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House Price Prediction Dataset

July 23, 2021

Importing the dataset. The notebook can be found [Here](#).

Ranabir_House Price Prediction.ipynb ☆

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

```
[2] path = '/content/drive/MyDrive/Work/Quantum AI Course/Assignments/House Price Prediction/ML Coding Test Dataset.csv'
```

```
[3] df2 = pd.read_csv(path)
    df1 = df2.copy()
    df1.head()
```

	LATITUDE	LONGITUDE	CITY_NUMBER	TAX_VALUE	MUNICIPAL_TAXES	PRIMARY_ROOM_AREA	USABLE_FLOOR_SPACE	GROSS_AREA	BEDROOMS	BUILT_YEAR	ENERGY_LABEL	TOTAL_PRICE
0	58.297768	7.834061	4223.0	505 398 kr	12 885 kr	160 m²	181 m²	193 m²	3.0	1961.0	NaN	1 440 420 kr
1	58.435657	8.747802	4203.0	608 500 kr	18 030 kr	132 m²	159 m²	176 m²	3.0	1964.0	F	2 668 742 kr
2	58.246155	7.945707	4223.0	537 010 kr	NaN	140 m²	163 m²	179 m²	3.0	1970.0	NaN	2 574 142 kr
3	58.149666	7.998533	4204.0	306 175 kr	6 108 kr	32 m²	32 m²	36 m²	1.0	1961.0	E	1 496 378 kr
4	58.171501	7.985000	4204.0	822 362 kr	NaN	140 m²	144 m²	158 m²	3.0	1997.0	NaN	3 806 021 kr

```
[4] df1.shape

(166768, 12)
```

Here is the dataset used in this notebook. A glimpse and the shape of the dataset are shown here. We can see there are some unnecessary strings attached to some of the columns. So have to strip them out.

```
df1['TAX_VALUE'] = df1.TAX_VALUE.str.replace(' kr', '')
df1['TAX_VALUE'] = df1.TAX_VALUE.str.replace('\xa0', '')
df1['TAX_VALUE'] = pd.to_numeric(df1['TAX_VALUE'], errors='ignore')

df1['MUNICIPAL_TAXES'] = df1.MUNICIPAL_TAXES.str.replace(' kr', '')
df1['MUNICIPAL_TAXES'] = df1.MUNICIPAL_TAXES.str.replace('\xa0', '')
df1['MUNICIPAL_TAXES'] = pd.to_numeric(df1['MUNICIPAL_TAXES'], errors='ignore')

df1['PRIMARY_ROOM_AREA'] = df1.PRIMARY_ROOM_AREA.str.replace(' m²', '')
df1['PRIMARY_ROOM_AREA'] = df1.PRIMARY_ROOM_AREA.str.replace('\xa0', '')
df1['PRIMARY_ROOM_AREA'] = pd.to_numeric(df1['PRIMARY_ROOM_AREA'], errors='ignore')

df1['USABLE_FLOOR_SPACE'] = df1.USABLE_FLOOR_SPACE.str.replace(' m²', '')
df1['USABLE_FLOOR_SPACE'] = df1.USABLE_FLOOR_SPACE.str.replace('\xa0', '')
df1['USABLE_FLOOR_SPACE'] = pd.to_numeric(df1['USABLE_FLOOR_SPACE'], errors='ignore')

df1['GROSS_AREA'] = df1.GROSS_AREA.str.replace(' m²', '')
df1['GROSS_AREA'] = df1.GROSS_AREA.str.replace('\xa0', '')
df1['GROSS_AREA'] = pd.to_numeric(df1['GROSS_AREA'], errors='ignore')

df1['TOTAL_PRICE'] = df1.TOTAL_PRICE.str.replace(' kr', '')
df1['TOTAL_PRICE'] = df1.TOTAL_PRICE.str.replace('\xa0', '')
df1['TOTAL_PRICE'] = pd.to_numeric(df1['TOTAL_PRICE'], errors='ignore')
```

After removing all the unnecessary strings attached with different columns, a description of the dataset is shown here.

```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 166768 entries, 0 to 166767
Data columns (total 12 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   LATITUDE            166768 non-null  float64
 1   LONGITUDE           166768 non-null  float64
 2   CITY_NUMBER         166624 non-null  float64
 3   TAX_VALUE           136381 non-null  float64
 4   MUNICIPAL_TAXES     93184 non-null   float64
 5   PRIMARY_ROOM_AREA   165095 non-null  float64
 6   USABLE_FLOOR_SPACE  165499 non-null  float64
 7   GROSS_AREA          117358 non-null  float64
 8   BEDROOMS            160814 non-null  float64
 9   BUILT_YEAR          164584 non-null  float64
 10  ENERGY_LABEL        127615 non-null  object
 11  TOTAL_PRICE         166768 non-null  int64
dtypes: float64(10), int64(1), object(1)
memory usage: 15.3+ MB
```

```
[6] df1.describe()
```

	LATITUDE	LONGITUDE	CITY_NUMBER	TAX_VALUE	MUNICIPAL_TAXES	PRIMARY_ROOM_AREA	USABLE_FLOOR_SPACE	GROSS_AREA	BEDROOMS	BUILT_YEAR	TOTAL_PRICE
count	166768.000000	166768.000000	166624.000000	1.363810e+05	93184.000000	165095.000000	165499.000000	117358.000000	160814.000000	164584.000000	1.667680e+05
mean	61.630107	10.176236	3021.201982	8.160642e+05	13089.871695	113.262918	130.674022	144.068624	2.774081	1977.007230	3.821578e+06
std	3.684552	4.387788	1694.339204	1.902400e+06	9213.134761	68.303253	92.857686	100.161577	1.473997	37.296304	3.238544e+06
min	0.000000	0.000000	0.000000	0.000000e+00	0.000000	0.000000	0.000000	1.000000	0.000000	1600.000000	1.000000e+00
25%	59.402578	6.913600	1507.000000	4.827710e+05	8530.000000	67.000000	70.000000	76.000000	2.000000	1956.000000	2.205092e+06
50%	60.201401	10.369204	3405.000000	6.812420e+05	12025.500000	95.000000	104.000000	115.000000	3.000000	1980.000000	3.167250e+06
75%	63.117500	11.007900	4601.000000	9.482580e+05	16229.000000	145.000000	171.000000	190.000000	3.000000	2009.000000	4.501288e+06
max	78.221336	31.118286	9911.000000	1.234568e+08	946024.000000	3912.000000	5152.000000	3000.000000	32.000000	2021.000000	1.281406e+08

Since the amount of data is huge in this dataset, it is normal for some of the rows to go missing. As we can see there are many rows with **NULL** values. So, we have to find a way to handle them.

```
df1.isnull().sum()
```

```
LATITUDE                  0
LONGITUDE                 0
CITY_NUMBER             144
TAX_VALUE             30387
MUNICIPAL_TAXES       73584
PRIMARY_ROOM_AREA      1673
USABLE_FLOOR_SPACE     1269
GROSS_AREA            49410
BEDROOMS               5954
BUILT_YEAR             2184
ENERGY_LABEL          39153
TOTAL_PRICE               0
dtype: int64
```

```
df1['CITY_NUMBER'].value_counts()
```

```
[9] df1['ENERGY_LABEL'].value_counts()
```

```
G    37168
F    21832
D    18870
C    18202
E    17539
B    12779
A     1225
Name: ENERGY_LABEL, dtype: int64
```

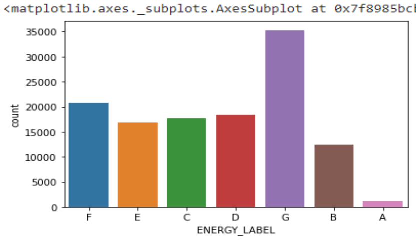
As we can see **'CITY_NUMBER', 'PRIMARY_ROOM_AREA', 'USABLE_FLOOR_SPACE', 'BUILT_YEAR'** has some **NULL** values. Since the size of data is huge here, so we can drop these **NULL** values. Here's how the data distribution currently is.

```
[10]  df1.dropna(how='any', subset=['CITY_NUMBER','PRIMARY_ROOM_AREA','USABLE_FLOOR_SPACE','BUILT_YEAR'], inplace=True)
      df1.isnull().sum()

      LATITUDE               0
      LONGITUDE              0
      CITY_NUMBER            0
      TAX_VALUE          28087
      MUNICIPAL_TAXES    71337
      PRIMARY_ROOM_AREA      0
      USABLE_FLOOR_SPACE     0
      GROSS_AREA         47209
      BEDROOMS            4988
      BUILT_YEAR             0
      ENERGY_LABEL       36497
      TOTAL_PRICE            0
      dtype: int64
```

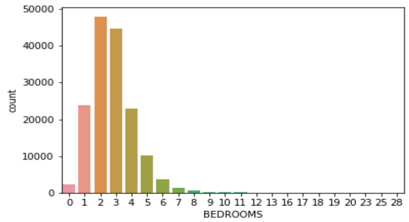
```
df1.shape

(162699, 12)
```

But there are still Columns with a high number of missing values. So we have to find a way to handle them. Before going to the process, there are two columns with categorical features. We have to encode them. There are some popular imputation techniques including **'Mean', 'Mode'**, but we will use a machine learning model to predict the output for the missing values in the column. Let's analyze the data to get the behavior of its nature.

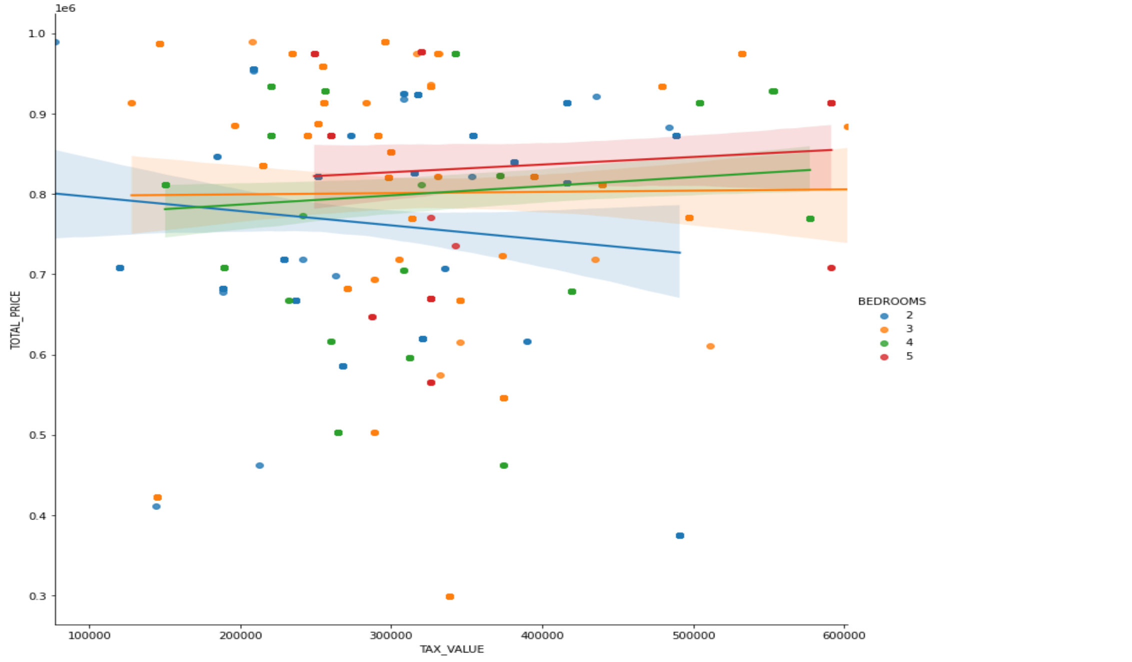
```
[74]  plt.figure()
      sns.countplot(x='ENERGY_LABEL', data=df1)

      <matplotlib.axes._subplots.AxesSubplot at 0x7f8985bcbe50>
```




```
[76]  plt.figure()
      sns.countplot(x='BEDROOMS', data=df1)

      <matplotlib.axes._subplots.AxesSubplot at 0x7f897bec9b50>
```

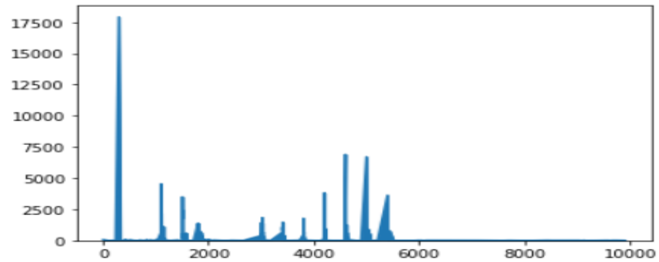


We can see the number of bedrooms and energy count in the graph. From here we can say that **"G"** level energy enabled house is more common and the max number of bedrooms is **2 or 3**.



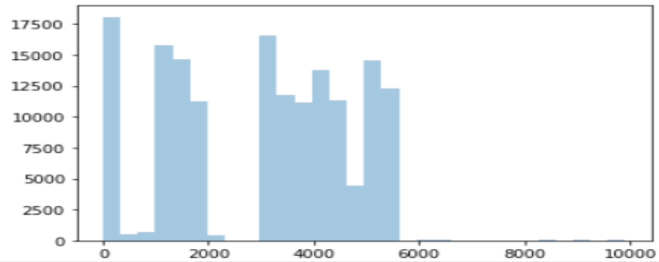
From this diagram, it is clear that as the number of **"Bedrooms"** increases the **Tax_Value** and **Price** also increases.

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f897d920f50>
```

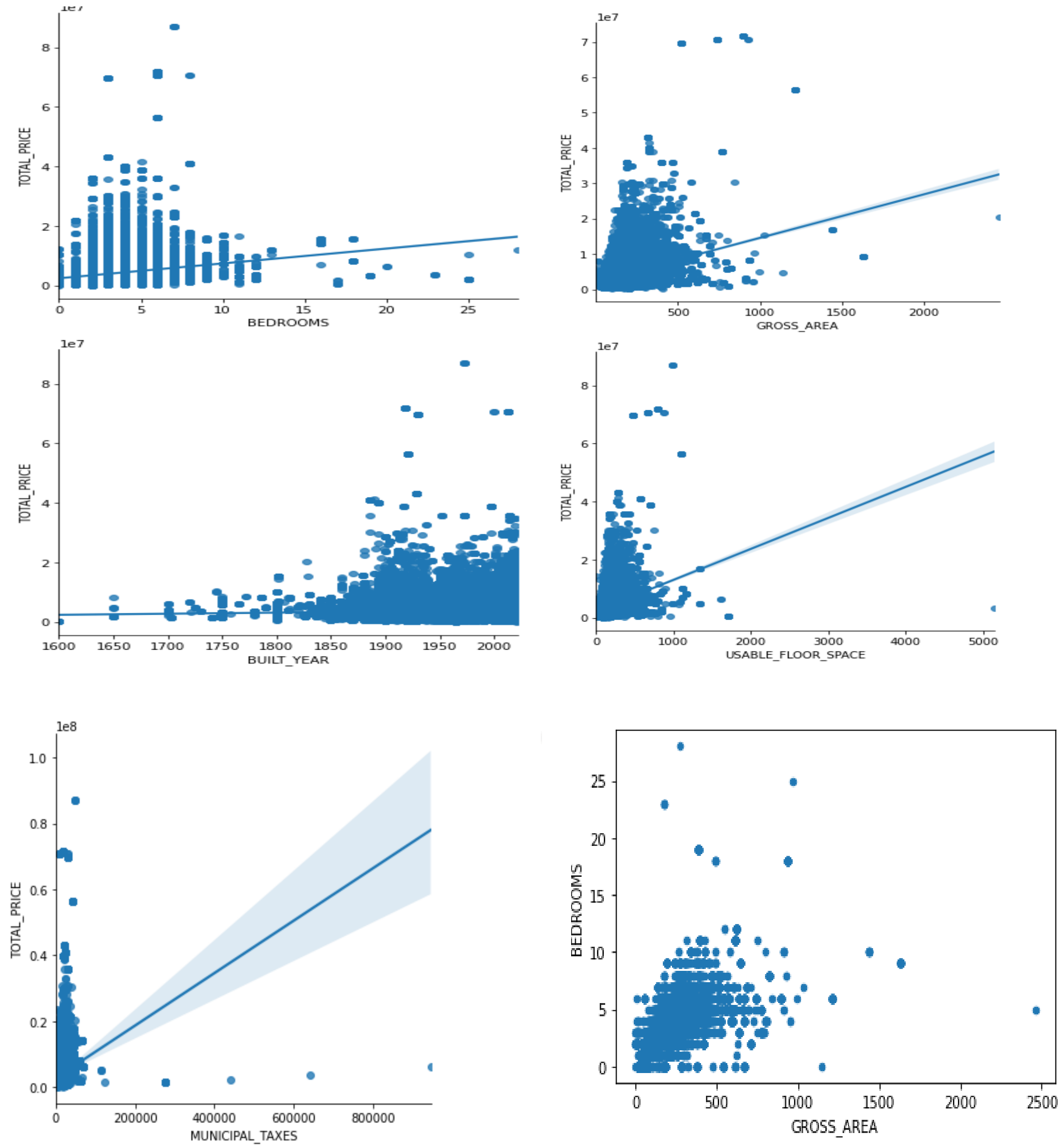



```
ax = sns.distplot(df1['CITY_NUMBER'], bins = 30, kde = False)
```

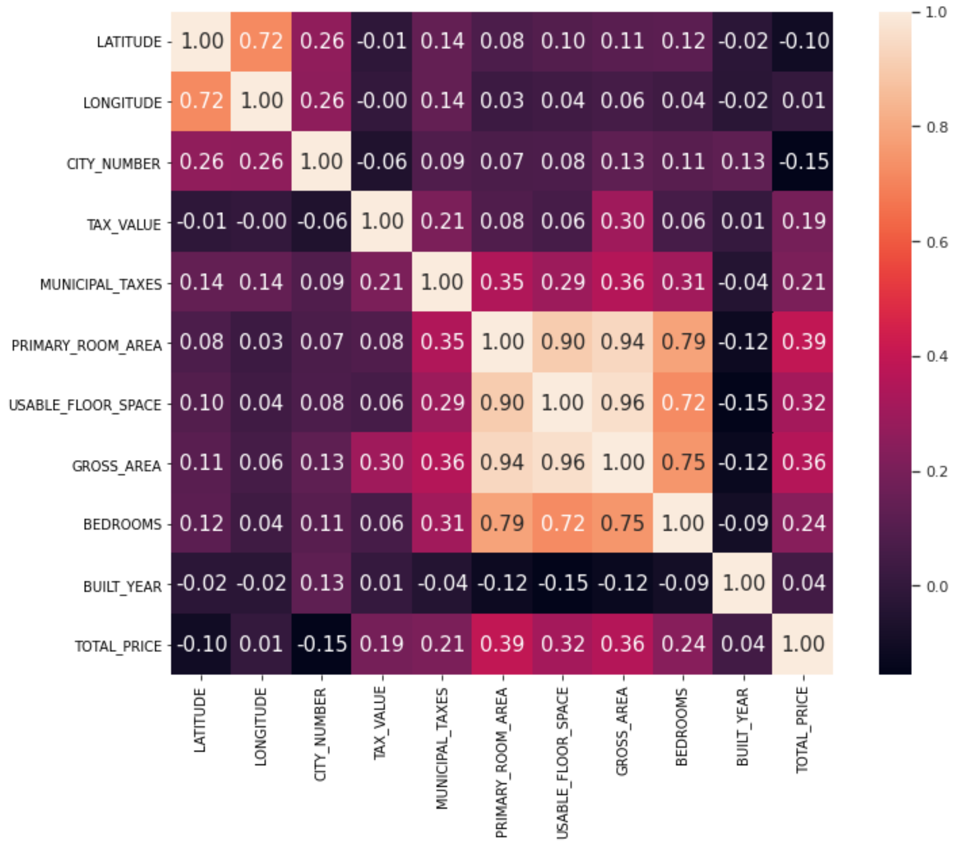
```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: `distplo
  warnings.warn(msg, FutureWarning)
```



Here is a simple distribution of the "CITY_NUMBER" column. We can see the count of Every City.



Here are some of the features with a huge number of NULL values that can affect the house price. We can see some relation between them. From a correlation matrix, we can see more details.



Here we can see the complete correlation between almost every variable. **"Energy Label"** is categorical data that's why it is missing here but we do know that the Energy label has an effect on the price prediction so we have to Encode them before filling up the missing values using '**K-Nearest Neighbour**". So here's how the "**Energy_Label**" looks like after encoding.

```
[162] cat_variables = df1[['ENERGY_LABEL']]
      cat_dummies = pd.get_dummies(cat_variables)
      cat_dummies.head()
```

	ENERGY_LABEL_A	ENERGY_LABEL_B	ENERGY_LABEL_C	ENERGY_LABEL_D	ENERGY_LABEL_E	ENERGY_LABEL_F	ENERGY_LABEL_G
0	0	0	0	0	0	0	0
1	0	0	0	0	0	1	0
2	0	0	0	0	0	0	0
3	0	0	0	0	1	0	0
4	0	0	0	0	0	0	0

```
df1 = df1.drop(['ENERGY_LABEL'], axis=1)
df1 = pd.concat([df1, cat_dummies], axis=1)
df1.head()
```

ITY_NUMBER	TAX_VALUE	MUNICIPAL_TAXES	PRIMARY_ROOM_AREA	USABLE_FLOOR_SPACE	GROSS_AREA	BEDROOMS	BUILT_YEAR	TOTAL_PRICE	ENERGY_LABEL_A	ENERGY_LABEL_B	ENERGY_LABEL_C	ENERGY_LABEL_D	ENERGY_LABEL_E	ENERGY_LABEL_F	ENERGY_LABEL_G
4223.0	505398.0	12885.0	160.0	181.0	193.0	3.0	1961.0	1440420	0	0	0	0	0	0	0
4203.0	608500.0	18030.0	132.0	159.0	176.0	3.0	1964.0	2668742	0	0	0	0	0	1	0
4223.0	537010.0	NaN	140.0	163.0	179.0	3.0	1970.0	2574142	0	0	0	0	0	0	0
4204.0	306175.0	6108.0	32.0	32.0	36.0	1.0	1961.0	1496378	0	0	0	0	1	0	0
4204.0	822362.0	NaN	140.0	144.0	158.0	3.0	1997.0	3806021	0	0	0	0	0	0	0

After applying KNN imputation, here's how the data looks like.

KNN imputation on whole dataset

```
[301]  df1_fill = imputer.fit_transform(df1)
```

```
df1_fill_pd = pd.DataFrame(df1_fill)

df1_fill_pd.rename(columns={0:'LATITUDE',
                            1:'LONGITUDE',
                            2:'CITY_NUMBER',
                            3:'TAX_VALUE',
                            4:'MUNICIPAL_TAXES',
                            5:'PRIMARY_ROOM_AREA',
                            6:'USABLE_FLOOR_SPACE',
                            7:'GROSS_AREA',
                            8:'BEDROOMS',
                            9:'BUILT_YEAR',
                            10:'TOTAL_PRICE',
                            11:'ENERGY_LABEL_A',
                            12:'ENERGY_LABEL_B',
                            13:'ENERGY_LABEL_C',
                            14:'ENERGY_LABEL_D',
                            15:'ENERGY_LABEL_E',
                            16:'ENERGY_LABEL_F',
                            17:'ENERGY_LABEL_G'},
                      inplace=True)
df1_fill_pd
```

```
[306]  df1_fill_pd.isnull().sum()
```

```
LATITUDE              0
LONGITUDE             0
CITY_NUMBER           0
TAX_VALUE             0
MUNICIPAL_TAXES       0
PRIMARY_ROOM_AREA     0
USABLE_FLOOR_SPACE    0
GROSS_AREA            0
BEDROOMS              0
BUILT_YEAR            0
TOTAL_PRICE           0
ENERGY_LABEL_A        0
ENERGY_LABEL_B        0
ENERGY_LABEL_C        0
ENERGY_LABEL_D        0
ENERGY_LABEL_E        0
ENERGY_LABEL_F        0
ENERGY_LABEL_G        0
dtype: int64
```

So we are ready for training.

Here we split the dataset into two parts by the ratio of (90-10).90% train and 10% test.

```
[312]  X=df1_fill_pd[['CITY_NUMBER', 'TAX_VALUE', 'MUNICIPAL_TAXES','PRIMARY_ROOM_AREA','USABLE_FLOOR_SPACE','GROSS_AREA','BEDROOMS','BUILT_YEAR', 'ENERGY_LABEL_A','ENERGY
       Y=df1_fill_pd[[ 'TOTAL_PRICE']]
```

```
[313]  x_train,x_test,y_train,y_test = train_test_split(X,Y, train_size=0.9, random_state=42)
```

```
[314]  print(x_train.shape)
       print(y_train.shape)
       print(x_test.shape)

(141939, 15)
(141939, 1)
(15772, 15)
```

Here is the Linear Regression Implementation and evaluation of this problem.

Linear Regression

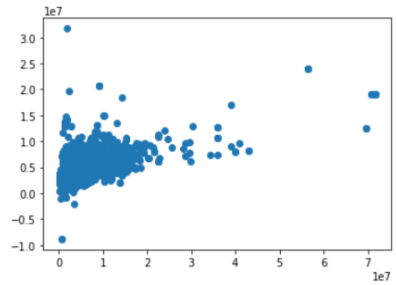
```
[9]   regressor = LinearRegression()

      # Fit model to training data
      regressor.fit(X_train,y_train)

LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

```
[10]  y_pred = regressor.predict(X_test)
```

```
[11]  regressor.score(X_test,y_test)

0.30157702083927684
```

```
print('MAE:',metrics.mean_absolute_error(y_test,y_pred))
print('MSE:',metrics.mean_squared_error(y_test,y_pred))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_test,y_pred)))

MAE: 1516933.7190646823
MSE: 6729516390214.582
RMSE: 2594131.1436036886
```

```
plt.scatter(y_test, y_pred)

<matplotlib.collections.PathCollection at 0x7f7e83dcee50>
```



Here is the Decision Tree Regressor implementation.

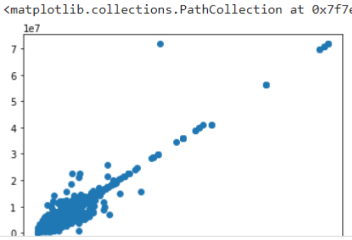
Decision Tree Regressor

```
[14]  tree = DecisionTreeRegressor()
      tree.fit(X_train,y_train)

DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None,
                      max_features=None, 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, presort='deprecated',
                      random_state=None, splitter='best')
```

```
[15]  y_pred_DT = tree.predict(X_test)
```

```
[16]  tree.score(X_test,y_test)

0.9597622802234412
```

```
plt.scatter(y_test, y_pred_DT)

<matplotlib.collections.PathCollection at 0x7f7e842c7f10>
```




```
print('MAE:',metrics.mean_absolute_error(y_test,y_pred_DT))
print('MSE:',metrics.mean_squared_error(y_test,y_pred_DT))
print('RMSE:',np.sqrt(metrics.mean_squared_error(y_test,y_pred_DT)))

MAE: 108821.14537391119
MSE: 387702585425.52905
RMSE: 622657.6791669151
```

So we are certain that Decision Tree Regressor has produced a better model than Linear Regression. Also More regression model can be applied for experiment.