titanic-prediction-model

June 27, 2024

Titanic Survival Prediction Model

By Elma Fortunate Phiri

About Dataset:

The sinking of the Titanic is one of the most infamous shipwrecks in history.

On April 15, 1912, during her maiden voyage, the widely considered "unsinkable" RMS Titanic sank after colliding with an iceberg. Unfortunately, there weren't enough lifeboats for everyone onboard, resulting in the death of 1502 out of 2224 passengers and crew.

While there was some element of luck involved in surviving, it seems some groups of people were more likely to survive than others.

Abstract: To perform data cleaning and exploratory data analysis (EDA) on the dataset. Explore the relationships between variables and identify patterns and trends in the data

Aim: To build a predictive model that answers the question: "what sorts of people were more likely to survive?" using passenger data (ie name, age, gender, socio-economic class, etc).

Data collection and Preprocessing

Importing Python Libraries

[269]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import ydata_profiling as pp
%matplotlib inline
```

[344]:
```
from sklearn. preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split, RandomizedSearchCV,␣
 ↪GridSearchCV
from sklearn.metrics import accuracy_score, confusion_matrix,␣
 ↪classification_report, precision_score, RocCurveDisplay
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from scipy.stats import randint
```

```
[271]: titanic = pd.read_csv("C:\\Users\\elmaf\\Desktop\\ProgidyInfoTech\\Titanic␣
       ↪dataset\\titanic3.csv")
titanic
```

```
[271]:       pclass  survived                                             name  \
0        1.0       1.0                    Allen, Miss. Elisabeth Walton
1        1.0       1.0                   Allison, Master. Hudson Trevor
2        1.0       0.0                     Allison, Miss. Helen Loraine
3        1.0       0.0             Allison, Mr. Hudson Joshua Creighton
4        1.0       0.0  Allison, Mrs. Hudson J C (Bessie Waldo Daniels)
…        …        …                                                 …
1305     3.0       0.0                            Zabour, Miss. Thamine
1306     3.0       0.0                        Zakarian, Mr. Mapriededer
1307     3.0       0.0                              Zakarian, Mr. Ortin
1308     3.0       0.0                               Zimmerman, Mr. Leo
1309     NaN       NaN                                              NaN

         sex      age  sibsp  parch  ticket      fare    cabin embarked boat  \
0     female  29.0000    0.0    0.0   24160  211.3375       B5        S    2
1       male   0.9167    1.0    2.0  113781  151.5500  C22 C26        S   11
2     female   2.0000    1.0    2.0  113781  151.5500  C22 C26        S  NaN
3       male  30.0000    1.0    2.0  113781  151.5500  C22 C26        S  NaN
4     female  25.0000    1.0    2.0  113781  151.5500  C22 C26        S  NaN
…        …       …      …     …       …        …      …  …
1305  female      NaN    1.0    0.0    2665   14.4542      NaN        C  NaN
1306    male  26.5000    0.0    0.0    2656    7.2250      NaN        C  NaN
1307    male  27.0000    0.0    0.0    2670    7.2250      NaN        C  NaN
1308    male  29.0000    0.0    0.0  315082    7.8750      NaN        S  NaN
1309     NaN      NaN    NaN    NaN     NaN       NaN      NaN      NaN  NaN

       body                        home.dest
0       NaN                     St Louis, MO
1       NaN  Montreal, PQ / Chesterville, ON
2       NaN  Montreal, PQ / Chesterville, ON
3     135.0  Montreal, PQ / Chesterville, ON
4       NaN  Montreal, PQ / Chesterville, ON
…      …                            …
1305    NaN                              NaN
1306  304.0                              NaN
1307    NaN                              NaN
1308    NaN                              NaN
1309    NaN                              NaN

[1310 rows x 14 columns]
```

Data Exploration

[272]:
```
titanic.head()
```

[272]:
```
   pclass  survived                                             name     sex  \
0     1.0       1.0                     Allen, Miss. Elisabeth Walton  female
1     1.0       1.0                    Allison, Master. Hudson Trevor    male
2     1.0       0.0                      Allison, Miss. Helen Loraine  female
3     1.0       0.0              Allison, Mr. Hudson Joshua Creighton    male
4     1.0       0.0  Allison, Mrs. Hudson J C (Bessie Waldo Daniels)  female

       age  sibsp  parch  ticket      fare    cabin embarked boat   body  \
0  29.0000    0.0    0.0   24160  211.3375       B5        S    2    NaN
1   0.9167    1.0    2.0  113781  151.5500  C22 C26        S   11    NaN
2   2.0000    1.0    2.0  113781  151.5500  C22 C26        S  NaN    NaN
3  30.0000    1.0    2.0  113781  151.5500  C22 C26        S  NaN  135.0
4  25.0000    1.0    2.0  113781  151.5500  C22 C26        S  NaN    NaN

                         home.dest
0                     St Louis, MO
1  Montreal, PQ / Chesterville, ON
2  Montreal, PQ / Chesterville, ON
3  Montreal, PQ / Chesterville, ON
4  Montreal, PQ / Chesterville, ON
```

[273]:
```
titanic.shape
```

[273]:
```
(1310, 14)
```

[274]:
```
titanic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1310 entries, 0 to 1309
Data columns (total 14 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   pclass     1309 non-null   float64
 1   survived   1309 non-null   float64
 2   name       1309 non-null   object
 3   sex        1309 non-null   object
 4   age        1046 non-null   float64
 5   sibsp      1309 non-null   float64
 6   parch      1309 non-null   float64
 7   ticket     1309 non-null   object
 8   fare       1308 non-null   float64
 9   cabin      295 non-null    object
 10  embarked   1307 non-null   object
 11  boat       486 non-null    object
 12  body       121 non-null    float64
```

```
 13  home.dest  745 non-null    object
dtypes: float64(7), object(7)
memory usage: 143.4+ KB
```

[275]:
```
titanic.describe()
```

[275]:
```
            pclass     survived          age        sibsp        parch  \
count  1309.000000  1309.000000  1046.000000  1309.000000  1309.000000
mean      2.294882     0.381971    29.881135     0.498854     0.385027
std       0.837836     0.486055    14.413500     1.041658     0.865560
min       1.000000     0.000000     0.166700     0.000000     0.000000
25%       2.000000     0.000000    21.000000     0.000000     0.000000
50%       3.000000     0.000000    28.000000     0.000000     0.000000
75%       3.000000     1.000000    39.000000     1.000000     0.000000
max       3.000000     1.000000    80.000000     8.000000     9.000000

              fare         body
count  1308.000000  121.000000
mean     33.295479  160.809917
std      51.758668   97.696922
min       0.000000    1.000000
25%       7.895800   72.000000
50%      14.454200  155.000000
75%      31.275000  256.000000
max     512.329200  328.000000
```

[276]:
```
titanic.columns
```

[276]:
```
Index(['pclass', 'survived', 'name', 'sex', 'age', 'sibsp', 'parch', 'ticket',
       'fare', 'cabin', 'embarked', 'boat', 'body', 'home.dest'],
      dtype='object')
```

[277]:
```
titanic.index
```

[277]:
```
RangeIndex(start=0, stop=1310, step=1)
```

[278]:
```
pp.ProfileReport(titanic)
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]

Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]

Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]

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

[278]:

The Profile report highlighted the following: 1. We have 14 variables in our dataset 2. We have 1310 observations 3. Age has 20.2% missing values 5. Cabin has 687 (77.5%) missing values 6.

Boat has 62.9% missing values 7. Body has 90.8% missing values 9. home.dest has 565 (43.1%) missing values

[279]:
```
titanic.dtypes
```

[279]:
```
pclass       float64
survived     float64
name          object
sex           object
age          float64
sibsp        float64
parch        float64
ticket        object
fare         float64
cabin         object
embarked      object
boat          object
body         float64
home.dest     object
dtype: object
```

Age has wrong data dtype. It should be int but its float

[280]:
```
titanic["sex"].value_counts()
```

[280]:
```
male      843
female    466
Name: sex, dtype: int64
```

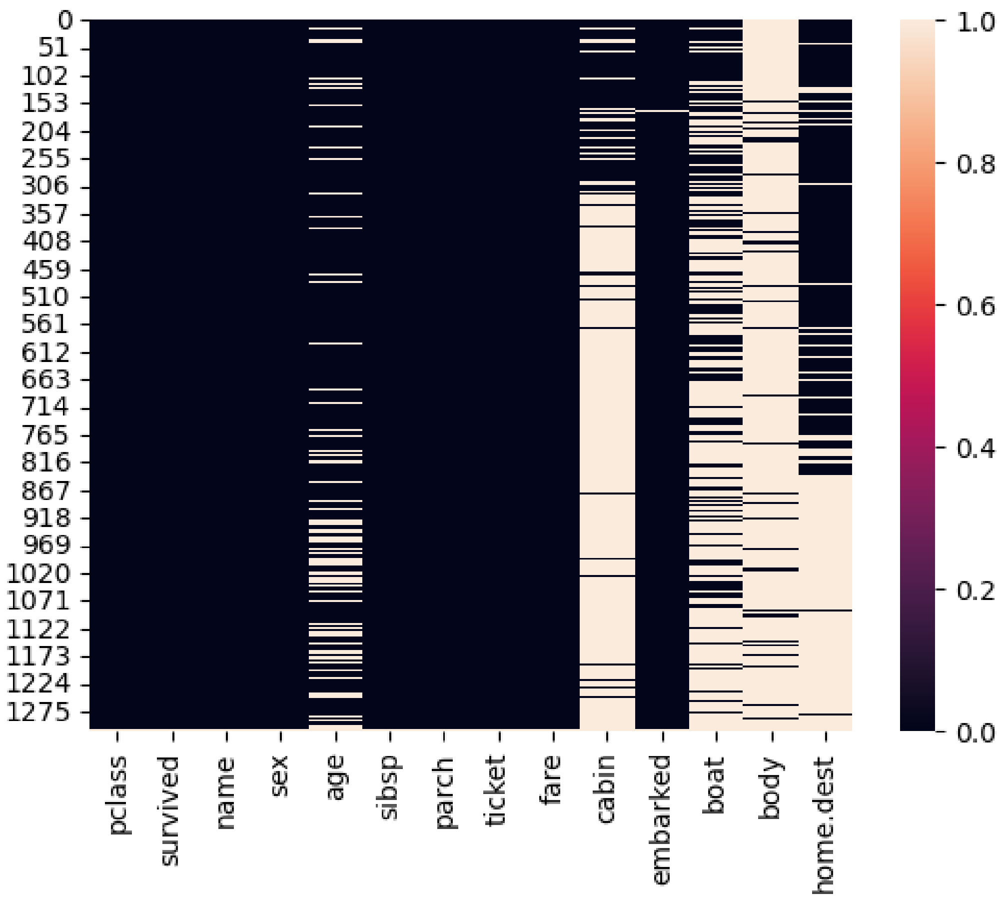
Data Preprocessing

[281]:
```
#Checking for null values
titanic.isnull().sum().sort_values(ascending=False)
```

[281]:
```
body         1189
cabin        1015
boat          824
home.dest     565
age           264
embarked        3
fare            2
pclass          1
survived        1
name            1
sex             1
sibsp           1
parch           1
ticket          1
```

```
dtype: int64
```

[282]:
```python
#Visualizing missing values
sns.heatmap(titanic.isnull())
plt.show()
```



[283]:
```python
#droping columns with more than 40% missing values
titanic = titanic.drop(["cabin", 'body','boat','home.dest'], axis=1)
titanic.head()
```

[283]:
```
   pclass  survived                                             name     sex  \
0     1.0       1.0                     Allen, Miss. Elisabeth Walton  female
1     1.0       1.0                    Allison, Master. Hudson Trevor    male
2     1.0       0.0                      Allison, Miss. Helen Loraine  female
3     1.0       0.0              Allison, Mr. Hudson Joshua Creighton    male
4     1.0       0.0   Allison, Mrs. Hudson J C (Bessie Waldo Daniels)  female

       age  sibsp  parch  ticket      fare embarked
```

```
0  29.0000    0.0    0.0   24160  211.3375        S
1   0.9167    1.0    2.0  113781  151.5500        S
2   2.0000    1.0    2.0  113781  151.5500        S
3  30.0000    1.0    2.0  113781  151.5500        S
4  25.0000    1.0    2.0  113781  151.5500        S
```

[284]:
```
#Renaming columns
titanic.rename(columns={
    " pclass": "Pclass",
    "survived": "Survived",
    "name": "Name",
    "sex": "Sex",
    "age": "Age",
    "sibsp": "No of Sibilings/ Spouse aboard",
    "parch": "No of Parents/Children",
    "ticket": "Ticket Number",
    "fare": "Fare",
    "embarked": "Embarked"
}, inplace=True)
titanic.head()
```

[284]:
```
   pclass  Survived                                             Name     Sex  \
0     1.0       1.0                    Allen, Miss. Elisabeth Walton  female
1     1.0       1.0                   Allison, Master. Hudson Trevor    male
2     1.0       0.0                     Allison, Miss. Helen Loraine  female
3     1.0       0.0             Allison, Mr. Hudson Joshua Creighton    male
4     1.0       0.0  Allison, Mrs. Hudson J C (Bessie Waldo Daniels)  female

       Age  No of Sibilings/ Spouse aboard  No of Parents/Children  \
0  29.0000                             0.0                     0.0
1   0.9167                             1.0                     2.0
2   2.0000                             1.0                     2.0
3  30.0000                             1.0                     2.0
4  25.0000                             1.0                     2.0

  Ticket Number      Fare Embarked
0         24160  211.3375        S
1        113781  151.5500        S
2        113781  151.5500        S
3        113781  151.5500        S
4        113781  151.5500        S
```

[285]:
```
titanic["Embarked"].value_counts()
```

[285]:
```
S    914
C    270
Q    123
```

```
Name: Embarked, dtype: int64
```

[286]:
```python
#Replace values in embarked column
titanic["Embarked"] = titanic["Embarked"].replace({"C": "Cherbourg", "Q":␣
↪"Queenstown", "S": "Southampton"})
titanic.sample(10)
```

[286]:
```
      pclass  Survived                                     Name     Sex  \
1147     3.0       0.0  Riihivouri, Miss. Susanna Juhantytar "Sanni"  female
719      3.0       1.0                    Cohen, Mr. Gurshon "Gus"    male
469      2.0       1.0                         Keane, Miss. Nora A  female
195      1.0       1.0                       Maioni, Miss. Roberta  female
384      2.0       0.0                 Cunningham, Mr. Alfred Fleming    male
1157     3.0       0.0                    Rosblom, Mr. Viktor Richard    male
847      3.0       0.0                          Hanna, Mr. Mansour    male
771      3.0       1.0                 Devaney, Miss. Margaret Delia  female
289      1.0       1.0                         Taussig, Miss. Ruth  female
414      2.0       0.0                          Gale, Mr. Shadrach    male

       Age  No of Sibilings/ Spouse aboard  No of Parents/Children  \
1147  22.0                             0.0                     0.0
719   18.0                             0.0                     0.0
469    NaN                             0.0                     0.0
195   16.0                             0.0                     0.0
384    NaN                             0.0                     0.0
1157  18.0                             1.0                     1.0
847   23.5                             0.0                     0.0
771   19.0                             0.0                     0.0
289   18.0                             0.0                     2.0
414   34.0                             1.0                     0.0

     Ticket Number     Fare     Embarked
1147       3101295  39.6875  Southampton
719       A/5 3540   8.0500  Southampton
469         226593  12.3500   Queenstown
195         110152  86.5000  Southampton
384         239853   0.0000  Southampton
1157        370129  20.2125  Southampton
847           2693   7.2292    Cherbourg
771         330958   7.8792   Queenstown
289         110413  79.6500  Southampton
414          28664  21.0000  Southampton
```

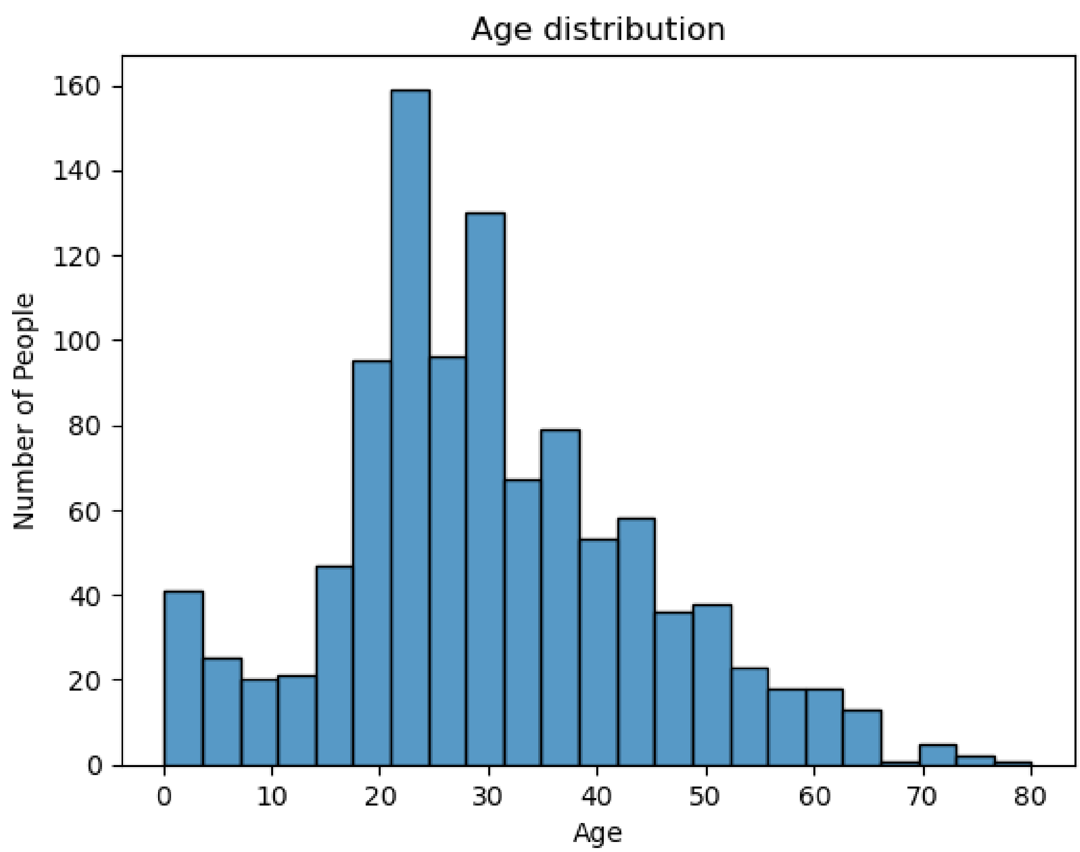
[287]:
```python
#Checking for null values
titanic.isnull().sum().sort_values(ascending=False)
```

[287]:

```
Age                              264
Embarked                           3
Fare                               2
pclass                             1
Survived                           1
Name                               1
Sex                                1
No of Sibilings/ Spouse aboard     1
No of Parents/Children             1
Ticket Number                      1
dtype: int64
```

[288]:

```
#Histogram for Age column
sns.histplot(x = "Age", data = titanic)
plt.title("Age distribution")
plt.ylabel("Number of People")
plt.show()
```



[289]:

```
#Handling Missing data in Age column  by filling na values
Age_mean = titanic["Age"].mean()
```

```
Age_mean
titanic['Age']=titanic['Age'].fillna(Age_mean)
```

[290]:
```
#Handling Missing values in Embarked column by filling na values
titanic["Embarked"] = titanic["Embarked"].fillna(titanic["Embarked"].
 ↪value_counts().idxmax())
```

[291]:
```
#Handling Missing values by filling na values
titanic["Fare"] = titanic["Fare"].fillna(titanic["Fare"].mean())
```

[292]:
```
#Checking for null values
titanic.isnull().sum().sort_values(ascending=False)
```

[292]:
```
pclass                          1
Survived                        1
Name                            1
Sex                             1
No of Sibilings/ Spouse aboard  1
No of Parents/Children          1
Ticket Number                   1
Age                             0
Fare                            0
Embarked                        0
dtype: int64
```

[293]:
```
#drop na values
titanic.dropna(inplace= True)
```

[294]:
```
#Checking for null values
titanic.isnull().sum().sort_values(ascending=False)
```

[294]:
```
pclass                          0
Survived                        0
Name                            0
Sex                             0
Age                             0
No of Sibilings/ Spouse aboard  0
No of Parents/Children          0
Ticket Number                   0
Fare                            0
Embarked                        0
dtype: int64
```

[295]:
```
titanic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1309 entries, 0 to 1308
```

```
Data columns (total 10 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   pclass                          1309 non-null   float64
 1   Survived                        1309 non-null   float64
 2   Name                            1309 non-null   object
 3   Sex                             1309 non-null   object
 4   Age                             1309 non-null   float64
 5   No of Sibilings/ Spouse aboard  1309 non-null   float64
 6   No of Parents/Children          1309 non-null   float64
 7   Ticket Number                   1309 non-null   object
 8   Fare                            1309 non-null   float64
 9   Embarked                        1309 non-null   object
dtypes: float64(6), object(4)
memory usage: 112.5+ KB
```

[296]:

```
#changing datatypes
titanic=titanic.astype({
    "Age":"int64",
    "pclass": "int64",
    "Survived": "int64"
   }
)
titanic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1309 entries, 0 to 1308
Data columns (total 10 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   pclass                          1309 non-null   int64
 1   Survived                        1309 non-null   int64
 2   Name                            1309 non-null   object
 3   Sex                             1309 non-null   object
 4   Age                             1309 non-null   int64
 5   No of Sibilings/ Spouse aboard  1309 non-null   float64
 6   No of Parents/Children          1309 non-null   float64
 7   Ticket Number                   1309 non-null   object
 8   Fare                            1309 non-null   float64
 9   Embarked                        1309 non-null   object
dtypes: float64(3), int64(3), object(4)
memory usage: 112.5+ KB
```

[297]:

```
titanic["No of Parents/Children"] = titanic["No of Parents/Children"].
 ↪astype("int64")
titanic['No of Sibilings/ Spouse aboard'] = titanic['No of Sibilings/ Spouse␣
 ↪aboard'].astype("int64")
```

```
titanic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1309 entries, 0 to 1308
Data columns (total 10 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   pclass                          1309 non-null   int64
 1   Survived                        1309 non-null   int64
 2   Name                            1309 non-null   object
 3   Sex                             1309 non-null   object
 4   Age                             1309 non-null   int64
 5   No of Sibilings/ Spouse aboard  1309 non-null   int64
 6   No of Parents/Children          1309 non-null   int64
 7   Ticket Number                   1309 non-null   object
 8   Fare                            1309 non-null   float64
 9   Embarked                        1309 non-null   object
dtypes: float64(1), int64(5), object(4)
memory usage: 112.5+ KB
```

[298]:
```
titanic.head()
```

[298]:
```
   pclass  Survived                                             Name     Sex  \
0       1         1                    Allen, Miss. Elisabeth Walton  female
1       1         1                   Allison, Master. Hudson Trevor    male
2       1         0                     Allison, Miss. Helen Loraine  female
3       1         0             Allison, Mr. Hudson Joshua Creighton    male
4       1         0  Allison, Mrs. Hudson J C (Bessie Waldo Daniels)  female

   Age  No of Sibilings/ Spouse aboard  No of Parents/Children Ticket Number  \
0   29                               0                       0         24160
1    0                               1                       2        113781
2    2                               1                       2        113781
3   30                               1                       2        113781
4   25                               1                       2        113781

       Fare     Embarked
0  211.3375  Southampton
1  151.5500  Southampton
2  151.5500  Southampton
3  151.5500  Southampton
4  151.5500  Southampton
```

[299]:
```
#Correlation matrix
corr_matrix = titanic.corr()
corr_matrix
```

```
C:\Users\elmaf\AppData\Local\Temp\ipykernel_16020\2987745338.py:2:
```

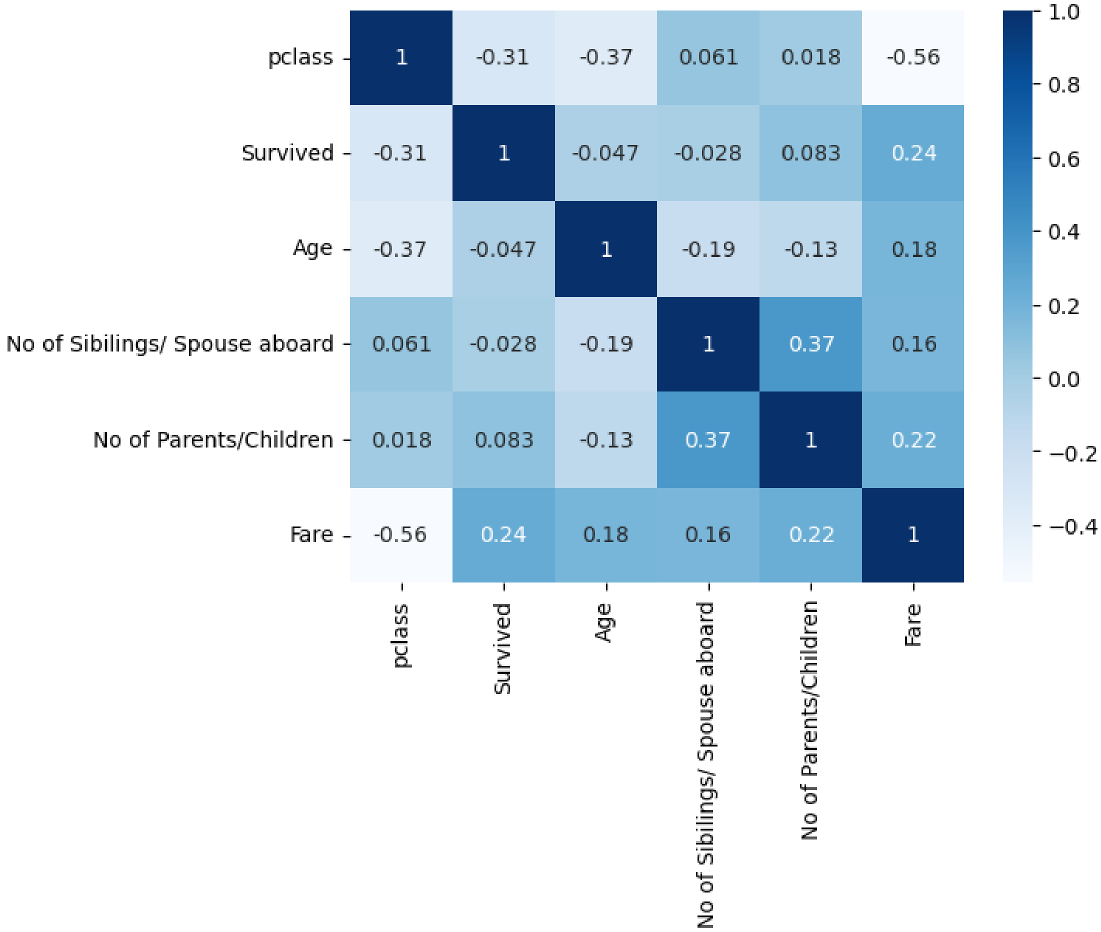
```
FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only valid
columns or specify the value of numeric_only to silence this warning.
  corr_matrix = titanic.corr()
```

[299]:

```
                             pclass  Survived       Age  \
pclass                     1.000000 -0.312469 -0.372115
Survived                  -0.312469  1.000000 -0.047021
Age                       -0.372115 -0.047021  1.000000
No of Sibilings/ Spouse aboard  0.060832 -0.027825 -0.190345
No of Parents/Children     0.018322  0.082660 -0.128821
Fare                      -0.558477  0.244208  0.175114

                                No of Sibilings/ Spouse aboard  \
pclass                                                0.060832
Survived                                             -0.027825
Age                                                  -0.190345
No of Sibilings/ Spouse aboard                        1.000000
No of Parents/Children                                0.373587
Fare                                                  0.160224

                                No of Parents/Children      Fare
pclass                                        0.018322 -0.558477
Survived                                      0.082660  0.244208
Age                                          -0.128821  0.175114
No of Sibilings/ Spouse aboard                0.373587  0.160224
No of Parents/Children                        1.000000  0.221522
Fare                                          0.221522  1.000000
```

[300]:

```
#Visualising our correlation matrix
sns.heatmap(corr_matrix, annot= True, cmap= 'Blues')
plt.show()
```

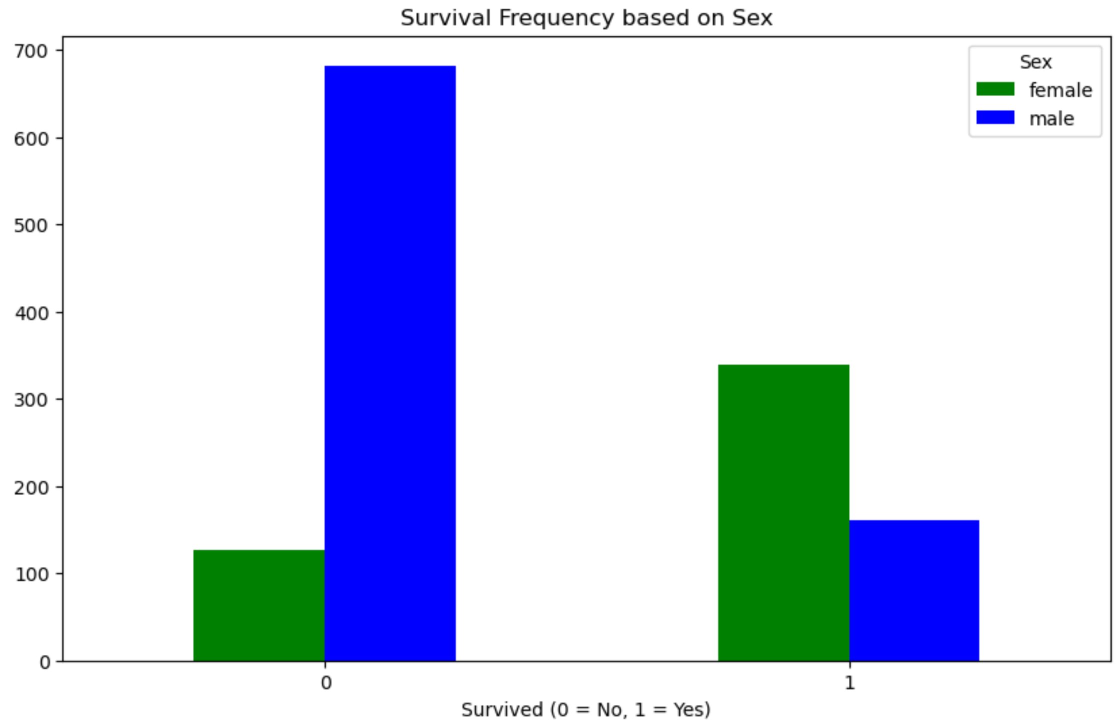


[301]:
```
#Survival frequency according to gender
pd.crosstab(titanic.Survived , titanic.Sex)
```

[301]:
```
Sex       female  male
Survived
0            127   682
1            339   161
```

[302]:
```
pd.crosstab(titanic.Survived , titanic.Sex).plot(kind = 'bar', figsize=(10,6),␣
 ↪color = ['green','blue'])
plt.xlabel("Survived (0 = No, 1 = Yes)")
plt.title("Survival Frequency based on Sex")
plt.xticks(rotation=0)
```

[302]:
```
(array([0, 1]), [Text(0, 0, '0'), Text(1, 0, '1')])
```



[303]:
```
#Survived frequency according to age
survival_age = pd.crosstab(titanic.Survived , titanic.Age)
survival_age
```

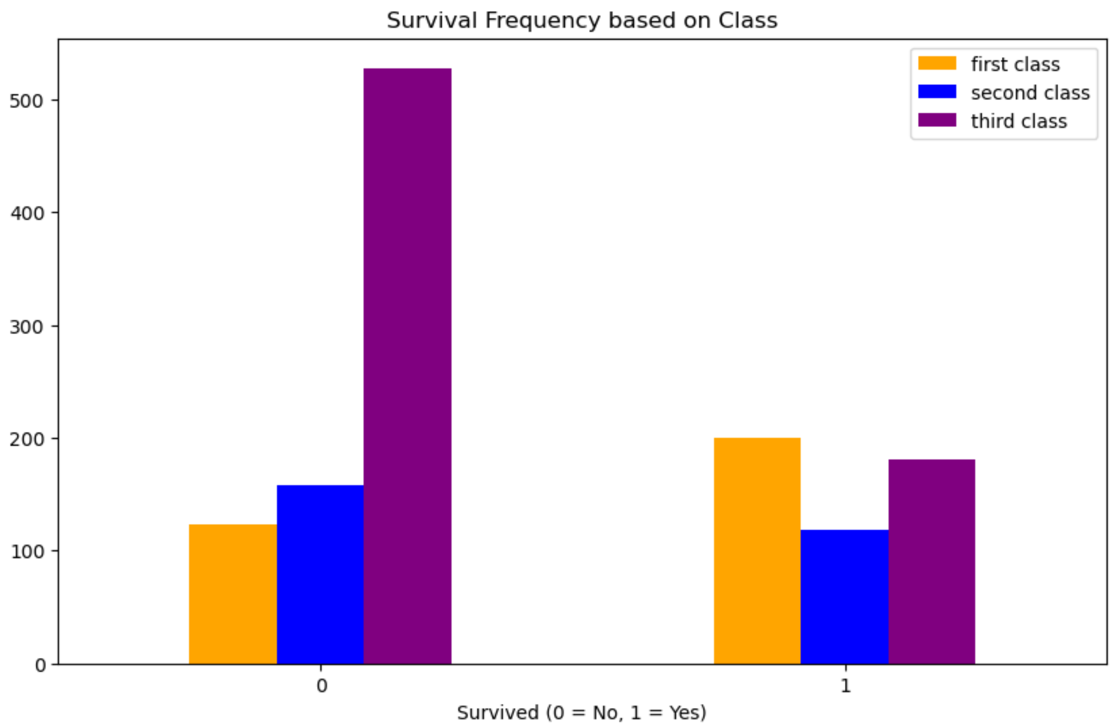
[303]:
```
Age        0   1   2   3   4   5   6   7   8   9  …  63  64  65  66  67  70  \
Survived                                          …
0          2   3   8   2   3   1   3   2   2   6  …   2   3   3   1   1   3
1         10   7   4   5   7   4   3   2   4   4  …   2   2   0   0   0   0

Age       71  74  76  80
Survived
0          2   1   0   0
1          0   0   1   1

[2 rows x 73 columns]
```

[304]:
```
#Survival frequency based on class
pd.crosstab(titanic.Survived, titanic.pclass)
```

[304]:
```
pclass      1    2    3
Survived
0         123  158  528
1         200  119  181
```

[305]:
```python
#Visualizing survival frequency based on  class
crosstab = pd.crosstab(titanic.Survived, titanic.pclass)
crosstab.plot(kind='bar', figsize=(10,6), color=['orange', 'blue', 'purple'])
plt.legend(["first class", "second class", "third class"])
plt.xlabel("Survived (0 = No, 1 = Yes)")
plt.title("Survival Frequency based on Class")
plt.xticks(rotation=0)
```

[305]: (array([0, 1]), [Text(0, 0, '0'), Text(1, 0, '1')])



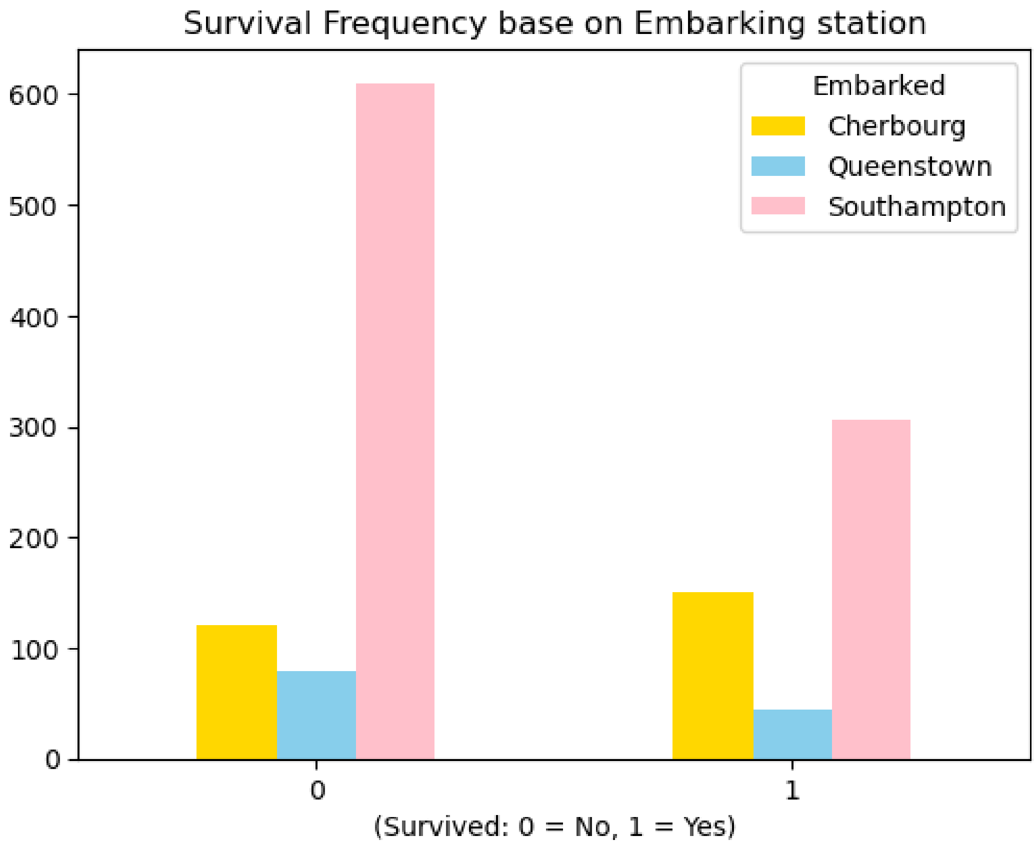
[306]:
```python
#Survival frequency based on embarking station
pd.crosstab(titanic.Survived, titanic.Embarked)
```

[306]:

Embarked	Cherbourg	Queenstown	Southampton
Survived			
0	120	79	610
1	150	44	306

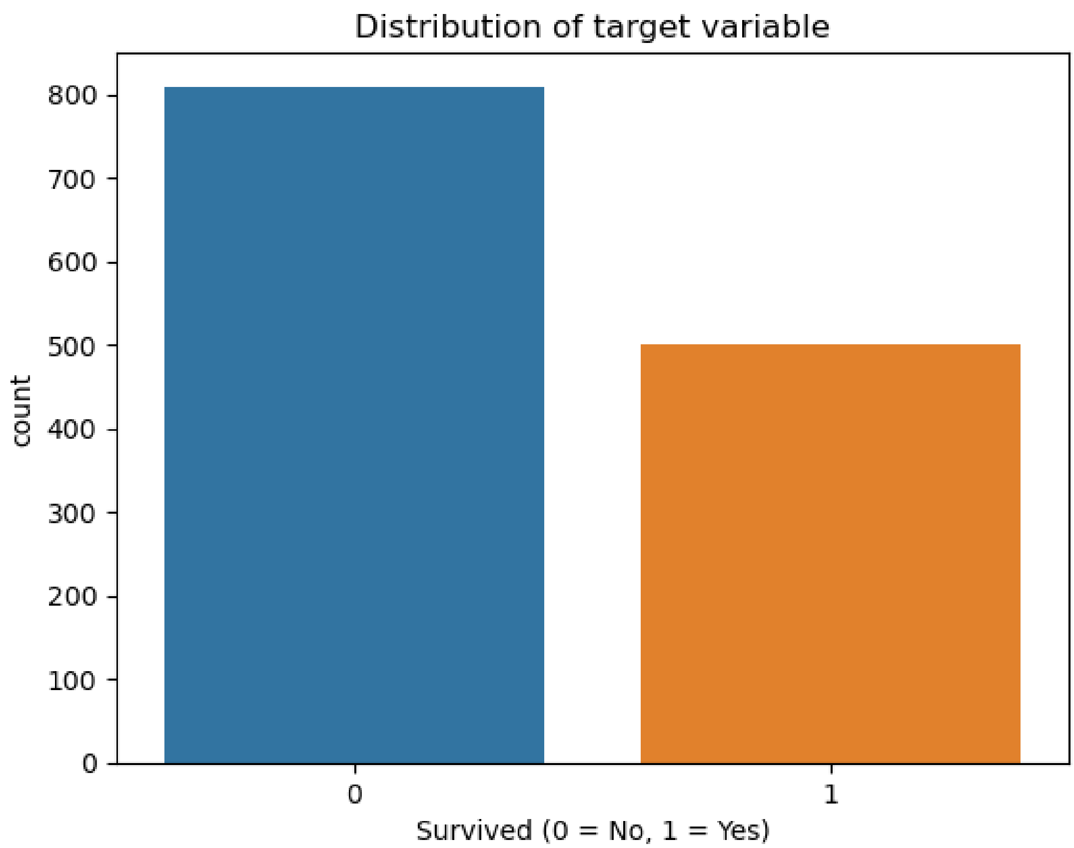
[307]:
```python
#Visualising the #Survival frequency based on embarking station
pd.crosstab(titanic.Survived, titanic.Embarked).plot(kind = "bar", color=␣
 ↪["gold", "skyblue", "pink"])
plt.title("Survival Frequency base on Embarking station")
plt.xlabel("(Survived: 0 = No, 1 = Yes)")
```

```
plt.xticks(rotation = 0)
plt.show()
```



[308]:

```
#Visualising the target variable
sns.countplot(x = "Survived", data = titanic)
plt.title("Distribution of target variable")
plt.xlabel("Survived (0 = No, 1 = Yes)")
plt.xticks(rotation = 0)
plt.show()
```



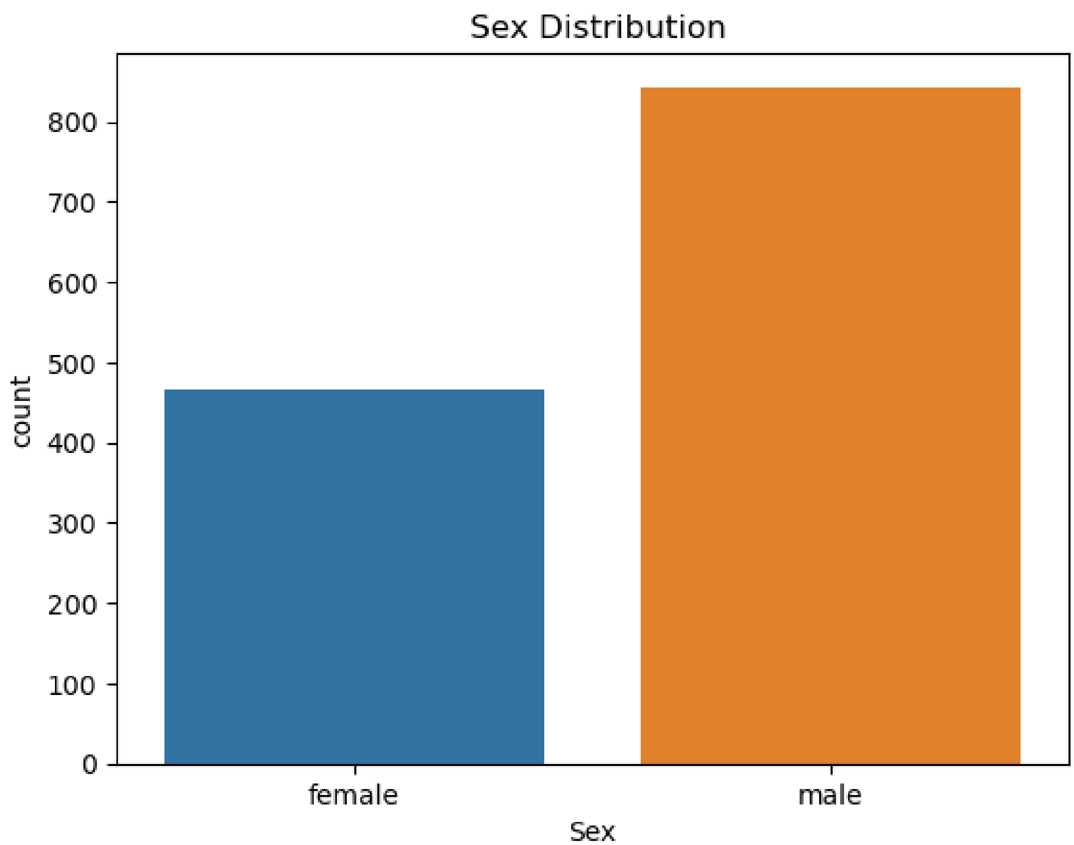
[309]:
```
#Visualising categorical values
titanic.select_dtypes('object')
```

[309]:
```
                                                 Name     Sex Ticket Number  \
0                       Allen, Miss. Elisabeth Walton  female         24160
1                      Allison, Master. Hudson Trevor    male        113781
2                        Allison, Miss. Helen Loraine  female        113781
3                Allison, Mr. Hudson Joshua Creighton    male        113781
4     Allison, Mrs. Hudson J C (Bessie Waldo Daniels)  female        113781
…                                                   …     …           …
1304                             Zabour, Miss. Hileni  female          2665
1305                            Zabour, Miss. Thamine  female          2665
1306                        Zakarian, Mr. Mapriededer    male          2656
1307                              Zakarian, Mr. Ortin    male          2670
1308                               Zimmerman, Mr. Leo    male        315082

         Embarked
0     Southampton
1     Southampton
2     Southampton
```

```
3     Southampton
4     Southampton
…             …
1304    Cherbourg
1305    Cherbourg
1306    Cherbourg
1307    Cherbourg
1308  Southampton

[1309 rows x 4 columns]
```

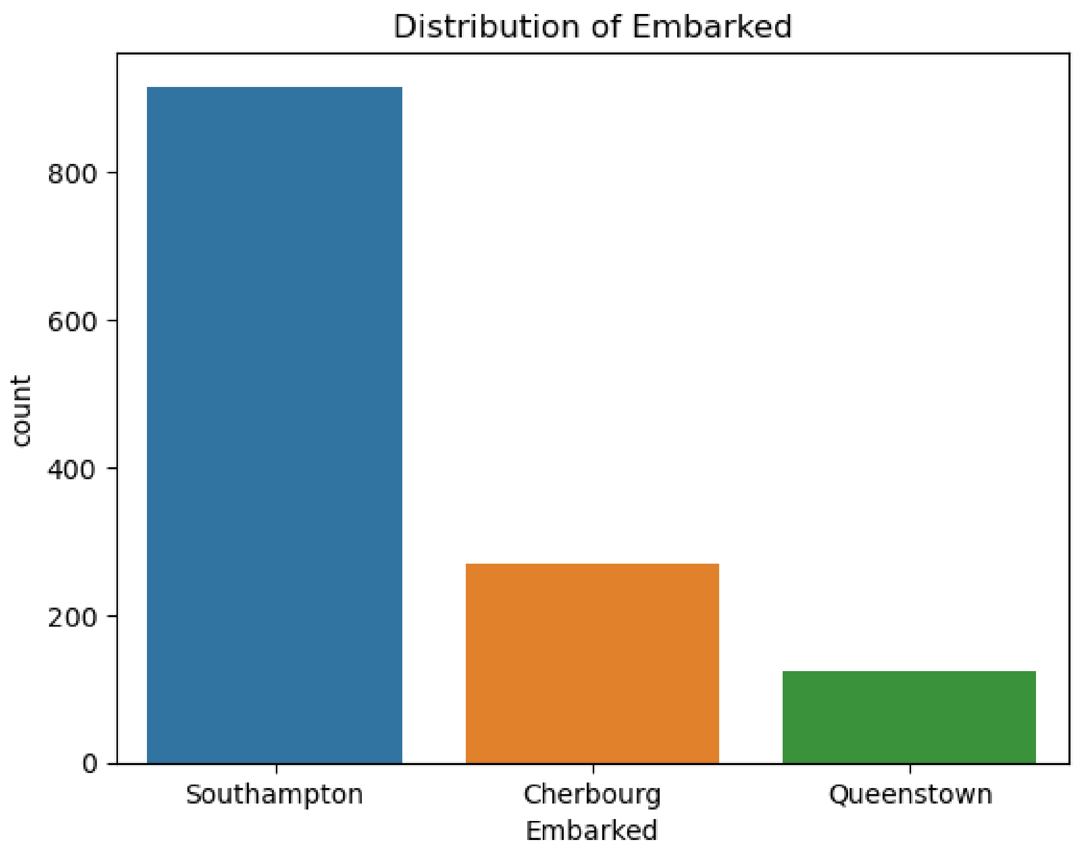
[310]:

```
#Visualising Categorical Variables
sns.countplot(x = 'Sex', data = titanic)
plt.title(" Sex Distribution")
plt.show()
```

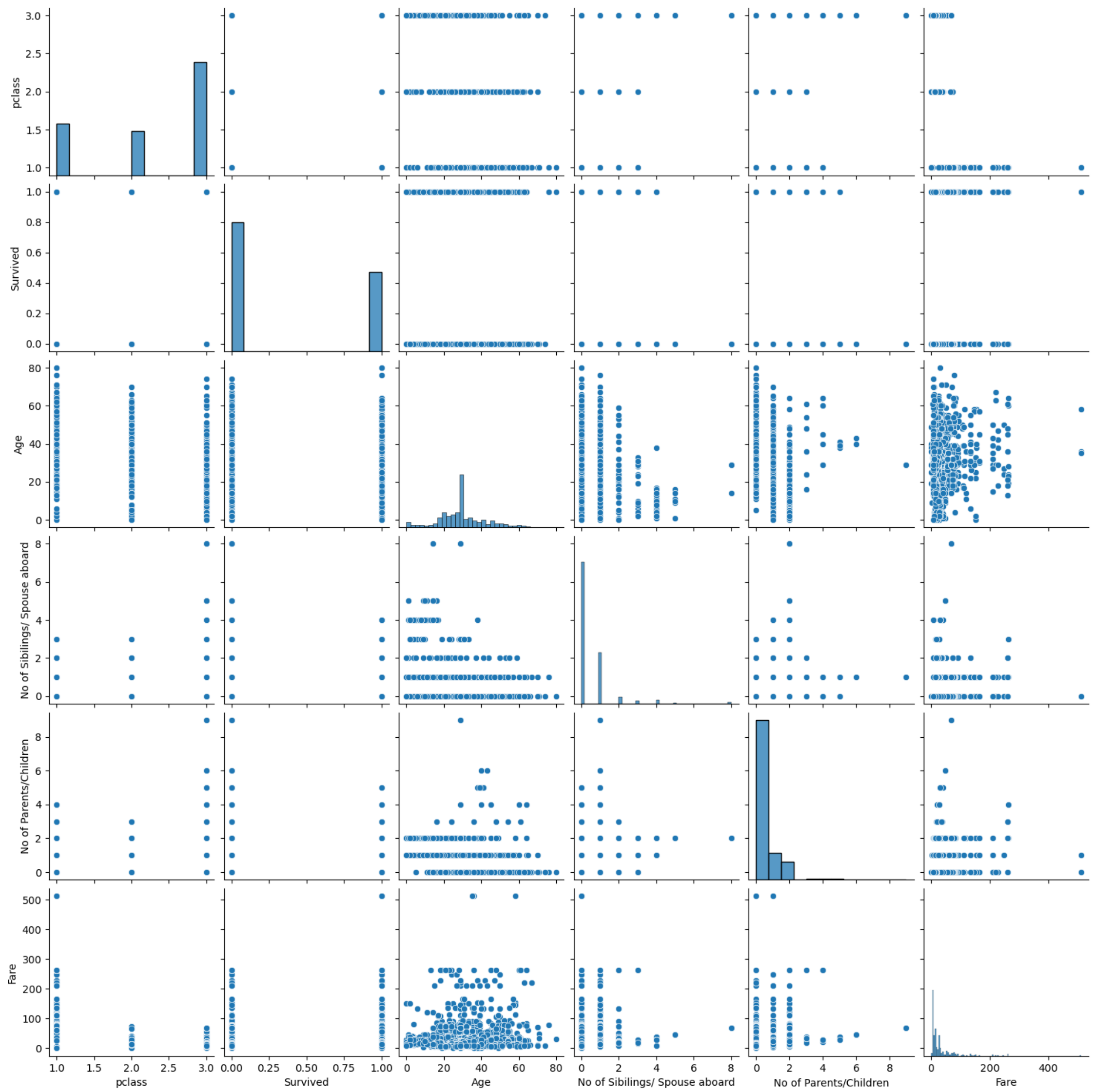


[311]:

```
sns.countplot(x = "Embarked", data = titanic)
plt.title("Distribution of Embarked")
plt.show()
```



[312]:
```
sns.pairplot(data = titanic)
plt.show()
```



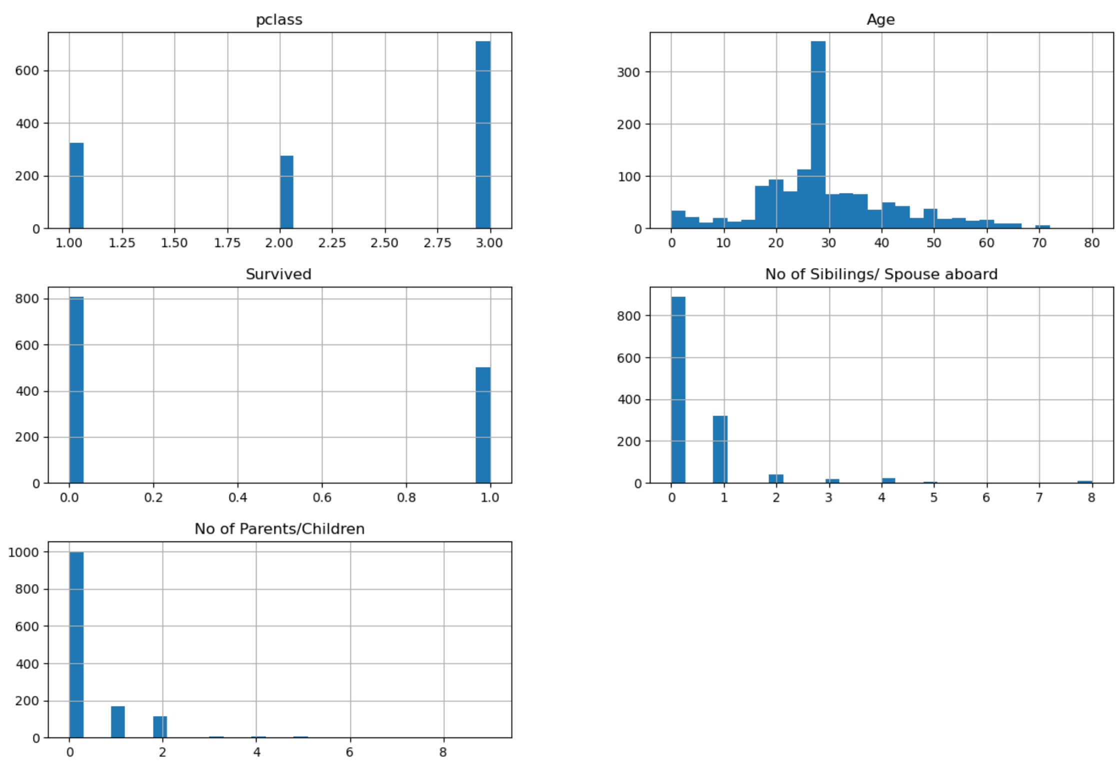
[313]:
```
#Exploring Numerical Values
titanic.select_dtypes('int')
```

[313]:

	pclass	Survived	Age	No of Sibilings/ Spouse aboard	\
0	1	1	29	0	
1	1	1	0	1	
2	1	0	2	1	
3	1	0	30	1	
4	1	0	25	1	
…	…	…	…	…	
1304	3	0	14	1	
1305	3	0	29	1	
1306	3	0	26	0	

```
1307         3          0    27                                0
1308         3          0    29                                0

      No of Parents/Children
0                          0
1                          2
2                          2
3                          2
4                          2
…                      …
1304                       0
1305                       0
1306                       0
1307                       0
1308                       0

[1309 rows x 5 columns]
```

[314]:
```
#VIsualising numerical features
numerical_features = ["pclass","Age","Survived","No of Sibilings/ Spouse␣
↪aboard", "No of Parents/Children"]
titanic[numerical_features].hist(bins = 30, figsize= (15,10))
plt.show()
```



Model Preprocessing

[315]:
```
#Encoding categorical values
cat_values =["Name", "Sex","Ticket Number","Embarked"]
titanic= pd.get_dummies(titanic, columns = cat_values, drop_first=True)
```

[316]:
```
#Label encoding the target variable
le = LabelEncoder()
titanic['Survived']= le.fit_transform( titanic['Survived'])
```

[317]:
```
#Feature Scaling
scaler = StandardScaler()
titanic[numerical_features] = scaler.fit_transform(titanic[numerical_features])
```

Model Building

[318]:
```
y = titanic["Survived"].info()
titanic["Survived"]=titanic["Survived"].astype("int64")
#y.astype(int)
#y_train.astype(int)
#y_train.info()
```

```
<class 'pandas.core.series.Series'>
Int64Index: 1309 entries, 0 to 1308
Series name: Survived
Non-Null Count  Dtype
--------------  -----
1309 non-null   float64
dtypes: float64(1)
memory usage: 20.5 KB
```

[319]:
```
#train_test split
X = titanic.drop("Survived", axis = 1)
y = titanic["Survived"]
X_standardised = scaler.fit_transform(X)
X_train,X_test,y_train,y_test = train_test_split(X_standardised,y, test_size= 0.
 ↪2, random_state=42)
```

[320]:
```
#Model Training using LogisticRegression
Lg = LogisticRegression()
Lg.fit(X_train,y_train)
```

[320]: LogisticRegression()

[321]:
```
#Model Training using RandomForestClassifier
rfc = RandomForestClassifier()
rfc.fit(X_train,y_train)
```

[321]: RandomForestClassifier()

HyperParameter Tuning

[322]:
```
#Hyperparameter tuning using gridsearchcv for RandomForest
# Define the hyperparameter grid
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_features': ['auto', 'sqrt', 'log2'],
    'max_depth': [10, 20, 30, None],
    'criterion': ['gini']
}
grid_search = GridSearchCV(estimator= rfc, param_grid= param_grid,cv = 3,␣
↪n_jobs= -1, verbose= 2)
grid_search.fit(X_train, y_train)

# Best hyperparameters
print("Best Hyperparameters:", grid_search.best_params_)

# Best estimator
best_rfc = grid_search.best_estimator_
```

```
Fitting 3 folds for each of 36 candidates, totalling 108 fits
```

```
c:\Users\elmaf\anaconda3\Lib\site-
packages\joblib\externals\loky\process_executor.py:700: UserWarning: A worker
stopped while some jobs were given to the executor. This can be caused by a too
short worker timeout or by a memory leak.
  warnings.warn(
c:\Users\elmaf\anaconda3\Lib\site-
packages\sklearn\model_selection\_validation.py:425: FitFailedWarning:
36 fits failed out of a total of 108.
The score on these train-test partitions for these parameters will be set to
nan.
If these failures are not expected, you can try to debug them by setting
error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
36 fits failed with the following error:
Traceback (most recent call last):
  File "c:\Users\elmaf\anaconda3\Lib\site-
packages\sklearn\model_selection\_validation.py", line 732, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "c:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\base.py", line 1144,
in wrapper
    estimator._validate_params()
  File "c:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\base.py", line 637,
```

```
in _validate_params
    validate_parameter_constraints(
  File "c:\Users\elmaf\anaconda3\Lib\site-
packages\sklearn\utils\_param_validation.py", line 95, in
validate_parameter_constraints
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'max_features'
parameter of RandomForestClassifier must be an int in the range [1, inf), a
float in the range (0.0, 1.0], a str among {'sqrt', 'log2'} or None. Got 'auto'
instead.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
c:\Users\elmaf\anaconda3\Lib\site-
packages\sklearn\model_selection\_search.py:976: UserWarning: One or more of the
test scores are non-finite: [       nan        nan        nan 0.69818529
0.70391595 0.69436485
 0.63514804 0.63514804 0.63514804        nan        nan        nan
 0.77936963 0.78127985 0.78319007 0.63514804 0.63610315 0.63705826
        nan        nan        nan 0.78796562 0.79465138 0.79369628
 0.65616046 0.65902579 0.6599809         nan        nan        nan
 0.80897803 0.80993314 0.80993314 0.79178606 0.80324737 0.80993314]
  warnings.warn(

Best Hyperparameters: {'criterion': 'gini', 'max_depth': None, 'max_features':
'sqrt', 'n_estimators': 200}
```

[345]:
```python
#MOdel Predictions
y_pred = best_rfc.predict(X_test)
y_pred
```

[345]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0,
       0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1,
       1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1,
       1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1,
       0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1,
       0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0,
       1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0,
       1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1],
      dtype=int64)
```

[346]:
```python
#Calculating accuracy
Accuracy = accuracy_score(y_pred,y_test)
Accuracy
```

[346]: 0.7862595419847328

[325]:
```python
#Hyperparameter tuning using gridsearchcv for Logistic Regression
# Define the hyperparameter grid
param_grid = {'C': [0.1, 1, 10],
              'solver': ['liblinear', 'saga']}
grid = GridSearchCV(estimator = Lg, param_grid=param_grid, cv=3)
grid.fit(X_train, y_train)
best_model = grid.best_estimator_
```

```
c:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
converge
  warnings.warn(
c:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
converge
  warnings.warn(
c:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
converge
  warnings.warn(
c:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
converge
  warnings.warn(
c:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
converge
  warnings.warn(
c:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
converge
  warnings.warn(
c:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
converge
  warnings.warn(
c:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
converge
  warnings.warn(
c:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
converge
  warnings.warn(
c:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
```

```
ConvergenceWarning: The max_iter was reached which means the coef_ did not
converge
  warnings.warn(
```

[347]:
```
#MOdel Predictions
y_pred = best_rfc.predict(X_test)
y_pred
```

[347]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0,
       0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1,
       1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1,
       1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1,
       0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1,
       0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0,
       1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0,
       1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1],
      dtype=int64)
```

[348]:
```
#Calculating accuracy
Accuracy = accuracy_score(y_pred,y_test)
Accuracy
```

[348]: 0.7862595419847328

[342]:
```
#Hyperparameter tuning using Randomizedsearchcv for RandomForestClassifier
param_grid = {
    'n_estimators': [100, 200,300],
    'max_features': ['auto', 'sqrt', 'log2'],
    'max_depth': [10, 20, 30, None],
    'criterion': ['gini']
}
# Setup random hyperparameter search for RandomForestClassifier
rs_rf = RandomizedSearchCV(RandomForestClassifier(),␣
 ↪param_distributions=param_grid, cv=5, n_iter=20, verbose=True)
rs_rf.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
```

```
c:\Users\elmaf\anaconda3\Lib\site-
packages\sklearn\model_selection\_validation.py:425: FitFailedWarning:
40 fits failed out of a total of 100.
The score on these train-test partitions for these parameters will be set to
nan.
If these failures are not expected, you can try to debug them by setting
```

```
error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
40 fits failed with the following error:
Traceback (most recent call last):
  File "c:\Users\elmaf\anaconda3\Lib\site-
packages\sklearn\model_selection\_validation.py", line 732, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "c:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\base.py", line 1144,
in wrapper
    estimator._validate_params()
  File "c:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\base.py", line 637,
in _validate_params
    validate_parameter_constraints(
  File "c:\Users\elmaf\anaconda3\Lib\site-
packages\sklearn\utils\_param_validation.py", line 95, in
validate_parameter_constraints
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'max_features'
parameter of RandomForestClassifier must be an int in the range [1, inf), a
float in the range (0.0, 1.0], a str among {'sqrt', 'log2'} or None. Got 'auto'
instead.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
c:\Users\elmaf\anaconda3\Lib\site-
packages\sklearn\model_selection\_search.py:976: UserWarning: One or more of the
test scores are non-finite: [0.63515152 0.63610845        nan        nan
0.63515152 0.63515152
 0.81564821        nan        nan        nan 0.81850535 0.77840966
        nan 0.7765049  0.6361039         nan        nan 0.65138756
 0.81181135 0.80226475]
  warnings.warn(
```

[342]:
```
RandomizedSearchCV(cv=5, estimator=RandomForestClassifier(), n_iter=20,
                   param_distributions={'criterion': ['gini'],
                                        'max_depth': [10, 20, 30, None],
                                        'max_features': ['auto', 'sqrt',
                                                         'log2'],
                                        'n_estimators': [100, 200, 300]},
                   verbose=True)
```

[349]:
```python
#Model Evaluation using RandomisedSearchCV - RandomForestClassifier
y_pred_rs_rf = rs_rf .predict(X_test)
y_pred_rs_rf
```

[349]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0,
       0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1,
       1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1,
       1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1,
       0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1,
       0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0,
       1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0,
       1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1],
      dtype=int64)
```

[350]:
```
#Model Accuracy
Accuracy_rnd = accuracy_score(y_pred_rs_rf,y_test)
Accuracy_rnd
```

[350]:
```
0.7900763358778626
```

[329]:
```
#Hyperparameter tuning using Randomizedsearchcv for Logistic Regression
# Define the hyperparameter grid
param_grid = {'C': [0.1, 1, 10],
               'solver': ['liblinear', 'saga']}
# Initialize RandomizedSearchCV
rs_log_reg = RandomizedSearchCV(estimator=LogisticRegression(),␣
 ↪param_distributions=param_grid,
                                cv=3, n_iter=20, verbose=True, random_state=42,␣
 ↪n_jobs=-1)

# Fit RandomizedSearchCV to the data
rs_log_reg.fit(X_train, y_train)
```

```
c:\Users\elmaf\anaconda3\Lib\site-
packages\sklearn\model_selection\_search.py:307: UserWarning: The total space of
parameters 6 is smaller than n_iter=20. Running 6 iterations. For exhaustive
searches, use GridSearchCV.
  warnings.warn(
```

```
Fitting 3 folds for each of 6 candidates, totalling 18 fits
```

```
c:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
converge
  warnings.warn(
```

[329]:
```
RandomizedSearchCV(cv=3, estimator=LogisticRegression(), n_iter=20, n_jobs=-1,
                   param_distributions={'C': [0.1, 1, 10],
```

```
                                        'solver': ['liblinear', 'saga']},
                    random_state=42, verbose=True)
```

Model Evaluation

[351]:
```
#Model Evaluation using RandomisedSearchCV - Logistic Regression
y_pred_rcv = rs_log_reg.predict(X_test)
y_pred_rcv
```

[351]:
```
array([0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0,
       0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 0,
       0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1,
       1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1,
       1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1,
       0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1,
       0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0,
       0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1,
       1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0,
       1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1],
      dtype=int64)
```

[352]:
```
#Model Accuracy
Accuracy_rnd_reg= accuracy_score(y_pred_rcv ,y_test)
Accuracy_rnd_reg
```

[352]:
```
0.7748091603053435
```

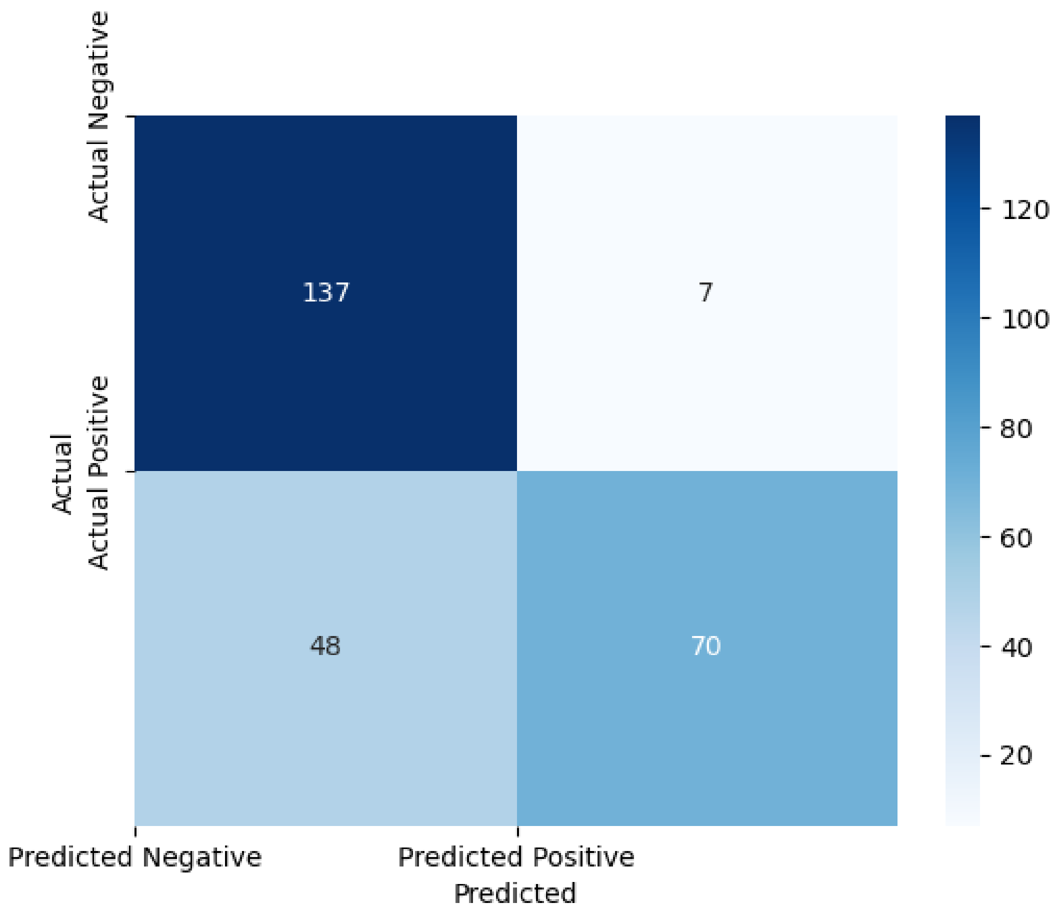
From the 2 models used Logistic Regression and RandomForest Classifier, the best performing model is RandomForestClassifier model hypertuned using RandomisedSearchCV

The model is 79% accurate

[361]:
```
# Evaluation metrics
print(confusion_matrix(y_test, y_pred_rs_rf))
print(classification_report(y_test, y_pred_rs_rf))
sns.heatmap(confusion_matrix(y_test, y_pred_rs_rf), annot=True, fmt='d', cmap=␣
 ↪'Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.xticks([0, 1], ['Predicted Negative', 'Predicted Positive'])
plt.yticks([0, 1], ['Actual Negative', 'Actual Positive'])
plt.show()
```

```
[[137   7]
 [ 48  70]]
              precision    recall  f1-score   support
```

```
              0       0.74      0.95      0.83       144
              1       0.91      0.59      0.72       118

       accuracy                           0.79       262
      macro avg       0.82      0.77      0.78       262
   weighted avg       0.82      0.79      0.78       262
```



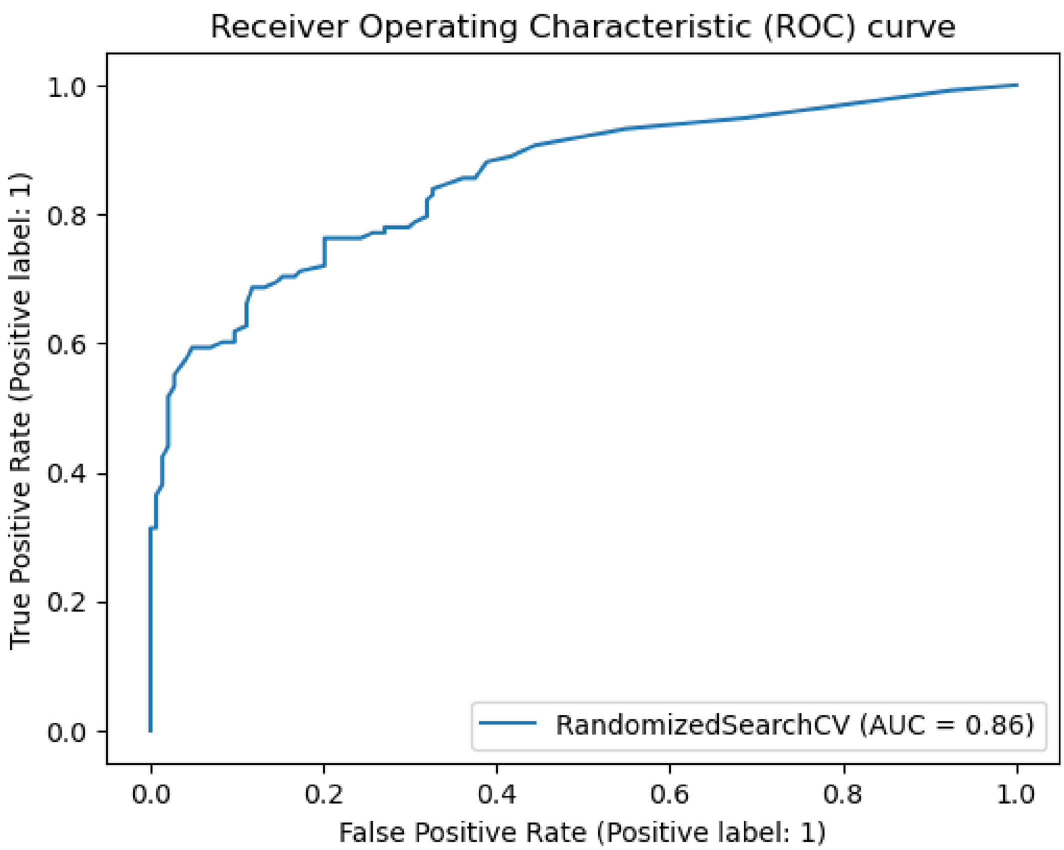
Explanation: True Positives (TP): Correctly predicted positive cases.

True Negatives (TN): Correctly predicted negative cases.

False Positives (FP): Incorrectly predicted positive cases. False Negatives (FN): Incorrectly predicted negative cases.

[359]:
```
#ROC display curve
RocCurveDisplay.from_estimator(estimator= rs_rf,X = X_test, y =y_test);
plt.title("Receiver Operating Characteristic (ROC) curve")
```

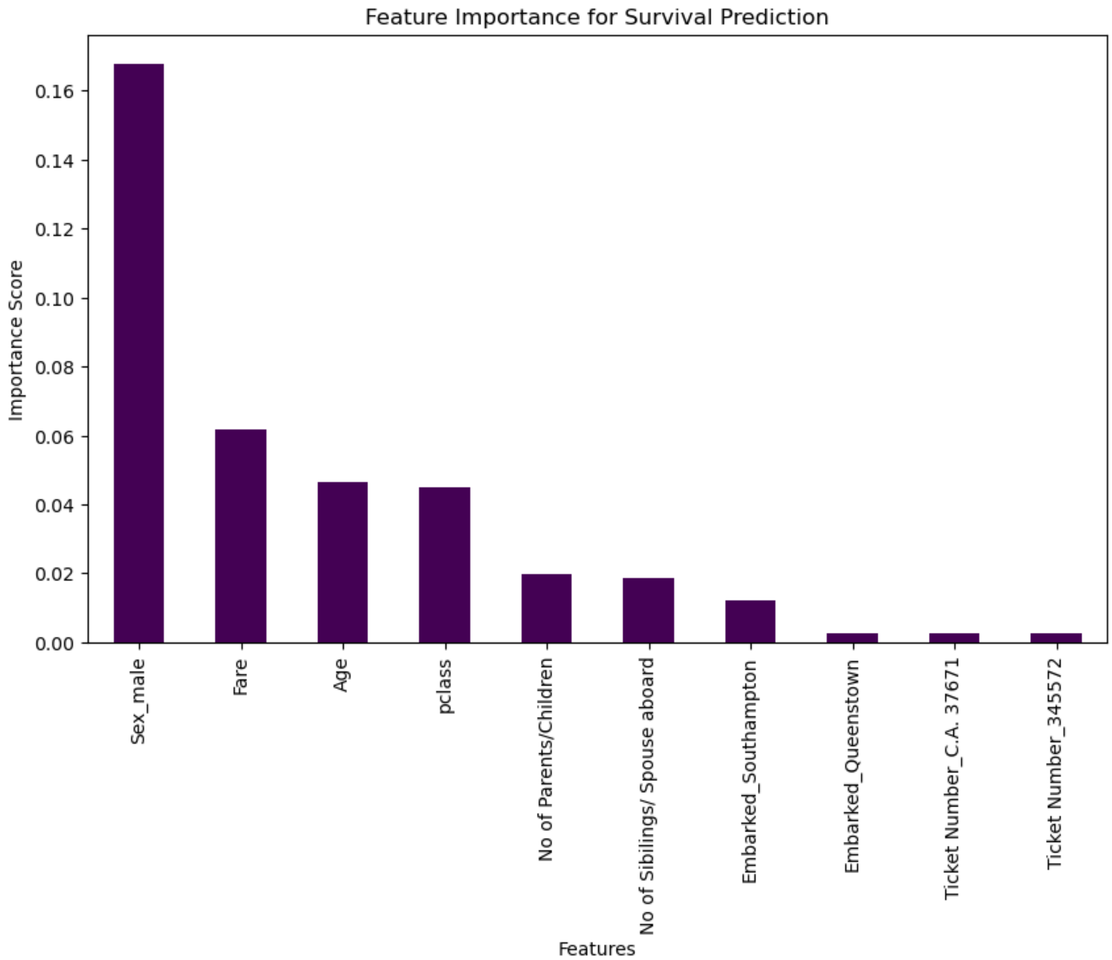
[359]:
```
Text(0.5, 1.0, 'Receiver Operating Characteristic (ROC) curve')
```



This is great, our model does far better with an AUC of 0.86, but a perfect model would achieve an AUC score of 1.0, so there's still room for improvement.

[379]:
```
#Feature Importance
best_rf = rs_rf.best_estimator_  # Retrieve the best estimator from␣
↪RandomizedSearchCV
features = X.columns

# Get feature importances from the best RandomForestClassifier model
feature_importances = best_rf.feature_importances_
feature_importances = pd.Series(feature_importances, index=features)
feature_importances = feature_importances.sort_values(ascending=False).head(10)
plt.figure(figsize=(10, 6))
feature_importances.plot(kind='bar', cmap='viridis')
plt.title('Feature Importance for Survival Prediction')
plt.xlabel('Features')
plt.ylabel('Importance Score')
```

[379]:
```
Text(0, 0.5, 'Importance Score')
```



The bar plot shows the importance of each feature in making predictions. Higher importance indicates a greater influence on the model's predictions.

Conclusion

Our model is 79% accurate. It is fairly reasonably but there is room for improvement

Key Findings

Gender is the most significant predictor of survival followed by class and age

Female passangers had a higher chance of surviving compared to male passangers