Diamond Price Modelling

This is my first ever machine learning project. I will be applying what I've learnt so far (since 2 weeks) on this data set.

In this notebook, we will explore the factors that affect the price of a diamond with a goal of finding a model to help predict the price of diamonds.

Notice

- The problem is requires **Supervised Learning**. The instances come with an expected output (*i.e* **the diamond's price**).
- Predicting the price of a diamond from dataset is a **Regression Task**. More specifically, a **Multivariate Regression Task**.
- We will be using the **Batch Learning** technique since the data is not live-fed from a source.
- We will also be the **Root Mean Square Error (RMSE)** for our performance measure (typical for Regression tasks).

If you like this notebook, please up-vote! It keeps me motivated. Thank you! :)

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

import warnings
warnings.filterwarnings("ignore")

%matplotlib inline

# Load the diamond's dataset
diamonds = pd.read_csv("diamonds.csv")
```

Take a quick look at the Data Structure

Let's take a quick look at our diamonds dataset.

```
# Preview the top (five) rows of the dataset
diamonds.head()
```

	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

A little more information about our dataset.

```
# Preview the little information about dataset
diamonds.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53940 entries, 0 to 53939
Data columns (total 11 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Unnamed: 0  53940 non-null  int64  
 1   carat       53940 non-null  float64
 2   cut         53940 non-null  object 
 3   color       53940 non-null  object 
 4   clarity     53940 non-null  object 
 5   depth       53940 non-null  float64
 6   table       53940 non-null  float64
 7   price       53940 non-null  int64  
 8   x           53940 non-null  float64
 9   y           53940 non-null  float64
 10  z           53940 non-null  float64
```

```
dtypes: float64(6), int64(2), object(3)
memory usage: 4.5+ MB
```

Noticed an unnecessary column `Unnamed: 0`. It just acts as index, it is not needed, thus that needs to be dropped.

```
# Drop the "Unnamed: 0" column
diamonds = diamonds.drop("Unnamed: 0", axis = 1)

# Price is int64, best if all numeric attributes have the same datatype, especial
diamonds["price"] = diamonds["price"].astype(float)

# Preview dataset again
diamonds.head()
```

	carat	cut	color	clarity	depth	table	price	x	y	z
0	0.23	Ideal	E	SI2	61.5	55.0	326.0	3.95	3.98	2.43
1	0.21	Premium	E	SI1	59.8	61.0	326.0	3.89	3.84	2.31
2	0.23	Good	E	VS1	56.9	65.0	327.0	4.05	4.07	2.31
3	0.29	Premium	I	VS2	62.4	58.0	334.0	4.20	4.23	2.63
4	0.31	Good	J	SI2	63.3	58.0	335.0	4.34	4.35	2.75

There are **53490** instances in the dataset. There are also no missing instances in the dataset. *That looks clean!*

It's easier to work a dataset when all its attributes are numerical. The **cut**, **color** and **clarity** attributes are non-numeric (They are *objects*). We still have to convert them to be numerical.

Let's find out what categories exist for each of them.

```
# The diamond cut categories
diamonds["cut"].value_counts()
```

```
Ideal        21551
Premium      13791
Very Good    12082
Good          4906
Fair          1610
Name: cut, dtype: int64
```

```
# The diamond color categories
diamonds["color"].value_counts()
```

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

```
# The diamond clarity categories
diamonds["clarity"].value_counts()
```

```
SI1     13065
VS2     12258
SI2      9194
VS1      8171
VVS2     5066
VVS1     3655
IF       1790
I1        741
Name: clarity, dtype: int64
```

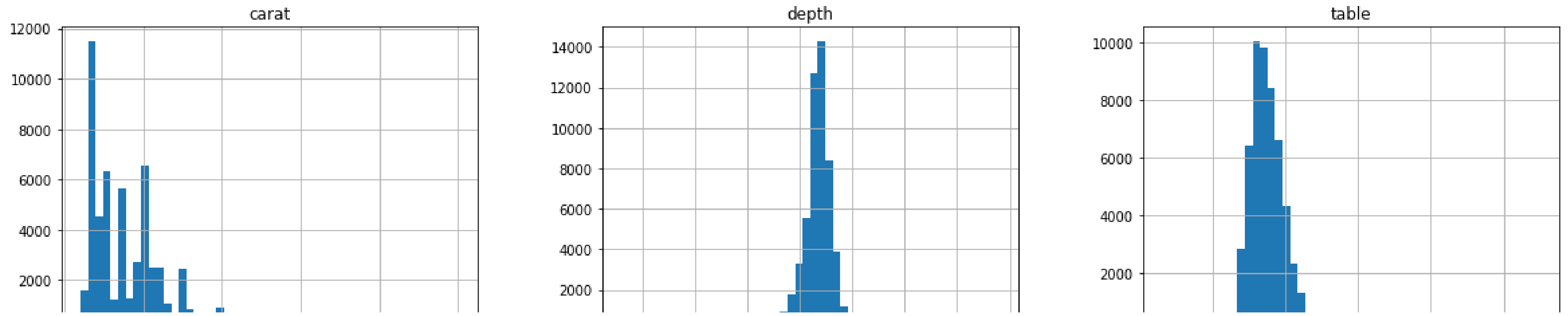
They each don't have so many categories, but still, we will be having a much longer table (*more columns*). That aside for now.

Let's take a preview of the summary of the numerical attributes and then an histogram on the dataset.

```
# Summary of each numerical attribute
# Summary of each numerical attribute
diamonds.describe()
```

	carat	depth	table	price	x	y	z
count	53940.000000	53940.000000	53940.000000	53940.000000	53940.000000	53940.000000	53940.000000
mean	0.797940	61.749405	57.457184	3932.799722	5.731157	5.734526	3.538734
std	0.474011	1.432621	2.234491	3989.439738	1.121761	1.142135	0.705699
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	5324.250000	6.540000	6.540000	4.040000
max	5.010000	79.000000	95.000000	18823.000000	10.740000	58.900000	31.800000

```
diamonds.hist(bins = 50, figsize = (20, 15))
plt.show()
```



Okay good! But what about the categorical attributes? What happens to them now? We are still going to make out a solution for them. But there's also something important we have to do and that is "**Creating a Test Set**".

Create a Test Set

I've learnt it is a good practice to separate your **Train Set** and **Test Set** (80% and 20% from your dataset respectively). The Test set will make us see our model's performance on the new instances.

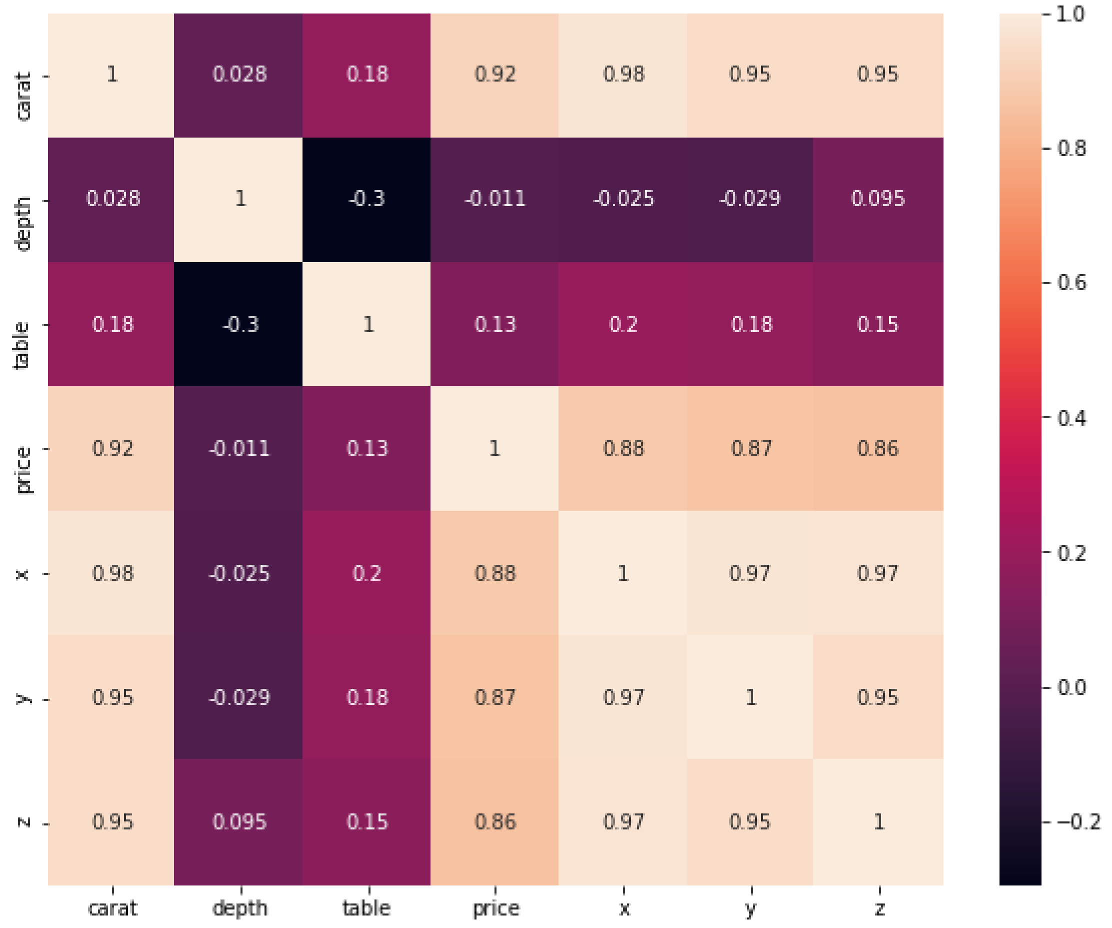
That's clear! **But**, even though we want to do this, it doesn't feel right taking purely random samples of the dataset, else we could introduce a significant **Sampling Bias**. A good solution is by performing **Stratified Sampling**. The dataset will be divided into homogeneous subgroups called strata, and the right number of instances is sampled from each stratum to guarantee that the test set is representative of the overall dataset. (*Hopefully, that's clear enough*)

To use this, we will need a very important attribute of the dataset to predict the of the diamond. How can we try select the attribute even though the team of those who gave you data didn't give you a clue? This is where we need to know the attributes that are most correlated to the price of the diamond. We use the **Standard Correlation Coefficient** (Pearson's r) to determine.

```
# Create a correlation matrix between every pair of attributes
corr_matrix = diamonds.corr()

# Plot the correlation with seaborn
plt.subplots(figsize = (10, 8))
sns.heatmap(corr_matrix, annot = True)
plt.show()
```

```
    plt.show()
```



	carat	depth	table	price	x	y	z
carat	1	0.028	0.18	0.92	0.98	0.95	0.95
depth	0.028	1	-0.3	-0.011	-0.025	-0.029	0.095
table	0.18	-0.3	1	0.13	0.2	0.18	0.15
price	0.92	-0.011	0.13	1	0.88	0.87	0.86
x	0.98	-0.025	0.2	0.88	1	0.97	0.97
y	0.95	-0.029	0.18	0.87	0.97	1	0.95
z	0.95	0.095	0.15	0.86	0.97	0.95	1

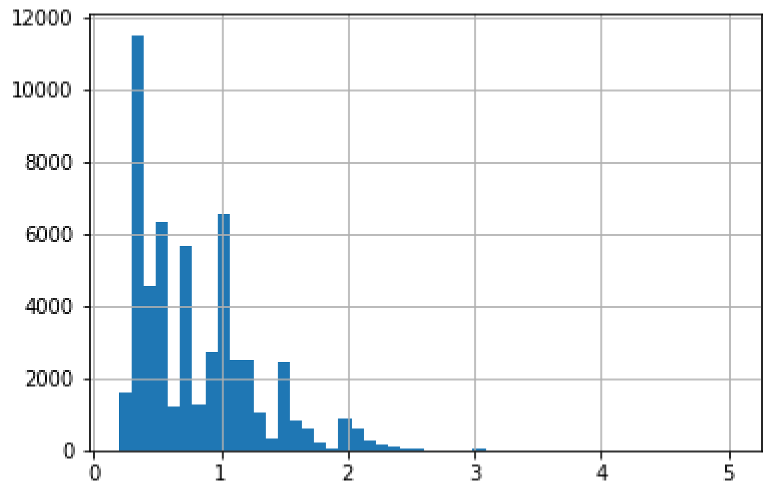
From the plot above, we could deduce that:

- `x`, `y`, `z` have strong correlations with `price`
- `carat` has the strongest correlation with `price` (0.92)
- `table` and `depth` have the weakest correlations

It is amazing so see that `carat` correlates best with price. Its score is pretty high! Now we use this for our *Stratified Sampling*.

Let's take a closer look at the `carat`'s histogram.

```
diamonds["carat"].hist(bins = 50)
plt.show()
```



Most diamonds are roughly between 0.3 and 1.5 Carats. Let's divide them into 5 categories, with those more than the 5th category merging into the 5th category.

```
# Divide the diamond carats by 0.4 to limit the number of carat categories
# Round up to have discrete categories
diamonds["carat_cat"] = np.ceil(diamonds["carat"] / 0.35)

# Merge categories > 5 in 5
diamonds["carat_cat"].where(diamonds["carat_cat"] < 5, 5.0, inplace = True)
```

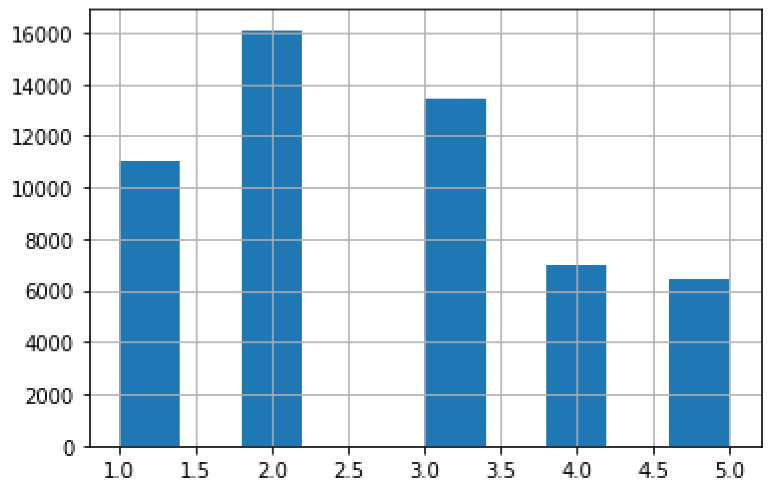
Now let's see how much the diamonds are distributed in relation to the carat categories.

```
# Check the distribution of the diamonds in the categories
diamonds["carat_cat"].value_counts()
```

```
2.0    16104
```

```
3.0    13399
1.0    11058
4.0     6970
5.0     6409
Name: carat_cat, dtype: int64
```

```
diamonds["carat_cat"].hist()
plt.show()
```



The distribution looks nice enough.

PS: I adjusted the divisor of `carat` until the distribution of the diamonds looked nice. *You could comment if you have any other ideas to doing this* :)

And yup! We can now perform a Stratified Sampling based on the carat categories :) I will use Scikit-Learn's `StratifiedShuffleSplit` class.

```
# Import the sklearn module
from sklearn.model_selection import StratifiedShuffleSplit

# Run the split. Creates on split and shares 20% of the dataset for the test set
split = StratifiedShuffleSplit(n_splits = 1, test_size = 0.2, random_state = 42)
```

```
# Separate the stratified train set and the test set
for train_index, test_index in split.split(diamonds, diamonds["carat_cat"]):
    strat_train_set = diamonds.loc[train_index]
    strat_test_set = diamonds.loc[test_index]
```

We now have our Train set and Test set, both stratified. From here, we don't need the `carat_cat` anylonger, hence we can drop it.

```
for set in (strat_train_set, strat_test_set):
    set.drop(["carat_cat"], axis = 1, inplace = True)
```

Our new `diamonds` dataset will now be the *Stratified Train set*.

```
# Redefined diamonds dataset
diamonds = strat_train_set.copy()
diamonds.head()
```

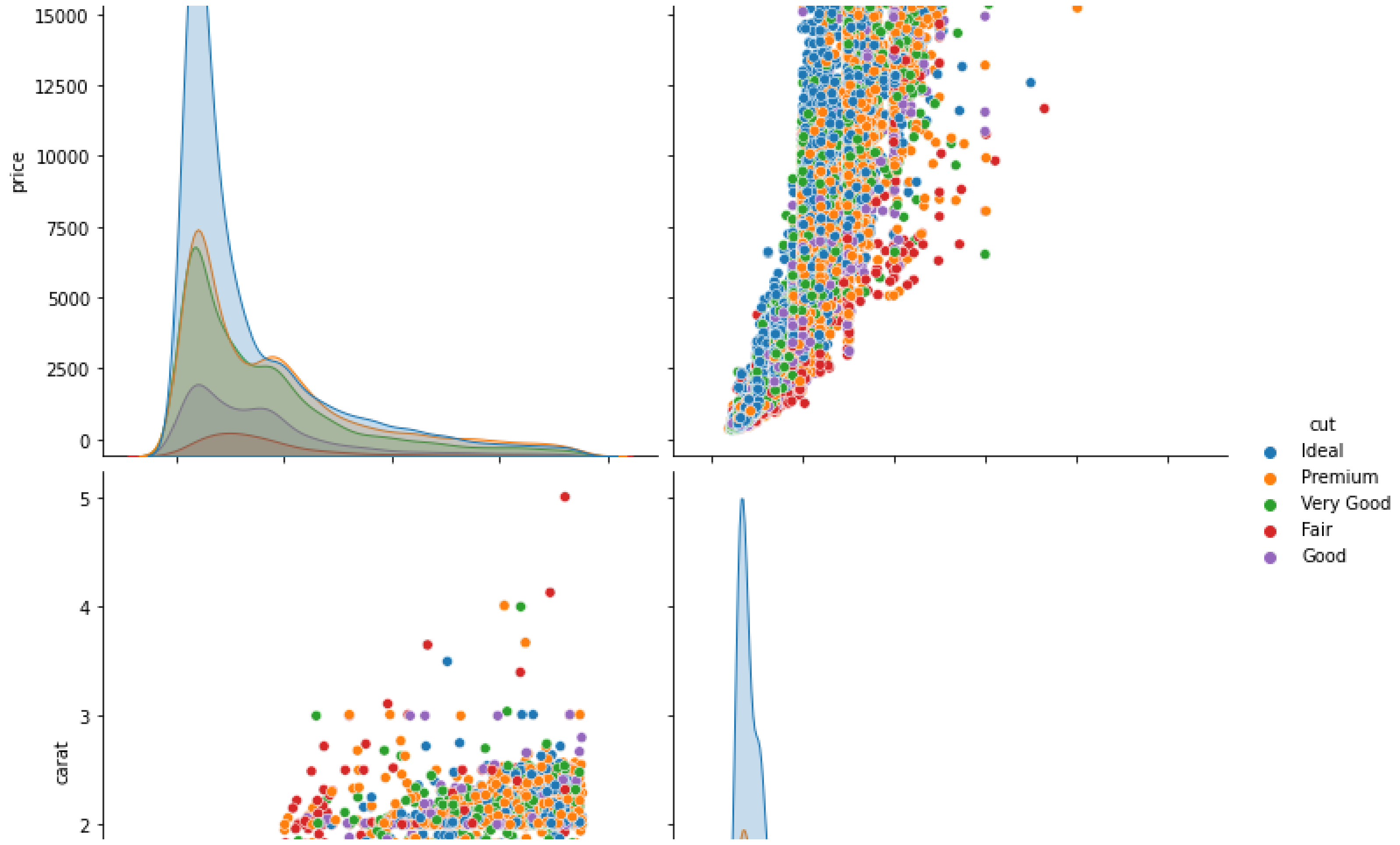
	carat	cut	color	clarity	depth	table	price	x	y	z
7663	1.06	Ideal	I	SI2	61.8	57.0	4270.0	6.57	6.60	4.07
25971	1.51	Premium	G	VVS2	60.9	58.0	15164.0	7.38	7.42	4.51
33471	0.32	Ideal	F	VS2	61.3	56.0	828.0	4.43	4.41	2.71
44281	0.53	Ideal	G	VS2	61.2	56.0	1577.0	5.19	5.22	3.19
53007	0.70	Premium	H	VVS2	61.0	57.0	2596.0	5.76	5.72	3.50

Data Visualization

Let's play around with some visualization of our dataset and make some observations out of it.

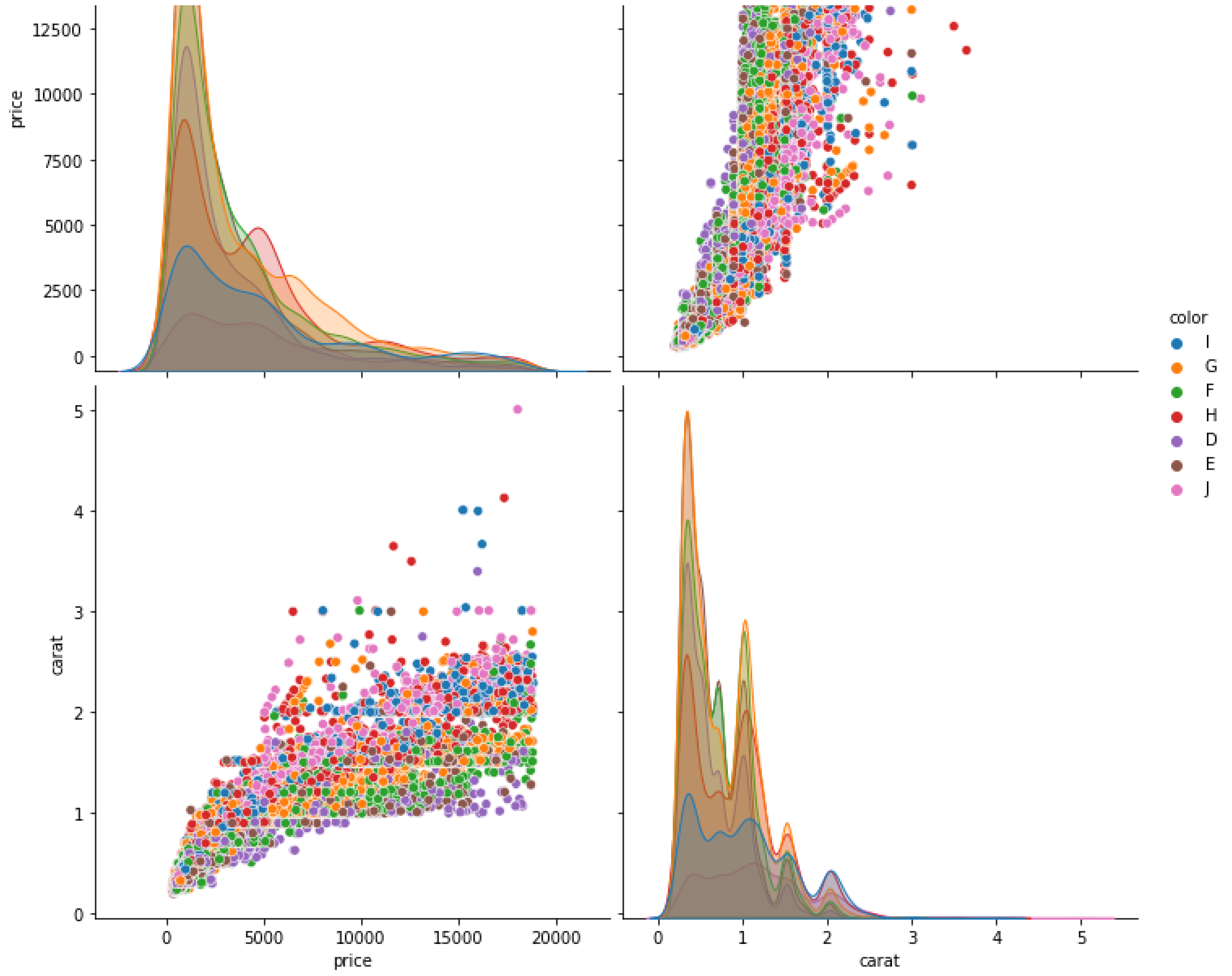
```
sns.pairplot(diamonds[["price", "carat", "cut"]], hue = "cut", height = 5)
plt.show()
```

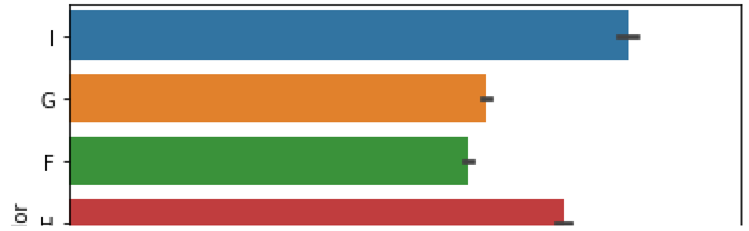
```
    plt.show()
    sns.barplot(x = "carat", y = "cut", data = diamonds)
    plt.show()
    sns.barplot(x = "price", y = "cut", data = diamonds)
    plt.show()
```

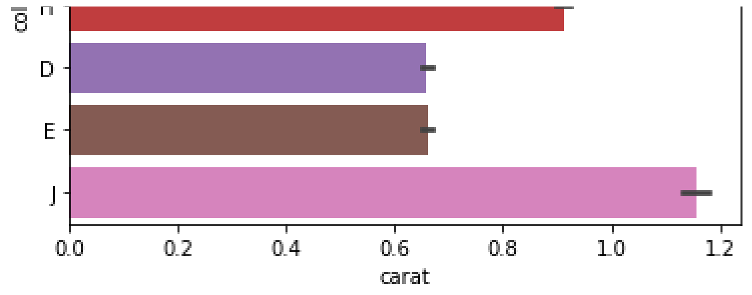


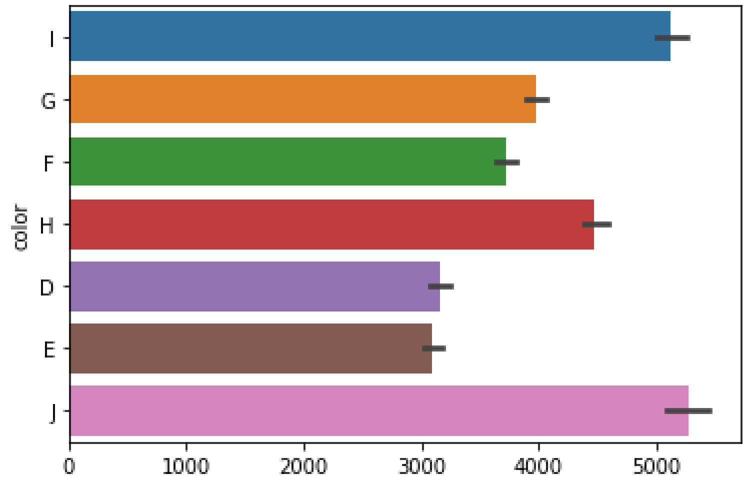
`Fair` cuts are most weighed, but they aren't the most expensive diamonds. `Premium` cuts weigh less than the fair and then cost more. `Ideal` cuts weigh way less and they are least expensive. The cut therefore is relatively considered while determining the price of the diamond.

```
sns.pairplot(diamonds[["price", "carat", "color"]], hue = "color", height = 5)
plt.show()
sns.barplot(x = "carat", y = "color", data = diamonds)
plt.show()
sns.barplot(x = "price", y = "color", data = diamonds)
plt.show()
```


price
carat
color
I
G
F
H
D
E
J

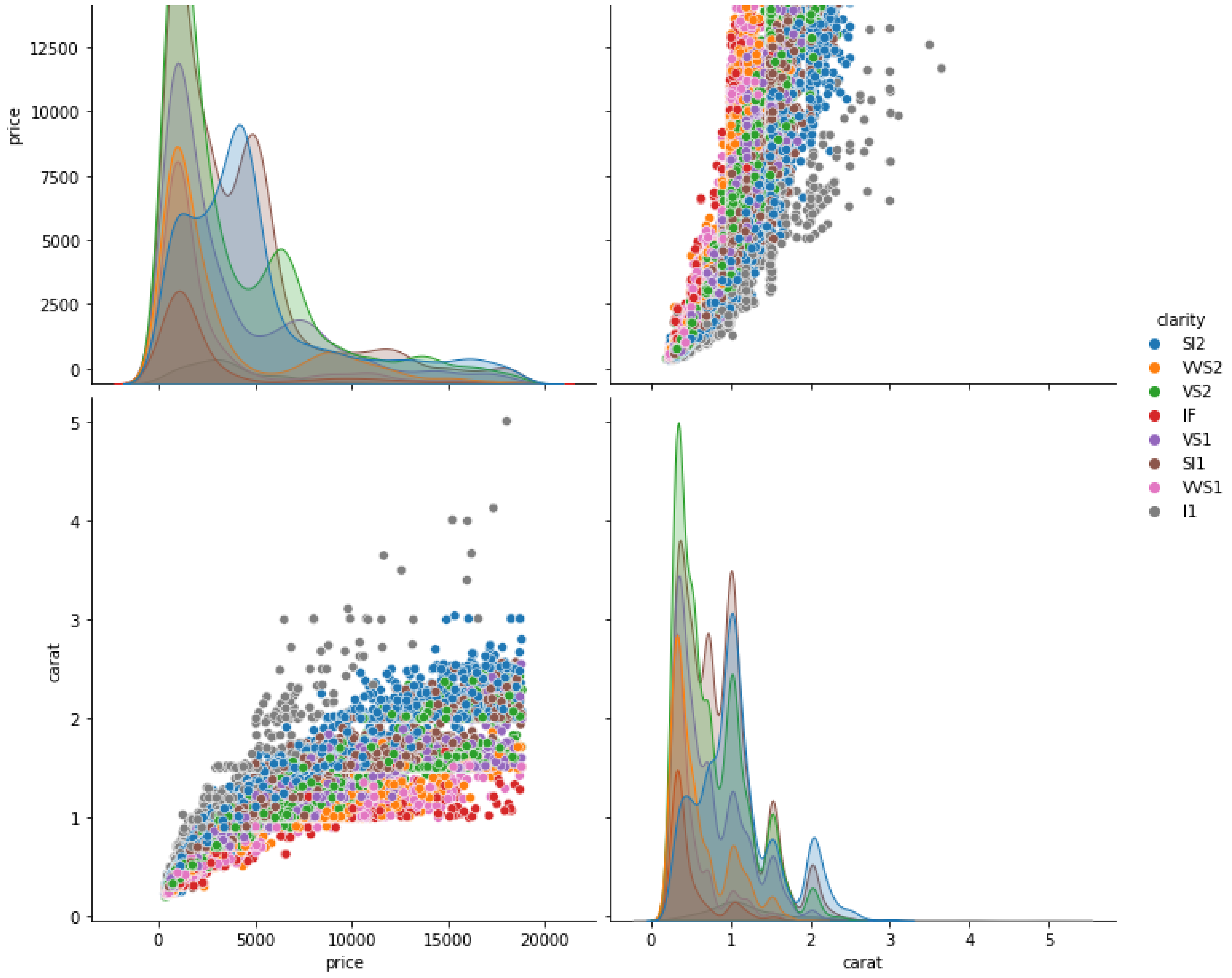

I
G
F

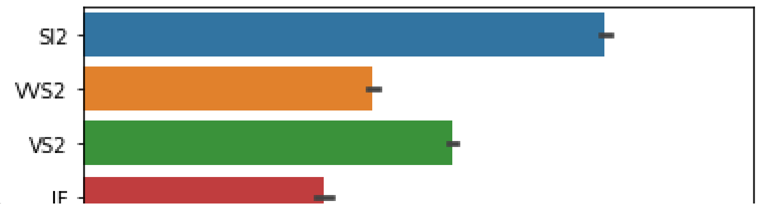


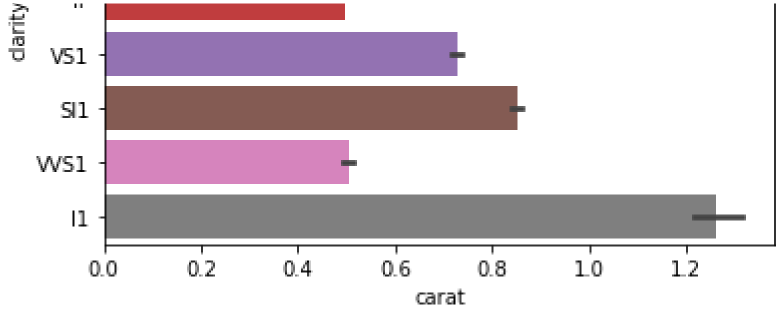


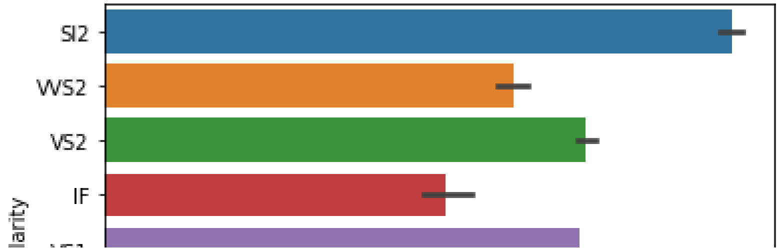
Here, we could see that the color `J` which is the most weighed is also the most priced. The last 2 plots are very similar. We could see here that the color of the diamond is also very dependent on its price.

```
sns.pairplot(diamonds[["price", "carat", "clarity"]], hue = "clarity", height = 5
plt.show()
sns.barplot(x = "carat", y = "clarity", data = diamonds)
plt.show()
sns.barplot(x = "price", y = "clarity", data = diamonds)
plt.show()
```


price
12500
10000
7500
5000
2500
0
carat
5
4
3
2
1
0
0
5000
10000
15000
20000
price
0
1
2
3
4
5
carat
clarity
SI2
VVS2
VS2
IF
VS1
SI1
VVS1
I1


SI2
VVS2
VS2
IF

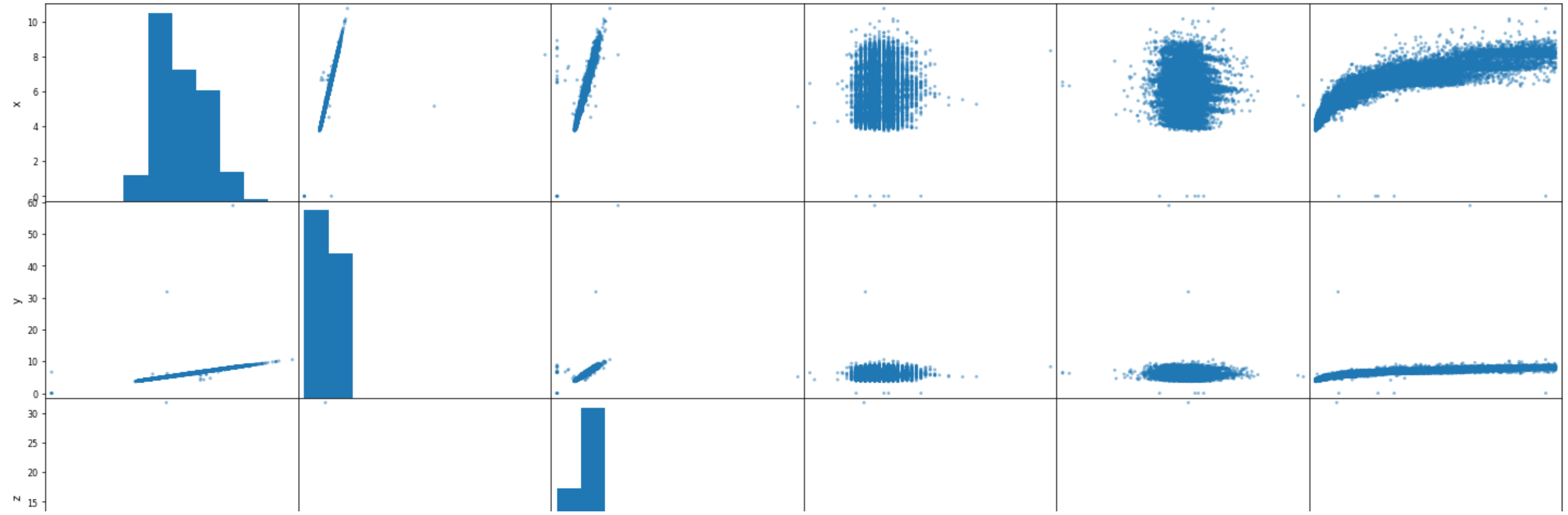




Here, we could see that `I1` doesn't hold the highest clarity, even though it is the most priced. But there's something else: Apart from `I1`, if the rest stays, the price of a diamond could **fairly** be relative to its clarity, to some extent.

```
from pandas.plotting import scatter_matrix

attributes = ["x", "y", "z", "table", "depth", "price"]
scatter_matrix(diamonds[attributes], figsize=(25, 20))
plt.show()
```



These visualizations have been met by our theories during correlation. And it's very obvious here that depth and table have very weak correlation with price.

Feature Scaling

With few exceptions, Machine Learning algrorithms don't perform well when the input numerical attributes have very different scales. We sure want our models to work well, so how can we go about it?

Feature scaling can be done in 2 ways: **Min-max scaling** and **Standardization**. I would preferably use Standardization, because it is much less affected by outliers. Scikit-Learn provides a transformer called `StandardScaler` for this transformation.

PS: You don't stratify your label, which is in our case `price`.

```
# Do not stratify the label
diamonds = strat_train_set.drop("price", axis = 1)

# Set a new dataset label variable
diamond_labels = strat_train_set["price"].copy()
```

```
# Drop all the category, so we could have only numeric
diamonds_num = diamonds.drop(["cut", "color", "clarity"], axis = 1)
diamonds_num.head()
```

	carat	depth	table	x	y	z
7663	1.06	61.8	57.0	6.57	6.60	4.07
25971	1.51	60.9	58.0	7.38	7.42	4.51
33471	0.32	61.3	56.0	4.43	4.41	2.71
44281	0.53	61.2	56.0	5.19	5.22	3.19
53007	0.70	61.0	57.0	5.76	5.72	3.50

```
from sklearn.preprocessing import StandardScaler

# Perform the feature scaling on the numeric attributes of the dataset
num_scaler = StandardScaler()
diamonds_num_scaled = num_scaler.fit_transform(diamonds_num)

# Preview
pd.DataFrame(diamonds_num_scaled).head()
```

	0	1	2	3	4	5
0	0.553529	0.036799	-0.205180	0.747755	0.752947	0.750367
1	1.503722	-0.590188	0.242472	1.470153	1.466739	1.371635
2	-1.009010	-0.311527	-0.652832	-1.160802	-1.153397	-1.169914
3	-0.565586	-0.381192	-0.652832	-0.482997	-0.448311	-0.492168
4	-0.206625	-0.520523	-0.205180	0.025357	-0.013072	-0.054456

That is what our data *will* look like during its processing. That's for the Machine Learning algorithm.

Handling Categorical Attributes

From above, we split the columns of our dataset, putting aside the category attributes. Remember we still wanted to convert these attributes to numericaal attributes. How to we go about this?

We create one binary attribute per category: one attribute will be one while the rest will be 0. This is called **One-Hot Encoding**. Scikit-Learn provides a `OneHotEncoder` encoder to convert our category attributes to One-Hot vectors.

```
# We need only the category attributes to work with here
diamonds_cat = diamonds[["cut", "color", "clarity"]]
diamonds_cat.head()
```

	cut	color	clarity
7663	Ideal	I	SI2
25971	Premium	G	VVS2
33471	Ideal	F	VS2
44281	Ideal	G	VS2
53007	Premium	H	VVS2

```
from sklearn.preprocessing import OneHotEncoder

# Perform the one-hot encoding on the category attributes of the dataset
cat_encoder = OneHotEncoder()
diamonds_cat_encoded = cat_encoder.fit_transform(diamonds_cat)

# Convert the encoded categories to arrays and Preview
pd.DataFrame(diamonds_cat_encoded.toarray()).head()
```

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
2	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
3	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
4	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0

Now that's what I meant by a longer table. What do we do next?

Transformation Pipeline

We have our tables reformed, what we do now to to merge the numeric feature scaled attributes and the encoded category attributes. An easy way to do this without writing so much like above is to Scikit-Learn's `ColumnTransformer` class. This merging provides a single pipeline for the whole dataset.

```
from sklearn.compose import ColumnTransformer

num_attribs = list(diamonds_num)
cat_attribs = ["cut", "color", "clarity"]

# Pipeline to transform our dataset
pipeline = ColumnTransformer([
    ("num", StandardScaler(), num_attribs), # Perform feaured scaling on numeric
    ("cat", OneHotEncoder(), cat_attribs) # Perform One-Hot encoding on the categ
])


# Transformed dataset to feed the ML Algorithm
diamonds_ready = pipeline.fit_transform(diamonds)

# Preview
pd.DataFrame(diamonds_ready).head()
```

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
0	0.553529	0.036799	-0.205180	0.747755	0.752947	0.750367	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
1	1.503722	-0.590188	0.242472	1.470153	1.466739	1.371635	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0
2	-1.009010	-0.311527	-0.652832	-1.160802	-1.153397	-1.169914	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
3	-0.565586	-0.381192	-0.652832	-0.482997	-0.448311	-0.492168	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0
4	-0.206625	-0.520523	-0.205180	0.025357	-0.013072	-0.054456	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0

We now have our newly transformed dataset that can easily be fed to our Machine Learning Algorithms.

Select and Train Model

We will create one function that will run through each algorithm. We'll also have variables that hold results of the algorithms for future comparisons. What does our fat function do?

- Fits the dataset into the model and create series of predictions to compare with labels. We check its performance with the **RMSE**.
- Performs some evaluation using Cross validation, which splits the training set into a number of CVs and train the model on the smaller sets. We then compare its mean with our intial RMSE.
- We view how well the model performs on our test set and compare its RMSE with that of the train set. Hopefully we don't have much difference.
- Some accuracy test of the model on the dataset is being evaluated
- We could also have a preview of what's going on. Some parts of the test set will be selected and then the model will run on them and we can then compare its result with the expected prices.
- We also get a preview this model's plot results and see how well it fits

```
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import cross_val_score
from random import randint

# Our test set

# Remove label from test set
X_test = strat_test_set.drop("price", axis = 1)
# Have label stand alone
y_test = strat_test_set["price"].copy()

# Our models performance holder
models_rmse = [] # Holds Models original RMSE
cvs_rmse_mean = [] # Holds the Cross Validation RMSE Mean
tests_rmse = [] # Holds the tests RMSE
tests_accuracy = [] # Holds the tests accuracy
models = [] # Holds the models name

def display_model_performance(model_name, model, diamonds = diamonds_ready, label
                              models_rmse = models_rmse, cvs_rmse_mean = cvs_rmse
                              tests_accuracy = tests_accuracy, pipeline = pipelin
                              y_test = y_test, cv = True):
    # Fit dataset in model
    model.fit(diamonds, labels)

    # Setup predictions
    predictions = model.predict(diamonds)

    # Get models performance
    model_mse = mean_squared_error(labels, predictions)
    model_rmse = np.sqrt(model_mse)

    # Cross validation
    cv_score = cross_val_score(model, diamonds, labels, scoring = "neg_mean_squar
    cv_rmse = np.sqrt(-cv_score)
    cv_rmse_mean = cv_rmse.mean()

    print("RMSE: %.4f" %model_rmse)
    models_rmse.append(model_rmse)
    print("CV-RMSE: %.4f" %cv_rmse_mean)
    cvs_rmse_mean.append(cv_rmse_mean)

    print("--- Test Performance ---")

    X_test_prepared = pipeline.transform(X_test)

    # Fit test dataset in model
    model.fit(X_test_prepared, y_test)

    # Setup test predictions
    test_predictions = model.predict(X_test_prepared)

    # Get models performance on test
    test_model_mse = mean_squared_error(y_test, test_predictions)
    test_model_rmse = np.sqrt(test_model_mse)
    print("RMSE: %.4f" %test_model_rmse)
    tests_rmse.append(test_model_rmse)

    # Tests accuracy
    test_accuracy = round(model.score(X_test_prepared, y_test) * 100, 2)
    print("Accuracy:", str(test_accuracy)+"%")
    tests_accuracy.append(test_accuracy)

    # Check how well model works on Test set by comparing prices
    start = randint(1, len(y_test))
    some_data = X_test.iloc[start:start + 7]
    some_labels = y_test.iloc[start:start + 7]
    some_data_prepared = pipeline.transform(some_data)
    print("Predictions:\t", model.predict(some_data_prepared))
    print("Labels:\t\t", list(some_labels))

    models.append(model_name)

    # Preview plot
    plt.scatter(diamond_labels, model.predict(diamonds_ready))
    plt.xlabel("Actual")
    plt.ylabel("Predicted")
    x_lim = plt.xlim()
    y_lim = plt.ylim()
    plt.plot(x_lim, y_lim, "k--")
    plt.show()

    print("------- Test -------")
    plt.scatter(y_test, model.predict(X_test_prepared))
    plt.xlabel("Actual")
    plt.ylabel("Predicted")
    plt.plot(x_lim, y_lim, "k--")
    plt.show()
```

We can now start fitting models and get their performance error. Remember we are using **Root Mean Squared Error** for our performance measure.

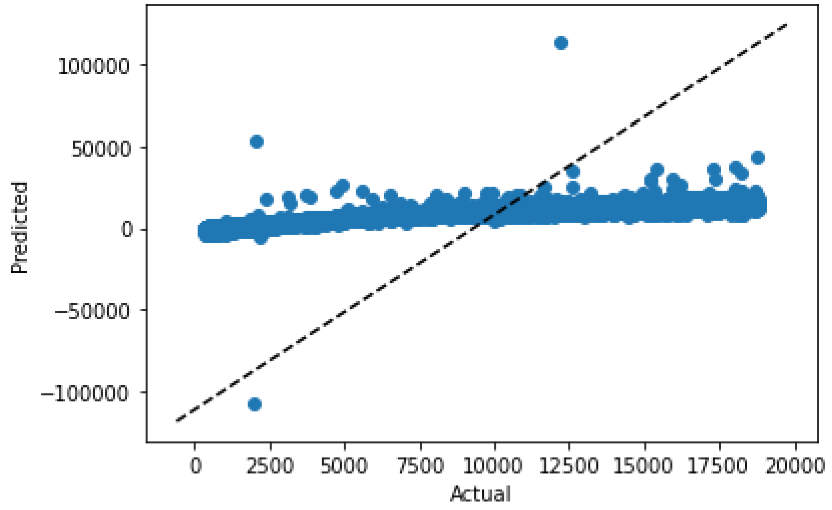
Let's start with the easiest model - `Linear Regression`

Linear Regression

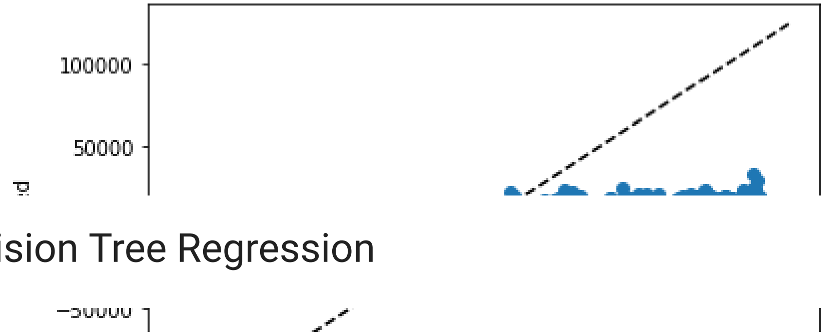
```
from sklearn.linear_model import LinearRegression

lin_reg = LinearRegression(normalize = True)
display_model_performance("Linear Regression", lin_reg)
```

```
RMSE: 1124.7191
CV-RMSE: 1126.2084
--- Test Performance ---
RMSE: 1142.2522
Accuracy: 91.87%
Predictions:     [ 1942.78882269   605.69870135  4265.56512817 -1352.66857764
  4107.11549782  8026.16201137   928.49790285]
Labels:          [1179.0, 1068.0, 4516.0, 418.0, 3462.0, 7092.0, 730.0]
```



```
------- Test -------
```

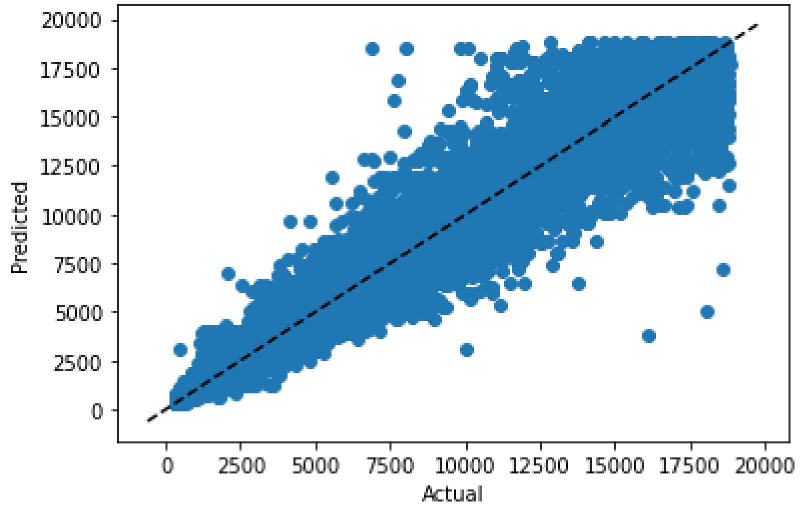


Decision Tree Regression

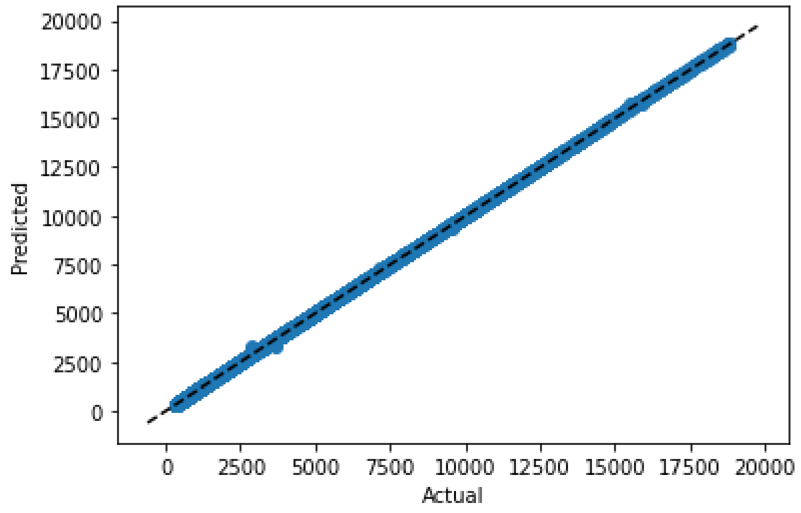
```
from sklearn.tree import DecisionTreeRegressor

tree_reg = DecisionTreeRegressor(random_state = 42)
display_model_performance("Decision Tree Regression", tree_reg)
```

```
RMSE: 8.6134
CV-RMSE: 742.1458
--- Test Performance ---
RMSE: 6.5552
Accuracy: 100.0%
Predictions:     [3977.  710. 1094. 7370. 8580. 2737.  517.]
Labels:          [3977.0, 710.0, 1094.0, 7370.0, 8580.0, 2737.0, 517.0]
```



```
------- Test -------
```



Random Forest Regression

```
from sklearn.ensemble import RandomForestRegressor

forest_reg = RandomForestRegressor(n_estimators = 10, random_state = 42)
display_model_performance("Random Forest Regression", forest_reg)
```

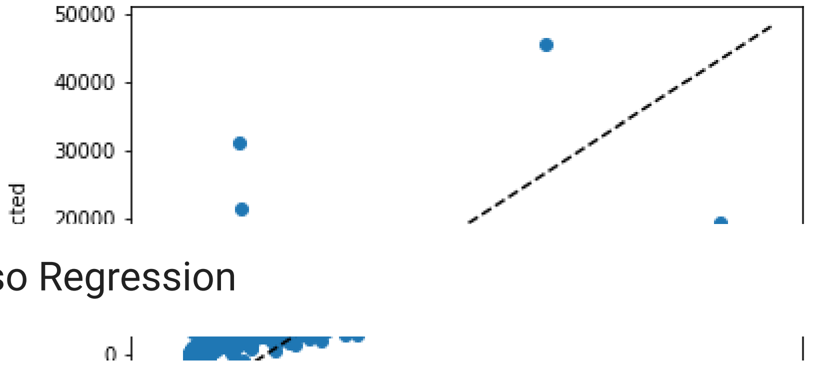
```
RMSE: 237.9667
CV-RMSE: 577.3906
--- Test Performance ---
RMSE: 282.6978
Accuracy: 99.5%
```

Ridge Regression

```
from sklearn.linear_model import Ridge

ridge_reg = Ridge(normalize = True)
display_model_performance("Ridge Regression", ridge_reg)
```

```
RMSE: 1782.0191
CV-RMSE: 1783.2610
--- Test Performance ---
RMSE: 1785.6677
Accuracy: 80.12%
Predictions:     [3156.07068488  883.67737432 5399.63357737 1256.77168655 5234.25563823
 3377.66992933  824.24353381]
Labels:          [1637.0, 781.0, 4560.0, 789.0, 3674.0, 2015.0, 814.0]
```

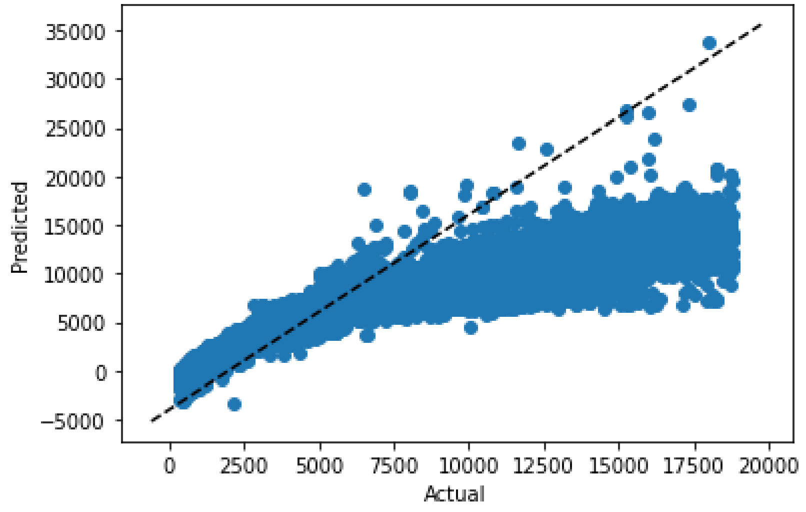


Lasso Regression

```
from sklearn.linear_model import Lasso

lasso_reg = Lasso(normalize = True)
display_model_performance("Lasso Regression", lasso_reg)
```

```
RMSE: 1401.3031
CV-RMSE: 1387.4085
--- Test Performance ---
RMSE: 1255.4279
Accuracy: 90.17%
Predictions:     [6027.07079186  379.51750369 -165.24378291  453.93512253 8906.9871423
 1155.53730433 6159.17000102]
Labels:          [6889.0, 596.0, 863.0, 749.0, 9384.0, 784.0, 5171.0]
```



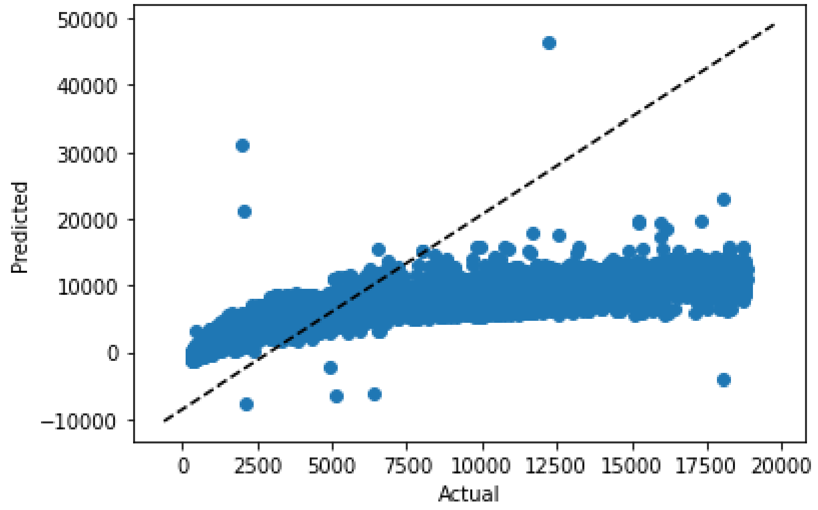
```
------- Test -------
```

Elastic Net Regression

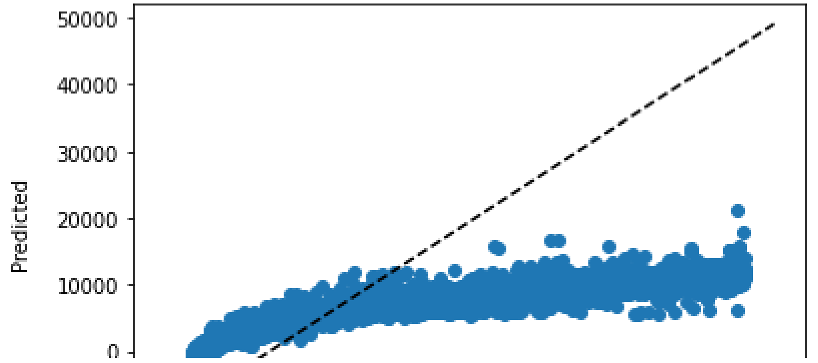
```
from sklearn.linear_model import ElasticNet

net_reg = ElasticNet()
display_model_performance("Elastic Net Regression", net_reg)
```

```
RMSE: 1725.9555
CV-RMSE: 1727.3482
--- Test Performance ---
RMSE: 1735.8126
Accuracy: 81.22%
Predictions:     [6031.4959745  7043.77020758 1088.52898221 4000.63351989  397.943458
 2325.70525022 5571.16531426]
Labels:          [10888.0, 7231.0, 971.0, 2401.0, 1046.0, 1072.0, 5206.0]
```



```
------- Test -------
```



AdaBoost Regression

```
from sklearn.ensemble import AdaBoostRegressor
```

```
ada_reg = AdaBoostRegressor(n_estimators = 100)
display_model_performance("AdaBoost Regression", ada_reg)
```

```
RMSE: 1346.1961
CV-RMSE: 1461.4723
```

GradientBoosting Regression

```
Predictions:     [ 2904.0989011  13442.7864764  1699.99591837  4217.92307692
```

```
from sklearn.ensemble import GradientBoostingRegressor

grad_reg = GradientBoostingRegressor(n_estimators = 100, learning_rate = 0.1,
                                     max_depth = 1, random_state = 42, loss = 'ls
display_model_performance("GradientBoosting Regression", grad_reg)
```

```
RMSE: 1229.1191
CV-RMSE: 1235.6116
--- Test Performance ---
RMSE: 1242.2006
Accuracy: 90.38%
Predictions:     [14555.09165695  3140.03274264  5552.23792393  2256.25608283
  1084.6442308   4214.85214511   869.43605277]
Labels:          [16462.0, 3856.0, 5231.0, 1971.0, 806.0, 3826.0, 765.0]
```

Compare Models Performance

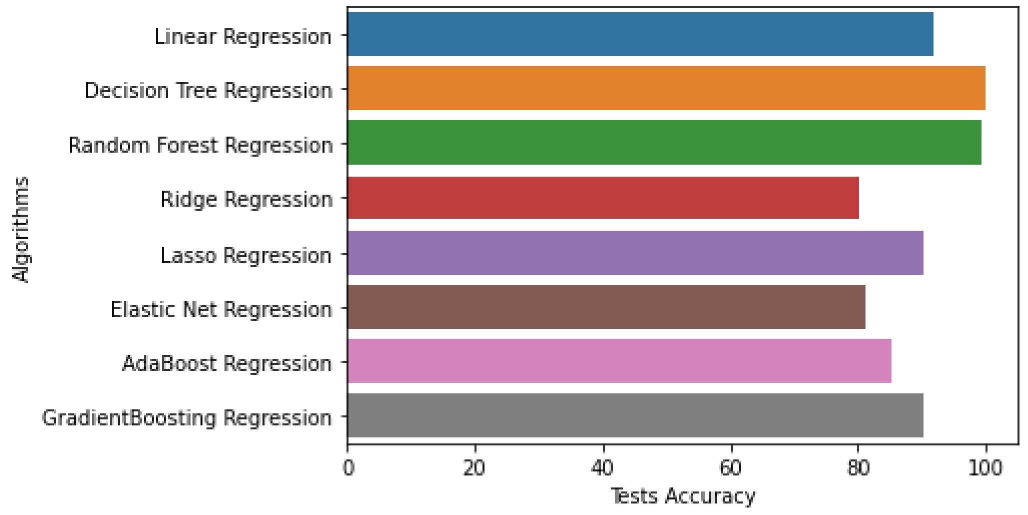
```
compare_models = pd.DataFrame({ "Algorithms": models, "Models RMSE": models_rmse,
                                 "Tests RMSE": tests_rmse, "Tests Accuracy": tests_a
compare_models.sort_values(by = "Tests Accuracy", ascending = False)
```

	Algorithms	Models RMSE	CV RMSE Mean	Tests RMSE	Tests Accuracy
1	Decision Tree Regression	8.613424	742.145838	6.555155	100.00
2	Random Forest Regression	237.966731	577.390633	282.697751	99.50
0	Linear Regression	1124.719103	1126.208443	1142.252184	91.87
7	GradientBoosting Regression	1229.119083	1235.611606	1242.200607	90.38
4	Lasso Regression	1401.303082	1387.408507	1255.427883	90.17
6	AdaBoost Regression	1346.196148	1461.472261	1539.898887	85.22
5	Elastic Net Regression	1725.955500	1727.348165	1735.812583	81.22
3	Ridge Regression	1782.019095	1783.261042	1785.667741	80.12

Okay. I was really surprised seeing some **100% accuracy** from the `Decision Tree Regression` Model. That is just too perfect. Noticed that some dataset from the test set were selected and compared and that was just right!

Another model that we could depend on is the `Random Forest Regression`. It works relatively fine in my opinion.

```
sns.barplot(x = "Tests Accuracy", y = "Algorithms", data = compare_models)
plt.show()
```



Save model

```
import pickle

with open('final_model.pkl', 'wb') as f:
    pickle.dump(tree_reg, f)
```

Conclusion

The **Decision Tree Algorithm** wins it all here!

What do you think about the deduced model? Could it really be? Please comment your opinions.

That's all for now. I'm still learning, so I would love some feedback!

If you find this notebook useful, Please upvote this notebook it keeps me motivated. Also I do look forward to suggestions, so please comment if any. Thank you!

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