```
#Importing important libraries

import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder,StandardScaler
from scipy import stats
from sklearn.linear_model import LinearRegression,Lasso
from sklearn.metrics import mean_squared_error,mean_absolute_error
from sklearn.ensemble import RandomForestRegressor
import warnings
warnings.filterwarnings("ignore")
```

```
#Impoting Data from .csv and saving in variable TD
TD = pd.read_csv('/content/diamonds.csv')
TD.head()# to show 1st 5 rows of data
```

	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

Next steps: Generate code with TD View recommended plots

```
TD.shape # to show the rows and colmns of the data
```

```
(53940, 11)
```

```
TD.isnull().sum() # to show the sum of all null fields
```

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

```
# EDA
TD.describe() # to show summary statistics of the data
```

	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

```
TD = TD.dropna() # this removes all data whcih contains null values, since there are no null values the data remains the same
TD.drop(TD.columns[0], axis=1, inplace=True) # removing the 1st columnn since the its just numbering
```

```
TD.isnull().sum() # repeating previous step to recheck
```

```
carat      0
cut        0
color      0
clarity    0
```

```
depth      0
table      0
price      0
x          0
y          0
z          0
dtype: int64
```

```
TD.dtypes # to show the datatypes of the data
```

```
carat      float64
cut         object
color       object
clarity     object
depth      float64
table      float64
price        int64
x          float64
y          float64
z          float64
dtype: object
```

```
# EDA
TD.describe() # to show summary statistics of the data
```

	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

```
print(TD[TD['x'] == 0]) # checking for x values where x = 0
print(TD[TD['y'] == 0]) # checking for y values where y = 0
print(TD[TD['z'] == 0]) # checking for z values where z = 0
```

```
       carat        cut color clarity  depth  table  price    x     y    z
11182   1.07      Ideal     F     SI2   61.6   56.0   4954  0.0  6.62  0.0
11963   1.00  Very Good     H     VS2   63.3   53.0   5139  0.0  0.00  0.0
15951   1.14       Fair     G     VS1   57.5   67.0   6381  0.0  0.00  0.0
24520   1.56      Ideal     G     VS2   62.2   54.0  12800  0.0  0.00  0.0
26243   1.20    Premium     D    VVS1   62.1   59.0  15686  0.0  0.00  0.0
27429   2.25    Premium     H     SI2   62.8   59.0  18034  0.0  0.00  0.0
49556   0.71       Good     F     SI2   64.1   60.0   2130  0.0  0.00  0.0
49557   0.71       Good     F     SI2   64.1   60.0   2130  0.0  0.00  0.0
       carat        cut color clarity  depth  table  price    x    y    z
11963   1.00  Very Good     H     VS2   63.3   53.0   5139  0.0  0.0  0.0
15951   1.14       Fair     G     VS1   57.5   67.0   6381  0.0  0.0  0.0
24520   1.56      Ideal     G     VS2   62.2   54.0  12800  0.0  0.0  0.0
26243   1.20    Premium     D    VVS1   62.1   59.0  15686  0.0  0.0  0.0
27429   2.25    Premium     H     SI2   62.8   59.0  18034  0.0  0.0  0.0
49556   0.71       Good     F     SI2   64.1   60.0   2130  0.0  0.0  0.0
49557   0.71       Good     F     SI2   64.1   60.0   2130  0.0  0.0  0.0
       carat        cut color clarity  depth  table  price     x     y    z
2207    1.00    Premium     G     SI2   59.1   59.0   3142  6.55  6.48  0.0
2314    1.01    Premium     H      I1   58.1   59.0   3167  6.66  6.60  0.0
4791    1.10    Premium     G     SI2   63.0   59.0   3696  6.50  6.47  0.0
5471    1.01    Premium     F     SI2   59.2   58.0   3837  6.50  6.47  0.0
10167   1.50       Good     G      I1   64.0   61.0   4731  7.15  7.04  0.0
11182   1.07      Ideal     F     SI2   61.6   56.0   4954  0.00  6.62  0.0
11963   1.00  Very Good     H     VS2   63.3   53.0   5139  0.00  0.00  0.0
13601   1.15      Ideal     G     VS2   59.2   56.0   5564  6.88  6.83  0.0
15951   1.14       Fair     G     VS1   57.5   67.0   6381  0.00  0.00  0.0
24394   2.18    Premium     H     SI2   59.4   61.0  12631  8.49  8.45  0.0
24520   1.56      Ideal     G     VS2   62.2   54.0  12800  0.00  0.00  0.0
26123   2.25    Premium     I     SI1   61.3   58.0  15397  8.52  8.42  0.0
26243   1.20    Premium     D    VVS1   62.1   59.0  15686  0.00  0.00  0.0
27112   2.20    Premium     H     SI1   61.2   59.0  17265  8.42  8.37  0.0
27429   2.25    Premium     H     SI2   62.8   59.0  18034  0.00  0.00  0.0
27503   2.02    Premium     H     VS2   62.7   53.0  18207  8.02  7.95  0.0
27739   2.80       Good     G     SI2   63.8   58.0  18788  8.90  8.85  0.0
49556   0.71       Good     F     SI2   64.1   60.0   2130  0.00  0.00  0.0
49557   0.71       Good     F     SI2   64.1   60.0   2130  0.00  0.00  0.0
51506   1.12    Premium     G      I1   60.4   59.0   2383  6.71  6.67  0.0
```

```
TD = TD[TD['x'] != 0] # removing data where x = 0
TD = TD[TD['y'] != 0] # removing data where x = 0
TD = TD[TD['z'] != 0] # removing data where x = 0
print(TD[TD['x'] == 0]) # rechecking for x values where x = 0
print(TD[TD['y'] == 0]) # rechecking for y values where y = 0
print(TD[TD['z'] == 0]) # rechecking for z values where z = 0
```

```
Empty DataFrame
Columns: [carat, cut, color, clarity, depth, table, price, x, y, z]
Index: []
Empty DataFrame
Columns: [carat, cut, color, clarity, depth, table, price, x, y, z]
Index: []
Empty DataFrame
Columns: [carat, cut, color, clarity, depth, table, price, x, y, z]
Index: []
```

```
TD.head()
```

	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

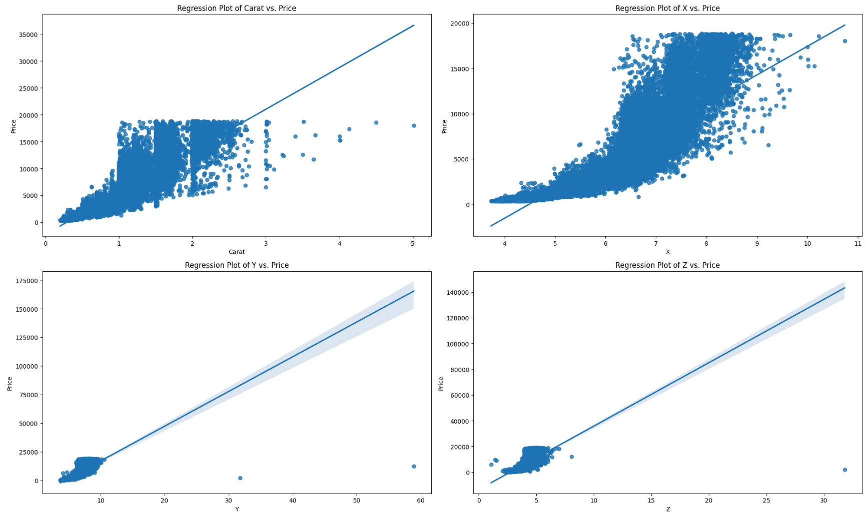
Next steps: Generate code with TD View recommended plots

```
TD.describe(include='object') # to show summary of objects/categories which without specifying gives summary without objects
```

	cut	color	clarity
count	53920	53920	53920
unique	5	7	8
top	Ideal	G	SI1
freq	21548	11284	13063

```
#Regression plot against all the categories
features = ['carat', 'x', 'y', 'z']
plt.figure(figsize=(20, 12))
for i, feature in enumerate(features):
    plt.subplot(2, 2, i + 1)
    sns.regplot(x=feature, y='price', data=TD)
    plt.title(f'Regression Plot of {feature.capitalize()} vs. Price')
    plt.xlabel(feature.capitalize())
    plt.ylabel('Price')

plt.tight_layout()
plt.show()
```

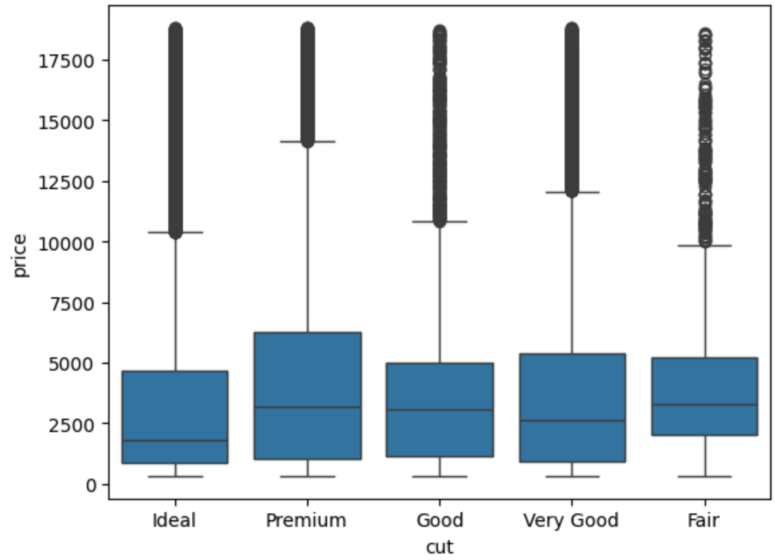



```
# Pearson Correlation Coefficient to show linear relationship
for feature in features:
    pcf, pvv = stats.pearsonr(TD[feature], TD['price'])
    print("The Pearson Correlation Coefficient is", pcf, " with a P-value of P =", pvv," for ",feature)
```

```
The Pearson Correlation Coefficient is 0.9215920634723974  with a P-value of P = 0.0  for  carat
The Pearson Correlation Coefficient is 0.887231372527643  with a P-value of P = 0.0  for  x
The Pearson Correlation Coefficient is 0.867864244674355  with a P-value of P = 0.0  for  y
The Pearson Correlation Coefficient is 0.8682064012988696  with a P-value of P = 0.0  for  z
```

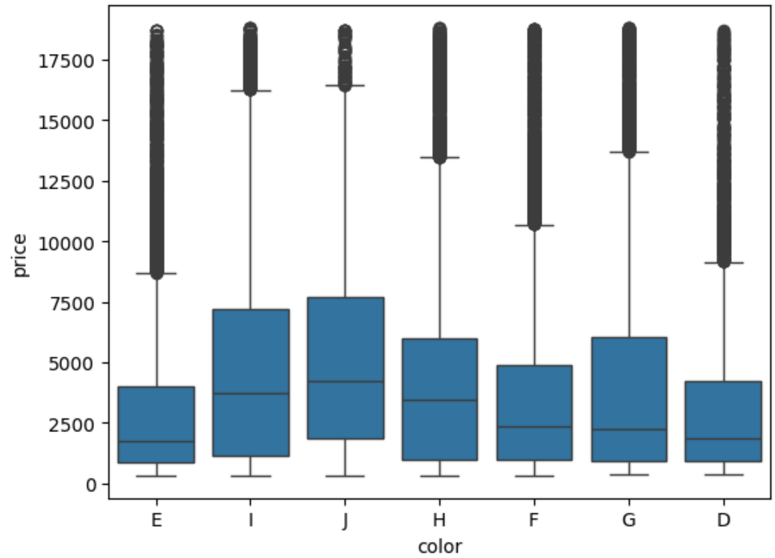
```
# box plot for the quality of cut
sns.boxplot(x='cut',y='price',data = TD)
```

```
<Axes: xlabel='cut', ylabel='price'>
```



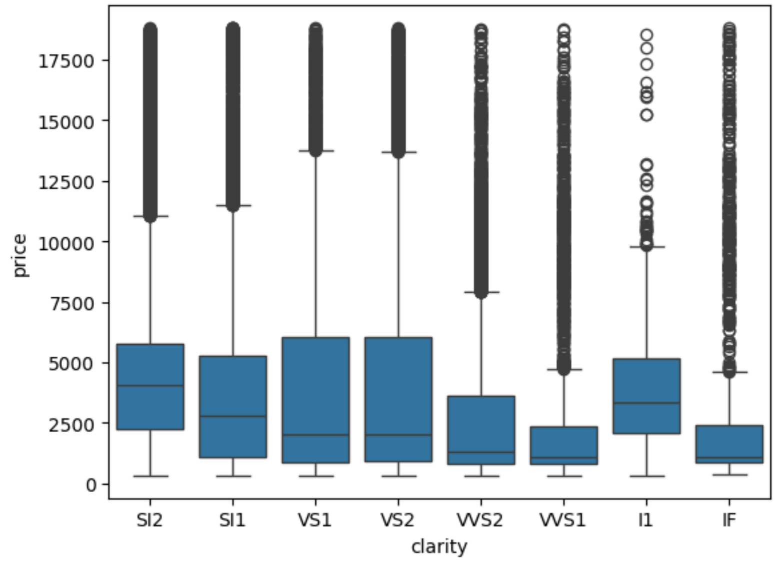

```
# box plot for color of the diamond
sns.boxplot(x='color',y='price',data = TD)
```

```
<Axes: xlabel='color', ylabel='price'>
```




```
# box plot for the clarity of the diamond
sns.boxplot(x='clarity',y='price',data = TD)
```

```
<Axes: xlabel='clarity', ylabel='price'>
```



```
#nothing to remove since all data is required and affects the price of the diamond
TD.shape
```

```
(53920, 10)
```

```
# Data Transformation
labelencoder = LabelEncoder()
TD.cut = labelencoder.fit_transform(TD.cut)
TD.color = labelencoder.fit_transform(TD.color)
TD.clarity = labelencoder.fit_transform(TD.clarity)
```

```
TD.head(10) # to check if label encoding is applied
```

	carat	cut	color	clarity	depth	table	price	x	y	z
0	0.23	2	1	3	61.5	55.0	326	3.95	3.98	2.43
1	0.21	3	1	2	59.8	61.0	326	3.89	3.84	2.31
2	0.23	1	1	4	56.9	65.0	327	4.05	4.07	2.31
3	0.29	3	5	5	62.4	58.0	334	4.20	4.23	2.63
4	0.31	1	6	3	63.3	58.0	335	4.34	4.35	2.75
5	0.24	4	6	7	62.8	57.0	336	3.94	3.96	2.48
6	0.24	4	5	6	62.3	57.0	336	3.95	3.98	2.47
7	0.26	4	4	2	61.9	55.0	337	4.07	4.11	2.53
8	0.22	0	1	5	65.1	61.0	337	3.87	3.78	2.49
9	0.23	4	4	4	59.4	61.0	338	4.00	4.05	2.39

Next steps: Generate code with TD | View recommended plots

```
# normalization
traindata = stats.zscore(TD)
traindata
```

	carat	cut	color	clarity	depth	table	price	
0	-1.198204	-0.538173	-0.936971	-0.484445	-0.174203	-1.099725	-0.904132	-1.5915
1	-1.240417	0.434877	-0.936971	-1.064312	-1.361090	1.585988	-0.904132	-1.6451
2	-1.198204	-1.511224	-0.936971	0.095422	-3.385781	3.376463	-0.903881	-1.5022
3	-1.071566	0.434877	1.414232	0.675289	0.454149	0.243131	-0.902125	-1.3682
4	-1.029353	-1.511224	2.002033	-0.484445	1.082501	0.243131	-0.901875	-1.2431
...	...	...	...	...	...	...	...	
53935	-0.163993	-0.538173	-1.524772	-1.064312	-0.662921	-0.204488	-0.294437	0.0164
53936	-0.163993	-1.511224	-1.524772	-1.064312	0.942868	-1.099725	-0.294437	-0.0371
53937	-0.206205	1.407928	-1.524772	-1.064312	0.733417	1.138369	-0.294437	-0.0639
53938	0.131496	0.434877	0.826431	-0.484445	-0.523288	0.243131	-0.294437	0.3737
53939	-0.100674	-0.538173	-1.524772	-0.484445	0.314515	-1.099725	-0.294437	0.0878

53920 rows × 10 columns

Next steps: Generate code with traindata | View recommended plots

```
# dividing the data wherein xt retains all the features while yt retains the target (price)
xt = traindata.drop('price',axis =1)
yt = traindata['price']
```

```
xt.head() # checking if data is split properly
```

	carat	cut	color	clarity	depth	table	x	y
0	-1.198204	-0.538173	-0.936971	-0.484445	-0.174203	-1.099725	-1.591573	-1.539219
1	-1.240417	0.434877	-0.936971	-1.064312	-1.361090	1.585988	-1.645173	-1.662014
2	-1.198204	-1.511224	-0.936971	0.095422	-3.385781	3.376463	-1.502241	-1.460280
3	-1.071566	0.434877	1.414232	0.675289	0.454149	0.243131	-1.368242	-1.319943
4	-1.029353	-1.511224	2.002033	-0.484445	1.082501	0.243131	-1.243176	-1.214690

Next steps: Generate code with xt View recommended plots

```
yt.head() # checking if data is split properly
```

```
0   -0.904132
1   -0.904132
2   -0.903881
3   -0.902125
4   -0.901875
Name: price, dtype: float64
```

```
from sklearn.model_selection import train_test_split #importing important library for training a model, to split the data properly acco
Xt,Xtt,Yt,Ytt = train_test_split(xt,yt,test_size=0.3,random_state=42)
```

```
# Multiple Linear Regression fitting training data into model
model = LinearRegression()
model_mlr = model.fit(Xt,Yt)
```

```
# making prediction after fitting data into mdoel
YpMLR = model_mlr.predict(Xtt)
```

```
# calculating the mean square error of the model with actual data
mse_MLR = mean_squared_error(Ytt,YpMLR)
print('The mean squared error for Multiple Linear Regression: ',mse_MLR)
```

```
The mean squared error for Multiple Linear Regression:  0.11096621872138686
```

```
# calculating the mean absolute error of the model with actual data
mae_MLR = mean_absolute_error(Ytt,YpMLR)
print('The mean absolute error for Multiple Linear Regression: ',mae_MLR)
```

```
The mean absolute error for Multiple Linear Regression:  0.21303238468283664
```

```
# fitting data into Random forest
rfModel = RandomForestRegressor()
model_rf = rfModel.fit(Xt,Yt)
```

```
# making prediction after fitting data
Yprf = model_rf.predict(Xtt)
```

```
# calculating the mean square error of the model with actual data
mse_RF = mean_squared_error(Ytt,Yprf)
print('The mean squared error for Random Forest: ',mse_RF)
```

```
The mean squared error for Random Forest:  0.017906355767287833
```

```
# calculating the mean absolute error of the model with actual data
mae_RF = mean_absolute_error(Ytt,Yprf)
print('The mean absolute error for Random Forest: ',mae_RF)
```

```
The mean absolute error for Random Forest:  0.06718954037281256
```

```
# fitting data into LASSO model
LassoModel = Lasso()
model_ls = LassoModel.fit(Xt,Yt)
```

```
# making prediction using testing data
YpLs = model_ls.predict(Xtt)
```

```
# calculating the mean square error of the model with actual data
mse_Ls = mean_squared_error(Ytt,YpLs)
print('The mean squared error for Lasso: ',mse_Ls)
```

```
The mean squared error for Lasso:  0.9810294848199543
```

```
# calculating the mean absolute error of the model with actual data
mae_Ls = mean_absolute_error(Ytt,YpLs)
print('The mean absolute error for Lasso: ',mae_Ls)
```

```
The mean absolute error for Lasso:  0.7532785276594522
```

```
# saving all the scores of mean squared error
scoresSE = [('MLR',mse_MLR),('Random Forest',mse_RF),('LASSO',mse_Ls)]
# saving all the scores of mean absolute error
scoresAE = [('MLR',mae_MLR),('Random Forest',mae_RF),('LASSO',mae_Ls)]
```

```
# Visualizing MSE and MAE in table format
mse = pd.DataFrame(data = scoresSE,columns=['Model','MSE Score'])
mae = pd.DataFrame(data = scoresAE,columns=['Model','MAE Score'])
cdf = pd.merge(mse,mae,on='Model')
cdf
```

	Model	MSE Score	MAE Score
0	MLR	0.110966	0.213032
1	Random Forest	0.017906	0.067190
2	LASSO	0.981029	0.753279

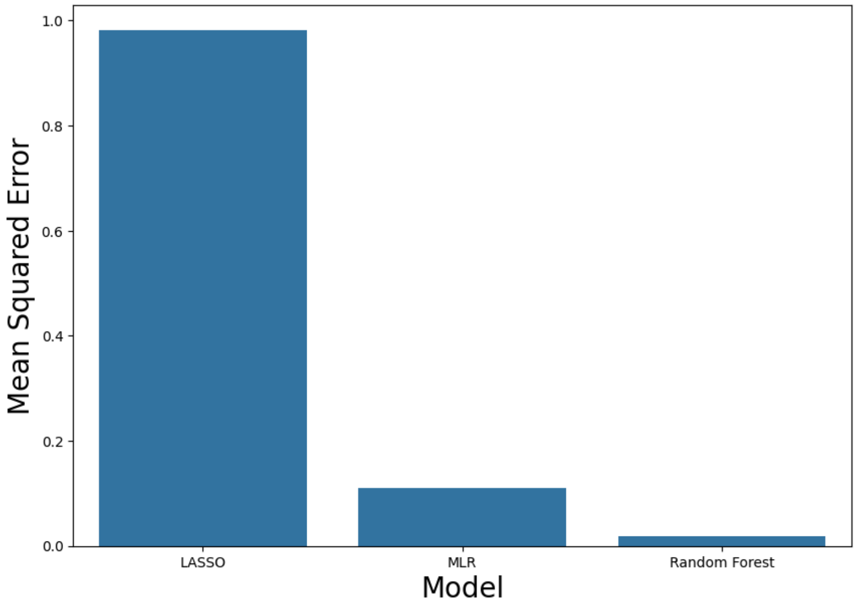
Next steps: Generate code with cdf View recommended plots

```
# Visualizing findings in diagram
mse.sort_values(by=(['MSE Score']), ascending=False, inplace=True)
f,axe = plt.subplots(1,1,figsize=(10,7))
sns.barplot(x=mse['Model'],y=mse['MSE Score'],ax = axe)
axe.set_xlabel('Model',size=20)
axe.set_ylabel('Mean Squared Error',size=20)
plt.show
```

```
matplotlib.pyplot.show
def show(*args, **kwargs)

/usr/local/lib/python3.10/dist-packages/matplotlib/pyplot.py
Display all open figures.

Parameters
----------
block : bool, optional
```



```
# Visualizing findings in diagram
mae.sort_values(by=(['MAE Score']), ascending=False, inplace=True)
f,axe = plt.subplots(1,1,figsize=(10,7))
sns.barplot(x=mae['Model'],y=mae['MAE Score'],ax = axe)
axe.set_xlabel('Model',size=20)
axe.set_ylabel('Mean Abdolute Error',size=20)
plt.show
```

```
matplotlib.pyplot.show
def show(*args, **kwargs)
```