Melbourne Housing Prices

Main Objective: To create a model able to predict the Housing Prices in Melbourne.

1) Fetch the Housing Prices Dataset
2) Data cleaning i.e A) Remove insignificant features , B) Deal with N.A values and drop the rest unimportant data records.
3) Train Test Split
4) Determine the best fit for our model
5) Predictions

In [4]:

```
#import libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

#Suppress Systems warnings
#Warnings.filterwarnings('ignore')
```

Load Melbourne Dataset

In [5]:

```
dataset = pd.read_csv('./Melbourne_Housing/Data/Melbourne_housing_FULL.csv')
```

Dataset before Cleaning

In [7]:

```
#View the entire Dataset
dataset.head()
```

Out[7]:

	Suburb	Address	Rooms	Type	Price	Method	SellerG	Date	Distance	Postcode	...	Bathroom	Car	La
0	Abbotsford	68 Studley St	2	h	NaN	SS	Jellis	3/09/2016	2.5	3067.0	...	1.0	1.0	
1	Abbotsford	85 Turner St	2	h	1480000.0	S	Biggin	3/12/2016	2.5	3067.0	...	1.0	1.0	
2	Abbotsford	25 Bloomburg St	2	h	1035000.0	S	Biggin	4/02/2016	2.5	3067.0	...	1.0	0.0	
3	Abbotsford	18/659 Victoria St	3	u	NaN	VB	Rounds	4/02/2016	2.5	3067.0	...	2.0	1.0	
4	Abbotsford	5 Charles St	3	h	1465000.0	SP	Biggin	4/03/2017	2.5	3067.0	...	2.0	0.0	

5 rows × 21 columns

In [8]:

```
#View the Dataset shape
dataset.shape
```

Out[8]:

```
(34857, 21)
```

The dataset has 34857 records and 21 Features. **Now there are some features that doesnot have much effect to our price prediction model. Mreover this dataset also include N.A values which need to be cleaned.**

DATA CLEANING

In [119]:

```
# 1) Listing the useful Features(Columns)
cols_to_use = ['Suburb' , 'Rooms' , 'Type' , 'Method' , 'SellerG' , 'Regionname' , 'Prop
ertycount' , 'Distance' ,
               'CouncilArea' , 'Bedroom2' ,'Bathroom' , 'Car' , 'Landsize' , 'BuildingAr
ea' , 'Price' ]

# 2) Filter out other insignificant Features
dataset = dataset[cols_to_use]
dataset.shape
```

Out[119]:

```
(34857, 15)
```

Thus, we reduced the number to columns to 15 significant features from overall 21 features.

In [120]:

```
# 3) Check for N.A values in the dataset
dataset.isna().sum()
```

Out[120]:

```
Suburb               0
Rooms                0
Type                 0
Method               0
SellerG              0
Regionname           3
Propertycount        3
Distance             1
CouncilArea          3
Bedroom2          8217
Bathroom          8226
Car               8728
Landsize         11810
BuildingArea     21115
Price             7610
dtype: int64
```

Feeding the N.A values in the dataset with 0 or mean values where ever needed and dropping the rest columns.

In [108]:

```
# Fill with Zero
cols_to_fill_zero = ['Propertycount' , 'Distance' , 'Bedroom2' , 'Bathroom' , 'Car']
dataset[cols_to_fill_zero] = dataset[cols_to_fill_zero].fillna(0)

# Fill with mean
dataset['Landsize'] = dataset['Landsize'].fillna(dataset.Landsize.mean())
dataset['BuildingArea'] = dataset['BuildingArea'].fillna(dataset.BuildingArea.mean())
```

```
# Drop the remaining
dataset.dropna(inplace=True)
```

Dataset after Data Filtering

In [109]:

```
# Clean N.A values
dataset.isna().sum()
```

Out[109]:

```
Suburb           0
Rooms            0
Type             0
Method           0
SellerG          0
Regionname       0
Propertycount    0
Distance         0
CouncilArea      0
Bedroom2         0
Bathroom         0
Car              0
Landsize         0
BuildingArea     0
Price            0
dtype: int64
```

Thus we cleaned all the N.A data records.

One Hot Encoding

In [36]:

```
dataset = pd.get_dummies(dataset , drop_first = True)
dataset.head()
```

Out[36]:

	Rooms	Propertycount	Distance	Bedroom2	Bathroom	Car	Landsize	BuildingArea	Price	Suburb_Aberfeldie	...	Co
1	2	4019.0	2.5	2.0	1.0	1.0	202.0	160.2564	1480000.0	0	...	
2	2	4019.0	2.5	2.0	1.0	0.0	156.0	79.0000	1035000.0	0	...	
4	3	4019.0	2.5	3.0	2.0	0.0	134.0	150.0000	1465000.0	0	...	
5	3	4019.0	2.5	3.0	2.0	1.0	94.0	160.2564	850000.0	0	...	
6	4	4019.0	2.5	3.0	1.0	2.0	120.0	142.0000	1600000.0	0	...	

5 rows × 745 columns

In [40]:

```
X = dataset.drop('Price' , axis=1)
Y = dataset['Price']
```

Train-Test Split

In [44]:

```
from sklearn.model_selection import train_test_split

train_X , test_X , train_Y , test_Y = train_test_split(X , Y, test_size = 0.3 , random_s
tate= 2 )
```

Linear Regression

In [51]:

```
from sklearn.linear_model import LinearRegression
lr = LinearRegression().fit(train_X ,train_Y)
lr_r2 = lr.score(test_X , test_Y)
print('R2 for Linear Regression : ' , lr_r2)
```

```
R2 for Linear Regression :  0.1385368316163994
```

Lasso Regression

In [67]:

```
from sklearn.linear_model import Lasso
lassoR = Lasso(alpha= 50 , max_iter= 1000 , tol=0.1)
lassoR.fit(train_X ,train_Y)
lasso_r2 = lassoR.score(test_X , test_Y)
print('R2 for Lasso Regression : ' , lasso_r2)
```

```
R2 for Lasso Regression :  0.6636280170612746
```

Ridge Regression

In [68]:

```
from sklearn.linear_model import Ridge
ridgeR = Ridge(alpha= 50 , max_iter= 1000 , tol = 0.1)
ridgeR.fit(train_X ,train_Y)
ridge_r2 = ridgeR.score(test_X , test_Y)
print('R2 for Ridge Regression : ' , ridge_r2)
```

```
R2 for Ridge Regression :  0.6670848945194958
```

In [72]:

```
methods_labels = ['Linear Regression' , 'Lasso Regression' ,'Ridge Regression']
r2_values = [ lr_r2 , lasso_r2, ridge_r2]
R2_results = pd.Series(r2_values , index= methods_labels).to_frame()
R2_results.rename(columns = {0: 'R2 Score'} , inplace=1)
R2_results
```

Out[72]:

	R2 Score
Linear Regression	0.138537
Lasso Regression	0.663628
Ridge Regression	0.667085

On comparing Linear, Lasso and Ridge Regression we got the best R2 score for Ridge Regression thus, we would be using Ridge Regression for our price prediction model.
Now we need to optimize the solution thus using RidgeCV which will find the optimal alpha value along with Cross Validation.

In [81]:

```
from sklearn.linear_model import RidgeCV
alphas = [0.005 ,0.05 , 0.1 ,0.3 , 1 ,5 , 10 ,15 , 30 ,80 ]
ridgeCV = RidgeCV(alphas = alphas , cv =4).fit(train_X ,train_Y)
ridgeCV_r2 = ridgeCV.score(test_X , test_Y)
```

In [87]:

```
print('\nRidge Regression ')
print('Optimal Alpha :' , ridgeCV.alpha_ , ' , R2 Score :', ridgeCV_r2)
```

```
Ridge Regression
Optimal Alpha : 5.0  , R2 Score : 0.6743855819360092
```

In [89]:

```
#Predicted value for RidgeCV Regression for alpha = 5.0
predicted_ridgeCV_X_test = ridgeCV.predict(test_X)

#Predicted value for Linear Regression
predicted_LR_X_test = lr.predict(test_X)
```

(Graph continued on next page)

Actual Values VS Predicted Values

In [97]:

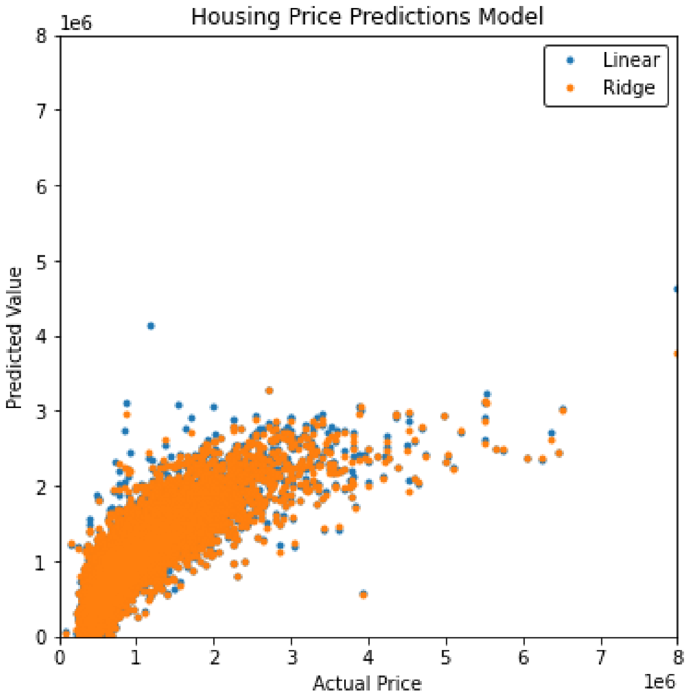
```
# Graph Actual Values VS Predicted Values

f =plt.figure(figsize= (6,6))
ax = plt.axes()
labels = ['Linear', 'Ridge']
predicted_values = [predicted_LR_X_test , predicted_ridgeCV_X_test]
for pred_val , lab in zip(predicted_values , labels):
    ax.plot(test_Y , pred_val , marker='o' , ls='' , ms=3.0 , label= lab)

leg = plt.legend(frameon =True)
leg.get_frame().set_edgecolor('black')
leg.get_frame().set_linewidth(1.0)
lim = (0 , test_Y.max())
ax.set(xlabel = 'Actual Price', ylabel='Predicted Value' , xlim =lim , ylim =lim , title
= 'Housing Price Predictions Model')
```

Out[97]:

```
[Text(0.5, 0, 'Actual Price'),
 Text(0, 0.5, 'Predicted Value'),
 (0.0, 8000000.0),
 (0.0, 8000000.0),
 Text(0.5, 1.0, 'Housing Price Predictions Model')]
```



Conclusion

Thus, I got best R2 score for Ridge Regression among other models for my Melbourne Housing Prediction Model. Moreover I to optimize my predictions I used RidgeCV that calculated the optimal alpha(alpha = 5.0) for this particular case along with Cross Validation. Currently my R2 score is 0.6743855819360092 (i.e. 67.44% accuracy).

FLAWS : For now I have just filled the Null values with 0 or their mean values but need to find the most accurate assumrd value. Also I have not considered Feature Transformation.
Thus, for increasing my accuracy I need to overcome my flaws and also test other predictive models ANOVA, Logistic Regression, Decision Trees, Neural Networks.