Diamond cut analysis

Objective

Objective of this project is to accurately predict the price of a diamond. There are various factors (variables) that affect the price of a diamond. In this project, we will analyze the price of a diamond based on those factors.

Data

Data Sourcing

The data is sourced from kaggle website. https://www.kaggle.com/shivam2503/diamonds (https://www.kaggle.com/shivam2503/diamonds)

Data description. We will use this for our analysis.</U>
price = price in US dollars ($326--$18,823)

carat =weight of the diamond (0.2--5.01)

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 (0--10.74)

y = width in mm (0--58.9)

z = depth in mm (0--31.8)

depth = total depth percentage = z / mean(x, y) = 2 * z / (x + y) (43--79)

table = width of top of diamond relative to widest point (43--95)

Exploratory Data Analysis

In [ ]:
```python
import pandas as pd
data = pd.read_csv('data_diamonds.csv')
data.head()
```

Out[ ]:

	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

In [ ]:
```python
data.shape
```

Out[ ]:
```
(53940, 11)
```

There are 53k records and 10 variables

In [ ]:
```python
data.dtypes
```

Out[ ]:
```
Unnamed: 0      int64
carat         float64
cut            object
color          object
clarity        object
depth         float64
table         float64
price           int64
x             float64
y             float64
z             float64
dtype: object
```

In [ ]:
```
data.describe()
```

Out[ ]:

	Unnamed: 0	carat	depth	table	price	x	y	z
count	53940.000000	53940.000000	53940.000000	53940.000000	53940.000000	53940.000000	53940.000000	53940.000000
mean	26970.500000	0.797940	61.749405	57.457184	3932.799722	5.731157	5.734526	3.538734
std	15571.281097	0.474011	1.432621	2.234491	3989.439738	1.121761	1.142135	0.705699
min	1.000000	0.200000	43.000000	43.000000	326.000000	0.000000	0.000000	0.000000
25%	13485.750000	0.400000	61.000000	56.000000	950.000000	4.710000	4.720000	2.910000
50%	26970.500000	0.700000	61.800000	57.000000	2401.000000	5.700000	5.710000	3.530000
75%	40455.250000	1.040000	62.500000	59.000000	5324.250000	6.540000	6.540000	4.040000
max	53940.000000	5.010000	79.000000	95.000000	18823.000000	10.740000	58.900000	31.800000

Remove unwated variables

In [ ]:
```
# the variable Unnamed: 0 is not relevent for the analysis. Its more of a ID column and it can be safely igno
red
data.drop(columns=['Unnamed: 0'], inplace=True)
data.columns.T
```

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

Analyze Missing values

In [ ]:
```
# quick check on null in the data
data.isnull().sum()
```

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

There are no missing values. All the column can be used for our analysis

In [ ]:

```
# Lets visualize the data 
# Correlation matrix visualisation
import seaborn as sns
import matplotlib.pyplot as plt
sns.set(style="whitegrid")
sns.set(font_scale=1.0)
corr = data.corr()
sns.heatmap(corr, xticklabels=corr.columns, yticklabels=corr.columns, annot=True, cmap=plt.cm.Reds)
plt.show()
```

From the correlation matrix, we can see that the variables price, x, y, z are highly correlated. we can remove x, y, z and keep price.

In [ ]:
```
# drop the variables with high correlation
# data.drop(columns=['y','z'], inplace=True)
```

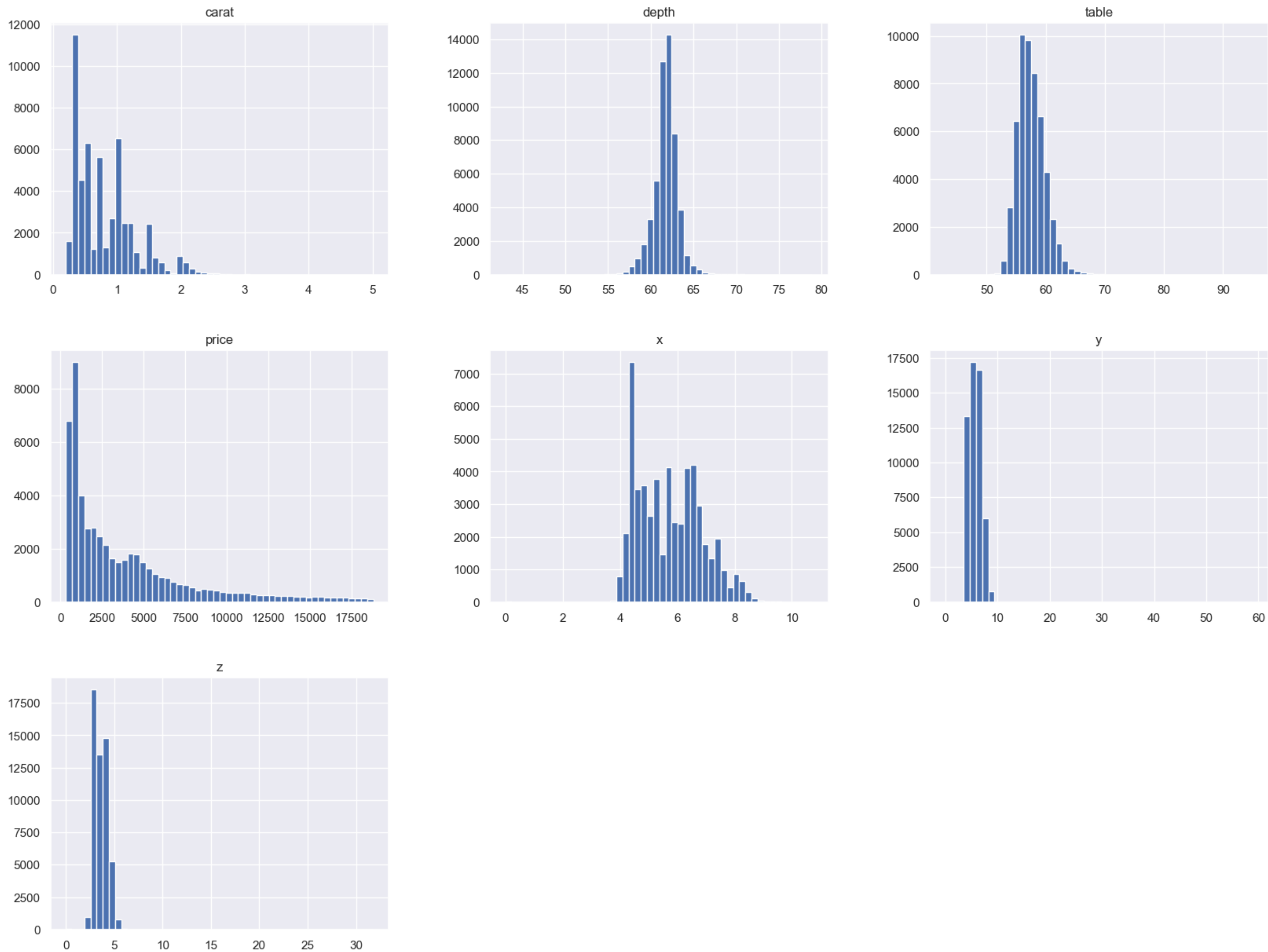
In [ ]:
```
data.head()
```

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

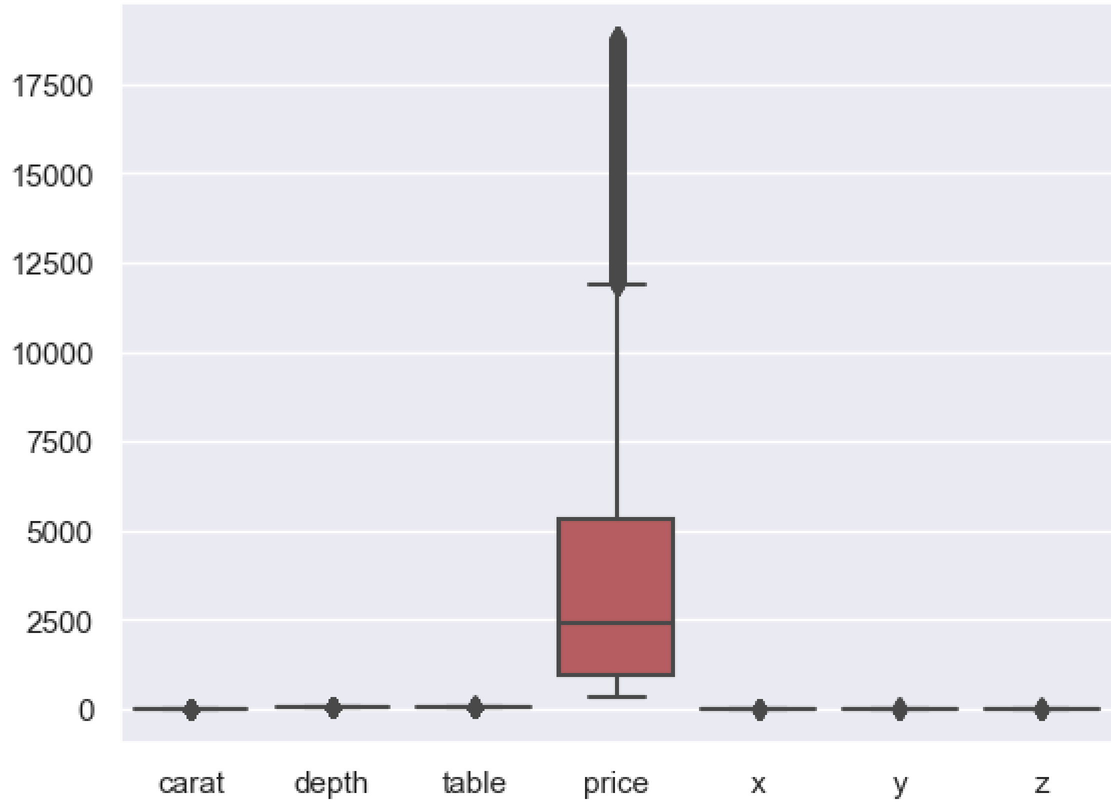
In [ ]:

```
# Lets check the distribution of the data
data.hist(bins=50, figsize=(20,15))
plt.show()
```


carat
0 2000 4000 6000 8000 10000 12000
0 1 2 3 4 5
depth
0 2000 4000 6000 8000 10000 12000 14000
45 50 55 60 65 70 75 80
table
0 2000 4000 6000 8000 10000
50 60 70 80 90
price
0 2000 4000 6000 8000
0 2500 5000 7500 10000 12500 15000 17500
x
0 1000 2000 3000 4000 5000 6000 7000
0 2 4 6 8 10
y
0 2500 5000 7500 10000 12500 15000 17500
0 10 20 30 40 50 60
z
0 2500 5000 7500 10000 12500 15000 17500
0 5 10 15 20 25 30

In [ ]:

```
# let check for any outliers
sns.boxplot(data=data)
plt.show()
```

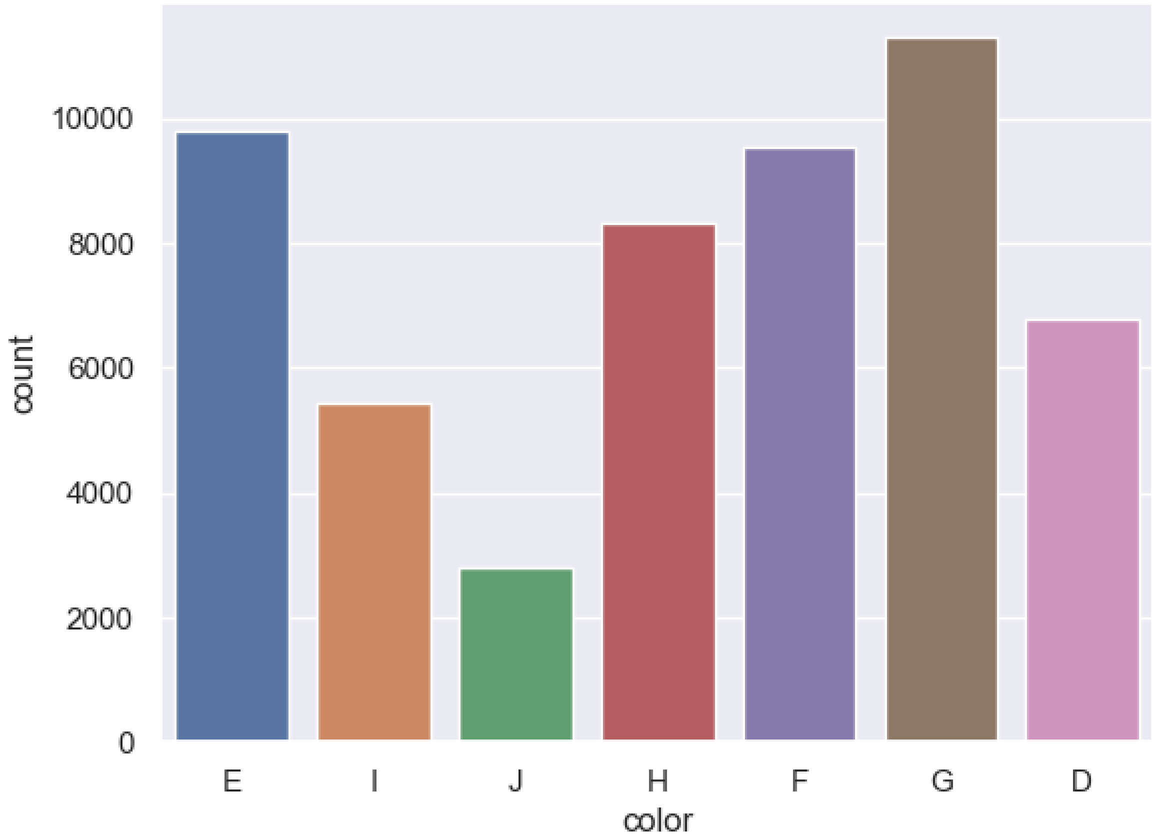


We could see there are some outliers in the price column. For now we do not remove it. Let us see if we can remove the outliers later.

Feature Engineering

In [ ]:

```
# for the categorical variables we can use the countplot to see the distribution of the data
sns.countplot(x='color', data=data)
plt.show()
```

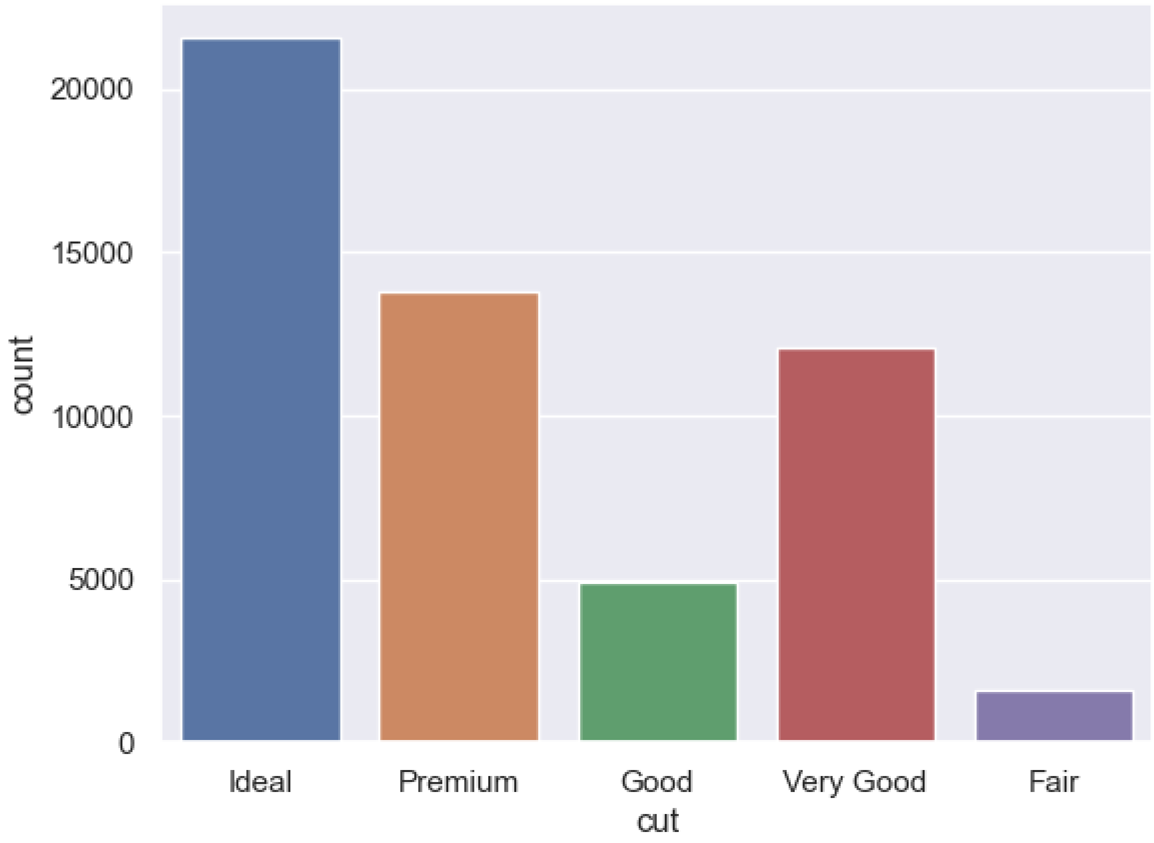


In [ ]:

```
sns.countplot(x='clarity', data=data)
plt.show()
```

In [ ]:

```
sns.countplot(x='cut', data=data)
plt.show()
```



In [ ]:

```
# we have below categorical variables. we need to transform them into numerical variables
# as per the requirement we need to use the dummy variables. The categories are ordinal
data['cut'] = data['cut'].map({'Fair':0, 'Good':1, 'Very Good':2, 'Premium':3, 'Ideal':4})
data['color'] = data['color'].map({'J':0, 'I':1, 'H':2, 'G':3, 'F':4, 'E':5, 'D':6})
data['clarity'] = data['clarity'].map({'I1':0, 'SI2':1, 'SI1':2, 'VS2':3, 'VS1':4, 'VVS2':5, 'VVS1':6, 'IF':7
})
data.head()
```

Out[ ]:

	carat	cut	color	clarity	depth	table	price	x	y	z
0	0.23	4	5	1	61.5	55.0	326	3.95	3.98	2.43
1	0.21	3	5	2	59.8	61.0	326	3.89	3.84	2.31
2	0.23	1	5	4	56.9	65.0	327	4.05	4.07	2.31
3	0.29	3	1	3	62.4	58.0	334	4.20	4.23	2.63
4	0.31	1	0	1	63.3	58.0	335	4.34	4.35	2.75

In [ ]:

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

Out[ ]:

```
carat       0
cut         0
color       0
clarity     0
depth       0
table       0
price       0
x           0
y           0
z           0
dtype: int64
```

Model Building

In [ ]:
```
# We will not scale the data first. We will scale the data after we have done the analysis
X = data.drop(columns=['price'])
y = data['price']
```

In [ ]:
```
# Lets split the data into train and test
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

In [ ]:
```
# define rmse function
import numpy as np
from sklearn.metrics import mean_squared_error
def rmse(y_true, y_pred):
    return np.sqrt(mean_squared_error(y_true, y_pred))
```

Models without Scaling

In [ ]:
```
# Lets use Linear Regression
from sklearn.linear_model import LinearRegression
linearRegression = LinearRegression()
linearRegression.fit(X_train, y_train)
```

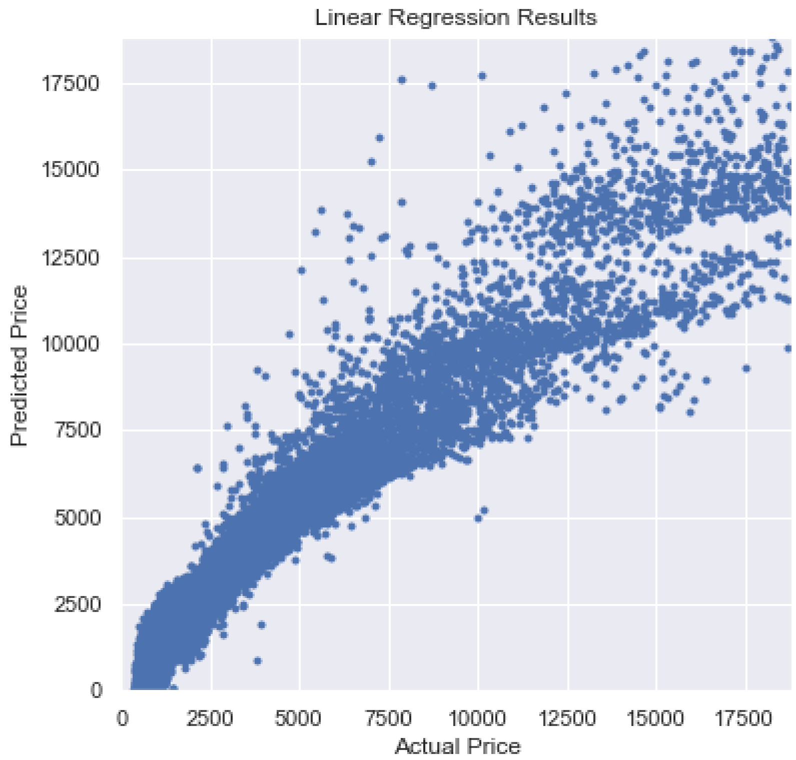
Out[ ]:
```
LinearRegression()
```

In [ ]:
```
linearRegression_rmse = rmse(y_test, linearRegression.predict(X_test))

print(linearRegression_rmse)
```

```
1201.2077317517576
```

In [ ]:

```
import matplotlib.pyplot as plt
%matplotlib inline
f = plt.figure(figsize=(6,6))
ax = plt.axes()

ax.plot(y_test, linearRegression.predict(X_test),
         marker='o', ls='', ms=3.0)

lim = (0, y_test.max())

ax.set(xlabel='Actual Price',
       ylabel='Predicted Price',
       xlim=lim,
       ylim=lim,
       title='Linear Regression Results');
```



In [ ]:
```
# Lets use the Lasso Regression
from sklearn.linear_model import Lasso
lassoRegression = Lasso()
lassoRegression.fit(X_train, y_train)
lassoRegression_rmse = rmse(y_test, lassoRegression.predict(X_test))
lassoRegression_rmse
```

Out[ ]:
```
1201.5721272188778
```

In [ ]:
```
# the score between Liner and Lasso Regression is very minor. Lets try with ridge regression
from sklearn.linear_model import Ridge
ridgeRegression = Ridge()
ridgeRegression.fit(X_train, y_train)
ridgeRegression_rmse = rmse(y_test, ridgeRegression.predict(X_test))
ridgeRegression_rmse
```

Out[ ]:
```
1201.2489660741646
```

Model with Scaling

In [ ]:
```
# we havnt used any custom alphas. Without scaling the scores between the models are very similar.
# Lets try with MinMax Scaling. We taken the reference from the link below
# https://datascience.stackexchange.com/questions/44009/scaling-label-encoded-values-for-linear-algorithms
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaler.fit(X_train)
X_train_scaled = scaler.transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [ ]:
```
linearRegression = LinearRegression()
linearRegression.fit(X_train_scaled, y_train)
linearRegression_rmse = rmse(y_test, linearRegression.predict(X_test_scaled))
lassoRegression = Lasso()
lassoRegression.fit(X_train_scaled, y_train)
lassoRegression_rmse = rmse(y_test, lassoRegression.predict(X_test_scaled))
ridgeRegression = Ridge()
ridgeRegression.fit(X_train_scaled, y_train)
ridgeRegression_rmse = rmse(y_test, ridgeRegression.predict(X_test_scaled))
(linearRegression_rmse, lassoRegression_rmse, ridgeRegression_rmse)
```

Out[ ]:
```
(1201.2077317517578, 1207.505274155642, 1204.0125324315045)
```

In [ ]:
```
# there are no improvement in the scores. We can conclude that the data is not scaled.
```

Models with Scaling and Cross Validation

In [ ]:
```
from sklearn.linear_model import RidgeCV
ridgeCV = RidgeCV(alphas = [0.005, 0.05, 0.1, 0.3, 1, 3, 5, 10, 15, 30, 80], cv=5)
ridgeCV.fit(X_train_scaled, y_train)
ridgeCV_rmse = rmse(y_test, ridgeCV.predict(X_test_scaled))
print(ridgeCV.alpha_, ridgeCV_rmse)
```

```
0.3 1201.7293422060393
```

In [ ]:
```
from sklearn.linear_model import LassoCV
lassoCV = LassoCV(alphas = [0.005, 0.05, 0.1, 0.3, 1, 3, 5, 10, 15, 30, 80], cv=5, max_iter=10000)
lassoCV.fit(X_train_scaled, y_train)
lassoCV_rmse = rmse(y_test, lassoCV.predict(X_test_scaled))
print(lassoCV.alpha_, lassoCV_rmse)
```

```
0.05 1201.377746019673
```

In [ ]:

```python
from sklearn.linear_model import ElasticNetCV
elasticNetCV = ElasticNetCV(alphas = [0.005, 0.05, 0.1, 0.3, 1, 3, 5, 10, 15, 30, 80], cv=5, max_iter=10000)
elasticNetCV.fit(X_train_scaled, y_train)
elasticNetCV_rmse = rmse(y_test, elasticNetCV.predict(X_test_scaled))
print(elasticNetCV.alpha_, elasticNetCV.l1_ratio_, elasticNetCV_rmse)
```

```
0.005 0.5 1436.3297976166275
```

In [ ]:

```python
rmse_vals = [linearRegression_rmse, ridgeCV_rmse, lassoCV_rmse, elasticNetCV_rmse]

labels = ['Linear', 'Ridge', 'Lasso', 'ElasticNet']

rmse_df = pd.Series(rmse_vals, index=labels).to_frame()
rmse_df.rename(columns={0: 'RMSE'}, inplace=1)
rmse_df
```

Out[ ]:

	RMSE
Linear	1201.207732
Ridge	1201.729342
Lasso	1201.377746
ElasticNet	1436.329798

In [ ]:

```python
f = plt.figure(figsize=(6,6))
ax = plt.axes()

labels = ['Ridge', 'Lasso', 'ElasticNet']

models = [ridgeCV, lassoCV, elasticNetCV]

for mod, lab in zip(models, labels):
    ax.plot(y_test, mod.predict(X_test), 
             marker='o', ls='', ms=3.0, label=lab)


leg = plt.legend(frameon=True)
leg.get_frame().set_edgecolor('black')
leg.get_frame().set_linewidth(1.0)

ax.set(xlabel='Actual Price', 
       ylabel='Predicted Price', 
       title='Linear Regression Results');
```

Other Regression Techniques

In [ ]:

```
# XGBoost Regressor
import xgboost as xgb
# random forest regressor
from sklearn.ensemble import RandomForestRegressor
# decision tree regressor
from sklearn.tree import DecisionTreeRegressor
# elastic net regressor
from sklearn.linear_model import ElasticNet
# import pipeline
from sklearn.pipeline import Pipeline
from sklearn.linear_model import SGDRegressor
# catboost regressor
from catboost import CatBoostRegressor
```

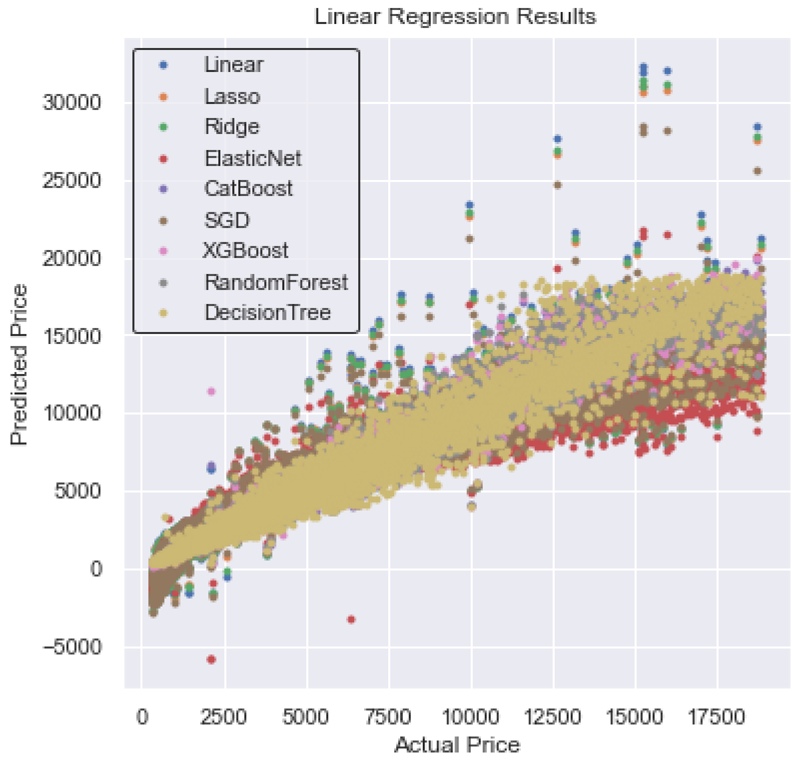
In [ ]:

```python
# create pipeline for each model
f = plt.figure(figsize=(6,6))
ax = plt.axes()
new_rmses = {}
model_pipelines = {
    'Linear': Pipeline([('scaler', scaler), ('linear', linearRegression)]),
    'Lasso': Pipeline([('scaler', scaler), ('lasso', lassoRegression)]),
    'Ridge': Pipeline([('scaler', scaler), ('ridge', ridgeRegression)]),
    'ElasticNet': Pipeline([('scaler', scaler), ('elasticNet', elasticNetCV)]),
    'CatBoost': Pipeline([ ('catboost', CatBoostRegressor(verbose=False))]), 
    'SGD': Pipeline([('scaler', scaler), ('SGD', SGDRegressor())]),
    'XGBoost': Pipeline([('scaler', scaler), ('XGBoost', xgb.XGBRegressor())]),
    'RandomForest': Pipeline([('scaler', scaler), ('RandomForest', RandomForestRegressor())]),
    'DecisionTree': Pipeline([('scaler', scaler), ('DecisionTree', DecisionTreeRegressor())]),
}
# fit each model
for model_label, model_pipeline in model_pipelines.items():
    print(f'Fitting {model_label}')
    model_pipeline.fit(X_train, y_train)
    new_rmses[model_label] = rmse(y_test, model_pipeline.predict(X_test))
    ax.plot(y_test, model_pipeline.predict(X_test),  marker='o', ls='',
     ms=3.0, label=model_label)
leg = plt.legend(frameon=True)
leg.get_frame().set_edgecolor('black')
leg.get_frame().set_linewidth(1.0)

ax.set(xlabel='Actual Price', 
       ylabel='Predicted Price', 
       title='Linear Regression Results');
# create dataframe of new rmse values
new_rmses_df = pd.Series(new_rmses, index=model_pipelines.keys()).to_frame()
new_rmses_df.rename(columns={0: 'RMSE'}, inplace=1)

new_rmses_df
```

```
Fitting Linear
Fitting Lasso
Fitting Ridge
Fitting ElasticNet
Fitting CatBoost
Fitting SGD
Fitting XGBoost
Fitting RandomForest
Fitting DecisionTree
```

Out[ ]:

	RMSE
Linear	1201.207732
Lasso	1207.505274
Ridge	1204.012532
ElasticNet	1436.329798
CatBoost	515.413999
SGD	1237.525854
XGBoost	543.243708
RandomForest	538.256622
DecisionTree	740.379380



Conclusion

Based on the analysis we could conclude that **Catboost** is the best model for this project. It has the best accuracy and the best performance. We can also revisit the same model if we get additional data about the diamonds in other categories.