Install and import kaggle library

Kaggle library is useful to connect to kaggle website and download datasets to local computer.

```
!pip install kaggle
```

```
Requirement already satisfied: kaggle in /usr/local/lib/python3.12/dist-packages (1.7.4.5)
Requirement already satisfied: bleach in /usr/local/lib/python3.12/dist-packages (from kaggle) (6.2.0)
Requirement already satisfied: certifi>=14.05.14 in /usr/local/lib/python3.12/dist-packages (from kaggle) (2025.8.3)
Requirement already satisfied: charset-normalizer in /usr/local/lib/python3.12/dist-packages (from kaggle) (3.4.3)
Requirement already satisfied: idna in /usr/local/lib/python3.12/dist-packages (from kaggle) (3.10)
Requirement already satisfied: protobuf in /usr/local/lib/python3.12/dist-packages (from kaggle) (5.29.5)
Requirement already satisfied: python-dateutil>=2.5.3 in /usr/local/lib/python3.12/dist-packages (from kaggle) (2.9.0.post0)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.12/dist-packages (from kaggle) (8.0.4)
Requirement already satisfied: requests in /usr/local/lib/python3.12/dist-packages (from kaggle) (2.32.4)
Requirement already satisfied: setuptools>=21.0.0 in /usr/local/lib/python3.12/dist-packages (from kaggle) (75.2.0)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.12/dist-packages (from kaggle) (1.17.0)
Requirement already satisfied: text-unidecode in /usr/local/lib/python3.12/dist-packages (from kaggle) (1.3)
Requirement already satisfied: tqdm in /usr/local/lib/python3.12/dist-packages (from kaggle) (4.67.1)
Requirement already satisfied: urllib3>=1.15.1 in /usr/local/lib/python3.12/dist-packages (from kaggle) (2.5.0)
Requirement already satisfied: webencodings in /usr/local/lib/python3.12/dist-packages (from kaggle) (0.5.1)
```

```
import kaggle
```

Download ecommerce datasets from kaggle website using kaggle library

Follow below steps before using kaggle library

```
1. Login to kaggle, go to settings and create new token
2. This will download kaggle.json
3. Now place this file to <home directory>/.kaggle folder
```

```
kaggle.api.authenticate()
```

```
kaggle.api.dataset_download_files('desalegngeb/students-exam-scores', path='.', unzip=True, quiet=False)
```

```
Dataset URL: https://www.kaggle.com/datasets/desalegngeb/students-exam-scores
Downloading students-exam-scores.zip to .
100%|████████████████████████████████████████████████████████████████| 695k/695k [00:00<00:00, 630MB/s]
```

Check the downloaded files using os library

```
import os
```

```
os.listdir()
```

```
['.ipynb_checkpoints',
 'Expanded_data_with_more_features.csv',
 'Original_data_with_more_rows.csv',
 'Student Performance Analysis.ipynb']
```

```
os.rename('Expanded_data_with_more_features.csv','student_scores.csv')
```

```
os.listdir()
```

```
['.ipynb_checkpoints',
 'Original_data_with_more_rows.csv',
 'Student Performance Analysis.ipynb',
 'student_scores.csv']
```

Check the file data using pandas dataframe and make corrections fi required

```
import pandas as pd
import numpy as np
```

```
df = pd.read_csv('student_scores.csv')
df.head()
```

	Unnamed: 0	Gender	EthnicGroup	ParentEduc	LunchType	TestPrep	ParentMaritalStatus	PracticeSport	IsFirstChild	NrSibling
0	0	female	NaN	bachelor's degree	standard	none	married	regularly	yes	3.
1	1	female	group C	some college	standard	NaN	married	sometimes	yes	0.
2	2	female	group B	master's degree	standard	none	single	sometimes	yes	4.
3	3	male	group A	associate's degree	free/reduced	none	married	never	no	1.
4	4	male	group C	some college	standard	none	married	sometimes	yes	0.

Drop unnamed column

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

	Gender	EthnicGroup	ParentEduc	LunchType	TestPrep	ParentMaritalStatus	PracticeSport	IsFirstChild	NrSiblings	Transpo
0	female	NaN	bachelor's degree	standard	none	married	regularly	yes	3.0	sch
1	female	group C	some college	standard	NaN	married	sometimes	yes	0.0	
2	female	group B	master's degree	standard	none	single	sometimes	yes	4.0	sch
3	male	group A	associate's degree	free/reduced	none	married	never	no	1.0	
4	male	group C	some college	standard	none	married	sometimes	yes	0.0	sch

Rename columns

```
df.columns
```

```
Index(['Gender', 'EthnicGroup', 'ParentEduc', 'LunchType', 'TestPrep',
       'ParentMaritalStatus', 'PracticeSport', 'IsFirstChild', 'NrSiblings',
       'TransportMeans', 'WklyStudyHours', 'MathScore', 'ReadingScore',
       'WritingScore'],
      dtype='object')
```

```
df.columns = ['gender', 'ethnic_group', 'parent_education', 'lunch_type', 'test_preparation',
              'parent_marital_status', 'practice_sport', 'is_first_child', 'no_of_siblings',
              'transport_means', 'weekly_study_hours', 'math_score', 'reading_score', 'writing_score']
df.head()
```

	gender	ethnic_group	parent_education	lunch_type	test_preparation	parent_marital_status	practice_sport	is_first_child
0	female	NaN	bachelor's degree	standard	none	married	regularly	yes
1	female	group C	some college	standard	NaN	married	sometimes	yes
2	female	group B	master's degree	standard	none	single	sometimes	yes
3	male	group A	associate's degree	free/reduced	none	married	never	no
4	male	group C	some college	standard	none	married	sometimes	yes

Load the environment variables (database details) using dotenv and os libraries

Create a **.env** file and add the environment variables to this file for security purpose.
Examples:
mssql=mssql://`dbname`/`schemaname`?driver=ODBC+DRIVER+17+FOR+SQL+SERVER

userid=`userid`

password=`password`

Note: Do not enclose variable information into single quotes.

```
import dotenv
```

```
dotenv.load_dotenv()
mssql_db = os.getenv('mssql')
```

Create database connection using sqlalchemy

```
from sqlalchemy import create_engine, text
engine = create_engine(mssql_db)
conn = engine.connect()
```

Create functions

- Create function to map python data type to SQL Server data type
- Create function to generate CREATE TABLE statement
- Create function to calculate elapsed time of data loading process

```
# Map python data type to sql data type
def get_sql_dtype(dtype):
    if pd.api.types.is_integer_dtype(dtype):
        return 'INT'
    elif pd.api.types.is_float_dtype(dtype):
        return 'FLOAT'
    elif pd.api.types.is_bool_dtype(dtype):
        return 'BOOL'
    elif pd.api.types.is_datetime64_any_dtype(dtype):
        return 'DATETIME'
    else:
        return 'VARCHAR'

# Generate create table statement
def create_table_stmt(df, table_name):
    col_list = []
    for col in df.columns:
        col_dtype = get_sql_dtype(df[col].dtype)

        # fetch max lengh of the column data if the column is of object type
        # requied to provide data type length in sql server
        if df[col].dtype == 'object':
            col_len = int(df[col].str.len().max()) + 10
            col_list.append(f'{col} {col_dtype}({col_len})')
        else:
            col_list.append(f'{col} {col_dtype}')

    query = f'create table {table_name} ({', '.join(col_list)})'
    return query

# Calculate elased time in hours, minutes, seconds
def calculate_elapsed_time(start_time, end_time):
    elapsed_time = end_time - start_time
    minutes, seconds = divmod(elapsed_time.total_seconds(), 60)
    hours, minutes = divmod(minutes, 60)
    return (round(hours), round(minutes), round(seconds))
```

Load student scores data to SQL Server using pandas and sqlalchemy libraries

Approach for data load process:

1. Generate create table statement from dataframe and execute into SQL Server
2. Load dataframe data to SQL Server
3. Calculate total time taken in loading process

```
import datetime
```

```
# fetch the current time before starting the load
start_time = datetime.datetime.now()

# generate create table statement for each dataframe
table_name = 'student_performance'
create_table_query = create_table_stmt(df, table_name)
# print(create_table_query)

# execute table statement
conn.execute(text(create_table_query))
conn.commit()

# load data to sql server
df.to_sql(table_name, con=conn, index=False, if_exists='append')
print(f'Successfully loaded {table_name} data to SQL Server')

# fetch the current time after completing the load
end_time = datetime.datetime.now()

# calculate elapsed time and print total time taken to complete the load process
print(f'Total Elapsed Time: {(end_time - start_time).total_seconds()}')
hh, mi, ss = calculate_elapsed_time(start_time, end_time)
print(f'Total time taken: {hh} hrs, {mi} minutes, {ss} seconds')
```

```
Successfully loaded student_performance data to SQL Server
Total Elapsed Time: 17.579607
Total time taken: 0 hrs, 0 minutes, 18 seconds
```

Close the database connection

```
conn.close()
```

Enable SQL magic function

Follow below steps to enable SQL Magic function:

- Load libraries ipython-sql and prettytable `!pip install ipython-sql prettytable` `import prettytable`
- Enable SQL magic by loading the SQL extension `%load_ext sql`
- Fetch the database connection details from environment file using dotenv and os libraries
- Establish connection between SQL magic module and SQL Server `%sql $mssql_db`

```
!pip install ipython-sql prettytable
```

```
Requirement already satisfied: ipython-sql in /usr/local/lib/python3.12/dist-packages (0.5.0)
Requirement already satisfied: prettytable in /usr/local/lib/python3.12/dist-packages (3.16.0)
Requirement already satisfied: ipython in /usr/local/lib/python3.12/dist-packages (from ipython-sql) (7.34.0)
Requirement already satisfied: sqlalchemy>=2.0 in /usr/local/lib/python3.12/dist-packages (from ipython-sql) (2.0.43)
Requirement already satisfied: sqlparse in /usr/local/lib/python3.12/dist-packages (from ipython-sql) (0.5.3)
Requirement already satisfied: six in /usr/local/lib/python3.12/dist-packages (from ipython-sql) (1.17.0)
Requirement already satisfied: ipython-genutils in /usr/local/lib/python3.12/dist-packages (from ipython-sql) (0.2.0)
Requirement already satisfied: wcwidth in /usr/local/lib/python3.12/dist-packages (from prettytable) (0.2.13)
Requirement already satisfied: greenlet>=1 in /usr/local/lib/python3.12/dist-packages (from sqlalchemy>=2.0->ipython-sql) (3.2
Requirement already satisfied: typing-extensions>=4.6.0 in /usr/local/lib/python3.12/dist-packages (from sqlalchemy>=2.0->ipytł
Requirement already satisfied: setuptools>=18.5 in /usr/local/lib/python3.12/dist-packages (from ipython->ipython-sql) (75.2.0)
Collecting jedi>=0.16 (from ipython->ipython-sql)
  Downloading jedi-0.19.2-py2.py3-none-any.whl.metadata (22 kB)
Requirement already satisfied: decorator in /usr/local/lib/python3.12/dist-packages (from ipython->ipython-sql) (4.4.2)
Requirement already satisfied: pickleshare in /usr/local/lib/python3.12/dist-packages (from ipython->ipython-sql) (0.7.5)
Requirement already satisfied: traitlets>=4.2 in /usr/local/lib/python3.12/dist-packages (from ipython->ipython-sql) (5.7.1)
Requirement already satisfied: prompt-toolkit!=3.0.0,!=3.0.1,<3.1.0,>=2.0.0 in /usr/local/lib/python3.12/dist-packages (from ip
Requirement already satisfied: pygments in /usr/local/lib/python3.12/dist-packages (from ipython->ipython-sql) (2.19.2)
Requirement already satisfied: backcall in /usr/local/lib/python3.12/dist-packages (from ipython->ipython-sql) (0.2.0)
Requirement already satisfied: matplotlib-inline in /usr/local/lib/python3.12/dist-packages (from ipython->ipython-sql) (0.1.7)
Requirement already satisfied: pexpect>4.3 in /usr/local/lib/python3.12/dist-packages (from ipython->ipython-sql) (4.9.0)
Requirement already satisfied: parso<0.9.0,>=0.8.4 in /usr/local/lib/python3.12/dist-packages (from jedi>=0.16->ipython->ipythc
Requirement already satisfied: ptyprocess>=0.5 in /usr/local/lib/python3.12/dist-packages (from pexpect>4.3->ipython->ipython-s
Downloading jedi-0.19.2-py2.py3-none-any.whl (1.6 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.6/1.6 MB 15.0 MB/s eta 0:00:00
Installing collected packages: jedi
Successfully installed jedi-0.19.2
```

```
import prettytable
prettytable.DEFAULT = 'DEFAULT'
```

```
%load_ext sql
```

```
# Not needed here as information already fetched while loading data to SQL Server
# import os, dotenv
# dotenv.load_dotenv()
# mssql_db = os.getenv('mssql')
```

```
%sql $mssql_db
```

Import data visualization libraries

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

Analyze student performance data using below methods:

1. Pandas Dataframe
2. SQL
3. Matplotlib/Seaborn

1. Statistical analysis using pandas dataframe

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30641 entries, 0 to 30640
Data columns (total 14 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   gender                30641 non-null  object
 1   ethnic_group          28801 non-null  object
 2   parent_education      28796 non-null  object
 3   lunch_type            30641 non-null  object
 4   test_preparation      28811 non-null  object
 5   parent_marital_status 29451 non-null  object
 6   practice_sport        30010 non-null  object
 7   is_first_child        29737 non-null  object
 8   no_of_siblings        29069 non-null  float64
 9   transport_means       27507 non-null  object
 10  weekly_study_hours    29686 non-null  object
 11  math_score            30641 non-null  int64
 12  reading_score         30641 non-null  int64
 13  writing_score         30641 non-null  int64
dtypes: float64(1), int64(3), object(10)
memory usage: 3.3+ MB
```

```
df.describe()
```

	no_of_siblings	math_score	reading_score	writing_score
count	29069.000000	30641.000000	30641.000000	30641.000000
mean	2.145894	66.558402	69.377533	68.418622
std	1.458242	15.361616	14.758952	15.443525
min	0.000000	0.000000	10.000000	4.000000
25%	1.000000	56.000000	59.000000	58.000000
50%	2.000000	67.000000	70.000000	69.000000
75%	3.000000	78.000000	80.000000	79.000000
max	7.000000	100.000000	100.000000	100.000000

2. Find Total number of records

Using dataframe

```
df.shape
```

```
(30641, 14)
```

Using SQL

```
%%capture --no-display
%sql select count(*) from student_performance;
```

30641

```
%%capture --no-display
%sql SELECT count(COLUMN_NAME) FROM INFORMATION_SCHEMA.COLUMNS WHERE TABLE_NAME = 'student_performance';
```

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3. Count null values in each column

Using dataframe

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

```
gender                    0
ethnic_group           1840
parent_education       1845
lunch_type                0
test_preparation       1830
parent_marital_status  1190
practice_sport          631
is_first_child          904
no_of_siblings         1572
transport_means        3134
weekly_study_hours      955
math_score                0
reading_score             0
writing_score             0
dtype: int64
```

Using SQL

```
%%capture --no-display
%%sql select count(*) - count(gender) null_gender,
count(*) - count(ethnic_group) null_ethnic_group,
count(*) - count(parent_education) null_parent_education,
count(*) - count(lunch_type) null_lunch_type,
count(*) - count(test_preparation) null_test_preparation,
count(*) - count(parent_marital_status) null_parent_marital_status,
count(*) - count(practice_sport) null_practice_sport,
count(*) - count(is_first_child) null_is_first_child,
count(*) - count(no_of_siblings) null_no_of_siblings,
count(*) - count(transport_means) null_transport_means,
count(*) - count(weekly_study_hours) null_weekly_study_hours,
count(*) - count(math_score) null_math_score,
count(*) - count(reading_score) null_reading_score,
count(*) - count(writing_score) null_writing_score
from student_performance;
```

null_gender	null_ethnic_group	null_parent_education	null_lunch_type	null_test_preparation	null_parent_marital_status	null_practice_sport	null_i
0	1840	1845	0	1830	1190	631	904

4. Fetch first 5 rows

Using dataframe

```
df.head()
```

	gender	ethnic_group	parent_education	lunch_type	test_preparation	parent_marital_status	practice_sport	is_first_child
0	female	NaN	bachelor's degree	standard	none	married	regularly	yes
1	female	group C	some college	standard	NaN	married	sometimes	yes
2	female	group B	master's degree	standard	none	single	sometimes	yes
3	male	group A	associate's degree	free/reduced	none	married	never	no
4	male	group C	some college	standard	none	married	sometimes	yes

Using SQL

```
%%capture --no-display
%sql select top 5 * from student_performance;
```

gender	ethnic_group	parent_education	lunch_type	test_preparation	parent_marital_status	practice_sport	is_first_child	no_of_siblings	transport_
female	None	bachelor's degree	standard	none	married	regularly	yes	3.0	school_bu
female	group C	some college	standard	None	married	sometimes	yes	0.0	None
female	group B	master's degree	standard	none	single	sometimes	yes	4.0	school_bu
male	group A	associate's degree	free/reduced	none	married	never	no	1.0	None
male	group C	some college	standard	none	married	sometimes	yes	0.0	school_bu

5. Analyze gender distribution (Count the number of records by gender)

Using dataframe

```
df['gender'].value_counts()
```

```
gender
female    15424
male      15217
Name: count, dtype: int64
```

Using SQL

```
%%capture --no-display
%%sql
select gender, count(*) from student_performance
group by gender;
```

gender	
male	15217
female	15424

Plot the gender distribution using countplot

```
ax = sns.countplot(data=df, x='gender')
ax.bar_label(ax.containers[0])
plt.show()
```

Conclusion: Above chart shows that there are more female students than male.

6. Analyze math_score distribution

Using dataframe - create categorical column for math_score using bins

```
bins = np.linspace(min(df['math_score']), max(df['math_score']), 11)
bins
```

```
array([  0.,  10.,  20.,  30.,  40.,  50.,  60.,  70.,  80.,  90., 100.])
```

```
# Create bins for math_score column using numpy linspace
bins = np.linspace(min(df['math_score']), max(df['math_score']), 11)

# Provide names for bins
group_names = ['0-9', '10-19', '20-29', '30-39', '40-49', '50-59', '60-69', '70-79', '80-89', '90-100']

# add new column for binned values
df['math_score_binned'] = pd.cut(df['math_score'], bins, labels=group_names, include_lowest=True, right=False)

# additionally update records where math_score = 100 as the above statement will exclude math_score = 100 due to parameter ri
df.loc[df['math_score'] == 100, 'math_score_binned'] = '90-100'

df.head()
```

	gender	ethnic_group	parent_education	lunch_type	test_preparation	parent_marital_status	practice_sport	is_first_child
0	female	NaN	bachelor's degree	standard	none	married	regularly	yes
1	female	group C	some college	standard	NaN	married	sometimes	yes
2	female	group B	master's degree	standard	none	single	sometimes	yes
3	male	group A	associate's degree	free/reduced	none	married	never	no
4	male	group C	some college	standard	none	married	sometimes	yes

```
# group by math_score_binned, and count number of records for each bin
# observed is a deprecated attribute, it gives warning with default value, giving observed=True to silent the warning message
df.groupby('math_score_binned', as_index=False, observed=True).size()
```

	math_score_binned	size
0	0-9	7
1	10-19	41
2	20-29	234
3	30-39	1014
4	40-49	2940
5	50-59	5629
6	60-69	7395
7	70-79	6923
8	80-89	4366
9	90-100	2092

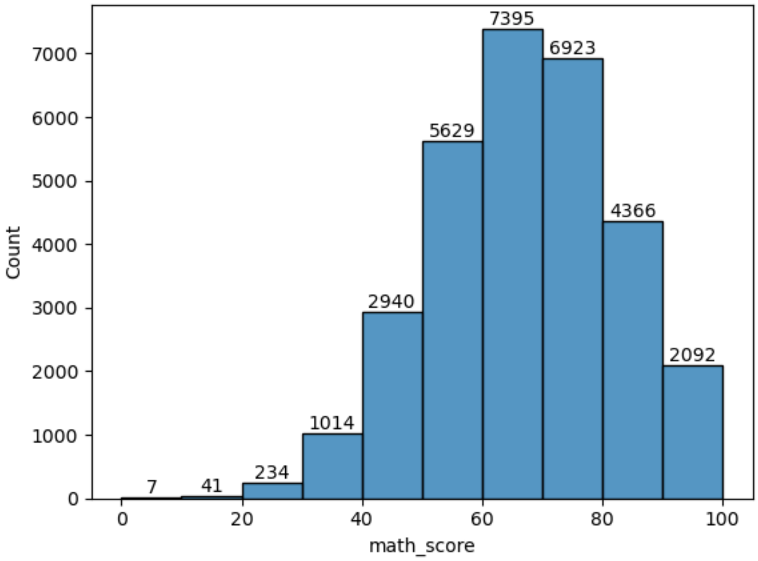
Using SQL

```
%%capture --no-display
%%sql
select math_score_binned, count from (
select sum(case when math_score >= 0 and math_score < 10 then 1 else 0 end) score_between_0_9,
sum(case when math_score >= 10 and math_score < 20 then 1 else 0 end) score_between_10_19,
sum(case when math_score >= 20 and math_score < 30 then 1 else 0 end) score_between_20_29,
sum(case when math_score >= 30 and math_score < 40 then 1 else 0 end) score_between_30_39,
sum(case when math_score >= 40 and math_score < 50 then 1 else 0 end) score_between_40_49,
sum(case when math_score >= 50 and math_score < 60 then 1 else 0 end) score_between_50_59,
sum(case when math_score >= 60 and math_score < 70 then 1 else 0 end) score_between_60_69,
sum(case when math_score >= 70 and math_score < 80 then 1 else 0 end) score_between_70_79,
sum(case when math_score >= 80 and math_score < 90 then 1 else 0 end) score_between_80_89,
sum(case when math_score >= 90 and math_score <= 100 then 1 else 0 end) score_between_90_100
from student_performance) p
unpivot (count for math_score_binned in (score_between_0_9, score_between_10_19, score_between_20_29, score_between_30_39,
score_between_40_49, score_between_50_59, score_between_60_69, score_between_70_79, score_between_80_89, score_between_90_100
order by math_score_binned;
```

math_score_binned	count
score_between_0_9	7
score_between_10_19	41
score_between_20_29	234
score_between_30_39	1014
score_between_40_49	2940
score_between_50_59	5629
score_between_60_69	7395
score_between_70_79	6923
score_between_80_89	4366
score_between_90_100	2092

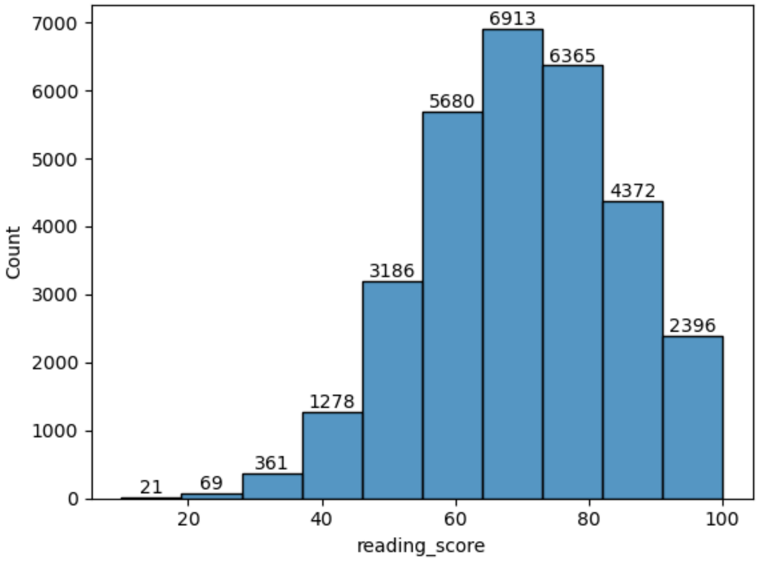
Plot math_score distribution by gender using seaborn's histogram plot - automatically creates bins

```
ax = sns.histplot(data=df, x='math_score', bins=10)
ax.bar_label(ax.containers[0])
plt.show()
```



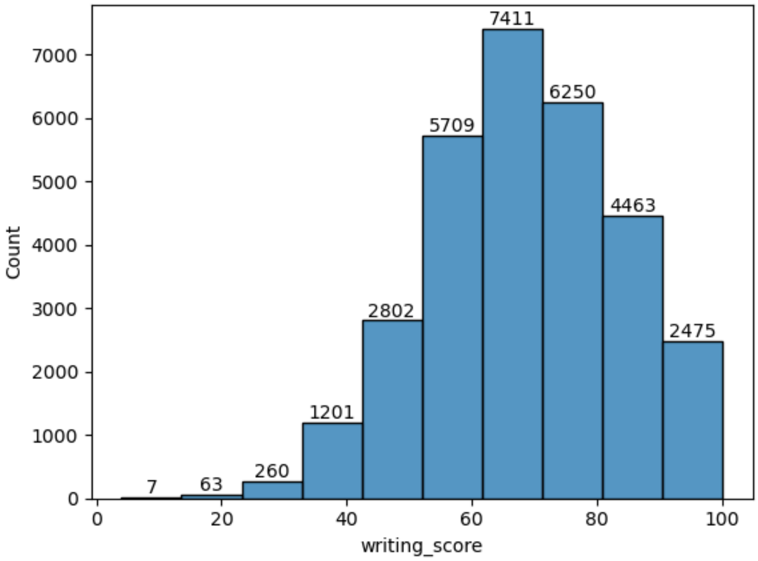
Plot reading_score distribution using seaborn's histogram plot

```
ax = sns.histplot(data=df, x='reading_score', bins=10)
ax.bar_label(ax.containers[0])
plt.show()
```



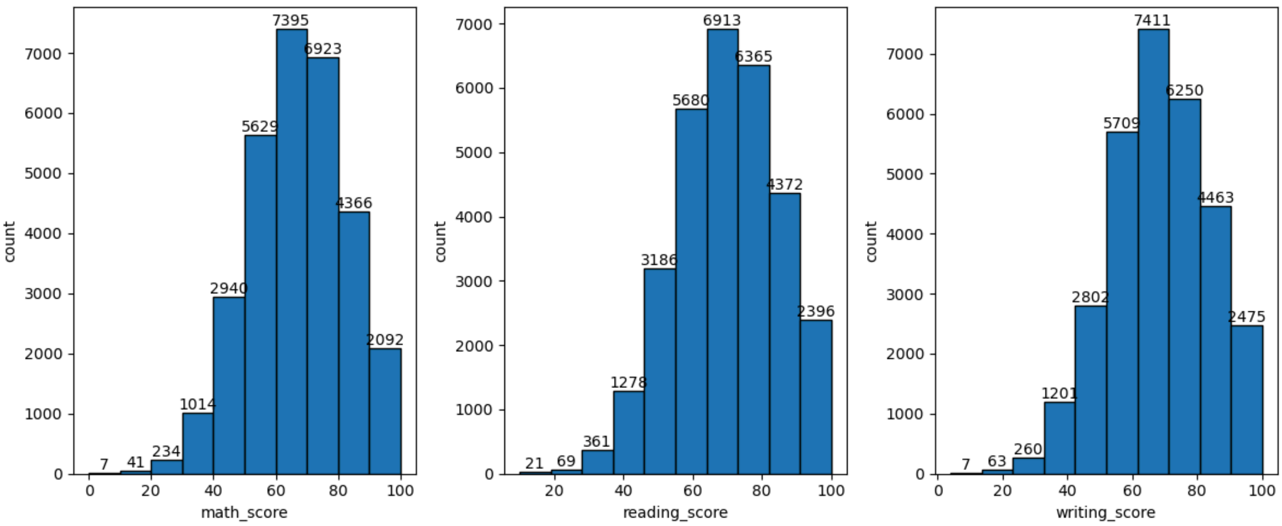
Plot writing_score distribution using seaborn's histogram plot

```
ax = sns.histplot(data=df, x='writing_score', bins=10)
ax.bar_label(ax.containers[0])
plt.show()
```

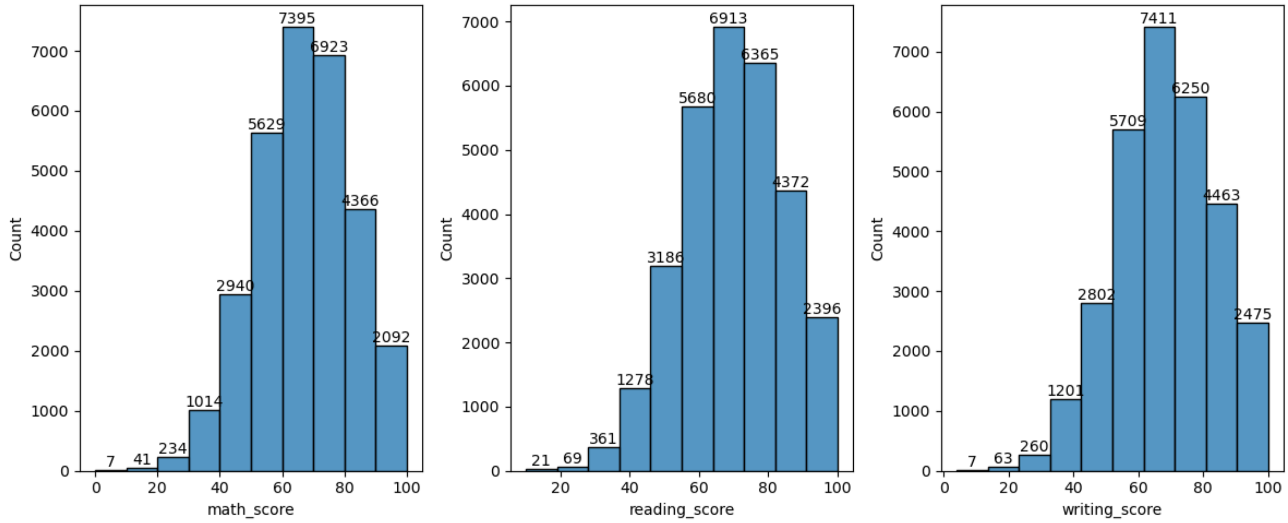


Plot math_score, reading_score and writing_score using matplotlib's subplot functionality

```
fig, axes = plt.subplots(nrows=1,ncols=3, figsize=(12,5))
axes[0].hist(df['math_score'], bins=10, edgecolor='black')
axes[0].bar_label(axes[0].containers[0])
axes[0].set_xlabel('math_score')
axes[0].set_ylabel('count')
axes[1].hist(df['reading_score'], bins=10, edgecolor='black')
axes[1].bar_label(axes[1].containers[0])
axes[1].set_xlabel('reading_score')
axes[1].set_ylabel('count')
axes[2].hist(df['writing_score'], bins=10, edgecolor='black')
axes[2].bar_label(axes[2].containers[0])
axes[2].set_xlabel('writing_score')
axes[2].set_ylabel('count')
plt.tight_layout()
```




```
# Another method by using seaborn's histogram
fig, axes = plt.subplots(nrows=1,ncols=3, figsize=(12,5))
sns.histplot(data=df, x='math_score', bins=10, ax=axes[0])
axes[0].bar_label(axes[0].containers[0])
sns.histplot(data=df, x='reading_score', bins=10, ax=axes[1])
axes[1].bar_label(axes[1].containers[0])
sns.histplot(data=df, x='writing_score', bins=10, ax=axes[2])
axes[2].bar_label(axes[2].containers[0])
plt.tight_layout()
```



Conclusion: Above charts show that most students scored between 50-80 on an average in all subjects.

7. Analyze math_score distribution by gender

Using dataframe

```
# group by gender and math_score_binned, and count number of records for each bin
# sort by math_score_binned and gender
# observed is a deprecated attribute, it gives warning with default value, giving observed=True to silent the warning message
df.groupby(['gender','math_score_binned'], as_index=False, observed=True).size().sort_values(['math_score_binned','gender'])
```

	gender	math_score_binned	size
0	female	0-9	6
10	male	0-9	1
1	female	10-19	32
11	male	10-19	9
2	female	20-29	157
12	male	20-29	77
3	female	30-39	698
13	male	30-39	316
4	female	40-49	1761
14	male	40-49	1179
5	female	50-59	3208
15	male	50-59	2421
6	female	60-69	3760
16	male	60-69	3635
7	female	70-79	3248
17	male	70-79	3675
8	female	80-89	1886
18	male	80-89	2480
9	female	90-100	668
19	male	90-100	1424

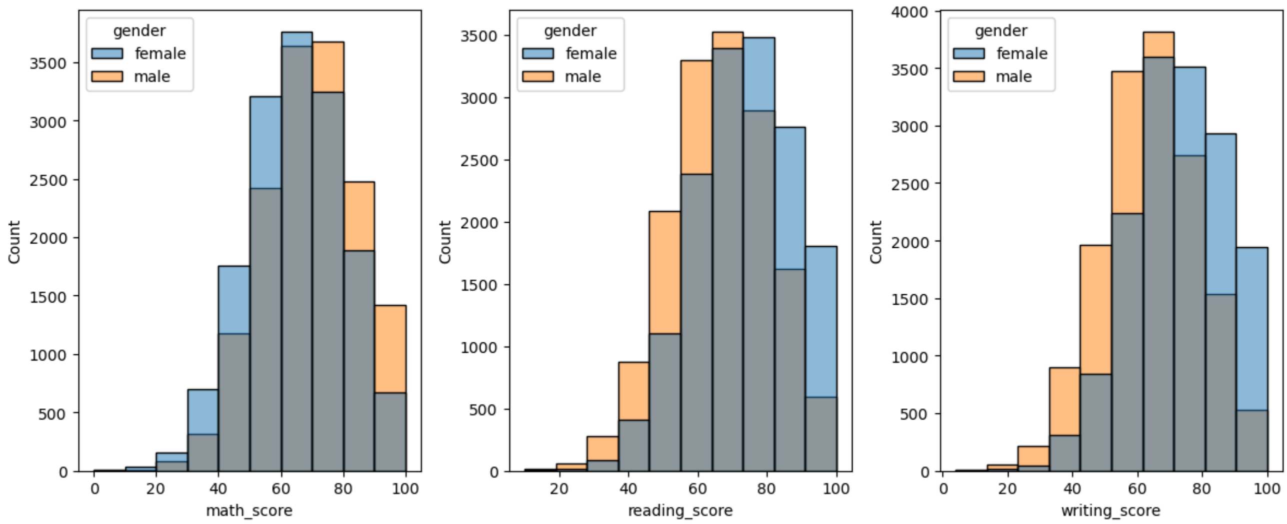
Using SQL

```
%%capture --no-display
%%sql
select gender, math_score_binned, count from (
select gender, sum(case when math_score >= 0 and math_score < 10 then 1 else 0 end) score_between_0_9,
sum(case when math_score >= 10 and math_score < 20 then 1 else 0 end) score_between_10_19,
sum(case when math_score >= 20 and math_score < 30 then 1 else 0 end) score_between_20_29,
sum(case when math_score >= 30 and math_score < 40 then 1 else 0 end) score_between_30_39,
sum(case when math_score >= 40 and math_score < 50 then 1 else 0 end) score_between_40_49,
sum(case when math_score >= 50 and math_score < 60 then 1 else 0 end) score_between_50_59,
sum(case when math_score >= 60 and math_score < 70 then 1 else 0 end) score_between_60_69,
sum(case when math_score >= 70 and math_score < 80 then 1 else 0 end) score_between_70_79,
sum(case when math_score >= 80 and math_score < 90 then 1 else 0 end) score_between_80_89,
sum(case when math_score >= 90 and math_score <= 100 then 1 else 0 end) score_between_90_100
from student_performance
group by gender) p
unpivot (count for math_score_binned in (score_between_0_9, score_between_10_19, score_between_20_29, score_between_30_39,
score_between_40_49, score_between_50_59, score_between_60_69, score_between_70_79, score_between_80_89, score_between_90_100
order by math_score_binned, gender;
```

gender	math_score_binned	count
female	score_between_0_9	6
male	score_between_0_9	1
female	score_between_10_19	32
male	score_between_10_19	9
female	score_between_20_29	157
male	score_between_20_29	77
female	score_between_30_39	698
male	score_between_30_39	316
female	score_between_40_49	1761
male	score_between_40_49	1179
female	score_between_50_59	3208
male	score_between_50_59	2421
female	score_between_60_69	3760
male	score_between_60_69	3635
female	score_between_70_79	3248
male	score_between_70_79	3675
female	score_between_80_89	1886
male	score_between_80_89	2480
female	score_between_90_100	668
male	score_between_90_100	1424

Plot math_score, reading_score and writing_score distribution by gender using matplotlib's subplot and seaborn's histogram plot

```
fig, axes = plt.subplots(nrows=1,ncols=3, figsize=(12,5))
sns.histplot(data=df, x='math_score', hue='gender', bins=10, ax=axes[0])
sns.histplot(data=df, x='reading_score', hue='gender', bins=10, ax=axes[1])
sns.histplot(data=df, x='writing_score', hue='gender', bins=10, ax=axes[2])
plt.tight_layout()
```



Conclusion: Above charts show that male students performed better in Maths while female students performed better in reading and writing.

8. Fetch distinct ethnic groups

Using dataframe

```
df['ethnic_group'].unique()
```

```
array([nan, 'group C', 'group B', 'group A', 'group D', 'group E'],
      dtype=object)
```

Using SQL

```
%%capture --no-display
%sql select distinct ethnic_group from student_performance;
```

ethnic_group
group A
group B
group C
None
group D
group E

9. Analyze the distribution of ethnic group

Using dataframe

```
df_ethnic = df['ethnic_group'].value_counts().to_frame().reset_index().sort_values('ethnic_group')
df_ethnic
```

	ethnic_group	count
4	group A	2219
2	group B	5826
0	group C	9212
1	group D	7503
3	group E	4041

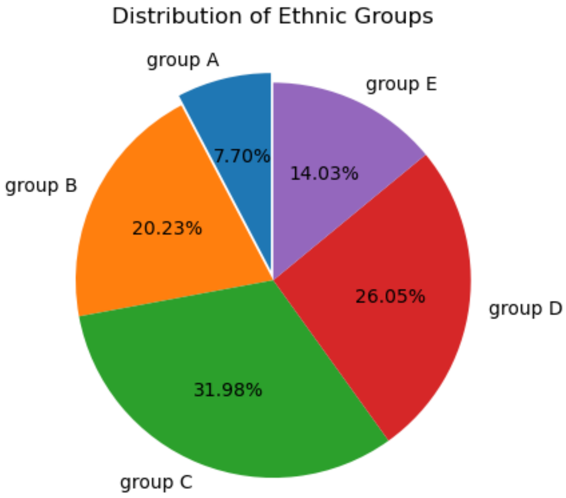
Using SQL

```
%%capture --no-display
%%sql
select ethnic_group, count(*) count
from student_performance
where ethnic_group is not null
group by ethnic_group
order by ethnic_group;
```

ethnic_group	count
group A	2219
group B	5826
group C	9212
group D	7503
group E	4041

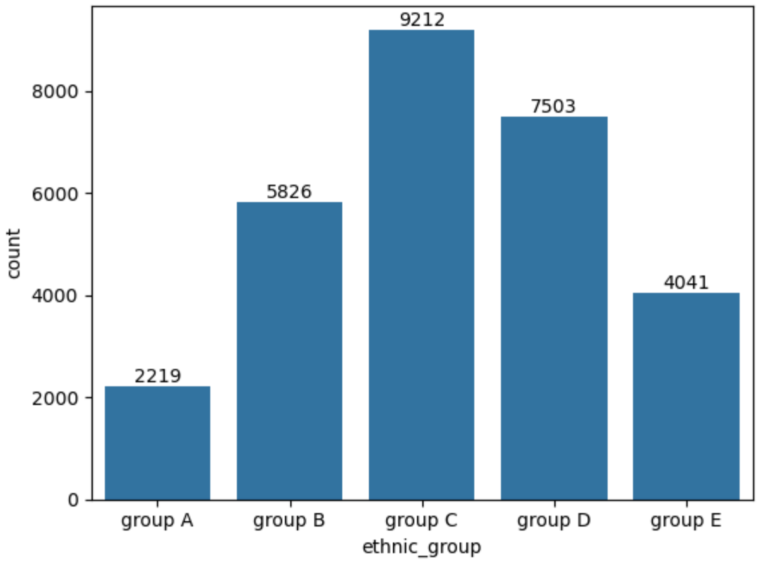
Plot ethnic group distribution using matplotlib's pie chart

```
plt.pie(data=df_ethnic, x='count', labels='ethnic_group', autopct='%1.2f%%', startangle=90, explode=[0.05,0,0,0,0])
plt.title('Distribution of Ethnic Groups')
plt.show()
```



Plot the ethnic group distribution using countplot

```
ax = sns.countplot(data=df, x='ethnic_group', order=['group A','group B','group C','group D','group E'])
ax.bar_label(ax.containers[0])
plt.show()
```



Conclusion: Above chart shows that the maximum number of students (31%) belong to Ethnic Group C and the least number of students (7%) belong to Ethnic Group A.

10. Analyze the distribution of ethnic group by gender

Using dataframe

```
df.groupby(['ethnic_group', 'gender'], as_index=False).size()
```

	ethnic_group	gender	size
0	group A	female	1123
1	group A	male	1096
2	group B	female	2959
3	group B	male	2867
4	group C	female	4613
5	group C	male	4599
6	group D	female	3768
7	group D	male	3735
8	group E	female	2036
9	group E	male	2005

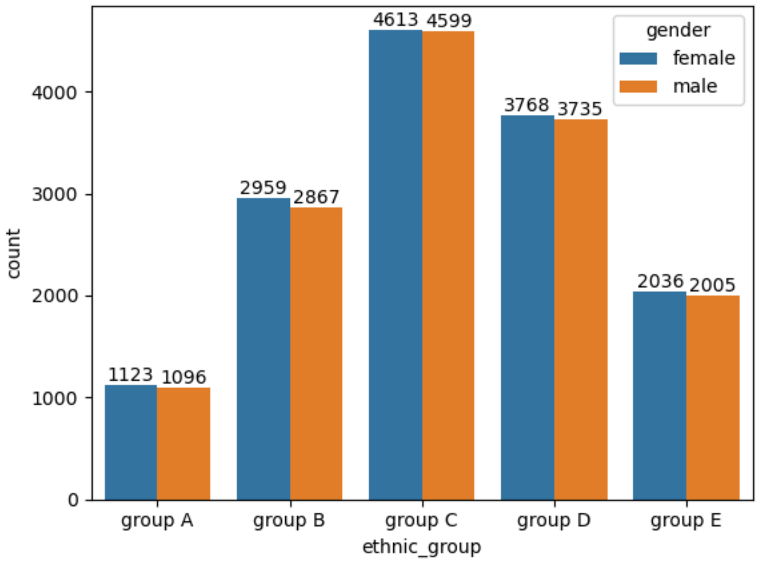
Using SQL

```
%%capture --no-display
%%sql
select ethnic_group, gender, count(*) count
from student_performance
where ethnic_group is not null
group by ethnic_group, gender
order by ethnic_group, gender;
```

ethnic_group	gender	count
group A	female	1123
group A	male	1096
group B	female	2959
group B	male	2867
group C	female	4613
group C	male	4599
group D	female	3768
group D	male	3735
group E	female	2036
group E	male	2005

Plot the ethinic group distribution by gender using countplot

```
ax = sns.countplot(data=df, x='ethnic_group', hue='gender', order=['group A','group B','group C','group D','group E'])
ax.bar_label(ax.containers[0])
ax.bar_label(ax.containers[1])
plt.show()
```



Conclusion: Above chart shows that there is not much impact of gender on ethnic group distribution.

11. Analyze the impact of parent's education on scores

Using dataframe

```
df_grouped_edu = df.groupby('parent_education')[['math_score','reading_score','writing_score']].mean().round(2)
df_grouped_edu
```

	math_score	reading_score	writing_score
parent_education			
associate's degree	68.37	71.12	70.30
bachelor's degree	70.47	73.06	73.33
high school	64.44	67.21	65.42
master's degree	72.34	75.83	76.36
some college	66.39	69.18	68.50
some high school	62.58	65.51	63.63

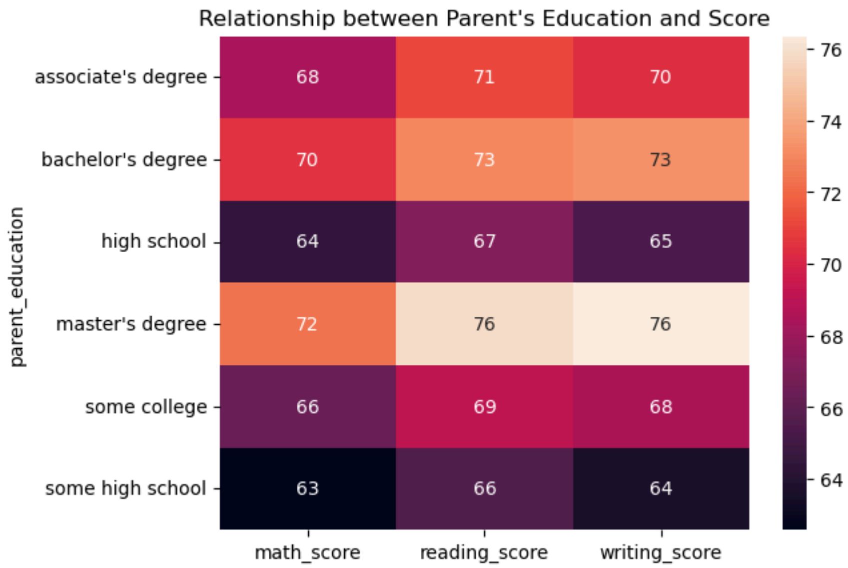
Using SQL

```
%%capture --no-display
%%sql
select parent_education, round(cast(avg(1.0 * math_score) as float), 2) avg_math_score,
round(cast(avg(1.0 * reading_score) as float), 2) avg_reading_score,
round(cast(avg(1.0 * writing_score) as float), 2) avg_writing_score
from student_performance
where parent_education is not null
group by parent_education
order by parent_education;
```

parent_education	avg_math_score	avg_reading_score	avg_writing_score
associate's degree	68.37	71.12	70.3
bachelor's degree	70.47	73.06	73.33
high school	64.44	67.21	65.42
master's degree	72.34	75.83	76.36
some college	66.39	69.18	68.5
some high school	62.58	65.51	63.63

Plot the data using seaborn's heatmap

```
sns.heatmap(data=df_grouped_edu, annot=True)
plt.title('Relationship between Parent\'s Education and Score')
plt.show()
```



Conclusion: Above chart shows that parent's education does have impact on student's scores. Students scored better whose parents have higher education than high school. Students whose parents have done masters, scored highest in all subjects.

12. Analyze the impact of parent's marital status on scores

Using dataframe

```
df_grouped_marital_sts = df.groupby('parent_marital_status').agg({'math_score':'mean','reading_score':'mean','writing_score':
df_grouped_marital_sts
```

parent_marital_status	math_score	reading_score	writing_score
divorced	66.69	69.66	68.80
married	66.66	69.39	68.42
single	66.17	69.16	68.17
widowed	67.37	69.65	68.56

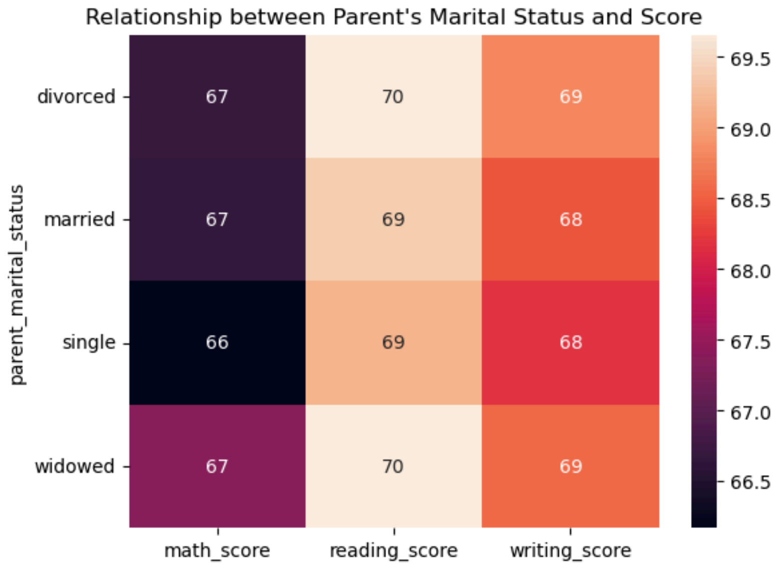
Using SQL

```
%%capture --no-display
%%sql
select parent_marital_status, round(cast(avg(1.0 * math_score) as float), 2) avg_math_score,
round(cast(avg(1.0 * reading_score) as float), 2) avg_reading_score,
round(cast(avg(1.0 * writing_score) as float), 2) avg_writing_score
from student_performance
where parent_marital_status is not null
group by parent_marital_status
order by parent_marital_status;
```

parent_marital_status	avg_math_score	avg_reading_score	avg_writing_score
divorced	66.69	69.66	68.8
married	66.66	69.39	68.42
single	66.17	69.16	68.17
widowed	67.37	69.65	68.56

Plot the data using seaborn's heatmap

```
sns.heatmap(data=df_grouped_marital_sts, annot=True)
plt.title('Relationship between Parent\'s Marital Status and Score')
plt.yticks(rotation=0)
plt.show()
```



Conclusion: Above chart shows that parent's marital status does not have any impact on student's scores.

13. Analyze the impact of student's sports activity on scores

Using dataframe

```
df_grouped_sports = df.groupby('practice_sport').agg({'math_score':'mean','reading_score':'mean','writing_score':'mean'}).rou
df_grouped_sports
```

	math_score	reading_score	writing_score
practice_sport			
never	64.17	68.34	66.52
regularly	67.84	69.94	69.60
sometimes	66.27	69.24	68.07

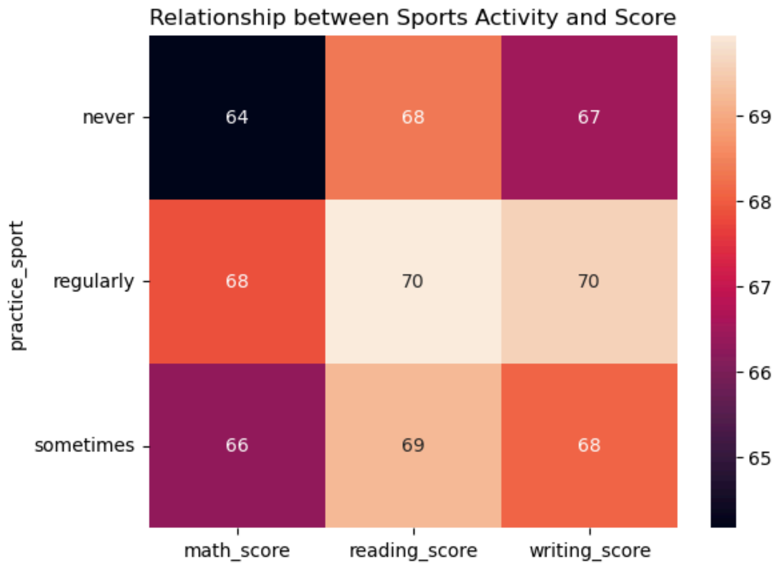
Using SQL

```
%%capture --no-display
%%sql
select practice_sport, round(cast(avg(1.0 * math_score) as float), 2) avg_math_score,
round(cast(avg(1.0 * reading_score) as float), 2) avg_reading_score,
round(cast(avg(1.0 * writing_score) as float), 2) avg_writing_score
from student_performance
where practice_sport is not null
group by practice_sport
order by practice_sport;
```

practice_sport	avg_math_score	avg_reading_score	avg_writing_score
never	64.17	68.34	66.52
regularly	67.84	69.94	69.6
sometimes	66.27	69.24	68.07

Plot the data using seaborn's heatmap

```
sns.heatmap(data=df_grouped_sports, annot=True)
plt.title('Relationship between Sports Activity and Score')
plt.yticks(rotation=0)
plt.show()
```



Conclusion: Above chart shows that students who play regularly, scored high in all subjects and students who never plays, scored lowest in all subjects.

14. Analyze the impact of student's weekly study hours on scores

Using dataframe

```
df_grouped_hours = df.groupby('weekly_study_hours').agg({'math_score':'mean','reading_score':'mean','writing_score':'mean'}).
df_grouped_hours
```

weekly_study_hours	math_score	reading_score	writing_score
5 - 10	66.87	69.66	68.64
< 5	64.58	68.18	67.09
> 10	68.70	70.37	69.78

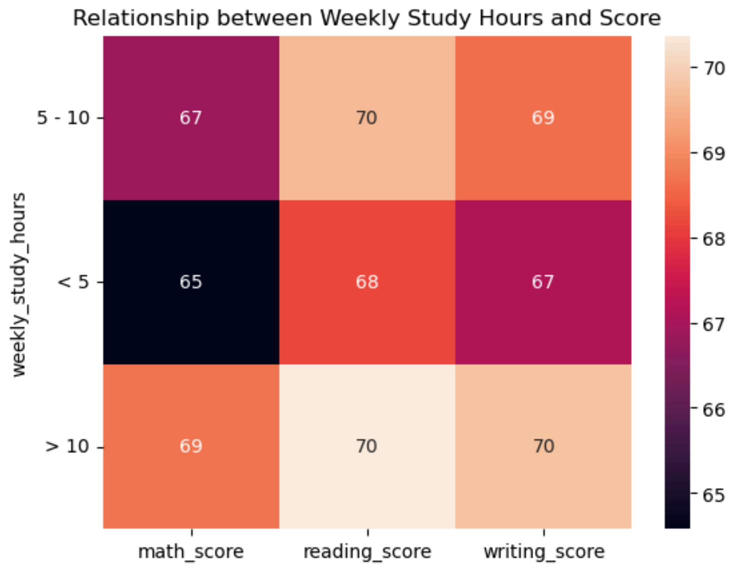
Using SQL

```
%%capture --no-display
%%sql
select weekly_study_hours, round(cast(avg(1.0 * math_score) as float), 2) avg_math_score,
round(cast(avg(1.0 * reading_score) as float), 2) avg_reading_score,
round(cast(avg(1.0 * writing_score) as float), 2) avg_writing_score
from student_performance
where weekly_study_hours is not null
group by weekly_study_hours
order by weekly_study_hours;
```

weekly_study_hours	avg_math_score	avg_reading_score	avg_writing_score
< 5	64.58	68.18	67.09
> 10	68.7	70.37	69.78
5 - 10	66.87	69.66	68.64

Plot the data using seaborn's heatmap

```
sns.heatmap(data=df_grouped_hours, annot=True)
plt.title('Relationship between Weekly Study Hours and Score')
plt.yticks(rotation=0)
plt.show()
```

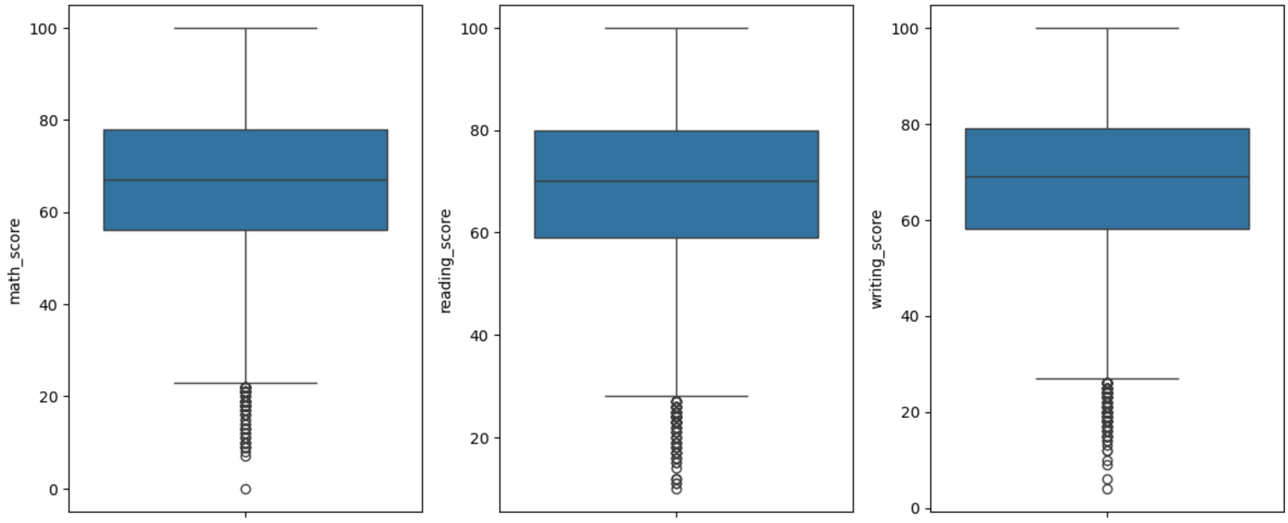


Conclusion: Above chart shows that students who studied more than 10 hours have scored high in all subjects.

Similarly, data can be further analyzed for lunch_type, test_preparation, is_first_child and transport_means columns.

15. Detect outliers for math, reading and writing scores

```
fig, axes = plt.subplots(nrows=1, ncols=3, figsize=(12,5))
sns.boxplot(data=df, y='math_score', ax=axes[0])
sns.boxplot(data=df, y='reading_score', ax=axes[1])
sns.boxplot(data=df, y='writing_score', ax=axes[2])
plt.tight_layout()
plt.show()
```



Conclusion: Above charts show that students are comparitively weak in maths as there are students who have scored zero and minimum score is also low as compared to reading and writing.

16. Identify the correlation between scores

Using dataframe

```
df_corr = df[['math_score','reading_score','writing_score']].corr()
df_corr
```

	math_score	reading_score	writing_score