Open in Colab

In [ ]:
```
!pip install matplotlib-venn
!pip install sns
```

```
Requirement already satisfied: matplotlib-venn in /usr/local/lib/python3.10/dist-packages (0.11.10)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (from matplotlib-venn) (3.7.1)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from matplotlib-venn) (1.25.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages (from matplotlib-venn) (1.11.4)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->matplotlib-venn) (1.2.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib->matplotlib-venn) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->matplotlib-venn) (4.48.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->matplotlib-venn) (1.4.5)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->matplotlib-venn) (23.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->matplotlib-venn) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->matplotlib-venn) (3.1.1)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib->matplotlib-venn) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib->matplotlib-venn) (1.16.0)
Collecting sns
  Downloading sns-0.1.tar.gz (2.1 kB)
  Preparing metadata (setup.py) ... done
Building wheels for collected packages: sns
  Building wheel for sns (setup.py) ... done
  Created wheel for sns: filename=sns-0.1-py3-none-any.whl size=2639 sha256=18545276a9e8ce7a9982f0553e9245a8abe82f159ef0fad9b0fd56cc9a37bac9
  Stored in directory: /root/.cache/pip/wheels/76/1a/47/c3b6a8b9d3ae47b1488f4be13c86586327c07e0ac1bb5b3337
Successfully built sns
Installing collected packages: sns
Successfully installed sns-0.1
```

Introduction

The dataset contains 53940 diamond data and 10 fields.

- **carat:** 1 carat = 0.2 grams = 200 mg
- **cut:** diamond cut grade. There are five values: Fair, Good, Very Good, Premium, and Ideal.
- **color:** The color grade of the diamond. Its value ranges from J (worst) to D (best)
- **clarity:** diamond clarity. It has a value of one of I1 (worst), SI2, SI1, VS2, VS1, VVS2, VVS1, IF (best).
- **depth:** depth ratio, calculated as = z / mean(x, y)
- **table:** the width of the top of the diamond relative to the widest point.
- **x:** the length of the diamond
- **y:** the width of the diamond
- **z:** the depth of the diamond price: the price of the diamond (USD)

In [ ]:
```
import numpy as np
```

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
# show the graph inline
%matplotlib inline
# color setting
color= sns.color_palette()

# precise setting
# pd.set_option('precision',3)

# Regression
from sklearn.linear_model import LinearRegression,Ridge,Lasso
from sklearn.ensemble import RandomForestRegressor,BaggingRegressor
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error #
# import data
df= pd. read_csv("/content/drive/MyDrive/diamonds.csv")
df. head(5)
```

Out[ ]:

	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 [ ]:

```python
# check null value and data types
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 [ ]:

```python
# overview the features of dataset
df.describe()
```

Out[ ]:

	carat	depth	table	price	x	
count	53940.000000	53940.000000	53940.000000	53940.000000	53940.000000	53940.0
mean	0.797940	61.749405	57.457184	3932.799722	5.731157	5.73
std	0.474011	1.432621	2.234491	3989.439738	1.121761	1.1
min	0.200000	43.000000	43.000000	326.000000	0.000000	0.00

min	0.200000	43.000000	43.000000	326.000000	0.000000	0.00
25%	0.400000	61.000000	56.000000	950.000000	4.710000	4.72
50%	0.700000	61.800000	57.000000	2401.000000	5.700000	5.7
75%	1.040000	62.500000	59.000000	5324.250000	6.540000	6.54
max	5.010000	79.000000	95.000000	18823.000000	10.740000	58.9

Data Preprocessing

- Check duplicated value
- Delete duplicated value
- Delect 0 in x, y, z fields

In [ ]:

```
df. duplicated(). sum() # count duplicated value
```

Out[ ]: 146

In [ ]:

```
df= df. drop_duplicates(ignore_index= True ) # Delete duplicated value
df= df.loc[(df.x!= 0)&(df.y!=0)&(df.z!=0)] # Delect 0 in x,y,z fields
```

In [ ]:

```
df.tail()
```

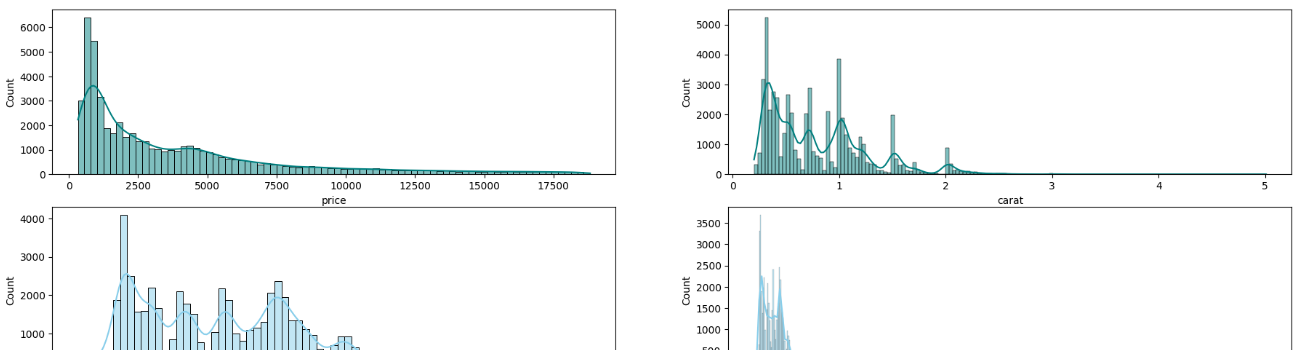
Out[ ]:

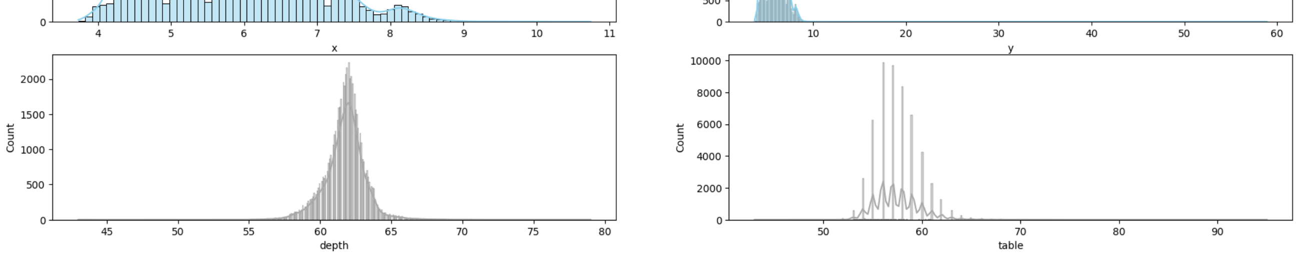
	carat	cut	color	clarity	depth	table	price	x	y	z
53789	0.72	Ideal	D	SI1	60.8	57.0	2757	5.75	5.76	3.50
53790	0.72	Good	D	SI1	63.1	55.0	2757	5.69	5.75	3.61
53791	0.70	Very Good	D	SI1	62.8	60.0	2757	5.66	5.68	3.56
53792	0.86	Premium	H	SI2	61.0	58.0	2757	6.15	6.12	3.74
53793	0.75	Ideal	D	SI2	62.2	55.0	2757	5.83	5.87	3.64

Single variable analysis

In [ ]:

```
# dimond numerial fields distribution
fig, axs = plt.subplots(3, 2, figsize=(22, 10))
sns.histplot(df['price'], kde=True, color="teal",ax=axs[0, 0])
sns.histplot(df['carat'],kde=True, color="teal",ax=axs[0, 1])
sns.histplot(df['x'],kde=True, color="skyblue",ax=axs[1, 0])
sns.histplot(df['y'],kde=True, color="skyblue",ax=axs[1, 1])
sns.histplot(df['depth'],kde=True, color="darkgrey",ax=axs[2, 0])
sns.histplot(df['table'],kde=True, color="darkgrey",ax=axs[2, 1])
plt.show()
```

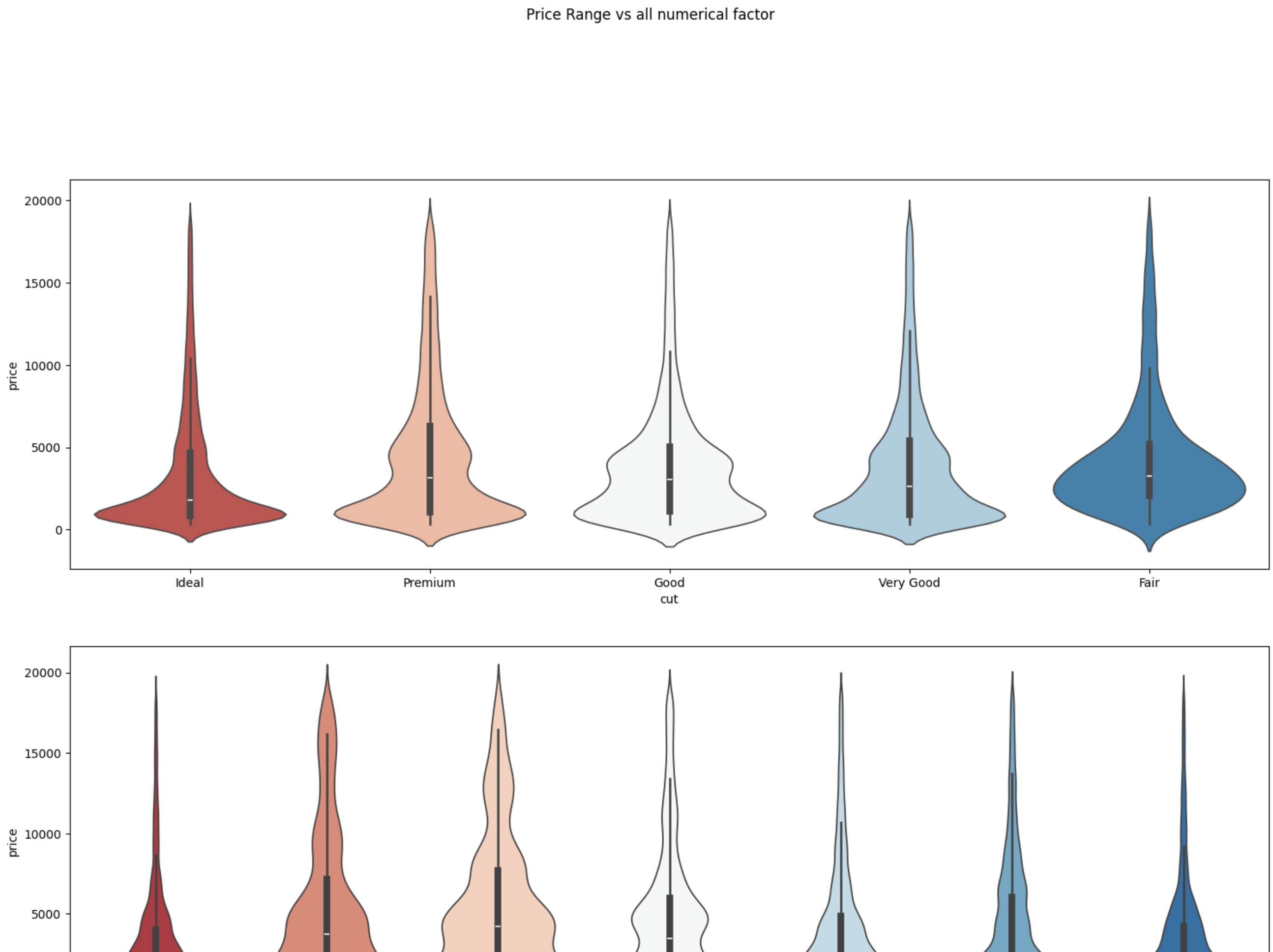


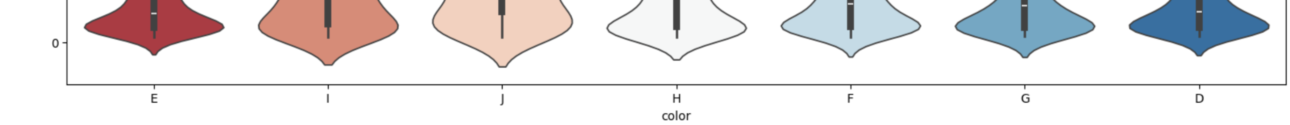


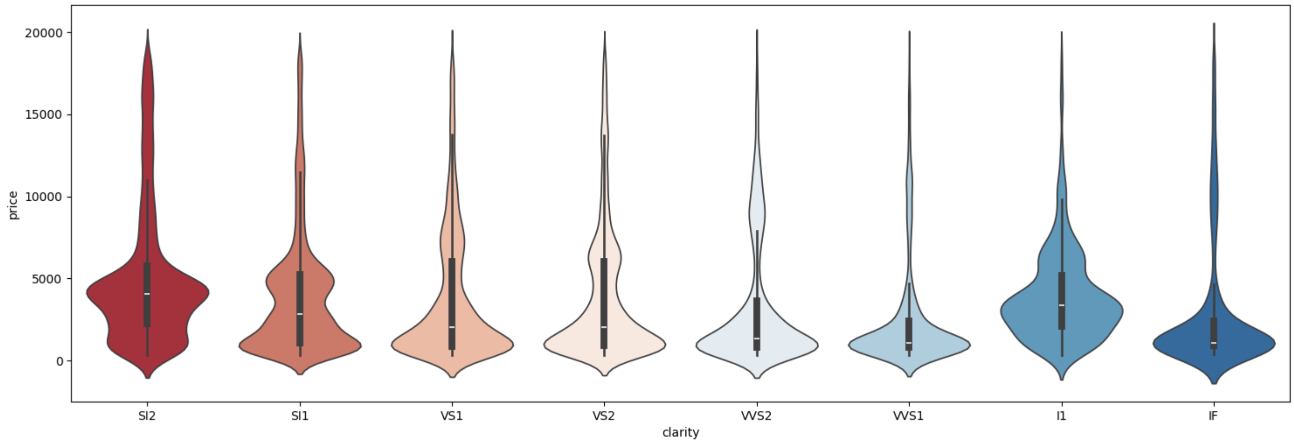
In [ ]:

```python
fig, axes = plt.subplots(3, 1, figsize=(18, 20))

fig.suptitle('Price Range vs all numerical factor')

sns.violinplot(ax=axes[0], data=df, x='cut', y='price', palette="RdBu")
sns.violinplot(ax=axes[1], data=df, x='color', y='price', palette="RdBu")
sns.violinplot(ax=axes[2], data=df, x='clarity', y='price', palette="RdBu")

plt.show()
```

```
<ipython-input-11-39f00a5ced78>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.
14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.violinplot(ax=axes[0], data=df, x='cut', y='price', palette="RdBu")
<ipython-input-11-39f00a5ced78>:6: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.
14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.violinplot(ax=axes[1], data=df, x='color', y='price', palette="RdBu")
<ipython-input-11-39f00a5ced78>:7: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.
14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.violinplot(ax=axes[2], data=df, x='clarity', y='price', palette="RdBu")
```







Heatmap of variable

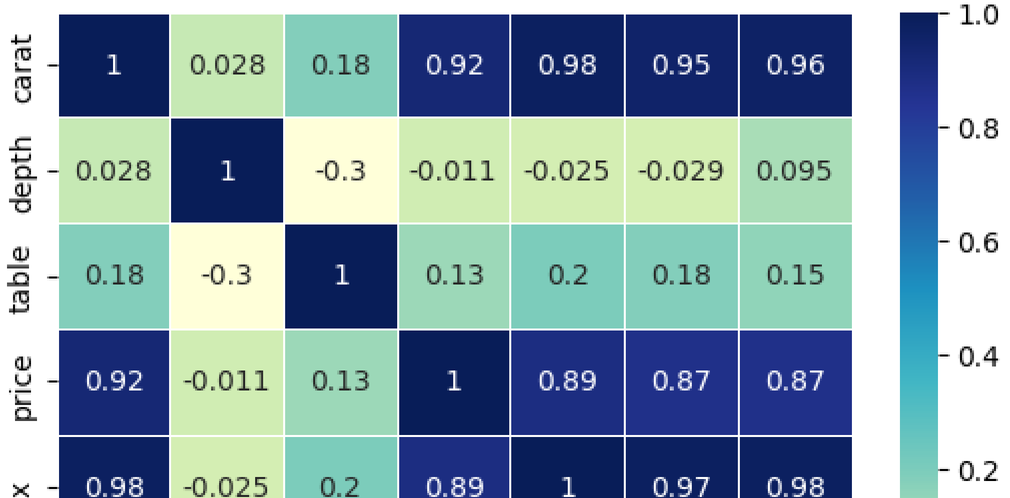
Sort variables according to their correlation with price.
There is a strong correlation between the attribute of diamond price and carat, and the length and width of diamond are closely related to the carat of diamond.

- carat
- x
- y
- z

In [ ]:

```
corr= df. corr()
print(corr)
sns.heatmap(corr,annot= True ,linewidths=0.5,cmap= "YlGnBu")
plt.show()
```

```
<ipython-input-13-b632ba75d6c5>:1: FutureWarning: The default value of numeric_onl
y in DataFrame.corr is deprecated. In a future version, it will default to False.
Select only valid columns or specify the value of numeric_only to silence this war
ning.
  corr= df. corr()
          carat     depth     table     price         x         y         z
carat  1.000000  0.027889  0.181113  0.921548  0.977857  0.953980  0.961030
depth  0.027889  1.000000 -0.297580 -0.011144 -0.025224 -0.029262  0.094678
table  0.181113 -0.297580  1.000000  0.126666  0.195451  0.183814  0.151683
price  0.921548 -0.011144  0.126666  1.000000  0.887137  0.867685  0.868030
x      0.977857 -0.025224  0.195451  0.887137  1.000000  0.974822  0.975382
y      0.953980 -0.029262  0.183814  0.867685  0.974822  1.000000  0.956623
z      0.961030  0.094678  0.151683  0.868030  0.975382  0.956623  1.000000
```

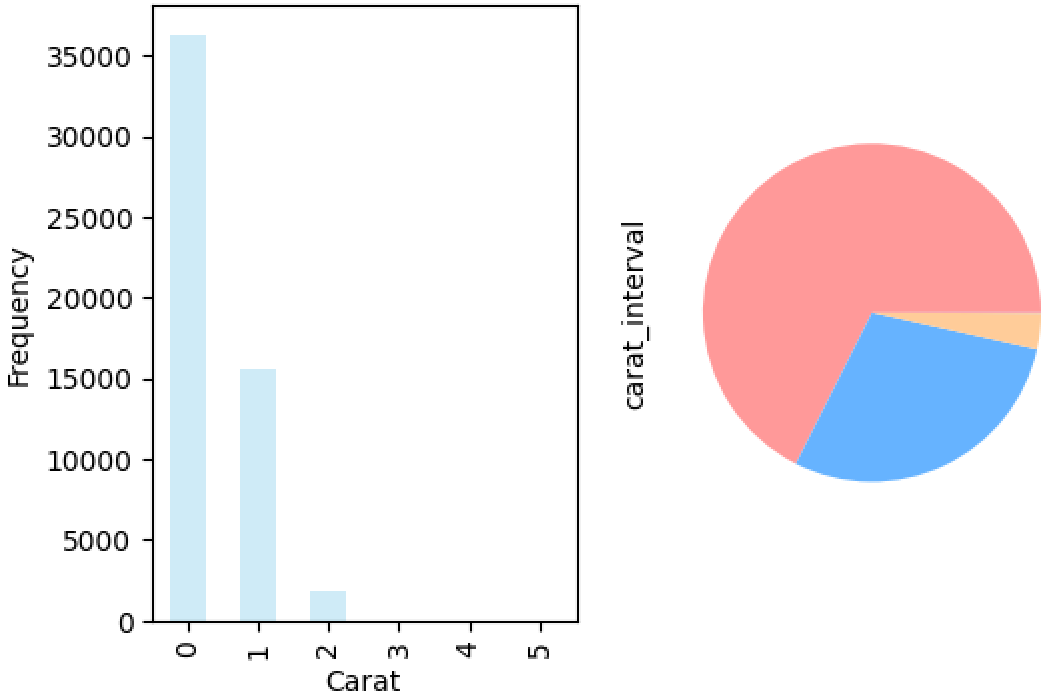


Analyze the relation of cut, color, clarity and other attributes on the price of diamonds

Due to the diamond carats in the data set are distributed between 0 and 3 carats, we mainly choose 0-3 carats diamonds as dataset.

In [ ]:

```
#Setting carat intervals
bins= [0,1,2,3,4,5,6]
label= [ 0,1,2,3,4,5]
df["carat_interval"] = pd.cut(df['carat'], bins=bins, labels=label, right=True)
plt. figure(figsize= (6,4))
# subplot1 - Bar plot
plt.subplot(1, 2, 1)
df_carat_interval_value = df["carat_interval"].value_counts()
df_carat_interval_value.plot.bar(color='#87CEEB', xlabel='Carat', ylabel='Freque

# subplot2 - Pie plot
plt.subplot(1, 2, 2)
df_carat_interval_value.plot(kind='pie', labels=None, colors=['#FF9999', '#66B3F

plt.show()
```



Blue for 0-1 carat diamonds, Orange for 1-2 carat diamonds, Green for 2-3.

Number of colour/clarity/cut that higher is the better.

- The first sub-chart shows that 30 point and 1 carat diamond rings are the most popular among diamond rings under 2 carats, and assuming this is an objective market data, companies should focus their productivity on 30 point and 1 carat diamond rings.

- The second sub-chart shows a skewed distribution, with the majority of people choosing a diamond ring in the 5,000 dollor range, and companies should set a reasonable price range.
- The third sub-chart shows the colour of diamonds, with most of the colour of diamonds under 2 carats concentrated above grade 3, but the distribution of 1-2 carat rings is approximately normal, with the highest point at the medium (grade 3), while the colour of diamonds under 1 carat is generally higher than that of 1-2 carat rings, with the highest point of the colour grade at the medium-high (grade 5).
- The fourth sub diagram depicts the clarity of the diamond, understanding that high quality clarity is rare, most diamonds have some inclusions, and that clarity is an innate property that cannot be altered by human intervention and therefore cannot be enhanced by human intervention.
- The fifth sub-picture depicts the cut of the diamond, which, in contrast to the fourth sub-picture, is a factor that can be interfered with, with the cut of diamonds under two carats mostly distributed in the better areas, most of which are of the highest grades.
- The sixth image shows the relationship between carat weight and price for diamonds under two carats. The relationship between carat weight and price is roughly. proportional, but there are other factors that influence the diamond, so we can see that even diamonds that are not dominant in weight can sometimes be overpriced.

In [ ]:

```
# Diamonds below 3 carat as sample, analyse the price influence of each variable
diamond_carat=df[df['carat_interval'] < 3].sort_values('price', ascending=False)
```

In [ ]:

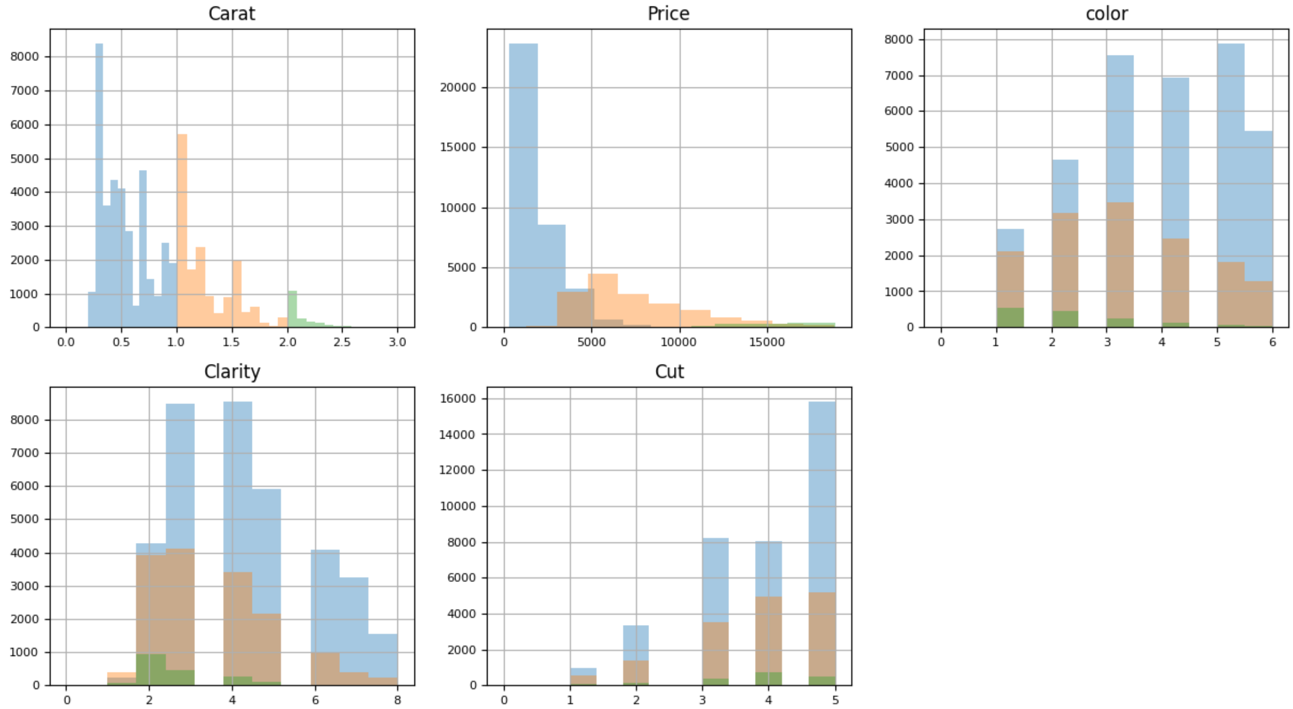
```
diamond_carat['cut']=diamond_carat['cut'].map({'Ideal':5,'Premium':4,'Very Good'
diamond_carat['color']= diamond_carat['color']. map({'D':6,'E':5,'F':4,'G':3,'H'
diamond_carat['clarity']= diamond_carat['clarity']. map({'IF':8,'VVS1':7,'VVS2':
                                                  'VS1':5,'VS2':4,'SI1':3
diamond_carat. drop(['depth','table','x','y','z'],axis= 1,inplace= True )
```

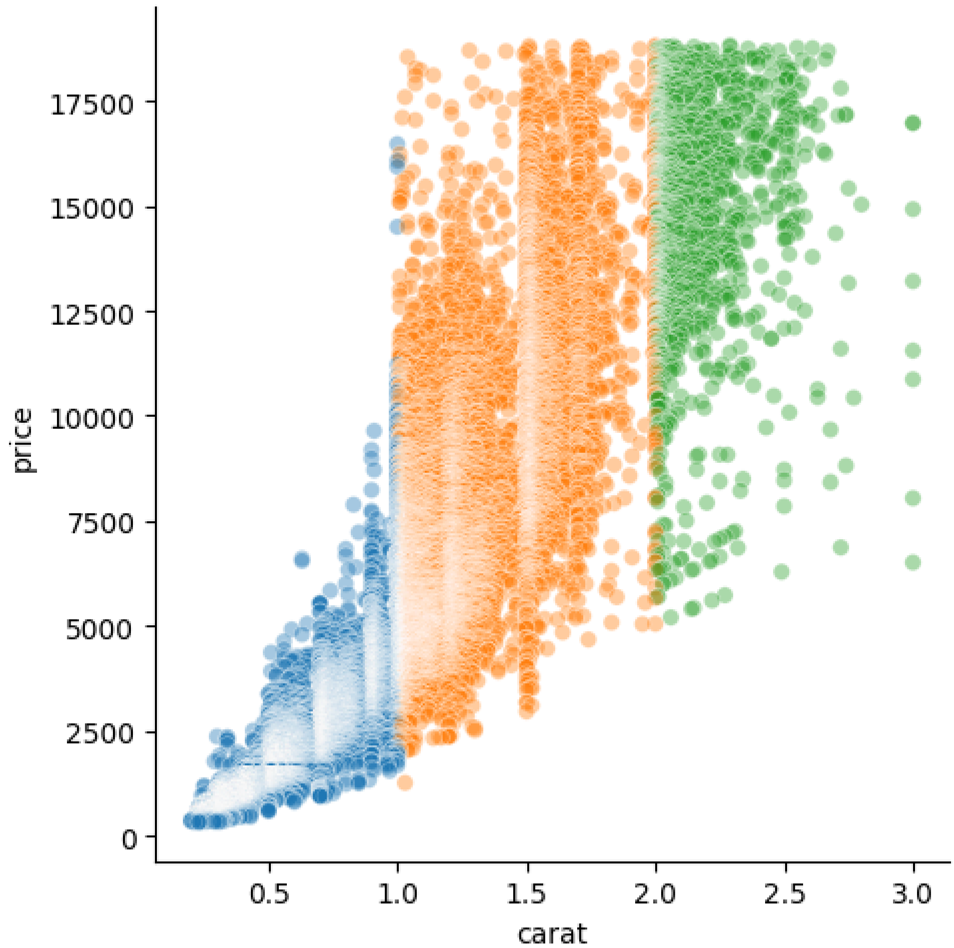
In [ ]:

```
plt. figure(figsize= (15,8))
# setting palette
custom_palette = {"blue": "blue", "red": "red"}


#subplot1
ax1= plt. subplot(231)
ax1. set_title('Carat')
diamond_carat.groupby("carat_interval")['carat'].hist(stacked=True,bins= 12,alph
plt.setp(ax1.get_xticklabels(), fontsize=8)
plt.setp(ax1.get_yticklabels(), fontsize=8)
#subplot2
ax2= plt. subplot(232)
ax2. set_title('Price')
diamond_carat. groupby("carat_interval")['price']. hist(alpha= 0.4)
plt.setp(ax2.get_xticklabels(), fontsize=8)
plt.setp(ax2.get_yticklabels(), fontsize=8)
#subplot3
ax3= plt. subplot(233)
ax3. set_title('color')
diamond_carat. groupby("carat_interval")['color']. hist(alpha= 0.4)
plt.setp(ax3.get_xticklabels(), fontsize=8)
plt.setp(ax3.get_yticklabels(), fontsize=8)
#subplot4
ax4= plt. subplot(234)
ax4. set_title('Clarity')
diamond_carat. groupby("carat_interval")['clarity']. hist(alpha= 0.4)
```

```
diamond_carat. groupby("carat_interval")['clarity']. hist(alpha= 0.4)
plt.setp(ax4.get_xticklabels(), fontsize=8)
plt.setp(ax4.get_yticklabels(), fontsize=8)

#subplot5
ax5= plt. subplot(235)
ax5. set_title('Cut')
diamond_carat. groupby("carat_interval")['cut']. hist(alpha= 0.4)
plt.setp(ax5.get_xticklabels(), fontsize=8)
plt.setp(ax5.get_yticklabels(), fontsize=8)
#subplot6
sns.relplot(data=diamond_carat, x = 'carat', y = 'price', hue = 'carat_interval'
```

Out[ ]: <seaborn.axisgrid.FacetGrid at 0x795610ed0d30>





Linear Regression

In [ ]:

```
# transform data format to mechine learning
def LABEL_ENCODING(c1):
    from sklearn import preprocessing
    label_encoder = preprocessing.LabelEncoder()
    df[c1]= label_encoder.fit_transform(df[c1])
    df[c1].unique()
LABEL_ENCODING("cut")
LABEL_ENCODING("color")
LABEL_ENCODING("clarity")
df
```

Out[ ]:

	carat	cut	color	clarity	depth	table	price	x	y	z	carat_interval
0	0.23	2	1	3	61.5	55.0	326	3.95	3.98	2.43	0
1	0.21	3	1	2	59.8	61.0	326	3.89	3.84	2.31	0
2	0.23	1	1	4	56.9	65.0	327	4.05	4.07	2.31	0
3	0.29	3	5	5	62.4	58.0	334	4.20	4.23	2.63	0
4	0.31	1	6	3	63.3	58.0	335	4.34	4.35	2.75	0
...	...	...	...	...	...	...	...	...	...	...	...
53789	0.72	2	0	2	60.8	57.0	2757	5.75	5.76	3.50	0
53790	0.72	1	0	2	63.1	55.0	2757	5.69	5.75	3.61	0
53791	0.70	4	0	2	62.8	60.0	2757	5.66	5.68	3.56	0
53792	0.86	3	4	3	61.0	58.0	2757	6.15	6.12	3.74	0

In [ ]:

```
X = df.drop('price',axis=1)
y = df['price']
```

In [ ]:

```
from sklearn.model_selection import train_test_split #split the data set
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,random_state=
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(43020, 10)
(10755, 10)
(43020,)
(10755,)
```

In [ ]:

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
linear = LinearRegression()
linear.fit(X_train,y_train)
```

Out[ ]: LinearRegression()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with

nbviewer.org.

In [ ]:

```
y_test_predict = linear.predict(X_test)
rmse = (np.sqrt(mean_squared_error(y_test,y_test_predict)))
# Root Mean Squared Error, RMSE.
# Used to measure the size of the model's prediction error
# The smaller the RMSE, the better the prediction performance of the model.
# evaluate accuracy of linearRegression
from sklearn.metrics import r2_score
r2 = r2_score(y_test,y_test_predict)
print("Accuracy: ",r2)
```

```
Accuracy:  0.8887973534652991
```

Decision Tree

In [ ]:

```
from sklearn.tree import DecisionTreeRegressor
DTR = DecisionTreeRegressor(max_depth=3)
DTR.fit(X_train,y_train)
```

Out[ ]: DecisionTreeRegressor(max_depth=3)

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [ ]:

```
train_score = DTR.score(X_train,y_train)
text_score = DTR.score(X_test,y_test)
print("Accuracy: ",text_score)
```

```
Accuracy:  0.8841342370572554
```

RandomForest Regressor

In [ ]:

```
from sklearn.ensemble import RandomForestRegressor
RF = RandomForestRegressor(n_estimators=5,random_state=0)
```

In [ ]:

```
RF.fit(X_train,y_train)
rf = RF.score(X_train,y_train)
rf_score = RF.score(X_test,y_test)
print("Accuracy: ",rf_score)
```

```
Accuracy:  0.9774645734611015
```