

About This Sheet

This notebook serves as a **beginner-friendly guide** to mastering the basics of Pandas. You'll learn how to:

1. Load data into Pandas.
2. Explore and analyze datasets.
3. Clean, transform and visualize data.
4. Save your work for future use.

By the end of this sheet, you'll have a solid foundation in Pandas to work on your data analysis projects. 🚀

What is Pandas? Pandas is a powerful Python library for data manipulation and analysis. It provides easy-to-use tools to handle structured data such as tables, making it an essential tool for data scientists and analysts.

With Pandas, you can:

- Load and explore datasets effortlessly.
 - Clean and preprocess messy data.
 - Perform statistical analysis.
 - Visualize data.
-

Let's Go 🌟

• Basics

1. Installation

```
In [1]: !pip install pandas
```

Requirement already satisfied: pandas in c:\users\eng mariam skoot\anaconda3\lib\site-packages (2.2.3)
Requirement already satisfied: numpy>=1.23.2 in c:\users\eng mariam skoot\anaconda3\lib\site-packages (from pandas) (1.26.4)
Requirement already satisfied: python-dateutil>=2.8.2 in c:\users\eng mariam skoot\anaconda3\lib\site-packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in c:\users\eng mariam skoot\anaconda3\lib\site-packages (from pandas) (2023.3.post 1)
Requirement already satisfied: tzdata>=2022.7 in c:\users\eng mariam skoot\anaconda3\lib\site-packages (from pandas) (2023.3)
Requirement already satisfied: six>=1.5 in c:\users\eng mariam skoot\anaconda3\lib\site-packages (from python-dateutil>=2.8.2->pandas) (1.16.0)

2. Importing pandas

```
In [2]: import pandas as pd          # pd is alternate name for referring to pandas
```

3. Pandas Series

A Pandas Series is a one-dimensional array holding data of any type (a column in a table)

```
In [3]: a = [10,20,30]
        myvar = pd.Series(a)
        print(myvar)
```

```
0    10
1    20
2    30
dtype: int64
```

```
In [4]: # The values are labeled with their index number
        a = [10,20,30]
        print(myvar[0])
```

```
10
```

```
In [5]: #With the index argument, you can name your own labels.
        a = [10,20,30]
        myvar = pd.Series(a, index = ["i", "ii", "iii"])
        print(myvar)
```

```
i      10
ii     20
iii    30
dtype: int64
```

In [6]: *# You can create a Pandas Series from a dictionary*

```
data = {'Name':['Mohamed', 'Youssef', 'Amira', 'Mariam'],
        'Age':[25, 10, 37, 19]}
ds = pd.Series(data)
print(ds)
```

```
Name    [Mohamed, Youssef, Amira, Mariam]
Age      [25, 10, 37, 19]
dtype: object
```

Pandas DataFrames

A Pandas DataFrame is a 2 dimensional data structure (table)

In [7]:

```
data = {'Name':['Mohamed', 'Youssef', 'Amira', 'Mariam'],
        'Age':[25, 10, 37, 19]}
df = pd.DataFrame(data)
print(df)
```

```
      Name  Age
0  Mohamed   25
1  Youssef   10
2    Amira   37
3   Mariam   19
```

In [8]: *# Column Selection ==> By []*

```
data = {'Name':['Mohamed', 'Youssef', 'Amira', 'Mariam'],
        'Age':[25, 10, 37, 19]}
df = pd.DataFrame(data)
print(df[['Age']])
```

	Age
0	25
1	10
2	37
3	19

```
In [9]: # Row Selection ==> By Loc[]
# Note : Loc[] returns pandas series
data = {'Name':['Mohamed', 'Youssef', 'Amira', 'Mariam'],
        'Age':[25, 10, 37, 19]}
df = pd.DataFrame(data)
print(df.loc[2])
```

```
Name    Amira
Age      37
Name: 2, dtype: object
```

```
In [10]: # Note : Loc[][] the result is a Pandas DataFrame
data = {'Name':['Mohamed', 'Youssef', 'Amira', 'Mariam'],
        'Age':[25, 10, 37, 19]}
df = pd.DataFrame(data)
print(df.loc[[1,2,3]])
```

	Name	Age
1	Youssef	10
2	Amira	37
3	Mariam	19

Read CSV Files

CSV files (comma separated files) is a plain text file used to store tabular data, where each line represents a row, and each value in the row is separated by a comma

Example:

Name, Age, City

Alice, 25, New York

Bob, 30, Los Angeles

Charlie, 35, Chicago go

```
data = pd.read_csv('data.csv') # 'data.csv' => this is the path of file print(data)
```

```
In [11]: url = "https://media.geeksforgeeks.org/wp-content/uploads/nba.csv"
data = pd.read_csv(url)
```

Analyzing DataFrames

```
In [12]: # The head() method returns the headers (starting from the top)
print(data.head())
```

	Name	Team	Number	Position	Age	Height	Weight	\
0	Avery Bradley	Boston Celtics	0.0	PG	25.0	6-2	180.0	
1	Jae Crowder	Boston Celtics	99.0	SF	25.0	6-6	235.0	
2	John Holland	Boston Celtics	30.0	SG	27.0	6-5	205.0	
3	R.J. Hunter	Boston Celtics	28.0	SG	22.0	6-5	185.0	
4	Jonas Jerebko	Boston Celtics	8.0	PF	29.0	6-10	231.0	

	College	Salary
0	Texas	7730337.0
1	Marquette	6796117.0
2	Boston University	NaN
3	Georgia State	1148640.0
4	NaN	5000000.0

```
In [13]: # The tail() method returns the headers (starting from the bottom)
print(data.tail())
```

	Name	Team	Number	Position	Age	Height	Weight	College	\
453	Shelvin Mack	Utah Jazz	8.0	PG	26.0	6-3	203.0	Butler	
454	Raul Neto	Utah Jazz	25.0	PG	24.0	6-1	179.0	NaN	
455	Tibor Pleiss	Utah Jazz	21.0	C	26.0	7-3	256.0	NaN	
456	Jeff Withey	Utah Jazz	24.0	C	26.0	7-0	231.0	Kansas	
457	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

	Salary
453	2433333.0
454	900000.0
455	2900000.0
456	947276.0
457	NaN

```
In [14]: # info() gives you more information about the data set
print(data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 458 entries, 0 to 457
Data columns (total 9 columns):
#   Column      Non-Null Count  Dtype
---  -
0   Name        457 non-null    object
1   Team        457 non-null    object
2   Number      457 non-null    float64
3   Position    457 non-null    object
4   Age         457 non-null    float64
5   Height      457 non-null    object
6   Weight      457 non-null    float64
7   College     373 non-null    object
8   Salary      446 non-null    float64
dtypes: float64(4), object(5)
memory usage: 32.3+ KB
None
```

```
In [15]: # describe() generates a statistical summary.
data.describe()
```

Out[15]:

	Number	Age	Weight	Salary
count	457.000000	457.000000	457.000000	4.460000e+02
mean	17.678337	26.938731	221.522976	4.842684e+06
std	15.966090	4.404016	26.368343	5.229238e+06
min	0.000000	19.000000	161.000000	3.088800e+04
25%	5.000000	24.000000	200.000000	1.044792e+06
50%	13.000000	26.000000	220.000000	2.839073e+06
75%	25.000000	30.000000	240.000000	6.500000e+06
max	99.000000	40.000000	307.000000	2.500000e+07

• Manipulating Data

It's an essential step before performing data analysis or modeling, ensuring that the data is organized and clean.

1. Empty cells
2. Data in wrong format
3. Remove Duplicates
4. Filtering Data
5. Sorting
6. Adding New Columns
7. Grouping
8. Merging

1. Empty cells

How to deal with empty cells ?

- Remove Rows

```
In [16]: url = "https://media.geeksforgeeks.org/wp-content/uploads/nba.csv"
data= pd.read_csv(url)
data
```

```
Out[16]:
```

	Name	Team	Number	Position	Age	Height	Weight	College	Salary
0	Avery Bradley	Boston Celtics	0.0	PG	25.0	6-2	180.0	Texas	7730337.0
1	Jae Crowder	Boston Celtics	99.0	SF	25.0	6-6	235.0	Marquette	6796117.0
2	John Holland	Boston Celtics	30.0	SG	27.0	6-5	205.0	Boston University	NaN
3	R.J. Hunter	Boston Celtics	28.0	SG	22.0	6-5	185.0	Georgia State	1148640.0
4	Jonas Jerebko	Boston Celtics	8.0	PF	29.0	6-10	231.0	NaN	5000000.0
...
453	Shelvin Mack	Utah Jazz	8.0	PG	26.0	6-3	203.0	Butler	2433333.0
454	Raul Neto	Utah Jazz	25.0	PG	24.0	6-1	179.0	NaN	900000.0
455	Tibor Pleiss	Utah Jazz	21.0	C	26.0	7-3	256.0	NaN	2900000.0
456	Jeff Withey	Utah Jazz	24.0	C	26.0	7-0	231.0	Kansas	947276.0
457	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

458 rows × 9 columns

```
In [17]: data.dropna()      # dropna() returns a new DataFrame, and will not change the original
```


Out[17]:

	Name	Team	Number	Position	Age	Height	Weight	College	Salary
0	Avery Bradley	Boston Celtics	0.0	PG	25.0	6-2	180.0	Texas	7730337.0
1	Jae Crowder	Boston Celtics	99.0	SF	25.0	6-6	235.0	Marquette	6796117.0
3	R.J. Hunter	Boston Celtics	28.0	SG	22.0	6-5	185.0	Georgia State	1148640.0
6	Jordan Mickey	Boston Celtics	55.0	PF	21.0	6-8	235.0	LSU	1170960.0
7	Kelly Olynyk	Boston Celtics	41.0	C	25.0	7-0	238.0	Gonzaga	2165160.0
...
449	Rodney Hood	Utah Jazz	5.0	SG	23.0	6-8	206.0	Duke	1348440.0
451	Chris Johnson	Utah Jazz	23.0	SF	26.0	6-6	206.0	Dayton	981348.0
452	Trey Lyles	Utah Jazz	41.0	PF	20.0	6-10	234.0	Kentucky	2239800.0
453	Shelvin Mack	Utah Jazz	8.0	PG	26.0	6-3	203.0	Butler	2433333.0
456	Jeff Withey	Utah Jazz	24.0	C	26.0	7-0	231.0	Kansas	947276.0

364 rows × 9 columns

If you want to change the original DataFrame: data.dropna(inplace = True)

- Replace Empty Values

```
In [18]: url = "https://media.geeksforgeeks.org/wp-content/uploads/nba.csv"
data= pd.read_csv(url)
data
```

Out[18]:

	Name	Team	Number	Position	Age	Height	Weight	College	Salary
0	Avery Bradley	Boston Celtics	0.0	PG	25.0	6-2	180.0	Texas	7730337.0
1	Jae Crowder	Boston Celtics	99.0	SF	25.0	6-6	235.0	Marquette	6796117.0
2	John Holland	Boston Celtics	30.0	SG	27.0	6-5	205.0	Boston University	NaN
3	R.J. Hunter	Boston Celtics	28.0	SG	22.0	6-5	185.0	Georgia State	1148640.0
4	Jonas Jerebko	Boston Celtics	8.0	PF	29.0	6-10	231.0	NaN	5000000.0
...
453	Shelvin Mack	Utah Jazz	8.0	PG	26.0	6-3	203.0	Butler	2433333.0
454	Raul Neto	Utah Jazz	25.0	PG	24.0	6-1	179.0	NaN	900000.0
455	Tibor Pleiss	Utah Jazz	21.0	C	26.0	7-3	256.0	NaN	2900000.0
456	Jeff Withey	Utah Jazz	24.0	C	26.0	7-0	231.0	Kansas	947276.0
457	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

458 rows × 9 columns

```
In [19]: data.fillna(130)           # Replace NULL values with the number 130:
```

Out[19]:

	Name	Team	Number	Position	Age	Height	Weight	College	Salary
0	Avery Bradley	Boston Celtics	0.0	PG	25.0	6-2	180.0	Texas	7730337.0
1	Jae Crowder	Boston Celtics	99.0	SF	25.0	6-6	235.0	Marquette	6796117.0
2	John Holland	Boston Celtics	30.0	SG	27.0	6-5	205.0	Boston University	130.0
3	R.J. Hunter	Boston Celtics	28.0	SG	22.0	6-5	185.0	Georgia State	1148640.0
4	Jonas Jerebko	Boston Celtics	8.0	PF	29.0	6-10	231.0	130	5000000.0
...
453	Shelvin Mack	Utah Jazz	8.0	PG	26.0	6-3	203.0	Butler	2433333.0
454	Raul Neto	Utah Jazz	25.0	PG	24.0	6-1	179.0	130	900000.0
455	Tibor Pleiss	Utah Jazz	21.0	C	26.0	7-3	256.0	130	2900000.0
456	Jeff Withey	Utah Jazz	24.0	C	26.0	7-0	231.0	Kansas	947276.0
457	130	130	130.0	130	130.0	130	130.0	130	130.0

458 rows × 9 columns

- **Replace Using Mean, Median, or Mode**

-> Mean = the average value (the sum of all values divided by number of values).

-> Median = the value in the middle, after you have sorted all values ascending.

-> Mode = the value that appears most frequently.

```
In [20]: url = "https://media.geeksforgeeks.org/wp-content/uploads/nba.csv"
data= pd.read_csv(url)
data
```

Out[20]:

	Name	Team	Number	Position	Age	Height	Weight	College	Salary
0	Avery Bradley	Boston Celtics	0.0	PG	25.0	6-2	180.0	Texas	7730337.0
1	Jae Crowder	Boston Celtics	99.0	SF	25.0	6-6	235.0	Marquette	6796117.0
2	John Holland	Boston Celtics	30.0	SG	27.0	6-5	205.0	Boston University	NaN
3	R.J. Hunter	Boston Celtics	28.0	SG	22.0	6-5	185.0	Georgia State	1148640.0
4	Jonas Jerebko	Boston Celtics	8.0	PF	29.0	6-10	231.0	NaN	5000000.0
...
453	Shelvin Mack	Utah Jazz	8.0	PG	26.0	6-3	203.0	Butler	2433333.0
454	Raul Neto	Utah Jazz	25.0	PG	24.0	6-1	179.0	NaN	900000.0
455	Tibor Pleiss	Utah Jazz	21.0	C	26.0	7-3	256.0	NaN	2900000.0
456	Jeff Withey	Utah Jazz	24.0	C	26.0	7-0	231.0	Kansas	947276.0
457	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

458 rows × 9 columns

```
In [21]: data['Salary'].fillna(data['Salary'].mean())      # Note the column with index 2 and 457
# data['Salary'] => because in this way the data must be a number
```

```
Out[21]: 0      7.730337e+06
          1      6.796117e+06
          2      4.842684e+06
          3      1.148640e+06
          4      5.000000e+06
          ...
          453    2.433333e+06
          454    9.000000e+05
          455    2.900000e+06
          456    9.472760e+05
          457    4.842684e+06
Name: Salary, Length: 458, dtype: float64
```

2. Wrong Format

To fix wrong format, you have two options: remove the rows, or convert all cells in the columns into the same format.

- Removing Rows

```
In [22]: data.dropna()
```

Out[22]:

	Name	Team	Number	Position	Age	Height	Weight	College	Salary
0	Avery Bradley	Boston Celtics	0.0	PG	25.0	6-2	180.0	Texas	7730337.0
1	Jae Crowder	Boston Celtics	99.0	SF	25.0	6-6	235.0	Marquette	6796117.0
3	R.J. Hunter	Boston Celtics	28.0	SG	22.0	6-5	185.0	Georgia State	1148640.0
6	Jordan Mickey	Boston Celtics	55.0	PF	21.0	6-8	235.0	LSU	1170960.0
7	Kelly Olynyk	Boston Celtics	41.0	C	25.0	7-0	238.0	Gonzaga	2165160.0
...
449	Rodney Hood	Utah Jazz	5.0	SG	23.0	6-8	206.0	Duke	1348440.0
451	Chris Johnson	Utah Jazz	23.0	SF	26.0	6-6	206.0	Dayton	981348.0
452	Trey Lyles	Utah Jazz	41.0	PF	20.0	6-10	234.0	Kentucky	2239800.0
453	Shelvin Mack	Utah Jazz	8.0	PG	26.0	6-3	203.0	Butler	2433333.0
456	Jeff Withey	Utah Jazz	24.0	C	26.0	7-0	231.0	Kansas	947276.0

364 rows × 9 columns

- **Convert Into a Correct Format**

This appears in the dates

```
In [23]: df = pd.DataFrame({'Date': {0: '26/1/2016', 1: '26/1/2016'}})
print (df)
```

```
      Date
0  26/1/2016
1  26/1/2016
```

```
In [24]: df['Date'] = pd.to_datetime(df.Date)
print (df)
# 26/1/2016 => 2016-01-26
```

```
    Date
0 2016-01-26
1 2016-01-26
```

```
C:\Users\Eng Mariam skoot\AppData\Local\Temp\ipykernel_22272\1954211441.py:1: UserWarning: Parsing dates in %d/%m/%Y format when dayfirst=False (the default) was specified. Pass `dayfirst=True` or specify a format to silence this warning.
df['Date'] = pd.to_datetime(df.Date)
```

• Converting Column type

1. `.astype()` is useful for explicit type conversion in pandas.
2. Use `errors = 'coerce'` with `pd.to_numeric()`, `pd.to_datetime()`, or `pd.to_timedelta()` if you need to handle errors by replacing invalid entries with `NaN`.

```
In [25]: # Create a DataFrame with columns of different types
data = {
    'String_to_Int': ['10', '20', '30', '40'],          # Strings to be converted to integers
    'String_to_Float': ['1.5', '2.5', '3.5', '4.5'],    # Strings to be converted to floats
    'Category_Column': ['A', 'B', 'A', 'C'],            # Values to be converted to categorical
    'Numeric_to_Bool': [1, 0, 1, 0],                   # Numeric values to be converted to boolean
    'Invalid_to_Coerce': ['100', 'abc', '200', '300']   # Values with invalid entries for coercion
}

df = pd.DataFrame(data)

# Print the results
print(df)
print("\nData Types:")
print(df.dtypes)          # Focus on the data types
```

	String_to_Int	String_to_Float	Category_Column	Numeric_to_Bool	\
0	10	1.5	A	1	
1	20	2.5	B	0	
2	30	3.5	A	1	
3	40	4.5	C	0	

	Invalid_to_Coerce
0	100
1	abc
2	200
3	300

```
Data Types:
String_to_Int      object
String_to_Float    object
Category_Column    object
Numeric_to_Bool    int64
Invalid_to_Coerce  object
dtype: object
```

```
In [26]: # Convert strings to integers
df['String_to_Int'] = df['String_to_Int'].astype(int)

# Convert strings to floats
df['String_to_Float'] = df['String_to_Float'].astype(float)

# Convert to categorical type
df['Category_Column'] = df['Category_Column'].astype('category')

# Convert numeric values to boolean
df['Numeric_to_Bool'] = df['Numeric_to_Bool'].astype(bool)

# Handle invalid values and convert strings to integers with errors='coerce'
df['Invalid_to_Coerce'] = pd.to_numeric(df['Invalid_to_Coerce'], errors='coerce')

# Print the results
print(df)
print("\nData Types:")
print(df.dtypes)          # Focus on the data types
```


	String_to_Int	String_to_Float	Category_Column	Numeric_to_Bool	\
0	10	1.5	A	True	
1	20	2.5	B	False	
2	30	3.5	A	True	
3	40	4.5	C	False	

	Invalid_to_Coerce
0	100.0
1	NaN
2	200.0
3	300.0

Data Types:

String_to_Int	int32
String_to_Float	float64
Category_Column	category
Numeric_to_Bool	bool
Invalid_to_Coerce	float64

dtype: object

3. Removing Duplicates

```
In [27]: data = {
    'A': [1, 2, 2, 3, 3, 3],
    'B': ['a', 'b', 'b', 'c', 'c', 'c']}
df = pd.DataFrame(data)
df
```

```
Out[27]:
```

	A	B
0	1	a
1	2	b
2	2	b
3	3	c
4	3	c
5	3	c

```
In [28]: df.duplicated()
```

```
Out[28]: 0    False
1    False
2     True
3    False
4     True
5     True
dtype: bool
```

```
In [29]: df.duplicated().sum()          # duplicated().sum() => summision of duplicated values
```

```
Out[29]: 3
```

```
In [30]: # Remove duplicate rows
df.drop_duplicates(inplace = True)
df
```

```
Out[30]:
```

	A	B
0	1	a
1	2	b
3	3	c

```
In [31]: df.duplicated().sum()
```

```
Out[31]: 0
```

4. Filtering Data

```
In [32]: data = {'Name': ['Alice', 'Bob', 'Charlie', 'David'],
                'Age': [24, 27, 22, 32],
                'Score': [85, 62, 90, 70]}
df = pd.DataFrame(data)

# Filter rows where Age is greater than 25
filtered_df = df[df['Age'] > 25]
filtered_df
```

```
Out[32]:
```

	Name	Age	Score
1	Bob	27	62
3	David	32	70

5. Sorting

```
In [33]: df = pd.DataFrame({
        'Name': ['Alice', 'Bob', 'Charlie', 'David'],
        'Age': [25, 30, 22, 35]}
    })

# Sort the DataFrame by the 'Age' column
sorted_df = df.sort_values(by='Age')
sorted_df
```

Out[33]:

	Name	Age
2	Charlie	22
0	Alice	25
1	Bob	30
3	David	35

6. Adding New Columns

```
In [34]: data = {  
    'Name': ['Jai', 'Princi', 'Gaurav', 'Anuj'],  
    'Height': [5.1, 6.2, 5.1, 5.2],  
    'Qualification': ['Msc', 'MA', 'Msc', 'Msc']  
}  
df = pd.DataFrame(data)  
df
```

Out[34]:

	Name	Height	Qualification
0	Jai	5.1	Msc
1	Princi	6.2	MA
2	Gaurav	5.1	Msc
3	Anuj	5.2	Msc

```
In [35]: address = ['NewYork', 'Chicago', 'Boston', 'Miami']  
df['Address'] = address      # Adding the column  
df
```

Out[35]:

	Name	Height	Qualification	Address
0	Jai	5.1	Msc	NewYork
1	Princi	6.2	MA	Chicago
2	Gaurav	5.1	Msc	Boston
3	Anuj	5.2	Msc	Miami

7. Grouping

```
In [36]: data = {
    'state': ['CA', 'NY', 'CA', 'NY', 'CA'],
    'value': [1, 2, 3, 4, 5]
}
df = pd.DataFrame(data)

# Group by 'state'
grouped = df.groupby('state')

# Apply a function to each group
result = grouped.sum()
result
```

Out[36]:

	value
CA	9
NY	6

8. Merging

```
In [37]: data1 = {
    'key': ['K0', 'K1', 'K2', 'K3'],
    'Name': ['Jai', 'Princi', 'Gaurav', 'Anuj'],
```

```

        'Age': [27, 24, 22, 32]
    }
data2 = {
    'key': ['K0', 'K1', 'K2', 'K3'],
    'Address': ['Nagpur', 'Kanpur', 'Allahabad', 'Kannuaj'],
    'Qualification': ['Btech', 'B.A', 'Bcom', 'B.hons']
}

df1 = pd.DataFrame(data1)
df2 = pd.DataFrame(data2)
print(df1, "\n\n", df2)

```

```

key    Name  Age
0  K0     Jai   27
1  K1  Princi   24
2  K2  Gaurav   22
3  K3   Anuj   32

```

```

key    Address Qualification
0  K0     Nagpur         Btech
1  K1     Kanpur          B.A
2  K2  Allahabad          Bcom
3  K3   Kannuaj         B.hons

```

```

In [38]: # Merge DataFrames on the 'key' column
result = pd.merge(df1, df2, on='key')           # on => 2-DataFrames have the same column named 'Key'
print(result)

```

```

key    Name  Age  Address Qualification
0  K0     Jai   27    Nagpur         Btech
1  K1  Princi   24    Kanpur          B.A
2  K2  Gaurav   22  Allahabad          Bcom
3  K3   Anuj   32   Kannuaj         B.hons

```

• Advanced

1. Correlations

2. Plotting (Data visualization)

1. Correlations

The `corr()` method calculates the relationship between each column in your data set.

```
In [39]: url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.csv"
# read dataset
df = pd.read_csv(url, header=None)

## Set column names instead of being in index
df.columns = ['Pregnancies', 'Glucose', 'BloodPressure',
              'SkinThickness', 'Insulin', 'BMI',
              'DiabetesPedigreeFunction', 'Age', 'Outcome']

df.head()
```

```
Out[39]:
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

```
In [40]: # Show the relationship between the columns:
df.corr()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age
Pregnancies	1.000000	0.129459	0.141282	-0.081672	-0.073535	0.017683	-0.033523	0.544341
Glucose	0.129459	1.000000	0.152590	0.057328	0.331357	0.221071	0.137337	0.263514
BloodPressure	0.141282	0.152590	1.000000	0.207371	0.088933	0.281805	0.041265	0.239528
SkinThickness	-0.081672	0.057328	0.207371	1.000000	0.436783	0.392573	0.183928	-0.113970
Insulin	-0.073535	0.331357	0.088933	0.436783	1.000000	0.197859	0.185071	-0.042163
BMI	0.017683	0.221071	0.281805	0.392573	0.197859	1.000000	0.140647	0.036242
DiabetesPedigreeFunction	-0.033523	0.137337	0.041265	0.183928	0.185071	0.140647	1.000000	0.033561
Age	0.544341	0.263514	0.239528	-0.113970	-0.042163	0.036242	0.033561	1.000000
Outcome	0.221898	0.466581	0.065068	0.074752	0.130548	0.292695	0.173844	0.238356

We can use Pyplot, a submodule of the Matplotlib library to visualize the diagram on the screen.

```
!pip install matplotlib
```

```
In [41]: import pandas as pd
import matplotlib.pyplot as plt

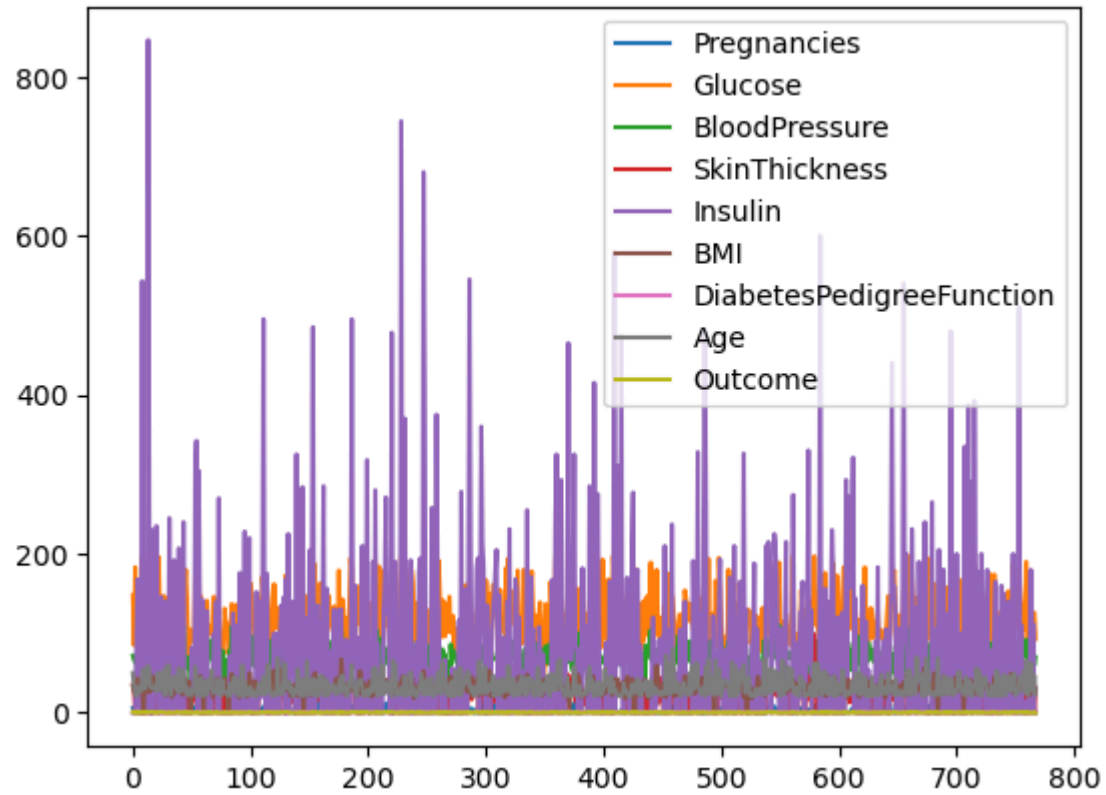
url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.csv"
df = pd.read_csv(url, header=None) # read dataset

## Set column names instead of being in index
df.columns = ['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness',
              'Insulin', 'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome']

df.plot() # visualize the DataFrame
```



```
plt.show()
```



```
In [42]: df.head()
```

```
Out[42]:
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

```
In [43]: data = {
    "Year": [2020, 2021, 2022, 2023, 2024],
    "Sales": [200, 300, 400, 500, 600],
    "Profit": [50, 100, 150, 200, 250]
}

df = pd.DataFrame(data)

plt.figure(figsize=(15, 10))                                # Figure setting with 2 axes

# plt.subplot(2, 3, 1)
# 2: The grid will have 2 rows.
# 3: The grid will have 3 columns.
# 1: Which position the current plot will occupy in the grid?

# Line Plot
plt.subplot(2, 3, 1)
plt.plot(df['Year'], df['Sales'], color='blue')             # x-axis as "Year" , y-axis as "Sales"
plt.title("Line Plot")                                       # title to the graph
plt.xlabel("Year")
plt.ylabel("Sales")

# Bar Plot
plt.subplot(2, 3, 2)
plt.bar(df['Year'], df['Sales'], color='green')             # x-axis as "Year" , y-axis as "Sales"
plt.title("Bar Plot")                                       # title to the graph
plt.xlabel("Year")
```

```

plt.ylabel("Sales")

# Histogram
plt.subplot(2, 3, 3)
plt.hist(df['Sales'], color='orange') # histogram to show the distribution of 'Sales'
plt.title("Histogram") # title to the graph
plt.xlabel("Sales")
plt.ylabel("Frequency")

# Box Plot
plt.subplot(2, 3, 4)
plt.boxplot(df['Sales'], vert=False, patch_artist=True) # Create a box plot of 'Sales' with horizontal orientation and color
plt.title("Box Plot")
plt.xlabel("Sales")

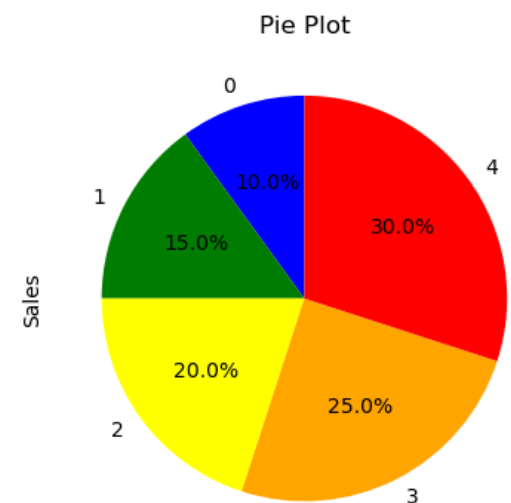
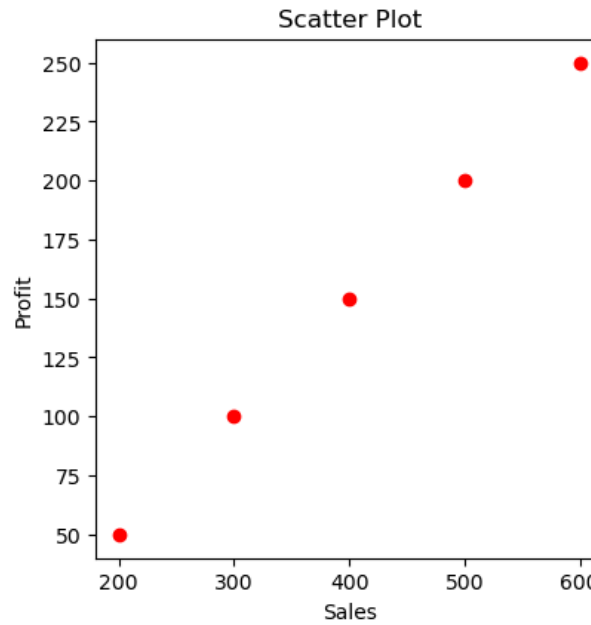
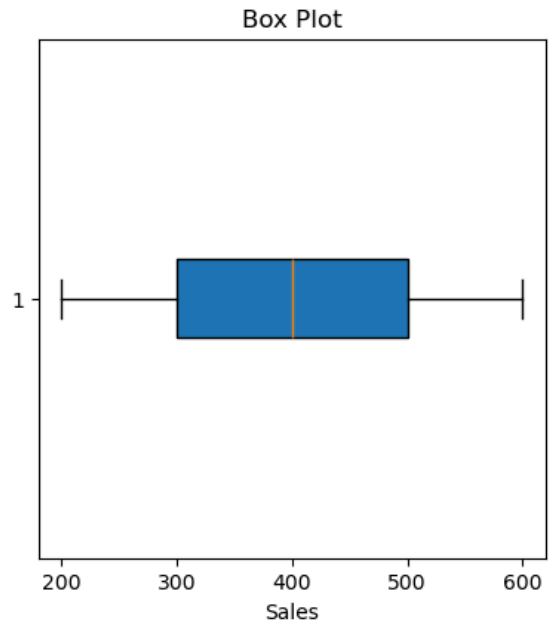
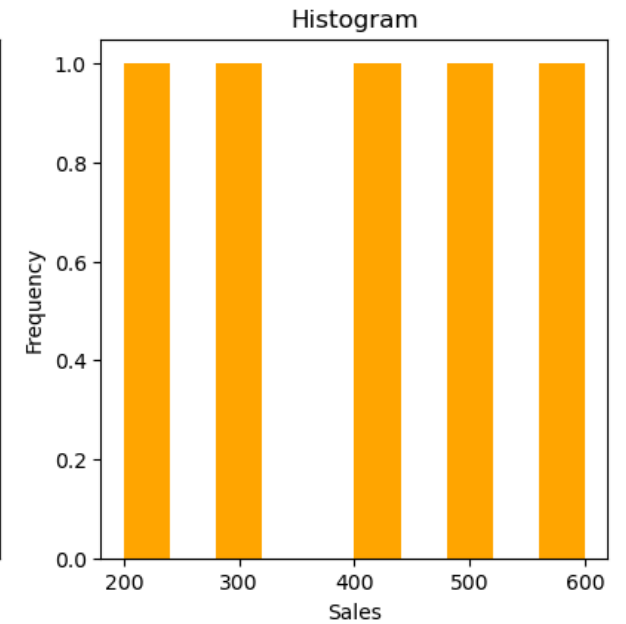
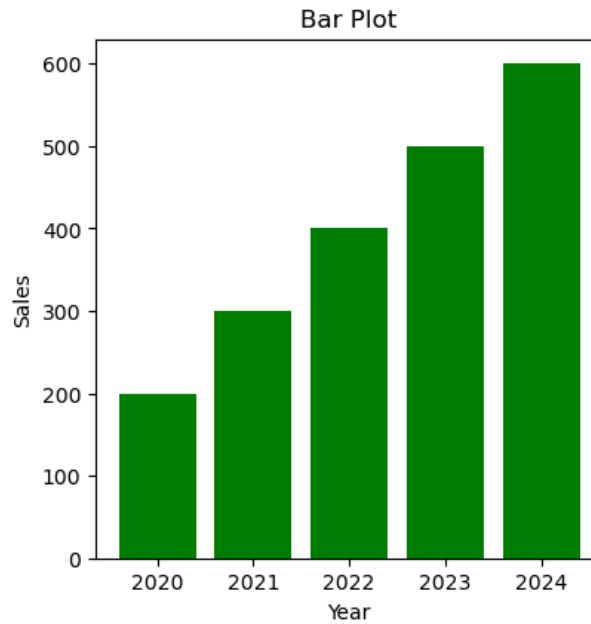
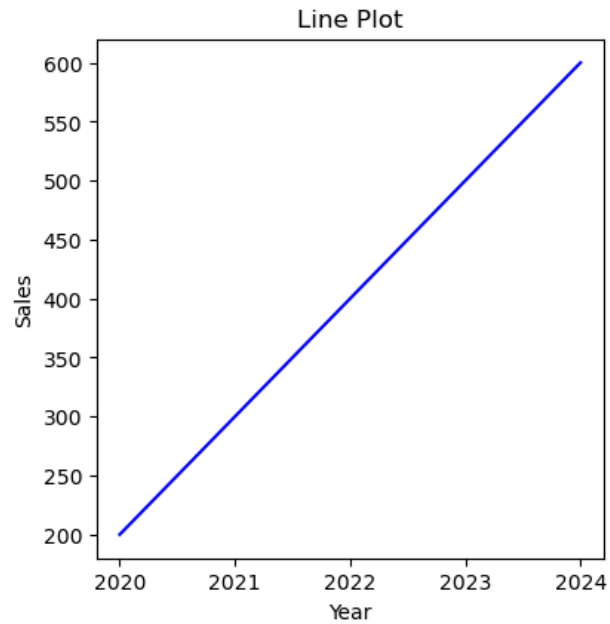
# Scatter Plot
plt.subplot(2, 3, 5)
plt.scatter(df['Sales'], df['Profit'], color='red') # x-axis as "Year" , y-axis as "Sales"
plt.title("Scatter Plot")
plt.xlabel("Sales")
plt.ylabel("Profit")

# Pie Plot
plt.subplot(2, 3, 6)
# Create a pie chart of 'Sales' with percentage values, specific colors, and starting angle of 90 degrees.
df['Sales'].plot(kind='pie', autopct='%1.1f%%', colors=['blue', 'green', 'yellow', 'orange', 'red'], startangle=90)
plt.title("Pie Plot")

# What is (autopct='%1.1f%%') ?
# autopct: Controls the display of percentages on the pie slices ()
# '%1.1f%%': Formats percentages with one decimal place followed by a % symbol.

plt.show() # Display all the plots in the 2x3 grid.

```



Saving Data

```
In [44]: #Saving Data as csv file
df.to_csv("output.csv", index=False)
```

```
In [45]: # Let's try it
data= pd.read_csv("output.csv")
data.head()          # it works 😊
```

```
Out[45]:
```

	Year	Sales	Profit
0	2020	200	50
1	2021	300	100
2	2022	400	150
3	2023	500	200
4	2024	600	250

I hope you found this notebook helpful! 😊 These are the key concepts we covered today:

- Pandas Basics
- Data Manipulation and Cleaning
- Data Visualization
- Exporting Processed Data

Data is the new gold, and your skills now make you able to extract their value! 🚀