Exercise 2

For this exercise , you will be working with the [Titanic Data Set from Kaggle (https://www.kaggle.com/c/titanic)](https://www.kaggle.com/c/titanic). This is a very famous data set and very often is a student's first step in Data Analytics!

The Dataset has been given to you on D2L. You need to download the .csv file from your assignment folder. The above link is just for a reference story about the data.

1- For this assignment, you need to perform explorotary data analysis and answer at least three hypotheses based on the dataset. You may need to use your knowledge of statiscts to analyze this data.

Here are three possible hypotheses that you can define for this dataset (you can define your own hypotheses as well):

- Determine if the survival rate is associated to the class of passenger
- Determine if the survival rate is associated to the gender
- Determine the survival rate is associated to the age

2- For each hypothesis, you need to make at least one plot.

3- Write a summary of your findings in one page (e.g., summary statistics, plots) and submit the pdf file. Therefore, for part 2 of your assignment, you need to submit one jupyter notebook file and one pdf file.

This will be your first end to end data analysis project. For this assignment, you will be graded on you overall analysis, and your final report.

4- Push your code and project to github and provide the link to your code here.

Ensure that your github project is organized to at least couple of main folders, ensure that you have the README file as well:

- Src
- Data
- Docs
- Results

Read this link for further info: [https://gist.github.com/ericmjl/27e50331f24db3e8f957d1fe7bbbe510 (https://gist.github.com/ericmjl/27e50331f24db3e8f957d1fe7bbbe510)](https://gist.github.com/ericmjl/27e50331f24db3e8f957d1fe7bbbe510)

Topic will be covered

```
The framework of this notebook is:

1. Explorotary data analysis\
    1) NaN Values\
    2) Survived\
    3) Pclass\
    4) Name Column\
    5) Age Column\
    6) Sex Column

2. Hypothesis\
```

```
1) Determine if the survival rate is associated to the class of passenger\
2) Determine if the survival rate is associated to the gender\
3) Determine the survival rate is associated to the age
```

In [58]:

```
import pandas as pd
import numpy as np
import pickle

# visualization
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

# Enable Jupyter Notebook's intellisense
%config IPCompleter.greedy=True

# We want to see whole content (non-truncated)
pd.set_option('display.max_colwidth', None)
```

In [59]:

```python
df = pd.read_csv("titanic.csv")
display(df.head())

print(df.info())
print(df.describe())
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Thayer)	female	38.0	1	0	PC 17599	71.2833
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500

```
<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
None
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000   
mean    446.000000    0.383838    2.308642   29.699118    0.523008   
std     257.353842    0.486592    0.836071   14.526497    1.102743   
min       1.000000    0.000000    1.000000    0.420000    0.000000   
25%     223.500000    0.000000    2.000000   20.125000    0.000000   
50%     446.000000    0.000000    3.000000   28.000000    0.000000   
```

```
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

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

Exploratory Data Analysis

NaN values

In [60]:

```
print(df.isnull().sum())
```

```
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
```

From the records, we can see that 4 features have missing values:

Age: Age is fractional if less than 1. -> Numerical Variable
Cabin: Cabin number -> Categorical variable
Embarked: Port of Embarkation (3 categories) -> Categorical variable
Fare: Numerical: Only 1 missing in the test dataset. Can be replace by the mean in the training set.

Survived

In [61]:

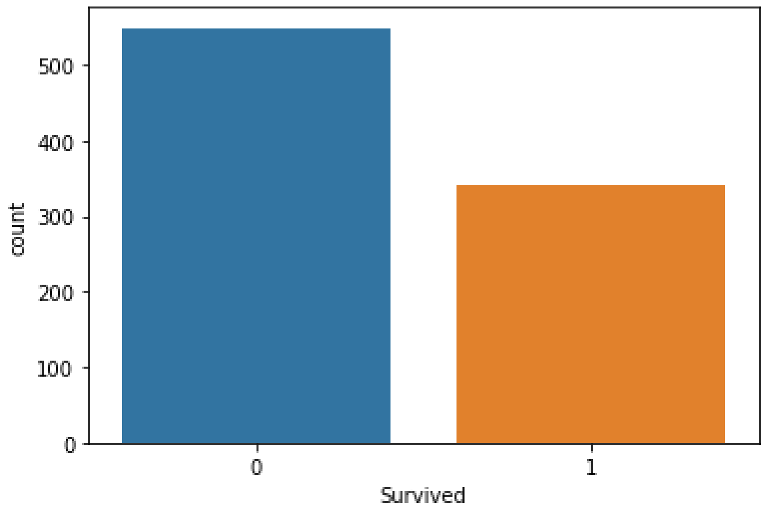
```
#COUNT THE SURVIVOURS AND UNSURVIVOURS
survivours = df.Survived.sum()
unsurvivours = len(df) - survivours

print(survivours, "people survived")
print(unsurvivours, "people didn't survive")

#Visualize Survived column. (1=Survived, 0=Not Survived)
sns.countplot(x="Survived", data=df)
plt.show()

#PRINT PROPORTIONS
print(df["Survived"].value_counts(normalize=True))
```

```
342 people survived
549 people didn't survive
```




```
0    0.616162
1    0.383838
Name: Survived, dtype: float64
```

Pclass

Pclass column contains the status of the passengers.

1 = Upper

2 = Middle

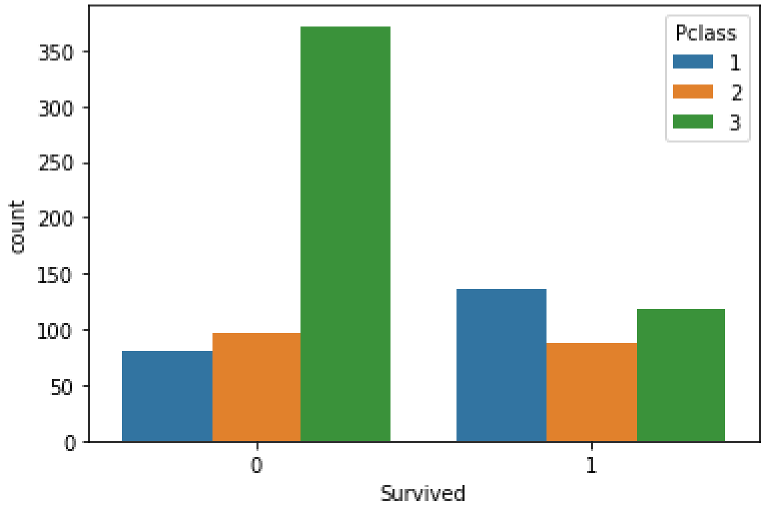
3 = Lower

In [62]:

```
#hue parameter represents which column in the data frame, you want to use for color encodin
sns.countplot(x="Survived",hue="Pclass",data=df)
```

Out[62]:

```
<AxesSubplot:xlabel='Survived', ylabel='count'>
```



Name Column

In [63]:

```
# Display first five rows of the Name column
display(df[["Name"]].head())
```

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

Age Column

In [64]:

```
# Print the missing values in Age column
print(df["Age"].isnull().sum())
```

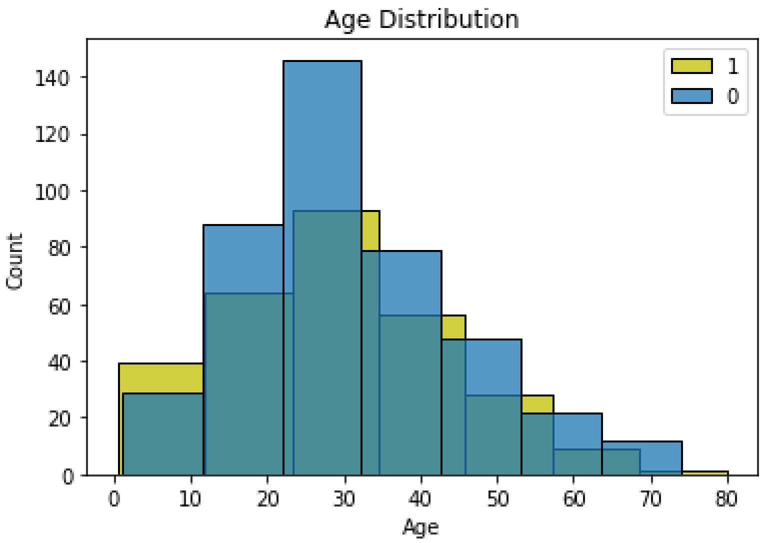
```
177
```

In [65]:

```
# There are 177 missing values in Age column. Now, let's look at the distribution of ages b

# Survived by age
sns.histplot(df[df.Survived==1]["Age"],color="y", bins=7, label="1")

# Death by age
sns.histplot(df[df.Survived==0]["Age"], bins=7, label="0")
plt.legend()
plt.title("Age Distribution")
plt.show()
```



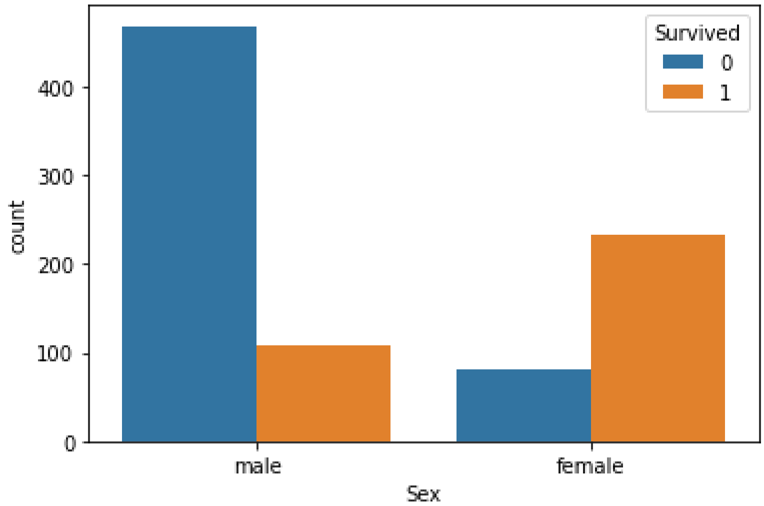
Sex Column

In [66]:

```
# Visualize with a countplot
sns.countplot(x="Sex", hue="Survived", data=df)
plt.show()

# Proportion of people survived for each class
print(df["Survived"].groupby(df["Sex"]).mean())

# How many people we have in each class?
print(df["Sex"].value_counts())
```




```
Sex
female    0.742038
male      0.188908
Name: Survived, dtype: float64
male      577
female    314
Name: Sex, dtype: int64
```

Hypothesis

1.Determine if the survival rate is associated to the class of passenger.

Let's check how the passesnger class (Pclass) impacted the survival of the passengers.

In [67]:

```
total_passenger_count = len(df['Pclass'])
first_count = (df['Pclass'] == 1).sum()
second_count = (df['Pclass'] == 2).sum()
third_count = (df['Pclass'] == 3).sum()

per_first =  first_count / total_passenger_count * 100
per_second = second_count / total_passenger_count * 100
per_third = third_count / total_passenger_count * 100
```

In [68]:

```
print('First class percentage = ', per_first_class, '  Count: ', first_class_count)
print('Second class percentage = ', per_second_class, '  Count: ', second_class_count)
print('Third class percentage = ', per_third_class, '  Count: ', third_class_count)
```

```
First class percentage =  24.242424242424242   Count:  216
Second class percentage =  20.65095398428732   Count:  184
Third class percentage =  55.106621773288445   Count:  491
```

With these survival rates, we can see that:

The first class represents ≈ 24% of the passengers, but ≈ 40% of the survivors
The second class represents ≈ 20% of the passengers, but ≈ 25% of the survivors
The third class representes ≈ 55% of the passengers, but ≈ 34% of the survivors

In [69]:

```
df[['Pclass', 'Survived']].groupby(['Pclass'], as_index=False).mean()
```

Out[69]:

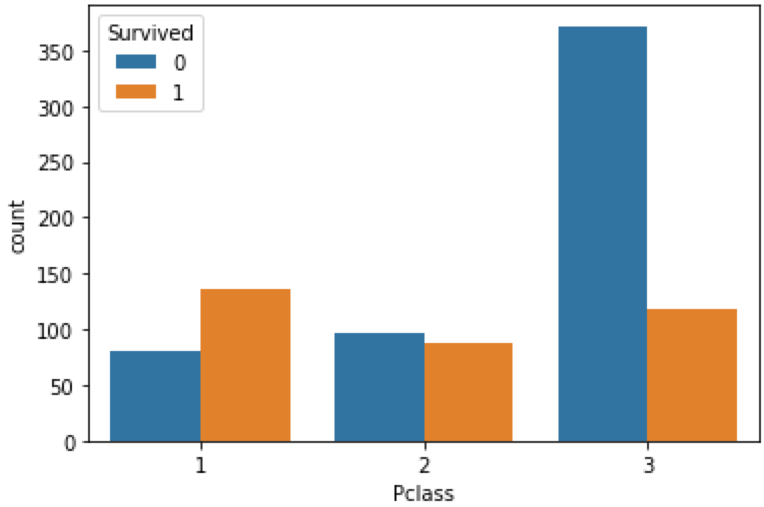
	Pclass	Survived
0	1	0.629630
1	2	0.472826
2	3	0.242363

In [72]:

```
# Visualize with a countplot                          (1=Survived, 0=Not Survived)
sns.countplot(x="Pclass", hue="Survived", data=df)
plt.show()

# Proportion of people survived for each class
print(df["Survived"].groupby(df["Pclass"]).mean())

# How many people we have in each class?
print(df["Pclass"].value_counts())
```



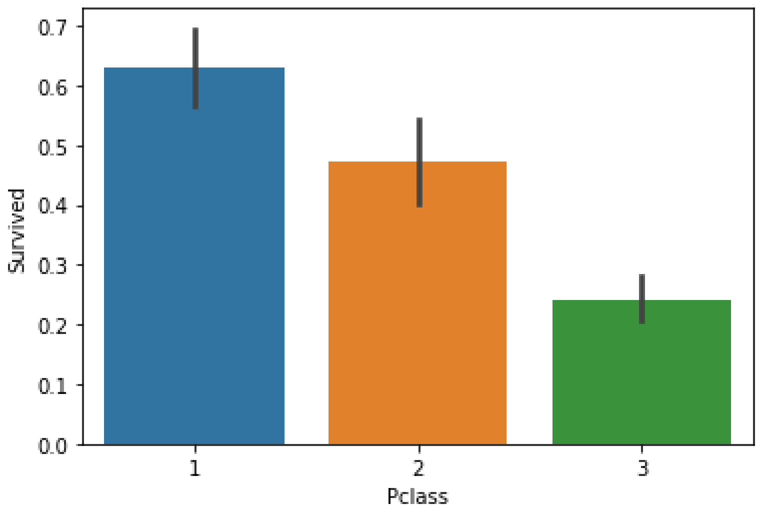

```
Pclass
1    0.629630
2    0.472826
3    0.242363
Name: Survived, dtype: float64
3    491
1    216
2    184
Name: Pclass, dtype: int64
```

In [73]:

```
#df.groupby('Pclass').Survived.mean().plot(kind='bar')
sns.barplot(x='Pclass', y='Survived', data=df)
```

Out[73]:

```
<AxesSubplot:xlabel='Pclass', ylabel='Survived'>
```



From the above two graph we can see that higher class passengers have better survival chance. Therefore, we can say that the hypothesis is correct, survival rate is associated to the class of passesnger.

2.Determine if the survival rate is associated to the gender

Now we will analyze if there is any relation between gender and survival rate. First, we'll get the count of survivals and deaths by gender.

In [74]:

```
df[['Sex', 'Survived']].groupby(['Sex'], as_index=False).mean()
```

Out[74]:

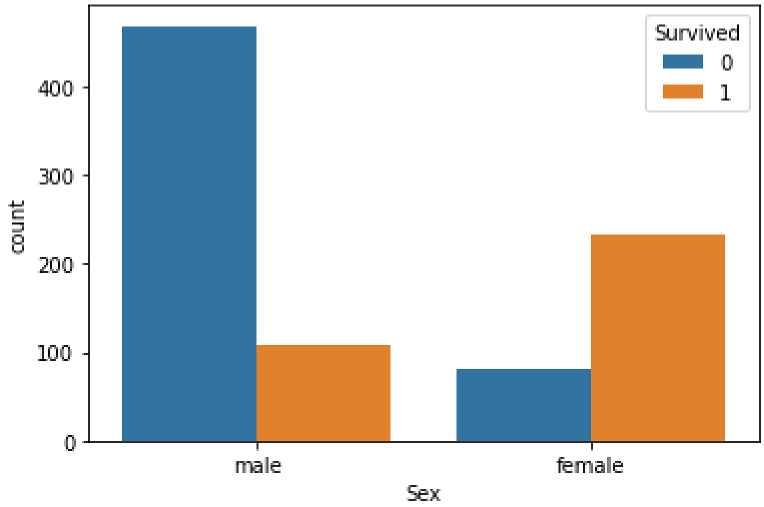
	Sex	Survived
0	female	0.742038
1	male	0.188908

In [41]:

```
# Visualize with a countplot
sns.countplot(x="Sex", hue="Survived", data=df)
plt.show()

# Proportion of people survived for each class
print(df["Survived"].groupby(df["Sex"]).mean())

# How many people we have in each class?
print(df["Sex"].value_counts())
```



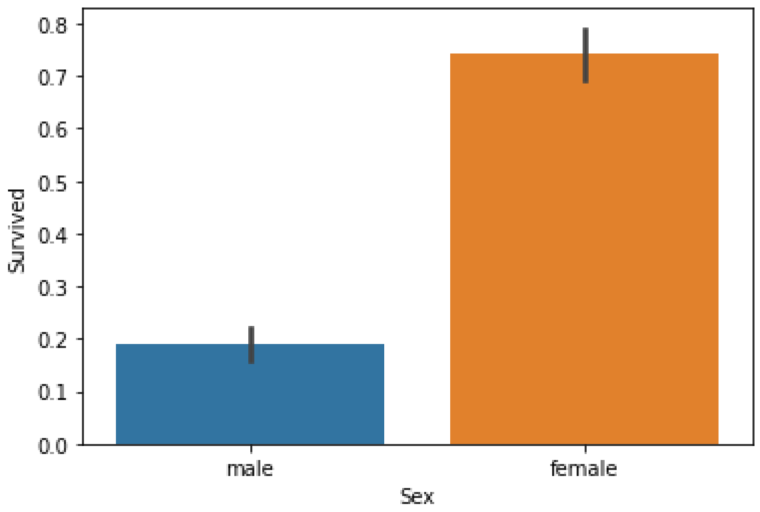

```
Sex
female    0.742038
male      0.188908
Name: Survived, dtype: float64
male      577
female    314
Name: Sex, dtype: int64
```

In [44]:

```
#df.groupby('Sex').Survived.mean().plot(kind='bar')
sns.barplot(x='Sex', y='Survived', data=df)
```

Out[44]:

```
<AxesSubplot:xlabel='Sex', ylabel='Survived'>
```



From the above two graph we can se that Females had better survival chance. Therefore, we can say that the survival rate is associated to the gender of the passesnger.

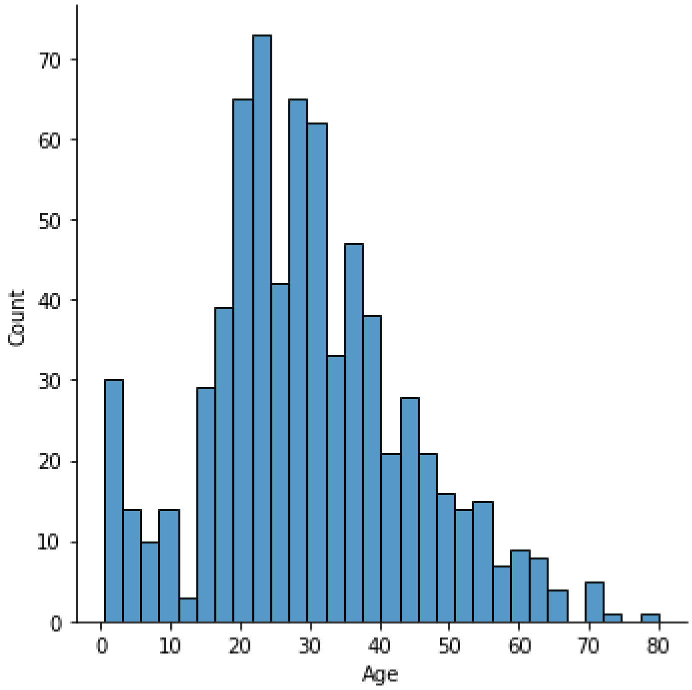
3.Determine the survival rate is associated to the age

In [12]:

```
#Determine the survival rate is associated to the age
sns.displot(df['Age'].dropna(), kde=False, bins=30)
```

Out[12]:

```
<seaborn.axisgrid.FacetGrid at 0x2b44fbbe910>
```



In [46]:

```
df_age = df[['Age' , 'Survived']].dropna(how='any')
df_age['Age'] = (np.floor(df_age['Age'])).astype(int)
df_age.shape
```

Out[46]:

```
(714, 2)
```

In [47]:

```
print('Yougest passenger: ' + str(df_age['Age'].min() * 12) + ' months old')
print('\nOldest passenger: ' + str(df_age['Age'].max()) + ' years old')
```

```
Yougest passenger: 0 months old

Oldest passenger: 80 years old
```

We rounded the ages up for the sake of this analysis, so the youngest passenger on board was a few months old, and the oldest was 80 years old.
Now let' order our data and create a new DataFrame df_ages_survival. It will Age indexed. Four each age, 4 columns will give us the following information:

Number of passengers of index age that survived
Number of passengers of index age that died
Total number of passengers of index age
Percentage of survivors of that index age

In [48]:

```
ages_list = df_age['Age'].unique()
ages_list.sort()
ages_list
```

Out[48]:

```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
       17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
       34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50,
       51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 70,
       71, 74, 80])
```

In [49]:

```
df_ages_survival = pd.DataFrame(index=ages_list, columns=['Survived', 'Deaths', 'Total', 'P

df_ages_survival['Survived'] = df_age.groupby('Age')['Survived'].sum()
df_ages_survival['Total'] = df_age.groupby('Age').count()
df_ages_survival['Deaths'] = df_ages_survival['Total'] - df_ages_survival['Survived']
df_ages_survival['Percentage'] = round(df_age.groupby('Age')['Survived'].mean() * 100, 2)

df_ages_survival.head()
```

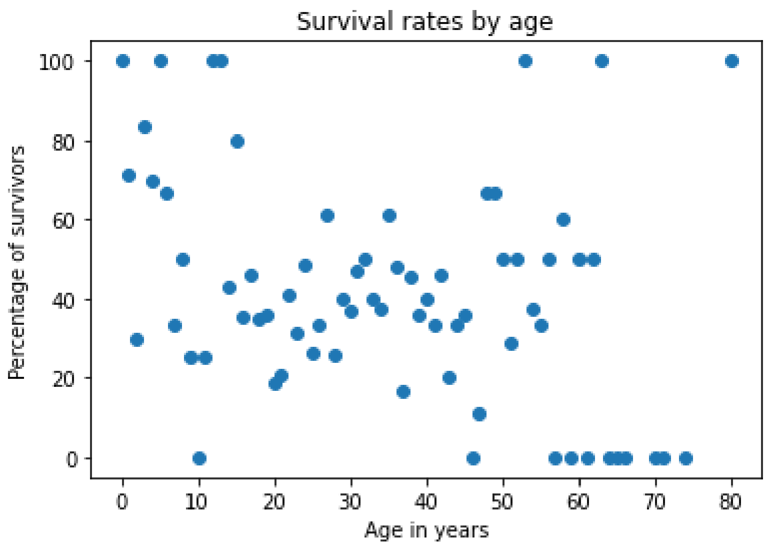
Out[49]:

	Survived	Deaths	Total	Percentage
0	7	0	7	100.00
1	5	2	7	71.43
2	3	7	10	30.00
3	5	1	6	83.33
4	7	3	10	70.00

Let's take a look at a scatter plot of our data, and see if we can identify any outliers.

In [50]:

```
x = df_ages_survival['Percentage'].index
y = df_ages_survival['Percentage']
plt.scatter(x, y)
m, b = np.polyfit(x, y, 1)
plt.plot(x, y, '.')
plt.title('Survival rates by age')
plt.xlabel('Age in years')
plt.ylabel('Percentage of survivors')
plt.show()
```

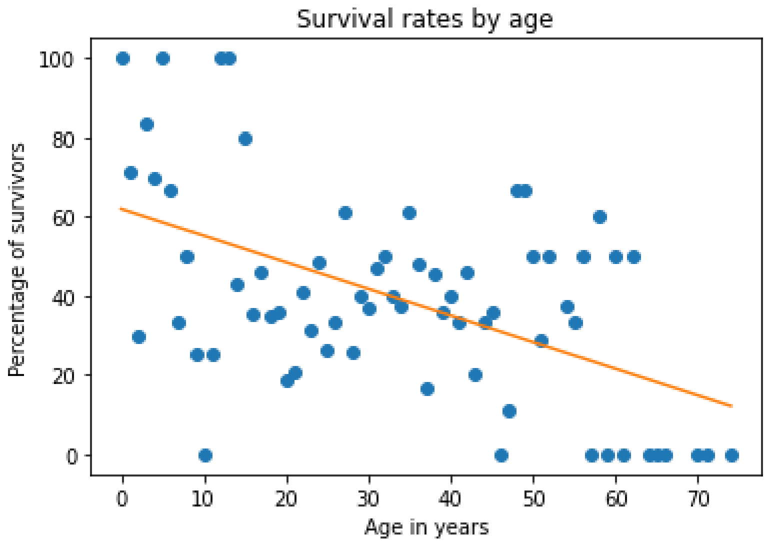


We can identify a tendency where the lower y values have high x coordinates, and high y values have low x coordinates. This means that apparently, the younger you are, the more chances you have to survive.

However, there are three dots on the upper right side of the graph that seem to be outliers. They are not representative of the general tendency: let's identify them, remove them from the DataFrame, plot it again and fit a regression line.

In [51]:

```
df_ages_survival = df_ages_survival.drop(df_ages_survival[(df_ages_survival['Percentage'] =
x = df_ages_survival['Percentage'].index
y = df_ages_survival['Percentage']
plt.scatter(x, y)
m, b = np.polyfit(x, y, 1)
plt.plot(x, y, '.')
plt.plot(x, m*x + b, '-')
plt.title('Survival rates by age')
plt.xlabel('Age in years')
plt.ylabel('Percentage of survivors')
plt.show()
```



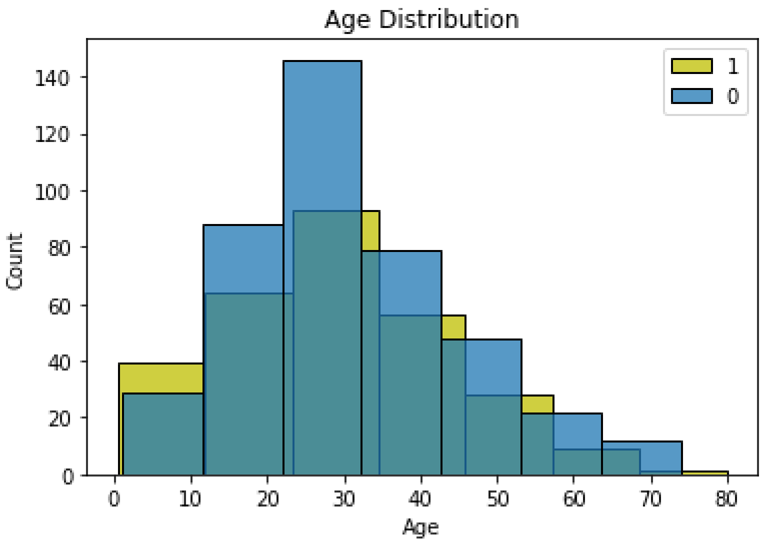
In [ ]:

```
The regression line clearly shows that the younger you were, the higher your chances to sur
```

In [52]:

```
# Survived by age
sns.histplot(df[df.Survived==1]["Age"],color="y", bins=7, label="1")

# Death by age
sns.histplot(df[df.Survived==0]["Age"], bins=7, label="0")
plt.legend()
plt.title("Age Distribution")
plt.show()
```



We can definitely see a spike in the distribution of survival passengers when the age is small, indicating children had a higher survival rate.

It would seem that children up to 10 years old had a higher chance of survival than people over 10 years old.

From the above graphs we can say that the younger you were, the higher your chances to survive. Therefore, we can say that the survival rate is associated with the age of the passenger.