```
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt

#dataset from seaborn:
df=sns.load_dataset("diamonds")

df.head()
```

```
   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
```

```
#Adding the logarithm of the price into a new column:
df['log_price']=np.log(df['price'])

df.head()
```

```
   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


   log_price
0   5.786897
1   5.786897
2   5.789960
3   5.811141
4   5.814131
```

```
#subset the dataset into (color,price,log_price) columns only
data=df[['color','price','log_price']]
data.tail()
```

```
      color  price  log_price
53935     D   2757   7.921898
53936     D   2757   7.921898
53937     D   2757   7.921898
53938     H   2757   7.921898
53939     D   2757   7.921898
```

Data Exploration

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53940 entries, 0 to 53939
Data columns (total 3 columns):
 #   Column     Non-Null Count  Dtype   
---  ------     --------------  -----   
 0   color      53940 non-null  category
 1   price      53940 non-null  int64   
 2   log_price  53940 non-null  float64 
dtypes: category(1), float64(1), int64(1)
memory usage: 896.0 KB
```

```
print("Rows: ",data.shape[0],", Columns: ",data.shape[1])
```

```
Rows:  53940 , Columns:  3
```

```
data.columns
```

```
Index(['color', 'price', 'log_price'], dtype='object')
```

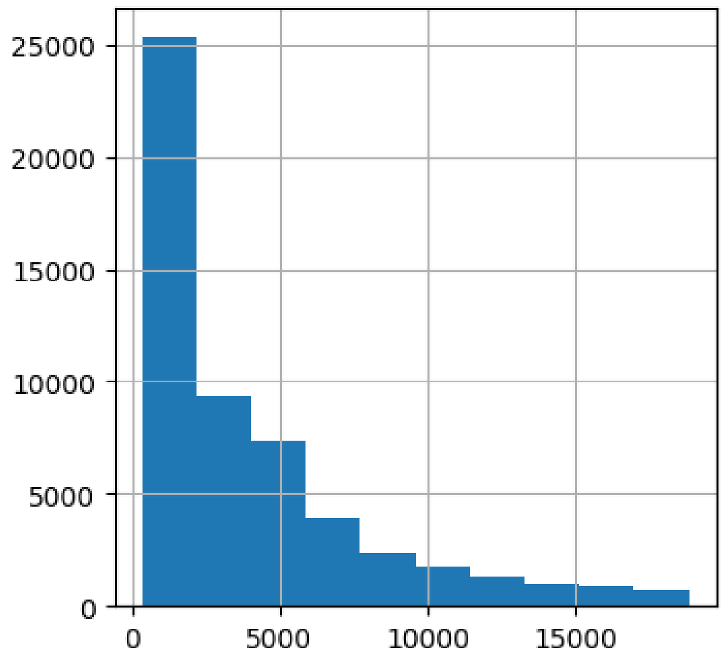
```
data.describe()
```

```
              price     log_price
count  53940.000000  53940.000000
mean    3932.799722      7.786768
std     3989.439738      1.014649
min      326.000000      5.786897
25%      950.000000      6.856462
50%     2401.000000      7.783641
75%     5324.250000      8.580027
max    18823.000000      9.842835
```

High standard deviation means that the data is more spread out

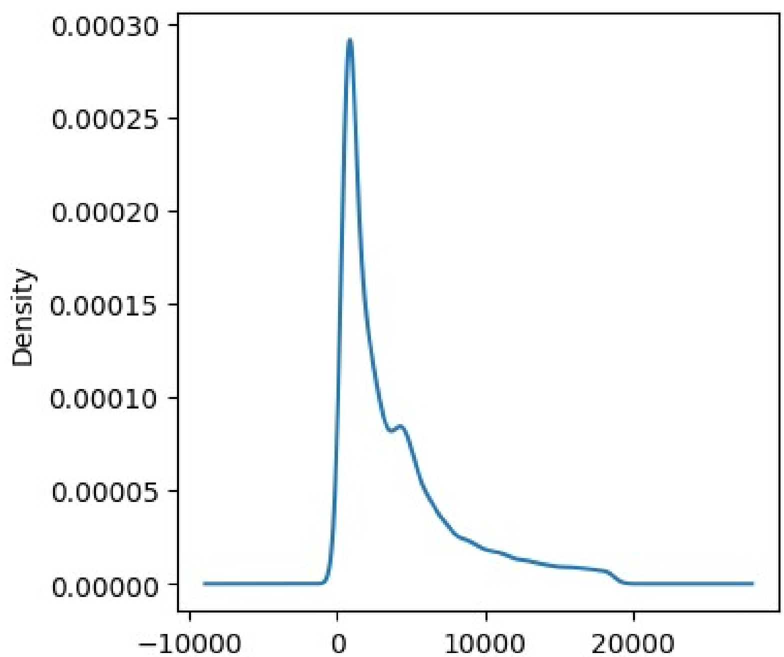
```
plt.figure(figsize=(4,4))
data['price'].hist()
```

```
<Axes: >
```

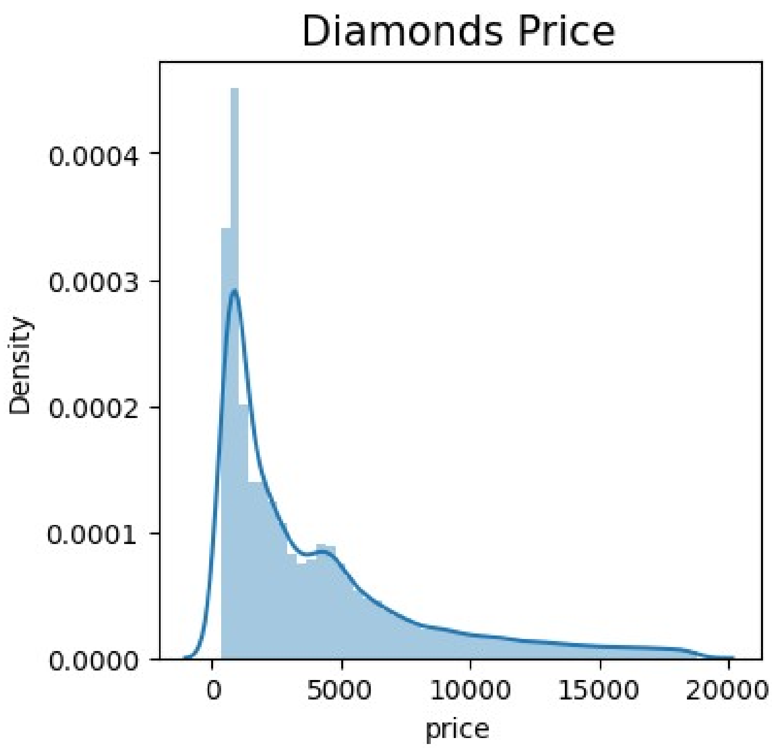



```
plt.figure(figsize=(4,4))
data['price'].plot(kind='kde')
print(data)
```

```
      color  price  log_price
0         E    326   5.786897
1         E    326   5.786897
2         E    327   5.789960
3         I    334   5.811141
4         J    335   5.814131
...     ...    ...        ...
53935     D   2757   7.921898
53936     D   2757   7.921898
53937     D   2757   7.921898
53938     H   2757   7.921898
53939     D   2757   7.921898

[53940 rows x 3 columns]
```




```
plt.figure(figsize=(4,4))
plt.title("Diamonds Price",fontsize=15)
sns.distplot(data['price'])
plt.show()

<ipython-input-13-74cdcdb4fa29>:3: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(data['price'])
```



Missing values

```
data.isnull().sum()
```

```
color        0
price        0
log_price    0
dtype: int64
```

There are no missing valeues in the whole dataset

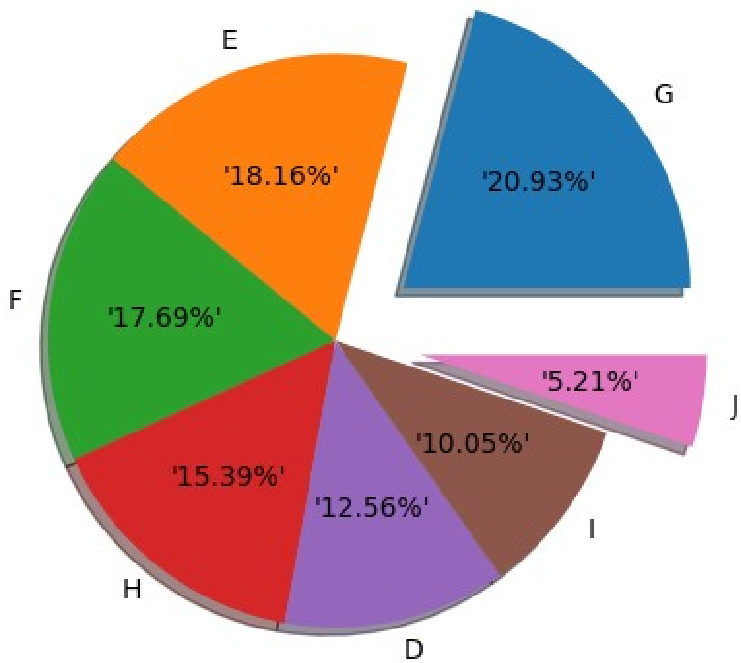
Exploring Catogrical data

```
data['color'].value_counts()
```

```
G    11292
E     9797
F     9542
H     8304
D     6775
I     5422
J     2808
Name: color, dtype: int64
```

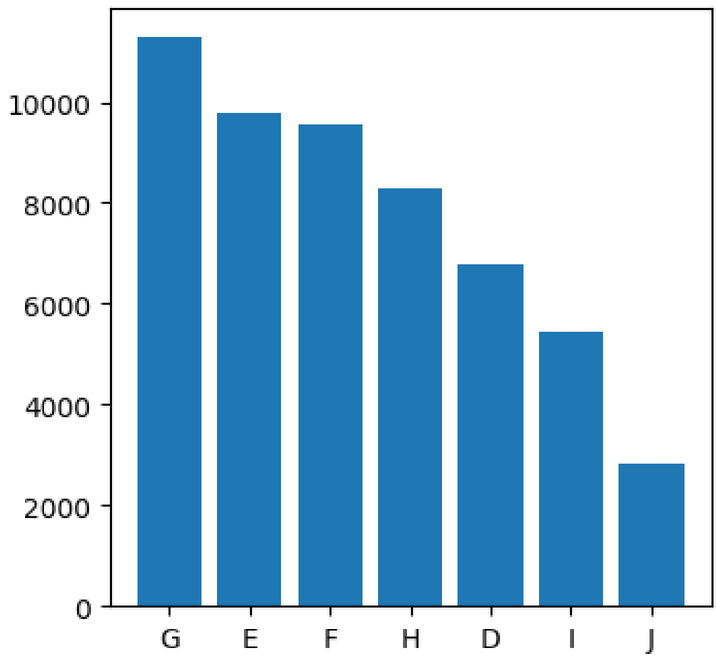
```
print('There are',
len(list(data['color'].value_counts().index)),'different colors for
diamonds')
```

```
There are 7 different colors for diamonds

color=list(data['color'].value_counts().index)
amount=list(data['color'].value_counts().values)

#we can display some percentage: showing the percentage of diamonds
color in the dataset
minvalue=min(amount)
mind=amount.index(minvalue)
maxvalue=max(amount)
maxind=amount.index(maxvalue)
explode=[0,0,0,0,0,0,0]
for i in range(8):
  if i==mind or i==maxind:
    explode[i]=0.3
plt.pie(amount, labels=color,  shadow = True, autopct="'%1.2f%
%'",explode=explode)
plt.show()
```



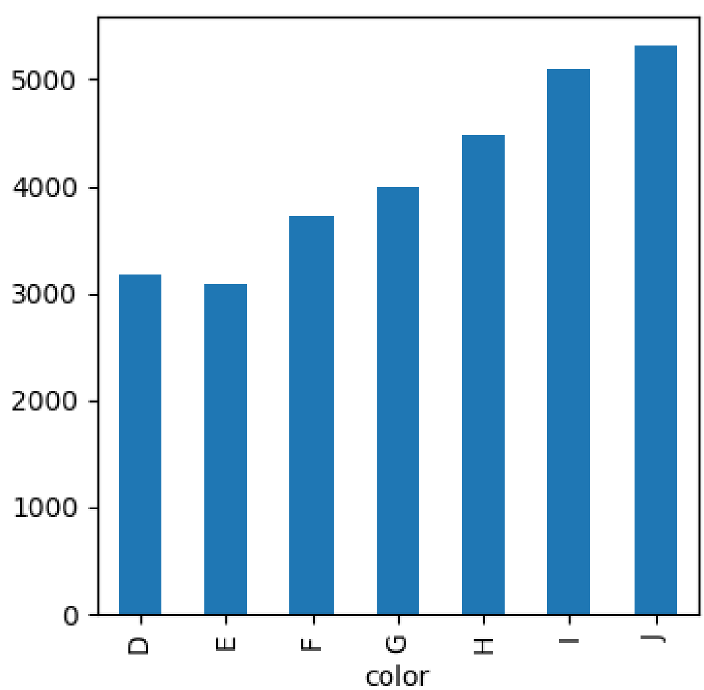
there are few diamonds with J color

```
#bar plot
plt.figure(figsize=(4,4))
plt.bar(color,amount)

<BarContainer object of 7 artists>
```



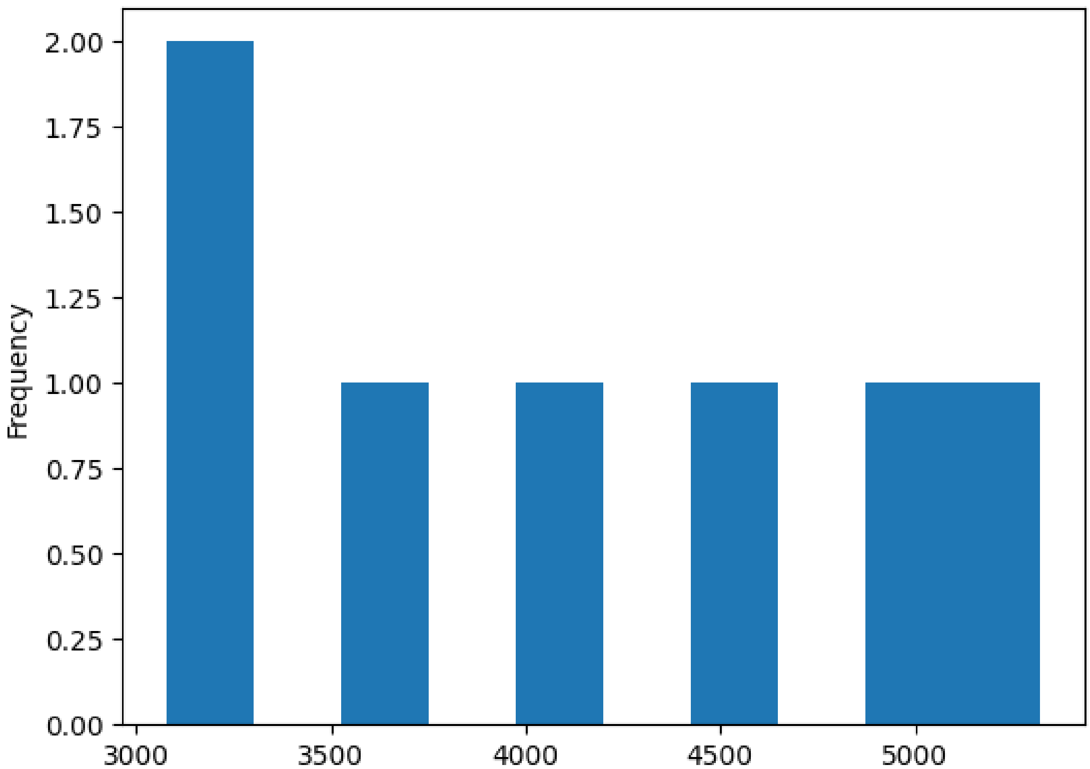

```
plt.figure(figsize=(4,4))
data.groupby('color')['price'].mean().plot.bar()
```

```
<Axes: xlabel='color'>
```




```
data.groupby('color')['price'].mean().plot.hist()
```

```
<Axes: ylabel='Frequency'>
```



This is an important plot, in the pie chart the J color countered the least percentage, but the average price for the diamonds with J color is the highest

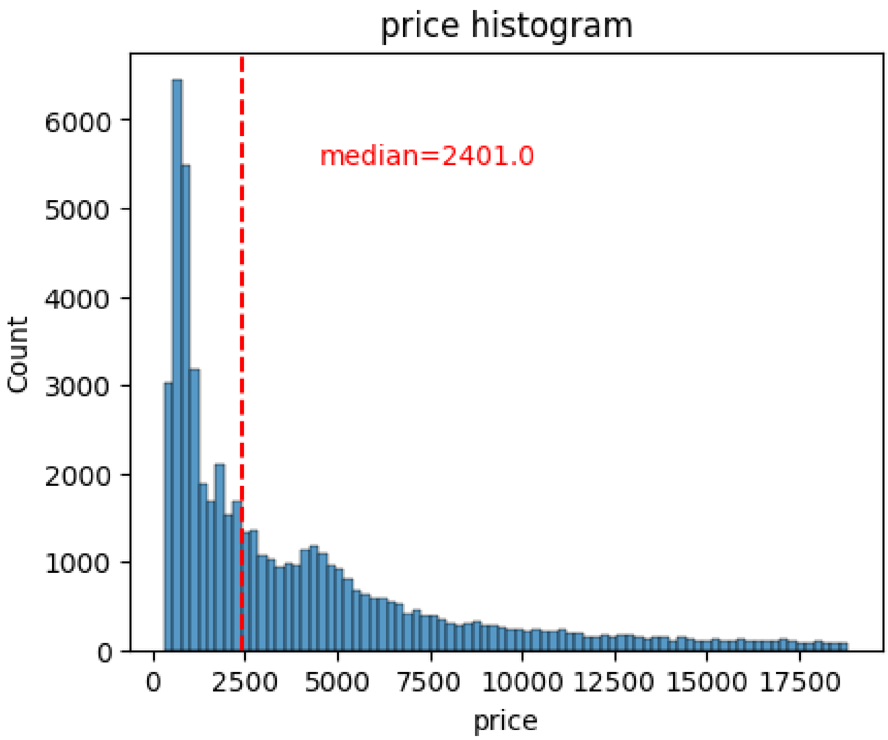
Outlier Detection

```
def boxplotter(column,xlabel,title): # Box plot
  fig, ax = plt.subplots(figsize=(5, 4))
  box = sns.boxplot(x=data[column])
  g = plt.gca()
  #box.set_xticklabels(np.array([readable_numbers(x) for x in g.
↪get_xticks()]))
  plt.xlabel(xlabel)
  plt.title(title)
  plt.show()

# Helper function to plot histograms based on the
# format of the `sessions` histogram
def histogrammer(column_str, median_text=True, **kwargs):    #
**kwargs = any keyword arguments
                                                             # from
the sns.histplot() function
    median=round(data[column_str].median(), 1)
    fig, ax = plt.subplots(figsize=(5, 4))
    ax = sns.histplot(x=data[column_str], **kwargs)           # Plot
```

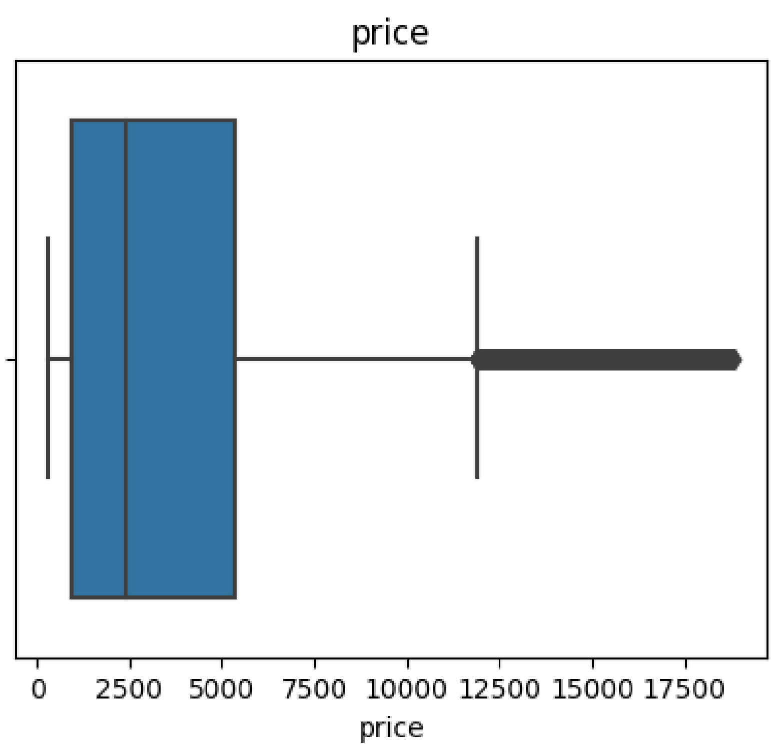
```
the histogram
    plt.axvline(median, color='red', linestyle='--')         # Plot
the median line
    if median_text==True:                                    # Add
median text unless set to False
        ax.text(0.25, 0.85, f'median={median}', color='red',
            ha="left", va="top", transform=ax.transAxes)
    else:
        print('Median:', median)
    plt.title(f'{column_str} histogram');

def skeweness(column):
   mean=np.mean(data[column])
   median=np.median(data[column])
   print("The mean: ",mean)
   #calculating the median
   print("The median: ",median)
   if mean>median:
     print('The data more likely to be skewed to the RIGHT!')
   else:
     print('The data more likely to be skewed to the LEFT!')

skeweness('price')
```

```
The mean:  3932.799721913237
The median:  2401.0
The data more likely to be skewed to the RIGHT!
```

```
histogrammer('price',True)
```

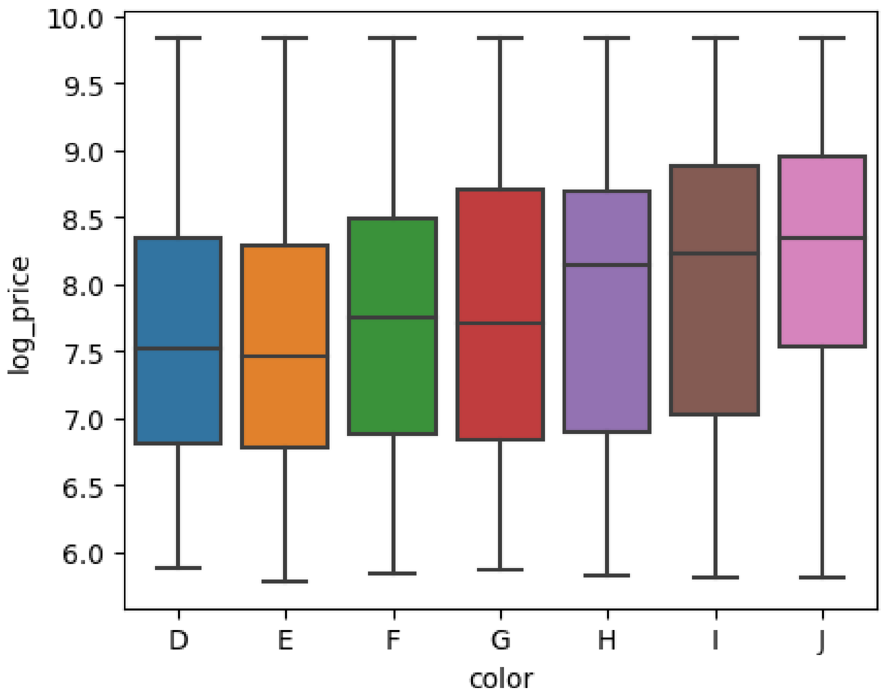



```
boxplotter('price','price','price')
```

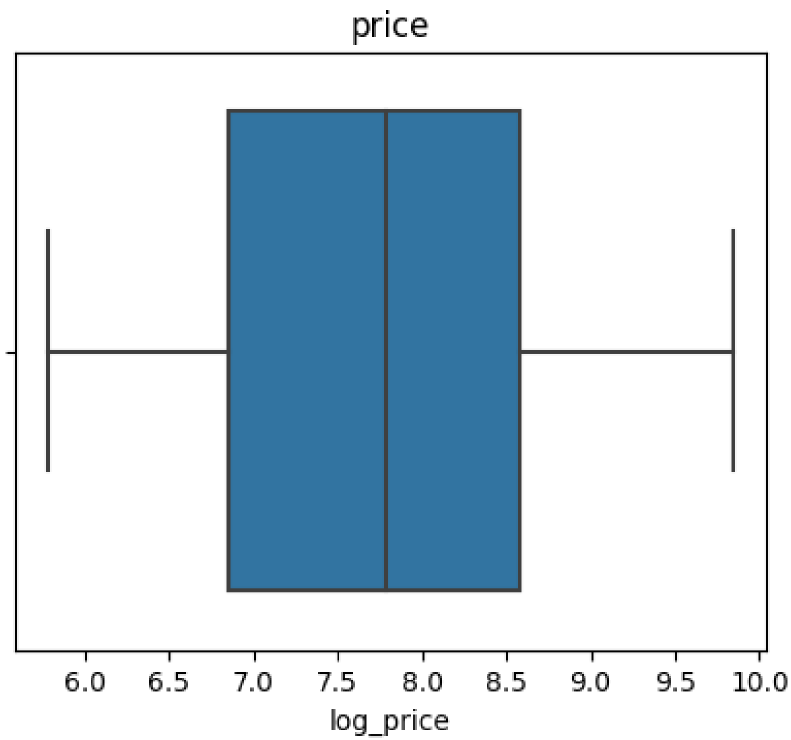


```
fig, ax = plt.subplots(figsize=(5, 4))
sns.boxplot(x='color',y='log_price',data=data)
```

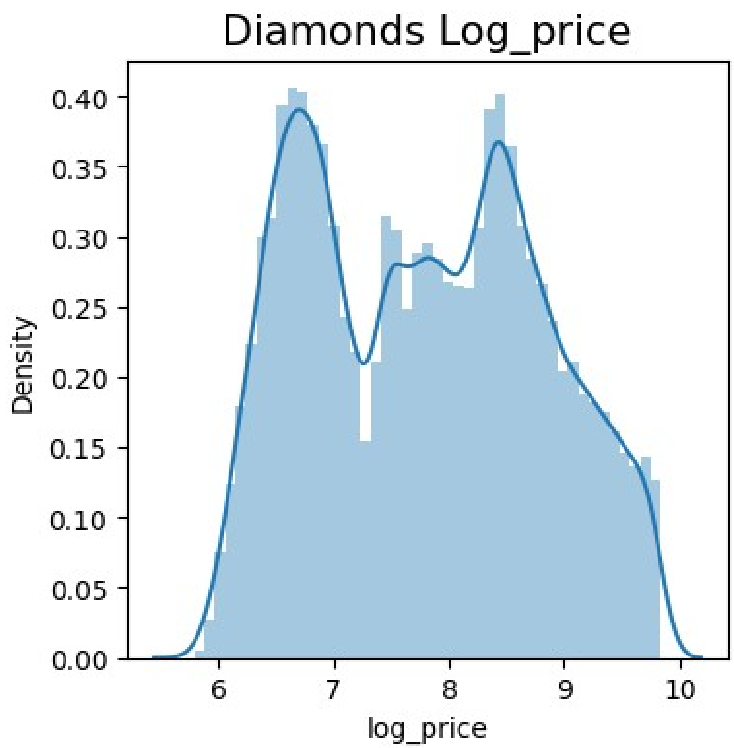
```
<Axes: xlabel='color', ylabel='log_price'>
```



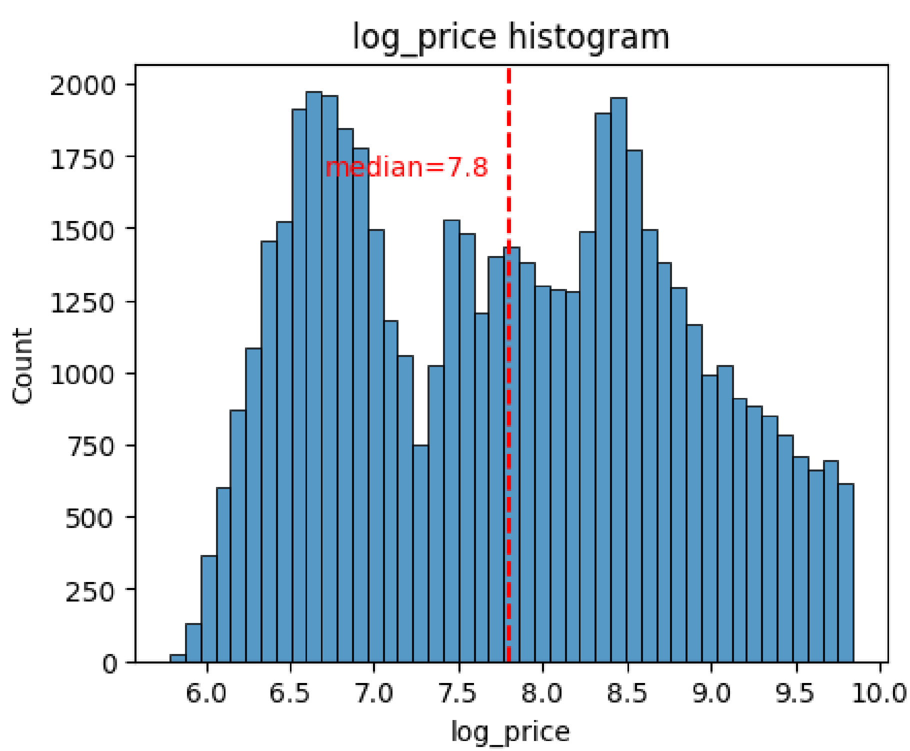

```
boxplotter('log_price','log_price','price')
```




```
skeweness('price')

The mean:  3932.799721913237
The median:  2401.0
The data more likely to be skewed to the RIGHT!

plt.figure(figsize=(4,4))
plt.title("Diamonds Log_price",fontsize=15)
sns.distplot(data['log_price'])
plt.show()

<ipython-input-31-98c02183ab69>:3: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn
v0.14.0.

Please adapt your code to use either `displot` (a figure-level
function with
similar flexibility) or `histplot` (an axes-level function for
histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(data['log_price'])
```




```
histogrammer('log_price',True)
```



OLS Regression Model

```
import statsmodels.api as st
from statsmodels.formula.api import ols

#Building the regression model using the ols model
olsmodel=ols(formula='log_price ~ C(color)',data=data).fit()

olsmodel.summary()

<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

======================================================================
========
Dep. Variable:              log_price   R-squared:
0.026
Model:                            OLS   Adj. R-squared:
0.026
Method:                 Least Squares   F-statistic:
237.8
Date:                Wed, 19 Jul 2023   Prob (F-statistic):
3.77e-301
Time:                        18:57:21   Log-Likelihood:
-76617.
No. Observations:               53940   AIC:
1.532e+05
Df Residuals:                   53933   BIC:
1.533e+05
Df Model:                           6

Covariance Type:            nonrobust

======================================================================
===========
                    coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
-----------
Intercept         7.6169      0.012    625.984      0.000       7.593
7.641
C(color)[T.E]    -0.0375      0.016     -2.370      0.018      -0.069
-0.006
C(color)[T.F]     0.1455      0.016      9.146      0.000       0.114
0.177
C(color)[T.G]     0.1727      0.015     11.219      0.000       0.143
0.203
C(color)[T.H]     0.3015      0.016     18.390      0.000       0.269
0.334
C(color)[T.I]     0.4061      0.018     22.250      0.000       0.370
```

```
0.442
C(color)[T.J]     0.5291      0.022     23.537      0.000       0.485
0.573
======================================================================
========
Omnibus:                    11794.122   Durbin-Watson:
0.059
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
2240.596
Skew:                           0.064   Prob(JB):
0.00
Kurtosis:                       2.010   Cond. No.
8.56
======================================================================
========

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

Running ANOVA Test model

The t-test is used to state the hypothisis on equal means among 2 groups of data, but when we have 3 groups or more we use anova test to state whether the 3 groups have the same mean or not?

- This is only the one way anova, because we are examining if the color of the diamond do affect the price of the diamond or not, Thus we are dealing only with one variable which is the "COLOR"

```
st.stats.anova_lm(olsmodel,type=2)

                df         sum_sq    mean_sq           F         PR(>F)
C(color)       6.0    1431.255783  238.54263  237.807767  3.767555e-301
Residual   53933.0   54099.661516    1.00309         NaN            NaN
```

- The p value tells us if we can reject or accept the null hypothisis.
- F: tells us how much the variable is affecting the outcome variable

A one-factor analysis of variance has shown that there is a significant difference between the categorical variable Place and the variable Salary F = 237.81, p = 3.767555e-301 Thus, with the available data, the null hypothesis is rejected.

Two-Way ANOVA

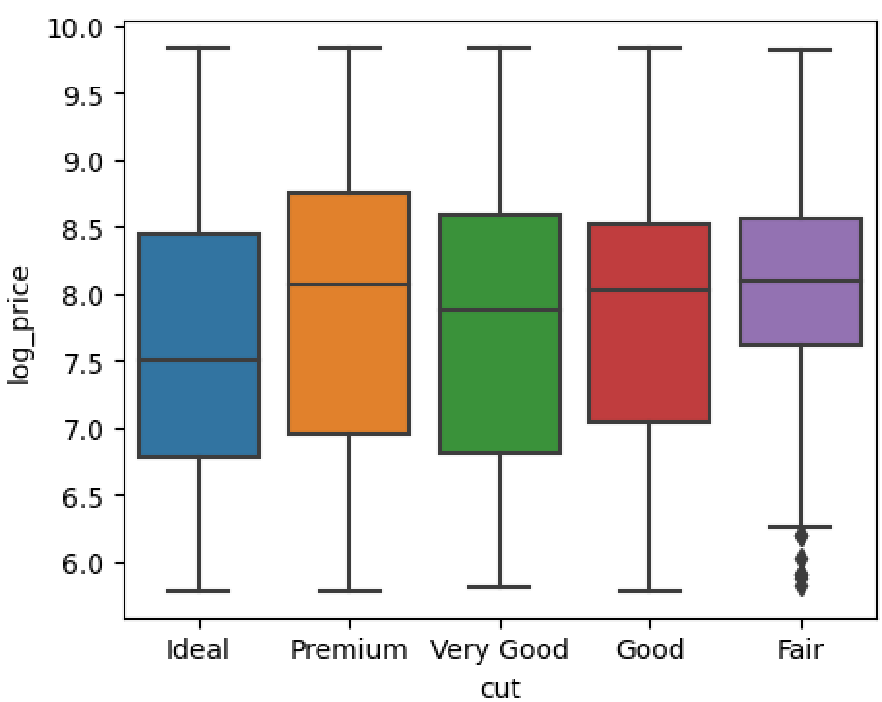
Two-Way ANOVA care about having two variables

```
#Add another catogrical data into the diamonds dataset
extracted_col = df["cut"]
data = data.join(extracted_col)

data.head()
```

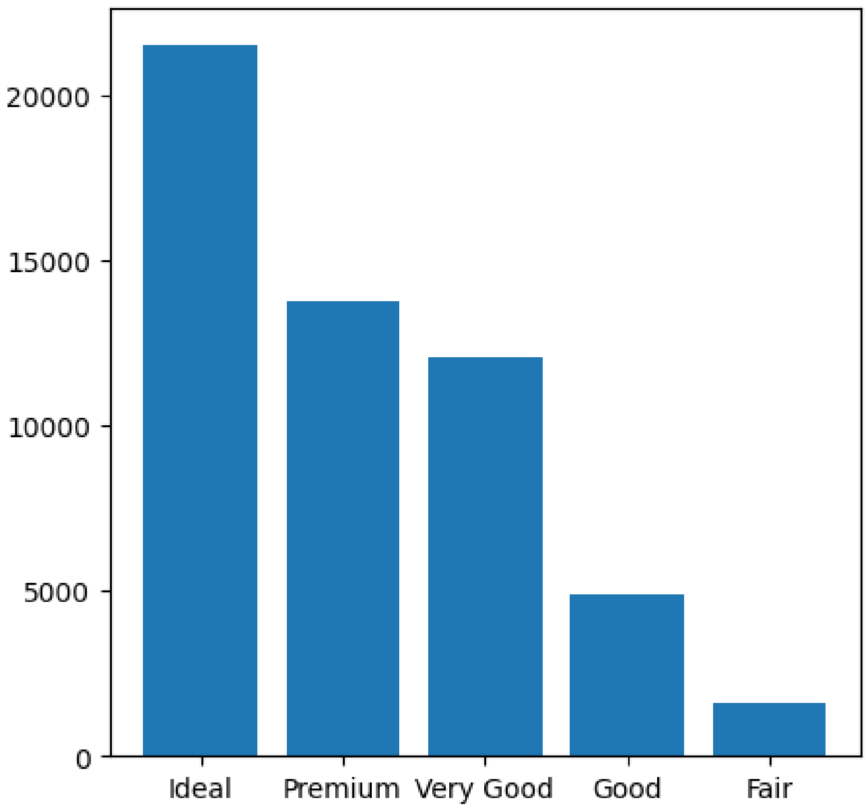
	color	price	log_price	cut
0	E	326	5.786897	Ideal
1	E	326	5.786897	Premium
2	E	327	5.789960	Good
3	I	334	5.811141	Premium
4	J	335	5.814131	Good

New column explortion

```
fig, ax = plt.subplots(figsize=(5, 4))
sns.boxplot(x='cut',y='log_price',data=data)

<Axes: xlabel='cut', ylabel='log_price'>
```

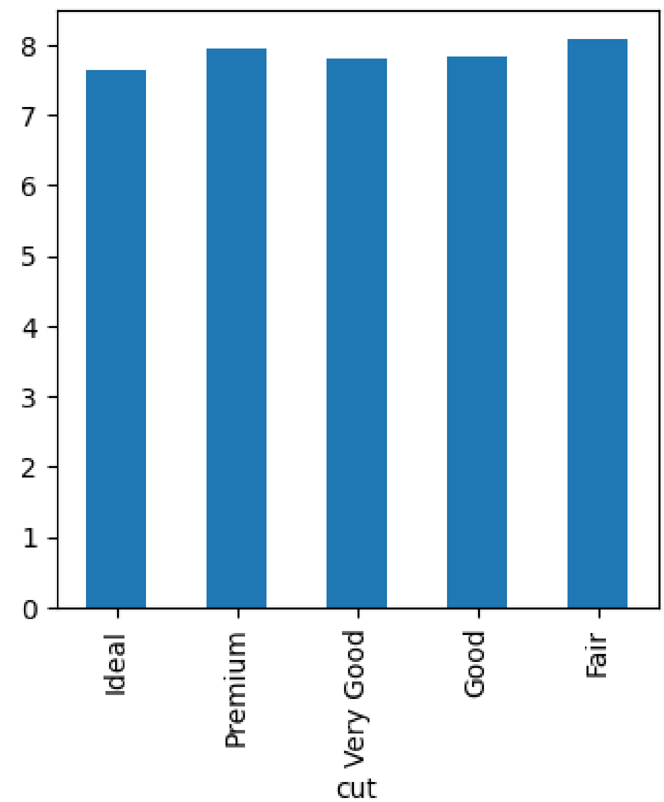



```
#bar plot
plt.figure(figsize=(5,5))
plt.bar(list(data['cut'].value_counts().index),list(data['cut'].value_
counts().values))

<BarContainer object of 5 artists>
```




```
plt.figure(figsize=(4,4))
data.groupby('cut')['log_price'].mean().plot.bar()
```

```
<Axes: xlabel='cut'>
```



- This indicate that the mean log price for the cut is almost the same!

```
#Building the regression model using the ols model
olsmodel2=ols(formula='log_price ~ C(color) + C(cut) +
C(color):C(cut)',data=data).fit()

olsmodel2.summary()

<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

======================================================================
========
Dep. Variable:              log_price   R-squared:
0.044
Model:                            OLS   Adj. R-squared:
0.043
Method:                 Least Squares   F-statistic:
72.53
Date:                Wed, 19 Jul 2023   Prob (F-statistic):
0.00
Time:                        18:57:26   Log-Likelihood:
-76115.
No. Observations:               53940   AIC:
1.523e+05
```

```
Df Residuals:                   53905   BIC:
1.526e+05
Df Model:                          34

Covariance Type:            nonrobust

======================================================================
===============================
                                            coef    std err          t
P>|t|      [0.025      0.975]
----------------------------------------------------------------------
-------------------------------
Intercept                                 7.4567      0.019    399.952
0.000       7.420       7.493
C(color)[T.E]                            -0.0056      0.024     -0.230
0.818      -0.054       0.042
C(color)[T.F]                             0.1755      0.025      7.136
0.000       0.127       0.224
C(color)[T.G]                             0.2352      0.023     10.035
0.000       0.189       0.281
C(color)[T.H]                             0.2756      0.026     10.695
0.000       0.225       0.326
C(color)[T.I]                             0.3787      0.029     13.240
0.000       0.323       0.435
C(color)[T.J]                             0.5457      0.038     14.345
0.000       0.471       0.620
C(cut)[T.Premium]                         0.2828      0.031      9.116
0.000       0.222       0.344
C(cut)[T.Very Good]                       0.2295      0.032      7.261
0.000       0.168       0.291
C(cut)[T.Good]                            0.2675      0.043      6.243
0.000       0.184       0.351
C(cut)[T.Fair]                            0.6610      0.080      8.268
0.000       0.504       0.818
C(color)[T.E]:C(cut)[T.Premium]          -0.0322      0.040     -0.797
0.426      -0.112       0.047
C(color)[T.F]:C(cut)[T.Premium]           0.0313      0.041      0.772
0.440      -0.048       0.111
C(color)[T.G]:C(cut)[T.Premium]          -0.0656      0.039     -1.695
0.090      -0.142       0.010
C(color)[T.H]:C(cut)[T.Premium]           0.0947      0.041      2.299
0.022       0.014       0.175
C(color)[T.I]:C(cut)[T.Premium]           0.0841      0.046      1.824
0.068      -0.006       0.174
C(color)[T.J]:C(cut)[T.Premium]           0.0610      0.057      1.065
0.287      -0.051       0.173
C(color)[T.E]:C(cut)[T.Very Good]        -0.0931      0.041     -2.284
0.022      -0.173      -0.013
C(color)[T.F]:C(cut)[T.Very Good]        -0.1013      0.041     -2.449
```

```
0.014      -0.182      -0.020
C(color)[T.G]:C(cut)[T.Very Good]    -0.1590      0.040     -3.941
0.000      -0.238      -0.080
C(color)[T.H]:C(cut)[T.Very Good]    -0.0247      0.043     -0.574
0.566      -0.109       0.060
C(color)[T.I]:C(cut)[T.Very Good]     0.0359      0.048      0.750
0.453      -0.058       0.130
C(color)[T.J]:C(cut)[T.Very Good]    -0.0979      0.060     -1.644
0.100      -0.215       0.019
C(color)[T.E]:C(cut)[T.Good]         -0.0112      0.056     -0.201
0.841      -0.121       0.099
C(color)[T.F]:C(cut)[T.Good]         -0.1196      0.056     -2.122
0.034      -0.230      -0.009
C(color)[T.G]:C(cut)[T.Good]         -0.0453      0.056     -0.805
0.421      -0.156       0.065
C(color)[T.H]:C(cut)[T.Good]         -0.1066      0.060     -1.788
0.074      -0.223       0.010
C(color)[T.I]:C(cut)[T.Good]         -0.0574      0.065     -0.886
0.376      -0.184       0.070
C(color)[T.J]:C(cut)[T.Good]         -0.2361      0.078     -3.012
0.003      -0.390      -0.082
C(color)[T.E]:C(cut)[T.Fair]         -0.1907      0.105     -1.815
0.070      -0.397       0.015
C(color)[T.F]:C(cut)[T.Fair]         -0.3459      0.099     -3.493
0.000      -0.540      -0.152
C(color)[T.G]:C(cut)[T.Fair]         -0.3024      0.099     -3.066
0.002      -0.496      -0.109
C(color)[T.H]:C(cut)[T.Fair]         -0.1040      0.100     -1.042
0.297      -0.300       0.092
C(color)[T.I]:C(cut)[T.Fair]         -0.2967      0.112     -2.655
0.008      -0.516      -0.078
C(color)[T.J]:C(cut)[T.Fair]         -0.4380      0.126     -3.488
0.000      -0.684      -0.192
======================================================================
========
Omnibus:                     8638.289   Durbin-Watson:
0.087
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
1985.296
Skew:                           0.069   Prob(JB):
0.00
Kurtosis:                       2.070   Cond. No.
60.0
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
```

```
correctly specified.
"""
```

	Null Hypothesis (H_0)	Alternative Hypothesis (H_1)
Color	There is no difference in diamond price based on color.	There is a difference in diamond price based on color.
Cut	There is no difference in diamond price based on cut.	There is a difference in diamond price based on cut.
Color & Cut Interaction Effect	The effect of color on diamond price is independent of the cut, and vice versa.	There is an interaction effect between color and cut on diamond price.

```
st.stats.anova_lm(olsmodel2,type=2)

                     df          sum_sq      mean_sq           F
PR(>F)
C(color)            6.0     1431.255783   238.542630  242.151273
1.206538e-306
C(cut)              4.0      901.918331   225.479583  228.890609
3.250547e-195
C(color):C(cut)    24.0       96.058742     4.002448    4.062996
8.168980e-11
Residual        53905.0    53101.684443     0.985098         NaN
NaN
```

Post hoc Test

```
from statsmodels.stats.multicomp import pairwise_tukeyhsd

tukeyhsd=pairwise_tukeyhsd(endog=data['log_price'],
groups=data['color'],alpha=0.05)

tukeyhsd.summary()

<class 'statsmodels.iolib.table.SimpleTable'>
```

The Reject column tells us if we can reject the null hypothisis or not:

- The null hypothisis: There are no difference in the mean of log price in different group of color
- Alternative hypothisis: There are IS difference in the mean of log price in different group of color

- True in the reject column tells us that we reject the null hypothisis and there is different mean log price between the 2 given color
- False in the reject column tells us that the null hypothisis is true and there is NO different in the mean log price between the 2 given color

Results:

1. Different color have different mean log price
2. Different cut have different mean log price
3. There is an interaction and dependability between the cut and color on the price of the diamonds

Similar log price mean in colors, Accepted null hypothisis "using Post hoc Test":

- D and E colors
- F and G colors

Running ANCOVA:

```
diamond=data
diamond=diamond.join(df['carat'])

diamond.head()
```

	color	price	log_price	cut	carat
0	E	326	5.786897	Ideal	0.23
1	E	326	5.786897	Premium	0.21
2	E	327	5.789960	Good	0.23
3	I	334	5.811141	Premium	0.29
4	J	335	5.814131	Good	0.31

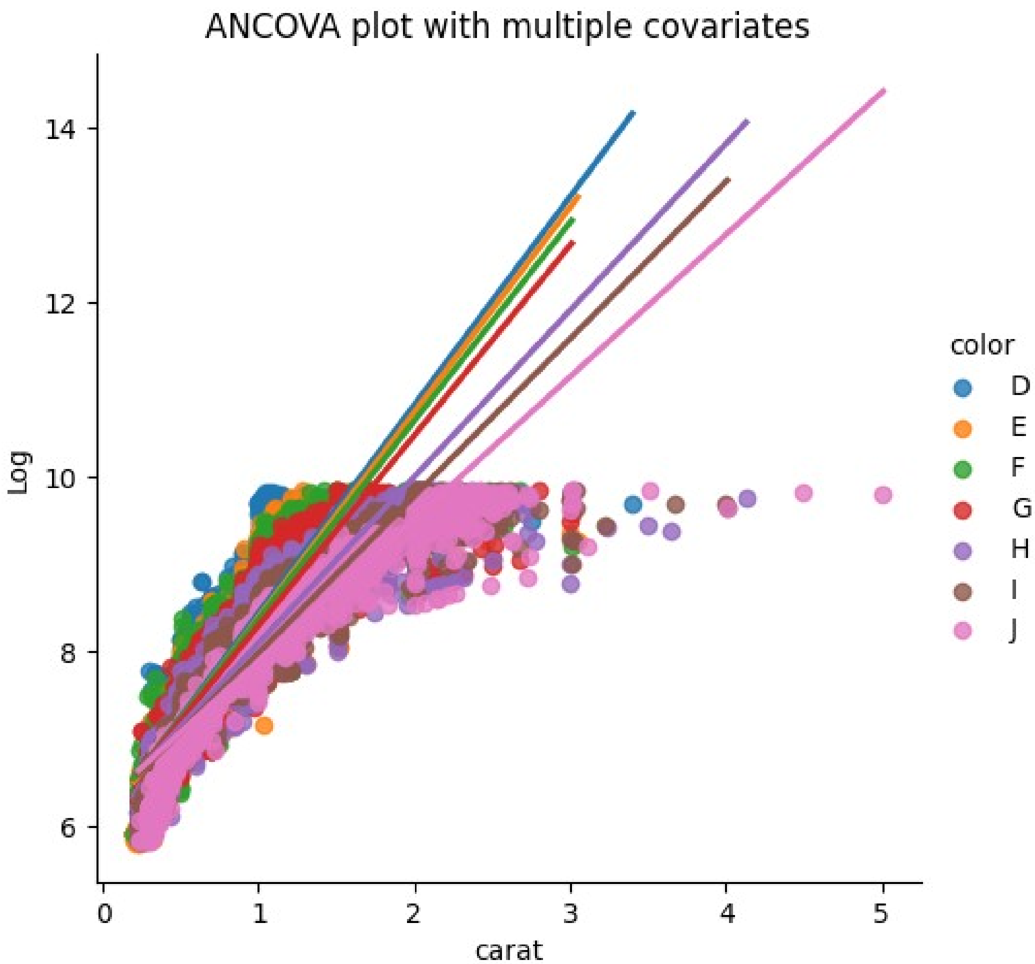
```
#formula = 'log_price ~ C(color) + carat'
model = ols('log_price ~ C(color) + carat', diamond).fit()

# Perform the ANCOVA
ancova_table = st.stats.anova_lm(model, typ=2)

print(ancova_table)
```

```
                 sum_sq       df              F  PR(>F)
C(color)    1017.040373      6.0    1220.311429     0.0
carat      46608.264906      1.0  335541.832021     0.0
Residual    7491.396610  53932.0            NaN     NaN
```

```
diamond['color'].value_counts()
```

```
G    11292
E     9797
F     9542
H     8304
D     6775
I     5422
```

```
J      2808
Name: color, dtype: int64

import matplotlib.pyplot as plt
import seaborn as sns

sns.lmplot(x='carat', y='log_price', hue='color', data=diamond,
ci=None)

plt.xlabel('carat')
plt.ylabel('Log')
plt.title('ANCOVA plot with multiple covariates')
plt.show()
```



Another way to perform ANCOVA Test

```
!pip3 install pingouin

from pingouin import ancova
ancova(data=diamond, dv='log_price', covar='carat', between='color')
```

```
     Source            SS     DF              F  p-unc       np2
0     color   1017.040373      6    1220.311429    0.0  0.119533
1     carat  46608.264906      1  335541.832021    0.0  0.861526
2  Residual   7491.396610  53932            NaN    NaN       NaN
```

Analyze the results obtained after performing ANCOVA.

ANCOVA() function after executing successfully it returns the following values.

ANCOVA summary:

- ‘Source’: Names of the factor considered
- ‘SS’: Sums of squares
- ‘DF’: Degrees of freedom
- ‘F’: F-values
- ‘p-unc’: Uncorrected p-values
- ‘np2’: Partial eta-squared

RESULT FROM ANCOVA TEST:

- According to the ANCOVA table, the p-value (p-unc = “uncorrected p-value”) for study methodology is 0.025542. Because this value is less than 0.05, we can reject the null hypothesis that each of the colors results in the same average log price, even after controlling for the carat variable.

MANOVA

We want to see if diamond log price and carat are associated with different diamond color using MANOVA.

```
diamond.groupby('color')['log_price'].describe()
```

```
         count      mean       std       min       25%       50%
75%  \
color

D       6775.0  7.616905  0.926359  5.877736  6.814543  7.516433
8.346049
E       9797.0  7.579405  0.925420  5.786897  6.782192  7.461066
8.294799
F       9542.0  7.762440  0.967514  5.834811  6.889591  7.759401
8.490490
G      11292.0  7.789583  1.027715  5.869297  6.836259  7.715124
8.707483
H       8304.0  7.918446  1.063218  5.820083  6.891626  8.149023
8.696218
I       5422.0  8.022962  1.105842  5.811141  7.021530  8.224164
8.882079
J       2808.0  8.145970  1.038166  5.814131  7.528600  8.350902
8.948326
```

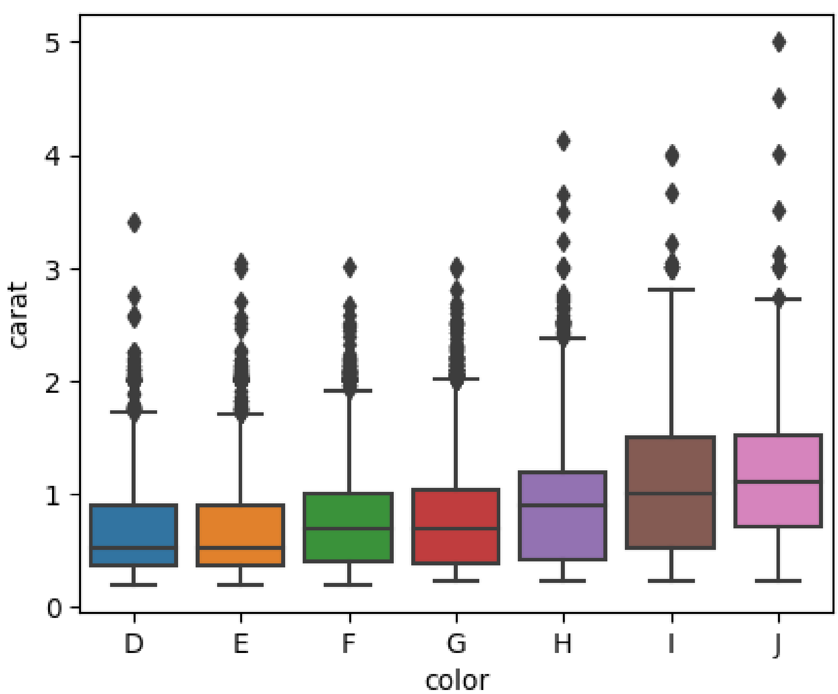
```
             max
color
D       9.835904
E       9.837935
F       9.841133
G       9.842569
H       9.841772
I       9.842835
J       9.836813
```

```
diamond.groupby('color')['carat'].describe()
```

	count	mean	std	min	25%	50%	75%	max
color								
D	6775.0	0.657795	0.359573	0.20	0.36	0.53	0.905	3.40
E	9797.0	0.657867	0.368566	0.20	0.36	0.53	0.900	3.05
F	9542.0	0.736538	0.397588	0.20	0.40	0.70	1.010	3.01
G	11292.0	0.771190	0.441436	0.23	0.39	0.70	1.040	3.01
H	8304.0	0.911799	0.521236	0.23	0.41	0.90	1.200	4.13
I	5422.0	1.026927	0.579173	0.23	0.52	1.00	1.500	4.01
J	2808.0	1.162137	0.595801	0.23	0.71	1.11	1.520	5.01

```
fig, ax = plt.subplots(figsize=(5, 4))
sns.boxplot(x='color',y='carat',data=diamond)
```

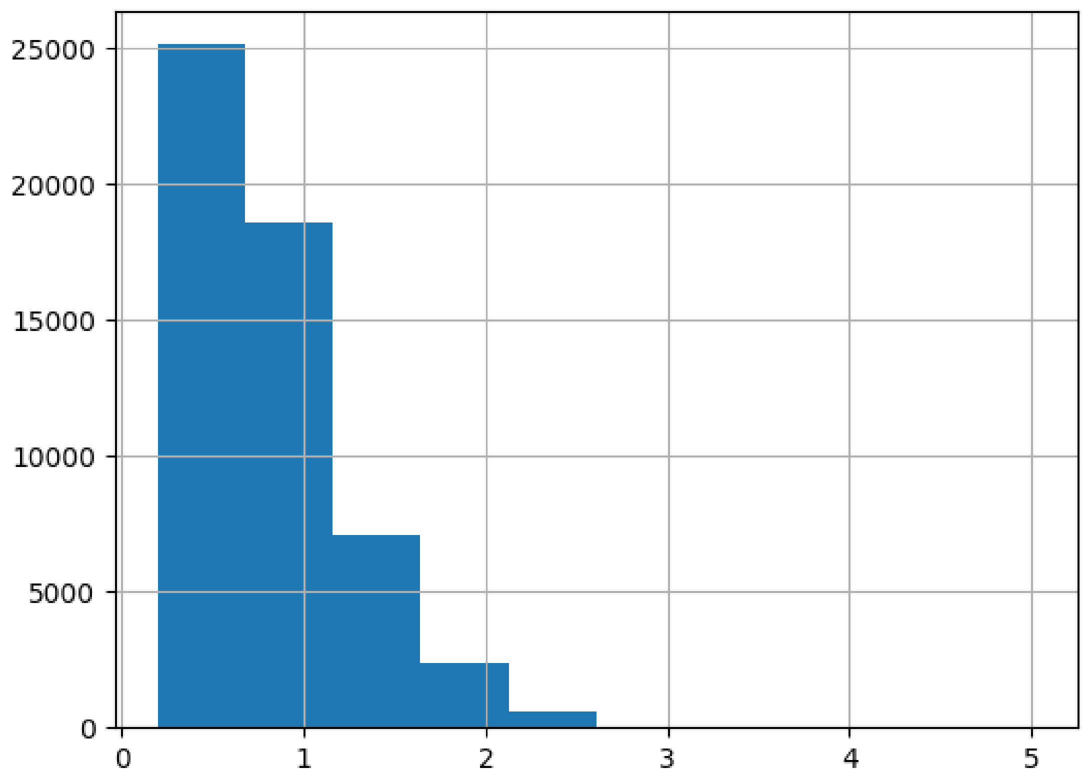
```
<Axes: xlabel='color', ylabel='carat'>
```



There alot of outliers in the carat variable

```python
diamond['carat'].hist()
```

```
<Axes: >
```



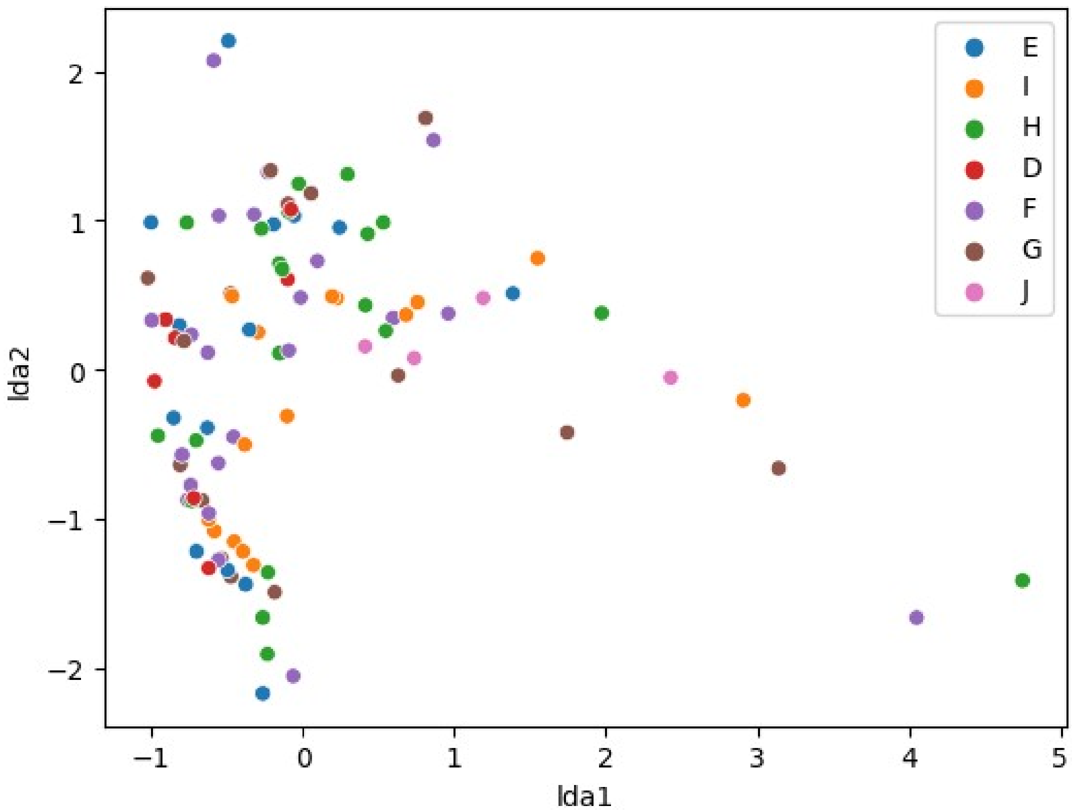

```python
from statsmodels.multivariate.manova import MANOVA
fit = MANOVA.from_formula('log_price + carat ~ color', data=diamond)
print(fit.mv_test())
```

```
                     Multivariate linear model
====================================================================

--------------------------------------------------------------------
       Intercept         Value  Num DF   Den DF     F Value    Pr > F
--------------------------------------------------------------------
          Wilks' lambda  0.0272 2.0000 53932.0000 963484.1583 0.0000
         Pillai's trace  0.9728 2.0000 53932.0000 963484.1583 0.0000
 Hotelling-Lawley trace 35.7296 2.0000 53932.0000 963484.1583 0.0000
    Roy's greatest root 35.7296 2.0000 53932.0000 963484.1583 0.0000
--------------------------------------------------------------------

--------------------------------------------------------------------
          color          Value   Num DF    Den DF    F Value   Pr > F
--------------------------------------------------------------------
           Wilks' lambda 0.7981 12.0000 107864.0000 1072.9205 0.0000
          Pillai's trace 0.2026 12.0000 107866.0000 1013.3180 0.0000
```

```
  Hotelling-Lawley trace 0.2521 12.0000  83891.1359 1132.8822 0.0000
     Roy's greatest root 0.2484  6.0000  53933.0000 2233.1743 0.0000
====================================================================
```

The Pillai's Trace test statistics is statistically significant [Pillai's Trace = 0.2026, p < 0.001] and indicates that plant color has a statistically significant association with both combined diamond carat and log price.

```
sample_data=diamond.sample(n=100,replace=True,random_state=32190)

sample_data[sample_data.index.duplicated()]

Empty DataFrame
Columns: [index, color, price, log_price, cut, carat]
Index: []

sample_data = sample_data.reset_index()

from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
as lda

X = sample_data[["log_price", "carat"]]
y = sample_data["color"]
# plot
X_ne = pd.DataFrame(lda().fit(X=X, y=y).transform(X), columns=["lda1",
"lda2"])
X_ne["color"] = sample_data["color"]
sns.scatterplot(data=X_ne, x="lda1", y="lda2",
hue=sample_data.color.tolist())
plt.show()
```




```
from google.colab import drive
drive.mount('/content/drive')

Mounted at /content/drive
```