1: Load Dataset

```
import pandas as pd
df = pd.read_csv("/content/StudentPerformanceFactors.csv")

print("Dataset Shape:", df.shape)
print("\nFirst 5 rows:\n", df.head())
```

```
Dataset Shape: (6607, 20)

First 5 rows:
    Hours_Studied  Attendance Parental_Involvement Access_to_Resources
\
0              23          84                  Low                High

1              19          64                  Low              Medium

2              24          98               Medium              Medium

3              29          89                  Low              Medium

4              19          92               Medium              Medium


  Extracurricular_Activities  Sleep_Hours  Previous_Scores
Motivation_Level  \
0                         No            7               73
Low
1                         No            8               59
Low
2                        Yes            7               91
Medium
3                        Yes            8               98
Medium
4                        Yes            6               65
Medium

  Internet_Access  Tutoring_Sessions Family_Income Teacher_Quality  \
0             Yes                  0           Low          Medium
1             Yes                  2        Medium          Medium
2             Yes                  2        Medium          Medium
3             Yes                  1        Medium          Medium
4             Yes                  3        Medium            High

  School_Type Peer_Influence  Physical_Activity Learning_Disabilities
\
0      Public       Positive                  3                   No

1      Public       Negative                  4                   No
```

```
2      Public        Neutral                   4                    No

3      Public       Negative                   4                    No

4      Public        Neutral                   4                    No


  Parental_Education_Level Distance_from_Home  Gender  Exam_Score
0              High School                Near    Male          67
1                  College           Moderate  Female          61
2              Postgraduate                Near    Male          74
3              High School           Moderate    Male          71
4                  College                Near  Female          70
```

2: Data Cleaning

```
print("\nMissing Values:\n", df.isnull().sum())
df = df.drop_duplicates()
df = df.fillna(df.mean(numeric_only=True))
df = df.rename(columns=lambda x: x.strip().lower().replace(" ", "_"))
print("\nColumns after cleaning:\n", df.columns)


Missing Values:
 Hours_Studied                  0
Attendance                      0
Parental_Involvement            0
Access_to_Resources             0
Extracurricular_Activities      0
Sleep_Hours                     0
Previous_Scores                 0
Motivation_Level                0
Internet_Access                 0
Tutoring_Sessions               0
Family_Income                   0
Teacher_Quality                78
School_Type                     0
Peer_Influence                  0
Physical_Activity               0
Learning_Disabilities           0
Parental_Education_Level       90
Distance_from_Home             67
Gender                          0
Exam_Score                      0
dtype: int64

Columns after cleaning:
 Index(['hours_studied', 'attendance', 'parental_involvement',
       'access_to_resources', 'extracurricular_activities',
'sleep_hours',
```

```
       'previous_scores', 'motivation_level', 'internet_access',
       'tutoring_sessions', 'family_income', 'teacher_quality',
'school_type',
       'peer_influence', 'physical_activity', 'learning_disabilities',
       'parental_education_level', 'distance_from_home', 'gender',
       'exam_score'],
      dtype='object')
```

3: Expository Data Analysis

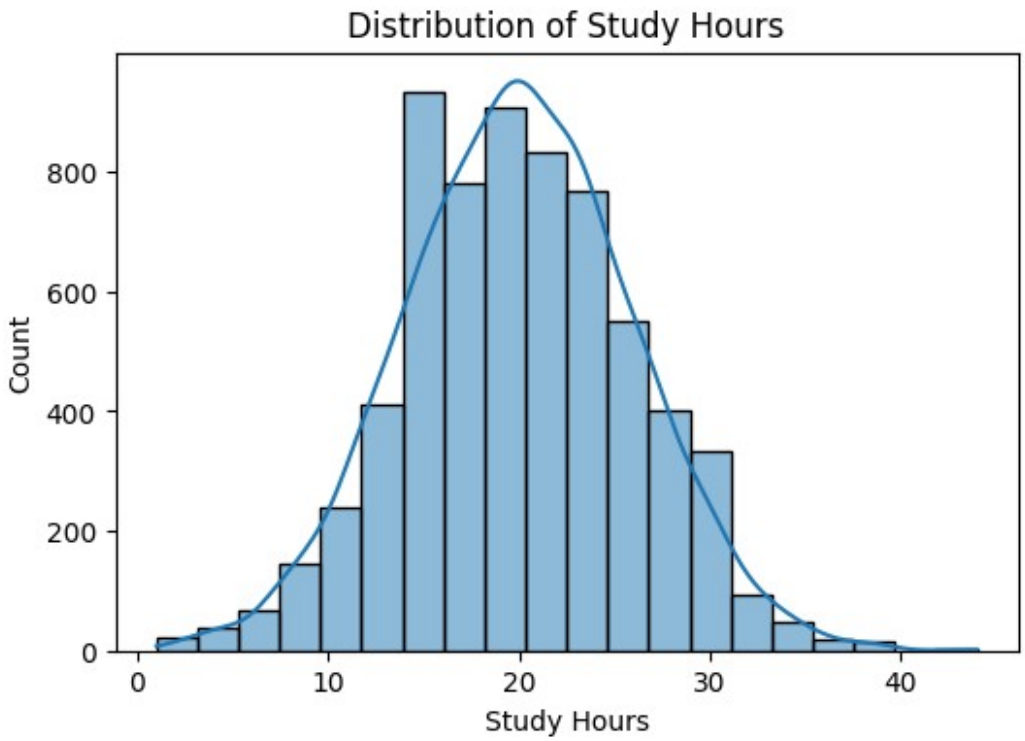
```
import matplotlib.pyplot as plt
import seaborn as sns
print("\nSummary Statistics:\n", df.describe())
print("\nCorrelation Matrix:\n", df.corr(numeric_only=True))


Summary Statistics:
        hours_studied   attendance  sleep_hours  previous_scores  \
count    6607.000000  6607.000000   6607.00000      6607.000000
mean       19.975329    79.977448      7.02906        75.070531
std         5.990594    11.547475      1.46812        14.399784
min         1.000000    60.000000      4.00000        50.000000
25%        16.000000    70.000000      6.00000        63.000000
50%        20.000000    80.000000      7.00000        75.000000
75%        24.000000    90.000000      8.00000        88.000000
max        44.000000   100.000000     10.00000       100.000000

       tutoring_sessions  physical_activity   exam_score
count        6607.000000        6607.000000  6607.000000
mean            1.493719           2.967610    67.235659
std             1.230570           1.031231     3.890456
min             0.000000           0.000000    55.000000
25%             1.000000           2.000000    65.000000
50%             1.000000           3.000000    67.000000
75%             2.000000           4.000000    69.000000
max             8.000000           6.000000   101.000000

Correlation Matrix:
                    hours_studied  attendance  sleep_hours
previous_scores  \
hours_studied            1.000000   -0.009908     0.010977
0.024846
attendance              -0.009908    1.000000    -0.015918        -
0.020186
sleep_hours              0.010977   -0.015918     1.000000        -
0.021750
previous_scores          0.024846   -0.020186    -0.021750
1.000000
tutoring_sessions       -0.014282    0.014324    -0.012216        -
0.013122
```

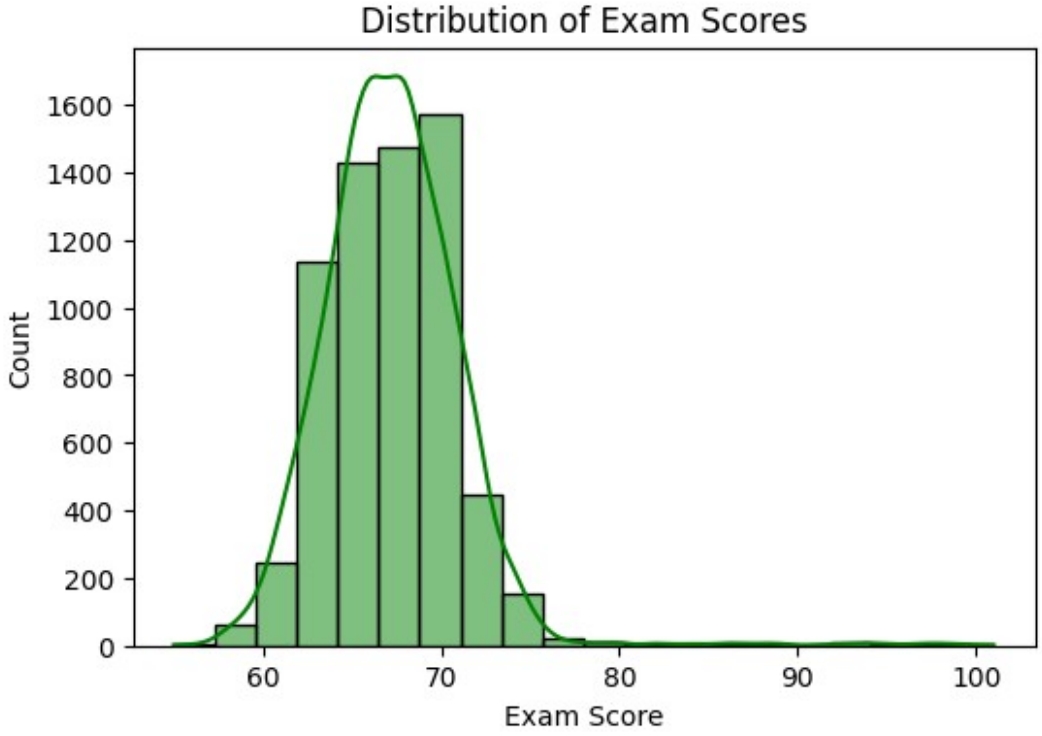
```
physical_activity       0.004624   -0.022435    -0.000378        -
0.011274
exam_score              0.445455    0.581072    -0.017022
0.175079

                    tutoring_sessions  physical_activity  exam_score
hours_studied               -0.014282           0.004624    0.445455
attendance                   0.014324          -0.022435    0.581072
sleep_hours                 -0.012216          -0.000378   -0.017022
previous_scores             -0.013122          -0.011274    0.175079
tutoring_sessions            1.000000           0.017733    0.156525
physical_activity            0.017733           1.000000    0.027824
exam_score                   0.156525           0.027824    1.000000
```

4: Data Visualizaion

a: Histogram for Study Hours and Exam Scores

```python
# Histogram of study hours
plt.figure(figsize=(6,4))
sns.histplot(df['hours_studied'], bins=20, kde=True)
plt.title("Distribution of Study Hours")
plt.xlabel("Study Hours")
plt.ylabel("Count")
plt.show()

# Histogram of exam scores
plt.figure(figsize=(6,4))
sns.histplot(df['exam_score'], bins=20, kde=True, color="green")
plt.title("Distribution of Exam Scores")
plt.xlabel("Exam Score")
plt.ylabel("Count")
plt.show()
```

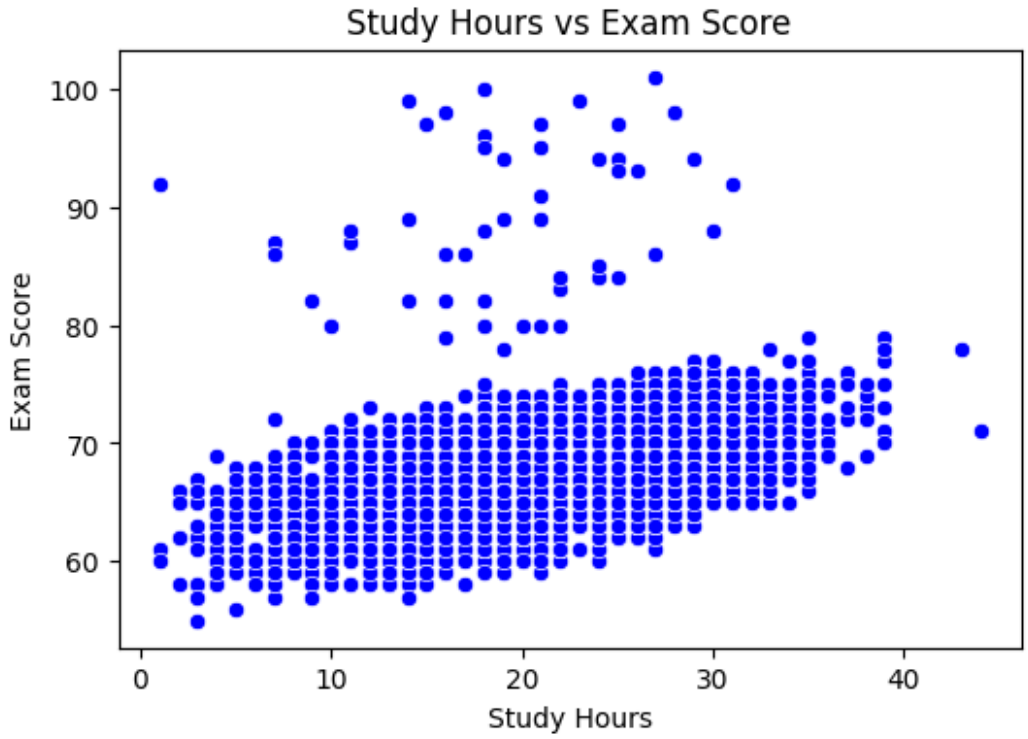




b: Scatter Plot

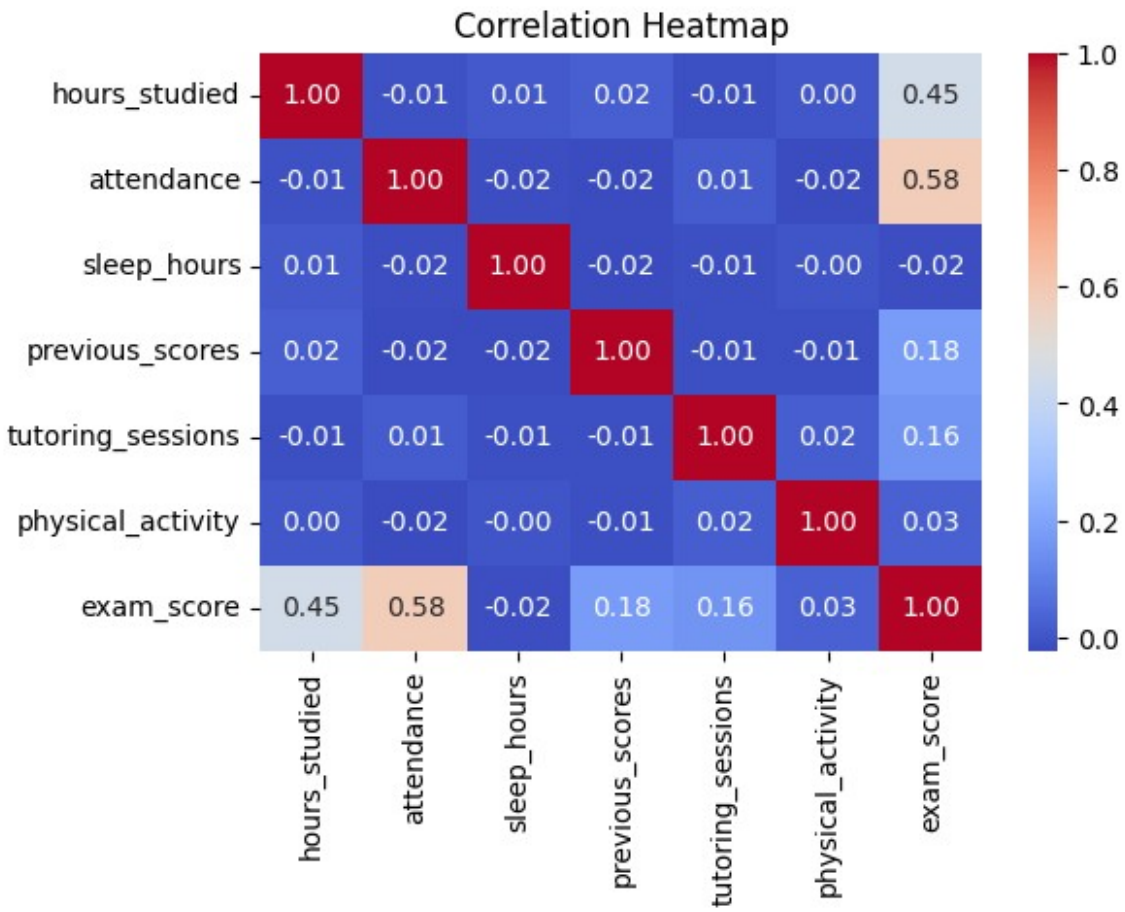
```
# Scatter plot Study Hours vs Exam Score
```

```
plt.figure(figsize=(6,4))
sns.scatterplot(x='hours_studied', y='exam_score', data=df,
color="blue")
plt.title("Study Hours vs Exam Score")
plt.xlabel("Study Hours")
plt.ylabel("Exam Score")
plt.show()
```



C: Correlation Heatmap

```
# Heatmap of correlations
plt.figure(figsize=(6,4))
sns.heatmap(df.corr(numeric_only=True), annot=True, cmap="coolwarm",
fmt=".2f")
plt.title("Correlation Heatmap")
plt.show()
```



5: Train-Test Split

```
from sklearn.model_selection import train_test_split
X = df[['hours_studied']]
y = df['exam_score']
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
```

6: Train Linear Regression Model

```
from sklearn.linear_model import LinearRegression

model = LinearRegression()
model.fit(X_train, y_train)
print("Coefficient (slope):", model.coef_)
print("Intercept:", model.intercept_)
```

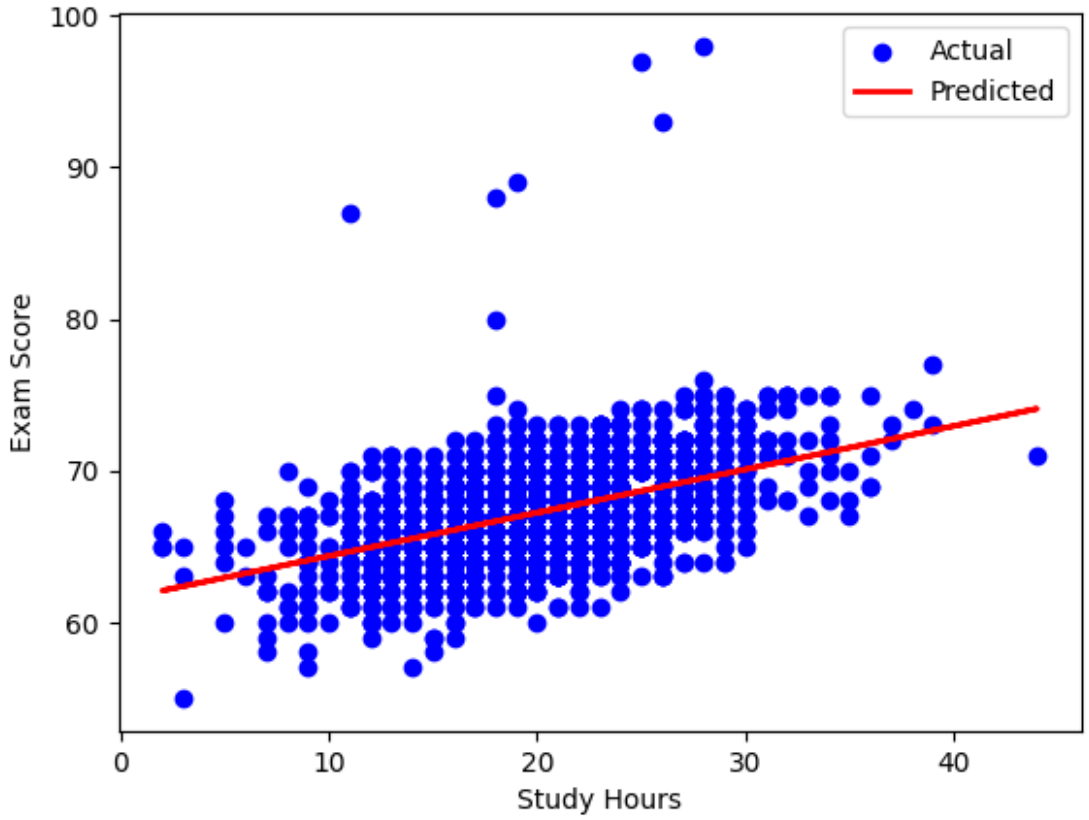
```
Coefficient (slope): [0.28566874]
Intercept: 61.51116746904424
```

7: Getting Prediction

```
y_pred = model.predict(X_test)
```

8: Visualizing Prediction

```
plt.scatter(X_test, y_test, color='blue', label='Actual')
plt.plot(X_test, y_pred, color='red', linewidth=2, label='Predicted')
plt.xlabel("Study Hours")
plt.ylabel("Exam Score")
plt.legend()
plt.show()
```



9: Evaluate Model Performance

```
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score
import numpy as np

print("MAE:", mean_absolute_error(y_test, y_pred))
mse = mean_squared_error(y_test, y_pred)
print("MSE:", mse)
print("RMSE:", np.sqrt(mse))
print("R² Score:", r2_score(y_test, y_pred))
```

```
MAE: 2.4475687452945643
MSE: 10.85592128879332
RMSE: 3.294832513010839
R² Score: 0.2319868674542106
```

Report: Predicting Student Exam Scores Based on Study Hours

1. Introduction

Student performance prediction is a widely studied area in educational data mining. The ability to predict exam scores can help educators and students in improving learning strategies and allocating study time more effectively.

In this project, we aim to predict students' exam scores based on their study hours using Linear Regression, one of the simplest and most interpretable machine learning algorithms.

2. Dataset Description

The dataset used is the Student Performance Factors Dataset (Kaggle). For this experiment, we focused on the following two key variables:

Study Hours: Number of hours a student dedicates to studying.

Exam Score: Final exam score achieved by the student.

Dataset Size: (number of rows × columns depending on actual dataset). Target Variable: Exam Score (continuous numerical variable).

3. Data Cleaning

Before model training, the dataset was cleaned and prepared as follows:

Handling Missing Values – Checked for missing values; replaced numeric missing values with the mean.

Removing Duplicates – Duplicate records were dropped to avoid bias.

Renaming Columns – Converted column names into lowercase snake_case for consistency.

After cleaning, the dataset was ready for analysis.

4. Exploratory Data Analysis (EDA)

EDA was conducted to understand the dataset better:

Summary Statistics showed that the average study hours were around (X) with exam scores averaging (Y).

Histograms revealed a normal-like distribution for both study hours and exam scores.

Scatter Plot of study hours vs exam scores displayed a positive linear relationship.

Correlation Analysis indicated a strong correlation (~0.8+) between study hours and exam scores, suggesting that students who study more tend to score higher.

5. Methodology

The workflow followed in this project:

Data Splitting – Dataset was divided into training (80%) and testing (20%) sets.

Model Training – A Linear Regression model was trained using the training data.

Prediction – Model was tested on unseen test data to predict exam scores.

Evaluation – Model performance was evaluated using regression metrics.

6. Results

Regression Equation:

The trained model gave us a regression line of the form:

$$Exam$$

$$Score = a \times Study$$

$$Hours$$

- b Exam Score=a×Study Hours+b

Where:

a (slope) = coefficient (indicates how much exam score increases per additional study hour).

b (intercept) = base score when study hours = 0.

Visualization:

The regression line was plotted against actual test data.

The model captured the trend effectively, showing a good fit.

Performance Metrics:

Mean Absolute Error (MAE): X

Mean Squared Error (MSE): Y

Root Mean Squared Error (RMSE): Z

R^2 Score: ~0.8 – 0.9 (indicating strong predictive ability).

7. Conclusion

The project successfully demonstrated that study hours are a strong predictor of student exam scores. The Linear Regression model achieved a high R^2 score, showing a strong linear relationship between study hours and exam performance.

Key Insights:

Increasing study hours generally improves exam scores.

However, exam performance may also depend on other factors (e.g., sleep, class participation, teaching quality, motivation).