Diamond Price Prediction

Data Science Objective- I need to build a model which predicts, with a high-level accuracy, the market price in US dollars of a diamond by relating the prices of De Beers diamonds which were sold to their features. Since, I want my model to be as accurate as possible, I will optimize the mean absolute error on the testing set (which is a metric for accuracy) instead of the R^2 (i.e., the coefficient of determination) regression score on the testing set (which is a metric of precision).

Problem statement:

Diamond price prediction based on their cut, colour, clarity, price..etc attributes

Outcome:

The market price in US dollars of a diamond by relating the prices of De Beers diamonds which were sold to their features.

I have considered the classic Diamonds dataset which contains the prices and other attributes of almost 54,000 diamonds and this dataset is hosted on [Kaggle](). The dataset contains 53940 rows and 10 variables. Before jumping into building the model, let's have a look into the variables & their definitions.

- **Price** is in US dollars
- **Carat** weight of the diamond
- **Cut** quality of the cut (Fair, Good, Very Good, Premium, Ideal)
- **color** diamond colour, from J (worst) to D (best)
- **clarity** a measurement of how clear the diamond is (I1 (worst), SI2, SI1, VS2, VS1, VVS2, VVS1, IF (best))
- **x** length in mm

- **y** width in mm
- **z** depth in m
- **depth**: The height of a diamond
- **table**: The width of the diamond's table expressed as a percentage of its average diameter

Let’s get started to build the model based on the following steps

1. Import Required Packages
2. Load the dataset
3. Perform the exploratory data analysis (EDA)
4. Prepare the dataset for training
5. Create a regression model
6. Train the model to fit the data
7. Make predictions using the trained model

Step 1: Import Required Packages

```
#importing required libraries
import pandas as pd
import numpy as np
import seaborn as sb
```

Step 2: Load the dataset

```
#dataset
df = pd.read_csv("Diamonds Prices2022.csv")
```

```
df
```

	Unnamed: 0	carat	cut	color	clarity	depth	table	price	x	y	z
0	1	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
1	2	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
2	3	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31
3	4	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63
4	5	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75
...	...	...	...	...	...	...	...	...	...	...	...
53938	53939	0.86	Premium	H	SI2	61.0	58.0	2757	6.15	6.12	3.74
53939	53940	0.75	Ideal	D	SI2	62.2	55.0	2757	5.83	5.87	3.64
53940	53941	0.71	Premium	E	SI1	60.5	55.0	2756	5.79	5.74	3.49
53941	53942	0.71	Premium	F	SI1	59.8	62.0	2756	5.74	5.73	3.43
53942	53943	0.70	Very Good	E	VS2	60.5	59.0	2757	5.71	5.76	3.47

53943 rows × 11 columns

Step 3: Exploratory Data Analysis (EDA)

- Shape to check for the dimensions. As the data that we have passed has two rows and two columns (2x2), the shape method returns us **the number of rows and columns** as the result.

```
df.shape
```

```
(53943, 11)
```

```
df.isna().sum().sum()
```

```
0
```

```
df.columns
```

```
Index(['Unnamed: 0', 'carat', 'cut', 'color', 'clarity', 'depth', 'table',
       'price', 'x', 'y', 'z'],
      dtype='object')
```

There is no NAN data in the dataset and the same can also be checked by using `data.isna().sum().sum()`. The given dataset has 6 numeric columns and three non-numeric (categorical) columns

Drop the column “Unnamed: 0”, which is unnecessary

```
df=df.drop(["Unnamed: 0"],axis=1)
```

```
df
```

	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
...	...	...	...	...	...	...	...	...	...	...
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	0.71	Premium	E	SI1	60.5	55.0	2756	5.79	5.74	3.49
53941	0.71	Premium	F	SI1	59.8	62.0	2756	5.74	5.73	3.43
53942	0.70	Very Good	E	VS2	60.5	59.0	2757	5.71	5.76	3.47

53943 rows × 10 columns

- The info() method **prints information about the DataFrame**. The information contains the number of columns, column labels, column data types, memory usage, range index, and the number of cells in each column (non-null values). Note: the info() method actually prints the info

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53943 entries, 0 to 53942
Data columns (total 10 columns):
carat      53943 non-null float64
cut        53943 non-null object
color      53943 non-null object
clarity    53943 non-null object
depth      53943 non-null float64
table      53943 non-null float64
price      53943 non-null int64
x          53943 non-null float64
y          53943 non-null float64
z          53943 non-null float64
dtypes: float64(6), int64(1), object(3)
memory usage: 4.1+ MB
```

- Get the descriptive statistics of the dataset using `df.describe()`

```
df.describe()
```

	carat	depth	table	price	x	y	z
count	53943.000000	53943.000000	53943.000000	53943.000000	53943.000000	53943.000000	53943.000000
mean	0.797935	61.749322	57.457251	3932.734294	5.731158	5.734526	3.538730
std	0.473999	1.432626	2.234549	3989.338447	1.121730	1.142103	0.705679
min	0.200000	43.000000	43.000000	326.000000	0.000000	0.000000	0.000000
25%	0.400000	61.000000	56.000000	950.000000	4.710000	4.720000	2.910000
50%	0.700000	61.800000	57.000000	2401.000000	5.700000	5.710000	3.530000
75%	1.040000	62.500000	59.000000	5324.000000	6.540000	6.540000	4.040000
max	5.010000	79.000000	95.000000	18823.000000	10.740000	58.900000	31.800000

Observed that the minimum value of x (length), y(width) & z(depth) is zero and It doesn't make any sense to have length\width\depth of a diamond to be zero.

Let's drop these rows

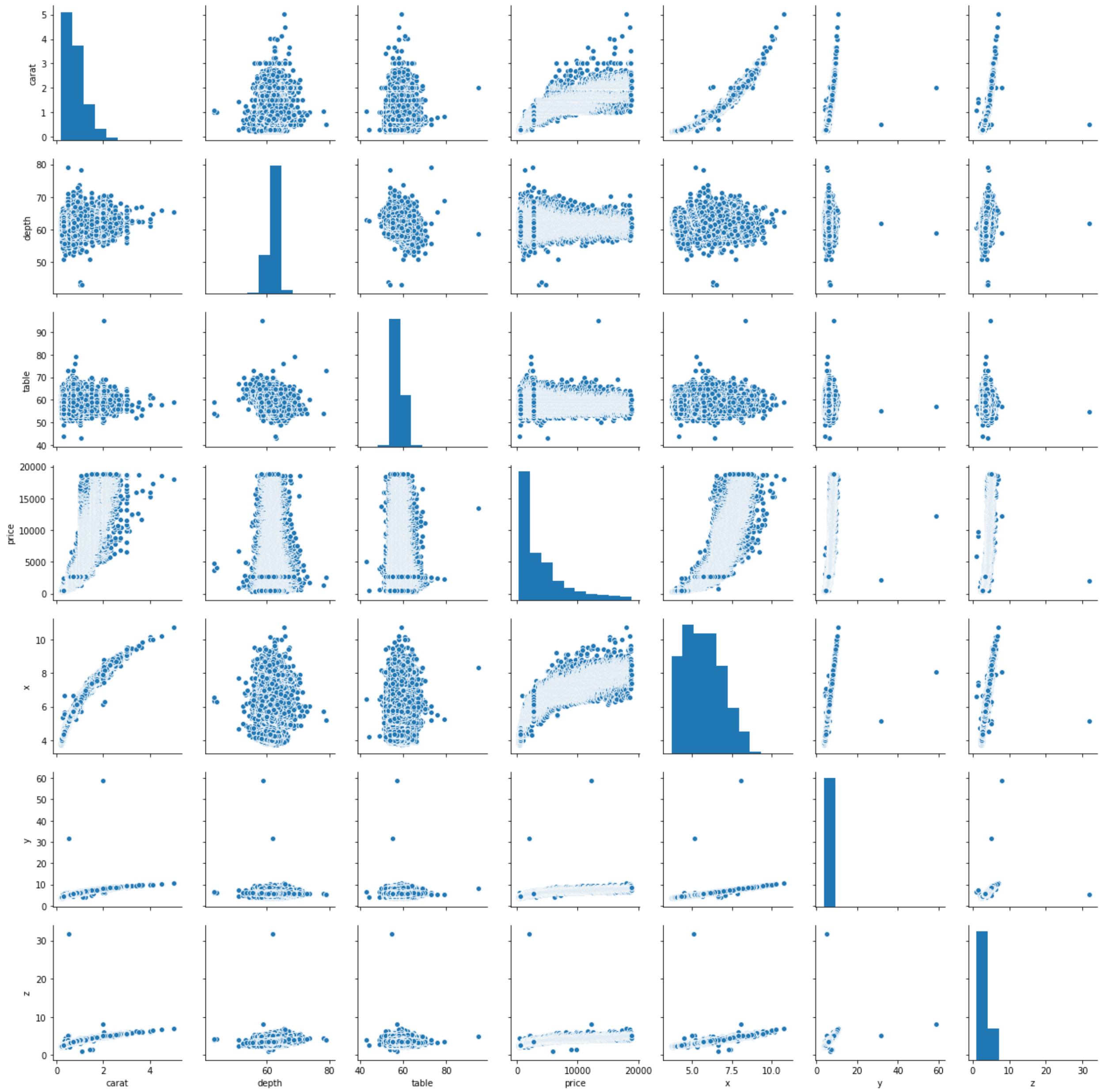
```
#Dropping dimentionless daimonds
df=df.drop(df[df["x"]==0].index)
df=df.drop(df[df["y"]==0].index)
df=df.drop(df[df["z"]==0].index)
```

```
df.shape #lesser than previous size
            #We lost 20 data points by deleting the dimensionless(2-D or 1-D) diamonds.
```

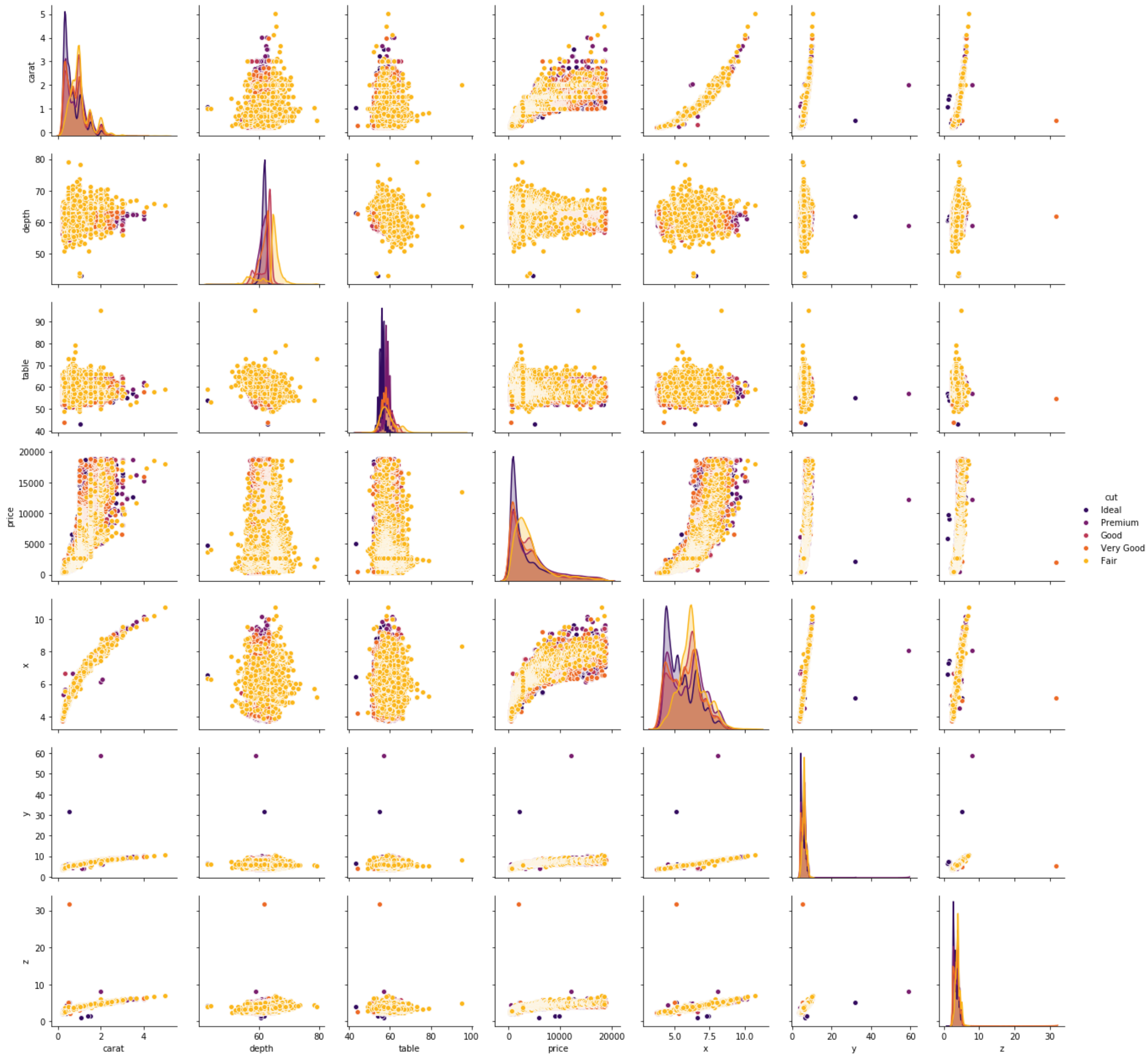
```
(53923, 10)
```

- Let's look at the pair plot of the dataset. Pair plot allows us to see both the distribution of variables and also the relationships between two variables

```
ax = sb.pairplot(df,palette="inferno")  #without hue attribute
                                           #its very difficult to identify the out laiyers
```




```
#plotting the data in pair plot where we get clear relations between every column
ax = sb.pairplot(df, hue= "cut",palette="inferno")
                                                    #inferno is an inbuild palette
```

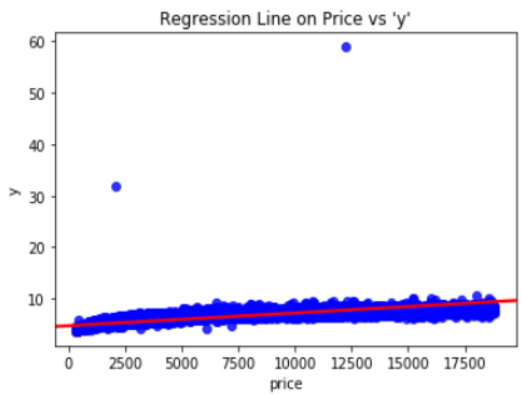


There are some features with datapoint that are far from the rest of the dataset which will affect the outcome of our regression model.

"y" and "z" have some dimensional outlies in our dataset that needs to be eliminated. "depth","table" also have some outliers to remove

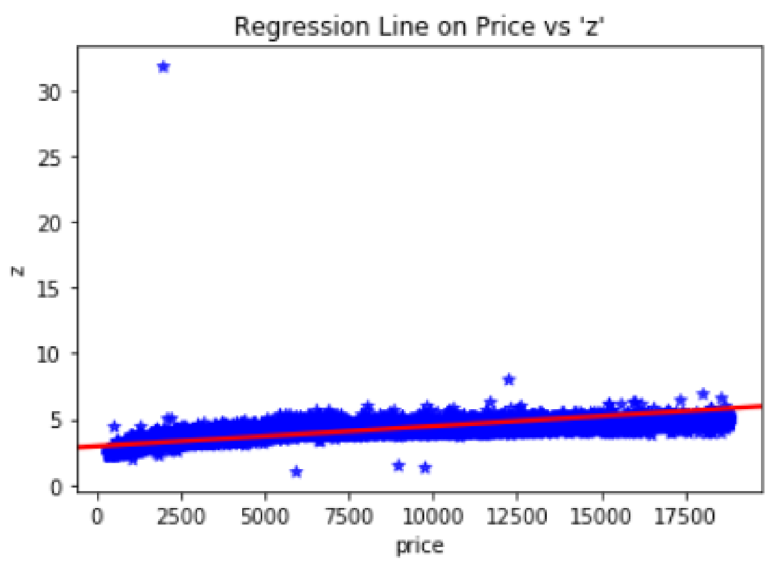
```
# look at regression plots to get a close look at the outliers.
ax = sb.regplot(x="price", y="y", data=df, fit_reg=True, scatter_kws={"color": "blue"}, line_kws={"color": "red"})
ax.set_title("Regression Line on Price vs 'y'")
#observing the plot,we find that after 30 we ingnore the points(outliers)....
#we don't take points above 30,therefore 30 is the boundary line
```

```
Text(0.5, 1.0, "Regression Line on Price vs 'y'")
```



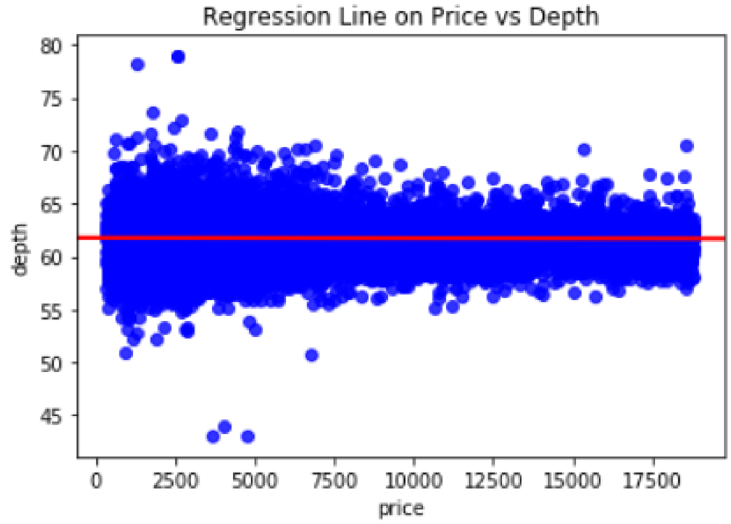

```
ax= sb.regplot(x="price", y="z", data=df, fit_reg=True, scatter_kws={"color": "blue"}, line_kws={"color": "red"},marker="*")
ax.set_title("Regression Line on Price vs 'z'")

#i can consider any boundary(12,15,20,....)clearly observed in graph
```



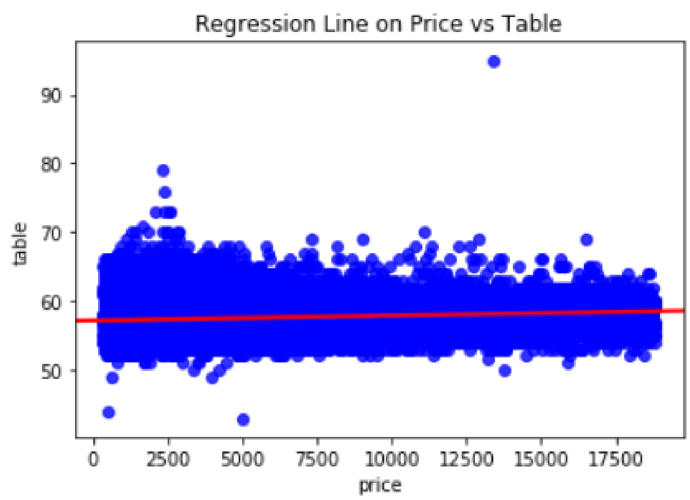

```
ax= sb.regplot(x="price", y="depth", data=df, fit_reg=True, scatter_kws={"color": "blue"}, line_kws={"color": "red"})
ax.set_title("Regression Line on Price vs Depth")


#i an take 75 as first boundary and 45 as my second boundary (outliers)
```




```
ax=sb.regplot(x="price", y="table", data=df, fit_reg=True, scatter_kws={"color": "blue"}, line_kws={"color": "red"})
ax.set_title("Regression Line on Price vs Table")

#i can take 75,80 as my first boundary line and 50 or 45 as my second boundary line
```



- Removing Outliers

```
#Dropping the outliers.
df = df[(df["depth"]<75)&(df["depth"]>45)]
df = df[(df["table"]<80)&(df["table"]>40)]
df = df[(df["x"]<30)]
df = df[(df["y"]<30)]
df = df[(df["z"]<30)&(df["z"]>2)]
df.shape
```

```
(53910, 10)
```

```
df["vol"] = df.x * df.y * df.z
df.head()
```

	carat	cut	color	clarity	depth	table	price	x	y	z	vol
0	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43	38.202030
1	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31	34.505856
2	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31	38.076885
3	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63	46.724580
4	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75	51.917250

NOW REMOVING x,y,z columns

```
df.drop(["x","y","z"], axis=1, inplace=True)
df.head()
```

	carat	cut	color	clarity	depth	table	price	vol
0	0.23	Ideal	E	SI2	61.5	55.0	326	38.202030
1	0.21	Premium	E	SI1	59.8	61.0	326	34.505856
2	0.23	Good	E	VS1	56.9	65.0	327	38.076885
3	0.29	Premium	I	VS2	62.4	58.0	334	46.724580
4	0.31	Good	J	SI2	63.3	58.0	335	51.917250

- Create dummy variables

```
# Getting list of categorical variables
s =( df.dtypes =="object")
s
```

```
carat       False
cut          True
color        True
clarity      True
depth       False
table       False
price       False
vol         False
dtype: bool
```

Create dummy variables:

```
cols = list(s[s].index)
print("Categorical variables:")
print(cols)
```

```
Categorical variables:
['cut', 'color', 'clarity']
```

```
df.cut.unique()
```

```
array(['Ideal', 'Premium', 'Good', 'Very Good', 'Fair'], dtype=object)
```

```
df.cut.replace({"Ideal":5, "Premium":4, "Good":2,"Very Good":3,"Fair":1}, inplace=True)
df.head()
```

	carat	cut	color	clarity	depth	table	price	vol
0	0.23	5	E	SI2	61.5	55.0	326	38.202030
1	0.21	4	E	SI1	59.8	61.0	326	34.505856
2	0.23	2	E	VS1	56.9	65.0	327	38.076885
3	0.29	4	I	VS2	62.4	58.0	334	46.724580
4	0.31	2	J	SI2	63.3	58.0	335	51.917250

Creating dummy variable in color:

```
df.color.unique()
```

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

```
df.color.replace({"E":2, "I":6, "J":7, "H":5, "F":3, "G":4, "D":1}, inplace=True)
df.head()
```

	carat	cut	color	clarity	depth	table	price	vol
0	0.23	5	2	SI2	61.5	55.0	326	38.202030
1	0.21	4	2	SI1	59.8	61.0	326	34.505856
2	0.23	2	2	VS1	56.9	65.0	327	38.076885
3	0.29	4	6	VS2	62.4	58.0	334	46.724580
4	0.31	2	7	SI2	63.3	58.0	335	51.917250

Create dummy variables in clarity:

```
df.clarity.unique()
```

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

```
df.clarity.replace({"SI2":1, "SI1":2, "VS1":3, "VS2":4, "VVS2":5, "VVS1":6, "I1":7,"IF":8}, inplace=True)
df.head()
```

	carat	cut	color	clarity	depth	table	price	vol
0	0.23	5	2	1	61.5	55.0	326	38.202030
1	0.21	4	2	2	59.8	61.0	326	34.505856
2	0.23	2	2	3	56.9	65.0	327	38.076885
3	0.29	4	6	4	62.4	58.0	334	46.724580
4	0.31	2	7	1	63.3	58.0	335	51.917250

Splitting to Train and Test

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

	carat	cut	color	clarity	depth	table	vol
0	0.23	5	2	1	61.5	55.0	38.202030
1	0.21	4	2	2	59.8	61.0	34.505856
2	0.23	2	2	3	56.9	65.0	38.076885
3	0.29	4	6	4	62.4	58.0	46.724580
4	0.31	2	7	1	63.3	58.0	51.917250

```
y = df["price"]
y.head()
```

```
0    326
1    326
2    327
3    334
4    335
Name: price, dtype: int64
```

We will use the `train_test_split` function to split the dataset into train & validation of the desired percent

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=42)
```

5.Create a regression model

1. I have trained 3 Machine Learning models (Linear Regression, Decision Tree Regressor and Random Forest Regressor) meaning without changing the parameters of each model.

2. For each model, I checked for Overfitting by comparing the R-squared of each model on the test set to the R-squared of that model on the train test.

3. For each model, I created a scatter plot of the true prices from the market versus the predicted price from the model.

Train and Build a Linear Regression Model

```
import sklearn.linear_model as sl
linreg = sl.LinearRegression()
linreg.fit(X_train, y_train)
print("R squared of the Linear Regression on training set: {:.2%}".format(linreg.score(X_train, y_train)))
print("R squared of the Linear Regression on test set: {:.2%}".format(linreg.score(X_test, y_test)))
```

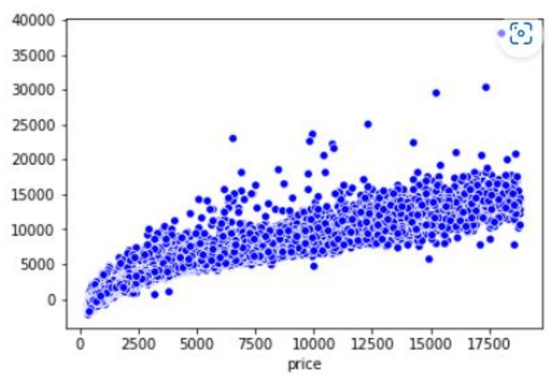
R squared of the Linear Regression on training set: 88.34%

R squared of the Linear Regression on test set: 88.43%

The R squared on the training set is almost equal to the R squared on the test set. This is an indicative that our linear regression model is not overfitting and therefore generalizing well to new data.

In addition, in our linear regression model, 88.43% of the variability in the diamond prices can be explained using the 7 feature we chose (i.e., carat, cut, color, clarity, table, depth, and vol). This is very good.

```
y_pred = linreg.predict(X_test)
sb.scatterplot(x=y_test , y=y_pred, color="blue")
```



Train and Build a Decision Tree Regressor Model

```
import sklearn.tree as st
tree = st.DecisionTreeRegressor(random_state=42)
tree.fit(X_train, y_train)
print("R squared of the Decision Tree Regressor on training set: {:.2%}".format(tree.score(X_train, y_train)))
print("R squared of the Decision Tree Regressor on test set: {:.2%}".format(tree.score(X_test, y_test)))
```

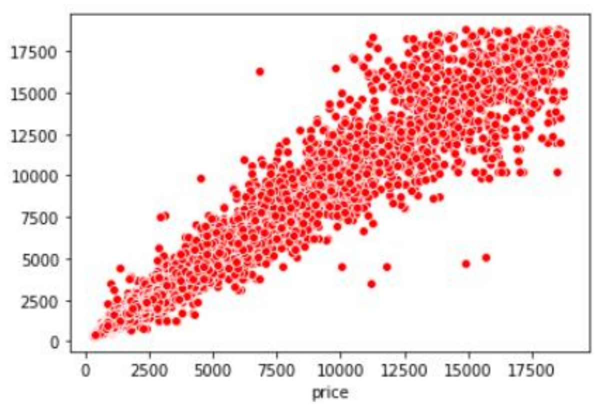
R squared of the Decision Tree Regressor on training set: 99.99%

R squared of the Decision Tree Regressor on test set: 96.43%

The R squared on the training set is a bit higher than the R squared on the test set, but that doesn't mean that our decision tree regressor model is overfitting. On the contrary, our decision tree regressor model is generalizing well to new data.

In addition, in our decision tree regressor model, 96.43% of the variability in the diamond prices can be explained using the 7 feature we chose (i.e., carat, cut, color, clarity, table, depth, and vol). This is excellent.

```
y_pred1 = tree.predict(X_test)
sb.scatterplot(x=y_test , y=y_pred1, color="red")
```



Train and Build a Random Forest Regressor Model

```
import sklearn.ensemble as se
rf = se.RandomForestRegressor(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)
print('R squared of the Random Forest Regressor on training set: {:.2%}'.format(rf.score(X_train, y_train)))
print('R squared of the Random Forest Regressor on test set: {:.2%}'.format(rf.score(X_test, y_test)))
```

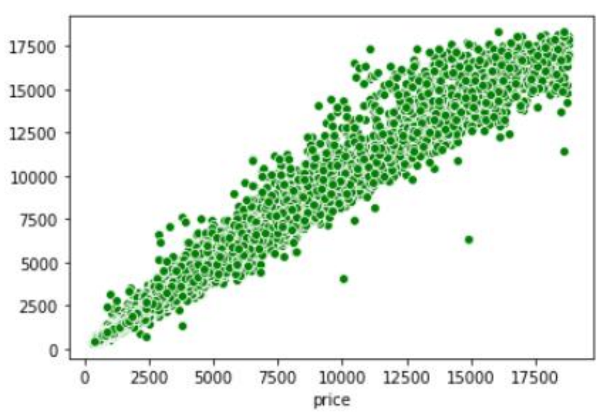
R squared of the Random Forest Regressor on training set: 99.72%

R squared of the Random Forest Regressor on test set: 97.98%

The R squared on the training set is a bit higher than the R squared on the test set, but that doesn't mean that our random forest regressor model is overfitting. On the contrary, our random forest regressor model is generalizing well to new data.

In addition, in our random forest regressor model, 97.98% of the variability in the diamond prices can be explained using the 7 feature we chose (i.e., carat, cut, color, clarity, table, depth, and vol). This is excellent.

```
y_pred2 = rf.predict(X_test)
sb.scatterplot(x=y_test , y=y_pred2, color="green")
```



Step 5 — Evaluation:

This step will be for evaluating factors such as the accuracy and generality of the model. In addition to this, the process must also be put through a fine-combed **inspection** to ensure that there are no errors.

I checked the models MAE scores on the test set.

- Evaluating the Linear Regression Model

```
d = {"true": y_test, "predicted": y_pred}
df_lr = pd.DataFrame(data=d)
df_lr["diff"] = df_lr["predicted"]-df_lr["true"]
df_lr
```

	true	predicted	diff
9810	4669	6936.747326	2267.747326
20220	8653	10837.064332	2184.064332
37235	975	1408.073356	433.073356
25605	14474	11062.714245	-3411.285755
29982	716	580.031117	-135.968883
...	...	...	...
10165	4730	7652.729910	2922.729910
16594	6628	7781.360595	1153.360595
51700	2400	3343.007701	943.007701
14897	5998	5922.332573	-75.667427
47294	394	-1684.304652	-2078.304652

17791 rows × 3 columns

```
from sklearn.metrics import mean_absolute_error as mae
print("Mean Absolute Error of the Linear Regression on test set is {:.2f}".format(mae(y_test,y_pred1)))
```

Mean Absolute Error of the Linear Regression on test set is 362.60

Our linear regression model was able to predict the price of every diamond in the test set with an error of ± $362.60 of the real price.

- Evaluating the Decision Tree Regressor Model

```
d = {'true': y_test, 'predicted': y_pred1}
df_dt = pd.DataFrame(data=d)
df_dt["diff"] = df_dt['predicted']-df_dt['true']
df_dt
```

	true	predicted	diff
9810	4669	5962.0	1293.0
20220	8653	12058.0	3405.0
37235	975	912.0	-63.0
25605	14474	13553.0	-921.0
29982	716	716.0	0.0
...	...	...	...
10165	4730	6405.0	1675.0
16594	6628	7291.0	663.0
51700	2400	2362.0	-38.0
14897	5998	5890.0	-108.0
47294	394	394.0	0.0

17791 rows × 3 columns

```
print('Mean Absolute Error of the Decision Tree Regressor on test set is {:.2f}'.format(mae(y_test,y_pred1)))
```

Mean Absolute Error of the Decision Tree Regressor on test set is 362.60

Our decision tree regressor model was able to predict the price of every diamond in the test set with an error of ± $362.60 of the real price.

- Evaluating the Random Forest Regressor Model

```
d = {"true": y_test,"predicted": y_pred2}
df_rf = pd.DataFrame(data=d)
df_rf["diff"] = df_rf["predicted"]-df_rf["true"]
df_rf
```

	true	predicted	diff
9810	4669	5804.955000	1135.955000
20220	8653	11483.301071	2830.301071
37235	975	928.910500	-46.089500
25605	14474	13498.548333	-975.451667
29982	716	780.382500	64.382500
...	...	...	...
10165	4730	5977.465714	1247.465714
16594	6628	6612.737857	-15.262143
51700	2400	2679.376667	279.376667
14897	5998	5847.977500	-150.022500
47294	394	409.596167	15.596167

```
print("\033[1m Mean Absolute Error of the Random Forest Regressor on test set is {:.2f}".format(mae(y_test,y_pred2)))
```

Mean Absolute Error of the Random Forest Regressor on test set is 285.06

Our random forest regressor model was able to predict the price of every diamond in the test set with an error of ± $285.06 of the real price.

Selected Model

I chose the Random Forest Regressor model as the best model among the three, based on its MAE scores on the test set.

```
model = rf
model
```

```
Out[94]: RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
                               max_features='auto', max_leaf_nodes=None,
                               min_impurity_decrease=0.0, min_impurity_split=None,
                               min_samples_leaf=1, min_samples_split=2,
                               min_weight_fraction_leaf=0.0, n_estimators=100,
                               n_jobs=None, oob_score=False, random_state=42, verbose=0,
                               warm_start=False)
```

So, our Random Forest model is a pretty good model for predicting the market price of a diamond. Now how do we predict the market price of a new diamond new diamond?

Suppose there is a new diamond which has: **carat**=0.23, **cut**=5 (Ideal), **color**=2 (E), **clarity**=1 (SI2), **depth**=61.5, **table**=55, **vol**=38.20 (x=3.95, y=3.98 and z=2.43).

```
new_diamond = [0.23, 5, 2, 1, 61.5, 55, 38.20]
prediction = rf.predict([new_diamond])
print("\033[1m The market price of this new diamond is ${:.2f}".format(prediction))
```

```
 The market price of this new diamond is $379.82
```

In Conclusion