# EDA on Student's Performance Dataset

In [1]:
```
#comment
#observations
```

## Import requirements

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

In [192…
```
#load dataset
df1=pd.read_csv('student.csv')
```

In [4]:
```
#first 5 rows
df1.head()
```

Out[4]:

| | gender | race/ethnicity | parental level of education | lunch | test preparation course | math score | reading score | writing score |
|---|---|---|---|---|---|---|---|---|
| 0 | female | group B | bachelor's degree | standard | none | 72 | 72 | 74 |
| 1 | female | group C | some college | standard | completed | 69 | 90 | 88 |
| 2 | female | group B | master's degree | standard | none | 90 | 95 | 93 |
| 3 | male | group A | associate's degree | free/reduced | none | 47 | 57 | 44 |
| 4 | male | group C | some college | standard | none | 76 | 78 | 75 |

In [6]:
```
#last 5 rows
df1.tail()
```

Out[6]:

| | gender | race/ethnicity | parental level of education | lunch | test preparation course | math score | reading score | writing score |
|---|---|---|---|---|---|---|---|---|
| 995 | female | group E | master's degree | standard | completed | 88 | 99 | 95 |
| 996 | male | group C | high school | free/reduced | none | 62 | 55 | 55 |
| 997 | female | group C | high school | free/reduced | completed | 59 | 71 | 65 |
| 998 | female | group D | some college | standard | completed | 68 | 78 | 77 |
| 999 | female | group D | some college | free/reduced | none | 77 | 86 | 86 |

In [10]:
```
#Data Types of all features

'''
gender                              -->Categorical Nominal(Nomianl or Ordinal)
race/ethnicity                      -->Categorical Nominal
parental level of education         -->Categorical Ordinal
lunch                               -->Categorical Nominal
test preparation course             -->Categorical Nominal
math score                          -->Numerical Continuous(Continuous or Discrete)
reading score                       -->Numerical Continuous
writing score                       -->Numerical Continuous
'''
```

Out[10]:
```
'\ngender                              -->Categorical Nominal(Nomianl or Ordinal)\nrace/ethnicity
-->Categorical Nominal\nparental level of education        -->Categorical Ordinal\nlunch
-->Categorical Nominal\ntest preparation course            -->Categorical Nominal\nmath score
-->Numerical Continuous(Continuous or Discrete)\nreading score                      -->Numerical Continuous\nwrit
ing score                       -->Numerical Continuous\n'
```

In [25]:
```
#number of rows and columns
df1.shape
```

Out[25]:
```
(1000, 8)
```

In [11]:
```
#Data Types using Python
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 8 columns):
 #   Column                       Non-Null Count  Dtype 
---  ------                       --------------  ----- 
 0   gender                       1000 non-null   object
 1   race/ethnicity               1000 non-null   object
 2   parental level of education  1000 non-null   object
 3   lunch                        1000 non-null   object
 4   test preparation course      1000 non-null   object
 5   math score                   1000 non-null   int64 
 6   reading score                1000 non-null   int64 
 7   writing score                1000 non-null   int64 
dtypes: int64(3), object(5)
memory usage: 62.6+ KB
```

In [12]:
```
#Data Type of any particular Column
df1['gender'].dtypes
```

Out[12]:
```
dtype('O')
```

In [15]:
```
#column names
df1.columns
```

Out[15]:
```
Index(['gender', 'race/ethnicity', 'parental level of education', 'lunch',
       'test preparation course', 'math score', 'reading score',
       'writing score'],
      dtype='object')
```

In [17]:
```
#Column names using list comprehenssion
[feature for feature in df1.columns]
```

Out[17]:
```
['gender',
 'race/ethnicity',
 'parental level of education',
 'lunch',
 'test preparation course',
 'math score',
 'reading score',
 'writing score']
```

In [23]:
```
#Segregate Data Types(categorical) using list comprehenssion
cat_fea=[fea for fea in df1.columns if df1[fea].dtypes=='O']
cat_fea
```

Out[23]:
```
['gender',
 'race/ethnicity',
 'parental level of education',
 'lunch',
 'test preparation course']
```

In [24]:
```
#Segregate Data Types(numerical) using list comprehenssion
num_fea=[fea for fea in df1.columns if df1[fea].dtypes!='O']
num_fea
```

Out[24]:
```
['math score', 'reading score', 'writing score']
```

In [30]:
```
#memory(in bytes) this data-set is consuming
```

```
df1.memory_usage()
```

Out[30]:
```
Index                          128
gender                        8000
race/ethnicity                8000
parental level of education    8000
lunch                         8000
test preparation course       8000
math score                    8000
reading score                 8000
writing score                 8000
dtype: int64
```

In [31]:
```
#total memory consumption
df1.memory_usage().sum()
```

Out[31]:
```
64128
```

# Exploratory Data Analysis(EDA)

## Missing Values

In [32]:
```
#column-wise missing values
df1.isnull().sum()
```

Out[32]:
```
gender                        0
race/ethnicity                0
parental level of education    0
lunch                         0
test preparation course       0
math score                    0
reading score                 0
writing score                 0
dtype: int64
```

In [33]:
```
#total missing values
df1.isnull().sum().sum()
```

Out[33]:
```
0
```

## Duplicate Rows

In [35]:
```
#total duplicate rows in dataframe
df1.duplicated().sum()
```

Out[35]:
```
0
```

## Number of Unique Values in a column

In [38]:
```
#number of unique values in all the columns
df1.nunique()
```

Out[38]:
```
gender                         2
race/ethnicity                 5
parental level of education    6
lunch                          2
test preparation course        2
math score                    81
reading score                 72
writing score                 77
dtype: int64
```

In [42]:
```
#number of unique values in particular column
df1['race/ethnicity'].nunique()
```

Out[42]:
```
5
```

In [43]:
```
#unique values in particular column
df1['race/ethnicity'].unique()
```

Out[43]:
```
array(['group B', 'group C', 'group A', 'group D', 'group E'],
      dtype=object)
```

In [63]:
```
#unique values for all columns
for fea in df1.columns:
    print(f'{fea}:{df1[fea].unique()}\n')
```

```
gender:['female' 'male']

race/ethnicity:['group B' 'group C' 'group A' 'group D' 'group E']

parental level of education:["bachelor's degree" 'some college' "master's degree" "associate's degree"
 'high school' 'some high school']

lunch:['standard' 'free/reduced']

test preparation course:['none' 'completed']

math score:[ 72  69  90  47  76  71  88  40  64  38  58  65  78  50  18  46  54  66
  44  74  73  67  70  62  63  56  97  81  75  57  55  53  59  82  77  33
  52   0  79  39  45  60  61  41  49  30  80  42  27  43  68  85  98  87
  51  99  84  91  83  89  22 100  96  94  48  35  34  86  92  37  28  24
  26  95  36  29  32  93  19  23   8]

reading score:[ 72  90  95  57  78  83  43  64  60  54  52  81  53  75  89  32  42  58
  69  73  71  74  70  65  87  56  61  84  55  44  41  85  59  17  39  80
  37  63  51  49  26  68  45  47  86  34  79  66  67  91 100  76  77  82
  92  93  62  88  50  28  48  46  23  38  94  97  99  31  96  24  29  40]

writing score:[ 74  88  93  44  75  78  92  39  67  50  52  43  73  70  58  86  28  46
  61  63  53  80  72  55  65  38  82  79  83  59  57  54  68  66  62  76
  48  42  87  49  10  34  71  37  56  41  22  81  45  36  89  47  90 100
  64  98  51  40  84  69  33  60  85  91  77  27  94  95  19  35  32  96
  97  99  15  30  23]
```

## Statistical Analysis

Applied only on Numerical Columns

### describe() data

In [45]:
```
#Central tendencies(mean, std, count), disperssion of data(min, 25%, 50%, 75%, max)(we find by using quartiles)
df1.describe()
```

Out[45]:

| | math score | reading score | writing score |
|---|---|---|---|
| **count** | 1000.00000 | 1000.000000 | 1000.000000 |
| **mean** | 66.08900 | 69.169000 | 68.054000 |
| **std** | 15.16308 | 14.600192 | 15.195657 |
| **min** | 0.00000 | 17.000000 | 10.000000 |
| **25%** | 57.00000 | 59.000000 | 57.750000 |
| **50%** | 66.00000 | 70.000000 | 69.000000 |
| **75%** | 77.00000 | 79.000000 | 79.000000 |
| **max** | 100.00000 | 100.000000 | 100.000000 |

In [50]:
```
#transpose
#df1.describe().transpose()
# OR
df1.describe().T
```

Out[50]:

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **math score** | 1000.0 | 66.089 | 15.163080 | 0.0 | 57.00 | 66.0 | 77.0 | 100.0 |
| **reading score** | 1000.0 | 69.169 | 14.600192 | 17.0 | 59.00 | 70.0 | 79.0 | 100.0 |
| **writing score** | 1000.0 | 68.054 | 15.195657 | 10.0 | 57.75 | 69.0 | 79.0 | 100.0 |

## Correlation among features(numerical)

In [53]:
```
#correlation between fetures
df1.corr()
#observation-->if we are good reader, then we are good writer (because correlation is 0.95...)
```

Out[53]:

| | math score | reading score | writing score |
|---|---|---|---|
| **math score** | 1.000000 | 0.817580 | 0.802642 |
| **reading score** | 0.817580 | 1.000000 | 0.954598 |
| **writing score** | 0.802642 | 0.954598 | 1.000000 |

## Covariance among features(numerical)

In [54]:
```
#covariance between features
df1.cov()
```

Out[54]:

| | math score | reading score | writing score |
|---|---|---|---|
| **math score** | 229.918998 | 180.998958 | 184.939133 |
| **reading score** | 180.998958 | 213.165605 | 211.786661 |
| **writing score** | 184.939133 | 211.786661 | 230.907992 |

## Skewness

In [55]:
```
#Skewness
df1.skew()
#observation-->data looks left skewed
```

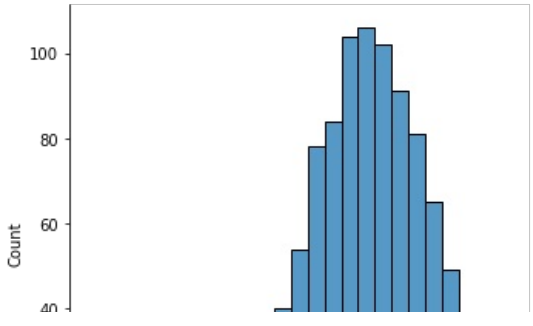
Out[55]:
```
math score      -0.278935
reading score   -0.259105
writing score   -0.289444
dtype: float64
```

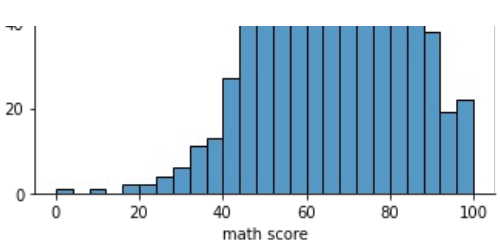
## displot(histograms), kdeplot and distplots(combination of both) for numerical features

distribution plots(tells about how data is distributed)

In [97]:
```
#displot(histogram) for 'math score'
sns.displot(df1['math score'])
```

Out[97]:
```
<seaborn.axisgrid.FacetGrid at 0x275b4f834c0>
```

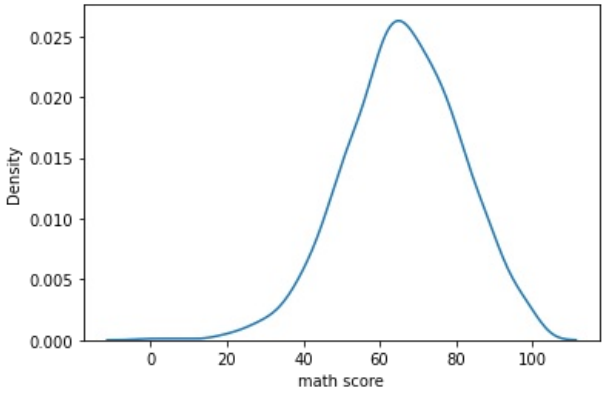





In [100…

```
#kdeplot for 'math score'
sns.kdeplot(df1['math score'])
```

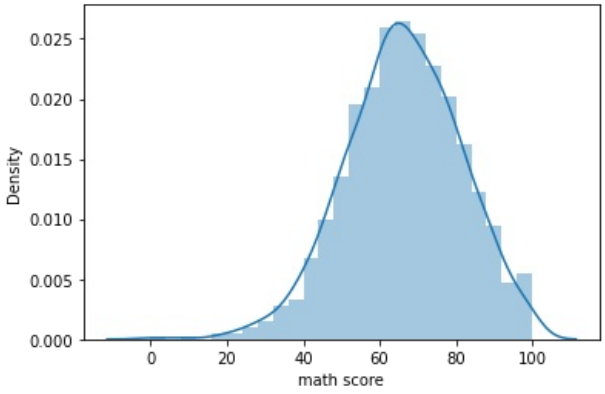
Out[100… <AxesSubplot:xlabel='math score', ylabel='Density'>




In [56]:

```
#distplot for 'math score'
sns.distplot(df1['math score'])
#looks left skewed
```

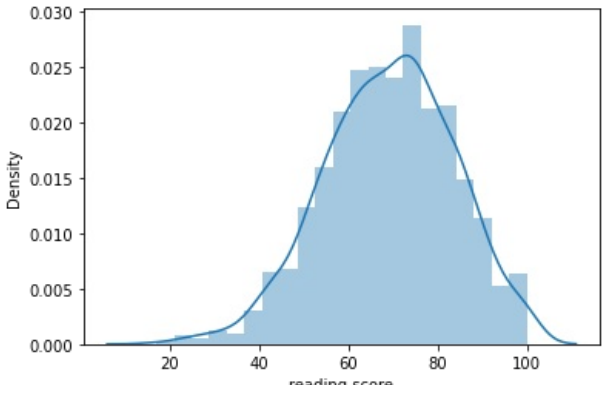
Out[56]: <AxesSubplot:xlabel='math score', ylabel='Density'>




In [57]:

```
#distplot for 'reading score'
sns.distplot(df1['reading score'])
#looks left skewed
```

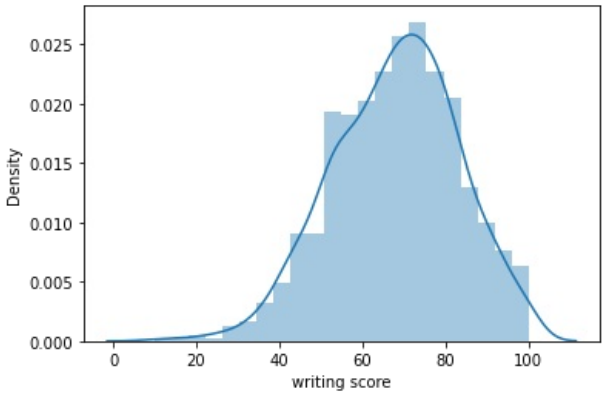
Out[57]: <AxesSubplot:xlabel='reading score', ylabel='Density'>



reading score

In [58]:
```
#distplot for 'writing score'
sns.distplot(df1['writing score'])
#looks left skewed
```

Out[58]:
```
<AxesSubplot:xlabel='writing score', ylabel='Density'>
```




**all plots looks normally dsitributed**

### row-wise average

Numerical Columns only

In [64]:
```
#row-wise average of numerical fetures
(df1['math score']+df1['reading score']+df1['writing score'])/3
```

Out[64]:
```
0      72.666667
1      82.333333
2      92.666667
3      49.333333
4      76.333333
         ...
995    94.000000
996    57.333333
997    65.000000
998    74.333333
999    83.000000
Length: 1000, dtype: float64
```

In [75]:
```
#add a new feature 'avg_score' in datafrane
df1['avg_score']=(df1['math score']+df1['reading score']+df1['writing score'])/3
df1.head()
```

Out[75]:

| | gender | race/ethnicity | parental level of education | lunch | test preparation course | math score | reading score | writing score | avg_score |
|---|---|---|---|---|---|---|---|---|---|
| **0** | female | group B | bachelor's degree | standard | none | 72 | 72 | 74 | 72.666667 |
| **1** | female | group C | some college | standard | completed | 69 | 90 | 88 | 82.333333 |
| **2** | female | group B | master's degree | standard | none | 90 | 95 | 93 | 92.666667 |
| **3** | male | group A | associate's degree | free/reduced | none | 47 | 57 | 44 | 49.333333 |
| **4** | male | group C | some college | standard | none | 76 | 78 | 75 | 76.333333 |

## Group-by operations

In [76]:
```
#group-by 'gender'
df1.groupby('gender')
```

Out[76]:
```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x00000275B5DD7910>
```

In [77]:
```
#group-by 'gender' and find mean of 'math score'
df1.groupby('gender')['math score'].mean()
```

Out[77]:
```
gender
female    63.633205
male      68.728216
Name: math score, dtype: float64
```

In [78]:
```
#group-by 'gender' and find mean of all features(numerical)
df1.groupby('gender').mean()
```

Out[78]:

| gender | math score | reading score | writing score | avg_score |
|---|---|---|---|---|
| **female** | 63.633205 | 72.608108 | 72.467181 | 69.569498 |
| **male** | 68.728216 | 65.473029 | 63.311203 | 65.837483 |

**Ques:** find number of students having 'math score' less than 30

In [85]:
```
#data of students having 'math score'<30
df1[df1['math score']<30]
```

Out[85]:

| | gender | race/ethnicity | parental level of education | lunch | test preparation course | math score | reading score | writing score | avg_score |
|---|---|---|---|---|---|---|---|---|---|
| **17** | female | group B | some high school | free/reduced | none | 18 | 32 | 28 | 26.000000 |
| **59** | female | group C | some high school | free/reduced | none | 0 | 17 | 10 | 9.000000 |
| **91** | male | group C | high school | free/reduced | none | 27 | 34 | 36 | 32.333333 |
| **145** | female | group C | some college | free/reduced | none | 22 | 39 | 33 | 31.333333 |
| **327** | male | group A | some college | free/reduced | none | 28 | 23 | 19 | 23.333333 |
| **338** | female | group B | some high school | free/reduced | none | 24 | 38 | 27 | 29.666667 |
| **363** | female | group D | some high school | free/reduced | none | 27 | 34 | 32 | 31.000000 |
| **466** | female | group D | associate's degree | free/reduced | none | 26 | 31 | 38 | 31.666667 |
| **528** | female | group D | bachelor's degree | free/reduced | none | 29 | 41 | 47 | 39.000000 |
| **601** | female | group C | high school | standard | none | 29 | 29 | 30 | 29.333333 |
| **683** | female | group C | some high school | free/reduced | completed | 29 | 40 | 44 | 37.666667 |
| **787** | female | group B | some college | standard | none | 19 | 38 | 32 | 29.666667 |
| **842** | female | group B | high school | free/reduced | completed | 23 | 44 | 36 | 34.333333 |
| **980** | female | group B | high school | free/reduced | none | 8 | 24 | 23 | 18.333333 |

In [84]:
```
#number of students having 'math score'<30
len(df1[df1['math score']<30])
```

Out[84]:
```
14
```

## Normality of features(numerical)

In [87]:
```
#numerical features only
num_fea
```

Out[87]:
```
['math score', 'reading score', 'writing score']
```

In [90]:
```
#numerical data only
df1_num=df1[num_fea]
df1_num.head()
```

Out[90]:

| | math score | reading score | writing score |
|---|---|---|---|
| **0** | 72 | 72 | 74 |
| **1** | 69 | 90 | 88 |
| **2** | 90 | 95 | 93 |
| **3** | 47 | 57 | 44 |
| **4** | 76 | 78 | 75 |

**when p>0.05 then data will be normally distributed**

In [91]:
```
#normaltest from scipy.stats library
from scipy.stats import normaltest
```

In [92]:
```
#check normality of 'math score'
normaltest(df1_num['math score'])
```

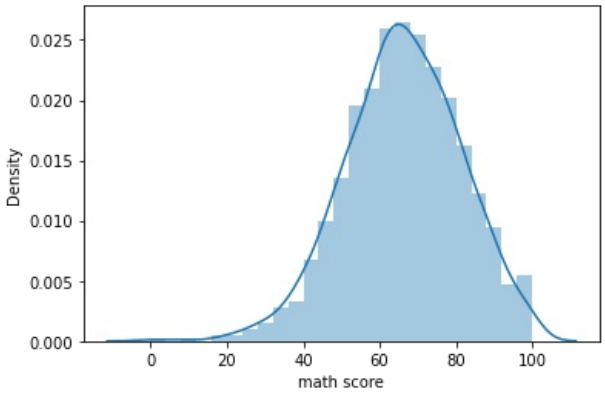
Out[92]:
```
NormaltestResult(statistic=15.408960513931822, pvalue=0.00045080293869937836)
```

In [96]:
```
#p-value of 'math score'
normaltest(df1_num['math score'])[1]*100
#observation->since p-value=0.045<0.05 ('math score' is non-normally distributed)
#whereas in distplot it looked like it is, but it was little left-skewed.
```

Out[96]:
```
0.04508029386993784
```

In [101…
```
#distplot for 'math score'
sns.distplot(df1['math score'])
#looks left skewed
```

Out[101…
```
<AxesSubplot:xlabel='math score', ylabel='Density'>
```




## Outlier Detection

Spread of data [Q0, Q1, Q2, Q3, Q4]=[0, 25, 50, 75, 100]percentile

Inter-Quartile Range(IQR)=Q3-Q1

upper-limit/upper-fence=Q3+1.5*IQR

lower-limit/lower-fence=Q1-1.5*IQR

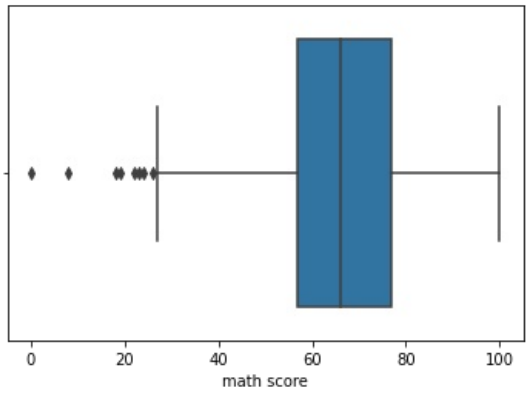
In [109…
```
#numerical features
num_fea
```

Out[109…
```
['math score', 'reading score', 'writing score']
```

In [104…
```
#outlier detection('math score') through boxplot
```

```
sns.boxplot(df1['math score']) # for horizontal plot
```

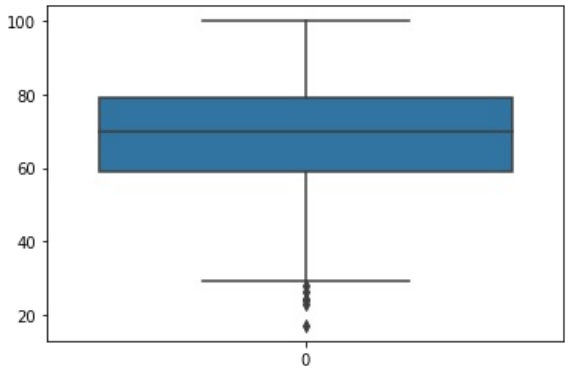
Out[104… <AxesSubplot:xlabel='math score'>




In [111…

```
#outlier detection('reading score') through boxplot
sns.boxplot(data=df1['reading score']) # for vertical plot
```

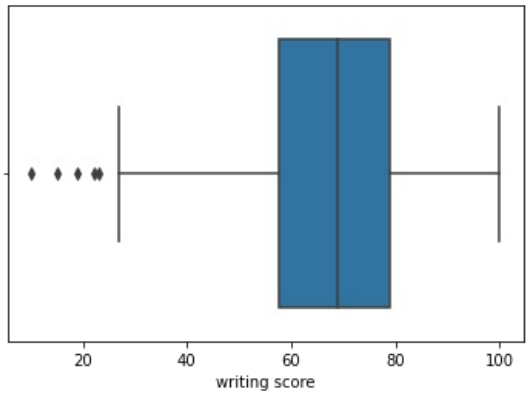
Out[111… <AxesSubplot:>




In [112…

```
#outlier detection('writing score') through boxplot
sns.boxplot(df1['writing score']) # for horizontal plot
```

Out[112… <AxesSubplot:xlabel='writing score'>




**also we have seen in distplots that plots were left skewed, and here we see plots are having left-outliers**

In [117…

```
#through python(find quantiles)

print(df1['math score'].min())          #minumum value
print(df1['math score'].quantile(0.10)) #10 percentile
print(df1['math score'].quantile(0.50)) #50 percentile
print(df1['math score'].quantile(0.90)) #90 percentile
print(df1['math score'].quantile(1.00)) #100 percentile
print(df1['math score'].max())          #maximum value
```

```
#observation-->looks like very few data(10%) in between 0 and 47-->so that's why we got left-outliers.

#How this spread of data happens?
#data is first sorted in ascending order then we find percentiles as required.
```

```
0
47.0
66.0
86.0
100.0
100
```

In [121…

```
#outlier detection through python(find min, max, q1, q3, IQR, lower-fence, upper-fence and finally outliers)
min_=df1['math score'].min()
max_=df1['math score'].max()
q1=df1['math score'].quantile(0.10) #we can set q1 to 25 percentile also(its upto us)
q3=df1['math score'].quantile(0.90) #we can set q3 to 75 percentile also(its upto us)
IQR=q3-q1
lower_fence=q1-(1.5*IQR)
upper_fence=q3+(1.5*IQR)
```

In [123…

```
#print all values
print(f'min:{min_}, max:{max_}, q1:{q1}, q3:{q3}, IQR:{IQR}, lower limit:{lower_fence}, upper limit:{upper_fence}
#observation-->minimum value=0 and lower limit=-11.5(no outliers)
#observation-->maximum value=100 and upper limit=144.5(no outliers

#so we need to change percentiles(q1 and q2)
```

```
min:0, max:100, q1:47.0, q3:86.0, IQR:39.0, lower limit:-11.5, upper limit:144.5
```

In [119…

```
#outliers?-->means data<lower_fence or data>upper_fence
```

In [130…

```
#create a function to get lower and upper limits of all numerical columns
def get_iqr(data, columns, q1_perc, q3_perc):
    for fea in columns:
        min_=data[fea].min()
        max_=data[fea].max()
        q1=data[fea].quantile(q1_perc)
        q3=data[fea].quantile(q3_perc)
        iqr=q3-q1
        lower_fence=q1-(1.5*iqr)
        upper_fence=q3+(1.5*iqr)
        print(f'feature:{fea}-->min:{min_}, max:{max_}, lower limit:{lower_fence}, upper limit:{upper_fence}\n')
```

In [131…

```
get_iqr(df1, num_fea, 0.25, 0.75)
```

```
feature:math score-->min:0, max:100, lower limit:27.0, upper limit:107.0

feature:reading score-->min:17, max:100, lower limit:29.0, upper limit:109.0

feature:writing score-->min:10, max:100, lower limit:25.875, upper limit:110.875
```

In [141…

```
#to drop outliers data?
```

## Graphical Analysis

In [143…

```
#data first 5 rows
df1.head()
```

Out[143…

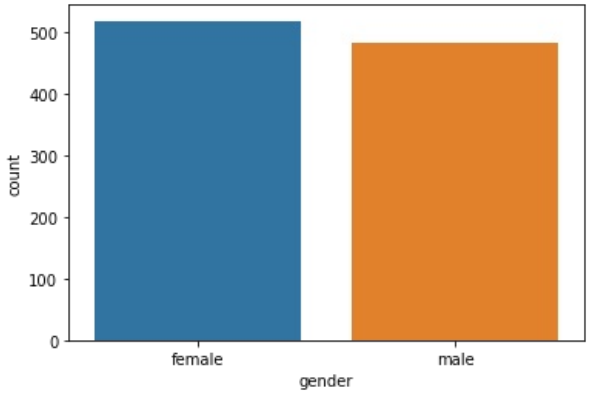
| | gender | race/ethnicity | parental level of education | lunch | test preparation course | math score | reading score | writing score | avg_score |
|---|---|---|---|---|---|---|---|---|---|
| **0** | female | group B | bachelor's degree | standard | none | 72 | 72 | 74 | 72.666667 |
| **1** | female | group C | some college | standard | completed | 69 | 90 | 88 | 82.333333 |
| **2** | female | group B | master's degree | standard | none | 90 | 95 | 93 | 92.666667 |
| **3** | male | group A | associate's degree | free/reduced | none | 47 | 57 | 44 | 49.333333 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **4** | male | group C | some college | standard | none | 76 | 78 | 75 | 76.333333 |

## Univariate Analysis

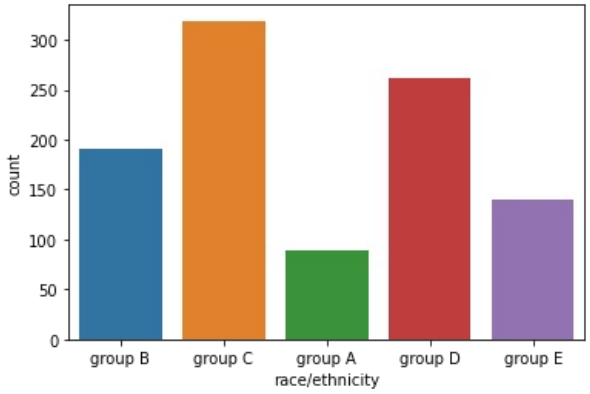
In [146…
```
#countplot --> 'gender'
sns.countplot(df1['gender'])
#observation-->balanced data
```

Out[146… <AxesSubplot:xlabel='gender', ylabel='count'>




In [145…
```
#countplot --> 'gender'
sns.countplot(df1['race/ethnicity'])
#observation-->imbalanced data
```

Out[145… <AxesSubplot:xlabel='race/ethnicity', ylabel='count'>




## Bivariate Analysis

In [149…
```
#groupby operation on gender
df1_gender=df1.groupby('gender').mean()
df1_gender
```

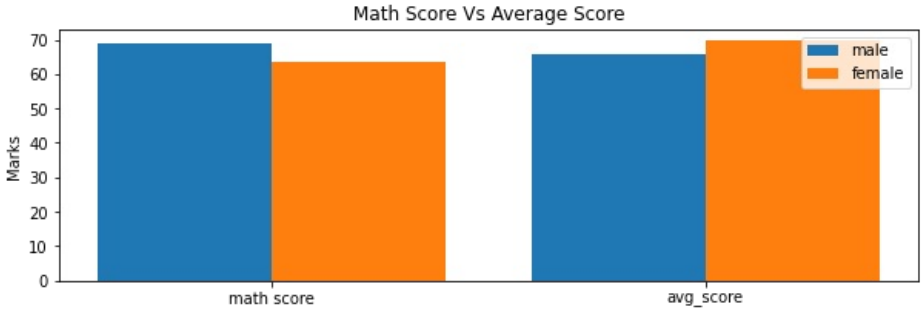
Out[149…

| gender | math score | reading score | writing score | avg_score |
|---|---|---|---|---|
| **female** | 63.633205 | 72.608108 | 72.467181 | 69.569498 |
| **male** | 68.728216 | 65.473029 | 63.311203 | 65.837483 |

In [154…
```
#math score and avg_score for female and male

#female
print(df1_gender['math score'][0])
print(df1_gender['avg_score'][0])

#male
print(df1_gender['math score'][1])
print(df1_gender['avg_score'][1])
```

```
63.633204633204635
69.56949806949811
68.72821576763485
65.83748271092671
```

In [160…
```
#bivarite analysis (math score, avg_score) for gender
plt.figure(figsize=(10,3))
X=['math score', 'avg_score']
female_score=df1_gender['math score'][0], df1_gender['avg_score'][0]
male_score  =df1_gender['math score'][1], df1_gender['avg_score'][1]
X_axis=np.arange(len(X))
plt.bar(X_axis-0.2, male_score, 0.4, label='male')
plt.bar(X_axis+0.2, female_score, 0.4, label='female')

plt.xticks(X_axis, X)
plt.ylabel("Marks")
plt.title("Math Score Vs Average Score")
plt.legend()
plt.show()
```




## Multivariate Analysis

1. heatmap
2. pairplot
3. violinplot

In [163…
```
#numerical data only
df1_num=df1[num_fea]
df1_num.head()
```

Out[163…

| | math score | reading score | writing score |
|---|---|---|---|
| **0** | 72 | 72 | 74 |
| **1** | 69 | 90 | 88 |
| **2** | 90 | 95 | 93 |
| **3** | 47 | 57 | 44 |
| **4** | 76 | 78 | 75 |

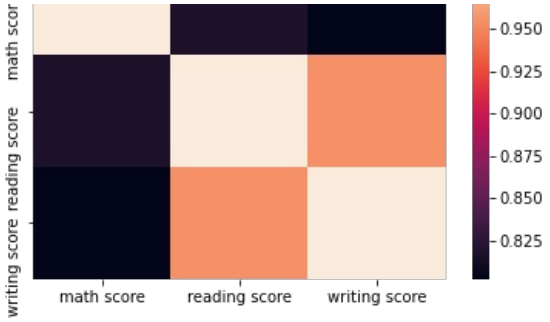
In [183…
```
#correlation between numerical features
df1_num.corr()
```

Out[183…

| | math score | reading score | writing score |
|---|---|---|---|
| **math score** | 1.000000 | 0.817580 | 0.802642 |
| **reading score** | 0.817580 | 1.000000 | 0.954598 |
| **writing score** | 0.802642 | 0.954598 | 1.000000 |

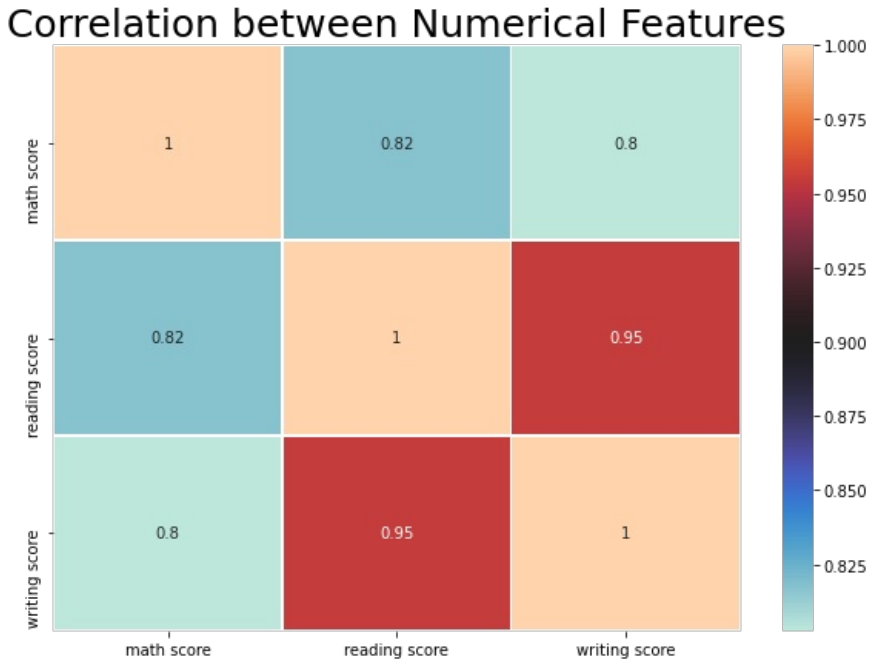
In [182…
```
#heatplot(onlt numerical data)
sns.heatmap(df1_num.corr())
```

Out[182… `<AxesSubplot:>`




In [181…

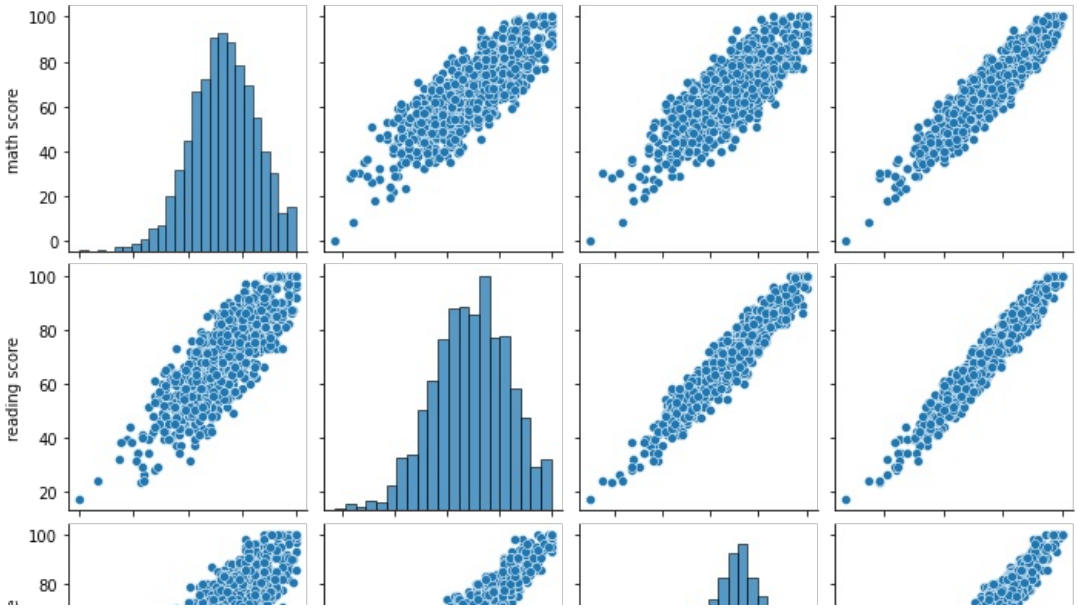
```
#heatplot(onlt numerical data) with styling
sns.heatmap(df1_num.corr(), annot=True, cmap='icefire', linewidths=0.3)
fig=plt.gcf()
fig.set_size_inches(10,7)
plt.title("Correlation between Numerical Features", size=25, color='black')
plt.show()

#cmap-->color combinations
#annot=True-->percentages show
#linewidths-->white spacing lines bw boxes
```

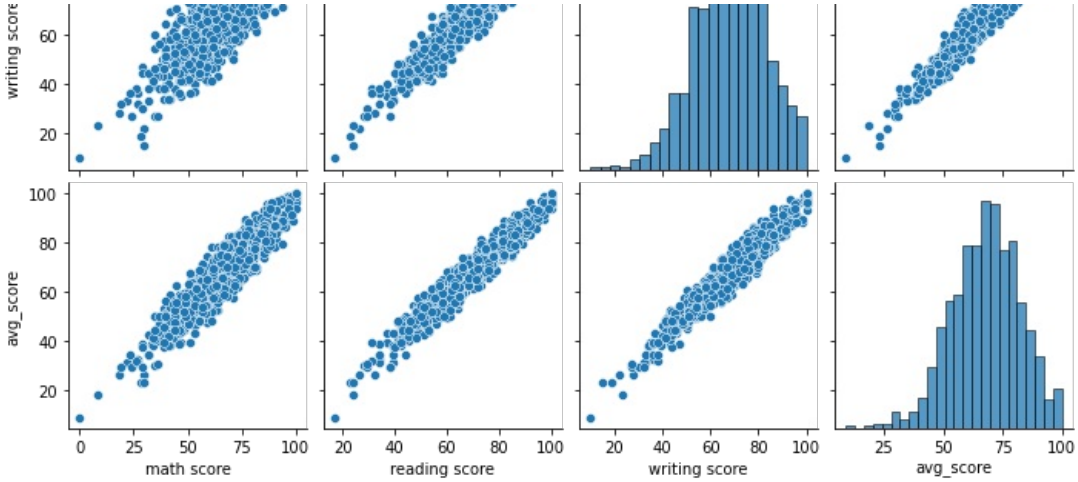



In [184…

```
#pairplot(numerical features), we can change types of plots in diagonal and non-diagonal
sns.pairplot(df1)
```

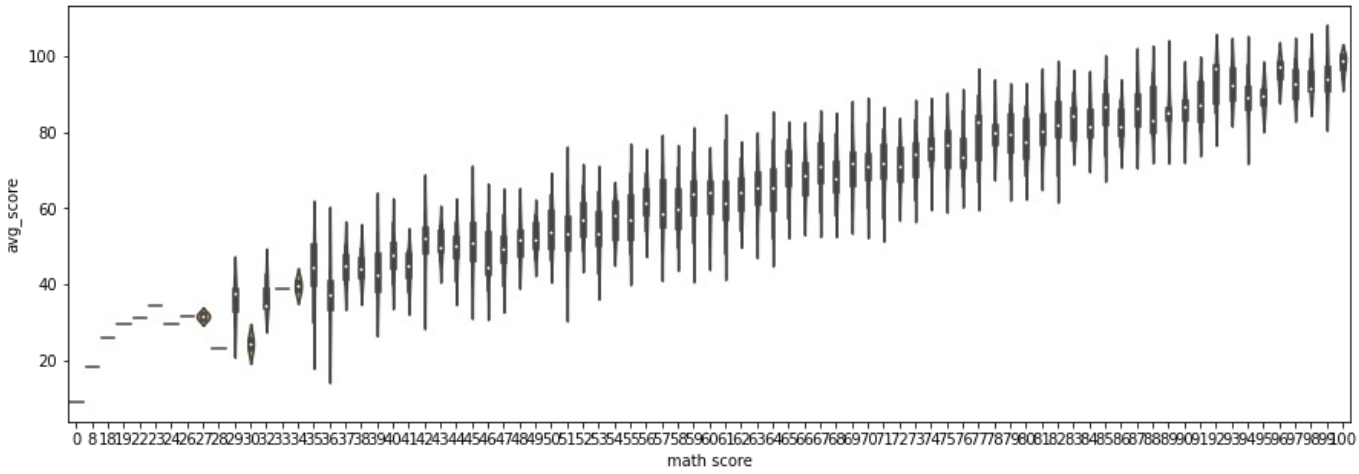
Out[184… <seaborn.axisgrid.PairGrid at 0x275b95339a0>






In [188…

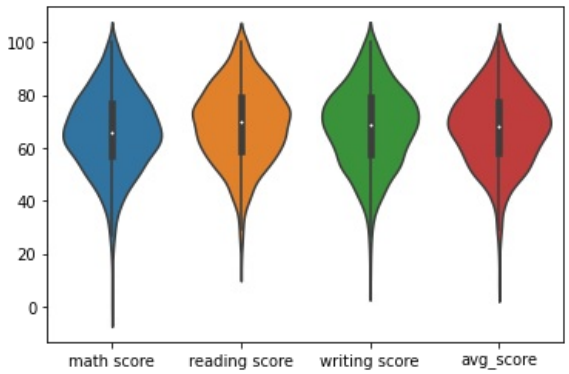
```
#violinplot of 'math score' wrt 'avg_score', shows distribution of data wrt each other
plt.figure(figsize=(15,5))
sns.violinplot(data=df1, x=df1['math score'], y=df1['avg_score'])
plt.show()
```




In [191…

```
#violinplot for all numerical features, shows distribution of data in a range
sns.violinplot(data=df1)
#observation-->outlier seems to be in lower side because of less data distribution
```

Out[191… <AxesSubplot:>




**End of Document**