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)

In [20]:

```
import pandas as pd
import numpy as np
import seaborn as sns

df = pd.read_csv('titanic.csv')
df.columns
```

Out[20]:

```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

In [9]:

```
df.head()
```

Out[9]:

	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 Th...	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

In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

In [10]:

```
def get_null_count(c_name):
    '''
    This function calculates the null value count of the column

    Arguments:
    c_name : Column name

    Return:
    n_count : count of null values in the column
    '''
    n_count = c_name.isnull().sum()
    return n_count
```

In [11]:

```
get_null_count(df['Survived'])
```

Out[11]:

```
0
```

In [12]:

```
get_null_count(df['Pclass'])
```

Out[12]:

```
0
```

In [13]:

```
get_null_count(df['Age'])
```

Out[13]:

```
177
```

In [14]:

```
get_null_count(df['Sex'])
```

Out[14]:

```
0
```

As we can see that there are no missing values for Sex and Ticket class. We will ignore the missing values of Age ,but since the column has 177 missing values out of 891 , the results will be less reliable

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

In [16]:

```
total_passenger = len(df['Pclass'])
first_class_count = (df['Pclass'] == 1).sum()
second_class_count = (df['Pclass'] == 2).sum()
third_class_count = (df['Pclass'] == 3).sum()

first_per =  first_class_count / total_passenger * 100
second_per = second_class_count / total_passenger * 100
third_per = third_class_count / total_passenger * 100

print('First class percentage = ', first_per, '\nCount: ', first_class_count)
print('Second class percentage = ', second_per, '\nCount: ', second_class_count)
print('Third class percentage = ', third_per, ' \nCount: ', third_class_count)
```

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

Here we can notice that 55% of the passengers are Third class ticket holders , 20% are second class and 24% are First class ticket holders.

Calculating the survival rates by Ticket class

In [8]:

```
survivor_count = df['Survived'].sum()
by_factor = df.groupby('Pclass')
count_by_factor = by_factor['Survived'].sum()
survival_rate = count_by_factor / survivor_count * 100
print('Survival rates:', survival_rate)
print('Counts: ', count_by_factor)
```

```
Survival rates: Pclass
1    39.766082
2    25.438596
3    34.795322
Name: Survived, dtype: float64

 Counts:  Pclass
1    136
2     87
3    119
Name: Survived, dtype: int64
```

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

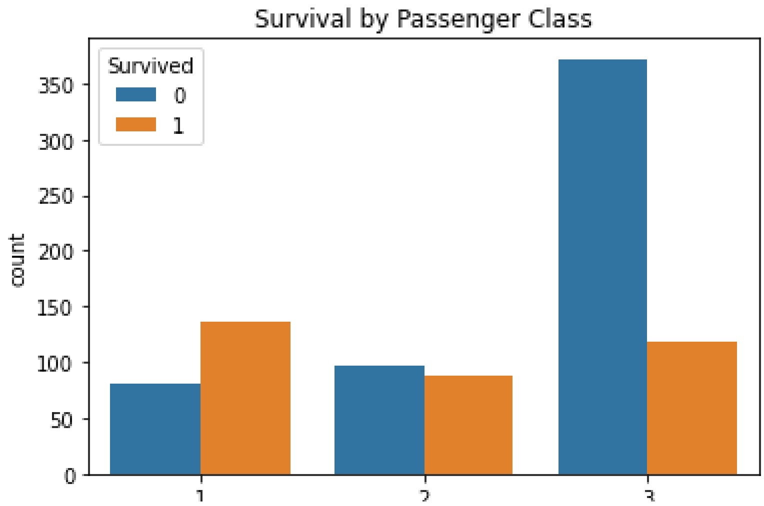
In [24]:

```
sns.countplot('Pclass',hue='Survived',data=df).set_title('Survival by Passenger Class')
```

```
  warnings.warn(
```

Out[24]:

```
Text(0.5, 1.0, 'Survival by Passenger Class')
```



Here we can see that the first class ticket holder has a better survival rate than that of a third class passenger.

Determine if the survival rate is associated to the gender

In [25]:

```
survivor_count = df['Survived'].sum()
by_factor = df.groupby('Sex')
count_by_factor = by_factor['Survived'].sum()
survival_rate = count_by_factor / survivor_count * 100
print('Survival rates:', survival_rate)
print('Counts: ', count_by_factor)
```

```
Survival rates: Sex
female    68.128655
male      31.871345
Name: Survived, dtype: float64
Counts:  Sex
female    233
male      109
Name: Survived, dtype: int64
```

In [ ]:

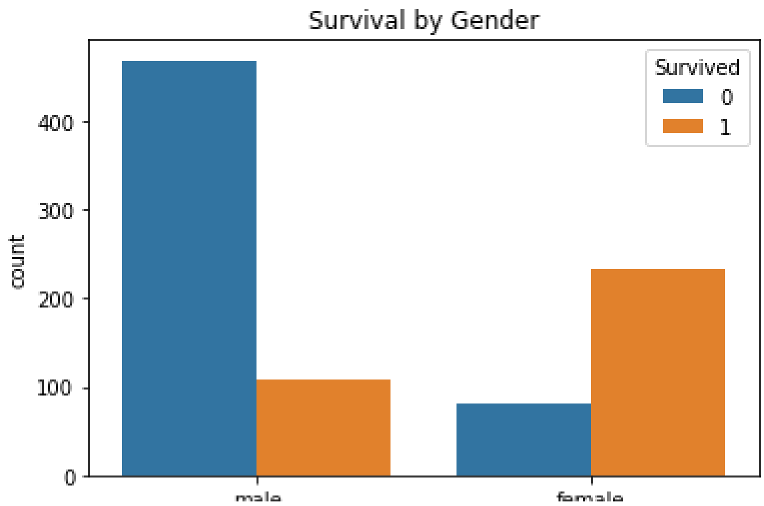
In [26]:

```
sns.countplot('Sex',hue='Survived',data=df).set_title('Survival by Gender')
```

```
  warnings.warn(
```

Out[26]:

```
Text(0.5, 1.0, 'Survival by Gender')
```



In this graph we can clearly see that Females had a better chance of survival i.e 68% and the male survival rate is just 32%.

Determine the survival rate is associated to the age

First we need to get rid of all the null values

In [70]:

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

Out[70]:

	Age	Survived
0	22	0
1	38	1
2	26	1
3	35	1
4	35	0

In [71]:

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

Out[71]:

```
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 [72]:

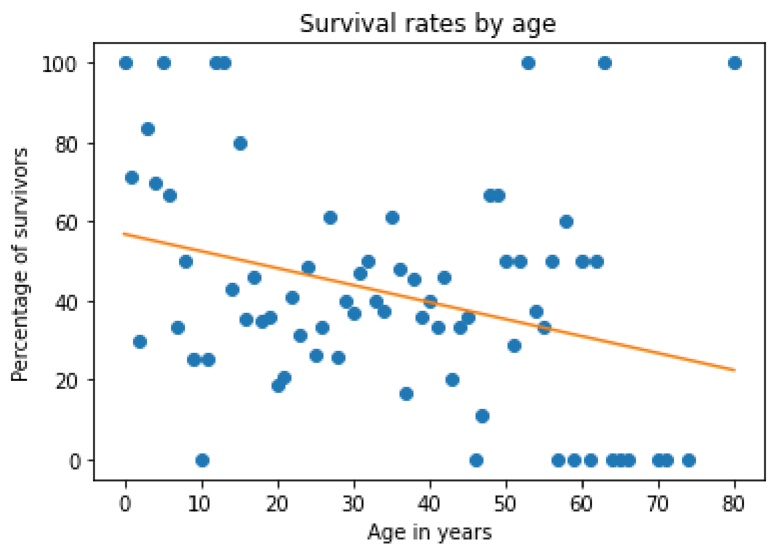
```
df_survival_age = pd.DataFrame(index=ages_list, columns=['Survived', 'Total', 'Percentage']

df_survival_age['Survived'] = df_age.groupby('Age')['Survived'].sum()
df_survival_age['Total'] = df_age.groupby('Age').count()
df_survival_age['Percentage'] = round(df_age.groupby('Age')['Survived'].mean() * 100, 2)
df_survival_age.head()
```

Out[72]:

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

In [77]:

```
import matplotlib.pyplot as plt
%matplotlib inline
x = df_survival_age['Percentage'].index
y = df_survival_age['Percentage']
plt.scatter(x, y)
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()
```



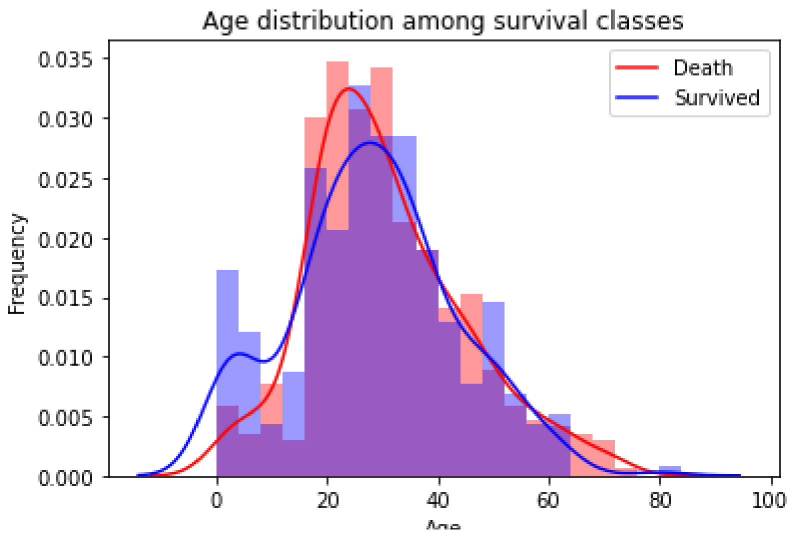

```
Here we can see that lower y values have high x values and the higher y values have low x
values which brings us to a conclusion that, the younger you are, the more chances you
have to survive.
However we can see that there are outliers in the top right corner which we will be
ignoring.
The regression line clearly shows that the younger you were, the higher your chances to
survive.
```

Plotting a distplot to determine the survival rate based on age

In [86]:

```
age_bins = np.arange(0, 100, 4)
sns.distplot(df.loc[(df['Survived']==0) & (~df['Age'].isnull()),'Age'], bins=age_bins, colo
sns.distplot(df.loc[(df['Survived']==1) & (~df['Age'].isnull()),'Age'], bins=age_bins, colo
plt.title('Age distribution among survival classes')
plt.ylabel('Frequency')
plt.legend(['Death', 'Survived'])
plt.show()
```

```
e-level function with similar flexibility) or `histplot` (an axes-level f
unction for histograms).
  warnings.warn(msg, FutureWarning)
```



We can see that the survival rate of younger passengers is higher than that of the passengers with old age.

In [89]:

```
sns.pairplot(df)
```

Out[89]:

<seaborn.axisgrid.PairGrid at 0x2997cd59310>