01_DS_101_DataScienceCrashCourse

July 29, 2022

1 DataScience Crash Course (DS-101)

- **Name: Muhammad Waleed Anjum**
- **Email: waleedanjum_2009@yahoo.com**

1.1 Basics Operators

[ ]:
```
print(1+2)
print(3-2)
print(3*2)
print(4/2)
print(9%2)
print(7//2)
```

```
3
1
6
2.0
1
3
```

1.2 Strings

[ ]:
```
print('Single Quote Test')
print('Double Quotes Test')
print('Triple Quotes Test')

print("What's up")
```

```
Single Quote Test
Double Quotes Test
Triple Quotes Test
What's up
```

1.3 Variables

Rules to assign a variable: 1. The variable should contain letters, numbers or underscores 2. Do not start with numbers 3. Spaces are not allowed 4. Do not use keywords used in functions (break, mean, test etc.) 5. Short and descriptive 6. Case sensitive

[ ]:
```python
# Variables: Objects containing Specific Values
x=5
print(x)

x=15
print(x)

print(type(x))
```

```
5
15
<class 'int'>
```

1.4 Input Variables

[ ]:
```python
# input function is used to get user input

fruit_basket = input('What is your favorite fruit?')
fruit_basket
```

[ ]:
```
'Mango'
```

[ ]:
```python
name = input('What is your Name?')
greeting = 'Hello!'
print(greeting, name)
```

```
Hello! Muhammad Waleed Anjum
```

1.5 Conditional Logics

- equal to ==
- not equal to !=
- less than <
- greater than >
- less than and equal to <=
- greater than and equal to >=

[ ]:
```python
age_at_school = 5
ahmed_age = int(input('What is Ahmed Age? '))
print(age_at_school==ahmed_age)
```

```
True
```

1.6 Type Conversion

[ ]:
```python
x = 10              # integer
y = 10.2            # Float
z = 'Hello'         # String

```

```
# Implicit type conversion
x = x + y
print(x, 'Type of x is: ', type(x))

# Explicit Type Conversion
age = int(input('What is your Age? '))
print(age, type(age))
```

```
20.2 Type of x is:  <class 'float'>
32 <class 'int'>
```

1.7 if else elif statements

[ ]:
```
req_age_at_school = 5
req_age_at_college = 14
ahmed_age = int(input('What is Ahmed Age? '))
# Can Ahmed go to school?
if ahmed_age >= req_age_at_college:
    print(f"Ahmed Age is: {ahmed_age}\nYes, Ahmed Can go to college")
elif ahmed_age >= req_age_at_school:
    print(f'Ahmed Age is: {ahmed_age}\nYes, Ahmed Can go to School')
else:
    print(f"Ahmed Age is: {ahmed_age}\nSorry, Ahmed is underage")
```

```
Ahmed Age is: 16
Yes, Ahmed Can go to college
```

1.8 Functions

[ ]:
```
# Defining a function (def)
# Method 1
def print_code():
    print('We are learning with babaAmmar')
    print('We are learning with babaAmmar')
    print('We are learning with babaAmmar')

# Method 1
def print_code2():
    text = 'We are learning with babaAmmar'
    print(text)
    print(text)
    print(text)

print_code()
print('--------------------------------')
print_code2()
```

```
We are learning with babaAmmar
We are learning with babaAmmar
```

```
We are learning with babaAmmar
-------------------------------
We are learning with babaAmmar
We are learning with babaAmmar
We are learning with babaAmmar
```

[ ]:
```
# School Age Calculator
def school_age_calc(age):
    if age == 5:
        print(f"Ahmed Age is: {age}\nAhmed Can join school")
    elif age > 5:
        print(f'Ahmed Age is: {age}\nAhmed should go to Higher School')
    else:
        print(f"Ahmed Age is: {age}\nSorry, Ahmed is underage")

school_age_calc(3)
```

```
Ahmed Age is: 3
Sorry, Ahmed is underage
```

[ ]:
```
# Defining a function of future
def future_age(age):
    new_age = age + 20
    return new_age

print('Future age is: ',future_age(18))
```

```
Future age is:  38
```

1.9 Loops

[ ]:
```
# While Loop

x = 0
while (x<=5):
    print(x)
    x = x + 1
```

```
0
1
2
3
4
5
```

[ ]:
```
# For Loop

for x in range(5,10):
    print(x)
```

5
6
7
8
9

[ ]:
```
# Array
days= ['Mon', 'Tues', 'Wed', 'Thur', 'Fri', 'Sat', 'Sun']

for d in days:
    #if (d == 'Fri'): break      #loop stops
    #if (d == 'Fri'): continue      #skips d
    print(d)
```

Mon
Tues
Wed
Thur
Fri
Sat
Sun

1.10 Import Libraries

[ ]:
```
# library is already developed codes
import math
print('The Value of pi is: ', math.pi)

import statistics
x = [150, 250, 350, 450]
print('Mean Value of x is: ',statistics.mean(x))
```

The Value of pi is: 3.141592653589793
Mean Value of x is: 300

1.11 Trouble Shooting

[ ]:
```
print(25/0)      # runtime error
print(we are learning python)       # syntax error
```

1.12 Indexing

[ ]:
```
a = 'samosa pakora'
print('First index is: ',a[0])       # Index starts from 0

# Length of indices
print('Length(Total Characters) of a are: ',len(a))
```

```
First index is:  s
Length(Total Characters) of a are:  13
```

[ ]:
```python
print('a is: ',a)
print('a[0:5]',a[0:5])
print('a[0:13]',a[0:13])    # last index is exclusive
print('a[:5]',a[:5])
print('a[-5]',a[-5])
print('a[0:-5]',a[0:-5])
print('a[-6:-1]',a[-6:-1])
```

```
a is:  samosa pakora
a[0:5] samos
a[0:13] samosa pakora
a[:5] samos
a[-5] a
a[0:-5] samosa p
a[-6:-1] pakor
```

1.13 String Methods

[ ]:
```python
food = 'biryani'

print('Capitilize: ', food.capitalize())
print('UpperCase: ', food.upper())
print('LowerCase: ', food.lower())

# Replace
print('Replacing b with Sh: ', food.replace('b', 'Sh'))

# Counting Specific alphabat in a string
name = 'Muhammad Waleed Anjum'
print(f"Number of 'a' in {name} are: ", name.count('a'))

# Finding index number in String
name = 'Muhammad Waleed Anjum'
print("Index number of 'h' is: ",name.find('h'))
print("Index number of 'a' is: ",name.find('a'))
print("Index number of 'ee' is: ",name.find('ee'))

# How to split a string
food = 'l love, samosa, pakora, biryani'
print('Spliting string based on specific charcter', food.split(','))
```

```
Capitilize:  Biryani
UpperCase:  BIRYANI
LowerCase:  biryani
Replacing b with Sh:  Shiryani
```

```
Number of 'a' in Muhammad Waleed Anjum are:  3
Index number of 'h' is:  2
Index number of 'a' is:  3
Index number of 'ee' is:  12
Spliting string based on specific charcter ['l love', ' samosa', ' pakora', '
biryani']
```

1.14 Basic Data Structure in Python

There are four basic Data Structures 1. Tuple 2. List 3. Dictionaries 4. Set

1.14.1 1. Tuple

- Ordered Collection of elements
- Enclosed in small brackets()
- Different kind of data can be stored
- Unmutatble

[ ]:
```
tup = (1, 'python', 3.5, True)
print(type(tup))
print('Number of elements in Tuple: ',len(tup))

tup2 = (2, 'Tuple', False)

concat = tup + tup2
print('Concatenation of two tuples: ', concat)

tup3 = (10, 723, 43, 11, 53)
print('Maximum Number in tup3 is: ', max(tup3))
```

```
<class 'tuple'>
Number of elements in Tuple:  4
Concatenation of two tuples:  (1, 'python', 3.5, True, 2, 'Tuple', False)
Maximum Number in tup3 is:  723
```

1.14.2 2. List

- Ordered Collection of Elements
- enclosed in [] brackets
- mutatable

[ ]:
```
list1 = [2, 'waleed', True]
print('list1 is: ', list1)

print(type(list1))

list1.reverse()
print('Reverse elements', list1)
```

```
list1.append('Pakistan')
print('Append something in list: ', list1)

print('Counting Something in list: ' ,list1.count(3))

list2 = [1,87,34,23,96,34]
print('list2 is: ', list2)
list2.sort()
print('Sorted list: ', list2)
```

```
list1 is:  [2, 'waleed', True]
<class 'list'>
Reverse elements [True, 'waleed', 2]
Append something in list:  [True, 'waleed', 2, 'Pakistan']
Counting Something in list:  0
list2 is:  [1, 87, 34, 23, 96, 34]
Sorted list:  [1, 23, 34, 34, 87, 96]
```

1.14.3 3. Dictionaries

- UnOrdered Collection of elements
- key and value
- Enclosed in curly brackets {}
- Unmutatble

[ ]:
```
d1 = {'samosa': 30,
'pakora': 50,
'Raita': 40,
'Roll': 100}

print('Dictionary d1 is: ',d1)
type(d1)

# extract data
k = d1.keys()
v = d1.values()
print('Keys in d1 are: ',k)
print('Values in d1 are: ',v)

# Adding new element
d1['shawarma'] = 120
print('After adding new element in d1 Dictionary is: ',d1)

# Updating existing value
d1['shawarma'] = 160
print('Updated d1 Dictionary is: ',d1)

# Concatenating two dictionaries
```

```
d2 = {'biryani': 200, 'Pulao': 160}

d1.update(d2)
print('concatenated dictionary: ', d1)
```

```
Dictionary d1 is:  {'samosa': 30, 'pakora': 50, 'Raita': 40, 'Roll': 100}
Keys in d1 are:  dict_keys(['samosa', 'pakora', 'Raita', 'Roll'])
Values in d1 are:  dict_values([30, 50, 40, 100])
After adding new element in d1 Dictionary is:  {'samosa': 30, 'pakora': 50,
'Raita': 40, 'Roll': 100, 'shawarma': 120}
Updated d1 Dictionary is:  {'samosa': 30, 'pakora': 50, 'Raita': 40, 'Roll':
100, 'shawarma': 160}
concatenated dictionary:  {'samosa': 30, 'pakora': 50, 'Raita': 40, 'Roll': 100,
'shawarma': 160, 'biryani': 200, 'Pulao': 160}
```

1.14.4 4. Set

- UnOrdered and unindexed
- Enclosed in only curly brackets {}
- No duplicates allowed

[ ]:
```
s1 = {1, 2.5, 7, 'waleed', 'Pakistan', True} # Sets cannot read boolain␣
 ↪operators
print('Set s1 is: ',s1)

# Adding same value again
s1.add('waleed')
print('Duplicates not allowed: ', s1)
```

```
Set s1 is:  {1, 2.5, 'waleed', 7, 'Pakistan'}
Duplicates not allowed:  {1, 2.5, 'waleed', 7, 'Pakistan'}
```

1.15 Numpy (Numerical Python)

[ ]:
```
# pip install numpy (installation)
# importing numpy
import numpy as np

# Creating an array using numpy
food = np.array(['Pakora', 'Samosa', 'Raita'])
print('food array: ', food)

price = np.array([5,5,5])
print('Data type of array: ', type(price))
print('length of food array: ', len(food))
```

```
food array:  ['Pakora' 'Samosa' 'Raita']
Data type of array:  <class 'numpy.ndarray'>
length of food array:  3
```

[ ]:
```
# zeros method
print('Zeros: ', np.zeros(5))

# ones
print('Ones: ', np.ones(5))

# empty
print('empty: ', np.empty(5))

# arange
print('arange: ', np.arange(6))
print('arange with specific start and end: ', np.arange(2, 10))
print('arange with specific interval: ', np.arange(2, 20, 3))

# linespace
print('linespace (same interval): ', np.linspace(1, 100, num=10))
```

```
Zeros:  [0. 0. 0. 0. 0.]
Ones:  [1. 1. 1. 1. 1.]
empty:  [1. 1. 1. 1. 1.]
arange:  [0 1 2 3 4 5]
arange with specific start and end:  [2 3 4 5 6 7 8 9]
arange with specific interval:  [ 2  5  8 11 14 17]
linespace (same interval):  [  1.  12.  23.  34.  45.  56.  67.  78.  89. 100.]
```

[ ]:
```
# specify data type
print('Array in int: ', np.ones(10, dtype=int))
print('Array in float: ', np.ones(10, dtype=float))
```

```
Array in int:  [1 1 1 1 1 1 1 1 1 1]
Array in float:  [1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

[ ]:
```
# Array functions
# 1-D Array
a = np.array([10, 12, 15, 65, 34, 93, 10.4])
print('array a: ', a)
a.sort()
print('Sorted a Array: ', a)

b = np.array([13, 52, 15, 69, 34, 91, 10.4])
concat = np.concatenate((a,b))
print('Concatenated Arrays', concat)
```

```
array a:  [10.  12.  15.  65.  34.  93.  10.4]
Sorted a Array:  [10.  10.4 12.  15.  34.  65.  93. ]
Concatenated Arrays [10.  10.4 12.  15.  34.  65.  93.  13.  52.  15.  69.  34.
91.  10.4]
```

[ ]:
```python
# 2-D Array
a = np.array([[0,1,2,3,4], [5,6,7,8,9]])
b = np.array([[0,1,2,3,4], [5,6,7,8,9]])
print('a Array: \n', a)
print('\nb Array: \n', b)

c = np.concatenate((a,b), axis=0) # Along Rows
d = np.concatenate((a,b), axis=1) # Along Columns
print('\nc Array: \n', c)
print('\nd Array: \n', d)
```

```
a Array:
 [[0 1 2 3 4]
 [5 6 7 8 9]]

b Array:
 [[0 1 2 3 4]
 [5 6 7 8 9]]

c Array:
 [[0 1 2 3 4]
 [5 6 7 8 9]
 [0 1 2 3 4]
 [5 6 7 8 9]]

d Array:
 [[0 1 2 3 4 0 1 2 3 4]
 [5 6 7 8 9 5 6 7 8 9]]
```

[ ]:
```python
# 3-D Array
a = np.array([[[0,1,2,3],
                        [4,5,6,7]],

                        [[0,1,2,3],
                        [4,5,6,7]],

                        [[0,1,2,3],
                        [4,5,6,7]]])
print('3D a Array: \n',a)

print('\nDimension of An Array: ', a.ndim)
print('Size of An Array: ', a.size)   # Number of elements
print('Shape of An Array: ', a.shape)   # (dimension, rows, columns)
```

```
3D a Array:
 [[[0 1 2 3]
  [4 5 6 7]]
```

```
 [[0 1 2 3]
  [4 5 6 7]]

 [[0 1 2 3]
  [4 5 6 7]]]

Dimension of An Array:  3
Size of An Array:  24
Shape of An Array:  (3, 2, 4)
```

[ ]:
```
# Reshape Method
# 2-D Array by using Reshape
a = np.arange(9)
b = a.reshape(3,3)
print('2-D Array by using Reshape:\n', b)

# 3-D Array by using Reshape
x = np.arange(24)
y = x.reshape(3,2,4)
print('\n3-D Array by using Reshape:\n', y)
```

```
2-D Array by using Reshape:
 [[0 1 2]
 [3 4 5]
 [6 7 8]]

3-D Array by using Reshape:
 [[[ 0  1  2  3]
  [ 4  5  6  7]]

 [[ 8  9 10 11]
  [12 13 14 15]]

 [[16 17 18 19]
  [20 21 22 23]]]
```

[ ]:
```
# Converting Array dimensions
# 1-D to 2-D
a = np.array([1,2,3,4,5,6,7,8,9])
print('Array a: ',a)
print('Dimension of a Array: ', a.ndim)
print('Shape of An a Array: ', a.shape)

b = a[np.newaxis, :]                # Row Conversion
print('\nArray b (Converted to 2D): ',b)
print('Dimensions of b Array: ', b.ndim)
print('Shape of b Array: ', b.shape)
```

```
c = a[:, np.newaxis]                    # Column Conversion
print('\nArray c (Converted to 2D): ',c)
print('Dimensions of c Array: ', c.ndim)
print('Shape of c Array: ', c.shape)
```

```
Array a:  [1 2 3 4 5 6 7 8 9]
Dimension of a Array:  1
Shape of An a Array:  (9,)

Array b (Converted to 2D):  [[1 2 3 4 5 6 7 8 9]]
Dimensions of b Array:  2
Shape of b Array:  (1, 9)

Array c (Converted to 2D):  [[1]
 [2]
 [3]
 [4]
 [5]
 [6]
 [7]
 [8]
 [9]]
Dimensions of c Array:  2
Shape of c Array:  (9, 1)
```

[ ]:
```
# Different operations
a = np.array([1,2,3,4,5,6,7,8,9])
print('a*6: ', a*6)
print('sum: ', a.sum())
print('Mean: ', a.mean())
```

```
a*6:  [ 6 12 18 24 30 36 42 48 54]
sum:  45
Mean:  5.0
```

1.16 Pandas (Pannel Data Analysis)

[ ]:
```
# pip install pandas
```

[ ]:
```
# Import libraries
import pandas as pd
import numpy as np
```

[ ]:
```
# object creation
s = pd.Series([1,3, np.nan,5,7,8,9])
print('Series s:\n',s)
```

```
Series s:
 0    1.0
```

```
1    3.0
2    NaN
3    5.0
4    7.0
5    8.0
6    9.0
dtype: float64
```

[ ]:
```
dates = pd.date_range('20220101', periods=20)
dates
```

[ ]:
```
DatetimeIndex(['2022-01-01', '2022-01-02', '2022-01-03', '2022-01-04',
               '2022-01-05', '2022-01-06', '2022-01-07', '2022-01-08',
               '2022-01-09', '2022-01-10', '2022-01-11', '2022-01-12',
               '2022-01-13', '2022-01-14', '2022-01-15', '2022-01-16',
               '2022-01-17', '2022-01-18', '2022-01-19', '2022-01-20'],
              dtype='datetime64[ns]', freq='D')
```

[ ]:
```
# DataFrame
df = pd.DataFrame(np.random.randn(20, 4), index=dates, columns=list('ABCD'))
df
```

[ ]:

	A	B	C	D
2022-01-01	-0.950106	0.666944	1.255174	0.620168
2022-01-02	0.679854	0.704714	1.847270	0.444161
2022-01-03	-0.549860	0.095673	-1.062794	-1.483643
2022-01-04	-0.840756	-1.541808	0.716966	-0.547674
2022-01-05	1.903297	0.829506	-0.492042	1.245799
2022-01-06	-2.087375	-1.134863	1.065108	-0.817172
2022-01-07	-0.333677	-0.782179	1.137580	-1.441844
2022-01-08	-0.588446	0.294438	1.343623	0.301845
2022-01-09	-0.096240	-1.650489	0.090041	0.954330
2022-01-10	-0.649596	0.941632	0.801956	0.756375
2022-01-11	0.593017	1.434123	1.115778	-0.751717
2022-01-12	-0.231228	1.241760	-2.217075	-1.623309
2022-01-13	0.810533	2.313326	-0.747402	-1.227251
2022-01-14	-0.446317	0.356303	0.430054	1.050609
2022-01-15	-1.143818	-0.885201	2.788002	0.056081
2022-01-16	-0.129958	-0.095443	1.490171	-1.012446
2022-01-17	-0.202072	0.562094	0.817439	-1.958470
2022-01-18	-0.002977	2.166893	-0.416769	-0.883259
2022-01-19	-1.469375	-0.034409	-0.486798	-1.216058
2022-01-20	0.297953	0.560134	-0.049372	0.240628

[ ]:
```
df2 = pd.DataFrame(
    {
        'A': 1.0,
        'B' : pd.Timestamp('20220314'),
```

```
        'C' : pd.Series(1, index=list(range(4)), dtype='float32'),
        'D' : np.array([3] * 4, dtype='int32'),
        'E' : pd.Categorical(['girl', 'woman', 'girl', 'woman']),
        'F' : 'female',
    }
)
df2
```

[ ]:
```
     A          B    C  D      E       F
0  1.0 2022-03-14  1.0  3   girl  female
1  1.0 2022-03-14  1.0  3  woman  female
2  1.0 2022-03-14  1.0  3   girl  female
3  1.0 2022-03-14  1.0  3  woman  female
```

[ ]:
```
df2.dtypes
```

[ ]:
```
A           float64
B    datetime64[ns]
C           float32
D             int32
E          category
F            object
dtype: object
```

[ ]:
```
# head method
df.head(4)  # shows first 4 rows
```

[ ]:
```
                   A         B         C         D
2022-01-01 -0.950106  0.666944  1.255174  0.620168
2022-01-02  0.679854  0.704714  1.847270  0.444161
2022-01-03 -0.549860  0.095673 -1.062794 -1.483643
2022-01-04 -0.840756 -1.541808  0.716966 -0.547674
```

[ ]:
```
df.tail(2)      # last 2 rows
```

[ ]:
```
                   A         B         C         D
2022-01-19 -1.469375 -0.034409 -0.486798 -1.216058
2022-01-20  0.297953  0.560134 -0.049372  0.240628
```

[ ]:
```
df.index
```

[ ]:
```
DatetimeIndex(['2022-01-01', '2022-01-02', '2022-01-03', '2022-01-04',
               '2022-01-05', '2022-01-06', '2022-01-07', '2022-01-08',
               '2022-01-09', '2022-01-10', '2022-01-11', '2022-01-12',
               '2022-01-13', '2022-01-14', '2022-01-15', '2022-01-16',
               '2022-01-17', '2022-01-18', '2022-01-19', '2022-01-20'],
              dtype='datetime64[ns]', freq='D')
```

[ ]:
```
# convert into numpy array
df.to_numpy()
```

[ ]:
```
array([[-0.95010582,  0.66694432,  1.25517431,  0.62016755],
       [ 0.67985399,  0.70471366,  1.84726953,  0.44416054],
       [-0.54985992,  0.0956732 , -1.06279356, -1.48364278],
       [-0.84075575, -1.54180846,  0.71696612, -0.54767372],
       [ 1.90329718,  0.82950604, -0.49204199,  1.24579925],
       [-2.0873748 , -1.13486316,  1.06510831, -0.8171724 ],
       [-0.3336765 , -0.782179  ,  1.13757981, -1.44184412],
       [-0.58844572,  0.29443818,  1.34362263,  0.30184502],
       [-0.09623966, -1.65048853,  0.09004135,  0.95432994],
       [-0.64959576,  0.94163212,  0.80195586,  0.75637494],
       [ 0.59301666,  1.43412276,  1.11577752, -0.75171684],
       [-0.2312285 ,  1.24176027, -2.21707466, -1.62330856],
       [ 0.8105335 ,  2.31332632, -0.7474015 , -1.22725142],
       [-0.44631672,  0.35630299,  0.43005431,  1.05060875],
       [-1.14381787, -0.88520068,  2.78800203,  0.05608148],
       [-0.12995805, -0.09544285,  1.49017146, -1.0124465 ],
       [-0.2020721 ,  0.56209436,  0.81743896, -1.95846952],
       [-0.00297664,  2.16689279, -0.41676885, -0.88325934],
       [-1.46937519, -0.03440855, -0.48679757, -1.21605849],
       [ 0.29795254,  0.56013394, -0.04937241,  0.2406284 ]])
```

[ ]:
```
df2.to_numpy()
```

[ ]:
```
array([[1.0, Timestamp('2022-03-14 00:00:00'), 1.0, 3, 'girl', 'female'],
       [1.0, Timestamp('2022-03-14 00:00:00'), 1.0, 3, 'woman', 'female'],
       [1.0, Timestamp('2022-03-14 00:00:00'), 1.0, 3, 'girl', 'female'],
       [1.0, Timestamp('2022-03-14 00:00:00'), 1.0, 3, 'woman', 'female']],
      dtype=object)
```

[ ]:
```
# describe function
df.describe()
```

[ ]:

	A	B	C	D
count	20.000000	20.000000	20.000000	20.000000
mean	-0.271857	0.302157	0.471346	-0.364642
std	0.877787	1.099836	1.153807	1.007529
min	-2.087375	-1.650489	-2.217075	-1.958470
25%	-0.697386	-0.267127	-0.434276	-1.218857
50%	-0.282453	0.458218	0.759461	-0.649695
75%	0.072256	0.857538	1.166978	0.488162
max	1.903297	2.313326	2.788002	1.245799

[ ]:
```
# transpose data
df2.T
```

```
[ ]:                     0                    1                    2  \
A                      1.0                  1.0                  1.0
B  2022-03-14 00:00:00  2022-03-14 00:00:00  2022-03-14 00:00:00
C                      1.0                  1.0                  1.0
D                        3                    3                    3
E                     girl                woman                 girl
F                   female               female               female

                         3
A                      1.0
B  2022-03-14 00:00:00
C                      1.0
D                        3
E                    woman
F                   female
```

```
[ ]: df.sort_index(axis=1, ascending=True)
```

```
[ ]:                   A         B         C         D
2022-01-01 -0.950106  0.666944  1.255174  0.620168
2022-01-02  0.679854  0.704714  1.847270  0.444161
2022-01-03 -0.549860  0.095673 -1.062794 -1.483643
2022-01-04 -0.840756 -1.541808  0.716966 -0.547674
2022-01-05  1.903297  0.829506 -0.492042  1.245799
2022-01-06 -2.087375 -1.134863  1.065108 -0.817172
2022-01-07 -0.333677 -0.782179  1.137580 -1.441844
2022-01-08 -0.588446  0.294438  1.343623  0.301845
2022-01-09 -0.096240 -1.650489  0.090041  0.954330
2022-01-10 -0.649596  0.941632  0.801956  0.756375
2022-01-11  0.593017  1.434123  1.115778 -0.751717
2022-01-12 -0.231228  1.241760 -2.217075 -1.623309
2022-01-13  0.810533  2.313326 -0.747402 -1.227251
2022-01-14 -0.446317  0.356303  0.430054  1.050609
2022-01-15 -1.143818 -0.885201  2.788002  0.056081
2022-01-16 -0.129958 -0.095443  1.490171 -1.012446
2022-01-17 -0.202072  0.562094  0.817439 -1.958470
2022-01-18 -0.002977  2.166893 -0.416769 -0.883259
2022-01-19 -1.469375 -0.034409 -0.486798 -1.216058
2022-01-20  0.297953  0.560134 -0.049372  0.240628
```

```
[ ]: df.sort_index(axis=0, ascending=True)
```

```
[ ]:                   A         B         C         D
2022-01-01 -0.950106  0.666944  1.255174  0.620168
2022-01-02  0.679854  0.704714  1.847270  0.444161
2022-01-03 -0.549860  0.095673 -1.062794 -1.483643
2022-01-04 -0.840756 -1.541808  0.716966 -0.547674
```

```
2022-01-05  1.903297  0.829506 -0.492042  1.245799
2022-01-06 -2.087375 -1.134863  1.065108 -0.817172
2022-01-07 -0.333677 -0.782179  1.137580 -1.441844
2022-01-08 -0.588446  0.294438  1.343623  0.301845
2022-01-09 -0.096240 -1.650489  0.090041  0.954330
2022-01-10 -0.649596  0.941632  0.801956  0.756375
2022-01-11  0.593017  1.434123  1.115778 -0.751717
2022-01-12 -0.231228  1.241760 -2.217075 -1.623309
2022-01-13  0.810533  2.313326 -0.747402 -1.227251
2022-01-14 -0.446317  0.356303  0.430054  1.050609
2022-01-15 -1.143818 -0.885201  2.788002  0.056081
2022-01-16 -0.129958 -0.095443  1.490171 -1.012446
2022-01-17 -0.202072  0.562094  0.817439 -1.958470
2022-01-18 -0.002977  2.166893 -0.416769 -0.883259
2022-01-19 -1.469375 -0.034409 -0.486798 -1.216058
2022-01-20  0.297953  0.560134 -0.049372  0.240628
```

[ ]:
```
df.sort_values(by='B')
```

[ ]:
```
                   A         B         C         D
2022-01-09 -0.096240 -1.650489  0.090041  0.954330
2022-01-04 -0.840756 -1.541808  0.716966 -0.547674
2022-01-06 -2.087375 -1.134863  1.065108 -0.817172
2022-01-15 -1.143818 -0.885201  2.788002  0.056081
2022-01-07 -0.333677 -0.782179  1.137580 -1.441844
2022-01-16 -0.129958 -0.095443  1.490171 -1.012446
2022-01-19 -1.469375 -0.034409 -0.486798 -1.216058
2022-01-03 -0.549860  0.095673 -1.062794 -1.483643
2022-01-08 -0.588446  0.294438  1.343623  0.301845
2022-01-14 -0.446317  0.356303  0.430054  1.050609
2022-01-20  0.297953  0.560134 -0.049372  0.240628
2022-01-17 -0.202072  0.562094  0.817439 -1.958470
2022-01-01 -0.950106  0.666944  1.255174  0.620168
2022-01-02  0.679854  0.704714  1.847270  0.444161
2022-01-05  1.903297  0.829506 -0.492042  1.245799
2022-01-10 -0.649596  0.941632  0.801956  0.756375
2022-01-12 -0.231228  1.241760 -2.217075 -1.623309
2022-01-11  0.593017  1.434123  1.115778 -0.751717
2022-01-18 -0.002977  2.166893 -0.416769 -0.883259
2022-01-13  0.810533  2.313326 -0.747402 -1.227251
```

[ ]:
```
df['A']
```

[ ]:
```
2022-01-01   -0.950106
2022-01-02    0.679854
2022-01-03   -0.549860
2022-01-04   -0.840756
```

```
2022-01-05    1.903297
2022-01-06   -2.087375
2022-01-07   -0.333677
2022-01-08   -0.588446
2022-01-09   -0.096240
2022-01-10   -0.649596
2022-01-11    0.593017
2022-01-12   -0.231228
2022-01-13    0.810533
2022-01-14   -0.446317
2022-01-15   -1.143818
2022-01-16   -0.129958
2022-01-17   -0.202072
2022-01-18   -0.002977
2022-01-19   -1.469375
2022-01-20    0.297953
Freq: D, Name: A, dtype: float64
```

[ ]:
```
# row wise selection
df[0:2]
```

[ ]:
```
                   A         B         C         D
2022-01-01 -0.950106  0.666944  1.255174  0.620168
2022-01-02  0.679854  0.704714  1.847270  0.444161
```

[ ]:
```
# select by label
df.loc[dates[0]]
```

[ ]:
```
A   -0.950106
B    0.666944
C    1.255174
D    0.620168
Name: 2022-01-01 00:00:00, dtype: float64
```

[ ]:
```
# column wise selection
df.loc[:, ['A', 'B']]
```

[ ]:
```
                   A         B
2022-01-01 -0.950106  0.666944
2022-01-02  0.679854  0.704714
2022-01-03 -0.549860  0.095673
2022-01-04 -0.840756 -1.541808
2022-01-05  1.903297  0.829506
2022-01-06 -2.087375 -1.134863
2022-01-07 -0.333677 -0.782179
2022-01-08 -0.588446  0.294438
2022-01-09 -0.096240 -1.650489
```

```
2022-01-10 -0.649596  0.941632
2022-01-11  0.593017  1.434123
2022-01-12 -0.231228  1.241760
2022-01-13  0.810533  2.313326
2022-01-14 -0.446317  0.356303
2022-01-15 -1.143818 -0.885201
2022-01-16 -0.129958 -0.095443
2022-01-17 -0.202072  0.562094
2022-01-18 -0.002977  2.166893
2022-01-19 -1.469375 -0.034409
2022-01-20  0.297953  0.560134
```

[ ]:
```
df.loc['20220102':'20220104', ['A', 'B']]
```

[ ]:
```
                   A         B
2022-01-02  0.679854  0.704714
2022-01-03 -0.549860  0.095673
2022-01-04 -0.840756 -1.541808
```

[ ]:
```
df.loc['20220102', ['A', 'B', 'C']]
```

[ ]:
```
A    0.679854
B    0.704714
C    1.847270
Name: 2022-01-02 00:00:00, dtype: float64
```

[ ]:
```
#specify value based on date
df.at[dates[0], 'A']
```

[ ]:
```
-0.9501058169930408
```

[ ]:
```
# iloc function
df.iloc[3]
```

[ ]:
```
A   -0.840756
B   -1.541808
C    0.716966
D   -0.547674
Name: 2022-01-04 00:00:00, dtype: float64
```

[ ]:
```
#implicity
df.iloc[0:5, 0:3]
```

[ ]:
```
                   A         B         C
2022-01-01 -0.950106  0.666944  1.255174
2022-01-02  0.679854  0.704714  1.847270
2022-01-03 -0.549860  0.095673 -1.062794
2022-01-04 -0.840756 -1.541808  0.716966
```

```
2022-01-05  1.903297  0.829506 -0.492042
```

[ ]:
```python
df.iloc[:, 0:2]
```

[ ]:
```
                   A         B
2022-01-01 -0.950106  0.666944
2022-01-02  0.679854  0.704714
2022-01-03 -0.549860  0.095673
2022-01-04 -0.840756 -1.541808
2022-01-05  1.903297  0.829506
2022-01-06 -2.087375 -1.134863
2022-01-07 -0.333677 -0.782179
2022-01-08 -0.588446  0.294438
2022-01-09 -0.096240 -1.650489
2022-01-10 -0.649596  0.941632
2022-01-11  0.593017  1.434123
2022-01-12 -0.231228  1.241760
2022-01-13  0.810533  2.313326
2022-01-14 -0.446317  0.356303
2022-01-15 -1.143818 -0.885201
2022-01-16 -0.129958 -0.095443
2022-01-17 -0.202072  0.562094
2022-01-18 -0.002977  2.166893
2022-01-19 -1.469375 -0.034409
2022-01-20  0.297953  0.560134
```

[ ]:
```python
df[df['A'] > 0]
```

[ ]:
```
                   A         B         C         D
2022-01-02  0.679854  0.704714  1.847270  0.444161
2022-01-05  1.903297  0.829506 -0.492042  1.245799
2022-01-11  0.593017  1.434123  1.115778 -0.751717
2022-01-13  0.810533  2.313326 -0.747402 -1.227251
2022-01-20  0.297953  0.560134 -0.049372  0.240628
```

[ ]:
```python
df[df > 0]
```

[ ]:
```
                   A         B         C         D
2022-01-01       NaN  0.666944  1.255174  0.620168
2022-01-02  0.679854  0.704714  1.847270  0.444161
2022-01-03       NaN  0.095673       NaN       NaN
2022-01-04       NaN       NaN  0.716966       NaN
2022-01-05  1.903297  0.829506       NaN  1.245799
2022-01-06       NaN       NaN  1.065108       NaN
2022-01-07       NaN       NaN  1.137580       NaN
2022-01-08       NaN  0.294438  1.343623  0.301845
2022-01-09       NaN       NaN  0.090041  0.954330
```

```
2022-01-10       NaN  0.941632  0.801956  0.756375
2022-01-11  0.593017  1.434123  1.115778       NaN
2022-01-12       NaN  1.241760       NaN       NaN
2022-01-13  0.810533  2.313326       NaN       NaN
2022-01-14       NaN  0.356303  0.430054  1.050609
2022-01-15       NaN       NaN  2.788002  0.056081
2022-01-16       NaN       NaN  1.490171       NaN
2022-01-17       NaN  0.562094  0.817439       NaN
2022-01-18       NaN  2.166893       NaN       NaN
2022-01-19       NaN       NaN       NaN       NaN
2022-01-20  0.297953  0.560134       NaN  0.240628
```

[ ]:
```
df2 = df.copy()
df2
```

[ ]:
```
                   A         B         C         D
2022-01-01 -0.950106  0.666944  1.255174  0.620168
2022-01-02  0.679854  0.704714  1.847270  0.444161
2022-01-03 -0.549860  0.095673 -1.062794 -1.483643
2022-01-04 -0.840756 -1.541808  0.716966 -0.547674
2022-01-05  1.903297  0.829506 -0.492042  1.245799
2022-01-06 -2.087375 -1.134863  1.065108 -0.817172
2022-01-07 -0.333677 -0.782179  1.137580 -1.441844
2022-01-08 -0.588446  0.294438  1.343623  0.301845
2022-01-09 -0.096240 -1.650489  0.090041  0.954330
2022-01-10 -0.649596  0.941632  0.801956  0.756375
2022-01-11  0.593017  1.434123  1.115778 -0.751717
2022-01-12 -0.231228  1.241760 -2.217075 -1.623309
2022-01-13  0.810533  2.313326 -0.747402 -1.227251
2022-01-14 -0.446317  0.356303  0.430054  1.050609
2022-01-15 -1.143818 -0.885201  2.788002  0.056081
2022-01-16 -0.129958 -0.095443  1.490171 -1.012446
2022-01-17 -0.202072  0.562094  0.817439 -1.958470
2022-01-18 -0.002977  2.166893 -0.416769 -0.883259
2022-01-19 -1.469375 -0.034409 -0.486798 -1.216058
2022-01-20  0.297953  0.560134 -0.049372  0.240628
```

[ ]:
```
# Adding new column
df2['Babakacolumn'] = ['one', 'one', 'two', 'three', 'four', 'three',
'one', 'one', 'two', 'three', 'four', 'three',
'one', 'one', 'two', 'three', 'four', 'three', 'four', 'three']
df2
```

[ ]:
```
                   A         B         C         D Babakacolumn
2022-01-01 -0.950106  0.666944  1.255174  0.620168          one
2022-01-02  0.679854  0.704714  1.847270  0.444161          one
2022-01-03 -0.549860  0.095673 -1.062794 -1.483643          two
```

```
2022-01-04 -0.840756 -1.541808  0.716966 -0.547674        three
2022-01-05  1.903297  0.829506 -0.492042  1.245799         four
2022-01-06 -2.087375 -1.134863  1.065108 -0.817172        three
2022-01-07 -0.333677 -0.782179  1.137580 -1.441844          one
2022-01-08 -0.588446  0.294438  1.343623  0.301845          one
2022-01-09 -0.096240 -1.650489  0.090041  0.954330          two
2022-01-10 -0.649596  0.941632  0.801956  0.756375        three
2022-01-11  0.593017  1.434123  1.115778 -0.751717         four
2022-01-12 -0.231228  1.241760 -2.217075 -1.623309        three
2022-01-13  0.810533  2.313326 -0.747402 -1.227251          one
2022-01-14 -0.446317  0.356303  0.430054  1.050609          one
2022-01-15 -1.143818 -0.885201  2.788002  0.056081          two
2022-01-16 -0.129958 -0.095443  1.490171 -1.012446        three
2022-01-17 -0.202072  0.562094  0.817439 -1.958470         four
2022-01-18 -0.002977  2.166893 -0.416769 -0.883259        three
2022-01-19 -1.469375 -0.034409 -0.486798 -1.216058         four
2022-01-20  0.297953  0.560134 -0.049372  0.240628        three
```

[ ]:
```
df2['new'] = [1,2,3,4,5,1,2,3,4,5,1,2,3,4,5,1,2,3,4,5]
df2
```

[ ]:
```
                   A         B         C         D Babakacolumn  new
2022-01-01 -0.950106  0.666944  1.255174  0.620168          one    1
2022-01-02  0.679854  0.704714  1.847270  0.444161          one    2
2022-01-03 -0.549860  0.095673 -1.062794 -1.483643          two    3
2022-01-04 -0.840756 -1.541808  0.716966 -0.547674        three    4
2022-01-05  1.903297  0.829506 -0.492042  1.245799         four    5
2022-01-06 -2.087375 -1.134863  1.065108 -0.817172        three    1
2022-01-07 -0.333677 -0.782179  1.137580 -1.441844          one    2
2022-01-08 -0.588446  0.294438  1.343623  0.301845          one    3
2022-01-09 -0.096240 -1.650489  0.090041  0.954330          two    4
2022-01-10 -0.649596  0.941632  0.801956  0.756375        three    5
2022-01-11  0.593017  1.434123  1.115778 -0.751717         four    1
2022-01-12 -0.231228  1.241760 -2.217075 -1.623309        three    2
2022-01-13  0.810533  2.313326 -0.747402 -1.227251          one    3
2022-01-14 -0.446317  0.356303  0.430054  1.050609          one    4
2022-01-15 -1.143818 -0.885201  2.788002  0.056081          two    5
2022-01-16 -0.129958 -0.095443  1.490171 -1.012446        three    1
2022-01-17 -0.202072  0.562094  0.817439 -1.958470         four    2
2022-01-18 -0.002977  2.166893 -0.416769 -0.883259        three    3
2022-01-19 -1.469375 -0.034409 -0.486798 -1.216058         four    4
2022-01-20  0.297953  0.560134 -0.049372  0.240628        three    5
```

[ ]:
```
# Getting first four columns
df2= df2.iloc[:, 0:4]
df2
```

[ ]:

```
                   A         B         C         D
2022-01-01 -0.950106  0.666944  1.255174  0.620168
2022-01-02  0.679854  0.704714  1.847270  0.444161
2022-01-03 -0.549860  0.095673 -1.062794 -1.483643
2022-01-04 -0.840756 -1.541808  0.716966 -0.547674
2022-01-05  1.903297  0.829506 -0.492042  1.245799
2022-01-06 -2.087375 -1.134863  1.065108 -0.817172
2022-01-07 -0.333677 -0.782179  1.137580 -1.441844
2022-01-08 -0.588446  0.294438  1.343623  0.301845
2022-01-09 -0.096240 -1.650489  0.090041  0.954330
2022-01-10 -0.649596  0.941632  0.801956  0.756375
2022-01-11  0.593017  1.434123  1.115778 -0.751717
2022-01-12 -0.231228  1.241760 -2.217075 -1.623309
2022-01-13  0.810533  2.313326 -0.747402 -1.227251
2022-01-14 -0.446317  0.356303  0.430054  1.050609
2022-01-15 -1.143818 -0.885201  2.788002  0.056081
2022-01-16 -0.129958 -0.095443  1.490171 -1.012446
2022-01-17 -0.202072  0.562094  0.817439 -1.958470
2022-01-18 -0.002977  2.166893 -0.416769 -0.883259
2022-01-19 -1.469375 -0.034409 -0.486798 -1.216058
2022-01-20  0.297953  0.560134 -0.049372  0.240628
```

[ ]:

```
df3 = df[df['A'] > 0]
df3
```

[ ]:

```
                   A         B         C         D
2022-01-02  0.679854  0.704714  1.847270  0.444161
2022-01-05  1.903297  0.829506 -0.492042  1.245799
2022-01-11  0.593017  1.434123  1.115778 -0.751717
2022-01-13  0.810533  2.313326 -0.747402 -1.227251
2022-01-20  0.297953  0.560134 -0.049372  0.240628
```

[ ]:

```
df3['mean'] = [(df3.iloc[0]).mean(),(df3.iloc[1]).mean(),(df3.iloc[2]).
 ↪mean(),(df3.iloc[3]).mean(),(df3.iloc[4]).mean()]
df3
```

```
C:\Users\Waleed\AppData\Local\Temp/ipykernel_9912/3693726348.py:1:
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-view-versus-a-copy
  df3['mean'] = [(df3.iloc[0]).mean(),(df3.iloc[1]).mean(),(df3.iloc[2]).mean(),
(df3.iloc[3]).mean(),(df3.iloc[4]).mean()]
```

[ ]:

```
                   A         B         C         D      mean
2022-01-02  0.679854  0.704714  1.847270  0.444161  0.918999
```

```
2022-01-05  1.903297  0.829506 -0.492042  1.245799  0.871640
2022-01-11  0.593017  1.434123  1.115778 -0.751717  0.597800
2022-01-13  0.810533  2.313326 -0.747402 -1.227251  0.287302
2022-01-20  0.297953  0.560134 -0.049372  0.240628  0.262336
```

1.16.1 Pandas Case Study

import save and analyze Data using Pandas (Titanic Dataset)

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

[ ]:
```
# import titanic (kashti) dataset
df = sns.load_dataset('titanic')
df.head()
```

[ ]:
```
   survived  pclass     sex   age  sibsp  parch     fare embarked  class  \
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

     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
```

[ ]:
```
# Saving dataset as csv file
df.to_csv('titanic.csv')
```

[ ]:
```
df.shape
```

[ ]: (891, 15)

[ ]:
```
# Basic Statistics or Summary
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
```

[ ]:
```
# Droping few columns and make a new dataset
df1 = df.drop(['deck', 'alone'], axis=1)
df1.head()
```

[ ]:
```
   survived  pclass     sex   age  sibsp  parch     fare embarked  class  \
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

     who  adult_male  embark_town alive
0    man        True  Southampton    no
1  woman       False    Cherbourg   yes
2  woman       False  Southampton   yes
3  woman       False  Southampton   yes
4    man        True  Southampton    no
```

[ ]:
```
df1.shape
```

[ ]:
```
(891, 13)
```

[ ]:
```
df1.mean()
```

```
C:\Users\Waleed\AppData\Local\Temp/ipykernel_9912/2053335143.py:1:
FutureWarning: Dropping of nuisance columns in DataFrame reductions (with
'numeric_only=None') is deprecated; in a future version this will raise
TypeError.  Select only valid columns before calling the reduction.
  df1.mean()
```

[ ]:
```
survived       0.383838
pclass         2.308642
age           29.699118
sibsp          0.523008
parch          0.381594
fare          32.204208
adult_male     0.602694
dtype: float64
```

[ ]:
```
# groupby
df1.groupby(['sex', 'class']).mean()
```

[ ]:
```
               survived  pclass        age     sibsp     parch        fare  \
sex    class
```

```
female First   0.968085     1.0  34.611765  0.553191  0.457447  106.125798
       Second  0.921053     2.0  28.722973  0.486842  0.605263   21.970121
       Third   0.500000     3.0  21.750000  0.895833  0.798611   16.118810
male   First   0.368852     1.0  41.281386  0.311475  0.278689   67.226127
       Second  0.157407     2.0  30.740707  0.342593  0.222222   19.741782
       Third   0.135447     3.0  26.507589  0.498559  0.224784   12.661633

               adult_male
sex    class
female First     0.000000
       Second    0.000000
       Third     0.000000
male   First     0.975410
       Second    0.916667
       Third     0.919308
```

[ ]:
```
df1.value_counts(['survived'])
```

[ ]:
```
survived
0           549
1           342
dtype: int64
```

[ ]:
```
df1.groupby(['sex']).mean()
```

[ ]:
```
        survived    pclass        age     sibsp     parch       fare  \
sex
female  0.742038  2.159236  27.915709  0.694268  0.649682  44.479818
male    0.188908  2.389948  30.726645  0.429809  0.235702  25.523893

        adult_male
sex
female    0.000000
male      0.930676
```

[ ]:
```
df1.groupby(['sex', 'class']).mean()
```

[ ]:
```
               survived  pclass        age     sibsp     parch        fare  \
sex    class
female First   0.968085     1.0  34.611765  0.553191  0.457447  106.125798
       Second  0.921053     2.0  28.722973  0.486842  0.605263   21.970121
       Third   0.500000     3.0  21.750000  0.895833  0.798611   16.118810
male   First   0.368852     1.0  41.281386  0.311475  0.278689   67.226127
       Second  0.157407     2.0  30.740707  0.342593  0.222222   19.741782
       Third   0.135447     3.0  26.507589  0.498559  0.224784   12.661633

               adult_male
```

```
sex     class
female  First     0.000000
        Second    0.000000
        Third     0.000000
male    First     0.975410
        Second    0.916667
        Third     0.919308
```

[ ]:
```
# Under 18 years
df1[df1['age'] < 18].groupby(['sex', 'class']).mean()
```

[ ]:
```
               survived  pclass        age     sibsp     parch        fare  \
sex    class
female First   0.875000     1.0  14.125000  0.500000  0.875000  104.083337
       Second  1.000000     2.0   8.333333  0.583333  1.083333   26.241667
       Third   0.542857     3.0   8.428571  1.571429  1.057143   18.727977
male   First   1.000000     1.0   8.230000  0.500000  2.000000  116.072900
       Second  0.818182     2.0   4.757273  0.727273  1.000000   25.659473
       Third   0.232558     3.0   9.963256  2.069767  1.000000   22.752523

               adult_male
sex    class
female First     0.000000
       Second    0.000000
       Third     0.000000
male   First     0.250000
       Second    0.181818
       Third     0.348837
```

1.17 Statistics

Statistics is a collection of methods for collecting, displaying, > analyzing and drawing conclusions from data. **Statistics is everywhere:**

- Weather Prediction
- USD Prediction
- ANOVA
- Un employment rate fallen
- etc

Language of Statistics:

- **Average** income in Pakistan
- Highest **(Maximum)** score in criket match
- 40% **(Percentage)** teachers in Pakistan are female
- Dollar kabhi uper jata hy kabhi neechay **(Varience)**
- Hostels main larkay zaida kharcha kartay hyn **(t-test)**
- Faislabad > Lahore > Karachi had jugtain ke ranking **(ANOVA)**

Types of Data

1. Cross Sectional Data
    - Data collected at one point
2. Time Series Data
    - Data Collected over different time points
3. Univariate
    - Data contains a single variable to measure entity e.g:
        1. Plant Height
4. Multi Variate
    - Data contains > 2 variables to measure something e.g:
        1. Plant Height
        2. Fertilizer Amount
        3. Irrigation Time

Types of Variables

1. Categorical (Nominal)
    1. Binomial (True or False)
    2. Multinomial (multiple choices e.g. how to go to office)
    3. Ordinal Variable: Data ranked or ordered (mery pass kitny phone hain?, categories can be compared)
2. Ratio Data:
    1. Data have a natural zero, Measurement in units and ratios are continuos variable
3. Interval Variable / Data:
    1. ordered and characterized data

Measure of Central Tendency

1. Mean:
    - Average, meaningful for inteval and ratio data
    - Outliers: change the mean of a data, therefore median is useful
2. Median:
    - Middle number in a sorted, ascending or descending, list of numbers
3. Mode:
    - The value that occurs most frequently

Measure of Dispersion

1. Dispersion:
    - How much data spread around mean
2. Standard Deviation (std)
    - **Mean** with a **SD** is more useful than only Mean by itself
3. Standard Error (se)
4. Variance
5. Bell Curve

Fundamentals of Visualization

Type of variable depends on the variable type

1. Categorical Variable: Qualitative (No numerical meaning)
    - Counts (plot type)

- Male vs Female
- True vs False
- 0 vs 1
- Yes vs NO

2. Continuous Variable: Quantitative Numerical (mostly represented in numbers)
   - Scatter plot
   - Statistical Proportions (means and their comparison)

1.18 Exploratory Data Analysis (EDA)

1.18.1 Three important steps to keep in mind:

- Understand the data
- Clean the data
- Find a relationship between data

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

[ ]:
```
ks = sns.load_dataset('titanic')
ks.head()
```

[ ]:
```
   survived  pclass     sex   age  sibsp  parch     fare embarked  class  \
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

     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
```

[ ]:
```
ks.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
```

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

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

[ ]:
```
# Provides details of numeric columns
ks.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

[ ]:
```
# Unique values in each column
ks.nunique()
```

[ ]:
```
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
```

[ ]:
```
# Column names
ks.columns
```

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

[ ]:
```
# unique values in specific column
ks['sex'].unique()
```

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

If you wanted to get all unique values for one column and then the second column use argument ‘K‘ to the ravel() function. The argument ’K’ tells the method to flatten the array in the order of the elements.

[ ]:
```
# Using pandas.unique() to get unique values in multiple columns
df = pd.unique(ks[['sex', 'class']].values.ravel('k'))
print(df)
```

```
['male' 'female' 'Third' 'First' 'Second']
```

[ ]:
```
# Use numpy.unique() to get unique values in multiple columns
column_values = ks[['sex', 'class']].values
df2 = np.unique(column_values)
print(df2)
```

```
['First' 'Second' 'Third' 'female' 'male']
```

Cleaning and Filtering Data

[ ]:
```
# find missing values inside
ks.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
```

[ ]:
```
# Removing missing values column (cleaning data)
ks_clean = ks.drop(['deck'], axis=1)
print('ks.shape: ', ks.shape)
print('ks_clean.shape: ', ks_clean.shape)
```

```
ks.shape:  (891, 15)
ks_clean.shape:  (891, 14)
```

[ ]:
```
# After removing deck column finding missing values again
ks_clean.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
embark_town      2
alive            0
alone            0
dtype: int64
```

[ ]:
```
# Removing all null values
ks_clean = ks_clean.dropna()
print('ks_clean.shape: ', ks_clean.shape)
ks_clean.isnull().sum()
```

```
ks_clean.shape:  (712, 14)
```

[ ]:
```
survived       0
pclass         0
sex            0
age            0
sibsp          0
parch          0
fare           0
embarked       0
class          0
```

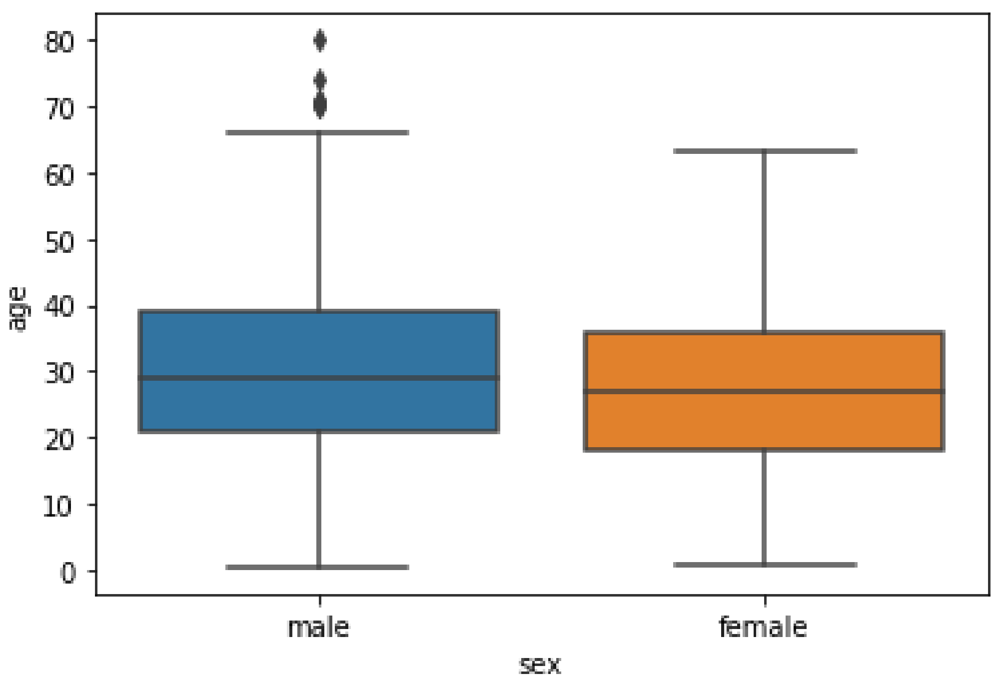
```
who            0
adult_male     0
embark_town    0
alive          0
alone          0
dtype: int64
```

[ ]:
```
# Counting Values in specific column
ks_clean['sex'].value_counts()
```

[ ]:
```
male      453
female    259
Name: sex, dtype: int64
```

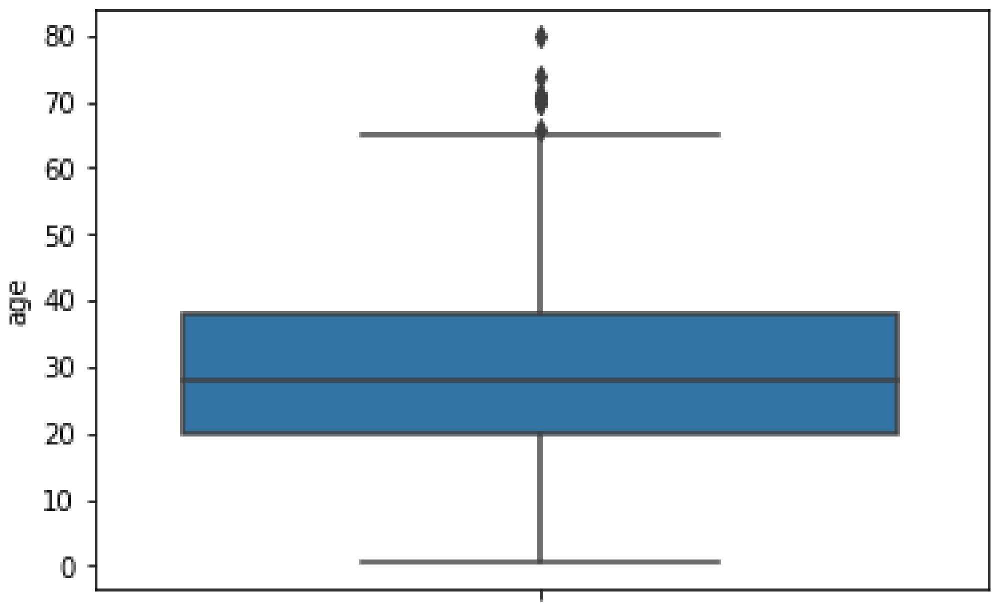
[ ]:
```
# Finding outliers
sns.boxplot(x='sex', y='age', data=ks_clean)
```

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



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

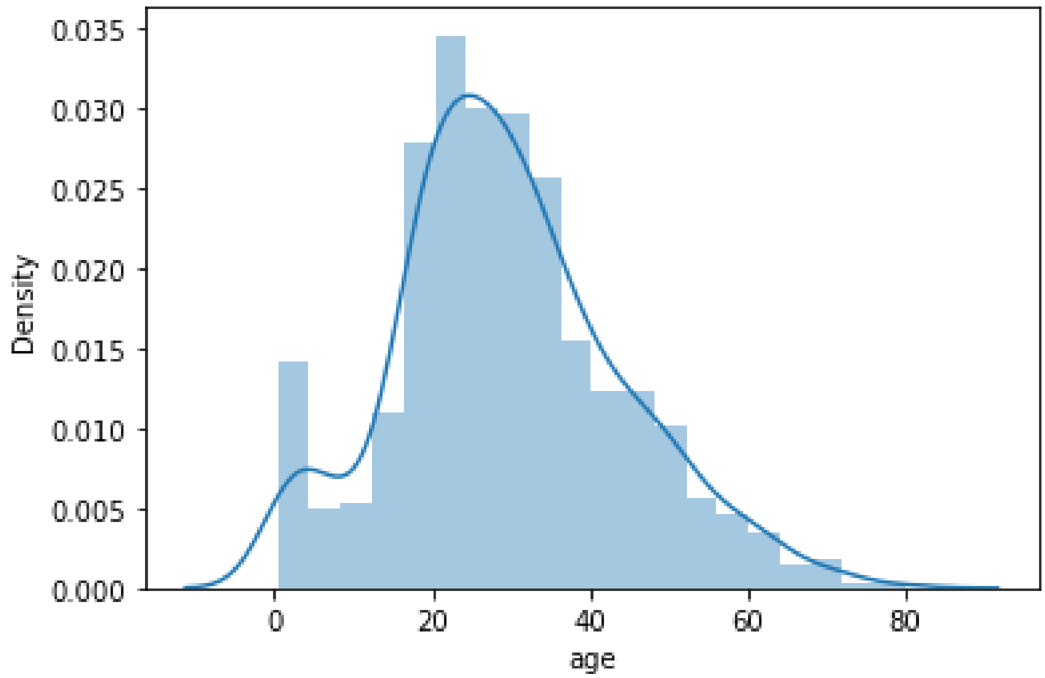
[ ]:
```
<AxesSubplot:ylabel='age'>
```



[ ]:
```
# Data Distribution
sns.distplot(ks_clean['age'])
```

```
c:\Users\Waleed\anaconda3\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'>
```



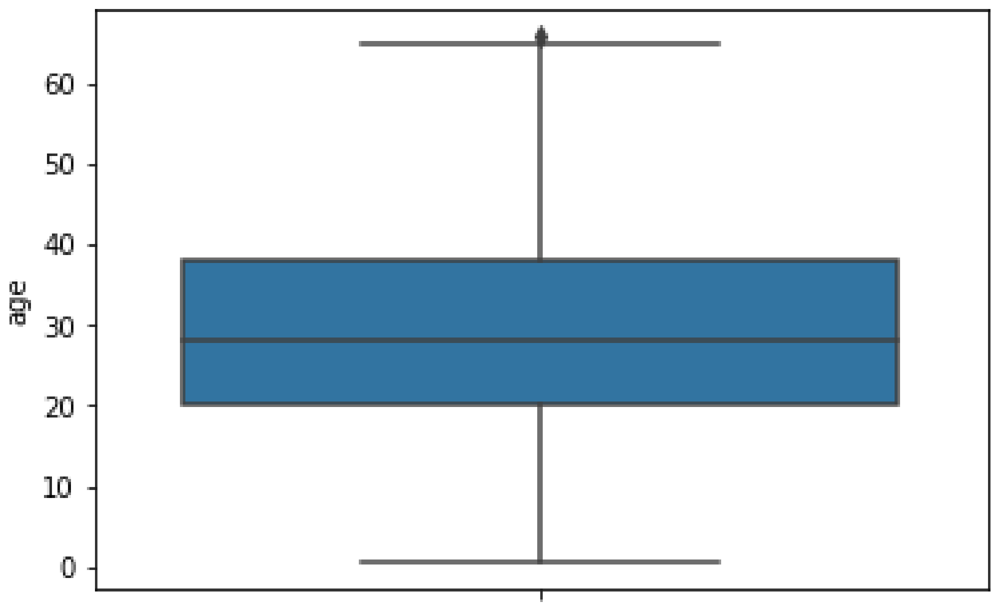
[ ]:
```
# Removing Outliers
ks_clean = ks_clean[ks_clean['age'] < 68]
ks_clean.head()
```

[ ]:
```
   survived  pclass     sex   age  sibsp  parch     fare embarked  class  \
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

     who  adult_male  embark_town alive  alone
0    man        True  Southampton    no  False
1  woman       False    Cherbourg   yes  False
2  woman       False  Southampton   yes   True
3  woman       False  Southampton   yes  False
4    man        True  Southampton    no   True
```

[ ]:
```
# After filtering outliers
sns.boxplot(y='age', data=ks_clean)
```

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

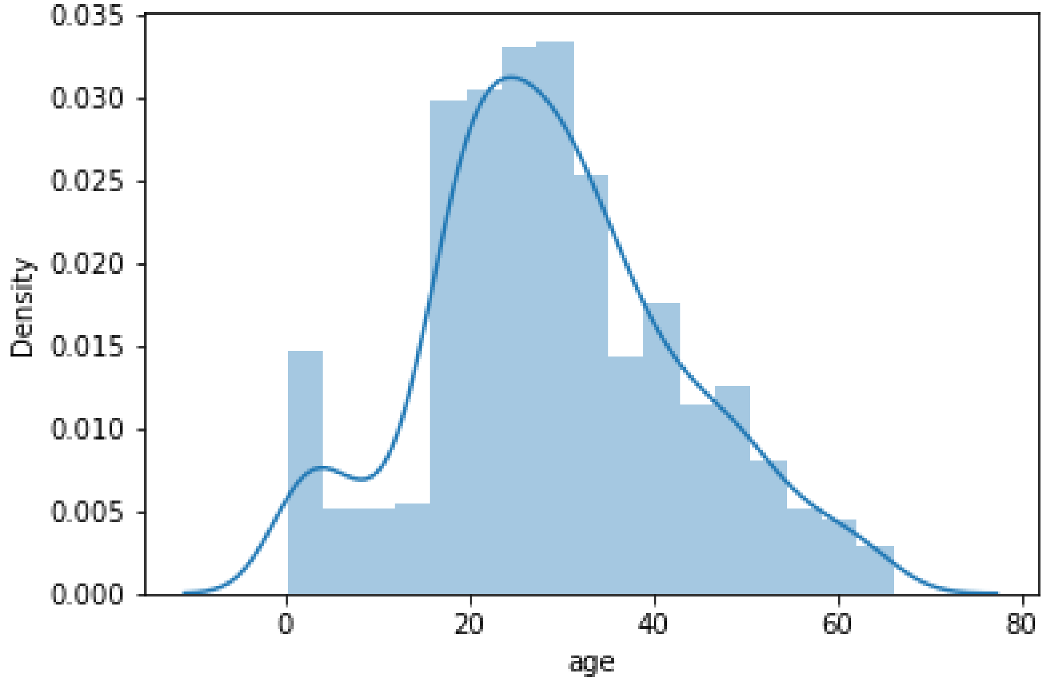


Looks Much Better

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

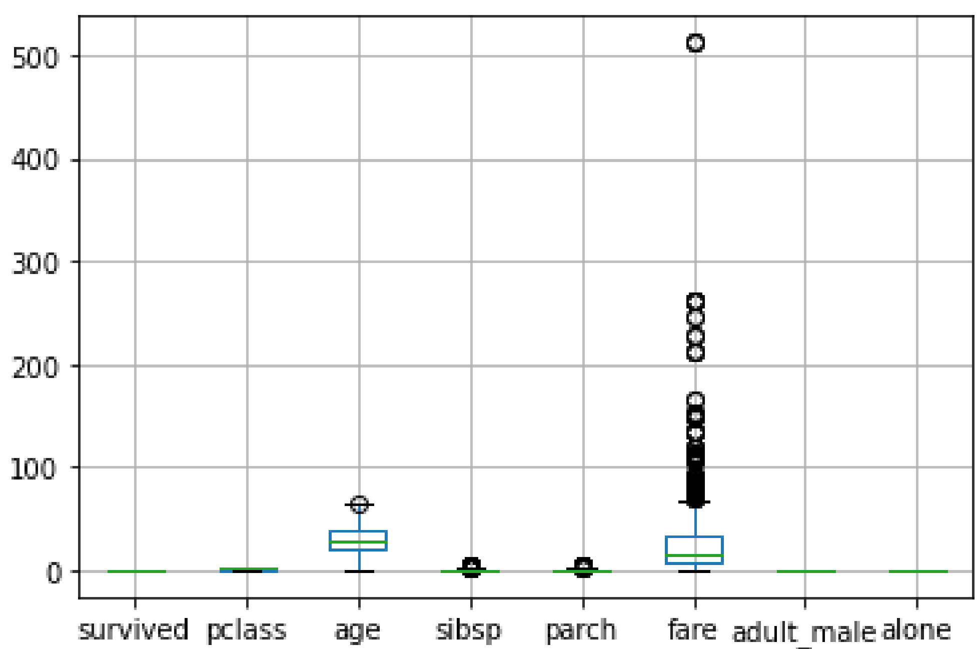
```
c:\Users\Waleed\anaconda3\lib\site-packages\seaborn\distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

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



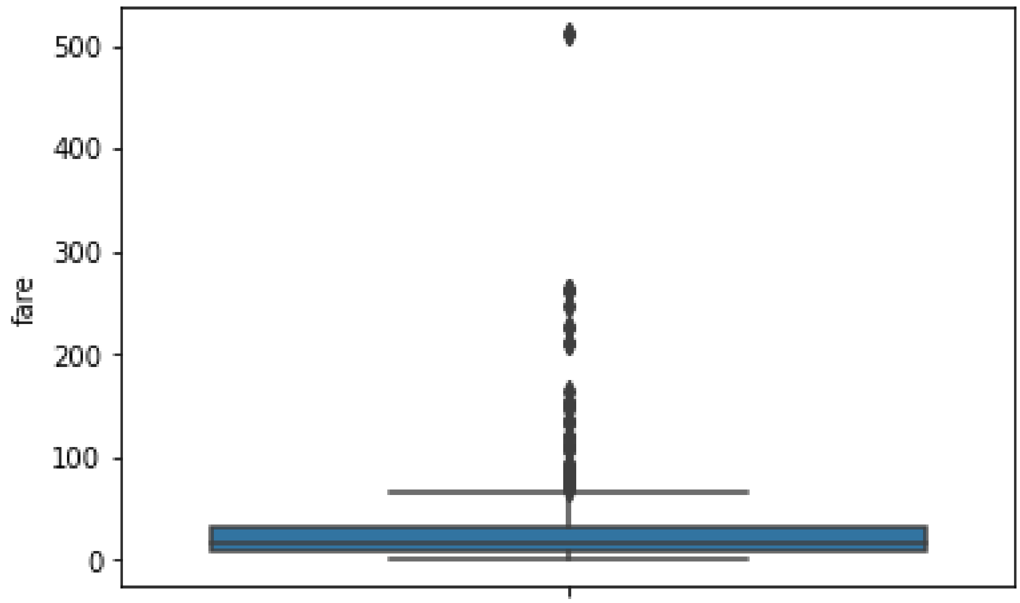

```
[ ]: # Whole Data BoxPlot
ks_clean.boxplot()
```

[ ]: <AxesSubplot:>



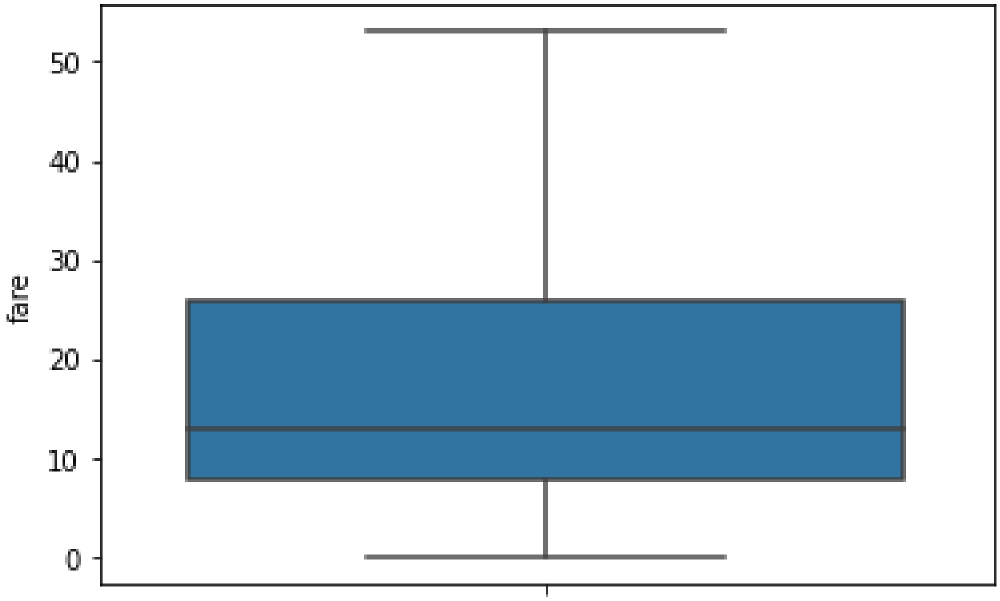
[ ]:
```
sns.boxplot(y='fare', data=ks_clean)
```

[ ]: <AxesSubplot:ylabel='fare'>



[ ]:
```
# cleaning fare column
ks_clean = ks_clean[ks_clean['fare'] < 55]
sns.boxplot(y='fare', data=ks_clean)
```

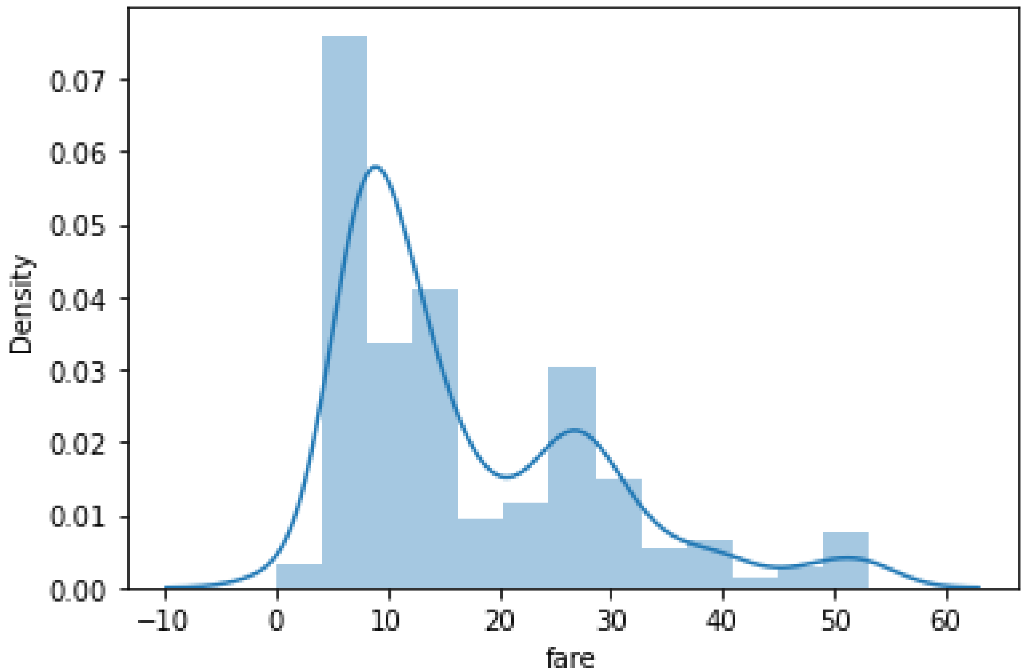
[ ]: <AxesSubplot:ylabel='fare'>



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

```
c:\Users\Waleed\anaconda3\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='fare', ylabel='Density'>
```

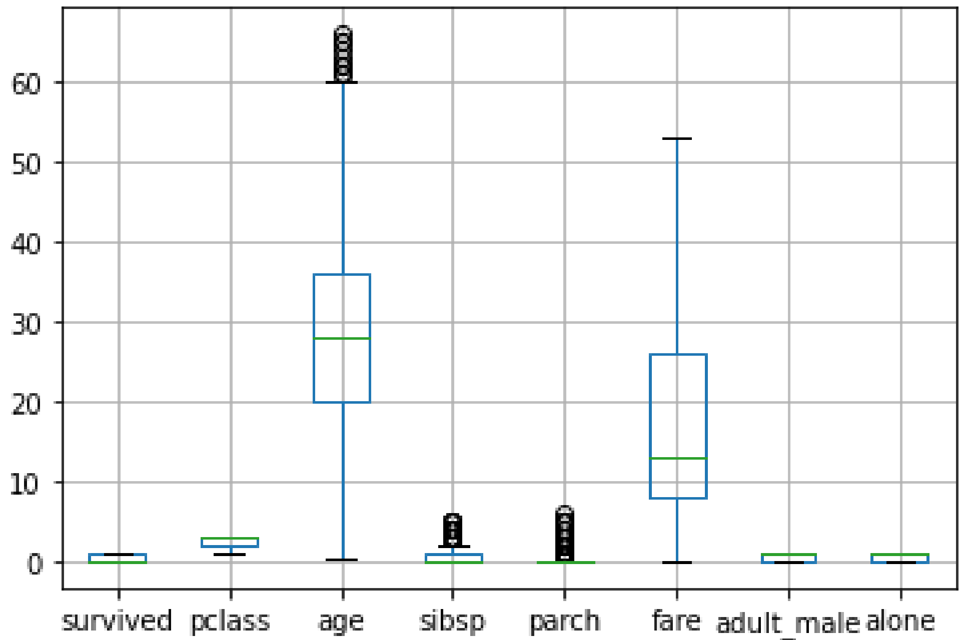


Data is not normaly distributd, log transformation can be used for resolve the issue.

[ ]:
```
# log transformation
ks_clean['fare_log'] = np.log(ks_clean['fare'])
```

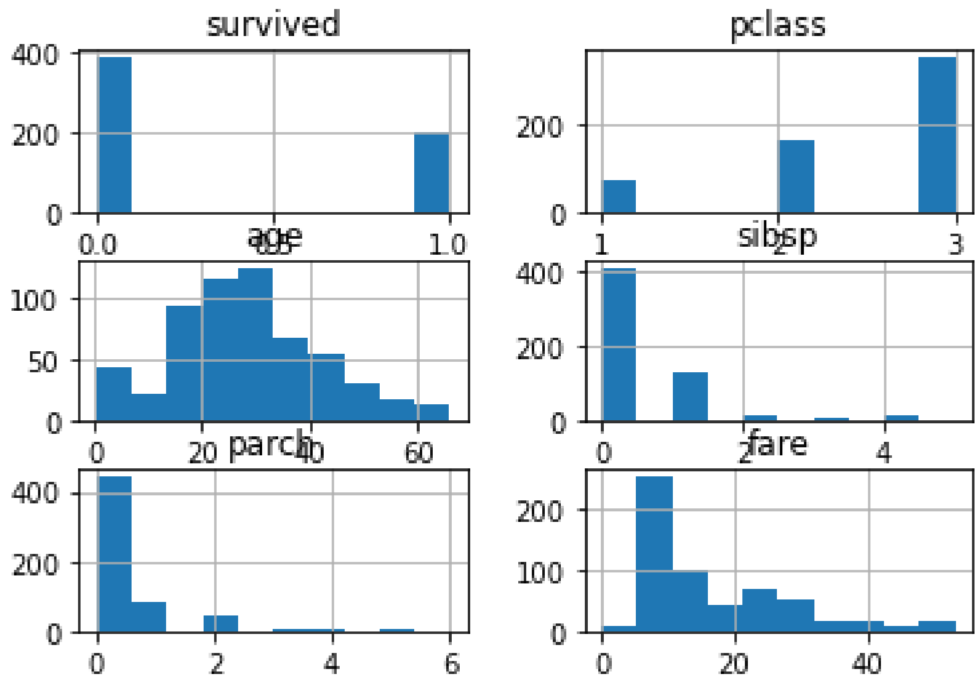
[ ]:
```
ks_clean.boxplot()
```

[ ]: <AxesSubplot:>



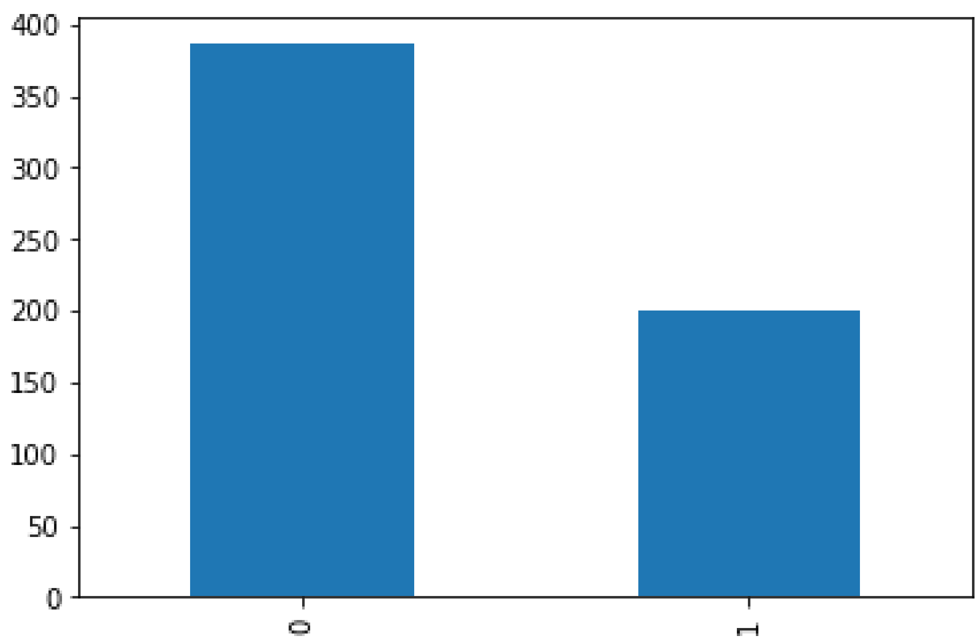
[ ]:
```
# Complete data histogram
ks_clean.hist()
```

[ ]:
```
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)
```



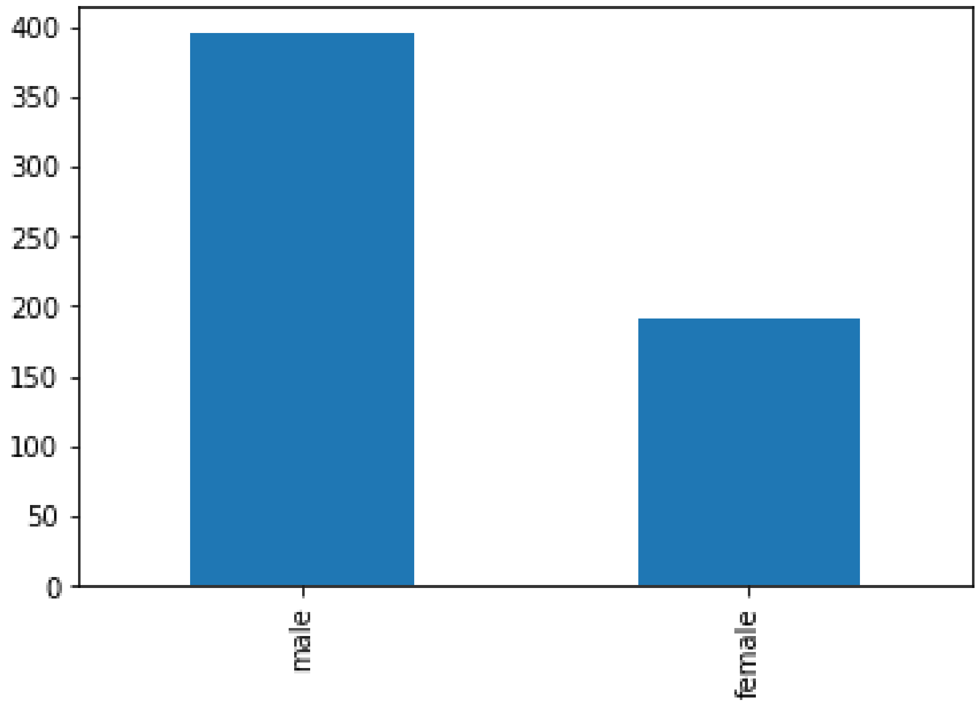

```
[ ]: pd.value_counts(ks_clean['survived']).plot.bar()
```

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



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

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



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

[ ]:
```
               survived  pclass        age     sibsp     parch       fare  \
sex    class
female First   0.941176     1.0  37.058824  0.411765  0.352941  38.962506
       Second  0.916667     2.0  28.520833  0.486111  0.583333  20.755267
       Third   0.460784     3.0  21.750000  0.823529  0.950980  15.875369
male   First   0.381818     1.0  42.772727  0.145455  0.036364  32.260680
       Second  0.161290     2.0  30.723978  0.333333  0.258065  18.410753
       Third   0.141700     3.0  26.088745  0.502024  0.263158  11.480379

               adult_male     alone
sex    class
female First     0.000000  0.470588
       Second    0.000000  0.416667
       Third     0.000000  0.372549
male   First     1.000000  0.836364
       Second    0.903226  0.645161
       Third     0.886640  0.732794
```

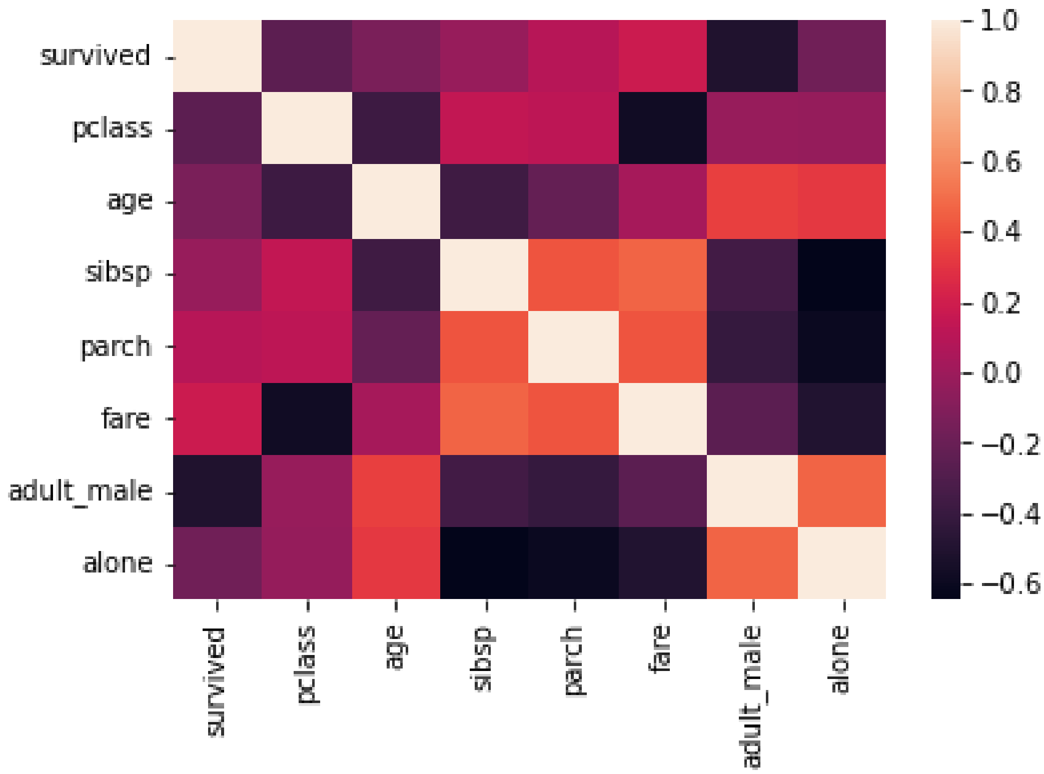
[ ]:
```
# corelation matrix 1 shows positive whereas neg value shows neg corelation
ks_clean.corr()
```

[ ]:
```
            survived    pclass       age     sibsp     parch      fare  \
survived    1.000000 -0.253421 -0.137448 -0.028300  0.098433  0.176168
pclass     -0.253421  1.000000 -0.380304  0.140866  0.120047 -0.573454
age        -0.137448 -0.380304  1.000000 -0.372958 -0.223097  0.033772
sibsp      -0.028300  0.140866 -0.372958  1.000000  0.411134  0.464386
parch       0.098433  0.120047 -0.223097  0.411134  1.000000  0.411263
fare        0.176168 -0.573454  0.033772  0.464386  0.411263  1.000000
adult_male -0.510726 -0.025996  0.341861 -0.362488 -0.412959 -0.260964
alone      -0.177098 -0.032915  0.312785 -0.648029 -0.599167 -0.503869

            adult_male     alone
survived     -0.510726 -0.177098
pclass       -0.025996 -0.032915
age           0.341861  0.312785
sibsp        -0.362488 -0.648029
parch        -0.412959 -0.599167
fare         -0.260964 -0.503869
adult_male    1.000000  0.463082
alone         0.463082  1.000000
```

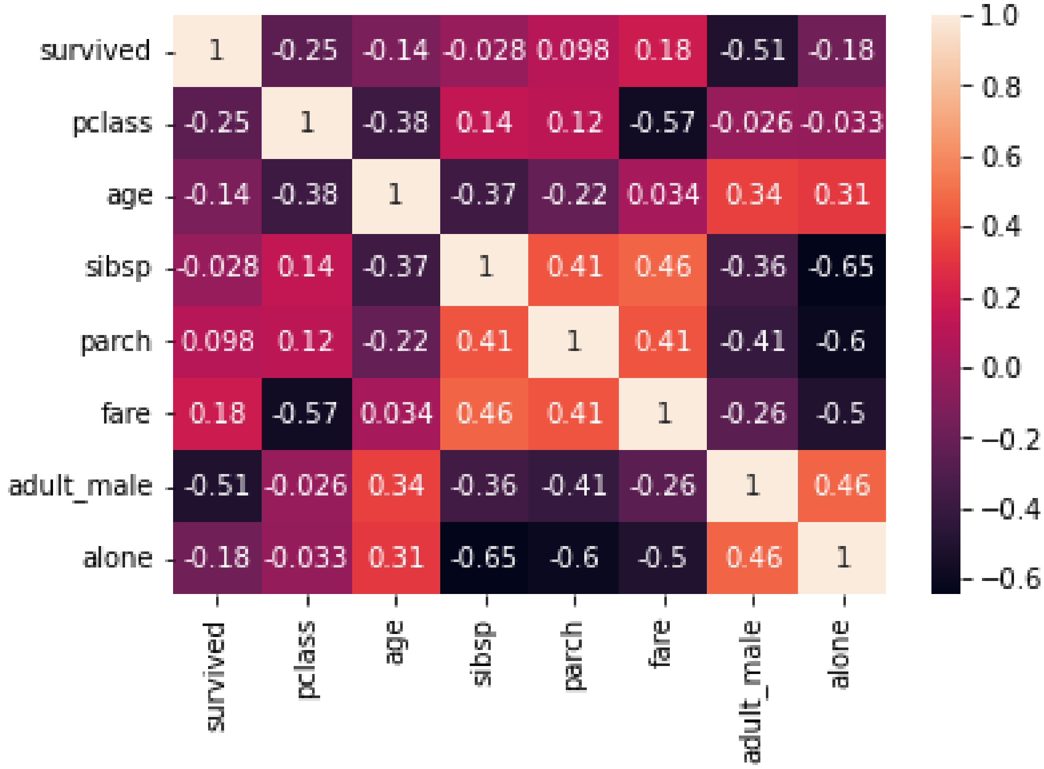
[ ]:
```
corr_ks_clean = ks_clean.corr()
sns.heatmap(corr_ks_clean)
```

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



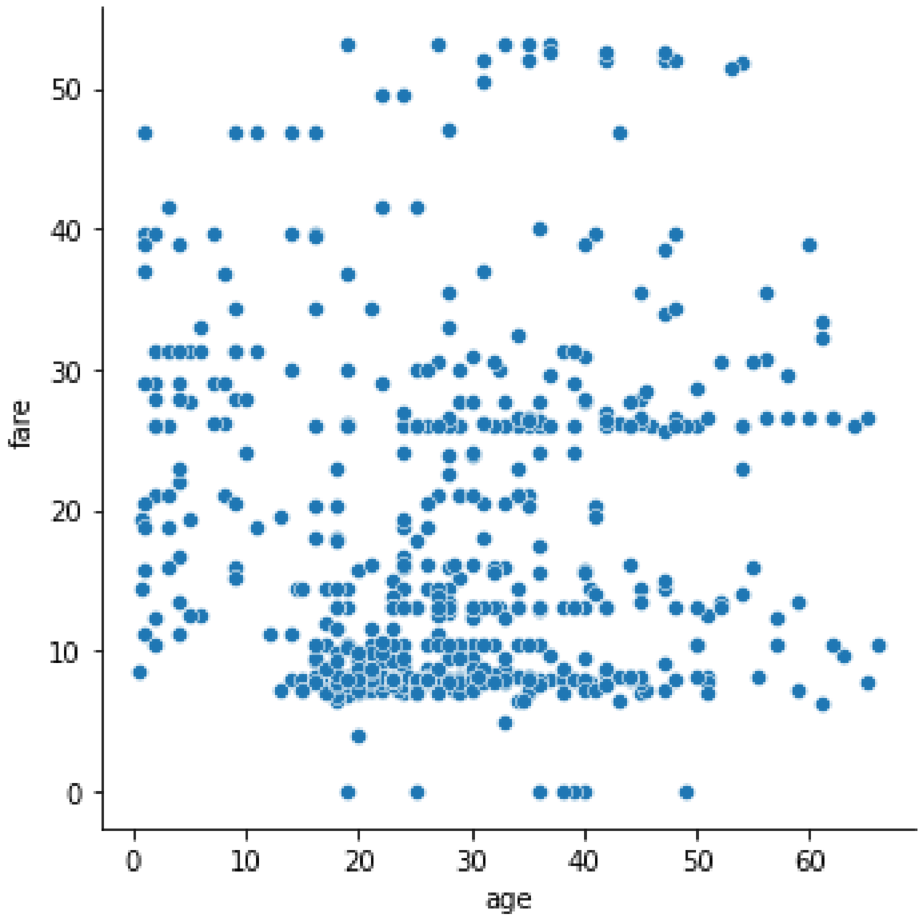

```
[ ]: sns.heatmap(corr_ks_clean, annot=True)
```

[ ]: <AxesSubplot:>



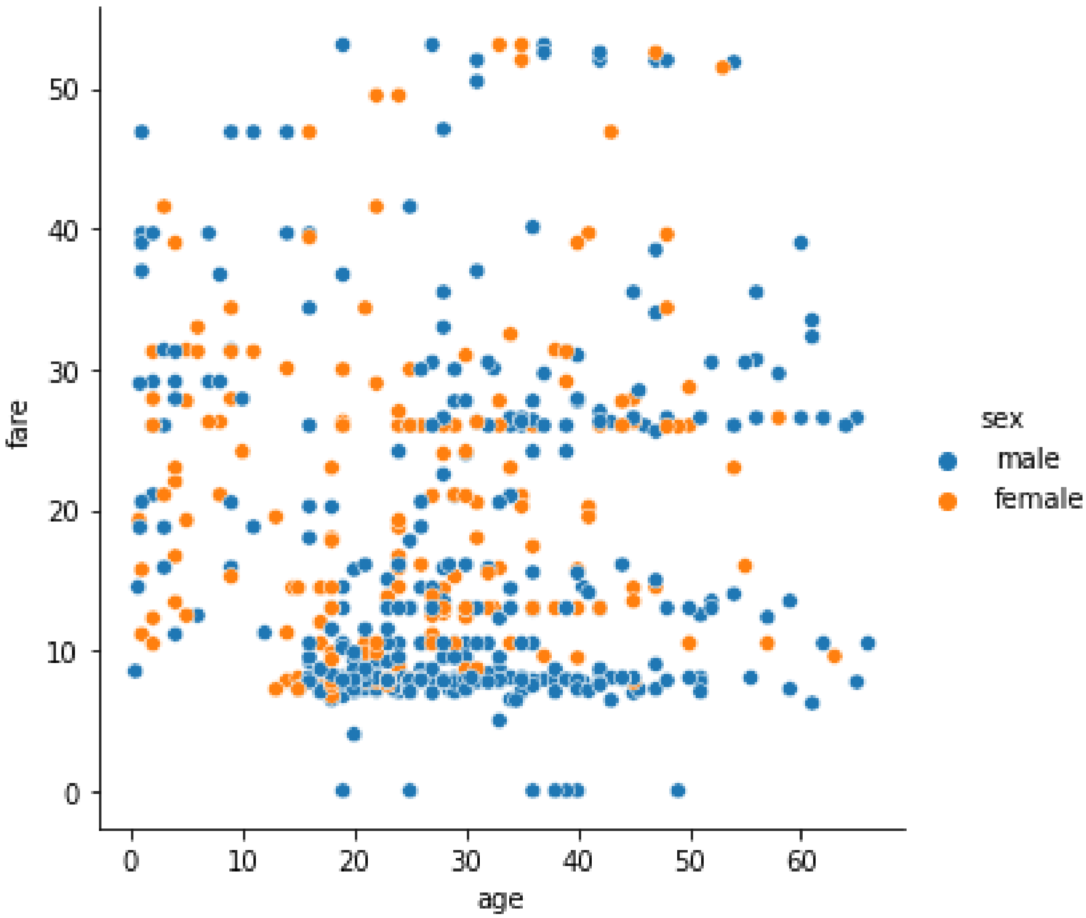
[ ]:
```
sns.relplot(x= 'age', y='fare', data=ks_clean)
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x1fdc67e8190>



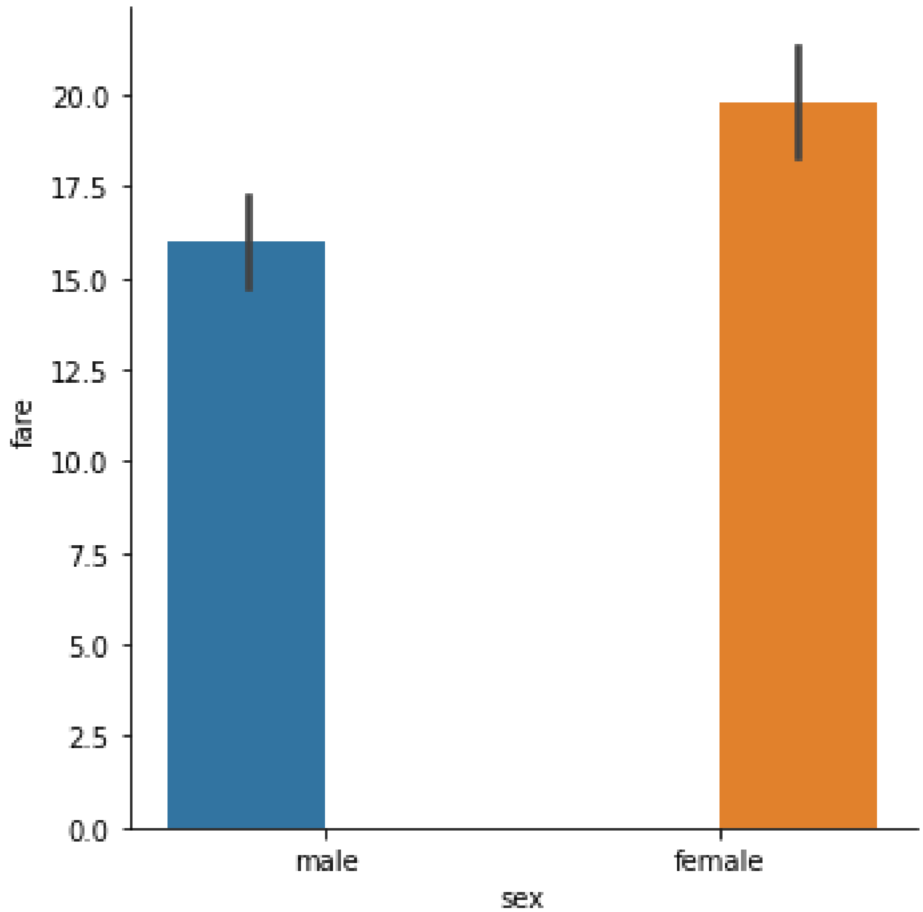
[ ]:
```
# Grouping
sns.relplot(x= 'age', y='fare',hue='sex', data=ks_clean)
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x1fdc677a3a0>



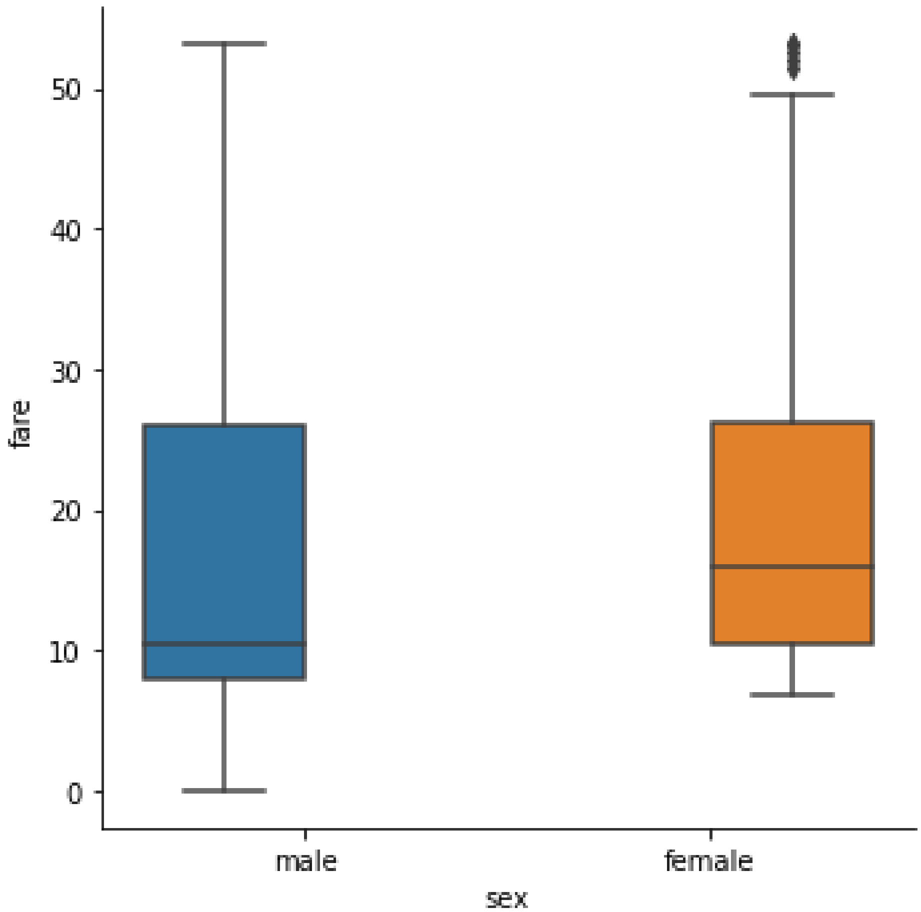

```
[ ]: # Category plot
     sns.catplot(x= 'sex', y='fare',hue='sex', data=ks_clean, kind='bar')
```

```
[ ]: <seaborn.axisgrid.FacetGrid at 0x1fdc79c2d90>
```



[ ]:
```
sns.catplot(x= 'sex', y='fare',hue='sex', data=ks_clean, kind='box')
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x1fdc7ad2dc0>



1.19 Data Wrangling

[ ]:
```
# Importing Required Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[ ]:
```
# Importing Dataset
kashti = sns.load_dataset('titanic')
kashti.head()
```

[ ]:
```
   survived  pclass     sex   age  sibsp  parch     fare embarked  class  \
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
```

```
     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
```

[ ]:
```
# Simple Operations (Math Operaters)
# Doing simple math operations on numeric value columns

(kashti['age'] * 6).head(10)
```

[ ]:
```
0    132.0
1    228.0
2    156.0
3    210.0
4    210.0
5      NaN
6    324.0
7     12.0
8    162.0
9     84.0
Name: age, dtype: float64
```

1.19.1 Dealing with missing values

- in a data set missing values are either? N/A or NaN or 0 or a blank cell.
- Jab kabhi data na ho kisi aik row main kisi b aik parameter ka

  - Steps: 1. Koshish karen dobra data collet kar len ya dekh len ager kahin ghalti hy. 2. Missing value wala variable (column) hi nikal den ager data per effect nahe hta ya simple row or data entry remove kar den. 3. Replace the missing values: 1. How? 1. Average value of entire variable or similar data point 2. frequency or MODE replacement 3. Replace based on other functions (Data sampler knows that) 4. ML algorithm can also be used 5. Leave it like that 2. Why? 1. Its better because no data is lost 2. Less accurate

[ ]:
```
# where exactly missing values are?
kashti.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
```

[ ]:
```
# Use drop.na method
print('Shape Before Removing deck col: ',kashti.shape)
# this will specifically removes deck column
# inplace = true modifies the data frame
kashti.dropna(subset=['deck'], axis=0, inplace=True)
print('Shape Before Removing deck col: ',kashti.shape)
```

```
Shape Before Removing deck col:  (891, 15)
Shape Before Removing deck col:  (203, 15)
```

[ ]:
```
# After removing 'deck' column, see again missing values
kashti.isnull().sum()
```

[ ]:
```
survived        0
pclass          0
sex             0
age            19
sibsp           0
parch           0
fare            0
embarked        2
class           0
who             0
adult_male      0
deck            0
embark_town     2
alive           0
alone           0
dtype: int64
```

[ ]:
```
# to update the main dataframe
kashti = kashti.dropna()     # Removes NAN values from whole dataframe
kashti.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
```

[ ]:
```
# After droping all NAN values let see how much data left
print('Shape After Removing all NaN Values: ',kashti.shape)
```

```
Shape After Removing all NaN Values:  (182, 15)
```

1.19.2 Replacing Missing values with mean of that column

[ ]:
```
# Now Using original data again in form of ks1
ks1 = sns.load_dataset('titanic')
ks1.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
```

[ ]:
```
# finding an average (mean)
mean_age = ks1['age'].mean()
mean_age
```

[ ]:
```
29.69911764705882
```

[ ]:
```
# Replacing NAN values in 'age' column with mean of that column (updating as␣
↪well)
ks1['age'] = ks1['age'].replace(np.nan, mean_age)

# After Replacing age col NaN values with mean of that col
ks1.isnull().sum()
```

[ ]:
```
survived         0
pclass           0
sex              0
age              0
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
```

[ ]:
```
ks1.shape
```

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

[ ]:
```
# Finding datatype of 'deck' column, can we replace missing values with mean or␣
↪not?
ks1.dtypes
```

[ ]:
```
survived          int64
pclass            int64
sex              object
age             float64
sibsp             int64
parch             int64
fare            float64
embarked         object
class          category
who              object
adult_male         bool
deck           category
embark_town      object
alive            object
alone              bool
```

```
dtype: object
```

> As 'deck' is categorical data column, we cannot replace it's NaN values with mean

> So, it's better to remove whole column because it contain too much missing data

[ ]:
```
# Removing 'deck' column, Because it's not possible to replace categorical col␣
↪with mean
print('Shape Before Removing deck col: ',ks1.shape)
ks1 = ks1.drop(['deck'], axis=1)
print('Shape After Removing deck col: ',ks1.shape)
ks1.isnull().sum()
```

```
Shape Before Removing deck col:  (891, 15)
Shape After Removing deck col:  (891, 14)
```

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

1.19.3 Data Formatting

- Data ko aik common standard per lana
- Ensures data is consistant and understandable
  - Easy to gather
  - Easy to workwith
  - Data ek hi unit main ho

[ ]:
```
# Know the data type and convert it into the known one
kashti.dtypes
```

[ ]:
```
survived          int64
pclass            int64
sex              object
age             float64
sibsp             int64
parch             int64
```

```
fare              float64
embarked           object
class            category
who                object
adult_male           bool
deck             category
embark_town        object
alive              object
alone                bool
dtype: object
```

[ ]:
```
# Use this Method to convert datatype / type casting
kashti['survived'] = kashti['survived'].astype('int64')
kashti.dtypes
```

[ ]:
```
survived           int64
pclass             int64
sex               object
age              float64
sibsp              int64
parch              int64
fare             float64
embarked          object
class           category
who               object
adult_male          bool
deck            category
embark_town       object
alive             object
alone               bool
dtype: object
```

[ ]:
```
# Here We will convert the age into days insted of years
ks1['age_in_days'] = ks1['age'] * 365    # New column added
ks1['age_in_days'] = ks1['age_in_days'].astype('int64')
ks1.head(10)
```

[ ]:
```
   survived  pclass     sex        age  sibsp  parch     fare embarked  \
0         0       3    male  22.000000      1      0   7.2500        S
1         1       1  female  38.000000      1      0  71.2833        C
2         1       3  female  26.000000      0      0   7.9250        S
3         1       1  female  35.000000      1      0  53.1000        S
4         0       3    male  35.000000      0      0   8.0500        S
5         0       3    male  29.699118      0      0   8.4583        Q
6         0       1    male  54.000000      0      0  51.8625        S
7         0       3    male   2.000000      3      1  21.0750        S
8         1       3  female  27.000000      0      2  11.1333        S
```

```
9         1       2  female  14.000000      1      0  30.0708        C

    class    who  adult_male  embark_town alive  alone  age_in_days
0   Third    man        True  Southampton    no  False         8030
1   First  woman       False    Cherbourg   yes  False        13870
2   Third  woman       False  Southampton   yes   True         9490
3   First  woman       False  Southampton   yes  False        12775
4   Third    man        True  Southampton    no   True        12775
5   Third    man        True   Queenstown    no   True        10840
6   First    man        True  Southampton    no   True        19710
7   Third  child       False  Southampton    no  False          730
8   Third  woman       False  Southampton   yes  False         9855
9  Second  child       False    Cherbourg   yes  False         5110
```

[ ]:
```python
# Rename the existing Column
ks1.rename(columns= {'age': 'age in days'}, inplace=True)
ks1.head()
```

[ ]:
```
   survived  pclass     sex  age in days  sibsp  parch     fare embarked  \
0         0       3    male         22.0      1      0   7.2500        S
1         1       1  female         38.0      1      0  71.2833        C
2         1       3  female         26.0      0      0   7.9250        S
3         1       1  female         35.0      1      0  53.1000        S
4         0       3    male         35.0      0      0   8.0500        S

   class    who  adult_male  embark_town alive  alone  age_in_days
0  Third    man        True  Southampton    no  False         8030
1  First  woman       False    Cherbourg   yes  False        13870
2  Third  woman       False  Southampton   yes   True         9490
3  First  woman       False  Southampton   yes  False        12775
4  Third    man        True  Southampton    no   True        12775
```

1.19.4 Data Normalization

- Uniform the data
- They have same impact
- aik machli samundar main or aik jar main
- Also for Computational reasons

[ ]:
```python
# Now Using original data again in form of ks2
#ks2 = sns.load_dataset('titanic')
ks1 = ks1.drop(['age in days'], axis=1)
ks1.head()
```

[ ]:
```
   survived  pclass     sex  sibsp  parch     fare embarked  class    who  \
0         0       3    male      1      0   7.2500        S  Third    man
1         1       1  female      1      0  71.2833        C  First  woman
2         1       3  female      0      0   7.9250        S  Third  woman
```

```
3           1         1  female       1       0  53.1000        S  First  woman
4           0         3    male       0       0   8.0500        S  Third    man

   adult_male  embark_town alive  alone  age_in_days
0        True  Southampton    no  False         8030
1       False    Cherbourg   yes  False        13870
2       False  Southampton   yes   True         9490
3       False  Southampton   yes  False        12775
4        True  Southampton    no   True        12775
```

[ ]:
```python
ks4 = ks1[['age_in_days', 'fare']]
ks4.head()
```

[ ]:
```
   age_in_days     fare
0         8030   7.2500
1        13870  71.2833
2         9490   7.9250
3        12775  53.1000
4        12775   8.0500
```

- The above data is really in wide range, it's hard to compare. So, we need to normalize
- Normalization changes the values to the range of 0-to-1 (now both variable has similar influence on our models)

1.19.5 Method for Normalization

1. Simple Feature Scaling
    1. x(new) = x(old) / x(max)
2. Min-Max method
3. Z-Score (standard score) -3 -to- +3
4. Log Transformation

[ ]:
```python
# simple feature scaling
ks4['fare'] = ks4['fare'] / ks4['fare'].max()
ks4['age_in_days'] = ks4['age_in_days'] / ks4['age_in_days'].max()
ks4.head()
```

```
C:\Users\Waleed\AppData\Local\Temp/ipykernel_11444/1927171063.py:2:
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-view-versus-a-copy
  ks4['fare'] = ks4['fare'] / ks4['fare'].max()
C:\Users\Waleed\AppData\Local\Temp/ipykernel_11444/1927171063.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-view-versus-a-copy
  ks4['age_in_days'] = ks4['age_in_days'] / ks4['age_in_days'].max()
```

[ ]:

	age_in_days	fare
0	0.2750	0.014151
1	0.4750	0.139136
2	0.3250	0.015469
3	0.4375	0.103644
4	0.4375	0.015713

[ ]:
```
ks5 = ks1[['age_in_days', 'fare']]
ks5.head()
```

[ ]:

	age_in_days	fare
0	8030	7.2500
1	13870	71.2833
2	9490	7.9250
3	12775	53.1000
4	12775	8.0500

[ ]:
```
# min - max method
ks5['fare'] = (ks5['fare'] - ks5['fare'].min()) / (ks5['fare'].max() -␣
↪ks5['fare'].min())
ks5.head()
```

```
C:\Users\Waleed\AppData\Local\Temp/ipykernel_11444/1487300651.py:2:
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-view-versus-a-copy
  ks5['fare'] = (ks5['fare'] - ks5['fare'].min()) / (ks5['fare'].max() -
ks5['fare'].min())
```

[ ]:

	age_in_days	fare
0	8030	0.014151
1	13870	0.139136
2	9490	0.015469
3	12775	0.103644
4	12775	0.015713

[ ]:
```
ks6 = ks1[['age_in_days', 'fare']]
ks6.head()
```

[ ]:

	age_in_days	fare
0	8030	7.2500
1	13870	71.2833
2	9490	7.9250
3	12775	53.1000
4	12775	8.0500

[ ]:

```
# z-score method (standard score)
ks6['fare'] = (ks6['fare'] - ks6['fare'].mean()) / ks6['fare'].std()
ks6.head()
```

```
C:\Users\Waleed\AppData\Local\Temp/ipykernel_11444/2270294703.py:2:
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-view-versus-a-copy
  ks6['fare'] = (ks6['fare'] - ks6['fare'].mean()) / ks6['fare'].std()
```

[ ]:

	age_in_days	fare
0	8030	-0.502163
1	13870	0.786404
2	9490	-0.488580
3	12775	0.420494
4	12775	-0.486064

[ ]:

```
ks7 = ks1[['age_in_days', 'fare']]
ks7.head()
```

[ ]:

	age_in_days	fare
0	8030	7.2500
1	13870	71.2833
2	9490	7.9250
3	12775	53.1000
4	12775	8.0500

[ ]:

```
# log transformation method
ks7['fare'] = np.log(ks7['fare'])
ks7.head()
```

```
c:\Users\Waleed\anaconda3\lib\site-packages\pandas\core\arraylike.py:364:
RuntimeWarning: divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
C:\Users\Waleed\AppData\Local\Temp/ipykernel_11444/3833499268.py:2:
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-view-versus-a-copy
  ks7['fare'] = np.log(ks7['fare'])
```

[ ]:

```
   age_in_days      fare
0         8030  1.981001
1        13870  4.266662
2         9490  2.070022
3        12775  3.972177
4        12775  2.085672
```

1.19.6 Binning

- Grouping of values into smaller number of values (bins)
- Convert numeric into categories (jawan, bachay, booray) etc
- To have better understanding of groups
  - low vs mid vs high price

- bins = number of times the data is being sliced
- labels = the range you are categorizing using labels.

[ ]:

```
df = sns.load_dataset('titanic')
#df.head()
#print((df['age']).describe())
bins = np.linspace(min(df['age']), max(df['age']), 4)
age_groups = ['Bachay', 'Jawan', 'Boorhay']
df['age'] = pd.cut(df['age'], bins, labels=age_groups, include_lowest=True)
(df['age']).head()

# How this will change the names in dataset based on grouping?
```

[ ]:

```
0    Bachay
1     Jawan
2    Bachay
3     Jawan
4     Jawan
Name: age, dtype: category
Categories (3, object): ['Bachay' < 'Jawan' < 'Boorhay']
```

[ ]:

```
df.head()
```

[ ]:

```
   survived  pclass     sex     age  sibsp  parch     fare embarked  class  \
0         0       3    male  Bachay      1      0   7.2500        S  Third
1         1       1  female   Jawan      1      0  71.2833        C  First
2         1       3  female  Bachay      0      0   7.9250        S  Third
3         1       1  female   Jawan      1      0  53.1000        S  First
4         0       3    male   Jawan      0      0   8.0500        S  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
```

Converting Categories into dummies - Easy to use for computation - Male Female (0, 1)

[ ]:
```
ks1.head()
```

[ ]:
```
   survived  pclass     sex  sibsp  parch     fare embarked  class    who  \
0         0       3    male      1      0   7.2500        S  Third    man
1         1       1  female      1      0  71.2833        C  First  woman
2         1       3  female      0      0   7.9250        S  Third  woman
3         1       1  female      1      0  53.1000        S  First  woman
4         0       3    male      0      0   8.0500        S  Third    man

   adult_male  embark_town alive  alone  age_in_days
0        True  Southampton    no  False         8030
1       False    Cherbourg   yes  False        13870
2       False  Southampton   yes   True         9490
3       False  Southampton   yes  False        12775
4        True  Southampton    no   True        12775
```

[ ]:
```
pd.get_dummies(ks1['sex'])
#ks1.head()
# how to append in dataframe
```

[ ]:
```
     0  1
0    0  1
1    1  0
2    1  0
3    1  0
4    0  1
..  .. ..
886  0  1
887  1  0
888  1  0
889  0  1
890  0  1

[891 rows x 2 columns]
```

[ ]:
```
#Replace multiple values with multiple new values.
ks1['sex'] = ks1['sex'].replace(['male','female'],[1,0])
ks1.head()
```

[ ]:

```
   survived  pclass  sex  sibsp  parch     fare embarked  class    who  \
0         0       3    1      1      0   7.2500        S  Third    man
1         1       1    0      1      0  71.2833        C  First  woman
2         1       3    0      0      0   7.9250        S  Third  woman
3         1       1    0      1      0  53.1000        S  First  woman
4         0       3    1      0      0   8.0500        S  Third    man

   adult_male  embark_town alive  alone  age_in_days
0        True  Southampton    no  False         8030
1       False    Cherbourg   yes  False        13870
2       False  Southampton   yes   True         9490
3       False  Southampton   yes  False        12775
4        True  Southampton    no   True        12775
```