
Group A
Assignment No: 9

Title of the Assignment: Data Visualization II

1. Use the inbuilt dataset 'titanic' as used in the above problem. Plot a box plot for distribution of age with respect to each gender along with the information about whether they
survived or not. (Column names : 'sex' and 'age')
2. Write observations on the inference from the above statistics.

Objective of the Assignment: Students should be able to perform the data Visualization
operation using Python on any open source dataset

Prerequisite:
1. Basic of Python Programming
2. Seaborn Library, Concept of Data Visualization.

What is EDA?

Exploratory Data Analysis (EDA) is a method used to analyze and summarize datasets. Majority of the EDA techniques involve the use of graphs.

Titanic Dataset –

It is one of the most popular datasets used for understanding machine learning basics. It contains information of all the passengers aboard the RMS Titanic, which unfortunately was shipwrecked. This dataset can be used to predict whether a given passenger survived or not. The csv file can be downloaded from Kaggle.

1. PassengerId: Unique Id of a passenger
2. Survived: If the passenger survived(0-No, 1-Yes)
3. Pclass: Passenger Class (1 = 1st, 2 = 2nd, 3 = 3rd)
4. Name: Name of the passenger
5. Sex: Male/Female
6. Age: Passenger age in years
7. SibSp: No of siblings/spouses aboard
8. Parch: No of parents/children aboard
9. Ticket: Ticket Number
10. Fare: Passenger Fare
11. Cabin: Cabin number
12. Embarked: Port of Embarkation (C = Cherbourg; Q = Queenstown; S = Southampton)

Code: Loading data using Pandas

```
#importing pandas library

import pandas as pd

#loading data

titanic = pd.read_csv('...\input\train.csv')
```

Seaborn:

It is a python library used to statistically visualize data. Seaborn, built over Matplotlib, provides a better interface and ease of usage. It can be installed using the following command, pip3 install seaborn

Code: Printing data head

```
# View first five rows of the dataset
titanic.head()
```

Output :

	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

Code: Checking the NULL values

```
titanic.isnull().sum()
```

Output:-

```
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
```

The columns having null values are: Age, Cabin, Embarked. They need to be filled up with appropriate values later on.

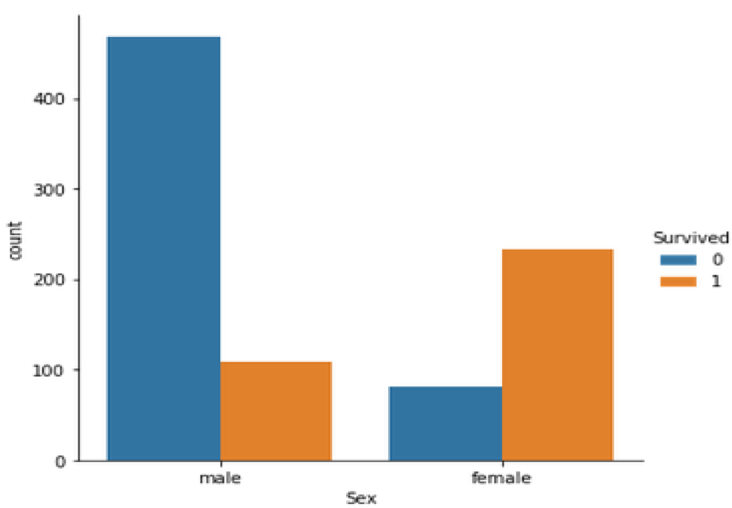
Features: The titanic dataset has roughly the following types of features:

- **Categorical/Nominal**: Variables that can be divided into multiple categories but having no order or priority.
  Eg. Embarked (C = Cherbourg; Q = Queenstown; S = Southampton)
- **Binary**: A subtype of categorical features, where the variable has only two categories.
  Eg: Sex (Male/Female)
- **Ordinal**: They are similar to categorical features but they have an order(i.e can be sorted).
  Eg. Pclass (1, 2, 3)
- **Continuous**: They can take up any value between the minimum and maximum values in a column.
  Eg. Age, Fare
- **Count**: They represent the count of a variable.
  Eg. SibSp, Parch
- **Useless**: They don't contribute to the final outcome of an ML model. Here, *PassengerId*, *Name*, *Cabin* and *Ticket* might fall into this category.

Code: Graphical Analysis

```
import seaborn as sns
import matplotlib.pyplot as plt

# Countplot
sns.catplot(x ="Sex", hue ="Survived",
kind ="count", data = titanic)
```

Output:-

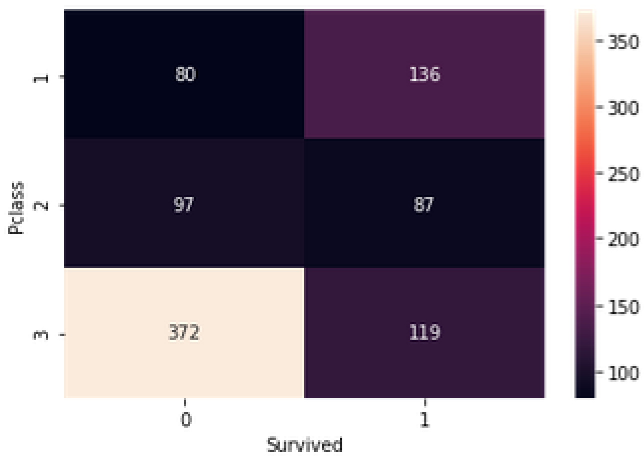


Just by observing the graph, it can be approximated that the survival rate of men is around *20%* and that of women is around *75%*. Therefore, whether a passenger is a male or a female plays an important role in determining if one is going to survive.

Code : Pclass (Ordinal Feature) vs Survived

```
# Group the dataset by Pclass and Survived and then unstack them
group = titanic.groupby(['Pclass', 'Survived'])
pclass_survived = group.size().unstack()

# Heatmap - Color encoded 2D representation of data.
sns.heatmap(pclass_survived, annot = True, fmt ="d")
```

Output:

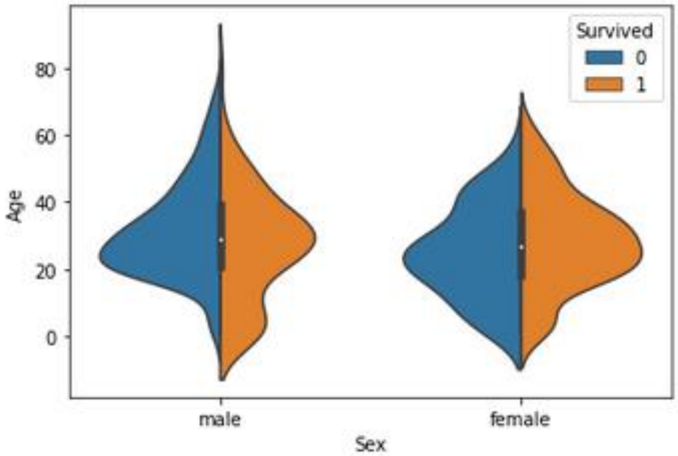


It helps in determining if higher-class passengers had more survival rate than the lower class ones or vice versa. Class 1 passengers have a higher survival chance compared to classes 2 and 3. It implies that Pclass contributes a lot to a passenger’s survival rate.

Code : Age (Continuous Feature) vs Survived

```
# Violinplot Displays distribution of data
# across all levels of a category.
sns.violinplot(x ="Sex", y ="Age", hue ="Survived",
data = titanic, split = True)
```

Output:-



This graph gives a summary of the age range of men, women and children who were saved. The survival rate is –

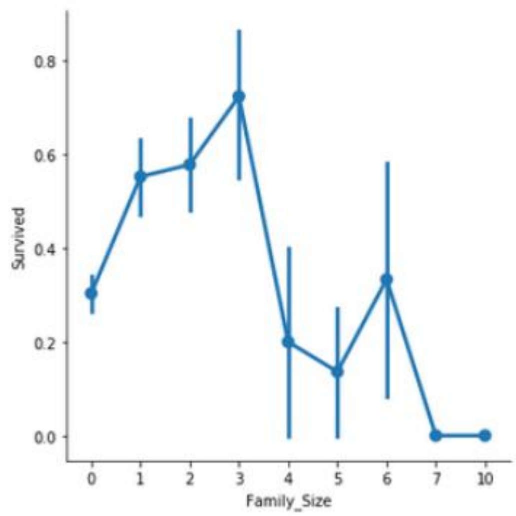
- Good for children.
- High for women in the age range 20-50.
- Less for men as the age increases.

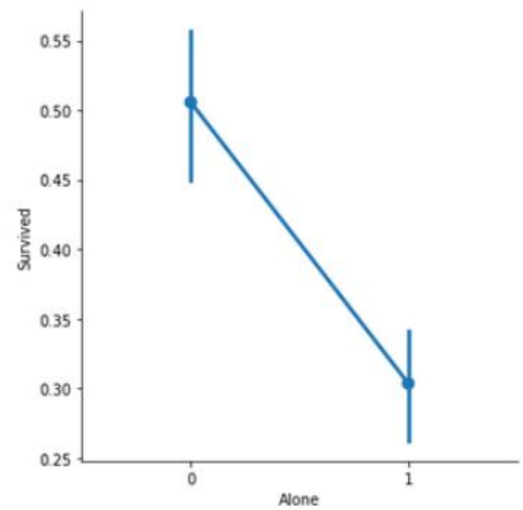
Since *Age* column is important, the missing values need to be filled, either by using the *Name* column(ascertaining age based on salutation – Mr, Mrs etc.) or by using a regressor. After this step, another column – *Age_Range* (based on age column) can be created and the data can be analyzed again.

Code : Factor plot for Family_Size (Count Feature) and Family Size.

```
# Adding a column Family_Size
titanic['Family_Size'] = 0
titanic['Family_Size'] = titanic['Parch']+titanic['SibSp']

# Adding a column Alone
titanic['Alone'] = 0
titanic.loc[titanic.Family_Size == 0, 'Alone'] = 1

# Factorplot for Family_Size
sns.factorplot(x ='Family_Size', y ='Survived', data = titanic)

# Factorplot for Alone
sns.factorplot(x ='Alone', y ='Survived', data = titanic)
```

Output:-





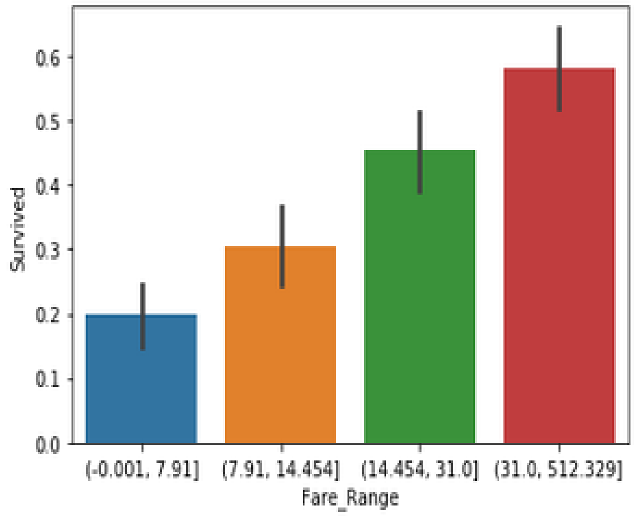
Family_Size denotes the number of people in a passenger's family. It is calculated by summing the **SibSp** and **Parch** columns of a respective passenger. Also, another column **Alone** is added to check the chances of survival of a lone passenger against the one with a family.
Important observations –

- If a passenger is alone, the survival rate is less.
- If the family size is greater than 5, chances of survival decrease considerably.

Code : Bar Plot for Fare (Continuous Feature)

```
# Divide Fare into 4 bins
titanic['Fare_Range'] = pd.qcut(titanic['Fare'], 4)

# Barplot - Shows approximate values based
# on the height of bars.
sns.barplot(x ='Fare_Range', y ='Survived',
data = titanic)
```

Output:-

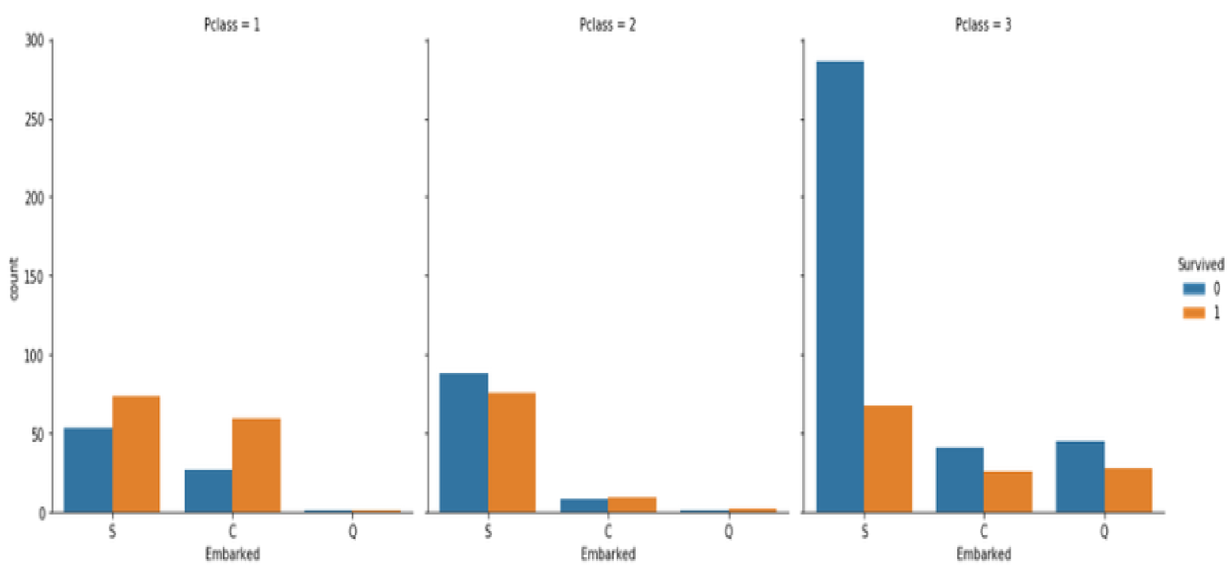


Fare denotes the fare paid by a passenger. As the values in this column are continuous, they need to be put in separate bins(as done for **Age** feature) to get a clear idea. It can be concluded that if a passenger paid a higher fare, the survival rate is more.

Code: Categorical Count Plots for Embarked Feature

```
# Countplot
sns.catplot(x ='Embarked', hue ='Survived',
kind ='count', col ='Pclass', data = titanic)
```

Output:-



Some notable observations are:

- Majority of the passengers boarded from *S*. So, the missing values can be filled with *S*.
- Majority of class 3 passengers boarded from *Q*.
- *S* looks lucky for class 1 and 2 passengers compared to class 3.

Conclusion :

- The columns that can be dropped are:
  - PassengerId, Name, Ticket, Cabin: They are strings, cannot be categorized and don't contribute much to the outcome.
  - Age, Fare: Instead, the respective range columns are retained.
- The titanic data can be analyzed using many more graph techniques and also more column correlations, than, as described in this article.
- Once the EDA is completed, the resultant dataset can be used for predictions.