In [1]:
```python
# Importing the requierd libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')

#plt.style.use('ggplot')
plt.style.use('fivethirtyeight')
```

In [2]:
```python
# Reading the csv file
df = pd.read_csv('Diamond_Price_Prediction.csv')
```

In [3]:
```python
df
```

Out[3]:

	id	carat	cut	color	clarity	depth	table	price	x	y	z
0	0	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
1	1	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
2	2	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31
3	3	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63
4	4	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75
...	...	...	...	...	...	...	...	...	...	...	...
53935	53935	0.72	Ideal	D	SI1	60.8	57.0	2757	5.75	5.76	3.50
53936	53936	0.72	Good	D	SI1	63.1	55.0	2757	5.69	5.75	3.61
53937	53937	0.70	Very Good	D	SI1	62.8	60.0	2757	5.66	5.68	3.56
53938	53938	0.86	Premium	H	SI2	61.0	58.0	2757	6.15	6.12	3.74
53939	53939	0.75	Ideal	D	SI2	62.2	55.0	2757	5.83	5.87	3.64

53940 rows × 11 columns

In [4]:
```python
df = df.drop("id", axis=1)
```

In [5]:
```python
df
```

Out[5]:

	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
...	...	...	...	...	...	...	...	...	...	...
53935	0.72	Ideal	D	SI1	60.8	57.0	2757	5.75	5.76	3.50
53936	0.72	Good	D	SI1	63.1	55.0	2757	5.69	5.75	3.61
53937	0.70	Very Good	D	SI1	62.8	60.0	2757	5.66	5.68	3.56
53938	0.86	Premium	H	SI2	61.0	58.0	2757	6.15	6.12	3.74
53939	0.75	Ideal	D	SI2	62.2	55.0	2757	5.83	5.87	3.64

53940 rows × 10 columns

In [6]:

```
# shape of the data
df.shape
```

Out[6]:

```
(53940, 10)
```

In [7]:

```
# top 5 rows of the data
df.head()
```

Out[7]:

	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

In [8]:

```
# last 5 rows of the data
df.tail()
```

Out[8]:

	carat	cut	color	clarity	depth	table	price	x	y	z
53935	0.72	Ideal	D	SI1	60.8	57.0	2757	5.75	5.76	3.50
53936	0.72	Good	D	SI1	63.1	55.0	2757	5.69	5.75	3.61
53937	0.70	Very Good	D	SI1	62.8	60.0	2757	5.66	5.68	3.56
53938	0.86	Premium	H	SI2	61.0	58.0	2757	6.15	6.12	3.74
53939	0.75	Ideal	D	SI2	62.2	55.0	2757	5.83	5.87	3.64

In [9]:

```
# information about data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53940 entries, 0 to 53939
Data columns (total 10 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   carat    53940 non-null  float64
 1   cut      53940 non-null  object 
 2   color    53940 non-null  object 
 3   clarity  53940 non-null  object 
 4   depth    53940 non-null  float64
 5   table    53940 non-null  float64
 6   price    53940 non-null  int64  
 7   x        53940 non-null  float64
 8   y        53940 non-null  float64
 9   z        53940 non-null  float64
dtypes: float64(6), int64(1), object(3)
memory usage: 4.1+ MB
```

In [10]:

```python
# Descriptive statistics of the data
df.describe()
```

Out[10]:

	carat	depth	table	price	x	y	
count	53940.000000	53940.000000	53940.000000	53940.000000	53940.000000	53940.000000	5394
mean	0.797940	61.749405	57.457184	3932.799722	5.731157	5.734526	3
std	0.474011	1.432621	2.234491	3989.439738	1.121761	1.142135	0
min	0.200000	43.000000	43.000000	326.000000	0.000000	0.000000	0
25%	0.400000	61.000000	56.000000	950.000000	4.710000	4.720000	2
50%	0.700000	61.800000	57.000000	2401.000000	5.700000	5.710000	3
75%	1.040000	62.500000	59.000000	5324.250000	6.540000	6.540000	4
max	5.010000	79.000000	95.000000	18823.000000	10.740000	58.900000	31

In [11]:

```python
# Duplicate values in data
df.duplicated().sum()
```

Out[11]:

146

In [12]:

```python
df = df.drop_duplicates()
```

In [13]:

```python
df
```

Out[13]:

	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
...	...	...	...	...	...	...	...	...	...	...
53935	0.72	Ideal	D	SI1	60.8	57.0	2757	5.75	5.76	3.50
53936	0.72	Good	D	SI1	63.1	55.0	2757	5.69	5.75	3.61
53937	0.70	Very Good	D	SI1	62.8	60.0	2757	5.66	5.68	3.56
53938	0.86	Premium	H	SI2	61.0	58.0	2757	6.15	6.12	3.74
53939	0.75	Ideal	D	SI2	62.2	55.0	2757	5.83	5.87	3.64

53794 rows × 10 columns

In [14]:

```
# Missing values check by using list comprehension
[feature for feature in df.columns if df[feature].isnull().sum()]
```

Out[14]:

```
[]
```

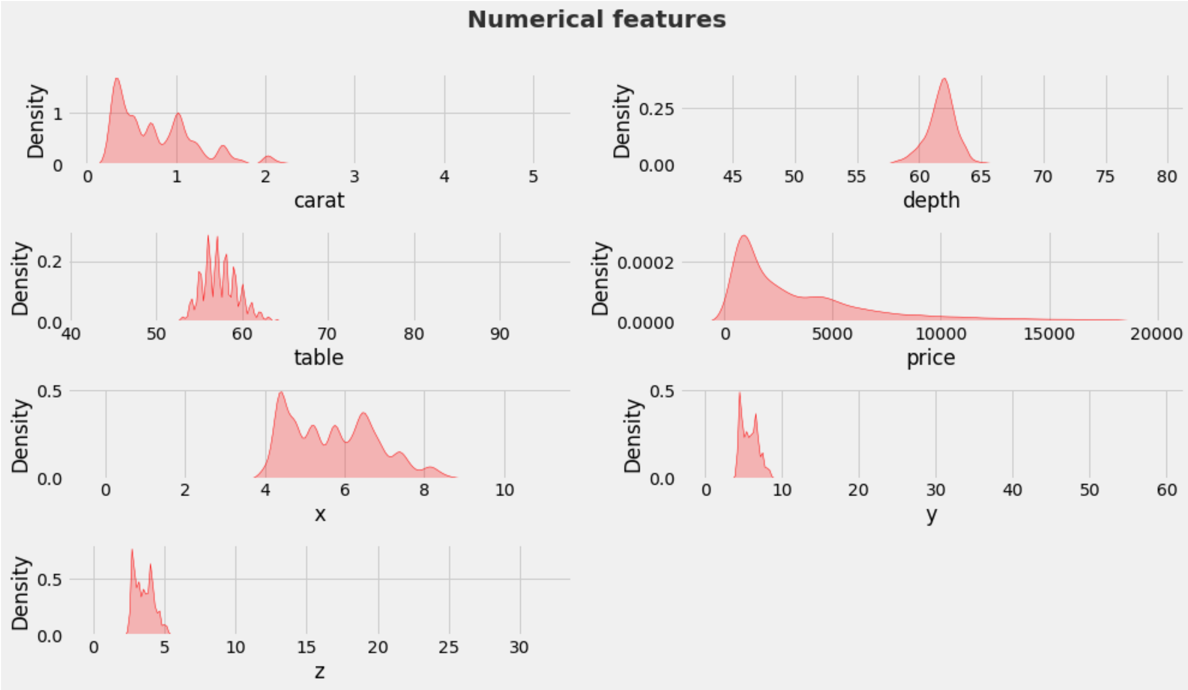
Numerical Feature

In [15]:

```
numerical_feature = [feature for feature in df.columns if df[feature].dtype != "O"]
```

In [16]:

```
plt.figure(figsize=(14,8))
plt.suptitle('Numerical features',fontsize=20, fontweight = 'bold', alpha=0.8,y=1)
for i in range(0, len(numerical_feature)):
    plt.subplot(4,2,i+1)
    sns.kdeplot(x=df[numerical_feature[i]],shade=True,color='red')
    plt.xlabel(numerical_feature[i])
    plt.tight_layout()
```

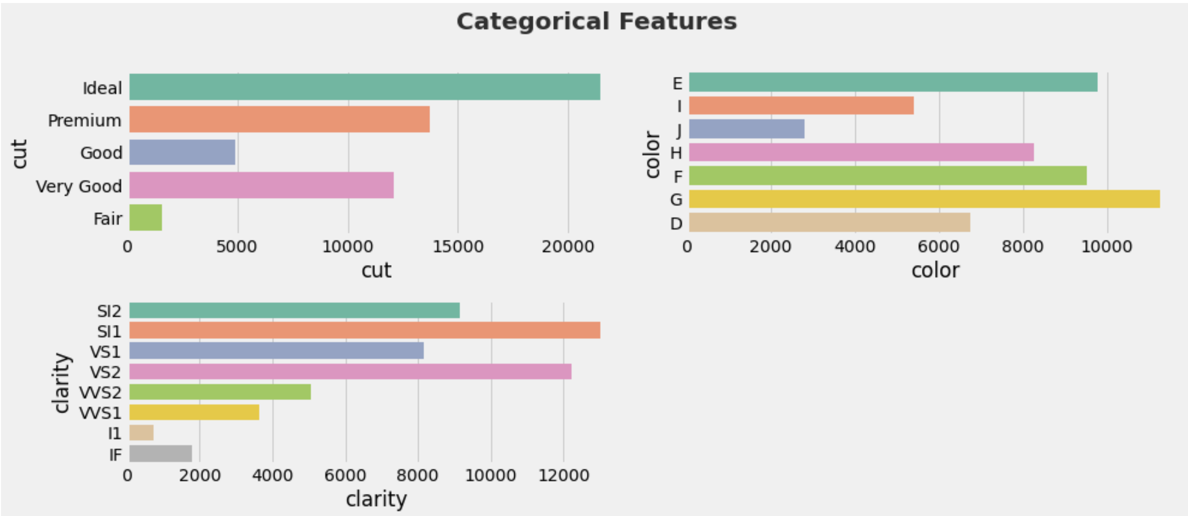


Categorical Features

In [17]:
```python
categorical_feature = [feature for feature in df.columns if df[feature].dtype=='O'
```

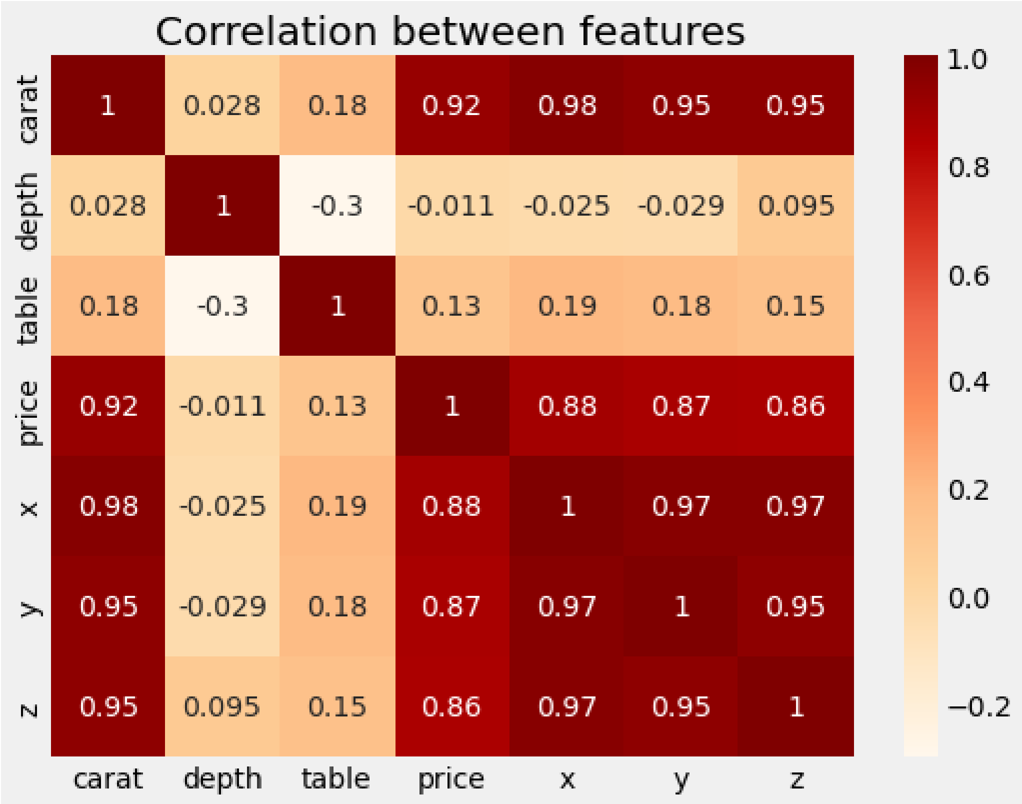
In [18]:
```python
plt.figure(figsize=(14,6))
plt.suptitle('Categorical Features',fontsize=20, fontweight = 'bold', alpha=0.8,y=

for i in range(0, len(categorical_feature)):
    plt.subplot(2,2,i+1)
    sns.countplot(y=df[categorical_feature[i]],palette="Set2")
    plt.xlabel(categorical_feature[i])
    plt.tight_layout()
```



Correlation Matrix

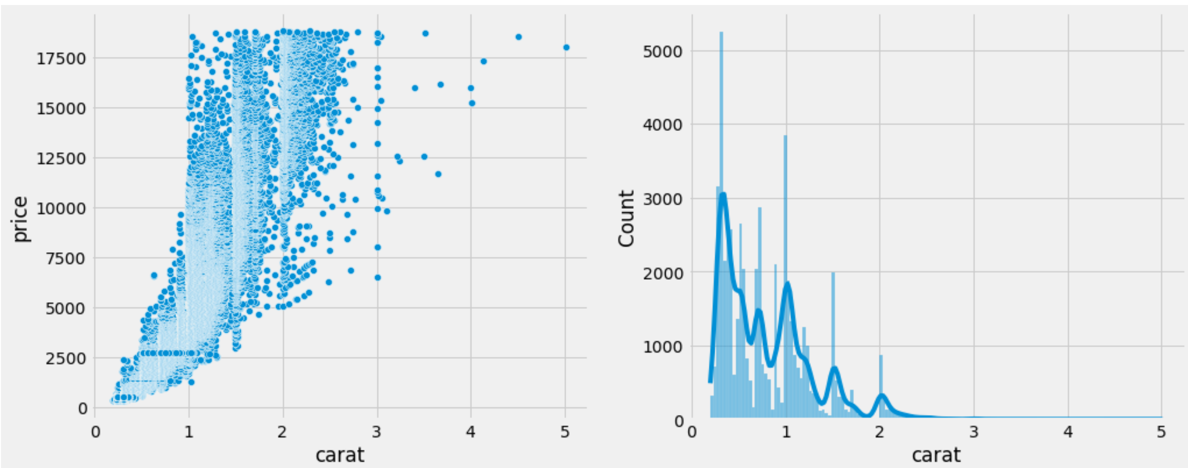
In [19]:
```python
plt.figure(figsize=(8,6))
sns.heatmap(df.corr(),cmap="OrRd", annot=True)
plt.title("Correlation between features")
plt.show()
```



- There is multicollinearity issue in the data x, y and z are highly correlated with each other.

Carat

In [20]:
```
# carat and price column analysis
fig = plt.figure()
ax1 = fig.add_subplot(121)
ax2 = fig.add_subplot(122)
sns.scatterplot(data=df,x='carat',y='price',ax=ax1)
sns.histplot(data=df,x='carat',kde=True,ax=ax2)
fig.set_size_inches(15,6)
plt.show()
```



We can clearly see a positive correlation between carat and price. • Our histplot shows that the majority of the data is located between 0.3 and 1.3 carats. • There are outliers, but they are important to the price since it rises as the carat size increases. Because bigger diamonds are uncommon, modeling can benefit significantly from these outliers.

Cut

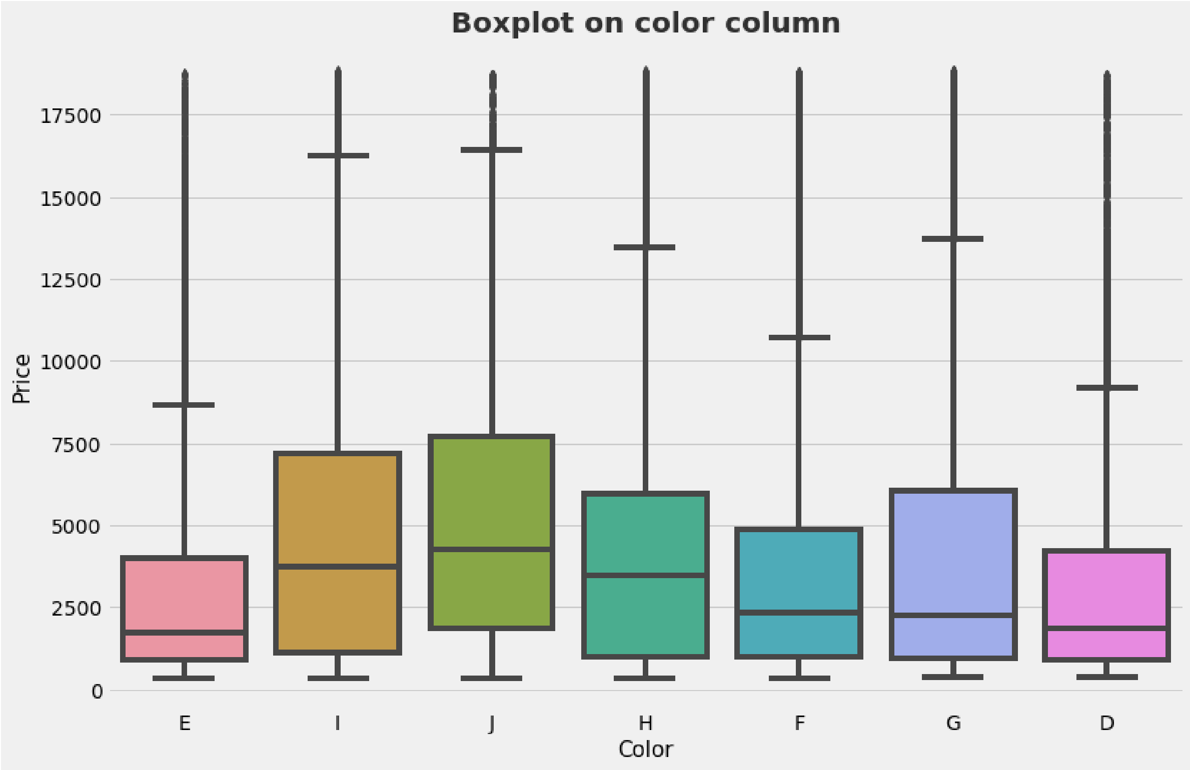
In [21]:
```
df1 = df.groupby(['cut']).mean().reset_index()
df2 = df.groupby(['cut']).median().reset_index()
plt.figure(figsize=(15,4))
plt.subplot(1,2,1)
plt.plot(df1['cut'],df1['price'] , 'go-', linewidth=2, markersize=12, c='red',labe
plt.plot(df2['cut'],df2['price'],'go-', linewidth=2, markersize=12, label="median 
plt.title("Cut with Price")
plt.xlabel("Cuts")
plt.ylabel("Price")
plt.legend()

plt.subplot(1,2,2)
plt.plot(df1['cut'],df1['carat'] , 'go-', linewidth=2, markersize=12, c='red',labe
plt.plot(df2['cut'],df2['carat'],'go-', linewidth=2, markersize=12, label="median 
plt.title("Cut with Carat")
plt.xlabel("Cuts")
plt.ylabel("Carat")
plt.legend()
plt.show()
```

This plot show the difference between cut such as Fair,Good,Very Good, Ideal and Premium. • All Good, Very Good and Ideal cut diamonds weigh less than 1 carat with medain < 1. • There are few fair cut diamonds where the weight is slightly higher than 1 carat but the median is still <=1 carat. • Premium cut diamonds has the highest range between mean price and median price w.r.t mean carat and median carat size.

Color

In [22]:
```
plt.figure(figsize=(12,8))
sns.boxplot(x=df['color'],y=df['price'])
plt.title("Boxplot on color column",fontsize=20, fontweight = 'bold', alpha=0.8,y=
plt.xlabel("Color",fontsize=15)
plt.ylabel("Price",fontsize=15)
plt.show()
```



The Gemological Institute of America (GIA) grades diamonds from D (colorless) to Z (faint yellow tinge). Diamonds with colors ranging from D to H can be difficult to identify for non-professionals. Key Points - D and E color grade diamonds are colorless and almost colorless, respectively. F grade diamonds are also almost colorless, but they can only be identified by professional gemologists. - We can see that these three color grades of diamonds have too many outliers compared to other grades. In fact, we can say that for smaller carat sizes, colorless diamonds have higher prices than diamonds of other color grades. - G and H grade diamonds are nearly colorless or next to colorless diamonds. As shown in the plot, these grades also have some outliers, but not as many as D, E, and F grades. Color is a major factor that defines the price of a diamond. - I and J grade diamonds have a very slight tint of color. J grade diamonds are always (10 to 20%) cheaper than I color grade diamonds. We can see that these grade diamonds do not have as many outliers, which means that their price is justified. As the carat size increases, the price also increases

Clarity

In [24]:

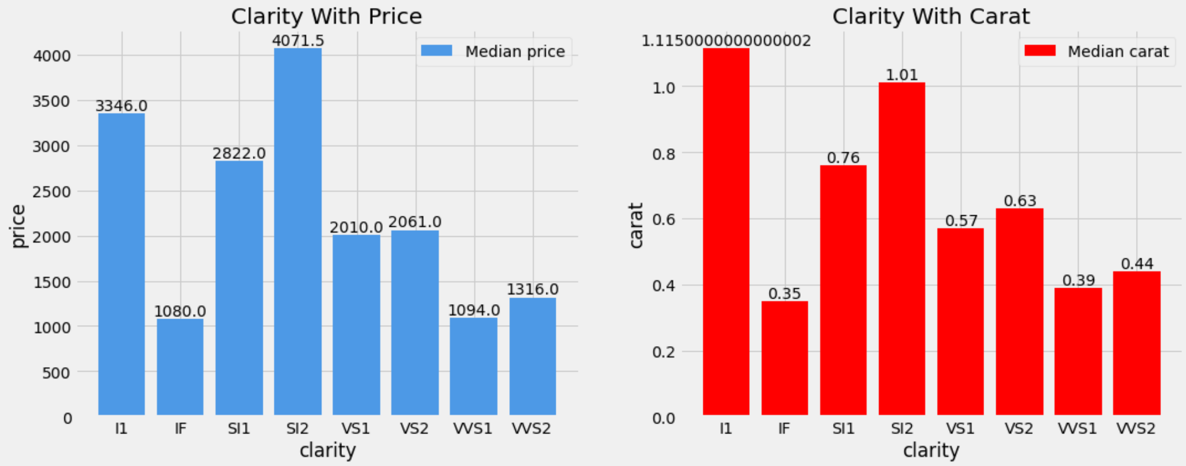
```
df1 = df.groupby(['clarity']).median().reset_index()
clarity = df1['clarity']
price = df1['price']
carat = df1['carat']

fig, (ax1,ax2) = plt.subplots(1,2,figsize=(16,6))
bars1 = ax1.bar(clarity,price,label="Median price",color=(0.3, 0.6, 0.9))
ax1.set_title('Clarity With Price')
ax1.set_xlabel("clarity")
ax1.set_ylabel("price")

for bar in bars1:
    height = bar.get_height()
    ax1.text(bar.get_x() + bar.get_width() / 2, height, height, ha='center', va='b
ax1.legend()
bars2 = ax2.bar(clarity,carat,label="Median carat",color='red')
ax2.set_title('Clarity With Carat')
ax2.set_xlabel("clarity")
ax2.set_ylabel("carat")

for bar in bars2:
    height = bar.get_height()
    ax2.text(bar.get_x() + bar.get_width() / 2, height, height, ha='center', va='b
```

```
ax2.legend()
plt.show()
```

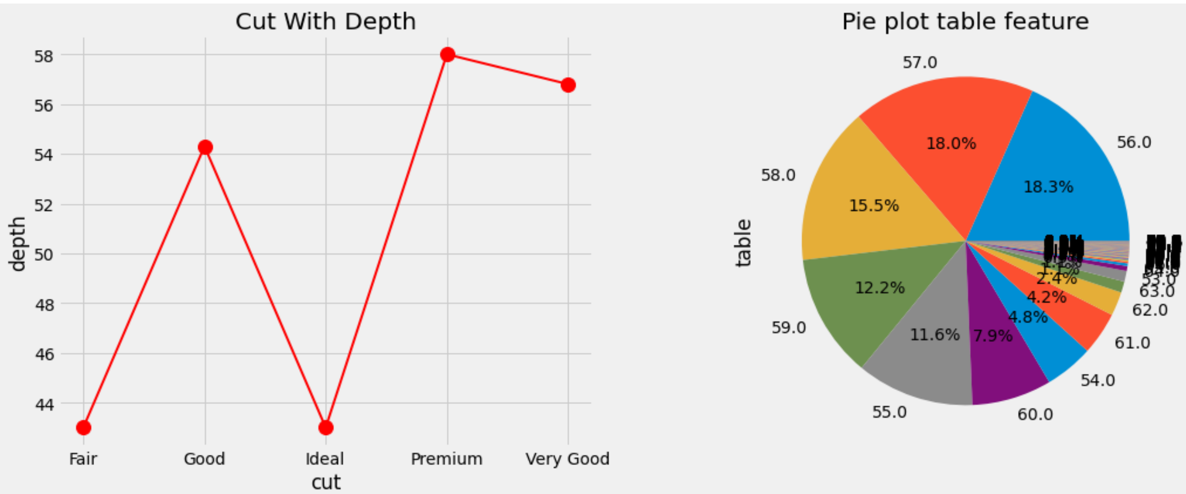


According to gia approval, there are 6 main categories of clarity ratings, and this figure illustrates how they differ. • IF, VVS1, VVS2, VS1, VS2, SI1, SI2, and I1 are the major and minor categories in our situation, and they are all ranked in the same order in terms of pricing as well. • We can see that I1, which is ranked low in clearity factor, has a median price of 3355 and a carat size of 1.02, which is significantly more expensive than our first rank clearity bar, while IF, which is ranked one in clearity factor, has a median price of 979 and a carat size of 0.33. • The median price of the S12 clearity bar is 4142, and the carat size in this clearity bar is 1.01; however, there is another important point that must be noted: the size of the carat is also larger. • Therefore, we may conclude that the prize and the carat are directly related, but the price will also rise as clarity improves

Depth & Table

In [25]:
```
df1 = df.groupby(['cut']).min().reset_index()
fig, (ax1,ax2) = plt.subplots(1,2,figsize=(16,6))

ax1.plot(df1['cut'],df1['depth'],'go-', linewidth=2, markersize=12,c='red')
ax1.set_title('Cut With Depth')
ax1.set_xlabel("cut")
ax1.set_ylabel("depth")
df['table'].value_counts().plot.pie(y=df['table'].value_counts().to_list()[:5],sta
autopct='%1.1f%%',textprops={'fontsize':14})
ax2.set_title('Pie plot table feature')
plt.show()
```



The depth of a diamond refers to its measurement from top to bottom. • We can observe from this plot that the cut depth increases depending on whether they choose an fair, ideal, premium, good or very good cut. • The majority of the carats in the pie chart only have table sizes of 56, 57, 58, 55, 59, and 60