Diamond Price Prediction

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.

Dataset Source Link : https://www.kaggle.com/competitions/playground-series-s3e8/data?select=train.csv (https://www.kaggle.com/competitions/playground-series-s3e8/data?select=train.csv) https://www.kaggle.com/datasets/colearninglounge/gemstone-price-prediction (https://www.kaggle.com/datasets/colearninglounge/gemstone-price-prediction)

In [51]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

import pickle
import json

import warnings
warnings.filterwarnings('ignore')
```

In [53]:
```
## Data Ingestions step
df=pd.read_csv('gemstone.csv')
df.head()
```

Out[53]:

	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

EDA and Feature Engineering

In [54]:
```
df.isnull().sum()
```

Out[54]:
```
id          0
carat       0
cut         0
color       0
clarity     0
depth       0
table       0
x           0
y           0
z           0
price       0
dtype: int64
```

In [4]:
```
### No missing values present in the data
```

In [55]:
```
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
```

In [56]:
```
df.head()
```

Out[56]:

	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

In [57]:
```
## Lets drop the id column
df=df.drop(labels=['id'],axis=1)
df.head()
```

Out[57]:

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

In [58]:
```
## check for duplicated records
df.duplicated().sum()
```

Out[58]: 0

In [59]:
```
## segregate numerical and categorical columns

numerical_columns=df.columns[df.dtypes!='object']
categorical_columns=df.columns[df.dtypes=='object']

print("Numerical columns:",numerical_columns)
print('Categorical Columns:',categorical_columns)
```

```
Numerical columns: Index(['carat', 'depth', 'table', 'x', 'y', 'z', 'price'],
dtype='object')
Categorical Columns: Index(['cut', 'color', 'clarity'], dtype='object')
```

In [60]:
```
df[categorical_columns].describe()
```

Out[60]:

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

In [61]:
```
df['cut'].value_counts()
```

Out[61]:
```
Ideal        92454
Premium      49910
Very Good    37566
Good         11622
Fair          2021
Name: cut, dtype: int64
```

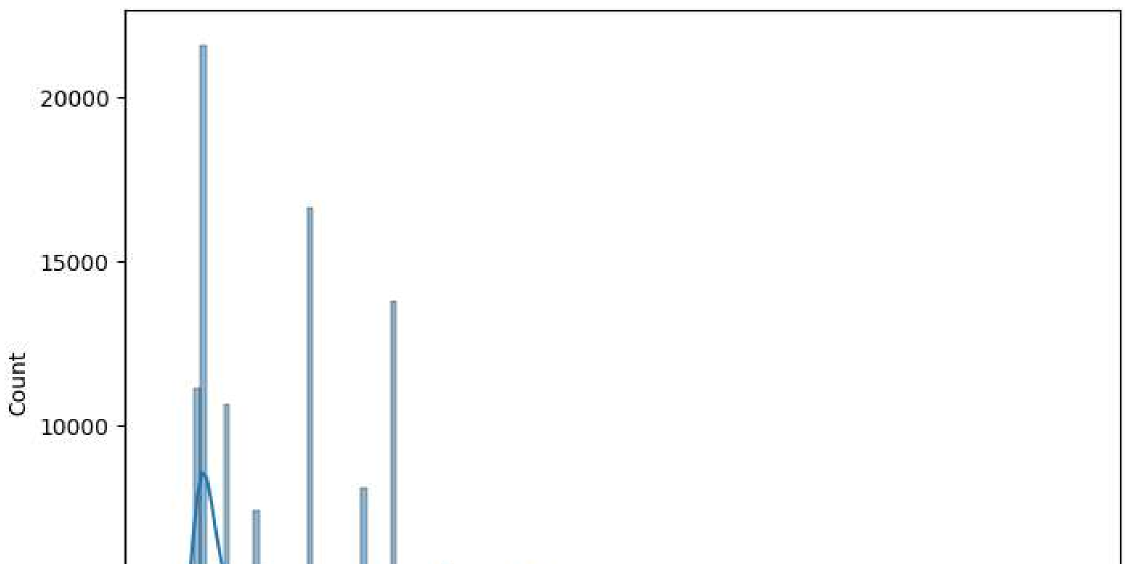
In [62]:
```
df['color'].value_counts()
```

Out[62]:
```
G    44391
E    35869
F    34258
H    30799
D    24286
I    17514
J     6456
Name: color, dtype: int64
```

In [63]:
```
df['clarity'].value_counts()
```

Out[63]:
```
SI1     53272
VS2     48027
VS1     30669
SI2     30484
VVS2    15762
VVS1    10628
IF       4219
I1        512
Name: clarity, dtype: int64
```

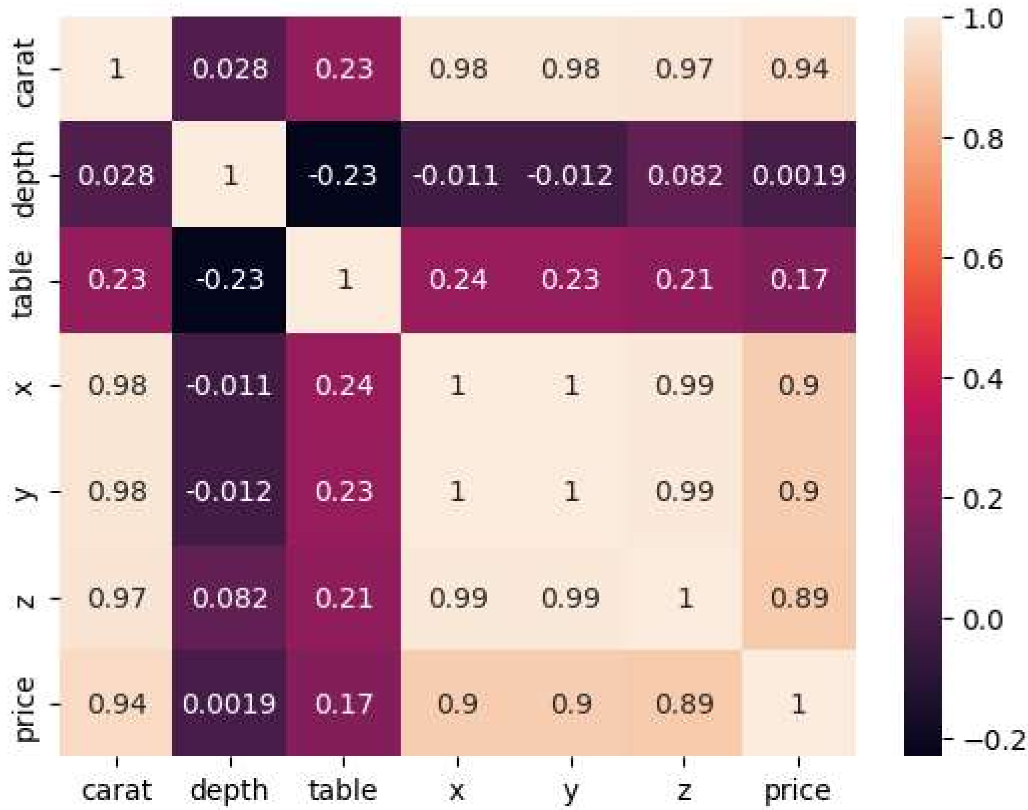
In [64]:
```
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(8,6))
x=0
for i in numerical_columns:
    sns.histplot(data=df,x=i,kde=True)
    print('\n')
    plt.show()
```



In [15]:
```
## Assignment Do the same for categorical data
```

In [65]:
```
## correlation
sns.heatmap(df[numerical_columns].corr(),annot=True)
```

Out[65]: <AxesSubplot: >



In [ ]:

In [66]:
```
df.head()
```

Out[66]:

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

In [67]:
```
## For Domain Purpose https://www.americangemsociety.org/ags-diamond-grading-s
df['cut'].unique()
```

Out[67]: array(['Premium', 'Very Good', 'Ideal', 'Good', 'Fair'], dtype=object)

In [68]:
```
cut_map={"Fair":1,"Good":2,"Very Good":3,"Premium":4,"Ideal":5}
```

In [69]:
```
df['clarity'].unique()
```

Out[69]:
```
array(['VS2', 'SI2', 'VS1', 'SI1', 'IF', 'VVS2', 'VVS1', 'I1'],
      dtype=object)
```

In [70]:
```
clarity_map = {"I1":1,"SI2":2 ,"SI1":3 ,"VS2":4 , "VS1":5 , "VVS2":6 , "VVS1":
```

In [71]:
```
df['color'].unique()
```

Out[71]:
```
array(['F', 'J', 'G', 'E', 'D', 'H', 'I'], dtype=object)
```

In [72]:
```
color_map = {"D":1 ,"E":2 ,"F":3 , "G":4 ,"H":5 , "I":6, "J":7}
```

In [73]:
```
df['cut']=df['cut'].map(cut_map)
df['clarity'] = df['clarity'].map(clarity_map)
df['color'] = df['color'].map(color_map)
```

In [74]:
```
df.head()
```

Out[74]:

	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

In [26]:
```
# # droping x,y,z cols

# df= df.drop(labels=['x','y','z'],axis=1)
```

In [ ]:
```

```

Model Training

In [27]:
```
## Independent and dependent features

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

In [28]:
```
y.head()
```

Out[28]:

	price
0	13619
1	13387
2	2772
3	666
4	14453

In [29]:
```
X.head()
```

Out[29]:

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

In [30]:
```
#Train Test Split

X_train, X_test, y_train, y_test= train_test_split(X,y,test_size=0.30,random_s
```

In [31]:
```
X_train.shape,X_test.shape
```

Out[31]:
```
((135501, 9), (58072, 9))
```

In [32]:
```
## Feature Selection based on correlaltion
X_train.corr()
```

Out[32]:

	carat	cut	color	clarity	depth	table	x	y	
carat	1.000000	-0.151887	0.289916	-0.348100	0.030080	0.225997	0.980467	0.980107	0.9
cut	-0.151887	1.000000	-0.020501	0.186134	-0.247813	-0.480045	-0.148002	-0.148379	-0.1
color	0.289916	-0.020501	1.000000	0.088890	0.037313	0.032545	0.266675	0.266793	0.2
clarity	-0.348100	0.186134	0.088890	1.000000	-0.062403	-0.183678	-0.375109	-0.373423	-0.3
depth	0.030080	-0.247813	0.037313	-0.062403	1.000000	-0.230617	-0.008943	-0.009873	0.0
table	0.225997	-0.480045	0.032545	-0.183678	-0.230617	1.000000	0.238178	0.233933	0.2
x	0.980467	-0.148002	0.266675	-0.375109	-0.008943	0.238178	1.000000	0.999074	0.9
y	0.980107	-0.148379	0.266793	-0.373423	-0.009873	0.233933	0.999074	1.000000	0.9
z	0.972516	-0.169213	0.267222	-0.375497	0.083483	0.212400	0.988007	0.987770	1.0

In [33]:
```
## Check for multicollinearity
plt.figure(figsize=(12,10))

corr= X_train.corr()
sns.heatmap(corr,annot=True)
```

Out[33]: <AxesSubplot: >

	carat	cut	color	clarity	depth	table	x	y	z
carat	1	-0.15	0.29	-0.35	0.03	0.23	0.98	0.98	0.97
cut	-0.15	1	-0.021	0.19	-0.25	-0.48	-0.15	-0.15	-0.17
color	0.29	-0.021	1	0.089	0.037	0.033	0.27	0.27	0.27
clarity	-0.35	0.19	0.089	1	-0.062	-0.18	-0.38	-0.37	-0.38
depth	0.03	-0.25	0.037	-0.062	1	-0.23	-0.0089	-0.0099	0.083
table	0.23	-0.48	0.033	-0.18	-0.23	1	0.24	0.23	0.21
x	0.98	-0.15	0.27	-0.38	-0.0089	0.24	1	1	0.99
y	0.98	-0.15	0.27	-0.37	-0.0099	0.23	1	1	0.99
z	0.97	-0.17	0.27	-0.38	0.083	0.21	0.99	0.99	1

In [34]:
```
### Linear regression Model
```

In [35]:
```
linear_reg = LinearRegression()
linear_reg.fit(X_train, y_train)
```

Out[35]: 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 [36]:
```
linear_reg.coef_
```

Out[36]:
```
array([[13908.5914125 ,    72.89534931,  -283.5924305 ,   433.73822644,
         -122.8355985 ,   -36.71694327, -1550.78910628,  -452.96841314,
          -91.86321724]])
```

In [37]:
```
linear_reg.intercept_
```

Out[37]:
```
array([13417.41178519])
```

Evaluation

In [38]:
```
y_pred = linear_reg.predict(X_test)

mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
print("RMSE :",rmse)

mae = mean_absolute_error(y_test, y_pred)
print("MAE :",mae)

r2_value = r2_score(y_test, y_pred)
print("R-Squared :",r2_value)
```

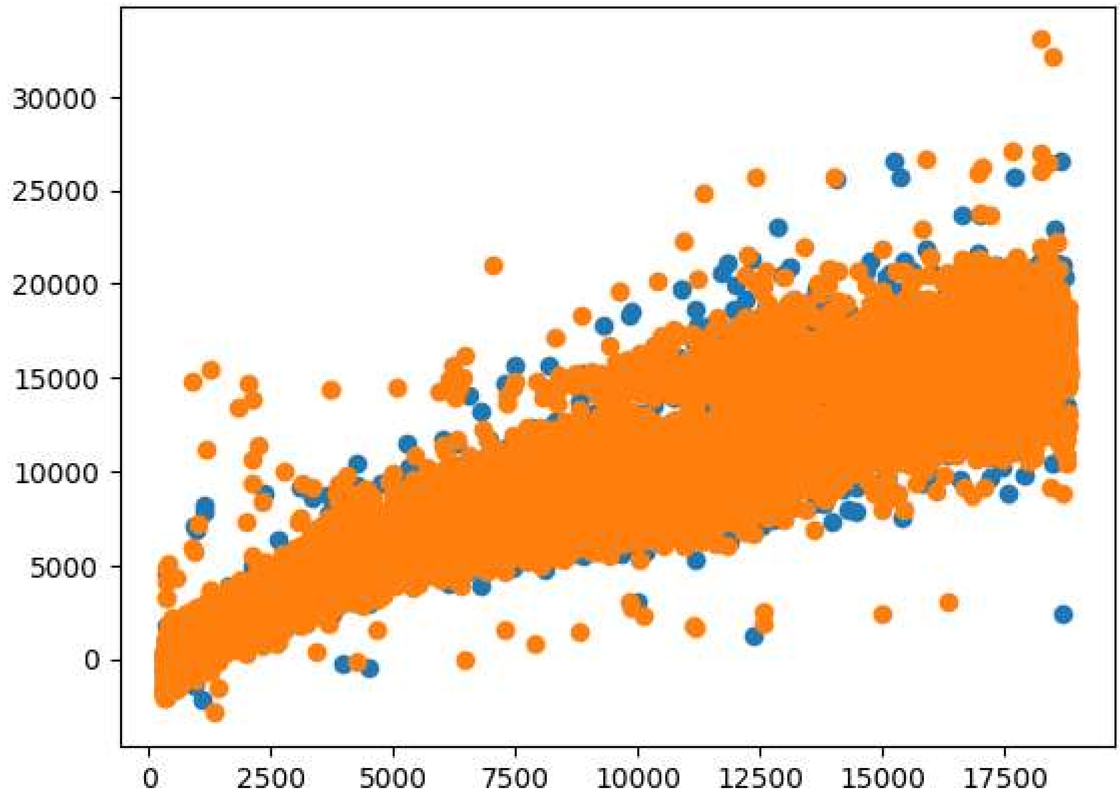
```
RMSE : 1013.9047094344014
MAE : 674.0255115796725
R-Squared : 0.936890824856751
```

In [39]:
```
y_pred_train = linear_reg.predict(X_train)

mse = mean_squared_error(y_train, y_pred_train)
rmse = np.sqrt(mse)
print("RMSE :",rmse)

mae = mean_absolute_error(y_train, y_pred_train)
print("MAE :",mae)

r2_value = r2_score(y_train, y_pred_train )
print("R-Squared :",r2_value)
```

```
RMSE : 1015.3275630072727
MAE : 675.6337012111566
R-Squared : 0.9366402738974493
```

In [40]:
```
plt.scatter(y_test,y_pred)
plt.scatter(y_train,y_pred_train)
```

Out[40]: `<matplotlib.collections.PathCollection at 0x1f37cf33f90>`



In [41]:
```
# single row testing

X_test[20:21]
```

Out[41]:

	carat	cut	color	clarity	depth	table	x	y	z
45797	2.0	3	4	2	63.5	60.0	7.98	7.93	5.04

In [42]:
```
# prediction

linear_reg.predict(X_test[20:21])[0]
```

Out[42]: `array([14752.98308863])`

In [43]:
```
X_test[20:21].T
```

Out[43]:

	45797
carat	2.00
cut	3.00
color	4.00
clarity	2.00
depth	63.50
table	60.00
x	7.98
y	7.93
z	5.04

```
carat=2.00
cut='Good'     #categorical
color='F'      #categorical
clarity="SI2"   #categorical
depth=63.50
table=60.00
x=7.98
y=7.93
z=5.04
```

In [44]:
```
column_names = X.columns.tolist()
column_names
```

Out[44]: ['carat', 'cut', 'color', 'clarity', 'depth', 'table', 'x', 'y', 'z']

In [45]:
```
X.shape[1]
```

Out[45]: 9

In [46]:
```
linear_reg.n_features_in_
```

Out[46]: 9

In [47]:
```
cut_map={"Fair":1,"Good":2,"Very Good":3,"Premium":4,"Ideal":5}
clarity_map = {"I1":1,"SI2":2 ,"SI1":3 ,"VS2":4 , "VS1":5 , "VVS2":6 , "VVS1":
color_map = {"D":1 ,"E":2 ,"F":3 , "G":4 ,"H":5 , "I":6, "J":7}
```

In [48]:
```
carat=2.00
cut='Very Good'
color='G'
clarity="SI2"
depth=63.50
table=60.00
x=7.98
y=7.93
z=5.04

cut     = cut_map[cut]
color   = color_map[color]
clarity = clarity_map[clarity]

test_array = np.zeros([1,linear_reg.n_features_in_])
test_array[0,0] = carat
test_array[0,1] = cut
test_array[0,2] = color
test_array[0,3] = clarity
test_array[0,4] = depth
test_array[0,5] = table
test_array[0,6] = x
test_array[0,7] = y
test_array[0,8] = z

predicted_charges = np.around(linear_reg.predict(test_array)[0],3)
predicted_charges
```

Out[48]:
```
array([14752.983])
```

MODELs

In [49]:
```
with open('linear_regression.pkl','wb') as f:
    pickle.dump(linear_reg, f)
```

In [50]:
```
project_data = {"cut": cut_map,
                "color": color_map,
                "clarity": clarity_map,
                "Column Names" : column_names}

with open('proj_data.json','w') as f:
    json.dump(project_data, f)
```

In [ ]:

In [ ]:

Type *Markdown* and LaTeX: α^2