# Exploratory Data Analysis -Real Estate Industry in Bangladesh

EDA summary (Group 3) In this EDA we tried to answer the following questions:

Question 4

a) How do property prices fluctuate for same location?

b) How do property prices fluctuate for same property size?

c) How do property prices fluctuate for same / similar amenities?

Answer Summary :

- 4.a) Average price for different cities observed very much fluctuating there is no pattern observed . Mean value followed range 0.2 to 0.5*10^7
- 4.b) Relation between price Vs Property size observed Linear for 80% data, after removing missing values ,
  - Missing values area Price-3%, area-6.37%
- 4.C) Answer in 7c & d

Question 7

a) Which amenities are the more frequent in Residential properties ?

- the percentage contribution of each amenity in Residential properties. The top Three amenities were "expendable_amenity_count" (26.9%),"maintenance_or_cleaning_amenity_count" (17.8%), "security_amenity_count" (17.6%), Unclassified amenities 41.45%t

b) Which amenities are the more frequent in Commercial properties ?

- the percentage contribution of each amenity in Commercialproperties. The top Three amenities were "expendable_amenity_count" (25.9%),"maintenance_or_cleaning_amenity_count" (17.6%), "security_amenity_count"(11.2%), Unclassified amenities 41.7%

c) & d) Which amenities have the more impact on price?

- security_amenity_count,maintenance_or_cleaning_amenity_count
  expendable_amenity_count OBSERVED Moderately positively co-related (0.35) with price and others amenities has no Relation with price

## Importing Required Libararies

```
pip install fancyimpute
```

```
# Importing required libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure
import plotly.express as px
from sklearn.impute import KNNImputer
import missingno as msno
import xgboost as xgb
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
from sklearn.linear_model import LinearRegression
from fancyimpute import KNN
```

## Basic Exploration of Real Estate Industry in Bangladesh

```
df=pd.read_csv(r"/content/drive/MyDrive/merged_datasets.csv")
df.head(10)
```

```
<ipython-input-39-01b66f3149a6>:1: DtypeWarning:

Columns (3,8) have mixed types. Specify dtype option on import or set low_memory=F
```

| | area | building_type | building_nature | image_url | num_bath_ |
|---|---|---|---|---|---|
| **0** | 1185.0 | Apartment | Residential | https://images-cdn.bproperty.com/thumbnails/15... | |
| **1** | 2464.0 | Apartment | Residential | https://images-cdn.bproperty.com/thumbnails/15... | |
| **2** | 1140.0 | Apartment | Residential | https://images-cdn.bproperty.com/thumbnails/15... | |
| **3** | 1920.0 | Apartment | Residential | https://images-cdn.bproperty.com/thumbnails/15... | |
| **4** | 1445.0 | Apartment | Residential | https://images-cdn.bproperty.com/thumbnails/15... | |
| **5** | 925.0 | Apartment | Residential | https://images-cdn.bproperty.com/thumbnails/15... | |
| **6** | 2468.0 | Apartment | Residential | https://images-cdn.bproperty.com/thumbnails/15... | |
| **7** | 1475.0 | Apartment | Residential | https://images-cdn.bproperty.com/thumbnails/15... | |
| **8** | 1066.0 | Apartment | Residential | https://images-cdn.bproperty.com/thumbnails/13... | |
| **9** | 950.0 | Apartment | Residential | https://images- | |

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35646 entries, 0 to 35645
Data columns (total 24 columns):
 #   Column                              Non-Null Count  Dtype  
---  ------                              --------------  -----  
 0   area                                33374 non-null  float64
 1   building_type                       35465 non-null  object 
 2   building_nature                     35646 non-null  object 
 3   image_url                           17312 non-null  object 
 4   num_bath_rooms                      35646 non-null  float64
 5   num_bed_rooms                       35646 non-null  float64
 6   price                               34578 non-null  float64
 7   property_description                18259 non-null  object 
 8   property_overview                   17553 non-null  object 
 9   property_url                        35621 non-null  object 
 10  purpose                             35632 non-null  object 
 11  city                                35110 non-null  object 
 12  locality                            35046 non-null  object 
 13  address                             30507 non-null  object 
 14  id                                  35646 non-null  object 
 15  garage                              35646 non-null  float64
 16  year_built                          256 non-null    float64
 17  relaxation_amenity_count            35646 non-null  int64  
 18  security_amenity_count              35646 non-null  int64  
 19  maintenance_or_cleaning_amenity_count  35646 non-null  int64  
 20  social_amenity_count                35646 non-null  int64  
 21  expendable_amenity_count            35646 non-null  int64  
 22  service_staff_amenity_count         35646 non-null  int64  
 23  unclassify_amenity_count            35646 non-null  int64  
dtypes: float64(6), int64(7), object(11)
memory usage: 6.5+ MB
```

# Exploring features

## Numerical Features

1. Area
2. num_bath_rooms
3. num_bed_rooms
4. price
5. garage
6. year_built
7. relaxation_amenity_count
8. security_amenity_count
9. maintenance_or_cleaning_amenity_count
10. social_amenity_count
11. Expendable_amenity_count
12. Service_staff_amenity_count
13. Unclassify_amenity_count

[ ] ↳ *1 cell hidden*

## Categorical Features

1. building_type
2. building_nature
3. image_url
4. property_description
5. property_overview
6. property_url
7. purpose
8. city
9. locality
10. address
11. id

[ ] ↳ *5 cells hidden*

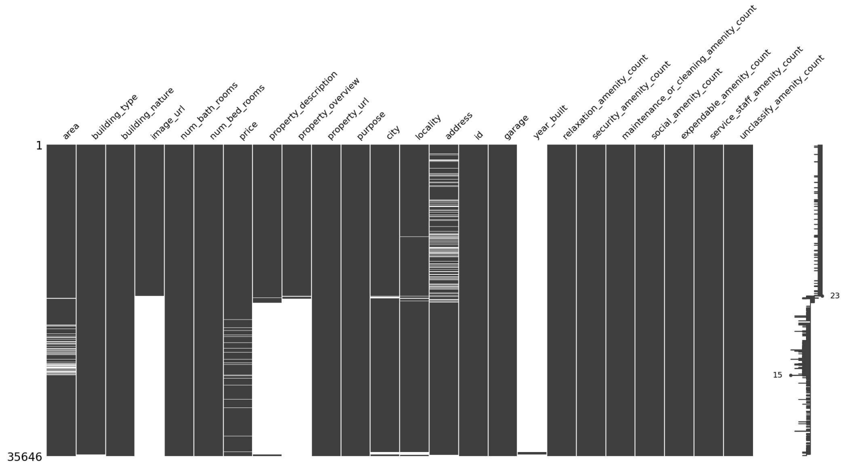
## Dealing With Missing Values

```
df.isnull().sum() # Gives Count of Missing values in perticular column
```

```
area                                      2272
building_type                              181
building_nature                              0
image_url                                18334
num_bath_rooms                               0
num_bed_rooms                                0
price                                     1068
property_description                     17387
property_overview                        18093
property_url                                25
purpose                                     14
city                                       536
locality                                   600
address                                   5139
id                                           0
garage                                       0
year_built                               35390
relaxation_amenity_count                     0
security_amenity_count                       0
maintenance_or_cleaning_amenity_count        0
social_amenity_count                         0
expendable_amenity_count                     0
service_staff_amenity_count                  0
unclassify_amenity_count                     0
dtype: int64
```

```
msno.matrix(df) # visualization of missing values
```

```
<Axes: >
```

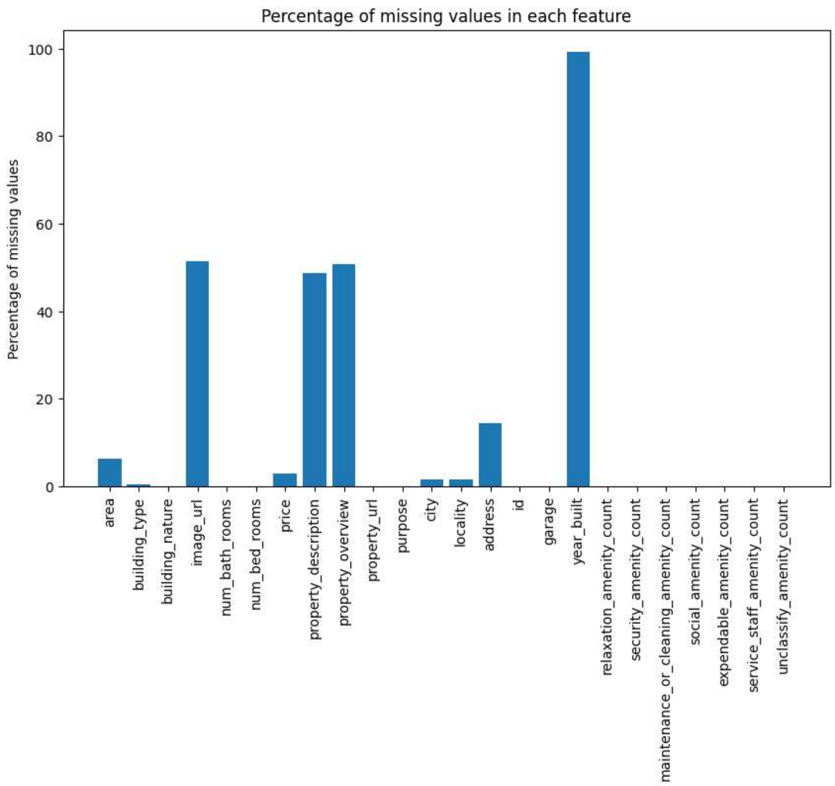



```
(df.isna().mean() * 100).round(2)
```

```
area                                     6.37
building_type                            0.51
building_nature                          0.00
image_url                               51.43
num_bath_rooms                           0.00
num_bed_rooms                            0.00
price                                    3.00
property_description                    48.78
property_overview                       50.76
property_url                             0.07
purpose                                  0.04
city                                     1.50
locality                                 1.68
address                                 14.42
id                                       0.00
garage                                   0.00
year_built                              99.28
relaxation_amenity_count                 0.00
security_amenity_count                   0.00
maintenance_or_cleaning_amenity_count    0.00
```

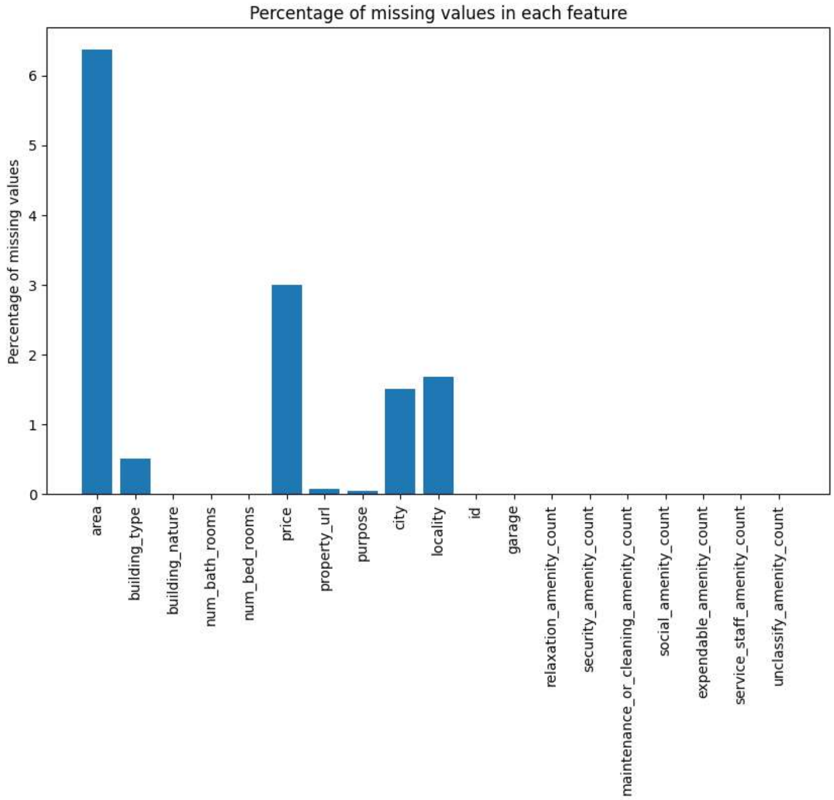
```
social_amenity_count                  0.00
expendable_amenity_count              0.00
service_staff_amenity_count           0.00
unclassify_amenity_count              0.00
dtype: float64
```

```
missing_percentages = (df.isna().mean() * 100).round(2)
plt.figure(figsize=(10,6))
plt.bar(missing_percentages.index, missing_percentages.values)
plt.xticks(rotation=90)
plt.ylabel('Percentage of missing values')
plt.title('Percentage of missing values in each feature')
plt.show()
```



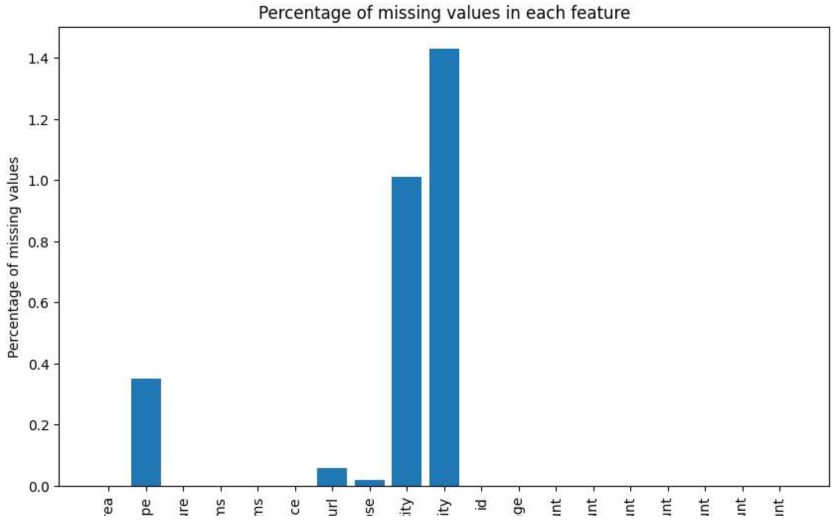

```
threshold = len(df) * 0.9 # set the threshold to 60% non-missing values
df.dropna(thresh=threshold, axis=1, inplace=True)
```

```
missing_percentages = (df.isna().mean() * 100).round(2)
plt.figure(figsize=(10,6))
plt.bar(missing_percentages.index, missing_percentages.values)
plt.xticks(rotation=90)
plt.ylabel('Percentage of missing values')
plt.title('Percentage of missing values in each feature')
plt.show()
```




```
from fancyimpute import IterativeImputer
# Area & Price fill with missing N-Computing technique
df1=df.loc[:,["price","area"]]
df3 = df1.copy(deep=True)
MICE_imputer = IterativeImputer()
df3.iloc[:, :] = MICE_imputer.fit_transform(df3)
df['price']=df3['price']
df['area']=df3['area']
```

```
missing_percentages = (df.isna().mean() * 100).round(2)
plt.figure(figsize=(10,6))
plt.bar(missing_percentages.index, missing_percentages.values)
plt.xticks(rotation=90)
plt.ylabel('Percentage of missing values')
plt.title('Percentage of missing values in each feature')
plt.show()
```




```
(df.isna().mean() * 100).round(2)
```

```
area                                  0.00
building_type                         0.51
building_nature                       0.00
num_bath_rooms                        0.00
num_bed_rooms                         0.00
price                                 0.00
property_url                          0.07
purpose                               0.04
city                                  1.50
locality                              1.68
id                                    0.00
garage                                0.00
relaxation_amenity_count              0.00
security_amenity_count                0.00
maintenance_or_cleaning_amenity_count 0.00
social_amenity_count                  0.00
expendable_amenity_count              0.00
service_staff_amenity_count           0.00
unclassify_amenity_count              0.00
dtype: float64
```

```
df.isnull().sum()
```

```
area                                     0
building_type                          181
building_nature                          0
num_bath_rooms                           0
num_bed_rooms                            0
price                                    0
property_url                            25
purpose                                 14
city                                   536
locality                               600
id                                       0
garage                                   0
relaxation_amenity_count                 0
security_amenity_count                   0
maintenance_or_cleaning_amenity_count    0
social_amenity_count                     0
expendable_amenity_count                 0
service_staff_amenity_count              0
unclassify_amenity_count                 0
dtype: int64
```

```
df.info()
```

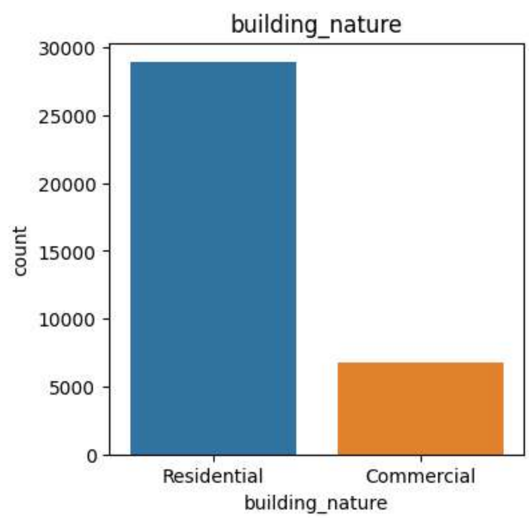
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35646 entries, 0 to 35645
Data columns (total 19 columns):
 #   Column                                 Non-Null Count  Dtype
---  ------                                 --------------  -----
 0   area                                   35646 non-null  float64
 1   building_type                          35465 non-null  object
 2   building_nature                        35646 non-null  object
 3   num_bath_rooms                         35646 non-null  float64
 4   num_bed_rooms                          35646 non-null  float64
 5   price                                  35646 non-null  float64
```

```
 6   property_url                         35621 non-null  object
 7   purpose                              35632 non-null  object
 8   city                                 35110 non-null  object
 9   locality                             35046 non-null  object
 10  id                                   35646 non-null  object
 11  garage                               35646 non-null  float64
 12  relaxation_amenity_count             35646 non-null  int64
 13  security_amenity_count               35646 non-null  int64
 14  maintenance_or_cleaning_amenity_count  35646 non-null  int64
 15  social_amenity_count                 35646 non-null  int64
 16  expendable_amenity_count             35646 non-null  int64
 17  service_staff_amenity_count          35646 non-null  int64
 18  unclassify_amenity_count             35646 non-null  int64
dtypes: float64(5), int64(7), object(7)
memory usage: 5.2+ MB
```

```
df['area'].describe()
```

```
count     35646.000000
mean       1993.137088
std        4473.131958
min           0.000000
25%        1100.000000
50%        1450.000000
75%        2000.000000
max      387360.000000
Name: area, dtype: float64
```

```
# building_nature
sns.set
plt.figure(figsize=(4,4))
sns.countplot(x ='building_nature', data = df)
plt.title('building_nature')
plt.show()
```

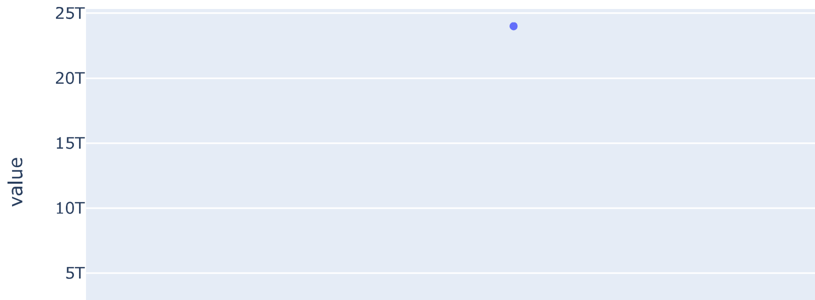



```
df['building_nature'].value_counts()
```

```
Residential    28892
Commercial      6754
Name: building_nature, dtype: int64
```

## Univariate Analysis

```
fig1 = px.box(df['price'],width=800, height=400)
fig1.show()
```



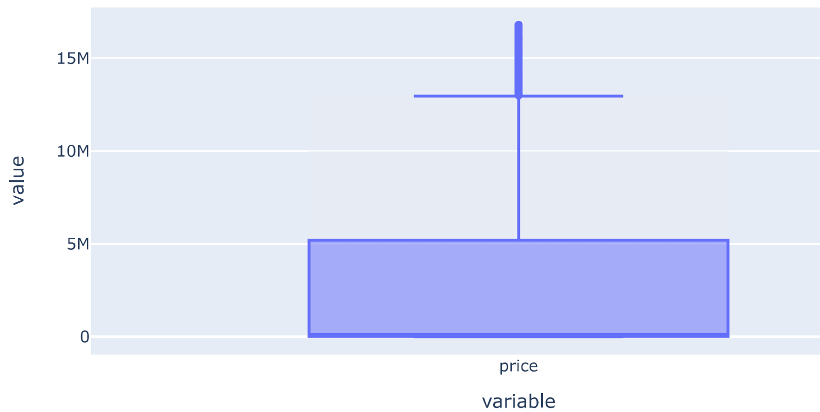

```
# Outlier finding for Area
Q1 = np.percentile(df['price'], 25, interpolation = 'midpoint')
Q2 = np.percentile(df['price'], 50, interpolation = 'midpoint')
Q3 = np.percentile(df['price'], 75, interpolation = 'midpoint')

IQR = Q3 - Q1
print('Interquartile range is',IQR)
low_lim = Q1 - 1.5 * IQR
up_lim = Q3 + 1.5 * IQR
Extreme_LL = Q1 - 3 * IQR
Extreme_UL = Q3 + 3 * IQR
print('low_limit is', low_lim)
print('up_limit is', up_lim)
outlier1 =[]
outlier2 =[]
for x in df['price']:
    if ((Extreme_UL>x> up_lim) or (Extreme_LL<x<low_lim)):
        outlier1.append(x)
    if ((x> Extreme_UL) or (x<Extreme_LL)):
        outlier2.append(x)
print(' outlier in the dataset is', outlier1+outlier2)
count1=0
for i in outlier1:
  count1+=1
print("Outliers", count1)
count2=0
for i in outlier2:
  count2+=1
print("Extreme Outlier", count2)
print(Q1,Q2,Q3)
df.shape
```

```
Interquartile range is 6723000.0
low_limit is -10057500.0
up_limit is 16834500.0
 outlier in the dataset is [20000000.0, 22500000.0, 21000000.0, 22000000.0, 17400000.0, 22000000.0, 24000000.0, 18000000.0, 18500000.0,
Outliers 1026
Extreme Outlier 2126
27000.0 220000.0 6750000.0
<ipython-input-62-f63a9be3d58e>:2: DeprecationWarning:

the `interpolation=` argument to percentile was renamed to `method=`, which has additional options.
Users of the modes 'nearest', 'lower', 'higher', or 'midpoint' are encouraged to review the method they. (Deprecated NumPy 1.22)

<ipython-input-62-f63a9be3d58e>:3: DeprecationWarning:

the `interpolation=` argument to percentile was renamed to `method=`, which has additional options.
Users of the modes 'nearest', 'lower', 'higher', or 'midpoint' are encouraged to review the method they. (Deprecated NumPy 1.22)

<ipython-input-62-f63a9be3d58e>:4: DeprecationWarning:

the `interpolation=` argument to percentile was renamed to `method=`, which has additional options.
Users of the modes 'nearest', 'lower', 'higher', or 'midpoint' are encouraged to review the method they. (Deprecated NumPy 1.22)

(35646, 19)
```

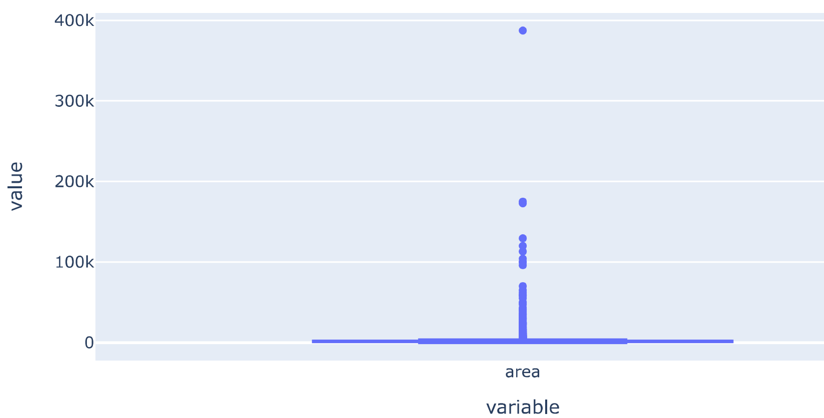
```
df = df[df.price < up_lim]
df = df[df.price > low_lim]
df.shape
```

```
(32494, 19)
```

```
fig1 = px.box(df['price'],width=800, height=400)
fig1.show()
```




```
fig1 = px.box(df['area'],width=800, height=400,
            labels={"area": "area"})
fig1.show()
```




```
# Outlier finding for Area
Q1 = np.percentile(df['area'], 25, interpolation = 'midpoint')
Q2 = np.percentile(df['area'], 50, interpolation = 'midpoint')
Q3 = np.percentile(df['area'], 75, interpolation = 'midpoint')

IQR = Q3 - Q1
print('Interquartile range is', IQR)
low_lim = Q1 - 1.5 * IQR
up_lim = Q3 + 1.5 * IQR
Extreme_LL = Q1 - 3 * IQR
Extreme_UL = Q3 + 3 * IQR
print('low_limit is', low_lim)
print('up_limit is', up_lim)
outlier1 =[]
outlier2 =[]
for x in df['area']:
    if ((Extreme_UL>x> up_lim) or (Extreme_LL<x<low_lim)):
         outlier1.append(x)
    if ((x> Extreme_UL) or (x<Extreme_LL)):
         outlier2.append(x)
print(' outlier in the dataset is', outlier1+outlier2)
count1=0
for i in outlier1:
  count1+=1
```

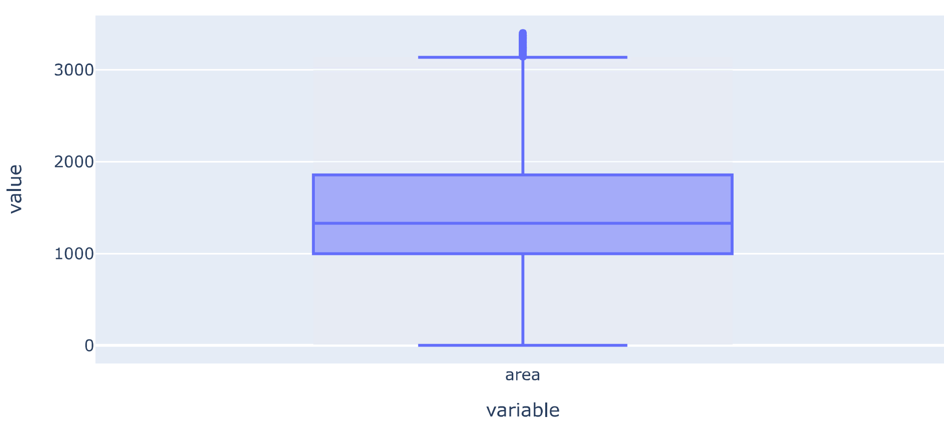
```
print("Outliers", count1)
count2=0
for i in outlier2:
  count2+=1
print("Extreme Outlier", count2)
print(Q1,Q2,Q3)
df.shape
```

```
Interquartile range is 942.6917393926219
low_limit is -364.03760908893287
up_limit is 3406.7293484815546
 outlier in the dataset is [3955.0, 3600.0, 3600.0, 3600.0, 3600.0, 3600.0, 3600.0, 4320.0, 3600.0, 4320.0, 3850.0, 3888.0, 3600.0, 3600
Outliers 1231
Extreme Outlier 1178
1050.0 1400.0 1992.691739392622
<ipython-input-66-b3ed9a1bc9cb>:2: DeprecationWarning:

the `interpolation=` argument to percentile was renamed to `method=`, which has additional options.
Users of the modes 'nearest', 'lower', 'higher', or 'midpoint' are encouraged to review the method they. (Deprecated NumPy 1.22)

<ipython-input-66-b3ed9a1bc9cb>:3: DeprecationWarning:

the `interpolation=` argument to percentile was renamed to `method=`, which has additional options.
Users of the modes 'nearest', 'lower', 'higher', or 'midpoint' are encouraged to review the method they. (Deprecated NumPy 1.22)

<ipython-input-66-b3ed9a1bc9cb>:4: DeprecationWarning:

the `interpolation=` argument to percentile was renamed to `method=`, which has additional options.
Users of the modes 'nearest', 'lower', 'higher', or 'midpoint' are encouraged to review the method they. (Deprecated NumPy 1.22)

(32494, 19)
```

```
df = df[df.area < up_lim]
df = df[df.area > low_lim]
df.shape
```

```
(30085, 19)
```

```
fig1 = px.box(df['area'],width=800, height=400,
            labels={"area": "area"})
fig1.show()
```

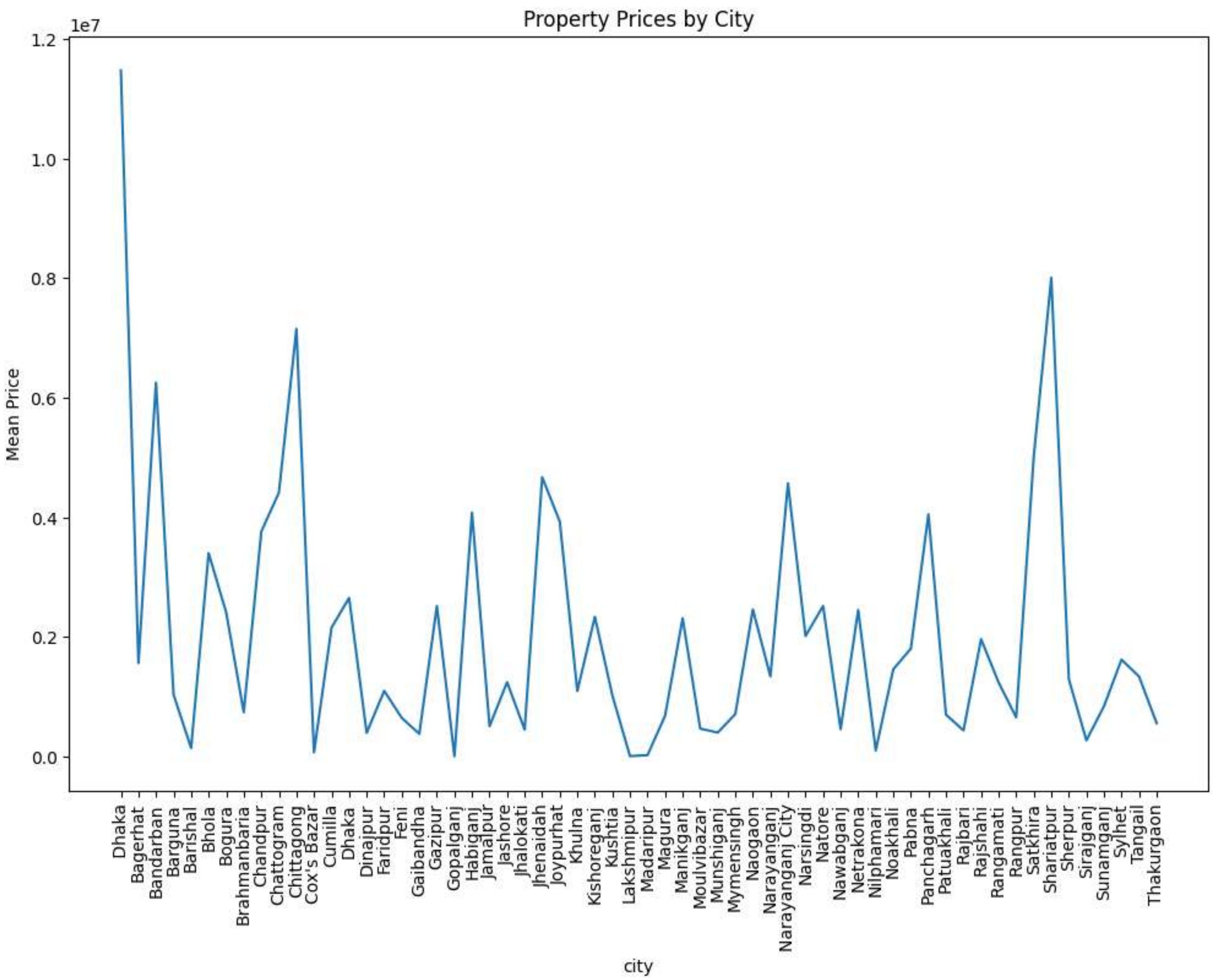



## 4.A) **How do property prices fluctuate for same location?**

The resulting line chart shows the mean property prices for each city in the dataset. It can be seen that some cities have higher mean prices than others, indicating that the cost of living and demand for real estate varies between different locations

```
import matplotlib.pyplot as plt
```

```
# group by location and calculate the mean price
price_by_location = df.groupby('city')['price'].mean()

# plot the results as a line chart
plt.figure(figsize=(12, 8))
plt.plot(price_by_location.index, price_by_location.values)
plt.xticks(rotation=90)
plt.xlabel('city')
plt.ylabel('Mean Price')
plt.title('Property Prices by City')
plt.show()
```




## Q.4 B) How do property prices fluctuate for same property size?

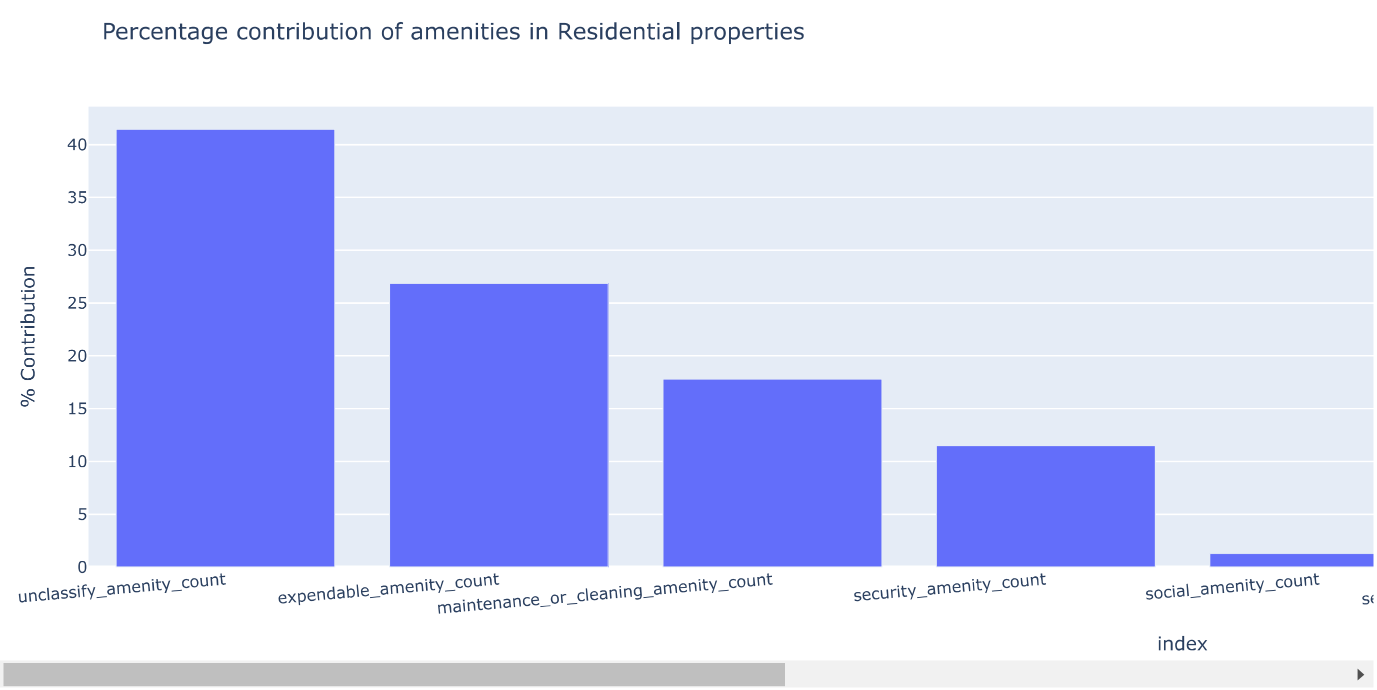
```
fig = px.scatter(df, x="price", y="area", width=800, height=400,
            labels={"area": "area", "price": "price"})
fig.show()
```


## 7.A) Which amenities are the more frequent in Residential properties ?

the percentage contribution of each amenity in Residential properties. The top Three amenities were "expendable_amenity_count" (26.9%),"maintenance_or_cleaning_amenity_count" (17.8%), "security_amenity_count" (17.6%), Unclassified amenities 41.45%

Double-click (or enter) to edit

```
# Step 1: Subset the DataFrame
amenities_columns = ['garage', 'relaxation_amenity_count', 'security_amenity_count',
                     'maintenance_or_cleaning_amenity_count', 'social_amenity_count',
                     'expendable_amenity_count', 'service_staff_amenity_count',
                     'unclassify_amenity_count']
df_amenities = df[['building_nature'] + amenities_columns]

# Step 2: Filter the DataFrame to only include Residential properties
df_residential = df_amenities[df_amenities['building_nature'] == 'Residential']

# Step 3: Calculate the frequency of each amenity
amenities_frequencies = df_residential[amenities_columns].sum().sort_values(ascending=False)

# Step 4: Sort the frequencies in descending order
amenities_frequencies_sorted = amenities_frequencies.sort_values(ascending=False)

# Step 5: Visualize the frequencies using a bar plot
fig = px.bar(amenities_frequencies, x=amenities_frequencies.index, y=amenities_frequencies.values,
             labels={'x': 'Amenity', 'y': 'Frequency'}, title='Frequencies of amenities in Residential properties')
fig.update_layout(xaxis_tickangle=-5)
fig.show()
```

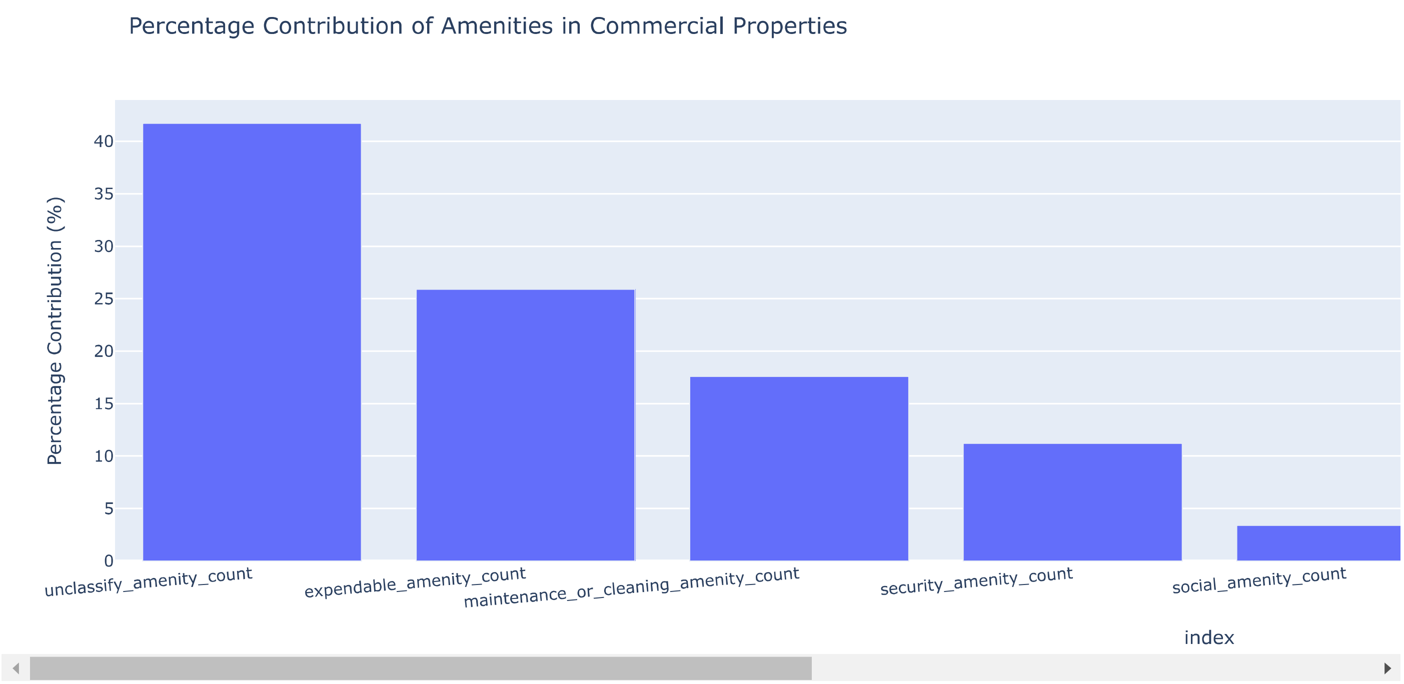



**Found expendable_Amenity_count,maintenance or cleaning amenity more frequent**

## Q.7 B) Which amenities are the more frequent in Commercial properties ?

the percentage contribution of each amenity in Commercialproperties. The top Three amenities were "expendable_amenity_count" (25.9%),"maintenance_or_cleaning_amenity_count" (17.6%), "security_amenity_count"(11.2%), Unclassified amenities 41.7%

```
# Step 2: Filter the DataFrame to only include Commercial properties
df_commercial = df_amenities[df_amenities['building_nature'] == 'Commercial']

# Step 3: Calculate the frequency of each amenity
amenities_frequencies = df_commercial[amenities_columns].sum().sort_values(ascending=False)

# Step 4: Calculate the percentage contribution of each amenity
amenities_percentages = round((amenities_frequencies / amenities_frequencies.sum()) * 100, 1)

# Step 5: Sort the percentages in descending order
amenities_percentages_sorted = amenities_percentages.sort_values(ascending=False)

# Step 6: Visualize the percentages using a bar plot
fig = px.bar(amenities_percentages_sorted, x=amenities_percentages_sorted.index, y=amenities_percentages_sorted.values,
             labels={'x': 'Amenity', 'y': 'Percentage Contribution (%)'},
             title='Percentage Contribution of Amenities in Commercial Properties')
fig.update_layout(xaxis_tickangle=-5)
fig.show()
```




Double-click (or enter) to edit

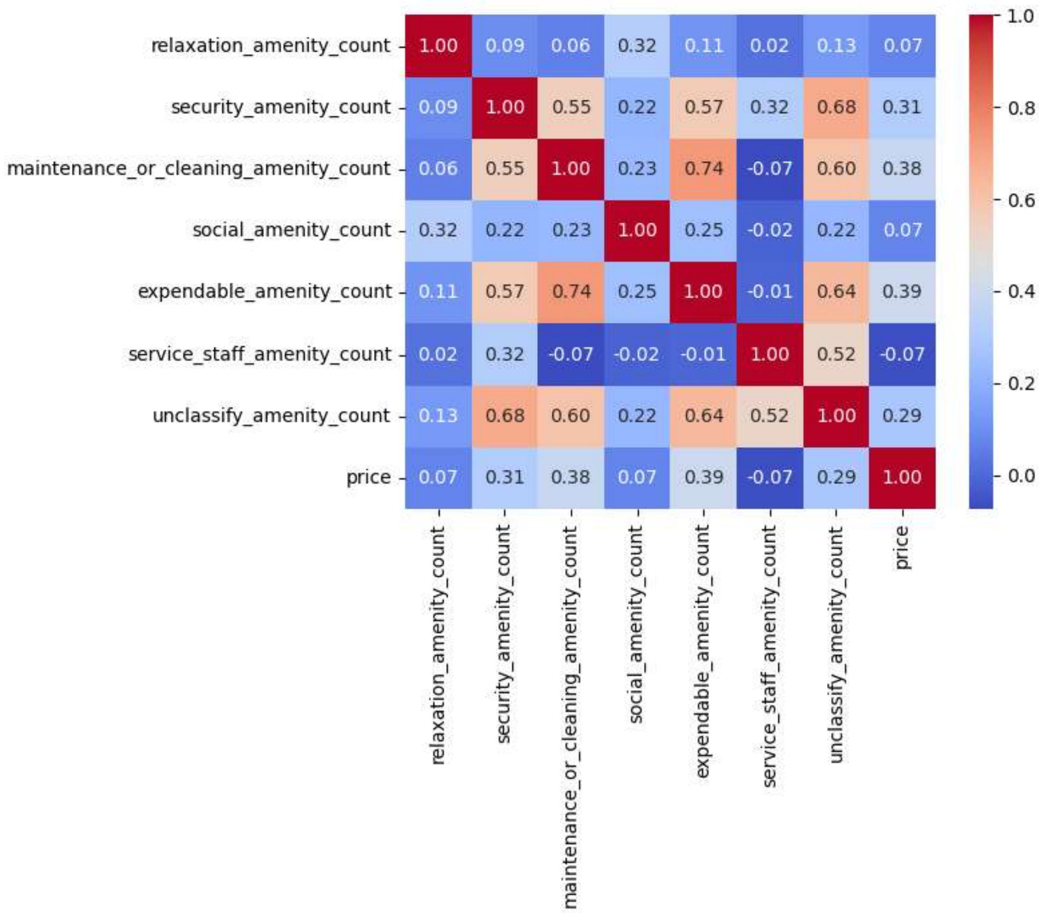
**Found expendable_Amenity_count,maintenance or cleaning amenity more frequent**

## Q.7 C) & Q.7 D) Which amenities have more/ less impact on price?

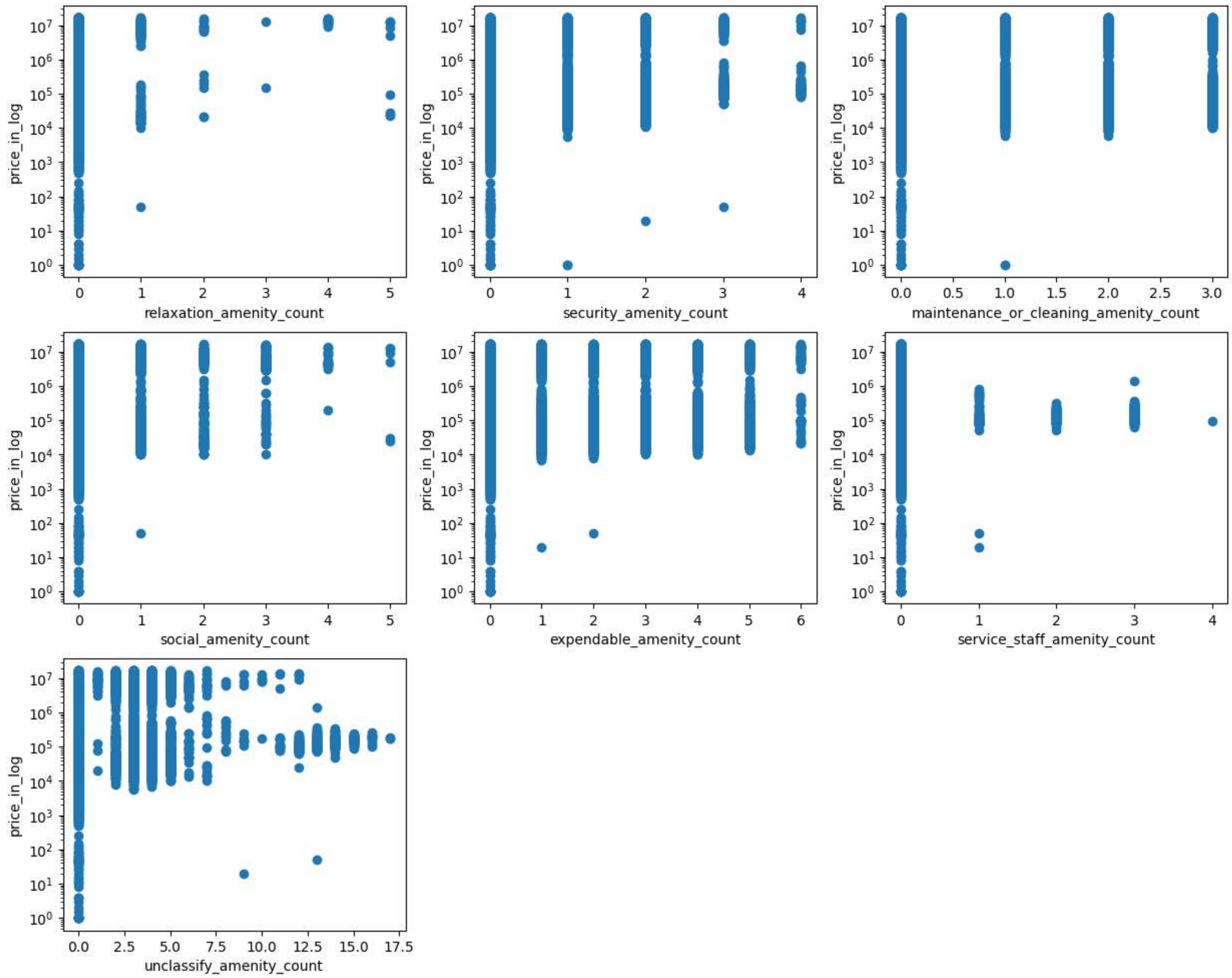
- security_amenity_count,maintenance_or_cleaning_amenity_count
  expendable_amenity_count OBSERVED Moderately positively co-related (0.35) with price and others amenities has no Relation with price

```
amenities_cols = ['relaxation_amenity_count', 'security_amenity_count',
                  'maintenance_or_cleaning_amenity_count', 'social_amenity_count',
                  'expendable_amenity_count', 'service_staff_amenity_count',
                  'unclassify_amenity_count', 'price']

# create a correlation matrix
corr = df[amenities_cols].corr()

# plot the heatmap
sns.heatmap(corr, cmap='coolwarm', annot=True, fmt='.2f')
```

<Axes: >




```
amenity_counts = ['relaxation_amenity_count','security_amenity_count','maintenance_or_cleaning_amenity_count','social_amenity_count','expenda

fig, axes = plt.subplots(nrows=3, ncols=3, figsize=(15, 12))

for i, ax in enumerate(axes.flat):
    if i >= len(amenity_counts):
        ax.axis('off')
    else:
        amenity_count = amenity_counts[i]
        ax.scatter(df[amenity_count],df['price'])
        ax.set_xlabel(amenity_count)
        ax.set_ylabel('price_in_log')
        ax.set_yscale('log')
```


price_in_log
relaxation_amenity_count
security_amenity_count
maintenance_or_cleaning_amenity_count
social_amenity_count
expendable_amenity_count
service_staff_amenity_count
unclassify_amenity_count