DHRUV JAIN

Predicting price of house depending upon the size of house

Introduction

Creating a Machine Learning model to predict the home prices in Bangalore, India. I used data set avaialble on Kaggle.com.

Below are the various concepts that are used in this project :

- Data loading and cleaning
- Outlier detection and removal
- Feature engineering
- Dimensionality reduction
- K fold cross validation
- Gridsearchcv for hyperparameter tunning

Technology and tools used i have used in this project :

- Python
- Numpy and Pandas for data cleaning
- Matplotlib for data visualization

- Sklearn for model building
- Python flask for http server
- Google Colaboratory Notebook
- HTML/CSS for website presentation

Steps

1. I will first build a model that uses sklearn and linear regression using banglore home prices dataset from kaggle.com.
2. Second step is to write a python flask server that uses the saved model to serve http requests.
3. I can try to build a website built in html, css and javascript that allows user to enter home square ft area, bedrooms etc and it will call python flask server to retrieve the predicted price.

Dataset Reference

- [Bengaluru House price data]
- I have also uploaed the csv file in this repository [Bengaluru_House_Data.csv]

Double-click (or enter) to edit

Step#1: Import Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import matplotlib
matplotlib.rcParams['figure.figsize'] = (20,10) # width, height in inches
from google.colab import files
import io
```

Step#2: Load the data

- Load the data in dataframe

```
# for local notebook
#df1 = pd.read_csv('Bengaluru_House_Data.csv')
#df1.head()
```

```
#For google colab
uploaded = files.upload()
```

```
df1 = pd.read_csv(io.StringIO(uploaded['Bengaluru_House_Data.csv'].decode('utf-8')))
df1.head()
```

Step#3: Understand the data

- Finalize the columns to work with and drop the rest of them

```
# Get the no of rows and columns
df1.shape
```

```
(13320, 9)
```

```
#Get all the column names
df1.columns
```

```
Index(['area_type', 'availability', 'location', 'size', 'society',
       'total_sqft', 'bath', 'balcony', 'price'],
      dtype='object')
```

```
#Lets check the unique values 'area_type' column
df1.area_type.unique()
```

```
array(['Super built-up  Area', 'Plot  Area', 'Built-up  Area',
       'Carpet  Area'], dtype=object)
```

```
#Let get the count of trianing examples for each area type
df1.area_type.value_counts()
```

```
Super built-up  Area    8790
Built-up  Area          2418
Plot  Area              2025
Carpet  Area              87
Name: area_type, dtype: int64
```

Dropping the columns

- As such all the columns are important for price prediction, but for the sake of this project I am going to drop few columns

```
# Note everytime we make change in dataset we store it in new dataframe
df2 = df1.drop(['area_type', 'availability', 'society', 'balcony'],axis='columns')

print('Rows and columns are = ', df2.shape)
df2.head()
```

Step#4: Data Cleaning

- Check for na values
- Verify unique values of each column
- Make sure values are correct (eg. 23 BHK home with only 2000 Sqrft size seems wrong)

Handling null values

```
# Get the sum of all na values from dataset
df2.isna().sum()
```

Since null values as comapre to total training examples(13320) is verry less we can safly drop those examples

```
df3 = df2.dropna()
df3.isnull().sum()
```

```
# Since all oor training examples containing null values are dropped lets check the
df3.shape
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-1-ecc2f55bda1c> in <cell line: 2>()
      1 # Since all oor training examples containing null values are dropped
lets check the shape of the dataset again
----> 2 df3.shape

NameError: name 'df3' is not defined
```

SEARCH STACK OVERFLOW

Feature Engineering

- 'size' column contgaines the size of house in terms of BHK(Bedroom Hall Kitchen)
- To simply it we can create new column by the name 'bhk' and add only numeric value of how many BHK's

```
df3['size'].unique()
```

```
array(['2 BHK', '4 Bedroom', '3 BHK', '4 BHK', '6 Bedroom', '3 Bedroom',
       '1 BHK', '1 RK', '1 Bedroom', '8 Bedroom', '2 Bedroom',
       '7 Bedroom', '5 BHK', '7 BHK', '6 BHK', '5 Bedroom', '11 BHK',
       '9 BHK', '9 Bedroom', '27 BHK', '10 Bedroom', '11 Bedroom',
       '10 BHK', '19 BHK', '16 BHK', '43 Bedroom', '14 BHK', '8 BHK',
       '12 Bedroom', '13 BHK', '18 Bedroom'], dtype=object)
```

```
df4 = df3.copy()

# Using lambda function we can get the BHK numeric value
df4['bhk'] = df3['size'].apply(lambda x: int(x.split(' ')[0]))
#df3['bhk'] = df3['size'].apply(lambda x: int(x.split(' ')[0]))
df4.bhk.unique()
```

```
array([ 2,  4,  3,  6,  1,  8,  7,  5, 11,  9, 27, 10, 19, 16, 43, 14, 12,
       13, 18])
```

From above data we can see that there are home with upto 43 BHK's in Bangalore.. must be apolitician :)

```
#Get the training examples with home size more than 20 BHK
df4[df4.bhk >20]
```

	location	size	total_sqft	bath	price	bhk
1718	2Electronic City Phase II	27 BHK	8000	27.0	230.0	27
4684	Munnekollal	43 Bedroom	2400	40.0	660.0	43

Note above 43 BHK home area is only 2400 sqrft only. I will remove this data error later. First lets clean the 'total_sqft' column

Now lets check the unique values in 'total_sqft' column

```
df4.total_sqft.unique()
```

```
array(['1056', '2600', '1440', ..., '1133 - 1384', '774', '4689'],
      dtype=object)
```

Note above, there are few records with range of the area like '1133 - 1384'. Lets write a function to identify such values

```
def is_float(x):
  try:
    float(x)
  except:
    return False
```

```
  return True


# Test the function
print('is this (123) float value = %s' % (is_float(123)))
print('is this (1133 - 1384) float value = %s' % (is_float('1133 - 1384')))
```

```
is this (123) float value = True
is this (1133 - 1384) float value = False
```

```
#Lets apply this function to 'total_sqft' column

#Showing training examples where 'total_sqft' vale is not float
df4[~df4['total_sqft'].apply(is_float)].head(10)
```

	location	size	total_sqft	bath	price	bhk
30	Yelahanka	4 BHK	2100 - 2850	4.0	186.000	4
122	Hebbal	4 BHK	3067 - 8156	4.0	477.000	4
137	8th Phase JP Nagar	2 BHK	1042 - 1105	2.0	54.005	2
165	Sarjapur	2 BHK	1145 - 1340	2.0	43.490	2
188	KR Puram	2 BHK	1015 - 1540	2.0	56.800	2
410	Kengeri	1 BHK	34.46Sq. Meter	1.0	18.500	1
549	Hennur Road	2 BHK	1195 - 1440	2.0	63.770	2
648	Arekere	9 Bedroom	4125Perch	9.0	265.000	9
661	Yelahanka	2 BHK	1120 - 1145	2.0	48.130	2
672	Bettahalsoor	4 Bedroom	3090 - 5002	4.0	445.000	4

- Since most the value are range of sqft, we can write afunction to get the average value from a range.
- There are few values like '34.46Sq. Meter' and '4125Perch' we can also try and convert those values into sqft but for now I amgoing to ignore them

```
def convert_range_to_sqft(x):
  try:
    tokens = x.split('-')

    if len(tokens) == 2:
      return (float(tokens[0]) + float(tokens[1]))/2
    else:
      return float(x)
  except:
    return None
```

```
#Lets test the convert_range_to_sqft()
print('Return value for i/p 12345 = %s' % (convert_range_to_sqft('12345')))
print('Return value for i/p 1133 - 1384 = %s' % (convert_range_to_sqft('1133 - 1384
print('Return value for i/p 34.46Sq. Meter = %s' % (convert_range_to_sqft('34.46Sq.
```

```
Return value for i/p 12345 = 12345.0
Return value for i/p 1133 - 1384 = 1258.5
Return value for i/p 34.46Sq. Meter = None
```

```
# Lets apply this function for total_sqft column
df5 = df4.copy()

df5.total_sqft = df4.total_sqft.apply(convert_range_to_sqft)
df5.head()
```

	location	size	total_sqft	bath	price	bhk
0	Electronic City Phase II	2 BHK	1056.0	2.0	39.07	2
1	Chikka Tirupathi	4 Bedroom	2600.0	5.0	120.00	4
2	Uttarahalli	3 BHK	1440.0	2.0	62.00	3
3	Lingadheeranahalli	3 BHK	1521.0	3.0	95.00	3
4	Kothanur	2 BHK	1200.0	2.0	51.00	2

```
# Since our converion function will return null for values like 34.46Sq. Meter. Let
df5.total_sqft.isnull().sum()
```

```
46
```

```
# Lets dro the null training sets from total_sqft
df6 = df5.dropna()
df6.total_sqft.isnull().sum()

# OR
#We can also select the not null training set using below filter
#df6 = df5[df5.total_sqft.notnull()]
```

```
0
```

```
# Lets cross check the values of 'total_sqft'
print('total_sqft value for 30th training set in df4 = %s' % (df4.total_sqft[30]))
print('total_sqft value for 30th training set in df6 = %s' % (df6.total_sqft[30]))
```

```
total_sqft value for 30th training set in df4 = 2100 - 2850
total_sqft value for 30th training set in df6 = 2475.0
```

Feature Engineering

- 'price' column containes the price of house in lacka (1 lakh = 100000)

- Price per square fit is important parameter in house prices.
- So we can create new column by the name 'price_per_sqft' and add price per sqft in it. formula = (price * 100000)/total_sqft

```
df7 = df6.copy()

df7['price_per_sqft'] = (df6['price'] * 100000)/df6['total_sqft']
df7.head()
```

	location	size	total_sqft	bath	price	bhk	price_per_sqft
0	Electronic City Phase II	2 BHK	1056.0	2.0	39.07	2	3699.810606
1	Chikka Tirupathi	4 Bedroom	2600.0	5.0	120.00	4	4615.384615
2	Uttarahalli	3 BHK	1440.0	2.0	62.00	3	4305.555556
3	Lingadheeranahalli	3 BHK	1521.0	3.0	95.00	3	6245.890861
4	Kothanur	2 BHK	1200.0	2.0	51.00	2	4250.000000

```
df7_stats = df7['price_per_sqft'].describe()
df7_stats
```

```
count    1.320000e+04
mean     7.920759e+03
std      1.067272e+05
min      2.678298e+02
25%      4.267701e+03
50%      5.438331e+03
75%      7.317073e+03
max      1.200000e+07
Name: price_per_sqft, dtype: float64
```

Dimesionality Reduction

- Dimensionality reduction is simply a process of reducing the dimension(or number of random variables) of your feature set
- In our dataset 'location' is categorical variable with 1287 categories.
- Before using One Hot Encoding to create dummy variables we must reduce the number of categories by using dimensionality reduction so that I will get less number of dummy variables.
- Our criteria for dimesionality reduction for 'location' is to use 'other' location for any location having less than 10 data points.

```
#Trim the location values
df7.location = df7.location.apply(lambda x: x.strip())
df7.head()
```

	location	size	total_sqft	bath	price	bhk	price_per_sqft
0	Electronic City Phase II	2 BHK	1056.0	2.0	39.07	2	3699.810606
1	Chikka Tirupathi	4 Bedroom	2600.0	5.0	120.00	4	4615.384615
2	Uttarahalli	3 BHK	1440.0	2.0	62.00	3	4305.555556
3	Lingadheeranahalli	3 BHK	1521.0	3.0	95.00	3	6245.890861
4	Kothanur	2 BHK	1200.0	2.0	51.00	2	4250.000000

```
#Lets get the count of each location
location_stats = df7.location.value_counts(ascending=False)
location_stats
```

```
Whitefield                                       533
Sarjapur  Road                                   392
Electronic City                                  304
Kanakpura Road                                   264
Thanisandra                                      235
                                                ...
Somanna Garden                                     1
Howthinarayanappa Garden                           1
Bharat Nagar                                       1
Annapoorneshwari Layout, JP nagar 7th phase        1
Kalkere Channasandra                               1
Name: location, Length: 1287, dtype: int64
```

```
#Total number unique location categories are
len(location_stats)
```

```
1287
```

We are going assign a category 'other' for every location where total datapoints are less than 10

```
#Get total number of categories where data points are less than 10
print('Total no of locations where data points are more than 10 = %s' % (len(locati
print('Total no of locations where data points are less than 10 = %s' % (len(locati
```

```
Total no of locations where data points are more than 10 = 240
Total no of locations where data points are less than 10 = 1047
```

Any location having less than 10 data points should be tagged as "other" location. This way number of categories can be reduced by huge amount. Later on when we do one hot encoding, it will help us with having fewer dummy columns

```
location_stats_less_than_10 = location_stats[location_stats <= 10]
location_stats_less_than_10
```

```
Gunjur Palya                                    10
Nagappa Reddy Layout                            10
Sector 1 HSR Layout                             10
Ganga Nagar                                     10
```

```
Naganathapura                                      10
                                                   ..
Somanna Garden                                      1
Howthinarayanappa Garden                            1
Bharat Nagar                                        1
Annapoorneshwari Layout, JP nagar 7th phase         1
Kalkere Channasandra                                1
Name: location, Length: 1047, dtype: int64
```

```
#Using lambda function assign the 'other' type to every element in 'location_stats_
df8 = df7.copy()

df8.location = df7.location.apply(lambda x: 'other' if x in location_stats_less_tha
len(df8.location.unique())
```

```
241
```

Since 1047 location with less than 10 data points are converted to one category 'other' Total no of unique location categories are = 240 +1 = 241

```
df8.head(10)
```

	location	size	total_sqft	bath	price	bhk	price_per_sqft
0	Electronic City Phase II	2 BHK	1056.0	2.0	39.07	2	3699.810606
1	Chikka Tirupathi	4 Bedroom	2600.0	5.0	120.00	4	4615.384615
2	Uttarahalli	3 BHK	1440.0	2.0	62.00	3	4305.555556
3	Lingadheeranahalli	3 BHK	1521.0	3.0	95.00	3	6245.890861
4	Kothanur	2 BHK	1200.0	2.0	51.00	2	4250.000000
5	Whitefield	2 BHK	1170.0	2.0	38.00	2	3247.863248
6	Old Airport Road	4 BHK	2732.0	4.0	204.00	4	7467.057101
7	Rajaji Nagar	4 BHK	3300.0	4.0	600.00	4	18181.818182
8	Marathahalli	3 BHK	1310.0	3.0	63.25	3	4828.244275
9	other	6 Bedroom	1020.0	6.0	370.00	6	36274.509804

Outlier Removal

- An outlier is an observation that is unlike the other observations. It is rare, or distinct, or does not fit in some way.
- Outliers are the data points that represent the extreame variation of dataset
- Outliers can be valid data points but since our model is generalization of the data, outliers can affect the performanace of the model. We are going to remove the otliers, but please note its not always a good practice to remove the outliers.

- To remove the outliers we can use domain knwoledge and standard deviation

Standard Deviation

- Standard deviation is measure of spread that is to khow how much does the data vary from the average
- A low standard deviation tells us that the data is closely clustered around the mean (or average), while a high standard deviation indicates that the data is dispersed over a wider range of values.
- It is used when the distribution of data is approximately normal, resembling a bell curve.
- One standard deviation(1 Sigma) of the mean will cover 68% of the data. i.e. Data between (mean - std deviation) & (mean + std deviation) is 1 Sigma and which is equal to 68%
- Here we are going to consider 1 Sigma as our threshold adn any data outside 1 Sigma will be considered as outlier
- How to Use Statistics to Identify Outliers in Data
- Reference

Using domain knowledge for outlier removal

- Normally square fit per bedroom is 300 (i.e. 2 bhk apartment is minimum 600 sqft)
- If you have for example 400 sqft apartment with 2 bhk than that seems suspicious and can be removed as an outlier.
- I will remove such outliers by keeping our minimum threshold per bhk to be 300 sqft

Double-click (or enter) to edit

Using domain knowledge for outlier removal

```
# Lets visualize the data where square fit per bedroom is less than 300
df8[(df8.total_sqft / df8.bhk) < 300]
```

	location	size	total_sqft	bath	price	bhk	price_per_sqft
9	other	6 Bedroom	1020.0	6.0	370.0	6	36274.509804
45	HSR Layout	8 Bedroom	600.0	9.0	200.0	8	33333.333333
70	other	3 Bedroom	500.0	3.0	100.0	3	20000.000000

Note abobe we have 744 training examples where square fit per bedroom is less than 300. These are outliers, so we can remove them

```
#Lets check current dataset shape before removing outliers
df8.shape
```

```
(13200, 7)
```

```
df9 = df8[~((df8.total_sqft / df8.bhk) < 300)]
df9.shape
```

```
(12456, 7)
```

744 rows × 7 columns

Outlier Removal - Using Standard Deviation and Mean

- One standard deviation(1 Sigma) of the mean will cover 68% of the data. i. e. Data between (mean - std deviation) & (mean + std deviation) is 1 Sigma and which is equal to 68%
- Here any datapin t outside the 1 Sigma deviation (68%) is outlier for us

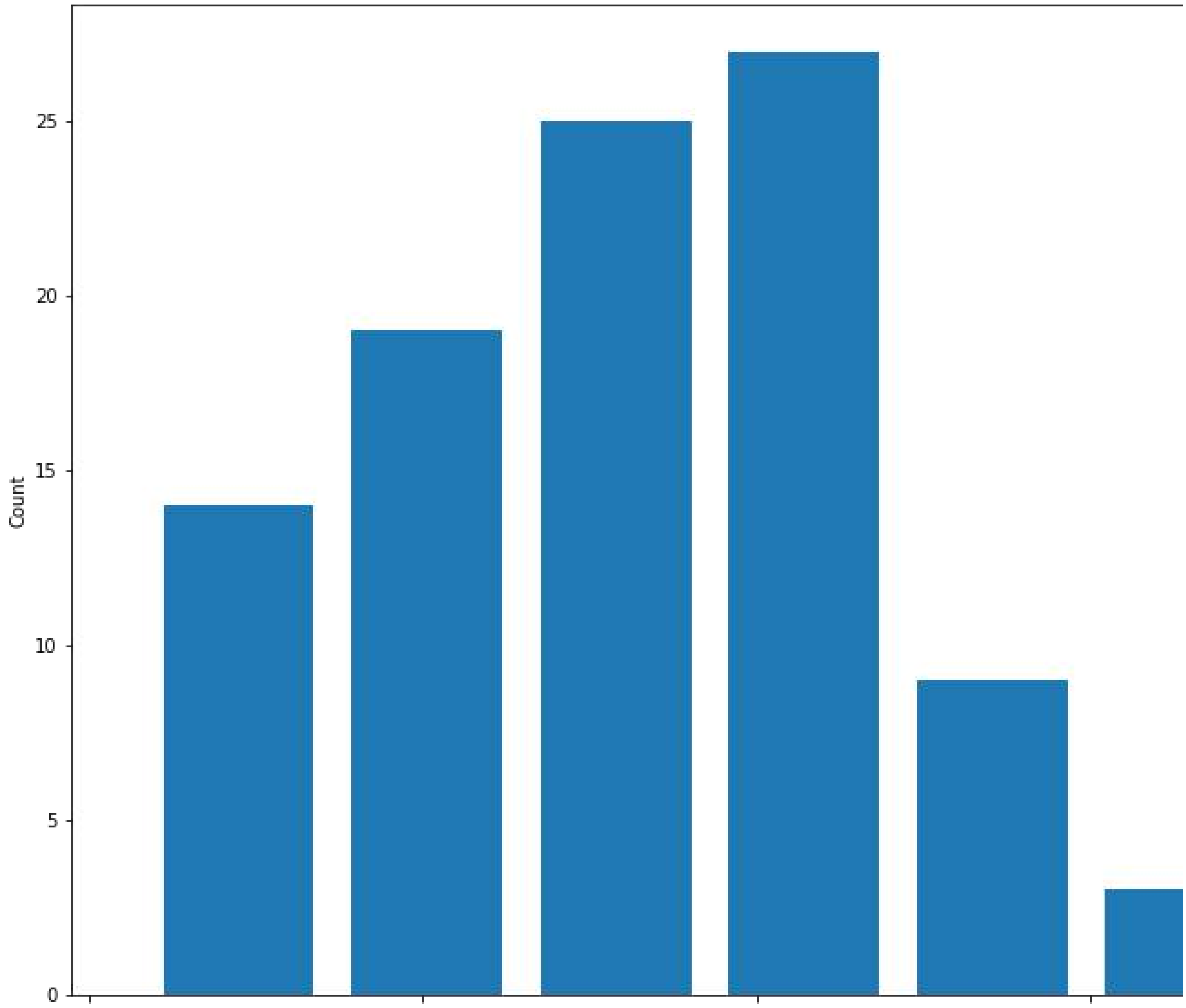
```
# Get basic stats of column 'price_per_sqft'
df9.price_per_sqft.describe()
```

```
count     12456.000000
mean       6308.502826
std        4168.127339
min         267.829813
25%        4210.526316
50%        5294.117647
75%        6916.666667
max      176470.588235
Name: price_per_sqft, dtype: float64
```

Note: Its important to understand that price of every house is location specific. We are going to remove outliers using 'price_per_sqft' for each location

```
# Data visualization for 'price_per_sqft' for location 'Rajaji Nagar'
# Note here its normal distribuation of data so outlier removal using stad deviatio
plt.hist(df9[df9.location == "Rajaji Nagar"].price_per_sqft,rwidth=0.8)
plt.xlabel("Price Per Square Feet")
plt.ylabel("Count")
```

```
Text(0, 0.5, 'Count')
```




```
#Lets check current dataset shape before removing outliers
df9.shape
```

```
(12456, 7)
```

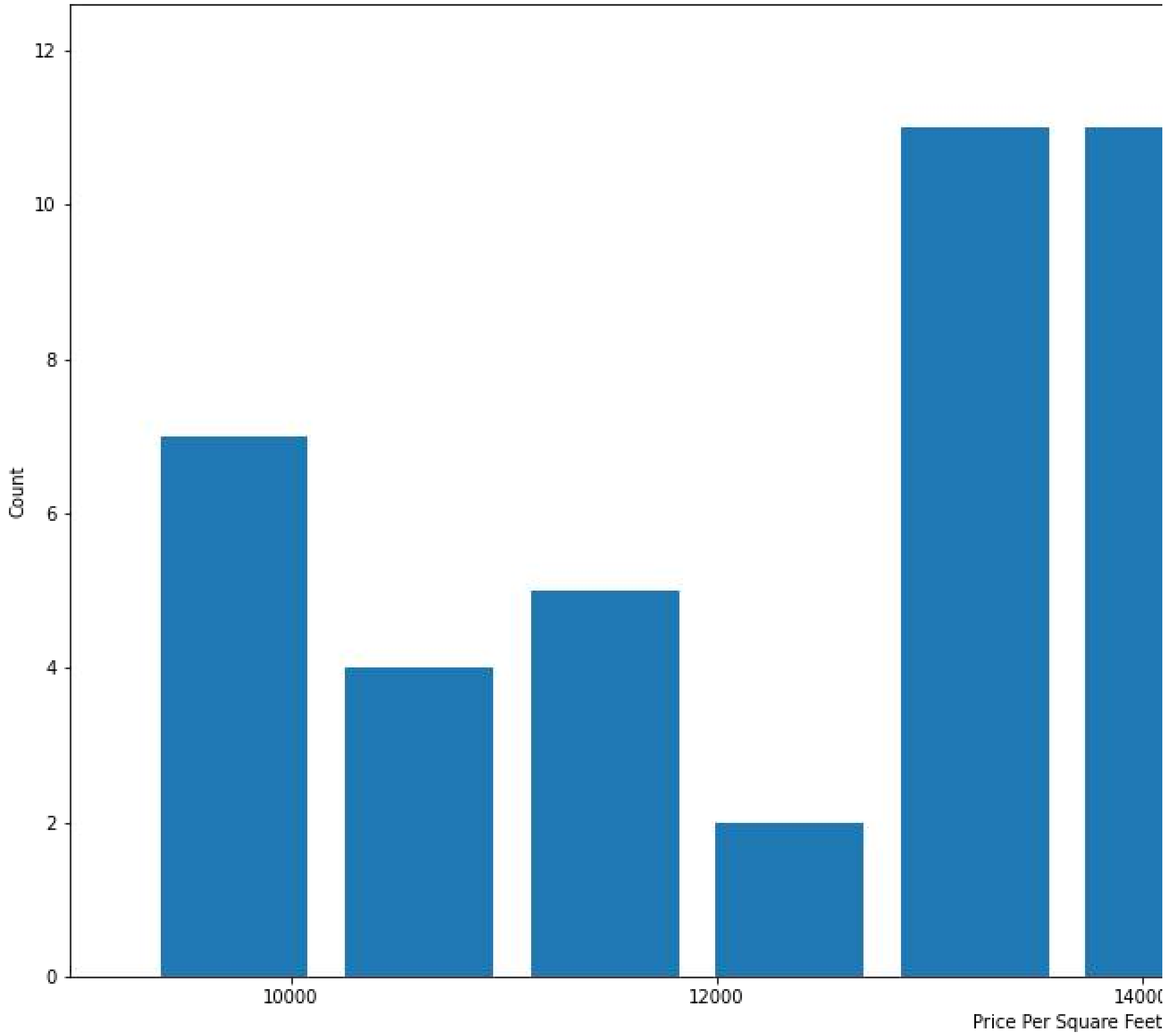
```
# Function to remove outliers using pps(price per sqft)
def remove_pps_outliers(df):
    df_out = pd.DataFrame()
    for key, subdf in df.groupby('location'):
        mean = np.mean(subdf.price_per_sqft)
        std = np.std(subdf.price_per_sqft)
        reduced_df = subdf[(subdf.price_per_sqft>(mean-std)) & (subdf.price_per_sqf
        df_out = pd.concat([df_out,reduced_df],ignore_index=True) # Storing data in
    return df_out

df10 = remove_pps_outliers(df9)
df10.shape
```

```
(10242, 7)
```

```
# Data visualization for 'price_per_sqft' for location 'Rajaji Nagar' after outlier
plt.hist(df10[df10.location == "Rajaji Nagar"].price_per_sqft,rwidth=0.8)
```

```
plt.xlabel("Price Per Square Feet")
plt.ylabel("Count")
```

```
Text(0, 0.5, 'Count')
```

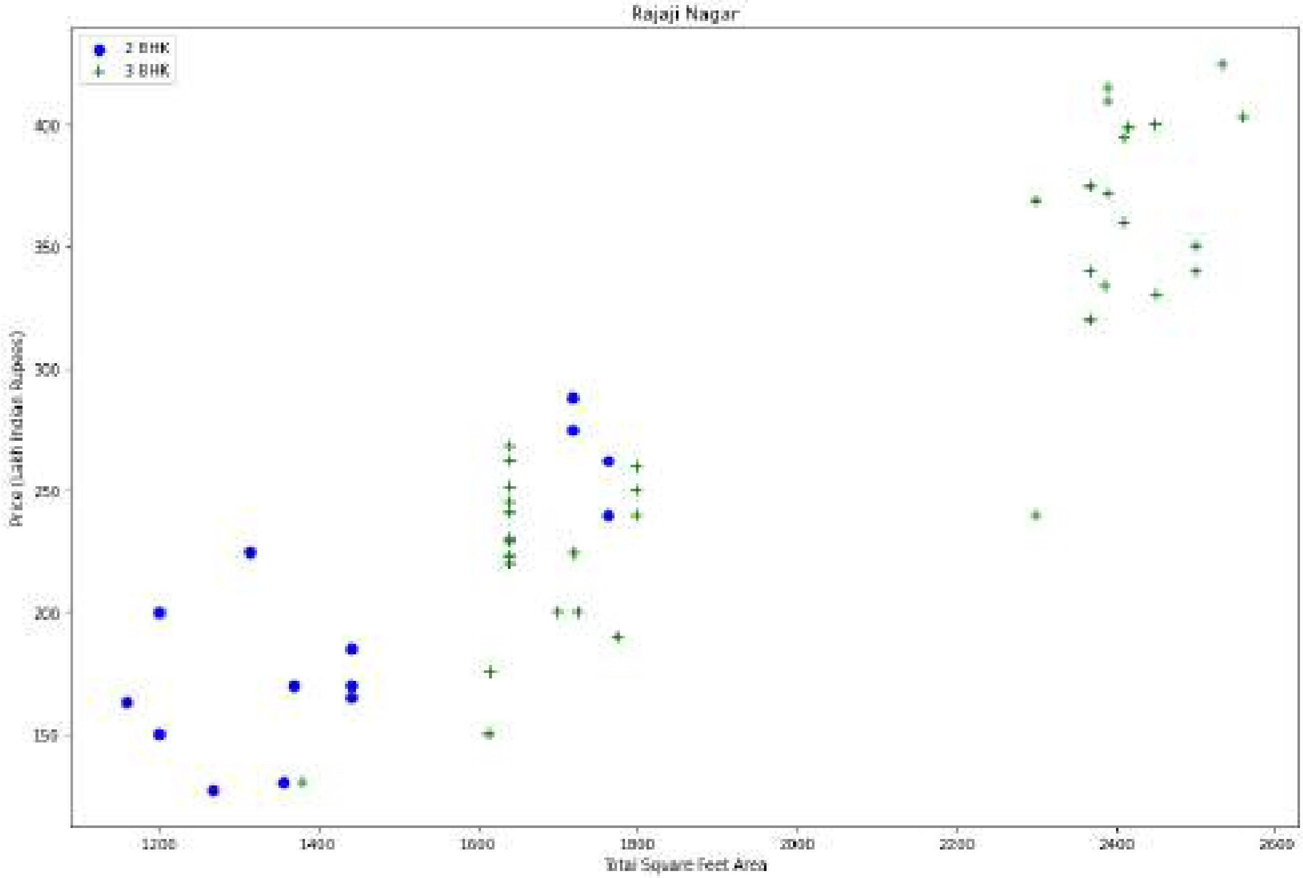


Using domain knowledge for outlier removal

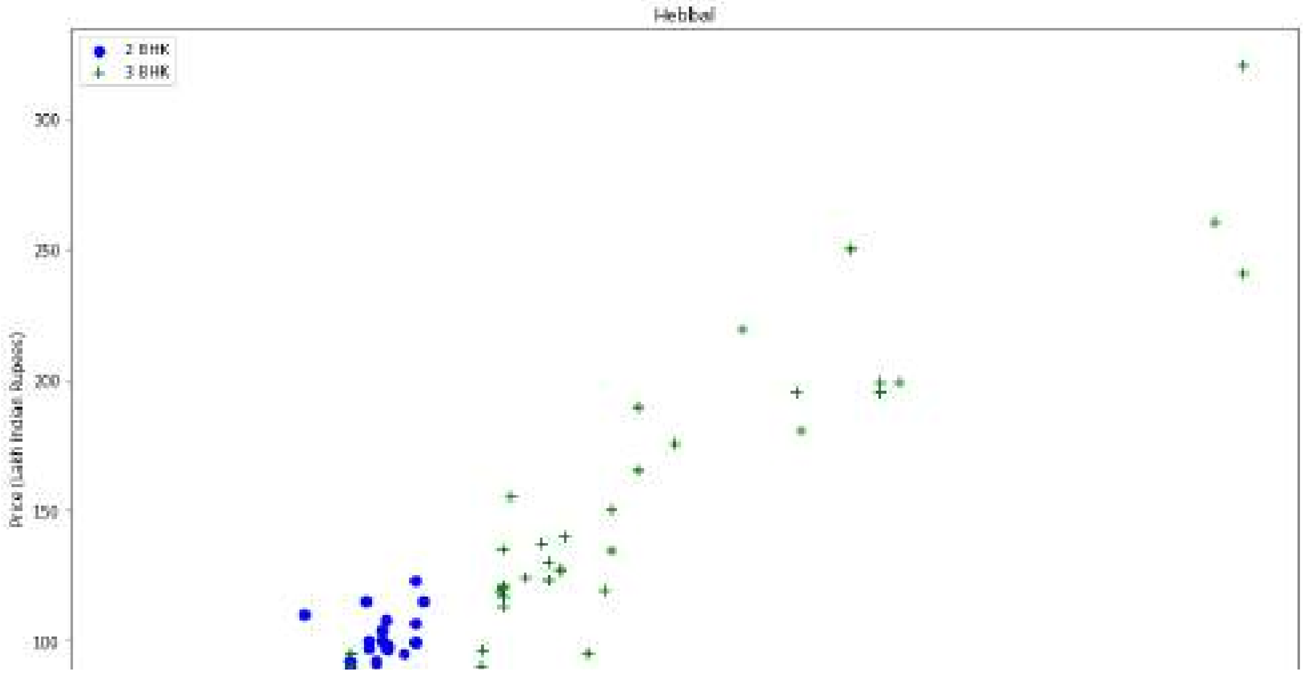
- If location and square foot area is aslo same then price of 3BHK should be more than 2 BHK
- There are other factors that also affect the price but for this exercise we are treating such values as outlier and remove them

```
# Let's check if for a given location how does the 2 BHK and 3 BHK property prices
def plot_scatter_chart(df,location):
    bhk2 = df[(df.location==location) & (df.bhk==2)]
    bhk3 = df[(df.location==location) & (df.bhk==3)]
    matplotlib.rcParams['figure.figsize'] = (15,10)
    plt.scatter(bhk2.total_sqft,bhk2.price,color='blue',label='2 BHK', s=50)
    plt.scatter(bhk3.total_sqft,bhk3.price,marker='+', color='green',label='3 BHK',
    plt.xlabel("Total Square Feet Area")
    plt.ylabel("Price (Lakh Indian Rupees)")
```

```
    plt.title(location)
    plt.legend()

plot_scatter_chart(df10,"Rajaji Nagar")
```




```
plot_scatter_chart(df10,"Hebbal")
```



We should also remove properties where for same location, the price of (for example) 3 bedroom apartment is less than 2 bedroom apartment (with same square ft area). What I will do is for a given location, I will build a dictionary by name 'bhk_stats' with below values of 'price_per_sqft'

```
{
    '1' : {
        'mean': 4000,
        'std: 2000,
        'count': 34
    },
    '2' : {
        'mean': 4300,
        'std: 2300,
        'count': 22
    },
}
```

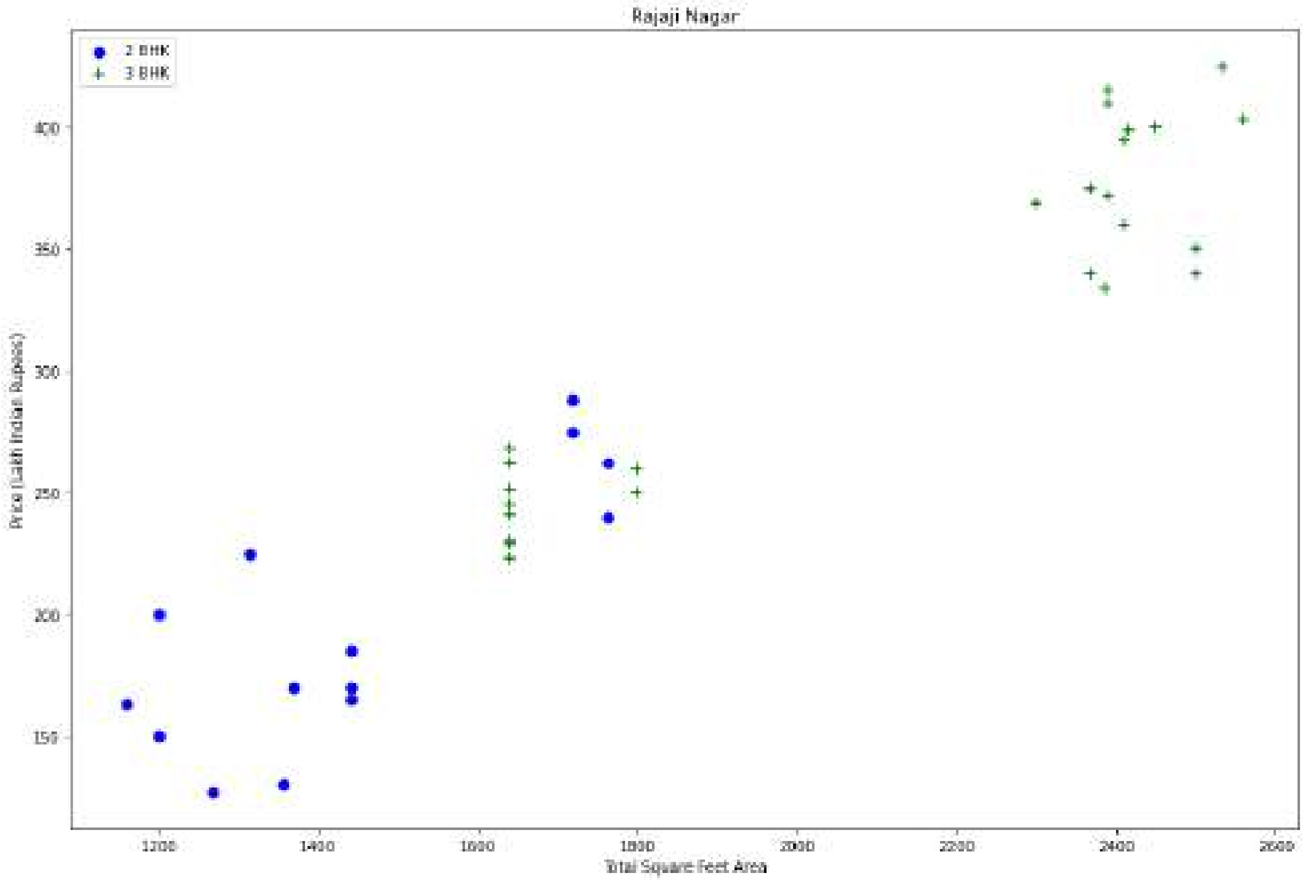
Now we can remove those 2 BHK apartments whose price_per_sqft is less than mean price_per_sqft of 1 BHK apartment

```
def remove_bhk_outliers(df):
    exclude_indices = np.array([])
    for location, location_df in df.groupby('location'):
        bhk_stats = {}
        for bhk, bhk_df in location_df.groupby('bhk'):
            bhk_stats[bhk] = {
                'mean': np.mean(bhk_df.price_per_sqft),
                'std': np.std(bhk_df.price_per_sqft),
                'count': bhk_df.shape[0]
            }
        for bhk, bhk_df in location_df.groupby('bhk'):
```

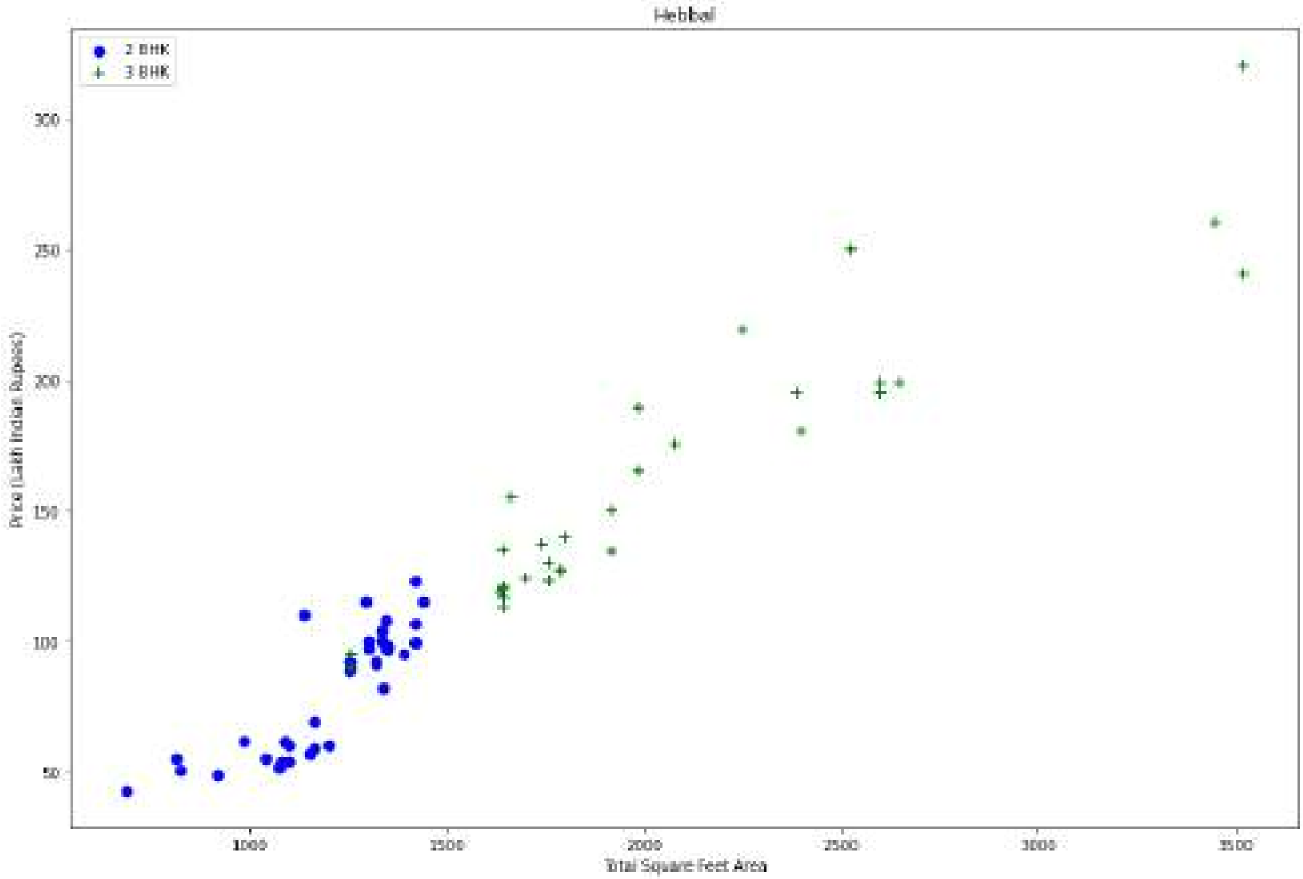
```
            stats = bhk_stats.get(bhk-1)
            if stats and stats['count']>5:
                exclude_indices = np.append(exclude_indices, bhk_df[bhk_df.price_pe
    return df.drop(exclude_indices,axis='index')

df11 = remove_bhk_outliers(df10)
df11.shape
```

```
(7317, 7)
```

```
#Plot same scatter chart again to visualize price_per_sqft for 2 BHK and 3 BHK prop
plot_scatter_chart(df11,"Rajaji Nagar")
```



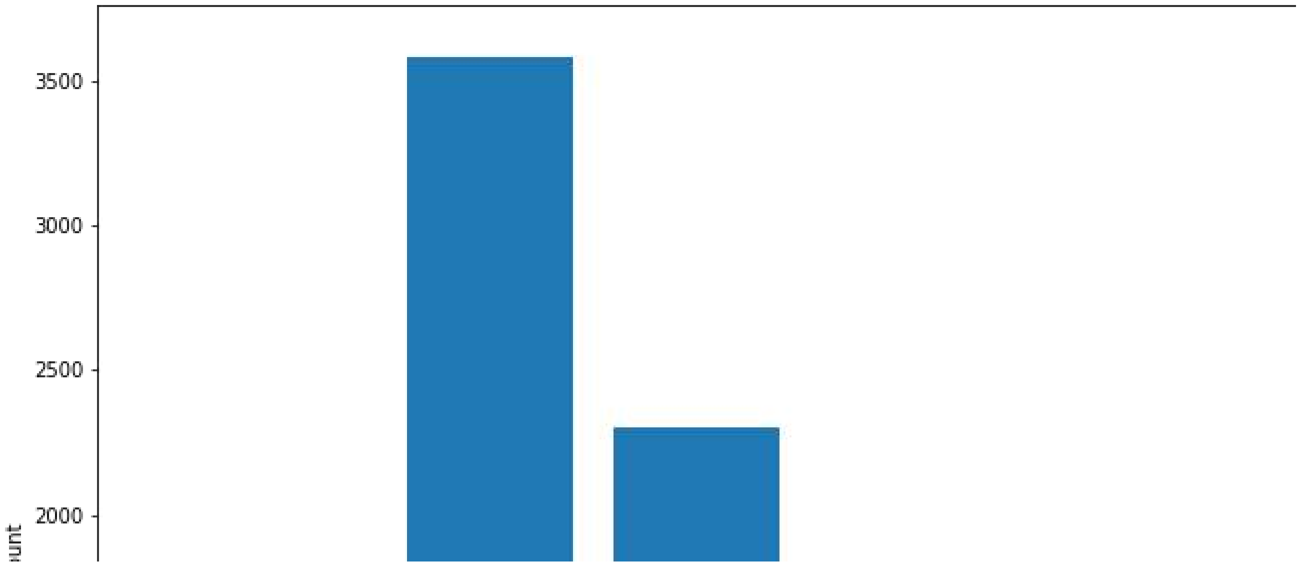

```
plot_scatter_chart(df11,"Hebbal")
```



Now you can campre the scatter plots for location(Hebbal and Rajaji Nagar) for before and after outlier removal

```
#Now lets plot the histogram and visualize the price_per_sqft data after outlier re

matplotlib.rcParams["figure.figsize"] = (20,10)
plt.hist(df11.price_per_sqft,rwidth=0.8)
plt.xlabel("Price Per Square Feet")
plt.ylabel("Count")
```

```
Text(0, 0.5, 'Count')
```



Using domain knowledge for outlier removal

- Generally number of bathrooms per BHK are (no of BHK) + 2.
- So using above understanding we can identify the outliers and remove them


```
#Get unique bath from dataset
df11.bath.unique()
```

```
array([ 4.,  3.,  2.,  5.,  8.,  1.,  6.,  7.,  9., 12., 16., 13.])
```

```
#Get the training examples where no of bath are more than (no of BHK +2)
df11[df11.bath > df11.bhk + 2]
```

	location	size	total_sqft	bath	price	bhk	price_per_sqft
1626	Chikkabanavar	4 Bedroom	2460.0	7.0	80.0	4	3252.032520
5238	Nagasandra	4 Bedroom	7000.0	8.0	450.0	4	6428.571429
6711	Thanisandra	3 BHK	1806.0	6.0	116.0	3	6423.034330
8408	other	6 BHK	11338.0	9.0	1000.0	6	8819.897689

We can remove above outliers from the datset

```
#Lets check current dataset shape before removing outliers
df11.shape
```

```
(7317, 7)
```

```
# Remove the outliers with more than (no of BHK + 2) bathrooms
df12 = df11[df11.bath < (df11.bhk + 2)]
df12.shape
```

```
(7239, 7)
```

This concludes our data cleaning, lets drop unnecessary columns

- Since we have 'bhk' feature lets drop 'size'
- We have crerated 'price_per_sqft' for outlier detection and removal purpose, so we can also drop it.

```
df13 = df11.drop(['size', 'price_per_sqft'], axis='columns')
df13.head()
```

	location	total_sqft	bath	price	bhk
0	1st Block Jayanagar	2850.0	4.0	428.0	4
1	1st Block Jayanagar	1630.0	3.0	194.0	3
2	1st Block Jayanagar	1875.0	2.0	235.0	3
3	1st Block Jayanagar	1200.0	2.0	130.0	3
4	1st Block Jayanagar	1235.0	2.0	148.0	2

One Hot Encoding

Since we have 'location' as categorical feature lets use One Hot Encoding to create separate column for each location category and assign binary value 1 or 0

```
dummies = pd.get_dummies(df13.location)
dummies.head()
```

	1st Block Jayanagar	1st Phase JP Nagar	2nd Phase Judicial Layout	2nd Stage Nagarbhavi	5th Block Hbr Layout	5th Phase JP Nagar	6th Phase JP Nagar	7th Phase JP Nagar	8th Phase JP Nagar	Pl Na
0	1	0	0	0	0	0	0	0	0	
1	1	0	0	0	0	0	0	0	0	
2	1	0	0	0	0	0	0	0	0	
3	1	0	0	0	0	0	0	0	0	
4	1	0	0	0	0	0	0	0	0	

5 rows × 241 columns

```
#To avoid dummy variable trap problem lets delete the one of the dummy variable col
dummies = dummies.drop(['other'],axis='columns')
dummies.head()
```

	1st Block Jayanagar	1st Phase JP Nagar	2nd Phase Judicial Layout	2nd Stage Nagarbhavi	5th Block Hbr Layout	5th Phase JP Nagar	6th Phase JP Nagar	7th Phase JP Nagar	8th Phase JP Nagar	Pl Na
0	1	0	0	0	0	0	0	0	0	
1	1	0	0	0	0	0	0	0	0	
2	1	0	0	0	0	0	0	0	0	
3	1	0	0	0	0	0	0	0	0	
4	1	0	0	0	0	0	0	0	0	

5 rows × 240 columns

```
#Now lets add dummies dataframe to original dataframe
df14 = pd.concat([df13,dummies],axis='columns')
df14.head()
```

	location	total_sqft	bath	price	bhk	1st Block Jayanagar	1st Phase JP Nagar	2nd Phase Judicial Layout	2nd Stag Nagarbhav
0	1st Block Jayanagar	2850.0	4.0	428.0	4	1	0	0	
1	1st Block Jayanagar	1630.0	3.0	194.0	3	1	0	0	
2	1st Block Jayanagar	1875.0	2.0	235.0	3	1	0	0	
3	1st Block Jayanagar	1200.0	2.0	130.0	3	1	0	0	
4	1st Block Jayanagar	1235.0	2.0	148.0	2	1	0	0	

5 rows × 245 columns

```
#Lets delete the location feature
df15 = df14.drop(['location'],axis='columns')
df15.head()m
```

	total_sqft	bath	price	bhk	1st Block Jayanagar	1st Phase JP Nagar	2nd Phase Judicial Layout	2nd Stage Nagarbhavi	5th Block Hbr Layout
2	1875.0	2.0	235.0	3	1	0	0	0	0

Step#5: Build Machine Learning Model

```
#Final shape of our dataset is
df15.shape
```

```
(7317, 244)
```

Now leats create X(independent variable/features) and y(dependent variables/target)

```
X = df15.drop(['price'],axis='columns')
X.head()
```

	total_sqft	bath	bhk	1st Block Jayanagar	1st Phase JP Nagar	2nd Phase Judicial Layout	2nd Stage Nagarbhavi	5th Block Hbr Layout	5th Phase JP Nagar
0	2850.0	4.0	4	1	0	0	0	0	0
1	1630.0	3.0	3	1	0	0	0	0	0
2	1875.0	2.0	3	1	0	0	0	0	0
3	1200.0	2.0	3	1	0	0	0	0	0
4	1235.0	2.0	2	1	0	0	0	0	0

5 rows × 243 columns

```
y = df15.price
y.head()
```

```
0    428.0
1    194.0
2    235.0
3    130.0
4    148.0
Name: price, dtype: float64
```

Split the dataset to training andtest dataset

```
from sklearn.model_selection import train_test_split

X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,random_state=10)
```

```
print('X_train shape = ',X_train.shape)
print('X_test shape = ',X_test.shape)
print('y_train shape = ',y_train.shape)
print('y_test shape = ',y_test.shape)
```

```
X_train shape =  (5853, 243)
X_test shape =  (1464, 243)
y_train shape =  (5853,)
y_test shape =  (1464,)
```

Linear Regression

- Lets test the score with LinearRegression model

```
from sklearn.linear_model import LinearRegression

lr_clf = LinearRegression()
lr_clf.fit(X_train, y_train)
lr_clf.score(X_test, y_test)
```

```
0.8175889965469311
```

Use K Fold cross validation to measure accuracy of our LinearRegression model

- Using Sklearn cross_val_score function
- Note: Sklearn's cross_val_score uses StratifiedKFold by default

```
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import ShuffleSplit

# ShuffleSplit is used to randomize the each fold
cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=0)
cross_val_score(LinearRegression(), X, y, cv = cv)
```

```
array([0.83458131, 0.8720703 , 0.77477801, 0.86043362, 0.87857309])
```

GridSearchCV

- From above scores its clear that with LinearRegresion we get max score of upto 87%
- Let use GridSearchCV to test other regression algorithm

```
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import Lasso
from sklearn.tree import DecisionTreeRegressor

from sklearn.linear_model import Ridge
```

```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.linear_model import ElasticNet

def find_best_model_using_gridsearchcv(X,y):
  algos ={
      'linear_regression':{
          'model':LinearRegression(),
          'params': {
              'normalize':[True,False]
          }
      },
        'lasso': {
            'model': Lasso(),
            'params': {
                'alpha': [1,2],
                'selection': ['random', 'cyclic']
            }
        },
        'decision_tree': {
            'model': DecisionTreeRegressor(),
            'params': {
                'criterion' : ['mse','friedman_mse'],
                'splitter': ['best','random']
            }
        }
  }

  scores= []
  cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=0)

  for algo_name, config in algos.items():
      gs =  GridSearchCV(config['model'], config['params'], cv=cv, return_train_sco
      gs.fit(X,y)
      scores.append({
          'model': algo_name,
          'best_score': gs.best_score_,
          'best_params': gs.best_params_
      })

  return pd.DataFrame(scores,columns=['model','best_score','best_params'])

find_best_model_using_gridsearchcv(X,y)
```

	model	best_score	best_params
0	linear_regression	0.844087	{'normalize': False}
1	lasso	0.710569	{'alpha': 1, 'selection': 'cyclic'}
2	decision_tree	0.668973	{'criterion': 'friedman_mse', 'splitter': 'ran...

Based on above results we can say that LinearRegression gives the best score. Hence I will use that.

Step#6: Testing The model

- Since all our locations are now columns in form of dummy variabales, all other dummy variables value should be 0 except the one(dummy variable column for our location) we are predicting for
- This(np.where(X.columns==location)[0][0]) code will give us index of dummy column for our location
- Now I will assign value '1' to this index and keep all other dummy variable columns as '0'

```
def predict_price(location, sqft, bath, bhk):
    loc_index = np.where(X.columns==location)[0][0]

    x = np.zeros(len(X.columns))
    x[0] = sqft
    x[1] = bath
    x[2] = bhk
    if loc_index >= 0:
        x[loc_index] = 1

    return lr_clf.predict([x])[0]
```

```
predict_price('1st Phase JP Nagar',1000, 2, 2)
```

```
83.16761667762826
```

```
predict_price('1st Phase JP Nagar',1000, 3, 3)
```

```
83.71323640897404
```

```
predict_price('Indira Nagar',1000, 2, 2)
```

```
158.07409801131223
```

```
predict_price('Indira Nagar',1000, 3, 3)
```

```
158.61971774265803
```

Step#7: Export the model to Pickle file

```
import pickle

with open('Real_Estate_Price_Prediction_Project.pickle','wb') as f:
    pickle.dump(lr_clf,f)
```

```
#Since we are using the Google colab, pickle will will be saved at current director
import os
```

```
os.listdir('.')
```

```
['.config',
 'Bengaluru_House_Data.csv',
 'Real_Estate_Price_Prediction_Project.pickle',
 'sample_data']
```

```
#Lets download it
from google.colab import files

files.download('Real_Estate_Price_Prediction_Project.pickle')
```

Step#8: Export any other important info

- since weare using One Hot Encoding for location column we need the final list of all the columns in our feature set

```
import json
columns = {
    'data_columns' : [col.lower() for col in X.columns]
}
with open("columns.json","w") as f:
    f.write(json.dumps(columns))
```

```
os.listdir('.')
```

```
['.config',
 'Bengaluru_House_Data.csv',
 'Real_Estate_Price_Prediction_Project.pickle',
 'columns.json',
 'sample_data']
```

```
files.download('columns.json')
```

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