DSC 540 - Topic 1- Assignment - Part 2

August 11, 2021

[54]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn import linear_model
from mpl_toolkits.mplot3d import Axes3D
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
import statsmodels.api as sm
import seaborn as sns
```

The data for Real Estate has been downloaded from https://archive.ics.uci.edu/ml/machine-learning-databases/00477/

[57]:
```
# Import the dataset as a dataframe using the pandas package
real= pd.read_csv("H:/Krishna/GCU/DSC 540/Topic 1/Real estate valuation data␣
↪set.csv",sep=',', header=0)
```

[58]:
```
# Get the structure of the dataframe
real.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 414 entries, 0 to 413
Data columns (total 8 columns):
 #   Column                                  Non-Null Count  Dtype
---  ------                                  --------------  -----
 0   No                                      414 non-null    int64
 1   X1 transaction date                     414 non-null    float64
 2   X2 house age                            414 non-null    float64
 3   X3 distance to the nearest MRT station  414 non-null    float64
 4   X4 number of convenience stores         414 non-null    int64
 5   X5 latitude                             414 non-null    float64
 6   X6 longitude                            414 non-null    float64
 7   Y house price of unit area              414 non-null    float64
dtypes: float64(6), int64(2)
memory usage: 26.0 KB
```

[59]:
```
# View sample of the dataset
real.head()
```

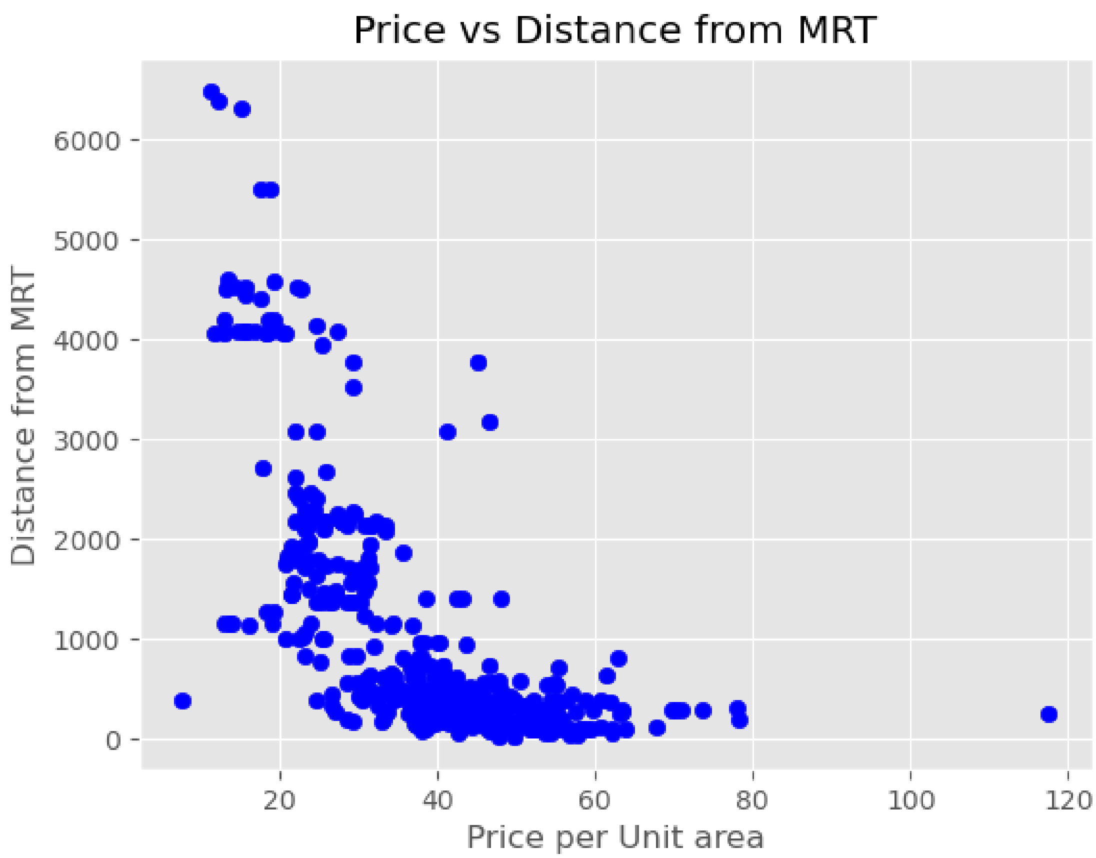
[59]:
```
   No  X1 transaction date  X2 house age  \
0   1              2012.917          32.0
1   2              2012.917          19.5
2   3              2013.583          13.3
3   4              2013.500          13.3
4   5              2012.833           5.0

   X3 distance to the nearest MRT station  X4 number of convenience stores  \
0                                84.87882                               10
1                               306.59470                                9
2                               561.98450                                5
3                               561.98450                                5
4                               390.56840                                5

   X5 latitude  X6 longitude  Y house price of unit area
0     24.98298     121.54024                        37.9
1     24.98034     121.53951                        42.2
2     24.98746     121.54391                        47.3
3     24.98746     121.54391                        54.8
4     24.97937     121.54245                        43.1
```

[64]:
```
# Let us try to plot and find how the Response variable Price per unit area␣
 ↪against all its predictor variables
# Price vs Distance from MRT station
plt.scatter(real[['Y house price of unit area']], real[['X3 distance to the␣
 ↪nearest MRT station']], c='blue')
plt.title('Price vs Distance from MRT')
plt.xlabel('Price per Unit area')
plt.ylabel('Distance from MRT')
```

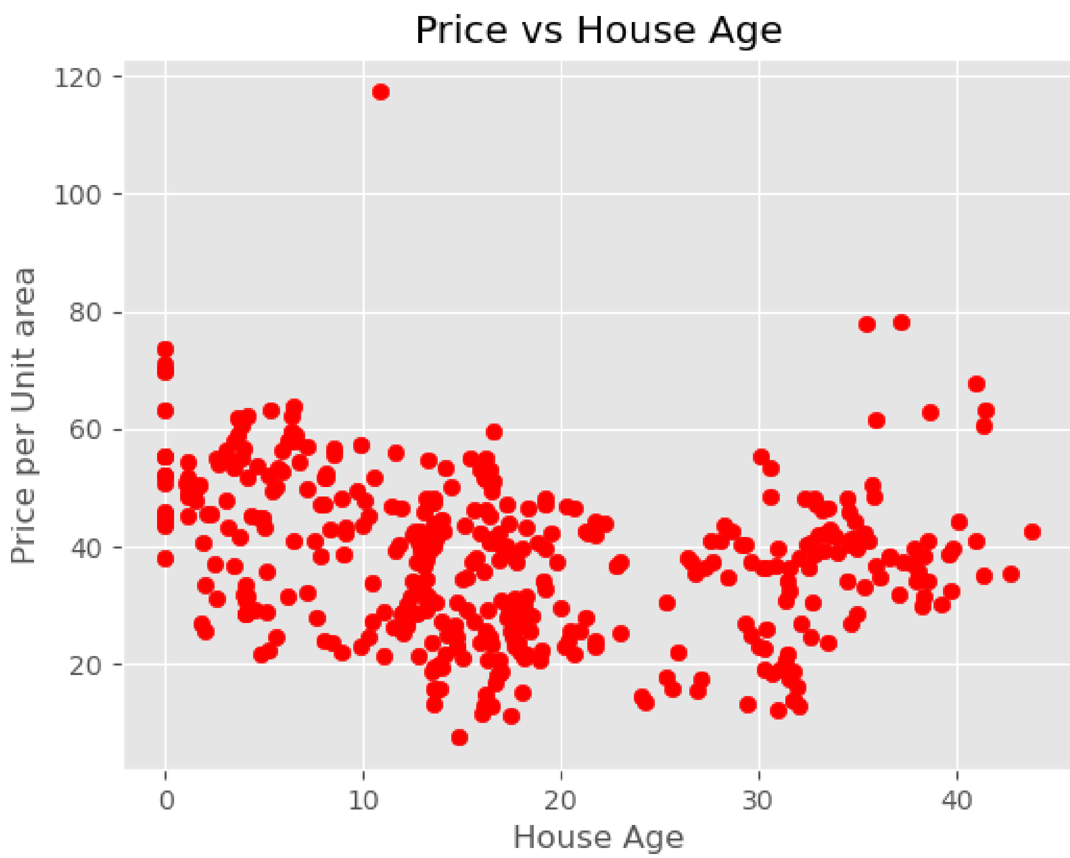
[64]:
```
Text(0, 0.5, 'Distance from MRT')
```



We can see that as the distance from the MRT increases the price of the house decreases

[68]:
```
# Price vs House Age
plt.scatter(real[['X2 house age']], real[['Y house price of unit area']],␣
 ↪c='red')
plt.title('Price vs House Age')
plt.xlabel('House Age')
plt.ylabel('Price per Unit area')
```

[68]:
```
Text(0, 0.5, 'Price per Unit area')
```



We do see some newly built homes are highly priced but overall we see that the price is evenly distributed across age with a slight drop in price when the houses age.

[69]:
```
# Price vs Convenience Stores
plt.scatter(real[['X4 number of convenience stores']], real[['Y house price of␣
↪unit area']], c='green')
plt.title('Price vs No of Convenience stores')
plt.xlabel('No of Convenience stores')
plt.ylabel('Price per Unit area')
```

[69]: Text(0, 0.5, 'Price per Unit area')

From the plot we can see that as the number of stores increase the price of the houses also tend to raise gradually.

[21]:
```
# Split the data into Test and Training dataset
real_train, real_test = train_test_split(real, test_size=0.4, random_state=123)
```

[22]:
```
real_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 248 entries, 396 to 365
Data columns (total 8 columns):
 #   Column                                  Non-Null Count  Dtype
---  ------                                  --------------  -----
 0   No                                      248 non-null    int64
 1   X1 transaction date                     248 non-null    float64
 2   X2 house age                            248 non-null    float64
 3   X3 distance to the nearest MRT station  248 non-null    float64
 4   X4 number of convenience stores         248 non-null    int64
 5   X5 latitude                             248 non-null    float64
 6   X6 longitude                            248 non-null    float64
 7   Y house price of unit area              248 non-null    float64
```

```
dtypes: float64(6), int64(2)
memory usage: 17.4 KB
```

[23]:
```
real_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 166 entries, 188 to 347
Data columns (total 8 columns):
 #   Column                                  Non-Null Count  Dtype
---  ------                                  --------------  -----
 0   No                                      166 non-null    int64
 1   X1 transaction date                     166 non-null    float64
 2   X2 house age                            166 non-null    float64
 3   X3 distance to the nearest MRT station  166 non-null    float64
 4   X4 number of convenience stores         166 non-null    int64
 5   X5 latitude                             166 non-null    float64
 6   X6 longitude                            166 non-null    float64
 7   Y house price of unit area              166 non-null    float64
dtypes: float64(6), int64(2)
memory usage: 11.7 KB
```

[24]:
```
# Split the test and training dataframe as response variable and Independent␣
↪variables
# The Response variable is the Price of Unit area of the house
# The independent variables are House age, Distance from Metro Rail and Number␣
↪of convenience stores closer to the house
X_train = real_train[['X2 house age','X3 distance to the nearest MRT␣
↪station','X4 number of convenience stores']]
y_train = real_train[['Y house price of unit area']]
X_test = real_test[['X2 house age','X3 distance to the nearest MRT station','X4␣
↪number of convenience stores']]
y_test = real_test[['Y house price of unit area']]
```

[25]:
```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 248 entries, 396 to 365
Data columns (total 3 columns):
 #   Column                                  Non-Null Count  Dtype
---  ------                                  --------------  -----
 0   X2 house age                            248 non-null    float64
 1   X3 distance to the nearest MRT station  248 non-null    float64
 2   X4 number of convenience stores         248 non-null    int64
dtypes: float64(2), int64(1)
memory usage: 7.8 KB
```

[26]:
```
y_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
Int64Index: 248 entries, 396 to 365
Data columns (total 1 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   Y house price of unit area  248 non-null    float64
dtypes: float64(1)
memory usage: 3.9 KB
```

[31]:
```
# Let us run the linear regression to predict the cost per unit area of the␣
↪house.
# We will use the Linearregression function from the Linear_Model
ols = linear_model.LinearRegression()
model = ols.fit(X_train, y_train)
```

[28]:
```
# The Coefficients of the Model can be given by the below function
model.coef_
```

[28]:
```
array([[-0.22667982, -0.00561765,  1.14814398]])
```

We can say from the above output the Model coefficients for all Input variable are

Coefficient of House age, b1-> -0.22667982 Coefficient of Distance to MRT station, b2 -> -0.00561765 Coefficient of Number of convenience store, b3 -> 1.14814398

[29]:
```
# The model intecept can be given as
model.intercept_
```

[29]:
```
array([43.34493233])
```

The Multiple Linear regression equation for the House Price per Unit area can be given as

House price per unit area (y) = 43.34 + (-0.227)* House Age + (-0.006)* Distinace to MRT station + 1.148* Number of Convenience stores

[30]:
```
# The model score (R-squared) can be identified by the score function
model.score(X_train,y_train)
```

[30]:
```
0.48179836059668957
```

The R-squared for the model is at 48.2%

[33]:
```
# The House price per unit area can be predicted for the test dataset as follows
y_pred=ols.predict(X_test)
```

[34]:
```
X_output = X_test
```

[36]:
```
X_output['Predicted Price'] = y_pred
X_output['Actual Price'] = y_test
```

```
<ipython-input-36-1acbb42baf74>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
```

```
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X_output['Predicted Price'] = y_pred
<ipython-input-36-1acbb42baf74>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X_output['Actual Price'] = y_test
```

[37]:
```
# The Predicted and the actual price of the test data can be seen in the dataframe below
X_output.head(5)
```

[37]:
```
     X2 house age  X3 distance to the nearest MRT station  \
188          34.8                                 190.0392
404          16.4                                 289.3248
191          13.2                                 750.0704
101          12.7                                 170.1289
210           5.2                                 390.5684

     X4 number of convenience stores  Predicted Price  Actual Price
188                                8        43.574053          44.3
404                                5        43.742778          41.2
191                                2        38.435415          37.8
101                                1        40.658518          32.9
210                                5        45.712841          52.2
```

[39]:
```
#The mean square error of the model can be given as
mean_squared_error(y_test, y_pred)
```

[39]:
```
62.86779419807648
```

[41]:
```
# We can also do Multiple lear regression using the statsmodels.api
# In order to do that we may need to add a constant for the intercept to our training Input variables first
X_train = sm.add_constant(X_train)
```

[42]:
```
# The model can be fitted using the OLS (Ordinary Least Square) function
model_sm = sm.OLS(y_train, X_train).fit()
```

[44]:
```
# The model summary can be found by
model_sm.summary()
```

[44]: <class 'statsmodels.iolib.summary.Summary'>

```
"""
                                  OLS Regression Results
==============================================================================
======
Dep. Variable:     Y house price of unit area   R-squared:
0.482
Model:                                    OLS   Adj. R-squared:
0.475
Method:                         Least Squares   F-statistic:
75.62
Date:                        Sun, 08 Aug 2021   Prob (F-statistic):
1.29e-34
Time:                                16:17:55   Log-Likelihood:
-922.62
No. Observations:                         248   AIC:
1853.
Df Residuals:                             244   BIC:
1867.
Df Model:                                   3
Covariance Type:                    nonrobust
==============================================================================
==========================
                                             coef    std err          t
P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
--------------------------
const                                     43.3449      1.852     23.410
0.000      39.698      46.992
X2 house age                              -0.2267      0.056     -4.084
0.000      -0.336      -0.117
X3 distance to the nearest MRT station    -0.0056      0.001     -8.879
0.000      -0.007      -0.004
X4 number of convenience stores            1.1481      0.268      4.289
0.000       0.621       1.675
=============================================================================
Omnibus:                      154.494   Durbin-Watson:                   1.899
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2283.134
Skew:                           2.155   Prob(JB):                         0.00
Kurtosis:                      17.226   Cond. No.                     4.73e+03
=============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 4.73e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

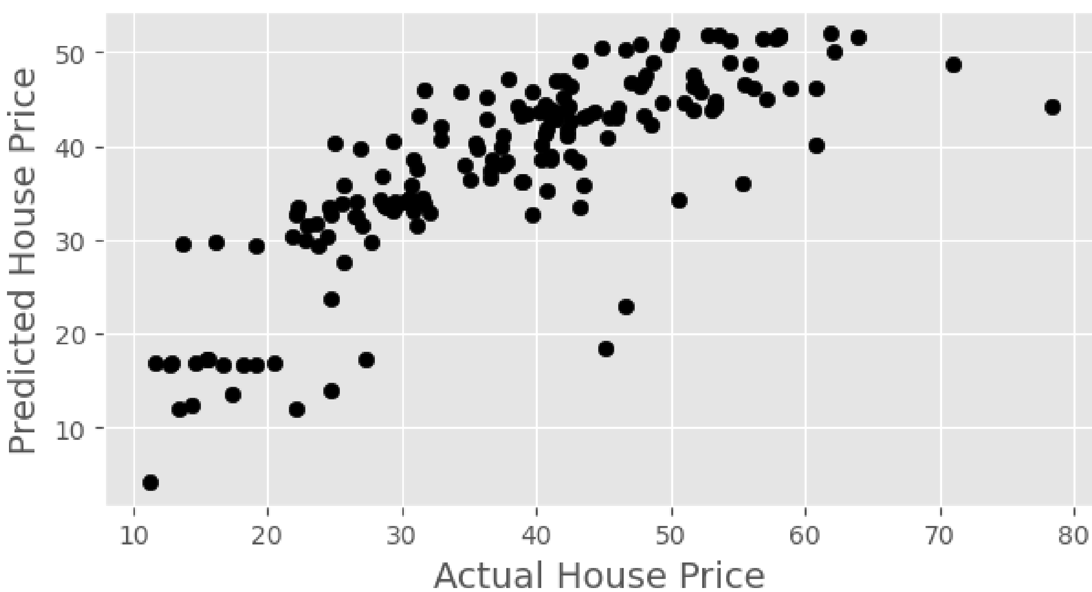
"""

The significance of using the statsmodels package is that we can use the summary function to print out all the important statistics of the model. The summary also provides the p-value of the Independent variable used. We can say that when the p value is greater than 0.05 (which is our Null hypothesis) we can safely say that the variance in the Independent variable do not have statistical impact on the Reponse variable. Here we can see that the p-value (P>|t|) of all the independent variable is less that 0.05, meaning we can safely reject the null hypothesis and say that all our three independent variable impact the prediction of the House price per square area.

We can also see that the result of Durbin Watson test is 1.9 and we can say that there are no issues with respect to aut-correlation between the variables selected for the model.

[53]:
```
# Scatter Plot for the Actual vs the Predicted House Price
plt.style.use('default')
plt.style.use('ggplot')
fig, ax = plt.subplots(figsize=(7, 3.5))
ax.scatter(y_test, y_pred, color='k', label='Predicted vs Actual Model')
ax.set_ylabel('Predicted House Price', fontsize=14)
ax.set_xlabel('Actual House Price', fontsize=14)
```

[53]:
```
Text(0.5, 0, 'Actual House Price')
```



[55]:
```
# In order to visually compare the performance of the Model we can use the
↪distplot function from the Seaborn package to see how the predicted value
↪compares with the actual value
ax1 = sns.distplot(y_test, hist=False, color="r", label="Actual Value")
sns.distplot(y_pred, hist=False, color="b", label="Fitted Values" , ax=ax1)
```

```
C:\Users\ua58809\Anaconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `kdeplot` (an axes-level function for
kernel density plots).
  warnings.warn(msg, FutureWarning)
C:\Users\ua58809\Anaconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `kdeplot` (an axes-level function for
kernel density plots).
  warnings.warn(msg, FutureWarning)
```

[55]: <AxesSubplot:ylabel='Density'>