Problem 1: Linear Regression

You are hired by a company Gem Stones co ltd, which is a cubic zirconia manufacturer. You are provided with the dataset containing the prices and other attributes of almost 27,000 cubic zirconia (which is an inexpensive diamond alternative with many of the same qualities as a diamond). The company is earning different profits on different prize slots. You have to help the company in predicting the price for the stone on the bases of the details given in the dataset so it can distinguish between higher profitable stones and lower profitable stones so as to have better profit share. Also, provide them with the best 5 attributes that are most important.

Data Dictionary:

Variable Name Description

Carat : Carat weight of the cubic zirconia.

Cut : Describe the cut quality of the cubic zirconia. Quality is increasing order Fair, Good, Very Good, Premium, Ideal.

Color: Colour of the cubic zirconia.With D being the best and J the worst.

Clarity: cubic zirconia Clarity refers to the absence of the Inclusions and Blemishes. (In order from Best to Worst, FL = flawless, I3= level 3 inclusions) FL, IF, VVS1, VVS2, VS1, VS2, SI1, SI2, I1, I2, I3

Depth: The Height of a cubic zirconia, measured from the Culet to the table, divided by its average Girdle Diameter.

Table: The Width of the cubic zirconia's Table expressed as a Percentage of its Average Diameter.

Price: the Price of the cubic zirconia.

X : Length of the cubic zirconia in mm.

Y :Width of the cubic zirconia in mm.

Z :Height of the cubic zirconia in mm.

1.1. Read the data and do exploratory data analysis. Describe the data briefly. (Check the null values, Data types, shape, EDA). Perform Univariate and Bivariate Analysis.

1.2 Impute null values if present, also check for the values which are equal to zero. Do they have any meaning or do we need to change them or drop them? Do you think scaling is necessary in this case?

1.3 Encode the data (having string values) for Modelling. Data Split: Split the data into train and test (70:30). Apply Linear regression. Performance Metrics: Check the performance of Predictions on Train and Test sets using Rsquare, RMSE.

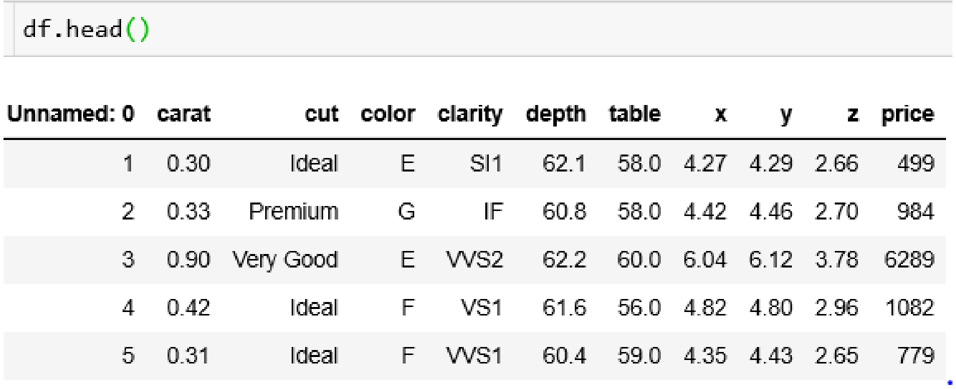
1.4 Inference: Basis on these predictions, what are the business insights and recommendations.

1.1. Read the data and do exploratory data analysis. Describe the data briefly. (Check the null values, Data types, shape, EDA). Perform Univariate and Bivariate Analysis.

Import all the necessary libraries required, like seaborn, matplotlib, sklearn, numpy, pandas, scipy etc.

After importing,

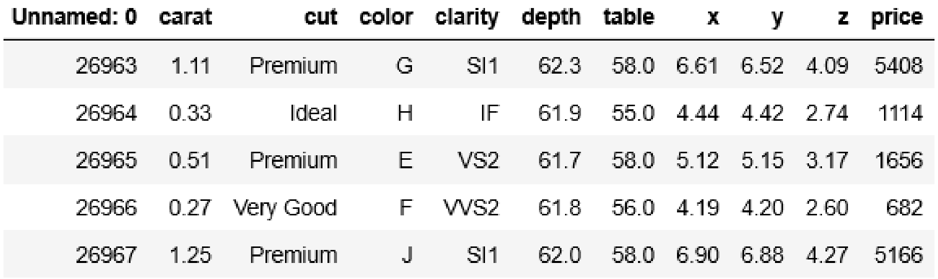
Head of the data



```
df.head()
```

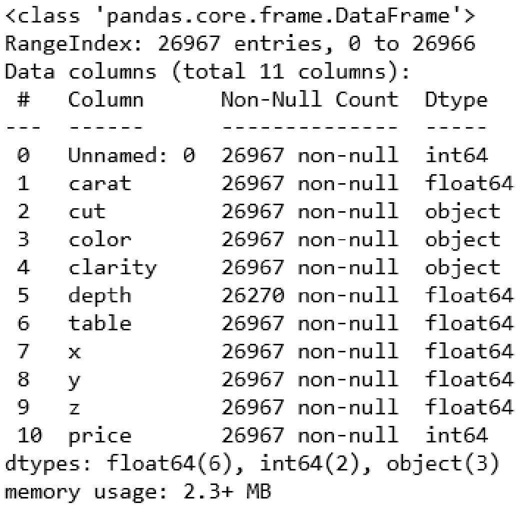
Unnamed: 0	carat	cut	color	clarity	depth	table	x	y	z	price
1	0.30	Ideal	E	SI1	62.1	58.0	4.27	4.29	2.66	499
2	0.33	Premium	G	IF	60.8	58.0	4.42	4.46	2.70	984
3	0.90	Very Good	E	VVS2	62.2	60.0	6.04	6.12	3.78	6289
4	0.42	Ideal	F	VS1	61.6	56.0	4.82	4.80	2.96	1082
5	0.31	Ideal	F	VVS1	60.4	59.0	4.35	4.43	2.65	779

Tail of the data,



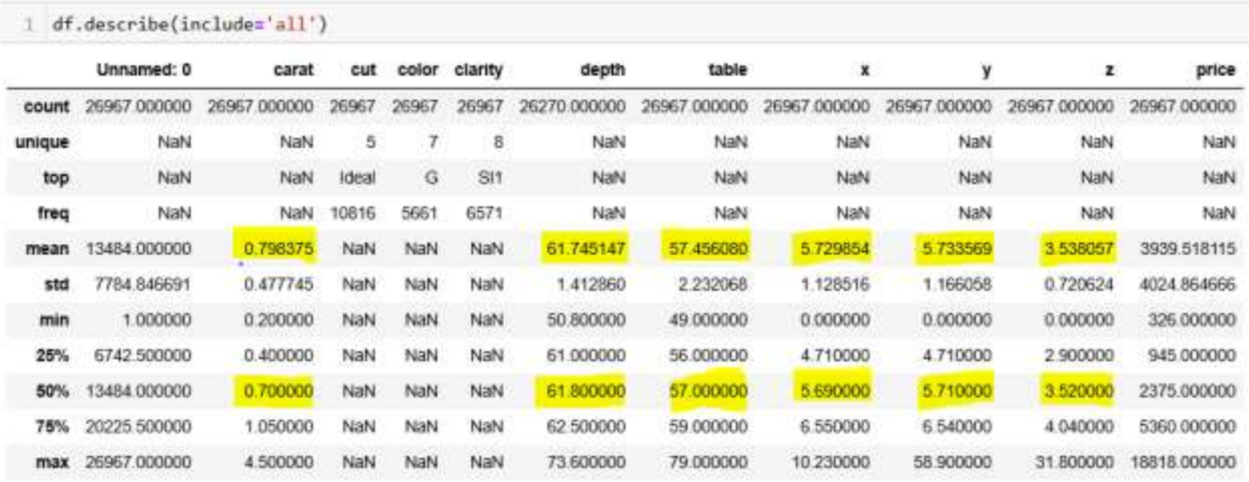
Unnamed: 0	carat	cut	color	clarity	depth	table	x	y	z	price
26963	1.11	Premium	G	SI1	62.3	58.0	6.61	6.52	4.09	5408
26964	0.33	Ideal	H	IF	61.9	55.0	4.44	4.42	2.74	1114
26965	0.51	Premium	E	VS2	61.7	58.0	5.12	5.15	3.17	1656
26966	0.27	Very Good	F	VVS2	61.8	56.0	4.19	4.20	2.60	682
26967	1.25	Premium	J	SI1	62.0	58.0	6.90	6.88	4.27	5166

Data Description:



```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26967 entries, 0 to 26966
Data columns (total 11 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Unnamed: 0  26967 non-null  int64  
 1   carat       26967 non-null  float64
 2   cut         26967 non-null  object 
 3   color       26967 non-null  object 
 4   clarity     26967 non-null  object 
 5   depth       26270 non-null  float64
 6   table       26967 non-null  float64
 7   x           26967 non-null  float64
 8   y           26967 non-null  float64
 9   z           26967 non-null  float64
 10  price       26967 non-null  int64  
dtypes: float64(6), int64(2), object(3)
memory usage: 2.3+ MB
```

By above Information we can say that there are 9 dependent Variables and 1 Independent variable which is Price. Unnamed is of no use, we will drop it ahead. Data Type of Variables is int,float and object. Cut, Color and clarity are three categorical variables, which we have to convert into numerical variables. All these three variables are Ordinal categorical variables, where Order matters. Total we have 26967 rows and 11 columns.



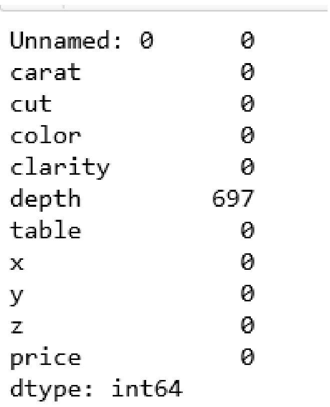
```
df.describe(include='all')
```

	Unnamed: 0	carat	cut	color	clarity	depth	table	x	y	z	price
count	26967.000000	26967.000000	26967	26967	26967	26270.000000	26967.000000	26967.000000	26967.000000	26967.000000	26967.000000
unique	NaN	NaN	5	7	8	NaN	NaN	NaN	NaN	NaN	NaN
top	NaN	NaN	Ideal	G	SI1	NaN	NaN	NaN	NaN	NaN	NaN
freq	NaN	NaN	10816	5661	6571	NaN	NaN	NaN	NaN	NaN	NaN
mean	13484.000000	0.798375	NaN	NaN	NaN	61.745147	57.456080	5.729854	5.733569	3.538057	3939.518115
std	7784.846691	0.477745	NaN	NaN	NaN	1.412860	2.232068	1.128516	1.166058	0.720624	4024.864666
min	1.000000	0.200000	NaN	NaN	NaN	50.800000	49.000000	0.000000	0.000000	0.000000	326.000000
25%	6742.500000	0.400000	NaN	NaN	NaN	61.000000	56.000000	4.710000	4.710000	2.900000	945.000000
50%	13484.000000	0.700000	NaN	NaN	NaN	61.800000	57.000000	5.690000	5.710000	3.520000	2375.000000
75%	20225.500000	1.050000	NaN	NaN	NaN	62.500000	59.000000	6.550000	6.540000	4.040000	5360.000000
max	26967.000000	4.500000	NaN	NaN	NaN	73.600000	79.000000	10.230000	58.900000	31.800000	18818.000000

Means and 50% are almost same so data is normally distributed.

From above table, we can see that mean and median are almost same. we will check further whether variables are normally distributed or not.

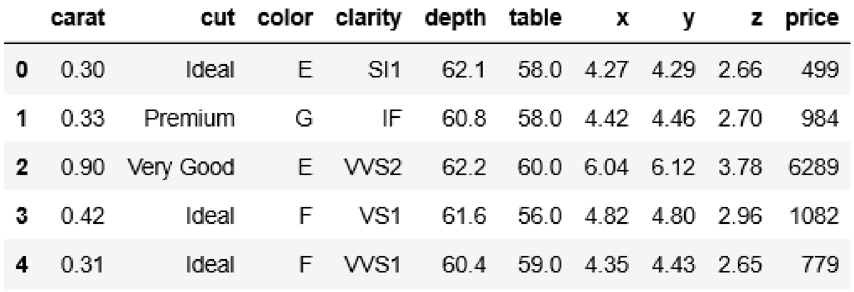
Null Value Check:



```
Unnamed: 0      0
carat           0
cut             0
color           0
clarity         0
depth         697
table           0
x               0
y               0
z               0
price           0
dtype: int64
```

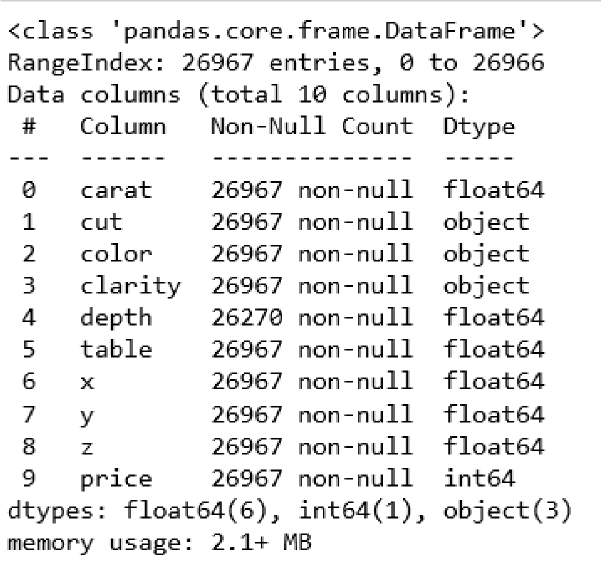
Here in Depth column total 697 values are missing out of 26967, so it is less that 3 percent so we can directly drop this observations or we can impute it with Median.

After Dropping the variable ‘unnamed:0’ Head of the dataset



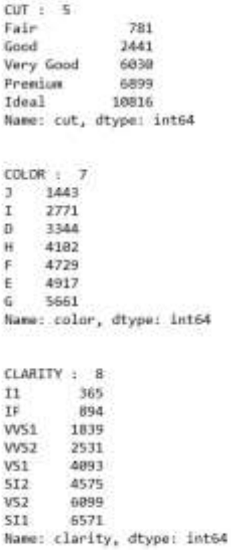
	carat	cut	color	clarity	depth	table	x	y	z	price
0	0.30	Ideal	E	SI1	62.1	58.0	4.27	4.29	2.66	499
1	0.33	Premium	G	IF	60.8	58.0	4.42	4.46	2.70	984
2	0.90	Very Good	E	VVS2	62.2	60.0	6.04	6.12	3.78	6289
3	0.42	Ideal	F	VS1	61.6	56.0	4.82	4.80	2.96	1082
4	0.31	Ideal	F	VVS1	60.4	59.0	4.35	4.43	2.65	779

Unwanted variable is removed.



```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26967 entries, 0 to 26966
Data columns (total 10 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   carat    26967 non-null  float64
 1   cut      26967 non-null  object 
 2   color    26967 non-null  object 
 3   clarity  26967 non-null  object 
 4   depth    26270 non-null  float64
 5   table    26967 non-null  float64
 6   x        26967 non-null  float64
 7   y        26967 non-null  float64
 8   z        26967 non-null  float64
 9   price    26967 non-null  int64  
dtypes: float64(6), int64(1), object(3)
memory usage: 2.1+ MB
```

Checking the unique values for categorical variables

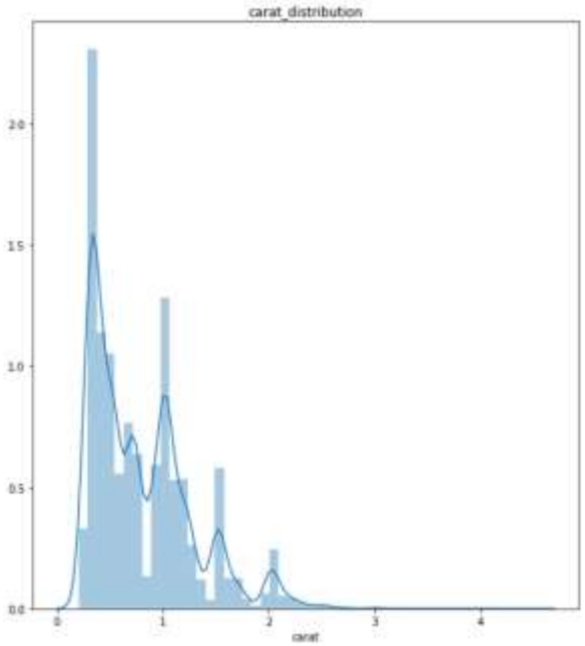


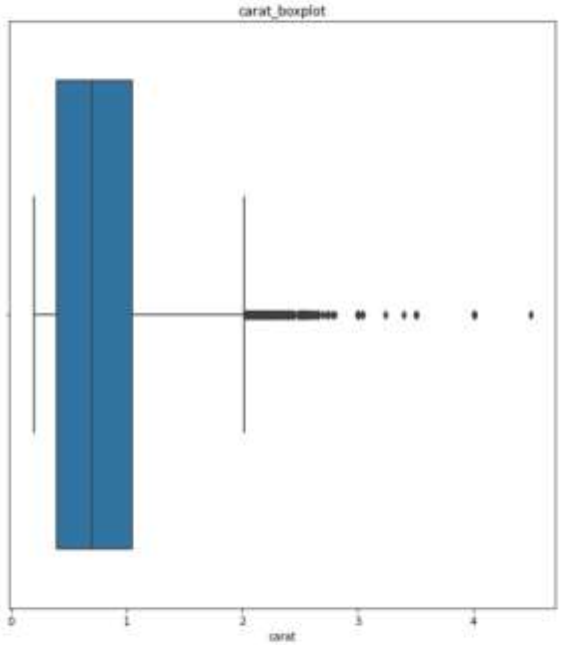
```
CUT :  5
Fair            781
Good           2441
Very Good      6030
Premium        6899
Ideal         10816
Name: cut, dtype: int64

COLOR :  7
J    1443
I    2771
D    3344
H    4102
F    4729
E    4917
G    5661
Name: color, dtype: int64

CLARITY :  8
I1       365
IF       894
VVS1    1839
VVS2    2531
VS1     4093
SI2     4575
VS2     6099
SI1     6571
Name: clarity, dtype: int64
```

All the three variables needs to be encoded, as variables are Ordinal we can use One hot encoding or Label encoding.

Univariate Analysis:

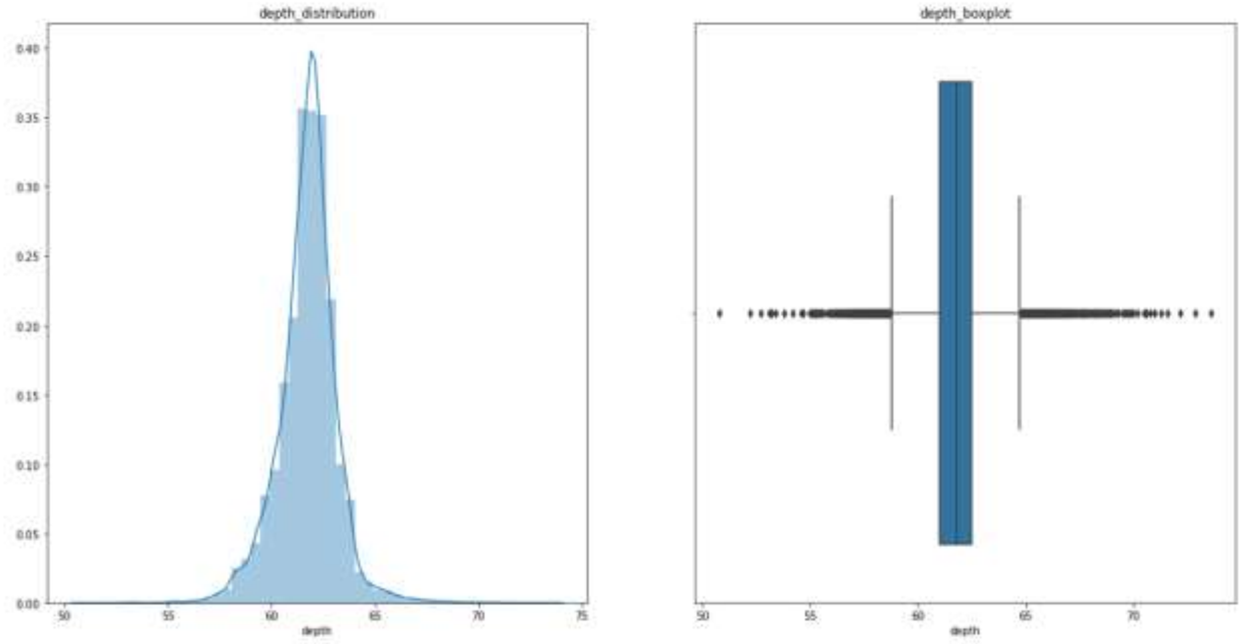
Now we will perform Univariate analysis, to see the Distributions, skewness and get general idea of data distribution.





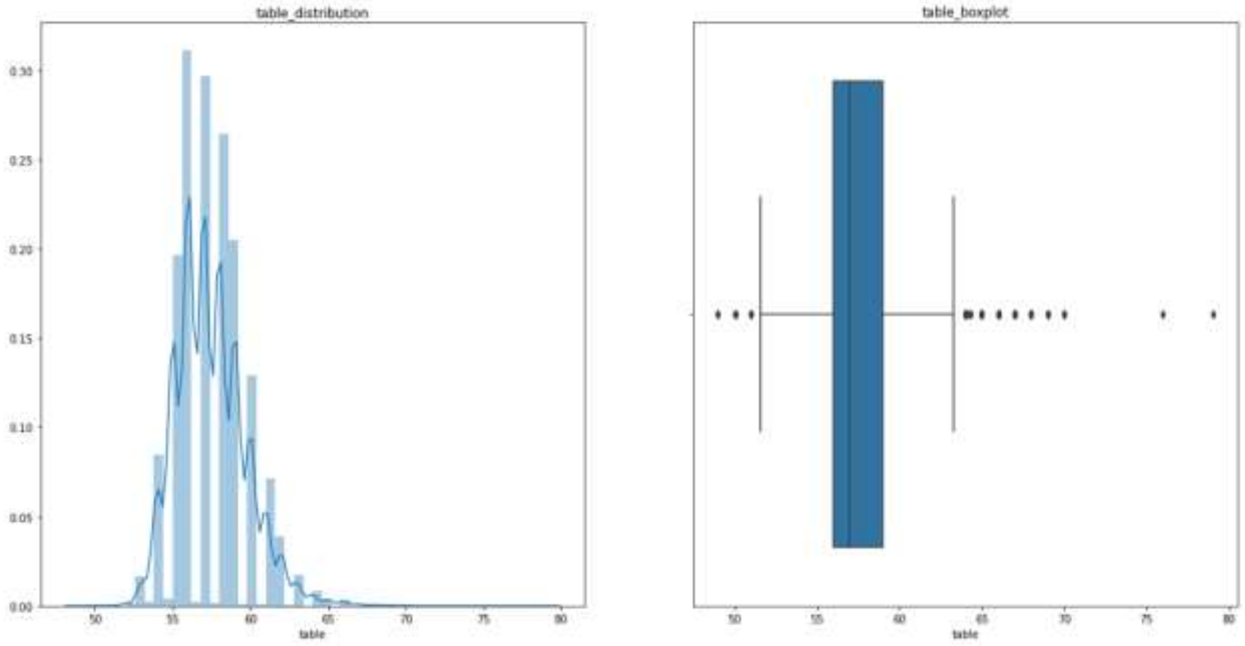
From above plots we get to know that carat variable is right skewed, and it has too many peaks so this variable seems to be inconsistent, and it has outliers that can be seen in boxplot.Maximum Data points ranges between 0 to 2.

plot the graph for depth variable



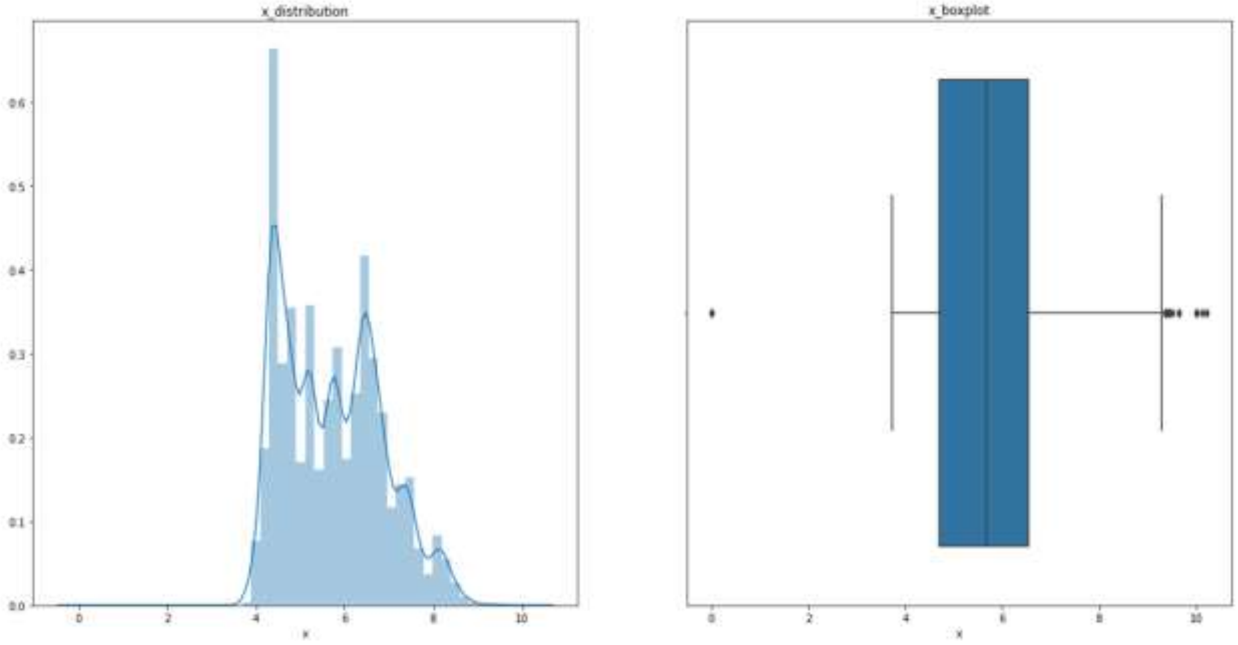
The Distribution of Depth variable seems to be Normal, it is normally distributed. It has too many outliers that can be seen in boxplot.Maximum data points are between 57 to 65.

Table Variable:



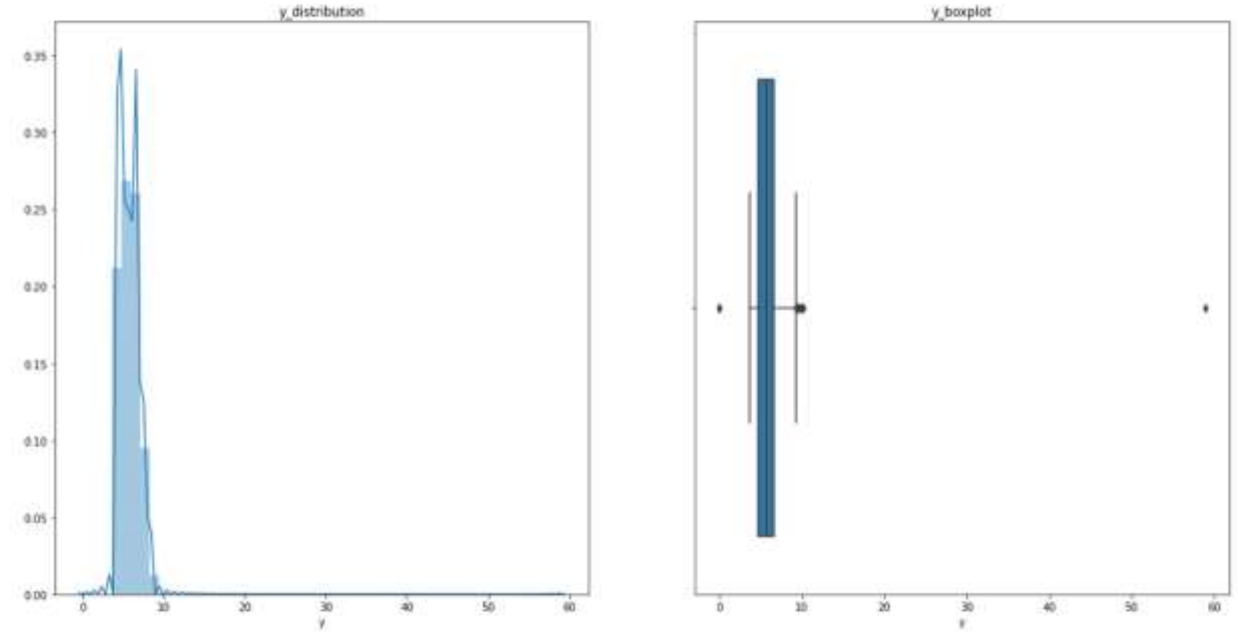
The Distribution of table variable seems to be right skewd and it has too many spikes due to inconsistent data.It also has outliers that can be seen in boxplot.Maximum data points are situated between 52 to 60. It has range of 50 to 65.

plot the graph for x variable



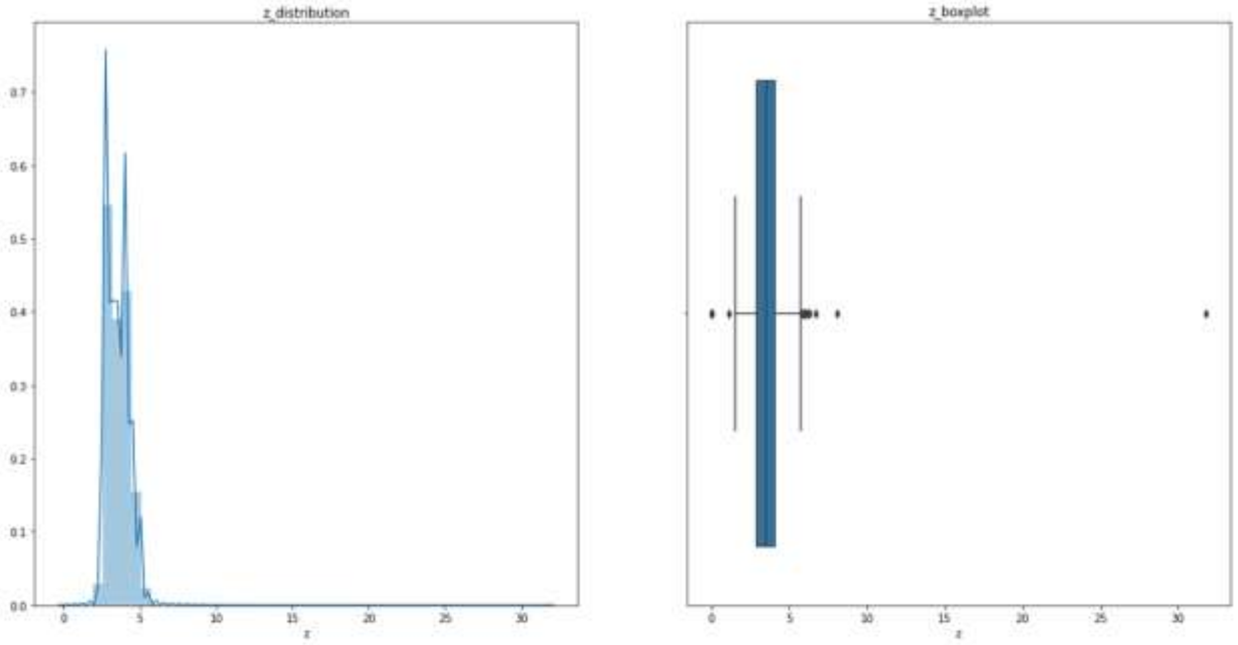
The Distribution of x variable seems to be left skewd and it has too many spikes due to inconsistent data.It also has outliers that can be seen in boxplot. It has range from 4 to 8.

plot the graph for y variable



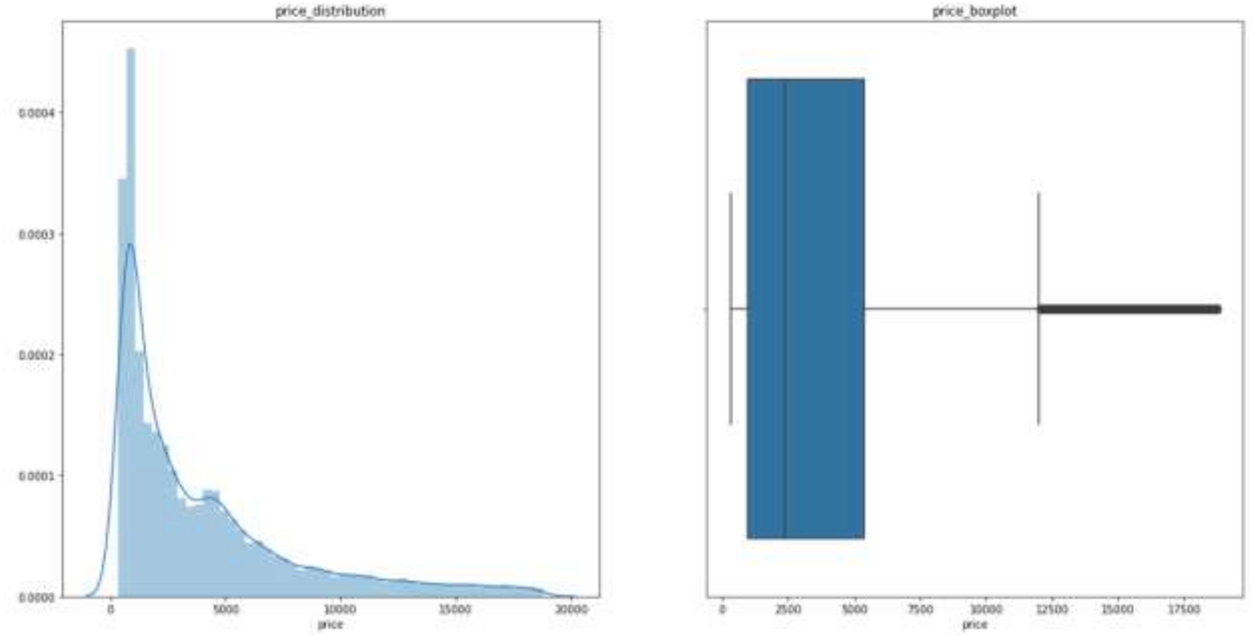
The Distribution of y variable seems to be right skewd and it has too many spikes due to inconsistent data.It also has less outliers that can be seen in boxplot.

Plot the graph for z variable



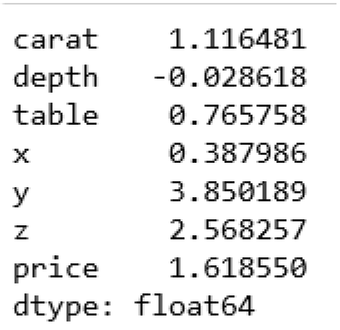
The Distribution of z variable seems to be right skewd and it has too many spikes due to inconsistent data.It also has less outliers that can be seen in boxplot.

Plot the graph for price variable- Target variable(Dependent)



The target Dependent 'Price' variable is also Right Skewed and it also has outliers. This is just for information, we will not treat this variable.

Skewness:

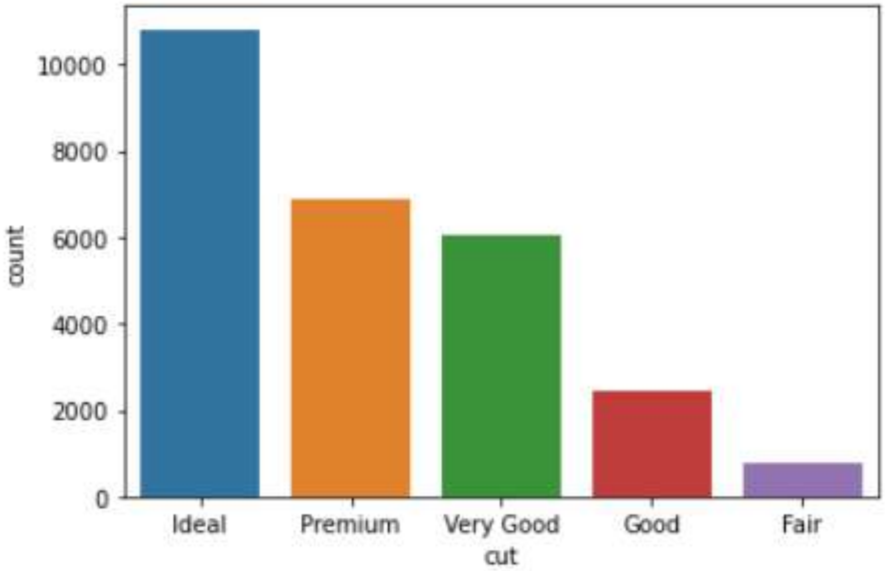


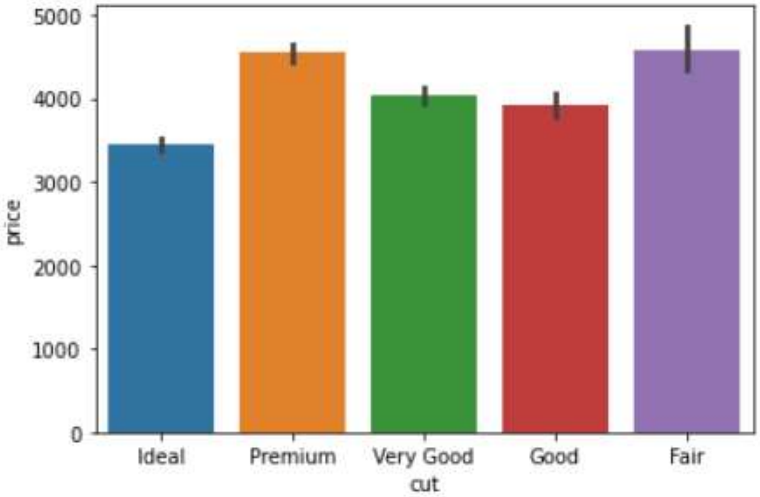
```
carat     1.116481
depth    -0.028618
table     0.765758
x         0.387986
y         3.850189
z         2.568257
price     1.618550
dtype: float64
```

We can see that depth, table, x are less skwed(Positive/Negative) while carat,y ,z are highly positive skwed .

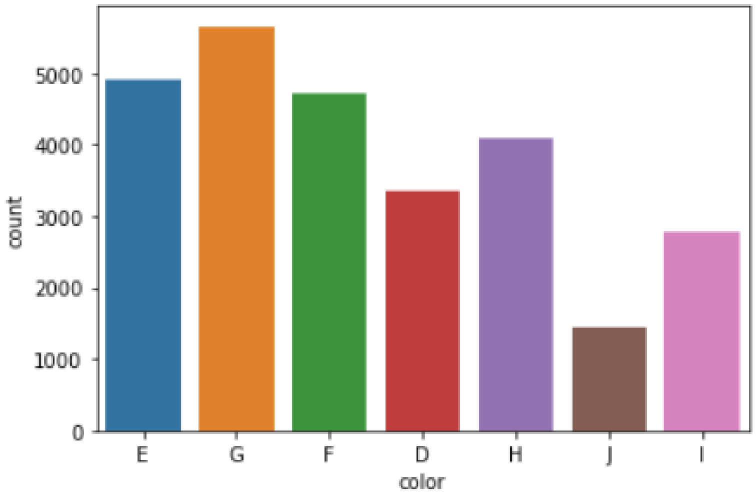
Bivariate Analysis

cut vs price



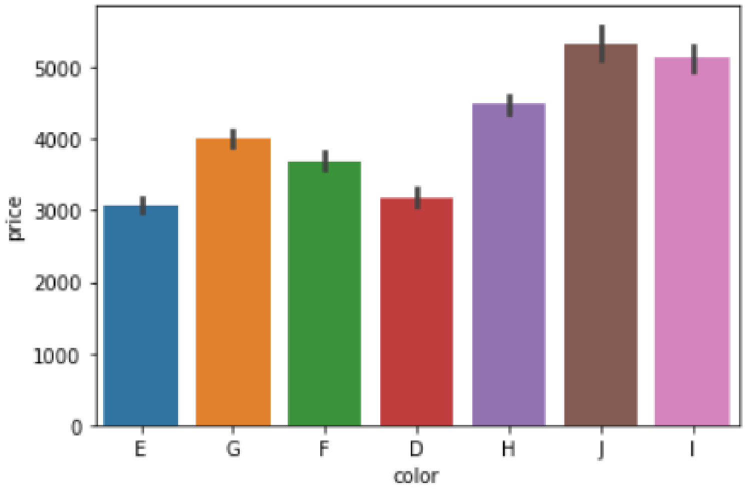


We can see, from given dataset count of Ideal cut is High, so it seems that people prefer this cut, the reason seems to be less price.



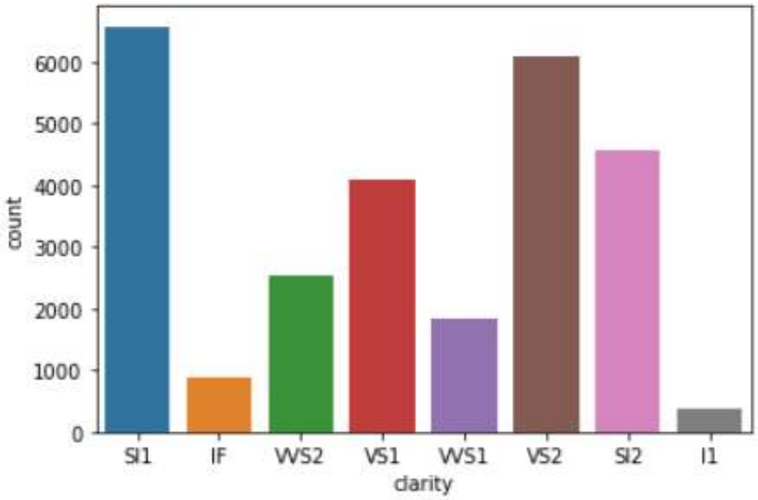
D is the best color while J is the worst color. J us the least used might because of it is worst. Count of users of Color G is high, It is Moderate level color, with the moderate price.

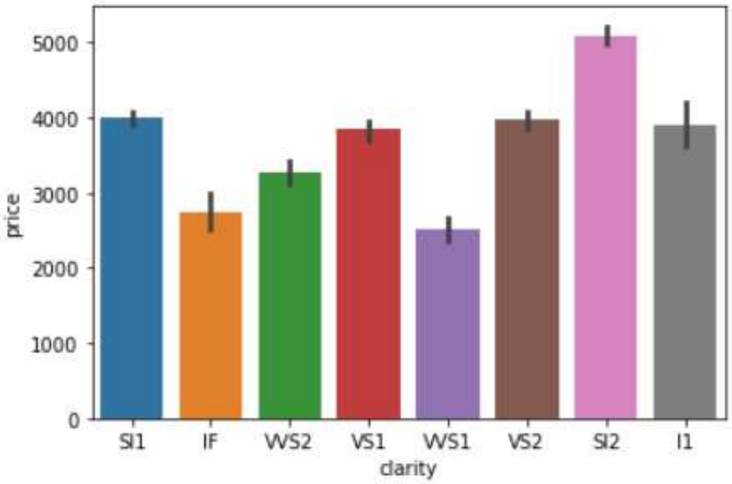
Color vs Price:



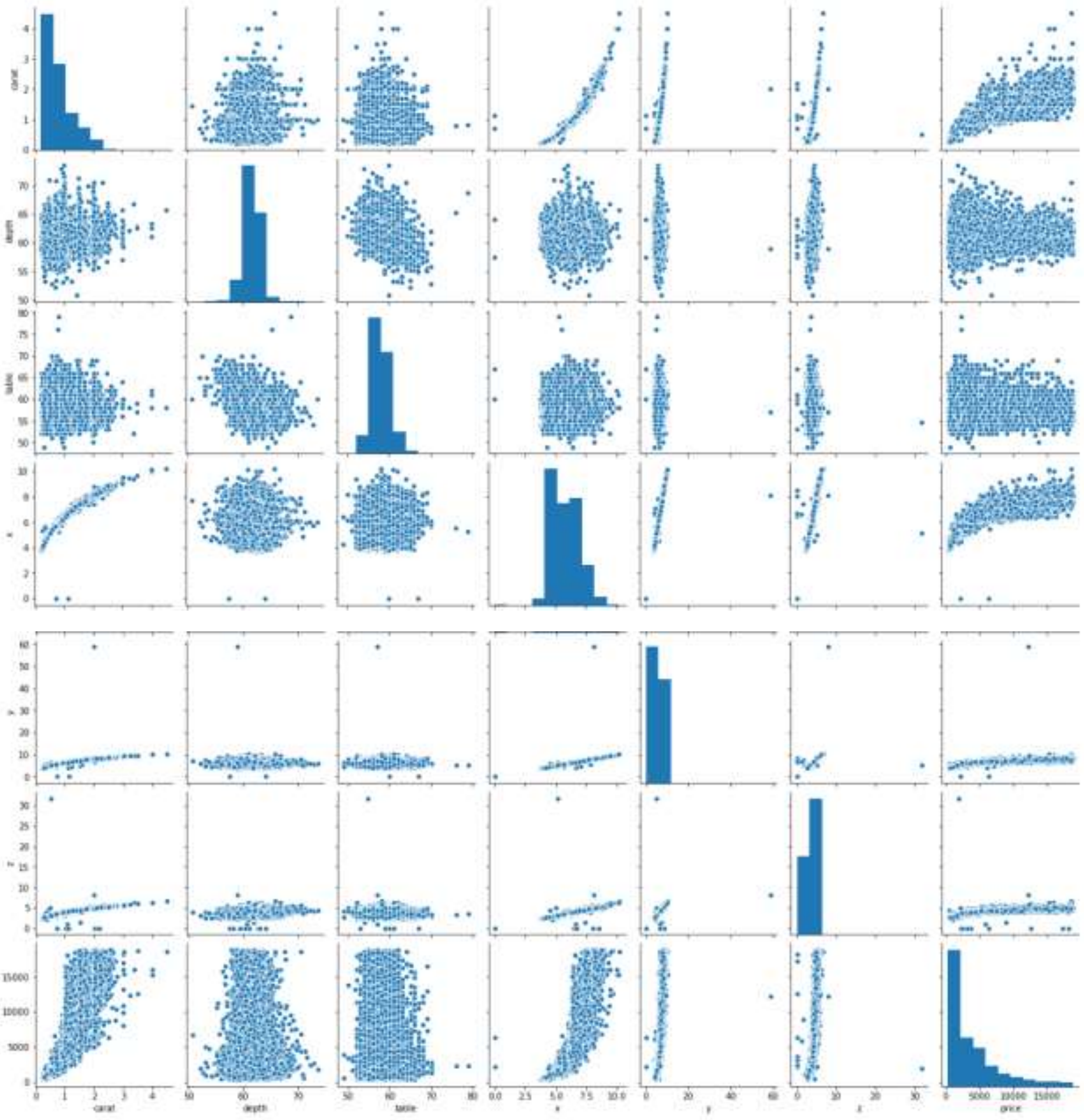
Another reason that less people select J color may be its Highest price, so Price and its color quality are two factors deciding the count here.

Clarity vs Price:



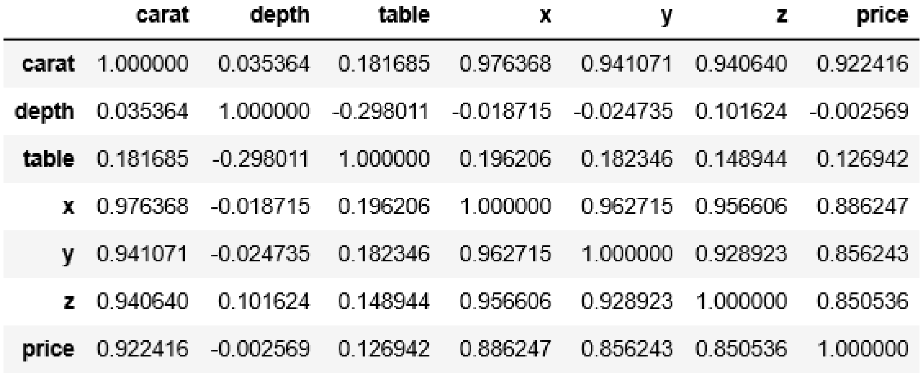


Pairplot: To analyse all possibilities



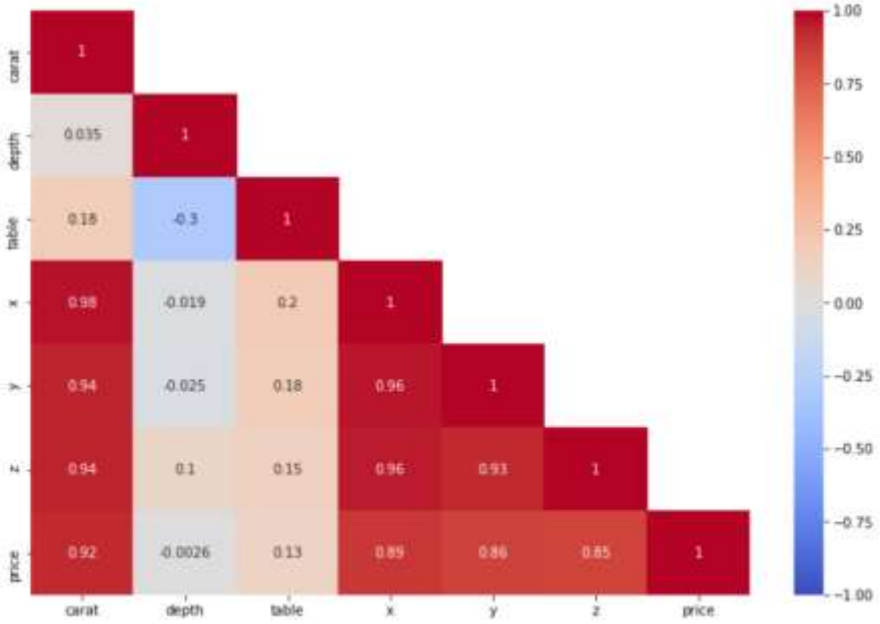
Order from best to worst: FL, IF, VVS1, VVS2, VS1, VS2, SI1, SI2, I1, I2, I3 : Flawless to Level 3
It seems that no one is buying Flawless diamonds, Level 2 and Level 3 diamonds, so production should be minimised. It means People are not much intersted in diamonds with Best and Worst Clarity. It seems that Diamonds with Clarity SI2, SI1, VS2 can bring Maximum profit.

Correlation :



	carat	depth	table	x	y	z	price
carat	1.000000	0.035364	0.181685	0.976368	0.941071	0.940640	0.922416
depth	0.035364	1.000000	-0.298011	-0.018715	-0.024735	0.101624	-0.002569
table	0.181685	-0.298011	1.000000	0.196206	0.182346	0.148944	0.126942
x	0.976368	-0.018715	0.196206	1.000000	0.962715	0.956606	0.886247
y	0.941071	-0.024735	0.182346	0.962715	1.000000	0.928923	0.856243
z	0.940640	0.101624	0.148944	0.956606	0.928923	1.000000	0.850536
price	0.922416	-0.002569	0.126942	0.886247	0.856243	0.850536	1.000000

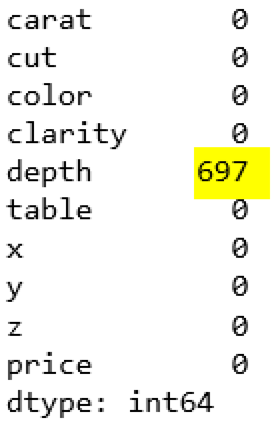
Heatmap:



The Multicollinearity can be seen in above heatmap.
For example, In between x and carat, y and carat, z and carat, x and y, x and z, y and z.

1.2 Impute null values if present, also check for the values which are equal to zero. Do they have any meaning or do we need to change them or drop them? Do you think scaling is necessary in this case?

Missing value treatment:

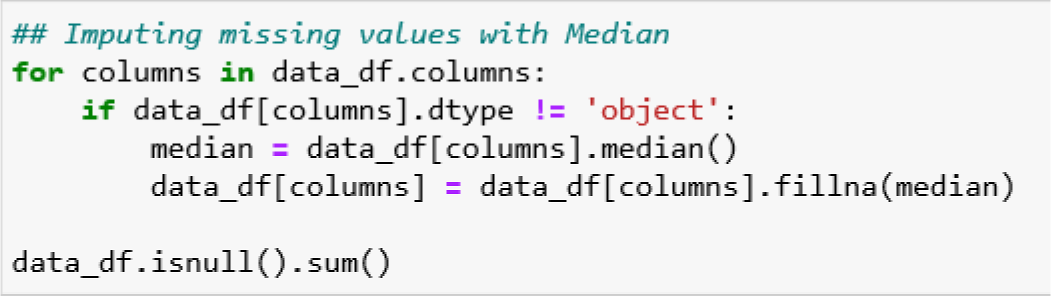


```
carat         0
cut           0
color         0
clarity       0
depth       697
table         0
x             0
y             0
z             0
price         0
dtype: int64
```

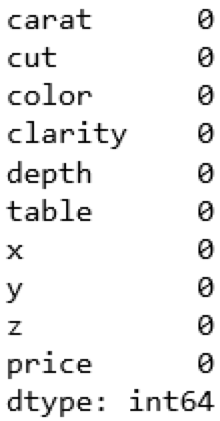
It seems that it has 697 missing values.

There are 697 missing values in depth variable, which is less than 3 % of whole dataset, so we can drop it. but here we will impute it with Median.

Lets impute missing values with median



```
## Imputing missing values with Median
for columns in data_df.columns:
    if data_df[columns].dtype != 'object':
        median = data_df[columns].median()
        data_df[columns] = data_df[columns].fillna(median)

data_df.isnull().sum()
```



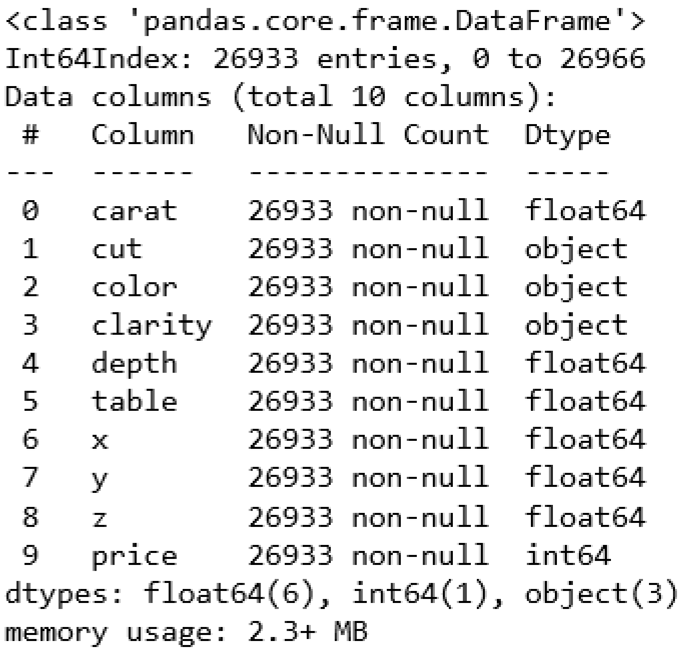
```
carat      0
cut        0
color      0
clarity    0
depth      0
table      0
x          0
y          0
z          0
price      0
dtype: int64
```

Now all missing values seems to be imputed with median.

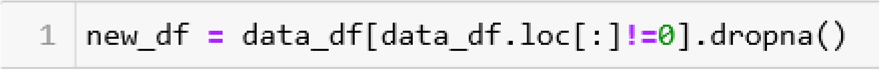
Checking for duplicates:

Number of duplicate rows = 34

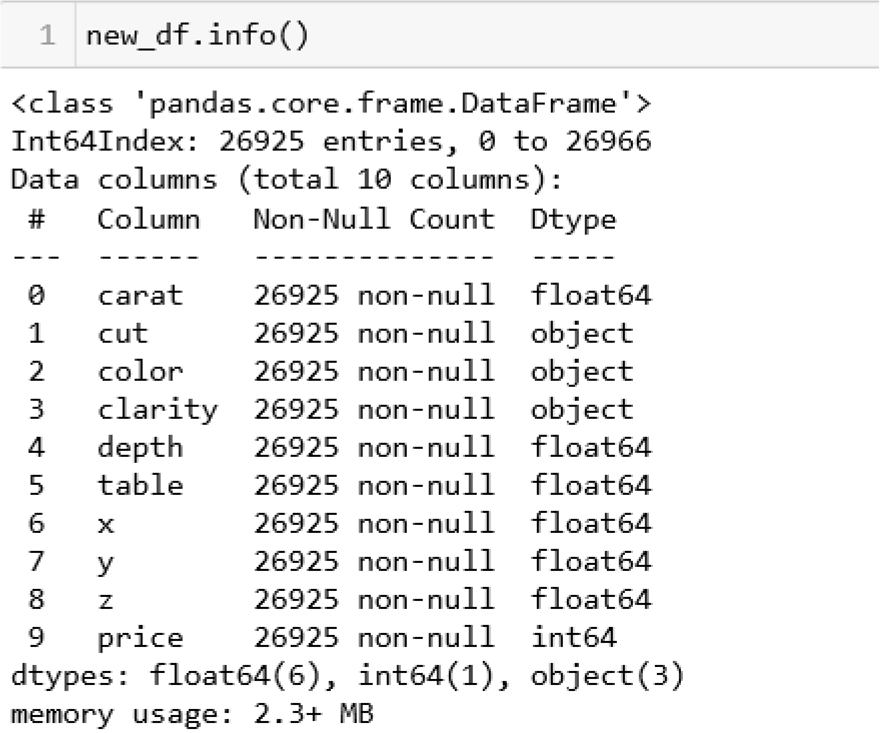
Here we will drop the 34 Duplicate values, rows count will be 26933 from 26967.



```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26933 entries, 0 to 26966
Data columns (total 10 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   carat    26933 non-null  float64
 1   cut      26933 non-null  object 
 2   color    26933 non-null  object 
 3   clarity  26933 non-null  object 
 4   depth    26933 non-null  float64
 5   table    26933 non-null  float64
 6   x        26933 non-null  float64
 7   y        26933 non-null  float64
 8   z        26933 non-null  float64
 9   price    26933 non-null  int64  
dtypes: float64(6), int64(1), object(3)
memory usage: 2.3+ MB
```

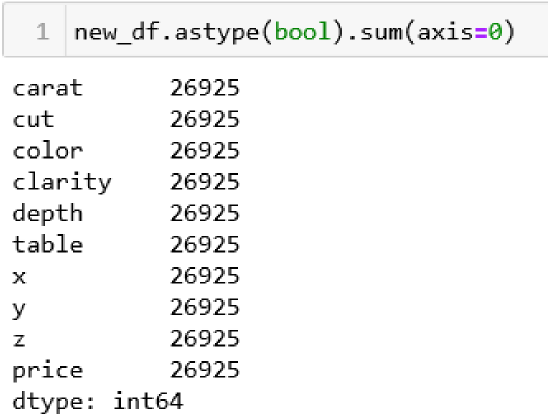


```
new_df = data_df[data_df.loc[:]!=0].dropna()
```



```
new_df.info()
```

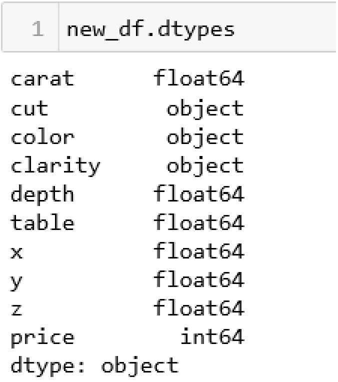
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26925 entries, 0 to 26966
Data columns (total 10 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   carat    26925 non-null  float64
 1   cut      26925 non-null  object 
 2   color    26925 non-null  object 
 3   clarity  26925 non-null  object 
 4   depth    26925 non-null  float64
 5   table    26925 non-null  float64
 6   x        26925 non-null  float64
 7   y        26925 non-null  float64
 8   z        26925 non-null  float64
 9   price    26925 non-null  int64  
dtypes: float64(6), int64(1), object(3)
memory usage: 2.3+ MB
```



```
new_df.astype(bool).sum(axis=0)
```

```
carat      26925
cut        26925
color      26925
clarity    26925
depth      26925
table      26925
x          26925
y          26925
z          26925
price      26925
dtype: int64
```

All zeros are removed now, dataset now needs a treatment of Label Encoding. Here Linear regression understands Numeric values, so we have to encode this Ordinal Categorical variables with Label Encoding.

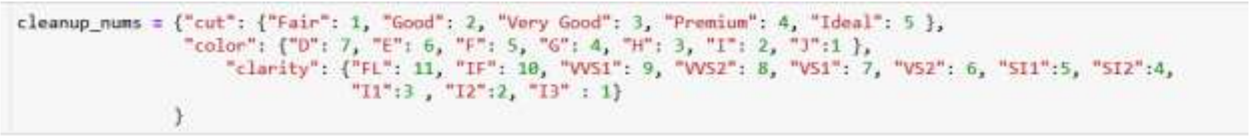


```
new_df.dtypes
```

```
carat       float64
cut          object
color        object
clarity      object
depth       float64
table       float64
x           float64
y           float64
z           float64
price         int64
dtype: object
```

Label Encoding:

For cut, color and clarity we are doing label encoding.

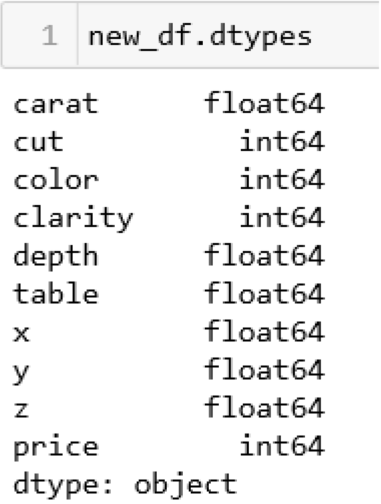


```
cleanup_nums = {"cut": {"Fair": 1, "Good": 2, "Very Good": 3, "Premium": 4, "Ideal": 5 },
                "color": {"D": 7, "E": 6, "F": 5, "G": 4, "H": 3, "I": 2, "J":1 },
                    "clarity": {"FL": 11, "IF": 10, "VVS1": 9, "VVS2": 8, "VS1": 7, "VS2": 6, "SI1":5, "SI2":4,
                                "I1":3 , "I2":2, "I3" : 1}
               }
```

Generally we have two techniques one hot encoding and label encoding. But for ordinal categorical variables we will use label encoding and assign values in ascending order.

If we use one hot encoding, No order will be considered, every level will considered as same.

Data types after label encoding:



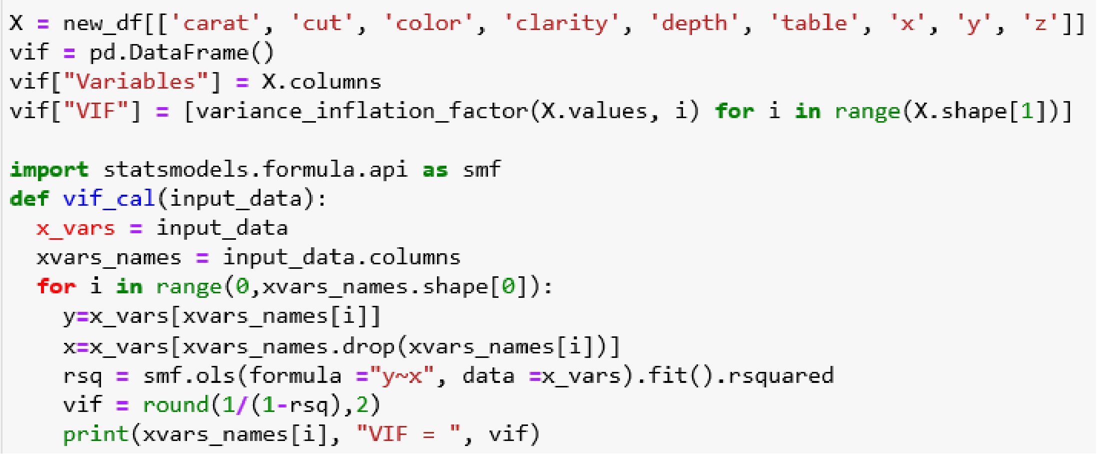
```
new_df.dtypes
```

```
carat       float64
cut           int64
color         int64
clarity       int64
depth       float64
table       float64
x           float64
y           float64
z           float64
price         int64
dtype: object
```

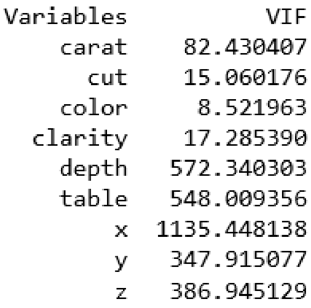
Now We have done Label Encoding and change the data type to Numeric value. Lets check for Multicollinearity by VIF.

Multicollinearity before Scaling:

Vif calculation:



```
X = new_df[['carat', 'cut', 'color', 'clarity', 'depth', 'table', 'x', 'y', 'z']]
vif = pd.DataFrame()
vif["Variables"] = X.columns
vif["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]

import statsmodels.formula.api as smf
def vif_cal(input_data):
  x_vars = input_data
  xvars_names = input_data.columns
  for i in range(0,xvars_names.shape[0]):
    y=x_vars[xvars_names[i]]
    x=x_vars[xvars_names.drop(xvars_names[i])]
    rsq = smf.ols(formula ="y~x", data =x_vars).fit().rsquared
    vif = round(1/(1-rsq),2)
    print(xvars_names[i], "VIF = ", vif)
```



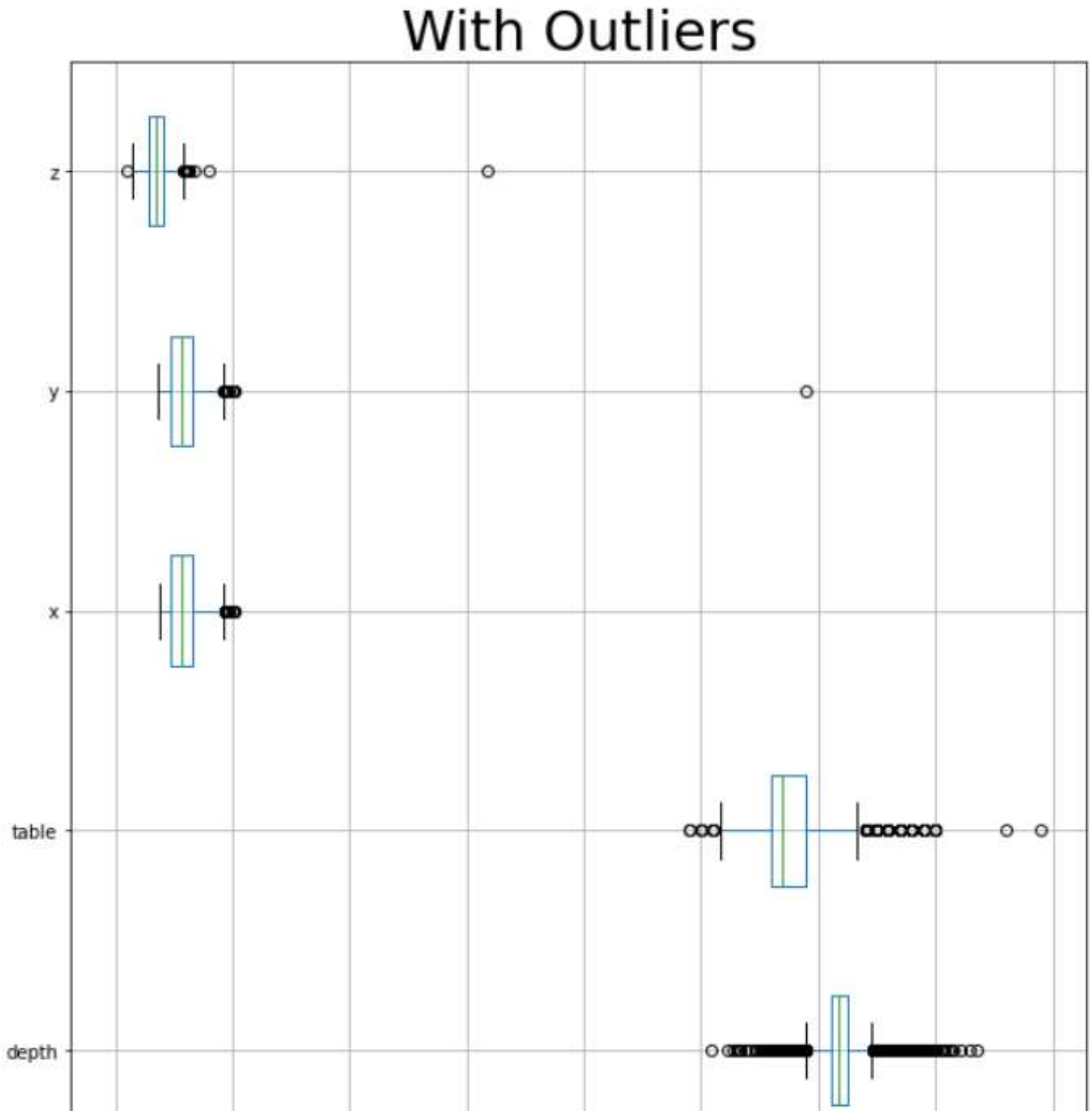
```
Variables           VIF
    carat     82.430407
      cut     15.060176
    color      8.521963
  clarity     17.285390
    depth    572.340303
    table    548.009356
        x   1135.448138
        y    347.915077
        z    386.945129
```

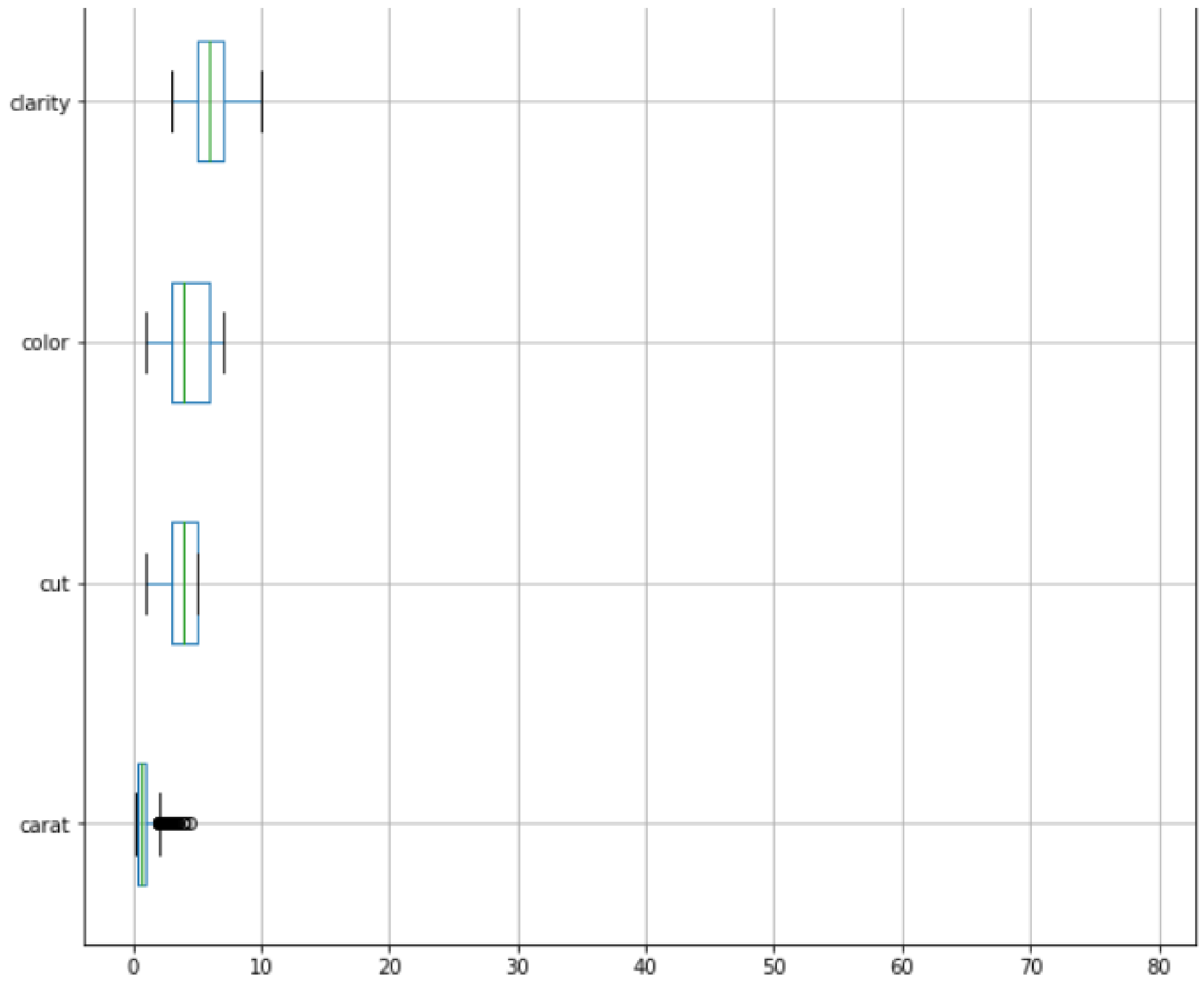
We can see the VIF is very high and this issue can be solved by scaling.

Scaling is necessary here and all variables are measured in different units and scale. VIF is very high for each variable, so we will do scaling to reduce VIF and Multicollinearity issue.

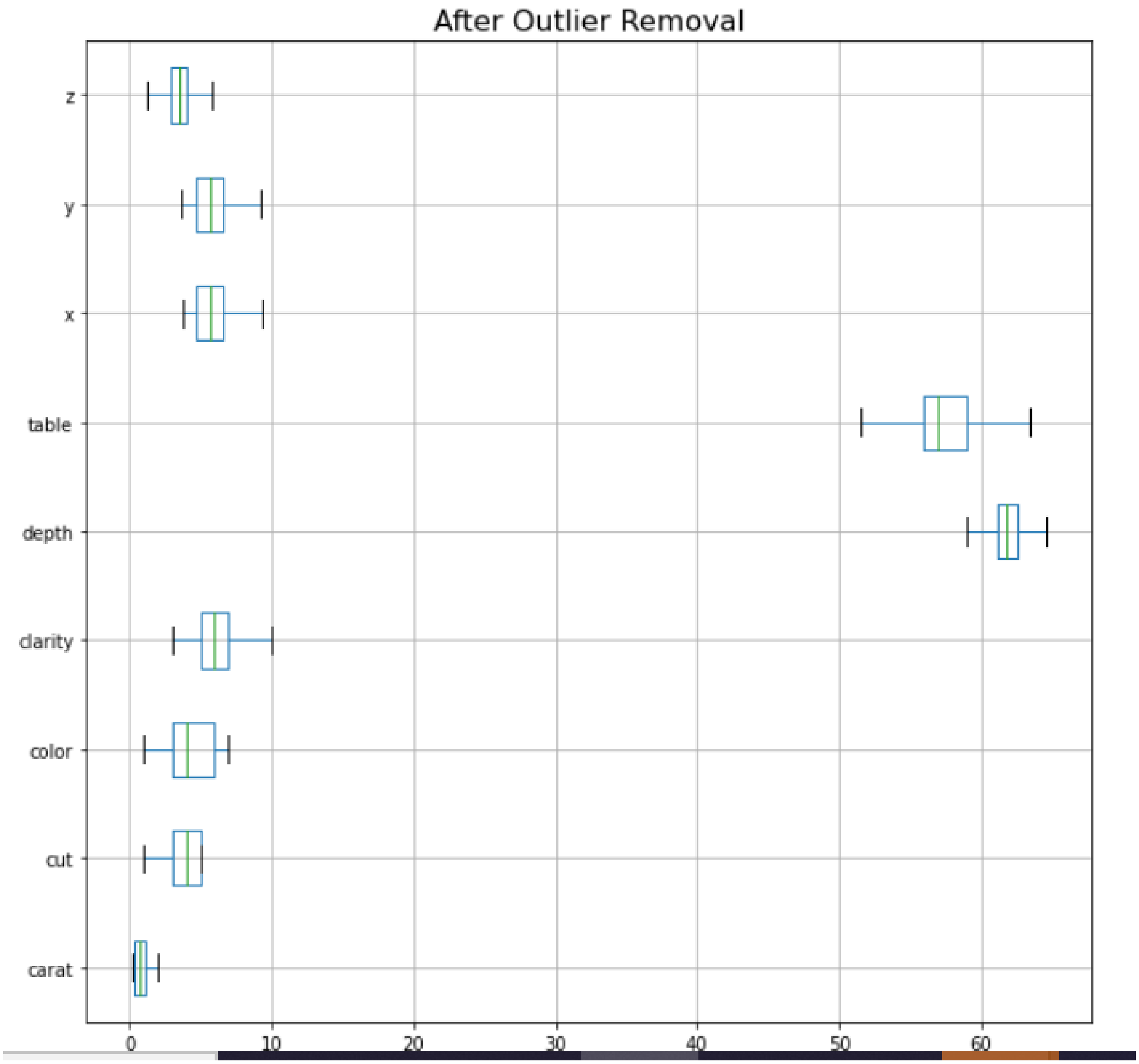
Outlier Treatment:

Boxplot with outliers:




clarity
color
cut
carat
0
10
20
30
40
50
60
70
80

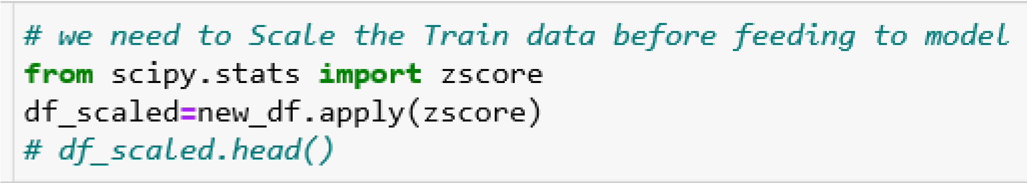
After outlier removal:



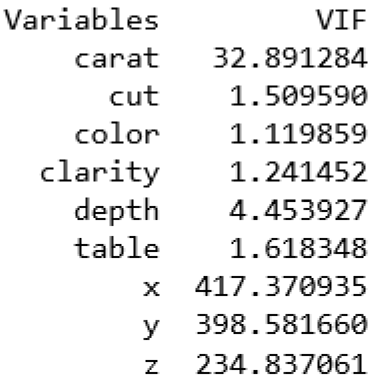
We cannot see any outlier, all outliers are removed.

Now we will do scaling:

We need to Scale the data before feeding to model.



```
# we need to Scale the Train data before feeding to model
from scipy.stats import zscore
df_scaled=new_df.apply(zscore)
# df_scaled.head()
```



```
Variables          VIF
    carat    32.891284
      cut     1.509590
    color     1.119859
  clarity     1.241452
    depth     4.453927
    table     1.618348
        x   417.370935
        y   398.581660
        z   234.837061
```

VIF is reduced for below Variables:

cut 1.509590

color 1.119859

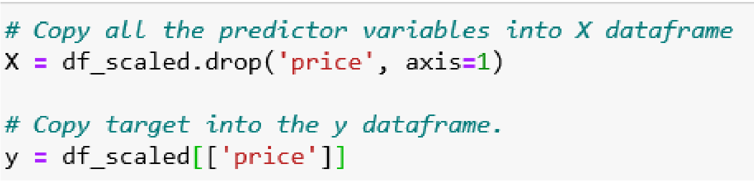
clarity 1.241452

depth 4.453927

table 1.618348

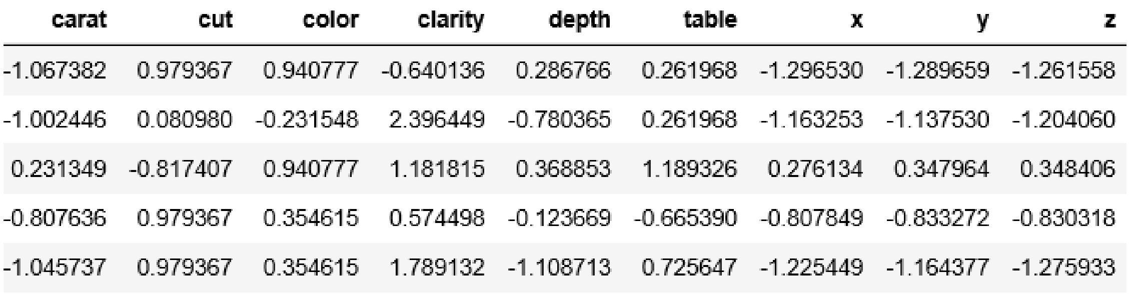
1.3 Encode the data (having string values) for Modelling. Data Split: Split the data into train and test (70:30). Apply Linear regression. Performance Metrics: Check the performance of Predictions on Train and Test sets using Rsquare, RMSE.

We have encoded the Data above, We have used Label Encoding here as variables are having Order. One hot encoding will induce Multicollinearity issue, so we will use label encoding.



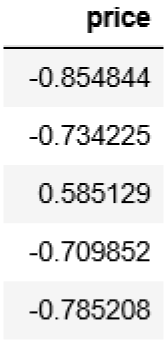
```
# Copy all the predictor variables into X dataframe
X = df_scaled.drop('price', axis=1)

# Copy target into the y dataframe.
y = df_scaled[['price']]
```

Head of Dependent Variables:



carat	cut	color	clarity	depth	table	x	y	z
-1.067382	0.979367	0.940777	-0.640136	0.286766	0.261968	-1.296530	-1.289659	-1.261558
-1.002446	0.080980	-0.231548	2.396449	-0.780365	0.261968	-1.163253	-1.137530	-1.204060
0.231349	-0.817407	0.940777	1.181815	0.368853	1.189326	0.276134	0.347964	0.348406
-0.807636	0.979367	0.354615	0.574498	-0.123669	-0.665390	-0.807849	-0.833272	-0.830318
-1.045737	0.979367	0.354615	1.789132	-1.108713	0.725647	-1.225449	-1.164377	-1.275933

Head of Independent Variable:



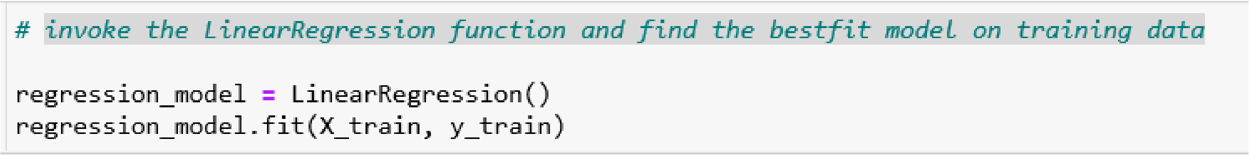
price
-0.854844
-0.734225
0.585129
-0.709852
-0.785208

Split X and y into training and test set in 70:30 ratio

Apply Linear Regression Model:

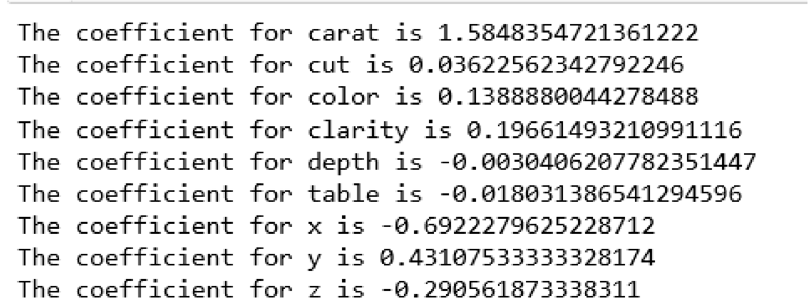
Invoke the LinearRegression function and find the bestfit model on training data.

Let us explore the coefficients for each of the independent attributes

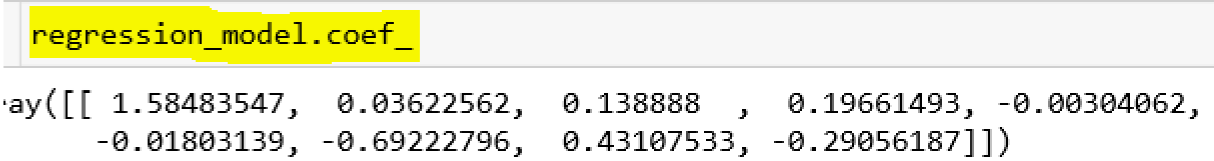


```
# invoke the LinearRegression function and find the bestfit model on training data

regression_model = LinearRegression()
regression_model.fit(X_train, y_train)
```

Coefficent for variables:



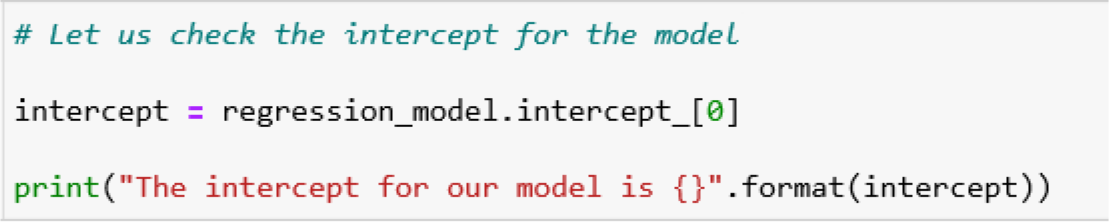
```
The coefficient for carat is 1.5848354721361222
The coefficient for cut is 0.036225623427922246
The coefficient for color is 0.1388880044278488
The coefficient for clarity is 0.19661493210991116
The coefficient for depth is -0.0030406207782351447
The coefficient for table is -0.018031386541294596
The coefficient for x is -0.6922279625228712
The coefficient for y is 0.43107533333328174
The coefficient for z is -0.290561873338311
```



```
regression_model.coef_
```

```
ay([[ 1.58483547,  0.03622562,  0.138888  ,  0.19661493, -0.00304062,
     -0.01803139, -0.69222796,  0.43107533, -0.29056187]])
```

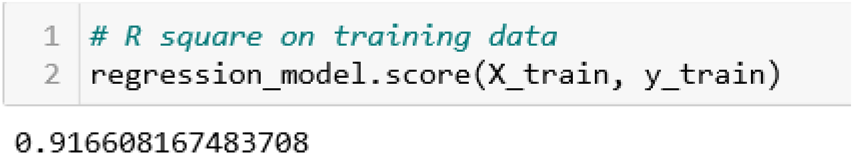
Intercept for the model:



```
# Let us check the intercept for the model

intercept = regression_model.intercept_[0]

print("The intercept for our model is {}".format(intercept))
```

```
The intercept for our model is 3.7585301438372446e-05
```

R square value:

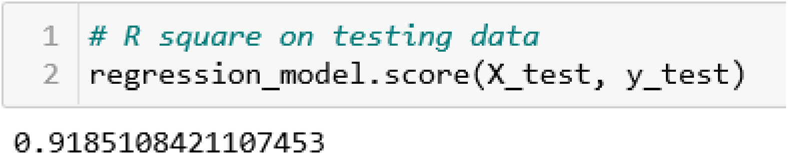


```
# R square on training data
regression_model.score(X_train, y_train)
```

```
0.916608167483708
```

50% of the variation in the log_price is explained by the predictors (Independent variable) in the model for train set

R Square value on Testing data:



```
# R square on testing data
regression_model.score(X_test, y_test)
```

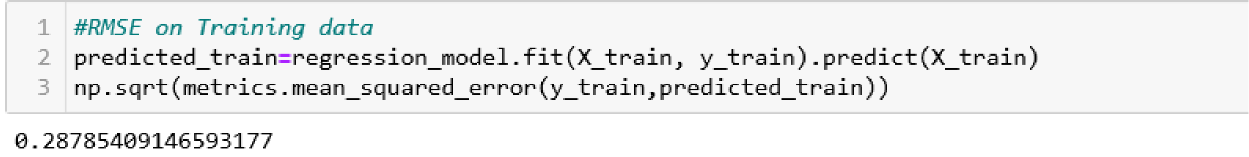
```
0.9185108421107453
```

RMSE on Training data:

0.28785409146593177

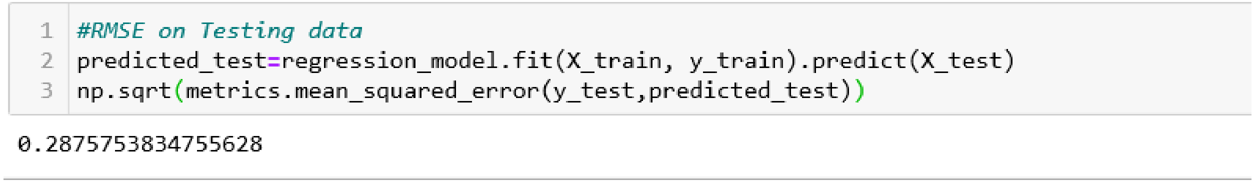
RMSE on Testing data

0.2875



```
#RMSE on Training data
predicted_train=regression_model.fit(X_train, y_train).predict(X_train)
np.sqrt(metrics.mean_squared_error(y_train,predicted_train))
```

```
0.28785409146593177
```

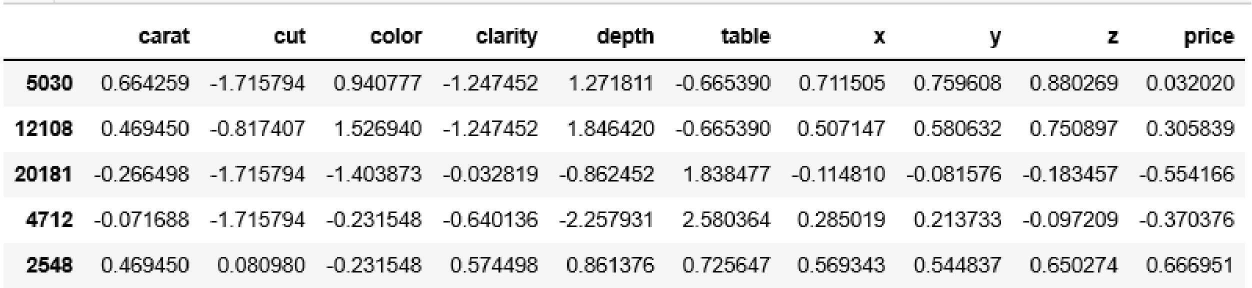


```
#RMSE on Testing data
predicted_test=regression_model.fit(X_train, y_train).predict(X_test)
np.sqrt(metrics.mean_squared_error(y_test,predicted_test))
```

```
0.2875753834755628
```

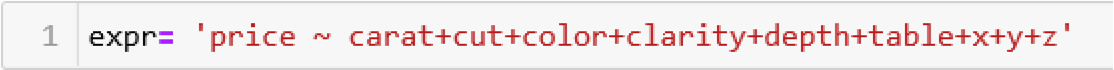
Now we will use stats model, to find contribution of variables, then we will drop the variable to improve RMSE and Reduce Multicollinearity issue

concatenate X and y into a single dataframe - Adding dependent and independent variable



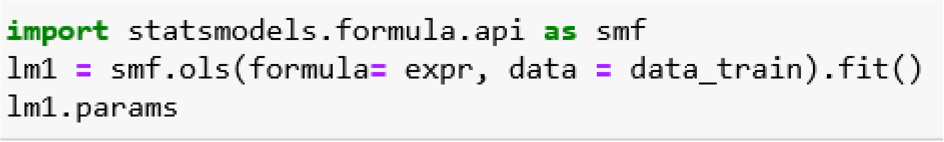
	carat	cut	color	clarity	depth	table	x	y	z	price
5030	0.664259	-1.715794	0.940777	-1.247452	1.271811	-0.665390	0.711505	0.759608	0.880269	0.032020
12108	0.469450	-0.817407	1.526940	-1.247452	1.846420	-0.665390	0.507147	0.580632	0.750897	0.305839
20181	-0.266498	-1.715794	-1.403873	-0.032819	-0.862452	1.838477	-0.114810	-0.081576	-0.183457	-0.554166
4712	-0.071688	-1.715794	-0.231548	-0.640136	-2.257931	2.580364	0.285019	0.213733	-0.097209	-0.370376
2548	0.469450	0.080980	-0.231548	0.574498	0.861376	0.725647	0.569343	0.544837	0.650274	0.666951

Expression:

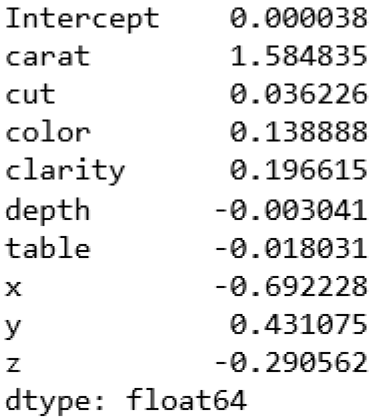


```
expr= 'price ~ carat+cut+color+clarity+depth+table+x+y+z'
```

Import Statsmodels:

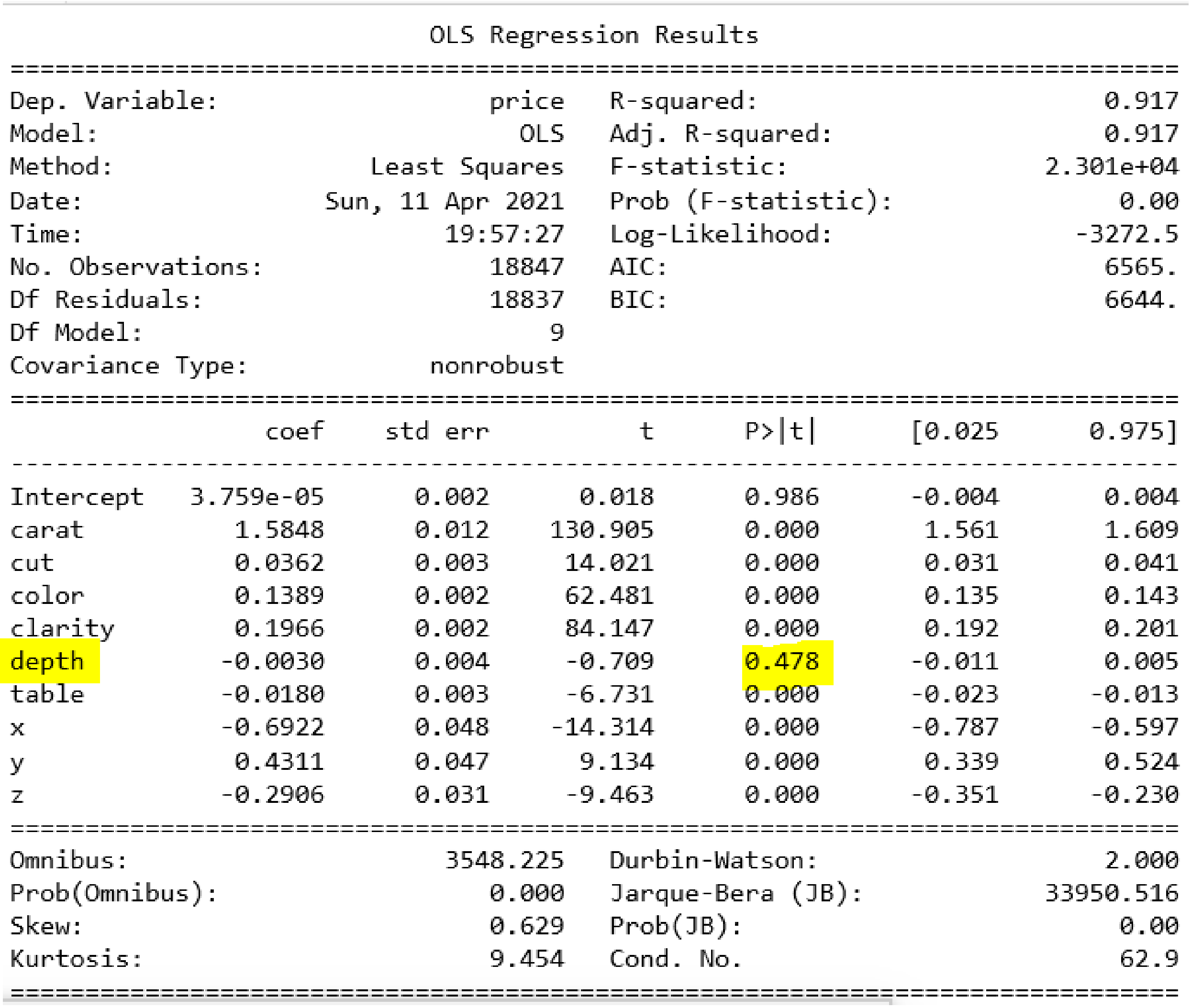


```
import statsmodels.formula.api as smf
lm1 = smf.ols(formula= expr, data = data_train).fit()
lm1.params
```



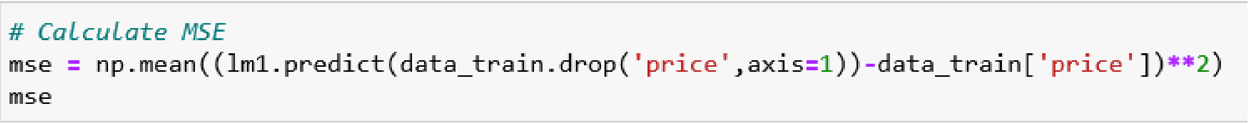
```
Intercept    0.000038
carat        1.584835
cut          0.036226
color        0.138888
clarity      0.196615
depth       -0.003041
table       -0.018031
x           -0.692228
y            0.431075
z           -0.290562
dtype: float64
```

Final Result:



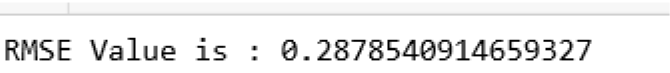
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.917
Model:                            OLS   Adj. R-squared:                  0.917
Method:                 Least Squares   F-statistic:                 2.301e+04
Date:                Sun, 11 Apr 2021   Prob (F-statistic):               0.00
Time:                        19:57:27   Log-Likelihood:                -3272.5
No. Observations:               18847   AIC:                             6565.
Df Residuals:                   18837   BIC:                             6644.
Df Model:                           9
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   3.759e-05      0.002      0.018      0.986      -0.004       0.004
carat          1.5848      0.012    130.905      0.000       1.561       1.609
cut            0.0362      0.003     14.021      0.000       0.031       0.041
color          0.1389      0.002     62.481      0.000       0.135       0.143
clarity        0.1966      0.002     84.147      0.000       0.192       0.201
depth         -0.0030      0.004     -0.709      0.478      -0.011       0.005
table         -0.0180      0.003     -6.731      0.000      -0.023      -0.013
x             -0.6922      0.048    -14.314      0.000      -0.787      -0.597
y              0.4311      0.047      9.134      0.000       0.339       0.524
z             -0.2906      0.031     -9.463      0.000      -0.351      -0.230
==============================================================================
Omnibus:                     3548.225   Durbin-Watson:                   2.000
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            33950.516
Skew:                           0.629   Prob(JB):                         0.00
Kurtosis:                       9.454   Cond. No.                         62.9
==============================================================================
```

Calculate MSE:



```
# Calculate MSE
mse = np.mean((lm1.predict(data_train.drop('price',axis=1))-data_train['price'])**2)
mse
```

Calculate RMSE:



```
RMSE Value is : 0.2878540914659327
```

Final Equation:

```
Price = (0.000038) * Intercept + (1.58) * carat + (0.04) * cut +
(0.14) * color + (0.2) * clarity + (-0.0) * depth + (-0.02) *
table + (-0.69) * x + (0.43) * y + (-0.29) * z
```

Now again We have seen that VIF value for Depth variable is High we can drop it to reduce Muliti collinearity issue.

1.4 Inference: Basis on these predictions, what are the business insights and recommendations.

This Case study is specifically created to predict the price of stone on the basis of different Dimensions or features. We have done EDA first, Done missing value treatment, Outlier treatment, Scaling, Label Encoding and finally Calculated VIF score and applied Linear Regression Model.

In EDA, We have some Business Insights:

- Count of Ideal cut is High, so it seems that people prefer this cut, the reason seems to be less price.

- D is the best color while J is the worst color. J is the least used, might be because of it is worst. Count of users of Color G is high, It is Moderate level color, with the moderate price

- Another reason that less people select J color may be its Highest price, so Price and its color quality are two factors deciding the count here.

- Order from best to worst: FL, IF, VVS1, VVS2, VS1, VS2, SI1, SI2, I1, I2, I3 : Flawless to Level 3. It seems that no one is buying Flawless diamonds, Level 2 and Level 3 diamonds, so production should be minimised. It means People are not much interested in diamonds with Best and Worst Clarity. It seems that Diamonds with Clarity SI2, SI1, VS2 can bring Maximum profit.

- In clarity if we could see there were no flawless stones and they were no profits coming from l1, l2, l3 stones. The ideal, premium and very good types of cut were bringing profits where as fair and good are not bringing profits.

Recommendations:

- Production of Ideal cut stones can be done in large amount to increase the profits due to high demand. Production of Diamond with color J can be mimised and company should focus on moderate color G.
- To Maximise Profit Company should start Production Diamonds with Clarity SI2, SI1, VS2 as this can bring Maximum profit
- Ideal Premium and very good cut type production should be done in High quantity.