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Titanic

# Titanic model

## Introduction

In this notebook we examine the Titanic dataset and then we build a model that can predict if a passenger survived the sinking or not. We start with finding feature types, missing values and we continue with feature analysis and visualization of the data. Feature engineering is implemented to create new attributes, encoding and imputation of the missing values. At last we test several classifiers and we evaluate them with the help of the ROC and CAP curves.

## History

RMS Titanic was a British passenger liner operated by the White Star Line that sank in the North Atlantic Ocean in the early morning hours of 15 April 1912, after striking an iceberg during her maiden voyage from Southampton to New York City. Of the estimated 2,224 passengers and crew aboard, more than 1,500 died, making the sinking one of modern history's deadliest peacetime commercial marine disasters.

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Machine learning Model

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### Importing Libraries

In [1]:

```
# This Python 3 environment comes with many helpful analytics libraries installed

# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
```

```
# For example, here's several helpful packages to load
%matplotlib inline


import pandas as pd            # Implemennts milti-dimensional array and matrices
import numpy as np             # For data manipulation and analysis
import matplotlib.pyplot as plt    # Plotting library for Python programming language and it's numerical mathematics extension NumPy
import seaborn as sns          # Provides a high level interface for drawing attractive and informative statistical graphics


# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory


import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))


# You can write up to 5GB to the current directory (/kaggle/working/) that gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current session
```

```
/kaggle/input/titanic/gender_submission.csv
/kaggle/input/titanic/test.csv
```

/kaggle/input/titanic/train.csv

In [2]:

```
# load dataset
train=pd.read_csv('/kaggle/input/titanic/train.csv')
test=pd.read_csv('/kaggle/input/titanic/test.csv')
gender_submission=pd.read_csv("../input/titanic/gender_submission.csv")
```

In [3]:

```
len(train),len(test),len(gender_submission)
```

Out[3]:

(891, 418, 418)

In [4]:

```
train.head()
```

Out[4]:

| | PassengerId | Survived | Pclass | Name | Sex | Age | SibSp | Parch | Ticket | Fare | Cabin | Embarked |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 0 | 3 | Braund, Mr. Owen Harris | male | 22.0 | 1 | 0 | A/5 21171 | 7.2500 | NaN | S |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 1 | 1 | Cumings, Mrs. John Bradley (Florence Briggs Th... | female | 38.0 | 1 | 0 | PC 17599 | 71.2833 | C85 | C |
| 2 | 3 | 1 | 3 | Heikkinen, Miss. Laina | female | 26.0 | 0 | 0 | STON/O2. 3101282 | 7.9250 | NaN | S |
| 3 | 4 | 1 | 1 | Futrelle, Mrs. Jacques Heath (Lily May Peel) | female | 35.0 | 1 | 0 | 113803 | 53.1000 | C123 | S |
| 4 | 5 | 0 | 3 | Allen, Mr. William Henry | male | 35.0 | 0 | 0 | 373450 | 8.0500 | NaN | S |

In [5]:

```
train.shape
```

Out[5]:

(891, 12)

In [6]:

```
train.describe(include='all')
```

Out[6]:

| | PassengerId | Survived | Pclass | Name | Sex | Age | SibSp | Parch | Ticket | Fare | Cabin | Embarked |
|---|---|---|---|---|---|---|---|---|---|---|---|---|

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| count | 891.000000 | 891.000000 | 891.000000 | 891 | 891 | 714.000000 | 891.000000 | 891.000000 | 891 | 891.000000 | 204 | 889 |
| unique | NaN | NaN | NaN | 891 | 2 | NaN | NaN | NaN | 681 | NaN | 147 | 3 |
| top | NaN | NaN | NaN | Kelly, Miss. Anna Katherine "Annie Kate" | male | NaN | NaN | NaN | 347082 | NaN | C23 C25 C27 | S |
| freq | NaN | NaN | NaN | 1 | 577 | NaN | NaN | NaN | 7 | NaN | 4 | 644 |
| mean | 446.000000 | 0.383838 | 2.308642 | NaN | NaN | 29.699118 | 0.523008 | 0.381594 | NaN | 32.204208 | NaN | NaN |
| std | 257.353842 | 0.486592 | 0.836071 | NaN | NaN | 14.526497 | 1.102743 | 0.806057 | NaN | 49.693429 | NaN | NaN |
| min | 1.000000 | 0.000000 | 1.000000 | NaN | NaN | 0.420000 | 0.000000 | 0.000000 | NaN | 0.000000 | NaN | NaN |
| 25% | 223.500000 | 0.000000 | 2.000000 | NaN | NaN | 20.125000 | 0.000000 | 0.000000 | NaN | 7.910400 | NaN | NaN |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 50% | 446.000000 | 0.000000 | 3.000000 | NaN | NaN | 28.000000 | 0.000000 | 0.000000 | NaN | 14.454200 | NaN | NaN |
| 75% | 668.500000 | 1.000000 | 3.000000 | NaN | NaN | 38.000000 | 1.000000 | 0.000000 | NaN | 31.000000 | NaN | NaN |
| max | 891.000000 | 1.000000 | 3.000000 | NaN | NaN | 80.000000 | 8.000000 | 6.000000 | NaN | 512.329200 | NaN | NaN |

## Some Observations:

- There are a total of 891 passengers in our training set.
- The Age feature is missing approximately 19.8% of its values. I'm guessing that the Age feature is pretty important to survival, so we should probably attempt to fill these gaps.
- The Cabin feature is missing approximately 77.1% of its values. Since so much of the feature is missing, it would be hard to fill in the missing values. We'll probably drop these values from our dataset.
- The Embarked feature is missing 0.22% of its values, which should be relatively harmless.

In [7]:

```
train.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
```

# Variables

From the data overview of the competition, we have a description of each variable:

- PassengerId - unique identifier

Survived:
0 = No

- 1 = Yes

Pclass: Ticket class
1 = 1st, Upper

2 = 2nd, Middle

- 3 = 3rd, Lower

- Name: full name with a title
- Sex: gender
- Age: Age is fractional if less than 1. If the age is estimated, is it in the form of xx.5

Sibsp: Number of siblings / spouses aboard the Titanic. The dataset defines family relations in this way:
Sibling = brother, sister, stepbrother, stepsister

- Spouse = husband, wife (mistresses and fiancés were ignored)

Parch: Number of parents / children aboard the Titanic. The dataset defines family relations in this way:
Parent = mother, father

Child = daughter, son, stepdaughter, stepson

- Some children travelled only with a nanny, therefore parch=0 for them.
- Ticket: Ticket number.
- Fare: Passenger fare.
- Cabin: Cabin number.

Embarked: Port of Embarkation:
C = Cherbourg

Q = Queenstown

- S = Southampton

# Handle missing data

Checking Missing value is **present or not** in our dataset

In [8]:

```
train.isnull().values.any()
```

Out[8]:

True

In [9]:

```
train.isnull().sum()
```

Out[9]:

PassengerId 0

Survived 0

```
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

In [10]:

```
test.isnull().sum()
```

Out[10]:

```
PassengerId      0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
```

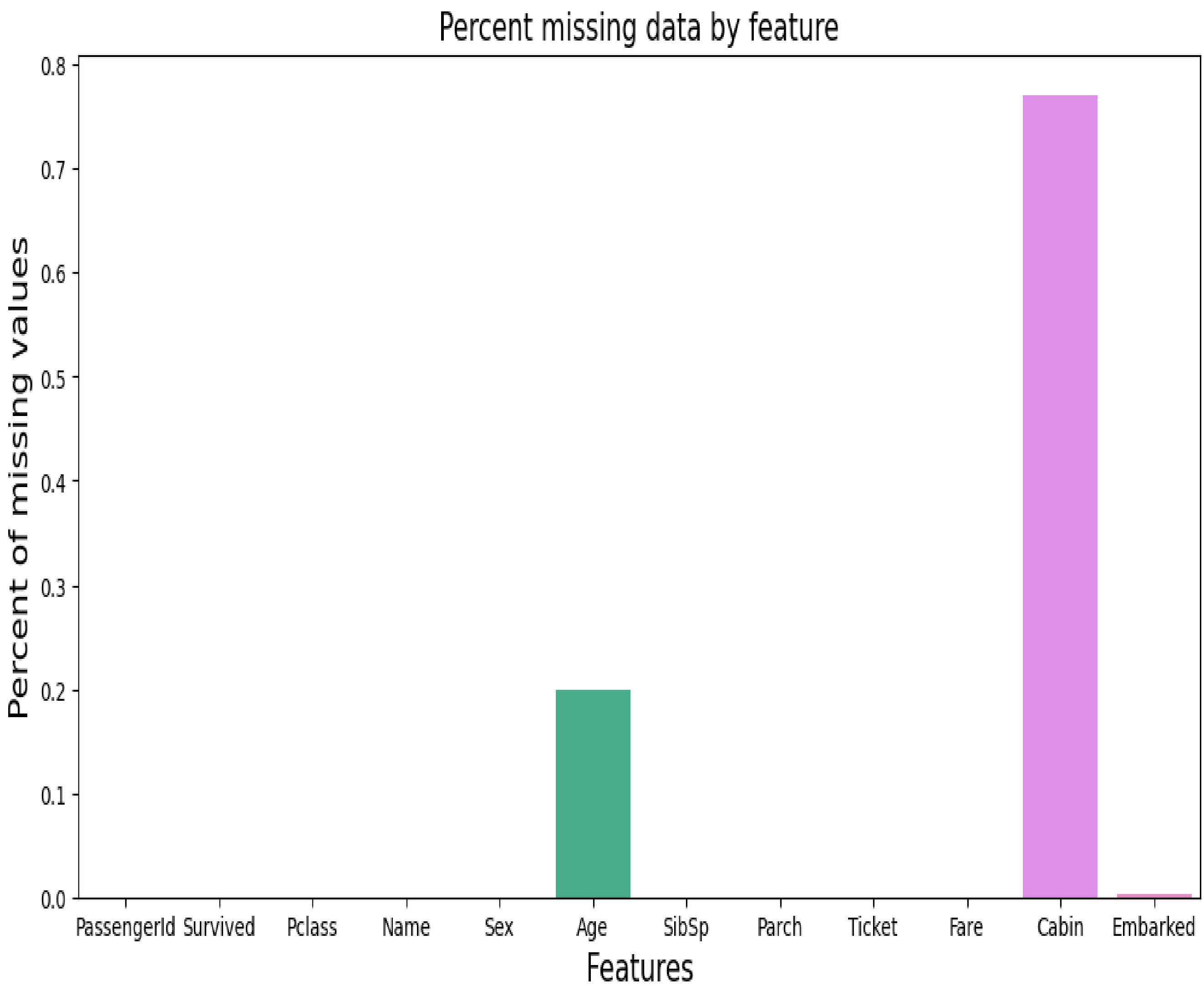
Cabin 327

Embarked 0

dtype: int64

In [11]:

```
plt.style.use('default')
total=train.isnull().sum()
percent=train.isnull().sum()/train.isnull().count()
missing_data=pd.concat([total,percent],axis=1, keys=['total', 'percent'])
#missing_data.sort_values(ascending=False)
ax = plt.subplots(figsize=(12, 6))
#plt.xticks(rotation='90')
sns.barplot(x=missing_data.index,y=missing_data['percent'])
plt.xlabel('Features', fontsize=15)
plt.ylabel('Percent of missing values', fontsize=15)
plt.title('Percent missing data by feature', fontsize=15)
plt.show()
```




**Missingno** library offers a very nice way to visualize the distribution of NaN values. Missingno is a Python library and compatible with Pandas.

In [12]:

```
import missingno as msno
```

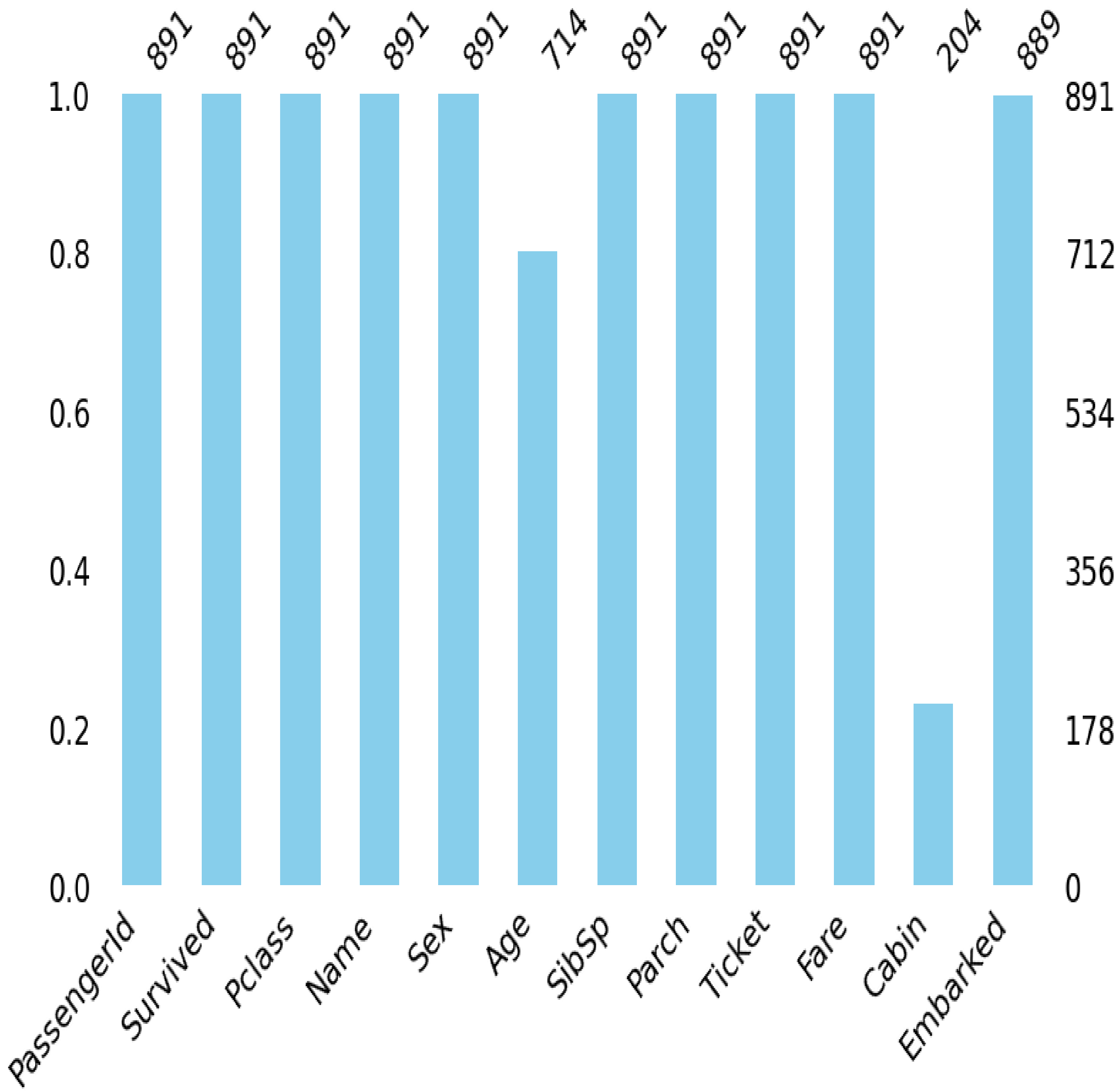
## Bar Chart :

This bar chart gives you an idea about how many missing values are there in each column.

In [13]:

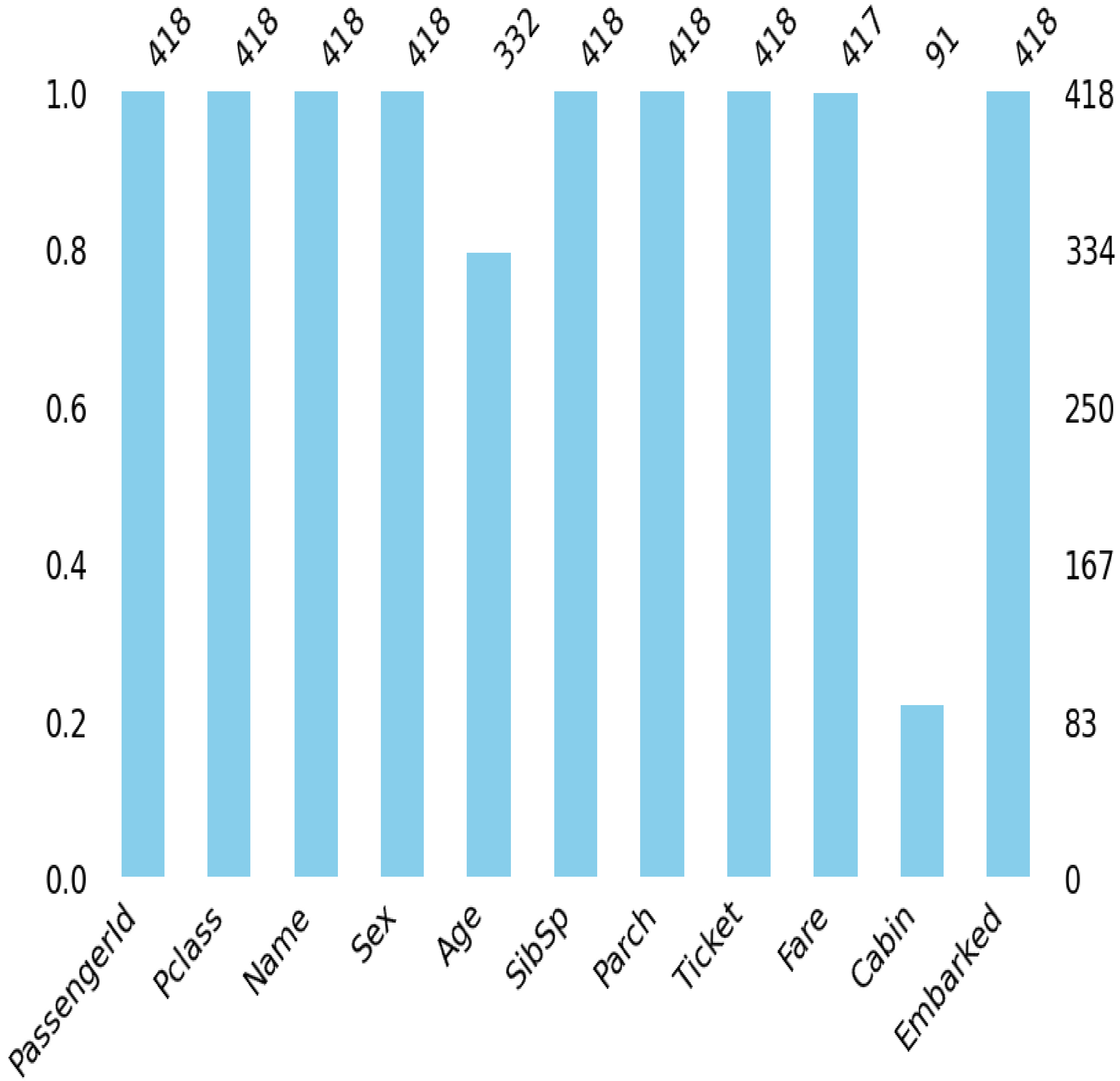
```
msno.bar(train,figsize=(10,6),color="skyblue")
```

```
plt.show()
```




In [14]:

```
msno.bar(test,figsize=(10,6),color="skyblue")

plt.show()
```

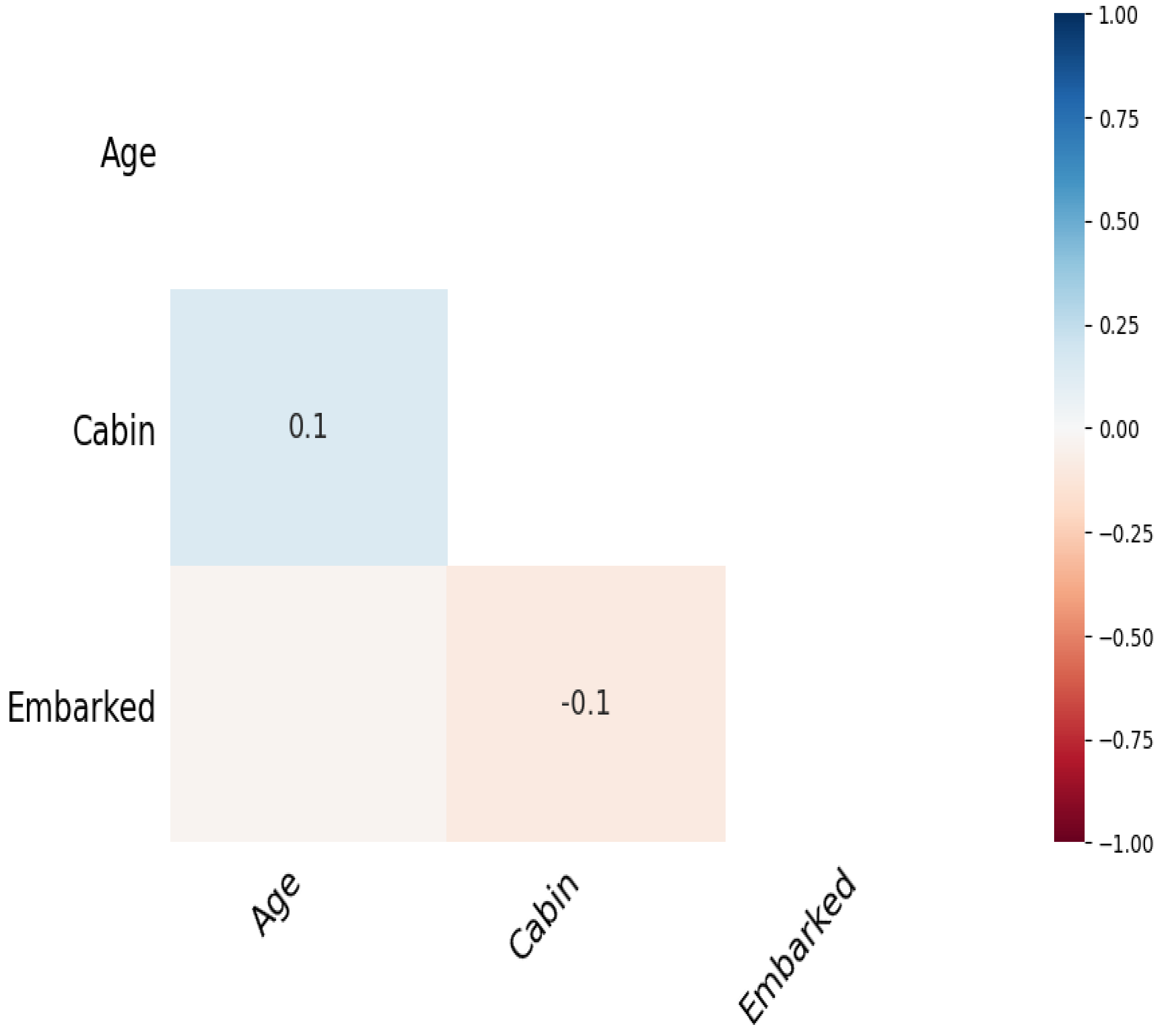



## Heatmap

The missingno correlation heatmap measures nullity correlation: how strongly the presence or absence of one variable affects the presence of another:

In [15]:

```
msno.heatmap(train,figsize=(10,6))

plt.show()
```

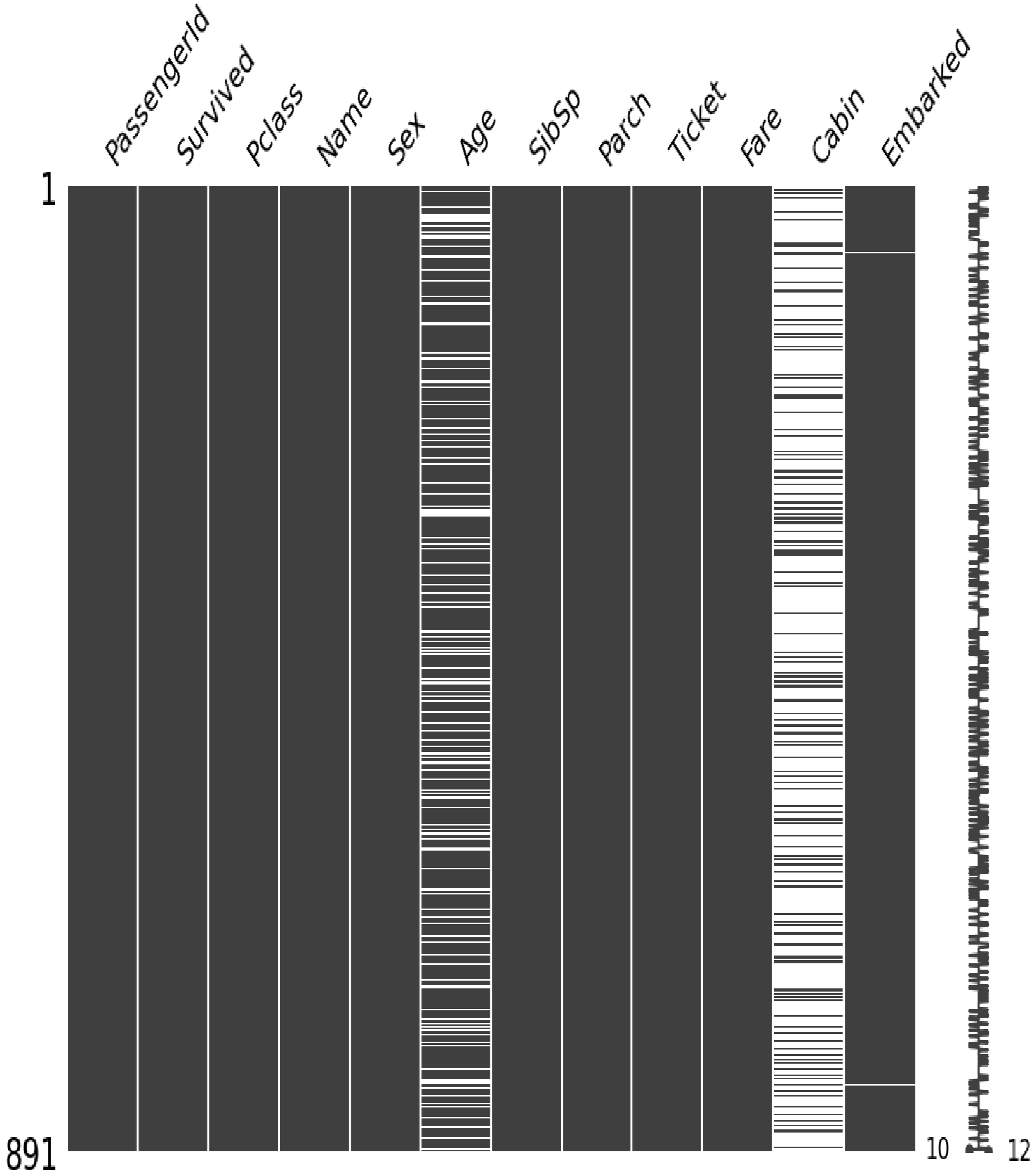



## Matrix:

Visualising missing values for a sample of 150 Using this matrix you can very quickly find the pattern of missingness in the dataset.

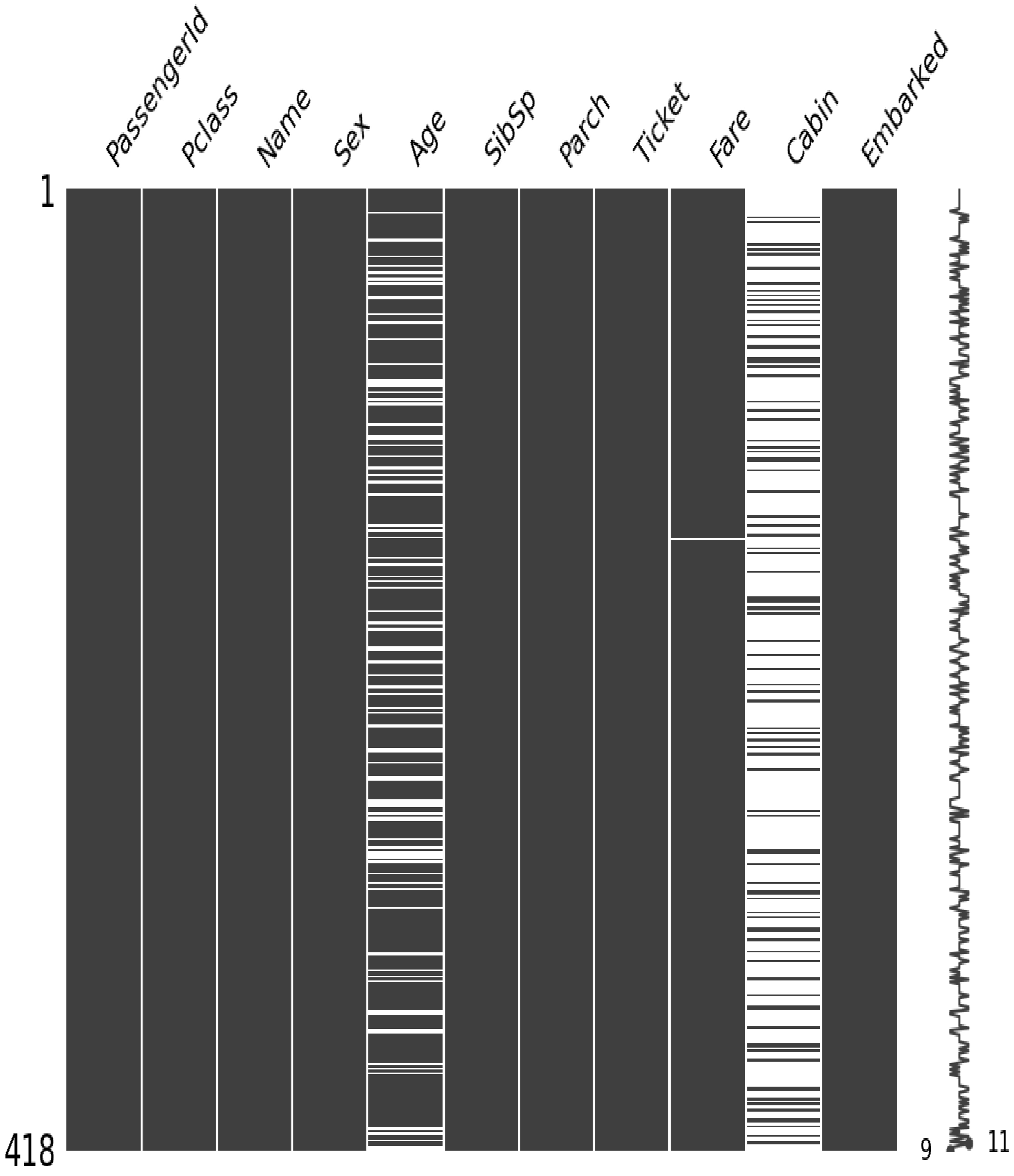
In [16]:

```
msno.matrix(train,figsize=(12,8))

plt.show()
```




In [17]:

```
msno.matrix(test,figsize=(12,8))

plt.show()
```




Replacing With Mean/Median/mode

MEAN: Suitable for continuous data without outliers MEDIAN : Suitable for continuous data with outliers Mode: For categorical feature we can select to fill in the missing values with the most common value(mode) as illustrated below.

- We are going to deal missing value(in **Age**) has numeric data by replace its **median value**

In [18]:

```
train['Age'].fillna(train['Age'].median(),inplace=True)

test['Age'].fillna(train['Age'].median(),inplace=True)
```

In [19]:

```
train['Age']
```

Out[19]:

```
0      22.0
1      38.0
2      26.0
3      35.0
4      35.0
       ...
886    27.0
887    19.0
888    28.0
889    26.0
890    32.0
Name: Age, Length: 891, dtype: float64
```

- We are going to deal missing value(in **Cabin** & **Embarked**) has categorical data by replace its by new category ie. 'unknown'

In [20]:

```
train['Cabin'].unique()
```

Out[20]:

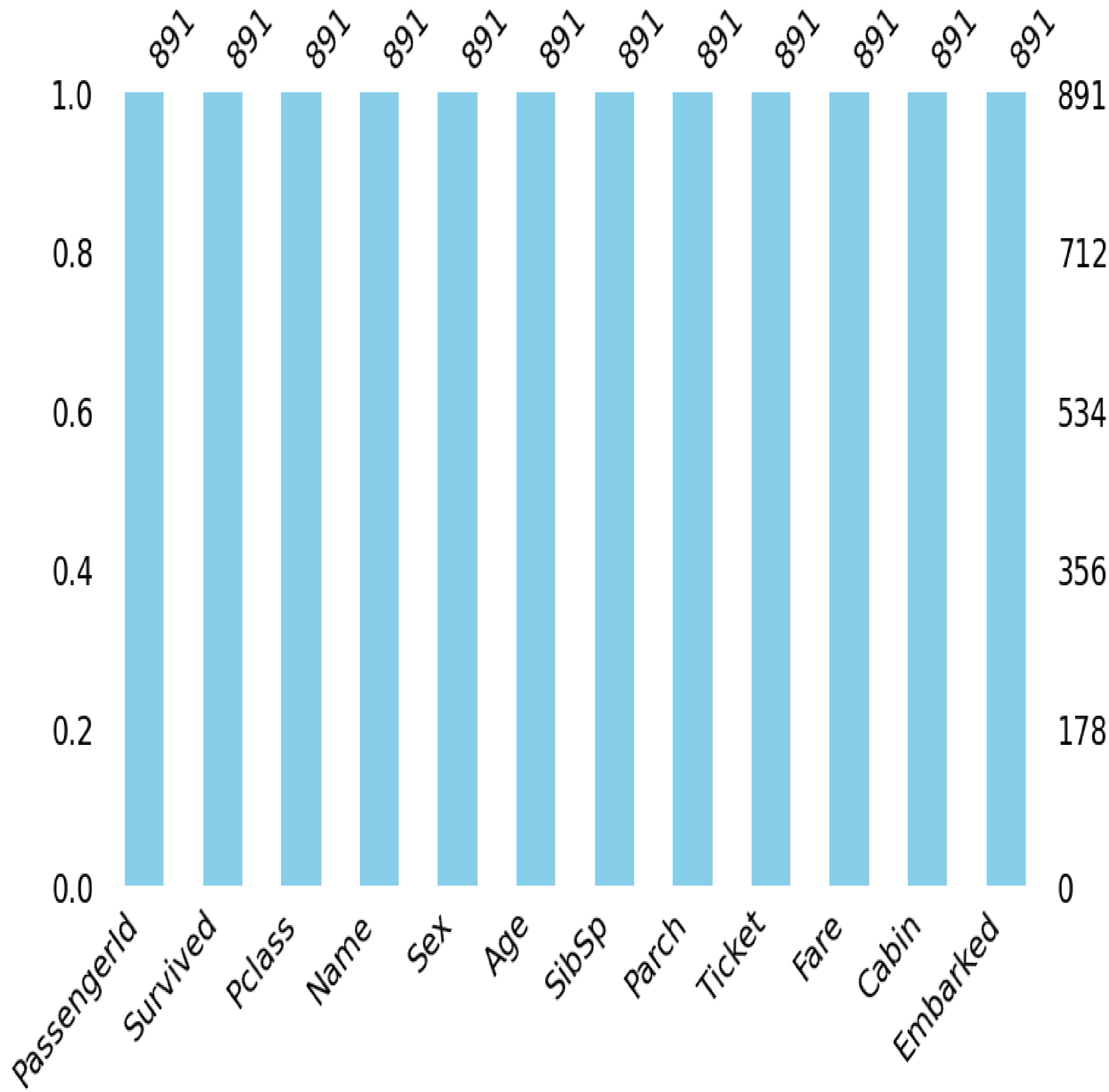
```
array([nan, 'C85', 'C123', 'E46', 'G6', 'C103', 'D56', 'A6',
       'C23 C25 C27', 'B78', 'D33', 'B30', 'C52', 'B28', 'C83', 'F33',
       'F G73', 'E31', 'A5', 'D10 D12', 'D26', 'C110', 'B58 B60', 'E101',
       'F E69', 'D47', 'B86', 'F2', 'C2', 'E33', 'B19', 'A7', 'C49', 'F4',
       'A32', 'B4', 'B80', 'A31', 'D36', 'D15', 'C93', 'C78', 'D35',
       'C87', 'B77', 'E67', 'B94', 'C125', 'C99', 'C118', 'D7', 'A19',
       'B49', 'D', 'C22 C26', 'C106', 'C65', 'E36', 'C54',
       'B57 B59 B63 B66', 'C7', 'E34', 'C32', 'B18', 'C124', 'C91', 'E40',
       'T', 'C128', 'D37', 'B35', 'E50', 'C82', 'B96 B98', 'E10', 'E44',
       'A34', 'C104', 'C111', 'C92', 'E38', 'D21', 'E12', 'E63', 'A14',
       'B37', 'C30', 'D20', 'B79', 'E25', 'D46', 'B73', 'C95', 'B38',
       'B39', 'B22', 'C86', 'C70', 'A16', 'C101', 'C68', 'A10', 'E68',
       'B41', 'A20', 'D19', 'D50', 'D9', 'A23', 'B50', 'A26', 'D48',
       'E58', 'C126', 'B71', 'B51 B53 B55', 'D49', 'B5', 'B20', 'F G63',
       'C62 C64', 'E24', 'C90', 'C45', 'E8', 'B101', 'D45', 'C46', 'D30',
       'E121', 'D11', 'E77', 'F38', 'B3', 'D6', 'B82 B84', 'D17', 'A36',
       'B102', 'B69', 'E49', 'C47', 'D28', 'E17', 'A24', 'C50', 'B42',
       'C148'], dtype=object)
```

In [21]:

```
train['Cabin'].fillna('Unknown',inplace=True)

train['Embarked'].fillna('Unknown',inplace=True)

test['Cabin'].fillna('Unknown',inplace=True)

test['Fare'].fillna(train['Fare'].median(),inplace=True)
```

In [22]:

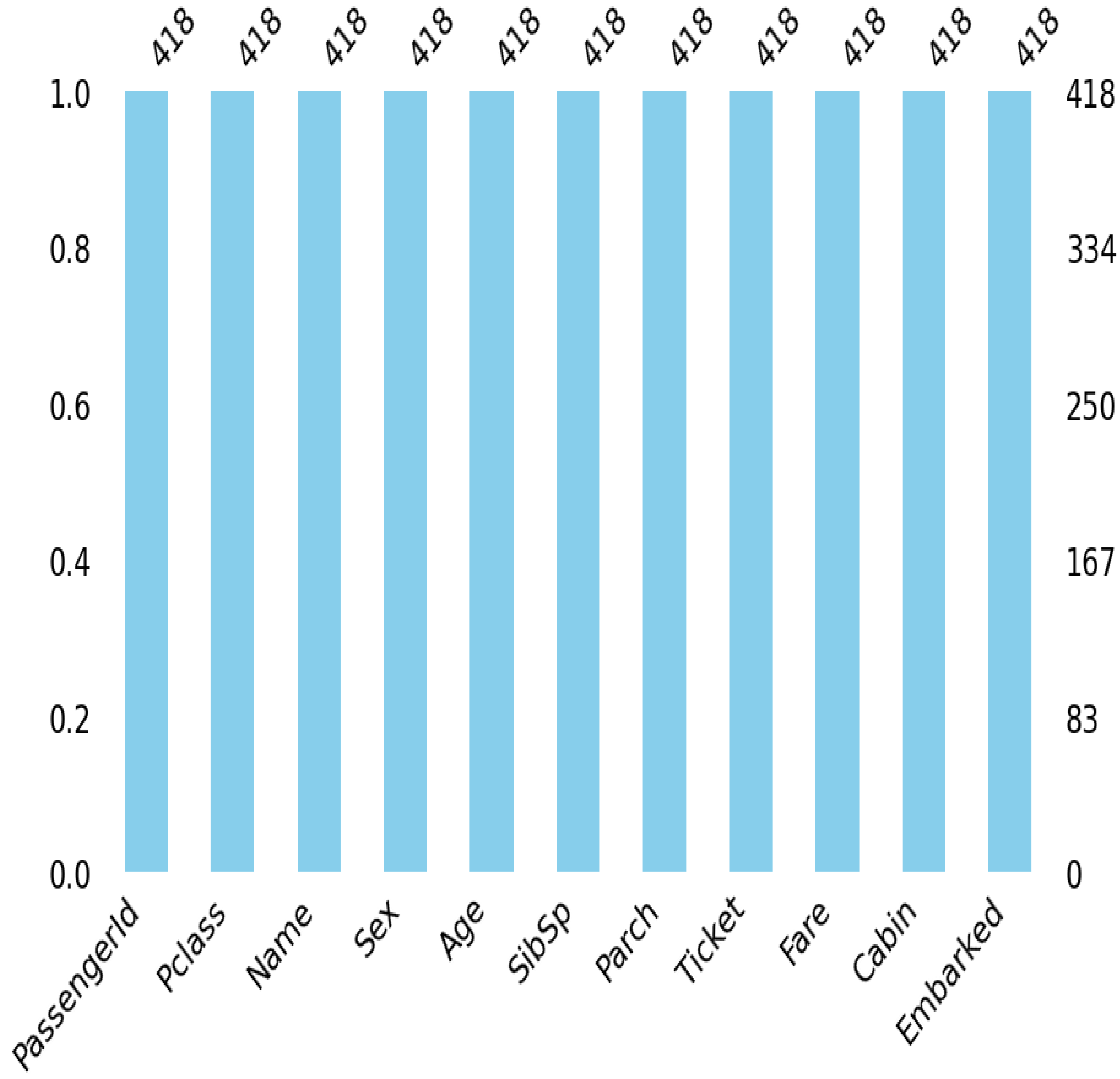
```
msno.bar(train,figsize=(10,6),color="skyblue")

plt.show()
```




As we see their is not any missing value

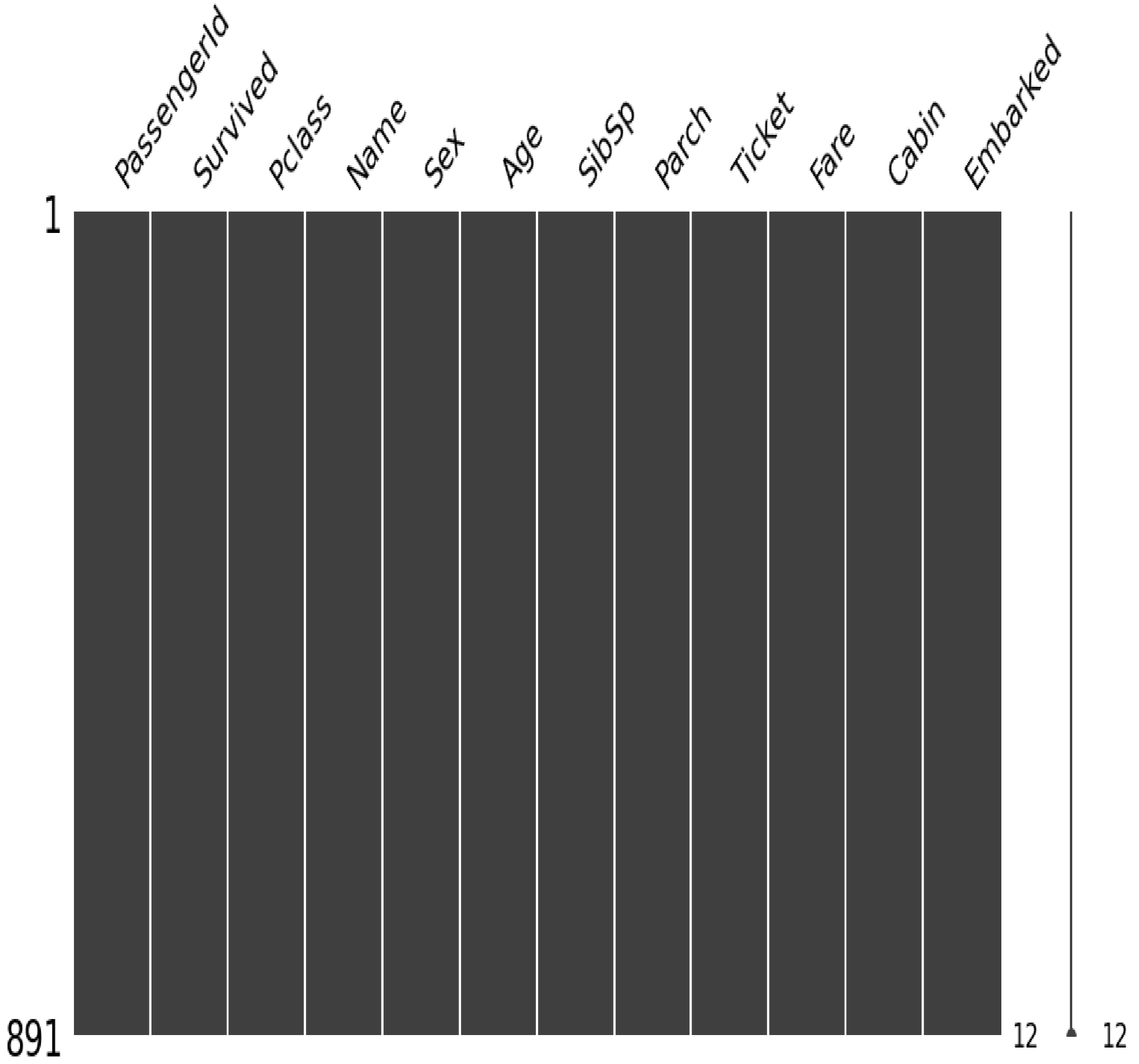
In [23]:

```
msno.bar(test,figsize=(10,6),color="skyblue")

plt.show()
```




In [24]:

```
msno.matrix(train,figsize=(12,6))

plt.show()
```




## Exploratory data analysis

Exploratory data analysis (EDA) is an approach to analyzing data sets to summarize their main characteristics, often with visual methods.

### 1. Survivals( Survived (1) or died (0))

In [25]:

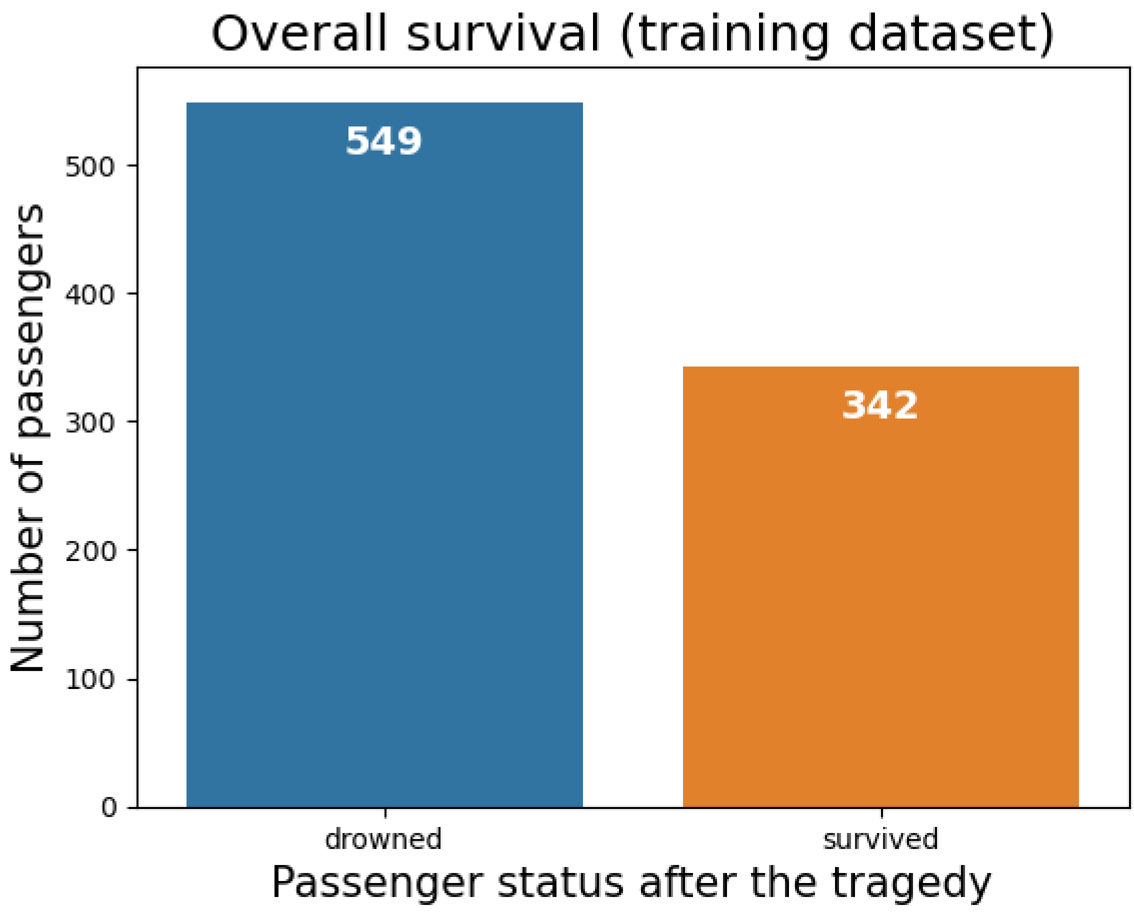
```
train['Survived'].value_counts(normalize=True)
```

Out[25]:

```
0    0.616162

1    0.383838

Name: Survived, dtype: float64
```

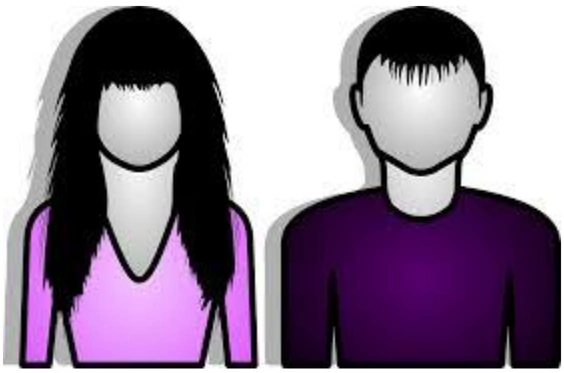
In [26]:

```
sns.countplot(x='Survived',data=train)

plt.xticks( np.arange(2), ['drowned', 'survived'] )

plt.title('Overall survival (training dataset)',fontsize= 18)

# set x label

plt.xlabel('Passenger status after the tragedy',fontsize = 15)

# set y label

plt.ylabel('Number of passengers',fontsize = 15)

labels = (train['Survived'].value_counts())

for i, v in enumerate(labels):

    plt.text(i, v-40, str(v), horizontalalignment = 'center', size = 14, color = 'w', fontweight = 'bold')



plt.show()
```




- We have 891 passengers in train dataset, 549 (61,6%) of them drowned and only 342 (38,4%) survived.
- more people died than survived (38% survived)

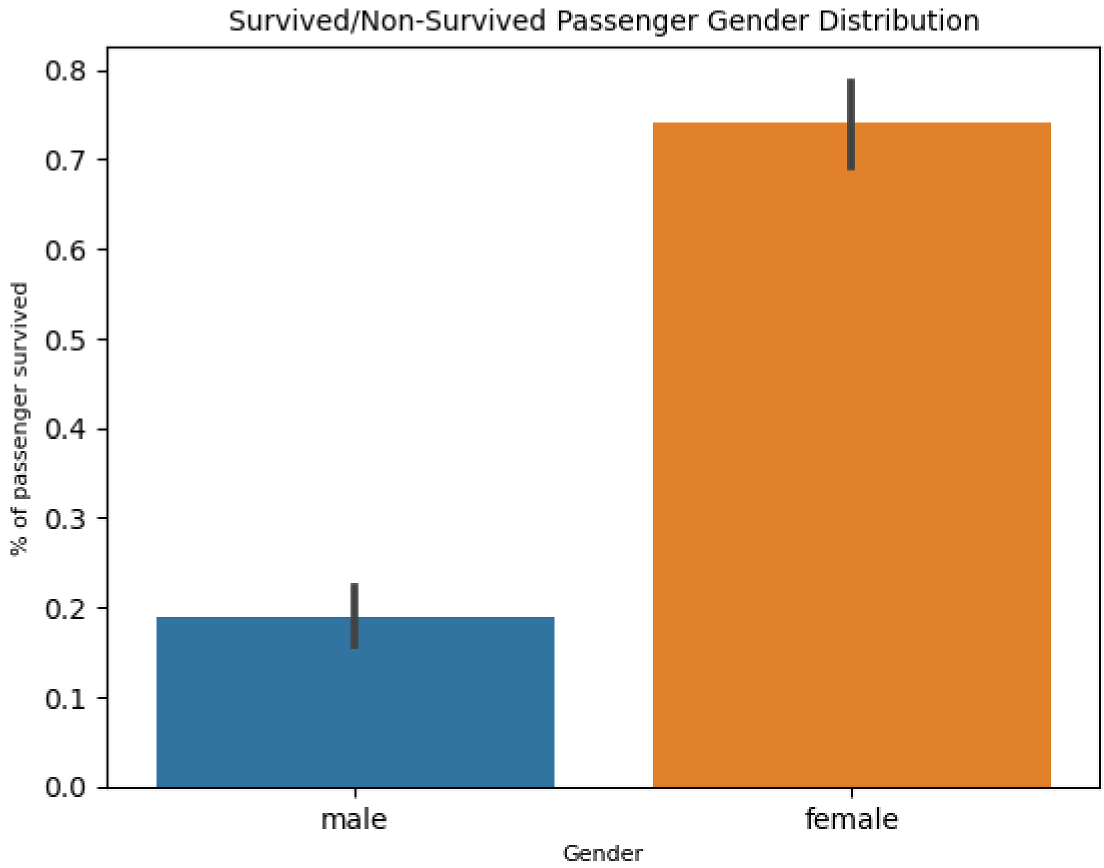
## 1.1 Sex



In [27]:

```
sns.barplot(x = "Sex", y = "Survived", data=train)
```

```
plt.title("Survived/Non-Survived Passenger Gender Distribution", fontsize =10)

labels = ['Female', 'Male']

plt.ylabel("% of passenger survived", fontsize = 8)

plt.xlabel("Gender",fontsize = 8)

plt.show()
```




In [28]:

```
print("% of women survived: " , train[train.Sex == 'female'].Survived.sum()/train[train.Sex ==
'female'].Survived.count())

print("% of men survived:   " , train[train.Sex == 'male'].Survived.sum()/train[train.Sex ==
'male'].Survived.count())
```

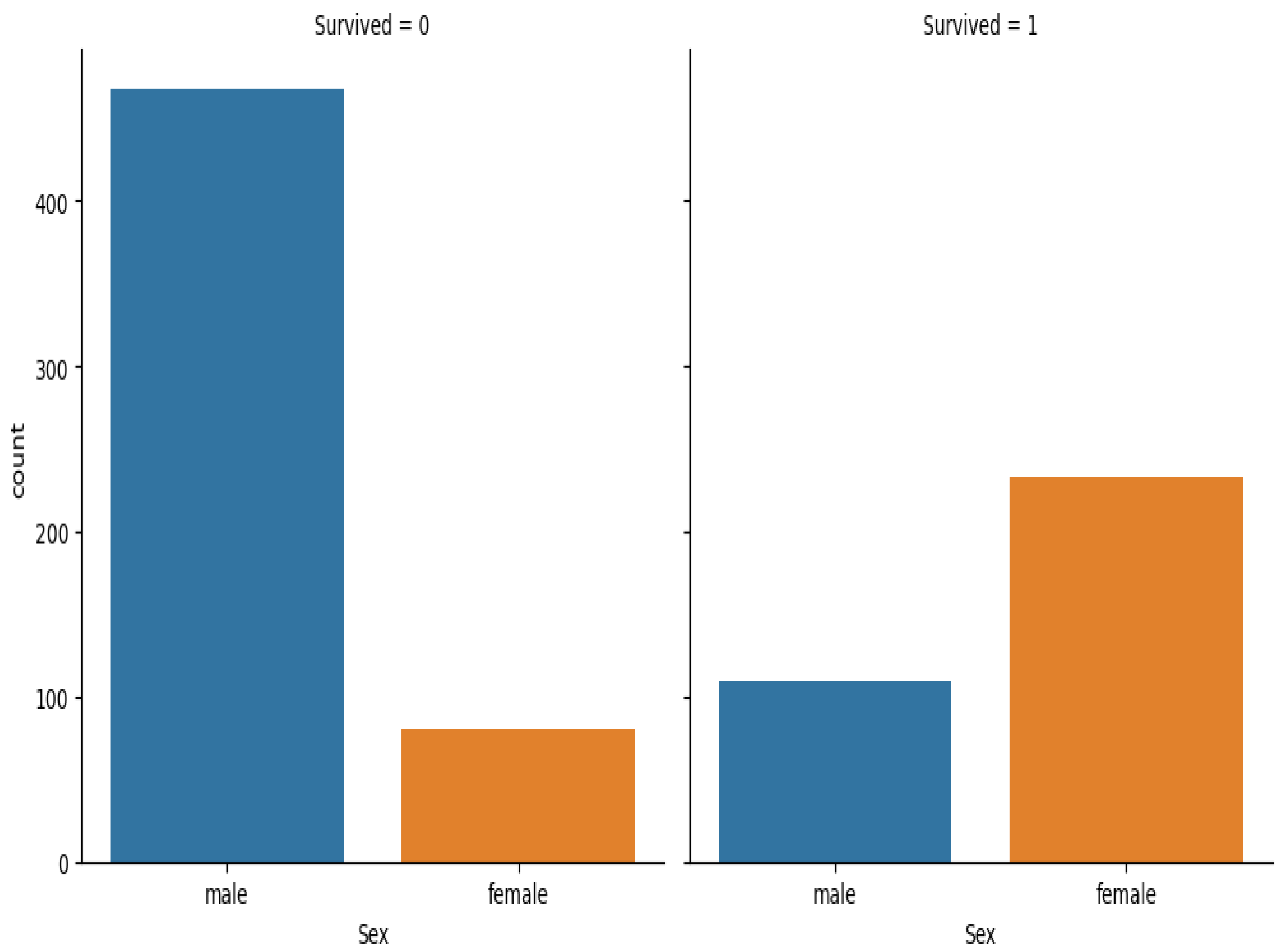
% of women survived:  0.7420382165605095

% of men survived:    0.18890814558058924

- As predicted, females have a much higher chance of survival than males.

In [29]:

```
sns.catplot(x='Sex', col='Survived', kind='count', data=train)

plt.show()
```




In [30]:

```
train.groupby(['Survived','Sex']).count()
```

Out[30]:

| | | PassengerId | Pclass | Name | Age | SibSp | Parch | Ticket | Fare | Cabin | Embarked |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Survived | Sex | | | | | | | | | | |
| 0 | female | 81 | 81 | 81 | 81 | 81 | 81 | 81 | 81 | 81 | 81 |
| | male | 468 | 468 | 468 | 468 | 468 | 468 | 468 | 468 | 468 | 468 |
| 1 | female | 233 | 233 | 233 | 233 | 233 | 233 | 233 | 233 | 233 | 233 |
| | male | 109 | 109 | 109 | 109 | 109 | 109 | 109 | 109 | 109 | 109 |

# 1.2 Pclss(Passenger’s class )

In [31]:

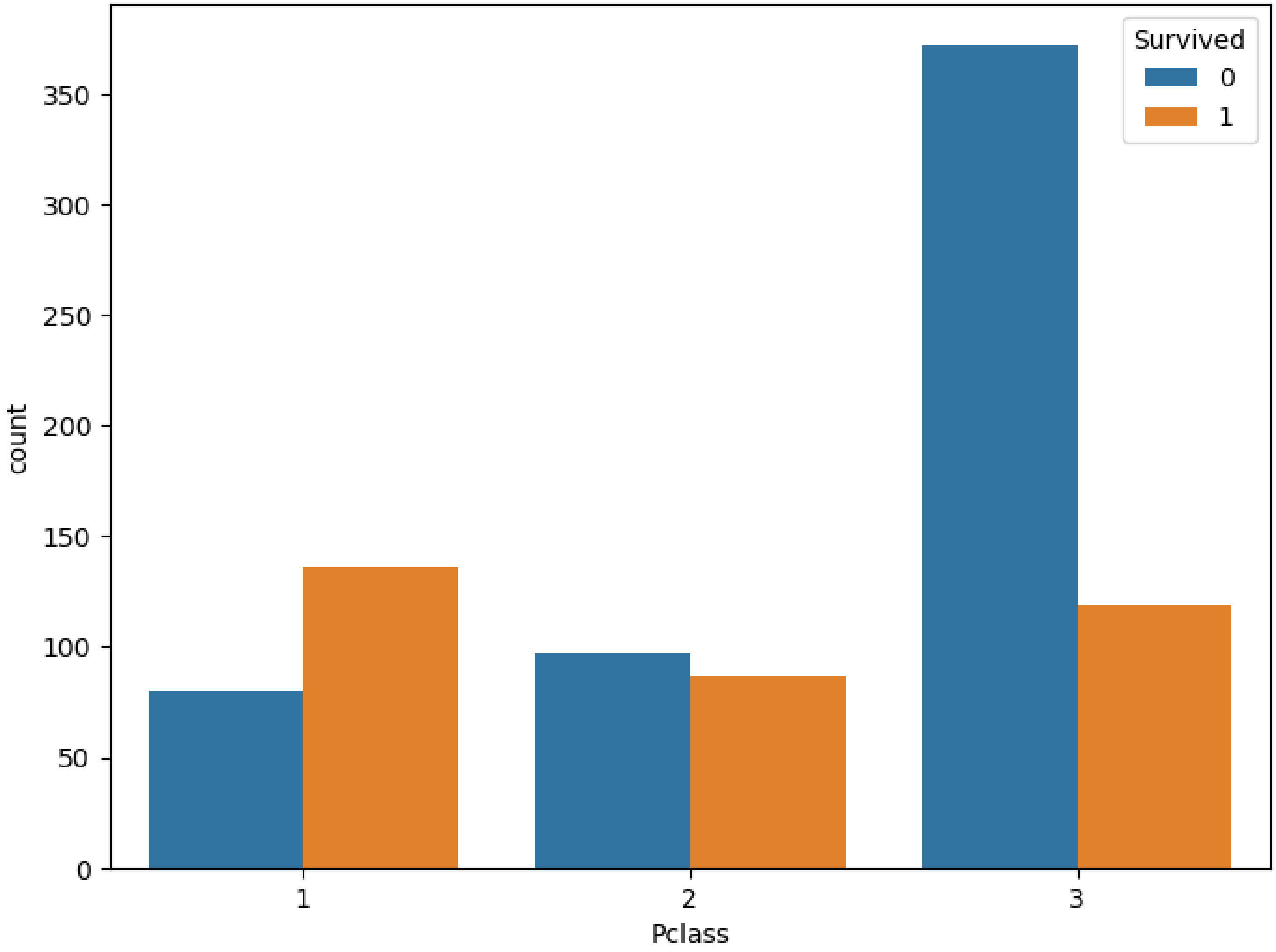
```
train['Pclass'].unique()
```

Out[31]:

array([3, 1, 2])

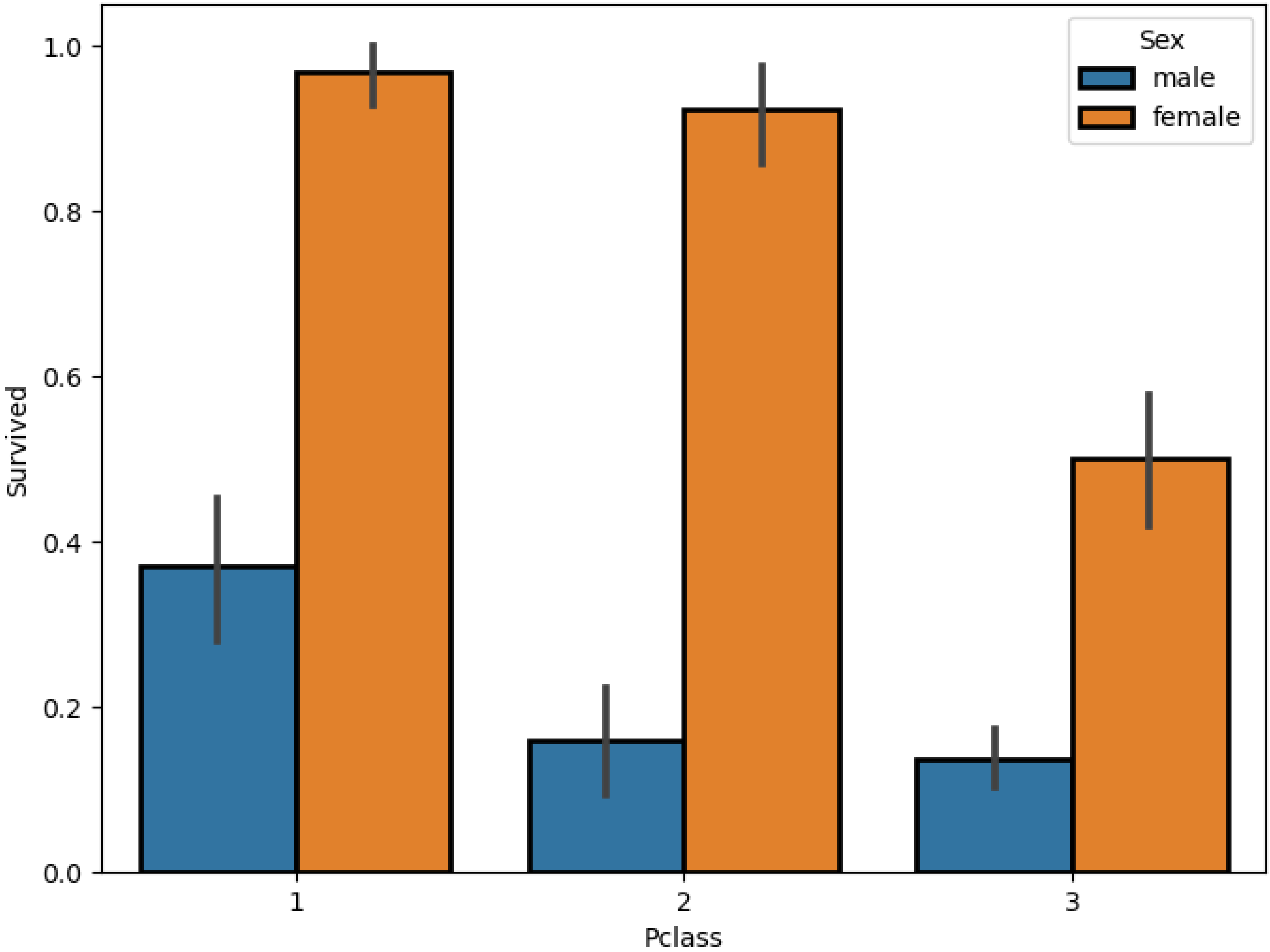
In [32]:

```
plt.subplots(figsize = (8,6))

sns.countplot('Pclass',hue='Survived',data=train)


plt.show()
```



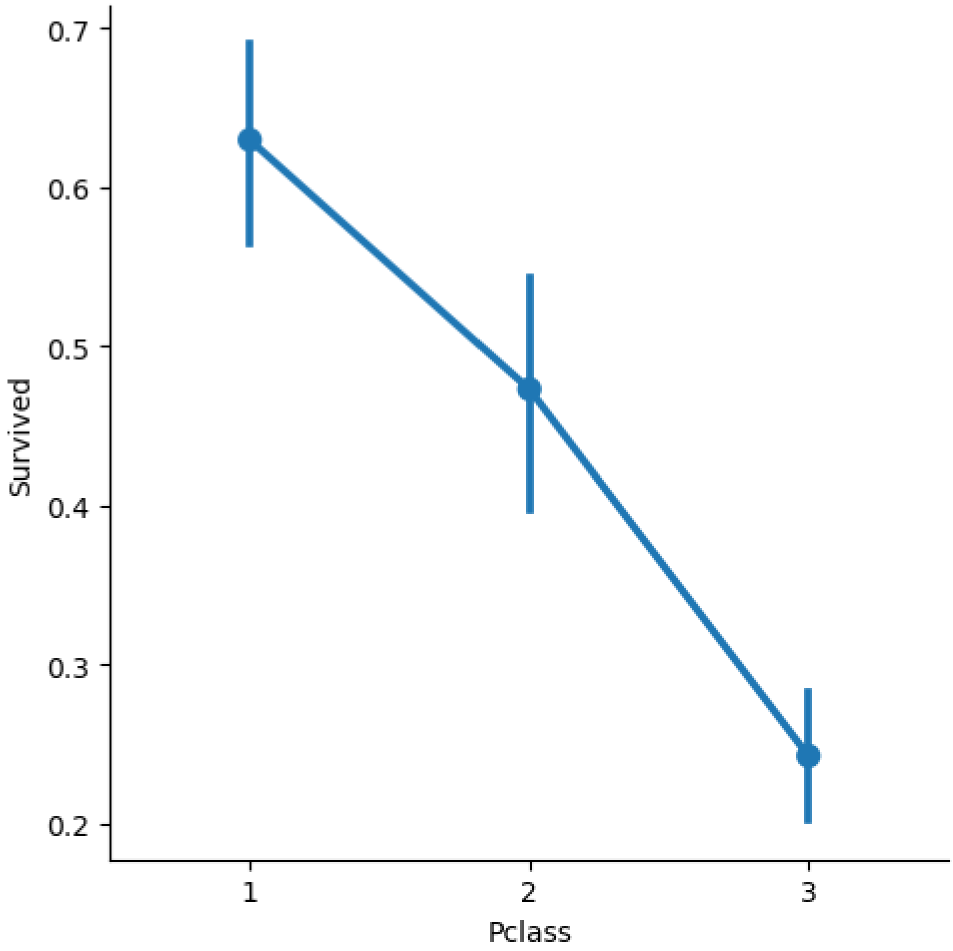

In [33]:

```
plt.subplots(figsize = (8,6))

sns.barplot('Pclass','Survived',data=train,hue='Sex',edgecolor=(0,0,0), linewidth=2)

plt.show()
```



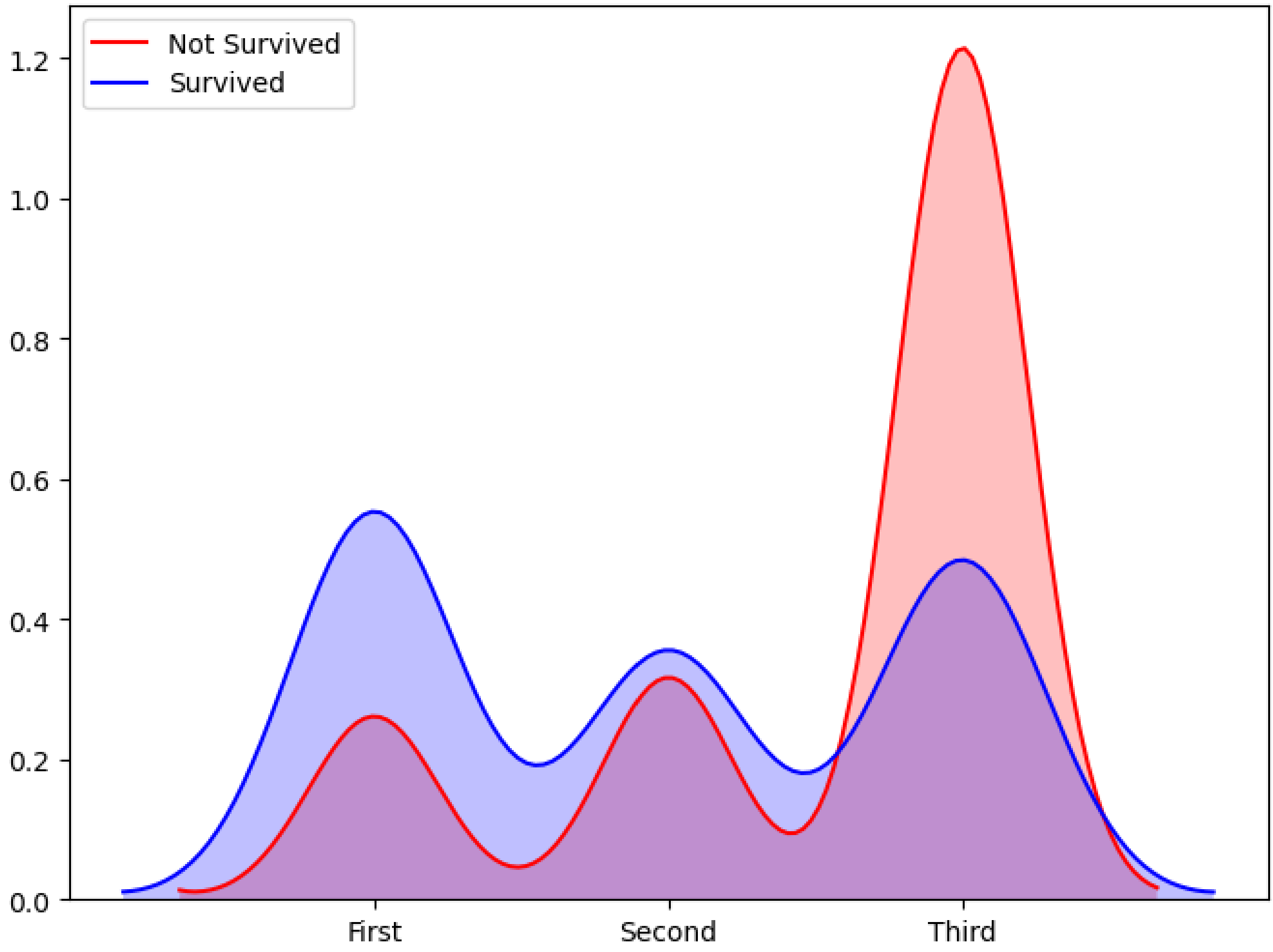

In [34]:

```
sns.catplot('Pclass','Survived', kind='point', data=train);
```




In [35]:

```
plt.subplots(figsize=(8,6))

sns.kdeplot(train.loc[(train['Survived'] == 0),'Pclass'],shade=True,color='r',label='Not Survived')

ax=sns.kdeplot(train.loc[(train['Survived'] == 1),'Pclass'],shade=True,color='b',label='Survived' )



labels = ['First', 'Second', 'Third']

plt.xticks(sorted(train.Pclass.unique()),labels)

plt.show()
```




In [36]:

```
print("% of survivals in")
print("Pclass=1 : ", train.Survived[train.Pclass == 1].sum()/train.Survived[train.Pclass == 1].count())
print("Pclass=2 : ", train.Survived[train.Pclass == 2].sum()/train.Survived[train.Pclass == 2].count())
print("Pclass=3 : ", train.Survived[train.Pclass == 3].sum()/train[train.Pclass == 3].Survived.count())
```

```
% of survivals in
Pclass=1 :  0.6296296296296297
Pclass=2 :  0.47282608695652173
Pclass=3 :  0.24236252545824846
```

So it clearly seems that,The survival of the people belong to 3rd class is very least. It looks like ...

- 63% first class passenger survived titanic tragedy, while
- 48% second class and
- only 24% third class passenger survived.

# 1.3 Age


## What was the age of passengers, how it correlated with chances to survive

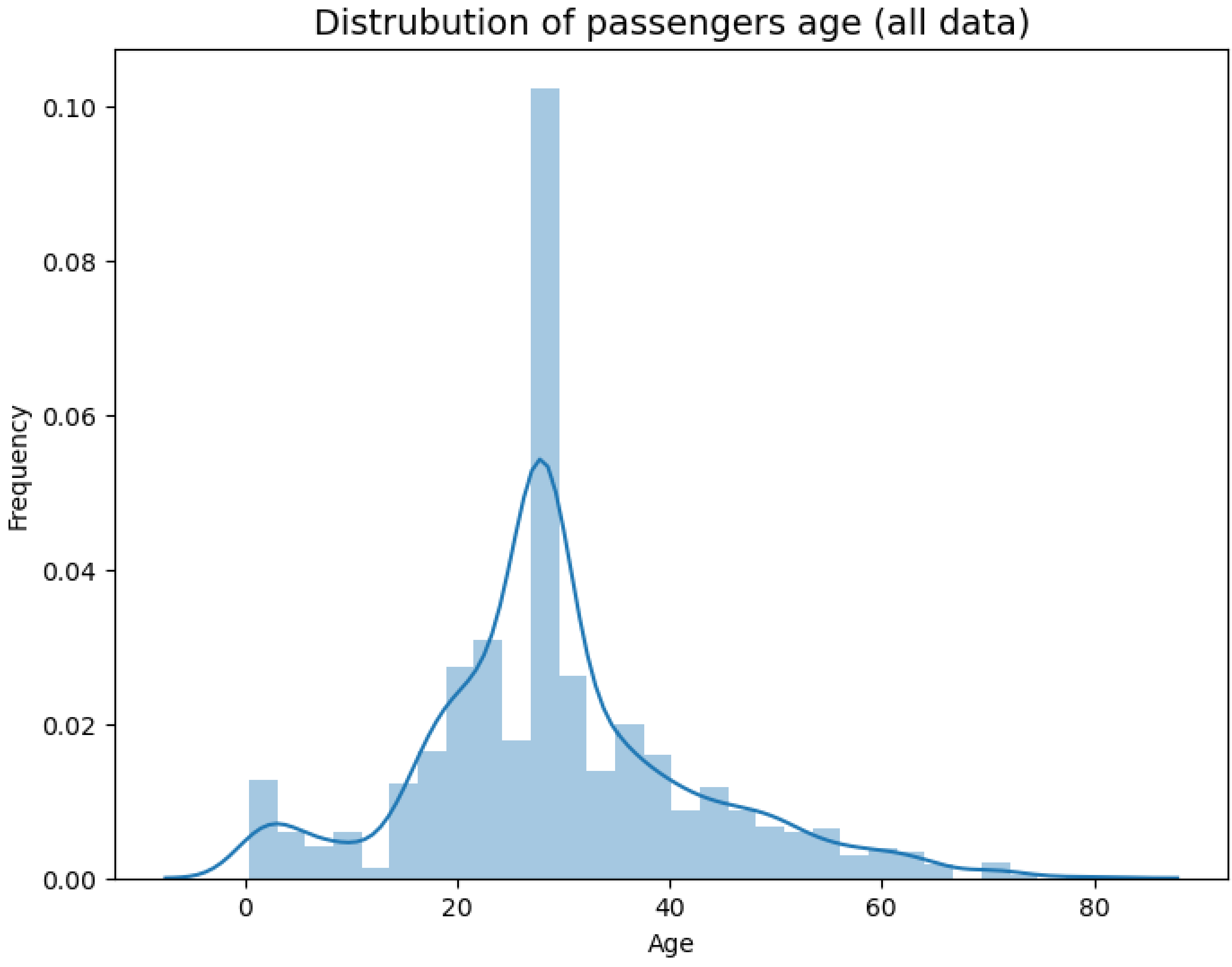
We have 263 missing values:

- 177 missing in the training dataset(**which had filled by age mean value**)
- 86 in the test dataset Overall age distribution (seaborn distplot) and descriptive statistics:

In [37]:

```
plt.subplots(figsize=(8,6))
```

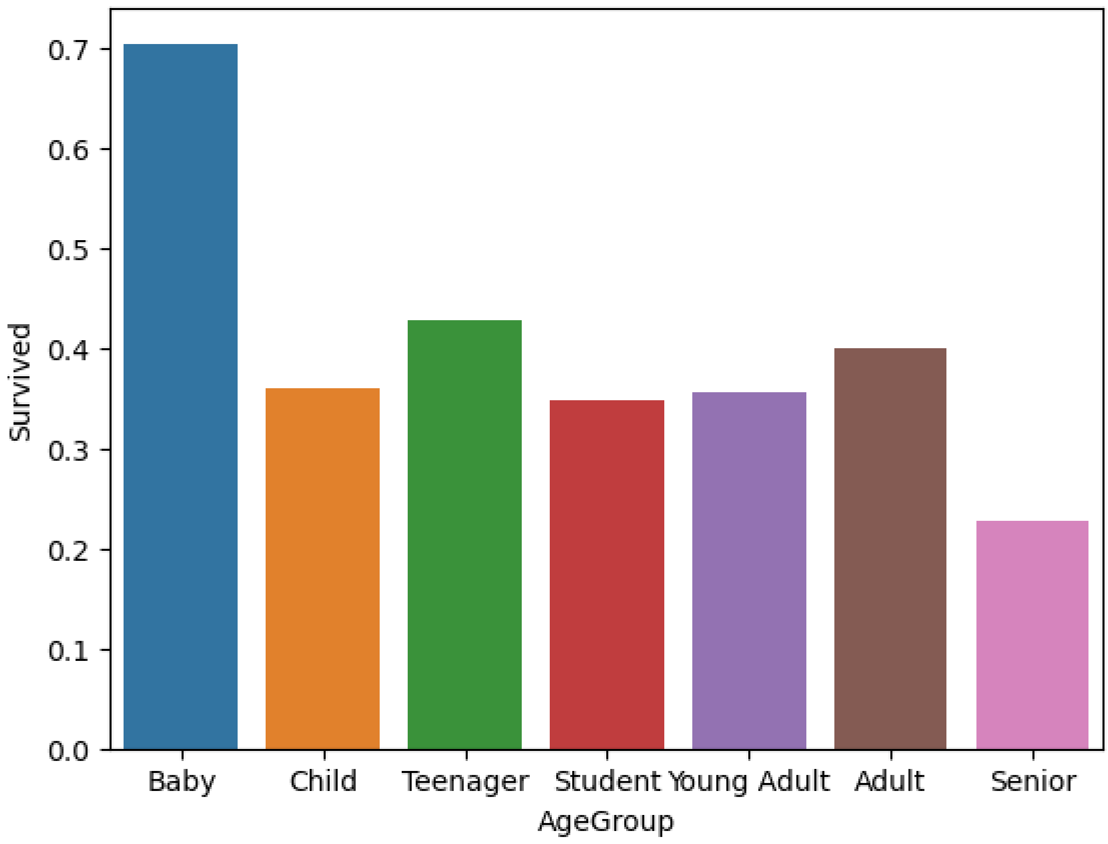
```
sns.distplot(train.Age)

plt.title('Distrubution of passengers age (all data)',fontsize= 14)

plt.xlabel('Age')

plt.ylabel('Frequency')

plt.show()
```




In [38]:

```
bins = [ 0, 5, 12, 18, 24, 35, 60, np.inf]

labels = ['Baby', 'Child', 'Teenager', 'Student', 'Young Adult', 'Adult', 'Senior']
```

```
train['AgeGroup'] = pd.cut(train["Age"], bins, labels = labels)

#draw a bar plot of Age vs. survival

sns.barplot(x="AgeGroup", y="Survived", data=train,ci=None)

plt.show()
```




- Babies are more likely to survive than any other age group.

# 1.4 Name

In [39]:

```
train.Name.head()
```

Out[39]:

```
0                          Braund, Mr. Owen Harris
1    Cumings, Mrs. John Bradley (Florence Briggs Th...
2                           Heikkinen, Miss. Laina
3         Futrelle, Mrs. Jacques Heath (Lily May Peel)
4                         Allen, Mr. William Henry
Name: Name, dtype: object
```

# linkcode

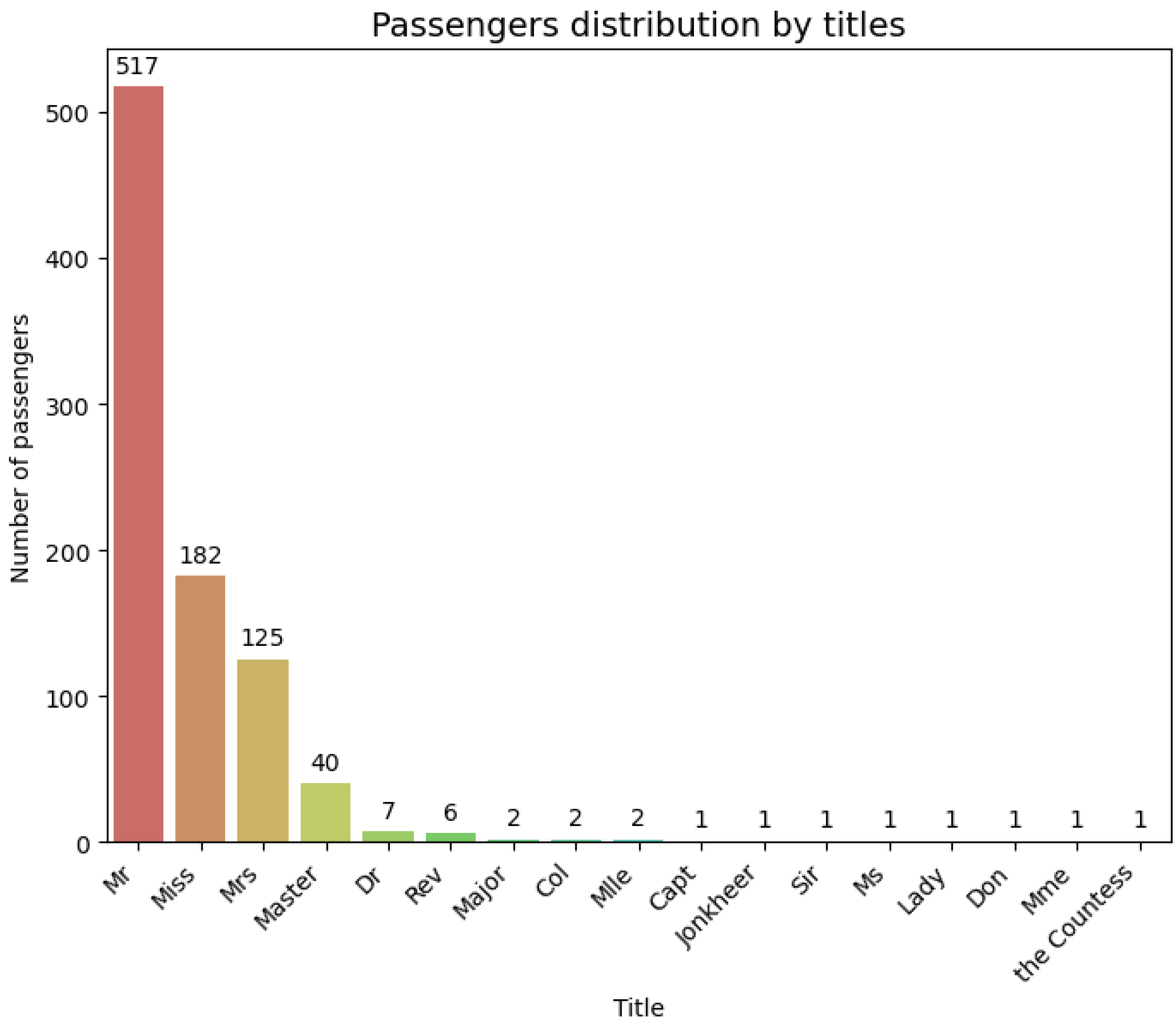
Each passenger Name value contains the title of the passenger which we can extract and discover. To create new variable "Title":

1. I am using method 'split' by comma to divide Name in two parts and save the second part
2. I am splitting saved part by dot and save first part of the result
3. To remove spaces around the title I am using 'split' method To visualize, how many passengers hold each title, I chose countplot.

In [40]:

```
train['Title'] = train['Name'].str.split(',', expand = True)[1].str.split('.', expand = True)[0].str.strip(' ')

test['Title'] = test['Name'].str.split(',', expand = True)[1].str.split('.', expand = True)[0].str.strip(' ')

plt.figure(figsize=(8, 6))

ax = sns.countplot( x = 'Title', data = train, palette = "hls", order = train['Title'].value_counts().index)

_ = plt.xticks(

    rotation=45,

    horizontalalignment='right',

    fontweight='light'

)



plt.title('Passengers distribution by titles',fontsize= 14)
```

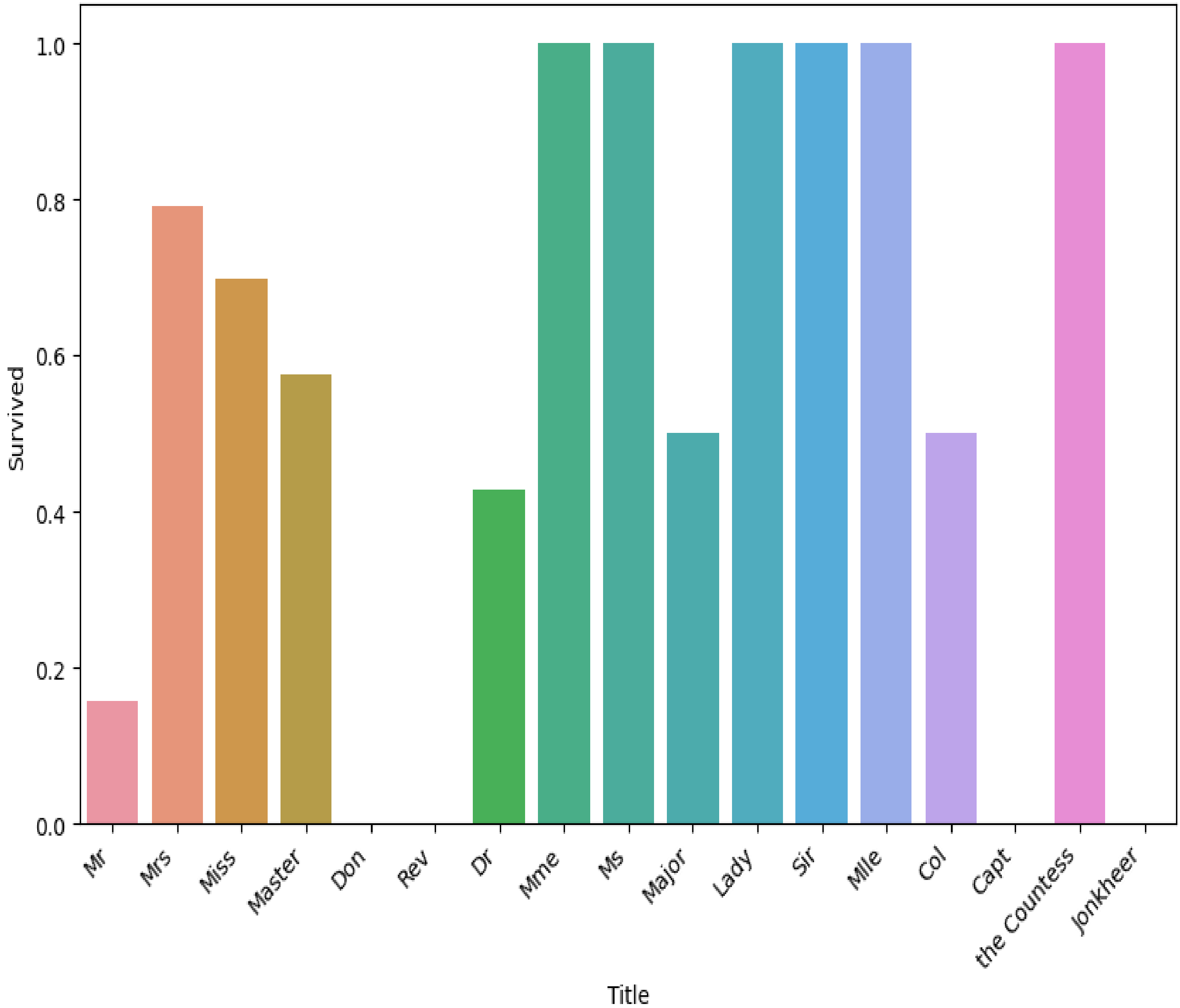
```
plt.ylabel('Number of passengers')


# calculate passengers for each category
labels = (train['Title'].value_counts())
# add result numbers on barchart
for i, v in enumerate(labels):
    ax.text(i, v+10, str(v), horizontalalignment = 'center', size = 10, color = 'black')


plt.show()
```



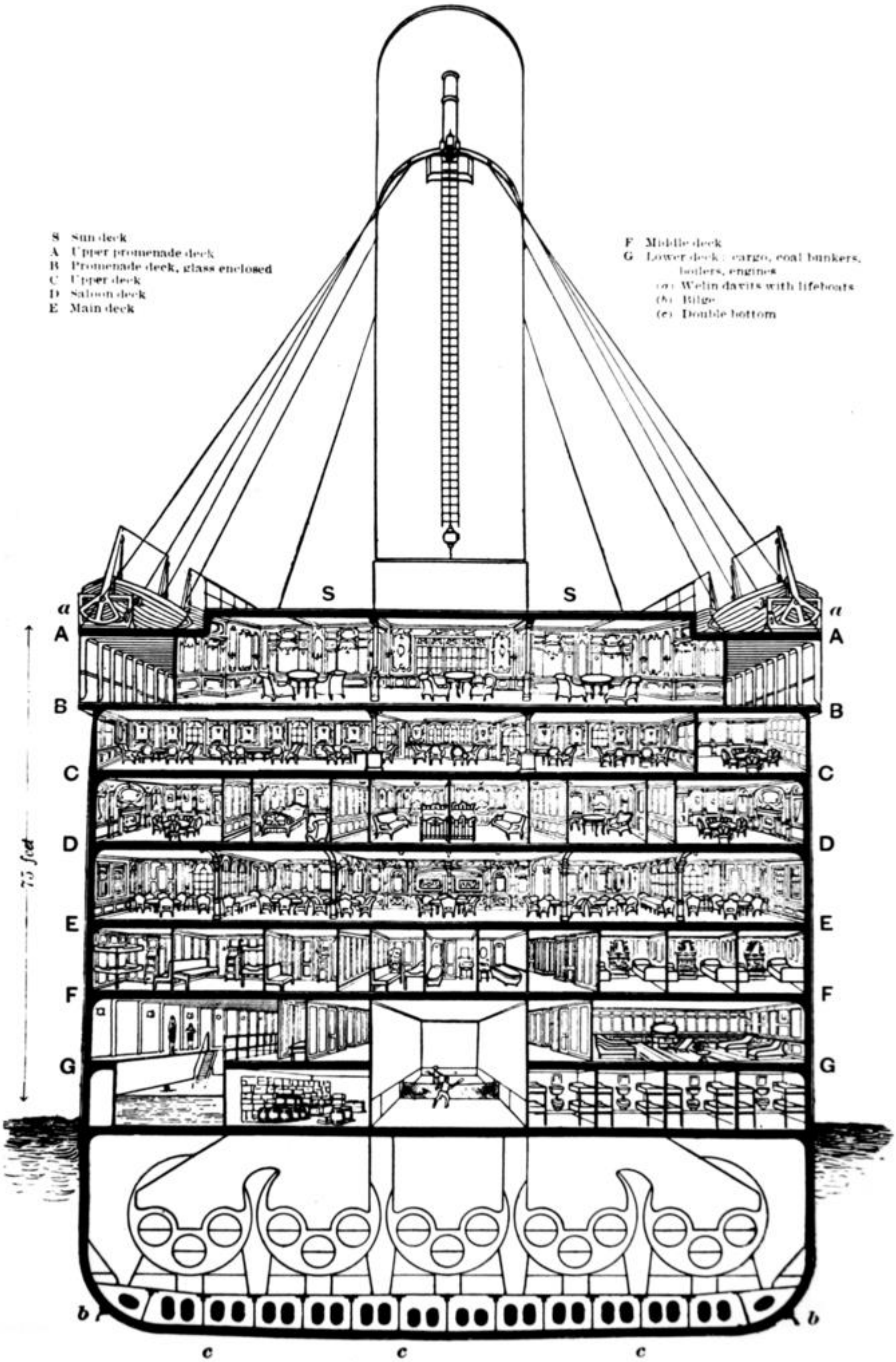

In [41]:

```
plt.figure(figsize=(10, 6))

sns.barplot(x="Title", y="Survived", data=train,ci=None)

plt.xticks(

    rotation=45,

    horizontalalignment='right',

    fontweight='light'

)
```

```
plt.show()
```




## 1.4 Cabin


S Sun deck
A Upper promenade deck
B Promenade deck, glass enclosed
C Upper deck
D Saloon deck
E Main deck
F Middle deck
G Lower deck: cargo, coal bunkers, boilers, engines
(a) Welin davits with lifeboats
(b) Bilge
(c) Double bottom
S
S
a
a
A
A
B
B
C
C
D
D
E
E
F
F
G
G
75 feet
b
b
c
c
c

In [42]:

```
train['Cabin']
```

Out[42]:

```
0      Unknown
1          C85
2      Unknown
3         C123
4      Unknown
        ...
886    Unknown
887        B42
888    Unknown
889       C148
890    Unknown
Name: Cabin, Length: 891, dtype: object
```

In [43]:

```
train['Cabin'].unique()
```

Out[43]:

```
array(['Unknown', 'C85', 'C123', 'E46', 'G6', 'C103', 'D56', 'A6',
       'C23 C25 C27', 'B78', 'D33', 'B30', 'C52', 'B28', 'C83', 'F33',
       'F G73', 'E31', 'A5', 'D10 D12', 'D26', 'C110', 'B58 B60', 'E101',
       'F E69', 'D47', 'B86', 'F2', 'C2', 'E33', 'B19', 'A7', 'C49', 'F4',
```

'A32', 'B4', 'B80', 'A31', 'D36', 'D15', 'C93', 'C78', 'D35',

'C87', 'B77', 'E67', 'B94', 'C125', 'C99', 'C118', 'D7', 'A19',

'B49', 'D', 'C22 C26', 'C106', 'C65', 'E36', 'C54',

'B57 B59 B63 B66', 'C7', 'E34', 'C32', 'B18', 'C124', 'C91', 'E40',

'T', 'C128', 'D37', 'B35', 'E50', 'C82', 'B96 B98', 'E10', 'E44',

'A34', 'C104', 'C111', 'C92', 'E38', 'D21', 'E12', 'E63', 'A14',

'B37', 'C30', 'D20', 'B79', 'E25', 'D46', 'B73', 'C95', 'B38',

'B39', 'B22', 'C86', 'C70', 'A16', 'C101', 'C68', 'A10', 'E68',

'B41', 'A20', 'D19', 'D50', 'D9', 'A23', 'B50', 'A26', 'D48',

'E58', 'C126', 'B71', 'B51 B53 B55', 'D49', 'B5', 'B20', 'F G63',

'C62 C64', 'E24', 'C90', 'C45', 'E8', 'B101', 'D45', 'C46', 'D30',

'E121', 'D11', 'E77', 'F38', 'B3', 'D6', 'B82 B84', 'D17', 'A36',

'B102', 'B69', 'E49', 'C47', 'D28', 'E17', 'A24', 'C50', 'B42',

'C148'], dtype=object)

- From the number of the cabin we can extract first letter, which will tell us about placement of the cabin on the ship!
- To the passengers without deck information I will imput U letter (as unknown).

In [44]:

```
train['deck']=train['Cabin'].str.split('',expand=True)[1]

test['deck']=test['Cabin'].str.split('',expand=True)[1]
```

In [45]:

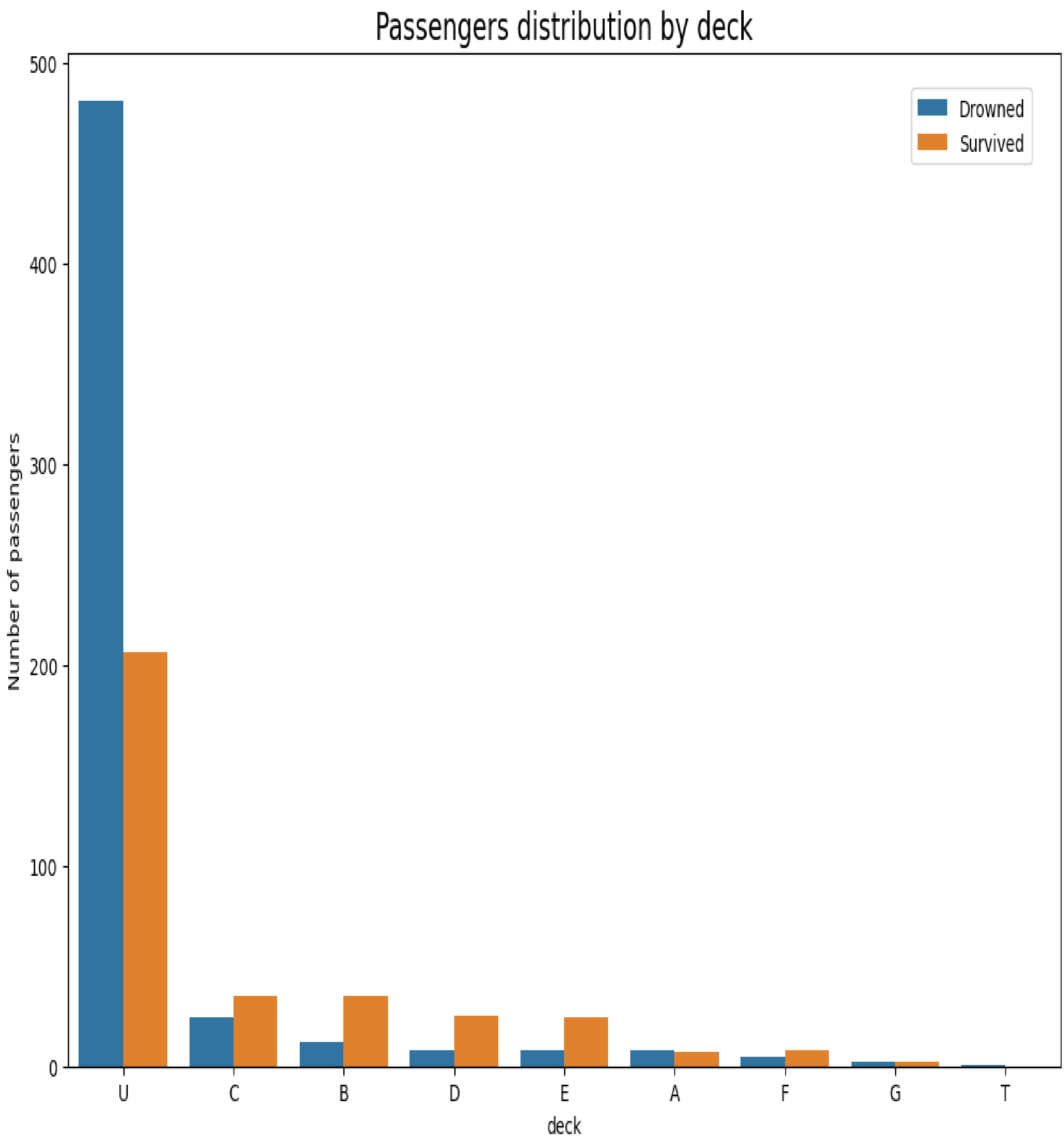
```
train['deck'].unique()
```

Out[45]:

```
array(['U', 'C', 'E', 'G', 'D', 'A', 'B', 'F', 'T'], dtype=object)
```

In [46]:

```
plt.figure(figsize=(12,8))

sns.countplot(x=train['deck'],data=train,hue='Survived',order = train['deck'].value_counts().index)

plt.title('Passengers distribution by deck',fontsize= 16)

plt.ylabel('Number of passengers')

plt.legend(( 'Drowned', 'Survived'), loc=(0.85,0.89))

plt.xticks(rotation = False)



plt.show()
```

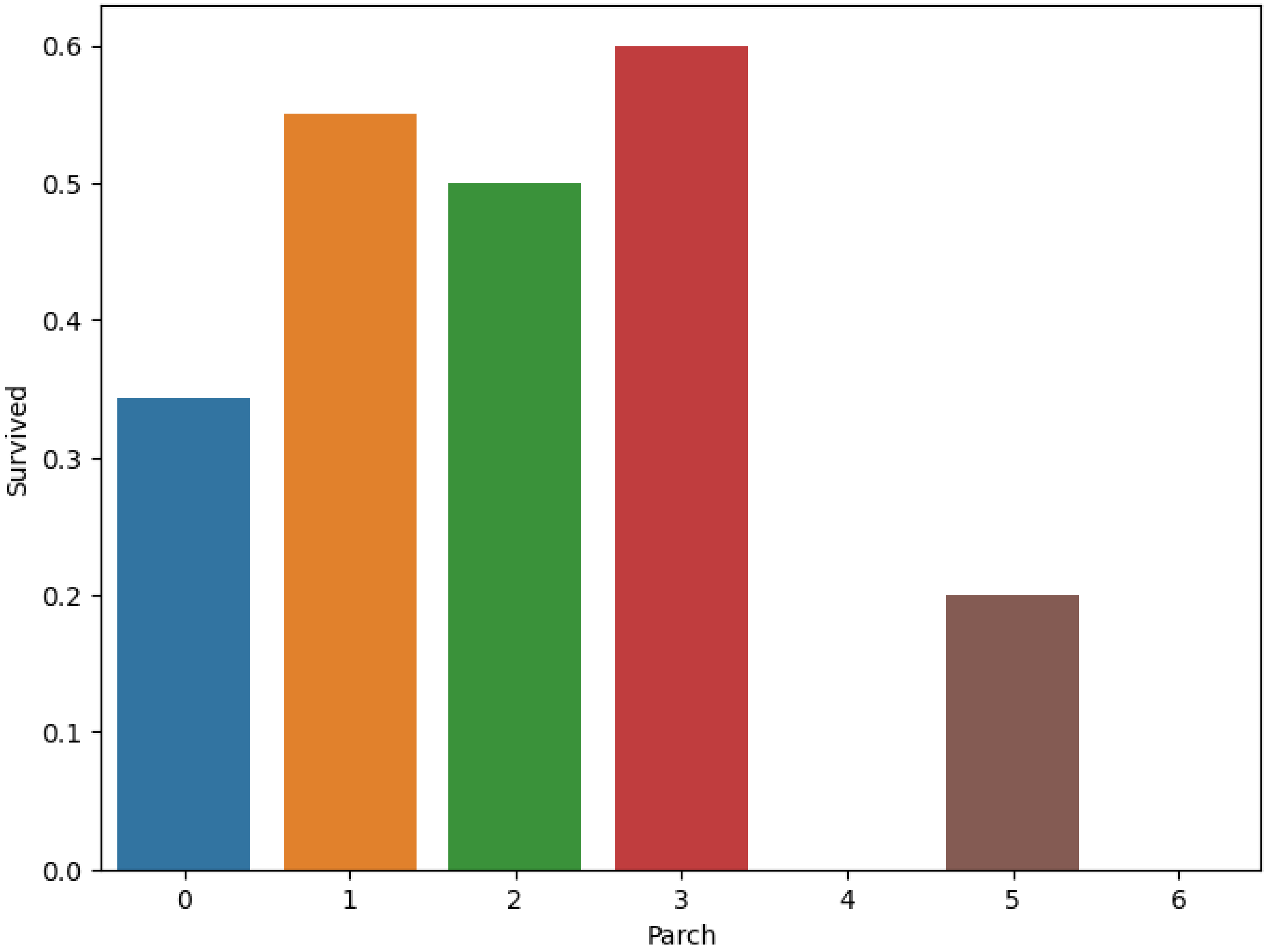



- Most passengers don't have cabin numbers ('U').
- The largest part of passengers with known cabin numbers were located on the 'C' deck . 'C' deck is fifth by a percentage of the survivor.
- The largest surviving rate (among passengers with known cabin numbers in training dataset) had passengers from deck 'D'.

## 1.5 Parch( Number of Parents/Children Aboard )

In [47]:

```
#draw a bar plot for Parch vs. survival
plt.figure(figsize=(8,6))
sns.barplot(x="Parch", y="Survived", data=train,ci=None)
plt.show()
```

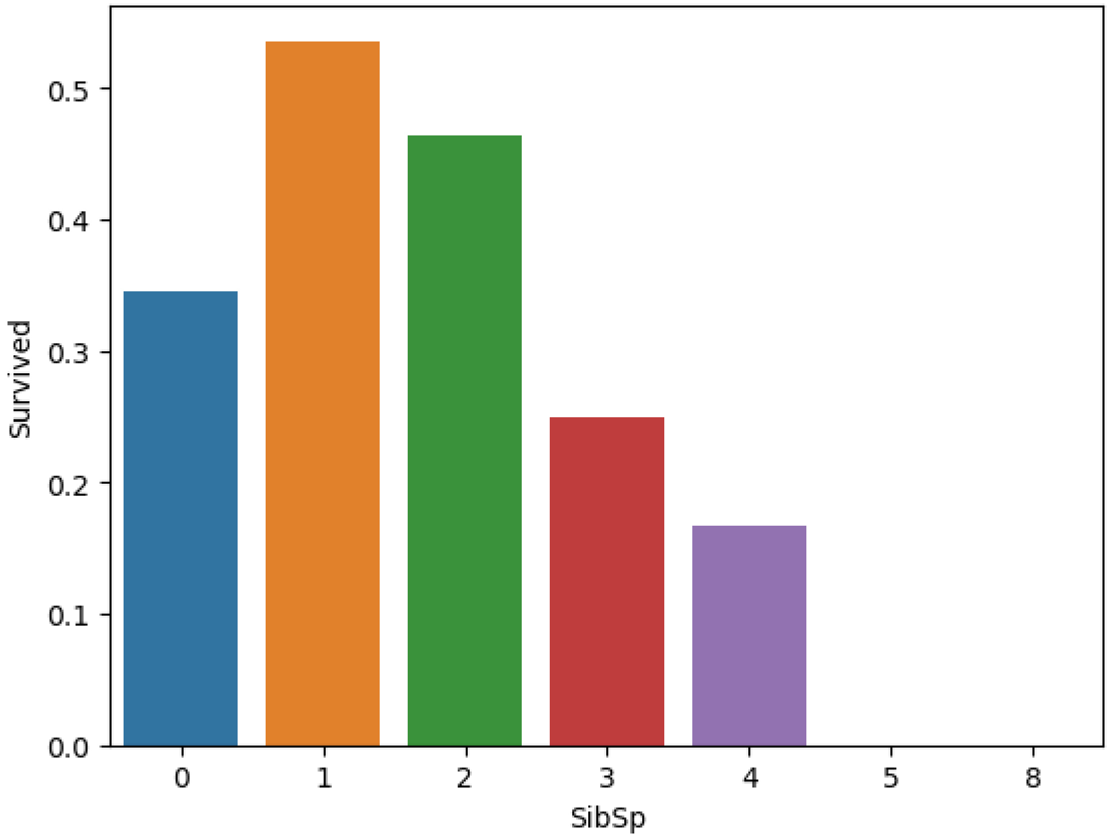



- People with less than four parents or children aboard are more likely to survive than those with four or more. Again, people traveling alone are less likely to survive than those with 1-3 parents or children.

# 1.6 SibSp( Number of Siblings/Spouses Aboard )

In [48]:

```
#draw a bar plot for SibSp vs. survival

sns.barplot(x="SibSp", y="Survived", data=train,ci=None)

plt.show()
```




In [49]:

```
train['SibSp'].sort_values().unique()
```

Out[49]:

```
array([0, 1, 2, 3, 4, 5, 8])
```

In [50]:

```
print("Percentage of SibSp = 0 who survived:", train["Survived"][train["SibSp"] == 0].value_counts(normalize = True)[1]*100)

print("Percentage of SibSp = 1 who survived:", train["Survived"][train["SibSp"] == 1].value_counts(normalize = True)[1]*100)

print("Percentage of SibSp = 2 who survived:", train["Survived"][train["SibSp"] == 2].value_counts(normalize = True)[1]*100)

print("Percentage of SibSp = 3 who survived:", train["Survived"][train["SibSp"] == 3].value_counts(normalize = True)[1]*100)
```

```
print("Percentage of SibSp = 4 who survived:", train["Survived"][train["SibSp"] ==
4].value_counts(normalize = True)[1]*100)
```

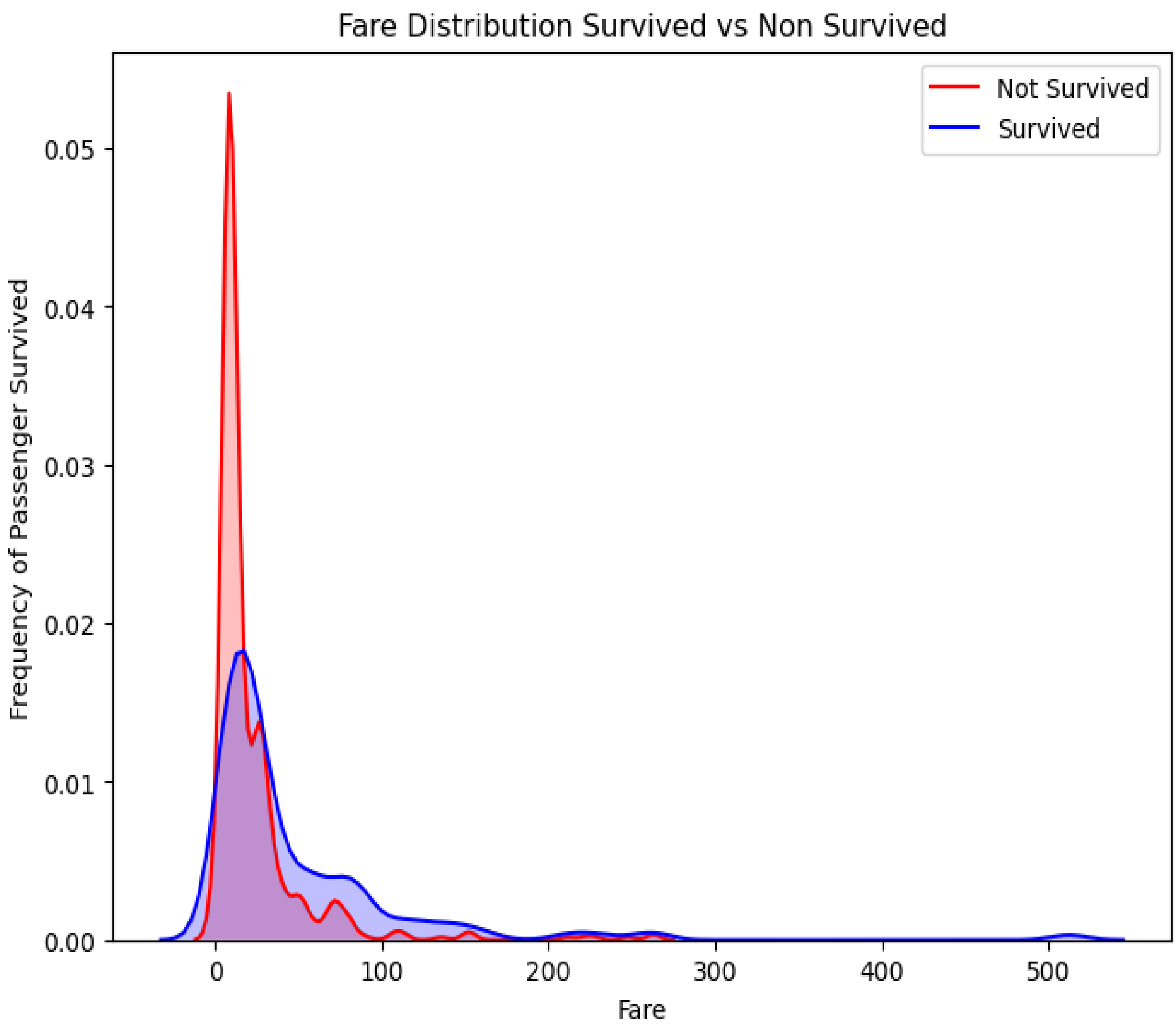
```
Percentage of SibSp = 0 who survived: 34.53947368421053

Percentage of SibSp = 1 who survived: 53.588516746411486

Percentage of SibSp = 2 who survived: 46.42857142857143

Percentage of SibSp = 3 who survived: 25.0

Percentage of SibSp = 4 who survived: 16.666666666666664
```

- In general, it's clear that people with more siblings or spouses aboard were less likely to survive. However, contrary to expectations, people with no siblings or spouses were less to likely to survive than those with one or two. (34.5% vs 53.4% vs. 46.4%)

# 1.7 Fare( Passenger Fare )

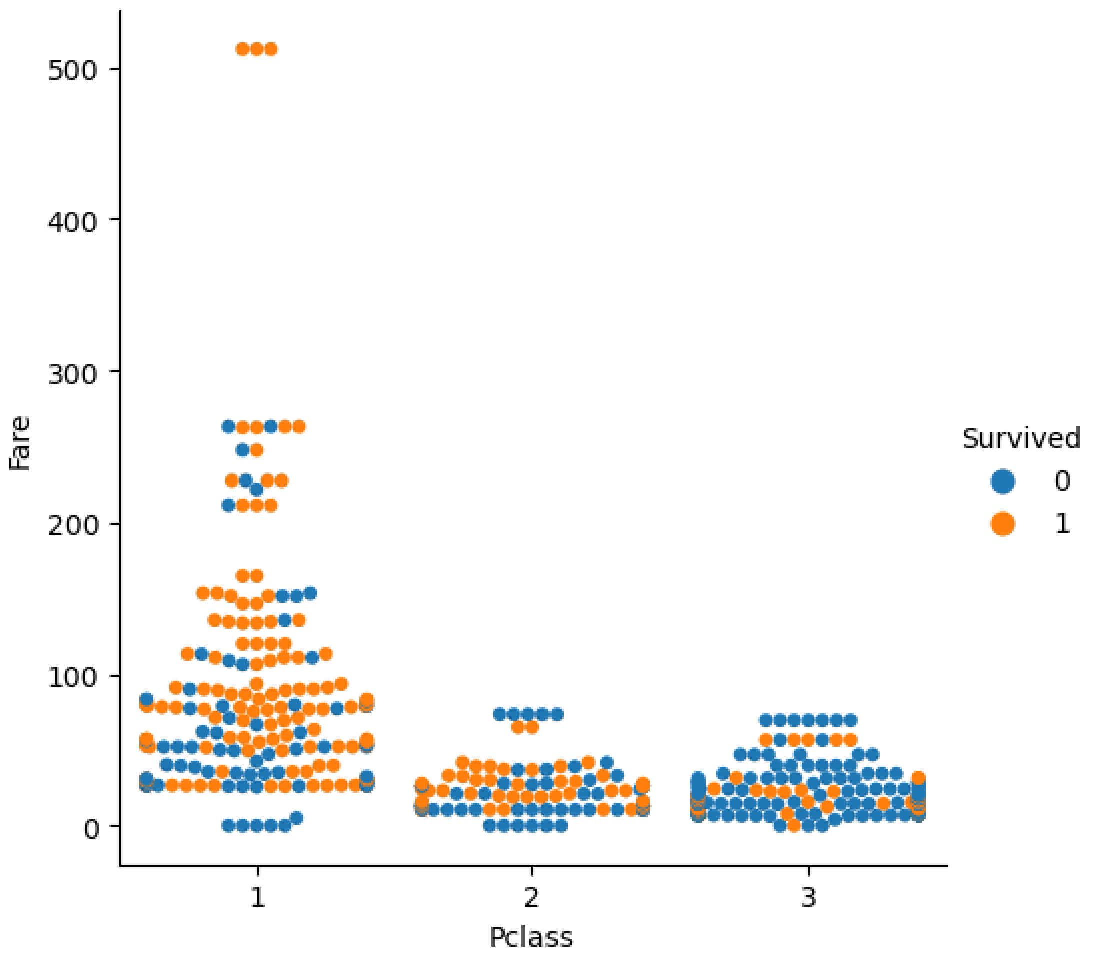
In [51]:

```
plt.subplots(figsize=(8,6))

ax=sns.kdeplot(train.loc[(train['Survived'] == 0),'Fare'],color='r',shade=True,label='Not Survived')

ax=sns.kdeplot(train.loc[(train['Survived'] == 1),'Fare'],color='b',shade=True,label='Survived' )

plt.title('Fare Distribution Survived vs Non Survived')

plt.ylabel('Frequency of Passenger Survived')

plt.xlabel('Fare')

plt.show()
```




In [52]:

```
sns.catplot(x="Pclass", y="Fare",hue='Survived', kind="swarm", data=train)

plt.show()
```




- We can observe that the distribution of prices for the second and third class is very similar.
- The distribution of first-class prices is very different, has a larger spread, and on average prices are higher.

Looks like the bigger passenger paid, the more chances to survive he had.

## 1.8 Embarked( Port of Embarkation )


Titanic had 3 embarkation points before the ship started its route to New York:

- Southampton
- Cherbourg
- Queenstown

Some passengers could leave Titanic in Cherbourg or Queenstown and avoid catastrophe. Also, the point of embarkation could have an influence on ticket fare and location on the ship.

In [53]:

```
train['Embarked'].unique()
```

Out[53]:

```
array(['S', 'C', 'Q', 'Unknown'], dtype=object)
```

In [54]:

```
train['Embarked'].describe()
```

Out[54]:

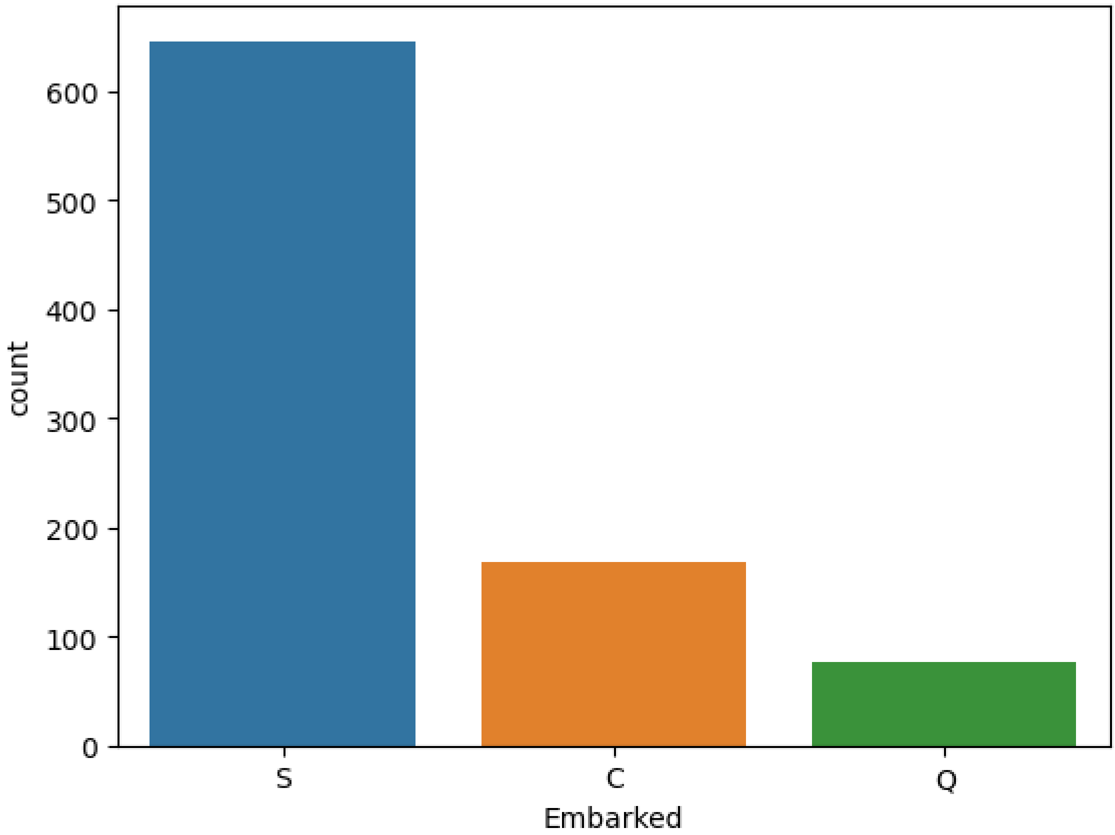
```
count     891
unique      4
top         S
freq      644
Name: Embarked, dtype: object
```

In [55]:

```
train['Embarked'] = train['Embarked'].replace('Unknown','S')
```

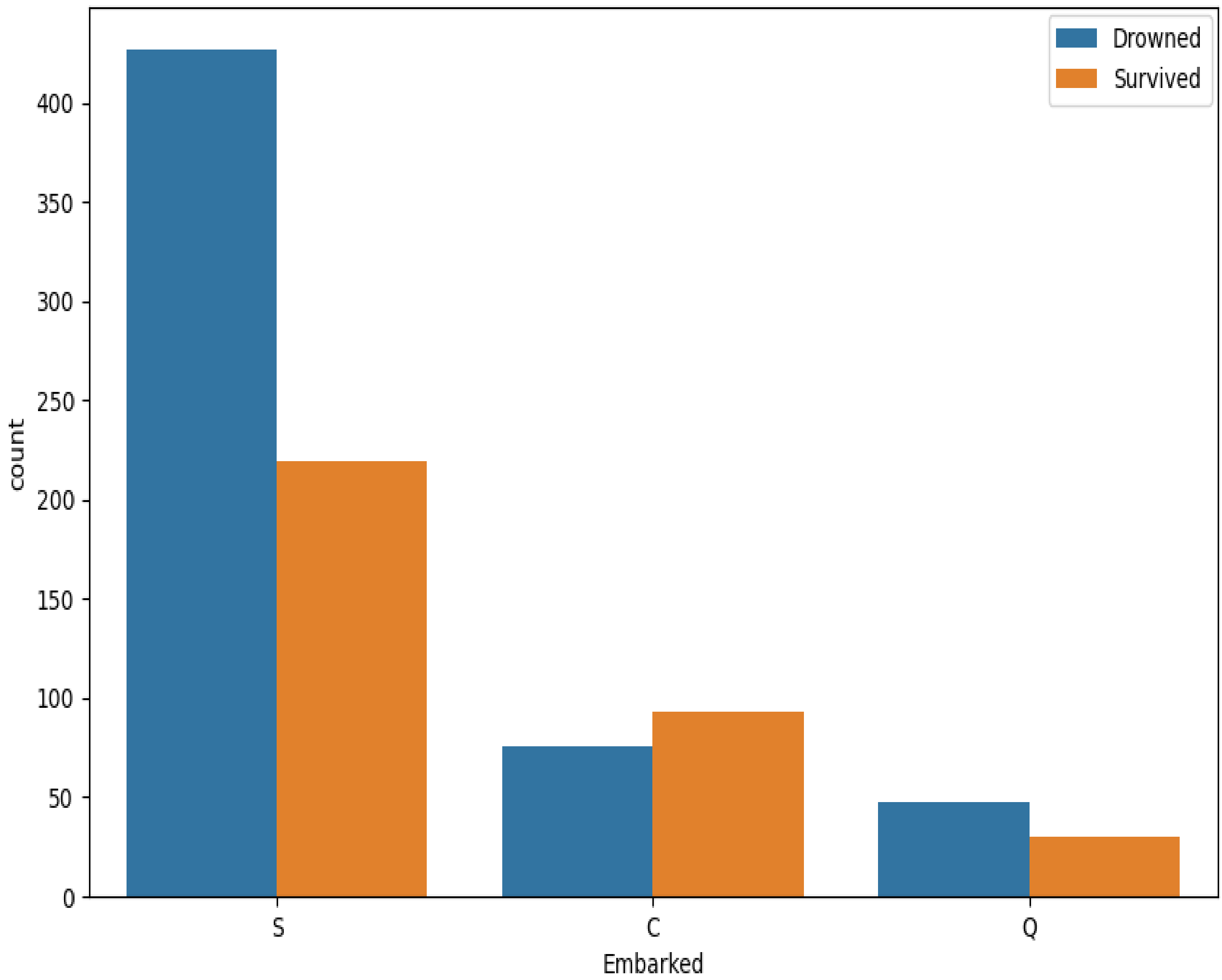
In [56]:

```
sns.countplot(train.Embarked)
labels = (train['Embarked'].value_counts())
```




In [57]:

```
plt.figure(figsize=(10,6))

sns.countplot(train['Embarked'],hue='Survived',data=train)

plt.legend(( 'Drowned', 'Survived'), loc=(0.85,0.89))

plt.show()
```




- Most number of passengers were embarked in Southampton. Also Southampton has the biggiest proportion of drowned passengers.
- Passengers emarked in Cherbourg and more than 50% of them survived (in the training dataset).

In [58]:

```
train.head()
```

Out[58]:

| | PassengerId | Survived | Pclass | Name | Sex | Age | SibSp | Parch | Ticket | Fare | Cabin | Embarked | AgeGroup | Title | deck |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 0 | 3 | Braund, Mr. Owen Harris | male | 22.0 | 1 | 0 | A/5 21171 | 7.2500 | Unknown | S | Student | Mr | U |
| 1 | 2 | 1 | 1 | Cumings, Mrs. John Bradley (Florence Briggs Th... | female | 38.0 | 1 | 0 | PC 17599 | 71.2833 | C85 | C | Adult | Mrs | C |
| 2 | 3 | 1 | 3 | Heikkinen, Miss. Laina | female | 26.0 | 0 | 0 | STON/O2. 3101282 | 7.9250 | Unknown | S | Young Adult | Miss | U |
| 3 | 4 | 1 | 1 | Futrelle, Mrs. Jacques Heath (Lily May Peel) | female | 35.0 | 1 | 0 | 113803 | 53.1000 | C123 | S | Young Adult | Mrs | C |
| 4 | 5 | 0 | 3 | Allen, Mr. William Henry | male | 35.0 | 0 | 0 | 373450 | 8.0500 | Unknown | S | Young Adult | Mr | U |

# 2. Feature Engineering

## 2.1 Creating Dummies Variables

Dummy variable is a categorical variable that has been transformed into numeric. For example the column Gender, we have "male" and "female" we will transform these variables into numeric. Creating a new column just for Men. and Women, where 1 will be set to positive and 0 to negative

In [59]:

```
total_data=train.append(test)
```

In [60]:

```
total_data.head()
```

Out[60]:

| | PassengerId | Survived | Pclass | Name | Sex | Age | SibSp | Parch | Ticket | Fare | Cabin | Embarked | AgeGroup | Title | deck |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 0.0 | 3 | Braund, Mr. Owen Harris | male | 22.0 | 1 | 0 | A/5 21171 | 7.2500 | Unknown | S | Student | Mr | U |
| 1 | 2 | 1.0 | 1 | Cumings, Mrs. John Bradley (Florence | female | 38.0 | 1 | 0 | PC 17599 | 71.2833 | C85 | C | Adult | Mrs | C |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Briggs Th... | | | | | | | | | | | |
| 2 | 3 | 1.0 | 3 | Heikkinen, Miss. Laina | female | 26.0 | 0 | 0 | STON/O2. 3101282 | 7.9250 | Unknown | S | Young Adult | Miss | U |
| 3 | 4 | 1.0 | 1 | Futrelle, Mrs. Jacques Heath (Lily May Peel) | female | 35.0 | 1 | 0 | 113803 | 53.1000 | C123 | S | Young Adult | Mrs | C |
| 4 | 5 | 0.0 | 3 | Allen, Mr. William Henry | male | 35.0 | 0 | 0 | 373450 | 8.0500 | Unknown | S | Young Adult | Mr | U |

In [61]:

```
total_data.shape
```

Out[61]:

(1309, 15)

In [62]:

```
total_data['Sex'] =total_data['Sex'].replace('male',0)

total_data['Sex'] =total_data['Sex'].replace('female',1)

total_data['Embarked'] =total_data['Embarked'].replace('S',0)
```

```
total_data['Embarked'] = total_data['Embarked'].replace('Q',1)

total_data['Embarked'] = total_data['Embarked'].replace('C',2)
```

## 2.2 Adding New Features and Filling the missing values

In [63]:

```
mapping = {'Mlle': 'Miss', 'Major': 'Rare', 'Col': 'Rare', 'Sir': 'Rare', 'Don': 'Rare', 'Mme': 'Mrs',

          'Jonkheer': 'Rare', 'Lady': 'Rare', 'Capt': 'Rare', 'Countess': 'Rare', 'Ms': 'Miss', 'Dona': 'Mrs',
'Rev':'Rare', 'Dr':'Rare'}



total_data.replace({'Title': mapping}, inplace=True)



total_data['Title'].value_counts(normalize=True)*100
```

Out[63]:

```
Mr            57.830405

Miss          20.168067

Mrs           15.202445

Master         4.660046

Rare           2.062643

the Countess     0.076394

Name: Title, dtype: float64
```

In [64]:

```
total_data['Title'] = total_data['Title'].map({'Mr':0, 'Miss':1, 'Mrs':2, 'Master':3, 'Rare':4})

total_data['Title'].fillna(total_data['Title'].median(),inplace=True)
```

In [65]:

```
cabin_category = {'A':1, 'B':2, 'C':3, 'D':4, 'E':5, 'F':6, 'G':7, 'T':8, 'U':9}
total_data['deck'] = total_data['deck'].map(cabin_category)
```

In [66]:

```
total_data['Family_size'] = total_data['SibSp'] + total_data['Parch'] + 1
```

In [67]:

```
total_data['Alone'] = 1
total_data['Alone'].loc[total_data['Family_size'] > 1] = 0
```

```
/opt/conda/lib/python3.7/site-packages/pandas/core/indexing.py:671: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self._setitem_with_indexer(indexer, value)
```

In this case I will use the age that was provided from our dataset to create the groups to find out if the passenger was a child, youth, adult, etc. In this case we are doing a Feacture Engineer where we transform a column to get another one through it

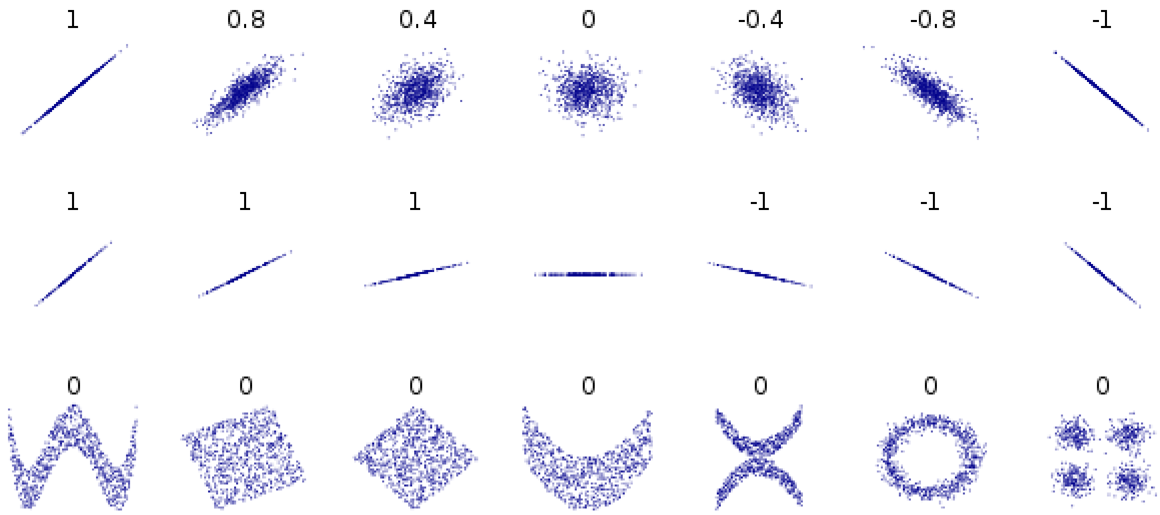
In [68]:

```
bins = [-1, 0, 18, 25, 35, 60, np.inf]
```

```
labels = ['Unknown', 'Child', 'Teenager', 'Young Adult', 'Adult', 'Senior']

total_data['AgeGroup'] = pd.cut(total_data["Age"], bins, labels = labels)

age_mapping = {'Unknown': None,'Child': 1, 'Teenager': 2, 'Young Adult': 3, 'Adult': 4, 'Senior': 5}

total_data['AgeGroup'] = total_data['AgeGroup'].map(age_mapping)
```

Correlation

Correlation is a statistical technique that can show whether and how strongly pairs of variables are related

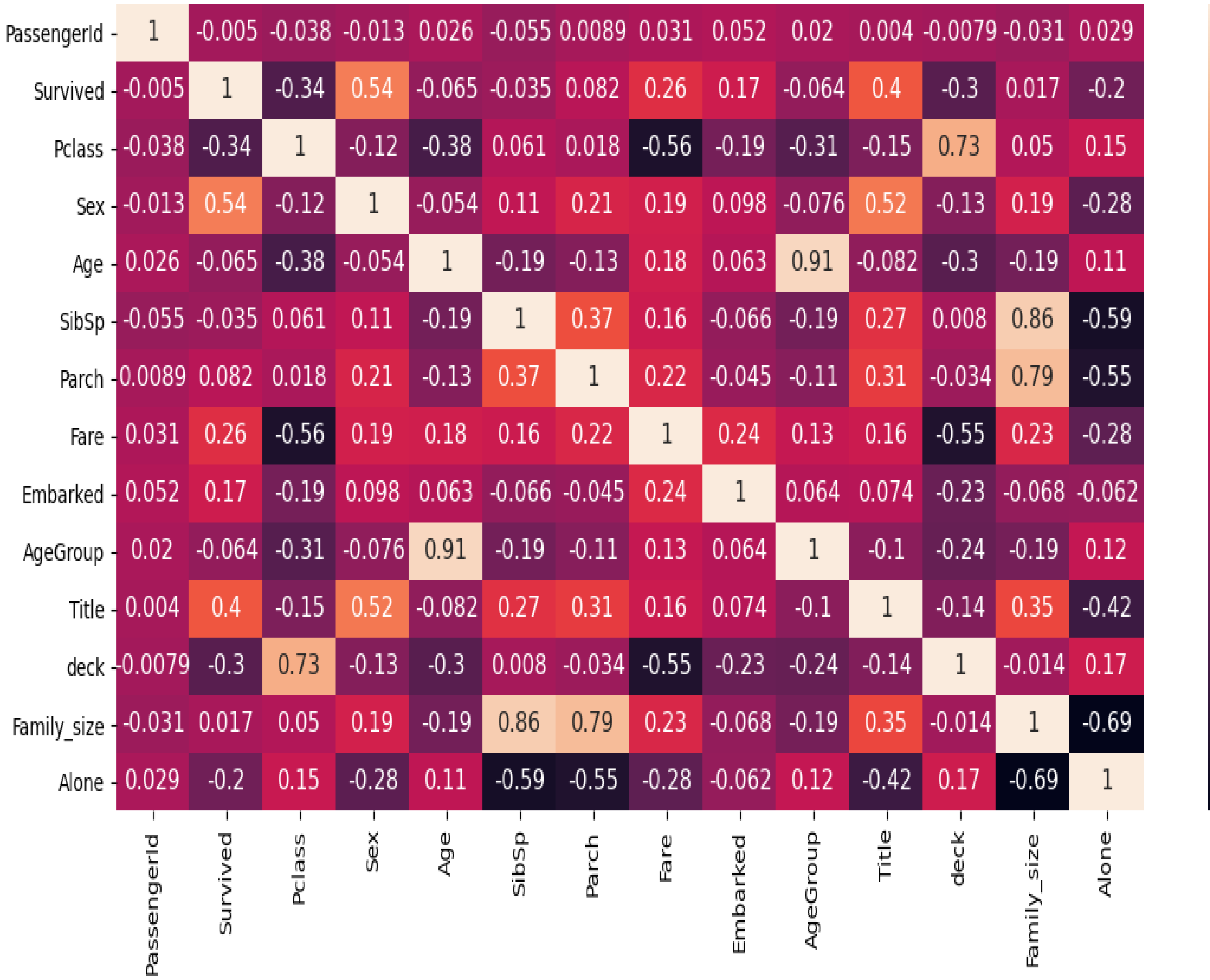



In [69]:

```
fig,ax=plt.subplots(figsize=(14,6))

sns.heatmap(total_data.corr(),annot=True,annot_kws={'size':12})
```

Out[69]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f721ae96610>




In [70]:

```
total_data.head()
```

Out[70]:

| | PassengerId | Survived | Pclass | Name | Sex | Age | SibSp | Parch | Ticket | Fare | Cabin | Emb |
|---|---|---|---|---|---|---|---|---|---|---|---|---|

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 0.0 | 3 | Braund, Mr. Owen Harris | 0 | 22.0 | 1 | 0 | A/5 21171 | 7.2500 | Unknown | 0 |
| 1 | 2 | 1.0 | 1 | Cumings, Mrs. John Bradley (Florence Briggs Th... | 1 | 38.0 | 1 | 0 | PC 17599 | 71.2833 | C85 | 2 |
| 2 | 3 | 1.0 | 3 | Heikkinen, Miss. Laina | 1 | 26.0 | 0 | 0 | STON/O2. 3101282 | 7.9250 | Unknown | 0 |
| 3 | 4 | 1.0 | 1 | Futrelle, Mrs. Jacques Heath (Lily May Peel) | 1 | 35.0 | 1 | 0 | 113803 | 53.1000 | C123 | 0 |
| 4 | 5 | 0.0 | 3 | Allen, Mr. William Henry | 0 | 35.0 | 0 | 0 | 373450 | 8.0500 | Unknown | 0 |

In [71]:

```
total_data.isna().sum()
```

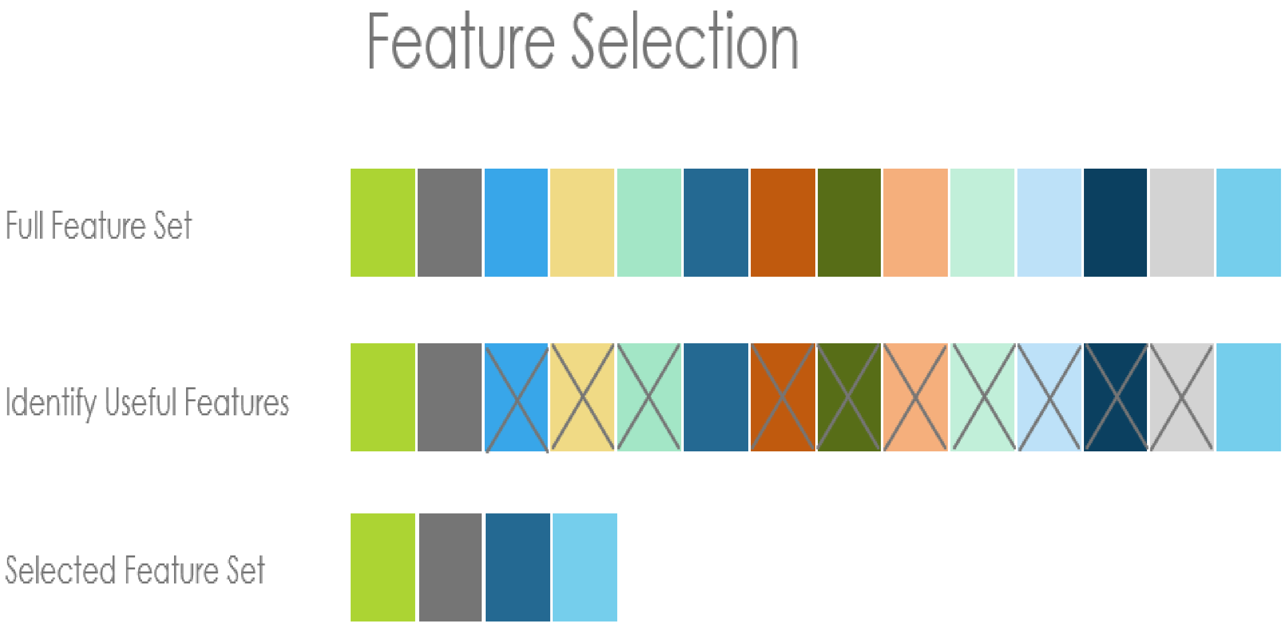
Out[71]:

```
PassengerId      0
Survived       418
Pclass           0
```

```
Name          0
Sex           0
Age           0
SibSp         0
Parch         0
Ticket        0
Fare          0
Cabin         0
Embarked      0
AgeGroup      0
Title         0
deck          0
Family_size   0
Alone         0
dtype: int64
```

**Dateset is completely ready now!**

## 2.3 Feature selection




We will now select the features (X) for our model. These features will help our model identify patterns. The features will be columns.

"When feature engineering is done, we usually tend to decrease the dimensionality by selecting the "right" number of features that capture the essential."

In [72]:

```
features = ['Embarked','Fare','Pclass','Sex','Title','Family_size','Alone']
```

# Building Machine Learning Models

In [73]:

```
#Modelos

from sklearn.ensemble import RandomForestClassifier



#Metrics

from sklearn.metrics import make_scorer, accuracy_score,precision_score

from sklearn.metrics import classification_report
```

```python
from sklearn.metrics import confusion_matrix

from sklearn.metrics import accuracy_score ,precision_score,recall_score,f1_score

from sklearn.metrics import roc_curve

from sklearn.metrics import roc_auc_score


#Model Select

from sklearn.model_selection import GridSearchCV

from sklearn.model_selection import train_test_split

from sklearn.linear_model import  LogisticRegression

from sklearn.ensemble import RandomForestClassifier

from sklearn import linear_model

from sklearn.linear_model import SGDClassifier

from sklearn.tree import DecisionTreeClassifier

from sklearn.neighbors import KNeighborsClassifier

from sklearn.svm import SVC, LinearSVC

from sklearn.naive_bayes import GaussianNB
```

In [74]:

```python
df_train = total_data[0:891]

df_test =  total_data[891:]

X = df_train[features]

y = df_train['Survived'].astype(int)
```

In [75]:

```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=78941)
```

Now we will train several Machine Learning models and compare their results. Note that because the dataset does not provide labels for their testing-set, we need to use the predictions on the training set to compare the algorithms with each other. Later on, we will use cross validation.

Random Forest:

In [76]:

```
random_forest = RandomForestClassifier(n_estimators=100)

random_forest.fit(X_train, y_train)


Y_prediction = random_forest.predict(X_test)


random_forest.score(X_train, y_train)

acc_random_forest = round(random_forest.score(X_train, y_train) * 100, 2)
```

Logistic Regression:

In [77]:

```
logreg = LogisticRegression(solver= 'lbfgs',max_iter=400)

logreg.fit(X_train, y_train)


Y_pred = logreg.predict(X_test)


acc_log = round(logreg.score(X_train, y_train) * 100, 2)
```

K Nearest Neighbor:

In [78]:

```
knn = KNeighborsClassifier(n_neighbors = 3)

knn.fit(X_train, y_train)

Y_pred = knn.predict(X_test)

acc_knn = round(knn.score(X_train, y_train) * 100, 2)
```

Gaussian Naive Bayes:

In [79]:

```
gaussian = GaussianNB()

gaussian.fit(X_train, y_train)

Y_pred = gaussian.predict(X_test)

acc_gaussian = round(gaussian.score(X_train, y_train) * 100, 2)
```

Linear Support Vector Machine:

In [80]:

```
linear_svc = LinearSVC()

linear_svc.fit(X_train, y_train)



Y_pred = linear_svc.predict(X_test)



acc_linear_svc = round(linear_svc.score(X_train, y_train) * 100, 2)
```

/opt/conda/lib/python3.7/site-packages/sklearn/svm/_base.py:947: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.

  "the number of iterations.", ConvergenceWarning)

Decision Tree

In [81]:

```
decision_tree = DecisionTreeClassifier()

decision_tree.fit(X_train, y_train)

Y_pred = decision_tree.predict(X_test)

acc_decision_tree = round(decision_tree.score(X_train, y_train) * 100, 2)
```

## Which is the best Model ?

In [82]:

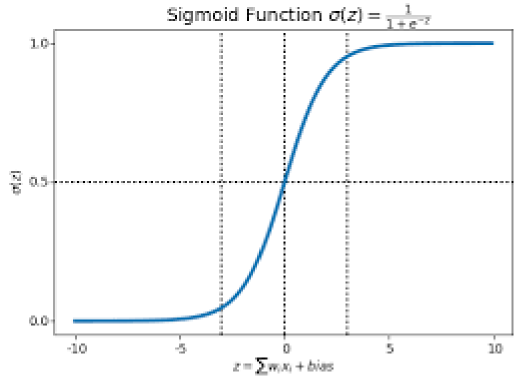
```
results = pd.DataFrame({

    'Model': [ 'KNN', 'Logistic Regression',

              'Random Forest', 'Naive Bayes',

              ' Support Vector Machine',

              'Decision Tree'],

    'Score': [ acc_knn, acc_log,

              acc_random_forest, acc_gaussian,

              acc_linear_svc, acc_decision_tree]})

result_df = results.sort_values(by='Score', ascending=False)

result_df = result_df.set_index('Score')

result_df.head(9)
```

Out[82]:

| | Model |
|---|---|
| Score | |
| 93.54 | Random Forest |
| 93.54 | Decision Tree |
| 85.11 | KNN |
| 81.46 | Naive Bayes |
| 80.76 | Logistic Regression |
| 72.47 | Support Vector Machine |

As we can see, the Random Forest classifier goes on the first place. But first, let us check, how random-forest performs & Logistic_Regression

# Logistic_Regression Model




Logistic regression is a supervised learning classification algorithm used to predict the probability of a target variable. The nature of target or dependent variable is dichotomous, which means there would be only two possible classes.

In simple words, the dependent variable is binary in nature having data coded as either 1 (stands for success/yes) or 0 (stands for failure/no).

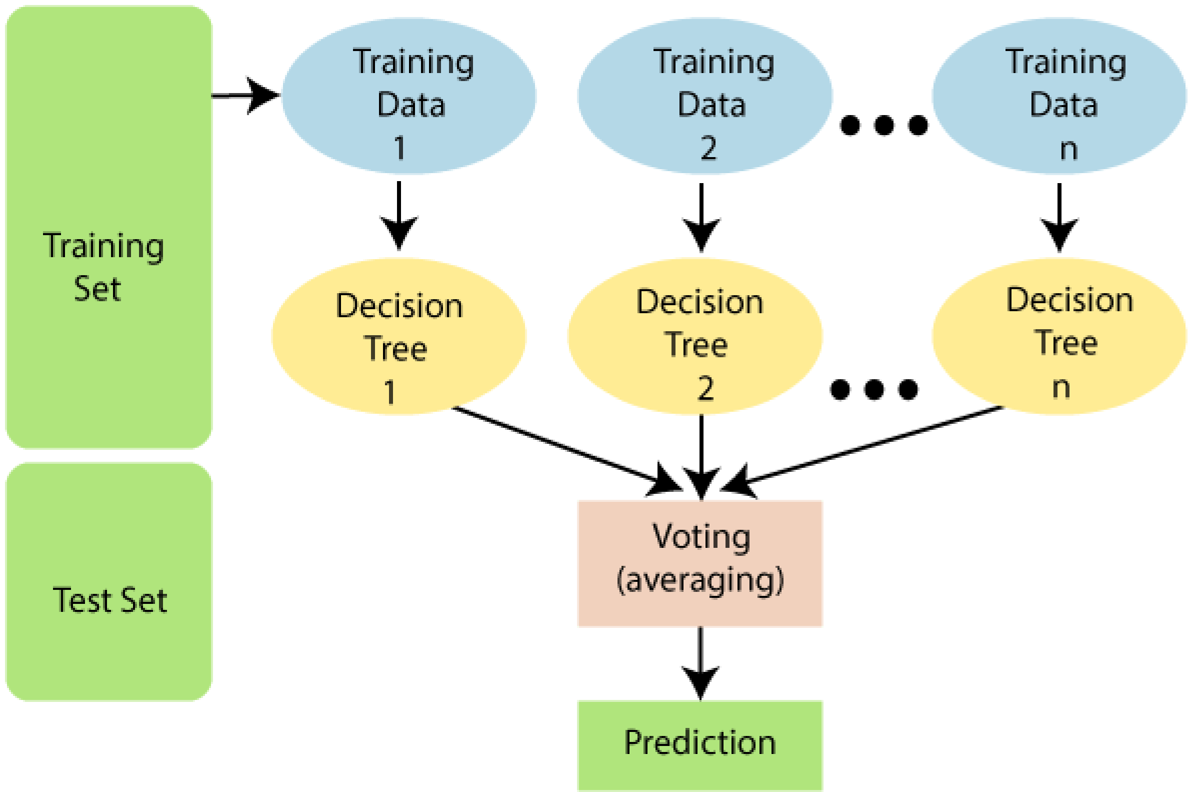
In [83]:

```
model= LogisticRegression(solver= 'lbfgs',max_iter=400)

model.fit(X_train, y_train)

predictions = model.predict(X_test)




cm_logit = confusion_matrix(y_test, predictions)

print('Confusion matrix for Logistic\n',cm_logit)



accuracy_logit = accuracy_score(y_test,predictions)

precision_logit =precision_score(y_test, predictions)

recall_logit =  recall_score(y_test, predictions)

f1_logit = f1_score(y_test, predictions)

print('accuracy_logistic : %.3f' %accuracy_logit)

print('precision_logistic : %.3f' %precision_logit)
```

```
print('recall_logistic : %.3f' %recall_logit)

print('f1-score_logistic : %.3f' %f1_logit)

auc_logit = roc_auc_score(y_test,predictions)

print('AUC_logistic : %.2f' % auc_logit)
```

```
Confusion matrix for Logistic

 [[97 18]

 [22 42]]

accuracy_logistic : 0.777

precision_logistic : 0.700

recall_logistic : 0.656

f1-score_logistic : 0.677

AUC_logistic : 0.75
```

## Random_Forest Model




Random forest is a supervised learning algorithm which is used for both classification as well as regression. But however, it is mainly used for classification problems. As we know that a forest is made up of trees and more trees means more robust forest. Similarly, random forest algorithm creates decision trees on data samples and then gets the prediction from each of them and finally selects the best solution by means of voting. It is an ensemble method which is better than a single decision tree because it reduces the over-fitting by averaging the result.

I would like to introduce one of the most popular algorithms for classification (but also regression, etc), Random Forest! In a nutshell, Random Forest is an ensembling learning algorithm which combines decision trees in order to increase performance and avoid overfitting.

## Hyperparameter Tuning

Below we set the hyperparameter grid of values with 4 lists of values:

**'criterion'** : A function which measures the quality of a split.

**'n_estimators'** : The number of trees of our random forest.

**'max_features'** : The number of features to choose when looking for the best way of splitting.

**'max_depth'** : the maximum depth of a decision tree.

In [84]:

```
randomForestFinalModel = RandomForestClassifier(random_state = 2,
bootstrap=False,min_samples_split=2,min_samples_leaf= 5, criterion = 'entropy', max_depth = 13,
max_features = 'sqrt', n_estimators = 200)

randomForestFinalModel.fit(X_train, y_train)

predictions_rf = randomForestFinalModel.predict(X_test)



cm_logit = confusion_matrix(y_test, predictions_rf)

print('Confusion matrix for Random Forest\n',cm_logit)



accuracy_logit = accuracy_score(y_test,predictions_rf)

precision_logit =precision_score(y_test, predictions_rf)

recall_logit =  recall_score(y_test, predictions_rf)

f1_logit = f1_score(y_test,predictions_rf)

print('accuracy_random_Forest : %.3f' %accuracy_logit)

print('precision_random_Forest : %.3f' %precision_logit)

print('recall_random_Forest : %.3f' %recall_logit)

print('f1-score_random_Forest : %.3f' %f1_logit)

auc_logit = roc_auc_score(y_test,predictions_rf)

print('AUC_random_Forest: %.2f' % auc_logit)
```

```
Confusion matrix for Random Forest

 [[101  14]

 [ 21  43]]
```

accuracy_random_Forest : 0.804

precision_random_Forest : 0.754

recall_random_Forest : 0.672

f1-score_random_Forest : 0.711

AUC_random_Forest: 0.78

## Roc_curve

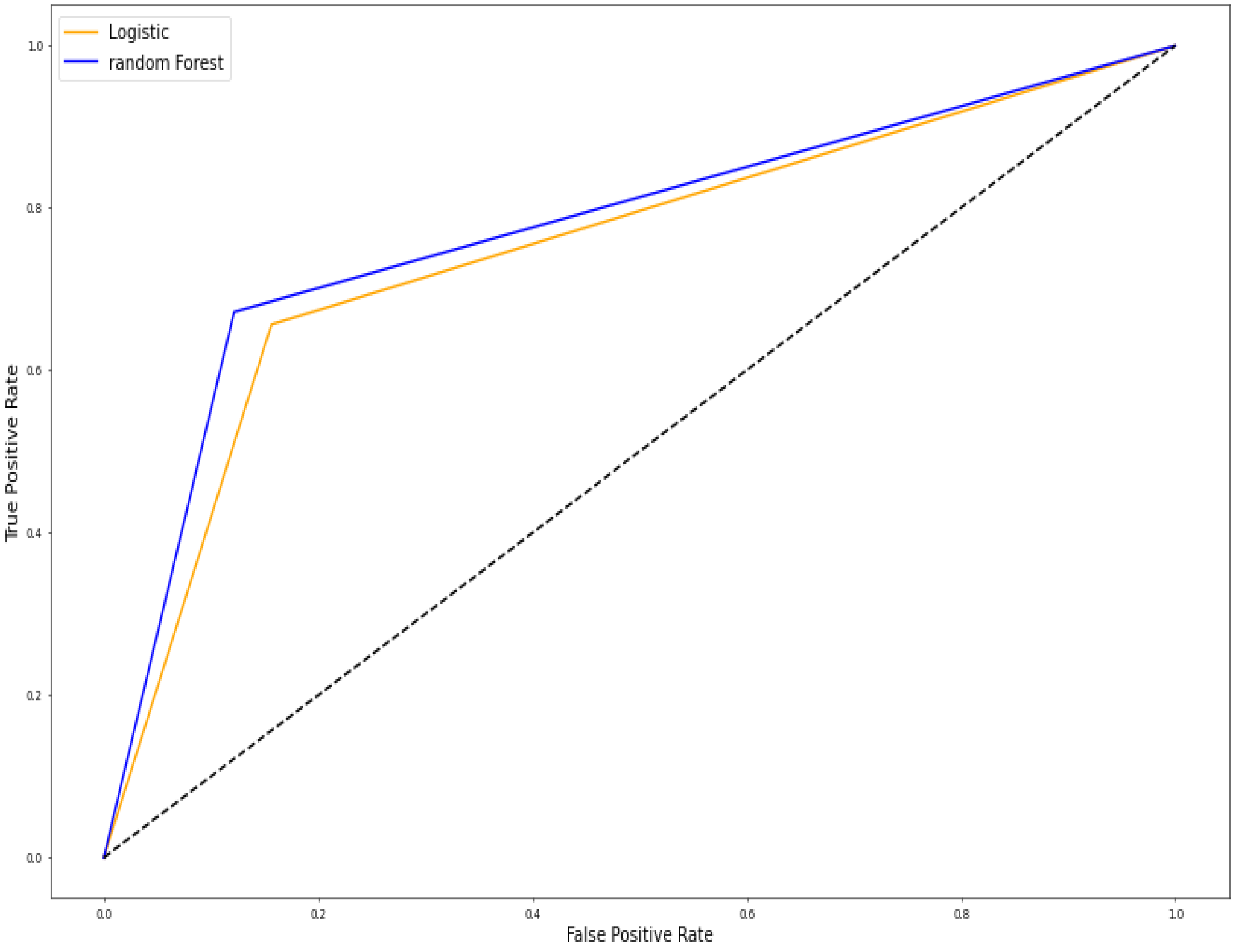
Another way to evaluate and compare your binary classifier is provided by the ROC AUC Curve. This curve plots the true positive rate (also called recall) against the false positive rate (ratio of incorrectly classified negative instances), instead of plotting the precision versus the recall.

In [85]:

```
a=[0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1]

b=[0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1]

fig =plt.figure(figsize=(20,12),dpi=50)

fpr, tpr, thresholds = roc_curve(y_test,predictions )

plt.plot(fpr, tpr,color ='orange',label ='Logistic',linewidth=2 )

fpr, tpr, thresholds = roc_curve(y_test,predictions_rf )

plt.plot(fpr, tpr,color ='blue',label ='random Forest',linewidth=2 )


plt.plot(a,b,color='black',linestyle ='dashed',linewidth=2)

plt.legend(fontsize=15)

plt.xlabel('False Positive Rate',fontsize=15)

plt.ylabel('True Positive Rate',fontsize=15)
```

Out[85]:

Text(0, 0.5, 'True Positive Rate')




## Let's submit our solutions

In [86]:

```
submission = pd.DataFrame({
    "PassengerId": df_test["PassengerId"],
    "Survived": randomForestFinalModel.predict( df_test[features])
})
```

In [87]:

```
submission.head()
```

Out[87]:

| | PassengerId | Survived |
|---|---|---|
| 0 | 892 | 0 |
| 1 | 893 | 1 |
| 2 | 894 | 0 |
| 3 | 895 | 0 |
| 4 | 896 | 1 |

In [88]:

```
submission.to_csv("titanic_s.csv",index=False)
```