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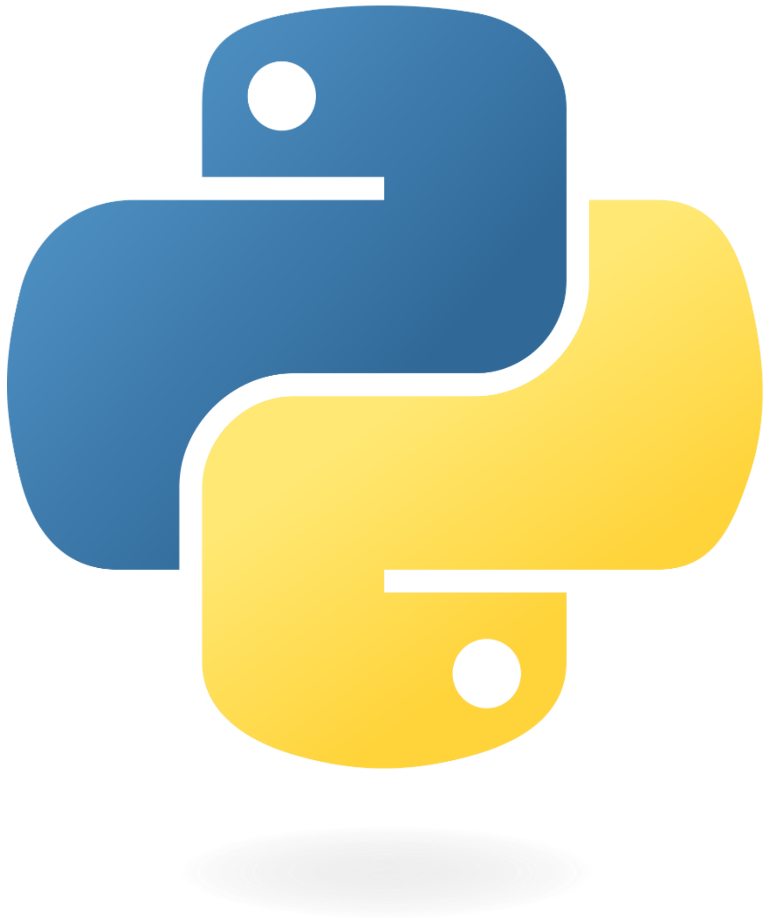
Python for Data Analysis

National Institute of Electronics & Information Technology

Why Python for Data Analysis?

- Simple and readable syntax
- Rich ecosystem: NumPy, Pandas, Matplotlib, etc.
- Excellent support for data manipulation and visualization
- Widely used in academia and industry



Tutorial Content

- Overview of Python Libraries for Data Scientists
- Reading Data; Selecting and Filtering the Data; Data manipulation, sorting, grouping, rearranging
- Plotting the data
- Descriptive statistics
- Inferential statistics

Python Libraries for Data Science

Many popular Python toolboxes/libraries:

- NumPy
- SciPy
- Pandas
- SciKit-Learn

All these libraries are installed on the SCC

Visualization libraries

- matplotlib
- Seaborn

and many more …

Python Libraries for Data Science

NumPy:

- introduces objects for multidimensional arrays and matrices, as well as functions that allow to easily perform advanced mathematical and statistical operations on those objects

- provides vectorization of mathematical operations on arrays and matrices which significantly improves the performance

- many other python libraries are built on NumPy

Link: http://www.numpy.org/

Python Libraries for Data Science

SciPy:

- collection of algorithms for linear algebra, differential equations, numerical integration, optimization, statistics and more

- part of SciPy Stack

- built on NumPy

Link: https://www.scipy.org/scipylib/

Python Libraries for Data Science

Pandas:

- adds data structures and tools designed to work with table-like data (similar to Series and Data Frames in R)

- provides tools for data manipulation: reshaping, merging, sorting, slicing, aggregation etc.

- allows handling missing data

Link: http://pandas.pydata.org/

Python Libraries for Data Science

SciKit-Learn:

- provides machine learning algorithms: classification, regression, clustering, model validation etc.

- built on NumPy, SciPy and matplotlib

Link: http://scikit-learn.org/

Python Libraries for Data Science

Matplotlib:

- python 2D plotting library which produces publication quality figures in a variety of hardcopy formats

- a set of functionalities similar to those of MATLAB

- line plots, scatter plots, barcharts, histograms, pie charts etc.

- relatively low-level; some effort needed to create advanced visualization

Link: https://matplotlib.org/

Python Libraries for Data Science

Seaborn:

- based on matplotlib
- provides high level interface for drawing attractive statistical graphics
- Similar (in style) to the popular ggplot2 library in R

Link: https://seaborn.pydata.org/

Introduction to Google Colab

What is Google Colab?

Google Colab (short for Colaboratory) is a cloud-based platform that provides an environment to run Python code in Jupyter notebooks without needing to install anything locally. Colab is built on Jupyter, an open-source project widely used for creating interactive code and data science projects.

Advantages:

- No Setup Required
- Free Access to GPUs/TPUs
- CollaborationCloud Storage Integration
- Supports Popular Libraries
- Easy Sharing and Publishing
- Free to Use
- **URL:** https://colab.research.google.com/

Key Features of Colab

- Live code execution in browser
- Markdown + Code combo
- Easily shareable notebooks
- Integrated with Google Drive
- Can install additional libraries with `!pip install`

Getting Started with Colab

How to open Colab:

1. Go to https://colab.research.google.com/
2. Click "New Notebook“
3. Start coding!

Code Example:

```
print("Hello, Google Colab!")
```

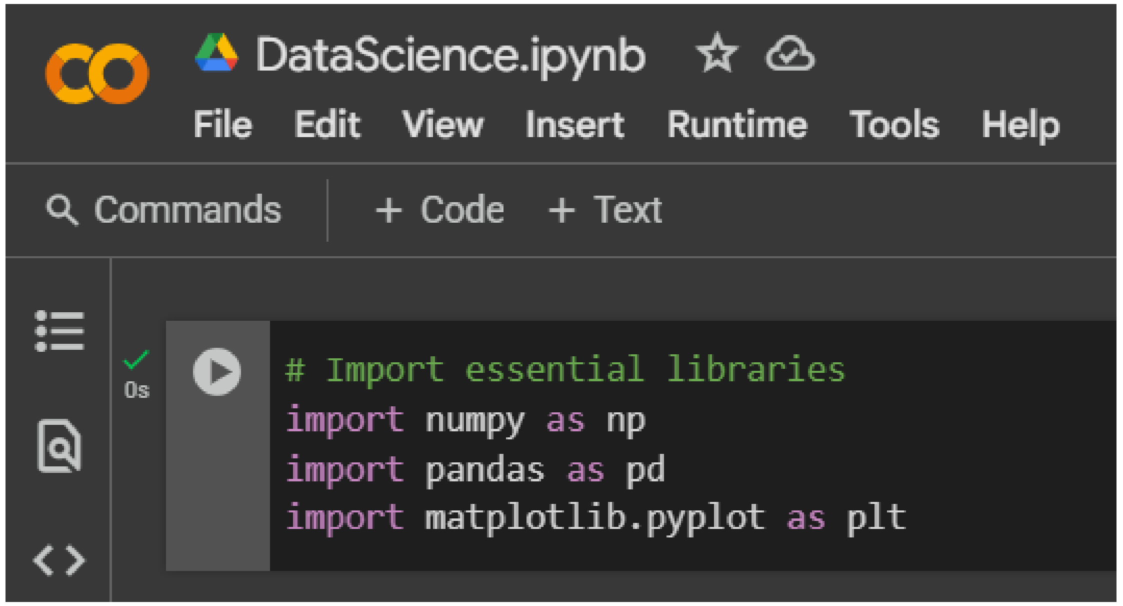
Installing and Importing Libraries

#Install a package (if needed)

```
!pip install pandas
```

#Import essential libraries

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



```
# Import essential libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

Reading data using pandas

```
#Basic Syntax to Read CSV
import pandas as pd

df = pd.read_csv("filename.csv")  # Load CSV into DataFrame
```

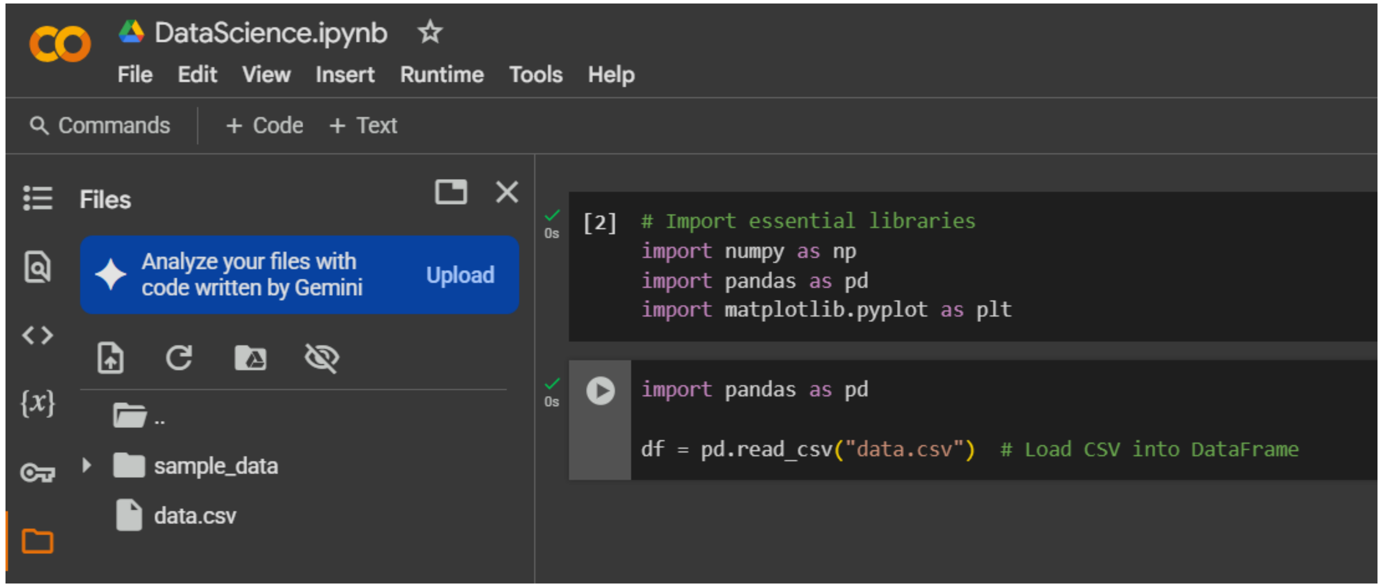
```
#Load CSV from a URL
url =
'https://raw.githubusercontent.com/lovnishverm
a/datasets/refs/heads/main/titanic.csv'
```

```
# Load CSV from URL
df = pd.read_csv(url)

# Show first few rows
df.head()
```

```
#Load from Google Drive
from google.colab import drive
drive.mount('/content/drive')

# Replace with actual path
file_path =
'/content/drive/MyDrive/mydata.csv'

df = pd.read_csv(file_path)
```

There is a number of pandas commands to read other data formats:

- pd.read_excel('myfile.xlsx',sheet_name='Sheet1', index_col=None, na_values=['NA'])
- pd.read_stata('myfile.dta')
- pd.read_sas('myfile.sas7bdat')
- pd.read_hdf('myfile.h5','df')

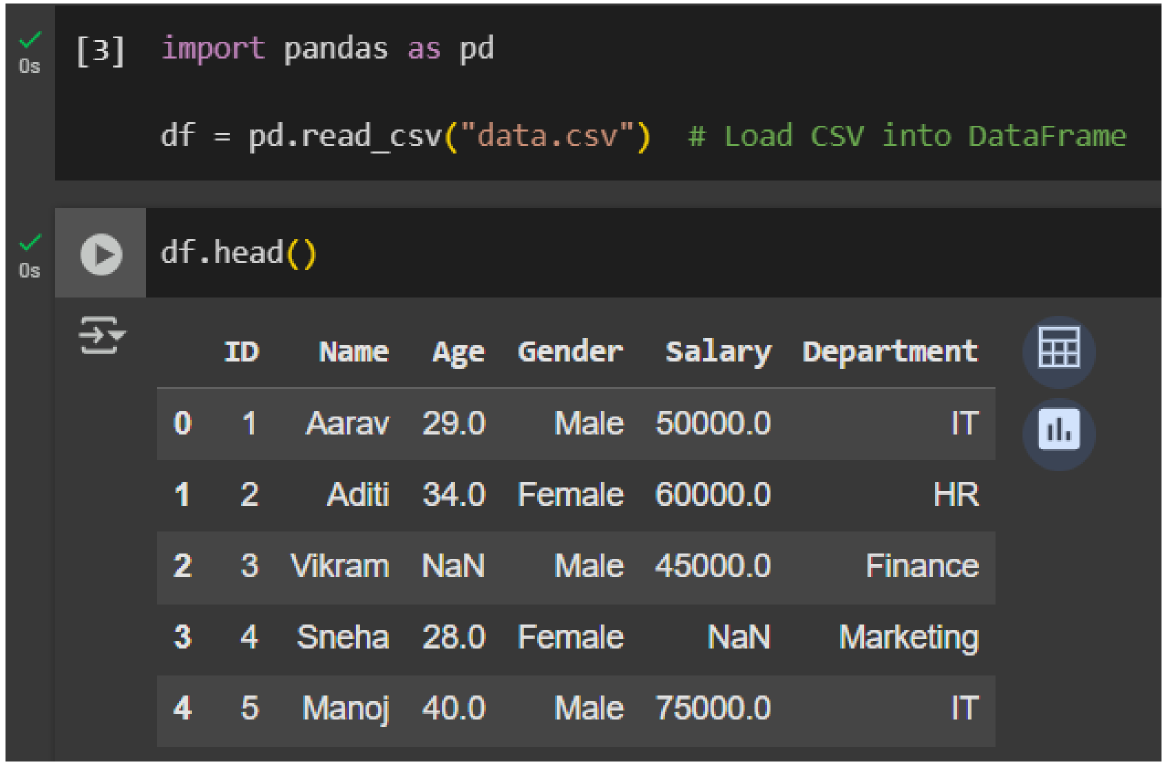

DataScience.ipynb
File Edit View Insert Runtime Tools Help
Commands
+ Code
+ Text
Files
Analyze your files with code written by Gemini
Upload
..
sample_data
data.csv

```
[2] # Import essential libraries
    import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
```

```
import pandas as pd

df = pd.read_csv("data.csv")  # Load CSV into DataFrame
```

Exploring data frames

```
#List first 5 records
df.head()
```



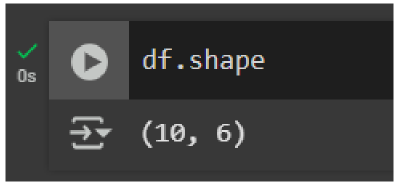
```
[3] import pandas as pd

    df = pd.read_csv("data.csv")  # Load CSV into DataFrame
```

```
df.head()
```

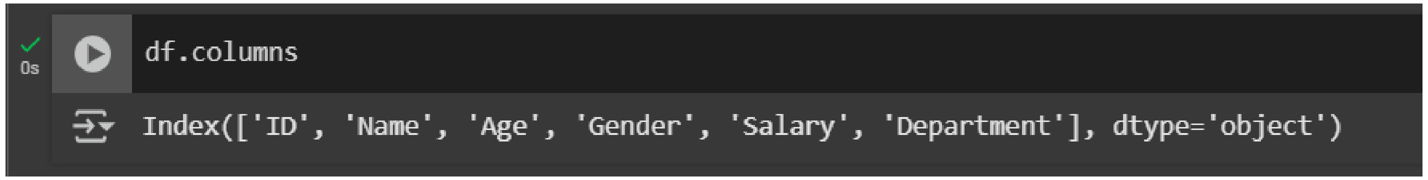
```
   ID    Name   Age  Gender   Salary  Department
0   1   Aarav  29.0    Male  50000.0          IT
1   2   Aditi  34.0  Female  60000.0          HR
2   3  Vikram   NaN    Male  45000.0     Finance
3   4  Sneha   28.0  Female      NaN   Marketing
4   5   Manoj  40.0    Male  75000.0          IT
```

After Reading: Inspect the Data

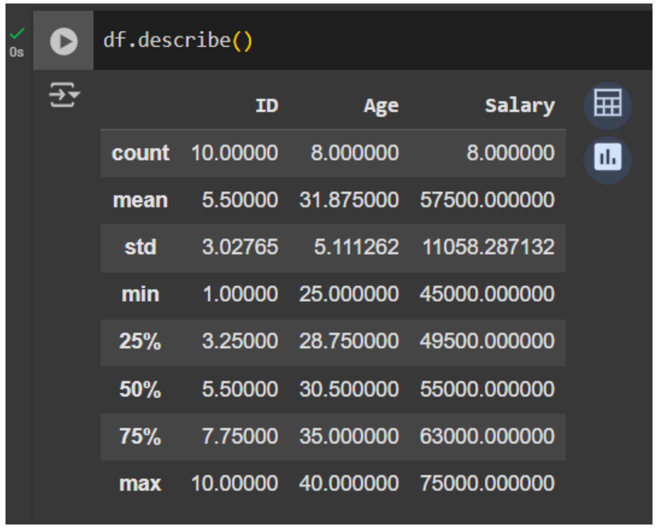
- ✓ df.head() # First 5 rows
- ✓ df.tail() # Last 5 rows
- ✓ df.shape # Rows & columns
- ✓ df.columns # Column names
- ✓ df.dtypes # Data types
- ✓ df.info() # Summary
- ✓ df.describe() # Statistical summary



```
df.shape
(10, 6)
```

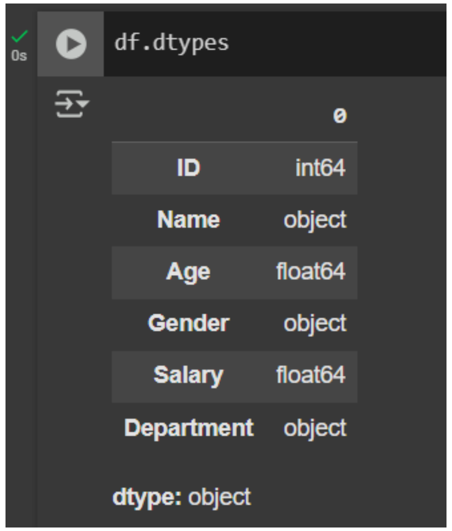


```
df.columns
Index(['ID', 'Name', 'Age', 'Gender', 'Salary', 'Department'], dtype='object')
```



```
df.describe()
```

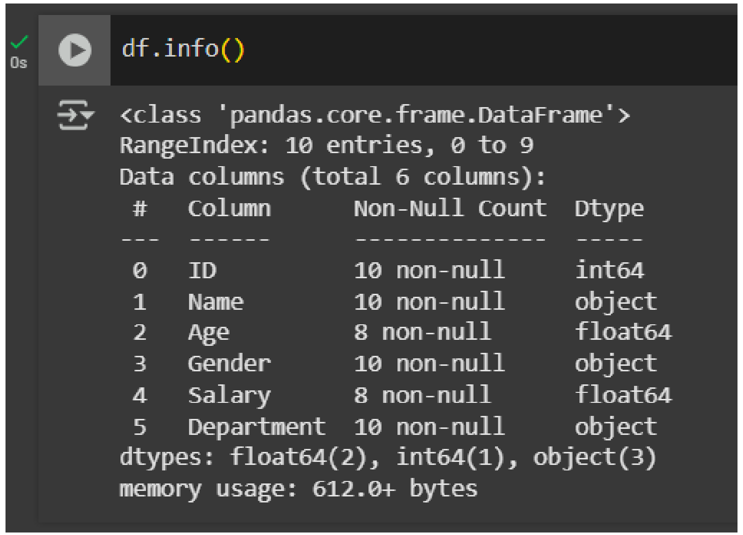
	ID	Age	Salary
count	10.00000	8.000000	8.000000
mean	5.50000	31.875000	57500.000000
std	3.02765	5.111262	11058.287132
min	1.00000	25.000000	45000.000000
25%	3.25000	28.750000	49500.000000
50%	5.50000	30.500000	55000.000000
75%	7.75000	35.000000	63000.000000
max	10.00000	40.000000	75000.000000



```
df.dtypes
```

	0
ID	int64
Name	object
Age	float64
Gender	object
Salary	float64
Department	object

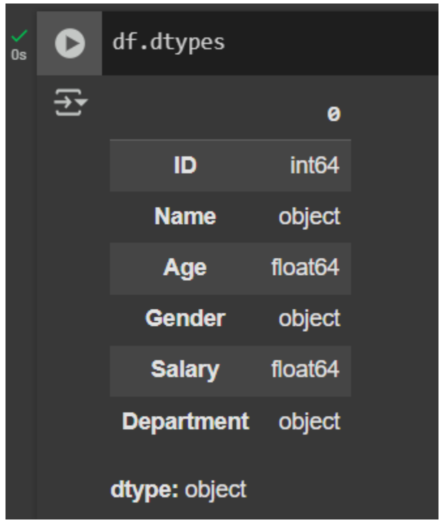
dtype: object



```
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   ID          10 non-null     int64  
 1   Name        10 non-null     object 
 2   Age         8 non-null      float64
 3   Gender      10 non-null     object 
 4   Salary      8 non-null      float64
 5   Department  10 non-null     object 
dtypes: float64(2), int64(1), object(3)
memory usage: 612.0+ bytes
```

Data Frame data types

Pandas Type	Native Python Type	Description
object	string	The most general dtype. Will be assigned to your column if column has mixed types (numbers and strings).
int64	int	Numeric characters. 64 refers to the memory allocated to hold this character.
float64	float	Numeric characters with decimals. If a column contains numbers and NaNs(see below), pandas will default to float64, in case your missing value has a decimal.
datetime64, timedelta[ns]	N/A (but see the datetime module in Python's standard library)	Values meant to hold time data. Look into these for time series experiments.



```
df.dtypes
```

```
                    0
        ID      int64
      Name     object
       Age    float64
    Gender     object
    Salary    float64
Department     object

dtype: object
```

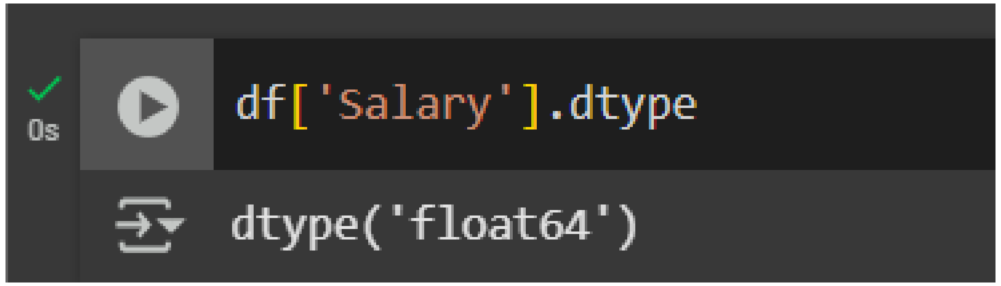
Data Frame data types

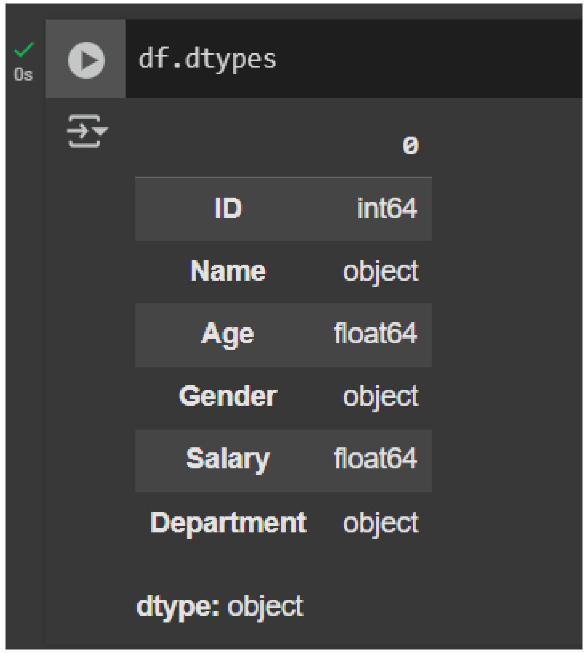
```
#Check a particular column type
df['Salary'].dtype
```

Output : dtype('float64')

```
#Check types for all the columns
df.dtypes
```

Output:
```
ID           int64
Name         object
Age          float64
Gender       object
Salary       float64
Department   object
dtype: object
```


```
df['Salary'].dtype
dtype('float64')
```


```
df.dtypes
```

	0
ID	int64
Name	object
Age	float64
Gender	object
Salary	float64
Department	object

dtype: object

Data Frames attributes

Python objects have *attributes* and *methods*.

df.attribute	description
dtypes	list the types of the columns
columns	list the column names
axes	list the row labels and column names
ndim	number of dimensions
size	number of elements
shape	return a tuple representing the dimensionality
values	numpy representation of the data

Hands-on exercises

- ✓ Find how many records this data frame has;
- ✓ How many elements are there?
- ✓ What are the column names?
- ✓ What types of columns we have in this data frame?

Data Frames methods

Unlike attributes, python methods have *parenthesis.*
All attributes and methods can be listed with a *dir()* function: `dir(df)`

df.method()	description
head([n]), tail([n])	first/last n rows
describe()	generate descriptive statistics (for numeric columns only)
max(), min()	return max/min values for all numeric columns
mean(), median()	return mean/median values for all numeric columns
std()	standard deviation
sample([n])	returns a random sample of the data frame
dropna()	drop all the records with missing values

Hands-on exercises

- ✓ Give the summary for the numeric columns in the dataset
- ✓ Calculate standard deviation for all numeric columns;
- ✓ What are the mean values of the first 50 records in the dataset?
- ✓ ***Hint:*** use head() method to subset the first 50 records and then calculate the mean

Selecting a column in a Data Frame

Method 1: Subset the data frame using column name:

df[‘Gender']

Method 2: Use the column name as an attribute:

df.Gender

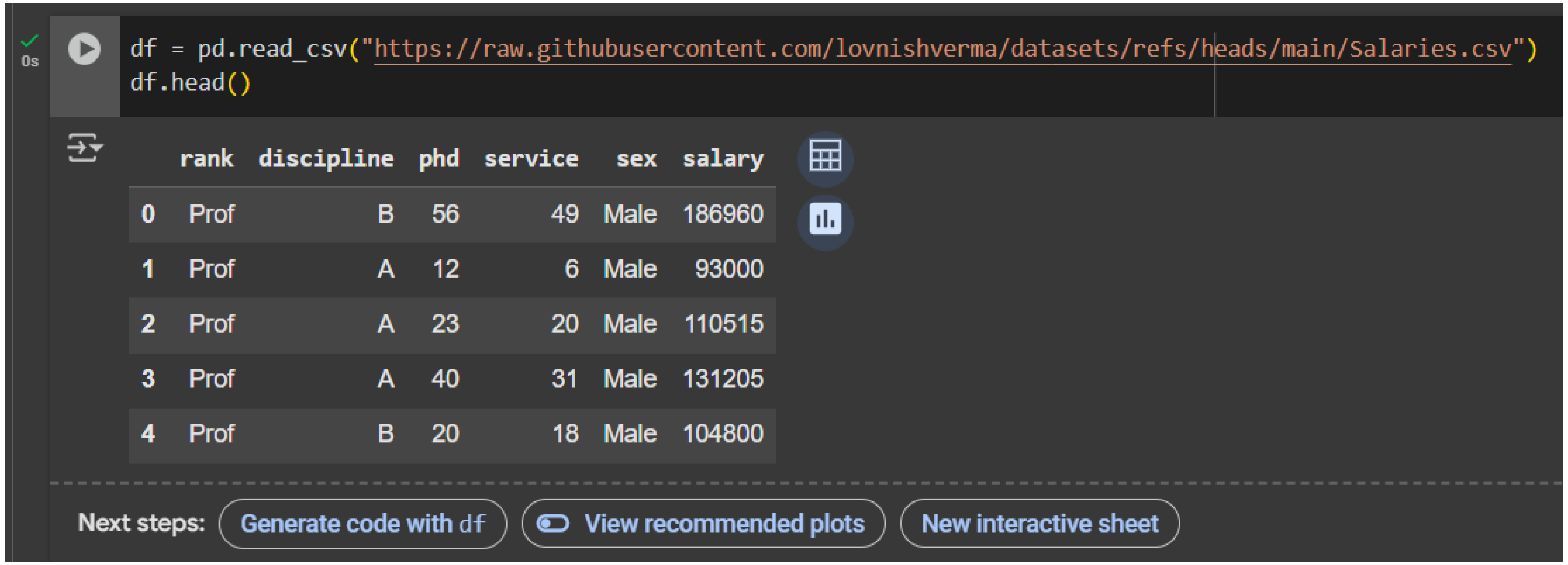
Note: there is an attribute *rank* for pandas data frames, so to select a column with a name "rank" we should use method 1.

Hands-on exercises

- ✓ Calculate the basic statistics for the *salary* column;
- ✓ Find how many values in the *salary* column (use *count* method);
- ✓ Calculate the average Salary;

Try This Dataset

```
df = pd.read_csv("https://raw.githubusercontent.com/lovnishverma/datasets/refs/heads/main/Salaries.csv")
df.head()
```



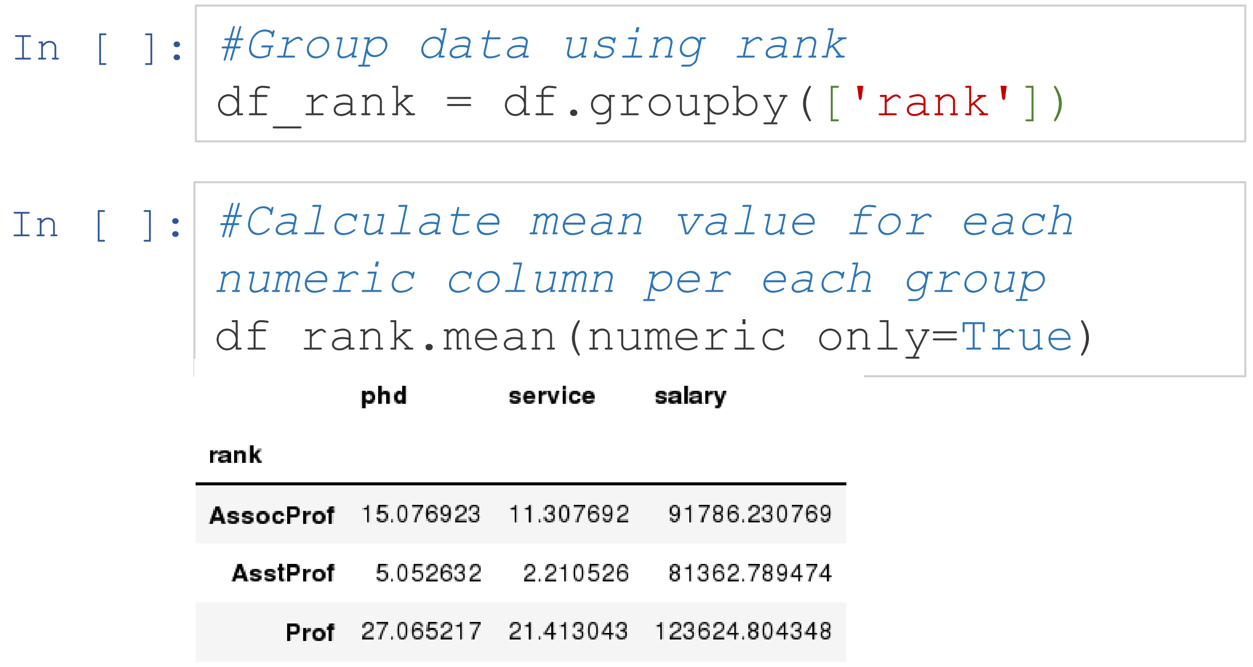
```
df = pd.read_csv("https://raw.githubusercontent.com/lovnishverma/datasets/refs/heads/main/Salaries.csv")
df.head()
```

```
   rank discipline  phd  service   sex  salary
0  Prof          B   56       49  Male  186960
1  Prof          A   12        6  Male   93000
2  Prof          A   23       20  Male  110515
3  Prof          A   40       31  Male  131205
4  Prof          B   20       18  Male  104800
```

Data Frames *groupby* method

Using "group by" method we can:

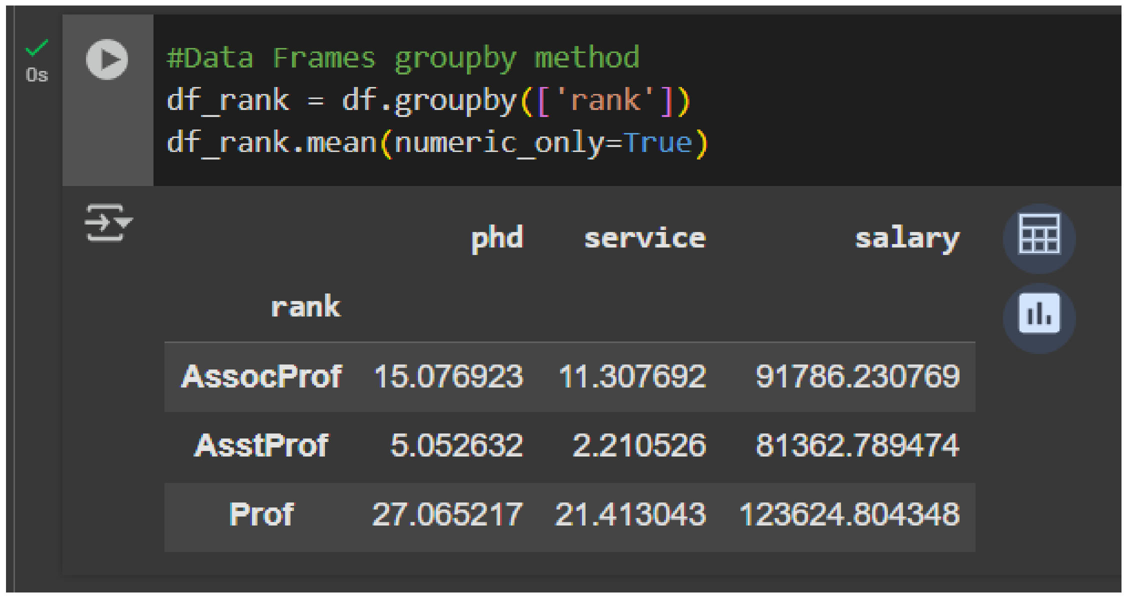
- Split the data into groups based on some criteria
- Calculate statistics (or apply a function) to each group
- Similar to dplyr() function in R



```
In [ ]: #Group data using rank
        df_rank = df.groupby(['rank'])
```

```
In [ ]: #Calculate mean value for each
        numeric column per each group
        df rank.mean(numeric only=True)
```

```
                 phd    service         salary
rank
AssocProf  15.076923  11.307692   91786.230769
 AsstProf   5.052632   2.210526   81362.789474
     Prof  27.065217  21.413043  123624.804348
```



```
#Data Frames groupby method
df_rank = df.groupby(['rank'])
df_rank.mean(numeric_only=True)
```

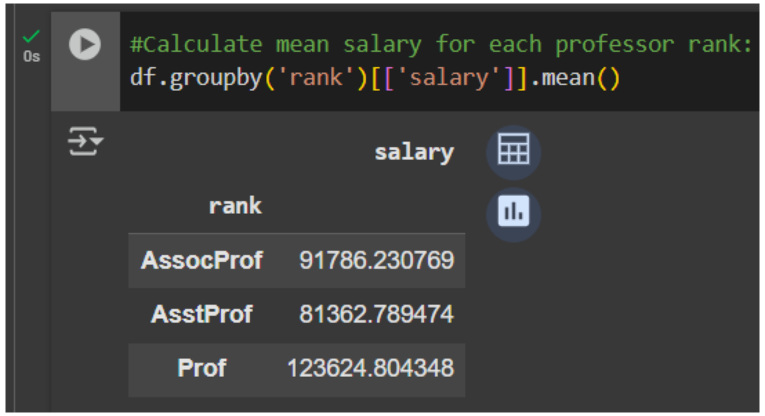
```
                 phd    service         salary
rank
AssocProf  15.076923  11.307692   91786.230769
 AsstProf   5.052632   2.210526   81362.789474
     Prof  27.065217  21.413043  123624.804348
```

Data Frames *groupby* method

Once groupby object is create we can calculate various statistics for each group:

```
In [ ]: #Calculate mean salary for each professor rank:
        df.groupby('rank')[['salary']].mean()
```

	salary
rank	
AssocProf	91786.230769
AsstProf	81362.789474
Prof	123624.804348



```
#Calculate mean salary for each professor rank:
df.groupby('rank')[['salary']].mean()
```

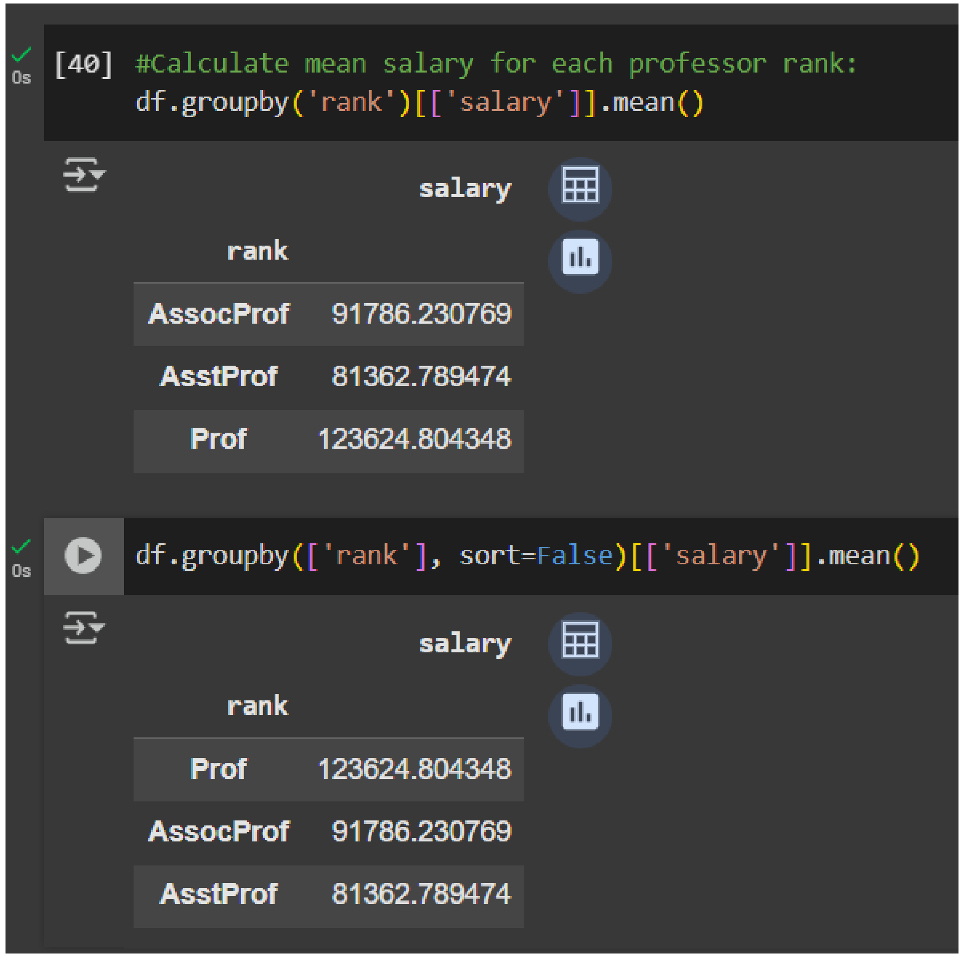
	salary
rank	
AssocProf	91786.230769
AsstProf	81362.789474
Prof	123624.804348

Note: If single brackets are used to specify the column (e.g. salary), then the output is Pandas Series object. When double brackets are used the output is a Data Frame

Data Frames *groupby* method

Why use sort=False?By default, groupby sorts the group keys alphabetically.
If you want to preserve the original order (like in your input dataset), use sort=False.
groupby performance notes:

- no grouping/splitting occurs until it's needed. Creating the *groupby* object only verifies that you have passed a valid mapping
- by default the group keys are sorted during the *groupby* operation. You may want to pass sort=False for potential speedup:



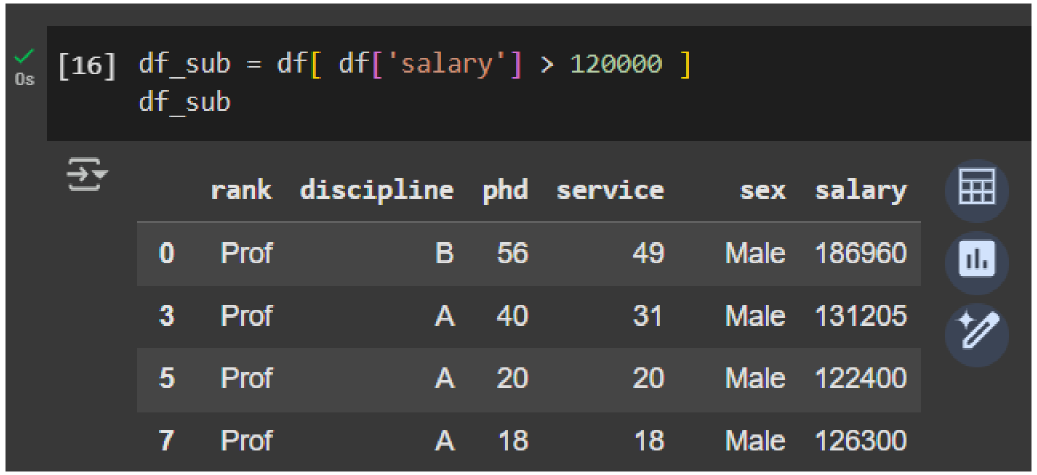
```
[40] #Calculate mean salary for each professor rank:
     df.groupby('rank')[['salary']].mean()

                  salary
rank
AssocProf   91786.230769
AsstProf    81362.789474
Prof       123624.804348
```

```
df.groupby(['rank'], sort=False)[['salary']].mean()

                  salary
rank
Prof       123624.804348
AssocProf   91786.230769
AsstProf    81362.789474
```

```
In [ ]: #Calculate mean salary for each professor rank:
        df.groupby(['rank'], sort=False)[['salary']].mean()
```

Data Frame: filtering

To subset the data we can apply Boolean indexing. This indexing is commonly known as a filter. For example, if we want to subset the rows in which the salary value is greater than 120K:



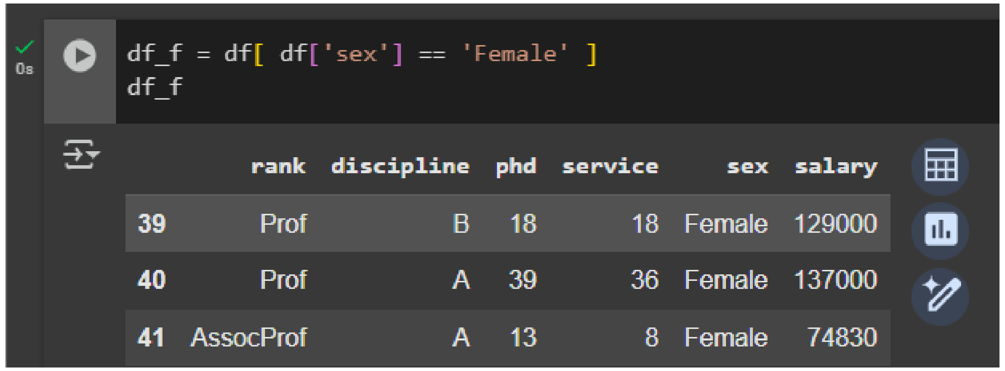
```
[16] df_sub = df[ df['salary'] > 120000 ]
     df_sub
```

```
   rank  discipline  phd  service   sex  salary
0  Prof           B   56       49  Male  186960
3  Prof           A   40       31  Male  131205
5  Prof           A   20       20  Male  122400
7  Prof           A   18       18  Male  126300
```

```
In [ ]: #Calculate mean salary for each professor rank:
        df_sub = df[ df['salary'] > 120000 ]
```

Any Boolean operator can be used to subset the data:

> greater;	>= greater or equal;
< less;	<= less or equal;
== equal;	!= not equal;



```
df_f = df[ df['sex'] == 'Female' ]
df_f
```

```
         rank  discipline  phd  service     sex  salary
39       Prof           B   18       18  Female  129000
40       Prof           A   39       36  Female  137000
41  AssocProf           A   13        8  Female   74830
```

```
In [ ]: #Select only those rows that contain
        female professors:
        df_f = df[ df['sex'] == 'Female' ]
```

Data Frames: Slicing

🧠 What is Slicing in Pandas?

Slicing means selecting specific rows or columns (or both) from a DataFrame — similar to slicing lists in Python.

There are a number of ways to subset the Data Frame:

- one or more columns
- one or more rows
- a subset of rows and columns

Rows and columns can be selected by their position or label

🔪 1. **Row Slicing (by index)**

```
df[0:3]
```

Returns rows 0, 1, 2:

📍 2. Column Slicing

```
df[['rank', 'salary’]]
```

🧮 3. Using .loc[] — Label-based slicing

```
df.loc[1:3, ['rank', 'phd’]]
```

Returns rows 1 to 3, columns 'rank' and 'phd’:

🔢 4. Using .iloc[] — Integer-position slicing

```
df.iloc[0:3, 0:2]
```

Returns first 3 rows and first 2 columns:

✅ 5. Conditional Slicing (Filtering)

```
df[ df['salary'] > 100000 ]
```

Returns only rows with salary > 100000.

🧪 Extra: Fancy Slicing

Select every other row:

```
df[::2]
```

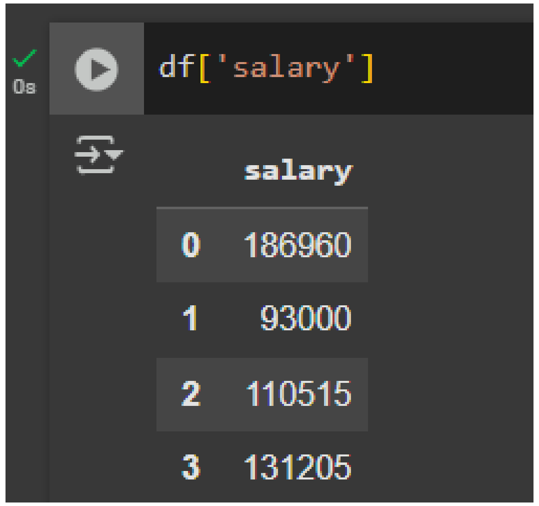
💡 **Tips:**

Use this	For this purpose
df[]	Select columns, slice rows
.loc[]	Label-based slicing
.iloc[]	Position-based slicing
df[df[col] > val]	Conditional filtering

Data Frames: Slicing

When selecting one column, it is possible to use single set of brackets, but the resulting object will be a Series (not a DataFrame):

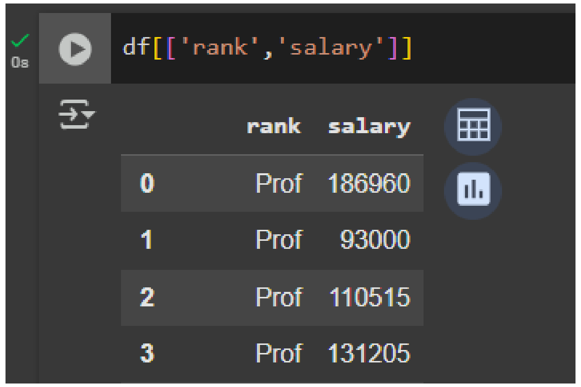
```
In [ ]: #Select column salary:
        df['salary']
```



```
df['salary']

   salary
0  186960
1   93000
2  110515
3  131205
```

When we need to select more than one column and/or make the output to be a DataFrame, we should use double brackets:

```
In [ ]: #Select column salary:
        df[['rank','salary']]
```



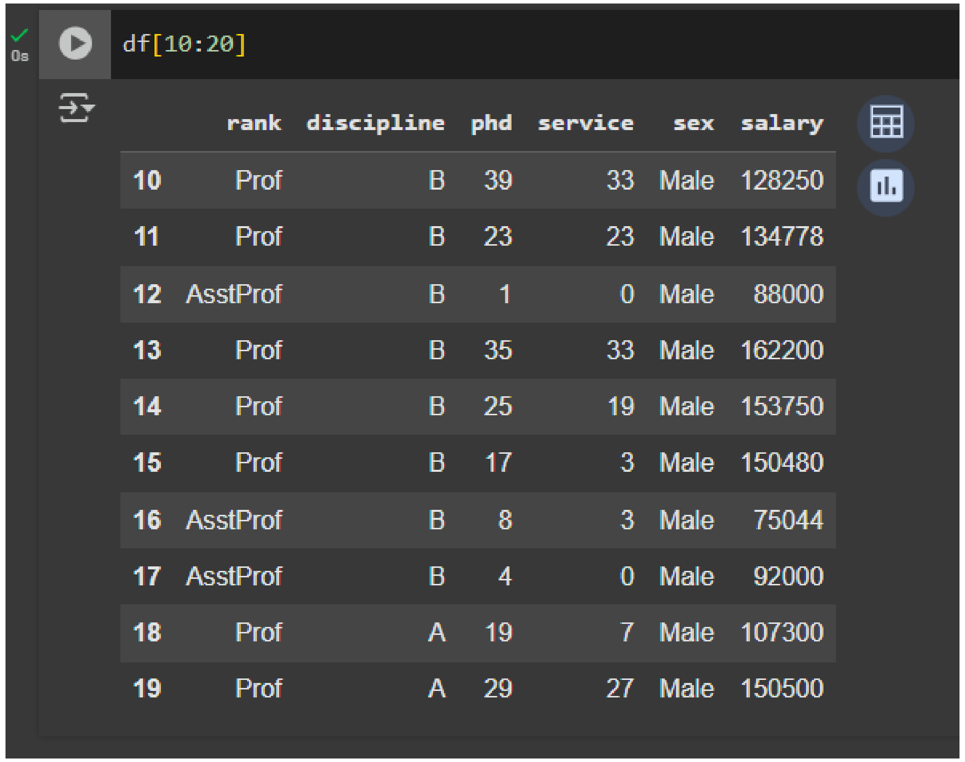
```
df[['rank','salary']]

   rank  salary
0  Prof  186960
1  Prof   93000
2  Prof  110515
3  Prof  131205
```

Data Frames: Selecting rows

If we need to select a range of rows, we can specify the range using ":"

```
In [ ]: #Select rows by their position:
        df[10:20]
```

Notice that the first row has a position 0, and the last value in the range is omitted:
So for 0:10 range the first 10 rows are returned with the positions starting with 0 and ending with 9



```
df[10:20]
```

	rank	discipline	phd	service	sex	salary
10	Prof	B	39	33	Male	128250
11	Prof	B	23	23	Male	134778
12	AsstProf	B	1	0	Male	88000
13	Prof	B	35	33	Male	162200
14	Prof	B	25	19	Male	153750
15	Prof	B	17	3	Male	150480
16	AsstProf	B	8	3	Male	75044
17	AsstProf	B	4	0	Male	92000
18	Prof	A	19	7	Male	107300
19	Prof	A	29	27	Male	150500

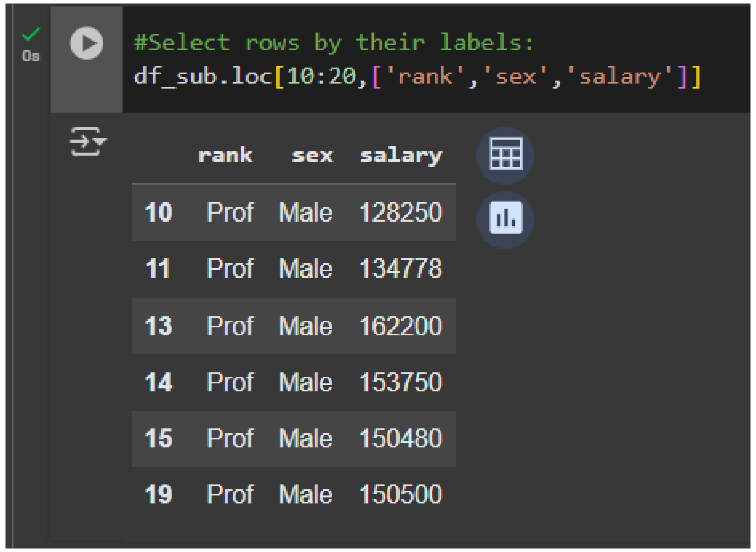
Data Frames: method loc

If we need to select a range of rows, using their labels we can use method loc:

```
In [ ]: #Select rows by their labels:
        df_sub.loc[10:20,['rank','sex','salary']]
```

Out[ ]:

	rank	sex	salary
10	Prof	Male	128250
11	Prof	Male	134778
13	Prof	Male	162200
14	Prof	Male	153750
15	Prof	Male	150480
19	Prof	Male	150500



```
#Select rows by their labels:
df_sub.loc[10:20,['rank','sex','salary']]
```

	rank	sex	salary
10	Prof	Male	128250
11	Prof	Male	134778
13	Prof	Male	162200
14	Prof	Male	153750
15	Prof	Male	150480
19	Prof	Male	150500

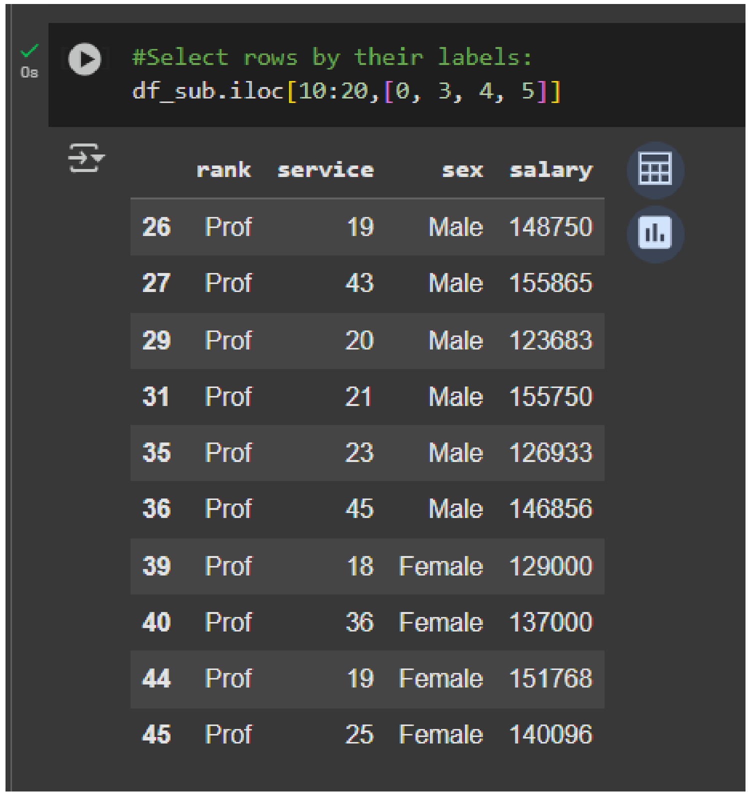
Data Frames: method iloc

If we need to select a range of rows and/or columns, using their positions we can use method iloc:

```
In [ ]: #Select rows by their labels:
        df_sub.iloc[10:20,[0, 3, 4, 5]]
```

Out[ ]:

	rank	service	sex	salary
26	Prof	19	Male	148750
27	Prof	43	Male	155865
29	Prof	20	Male	123683
31	Prof	21	Male	155750
35	Prof	23	Male	126933
36	Prof	45	Male	146856
39	Prof	18	Female	129000
40	Prof	36	Female	137000
44	Prof	19	Female	151768
45	Prof	25	Female	140096



```
#Select rows by their labels:
df_sub.iloc[10:20,[0, 3, 4, 5]]
```

	rank	service	sex	salary
26	Prof	19	Male	148750
27	Prof	43	Male	155865
29	Prof	20	Male	123683
31	Prof	21	Male	155750
35	Prof	23	Male	126933
36	Prof	45	Male	146856
39	Prof	18	Female	129000
40	Prof	36	Female	137000
44	Prof	19	Female	151768
45	Prof	25	Female	140096

Data Frames: method iloc (summary)

```
df.iloc[0]   # First row of a data frame
df.iloc[i]   #(i+1)th row
df.iloc[-1] # Last row
```

```
df.iloc[:, 0]   # First column
df.iloc[:, -1] # Last column
```

```
df.iloc[0:7]        #First 7 rows
df.iloc[:, 0:2]     #First 2 columns
df.iloc[1:3, 0:2]   #Second through third rows and first 2 columns
df.iloc[[0,5], [1,3]]  #1st and 6th rows and 2nd and 4th columns
```

Data Frames: Sorting

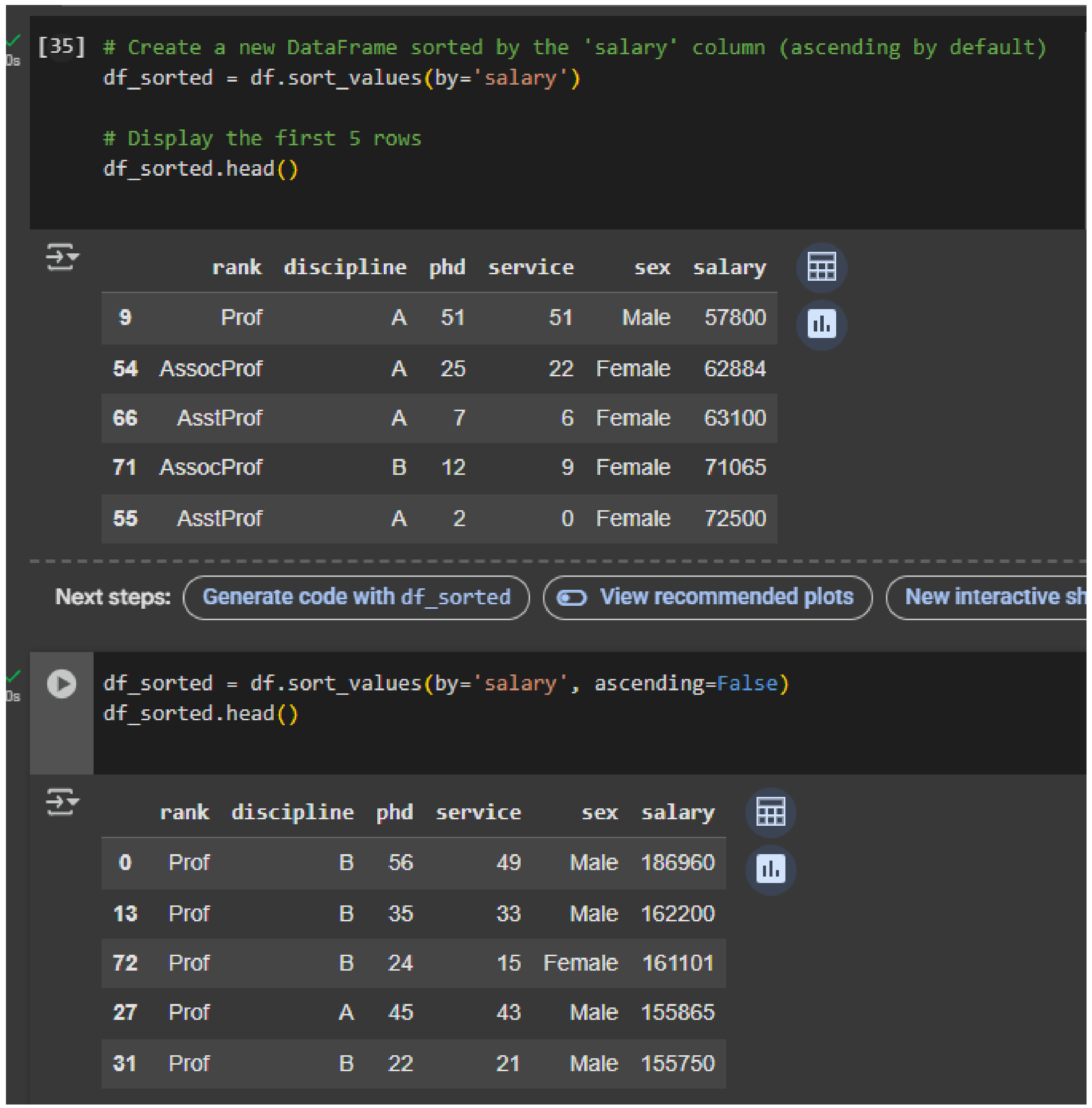
📦 What Is DataFrame Sorting?

- Pandas allows you to sort your data either:
- By index (row/column labels)
- By values in one or more columns

We can sort the data by a value in the column. By default, the sorting will occur in ascending order and a new data frame is return.

In [ ]:

```
# Create a new data frame from the original sorted by the column Salary

df_sorted = df.sort_values( by ='salary')

df_sorted.head()
```



```
[35] # Create a new DataFrame sorted by the 'salary' column (ascending by default)
     df_sorted = df.sort_values(by='salary')

     # Display the first 5 rows
     df_sorted.head()
```

```
        rank  discipline  phd  service     sex  salary
9       Prof           A   51       51    Male   57800
54  AssocProf          A   25       22  Female   62884
66    AsstProf         A    7        6  Female   63100
71  AssocProf          B   12        9  Female   71065
55    AsstProf         A    2        0  Female   72500
```

Next steps: Generate code with df_sorted | View recommended plots | New interactive sh

```
df_sorted = df.sort_values(by='salary', ascending=False)
df_sorted.head()
```

```
    rank  discipline  phd  service     sex  salary
0   Prof           B   56       49    Male  186960
13  Prof           B   35       33    Male  162200
72  Prof           B   24       15  Female  161101
27  Prof           A   45       43    Male  155865
31  Prof           B   22       21    Male  155750
```

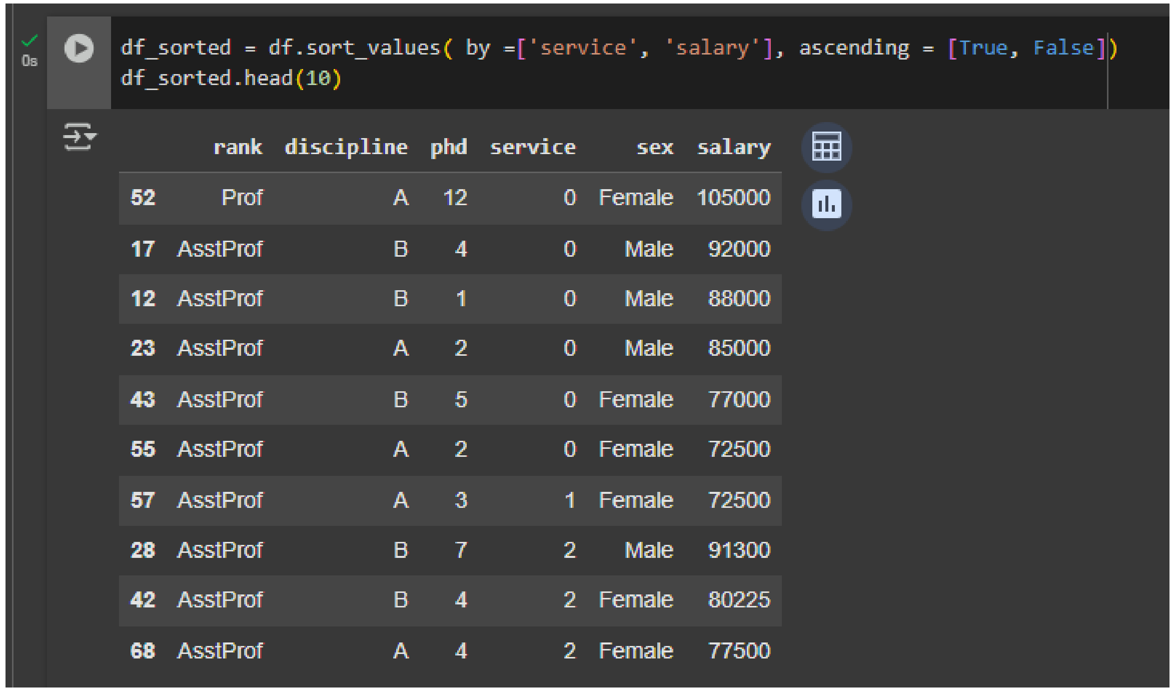
Data Frames: Sorting

We can sort the data using 2 or more columns:

```
In [ ]: df_sorted = df.sort_values( by =['service', 'salary'], ascending = [True, False])
        df_sorted.head(10)
```

Out[ ]:

	rank	discipline	phd	service	sex	salary
52	Prof	A	12	0	Female	105000
17	AsstProf	B	4	0	Male	92000
12	AsstProf	B	1	0	Male	88000
23	AsstProf	A	2	0	Male	85000
43	AsstProf	B	5	0	Female	77000
55	AsstProf	A	2	0	Female	72500
57	AsstProf	A	3	1	Female	72500
28	AsstProf	B	7	2	Male	91300
42	AsstProf	B	4	2	Female	80225
68	AsstProf	A	4	2	Female	77500



```
df_sorted = df.sort_values( by =['service', 'salary'], ascending = [True, False])
df_sorted.head(10)
```

	rank	discipline	phd	service	sex	salary
52	Prof	A	12	0	Female	105000
17	AsstProf	B	4	0	Male	92000
12	AsstProf	B	1	0	Male	88000
23	AsstProf	A	2	0	Male	85000
43	AsstProf	B	5	0	Female	77000
55	AsstProf	A	2	0	Female	72500
57	AsstProf	A	3	1	Female	72500
28	AsstProf	B	7	2	Male	91300
42	AsstProf	B	4	2	Female	80225
68	AsstProf	A	4	2	Female	77500

Missing Values

Missing values are marked as NaN

```
In [ ]: # Read a dataset with missing values
        flights =
        pd.read_csv("https://raw.githubusercontent.com/lovnishverma/datasets/refs/heads/main/
        flights.csv")
```

```
In [ ]: # Select the rows that have at least one missing value
        flights[flights.isnull().any(axis=1)].head()
```

Out[ ]:

	year	month	day	dep_time	dep_delay	arr_time	arr_delay	carrier	tailnum	flight	origin	dest	air_time	distance	hour	minute
330	2013	1	1	1807.0	29.0	2251.0	NaN	UA	N31412	1228	EWR	SAN	NaN	2425	18.0	7.0
403	2013	1	1	NaN	NaN	NaN	NaN	AA	N3EHAA	791	LGA	DFW	NaN	1389	NaN	NaN
404	2013	1	1	NaN	NaN	NaN	NaN	AA	N3EVAA	1925	LGA	MIA	NaN	1096	NaN	NaN
855	2013	1	2	2145.0	16.0	NaN	NaN	UA	N12221	1299	EWR	RSW	NaN	1068	21.0	45.0
858	2013	1	2	NaN	NaN	NaN	NaN	AA	NaN	133	JFK	LAX	NaN	2475	NaN	NaN

Missing Values

There are a number of methods to deal with missing values in the data frame:

df.method()	description
dropna()	Drop missing observations
dropna(how='all')	Drop observations where all cells is NA
dropna(axis=1, how='all')	Drop column if all the values are missing
dropna(thresh = 5)	Drop rows that contain less than 5 non-missing values
fillna(0)	Replace missing values with zeros
isnull()	returns True if the value is missing
notnull()	Returns True for non-missing values

Missing Values

- When summing the data, missing values will be treated as zero
- If all values are missing, the sum will be equal to NaN
- cumsum() and cumprod() methods ignore missing values but preserve them in the resulting arrays
- Missing values in GroupBy method are excluded (just like in R)
- Many descriptive statistics methods have *skipna* option to control if missing data should be excluded . This value is set to *True* by default (unlike R)

Aggregation Functions in Pandas

Aggregation - computing a summary statistic about each group, i.e.

- compute group sums or means
- compute group sizes/counts

Common aggregation functions:

min, max
count, sum, prod
mean, median, mode, mad
std, var

Aggregation Functions in Pandas

agg() method are useful when multiple statistics are computed per column:

```
In [ ]: flights[['dep_delay','arr_delay']].agg(['min','mean','max'])
```

```
Out[ ]:
```

	dep_delay	arr_delay
min	-16.000000	-62.000000
mean	9.384302	2.298675
max	351.000000	389.000000

Basic Descriptive Statistics

df.method()	description
describe	Basic statistics (count, mean, std, min, quantiles, max)
min, max	Minimum and maximum values
mean, median, mode	Arithmetic average, median and mode
var, std	Variance and standard deviation
sem	Standard error of mean
skew	Sample skewness
kurt	kurtosis

Graphics to explore the data

Seaborn package is built on matplotlib but provides high level interface for drawing attractive statistical graphics, similar to ggplot2 library in R.
It specifically targets statistical data visualization

To show graphs within Python notebook include inline directive:

```
In [ ]: %matplotlib inline
```

It is a magic command used in Jupyter Notebooks (or IPython environments). It tells the notebook to: 🖼️ Render plots inline, meaning the output of matplotlib plotting commands will be displayed directly below the code cells that produce them.

Note:
Google Colab, you don't need to manually include `%matplotlib inline` —
it's enabled by default behind the scenes.

Why?
Google Colab is built on Jupyter Notebook, and it: Automatically detects matplotlib plots, Renders them inline below your code without extra commands.

Graphics

	description
distplot	histogram
barplot	estimate of central tendency for a numeric variable
violinplot	similar to boxplot, also shows the probability density of the data
jointplot	Scatterplot
regplot	Regression plot
pairplot	Pairplot
boxplot	boxplot
swarmplot	categorical scatterplot
factorplot	General categorical plot

Basic statistical Analysis

statsmodel and scikit-learn - both have a number of function for statistical analysis

The first one is mostly used for regular analysis using R style formulas, while scikit-learn is more tailored for Machine Learning.

statsmodels:

- linear regressions
- ANOVA tests
- hypothesis testings
- many more ...

scikit-learn:

- kmeans
- support vector machines
- random forests
- many more ...

See examples in these Colab Notebooks: https://github.com/lovnishverma/Python-Getting-Started

Thank you