Experiment - 1

1. Dataset Source

The dataset used for this experiment is a **synthetic student performance dataset** commonly used for demonstrating data preprocessing and exploratory data analysis techniques in machine learning.

Dataset Source:
student_performance.csv

2. Dataset Description

The dataset contains academic performance records of students and is used to analyze relationships between study habits, attendance, and examination scores.

Dataset Characteristics

- **Number of Records:** ~10–50 students
- **Type:** Structured, tabular data
- **Domain:** Education / Academic Analytics

Features (Independent Variables)

Feature Name	Description
`Hours_Studied`	Number of hours spent studying
`Attendance`	Attendance percentage of the student
`Assignment_Score`	Score obtained in assignments
`Midterm_Score`	Score obtained in midterm examination

Target / Analysis Variable

- `Midterm_Score` (used for statistical analysis and visualization)

Derived Categorical Feature

- `Performance` – classified based on **Attendance**:
    - High (≥ 85%)
    - Medium (70–84%)
    - Low (< 70%)

3. Mathematical Formulation of the Algorithm

This experiment does **not use a predictive machine learning algorithm**. Instead, it focuses on **statistical analysis and data normalization**, which are foundational steps in ML pipelines.

Statistical Measures

- **Mean**

$\mu=\frac{1}{N}\sum_{i=1}^{N}xi$μ=N1i=1∑Nxi

- **Median**
  The middle value of the sorted dataset.
- **Standard Deviation**

$\sigma=\frac{1}{N}\sum_{i=1}^{N}(xi-\mu)2$σ=N1i=1∑N(xi−μ)2

Min-Max Normalization

Used to scale values between 0 and 1:

$Xnorm=\frac{X-Xmin}{Xmax-Xmin}$Xnorm=Xmax−XminX−Xmin

This technique is widely used in machine learning preprocessing to ensure uniform feature scaling.

4. Algorithm Limitations

Since this experiment relies on **Exploratory Data Analysis (EDA)** techniques rather than predictive models, the following limitations apply:

- No predictions or classifications are performed
- Cannot be used to infer causality
- Visual interpretations may vary depending on dataset size
- Sensitive to outliers in normalization and correlation analysis
- Not suitable for automated decision-making without a trained ML model

EDA is **descriptive**, not **prescriptive or predictive**.

5. Methodology / Workflow

Step-by-Step Workflow

1. **Dataset Loading**
    - Loaded CSV file using Pandas
2. **Data Inspection**
    - Checked shape, columns, and missing values
3. **NumPy Operations**
    - Converted `Midterm_Score` into NumPy array
    - Calculated mean, median, standard deviation
    - Applied Min-Max normalization
4. **Feature Engineering**
    - Created `Performance` category based on attendance
5. **Data Visualization**
    - Line plot: Assignment Score vs Midterm Score
    - Histogram: Distribution of Midterm Scores
    - Scatter plot: Attendance vs Midterm Score
    - Heatmap: Correlation between numerical features
    - Boxplot: Performance category vs Midterm Score

Workflow Diagram

```
Dataset → Cleaning → Statistical Analysis →
Feature Engineering → Visualization → Insights
```

6. Performance Analysis

Since no predictive model is trained, **traditional ML metrics** such as accuracy, precision, recall, or RMSE are **not applicable**.

Analytical Observations

- Strong positive correlation observed between:
    - Assignment_Score and Midterm_Score
    - Attendance and academic performance
- Students with **High attendance** tend to score higher in midterm exams
- Normalized scores enable fair comparison across students

- Heatmap reveals inter-feature dependencies useful for future model selection

This analysis helps determine **feature importance** for downstream machine learning tasks.

7. Hyperparameter Tuning

Hyperparameter tuning is **not applicable** in this experiment because:

- No machine learning model is implemented
- No training or optimization process is involved

However, this experiment serves as a **preparatory step** for ML pipelines where:

- Feature scaling parameters
- Model hyperparameters
- Feature selection thresholds

would be tuned in subsequent experiments.

Exercise -1

```
import numpy as np

df = pd.read_csv('/content/student_performance.csv')

final_scores = df['Final_Score'].to_numpy()

print(final_scores)

mean_score = np.mean(final_scores)
median_score = np.median(final_scores)
std_score = np.std(final_scores)

print("Mean:", mean_score)
print("Median:", median_score)
print("Standard Deviation:", std_score)

min_score = np.min(final_scores)
max_score = np.max(final_scores)

normalized_scores = (final_scores - min_score) / (max_score - min_score)

normalized_scores
```

Output -

```
[52 57 60 64 68 71 74 77 79 83 63 70 75 56 69 73 80 58 72 78]
Mean: 68.95
Median: 70.5
Standard Deviation: 8.71478628538876
array([0.        , 0.16129032, 0.25806452, 0.38709677, 0.51612903,
       0.61290323, 0.70967742, 0.80645161, 0.87096774, 1.        ,
       0.35483871, 0.58064516, 0.74193548, 0.12903226, 0.5483871 ,
       0.67741935, 0.90322581, 0.19354839, 0.64516129, 0.83870968])
```

Exercise - 2

```python
import pandas as pd
df = pd.read_csv('/content/student_performance.csv')
df.head()
print("Shape:", df.shape)

print("Columns:", df.columns)

print("\nMissing Values:\n", df.isnull().sum())
def performance_label(score):
    if score >= 75:
        return "Excellent"
    elif score >= 60:
        return "Good"
    else:
        return "Average"

df['Performance'] = df['Final_Score'].apply(performance_label)

df.head()
```

Output -

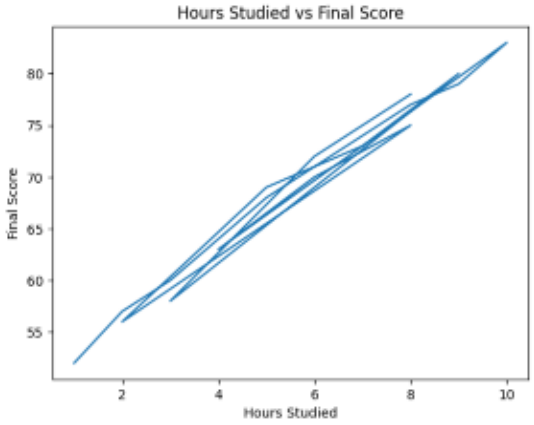
```
Shape: (20, 5)
Columns: Index(['Hours_Studied', 'Attendance', 'Assignment_Score', 'Midterm_Score',
       'Final_Score'],
      dtype='object')

Missing Values:
 Hours_Studied       0
Attendance           0
Assignment_Score     0
Midterm_Score        0
Final_Score          0
dtype: int64
```

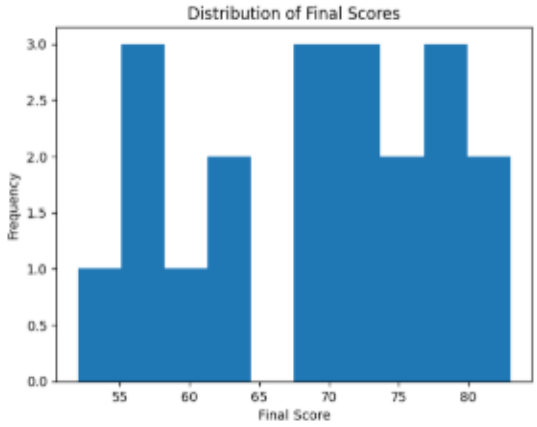
	Hours_Studied	Attendance	Assignment_Score	Midterm_Score	Final_Score	Performance
0	1	60	55	50	52	Average
1	2	65	58	55	57	Average
2	3	70	60	58	60	Good
3	4	75	65	62	64	Good
4	5	80	68	65	68	Good

Exercise 3 -

```python
import matplotlib.pyplot as plt
plt.figure()
plt.plot(df['Hours_Studied'], df['Final_Score'])
plt.xlabel('Hours Studied')
plt.ylabel('Final Score')
plt.title('Hours Studied vs Final Score')
plt.show()

plt.figure()
plt.hist(df['Final_Score'])
plt.xlabel('Final Score')
plt.ylabel('Frequency')
plt.title('Distribution of Final Scores')
plt.show()
```

Output -

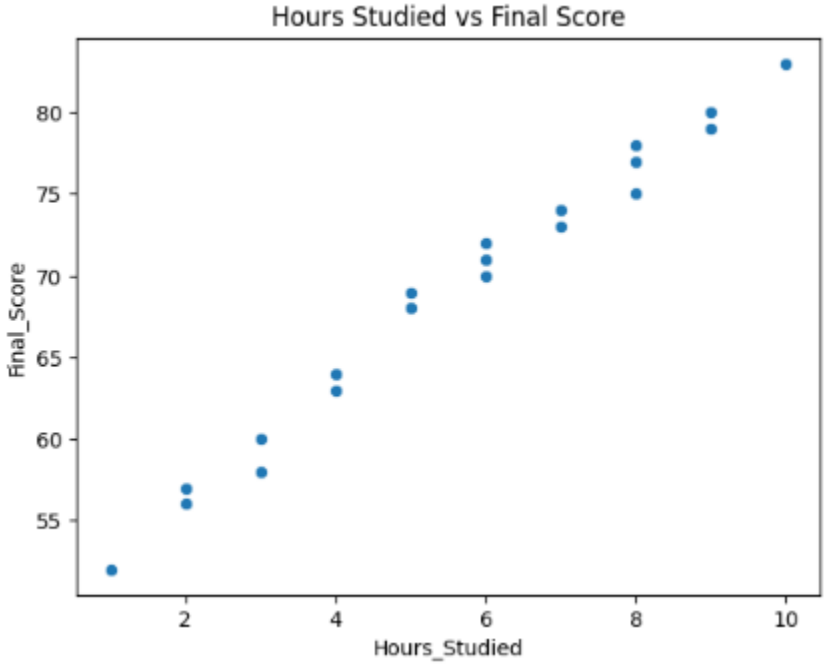


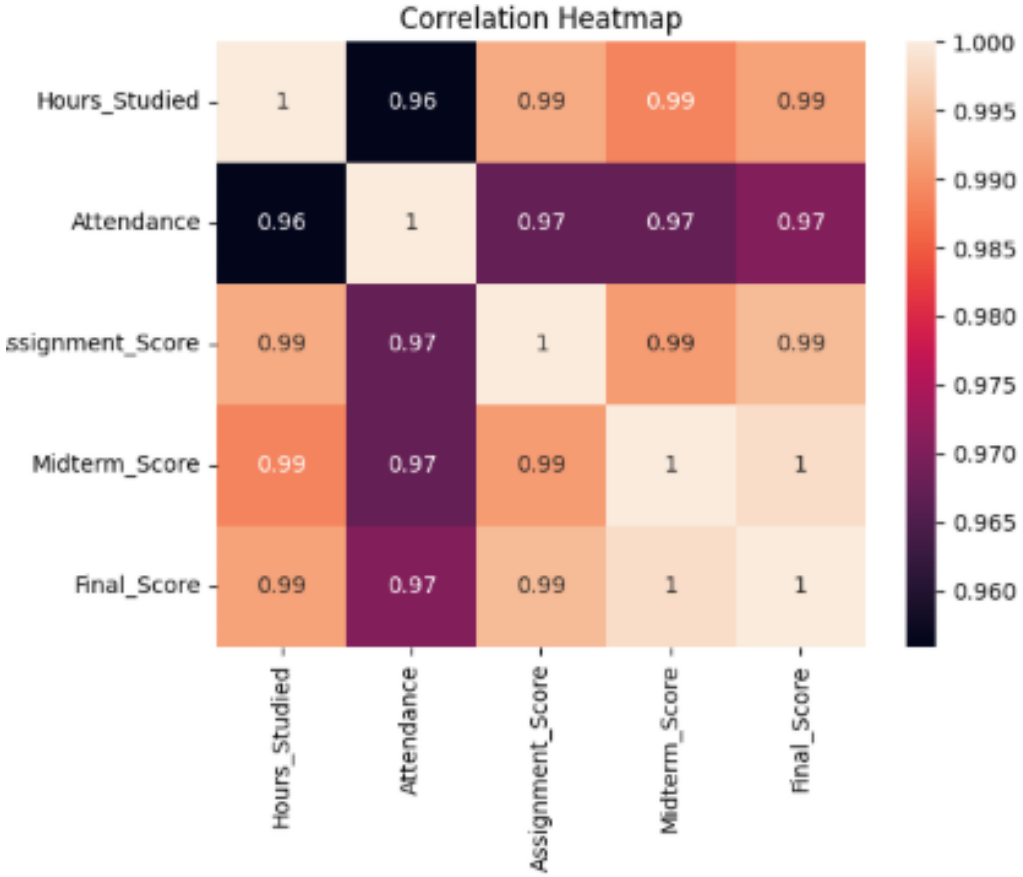


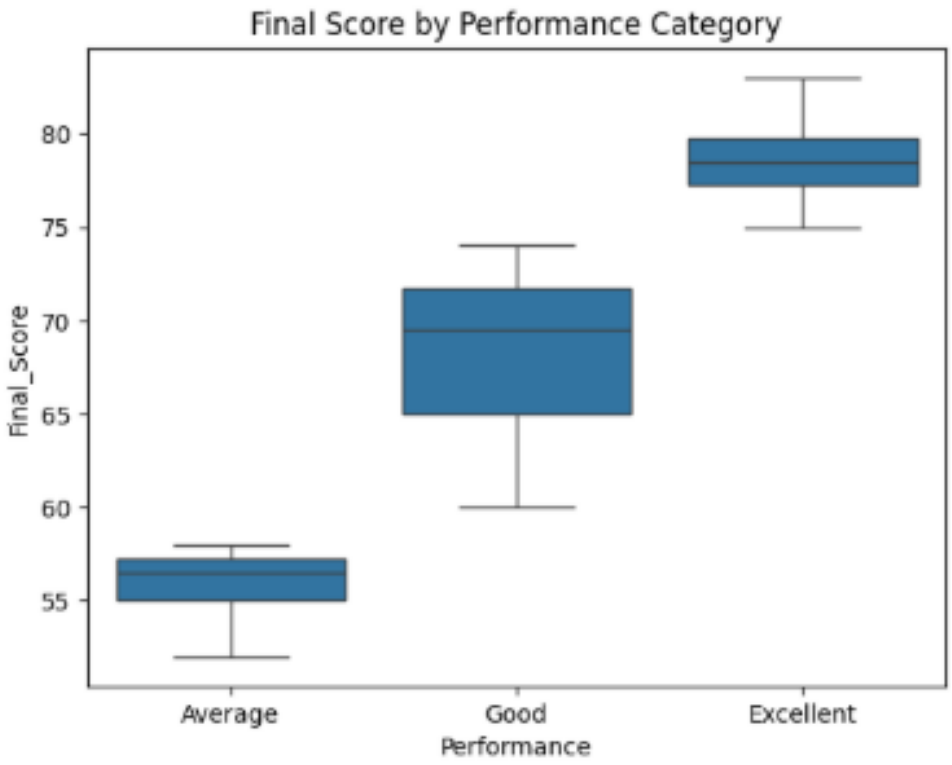
Exercise - 4\

```
import seaborn as sns

sns.scatterplot(
    x='Hours_Studied',
    y='Final_Score',
    data=df
)
plt.title('Hours Studied vs Final Score')
plt.show()

correlation_matrix = df.corr(numeric_only=True)

sns.heatmap(
    correlation_matrix,
    annot=True
)
plt.title('Correlation Heatmap')
plt.show()

sns.boxplot(
    x='Performance',
    y='Final_Score',
    data=df
)
plt.title('Final Score by Performance Category')
plt.show()
```

Output -


Hours Studied vs Final Score
Final_Score
Hours_Studied
80
75
70
65
60
55
2
4
6
8
10


Correlation Heatmap
Hours_Studied
Attendance
ssignment_Score
Midterm_Score
Final_Score
1
0.96
0.99
0.99
0.99
0.96
1
0.97
0.97
0.97
0.99
0.97
1
0.99
0.99
0.99
0.97
0.99
1
1
0.99
0.97
0.99
1
1
Hours_Studied
Attendance
Assignment_Score
Midterm_Score
Final_Score
1.000
0.995
0.990
0.985
0.980
0.975
0.970
0.965
0.960



Conclusion

This experiment successfully demonstrated the use of **NumPy, Pandas, Matplotlib, and Seaborn** for data handling, normalization, and exploratory data analysis. By modifying the parameters and analysis focus, deeper insights into student academic behavior were obtained. The results emphasize the importance of EDA as a foundational step before applying machine learning algorithms.