FUNDAMENTAL BUSINESS DATA VISUALIZATION NOTES

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Based on course material provided through King Mongkut's University of Technology Thonburi (KMUTT)

All Learning Unit Documents

Course Introduction

Human interprets picture better from words

↳ like plotting chart to look pattern

- Start by asking Question
- Understand data collection

  transform data to proper data

  - data cleaning
- 3 Libraries

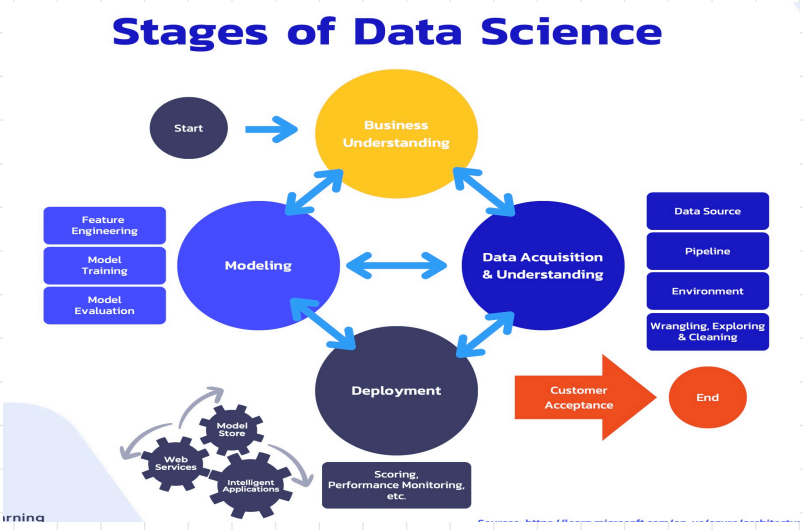
With data visualization → for users

→ for team

Introduction to Data Science for Business

Stages of Data Science

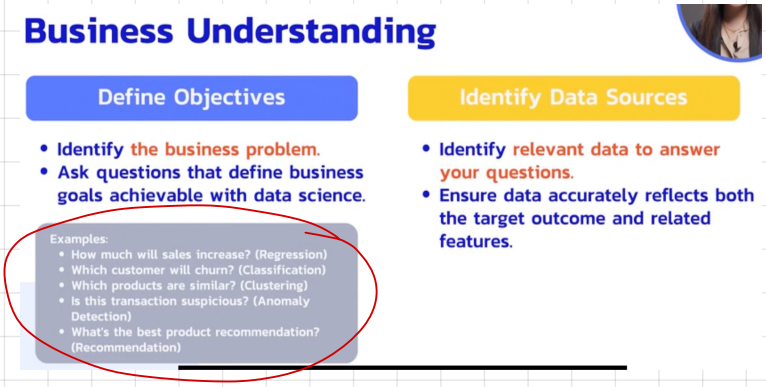
1. Data Acquisition & Understanding
   - involves collecting raw data from various sources like databases, API, web scraping
2. Data Modeling
   - analyze and process data to create model that can identify pattern & prediction
   - involves STATISTICAL ANALYSIS
3. Deployment
   - used to make prediction and decision in REAL TIME
4. Customer Acceptance
   - presented to stake holders / end user for feedback



Before data analysis, we need to understand Business

① What problem are we solving?

- ask the right questions
- find the right data



Data Acquisiton and Understanding

- prepare data before analyzing

Ingest the data

- get the data into the system

Explore the data

- check quality of data, ensure clean (data cleaning)

Set up the data Pipeline

Modeling

Feature engineering

- process in which we transform raw data into features so that the model can understand

Model training

- test model and pick that solves problem accurately

Determine if your model is suitable for production

- test in real time

Deployment

Operationalize the model

transfer model to the special environment

Expose model with an API interface

API allows applications to easily talk to the model and get predictions

Customer Acceptance

System Validation

Project handoff

Overview of Data Visualization in Business Intelligent

Topics

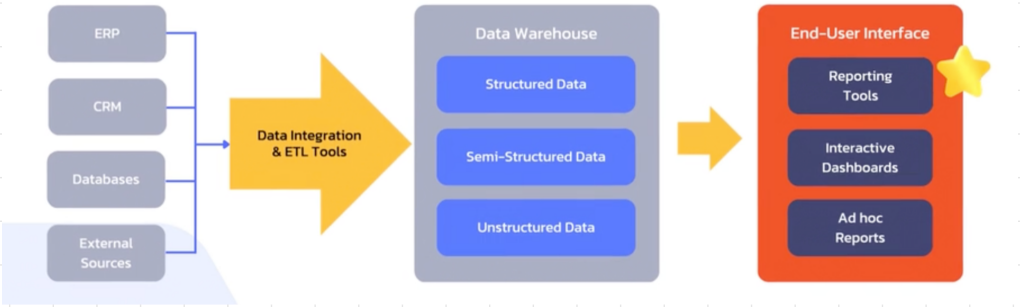
- What is Business Intelligence (BI)?
- Why is Data Visualization so important for BI?
- How can businesses use Data Visualization to make decisions?
- Trends of Data visualization

What is Business Intelligence (BI)

- tool to organize, analyze and understand data

BI takes raw numbers from count to actionable insights

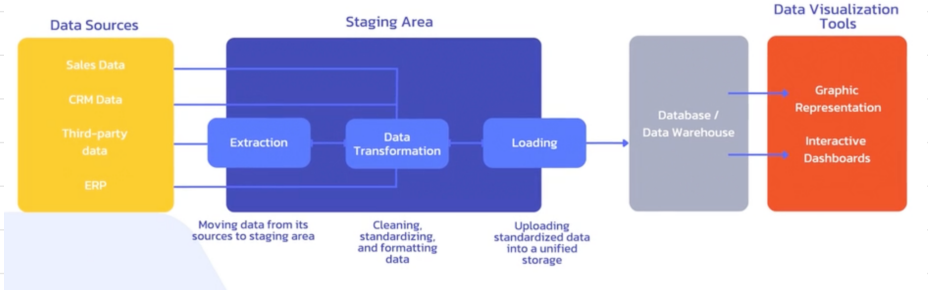
Business Intelligence Architecture (for Small Business)



Why data visualization Important?

- our brain grasp picture easier than numbers
- easily spot pattern
- see the bigger picture
- significant numbers → Opportunity / issue

Data Processing and ETL steps



By analyzing patterns and trends in visualized data, business can:

- Improve Operational Process
- Predict Future Trends

Example Trends of Data visualization

Emergence of High-Fidelity Digital Twins

Virtual model of physical object or system on stream to physical asset

Powerful Javascript Visualizations

Powerful JavaScript frameworks like React, Angular, Babylon.js, and Three.js are making it easier to create stunning 3D and immersive reality (VR) data visualizations.

Verficalized Data Visualization Offerings

Industry-specific insights

→ ex. Use to monitor performance of Robot

Data Visualization Technique

Topics

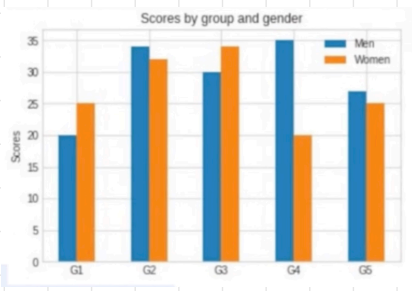
- Basic 2D Data Visualization
- Types of Connection
- 8 Common Chart types

Key of Data Visualization

1. Know your data
   - what to show, and how to use the chart to explain it
2. Types of connection
   - Comparison
   - Composition
   - Relationship
   - Distribution

8 Common Chart Types

1. Bar Chart → Comparison Type
   - comparing data units
   - can be clustered or stack bars
   * Use HORIZONTAL BARCHART for long data label



2. Pie chart → Composition
   - composition of whole, percentage

3. Line Graph → Comparison, relationship

- change data over time
- can combine 1 or more line graph
- Useful for trends, pattern and make prediction

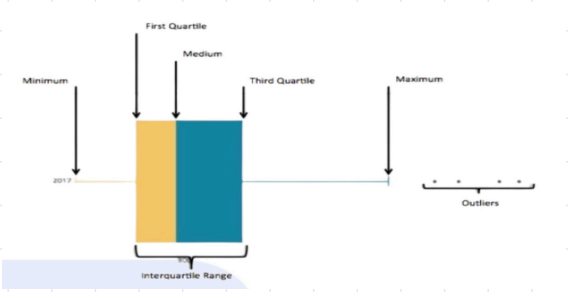
4. Box Plot → Distribution

- makes it easy to see data spread, skewness, variability & Outliers

Shows:

1. **Minimum** – lowest non-outlier value
2. **Q1 (First Quartile)** – 25% of data is below this
3. **Median (Q2)** – the midpoint of the data
4. **Q3 (Third Quartile)** – 75% of data is below this
5. **Maximum** – highest non-outlier value
6. **Outliers** – unusually high or low values (shown as small dots)

Together these form the **box** (Q1–Q3) and the **whiskers** (min–max), making it easy to see:

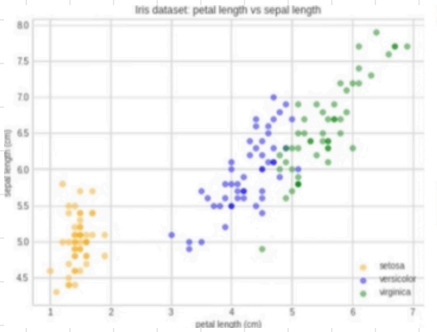


5. Scatter Plot → distribution

- shows dots.

Use to show if there are

- cluster
- wider Spread



6. Radar or Spider chart → distribution

- Compare multiple objects with different dimensions
- commonly used in

games, athlete stats, student performance

7. Density Map / dot map → distribution

↳ Geographical

- use dot or color density to represent the geographical distribution of data

example use:

typhoon, covid-cases, location that sells best

8. funnel chart → Flow with Trends

- use how data move through a process in Stages

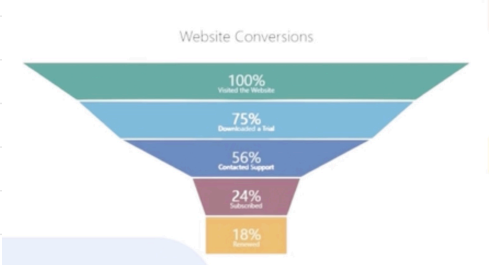
A funnel chart typically displays:

1. A process with **sequential stages**
2. The **number of items** (customers, leads, tasks, etc.) at each stage
3. How many are **lost** or **drop off** between stages
4. The **conversion rate** from one stage to the next

The chart shape makes it visually clear where the biggest reductions happen.

🔍 **What Makes Funnel Charts Valuable**

- ✓ **Immediate insight** into conversion and loss
- ✓ **Easy comparison** of performance month to month
- ✓ **Helps identify bottlenecks** and areas needing improvement
- ✓ **Supports forecasting** (e.g., expected revenue from leads)



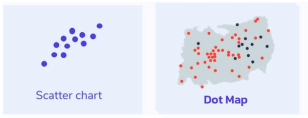
Overall Chart Types

Composition

Comparison

Relationship

Distribution



Keys for Choosing the right chart

1. What you want your data to tell
2. Do you want to compare things, show trends, or show geographical patterns?

Introduction to Basic Python

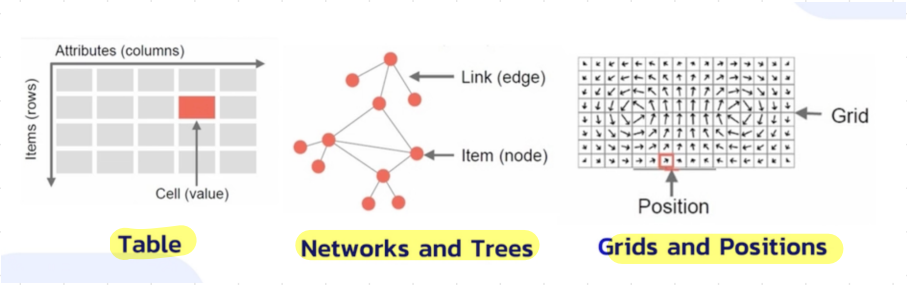
Already have background in Python

I'll be using Jupyter Notebook

Short Review

Data Collection

Data Types



Table

- created using items (rows) and attribute (column)

Network and Trees

- include items called nodes which are connected with link (edges)

Grids & Positions

- grids are like table
- positions are the coordinate (rows, column)

Data Structure

- organize your data by storing and structuring it making it easier to access

Data Structure

- Foundation: Lists and Tuples
- Complex: Sets and Dictionaries
- Advanced: Series and Data frames

LIST ↳ [ ]

TUPLES ↳ ( )

Feature	List	Tuple
Changeable (mutable)	✅ Yes	❌ No
Syntax	`[ ]`	`( )`
Speed	⏳ Slower	⚡ Faster
Use case	Data that changes	Data that stays constant
Methods available	Many (append, remove, etc.)	Very few
Memory usage	More	Less

List Example

```python
fruits = ["apple", "banana"]
fruits.append("orange")
# Now: ["apple", "banana", "orange"]
```

Tuple Example

```python
colors = ("red", "green", "blue")
colors.append("yellow")  # ❌ Error
```

🎯 When to Use Which?

✔ **Use a LIST when:**

- Items will change
- You want to add/remove stuff
- You're making dynamic data (e.g., user input, database data)

✔ **Use a TUPLE when:**

- Data should NEVER change
- You want faster performance
- You need something unchangeable (keys, constants, coordinates)

Example:

```python
position = (10, 20)   # A tuple makes sense for coordinates
```

Set

- { }
- no duplicate, no order

If you do this:

```python
my_set = {1, 2, 2, 3}
```

Python turns it into:

```python
{1, 2, 3}
```

Because duplicates are automatically removed.

Dictionary

- key + value pairs

Think of it like a **real dictionary**:

- The **word** is the key
- The **definition** is the value

```python
my_dict = {
  "name": "John",
  "age": 20
}
```

You look things up by their **key**.

SERIES

↳ we use pandas library

import pandas as pd

pd.Series([..,..,])

🟢 SERIES = One column

A **Series** is basically **a single column of data**.

Think of it like **one column in Excel**:

```
css

0    John
1    Mark
2    Ana
```

This is a **Series**.

Code example:

```
python

import pandas as pd

s = pd.Series(["John", "Mark", "Ana"])
```

Data Frame

A **DataFrame** is basically **a whole table** — multiple columns, multiple rows.

Think of it like an **Excel sheet with many columns**:

```
css

   name   age
0  John   30
1  Mark   22
2  Ana    28
```

pd.DataFrame ({
"key": [.., .., ..],
:
})

This is a **DataFrame**.

Code example:

```
python

df = pd.DataFrame({
    "name": ["John", "Mark", "Ana"],
    "age": [30, 22, 28]
})
```

Series = 1D array
Dataframe = 2D array

Why use Series & Dataframe?

Series has an index

```
makefile

Index: 0  1  2
Value: 10 20 30
```

You can change the index:

```
makefile

Index: age1  age2  age3
Value: 10    20    30
```

Try that in a normal array → ❌ impossible.

🟨 2. DataFrame has column names

A DataFrame looks like this:

```
css

 name   age   salary
 John    30    50000
 Mark    22    45000
```

This is **NOT** just a 2D array — because:

- Each column has a **name**
- Rows have **index labels**
- You can access data by **column name**, not just by number

Example:

```
python

df["age"]
```

A normal 2D array **cannot** do that.

Key Characteristics

M — **Mutability: Refers to whether the collection can be changed after creation.**

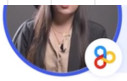
O — **Order: Refers to whether elements have a specific sequence.**

D — **Duplicate: Refers to whether the collection can contain the same element multiple time.**

	Mutability	Order	Duplicate
List	✓	✓	✓
Tuples	✗	✓	✓
Dictionary	✓	✗	✓
Sets	✓	✗	✗
Series	✓	✓	✓

EP.5 Data Collection

List



Adding/Removing Elements:

- append(x): Adds an element x to the end of the list.
- insert(i, x): Inserts an element x at a specific index i.
- remove(x): Removes the first occurrence of element x from the list.
- pop(i): Removes and returns the element at index i (defaults to the last element if no index provided).
- clear(): Removes all elements from the list.

Ordering:

- sort(): Sorts the list elements in ascending order (in-place modification).
- reverse(): Reverses the order of elements in the list (in-place modification).

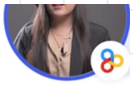
Finding Elements:

- index(x): Returns the index of the first occurrence of element x (raises an error if not found).
- count(x): Returns the number of times element x appears in the list.

Length

- len(list_name): Returns the number of elements in the list.

Tuples



Concatenate

```
# Create Tuples
MarksCIS=(70,85,55)
MarksCIN=(90,75,60)
# Concatenating Tuples
Combined=MarksCIS + MarksCIN
print(Combined)
```

```
(70, 85, 55, 90, 75, 60)
```

Access

```
# Create Tuples
MarksCIS = (70, 85, 55)
MarksCIN = (90, 75, 60)
print ("The third mark in CIS is ", MarksCIS[2])
print ("The third mark in CIN is ", MarksCIN[2])
```

```
The third mark in CIS is  55
The third mark in CIN is  60
```

Basic Tuples Operations

Expression	Results	Description
len((5, 7, 2,6))	4	Length
(1, 2, 3,10) + (4, 5, 6,7)	(1, 2, 3,10, 4, 5, 6,7)	Concatenation
('Hi!',) * 4	('Hi!', 'Hi!', 'Hi!', 'Hi!')	Repetition
10 in (10, 2, 3)	True	Membership
for x in (10, 1, 5): print x,	10 1 5	Iteration

Tuples

- Finding Elements:
  - index(x): Returns the index of the first occurrence of element x (raises an error if not found).
  - count(x): Returns the number of times element x appears in the tuple.
- Length:
  - len(tuple_name): Returns the number of elements in the tuple.
- Slicing: Accessing elements by position range (similar to lists).
  - tuple[start:end:step]: Returns a new tuple containing elements from index start (inclusive) to end (exclusive) with a step of step (defaults to 1).
- Conversion:
  - tuple(iterable): Converts an iterable (like a list or string) to a tuple.

EP.5 Data Collection

Dictionary

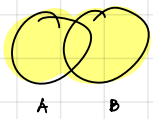
Methods and Functions:

- get(key, default): Retrieves the value associated with the key. If the key is not found, returns the default value (optional).
- pop(key, default): Removes the key-value pair and returns the value. If the key is not found, returns the default value (optional).
- keys(): Returns a view of all keys as a dictionary view object.
- values(): Returns a view of all values as a dictionary view object.
- items(): Returns a view of all key-value pairs as tuples in a dictionary view object.
- update(dictionary): Updates the dictionary with key-value pairs from another dictionary (modifies the original dictionary).
  - dict(iterable): Converts an iterable of key-value pairs into a dictionary.

Mathematic Set Operation

- Union
- Intersection
- Difference
- Symmetric Difference

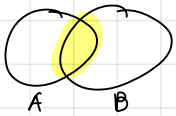
1. Union




```
A = {1, 2, 3, 4, 5}
B = {4, 5, 6, 7, 8}

# use | operator
# Output: {1, 2, 3, 4, 5, 6, 7, 8}
print(A | B)
print(A.union(B))
```

```
{1, 2, 3, 4, 5, 6, 7, 8}
{1, 2, 3, 4, 5, 6, 7, 8}
```

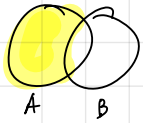
2. Intersection




```
print(A & B)
print(A.intersection(B))
```

```
{4, 5}
{4, 5}
```

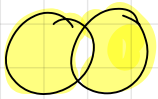
3. Difference




```
print(A - B)
print(A.difference(B))
```

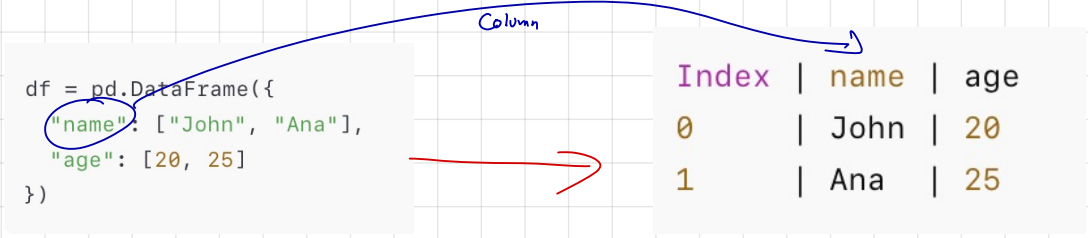
```
{1, 2, 3}
{1, 2, 3}
```

4. Symmetric Difference



```
print(A ^ B)
print(A.symmetric_difference(B))
```

```
{1, 2, 3, 6, 7, 8}
{1, 2, 3, 6, 7, 8}
```



Index in Pandas

You can change index name using

df.index

Example:

```python
df = pd.DataFrame({"name": ["A", "B", "C"]})
print(df)
```

Output:

```
  name
0   A
1   B
2   C
```

Rows automatically numbered.

🟩 2. Custom Index

You can replace the index with anything:

```python
df.index = ["a", "b", "c"]
```

Output:

```
  name
a   A
b   B
c   C
```

Now rows are labeled "a", "b", "c"

🟧 4. Resetting the Index

You can convert the index BACK to a normal column:

```python
df.reset_index()
```

This will make the old index a column and create a new default index.

Example:

Before:

```
      name
id
101   Mark
102   Jay
```

After:

```
   id   name
0 101   Mark
1 102   Jay
```

Setting a column as index

df.set_index()

Most real datasets have a column like "id", "code", or "email" to uniquely identify row.

You can turn that into the index:

```python
df = df.set_index("id")
```

Example:

Before:

```
   id   name   age
0  1    John   20
1  2    Ana    22
```

After:

```
      name   age
id
1     John   20
2     Ana    22
```

The column "id" is now the row identifier.

Index must be UNIQUE

LOC vs ILOC

🟦 2. Selecting Data (loc vs iloc)

⭐ `loc` = label-based

Use **names**, not numbers.

```python
df.loc["row1"]        # select row with label "row1"
df.loc[:, "age"]      # select age column
df.loc["row1", "age"] # specific cell
```

⭐ `iloc` = position-based

Use **numbers only** (like array indexing).

```python
df.iloc[0]            # first row
df.iloc[:, 1]         # second column
df.iloc[0, 1]         # row 0, column 1
```

🤓 Easy memory trick:

- **loc = label**
- **iloc = integer index**

How to add or change data in pandas df and series

📌 1. INDEX in a Series

✔ Example Series

```python
import pandas as pd

s = pd.Series([10, 20, 30], index=["a", "b", "c"])
print(s)
```

✅ Visual:

index	value
a	10
b	20
c	30

📌 2. ADDING a new index + value to Series

Method 1 — direct assignment

```python
s["d"] = 40
```

Result:

index	value
a	10
b	20
c	30
d	40

📌 3. MODIFYING an existing index's value

```python
s["b"] = 999
```

Result:

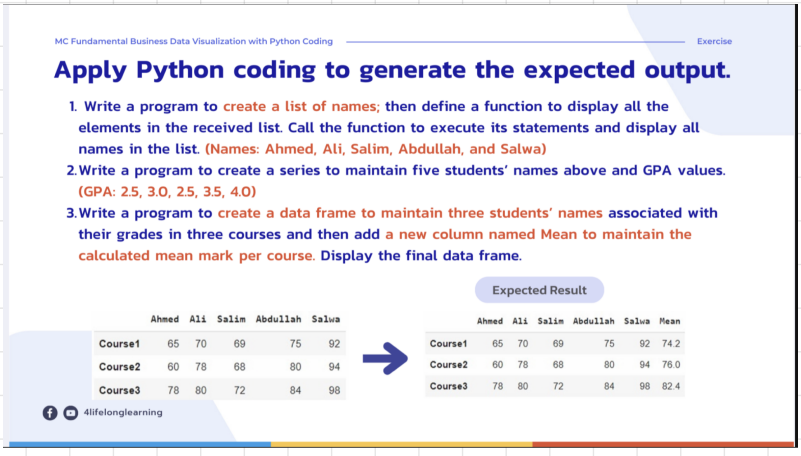
index	value
a	10
b	999
c	30
d	40

📌 4. RENAMING index labels (Series)

```python
s = s.rename({"a": "alpha", "b": "beta"})
```

Result:

index	value
alpha	10
beta	999
c	30
d	40



```
import pandas as pd
```

1. Make List of names

Write a program to create a list of names; then define a function to display all the elements in the received list. Call the function to execute its statements and display all names in the list. (Names: Ahmed, Ali, Salim, Abdullah, and Salwa)

```
names = ["Ahmed", "Ali", "Salim", "Abdulla", "Salwa"]
print(names)
```

```
['Ahmed', 'Ali', 'Salim', 'Abdulla', 'Salwa']
```

3. Create a Series of grades

Write a program to create a series to maintain five students' names above and GPA values. (GPA: 2.5, 3.0, 2.5, 3.5, 4.0)

```
grades = pd.Series([2.5, 3.0, 2.5, 3.5, 4.0])
print(grades)
```

```
0    2.5
1    3.0
2    2.5
3    3.5
4    4.0
dtype: float64
```

3. Create dataframe

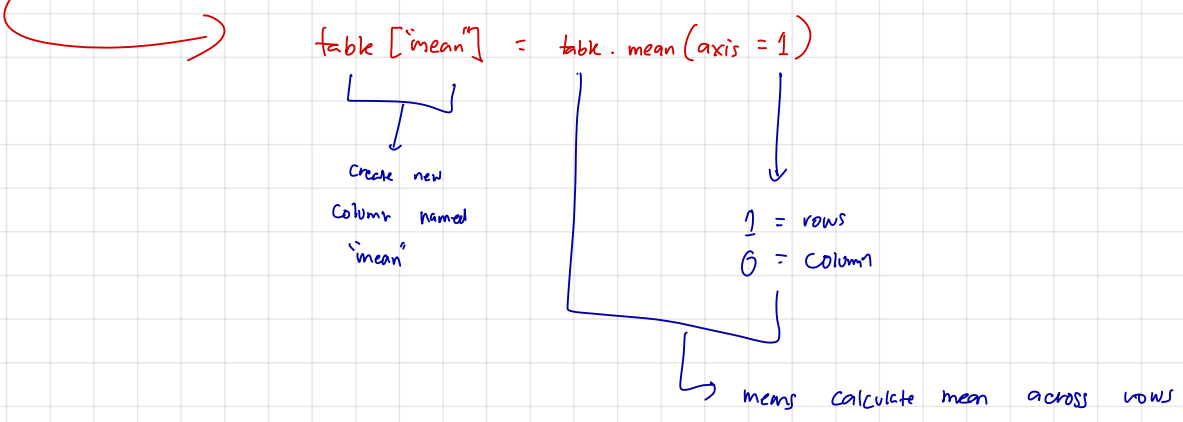
Write a program to create a data frame to maintain three students' names associated with their grades in three courses and then add a new column named Mean to maintain the calculated mean mark per course. Display the final data frame.

```
table = pd.DataFrame({
    "": ["Course1", "Course2", "Course3"],
    "Ahmed": [65, 60, 78],
    "Ali": [70, 78, 80],
    "Salim": [69, 68, 72],
    "Abdullah": [75, 80, 84],
    "Salwa": [92, 94, 98],
})

# Set 'Course1' as index
table = table.set_index("") # or use table.set_index("Course1", inplace=True)

print(table)
```

```
         Ahmed  Ali  Salim  Abdullah  Salwa
Course1     65   70     69        75     92
Course2     60   78     68        80     94
Course3     78   80     72        84     98
```

```
table["Mean"] = table.mean(axis=1)
print(table)
```

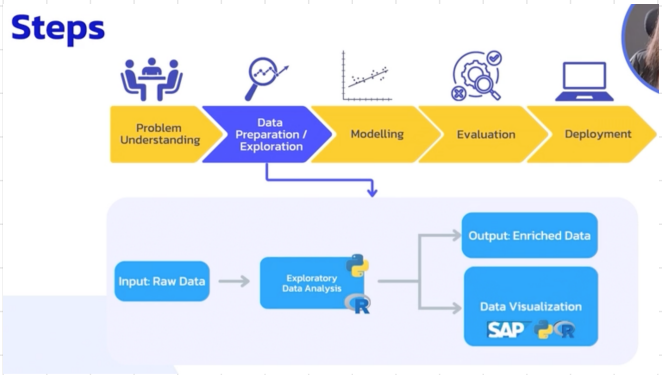
```
         Ahmed  Ali  Salim  Abdullah  Salwa  Mean
Course1     65   70     69        75     92  74.2
Course2     60   78     68        80     94  76.0
Course3     78   80     72        84     98  82.4
```



6. Data Exploring and Analysis

What is Exploratory Data Analysis?

- describe the data by means of statistical and visualization techniques to recognize hidden pattern and insight within data for further analysis



Foundation of Statistics

- numbers that summarize the whole data set

1. frequency
   - how many times data occurs
2. Location
   - mean ($\bar{x}$)
3. Spread
   - range like min & max
   - Variance or Standard deviation (σ)

Data Preprocessing

- Missing values
  - convert missing values from data to Null

example csv

```python
import pandas as pd

df = pd.read_csv("file.csv")
print(df)
```

Output:

```
   name   age    city
0  John    25   Manila
1  Anna   NaN     Cebu
2   NaN    30   Davao
3  Mark       NaN
```

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

Output might look like:

```
name    1
age     1
city    1
dtype: int64
```

isnull() . sum()

- isnull(): returns True if data has Null
- sum(): adds how many null is in the column

- Duplicate Rows
  - sometimes, data gets copied accidentally

df. duplicate() . sum() variable = df. drop_duplicates()

- duplicate(): Counts how many rows are duplicated
- drop_duplicates(): removes duplicates

```
   name   age
0  John    25
1  Anna    30
2  John    25
3  Mark    40
4  Anna    30
```

```
df_clean = df.drop_duplicates()
print(df_clean)
```

Output:

```
   name   age
0  John    25
1  Anna    30
3  Mark    40
```

Pandas Profiling for Quick EDA with Python

`df.head()`

- shows first 5 rows

`df.describe()`

- quick statistical summary

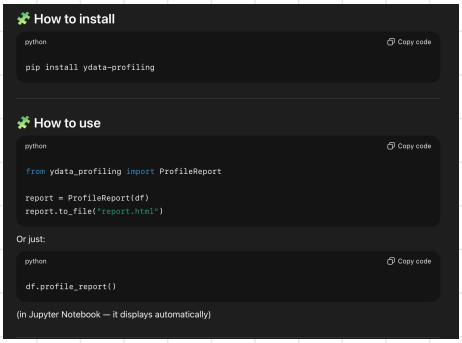
	age	height	weight
count	3.000000	3.000000	3.000000
mean	27.666667	175.000000	70.000000
std	2.516611	5.000000	5.000000
min	25.000000	170.000000	65.000000
25%	26.500000	172.500000	67.500000
50%	28.000000	175.000000	70.000000
75%	29.000000	177.500000	72.500000
max	30.000000	180.000000	75.000000

`df.profile_report()`

↳ NOT built in pandas

Automatically make reports in WEB FORMAT

- df.describe() is limited, profile_report is professional



Basic Data Manipulation

1. GROUPING

`df.groupby("column_name")`

df

	name	city	sales
0	John	Manila	100
1	Anna	Cebu	80
2	Mark	Manila	120
3	Liza	Cebu	90
4	Paul	Davao	150

`grouped = df.groupby("city")`

↳ what this does is it creates something like this

```
Folder: Manila
Rows: John(100), Mark(120)

Folder: Cebu
Rows: Anna(80), Liza(90)

Folder: Davao
Rows: Paul(150)
```

← groups rows based on the "city"

`.get_group("column_value")`

- after grouping, to check specific value

```
print(grouped.get_group("Manila"))
```

Output:

```
   name   city  sales
0  John  Manila    100
2  Mark  Manila    120
```

2. Aggregation

- compute something for each group

treat this as array — Index of that array

```
total_sales = df.groupby("city")["sales"].sum()
print(total_sales)
```

Output:

```
city
Cebu      170
Davao     150
Manila    220
Name: sales, dtype: int64
```

3 Other aggregations

You can calculate many things:

```python
df.groupby("city")["sales"].mean()   # average
df.groupby("city")["sales"].min()    # smallest sale
df.groupby("city")["sales"].max()    # biggest sale
df.groupby("city")["sales"].count()  # number of people in city
```

You can combine this in 1 single line of code using the

- agg(["operation", ...])

```
df.groupby("city")["sales"].agg(["sum", "mean", "min", "max"])
```

Output:

```
        sum   mean  min  max
city
Cebu    170  85.0   80   90
Davao   150 150.0  150  150
Manila  220 110.0  100  120
```

Transformation

Review : Lamda functions

```
lambda x, y : x + y
```

lambda — function with no name
x, y — parameter
x + y — returned value

df

	name	city	sales
0	John	Manila	100
1	Anna	Cebu	80
2	Mark	Manila	120
3	Liza	Cebu	90
4	Paul	Davao	150

df.groupby("city")["sales"]

```
Folder: Manila
Rows: John(100), Mark(120)

Folder: Cebu
Rows: Anna(80), Liza(90)

Folder: Davao
Rows: Paul(150)
```

- transform(function)

apply this in all array in our case in (Groups) using the function inside

assign new column

```
df["sales_diff"] = df.groupby("city")["sales"].transform(lambda x: x - x.mean())
```

Step by step:

1. Group by city:
   - Manila → [100, 120]
   - Cebu → [80, 90]
   - Davao → [150]
2. Apply function to each group (`lambda x: x - x.mean()`):
   - Manila → [100-110, 120-110] = [-10, 10]
   - Cebu → [80-85, 90-85] = [-5, 5]
   - Davao → [150-150] = [0]
3. Combine results → **same rows as original DataFrame:**

nginx

```
City   Sales  sales_diff
Manila  100       -10
Manila  120        10
Cebu     80        -5
Cebu     90         5
Davao   150         0
```

filtration

Python refresher

df["age"] → select 1 column

df[["age","name"]] → select multiple column and do function with it (automatic loop)

df[condition] → Filter rows

	name	city	sales
0	John	Manila	100
1	Anna	Cebu	80
2	Mark	Manila	120
3	Liza	Cebu	90
4	Paul	Davao	150

```python
df_filtered = df[df["sales"] > 90]
print(df_filtered)
```

Output:

```
   name   city  sales
0  John  Manila    100
2  Mark  Manila    120
4  Paul   Davao    150
```

Example: Keep only Cebu rows

```python
df[df["city"] == "Cebu"]
```

Output:

```
   name  city  sales
1  Anna  Cebu     80
3  Liza  Cebu     90
```

If you want to operate in group → .filter(function condition)

ex.

```python
filtered = df.groupby("city").filter(lambda x: x["sales"].sum() > 200)
print(filtered)
```

Output:

```
   name   city  sales
0  John  Manila    100
2  Mark  Manila    120
```

✅ Explanation:

1. Group by city:
   - Manila → [100, 120] → sum = 220 ✅ keep
   - Cebu → [80, 90] → sum = 170 ❌ remove
   - Davao → [150] → sum = 150 ❌ remove
2. Only **Manila rows are kept**, all others removed.