```
import pandas as pd
data = pd.read_csv("diamonds.csv")
```

data.tail()

	Unnamed: 0	carat	cut	color	clarity	depth	table	price	x	у	z
53935	53936	0.72	Ideal	D	SI1	60.8	57.0	2757	5.75	5.76	3.50
53936	53937	0.72	Good	D	SI1	63.1	55.0	2757	5.69	5.75	3.61
53937	53938	0.70	Very Good	D	SI1	62.8	60.0	2757	5.66	5.68	3.56
1	50000	2.22	· ·		010	24.2	50.0	0757	0.45	0.40	<b>1</b>

data.shape

(53940, 11)

data.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 53940 entries, 0 to 53939 Data columns (total 11 columns):

	COTA ( CO.		
#	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	х	53940 non-null	float64
9	у	53940 non-null	float64
10	Z	53940 non-null	float64
dtype	es: float64(	5), int64(2), ob	ject(3)

memory usage: 4.5+ MB

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

data.head()

	carat	cut	color	clarity	depth	table	price	x	У	z
0	0.23	Ideal	Е	SI2	61.5	55.0	326	3.95	3.98	2.43
1	0.21	Premium	Е	SI1	59.8	61.0	326	3.89	3.84	2.31
2	0.23	Good	Е	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

data.describe()

	carat	depth	table	price	х	у	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

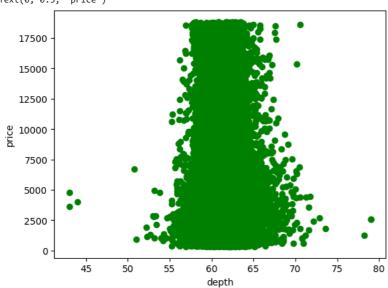
#Dropping dimentionless diamonds data = data.drop(data[data["x"]==0].index)

```
data = data.drop(data[data["y"]==0].index)
data = data.drop(data[data["z"]==0].index)
data.shape
```

(53920, 10)

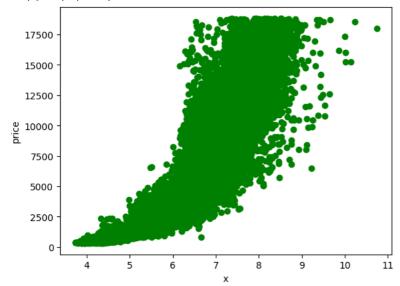
import matplotlib.pyplot as plt
x=data["depth"].values
y=data["price"].values
plt.scatter(x,y,color='green')
plt.xlabel("depth")
plt.ylabel("price")

Text(0, 0.5, 'price')



x=data["x"].values
y=data["price"].values
plt.scatter(x,y,color='green')
plt.xlabel("x")
plt.ylabel("price")

Text(0, 0.5, 'price')



x=data["y"].values
y=data["price"].values
plt.scatter(x,y,color='green')
plt.xlabel("y")
plt.ylabel("price")

```
Text(0, 0.5, 'price')
         17500
         15000
         12500
      <u>pr</u> 10000
          7500
          5000
x=data["z"].values
y=data["price"].values
plt.scatter(x,y,color='green')
plt.xlabel("z")
plt.ylabel("price")
     Text(0, 0.5, 'price')
         17500
         15000
         12500
      97.0000
10000
          7500
          5000
          2500
              0
                                   10
                                             15
                                                      20
                                                                25
                0
                          5
                                                                          30
#Dropping the outliers.
data = data[(data["depth"]<75)&(data["depth"]>45)]
data = data[(data["table"]<80)&(data["table"]>40)]
data = data[(data["x"]<30)]</pre>
data = data[(data["y"]<30)]
data = data[(data["z"]<30)&(data["z"]>2)]
data.shape
     (53907, 10)
data.info()
     <class 'pandas.core.frame.DataFrame'>
     Int64Index: 53907 entries, 0 to 53939
     Data columns (total 10 columns):
     # Column Non-Null Count Dtype
                   53907 non-null float64
     0
         carat
                   53907 non-null object
      1
          cut
      2
          color
                   53907 non-null object
      3
          clarity
                   53907 non-null object
      4
          depth
                   53907 non-null float64
      5
          table
                   53907 non-null float64
          price
                   53907 non-null
                                   int64
                   53907 non-null float64
      8
                   53907 non-null float64
         У
                   53907 non-null float64
     dtypes: float64(6), int64(1), object(3)
```

data.describe()

memory usage: 4.5+ MB

	carat	depth	table	price	х	у	z
count	53907.000000	53907.000000	53907.000000	53907.000000	53907.000000	53907.000000	53907.000000
mean	0.797628	61.749741	57.455948	3930.584470	5.731463	5.733292	3.539441
std	0.473765	1.420119	2.226153	3987.202815	1.119384	1.111252	0.691434
min	0.200000	50.800000	43.000000	326.000000	3.730000	3.680000	2.060000
25%	0.400000	61.000000	56.000000	949.000000	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	5322.000000	6.540000	6.540000	4.040000
max	5.010000	73.600000	79.000000	18823.000000	10.740000	10.540000	6.980000

```
s = (data.dtypes =="object")
object_cols = list(s[s].index)
print("Categorical variables:")
print(object_cols)

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

from sklearn.preprocessing import OneHotEncoder, LabelEncoder

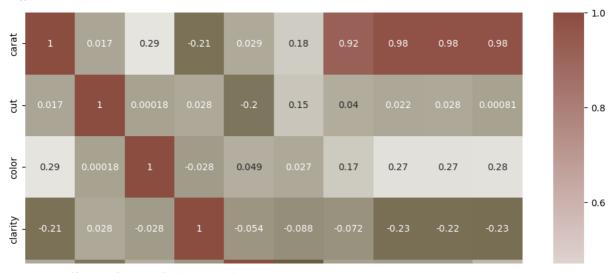
```
label_data = data.copy()

label_encoder = LabelEncoder()
for col in object_cols:
    label_data[col] = label_encoder.fit_transform(label_data[col])
label_data.head()
```

	carat	cut	color	clarity	depth	table	price	x	у	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

```
cmap = sns.diverging_palette(70,20,s=50, l=40, n=6,as_cmap=True)
corrmat= label_data.corr()
f, ax = plt.subplots(figsize=(12,12))
sns.heatmap(corrmat,cmap=cmap,annot=True, )
```

<Axes: >



X= label\_data.drop(["price"],axis =1) #features 9features

y= label\_data["price"] #target value

```
print(X)
```

```
carat
              cut
                   color clarity
                                   depth
                                         table
0
        0.23
                                    61.5
                                           55.0
                                                3.95
                                                      3.98
                                                            2.43
1
        0.21
               3
                      1
                               2
                                    59.8
                                           61.0
                                                3.89
                                                      3.84
                                                            2.31
2
        0.23
               1
                                    56.9
                                           65.0
                                                4.05
                                                      4.07
                                                4.20
                                    62.4
                                           58.0
                                               4.34
        0.31
               1
                      6
                               3
                                    63.3
                                          58.0
                                                      4.35
                      0
                               2
                                    60.8
                                           57.0
                                                5.75
53935
       0.72
                                                      5.76
                                                            3.50
53936
       0.72
                                                5.69
                                                       5.75
                      0
                                    63.1
                                           55.0
                                                            3.61
               1
53937
       0.70
               4
                      0
                               2
                                    62.8
                                           60.0
                                                5.66
                                                      5.68
                                                            3.56
53938
       0.86
               3
                      4
                               3
                                    61.0
                                          58.0
                                                6.15
                                                      6.12
                                                            3.74
53939
       0.75
                                    62.2
                                          55.0 5.83
                                                     5.87 3.64
[53907 rows x 9 columns]
```

## print(y)

```
0
           326
           326
1
           327
2
3
           334
          335
53935
          2757
53936
          2757
53937
53938
          2757
53939
         2757
```

Name: price, Length: 53907, dtype: int64

from sklearn.model\_selection import train\_test\_split

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y,test\_size=0.25, random\_state=7)

## print(X\_train)

```
color
                                       table
      carat
             cut
                        clarity
                                 depth
8778
                                         63.0 6.21 6.30 3.66
47001
       0.53
                      3
                                  62.5
                                         54.0 5.19
                                                     5.21
40421
                                         58.0 4.95
                                                    4.84
                                                          3.26
       0.50
               0
                                  66.6
44023
                                         57.0 5.12
                                                    5.08
       0.51
                      1
                              2
                                  62.2
                                                          3.17
                              7
13402
       0.32
               3
                      4
                                  62.2
                                         58.0 4.33
                                                    4.38
                                                          2.71
                                         69.0 5.93
                                                    5.77
919
       0.72
                      2
                                  56.9
                                                          3.33
               0
                              4
53492
       0.75
               3
                      2
                              2
                                  61.5
                                         58.0 5.83
                                                    5.87 3.60
38492
       0.42
                      2
                              4
                                  61.2
                                         58.0 4.82
                                                    4.86
                                                          2.96
10750
       1.12
                                  60.2
                                         59.0 6.70 6.85 4.08
                                         57.0
                                               5.74
                                                     5.77
49719
       0.72
                                  61.5
```

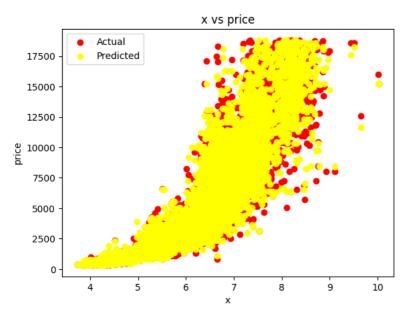
[40430 rows x 9 columns]

print(y\_train)

```
8778
              4469
     47001
              1818
     40421
              1134
     44023
              1546
     13402
               602
              2879
     919
     53492
              2683
     38492
              1031
     10750
              4852
     49719
              2150
     Name: price, Length: 40430, dtype: int64
from sklearn.linear_model import LinearRegression
mymodel = LinearRegression()
mymodel.fit(X_train,y_train)
     ▼ LinearRegression
     LinearRegression()
pred = mymodel.predict(X_test)
from sklearn.model_selection import cross_val_score
from sklearn.metrics import mean_squared_error
from sklearn import metrics
import numpy as np
# Model Evaluation
print("R^2:",metrics.r2_score(y_test, pred))
print("Adjusted R^2:",1 - (1-metrics.r2\_score(y\_test, pred))*(len(y\_test)-1)/(len(y\_test)-X\_test.shape[1]-1))
print("MAE:",metrics.mean_absolute_error(y_test, pred))
\verb|print("MSE:",metrics.mean_squared_error(y_test, pred))|\\
print("RMSE:",np.sqrt(metrics.mean_squared_error(y_test, pred)))
     R^2: 0.8890105065854332
     Adjusted R^2: 0.888936332274842
     MAE: 849.3507396470712
     MSE: 1741183.667805709
     RMSE: 1319.5391876733745
import matplotlib.pyplot as plt
plt.scatter(X_test['x'],y_test,color="red")
plt.scatter(X_test['x'],output,color="yellow")
plt.legend(["Actual" , "Predicted"])
plt.xlabel('x')
plt.ylabel('price')
plt.title('x vs price')
plt.show()
```



```
from sklearn.tree import DecisionTreeRegressor
decisiontreemodel = DecisionTreeRegressor()
decisiontreemodel.fit(X train,y train)
      ▼ DecisionTreeRegressor
      DecisionTreeRegressor()
treeoutput = decisiontreemodel.predict(X_test)
print(treeoutput[:5])
     [6055. 2564. 4339. 3655. 700.]
print(y_test[:5])
     16087
               6426
     164
               2771
     5785
               3903
     4703
               3678
     28059
                660
     Name: price, dtype: int64
# Model Evaluation
print("R^2:",metrics.r2_score(y_test, treeoutput))
print("Adjusted R^2:",1 - (1-metrics.r2\_score(y\_test, treeoutput))*(len(y\_test)-1)/(len(y\_test)-X\_test.shape[1]-1))
\verb|print("MAE:",metrics.mean_absolute_error(y_test, treeoutput))| \\
\verb|print("MSE:",metrics.mean_squared_error(y_test, treeoutput))|\\
print("RMSE:",np.sqrt(metrics.mean_squared_error(y_test, treeoutput)))
     R^2: 0.9647179178635343
     Adjusted R^2: 0.964694338837825
     MAE: 359.7847443793129
     MSE: 553499.1042145878
     RMSE: 743.9752040320885
{\tt import\ matplotlib.pyplot\ as\ plt}
plt.scatter(X_test['x'],y_test,color="red")
plt.scatter(X_test['x'],treeoutput,color="yellow")
plt.legend(["Actual" , "Predicted"])
plt.xlabel('x')
plt.ylabel('price')
plt.title('x vs price')
plt.show()
```



from sklearn.ensemble import RandomForestRegressor

forestmodel = RandomForestRegressor()

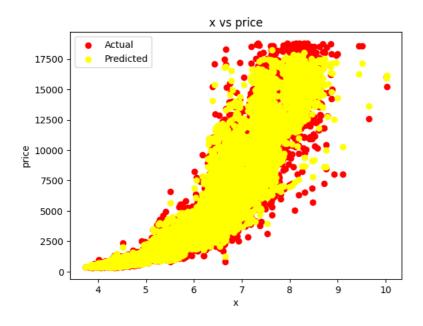
plt.show()

```
forestmodel.fit(X_train,y_train)
```

```
* RandomForestRegressor
RandomForestRegressor()
```

```
forestoutput = forestmodel.predict(X_test)

plt.scatter(X_test['x'],y_test,color="red")
plt.scatter(X_test['x'],forestoutput,color="yellow")
plt.legend(["Actual" , "Predicted"])
plt.xlabel('x')
plt.ylabel('price')
plt.title('x vs price')
```

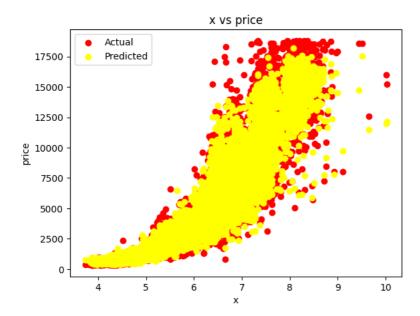


```
# Model Evaluation
print("R^2:",metrics.r2_score(y_test, forestoutput))
print("Adjusted R^2:",1 - (1-metrics.r2\_score(y\_test, forestoutput))*(len(y\_test)-1)/(len(y\_test)-X\_test.shape[1]-1))
print("MAE:",metrics.mean_absolute_error(y_test, forestoutput))
print("MSE:",metrics.mean_squared_error(y_test, forestoutput))
print("RMSE:",np.sqrt(metrics.mean_squared_error(y_test, forestoutput)))
     R^2: 0.9807999016737576
     Adjusted R^2: 0.9807870702424859
     MAE: 270.960836614055
     MSE: 301207.7683880054
     RMSE: 548.8239867097697
from sklearn.neighbors import KNeighborsRegressor
neighbormodel = KNeighborsRegressor()
neighbormodel.fit(X\_train,y\_train)
      ▼ KNeighborsRegressor
      KNeighborsRegressor()
neighboroutput = neighbormodel.predict(X_test)
# Model Evaluation
\verb"print("R^2:", \verb"metrics.r2_score(y_test, neighboroutput))"
print("Adjusted R^2:",1 - (1-metrics.r2\_score(y\_test, neighboroutput))*(len(y\_test)-1)/(len(y\_test)-X\_test.shape[1]-1))
print("MAE:",metrics.mean_absolute_error(y_test, neighboroutput))
\verb|print("MSE:",metrics.mean_squared_error(y_test, neighboroutput))| \\
\verb|print("RMSE:",np.sqrt(metrics.mean_squared\_error(y\_test, neighboroutput)))| \\
     R^2: 0.9488465711208338
Adjusted R^2: 0.9488123852695
```

plt.show()

MAE: 477.70471173109746
MSE: 802486.00274245
RMSE: 895.8158308170547

plt.scatter(X\_test['x'],y\_test,color="red")
plt.scatter(X\_test['x'],neighboroutput,color="yellow")
plt.legend(["Actual" , "Predicted"])
plt.xlabel('x')
plt.ylabel('price')
plt.title('x vs price')



## print(X\_train)

			_						
	carat	cut	color	clarity	depth	table	X	У	Z
8778	0.90	1	0	2	58.5	63.0	6.21	6.30	3.66
47001	0.53	2	3	7	62.5	54.0	5.19	5.21	3.25
40421	0.50	0	4	4	66.6	58.0	4.95	4.84	3.26
44023	0.51	2	1	2	62.2	57.0	5.12	5.08	3.17
13402	0.32	3	4	7	62.2	58.0	4.33	4.38	2.71
919	0.72	0	2	4	56.9	69.0	5.93	5.77	3.33
53492	0.75	3	2	2	61.5	58.0	5.83	5.87	3.60
38492	0.42	3	2	4	61.2	58.0	4.82	4.86	2.96
10750	1.12	4	3	3	60.2	59.0	6.70	6.85	4.08
49719	0.72	2	6	7	61.5	57.0	5.74	5.77	3.54

[40430 rows x 9 columns]

forestmodel.predict([[0.90,1,0,2,58.5,63.0,6.21,6.30,3.66]])

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but RandomForestRegr warnings.warn(
array([4354.75])

4