TC2-DS- Experiment 6

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• AIM - To perform feature engineering on "TITANIC" dataset

• To Do -

1. Handling of Missing Values:
   - For Numerical Variables.
   - Categorical Variables.
2. Handling of Outliers at least for 1 variable.
3. Handling of Rare Variables.

In [1]:
```
%matplotlib inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import category_encoders as ce
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
#Loading the Titanic Dataset =
Titanic_df = pd.read_csv(r'C:\sia\Titanic_Dataset.csv')
print("The Dataset is as Follows:")
print(Titanic_df.dropna(), '\n')
```

```
The Dataset is as Follows:
     PassengerId  Survived  Pclass  \
1              2         1       1
3              4         1       1
6              7         0       1
10            11         1       3
11            12         1       1
..           ...       ...     ...
871          872         1       1
872          873         0       1
879          880         1       1
887          888         1       1
889          890         1       1

                                                 Name  Gender   Age  SibSp  \
1    Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
3         Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
6                              McCarthy, Mr. Timothy J    male  54.0      0
10                    Sandstrom, Miss. Marguerite Rut  female   4.0      1
11                           Bonnell, Miss. Elizabeth  female  58.0      0
..                                                ...     ...   ...    ...
871   Beckwith, Mrs. Richard Leonard (Sallie Monypeny)  female  47.0      1
872                           Carlsson, Mr. Frans Olof    male  33.0      0
879      Potter, Mrs. Thomas Jr (Lily Alexenia Wilson)  female  56.0      0
887                       Graham, Miss. Margaret Edith  female  19.0      0
889                            Behr, Mr. Karl Howell    male  26.0      0

     Parch    Ticket     Fare        Cabin Embarked
1        0  PC 17599  71.2833          C85        C
3        0    113803  53.1000         C123        S
6        0     17463  51.8625          E46        S
10       1   PP 9549  16.7000           G6        S
11       0    113783  26.5500         C103        S
..     ...       ...      ...          ...      ...
871      1     11751  52.5542          D35        S
872      0       695   5.0000  B51 B53 B55        S
879      1     11767  83.1583          C50        C
887      0    112053  30.0000          B42        S
889      0    111369  30.0000         C148        C

[183 rows x 12 columns]
```

In [3]:
```
#Shaping the DataSet
Titanic_df.shape
```

Out[3]:
```
(891, 12)
```

In [4]:
```
#DataSet Information
Titanic_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   Gender       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 [5]:
```
#Descriptive Stats
Titanic_df.describe()
```

Out[5]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

~ Handling Missing Values

In [6]:
```
Titanic_df.isna().sum()
```

Out[6]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Gender           0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

In [7]:
```
na_variables = []

for series in Titanic_df.columns:
    if Titanic_df[series].isna().sum() > 0:
        na_variables.append(series)
        print(f"Column which consists null values: {series}")
```

```
Column which consists null values: Age
Column which consists null values: Cabin
Column which consists null values: Embarked
```

In [8]:
```
numerical_na_variables = []
categorical_na_variables = []

for series in na_variables:
    if Titanic_df[series].dtype == 'float64' or Titanic_df[series].dtype == 'int64':
        numerical_na_variables.append(series)
    elif Titanic_df[series].dtype == "O":
      categorical_na_variables.append(series)
    else:
        pass
```

Here, The categorical and numerical variables that have null values have been identified; and in the following steps, we will fill in the values for each variable.

In [9]:
```
for series in na_variables:
    print("{}: {}% missing values".format(series,np.round(Titanic_df[series].isnull().mean())))
```

```
Age: 0.0% missing values
Cabin: 1.0% missing values
Embarked: 0.0% missing values
```

a) Numerical Variables -

In [10]:
```
numerical_na_variables
```

Out[10]:
```
['Age']
```

In [11]:
```
#Filling the missing value with median

for series in numerical_na_variables:
 Titanic_df[series].fillna(Titanic_df[series].median(), inplace=True)

Titanic_df.head()
```

Out[11]:

	PassengerId	Survived	Pclass	Name	Gender	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 [12]:
```
Titanic_df.isna().sum()
```

Out[12]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Gender           0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

a) Categorical Variables -

In [13]:
```
#Filling up the missing values with 'Missing

for series in categorical_na_variables:
 Titanic_df[series].fillna('Missing', inplace=True)

Titanic_df.head()
```

Out[13]:

	PassengerId	Survived	Pclass	Name	Gender	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	Missing	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	Missing	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	Missing	S

In [14]:
```
Titanic_df.isna().sum()
```

Out[14]:
```
PassengerId    0
Survived       0
Pclass         0
Name           0
Gender         0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Cabin          0
Embarked       0
dtype: int64
```

As we can see that the cabin series contains a lot of missing data, which is not helpful for the model, we can drop the column.

In [15]:
```
Titanic_df.drop("Cabin", axis=1, inplace=True)
```

In [16]:
```
Titanic_df.head()
```

Out[16]:

	PassengerId	Survived	Pclass	Name	Gender	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

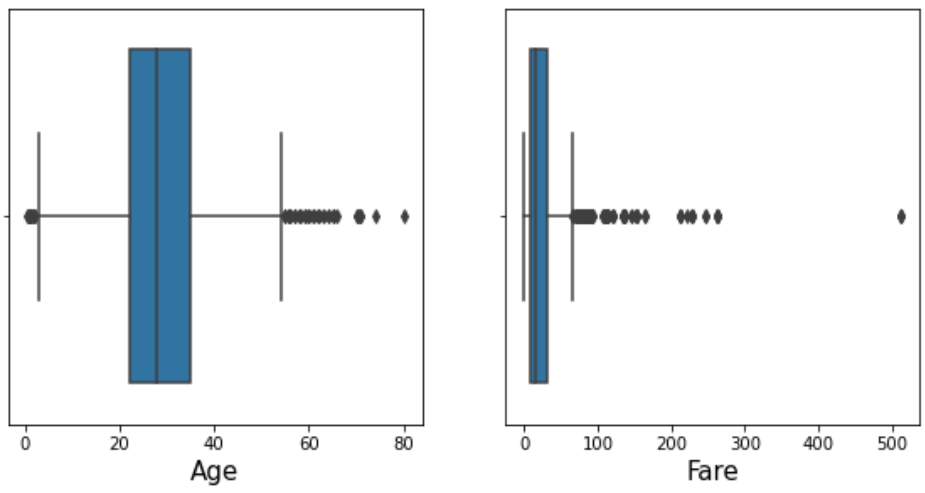
Here, we have successfully cleaned the data and filled in the missing values with the required parameters. I've also dropped the Cabin Series as it contains a lot of missing values which will not be important features in the feature.

In [17]:
```
#Here we can Identify the Numerical Variables:
numerical_variables = ["Age", "Fare"]
```

In [18]:
```
#Also, here we can Identify the Categorical Variables:
categorical_variables = ["Survived", "Pclass", "Sex", "SibSp", "Parch", "Embarked"]
```

~ Handling The Outliers

In [19]:
```
plt.figure(figsize = (15,10), facecolor='white')
graphplot = 1
for column in numerical_variables:
    if graphplot<=6:
        ax = plt.subplot(2,3,graphplot)
        sns.boxplot(Titanic_df[column])
        plt.xlabel(column,fontsize=15)
    graphplot+=1
plt.show()
```



Here, we can understand from the plots that for:

1. Age: All values greater than 65 approximately can be said as outliers
2. Fare: Mostly the values greater than 200 can be said as outliers. And the outlier lies at greater than 500

In [20]:
```
Titanic_df[Titanic_df["Age"] > 65]
```

Out[20]:

	PassengerId	Survived	Pclass	Name	Gender	Age	SibSp	Parch	Ticket	Fare	Embarked
33	34	0	2	Wheadon, Mr. Edward H	male	66.0	0	0	C.A. 24579	10.5000	S
96	97	0	1	Goldschmidt, Mr. George B	male	71.0	0	0	PC 17754	34.6542	C
116	117	0	3	Connors, Mr. Patrick	male	70.5	0	0	370369	7.7500	Q
493	494	0	1	Artagaveytia, Mr. Ramon	male	71.0	0	0	PC 17609	49.5042	C
630	631	1	1	Barkworth, Mr. Algernon Henry Wilson	male	80.0	0	0	27042	30.0000	S
672	673	0	2	Mitchell, Mr. Henry Michael	male	70.0	0	0	C.A. 24580	10.5000	S
745	746	0	1	Crosby, Capt. Edward Gifford	male	70.0	1	1	WE/P 5735	71.0000	S
851	852	0	3	Svensson, Mr. Johan	male	74.0	0	0	347060	7.7750	S

In [21]:
```
Titanic_df[Titanic_df["Fare"] > 200]
```

Out[21]:

	PassengerId	Survived	Pclass	Name	Gender	Age	SibSp	Parch	Ticket	Fare	Embarked
27	28	0	1	Fortune, Mr. Charles Alexander	male	19.0	3	2	19950	263.0000	S
88	89	1	1	Fortune, Miss. Mabel Helen	female	23.0	3	2	19950	263.0000	S
118	119	0	1	Baxter, Mr. Quigg Edmond	male	24.0	0	1	PC 17558	247.5208	C
258	259	1	1	Ward, Miss. Anna	female	35.0	0	0	PC 17755	512.3292	C
299	300	1	1	Baxter, Mrs. James (Helene DeLaudeniere Chaput)	female	50.0	0	1	PC 17558	247.5208	C
311	312	1	1	Ryerson, Miss. Emily Borie	female	18.0	2	2	PC 17608	262.3750	C
341	342	1	1	Fortune, Miss. Alice Elizabeth	female	24.0	3	2	19950	263.0000	S
377	378	0	1	Widener, Mr. Harry Elkins	male	27.0	0	2	113503	211.5000	C
380	381	1	1	Bidois, Miss. Rosalie	female	42.0	0	0	PC 17757	227.5250	C
438	439	0	1	Fortune, Mr. Mark	male	64.0	1	4	19950	263.0000	S
527	528	0	1	Farthing, Mr. John	male	28.0	0	0	PC 17483	221.7792	S
557	558	0	1	Robbins, Mr. Victor	male	28.0	0	0	PC 17757	227.5250	C
679	680	1	1	Cardeza, Mr. Thomas Drake Martinez	male	36.0	0	1	PC 17755	512.3292	C
689	690	1	1	Madill, Miss. Georgette Alexandra	female	15.0	0	1	24160	211.3375	S
700	701	1	1	Astor, Mrs. John Jacob (Madeleine Talmadge Force)	female	18.0	1	0	PC 17757	227.5250	C
716	717	1	1	Endres, Miss. Caroline Louise	female	38.0	0	0	PC 17757	227.5250	C
730	731	1	1	Allen, Miss. Elisabeth Walton	female	29.0	0	0	24160	211.3375	S
737	738	1	1	Lesurer, Mr. Gustave J	male	35.0	0	0	PC 17755	512.3292	C
742	743	1	1	Ryerson, Miss. Susan Parker "Suzette"	female	21.0	2	2	PC 17608	262.3750	C
779	780	1	1	Robert, Mrs. Edward Scott (Elisabeth Walton Mc...	female	43.0	0	1	24160	211.3375	S

In [22]:
```
Titanic_df[Titanic_df["Fare"] > 500]
```

Out[22]:

	PassengerId	Survived	Pclass	Name	Gender	Age	SibSp	Parch	Ticket	Fare	Embarked
258	259	1	1	Ward, Miss. Anna	female	35.0	0	0	PC 17755	512.3292	C
679	680	1	1	Cardeza, Mr. Thomas Drake Martinez	male	36.0	0	1	PC 17755	512.3292	C
737	738	1	1	Lesurer, Mr. Gustave J	male	35.0	0	0	PC 17755	512.3292	C

In [23]:
```
Q1_Fare = np.quantile(Titanic_df["Fare"], 0.25)
Q3_Fare = np.quantile(Titanic_df["Fare"], 0.75)

IQR_Fare = Q3_Fare - Q1_Fare
```

In [24]:
```
Q1_Age = np.quantile(Titanic_df["Age"], 0.25)
Q3_Age = np.quantile(Titanic_df["Age"], 0.75)

IQR_Age = Q3_Age - Q1_Age
```

In [25]:
```
MIN_VALUE_Age = Q1_Fare - 1.5 * IQR_Age
print(f"The Minimum Value: {MIN_VALUE_Age}")
```

```
The Minimum Value: -11.5896
```

In [26]:
```
MAX_VALUE_Age = Q3_Age + 1.5 * IQR_Age
print(f"The Maximum Value: {MAX_VALUE_Age}")
```

```
The Maximum Value: 54.5
```

In [27]:
```
MIN_VALUE_Fare = Q1_Fare - 1.5 * IQR_Fare
print(f"The Minimum Value: {MIN_VALUE_Fare}")
```

```
The Minimum Value: -26.724
```

In [28]:
```
MAX_VALUE_fare = Q3_Fare + 1.5 * IQR_Fare
print(f"The Maximum Value: {MAX_VALUE_fare}")
```

```
The Maximum Value: 65.6344
```

We can identify the outliers by considering the Min and Max values of the range for Age and Fare respectively and we are able to recognize the Outliers by finding the values below Min value and above max value respectively

---

~ Handling Rare Variables

In [29]:
```
# Here, we can define the rare variables which can exist rarely in the dataset
rare_variables = ["Name", "Ticket"]
```

In [30]:
```
for feature in rare_variables:
 temp = Titanic_df.groupby(feature)["Fare"].count() / len(Titanic_df)
 temp_df = temp[temp > 0.01].index
 Titanic_df[feature] = np.where(Titanic_df[feature].isin(temp_df), Titanic_df[feature], 'Rare Variables')
Titanic_df.head()
```

Out[30]:

	PassengerId	Survived	Pclass	Name	Gender	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	3	Rare Variables	male	22.0	1	0	Rare Variables	7.2500	S
1	2	1	1	Rare Variables	female	38.0	1	0	Rare Variables	71.2833	C
2	3	1	3	Rare Variables	female	26.0	0	0	Rare Variables	7.9250	S
3	4	1	1	Rare Variables	female	35.0	1	0	Rare Variables	53.1000	S
4	5	0	3	Rare Variables	male	35.0	0	0	Rare Variables	8.0500	S

In [31]:
```
for feature in rare_variables:
 temp = Titanic_df.groupby(feature)["Age"].count() / len(Titanic_df)
 temp_df = temp[temp > 0.01].index
 Titanic_df[feature] = np.where(Titanic_df[feature].isin(temp_df), Titanic_df[feature], 'Rare Variables')
Titanic_df.head()
```

Out[31]:

	PassengerId	Survived	Pclass	Name	Gender	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	3	Rare Variables	male	22.0	1	0	Rare Variables	7.2500	S
1	2	1	1	Rare Variables	female	38.0	1	0	Rare Variables	71.2833	C
2	3	1	3	Rare Variables	female	26.0	0	0	Rare Variables	7.9250	S
3	4	1	1	Rare Variables	female	35.0	1	0	Rare Variables	53.1000	S
4	5	0	3	Rare Variables	male	35.0	0	0	Rare Variables	8.0500	S

In [32]:
```
for feature in rare_variables:
 labels = Titanic_df.groupby(feature)['Fare'].mean().sort_values().index
 labels = {j:i for i, j in enumerate(labels, 0)}
 Titanic_df[feature] = Titanic_df[feature].map(labels)
Titanic_df.head()
```

Out[32]:

	PassengerId	Survived	Pclass	Name	Gender	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	3	0	male	22.0	1	0	0	7.2500	S
1	2	1	1	0	female	38.0	1	0	0	71.2833	C
2	3	1	3	0	female	26.0	0	0	0	7.9250	S
3	4	1	1	0	female	35.0	1	0	0	53.1000	S
4	5	0	3	0	male	35.0	0	0	0	8.0500	S

In [33]:
```
for feature in rare_variables:
 labels = Titanic_df.groupby(feature)['Age'].mean().sort_values().index
 labels = {j:i for i, j in enumerate(labels, 0)}
 Titanic_df[feature] = Titanic_df[feature].map(labels)

Titanic_df.head()
```

Out[33]:

	PassengerId	Survived	Pclass	Name	Gender	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	3	0	male	22.0	1	0	0	7.2500	S
1	2	1	1	0	female	38.0	1	0	0	71.2833	C
2	3	1	3	0	female	26.0	0	0	0	7.9250	S
3	4	1	1	0	female	35.0	1	0	0	53.1000	S
4	5	0	3	0	male	35.0	0	0	0	8.0500	S

~ Encoding on the nominal and ordinal & categorical variables

> One-hot encoding: keeps all information about variable, but create a lot of new features
>
> Binary encoding: keeps all information about variable, creates new dimensions, but less than one-hot encoder
>
> Ordinal numbering encoding: keeps semantical info about variable, but treats 2-1 as 3-2 and can be missleading, doesn't create new dimensions

---

Ordinal Encoding

In [34]:
```
ordinal_features = Titanic_df[['Embarked']].copy()
ordinal_features.head(10)
```

Out[34]:

	Embarked
0	S
1	C
2	S
3	S
4	S
5	Q
6	S
7	S
8	S
9	C

In [35]:
```
def encode_ordinal_features(Titanic_df):
 Embarked = {'S':1, 'C':2, 'Q':3}
 Titanic_df['Embarked'] =Titanic_df.Embarked.map(Embarked)
 return Titanic_df
ordinal_features = encode_ordinal_features(ordinal_features)
ordinal_features.head(10)
```

Out[35]:

	Embarked
0	1.0
1	2.0
2	1.0
3	1.0
4	1.0
5	3.0
6	1.0
7	1.0
8	1.0
9	2.0

One Hot Encoding:

In [36]:
```
pd.get_dummies(Titanic_df['Gender']).head()
pd.concat([Titanic_df['Gender'], pd.get_dummies(Titanic_df['Gender'])], axis=1).head(10)
```

Out[36]:

	Gender	female	male
0	male	0	1
1	female	1	0
2	female	1	0
3	female	1	0
4	male	0	1
5	male	0	1
6	male	0	1
7	male	0	1
8	female	1	0
9	female	1	0

Conclusion:

In conclusion, the data has been cleaned, and the outliers and rare variables have been identified. In addition, we have integrated the necessary methods for both the exploratory data analysis and feature engineering. On the nominal and ordinal categorical variables of the provided Titanic Dataset, we applied Feature Encoding Techniques.