House Price Prediction Using Polynomial Regression

Importing Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

Reading The TrainSet

```
df = pd.read_excel("train.xlsx")
```

Null value percentages

```
Null=[]
for i in df:
    Null.append((i,df[i].isna().mean()*100))
Null=pd.DataFrame(Null,columns=['class','per'])
Null
```

	class	per
0	id	0.0
1	date	0.0
2	price	0.0
3	bedrooms	0.0
4	bathrooms	0.0
5	sqft_living	0.0
6	sqft_lot	0.0
7	floors	0.0
8	waterfront	0.0
9	view	0.0
10	condition	0.0
11	grade	0.0
12	sqft_above	0.0
13	sqft_basement	0.0
14	yr_built	0.0

Data is clean and doesnt have any *null* values. So no need for data cleaning in this case.

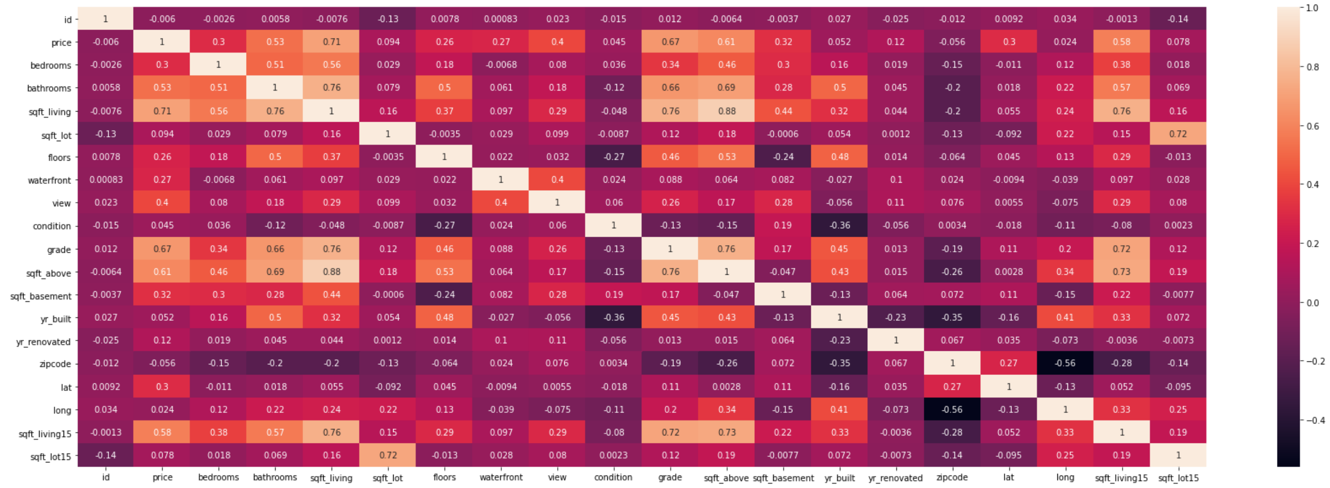
[illegible]	zipcode	[illegible]

Pearson Correlations Heat map

18	long	0.0

```
plt.figure(figsize=(30,10))
sns.heatmap(df.corr(),annot = True)
```

```
&lt;matplotlib.axes._subplots.AxesSubplot at 0x7f7cbb393d30&gt;
```



Based on the Heat map of pearson correlation, There is very less intra correlation. On inspecting the price column the very few columns are have a good correlation.

Seeing the correlation value for price column

```
df.corr()['price'].sort_values(ascending=False)
```

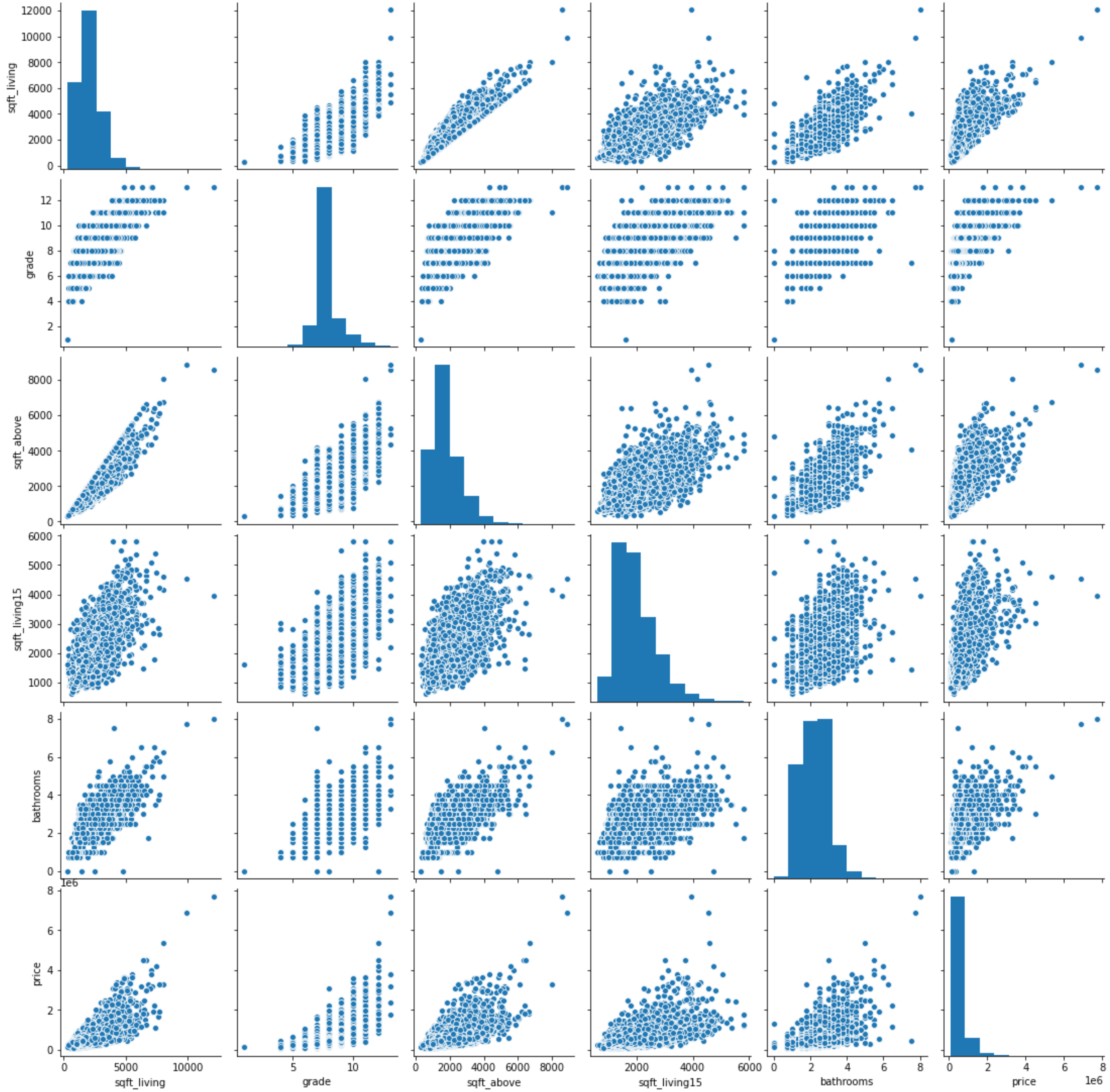
```
price            1.000000
sqft_living      0.705052
grade            0.665567
sqft_above       0.611453
sqft_living15    0.584807
bathrooms        0.527532
view             0.399658
sqft_basement    0.322383
bedrooms         0.300808
lat              0.299280
waterfront       0.274977
floors           0.262954
yr_renovated     0.120472
sqft_lot         0.094143
sqft_lot15       0.077943
yr_built         0.051759
condition        0.044732
long             0.023754
```

Quick Inspection of Columns having correlation greater than 0.5

```
Name: price, dtype: float64
```

```
c=["sqft_living", "grade", "sqft_above","sqft_living15","bathrooms","price"]
df1 = df[c]
import seaborn as sns
sns.pairplot(df1)
```

<seaborn.axisgrid.PairGrid at 0x7f7cb7c3eb70>



The Distribution of data is not normal so we need to normalize the data. The graph of grade and price show a exponential growth.

```
df1 = (df1-df1.min()) / (df1.max()-df1.min()) # MIN MAX scaling
```

```
c1=["sqft_living", "grade", "sqft_above","sqft_living15","bathrooms"] # feature lsit
```

Model

```
train = df1[c1]
y = df1['price']
from sklearn.preprocessing import PolynomialFeatures
poly = PolynomialFeatures(degree = 3)
X_poly = poly.fit_transform(train)
from sklearn.linear_model import LinearRegression
lin = LinearRegression()
lin.fit(X_poly,y)
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

Degree of the polynomial features is selected using trial and error

RMSE on Train and Test values

```
from sklearn.metrics import mean_squared_error as mse
yp = lin.predict(X_poly)
np.sqrt(mse(y,yp))
```

```
0.029129840468804003
```

As the values have been normalized the value of price will be in between 0-1. So, around 3% error on train values

```
test=pd.read_excel('test.xlsx')
test  = test[c]
test = (test-test.min()) / (test.max()-test.min()) # MIN MAX scaling
x=test[c1]
```

```
X_poly_test = poly.fit_transform(x)
y=test['price']
yp=lin.predict(X_poly_test)
np.sqrt(mse(y,yp))
```

```
0.0834663873986489
```

And around 8% erron onthe test data

As there is no much difference between the test and train error we can say that there is no overfit on the data.