

Name – SURANA GAURAV

REG NO – 20BEE0371

```
In [30]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import os
```

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

Out[30]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alone
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN	Southampton	no	False
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes	False
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN	Southampton	yes	True
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton	yes	False
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN	Southampton	no	True
...
886	0	2	male	27.0	0	0	13.0000	S	Second	man	True	NaN	Southampton	no	True
887	1	1	female	19.0	0	0	30.0000	S	First	woman	False	B	Southampton	yes	True
888	0	3	female	NaN	1	2	23.4500	S	Third	woman	False	NaN	Southampton	no	False
889	1	1	male	26.0	0	0	30.0000	C	First	man	True	C	Cherbourg	yes	True
890	0	3	male	32.0	0	0	7.7500	Q	Third	man	True	NaN	Queenstown	no	True

891 rows x 15 columns

```
In [18]: #Handle the missing values(Mean mode median imputation)
df.isnull().sum()
```

```
Out[18]: survived      0
pclass      0
sex          0
age         177
sibsp       0
parch       0
fare        0
embarked     2
class       0
who         0
```

```
fare      0
embarked  2
class     0
who       0
adult_male 0
deck     588
embark_town 2
alive     0
alone     0
dtype: int64
```

```
In [20]: def mean_median(df,variable):
         df[variables+'_mean'] = df[variable].fillna(df[variable].mean())
         df[variables+'_median'] = df[variable].fillna(df[variable].median())
```

```
In [23]: mean_median(df,'age')
df.head()
```

```
Out[23]:
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alone	age_mean	age_median
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN	Southampton	no	False	22.0	22.0
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes	False	38.0	38.0
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN	Southampton	yes	True	26.0	26.0
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton	yes	False	35.0	35.0
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN	Southampton	no	True	35.0	35.0

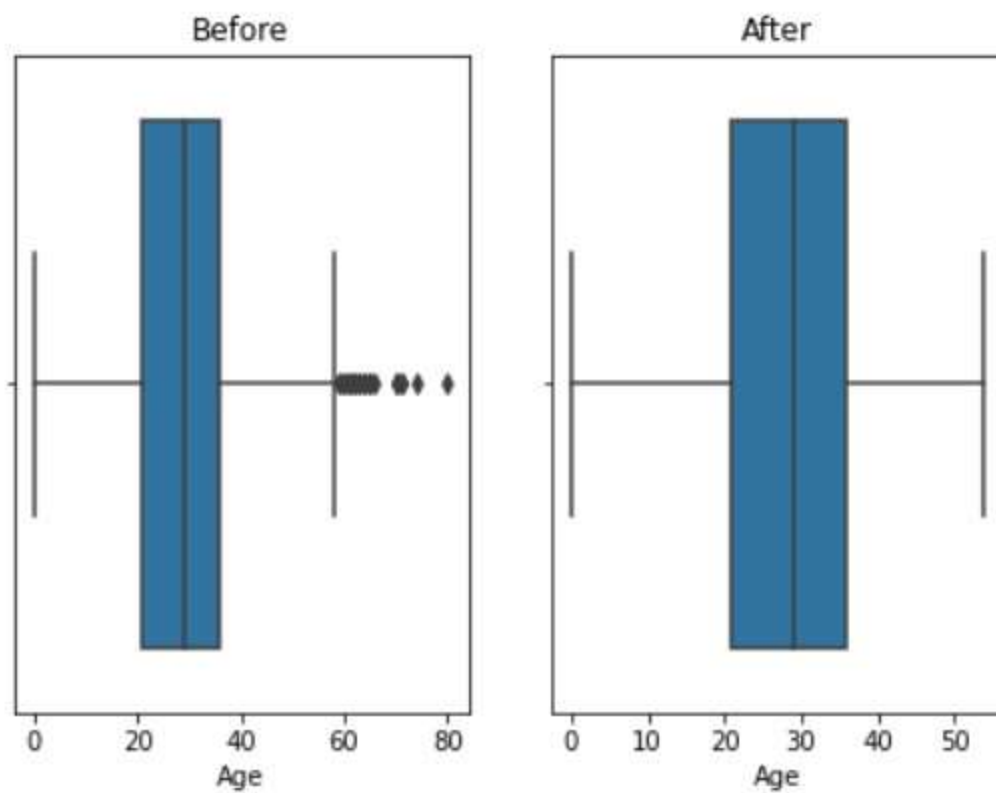
```
In [32]: #Finding the outliers(using INTER QUARTILE RANGE)
Q1=df['fare'].quantile(0.25)
Q3=df['fare'].quantile(0.75)
IQR=Q3-Q1
```

```
In [33]: Q1 = df['fare'].quantile(0.25)
Q3 = df['fare'].quantile(0.75)
IQR = Q3 - Q1
whisker_width = 1.5
fare_outliers = df[(df['fare'] < Q1 - whisker_width*IQR) | (df['fare'] > Q3 + whisker_width*IQR)]
fare_outliers.head()
```

```
Out[33]:
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alone
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes	False
27	0	1	male	19.0	3	2	263.0000	S	First	man	True	C	Southampton	no	False

Previous Shape With Outlier: (891, 11)
Shape After Removing Outliers: (891, 11)



```

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File Edit View Insert Cell Kernel Widgets Help Notebook saved Trusted Python 3 (ipykernel)

In [58]: #split the data into training and testing
X_train, X_test, y_train, y_test = train_test_split(
    df[['embarked'],
        df['survived']],

    test_size=0.3,
    random_state=8,
)

In [52]: #categorical columns encoding
X_train_enc = pd.get_dummies(X_train, drop_first=True)
X_test_enc = pd.get_dummies(X_test, drop_first=True)
X_train_enc.head()

Out[52]:
   Q  S
857  0  1
   52  0  0
  306  0  1
   124  0  1
   578  0  0

In [59]: # Splitting Dataset into the Independent variables:
X = df.iloc[:, :-1].values
print(X)

[[0 3 'male' ... nan 'Southampton' 'no']
 [1 1 'female' ... 'C' 'Cherbourg' 'yes']
 [1 3 'female' ... nan 'Southampton' 'yes']
 ...
 [0 3 'female' ... nan 'Southampton' 'no']
 [1 1 'male' ... 'C' 'Cherbourg' 'yes']
 [0 3 'male' ... nan 'Queenstown' 'no']]

In [60]: ## Splitting Dataset into the dependent variables:
Y = df.iloc[:, -1].values
print(Y)

[False False  True False  True  True  True False False False  True
 True False  True  True False  True False  True  True  True  True
 False False  True False  True  True  True False  True  True False False
 True  True False False False False  True False  True  True False  True

```

SCALING OF INDEPENDENT VARIABLE

```

In [51]: #Using the concept of feature scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train[:,3:] = sc.fit_transform(X_train[:,3:])
X_test[:,3:] = sc.transform(X_test[:,3:])

In [52]: print(X_train)

[[ 2.03000000e+02  3.40000000e+01  0.00000000e+00 ... -4.88677777e-01
 -1.93649167e-01  5.44862368e-01]
 [ 4.40000000e+02  3.10000000e+01  0.00000000e+00 ... -4.88677777e-01
 -1.93649167e-01  5.44862368e-01]
 [ 1.03000000e+02  2.10000000e+01  0.00000000e+00 ... -4.88677777e-01
 -1.93649167e-01  5.44862368e-01]
 ...
 [ 7.92000000e+02  1.60000000e+01  0.00000000e+00 ... -4.88677777e-01
 -1.93649167e-01  5.44862368e-01]
 [ 7.06000000e+02  3.90000000e+01  0.00000000e+00 ... -4.88677777e-01
 -1.93649167e-01  5.44862368e-01]
 [ 8.59000000e+02  2.40000000e+01  0.00000000e+00 ...  2.04633819e+00
 -1.93649167e-01 -1.83532587e+00]]

```

```
In [67]: #DESCRIPTIVE STATS
df.describe
```

```
Out[67]: <bound method NDFrame.describe of
0      0      3      male  22.0      1      0      7.2500      S      Third
1      1      1      female  38.0      1      0      71.2833      C      First
2      1      3      female  26.0      0      0      7.9250      S      Third
3      1      1      female  35.0      1      0      53.1000      S      First
4      0      3      male   35.0      0      0      8.0500      S      Third
...
886     0      2      male   27.0      0      0      13.0000      S      Second
887     1      1      female  19.0      0      0      30.0000      S      First
888     0      3      female   NaN      1      2      23.4500      S      Third
889     1      1      male   26.0      0      0      30.0000      C      First
890     0      3      male   32.0      0      0      7.7500      Q      Third

      who  adult_male  deck  embark_town  alive  alone
0      man         True   NaN  Southampton    no  False
1  woman         False    C   Cherbourg    yes  False
2  woman         False   NaN  Southampton    yes  True
3  woman         False    C   Southampton    yes  False
4      man         True   NaN  Southampton    no  True
...
886  man         True   NaN  Southampton    no  True
887 woman         False    B   Southampton    yes  True
888 woman         False   NaN  Southampton    no  False
889  man         True    C   Cherbourg    yes  True
890  man         True   NaN  Queenstown    no  True

[891 rows x 15 columns]>
```

```
In [69]: df2 = df["age"].mean()
df2
```

```
Out[69]: 29.89911764705882
```

```
In [70]: df3=df["age"].median
df3
```

```
Out[70]: <bound method NDFrame._add_numeric_operations.<locals>.median of 0      22.0
1      38.0
2      26.0
3      35.0
4      35.0
...
886    27.0
887    19.0
888     NaN
889    26.0
890    32.0
Name: age, Length: 891, dtype: float64>
```

```
In [72]: df4=df["age"].mode
df4
```

```
Out[72]: <bound method Series.mode of 0      22.0
1      38.0
2      26.0
3      35.0
4      35.0
...
886    27.0
887    19.0
888     NaN
889    26.0
890    32.0
Name: age, Length: 891, dtype: float64>
```

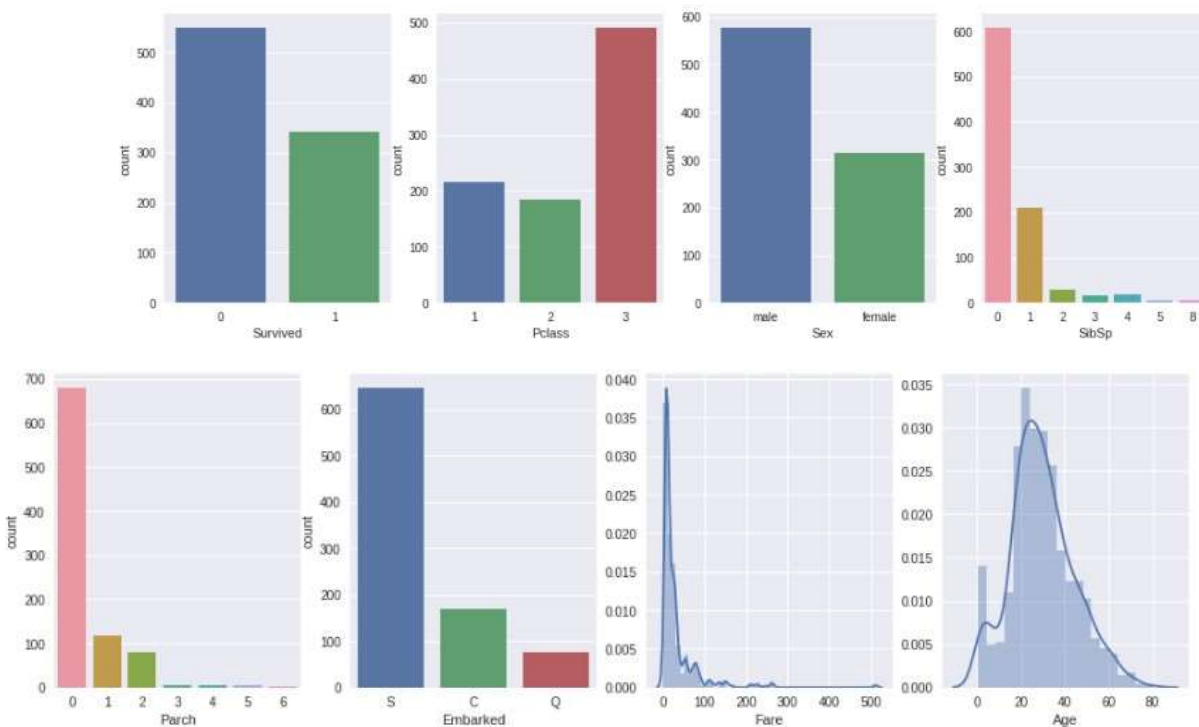
#UNIVARIATE ANALYSIS

In [17]:

```
fig, axes = plt.subplots(2, 4, figsize=(16, 10))
sns.countplot('Survived', data=train, ax=axes[0,0])
sns.countplot('Pclass', data=train, ax=axes[0,1])
sns.countplot('Sex', data=train, ax=axes[0,2])
sns.countplot('SibSp', data=train, ax=axes[0,3])
sns.countplot('Parch', data=train, ax=axes[1,0])
sns.countplot('Embarked', data=train, ax=axes[1,1])
sns.distplot(train['Fare'], kde=True, ax=axes[1,2])
sns.distplot(train['Age'].dropna(), kde=True, ax=axes[1,3])
```

Out[17]:

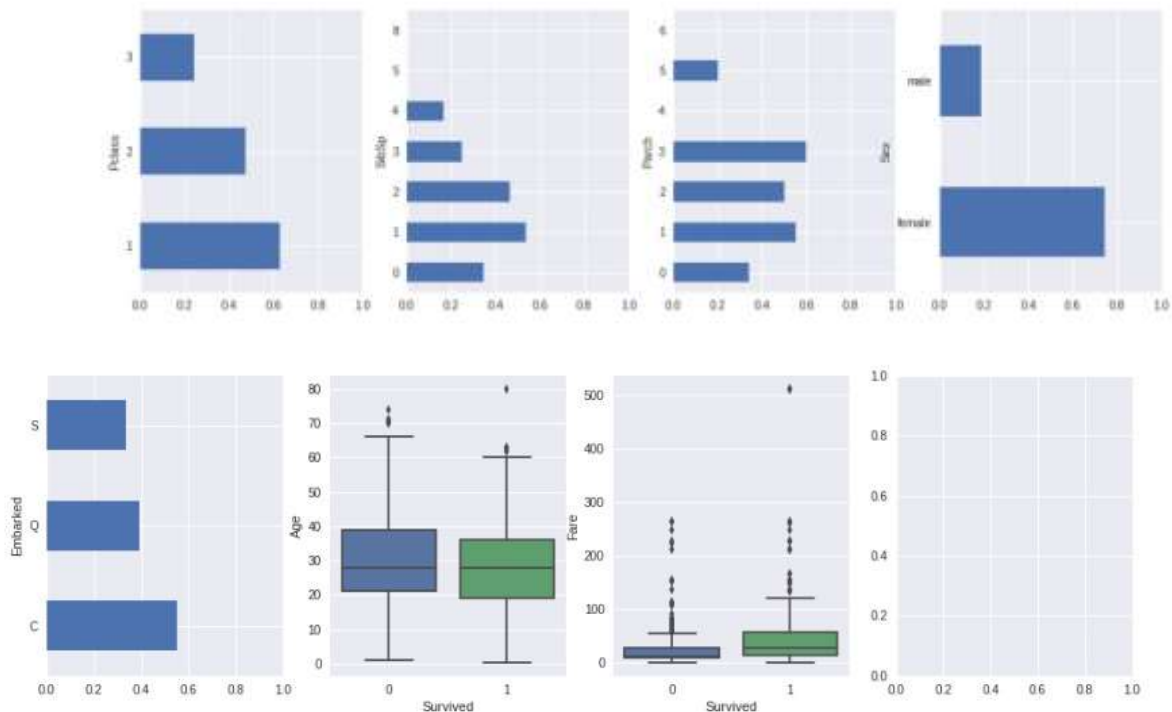
<matplotlib.axes._subplots.AxesSubplot at 0x7ffa6366bdd8>



BIVRIATE ANALYSIS

```
In [18]: figbi, axesbi = plt.subplots(2, 4, figsize=(16, 10))
train.groupby('Pclass')['Survived'].mean().plot(kind='barh', ax=axesbi[0,0], xlim=[0,1])
train.groupby('SibSp')['Survived'].mean().plot(kind='barh', ax=axesbi[0,1], xlim=[0,1])
train.groupby('Parch')['Survived'].mean().plot(kind='barh', ax=axesbi[0,2], xlim=[0,1])
train.groupby('Sex')['Survived'].mean().plot(kind='barh', ax=axesbi[0,3], xlim=[0,1])
train.groupby('Embarked')['Survived'].mean().plot(kind='barh', ax=axesbi[1,0], xlim=[0,1])
sns.boxplot(x="Survived", y="Age", data=train, ax=axesbi[1,1])
sns.boxplot(x="Survived", y="Fare", data=train, ax=axesbi[1,2])
```

```
Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffa631ff9e8>
```



MULTIVARIATE ANALYSIS

In [20]:

```
import seaborn as sns

f, ax = plt.subplots(figsize=(10, 8))
corr = train.corr()
sns.heatmap(corr,
            mask=np.zeros_like(corr, dtype=np.bool),
            cmap=sns.diverging_palette(220, 10, as_cmap=True),
            square=True, ax=ax)
```

Out[20]:

<matplotlib.axes._subplots.AxesSubplot at 0x7ffa590f7160>

