

```
In [33]: #There isnt enough data
import numpy as np
import pandas as pd

stand_test = pd.read_csv(r"C:\Users\djbro\OneDrive\Desktop\Multiple Linear Regression\Te
stand_test1= pd.read_csv(r"C:\Users\djbro\OneDrive\Desktop\Multiple Linear Regression\Te
```

```
In [34]: #Concatenate wine and wine1
a=[stand_test,stand_test1]
dataset = pd.concat(a)
dataset
```

```
Out[34]:
```

	grade	male	raceeth	preschool	expectBachelors	motherHS	motherBachelors	motherWork	fatherHS	fa
0	10	0	White	1.0	0.0	1.0	1.0	1.0	1.0	
1	10	1	White	0.0	0.0	1.0	0.0	1.0	1.0	
2	10	0	White	1.0	0.0	1.0	0.0	1.0	1.0	
3	10	0	White	1.0	0.0	1.0	1.0	1.0	1.0	
4	10	0	White	1.0	1.0	1.0	0.0	0.0	1.0	
...
3658	9	1	White	0.0	1.0	1.0	NaN	0.0	1.0	
3659	9	1	White	0.0	0.0	1.0	0.0	1.0	1.0	
3660	10	1	Hispanic	1.0	1.0	1.0	0.0	1.0	1.0	
3661	11	1	Black	0.0	0.0	1.0	0.0	NaN	NaN	
3662	10	0	White	0.0	1.0	1.0	0.0	1.0	1.0	

5233 rows × 24 columns

```
In [35]: #Checking for missing values
dataset.isnull().sum()
```

```
Out[35]:
```

grade	0
male	0
raceeth	48
preschool	77
expectBachelors	85
motherHS	142
motherBachelors	585
motherWork	129
fatherHS	370
fatherBachelors	857
fatherWork	346
selfBornUS	93
motherBornUS	94
fatherBornUS	171
englishAtHome	98
computerForSchoolwork	95
read30MinsADay	55
minutesPerWeekEnglish	289
studentsInEnglish	363
schoolHasLibrary	201
publicSchool	0
urban	0
schoolSize	231

```
readingScore      0
dtype: int64
```

```
In [36]: dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5233 entries, 0 to 3662
Data columns (total 24 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   grade                                5233 non-null   int64
1   male                                5233 non-null   int64
2   raceeth                             5185 non-null   object
3   preschool                           5156 non-null   float64
4   expectBachelors                     5148 non-null   float64
5   motherHS                             5091 non-null   float64
6   motherBachelors                     4648 non-null   float64
7   motherWork                           5104 non-null   float64
8   fatherHS                             4863 non-null   float64
9   fatherBachelors                     4376 non-null   float64
10  fatherWork                           4887 non-null   float64
11  selfBornUS                           5140 non-null   float64
12  motherBornUS                         5139 non-null   float64
13  fatherBornUS                         5062 non-null   float64
14  englishAtHome                       5135 non-null   float64
15  computerForSchoolwork               5138 non-null   float64
16  read30MinsADay                     5178 non-null   float64
17  minutesPerWeekEnglish               4944 non-null   float64
18  studentsInEnglish                   4870 non-null   float64
19  schoolHasLibrary                    5032 non-null   float64
20  publicSchool                        5233 non-null   int64
21  urban                               5233 non-null   int64
22  schoolSize                          5002 non-null   float64
23  readingScore                        5233 non-null   float64
dtypes: float64(19), int64(4), object(1)
memory usage: 1022.1+ KB
```

```
In [37]: dataset = dataset.dropna()
```

```
In [38]: #Checking for missing values
dataset.isnull().sum()
```

```
Out[38]: grade                                0
male                                           0
raceeth                                       0
preschool                                    0
expectBachelors                             0
motherHS                                     0
motherBachelors                             0
motherWork                                  0
fatherHS                                     0
fatherBachelors                             0
fatherWork                                  0
selfBornUS                                  0
motherBornUS                                0
fatherBornUS                                0
englishAtHome                               0
computerForSchoolwork                       0
read30MinsADay                             0
minutesPerWeekEnglish                       0
studentsInEnglish                           0
schoolHasLibrary                            0
publicSchool                               0
urban                                        0
schoolSize                                  0
```

```
readingScore
dtype: int64
```

```
In [39]: #Import label encoder
from sklearn import preprocessing

#label_encoder object knows how to understand word labels
label_encoder = preprocessing.LabelEncoder()

#Encode labels in column Sex and Embarked
dataset['raceeth']= label_encoder.fit_transform(dataset['raceeth'])
```

```
C:\Users\djbro\AppData\Local\Temp\ipykernel_14736\2164675448.py:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
dataset['raceeth']= label_encoder.fit_transform(dataset['raceeth'])
```

```
In [40]: # Checking for null values
print(dataset.info())

# Checking for outliers
print(dataset.describe())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3404 entries, 0 to 3662
Data columns (total 24 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   grade                                3404 non-null   int64
1   male                                3404 non-null   int64
2   raceeth                             3404 non-null   int32
3   preschool                           3404 non-null   float64
4   expectBachelors                     3404 non-null   float64
5   motherHS                            3404 non-null   float64
6   motherBachelors                     3404 non-null   float64
7   motherWork                           3404 non-null   float64
8   fatherHS                            3404 non-null   float64
9   fatherBachelors                     3404 non-null   float64
10  fatherWork                           3404 non-null   float64
11  selfBornUS                           3404 non-null   float64
12  motherBornUS                         3404 non-null   float64
13  fatherBornUS                         3404 non-null   float64
14  englishAtHome                       3404 non-null   float64
15  computerForSchoolwork               3404 non-null   float64
16  read30MinsADay                     3404 non-null   float64
17  minutesPerWeekEnglish               3404 non-null   float64
18  studentsInEnglish                   3404 non-null   float64
19  schoolHasLibrary                    3404 non-null   float64
20  publicSchool                        3404 non-null   int64
21  urban                                3404 non-null   int64
22  schoolSize                           3404 non-null   float64
23  readingScore                         3404 non-null   float64
```

```
dtypes: float64(19), int32(1), int64(4)
```

```
memory usage: 651.5 KB
```

```
None
```

	grade	male	raceeth	preschool	expectBachelors	\
count	3404.000000	3404.000000	3404.000000	3404.000000	3404.000000	
mean	10.126910	0.498531	4.685370	0.725911	0.827556	
std	0.520284	0.500071	1.751875	0.446120	0.377822	
min	8.000000	0.000000	0.000000	0.000000	0.000000	
25%	10.000000	0.000000	3.000000	0.000000	1.000000	
50%	10.000000	0.000000	6.000000	1.000000	1.000000	

75%	10.000000	1.000000	6.000000	1.000000	1.000000
max	12.000000	1.000000	6.000000	1.000000	1.000000

	motherHS	motherBachelors	motherWork	fatherHS	\
count	3404.000000	3404.000000	3404.000000	3404.000000	
mean	0.889542	0.354289	0.730905	0.867215	
std	0.313506	0.478368	0.443555	0.339392	
min	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	0.000000	0.000000	1.000000	
50%	1.000000	0.000000	1.000000	1.000000	
75%	1.000000	1.000000	1.000000	1.000000	
max	1.000000	1.000000	1.000000	1.000000	

	fatherBachelors	...	englishAtHome	computerForSchoolwork	\
count	3404.000000	...	3404.000000	3404.000000	
mean	0.341069	...	0.876616	0.917156	
std	0.474138	...	0.328926	0.275686	
min	0.000000	...	0.000000	0.000000	
25%	0.000000	...	1.000000	1.000000	
50%	0.000000	...	1.000000	1.000000	
75%	1.000000	...	1.000000	1.000000	
max	1.000000	...	1.000000	1.000000	

	read30MinsADay	minutesPerWeekEnglish	studentsInEnglish	\
count	3404.000000	3404.000000	3404.000000	
mean	0.299941	269.029377	24.591951	
std	0.458299	141.631752	6.966783	
min	0.000000	0.000000	1.000000	
25%	0.000000	225.000000	20.000000	
50%	0.000000	250.000000	25.000000	
75%	1.000000	300.000000	30.000000	
max	1.000000	2025.000000	90.000000	

	schoolHasLibrary	publicSchool	urban	schoolSize	readingScore
count	3404.000000	3404.000000	3404.000000	3404.000000	3404.000000
mean	0.969741	0.916275	0.360165	1372.634841	518.515875
std	0.171323	0.277016	0.480118	855.541812	89.164390
min	0.000000	0.000000	0.000000	100.000000	242.640000
25%	1.000000	1.000000	0.000000	690.000000	457.120000
50%	1.000000	1.000000	0.000000	1233.000000	520.205000
75%	1.000000	1.000000	1.000000	1900.000000	581.980000
max	1.000000	1.000000	1.000000	6694.000000	772.460000

[8 rows x 24 columns]

In [41]: dataset.raceeth.unique()

Out[41]: array([6, 0, 3, 2, 4, 1, 5])

In [42]: dataset.head(5)

	grade	male	raceeth	preschool	expectBachelors	motherHS	motherBachelors	motherWork	fatherHS	father
0	10	0	6	1.0	0.0	1.0	1.0	1.0	1.0	
4	10	0	6	1.0	1.0	1.0	0.0	0.0	1.0	
6	10	0	0	1.0	0.0	1.0	0.0	0.0	1.0	
7	10	0	6	1.0	0.0	1.0	0.0	1.0	1.0	
8	11	0	6	0.0	0.0	1.0	1.0	1.0	1.0	

5 rows x 24 columns

```
In [43]: dataset.columns

Out[43]: Index(['grade', 'male', 'raceeth', 'preschool', 'expectBachelors', 'motherHS',
        'motherBachelors', 'motherWork', 'fatherHS', 'fatherBachelors',
        'fatherWork', 'selfBornUS', 'motherBornUS', 'fatherBornUS',
        'englishAtHome', 'computerForSchoolwork', 'read30MinsADay',
        'minutesPerWeekEnglish', 'studentsInEnglish', 'schoolHasLibrary',
        'publicSchool', 'urban', 'schoolSize', 'readingScore'],
        dtype='object')
```

```
In [44]: dataset.corr()
```

```
Out[44]:
```

	grade	male	raceeth	preschool	expectBachelors	motherHS	motherBachelors
grade	1.000000	-0.088510	-0.023883	0.008111	0.115848	0.015706	0.035358
male	-0.088510	1.000000	0.020437	0.012026	-0.092327	0.030829	0.052541
raceeth	-0.023883	0.020437	1.000000	0.058449	0.033880	0.227232	0.159000
preschool	0.008111	0.012026	0.058449	1.000000	0.103052	0.138550	0.167373
expectBachelors	0.115848	-0.092327	0.033880	0.103052	1.000000	0.119481	0.177169
motherHS	0.015706	0.030829	0.227232	0.138550	0.119481	1.000000	0.243386
motherBachelors	0.035358	0.052541	0.159000	0.167373	0.177169	0.243386	1.000000
motherWork	0.032151	-0.015031	0.069507	0.083065	0.071965	0.160225	0.132301
fatherHS	0.055522	0.028285	0.229714	0.134133	0.160543	0.511132	0.202969
fatherBachelors	0.057963	0.058505	0.170622	0.161456	0.220153	0.229800	0.550203
fatherWork	0.016955	0.039694	0.096688	0.059649	0.033112	0.004112	0.076205
selfBornUS	-0.028336	0.026843	0.244736	0.089791	-0.003177	0.204745	0.034493
motherBornUS	-0.073732	0.000600	0.497586	0.093709	-0.001411	0.375398	0.133455
fatherBornUS	-0.069322	0.011960	0.482441	0.093035	-0.011533	0.346970	0.108897
englishAtHome	-0.009784	-0.006462	0.390556	0.119919	0.051012	0.403534	0.158373
computerForSchoolwork	0.083564	-0.017935	0.086566	0.116375	0.153392	0.162692	0.137949
read30MinsADay	0.041193	-0.200024	-0.008331	-0.013158	0.113816	0.011817	0.029851
minutesPerWeekEnglish	0.038795	-0.004372	0.017388	-0.019020	0.012247	0.009788	0.015066
studentsInEnglish	0.054908	-0.036653	-0.070715	-0.030417	0.032652	-0.044187	-0.041785
schoolHasLibrary	-0.026137	0.032066	-0.011168	0.006801	0.032860	0.008879	-0.005408
publicSchool	-0.048588	-0.088922	-0.048847	-0.100144	-0.109911	-0.076067	-0.186335
urban	0.080475	0.025459	-0.285179	-0.015045	0.024974	-0.108504	-0.023489
schoolSize	0.068044	-0.003000	-0.197085	-0.012268	0.038534	-0.081655	-0.003737
readingScore	0.222190	-0.120640	0.247034	0.075072	0.343326	0.152614	0.228640

24 rows × 24 columns

```
In [45]: from sklearn.model_selection import train_test_split

# We specify random seed so that the train and test data set always have the same rows,
np.random.seed(0)
df_train, df_test = train_test_split(dataset, train_size = 0.7, test_size = 0.3, random_
```

```
In [46]: #Re-scaling the Features
#We can see that all the columns have
#smaller integer values in the dataset
#except the area column. So it is important to
#re-scale the variables so that they all have a comparable scale.
#If we don't have relative scales, then some of the regression model
#coefficients will be of different units compared to the other coefficients.

#To do that, we use the MinMax scaling method.
```

```
In [47]: from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()

#Applying scaler() to all the columns except the 'yes-no' and 'dummy' variables
num_vars = ['minutesPerWeekEnglish', 'studentsInEnglish', 'schoolSize', 'readingScore', '
df_train[num_vars] = scaler.fit_transform(df_train[num_vars])

df_train
```

```
Out[47]:
```

	grade	male	raceeth	preschool	expectBachelors	motherHS	motherBachelors	motherWork	fatherHS	f
1938	0.50	1	0.333333	1.0	1.0	1.0	0.0	1.0	1.0	
611	0.25	0	1.000000	0.0	1.0	0.0	1.0	0.0	1.0	
48	0.50	0	0.166667	1.0	1.0	1.0	0.0	1.0	1.0	
1169	0.50	1	0.333333	1.0	1.0	1.0	1.0	1.0	1.0	
745	0.50	1	1.000000	1.0	1.0	1.0	0.0	1.0	1.0	
...
1309	0.75	0	0.333333	0.0	1.0	0.0	0.0	0.0	1.0	
3439	0.25	1	0.500000	1.0	1.0	1.0	0.0	1.0	1.0	
1017	0.50	0	0.500000	1.0	1.0	0.0	0.0	0.0	0.0	
2450	0.50	1	1.000000	1.0	1.0	1.0	1.0	1.0	1.0	
2631	0.50	1	0.666667	1.0	0.0	1.0	1.0	1.0	1.0	

2382 rows × 24 columns

```
In [48]: # Dividing the training data set into X and Y
y_train = df_train.pop('readingScore')
X_train = df_train
```

```
In [49]: #Build a linear model

import statsmodels.api as sm
X_train_lm = sm.add_constant(X_train)

lr_1 = sm.OLS(y_train, X_train_lm).fit()

lr_1.summary()
```

```
Out[49]:
```

OLS Regression Results			
Dep. Variable:	readingScore	R-squared:	0.290
Model:	OLS	Adj. R-squared:	0.283
Method:	Least Squares	F-statistic:	41.94
Date:	Sat, 24 Dec 2022	Prob (F-statistic):	9.41e-157

Time:	13:49:20	Log-Likelihood:	1276.6
No. Observations:	2382	AIC:	-2505.
Df Residuals:	2358	BIC:	-2367.
Df Model:	23		
Covariance Type:	nonrobust		

	coef	std err	t	P> t 	[0.025	0.975]
const	0.1484	0.032	4.575	0.000	0.085	0.212
grade	0.2120	0.023	9.146	0.000	0.167	0.257
male	-0.0206	0.006	-3.416	0.001	-0.032	-0.009
raceeth	0.1335	0.012	10.883	0.000	0.109	0.158
preschool	-0.0009	0.007	-0.136	0.892	-0.014	0.012
expectBachelors	0.0954	0.008	11.520	0.000	0.079	0.112
motherHS	0.0103	0.012	0.873	0.383	-0.013	0.034
motherBachelors	0.0213	0.008	2.820	0.005	0.006	0.036
motherWork	0.0009	0.007	0.126	0.900	-0.013	0.014
fatherHS	0.0213	0.011	1.998	0.046	0.000	0.042
fatherBachelors	0.0427	0.008	5.519	0.000	0.028	0.058
fatherWork	0.0044	0.008	0.517	0.605	-0.012	0.021
selfBornUS	-0.0001	0.013	-0.008	0.994	-0.026	0.026
motherBornUS	-0.0328	0.013	-2.595	0.010	-0.058	-0.008
fatherBornUS	0.0110	0.012	0.903	0.366	-0.013	0.035
englishAtHome	0.0076	0.013	0.580	0.562	-0.018	0.033
computerForSchoolwork	0.0353	0.011	3.198	0.001	0.014	0.057
read30MinsADay	0.0643	0.007	9.781	0.000	0.051	0.077
minutesPerWeekEnglish	0.0443	0.036	1.229	0.219	-0.026	0.115
studentsInEnglish	-0.0050	0.034	-0.148	0.882	-0.072	0.062
schoolHasLibrary	0.0047	0.017	0.278	0.781	-0.028	0.038
publicSchool	-0.0369	0.013	-2.918	0.004	-0.062	-0.012
urban	-2.712e-05	0.008	-0.003	0.997	-0.015	0.015
schoolSize	0.0787	0.028	2.802	0.005	0.024	0.134

Omnibus:	2.001	Durbin-Watson:	1.989
Prob(Omnibus):	0.368	Jarque-Bera (JB):	1.934
Skew:	-0.067	Prob(JB):	0.380
Kurtosis:	3.041	Cond. No.	47.3

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
In [50]: #Recursive Feature Elimination (RFE)
#RFE is an automatic process where we don't need to select
#variables manually. We follow the same steps we have done earlier
#until Re-scaling the features and dividing the data into X and Y.

#We will use the LinearRegression function from sklearn
#for RFE (which is a utility from sklearn)
```

```
In [51]: # Importing RFE and LinearRegression
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
```

```
In [52]: # Running RFE with the output number of the variable equal to 10
lm = LinearRegression()
lm.fit(X_train, y_train)

rfe = RFE(lm,n_features_to_select=10)          # running RFE
rfe = rfe.fit(X_train, y_train)

list(zip(X_train.columns,rfe.support_,rfe.ranking_))
```

```
Out[52]: [('grade', True, 1),
('male', False, 3),
('raceeth', True, 1),
('preschool', False, 11),
('expectBachelors', True, 1),
('motherHS', False, 6),
('motherBachelors', False, 2),
('motherWork', False, 12),
('fatherHS', True, 1),
('fatherBachelors', True, 1),
('fatherWork', False, 10),
('selfBornUS', False, 13),
('motherBornUS', False, 4),
('fatherBornUS', False, 5),
('englishAtHome', False, 7),
('computerForSchoolwork', True, 1),
('read30MinsADay', True, 1),
('minutesPerWeekEnglish', True, 1),
('studentsInEnglish', False, 8),
('schoolHasLibrary', False, 9),
('publicSchool', True, 1),
('urban', False, 14),
('schoolSize', True, 1)]
```

```
In [53]: # Creating X_test dataframe with RFE selected variables
col = ['grade','raceeth','expectBachelors','motherBachelors','fatherHS','fatherBachelors']
X_train_rfe = X_train[col]

# Adding a constant variable
import statsmodels.api as sm
X_train_rfe = sm.add_constant(X_train_rfe)

lm = sm.OLS(y_train,X_train_rfe).fit()    # Running the linear model

print(lm.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          readingScore    R-squared:                0.283
Model:                  OLS            Adj. R-squared:           0.280
Method:                 Least Squares   F-statistic:              93.63
```


Date: Sat, 24 Dec 2022 Prob (F-statistic): 2.41e-163
Time: 13:49:20 Log-Likelihood: 1264.5
No. Observations: 2382 AIC: -2507.
Df Residuals: 2371 BIC: -2444.
Df Model: 10
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.97
5]						

-						
const	0.1532	0.021	7.250	0.000	0.112	0.19
5						
grade	0.2231	0.023	9.710	0.000	0.178	0.26
8						
raceeth	0.1329	0.012	11.221	0.000	0.110	0.15
6						
expectBachelors	0.0995	0.008	12.110	0.000	0.083	0.11
6						
motherBachelors	0.0220	0.007	2.967	0.003	0.007	0.03
7						
fatherHS	0.0260	0.010	2.705	0.007	0.007	0.04
5						
fatherBachelors	0.0433	0.008	5.627	0.000	0.028	0.05
8						
motherBornUS	-0.0237	0.009	-2.743	0.006	-0.041	-0.00
7						
computerForSchoolwork	0.0390	0.011	3.571	0.000	0.018	0.06
0						
read30MinsADay	0.0680	0.006	10.551	0.000	0.055	0.08
1						
publicSchool	-0.0226	0.010	-2.165	0.030	-0.043	-0.00
2						
=====						
Omnibus:	1.921	Durbin-Watson:			1.988	
Prob(Omnibus):	0.383	Jarque-Bera (JB):			1.844	
Skew:	-0.063	Prob(JB):			0.398	
Kurtosis:	3.052	Cond. No.			23.4	
=====						

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
In [54]: from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
X = X_train_rfe
vif['Features'] = X.columns
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
print(vif)
```

	Features	VIF
0	const	52.263214
1	grade	1.027453
2	raceeth	1.383522
3	expectBachelors	1.116988
4	motherBachelors	1.478825
5	fatherHS	1.260773
6	fatherBachelors	1.557503
7	motherBornUS	1.484564
8	computerForSchoolwork	1.071096
9	read30MinsADay	1.018813
10	publicSchool	1.060722

```
In [55]: X_train_new = X_train_rfe.drop(["const"], axis = 1)
```

```

# Adding a constant variable
import statsmodels.api as sm
X_train_lm = sm.add_constant(X_train_new)

lm = sm.OLS(y_train,X_train_lm).fit()    # Running the linear model
print(lm.summary())

vif = pd.DataFrame()
X = X_train_new
vif['Features'] = X.columns
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
print(vif)

```

OLS Regression Results

```

=====
Dep. Variable:          readingScore    R-squared:                0.283
Model:                  OLS            Adj. R-squared:           0.280
Method:                 Least Squares   F-statistic:              93.63
Date:                   Sat, 24 Dec 2022 Prob (F-statistic):       2.41e-163
Time:                   13:49:20        Log-Likelihood:          1264.5
No. Observations:      2382            AIC:                     -2507.
Df Residuals:          2371            BIC:                     -2444.
Df Model:               10
Covariance Type:        nonrobust
=====
=

```

	coef	std err	t	P> t	[0.025	0.97
5]						

-						
const	0.1532	0.021	7.250	0.000	0.112	0.19
5						
grade	0.2231	0.023	9.710	0.000	0.178	0.26
8						
raceeth	0.1329	0.012	11.221	0.000	0.110	0.15
6						
expectBachelors	0.0995	0.008	12.110	0.000	0.083	0.11
6						
motherBachelors	0.0220	0.007	2.967	0.003	0.007	0.03
7						
fatherHS	0.0260	0.010	2.705	0.007	0.007	0.04
5						
fatherBachelors	0.0433	0.008	5.627	0.000	0.028	0.05
8						
motherBornUS	-0.0237	0.009	-2.743	0.006	-0.041	-0.00
7						
computerForSchoolwork	0.0390	0.011	3.571	0.000	0.018	0.06
0						
read30MinsADay	0.0680	0.006	10.551	0.000	0.055	0.08
1						
publicSchool	-0.0226	0.010	-2.165	0.030	-0.043	-0.00
2						
=====						
Omnibus:	1.921		Durbin-Watson:		1.988	
Prob (Omnibus):	0.383		Jarque-Bera (JB):		1.844	
Skew:	-0.063		Prob (JB):		0.398	
Kurtosis:	3.052		Cond. No.		23.4	
=====						

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

	Features	VIF
0	grade	13.334303
1	raceeth	10.784652

2	expectBachelors	6.273012
3	motherBachelors	2.295383
4	fatherHS	9.107929
5	fatherBachelors	2.357636
6	motherBornUS	6.824334
7	computerForSchoolwork	11.198686
8	read30MinsADay	1.448749
9	publicSchool	8.536986

In [56]: *#Since the p-values and VIF are in the desired range, we'll move forward with the analysis*

In [57]: *#The next step is the residual analysis of error terms.*

#Residual Analysis

#So, let's check if the error terms are also normally distributed using a histogram.

In [58]: `y_train_price = lm.predict(X_train_lm)`

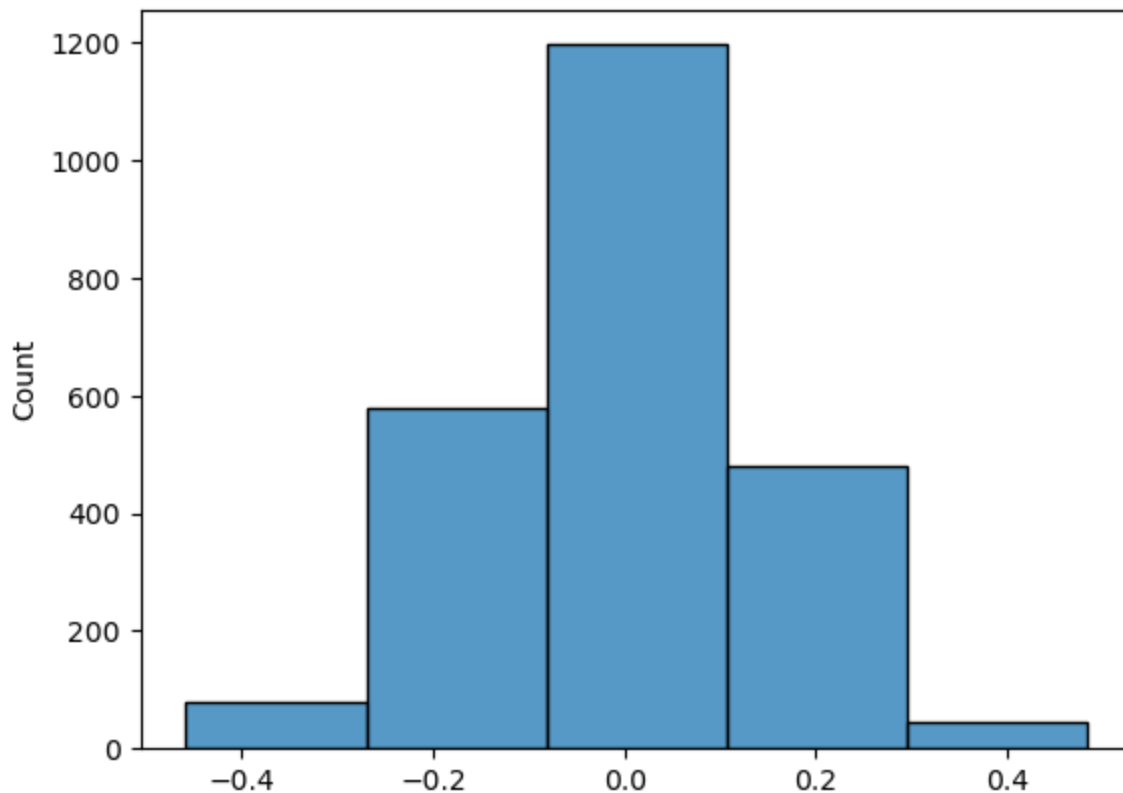
Importing the required libraries for plots.

```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Plot the histogram of the error terms

```
fig = plt.figure()
sns.histplot((y_train - y_train_price), bins = 5)
```

Out[58]: `<AxesSubplot:ylabel='Count'>`



In [59]: `num_vars = ['minutesPerWeekEnglish', 'studentsInEnglish', 'schoolSize', 'readingScore', 'df_test[num_vars] = scaler.transform(df_test[num_vars])`

```
y_test = df_test.pop('readingScore')
X_test = df_test
```

Now let's use our model to make predictions.

Creating X_test_new dataframe by dropping variables from X_test

```
X_test_new = X_test[X_train_new.columns]
```

```
# Adding a constant variable
X_test_new = sm.add_constant(X_test_new)

# Making predictions
y_pred = lm.predict(X_test_new)
```

```
In [60]: from sklearn.metrics import r2_score
r2_score(y_true = y_test, y_pred = y_pred)
```

```
Out[60]: 0.2823514158060685
```

```
In [61]: from sklearn import metrics
print(metrics.mean_absolute_error(y_test, y_pred))
print(metrics.mean_squared_error(y_test, y_pred))
print(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
0.11335678625972335
0.020431053528085375
0.14293723632449795
```

```
In [62]: #The R2 value for the test data = 0.6481740917926483,
#which is pretty similar to the train data.

#Since the R2 values for both the train and
#test data are almost equal, the model we built is the best-fitted model.
```