London House Price Prediction

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Step 1 : Loading the libraries

In [1]:
```
import matplotlib.pyplot as plt
import numpy as np
from sklearn import datasets, linear_model
from sklearn.metrics import mean_squared_error, r2_score
import pandas as pd
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

Step 2 : Loading the dataset

In [2]:
```
import os
working_directory = os.getcwd()
path  = working_directory + '/London_housingdata_copy.csv'
df = pd.read_csv(path)
```

In [3]:
```
df.head()
```

Out[3]:

	Unnamed: 0	Property Name	Price	House Type	AreainSQFT	Bedroom	Bathroom	Location
0	0	Queens Road	1675000	House	2716	5.0	5.0	Wimbledon
1	1	Seward Street	650000	Flat / Apartment	814	2.0	2.0	Clerkenwell
2	2	Hotham Road	735000	Flat / Apartment	761	2.0	2.0	Putney
3	3	Festing Road	1765000	House	1986	4.0	4.0	Putney
4	4	Spencer Walk	675000	Flat / Apartment	700	2.0	2.0	Putney

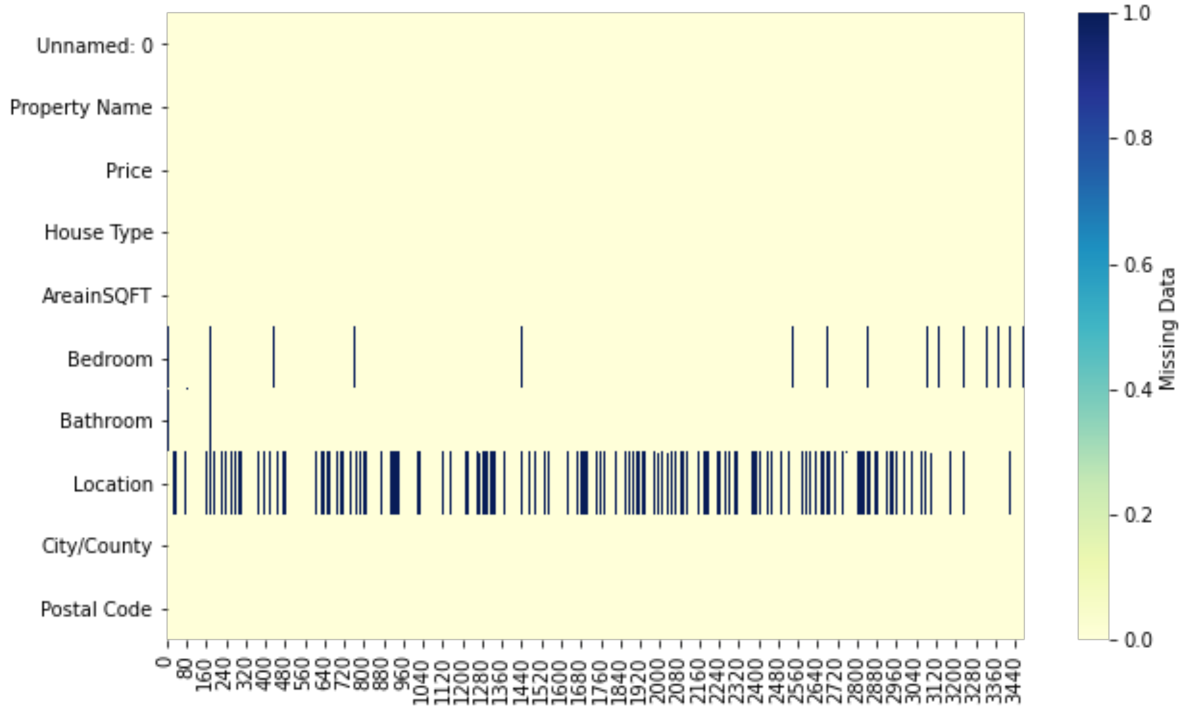
In [4]:
```
df.shape
```

Out[4]:
```
(3480, 10)
```

Heatmap

In [5]:
```
plt.figure(figsize=(10,6))
sns.heatmap(df.isna().transpose(),
            cmap="YlGnBu",

            cbar_kws={'label': 'Missing Data'})
#plt.savefig("visualizing_missing_data_with_heatmap_Seaborn_Python.
```

Out[5]:
```
<AxesSubplot:>
```



In [ ]:

Step 3 : Cleaning the dataset

In [6]:
```
df.groupby("Property Name")["Property Name"].agg("count")
```

Out[6]:
```
Property Name
1 Eastfields Avenue    1
10 Park Drive          3
17 Lillie Square       7
23 Maud Street         1
28 Narrow Street       1
                      ..
Youngs Court           1
Yukon Road             1
Yvon House             2
Ziggurat Building      1
Zulu Mews              1
Name: Property Name, Length: 2380, dtype: int64
```

In [7]:
```
df.groupby("Location")["Location"].agg("count")
```

Out[7]:
```
Location
 161 Millbank          1
 35 Salusbury Road     1
 352 Queenstown Road   1
 372 Queenstown Road   1
 50 Shad Thames        1
                      ..
Winchester Road        1
Windsor Street         1
Woodberry Grove        1
Woodford Green        12
Woodstock Road         1
Name: Location, Length: 679, dtype: int64
```

Step 3.1 : Converting price to millions

For easy intrepretation we convert the price to millions.

In [8]:
```
df["price_in_million"]=df["Price"]/[1000000]
df.head()
```

Out[8]:

	Unnamed: 0	Property Name	Price	House Type	AreainSQFT	Bedroom	Bathroom	Location
0	0	Queens Road	1675000	House	2716	5.0	5.0	Wimbledon
1	1	Seward Street	650000	Flat / Apartment	814	2.0	2.0	Clerkenwell
2	2	Hotham Road	735000	Flat / Apartment	761	2.0	2.0	Putney
3	3	Festing Road	1765000	House	1986	4.0	4.0	Putney
4	4	Spencer Walk	675000	Flat / Apartment	700	2.0	2.0	Putney

In [9]:
```
df["House Type"].unique()
```

Out[9]:
```
array(['House', 'Flat / Apartment', 'New development', 'Duplex',
       'Penthouse', 'Studio', 'Bungalow', 'Mews'], dtype=object)
```

In [10]:
```
Housetype_stats=df.groupby("House Type")["House Type"].agg("count")
print(Housetype_stats)
```

```
House Type
Flat / Apartment    1565
House               1430
New development      357
Penthouse            100
Studio                10
Bungalow               9
Duplex                 7
Mews                   2
Name: House Type, dtype: int64
```

Step 3.2 : Dropping two columns

Since in this project we are taking a overlaying approach of predictig the average house prices we drop the House Type and we will take care of the outliers in the later stage.

In [11]:
```
df1=df.drop(["Unnamed: 0","House Type" ],axis="columns")
df1.head()
```

Out[11]:

	Property Name	Price	AreainSQFT	Bedroom	Bathroom	Location	City/County	Postal Code	p
0	Queens Road	1675000	2716	5.0	5.0	Wimbledon	London	SW19 8NY	
1	Seward Street	650000	814	2.0	2.0	Clerkenwell	London	EC1V 3PA	
2	Hotham Road	735000	761	2.0	2.0	Putney	London	SW15 1QL	
3	Festing Road	1765000	1986	4.0	4.0	Putney	London	SW15 1LP	
4	Spencer Walk	675000	700	2.0	2.0	Putney	London	SW15 1PL	

In [12]:
```
df1.shape
```

Out[12]: (3480, 9)

In [13]:
```
df1.describe()
```

Out[13]:

	Price	AreainSQFT	Bedroom	Bathroom	price_in_million
count	3.480000e+03	3480.000000	3407.000000	3471.000000	3480.000000
mean	1.864173e+06	1712.973563	3.104784	3.101988	1.864173
std	2.267283e+06	1364.259351	1.520036	1.518559	2.267283
min	1.800000e+05	274.000000	0.000000	0.000000	0.180000
25%	7.500000e+05	834.000000	2.000000	2.000000	0.750000
50%	1.220000e+06	1310.000000	3.000000	3.000000	1.220000
75%	2.150000e+06	2157.250000	4.000000	4.000000	2.150000
max	3.975000e+07	15405.000000	10.000000	10.000000	39.750000

Step 3.3 : Comparing Price to other metrics

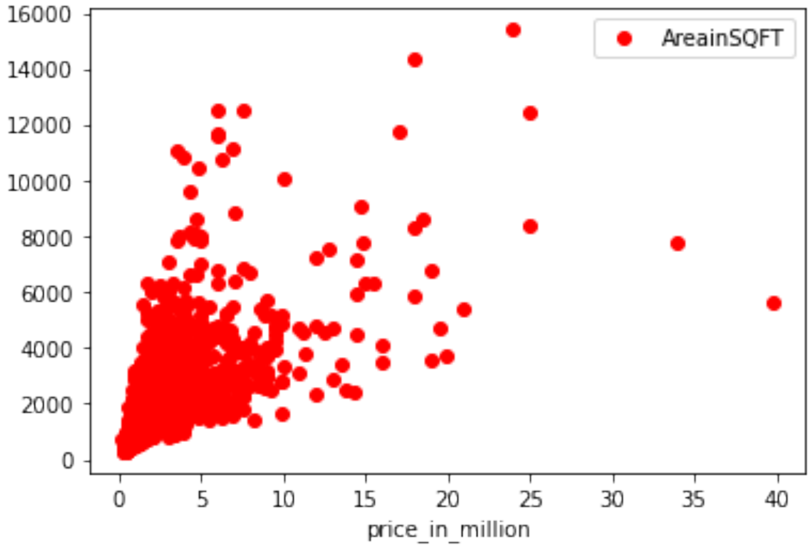
Confusion Matrix

In [14]:
```
corrMatrix = df1.corr()
sns.heatmap(corrMatrix, annot=True)
plt.show()
```

Comparing the Prices to Area

In [15]:
```
df1.plot(x='price_in_million', y='AreainSQFT', style='o' ,  color =
```

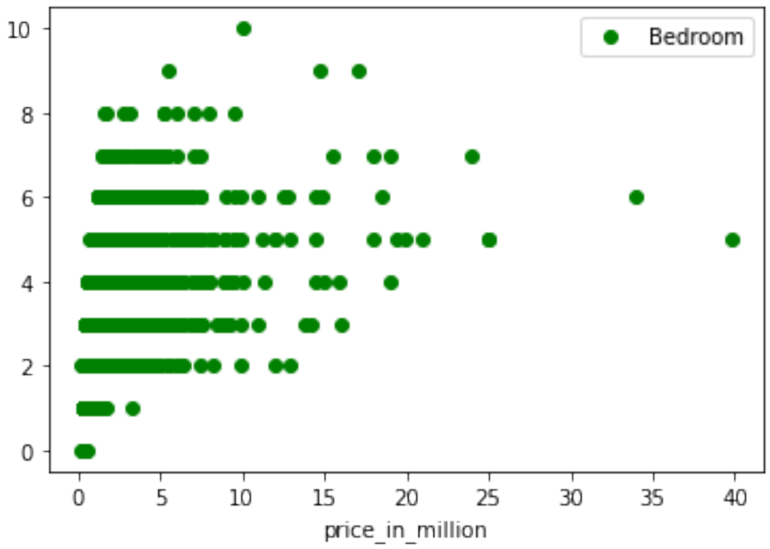
Out[15]: <AxesSubplot:xlabel='price_in_million'>



Comparing the Prices to Area

In [16]:
```
df1.plot(x='price_in_million', y='Bedroom', style='o' ,  color = "g
```

Out[16]: <AxesSubplot:xlabel='price_in_million'>



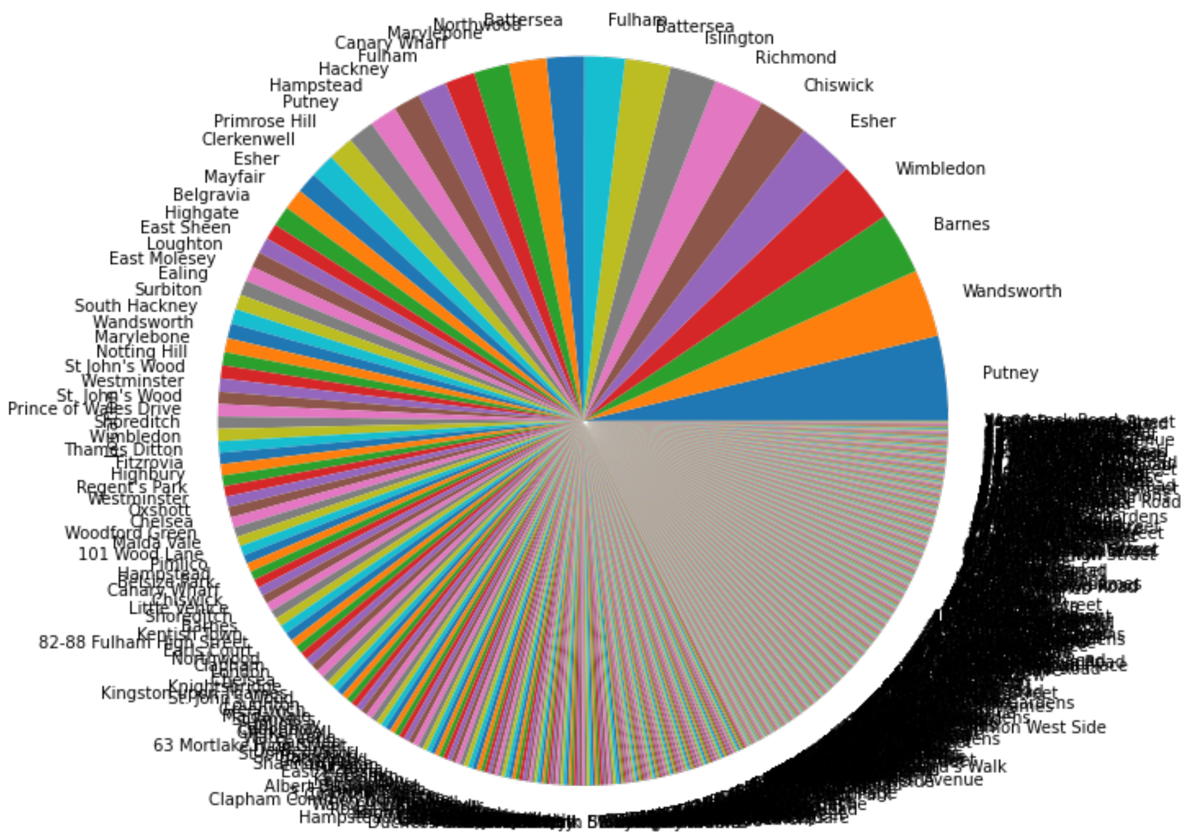
In [17]:
```
Locationtype_stats=df1.groupby("Location")["Location"].agg("count")
print(Locationtype_stats)
```

```
Location
Putney                 97
Wandsworth             77
Barnes                 71
Wimbledon              69
Esher                  64
                       ..
35 Pembroke Road        1
35 Kensington Court     1
348 Queenstown Road     1
34-37 Beaumont Street   1
Woodstock Road          1
Name: Location, Length: 679, dtype: int64
```

Comparing the Location density

In [18]:
```
Locationtype_stats.plot(kind='pie',figsize=(10,50))
```

Out[18]: <AxesSubplot:ylabel='Location'>



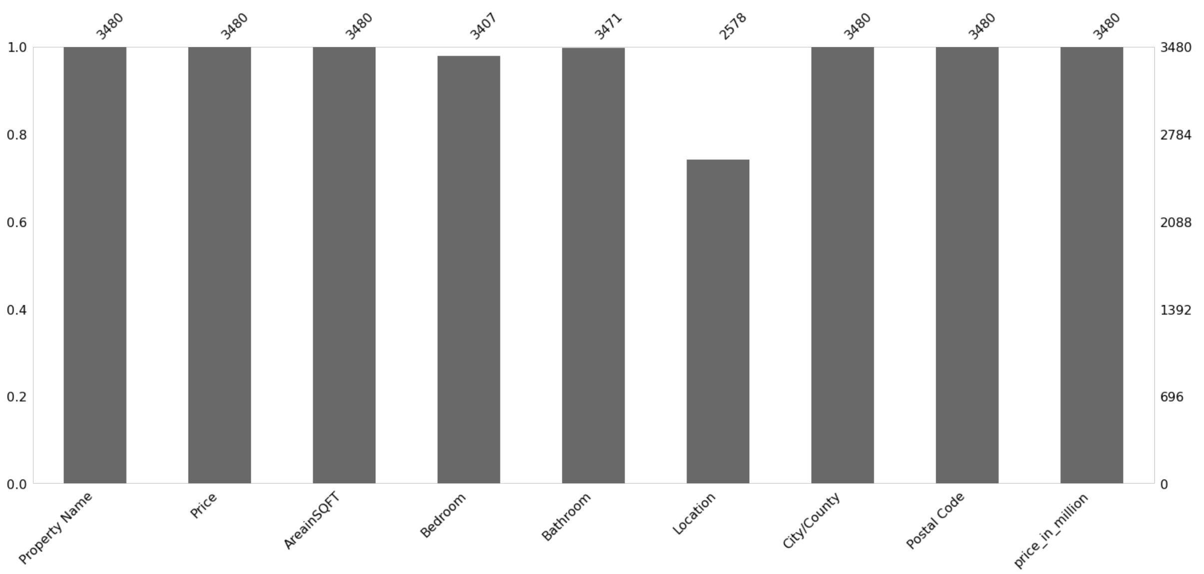
Step 3.4 : Handling Null values

In [19]:
```
df1.isnull().sum()
```

Out[19]:
```
Property Name        0
Price                0
AreainSQFT           0
Bedroom             73
Bathroom             9
Location           902
City/County          0
Postal Code          0
price_in_million     0
dtype: int64
```

In [20]:
```
import missingno as msno



# values as a bar chart
msno.bar(df1)
```

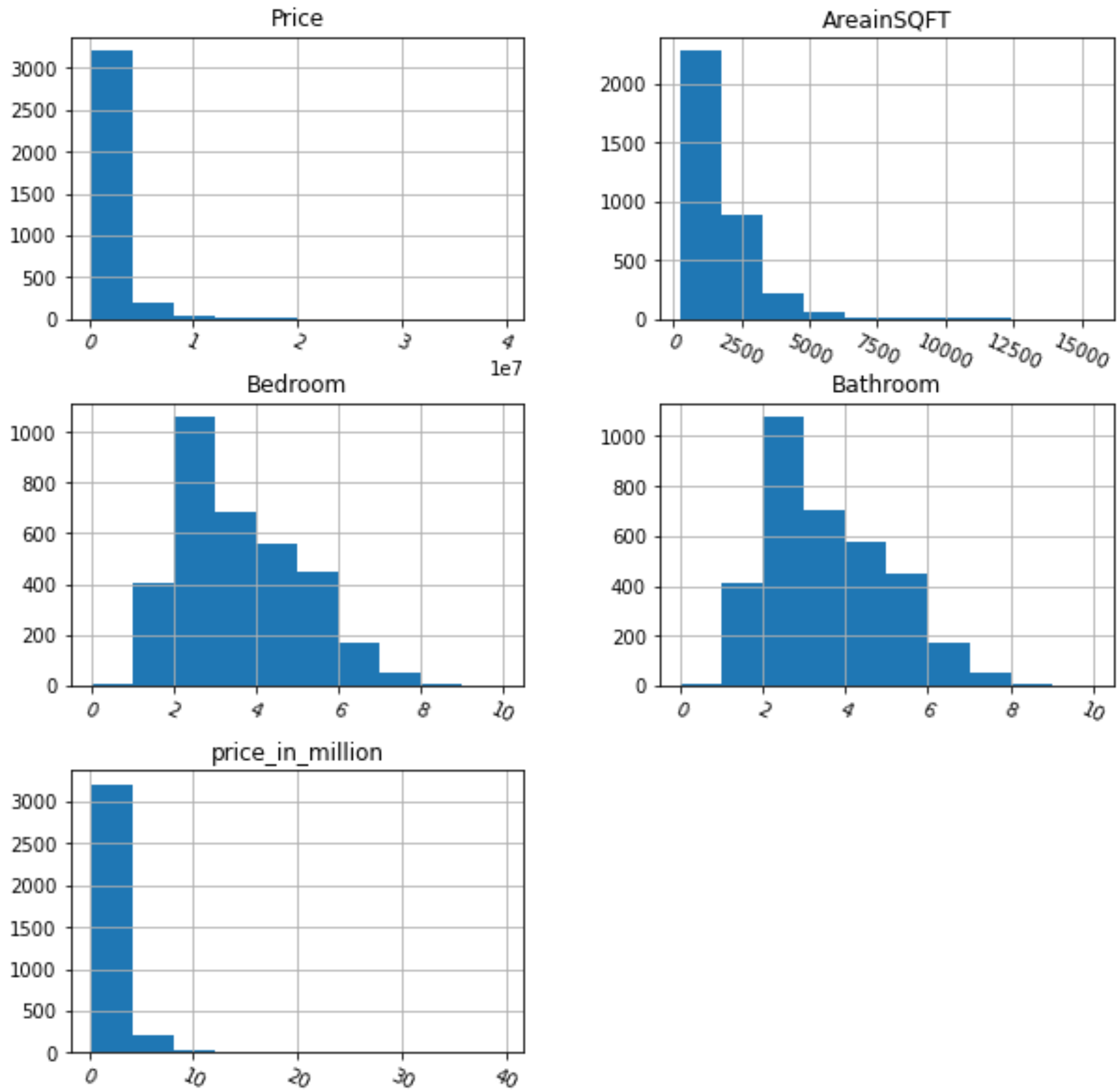
Out[20]: <AxesSubplot:>



In [21]:
```
df1.dtypes[df1.dtypes!= "object"]
```

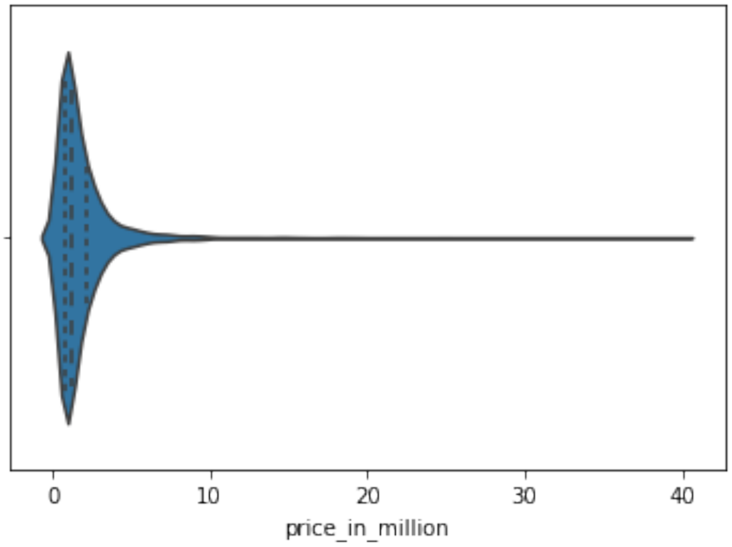
Out[21]:
```
Price                 int64
AreainSQFT            int64
Bedroom             float64
Bathroom            float64
price_in_million    float64
dtype: object
```

In [22]:
```
df1.hist(figsize=(10,10), xrot=-25)
plt.ticklabel_format(style='plain')
```



In [23]:
```
sns.violinplot(data=df1, x="price_in_million" , fmt = "g",plit=True
```

Out[23]: <AxesSubplot:xlabel='price_in_million'>



Since the null values are scarce we drop the same

In [24]:
```
df2 = df1.dropna()
df2.shape
```

Out[24]: (2532, 9)

In [25]:
```
df2.head()
```

Out[25]:

	Property Name	Price	AreainSQFT	Bedroom	Bathroom	Location	City/County	Postal Code	p
0	Queens Road	1675000	2716	5.0	5.0	Wimbledon	London	SW19 8NY	
1	Seward Street	650000	814	2.0	2.0	Clerkenwell	London	EC1V 3PA	
2	Hotham Road	735000	761	2.0	2.0	Putney	London	SW15 1QL	
3	Festing Road	1765000	1986	4.0	4.0	Putney	London	SW15 1LP	
4	Spencer Walk	675000	700	2.0	2.0	Putney	London	SW15 1PL	

In [26]:
```
df2.isnull().sum()
```

Out[26]:
```
Property Name       0
Price               0
AreainSQFT          0
Bedroom             0
Bathroom            0
Location            0
City/County         0
Postal Code         0
price_in_million    0
dtype: int64
```

In [27]:
```
df2.head()
```

Out[27]:

	Property Name	Price	AreainSQFT	Bedroom	Bathroom	Location	City/County	Postal Code	p
0	Queens Road	1675000	2716	5.0	5.0	Wimbledon	London	SW19 8NY	
1	Seward Street	650000	814	2.0	2.0	Clerkenwell	London	EC1V 3PA	
2	Hotham Road	735000	761	2.0	2.0	Putney	London	SW15 1QL	
3	Festing Road	1765000	1986	4.0	4.0	Putney	London	SW15 1LP	
4	Spencer Walk	675000	700	2.0	2.0	Putney	London	SW15 1PL	

Step 4 : Feature Engineering

In [28]:
```
df2["Bedroom"].unique()
```

Out[28]:
```
array([ 5.,  2.,  4.,  1.,  3.,  6.,  0., 10.,  7.,  8.,  9.])
```

Step 4.1 : Removing houses with high counts of bedroom

As 7 Bedooms is high number for an ideal home we shall remove the houses with more than 7 bedrooms to create a perfect model.

In [29]:
```
df2[df2.Bedroom>7]
```

Out[29]:

	Property Name	Price	AreainSQFT	Bedroom	Bathroom	Location	City/County
43	Old Battersea House	9975000	10100	10.0	10.0	Battersea	London
224	Harper Lane	1650000	4016	8.0	8.0	Radlett	Hertfordshire
800	Upper Park Road	5250000	3782	8.0	8.0	Belsize Park	London
1818	Parkside Avenue	8000000	6713	8.0	8.0	Wimbledon	London
2619	Courtenay Avenue	16999999	11733	9.0	9.0	Highgate	London
2687	Christchurch Road	7000000	6388	8.0	8.0	East Sheen	London
3063	Macaulay Road	5950000	6776	8.0	8.0	Clapham	London
3282	Manor Road	2800000	4378	8.0	8.0	Chigwell	Essex
3336	Bryanston Mews West	5250000	3108	8.0	8.0	Marylebone	London
3394	Upper Wimpole Street	14750000	9053	9.0	9.0	Marylebone	London
3426	Norfolk Road	9500000	3974	8.0	8.0	St John's Wood	London

In [30]:
```
df2[df2.Bedroom>7].head(10)
```

Out[30]:

	Property Name	Price	AreainSQFT	Bedroom	Bathroom	Location	City/County	F
43	Old Battersea House	9975000	10100	10.0	10.0	Battersea	London	!
224	Harper Lane	1650000	4016	8.0	8.0	Radlett	Hertfordshire	
800	Upper Park Road	5250000	3782	8.0	8.0	Belsize Park	London	
1818	Parkside Avenue	8000000	6713	8.0	8.0	Wimbledon	London	!
2619	Courtenay Avenue	16999999	11733	9.0	9.0	Highgate	London	
2687	Christchurch Road	7000000	6388	8.0	8.0	East Sheen	London	!
3063	Macaulay Road	5950000	6776	8.0	8.0	Clapham	London	
3282	Manor Road	2800000	4378	8.0	8.0	Chigwell	Essex	
3336	Bryanston Mews West	5250000	3108	8.0	8.0	Marylebone	London	
3394	Upper Wimpole Street	14750000	9053	9.0	9.0	Marylebone	London	

Negating the same

In [31]:
```
df2 = df2[~(df2.Bedroom>7)]
df2.shape
```

Out[31]: (2521, 9)

Step 4.2 : Calculation the price per SQFT

For easy interpretation we calculate the Price in Sqft

In [32]:
```
df2.AreainSQFT.unique()
```

Out[32]: array([2716, 814, 761, ..., 3698, 4435, 1506])

In [33]:
```
df3 = df2.copy()
```

In [34]:
```
df3.head()
```

Out[34]:

	Property Name	Price	AreainSQFT	Bedroom	Bathroom	Location	City/County	Postal Code	p
0	Queens Road	1675000	2716	5.0	5.0	Wimbledon	London	SW19 8NY	
1	Seward Street	650000	814	2.0	2.0	Clerkenwell	London	EC1V 3PA	
2	Hotham Road	735000	761	2.0	2.0	Putney	London	SW15 1QL	
3	Festing Road	1765000	1986	4.0	4.0	Putney	London	SW15 1LP	
4	Spencer Walk	675000	700	2.0	2.0	Putney	London	SW15 1PL	

In [35]:
```
df3["price_per_sqft"]=df["Price"]/df2["AreainSQFT"]

df3.head()
```

Out[35]:

	Property Name	Price	AreainSQFT	Bedroom	Bathroom	Location	City/County	Postal Code	p
0	Queens Road	1675000	2716	5.0	5.0	Wimbledon	London	SW19 8NY	
1	Seward Street	650000	814	2.0	2.0	Clerkenwell	London	EC1V 3PA	
2	Hotham Road	735000	761	2.0	2.0	Putney	London	SW15 1QL	
3	Festing Road	1765000	1986	4.0	4.0	Putney	London	SW15 1LP	
4	Spencer Walk	675000	700	2.0	2.0	Putney	London	SW15 1PL	

Step 4.3 : Stripping the Location name using Lamda fucntion

Since some location names are merged together we use the lambda function to strip into identifiable names

In [36]:
```
len(df3.Location.unique())
```

Out[36]: 667

In [37]:
```
df3.Location.apply(lambda x:x.strip())
```

Out[37]:
```
0                    Wimbledon
1                  Clerkenwell
2                       Putney
3                       Putney
4                       Putney
                 ...
3474              Queen's gate
3475                    Fulham
3476                St James's
3477    Hampstead Garden Suburb
3478                   Mayfair
Name: Location, Length: 2521, dtype: object
```

Step 4.4 : Change name of scare location to 'Others'

In [38]:
```
Location_stats=df3.groupby("Location")["Location"].agg("count").sor
print(Location_stats)
```

```
Location
Putney                 96
Wandsworth             77
Barnes                 71
Wimbledon              68
Esher                  62
                       ..
350 The Highway         1
35 Pembroke Road        1
35 Kensington Court     1
348 Queenstown Road     1
Woodstock Road          1
Name: Location, Length: 667, dtype: int64
```

To prevent outliers, we shall consider the locations where there are instances less than or equal to 5 as 'Others'

In [39]:
```
len(Location_stats[Location_stats<=5])
```

Out[39]:
```
579
```

In [40]:
```
Location_stats_less_than_5=Location_stats[Location_stats<=5]
Location_stats_less_than_5
```

Out[40]:
```
Location
St. James's                   5
Brook Green                   5
Albert Bridge Road            5
Acton                         5
Clapham Common North Side     5
                             ..
350 The Highway               1
35 Pembroke Road              1
35 Kensington Court           1
348 Queenstown Road           1
Woodstock Road                1
Name: Location, Length: 579, dtype: int64
```

In [41]:
```
len(df3.Location.unique())
```

Out[41]:
```
667
```

In [42]:
```
df3.Location=df3.Location.apply(lambda x:"other" if x in Location_s

len(df3.Location.unique())
```

Out[42]:
```
89
```

In [43]:
```
df3.head(15)
```

Out[43]:

	Property Name	Price	AreainSQFT	Bedroom	Bathroom	Location	City/County	Postal Code
0	Queens Road	1675000	2716	5.0	5.0	Wimbledon	London	SW19 8NY
1	Seward Street	650000	814	2.0	2.0	Clerkenwell	London	EC1V 3PA
2	Hotham Road	735000	761	2.0	2.0	Putney	London	SW15 1QL
3	Festing Road	1765000	1986	4.0	4.0	Putney	London	SW15 1LP
4	Spencer Walk	675000	700	2.0	2.0	Putney	London	SW15 1PL
5	Craven Hill Gardens	420000	403	1.0	1.0	other	London	W2 3EA
6	Alfriston Road	1475000	1548	4.0	4.0	Battersea	London	SW11 6NW
7	Bishops Gate	650000	560	1.0	1.0	Fulham	London	SW6 3LF
8	Adam & Eve Mews	2500000	1308	3.0	3.0	other	London	W8 6UG
9	Hornton Street	925000	646	2.0	2.0	other	London	W8 4NT
11	Cromwell Avenue	2500000	2974	6.0	6.0	Highgate	London	N6 5HQ
12	Ashley Park Avenue	2795000	5294	5.0	5.0	other	Surrey	KT12 1ER
13	Grove End House	725000	778	2.0	2.0	St. John's Wood	London	NW8 9HP
14	Abercorn Mansions	750000	647	2.0	2.0	other	London	NW8 9DY
15	Chester Terrace	12500000	4596	6.0	6.0	other	London	NW1 4ND

In [44]:
```
len(df3.Location.unique())
```

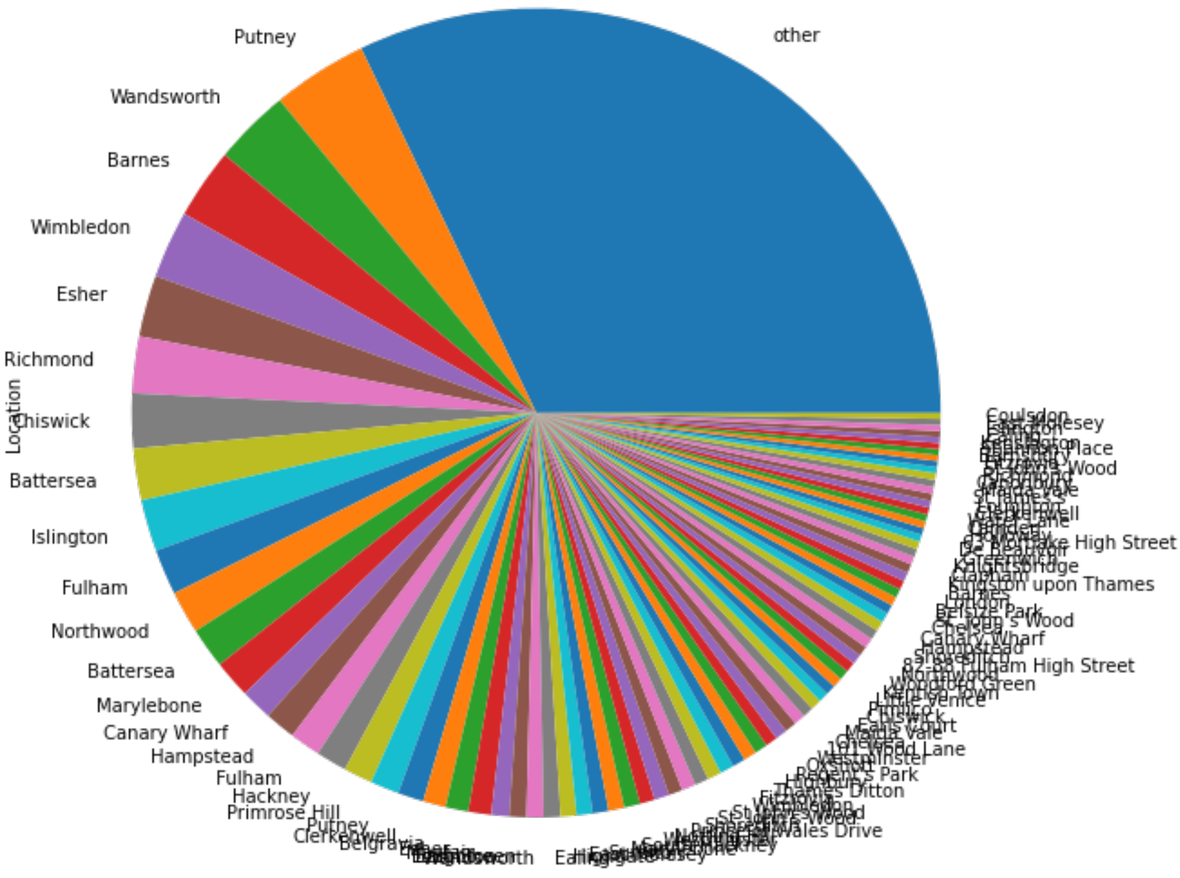
Out[44]: 89

In [45]:
```
Location_stats=df3.groupby("Location")["Location"].agg("count").sor
print(Location_stats)
```

```
Location
other            810
Putney            96
Wandsworth        77
Barnes            71
Wimbledon         68
                ... 
Kensington         6
 Ealing            6
 Islington         6
 East Molesey      6
 Coulsdon          6
Name: Location, Length: 89, dtype: int64
```

In [46]:
```
Location_stats.plot(kind='pie',figsize=(10,50))
```

Out[46]: <AxesSubplot:ylabel='Location'>



Step 4.5 : Remvoing houses which dont have bedroom for atleast 250 sq ft

In [47]:
```
df4 = df3.copy()
```

As an ideal house of 250 squarefeet should have one bedroom at least.If houses having at least a bedroom for every 250 sqft we accept otherwise we shall reject the same and remove from the data

In [48]:
```
df4[df4.AreainSQFT/df4.Bedroom<250].head()
```

Out[48]:

	Property Name	Price	AreainSQFT	Bedroom	Bathroom	Location	City/County	Pc C
463	Disraeli Road	1295000	876	4.0	4.0	Putney	London	S'
1909	Samford House	525000	779	4.0	4.0	other	London	
2362	Landmark Court	550000	469	2.0	2.0	Marylebone	London	I
2656	St. George's Drive	650000	458	2.0	2.0	Pimlico	London	S'
3041	Broomwood Road	600000	736	3.0	3.0	Wandsworth	London	S'

In [49]:
```
df4.shape
```

Out[49]: (2521, 10)

We shall negate the same

In [50]:
```
df5 = df4[~(df4.AreainSQFT/df4.Bathroom<250)]
df5.shape
```

Out[50]: (2514, 10)

In [51]:
```
df5.describe()
```

Out[51]:

	Price	AreainSQFT	Bedroom	Bathroom	price_in_million	price_per_sq
count	2.514000e+03	2514.000000	2514.000000	2514.000000	2514.000000	2514.00000
mean	1.865896e+06	1743.635243	3.091488	3.091488	1.865896	1057.44141
std	2.289145e+06	1411.670875	1.505654	1.505654	2.289145	582.02692
min	1.800000e+05	274.000000	0.000000	0.000000	0.180000	241.61073
25%	7.250000e+05	834.000000	2.000000	2.000000	0.725000	717.34776
50%	1.200000e+06	1308.000000	3.000000	3.000000	1.200000	907.42908
75%	2.250000e+06	2206.500000	4.000000	4.000000	2.250000	1196.04223
max	3.975000e+07	15405.000000	7.000000	7.000000	39.750000	7069.18015

In [52]:
```
df5.price_per_sqft.describe()
```

Out[52]:
```
count    2514.000000
mean     1057.441411
std       582.026929
min       241.610738
25%       717.347765
50%       907.429083
75%      1196.042230
max      7069.180153
Name: price_per_sqft, dtype: float64
```

Step 4.6 : Removing the outliers one standard deviation from the mean

Removing the outliers which are one startdard deviation away from the mean to create a normal distrubution

In [53]:
```
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))&(subdf.price_
        df_out=pd.concat([df_out,reduced_df],ignore_index=True)
    return df_out
```

In [54]:
```
df6 = remove_pps_outliers(df5)
df6.shape
```

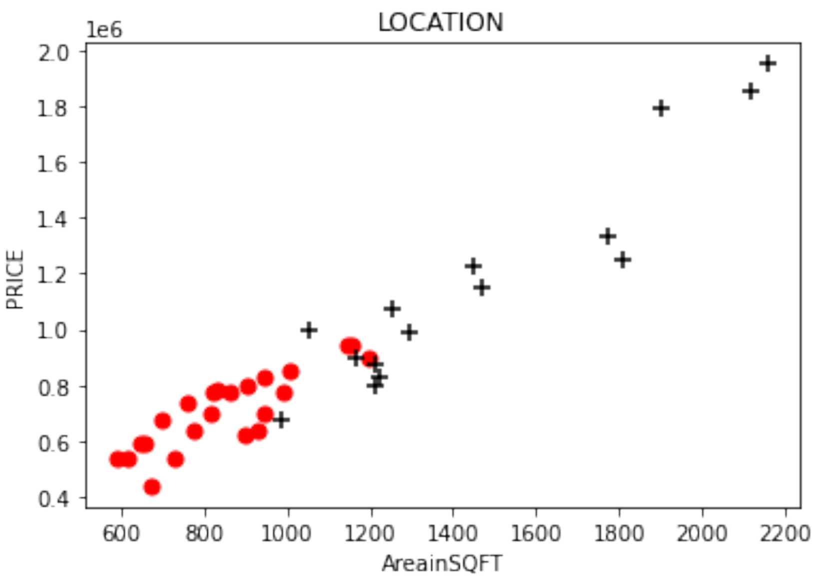
Out[54]: (1866, 10)

Step 4.7 : Removing houses with irregular area.

For example some 2 bedroom house has more area than some 3 bedroom places.We are removing such outliers to create the ideal home for modelling.

In [55]:
```
def plot_scatter_chart(df,Location):
    Bedroom2=df[(df.Location==Location)&(df.Bedroom==2)]
    Bedroom3=df[(df.Location==Location)&(df.Bedroom==3)]

    #matplotlib.reParams["figure.figsize"]=(15,10)
    plt.scatter(Bedroom2.AreainSQFT,Bedroom2.Price,color="red",labe
    plt.scatter(Bedroom3.AreainSQFT,Bedroom3.Price,marker="+",color
    plt.xlabel("AreainSQFT")
    plt.ylabel("PRICE")
    plt.title("LOCATION")
```

In [56]:
```
plot_scatter_chart(df6,"Putney")
```

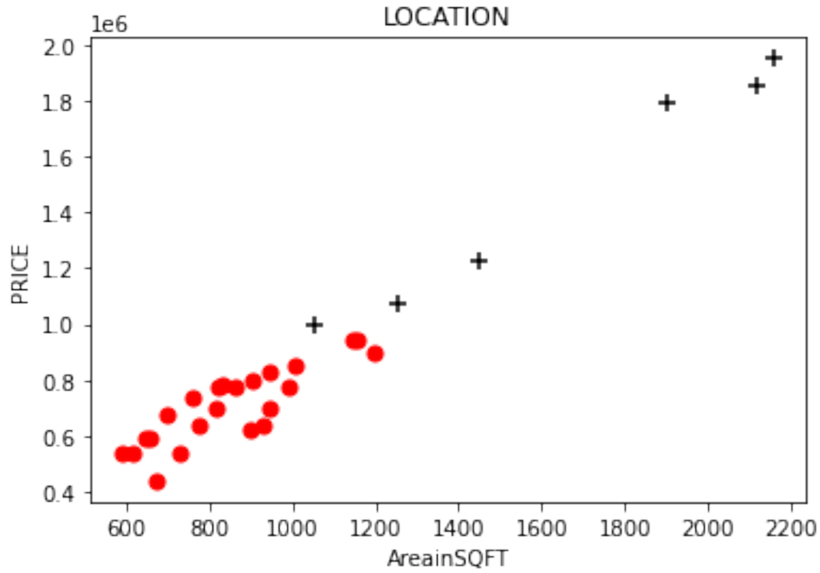


In [57]:
```
def remove_bhk_outliers(df):
    exclude_indices=np.array([])
    for Location,Location_df in df.groupby("Location"):
        Bedroom_stats={}
        for Bedroom,Bedroom_df in Location_df.groupby("Bedroom"):
            Bedroom_stats[Bedroom]={
            "mean":np.mean(Bedroom_df.price_per_sqft),
            "std":np.std(Bedroom_df.price_per_sqft),
            "count":Bedroom_df.shape[0]
            }
        for Bedroom,Bedroom_df in Location_df.groupby("Bedroom"):
            stats=Bedroom_stats.get(Bedroom-1)

            if stats and stats["count"]>5:
                exclude_indices=np.append(exclude_indices,Bedroom_d

    return df.drop(exclude_indices,axis="index")
```

In [58]:
```
df7=remove_bhk_outliers(df6)
df7.shape
```

Out[58]: (1340, 10)

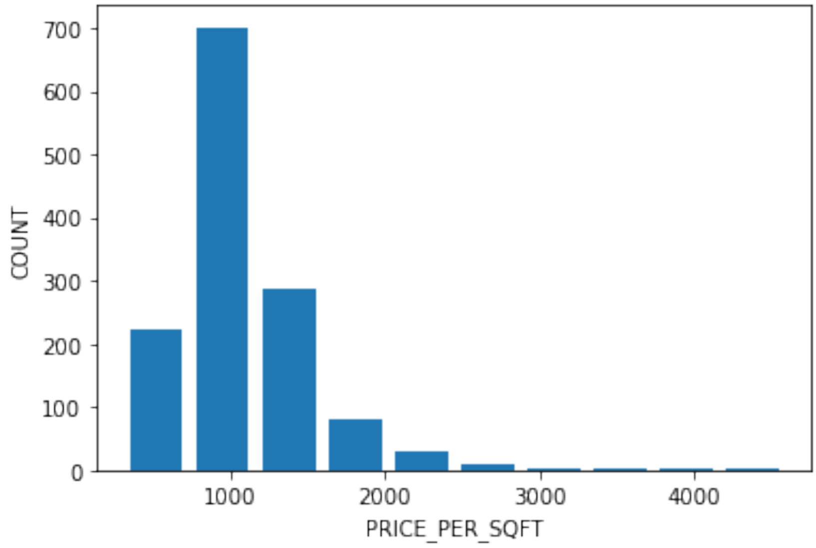
In [59]:
```
plot_scatter_chart(df7,"Putney")
```



After removed some of the said outliers a standard deviation is formed

In [60]:
```
import matplotlib
plt.hist(df7.price_per_sqft,rwidth=0.8)
plt.xlabel("PRICE_PER_SQFT")
plt.ylabel("COUNT")
```

Out[60]: Text(0, 0.5, 'COUNT')



In [61]:
```
df7.head()
```

Out[61]:

	Property Name	Price	AreainSQFT	Bedroom	Bathroom	Location	City/County	Postal Code	p
0	Castelnau Court	575000	793	3.0	3.0	Barnes	London	SW13 9DH	
1	Carmichael Court	685000	783	3.0	3.0	Barnes	London	SW13 0HA	
2	Richard Burbidge Mansions	1700000	1796	3.0	3.0	Barnes	London	SW13 8RB	
3	The Old Sorting Office	700000	736	1.0	1.0	Barnes	London	SW13 0LF	
4	William Hunt Mansions	1150000	1349	2.0	2.0	Barnes	London	SW13 8HS	

Step 4.8 : Removing various other columns for model building

In [62]:
```
df7=df6.drop(["price_per_sqft", "Postal Code" ,"Property Name" ,"Ci
df7.head()
```

Out[62]:

	Price	AreainSQFT	Bedroom	Bathroom	Location
0	575000	793	3.0	3.0	Barnes
1	685000	783	3.0	3.0	Barnes
2	1700000	1796	3.0	3.0	Barnes
3	700000	736	1.0	1.0	Barnes
4	1150000	1349	2.0	2.0	Barnes

In [63]:
```
df7.shape
```

Out[63]: (1866, 5)

In [64]:
```
df8 = df7.copy()
```

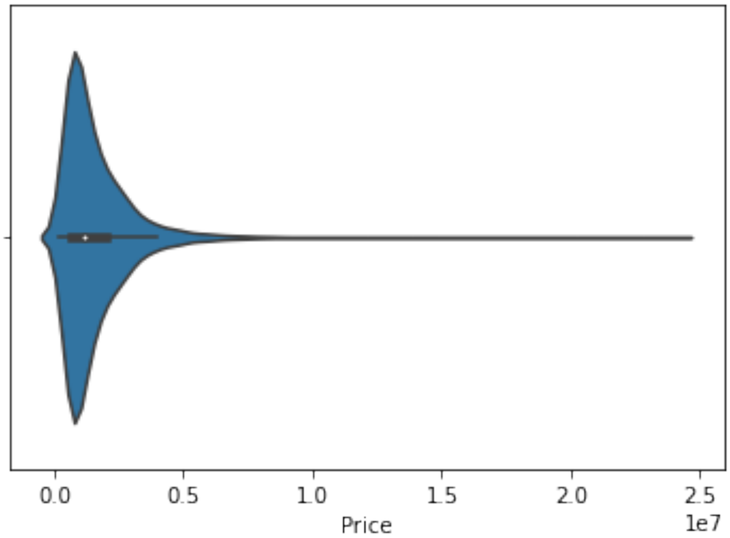
In [65]:
```
df8.describe()
```

Out[65]:

	Price	AreainSQFT	Bedroom	Bathroom
count	1.866000e+03	1866.000000	1866.000000	1866.000000
mean	1.605539e+06	1625.708467	3.013398	3.013398
std	1.597997e+06	1309.871592	1.495062	1.495062
min	2.100000e+05	274.000000	0.000000	0.000000
25%	6.999500e+05	798.250000	2.000000	2.000000
50%	1.125000e+06	1213.500000	3.000000	3.000000
75%	2.000000e+06	2046.250000	4.000000	4.000000
max	2.395000e+07	15405.000000	7.000000	7.000000

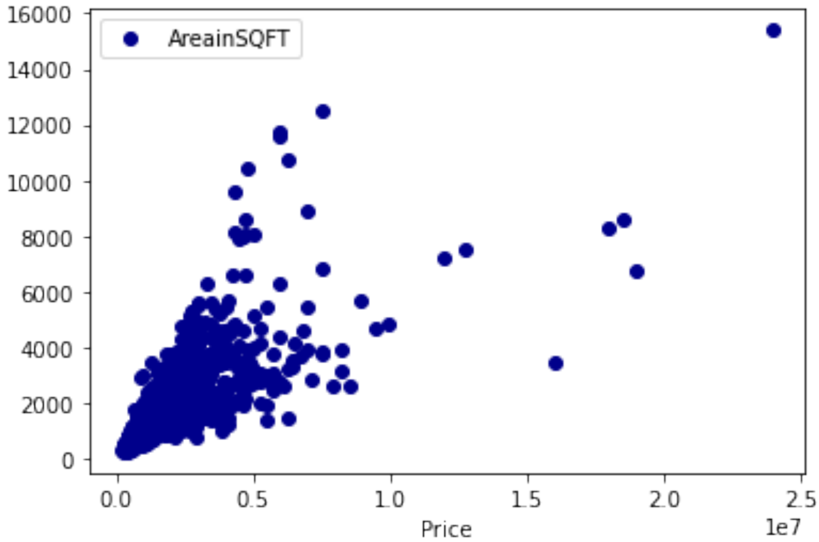
In [66]:
```
sns.violinplot(data=df8, x="Price" , fmt = "g")
```

Out[66]: <AxesSubplot:xlabel='Price'>



In [67]:
```
df8.plot(x='Price', y='AreainSQFT', style='o' ,c='DarkBlue' )
```

Out[67]: <AxesSubplot:xlabel='Price'>



Step 5 : Creating Dummies for the location¶

In [68]:
```
dummies=pd.get_dummies(df8.Location)
dummies.head()
```

Out[68]:

	Barnes	Battersea	Canary Wharf	Chelsea	Chiswick	Clerkenwell	Coulsdon	Ealing	Earls Court	M
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 × 89 columns

In [69]:
```
df9=pd.concat([df8,dummies.drop("other",axis="columns")],axis="colu
df9.head()
```

Out[69]:

	Price	AreainSQFT	Bedroom	Bathroom	Location	Barnes	Battersea	Canary Wharf	Chels
0	575000	793	3.0	3.0	Barnes	1	0	0	
1	685000	783	3.0	3.0	Barnes	1	0	0	
2	1700000	1796	3.0	3.0	Barnes	1	0	0	
3	700000	736	1.0	1.0	Barnes	1	0	0	
4	1150000	1349	2.0	2.0	Barnes	1	0	0	

5 rows × 93 columns

In [70]:
```
df9.shape
```

Out[70]: (1866, 93)

After creating dummies we drop the location column

In [71]:
```
df10=df9.drop("Location", axis="columns")
df10.head()
```

Out[71]:

	Price	AreainSQFT	Bedroom	Bathroom	Barnes	Battersea	Canary Wharf	Chelsea	Chiswi
0	575000	793	3.0	3.0	1	0	0	0	
1	685000	783	3.0	3.0	1	0	0	0	
2	1700000	1796	3.0	3.0	1	0	0	0	
3	700000	736	1.0	1.0	1	0	0	0	
4	1150000	1349	2.0	2.0	1	0	0	0	

5 rows × 92 columns

In [72]:
```
df10.shape
```

Out[72]: (1866, 92)

Step 6 : Model Building

Step 6.1 : Splitting Training set and test set

In [73]:
```
x=df10.drop("Price",axis="columns")
x.head()
```

Out[73]:

	AreainSQFT	Bedroom	Bathroom	Barnes	Battersea	Canary Wharf	Chelsea	Chiswick	Clerk
0	793	3.0	3.0	1	0	0	0	0	
1	783	3.0	3.0	1	0	0	0	0	
2	1796	3.0	3.0	1	0	0	0	0	
3	736	1.0	1.0	1	0	0	0	0	
4	1349	2.0	2.0	1	0	0	0	0	

5 rows × 91 columns

In [74]:
```
y=df10.Price
y.head()
```

Out[74]:
```
0     575000
1     685000
2    1700000
3     700000
4    1150000
Name: Price, dtype: int64
```

Considering 75% for training and 25 % for testing

In [75]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25,r
```

Step 6.2 : Linear Regression

In [76]:
```
from sklearn.linear_model import LinearRegression
lr_clf=LinearRegression()
lr_clf.fit(x_train,y_train)
```

Out[76]:
```
LinearRegression()
```

In [77]:
```
print('R squared training set : ', round(lr_clf.score(x_train, y_tr
print('R squared test set : ', round(lr_clf.score(x_test, y_test)*1
```

```
R squared training set :  82.68
R squared test set :  84.7
```

Step 6.3 : Decision tree Regressor

In [78]:
```
from sklearn.tree import DecisionTreeRegressor
dtr = DecisionTreeRegressor()
dtr.fit(x_train, y_train)
```

Out[78]:
```
DecisionTreeRegressor()
```

In [79]:
```
print('R squared training set : ', round(dtr.score(x_train, y_train
print('R squared test set : ', round(dtr.score(x_test, y_test)*100,
```

```
R squared training set :  99.94
R squared test set :  78.52
```

Step 6.4 : Lasso Regression

In [80]:
```
from sklearn.linear_model import Lasso

reg = Lasso(alpha=1)
reg.fit(x_train, y_train)
```

Out[80]:
```
Lasso(alpha=1)
```

In [81]:
```
print('R squared training set', round(reg.score(x_train, y_train)*1
print('R squared test set', round(reg.score(x_test, y_test)*100, 2)
```

```
R squared training set 82.68
R squared test set 84.7
```

Step 7 : K Fold Cross Validation

We shuffle the data to make a very even and effecient prediction

In [82]:
```
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[82]:
```
array([0.76944168, 0.82364859, 0.80857668, 0.79183952, 0.79979947]
)
```

In [83]:
```
cross_val_score(Lasso(),x,y,cv=cv)
```

Out[83]:
```
array([0.7694462 , 0.82364736, 0.80858054, 0.79184593, 0.79980399]
)
```

In [84]:
```
cross_val_score(DecisionTreeRegressor(),x,y,cv=cv)
```

Out[84]:
```
array([0.70499489, 0.80270472, 0.55621021, 0.71785686, 0.77179405]
)
```

Step 8 : Hyperparameter Tuning - GridSearch

After shuffle split to create a very effecidnt prediction we attempe to do Hyperparameter Tuning unsing GridSearchCV to improve the efficiency of the model for deployment.

In [85]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import Lasso
```

```
def find_best_model_using_gridsearchcv(x,y):
    algos={
        "linear_regressor":{
            "model":LinearRegression(),
            "parms":{
                "normalize":[True,False]
            }
        },
        "lasso":{
            "model":Lasso(),
            "parms":{
                "alpha":[1,2],
                "selection":["random","cyclic"]
            }
       },
       "decision_tree":{
            "model":DecisionTreeRegressor(),
            "parms":{
                "criterion":["mse","freidman_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["parms"],cv=cv,retur
        gs.fit(x,y)

        scores.append({

            "model":algo_name,

            "best_score":gs.best_score_,

            "best_parms":gs.best_params_


        })
    return pd.DataFrame(scores,columns=["model","best_score","best_


find_best_model_using_gridsearchcv(x,y)
```

Out[85]:

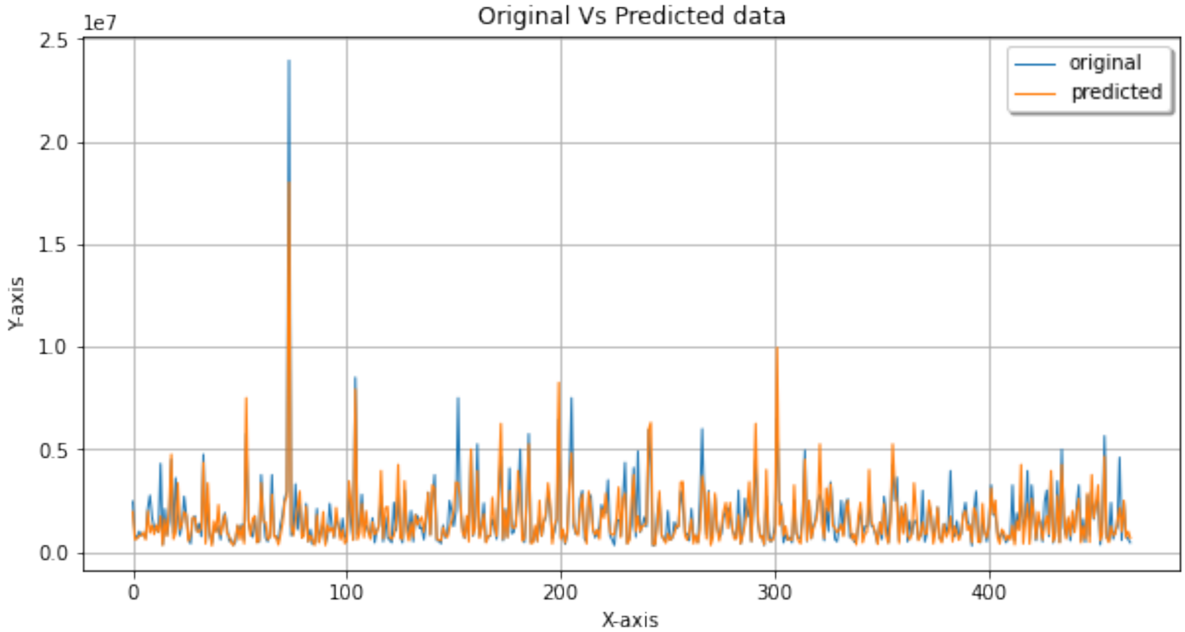
	model	best_score	best_parms
0	linear_regressor	0.798661	{'normalize': True}
1	lasso	0.798668	{'alpha': 2, 'selection': 'cyclic'}
2	decision_tree	0.688520	{'criterion': 'mse', 'splitter': 'best'}

Step 9 : Comparing Original and Predicted data

In [86]:
```
y_pred = dtr.predict(x_test)

mse = mean_squared_error(y_test, y_pred)
print("MSE: ", mse)
print("RMSE: ", mse*(1/2.0))
```

```
MSE:  572726019390.4103
RMSE:  286363009695.20514
```

In [87]:
```
x_ax = range(len(y_test))
plt.rcParams["figure.figsize"] = (10,5)
plt.plot(x_ax, y_test, linewidth=1, label="original")
plt.plot(x_ax, y_pred, linewidth=1.1, label="predicted")
plt.title("Original Vs Predicted data")
plt.xlabel('X-axis')
plt.ylabel('Y-axis')
plt.legend(loc='best',fancybox=True, shadow=True)
plt.grid(True)
plt.show()
```



Step 10 : Model Deployment using the best model.

In [88]:
```
x.columns
```

Out[88]:
```
Index(['AreainSQFT', 'Bedroom', 'Bathroom', ' Barnes', ' Battersea
',
       ' Canary Wharf', ' Chelsea', ' Chiswick', ' Clerkenwell', '
Coulsdon',
       ' Ealing', ' Earls Court', ' East Molesey', ' Esher', ' Fit
zrovia',
       ' Fulham', ' Greenwich', ' Hampstead', ' Holloway', ' Islin
gton',
       ' London', ' Loughton', ' Maida Vale', ' Marylebone', ' Nor
thwood',
       ' Putney', ' Richmond', ' Shoreditch', ' St John's Wood',
       ' St. John's Wood', ' Wandsworth', ' Westminster', ' Wimble
don',
       '101 Wood Lane', '63 Mortlake High Street', '82-88 Fulham H
igh Street',
       'Barnes', 'Barnsbury', 'Battersea', 'Belgravia', 'Belsize P
ark',
       'Camden', 'Canary Wharf', 'Canonbury', 'Chelsea', 'Chiswick
', 'Clapham',
       'Clerkenwell', 'De Beauvoir', 'Ealing', 'East Molesey', 'Ea
st Sheen',
       'Esher', 'Fitzrovia', 'Fulham', 'Hackney', 'Hampstead', 'Hi
ghbury',
       'Highgate', 'Islington', 'Kensington', 'Kentish Town',
       'Kingston upon Thames', 'Knightsbridge', 'Little Venice', '
Loughton',
       'Maida Vale', 'Marylebone', 'Mayfair', 'Northwood', 'Nottin
g Hill',
       'Oxshott', 'Pimlico', 'Primrose Hill', 'Prince of Wales Dri
ve',
       'Putney', 'Regent's Park', 'Richmond', 'Shannon Place', 'Sh
oreditch',
       'South Hackney', 'St James's', 'St John's Wood', 'St. John'
s Wood',
       'Surbiton', 'Thames Ditton', 'Wandsworth', 'Water Lane', 'W
estminster',
       'Wimbledon', 'Woodford Green'],
      dtype='object')
```

In [89]:
```
np.where(x.columns =="Putney")[0][0]
```

Out[89]:
```
75
```

Linear regressiion is the best model hence we deploy it

In [90]:
```
#WE SEE LINEAR REGRESSION IS THE BEST WITH NORMALIZE=TRUE
def predict_price(Location,AreainSQFT,Bathroom,Bedroom):

    loc_index=np.where(x.columns==Location)[0][0]

    z=np.zeros(len(x.columns))

    z[0]=AreainSQFT
    z[1]=Bathroom
    z[2]=Bedroom

    if loc_index>=0:

        z[loc_index]=1


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

In [91]:
```
Price = predict_price("Putney",2000,4,4)

Price
```

Out[91]: 1634319.6862044318

In [92]:
```
Price = predict_price("Putney",2500,5,5)

Price
```

Out[92]: 2118513.6862044316

In [93]:
```
Price_in_millions = "The cost of house is: " + str(round(Price/1000(
Price_in_millions
```

Out[93]: 'The cost of house is: 2.12 million'

In [ ]:
```
```