```python
#Importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Loading and describing datasets

```python
student_df = pd.read_csv('student.csv')
student_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]
```

```
student_df.info()
```

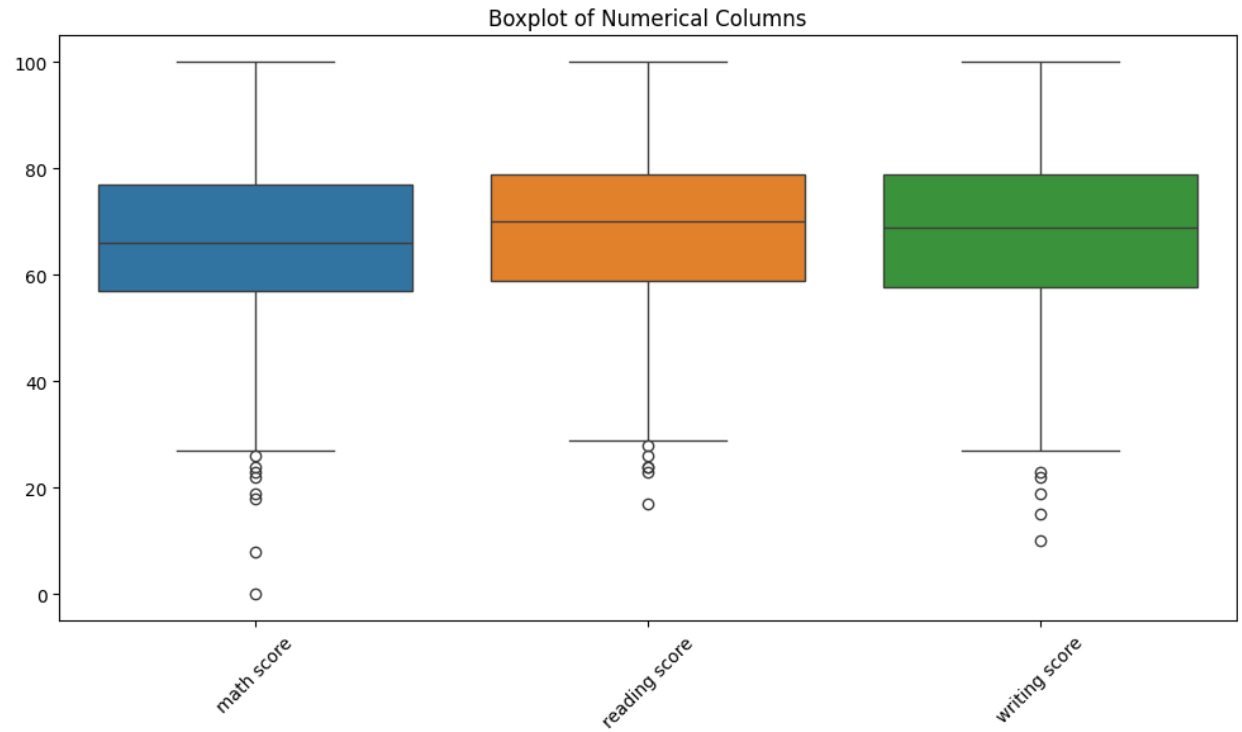
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 8 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   gender                       1000 non-null   object
 1   race/ethnicity               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
```

```
student_df.describe()
```

```
       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
```

```
#handing missing values
student_df.dropna(inplace=True) # Handle missing values

#handing duplicate values
student_df.drop_duplicates(inplace=True)

#handling outliers
plt.figure(figsize=(12, 6))
sns.boxplot(data=student_df)
```

```
plt.title('Boxplot of Numerical Columns')
plt.xticks(rotation=45)
plt.show()
```




```
# Removing outliers using IQR method
def remove_outliers_iqr(student_df, column):
    Q1 = student_df[column].quantile(0.25)
    Q3 = student_df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return student_df[(student_df[column] >= lower_bound) &
(student_df[column] <= upper_bound)]

# Removing outliers from math score
student_df = remove_outliers_iqr(student_df, 'math score')

# Removing outliers from reading score
student_df = remove_outliers_iqr(student_df, 'reading score')

# Removing outliers from writing score
student_df = remove_outliers_iqr(student_df, 'writing score')
```

Lets create a new column representing total marks which is nothing but sum of math, reading and writing scores. This can be useful for analyzing the overall performance of students across these subjects.

```python
student_df['total score']=student_df['math score']+student_df['reading score']+student_df['writing score']
student_df.head()
```

```
   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
0          218
1          247
2          278
3          148
4          229
```

Converting Categorical Features Into Numerical: To predict the total score of any student in the table, we need to take into consideration all the columns. So, let's convert the categorial data columns into numerical ones by using LabelEncoder function.

```python
# Encoding categorical variables
from sklearn.preprocessing import LabelEncoder

label_encoder = LabelEncoder()
student_df['gender'] =
label_encoder.fit_transform(student_df['gender'])
student_df['race/ethnicity'] =
label_encoder.fit_transform(student_df['race/ethnicity'])
student_df['parental level of education'] =
label_encoder.fit_transform(student_df['parental level of education'])
student_df['lunch'] = label_encoder.fit_transform(student_df['lunch'])
student_df['test preparation course'] =
label_encoder.fit_transform(student_df['test preparation course'])

student_df.head()
```

```
   gender  race/ethnicity  parental level of education  lunch  \
0       0               1                            1      1
1       0               2                            4      1
2       0               1                            3      1
3       1               0                            0      0
```

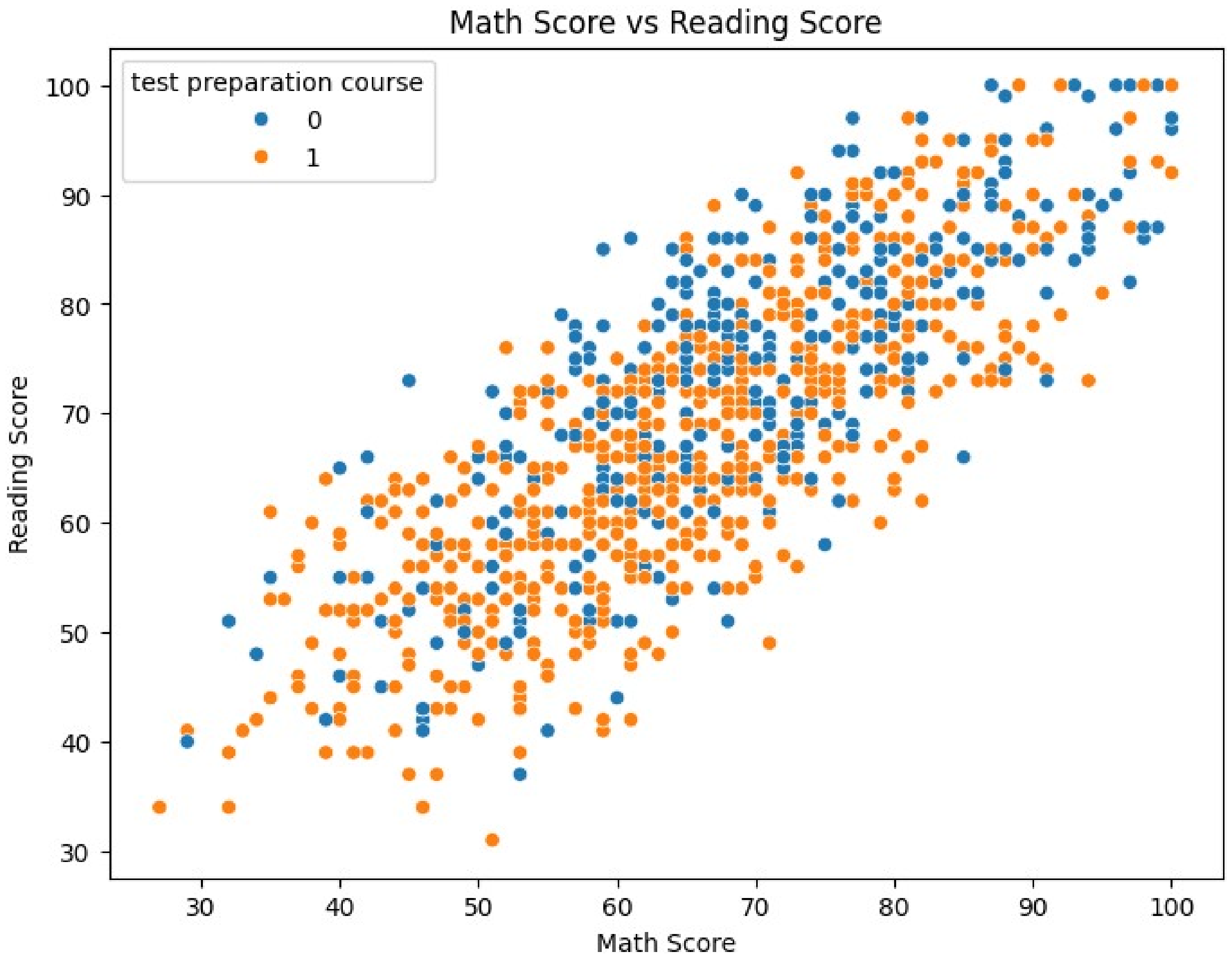
```
4       1               2                            4      1

   test preparation course  math score  reading score  writing
score  \
0                        1          72             72             74

1                        0          69             90             88

2                        1          90             95             93

3                        1          47             57             44

4                        1          76             78             75


   total score
0          218
1          247
2          278
3          148
4          229
```

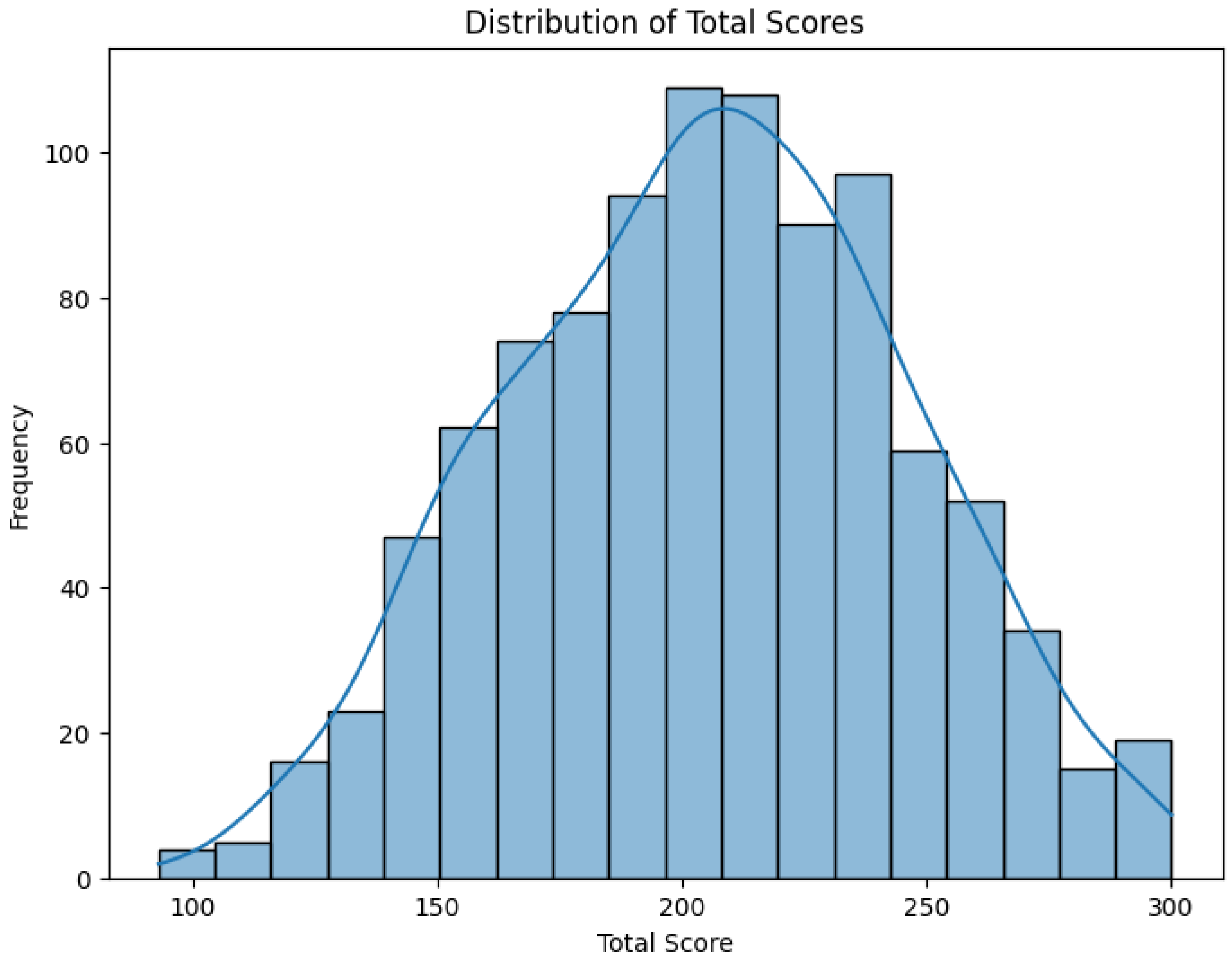
Defining features and target variable

```
X=student_df.drop(['total score'], axis=1)
y=student_df['total score']
```

Basic EDA:

```
plt.figure(figsize=(12, 5))


# Visualizing the relationship between math score and reading score
plt.figure(figsize=(8, 6))
sns.scatterplot(data=student_df, x='math score', y='reading score',
hue='test preparation course')
plt.title('Math Score vs Reading Score')
plt.xlabel('Math Score')
plt.ylabel('Reading Score')
plt.show()

# Visualize the distribution of total scores
plt.figure(figsize=(8, 6))
sns.histplot(student_df['total score'], kde=True)
plt.title('Distribution of Total Scores')
plt.xlabel('Total Score')
plt.ylabel('Frequency')
plt.show()

<Figure size 1200x500 with 0 Axes>
```

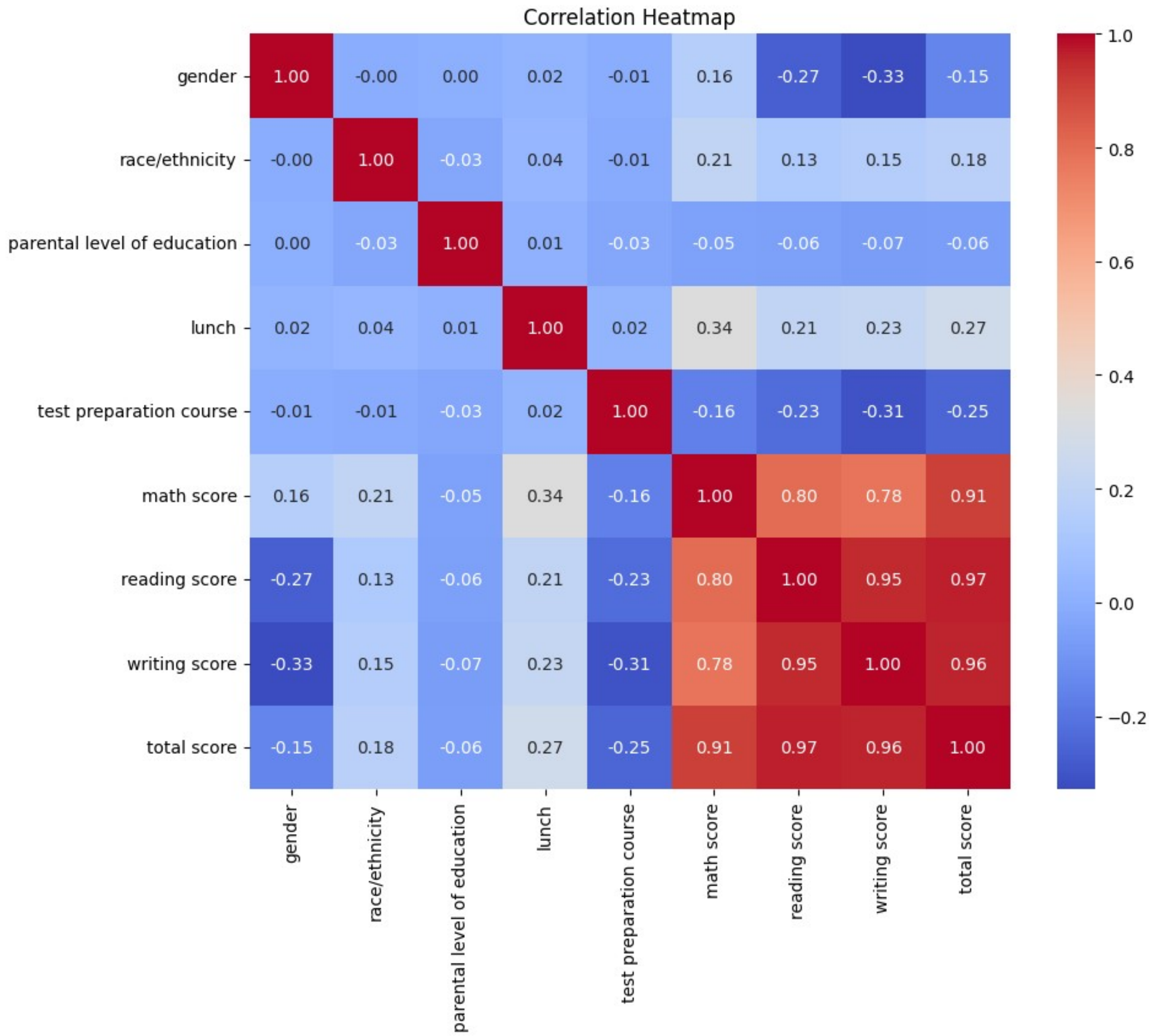

Math Score vs Reading Score
test preparation course
0
1
Reading Score
Math Score
30
40
50
60
70
80
90
100



Looking at the scatter plot, you can see that a positive linear relationship does appear between the math score and the reading. The above histogram depicts that our data set is normally distributed or symmetric. The mean, median, and mode are approximately equal.

Heatmap:

```
# Heatmap of correlation between features and target variable
plt.figure(figsize=(10, 8))
sns.heatmap(student_df.corr(), annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap')
plt.show()
```



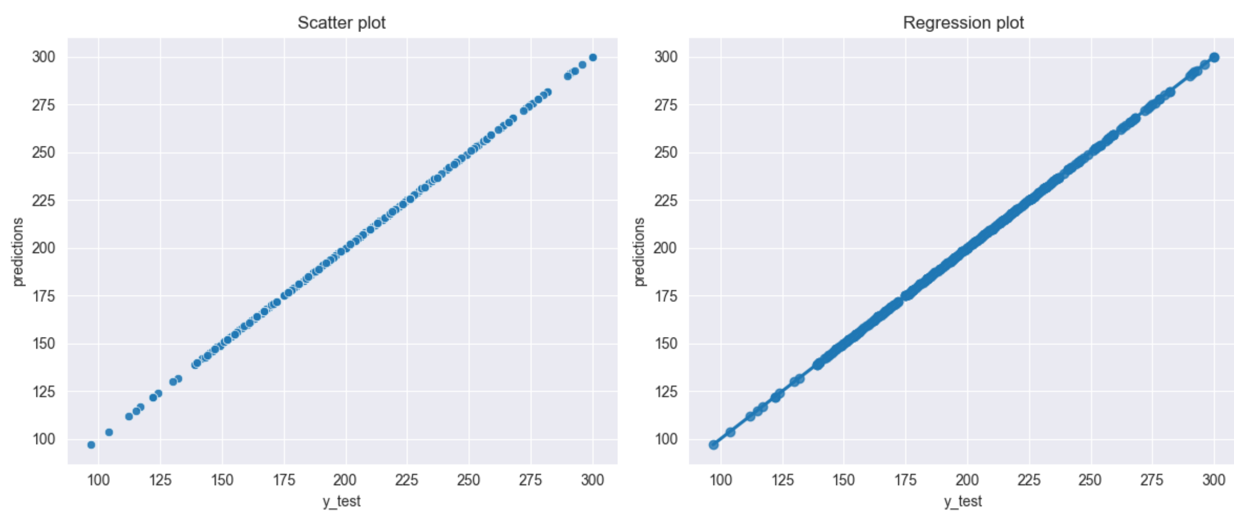

```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn import metrics #for evaluation of the model
from sklearn.preprocessing import StandardScaler

#train test split
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)
```

Standard Scaling

```
# Standardize features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Linear Regression:

```
# create a linear regression object
LR = LinearRegression()
# fit the model
LR.fit(X_train, y_train)
# predict the values for test data
predictions = LR.predict(X_test)

plt.figure(figsize=(12,5))
sns.set_style("darkgrid")
plt.subplot(1,2,1)
sns.scatterplot(x=y_test, y=predictions, alpha=0.9);
plt.xlabel('y_test')
plt.ylabel('predictions')
plt.title('Scatter plot')

plt.subplot(1,2,2)
sns.regplot(x=y_test, y=predictions)
plt.xlabel('y_test')
plt.ylabel('predictions')
plt.title('Regression plot')

plt.tight_layout()
plt.show()
```



Well as above plot shows our model fits very well and showing that the reg score is almost equal to 1, But still we can evaluate the model by the help of the cost functions

Evaluation Metrics:

In case of linear regression, we mostly use mean absolute error, mean squared error & root mean squared error as an evaluation metrics. So lets import them and evaluate our model.

```
print('The regression score on training data :
{}'.format(LR.score(X_train, y_train)))
print('The regression score on testing data :
{}'.format(LR.score(X_test, y_test)))
print('\n')
print('The Mean absolute error:', metrics.mean_absolute_error(y_test,
predictions))
print('The mean squared error:', metrics.mean_squared_error(y_test,
predictions))
print('The root mean squared error:',
np.sqrt(metrics.mean_squared_error(y_test, predictions)))
```

```
The regression score on training data : 1.0
The regression score on testing data : 1.0


The Mean absolute error: 1.5219057245672418e-14
The mean squared error: 4.441500102044356e-28
The root mean squared error: 2.1074866789719823e-14
```

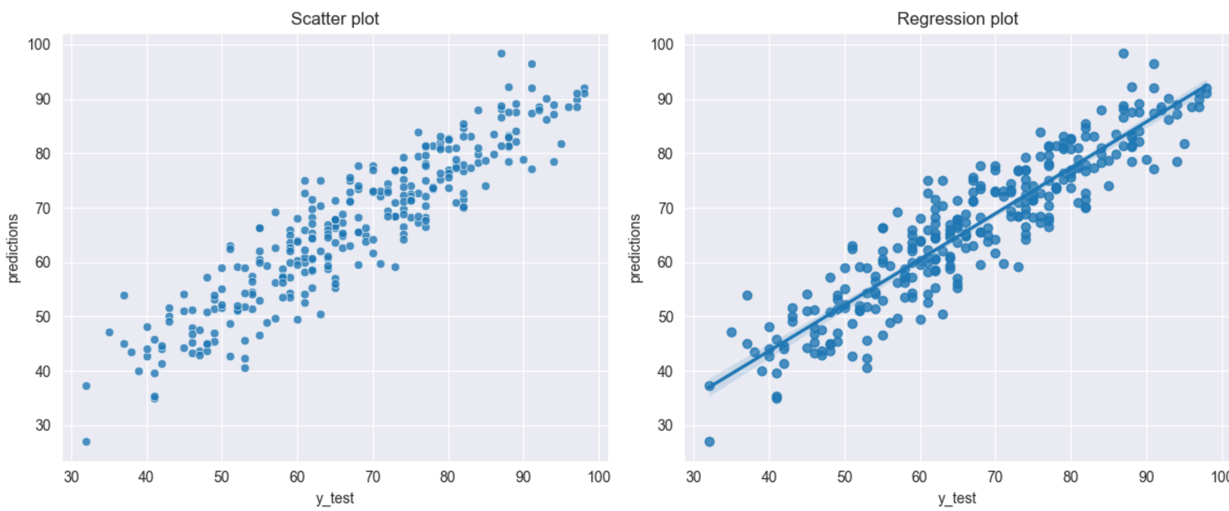
Pretty well! That shows our model is best fitted on the given dataset

Lets create models to predict the math score, reading score and writing score and compare the result

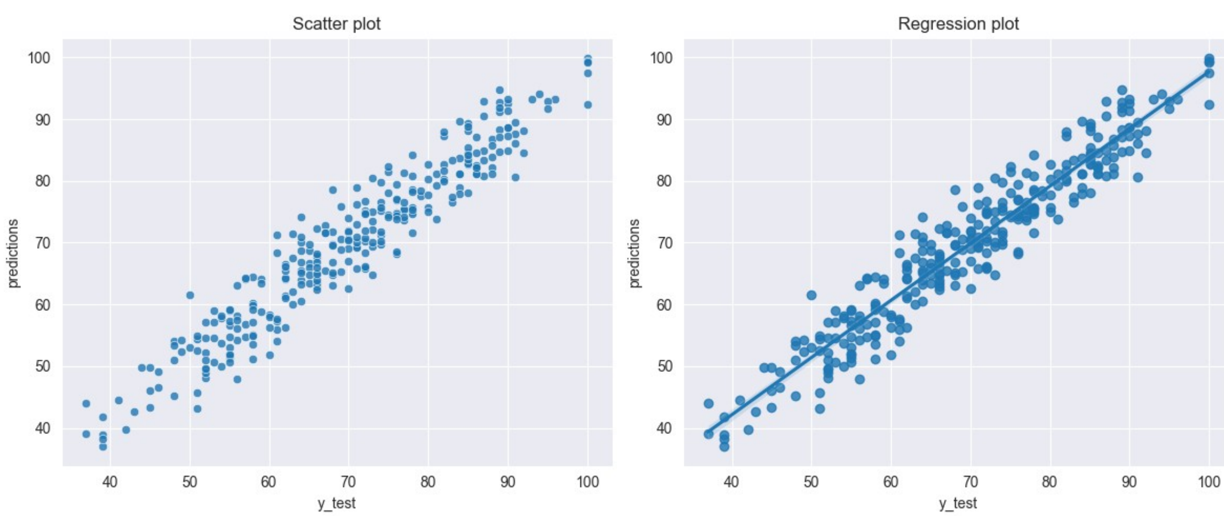
```
student_df2=student_df.drop('total score', axis=1)
sns.set_style("darkgrid")
for i in ['math score', 'reading score', 'writing score']:
    X_train, X_test, y_train, y_test =
train_test_split(student_df2.drop([i], axis=1), student_df2[i],
test_size=0.3, random_state=101)

    LR.fit(X_train, y_train)
    predictions = LR.predict(X_test)

    print('\n')
    print('Plot between y_test and predictions ')
    plt.figure(figsize=(12,5))

    plt.subplot(1,2,1)
    sns.scatterplot(x=y_test, y=predictions, alpha=0.8);
    plt.xlabel('y_test')
    plt.ylabel('predictions')
    plt.title('Scatter plot')

    plt.subplot(1,2,2)
    sns.regplot(x=y_test, y=predictions)
    plt.xlabel('y_test')
    plt.ylabel('predictions')
    plt.title('Regression plot')
```

```
    plt.tight_layout()
    plt.show()
    print('The regression score on training data :
{}'.format(LR.score(X_train, y_train)))
    print('The regression score on testing data :
{}'.format(LR.score(X_test, y_test)))
```

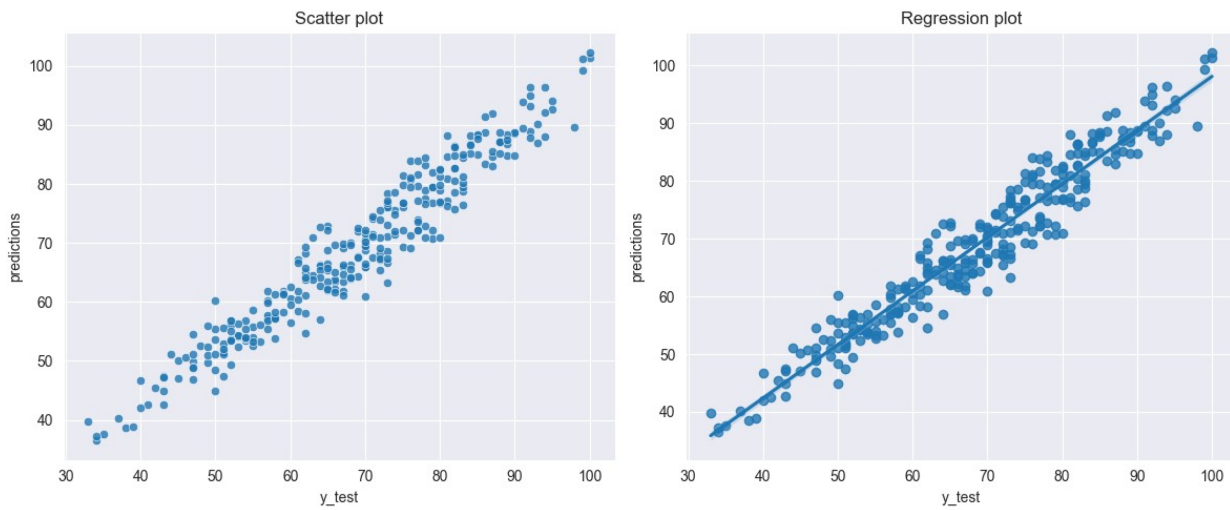
```
Plot between y_test and predictions
```




```
The regression score on training data : 0.8526127947829331
The regression score on testing data : 0.8459414548882465


Plot between y_test and predictions
```



```
The regression score on training data : 0.9140107447213139
The regression score on testing data : 0.9192974057384575


Plot between y_test and predictions
```




```
The regression score on training data : 0.9325397602090365
The regression score on testing data : 0.9361574638607061
```