

All about Data Engineering

Python Pandas The definitive hands on guide

Swipe Right



Pandas from basic to advanced

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Table of Content

1. Introduction
 - 1.1 What is pandas? and Why it is important?
 - 1.2 What is the version of pandas used in this notebook?
2. Pandas' fundamental operations
 - 2.1 Series
 - 2.1.1 Create series
 - 2.1.2 Info. about the series
 - 2.1.3 How to access and slice data in a Series?
 - 2.1.4 Customize the index
 - 2.2 List and List operations by Pandas
3. Data Visualization with Pandas
4. DataFrames
 - 4.1 Creating DataFrame
 - 4.1.1 Creating DF from array
 - 4.1.2 Creating DF from list
 - 4.1.3 Creating DF from many Series
 - 4.1.4 Creating DF by Dictionary Method
 - 4.1.5 Creating DF by function (advanced method)
 - 4.2 Basic Operations on DataFrame

- 4.2.1 Slicing or accessing columns in the DF
- 4.2.2 Transpose the DF
- 4.2.3 Accessing only keys or values from the DF
- 4.2.4 Applying conditions to specific keys or values in the DF
- 4.2.5 Vertical representation of elements with keys and values
- 4.2.6 Locating specific elements for slicing and searching within the DF
- 4.2.7 Access names of all columns and the index in the DF
- 4.2.8 Sort the elements in the DF
- 4.2.9 Statistics for the entire DF or per column
- 4.2.10 The correlation between elements in the DF
- 4.2.11 The skewness among the elements of each column in the DF
- 4.2.12 Arithmetic operations between Columns
- 4.2.13 Selecting a Specific Row by Conditions

4.3 Table Concatenation and Merging

- 4.3.1 Simple Concatenation
- 4.3.2 Set logic on the other axes
- 4.3.3 Ignoring indexes on the concatenation axis
- 4.3.4 Merging DataFrames
- 4.3.5 Set logic on the other axes during merging

4.4 Advanced operations on DataFrames

- 4.4.1 Statistics for the entire DF
- 4.4.2 Statistics on one Column of the DF
- 4.4.3 Statistics on all columns of the DF
- 4.4.4 Statistics on all rows of the DF
- 4.4.5 Statistics on the entire DF using the Describe method
- 4.4.6 Groupby
- 4.4.7 Grouping with the Describe Method

4.5 Data Transformation and Handling Missing Data

- 4.5.1 How to Address Missing Data ?
- 4.5.2 Dropping Unnecessary Data
- 4.5.3 Dropping Rows with Any Missing Values
- 4.5.4 Detecting All Missing Values
- 4.5.5 Eliminating Duplicates
- 4.5.6 Control Eliminating Duplicates
- 4.5.7 Transforming Data Using the replace() Function
- 4.5.8 Analysis of Categorical Data

5. Multi Index

5.1 Creating a 3D hierarchical table using MultiIndex or other methods.

- 5.1.1 Creating a hierarchical table with a MultiIndex
- 5.1.2 Creating a hierarchical table with a DataFrame
- 5.1.3 Creating a hierarchical table with a dictionary

5.2 Searching in the 3D Table by Year

5.3 Transforming the hierarchical table to a regular format using the unstack method

5.4 Adding one more column to the DataFrame

5.5 Examples of Complicated Tables with MultiIndex

6. Strings in pandas

7. Date & Time

7.1 Write Date in Pandas

7.2 Range between past and future dates

7.3 Write Dates & Tables

- 7.3.1 Creating a Table for Dates

- 7.3.2 Filtering based on dates: days, months, or years
- 7.3.3 Creating a table for dates with a range between two dates or starting from a specific day
- 7.3.4 Creating a table for dates with a range specified by hours only, excluding dates

8. File Handling (CSV files)

- 8.1 Read CSV or Excel file

- 8.2 Save DF as CSV or Excel file

- 8.3 Applying different methods while reading the DataFrame

- 8.3.1 Specify one column to be the index column
- 8.3.2 Skip some rows
- 8.3.3 Classify Data
- 8.3.4 Correlation and Skew

9. The Key Resources

1. Introduction

1.1 What is pandas? and Why it is important?

- Pandas offers an extensive array of tools designed for handling tabular data, encompassing tasks such as data cleaning, aggregation, and visualization.
- At the heart of Pandas is its core data structure, the DataFrame (DF), which represents a versatile two-dimensional table with flexible data types and operations.
- This structure facilitates efficient data manipulation, allowing for actions like indexing, slicing, and filtering.
- This notebook constitutes a component of my preparation for the application of machine learning (ML) models for drug design. Within this notebook, I aim to

curate a thorough compilation of commands, spanning from basic to advanced levels, for utilizing the Pandas library.

The version of pandas used in this notebook is '2.1.4'

1.2 What is the version of pandas used in this notebook?

The version of pandas used in this notebook is '2.1.4'

```
In [ ]: import pandas as pd  
pd.__version__
```

```
Out[ ]: '2.1.4'
```

2. Pandas' fundamental operations

2.1 Series

- Series in pandas is a one-dimensional labeled array, capable of holding data of any type and facilitating efficient data manipulation.
- We use Series to create 1D arrays or vectors, also known as 1D matrices

2.1.1 Create series

```
In [ ]: data = pd.Series([0.25, 0.5, 0.75, 1.0])  
print(data)
```

```
0    0.25  
1    0.50  
2    0.75  
3    1.00  
dtype: float64
```

2.1.2 Info. about the series

When seeking information about our data, we can obtain it through:

- **value** --> to retrieve the values within the dataset.
- **index** --> to ascertain the range of indices for all elements in the dataset.

```
In [ ]: data = pd.Series((0.25, 0.5, 0.75, 1.0))
# print(data.values)
# print(data.index)
print(data.keys)
```

```
<bound method Series.keys of 0    0.25
1    0.50
2    0.75
3    1.00
dtype: float64>
```

- The `describe` function provides statistical insights into our data, we used to use different function in numpy to obtain such information, but with pandas employing `describe` alone is sufficient.
- we have the flexibility to tailor the information obtained from `describe` using the `agg` command based on our specific requirements.

```
In [ ]: data = pd.Series((3,6,9,8,5,4,2,6,3,5,8))
print(data.describe())
```

```
count    11.000000
mean     5.363636
std      2.292280
min     2.000000
25%    3.500000
50%    5.000000
75%    7.000000
max    9.000000
dtype: float64
```

```
In [ ]: data = pd.Series((3,6,9,8,5,4,2,6,3,5,8))
print(data.agg(['max','min','sum','mean','std']))
```

```
max    9.000000
min    2.000000
sum   59.000000
mean   5.363636
std    2.292280
dtype: float64
```

2.1.3 How to access and slice data in a Series?

 Keep in your mind 🧐 --> `data[start : end : steps]`

```
In [ ]: data = pd.Series((0.25, 0.5, 0.75, 1.0))
print(data[1])
print(data[1:3])
print(data[1:3:2])
```

```
0.5  
1    0.50  
2    0.75  
dtype: float64  
1    0.5  
dtype: float64
```

2.1.4 Customize the index

How to manually manage and customize the index in Pandas for those who prefer not to use the default index provided by the library ?

- Method 1: List of Index - You can specify the index by providing a list with the number of indexes equal to the number of elements.
- Method 2: Dictionary Approach - You can utilize the dictionary format to define the index.

```
In [ ]: data1 = pd.Series([1,2,3,4], index=['a', 'b', 'c', 'd'])  
  
data2 = pd.Series({'a':1,'b':2,'c':3,'d':4})  
  
print(data1)  
print(data2)
```

```
a    1  
b    2  
c    3  
d    4  
dtype: int64  
a    1  
b    2  
c    3  
d    4  
dtype: int64
```

Then, we can access or slice by new indexes

```
In [ ]: import pandas as pd  
data1 = pd.Series([1,2,3,4], index=['a', 'b', 'c', 'd'])  
data2 = pd.Series({'a':1,'b':2,'c':3,'d':4})  
print(data1['a'])  
print(data2['b'])
```

```
1  
2
```

2.2 List and List operations by Pandas

In Pandas you can create list by use the `Index` class

```
In [ ]: x = pd.Index([2,3,5,7,11])
print(x)

Index([2, 3, 5, 7, 11], dtype='int64')
```

Then it is easy to deal with it as list and do other operations such as logic gates

```
In [ ]: import pandas as pd
a = pd.Index([1, 3, 5, 7, 9])
b = pd.Index([2, 3, 5, 7, 11])

print(a)
print(b)
print(a & b)
print(a | b)
print(a ^ b)

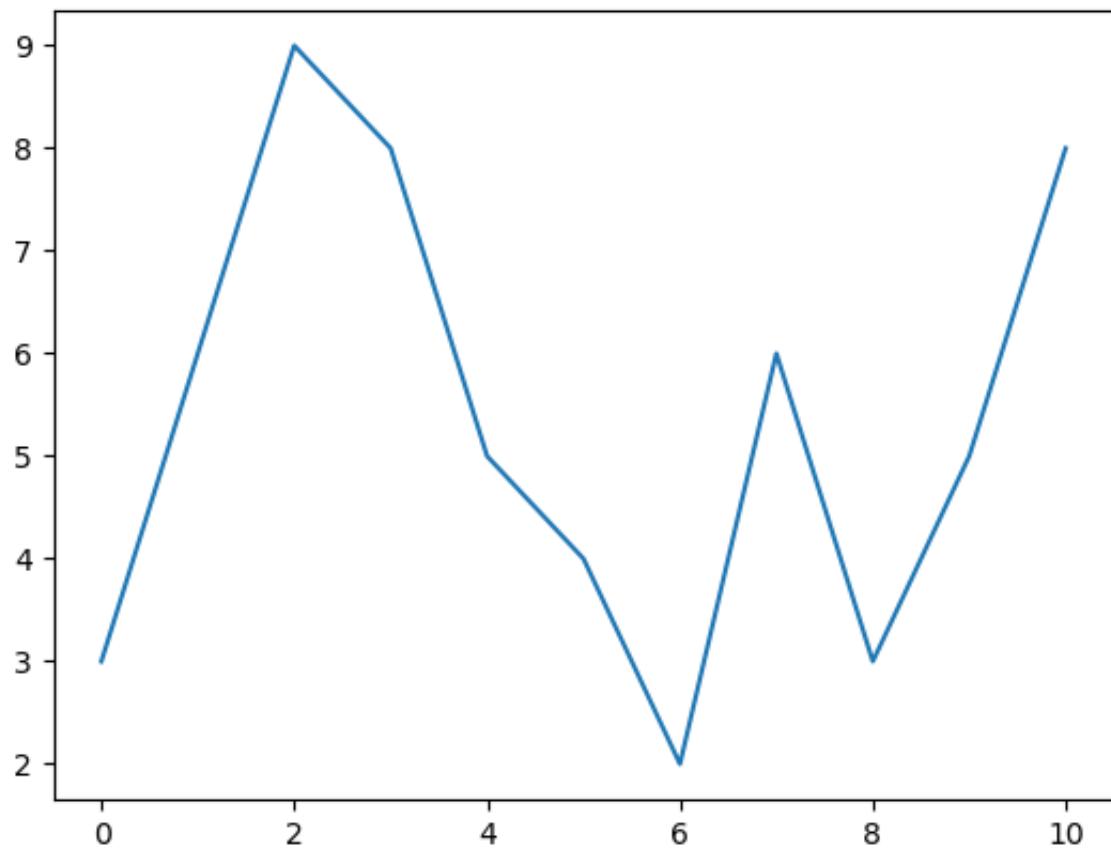
Index([1, 3, 5, 7, 9], dtype='int64')
Index([2, 3, 5, 7, 11], dtype='int64')
Index([0, 3, 5, 7, 9], dtype='int64')
Index([3, 3, 5, 7, 11], dtype='int64')
Index([3, 0, 0, 0, 2], dtype='int64')
```

3. Data Visualization with Pandas

Important Notes

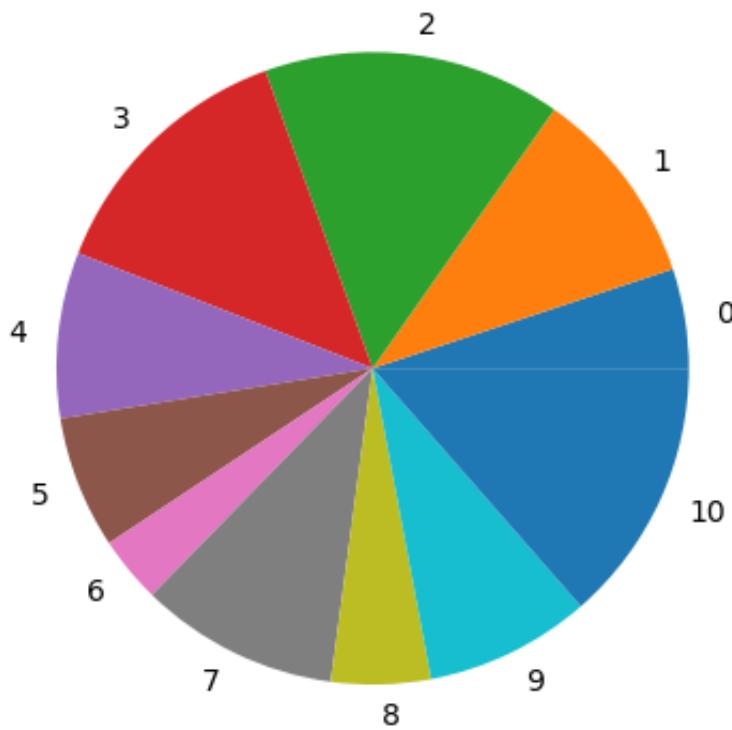
- When supplying only the 'y' data, Pandas plot will automatically create the x-axis data as 1, 2, 3, ..., aligning with the quantity of input data on the y-axis.
- The default `kind` parameter in the plot command is set to `line`. Therefore, if you desire a different plot type, you will need to specify it accordingly.
- Plot as line

```
In [ ]: data = pd.Series((3,6,9,8,5,4,2,6,3,5,8))
# data.plot()
data.plot(kind='line');
```



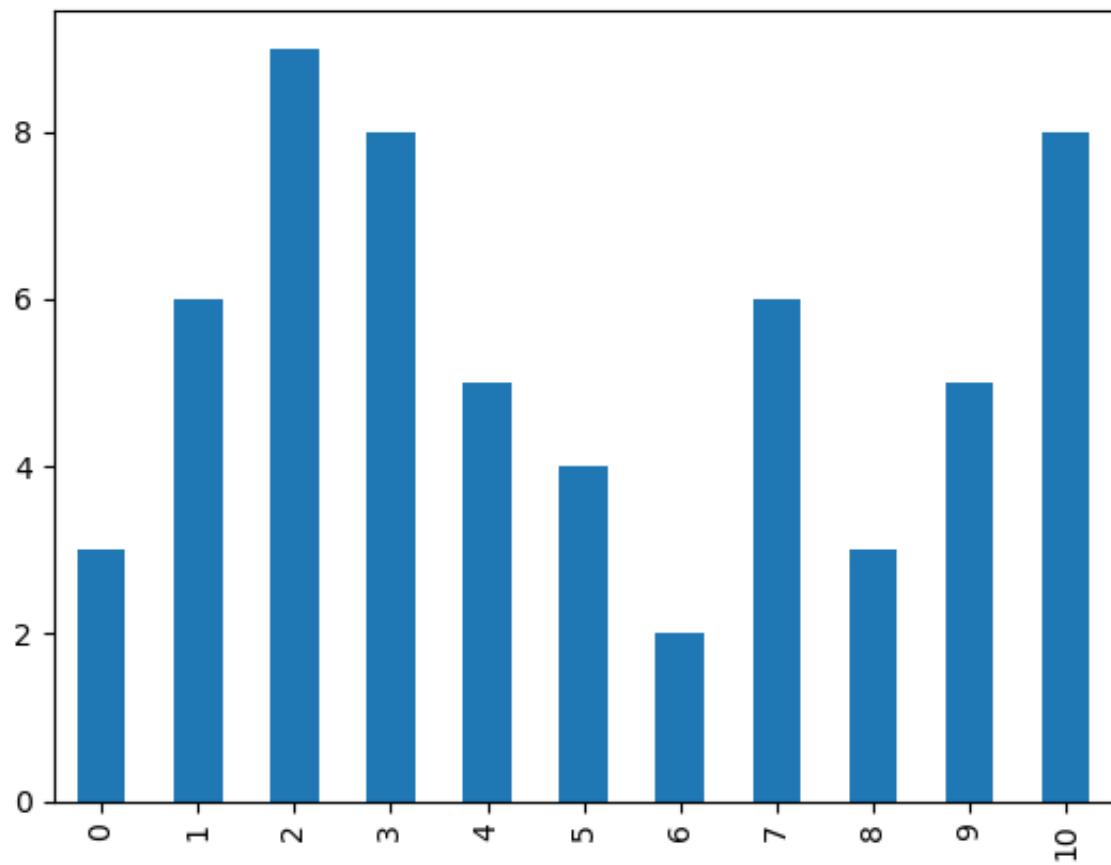
- Plot as Pie

```
In [ ]: import pandas as pd  
data = pd.Series((3,6,9,8,5,4,2,6,3,5,8))  
data.plot(kind='pie');
```

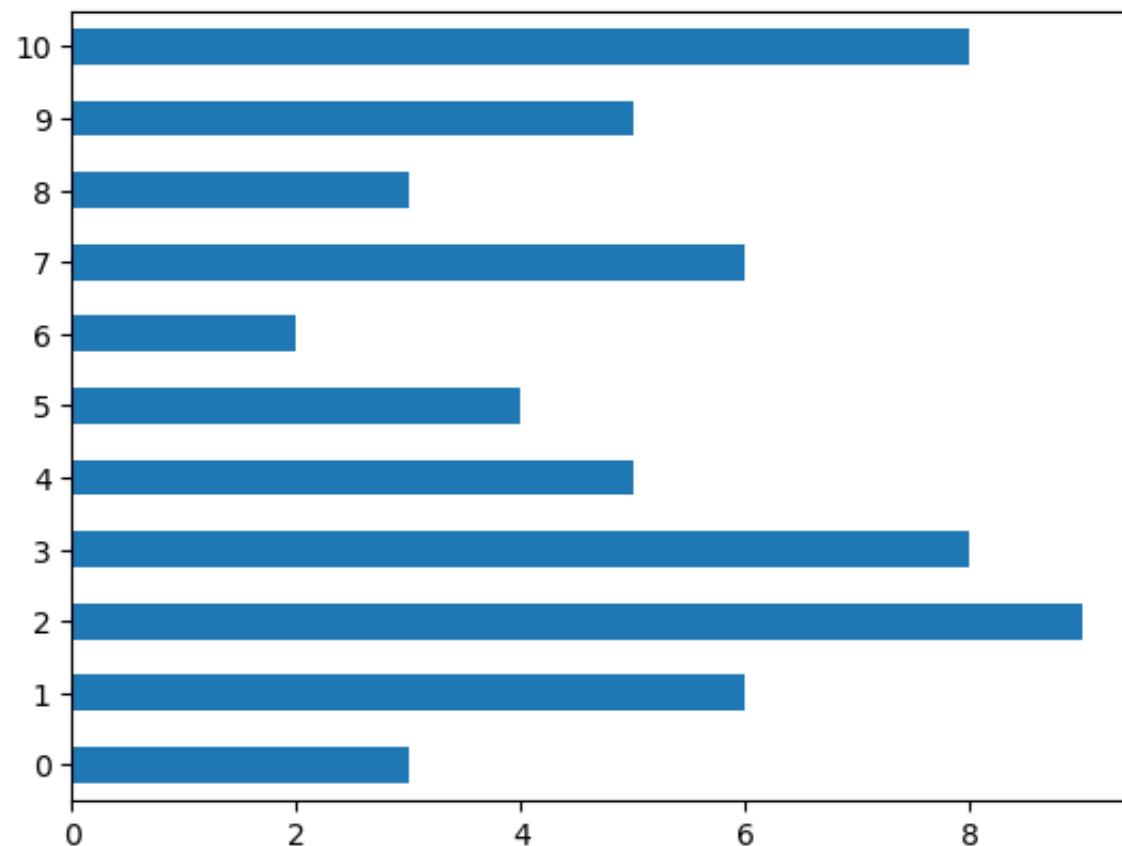


- Plot as Bar

```
In [ ]: import pandas as pd  
data = pd.Series((3,6,9,8,5,4,2,6,3,5,8))  
data.plot(kind='bar');
```



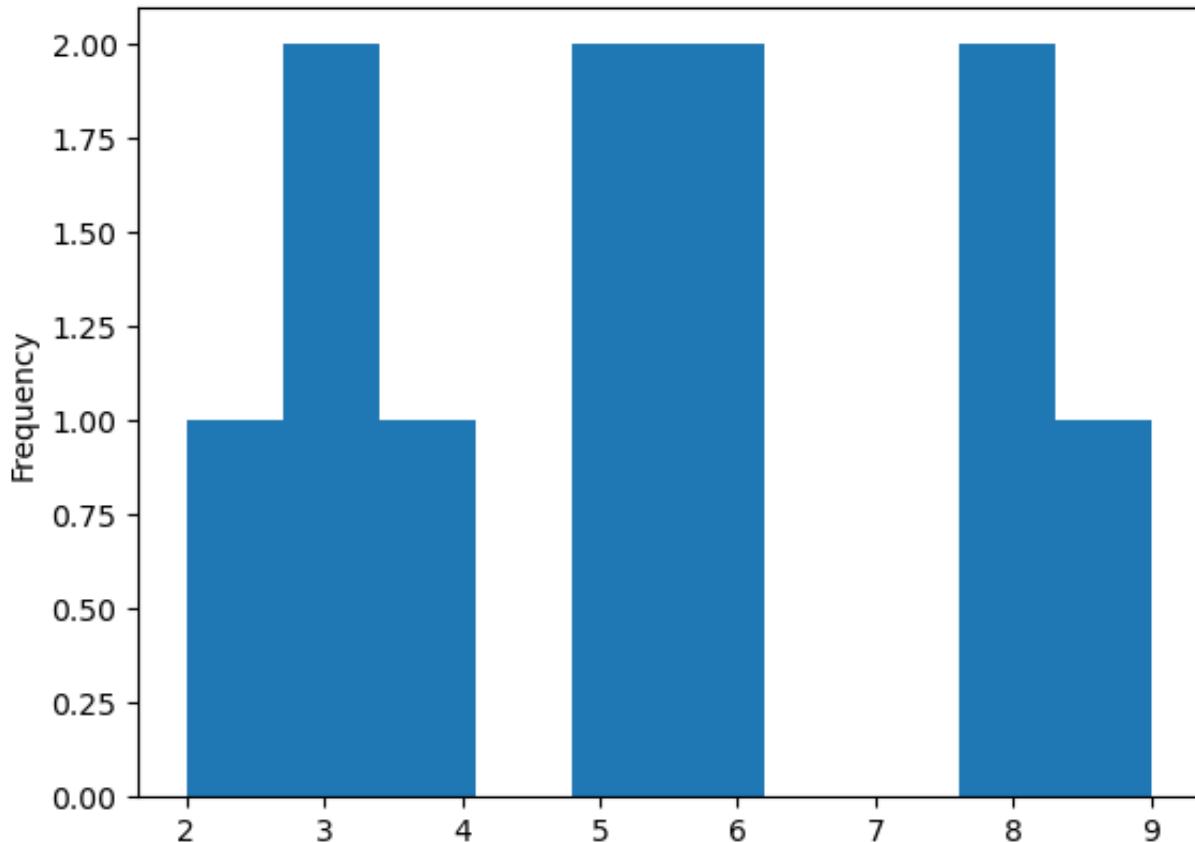
```
In [ ]: import pandas as pd  
data = pd.Series([3,6,9,8,5,4,2,6,3,5,8])  
data.plot(kind='barh');
```



- **Plot as Histogram**

- The concept behind a histogram is to determine the frequency of each element in the provided list.
- It requires a single column as input to analyze and display the distribution.

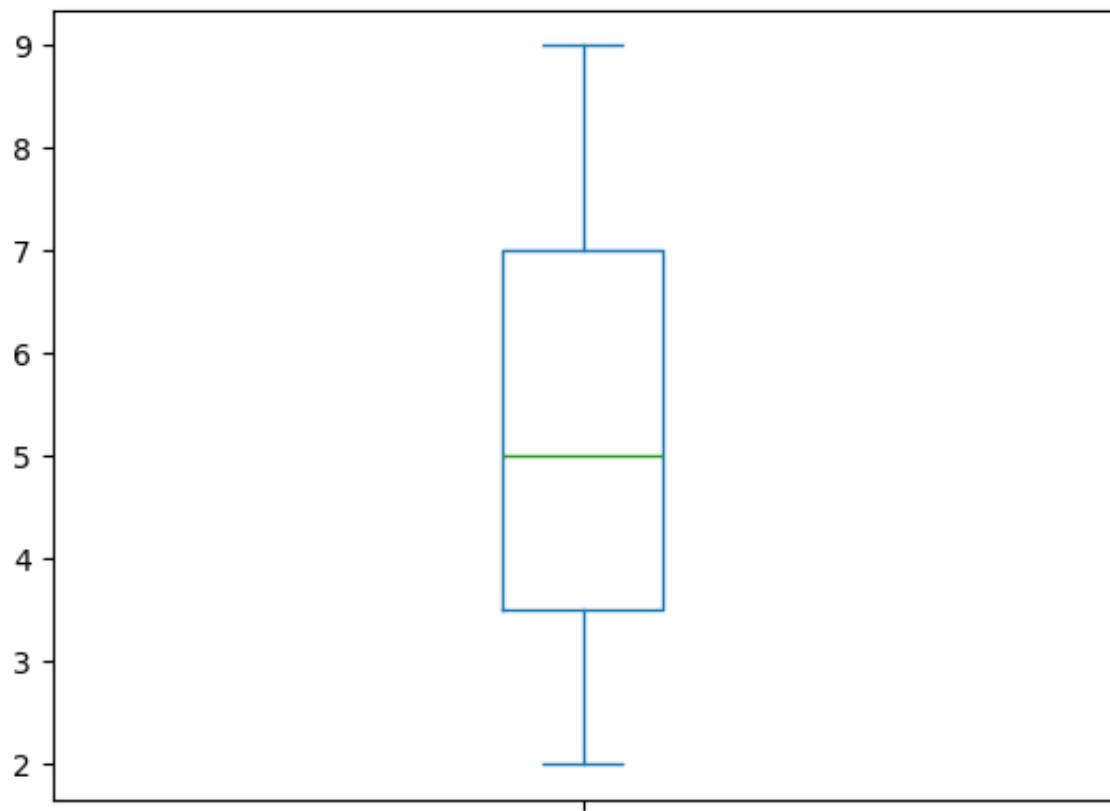
```
In [ ]: import pandas as pd  
data = pd.Series((3,6,9,8,5,4,2,6,3,5,8))  
data.plot(kind='hist');
```



- **Plot as box**

- The box plotted based on the maximum, lower, and median for the given data

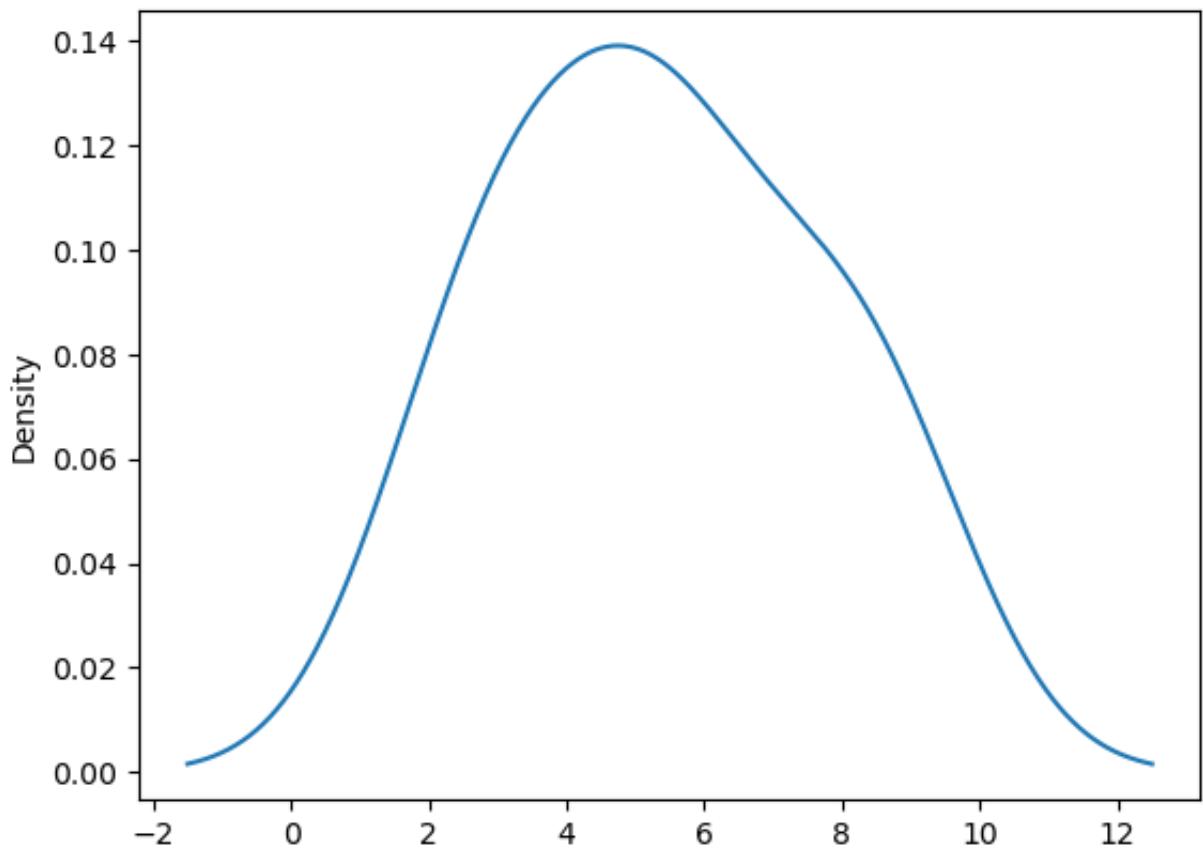
```
In [ ]: data = pd.Series((3,6,9,8,5,4,2,6,3,5,8))  
data.plot(kind='box');
```



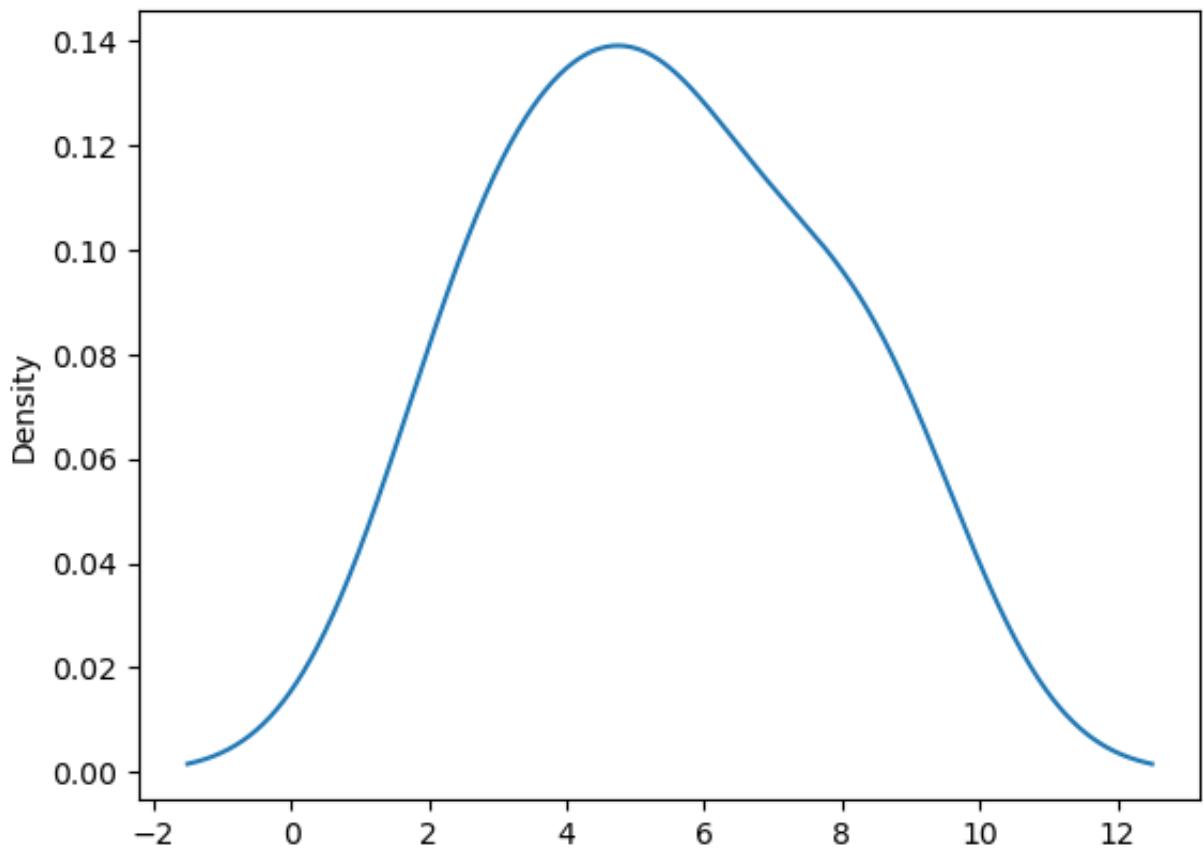
- **Plot by KDE**

- It is something related to the density distribution from the number of repetition of each value

```
In [ ]: data = pd.Series((3,6,9,8,5,4,2,6,3,5,8))
data.plot(kind='kde');
```

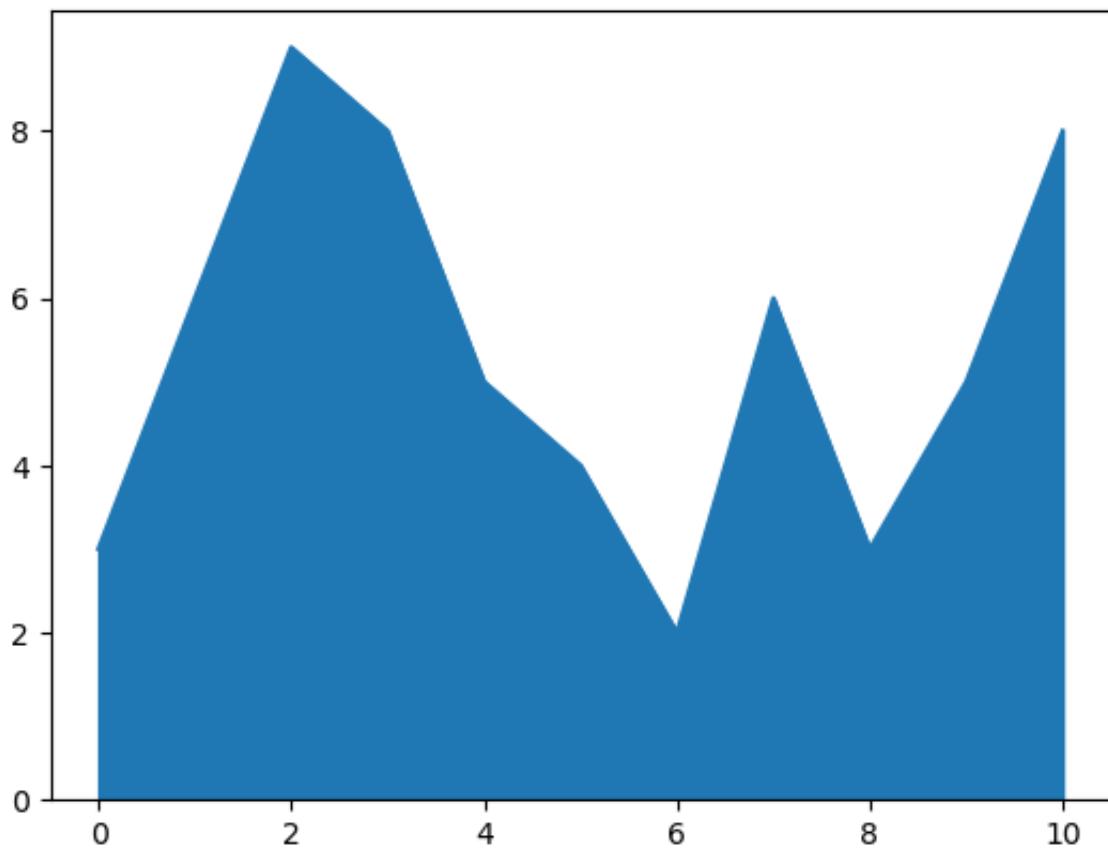


```
In [ ]: import pandas as pd  
data = pd.Series([3,6,9,8,5,4,2,6,3,5,8])  
data.plot(kind='density');
```



- Plot by the area under the curve
 - We can plot the area under the curve for our data by the **area** kind in the `plot` command

```
In [ ]: data = pd.Series((3,6,9,8,5,4,2,6,3,5,8))
data.plot(kind='area');
```



4. DataFrames

One of the crucial roles played by Pandas is through its DataFrame tool, specifically designed for working with tables and managing **Big Data in Data Science**

4.1 Creating DataFrame

- There are various ways to create Data frames (DF) in pandas, including using arrays and series.
- We will explore each method in this notebook, but you will notice that the DF class requires several optional parameters, such as index, column names, and others.
- However, one parameter is mandatory—the data itself (either an array or a series)

4.1.1 Creating DF from array

It's essential to note that the length of the index list should match the number of rows in the data, and similarly, the length of the columns list should correspond to the number of columns in the provided data.

```
In [ ]: import pandas as pd
import numpy as np
myarray = np.array([[6,9,8,5,4,2],[0,2,5,6,3,9],
[8,5,4,1,2,3],[6,9,8,5,4,2],
[0,5,3,6,9,8],[8,7,4,5,2,3]])
row_names = ['a', 'b','c','d','e','f']
col_names = ['one', 'two', 'three','four','five','six']
df = pd.DataFrame(myarray, index=row_names, columns=col_names)
print(df)
```

| | one | two | three | four | five | six |
|---|-----|-----|-------|------|------|-----|
| a | 6 | 9 | 8 | 5 | 4 | 2 |
| b | 0 | 2 | 5 | 6 | 3 | 9 |
| c | 8 | 5 | 4 | 1 | 2 | 3 |
| d | 6 | 9 | 8 | 5 | 4 | 2 |
| e | 0 | 5 | 3 | 6 | 9 | 8 |
| f | 8 | 7 | 4 | 5 | 2 | 3 |

4.1.2 Creating DF from list

```
In [ ]: import pandas as pd

# Example list of lists
data_list = [
    ['Alice', 25, 'Engineer'],
    ['Bob', 30, 'Data Scientist'],
    ['Charlie', 28, 'Designer']
]

# Define column names
columns = ['Name', 'Age', 'Occupation']

# Create DataFrame
df = pd.DataFrame(data_list, columns=columns)

# Display the DataFrame
print(df)
```

| | Name | Age | Occupation |
|---|---------|-----|----------------|
| 0 | Alice | 25 | Engineer |
| 1 | Bob | 30 | Data Scientist |
| 2 | Charlie | 28 | Designer |

4.1.3 Create DF from many Series

As previously mentioned, a Series is essentially a 1D matrix. If you have multiple Series, you can combine them to create a DataFrame.

```
In [ ]: import pandas as pd
w = pd.Series({'a':1 , 'b':2 , 'c':3 , 'd':4 , 'e':5})
x = pd.Series({'a':6 , 'b':7 , 'c':8 , 'd':9 , 'e':10})
```

```
y = pd.Series({'a':11 , 'b':12 , 'c':13 , 'd':14 , 'e':15})
z = pd.Series({'a':16 , 'b':17 , 'c':18 , 'd':19 , 'e':20})

grades = pd.DataFrame({'Math':w,'Physics':x,'French':y,'Chemistry':z})

print(grades)
```

| | Math | Physics | French | Chemistry |
|---|------|---------|--------|-----------|
| a | 1 | 6 | 11 | 16 |
| b | 2 | 7 | 12 | 17 |
| c | 3 | 8 | 13 | 18 |
| d | 4 | 9 | 14 | 19 |
| e | 5 | 10 | 15 | 20 |

Alternatively, in Pandas, you can use a list to serve as the index for your DataFrame.

```
In [ ]: import pandas as pd
data1 = pd.Index([3,5,6,0,18,38,48,54,3,5])
data2 = pd.Index([13,15,16,10,118,138,148,154,13,15])
row_names = ["Row no 1 ", "Row no 2 ", "Row no 3 ", "Row no 4 ", "Row no
df= pd.DataFrame({"Column No 1":data1,"Column No 2":data2},index=row_name
df
```

| | Column No 1 | Column No 2 |
|------------------|-------------|-------------|
| Row no 1 | 3 | 13 |
| Row no 2 | 5 | 15 |
| Row no 3 | 6 | 16 |
| Row no 4 | 0 | 10 |
| Row no 5 | 18 | 118 |
| Row no 6 | 38 | 138 |
| Row no 7 | 48 | 148 |
| Row no 8 | 54 | 154 |
| Row no 9 | 3 | 13 |
| Row no 10 | 5 | 15 |

4.1.4 Creating DF by Dictionary Method

We can create DF by dictionary methods column by column and using the conditions for fill the values

```
In [ ]: import pandas as pd
```

```
data = [ {'square': i**2} for i in range(10) ]  
df = pd.DataFrame(data)  
print(df)
```

```
    square  
0      0  
1      1  
2      4  
3      9  
4     16  
5     25  
6     36  
7     49  
8     64  
9     81
```

```
In [ ]: import pandas as pd  
data = [ {'square': i**2, 'cube': i**3  
        , 'root': i**0.5} for i in range(10) ]  
  
df = pd.DataFrame(data)  
  
print(df)
```

| | square | cube | root |
|---|--------|------|----------|
| 0 | 0 | 0 | 0.000000 |
| 1 | 1 | 1 | 1.000000 |
| 2 | 4 | 8 | 1.414214 |
| 3 | 9 | 27 | 1.732051 |
| 4 | 16 | 64 | 2.000000 |
| 5 | 25 | 125 | 2.236068 |
| 6 | 36 | 216 | 2.449490 |
| 7 | 49 | 343 | 2.645751 |
| 8 | 64 | 512 | 2.828427 |
| 9 | 81 | 729 | 3.000000 |

```
In [ ]: import pandas as pd  
d = pd.DataFrame([{'a':1,'b':2},{'a':3,'b':4},{'a':5,'b':6}])  
  
print(d)
```

| | a | b |
|---|---|---|
| 0 | 1 | 2 |
| 1 | 3 | 4 |
| 2 | 5 | 6 |

Note : if there is value missing for any element will add Nan instead

```
In [ ]: import pandas as pd  
  
d = pd.DataFrame([{'a':1,'b':2},{'b':3,'c':4},{'d':5,'e':6}])  
  
print(d)
```

```
a    b    c    d    e
0  1.0  2.0  NaN  NaN  NaN
1  NaN  3.0  4.0  NaN  NaN
2  NaN  NaN  NaN  5.0  6.0
```

```
In [ ]: import pandas as pd
import numpy as np

d = pd.DataFrame(np.random.rand(3, 2),
                  columns=['food', 'drink'], index=['a', 'b', 'c'])
print(d)

      food      drink
a  0.903192  0.006704
b  0.222576  0.001998
c  0.236427  0.224673
```

4.1.5 Creating DF by function (advanced method)

```
In [ ]: import pandas as pd

def make_df(cols, ind):
    data = {c: [str(c) + str(i) for i in ind] for c in cols}
    return pd.DataFrame(data, ind)

print(make_df('ABC', range(3)))

      A      B      C
0  A0    B0    C0
1  A1    B1    C1
2  A2    B2    C2
```

4.2 Basic Operations on DataFrame

You can perform various operations on a DataFrame, including slicing and handling a multitude of tasks.

4.2.1 Slicing or accessing columns in the DF

When you retrieve a single column, it includes the index. If you prefer excluding the index, you can utilize the keys and values options to precisely customize the output based on your requirements.

```
In [ ]: import pandas as pd
w = pd.Series({'a':1 , 'b':2 , 'c':3 , 'd':4 , 'e':5})
x = pd.Series({'a':6 , 'b':7 , 'c':8 , 'd':9 , 'e':10})
y = pd.Series({'a':11 , 'b':12 , 'c':13 , 'd':14 , 'e':15})
z = pd.Series({'a':16 , 'b':17 , 'c':18 , 'd':19 , 'e':20})
```

```
grades = pd.DataFrame({'Math':w,'Physics':x,'French':y,'Chemistry':z})
print(grades)
print(grades['Chemistry'])
```

| | Math | Physics | French | Chemistry |
|---|------|---------|--------|-----------|
| a | 1 | 6 | 11 | 16 |
| b | 2 | 7 | 12 | 17 |
| c | 3 | 8 | 13 | 18 |
| d | 4 | 9 | 14 | 19 |
| e | 5 | 10 | 15 | 20 |
| a | 16 | | | |
| b | 17 | | | |
| c | 18 | | | |
| d | 19 | | | |
| e | 20 | | | |

Name: Chemistry, dtype: int64

4.2.2 Transpose the DF

```
In [ ]: import pandas as pd
w = pd.Series({'a':1 , 'b':2 , 'c':3 , 'd':4 , 'e':5})
x = pd.Series({'a':6 , 'b':7 , 'c':8 , 'd':9 , 'e':10})
y = pd.Series({'a':11 , 'b':12 , 'c':13 , 'd':14 , 'e':15})
z = pd.Series({'a':16 , 'b':17 , 'c':18 , 'd':19 , 'e':20})

grades = pd.DataFrame({'Math':w,'Physics':x,'French':y,'Chemistry':z})

print(grades.T)
```

| | a | b | c | d | e |
|-----------|----|----|----|----|----|
| Math | 1 | 2 | 3 | 4 | 5 |
| Physics | 6 | 7 | 8 | 9 | 10 |
| French | 11 | 12 | 13 | 14 | 15 |
| Chemistry | 16 | 17 | 18 | 19 | 20 |

4.2.3 Accessing only keys or values from the DF

```
In [ ]: import pandas as pd
w = pd.Series({'a':1 , 'b':2 , 'c':3 , 'd':4 , 'e':5})
x = pd.Series({'a':6 , 'b':7 , 'c':8 , 'd':9 , 'e':10})
y = pd.Series({'a':11 , 'b':12 , 'c':13 , 'd':14 , 'e':15})
z = pd.Series({'a':16 , 'b':17 , 'c':18 , 'd':19 , 'e':20})

grades = pd.DataFrame({'Math':w,'Physics':x,'French':y,'Chemistry':z})
print(grades.keys())
print(grades.values)
```

```
Index(['Math', 'Physics', 'French', 'Chemistry'], dtype='object')
[[ 1  6 11 16]
 [ 2  7 12 17]
 [ 3  8 13 18]
 [ 4  9 14 19]
 [ 5 10 15 20]]
```

4.2.4 Applying conditions to specific keys or values in the DF

Note : Keys --> Columns header

```
In [ ]: import pandas as pd

w = pd.Series({'a':1 , 'b':2 , 'c':3 , 'd':4 , 'e':5})
x = pd.Series({'a':6 , 'b':7 , 'c':8 , 'd':9 , 'e':10})
y = pd.Series({'a':11 , 'b':12 , 'c':13 , 'd':14 , 'e':15})
z = pd.Series({'a':16 , 'b':17 , 'c':18 , 'd':19 , 'e':20})

grades = pd.DataFrame({'Math':w,'Physics':x,'French':y,'Chemistry':z})

print('Math' in grades.keys())
print('math' in grades.keys())
print(12 in grades.values)
print(55 in grades.values)
```

```
True
False
True
False
```

4.2.5 Vertical representation of elements with keys and values

```
In [ ]: import pandas as pd

w = pd.Series({'a':1 , 'b':2 , 'c':3 , 'd':4 , 'e':5})
x = pd.Series({'a':6 , 'b':7 , 'c':8 , 'd':9 , 'e':10})
y = pd.Series({'a':11 , 'b':12 , 'c':13 , 'd':14 , 'e':15})
z = pd.Series({'a':16 , 'b':17 , 'c':18 , 'd':19 , 'e':20})

grades = pd.DataFrame({'Math':w,'Physics':x,'French':y,'Chemistry':z})

print(grades.stack())
```

```
a   Math      1
    Physics    6
    French     11
    Chemistry   16
b   Math      2
    Physics    7
    French     12
    Chemistry   17
c   Math      3
    Physics    8
    French     13
    Chemistry   18
d   Math      4
    Physics    9
    French     14
    Chemistry   19
e   Math      5
    Physics   10
    French     15
    Chemistry   20
dtype: int64
```

4.2.6 Locating specific elements for slicing and searching within the DF

We have two primary methods for this task:

Method 1: iloc (i for index) - It locates the position by index, similar to the method we are familiar with in lists.

Example: --> iloc[:3, :2]

Method 2: loc - You need to specify the names of the elements, rows, and columns you are searching for.

Example: --> loc["b":"c", "Math":] This implies selecting rows from 'b' to 'c' and columns from 'Math' to the end.

Note: In this method, you need to reference columns by their names. If the index is numeric, you can use numbers.

Example: df.loc[3:6, : "Square of x"]

```
In [ ]: import pandas as pd

w = pd.Series({'a':1 , 'b':2 , 'c':3 , 'd':4 , 'e':5})
x = pd.Series({'a':6 , 'b':7 , 'c':8 , 'd':9 , 'e':10})
y = pd.Series({'a':11 , 'b':12 , 'c':13 , 'd':14 , 'e':15})
z = pd.Series({'a':16 , 'b':17 , 'c':18 , 'd':19 , 'e':20})

grades = pd.DataFrame({'Math':w, 'Physics':x, 'French':y, 'Chemistry':z})
```

```
print(grades.iloc[:3, :2])
```

| | Math | Physics |
|---|------|---------|
| a | 1 | 6 |
| b | 2 | 7 |
| c | 3 | 8 |

In []: `import pandas as pd`

```
w = pd.Series({'a':1 , 'b':2 , 'c':3 , 'd':4 , 'e':5})
x = pd.Series({'a':6 , 'b':7 , 'c':8 , 'd':9 , 'e':10})
y = pd.Series({'a':11 , 'b':12 , 'c':13 , 'd':14 , 'e':15})
z = pd.Series({'a':16 , 'b':17 , 'c':18 , 'd':19 , 'e':20})

grades = pd.DataFrame({'Math':w, 'Physics':x, 'French':y, 'Chemistry':z})

print(grades.loc['b':'c', 'Math'])
```

| | Math | Physics | French | Chemistry |
|---|------|---------|--------|-----------|
| b | 2 | 7 | 12 | 17 |
| c | 3 | 8 | 13 | 18 |

You can apply conditions with `loc` command

In []: `import pandas as pd`

```
w = pd.Series({'a':1 , 'b':2 , 'c':3 , 'd':4 , 'e':5})
x = pd.Series({'a':6 , 'b':7 , 'c':8 , 'd':9 , 'e':10})
y = pd.Series({'a':11 , 'b':12 , 'c':13 , 'd':14 , 'e':15})
z = pd.Series({'a':16 , 'b':17 , 'c':18 , 'd':19 , 'e':20})

grades = pd.DataFrame({'Math':w, 'Physics':x, 'French':y, 'Chemistry':z})

print(grades.loc[grades.Math >3])
```

| | Math | Physics | French | Chemistry |
|---|------|---------|--------|-----------|
| d | 4 | 9 | 14 | 19 |
| e | 5 | 10 | 15 | 20 |

Applying conditions to rows and selecting specific columns for display using the `loc` command.

In []: `import pandas as pd`

```
w = pd.Series({'a':1 , 'b':2 , 'c':3 , 'd':4 , 'e':5})
x = pd.Series({'a':6 , 'b':7 , 'c':8 , 'd':9 , 'e':10})
y = pd.Series({'a':11 , 'b':12 , 'c':13 , 'd':14 , 'e':15})
z = pd.Series({'a':16 , 'b':17 , 'c':18 , 'd':19 , 'e':20})

grades = pd.DataFrame({'Math':w, 'Physics':x, 'French':y, 'Chemistry':z})

print(grades.loc[grades.Math >3, ['French' , 'Math']])
```

| | French | Math |
|---|--------|------|
| d | 14 | 4 |
| e | 15 | 5 |

4.2.7 Access names of all columns and the index in the DF

```
In [ ]: import pandas as pd

w = pd.Series({'a':1 , 'b':2 , 'c':3 , 'd':4 , 'e':5})
x = pd.Series({'a':6 , 'b':7 , 'c':8 , 'd':9 , 'e':10})
y = pd.Series({'a':11 , 'b':12 , 'c':13 , 'd':14 , 'e':15})
z = pd.Series({'a':16 , 'b':17 , 'c':18 , 'd':19 , 'e':20})

grades = pd.DataFrame({'Math':w, 'Physics':x, 'French':y, 'Chemistry':z})

print(grades.columns)    ## same as df.keys()
print(grades.index)
```

Index(['Math', 'Physics', 'French', 'Chemistry'], dtype='object')
Index(['a', 'b', 'c', 'd', 'e'], dtype='object')

```
In [ ]: import pandas as pd

w = pd.Series({'a':1 , 'b':2 , 'c':3 , 'd':4 , 'e':5})
x = pd.Series({'a':6 , 'b':7 , 'c':8 , 'd':9 , 'e':10})
y = pd.Series({'a':11 , 'b':12 , 'c':13 , 'd':14 , 'e':15})
z = pd.Series({'a':16 , 'b':17 , 'c':18 , 'd':19 , 'e':20})

grades = pd.DataFrame({'Math':w, 'Physics':x, 'French':y, 'Chemistry':z})

print(grades['Math'])
```

a 1
b 2
c 3
d 4
e 5
Name: Math, dtype: int64

Example: Changing the index to one of the columns in the DF

```
In [ ]: import pandas as pd
df1 = pd.DataFrame({'employee': ['Bob', 'Jake', 'Lisa', 'Sue'],
                     'group': ['Accounting', 'Engineering',
                               'Engineering', 'HR']})
df2 = pd.DataFrame({'employee': ['Lisa', 'Bob', 'Jake', 'Sue'],
                     'hire_date': [2004, 2008, 2012, 2014]})

df3 = pd.DataFrame({'name': ['Bob', 'Jake', 'Lisa', 'Sue'],
                     'salary': [70000, 80000, 120000, 90000]})

print(df1)
```

```
df2 = df1.set_index('employee')

print(df2)
```

| | employee | group |
|---|----------|-------------|
| 0 | Bob | Accounting |
| 1 | Jake | Engineering |
| 2 | Lisa | Engineering |
| 3 | Sue | HR |

| | employee | group |
|------|----------|-------------|
| Bob | | Accounting |
| Jake | | Engineering |
| Lisa | | Engineering |
| Sue | | HR |

4.2.8 Sort the elements in the DF

Sorting the DataFrame based on the values of a specific column in ascending or descending order (using the parameter **ascending=False** if needed).

```
In [ ]: import pandas as pd

w = pd.Series({'a':1 , 'b':2 , 'c':3 , 'd':4 , 'e':5})
x = pd.Series({'a':6 , 'b':7 , 'c':8 , 'd':9 , 'e':10})
y = pd.Series({'a':11 , 'b':12 , 'c':13 , 'd':14 , 'e':15})
z = pd.Series({'a':16 , 'b':17 , 'c':18 , 'd':19 , 'e':20})

grades = pd.DataFrame({'Math':w, 'Physics':x, 'French':y, 'Chemistry':z})

print(grades.sort_values(['Math'], ascending= False))
print(grades.sort_values(['French'], ascending= True))
```

| | Math | Physics | French | Chemistry |
|---|------|---------|--------|-----------|
| e | 5 | 10 | 15 | 20 |
| d | 4 | 9 | 14 | 19 |
| c | 3 | 8 | 13 | 18 |
| b | 2 | 7 | 12 | 17 |
| a | 1 | 6 | 11 | 16 |

| | Math | Physics | French | Chemistry |
|---|------|---------|--------|-----------|
| a | 1 | 6 | 11 | 16 |
| b | 2 | 7 | 12 | 17 |
| c | 3 | 8 | 13 | 18 |
| d | 4 | 9 | 14 | 19 |
| e | 5 | 10 | 15 | 20 |

4.2.9 Statistics for the entire DF or per column

```
In [ ]: import pandas as pd
```

```
w = pd.Series({'a':1 , 'b':2 , 'c':3 , 'd':4 , 'e':5})
x = pd.Series({'a':6 , 'b':7 , 'c':8 , 'd':9 , 'e':10})
y = pd.Series({'a':11 , 'b':12 , 'c':13 , 'd':14 , 'e':15})
z = pd.Series({'a':16 , 'b':17 , 'c':18 , 'd':19 , 'e':20})

grades = pd.DataFrame({'Math':w,'Physics':x,'French':y,'Chemistry':z})

print("The max. for DF all columns\n", grades.max())
print("The min. for DF all columns\n ",grades.min())
print("The mean for DF all columns\n ",grades.mean())
print("The std. for DF all columns\n ",grades.std())
```

The max. for DF all columns

```
Math      5
Physics   10
French    15
Chemistry 20
dtype: int64
```

The min. for DF all columns

```
Math      1
Physics   6
French    11
Chemistry 16
dtype: int64
```

The mean for DF all columns

```
Math      3.0
Physics   8.0
French    13.0
Chemistry 18.0
dtype: float64
```

The std. for DF all columns

```
Math      1.581139
Physics   1.581139
French    1.581139
Chemistry 1.581139
dtype: float64
```

In []: `import pandas as pd`

```
w = pd.Series({'a':1 , 'b':2 , 'c':3 , 'd':4 , 'e':5})
x = pd.Series({'a':6 , 'b':7 , 'c':8 , 'd':9 , 'e':10})
y = pd.Series({'a':11 , 'b':12 , 'c':13 , 'd':14 , 'e':15})
z = pd.Series({'a':16 , 'b':17 , 'c':18 , 'd':19 , 'e':20})

grades = pd.DataFrame({'Math':w,'Physics':x,'French':y,'Chemistry':z})

print(grades['Math'].max())
print(grades['French'].min())
print(grades['Physics'].mean())
print(grades['Chemistry'].std())
```

```
5  
11  
8.0  
1.5811388300841898
```

4.2.10 The correlation between elements in the DF

When the numbers are closely aligned, the correlation tends to approach 1, and conversely, when they are distant, the correlation tends to be closer to -1.

```
In [ ]: import pandas as pd  
import numpy as np  
  
df = pd.DataFrame(np.random.rand(5, 3), columns=['A', 'B', 'C'])  
  
print(df)  
print(df.corr())
```

| | A | B | C |
|---|----------|----------|----------|
| 0 | 0.124522 | 0.802319 | 0.508907 |
| 1 | 0.082320 | 0.473766 | 0.173403 |
| 2 | 0.050012 | 0.651602 | 0.569051 |
| 3 | 0.926583 | 0.744118 | 0.619364 |
| 4 | 0.572466 | 0.403565 | 0.449702 |

| | A | B | C |
|---|----------|----------|----------|
| A | 1.000000 | 0.045352 | 0.455363 |
| B | 0.045352 | 1.000000 | 0.637697 |
| C | 0.455363 | 0.637697 | 1.000000 |

4.2.11 The skewness among the elements of each column in the DF

The `df.skew()` function yields a Series, providing one value for each column in the DataFrame. These Series values represent the skewness of each corresponding column.

انحراف == Skewness

```
In [ ]: import pandas as pd  
import numpy as np  
  
df = pd.DataFrame(np.random.rand(5, 3), columns=['A', 'B', 'C'])  
  
print(df)  
print(df.skew())
```

```

          A         B         C
0  0.235355  0.389166  0.181239
1  0.726775  0.072747  0.996716
2  0.351588  0.133315  0.599001
3  0.510098  0.833063  0.328395
4  0.219143  0.561235  0.131055
A    0.914599
B    0.460093
C    1.073441
dtype: float64

```

4.2.12 Arithmetic operations between Columns

We have two options:

- Applying the arithmetic operation directly
- Utilizing the DataFrame method (`eval`).

However, please note that when using the pandas method, you need to specify the operation as text.

```

In [ ]: import pandas as pd

w = pd.Series({'a':1 , 'b':2 , 'c':3 , 'd':4 , 'e':5})
x = pd.Series({'a':6 , 'b':7 , 'c':8 , 'd':9 , 'e':10})
y = pd.Series({'a':11 , 'b':12 , 'c':13 , 'd':14 , 'e':15})
z = pd.Series({'a':16 , 'b':17 , 'c':18 , 'd':19 , 'e':20})

grades = pd.DataFrame({'Math':w,'Physics':x,'French':y,'Chemistry':z})

grades['Total'] = (grades['Math'] + grades['French'] +
                    grades['Chemistry']+ grades['Physics']) /100

print(grades)

```

| | Math | Physics | French | Chemistry | Total |
|---|------|---------|--------|-----------|-------|
| a | 1 | 6 | 11 | 16 | 0.34 |
| b | 2 | 7 | 12 | 17 | 0.38 |
| c | 3 | 8 | 13 | 18 | 0.42 |
| d | 4 | 9 | 14 | 19 | 0.46 |
| e | 5 | 10 | 15 | 20 | 0.50 |

Performing calculations through direct arithmetic operations

```

In [ ]: import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.rand(5, 3), columns=['A', 'B', 'C'])

```

```
result = (df['A'] + df['B']) / (df['C'] - 1)

print(df)
print(result)
```

```
          A         B         C
0  0.997893  0.933147  0.630340
1  0.013309  0.722930  0.126046
2  0.372473  0.378301  0.846271
3  0.700943  0.540816  0.077703
4  0.864855  0.524521  0.439235
0   -5.223823
1   -0.842422
2   -4.883745
3   -1.346377
4   -2.477642
dtype: float64
```

Performing calculations using the evaluation method of Pandas

```
In [ ]: import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.rand(5, 3), columns=['A', 'B', 'C'])

result = pd.eval("(df.A + df.B) / (df.C - 1)")

print(df)
print(result)
```

```
          A         B         C
0  0.192101  0.036617  0.135488
1  0.810343  0.320694  0.475438
2  0.023259  0.276737  0.777996
3  0.399341  0.928936  0.560557
4  0.988831  0.058670  0.399062
0   -0.264563
1   -2.156157
2   -1.351307
3   -3.022635
4   -1.743111
dtype: float64
```

4.2.13 Selecting a Specific Row by Conditions

Similarly, for selection, you can either do it manually or use the Pandas method (**query**).

- However, when utilizing the Pandas method, remember to express the operation

as text.

```
In [ ]: import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.rand(5, 3), columns=['A', 'B', 'C'])

result = df.query('A < 0.5 and B < 0.5')

print(df)
print(result)
```

| | A | B | C |
|---|----------|----------|----------|
| 0 | 0.869640 | 0.652818 | 0.211815 |
| 1 | 0.549392 | 0.466400 | 0.347395 |
| 2 | 0.319789 | 0.239428 | 0.212668 |
| 3 | 0.052973 | 0.569942 | 0.686194 |
| 4 | 0.730785 | 0.442917 | 0.276722 |

| | A | B | C |
|---|----------|----------|----------|
| 2 | 0.319789 | 0.239428 | 0.212668 |

```
In [ ]: import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.rand(5, 3), columns=['A', 'B', 'C'])

tmp1 = df.A < 0.5
tmp2 = df.B < 0.5
tmp3 = tmp1 & tmp2
result1 = df[tmp3]
result2 = df[(df.A < 0.5) & (df.B < 0.5)]
result3 = df[(df.A < 0.5) | (df.B < 0.5)]

print(df)
print(result1)
print(result2)
print(result3)
```

| | A | B | C |
|---|----------|----------|----------|
| 0 | 0.891539 | 0.142778 | 0.229673 |
| 1 | 0.578983 | 0.223848 | 0.746335 |
| 2 | 0.114691 | 0.885383 | 0.815843 |
| 3 | 0.628647 | 0.439630 | 0.800615 |
| 4 | 0.022767 | 0.307606 | 0.918541 |

| | A | B | C |
|---|----------|----------|----------|
| 4 | 0.022767 | 0.307606 | 0.918541 |

| | A | B | C |
|---|----------|----------|----------|
| 4 | 0.022767 | 0.307606 | 0.918541 |

| | A | B | C |
|---|----------|----------|----------|
| 0 | 0.891539 | 0.142778 | 0.229673 |
| 1 | 0.578983 | 0.223848 | 0.746335 |
| 2 | 0.114691 | 0.885383 | 0.815843 |
| 3 | 0.628647 | 0.439630 | 0.800615 |
| 4 | 0.022767 | 0.307606 | 0.918541 |

Note here : this sign " | " means "**or**"

```
In [ ]: import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.rand(5, 3), columns=['A', 'B', 'C'])

result = df[(df.A < 0.5) | (df.B < 0.5)]

print(df)
print(result)
```

| | A | B | C |
|---|----------|----------|----------|
| 0 | 0.551104 | 0.540216 | 0.482121 |
| 1 | 0.607297 | 0.441072 | 0.829768 |
| 2 | 0.360749 | 0.134419 | 0.994606 |
| 3 | 0.928518 | 0.858054 | 0.772040 |
| 4 | 0.328330 | 0.648579 | 0.807195 |

| | A | B | C |
|---|----------|----------|----------|
| 1 | 0.607297 | 0.441072 | 0.829768 |
| 2 | 0.360749 | 0.134419 | 0.994606 |
| 4 | 0.328330 | 0.648579 | 0.807195 |

4.3 Table Concatenation and Merging

4.3.1 Simple Concatenation

The `concat()` function does all of the heavy lifting of performing concatenation operations along an axis while performing optional set logic (union or intersection) of the indexes (if any) on the other axes.

Concatenation simple example

| df1 | | | | | Result | | | | |
|-----|----|----|----|----|--------|----|----|----|----|
| | A | B | C | D | | A | B | C | D |
| 0 | A0 | B0 | C0 | D0 | 0 | A0 | B0 | C0 | D0 |
| 1 | A1 | B1 | C1 | D1 | 1 | A1 | B1 | C1 | D1 |
| 2 | A2 | B2 | C2 | D2 | 2 | A2 | B2 | C2 | D2 |
| 3 | A3 | B3 | C3 | D3 | 3 | A3 | B3 | C3 | D3 |

| df2 | | | | | Result | | | | |
|-----|----|----|----|----|--------|----|----|----|----|
| | A | B | C | D | | A | B | C | D |
| 4 | A4 | B4 | C4 | D4 | 4 | A4 | B4 | C4 | D4 |
| 5 | A5 | B5 | C5 | D5 | 5 | A5 | B5 | C5 | D5 |
| 6 | A6 | B6 | C6 | D6 | 6 | A6 | B6 | C6 | D6 |
| 7 | A7 | B7 | C7 | D7 | 7 | A7 | B7 | C7 | D7 |

| df3 | | | | | Result | | | | |
|-----|-----|-----|-----|-----|--------|-----|-----|-----|-----|
| | A | B | C | D | | A | B | C | D |
| 8 | AB | BB | CB | DB | 8 | AB | BB | CB | DB |
| 9 | A9 | B9 | C9 | D9 | 9 | A9 | B9 | C9 | D9 |
| 10 | A10 | B10 | C10 | D10 | 10 | A10 | B10 | C10 | D10 |
| 11 | A11 | B11 | C11 | D11 | 11 | A11 | B11 | C11 | D11 |

How Concatenation working

```
In [ ]: df1 = pd.DataFrame(
    {
        "A": ["A0", "A1", "A2", "A3"],
        "B": ["B0", "B1", "B2", "B3"],
        "C": ["C0", "C1", "C2", "C3"],
        "D": ["D0", "D1", "D2", "D3"],
    },
    index=[0, 1, 2, 3],
)

df2 = pd.DataFrame(
    {
        "A": ["A4", "A5", "A6", "A7"],
        "B": ["B4", "B5", "B6", "B7"],
        "C": ["C4", "C5", "C6", "C7"],
        "D": ["D4", "D5", "D6", "D7"],
    },
    index=[4, 5, 6, 7],
)

df3 = pd.DataFrame(
    {
        "A": ["A8", "A9", "A10", "A11"],
        "B": ["B8", "B9", "B10", "B11"],
        "C": ["C8", "C9", "C10", "C11"],
        "D": ["D8", "D9", "D10", "D11"],
    },
)
```

```
        index=[8, 9, 10, 11],  
    )  
  
frames = [df1, df2, df3]  
result = pd.concat(frames)  
result
```

Out[]:

| | A | B | C | D |
|----|-----|-----|-----|-----|
| 0 | A0 | B0 | C0 | D0 |
| 1 | A1 | B1 | C1 | D1 |
| 2 | A2 | B2 | C2 | D2 |
| 3 | A3 | B3 | C3 | D3 |
| 4 | A4 | B4 | C4 | D4 |
| 5 | A5 | B5 | C5 | D5 |
| 6 | A6 | B6 | C6 | D6 |
| 7 | A7 | B7 | C7 | D7 |
| 8 | A8 | B8 | C8 | D8 |
| 9 | A9 | B9 | C9 | D9 |
| 10 | A10 | B10 | C10 | D10 |
| 11 | A11 | B11 | C11 | D11 |

To add key for each DF in the resultant DF

In []:

```
result = pd.concat(frames, keys=["x", "y", "z"])  
result
```

Out[]:

| | | A | B | C | D |
|---|----|-----|-----|-----|-----|
| x | 0 | A0 | B0 | C0 | D0 |
| y | 1 | A1 | B1 | C1 | D1 |
| | 2 | A2 | B2 | C2 | D2 |
| | 3 | A3 | B3 | C3 | D3 |
| | 4 | A4 | B4 | C4 | D4 |
| | 5 | A5 | B5 | C5 | D5 |
| | 6 | A6 | B6 | C6 | D6 |
| | 7 | A7 | B7 | C7 | D7 |
| z | 8 | A8 | B8 | C8 | D8 |
| | 9 | A9 | B9 | C9 | D9 |
| | 10 | A10 | B10 | C10 | D10 |
| | 11 | A11 | B11 | C11 | D11 |

4.3.2 Set logic on the other axes (join outer and inner)

When gluing together multiple DataFrames, you have a choice of how to handle the other axes (other than the one being concatenated). This can be done in the following two ways:

- Take the union of them all, join='outer'. This is the default option as it results in zero information loss.
- Take the intersection, join='inner'.

Example for the default case, the outer

| df1 | | | | df4 | | | Result | | | | | | | | | |
|-----|----|----|----|-----|---|----|--------|----|---|----|----|----|----|-----|-----|-----|
| | A | B | C | D | B | D | F | A | B | C | D | B | D | F | | |
| 0 | A0 | B0 | C0 | D0 | 2 | B2 | D2 | F2 | 0 | A0 | B0 | C0 | D0 | NaN | NaN | NaN |
| 1 | A1 | B1 | C1 | D1 | 3 | B3 | D3 | F3 | 1 | A1 | B1 | C1 | D1 | NaN | NaN | NaN |
| 2 | A2 | B2 | C2 | D2 | 6 | B6 | D6 | F6 | 2 | A2 | B2 | C2 | D2 | B2 | D2 | F2 |
| 3 | A3 | B3 | C3 | D3 | 7 | B7 | D7 | F7 | 3 | A3 | B3 | C3 | D3 | B3 | D3 | F3 |

How joining outer working

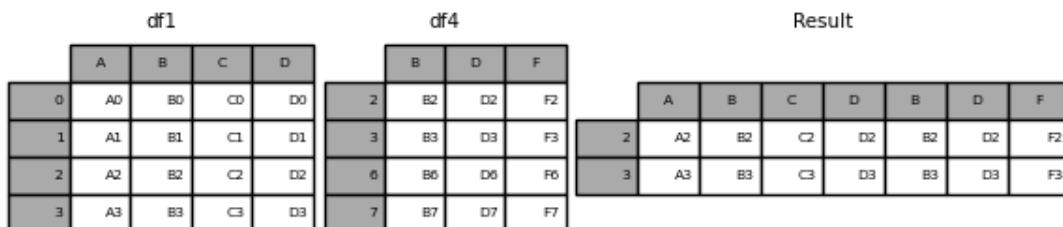
```
In [ ]: df4 = pd.DataFrame(
    {
        "B": ["B2", "B3", "B6", "B7"],
        "D": ["D2", "D3", "D6", "D7"],
        "F": ["F2", "F3", "F6", "F7"],
    },
    index=[2, 3, 6, 7],
)

result = pd.concat([df1, df4], axis=1)
result
```

Out []:

| | A | B | C | D | B | D | F |
|----------|-----|-----|-----|-----|-----|-----|-----|
| 0 | A0 | B0 | C0 | D0 | NaN | NaN | NaN |
| 1 | A1 | B1 | C1 | D1 | NaN | NaN | NaN |
| 2 | A2 | B2 | C2 | D2 | B2 | D2 | F2 |
| 3 | A3 | B3 | C3 | D3 | B3 | D3 | F3 |
| 6 | NaN | NaN | NaN | NaN | B6 | D6 | F6 |
| 7 | NaN | NaN | NaN | NaN | B7 | D7 | F7 |

Example for the inner case



How joining inner working

```
In [ ]: result = pd.concat([df1, df4], axis=1, join="inner")
result
```

Out []:

| | A | B | C | D | B | D | F |
|----------|----|----|----|----|----|----|----|
| 2 | A2 | B2 | C2 | D2 | B2 | D2 | F2 |
| 3 | A3 | B3 | C3 | D3 | B3 | D3 | F3 |

4.3.3 Ignoring indexes on the concatenation axis

For DataFrame objects which don't have a meaningful index, you may wish to append

them and ignore the fact that they may have overlapping indexes.

To do this, use the `ignore_index` argument:

| df1 | | | | | Result | | | | | | |
|-----|----|----|----|----|--------|---|-----|----|-----|----|-----|
| | A | B | C | D | | A | B | C | D | F | |
| 0 | A0 | B0 | C0 | D0 | | 0 | A0 | B0 | C0 | D0 | NaN |
| 1 | A1 | B1 | C1 | D1 | | 1 | A1 | B1 | C1 | D1 | NaN |
| 2 | A2 | B2 | C2 | D2 | | 2 | A2 | B2 | C2 | D2 | NaN |
| 3 | A3 | B3 | C3 | D3 | | 3 | A3 | B3 | C3 | D3 | NaN |
| df4 | | | | | | | | | | | |
| | B | D | F | | | | | | | | |
| 2 | B2 | D2 | F2 | | | 4 | NaN | B2 | NaN | D2 | F2 |
| 3 | B3 | D3 | F3 | | | 5 | NaN | B3 | NaN | D3 | F3 |
| 6 | B6 | D6 | F6 | | | 6 | NaN | B6 | NaN | D6 | F6 |
| 7 | B7 | D7 | F7 | | | 7 | NaN | B7 | NaN | D7 | F7 |

How to ignore index

```
In [ ]: result = pd.concat([df1, df4], ignore_index=True, sort=False)
result
```

```
Out[ ]:      A   B   C   D   F
0    A0  B0  C0  D0  NaN
1    A1  B1  C1  D1  NaN
2    A2  B2  C2  D2  NaN
3    A3  B3  C3  D3  NaN
4    NaN  B2  NaN  D2  F2
5    NaN  B3  NaN  D3  F3
6    NaN  B6  NaN  D6  F6
7    NaN  B7  NaN  D7  F7
```

4.3.4 Merging DataFrames

When merging two DataFrames, Pandas will search for any common column and use it as the basis for the merge. If no common column is found, Pandas will introduce NaN values in the resulting DataFrame.

```
In [ ]: import pandas as pd
```

```
df1 = pd.DataFrame({'employee': ['Bob', 'Jake', 'Lisa', 'Sue'],
                    'group': ['Accounting', 'Engineering',
                              'Engineering', 'HR']})

df2 = pd.DataFrame({'employee': ['Lisa', 'Bob', 'Jake', 'Sue'],
                    'hire_date': [2004, 2008, 2012, 2014]})

print(df1)
print(df2)
df3 = pd.merge(df1, df2)
print('-----')
print(df3)
```

```
employee      group
0      Bob  Accounting
1      Jake  Engineering
2      Lisa  Engineering
3      Sue        HR
employee  hire_date
0      Lisa       2004
1      Bob        2008
2      Jake       2012
3      Sue       2014
-----
employee      group  hire_date
0      Bob  Accounting       2008
1      Jake  Engineering     2012
2      Lisa  Engineering     2004
3      Sue        HR       2014
```

Example: Adding more than two DataFrames

```
In [ ]: import pandas as pd

df1 = pd.DataFrame({'employee': ['Bob', 'Jake', 'Lisa', 'Sue'],
                    'group': ['Accounting', 'Engineering',
                              'Engineering', 'HR']})

df2 = pd.DataFrame({'employee': ['Lisa', 'Bob', 'Jake', 'Sue'],
                    'hire_date': [2004, 2008, 2012, 2014]})

df3 = pd.merge(df1, df2)
print(df3)
print('-----')

df4 = pd.DataFrame({'group': ['Accounting', 'Engineering', 'HR'],
                    'supervisor': ['Carly', 'Guido', 'Steve']})
df5 = pd.merge(df3, df4)
print(df4)
print('-----')
print(df5)
```

```

      employee      group  hire_date
0      Bob  Accounting    2008
1     Jake  Engineering   2012
2     Lisa  Engineering   2004
3      Sue          HR    2014
-----
      group supervisor
0  Accounting      Carly
1  Engineering      Guido
2          HR       Steve
-----
      employee      group  hire_date supervisor
0      Bob  Accounting    2008      Carly
1     Jake  Engineering   2012      Guido
2     Lisa  Engineering   2004      Guido
3      Sue          HR    2014      Steve

```

Example: Merging two DataFrames and specifying which one is on the left and which one is on the right.

```
In [ ]: import pandas as pd
df1 = pd.DataFrame({'employee': ['Bob', 'Jake', 'Lisa', 'Sue'],
                     'group': ['Accounting', 'Engineering',
                               'Engineering', 'HR']})
df2 = pd.DataFrame({'employee': ['Lisa', 'Bob', 'Jake', 'Sue'],
                     'hire_date': [2004, 2008, 2012, 2014]})

df3 = pd.DataFrame({'name': ['Bob', 'Jake', 'Lisa', 'Sue'],
                     'salary': [70000, 80000, 120000, 90000]})

print(df1)
print(df3)
print(pd.merge(df1, df3, left_on="employee", right_on="name"))
```

```

      employee      group
0      Bob  Accounting
1     Jake  Engineering
2     Lisa  Engineering
3      Sue          HR
      name  salary
0     Bob    70000
1    Jake    80000
2    Lisa   120000
3    Sue    90000
      employee      group  name  salary
0      Bob  Accounting    Bob    70000
1     Jake  Engineering   Jake   80000
2     Lisa  Engineering   Lisa  120000
3      Sue          HR    Sue   90000

```

4.3.4 Set logic on the other axes during merging

Important Note:

- In pandas axis = 1 parameter specifies that the operation should be performed on the columns of the DataFrame
- In pandas axis = 0 parameter specifies that the operation should be performed on the rows of the DataFrame

```
In [ ]: import pandas as pd
df1 = pd.DataFrame({'employee': ['Bob', 'Jake', 'Lisa', 'Sue'],
                     'group': ['Accounting', 'Engineering',
                               'Engineering', 'HR']})
df2 = pd.DataFrame({'employee': ['Lisa', 'Bob', 'Jake', 'Sue'],
                     'hire_date': [2004, 2008, 2012, 2014]})

df3 = pd.DataFrame({'name': ['Bob', 'Jake', 'Lisa', 'Sue'],
                     'salary': [70000, 80000, 120000, 90000]})

print(df1)
print(df3)
print(pd.merge(df1, df3, left_on="employee",
               right_on="name").drop('name', axis=1))
```

| | employee | group |
|---|----------|-------------|
| 0 | Bob | Accounting |
| 1 | Jake | Engineering |
| 2 | Lisa | Engineering |
| 3 | Sue | HR |

| | name | salary |
|---|------|--------|
| 0 | Bob | 70000 |
| 1 | Jake | 80000 |
| 2 | Lisa | 120000 |
| 3 | Sue | 90000 |

| | employee | group | salary |
|---|----------|-------------|--------|
| 0 | Bob | Accounting | 70000 |
| 1 | Jake | Engineering | 80000 |
| 2 | Lisa | Engineering | 120000 |
| 3 | Sue | HR | 90000 |

Example: When merging, only the intersecting elements in the common column will appear in the resulting DataFrame.

```
In [ ]: import pandas as pd
df1 = pd.DataFrame({'name': ['Peter', 'Paul', 'Mary'],
                     'food': ['fish', 'beans', 'bread']},
                     columns=['name', 'food'])

df2 = pd.DataFrame({'name': ['Mary', 'Joseph'],
                     'drink': ['cola', '7 up']},
                     columns=['name', 'drink'])
print(df1)
```

```
print('-----')
print(df2)
print('-----')
df3 = pd.merge(df1, df2)
print(df3)
```

```
      name  food
0  Peter   fish
1  Paul   beans
2  Mary   bread
-----
      name  drink
0    Mary   cola
1  Joseph  7 up
-----
      name  food  drink
0  Mary   bread   cola
```

- Example for the inner case

The same intersection between DataFrames can be achieved by using the "**inner**" parameter.

It's worth noting that "inner" is the default value for the parameter in the Pandas merge method.

```
In [ ]: import pandas as pd
df1 = pd.DataFrame({'name': ['Peter', 'Paul', 'Mary'],
                     'food': ['fish', 'beans', 'bread']},
                     columns=['name', 'food'])

df2 = pd.DataFrame({'name': ['Mary', 'Joseph'],
                     'drink': ['cola', '7 up']},
                     columns=['name', 'drink'])

print(df1)
print('-----')
print(df2)
print('-----')
df3 = pd.merge(df1, df2, how='inner')
print(df3)
```

```
      name  food
0  Peter   fish
1  Paul   beans
2  Mary   bread
-----
      name  drink
0    Mary   cola
1  Joseph  7 up
-----
      name  food  drink
0  Mary   bread   cola
```

- Example for the outer case

Merging to obtain all elements, with NaN filling in the missing values, using the "outer" parameter.

```
In [ ]: import pandas as pd
df1 = pd.DataFrame({'name': ['Peter', 'Paul', 'Mary'],
                     'food': ['fish', 'beans', 'bread']},
                     columns=['name', 'food'])

df2 = pd.DataFrame({'name': ['Mary', 'Joseph'],
                     'drink': ['cola', '7 up']},
                     columns=['name', 'drink'])

print(df1)
print('-----')
print(df2)
print('-----')
df3 = pd.merge(df1, df2, how='outer')
print(df3)
```

```
      name    food
0   Peter    fish
1   Paul    beans
2   Mary   bread
-----
      name  drink
0     Mary   cola
1  Joseph   7 up
-----
      name    food  drink
0   Peter    fish    NaN
1   Paul    beans    NaN
2   Mary   bread   cola
3  Joseph     NaN   7 up
```

- Example for the right case

Merging to obtain all elements from one DataFrame and filling in missing values in the other DataFrame with NaN, using the "right" parameter.

```
In [ ]: import pandas as pd
df1 = pd.DataFrame({'name': ['Peter', 'Paul', 'Mary'],
                     'food': ['fish', 'beans', 'bread']},
                     columns=['name', 'food'])

df2 = pd.DataFrame({'name': ['Mary', 'Joseph'],
                     'drink': ['cola', '7 up']},
                     columns=['name', 'drink'])

print(df1)
```

```
print('-----')
print(df2)
print('-----')
df3 = pd.merge(df1, df2, how='right')
print(df3)
```

```
      name    food
0  Peter    fish
1  Paul    beans
2  Mary   bread
-----
      name   drink
0    Mary    cola
1  Joseph   7 up
-----
      name    food   drink
0  Mary   bread    cola
1  Joseph     NaN   7 up
```

- Example for the left case

Merging to obtain all elements from one DataFrame and filling in missing values in the other DataFrame with NaN, using the "left" parameter.

```
In [ ]: import pandas as pd
df1 = pd.DataFrame({'name': ['Peter', 'Paul', 'Mary'],
                     'food': ['fish', 'beans', 'bread']},
                     columns=['name', 'food'])

df2 = pd.DataFrame({'name': ['Mary', 'Joseph'],
                     'drink': ['cola', '7 up']},
                     columns=['name', 'drink'])

print(df1)
print('-----')
print(df2)
print('-----')
df3 = pd.merge(df1, df2, how='left')
print(df3)
```

```
      name    food
0  Peter    fish
1  Paul    beans
2  Mary   bread
-----
      name  drink
0   Mary   cola
1 Joseph   7 up
-----
      name    food  drink
0  Peter    fish    NaN
1  Paul    beans    NaN
2  Mary   bread   cola
```

4.4 Advanced operations on DataFrames

4.4.1 Statistics for the entire DF

```
In [ ]: import pandas as pd
import numpy as np

df = pd.DataFrame({'A': np.random.rand(10), 'B': np.random.rand(10)})
print(df)
print('-----')
print(df.sum())
print('-----')
print(df.prod())
print('-----')
print(df.mean())
```

```
          A            B
0  0.005275  0.590053
1  0.319625  0.230584
2  0.937504  0.333223
3  0.545917  0.104463
4  0.501140  0.597576
5  0.998301  0.465496
6  0.017465  0.196450
7  0.793709  0.366809
8  0.879614  0.028697
9  0.858705  0.389454
-----
A    5.857254
B    3.302805
dtype: float64
-----
A    0.000005
B    0.000001
dtype: float64
-----
A    0.585725
B    0.330280
dtype: float64
```

4.4.2 Statistics on one Column of the DF

```
In [ ]: import pandas as pd
import numpy as np

df = pd.DataFrame({'A': np.random.rand(10), 'B': np.random.rand(10)})
print(df)
print('-----')
print(df['A'].sum())
print('-----')
print(df['B'].prod())
print('-----')
print(df['A'].mean())
```

```
          A            B  
0  0.151915  0.384361  
1  0.157454  0.137242  
2  0.194169  0.637392  
3  0.836226  0.316493  
4  0.235182  0.972446  
5  0.423518  0.418742  
6  0.381023  0.182254  
7  0.143662  0.506586  
8  0.531885  0.204914  
9  0.877983  0.488592  
-----  
3.9330174514184097  
-----  
4.005510831011704e-05  
-----  
0.39330174514184096
```

4.4.3 Statistics on all columns of the DF

This is the default behavior, and you can specify to compute by rows. For example, computing the average for all rows will return the average of the elements across the entire column.

```
In [ ]: import pandas as pd  
import numpy as np  
  
df = pd.DataFrame({'A': np.random.rand(10), 'B': np.random.rand(10)})  
print(df)  
print('-----')  
print(df.mean(axis='rows'))  
print('-----')  
print(df.count())  
print('-----')  
print(df.min())  
print('-----')  
print(df.max())  
print('-----')  
print(df.std())  
print('-----')
```

```
          A            B
0  0.620815  0.940360
1  0.865903  0.801033
2  0.374614  0.307738
3  0.970911  0.176068
4  0.735641  0.536717
5  0.369581  0.591873
6  0.413798  0.072219
7  0.098215  0.288579
8  0.144818  0.194250
9  0.305043  0.910270
-----
A    0.489934
B    0.481910
dtype: float64
-----
A    10
B    10
dtype: int64
-----
A    0.098215
B    0.072219
dtype: float64
-----
A    0.970911
B    0.940360
dtype: float64
-----
A    0.296368
B    0.320148
dtype: float64
-----
```

4.4.4 Statistics on all rows of the DF

In this case, you need to pass the parameter **axis="column"**. This allows the process to be applied to all elements by column and return results for each row.

```
In [ ]: import pandas as pd
import numpy as np

df = pd.DataFrame({'A': np.random.rand(10), 'B': np.random.rand(10)})
print(df)
print('-----')
print(df.mean(axis='columns'))
```

```
          A            B  
0  0.409199  0.838762  
1  0.520183  0.080766  
2  0.928907  0.882454  
3  0.605618  0.086910  
4  0.456624  0.702574  
5  0.620493  0.309700  
6  0.780535  0.672074  
7  0.534290  0.996859  
8  0.247131  0.935650  
9  0.900387  0.839409  
-----  
0    0.623981  
1    0.300474  
2    0.905681  
3    0.346264  
4    0.579599  
5    0.465096  
6    0.726305  
7    0.765575  
8    0.591391  
9    0.869898  
dtype: float64
```

4.4.5 Statistics on the entire DF using the Describe method

```
In [ ]: import pandas as pd  
  
df = pd.DataFrame({'key': ['A', 'B', 'C', 'A', 'B', 'C'],  
                   'data': range(6)}, columns=['key', 'data'])  
  
print(df)  
print(df.describe())
```

```
   key  data  
0   A    0  
1   B    1  
2   C    2  
3   A    3  
4   B    4  
5   C    5  
      data  
count  6.000000  
mean   2.500000  
std    1.870829  
min   0.000000  

```

4.4.6 Groupby

Groupby is a crucial method in Pandas that facilitates grouping similar elements and applying various operations on each group.

```
In [ ]: import pandas as pd

df = pd.DataFrame({'key': ['A', 'B', 'C', 'A', 'B', 'C'],
                   'data': range(6)}, columns=['key', 'data'])

print(df)
print(df.groupby('key').sum())
```

| | key | data |
|---|-----|------|
| 0 | A | 0 |
| 1 | B | 1 |
| 2 | C | 2 |
| 3 | A | 3 |
| 4 | B | 4 |
| 5 | C | 5 |

| | key | data |
|--|-----|------|
| | A | 3 |
| | B | 5 |
| | C | 7 |

4.4.7 Grouping with the Describe Method

```
In [ ]: import pandas as pd

df = pd.DataFrame({'key': ['A', 'B', 'C', 'A', 'B', 'C'],
                   'data': range(6)}, columns=['key', 'data'])

print(df)
print(df.groupby('key').describe())
```

| | key | data |
|---|-----|------|
| 0 | A | 0 |
| 1 | B | 1 |
| 2 | C | 2 |
| 3 | A | 3 |
| 4 | B | 4 |
| 5 | C | 5 |

| | key | data | count | mean | std | min | 25% | 50% | 75% | max |
|--|-----|------|-------|---------|-----|------|-----|------|-----|-----|
| | A | 2.0 | 1.5 | 2.12132 | 0.0 | 0.75 | 1.5 | 2.25 | 3.0 | |
| | B | 2.0 | 2.5 | 2.12132 | 1.0 | 1.75 | 2.5 | 3.25 | 4.0 | |
| | C | 2.0 | 3.5 | 2.12132 | 2.0 | 2.75 | 3.5 | 4.25 | 5.0 | |

Example: **Unstack** the returned data from the describe method.

```
In [ ]: import pandas as pd

df = pd.DataFrame({'key': ['A', 'B', 'C', 'A', 'B', 'C'],
                   'data': range(6)}, columns=['key', 'data'])

print(df)
print(df.groupby('key').describe().unstack())
```

```
key  data
0    A    0
1    B    1
2    C    2
3    A    3
4    B    4
5    C    5

      key
data  count   A    2.00000
                  B    2.00000
                  C    2.00000
        mean   A    1.50000
                  B    2.50000
                  C    3.50000
        std    A    2.12132
                  B    2.12132
                  C    2.12132
        min    A    0.00000
                  B    1.00000
                  C    2.00000
        25%    A    0.75000
                  B    1.75000
                  C    2.75000
        50%    A    1.50000
                  B    2.50000
                  C    3.50000
        75%    A    2.25000
                  B    3.25000
                  C    4.25000
        max    A    3.00000
                  B    4.00000
                  C    5.00000

dtype: float64
```

```
In [ ]: import pandas as pd
import numpy as np

df = pd.DataFrame({'key': ['A', 'B', 'C', 'A', 'B', 'C'],
                   'data1': range(6),
                   'data2': np.random.randint(0, 10, 6)},
                   columns = ['key', 'data1', 'data2'])

print(df)
df2 = df.groupby('key').aggregate({'data1': 'min', 'data2': 'max'})
print(df2)
```

```

key  data1  data2
0   A      0      0
1   B      1      6
2   C      2      6
3   A      3      9
4   B      4      5
5   C      5      1
      data1  data2
key
A      0      9
B      1      6
C      2      6

```

Example: **filter** the returned data based on function.

```

In [ ]: import pandas as pd
import numpy as np

df = pd.DataFrame({'key': ['A', 'B', 'C', 'A', 'B', 'C'],
                   'data1': range(6),
                   'data2': np.random.randint(0, 10, 6)},
                  columns = ['key', 'data1', 'data2'])

print(df)
def filter_func(x):
    return x['data2'].std() > 4

df2 = df.groupby('key').filter(filter_func)
print(df2)

```

```

key  data1  data2
0   A      0      0
1   B      1      6
2   C      2      5
3   A      3      5
4   B      4      1
5   C      5      5
Empty DataFrame
Columns: [key, data1, data2]
Index: []

```

```

In [ ]: import pandas as pd
import numpy as np

df = pd.DataFrame({'key': ['A', 'B', 'C', 'A', 'B', 'C'],
                   'data1': range(6),
                   'data2': np.random.randint(0, 10, 6)},
                  columns = ['key', 'data1', 'data2'])

print(df)

df2 = df.groupby('key').transform(lambda x: x**2)

```

```
print(df2)

  key  data1  data2
0   A      0      9
1   B      1      6
2   C      2      5
3   A      3      1
4   B      4      4
5   C      5      5
  data1  data2
0      0     81
1      1     36
2      4     25
3      9      1
4     16     16
5     25     25
```

4.5 Data Transformation and Handling Missing Data

4.5.1 How to Address Missing Data ?

- Why Handling Missing Data is Essential ?
 - Real-world data often contains missing values for various reasons.
 - Many machine learning models and statistical methods cannot effectively process data with missing values.
 - In such cases, it becomes essential to determine how to handle this missing data.
 - When reading data with missing values, Pandas represents them as NaN values.
- Options for handling missing data include:
 1. Keeping the missing data:
 - Pros: Does not manipulate or alter the true data.
 - Cons: Many methods or models do not support NaN values.
 2. Dropping or Removing the missing data:
 - Pros: Easy and can be based on predefined rules.
 - Cons: May result in the loss of a significant amount of data or valuable information.
 3. Filling the missing data:
 - Pros: Has the potential to retain a substantial amount of data for training a model.
 - Cons: Can be challenging and somewhat arbitrary, with the potential to lead to false conclusions.

4.5.2 Dropping Unnecessary Data

Dropping helps in focusing on what's essential by removing unneeded data.

Example to drop unneeded columns

```
In [ ]: # Sample DataFrame with unnecessary data
data = {'Name': ['Alice', 'Bob', 'Charlie'],
        'Age': [25, 30, 22],
        'Unneeded_Column': ['A', 'B', 'C']}
df = pd.DataFrame(data)

# Displaying the original DataFrame
print("Original DataFrame:")
print(df)

# Dropping the unneeded column
df = df.drop(columns=['Unneeded_Column'])

# Displaying the DataFrame after dropping the column
print("\nDataFrame after streamlining data:")
print(df)
```

Original DataFrame:

| | Name | Age | Unneeded_Column |
|---|---------|-----|-----------------|
| 0 | Alice | 25 | A |
| 1 | Bob | 30 | B |
| 2 | Charlie | 22 | C |

DataFrame after streamlining data:

| | Name | Age |
|---|---------|-----|
| 0 | Alice | 25 |
| 1 | Bob | 30 |
| 2 | Charlie | 22 |

4.5.3 Dropping Rows with Any Missing Values

Method one : Using **dropna** function.

```
In [ ]: import pandas as pd

# Sample DataFrame with missing values
data = {'Name': ['Alice', 'Bob', None, 'Charlie'],
        'Age': [25, 30, None, 22],
        'Salary': [50000, None, 60000, 70000]}
```

```
df = pd.DataFrame(data)

# Displaying the original DataFrame
print("Original DataFrame:")
print(df)

# Drop the entire row if there is any one missing data
df_clean = df.dropna()
print("\nDataFrame with all rows without missing value ")
print(df_clean)
```

Original DataFrame:

| | Name | Age | Salary |
|---|---------|------|---------|
| 0 | Alice | 25.0 | 50000.0 |
| 1 | Bob | 30.0 | NaN |
| 2 | None | NaN | 60000.0 |
| 3 | Charlie | 22.0 | 70000.0 |

DataFrame with all rows without missing value

| | Name | Age | Salary |
|---|---------|------|---------|
| 0 | Alice | 25.0 | 50000.0 |
| 3 | Charlie | 22.0 | 70000.0 |

Another Method : Using **drop** function; Dropping an entire row containing missing values can be achieved by specifying a single label, index, or column

In []: `import pandas as pd`

```
# Sample DataFrame with missing values
data = {'Name': ['Alice', 'Bob', None, 'Charlie'],
        'Age': [25, 30, None, 22],
        'Salary': [50000, None, 60000, 70000]}

df = pd.DataFrame(data)

# Displaying the original DataFrame
print("Original DataFrame:")
print(df)

# Drop the entire row if there is any one missing data
df_clean = df.drop(2, axis=0)
print("\nDataFrame with all rows without missing value ")
print(df_clean)
```

Original DataFrame:

```
Name    Age   Salary
0     Alice  25.0  50000.0
1      Bob   30.0      NaN
2     None   NaN  60000.0
3   Charlie  22.0  70000.0
```

DataFrame with all rows without missing value

```
Name    Age   Salary
0     Alice  25.0  50000.0
1      Bob   30.0      NaN
3   Charlie  22.0  70000.0
```

4.5.4 Detecting All Missing Values

- Detecting missing values is crucial for maintaining data integrity, and it can be achieved using the **isnull()** function.
- Additionally, there is another function named **notnull()**, which, when used in reverse, indicates false wherever there is a missing value.

```
In [ ]: import pandas as pd

# Sample DataFrame with missing values
data = {'Name': ['Alice', 'Bob', None, 'Charlie'],
        'Age': [25, 30, None, 22],
        'Salary': [50000, None, 60000, 70000]}

df = pd.DataFrame(data)

# Displaying the original DataFrame
print("Original DataFrame:")
print(df)

# Checking for missing values
missing_values = df.isnull()

# Displaying the DataFrame with missing value indicators
print("\nDataFrame with Missing Value Indicators:")
print(missing_values)

# Show rows where any one of them have missing value in the Salary column
rows_with_missing = df[df["Salary"].isnull()]
print("\nDataFrame with all rows contain Missing Value ")
print(rows_with_missing)
```

Original DataFrame:

| | Name | Age | Salary |
|---|---------|------|---------|
| 0 | Alice | 25.0 | 50000.0 |
| 1 | Bob | 30.0 | NaN |
| 2 | None | NaN | 60000.0 |
| 3 | Charlie | 22.0 | 70000.0 |

DataFrame with Missing Value Indicators:

| | Name | Age | Salary |
|---|-------|-------|--------|
| 0 | False | False | False |
| 1 | False | False | True |
| 2 | True | True | False |
| 3 | False | False | False |

DataFrame with all rows contain Missing Value

| | Name | Age | Salary |
|---|------|------|--------|
| 1 | Bob | 30.0 | NaN |

4.5.5 Eliminating Duplicates

Duplicate data can distort your analysis. The **drop_duplicates()** function is instrumental in preserving data integrity.

In []: `import pandas as pd`

```
# Sample DataFrame with duplicate data
data = {'Name': ['Alice', 'Bob', 'Alice', 'Charlie', 'Bob'],
        'Age': [25, 30, 25, 22, 30],
        'Salary': [50000, 60000, 50000, 70000, 60000]}

df = pd.DataFrame(data)

# Displaying the original DataFrame
print("Original DataFrame:")
print(df)

# Dropping duplicates based on all columns
df_no_duplicates = df.drop_duplicates()

# Displaying the DataFrame after dropping duplicates
print("\nDataFrame after dropping duplicates:")
print(df_no_duplicates)
```

Original DataFrame:

| | Name | Age | Salary |
|---|---------|-----|--------|
| 0 | Alice | 25 | 50000 |
| 1 | Bob | 30 | 60000 |
| 2 | Alice | 25 | 50000 |
| 3 | Charlie | 22 | 70000 |
| 4 | Bob | 30 | 60000 |

DataFrame after dropping duplicates:

| | Name | Age | Salary |
|---|---------|-----|--------|
| 0 | Alice | 25 | 50000 |
| 1 | Bob | 30 | 60000 |
| 3 | Charlie | 22 | 70000 |

Another example to eliminating duplicates

```
In [ ]: # create DataFrame with duplicate entries
df = pd.DataFrame({'k1':['one']*3 + ['two']*4, 'k2':[1,1,2,3,3,4,4]})

# Displaying the original DataFrame
print("Original DataFrame:")
print(df)

# see the duplicate entries
duplicates = df.duplicated()
# Displaying the duplicates to look at them
print("\nThe duplicate entries :")
print(duplicates)

# Dropping duplicates based on all columns
df_no_duplicates = df.drop_duplicates()

# Displaying the DataFrame after dropping duplicates
print("\nDataFrame after dropping duplicates:")
print(df_no_duplicates)
```

Original DataFrame:

| | k1 | k2 |
|---|-----|----|
| 0 | one | 1 |
| 1 | one | 1 |
| 2 | one | 2 |
| 3 | two | 3 |
| 4 | two | 3 |
| 5 | two | 4 |
| 6 | two | 4 |

The duplicate entries :

| | |
|---|-------|
| 0 | False |
| 1 | True |
| 2 | False |
| 3 | False |
| 4 | True |
| 5 | False |
| 6 | True |

dtype: bool

DataFrame after dropping duplicates:

| | k1 | k2 |
|---|-----|----|
| 0 | one | 1 |
| 2 | one | 2 |
| 3 | two | 3 |
| 5 | two | 4 |

4.5.6 Control Eliminating Duplicates

- Keep The last entry ;

The drop_duplicates command currently removes the last entry. If there is a need to retain the last entry, the 'keep' keyword can be employed.

In []: df.drop_duplicates(keep="last")

Out[]:

| | k1 | k2 |
|---|-----|----|
| 1 | one | 1 |
| 2 | one | 2 |
| 4 | two | 3 |
| 6 | two | 4 |

We can eliminate all duplicate values based on specific columns as well.

```
In [ ]: # create DataFrame with duplicate entries
df = pd.DataFrame({'k1':['one']*3 + ['two']*4, 'k2':[1,1,2,3,3,4,4]})

# Displaying the original DataFrame
print("Original DataFrame:")
print(df)

# drop duplicate entries based on k1 only
df_k1 = df.drop_duplicates(['k1'])

# Displaying the df after drop the duplicates based on k1
print("\n The DF without duplicate (k1 based) :")
print(df_k1)

# drop if k1 and k2 column matched
df_k1_k2 = df.drop_duplicates(['k1', 'k2'])

# Displaying the df after drop the duplicates based on k1 and k2
print("\n The DF without duplicate (k1_k2 based) :")
print(df_k1_k2)
```

Original DataFrame:

| | k1 | k2 |
|---|-----|----|
| 0 | one | 1 |
| 1 | one | 1 |
| 2 | one | 2 |
| 3 | two | 3 |
| 4 | two | 3 |
| 5 | two | 4 |
| 6 | two | 4 |

The DF without duplicate (k1 based) :

| | k1 | k2 |
|---|-----|----|
| 0 | one | 1 |
| 3 | two | 3 |

The DF without duplicate (k1_k2 based) :

| | k1 | k2 |
|---|-----|----|
| 0 | one | 1 |
| 2 | one | 2 |
| 3 | two | 3 |
| 5 | two | 4 |

4.5.7 Transforming Data Using the replace() Function

The replace() function can customize your dataset by substituting values. It is commonly used for data cleaning, allowing correction of mislabeled data or handling outliers.

```
In [ ]: import pandas as pd
```

```
# Sample DataFrame with a column containing specific values to be replace
data = {'Category': ['Fruit', 'Vegetable', 'Fruit', 'Meat', 'Vegetable',
                    'Price': [2.5, 1.8, 3.0, 5.5, 2.0, 3.2, 6.0]}
```

```
df = pd.DataFrame(data)

# Displaying the original DataFrame
print("Original DataFrame:")
print(df)

# Replacing 'Fruit' with 'Healthy Snack' in the 'Category' column
df['Category'] = df['Category'].replace('Fruit', 'Healthy Snack')

# Displaying the DataFrame after replacement
print("\nDataFrame after Replacement:")
print(df)
```

Original DataFrame:

| | Category | Price |
|---|-----------|-------|
| 0 | Fruit | 2.5 |
| 1 | Vegetable | 1.8 |
| 2 | Fruit | 3.0 |
| 3 | Meat | 5.5 |
| 4 | Vegetable | 2.0 |
| 5 | Fruit | 3.2 |
| 6 | Meat | 6.0 |

DataFrame after Replacement:

| | Category | Price |
|---|---------------|-------|
| 0 | Healthy Snack | 2.5 |
| 1 | Vegetable | 1.8 |
| 2 | Healthy Snack | 3.0 |
| 3 | Meat | 5.5 |
| 4 | Vegetable | 2.0 |
| 5 | Healthy Snack | 3.2 |
| 6 | Meat | 6.0 |

Another example for data transformation by replacing

```
In [ ]: # create DataFrame with duplicate entries
df = pd.DataFrame({'k1':['one']*3 + ['two']*4, 'k2':[1,1,2,3,3,4,4]})

# Displaying the original DataFrame
print("Original DataFrame:")
print(df)

df_replaced=df.replace(['one', 3], ['One', '30'])

# Displaying the DataFrame after replacement
print("\nDataFrame after Replacement:")
print(df_replaced)
```

Original DataFrame:

| | k1 | k2 |
|---|-----|----|
| 0 | one | 1 |
| 1 | one | 1 |
| 2 | one | 2 |
| 3 | two | 3 |
| 4 | two | 3 |
| 5 | two | 4 |
| 6 | two | 4 |

DataFrame after Replacement:

| | k1 | k2 |
|---|-----|----|
| 0 | One | 1 |
| 1 | One | 1 |
| 2 | One | 2 |
| 3 | two | 30 |
| 4 | two | 30 |
| 5 | two | 4 |
| 6 | two | 4 |

4.5.8 Analysis of Categorical Data

A) Identifying Distinct Elements Using unique()

The unique function reveals the uniqueness within your data, providing insights into its diversity.

```
In [ ]: import pandas as pd

# Sample DataFrame with a column containing repeated elements
data = {'Category': ['Fruit', 'Vegetable', 'Fruit', 'Meat', 'Vegetable',
                     'Fruit', 'Meat', 'Vegetable', 'Fruit', 'Vegetable']}
df = pd.DataFrame(data)

# Displaying the original DataFrame
print("Original DataFrame:")
print(df)

# Extracting unique elements from the 'Category' column
unique_categories = df['Category'].unique()

# Displaying the unique elements
print("\nUnique Categories:")
print(unique_categories)
```

Original DataFrame:

```
Category
0      Fruit
1  Vegetable
2      Fruit
3      Meat
4  Vegetable
5      Fruit
6      Meat
```

Unique Categories:

```
['Fruit' 'Vegetable' 'Meat']
```

B) Counting Uniqueness with nunique()

The **nunique()** function offers a quick method to comprehend the variation within your dataset.

```
In [ ]: import pandas as pd
```

```
# Sample DataFrame with a column containing repeated elements
data = {'Category': ['Fruit', 'Vegetable', 'Fruit', 'Meat', 'Vegetable',
                     'Fruit', 'Meat']}
df = pd.DataFrame(data)

# Displaying the original DataFrame
print("Original DataFrame:")
print(df)

# Counting the number of unique elements in the 'Category' column
num_unique_categories = df['Category'].nunique()

# Displaying the number of unique elements
print("\nNumber of Unique Categories:", num_unique_categories)
```

Original DataFrame:

```
Category
0      Fruit
1  Vegetable
2      Fruit
3      Meat
4  Vegetable
5      Fruit
6      Meat
```

Number of Unique Categories: 3

5. Multi Index

- MultiIndex: Used to create a hierarchical index for a DataFrame. This implies that

the DataFrame's index can have multiple levels instead of just a single level.

5.1 Creating a 3D hierarchical table using MultiIndex or other methods.

5.1.1 Creating a hierarchical table with a MultiIndex

```
In [ ]: import pandas as pd

index = [('California', 2000), ('California', 2010),
          ('New York', 2000), ('New York', 2010),
          ('Texas', 2000), ('Texas', 2010)]

populations = [10000, 15000,
                20000, 25000,
                30000, 35000]

index = pd.MultiIndex.from_tuples(index)
pop = pd.Series(populations, index=index)
pop = pop.reindex(index)

print(pop)
```

| | | |
|------------|------|-------|
| California | 2000 | 10000 |
| | 2010 | 15000 |
| New York | 2000 | 20000 |
| | 2010 | 25000 |
| Texas | 2000 | 30000 |
| | 2010 | 35000 |

dtype: int64

5.1.2 Creating a hierarchical table with a DataFrame

The concept involves adding an index in 2D, considering the existing columns as 1D, resulting in a total of 3D structure.

```
In [ ]: import pandas as pd
import numpy as np
df = pd.DataFrame(np.random.rand(4, 2),
                  index=[['a', 'a', 'b', 'b'],
                         [1, 2, 1, 2]], columns=['income', 'profit'])
print(df)
```

| | income | profit |
|-----|------------|----------|
| a 1 | 0.434272 | 0.849378 |
| | 2 0.930367 | 0.951611 |
| b 1 | 0.874657 | 0.133630 |
| | 2 0.160487 | 0.983924 |

5.1.3 Creating a hierarchical table with a dictionary

The approach involves structuring the data in a dictionary, organizing it with nested dictionaries to achieve a hierarchical arrangement.

```
In [ ]: import pandas as pd  
data = {('California', 2000): 10000, ('California', 2010): 15000,  
        ('Texas', 2000): 20000, ('Texas', 2010): 25000,  
        ('New York', 2000): 30000, ('New York', 2010): 35000}  
df = pd.Series(data)  
print(df)
```

```
California 2000    10000  
           2010    15000  
Texas     2000    20000  
           2010    25000  
New York  2000    30000  
           2010    35000  
dtype: int64
```

5.2 Searching in the 3D Table by Year

```
In [ ]: import pandas as pd  
  
index = [('California', 2000), ('California', 2010),  
         ('New York', 2000), ('New York', 2010),  
         ('Texas', 2000), ('Texas', 2010)]  
  
populations = [10000, 15000,  
                20000, 25000,  
                30000, 35000]  
  
index = pd.MultiIndex.from_tuples(index)  
pop = pd.Series(populations, index=index)  
pop = pop.reindex(index)  
  
print(pop[:, 2010])
```

```
California    15000  
New York     25000  
Texas        35000  
dtype: int64
```

5.3 Transforming the hierarchical table to a regular format using the unstack method.

```
In [ ]: import pandas as pd  
  
index = [('California', 2000), ('California', 2010),  
         ('New York', 2000), ('New York', 2010),
```

```
( 'Texas', 2000),('Texas', 2010)]  
  
populations = [10000,15000,  
                20000,25000,  
                30000,35000]  
  
index = pd.MultiIndex.from_tuples(index)  
pop = pd.Series(populations, index=index)  
pop = pop.reindex(index)  
  
print(pop.unstack())
```

| | 2000 | 2010 |
|------------|-------|-------|
| California | 10000 | 15000 |
| New York | 20000 | 25000 |
| Texas | 30000 | 35000 |

5.4 Adding one more column to the DataFrame

```
In [ ]: import pandas as pd  
  
index = [('California', 2000),('California', 2010),  
         ('New York', 2000),('New York', 2010),  
         ('Texas', 2000),('Texas', 2010)]  
  
populations = [10000,15000,  
                20000,25000,  
                30000,35000]  
  
index = pd.MultiIndex.from_tuples(index)  
pop = pd.Series(populations, index=index)  
pop = pop.reindex(index)  
  
pop_df = pd.DataFrame({'total': pop,  
                       'under18':[9267089, 9284094,4687374,  
                                  4318033,5906301, 6879014]})  
  
print(pop)  
print(pop_df)
```

```

California 2000    10000
              2010    15000
New York   2000    20000
              2010    25000
Texas      2000    30000
              2010    35000
dtype: int64
          total  under18
California 2000  10000  9267089
              2010  15000  9284094
New York   2000  20000  4687374
              2010  25000  4318033
Texas      2000  30000  5906301
              2010  35000  6879014

```

5.5 Examples of Complicated Tables with MultiIndex

```

In [ ]: import pandas as pd
import numpy as np

index = pd.MultiIndex.from_product([[2013, 2014], [1, 2]],
                                   names=['year', 'visit'])

columns = pd.MultiIndex.from_product([('Bob', 'Guido', 'Sue'),
                                      ['HR', 'Temp']],
                                    names=['subject', 'type'])

data = np.round(np.random.randn(4, 6))
health_data = pd.DataFrame(data, index=index, columns=columns)
print(health_data)

```

| subject | Bob | Guido | Sue | | | | |
|---------|-------|-------|------|------|------|------|-----|
| type | HR | Temp | HR | Temp | HR | Temp | |
| year | visit | | | | | | |
| 2013 | 1 | -1.0 | 1.0 | -0.0 | 0.0 | -1.0 | 1.0 |
| | 2 | 0.0 | -1.0 | -2.0 | -1.0 | -0.0 | 1.0 |
| 2014 | 1 | -0.0 | 0.0 | 0.0 | -1.0 | -0.0 | 0.0 |
| | 2 | 0.0 | -0.0 | 1.0 | -1.0 | -0.0 | 2.0 |

```

In [ ]: import pandas as pd
import numpy as np

index = pd.MultiIndex.from_product([[2013, 2014], [1, 2]],
                                   names=['year', 'visit'])

columns = pd.MultiIndex.from_product([('Bob', 'Guido', 'Sue'),
                                      ['HR', 'Temp']],
                                    names=['subject', 'type'])

data = np.round(np.random.randn(4, 6))
health_data = pd.DataFrame(data, index=index, columns=columns)

print(health_data['Guido', 'HR'])

```

```
year  visit
2013 1      -1.0
      2      0.0
2014 1      -0.0
      2      1.0
Name: (Guido, HR), dtype: float64
```

```
In [ ]: import pandas as pd
import numpy as np

index = pd.MultiIndex.from_product([[2013, 2014], [1, 2]],
                                   names=['year', 'visit'])

columns = pd.MultiIndex.from_product([('Bob', 'Guido', 'Sue'),
                                      ('HR', 'Temp')],
                                    names=['subject', 'type'])

data = np.round(np.random.randn(4, 6))
health_data = pd.DataFrame(data, index=index, columns=columns)

print(health_data.loc[:, ('Bob', 'HR')])
```

```
year  visit
2013 1      -2.0
      2      -0.0
2014 1      -1.0
      2      -0.0
Name: (Bob, HR), dtype: float64
```

```
In [ ]: import pandas as pd
import numpy as np

index = pd.MultiIndex.from_product([[2013, 2014], [1, 2]],
                                   names=['year', 'visit'])

columns = pd.MultiIndex.from_product([('Bob', 'Guido', 'Sue'),
                                      ('HR', 'Temp')],
                                    names=['subject', 'type'])

data = np.round(np.random.randn(4, 6))
health_data = pd.DataFrame(data, index=index, columns=columns)

idx = pd.IndexSlice
print(health_data.loc[idx[:, 1], idx[:, 'HR']])
```

| subject | Bob | Guido | Sue | |
|---------|-------|-------|------|------|
| type | HR | HR | HR | |
| year | visit | | | |
| 2013 | 1 | 1.0 | 2.0 | -0.0 |
| 2014 | 1 | -0.0 | -1.0 | -1.0 |

6. String in pandas

- Pandas handles strings through various methods, offering a range of functionalities for string manipulation.
- It's important to note that you can access the data as a series and then use the str class, which contains numerous functions for applying operations element-wise and returning the result for each element.

```
In [ ]: import pandas as pd
data = ['peter', 'Paul', 'MARY', '15' , ' ' ]
print( pd.Series(data).str.len() ) # length
print( pd.Series(data).str.startswith('p'))# is it start with "p"
print( pd.Series(data).str.endswith('Y')) #does is end with "r"
print( pd.Series(data).str.find('t')) # find this letter
print( pd.Series(data).str.rfind('A'))# find it from right

0      5
1      4
2      4
3      2
4      2
dtype: int64
0    True
1   False
2   False
3   False
4   False
dtype: bool
0   False
1   False
2   True
3   False
4   False
dtype: bool
0      2
1     -1
2     -1
3     -1
4     -1
dtype: int64
0     -1
1     -1
2      1
3     -1
4     -1
dtype: int64
```

```
In [ ]: import pandas as pd
data = ['peter', 'Paul', 'MARY', '15' , ' ' ]
print( pd.Series(data).str.rjust(20))# adjust from right
print( pd.Series(data).str.ljust(50))# adjust from left
print( pd.Series(data).str.center(10))# make it center
print( pd.Series(data).str.zfill(5))# fill zeros
```

```
0          peter
1          Paul
2         MARY
3         15
4
dtype: object
0          peter
1          Paul
2         MARY
3         15
4
dtype: object
0          peter
1          Paul
2         MARY
3         15
4
dtype: object
0          peter
1          0Paul
2          0MARY
3          00015
4          000
dtype: object
```

```
In [ ]: import pandas as pd
data = ['peter', 'Paul', 'MARY', '15' , ' ' ]
print( pd.Series(data).str.isupper() )# is it all capital
print( pd.Series(data).str.islower() )# is it lower ?
print( pd.Series(data).str.istitle() )# is like like "This"
print( pd.Series(data).str.isspace() )# is it all spaces ?
print( pd.Series(data).str.isdigit() )# is it numbers ?
print( pd.Series(data).str.isalpha() )# is it all letters ?
print( pd.Series(data).str.isalnum() )# is it not got any spaces ?
print( pd.Series(data).str.isdecimal() )# is it decimals ?
print( pd.Series(data).str.isnumeric() )# is it number
print( pd.Series(data).str.upper() )# make it capital
print( pd.Series(data).str.capitalize() )# make it like 'This'
print( pd.Series(data).str.lower() )# make it lower
print( pd.Series(data).str.swapcase() )# switch capital & small
```

```
0    False
1    False
2     True
3    False
4    False
dtype: bool
0     True
1    False
2    False
3    False
4    False
dtype: bool
0    False
```

```
1      True
2     False
3     False
4     False
dtype: bool
0     False
1     False
2     False
3     False
4     True
dtype: bool
0     False
1     False
2     False
3     True
4     False
dtype: bool
0     True
1     True
2     True
3    False
4    False
dtype: bool
0     True
1     True
2     True
3     True
4    False
dtype: bool
0     False
1     False
2     False
3     True
4    False
dtype: bool
0     False
1     False
2     False
3     True
4    False
dtype: bool
0    PETER
1    PAUL
2    MARY
3     15
4
dtype: object
0   Peter
1   Paul
2   Mary
3    15
4
dtype: object
```

```
0    peter
1    paul
2   mary
3    15
4
dtype: object
0    PETER
1    pAUL
2   mary
3    15
4
dtype: object
```

7. Date & Time

7.1 Write Date in Pandas

- In Pandas, dates are typically represented in the format of year, month, day, hour, minute, and second.
- This format allows for easy access to individual components such as year, month, day, hour, minute, and second.

```
In [ ]: import pandas as pd
x = pd.to_datetime("4th of July, 2018")
print(x)
```

```
2018-07-04 00:00:00
```

7.2 Range between past and future dates

```
In [ ]: import pandas as pd
import numpy as np
x = pd.to_datetime("4th of July, 2018")

y = x + pd.to_timedelta(np.arange(20), 'D')
z = x - pd.to_timedelta(np.arange(20), 'D')

print(x)
print(y)
print(z)
```

```
2018-07-04 00:00:00
DatetimeIndex(['2018-07-04', '2018-07-05', '2018-07-06', '2018-07-07',
               '2018-07-08', '2018-07-09', '2018-07-10', '2018-07-11',
               '2018-07-12', '2018-07-13', '2018-07-14', '2018-07-15',
               '2018-07-16', '2018-07-17', '2018-07-18', '2018-07-19',
               '2018-07-20', '2018-07-21', '2018-07-22', '2018-07-23'],
              dtype='datetime64[ns]', freq=None)
DatetimeIndex(['2018-07-04', '2018-07-03', '2018-07-02', '2018-07-01',
               '2018-06-30', '2018-06-29', '2018-06-28', '2018-06-27',
               '2018-06-26', '2018-06-25', '2018-06-24', '2018-06-23',
               '2018-06-22', '2018-06-21', '2018-06-20', '2018-06-19',
               '2018-06-18', '2018-06-17', '2018-06-16', '2018-06-15'],
              dtype='datetime64[ns]', freq=None)
```

7.3 Write Dates & Tables

7.3.1 Creating a Table for Dates

```
In [ ]: import pandas as pd
index = pd.DatetimeIndex(['2014-07-04', '2014-08-04',
                           '2015-07-04', '2015-08-04'])
data = pd.Series([0, 1, 2, 3], index=index)
print(data)
```

```
2014-07-04    0
2014-08-04    1
2015-07-04    2
2015-08-04    3
dtype: int64
```

7.3.2 Filtering based on dates: days, months, or years

```
In [ ]: import pandas as pd
index = pd.DatetimeIndex(['2011-03-12', '2012-08-21',
                           '2013-07-11', '2014-11-08'])
data = pd.Series([0, 1, 2, 3], index=index)
print(data['2011-01-01':'2012-12-31'])
```

```
2011-03-12    0
2012-08-21    1
dtype: int64
```

```
In [ ]: import pandas as pd
index = pd.DatetimeIndex(['2011-03-12', '2012-08-21',
                           '2013-07-11', '2014-11-08'])

data = pd.Series([0, 1, 2, 3], index=index)
print(data['2012'])
```

```
2012-08-21    1
dtype: int64
```

```
In [ ]: import pandas as pd  
index = pd.DatetimeIndex(['2011-03-12', '2012-08-21',  
                           '2013-07-11', '2014-11-08'])  
  
data = pd.Series([0, 1, 2, 3], index=index)  
print(data['2012-08'])
```

```
2012-08-21    1  
dtype: int64
```

7.3.3 Creating a table for dates with a range between two dates or starting from a specific day.

```
In [ ]: import pandas as pd  
data = pd.date_range('2011-12-25', '2012-01-08')  
print(data)
```



```
DatetimeIndex(['2011-12-25', '2011-12-26', '2011-12-27', '2011-12-28',  
                '2011-12-29', '2011-12-30', '2011-12-31', '2012-01-01',  
                '2012-01-02', '2012-01-03', '2012-01-04', '2012-01-05',  
                '2012-01-06', '2012-01-07', '2012-01-08'],  
               dtype='datetime64[ns]', freq='D')
```

```
In [ ]: import pandas as pd  
data = pd.date_range('2011-12-25', periods=8)  
print(data)
```



```
DatetimeIndex(['2011-12-25', '2011-12-26', '2011-12-27', '2011-12-28',  
                '2011-12-29', '2011-12-30', '2011-12-31', '2012-01-01'],  
               dtype='datetime64[ns]', freq='D')
```

```
In [ ]: import pandas as pd  
data = pd.date_range('2011-12-25', periods=8, freq='H')  
print(data)
```



```
DatetimeIndex(['2011-12-25 00:00:00', '2011-12-25 01:00:00',  
                '2011-12-25 02:00:00', '2011-12-25 03:00:00',  
                '2011-12-25 04:00:00', '2011-12-25 05:00:00',  
                '2011-12-25 06:00:00', '2011-12-25 07:00:00'],  
               dtype='datetime64[ns]', freq='H')
```

7.3.4 Creating a table for dates with a range specified by hours only, excluding dates.

```
In [ ]: import pandas as pd  
data = pd.timedelta_range(0, periods=10, freq='H')  
print(data)
```

```
TimedeltaIndex(['0 days 00:00:00', '0 days 01:00:00', '0 days 02:00:00',
                 '0 days 03:00:00', '0 days 04:00:00', '0 days 05:00:00',
                 '0 days 06:00:00', '0 days 07:00:00', '0 days 08:00:00',
                 '0 days 09:00:00'],
                dtype='timedelta64[ns]', freq='H')
```

```
In [ ]: import pandas as pd
data = pd.timedelta_range(0, periods=9, freq="2H30T40S")
print(data)
```

```
TimedeltaIndex(['0 days 00:00:00', '0 days 02:30:40', '0 days 05:01:20',
                 '0 days 07:32:00', '0 days 10:02:40', '0 days 12:33:20',
                 '0 days 15:04:00', '0 days 17:34:40', '0 days 20:05:20'],
                dtype='timedelta64[ns]', freq='9040S')
```

```
In [ ]: import pandas as pd
from pandas.tseries.offsets import BDay
data = pd.date_range('2018-07-01', periods=5, freq=BDay())
print(data)
```

```
DatetimeIndex(['2018-07-02', '2018-07-03', '2018-07-04', '2018-07-05',
                 '2018-07-06'],
                dtype='datetime64[ns]', freq='B')
```

8. File Handling (CSV files)

The **CSV** (Comma-Separated Values) file --> is a text file format that uses commas to separate values

8.1 Read CSV or Excel file

(Comma-Separated Values) is a text file format that uses commas to separate values

```
In [ ]: iris = 'http://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.csv'
df = pd.read_csv(iris, sep=',')
df.columns = ["sepal_length", "sepal_width", "petal_length", "petal_width"]
print(df.head(10))
```

| | sepal_length | sepal_width | petal_length | petal_width | class |
|---|--------------|-------------|--------------|-------------|-------------|
| 0 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| 1 | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| 2 | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| 3 | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |
| 4 | 5.4 | 3.9 | 1.7 | 0.4 | Iris-setosa |
| 5 | 4.6 | 3.4 | 1.4 | 0.3 | Iris-setosa |
| 6 | 5.0 | 3.4 | 1.5 | 0.2 | Iris-setosa |
| 7 | 4.4 | 2.9 | 1.4 | 0.2 | Iris-setosa |
| 8 | 4.9 | 3.1 | 1.5 | 0.1 | Iris-setosa |
| 9 | 5.4 | 3.7 | 1.5 | 0.2 | Iris-setosa |

```
In [ ]: import pandas as pd

grades1 = pd.read_csv('dataframe1.csv')
grades2 = pd.read_excel('dataframe1.xlsx')

print(grades1)
print(grades2)
```

| | Unnamed: 0 | Math | Physics | French | Chemistry |
|---|------------|------|---------|--------|-----------|
| 0 | a | 1 | 6 | 11 | 16 |
| 1 | b | 2 | 7 | 12 | 17 |
| 2 | c | 3 | 8 | 13 | 18 |
| 3 | d | 4 | 9 | 14 | 19 |
| 4 | e | 5 | 10 | 15 | 20 |

| | Unnamed: 0 | Math | Physics | French | Chemistry |
|---|------------|------|---------|--------|-----------|
| 0 | a | 1 | 6 | 11 | 16 |
| 1 | b | 2 | 7 | 12 | 17 |
| 2 | c | 3 | 8 | 13 | 18 |
| 3 | d | 4 | 9 | 14 | 19 |
| 4 | e | 5 | 10 | 15 | 20 |

8.2 Save DF as CSV or Excel file

```
In [ ]: import pandas as pd
w = pd.Series({'a':1 , 'b':2 , 'c':3 , 'd':4 , 'e':5})
x = pd.Series({'a':6 , 'b':7 , 'c':8 , 'd':9 , 'e':10})
y = pd.Series({'a':11 , 'b':12 , 'c':13 , 'd':14 , 'e':15})
z = pd.Series({'a':16 , 'b':17 , 'c':18 , 'd':19 , 'e':20})
grades = pd.DataFrame({'Math':w,'Physics':x,'French':y,'Chemistry':z})

print(grades)
grades.to_csv('dataframe1.csv')
```

| | Math | Physics | French | Chemistry |
|---|------|---------|--------|-----------|
| a | 1 | 6 | 11 | 16 |
| b | 2 | 7 | 12 | 17 |
| c | 3 | 8 | 13 | 18 |
| d | 4 | 9 | 14 | 19 |
| e | 5 | 10 | 15 | 20 |

```
In [ ]: import pandas as pd
```

```
w = pd.Series({'a':1 , 'b':2 , 'c':3 , 'd':4 , 'e':5})
x = pd.Series({'a':6 , 'b':7 , 'c':8 , 'd':9 , 'e':10})
y = pd.Series({'a':11 , 'b':12 , 'c':13 , 'd':14 , 'e':15})
z = pd.Series({'a':16 , 'b':17 , 'c':18 , 'd':19 , 'e':20})

grades = pd.DataFrame({'Math':w,'Physics':x,'French':y,'Chemistry':z})

print(grades)
grades.to_excel('dataframe1.xlsx',sheet_name ='Sheet1')
```

| | Math | Physics | French | Chemistry |
|---|------|---------|--------|-----------|
| a | 1 | 6 | 11 | 16 |
| b | 2 | 7 | 12 | 17 |
| c | 3 | 8 | 13 | 18 |
| d | 4 | 9 | 14 | 19 |
| e | 5 | 10 | 15 | 20 |

8.3 Applying different methods while reading the DataFrame

8.3.1 Specify one column to be the index column

```
In [ ]: import pandas as pd
data=pd.read_csv("dataframe1.csv", index_col= "Math")
print(data)
```

| | Math | Unnamed: 0 | Physics | French | Chemistry |
|---|------|------------|---------|--------|-----------|
| 1 | a | 1 | 6 | 11 | 16 |
| 2 | b | 2 | 7 | 12 | 17 |
| 3 | c | 3 | 8 | 13 | 18 |
| 4 | d | 4 | 9 | 14 | 19 |
| 5 | e | 5 | 10 | 15 | 20 |

8.3.2 Skip some rows

Example for reading data and displaying from a CSV file:

- In this example, we skip the first three rows in the CSV file since they contain comments that I want to keep in the CSV file. Adjust the number accordingly based on your specific file.

```
In [ ]: import pandas as pd
filename= "pima-indians-diabetes.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'df
df = pd.read_csv(filename, skiprows=9, names = names)
# df.head(10)
description = data.describe()
```

```
print(description)

      Physics    French  Chemistry
count  5.000000  5.000000  5.000000
mean   8.000000 13.000000 18.000000
std    1.581139  1.581139  1.581139
min   6.000000 11.000000 16.000000
25%   7.000000 12.000000 17.000000
50%   8.000000 13.000000 18.000000
75%   9.000000 14.000000 19.000000
max  10.000000 15.000000 20.000000
```

8.3.3 Classify Data

Example for classifying this data based on class (0,0) using groupby.

```
In [ ]: # Class Distribution
import pandas as pd
filename= "pima-indians-diabetes.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
data = pd.read_csv(filename, skiprows=9, names = names)
class_counts = data.groupby('class').size()
print(class_counts)

class
0    496
1    263
dtype: int64
```

8.3.4 Correlation and Skew

- Example for correlation of reading data from a file and skew:
 - A positive skew indicates that the distribution is skewed to the right, with more values above the mean than below the mean.
 - Conversely, a negative skew indicates that the distribution is skewed to the left, with more values below the mean than above the mean.

```
In [ ]: import pandas as pd
filename= "pima-indians-diabetes.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
data = pd.read_csv(filename, skiprows=9, names = names)
correlations = data.corr(method='pearson')
print(correlations)
skew = data.skew()
print(skew)
```

```

          preg      plas      pres      skin      test      mass      ped
i \
preg  1.000000  0.127728  0.149506 -0.074168 -0.067703  0.019442 -0.02701
2
plas  0.127728  1.000000  0.154069  0.056797  0.327046  0.224216  0.13566
7
pres  0.149506  0.154069  1.000000  0.207468  0.089140  0.289950  0.04819
1
skin -0.074168  0.056797  0.207468  1.000000  0.433753  0.392981  0.18311
9
test -0.067703  0.327046  0.089140  0.433753  1.000000  0.198878  0.19044
5
mass  0.019442  0.224216  0.289950  0.392981  0.198878  1.000000  0.13321
6
pedi -0.027012  0.135667  0.048191  0.183119  0.190445  0.133216  1.00000
0
age   0.549304  0.257701  0.240014 -0.120604 -0.051139  0.035393  0.03323
9
class 0.225405  0.464388  0.067412  0.068956  0.124995  0.293990  0.16712
7

          age      class
preg  0.549304  0.225405
plas  0.257701  0.464388
pres  0.240014  0.067412
skin -0.120604  0.068956
test -0.051139  0.124995
mass  0.035393  0.293990
pedi  0.033239  0.167127
age   1.000000  0.235132
class 0.235132  1.000000
preg  0.905962
plas  0.162860
pres -1.850360
skin  0.115403
test  2.266363
mass -0.436700
pedi  1.828278
age   1.131371
class 0.646393
dtype: float64

```

The Key Resources :

- Codes and examples in this notebook based heavily on [Hesham Asem Python Playlist for ML.](#)