Introduction About the Data :

The dataset The goal is to predict `price` of given diamond (Regression Analysis).

There are 10 independent variables (including `id`):

- `id` : unique identifier of each diamond
- `carat` : Carat (ct.) refers to the unique unit of weight measurement used exclusively to weigh gemstones and diamonds.
- `cut` : Quality of Diamond Cut
- `color` : Color of Diamond
- `clarity` : Diamond clarity is a measure of the purity and rarity of the stone, graded by the visibility of these characteristics under 10-power magnification.
- `depth` : The depth of diamond is its height (in millimeters) measured from the culet (bottom tip) to the table (flat, top surface)
- `table` : A diamond's table is the facet which can be seen when the stone is viewed face up.
- `x` : Diamond X dimension
- `y` : Diamond Y dimension
- `x` : Diamond Z dimension

Target variable:

- `price`: Price of the given Diamond.

Read the Dataset

Read Dataset

In [ ]:
```
import pandas as pd
df = pd.read_csv("./data/gemstone.csv")
df.head()
```

Out[ ]:

	id	carat	cut	color	clarity	depth	table	x	y	z	price
0	0	1.52	Premium	F	VS2	62.2	58.0	7.27	7.33	4.55	13619
1	1	2.03	Very Good	J	SI2	62.0	58.0	8.06	8.12	5.05	13387
2	2	0.70	Ideal	G	VS1	61.2	57.0	5.69	5.73	3.50	2772
3	3	0.32	Ideal	G	VS1	61.6	56.0	4.38	4.41	2.71	666
4	4	1.70	Premium	G	VS2	62.6	59.0	7.65	7.61	4.77	14453

Dataset Info

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 193573 entries, 0 to 193572
Data columns (total 11 columns):
 #   Column   Non-Null Count   Dtype  
---  ------   --------------   -----  
 0   id       193573 non-null  int64  
 1   carat    193573 non-null  float64
 2   cut      193573 non-null  object 
 3   color    193573 non-null  object 
 4   clarity  193573 non-null  object 
 5   depth    193573 non-null  float64
 6   table    193573 non-null  float64
 7   x        193573 non-null  float64
 8   y        193573 non-null  float64
 9   z        193573 non-null  float64
 10  price    193573 non-null  int64  
dtypes: float64(6), int64(2), object(3)
memory usage: 16.2+ MB
```

Drop id column as it is statistically insignificant

In [ ]:
```
df = df.drop(labels=['id'],axis=1)
```

Check Missing Values in Dataset

In [ ]:
```
df.isna().sum()
```

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

No Missing Values found in the dataset

Check Duplicates in Dataset

In [ ]:
```
df.duplicated().sum()
```

Out[ ]:
```
0
```

No Duplicated data found

Descriptive Statistics

Numerical and Categorical columns seperation

In [ ]:
```
numerical_columns = list(df.columns[df.dtypes!='object'])
categorical_columns = list(df.columns[df.dtypes=='object'])
print(f'Numerical Columns   : {numerical_columns}')
print(f'Categorical Columns : {categorical_columns}')
```

```
Numerical Columns   : ['carat', 'depth', 'table', 'x', 'y', 'z', 'price']
Categorical Columns : ['cut', 'color', 'clarity']
```

Numerical Columns Description

In [ ]:
```
df.describe().T
```

Out[ ]:

	count	mean	std	min	25%	50%	75%	max
carat	193573.0	0.790688	0.462688	0.2	0.40	0.70	1.03	3.50
depth	193573.0	61.820574	1.081704	52.1	61.30	61.90	62.40	71.60
table	193573.0	57.227675	1.918844	49.0	56.00	57.00	58.00	79.00
x	193573.0	5.715312	1.109422	0.0	4.70	5.70	6.51	9.65
y	193573.0	5.720094	1.102333	0.0	4.71	5.72	6.51	10.01
z	193573.0	3.534246	0.688922	0.0	2.90	3.53	4.03	31.30
price	193573.0	3969.155414	4034.374138	326.0	951.00	2401.00	5408.00	18818.00

Categorical Columns Description

In [ ]:

```
df[categorical_columns].describe().T
```

Out[ ]:

	count	unique	top	freq
cut	193573	5	Ideal	92454
color	193573	7	G	44391
clarity	193573	8	SI1	53272

All unique values in dataset

In [ ]:

```
df.nunique()
```

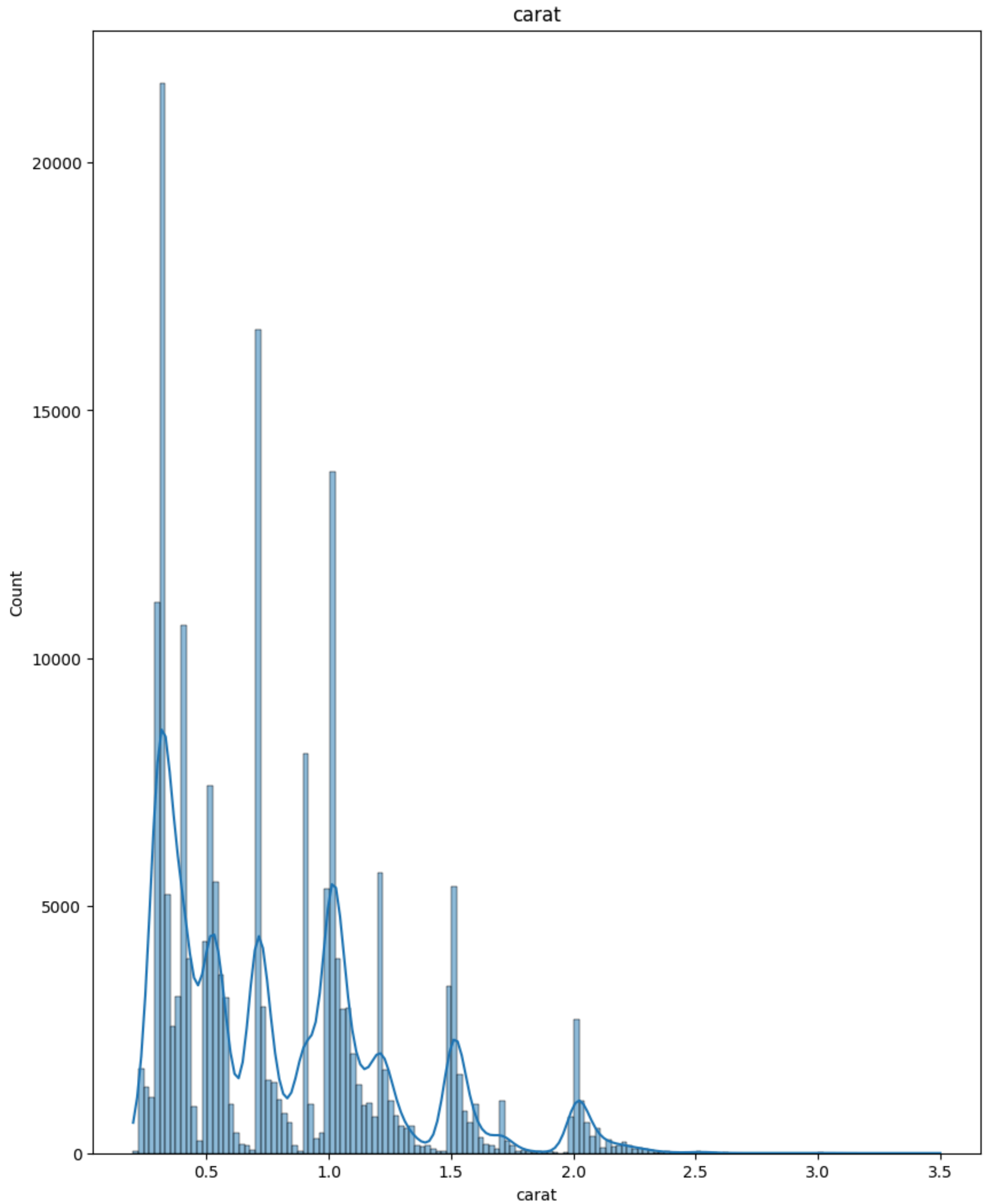
Out[ ]:

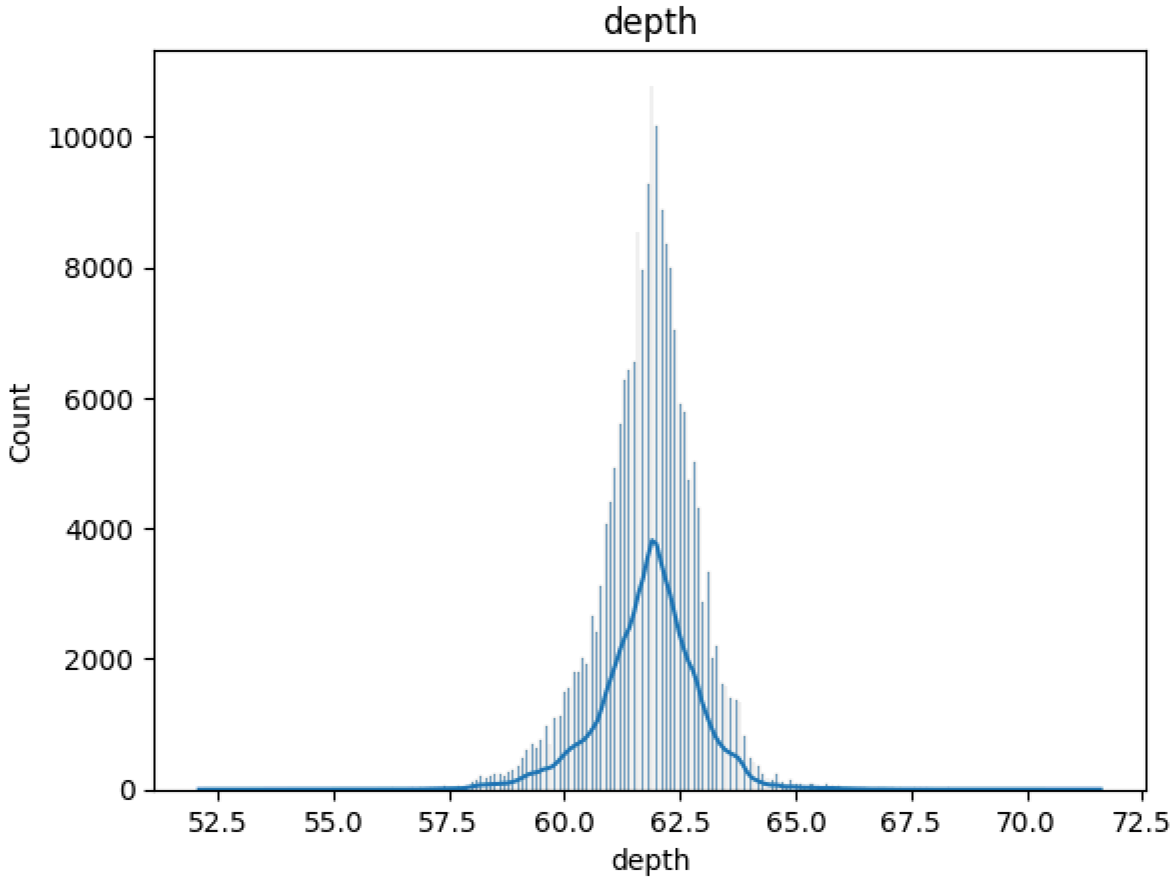
```
carat       248
cut           5
color         7
clarity       8
depth       153
table       108
x           522
y           521
z           349
price      8738
dtype: int64
```

Univariate Analysis with Visualisation

Univariate Analysis of Numerical Variables

In [ ]:
```
import seaborn as sb
import matplotlib.pyplot as plt
plt.figure(figsize=(10,10))
plt.subplots_adjust(top = 0.99, bottom=0.01, hspace=0.5, wspace=0.5)
x = 1
for i in numerical_columns:
    sb.histplot(data = df, x = i, kde=True)
    plt.title(i)
    print('\n')
    plt.show()
```


carat
Count
carat
0
5000
10000
15000
20000
0.5
1.0
1.5
2.0
2.5
3.0
3.5


depth
Count
depth
0
2000
4000
6000
8000
10000
52.5
55.0
57.5
60.0
62.5
65.0
67.5
70.0
72.5

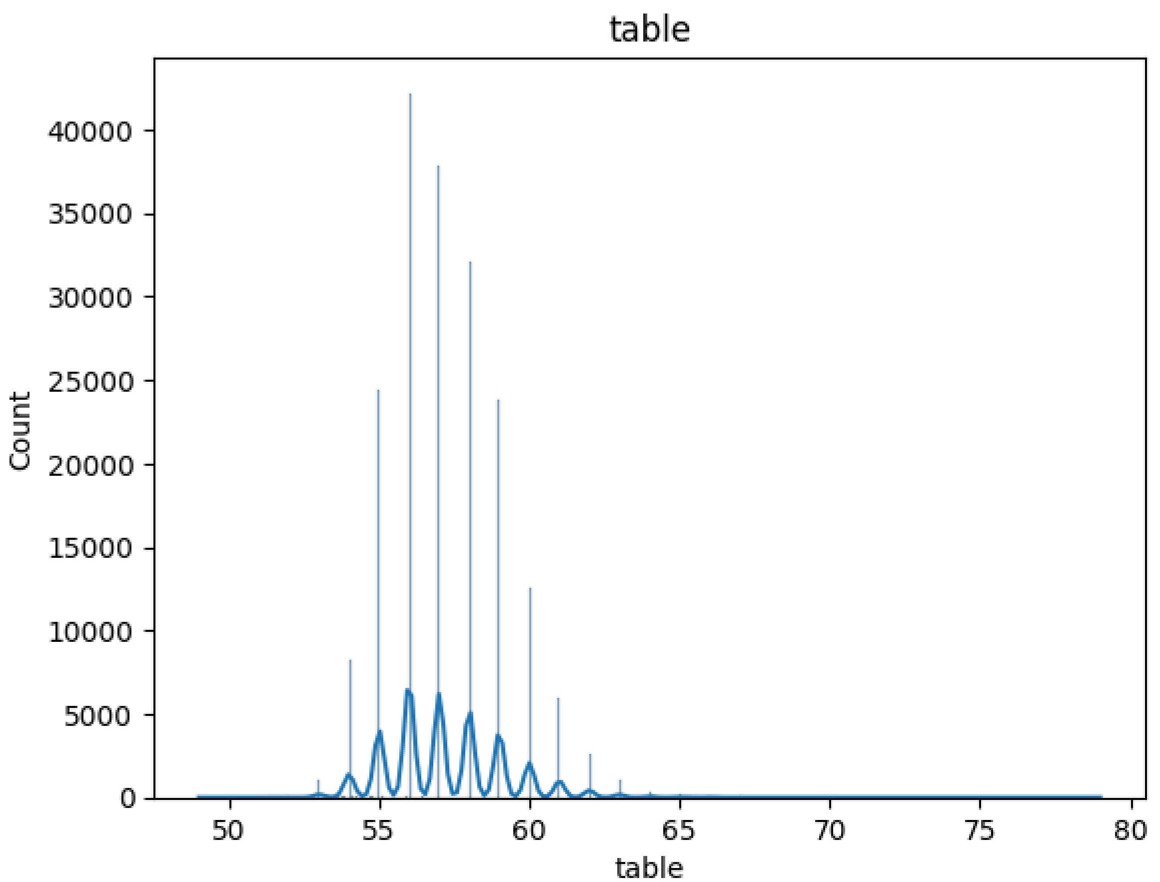
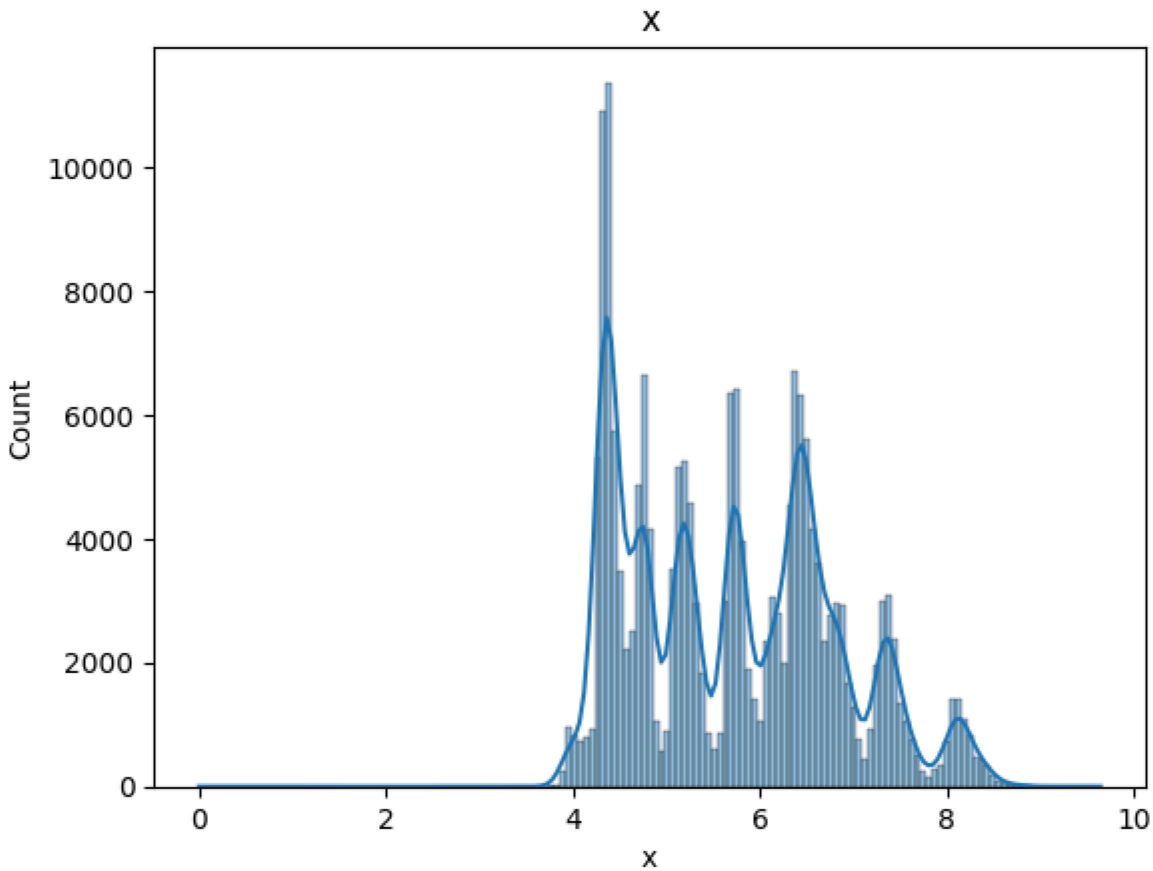
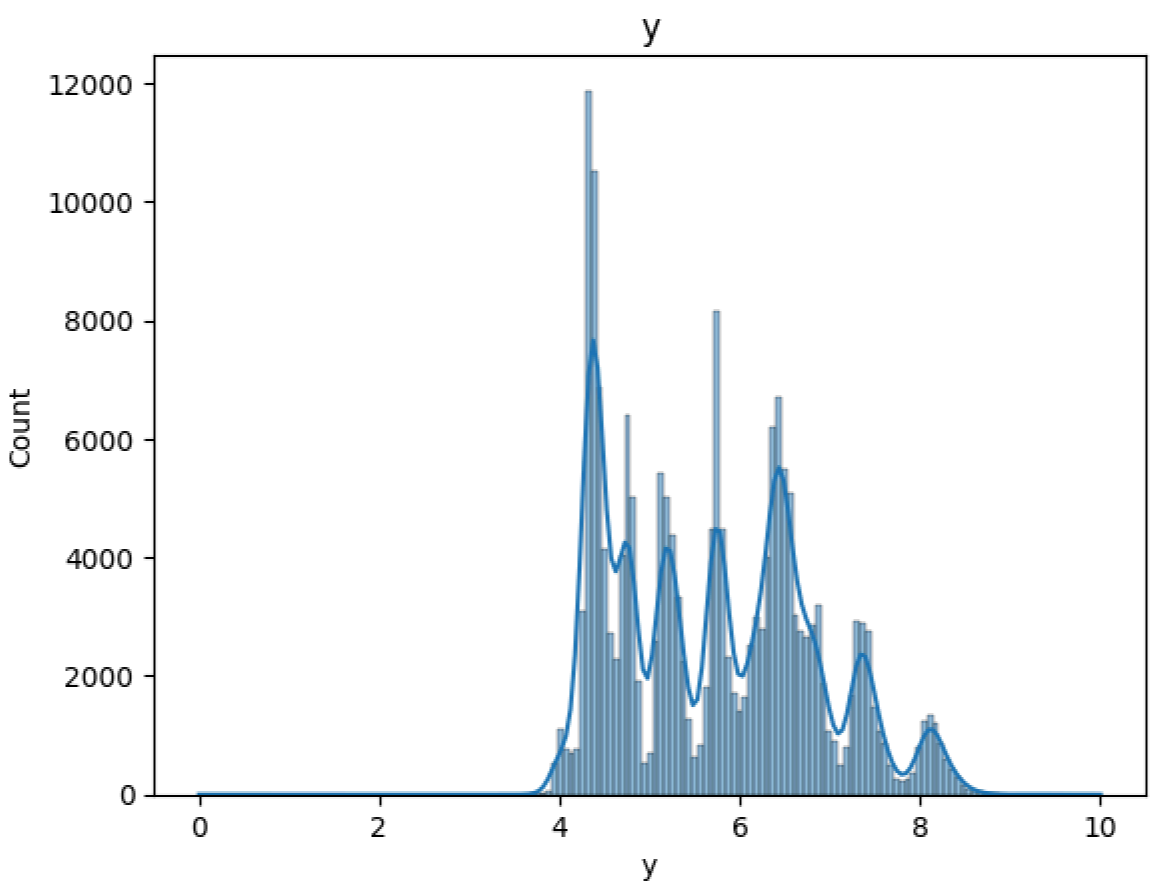
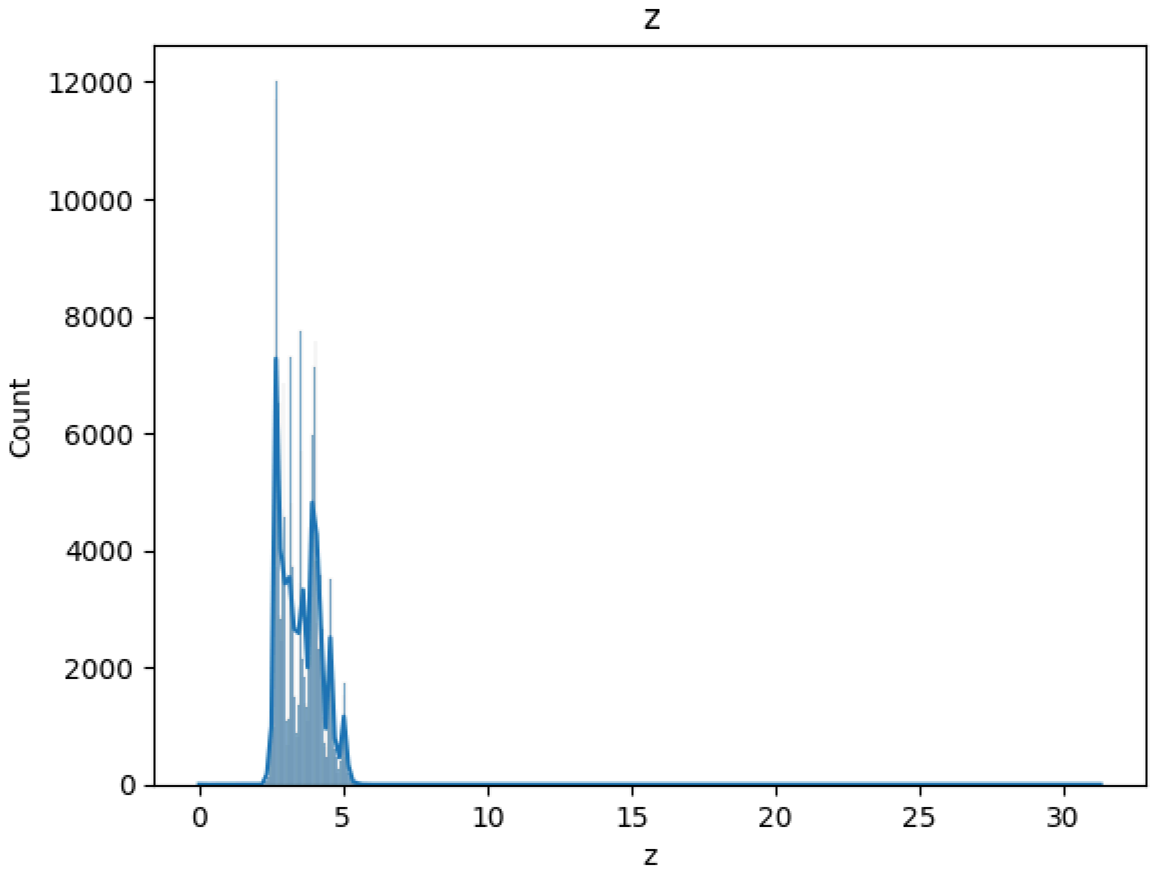
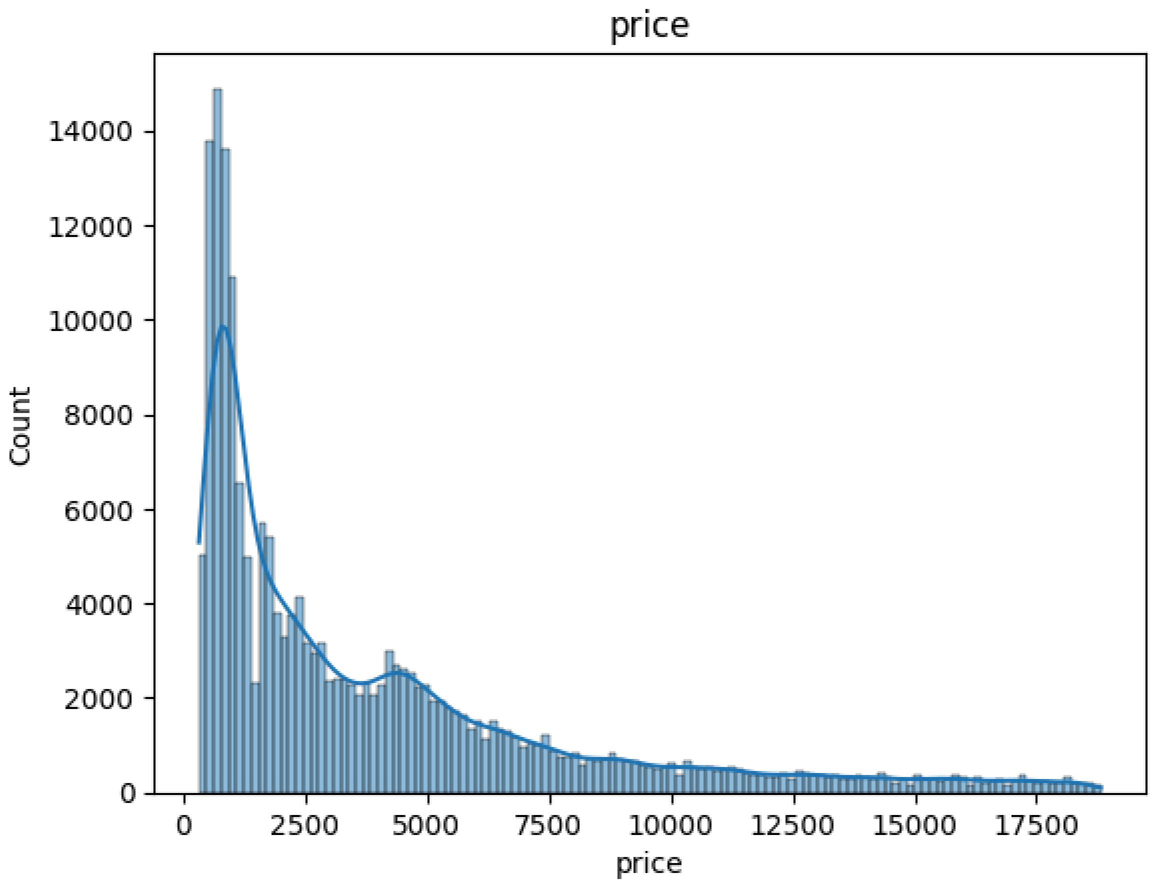


table
Count
table
0
5000
10000
15000
20000
25000
30000
35000
40000
50
55
60
65
70
75
80


x
Count
10000
8000
6000
4000
2000
0
0
2
4
6
8
10
x

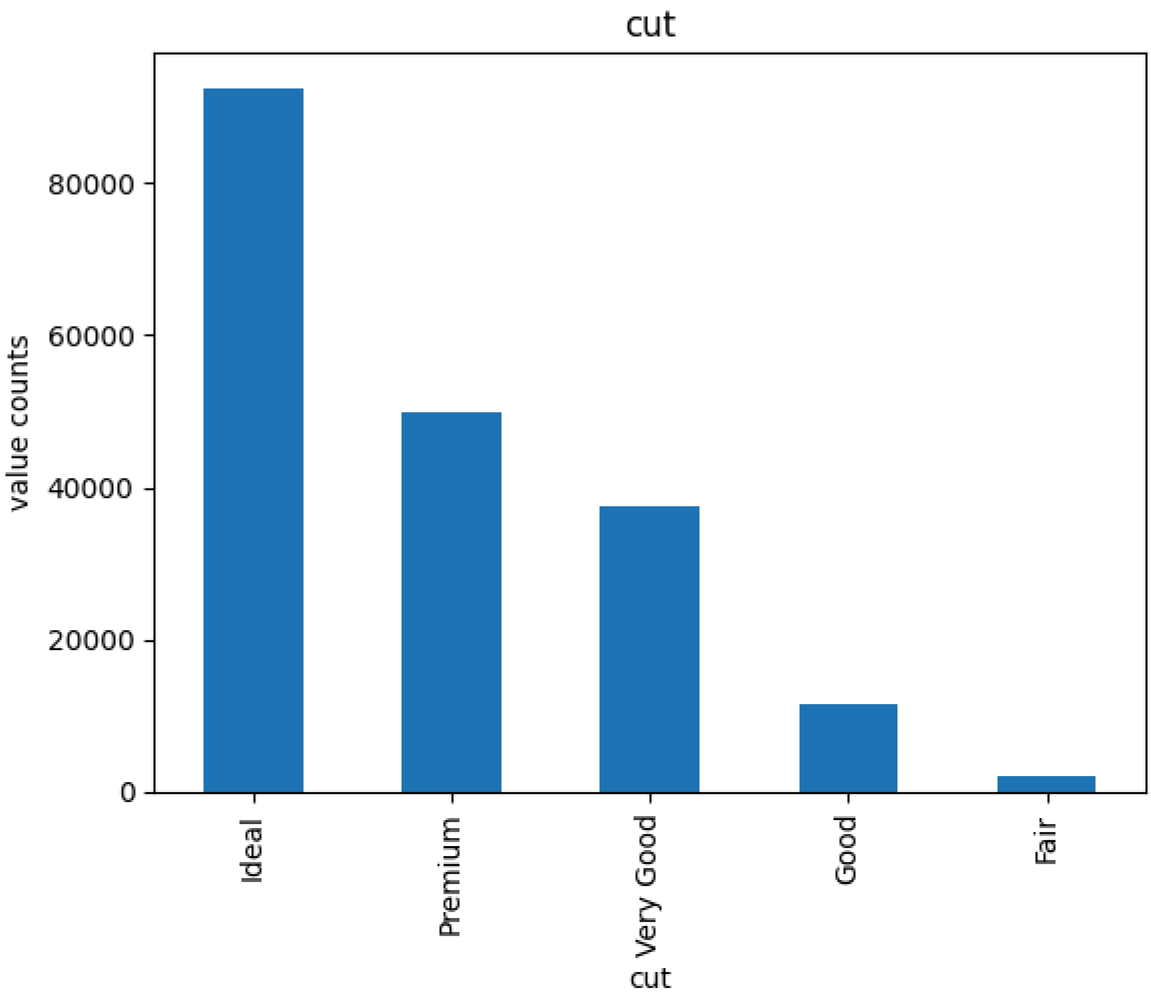

y
Count
12000
10000
8000
6000
4000
2000
0
0
2
4
6
8
10
y

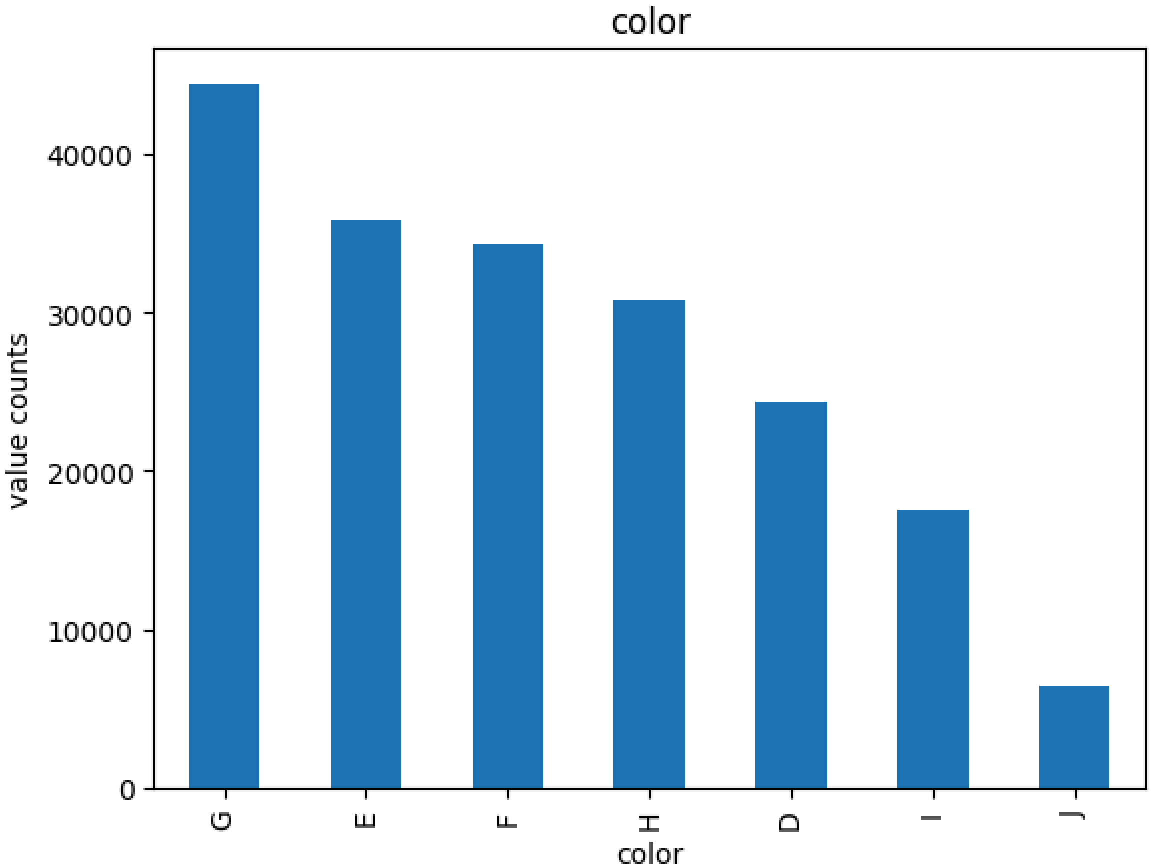

z
Count
z
12000
10000
8000
6000
4000
2000
0
0
5
10
15
20
25
30

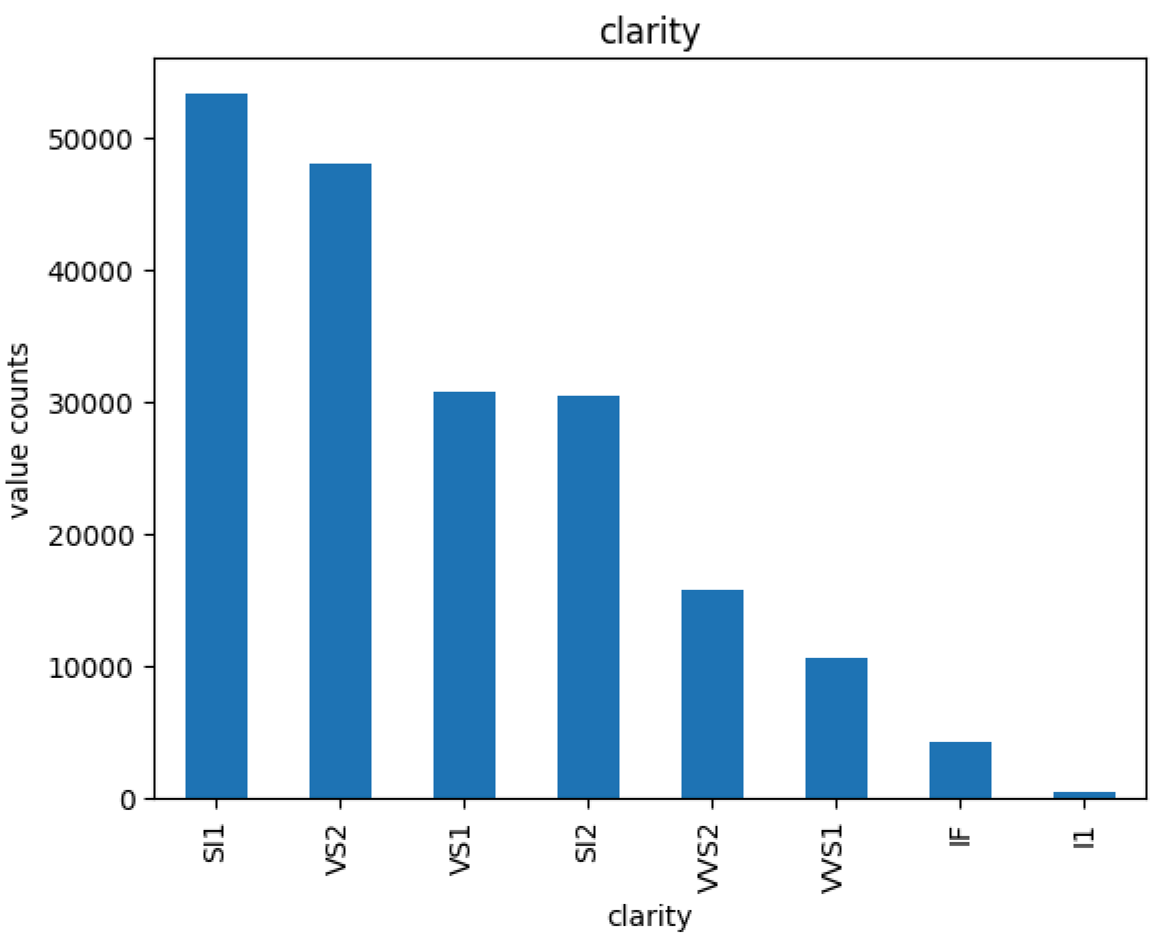

price
Count
price
14000
12000
10000
8000
6000
4000
2000
0
0
2500
5000
7500
10000
12500
15000
17500

Univariate analysis for categorical variables

In [ ]:
```
for i in categorical_columns:
    df[i].value_counts().plot(kind='bar', xlabel = i , ylabel='value counts', title
    print('\n')
    plt.show()
```



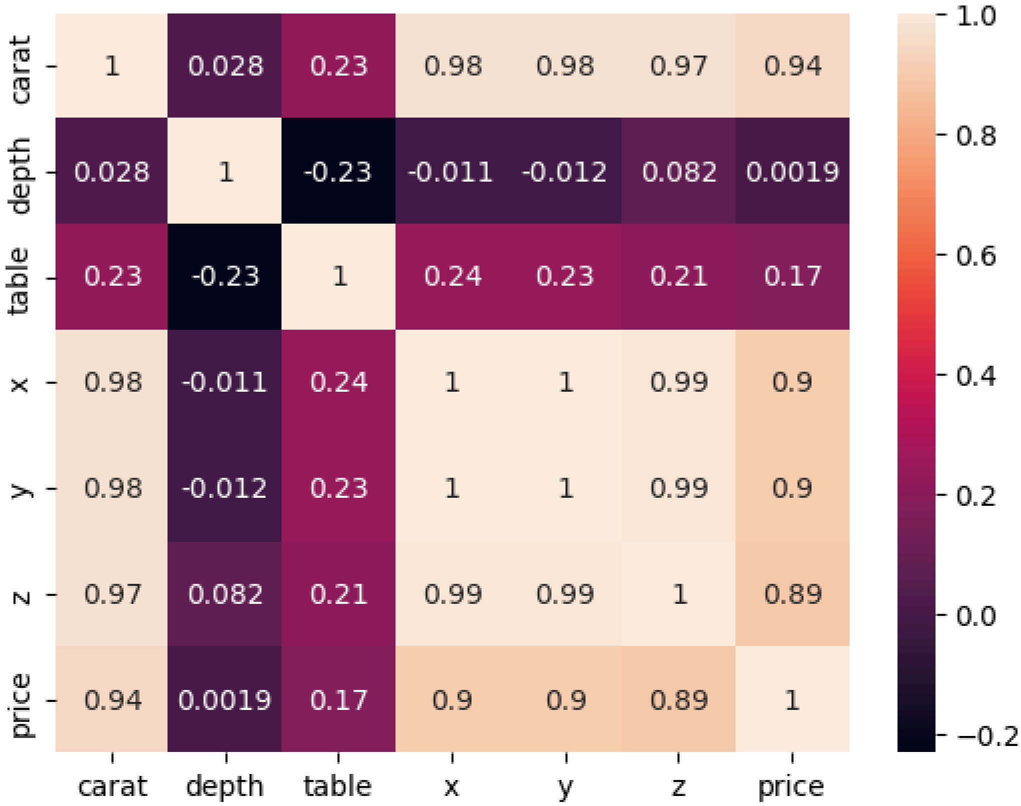

color
value counts
0
10000
20000
30000
40000
G
E
F
H
D
I
J
color


clarity
value counts
0
10000
20000
30000
40000
50000
SI1
VS2
VS1
SI2
VVS2
VVS1
IF
I1
clarity

Bivariate Analysis with Visualisation

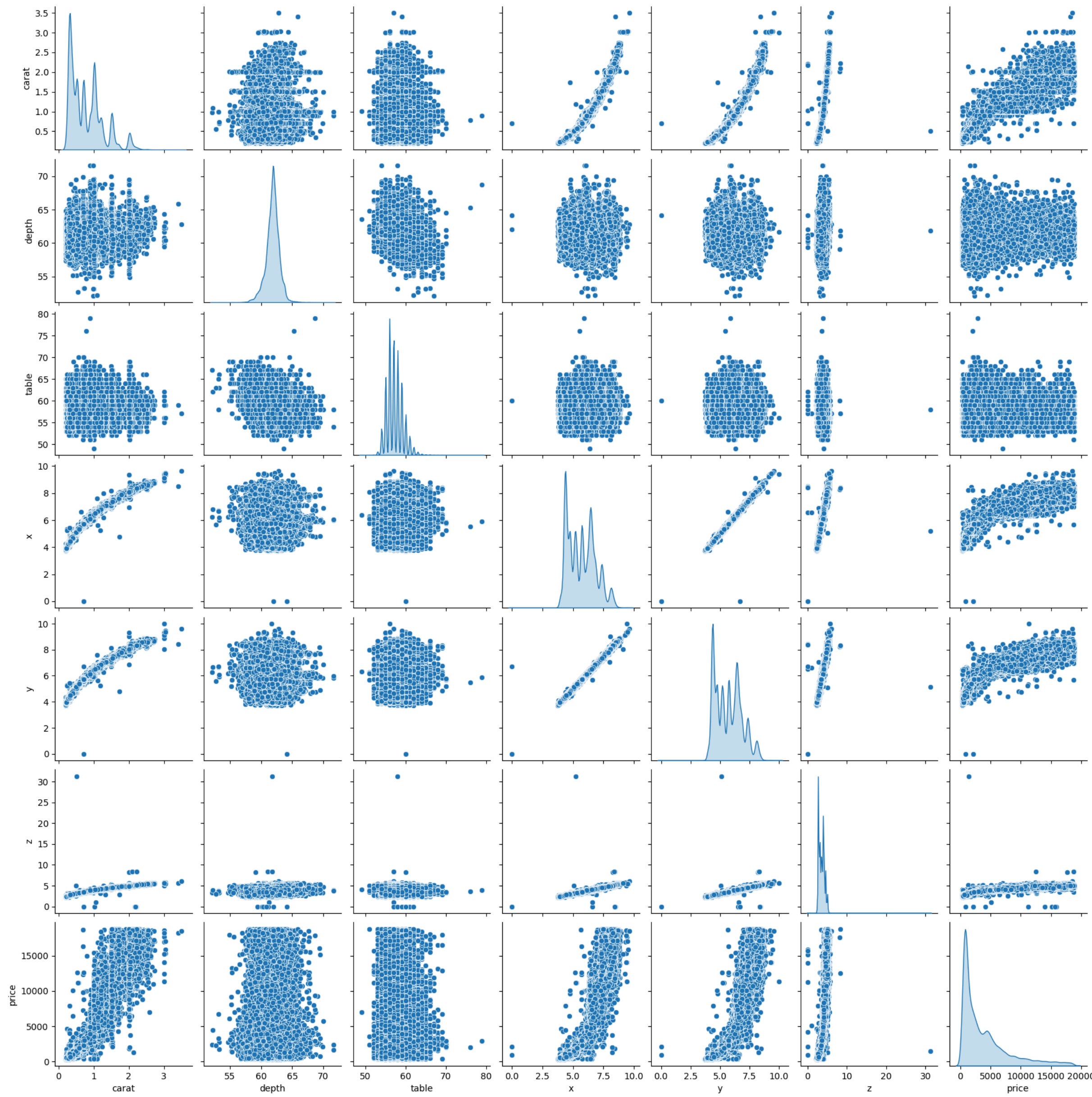
Correlation heatmap

In [ ]:
```
sb.heatmap(df.corr(numeric_only=True),annot=True)
plt.show()
```



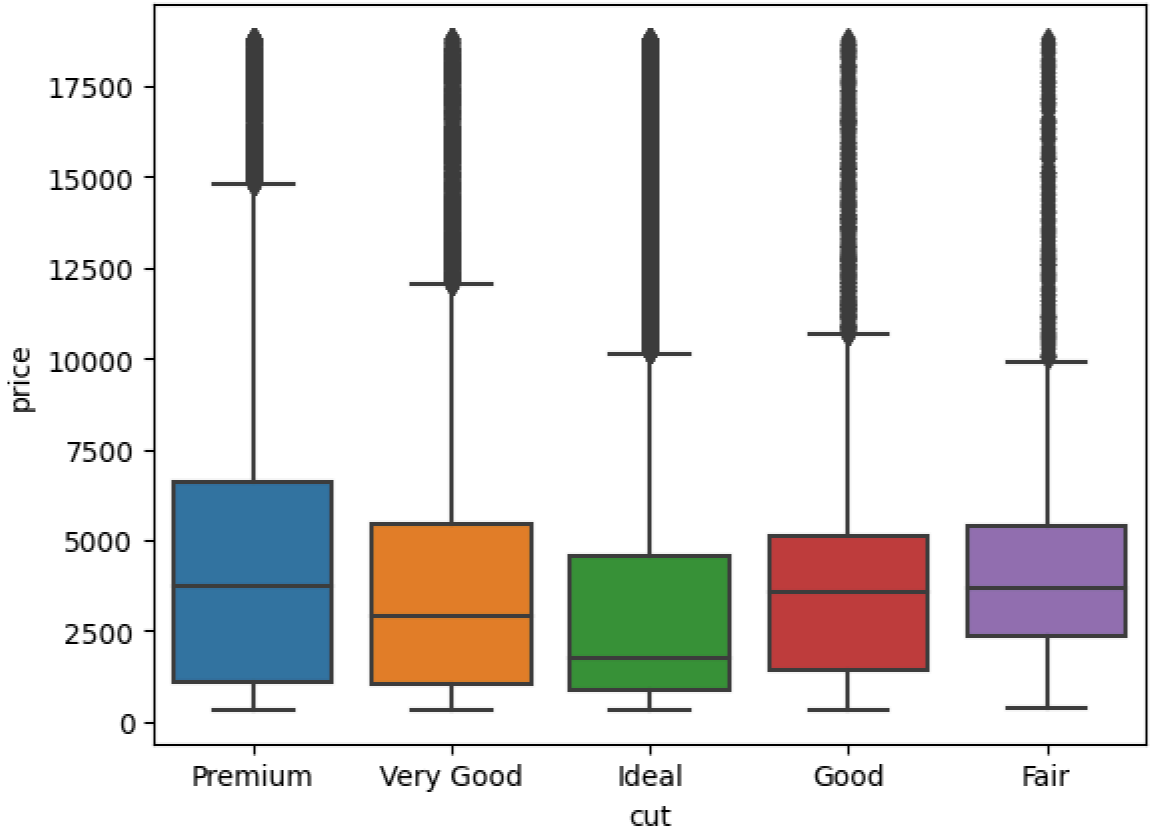
Pairplot

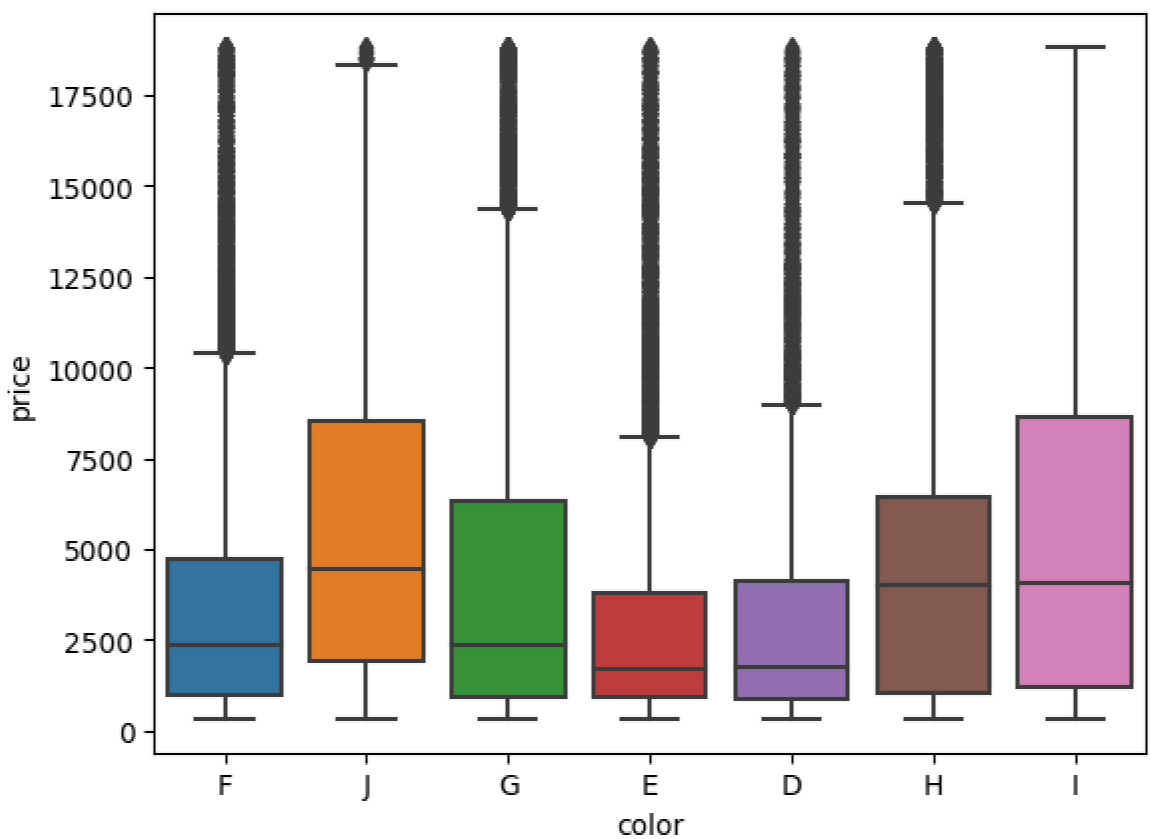
In [ ]:
```
sb.pairplot(df,diag_kind='kde')
plt.show()
```

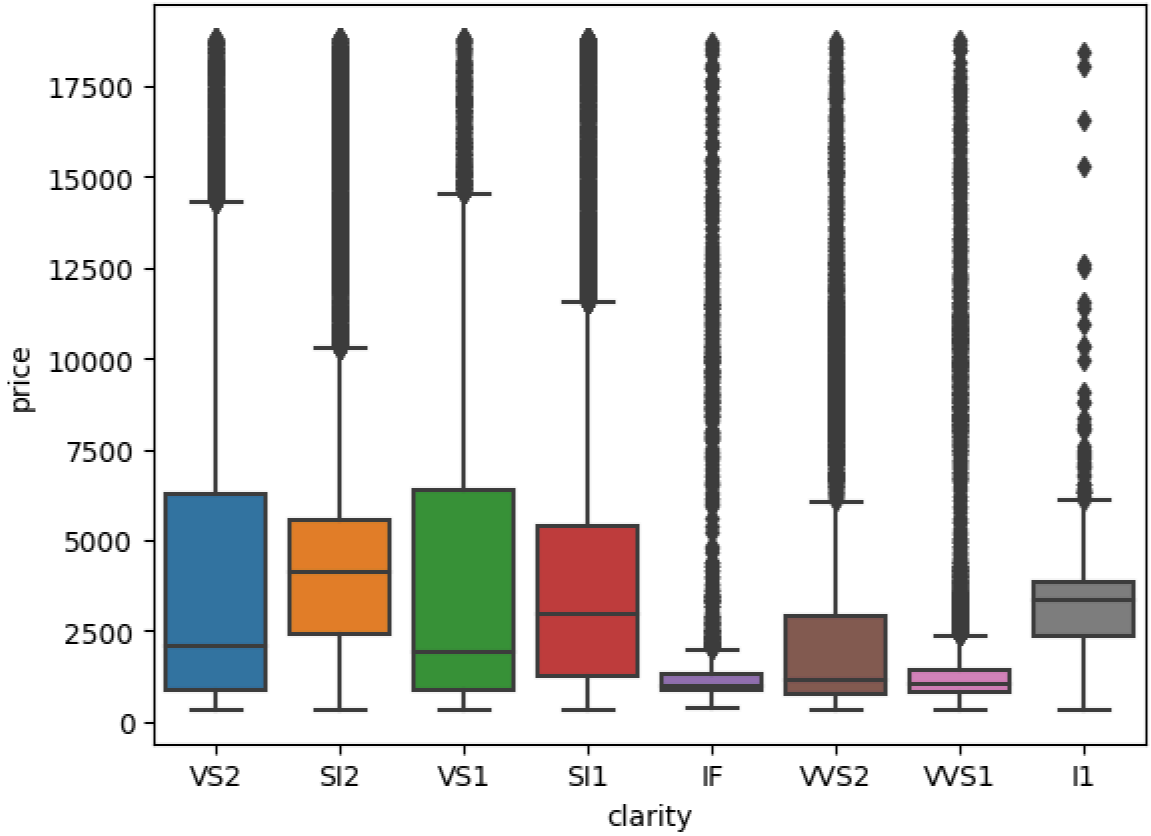


Categorical Features vs Target Feature Price Boxplot

In [ ]:
```
for i in categorical_columns:
    sb.boxplot(data=df, x=i , y='price')
    plt.show()
```


price
17500
15000
12500
10000
7500
5000
2500
0
Premium
Very Good
Ideal
Good
Fair
cut


price
17500
15000
12500
10000
7500
5000
2500
0
F
J
G
E
D
H
I
color



Ordinal Mapping of categorical features

It is observed that the categorical variables 'cut', 'color' and 'clarity' are ordinal in nature

Creating Mapper for each categorical variable

In [ ]:
```
cut_mapper = {"Fair":1, "Good":2, "Very Good":3 , "Premium":4 ,"Ideal":5}
clarity_mapper = {"I1":1,"SI2":2 ,"SI1":3 ,"VS2":4 , "VS1":5 , "VVS2":6 , "VVS1":7
color_mapper = {"D":1 ,"E":2 ,"F":3 , "G":4 ,"H":5 , "I":6, "J":7}
```

Applying the mapper to the dataframe

In [ ]:
```
df['cut'] = df['cut'].replace(cut_mapper)
df['clarity'] = df['clarity'].replace(clarity_mapper)
df['color'] = df['color'].replace(color_mapper)
```

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

Out[ ]:

	carat	cut	color	clarity	depth	table	x	y	z	price
0	1.52	4	3	4	62.2	58.0	7.27	7.33	4.55	13619
1	2.03	3	7	2	62.0	58.0	8.06	8.12	5.05	13387
2	0.70	5	4	5	61.2	57.0	5.69	5.73	3.50	2772
3	0.32	5	4	5	61.6	56.0	4.38	4.41	2.71	666
4	1.70	4	4	4	62.6	59.0	7.65	7.61	4.77	14453

Mutual Information Scores

Seperating X and Y

In [ ]:
```
X = df.drop(labels=['price'],axis=1)
Y = df[['price']]
```

Calculating Mutual Information scores for regression

In [ ]:
```
from sklearn.feature_selection import mutual_info_regression
mi_scores = mutual_info_regression(X,Y.values.flatten(),random_state=42)
mi_scores = pd.Series(mi_scores, name="MI Scores",index=X.columns)
mi_scores = mi_scores.sort_values(ascending=False)
```

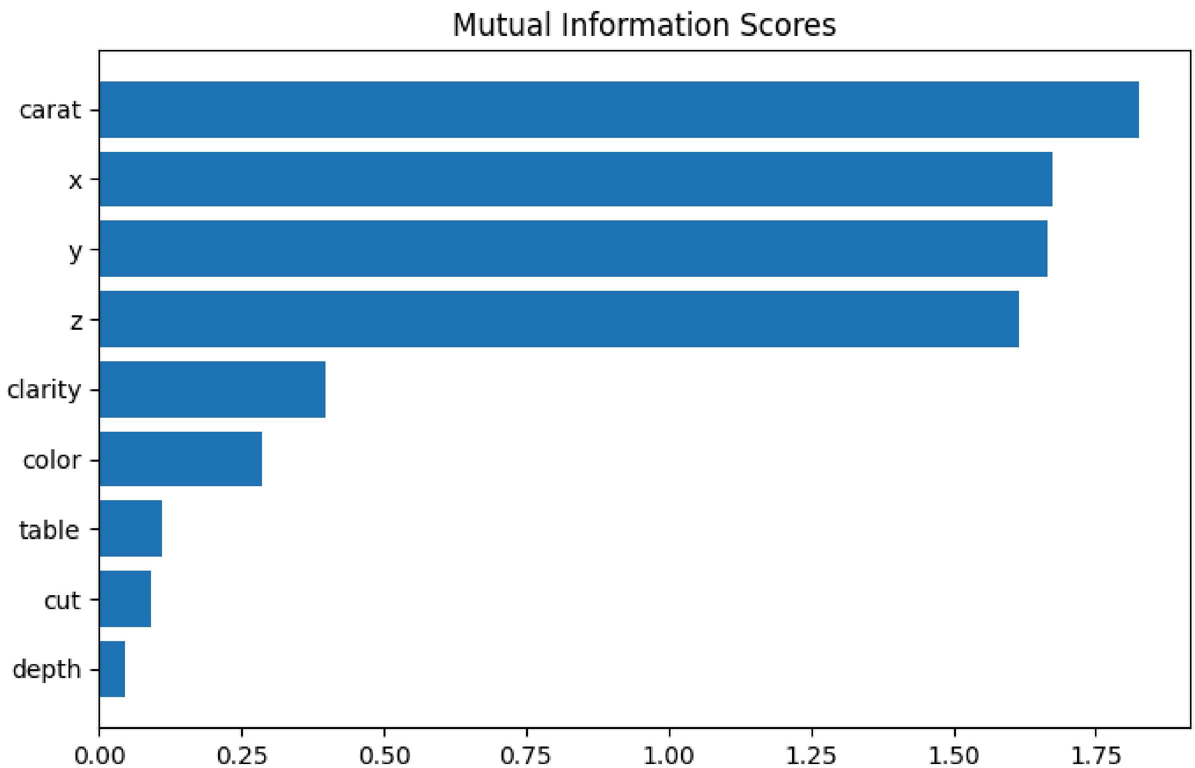
In [ ]:
```
import numpy as np

def plot_mi_scores(scores):
    scores = scores.sort_values(ascending=True)
    width = np.arange(len(scores))
    ticks = list(scores.index)
    plt.barh(width, scores)
    plt.yticks(width, ticks)
    plt.title("Mutual Information Scores")
    plt.show()
```

Visualizing Mutual Information Scores

In [ ]:
```
print(mi_scores)
plt.figure(dpi=100, figsize=(8, 5))
plot_mi_scores(mi_scores)
```

```
carat      1.825115
x          1.674011
y          1.666632
z          1.615992
clarity    0.397911
color      0.285518
table      0.109664
cut        0.092104
depth      0.045643
Name: MI Scores, dtype: float64
```



Conclusion : Above shows that carat and x, y, z are most important features to predict the price of a gemstone