Exploratory Data Analysis

This will show us how can we do EDA using python

Three important steps to keep in minda are:

```
1- Understand the Data.
2- clean the data.
3- Find a relationship between data.
```

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

load seaborn library dataset

In [ ]:
```
kashti = sns.load_dataset('titanic')
kashti
```

Out[ ]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True
...	...	...	...	...	...	...	...	...	...	...	...
886	0	2	male	27.0	0	0	13.0000	S	Second	man	True
887	1	1	female	19.0	0	0	30.0000	S	First	woman	False
888	0	3	female	NaN	1	2	23.4500	S	Third	woman	False
889	1	1	male	26.0	0	0	30.0000	C	First	man	True
890	0	3	male	32.0	0	0	7.7500	Q	Third	man	True

891 rows × 15 columns

to save titanic data set as csv file

In [ ]:
```
kashti.to_csv('kashti.csv')
```

1- Understanding the data

to get full information of kashti dataset

In [ ]:
```
kashti.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    category
 9   who          891 non-null    object
 10  adult_male   891 non-null    bool
 11  deck         203 non-null    category
 12  embark_town  889 non-null    object
 13  alive        891 non-null    object
 14  alone        891 non-null    bool
dtypes: bool(2), category(2), float64(2), int64(4), object(5)
memory usage: 80.7+ KB
```

In [ ]:
```
ks = kashti
```

to print header of data

In [ ]:
```
ks.head()
```

Out[ ]:

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

to print shape of dataset

In [ ]:
```
ks.shape
```

Out[ ]:
```
(891, 15)
```

to print tail of dataset

In [ ]:
```
ks.tail()
```

Out[ ]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	d
886	0	2	male	27.0	0	0	13.00	S	Second	man	True	N
887	1	1	female	19.0	0	0	30.00	S	First	woman	False	
888	0	3	female	NaN	1	2	23.45	S	Third	woman	False	N
889	1	1	male	26.0	0	0	30.00	C	First	man	True	

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	d
890	0	3	male	32.0	0	0	7.75	Q	Third	man	True	N

to get information of numeric variable

In [ ]:
```
ks.describe()
```

Out[ ]:

	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

to print unique values of a column in dataset

In [ ]:
```
ks.nunique()
```

Out[ ]:
```
survived         2
pclass           3
sex              2
age             88
sibsp            7
parch            7
fare           248
embarked         3
class            3
who              3
adult_male       2
deck             7
embark_town      3
alive            2
alone            2
dtype: int64
```

to print all column names of dataset

In [ ]:
```
ks.columns
```

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

In [ ]:
```
ks['sex'].unique()   #nunique print number of unique values and unique print the val
```

Out[ ]:
```
array(['male', 'female'], dtype=object)
```

In [ ]:
```
ks['embarked'].unique()
```

Out[ ]:
```
array(['S', 'C', 'Q', nan], dtype=object)
```

Assignment:

HOw to print unique values of all column in one line of code.

In [ ]:
```
ks_series=ks.columns
for i in ks_series:
    print("The unique value of:", i)
    print(ks[i].unique())
```

```
The unique value of: survived
[0 1]
The unique value of: pclass
[3 1 2]
The unique value of: sex
['male' 'female']
The unique value of: age
[22.   38.   26.   35.     nan 54.    2.   27.   14.    4.   58.   20.
 39.   55.   31.   34.   15.   28.    8.   19.   40.   66.   42.   21.
 18.    3.    7.   49.   29.   65.   28.5   5.   11.   45.   17.   32.
 16.   25.    0.83 30.   33.   23.   24.   46.   59.   71.   37.   47.
 14.5  70.5  32.5  12.    9.   36.5  51.   55.5  40.5  44.    1.   61.
 56.   50.   36.   45.5  20.5  62.   41.   52.   63.   23.5   0.92 43.
 60.   10.   64.   13.   48.    0.75 53.   57.   80.   70.   24.5   6.
  0.67 30.5   0.42 34.5  74.  ]
The unique value of: sibsp
[1 0 3 4 2 5 8]
The unique value of: parch
[0 1 2 5 3 4 6]
The unique value of: fare
[  7.25    71.2833   7.925   53.1      8.05     8.4583  51.8625  21.075
  11.1333  30.0708  16.7     26.55    31.275    7.8542  16.      29.125
  13.      18.       7.225   26.       8.0292  35.     31.3875 263.
   7.8792   7.8958  27.7208 146.5208   7.75    10.5     82.1708  52.
   7.2292  11.2417   9.475   21.      41.5792  15.5     21.6792  17.8
  39.6875   7.8     76.7292  61.9792  27.75    46.9     80.      83.475
  27.9     15.2458   8.1583   8.6625  73.5     14.4542  56.4958   7.65
  29.      12.475    9.       9.5      7.7875  47.1     15.85    34.375
  61.175   20.575   34.6542  63.3583  23.      77.2875   8.6542   7.775
  24.15     9.825   14.4583 247.5208   7.1417  22.3583   6.975    7.05
  14.5     15.0458  26.2833   9.2167  79.2      6.75    11.5     36.75
   7.7958  12.525   66.6      7.3125  61.3792   7.7333  69.55    16.1
  15.75    20.525   55.      25.925   33.5     30.6958  25.4667  28.7125
   0.      15.05    39.      22.025   50.       8.4042   6.4958  10.4625
  18.7875  31.     113.275   27.      76.2917  90.       9.35    13.5
   7.55    26.25    12.275    7.125   52.5542  20.2125  86.5    512.3292
  79.65   153.4625 135.6333  19.5     29.7     77.9583  20.25    78.85
  91.0792  12.875    8.85   151.55    30.5     23.25    12.35   110.8833
 108.9     24.      56.9292  83.1583 262.375   14.     164.8667 134.5
   6.2375  57.9792  28.5    133.65    15.9      9.225   35.      75.25
  69.3     55.4417 211.5      4.0125 227.525   15.7417   7.7292  12.
 120.      12.65    18.75     6.8583  32.5      7.875   14.4     55.9
   8.1125  81.8583  19.2583  19.9667  89.1042  38.5      7.725   13.7917
   9.8375   7.0458   7.5208  12.2875   9.5875  49.5042  78.2667  15.1
   7.6292  22.525   26.2875  59.4      7.4958  34.0208  93.5    221.7792
 106.425   49.5     71.      13.8625   7.8292  39.6     17.4     51.4792
  26.3875  30.      40.125    8.7125  15.      33.      42.4     15.55
  65.      32.3208   7.0542   8.4333  25.5875   9.8417   8.1375  10.1708
```

```
 211.3375  57.      13.4167   7.7417   9.4833   7.7375   8.3625  23.45
  25.9292   8.6833   8.5167   7.8875  37.0042   6.45     6.95     8.3
   6.4375  39.4     14.1083  13.8583  50.4958   5.       9.8458  10.5167]
The unique value of: embarked
['S' 'C' 'Q' nan]
The unique value of: class
['Third', 'First', 'Second']
Categories (3, object): ['First', 'Second', 'Third']
The unique value of: who
['man' 'woman' 'child']
The unique value of: adult_male
[ True False]
The unique value of: deck
[NaN, 'C', 'E', 'G', 'D', 'A', 'B', 'F']
Categories (7, object): ['A', 'B', 'C', 'D', 'E', 'F', 'G']
The unique value of: embark_town
['Southampton' 'Cherbourg' 'Queenstown' nan]
The unique value of: alive
['no' 'yes']
The unique value of: alone
[False  True]
```

2- Cleaning and filtering the data

to find missing values in dataset

In [ ]:
```
ks.isnull().sum()
```

Out[ ]:
```
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
```

to remove the column with most missing values (cleaning)

In [ ]:
```
ks_clean = ks.drop(['deck'], axis=1)
ks_clean.head()
```

Out[ ]:

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

In [ ]:
```
ks_clean.isnull().sum()
```

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

In [ ]:
```
ks_clean.shape
```

Out[ ]:
```
(891, 14)
```

to drop all NaN from dataframe

In [ ]:
```
ks_clean = ks_clean.dropna()
```

In [ ]:
```
ks_clean.isnull().sum()
```

Out[ ]:
```
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
```

In [ ]:
```
ks_clean.shape
```

Out[ ]:
```
(712, 14)
```

In [ ]:
```
ks_clean.describe()
```

Out[ ]:

	survived	pclass	age	sibsp	parch	fare
count	712.000000	712.000000	712.000000	712.000000	712.000000	712.000000
mean	0.404494	2.240169	29.642093	0.514045	0.432584	34.567251
std	0.491139	0.836854	14.492933	0.930692	0.854181	52.938648
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000

	survived	pclass	age	sibsp	parch	fare
25%	0.000000	1.000000	20.000000	0.000000	0.000000	8.050000
50%	0.000000	2.000000	28.000000	0.000000	0.000000	15.645850
75%	1.000000	3.000000	38.000000	1.000000	1.000000	33.000000
max	1.000000	3.000000	80.000000	5.000000	6.000000	512.329200

In [ ]:
```
ks.describe()
```

Out[ ]:

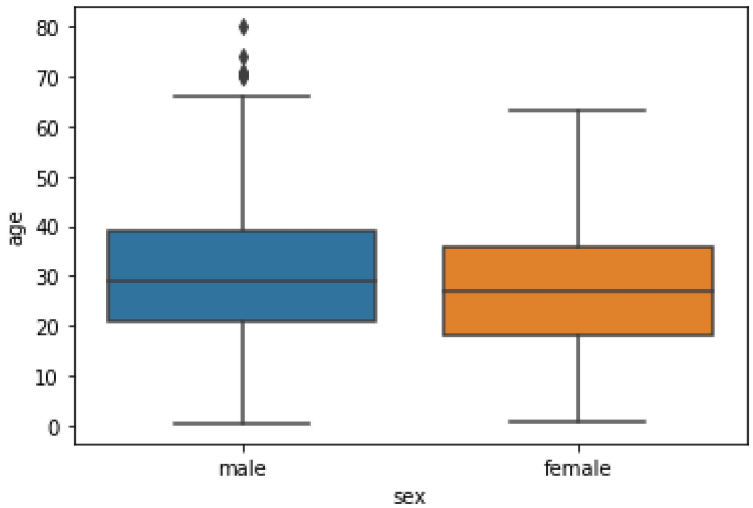
	survived	pclass	age	sibsp	parch	fare
count	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	0.000000	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

In [ ]:
```
ks_clean.columns
```

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

In [ ]:
```
sns.boxplot(x = 'sex', y = 'age', data=ks_clean)
```

Out[ ]:
```
<AxesSubplot:xlabel='sex', ylabel='age'>
```

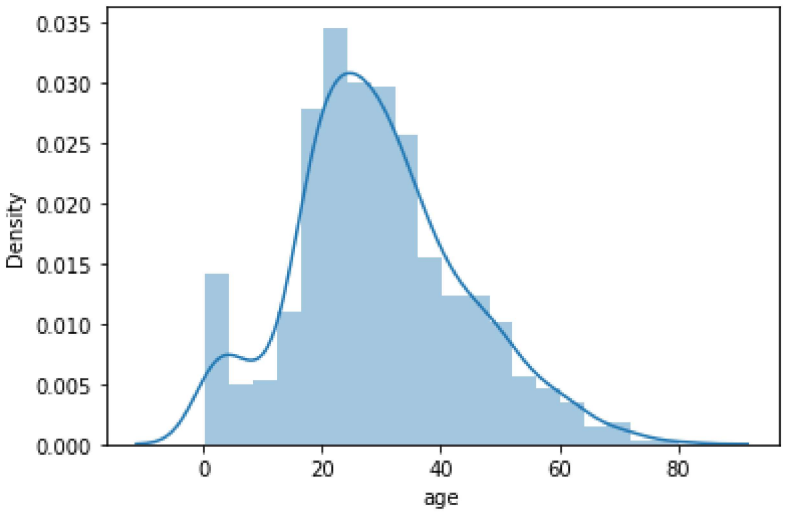


In [ ]:
```
sns.distplot(ks_clean['age'])  # the below graph is called bell curve, histogram, no
```

```
C:\Users\Faisal Hayat\AppData\Local\Programs\Python\Python310\lib\site-packages\seab
```

```
orn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and wi
ll be removed in a future version. Please adapt your code to use either `displot` (a
figure-level function with similar flexibility) or `histplot` (an axes-level functio
n for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[ ]:
```
<AxesSubplot:xlabel='age', ylabel='Density'>
```



Remarks:To make bell shape curve we apply diff method one method is to remove outlier

Dispersion and mean has to be seen

In [ ]:
```
# To remove outliers
ks_clean['age'].mean()
```

Out[ ]:
```
29.64209269662921
```

In [ ]:
```
ks_clean = ks_clean[ks_clean['age']<65]
ks_clean
```

Out[ ]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True
...	...	...	...	...	...	...	...	...	...	...	...
885	0	3	female	39.0	0	5	29.1250	Q	Third	woman	False
886	0	2	male	27.0	0	0	13.0000	S	Second	man	True
887	1	1	female	19.0	0	0	30.0000	S	First	woman	False
889	1	1	male	26.0	0	0	30.0000	C	First	man	True
890	0	3	male	32.0	0	0	7.7500	Q	Third	man	True

701 rows × 14 columns

In [ ]:
```
ks_clean.shape
```

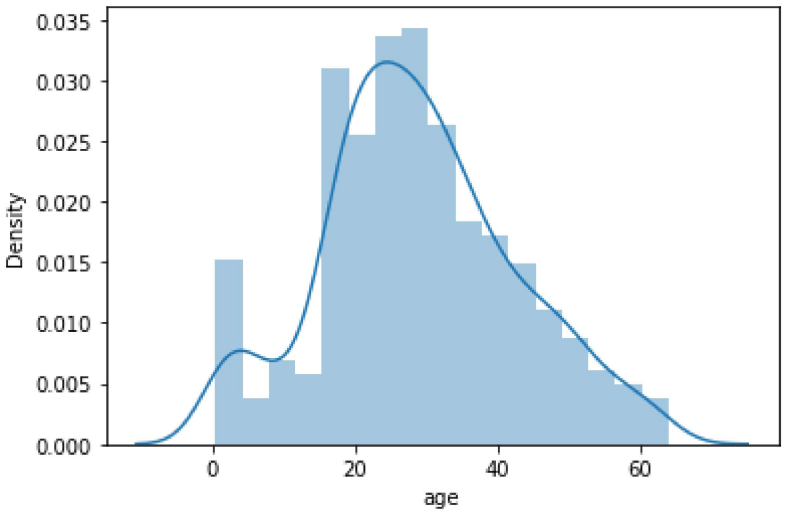
Out[ ]:
```
(701, 14)
```

In [ ]:
```
ks_clean['age'].mean()
```

Out[ ]:
```
29.01236804564907
```

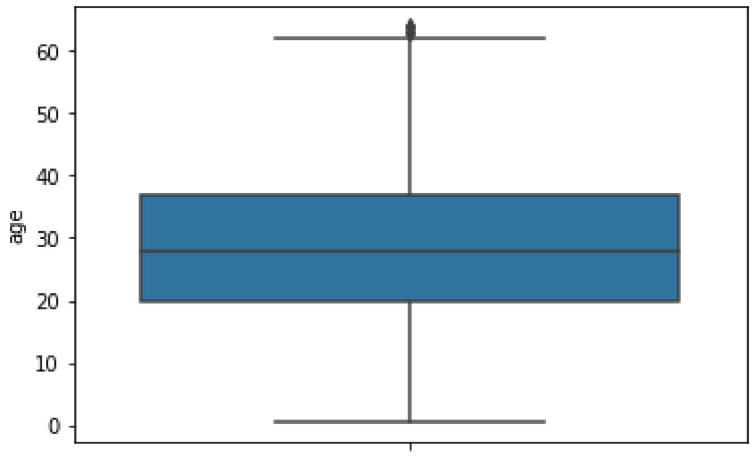
In [ ]:
```
sns.distplot(ks_clean['age'])
```

Out[ ]:
```
C:\Users\Faisal Hayat\AppData\Local\Programs\Python\Python310\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
<AxesSubplot:xlabel='age', ylabel='Density'>
```



In [ ]:
```
sns.boxplot(y='age', data=ks_clean)
```

Out[ ]:
```
<AxesSubplot:ylabel='age'>
```



In [ ]:
```
ks_clean.head()
```

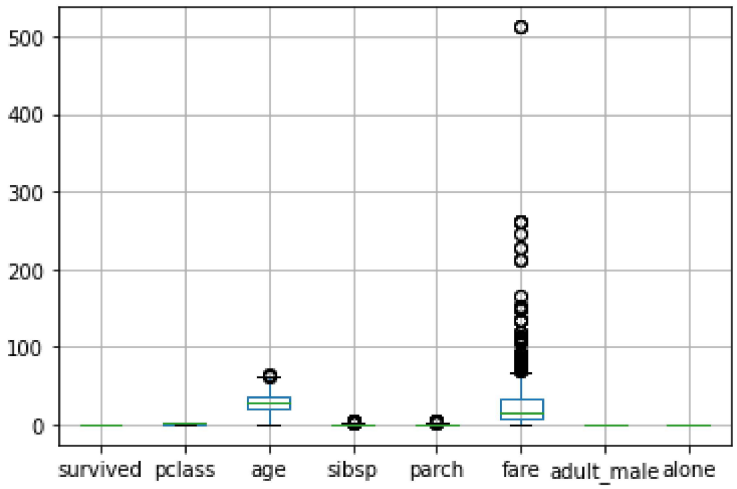
Out[ ]:

survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	emb

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

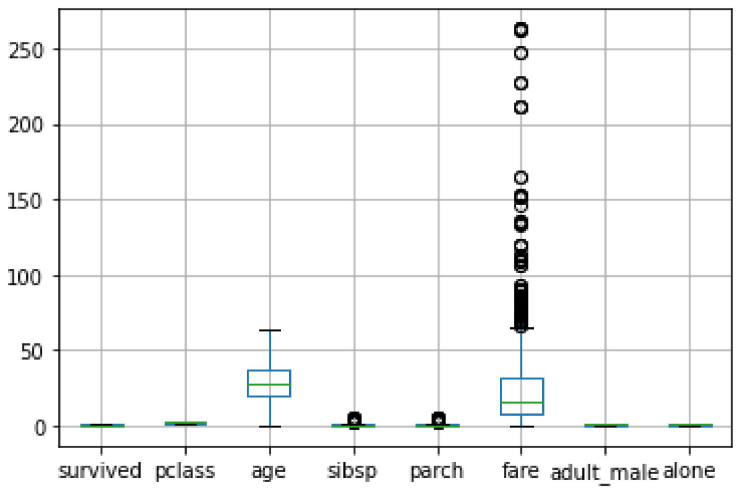
In [ ]:
```
ks_clean.boxplot()
```

Out[ ]:
```
<AxesSubplot:>
```



In [ ]:
```
ks_clean = ks_clean[ks_clean['fare']<300]
ks_clean.boxplot()
```

Out[ ]:
```
<AxesSubplot:>
```

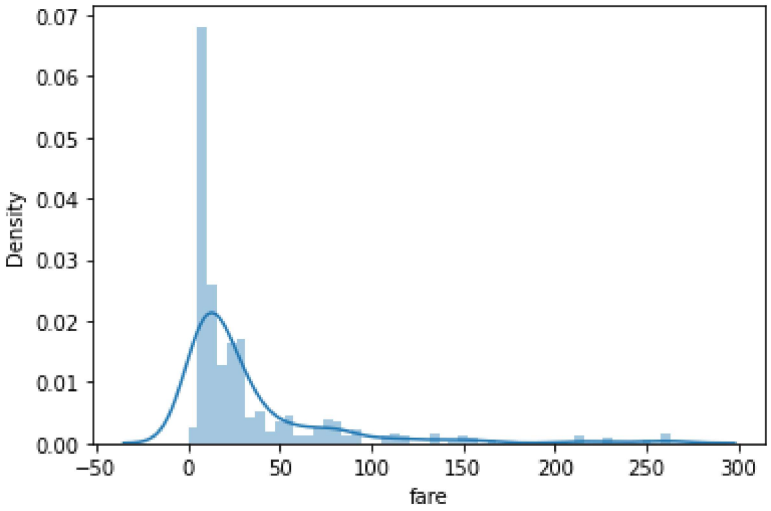


In [ ]:
```
sns.distplot(ks_clean['fare'])
```

```
C:\Users\Faisal Hayat\AppData\Local\Programs\Python\Python310\lib\site-packages\seab
orn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and wi
ll be removed in a future version. Please adapt your code to use either `displot` (a
figure-level function with similar flexibility) or `histplot` (an axes-level functio
```

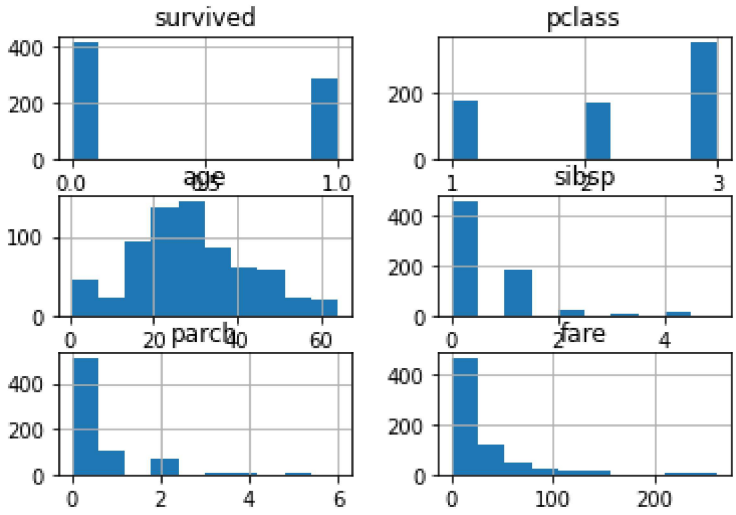
```
n for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[ ]:
```
<AxesSubplot:xlabel='fare', ylabel='Density'>
```



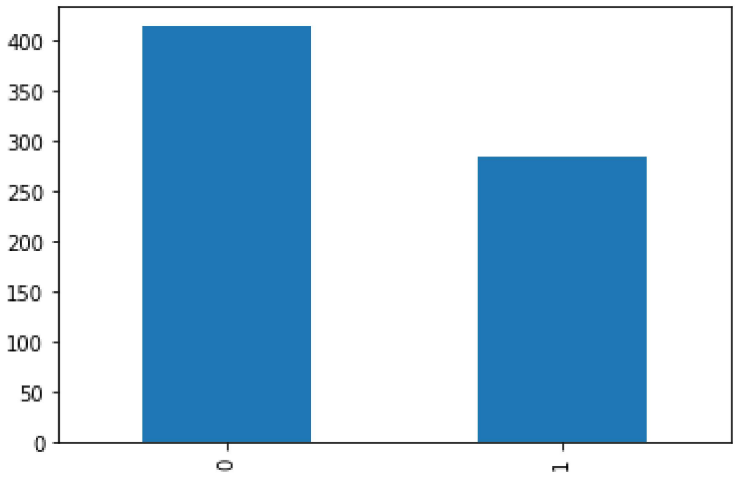
In [ ]:
```
# to make histogram of whole dataset
ks_clean.hist()
```

Out[ ]:
```
array([[<AxesSubplot:title={'center':'survived'}>,
        <AxesSubplot:title={'center':'pclass'}>],
       [<AxesSubplot:title={'center':'age'}>,
        <AxesSubplot:title={'center':'sibsp'}>],
       [<AxesSubplot:title={'center':'parch'}>,
        <AxesSubplot:title={'center':'fare'}>]], dtype=object)
```



In [ ]:
```
pd.value_counts(ks_clean['survived']).plot.bar()
```

Out[ ]:
```
<AxesSubplot:>
```



In [ ]:
```
ks_clean.groupby(['sex']).mean()
```

Out[ ]:

sex	survived	pclass	age	sibsp	parch	fare	adult_male	alone
female	0.751938	2.077519	27.717054	0.647287	0.717054	45.530120	0.000000	0.375969
male	0.204545	2.356818	29.728795	0.450000	0.272727	25.023095	0.909091	0.668182

In [ ]:
```
ks_clean.groupby(['sex','class']).mean()
```

Out[ ]:

sex	class	survived	pclass	age	sibsp	parch	fare	adult_male	alone
female	**First**	0.963415	1.0	34.231707	0.560976	0.512195	103.696393	0.000000	0.353659
	Second	0.918919	2.0	28.722973	0.500000	0.621622	21.951070	0.000000	0.405405
	Third	0.460784	3.0	21.750000	0.823529	0.950980	15.875369	0.000000	0.372549
male	**First**	0.397849	1.0	39.531398	0.397849	0.333333	63.301881	0.967742	0.526882
	Second	0.154639	2.0	29.972474	0.381443	0.247423	21.331959	0.907216	0.628866
	Third	0.152000	3.0	25.987680	0.496000	0.260000	12.215548	0.888000	0.736000

In [ ]:
```
ks_clean
```

Out[ ]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True
...	...	...	...	...	...	...	...	...	...	...	...
885	0	3	female	39.0	0	5	29.1250	Q	Third	woman	False
886	0	2	male	27.0	0	0	13.0000	S	Second	man	True

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male
887	1	1	female	19.0	0	0	30.0000	S	First	woman	False
889	1	1	male	26.0	0	0	30.0000	C	First	man	True
890	0	3	male	32.0	0	0	7.7500	Q	Third	man	True

698 rows × 14 columns

In [ ]:
```
ks
```

Out[ ]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True
...	...	...	...	...	...	...	...	...	...	...	...
886	0	2	male	27.0	0	0	13.0000	S	Second	man	True
887	1	1	female	19.0	0	0	30.0000	S	First	woman	False
888	0	3	female	NaN	1	2	23.4500	S	Third	woman	False
889	1	1	male	26.0	0	0	30.0000	C	First	man	True
890	0	3	male	32.0	0	0	7.7500	Q	Third	man	True

891 rows × 15 columns

3- Relationship

In [ ]:
```
# to find correlation of data set, below function will give us correlation matrix
ks_clean.corr()
```

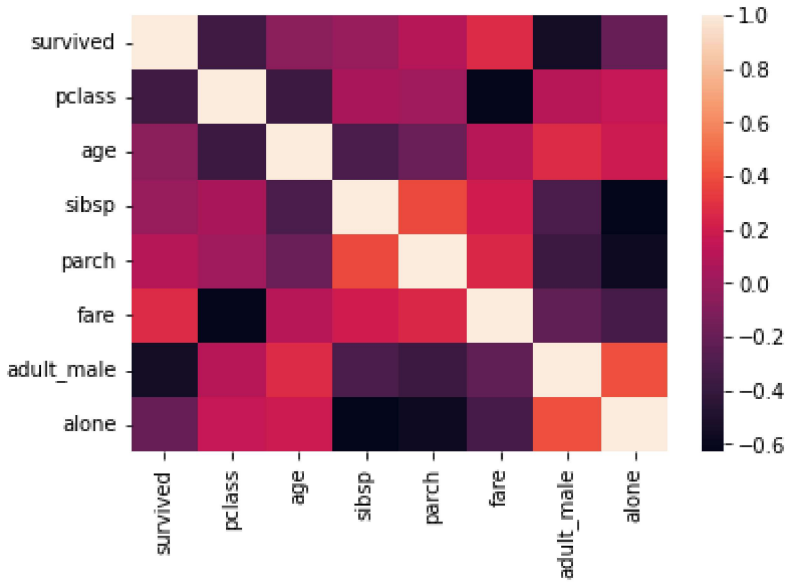
Out[ ]:

	survived	pclass	age	sibsp	parch	fare	adult_male	alone
survived	1.000000	-0.361495	-0.063460	-0.017159	0.094668	0.273631	-0.552755	-0.200286
pclass	-0.361495	1.000000	-0.364680	0.059720	0.023379	-0.618783	0.106530	0.155759
age	-0.063460	-0.364680	1.000000	-0.306870	-0.186806	0.107324	0.268049	0.185661
sibsp	-0.017159	0.059720	-0.306870	1.000000	0.381779	0.197847	-0.309813	-0.630175
parch	0.094668	0.023379	-0.186806	0.381779	1.000000	0.258839	-0.366564	-0.573696
fare	0.273631	-0.618783	0.107324	0.197847	0.258839	1.000000	-0.228663	-0.332415
adult_male	-0.552755	0.106530	0.268049	-0.309813	-0.366564	-0.228663	1.000000	0.402231
alone	-0.200286	0.155759	0.185661	-0.630175	-0.573696	-0.332415	0.402231	1.000000

In [ ]:
```
cor_var = ks_clean.corr()
```

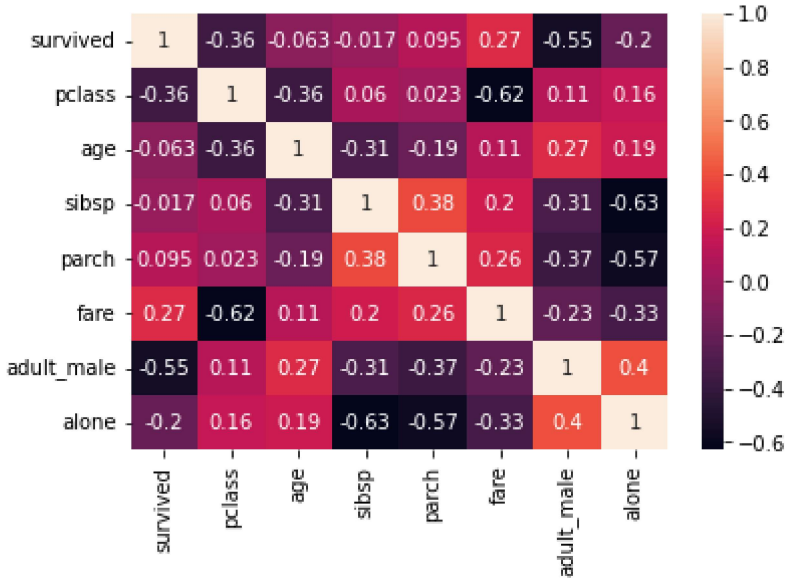
In [ ]:
```
# drawing heatmap
sns.heatmap(cor_var)
```

Out[ ]:
```
<AxesSubplot:>
```



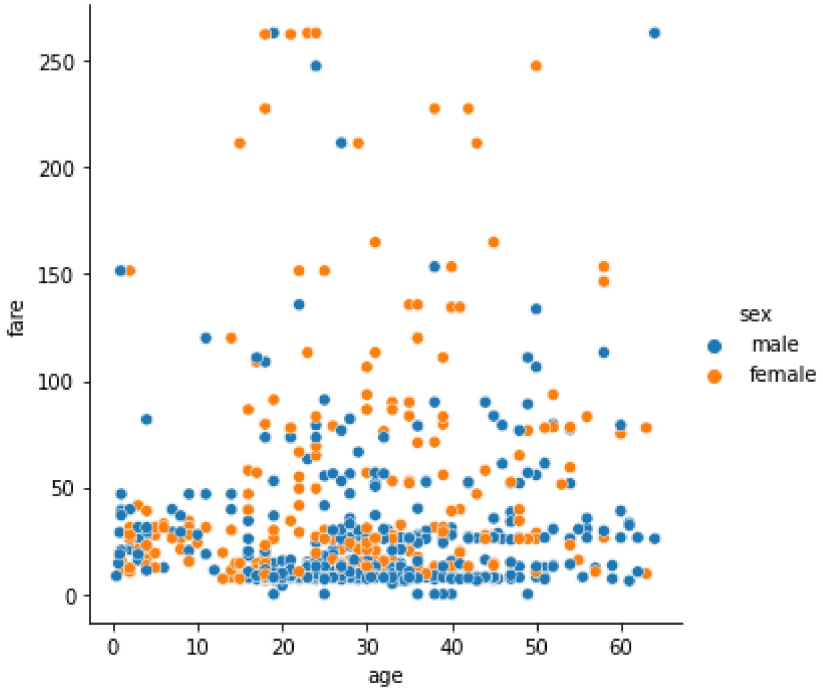
In [ ]:
```
sns.heatmap(cor_var, annot=True)
```

Out[ ]:
```
<AxesSubplot:>
```



In [ ]:
```
# correlation is actually for numerical variable
sns.relplot(x='age', y='fare', hue='sex', data=ks_clean)
```

Out[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x286d5f76da0>
```



In [ ]:
```
sns.catplot(x='sex', y='fare', hue='sex', data=ks_clean, kind='bar')  # kind can be
```

Out[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x286d5ea0e80>
```