Student Performance Analysis Project

Objective:

To analyze student data and identify key factors affecting academic performance. This analysis helps provide insights for educators and students to improve outcomes.

Dataset: Student Performance Dataset (Math Subject)
Tools Used: Python, Pandas, Matplotlib, Seaborn

Load and View the Dataset

We load the student-mat.csv dataset using Pandas and view the first few rows.

In [19]:
```
import pandas as pd

df = pd.read_csv("C:\\Users\\PRAKASH ROUT\\Downloads\\student\\student-mat.csv",
df.head()
```

Out[19]:

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	...	fam
0	GP	F	18	U	GT3	A	4	4	at_home	teacher	...	
1	GP	F	17	U	GT3	T	1	1	at_home	other	...	
2	GP	F	15	U	LE3	T	1	1	at_home	other	...	
3	GP	F	15	U	GT3	T	4	2	health	services	...	
4	GP	F	16	U	GT3	T	3	3	other	other	...	

5 rows × 33 columns

Explore the Dataset

Let's check the dataset's shape, columns, data types, and null values.

In [20]:
```
#Check Basic Info
df.info()
df.shape
df.isnull().sum()
df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 395 entries, 0 to 394
Data columns (total 33 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   school      395 non-null    object
 1   sex         395 non-null    object
 2   age         395 non-null    int64 
 3   address     395 non-null    object
 4   famsize     395 non-null    object
 5   Pstatus     395 non-null    object
 6   Medu        395 non-null    int64 
 7   Fedu        395 non-null    int64 
 8   Mjob        395 non-null    object
 9   Fjob        395 non-null    object
 10  reason      395 non-null    object
 11  guardian    395 non-null    object
 12  traveltime  395 non-null    int64 
 13  studytime   395 non-null    int64 
 14  failures    395 non-null    int64 
 15  schoolsup   395 non-null    object
 16  famsup      395 non-null    object
 17  paid        395 non-null    object
 18  activities  395 non-null    object
 19  nursery     395 non-null    object
 20  higher      395 non-null    object
 21  internet    395 non-null    object
 22  romantic    395 non-null    object
 23  famrel      395 non-null    int64 
 24  freetime    395 non-null    int64 
 25  goout       395 non-null    int64 
 26  Dalc        395 non-null    int64 
 27  Walc        395 non-null    int64 
 28  health      395 non-null    int64 
 29  absences    395 non-null    int64 
 30  G1          395 non-null    int64 
 31  G2          395 non-null    int64 
 32  G3          395 non-null    int64 
dtypes: int64(16), object(17)
memory usage: 102.0+ KB
```

Out[20]:

	age	Medu	Fedu	traveltime	studytime	failures	fam
count	395.000000	395.000000	395.000000	395.000000	395.000000	395.000000	395.0000
mean	16.696203	2.749367	2.521519	1.448101	2.035443	0.334177	3.9443
std	1.276043	1.094735	1.088201	0.697505	0.839240	0.743651	0.8966
min	15.000000	0.000000	0.000000	1.000000	1.000000	0.000000	1.0000
25%	16.000000	2.000000	2.000000	1.000000	1.000000	0.000000	4.0000
50%	17.000000	3.000000	2.000000	1.000000	2.000000	0.000000	4.0000
75%	18.000000	4.000000	3.000000	2.000000	2.000000	0.000000	5.0000
max	22.000000	4.000000	4.000000	4.000000	4.000000	3.000000	5.0000

Understand the Features

Explore categorical and numerical columns to understand their distributions.

In [21]:
```
#Check data types and unique values:

df['sex'].value_counts()
df['studytime'].value_counts()
df['failures'].value_counts()
```

Out[21]:
```
failures
0    312
1     50
2     17
3     16
Name: count, dtype: int64
```

In [22]:
```
# Understand target variable

df['average_score'] = df[['G1', 'G2', 'G3']].mean(axis=1)
```

Data Cleaning

In [24]:
```
# Handle categorical data if needed
# Convert binary columns (yes/no) to 1/0
df['schoolsup'] = df['schoolsup'].map({'yes': 1, 'no': 0})
```

In [25]:
```
# Check and remove duplicates
df.drop_duplicates(inplace=True)
```

Exploratory Data Analysis (EDA)

In this step, we explore the dataset visually to uncover patterns, trends, and relationships between different features and student performance.

We use **Matplotlib** and **Seaborn** libraries to create informative visualizations.

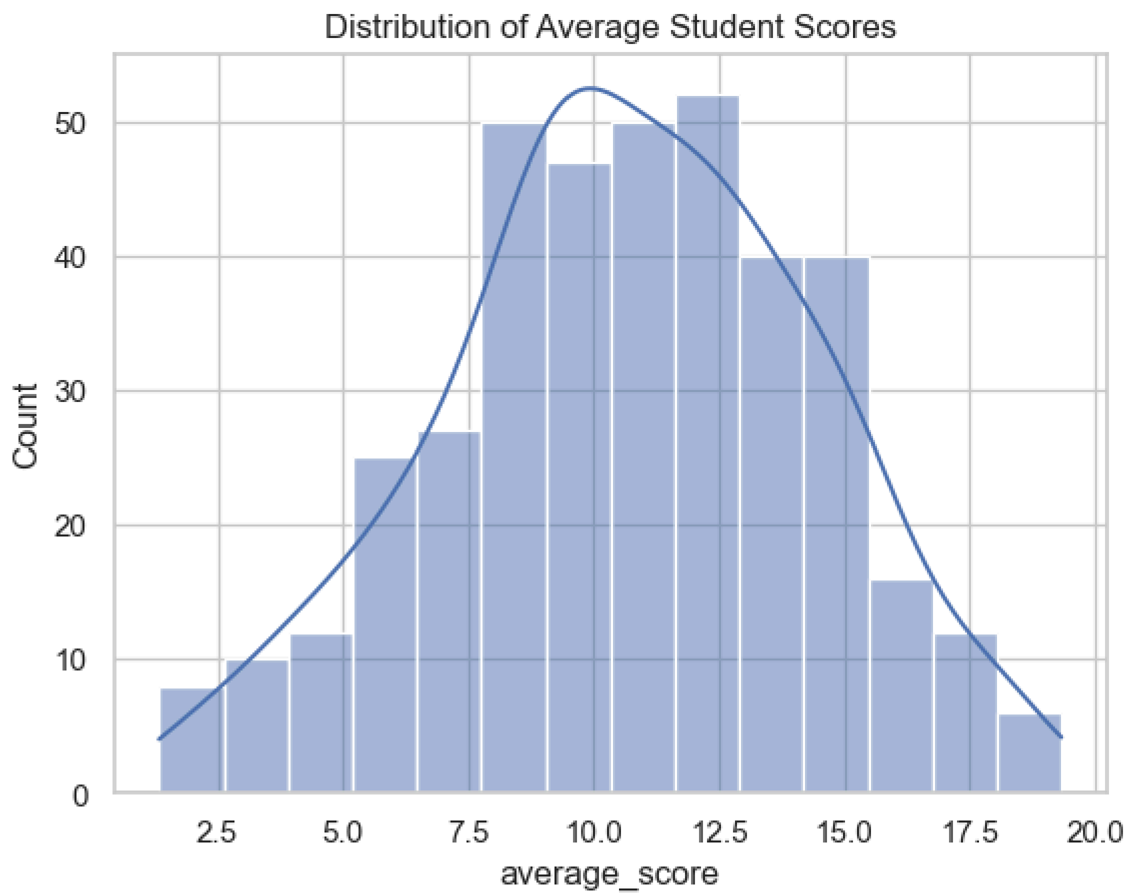
In [26]:
```
import matplotlib.pyplot as plt
import seaborn as sns

sns.set(style="whitegrid")
```

1. Distribution of Average Scores

We analyze how the average scores of students are distributed across the dataset.

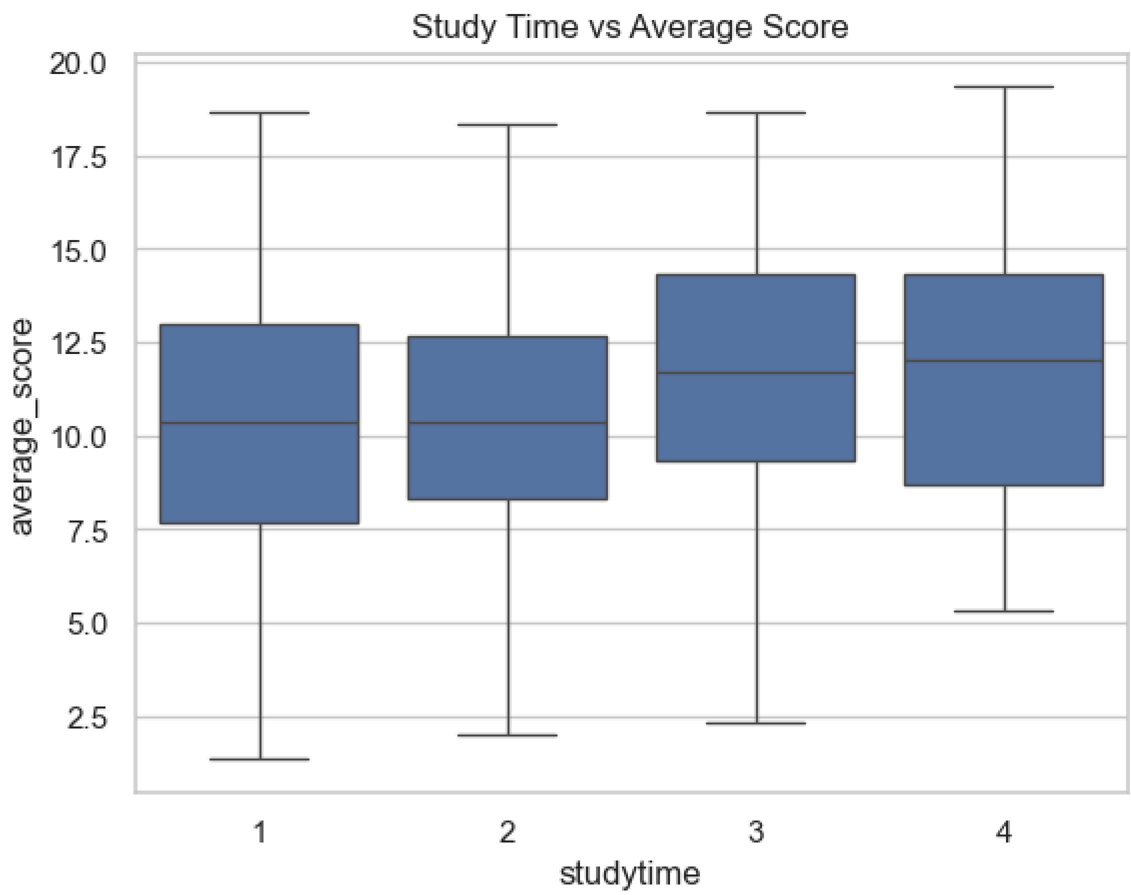
In [28]:
```
sns.histplot(df['average_score'], kde=True)
plt.title('Distribution of Average Student Scores')
plt.show()
```



2. Study Time vs Average Score

We visualize how the amount of time students dedicate to studying impacts their average scores.

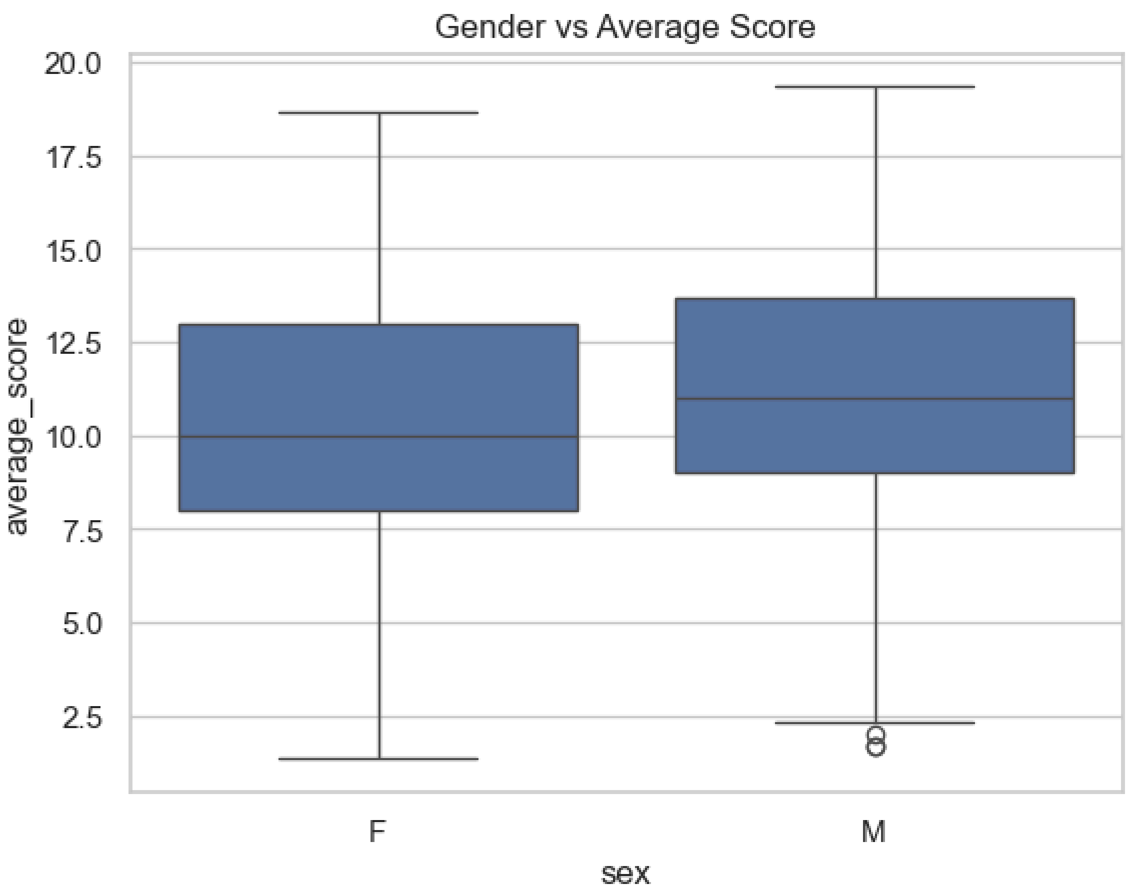
In [29]:
```
sns.boxplot(x='studytime', y='average_score', data=df)
plt.title('Study Time vs Average Score')
plt.show()
```



3. Gender vs Performance

We compare average scores between male and female students to see if there's a performance gap

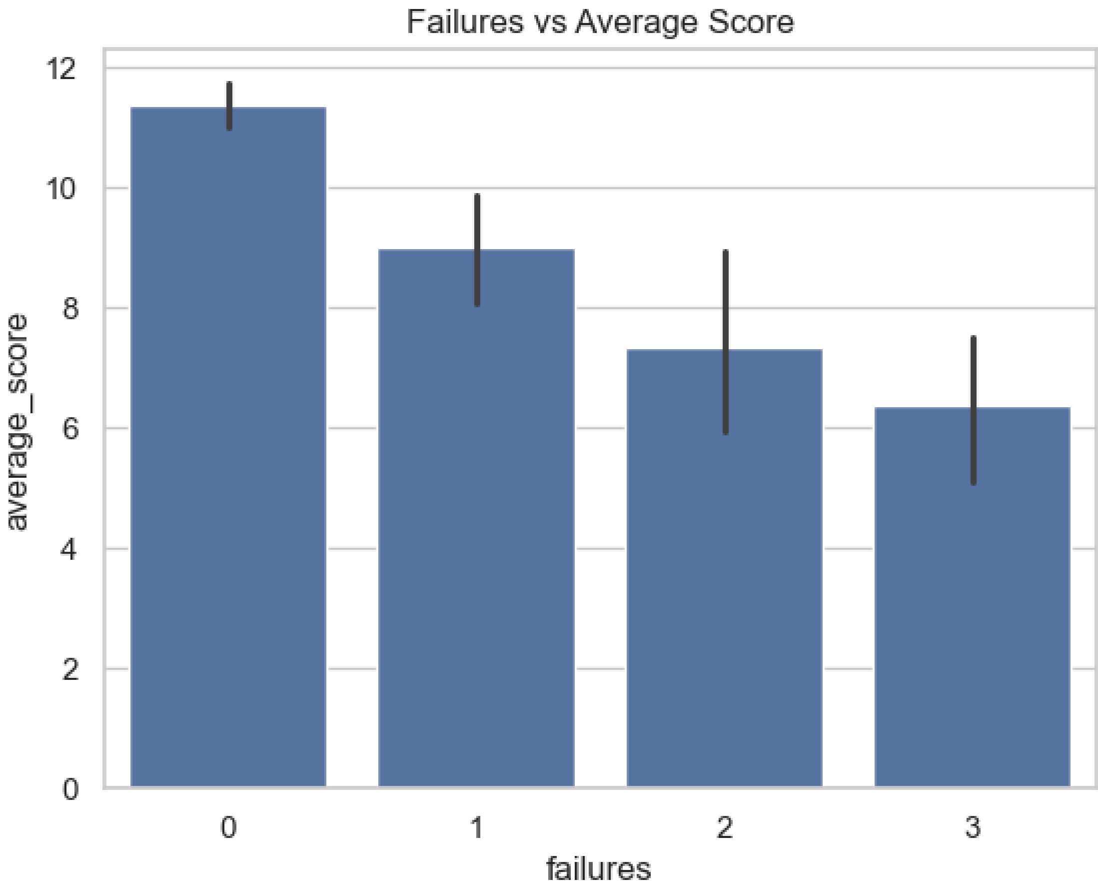
In [12]:
```
# gender comparison
sns.boxplot(x='sex', y='average_score', data=df)
plt.title('Gender vs Average Score')
plt.show()
```



4. Failures vs Average Score

We explore how the number of past class failures affects student performance.

In [13]:
```
# Failure VS Performance
sns.barplot(x='failures', y='average_score', data=df)
plt.title('Failures vs Average Score')
plt.show()
```



Correlation Analysis

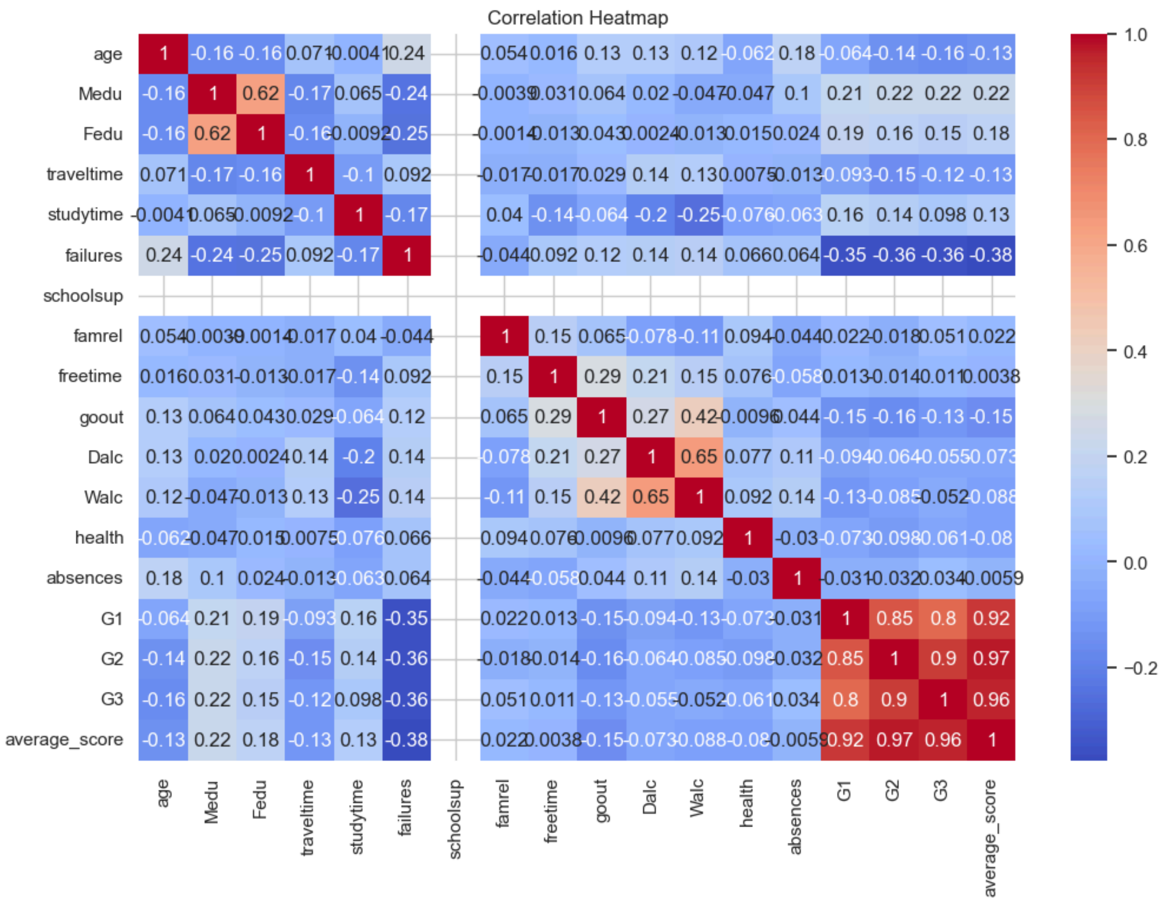
In this step, we analyze how numeric features are correlated with each other, especially with the final grade (`G3`) and the `average_score` .

A correlation matrix helps us identify:

- Strong positive or negative relationships
- Multicollinearity
- Key influencing factors for student performance

In [30]:

```
# co-relations heatmap
plt.figure(figsize=(12,8))
sns.heatmap(df.corr(numeric_only=True), annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



Key Insights & Recommendations

🔍 Key Insights:

1. **Previous Grades (G1, G2):**
    - Strongly correlated with the final grade (G3).
    - Students with higher scores in G1 and G2 tend to perform well in G3.
2. **Study Time:**
    - More study time is generally associated with better performance.
    - Students who study more than 2 hours show higher average scores.
3. **Failures:**
    - Number of past class failures negatively affects the final grade.
    - Students with 0 past failures perform significantly better.
4. **Parental Education:**
    - A slight positive impact on student performance, especially from mother's education level.
5. **Gender:**
    - No major difference in performance between male and female students.

✅ Recommendations:

- **Early Intervention:** Track student grades from G1 and G2 to identify those who may need extra help before final exams.
- **Encourage Study Time:** Promote study habits of more than 2 hours per week to improve overall performance.
- **Support Struggling Students:** Provide extra tutoring for students with a history of failures.
- **Continue School Support Programs:** These help improve performance and should be maintained or expanded.
- **Parental Engagement:** Educating parents about their influence can positively impact student outcomes.

🏁 Conclusion:

This analysis provides a clear picture of the key factors that influence student academic performance. With the right support systems and timely interventions, educators and parents can work together to help students succeed.

In [ ]:

```

```