1.1 Importing libraries

```
# This Python 3 environment comes with many helpful analytics
libraries installed
# It is defined by the kaggle/python Docker image:
https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
from sklearn.preprocessing import OrdinalEncoder # for converting
categorical features to discrete numerical values

import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
import seaborn as sb


# Input data files are available in the read-only "../input/"
directory
# For example, running this (by clicking run or pressing Shift+Enter)
will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        path = os.path.join(dirname, filename)

# You can write up to 20GB to the current directory (/kaggle/working/)
that gets preserved as output when you create a version using "Save &
Run All"
# You can also write temporary files to /kaggle/temp/, but they won't
be saved outside of the current session

df = pd.read_csv(path)
df
```

```
     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
```

```
..      ...            ...                          ...           ...
995  female        group E            master's degree      standard
996    male        group C                high school  free/reduced
997  female        group C                high school  free/reduced
998  female        group D               some college      standard
999  female        group D               some college  free/reduced

    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
..                      ...         ...            ...            ...
995               completed          88             99             95
996                    none          62             55             55
997               completed          59             71             65
998               completed          68             78             77
999                    none          77             86             86

[1000 rows x 8 columns]
```

Identify categorical and numerical features

```python
cols = df.columns

num_cols = df._get_numeric_data().columns.to_list()
print(num_cols)

# get complement of set of columns and numerical columns
```

```
cat_cols = list(set(cols) - set(num_cols))
print(cat_cols)
```

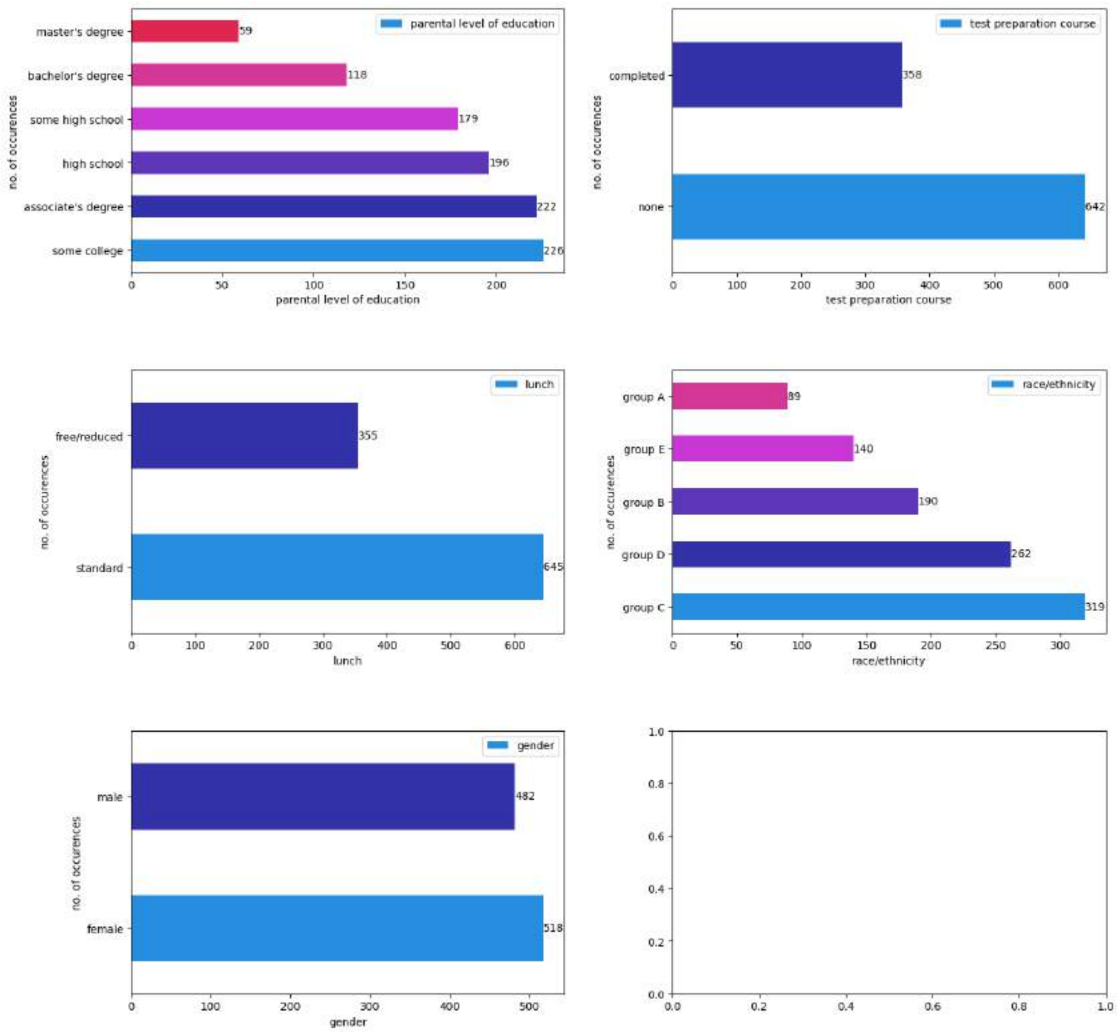
```
['math score', 'reading score', 'writing score']
['parental level of education', 'test preparation course', 'lunch',
'race/ethnicity', 'gender']
```

Display mode, median of categorical variables/features

```
def disp_cat_feat():
    fig, axes = plt.subplots(3, 2, figsize=(15, 15),
gridspec_kw={'width_ratios': [3, 3], 'height_ratios': [5, 5, 5]})
    axes = axes.flat
    fig.tight_layout(pad=7)

    for index, col in enumerate(cat_cols):
        keys = list(df[col].value_counts().keys())
        print(keys)

        # list all categorical columns no of occurences of each of
their unique values
        ax = df[col].value_counts().plot(kind='barh', ax=axes[index],
color=['#268ede', '#3432a8', '#5e36ba', '#c937d4', '#d43795',
'#de2651'])

        # annotate bars using axis.containers[0] since it contains
        # all
        print(ax.containers[0])
        ax.bar_label(ax.containers[0])
        ax.set_ylabel('no. of occurences')
        ax.set_xlabel(col)
        ax.legend()

        # current column
        print(col)

    plt.show()

disp_cat_feat()
```

```
['some college', "associate's degree", 'high school', 'some high
school', "bachelor's degree", "master's degree"]
<BarContainer object of 6 artists>
parental level of education
['none', 'completed']
<BarContainer object of 2 artists>
test preparation course
['standard', 'free/reduced']
<BarContainer object of 2 artists>
lunch
```

```
['group C', 'group D', 'group B', 'group E', 'group A']
<BarContainer object of 5 artists>
race/ethnicity
['female', 'male']
<BarContainer object of 2 artists>
gender
```



convert nominal/categorical features to ordinal features

1. check also if in each column the number of categories still stay the same

```
oe = OrdinalEncoder()
df_t = oe.fit_transform(df[cat_cols])
df_t
```

```
array([[1., 1., 1., 1., 0.],
       [4., 0., 1., 2., 0.],
       [3., 1., 1., 1., 0.],
       ...,
       [2., 0., 0., 2., 0.],
```

```
       [4., 0., 1., 3., 0.],
       [4., 1., 0., 3., 0.]])
```

```python
unique, freq = np.unique(df_t[:, 0], return_counts=True)
unique, freq
```

```
(array([0., 1., 2., 3., 4., 5.]), array([222, 118, 196,  59, 226,
179]))
```

```python
for cat in cat_cols:
    df[cat] = oe.fit_transform(np.array(df[cat]).reshape(-1, 1))
```

```python
df
```

```
     gender  race/ethnicity  parental level of education  lunch  \
0       0.0             1.0                          1.0    1.0
1       0.0             2.0                          4.0    1.0
2       0.0             1.0                          3.0    1.0
3       1.0             0.0                          0.0    0.0
4       1.0             2.0                          4.0    1.0
..      ...             ...                          ...    ...
995     0.0             4.0                          3.0    1.0
996     1.0             2.0                          2.0    0.0
997     0.0             2.0                          2.0    0.0
998     0.0             3.0                          4.0    1.0
999     0.0             3.0                          4.0    0.0

     test preparation course  math score  reading score  writing score

0                        1.0          72             72             74

1                        0.0          69             90             88

2                        1.0          90             95             93

3                        1.0          47             57             44

4                        1.0          76             78             75

..                       ...         ...            ...            ...

995                      0.0          88             99             95

996                      1.0          62             55             55

997                      0.0          59             71             65

998                      0.0          68             78             77
```

```
999                         1.0          77             86             86

[1000 rows x 8 columns]
```

check if there are also any null/missing values in the dataframe

```
df.isna().sum()
```

```
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
```

1.2 Checking for outliers in dataset

Display standard deviation, variance, and mean of numerical variables/features math score, reading score, writing score

```
# calculate mean of writing score, reading score, and math score

num_cols_desc = df[num_cols].describe()
print(num_cols_desc)

math_median = df['math score'].median()
read_median = df['reading score'].median()
write_median = df['writing score'].median()
```

```
       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
```

calculate interquartile range of numerical variables

```
_75_p = num_cols_desc.loc['75%', ['math score', 'reading score',
'writing score']]
print(f'{_75_p}\n')

_25_p = num_cols_desc.loc['25%', ['math score', 'reading score',
'writing score']]
```

```
print(f'{_25_p}\n')

# calculate interquartile range of each numerical variable
iqr = _75_p - _25_p
print(f'interquartile range of each feature:\n{iqr}\n')
```

```
math score       77.0
reading score    79.0
writing score    79.0
Name: 75%, dtype: float64

math score       57.00
reading score    59.00
writing score    57.75
Name: 25%, dtype: float64

interquartile range of each feature:
math score       20.00
reading score    20.00
writing score    21.25
dtype: float64
```

find upper bound and lower bound without the outliers

```
upper_bound = _75_p + (1.5 * iqr)
lower_bound = _25_p - (1.5 * iqr)
print(f'lower bounds/whiskers are:\n{lower_bound}\n')
print(f'upper bounds/whiskers are:\n{upper_bound}')
```

```
lower bounds/whiskers are:
math score       27.000
reading score    29.000
writing score    25.875
dtype: float64

upper bounds/whiskers are:
math score       107.000
reading score    109.000
writing score    110.875
dtype: float64
```

once upper and lower bounds have been calculated anything greater or lesser than these bounds respectively are the outliers

```
math_outliers = df.loc[(df['math score'] <= lower_bound['math score'])
| (df['math score'] >= upper_bound['math score']),'math score']
math_outliers
```

```
17     18
59      0
91     27
```

```
145    22
338    24
363    27
466    26
787    19
842    23
980     8
Name: math score, dtype: int64
```

```
read_outliers = df.loc[(df['reading score'] <= lower_bound['reading
score']) | (df['reading score'] >= upper_bound['reading
score']),'reading score']
read_outliers
```

```
59     17
76     26
211    28
327    23
596    24
601    29
896    29
980    24
Name: reading score, dtype: int64
```

```
write_outliers = df.loc[(df['writing score'] <= lower_bound['writing
score']) | (df['writing score'] >= upper_bound['writing
score']),'writing score']
write_outliers
```

```
59     10
76     22
327    19
596    15
980    23
Name: writing score, dtype: int64
```

1.3 identifying the variables with outliers

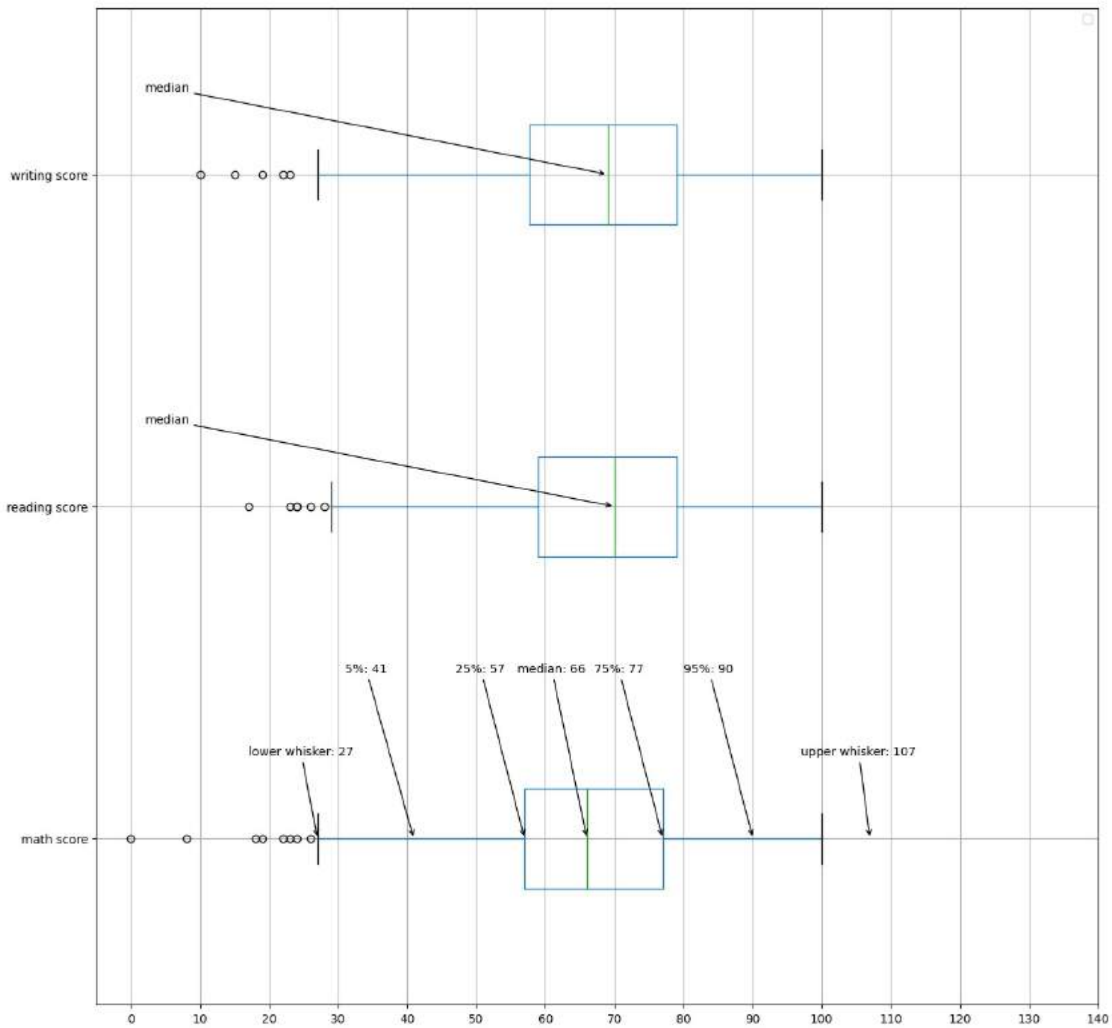
As we can see in our revealed outliers we observe that the outliers occur mostly on the left side of the distribution meaning it is postively skewed

```
axis = df.boxplot(column=num_cols, vert=False, figsize=(15, 15))
```

```
xy = {
    'math': {
        'median': math_median,
        '75%': num_cols_desc.loc['75%', 'math score'],
        '25%': num_cols_desc.loc['25%', 'math score'],
        '95%': np.quantile(df['math score'], .95),
        '5%': np.quantile(df['math score'], .05),
```

```python
        'lower whisker': lower_bound['math score'],
        'upper whisker': upper_bound['math score']
    },
    'reading': {
        'median': read_median,
    },
    'writing': {
        'median': write_median,
    }
}

# shifts the
offset = -10

arrowprops = {
    'arrowstyle': '->'
}


# for math
axis.annotate('median: {}'.format(round(xy['math']['median']), 2),
xy=(xy['math']['median'], 1), xytext=(xy['math']['median'] + offset,
1.5), arrowprops=arrowprops)
axis.annotate('75%: {}'.format(round(xy['math']['75%']), 2),
xy=(xy['math']['75%'], 1), xytext=(xy['math']['75%'] + offset, 1.5),
arrowprops=arrowprops)
axis.annotate('25%: {}'.format(round(xy['math']['25%']), 2),
xy=(xy['math']['25%'], 1), xytext=(xy['math']['25%'] + offset, 1.5),
arrowprops=arrowprops)
axis.annotate('95%: {}'.format(round(xy['math']['95%']), 2),
xy=(xy['math']['95%'], 1), xytext=(xy['math']['95%'] + offset, 1.5),
arrowprops=arrowprops)
axis.annotate('5%: {}'.format(round(xy['math']['5%']), 2),
xy=(xy['math']['5%'], 1), xytext=(xy['math']['5%'] + offset, 1.5),
arrowprops=arrowprops)
axis.annotate('lower whisker: {}'.format(round(xy['math']['lower
whisker']), 2), xy=(xy['math']['lower whisker'], 1),
xytext=(xy['math']['lower whisker'] + offset, 1.25),
arrowprops=arrowprops)
axis.annotate('upper whisker: {}'.format(round(xy['math']['upper
whisker']), 2), xy=(xy['math']['upper whisker'], 1),
xytext=(xy['math']['upper whisker'] + offset, 1.25),
arrowprops=arrowprops)

# for reading
axis.annotate('median', xy=(xy['reading']['median'], 2), xytext=(2,
2.25), arrowprops=arrowprops)

# for writing
axis.annotate('median', xy=(xy['writing']['median'], 3), xytext=(2,
```

```
3.25), arrowprops=arrowprops)


tick_range = 150
plt.xticks([i for i in range(0, tick_range) if i % 10 == 0])
# plt.grid()

# plt.gca().margins(x=0)
# plt.gcf().canvas.draw()
# tl = plt.gca().get_xticklabels()
# maxsize = max([t.get_window_extent().width for t in tl])
# m = 0.2 # inch margin
# s = maxsize / plt.gcf().dpi * tick_range + 2 * m
# margin = m / plt.gcf().get_size_inches()[0]

# plt.gcf().subplots_adjust(left=margin, right=1. - margin)
# plt.gcf().set_size_inches(s, plt.gcf().get_size_inches()[1])


plt.legend()
plt.show()
```



1.4 Handling the outliers

However the first question that should be asked before even attempting to follow the first method of dealing with outliers in our data is where such data points even came from? Was there a purpose? Was it a naturally occuring minority? Or simply just a human error?

- because numerical features are naturally occuring and not a mere human error, transformation via log, square root, or mean normalization which implies it ought to be within/forced into the inter quartile range, it would be counter productive, because naturally occuring values, can simply be just removed and not forced into a vlaue which it is not
- the solution for the outliers in this case would simply be to remove them
- from this it can just be concluded that anything beyond the calculated lower bounds and upper bounds of each numerical feature would be the outliers and thus should

be removed. Conversely anything within these lower and upper bounds are the passed remarks

```
new_df = df.loc[~((df['math score'] <= lower_bound['math score']) |
(df['math score'] >= upper_bound['math
score']))].reset_index().drop(columns='index')
new_df = new_df.loc[~((new_df['reading score'] <= lower_bound['reading
score']) | (new_df['reading score'] >= upper_bound['reading
score']))].reset_index().drop(columns='index')
new_df = new_df.loc[~((new_df['writing score'] <= lower_bound['writing
score']) | (new_df['writing score'] >= upper_bound['writing
score']))].reset_index().drop(columns='index')
new_df.shape
```

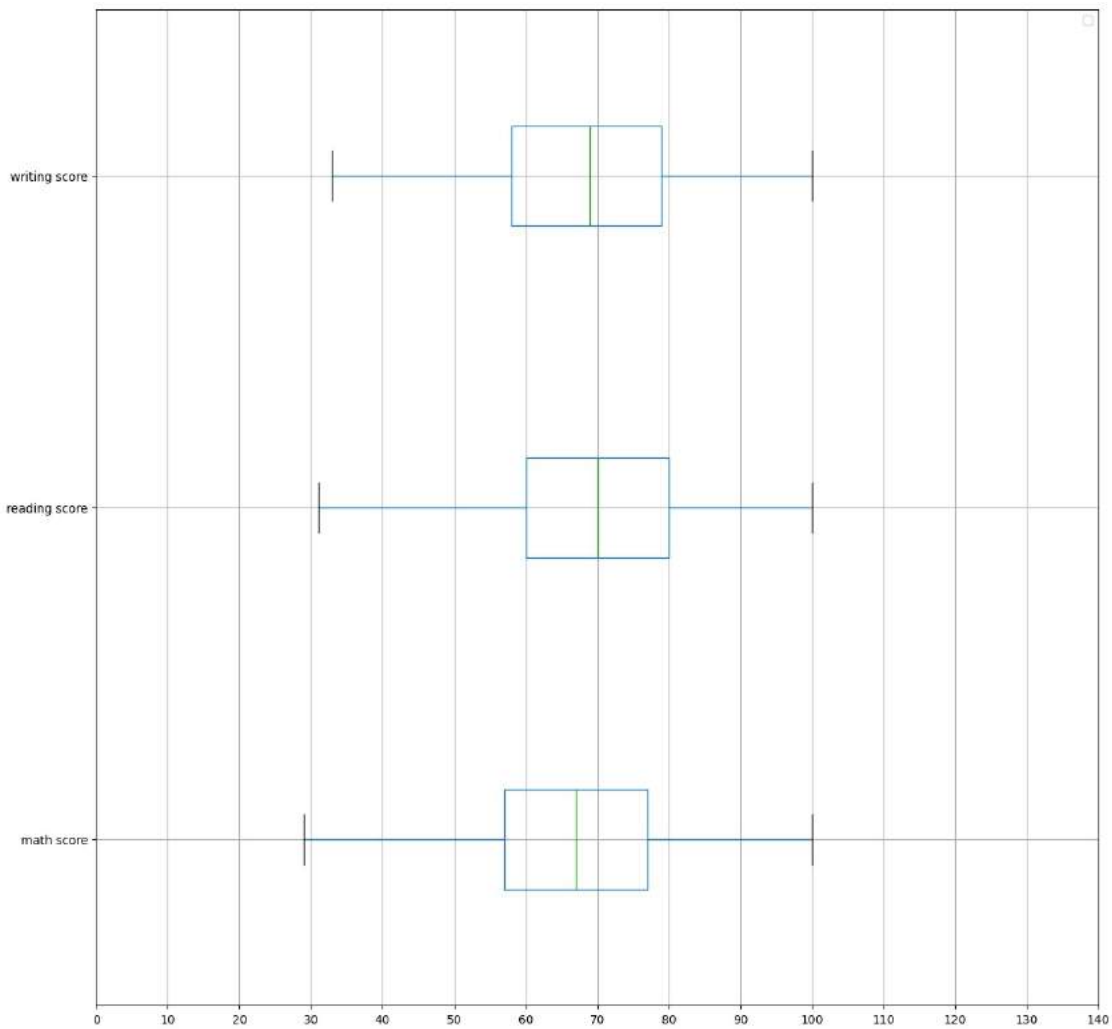
```
(984, 8)
```

```
new_df
```

```
     gender  race/ethnicity  parental level of education  lunch  \
0       0.0             1.0                          1.0    1.0
1       0.0             2.0                          4.0    1.0
2       0.0             1.0                          3.0    1.0
3       1.0             0.0                          0.0    0.0
4       1.0             2.0                          4.0    1.0
..      ...             ...                          ...    ...
979     0.0             4.0                          3.0    1.0
980     1.0             2.0                          2.0    0.0
981     0.0             2.0                          2.0    0.0
982     0.0             3.0                          4.0    1.0
983     0.0             3.0                          4.0    0.0

     test preparation course  math score  reading score  writing score

0                        1.0          72             72             74

1                        0.0          69             90             88

2                        1.0          90             95             93

3                        1.0          47             57             44

4                        1.0          76             78             75

..                       ...         ...            ...            ...

979                      0.0          88             99             95

980                      1.0          62             55             55

981                      0.0          59             71             65
```

```
982                         0.0          68              78              77

983                         1.0          77              86              86


[984 rows x 8 columns]
```

```python
# plot the numerical columns now without outliers, again
new_df.boxplot(column=num_cols, vert=False, figsize=(15, 15))

tick_range = 150
plt.xticks([i for i in range(0, tick_range) if i % 10 == 0])
plt.legend()
plt.show()
```




```python
new_df.describe()
```

```
          gender  race/ethnicity  parental level of education
lunch  \
count  984.00000      984.000000                   984.000000
984.000000
mean     0.48374        2.181911                     2.472561
0.652439
std      0.49999        1.158119                     1.830914
0.476438
min      0.00000        0.000000                     0.000000
0.000000
25%      0.00000        1.000000                     1.000000
0.000000
50%      0.00000        2.000000                     2.000000
1.000000
75%      1.00000        3.000000                     4.000000
1.000000
max      1.00000        4.000000                     5.000000
1.000000

       test preparation course  math score  reading score  writing
score
count               984.000000  984.000000     984.000000
984.000000
mean                  0.637195   66.775407      69.795732
68.718496
std                   0.481054   14.243035      13.831126
14.356492
min                   0.000000   29.000000      31.000000
33.000000
25%                   0.000000   57.000000      60.000000
58.000000
50%                   1.000000   67.000000      70.000000
69.000000
75%                   1.000000   77.000000      80.000000
79.000000
max                   1.000000  100.000000     100.000000
100.000000
```

1.5 Exploratory Data Analysis

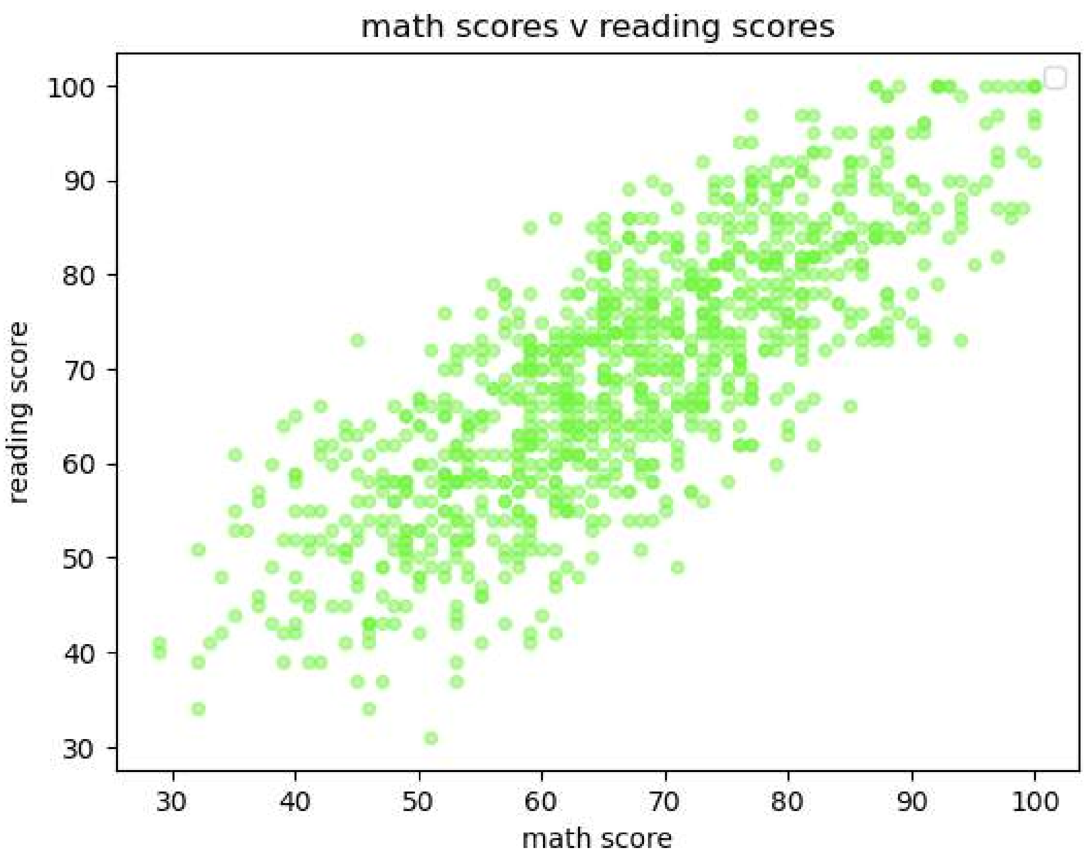
Some useful questions to ask are the ff:

1. How to imporve the students performance in each test?
2. What are the major factors influencing the test scores?
3. Effectiveness of test preparation course?
4. how many students passed in math (to do this set a standard passing rate say 50%, if max is 100 in all subjects)
5. how many students passed in writing

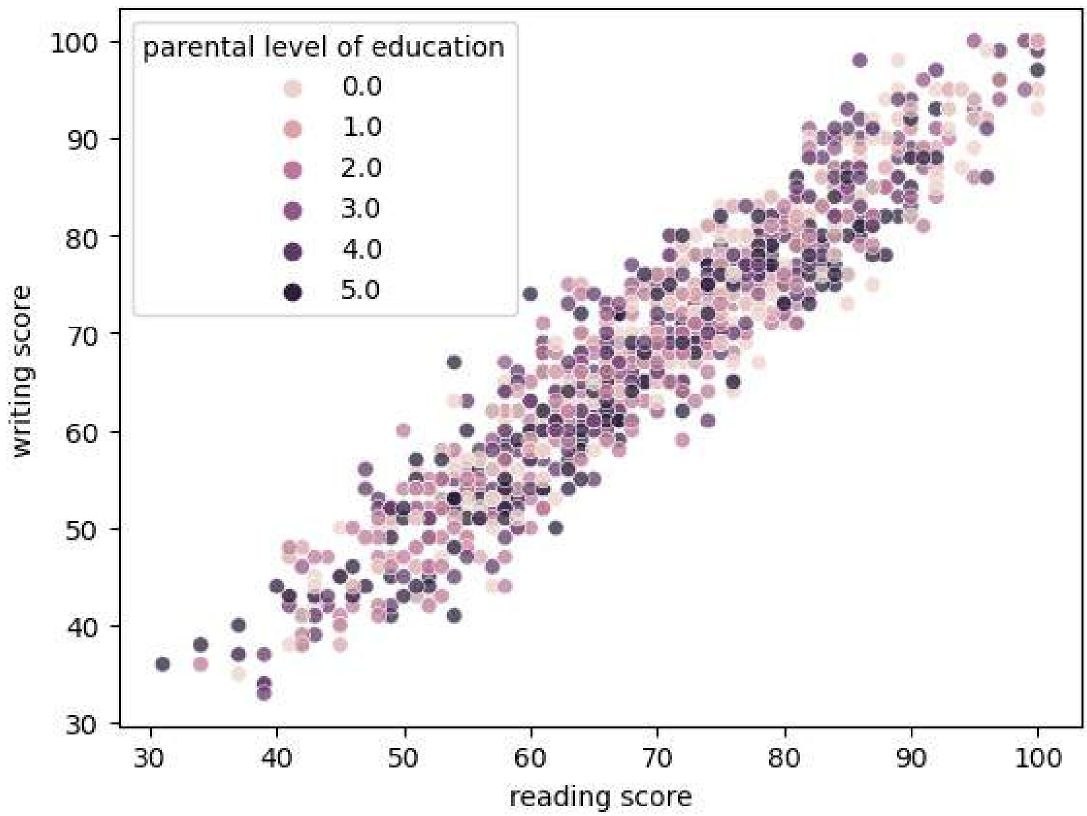
6. how many students passed in reading
7. how many students passed in all subjects

Compare two features with one another

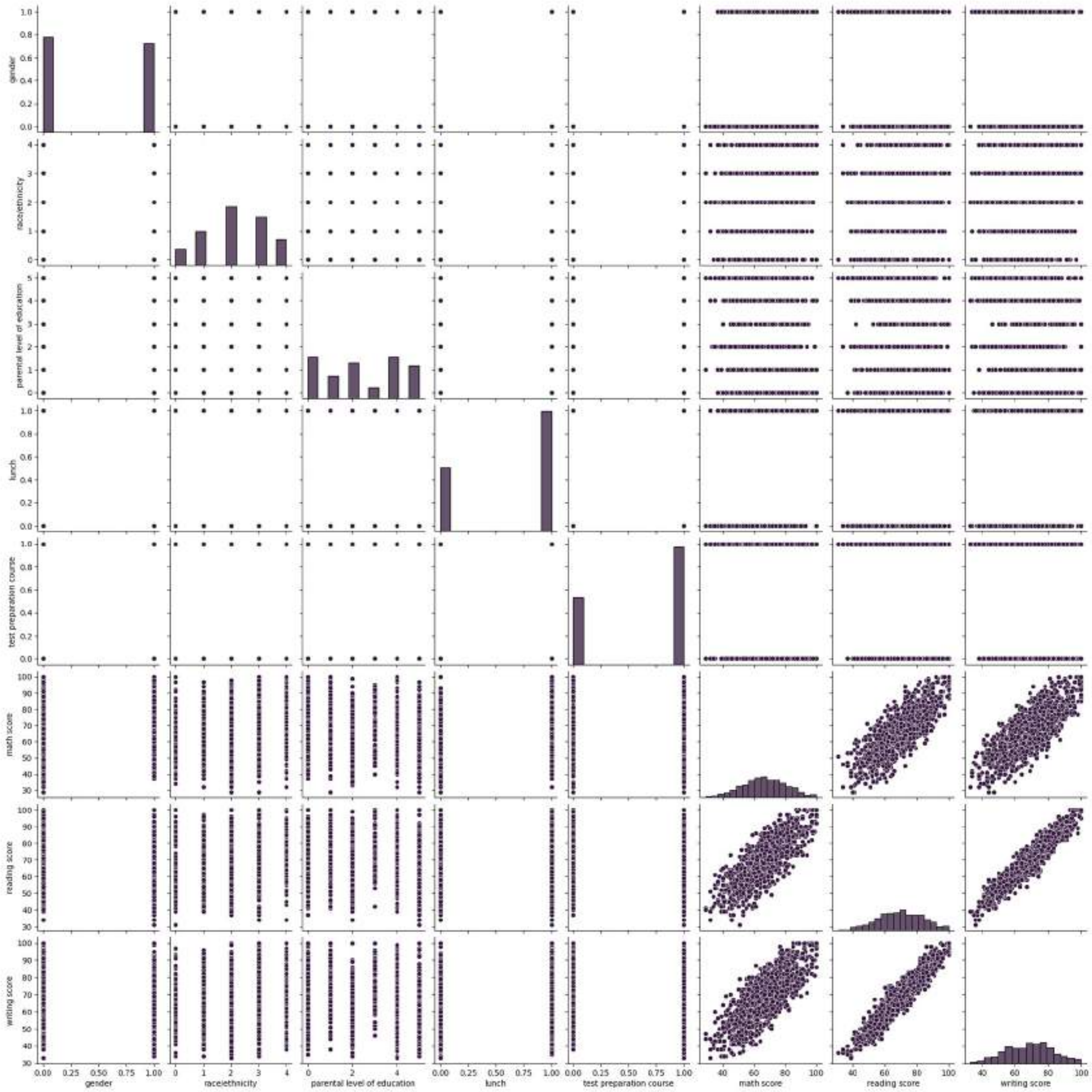
```
ax = new_df.plot(kind='scatter', x='math score', y='reading score',
color='#75f542', alpha=0.5, title='math scores v reading scores')
ax.legend()
plt.show()
```




```
# plot 3 variables x, y, z where x, y still remain on their axes, but
z
# represents different colors of different value of the third variable
# see if there is a correlation to reading and writing with level of
education of parents
sb.set_palette('rocket')
sb.scatterplot(x='reading score', y='writing score', hue='parental
level of education', alpha=0.75, data=new_df)
plt.show()
```




```
sb.set_palette('rocket')
sb.pairplot(new_df)
plt.show()
```



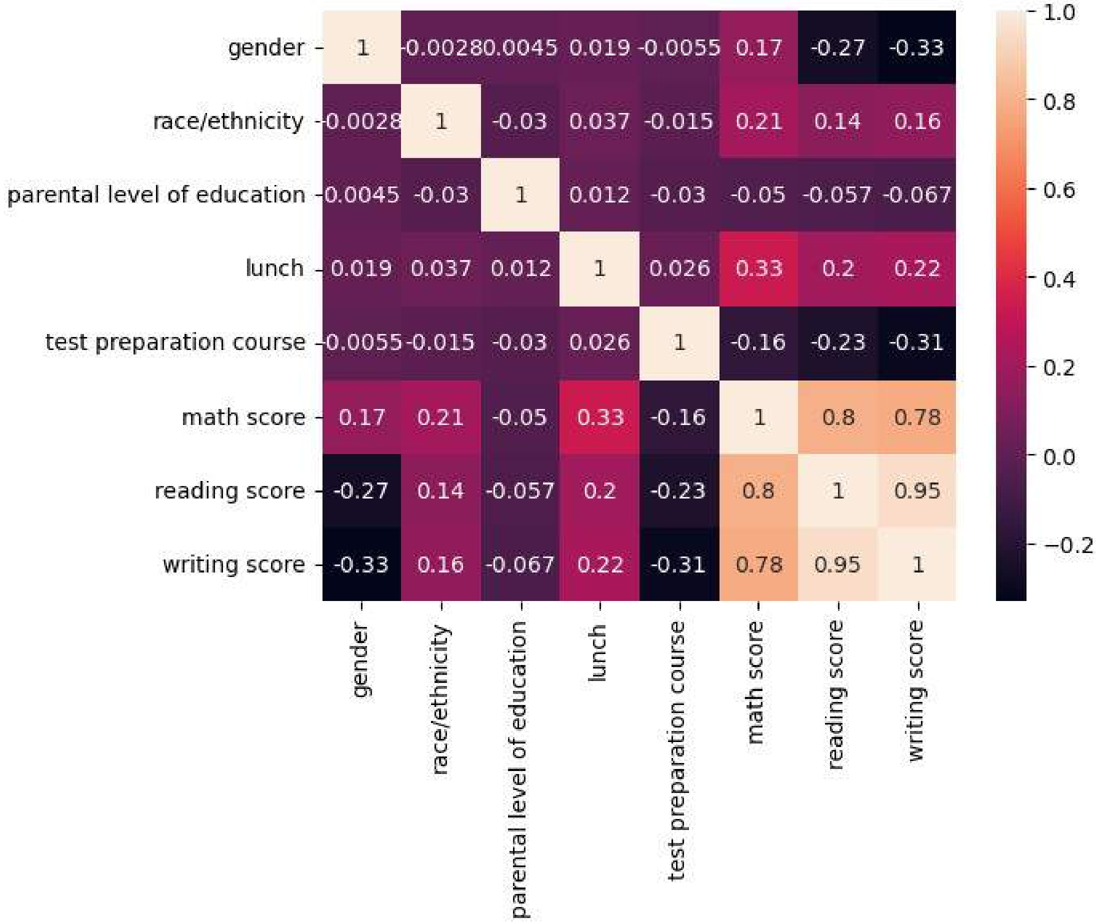
see correlations between each variable

```
df_corr = new_df.corr()
df_corr

                               gender  race/ethnicity  \
gender                       1.000000       -0.002792
race/ethnicity              -0.002792        1.000000
parental level of education  0.004513       -0.030028
lunch                        0.018957        0.037267
test preparation course     -0.005519       -0.014714
math score                   0.165122        0.212227
reading score               -0.269021        0.136644
writing score               -0.331630        0.156841

                             parental level of education     lunch  \
gender                                          0.004513  0.018957
```

```
race/ethnicity                                     -0.030028  0.037267
parental level of education                         1.000000  0.012380
lunch                                               0.012380  1.000000
test preparation course                            -0.030372  0.026280
math score                                         -0.049799  0.333434
reading score                                      -0.056522  0.203027
writing score                                      -0.066726  0.220076

                             test preparation course  math score  \
gender                                     -0.005519    0.165122
race/ethnicity                             -0.014714    0.212227
parental level of education                -0.030372   -0.049799
lunch                                       0.026280    0.333434
test preparation course                     1.000000   -0.161715
math score                                 -0.161715    1.000000
reading score                              -0.228262    0.795963
writing score                              -0.305427    0.777785

                             reading score  writing score
gender                           -0.269021      -0.331630
race/ethnicity                    0.136644       0.156841
parental level of education      -0.056522      -0.066726
lunch                             0.203027       0.220076
test preparation course          -0.228262      -0.305427
math score                        0.795963       0.777785
reading score                     1.000000       0.949253
writing score                     0.949253       1.000000
```

```python
sb.set_palette('mako')
sb.heatmap(df_corr, annot=True)
```

```
<AxesSubplot:>
```



Seeing both categorical and numerical features of the dataset, it can be deduced that:

- in the numerical features there are indeed known outliers in which the rows which indeed contain these outliers can either be dropped/removed altogether as if it were a data point not worthy of our time. In this case however, these were naturally occuring values which is a justification for removal of these outliers
- transformation of the outliers into a much more useful value without having to waste a data point which could be even beneficial perhaps in training a predictive model using either logarithmic, cubic root, square root transformation, or mean normalization. However in this case such an application was not applicable because of the outliers having again be naturally occuring values and not merely a human error
- in the categorical features test preparation course, lunch, race/ethnicity, gender, parental level of education we see that in each feature the most frequently occuring values are none, standard, group C, female, and some college respectively