Data Science Regression Project: Predicting Home Prices in Banglore

Dataset is downloaded from here: [https://www.kaggle.com/amitabhajoy/bengaluru-house-price-data (https://www.kaggle.com/amitabhajoy/bengaluru-house-price-data)](https://www.kaggle.com/amitabhajoy/bengaluru-house-price-data)

In [1]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
%matplotlib inline
import matplotlib
matplotlib.rcParams["figure.figsize"] = (20,10)
```

Data Load: Load banglore home prices into a dataframe

In [2]:
```
df1 = pd.read_csv("bengaluru_house_prices.csv")
df1.head()
```

Out[2]:

	area_type	availability	location	size	society	total_sqft
0	Super built-up Area	19-Dec	Electronic City Phase II	2 BHK	Coomee	1056
1	Plot Area	Ready To Move	Chikka Tirupathi	4 Bedroom	Theanmp	2600
2	Built-up Area	Ready To Move	Uttarahalli	3 BHK	NaN	1440
3	Super built-up Area	Ready To Move	Lingadheeranahalli	3 BHK	Soiewre	1521
4	Super built-up Area	Ready To Move	Kothanur	2 BHK	NaN	1200

In [3]:
```
df1.shape
```

Out[3]:
```
(13320, 9)
```

In [4]:
```
df1.columns
```

Out[4]:
```
Index(['area_type', 'availability', 'location', 'size', 'so
ciety',
       'total_sqft', 'bath', 'balcony', 'price'],
      dtype='object')
```

In [5]:
```
df1['area_type'].unique()
```

Out[5]:
```
array(['Super built-up  Area', 'Plot  Area', 'Built-up  Are
a',
       'Carpet  Area'], dtype=object)
```

In [6]:
```
df1['area_type'].value_counts()
```

Out[6]:
```
Super built-up  Area    8790
Built-up  Area          2418
Plot  Area              2025
Carpet  Area              87
Name: area_type, dtype: int64
```

Drop features that are not required to build our model

In [7]:
```
df2 = df1.drop(['area_type','society','balcony','availabilit
df2.shape
```

Out[7]:
```
(13320, 5)
```

Data Cleaning: Handle NA values

In [8]:
```
df2.isnull().sum()
```

Out[8]:
```
location       1
size          16
total_sqft     0
bath          73
price          0
dtype: int64
```

In [9]:
```
df2.shape
```

Out[9]:
```
(13320, 5)
```

In [10]:
```
df3 = df2.dropna()
df3.isnull().sum()
```

Out[10]:
```
location      0
size          0
total_sqft    0
bath          0
price         0
dtype: int64
```

In [11]:
```
df3.shape
```

Out[11]:
```
(13246, 5)
```

Feature Engineering

Add new feature(integer) for bhk (Bedrooms Hall Kitchen)

In [12]:
```
df3['bhk'] = df3['size'].apply(lambda x: int(x.split(' ')[0])
df3.bhk.unique()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launch
er.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a Dat
aFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.
org/pandas-docs/stable/indexing.html#indexing-view-versus-c
opy (http://pandas.pydata.org/pandas-docs/stable/indexing.h
tml#indexing-view-versus-copy)
  """Entry point for launching an IPython kernel.
```

Out[12]:
```
array([ 2,  4,  3,  6,  1,  8,  7,  5, 11,  9, 27, 10, 19,
16, 43, 14, 12,
       13, 18], dtype=int64)
```

Explore total_sqft feature

In [13]:
```
def is_float(x):
    try:
        float(x)
    except:
        return False
    return True
```

In [14]:
```
2+3
```

Out[14]: 5

In [15]:
```
df3[~df3['total_sqft'].apply(is_float)].head(10)
```

Out[15]:

	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

Above shows that total_sqft can be a range (e.g. 2100-2850). For such case we can just take average of min and max value in the range. There are other cases such as 34.46Sq. Meter which one can convert to square ft using unit conversion. I am going to just drop such corner cases to keep things simple

In [16]:
```
def convert_sqft_to_num(x):
    tokens = x.split('-')
    if len(tokens) == 2:
        return (float(tokens[0])+float(tokens[1]))/2
    try:
        return float(x)
    except:
        return None
```

In [17]:
```
df4 = df3.copy()
df4.total_sqft = df4.total_sqft.apply(convert_sqft_to_num)
df4 = df4[df4.total_sqft.notnull()]
df4.head(2)
```

Out[17]:

	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

For below row, it shows total_sqft as 2475 which is an average of the range 2100-2850

In [18]:
```
df4.loc[30]
```

Out[18]:
```
location      Yelahanka
size              4 BHK
total_sqft         2475
bath                  4
price               186
bhk                   4
Name: 30, dtype: object
```

In [19]:
```
(2100+2850)/2
```

Out[19]:
```
2475.0
```

Feature Engineering

Add new feature called price per square feet

In [20]:
```
df5 = df4.copy()
df5['price_per_sqft'] = df5['price']*100000/df5['total_sqft'
df5.head()
```

Out[20]:

	location	size	total_sqft	bath	price	bhk	price_per_sq
0	Electronic City Phase II	2 BHK	1056.0	2.0	39.07	2	3699.81060
1	Chikka Tirupathi	4 Bedroom	2600.0	5.0	120.00	4	4615.38461
2	Uttarahalli	3 BHK	1440.0	2.0	62.00	3	4305.55555
3	Lingadheeranahalli	3 BHK	1521.0	3.0	95.00	3	6245.89086
4	Kothanur	2 BHK	1200.0	2.0	51.00	2	4250.00000

In [21]:
```
df5_stats = df5['price_per_sqft'].describe()
df5_stats
```

Out[21]:
```
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
```

In [69]:
```
df5.to_csv("bhp.csv",index=False)
```

Examine locations which is a categorical variable. We need to apply dimensionality reduction technique here to reduce number of locations

In [22]:
```
df5.location = df5.location.apply(lambda x: x.strip())
location_stats = df5['location'].value_counts(ascending=Fals
location_stats
```

Out[22]:

```
Whitefield                                    533
Sarjapur  Road                                392
Electronic City                               304
Kanakpura Road                                264
Thanisandra                                   235
Yelahanka                                     210
Uttarahalli                                   186
Hebbal                                        176
Marathahalli                                  175
Raja Rajeshwari Nagar                         171
Bannerghatta Road                             151
Hennur Road                                   150
7th Phase JP Nagar                            148
Haralur Road                                  141
Electronic City Phase II                      131
Rajaji Nagar                                  106
Chandapura                                     98
Bellandur                                      96
KR Puram                                       88
Hoodi                                          88
Electronics City Phase 1                       87
Yeshwanthpur                                   85
Begur Road                                     84
Sarjapur                                       80
Kasavanhalli                                   79
Harlur                                         79
Hormavu                                        74
Banashankari                                   74
Ramamurthy Nagar                               72
Koramangala                                    72
                                             ...
Ckikkakammana Halli                             1
Neelasandra                                     1
Gangondanahalli                                 1
Agara Village                                   1
Sundara Nagar                                   1
Binny Mills Employees Colony                    1
Adugodi                                         1
Uvce Layout                                     1
Kenchanehalli R R Nagar                         1
Whietfield,                                     1
manyata                                         1
Air View Colony                                 1
Thavarekere                                     1
Muthyala Nagar                                  1
Haralur Road,                                   1
Manonarayanapalya                               1
GKW Layout                                      1
Marathalli bridge                               1
Banashankari 6th Stage ,Subramanyapura          1
```

```
anjananager magdi road                                 1
akshaya nagar t c palya                                1
Indiranagar HAL 2nd Stage                              1
Maruthi HBCS Layout                                    1
Gopal Reddy Layout                                     1
High grounds                                           1
CMH Road                                               1
Chambenahalli                                          1
Sarvobhogam Nagar                                      1
Ex-Servicemen Colony Dinnur Main Road R.T.Nagar        1
Bilal Nagar                                            1
Name: location, Length: 1287, dtype: int64
```

In [23]:
```
location_stats.values.sum()
```

Out[23]:
```
13200
```

In [24]:
```
len(location_stats[location_stats>10])
```

Out[24]:
```
240
```

In [25]:
```
len(location_stats)
```

Out[25]:
```
1287
```

In [26]:
```
len(location_stats[location_stats<=10])
```

Out[26]:
```
1047
```

Dimensionality Reduction

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

In [27]:
```
location_stats_less_than_10 = location_stats[location_stats<
location_stats_less_than_10
```

Out[27]:
```
BTM 1st Stage                                10
Sector 1 HSR Layout                          10
Ganga Nagar                                  10
Naganathapura                                10
1st Block Koramangala                        10
Thyagaraja Nagar                             10
Dairy Circle                                 10
Nagadevanahalli                              10
Sadashiva Nagar                              10
Gunjur Palya                                 10
Dodsworth Layout                             10
Basapura                                     10
Kalkere                                      10
Nagappa Reddy Layout                         10
2nd Phase JP Nagar                            9
Yemlur                                        9
Medahalli                                     9
Kaverappa Layout                              9
Ejipura                                       9
Mathikere                                     9
Lingarajapuram                                9
Peenya                                        9
Vignana Nagar                                 9
B Narayanapura                                9
Chandra Layout                                9
Jakkur Plantation                             9
Banagiri Nagar                                9
Chennammana Kere                              9
Richmond Town                                 9
Vishwanatha Nagenahalli                       9
                                             ..
Ckikkakammana Halli                           1
Neelasandra                                   1
Gangondanahalli                               1
Agara Village                                 1
Sundara Nagar                                 1
Binny Mills Employees Colony                  1
Adugodi                                       1
Uvce Layout                                   1
Kenchanehalli R R Nagar                       1
Whietfield,                                   1
manyata                                       1
Air View Colony                               1
Thavarekere                                   1
Muthyala Nagar                                1
Haralur Road,                                 1
Manonarayanapalya                             1
GKW Layout                                    1
Marathalli bridge                             1
Banashankari 6th Stage ,Subramanyapura        1
```

```
anjananager magdi road                                  1
akshaya nagar t c palya                                 1
Indiranagar HAL 2nd Stage                               1
Maruthi HBCS Layout                                     1
Gopal Reddy Layout                                      1
High grounds                                            1
CMH Road                                                1
Chambenahalli                                           1
Sarvobhogam Nagar                                       1
Ex-Servicemen Colony Dinnur Main Road R.T.Nagar         1
Bilal Nagar                                             1
Name: location, Length: 1047, dtype: int64
```

In [28]:
```
len(df5.location.unique())
```

Out[28]:
```
1287
```

In [29]:
```
df5.location = df5.location.apply(lambda x: 'other' if x in
len(df5.location.unique())
```

Out[29]:
```
241
```

In [30]:
```
df5.head(10)
```

Out[30]:

	location	size	total_sqft	bath	price	bhk	price_per_sq
0	Electronic City Phase II	2 BHK	1056.0	2.0	39.07	2	3699.81060
1	Chikka Tirupathi	4 Bedroom	2600.0	5.0	120.00	4	4615.38461
2	Uttarahalli	3 BHK	1440.0	2.0	62.00	3	4305.55555
3	Lingadheeranahalli	3 BHK	1521.0	3.0	95.00	3	6245.89086
4	Kothanur	2 BHK	1200.0	2.0	51.00	2	4250.00000
5	Whitefield	2 BHK	1170.0	2.0	38.00	2	3247.86324
6	Old Airport Road	4 BHK	2732.0	4.0	204.00	4	7467.05710
7	Rajaji Nagar	4 BHK	3300.0	4.0	600.00	4	18181.81818
8	Marathahalli	3 BHK	1310.0	3.0	63.25	3	4828.24427
9	other	6 Bedroom	1020.0	6.0	370.00	6	36274.50980

Outlier Removal Using Business Logic

As a data scientist when you have a conversation with your business manager (who has expertise in real estate), he will tell you that normally square ft 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. We will remove such outliers by keeping our minimum thresold per bhk to be 300 sqft

In [31]:
```
df5[df5.total_sqft/df5.bhk<300].head()
```

Out[31]:

	location	size	total_sqft	bath	price	bhk	price_per_s
9	other	6 Bedroom	1020.0	6.0	370.0	6	36274.5098
45	HSR Layout	8 Bedroom	600.0	9.0	200.0	8	33333.3333
58	Murugeshpalya	6 Bedroom	1407.0	4.0	150.0	6	10660.9808
68	Devarachikkanahalli	8 Bedroom	1350.0	7.0	85.0	8	6296.2962
70	other	3 Bedroom	500.0	3.0	100.0	3	20000.0000

Check above data points. We have 6 bhk apartment with 1020 sqft. Another one is 8 bhk and total sqft is 600. These are clear data errors that can be removed safely

In [32]:
```
df5.shape
```

Out[32]: (13200, 7)

In [33]:
```
df6 = df5[~(df5.total_sqft/df5.bhk<300)]
df6.shape
```

Out[33]: (12456, 7)

Outlier Removal Using Standard Deviation and Mean

In [34]:
```
df6.price_per_sqft.describe()
```

Out[34]:
```
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
```

Here we find that min price per sqft is 267 rs/sqft whereas max is 12000000, this shows a wide variation in property prices. We should remove outliers per location using mean and one standard deviation

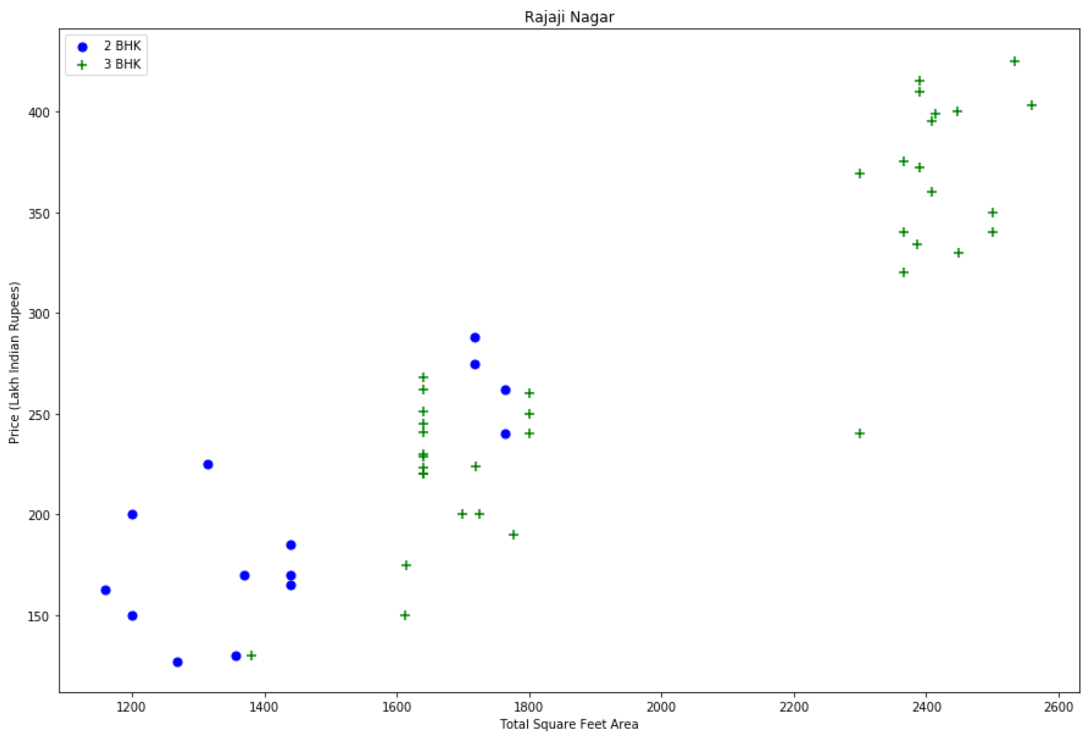
In [35]:
```
def remove_pps_outliers(df):
    df_out = pd.DataFrame()
    for key, subdf in df.groupby('location'):
        m = np.mean(subdf.price_per_sqft)
        st = np.std(subdf.price_per_sqft)
        reduced_df = subdf[(subdf.price_per_sqft>(m-st)) & (
        df_out = pd.concat([df_out,reduced_df],ignore_index=
    return df_out
df7 = remove_pps_outliers(df6)
df7.shape
```

Out[35]:
```
(10242, 7)
```

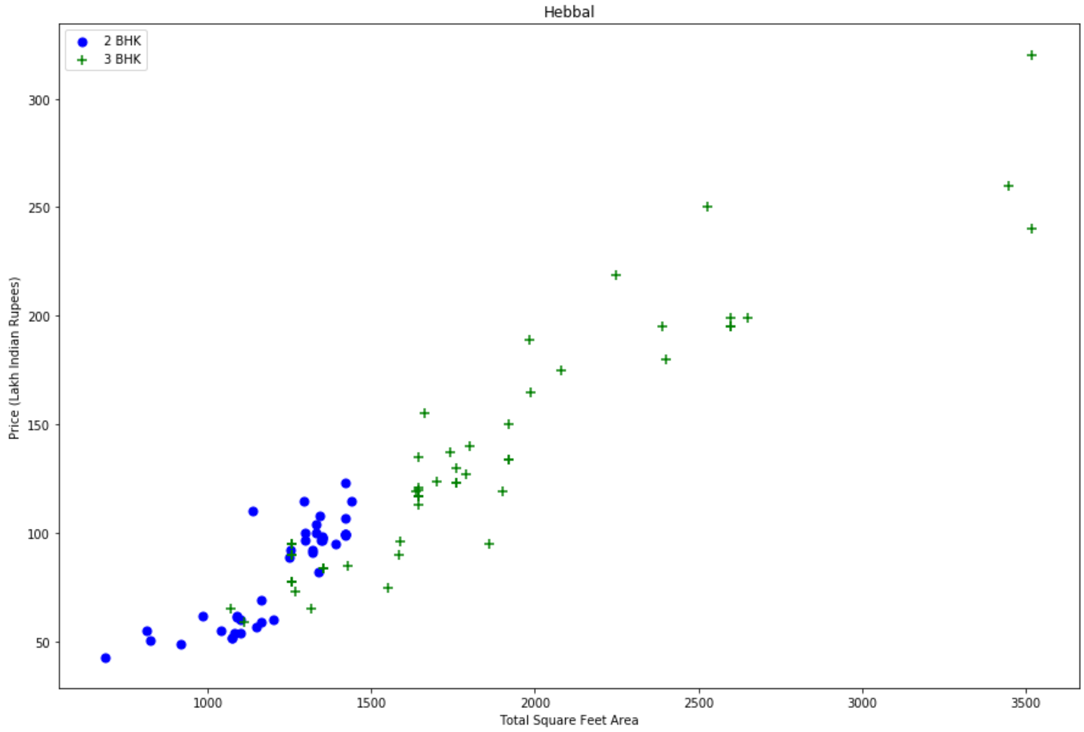
Let's check if for a given location how does the 2 BHK and 3 BHK property prices look like

In [36]:
```
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',labe
    plt.scatter(bhk3.total_sqft,bhk3.price,marker='+', color
    plt.xlabel("Total Square Feet Area")
    plt.ylabel("Price (Lakh Indian Rupees)")
    plt.title(location)
    plt.legend()

plot_scatter_chart(df7,"Rajaji Nagar")
```



In [37]:
```
plot_scatter_chart(df7,"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 we will do is for a given location, we will build a dictionary of stats per bhk, i.e.

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

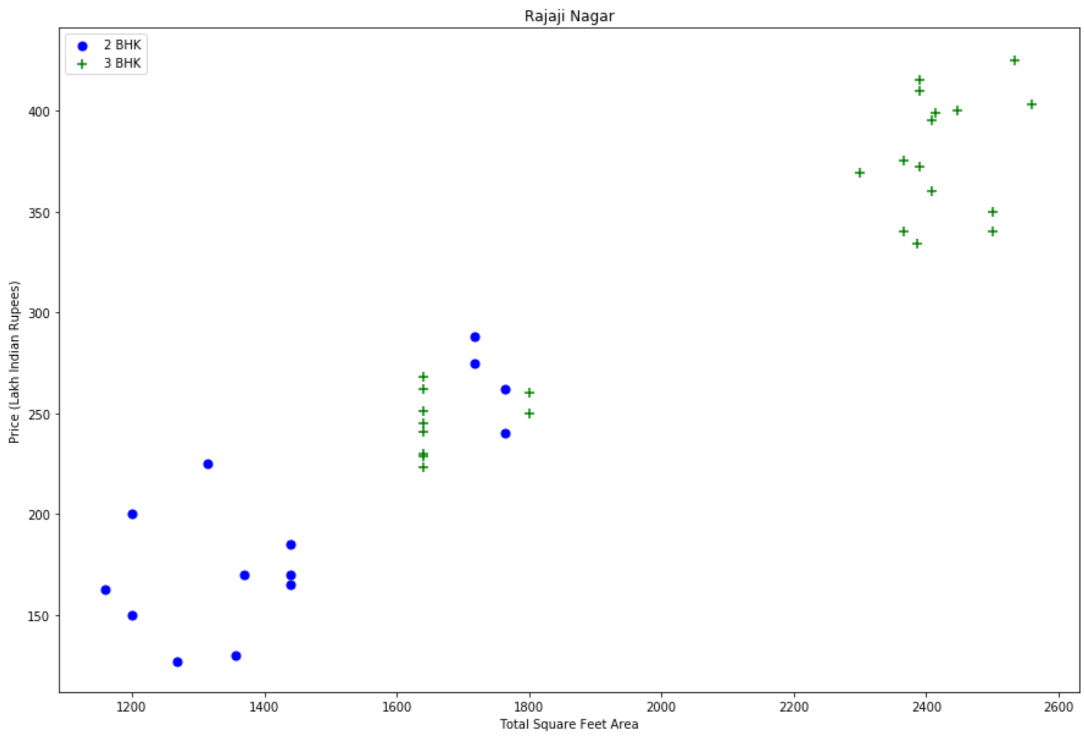
Now we can remove those 2 BHK apartments whose price_per_sqft is less than mean price_per_sqft of 1 BHK apartment

In [38]:
```
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,
    return df.drop(exclude_indices,axis='index')
df8 = remove_bhk_outliers(df7)
# df8 = df7.copy()
df8.shape
```

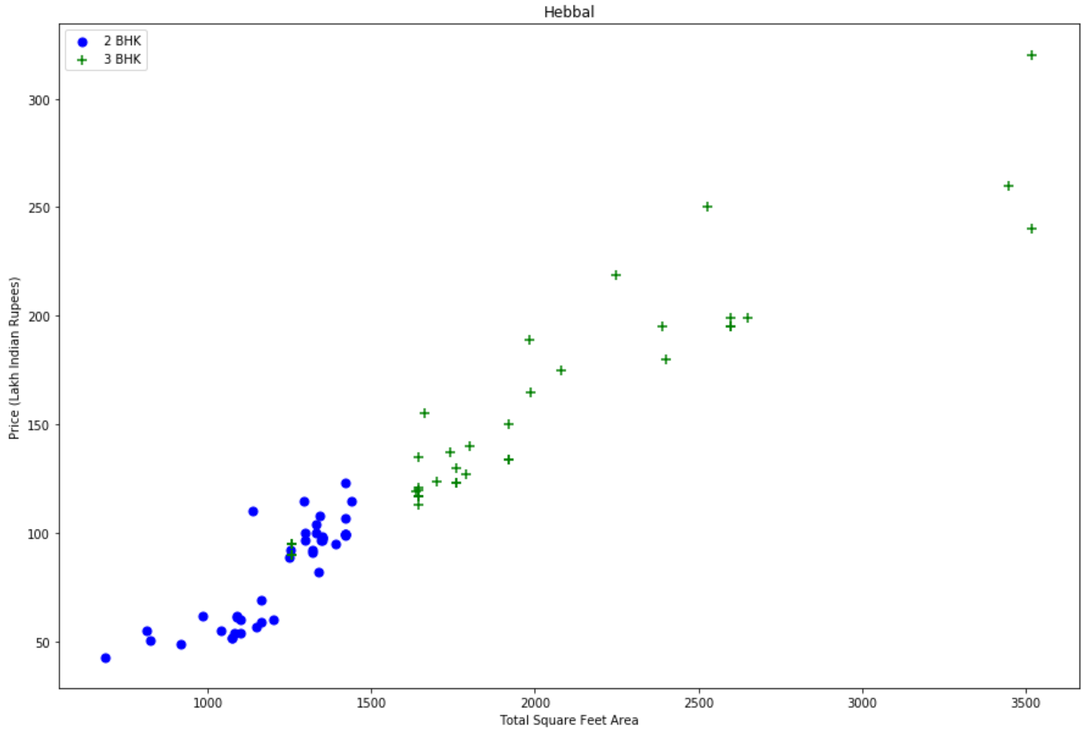
Out[38]: (7317, 7)

Plot same scatter chart again to visualize price_per_sqft for 2 BHK and 3 BHK properties

In [39]:
```
plot_scatter_chart(df8,"Rajaji Nagar")
```



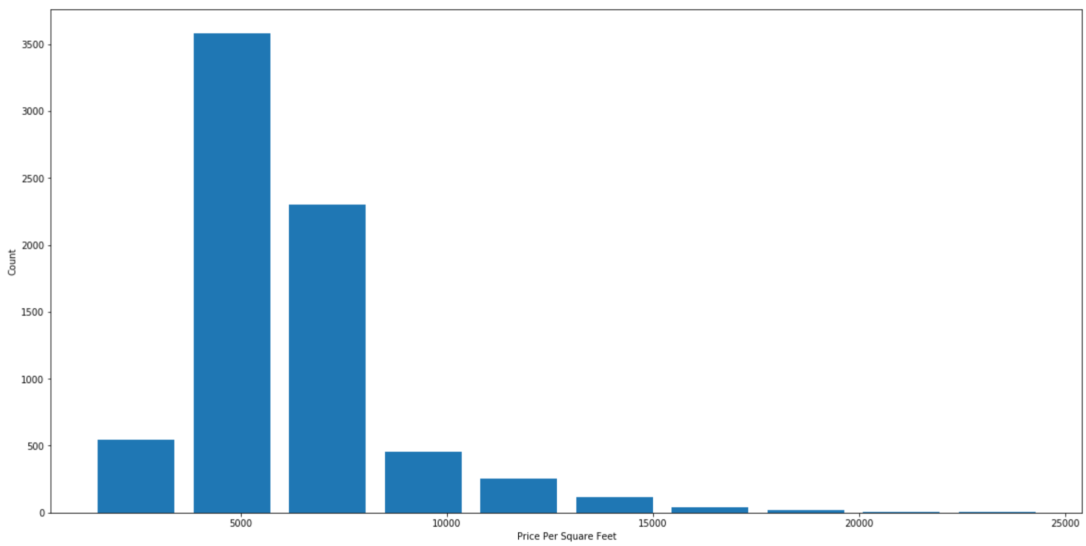
In [40]:
```
plot_scatter_chart(df8,"Hebbal")
```



Based on above charts we can see that data points highlighted in red below are outliers and they are being removed due to remove_bhk_outliers function

In [41]:
```
import matplotlib
matplotlib.rcParams["figure.figsize"] = (20,10)
plt.hist(df8.price_per_sqft,rwidth=0.8)
plt.xlabel("Price Per Square Feet")
plt.ylabel("Count")
```

Out[41]: Text(0, 0.5, 'Count')



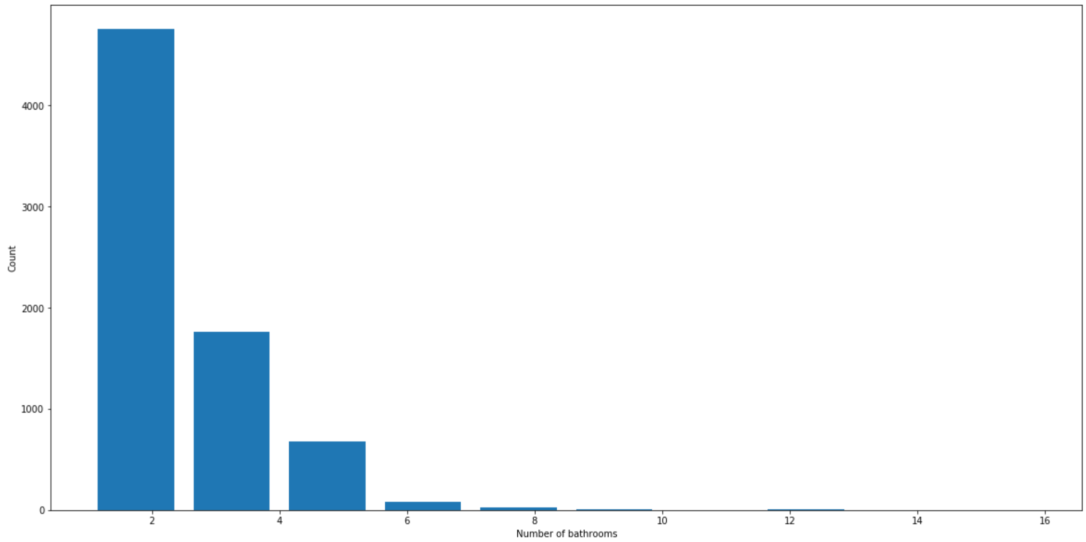
Outlier Removal Using Bathrooms Feature

In [42]:
```
df8.bath.unique()
```

Out[42]:
```
array([ 4.,  3.,  2.,  5.,  8.,  1.,  6.,  7.,  9., 12., 1
6., 13.])
```

In [43]:
```
plt.hist(df8.bath,rwidth=0.8)
plt.xlabel("Number of bathrooms")
plt.ylabel("Count")
```

Out[43]:
```
Text(0, 0.5, 'Count')
```



In [44]:
```
df8[df8.bath>10]
```

Out[44]:

	location	size	total_sqft	bath	price	bhk	price_per_sqft
5277	Neeladri Nagar	10 BHK	4000.0	12.0	160.0	10	4000.000000
8483	other	10 BHK	12000.0	12.0	525.0	10	4375.000000
8572	other	16 BHK	10000.0	16.0	550.0	16	5500.000000
9306	other	11 BHK	6000.0	12.0	150.0	11	2500.000000
9637	other	13 BHK	5425.0	13.0	275.0	13	5069.124424

It is unusual to have 2 more bathrooms than number of bedrooms in a home

In [45]:
```
df8[df8.bath>df8.bhk+2]
```

Out[45]:

	location	size	total_sqft	bath	price	bhk	price_per_sqf
1626	Chikkabanavar	4 Bedroom	2460.0	7.0	80.0	4	3252.03252(
5238	Nagasandra	4 Bedroom	7000.0	8.0	450.0	4	6428.57142!
6711	Thanisandra	3 BHK	1806.0	6.0	116.0	3	6423.03433(
8408	other	6 BHK	11338.0	9.0	1000.0	6	8819.89768!

Again the business manager has a conversation with you (i.e. a data scientist) that if you have 4 bedroom home and even if you have bathroom in all 4 rooms plus one guest bathroom, you will have total bath = total bed + 1 max. Anything above that is an outlier or a data error and can be removed

In [46]:
```
df9 = df8[df8.bath<df8.bhk+2]
df9.shape
```

Out[46]: (7239, 7)

In [47]:
```
df9.head(2)
```

Out[47]:

	location	size	total_sqft	bath	price	bhk	price_per_sqft
0	1st Block Jayanagar	4 BHK	2850.0	4.0	428.0	4	15017.543860
1	1st Block Jayanagar	3 BHK	1630.0	3.0	194.0	3	11901.840491

In [48]:
```
df10 = df9.drop(['size','price_per_sqft'],axis='columns')
df10.head(3)
```

Out[48]:

	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

Use One Hot Encoding For Location

In [49]:
```
dummies = pd.get_dummies(df10.location)
dummies.head(3)
```

Out[49]:

	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
0	1	0	0	0	0	0	0	0
1	1	0	0	0	0	0	0	0
2	1	0	0	0	0	0	0	0

3 rows × 241 columns

In [50]:
```
df11 = pd.concat([df10,dummies.drop('other',axis='columns')]
df11.head()
```

Out[50]:

	location	total_sqft	bath	price	bhk	1st Block Jayanagar	1st Phase JP Nagar	2nd Phase Judicial Layout	2 Na
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

In [51]:
```
df12 = df11.drop('location',axis='columns')
df12.head(2)
```

Out[51]:

	total_sqft	bath	price	bhk	1st Block Jayanagar	1st Phase JP Nagar	2nd Phase Judicial Layout	2nd Stage Nagarbhavi	L
0	2850.0	4.0	428.0	4	1	0	0	0	
1	1630.0	3.0	194.0	3	1	0	0	0	

2 rows × 244 columns

Build a Model Now...

In [52]:
```
df12.shape
```

Out[52]:
```
(7239, 244)
```

In [53]:
```
X = df12.drop(['price'],axis='columns')
X.head(3)
```

Out[53]:

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

3 rows × 243 columns

In [54]:
```
X.shape
```

Out[54]:
```
(7239, 243)
```

In [55]:
```
y = df12.price
y.head(3)
```

Out[55]:
```
0    428.0
1    194.0
2    235.0
Name: price, dtype: float64
```

In [56]:
```
len(y)
```

Out[56]:
```
7239
```

In [57]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test
```

In [58]:
```
from sklearn.linear_model import LinearRegression
lr_clf = LinearRegression()
lr_clf.fit(X_train,y_train)
lr_clf.score(X_test,y_test)
```

Out[58]:
```
0.8629132245229449
```

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

In [59]:
```
from sklearn.model_selection import ShuffleSplit
from sklearn.model_selection import cross_val_score

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

cross_val_score(LinearRegression(), X, y, cv=cv)
```

Out[59]:
```
array([0.82702546, 0.86027005, 0.85322178, 0.8436466 , 0.85
481502])
```

We can see that in 5 iterations we get a score above 80% all the time. This is pretty good but we want to test few other algorithms for regression to see if we can get even better score. We will use GridSearchCV for this purpose

Find best model using GridSearchCV

In [60]:
```
from sklearn.model_selection import GridSearchCV

from sklearn.linear_model import Lasso
from sklearn.tree import DecisionTreeRegressor

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_stat
    for algo_name, config in algos.items():
        gs =  GridSearchCV(config['model'], config['params']
        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'

find_best_model_using_gridsearchcv(X,y)
```

Out[60]:

	model	best_score	best_params
0	linear_regression	0.847796	{'normalize': False}
1	lasso	0.726738	{'alpha': 2, 'selection': 'cyclic'}
2	decision_tree	0.716064	{'criterion': 'friedman_mse', 'splitter': 'best'}

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

Test the model for few properties

In [61]:
```
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]
```

In [62]:
```
predict_price('1st Phase JP Nagar',1000, 2, 2)
```

Out[62]: 83.86570258311222

In [63]:
```
predict_price('1st Phase JP Nagar',1000, 3, 3)
```

Out[63]: 86.08062284985995

In [64]:
```
predict_price('Indira Nagar',1000, 2, 2)
```

Out[64]: 193.31197733179556

In [65]:
```
predict_price('Indira Nagar',1000, 3, 3)
```

Out[65]: 195.52689759854331

Export the tested model to a pickle file

In [66]:
```
import pickle
with open('banglore_home_prices_model.pickle','wb') as f:
    pickle.dump(lr_clf,f)
```

Export location and column information to a file that will be useful later on in our prediction application

In [67]:
```
import json
columns = {
    'data_columns' : [col.lower() for col in X.columns]
}
with open("columns.json","w") as f:
    f.write(json.dumps(columns))
```