titanic-eda-1

December 20, 2023

#Exploratory Data Analysis with Titanic dataset

Column Descriptions :

- PassengerId - unique ID, not relevant
- Survived - target, what we are trying to predict
- Pclass - ticket class, (1-3 for 1st/2nd/3rd class)
- Name - text field for passenger name, including title
- Sex - passenger gender (male or female)
- SibSp - # of siblings or spouses onboard
- Parch - # of parents or children onboard
- Ticket - ticket number
- Fare - cost of ticket
- Cabin - cabin number
- Embarked - port of embarkation (C = Cherbourg, Q = Queenstown, S = Southampton)

#Importing Necessary Libraries

[80]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix

from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
```

[81]:
```
from google.colab import files
dataset= files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving train.csv to train (1).csv
```

[82]:
```
df=pd.read_csv("train.csv")
df
```

[82]:

```
     PassengerId  Survived  Pclass  \
0              1         0       3
1              2         1       1
2              3         1       3
3              4         1       1
4              5         0       3
..           …         …     …
886          887         0       2
887          888         1       1
888          889         0       3
889          890         1       1
890          891         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
..                                                 …     …   …    …
886                              Montvila, Rev. Juozas    male  27.0      0
887                       Graham, Miss. Margaret Edith  female  19.0      0
888           Johnston, Miss. Catherine Helen "Carrie"  female   NaN      1
889                              Behr, Mr. Karl Howell    male  26.0      0
890                                Dooley, Mr. Patrick    male  32.0      0

     Parch            Ticket     Fare Cabin Embarked
0        0         A/5 21171   7.2500   NaN        S
1        0          PC 17599  71.2833   C85        C
2        0  STON/O2. 3101282   7.9250   NaN        S
3        0            113803  53.1000  C123        S
4        0            373450   8.0500   NaN        S
..     …               …      …   …      …
886      0            211536  13.0000   NaN        S
887      0            112053  30.0000   B42        S
888      2        W./C. 6607  23.4500   NaN        S
889      0            111369  30.0000  C148        C
890      0            370376   7.7500   NaN        Q

[891 rows x 12 columns]
```

[83]:

```
df.shape
```

[83]: (891, 12)

[84]:

```
df.head(5)
```

[84]:
```
   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
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

[85]:
```
df.tail()
```

[85]:
```
     PassengerId  Survived  Pclass                                      Name  \
886          887         0       2                     Montvila, Rev. Juozas
887          888         1       1              Graham, Miss. Margaret Edith
888          889         0       3  Johnston, Miss. Catherine Helen "Carrie"
889          890         1       1                     Behr, Mr. Karl Howell
890          891         0       3                       Dooley, Mr. Patrick

        Sex   Age  SibSp  Parch      Ticket   Fare Cabin Embarked
886    male  27.0      0      0      211536  13.00   NaN        S
887  female  19.0      0      0      112053  30.00   B42        S
888  female   NaN      1      2  W./C. 6607  23.45   NaN        S
889    male  26.0      0      0      111369  30.00  C148        C
890    male  32.0      0      0      370376   7.75   NaN        Q
```

[86]:
```
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          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
```

[87]:
```
df.isnull().sum()
```

[87]:
```
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
```

##**Handling Missing Values**

[88]:
```
miss_val = list(df.isna().sum())

#then we create a list of columns and their missing values as inner list to a
 ↪separate list
lst= []
i=0
for col in df.columns:
    l = [col,miss_val[i]]
    lst.append(l)
    i+=1

miss_val_df = pd.DataFrame(data=lst,columns=['Column_Name','Missing_Values'])
```

[89]:
```
miss_val_df[miss_val_df['Missing_Values']>0].sort_values(by='Missing_Values',
                                                   ascending=False).
 ↪reset_index(drop=True).style.background_gradient(cmap='Reds')
```

[89]:
```
<pandas.io.formats.style.Styler at 0x7cd436dd8b50>
```

[90]:
```
round((df.isnull().sum()/df.shape[0])*100,2)
```

[90]:
```
PassengerId     0.00
Survived        0.00
Pclass          0.00
Name            0.00
Sex             0.00
Age            19.87
SibSp           0.00
Parch           0.00
Ticket          0.00
Fare            0.00
Cabin          77.10
Embarked        0.22
dtype: float64
```

As we can see from the above result that Cabin has 77% null values and Age has 19.87% and Embarked has 0.22% of null values.

[91]:
```
df['Age'].mean()
```

[91]:
```
29.69911764705882
```

[92]:
```
df['Age'].median()
```

[92]:
```
28.0
```

[93]:
```
df['Age'].fillna(df['Age'].mean(), inplace=True)
df['Age'].isnull().sum()
```

[93]:
```
0
```

[94]:
```
df['Cabin'].isnull().sum()
```

[94]:
```
687
```

[95]:
```
df['Cabin'].value_counts()
```

[95]:
```
B96 B98        4
G6             4
C23 C25 C27    4
C22 C26        3
F33            3
              ..
E34            1
C7             1
C54            1
E36            1
```

```
C148           1
Name: Cabin, Length: 147, dtype: int64
```

[96]:
```python
df['Cabin'].mode()[0]
```

[96]:
```
'B96 B98'
```

[97]:
```python
df['Cabin'].fillna(df['Cabin'].mode()[0], inplace=True)
df['Cabin'].isnull().sum()
```

[97]:
```
0
```

[98]:
```python
df.describe()
```

[98]:
```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  891.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   13.002015    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   22.000000    0.000000
50%     446.000000    0.000000    3.000000   29.699118    0.000000
75%     668.500000    1.000000    3.000000   35.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

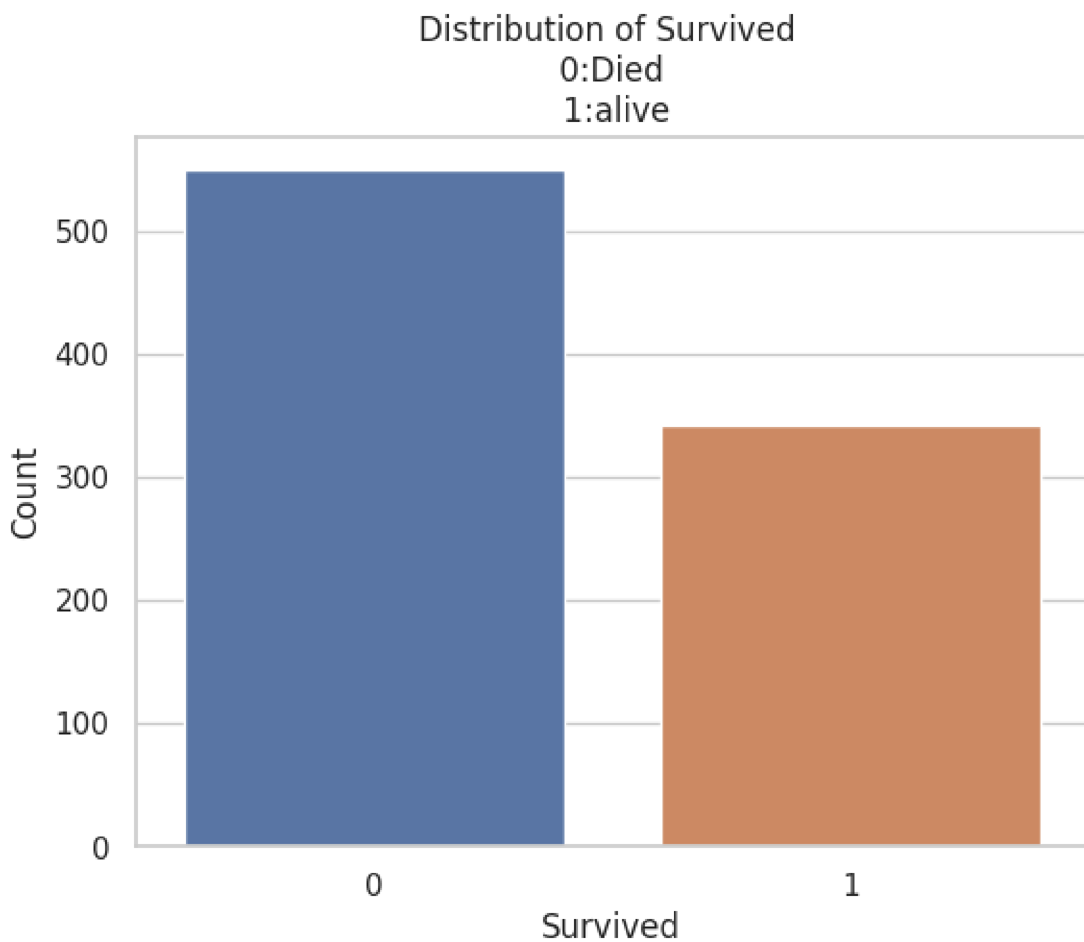
From above we can see * 38.3% people are survived * More number of people were actually in 3rd class * 50% of passengers were in between the age of 20 to 38

##**Survived Column**

[99]:
```python
died = (df["Survived"] == 0).sum()
print("Died ",died)
survived= (df["Survived"] == 1).sum()
print("Survived ",survived)
```

```
Died  549
Survived  342
```

[100]:
```
sns.countplot(x='Survived', data=df)
plt.title('Distribution of Survived \n 0:Died \n 1:alive')
plt.xlabel('Survived')
plt.ylabel('Count')

plt.show()
```

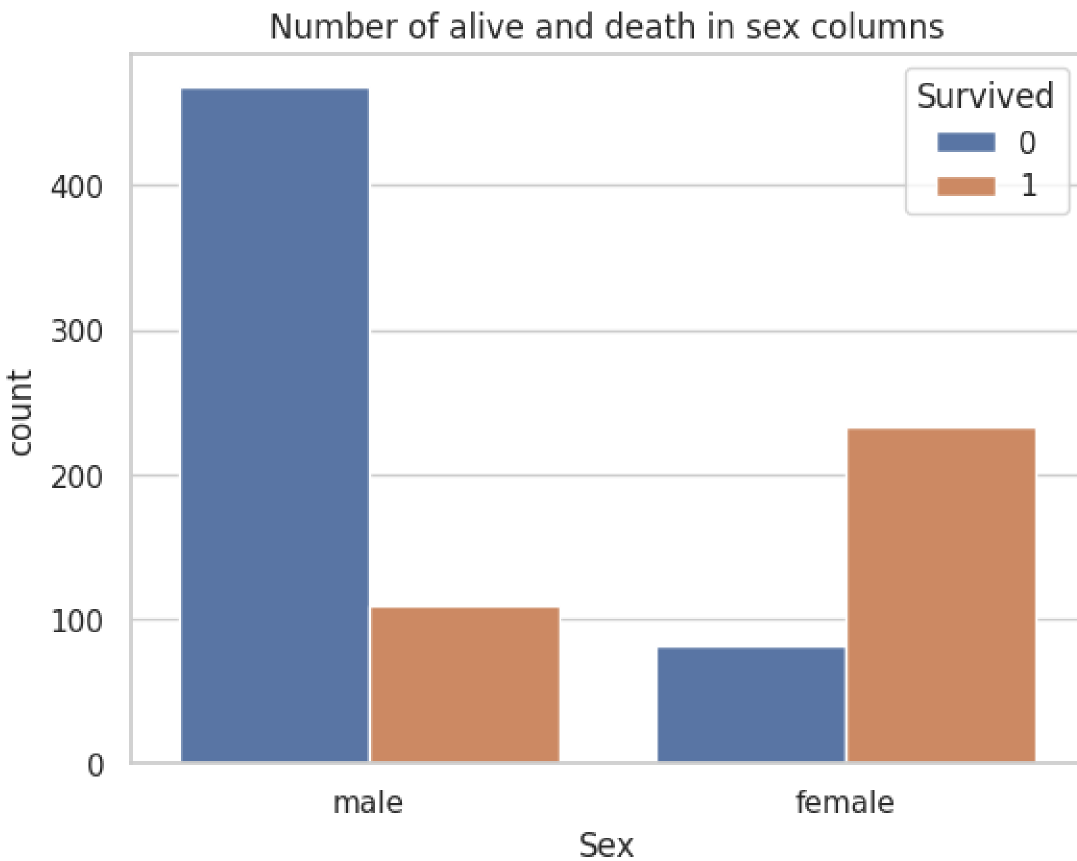


[146]:
```
df.groupby(['Survived','Sex'])['Survived'].count()
```

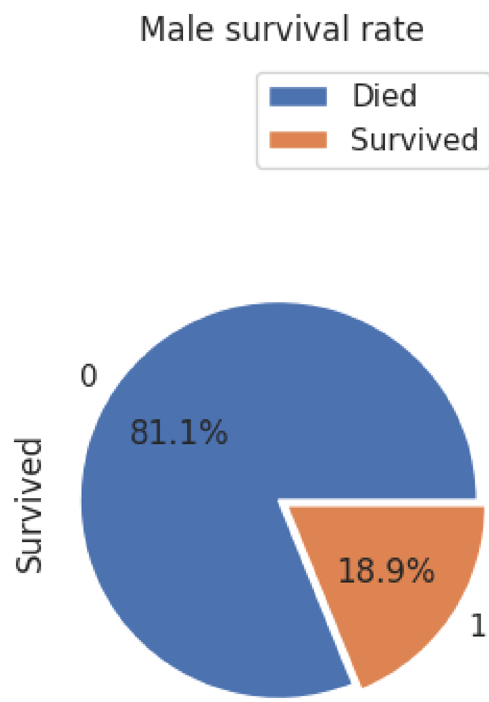
[146]:
```
Survived  Sex
0         0       81
          1      468
1         0      233
          1      109
Name: Survived, dtype: int64
```

[102]:
```
sns.countplot(data=df,x='Sex',hue='Survived',palette='deep').set(
    title='Number of alive and death in sex columns')
```

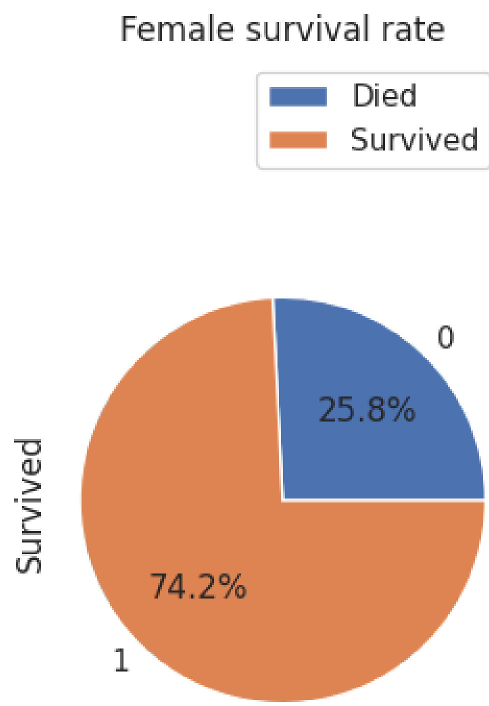
[102]: [Text(0.5, 1.0, 'Number of alive and death in sex columns')]



[103]:
```
df[df['Sex'] == 'male'].Survived.groupby(df.Survived).count().plot(kind='pie',␣
 ↪figsize=(3, 6),explode=[0,0.05],autopct='%1.1f%%')
plt.axis('equal')
plt.legend(["Died","Survived"])
plt.title("Male survival rate")
plt.show()
```



[104]:
```
df[df['Sex'] == 'female'].Survived.groupby(df.Survived).count().
    ↪plot(kind='pie',autopct='%1.1f%%',figsize=(3, 6))
plt.axis('equal')
plt.title("Female survival rate")
plt.legend(["Died","Survived"])
plt.show()
```



The above 2 plots says the females were given more priority than male in the survival process

##**Pclass vs Survived**

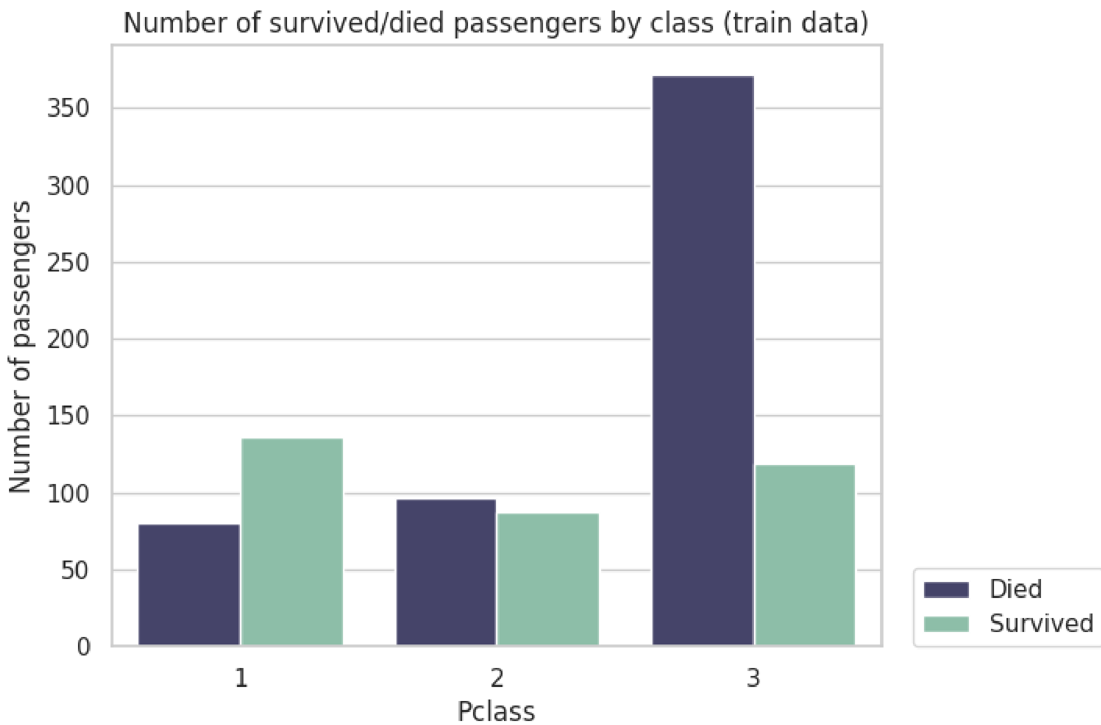
[105]:
```
pd.crosstab(df.Pclass, df.Survived, margins=True)
```

[105]:
```
Survived    0    1  All
Pclass
1          80  136  216
2          97   87  184
3         372  119  491
All       549  342  891
```

[147]:
```
fig = plt.figure(figsize=(14, 5))

ax1 = fig.add_subplot(121)
sns.countplot(x = 'Pclass', hue = 'Survived', data = df, palette=["#3f3e6fd1",␣
↪"#85c6a9"], ax = ax1)
```

```
plt.title('Number of survived/died passengers by class (train data)')
plt.ylabel('Number of passengers')
plt.legend(( 'Died', 'Survived'), loc=(1.04,0))
plt.xticks(rotation=False)
```

[147]: (array([0, 1, 2]), [Text(0, 0, '1'), Text(1, 0, '2'), Text(2, 0, '3')])

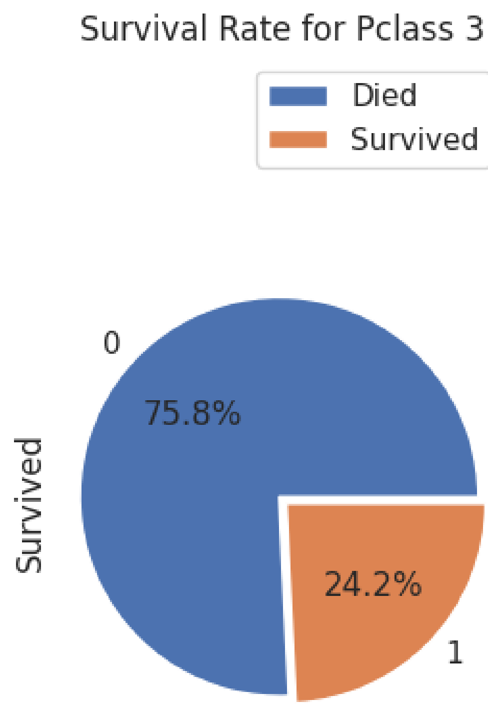


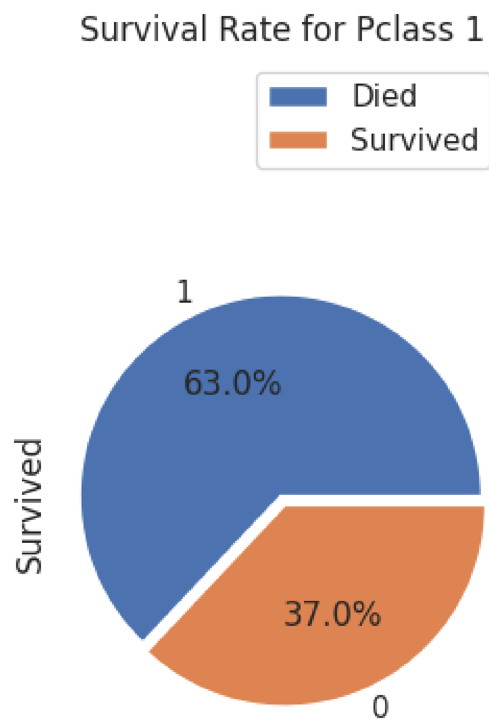
The first class has the largest number of survivors and the proportion of survivors within the class is the largest. Third-class had the highest number of drowned passengers, and most of the third-class passengers drowned.

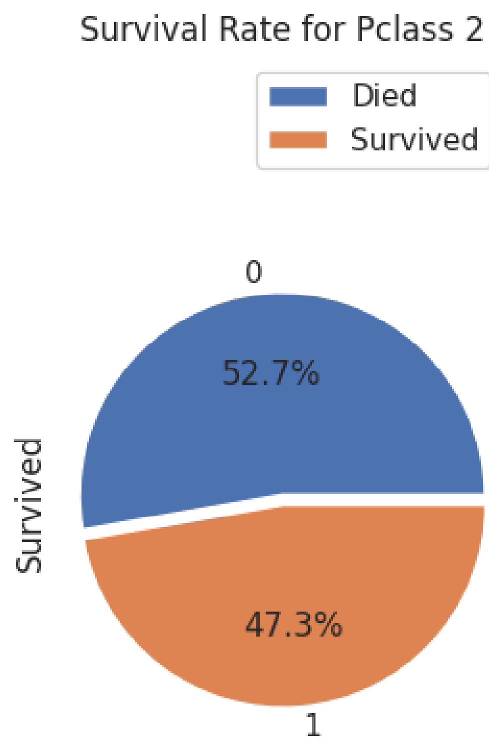
[107]:
```
values = df['Pclass'].unique()
print(values)
# Plotting pie charts for each Pclass
for pclass in values:
    pclass_data = df[df['Pclass'] == pclass].Survived.value_counts()

    plt.figure()
    pclass_data.plot(kind='pie', figsize=(3, 6), explode=[0, 0.05], autopct='%1.
↪1f%%')

    plt.axis('equal')
    plt.legend(["Died", "Survived"])
```

```
    plt.title(f"Survival Rate for Pclass {pclass}")
    plt.show()
```

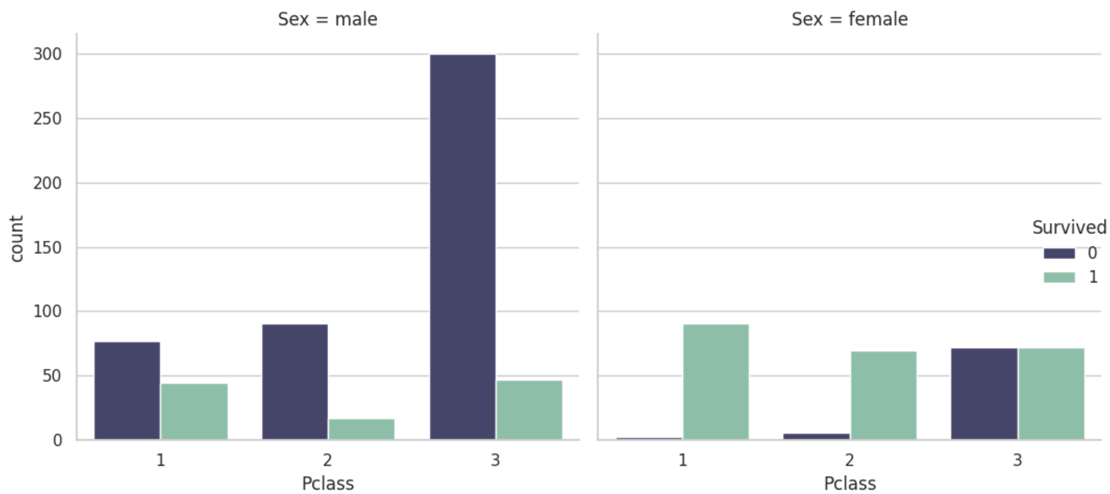
```
[3 1 2]
```




Survival Rate for Pclass 1
Died
Survived
1
63.0%
Survived
37.0%
0



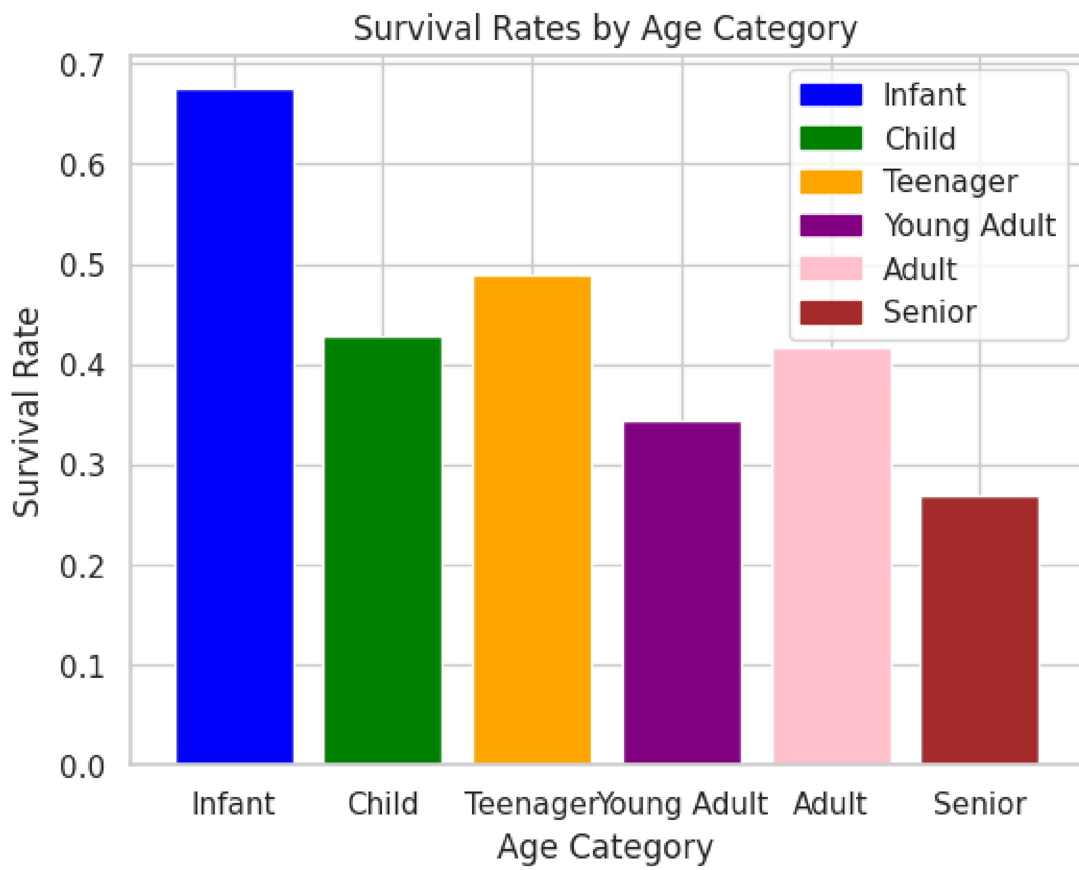
[108]:
```
sns.catplot(x = 'Pclass', hue = 'Survived', col = 'Sex', kind = 'count', data =␣
↪df,palette=["#3f3e6fd1", "#85c6a9"] )

plt.tight_layout()
```



Most of the male passengers of the first class drowned, and the female almost all survived. In the third class half of the female survived.

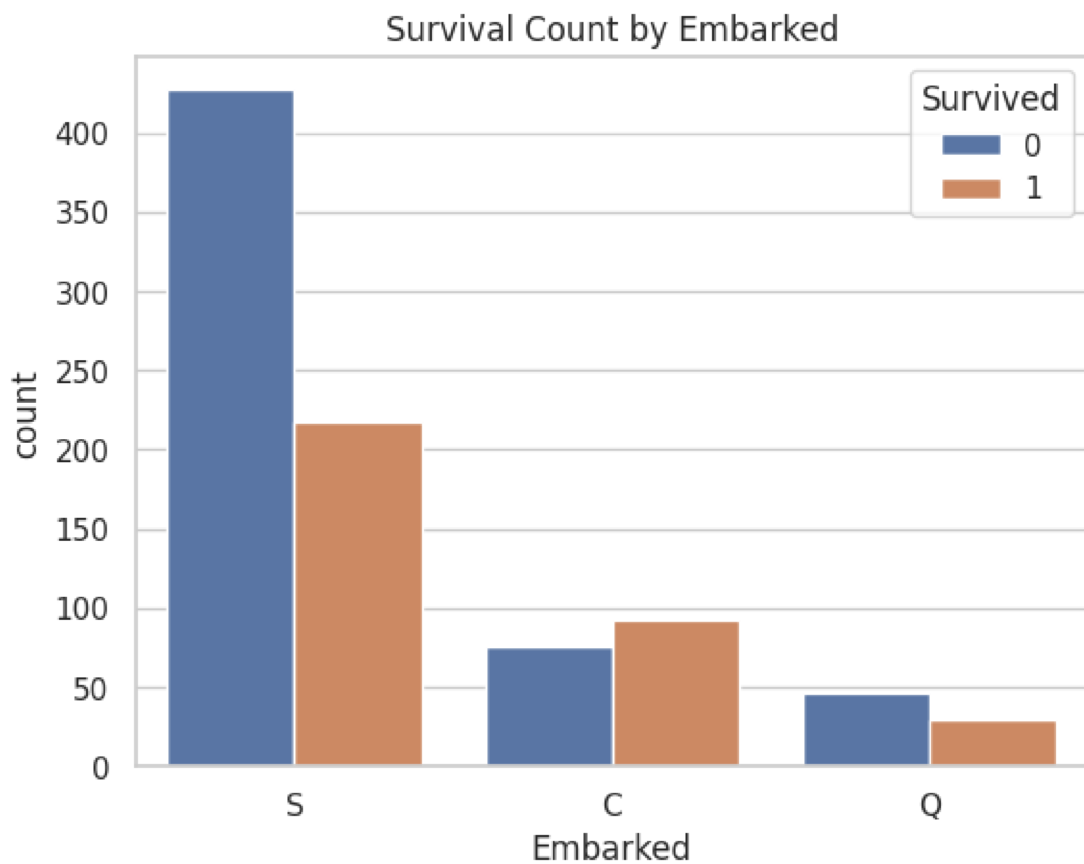
[112]:
```
# Define cut points and label names
cut_points = [ 0, 5, 12, 18, 35, 60, 100]
label_names = [ 'Infant', "Child", 'Teenager', "Young Adult", 'Adult', 'Senior']

# Create the "Age_categories" column
df['Age_categories'] = pd.cut(df['Age'], bins=cut_points, labels=label_names,␣
↪right=False)

# Creating a pivot table for survival rates based on age categories
age_cat_pivot = df.pivot_table(index="Age_categories", values="Survived")

# Define colors for each bar
colors = ['blue', 'green', 'orange', 'purple', 'pink', 'brown']

# Plotting the bar chart with different colors for each bar
fig, ax = plt.subplots()
bars = ax.bar(age_cat_pivot.index, age_cat_pivot['Survived'], color=colors)

# Adding a legend with the specified colors
handles = [plt.Rectangle((0, 0), 1, 1, color=colors[i]) for i in␣
↪range(len(colors))]
ax.legend(handles, label_names)

ax.set_title('Survival Rates by Age Category')
ax.set_xlabel('Age Category')
ax.set_ylabel('Survival Rate')
```

```
plt.show()
```



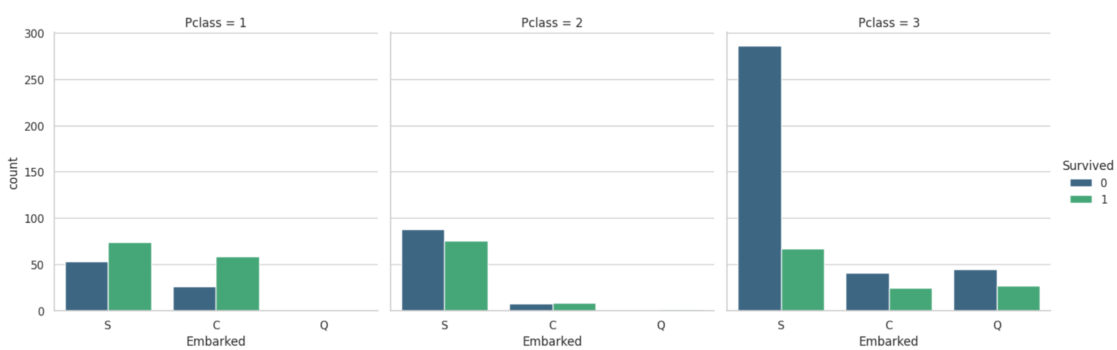
##**Analysis on Parch, Embarked and SibSp**

[148]:
```
sns.countplot(x='Embarked', hue='Survived', data=df)
plt.title('Survival Count by Embarked')
plt.show()
```




```
[113]: sns.catplot(x ='Embarked', hue ='Survived',
       kind ='count', col ='Pclass', data = df,palette='viridis')
```

[113]: <seaborn.axisgrid.FacetGrid at 0x7cd430e2cc70>



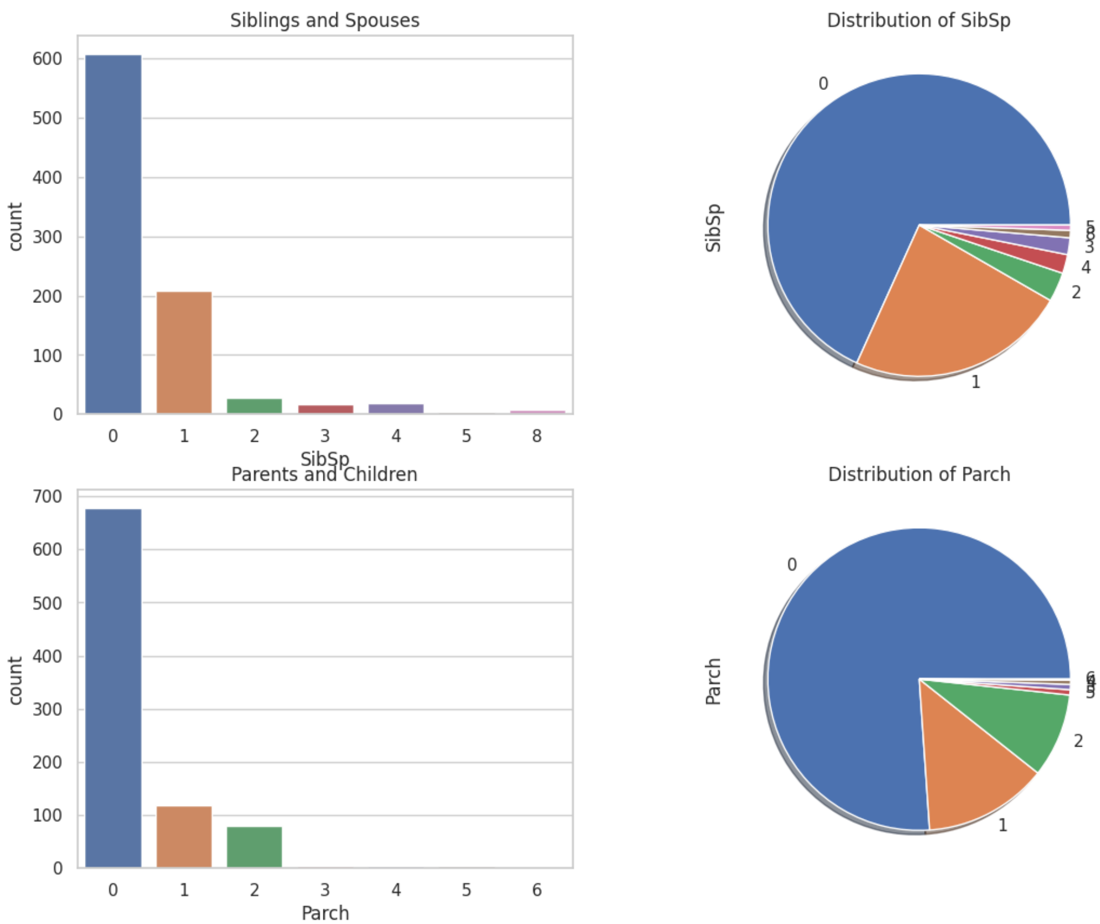
From above graph

- Majority of the passengers boarded from 'S'

- Majority of class 3 passengers boarded from Q.
- S looks lucky for class 1 and 2 passengers compared to class 3.

[114]:
```python
fig6, ax6 = plt.subplots(2, 2, figsize=(13, 10))

# SibSp
sns.countplot(data=df, x="SibSp", ax=ax6[0, 0]).set_title("Siblings and␣
↪Spouses")
df["SibSp"].value_counts().plot.pie(ax=ax6[0, 1], shadow=True,␣
↪title="Distribution of SibSp")

# Parch
sns.countplot(data=df, x="Parch", ax=ax6[1, 0]).set_title("Parents and␣
↪Children")
df["Parch"].value_counts().plot.pie(ax=ax6[1, 1], shadow=True,␣
↪title="Distribution of Parch")
```

[114]:
```
<Axes: title={'center': 'Distribution of Parch'}, ylabel='Parch'>
```



##Fare Column

[115]:
```
max_fare, min_fare = df["Fare"].max(), df["Fare"].min()

print(f"Number of passengers who paid ${min_fare}: ", df[df["Fare"] ==␣
↪min_fare].shape[0])
print(f"Number of passengers who paid ${max_fare}: ", df[df["Fare"] ==␣
↪max_fare].shape[0])
print(f"Fare given by maximum number of passengers: $", list(dict(df["Fare"].
↪value_counts()).keys())[0])
```

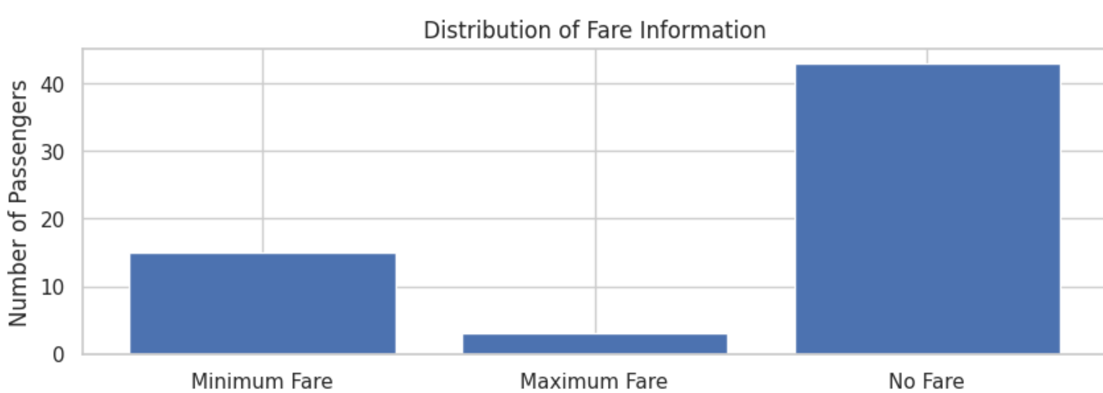
```
Number of passengers who paid $0.0:  15
Number of passengers who paid $512.3292:  3
Fare given by maximum number of passengers: $ 8.05
```

From above we can observe :

- only 3 people paid 512 dollars to be on Titanic
- 15 people paid no fare to be on Titanic

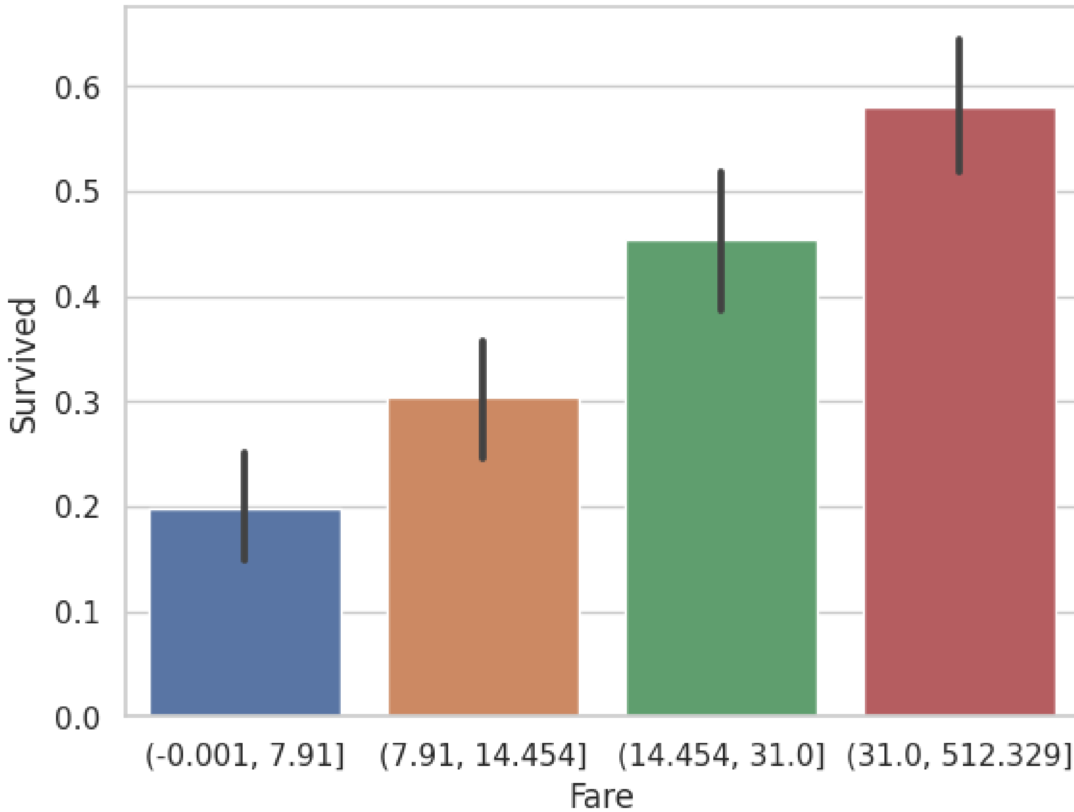
- Maximum people paid approximately 8 dollars

[116]:
```
# Count the number of passengers who paid the maximum and minimum fare
passengers_min_fare = df[df["Fare"] == min_fare].shape[0]
passengers_max_fare = df[df["Fare"] == max_fare].shape[0]

fig, ax = plt.subplots(figsize=(10, 3))

# Plotting the bars
ax.bar(["Minimum Fare", "Maximum Fare", "No Fare"], [passengers_min_fare,␣
↪passengers_max_fare, df["Fare"].value_counts().max()])

# Adding labels and title
ax.set_ylabel("Number of Passengers")
ax.set_title("Distribution of Fare Information")
plt.show()
```



[117]:
```
df['Fare'] = pd.qcut(df['Fare'], 4)
sns.barplot(x ='Fare', y ='Survived',
data = df)
```

[117]: <Axes: xlabel='Fare', ylabel='Survived'>



[118]:
```
df[df['Fare'] == min(df['Fare'] )]
```

[118]:
```
     PassengerId  Survived  Pclass                               Name  \
0              1         0       3            Braund, Mr. Owen Harris
14            15         0       3  Vestrom, Miss. Hulda Amanda Adolfina
19            20         1       3                Masselmani, Mrs. Fatima
26            27         0       3               Emir, Mr. Farred Chehab
28            29         1       3          O'Dwyer, Miss. Ellen "Nellie"
..           …         …      …                                    …
877          878         0       3                  Petroff, Mr. Nedelio
878          879         0       3                    Laleff, Mr. Kristo
881          882         0       3                    Markun, Mr. Johann
```

```
884          885          0       3                Sutehall, Mr. Henry Jr
890          891          0       3                   Dooley, Mr. Patrick

        Sex        Age  SibSp  Parch         Ticket            Fare  \
0      male  22.000000      1      0      A/5 21171  (-0.001, 7.91]
14   female  14.000000      0      0         350406  (-0.001, 7.91]
19   female  29.699118      0      0           2649  (-0.001, 7.91]
26     male  29.699118      0      0           2631  (-0.001, 7.91]
28   female  29.699118      0      0         330959  (-0.001, 7.91]
..      …          …    …     …           …              …
877    male  19.000000      0      0         349212  (-0.001, 7.91]
878    male  29.699118      0      0         349217  (-0.001, 7.91]
881    male  33.000000      0      0         349257  (-0.001, 7.91]
884    male  25.000000      0      0  SOTON/OQ 392076  (-0.001, 7.91]
890    male  32.000000      0      0         370376  (-0.001, 7.91]

       Cabin Embarked Age_categories
0    B96 B98        S    Young Adult
14   B96 B98        S       Teenager
19   B96 B98        C    Young Adult
26   B96 B98        C    Young Adult
28   B96 B98        Q    Young Adult
..       …       …            …
877  B96 B98        S    Young Adult
878  B96 B98        S    Young Adult
881  B96 B98        S    Young Adult
884  B96 B98        S    Young Adult
890  B96 B98        Q    Young Adult

[223 rows x 13 columns]
```

[119]:
```
df[df["Fare"] == min_fare]
```

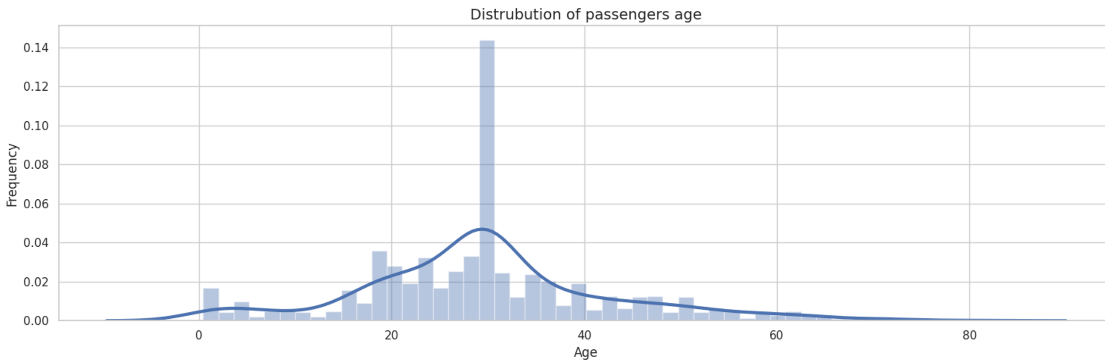
[119]:
```
Empty DataFrame
Columns: [PassengerId, Survived, Pclass, Name, Sex, Age, SibSp, Parch, Ticket,
Fare, Cabin, Embarked, Age_categories]
Index: []
```

Above dataframe represent that People who paid no fare to be on titanic

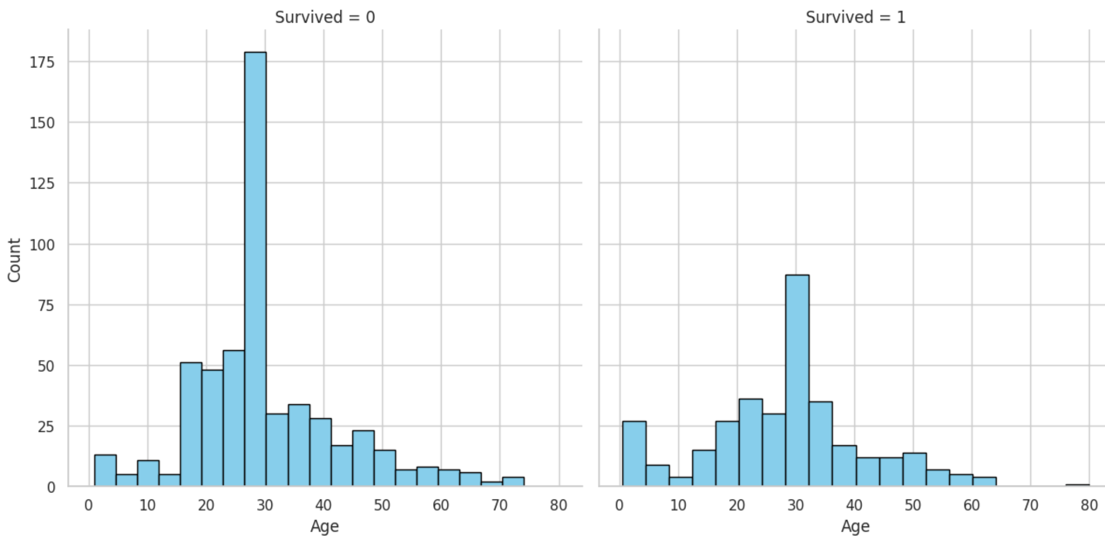
##**Age Column**

[120]:
```
plt.figure(figsize=(15, 5))
sns.distplot(df[(df["Age"] > 0)].Age, kde_kws={"lw": 3}, bins = 50)
plt.title('Distrubution of passengers age',fontsize= 14)
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.tight_layout()
```

```
<ipython-input-120-e467bcf6aaca>:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df[(df["Age"] > 0)].Age, kde_kws={"lw": 3}, bins = 50)
```



[109]:
```python
sns.set(style="whitegrid")

# Create a FacetGrid with Seaborn
g = sns.FacetGrid(df, col="Survived", height=6)
g.map(plt.hist, 'Age', bins=20, color='skyblue', edgecolor='black')

# Set labels and title
g.set_axis_labels('Age', 'Count')
g.set_titles(col_template='Survived = {col_name}')

plt.show()
```




```
[121]: age = pd.DataFrame(df['Age'].describe())
       age.transpose()
```

```
[121]:      count       mean        std   min   25%        50%   75%   max
       Age  891.0  29.699118  13.002015  0.42  22.0  29.699118  35.0  80.0
```

```
[122]: pd.DataFrame(df.groupby('Survived')['Age'].describe())
```

```
[122]:           count       mean        std   min   25%        50%   75%   max
       Survived
       0         549.0  30.415100  12.457370  1.00  23.0  29.699118  35.0  74.0
       1         342.0  28.549778  13.772498  0.42  21.0  29.699118  35.0  80.0
```

The mean age of survived passenger is **28.54** which on **1.87** smaller than the mean age of Died passengers

The minimum age of died passengers is 1 y.o The maximum age of survived passenger is 80 y.o

```
[123]: df[df['Age'] == min(df['Age'] )]
```

```
[123]:      PassengerId  Survived  Pclass                            Name   Sex  \
       803          804         1       3  Thomas, Master. Assad Alexander  male

             Age  SibSp  Parch Ticket            Fare    Cabin Embarked  \
       803  0.42      0      1   2625  (7.91, 14.454]  B96 B98        C

           Age_categories
       803         Infant
```

```
[124]: df[df['Age'] == max(df['Age'] )]
```

[124]:
```
     PassengerId  Survived  Pclass                                Name  \
630          631         1       1  Barkworth, Mr. Algernon Henry Wilson

      Sex   Age  SibSp  Parch Ticket            Fare Cabin Embarked  \
630  male  80.0      0      0  27042  (14.454, 31.0]   A23        S

    Age_categories
630         Senior
```

#Model Buliding

###Using Logistic Regression ###Survival Prediction Model Based on Age

[125]:
```
lr = LogisticRegression()
```

[126]:
```
X_Age = df[['Age']].values
y = df['Survived'].values
lr.fit(X_Age,y)
y_predict = lr.predict(X_Age)
print(y_predict[:10])
age_accuracy = (y == y_predict.round()).mean()
print("Age Accuracy:", age_accuracy)
```

```
[0 0 0 0 0 0 0 0 0 0]
Age Accuracy: 0.6161616161616161
```

###Survival Prediction Model Based on Pclass

[127]:
```
X_sex = pd.get_dummies(df['Pclass']).values
y = df['Survived'].values
lr.fit(X_sex, y)
y_predict = lr.predict(X_sex)
print(y_predict[:10])
pclass_accuracy = (y == y_predict.round()).mean()
print("Pclas Accuracy:", pclass_accuracy )
```

```
[0 1 0 1 0 0 1 0 0 0]
Pclas Accuracy: 0.6790123456790124
```

###Survival Prediction Model Based on Sex

[128]:
```
X_sex = pd.get_dummies(df['Sex']).values
y = df['Survived'].values
lr.fit(X_sex, y)
y_predict = lr.predict(X_sex)
print(y_predict[:10])
sex_accuracy = (y == y_predict.round()).mean()
print("Sex Accuracy:", sex_accuracy)
```

```
[0 1 1 1 0 0 0 0 1 1]
Sex Accuracy: 0.7867564534231201
```

[129]:
```python
pd.DataFrame([age_accuracy,pclass_accuracy,sex_accuracy],␣
↪index=["age_accuracy","pclass_accuracy","sex_accuracy"],␣
↪columns=['Accuracy'])
```

[129]:

	Accuracy
age_accuracy	0.616162
pclass_accuracy	0.679012
sex_accuracy	0.786756

The gender of passenger is a strong predictor and purely predciting based on gender, the model accuracy increased to **78%**

[130]:
```python
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
```

[131]:
```python
df["Sex"]=le.fit_transform(df['Sex'])
df["Cabin"]=le.fit_transform(df['Cabin'])
```

##**Machine Learning Algorithms**

###**Logistic Regression**

[132]:
```python
lr = LogisticRegression()
```

[133]:
```python
columns = ['Pclass', 'Sex','Age','Cabin','SibSp', 'Parch']
X = df[columns]
Y = df["Survived"]
lr.fit(X,Y)
```

[133]:
```
LogisticRegression()
```

[134]:
```python
columns = ['Pclass', 'Sex','Age','Cabin','SibSp', 'Parch']

all_X = df[columns]
all_y = df['Survived']

train_X, test_X, train_y, test_y = train_test_split(
    all_X, all_y, test_size=0.2,random_state=0)
```

[135]:
```python
lr = LogisticRegression()
lr.fit(train_X, train_y)
predictions = lr.predict(test_X)
```

[136]:
```python
accuracy = accuracy_score(test_y, predictions)
```

[137]:
```
predictions = lr.predict(test_X)
lr_accuracy = accuracy_score(test_y, predictions)
print("Lr_accuracy : ", lr_accuracy)
```

```
Lr_accuracy :  0.8212290502793296
```

[138]:
```
conf_matrix = confusion_matrix(test_y, predictions)
pd.DataFrame(conf_matrix, columns=['Survived', 'Died'], index=[['Survived',␣
↪'Died']])
```

[138]:

	Survived	Died
Survived	95	15
Died	17	52

[139]:
```
X=df[['Pclass', 'Sex','Age','Cabin','SibSp', 'Parch']].values # Taking all the␣
↪numerical values
y = df['Survived'].values
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X, y)
```

[139]: KNeighborsClassifier(n_neighbors=3)

[140]:
```
predictions = knn.predict(test_X)
knn_accuracy = accuracy_score(test_y, predictions)
print("Knn_accuracy : ", knn_accuracy)
```

```
Knn_accuracy :  0.8324022346368715

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432: UserWarning: X has
feature names, but KNeighborsClassifier was fitted without feature names
  warnings.warn(
```

[141]:
```
X=df[['Pclass', 'Sex','Age','Cabin','SibSp', 'Parch']].values # Taking all the␣
↪numerical values
y = df['Survived'].values
rfc = RandomForestClassifier()
rfc.fit(X, y)
```

[141]: RandomForestClassifier()

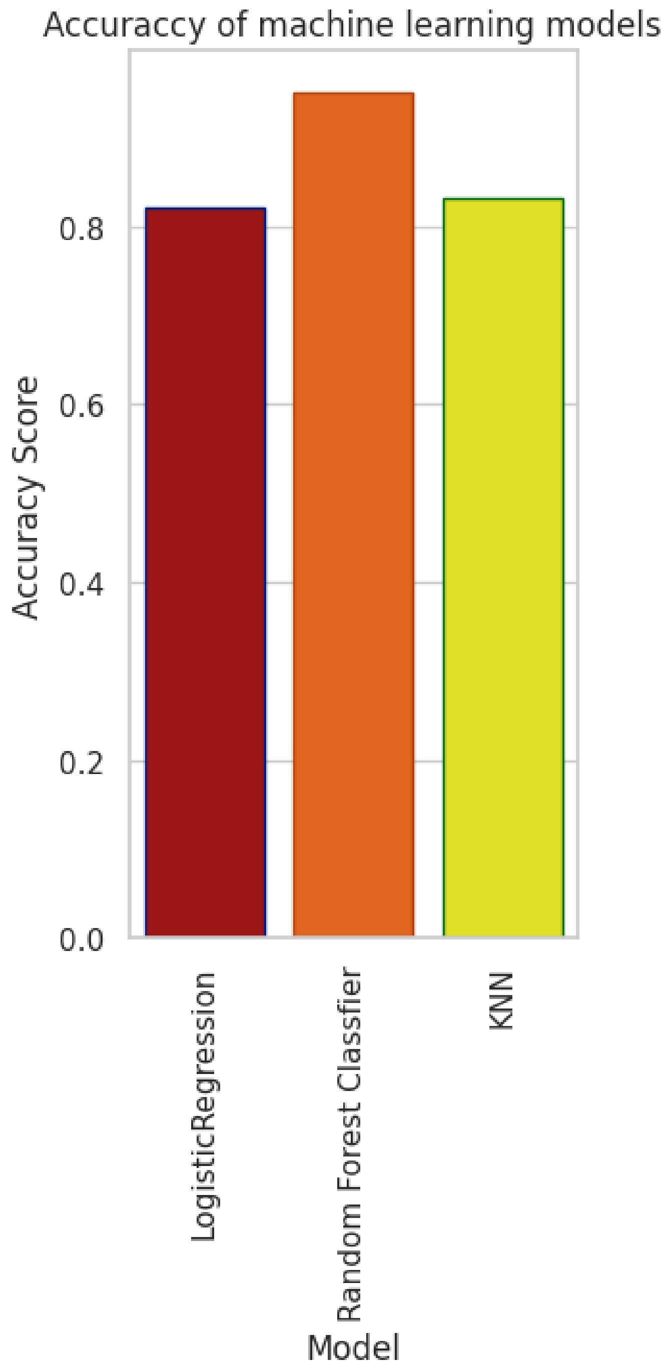
[142]:
```
predictions = rfc.predict(test_X)
rfc_accuracy = accuracy_score(test_y, predictions)
print("Rfc_accuracy : ", rfc_accuracy)
```

```
Rfc_accuracy :  0.9497206703910615

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432: UserWarning: X has
feature names, but RandomForestClassifier was fitted without feature names
  warnings.warn(
```

[143]:
```
results=pd.DataFrame({'Model':['LogisticRegression','Random Forest␣
↪Classfier','KNN'],
                    'Accuracy Score':[lr_accuracy,rfc_accuracy,knn_accuracy]})
result_df=results.sort_values(by='Accuracy Score', ascending=False)
result_df=result_df.set_index('Model')
result_df
```

[143]:
```
                         Accuracy Score
Model
Random Forest Classfier        0.949721
KNN                            0.832402
LogisticRegression             0.821229
```

[144]:
```
plt.subplots(figsize=(3,6))
sns.barplot(x="Model", y="Accuracy␣
↪Score",data=results,palette='hot',edgecolor=sns.color_palette('dark',7))
plt.xticks(rotation=90)
plt.title('Accuraccy of machine learning models')
plt.show()
```



Accuraccy of machine learning models
Accuracy Score
0.0
0.2
0.4
0.6
0.8
LogisticRegression
Random Forest Classfier
KNN
Model