### Generic Elective – Computer Science

# Data Analysis and Visualisation using Python Semester – II

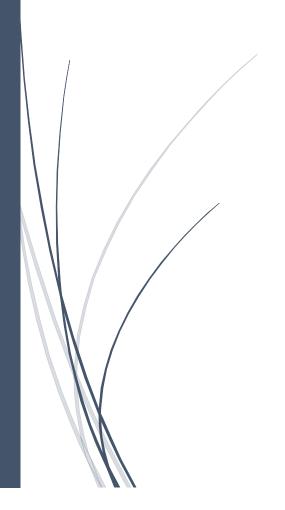
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## **PRACTICAL FILE**

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B.Sc. (Hons.) Mathematics

23BMAT019



- **Q1.** Write programs in Python using NumPy library to do the following:
  - a. Compute the mean, standard deviation, and variance of a two dimensional random integer array along the second axis.

### **Code:**

```
import numpy as np

m = int(input("Enter m (rows): "))
n = int(input("Enter n (columns): "))

arr = np.random.randint(10, size=(m, n))
print("\nOriginal Array:")
print(arr)

print("\nMean of the Array along the second axis:", np.mean(arr, axis=1))
print("Standard Deviation of Array along the second axis:", np.std(arr, axis=1))
print("Variance of Array along the second axis:", np.var(arr, axis=1))
```

```
Enter m (rows): 3
Enter n (columns): 4

Original Array:
[[5 4 6 6]
  [6 3 0 3]
  [1 5 3 6]]

Mean of the Array along the second axis: [5.25 3. 3.75]
Standard Deviation of Array along the second axis: [0.8291562 2.12132034 1.92028644]
Variance of Array along the second axis: [0.6875 4.5 3.6875]
```

b. Create a 2-dimensional array of size m x n integer elements, also print the shape, type and data type of the array and then reshape it into an n x m array, where n and m are user inputs given at the run time.

#### Code:

```
import numpy as np

m = int(input("Enter m (rows): "))
n = int(input("Enter n (columns): "))

arr = np.random.randint(10, size=(m,n))
print("\nOriginal Array:")
print(arr)

print("Shape of Array:", arr.shape)
print("Dimension of Array:", arr.ndim)
print("Data type of Array:", arr.dtype)

# Re-shaping the array
arr_new = np.reshape(arr, (n, m))
print("\nRe-shaped Array:")
print(arr_new)
```

```
Enter m (rows): 3
Enter n (columns): 4

Original Array:
[[9 9 6 8]
    [3 7 9 5]
    [3 5 3 8]]

Shape of Array: (3, 4)
Dimension of Array: 2
Data type of Array: int32

Re-shaped Array:
[[9 9 6]
    [8 3 7]
    [9 5 3]
    [5 3 8]]
```

c. Test whether the elements of a given 1D array are zero, non-zero and NaN. Record the indices of these elements in three separate arrays.

#### Code:

```
import numpy as np
# Creating an array containing zero, non-zero and NaN elements
ar = np.zeros(15)
print(f'Original array is:\n{ar}')
ar[3:6] = 100
ar[7:9] = float('Nan')
ar[12:14] = float('Nan')
print(f'\nNew array is:\n{ar}')
# Creating a boolean array representing indices with 0 as the element
bool zero = (ar == 0)
print(f'\nBoolean Array with zero-indicators:\n{bool zero}')
# Creating a boolean array representing indices with a non-zero element
bool nonzero = (ar!=0 & np.isnan(ar))
print(f'\nBoolean Array with non-zero-indicators:\n{bool_nonzero}')
# Creating a boolean array representing indices with a null/NaN element
bool_nan = np.isnan(ar)
print(f'\nBoolean Array with null-indicators:\n{bool_nan}')
# Creating an index array representing the indices of 'ar'
index=np.arange(15)
print(f'\nIndex Array:\n{index}')
# Using boolean indexing to retrieve index arrays - zero, non-zero and nan elements of ar.
zero_index = index[bool_zero == True]
print(f'\nArray containing indices of zero entries:\n{zero index}')
non_zero_index = index[bool_nonzero == True]
print(f'\nArray containing indices of non-zero entries:\n{non zero index}')
nan_index = index[bool_nan == True]
print(f'\nArray containing indices of NaN enries:\n{nan_index}')
```

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```
Original array is:
New array is:
[ 0. 0. 0.100.100.100. 0. nan nan 0. 0. 0. nan nan
  0.]
Boolean Array with zero-indicators:
[ True True True False False False True False False True True
False False True]
Boolean Array with non-zero-indicators:
[False False False True True False True False False False
 True True False]
Boolean Array with null-indicators:
[False False False False False False True True False False False
 True True False]
Index Array:
[0 1 2 3 4 5 6 7 8 9 10 11 12 13 14]
Array containing indices of zero entries:
[0 1 2 6 9 10 11 14]
Array containing indices of non-zero entries:
[ 3 4 5 7 8 12 13]
Array containing indices of NaN enries:
[ 7 8 12 13]
```

d. Create three random arrays of the same size: Array1, Array2 and Array3. Subtract Array 2 from Array3 and store in Array4. Create another array Array5 having two times the values in Array1. Find Co-variance and Correlation of Array1 with Array4 and Array5 respectively.

### **Code:**

```
import numpy as np
Array1 = np.random.random((3, 3))
print("Array1:")
print(Array1)
Array2 = np.random.random((3, 3))
print("\nArray2:")
print(Array2)
Array3 = np.random.random((3, 3))
print("\nArray3:")
print(Array3)
Array4 = Array2 - Array3
print("\nArray4 (Array2 - Array3):")
print(Array4)
Array5 = 2 * Array1
print("\nArray4 (2 * Array1):")
print(Array5)
print("\nCo-variance between Array1 and Array4:")
print(np.cov(Array4, Array1))
print("\nCorrelation between Array1 and Array5:")
print(np.corrcoef(Array5, Array1))
```

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```
Array1:
[[0.25388684 0.09025092 0.31568552]
[0.89595299 0.36696187 0.26172833]
[0.30998816 0.62019591 0.90459939]]
Array2:
[[0.29110749 0.11162578 0.88486029]
[0.51512098 0.48241184 0.90833106]
[0.97358125 0.06691973 0.01388881]]
Array3:
[[0.22997612 0.48743758 0.63734098]
[0.99849213 0.46402001 0.00191505]
[0.17207097 0.1624605 0.25289828]]
Array4 (Array2 - Array3):
[-0.48337115 0.01839183 0.90641601]
[ 0.80151028 -0.09554077 -0.23900947]]
Array4 (2 * Array1):
[[0.50777367 0.18050184 0.63137104]
[1.79190599 0.73392374 0.52345667]
[0.61997631 1.24039182 1.80919878]]
Co-variance between Array1 and Array4:
[[ 0.10236691  0.09888846  0.01809858  0.03725642  0.00788865  0.02542712]
[ 0.00788865 -0.20671923  0.19159218  0.00394074  0.11552444 -0.09519051]
Correlation between Array1 and Array5:
     0.09953132 0.2410247 1.
                            0.09953132 0.2410247 ]
[ 0.09953132 1. -0.94171029 0.09953132 1. -0.94171029]
[1. 0.09953132 0.2410247 1. 0.09953132 0.2410247 ]
[ 0.09953132 1. -0.94171029 0.09953132 1. -0.94171029]
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```

e. Create two random arrays of the same size 10: Array1, and Array2. Find the sum of the first half of both the arrays and product of the second half of both the arrays.

### **Code:**

```
import numpy as np

Array1 = np.random.random(size=10)
print("Array1:")
print(Array1)

Array2 = np.random.random(size=10)
print("\nArray2:")
print(Array2)

print(Array2)

print(Array1:5] + Array2:5])

print("\nProduct of the second half of both arrays:")
print(Array1:5:] * Array2:])
```

```
Array1:
[0.03582014 0.08651176 0.18055458 0.04456098 0.26991844 0.31331365 0.65042008 0.87145045 0.15883223 0.88449827]

Array2:
[0.5640922 0.97819022 0.1556042 0.06088445 0.50372476 0.00971907 0.87853942 0.67353239 0.55051318 0.9528223 ]

Sum of the first half of both arrays:
[0.59991234 1.06470198 0.33615877 0.10544543 0.7736432 ]

Product of the second half of both arrays:
[0.00304512 0.57141968 0.5869501 0.08743924 0.84276968]
```

- **Q2.** Do the following using PANDAS Series:
  - a. Create a series with 5 elements. Display the series sorted on index and also sorted on values separately

### **Code:**

```
import pandas as pd

s1 = pd.Series([7, 8, 9, 4, 5], index=['a', 'b', 'c', 'd', 'e'])
print(f"The original series is:\n{s1}")

x = s1.sort_index()
print(f"\nThe series sorted on the basis of index is:\n{x}")

y = s1.sort_values()
print(f"\nThe series sorted on the basis of values is:\n{y}")
```

```
The original series is:
    7
    8
   9
    4
    5
dtype: int64
The series sorted on the basis of index is:
b
    8
   9
d 4
    5
dtype: int64
The series sorted on the basis of values is:
    5
    7
а
b
    9
dtype: int64
```

b. Create a series with N elements with some duplicate values. Find the minimum and maximum ranks assigned to the values using 'first' and 'max' methods

### **Code:**

```
import pandas as pd
s = pd.Series([2, 10, 5, 7, 10, 3, 2, 9, 4, 8], index=list("abcdefghij"))
print(f"Ranks through 'first' method are:\n{s.rank(method='first')}")
print(f"\nRanks through 'max' method are:\n{s.rank(method='max')}")
```

```
Ranks through 'first' method are:
      1.0
b
      9.0
c
     5.0
     6.0
    10.0
f
     3.0
     2.0
     8.0
h
i
     4.0
j
     7.0
dtype: float64
Ranks through 'max' method are:
     2.0
b
     10.0
c
     5.0
     6.0
    10.0
f
     3.0
     2.0
g
      8.0
     4.0
     7.0
dtype: float64
```

c. Display the index value of the minimum and maximum element of a Series

### **Code:**

```
import numpy as np
import pandas as pd

obj1 = pd.Series(np.arange(10), index=list("abcdefghij"))
print(f"The series is:\n{obj1}")

print(f"\nIndex value for the minimum element of the series is: {obj1.idxmin()}")
print(f"\nIndex value for the maximum element of the series is: {obj1.idxmax()}")
```

```
The series is:
     0
b
     1
c
     2
     3
    4
f
     5
     6
h
    7
i
j
     9
dtype: int32
Index value for the minimum element of the series is: a
Index value for the maximum element of the series is: j
```

**Q3.** Create a data frame having at least 3 columns and 50 rows to store numeric data generated using a random function. Replace 10% of the values by null values whose index positions are generated using random function.

**<u>Code:</u>** (Creating the required data frame)

```
import numpy as np
import pandas as pd

data = np.random.randint(0, 500, size=(50,3))
df = pd.DataFrame(data)
print(f"The original dataframe is:\n{df}")

for i in range(15):
    a = np.random.randint(0, 50)
    b = np.random.randint(0, 3)
    df.iloc[a,b] = np.nan
print(f"The updated dataframe is:\n{df}")
```

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| The      | orig      | inal | dataframe | is: | The | update | d dataf | rame is: | : |
|----------|-----------|------|-----------|-----|-----|--------|---------|----------|---|
|          | 0         | 1    | 2         |     |     | 0      | 1       | 2        |   |
| 0        | 12        | 358  | 248       |     | 0   | 12.0   | 358.0   | 248.0    |   |
| 1        | 10        | 379  | 90        |     | 1   | 10.0   | 379.0   |          |   |
| 2        | 287       | 57   | 460       |     | 2   |        | 57.0    |          |   |
| 3        | 113       | 228  | 497       |     | 3   | 113.0  |         | 497.0    |   |
| 4        | 438       | 390  | 159       |     | 4   | 438.0  |         |          |   |
| 5        | 69        | 70   | 35        |     | 5   |        | 70.0    | 35.0     |   |
| 6        | 78        | 404  | 326       |     | 6   | 78.0   |         | NaN      |   |
| 7        | 395       | 130  | 410       |     | 7   | 395.0  | 130.0   |          |   |
| 8        | 35        | 79   | 128       |     | 8   |        | 79.0    |          |   |
| 9        | 33        | 172  | 353       |     | 9   | 33.0   | 172.0   |          |   |
| 10       | 119       | 338  | 104       |     | 10  | 119.0  |         |          |   |
| 11       | 69        | 498  | 370       |     | 11  | 69.0   |         |          |   |
| 12       | 265       | 114  | 156       |     | 12  |        | 114.0   |          |   |
| 13       | 423       | 190  | 347       |     | 13  |        |         |          |   |
| 14       | 453       | 424  |           |     |     | 423.0  |         |          |   |
| 15       | 25        | 155  | 169       |     | 14  | 453.0  |         |          |   |
| 16       | 408       | 443  | 49        |     | 15  | 25.0   | 155.0   | NaN      |   |
| 17       | 303       | 404  | 119       |     | 16  | 408.0  | 443.0   |          |   |
| 18       | 32        | 10   | 355       |     | 17  | 303.0  | 404.0   |          |   |
| 19       | 77        | 438  | 65        |     | 18  |        | 10.0    |          |   |
| 20       | 179       | 379  | 38        |     | 19  | 77.0   |         | 65.0     |   |
| 21       | 456       | 171  | 423       |     | 20  | NaN    | 379.0   |          |   |
| 22       | 58        | 336  | 24        |     | 21  | NaN    | 171.0   | NaN      |   |
| 23       | 35        | 466  | 272       |     | 22  | NaN    | 336.0   |          |   |
| 24       |           | 400  | 59        |     | 23  | 35.0   |         | NaN      |   |
|          | 199       |      |           |     | 24  | 199.0  | 400.0   |          |   |
| 25       | 409       | 207  | 149       |     | 25  | 409.0  | 207.0   |          |   |
| 26<br>27 | 283<br>90 | 177  | 338       |     | 26  | 283.0  | 177.0   |          |   |
|          |           | 374  | 309       |     | 27  | 90.0   | NaN     |          |   |
| 28       | 118       | 489  | 327       |     | 28  | 118.0  |         |          |   |
| 29       | 199       | 180  | 63        |     | 29  | 199.0  |         | 63.0     |   |
| 30       | 224       | 374  |           |     | 30  | 224.0  | 374.0   | NaN      |   |
| 31       | 491       | 65   | 164       |     | 31  |        | 65.0    | 164.0    |   |
| 32       | 483       | 274  | 120       |     | 32  | 483.0  |         |          |   |
| 33       | 216       | 387  |           |     |     | 216.0  |         |          |   |
| 34       | 402       | 188  | 103       |     |     | 402.0  |         |          |   |
| 35       | 58        | 185  | 468       |     | 35  | 58.0   | 185.0   | 468.0    |   |
| 36       | 433       | 283  | 237       |     | 36  | 433.0  |         |          |   |
| 37       | 473       | 354  |           |     | 37  | 473.0  | 354.0   | 448.0    |   |
| 38       | 474       | 276  |           |     | 38  | 474.0  | 276.0   | 345.0    |   |
| 39       | 225       | 84   |           |     | 39  | 225.0  | 84.0    | NaN      |   |
| 40       | 437       | 116  | 326       |     | 40  | NaN    | 116.0   | 326.0    |   |
| 41       | 213       | 279  | 286       |     | 41  | 213.0  | 279.0   | 286.0    |   |
| 42       | 396       | 226  | 258       |     | 42  | 396.0  | 226.0   | NaN      |   |
| 43       | 10        | 331  | 136       |     | 43  | 10.0   | 331.0   | 136.0    |   |
| 44       | 432       | 1    |           |     | 44  | 432.0  | 1.0     | 306.0    |   |
| 45       | 410       | 203  | 72        |     | 45  | 410.0  | 203.0   | NaN      |   |
| 46       | 335       | 202  | 140       |     | 46  | 335.0  | 202.0   | 140.0    |   |
| 47       | 402       | 455  | 433       |     | 47  | 402.0  | 455.0   | 433.0    |   |
| 48       | 163       | 411  | 173       |     | 48  | 163.0  | 411.0   | 173.0    |   |
| 49       | 399       | 470  | 256       |     | 49  | 399.0  | 470.0   | 256.0    |   |
|          |           |      |           |     |     |        |         |          |   |

Do the following:

a. Identify and count missing values in a data frame.

### **Code:**

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

### **Output:**

```
0 5
1 2
2 8
dtype: int64
```

b. Drop the column having more than 5 null values.

### **Code:**

```
print(df.dropna(axis=1, thresh=45))
```

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```
0 1
  12.0 358.0
0
1 10.0 379.0
2 287.0 57.0
3 113.0 228.0
  438.0 390.0
5
   69.0
         70.0
6 78.0 404.0
7 395.0 130.0
8
   NaN 79.0
9
   33.0 172.0
10 119.0 338.0
11 69.0 498.0
12 265.0 114.0
13 423.0 190.0
14 453.0 424.0
   25.0 155.0
15
16 408.0 443.0
17 303.0 404.0
18 32.0 10.0
19 77.0 438.0
20 NaN 379.0
21 NaN 171.0
22
   NaN 336.0
23 35.0 466.0
24 199.0 400.0
25 409.0 207.0
26 283.0 177.0
27 90.0 NaN
28 118.0 489.0
29 199.0 180.0
30 224.0 374.0
31 491.0 65.0
32 483.0 274.0
33 216.0 NaN
34 402.0 188.0
35 58.0 185.0
36 433.0 283.0
37 473.0 354.0
38 474.0 276.0
39 225.0 84.0
40 NaN 116.0
41 213.0 279.0
42 396.0 226.0
43 10.0 331.0
44 432.0 1.0
45 410.0 203.0
46 335.0 202.0
47 402.0 455.0
48 163.0 411.0
49 399.0 470.0
```

c. Identify the row label having maximum of the sum of all values in a row and drop that row.

### **Code:**

```
max_row = df.sum(axis=1).idxmax()
print("The row with maximum sum value is:", max_row)
print(df.drop(max_row))
```

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```
The row with maximum sum value is: 47
      0
          1 2
    12.0 358.0 248.0
1
   10.0 379.0 90.0
2
   287.0 57.0 460.0
3
   113.0 228.0 497.0
4
  438.0 390.0 159.0
5
   69.0
         70.0 35.0
6
   78.0 404.0
               NaN
7
  395.0 130.0 410.0
   NaN 79.0 128.0
8
9
   33.0 172.0 353.0
10 119.0 338.0 104.0
  69.0 498.0 370.0
11
12 265.0 114.0 156.0
13 423.0 190.0 347.0
14 453.0 424.0 280.0
   25.0 155.0
15
               NaN
16 408.0 443.0 49.0
17 303.0 404.0 119.0
18 32.0 10.0 355.0
  77.0 438.0 65.0
19
20 NaN 379.0
               38.0
21
  NaN 171.0
               NaN
22
   NaN 336.0
               24.0
23 35.0 466.0 NaN
24 199.0 400.0 59.0
25 409.0 207.0 149.0
26 283.0 177.0 338.0
27
  90.0 NaN 309.0
28 118.0 489.0 327.0
29 199.0 180.0 63.0
30 224.0 374.0
31 491.0 65.0 164.0
32 483.0 274.0 120.0
33 216.0 NaN 292.0
34 402.0 188.0 103.0
35 58.0 185.0 468.0
36 433.0 283.0 237.0
37 473.0 354.0 448.0
38 474.0 276.0 345.0
39 225.0 84.0
               NaN
40
   NaN 116.0 326.0
41 213.0 279.0 286.0
42 396.0 226.0
               NaN
43
  10.0 331.0 136.0
44 432.0 1.0 306.0
               NaN
45 410.0 203.0
46 335.0 202.0 140.0
48 163.0 411.0 173.0
49 399.0 470.0 256.0
```

d. Sort the data frame on the basis of the first column.

### **Code:**

print(df.sort\_values([0]))

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| 1 10.0 379.0 90.0 43 10.0 331.0 136.0 0 12.0 358.0 248.0 15 25.0 155.0 NaN 18 32.0 10.0 355.0 9 33.0 172.0 353.0 23 35.0 466.0 NaN 35 58.0 185.0 468.0 5 69.0 70.0 35.0 11 69.0 498.0 370.0 19 77.0 438.0 65.0 6 78.0 404.0 NaN 27 90.0 NaN 309.0 3 113.0 228.0 497.0 28 118.0 489.0 327.0 10 119.0 338.0 104.0 48 163.0 411.0 173.0 29 199.0 180.0 63.0 24 199.0 400.0 59.0 41 213.0 279.0 286.0 33 216.0 NaN 292.0 30 224.0 374.0 NaN 292.0 30 224.0 374.0 NaN 292.0 30 225.0 84.0 NaN 12 265.0 114.0 156.0 26 283.0 177.0 338.0 2 287.0 57.0 460.0 17 303.0 404.0 119.0 46 335.0 202.0 140.0 7 395.0 130.0 410.0 42 396.0 226.0 NaN 49 399.0 470.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 256.0 47 402.0 455.0 433.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 244.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0 346.0 340.0 34 |    |       |       | _     |
|--|----|-------|-------|-------|
| 43   | _  |       |       |       |
| 0       12.0       358.0       248.0         15       25.0       155.0       NaN         18       32.0       10.0       355.0         9       33.0       172.0       353.0         23       35.0       466.0       NaN         35       58.0       185.0       468.0         5       69.0       70.0       35.0         11       69.0       498.0       370.0         19       77.0       438.0       65.0         6       78.0       404.0       NaN         27       90.0       NaN       309.0         3       113.0       228.0       497.0         28       118.0       489.0       327.0         10       119.0       338.0       104.0         48       163.0       411.0       173.0         29       199.0       180.0       63.0         24       199.0       400.0       59.0         41       213.0       279.0       286.0         33       216.0       NaN       292.0         30       224.0       374.0       NaN         12       265.0       114.0   |    |       |       |       |
| 15   |    |       |       |       |
| 18       32.0       10.0       355.0         9       33.0       172.0       353.0         23       35.0       466.0       NaN         35       58.0       185.0       468.0         5       69.0       70.0       35.0         11       69.0       498.0       370.0         19       77.0       438.0       65.0         6       78.0       404.0       NaN         27       90.0       NaN       309.0         3       113.0       228.0       497.0         28       118.0       489.0       327.0         10       119.0       338.0       104.0         48       163.0       411.0       173.0         29       199.0       180.0       63.0         24       199.0       400.0       59.0         41       213.0       279.0       286.0         33       216.0       NaN       292.0         30       224.0       374.0       NaN         12       265.0       114.0       156.0         2       287.0       57.0       460.0         17       303.0       404.0 </td <td></td> <td></td> <td></td> <td></td>   |    |       |       |       |
| 9 33.0 172.0 353.0 23 35.0 466.0 NaN 35 58.0 185.0 468.0 5 69.0 70.0 35.0 11 69.0 498.0 370.0 19 77.0 438.0 65.0 6 78.0 404.0 NaN 27 90.0 NaN 309.0 3 113.0 228.0 497.0 28 118.0 489.0 327.0 10 119.0 338.0 104.0 48 163.0 411.0 173.0 29 199.0 180.0 63.0 24 199.0 400.0 59.0 41 213.0 279.0 286.0 33 216.0 NaN 292.0 30 224.0 374.0 NaN 39 225.0 84.0 NaN 12 265.0 114.0 156.0 26 283.0 177.0 338.0 2 287.0 57.0 460.0 17 303.0 404.0 119.0 46 335.0 202.0 140.0 7 395.0 130.0 410.0 42 396.0 226.0 NaN 49 399.0 470.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 25 409.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 188.0 103.0 16 408.0 443.0 49.0 25 409.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 347.0 44 432.0 1.0 306.0 347.0 44 432.0 1.0 306.0 347.0 44 432.0 1.0 306.0 347.0 44 432.0 1.0 306.0 347.0 44 432.0 1.0 306.0 347.0 44 432.0 1.0 306.0 347.0 44 432.0 1.0 306.0 347.0 44 432.0 1.0 306.0 347.0 44 432.0 1.0 306.0 347.0 44 432.0 1.0 306.0 347.0 44 432.0 1.0 306.0 347.0 448.0 390.0 159.0 149.0 347.0 448.0 390.0 159.0 149.0 453.0 347.0 448.0 390.0 159.0 149.0 347.0 448.0 390.0 159.0 149.0 347.0 448.0 390.0 159.0 149.0 347.0 448.0 390.0 159.0 149.0 347.0 448.0 390.0 159.0 149.0 347.0 448.0 390.0 159.0 149.0 347.0 448.0 390.0 159.0 149.0 347.0 448.0 390.0 159.0 149.0 347.0 348.0 390.0 159.0 149.0 347.0 348.0 390.0 159.0 149.0 347.0 348.0 390.0 159.0 149.0 347.0 348.0 390.0 159.0 149.0 347.0 348.0 390.0 159.0 347.0 348.0 390.0 159.0 347.0 348.0 390.0 159.0 347.0 348.0 390.0 159.0 347.0 348.0 390.0 159.0 348.0 349.0 34 |    |       |       |       |
| 23       35.0       466.0       NaN         35       58.0       185.0       468.0         5       69.0       70.0       35.0         11       69.0       498.0       370.0         19       77.0       438.0       65.0         6       78.0       404.0       NaN         27       90.0       NaN       309.0         3       113.0       228.0       497.0         28       118.0       489.0       327.0         10       119.0       338.0       104.0         48       163.0       411.0       173.0         29       199.0       180.0       63.0         24       199.0       400.0       59.0         41       213.0       279.0       286.0         33       216.0       NaN       292.0         30       224.0       374.0       NaN         12       265.0       114.0       156.0         2       287.0       57.0       460.0         17       303.0       404.0       119.0         46       335.0       202.0       140.0         7       395.0       130.  |    |       |       |       |
| 35 58.0 185.0 468.0 5 69.0 70.0 35.0 11 69.0 498.0 370.0 19 77.0 438.0 65.0 6 78.0 404.0 NaN 27 90.0 NaN 309.0 3 113.0 228.0 497.0 28 118.0 489.0 327.0 10 119.0 338.0 104.0 48 163.0 411.0 173.0 29 199.0 180.0 63.0 24 199.0 400.0 59.0 41 213.0 279.0 286.0 33 216.0 NaN 292.0 30 224.0 374.0 NaN 292.0 30 224.0 374.0 NaN 12 265.0 114.0 156.0 26 283.0 177.0 338.0 2 287.0 57.0 460.0 17 303.0 404.0 119.0 46 335.0 202.0 140.0 7 395.0 130.0 410.0 42 396.0 226.0 NaN 49 399.0 470.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 25 409.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 149.0 453.0 344.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 390.0 159.0 14 453.0 344.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 344.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 38 474.0 |    |       |       |       |
| 5       69.0       70.0       35.0         11       69.0       498.0       370.0         19       77.0       438.0       65.0         6       78.0       404.0       NaN         27       90.0       NaN       309.0         3       113.0       228.0       497.0         28       118.0       489.0       327.0         10       119.0       338.0       104.0         48       163.0       411.0       173.0         29       199.0       180.0       63.0         24       199.0       400.0       59.0         41       213.0       279.0       286.0         33       216.0       NaN       292.0         41       213.0       279.0       286.0         33       216.0       NaN       292.0         41       213.0       279.0       286.0         33       216.0       NaN       292.0         41       213.0       374.0       NaN         12       265.0       114.0       156.0         26       283.0       177.0       338.0         2       287.0       57  |    |       |       |       |
| 11 69.0 498.0 370.0 19 77.0 438.0 65.0 6 78.0 404.0 NaN 309.0 3 113.0 228.0 497.0 28 118.0 489.0 327.0 10 119.0 338.0 104.0 48 163.0 411.0 173.0 29 199.0 400.0 59.0 41 213.0 279.0 286.0 33 216.0 NaN 292.0 30 224.0 374.0 NaN 12 265.0 114.0 156.0 26 283.0 177.0 338.0 2 287.0 57.0 460.0 17 303.0 404.0 119.0 46 335.0 202.0 140.0 7 395.0 130.0 410.0 42 396.0 226.0 NaN 49 399.0 470.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 25 409.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 237.0 44 438.0 390.0 159.0 14 453.0 320.0 140.0 37 473.0 354.0 428.0 337.0 438.0 237.0 438.0 237.0 438.0 390.0 159.0 14 453.0 300.0 14 450.0 30 |    |       |       |       |
| 19   |    |       |       |       |
| 6       78.0       404.0       NaN         27       90.0       NaN       309.0         3       113.0       228.0       497.0         28       118.0       489.0       327.0         10       119.0       338.0       104.0         48       163.0       411.0       173.0         29       199.0       180.0       63.0         24       199.0       400.0       59.0         41       213.0       279.0       286.0         33       216.0       NaN       292.0         30       224.0       374.0       NaN         39       225.0       84.0       NaN         12       265.0       114.0       156.0         26       283.0       177.0       338.0         2       287.0       57.0       460.0         17       303.0       404.0       119.0         46       335.0       202.0       140.0         7       395.0       130.0       410.0         49       399.0       470.0       256.0         47       402.0       455.0       433.0         34       402.0   |    |       |       |       |
| 27       90.0       NaN       309.0         3       113.0       228.0       497.0         28       118.0       489.0       327.0         10       119.0       338.0       104.0         48       163.0       411.0       173.0         29       199.0       180.0       63.0         24       199.0       400.0       59.0         41       213.0       279.0       286.0         33       216.0       NaN       292.0         30       224.0       374.0       NaN         39       225.0       84.0       NaN         12       265.0       114.0       156.0         26       283.0       177.0       338.0         2       287.0       57.0       460.0         17       303.0       404.0       119.0         46       335.0       202.0       140.0         7       395.0       130.0       410.0         42       396.0       226.0       NaN         49       399.0       470.0       256.0         47       402.0       455.0       433.0         34       402.0   |    |       |       |       |
| 3       113.0       228.0       497.0         28       118.0       489.0       327.0         10       119.0       338.0       104.0         48       163.0       411.0       173.0         29       199.0       180.0       63.0         24       199.0       400.0       59.0         41       213.0       279.0       286.0         33       216.0       NaN       292.0         30       224.0       374.0       NaN         39       225.0       84.0       NaN         12       265.0       114.0       156.0         26       283.0       177.0       338.0         2       287.0       57.0       460.0         17       303.0       404.0       119.0         46       335.0       202.0       140.0         7       395.0       130.0       410.0         42       396.0       226.0       NaN         49       399.0       470.0       256.0         47       402.0       455.0       433.0         34       402.0       188.0       103.0         45       410.0  |    |       |       |       |
| 28       118.0       489.0       327.0         10       119.0       338.0       104.0         48       163.0       411.0       173.0         29       199.0       180.0       63.0         24       199.0       400.0       59.0         41       213.0       279.0       286.0         33       216.0       NaN       292.0         30       224.0       374.0       NaN         39       225.0       84.0       NaN         12       265.0       114.0       156.0         26       283.0       177.0       338.0         2       287.0       57.0       460.0         17       303.0       404.0       119.0         46       335.0       202.0       140.0         7       395.0       130.0       410.0         42       396.0       226.0       NaN         49       399.0       470.0       256.0         47       402.0       455.0       433.0         34       402.0       188.0       103.0         45       410.0       203.0       NaN         13       423.0   |    |       |       |       |
| 10 119.0 338.0 104.0 48 163.0 411.0 173.0 29 199.0 180.0 63.0 24 199.0 400.0 59.0 41 213.0 279.0 286.0 33 216.0 NaN 292.0 30 224.0 374.0 NaN 12 265.0 114.0 156.0 26 283.0 177.0 338.0 2 287.0 57.0 460.0 17 303.0 404.0 119.0 46 335.0 202.0 140.0 7 395.0 130.0 410.0 42 396.0 226.0 NaN 49 399.0 470.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 404.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 448.0 390.0 159.0 14 453.0 340.0 360.0 36 433.0 340.0 250.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0 345.0  |    |       |       |       |
| 48 163.0 411.0 173.0 29 199.0 180.0 63.0 24 199.0 400.0 59.0 41 213.0 279.0 286.0 33 216.0 NaN 292.0 30 224.0 374.0 NaN 292.0 84.0 NaN 225.0 84.0 NaN 22 265.0 114.0 156.0 26 283.0 177.0 338.0 2 287.0 57.0 460.0 17 303.0 404.0 119.0 46 335.0 202.0 140.0 7 395.0 130.0 410.0 42 396.0 226.0 NaN 49 399.0 470.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 25 409.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 3283.0 237.0 4 438.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 171.0 NaN 22 NaN 336.0 24.0  | 28 | 118.0 | 489.0 | 327.0 |
| 29       199.0       180.0       63.0         24       199.0       400.0       59.0         41       213.0       279.0       286.0         33       216.0       NaN       292.0         30       224.0       374.0       NaN         39       225.0       84.0       NaN         12       265.0       114.0       156.0         26       283.0       177.0       338.0         2       287.0       57.0       460.0         17       303.0       404.0       119.0         46       335.0       202.0       140.0         7       395.0       130.0       410.0         42       396.0       226.0       NaN         49       399.0       470.0       256.0         47       402.0       455.0       433.0         34       402.0       188.0       103.0         16       408.0       443.0       49.0         25       409.0       207.0       149.0         45       410.0       203.0       NaN         13       423.0       190.0       347.0         4       438.0   | 10 |       |       |       |
| 24       199.0       400.0       59.0         41       213.0       279.0       286.0         33       216.0       NaN       292.0         30       224.0       374.0       NaN         39       225.0       84.0       NaN         12       265.0       114.0       156.0         26       283.0       177.0       338.0         2       287.0       57.0       460.0         17       303.0       404.0       119.0         46       335.0       202.0       140.0         7       395.0       130.0       410.0         42       396.0       226.0       NaN         49       399.0       470.0       256.0         47       402.0       455.0       433.0         34       402.0       188.0       103.0         16       408.0       443.0       49.0         25       409.0       207.0       149.0         45       410.0       203.0       NaN         13       423.0       190.0       347.0         44       432.0       1.0       306.0         36       433.0   | 48 | 163.0 | 411.0 |       |
| 41 213.0 279.0 286.0 33 216.0 NaN 292.0 30 224.0 374.0 NaN 39 225.0 84.0 NaN 12 265.0 114.0 156.0 26 283.0 177.0 338.0 2 287.0 57.0 460.0 17 303.0 404.0 119.0 46 335.0 202.0 140.0 7 395.0 130.0 410.0 42 396.0 226.0 NaN 49 399.0 470.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 25 409.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 324.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0   | 29 | 199.0 | 180.0 | 63.0  |
| 33 216.0 NaN 292.0 30 224.0 374.0 NaN 39 225.0 84.0 NaN 12 265.0 114.0 156.0 26 283.0 177.0 338.0 2 287.0 57.0 460.0 17 303.0 404.0 119.0 46 335.0 202.0 140.0 7 395.0 130.0 410.0 42 396.0 226.0 NaN 49 399.0 470.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 25 409.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0   | 24 |       | 400.0 | 59.0  |
| 30 224.0 374.0 NaN 39 225.0 84.0 NaN 12 265.0 114.0 156.0 26 283.0 177.0 338.0 2 287.0 57.0 460.0 17 303.0 404.0 119.0 46 335.0 202.0 140.0 7 395.0 130.0 410.0 42 396.0 226.0 NaN 49 399.0 470.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 25 409.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 38 474.0 276.0 345.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0   | 41 |       | 279.0 | 286.0 |
| 39 225.0 84.0 NaN 12 265.0 114.0 156.0 26 283.0 177.0 338.0 2 287.0 57.0 460.0 17 303.0 404.0 119.0 46 335.0 202.0 140.0 7 395.0 130.0 410.0 42 396.0 226.0 NaN 49 399.0 470.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 25 409.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 38 474.0 276.0 345.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0  | 33 | 216.0 | NaN   | 292.0 |
| 12 265.0 114.0 156.0 26 283.0 177.0 338.0 2 287.0 57.0 460.0 17 303.0 404.0 119.0 46 335.0 202.0 140.0 7 395.0 130.0 410.0 42 396.0 226.0 NaN 49 399.0 470.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 25 409.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0  | 30 | 224.0 | 374.0 | NaN   |
| 26       283.0       177.0       338.0         2       287.0       57.0       460.0         17       303.0       404.0       119.0         46       335.0       202.0       140.0         7       395.0       130.0       410.0         42       396.0       226.0       NaN         49       399.0       470.0       256.0         47       402.0       455.0       433.0         34       402.0       188.0       103.0         16       408.0       443.0       49.0         25       409.0       207.0       149.0         45       410.0       203.0       NaN         13       423.0       190.0       347.0         44       432.0       1.0       306.0         36       433.0       283.0       237.0         4       438.0       390.0       159.0         14       453.0       424.0       280.0         37       473.0       354.0       448.0         38       474.0       276.0       345.0         31       491.0       65.0       164.0         8       NaN  | 39 | 225.0 | 84.0  | NaN   |
| 2 287.0 57.0 460.0 17 303.0 404.0 119.0 46 335.0 202.0 140.0 7 395.0 130.0 410.0 42 396.0 226.0 NaN 49 399.0 470.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 25 409.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0  | 12 |       |       | 156.0 |
| 17 303.0 404.0 119.0 46 335.0 202.0 140.0 7 395.0 130.0 410.0 42 396.0 226.0 NaN 49 399.0 470.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 25 409.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0   | 26 |       | 177.0 | 338.0 |
| 46 335.0 202.0 140.0 7 395.0 130.0 410.0 42 396.0 226.0 NaN 49 399.0 470.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 25 409.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0  | 2  | 287.0 | 57.0  | 460.0 |
| 7 395.0 130.0 410.0 42 396.0 226.0 NaN 49 399.0 470.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 25 409.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0   | 17 | 303.0 | 404.0 | 119.0 |
| 42 396.0 226.0 NaN 49 399.0 470.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 25 409.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0   | 46 | 335.0 | 202.0 | 140.0 |
| 49 399.0 470.0 256.0 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 458.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0  |    | 395.0 | 130.0 | 410.0 |
| 47 402.0 455.0 433.0 34 402.0 188.0 103.0 16 408.0 443.0 49.0 25 409.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 458.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0   | 42 | 396.0 | 226.0 | NaN   |
| 34 402.0 188.0 103.0 16 408.0 443.0 49.0 25 409.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0  | 49 | 399.0 | 470.0 | 256.0 |
| 16 408.0 443.0 49.0 25 409.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0   | 47 | 402.0 | 455.0 | 433.0 |
| 25 409.0 207.0 149.0 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0   | 34 | 402.0 | 188.0 | 103.0 |
| 45 410.0 203.0 NaN 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0  | 16 | 408.0 | 443.0 | 49.0  |
| 13 423.0 190.0 347.0 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0   | 25 | 409.0 | 207.0 | 149.0 |
| 44 432.0 1.0 306.0 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0  | 45 | 410.0 | 203.0 | NaN   |
| 36 433.0 283.0 237.0 4 438.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0   | 13 | 423.0 | 190.0 | 347.0 |
| 4 438.0 390.0 159.0 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0  | 44 | 432.0 | 1.0   | 306.0 |
| 14 453.0 424.0 280.0 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0  | 36 | 433.0 | 283.0 | 237.0 |
| 37 473.0 354.0 448.0 38 474.0 276.0 345.0 32 483.0 274.0 120.0 31 491.0 65.0 164.0 8 NaN 79.0 128.0 20 NaN 379.0 38.0 21 NaN 171.0 NaN 22 NaN 336.0 24.0   | 4  | 438.0 | 390.0 | 159.0 |
| 38 474.0 276.0 345.0<br>32 483.0 274.0 120.0<br>31 491.0 65.0 164.0<br>8 NaN 79.0 128.0<br>20 NaN 379.0 38.0<br>21 NaN 171.0 NaN<br>22 NaN 336.0 24.0  | 14 | 453.0 | 424.0 | 280.0 |
| 32 483.0 274.0 120.0<br>31 491.0 65.0 164.0<br>8 NaN 79.0 128.0<br>20 NaN 379.0 38.0<br>21 NaN 171.0 NaN<br>22 NaN 336.0 24.0  | 37 | 473.0 | 354.0 | 448.0 |
| 31 491.0 65.0 164.0<br>8 NaN 79.0 128.0<br>20 NaN 379.0 38.0<br>21 NaN 171.0 NaN<br>22 NaN 336.0 24.0  | 38 | 474.0 | 276.0 | 345.0 |
| 8 NaN 79.0 128.0<br>20 NaN 379.0 38.0<br>21 NaN 171.0 NaN<br>22 NaN 336.0 24.0   | 32 | 483.0 | 274.0 | 120.0 |
| 20 NaN 379.0 38.0<br>21 NaN 171.0 NaN<br>22 NaN 336.0 24.0   | 31 | 491.0 | 65.0  | 164.0 |
| 21 NaN 171.0 NaN<br>22 NaN 336.0 24.0  | 8  | NaN   | 79.0  | 128.0 |
| 22 NaN 336.0 24.0  | 20 | NaN   | 379.0 | 38.0  |
|  | 21 | NaN   | 171.0 | NaN   |
| 40 NaN 116.0 326.0   | 22 | NaN   | 336.0 | 24.0  |
|  | 40 | NaN   | 116.0 | 326.0 |

e. Remove all duplicates from the first column.

### **Code:**

```
print(df.drop_duplicates([0]))
```

```
0
            1
    12.0 358.0 248.0
0
1
   10.0 379.0
               90.0
2
   287.0
         57.0 460.0
   113.0 228.0 497.0
  438.0 390.0 159.0
5
   69.0
         70.0
               35.0
6
  78.0 404.0
                NaN
7
  395.0 130.0 410.0
         79.0 128.0
8
   NaN
9
   33.0 172.0 353.0
10 119.0 338.0 104.0
12 265.0 114.0 156.0
13 423.0 190.0 347.0
14 453.0 424.0 280.0
15
   25.0 155.0
               NaN
16 408.0 443.0
               49.0
17 303.0 404.0 119.0
18
   32.0
         10.0 355.0
   77.0 438.0 65.0
19
23 35.0 466.0
               NaN
24 199.0 400.0
              59.0
25 409.0 207.0 149.0
26 283.0 177.0 338.0
   90.0
27
         NaN 309.0
28 118.0 489.0 327.0
30 224.0 374.0
                NaN
31 491.0 65.0 164.0
32 483.0 274.0 120.0
33 216.0
         NaN 292.0
34 402.0 188.0 103.0
   58.0 185.0 468.0
35
36 433.0 283.0 237.0
37 473.0 354.0 448.0
38 474.0 276.0 345.0
39 225.0
         84.0
41 213.0 279.0 286.0
42 396.0 226.0
               NaN
44 432.0
         1.0 306.0
45 410.0 203.0
               NaN
46 335.0 202.0 140.0
48 163.0 411.0 173.0
49 399.0 470.0 256.0
```

f. Find the correlation between first and second column and covariance between second and third column.

### **Code:**

```
print(df[0].corr(df[1]))
print(df[1].corr(df[2]))
```

### **Output:**

- -0.10775273312299381 -0.17241754130534206
  - g. Discretize the second column and create 5 bins.

### **Code:**

```
bins = [0, 100, 200, 300, 400, 500]
pd.cut(df[1], bins)
```

(Output on Next Page)

```
(300.0, 400.0]
0
      (300.0, 400.0]
       (0.0, 100.0]
2
    (200.0, 300.0]
3
     (300.0, 400.0]
4
5
       (0.0, 100.0]
6
     (400.0, 500.0]
7
     (100.0, 200.0]
       (0.0, 100.0]
8
     (100.0, 200.0]
9
10
     (300.0, 400.0]
      (400.0, 500.0]
11
      (100.0, 200.0]
12
13
      (100.0, 200.0]
      (400.0, 500.0]
14
15
      (100.0, 200.0]
16
      (400.0, 500.0]
      (400.0, 500.0]
17
       (0.0, 100.0]
18
      (400.0, 500.0]
19
20
      (300.0, 400.0]
      (100.0, 200.0]
21
      (300.0, 400.0]
22
      (400.0, 500.0]
23
24
      (300.0, 400.0]
25
      (200.0, 300.0]
26
      (100.0, 200.0]
27
      (400.0, 500.0]
28
29
     (100.0, 200.0]
     (300.0, 400.0]
30
31
       (0.0, 100.0]
      (200.0, 300.0]
32
33
      (100.0, 200.0]
34
     (100.0, 200.0]
35
36
      (200.0, 300.0]
37
      (300.0, 400.0]
      (200.0, 300.0]
38
39
       (0.0, 100.0]
      (100.0, 200.0]
40
41
      (200.0, 300.0]
      (200.0, 300.0]
42
      (300.0, 400.0]
43
44
       (0.0, 100.0]
      (200.0, 300.0]
45
46
      (200.0, 300.0]
      (400.0, 500.0]
47
48
      (400.0, 500.0]
      (400.0, 500.0]
Name: 1, dtype: category
Categories (5, interval[int64, right]): [(0, 100] < (100, 200] < (200, 300] < (300, 400] <
(400, 500]]
```

**Q4.** Consider two excel files having attendance of two workshops. Each file has three fields 'Name', 'Date', 'Duration (in minutes)' where names are unique within a file. Note that duration may take one of three values (30, 40, 50) only. Import the data into two data frames.

### File contents: (work1.csv and work2.csv respectively)

|   | Α      | В          | С        |
|---|--------|------------|----------|
| 1 | Name   | Date       | Duration |
| 2 | Anya   | 01-07-2023 | 30       |
| 3 | Amit   | 01-07-2023 | 40       |
| 4 | Geeti  | 01-07-2023 | 50       |
| 5 | Shikha | 01-07-2023 | 30       |

|   | Α      | В          | С        |
|---|--------|------------|----------|
| 1 | Name   | Date       | Duration |
| 2 | Shikha | 02-07-2023 | 50       |
| 3 | Amit   | 02-07-2023 | 50       |
| 4 | Arun   | 02-07-2023 | 30       |

**Code:** (Importing the data into data frames)

```
import numpy as np
import pandas as pd

work1_df = pd.read_csv("C:\\Users\\Student_2\\Desktop\\work1.csv")
work2_df = pd.read_csv("C:\\Users\\Student_2\\Desktop\\work2.csv")
print(work1_df)
print(work2_df)
```

|   | Name   | Date       | Duration |
|---|--------|------------|----------|
| 0 | Anya   | 01-07-2023 | 30       |
| 1 | Amit   | 01-07-2023 | 40       |
| 2 | Geeti  | 01-07-2023 | 50       |
| 3 | Shikha | 01-07-2023 | 30       |
|   | Name   | Date       | Duration |
| 0 | Shikha | 02-07-2023 | 50       |
| 1 | Amit   | 02-07-2023 | 50       |
| 2 | Arun   | 02-07-2023 | 30       |

Now, do the following:

a. Perform merging of the two data frames to find the names of students who had attended both workshops.

### Code:

```
print("Students who have attended both the workshops are...\n",
    pd.merge(work1_df, work2_df, on="Name"))
```

### **Output:**

```
        Students who have attended both the workshops are...

        Name
        Date_x
        Duration_x
        Date_y
        Duration_y

        0
        Amit 01-07-2023
        40 02-07-2023
        50

        1
        Shikha 01-07-2023
        30 02-07-2023
        50
```

b. Find names of all students who have attended a single workshop only.

#### Code:

```
print("Students who have attended a single workshop are...\n",
    pd.concat([work1_df, work2_df]).drop_duplicates("Name", keep=False))
```

```
Students who have attended a single workshop are...

Name Date Duration

Anya 01-07-2023 30

Geeti 01-07-2023 50

Arun 02-07-2023 30
```

c. Merge two data frames row-wise and find the total number of records in the data frames.

### **Code:**

```
mer_row = pd.concat([work1_df, work2_df]).reset_index(drop=True)
print("Merging data frames row wise\n", mer_row)
print("Total number of records in the data frames:", mer_row.shape[0])
```

### Output:

```
Merging data frames row wise
    Name Date Duration
  Anya 01-07-2023
                        30
1 Amit 01-07-2023
                        40
2 Geeti 01-07-2023
                       50
3 Shikha 01-07-2023
                       30
4 Shikha 02-07-2023
                       50
   Amit 02-07-2023
   Arun 02-07-2023
                       30
Total number of records in the data frames: 7
```

d. Merge two data frames row-wise and use two columns viz. names and dates as multi-row indexes.

### **Code:**

|        |            | Duration |
|--------|------------|----------|
| Name   | Date       |          |
| Anya   | 01-07-2023 | 30       |
| Amit   | 01-07-2023 | 40       |
| Geeti  | 01-07-2023 | 50       |
| Shikha | 01-07-2023 | 30       |
|        | 02-07-2023 | 50       |
| Amit   | 02-07-2023 | 50       |
| Arun   | 02-07-2023 | 30       |

Generate descriptive statistics for this hierarchical data frame.

### **Code:**

```
des_stats = multi_index.describe()
print(des_stats)
```

|       | Duration |
|-------|----------|
| count | 7.0      |
| mean  | 40.0     |
| std   | 10.0     |
| min   | 30.0     |
| 25%   | 30.0     |
| 50%   | 40.0     |
| 75%   | 50.0     |
| max   | 50.0     |

**Q5.** Using Iris data, plot the following with proper legend and axis labels: (Download IRIS data from: <a href="https://archive.ics.uci.edu/ml/datasets/iris">https://archive.ics.uci.edu/ml/datasets/iris</a> or import it from sklearn datasets)

### **Code:**

(Importing necessary libraries)

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from scipy import stats
```

### (Loading IRIS data)

```
iris = load_iris()
data = pd.DataFrame(data=iris.data, columns=iris.feature_names)
target = iris.target
target_names = iris.target_names
print(data)
```

### **Output:**

|     | sepal length (cm) | sepal width (cm) | petal length (cm) | petal width (cm) |
|-----|-------------------|------------------|-------------------|------------------|
| 0   | 5.1               | 3.5              | 1.4               | 0.2              |
| 1   | 4.9               | 3.0              | 1.4               | 0.2              |
| 2   | 4.7               | 3.2              | 1.3               | 0.2              |
| 3   | 4.6               | 3.1              | 1.5               | 0.2              |
| 4   | 5.0               | 3.6              | 1.4               | 0.2              |
|     |                   |                  |                   |                  |
| 145 | 6.7               | 3.0              | 5.2               | 2.3              |
| 146 | 6.3               | 2.5              | 5.0               | 1.9              |
| 147 | 6.5               | 3.0              | 5.2               | 2.0              |
| 148 | 6.2               | 3.4              | 5.4               | 2.3              |
| 149 | 5.9               | 3.0              | 5.1               | 1.8              |

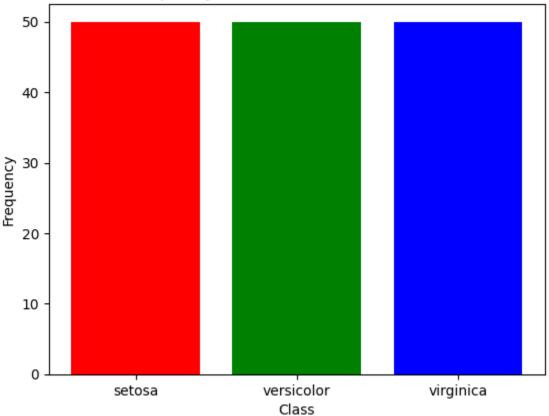
[150 rows x 4 columns]

a. Plot bar chart to show the frequency of each class label in the data.

### **Code:**

```
class_counts = data.groupby(target_names[target]).size()
plt.bar(target_names, class_counts, color=["red","green","blue"])
plt.xlabel("Class")
plt.ylabel("Frequency")
plt.title("Frequency of Class Labels in Iris Dataset")
plt.show()
```

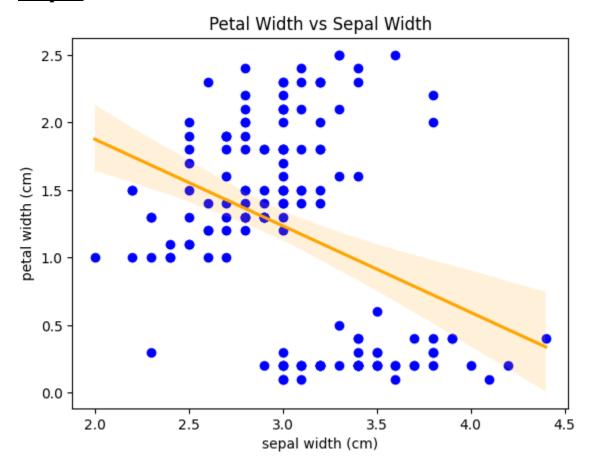




b. Draw a scatter plot for Petal width vs sepal width and fit a regression line

### **Code:**

```
plt.scatter(data["sepal width (cm)"], data["petal width (cm)"], color="blue")
plt.xlabel("Sepal Width (cm)")
plt.ylabel("Petal Width (cm)")
plt.title("Petal Width vs Sepal Width")
sns.regplot(x="sepal width (cm)", y="petal width (cm)", data=data, scatter=False, color="orange")
plt.show()
```

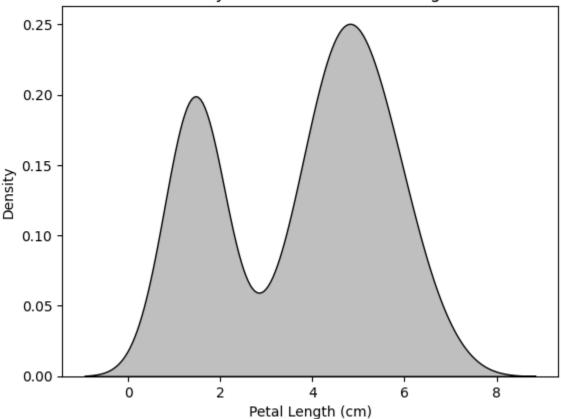


c. Plot density distribution for feature petal length.

### **Code:**

```
sns.kdeplot(data["petal length (cm)"], fill=True, color="black")
plt.xlabel("Petal Length (cm)")
plt.ylabel("Density")
plt.title("Density Distribution of Petal Length")
plt.show()
```

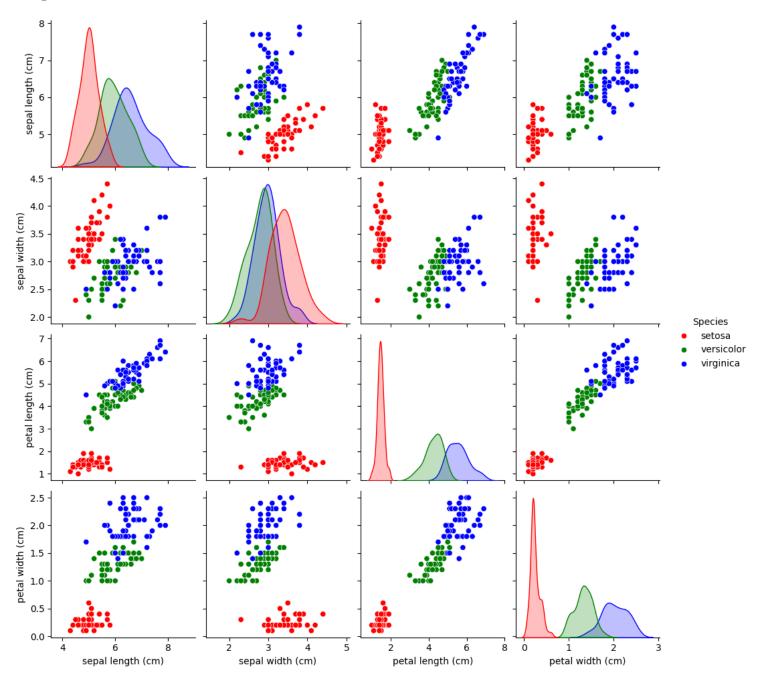




d. Use a pair plot to show pairwise bivariate distribution in the Iris Dataset.

### **Code:**

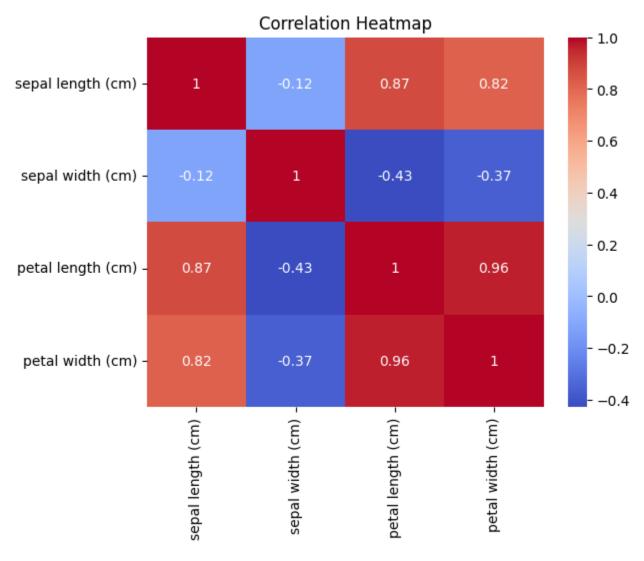
```
classes = {0:"setosa", 1:"versicolor", 2:"virginica"}
data["Target"] = iris.target
data["Species"] = data["Target"].map(classes)
data.drop("Target", axis=1, inplace=True)
sns.pairplot(data=data, hue="Species", palette=["Red", "Green", "Blue"])
plt.show()
```



### e. Draw heatmap for the four numeric attributes

### **Code:**

```
data.drop("Species", axis=1, inplace=True)
sns.heatmap(data.corr(), annot=True, cmap="coolwarm")
plt.title("Correlation Heatmap")
plt.show()
```



f. Compute mean, mode, median, standard deviation, confidence interval and standard error for each feature

#### **Code:**

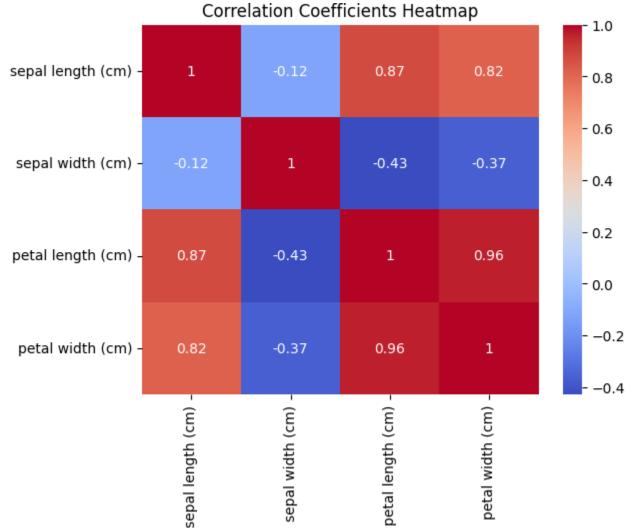
```
sepal length (cm) sepal width (cm) petal length (cm) \
Mean
                            5.843333
                                             3.057333
                                                                3.758000
                            0.828066
                                                                1.765298
Standard Deviation
                                             0.435866
Mode
                            5.000000
                                             3.000000
                                                                1.400000
CI
                                                  Nan
                                                                     Nan
                                NaN
                  petal width (cm) \
Mean
                           1.199333
Standard Deviation
                           0.762238
Median
                           1.300000
Mode
                           0.200000
CI
                               NaN
                                                         95% CI Min \
Mean
                                                                NaN
Standard Deviation
Median
Mode
CI
                   [5.709732481507367, 2.9870103180785437, 3.4731...
                                                         95% CI Max
Mean
                                                                NaN
Standard Deviation
Median
Mode
                                                                NaN
                   [5.976934185159302, 3.1276563485881246, 4.0428...
```

g. Compute correlation coefficients between each pair of features and plot heatmap

### **Code:**

```
correlation_matrix = data.corr()
print(correlation_matrix)
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm")
plt.title("Correlation Coefficients Heatmap")
plt.show()
```

```
sepal length (cm) sepal width (cm) petal length (cm) \
sepal length (cm)
                           1.000000
                                            -0.117570
                                                                 0.871754
sepal width (cm)
                           -0.117570
                                             1.000000
                                                                -0.428440
petal length (cm)
                           0.871754
                                             -0.428440
                                                                1.000000
petal width (cm)
                           0.817941
                                            -0.366126
                                                                 0.962865
                   petal width (cm)
sepal length (cm)
                          0.817941
sepal width (cm)
                         -0.366126
petal length (cm)
                          0.962865
petal width (cm)
                          1.000000
```



**Q6.** Consider the following data frame containing a family name, gender of the family member and her/his monthly income in each record.

| Name  | Gender | MonthlyIncome (Rs.) |
|-------|--------|---------------------|
| Shah  | Male   | 114000.00           |
| Vats  | Male   | 65000.00            |
| Vats  | Female | 43150.00            |
| Kumar | Female | 69500.00            |
| Vats  | Female | 155000.00           |
| Kumar | Male   | 103000.00           |
| Shah  | Male   | 55000.00            |
| Shah  | Female | 112400.00           |
| Kumar | Female | 81030.00            |
| Vats  | Male   | 71900.00            |

### **Code:** (Creating the required data frame)

```
import numpy as np
import pandas as pd
df = pd.read_csv("family.csv")
print(df)
```

|   | Name  | Gender | MonthlyIncome |
|---|-------|--------|---------------|
| 0 | Shah  | Male   | 114000.0      |
| 1 | Vats  | Male   | 65000.0       |
| 2 | Vats  | Female | 43150.0       |
| 3 | Kumar | Female | 69500.0       |
| 4 | Vats  | Female | 155000.0      |
| 5 | Kumar | Male   | 103000.0      |
| 6 | Shah  | Male   | 55000.0       |
| 7 | Shah  | Female | 112400.0      |
| 8 | Kumar | Female | 81030.0       |
| 9 | Vats  | Male   | 71900.0       |

Write a program in Python using Pandas to perform the following:

a. Calculate and display familywise gross monthly income.

### **Code:**

```
print("The familywise gross monthly income is:")
df.groupby(['Name'])['MonthlyIncome'].sum()
```

### **Output:**

```
The familywise gross monthly income is:
Name
Kumar 253530.0
Shah 281400.0
Vats 335050.0
Name: MonthlyIncome, dtype: float64
```

b. Calculate and display the member with the highest monthly income.

### **Code:**

```
print("Highest monthly income in each family:")
df.groupby(['Name'])['MonthlyIncome'].max()
```

```
Highest monthly income in each family:
Name
Kumar 103000.0
Shah 114000.0
Vats 155000.0
Name: MonthlyIncome, dtype: float64
```

c. Calculate and display monthly income of all members with income greater than  ${\rm Rs.}\,60000.00$ .

### **Code:**

```
print("Members with monthly income more than Rs. 60000:")
df[df["MonthlyIncome"]>60000]
```

### **Output:**

Members with monthly income more than Rs. 60000:

|   | Name  | Gender | MonthlyIncome |
|---|-------|--------|---------------|
| 0 | Shah  | Male   | 114000.0      |
| 1 | Vats  | Male   | 65000.0       |
| 3 | Kumar | Female | 69500.0       |
| 4 | Vats  | Female | 155000.0      |
| 5 | Kumar | Male   | 103000.0      |
| 7 | Shah  | Female | 112400.0      |
| 8 | Kumar | Female | 81030.0       |
| 9 | Vats  | Male   | 71900.0       |

d. Calculate and display the average monthly income of the female members

### **Code:**

### **Output:**

The average monthly income of the female members is Rs. 92216.0

**Q7.** Using Titanic dataset, to do the following:

**Code:** (Importing **seaborn** and loading TITANIC data)

```
import seaborn as sns
sns.set_style("whitegrid")
titanic = sns.load_dataset("titanic")
titanic
```

### **Output:**

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

891 rows × 15 columns

a. Find total number of passengers with age less than 30

### **Code:**

```
print("There are", sum(titanic.age < 30), "passengers under the age of 30.")</pre>
```

### Output:

There are 384 passengers under the age of 30.

b. Find total fare paid by passengers of first class

### **Code:**

```
print("Total fare paid by first class passengers:", titanic[titanic.pclass == 1].fare.sum())
```

### Output:

Total fare paid by first class passengers: 18177.4125

c. Compare number of survivors of each passenger class

### **Code:**

```
print("Number of survivors of each passenger class")
titanic.groupby("pclass").survived.sum()
```

### **Output:**

```
Number of survivors of each passenger class
pclass
1 136
2 87
3 119
Name: survived, dtype: int64
```

d. Compute descriptive statistics for any numeric attribute genderwise

### **Code:**

```
print("Genderwise age descriptive statistics:")
titanic.groupby("sex").age.describe()
```

### **Output:**

Genderwise age descriptive statistics:

|        | count | mean      | std       | min  | 25%  | 50%  | <b>75</b> % | max  |
|--------|-------|-----------|-----------|------|------|------|-------------|------|
| sex    |       |           |           |      |      |      |             |      |
| female | 261.0 | 27.915709 | 14.110146 | 0.75 | 18.0 | 27.0 | 37.0        | 63.0 |
| male   | 453.0 | 30.726645 | 14.678201 | 0.42 | 21.0 | 29.0 | 39.0        | 80.0 |