Real Estate Valuation Data Set

This research aimed at predicting housing prices within New Taipei City, Taiwan.

Data downloaded from: https://archive.ics.uci.edu/ml/datasets/Real+estate+valuation+data+set (https://archive.ics.uci.edu/ml/datasets/Real+estate+valuation+data+set)

Section Order

- Exploratory Data Analysis (Data understanding)
- Normalization (Data preparation)
- Train-Test Split (Validation)
- Linear Regression (Algorithm)
- R2 (Evaluation)

Exploratory Data Analysis (Data understanding)

In [1]:
```
# Load up the packages and data
import pandas as pd
import seaborn as sns
import sklearn
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: Futu
reWarning: pandas.util.testing is deprecated. Use the functions in the public
API at pandas.testing instead.
  import pandas.util.testing as tm
```

In [2]:
```
# Loading the data
housingdata=pd.read_excel("Real estate valuation data set.xlsx")

# Example on how to run data from URL link (commented out)
##housingdata=pd.read_excel("https://archive.ics.uci.edu/ml/machine-learning-d
atabases/00477/Real%20estate%20valuation%20data%20set.xlsx")

# Examining a few top rows
housingdata
```

Out[2]:

	No	X1 transaction date	X2 house age	X3 distance to the nearest MRT station	X4 number of convenience stores	X5 latitude	X6 longitude	Y house price of unit area
0	1	2012.916667	32.0	84.87882	10	24.98298	121.54024	37.9
1	2	2012.916667	19.5	306.59470	9	24.98034	121.53951	42.2
2	3	2013.583333	13.3	561.98450	5	24.98746	121.54391	47.3
3	4	2013.500000	13.3	561.98450	5	24.98746	121.54391	54.8
4	5	2012.833333	5.0	390.56840	5	24.97937	121.54245	43.1
...	...	...	...	...	...	...	...	...
409	410	2013.000000	13.7	4082.01500	0	24.94155	121.50381	15.4
410	411	2012.666667	5.6	90.45606	9	24.97433	121.54310	50.0
411	412	2013.250000	18.8	390.96960	7	24.97923	121.53986	40.6
412	413	2013.000000	8.1	104.81010	5	24.96674	121.54067	52.5
413	414	2013.500000	6.5	90.45606	9	24.97433	121.54310	63.9

414 rows × 8 columns

In [3]:

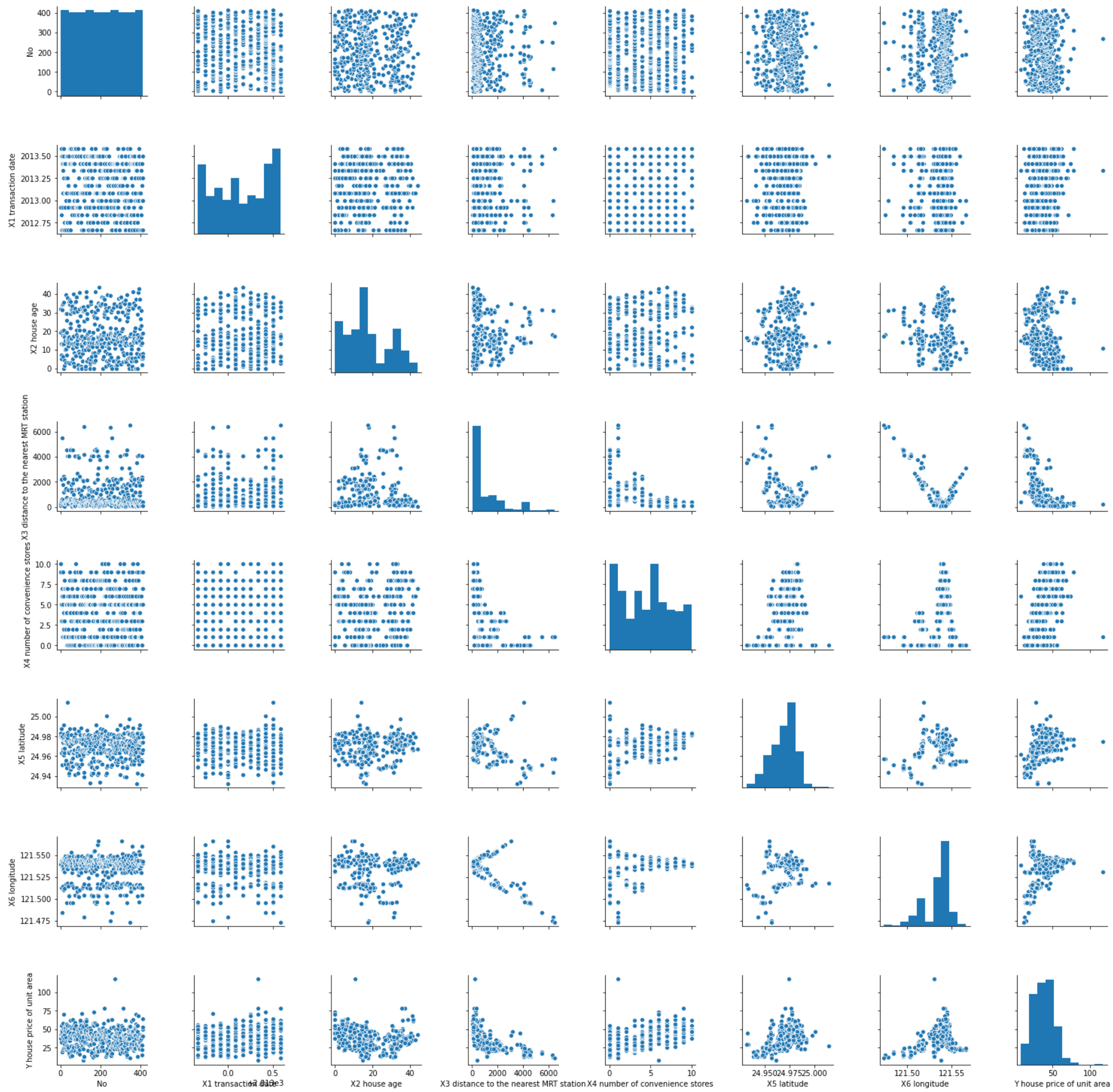
```
#Summary statistics
housingdata.describe()
```

Out[3]:

	No	X1 transaction date	X2 house age	X3 distance to the nearest MRT station	X4 number of convenience stores	X5 latitude	X6 longitude
count	414.000000	414.000000	414.000000	414.000000	414.000000	414.000000	414.000000
mean	207.500000	2013.148953	17.712560	1083.885689	4.094203	24.969030	121.533361
std	119.655756	0.281995	11.392485	1262.109595	2.945562	0.012410	0.015347
min	1.000000	2012.666667	0.000000	23.382840	0.000000	24.932070	121.473530
25%	104.250000	2012.916667	9.025000	289.324800	1.000000	24.963000	121.528085
50%	207.500000	2013.166667	16.100000	492.231300	4.000000	24.971100	121.538630
75%	310.750000	2013.416667	28.150000	1454.279000	6.000000	24.977455	121.543305
max	414.000000	2013.583333	43.800000	6488.021000	10.000000	25.014590	121.566270

In [4]:
```
#Getting an idea of the patterns of the data
sns.pairplot(housingdata)
```

Out[4]: <seaborn.axisgrid.PairGrid at 0x7fdd05791080>



Normalization (Data preparation)

In [5]:
```
#Correlation plots
##Feature selecting out transaction date
##since we are not taking time into account
sns.pairplot(housingdata.iloc[:,2:])
```

Out[5]: <seaborn.axisgrid.PairGrid at 0x7fdcf5ab0828>

In [6]:
```
#Summary statistics on numeric columns (removing No column- only an ID)
#Also removing transaction date
housingdata.iloc[:,2:].describe()
```

Out[6]:

	X2 house age	X3 distance to the nearest MRT station	X4 number of convenience stores	X5 latitude	X6 longitude	Y house price of unit area
count	414.000000	414.000000	414.000000	414.000000	414.000000	414.000000
mean	17.712560	1083.885689	4.094203	24.969030	121.533361	37.980193
std	11.392485	1262.109595	2.945562	0.012410	0.015347	13.606488
min	0.000000	23.382840	0.000000	24.932070	121.473530	7.600000
25%	9.025000	289.324800	1.000000	24.963000	121.528085	27.700000
50%	16.100000	492.231300	4.000000	24.971100	121.538630	38.450000
75%	28.150000	1454.279000	6.000000	24.977455	121.543305	46.600000
max	43.800000	6488.021000	10.000000	25.014590	121.566270	117.500000

In [7]:
```
#Getting non-null values from dataset
housingdata.iloc[:,2:].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 414 entries, 0 to 413
Data columns (total 6 columns):
 #   Column                                  Non-Null Count  Dtype  
---  ------                                  --------------  -----  
 0   X2 house age                            414 non-null    float64
 1   X3 distance to the nearest MRT station  414 non-null    float64
 2   X4 number of convenience stores         414 non-null    int64  
 3   X5 latitude                             414 non-null    float64
 4   X6 longitude                            414 non-null    float64
 5   Y house price of unit area              414 non-null    float64
dtypes: float64(5), int64(1)
memory usage: 19.5 KB
```

In [8]:

```
#normalizing the data:
from sklearn import preprocessing
housingdata_norm=preprocessing.normalize(housingdata.iloc[:,2:])
housingdata_norm=pd.DataFrame(housingdata_norm)

#code to place the header columns in the normalized dataset
housingdata_norm.columns=housingdata.iloc[:,2:].columns

#we do not need to normalize out output/target variable
housingdata_norm['Y house price of unit area'] = housingdata['Y house price of unit area']
housingdata_norm
```

Out[8]:

	X2 house age	X3 distance to the nearest MRT station	X4 number of convenience stores	X5 latitude	X6 longitude	Y house price of unit area
0	0.201737	0.535100	0.063043	0.157500	0.766225	37.9
1	0.058362	0.917610	0.026936	0.074764	0.363757	42.2
2	0.023025	0.972905	0.008656	0.043258	0.210416	47.3
3	0.022999	0.971790	0.008646	0.043209	0.210175	54.8
4	0.012132	0.947692	0.012132	0.060611	0.294916	43.1
...	...	...	...	...	...	...
409	0.003355	0.999526	0.000000	0.006107	0.029752	15.4
410	0.034603	0.558934	0.055612	0.154318	0.751023	50.0
411	0.045556	0.947394	0.016962	0.060529	0.294514	40.6
412	0.047379	0.613066	0.029247	0.146038	0.710928	52.5
413	0.038995	0.542664	0.053993	0.149826	0.729161	63.9

414 rows × 6 columns

Side note: it is also common to use logarithm instead of normalization when doing money values.

In [9]:
```
#splitting x (train set) and y (test set).  Also getting rid of
x=housingdata_norm.iloc[:,:5]
x
```

Out[9]:

	X2 house age	X3 distance to the nearest MRT station	X4 number of convenience stores	X5 latitude	X6 longitude
0	0.201737	0.535100	0.063043	0.157500	0.766225
1	0.058362	0.917610	0.026936	0.074764	0.363757
2	0.023025	0.972905	0.008656	0.043258	0.210416
3	0.022999	0.971790	0.008646	0.043209	0.210175
4	0.012132	0.947692	0.012132	0.060611	0.294916
...	...	...	...	...	...
409	0.003355	0.999526	0.000000	0.006107	0.029752
410	0.034603	0.558934	0.055612	0.154318	0.751023
411	0.045556	0.947394	0.016962	0.060529	0.294514
412	0.047379	0.613066	0.029247	0.146038	0.710928
413	0.038995	0.542664	0.053993	0.149826	0.729161

414 rows × 5 columns

In [10]:
```
y=housingdata_norm.iloc[:,5:6]
y
```

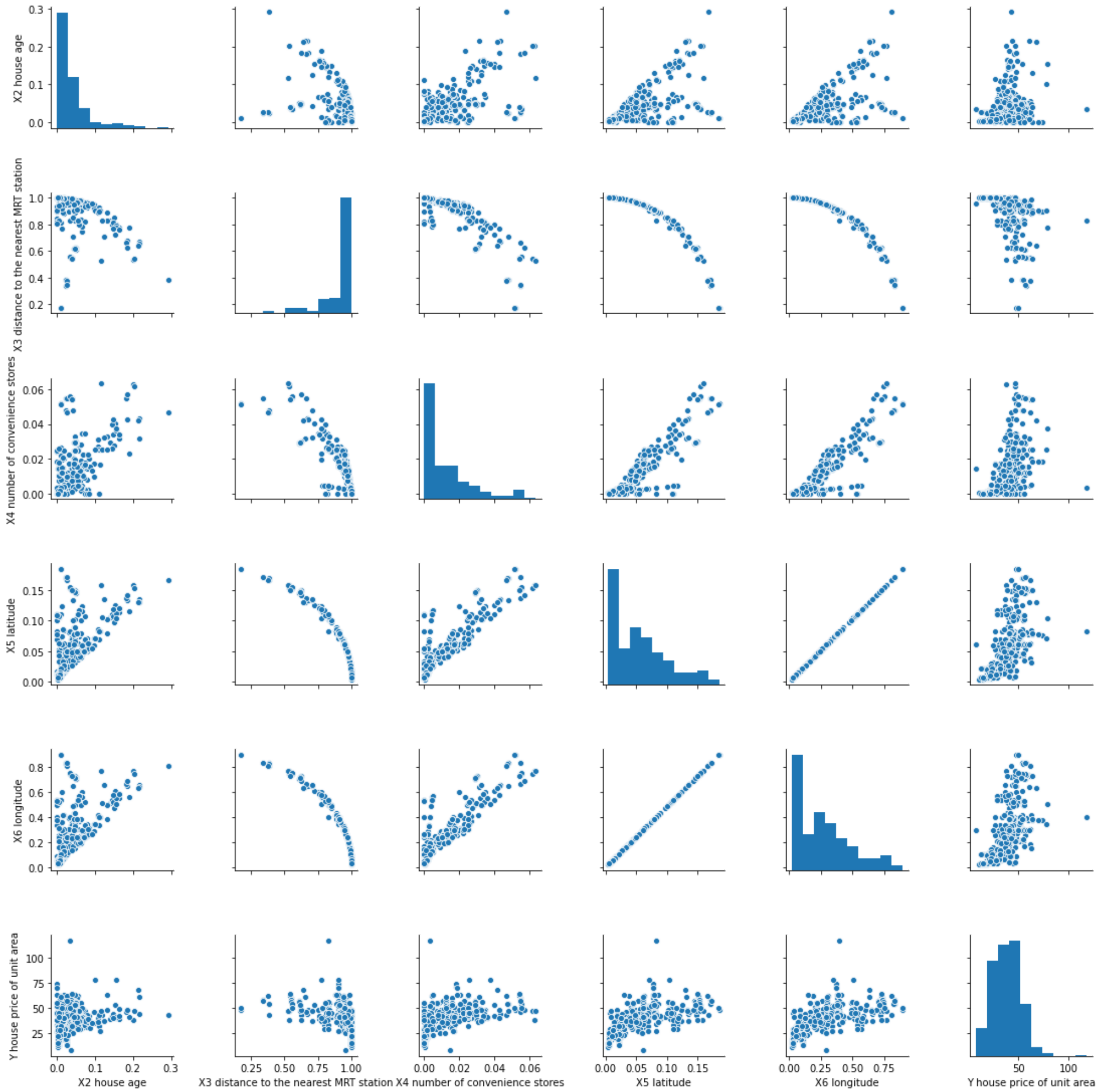
Out[10]:

	Y house price of unit area
0	37.9
1	42.2
2	47.3
3	54.8
4	43.1
...	...
409	15.4
410	50.0
411	40.6
412	52.5
413	63.9

414 rows × 1 columns

In [11]:
```
#correlation plot for normalized data:
sns.pairplot(housingdata_norm)
```

Out[11]: <seaborn.axisgrid.PairGrid at 0x7fdcf63aeb38>



In [12]:
```
#In case you wanted the correlations in a table form
housingdata_norm.corr()
```

Out[12]:

	X2 house age	X3 distance to the nearest MRT station	X4 number of convenience stores	X5 latitude	X6 longitude	Y house price of unit area
X2 house age	1.000000	-0.421179	0.556401	0.537865	0.537767	0.277851
X3 distance to the nearest MRT station	-0.421179	1.000000	-0.858782	-0.908956	-0.909024	-0.509469
X4 number of convenience stores	0.556401	-0.858782	1.000000	0.877750	0.877721	0.579531
X5 latitude	0.537865	-0.908956	0.877750	1.000000	1.000000	0.662669
X6 longitude	0.537767	-0.909024	0.877721	1.000000	1.000000	0.662566
Y house price of unit area	0.277851	-0.509469	0.579531	0.662669	0.662566	1.000000

Train-Test Split (Validation)

In [13]:
```
#A common train-test split is 20% of the data for the test set, which is also
 known as an 80/20 train test split
from sklearn import model_selection
x_train,x_test,y_train,y_test = model_selection.train_test_split(x,y,test_size
=0.2,random_state=55)
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(331, 5)
(83, 5)
(331, 1)
(83, 1)
```

Linear Regression (Algorithm)

In [14]:
```
#Sets up the linear regression model
from sklearn import linear_model
lm=linear_model.LinearRegression(fit_intercept=True)

#Trains the linear regression algorithm on the training dataset
model=lm.fit(x_train,y_train)
```

The linear regression model boils down to the formula y = mx + b. The slope (m) are the coefficent values, while the intercept (b) explains where the line would start if the slopes were 0.

In [15]:
```
#Intercept value
model.intercept_
```

Out[15]:
```
array([-34.91939464])
```

In [16]:
```
#Coefficent values
coeff_df = pd.DataFrame(model.coef_.T, x.columns, columns=['Coefficient'])
coeff_df
```

Out[16]:

	Coefficient
X2 house age	-86.382891
X3 distance to the nearest MRT station	58.368546
X4 number of convenience stores	200.712176
X5 latitude	104529.407984
X6 longitude	-21403.405846

In [17]:
```
#Display more data on linear regression
from statsmodels import regression
import statsmodels.api as sm
import numpy as np

def linreg(X,Y):
    # Running the linear regression
    X = sm.add_constant(X)
    model = regression.linear_model.OLS(Y, X).fit()
    a = model.params[0]
    b = model.params[1]
    X = X[:, 1]
    return model.summary()

linreg(x_train.values, y_train.values)
```

Out[17]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.535
Model:	OLS	**Adj. R-squared:**	0.528
Method:	Least Squares	**F-statistic:**	74.73
Date:	Mon, 27 Jul 2020	**Prob (F-statistic):**	6.07e-52
Time:	15:37:57	**Log-Likelihood:**	-1212.0
No. Observations:	331	**AIC:**	2436.
Df Residuals:	325	**BIC:**	2459.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-34.9194	10.999	-3.175	0.002	-56.558	-13.280
x1	-86.3829	15.386	-5.614	0.000	-116.652	-56.113
x2	58.3685	10.411	5.606	0.000	37.887	78.850
x3	200.7122	82.604	2.430	0.016	38.207	363.218
x4	1.045e+05	2.62e+04	3.993	0.000	5.3e+04	1.56e+05
x5	-2.14e+04	5379.895	-3.978	0.000	-3.2e+04	-1.08e+04

Omnibus:	186.472	**Durbin-Watson:**	1.930
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2673.807
Skew:	1.999	**Prob(JB):**	0.00
Kurtosis:	16.338	**Cond. No.**	7.08e+04

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 7.08e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

In [18]:

```
#Make predictions of train and test set
pred=lm.predict(x_train)
predd=lm.predict(x_test)
```

R2 (Evaluation)

In [19]:
```
#checking accuracy using r2:
from sklearn.metrics import r2_score

#Training r2
train_r2_score = r2_score(y_train,pred)
print('Training coefficient of determination:', train_r2_score)
```

```
Training coefficient of determination: 0.5348106470660416
```

In [20]:
```
#Test r2
test_r2_score = r2_score(y_test,predd)
print('Test coefficient of determination:', test_r2_score)
```

```
Test coefficient of determination: 0.5488671559665579
```

In [21]:
```
#Examining actual values against the predictions of test set
compare = y_test.copy()
compare['predictions'] = predd
compare.head(10)
```

Out[21]:

	Y house price of unit area	predictions
293	42.5	41.657872
84	43.7	41.085185
184	21.8	25.470754
85	50.8	47.571174
231	14.7	24.701607
151	44.7	47.968147
404	41.2	48.068743
67	56.8	50.727744
145	45.5	42.340210
195	34.6	35.410380

In [22]:
```
from sklearn import metrics

#Training set
print('Train Mean Absolute Error (MAE):', metrics.mean_absolute_error(y_train, pred))
print('Train Mean Squared Error (MSE):', metrics.mean_squared_error(y_train, pred))

#Test set
print('Test Mean Absolute Error (MAE):', metrics.mean_absolute_error(y_test, predd))
print('Test Mean Squared Error (MSE):', metrics.mean_squared_error(y_test, predd))
```

```
Train Mean Absolute Error (MAE): 6.315969043748797
Train Mean Squared Error (MSE): 88.71795847258532
Test Mean Absolute Error (MAE): 5.961437743461353
Test Mean Squared Error (MSE): 69.61245394528389
```

In [24]:
```
#Removing X3 variable for improvement - Better feature selection
housingdata=pd.read_excel("Real estate valuation data set.xlsx")
housingdata=housingdata.drop(housingdata.columns[3], axis=1)
housingdata_norm=preprocessing.normalize(housingdata.iloc[:,2:])
housingdata_norm=pd.DataFrame(housingdata_norm)

#code to place the header columns in the normalized dataset
housingdata_norm.columns=housingdata.iloc[:,2:].columns

#we do not need to normalize out output/target variable
housingdata_norm['Y house price of unit area'] = housingdata['Y house price of
unit area']

#data split
x=housingdata_norm.iloc[:,:4]
y=housingdata_norm.iloc[:,4:5]
x_train,x_test,y_train,y_test = model_selection.train_test_split(x,y,test_size
=0.2,random_state=55)

#Trains the linear regression algorithm on the training dataset
lm=linear_model.LinearRegression()
model=lm.fit(x_train,y_train)

#Make predictions of train and test set
pred=lm.predict(x_train)
predd=lm.predict(x_test)

#Training r2
train_r2_score = r2_score(y_train,pred)
print('Training coefficient of determination:', train_r2_score)

#Test r2
test_r2_score = r2_score(y_test,predd)
print('Test coefficient of determination:', test_r2_score)

#Training set
print('Train Mean Absolute Error (MAE):', metrics.mean_absolute_error(y_train,
pred))
print('Train Mean Squared Error (MSE):', metrics.mean_squared_error(y_train, p
red))

#Test set
print('Test Mean Absolute Error (MAE):', metrics.mean_absolute_error(y_test, p
redd))
print('Test Mean Squared Error (MSE):', metrics.mean_squared_error(y_test, pre
dd))
```

```
Training coefficient of determination: 0.9721139488268009
Test coefficient of determination: 0.9712254065634646
Train Mean Absolute Error (MAE): 1.7631625597348313
Train Mean Squared Error (MSE): 5.318250545384896
Test Mean Absolute Error (MAE): 1.7485062306065744
Test Mean Squared Error (MSE): 4.440089181905381
```

In [25]:
```
#Display Linear Regression statistics
linreg(x_train.values, y_train.values)
```

Out[25]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.972
Model:	OLS	**Adj. R-squared:**	0.972
Method:	Least Squares	**F-statistic:**	2841.
Date:	Mon, 27 Jul 2020	**Prob (F-statistic):**	6.32e-252
Time:	15:39:31	**Log-Likelihood:**	-746.24
No. Observations:	331	**AIC:**	1502.
Df Residuals:	326	**BIC:**	1521.
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	415.9132	4.930	84.362	0.000	406.214	425.612
x1	-61.9275	1.537	-40.297	0.000	-64.951	-58.904
x2	32.3558	6.998	4.624	0.000	18.589	46.123
x3	1.256e+04	1589.938	7.901	0.000	9433.763	1.57e+04
x4	-2983.4327	325.195	-9.174	0.000	-3623.178	-2343.688

Omnibus:	55.380	**Durbin-Watson:**	2.092
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	113.802
Skew:	-0.875	**Prob(JB):**	1.94e-25
Kurtosis:	5.277	**Cond. No.**	1.75e+04

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.75e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

In [ ]: