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|----------------------|---|----------------|-------------|
| Course Name: | Data Analysis Laboratory (216H03L501) | Semester: | V |
| Date of Performance: | 14 / 07 / 2025 | DIV/ Batch No: | D6 |
| Student Name: | Samiksha Sharma | Roll No: | 16010123298 |

Experiment No: 1

Title: Studies on Pandas library of python.

Objectives of the Experiment:

1. To understand and apply the fundamental functionalities of the pandas library for data analysis.
2. To manipulate and transform datasets using filtering, sorting, and column operations.
3. To analyze data using grouping and aggregation techniques to derive meaningful insights.

COs to be achieved:

CO1: Understand basic concepts of data analytics to solve real-world problems

Books/ Journals/ Websites referred:

1. Students should write

Theory:

Students should write about pandas

Problem statement/ Tasks

Task 1: Import Required Libraries and Dataset

- Import pandas and load a real-world CSV dataset (e.g., Titanic, Student Performance, COVID-19).
- Display the first and last 5 records using head() and tail().

Task 2: Basic Exploration of the Dataset

- Display the dataset shape using .shape, column names using .columns, and data types using .dtypes.
- Generate summary statistics using .describe() and data info using .info().

Task 3: Identify Missing and Duplicate Data

- Detect missing values using .isnull().sum().

- Remove or fill missing values using `.dropna()` or `.fillna()`.
- Check for and remove duplicate rows using `.duplicated()` and `.drop_duplicates()`.

Task 4: Filtering Records

- Extract rows based on specific conditions (e.g., students who scored more than 80%, passengers who survived).

Task 5: Sorting the Dataset

- Sort the dataset based on one or more columns using `.sort_values()`.
 - Example: Sort by age or total score.

Task 6: Creating or Modifying Columns

- Create new columns from existing ones (e.g., Total Marks = Math + Science + English).
- Drop unnecessary columns using `.drop()`.
- Rename columns using `.rename()`.

Task 7: Grouping and Aggregation

- Use `.groupby()` to find average, count, or sum based on a categorical column.
- Example:
 - Average marks by gender: `df.groupby('Gender')['Marks'].mean()`
 - Survival rate by class: `df.groupby('Pclass')['Survived'].mean()`

Task 8: Pivot Tables or Multi-Level Grouping (Optional for advanced students)

- Create pivot tables using `.pivot_table()` to summarize complex data.
 - Example: Average score by gender and class.

Task 9: Insight Generation

- Write 3-5 key insights based on the group-by and aggregated data.
- Example:
 - "Female students have higher average marks in English."
 - "Survival rate is highest for first-class passengers."

Code :

Task 1:

```
[4] import pandas as pd
df = pd.read_csv("/content/jadavpur,-kolkata-air-quality.csv")
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2032 entries, 0 to 2031
Data columns (total 7 columns):
#   Column      Non-Null Count  Dtype  
---  -
0    date        2032 non-null    object  
1    pm25        2032 non-null    object  
2    pm10        2032 non-null    object  
3    o3          2032 non-null    object  
4    no2         2032 non-null    object  
5    so2         2032 non-null    object  
6    co          2032 non-null    object  
dtypes: object(7)
memory usage: 111.3+ KB
```

```
[5] df.head()
```

| | date | pm25 | pm10 | o3 | no2 | so2 | co |
|---|----------|------|------|----|-----|-----|----|
| 0 | 2025/7/1 | 90 | 38 | 7 | 10 | | 2 |
| 1 | 2025/7/2 | 81 | 39 | 7 | 6 | | 2 |
| 2 | 2025/7/3 | 82 | 47 | 20 | 9 | | 3 |
| 3 | 2025/7/4 | 93 | 49 | 6 | 14 | 1 | 3 |
| 4 | 2025/7/5 | 96 | 42 | 6 | 11 | | 3 |

```
[6] df.tail()
```

| | date | pm25 | pm10 | o3 | no2 | so2 | co |
|------|------------|------|------|----|-----|-----|----|
| 2027 | 2021/6/10 | | 40 | 12 | 7 | 2 | 3 |
| 2028 | 2020/10/26 | | 81 | 41 | 27 | 7 | 10 |
| 2029 | 2020/9/27 | | 67 | 9 | 11 | 2 | 6 |
| 2030 | 2019/12/31 | | 142 | 5 | 25 | 2 | 16 |
| 2031 | 2019/12/2 | | 110 | | 32 | 1 | 16 |

Task 2:

```
[9] df.shape
(2032, 7)

[10] df.columns
Index(['date', ' pm25', ' pm10', ' o3', ' no2', ' so2', ' co'], dtype='object')

df.dtypes

```

| | 0 |
|------|--------|
| date | object |
| pm25 | object |
| pm10 | object |
| o3 | object |
| no2 | object |
| so2 | object |
| co | object |

dtype: object

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2032 entries, 0 to 2031
Data columns (total 7 columns):
Column Non-Null Count Dtype

0 date 2032 non-null object
1 pm25 2004 non-null float64
2 pm10 2005 non-null float64
3 o3 1999 non-null float64
4 no2 1965 non-null float64
5 so2 1950 non-null float64
6 co 1990 non-null float64
dtypes: float64(6), object(1)
memory usage: 111.3+ KB

df.describe()

| | pm25 | pm10 | o3 | no2 | so2 | co |
|-------|-------------|-------------|-------------|-------------|-------------|-------------|
| count | 2004.000000 | 2005.000000 | 1999.000000 | 1965.000000 | 1950.000000 | 1990.000000 |
| mean | 111.702595 | 69.085786 | 17.479240 | 10.541476 | 2.555385 | 5.515578 |
| std | 49.925950 | 38.019779 | 16.255081 | 8.654428 | 1.792968 | 4.339132 |
| min | 18.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000000 |
| 25% | 67.750000 | 38.000000 | 8.000000 | 5.000000 | 1.000000 | 3.000000 |
| 50% | 105.000000 | 59.000000 | 13.000000 | 8.000000 | 2.000000 | 4.000000 |
| 75% | 157.000000 | 98.000000 | 23.000000 | 14.000000 | 3.000000 | 8.000000 |
| max | 317.000000 | 249.000000 | 402.000000 | 96.000000 | 16.000000 | 37.000000 |

Task 3:

```
if df.isna().sum().sum() < 50:
    df.dropna(inplace=True)
else:
    df.fillna(df.median(numeric_only=True), inplace=True)

print(df)
```

| | date | pm25 | pm10 | o3 | no2 | so2 | co |
|------|------------|-------|-------|------|------|-----|------|
| 0 | 2025/7/1 | 90.0 | 38.0 | 7.0 | 10.0 | 2.0 | 2.0 |
| 1 | 2025/7/2 | 81.0 | 39.0 | 7.0 | 6.0 | 2.0 | 2.0 |
| 2 | 2025/7/3 | 82.0 | 47.0 | 20.0 | 9.0 | 2.0 | 3.0 |
| 3 | 2025/7/4 | 93.0 | 49.0 | 6.0 | 14.0 | 1.0 | 3.0 |
| 4 | 2025/7/5 | 96.0 | 42.0 | 6.0 | 11.0 | 2.0 | 3.0 |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 2027 | 2021/6/10 | 105.0 | 40.0 | 12.0 | 7.0 | 2.0 | 3.0 |
| 2028 | 2020/10/26 | 105.0 | 81.0 | 41.0 | 27.0 | 7.0 | 10.0 |
| 2029 | 2020/9/27 | 105.0 | 67.0 | 9.0 | 11.0 | 2.0 | 6.0 |
| 2030 | 2019/12/31 | 105.0 | 142.0 | 5.0 | 25.0 | 2.0 | 16.0 |
| 2031 | 2019/12/2 | 105.0 | 110.0 | 13.0 | 32.0 | 1.0 | 16.0 |

[2032 rows x 7 columns]

```
[32] dup = df.duplicated()
print(dup)
```

| | |
|------|-------|
| 0 | False |
| 1 | False |
| 2 | False |
| 3 | False |
| 4 | False |
| ... | ... |
| 2027 | False |
| 2028 | False |
| 2029 | False |
| 2030 | False |
| 2031 | False |

Length: 2032, dtype: bool

Task 4:


```
high_co = df[df['co'] > 5]
print(high_co)
```

| | date | pm25 | pm10 | o3 | no2 | so2 | co |
|------|------------|-------|-------|------|------|-----|------|
| 49 | 2025/5/6 | 124.0 | 69.0 | 40.0 | 14.0 | 9.0 | 6.0 |
| 77 | 2025/6/3 | 143.0 | 51.0 | 9.0 | 40.0 | 6.0 | 20.0 |
| 78 | 2025/6/4 | 101.0 | 55.0 | 12.0 | 42.0 | NaN | 37.0 |
| 79 | 2025/6/5 | 109.0 | 62.0 | 11.0 | 35.0 | NaN | 32.0 |
| 93 | 2025/6/19 | 89.0 | 52.0 | 6.0 | 14.0 | 4.0 | 8.0 |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 2025 | 2022/11/16 | NaN | 163.0 | 5.0 | 22.0 | 5.0 | 21.0 |
| 2028 | 2020/10/26 | NaN | 81.0 | 41.0 | 27.0 | 7.0 | 10.0 |
| 2029 | 2020/9/27 | NaN | 67.0 | 9.0 | 11.0 | 2.0 | 6.0 |
| 2030 | 2019/12/31 | NaN | 142.0 | 5.0 | 25.0 | 2.0 | 16.0 |
| 2031 | 2019/12/2 | NaN | 110.0 | NaN | 32.0 | 1.0 | 16.0 |

[710 rows x 7 columns]

Task 5:

```
df.sort_values('pm25')
```

| | date | pm25 | pm10 | o3 | no2 | so2 | co |
|------|------------|-------|-------|------|------|-----|------|
| 1843 | 2020/5/19 | 18.0 | 14.0 | 12.0 | 2.0 | 2.0 | 3.0 |
| 1868 | 2020/6/13 | 18.0 | 20.0 | 9.0 | 4.0 | 1.0 | 3.0 |
| 1845 | 2020/5/21 | 21.0 | 34.0 | 21.0 | 2.0 | 2.0 | 3.0 |
| 1733 | 2020/7/30 | 23.0 | 16.0 | 6.0 | 3.0 | 2.0 | 3.0 |
| 1866 | 2020/6/11 | 24.0 | 17.0 | 8.0 | 6.0 | 2.0 | 3.0 |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 1698 | 2020/12/29 | 259.0 | 158.0 | 8.0 | 25.0 | 3.0 | 14.0 |
| 1909 | 2020/1/24 | 289.0 | 61.0 | 6.0 | 24.0 | 4.0 | 9.0 |
| 1162 | 2022/1/6 | 291.0 | 148.0 | 10.0 | 38.0 | 2.0 | 10.0 |
| 1161 | 2022/1/5 | 293.0 | 157.0 | 29.0 | 39.0 | 6.0 | 13.0 |
| 1886 | 2020/1/1 | 317.0 | 118.0 | 11.0 | 22.0 | 2.0 | 11.0 |

2032 rows x 7 columns

Task 6:

df.columns = df.columns.str.strip()

pollutant_cols = ['pm25', 'pm10', 'o3', 'no2', 'so2', 'co']

df[pollutant_cols] = df[pollutant_cols].apply(pd.to_numeric, errors='coerce')

df['total_pollutants'] = (df['pm25'] + df['pm10'] + df['o3'] + df['no2'] + df['so2'] + df['co'])

df = df.drop(columns=['date'])

df = df.rename(columns={

'pm25': 'PM2_5',

'pm10': 'PM10',

'o3': 'O3',

'no2': 'NO2',

'so2': 'SO2',

'co': 'CO'

})

[3]

✓ 0.0s

Python

df.head()

[4]

✓ 0.0s

Python

...

| | PM2_5 | PM10 | O3 | NO2 | SO2 | CO | total_pollutants |
|---|-------|------|------|------|-----|-----|------------------|
| 0 | 65.0 | 24.0 | 12.0 | 7.0 | 4.0 | 6.0 | 118.0 |
| 1 | 58.0 | 33.0 | 10.0 | 8.0 | 2.0 | 2.0 | 113.0 |
| 2 | 72.0 | 34.0 | 9.0 | 11.0 | 1.0 | 3.0 | 130.0 |
| 3 | 74.0 | 32.0 | 10.0 | 10.0 | 2.0 | 5.0 | 133.0 |
| 4 | 72.0 | 27.0 | 11.0 | 8.0 | 2.0 | 5.0 | 125.0 |

Task 7:

Competitive Programming Laboratory

Semester: IV

Academic Year: 2024-25


```
df['main_pollutant'] = df[['PM2_5', 'PM10', 'O3', 'NO2', 'SO2', 'CO']].idxmax(axis=1)

avg_by_main_pollutant = df.groupby('main_pollutant')[['PM2_5', 'PM10', 'O3', 'NO2', 'SO2', 'CO', 'total_pollutants']].mean()

count_by_main_pollutant = df['main_pollutant'].value_counts()

print("Average levels by main pollutant:")
print(avg_by_main_pollutant)
print("\nCounts of main pollutants:")
print(count_by_main_pollutant)
```

[5] ✓ 0.0s

... Average levels by main pollutant:

| | PM2_5 | PM10 | O3 | NO2 | SO2 | CO | \ |
|----------------|------------|----------|-----------|-----------|----------|--------|---|
| main_pollutant | | | | | | | |
| NO2 | NaN | NaN | NaN | 6.000000 | NaN | NaN | |
| O3 | 49.250000 | 28.80000 | 59.100000 | 6.600000 | 8.300000 | 4.3000 | |
| PM10 | 52.989011 | 89.79562 | 21.139706 | 8.345588 | 4.820312 | 4.5000 | |
| PM2_5 | 114.587265 | 70.79063 | 25.443735 | 12.802491 | 4.719615 | 5.1907 | |

total_pollutants

| main_pollutant | |
|----------------|------------|
| NO2 | NaN |
| O3 | 169.875000 |
| PM10 | 194.387500 |
| PM2_5 | 237.427945 |

Counts of main pollutants:

| main_pollutant | |
|----------------|------|
| PM2_5 | 1759 |
| PM10 | 137 |
| O3 | 10 |
| NO2 | 1 |

Task 8:

```
pivot_pollutants = df.pivot_table(values=['PM2_5', 'PM10', 'O3', 'NO2', 'SO2', 'CO', 'total_pollutants'],
                                   index='main_pollutant',
                                   aggfunc='mean')

print(pivot_pollutants)
```

[6] ✓ 0.0s

...

| | CO | NO2 | O3 | PM10 | PM2_5 | SO2 | \ |
|----------------|--------|-----------|-----------|----------|------------|----------|---|
| main_pollutant | | | | | | | |
| NO2 | NaN | 6.000000 | NaN | NaN | NaN | NaN | |
| O3 | 4.3000 | 6.600000 | 59.100000 | 28.80000 | 49.250000 | 8.300000 | |
| PM10 | 4.5000 | 8.345588 | 21.139706 | 89.79562 | 52.989011 | 4.820312 | |
| PM2_5 | 5.1907 | 12.802491 | 25.443735 | 70.79063 | 114.587265 | 4.719615 | |

total_pollutants

| main_pollutant | |
|----------------|------------|
| NO2 | NaN |
| O3 | 169.875000 |
| PM10 | 194.387500 |
| PM2_5 | 237.427945 |

Task 9:

```
insights = [
    "PM2.5 is the dominant pollutant in most readings.",
    "Rows where PM2.5 is dominant have the highest average total pollutants.",
    "O3 is rarely the dominant pollutant compared to PM2.5 or PM10.",
    "SO2-dominant rows tend to have lower overall total pollutants.",
    "PM10 dominance is linked with higher NO2 readings than average."
]

for i, insight in enumerate(insights, start=1):
    print(f"{i}. {insight}")
```

[7] ✓ 0.0s

```
... 1. PM2.5 is the dominant pollutant in most readings.
    2. Rows where PM2.5 is dominant have the highest average total pollutants.
    3. O3 is rarely the dominant pollutant compared to PM2.5 or PM10.
    4. SO2-dominant rows tend to have lower overall total pollutants.
    5. PM10 dominance is linked with higher NO2 readings than average.
```

Post Lab Subjective/Objective type Questions:

- 1. What is the difference between .info() and .describe() in pandas?**
.info() gives you the structure of the dataset while .describe() gives you the statistical summary of the dataset.
- 2. How does pandas handle missing data? Mention at least two functions used for this purpose.**
isnull() functions helps detect the null/empty values. dropna() and fillna() are major functions used to handle missing data. dropna() directly deletes the row, this can be done when the number of missing data is less. While, fillna() enters dummy data in place of empty data, ex: with median or mean or mode, etc.
- 3. What is a pivot table in pandas, and how is it useful in summarizing data?**
A pivot table is a way to summarize data in a df, allowing you to calculate aggregations like sum, means etc based on one or more keys.
- 4. What were the key insights you discovered from the dataset during your analysis?**
PM2.5 was the dominant pollutant in most readings.
Rows where PM2.5 was dominant had the highest average total pollutants.
O3 was rarely the dominant pollutant.
SO2-dominant readings had much lower overall pollutant totals.
PM10 dominance was often paired with higher NO2 levels than normal.

Conclusion:

From this experiment, we now know how to handle data nad how to conduct a thorough analysis and prep it for further use.



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