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.<\li>

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.

Import necessary libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

1. Download the dataset:

```
# titanic.csv dataset downloaded and placed in the working directory
```

2. Load the dataset.

```
data = pd.read_csv("/content/titanic.csv")
```

```
data.head()
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN	Southampton
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN	Southampton
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN	Southampton

```
data.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
```

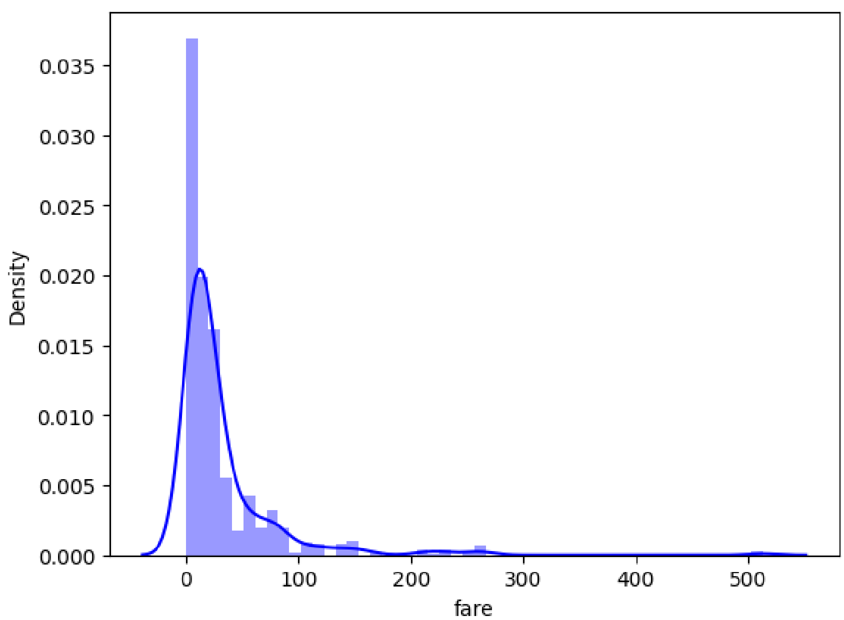
3. Perform Below Visualizations.
    - Univariate Analysis
    - Bi - Variate Analysis
    - Multi - Variate Analysis

Univariate Analysis

Distribution plot

```
sns.distplot(data['fare'], color = 'b')
```

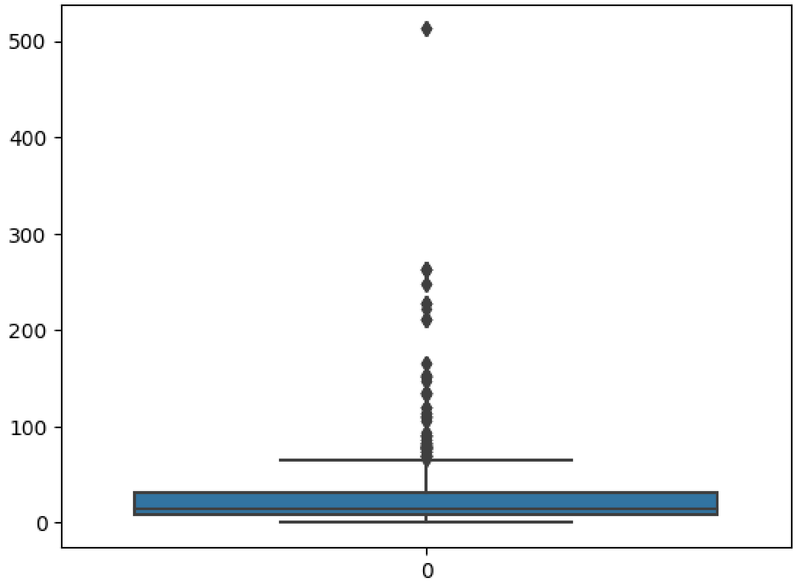
```
<ipython-input-6-41d06f94492f>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(data['fare'], color = 'b')
<Axes: xlabel='fare', ylabel='Density'>
```



Box plot

```
sns.boxplot(data['fare'])
```

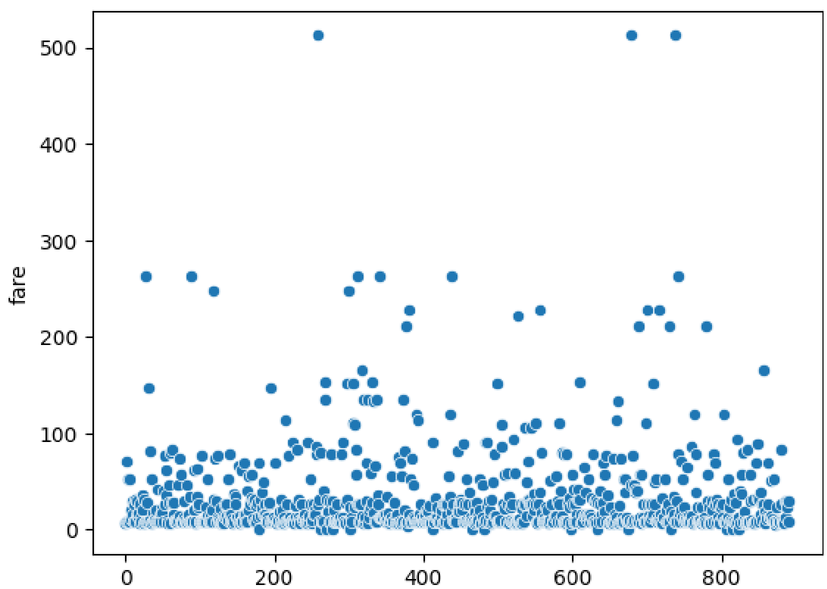
```
<Axes: >
```



Scatter plot

```
sns.scatterplot(data['fare'])
```

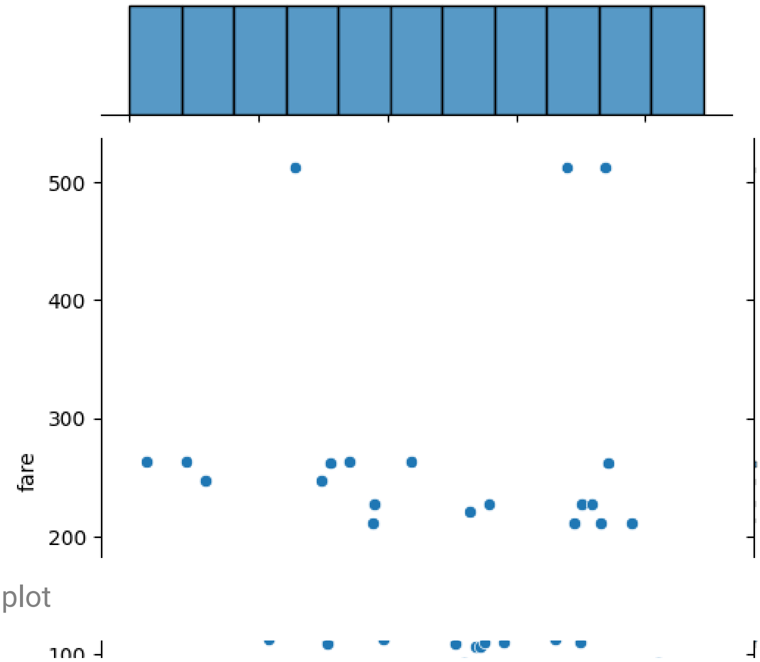
```
<Axes: ylabel='fare'>
```



Joint plot

```
sns.jointplot(data['fare'])
```

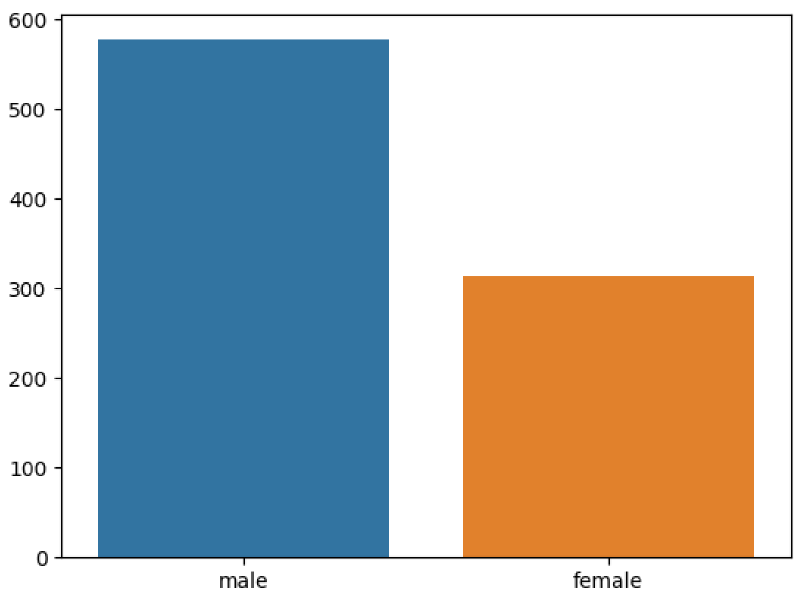
```
&lt;seaborn.axisgrid.JointGrid at 0x7f3741e036d0&gt;
```



Bar plot

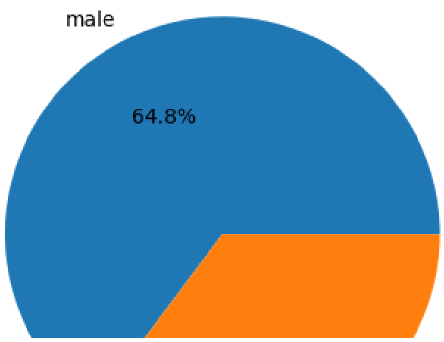
```
x = data.sex.value_counts()
sns.barplot(x=x.index, y=x.values)
```

```
&lt;Axes: &gt;
```



Pie plot

```
x = data['sex'].value_counts()
plt.pie(x.values,
        labels=x.index,
        autopct='%1.1f%%')
plt.show()
```

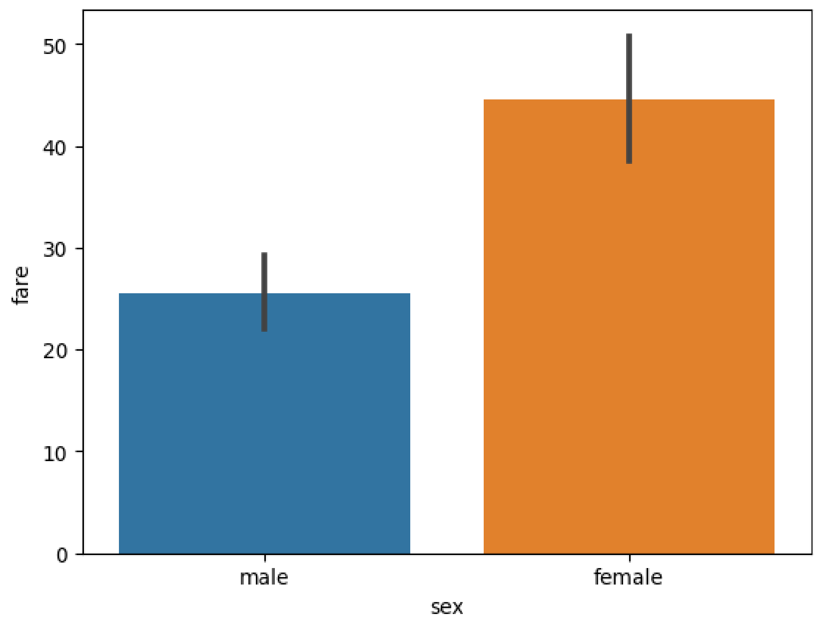


Bivariate analysis

Bar plot

```
sns.barplot(x=data.sex, y=data.fare)
```

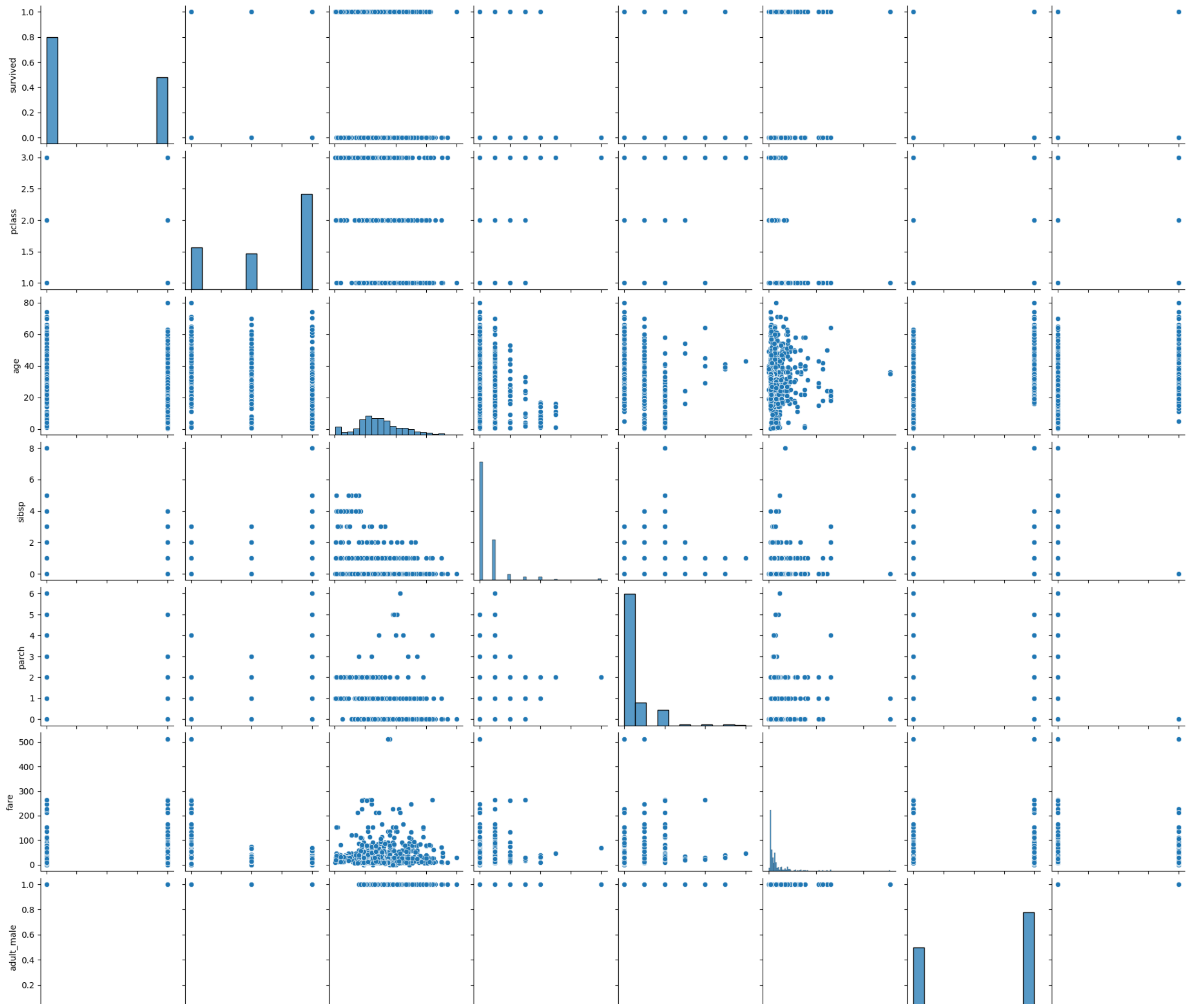
```
<Axes: xlabel='sex', ylabel='fare'>
```



Pair plot

```
sns.pairplot(data)
```

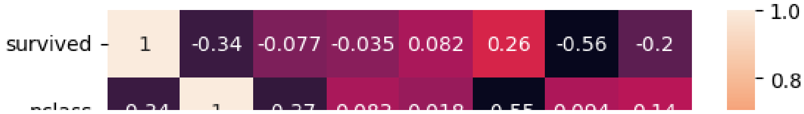
```
<__array_function__ internals>:180: RuntimeWarning: Converting input from bool to <class 'numpy.uint8'> for com
<__array_function__ internals>:180: RuntimeWarning: Converting input from bool to <class 'numpy.uint8'> for com
<seaborn.axisgrid.PairGrid at 0x7f374188e020>
```



Multivariate Analysis

```
sns.heatmap(data.corr(), annot=True)
```

```
<ipython-input-14-b699050ce883>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprec
  sns.heatmap(data.corr(), annot=True)
<Axes: >
```



4. Perform descriptive statistics on the dataset.

Measure of central tendency - Mean, Median and Mode

```
data.mean()
```

```
<ipython-input-15-abc01cf6c622>:1: FutureWarning: The default value of numeric_only in DataFrame.mean is deprecated. In a
  data.mean()
survived       0.383838
pclass         2.308642
age           29.699118
sibsp          0.523008
parch          0.381594
fare          32.204208
adult_male     0.602694
alone          0.602694
dtype: float64
```

```
data.median()
```

```
<ipython-input-16-135339ac59ce>:1: FutureWarning: The default value of numeric_only in DataFrame.median is deprecated. In
  data.median()
survived       0.0000
pclass         3.0000
age           28.0000
sibsp          0.0000
parch          0.0000
fare          14.4542
adult_male     1.0000
alone          1.0000
dtype: float64
```

```
data.mode()
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive
0	0	3	male	24.0	0	0	8.05	S	Third	man	True	C	Southampton	no

Measure of variability

Kurtosis

```
data.kurt()
```

```
<ipython-input-18-de7992f92dad>:1: FutureWarning: The default value of numeric_only in DataFrame.kurt is deprecated. In a
  data.kurt()
survived      -1.775005
pclass        -1.280015
age            0.178274
sibsp         17.880420
parch          9.778125
fare          33.398141
adult_male    -1.827345
```

```
alone         -1.827345
dtype: float64
```

Range

```
data.max()
```

```
<ipython-input-19-8637789457d2>:1: FutureWarning: The default value of numeric_only in DataFrame.max is deprecated. In a f
  data.max()
survived            1
pclass              3
sex              male
age              80.0
sibsp               8
parch               6
fare         512.3292
class           Third
who             woman
adult_male       True
alive             yes
alone            True
dtype: object
```

```
data.min()
```

```
/var/folders/03/k1p5_v6d69bg7b999gdktlgw0000gn/T/ipykernel_3411/927168777.py:1: FutureWarning: The default value of numeri
  data.min()
survived          0
pclass            1
sex          female
age            0.42
sibsp             0
parch             0
fare            0.0
class         First
who           child
adult_male    False
alive            no
alone         False
dtype: object
```

```
Range = data.max()[['age', 'fare']] - data.min()[['age', 'fare']]
print(Range)
```

```
age        79.58
fare    512.3292
dtype: object
/var/folders/03/k1p5_v6d69bg7b999gdktlgw0000gn/T/ipykernel_3411/1058199015.py:1: FutureWarning: The default value of numer
  Range = data.max()[['age', 'fare']] - data.min()[['age', 'fare']]
/var/folders/03/k1p5_v6d69bg7b999gdktlgw0000gn/T/ipykernel_3411/1058199015.py:1: FutureWarning: The default value of numer
  Range = data.max()[['age', 'fare']] - data.min()[['age', 'fare']]
```

Skewness

```
data.skew()
```

```
/var/folders/03/k1p5_v6d69bg7b999gdktlgw0000gn/T/ipykernel_3411/1188251951.py:1: FutureWarning: The default value of numer
  data.skew()
survived      0.478523
pclass       -0.630548
age           0.389108
sibsp         3.695352
parch         2.749117
```

```
fare          4.787317
adult_male   -0.420431
alone        -0.420431
dtype: float64
```

Interquartile range

```
quantiles = data[['age', 'fare']].quantile(q=[0.75, 0.25])
quantiles
```

	age	fare
0.75	38.000	31.0000
0.25	20.125	7.9104

```
#Q3
quantiles.iloc[0]
```

```
age     38.0
fare    31.0
Name: 0.75, dtype: float64
```

```
#Q1
quantiles.iloc[1]
```

```
age     20.1250
fare     7.9104
Name: 0.25, dtype: float64
```

```
IQR = quantiles.iloc[0]-quantiles.iloc[1]
IQR
```

```
age     17.8750
fare    23.0896
dtype: float64
```

Upper extreme

Q3 + 1.5*IQR

```
quantiles.iloc[0] + (1.5*IQR)
```

```
age     64.8125
fare    65.6344
dtype: float64
```

Lower extreme

Q1 - 1.5*IQR

```
quantiles.iloc[1] - (1.5*IQR)
```

```
age     -6.6875
fare   -26.7240
dtype: float64
```

Standard deviation

```
data.std()
```

```
/var/folders/03/k1p5_v6d69bg7b999gdktlgw0000gn/T/ipykernel_3411/2723740006.py:1: FutureWarning: The default value of numer
  data.std()
survived       0.486592
pclass         0.836071
age           14.526497
sibsp          1.102743
parch          0.806057
fare          49.693429
adult_male     0.489615
alone          0.489615
dtype: float64
```

Variance

```
data.var()
```

```
/var/folders/03/k1p5_v6d69bg7b999gdktlgw0000gn/T/ipykernel_3411/445316826.py:1: FutureWarning: The default value of numeri
  data.var()
survived         0.236772
pclass           0.699015
age            211.019125
sibsp            1.216043
parch            0.649728
fare          2469.436846
adult_male       0.239723
alone            0.239723
dtype: float64
```

```
data.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. Handle the Missing values.

```
data.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
```

Handling missing value

```
data['age'].fillna(data['age'].mean(), inplace=True)
```

```
data['embarked'].fillna(data['embarked'].mode()[0], inplace=True)
```

```
data['deck'].fillna(data['deck'].mode()[0], inplace=True)
```

```
data['embark_town'].fillna(data['embark_town'].mode()[0], inplace=True)
```

```
data.isnull().sum()
```

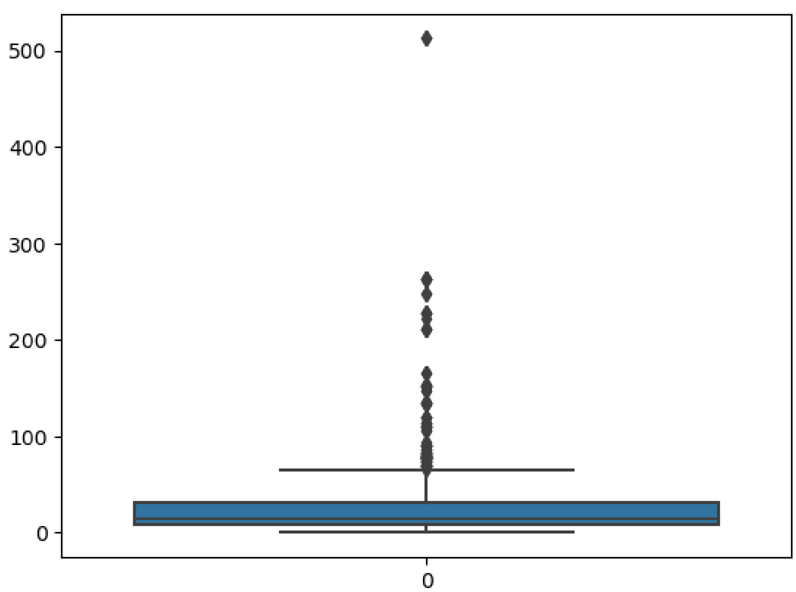
```
survived       0
pclass         0
sex            0
age            0
sibsp          0
parch          0
fare           0
embarked       0
class          0
who            0
adult_male     0
deck           0
embark_town    0
alive          0
alone          0
dtype: int64
```

6. Find the outliers and replace the outliers

Removing outliers

```
sns.boxplot(data.fare)
```

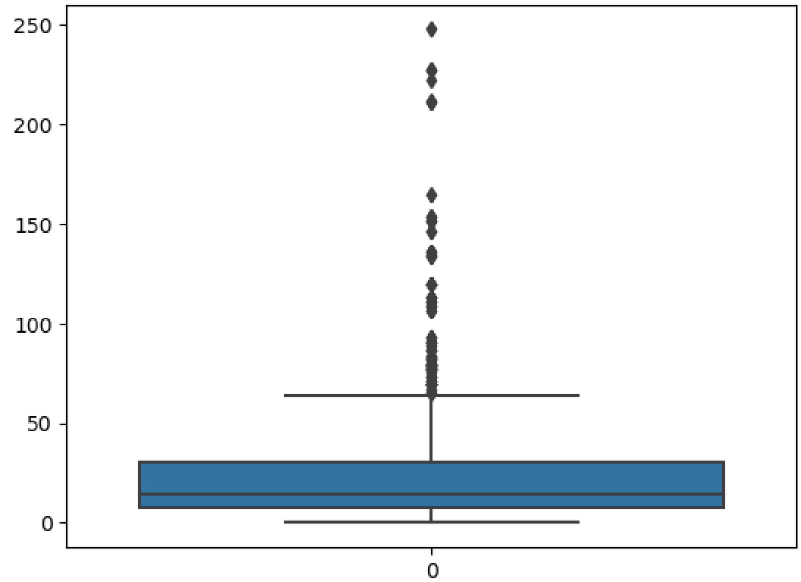
```
<Axes: >
```



```
quant99 = data.fare.quantile(0.99)
data = data[data.fare<quant99]
```

```
sns.boxplot(data.fare)
```

```
<Axes: >
```



7. Check for Categorical columns and perform encoding.

Encoding techniques

Label encoding

```
from sklearn.preprocessing import LabelEncoder
```

```
le = LabelEncoder()
```

```
data.head()
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	C	Southampton
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	C	Southampton
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	C	Southampton

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 882 entries, 0 to 890
Data columns (total 15 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   survived     882 non-null    int64
 1   pclass       882 non-null    int64
```

```
 2   sex          882 non-null    object
 3   age          882 non-null    float64
 4   sibsp        882 non-null    int64
 5   parch        882 non-null    int64
 6   fare         882 non-null    float64
 7   embarked     882 non-null    object
 8   class        882 non-null    object
 9   who          882 non-null    object
 10  adult_male   882 non-null    bool
 11  deck         882 non-null    object
 12  embark_town  882 non-null    object
 13  alive        882 non-null    object
 14  alone        882 non-null    bool
dtypes: bool(2), float64(2), int64(4), object(7)
memory usage: 130.5+ KB
```

```
columns = ['sex', 'embarked', 'class', 'who', 'deck', 'alive']
for col in columns:
 data[col] = le.fit_transform(data[col])
```

```
/var/folders/03/k1p5_v6d69bg7b999gdktlgw0000gn/T/ipykernel_3411/462314644.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-vi
  data[col] = le.fit_transform(data[col])
/var/folders/03/k1p5_v6d69bg7b999gdktlgw0000gn/T/ipykernel_3411/462314644.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-vi
  data[col] = le.fit_transform(data[col])
/var/folders/03/k1p5_v6d69bg7b999gdktlgw0000gn/T/ipykernel_3411/462314644.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-vi
  data[col] = le.fit_transform(data[col])
/var/folders/03/k1p5_v6d69bg7b999gdktlgw0000gn/T/ipykernel_3411/462314644.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-vi
  data[col] = le.fit_transform(data[col])
/var/folders/03/k1p5_v6d69bg7b999gdktlgw0000gn/T/ipykernel_3411/462314644.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-vi
  data[col] = le.fit_transform(data[col])
/var/folders/03/k1p5_v6d69bg7b999gdktlgw0000gn/T/ipykernel_3411/462314644.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-vi
  data[col] = le.fit_transform(data[col])
```

```
data.head()
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive
0	0	3	1	22.0	1	0	7.2500	2	2	1	True	2	Southampton	0
1	1	1	0	38.0	1	0	71.2833	0	0	2	False	2	Cherbourg	1
2	1	3	0	26.0	0	0	7.9250	2	2	2	False	2	Southampton	1
3	1	1	0	35.0	1	0	53.1000	2	0	2	False	2	Southampton	1
4	0	3	1	35.0	0	0	8.0500	2	2	1	True	2	Southampton	0

One Hot Encoding

```
data = pd.get_dummies(data, columns=['embark_town'])
```

```
data
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	alive	alon
0	0	3	1	22.000000	1	0	7.2500	2	2	1	True	2	0	Fals
1	1	1	0	38.000000	1	0	71.2833	0	0	2	False	2	1	Fals
2	1	3	0	26.000000	0	0	7.9250	2	2	2	False	2	1	Tru
3	1	1	0	35.000000	1	0	53.1000	2	0	2	False	2	1	Fals
4	0	3	1	35.000000	0	0	8.0500	2	2	1	True	2	0	Tru
...	...	...	...	...	...	...	...	...	...	...	...	...	...	.
886	0	2	1	27.000000	0	0	13.0000	2	1	1	True	2	0	Tru
887	1	1	0	19.000000	0	0	30.0000	2	0	2	False	1	1	Tru
888	0	3	0	29.699118	1	2	23.4500	2	2	2	False	2	0	Fals
889	1	1	1	26.000000	0	0	30.0000	0	0	1	True	2	1	Tru
890	0	3	1	32.000000	0	0	7.7500	1	2	1	True	2	0	Tru

882 rows × 17 columns

8. Split the data into dependent and independent variables.

Dependent variable

```
y = data.loc[:, 'alive':'alive']
y
```

	alive
0	0
1	1
2	1
3	1
4	0
...	...
886	0
887	1
888	0
889	1
890	0

882 rows × 1 columns

Independent variable

```
X = data.drop(columns=['alive'], axis=1)
X
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	alone	emba
0	0	3	1	22.000000	1	0	7.2500	2	2	1	True	2	False	
1	1	1	0	38.000000	1	0	71.2833	0	0	2	False	2	False	
2	1	3	0	26.000000	0	0	7.9250	2	2	2	False	2	True	
3	1	1	0	35.000000	1	0	53.1000	2	0	2	False	2	False	
4	0	3	1	35.000000	0	0	8.0500	2	2	1	True	2	True	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
886	0	2	1	27.000000	0	0	13.0000	2	1	1	True	2	True	
887	1	1	0	19.000000	0	0	30.0000	2	0	2	False	1	True	
888	0	3	0	29.699118	1	2	23.4500	2	2	2	False	2	False	
889	1	1	1	26.000000	0	0	30.0000	0	0	1	True	2	True	
890	0	3	1	32.000000	0	0	7.7500	1	2	1	True	2	True	

882 rows × 16 columns

9. Scale the independent variables

Scaling

StandardScaler --> mean=0 std=1

MinMaxScaler --> scale between 0 to 1

```
from sklearn.preprocessing import MinMaxScaler
scale = MinMaxScaler()
```

```
name = X.columns
X_scaled = scale.fit_transform(X)
```

```
X_scaled
```

```
array([[0., 1., 1., ..., 0., 0., 1.],
       [1., 0., 0., ..., 1., 0., 0.],
       [1., 1., 0., ..., 0., 0., 1.],
       ...,
       [0., 1., 0., ..., 0., 0., 1.],
       [1., 0., 1., ..., 1., 0., 0.],
       [0., 1., 1., ..., 0., 1., 0.]])
```

```
X = pd.DataFrame(X_scaled, columns=name)
X
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	alone
0	0.0	1.0	1.0	0.271174	0.125	0.000000	0.029290	1.0	1.0	0.5	1.0	0.333333	0.(
1	1.0	0.0	0.0	0.472229	0.125	0.000000	0.287989	0.0	0.0	1.0	0.0	0.333333	0.(
2	1.0	1.0	0.0	0.321438	0.000	0.000000	0.032018	1.0	1.0	1.0	0.0	0.333333	1.(
3	1.0	0.0	0.0	0.434531	0.125	0.000000	0.214527	1.0	0.0	1.0	0.0	0.333333	0.(
4	0.0	1.0	1.0	0.434531	0.000	0.000000	0.032523	1.0	1.0	0.5	1.0	0.333333	1.(
...	...	...	...	...	...	...	...	...	...	...	...	...	..
878	1.0	0.0	0.0	0.233476	0.000	0.000000	0.121202	1.0	0.0	1.0	0.0	0.166667	1.(

10. Split the data into training and testing

882 rows × 16 columns

Train-Test Split

```
from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)
```

```
X_train
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	alone
222	1.0	0.0	1.0	0.472229	0.125	0.000000	0.363606	1.0	0.0	0.5	1.0	0.333333	0.(
200	0.0	1.0	1.0	0.421965	0.000	0.000000	0.026243	1.0	1.0	0.5	1.0	0.333333	1.(
162	0.0	1.0	1.0	0.007288	0.500	0.166667	0.160340	1.0	1.0	0.0	0.0	0.333333	0.(
576	0.0	0.5	1.0	0.673285	0.000	0.000000	0.105042	1.0	0.5	0.5	1.0	0.333333	1.(
841	0.0	1.0	1.0	0.044986	0.500	0.333333	0.126353	1.0	1.0	0.0	0.0	0.333333	0.(
...	...	...	...	...	...	...	...	...	...	...	...	...	..
835	0.0	1.0	1.0	0.208344	0.000	0.000000	0.034997	1.0	1.0	0.5	1.0	0.333333	1.(
192	1.0	0.0	0.0	0.547625	0.000	0.000000	0.111994	0.0	0.0	1.0	0.0	0.166667	1.(
629	1.0	0.5	0.0	0.346569	0.000	0.000000	0.052521	1.0	0.5	1.0	0.0	0.333333	1.(
559	0.0	1.0	1.0	0.296306	0.250	0.000000	0.097568	1.0	1.0	0.5	1.0	0.333333	0.(
684	1.0	1.0	0.0	0.044986	0.000	0.166667	0.054204	0.0	1.0	0.0	0.0	0.333333	0.(

705 rows × 16 columns

```
y_train
```

	alive
224	1
202	0

X_test

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	alon
150	0.0	1.0	1.0	0.692134	0.000	0.000000	0.032523	1.0	1.0	0.5	1.0	0.333333	1.(
406	0.0	1.0	1.0	0.367921	0.000	0.000000	0.027708	0.5	1.0	0.5	1.0	0.333333	1.(
513	0.0	1.0	1.0	0.396833	0.000	0.000000	0.031900	1.0	1.0	0.5	1.0	0.333333	1.(
101	0.0	1.0	1.0	0.409399	0.000	0.000000	0.034964	1.0	1.0	0.5	1.0	0.333333	1.(
584	0.0	1.0	1.0	0.434531	0.000	0.000000	0.028785	1.0	1.0	0.5	1.0	0.333333	1.(
...	...	...	...	...	...	...	...	...	...	...	...	...	..
362	1.0	1.0	0.0	0.367921	0.000	0.000000	0.029206	0.0	1.0	1.0	0.0	0.333333	1.(
367	0.0	1.0	1.0	0.233476	0.000	0.000000	0.032523	1.0	1.0	0.5	1.0	0.333333	1.(
264	1.0	1.0	1.0	0.308872	0.125	0.000000	0.031412	1.0	1.0	0.5	1.0	0.333333	0.(
320	0.0	1.0	1.0	0.367921	1.000	0.333333	0.280986	1.0	1.0	0.5	1.0	0.333333	0.(
466	1.0	0.5	0.0	0.409399	0.125	0.333333	0.112112	1.0	0.5	1.0	0.0	0.333333	0.(

177 rows × 16 columns

y_test

	alive
152	0
411	0
519	0
103	0
590	0
...	...
367	1
372	0
267	1
324	0
472	1

177 rows × 1 columns

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