Assignment 1

January 27, 2025

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

IMPORTING THE DATA

[2]:
```
df=pd.read_csv("StudentsPerformance.csv")
```

0.0.1 EDA

[3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 8 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   gender                       999 non-null    object 
 1   race/ethnicity               999 non-null    object 
 2   parental level of education  998 non-null    object 
 3   lunch                        994 non-null    object 
 4   test preparation course      999 non-null    object 
 5   math score                   999 non-null    float64
 6   reading score                996 non-null    float64
 7   writing score                997 non-null    float64
dtypes: float64(3), object(5)
memory usage: 62.6+ KB
```

[4]:
```
df.describe(include='all')
```

[4]:

	gender	race/ethnicity	parental level of education	lunch	\
count	999	999	998	994	
unique	2	5	6	2	
top	female	group C	some college	standard	
freq	517	319	226	642	
mean	NaN	NaN	NaN	NaN	
std	NaN	NaN	NaN	NaN	
min	NaN	NaN	NaN	NaN	

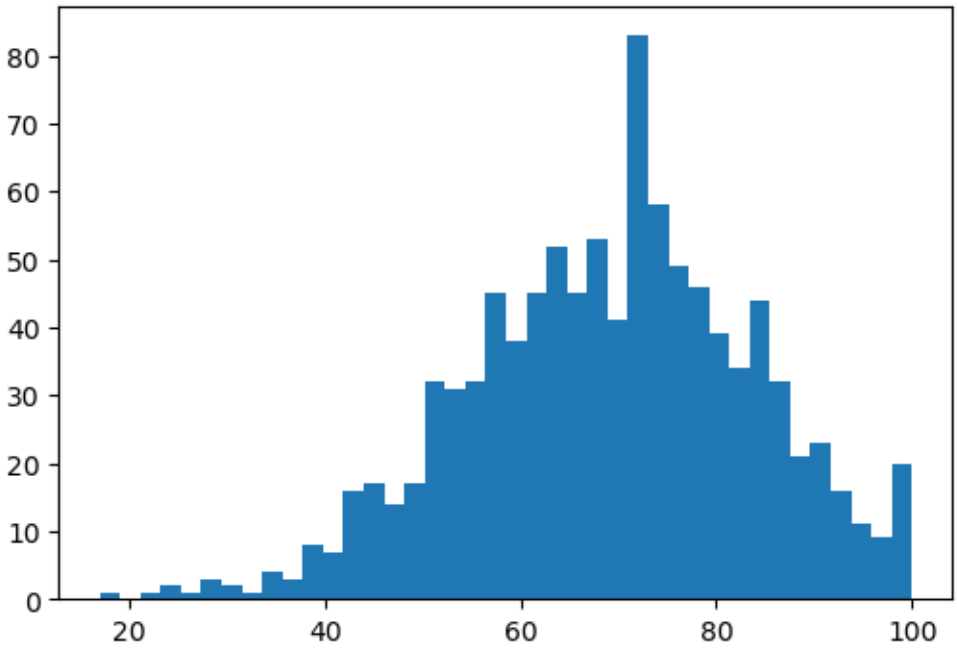
25%	NaN	NaN		NaN	NaN
50%	NaN	NaN		NaN	NaN
75%	NaN	NaN		NaN	NaN
max	NaN	NaN		NaN	NaN

	test preparation course	math score	reading score	writing score
count	999	999.000000	996.000000	997.000000
unique	2	NaN	NaN	NaN
top	none	NaN	NaN	NaN
freq	641	NaN	NaN	NaN
mean	NaN	66.093093	69.173695	68.058175
std	NaN	15.170122	14.625542	15.215409
min	NaN	0.000000	17.000000	10.000000
25%	NaN	57.000000	59.000000	57.000000
50%	NaN	66.000000	70.000000	69.000000
75%	NaN	77.000000	79.250000	79.000000
max	NaN	100.000000	100.000000	100.000000

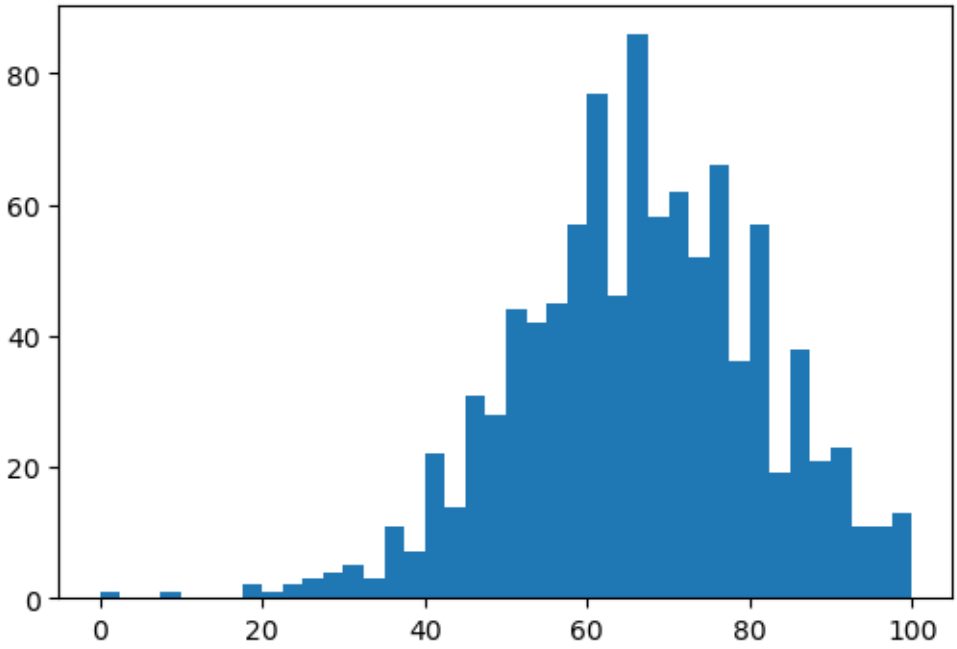
The given dataset belongs to an analysis of Students Performace. It has total 8 columns, 5 categorical and 3 numerical. Considering that the performance of the students is to be evaluated on the basis of all the three scores we will be combining the three scores later on. Null values are present in all columns.

0.0.2 Visualization

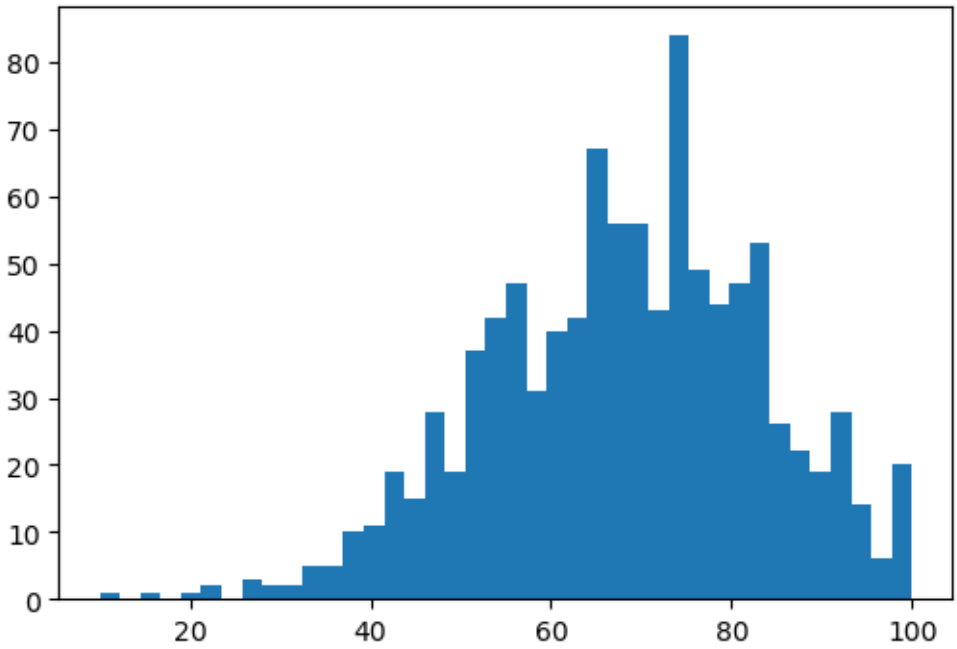
[5]:
```
def histplot(column):
    plt.figure(figsize=(6,4))
    plt.hist(df[column],bins=40)
    plt.show()

histplot('reading score')
```



[6]:
```
histplot('math score')
```

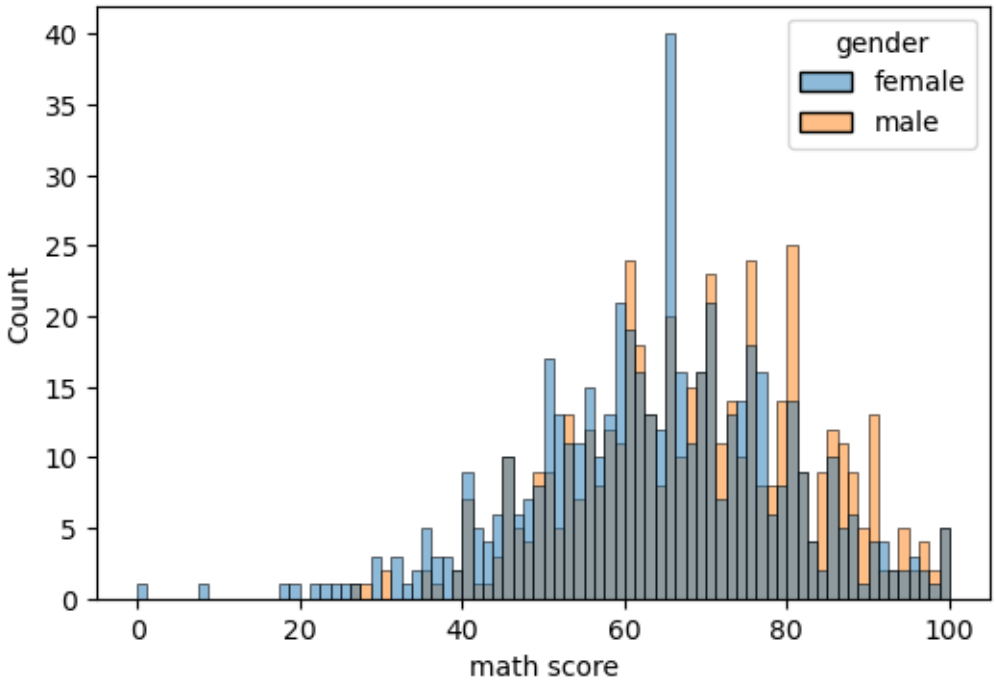


[7]:
```
histplot('writing score')
```

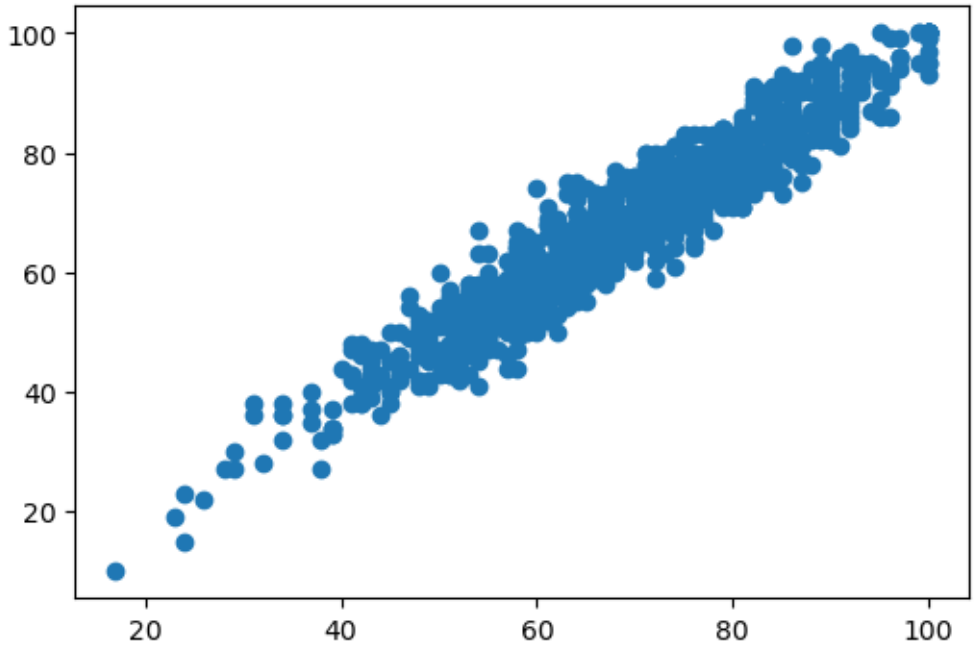


Maximum number of students have marks between 60 to 80 further more very less number of students have marks below 40

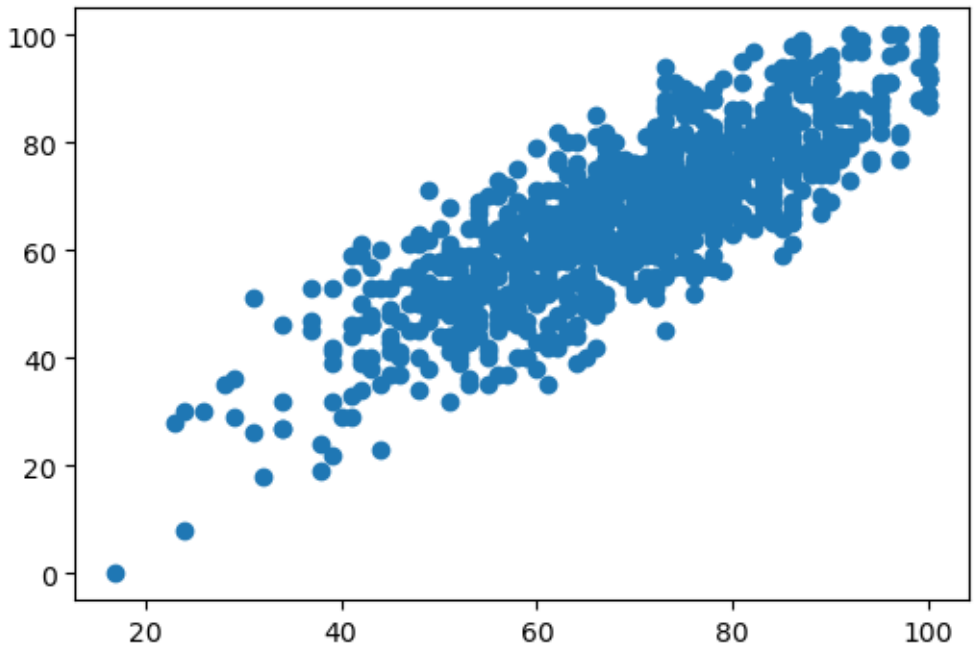
[8]:
```
plt.figure(figsize=(6,4))
sns.histplot(df,x='math score',hue='gender',bins=80)
plt.show()
```



[9]:
```
plt.figure(figsize=(6,4))
plt.scatter(df['reading score'],df['writing score'])
plt.show()
```

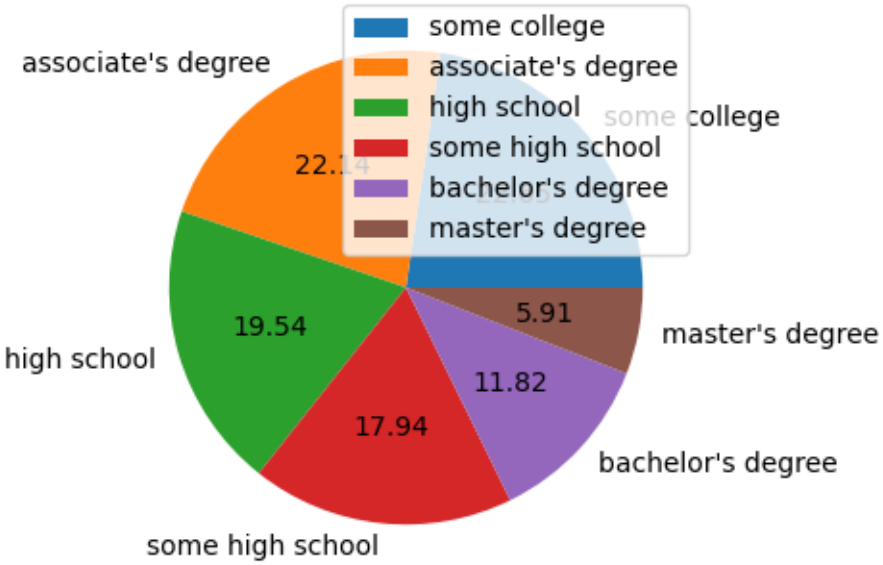


[10]:
```
plt.figure(figsize=(6,4))
plt.scatter(df['reading score'],df['math score'])
plt.show()
```

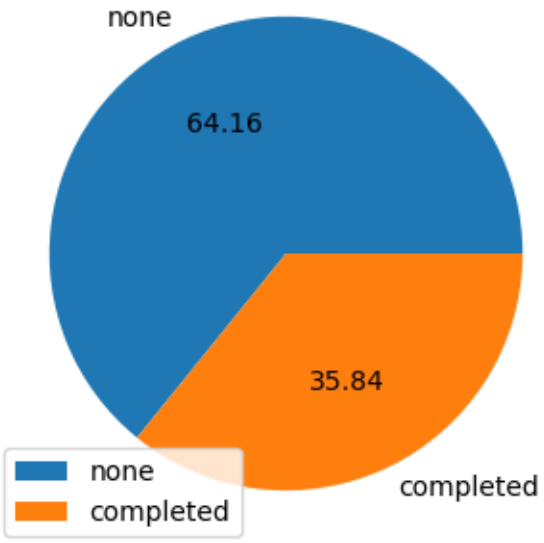


writing and reading score are closely linearly related with each other while math score is a bit different though also having linear relation with the two

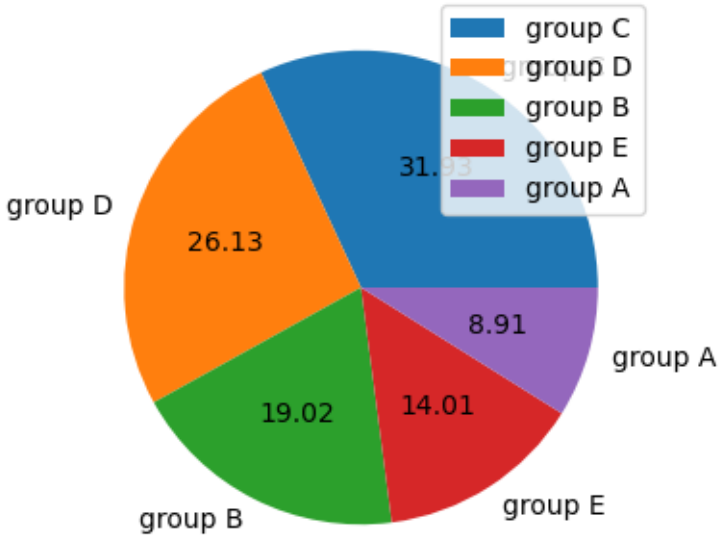
[11]:
```
def pieplot(column):
    plt.figure(figsize=(6,4))
    plt.pie(df[column].value_counts().values,labels=df[column].value_counts().
 ↪index,autopct='%1.2f')
    plt.legend()
pieplot('parental level of education')
```



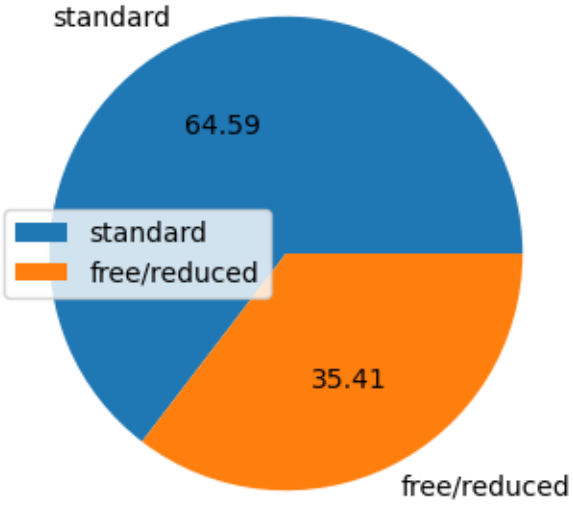
[12]:
```
pieplot('test preparation course')
```



[13]:
```
pieplot('race/ethnicity')
```



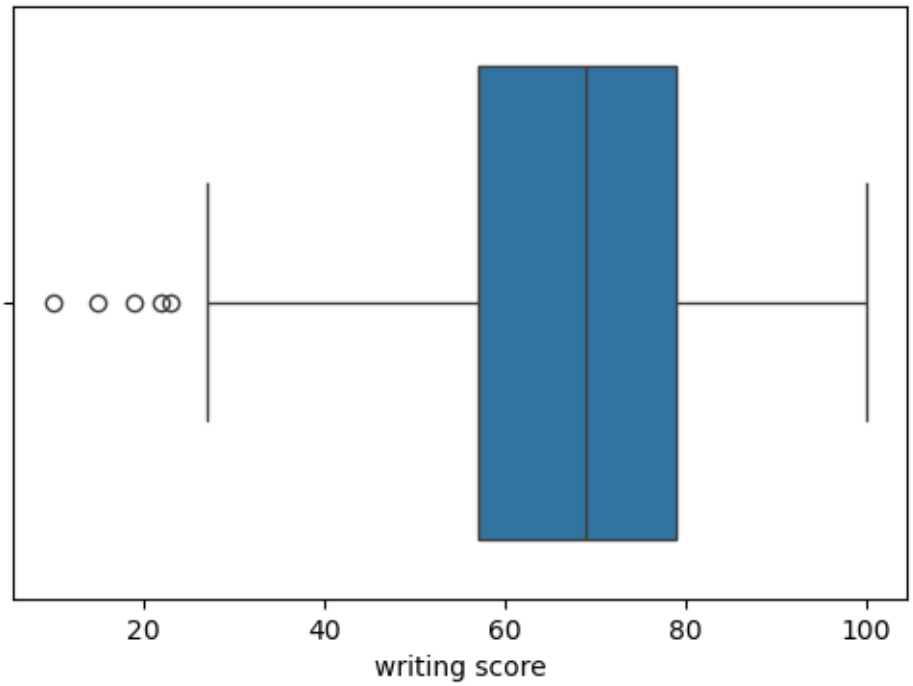
[14]:
```
pieplot('lunch')
```



Very less number of parents have a masters degree. Very less number of students have completed the test preperation course. Most of the students bring a standard lunch

0.0.3 Outlier handling

[15]:
```
def boxplot(column):
    plt.figure(figsize=(6,4))
    sns.boxplot(x=column,data=df)
    plt.show()
boxplot('writing score')
```

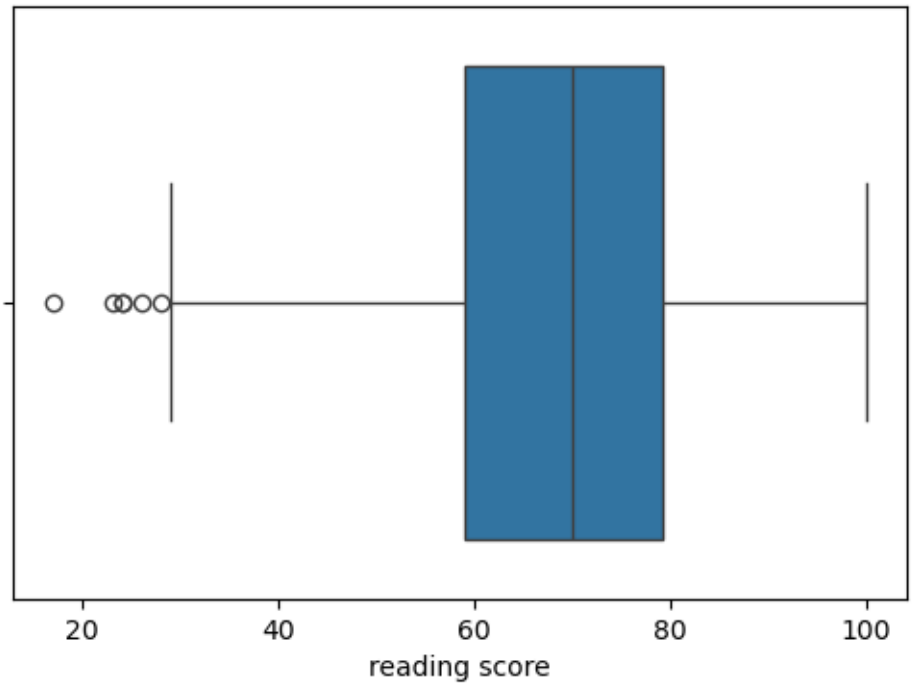


[16]:
```
## as we can see that some of the scores are outliers which are the onces below␣
 ↪30, and most of the scores are between 60 to 80. we will be handling these␣
 ↪outliers with capping
print(df['writing score'].quantile(0.02))
```

```
36.0
```

[17]:
```
df['writing score']=np.where(df['writing score']<36,36,df['writing score'])
```

[18]:
```
boxplot('reading score')
```

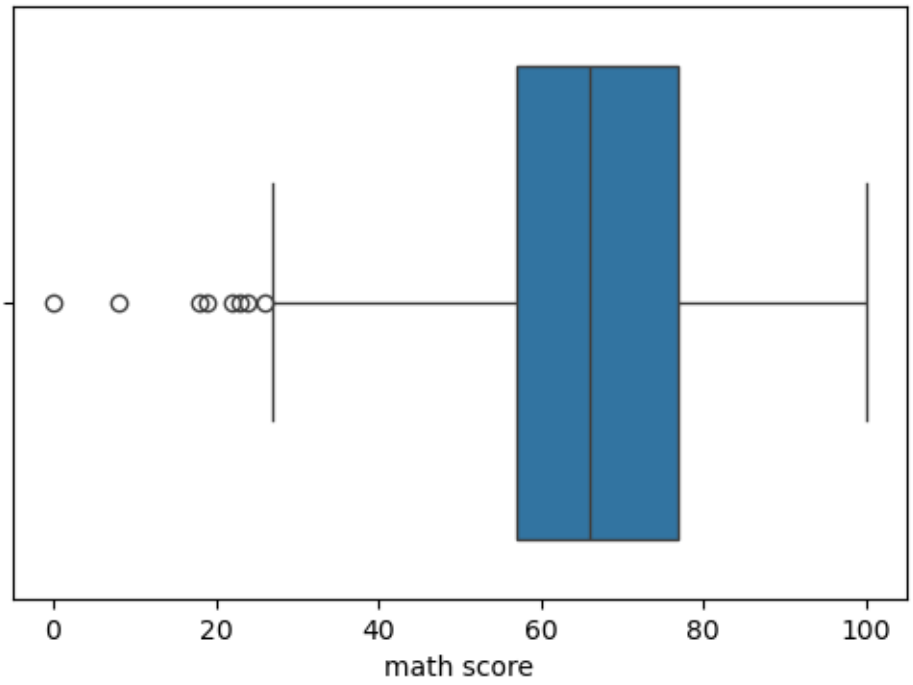


[19]:
```
print(df['reading score'].quantile(0.02))
```

```
38.900000000000006
```

[20]:
```
df['reading score']=np.where(df['reading score']<38.900000000000006,38.
↪900000000000006,df['reading score'])
```

[21]:
```
boxplot('math score')
```



[22]:
```
print(df['math score'].quantile(0.02))
```

```
33.96
```

[23]:
```
df['math score']=np.where(df['math score']<33.96,33.96,df['math score'])
```

0.0.4 Handling Missing Values

[24]:
```
df.isna().sum()
```

[24]:
```
gender                         1
race/ethnicity                 1
parental level of education    2
lunch                          6
test preparation course        1
math score                     1
reading score                  4
writing score                  3
dtype: int64
```

We will be handling missing values of numerical data with mean and categorical data with mode

[25]:
```
for column in df.columns:
    if df[column].dtype!='float64':
        df[column]=df[column].fillna(df[column].mode()[0])
```

```
    else:
        df[column]=df[column].fillna(df[column].median())
```

0.0.5 Handling Categorical Variables

lets convert the categorical data to numerical with one hot encoding and label encoding

[26]:
```
from sklearn import preprocessing
label_encoder=preprocessing.LabelEncoder()
```

[27]:
```
df['gender']=label_encoder.fit_transform(df['gender'])
```

[28]:
```
df['race/ethnicity']=label_encoder.fit_transform(df['race/ethnicity'])
```

[29]:
```
df['lunch']=label_encoder.fit_transform(df['lunch'])
```

[30]:
```
ordinal_encoder=preprocessing.OrdinalEncoder()
```

[31]:
```
df['test preparation course']=ordinal_encoder.fit_transform(df[['test␣
 ↪preparation course']])
```

[32]:
```
df['parental level of education']=ordinal_encoder.fit_transform(df[['parental␣
 ↪level of education']])
```

0.0.6 Standardization

[33]:
```
df['read/write score']=df['reading score']+df['writing score']
```

[34]:
```
df=df.drop('reading score',axis=1)
df=df.drop('writing score',axis=1)
```

[35]:
```
df['math score']=((df['math score']-df['math score'].mean())/df['math score'].
 ↪std())
df['read/write score']=((df['read/write score']-df['read/write score'].mean())/
 ↪df['read/write score'].std())
```

[36]:
```
y_math=df['math score']
y_read_write=df['read/write score']
X=df.drop('math score',axis=1)
X=X.drop('read/write score',axis=1)
```

[37]:
```
## predicting math score
from sklearn.model_selection import train_test_split
X_math_train,X_math_test,y_math_train,y_math_test=train_test_split(X,y_math,test_size=0.
 ↪2,random_state=42)
X_rw_train,X_rw_test,y_rw_train,y_rw_test=train_test_split(X,y_read_write,test_size=0.
 ↪2,random_state=42)
```

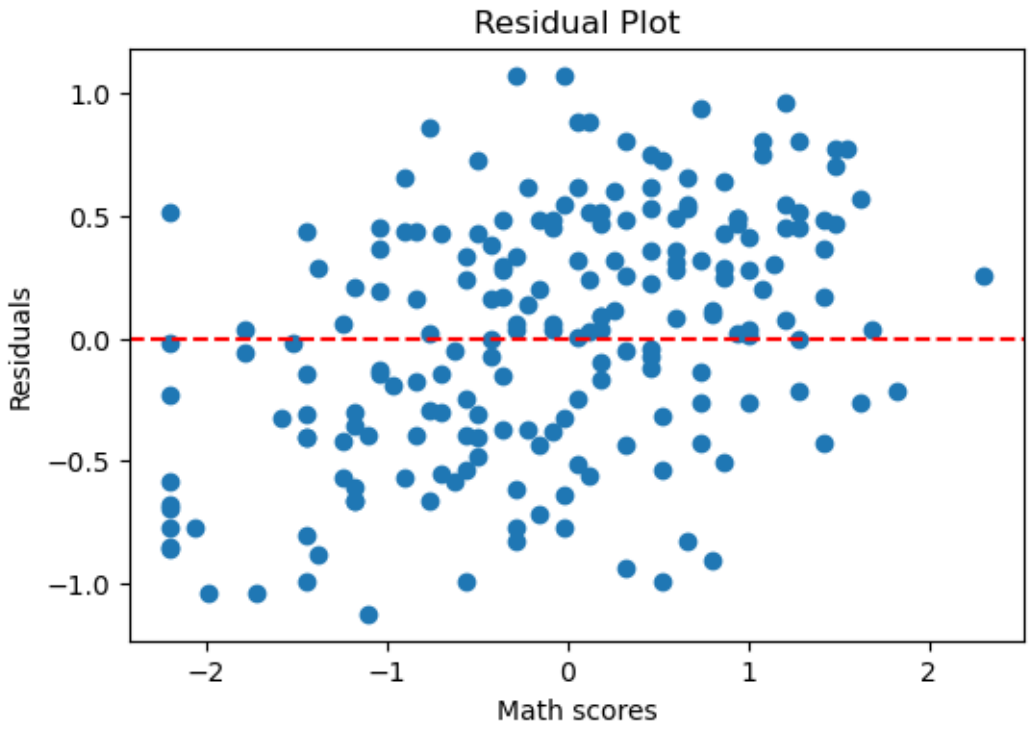
[38]:
```
from sklearn.linear_model import LinearRegression
math_model=LinearRegression().fit(X_math_train,y_math_train)
rw_model=LinearRegression().fit(X_rw_train,y_rw_train)
```

[39]:
```
y_math_pred=math_model.predict(X_math_test)
y_rw_pred=rw_model.predict(X_rw_test)
```

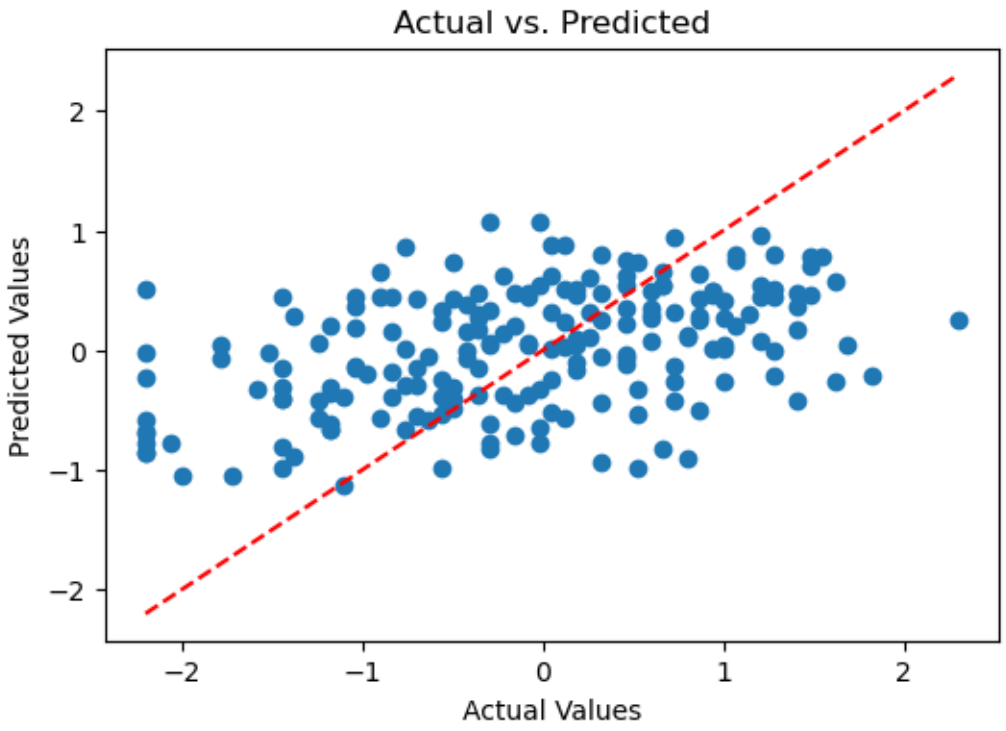
[40]:
```
from sklearn.metrics import mean_squared_error
math_mse=mean_squared_error(y_math_test,y_math_pred)
rw_mse=mean_squared_error(y_rw_test,y_rw_pred)
print("Math RMSE:",np.sqrt(math_mse))
print("Reading/Writing RMSE:",np.sqrt(rw_mse))
```

```
Math RMSE: 0.9035927938583902
Reading/Writing RMSE: 0.8954409352422096
```

[41]:
```
import seaborn as sns

math_residuals = y_math_pred

# Plot residuals
plt.figure(figsize=(6,4))
plt.scatter(y_math_test, math_residuals)
plt.axhline(0, color='red', linestyle='--')
plt.xlabel("Math scores")
plt.ylabel("Residuals")
plt.title("Residual Plot")
plt.show()
```



[42]:
```
plt.figure(figsize=(6,4))
plt.scatter(y_math_test, y_math_pred)
plt.plot([y_math_test.min(), y_math_test.max()], [y_math_test.min(),␣
 ↪y_math_test.max()], color="red", linestyle="--")  # 45-degree line
plt.xlabel("Actual Values")
plt.ylabel("Predicted Values")
plt.title("Actual vs. Predicted")
plt.show()
```


Actual vs. Predicted
Predicted Values
Actual Values
2
1
0
−1
−2
−2
−1
0
1
2