In [1]:
```
# Import all necessary libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
house_price_df = pd.read_csv('banglore.csv')
```

In [3]:
```
# Displaying 1st 5 records

house_price_df.head()
```

Out[3]:

	area_type	availability	location	size	society	total_sqft	bath	balcony	price
0	Super built-up Area	19-Dec	Electronic City Phase II	2 BHK	Coomee	1056	2.0	1.0	39.07
1	Plot Area	Ready To Move	Chikka Tirupathi	4 Bedroom	Theanmp	2600	5.0	3.0	120.00
2	Built-up Area	Ready To Move	Uttarahalli	3 BHK	NaN	1440	2.0	3.0	62.00
3	Super built-up Area	Ready To Move	Lingadheeranahalli	3 BHK	Soiewre	1521	3.0	1.0	95.00
4	Super built-up Area	Ready To Move	Kothanur	2 BHK	NaN	1200	2.0	1.0	51.00

In [4]:
```
# total number of rows and columns in dataframe(r,c)
house_price_df.shape
```

Out[4]:
```
(13320, 9)
```

In [5]:
```
# displaying only columns
house_price_df.columns
```

Out[5]:
```
Index(['area_type', 'availability', 'location', 'size', 'society',
       'total_sqft', 'bath', 'balcony', 'price'],
      dtype='object')
```

In [6]:
```
# basic information about dataframe
house_price_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13320 entries, 0 to 13319
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   area_type     13320 non-null  object 
 1   availability  13320 non-null  object 
 2   location      13319 non-null  object 
 3   size          13304 non-null  object 
 4   society       7818 non-null   object 
 5   total_sqft    13320 non-null  object 
 6   bath          13247 non-null  float64
 7   balcony       12711 non-null  float64
 8   price         13320 non-null  float64
dtypes: float64(3), object(6)
memory usage: 936.7+ KB
```

It shows us total number of non-null values in each column and their datatype

In [7]:
```
# datatype of each column
house_price_df.dtypes
```

Out[7]:
```
area_type        object
availability     object
location         object
size             object
society          object
total_sqft       object
bath            float64
balcony         float64
price           float64
dtype: object
```

In [8]:
```
# statistical information of numerical column
house_price_df.describe()
```

Out[8]:

	bath	balcony	price
count	13247.000000	12711.000000	13320.000000
mean	2.692610	1.584376	112.565627
std	1.341458	0.817263	148.971674
min	1.000000	0.000000	8.000000
25%	2.000000	1.000000	50.000000
50%	2.000000	2.000000	72.000000
75%	3.000000	2.000000	120.000000
max	40.000000	3.000000	3600.000000

In [9]:
```
# statistical information about categorical columns
house_price_df.describe(include='O')
```

Out[9]:

	area_type	availability	location	size	society	total_sqft
count	13320	13320	13319	13304	7818	13320
unique	4	81	1305	31	2688	2117
top	Super built-up Area	Ready To Move	Whitefield	2 BHK	GrrvaGr	1200
freq	8790	10581	540	5199	80	843

In [ ]:

1. NaN values

In [10]:
```
# total number of nan values in each column
house_price_df.isnull().sum()
```

Out[10]:
```
area_type          0
availability       0
location           1
size              16
society         5502
total_sqft         0
bath              73
balcony          609
price              0
dtype: int64
```

In [11]:
```
# NaN values in each column in percentage
house_price_df.isnull().sum()/len(house_price_df)*100
```

Out[11]:
```
area_type        0.000000
availability     0.000000
location         0.007508
size             0.120120
society         41.306306
total_sqft       0.000000
bath             0.548048
balcony          4.572072
price            0.000000
dtype: float64
```

Handling NaN values

Society

In [12]:
```
# Since Society column contains more than 40% NaN values we drop the society colu

house_price_df.drop(['society'],axis=1,inplace=True)
```

location

In [13]:
```
# Since location column has few nan values we can fill those values using mode()

house_price_df['location'].fillna(house_price_df['location'].mode()[0],inplace=Tr
```

size

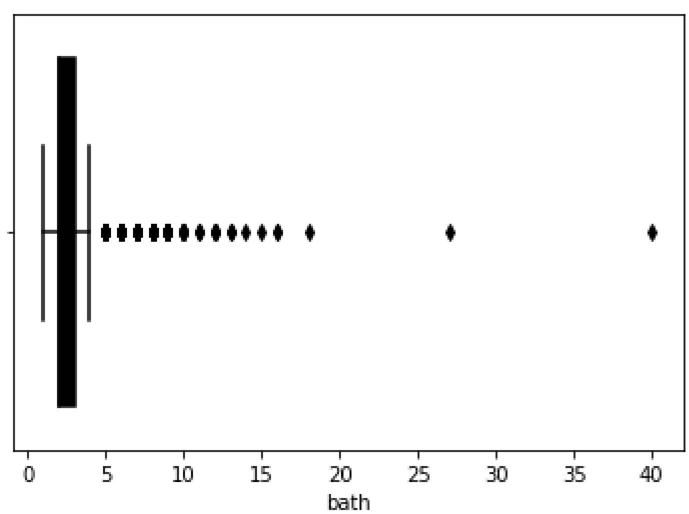
In [14]:
```
# again filling size column with mode as it has less number of nan values

house_price_df['size'].fillna(house_price_df['size'].mode()[0],inplace=True)
```

bath

In [15]:
```
# 1st we will check if outliers present in bath if outliers are present we will f

sns.boxplot(x=house_price_df['bath'],color='Black')
plt.show()
```



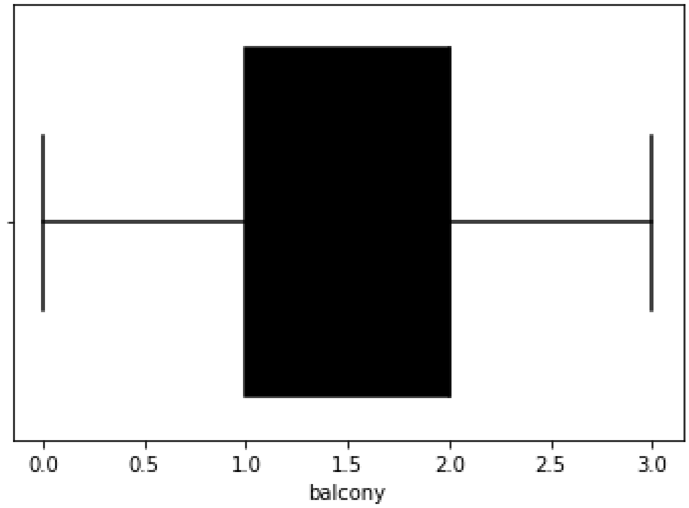
From the graph we can conclude that bath column has outliers in it so we will use median() to fill nan values

In [16]:
```
house_price_df['bath'].fillna(house_price_df['bath'].median(),inplace=True)
```

balcony

In [17]:
```
# 1st we need to check if outliers present in balcony column if outliers are pres

sns.boxplot(x=house_price_df['balcony'],color='Black')
plt.show()
```



Balcony column doesnt have any outlier present in it

In [18]:
```
house_price_df['balcony'].mean()
```

Out[18]: 1.5843757375501535

In [19]:
```
house_price_df['balcony'].median()
```

Out[19]: 2.0

In [20]:
```
# Since balcony cannot be 1.5 balcony it either can be 1 balcony or 2 balconys
# so we fill nan values with median()

house_price_df['balcony'].fillna(house_price_df['balcony'].median(),inplace=True)
```

now we check for nan values and their dtypes to ensure that we didnt mess things up

In [21]:
```
house_price_df.dtypes
```

Out[21]:
```
area_type        object
availability     object
location         object
size             object
total_sqft       object
bath            float64
balcony         float64
price           float64
dtype: object
```

In [22]:
```
house_price_df.isnull().any()
```

Out[22]:
```
area_type       False
availability    False
location        False
size            False
total_sqft      False
bath            False
balcony         False
price           False
dtype: bool
```

In [ ]:
```

```

2. Duplicates

In [23]:
```
house_price_df.duplicated().any()
```

Out[23]:
```
True
```

In [24]:
```
house_price_df.drop_duplicates(inplace=True)
```

In [ ]:
```

```

3. Cleaning Data

size

In [25]:
```
# total number of unique records in size

house_price_df['size'].nunique()
```

Out[25]:
```
31
```

In [26]:
```
# checking unique data and their total numbers

house_price_df['size'].value_counts()
```

Out[26]:
```
2 BHK          4919
3 BHK          4108
4 Bedroom       824
4 BHK           574
3 Bedroom       535
1 BHK           521
2 Bedroom       314
5 Bedroom       291
6 Bedroom       191
1 Bedroom       104
8 Bedroom        84
7 Bedroom        82
5 BHK            59
9 Bedroom        46
6 BHK            30
7 BHK            17
1 RK             13
10 Bedroom       12
9 BHK             8
8 BHK             5
11 BHK            2
11 Bedroom        2
10 BHK            2
14 BHK            1
13 BHK            1
12 Bedroom        1
27 BHK            1
43 Bedroom        1
16 BHK            1
19 BHK            1
18 Bedroom        1
Name: size, dtype: int64
```

In [27]:
```
# size column has various units like bedroom, bhk ,rk
# we will convert it into single unit - BHK and remove 1rk
```

In [28]:
```
def clean_size(x):
    if 'BHK' in x:
        x = x.split(' ')[0]
        return int(x)
    elif 'Bedroom' in x:
        x = x.split(' ')[0]
        return int(x)
    elif 'RK' in x:
        x = np.nan
    else :
        int(x)
```

In [29]:
```
house_price_df['size_in_BHK'] = house_price_df['size'].map(clean_size)
```

In [30]:
```
house_price_df.dropna(subset='size_in_BHK',inplace=True)
```

In [31]:
```
house_price_df.shape
```

Out[31]:
```
(12738, 9)
```

total_sqft

In [32]:
```
# total number of unique records in total_sqft column
house_price_df.total_sqft.nunique()
```

Out[32]:
```
2113
```

In [33]:
```
#  unique records and their total

house_price_df.total_sqft.value_counts()
```

Out[33]:
```
1200           803
1100           209
1500           202
2400           196
600            178
              ...
785              1
2563 - 2733      1
2005             1
605 - 624        1
4689             1
Name: total_sqft, Length: 2113, dtype: int64
```

In [34]:
```
# generally area for room is in square feet and it is in numerical format
# so converting it into numerical col
def clean_sqft(x):
    if '-' in x:
        x1, x2 = x.split('-')
        x = (float(x1.strip()) + float(x2.strip()))/2
        return float(x)
    elif 'Sq. Meter' in x:
        return np.nan
    elif 'Guntha' in x:
        return np.nan
    elif 'Acres' in x:
        return np.nan
    elif 'Cents' in x:
        return np.nan
    elif 'Sq. Yards' in x:
        return np.nan
    elif 'Perch' in x:
        return np.nan
    elif 'Grounds' in x:
        return np.nan
    else:
        try:
            if x:
                return float(x)
        except:
            return np.nan
```

In [35]:
```
# assigning numeric sqft to sqft column

house_price_df['sqft']=house_price_df['total_sqft'].map(clean_sqft)
house_price_df.columns
```

Out[35]:
```
Index(['area_type', 'availability', 'location', 'size', 'total_sqft', 'bath',
       'balcony', 'price', 'size_in_BHK', 'sqft'],
      dtype='object')
```

In [36]:
```
# deleting NaN values which we introduced in sqft column

house_price_df.dropna(subset=['sqft'],inplace = True)
```

In [37]:
```
house_price_df['sqft'].isnull().sum()
```

Out[37]:
```
0
```

In [38]:
```
# creating new column for price per sqft

house_price_df['price_per_sqft'] = (house_price_df['price'] * 100000 / house_pric
```

Converting datatype of bath, size_in_BHK and balcony in int datatype

In [39]:
```
house_price_df.dtypes
```

Out[39]:
```
area_type          object
availability       object
location           object
size               object
total_sqft         object
bath              float64
balcony           float64
price             float64
size_in_BHK       float64
sqft              float64
price_per_sqft    float64
dtype: object
```

In [40]:
```
house_price_df=house_price_df.astype({'size_in_BHK':'int','bath':'int','balcony':
```

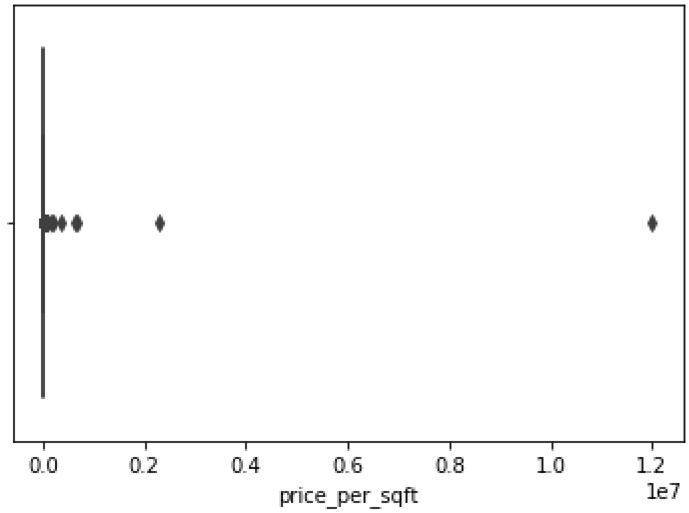
In [41]:
```
house_price_df.dtypes
```

Out[41]:
```
area_type          object
availability       object
location           object
size               object
total_sqft         object
bath                int32
balcony             int32
price             float64
size_in_BHK         int32
sqft              float64
price_per_sqft    float64
dtype: object
```

4. Outliers

Price per feet

In [42]:
```
sns.boxplot(x=house_price_df['price_per_sqft'])
plt.show()
```



In [43]:
```
# handling outliers using standard deviation

sd_sqft = house_price_df['price_per_sqft'].std()
print(f'standard deviation for sqft{sd_sqft}')
mean_sqft = house_price_df['price_per_sqft'].mean()
print(f'mean sqft: {mean_sqft}')

lower_limit =  mean_sqft - 3 * sd_sqft
print(f'lower limit: {lower_limit}')
upper_limit = mean_sqft + 3 * sd_sqft
print(f'upper limit: {upper_limit}')
```

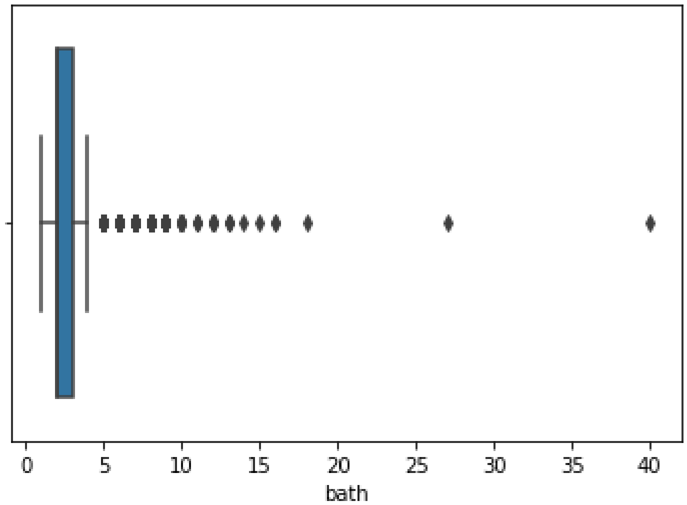
```
standard deviation for sqft108839.78118184546
mean sqft: 8036.0871828610725
lower limit: -318483.25636267534
upper limit: 334555.43072839745
```

In [44]:
```
non_outlier = house_price_df[(house_price_df['price_per_sqft'] > lower_limit) & (
non_outlier.shape
```

Out[44]:
```
(12687, 11)
```

bath

In [45]:
```
sns.boxplot(house_price_df['bath'])
plt.show()
```



In [46]:
```
# handling outliers using IQR

q1 = house_price_df['bath'].quantile(0.25)
q3 = house_price_df['bath'].quantile(0.75)
IQR = q3-q1

lower_limit = q1 - 1.5*IQR
print(f'lower limit for bath: {lower_limit}')
upper_limit = q3 + 1.5*IQR
print(f'upper limit for bath:{upper_limit}')
```

```
lower limit for bath: 0.5
upper limit for bath:4.5
```

In [47]:
```
non_outlier.shape
```

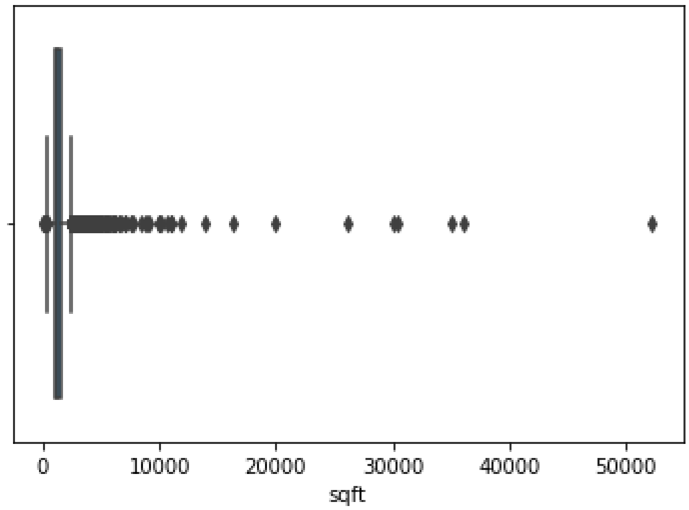
Out[47]: (12687, 11)

In [48]:
```
non_outlier = non_outlier[(non_outlier['bath'] > lower_limit) &(non_outlier['bath
```

In [49]:
```
non_outlier.shape
```

Out[49]: (11665, 11)

In [50]:
```
sns.boxplot(non_outlier['sqft'])
plt.show()
```



In [51]:
```
q1 = non_outlier['sqft'].quantile(0.25)
q3 = non_outlier['sqft'].quantile(0.75)
IQR = q3-q1

lower_limit = q1 - 1.5*IQR
print(f'lower limit for sqft: {lower_limit}')
upper_limit = q3 + 1.5*IQR
print(f'upper limit for sqft:{upper_limit}')
```

```
lower limit for sqft: 317.0
upper limit for sqft:2397.0
```

In [52]:
```
non_outlier = non_outlier[(non_outlier['sqft'] > lower_limit) & (non_outlier['sq
non_outlier.shape
```

Out[52]:
```
(10726, 11)
```

Dropping irrelevant columns

In [53]:
```
non_outlier.dtypes
```

Out[53]:
```
area_type          object
availability       object
location           object
size               object
total_sqft         object
bath                int32
balcony             int32
price             float64
size_in_BHK         int32
sqft              float64
price_per_sqft    float64
dtype: object
```

In [54]:
```
non_outlier.head()
```

Out[54]:

	area_type	availability	location	size	total_sqft	bath	balcony	price	size_in_BHK	
0	Super built-up Area	19-Dec	Electronic City Phase II	2 BHK	1056	2	1	39.07	2	10
2	Built-up Area	Ready To Move	Uttarahalli	3 BHK	1440	2	3	62.00	3	14
3	Super built-up Area	Ready To Move	Lingadheeranahalli	3 BHK	1521	3	1	95.00	3	15
4	Super built-up Area	Ready To Move	Kothanur	2 BHK	1200	2	1	51.00	2	12
5	Super built-up Area	Ready To Move	Whitefield	2 BHK	1170	2	1	38.00	2	11

In [55]:
```
non_outlier.drop(columns=['size','total_sqft','price'],axis=1,inplace=True)
```

In [56]:
```
non_outlier.head()
```

Out[56]:

	area_type	availability	location	bath	balcony	size_in_BHK	sqft	price_per_sqft
0	Super built-up Area	19-Dec	Electronic City Phase II	2	1	2	1056.0	3699.810606
2	Built-up Area	Ready To Move	Uttarahalli	2	3	3	1440.0	4305.555556
3	Super built-up Area	Ready To Move	Lingadheeranahalli	3	1	3	1521.0	6245.890861
4	Super built-up Area	Ready To Move	Kothanur	2	1	2	1200.0	4250.000000
5	Super built-up Area	Ready To Move	Whitefield	2	1	2	1170.0	3247.863248

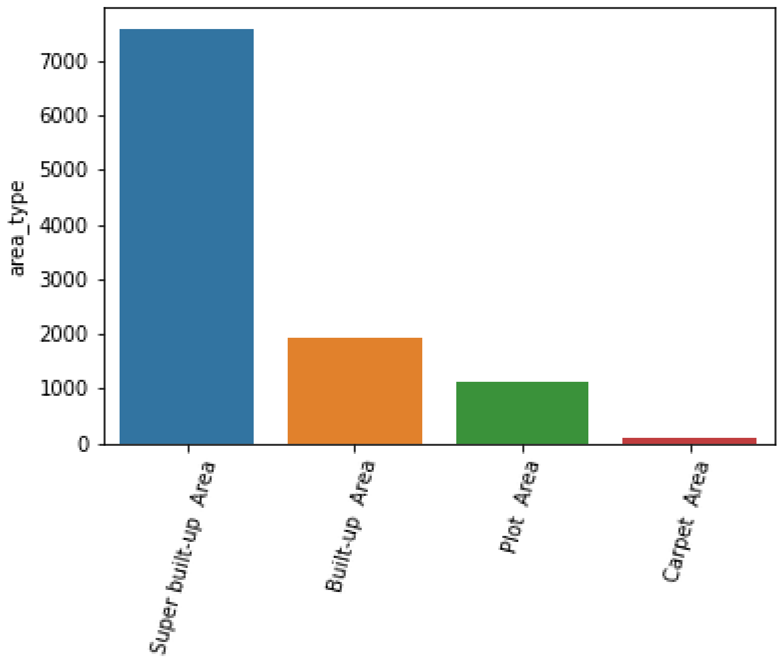
Analysing the data

area_type

In [57]:
```
area_type = non_outlier['area_type'].value_counts()
area_type
```

Out[57]:
```
Super built-up  Area    7593
Built-up  Area          1940
Plot  Area              1115
Carpet  Area              78
Name: area_type, dtype: int64
```

In [58]:
```
# barplot for area_type
sns.barplot(x=area_type.index, y = area_type )
plt.xticks(rotation=75)
plt.show()
```

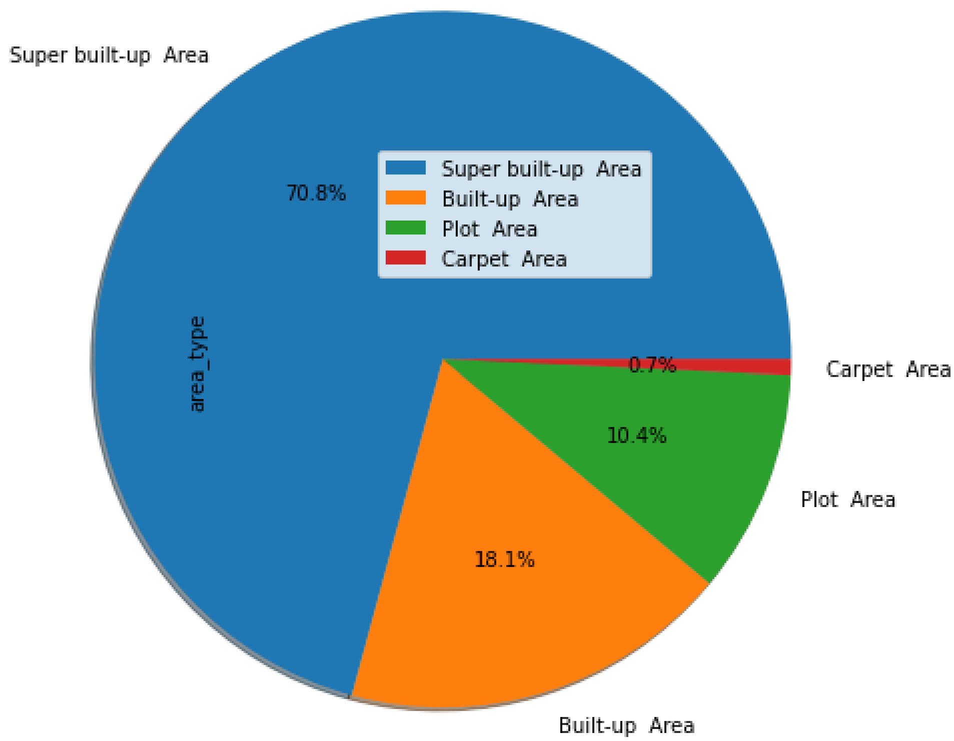


super built-up area is most frequent area type where as carpet area is least

In [59]:
```
# barplot

mylabels = area_type.index
plt.figure(figsize=(4,4))
(area_type).plot.pie(autopct="%.1f%%",shadow=True,labels=mylabels,radius=2)
plt.legend(loc ='best')
plt.show()

# area_type.plot.pie(autopct="%.1f%%",figsize=(7,7))
# plt.show()
```



super built-up area is 71% -the most where as carpet area is least 0.7%

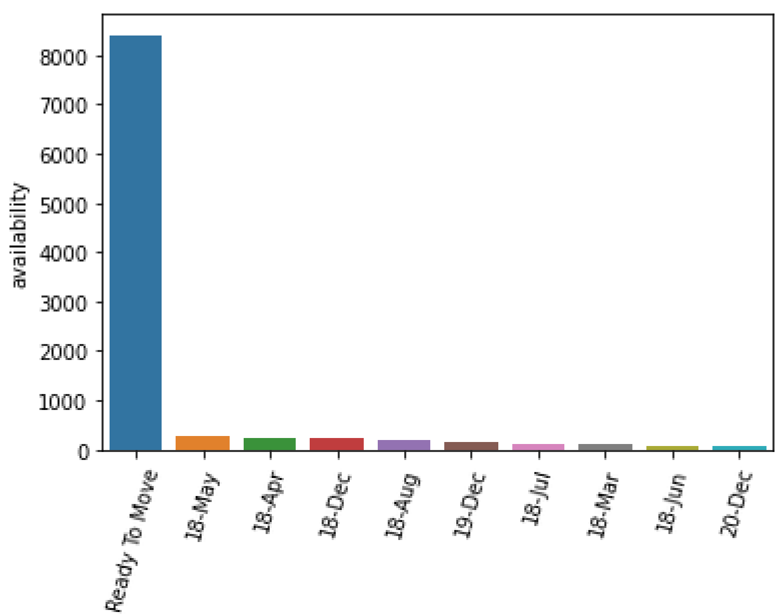
In [ ]:

availability

In [60]:
```
availability = non_outlier['availability'].value_counts().head(10)
availability
```

Out[60]:
```
Ready To Move    8411
18-May            262
18-Apr            244
18-Dec            239
18-Aug            179
19-Dec            152
18-Jul            121
18-Mar            106
18-Jun             89
20-Dec             87
Name: availability, dtype: int64
```

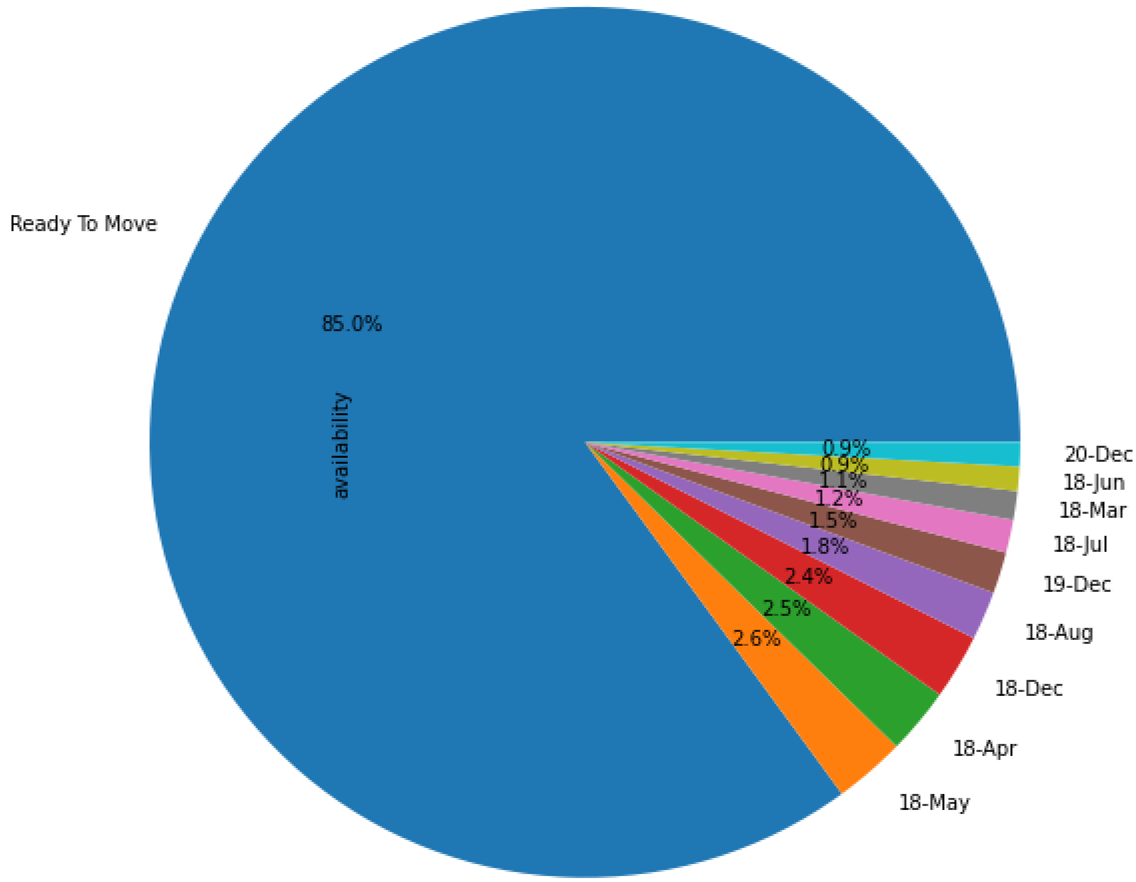
In [61]:
```
sns.barplot(x = availability.index, y = availability)
plt.xticks(rotation= 75)
plt.show()
```



More than 8000 houses are ready to move among the top 10 availability

In [62]:
```
# pie chart
availability.plot.pie(autopct="%.1f%%",radius=2.5)
```

Out[62]: <AxesSubplot:ylabel='availability'>



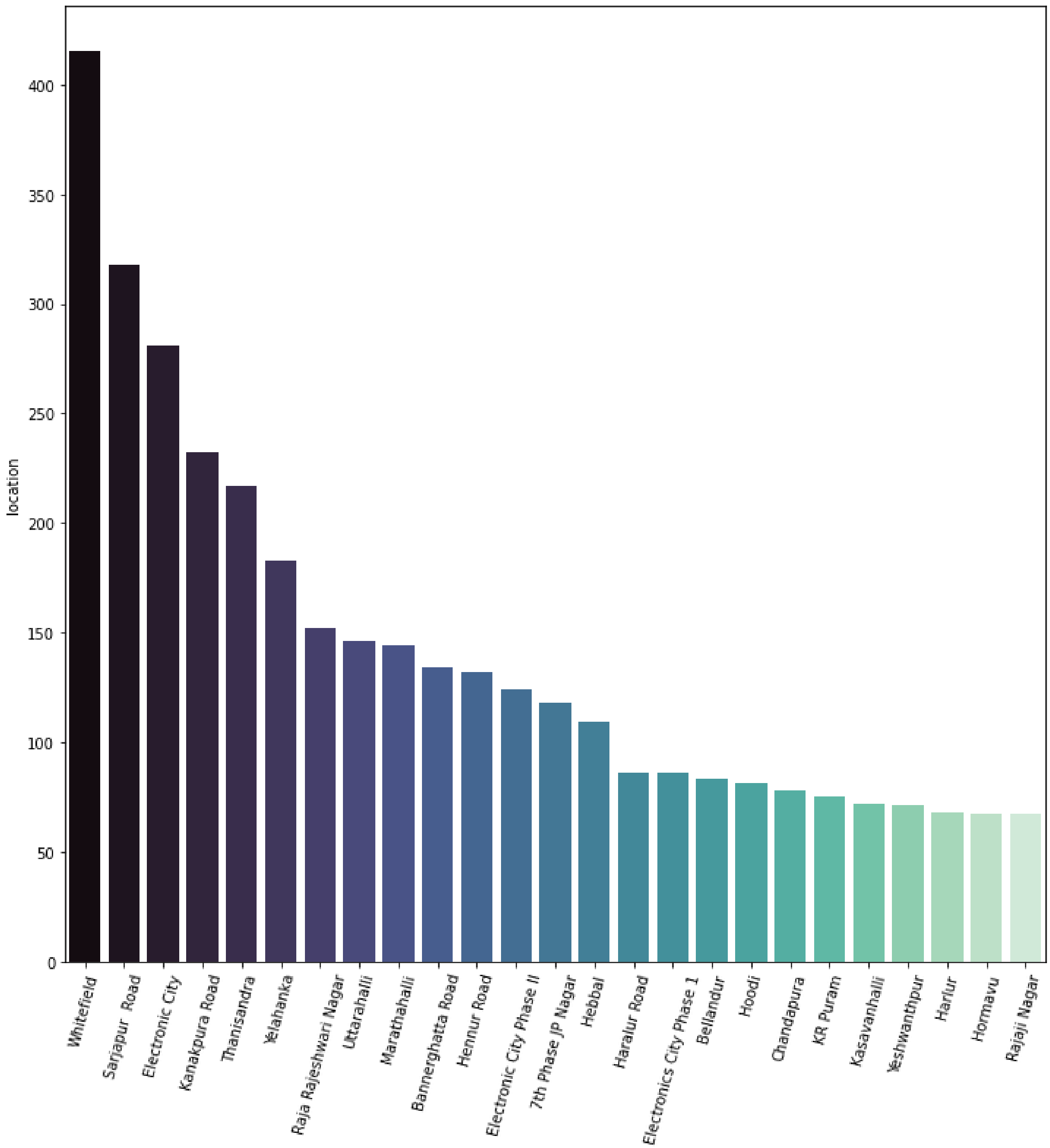
85% percent houses are ready to move among the top 10 availability

Location

In [63]:
```python
#  first 25 most frequent loaction
location = non_outlier['location'].value_counts().head(25)
location
```

Out[63]:
```
Whitefield                  415
Sarjapur  Road              318
Electronic City             281
Kanakpura Road              232
Thanisandra                 217
Yelahanka                   183
Raja Rajeshwari Nagar       152
Uttarahalli                 146
Marathahalli                144
Bannerghatta Road           134
Hennur Road                 132
Electronic City Phase II    124
7th Phase JP Nagar          118
Hebbal                      109
Haralur Road                 86
Electronics City Phase 1     86
Bellandur                    83
Hoodi                        81
Chandapura                   78
KR Puram                     75
Kasavanhalli                 72
Yeshwanthpur                 71
Harlur                       68
Hormavu                      67
Rajaji Nagar                 67
Name: location, dtype: int64
```

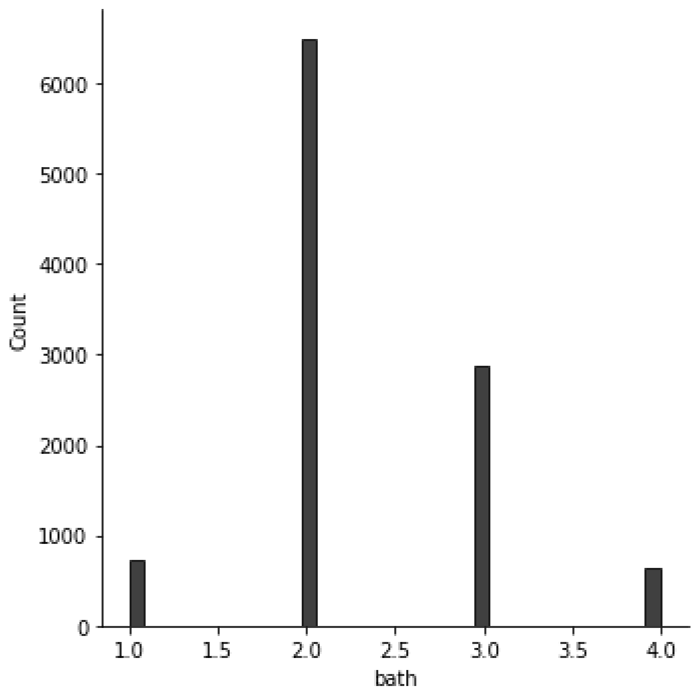
In [64]:
```
sns.color_palette("mako", as_cmap=True)
plt.figure(figsize=(12,12))
sns.barplot(x = location.index, y = location,palette='mako')
plt.xticks(rotation=75)
plt.show()
```



The most frequent location among the top 25 location is Whitefield with almost 400 counts

bath

In [65]:
```
# histogram
sns.displot(x = non_outlier['bath'],color='black')
plt.show()
```

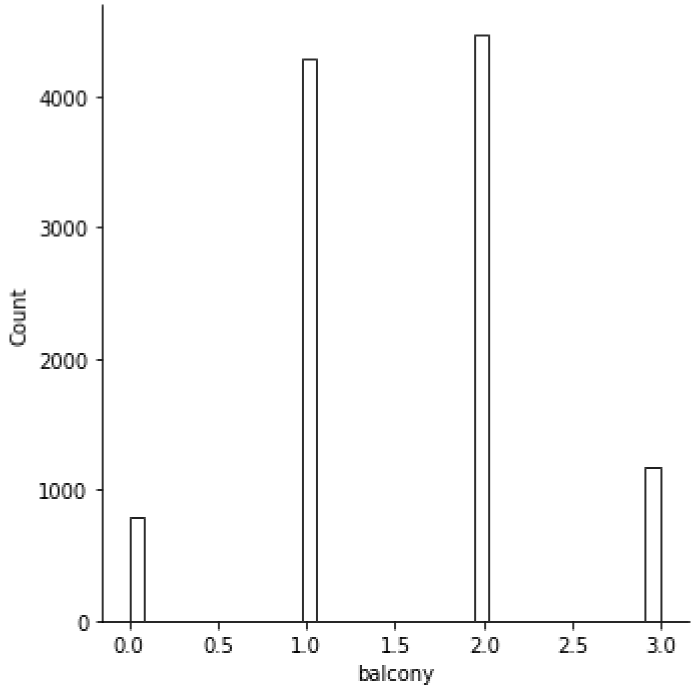


The most common number of bath per house is 2 and the least is 1 and 4

balcony

In [66]:
```
sns.displot(x = non_outlier['balcony'],color='white')
```

Out[66]: <seaborn.axisgrid.FacetGrid at 0x2214d478d90>

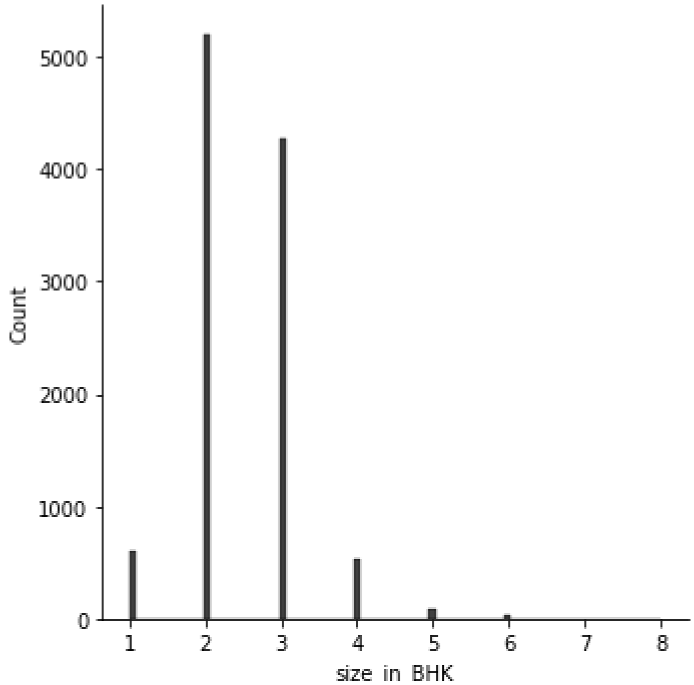


The most common number for balcony is 1 and 2

both balcony 1 and 2 have count more than 4000

size_in_BHK

In [67]:
```
sns.displot(x= non_outlier['size_in_BHK'],color='black')
plt.show()
```

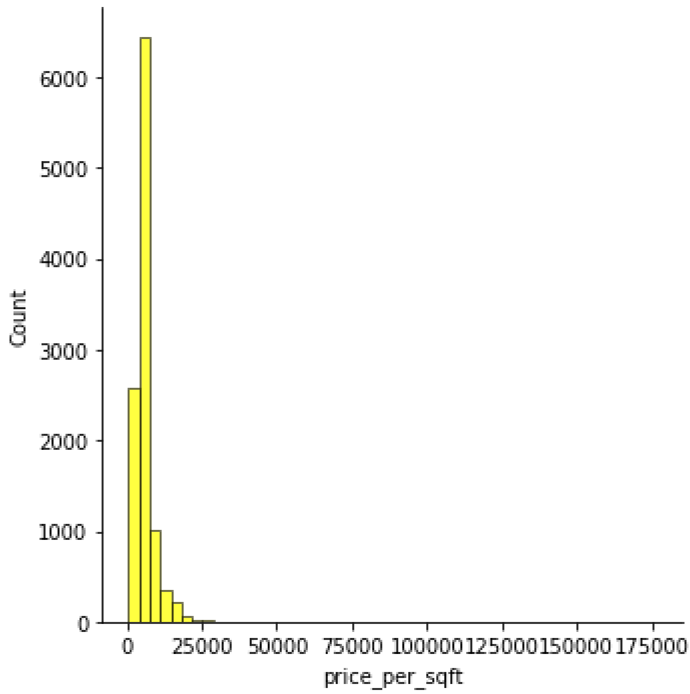


The most number of house sizes are 2 which is more than 5000

and 3BHK are the 2nd most preference

price per sqft

In [68]:
```
sns.displot(x = non_outlier['price_per_sqft'], color= 'yellow',bins=50)
plt.show()
```

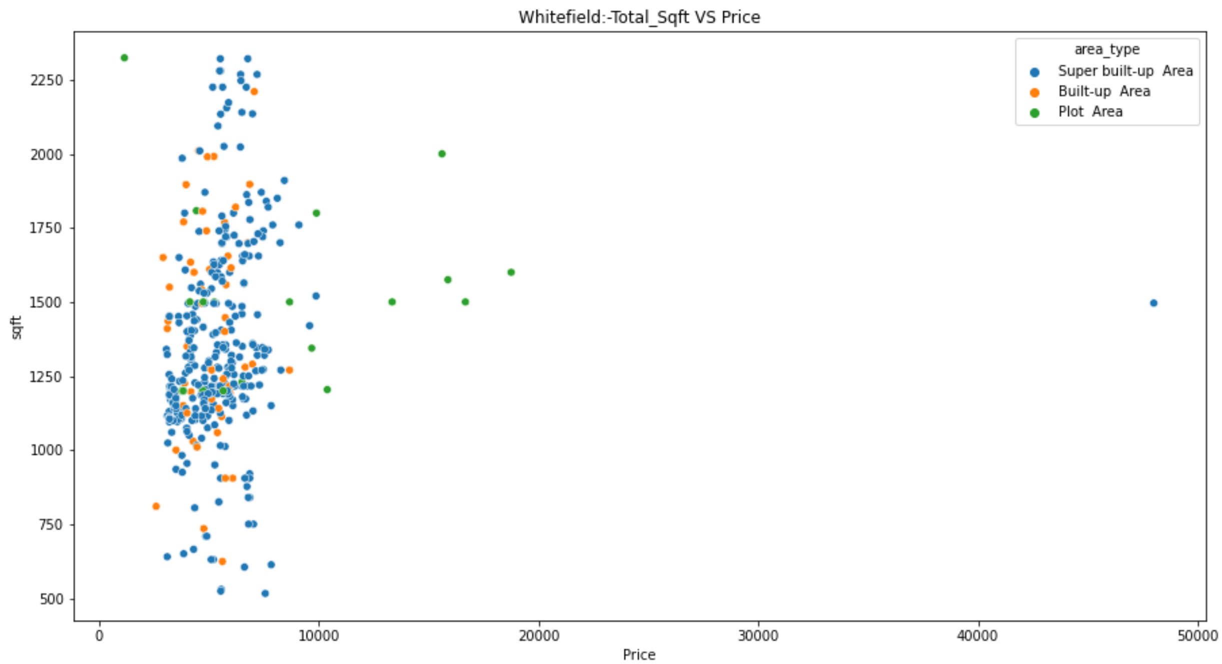


The price per sq feet range is somewhere around between 1800 to 10000

the graph is highly right skewed

In [69]:
```
# scatterplot between price and total_sqft for whitfield area
plt.figure(figsize=(15,8))
place = 'Whitefield'   # here location can be changed,as whitefield had highest r
df = non_outlier[non_outlier['location']== place]
sns.scatterplot(df['price_per_sqft'],df['sqft'],hue=df['area_type'])
plt.title('Whitefield:-Total_Sqft VS Price')
plt.xlabel('Price')
```

Out[69]:
```
Text(0.5, 0, 'Price')
```



from 500 sqft to more than 2250 super built up area areatype is available at around 10000 or less price in whitefield location

built up area and plot area are very less as compared to super built up area in whitefield locatoin

In [70]:
```
non_outlier.columns
```

Out[70]:
```
Index(['area_type', 'availability', 'location', 'bath', 'balcony',
       'size_in_BHK', 'sqft', 'price_per_sqft'],
      dtype='object')
```

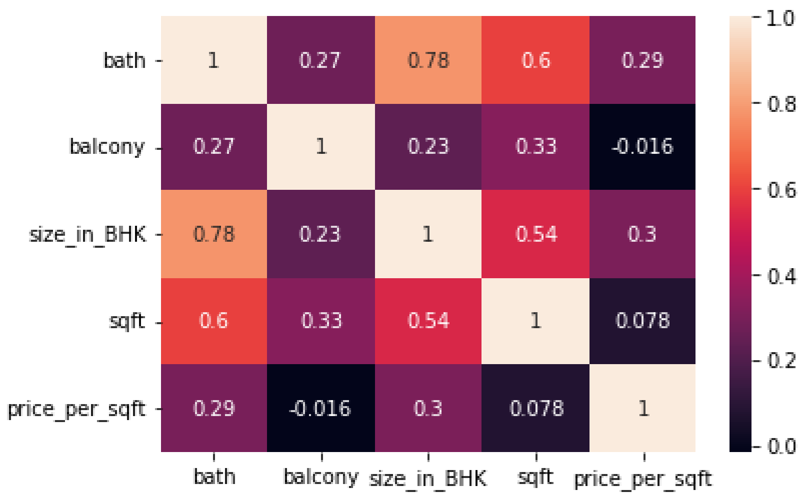
In [71]:
```
corr=non_outlier.corr()
corr
```

Out[71]:

	bath	balcony	size_in_BHK	sqft	price_per_sqft
bath	1.000000	0.273641	0.777301	0.598871	0.294996
balcony	0.273641	1.000000	0.230407	0.326120	-0.015717
size_in_BHK	0.777301	0.230407	1.000000	0.535042	0.302141
sqft	0.598871	0.326120	0.535042	1.000000	0.077571
price_per_sqft	0.294996	-0.015717	0.302141	0.077571	1.000000

In [72]:
```
sns.heatmap(corr,annot=True)
```

Out[72]: <AxesSubplot:>



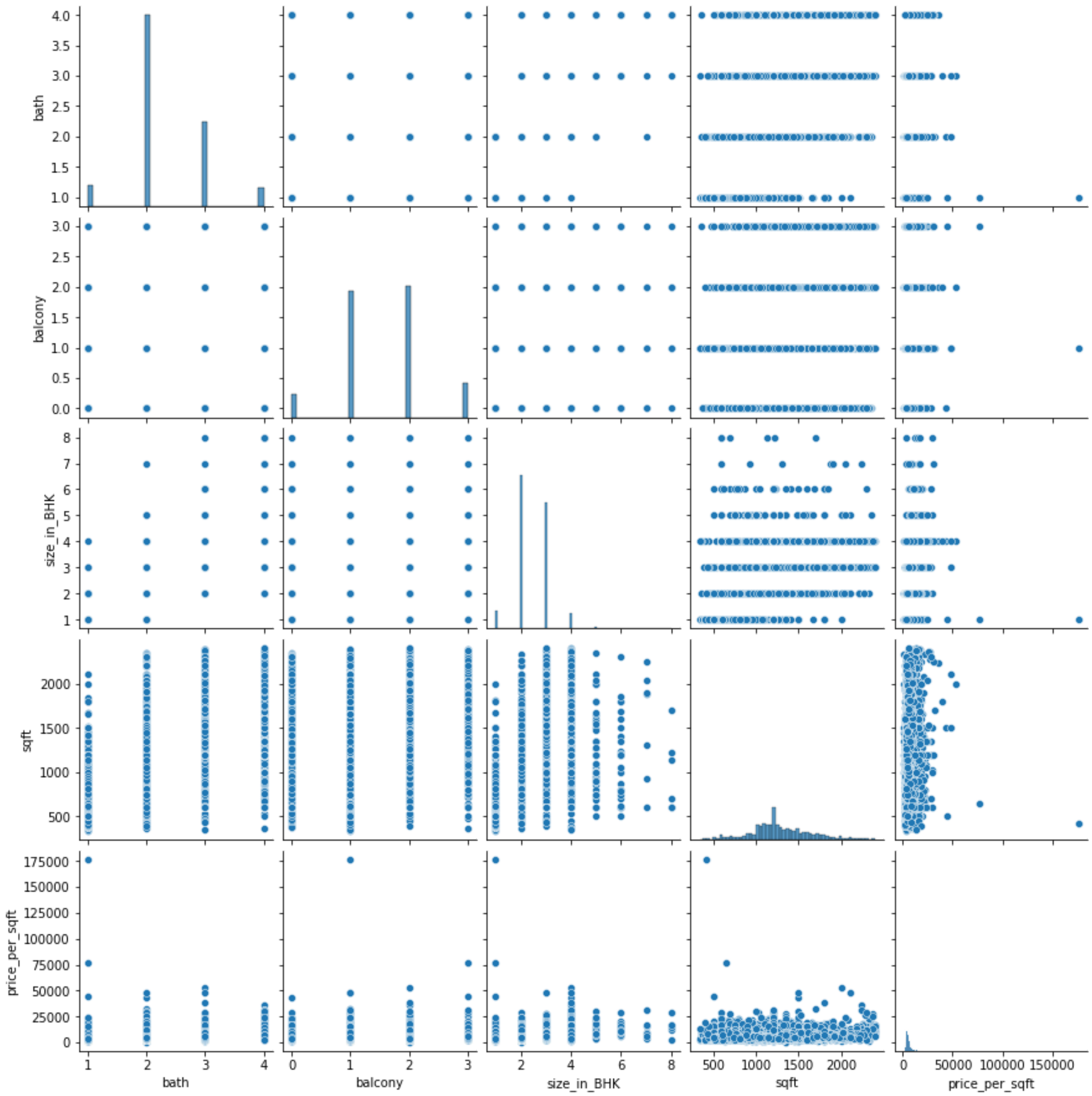
as the bath increases balcony and price_per_sqft also minorly increases but size_in_bhk and sqft significantly increases.

as size_in_BHK increases ofc bath,balcony,sqft,price_per_sqft also increases

it is very rare case that as the balcony has increased price_per_sqft decreased

In [73]:
```
sns.pairplot(non_outlier)
```

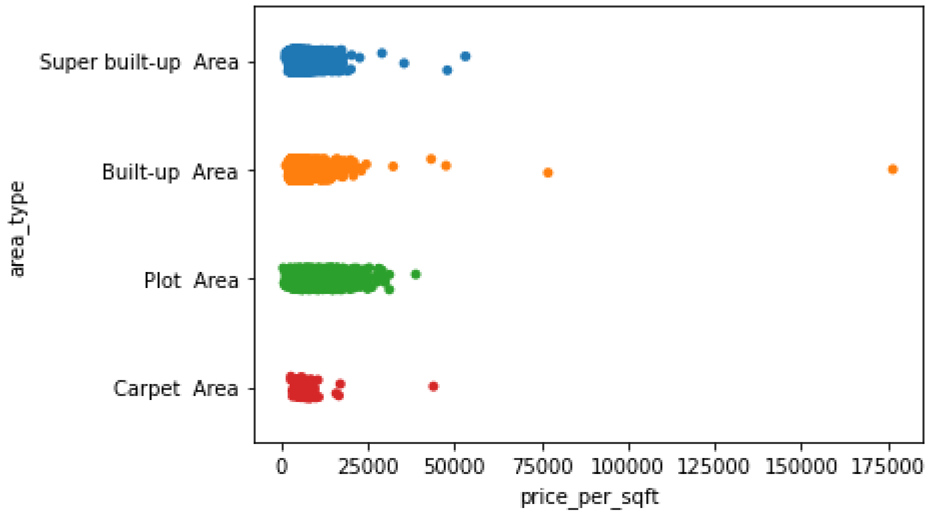
Out[73]: <seaborn.axisgrid.PairGrid at 0x2214d415b40>



In [74]:
```
#strip plot 1numeric 1 categorical

sns.stripplot('price_per_sqft','area_type',data=non_outlier)
```

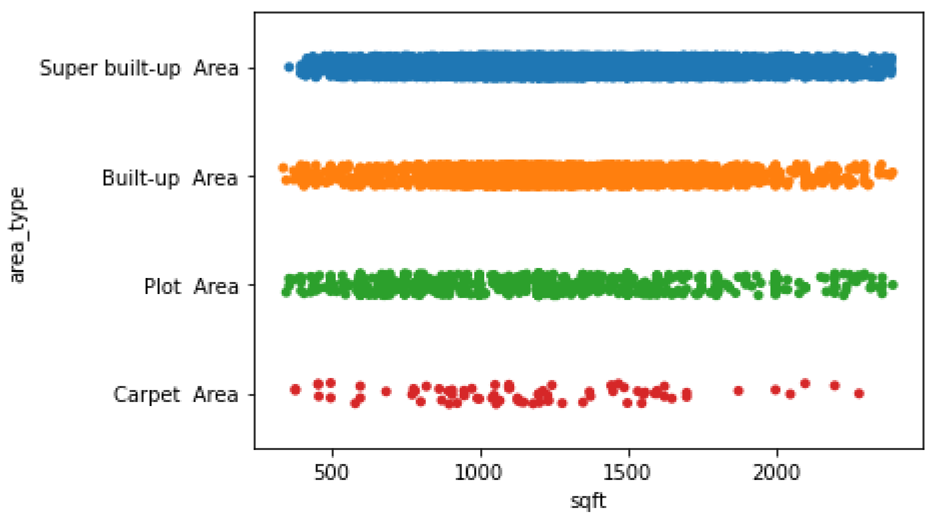
Out[74]: <AxesSubplot:xlabel='price_per_sqft', ylabel='area_type'>



regardless of area_type price per sqft is same for most of the data

In [75]:
```
sns.stripplot('sqft','area_type',data=non_outlier)
```

Out[75]: <AxesSubplot:xlabel='sqft', ylabel='area_type'>



super built-up area provides wide range of sqft choices whereas

next to super built-up area built up area provides wide range of sqft choices

next to builtup area area plot area provides sqft choices

and carpet area type provides leaset sqft choices

In [ ]:

In [ ]: