

ADS Assignment 2

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Titanic Ship Case Study

Problem Description: On April 15, 1912, during her maiden voyage, the Titanic sank after colliding with an iceberg, killing 1502 out of 2224 passengers and crew. Translated 32% survival rate.

- One of the reasons that the shipwreck led to such loss of life was that there were not enough lifeboats for the passengers and crew.
- Although there was some element of luck involved in surviving the sinking, some groups of people were more likely to survive than others, such as women, children, and the upper-class.

The problem associated with the Titanic dataset is to predict whether a passenger survived the disaster or not. The dataset contains various features such as passenger class, age, gender, cabin, fare, and whether the passenger had any siblings or spouses on board. These features can be used to build a predictive model to determine the likelihood of a passenger surviving the disaster. The dataset offers opportunities for feature engineering, data visualization, and model selection, making it a valuable resource for developing and testing data analysis and machine learning skills.

Perform Below Tasks to complete the assignment:-

1. Download the dataset: [Dataset](#)
2. Load the dataset.
3. Perform Below Visualizations.
 - Univariate Analysis
 - Bi - Variate Analysis
 - Multi - Variate Analysis
4. Perform descriptive statistics on the dataset.
5. Handle the Missing values.
6. Find the outliers and replace the outliers
7. Check for Categorical columns and perform encoding.
8. Split the data into dependent and independent variables.
9. Scale the independent variables
10. Split the data into training and testing

1)

```
#1
# Download the dataset: Dataset

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

2)

```
#2
# Load the dataset.

from google.colab import files
uploaded = files.upload()
```

Choose Files titanic.csv
• titanic.csv (text/csv) - 57018 bytes, last modified: 5/28/2023 - 100% done
Saving titanic.csv to titanic.csv

```
df = pd.read_csv("titanic.csv")
df.head()
```

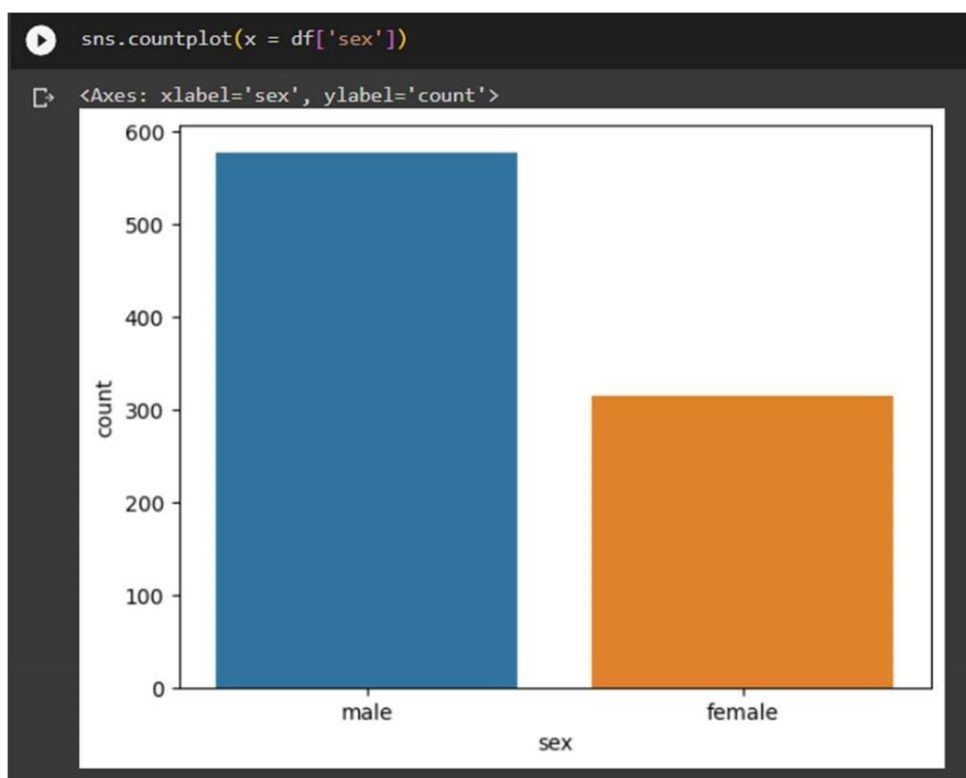
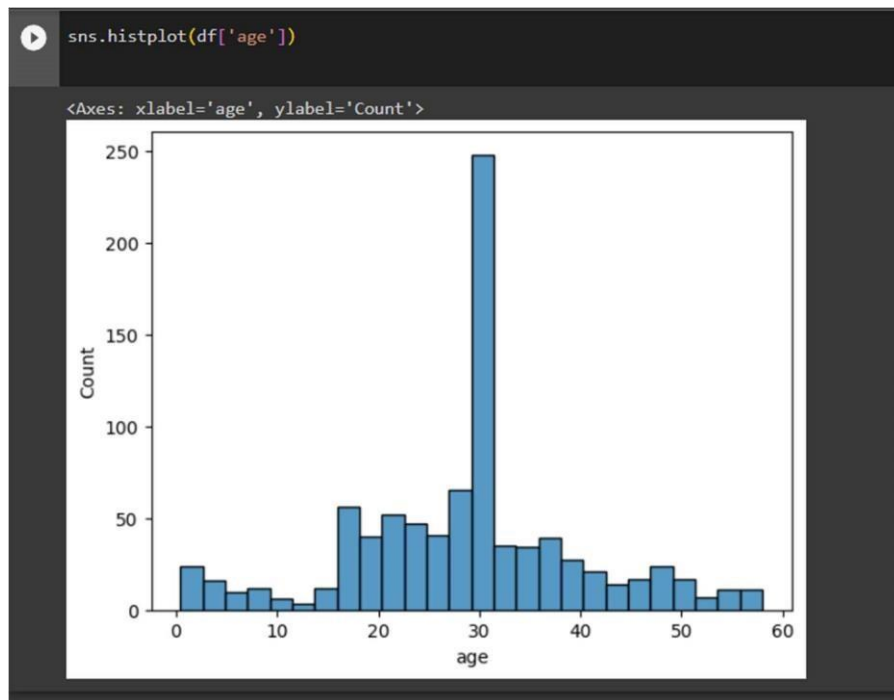
| | survived | pclass | sex | age | sibsp | parch | fare | embarked | class | who | adult_male | deck | embark_town | alive | alone |
|---|----------|--------|--------|------|-------|-------|---------|----------|-------|-------|------------|------|-------------|-------|-------|
| 0 | 0 | 3 | male | 22.0 | 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 |

```
[5]
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 15 columns):
#   Column      Non-Null Count  Dtype
---  -
0   survived    891 non-null    int64
1   pclass      891 non-null    int64
2   sex         891 non-null    object
3   age         714 non-null    float64
4   sibsp       891 non-null    int64
5   parch       891 non-null    int64
6   fare        891 non-null    float64
7   embarked    889 non-null    object
8   class       891 non-null    object
9   who         891 non-null    object
10  adult_male  891 non-null    bool
11  deck        203 non-null    object
12  embark_town 889 non-null    object
13  alive       891 non-null    object
14  alone       891 non-null    bool
dtypes: bool(2), float64(2), int64(4), object(7)
memory usage: 92.4+ KB
```

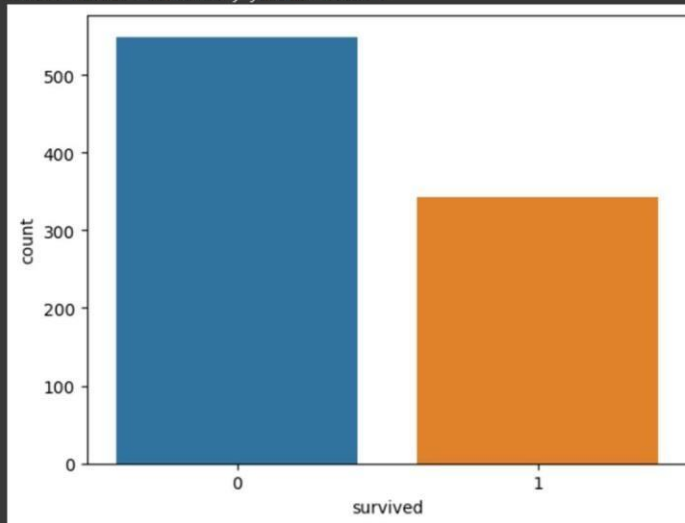
3)

- Univariate Analysis



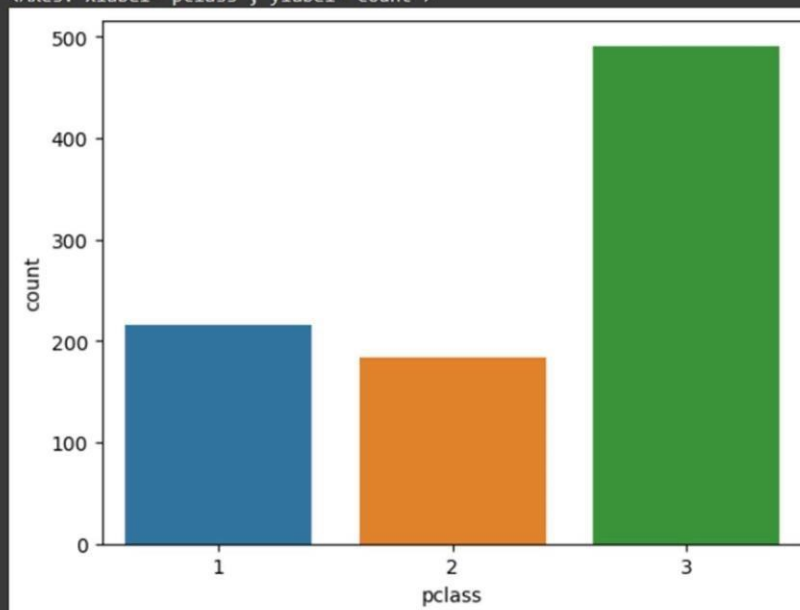
```
[8] sns.countplot(x = df['survived'])
```

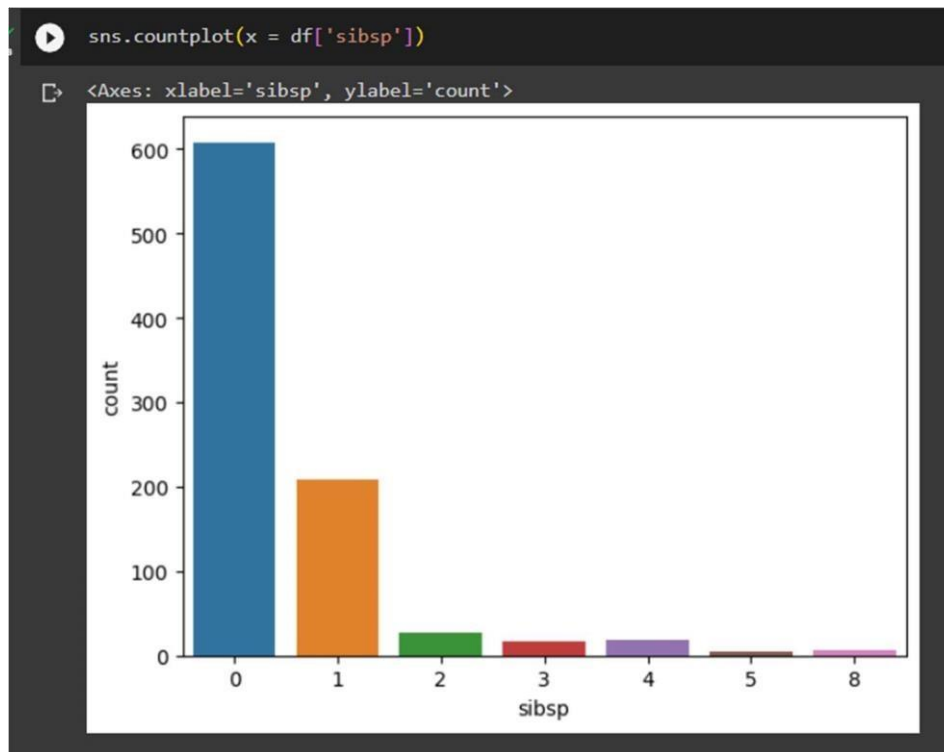
```
<Axes: xlabel='survived', ylabel='count'>
```

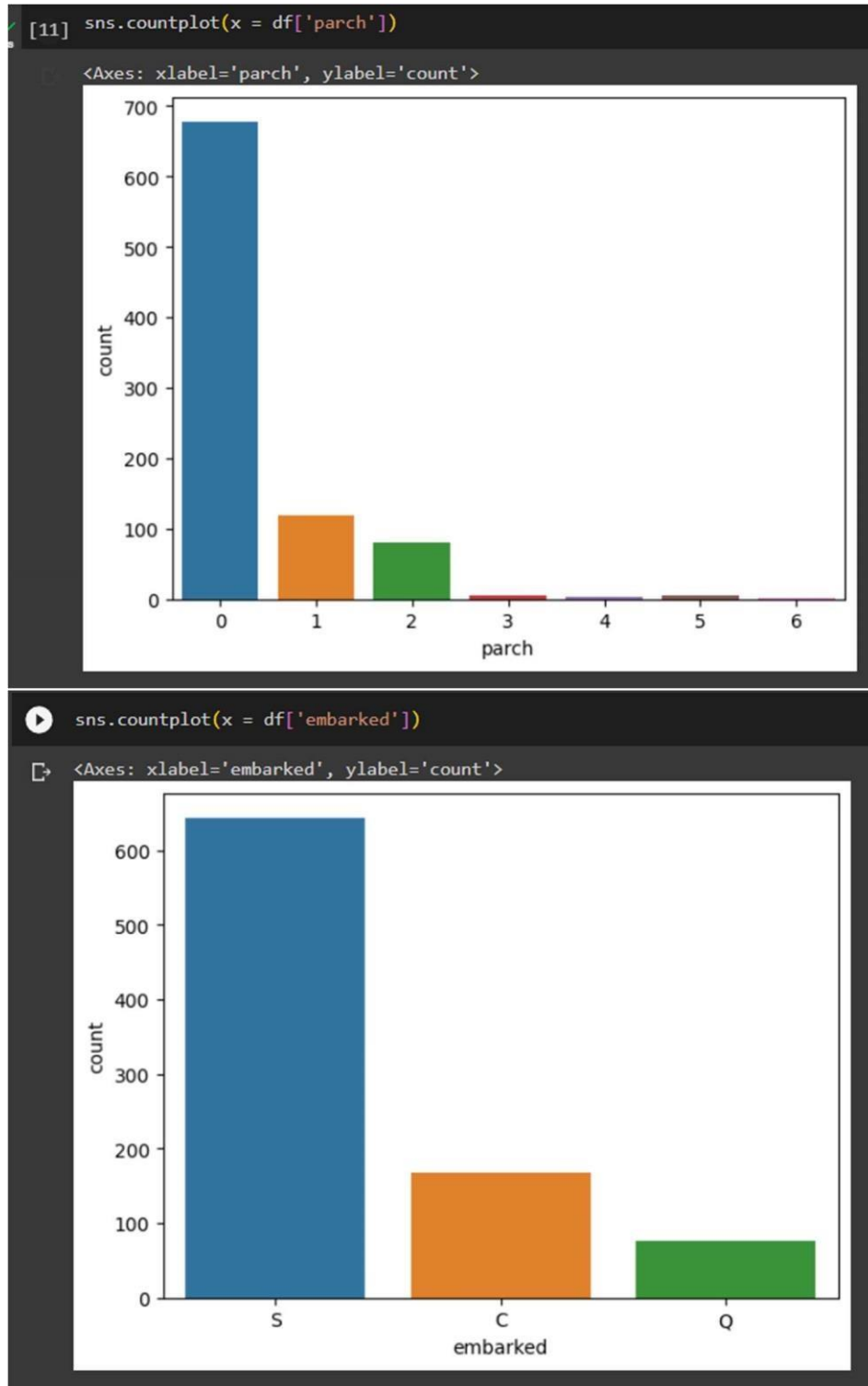


```
sns.countplot(x = df['pclass'])
```

```
<Axes: xlabel='pclass', ylabel='count'>
```





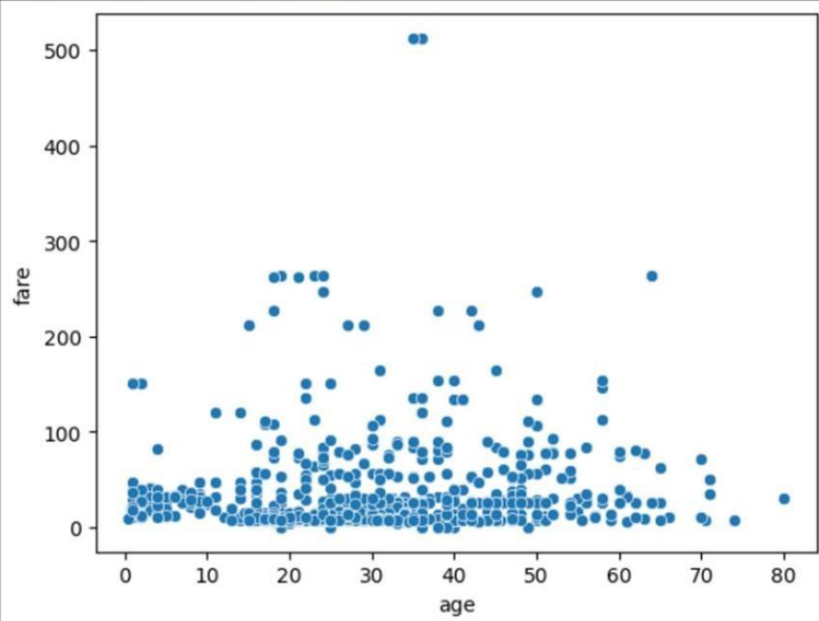


- bivariate analysis



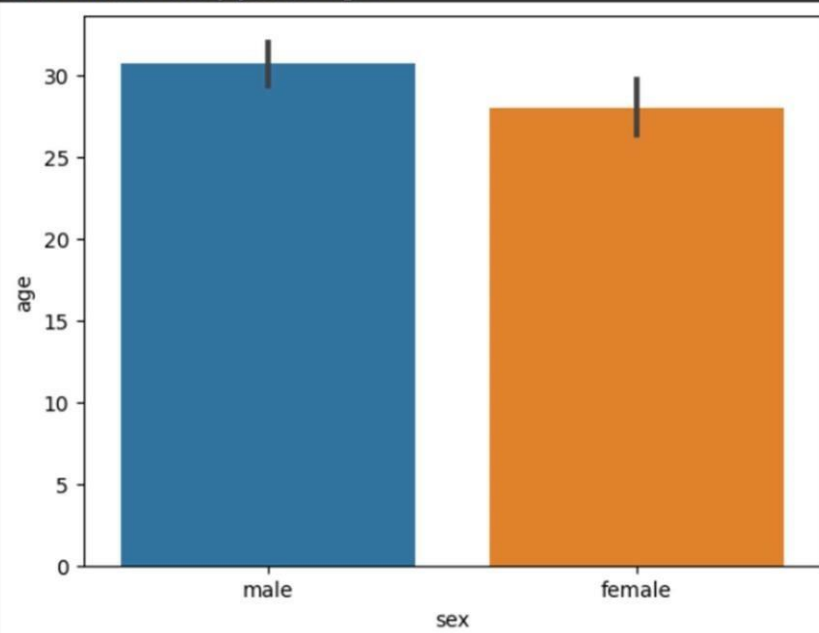
```
sns.scatterplot(data = df, x = 'age', y = 'fare')
```

<Axes: xlabel='age', ylabel='fare'>



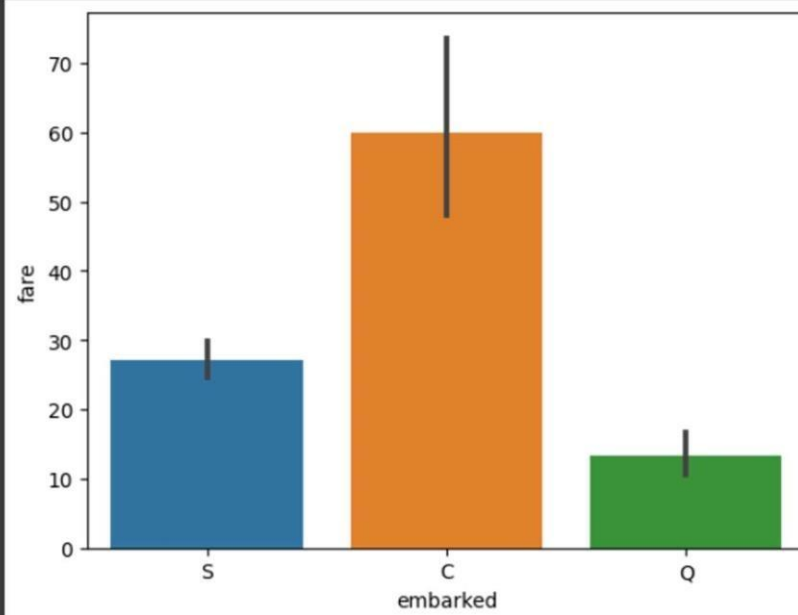
```
sns.barplot(data = df, x = 'sex', y = 'age')
```

<Axes: xlabel='sex', ylabel='age'>



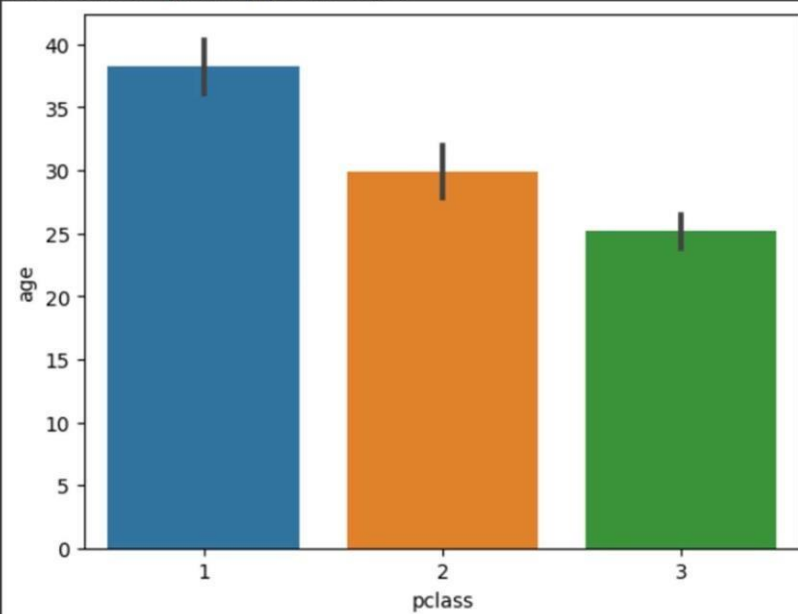
```
sns.barplot(data = df, x = 'embarked', y = 'fare')
```

```
<Axes: xlabel='embarked', ylabel='fare'>
```



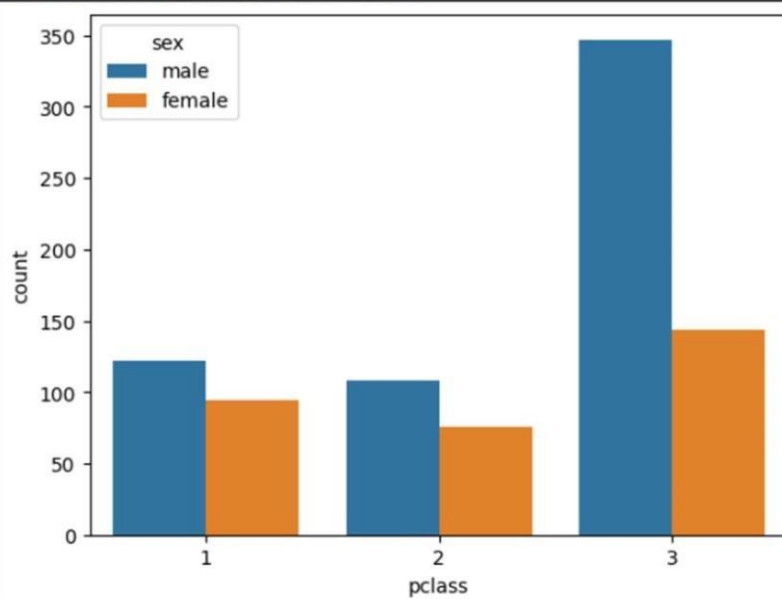
```
sns.barplot(data = df, x = 'pclass', y = 'age')
```

```
<Axes: xlabel='pclass', ylabel='age'>
```



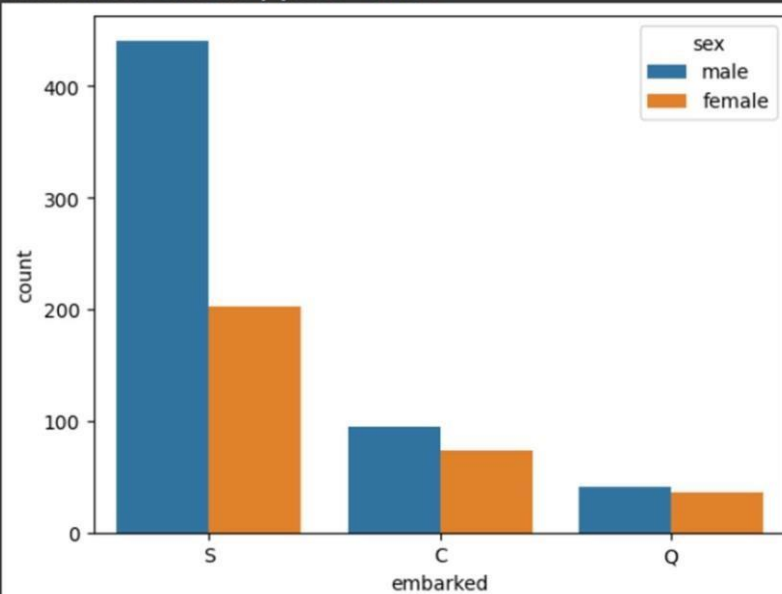

```
[17] sns.countplot(x = df['pclass'], hue = df['sex'])
```

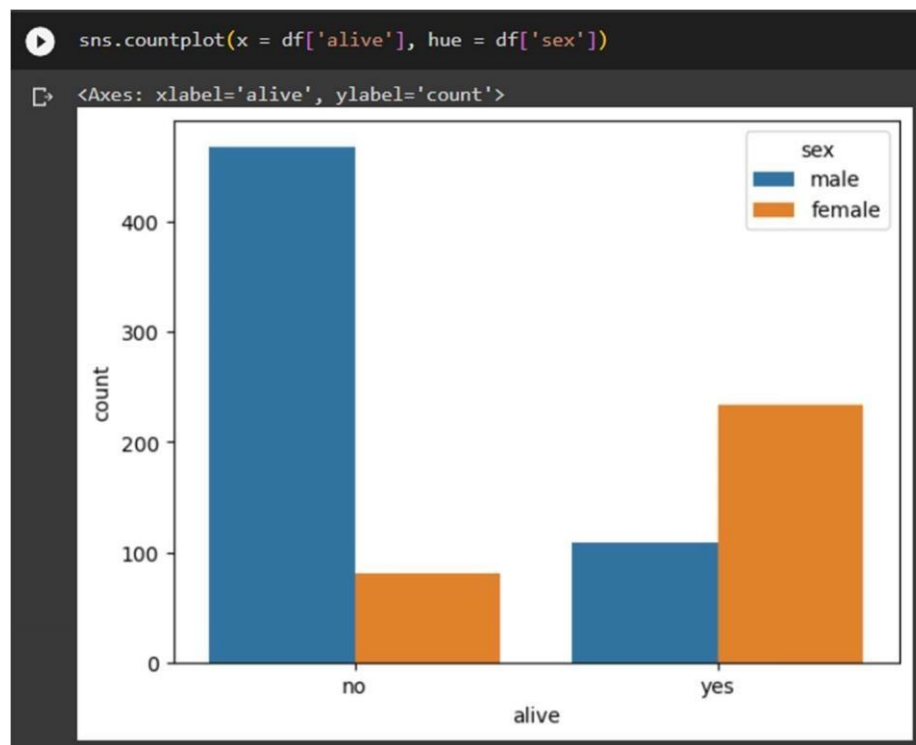
<Axes: xlabel='pclass', ylabel='count'>



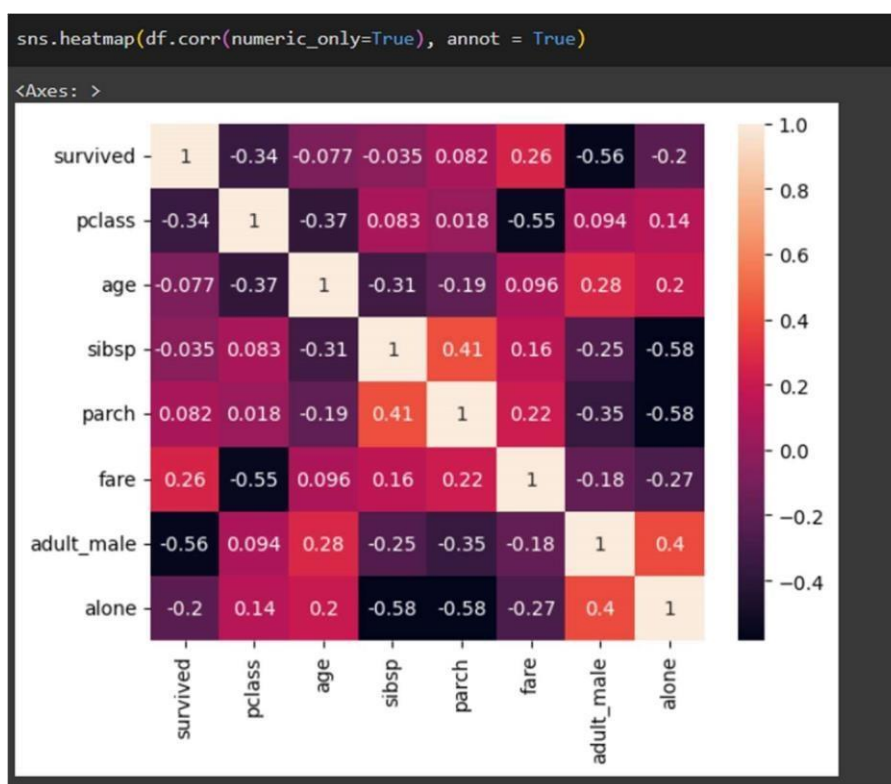
```
sns.countplot(x = df['embarked'], hue = df['sex'])
```

<Axes: xlabel='embarked', ylabel='count'>





- mul variate analysis



```
df.describe()
```

| | survived | pclass | age | sibsp | parch | fare |
|-------|------------|------------|------------|------------|------------|------------|
| count | 891.000000 | 891.000000 | 714.000000 | 891.000000 | 891.000000 | 891.000000 |
| mean | 0.383838 | 2.308642 | 29.699118 | 0.523008 | 0.381594 | 32.204208 |
| std | 0.486592 | 0.836071 | 14.526497 | 1.102743 | 0.806057 | 49.693429 |
| min | 0.000000 | 1.000000 | 0.420000 | 0.000000 | 0.000000 | 0.000000 |
| 25% | 0.000000 | 2.000000 | 20.125000 | 0.000000 | 0.000000 | 7.910400 |
| 50% | 0.000000 | 3.000000 | 28.000000 | 0.000000 | 0.000000 | 14.454200 |
| 75% | 1.000000 | 3.000000 | 38.000000 | 1.000000 | 0.000000 | 31.000000 |
| max | 1.000000 | 3.000000 | 80.000000 | 8.000000 | 6.000000 | 512.329200 |

5)

```
df.isnull().sum()
```

```
survived      0
pclass        0
sex           0
age          177
sibsp         0
parch         0
fare          0
embarked      2
class         0
who           0
adult_male    0
deck         688
embark_town    2
alive         0
alone         0
dtype: int64
```

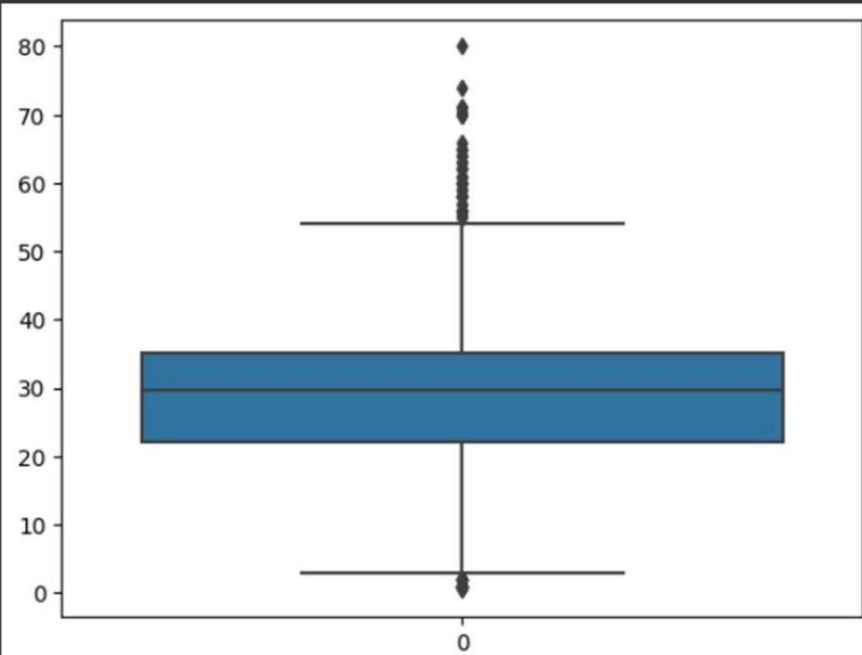
```
df.dropna(subset=['embark_town'], how='all', inplace = True)
df['age'] = df['age'].fillna(df['age'].mean())
df.drop(['deck'], axis = 1,inplace = True)
df.isnull().sum()
```

```
survived      0
pclass        0
sex           0
age           0
sibsp         0
parch         0
fare          0
embarked      0
class         0
who           0
adult_male    0
embark_town    0
alive         0
alone         0
dtype: int64
```

6)

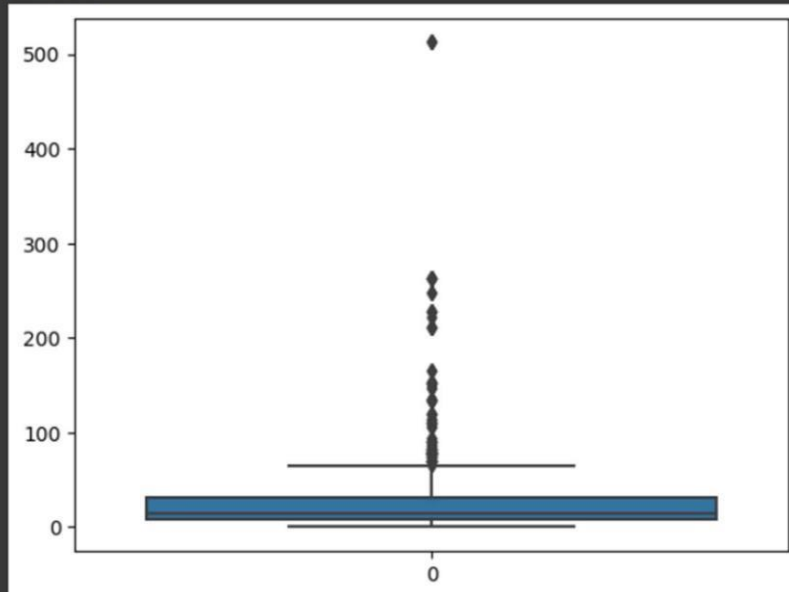
```
sns.boxplot(df['age'])
```

<Axes: >



```
[26] sns.boxplot(df['fare'])
```

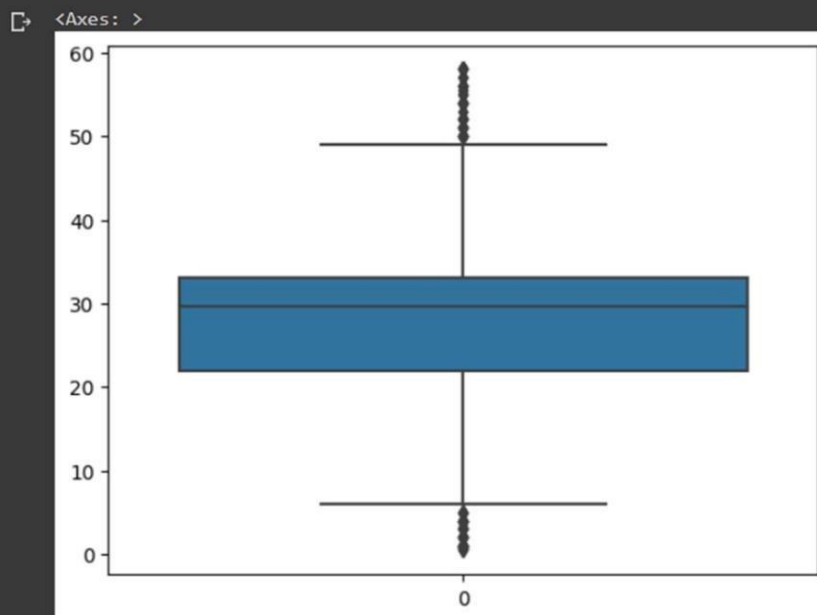
<Axes: >



```

median_age = df['age'].median()
df["age"] = np.where(df["age"] > 58, median_age, df['age'])
sns.boxplot(df['age'])

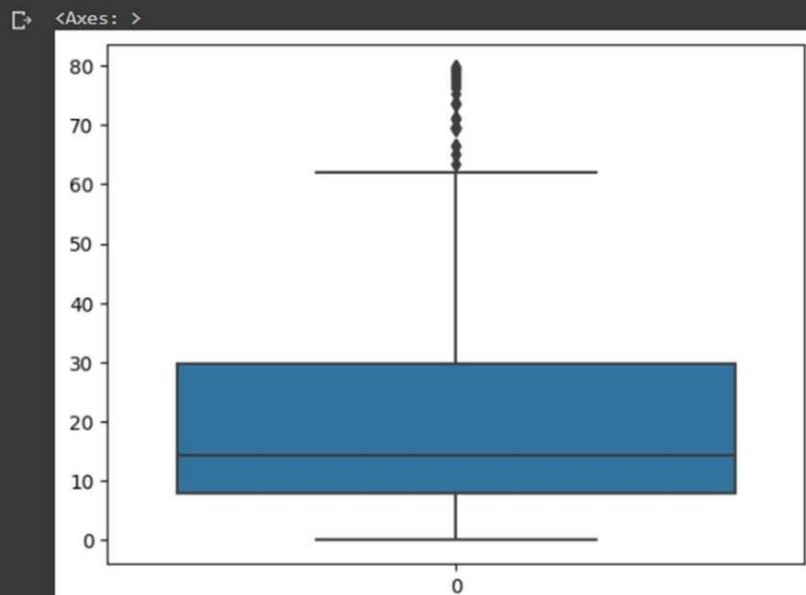
```



```

median_fare = df['fare'].median()
df["fare"] = np.where(df["fare"] > 80, median_fare, df['fare'])
sns.boxplot(df['fare'])

```



```
#7
# Check for Categorical columns and perform encoding.

from sklearn.preprocessing import OneHotEncoder
encoding = pd.get_dummies(df, columns = ['sex', 'embarked', 'class', 'who', 'adult_male', 'embark_town', 'alone'])
encoding.head()
```

| | survived | pclass | age | sibsp | parch | fare | alive | sex_female | sex_male | embarked_C | ... | who_child | who_man | who_woman | ad |
|---|----------|--------|------|-------|-------|---------|-------|------------|----------|------------|-----|-----------|---------|-----------|----|
| 0 | 0 | 3 | 22.0 | 1 | 0 | 7.2500 | no | 0 | 1 | 0 | ... | 0 | 1 | 0 | |
| 1 | 1 | 1 | 38.0 | 1 | 0 | 71.2833 | yes | 1 | 0 | 1 | ... | 0 | 0 | 1 | |
| 2 | 1 | 3 | 26.0 | 0 | 0 | 7.9250 | yes | 1 | 0 | 0 | ... | 0 | 0 | 1 | |
| 3 | 1 | 1 | 35.0 | 1 | 0 | 53.1000 | yes | 1 | 0 | 0 | ... | 0 | 0 | 1 | |
| 4 | 0 | 3 | 35.0 | 0 | 0 | 8.0500 | no | 0 | 1 | 0 | ... | 0 | 1 | 0 | |

5 rows x 25 columns

8)

```
df.columns

Index(['survived', 'pclass', 'sex', 'age', 'sibsp', 'parch', 'fare',
      'embarked', 'class', 'who', 'adult_male', 'embark_town', 'alive',
      'alone'],
      dtype='object')
```

```
X = encoding.drop(['survived', 'alive'], axis = 1)
X.head()
```

| | pclass | age | sibsp | parch | fare | sex_female | sex_male | embarked_C | embarked_Q | embarked_S | ... | who_child | who_ |
|---|--------|------|-------|-------|---------|------------|----------|------------|------------|------------|-----|-----------|------|
| 0 | 3 | 22.0 | 1 | 0 | 7.2500 | 0 | 1 | 0 | 0 | 1 | ... | 0 | |
| 1 | 1 | 38.0 | 1 | 0 | 71.2833 | 1 | 0 | 1 | 0 | 0 | ... | 0 | |
| 2 | 3 | 26.0 | 0 | 0 | 7.9250 | 1 | 0 | 0 | 0 | 1 | ... | 0 | |
| 3 | 1 | 35.0 | 1 | 0 | 53.1000 | 1 | 0 | 0 | 0 | 1 | ... | 0 | |
| 4 | 3 | 35.0 | 0 | 0 | 8.0500 | 0 | 1 | 0 | 0 | 1 | ... | 0 | |

5 rows x 23 columns

```
v = df[['survived', 'alive']]
```

Run cell (Ctrl+Enter)
cell has not been executed in this session

executed by Pratham Mohanty
16:30 (1 hour ago)
executed in 0.499 s

| | | |
|---|---|-----|
| 1 | 1 | yes |
| 2 | 1 | yes |
| 3 | 1 | yes |
| 4 | 0 | no |

9)

```
[ ] #9
# Scale the independent variables

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
x_std = scaler.fit_transform(X)
x_std

array([[ 0.82520863, -0.57985934,  0.43135024, ...,  0.61679395,
         1.22934919, -1.22934919],
       [-1.57221121,  0.83108889,  0.43135024, ..., -1.62128697,
         1.22934919, -1.22934919],
       [ 0.82520863, -0.22712228, -0.47519908, ...,  0.61679395,
        -0.81343853,  0.81343853],
       ...,
       [ 0.82520863,  0.09405298,  0.43135024, ...,  0.61679395,
         1.22934919, -1.22934919],
       [-1.57221121, -0.22712228, -0.47519908, ..., -1.62128697,
        -0.81343853,  0.81343853],
       [ 0.82520863,  0.3019833 , -0.47519908, ..., -1.62128697,
        -0.81343853,  0.81343853]])
```

10)

```
[ ] # 10
# Split the data into training and testing

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y['survived'], test_size=0.33)

[ ]
```