College : VIT Data Analysis Batch
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Data Analysis Report Project - Student Result Analysis on examscores.csv dataset downloaded from Kaagle Datasets

1. Introduction

This report aims to analyze the student scores dataset to uncover patterns and insights that can help in understanding the factors affecting student performance in Math, Reading, and Writing.

2. Data Dictionary (column description)

1. Gender: Gender of the student (male/female)

2. EthnicGroup: Ethnic group of the student (group A to E)

3. ParentEduc: Parent(s) education background (from some_highschool to master's degree)

4. LunchType: School lunch type (standard or free/reduced)

5. TestPrep: Test preparation course followed (completed or none)

6. ParentMaritalStatus: Parent(s) marital status (married/single/widowed/divorced)

7. PracticeSport: How often the student parctice sport (never/sometimes/regularly)

8. IsFirstChild: If the child is first child in the family or not (yes/no)

9. NrSiblings: Number of siblings the student has (0 to 7)

10. TransportMeans: Means of transport to school (schoolbus/private)

11. WklyStudyHours: Weekly self-study hours(less that 5hrs; between 5 and 10hrs; more than 10hrs)

12. MathScore: math test score(0-100)

13. ReadingScore: reading test score(0-100)

14. WritingScore: writing test score(0-100)

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

3. Data Understanding

3.1 Printing the top 5 values of the data

```
df= pd.read_csv("examscores.csv")
print(df.head())
```

```
   Unnamed: 0  Gender EthnicGroup          ParentEduc     LunchType TestPrep  \
0           0  female         NaN   bachelor's degree      standard     none
1           1  female     group C        some college      standard      NaN
2           2  female     group B     master's degree      standard     none
3           3    male     group A  associate's degree  free/reduced     none
4           4    male     group C        some college      standard     none

  ParentMaritalStatus PracticeSport IsFirstChild  NrSiblings TransportMeans  \
0             married     regularly          yes         3.0     school_bus
1             married     sometimes          yes         0.0            NaN
2              single     sometimes          yes         4.0     school_bus
3             married         never           no         1.0            NaN
4             married     sometimes          yes         0.0     school_bus

  WklyStudyHours  MathScore  ReadingScore  WritingScore
0            < 5         71            71            74
1         5 - 10         69            90            88
2            < 5         87            93            91
3         5 - 10         45            56            42
4         5 - 10         76            78            75
```

3.2 Descriptive Statistics of the data

```
df.describe()
```

```
        Unnamed: 0    NrSiblings     MathScore  ReadingScore  WritingScore
count  30641.000000  29069.000000  30641.000000  30641.000000  30641.000000
mean     499.556607      2.145894     66.558402     69.377533     68.418622
std      288.747894      1.458242     15.361616     14.758952     15.443525
min        0.000000      0.000000      0.000000     10.000000      4.000000
25%      249.000000      1.000000     56.000000     59.000000     58.000000
50%      500.000000      2.000000     67.000000     70.000000     69.000000
75%      750.000000      3.000000     78.000000     80.000000     79.000000
max      999.000000      7.000000    100.000000    100.000000    100.000000
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30641 entries, 0 to 30640
Data columns (total 15 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   Unnamed: 0           30641 non-null  int64  
 1   Gender               30641 non-null  object 
 2   EthnicGroup          28801 non-null  object 
 3   ParentEduc           28796 non-null  object 
 4   LunchType            30641 non-null  object 
 5   TestPrep             28811 non-null  object 
 6   ParentMaritalStatus  29451 non-null  object 
 7   PracticeSport        30010 non-null  object 
 8   IsFirstChild         29737 non-null  object 
 9   NrSiblings           29069 non-null  float64
 10  TransportMeans       27507 non-null  object 
 11  WklyStudyHours       29686 non-null  object 
 12  MathScore            30641 non-null  int64  
 13  ReadingScore         30641 non-null  int64  
 14  WritingScore         30641 non-null  int64  
dtypes: float64(1), int64(4), object(10)
memory usage: 3.5+ MB
```

3.3 Calculating the null values in the exam scores data

```
df.isnull().sum()
```

```
Unnamed: 0                0
Gender                    0
EthnicGroup            1840
ParentEduc             1845
LunchType                 0
TestPrep               1830
ParentMaritalStatus    1190
PracticeSport           631
IsFirstChild            904
NrSiblings             1572
TransportMeans         3134
WklyStudyHours          955
MathScore                 0
ReadingScore              0
WritingScore              0
dtype: int64
```

4. Data Cleaning

4.1 Drop Unnamed Column

```
df= df.drop("Unnamed: 0",axis =1)
print(df.head())
```

```
   Gender EthnicGroup          ParentEduc     LunchType TestPrep  \
0  female         NaN   bachelor's degree      standard     none   
1  female     group C        some college      standard      NaN   
2  female     group B     master's degree      standard     none   
3    male     group A  associate's degree  free/reduced     none   
4    male     group C        some college      standard     none   

  ParentMaritalStatus PracticeSport IsFirstChild  NrSiblings TransportMeans  \
0             married     regularly          yes         3.0     school_bus   
1             married     sometimes          yes         0.0            NaN   
2              single     sometimes          yes         4.0     school_bus   
3             married         never           no         1.0            NaN   
4             married     sometimes          yes         0.0     school_bus   

  WklyStudyHours  MathScore  ReadingScore  WritingScore  
0            < 5         71            71            74  
1         5 - 10         69            90            88  
2            < 5         87            93            91  
3         5 - 10         45            56            42  
4         5 - 10         76            78            75  
```

5. Data Transformation

5.1 change Weekly study hours column

```
df["WklyStudyHours"]=df["WklyStudyHours"].str.replace("05-Oct","5 - 10")
df.head()
```

```
  Gender EthnicGroup          ParentEduc     LunchType TestPrep  \
0  female         NaN   bachelor's degree      standard     none
1  female     group C        some college      standard      NaN
2  female     group B     master's degree      standard     none
3    male     group A  associate's degree  free/reduced     none
4    male     group C        some college      standard     none

  ParentMaritalStatus PracticeSport IsFirstChild  NrSiblings TransportMeans  \
0             married     regularly          yes         3.0     school_bus
1             married     sometimes          yes         0.0            NaN
2              single     sometimes          yes         4.0     school_bus
3             married         never           no         1.0            NaN
4             married     sometimes          yes         0.0     school_bus

  WklyStudyHours  MathScore  ReadingScore  WritingScore
0            < 5         71            71            74
1         5 - 10         69            90            88
2            < 5         87            93            91
3         5 - 10         45            56            42
4         5 - 10         76            78            75
```

6. Exploratory Data Analysis

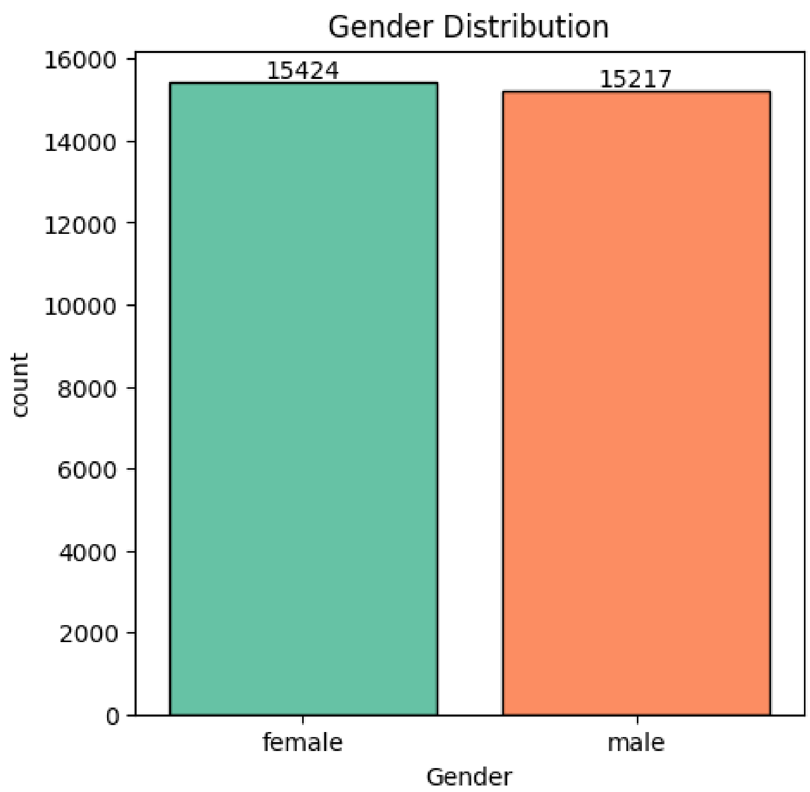
6.1 Gender Distribution

```
plt.figure(figsize=(5,5))
ax= sns.countplot(data= df, x="Gender",palette="Set2",saturation=2,edgecolor = "black")
plt.title("Gender Distribution")
ax.bar_label(ax.containers[0])
ax.bar_label(ax.containers[1])
plt.show()
```

```
C:\Users\asmika\AppData\Local\Temp\ipykernel_11664\1595413645.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the
`x` variable to `hue` and set `legend=False` for the same effect.

  ax= sns.countplot(data= df, x="Gender",palette="Set2",saturation=2,edgecolor = "black")
```



from the above chart we have analysed that:the number of females in the data is more than the number of males

6.2 Relationship Comparison between Gender and Students Score

```
gb2=df.groupby("Gender").agg({"MathScore":'mean',"ReadingScore":'mean',"WritingScore":"mean"})
print(gb2)
```

```
        MathScore  ReadingScore  WritingScore
Gender
female  64.080654     72.853216     72.856457
male    69.069856     65.854571     63.920418
```

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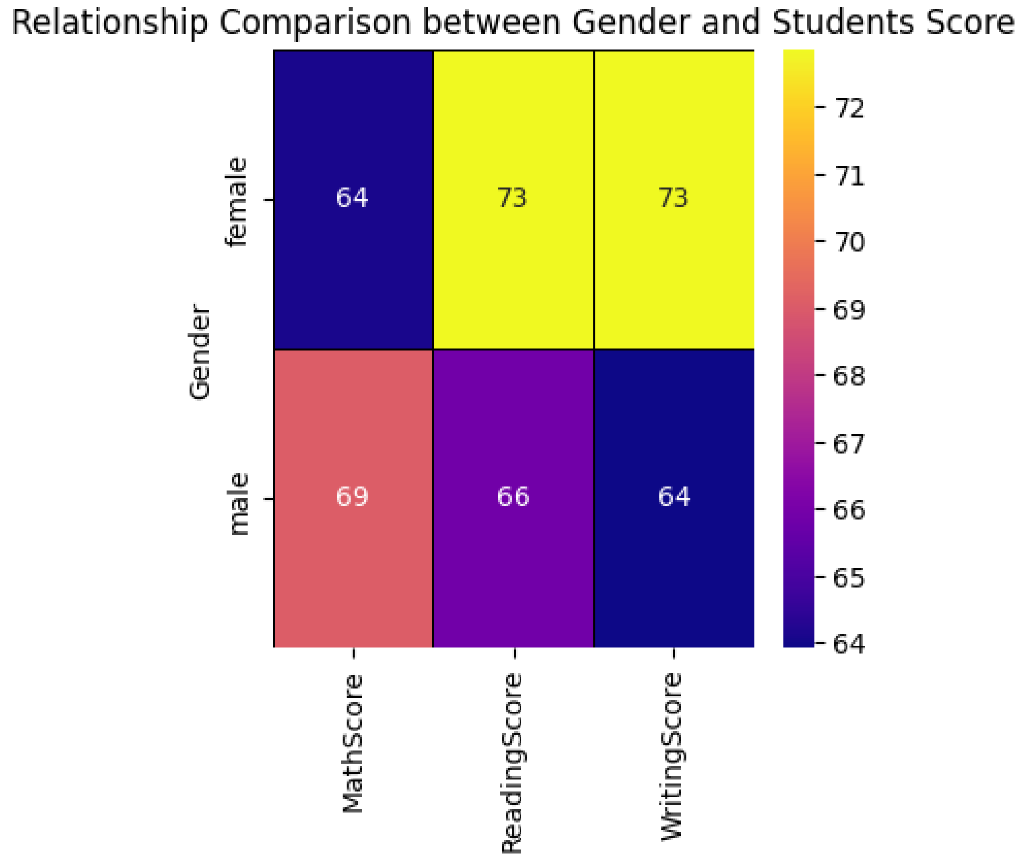
```
plt.figure(figsize=(4,4))
plt.title("Relationship Comparison between Gender and Students Score")
sns.heatmap(gb2, annot=True,cmap="plasma",linewidths=0.5, linecolor='black',cbar=True)
plt.show()
```



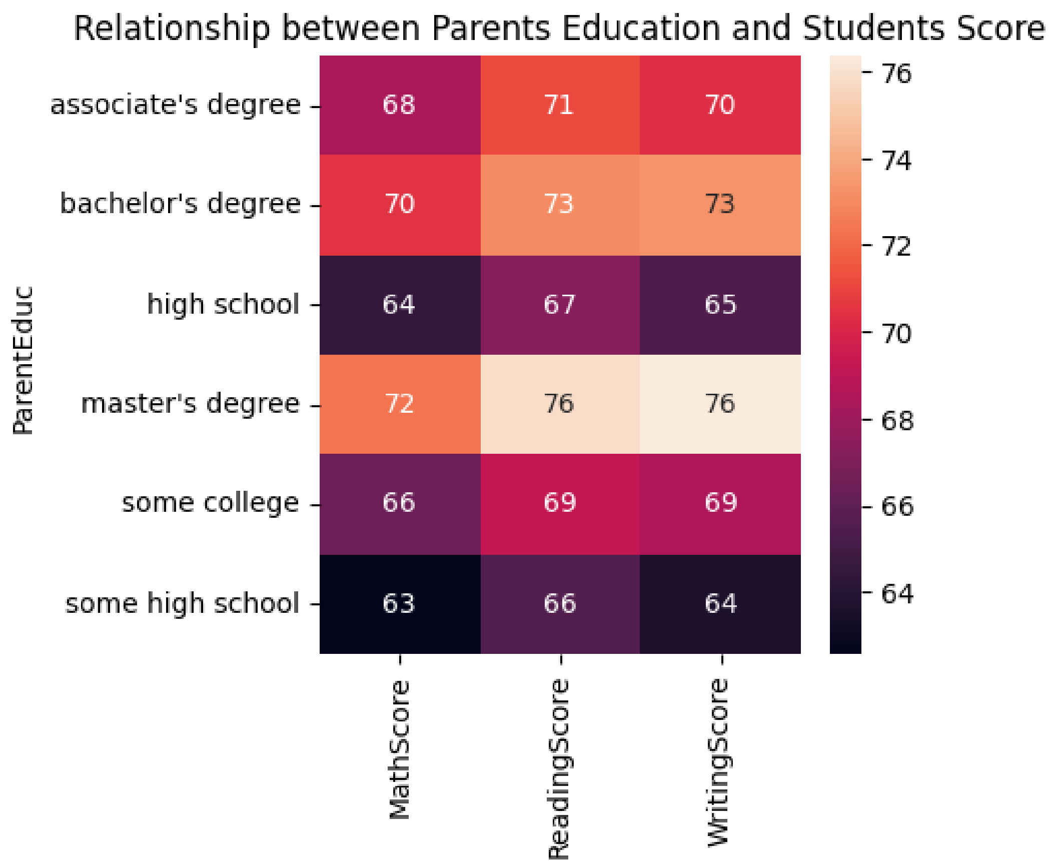
from the above chart we have concluded that males have obtained more marks in Maths comparatively to females and females have obtained more marks in Reading and Writing Scores compared to males

6.3 Relationship between Parents Education and Students Score

```
gb=df.groupby("ParentEduc").agg({"MathScore":'mean',"ReadingScore":'mean',"WritingScore":"mean"})
print(gb)
```

```
                   MathScore  ReadingScore  WritingScore
ParentEduc
associate's degree  68.365586     71.124324     70.299099
bachelor's degree   70.466627     73.062020     73.331069
high school         64.435731     67.213997     65.421136
master's degree     72.336134     75.832921     76.356896
some college        66.390472     69.179708     68.501432
some high school    62.584013     65.510785     63.632409
```

```
plt.figure(figsize=(4,4))
plt.title("Relationship between Parents Education and Students Score")
sns.heatmap(gb, annot=True)
plt.show()
```



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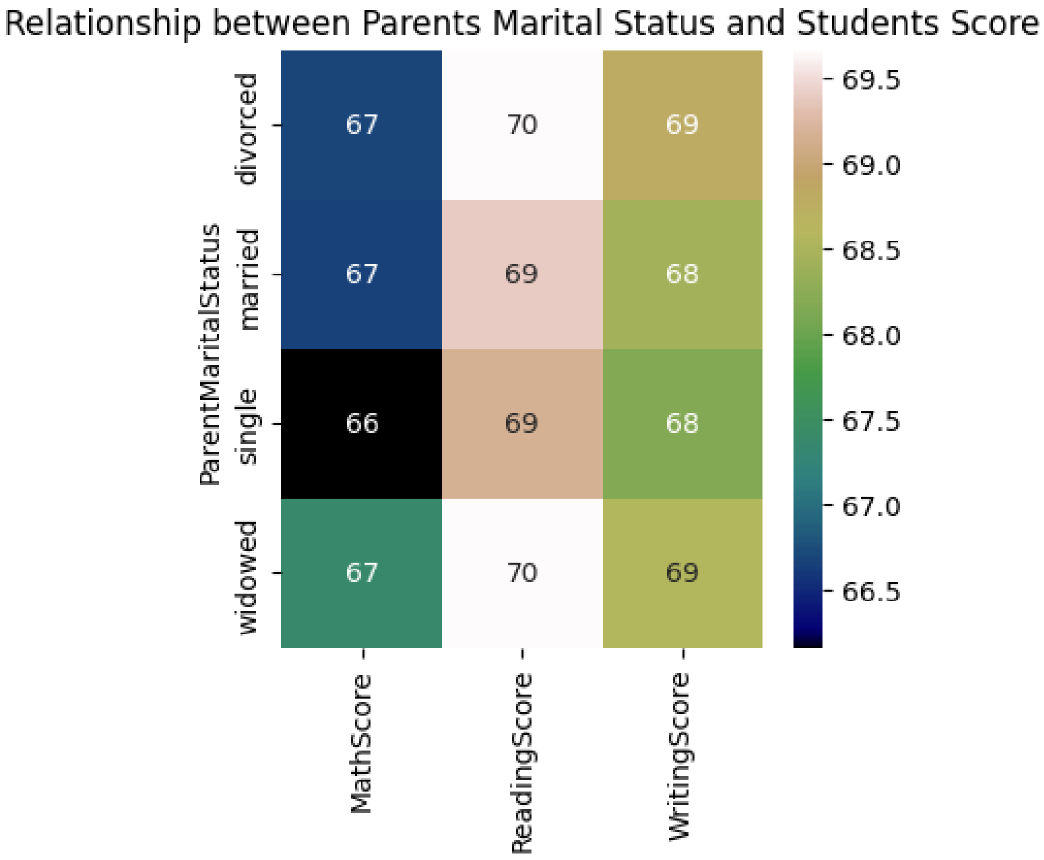
from the above chart we have concluded that the education of the parents have a good impact on their scores

6.4 Relationship between Parents Marital Status and Students Score

```
gb1=df.groupby("ParentMaritalStatus").agg({"MathScore":'mean',"ReadingScore":'mean',"WritingScore":
"mean"})
print(gb1)
```

```
                     MathScore  ReadingScore  WritingScore
ParentMaritalStatus
divorced             66.691197     69.655011     68.799146
married              66.657326     69.389575     68.420981
single               66.165704     69.157250     68.174440
widowed              67.368866     69.651438     68.563452
```

```
plt.figure(figsize=(4,4))
plt.title("Relationship between Parents Marital Status and Students Score")
sns.heatmap(gb1, annot=True,cmap='gist_earth')
plt.show()
```



from the above chart we have concluded there is no/negligible impact on the scores of the students based on their marital status

6.5 Distribution of Scores

6.5.1 Calculated the Frequency of Math Scores

```
import seaborn as sns
import matplotlib.pyplot as plt

math_score_counts = df['MathScore'].value_counts().sort_index()
# Create a line plot for MathScore
plt.figure(figsize=(9,5))
sns.lineplot(x=math_score_counts.index, y=math_score_counts.values)
plt.title('Distribution of Math Scores')
plt.xlabel('Math Score')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```

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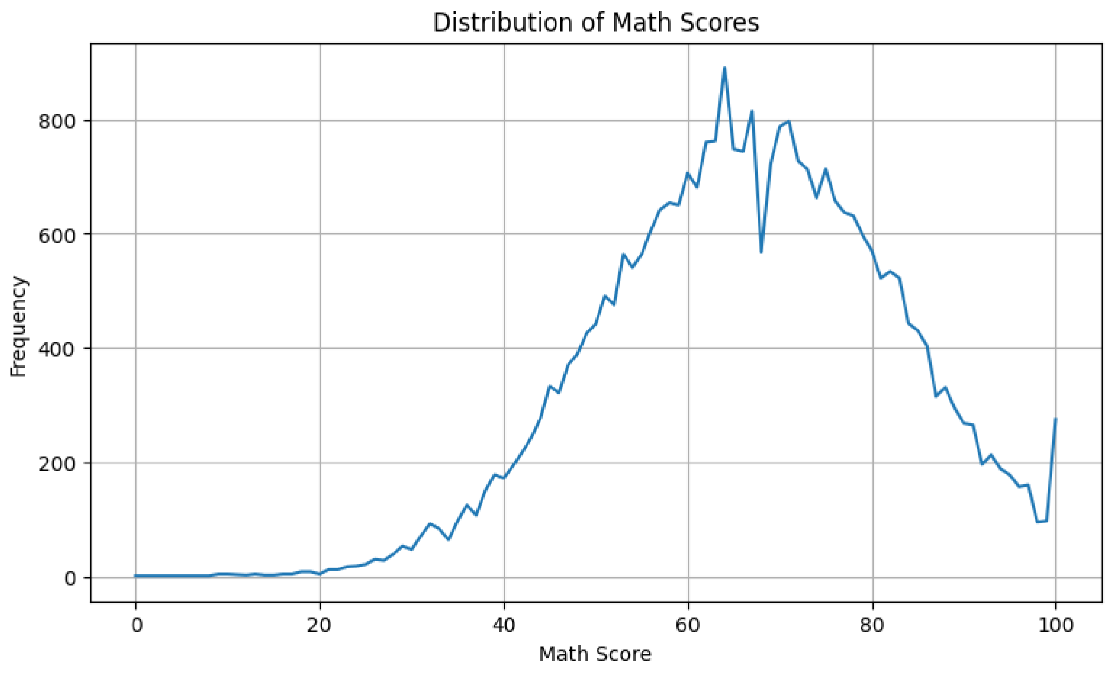
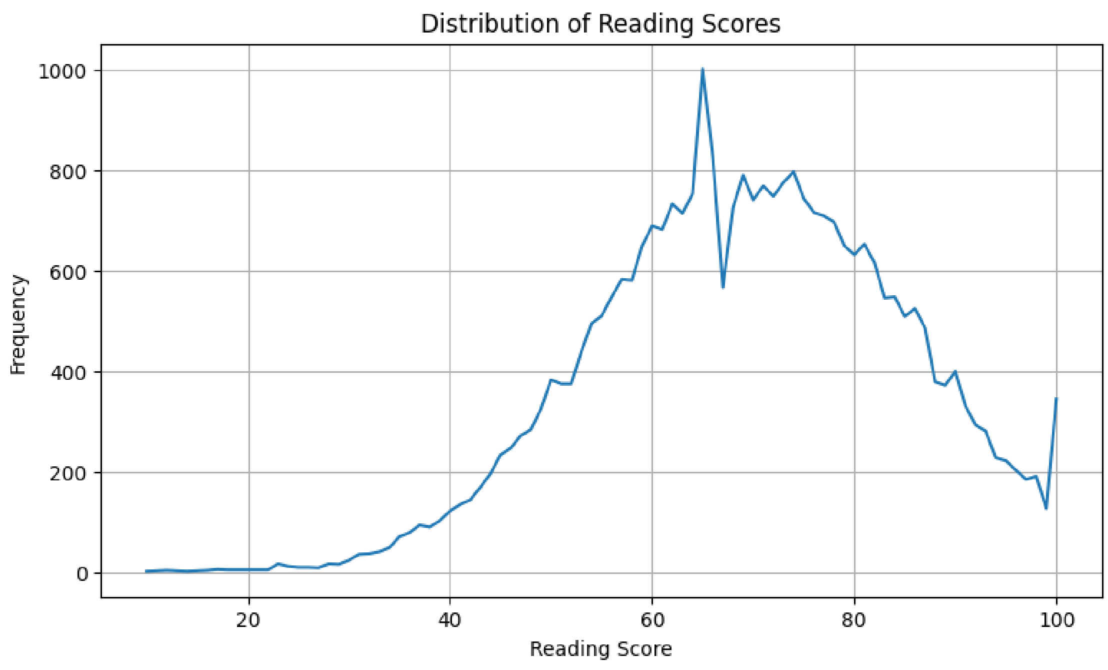


6.5.2 Calculated the Frequency of Reading Scores

```
import seaborn as sns
import matplotlib.pyplot as plt

# Assuming df is your DataFrame and 'ReadingScore' is the column name for reading scores
reading_score_counts = df['ReadingScore'].value_counts().sort_index()

# Create a line plot for ReadingScore
plt.figure(figsize=(9, 5))
sns.lineplot(x=reading_score_counts.index, y=reading_score_counts.values)
plt.title('Distribution of Reading Scores')
plt.xlabel('Reading Score')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```



6.5.3 Calculated the Frequency of Writing Scores

```
import seaborn as sns
import matplotlib.pyplot as plt

# Assuming df is your DataFrame and 'WritingScore' is the column name for writing scores
writing_score_counts = df['WritingScore'].value_counts().sort_index()

# Create a line plot for WritingScore
plt.figure(figsize=(9, 5))
sns.lineplot(x=writing_score_counts.index, y=writing_score_counts.values)
plt.title('Distribution of Writing Scores')
plt.xlabel('Writing Score')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```

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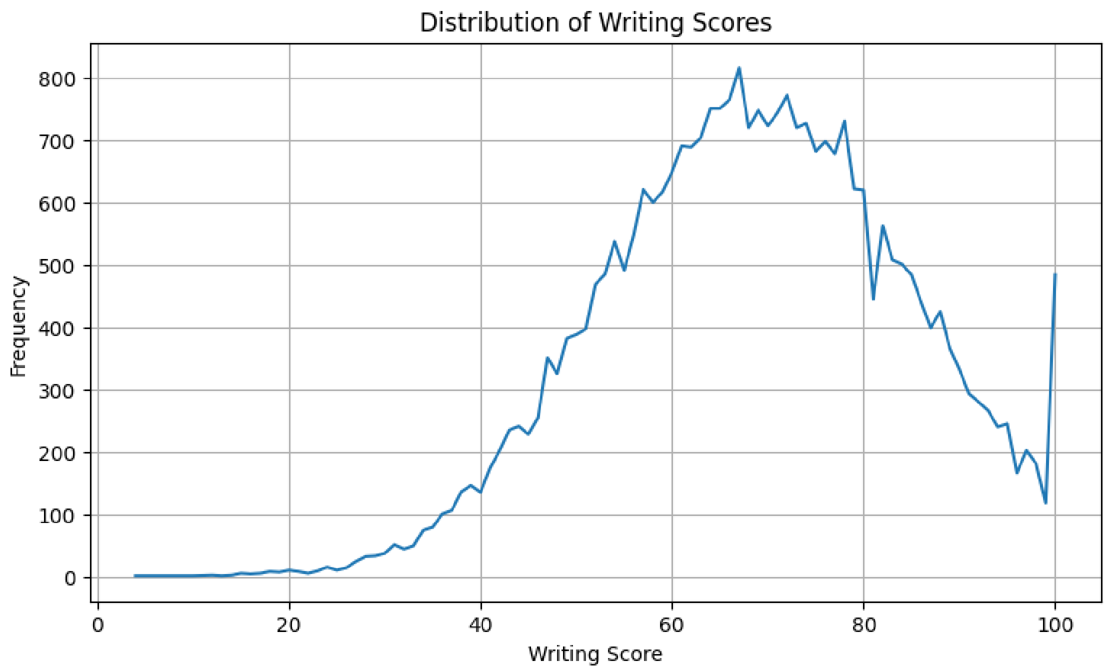


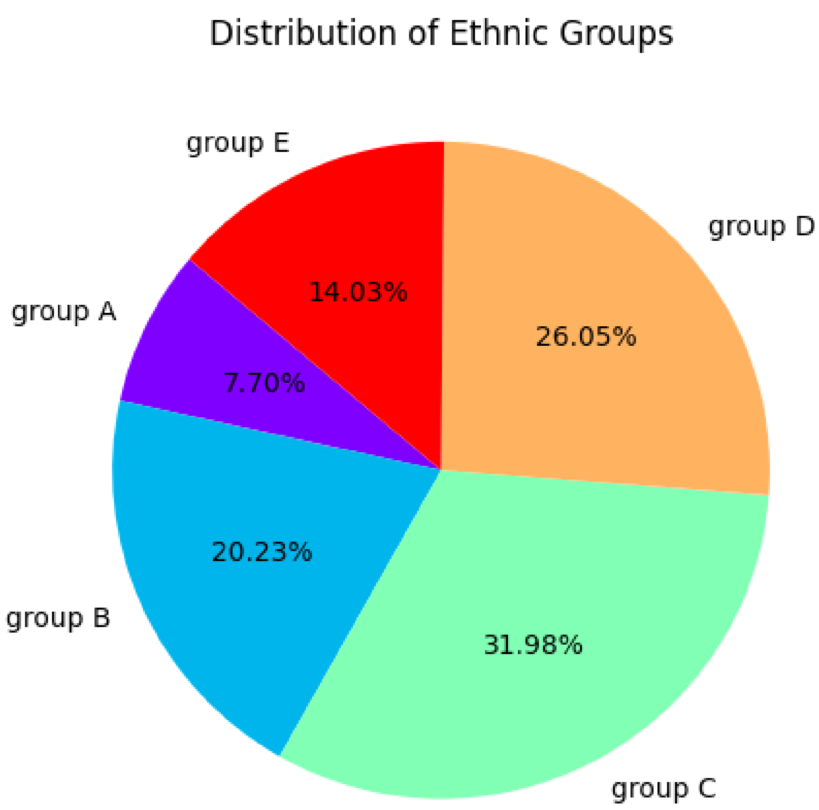
from the above 3 Scores Line Graphs we can conclude that the students are basically weak in Maths than the 2 rest of subjects

6.6. Distribution of Ethinic Groups

```
print(df["EthnicGroup"].unique())
```

```
[nan 'group C' 'group B' 'group A' 'group D' 'group E']
```

```
import seaborn as sns
import matplotlib.pyplot as plt

# Calculate counts for each ethnic group
groupA = df.loc[df['EthnicGroup'] == "group A"].count()
groupB = df.loc[df['EthnicGroup'] == "group B"].count()
groupC = df.loc[df['EthnicGroup'] == "group C"].count()
groupD = df.loc[df['EthnicGroup'] == "group D"].count()
groupE = df.loc[df['EthnicGroup'] == "group E"].count()

# Labels and data for the pie chart
labels = ["group A", "group B", "group C", "group D", "group E"]
sizes = [groupA["EthnicGroup"], groupB["EthnicGroup"], groupC["EthnicGroup"],
groupD["EthnicGroup"], groupE["EthnicGroup"]]

# Define colors and explode
colors = plt.get_cmap('rainbow')(np.linspace(0, 1, len(labels)))

# Create pie chart
plt.figure(figsize=(5.5,5.5))
plt.pie(sizes, labels=labels, autopct="%1.2f%%", startangle=140, colors=colors)
plt.title("Distribution of Ethnic Groups")

# Show plot
plt.show()
```



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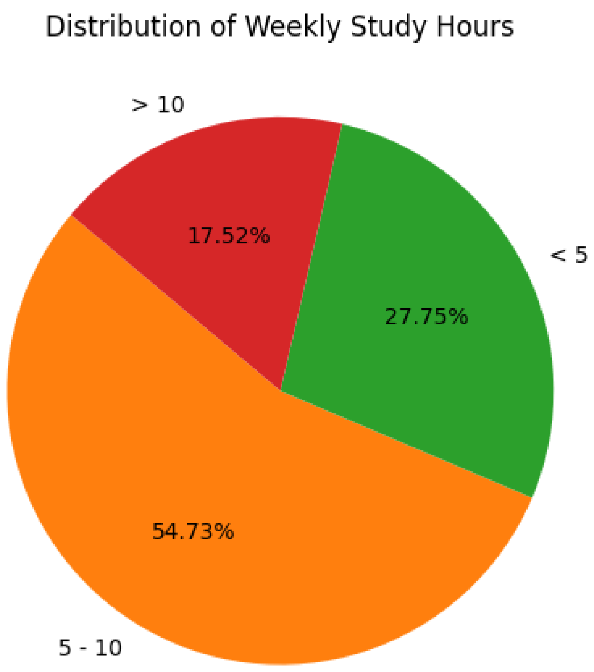
from this we can conclude that Group C has the most distribution among the Ethnic Groups with a percentage of 31.98%

6.7.1. Distribution of Scores of Students according to Weakly Study Hours

```
gb4=df.groupby("WklyStudyHours").agg({"MathScore":'mean',"ReadingScore":'mean',"WritingScore":"mean
"})
gb4['AllScoresMean'] = (gb4['MathScore'] + gb4['ReadingScore'] + gb4['WritingScore']) / 3
print(gb4)
```

```
                MathScore  ReadingScore  WritingScore  AllScoresMean
WklyStudyHours
5 - 10          66.870491     69.660532     68.636280      68.389101
< 5             64.580359     68.176135     67.090192      66.615562
> 10            68.696655     70.365436     69.777778      69.613290
```

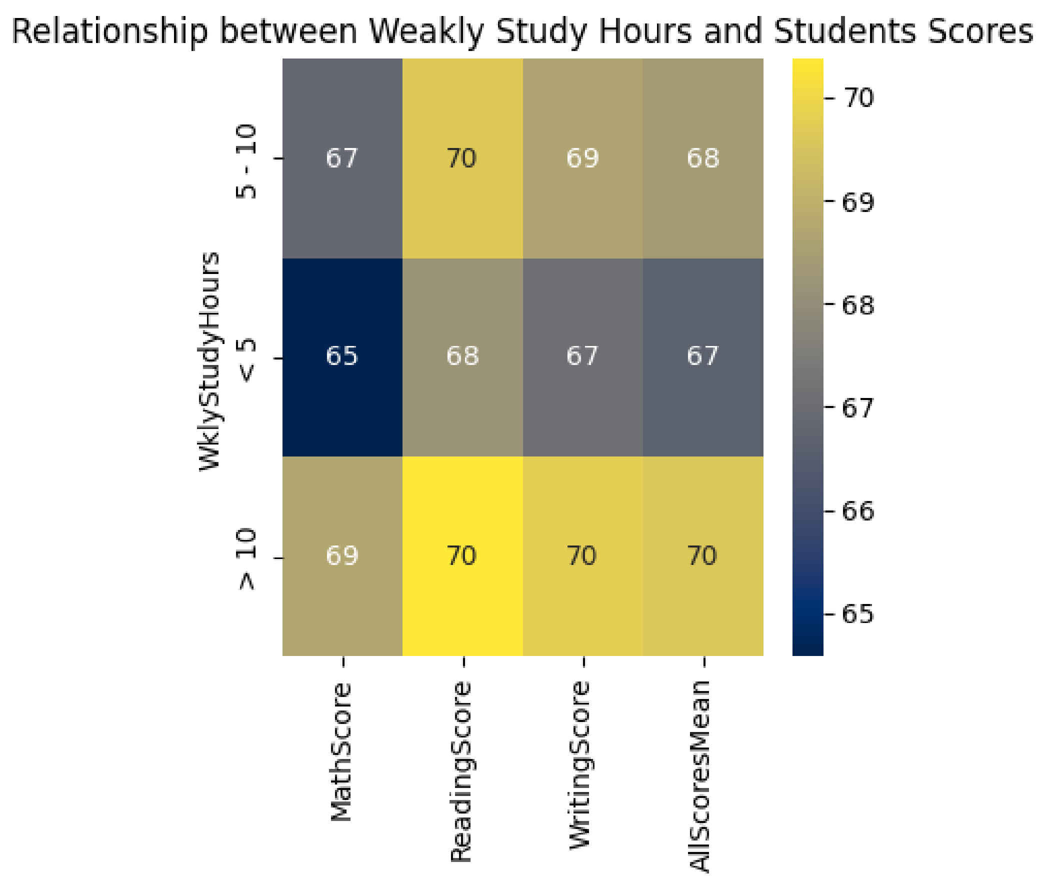
```
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

# Calculate counts for each category of weekly study hours
study_hours_counts = df['WklyStudyHours'].value_counts()

# Labels and data for the pie chart
labels = study_hours_counts.index.tolist()
sizes = study_hours_counts.values.tolist()

# Define colors
colors = ['tab:orange', 'tab:green', 'tab:red']

# Create pie chart
plt.figure(figsize=(5.5,5.5))
plt.pie(sizes, labels=labels, autopct="%1.2f%%", startangle=140, colors=colors)
plt.title("Distribution of Weekly Study Hours")

# Show plot

plt.show()
```



from this we can conclude that Student's study upto maximum 5 - 10 hours of study with the maximum percentage of 54.73%

6.7.2. Relationship between Weakly Study Hours studied by student and Students Scores

```
plt.figure(figsize=(4,4))
plt.title("Relationship between Weakly Study Hours and Students Scores")
sns.heatmap(gb4, annot=True,cmap='cividis')
plt.show()
```



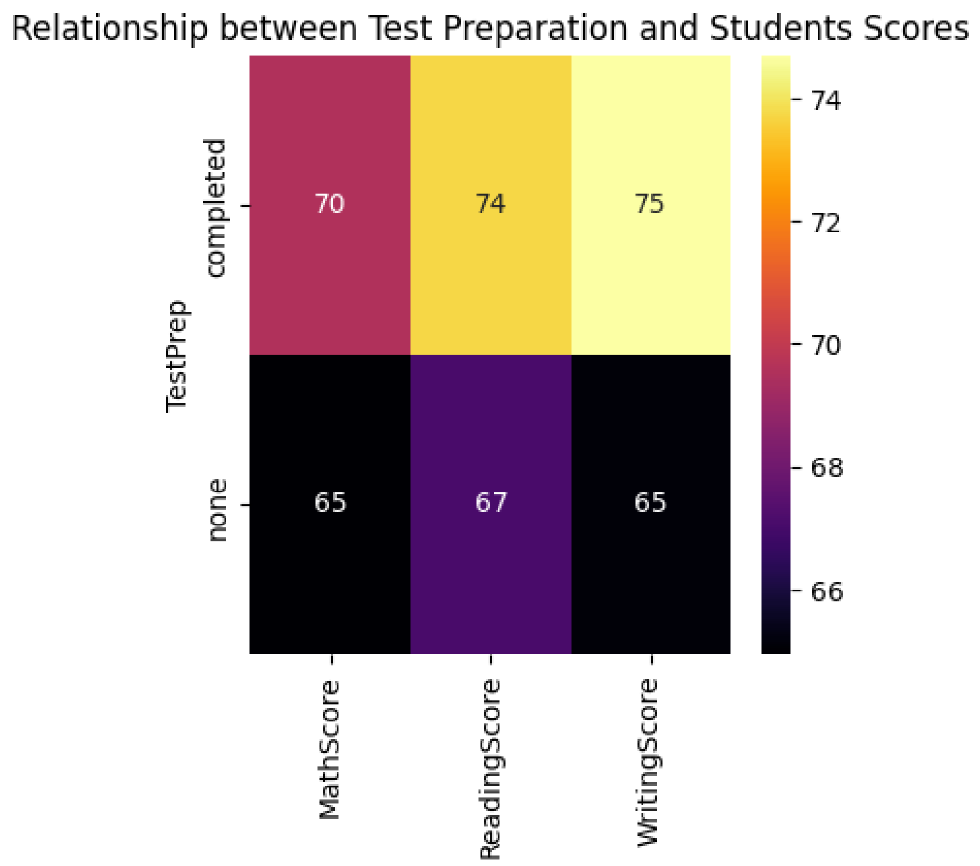
from this we can conclude that Student's who study more than 10 hours have more overall marks average of 70 than 5-10 hours with overall average of 68 and less than 5 hours with overall average of 67 respectively

6.8. Relationship between Test Preparation and Students Scores

```
gb5=df.groupby("TestPrep").agg({"MathScore":'mean',"ReadingScore":'mean',"WritingScore":"mean"})
print(gb5)
```

```
           MathScore  ReadingScore  WritingScore
TestPrep
completed   69.54666     73.732998     74.703265
none        64.94877     67.051071     65.092756
```

```
plt.figure(figsize=(4,4))
plt.title("Relationship between Test Preparation and Students Scores")
sns.heatmap(gb5, annot=True,cmap='inferno')
plt.show()
```



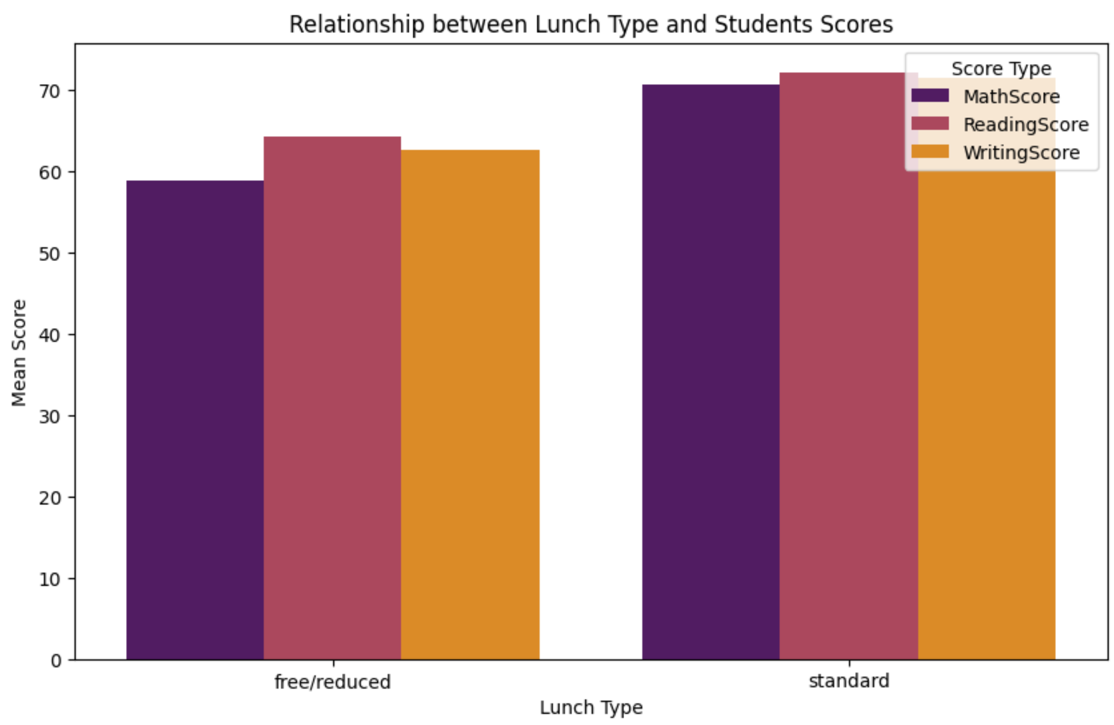
from this we can conclude that the Students those who have completed their Test Preparation have more mean marks in all the subjects comparatively to those haven't done any preparation

6.9. Relationship between Lunch Type and Student Scores

```
gb3=df.groupby("LunchType").agg({"MathScore":'mean',"ReadingScore":'mean',"WritingScore":"mean"}).r
eset_index()
print(gb3)
```

```
      LunchType  MathScore  ReadingScore  WritingScore
0  free/reduced  58.862332     64.189735     62.650522
1      standard  70.709370     72.175634     71.529716
```

```
# Reshape data for plotting as a bar graph
gb3_melted = pd.melt(gb3, id_vars=['LunchType'], value_vars=['MathScore', 'ReadingScore',
'WritingScore'],
                     var_name='ScoreType', value_name='MeanScore')
# Plotting as a bar graph
plt.figure(figsize=(10, 6))
sns.barplot(x='LunchType', y='MeanScore', hue='ScoreType', data=gb3_melted, palette='inferno')
plt.title("Relationship between Lunch Type and Students Scores")
plt.xlabel("Lunch Type")
plt.ylabel("Mean Score")
plt.legend(title='Score Type', loc='upper right')
plt.show()
```



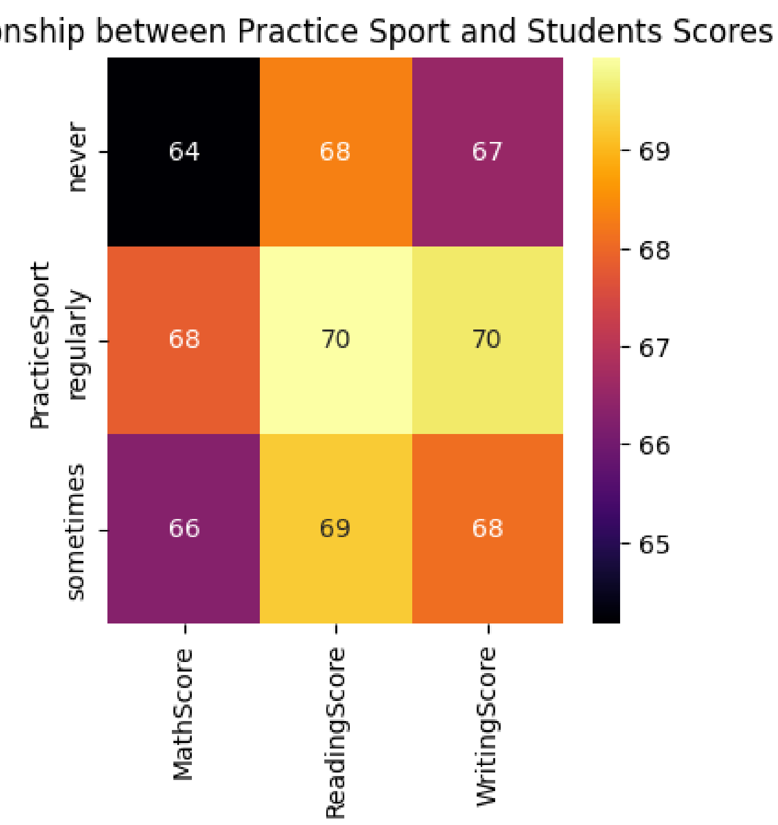
from this we can conclude that the Students those who have Standard Lunch have more mean marks in all the subjects comparatively to those have free or reduced food

6.10. Relationship between Practicing Sport and Student Scores

```
gb6=df.groupby("PracticeSport").agg({"MathScore":'mean',"ReadingScore":'mean',"WritingScore":"mean"
})
print(gb6)
```

```
               MathScore  ReadingScore  WritingScore
PracticeSport
never          64.171079     68.337662     66.522727
regularly      67.839155     69.943019     69.604003
sometimes      66.274831     69.241307     68.072438
```

```
plt.figure(figsize=(4,4))
plt.title("Relationship between Practice Sport and Students Scores")
sns.heatmap(gb6, annot=True,cmap='inferno')
plt.show()
```



from the above chart we can conclude that the students that Practice sports regularly and even sometimes remain fresh and active and hence their scores gradually increase comparative to those students who never Practice sports

Dashboard.py

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Roll No: 23101A2002

```
import streamlit as st
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Load the data
df = pd.read_csv("examscores.csv")

# Data Cleaning
df = df.drop("Unnamed: 0", axis=1)
df["WklyStudyHours"] = df["WklyStudyHours"].str.replace("05-Oct", "5 - 10")

# Streamlit App Title
st.title("Student Exam Scores Dashboard")

# Display the DataFrame
st.header("Dataset Overview")
st.write(df.head())

# Display summary statistics
st.header("Summary Statistics")
st.write(df.describe())

# Check for missing values
st.header("Missing Values")
st.write(df.isnull().sum())

# Gender Distribution
st.header("Gender Distribution")
plt.figure(figsize=(5, 5))
ax = sns.countplot(data=df, x="Gender", palette="Set2", saturation=2, edgecolor="black")
plt.title("Gender Distribution")
ax.bar_label(ax.containers[0])
ax.bar_label(ax.containers[1])
st.pyplot(plt)

# Gender vs Scores Heatmap
st.header("Gender vs Scores")
gb2 = df.groupby("Gender").agg({"MathScore": 'mean', "ReadingScore": 'mean', "WritingScore": "mean"})
st.write(gb2)
plt.figure(figsize=(4, 4))
plt.title("Relationship Comparison between Gender and Students Score")
sns.heatmap(gb2, annot=True, cmap="plasma", linewidths=0.5, linecolor='black', cbar=True)
st.pyplot(plt)

# Parent Education vs Scores Heatmap
st.header("Parent Education vs Scores")
gb = df.groupby("ParentEduc").agg({"MathScore": 'mean', "ReadingScore": 'mean', "WritingScore":
"mean"})
st.write(gb)
plt.figure(figsize=(4, 4))
plt.title("Relationship between Parents Education and Students Score")
sns.heatmap(gb, annot=True)
st.pyplot(plt)

# Parent Marital Status vs Scores Heatmap
st.header("Parent Marital Status vs Scores")
gb1 = df.groupby("ParentMaritalStatus").agg({"MathScore": 'mean', "ReadingScore": 'mean',
"WritingScore": "mean"})
st.write(gb1)
plt.figure(figsize=(4, 4))
plt.title("Relationship between Parents Marital Status and Students Score")
sns.heatmap(gb1, annot=True, cmap='gist_earth')
st.pyplot(plt)

# Math Score Distribution
st.header("Distribution of Math Scores")
math_score_counts = df['MathScore'].value_counts().sort_index()
plt.figure(figsize=(9, 5))
sns.lineplot(x=math_score_counts.index, y=math_score_counts.values)
plt.title('Distribution of Math Scores')
plt.xlabel('Math Score')
plt.ylabel('Frequency')
plt.grid(True)
```

```
st.pyplot(plt)

# Reading Score Distribution
st.header("Distribution of Reading Scores")
reading_score_counts = df['ReadingScore'].value_counts().sort_index()
plt.figure(figsize=(9, 5))
sns.lineplot(x=reading_score_counts.index, y=reading_score_counts.values)
plt.title('Distribution of Reading Scores')
plt.xlabel('Reading Score')
plt.ylabel('Frequency')
plt.grid(True)
st.pyplot(plt)

# Writing Score Distribution
st.header("Distribution of Writing Scores")
writing_score_counts = df['WritingScore'].value_counts().sort_index()
plt.figure(figsize=(9, 5))
sns.lineplot(x=writing_score_counts.index, y=writing_score_counts.values)
plt.title('Distribution of Writing Scores')
plt.xlabel('Writing Score')
plt.ylabel('Frequency')
plt.grid(True)
st.pyplot(plt)

# Ethnic Group Distribution
st.header("Distribution of Ethnic Groups")
groupA = df.loc[df['EthnicGroup'] == "group A"].count()
groupB = df.loc[df['EthnicGroup'] == "group B"].count()
groupC = df.loc[df['EthnicGroup'] == "group C"].count()
groupD = df.loc[df['EthnicGroup'] == "group D"].count()
groupE = df.loc[df['EthnicGroup'] == "group E"].count()
labels = ["group A", "group B", "group C", "group D", "group E"]
sizes = [groupA["EthnicGroup"], groupB["EthnicGroup"], groupC["EthnicGroup"], groupD["EthnicGroup"],
groupE["EthnicGroup"]]
colors = plt.get_cmap('rainbow')(np.linspace(0, 1, len(labels)))
plt.figure(figsize=(5.5, 5.5))
plt.pie(sizes, labels=labels, autopct="%1.2f%%", startangle=140, colors=colors)
plt.title("Distribution of Ethnic Groups")
st.pyplot(plt)

# Weekly Study Hours vs Scores
st.header("Weekly Study Hours vs Scores")
gb4 = df.groupby("WklyStudyHours").agg({"MathScore": 'mean', "ReadingScore": 'mean', "WritingScore":
"mean"})
gb4['AllScoresMean'] = (gb4['MathScore'] + gb4['ReadingScore'] + gb4['WritingScore']) / 3
st.write(gb4)
study_hours_counts = df['WklyStudyHours'].value_counts()
labels = study_hours_counts.index.tolist()
sizes = study_hours_counts.values.tolist()
colors = ['tab:orange', 'tab:green', 'tab:red']
plt.figure(figsize=(5.5, 5.5))
plt.pie(sizes, labels=labels, autopct="%1.2f%%", startangle=140, colors=colors)
plt.title("Distribution of Weekly Study Hours")
st.pyplot(plt)
plt.figure(figsize=(4, 4))
plt.title("Relationship between Weekly Study Hours and Students Scores")
sns.heatmap(gb4, annot=True, cmap='cividis')
st.pyplot(plt)

# Test Preparation vs Scores
st.header("Test Preparation vs Scores")
gb5 = df.groupby("TestPrep").agg({"MathScore": 'mean', "ReadingScore": 'mean', "WritingScore": "mean"})
st.write(gb5)
plt.figure(figsize=(4, 4))
plt.title("Relationship between Test Preparation and Students Scores")
sns.heatmap(gb5, annot=True, cmap='inferno')
st.pyplot(plt)

# Lunch Type vs Scores
st.header("Lunch Type vs Scores")
gb3 = df.groupby("LunchType").agg({"MathScore": 'mean', "ReadingScore": 'mean', "WritingScore":
"mean"}).reset_index()
gb3_melted = pd.melt(gb3, id_vars=['LunchType'], value_vars=['MathScore', 'ReadingScore',
'WritingScore'], var_name='ScoreType', value_name='MeanScore')
plt.figure(figsize=(10, 6))
```

```
sns.barplot(x='LunchType', y='MeanScore', hue='ScoreType', data=gb3_melted, palette='inferno')
plt.title("Relationship between Lunch Type and Students Scores")
plt.xlabel("Lunch Type")
plt.ylabel("Mean Score")
plt.legend(title='Score Type', loc='upper right')
st.pyplot(plt)

# Practice Sport vs Scores
st.header("Practice Sport vs Scores")
gb6 = df.groupby("PracticeSport").agg({"MathScore": 'mean', "ReadingScore": 'mean', "WritingScore":
"mean"})
st.write(gb6)
plt.figure(figsize=(4, 4))
plt.title("Relationship between Practice Sport and Students Scores")
sns.heatmap(gb6, annot=True, cmap='inferno')
st.pyplot(plt)
```

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Roll No: 23101A2002

Student Exam Scores Dashboard using Streamlit

Dataset Overview

	Gender	EthnicGroup	ParentEduc	LunchType	TestPrep	ParentMaritalStatus	PracticeSport
0	female	None	bachelor's degree	standard	none	married	regularly
1	female	group C	some college	standard	None	married	sometimes
2	female	group B	master's degree	standard	none	single	sometimes
3	male	group A	associate's degree	free/reduced	none	married	never
4	male	group C	some college	standard	none	married	sometimes

Summary Statistics

	NrSiblings	MathScore	ReadingScore	WritingScore
count	29,069	30,641	30,641	30,641
mean	2.1459	66.5584	69.3775	68.4186
std	1.4582	15.3616	14.759	15.4435
min	0	0	10	4
25%	1	56	59	58
50%	2	67	70	69
75%	3	78	80	79
max	7	100	100	100

Missing Values

	0
Gender	0
EthnicGroup	1,840
ParentEduc	1,845
LunchType	0
TestPrep	1,830
ParentMaritalStatus	1,190
PracticeSport	631
IsFirstChild	904
NrSiblings	1,572
TransportMeans	3,134

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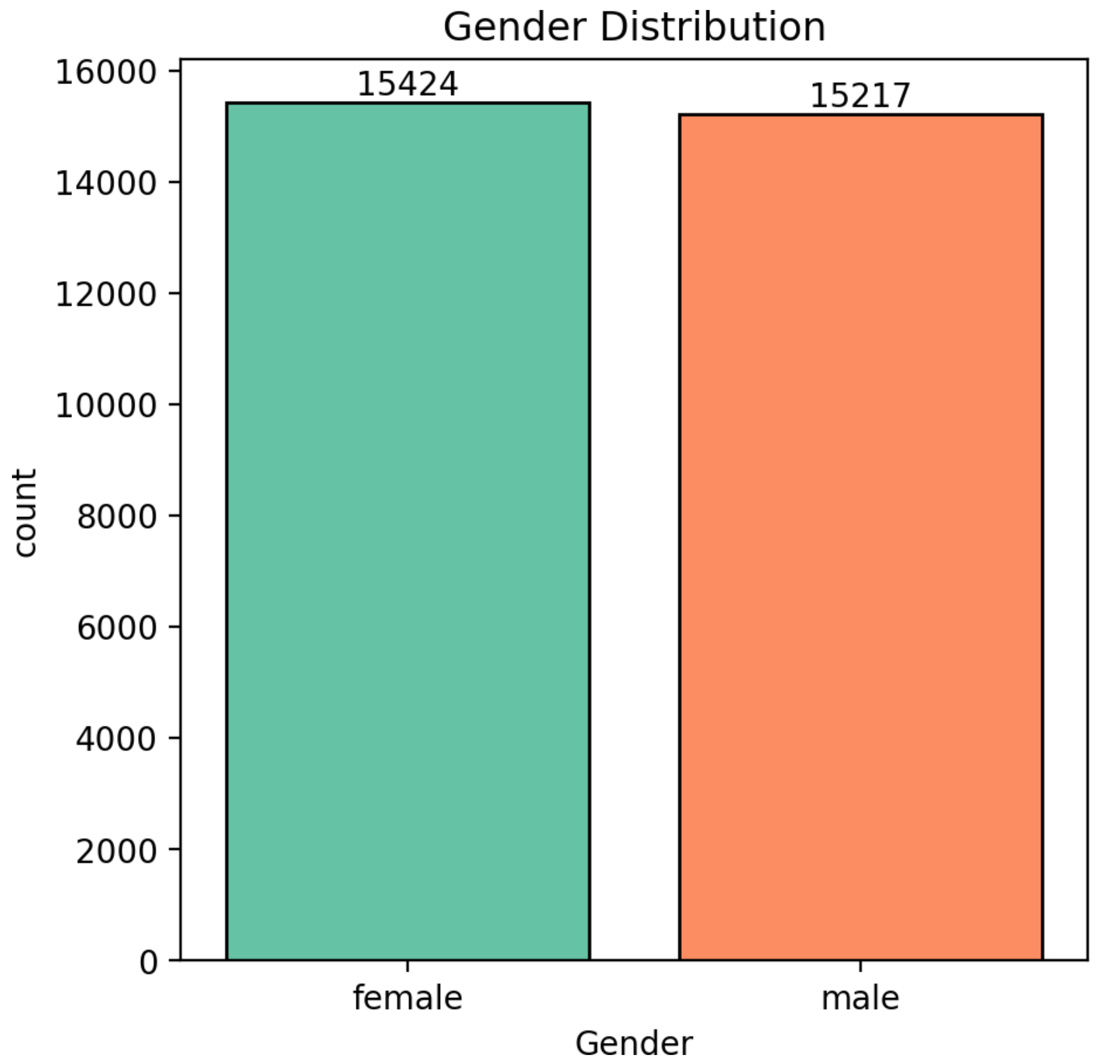
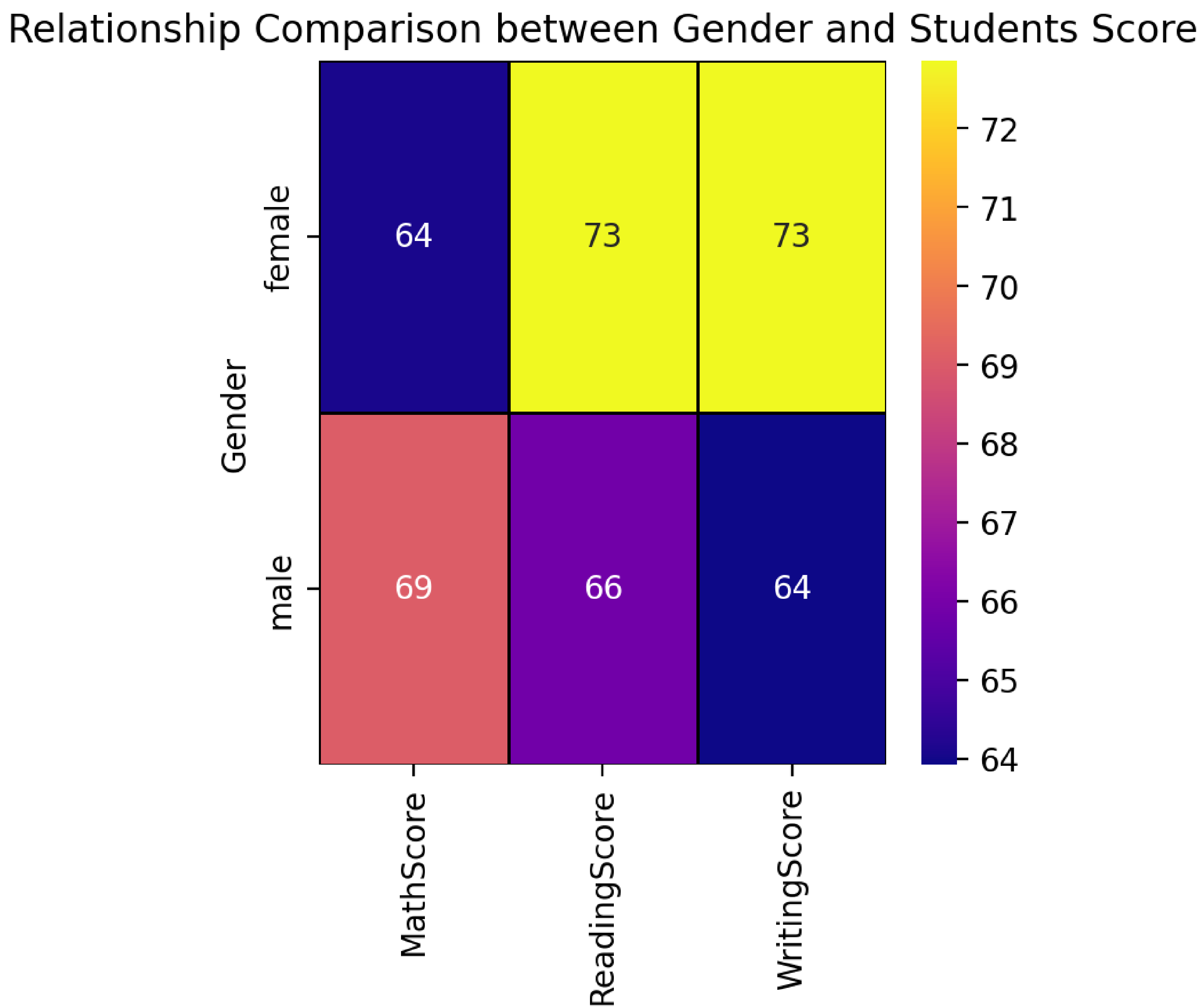
Gender Distribution



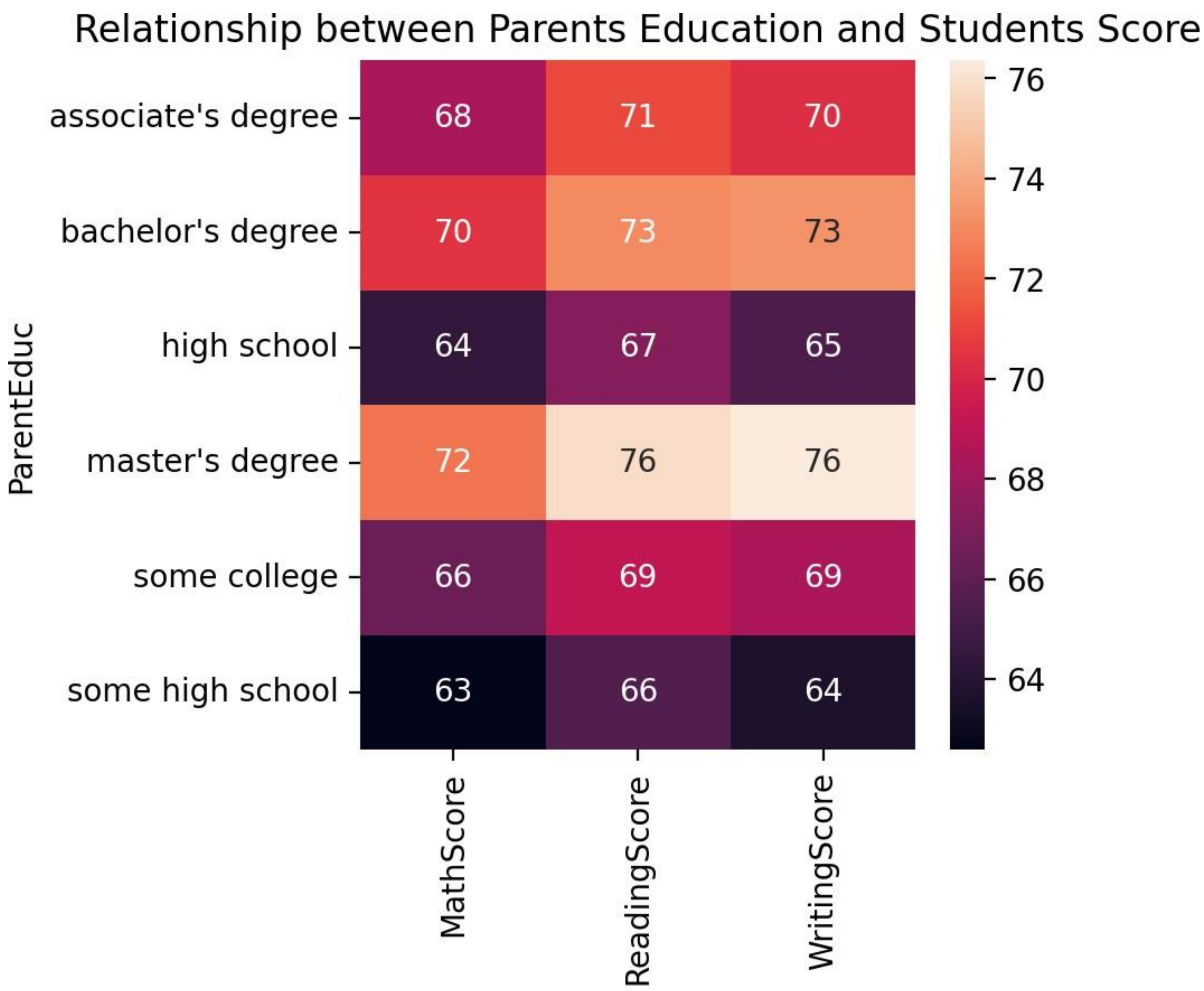
Gender vs Scores

Gender	MathScore	ReadingScore	WritingScore
female	64.0807	72.8532	72.8565
male	69.0699	65.8546	63.9204



Parent Education vs Scores

ParentEduc	MathScore	ReadingScore	WritingScore
associate's degree	68.3656	71.1243	70.2991
bachelor's degree	70.4666	73.062	73.3311
high school	64.4357	67.214	65.4211
master's degree	72.3361	75.8329	76.3569
some college	66.3905	69.1797	68.5014
some high school	62.584	65.5108	63.6324



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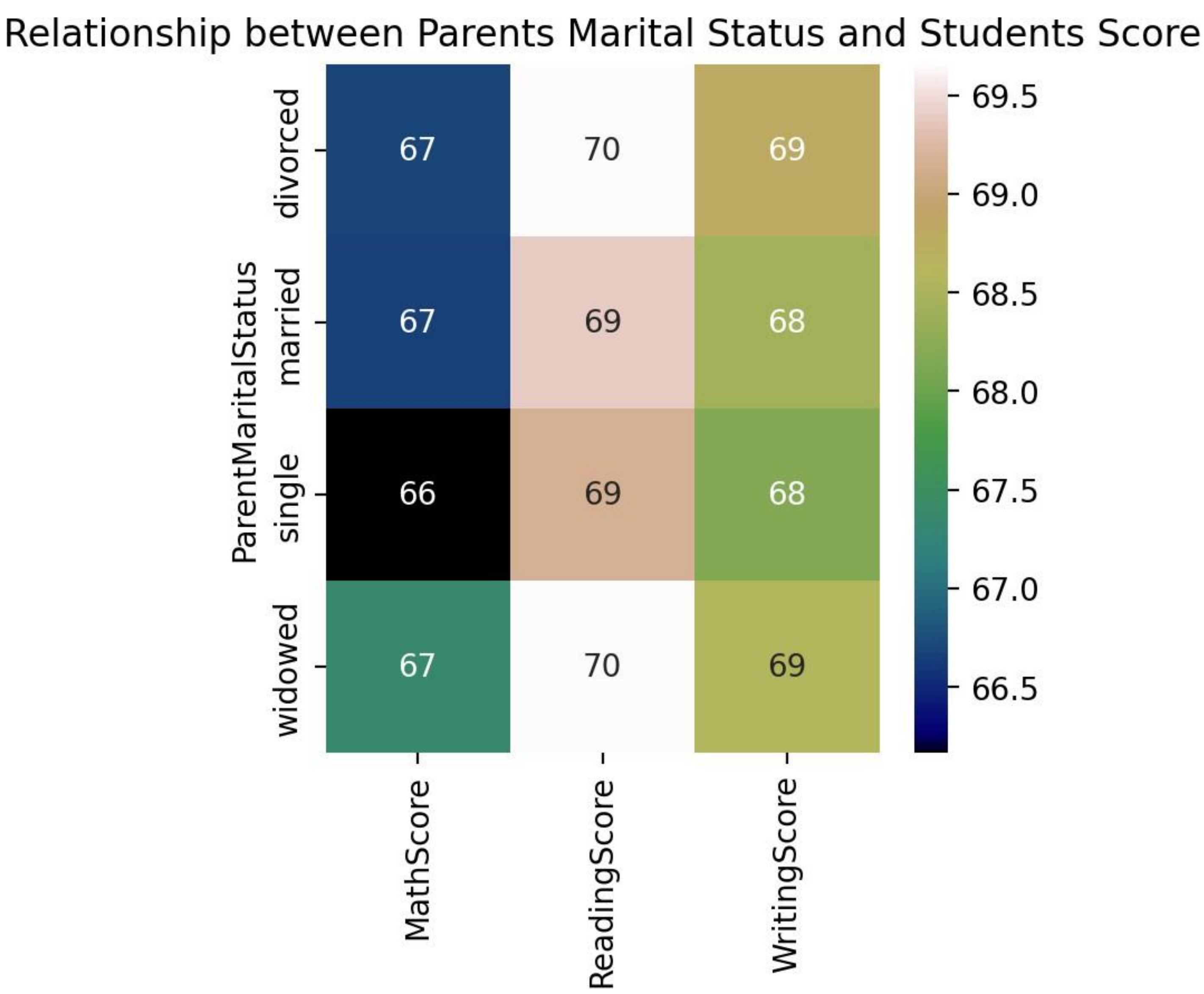
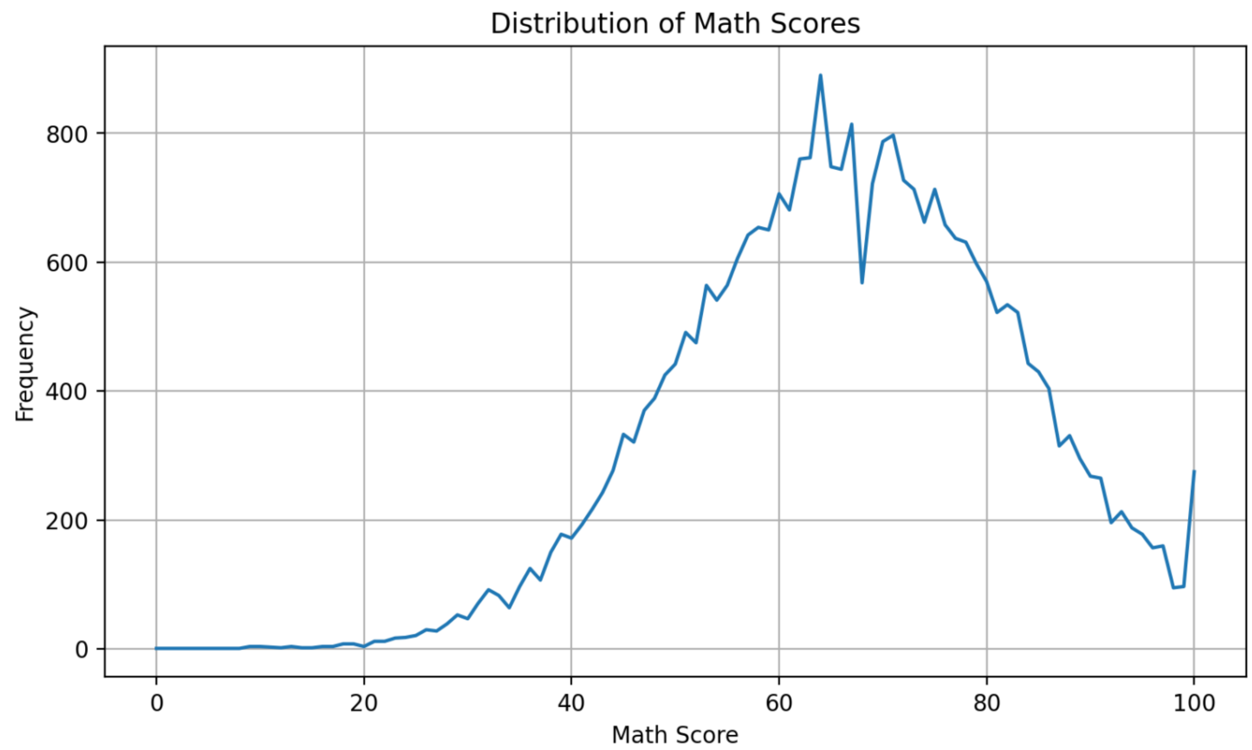
Parent Marital Status vs Scores

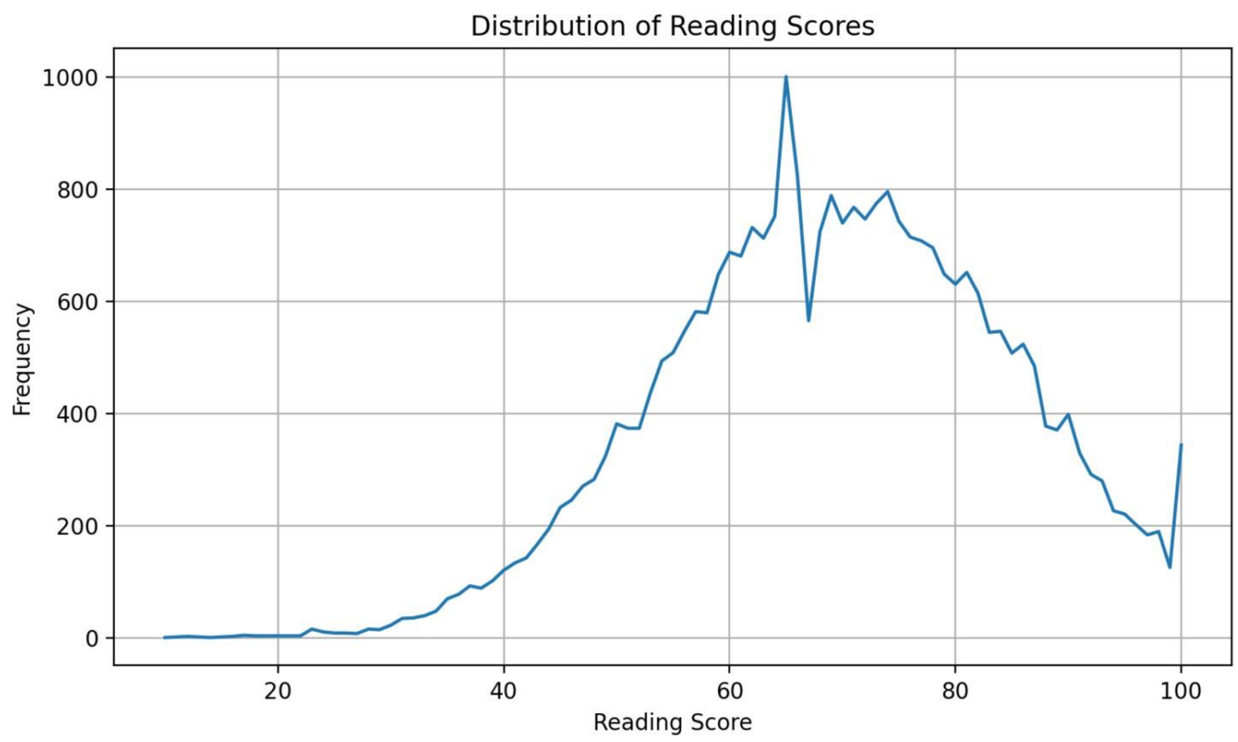
ParentMaritalStatus	MathScore	ReadingScore	WritingScore
divorced	66.6912	69.655	68.7991
married	66.6573	69.3896	68.421
single	66.1657	69.1572	68.1744
widowed	67.3689	69.6514	68.5635



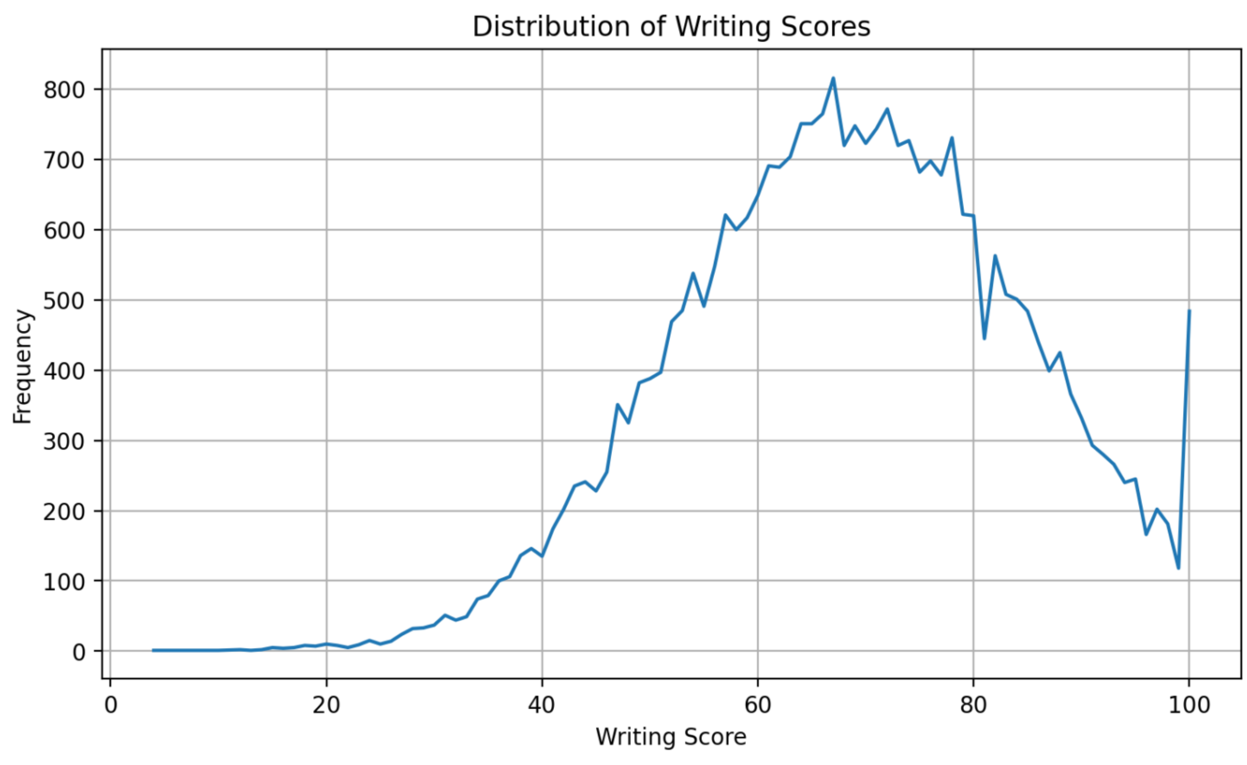
Distribution of Math Scores



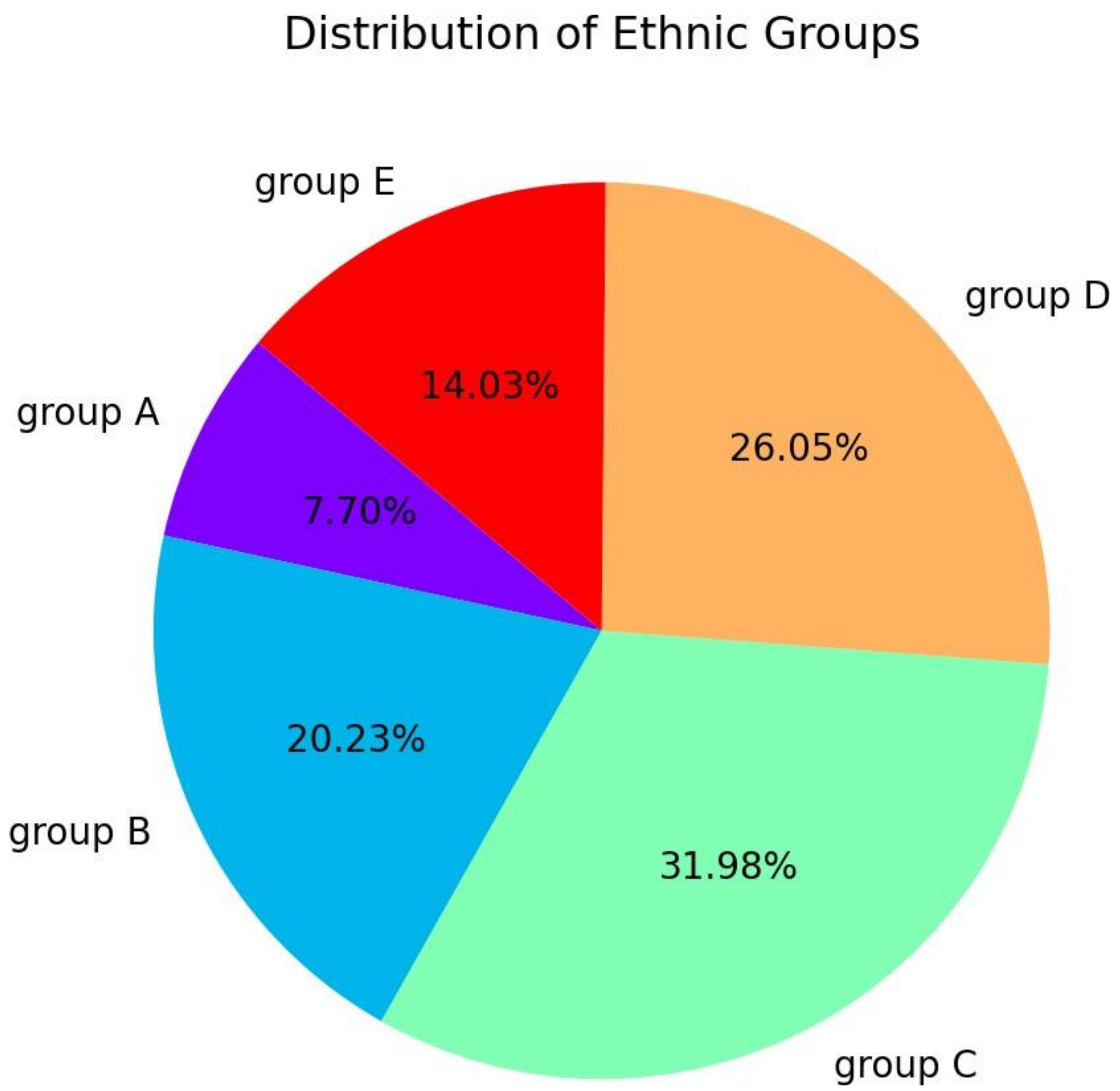
Distribution of Reading Scores



Distribution of Writing Scores



Distribution of Ethnic Groups



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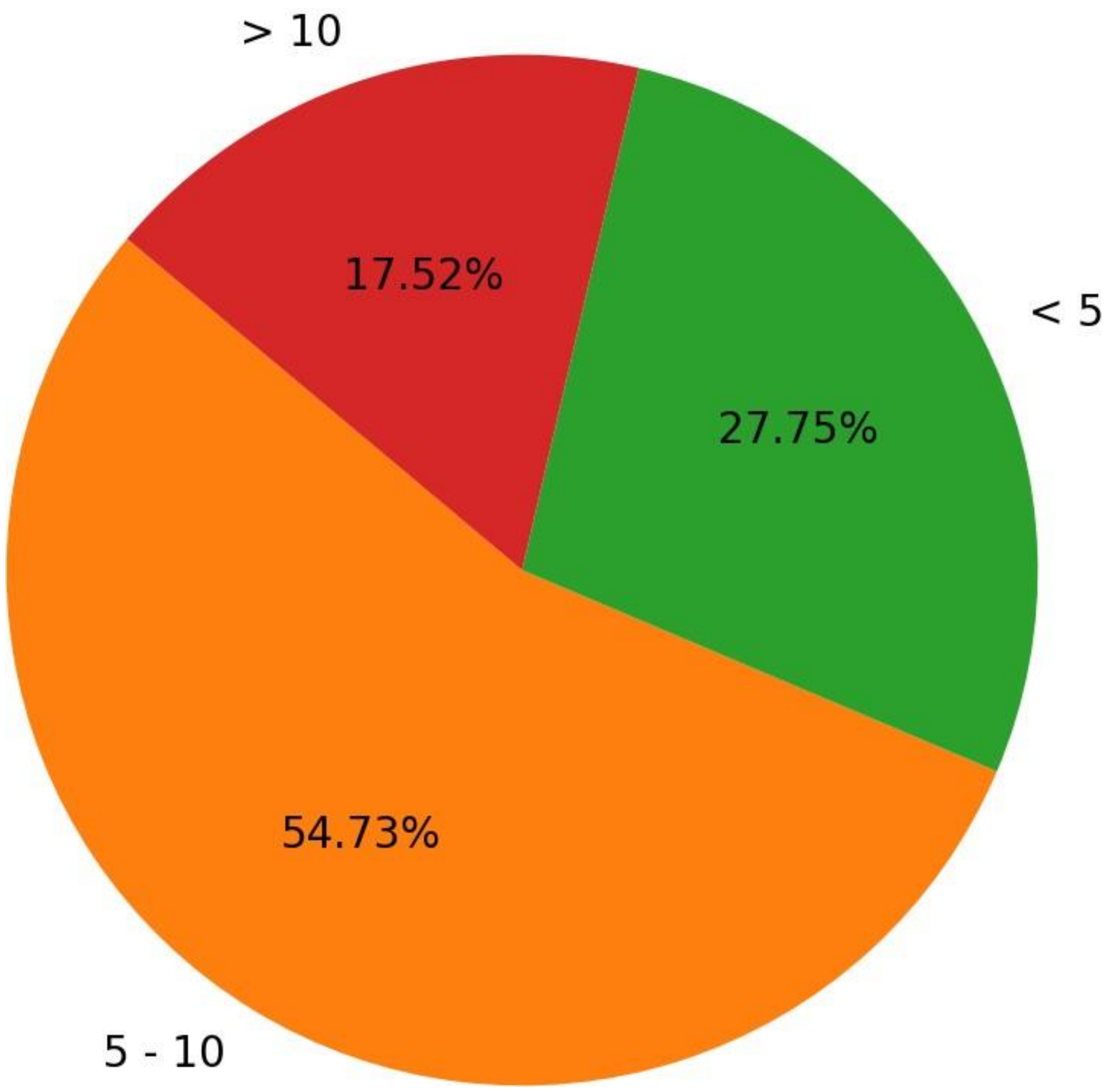
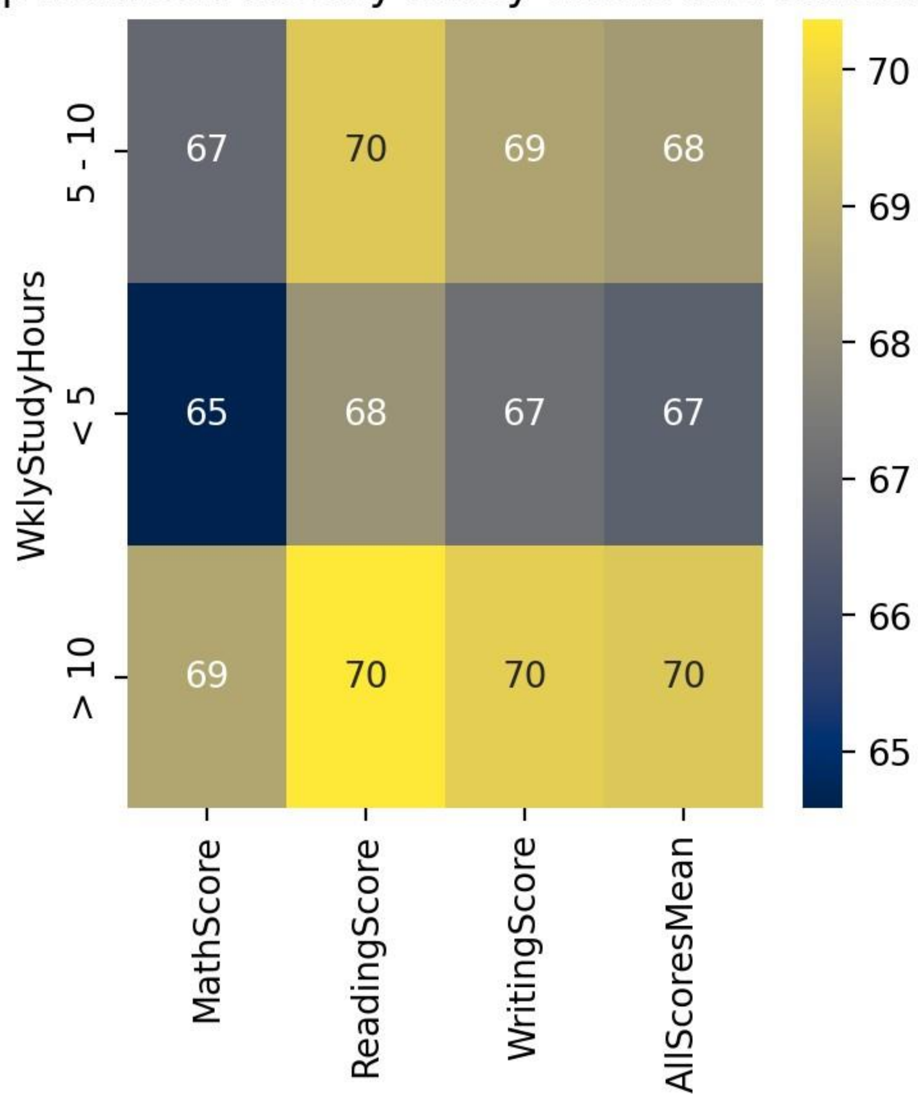
Weekly Study Hours vs Scores

WklyStudyHours	MathScore	ReadingScore	WritingScore	AllScoresMean
5 - 10	66.8705	69.6605	68.6363	68.3891
< 5	64.5804	68.1761	67.0902	66.6156
> 10	68.6967	70.3654	69.7778	69.6133

Distribution of Weekly Study Hours



Relationship between Weekly Study Hours and Students Scores



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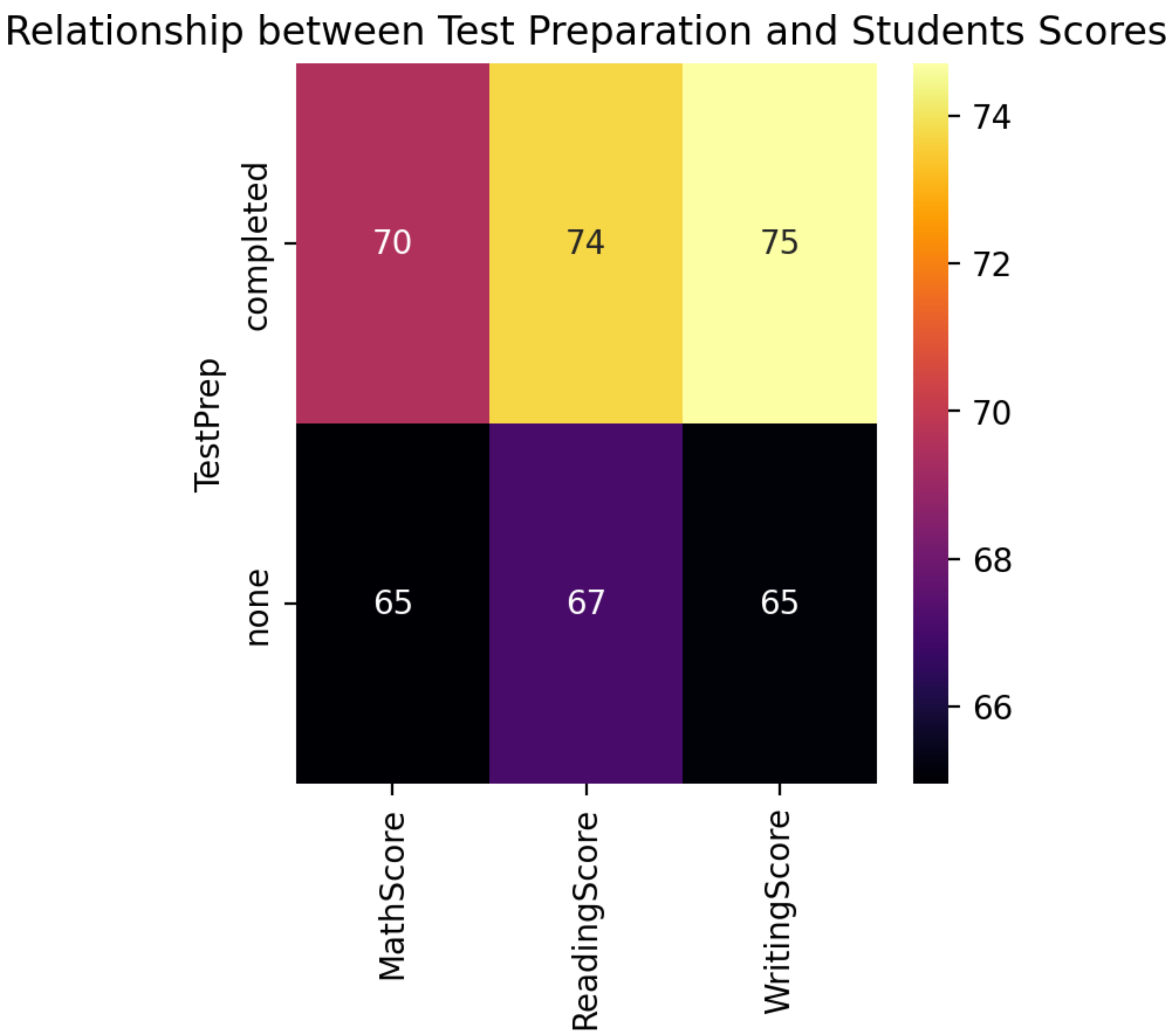
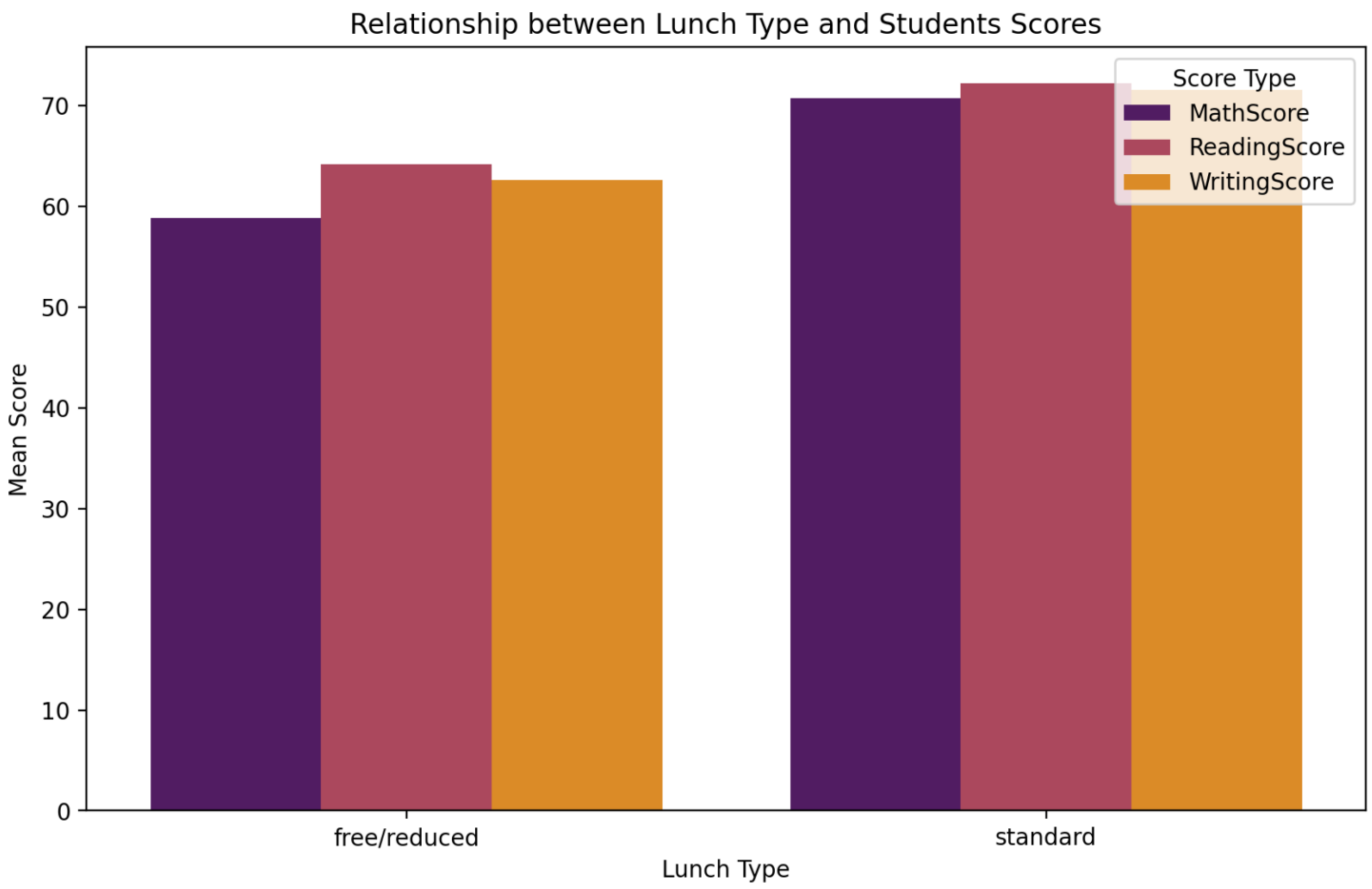
Test Preparation vs Scores

TestPrep	MathScore	ReadingScore	WritingScore
completed	69.5467	73.733	74.7033
none	64.9488	67.0511	65.0928



Lunch Type vs Scores



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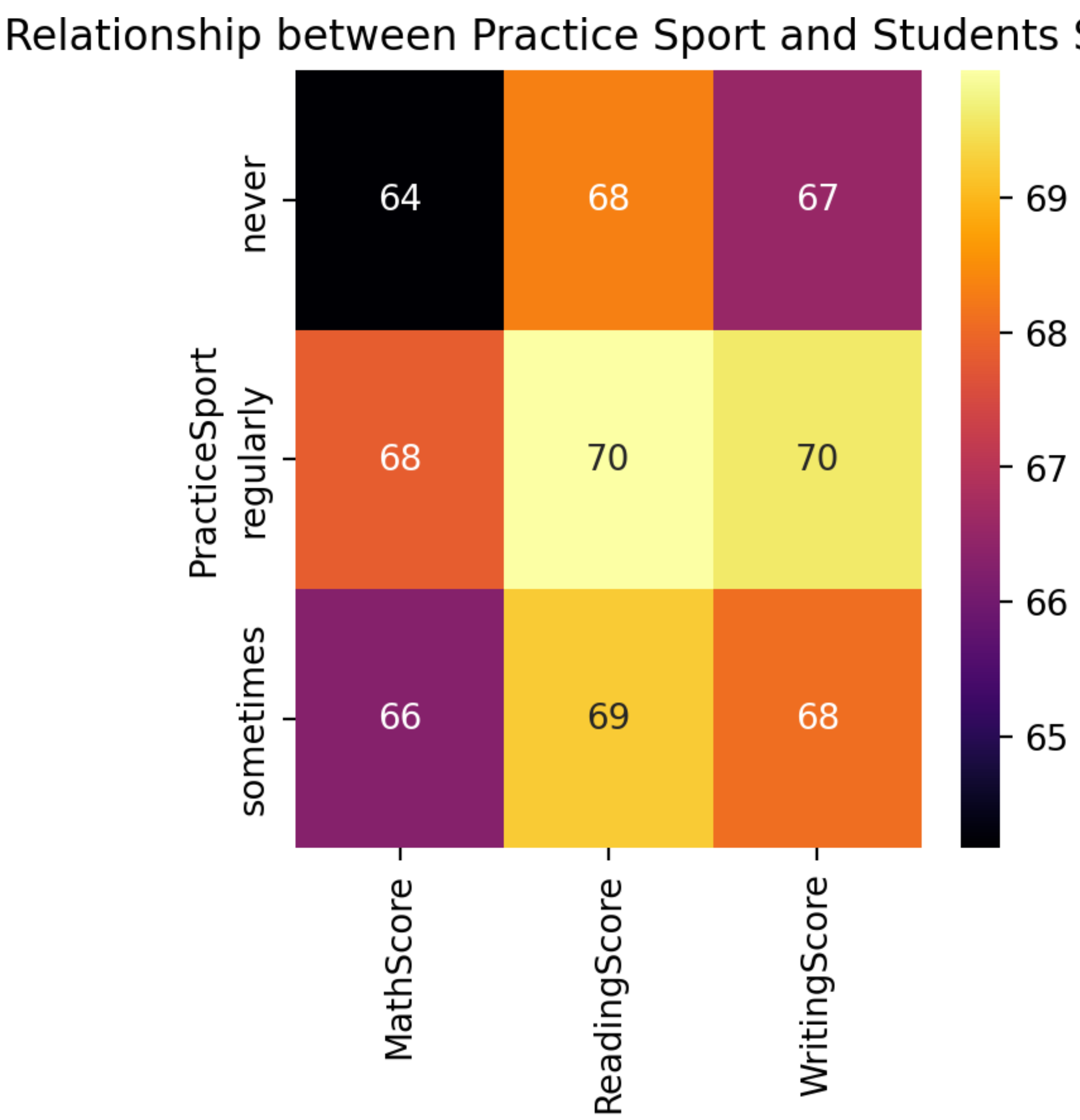
Practice Sport vs Scores

PracticeSport	MathScore	ReadingScore	WritingScore
never	64.1711	68.3377	66.5227
regularly	67.8392	69.943	69.604
sometimes	66.2748	69.2413	68.0724



Key Findings from this Project:

1. Distribution of Ethnic Groups: The pie chart for ethnic groups showed that the population of students is distributed across five ethnic groups, with each group making up a significant portion of the sample.
2. Relationship between Weekly Study Hours and Scores: The heatmap revealed a positive correlation between weekly study hours and student scores in Math, Reading, and Writing. More study hours tend to correlate with higher scores in all three subjects.
3. Relationship between Parent Education and Student Scores: The heatmap for parent education indicated that higher parent education levels are associated with higher student scores in Math, Reading, and Writing. Specifically, students with parents having a master's degree scored the highest on average.
4. Practice Sport and Student Scores: The analysis showed that students who practice sports regularly tend to have slightly higher scores compared to those who never practice sports. However, the differences were not very pronounced.
5. Lunch Type and Student Scores: Students who receive standard lunches tend to have higher average scores compared to those who receive free/reduced lunches.
6. Number of Siblings and Student Scores: There is a slight negative correlation between the number of siblings and student scores. Students with more siblings tend to have slightly lower scores on average.

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Conclusions:

Based on the analysis of the student scores dataset, several key insights can be drawn:

1. Parental Influence: The educational background of parents plays a significant role in student performance. Higher levels of parental education are associated with better student outcomes across all subjects.
2. Study Habits: Regular study habits are crucial for achieving higher scores. Students who dedicate more hours to studying each week tend to perform better in Math, Reading, and Writing.
3. Practice Sports: Engaging in sports appears to have a positive impact on student performance, albeit modest. Students who practice sports regularly tend to score slightly higher than their peers who do not engage in sports.
4. Socioeconomic Factors: Socioeconomic status, as indicated by lunch type, influences student performance. Students who have access to standard lunches generally perform better than those who receive free/reduced lunches.
5. Family Size: There is a slight negative impact of having more siblings on student performance. This may be due to resource dilution or less individual attention.

Recommendations on this Data:

1. Encourage Parental Involvement: Schools and educators should encourage parental involvement and provide resources to help parents support their children's education.
2. Promote Regular Study Habits: Implement programs and workshops to help students develop effective study habits and time management skills.
3. Support Physical Activity: Schools should provide ample opportunities for students to engage in sports and physical activities, as it has a positive impact on overall student well-being and performance.
4. Address Socioeconomic Disparities: Implement initiatives to support students from lower socioeconomic backgrounds, ensuring they have access to necessary resources and support systems.
5. Tailored Support for Larger Families: Provide additional support and resources to students from larger families to ensure they receive adequate attention and resources for their education.