04.ml.model

August 20, 2024

0.1 Real Estate Model Building

0.2 1. Import sklearn Libraries

[ ]:
```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.pylab as pylab
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split

import warnings
warnings.filterwarnings('ignore')
```

0.3 2. Import Dataset

[ ]:
```python
mum_prop = pd.read_csv('Final_Project.csv')
mum_prop
```

[ ]:
```
                      Property_Name  \
0                  Omkar Alta Monte
1      T Bhimjyani Neelkanth Woods
2             Legend 1 Pramila Nagar
3                  Unnamed Property
4                  Unnamed Property
…                               …
2526            Shagun White Woods
2527                    Guru Anant
2528          Balaji Mayuresh Delta
2529          Balaji Mayuresh Delta
2530        Gurukrupa Tulsi Heights

                                          Location            Region  \
0                      W E Highway Malad East Mumbai      Malad Mumbai
1                               Manpada Thane Mumbai     Manpada Thane
2                                Dahisar West Mumbai    Dahisar Mumbai
3      Vidyavihar West Vidyavihar West Central Mumbai…    Central Mumbai
```

```
4     176 Cst Road Kalina Mumbai 400098 Santacruz Ea…  Santacruz Mumbai
…                                                …              …
2526                Sector 23 Ulwe Navi Mumbai Mumbai  Ulwe Navi-Mumbai
2527                 Sector 2 Ulwe Navi Mumbai Mumbai  Ulwe Navi-Mumbai
2528                          Ulwe Navi Mumbai Mumbai  Ulwe Navi-Mumbai
2529                          Ulwe Navi Mumbai Mumbai  Ulwe Navi-Mumbai
2530                          Ulwe Navi Mumbai Mumbai  Ulwe Navi-Mumbai

     Property_Age   Availability            Area_Tpye  Area_SqFt  Rate_SqFt  \
0      0 to 1 Year  Ready To Move  Super Built Up Area     2900.0      17241
1      1 to 5 Year  Ready To Move  Super Built Up Area     1900.0      12631
2         10+ Year  Ready To Move  Super Built Up Area      595.0      15966
3     5 to 10 Year  Ready To Move        Built Up Area     1450.0      25862
4     5 to 10 Year  Ready To Move          Carpet Area      876.0      39954
…              …              …                   …        …          …
2526   1 to 5 Year  Ready To Move        Built Up Area     1180.0      10338
2527   0 to 1 Year  Ready To Move        Built Up Area     1090.0       8073
2528   1 to 5 Year  Ready To Move        Built Up Area     1295.0      10579
2529   1 to 5 Year  Ready To Move        Built Up Area     1850.0       9243
2530   0 to 1 Year  Ready To Move        Built Up Area     1100.0       8636

     Floor_No  Bedroom  Bathroom  Price_Lakh
0          14        3         4       500.0
1           8        3         3       240.0
2           3        1         2        95.0
3           1        3         3       375.0
4           5        2         2       350.0
…        …       …        …          …
2526        2        2         2       122.0
2527       11        2         2        88.0
2528        6        2         2       137.0
2529        6        3         3       171.0
2530        4        2         2        95.0

[2531 rows x 12 columns]
```

0.4 3. Data Understanding

[ ]:
```
mum_prop.shape
```

[ ]:
```
(2531, 12)
```

[ ]:
```
mum_prop.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2531 entries, 0 to 2530
Data columns (total 12 columns):
 #   Column         Non-Null Count  Dtype
```

```
---  ------          --------------  -----
 0   Property_Name   2531 non-null   object
 1   Location        2531 non-null   object
 2   Region          2531 non-null   object
 3   Property_Age    2531 non-null   object
 4   Availability    2531 non-null   object
 5   Area_Tpye       2531 non-null   object
 6   Area_SqFt       2531 non-null   float64
 7   Rate_SqFt       2531 non-null   int64
 8   Floor_No        2531 non-null   int64
 9   Bedroom         2531 non-null   int64
 10  Bathroom        2531 non-null   int64
 11  Price_Lakh      2531 non-null   float64
dtypes: float64(2), int64(4), object(6)
memory usage: 257.1+ KB
```

[ ]:
```
mum_prop.isna().sum()
```

[ ]:
```
Property_Name    0
Location         0
Region           0
Property_Age     0
Availability     0
Area_Tpye        0
Area_SqFt        0
Rate_SqFt        0
Floor_No         0
Bedroom          0
Bathroom         0
Price_Lakh       0
dtype: int64
```

[ ]:
```
mum_prop.describe().round()
```

[ ]:

	Area_SqFt	Rate_SqFt	Floor_No	Bedroom	Bathroom	Price_Lakh
count	2531.0	2531.0	2531.0	2531.0	2531.0	2531.0
mean	949.0	16554.0	9.0	2.0	2.0	161.0
std	487.0	10204.0	8.0	1.0	1.0	162.0
min	185.0	1808.0	-1.0	1.0	1.0	13.0
25%	634.0	8751.0	3.0	1.0	2.0	66.0
50%	850.0	13636.0	6.0	2.0	2.0	110.0
75%	1150.0	22314.0	12.0	2.0	2.0	197.0
max	5000.0	55611.0	55.0	6.0	7.0	1900.0

0.5 4. Feature Engineering

0.5.1 4.1 Drop Unwanted Columns

[ ]:
```
mum_prop.head()
```

[ ]:
```
                   Property_Name  \
0             Omkar Alta Monte
1  T Bhimjyani Neelkanth Woods
2       Legend 1 Pramila Nagar
3             Unnamed Property
4             Unnamed Property

                                          Location           Region  \
0                     W E Highway Malad East Mumbai      Malad Mumbai
1                              Manpada Thane Mumbai     Manpada Thane
2                               Dahisar West Mumbai    Dahisar Mumbai
3  Vidyavihar West Vidyavihar West Central Mumbai…    Central Mumbai
4  176 Cst Road Kalina Mumbai 400098 Santacruz Ea…  Santacruz Mumbai

  Property_Age   Availability           Area_Tpye  Area_SqFt  Rate_SqFt  \
0   0 to 1 Year  Ready To Move  Super Built Up Area     2900.0      17241
1   1 to 5 Year  Ready To Move  Super Built Up Area     1900.0      12631
2      10+ Year  Ready To Move  Super Built Up Area      595.0      15966
3  5 to 10 Year  Ready To Move        Built Up Area     1450.0      25862
4  5 to 10 Year  Ready To Move          Carpet Area      876.0      39954

   Floor_No  Bedroom  Bathroom  Price_Lakh
0        14        3         4       500.0
1         8        3         3       240.0
2         3        1         2        95.0
3         1        3         3       375.0
4         5        2         2       350.0
```

[ ]:
```
mum_prop.drop(columns=['Property_Name', 'Location','Availability','Bathroom'],␣
↪inplace =  True)
print('Shape of data :', mum_prop.shape)
```

```
Shape of data : (2531, 8)
```

0.5.2 4.2 Label Encoding for Categorical Columns

[ ]:
```
le = LabelEncoder()
```

[ ]:
```
for column in mum_prop.describe(include='object').columns:
    mum_prop[column] = le.fit_transform(mum_prop[column])
```

[ ]:
```
mum_prop.describe().round(2).T
```

[ ]:

	count	mean	std	min	25%	50%	75%	\
Region	2531.0	67.56	40.60	0.0	31.0	60.0	107.0	
Property_Age	2531.0	1.30	1.09	0.0	0.0	1.0	2.0	
Area_Tpye	2531.0	1.74	1.18	0.0	1.0	1.0	3.0	
Area_SqFt	2531.0	948.77	486.83	185.0	634.5	850.0	1150.0	
Rate_SqFt	2531.0	16553.69	10204.27	1808.0	8751.0	13636.0	22314.0	
Floor_No	2531.0	8.78	7.98	-1.0	3.0	6.0	12.0	
Bedroom	2531.0	1.95	0.83	1.0	1.0	2.0	2.0	
Price_Lakh	2531.0	161.35	162.32	13.0	66.0	110.0	197.0	

	max
Region	144.0
Property_Age	4.0
Area_Tpye	3.0
Area_SqFt	5000.0
Rate_SqFt	55611.0
Floor_No	55.0
Bedroom	6.0
Price_Lakh	1900.0

[ ]:
```
mum_prop
```

[ ]:

	Region	Property_Age	Area_Tpye	Area_SqFt	Rate_SqFt	Floor_No	\
0	69	0	3	2900.0	17241	14	
1	73	1	3	1900.0	12631	8	
2	24	2	3	595.0	15966	3	
3	18	3	0	1450.0	25862	1	
4	107	3	1	876.0	39954	5	
…	…	…	…	…	…	…	
2526	130	1	0	1180.0	10338	2	
2527	130	0	0	1090.0	8073	11	
2528	130	1	0	1295.0	10579	6	
2529	130	1	0	1850.0	9243	6	
2530	130	0	0	1100.0	8636	4	

	Bedroom	Price_Lakh
0	3	500.0
1	3	240.0
2	1	95.0
3	3	375.0
4	2	350.0
…	…	…
2526	2	122.0
2527	2	88.0
2528	2	137.0
2529	3	171.0
2530	2	95.0

```
[2531 rows x 8 columns]
```

[ ]:
```
mum_prop.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2531 entries, 0 to 2530
Data columns (total 8 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Region        2531 non-null   int32
 1   Property_Age  2531 non-null   int32
 2   Area_Tpye     2531 non-null   int32
 3   Area_SqFt     2531 non-null   float64
 4   Rate_SqFt     2531 non-null   int64
 5   Floor_No      2531 non-null   int64
 6   Bedroom       2531 non-null   int64
 7   Price_Lakh    2531 non-null   float64
dtypes: float64(2), int32(3), int64(3)
memory usage: 148.3 KB
```

0.5.3 4.3 Looking for Minimum & Maximum

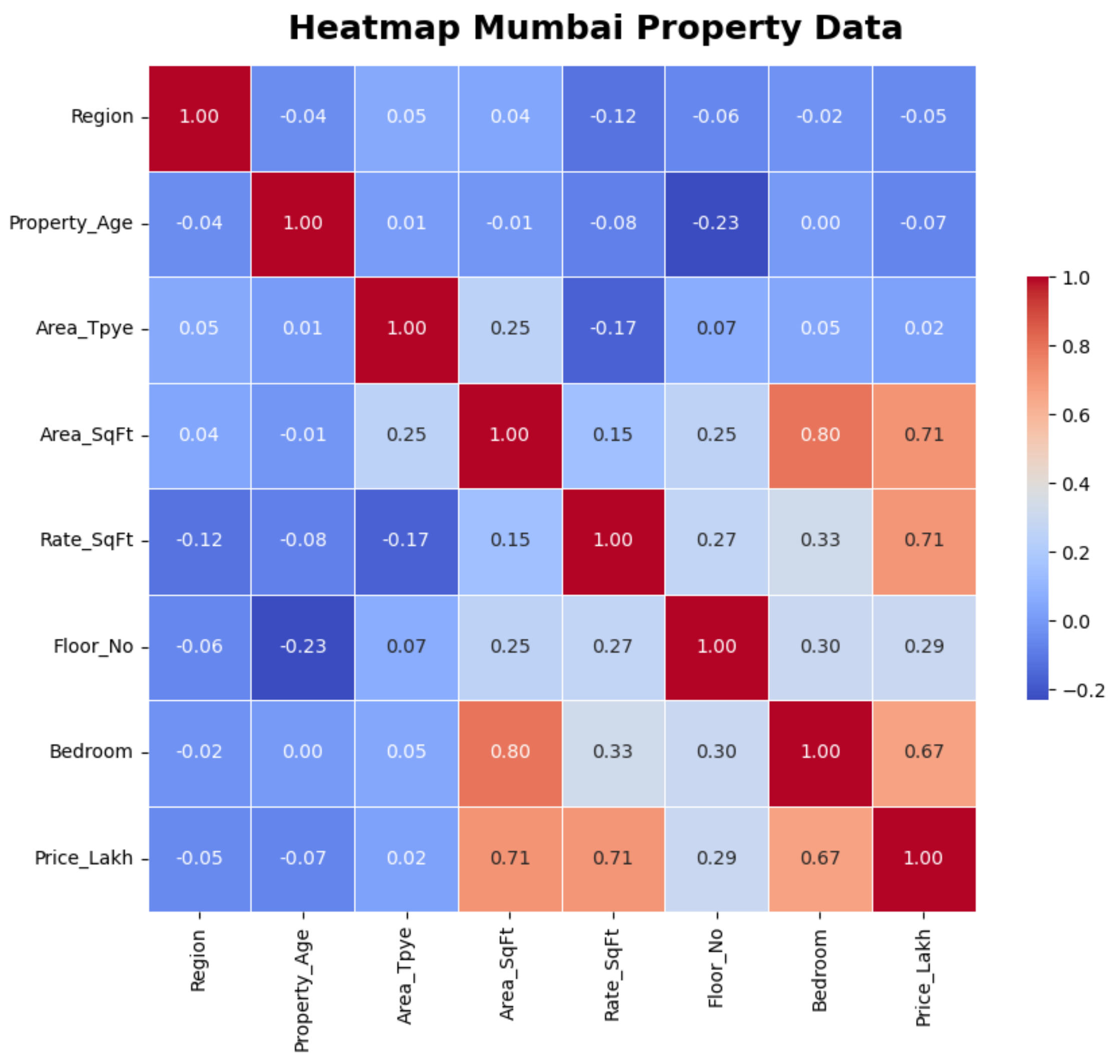
[ ]:
```
for i in mum_prop.columns:
    print(i,'Min value :', mum_prop[i].min(),'Max value :', mum_prop[i].max())
```

```
Region Min value : 0 Max value : 144
Property_Age Min value : 0 Max value : 4
Area_Tpye Min value : 0 Max value : 3
Area_SqFt Min value : 185.0 Max value : 5000.0
Rate_SqFt Min value : 1808 Max value : 55611
Floor_No Min value : -1 Max value : 55
Bedroom Min value : 1 Max value : 6
Price_Lakh Min value : 13.0 Max value : 1900.0
```

0.5.4 4.4 Correlation Heatmap

[ ]:
```
fig = plt.figure( figsize =(9,8))
rcParams = {'xtick.labelsize':'14','ytick.labelsize':'14','axes.labelsize':'16'}
sns.heatmap(mum_prop.corr(),annot = True, linewidths=.5, cbar_kws={"shrink": .
 ↪5},fmt='.2f', cmap='coolwarm')
fig.suptitle('Heatmap Mumbai Property Data',fontsize=18, fontweight="bold")
pylab.rcParams.update(rcParams)
fig.tight_layout()
plt.show()

fig.savefig('Heatmap_Encoding', dpi = 250)
```



0.6 5. Model Building

[ ]:
```
mum_prop.head()
```

[ ]:
```
   Region  Property_Age  Area_Tpye  Area_SqFt  Rate_SqFt  Floor_No  Bedroom  \
0      69             0          3     2900.0      17241        14        3
1      73             1          3     1900.0      12631         8        3
2      24             2          3      595.0      15966         3        1
3      18             3          0     1450.0      25862         1        3
4     107             3          1      876.0      39954         5        2

   Price_Lakh
0       500.0
1       240.0
```

```
2        95.0
3       375.0
4       350.0
```

0.6.1 5.1 Train Test Split

[ ]:
```
X =  mum_prop.drop('Price_Lakh', axis = 1)
y =  mum_prop['Price_Lakh']
```

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size= 0.20,␣
 ↪random_state = 12)
```

[ ]:
```
print(X_train.shape, X_test.shape)
```

```
(2024, 7) (507, 7)
```

0.6.2 5.2 Linear Regression

[ ]:
```
from sklearn.linear_model import LinearRegression

linear = LinearRegression()
linear.fit(X_train, y_train)

print("Training Accuracy = ", linear.score(X_train, y_train))
print("Test Accuracy     = ", linear.score(X_test, y_test))
```

```
Training Accuracy =  0.8729615274576085
Test Accuracy     =  0.8696528670699649
```

0.6.3 5.3 Decision Tree Regressor

[ ]:
```
from sklearn.tree import DecisionTreeRegressor

dt = DecisionTreeRegressor(min_samples_split=2)
dt.fit(X_train, y_train)

print("Training Accuracy = ", dt.score(X_train, y_train))
print("Test Accuracy     = ", dt.score(X_test, y_test))
```

```
Training Accuracy =  1.0
Test Accuracy     =  0.9606113566682924
```

0.6.4 5.4 Random Forest Regressor

[ ]:
```
from sklearn.ensemble import RandomForestRegressor

rf = RandomForestRegressor(n_estimators = 1000, max_depth=5, random_state = 12)
rf.fit(X_train, y_train);
```

```
print("Training Accuracy = ", rf.score(X_train, y_train))
print("Test Accuracy     = ", rf.score(X_test, y_test))
```

```
Training Accuracy =  0.9753917006228885
Test Accuracy     =  0.9641944588626601
```

0.6.5 5.5 Polynomial Features

[ ]:
```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import PolynomialFeatures

poly = PolynomialFeatures(degree=2)
poly.fit_transform(X)

# Define the pipeline and train model
poly_model = Pipeline([('poly', PolynomialFeatures(degree=2)),
                       ('rf', RandomForestRegressor(n_estimators = 1000,␣
 ↪max_depth=5, random_state = 12))])
poly_model.fit(X_train, y_train)

# Calculate the Score
print("Training Accuracy = ", poly_model.score(X_train, y_train))
print("Test Accuracy     = ", poly_model.score(X_test, y_test))
```

```
Training Accuracy =  0.9903850350980973
Test Accuracy     =  0.9821027587862007
```

[ ]:
```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import PolynomialFeatures

poly = PolynomialFeatures(degree=2)
poly.fit_transform(X)

# Define the pipeline and train model
poly_model = Pipeline([('poly', PolynomialFeatures(degree=2)), ('linear',␣
 ↪LinearRegression(fit_intercept=False))])
poly_model.fit(X_train, y_train)

# Calculate the Score
print("Training Accuracy = ", poly_model.score(X_train, y_train))
print("Test Accuracy     = ", poly_model.score(X_test, y_test))
```

```
Training Accuracy =  0.9832978154650837
Test Accuracy     =  0.9873735094928728
```

0.7 Obeservaion :

0.7.1 1. We select the final model - Polynomial Feature.

0.7.2 2. We got 98.73 % Model Accuracy.

0.8 6. Final Model Evaluation

[ ]:
```
def evaluate(model, test_features, test_labels):
    predictions = model.predict(test_features)
    errors = abs(predictions - test_labels)
    accuracy = model.score(test_features, test_labels)

    print('Average Error  = {:0.4f} degrees'.format(np.mean(errors)))
    print('Model Accuracy = {:0.4f} %'.format(accuracy))
```

[ ]:
```
evaluate(poly_model, X_train, y_train)
```

```
Average Error  = 8.1346 degrees
Model Accuracy = 0.9833 %
```

[ ]:
```
evaluate(poly_model, X_test, y_test)
```

```
Average Error  = 8.7685 degrees
Model Accuracy = 0.9874 %
```

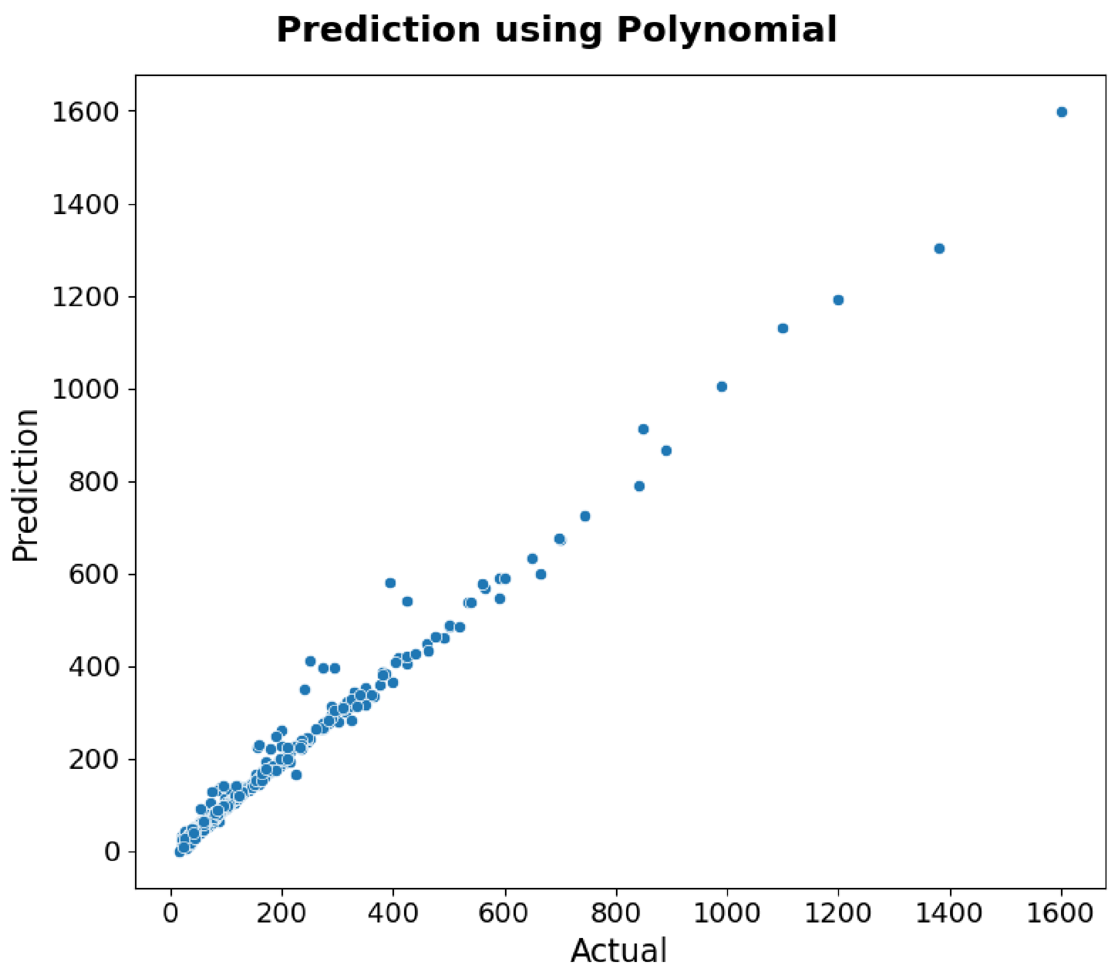
0.8.1 6.1 Visualizing Results

[ ]:
```
pred = poly_model.predict(X_test)
```

[ ]:
```
fig = plt.figure(figsize=(8,7))

sns.scatterplot(y_test, pred)
fig.suptitle('Prediction using Polynomial', fontsize= 18 , fontweight='bold')
plt.xlabel("Actual")
plt.ylabel("Prediction")
pylab.rcParams.update(rcParams)
fig.tight_layout()
fig.subplots_adjust(top=0.92)
plt.show()

#fig.savefig('Prediction_Polynomial', dpi = 500)
```



0.9 7. Model Deployement

[ ]:
```
from pickle import dump
```

[ ]:
```
dump(poly_model,open('regression_model.pkl','wb'))
```

1 The End !!!