IBM Machine Learning Professional Certificate

Exploratory data analysis - Assignment 1
Submitted by Sharon Rose S

Introduction

For this assignment we will be working with the ***Titanic Dataset from Kaggle.***

During her maiden voyage on April 15, 1912, the largest passenger ship ever built collided with an iceberg. The Titanic sank, killing 1502 passengers and crew members out of a total of 2224. The international society was shocked by the disaster, which resulted in improved ship safety rules. There were not enough lifeboats for the passengers and crew, which was one of the reasons for the shipwreck's high death toll. Despite the fact that some persons were more likely to survive the sinking than others, there were other groups of people who were more likely to survive.

The Dataset (titanic.csv) file provides information on 891 actual Titanic passengers. Each row represents a single individual. The columns include many aspects of the person's life, such as whether or not they Survived, their Age, Passenger-class, Sex, Fare paid, Name, Cabin, Ticket, Embarked, Sibling Spouse(SibSp) and Parent Child(Parch).

Exploratory Data Analysis

Let's import the necessary libraries

```
In [2]: #Done by Sharon Rose S
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        %matplotlib inline
```

The Data: To begin, let's start by reading in the titanic_train.csv file into a pandas dataframe.

```
In [3]: train = pd.read_csv(r"C:\Users\Sharon\Desktop\IBM_ML\EDA\titanic_train.csv")
```

Exploratory Data Analysis

Let's explore the details of the dataset using info() and head() function

```
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
```

Exploratory Data Analysis

```
In [8]: train.head()
```

Out[8]:

	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

EDA

Let's get started with some data exploration! We'll strategize by looking for missing data.

Exploratory Data Analysis and Feature Engineering

Missing Data

To check for missing data, we'll utilise the built-in function isnull(), which is available within the dataframe.

In [6]:
```
train.isnull()
```

Out[6]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	False	False	False	False	False	False	False	False	False	False	True	False
1	False	False	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	True	False
3	False	False	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	True	False
...	...	...	...	...	...	...	...	...	...	...	...	...
886	False	False	False	False	False	False	False	False	False	False	True	False
887	False	False	False	False	False	False	False	False	False	False	False	False
888	False	False	False	False	False	True	False	False	False	False	True	False
889	False	False	False	False	False	False	False	False	False	False	False	False
890	False	False	False	False	False	False	False	False	False	False	True	False

891 rows × 12 columns

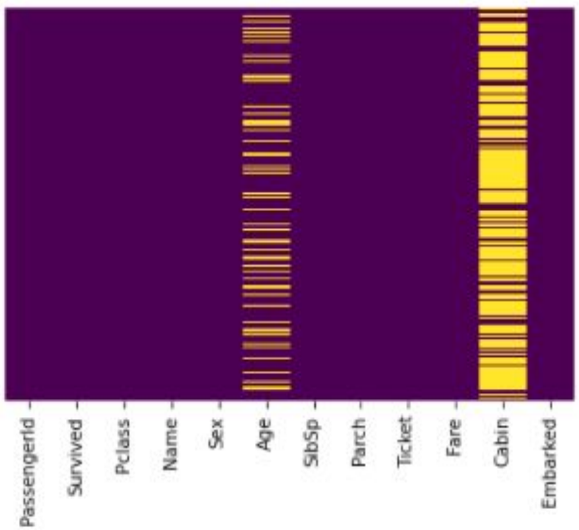
Exploratory Data Analysis and Feature Engineering

Data Exploration and Visualization

Let's utilise the seaborn library to develop a simple heatmap to visualize the null values.

More NaN values is observed in the
 Age and Cabin columns in the above
visualisation.Approximately 20% of the Age
 data is missing. The percentage of Age
that is missing is likely minimal enough to
be replaced reasonably with some sort
of imputation. Looking at the Cabin
column, it appears that we are lacking far
 too much information to accomplish
anything useful with at a basic level.
We'll probably remove
 that or replace it with something
like "Cabin Known: 1 or 0" eventually.

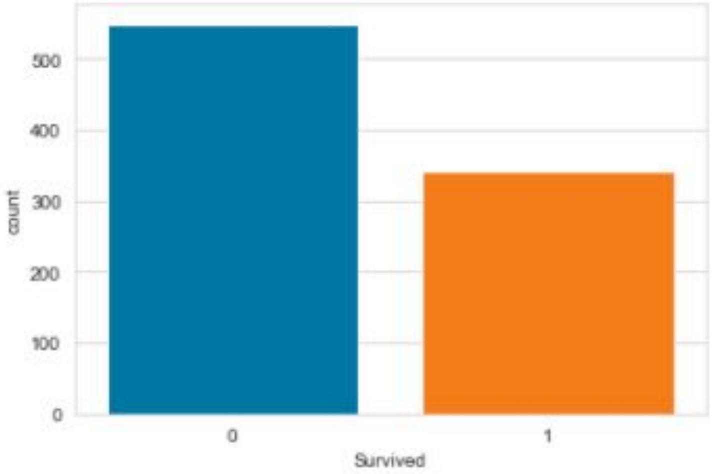
```
In [7]: sns.heatmap(train.isnull(),yticklabels=False,cbar=False,cmap='viridis')

Out[7]: <AxesSubplot:>
```



Exploratory Data Analysis and Feature Engineering

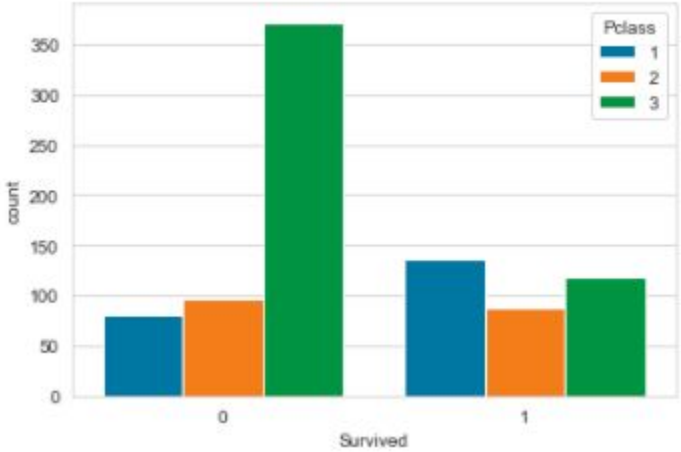
Now let's use counterplot to our advantage. Let's make a countplot based on the survived column. Countplots allow us to see how many people died and how many people survived from the 891 records.

```
In [8]: sns.set_style('whitegrid')
        sns.countplot(x='Survived',data=train)

Out[8]: <AxesSubplot:xlabel='Survived', ylabel='count'>
```



Exploratory Data Analysis and Feature Engineering

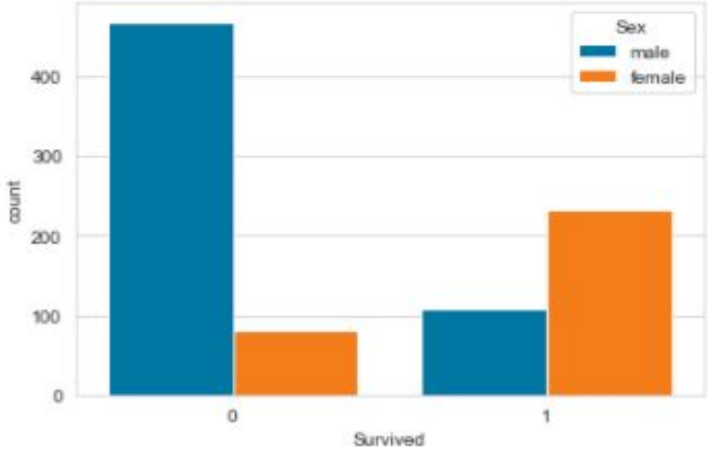
```
In [9]: sns.set_style('whitegrid')
        sns.countplot(x='Survived',hue='Pclass',data=train)

Out[9]: <AxesSubplot:xlabel='Survived', ylabel='count'>
```



We can see from the graph above that travellers from pclass 3 have died in greater numbers than passengers from pclass 1 and 2

Exploratory Data Analysis and Feature Engineering

```
In [10]: sns.set_style('whitegrid')
         sns.countplot(x='Survived',hue='Sex',data=train)

Out[10]: <AxesSubplot:xlabel='Survived', ylabel='count'>
```

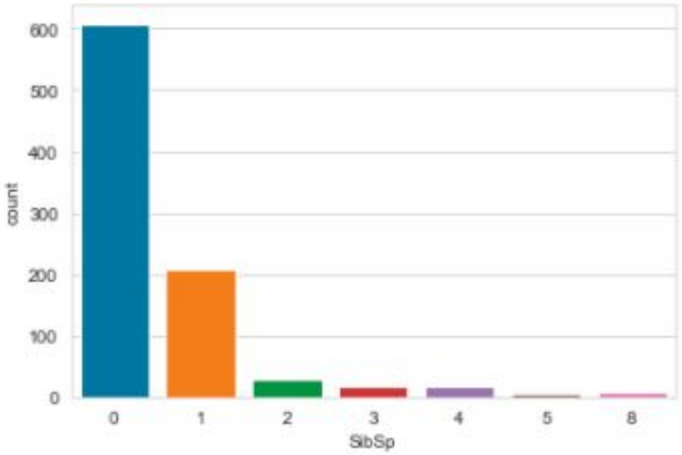


We can see from the graph above that male passengers have died in greater numbers than female passengers considering the 891 records of the dataset.

Exploratory Data Analysis and Feature Engineering

```
In [11]: sns.countplot(x='SibSp',data=train)
```

```
Out[11]: <AxesSubplot:xlabel='SibSp', ylabel='count'>
```



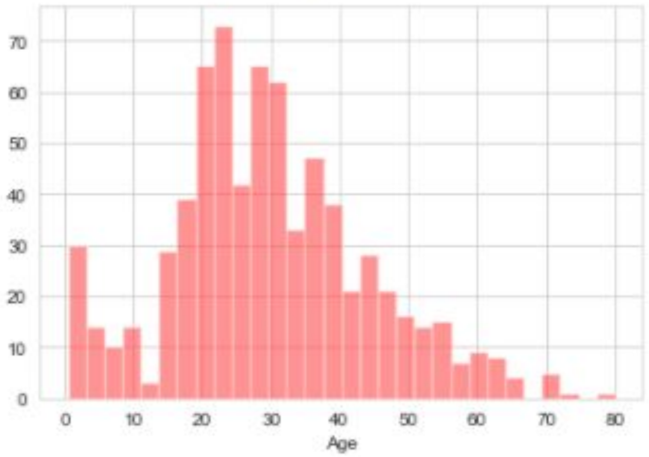
The graph above shows the number of travellers who did not have a spouse or sibling. As can be seen, many travellers did not have a spouse or sibling.

Exploratory Data Analysis and Feature Engineering

Now, using the distplot, we can observe if the age follows a normal distribution or not, which will help us figure out what the average age of the travellers on the boat was.

```
In [21]: sns.distplot(train['Age'].dropna(),kde=False,color='red',bins=30)
```

```
Out[21]: <AxesSubplot:xlabel='Age'>
```



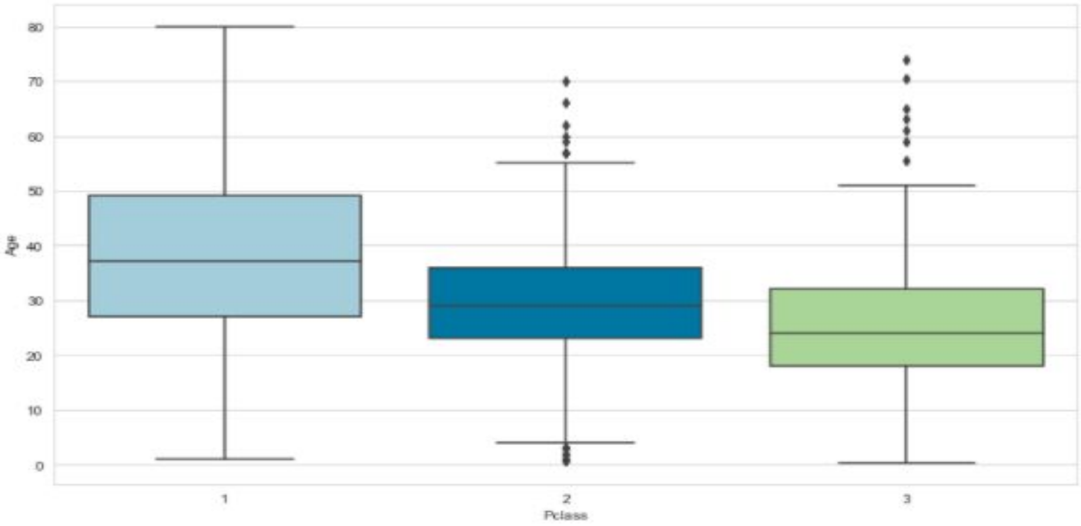
The graph above shows that the average age between 17 and 30 is the greatest, while the number of senior individuals who have travelled is the lowest.

Exploratory Data Analysis and Feature Engineering

Data Cleaning

Instead of discarding the missing age data rows, we'd like to fill up the gaps. Filling in the average age of all passengers is one method to do this. We can, however, smarter about this and check the average age by passenger class by making use of boxplot and a simple function to replace null values. For example:

```
In [23]: plt.figure(figsize=(12, 7))
         sns.boxplot(x='Pclass',y='Age',data=train,palette='Paired')

Out[23]: <AxesSubplot:xlabel='Pclass', ylabel='Age'>
```



Exploratory Data Analysis and Feature Engineering

We can see that the wealthy passengers in the upper classes are older, which is understandable from the boxplot. We'll infer based on Pclass for Age using these average age values.

```
In [24]: def impute_age(cols):
             Age = cols[0]
             Pclass = cols[1]

             if pd.isnull(Age):

                 if Pclass == 1:
                     return 37

                 elif Pclass == 2:
                     return 29

                 else:
                     return 24

             else:
                 return Age
```

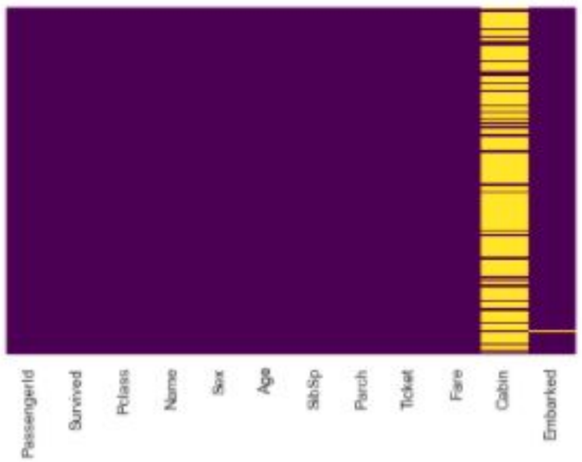
Now, let's use the function we just defined

```
In [25]: train['Age'] = train[['Age','Pclass']].apply(impute_age,axis=1)
```

Exploratory Data Analysis and Feature Engineering

Let's take a look at that heat map once more!

```
In [26]: sns.heatmap(train.isnull(),yticklabels=False,cbar=False,cmap='viridis')

Out[26]: <AxesSubplot:>
```



The null values in the Age column have now been replaced with values pertaining to the passenger class.

Exploratory Data Analysis and Feature Engineering

Great! Let's get rid of the Cabin column and the NaN-filled row in Embarked.

```
In [27]: train.drop('Cabin',axis=1,inplace=True)
```

```
In [28]: train.head()
```

Out[28]:

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

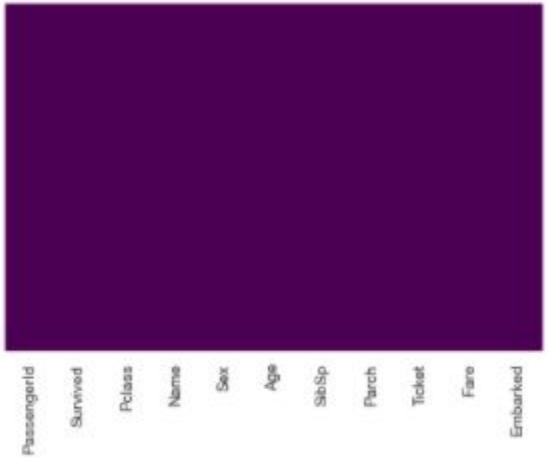
```
In [30]: train.dropna(inplace=True)
```

we cleansed the data and it is ready for further analysis.

Exploratory Data Analysis and Feature Engineering

Let's take a look at that heat map once more to check if the NaN are replaced or removed completely.

```
In [19]: sns.heatmap(train.isnull(),yticklabels=False,cbar=False,cmap='viridis')

Out[19]: <AxesSubplot:>
```



we cleansed the data and it is ready for further analysis.

Hypothesis

Hypothesis testing is a form of statistical inference that uses data from a sample to draw conclusions about a population parameter or a population probability distribution. First, a tentative assumption is made about the parameter or distribution. This assumption is called the null hypothesis and is denoted by H0. An alternative hypothesis (denoted HA), which is the opposite of what is stated in the null hypothesis, is then defined. The hypothesis-testing procedure involves using sample data to determine whether or not H0 can be rejected. If H0 is rejected, the statistical conclusion is that the alternative hypothesis HA is true.

First

The hypothesis for this question is that people's socio-economic level had an impact on their survival rate.

<u>Null Hypothesis(H0) :</u> The socio-economic class of the people didn’t have an effect on the survival rate.

<u>Alternative Hypothesis(HA) </u>: The socio-economic class of the people affected their survival rate.

Hypothesis

Second

The hypothesis for this question is that more than half of the passengers who survived the Titanic were between the ages of 20 and 40.

Null Hypothesis(H0) : Less than 50% of passengers who survived in Titanic are in the age group of 20–40

Alternative Hypothesis(HA) : Greater than 50% of passengers who survived in Titanic are in the age group of 20–40

Third

The hypothesis for this question is that age affects survival chances.

Null Hypothesis(H0) : The age group has an effect on survival odds

Alternative Hypothesis(HA) : Survivability is unaffected by age group

Hypothesis testing - chi-sqaure test

Solution for Hypothesis no.3

```
In [44]: #Solution for Hypothesis no.3
         from scipy import stats

In [49]: table = pd.crosstab([train['Survived']], train['Age'])
         chi2, p, dof, expected = stats.chi2_contingency(table.values)
         results = [

             ['Chi-Square Test',chi2],
             ['P-Value', p]
         ]
         print(results)

         [['Chi-Square Test', 110.20372747951563], ['P-Value', 0.047184688944026235]]
```

Because the P-Value is less than 0.05, the likelihood that the survivability is unaffected by age group is high. As a result, I believe we can rule out the null hypothesis.

Conclusion with Next Step

The more information we have, like with most datasets, the better we can analyze it.
I suppose the following variables could be added:

Lifeboat Count: There were not enough lifeboats on board the Titanic, which is why there were so many casualties. I feel that if we knew the number of lifeboats available and their capacity, we could evaluate whether or not more people could survive.

Passenger or crew: The current dataset makes no distinction between the two, but we know from history that a mixture of both survived.

Following the Eda, a machine learning logistic regression model is built using training and test splits.

Thank you!!