In [58]:
```
import numpy as np
import pandas as pd
import seaborn as sns
from matplotlib import pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_validate
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, LabelEncoder
from sklearn.metrics import mean_squared_error,r2_score
SEED=42
```

In [2]:
```
path=r"C:\Users\JAYADEVA JAVALI\Desktop\cs\diamonds.csv"
df = pd.read_csv(path)
df.head()
```

Out[2]:

	Unnamed: 0	carat	cut	color	clarity	depth	table	price	x	y	z
0	1	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
1	2	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
2	3	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31
3	4	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63
4	5	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75

- **carat** - Carat weight of the diamond.
- **cut** - Describes the cut quality of the diamond (from the best to worst: Ideal, Premium, Very Good, Good and Fair).
- **color** - Color of the diamond (from the best to worst: D, E, F, G, H, I and J).
- **clarity** - A measurement of how clear the diamond is (from the best to worst: IF, VVS1, VVS2, VS1, VS2, SI1, SI2 and I1).
- **depth** - The height of a diamond, measured from the culet to the table, divided by the average girdle diameter (%).
- **table** - The width of a diamond table expressed as a percentage of the average diameter (%).
- **x** - Diamond length (mm).
- **y** - Diamond width (mm).
- **z** - Diamond depth (mm).
- **price** - Diamond price.

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53940 entries, 0 to 53939
Data columns (total 11 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Unnamed: 0  53940 non-null  int64
 1   carat       53940 non-null  float64
 2   cut         53940 non-null  object
 3   color       53940 non-null  object
```

```
 4   clarity     53940 non-null  object
 5   depth       53940 non-null  float64
 6   table       53940 non-null  float64
 7   price       53940 non-null  int64
 8   x           53940 non-null  float64
 9   y           53940 non-null  float64
 10  z           53940 non-null  float64
dtypes: float64(6), int64(2), object(3)
memory usage: 4.5+ MB
```

In [4]:
```
df.shape
```

Out[4]:
```
(53940, 11)
```

Missing Values

In [5]:
```
df.isnull().sum()
```

Out[5]:
```
Unnamed: 0    0
carat         0
cut           0
color         0
clarity       0
depth         0
table         0
price         0
x             0
y             0
z             0
dtype: int64
```

In [6]:
```
if df.isnull().sum().any() == False:
    print("There are no missing values")
else:
    print("There are missing values")
```

```
There are no missing values
```

Checking for duplicate rows and removing unnecessary columns

In [7]:
```
# Dropping "Unnamed: 0" column
df = df.drop(["Unnamed: 0"], axis = 1)
```

In [8]:
```
# Checking for duplicate rows
print("number of duplicate rows: ", df.duplicated().sum())
```

```
number of duplicate rows:  146
```

In [9]:
```
df.head()
```

Out[9]:

	carat	cut	color	clarity	depth	table	price	x	y	z
0	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
1	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
2	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31
3	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63
4	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75

High Level Information

In [10]:
```
df.describe().T
#df.describe()
#Numerical Data
```

Out[10]:

	count	mean	std	min	25%	50%	75%	max
carat	53940.0	0.797940	0.474011	0.2	0.40	0.70	1.04	5.01
depth	53940.0	61.749405	1.432621	43.0	61.00	61.80	62.50	79.00
table	53940.0	57.457184	2.234491	43.0	56.00	57.00	59.00	95.00
price	53940.0	3932.799722	3989.439738	326.0	950.00	2401.00	5324.25	18823.00
x	53940.0	5.731157	1.121761	0.0	4.71	5.70	6.54	10.74
y	53940.0	5.734526	1.142135	0.0	4.72	5.71	6.54	58.90
z	53940.0	3.538734	0.705699	0.0	2.91	3.53	4.04	31.80

In [11]:
```
# Categorical data
df.describe(include = "O").T
```

Out[11]:

	count	unique	top	freq
cut	53940	5	Ideal	21551
color	53940	7	G	11292
clarity	53940	8	SI1	13065

In [12]:
```
format_dict = {"carat" : "{:.2f}", "depth" : "{:.1f}", "table" : "{:.1f}", "x" : "{:
```

In [13]:
```
df_zero = df.loc[(df["x"] == 0) | (df["y"] == 0) | (df["z"] == 0)]
df_zero.style.apply(lambda x: ["background: yellow" if n == 0 else "" for n in x], a
```

Out[13]:

	carat	cut	color	clarity	depth	table	price	x	y	z
2207	1.00	Premium	G	SI2	59.1	59.0	3142	6.55	6.48	0.00
2314	1.01	Premium	H	I1	58.1	59.0	3167	6.66	6.60	0.00
4791	1.10	Premium	G	SI2	63.0	59.0	3696	6.50	6.47	0.00
5471	1.01	Premium	F	SI2	59.2	58.0	3837	6.50	6.47	0.00
10167	1.50	Good	G	I1	64.0	61.0	4731	7.15	7.04	0.00
11182	1.07	Ideal	F	SI2	61.6	56.0	4954	0.00	6.62	0.00
11963	1.00	Very Good	H	VS2	63.3	53.0	5139	0.00	0.00	0.00
13601	1.15	Ideal	G	VS2	59.2	56.0	5564	6.88	6.83	0.00
15951	1.14	Fair	G	VS1	57.5	67.0	6381	0.00	0.00	0.00
24394	2.18	Premium	H	SI2	59.4	61.0	12631	8.49	8.45	0.00
24520	1.56	Ideal	G	VS2	62.2	54.0	12800	0.00	0.00	0.00
26123	2.25	Premium	I	SI1	61.3	58.0	15397	8.52	8.42	0.00
26243	1.20	Premium	D	VVS1	62.1	59.0	15686	0.00	0.00	0.00
27112	2.20	Premium	H	SI1	61.2	59.0	17265	8.42	8.37	0.00
27429	2.25	Premium	H	SI2	62.8	59.0	18034	0.00	0.00	0.00

	carat	cut	color	clarity	depth	table	price	x	y	z
27503	2.02	Premium	H	VS2	62.7	53.0	18207	8.02	7.95	0.00
27739	2.80	Good	G	SI2	63.8	58.0	18788	8.90	8.85	0.00
49556	0.71	Good	F	SI2	64.1	60.0	2130	0.00	0.00	0.00
49557	0.71	Good	F	SI2	64.1	60.0	2130	0.00	0.00	0.00
51506	1.12	Premium	G	I1	60.4	59.0	2383	6.71	6.67	0.00

We know that length,width and depth cannot be 0,therefore the data is wrong,lets treat these values

In [14]:
```
# Transforming them into NaN values
df.loc[df["x"] == 0, "x"] = np.nan
df.loc[df["y"] == 0, "y"] = np.nan
df.loc[df["z"] == 0, "z"] = np.nan
```

In [15]:
```
# Seeing the number of the new missing values
df[["x", "y", "z"]].isnull().sum()
```

Out[15]:
```
x     8
y     7
z    20
dtype: int64
```

After Transformation we see the count of missing values,now lets treat the missing values.

Checking Correlations

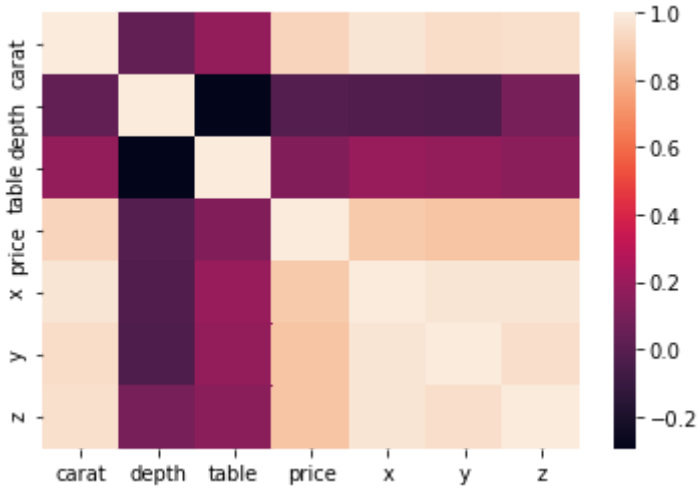
In [16]:
```
df.corr().T
```

Out[16]:

	carat	depth	table	price	x	y	z
carat	1.000000	0.028224	0.181618	0.921591	0.977765	0.953989	0.961048
depth	0.028224	1.000000	-0.295779	-0.010647	-0.025097	-0.029142	0.095023
table	0.181618	-0.295779	1.000000	0.127134	0.196130	0.184519	0.152483
price	0.921591	-0.010647	0.127134	1.000000	0.887227	0.867870	0.868206
x	0.977765	-0.025097	0.196130	0.887227	1.000000	0.974933	0.975435
y	0.953989	-0.029142	0.184519	0.867870	0.974933	1.000000	0.956744
z	0.961048	0.095023	0.152483	0.868206	0.975435	0.956744	1.000000

In [17]:
```
sns.heatmap(df.corr())
```

Out[17]:
```
<AxesSubplot:>
```



In [18]:
```
def get_corr(col):
    return df.corr().unstack()[col].sort_values(ascending = False)
```

In [19]:
```
print("x correlations\n\n{0}\n\n{3}\n\ny correlations\n\n{1}\n\n{3}\n\nz correlation
```

```
x correlations

x        1.000000
carat    0.977765
z        0.975435
y        0.974933
price    0.887227
table    0.196130
depth   -0.025097
dtype: float64

-------------------------

y correlations

y        1.000000
x        0.974933
z        0.956744
carat    0.953989
price    0.867870
table    0.184519
depth   -0.029142
dtype: float64

-------------------------

z correlations

z        1.000000
x        0.975435
carat    0.961048
y        0.956744
price    0.868206
table    0.152483
depth    0.095023
dtype: float64
```

Imputing Missing Values

x,y,z has values of 0

In [20]:
```
def missing_values_imputation(col):
    carat = df.groupby(["carat"])[col].median()
    index_list = list(df.loc[df[col].isnull() == True].sort_values(by = "carat", asc
```

```
    for i in index_list:
        carat_value = df.loc[i, "carat"]
        new_value = carat[carat_value]
        df.loc[i, col] = new_value
        print("carat: {0} / median {1} value: {2}".format(carat_value, col, new_valu
    return df.iloc[index_list].style.applymap(lambda x: "background-color: limegreen
```

In [21]:
```
missing_values_imputation("x")
```

```
carat: 2.25 / median x value: 8.47
carat: 1.56 / median x value: 7.46
carat: 1.2 / median x value: 6.78
carat: 1.14 / median x value: 6.71
carat: 1.07 / median x value: 6.57
carat: 1.0 / median x value: 6.38
carat: 0.71 / median x value: 5.72
carat: 0.71 / median x value: 5.72
```

Out[21]:

	carat	cut	color	clarity	depth	table	price	x	y	z
27429	2.25	Premium	H	SI2	62.8	59.0	18034	8.47	nan	nan
24520	1.56	Ideal	G	VS2	62.2	54.0	12800	7.46	nan	nan
26243	1.20	Premium	D	VVS1	62.1	59.0	15686	6.78	nan	nan
15951	1.14	Fair	G	VS1	57.5	67.0	6381	6.71	nan	nan
11182	1.07	Ideal	F	SI2	61.6	56.0	4954	6.57	6.62	nan
11963	1.00	Very Good	H	VS2	63.3	53.0	5139	6.38	nan	nan
49556	0.71	Good	F	SI2	64.1	60.0	2130	5.72	nan	nan
49557	0.71	Good	F	SI2	64.1	60.0	2130	5.72	nan	nan

In [22]:
```
missing_values_imputation("y")
```

```
carat: 2.25 / median y value: 8.39
carat: 1.56 / median y value: 7.46
carat: 1.2 / median y value: 6.79
carat: 1.14 / median y value: 6.72
carat: 1.0 / median y value: 6.38
carat: 0.71 / median y value: 5.73
carat: 0.71 / median y value: 5.73
```

Out[22]:

	carat	cut	color	clarity	depth	table	price	x	y	z
27429	2.25	Premium	H	SI2	62.8	59.0	18034	8.47	8.39	nan
24520	1.56	Ideal	G	VS2	62.2	54.0	12800	7.46	7.46	nan
26243	1.20	Premium	D	VVS1	62.1	59.0	15686	6.78	6.79	nan
15951	1.14	Fair	G	VS1	57.5	67.0	6381	6.71	6.72	nan
11963	1.00	Very Good	H	VS2	63.3	53.0	5139	6.38	6.38	nan
49556	0.71	Good	F	SI2	64.1	60.0	2130	5.72	5.73	nan
49557	0.71	Good	F	SI2	64.1	60.0	2130	5.72	5.73	nan

In [23]:
```
missing_values_imputation("z")
```

```
carat: 2.8 / median z value: 5.5
carat: 2.25 / median z value: 5.19
carat: 2.25 / median z value: 5.19
carat: 2.2 / median z value: 5.17
carat: 2.18 / median z value: 5.16
carat: 2.02 / median z value: 5.0
```

```
carat: 1.56 / median z value: 4.59
carat: 1.5 / median z value: 4.53
carat: 1.2 / median z value: 4.21
carat: 1.15 / median z value: 4.16
carat: 1.14 / median z value: 4.14
carat: 1.12 / median z value: 4.11
carat: 1.1 / median z value: 4.09
carat: 1.07 / median z value: 4.05
carat: 1.01 / median z value: 3.98
carat: 1.01 / median z value: 3.98
carat: 1.0 / median z value: 3.96
carat: 1.0 / median z value: 3.96
carat: 0.71 / median z value: 3.54
carat: 0.71 / median z value: 3.54
```

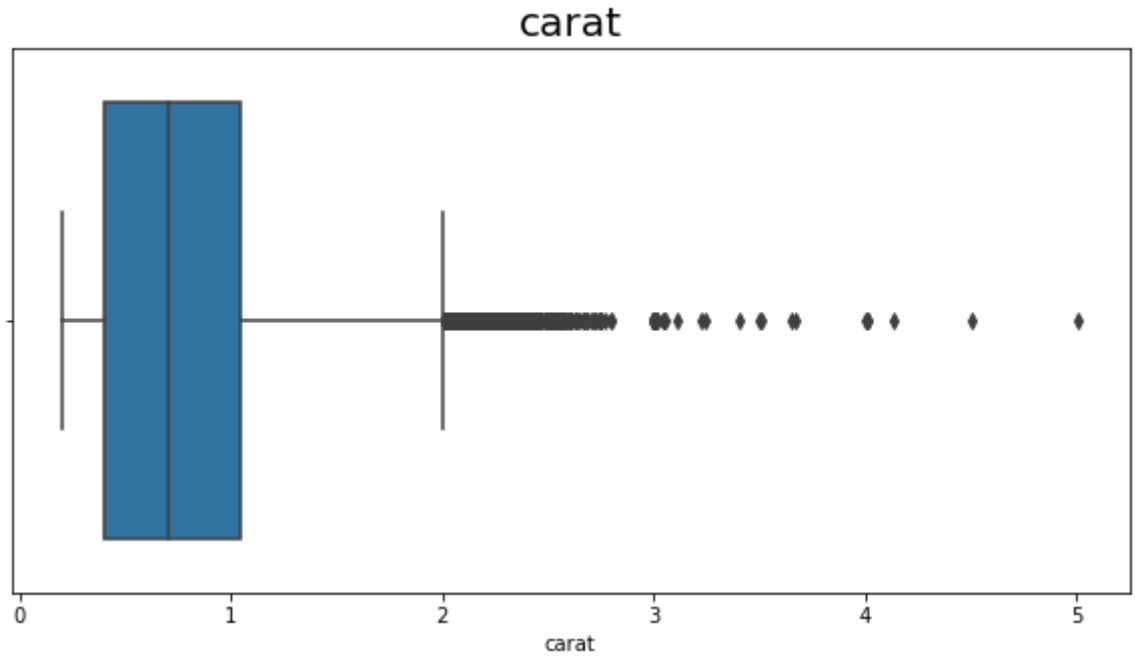
Out[23]:

	carat	cut	color	clarity	depth	table	price	x	y	z
27739	2.80	Good	G	SI2	63.8	58.0	18788	8.90	8.85	5.50
26123	2.25	Premium	I	SI1	61.3	58.0	15397	8.52	8.42	5.19
27429	2.25	Premium	H	SI2	62.8	59.0	18034	8.47	8.39	5.19
27112	2.20	Premium	H	SI1	61.2	59.0	17265	8.42	8.37	5.17
24394	2.18	Premium	H	SI2	59.4	61.0	12631	8.49	8.45	5.16
27503	2.02	Premium	H	VS2	62.7	53.0	18207	8.02	7.95	5.00
24520	1.56	Ideal	G	VS2	62.2	54.0	12800	7.46	7.46	4.59
10167	1.50	Good	G	I1	64.0	61.0	4731	7.15	7.04	4.53
26243	1.20	Premium	D	VVS1	62.1	59.0	15686	6.78	6.79	4.21
13601	1.15	Ideal	G	VS2	59.2	56.0	5564	6.88	6.83	4.16
15951	1.14	Fair	G	VS1	57.5	67.0	6381	6.71	6.72	4.14
51506	1.12	Premium	G	I1	60.4	59.0	2383	6.71	6.67	4.11
4791	1.10	Premium	G	SI2	63.0	59.0	3696	6.50	6.47	4.09
11182	1.07	Ideal	F	SI2	61.6	56.0	4954	6.57	6.62	4.05
2314	1.01	Premium	H	I1	58.1	59.0	3167	6.66	6.60	3.98
5471	1.01	Premium	F	SI2	59.2	58.0	3837	6.50	6.47	3.98
11963	1.00	Very Good	H	VS2	63.3	53.0	5139	6.38	6.38	3.96
2207	1.00	Premium	G	SI2	59.1	59.0	3142	6.55	6.48	3.96
49556	0.71	Good	F	SI2	64.1	60.0	2130	5.72	5.73	3.54
49557	0.71	Good	F	SI2	64.1	60.0	2130	5.72	5.73	3.54

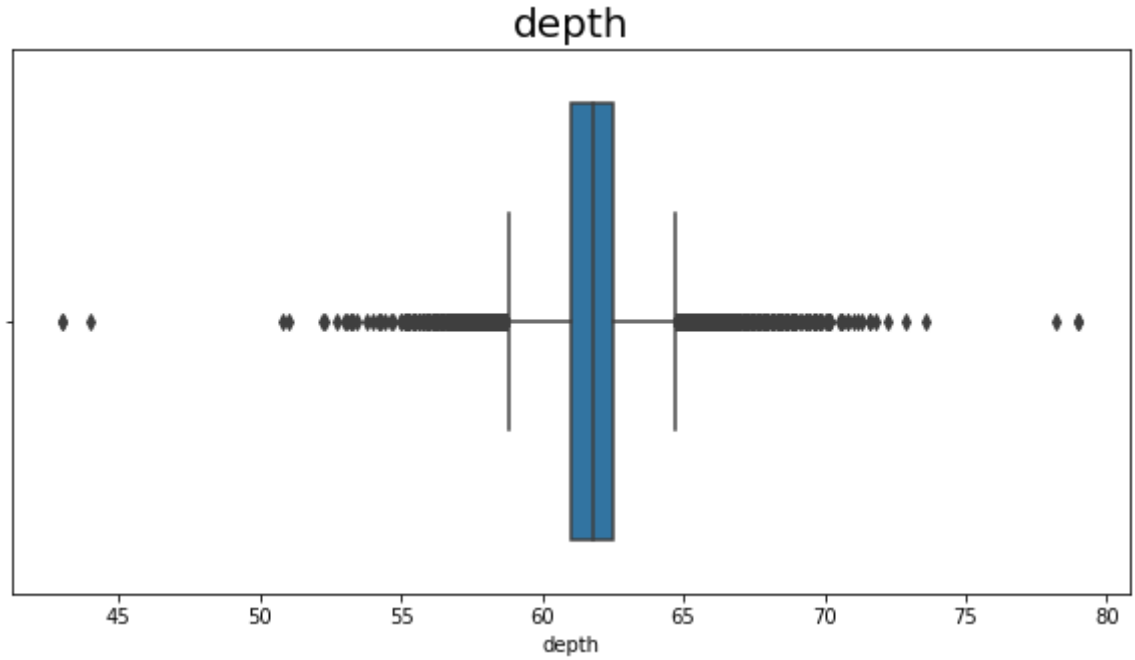
In [24]:

```
for c in ['carat', 'depth', 'table', 'price', 'x', 'y', 'z']:
    plt.figure(figsize=(10, 5))
    sns.boxplot(df[c])
    plt.title(c, fontsize=20)
    plt.show()
```

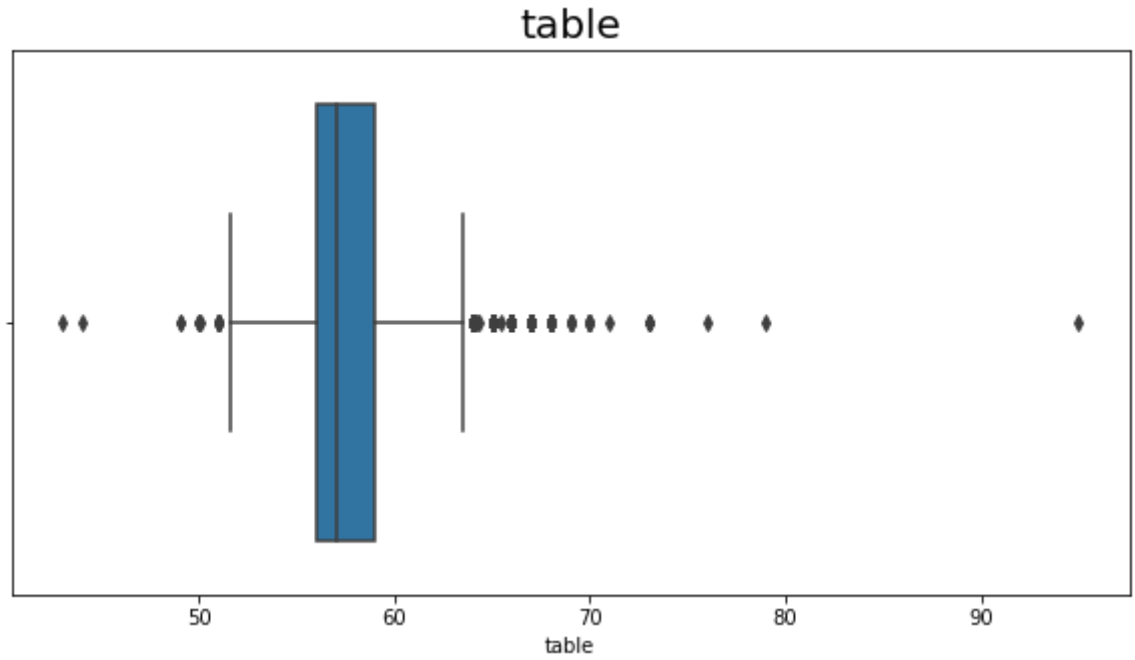
```
E:\anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the fol
lowing variable as a keyword arg: x. From version 0.12, the only valid positional ar
gument will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
```



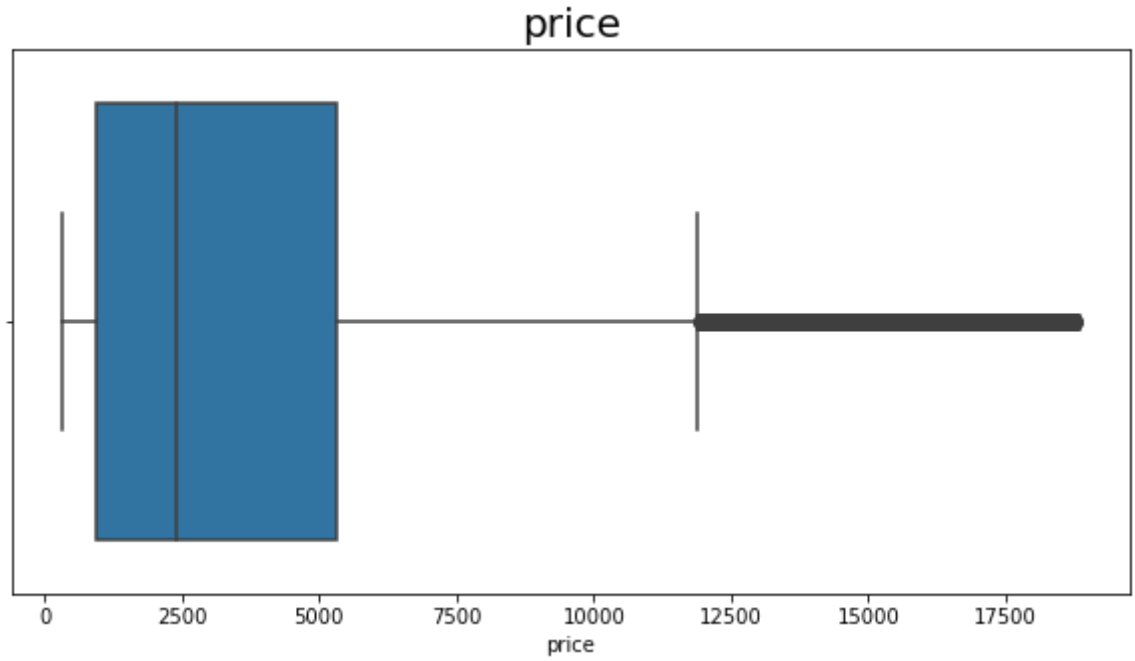

```
E:\anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the fol
lowing variable as a keyword arg: x. From version 0.12, the only valid positional ar
gument will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
```



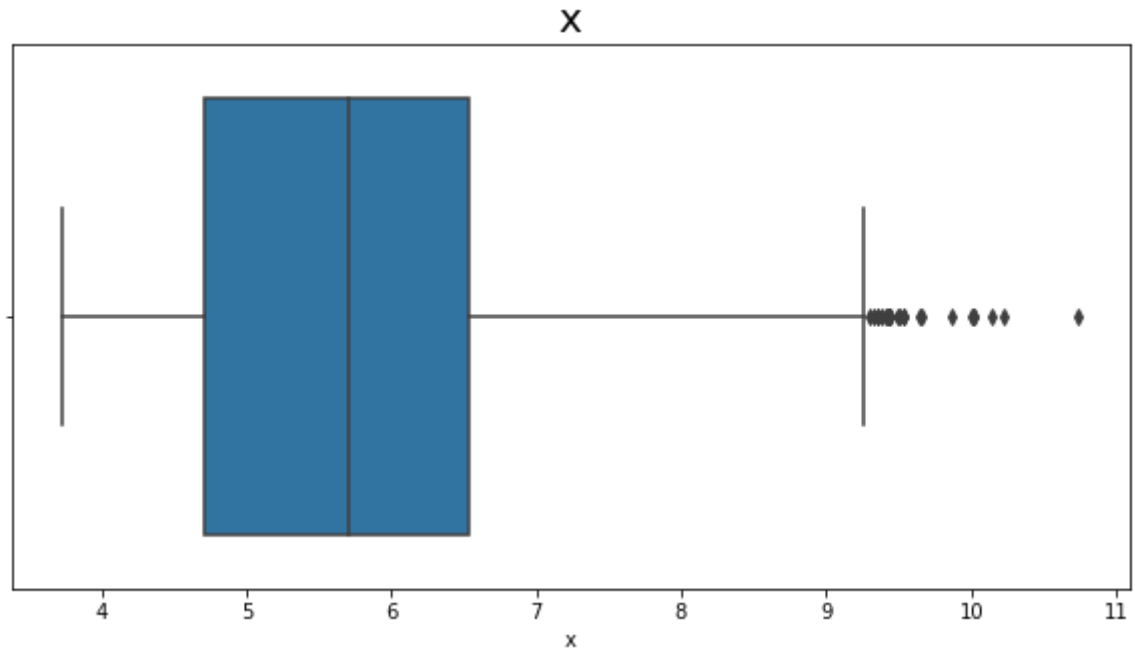

```
E:\anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the fol
lowing variable as a keyword arg: x. From version 0.12, the only valid positional ar
gument will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
```



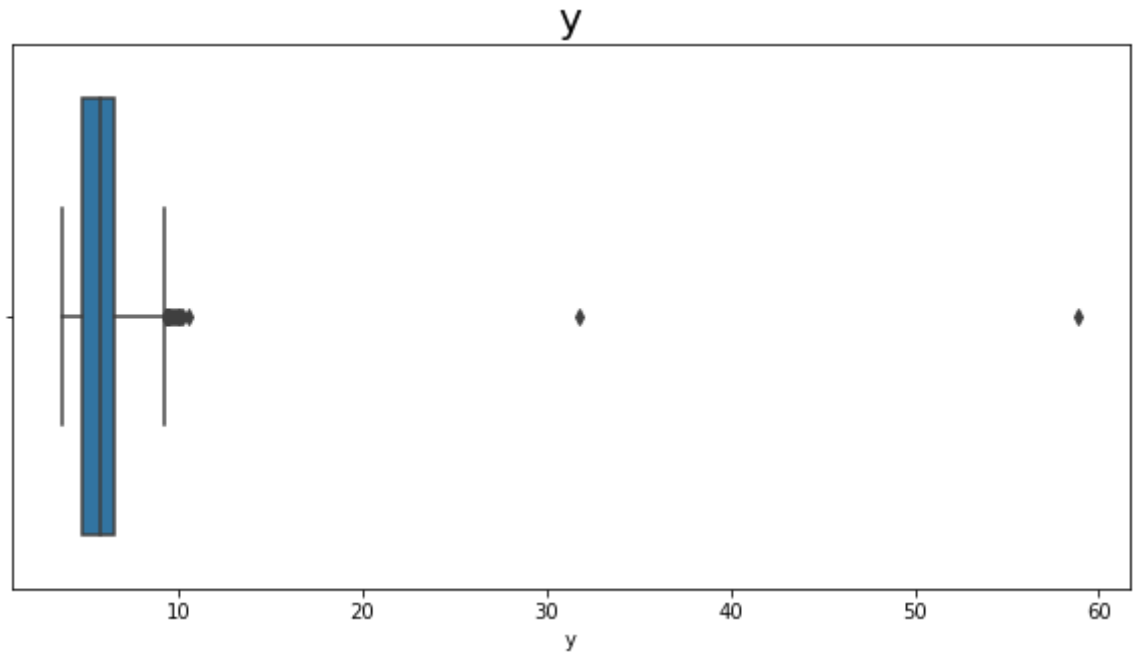

```
E:\anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the fol
lowing variable as a keyword arg: x. From version 0.12, the only valid positional ar
gument will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
```



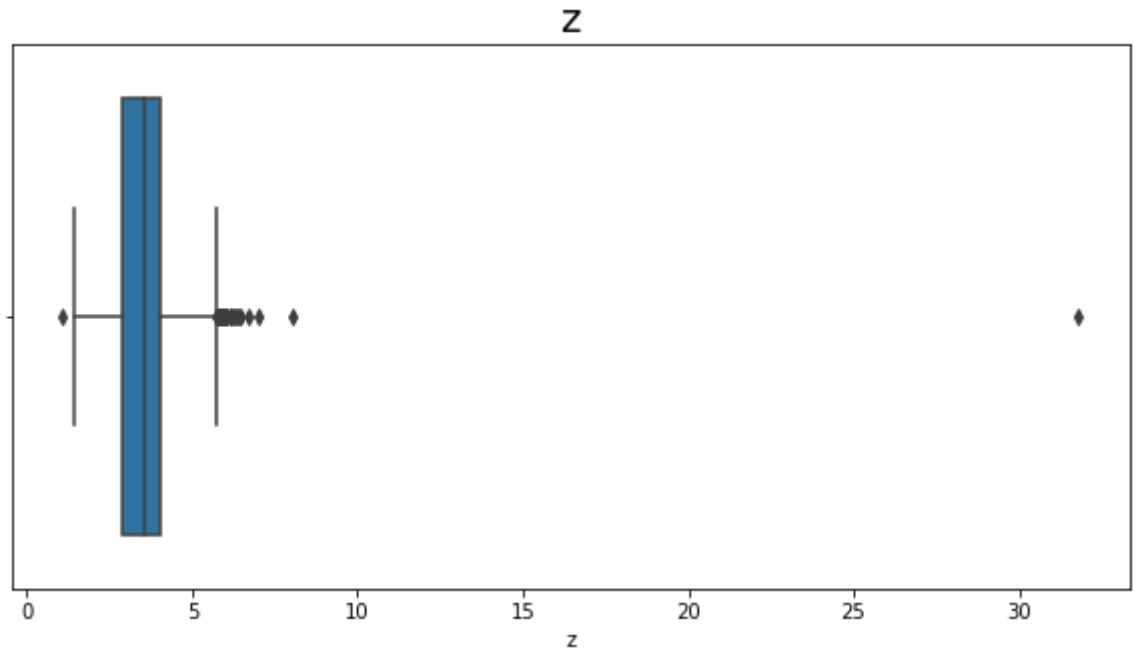

```
E:\anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the fol
lowing variable as a keyword arg: x. From version 0.12, the only valid positional ar
gument will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
```




```
E:\anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the fol
lowing variable as a keyword arg: x. From version 0.12, the only valid positional ar
gument will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
```



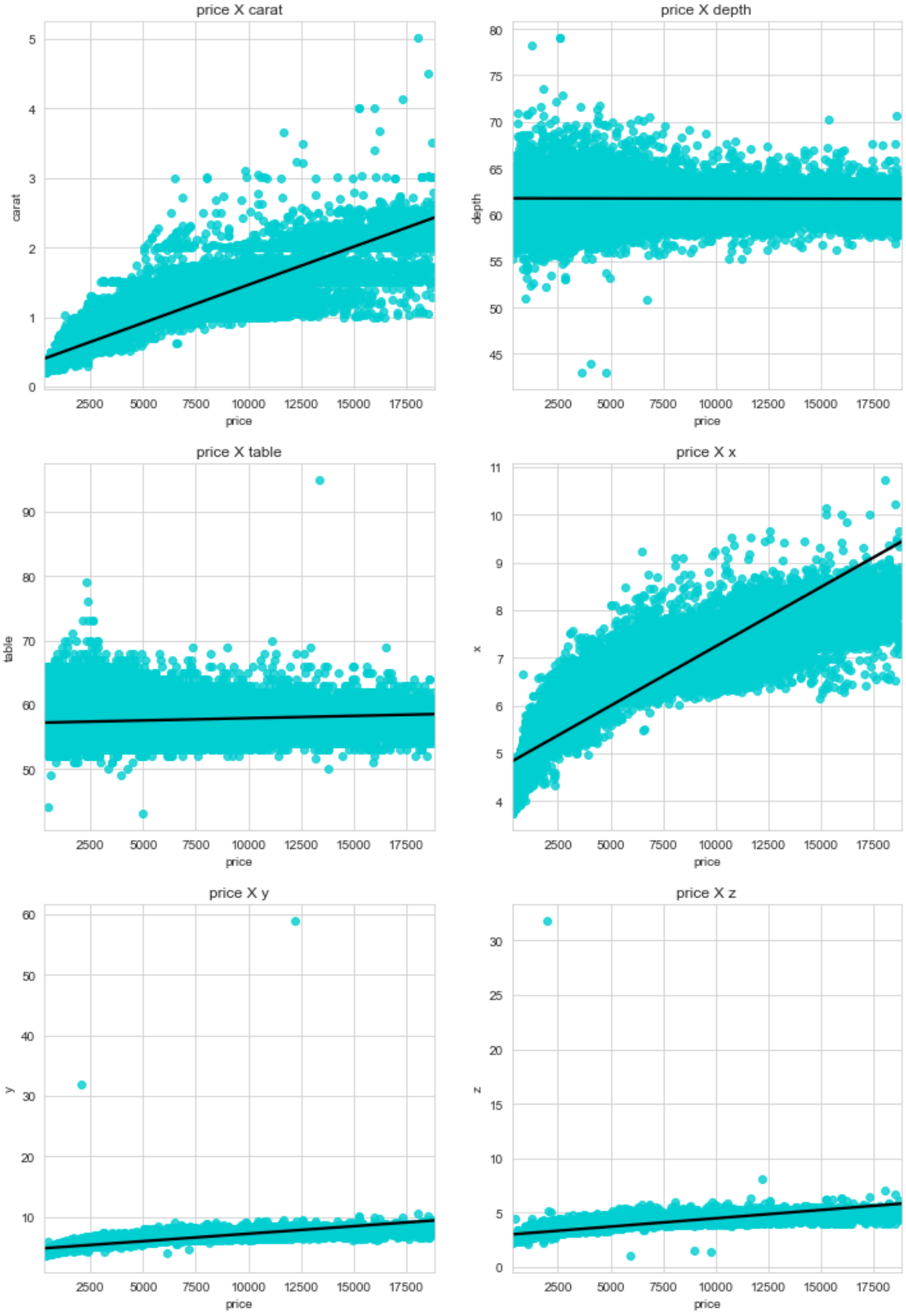

```
E:\anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the fol
lowing variable as a keyword arg: x. From version 0.12, the only valid positional ar
gument will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
```



Plotting Regression Fit with respect to target variable to visualize and find outliers

In [25]:
```
sns.set_style("whitegrid")
c = "darkturquoise"
#c = "lightsalmon"
#c = "crimson"

plt.figure(figsize = (12, 18))
plt.subplot(3, 2, 1)
plt.title("price X carat")
sns.regplot(data = df, x = "price", y = "carat", color = c, line_kws = {"color" : "b
plt.subplot(3, 2, 2)
plt.title("price X depth")
sns.regplot(data = df, x = "price", y = "depth", color = c, line_kws = {"color" : "b
plt.subplot(3, 2, 3)
plt.title("price X table")
sns.regplot(data = df, x = "price", y = "table", color = c, line_kws = {"color" : "b
plt.subplot(3, 2, 4)
plt.title("price X x")
sns.regplot(data = df, x = "price", y = "x", color = c, line_kws = {"color" : "black
plt.subplot(3, 2, 5)
plt.title("price X y")
sns.regplot(data = df, x = "price", y = "y", color = c, line_kws = {"color" : "black
plt.subplot(3, 2, 6)
plt.title("price X z")
sns.regplot(data = df, x = "price", y = "z", color = c, line_kws = {"color" : "black
plt.show()
```



From the above interpretation we see that Outliers exist in

- **Price vs y**
- **Price vs z**

In [26]:
```
def highlight_outliers(outliers, col):
    outliers_index = outliers.index
```

```
    i = pd.IndexSlice[outliers_index, col]
    return outliers.style.applymap(lambda x: "background-color: red", subset = i).fo
```

- **Price vs y**

In [27]:
```
df_outliers = df.loc[df["y"] > 30].copy()
highlight_outliers(df_outliers, "y")
```

Out[27]:

	carat	cut	color	clarity	depth	table	price	x	y	z
24067	2.00	Premium	H	SI2	58.9	57.0	12210	8.09	58.90	8.06
49189	0.51	Ideal	E	VS1	61.8	55.0	2075	5.15	31.80	5.12

- **Price vs z**

In [28]:
```
df_outliers = df.loc[df["z"] > 30].copy()
highlight_outliers(df_outliers, "z")
```

Out[28]:

	carat	cut	color	clarity	depth	table	price	x	y	z
48410	0.51	Very Good	E	VS1	61.8	54.7	1970	5.12	5.15	31.80

In [29]:
```
# Transforming them into NaN values
df.loc[df["y"] > 30, "y"] = np.nan
df.loc[df["z"] > 30, "z"] = np.nan
```

Let us impute these outliers

In [30]:
```
missing_values_imputation("y")
```

```
carat: 2.0 / median y value: 8.01
carat: 0.51 / median y value: 5.14
```

Out[30]:

	carat	cut	color	clarity	depth	table	price	x	y	z
24067	2.00	Premium	H	SI2	58.9	57.0	12210	8.09	8.01	8.06
49189	0.51	Ideal	E	VS1	61.8	55.0	2075	5.15	5.14	5.12

In [31]:
```
missing_values_imputation("z")
```

```
carat: 0.51 / median z value: 3.17
```

Out[31]:

	carat	cut	color	clarity	depth	table	price	x	y	z
48410	0.51	Very Good	E	VS1	61.8	54.7	1970	5.12	5.15	3.17

Checking for other outliers

- **price vs depth**

In [32]:
```
df_outliers = df.loc[(df["depth"] > 75) | (df["depth"] < 45)].copy()
highlight_outliers(df_outliers, "depth")
```

Out[32]:

	carat	cut	color	clarity	depth	table	price	x	y	z
4518	1.00	Fair	G	SI1	43.0	59.0	3634	6.32	6.27	3.97
6341	1.00	Fair	G	VS2	44.0	53.0	4032	6.31	6.24	4.12

	carat	cut	color	clarity	depth	table	price	x	y	z
10377	1.09	Ideal	J	VS2	43.0	54.0	4778	6.53	6.55	4.12
41918	1.03	Fair	E	I1	78.2	54.0	1262	5.72	5.59	4.42
52860	0.50	Fair	E	VS2	79.0	73.0	2579	5.21	5.18	4.09
52861	0.50	Fair	E	VS2	79.0	73.0	2579	5.21	5.18	4.09

They are not absurd values ,so let us not impute them and keep actual values for analysis

- **price vs table**

In [33]:
```
df_outliers = df.loc[(df["table"] > 90) | (df["table"] < 45)].copy()
highlight_outliers(df_outliers, "table")
```

Out[33]:

	carat	cut	color	clarity	depth	table	price	x	y	z
11368	1.04	Ideal	I	VS1	62.9	43.0	4997	6.45	6.41	4.04
24932	2.01	Fair	F	SI1	58.6	95.0	13387	8.32	8.31	4.87
35633	0.29	Very Good	E	VS1	62.8	44.0	474	4.20	4.24	2.65

We see it to be similar with depth,therefore let's keep it actual.

- **Price vs z**

In [34]:
```
df_outliers = df.loc[df["z"] < 2].copy()
highlight_outliers(df_outliers, "z")
```

Out[34]:

	carat	cut	color	clarity	depth	table	price	x	y	z
14635	1.07	Ideal	F	SI1	60.6	57.0	5909	6.62	6.67	1.07
20694	1.53	Ideal	I	SI1	61.9	54.0	8971	7.43	7.50	1.53
21654	1.41	Ideal	H	VS1	60.7	56.0	9752	7.31	7.22	1.41

We see that there are few values same as carat,which is not right,so let us impute them

In [36]:
```
df.loc[df["carat"] == df["z"], ["carat", "z"]]
```

Out[36]:

	carat	z
14635	1.07	1.07
20694	1.53	1.53
21654	1.41	1.41

In [37]:
```
# Transforming them into NaN values
df.loc[df["z"] < 2, "z"] = np.nan
```

In [38]:
```
missing_values_imputation("z")
```

```
carat: 1.53 / median z value: 4.56
carat: 1.41 / median z value: 4.44
carat: 1.07 / median z value: 4.05
```

Out[38]:

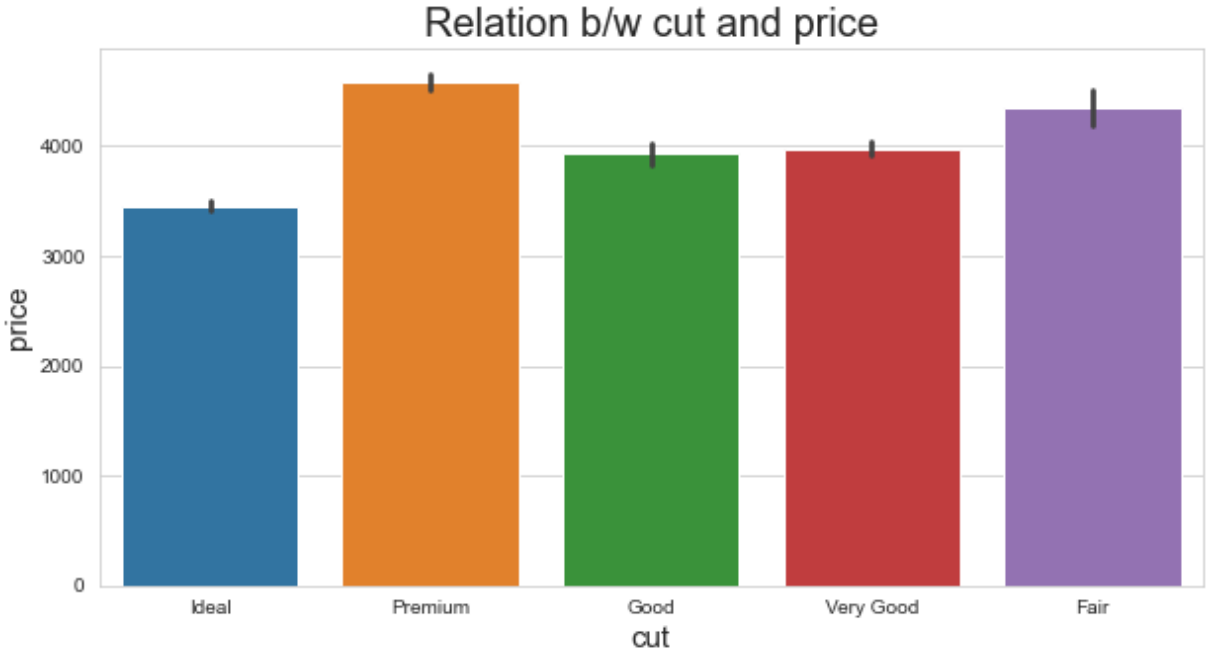
	carat	cut	color	clarity	depth	table	price	x	y	z
20694	1.53	Ideal	I	SI1	61.9	54.0	8971	7.43	7.50	4.56

	carat	cut	color	clarity	depth	table	price	x	y	z
21654	1.41	Ideal	H	VS1	60.7	56.0	9752	7.31	7.22	4.44
14635	1.07	Ideal	F	SI1	60.6	57.0	5909	6.62	6.67	4.05

Data Visualization

Bar Plot between cut and price

In [39]:
```
plt.figure(figsize=(10, 5))
sns.barplot(x='cut', y='price', data=df)
plt.title('Relation b/w cut and price', fontsize=20);
plt.xlabel('cut', fontsize=15)
plt.ylabel('price', fontsize=15);
```

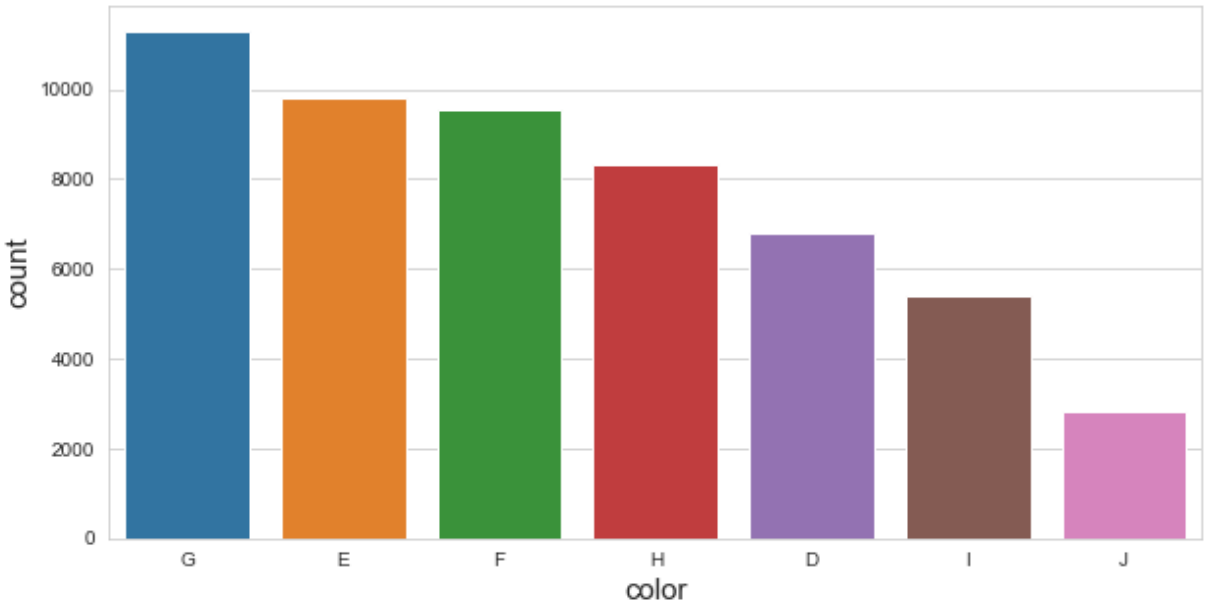


In [40]:
```
df.corr()['price'].sort_values(ascending=False)[1:]
```

Out[40]:
```
carat    0.921591
y        0.888800
x        0.887206
z        0.882368
table    0.127134
depth   -0.010647
Name: price, dtype: float64
```

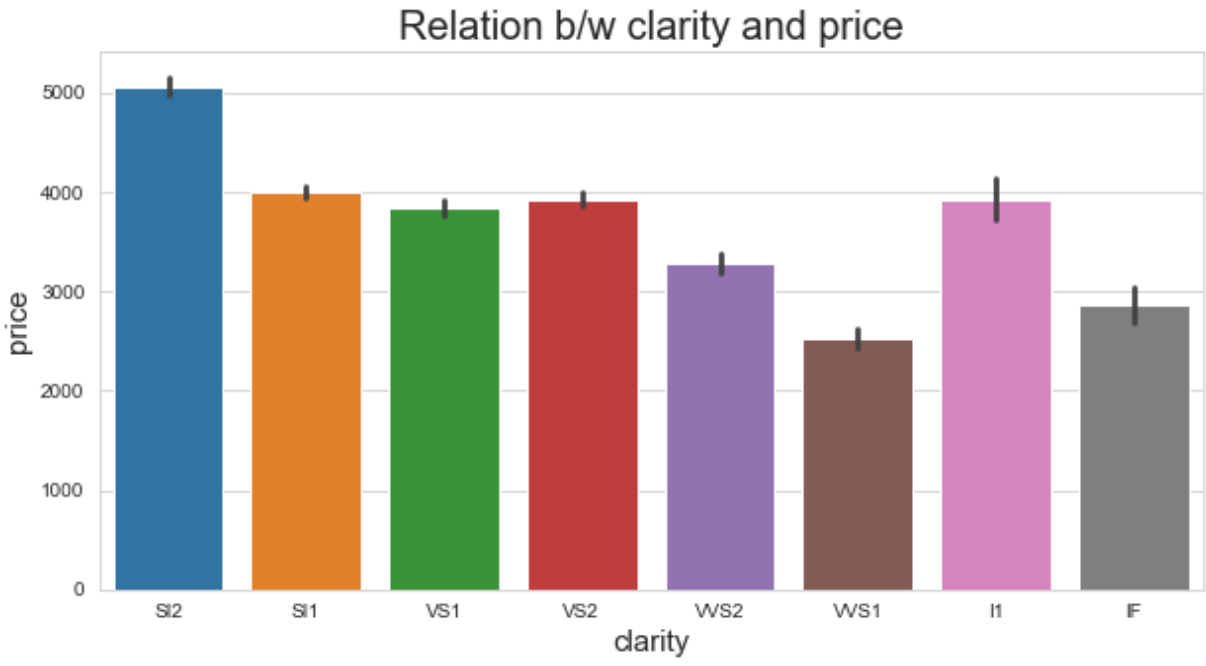
In [41]:
```
''' color category '''
color_label = df.color.value_counts()
plt.figure(figsize=(10, 5))
sns.barplot(color_label.index, color_label);
plt.ylabel('count', fontsize=15)
plt.xlabel('color', fontsize=15);
```

```
E:\anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the fol
lowing variables as keyword args: x, y. From version 0.12, the only valid positional
argument will be `data`, and passing other arguments without an explicit keyword wil
l result in an error or misinterpretation.
  warnings.warn(
```



Bar Plot between clarity and price

In [42]:
```
plt.figure(figsize=(10, 5))
sns.barplot(x='clarity', y='price', data=df);
plt.title('Relation b/w clarity and price', fontsize=20)
plt.xlabel('clarity', fontsize=15)
plt.ylabel('price', fontsize=15);
```



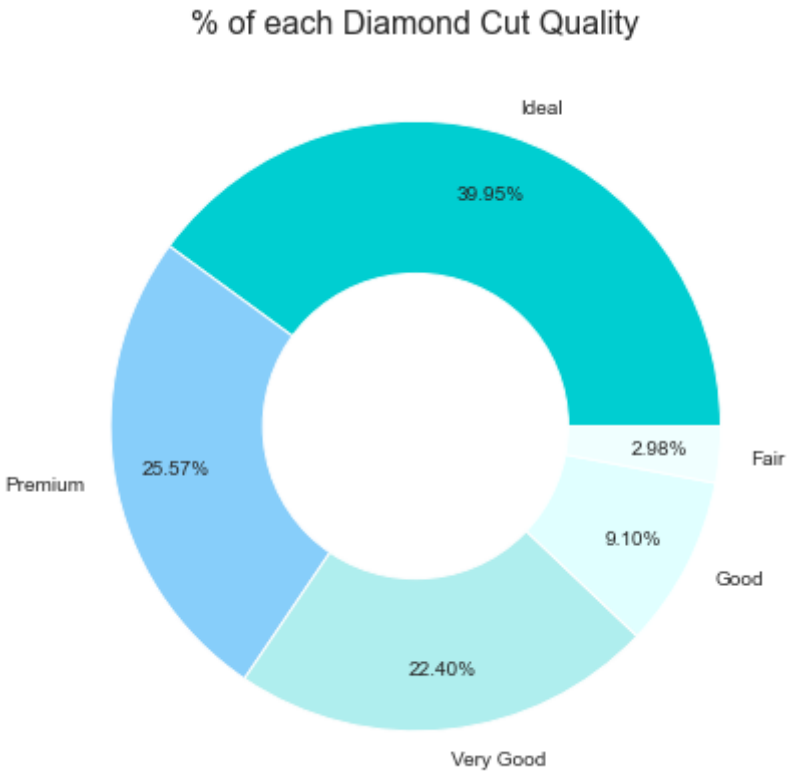
In [44]:
```
cut_palette = ["darkturquoise", "lightskyblue", "paleturquoise", "lightcyan", "azure
color_palette = ["cadetblue", "deepskyblue", "darkturquoise", "lightskyblue", "palet
clarity_palette = ["cadetblue", "deepskyblue", "darkturquoise", "lightskyblue", "pal

df["cut"] = pd.Categorical(df["cut"], categories = ["Ideal", "Premium", "Very Good",
df["color"] = pd.Categorical(df["color"], categories = ["D", "E", "F", "G", "H", "I"
df["clarity"] = pd.Categorical(df["clarity"], categories = ["IF", "VVS1", "VVS2", "V
```

In [45]:
```
df_cut = df["cut"].value_counts()

plt.figure(figsize = (7,7))
plt.pie(data = df_cut, x = df_cut.values, labels = df_cut.index, autopct = "%.2f%%",
circle = plt.Circle(xy = (0, 0), radius = 0.5, facecolor = 'white')
```

```
plt.gca().add_artist(circle)
plt.title("% of each Diamond Cut Quality", size = 16)
plt.show()
```



Ideal>Premium>VeryGood>Good>Fair

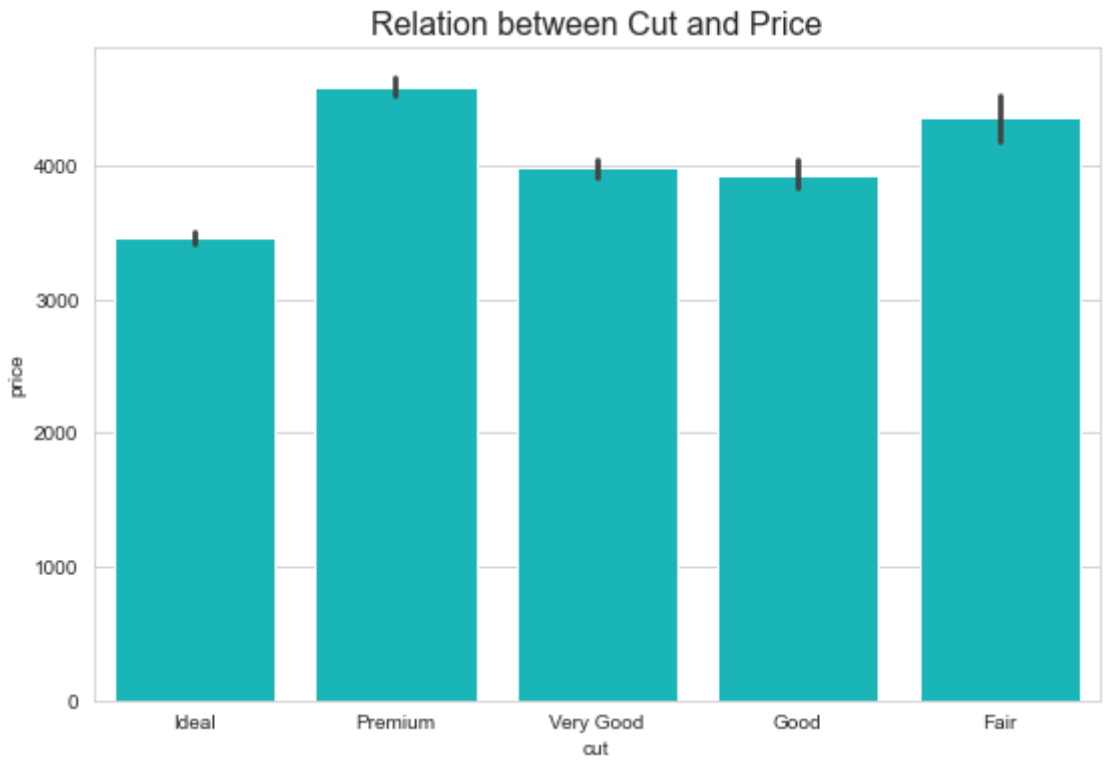
In [46]:
```
position = 0
for cut in df_cut:
    print("{0} quality cuts: {1}".format(df_cut.index[position], df_cut.values[posit
    position += 1
```

```
Ideal quality cuts: 21551
Premium quality cuts: 13791
Very Good quality cuts: 12082
Good quality cuts: 4906
Fair quality cuts: 1610
```

We can come to a conclusion that there are more number of high and well cut diamonds.

Checking cut with regards to price

In [47]:
```
plt.figure(figsize = (9, 6))
sns.barplot(data = df, x = "cut", y = "price", color = c)
plt.title("Relation between Cut and Price", size = 16)
plt.show()
```



Here we see a unusual interpretation,let us check the correlation

In [48]:
```
get_corr("price")
```

Out[48]:
```
price    1.000000
carat    0.921591
y        0.888800
x        0.887206
z        0.882368
table    0.127134
depth   -0.010647
dtype: float64
```

carat is the most important thing with regards to price,diamonds with ideal cuts should have lower carat value

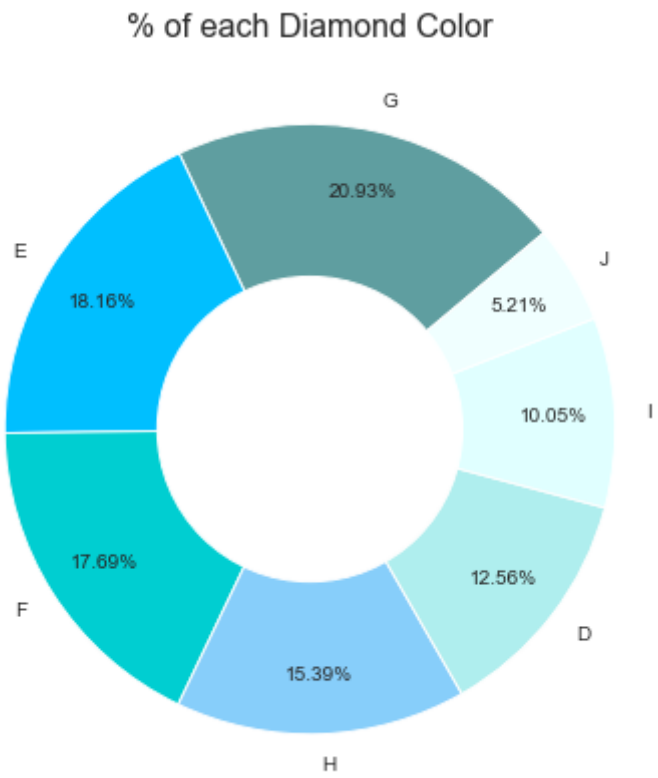
In [49]:
```
df.groupby(["cut"])["carat"].mean()
```

Out[49]:
```
cut
Ideal        0.702837
Premium      0.891955
Very Good    0.806381
Good         0.849185
Fair         1.046137
Name: carat, dtype: float64
```

Here we see the mean of Ideal cuts is very low compared to others,therefore the affect in graph.

In [50]:
```
df_color = df["color"].value_counts()

plt.figure(figsize = (7,7))
plt.pie(data = df_color, x = df_color.values, labels = df_color.index, autopct = "%.
circle = plt.Circle(xy = (0, 0), radius = 0.5, facecolor = 'white')
plt.gca().add_artist(circle)
plt.title("% of each Diamond Color", size = 16)
plt.show()
```



D>E>F>G>H>I>J

In [51]:
```
position = 0
for color in df_color:
    print("{0} color diamonds: {1}".format(df_color.index[position], df_color.values
    position += 1
```

```
G color diamonds: 11292
E color diamonds: 9797
F color diamonds: 9542
H color diamonds: 8304
D color diamonds: 6775
I color diamonds: 5422
J color diamonds: 2808
```

In [52]:
```
plt.figure(figsize = (9, 6))
sns.barplot(data = df, x = "color", y = "price", color = c)
plt.title("Relation between Diamond Color and Price", size = 16)
plt.show()
```

Again, the mean price of diamonds with better colors are lower than all other diamonds with worst colors.

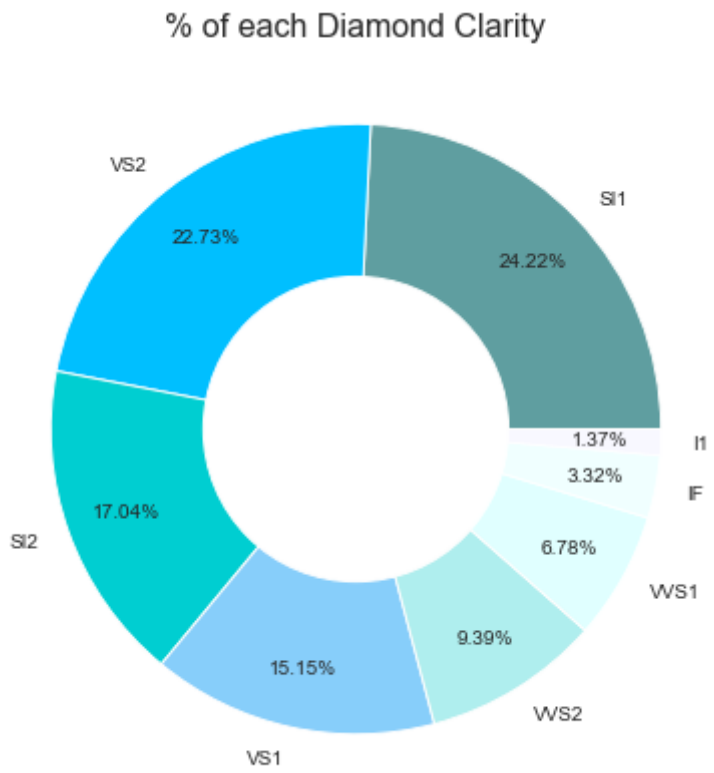
In [53]:
```
df.groupby(["color"])["carat"].mean()
```

Out[53]:
```
color
D    0.657795
E    0.657867
F    0.736538
G    0.771190
H    0.911799
I    1.026927
J    1.162137
Name: carat, dtype: float64
```

We observe the same here,D has the lowest mean value

In [54]:
```
df_clarity = df["clarity"].value_counts()

plt.figure(figsize = (7,7))
plt.pie(data = df_clarity, x = df_clarity.values, labels = df_clarity.index, autopct
circle = plt.Circle(xy = (0, 0), radius = 0.5, facecolor = 'white')
plt.gca().add_artist(circle)
plt.title("% of each Diamond Clarity", size = 16)
plt.show()
```

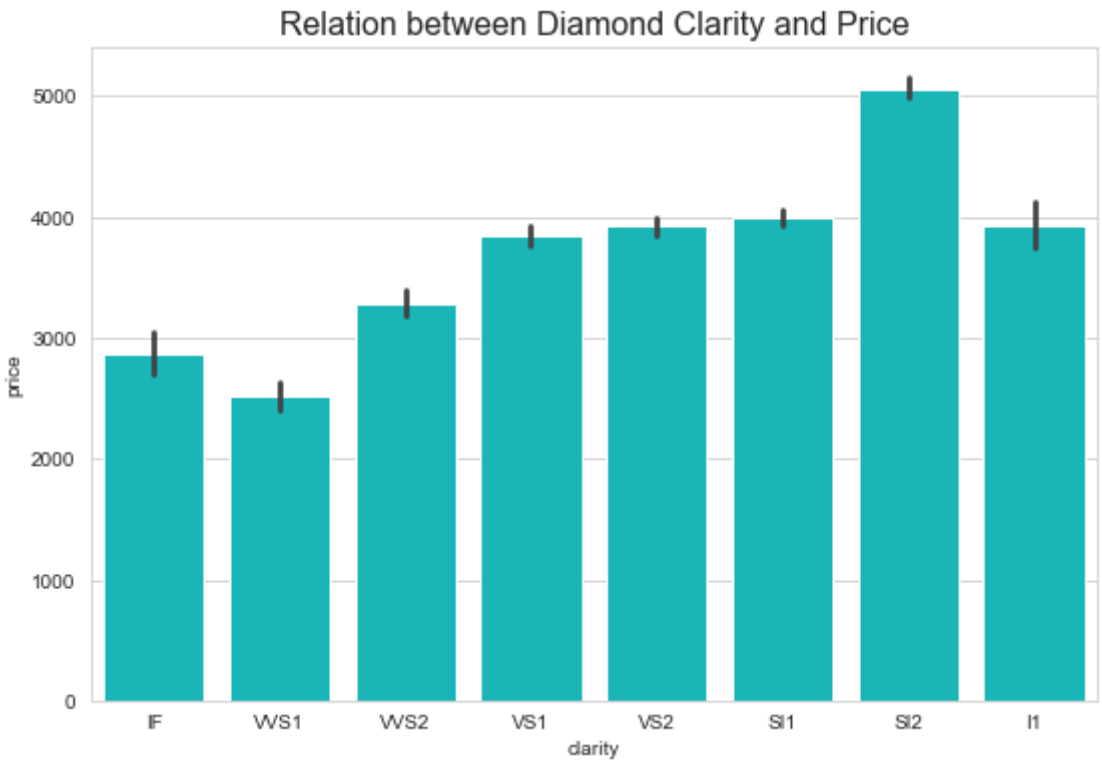


IF > VVS1 > VVS2 > VS1 > VS2 > SI1 > SI2 > I1

In [55]:
```
position = 0
for color in df_clarity:
    print("{0} clarity diamonds: {1}".format(df_clarity.index[position], df_clarity.
    position += 1
```

```
SI1 clarity diamonds: 13065
VS2 clarity diamonds: 12258
SI2 clarity diamonds: 9194
VS1 clarity diamonds: 8171
VVS2 clarity diamonds: 5066
VVS1 clarity diamonds: 3655
IF clarity diamonds: 1790
I1 clarity diamonds: 741
```

In [56]:
```
plt.figure(figsize = (9, 6))
sns.barplot(data = df, x = "clarity", y = "price", color = c)
plt.title("Relation between Diamond Clarity and Price", size = 16)
plt.show()
```



In [57]:
```
df.groupby(["clarity"])["carat"].mean()
```

Out[57]:
```
clarity
IF      0.505123
VVS1    0.503321
VVS2    0.596202
VS1     0.727158
VS2     0.763935
SI1     0.850482
SI2     1.077648
I1      1.283846
Name: carat, dtype: float64
```

We observe the same again,VVS1 has the lowest mean.

DATA PREPROCESSING TO IMPLEMENT VARIOUS MODELS

In [59]:
```
label_cut = LabelEncoder()
label_color = LabelEncoder()
label_clarity = LabelEncoder()


df['cut'] = label_cut.fit_transform(df['cut'])
df['color'] = label_color.fit_transform(df['color'])
df['clarity'] = label_clarity.fit_transform(df['clarity'])
```

In [60]:
```
df.head()
```

Out[60]:

	carat	cut	color	clarity	depth	table	price	x	y	z
0	0.23	2	1	3	61.5	55.0	326	3.95	3.98	2.43
1	0.21	3	1	2	59.8	61.0	326	3.89	3.84	2.31
2	0.23	1	1	4	56.9	65.0	327	4.05	4.07	2.31
3	0.29	3	5	5	62.4	58.0	334	4.20	4.23	2.63
4	0.31	1	6	3	63.3	58.0	335	4.34	4.35	2.75

In [61]:
```
X = df.drop(["price"], axis = 1).copy()
y = df["price"].copy()
```

In [62]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.1, random_state=
```

Linear Regression

In [70]:
```
regressor = LinearRegression()
regressor.fit(X_train, y_train)
prediction = regressor.predict(X_test)
rmse_Lreg = np.sqrt(mean_squared_error(y_test, prediction))
print('RMSE value is = {}'.format(rmse_Lreg))
r2_Lreg = r2_score(y_test, prediction)
print('R-squared value is {}'.format(r2_Lreg))
```

```
RMSE value is = 1376.6250458046643
R-squared value is 0.8841897788553627
```

Random Forest Regressor

In [71]:
```
RFreg_model = RandomForestRegressor()
RFreg_model.fit(X_train,y_train)
prediction2 = RFreg_model.predict(X_test)
rmse_RFreg = np.sqrt(mean_squared_error(y_test, prediction2))
print('RMSE value is = {}'.format(rmse_RFreg))
r2_RFreg = r2_score(y_test, prediction2)
print('R-squared value is {}'.format(r2_RFreg))
```

```
RMSE value is = 522.9692644787389
R-squared value is 0.9832864814086221
```

Polynomial Regressor

In [72]:
```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
poly_reg = PolynomialFeatures(degree = 4)
X_poly = poly_reg.fit_transform(X_train)
regressor = LinearRegression()
regressor.fit(X_poly, y_train)
prediction3 = regressor.predict(poly_reg.transform(X_test))

ploy_reg = np.sqrt(mean_squared_error(y_test, prediction3))
print('RMSE value is = {}'.format(ploy_reg))
r2_poly_reg = r2_score(y_test, prediction3)
print('R-squared value is {}'.format(r2_poly_reg))
```

```
RMSE value is = 977.721538221508
R-squared value is 0.9415821025119236
```

Decision Tree Regressor

In [73]:
```
regressor1 = DecisionTreeRegressor(random_state = 0)
regressor1.fit(X_train, y_train)
prediction4 = regressor1.predict(X_test)
dt_reg = np.sqrt(mean_squared_error(y_test, prediction4))
print('RMSE value is = {}'.format(dt_reg))
r2_dt_reg = r2_score(y_test, prediction4)
print('R-squared value is {}'.format(r2_dt_reg))
```

```
RMSE value is = 746.5701536975055
R-squared value is 0.9659390462125902
```

XGB Regressor

In [82]:
```
xgbr = XGBRegressor(learning_rate = 0.1, n_estimators = 200, random_state = SEED)
xgbr.fit(X_train,y_train)
prediction5 = xgbr.predict(X_test)
xgbr_reg = np.sqrt(mean_squared_error(y_test, prediction5))
print('RMSE value is = {}'.format(xgbr_reg))
r2_xgbr_reg = r2_score(y_test, prediction5)
print('R-squared value is {}'.format(r2_xgbr_reg))
```

```
RMSE value is = 7878.687711787642
R-squared value is -2.7933536281218787
```

In [86]:
```
Result= pd.DataFrame({'Actual Price':y_test,'Predicted Price By LinearRegression':pr
Result
```

Out[86]:

	Actual Price	Predicted Price By LinearRegression	Predicted Price By RandomForest	Predicted Price By PolynomialRegressor	Predicted Price By DecisionTreeRegressor	Pr I XgbRe
38807	1046	593.816379	964.320000	1024.250603	945.0	7827
36031	923	44.287825	897.290000	1165.927381	876.0	7684
28575	675	-217.498219	639.380000	472.529553	675.0	7827
51189	2348	2156.030710	2403.400000	2470.500218	2268.0	11018
10962	4903	5894.883014	4565.410000	5233.516574	3961.0	14496
...	...	...	...	...	...	
22076	10096	8031.807571	9773.700000	8380.688853	10359.0	11961
5647	3880	4506.737377	4034.660000	4018.571097	3846.0	11931
29488	702	930.971486	760.520000	804.506712	702.0	10041
33900	844	928.001216	868.680000	726.699063	911.0	9573
12966	5390	5896.288496	5775.486667	5757.349361	5102.0	11321

5394 rows × 6 columns

In [87]:
```
Result.head()
```

Out[87]:

	Actual Price	Predicted Price By LinearRegression	Predicted Price By RandomForest	Predicted Price By PolynomialRegressor	Predicted Price By DecisionTreeRegressor	Pr I XgbRe
38807	1046	593.816379	964.32	1024.250603	945.0	7827
36031	923	44.287825	897.29	1165.927381	876.0	7684
28575	675	-217.498219	639.38	472.529553	675.0	7827
51189	2348	2156.030710	2403.40	2470.500218	2268.0	11018
10962	4903	5894.883014	4565.41	5233.516574	3961.0	14496

In [ ]:

In [ ]: