House Price Prediction Multi-Linear Regression

February 20, 2025

Step 1: Importing Libraries

[82]:
```
# Import numpy and pandas package
import pandas as pd
import numpy as np
# Data visualization
from matplotlib import pyplot as plot
import statsmodels.api as sm
import seaborn as sns
```

Step 2: Reading the Dataset and Inspecting

[83]:
```
data = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/ML-DSE4/
↪Project_College/Housing.csv')
```

[84]:
```
data.head(10)
```

[84]:
```
      price   area  bedrooms  bathrooms  stories mainroad guestroom basement  \
0  13300000   7420         4          2        3      yes        no       no
1  12250000   8960         4          4        4      yes        no       no
2  12250000   9960         3          2        2      yes        no      yes
3  12215000   7500         4          2        2      yes        no      yes
4  11410000   7420         4          1        2      yes       yes      yes
5  10850000   7500         3          3        1      yes        no      yes
6  10150000   8580         4          3        4      yes        no       no
7  10150000  16200         5          3        2      yes        no       no
8   9870000   8100         4          1        2      yes       yes      yes
9   9800000   5750         3          2        4      yes       yes       no

  hotwaterheating airconditioning  parking prefarea furnishingstatus
0              no             yes        2      yes        furnished
1              no             yes        3       no        furnished
2              no              no        2      yes   semi-furnished
3              no             yes        3      yes        furnished
4              no             yes        2       no        furnished
5              no             yes        2      yes   semi-furnished
6              no             yes        2      yes   semi-furnished
7              no              no        0       no      unfurnished
```

```
8              no              yes          2       yes        furnished
9              no              yes          1       yes      unfurnished
```

[85]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 545 entries, 0 to 544
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   price             545 non-null    int64
 1   area              545 non-null    int64
 2   bedrooms          545 non-null    int64
 3   bathrooms         545 non-null    int64
 4   stories           545 non-null    int64
 5   mainroad          545 non-null    object
 6   guestroom         545 non-null    object
 7   basement          545 non-null    object
 8   hotwaterheating   545 non-null    object
 9   airconditioning   545 non-null    object
 10  parking           545 non-null    int64
 11  prefarea          545 non-null    object
 12  furnishingstatus  545 non-null    object
dtypes: int64(6), object(7)
memory usage: 55.5+ KB
```

[86]:
```
data.describe()
```

[86]:

	price	area	bedrooms	bathrooms	stories	\
count	5.450000e+02	545.000000	545.000000	545.000000	545.000000	
mean	4.766729e+06	5150.541284	2.965138	1.286239	1.805505	
std	1.870440e+06	2170.141023	0.738064	0.502470	0.867492	
min	1.750000e+06	1650.000000	1.000000	1.000000	1.000000	
25%	3.430000e+06	3600.000000	2.000000	1.000000	1.000000	
50%	4.340000e+06	4600.000000	3.000000	1.000000	2.000000	
75%	5.740000e+06	6360.000000	3.000000	2.000000	2.000000	
max	1.330000e+07	16200.000000	6.000000	4.000000	4.000000	

	parking
count	545.000000
mean	0.693578
std	0.861586
min	0.000000
25%	0.000000
50%	0.000000
75%	1.000000
max	3.000000

[87]:
```
data.shape
```

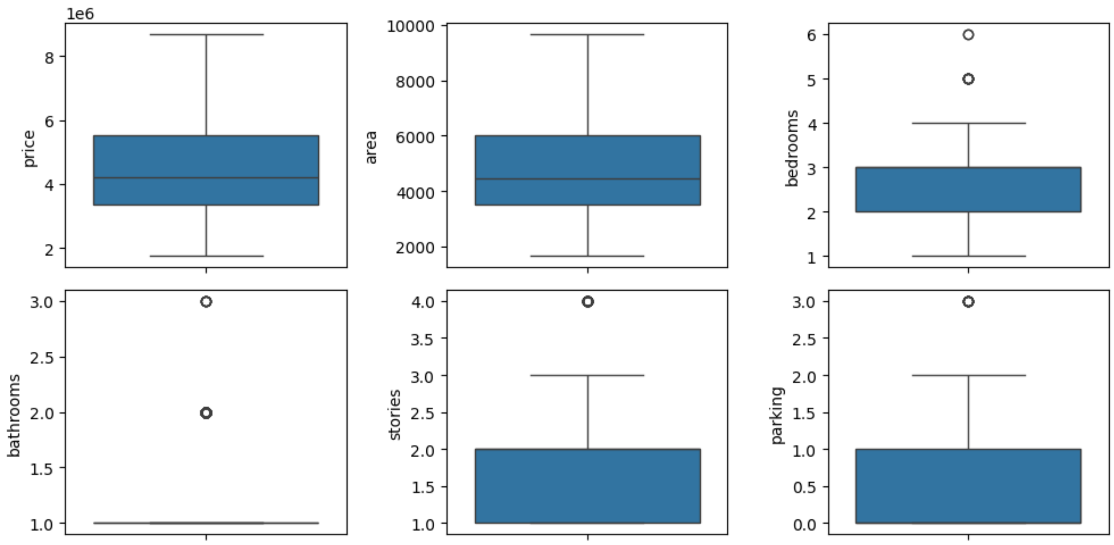
[87]:
```
(545, 13)
```

Step 3: Data Preprocessing

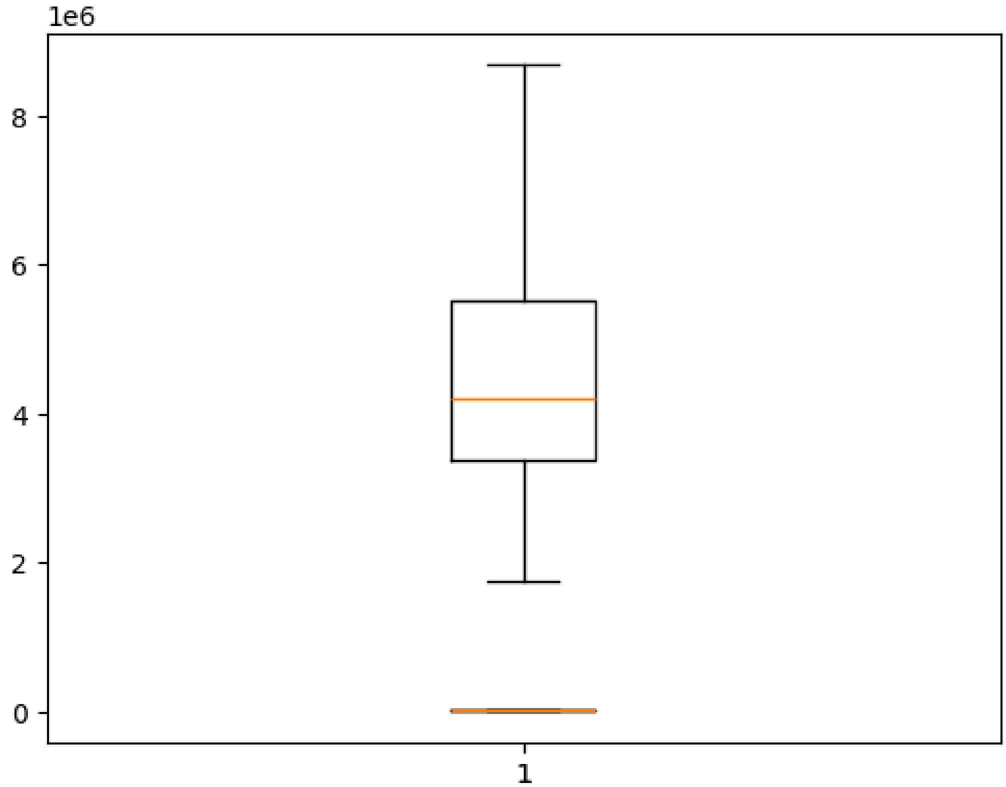
[ ]:
```
#Data Cleaning
data.isnull().sum()
```

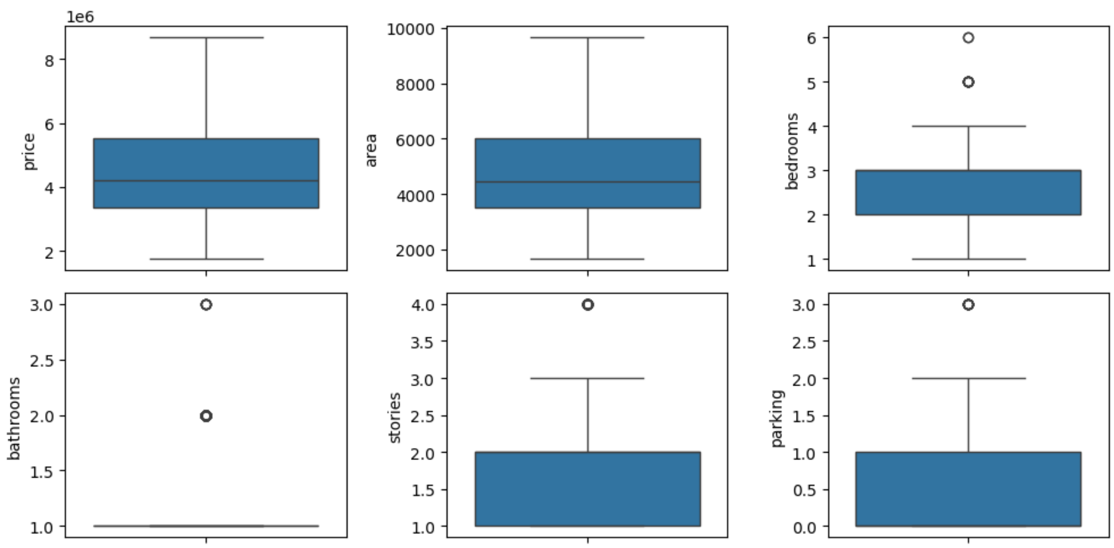
[ ]:
```
price               0
area                0
bedrooms            0
bathrooms           0
stories             0
mainroad            0
guestroom           0
basement            0
hotwaterheating     0
airconditioning     0
parking             0
prefarea            0
furnishingstatus    0
dtype: int64
```

[105]:
```
#Detecting for Outliers
def detectOutliers():
    fig, axs = plot.subplots(2,3, figsize = (10,5))
    plt1 = sns.boxplot(data['price'], ax = axs[0,0])
    plt2 = sns.boxplot(data['area'], ax = axs[0,1])
    plt3 = sns.boxplot(data['bedrooms'], ax = axs[0,2])
    plt1 = sns.boxplot(data['bathrooms'], ax = axs[1,0])
    plt2 = sns.boxplot(data['stories'], ax = axs[1,1])
    plt3 = sns.boxplot(data['parking'], ax = axs[1,2])
    plot.tight_layout()
detectOutliers()
```



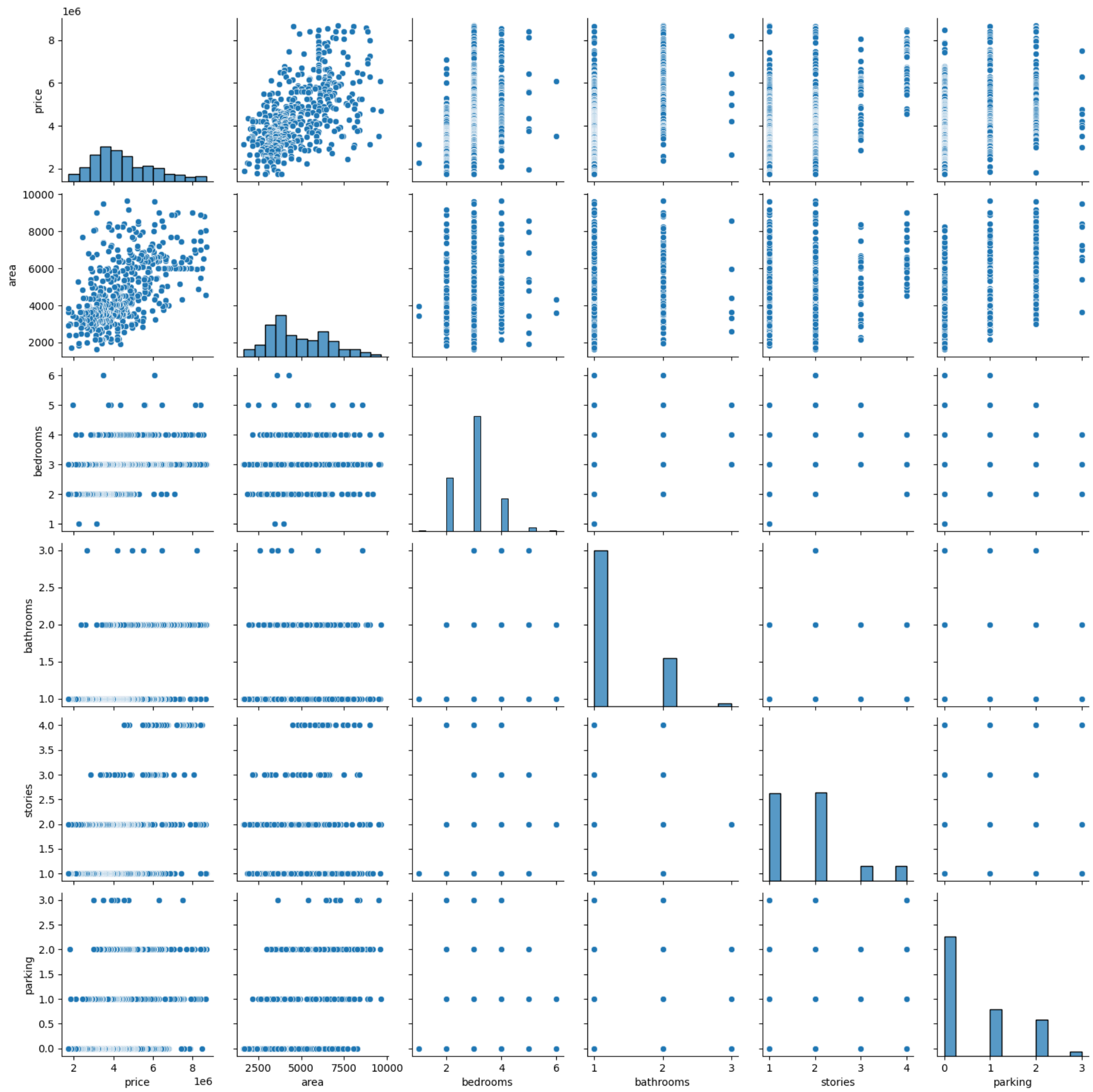
[104]:
```
#Removing Outliers
# Outlier reduction for price
plot.boxplot(data.price)
Q1 = data.price.quantile(0.25)
Q3 = data.price.quantile(0.75)
IQR = Q3 - Q1
data = data[(data.price >= Q1 - 1.5*IQR) & (data.price <= Q3 + 1.5*IQR)]
# Outlier reduction for area
plot.boxplot(data.area)
Q1 = data.area.quantile(0.25)
Q3 = data.area.quantile(0.75)
IQR = Q3 - Q1
data = data[(data.area >= Q1 - 1.5*IQR) & (data.area <= Q3 + 1.5*IQR)]

#To verify the outlier is still existing
detectOutliers()
```





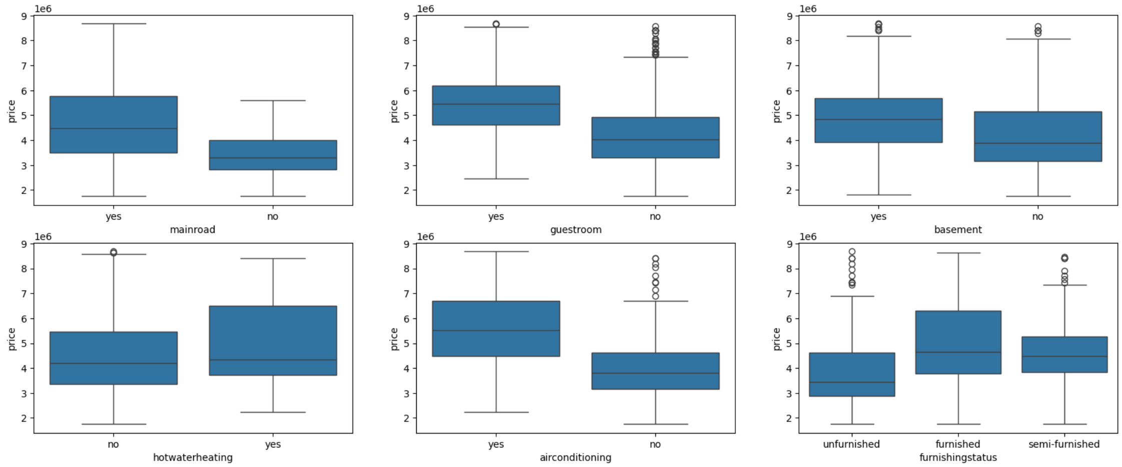
Step 4: Data Visualizations

[106]:
```
sns.pairplot(data)
plot.show()
```



[107]:
```
#Visualizing the Categorical Variables
plot.figure(figsize=(20, 12))
plot.subplot(3,3,1)
sns.boxplot(x='mainroad', y='price', data=data)
plot.subplot(3,3,2)
sns.boxplot(x='guestroom', y='price', data=data)
plot.subplot(3,3,3)
sns.boxplot(x='basement', y='price', data=data)
plot.subplot(3,3,4)
sns.boxplot(x='hotwaterheating', y='price', data=data)
```

```python
plot.subplot(3,3,5)
sns.boxplot(x='airconditioning', y='price', data=data)
plot.subplot(3,3,6)
sns.boxplot(x='furnishingstatus', y='price', data=data)
plot.show()
```



Step 5: Data Preparations

To fit the data in the regression line, we need of numeric data not string.So, need to convert those string values to int.

[108]:
```python
def toNumeric(x):
    return x.map({"no":0,"yes":1})
def convert_binary():
    for column in list(data.select_dtypes(['object']).columns):
        if(column != 'furnishingstatus'):
            data[[column]] = data[[column]].apply(toNumeric)
convert_binary()
```

Splitting the column for furnishing status that holds the value in three levels namely furnished/unfurnished/semi-furnished. To implement this we need dummy variables

[109]:
```python
status = pd.get_dummies(data['furnishingstatus'])
status
```

[109]:

	furnished	semi-furnished	unfurnished
21	False	False	True
22	True	False	False
23	True	False	False
24	True	False	False
25	True	False	False
..	…	…	…

```
540      False          False         True
541      False           True        False
542      False          False         True
543       True          False        False
544      False          False         True

[506 rows x 3 columns]
```

Now, you don't need three columns. You can drop the furnished column, as the type of furnishing can be identified with just the last two columns where

1. 00 will correspond to furnished
2. 01 will correspond to unfurnished
3. 10 will correspond to semi-furnished

[110]:
```
#To drop the very first column of furnished
status = pd.get_dummies(data['furnishingstatus'], drop_first=True)
#Concat the status and main data frame as below,
data = pd.concat([data, status], axis=1)
#Remove the column furnishing status which is no longer needed.
data.drop(columns='furnishingstatus',inplace=True)
```

After all the changes, the data frame looks like

[111]:
```
data
```

[111]:
```
       price  area  bedrooms  bathrooms  stories  mainroad  guestroom  \
21   8680000  7155         3          2        1         1          1
22   8645000  8050         3          1        1         1          1
23   8645000  4560         3          2        2         1          1
24   8575000  8800         3          2        2         1          0
25   8540000  6540         4          2        2         1          1
..       …     …       …         …       …        …         …
540  1820000  3000         2          1        1         1          0
541  1767150  2400         3          1        1         0          0
542  1750000  3620         2          1        1         1          0
543  1750000  2910         3          1        1         0          0
544  1750000  3850         3          1        2         1          0

     basement  hotwaterheating  airconditioning  parking  prefarea  \
21          1                0                1        2         0
22          1                0                1        1         0
23          1                0                1        1         0
24          0                0                1        2         0
25          1                0                1        2         1
..        …              …               …      …       …
540         1                0                0        2         0
```

```
541          0                 0                 0        0         0
542          0                 0                 0        0         0
543          0                 0                 0        0         0
544          0                 0                 0        0         0

     semi-furnished  unfurnished
21            False         True
22            False        False
23            False        False
24            False        False
25            False        False
..              …            …
540           False         True
541            True        False
542           False         True
543           False        False
544           False         True

[506 rows x 14 columns]
```

[112]:
```
#Including the fields other than prices for the X data frame. For Y including␣
↪the price field alone.
Y = data.price
# includes the fields other than prices
X = data.iloc[:,1:]
```

Checking for Multi-Collinearity

[113]:
```
# Import necessary libraries
from sklearn.preprocessing import MinMaxScaler, LabelEncoder, OneHotEncoder
from statsmodels.stats.outliers_influence import variance_inflation_factor
import pandas as pd
import numpy as np

def preprocessing(X):
    # Separate numeric and categorical features
    numeric_features = X.select_dtypes(include=np.number).columns
    categorical_features = X.select_dtypes(include=['object']).columns

    # Handle numeric features: Scaling and VIF calculation
    X_numeric = X[numeric_features]
    scaler = MinMaxScaler()
    X_numeric_scaled = scaler.fit_transform(X_numeric)
    X_numeric_scaled = pd.DataFrame(X_numeric_scaled, columns=numeric_features,␣
↪index=X.index)

    # Handle categorical features: One-hot encoding
```

```
    if len(categorical_features) > 0: # Only if there are categorical features
        encoder = OneHotEncoder(sparse_output=False, handle_unknown='ignore') #␣
↪sparse=False for compatibility with statsmodels
        X_categorical_encoded = encoder.fit_transform(X[categorical_features])
        X_categorical_encoded = pd.DataFrame(X_categorical_encoded,␣
↪columns=encoder.get_feature_names_out(categorical_features), index=X.index)

        # Combine scaled numeric and encoded categorical features
        X_processed = pd.concat([X_numeric_scaled, X_categorical_encoded],␣
↪axis=1)
    else:
        X_processed = X_numeric_scaled

    # Calculate VIF for numeric features
    variables = X_processed[numeric_features].values
    vif = pd.DataFrame()
    vif["VIF"] = [variance_inflation_factor(variables, i) for i in␣
↪range(variables.shape[1])]
    vif["Features"] = numeric_features
    print(vif)

    return X_processed  # Return the preprocessed DataFrame

# ... (Rest of your code) ...

# Before train_test_split
X = preprocessing(X)

# ... (Continue with your code) ...
```

```
         VIF          Features
0   5.819700              area
1   6.225434          bedrooms
2   1.596261         bathrooms
3   2.689909           stories
4   5.432064          mainroad
5   1.520775         guestroom
6   2.024715          basement
7   1.068902   hotwaterheating
8   1.728249   airconditioning
9   1.850638           parking
10  1.426323          prefarea
```

As a thumb rule, a VIF value greater than 5 means very severe multicollinearity. From the above results area and bedrooms having severe collinearity.

We need to drop those columns and confirm the collinearity is still exists.

[114]:
```
X.drop(['area','bedrooms'], axis=1, inplace=True)
preprocessing(X)
```

```
        VIF          Features
0  1.536585         bathrooms
1  2.251750           stories
2  3.080967          mainroad
3  1.474810         guestroom
4  1.876139          basement
5  1.061477  hotwaterheating
6  1.654247  airconditioning
7  1.673949           parking
8  1.414061          prefarea
```

[114]:

```
     bathrooms   stories  mainroad  guestroom  basement  hotwaterheating  \
21         0.5  0.000000       1.0        1.0       1.0              0.0
22         0.0  0.000000       1.0        1.0       1.0              0.0
23         0.5  0.333333       1.0        1.0       1.0              0.0
24         0.5  0.333333       1.0        0.0       0.0              0.0
25         0.5  0.333333       1.0        1.0       1.0              0.0
..         …         …        …         …        …               …
540        0.0  0.000000       1.0        0.0       1.0              0.0
541        0.0  0.000000       0.0        0.0       0.0              0.0
542        0.0  0.000000       1.0        0.0       0.0              0.0
543        0.0  0.000000       0.0        0.0       0.0              0.0
544        0.0  0.333333       1.0        0.0       0.0              0.0

     airconditioning   parking  prefarea
21               1.0  0.666667       0.0
22               1.0  0.333333       0.0
23               1.0  0.333333       0.0
24               1.0  0.666667       0.0
25               1.0  0.666667       1.0
..               …         …       …
540              0.0  0.666667       0.0
541              0.0  0.000000       0.0
542              0.0  0.000000       0.0
543              0.0  0.000000       0.0
544              0.0  0.000000       0.0

[506 rows x 9 columns]
```

Step 6: Splitting the Data into Training and Testing Sets

[115]:
```
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=355)
```

Step 7: Traning the model using Multi-Linear Regression

[116]:
```
from sklearn.linear_model import LinearRegression
regression = LinearRegression()
regression.fit(x_train,y_train)
```

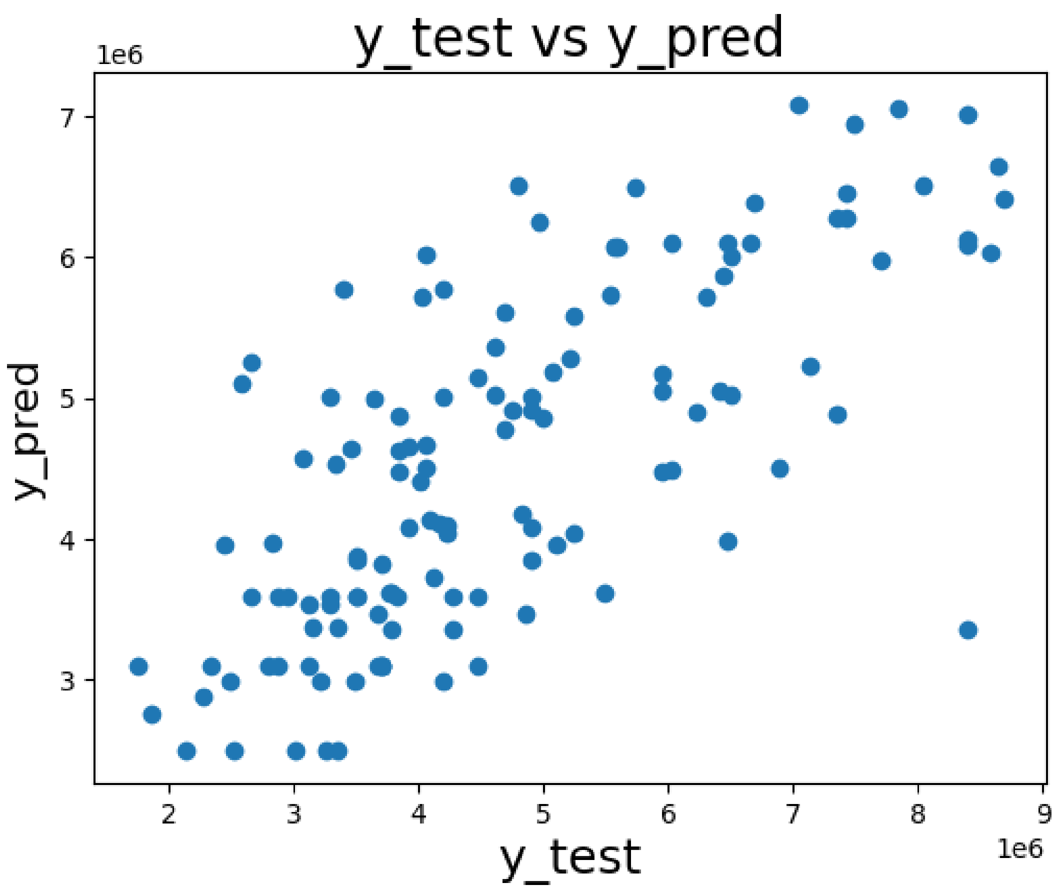
[116]:
```
LinearRegression()
```

Step 8: Making Predictions

[117]:
```
y_predict = regression.predict(x_test)
```

Step 9: Plotting y__test and y__pred to understand the spread

[119]:
```
#Import necessary library
import matplotlib.pyplot as plt

#Your plotting code:
plt.scatter(y_test,y_predict)
plt.title('y_test vs y_pred', fontsize=20) # Changed from fig.suptitle to plt.
 ↪title
plt.xlabel('y_test', fontsize=18)
plt.ylabel('y_pred', fontsize=16)
plt.show()
```



Step 10: Evaluating the model

[120]:
```
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler

mse = mean_squared_error(y_test,y_predict)
rmse = np.sqrt(mse)
r2 = r2_score(y_test,y_predict)

print(f'Mean Squared Error (MSE): {mse}')
print(f'Root Mean Squared Error (RMSE): {rmse}')
print(f'R-Sqaured (R2-Score): {r2}')
print("Model Coefficients:")
print(regression.coef_)
```

```
Mean Squared Error (MSE): 1396590759756.7407
Root Mean Squared Error (RMSE): 1181774.4115340882
R-Sqaured (R2-Score): 0.5154735302953686
Model Coefficients:
[1767879.26522718 1475368.92119728  598690.19657082  500675.44444703
```

```
376416.68297797  724872.17600083 1043865.90913399  777512.22815843
561347.53843054]
```