gurgaon-house-price-1

September 21, 2024

1 Analysis by Prisca

1.1 About the dataset

[ ]:
```
# Predicting the house price of Gurgaon
```

[411]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[412]:
```
df_clean=pd.read_csv(r'C:\Users\USER\Documents\india house␣
↪prediction\house_cleaned.csv')
```

[413]:
```
df_uncleaned=pd.read_csv(r'C:\Users\USER\Documents\india house␣
↪prediction\houses.csv')
```

[414]:
```
df_clean.head()
```

[414]:

	property_name	property_type	society	price	price_per_sqft	area	areaWithType	bedRoom	bathroom	balcony
0	5 Bedroom House for sale in Sector 70A Gurgaon	house	bptp visionnaire	5.25	20115.0	2610.0	Plot area 290(242.48 sq.m.)	5	4	3+
1	5 Bedroom House for sale in Sector 21A Faridabad	house	independent	5.70	105751.0	539.0	Plot area 539(50.07 sq.m.)	5	4	2
2	10 Bedroom House for sale in Sushant Lok Phase 1	house	independent	2.10	38251.0	549.0	Plot area 61(51 sq.m.)	10	10	3+
3	21 Bedroom House for sale in Sector 54 Gurgaon	house	independent	5.00	43066.0	1161.0	Plot area 129(107.86 sq.m.)	21	21	3+
4	12 Bedroom House for sale in Sushant Lok Phase 1	house	independent	3.00	53763.0	558.0				

```
4    Plot area 62(51.84 sq.m.)       12        12      3+

                      additionalRoom  \
0                       servant room
1  store room,pooja room,servant room
2                       servant room
3                       servant room
4                             others

                                    address  floorNum      facing  \
0    29b, Sector 70A Gurgaon, Gurgaon, Haryana       3.0  North-East
1       Sector 21A Faridabad, Gurgaon, Haryana       2.0         NaN
2        Sushant Lok Phase 1, Gurgaon, Haryana       5.0        West
3          Sector 54 Gurgaon, Gurgaon, Haryana       5.0       North
4  1228, Sushant Lok Phase 1, Gurgaon, Haryana       5.0        West

      agePossession                                    nearbyLocations  \
0   0 to 1 Year Old  ['Good Earth City Center 2', 'Kunskapsskolan I…
1  5 to 10 Year Old                                                NaN
2   0 to 1 Year Old  ['Sector 42-43 metro station', 'Huda city cent…
3   1 to 5 Year Old  ['Sector 53-54 metro station', 'Sector 54 chow…
4   Within 6 months  ['Sector 42-43 metro station', 'Huda city cent…

                                       description  \
0  Do you wish to buy an independent house in sec…
1  Hi, we have an independent house/villa availab…
2  Monthly rental income is rs1,40,000/- Best opt…
3  129 sq yd plot size. 5 floors built up , fully…
4  Best for investment purpose. Fully furnished b…

                                     furnishDetails  \
0  ['1 Wardrobe', '1 Fan', '1 Exhaust Fan', '1 Ge…
1  ['1 Water Purifier', '5 Fan', '1 Exhaust Fan',…
2  ['10 Bed', '3 Fan', '10 Geyser', '2 Light', 'N…
3  ['1 Water Purifier', '21 Fan', '1 Fridge', '1 …
4  ['1 Water Purifier', '1 Fridge', '12 Fan', '1 …

                                          features  \
0  ['Feng Shui / Vaastu Compliant', 'Private Gard…
1  ['Private Garden / Terrace', 'Park', 'Visitor …
2  ['Maintenance Staff', 'Water Storage', 'Visito…
3  ['Feng Shui / Vaastu Compliant', 'Private Gard…
4  ['Maintenance Staff', 'Water Storage', 'Visito…

                                           rating
0  ['Environment5 out of 5', 'Lifestyle4 out of 5…
1                                             NaN
```

```
2  ['Environment5 out of 5', 'Lifestyle5 out of 5…
3  ['Environment4 out of 5', 'Lifestyle5 out of 5…
4  ['Environment5 out of 5', 'Lifestyle5 out of 5…
```

[415]:
```
df_clean.columns
```

[415]:
```
Index(['property_name', 'property_type', 'society', 'price', 'price_per_sqft',
       'area', 'areaWithType', 'bedRoom', 'bathroom', 'balcony',
       'additionalRoom', 'address', 'floorNum', 'facing', 'agePossession',
       'nearbyLocations', 'description', 'furnishDetails', 'features',
       'rating'],
      dtype='object')
```

2 data structure

[416]:
```
# the columns are much , here i chose the columns that can help in price␣
↪predictions in the future
```

[417]:
```
df_price  = df_clean[['price', 'price_per_sqft','area','bedRoom', 'balcony']] #␣
↪i remove bathroom because it has high correlation with bedroom
```

[418]:
```
df_price
```

[418]:

	price	price_per_sqft	area	bedRoom	balcony
0	5.25	20115.0	2610.0	5	3+
1	5.70	105751.0	539.0	5	2
2	2.10	38251.0	549.0	10	3+
3	5.00	43066.0	1161.0	21	3+
4	3.00	53763.0	558.0	12	3+
..	…	…	…	…	…
959	5.50	30556.0	1800.0	4	3
960	4.25	31481.0	1350.0	3	3
961	4.50	33333.0	1350.0	3	2
962	3.25	33129.0	981.0	3	3
963	3.60	14815.0	2430.0	3	2

[964 rows x 5 columns]

3 data cleaning

[419]:
```
import warnings
warnings.filterwarnings('ignore')
```

[420]:
```
df_price['balcony'].unique() # getting the unique values contained in balcony␣
↪columns
```

[420]:
```
array(['3+', '2', '1', '3', '0'], dtype=object)
```

[421]:
```
df_price['balcony']=df_price['balcony'].str.replace('+','')
```

[422]:
```
df_price['balcony'] =df_price['balcony'].astype(int)  # balcony cleaned and␣
 ↪data type changed from object to int
```

[423]:
```
df_price.isnull().sum()
```

[423]:
```
price             19
price_per_sqft    19
area              19
bedRoom            0
balcony            0
dtype: int64
```

[424]:
```
dfr=df_price.dropna(inplace=True) # null values handled
```

[425]:
```
df_price.duplicated().sum()
```

[425]:
```
22
```

[426]:
```
dfr1=df_price.drop_duplicates(inplace=True) #duplicates handled
```

4 data exploration

[427]:
```
df_price.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 923 entries, 0 to 963
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   price           923 non-null    float64
 1   price_per_sqft  923 non-null    float64
 2   area            923 non-null    float64
 3   bedRoom         923 non-null    int64
 4   balcony         923 non-null    int32
dtypes: float64(3), int32(1), int64(1)
memory usage: 39.7 KB
```

[428]:
```
df_price.shape  # size of the data
```

[428]:
```
(923, 5)
```

[429]:
```
df_price.describe() #statistical analysis
```

[429]:

	price	price_per_sqft	area	bedRoom	balcony
count	923.000000	923.000000	9.230000e+02	923.000000	923.000000
mean	4.866035	28287.669556	1.074597e+04	5.102925	2.171181
std	4.658554	43326.560545	2.387085e+05	3.278012	1.053325
min	0.070000	2.000000	4.500000e+01	1.000000	0.000000
25%	1.160000	10017.500000	9.190000e+02	3.000000	2.000000
50%	3.500000	18889.000000	1.800000e+03	4.000000	3.000000
75%	7.000000	29788.500000	3.175000e+03	6.000000	3.000000
max	31.500000	600000.000000	7.250000e+06	36.000000	3.000000

[430]:
```
# correlation
```

[431]:
```
df_corr=df_price.corr()
```

[432]:
```
df_corr
```

[432]:

	price	price_per_sqft	area	bedRoom	balcony
price	1.000000	0.230972	-0.017679	0.282310	0.408199
price_per_sqft	0.230972	1.000000	-0.024713	0.136255	0.111310
area	-0.017679	-0.024713	1.000000	-0.008064	0.029419
bedRoom	0.282310	0.136255	-0.008064	1.000000	0.379689
balcony	0.408199	0.111310	0.029419	0.379689	1.000000

[433]:
```
# checking for multicollinearity
```

[434]:
```
pd.DataFrame(np.linalg.inv(df_corr.values),columns=df_corr.
↪columns,index=df_corr.index)
```

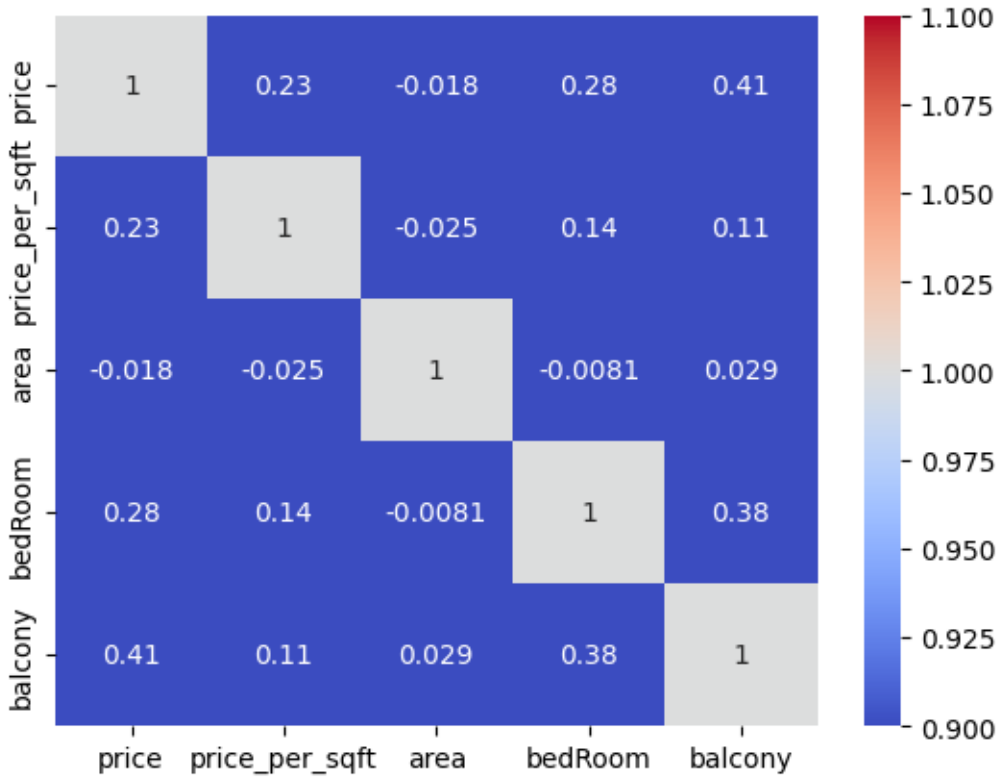
[434]:

	price	price_per_sqft	area	bedRoom	balcony
price	1.275802	-0.223199	0.028487	-0.164645	-0.434261
price_per_sqft	-0.223199	1.062991	0.021546	-0.083053	0.003689
area	0.028487	0.021546	1.002623	0.015929	-0.049571
bedRoom	-0.164645	-0.083053	0.015929	1.202421	-0.380562
balcony	-0.434261	0.003689	-0.049571	-0.380562	1.322808

[435]:
```
# price has high correlation with bedroom means bedroom is the most important␣
↪factor in determing the house of prices
```

[584]:
```
sns.heatmap(df_corr,annot=True,vmin=1,vmax=1,cmap='coolwarm')
```

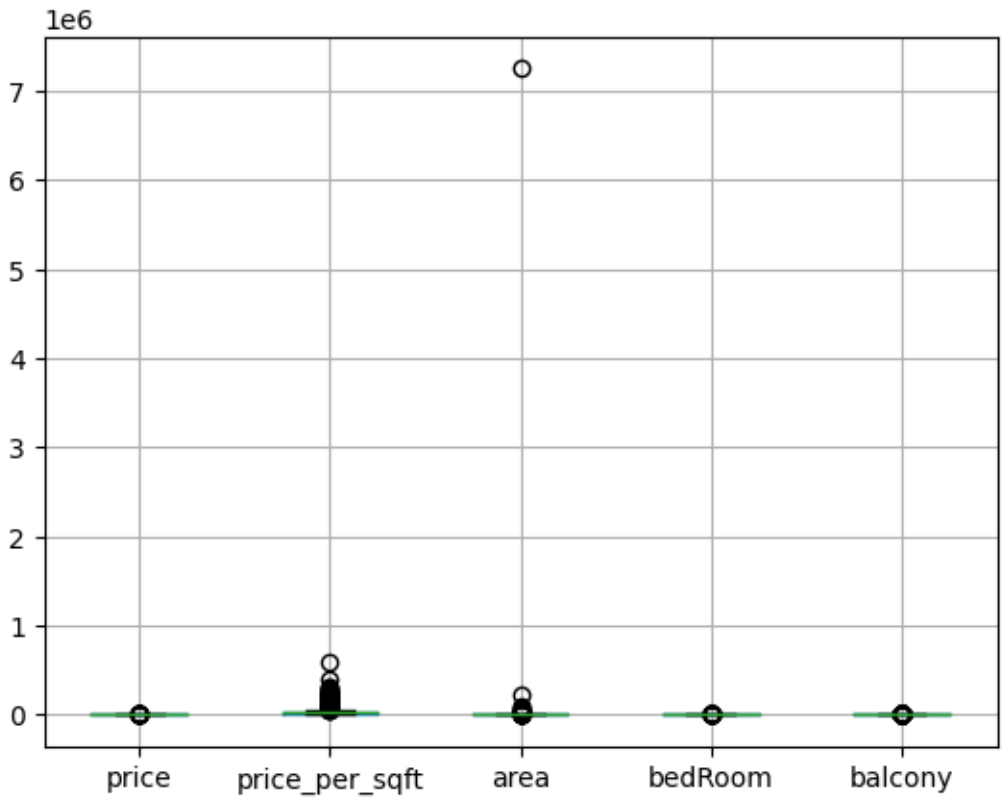
[584]: <Axes: >



5 outliers

[437]:
```
df_price.boxplot(column=['price', 'price_per_sqft', 'area', 'bedRoom',␣
↪'balcony'])
```

[437]: <Axes: >



[438]:
```
# handling outlier
```

[439]:
```
new_df=df_price.copy()
```

[440]:
```
q1=new_df['balcony'].quantile(0.25)
q3=new_df['balcony'].quantile(0.75)
iqr=q3-q1
upper_limit=q1+(1.5*iqr)
lower_limit=q3-(1.5*iqr)
upper_limit,lower_limit
```

[440]: (3.5, 1.5)

[441]:
```
dfr4=new_df.loc[(new_df['balcony']>upper_limit)|(new_df['balcony']<lower_limit)]
```

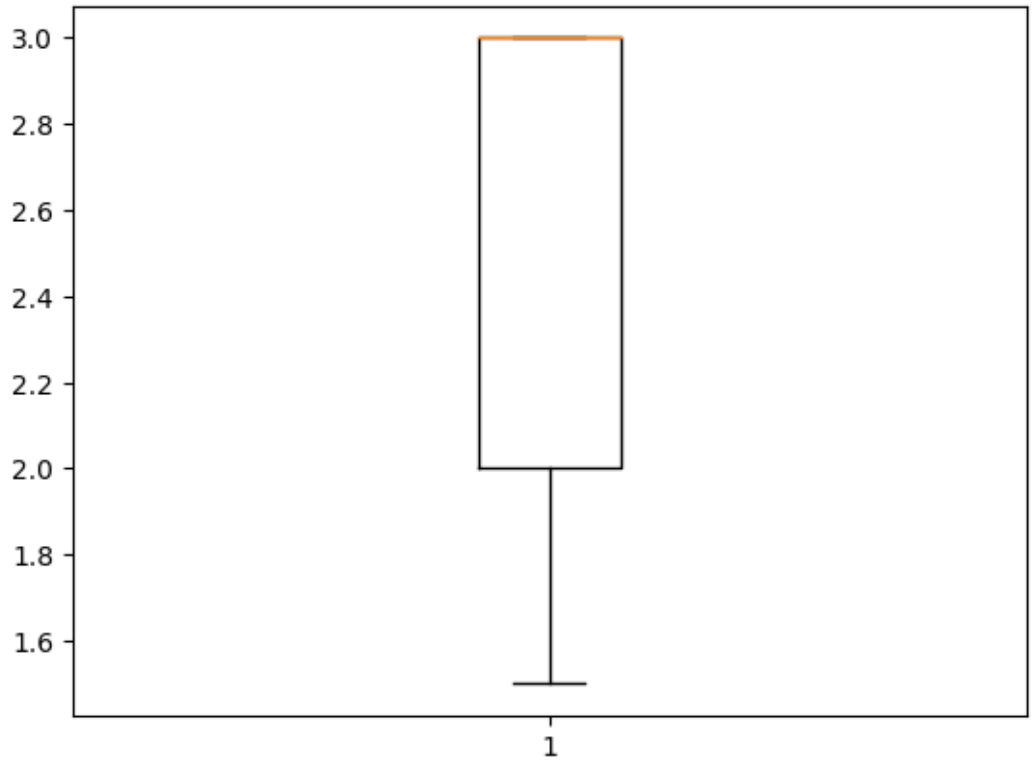
[442]:
```
len(dfr4)
```

[442]: 218

[443]:
```
new_df.loc[(new_df['balcony']>upper_limit,'balcony')]=upper_limit
new_df.loc[(new_df['balcony']<lower_limit,'balcony')]=lower_limit
```

[444]:
```
plt.boxplot(new_df['balcony'])
```

[444]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x1b661368040>,
  <matplotlib.lines.Line2D at 0x1b6613682e0>],
 'caps': [<matplotlib.lines.Line2D at 0x1b661368580>,
  <matplotlib.lines.Line2D at 0x1b661368820>],
 'boxes': [<matplotlib.lines.Line2D at 0x1b661359d60>],
 'medians': [<matplotlib.lines.Line2D at 0x1b661368ac0>],
 'fliers': [<matplotlib.lines.Line2D at 0x1b661368d60>],
 'means': []}
```



[445]:
```
q1=new_df['bedRoom'].quantile(0.25)
q3=new_df['bedRoom'].quantile(0.75)
iqr=q3-q1
upper_limit=q1+(1.5*iqr)
lower_limit=q3-(1.5*iqr)
upper_limit,lower_limit
```

[445]:
```
(7.5, 1.5)
```

[446]:
```
df4=new_df.loc[(new_df['bedRoom']>upper_limit)|(new_df['bedRoom']<lower_limit)]
```

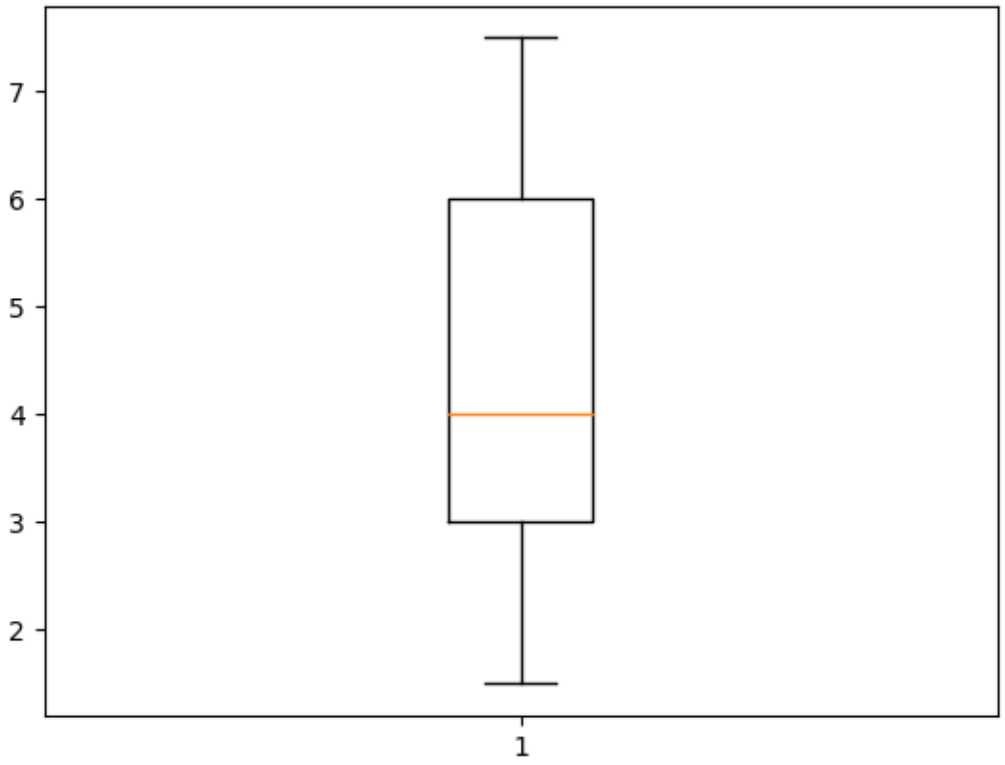
[447]:
```
len(df4)
```

[447]:
```
187
```

[448]:
```
new_df.loc[(new_df['bedRoom']>upper_limit,'bedRoom')]=upper_limit
new_df.loc[(new_df['bedRoom']<lower_limit,'bedRoom')]=lower_limit
```

[449]:
```
plt.boxplot(new_df['bedRoom'])
```

[449]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x1b6613d9340>,
  <matplotlib.lines.Line2D at 0x1b6613d95e0>],
 'caps': [<matplotlib.lines.Line2D at 0x1b6613d9880>,
  <matplotlib.lines.Line2D at 0x1b6613d9b20>],
 'boxes': [<matplotlib.lines.Line2D at 0x1b6613d90a0>],
 'medians': [<matplotlib.lines.Line2D at 0x1b6613d9dc0>],
 'fliers': [<matplotlib.lines.Line2D at 0x1b6613e80a0>],
 'means': []}
```



[450]:
```
q1=new_df['price_per_sqft'].quantile(0.25)
q3=new_df['price_per_sqft'].quantile(0.75)
iqr=q3-q1
upper_limit=q1+(1.5*iqr)
```

```
lower_limit=q3-(1.5*iqr)
upper_limit,lower_limit
```

[450]:
```
(39674.0, 132.0)
```

[451]:
```
dft=new_df.
  ↪loc[(new_df['price_per_sqft']>upper_limit)|(new_df['price_per_sqft']<lower_limit)]
```

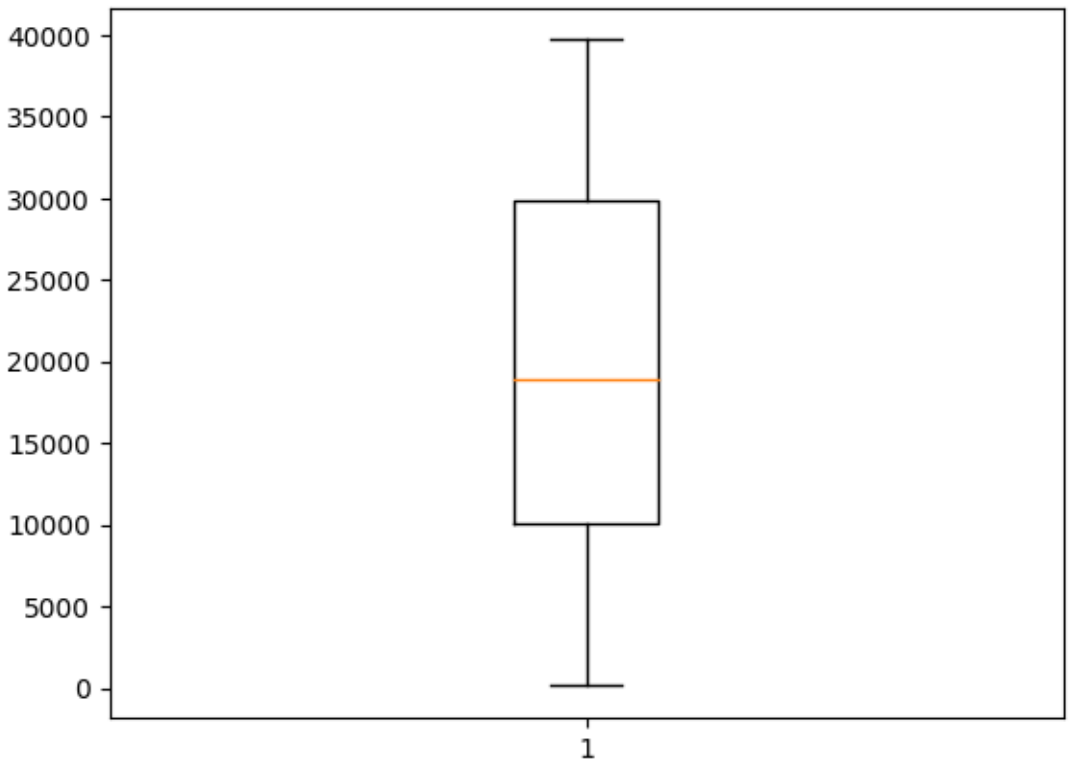
[452]:
```
len(dft)
```

[452]:
```
113
```

[453]:
```
new_df.loc[(new_df['price_per_sqft']>upper_limit),'price_per_sqft']=upper_limit
new_df.loc[(new_df['price_per_sqft']<lower_limit),'price_per_sqft']=lower_limit
```

[454]:
```
plt.boxplot(new_df['price_per_sqft'])
```

[454]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x1b66143f0a0>,
  <matplotlib.lines.Line2D at 0x1b66143f340>],
 'caps': [<matplotlib.lines.Line2D at 0x1b66143f5e0>,
  <matplotlib.lines.Line2D at 0x1b66143f880>],
 'boxes': [<matplotlib.lines.Line2D at 0x1b661431dc0>],
 'medians': [<matplotlib.lines.Line2D at 0x1b66143fb20>],
 'fliers': [<matplotlib.lines.Line2D at 0x1b66143fdc0>],
 'means': []}
```



[493]:
```
q1=new_df['price'].quantile(0.25)
q3=new_df['price'].quantile(0.75)
iqr=q3-q1
upper_limit=q1+(1.5*iqr)
lower_limit=q3-(1.5*iqr)
upper_limit,lower_limit
```

[493]: (9.92, -1.7599999999999998)

[494]:
```
df9=new_df.loc[(new_df['price']>upper_limit)|(new_df['price']<lower_limit)]
```

[495]:
```
len(df9)
```

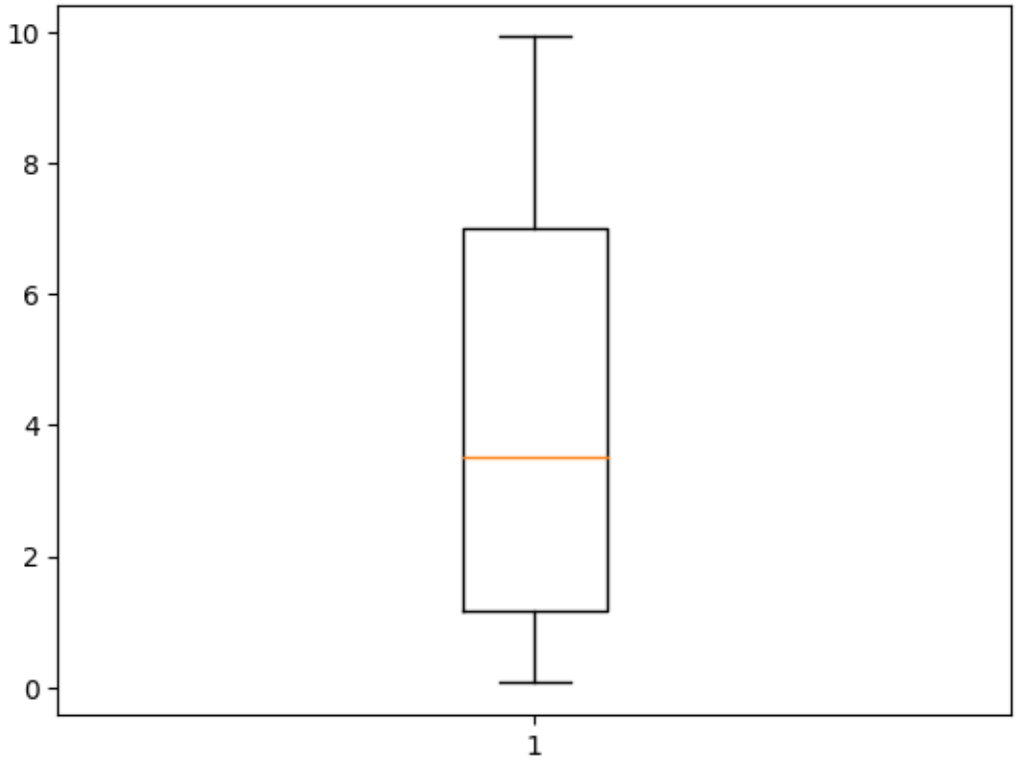
[495]: 118

[496]:
```
new_df.loc[(new_df['price']>upper_limit),'price']=upper_limit
new_df.loc[(new_df['price']<lower_limit),'price']=lower_limit
```

[497]:
```
plt.boxplot(new_df['price'])
```

[497]: {'whiskers': [<matplotlib.lines.Line2D at 0x1b6577db9a0>,
<matplotlib.lines.Line2D at 0x1b65c1a1b80>],

```
'caps': [<matplotlib.lines.Line2D at 0x1b65c1a1bb0>,
 <matplotlib.lines.Line2D at 0x1b65c1a11f0>],
'boxes': [<matplotlib.lines.Line2D at 0x1b65c664a90>],
'medians': [<matplotlib.lines.Line2D at 0x1b65c1a1e50>],
'fliers': [<matplotlib.lines.Line2D at 0x1b65c1a1940>],
'means': []}
```



[ ]:

[478]:
```
q1=new_df['area'].quantile(0.25)
q3=new_df['area'].quantile(0.75)
iqr=q3-q1
upper_Limit=q3+(1.5*iqr)
lower_limit=q1-(1.5*iqr)
upper_limit,lower_limit
```

[478]: (39674.0, -2465.0)

[479]:
```
# printing outlier in area
df5=new_df.loc[(new_df['area']>upper_limit)|(new_df['area']<lower_limit)]
```

[480]:
```
len(df5)
```

[480]: 0

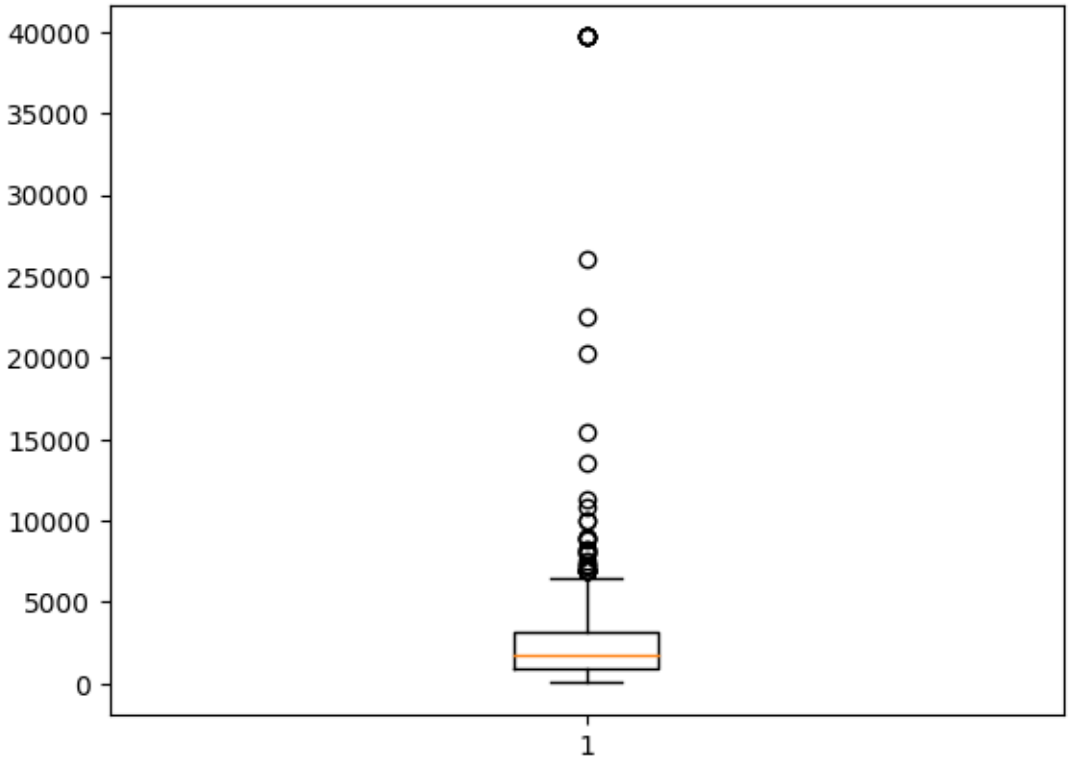
[481]:
```
new_df.loc[(new_df['area']>upper_limit),'area']=upper_limit
new_df.loc[(new_df['area']<lower_limit),'area']=lower_limit
```

[482]:
```
len(df5)
```

[482]: 0

[498]:
```
plt.boxplot(new_df['area'])
```

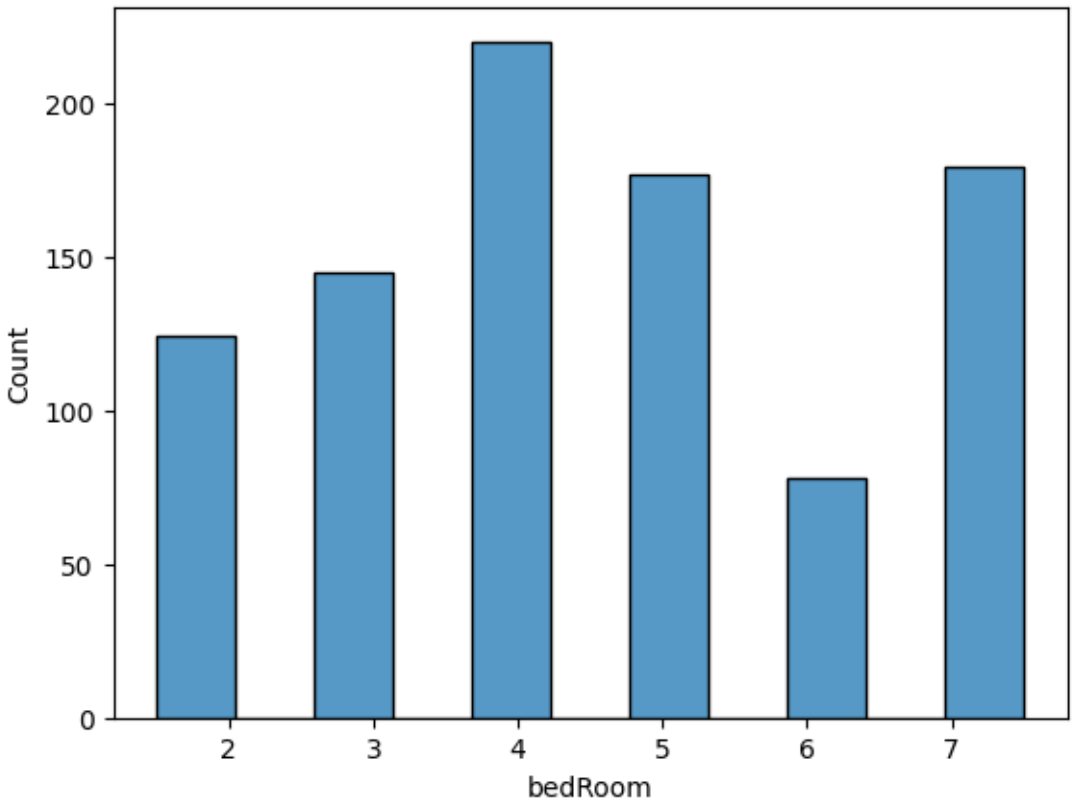
[498]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x1b65d5647f0>,
  <matplotlib.lines.Line2D at 0x1b65d564940>],
 'caps': [<matplotlib.lines.Line2D at 0x1b65d564bb0>,
  <matplotlib.lines.Line2D at 0x1b65d564d00>],
 'boxes': [<matplotlib.lines.Line2D at 0x1b65d564400>],
 'medians': [<matplotlib.lines.Line2D at 0x1b65d5640a0>],
 'fliers': [<matplotlib.lines.Line2D at 0x1b6631c3730>],
 'means': []}
```



6 visualization

[460]:
```
sns.histplot(x='bedRoom',data=new_df) # most house has 4 bedroom,the houses␣
↪with 6 bed isnt much
```

[460]:
```
<Axes: xlabel='bedRoom', ylabel='Count'>
```

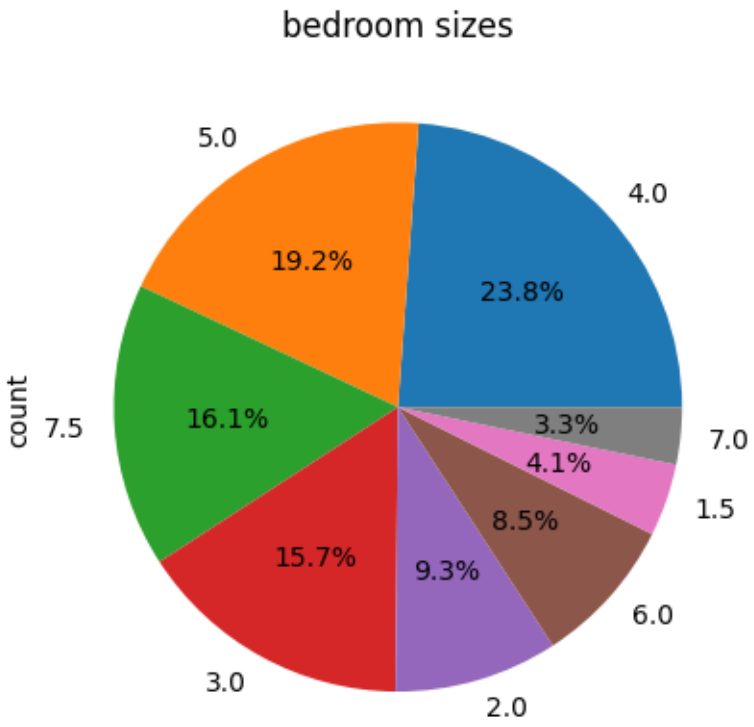


[461]:
```
new_df['bedRoom'].unique()
```

[461]:
```
array([5. , 7.5, 6. , 3. , 4. , 7. , 2. , 1.5])
```

[462]:
```
value_df=new_df['bedRoom'].value_counts().plot(kind='pie',autopct='%1.1f%%')
plt.title( 'bedroom sizes')
# 23% of houses in gurgaon has 4 bedroom, it means people prefer house with 4␣
↪bedroom or people buy houses with 4 bedroom
# 1.5 bed are of low demand
```

[462]:
```
Text(0.5, 1.0, 'bedroom sizes')
```



[463]:
```
new_df.head()
```

[463]:

	price	price_per_sqft	area	bedRoom	balcony
0	5.25	20115.0	2610.0	5.0	3.0
1	5.70	39674.0	539.0	5.0	2.0
2	2.10	38251.0	549.0	7.5	3.0
3	5.00	39674.0	1161.0	7.5	3.0
4	3.00	39674.0	558.0	7.5	3.0

[464]:
```
bal_value=new_df['balcony'].value_counts()
```

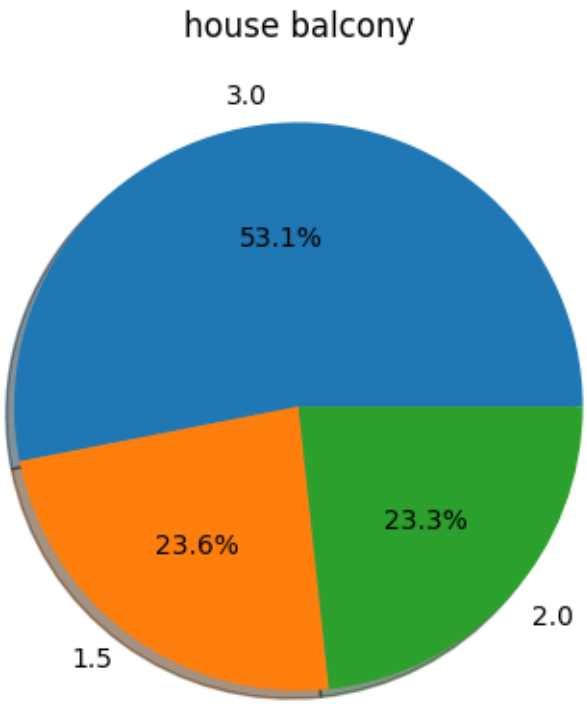
[465]:
```
bal_value
```

[465]:
```
balcony
3.0    490
1.5    218
2.0    215
Name: count, dtype: int64
```

[466]:
```
plt.pie(bal_value,autopct='%1.1f%%', labels=[3.0,1.5,2.0],shadow=True)
plt.title('house balcony')
```

```
# 53% of most house in gurgaon has 3 balconies in it ,they prefer houses with␣
 ↪more balcony
```

[466]: Text(0.5, 1.0, 'house balcony')



[467]:
```
new_df['balcony'].unique()
```

[467]: array([3. , 2. , 1.5])

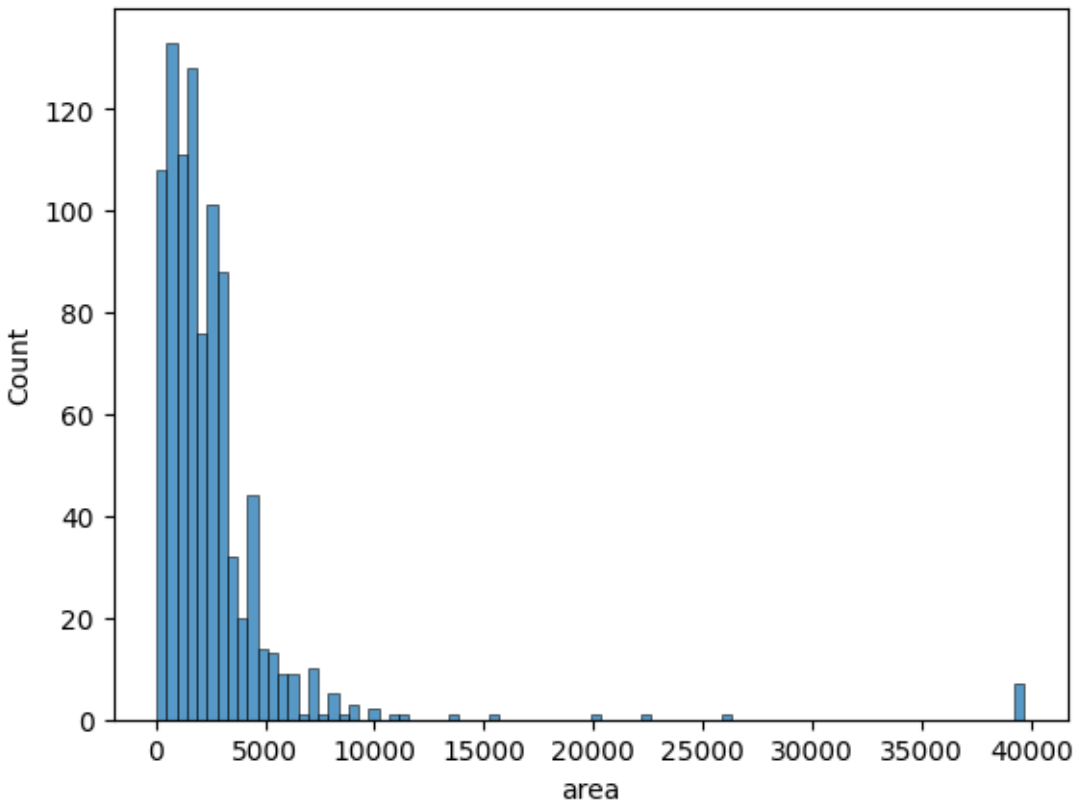
[468]:
```
new_df.head()
```

[468]:

	price	price_per_sqft	area	bedRoom	balcony
0	5.25	20115.0	2610.0	5.0	3.0
1	5.70	39674.0	539.0	5.0	2.0
2	2.10	38251.0	549.0	7.5	3.0
3	5.00	39674.0	1161.0	7.5	3.0
4	3.00	39674.0	558.0	7.5	3.0

[501]:
```
sns.histplot(x='area',data=new_df)
```

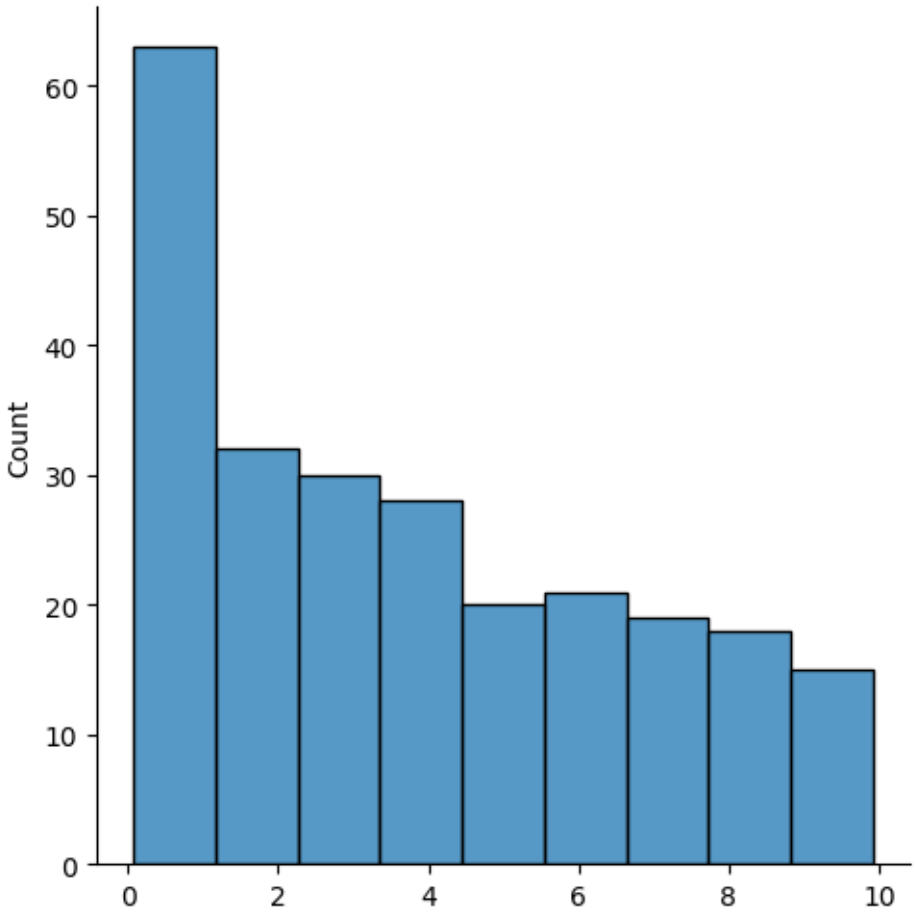
[501]: <Axes: xlabel='area', ylabel='Count'>



[503]:
```
df6=new_df['price'].unique()
```

[505]:
```
sns.displot(df6)
# the price of houses in gurgaon is decreasing with time
# from 9.9 to 0.07, thats alot of decrease
```

[505]: <seaborn.axisgrid.FacetGrid at 0x1b6643111c0>



[507]:
```
new_df['price'].agg(['min','max'])
```

[507]:
```
min    0.07
max    9.92
Name: price, dtype: float64
```

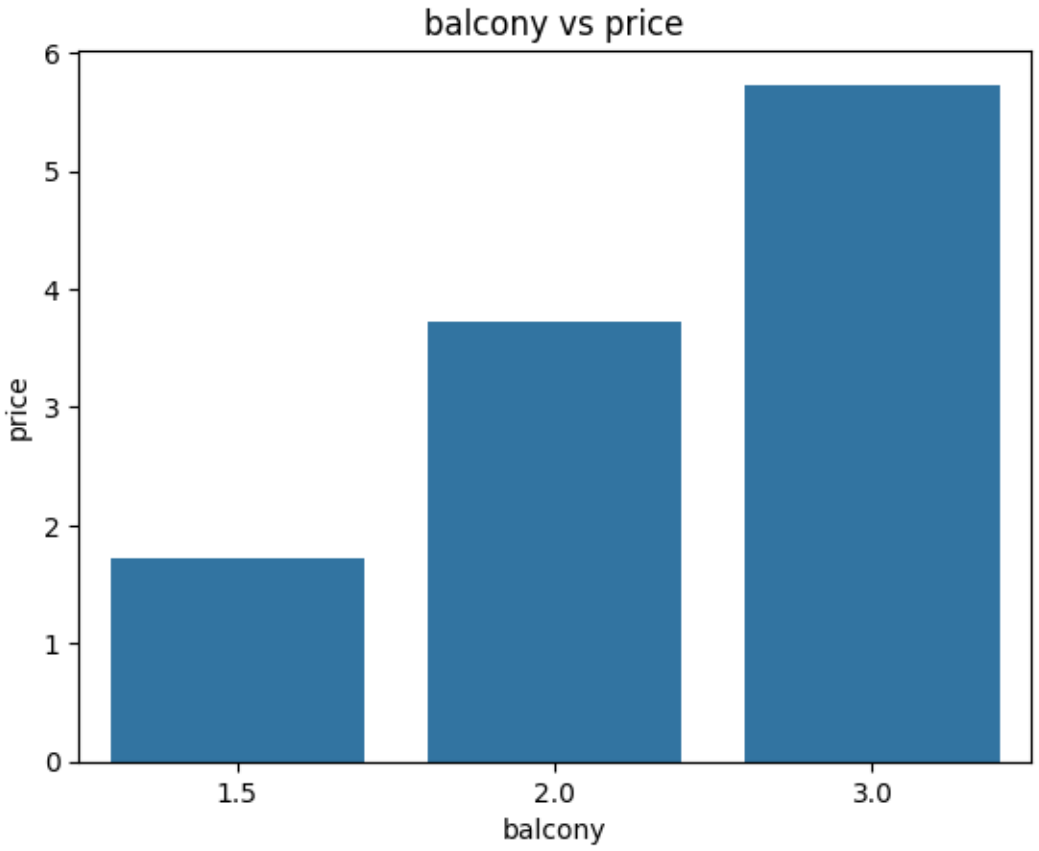
[508]:
```
df6 #unique house prices
```

[508]:
```
array([5.25, 5.7 , 2.1 , 5.  , 3.  , 4.5 , 9.92, 1.95, 4.45, 9.  , 8.25,
       2.  , 7.35, 3.4 , 8.4 , 8.5 , 7.6 , 7.  , 4.75, 3.5 , 5.46, 3.3 ,
       7.2 , 6.  , 5.8 , 0.55, 7.49, 6.25, 5.4 , 5.75, 2.55, 5.6 , 7.99,
       3.75, 7.25, 3.55, 2.5 , 6.5 , 9.5 , 5.5 , 5.65, 8.8 , 3.25, 7.5 ,
       0.67, 3.2 , 7.69, 1.55, 3.85, 3.1 , 2.25, 8.7 , 6.8 , 6.2 , 3.6 ,
       3.05, 5.9 , 5.85, 4.  , 5.35, 6.6 , 6.3 , 0.65, 0.85, 0.58, 0.61,
       7.05, 3.69, 6.95, 4.02, 1.  , 0.66, 0.7 , 1.45, 0.95, 0.9 , 0.45,
       0.6 , 3.93, 0.75, 2.75, 0.5 , 0.42, 0.48, 0.35, 2.4 , 2.2 , 1.1 ,
       8.  , 0.82, 1.3 , 0.36, 0.8 , 0.15, 2.8 , 1.75, 1.16, 0.34, 1.5 ,
       0.37, 1.15, 0.49, 1.6 , 0.62, 4.12, 1.87, 1.2 , 0.3 , 1.35, 4.7 ,
```

```
0.22, 1.65, 2.3 , 1.25, 1.7 , 3.12, 0.07, 2.58, 2.95, 8.95, 0.51,
0.53, 0.63, 1.72, 1.8 , 0.32, 0.78, 1.52, 1.05, 1.4 , 5.15, 0.92,
0.52, 4.25, 1.85, 4.65, 6.1 , 0.68, 1.07, 4.6 , 5.2 , 0.4 , 4.3 ,
0.43, 0.47, 0.71, 0.38, 1.44, 3.71, 0.18, 3.08, 0.29, 0.24, 0.44,
0.83, 0.98, 3.35, 3.09, 3.15, 0.74, 0.69, 2.43, 0.13, 0.96, 1.9 ,
0.89, 1.34, 9.9 , 2.15, 0.46, 2.6 , 3.87, 1.39, 0.59, 2.9 , 6.75,
0.27, 8.1 , 9.54, 3.65, 7.46, 3.99, 6.81, 8.81, 8.9 , 4.49, 4.15,
7.3 , 4.35, 8.31, 6.21, 1.83, 5.1 , 3.9 , 2.01, 9.25, 5.88, 6.4 ,
3.51, 9.4 , 8.45, 6.15, 2.47, 3.7 , 4.4 , 0.99, 2.65, 1.27, 8.49,
4.31, 8.48, 8.2 , 5.51, 3.49, 2.99, 9.19, 1.64, 9.35, 4.05, 8.75,
2.45, 7.85, 2.68, 2.7 , 1.04, 9.85, 1.18, 9.01, 9.8 , 4.95, 4.99,
7.1 , 8.6 , 9.55, 2.35, 5.3 , 4.1 , 7.65, 6.46, 6.44, 7.8 , 3.8 ,
7.45, 7.42, 6.09, 2.98])
```

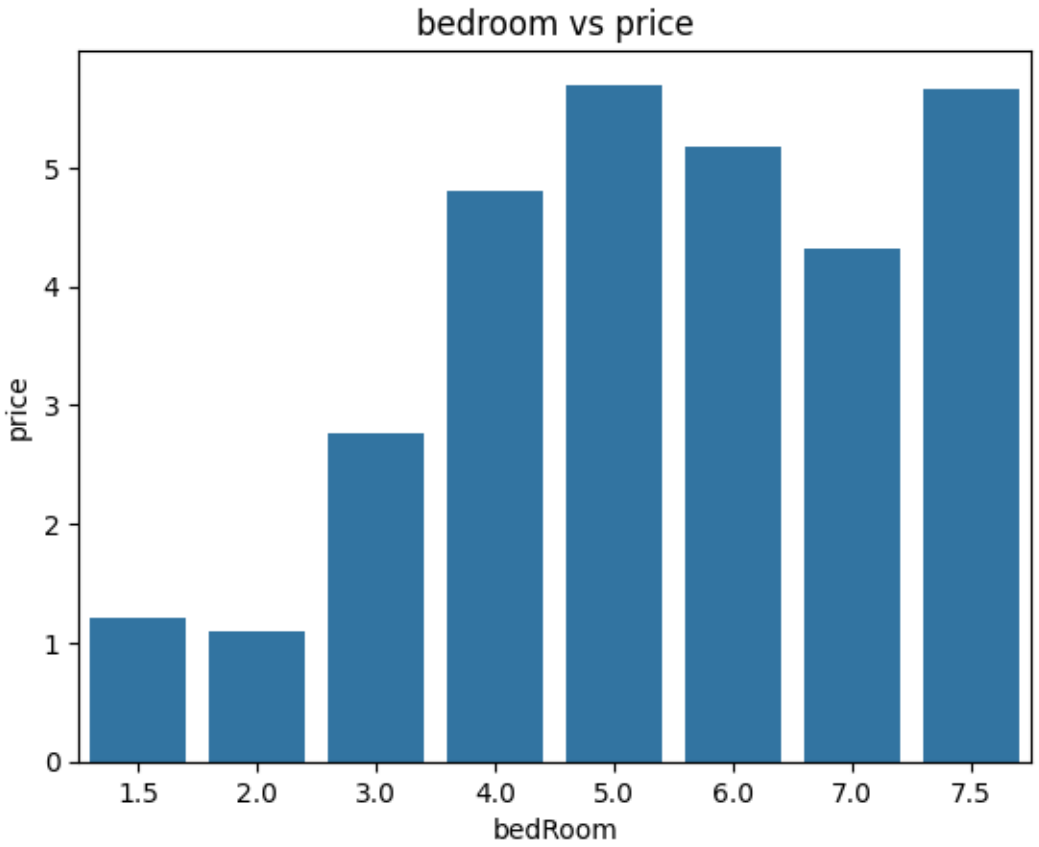
[513]:
```
sns.barplot(x='balcony',y='price',data=new_df,ci=None)
plt.title('balcony vs price')
```

[513]:
```
Text(0.5, 1.0, 'balcony vs price')
```



[516]:
```
sns.barplot(x='bedRoom',y='price',data=new_df,ci=None)
plt.title( 'bedroom vs price')
```

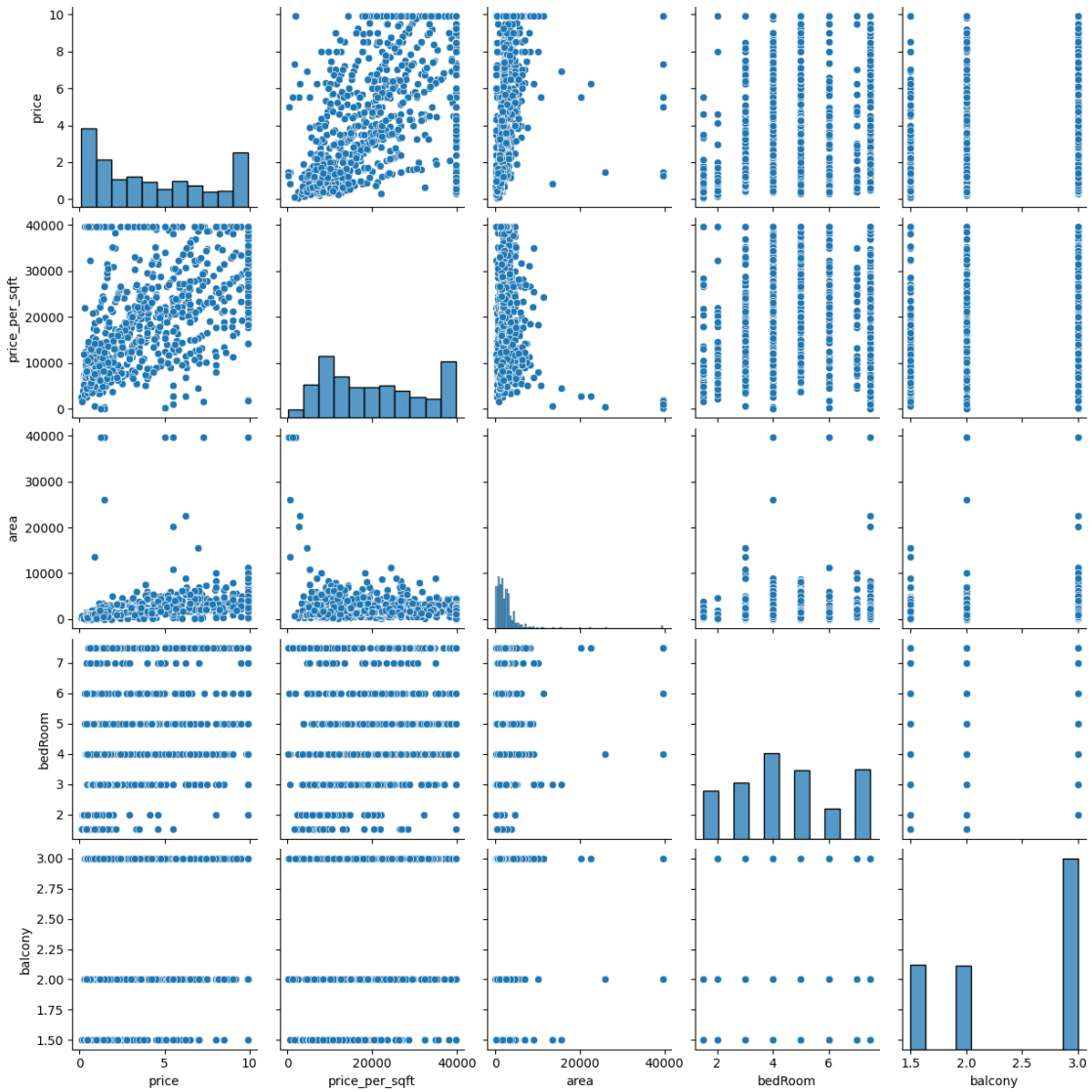
[516]:
```
Text(0.5, 1.0, 'bedroom vs price')
```



[517]:
```
# overall visualization
```

[509]:
```
sns.pairplot(new_df)
```

[509]:
```
<seaborn.axisgrid.PairGrid at 0x1b664394040>
```



[518]:
```
new_df.columns
```

[518]:
```
Index(['price', 'price_per_sqft', 'area', 'bedRoom', 'balcony'], dtype='object')
```

[519]:
```
x=new_df[['price_per_sqft', 'area', 'bedRoom', 'balcony']]
y=new_df['price']
```

7 data spliting

[520]:
```
from sklearn .model_selection import train_test_split
```

[522]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=1)
```

8 normalization

[524]:
```
from sklearn .preprocessing import MinMaxScaler
```

[526]:
```
scaler=MinMaxScaler(feature_range=(0,1))
```

[527]:
```
x_train=scaler.fit_transform(x_train)
x_test=scaler.transform(x_test)
```

[528]:
```
x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

[528]:
```
((738, 4), (185, 4), (738,), (185,))
```

9 model building

[529]:
```
from sklearn .linear_model import LinearRegression
```

[530]:
```
house_model=LinearRegression()
```

[531]:
```
house_model.fit(x_train,y_train)
```

[531]:
```
LinearRegression()
```

[532]:
```
house_model.score(x_train,y_train)
```

[532]:
```
0.5786230767343259
```

[534]:
```
ypred=house_model.predict(x_test)
```

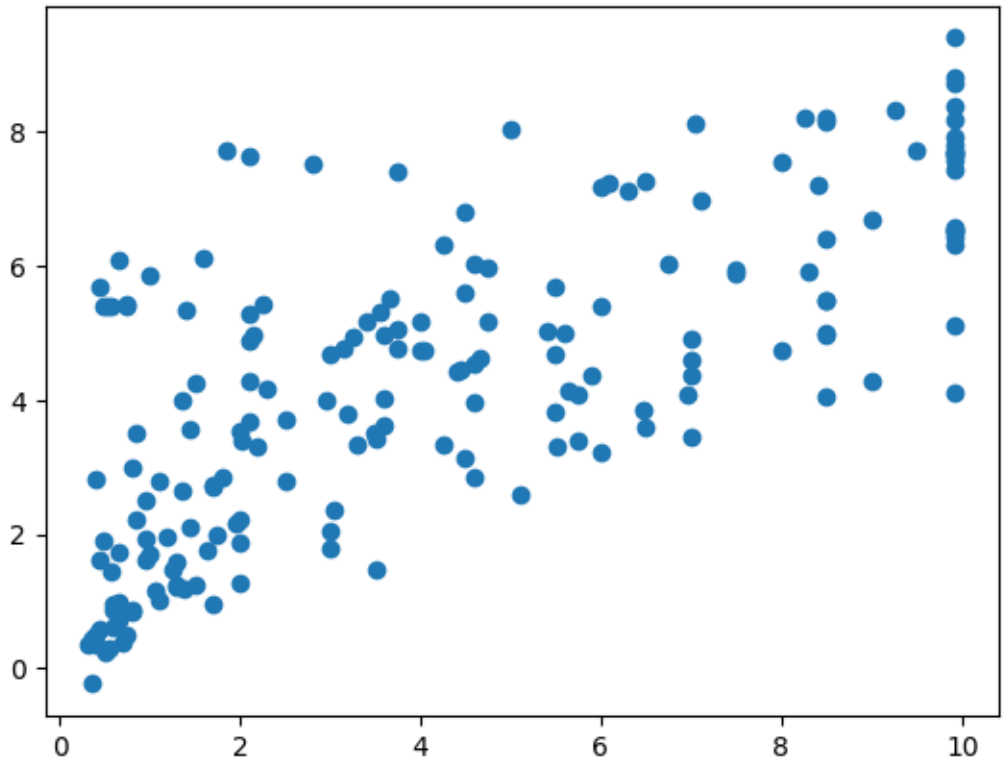
[535]:
```
from sklearn.metrics import r2_score
```

[536]:
```
r2_score(y_test,ypred)
```

[536]:
```
0.5250483038302602
```

[539]:
```
plt.scatter(y_test,ypred)
```

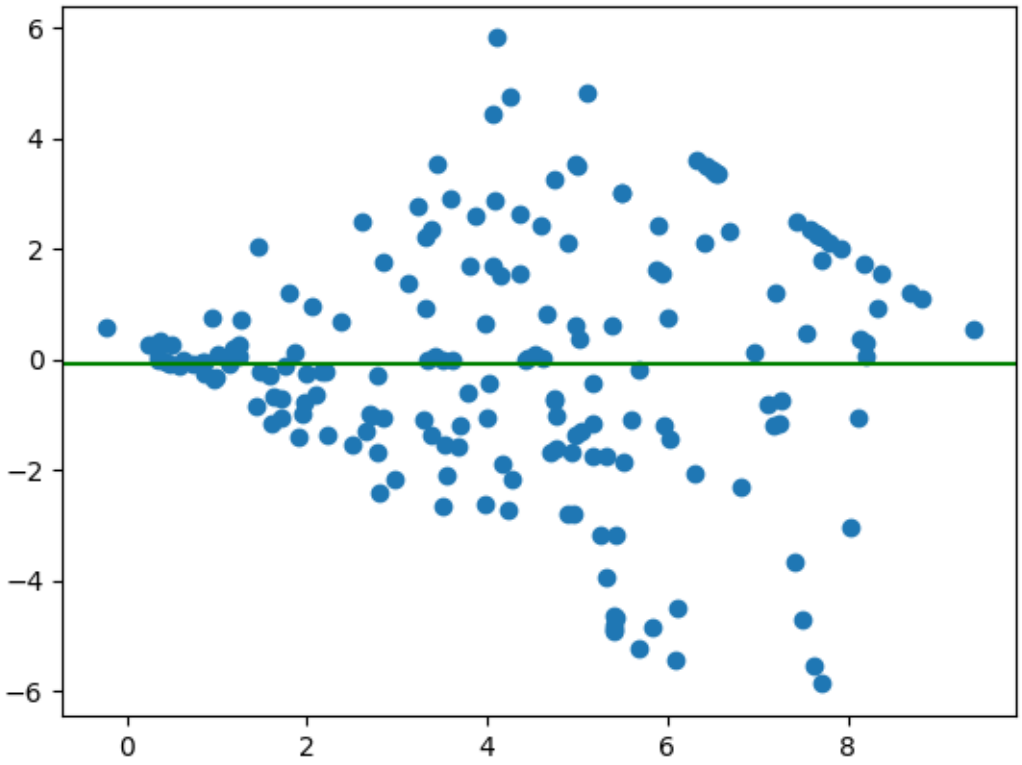
[539]:
```
<matplotlib.collections.PathCollection at 0x1b6687c4700>
```



[543]:
```
residuals=y_test-ypred
```

[546]:
```
plt.scatter(ypred,residuals)
plt.axhline(residuals.mean(),color='green') # no residual found
```

[546]:
```
<matplotlib.lines.Line2D at 0x1b657d82f70>
```



[ ]:

[550]:
```
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR
```

[594]:
```
knn=KNeighborsRegressor(n_neighbors=3)
```

[595]:
```
knn.fit(x_train,y_train)
```

[595]:
```
KNeighborsRegressor(n_neighbors=3)
```

[596]:
```
knn.score(x_train,y_train)
```

[596]:
```
0.8796200149822822
```

[597]:
```
sv=SVR()
```

[598]:
```
sv.fit(x_train,y_train)
```

[598]:
```
SVR()
```

[599]:
```
sv.score(x_train,y_train)
```

[599]: 0.7577462942070485

10 from the above models, knn model is doing better than all other model, therefore, chose knn for this analysis

[600]:
```
y_pred=knn.predict(x_test)
```

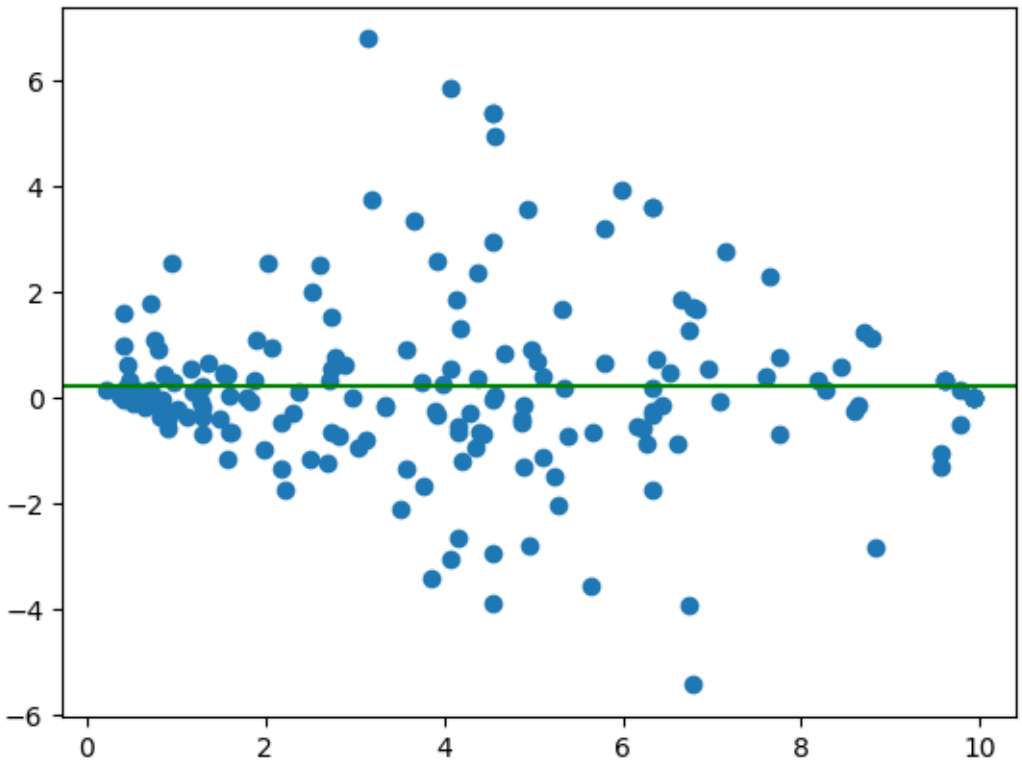
[601]:
```
r2_score(y_test,y_pred)
```

[601]: 0.7217234777561636

[615]:
```
residual=y_test-y_pred
```

[616]:
```
plt.scatter(y_pred,residual)
plt.axhline(residual.mean(),color='green') # no residual found
```

[616]: <matplotlib.lines.Line2D at 0x1b66b8e9f10>



11 knn evaluation

[602]:
```
from sklearn.metrics import mean_squared_error
```

[603]:
```
mean_squared_error(y_test,y_pred)
```

[603]:
```
2.8555503303303302
```

[604]:
```
np.sqrt(mean_squared_error(y_test,y_pred))
```

[604]:
```
1.6898373680121794
```

[605]:
```
# the error in the model is less than 5, this model i great
```

12 model validation

[606]:
```
from sklearn.model_selection import KFold,cross_val_score
```

[607]:
```
kf=KFold(n_splits=5)
```

[608]:
```
score=cross_val_score(knn, x_train,y_train,cv=kf)
```

[609]:
```
score # model did great after being trained 5 times
```

[609]:
```
array([0.7284731 , 0.60718697, 0.59428468, 0.75164998, 0.76069795])
```

13 model testing

[613]:
```
knn.predict(scaler.transform([[38251.0,        549.0,        7.5,        3.0]]))
```

[613]:
```
array([5.65])
```

[614]:
```
knn.predict(scaler.transform([[20115.0        ,2610.0,        5.0        ,3.
↪0]])) # nicely predicted
```

[614]:
```
array([4.5])
```

14 conclusion

[583]:
```
# model is ready for use
```

[ ]:
```

```