eda-student-performance

February 25, 2024

1 Problem Statement

This project aims to understand how the students performance (test scores) is affected by other variables such as Gender, Ethnicity, Parental level of education, Lunch and Test preparation course

2 Data Collection

2.0.1 Dataset source: https://www.kaggle.com/datasets/spscientist/students-performance-in-exams?datasetId=74977

2.0.2 The data contains 8 columns and 1000 rows

3 Import Data and Required Packages

[5]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

[6]:
```
df = pd.read_csv('data/StudentsPerformance.csv')
```

[7]:
```
df.head()
```

[7]:
```
   gender race/ethnicity parental level of education         lunch  \
0  female        group B           bachelor's degree      standard
1  female        group C                some college      standard
2  female        group B             master's degree      standard
3    male        group A          associate's degree  free/reduced
4    male        group C                some college      standard

  test preparation course  math score  reading score  writing score
0                    none          72             72             74
1               completed          69             90             88
2                    none          90             95             93
```

```
3                    none           47             57             44
4                    none           76             78             75
```

[8]:
```
df.shape
```

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

4 Dataset information

4.0.1 gender: sex of students -> (Male/Female)

4.0.2 race/ethnicity : ethnicity of students -> (Group A,B,C,D,E)

4.0.3 parental level of education : parents final education -> (bechelor's degree, some college degree, master's degree, associate's degree, high school)

4.0.4 lunch : having lunch before test (standard or free/reduced)

4.0.5 test preparation course : complete or not complete before test

4.0.6 math score

4.0.7 reading score

4.0.8 writing score

4.1 We perform Data Checks in the order:

4.1.1 Check Missing values

4.1.2 Check data type

4.1.3 Check the number of unique values of each column

4.1.4 Check statistics of data set

4.1.5 Check various categories present in the different categorical column

[9]:
```
df.isna().sum()
```

[9]:
```
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
```

[10]:
```
df.duplicated().sum()
```

[10]:
```
0
```

[11]:
```
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                       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
```

[13]:
```
df.nunique()
```

[13]:
```
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
```

[14]:
```
df.describe()
```

[14]:

	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

4.2 Insight

4.2.1 From above description of numerical data, all means cann be seen very close to each other - between 66 and 68.05

4.2.2 All standard deviations are also close - between 14.6 and 15.19

4.2.3 While there is a minimum score 0 for math, for writing , the minimum is much higher = 10 and for reading, its even higher = 17

5 Exploring Data

[16]:
```
print("Categories in 'gender' variable:     ", end=" ")
print(df['gender'].unique())

print("Categories in 'race/ethnicity' variable:   ", end=" ")
print(df['race/ethnicity'].unique())

print("Categories in 'parental level of eduation' variable:     ", end=" ")
print(df['parental level of education'].unique())

print("Categories in 'lunch' variable:     ", end=" ")
print(df['lunch'].unique())

print("Categories in 'test preparation course' variable:     ", end=" ")
print(df['test preparation course'].unique())
```

```
Categories in 'gender' variable:      ['female' 'male']
Categories in 'race/ethnicity' variable:     ['group B' 'group C' 'group A'
'group D' 'group E']
Categories in 'parental level of eduation' variable:      ["bachelor's degree"
'some college' "master's degree" "associate's degree"
 'high school' 'some high school']
Categories in 'lunch' variable:      ['standard' 'free/reduced']
Categories in 'test preparation course' variable:      ['none' 'completed']
```

[17]:
```
# define numerical & categorical columns
numeric_features = [feature for feature in df.columns if df[feature].dtype !=␣
↪'O']
categorical_features = [feature for feature in df.columns if df[feature].dtype␣
↪== 'O']

# print columns
print('We have {} numerical features : {}'.format(len(numeric_features),␣
↪numeric_features))
print('\nWe have {} categorical features : {}'.
↪format(len(categorical_features), categorical_features))
```

```
We have 3 numerical features : ['math score', 'reading score', 'writing score']
```

We have 5 categorical features : ['gender', 'race/ethnicity', 'parental level of education', 'lunch', 'test preparation course']

5.1 Adding columns for "Total Score" and "Average"

[18]:
```
# We do feature engineering to create new columns

df['total score'] = df['math score'] + df['reading score'] + df['writing score']
df['average'] = df['total score']/3
df.head()
```

[18]:
```
   gender race/ethnicity parental level of education         lunch  \
0  female        group B           bachelor's degree      standard
1  female        group C                some college      standard
2  female        group B             master's degree      standard
3    male        group A          associate's degree  free/reduced
4    male        group C                some college      standard

  test preparation course  math score  reading score  writing score  \
0                    none          72             72             74
1               completed          69             90             88
2                    none          90             95             93
3                    none          47             57             44
4                    none          76             78             75

   total score    average
0          218  72.666667
1          247  82.333333
2          278  92.666667
3          148  49.333333
4          229  76.333333
```

[19]:
```
reading_full = df[df['reading score'] == 100]['average'].count()
writing_full = df[df['writing score'] == 100]['average'].count()
math_full = df[df['math score'] == 100]['average'].count()

print(f'Number of students with full marks in maths: {math_full}')
print(f'Number of students with full marks in writing: {writing_full}')
print(f'Number of students with full marks in reading: {reading_full}')
```

```
Number of students with full marks in maths: 7
Number of students with full marks in writing: 14
Number of students with full marks in reading: 17
```

[20]:
```
reading_less_20 = df[df['reading score'] <= 20]['average'].count()
writing_less_20 = df[df['writing score'] <= 20]['average'].count()
```

```
math_less_20 = df[df['math score'] <= 20]['average'].count()

print(f'Numer of students with less than 20 marks in Maths: {math_less_20}')
print(f'Number of students with less than 20 marks in writing:␣
 ↪{writing_less_20}')
print(f'Number of students with less than 20 marks in reading:␣
 ↪{reading_less_20}')
```

```
Numer of students with less than 20 marks in Maths: 4
Number of students with less than 20 marks in writing: 3
Number of students with less than 20 marks in reading: 1
```

5.2 Insights

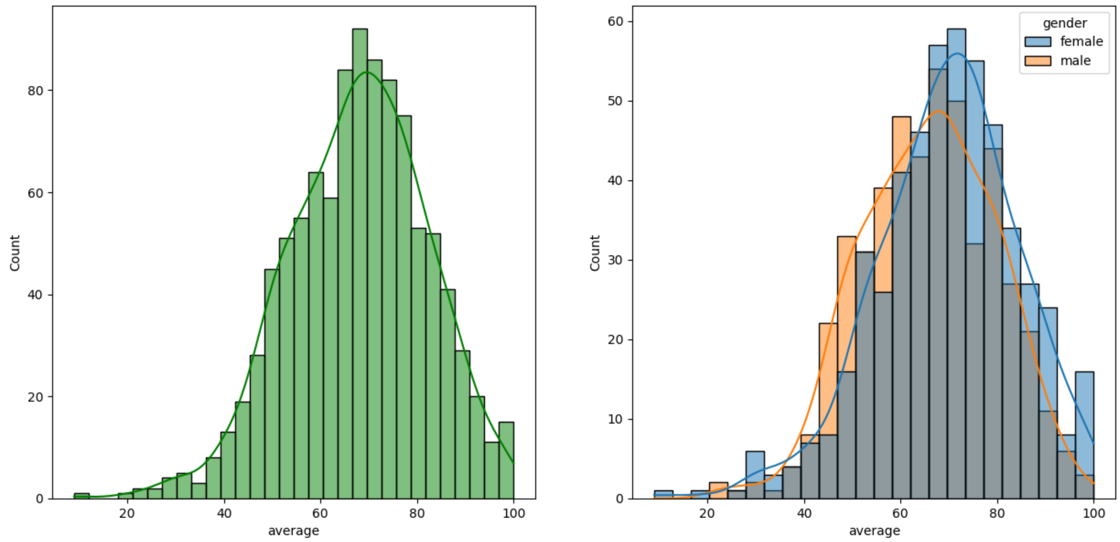
5.2.1 From above values we conclude that students have performed the worst in Maths

5.2.2 Best performance is in reading section

6 Exploring Data (Visualisation)

6.1 Visualise average score distribution to make some conclusion

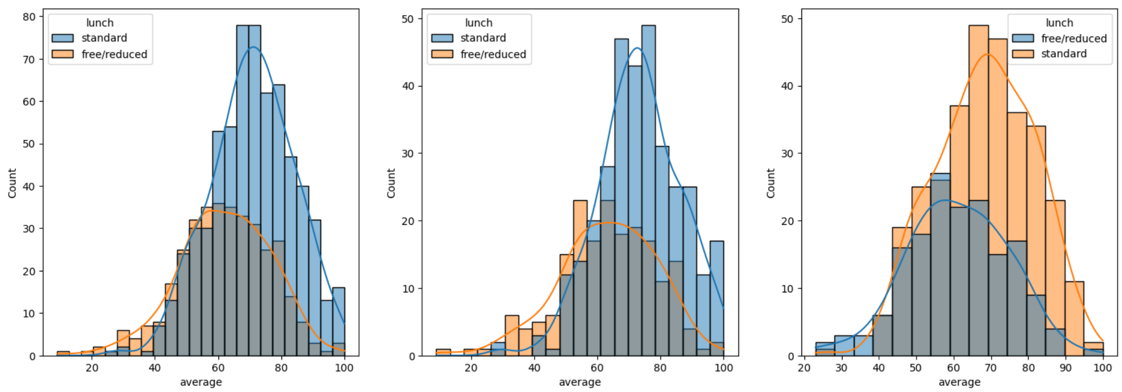
[21]:
```
# Gender wise comparison

fig,axs = plt.subplots(1,2, figsize=(15,7))
plt.subplot(121)
sns.histplot(data=df,x='average',bins=30,kde=True,color='g')
plt.subplot(122)
sns.histplot(data=df,x='average',kde=True,hue='gender')
plt.show()
```



6.2 INSIGHTS

6.2.1 Female tend to perform better than male students

[22]:
```
# Effect of lunch on genderwise performance

plt.subplots(1,3,figsize=(25,6))
plt.subplot(141)
sns.histplot(data=df,x='average',kde=True,hue='lunch')
plt.subplot(142)
sns.histplot(data=df[df.gender=='female'],x='average',kde=True,hue='lunch')
plt.subplot(143)
sns.histplot(data=df[df.gender=='male'],x='average',kde=True,hue='lunch')
plt.show()
```



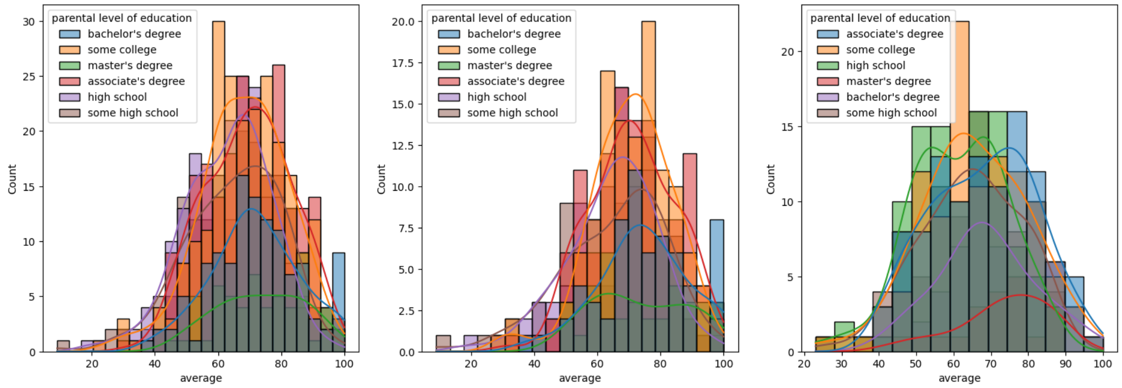
6.3 INSIGHTS

6.3.1 Standard lunch helps perform better in exams

6.3.2 Standard lunch helps perform better irrespective of gender

[23]:
```
# Gender wise performance with respect to the parental's level of education

plt.subplots(1,3,figsize=(25,6))
plt.subplot(141)
sns.histplot(data=df,x='average',kde=True,hue='parental level of education')
plt.subplot(142)
sns.histplot(data=df[df.gender=='female'],x='average',kde=True,hue='parental␣
↪level of education')
plt.subplot(143)
sns.histplot(data=df[df.gender=='male'],x='average',kde=True,hue='parental␣
↪level of education')
```

```
plt.show()
```



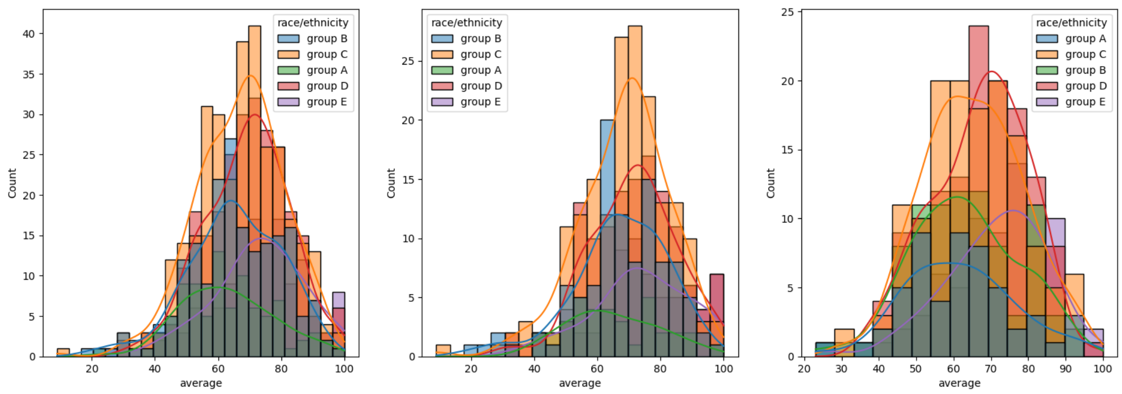
6.4 INSIGHTS

6.4.1 Parent's education don't tend to affect much. However, there is a noticeable difference between genders

6.4.2 2nd plot shows that if parent's education level is of master's or associate level, their male child tends to perform better

6.4.3 3rd plot shows that there is no effect of parent's education level on the performance of their female child

[24]:
```
# Gender wise performance with respect to the race/ethnicity

plt.subplots(1,3,figsize=(25,6))
plt.subplot(141)
sns.histplot(data=df,x='average',kde=True,hue='race/ethnicity')
plt.subplot(142)
sns.histplot(data=df[df.gender=='female'],x='average',kde=True,hue='race/
 ↪ethnicity')
plt.subplot(143)
sns.histplot(data=df[df.gender=='male'],x='average',kde=True,hue='race/
 ↪ethnicity')
plt.show()
```



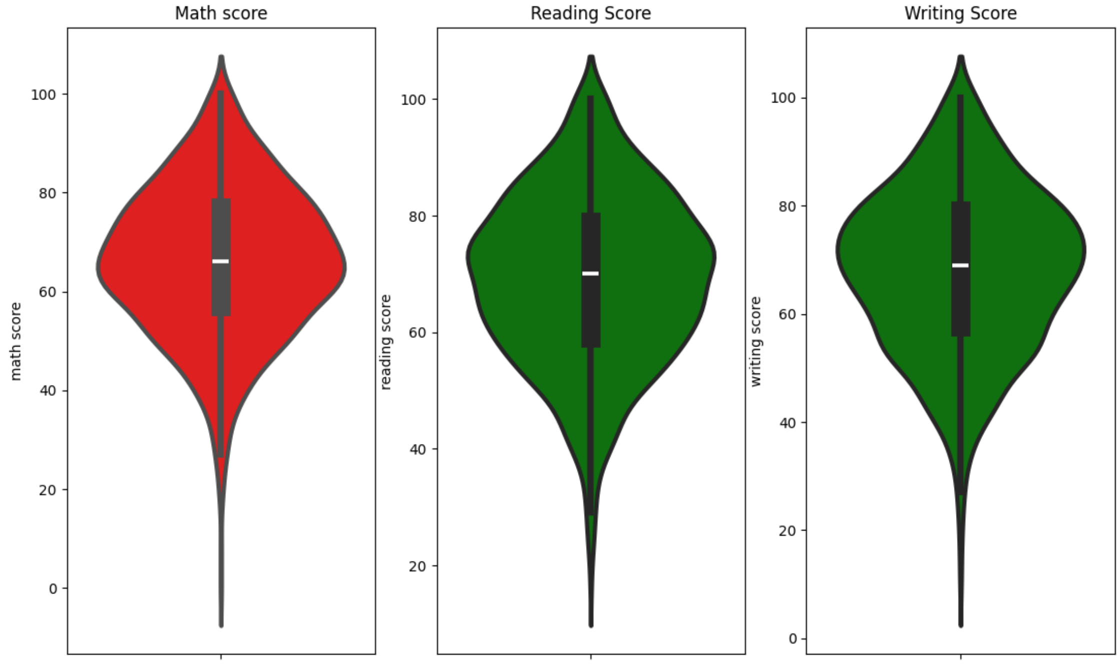
6.5 INSIGHTS

6.5.1 Students of group A and group B tend to perform poorly as compared to group C, group D, and group E students who perform consistently well

6.5.2 Students of group A and group B tend to perform poorly irrespective of gender.

6.5.3 There is more variation in group performance with respect to male students (3rd plot)

[25]:
```
# Variation in maximum score of all three subjects

plt.figure(figsize=(18,8))
plt.subplot(1,4,1)
plt.title('Math score')
sns.violinplot(data=df,y='math score',color='red',linewidth=3)
plt.subplot(1,4,2)
plt.title('Reading Score')
sns.violinplot(data=df,y='reading score',color='green',linewidth=3)
plt.subplot(1,4,3)
plt.title('Writing Score')
sns.violinplot(data=df,y='writing score',color='green',linewidth=3)
plt.show()
```



6.6 INSIGHTS

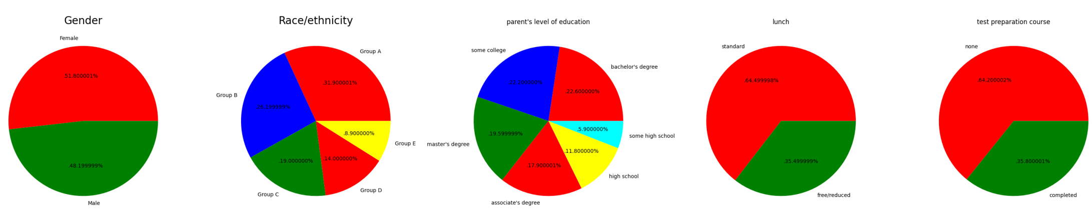
6.6.1 The distribution of math score is sharp and narrow indicating that most of the students score lie in the range of 60-80

6.6.2 The distibution of reading and writing score is broad indicating that most of the students score lie in the range of 50-90

6.7 Multivariate analysis using pieplot

[32]:
```
plt.rcParams['figure.figsize'] = (30,12)

plt.subplot(1,5,1)
size = df['gender'].value_counts()
labels = 'Female', 'Male'
color = ['red','green']

plt.pie(size, colors=color, labels=labels, autopct='.%2f%%')
plt.title('Gender', fontsize=20)
plt.axis('off')

plt.subplot(1,5,2)
size = df['race/ethnicity'].value_counts()
labels = 'Group A', 'Group B', 'Group C', 'Group D', 'Group E'
color = ['red','blue','green','red','yellow']
```

```
plt.pie(size, colors=color, labels=labels, autopct='.%2f%%')
plt.title('Race/ethnicity', fontsize=20)
plt.axis('off')

plt.subplot(1,5,3)
size = df['parental level of education'].value_counts()
labels = "bachelor's degree", 'some college', "master's degree", "associate's degree", 'high school', 'some high school'
color = ['red','blue','green','red','yellow','cyan']

plt.pie(size, colors=color, labels=labels, autopct='.%2f%%')
plt.title("parent's level of education")
plt.axis('off')

plt.subplot(1,5,4)
size = df['lunch'].value_counts()
labels = 'standard', 'free/reduced'
color = ['red','green']

plt.pie(size, colors=color, labels=labels, autopct='.%2f%%')
plt.title('lunch')
plt.axis('off')

plt.subplot(1,5,5)
size = df['test preparation course'].value_counts()
labels = 'none', 'completed'
colors = ['red', 'green']

plt.pie(size, colors=color, labels=labels, autopct='.%2f%%')
plt.title('test preparation course')
plt.axis('off')

plt.tight_layout()
plt.grid()

plt.show()
```



6.8 INSIGHTS

6.8.1 The proportion of male and female students is almost same

6.8.2 Group C has the most students

6.8.3 Number of students having standard lunch is greater

6.8.4 Most of the students haven't done the test preparation course

6.8.5 Parent's education level is unfiromly distributed except for the high school

6.9 Feature Wise Visualisation

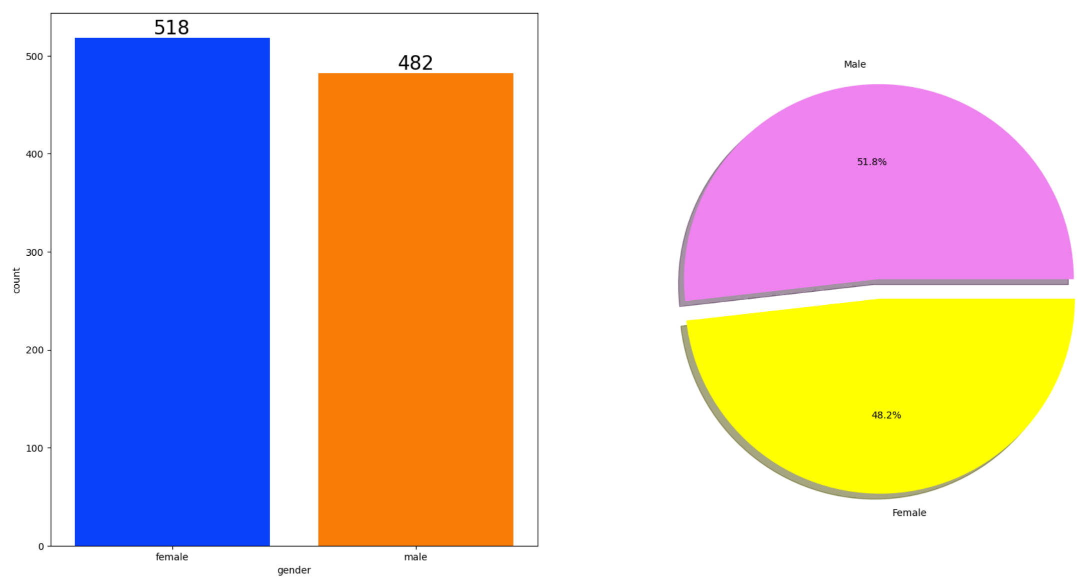
6.10 Gender Column

6.10.1 -> Distribution of gender

6.10.2 -> Does gender have any impact on student's performance

6.11 UNIVARIATE ANALYSIS (for distribution of gender)

[34]:
```
f,ax = plt.subplots(1,2,figsize=(20,10))
sns.countplot(x=df['gender'],data=df,palette='bright',ax=ax[0],saturation=0.95)

for container in ax[0].containers:
    ax[0].bar_label(container,color='black',size=20)

plt.pie(x=df['gender'].value_counts(),labels=['Male','Female'],explode=[0,0.
 ↪1],autopct='%1.1f%%',shadow=True,colors=['violet','yellow'])
plt.show()
```



6.12 INSIGHTS

6.12.1 We have a balanced gender data

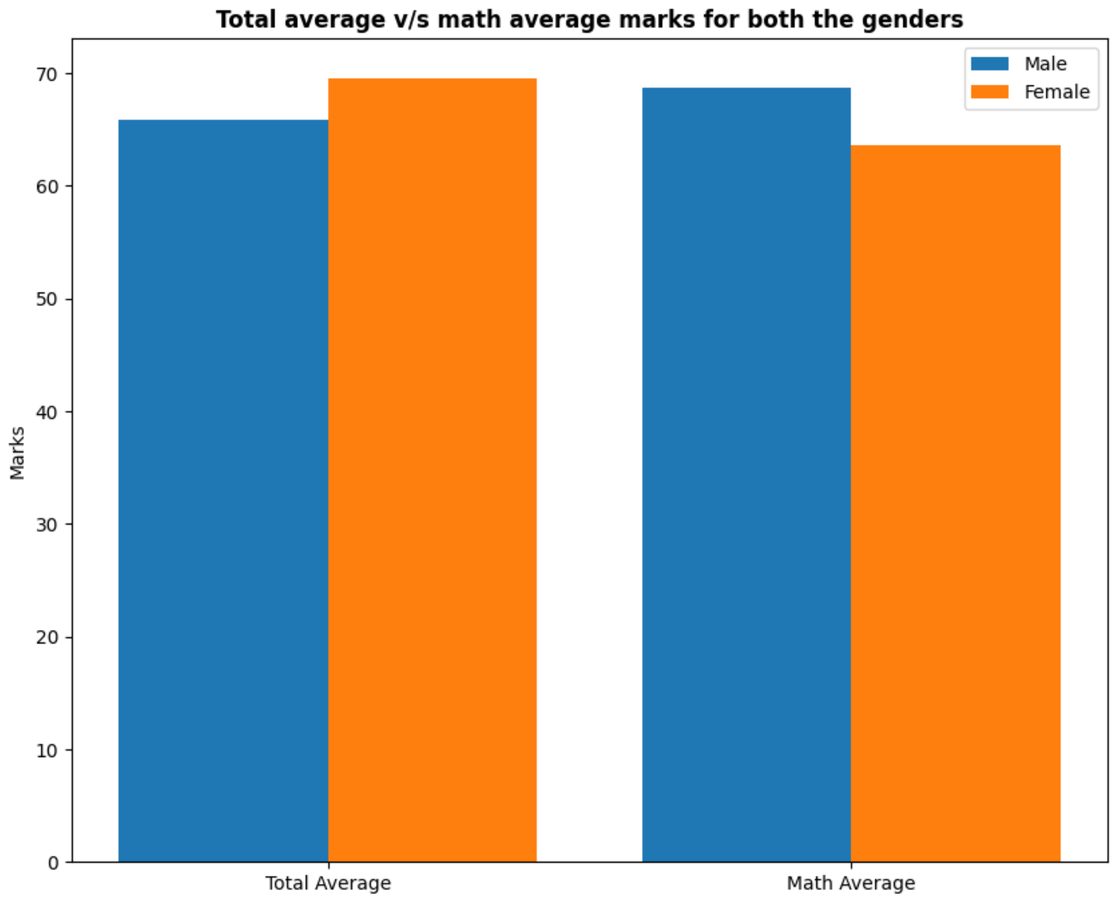
6.13 BIVARIATE ANALYSIS (Does gender have any impact on student's performance)

[40]:
```
# We can perform groupby operation on only the numeric columns
numeric_columns = df.select_dtypes(include=['int','float']).columns
gender_group = df.groupby('gender')[numeric_columns].mean()
gender_group
```

[40]:

	math score	reading score	writing score	total score	average
gender					
female	63.633205	72.608108	72.467181	208.708494	69.569498
male	68.728216	65.473029	63.311203	197.512448	65.837483

[43]:
```
plt.figure(figsize=(10,8))

x = ['Total Average', 'Math Average']

female_scores = [gender_group['average'][0], gender_group['math score'][0]]
male_scores = [gender_group['average'][1], gender_group['math score'][1]]

x_axis = np.arange(len(x))

plt.bar(x_axis-0.2,male_scores,0.4,label='Male')
plt.bar(x_axis+0.2,female_scores,0.4,label='Female')

plt.xticks(x_axis,x)
plt.ylabel('Marks')
plt.title('Total average v/s math average marks for both the genders',␣
↪fontweight='bold')
plt.legend()
plt.show()
```



6.14 INSIGHTS

6.14.1 Females perform overall better than men

6.14.2 Males perform better at maths than females

6.15 RACE/ETHNICITY COLUMN

6.15.1 How is group wise distribution

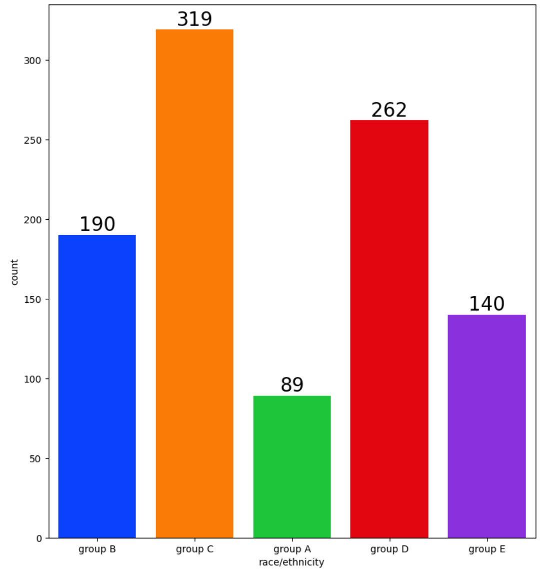
6.15.2 Does race ethnicity have an impact on student's performance

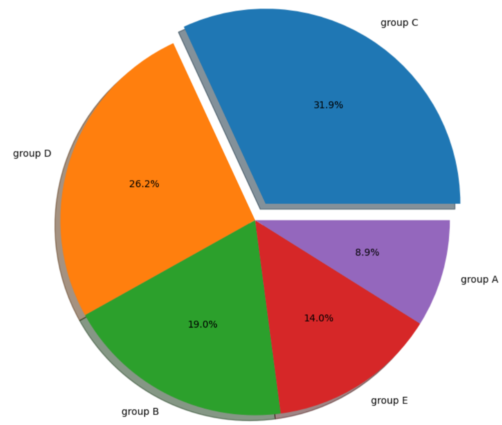
6.16 UNIVARIATE ANALYSIS (Group wise distribution)

[45]:

```
f,ax = plt.subplots(1,2,figsize=(20,10))
sns.countplot(x=df['race/
 ↪ethnicity'],data=df,palette='bright',ax=ax[0],saturation=0.95)

for container in ax[0].containers:
    ax[0].bar_label(container,color='black',size=20)
```

```
plt.pie(x=df['race/ethnicity'].value_counts(),labels=df['race/ethnicity'].
 ↪value_counts().index,explode=[0.1,0,0,0,0],autopct='%1.1f%%',shadow=True)
plt.show()
```





6.17 INSIGHTS

6.17.1 Most of the students belong to group-C/group-D

6.17.2 Lowest number of students belong to groupA

6.18 BIVARIATE ANALYSIS (Does Race/Ethnicity have any impact on student's performance)

[47]:
```
Group_data2 = df.groupby('race/ethnicity')
f,ax = plt.subplots(1,3,figsize=(20,8))

sns.barplot(x=Group_data2['math score'].mean().index, y=Group_data2['math␣
 ↪score'].mean().values,palette='mako',ax=ax[0])
ax[0].set_title('Math score',color='#005ce6',size=20)

for container in ax[0].containers:
    ax[0].bar_label(container,color='black',size=15)

sns.barplot(x=Group_data2['reading score'].mean().index, y=Group_data2['reading␣
 ↪score'].mean().values,palette='flare',ax=ax[1])
ax[1].set_title('Reading score',color='#005ce6',size=20)

for container in ax[1].containers:
    ax[1].bar_label(container,color='black',size=15)
```

```
sns.barplot(x=Group_data2['writing score'].mean().index, y=Group_data2['writing␣
↪score'].mean().values,palette='coolwarm',ax=ax[2])
ax[2].set_title('Writing score',color='#005ce6',size=20)

for container in ax[2].containers:
    ax[2].bar_label(container,color='black',size=15)
```

6.19 INSIGHTS

6.19.1 Group E students performs the best in all 3 subjects

6.19.2 Group A students performs the worst in all 3 subjects

6.19.3 We conclude that socioeconomic status affects performance

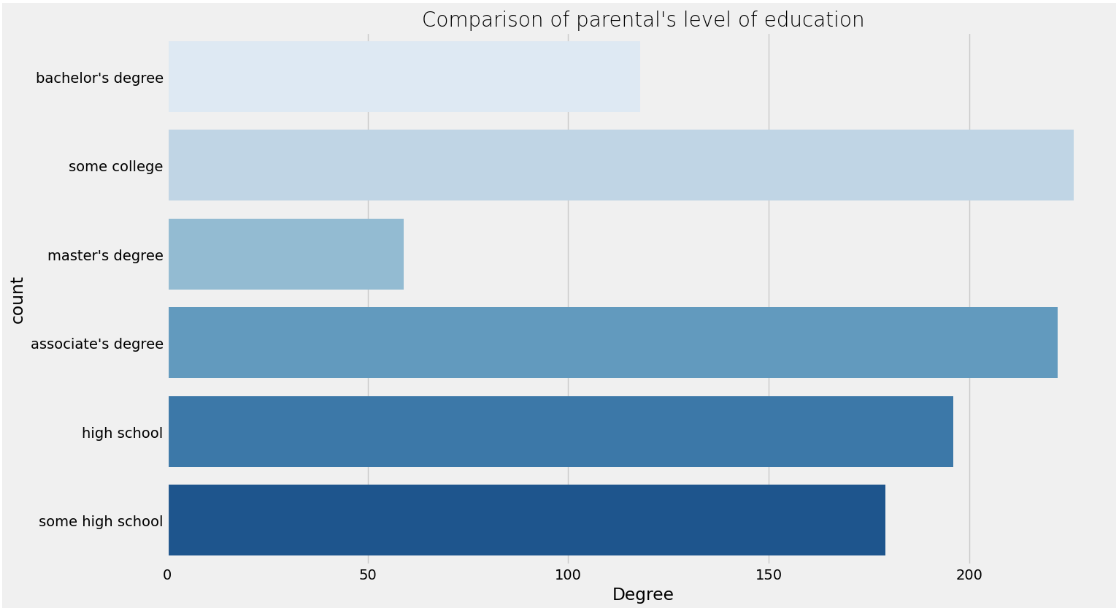
6.20 PARENTAL LEVEL OF EDUCATION COLUMN

6.20.1 What is educational background of student's parent

6.20.2 Does parental education have any impact in performance

6.21 UNIVARIATE ANALYSIS (Educational background of parents)

[48]:
```
plt.rcParams['figure.figsize'] = (15,9)
plt.style.use('fivethirtyeight')
sns.countplot(df['parental level of education'], palette='Blues')
plt.title("Comparison of parental's level of education", fontweight=30,␣
↪fontsize=20)
plt.xlabel('Degree')
plt.ylabel('count')
plt.show()
```

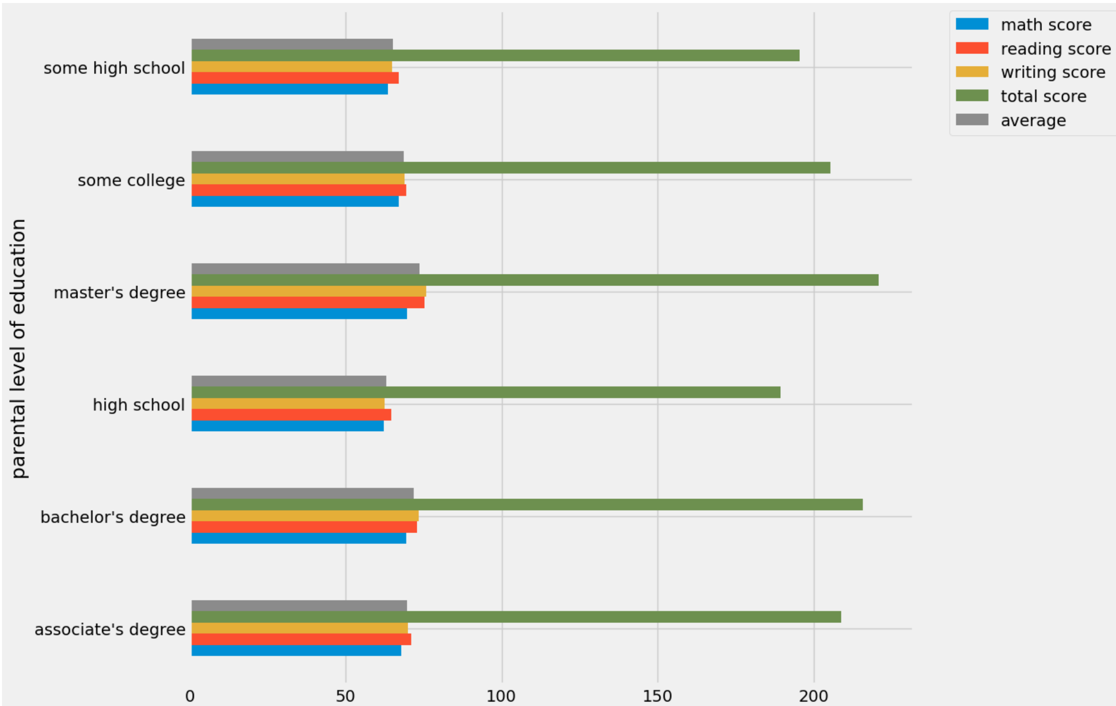


6.22 INSIGHTS

6.22.1 Most of the student's parents have attended some college

6.23 BIVARIATE ANALYSIS (Does parental's level of education affect student's performance)

[50]:
```
numeric_columns = df.select_dtypes(include=['int','float']).columns
df.groupby('parental level of education')[numeric_columns].agg('mean').
  ↪plot(kind='barh',figsize=(10,10))
plt.legend(bbox_to_anchor=(1.05,1),loc=2,borderaxespad=0.)
plt.show()
```



6.24 INSIGHTS

6.24.1 Student's whose parent's have Bachelor's and Master's degree tend to perform better than other groups

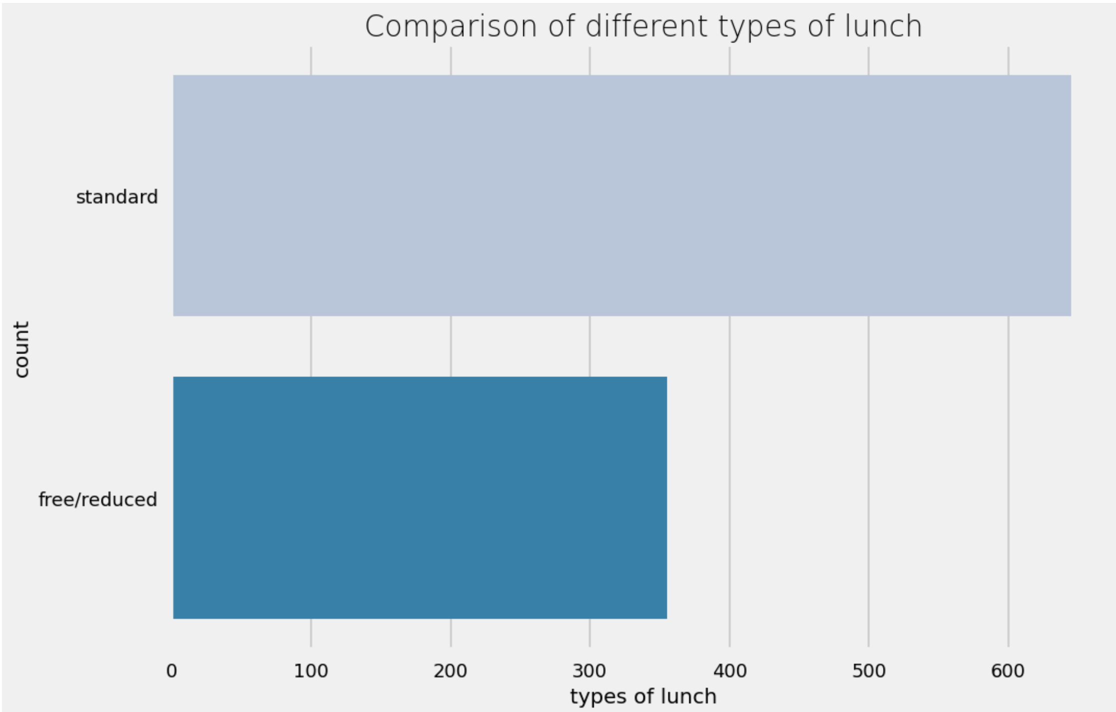
6.25 LUNCH COLUMN

6.25.1 Which type of lunch is most common among students

6.25.2 What is the effect of lunch type on student's performance

6.26 UNIVARIATE ANALYSIS (Most common lunch)

[51]:
```
plt.rcParams['figure.figsize'] = (15,9)
plt.style.use('seaborn-talk')
sns.countplot(df['lunch'],palette='PuBu')
plt.title('Comparison of different types of lunch',fontweight=30,fontsize=20)
plt.xlabel('types of lunch')
plt.ylabel('count')
plt.show()
```

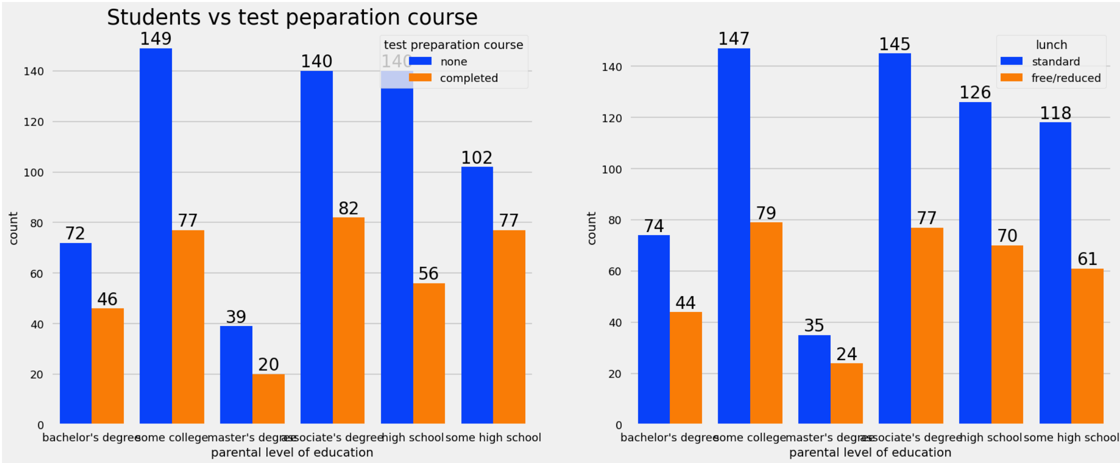


6.27 INSIGHTS

6.27.1 Most of the students are served lunch

6.28 BIVARIATE ANALYSIS (Does lunch type have any impact on student's performance)

[55]:
```
f,ax = plt.subplots(1,2,figsize=(20,8))
sns.countplot(x=df['parental level of␣
↪education'],data=df,palette='bright',hue='test preparation course',␣
↪saturation=0.95, ax=ax[0])
ax[0].set_title('Students vs test peparation course', color='black',size=25)
for container in ax[0].containers:
    ax[0].bar_label(container,color='black',size=20)

sns.countplot(x=df['parental level of␣
↪education'],data=df,palette='bright',hue='lunch',saturation=0.95,ax=ax[1])
for container in ax[1].containers:
    ax[1].bar_label(container,color='black',size=20)
```



6.29 INSIGHTS

6.29.1 Students who haven't done test preparation varies uniformly with their parent's level of education. However, there is a slight discrepancy that can be noticed.

6.29.2 The proportion of students getting served standard lunch varies uniformly with the parent's level of education

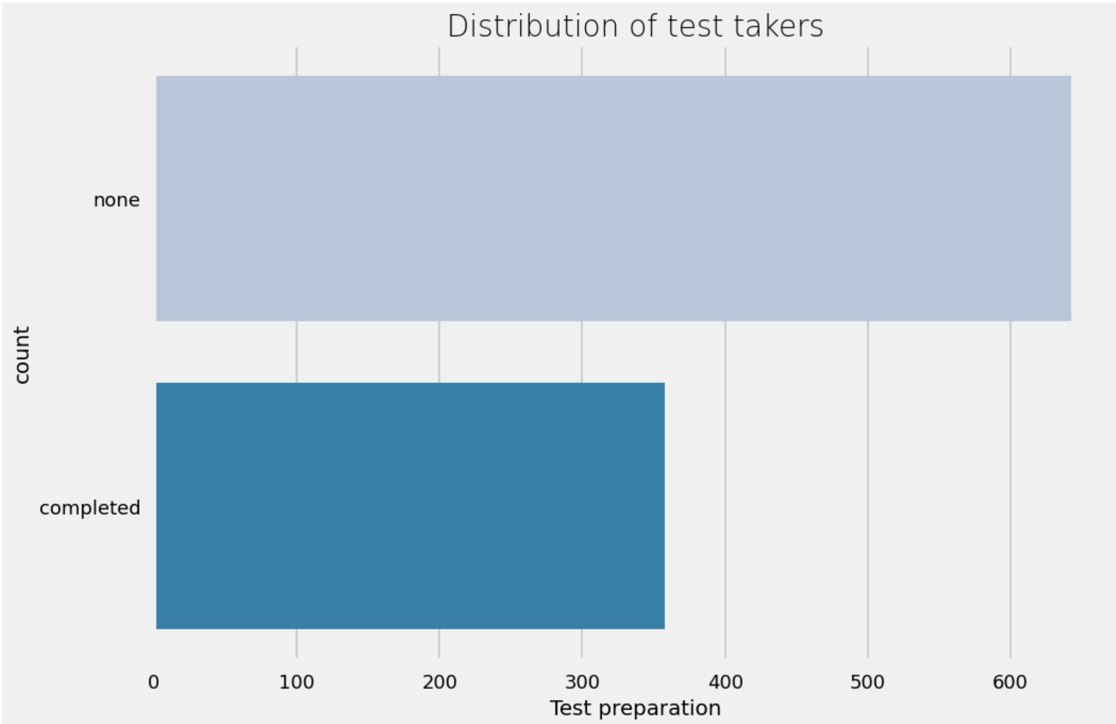
6.30 TEST PREPARATION COLUMN

6.30.1 What is the distribution of test takers

6.30.2 Does test preparation course have any impact on student's performance

6.31 UNIVARAITE ANALYSIS (distribution of test takers)

[56]:
```
plt.rcParams['figure.figsize'] = (15,9)
plt.style.use('seaborn-talk')
sns.countplot(df['test preparation course'],palette='PuBu')
plt.title('Distribution of test takers',fontweight=30,fontsize=20)
plt.xlabel('Test preparation')
plt.ylabel('count')
plt.show()
```



6.32 INSIGHTS

6.32.1 Most of the students haven't taken a test preapartion course

6.33 BIVARIATE ANALYSIS (Does test preparation have an impact on performance)

[58]:
```
plt.figure(figsize=(12,6))
plt.subplot(1,3,1)
sns.barplot(x=df['lunch'],y=df['math score'], hue=df['test preparation course'])
plt.subplot(1,3,2)
sns.barplot(x=df['lunch'],y=df['reading score'], hue=df['test preparation␣
↪course'])
plt.subplot(1,3,3)
sns.barplot(x=df['lunch'],y=df['writing score'], hue=df['test preparation␣
↪course'])
```

[58]:
```
<Axes: xlabel='lunch', ylabel='writing score'>
```

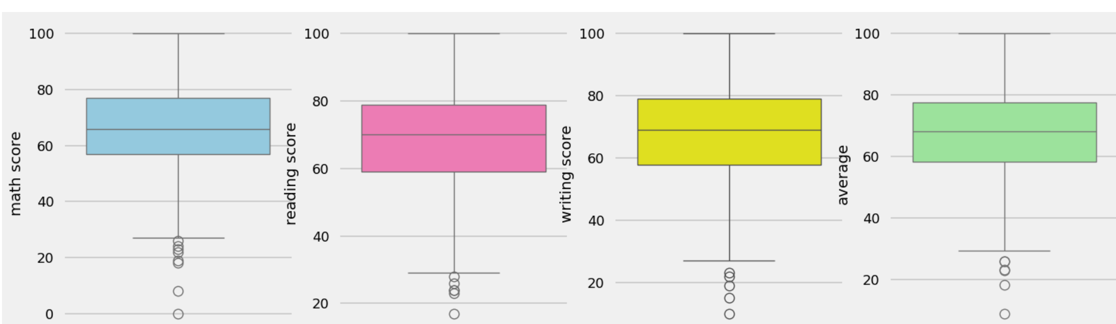
6.34 INSIGHTS

6.34.1 Students who have taken test preparation course perform better

6.34.2 Students perform better with test preparation course irrespective of the type of lunch they are served

7 CHECKING OUTLIERS

[59]:
```
plt.subplots(1,4,figsize=(16,5))
plt.subplot(141)
sns.boxplot(df['math score'],color='skyblue')
plt.subplot(142)
sns.boxplot(df['reading score'],color='hotpink')
plt.subplot(143)
sns.boxplot(df['writing score'],color='yellow')
plt.subplot(144)
sns.boxplot(df['average'],color='lightgreen')
plt.show()
```



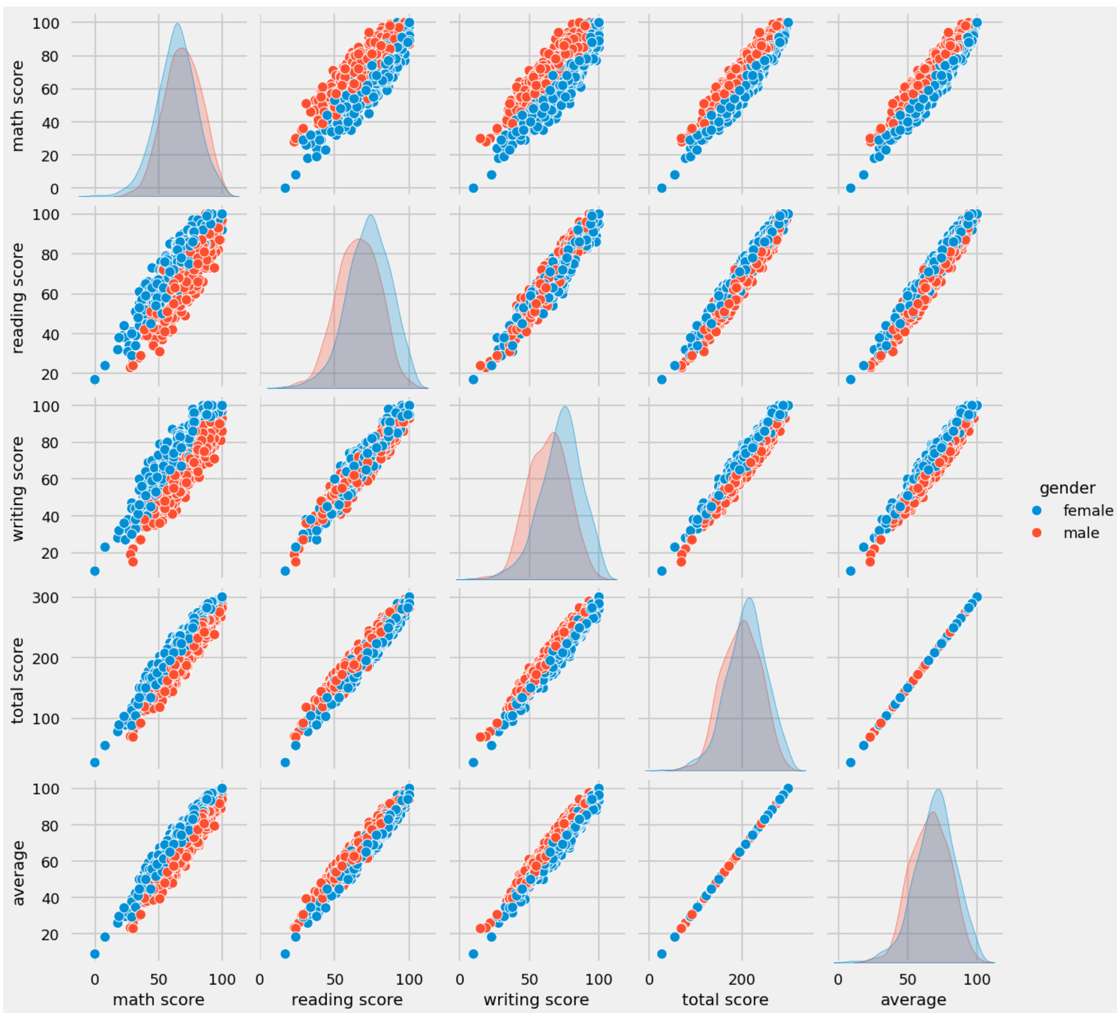
7.1 INSIGHTS

7.1.1 Most of the student score between an interval of 60-80 for all the 3 subjects

7.1.2 But there are students who have scored less than 20. We can't consider them outliers as their number is significant.

7.2 MULTIVARAITE ANALYSIS USING PAIRPLOT

[60]:
```
sns.pairplot(df,hue='gender')
plt.show()
```



7.3 INSIGHTS

7.3.1 We can clearly see that all the features vary linearly with respect to each other

7.4 CONCLUSIONS

7.4.1 Student’s performance is related to lunch, race, parental level of education

7.4.2 Females score more than males and are consistent top scorers

7.4.3 Student’s performance isn’t much dependent on the test preparation course

7.4.4 But, finishing test preparation course is beneficial