Group_2-EDA-Umesh

May 2, 2023

1 EDA summary (Group 2)

In this EDA we tried to answer the following questions:

Question 2 - (a) Impact of the basic facilities (e.g. num_bath_room, num_bed_room) we recorded on the property prices - (b) Impact of facilities (malls, educational institutions, business hubs, hospitals, …) in the vicinity on the prices - (c) Impact of internal amenities (play area, number of car parks, height of the building, number of storeys, number of total amenities) on the prices - (d) How do they influence the price: linearly / non-linearly / stepwise?

Question 8 - Mean prices per building_type (apartment/shop/…); the goal is to understand if it is worth it to have such an attribute, or if building_nature (commercial/residential) is enough.

Summary of answers:

- Answers to Question 2 (a+d)
  - We see that the influence of 'area' (size in Sq. ft) on price is more straightforwardly visible for "Aparments" under "Sale" purpose such that there is a linear increase in price with increase in area. For "Aparments" under "Rent" the picture is not that clear–there doesn't seem to be a direct linear relationship (see this). Note that:
    - There are only about 20% properties in the dataset that have some info about the area of the property (see this).
    - Close to 80% of the properties are of type 'Apartment' (see this).
    - → **This possibly means that we have very little info about other property types, and the number of data points with info about 'area' is probably not sufficient**
  - The impact of both, the number of bathrooms and bedrooms on price *seems to be* linear (could even be exponential), and again the pattern is clearer for "Sale" purpose than for "Rent" purpose (for bathrooms see this and for bedrooms see this). Note that:
    - The info is not available (or is zero) for bathrooms in around 40%, and for bedrooms, in around 20% of the data (see this)
- Answer to Question 2 (b)
  - This question cannot be answered because the required info about these facilities is not available in the dataset
- Answer to Question 2 (c)
  - Since we don't have separate info about these amenities, we analyzed the impact of different types of amenities on price. Again, the picture is clearer for "Sale" purpose than for "Rent" purpose, and the relationship seems exponetial such that the price increases exponetially with the number of amenities (see this). Note that:

    * For almost all the amenities in around 60-90% of the data, the amenity value is missing (or is zero) (see this)
- Answer to Question 8
  - This plot answers the question.

[1141]:
```
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.gridspec as gridspec
import seaborn as sns
import numpy as np

from numpy import median
```

[1142]:
```
# Dataset downloaded on 01 May 2023 at 08:30 hrs (CEST)
df_merged = pd.read_csv("merged_datasets_01_05_2023.csv")
```

[1143]:
```
df_merged.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41546 entries, 0 to 41545
Data columns (total 24 columns):
 #   Column                               Non-Null Count  Dtype
---  ------                               --------------  -----
 0   area                                 39274 non-null  object
 1   building_type                        41248 non-null  object
 2   building_nature                      41546 non-null  object
 3   image_url                            17312 non-null  object
 4   num_bath_rooms                       41546 non-null  float64
 5   num_bed_rooms                        41546 non-null  float64
 6   price                                40466 non-null  float64
 7   property_description                 23665 non-null  object
 8   property_overview                    20194 non-null  object
 9   property_url                         39146 non-null  object
 10  purpose                              40841 non-null  object
 11  city                                 40069 non-null  object
 12  locality                             36748 non-null  object
 13  address                              33619 non-null  object
 14  id                                   41546 non-null  object
 15  garage                               41546 non-null  float64
 16  year_built                           256 non-null    float64
 17  relaxation_amenity_count             41546 non-null  int64
 18  security_amenity_count               41546 non-null  int64
 19  maintenance_or_cleaning_amenity_count  41546 non-null  int64
 20  social_amenity_count                 41546 non-null  int64
 21  expendable_amenity_count             41546 non-null  int64
 22  service_staff_amenity_count          41546 non-null  int64
 23  unclassify_amenity_count             41546 non-null  int64
dtypes: float64(5), int64(7), object(12)
```

```
memory usage: 7.6+ MB
```

1.0.1 First, some data wrangling!!

Correct '*area*' values NOTE: Area is not numeric because some values have extra string: 'sft', '(Sft)' and ' gross' Get rid of extra strings and convert it to numeric values (float)

[1144]:
```
df_merged['area'] = np.where(df_merged['area'].str.contains(' sft'),␣
↪df_merged['area'].str.split(' ')[0],
                             np.where(df_merged['area'].str.contains('\(Sft\)'),␣
↪df_merged['area'].str.split('\(')[0],
                                      np.where(df_merged['area'].str.contains('␣
↪gross'),
                                          df_merged['area'].str.split(' ')[0],␣
↪df_merged['area'])
                                     )
                            )
```

[1145]:
```
df_merged['area'] = df_merged['area'].astype(float)
```

[1146]:
```
df_merged.area.describe(percentiles=[.1, .3, .6, .9, 0.95, .99])
```

[1146]:
```
count    8.775000e+03
mean     8.065880e+03
std      2.754335e+05
min      0.000000e+00
10%      0.000000e+00
30%      6.000000e+02
50%      1.050000e+03
60%      1.200000e+03
90%      2.160000e+03
95%      2.762300e+03
99%      7.940800e+03
max      1.450147e+07
Name: area, dtype: float64
```

Make '*building_type*' types as smaller set NOTE: There seems to be some repetitions of types. Let's combine the related values into unique types

[1147]:
```
df_merged['building_type'].value_counts()
```

[1147]:
```
Apartment                       28990
 Apartment                       2374
Office                           2340
Building                         1422
Land                             1342
```

```
Shop                             1064
Floor                             885
Plot                              809
Apartment/Flats                   611
Garage                            457
Commercial Space                  249
House                             221
Residential Plot                  164
Duplex                             91
Office space                       52
Warehouse                          39
Factory                            26
Land Sharing Flat                  24
Office Space                       24
Showroom/Shop/Restaurant           16
Independent House                   9
Duplex Home                         9
Commercial Plot                     8
Industrial Space                    6
Commerical - Other                  4
Sublet/Room                         4
Commercial property                 2
Apartment, Commercial               2
Showroom / Shop / Restaurant        2
Agriculture/Farm Land               1
 Condos                             1
Name: building_type, dtype: int64
```

[1148]:

```
# Combine the related values into one

# The following types are combined into one
#
# Apartment: Apartment;  Apartment/Flats;  Apartment, Commercial
# Office:  Office;  Office space
# Commercial Space:  Commercial Space;  Commerical - Other;  Commercial property
# Shop:  Shop;  Showroom / Shop / Restaurant
# House:  House;  Independent House
# Duplex:  Duplex;  Duplex Home

# Create a new column
df_merged['building_type_comb'] = df_merged['building_type']

df_merged['building_type_comb'] = np.where(df_merged['building_type_comb'].str.
 ↪contains('Apartment'),
                                          'Apartment',␣
 ↪df_merged['building_type_comb'])
```

```
df_merged['building_type_comb'] = np.where(df_merged['building_type_comb'].str.
 ↪contains('Office'),
                                           'Office', df_merged['building_type_comb'])

df_merged['building_type_comb'] = np.where(df_merged['building_type_comb'].str.
 ↪contains('Commercial'),
                                               'Commercial Space',␣
 ↪df_merged['building_type_comb'])

# Correct the typo!
df_merged['building_type_comb'] = np.where(df_merged['building_type_comb'].str.
 ↪contains('Commerical'),
                                               'Commercial Space',␣
 ↪df_merged['building_type_comb'])

df_merged['building_type_comb'] = np.where(df_merged['building_type_comb'].str.
 ↪contains('Shop'),
                                             'Shop', df_merged['building_type_comb'])

df_merged['building_type_comb'] = np.where(df_merged['building_type_comb'].str.
 ↪contains('House'),
                                            'House', df_merged['building_type_comb'])

# Although a 'Duplex' is a special kind of 'House', let's keep it as a separate␣
 ↪type
df_merged['building_type_comb'] = np.where(df_merged['building_type_comb'].str.
 ↪contains('Duplex'),
                                           'Duplex', df_merged['building_type_comb'])
```

[1149]:
```
df_merged['building_type_comb'].value_counts()
```

[1149]:
```
Apartment             32275
Office                 2416
Building               1422
Land                   1342
Shop                   1082
Floor                   885
Plot                    809
Garage                  457
Commercial Space        263
House                   230
Residential Plot        164
Duplex                  100
Warehouse                39
Factory                  26
Land Sharing Flat        24
```

```
Industrial Space            6
Sublet/Room                 4
Agriculture/Farm Land       1
 Condos                     1
Name: building_type_comb, dtype: int64
```

[1150]:
```
# And since the rest of the property types have very few occurences, let's club␣
↪them together as 'other'
df_merged['building_type_comb'] = np.where(df_merged['building_type_comb'].str.
↪contains(
    'Warehouse|Factory|Land Sharing Flat|Industrial Space|Sublet/
↪Room|Agriculture/Farm Land| Condos'),
                                           'other', df_merged['building_type_comb'])
```

[1151]:
```
df_merged['building_type_comb'].value_counts()
```

[1151]:
```
Apartment            32275
Office                2416
Building              1422
Land                  1342
Shop                  1082
Floor                  885
Plot                   809
Garage                 457
Commercial Space       263
House                  230
Residential Plot       164
other                  101
Duplex                 100
Name: building_type_comb, dtype: int64
```

[1152]:
```
df_merged['building_type_comb'].value_counts().sum()
```

[1152]: 41546

[1153]:
```
df_merged.shape
```

[1153]: (41546, 25)

Make 'num_bath_rooms' and 'num_bed_rooms' integer from float

[1154]:
```
df_merged['num_bath_rooms'] = df_merged['num_bath_rooms'].astype('int64')
df_merged['num_bed_rooms'] = df_merged['num_bed_rooms'].astype('int64')
```

Correct the values in '*purpose*'

[1155]:
```
df_merged['purpose'].unique()
```

[1155]:
```
array(['Sale', 'Rent', nan, 'sale', 'SALE', 'rent'], dtype=object)
```

[1156]:
```
df_merged['purpose'].value_counts()
```

[1156]:
```
Rent    23428
Sale    16813
sale      598
SALE        1
rent        1
Name: purpose, dtype: int64
```

[1157]:
```
df_merged['purpose'] = np.where(df_merged['purpose'].str.contains('sale|SALE'),␣
 ↪'Sale',
                             np.where(df_merged['purpose'].str.contains('rent'),␣
 ↪'Rent',
                                        df_merged['purpose'])
                                      )
```

[1158]:
```
df_merged['purpose'].value_counts()
```

[1158]:
```
Rent    23429
Sale    18117
Name: purpose, dtype: int64
```

[1159]:
```
df_merged['garage'].value_counts()
```

[1159]:
```
0.0    41347
1.0      190
2.0        8
4.0        1
Name: garage, dtype: int64
```

2 Question: 2

- (a) Impact of the basic facilities (e.g. num_bath_room, num_bed_room) we recorded on the property prices
- (b) Impact of facilities (malls, educational institutions, business hubs, hospitals, …) in the vicinity on the prices
- (c) Impact of internal amenities (play area, number of car parks, height of the building, number of storeys, number of total amenities) on the prices
- (d) How do they influence the price: linearly / non-linearly / stepwise?

(a) Impact of the basic facilities on property prices **{*area*, *num_bath_rooms*, _num_bed_rooms}**

(possible) Sub-questions:

- (i) What kind of properties have more than 3 or 4 bathrooms?
- (ii) What kind of properties have 0 bathrooms?

2.0.1 Impact of '*area*'

[ ]:

```

```

[1160]:

```python
# Distribution of prices for 'Rent'
percl_price_Rent = df_merged[(df_merged.purpose == 'Rent')
                              ].price.describe(percentiles=[0.02, .3, .6, .9, 0.
 ↪95, .99])
print(percl_price_Rent)
```

```
count    2.315600e+04
mean     1.092878e+07
std      8.266022e+08
min      0.000000e+00
2%       0.000000e+00
30%      1.800000e+04
50%      3.200000e+04
60%      5.000000e+04
90%      4.500000e+05
95%      8.000000e+05
99%      2.500000e+06
max      1.000000e+11
Name: price, dtype: float64
```

[1161]:

```python
# Distribution of prices for 'Sale'
percl_price_Sale = df_merged[(df_merged.purpose == 'Sale')
                              ].price.describe(percentiles=[0.02, .3, .6, .9, 0.
 ↪95, .99])
print(percl_price_Sale)
```

```
count    1.731000e+04
mean     2.077500e+09
std      1.839185e+11
min      0.000000e+00
2%       4.500000e+05
30%      5.337000e+06
50%      7.200000e+06
60%      8.220000e+06
```

```
90%      2.000000e+07
95%      3.500000e+07
99%      6.500000e+08
max      2.400000e+13
Name: price, dtype: float64
```

[1162]:
```
# Distribution of area for 'Rent'
percl_area_Rent = df_merged[(df_merged.purpose == 'Rent')
                              ].area.describe(percentiles=[0.05, .3, .6, .9, 0.
 ↪95, .99])
print(percl_area_Rent)
```

```
count    5.465000e+03
mean     1.190663e+04
std      3.489082e+05
min      0.000000e+00
5%       0.000000e+00
30%      0.000000e+00
50%      6.500000e+02
60%      8.000000e+02
90%      2.000000e+03
95%      2.650000e+03
99%      1.000000e+04
max      1.450147e+07
Name: area, dtype: float64
```

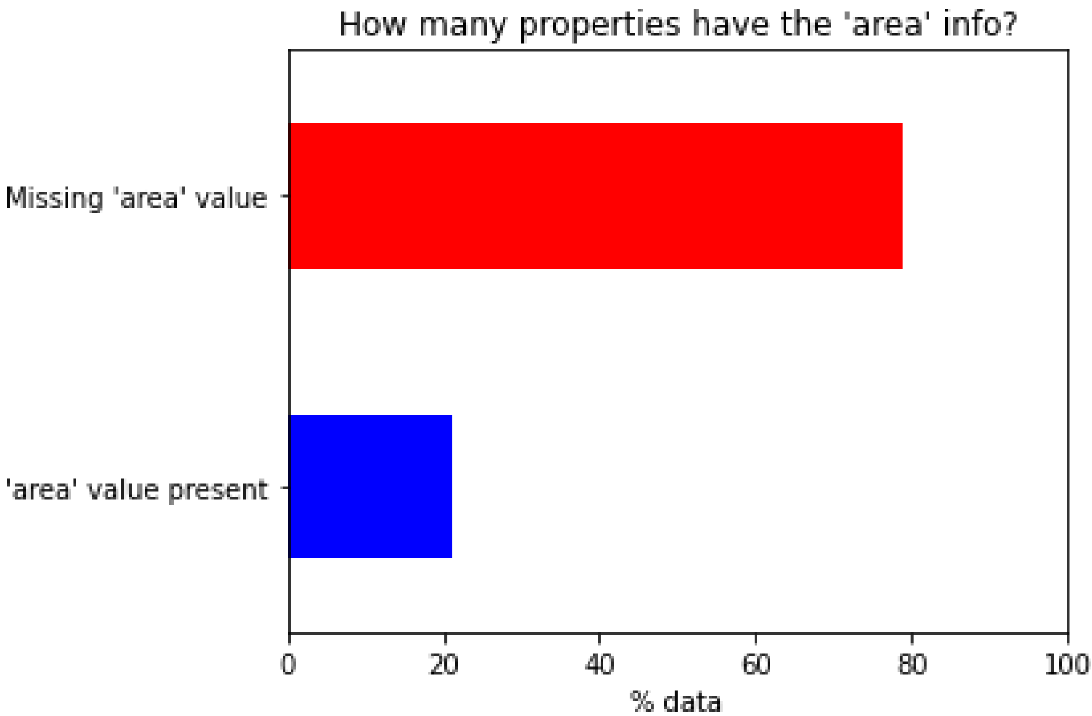
[1163]:
```
# Distribution of area for 'Sale'
percl_area_Sale = df_merged[(df_merged.purpose == 'Sale')
                              ].area.describe(percentiles=[0.05, .3, .6, .9, 0.
 ↪95, .99])
print(percl_area_Sale)
```

```
count      3310.000000
mean       1724.581420
std        8567.220496
min           3.000000
5%          830.900000
30%        1200.000000
50%        1375.000000
60%        1480.000000
90%        2200.000000
95%        2900.000000
99%        4350.000000
max      490000.000000
Name: area, dtype: float64
```

```
[1164]: # df_rent_all_area = df_merged[df_merged.purpose == 'Rent']
# df_rent_upto95_area = df_rent_all_area[df_rent_all_area.area <=␣
↪percl_area_Rent['95%']]

# print(df_rent_all_area.shape)
# print(df_rent_upto95_area.shape)
```

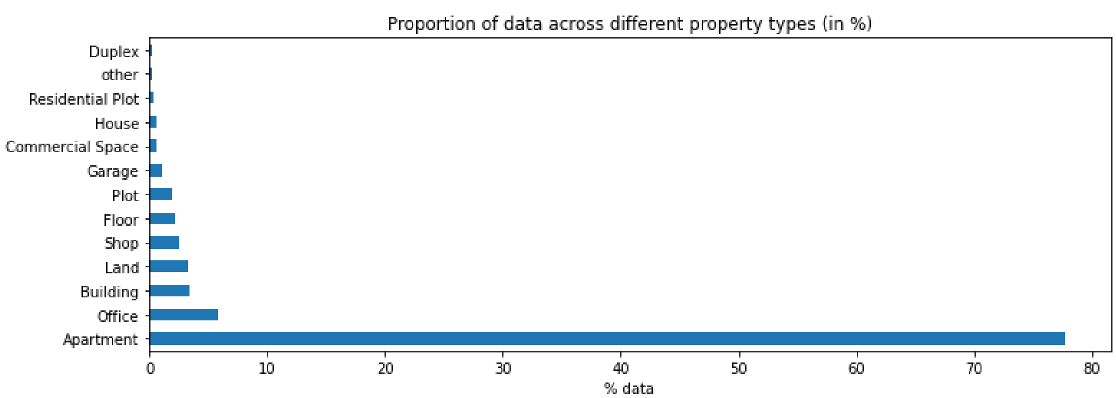
How many properties have the '*area*' info?

```
[1165]: df_TMP = pd.Series(np.where(df_merged['area'].isna(), "Missing 'area' value",␣
↪"'area' value present"))
percentages = (df_TMP.value_counts() / df_TMP.value_counts().sum()) * 100

#     print()
#     print("------------------------------------")
#     print(percentages)

fig, ax = plt.subplots(figsize=(6, 4))
percentages.sort_index().plot.barh(color=['blue', 'red'])

# Set x and y axis labels
plt.xlabel('% data')
plt.ylabel('')
# plt.title(f"'{col_name}': zero vs. non-zero entries")
plt.title("How many properties have the 'area' info?")
ax.set_xlim(0, 100)

plt.tight_layout()

# Show the plot
plt.show()
```



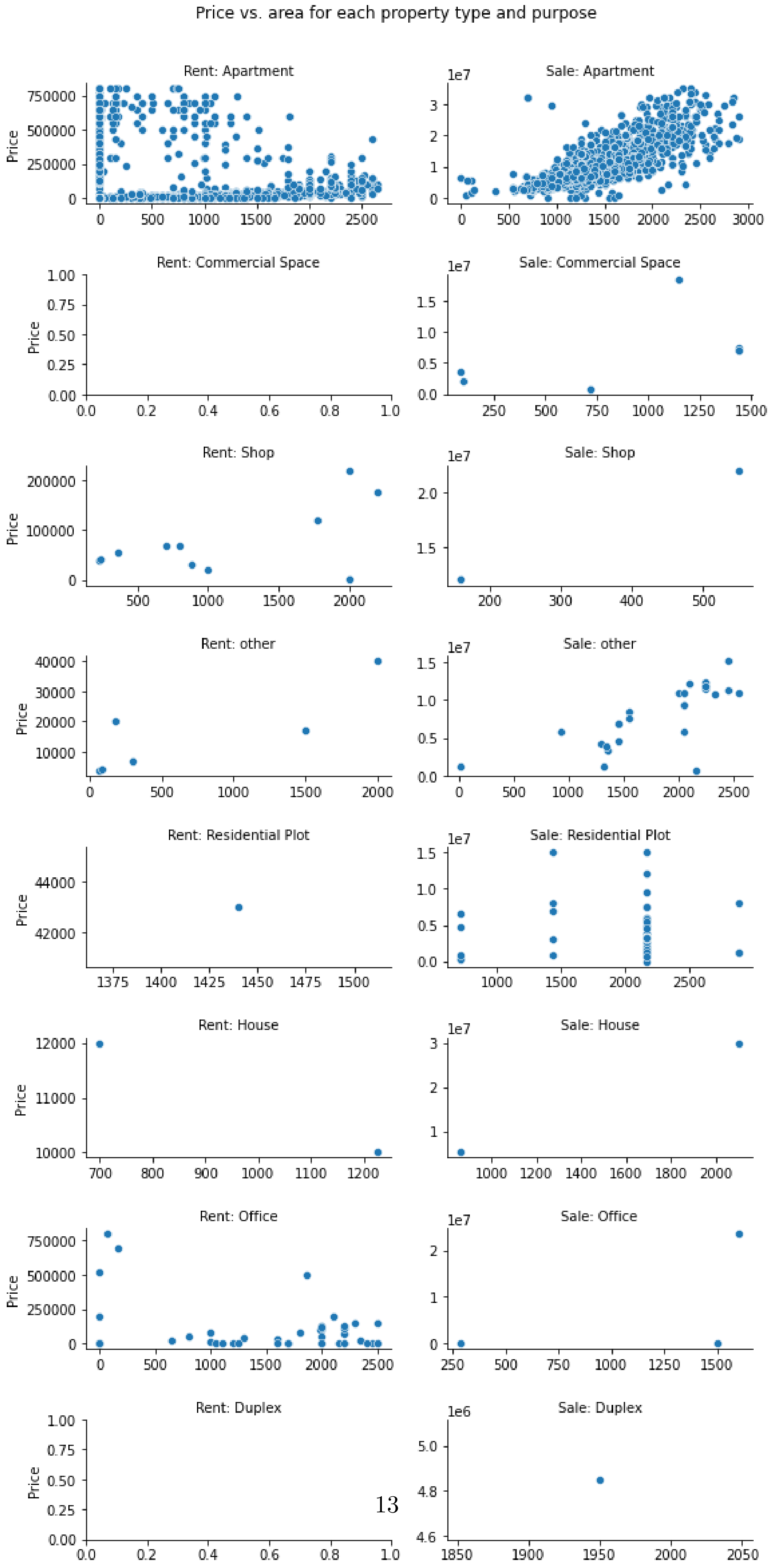
How many data points do we have for each type of property?

[1166]:
```
freq = (df_merged['building_type_comb'].value_counts() /␣
↪df_merged['building_type_comb'].value_counts().sum()) * 100

fig, ax = plt.subplots(figsize=(12, 4))
freq.plot.barh()

plt.title("Proportion of data across different property types (in %)")
plt.xlabel("% data")

plt.show()
```



[1167]:

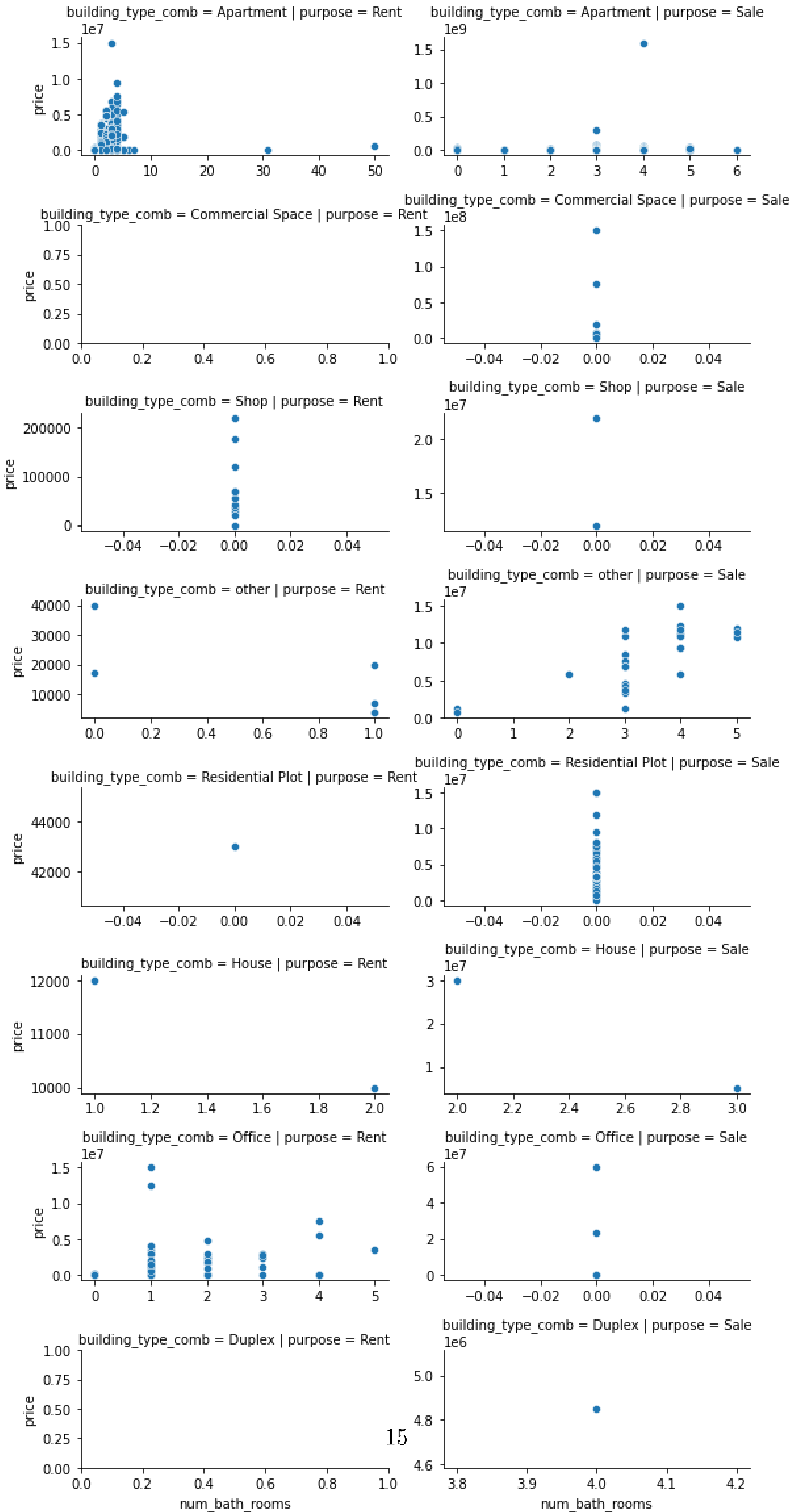
```
# Prepare / subset the data:
# Get all the data that has price and area outliers removed (= all values above␣
↪95 percentile)
data = df_merged[((df_merged.purpose == 'Rent') &
                  (df_merged.area <= percl_area_Rent['95%']) &
                  (df_merged.price <= percl_price_Rent['95%'])
                 ) |
                 ((df_merged.purpose == 'Sale') &
                  (df_merged.area <= percl_area_Sale['95%']) &
                  (df_merged.price <= percl_price_Sale['95%'])
                 )
                 ]

g = sns.relplot(y="price", x="area",
                data = data,
                col = "purpose",
                row = "building_type_comb",
                kind="scatter",
                facet_kws={'sharey': False, 'sharex': False},
                height=2, aspect=2
               )

g.set_titles('{col_name}: {row_name}')
g.set_axis_labels('Area', 'Price')

g.fig.suptitle('Price vs. area for each property type and purpose',␣
↪fontsize=12, y=1.02)
plt.plot()

g.savefig('Price-vs-Area-Scatterplot.jpg')
```


Price vs. area for each property type and purpose
Rent: Apartment
Sale: Apartment
Rent: Commercial Space
Sale: Commercial Space
Rent: Shop
Sale: Shop
Rent: other
Sale: other
Rent: Residential Plot
Sale: Residential Plot
Rent: House
Sale: House
Rent: Office
Sale: Office
Rent: Duplex
Sale: Duplex
Price
Area
1e7
1e6

2.0.2 Impact of '*num_bath_rooms*' and '*num_bed_rooms*'

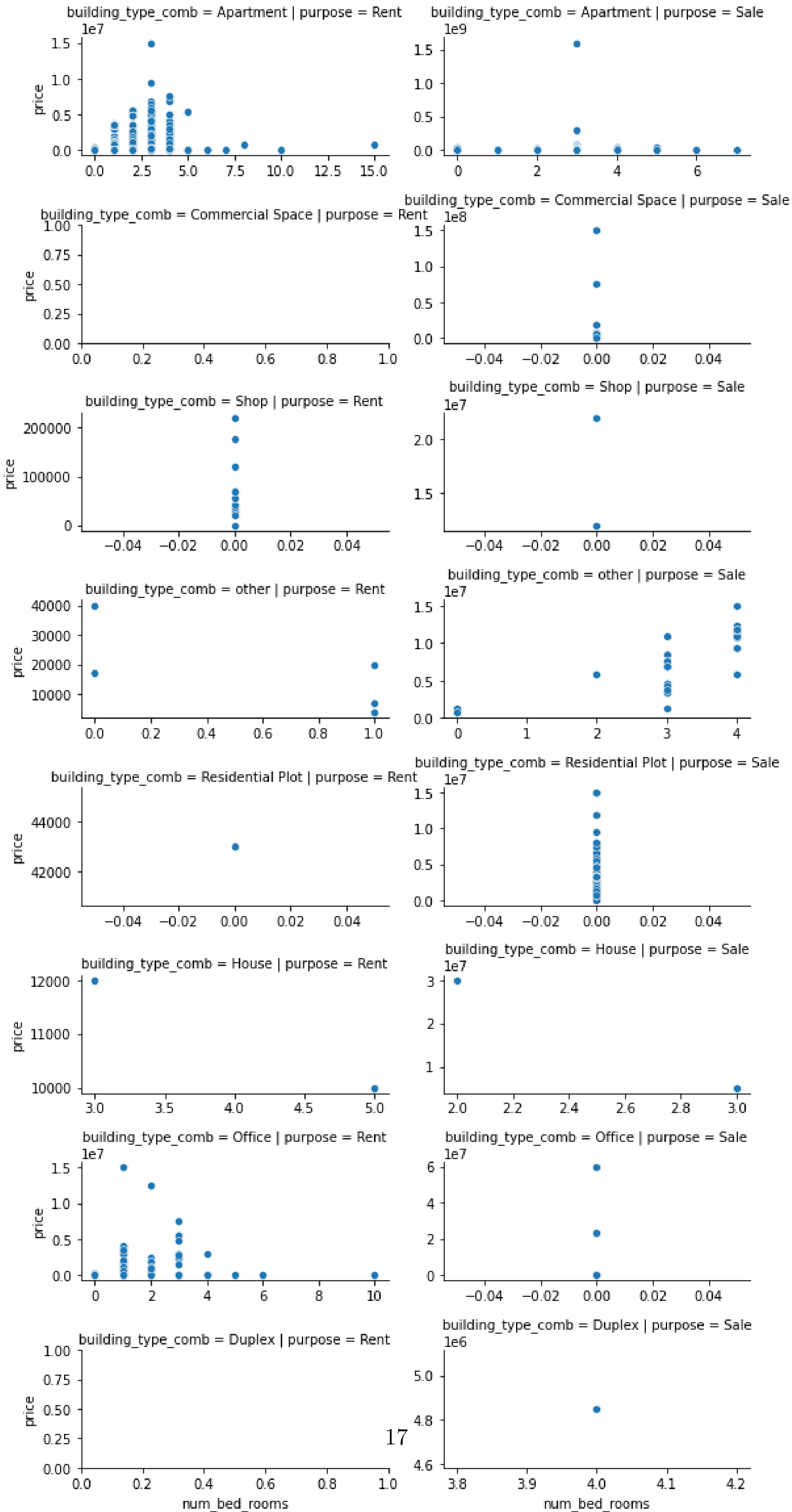
[1168]:
```
g = sns.relplot(y="price", x="num_bath_rooms",
                data = df_merged[(((df_merged.purpose == 'Rent') &
                                    (df_merged.area <= percl_area_Rent['95%'])) |
                                     ((df_merged.purpose == 'Sale') &
                                      (df_merged.area <= percl_area_Sale['95%'])
                                     ))],
                col = "purpose",
                row = "building_type_comb",
                kind="scatter",
                facet_kws={'sharey': False, 'sharex': False},
                height=2, aspect=2
               )
# g.fig.set_size_inches(10, 10)
plt.plot()
```

[1168]:
```
[]
```


building_type_comb = Apartment | purpose = Rent
building_type_comb = Apartment | purpose = Sale
building_type_comb = Commercial Space | purpose = Rent
building_type_comb = Commercial Space | purpose = Sale
building_type_comb = Shop | purpose = Rent
building_type_comb = Shop | purpose = Sale
building_type_comb = other | purpose = Rent
building_type_comb = other | purpose = Sale
building_type_comb = Residential Plot | purpose = Rent
building_type_comb = Residential Plot | purpose = Sale
building_type_comb = House | purpose = Rent
building_type_comb = House | purpose = Sale
building_type_comb = Office | purpose = Rent
building_type_comb = Office | purpose = Sale
building_type_comb = Duplex | purpose = Rent
building_type_comb = Duplex | purpose = Sale
price
num_bath_rooms

[1169]:
```
g = sns.relplot(y="price", x="num_bed_rooms",
                data = df_merged[(((df_merged.purpose == 'Rent') &
                                    (df_merged.area <= percl_area_Rent['95%'])) |
                                     ((df_merged.purpose == 'Sale') &
                                      (df_merged.area <= percl_area_Sale['95%'])
                                     ))],
                col = "purpose",
                row = "building_type_comb",
                kind="scatter",
                facet_kws={'sharey': False, 'sharex': False},
                height=2, aspect=2
               )
# g.fig.set_size_inches(50, 5)
plt.plot()
```

[1169]:
```
[]
```


building_type_comb = Apartment | purpose = Rent
building_type_comb = Apartment | purpose = Sale
building_type_comb = Commercial Space | purpose = Rent
building_type_comb = Commercial Space | purpose = Sale
building_type_comb = Shop | purpose = Rent
building_type_comb = Shop | purpose = Sale
building_type_comb = other | purpose = Rent
building_type_comb = other | purpose = Sale
building_type_comb = Residential Plot | purpose = Rent
building_type_comb = Residential Plot | purpose = Sale
building_type_comb = House | purpose = Rent
building_type_comb = House | purpose = Sale
building_type_comb = Office | purpose = Rent
building_type_comb = Office | purpose = Sale
building_type_comb = Duplex | purpose = Rent
building_type_comb = Duplex | purpose = Sale
price
num_bed_rooms

The individual scatterplots by 'building_type' for 'price' vs. 'num_bath_rooms' / 'num_bed_rooms' don't seem very informative ==> Let's use plot the distribution of 'price' for each value of 'num_bath_rooms' / 'num_bed_rooms'

[1170]:
```
print(df_merged[df_merged.num_bath_rooms == 0].shape)
print(df_merged[df_merged.num_bed_rooms == 0].shape)
```

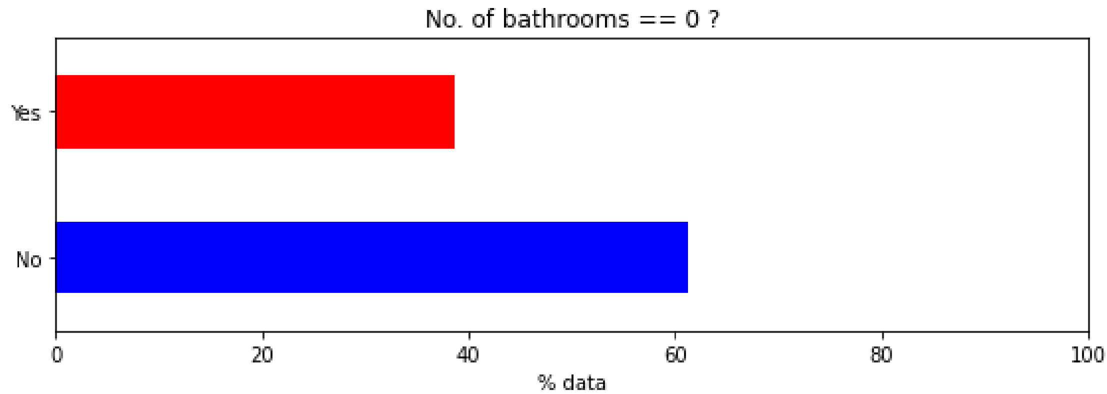
```
(16060, 25)
(9118, 25)
```

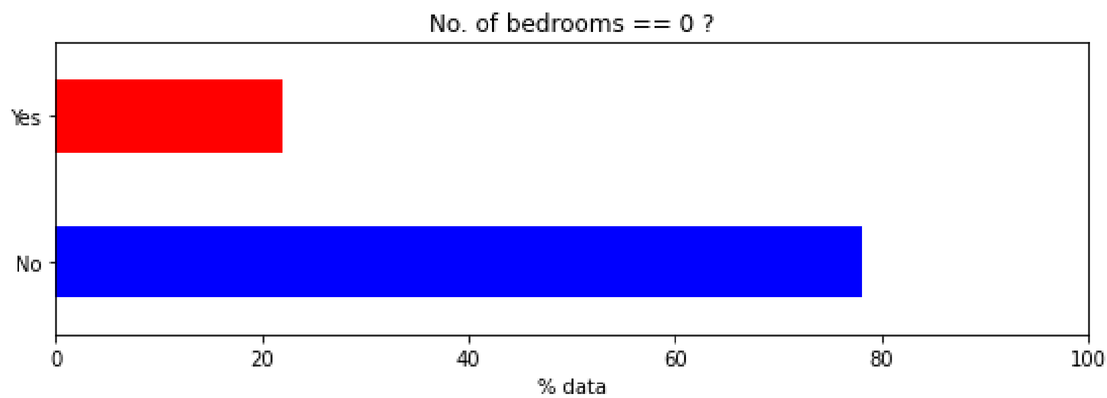
Missing or zero values for 'num_bath_rooms' / 'num_bed_rooms'

[1171]:
```
df_merged['is_num_bath_ZERO'] = np.where(df_merged['num_bath_rooms'] == 0,␣
↪'Yes', 'No')
df_merged['is_num_bed_ZERO'] = np.where(df_merged['num_bed_rooms'] == 0, 'Yes',␣
↪'No')
```

[1172]:
```
# BATHROOMS
freq = (df_merged['is_num_bath_ZERO'].value_counts() /␣
↪df_merged['is_num_bath_ZERO'].value_counts().sum()) * 100

fig, ax = plt.subplots(figsize=(8, 3))
freq.plot.barh(color=['blue', 'red'])

plt.title("No. of bathrooms == 0 ?")
plt.xlabel("% data")
ax.set_xlim(0, 100)
plt.tight_layout()

plt.show()


# BEDROOMS
freq = (df_merged['is_num_bed_ZERO'].value_counts() /␣
↪df_merged['is_num_bed_ZERO'].value_counts().sum()) * 100

fig, ax = plt.subplots(figsize=(8, 3))
freq.plot.barh(color=['blue', 'red'])

plt.title("No. of bedrooms == 0 ?")
plt.xlabel("% data")
ax.set_xlim(0, 100)
plt.tight_layout()
```

```
plt.show()
```





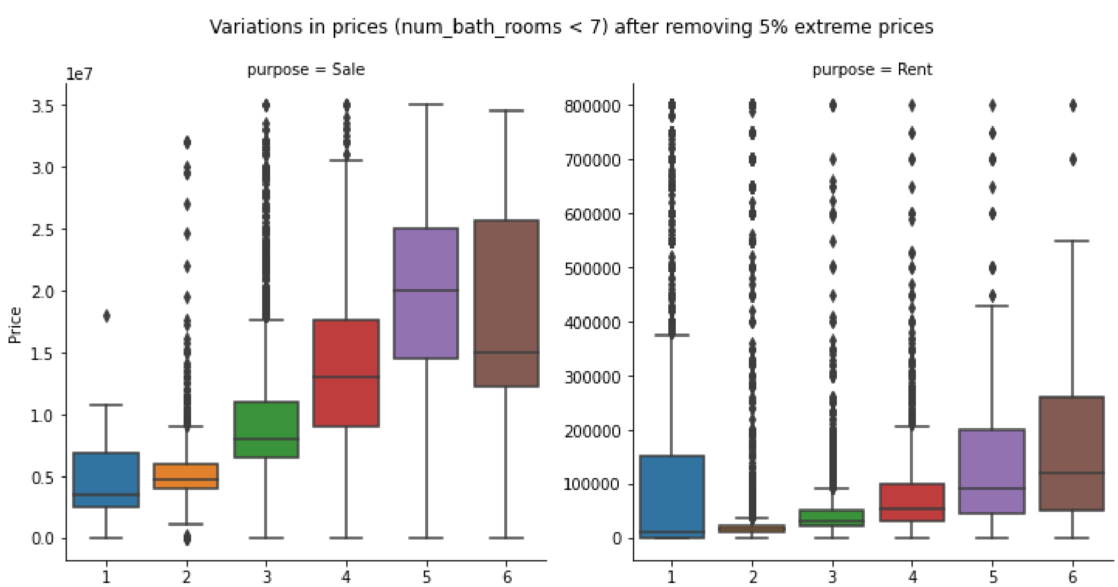
[1173]:
```
max_bath_sale = df_merged[df_merged['purpose'] == 'Sale'].num_bath_rooms.max()
print(max_bath_sale)

max_bath_rent = df_merged[df_merged['purpose'] == 'Rent'].num_bath_rooms.max()
print(max_bath_rent)
```

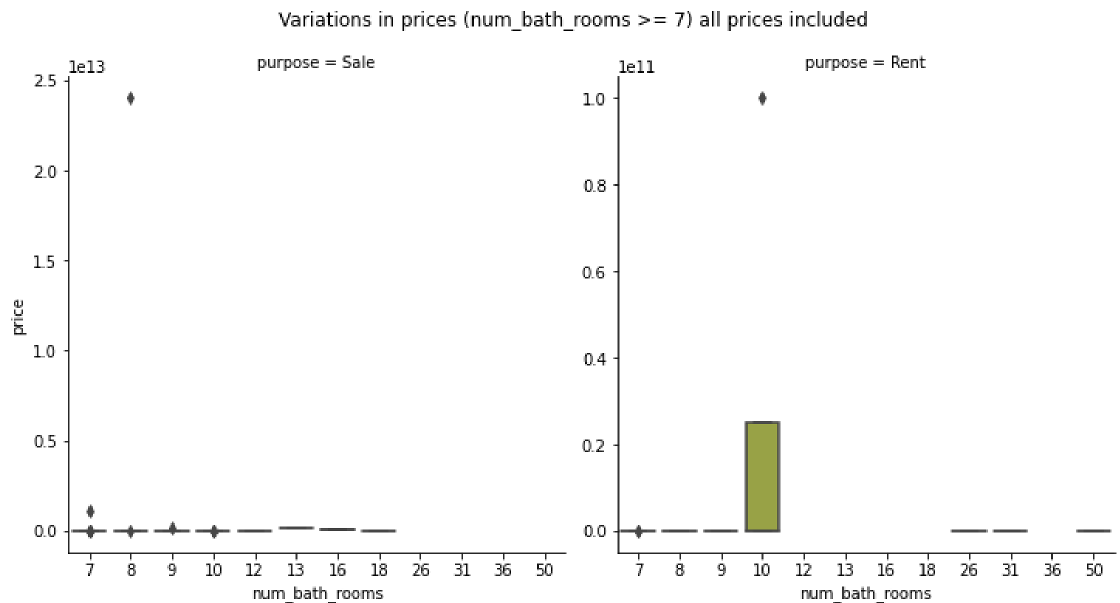
36
50

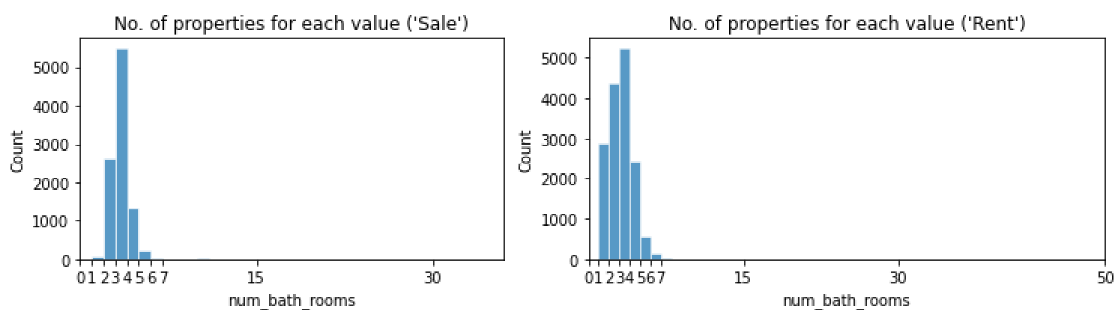
[1174]:
```
# First row ==============>
#
# plt.figure(figsize=(12, 3))
g = sns.catplot(y="price", x="num_bath_rooms",
            data = df_merged[(((df_merged.purpose == 'Rent') &
                                (df_merged.price <= percl_price_Rent['95%'])
                               ) |
```

```
                              ((df_merged.purpose == 'Sale') &
                               (df_merged.price <= percl_price_Sale['95%'])
                              )
                             ) &
                             (df_merged.num_bath_rooms > 0) &
                             (df_merged.num_bath_rooms <= 6)
                                ],
                kind="box",
               col= "purpose",
               sharey = False
           )

g.set_axis_labels('', 'Price')

# Add row title
fig = g.fig
# fig.suptitle(f'Row: {row_var}', y=1.05)
fig.suptitle('Variations in prices (num_bath_rooms < 7) after removing 5%␣
↪extreme prices', y=1.05)

plt.plot()


# Second row ==============>
#
# plt.figure(figsize=(12, 3))
g = sns.catplot(y="price", x="num_bath_rooms",
            data = df_merged[(df_merged.num_bath_rooms > 6)],
                kind="box",
               col= "purpose",
               sharey = False
           )

# Add row title
fig = g.fig
fig.suptitle('Variations in prices (num_bath_rooms >= 7) all prices included',␣
↪y=1.05)

# plt.title("")
plt.plot()


# Third row ==============>
#
# Create subplots with different widths
fig = plt.figure(figsize=(10.5, 3))
gs = gridspec.GridSpec(1, 2, width_ratios=[0.45, 0.55])
```

```
# Plot histogram 1
ax1 = plt.subplot(gs[0])
sns.histplot(x="num_bath_rooms",
             data = df_merged[(df_merged.num_bath_rooms > 0) &␣
 ↪(df_merged['purpose'] == 'Sale')],
             binwidth=1, edgecolor='white', ax=ax1)
ax1.set_xlim(0, max_bath_sale)
ax1.set_title("No. of properties for each value ('Sale')")
# plt.title("No. of properties for each value of num_bath_rooms ('Sale' +␣
 ↪'Rent')")
plt.xticks([0, 1, 2, 3, 4, 5, 6, 7, 15, 30])

ax2 = plt.subplot(gs[1])
sns.histplot(x="num_bath_rooms",
             data = df_merged[(df_merged.num_bath_rooms > 0) &␣
 ↪(df_merged['purpose'] == 'Rent')],
             binwidth=1, edgecolor='white', ax=ax2)
ax2.set_xlim(0, max_bath_rent)
ax2.set_title("No. of properties for each value ('Rent')")
plt.xticks([0, 1, 2, 3, 4, 5, 6, 7, 15, 30, 50])
# plt.xticks([0, 1, 2, 3, 4, 5, 6, 7, 10, 20, 35])

# Adjust spacing between subplots
plt.tight_layout()

# plt.plot()
plt.show()
```



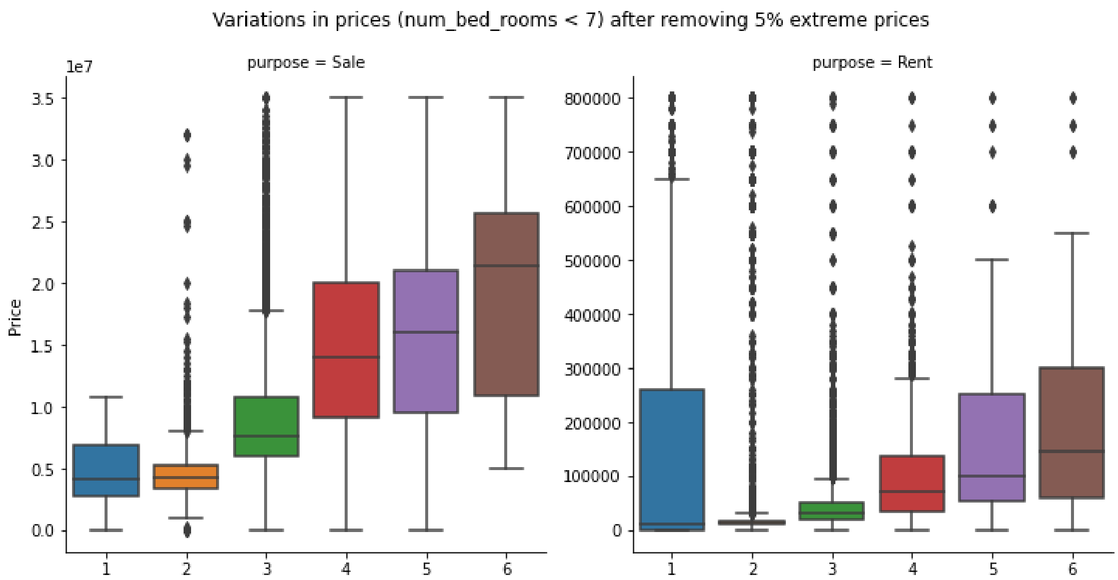


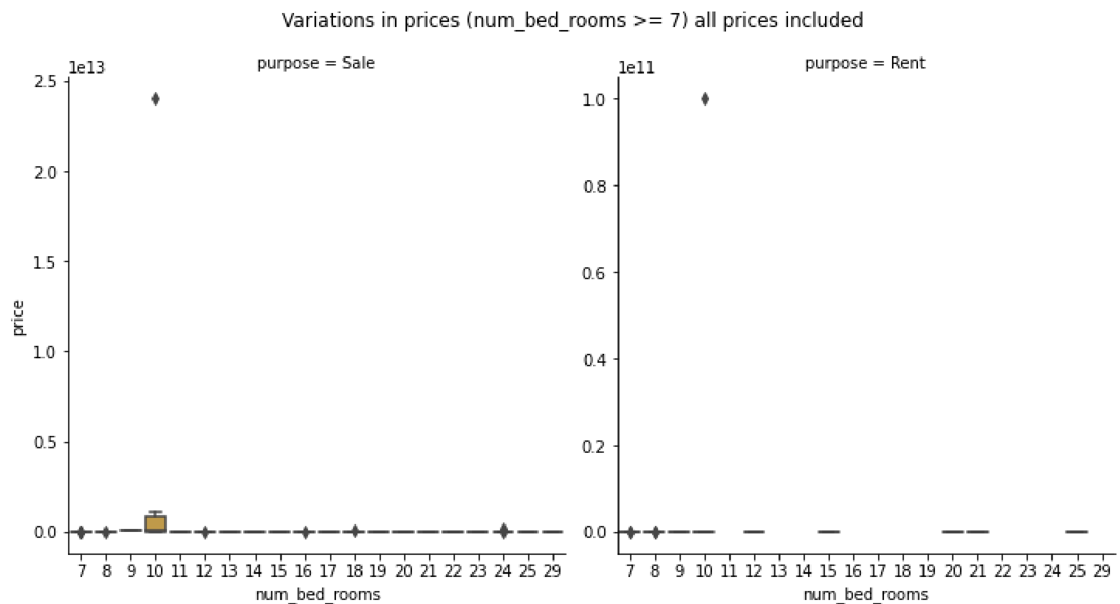


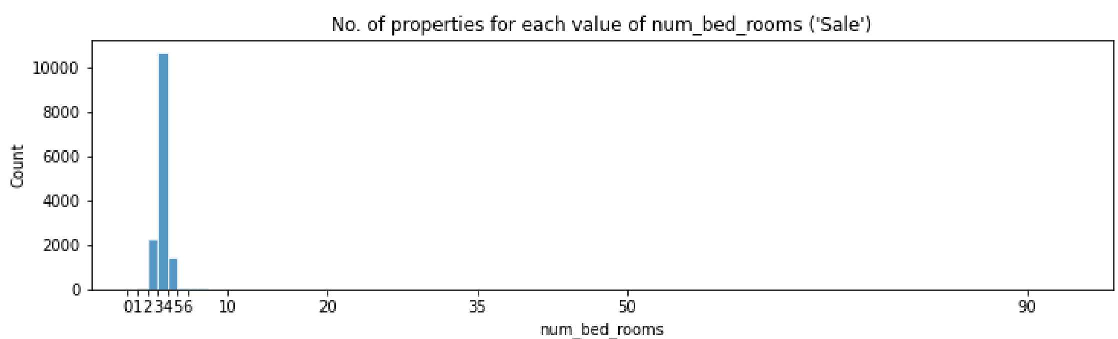
[1175]:
```
# First row ==============>
#
# plt.figure(figsize=(12, 3))
g = sns.catplot(y="price", x="num_bed_rooms",
            data = df_merged[(((df_merged.purpose == 'Rent') &
                               (df_merged.price <= percl_price_Rent['95%'])
                              ) |
                              ((df_merged.purpose == 'Sale') &
                               (df_merged.price <= percl_price_Sale['95%'])
                              )
                             ) &
                             (df_merged.num_bed_rooms > 0) &
                             (df_merged.num_bed_rooms <= 6)
```

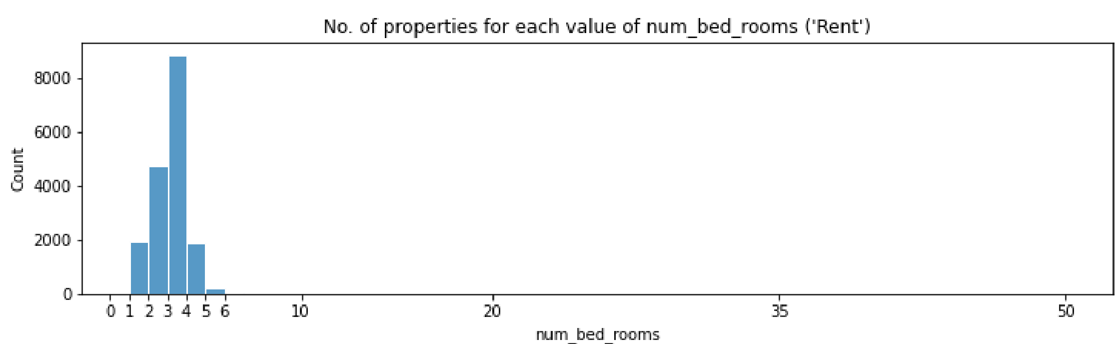
```
                                    ],
                 kind="box",
                col= "purpose",
                sharey = False
            )

g.set_axis_labels('', 'Price')

# Add row title
fig = g.fig
# fig.suptitle(f'Row: {row_var}', y=1.05)
fig.suptitle('Variations in prices (num_bed_rooms < 7) after removing 5%␣
↪extreme prices', y=1.05)

plt.plot()


# Second row ==============>
#
# plt.figure(figsize=(12, 3))
g = sns.catplot(y="price", x="num_bed_rooms",
            data = df_merged[(df_merged.num_bed_rooms > 6) &
                                (df_merged.num_bed_rooms < 30)
                                    ],
                 kind="box",
                col= "purpose",
                sharey = False
            )

# Add row title
fig = g.fig
fig.suptitle('Variations in prices (num_bed_rooms >= 7) all prices included',␣
↪y=1.05)

# plt.title("")
plt.plot()


plt.show()


# # Third row ==============>

plt.figure(figsize=(12, 3))

sns.histplot(x="num_bed_rooms",
```

```
                data = df_merged[(df_merged.num_bed_rooms > 0) &␣
 ↪(df_merged['purpose'] == 'Sale')],
                binwidth=1, edgecolor='white')
plt.title("No. of properties for each value of num_bed_rooms ('Sale')")
plt.xticks([0, 1, 2, 3, 4, 5, 6, 10, 20, 35, 50, 90])
plt.plot()

plt.figure(figsize=(12, 3))

sns.histplot(x="num_bed_rooms",
                data = df_merged[(df_merged.num_bed_rooms > 0) &␣
 ↪(df_merged['purpose'] == 'Rent')],
                binwidth=1, edgecolor='white')
plt.title("No. of properties for each value of num_bed_rooms ('Rent')")
plt.xticks([0, 1, 2, 3, 4, 5, 6, 10, 20, 35, 50])
plt.plot()

plt.show()
```









(b) Impact of facilities (malls, educational institutions, business hubs, hospitals, …) in the vicinity on the prices

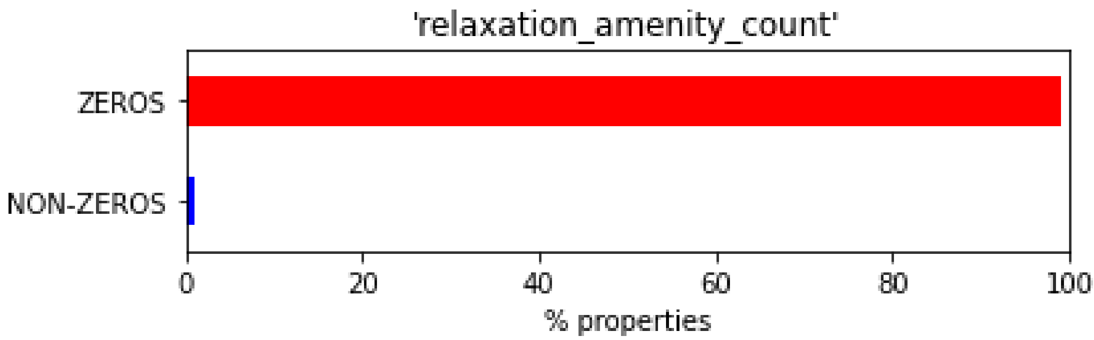
This question cannot be answered because the required info about these facilities is not available in the dataset ## (c) Impact of internal amenities (play area, number of car parks, height of the building, number of storeys, number of total amenities) on the prices

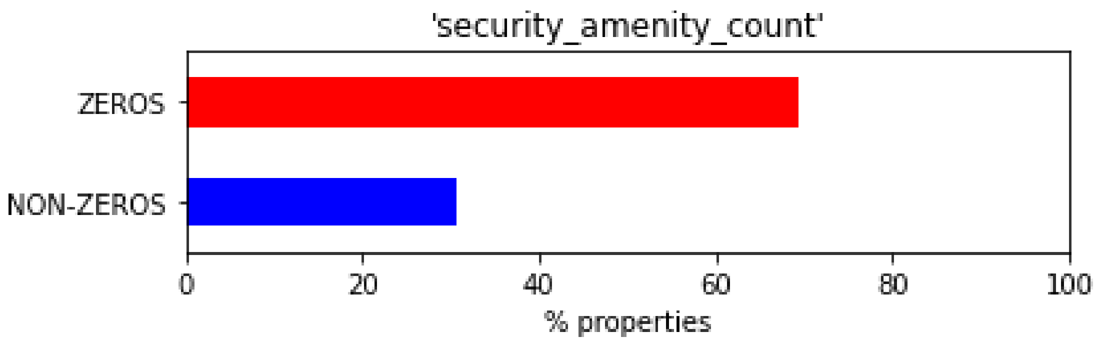
We don't have separate info about these amenities; so let's plot the impact of all the amenities we have

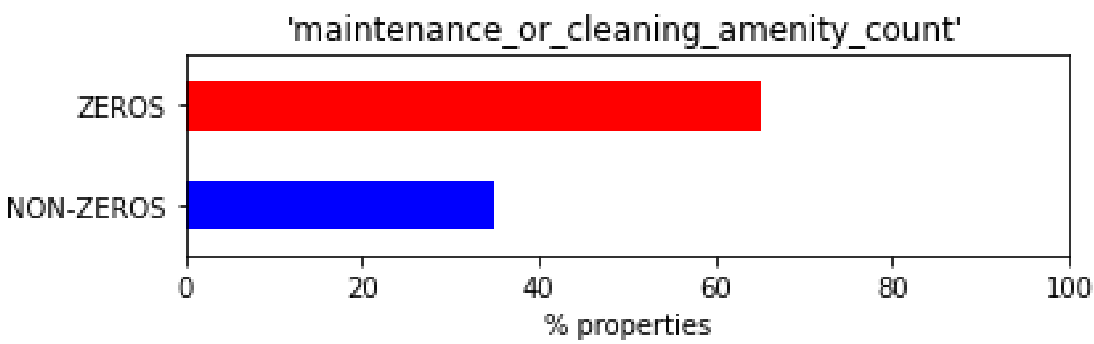
[1177]:
```
amenities = df_merged.iloc[:, 17:24].columns.tolist()

print(amenities)
```

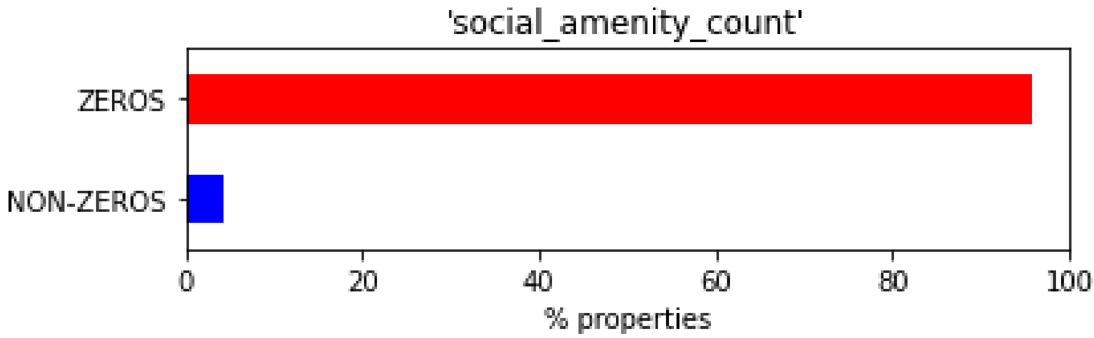
```
['relaxation_amenity_count', 'security_amenity_count',
'maintenance_or_cleaning_amenity_count', 'social_amenity_count',
'expendable_amenity_count', 'service_staff_amenity_count',
'unclassify_amenity_count']
```

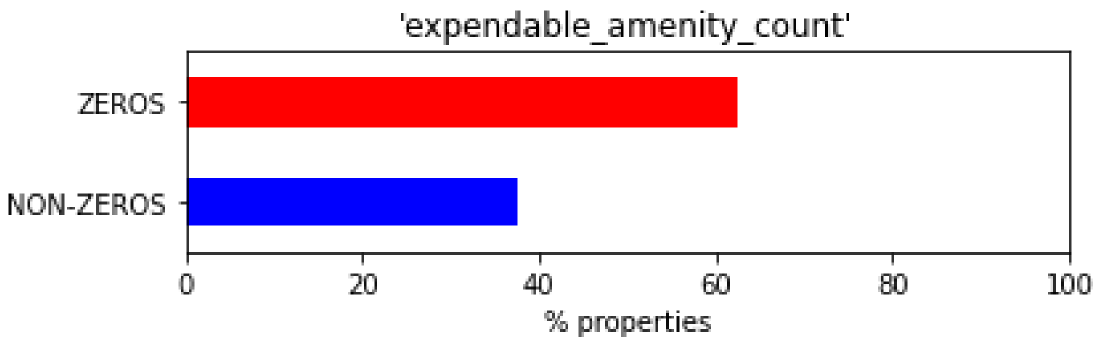
[1178]:
```
for col_name in amenities:
    # col_name = 'security_amenity_count'
    # print(df_merged[col_name].value_counts())

    df_TMP = pd.Series(np.where(df_merged[col_name] == 0, 'ZEROS', 'NON-ZEROS'))
    percentages = (df_TMP.value_counts() / df_TMP.value_counts().sum()) * 100

#     print()
#     print("------------------------------------")
#     print(percentages)

    fig, ax = plt.subplots(figsize=(6, 2))
    percentages.sort_index().plot.barh(color=['blue', 'red'])

    # Set x and y axis labels
    plt.xlabel('% properties')
    plt.ylabel('')
    # plt.title(f"'{col_name}': zero vs. non-zero entries")
    plt.title(f"'{col_name}'")
    ax.set_xlim(0, 100)

    plt.tight_layout()

    # Show the plot
    plt.show()
```

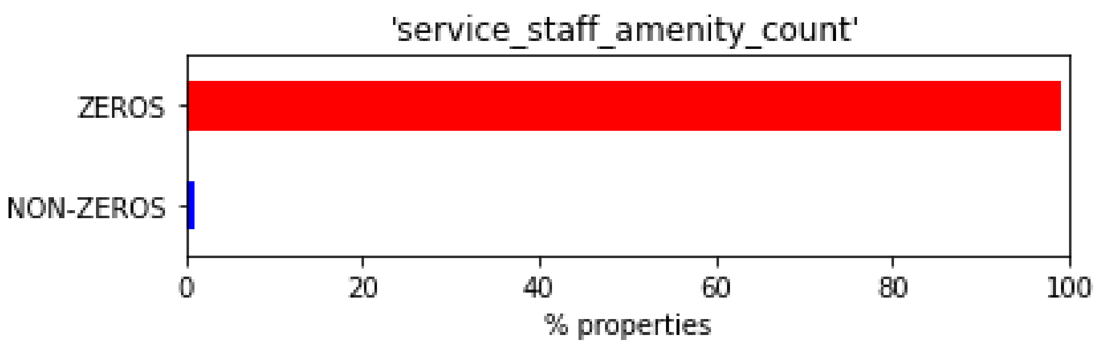

'relaxation_amenity_count'
ZEROS
NON-ZEROS
0
20
40
60
80
100
% properties

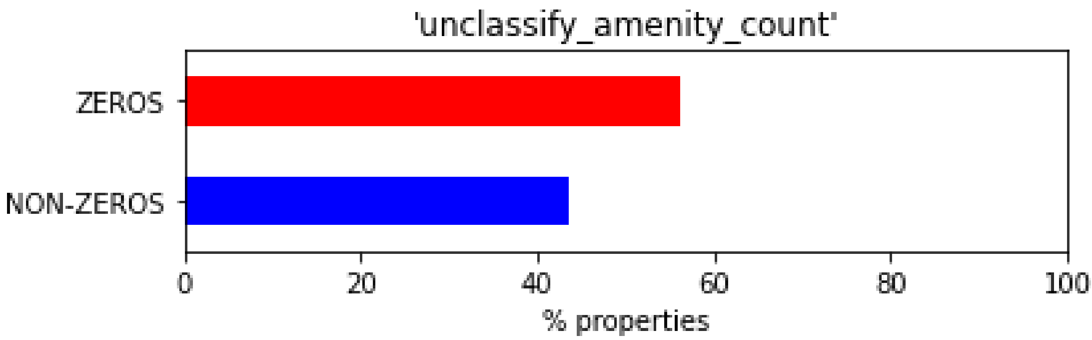

'security_amenity_count'
ZEROS
NON-ZEROS
0
20
40
60
80
100
% properties


'maintenance_or_cleaning_amenity_count'
ZEROS
NON-ZEROS
0
20
40
60
80
100
% properties


'social_amenity_count'
ZEROS
NON-ZEROS
0
20
40
60
80
100
% properties


'expendable_amenity_count'
ZEROS
NON-ZEROS
0
20
40
60
80
100
% properties


'service_staff_amenity_count'
ZEROS
NON-ZEROS
0
20
40
60
80
100
% properties



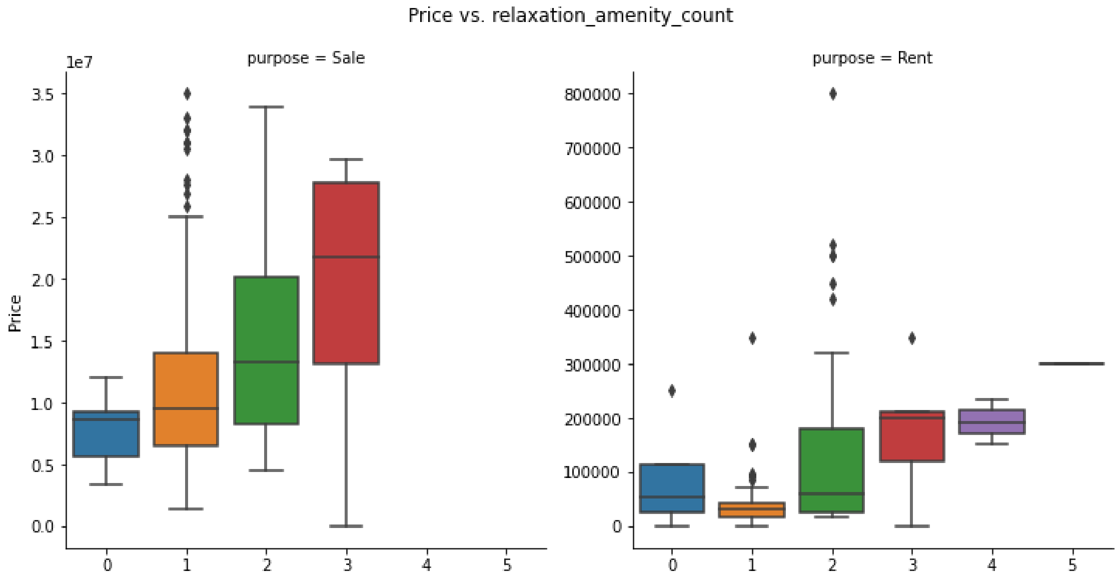
[1179]:
```
# amenities
```

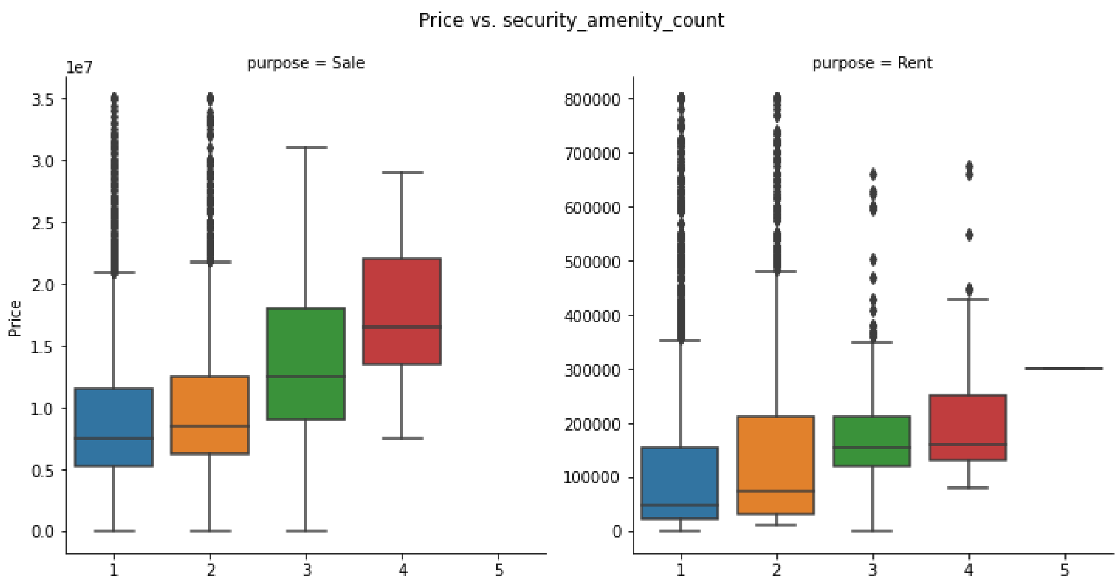
[1180]:
```
print("Price percentile range for 'Rent'")
print()
print(percl_price_Rent)
print()
print()
print("Price percentile range for 'Sale'")
print()
print(percl_price_Sale)
```

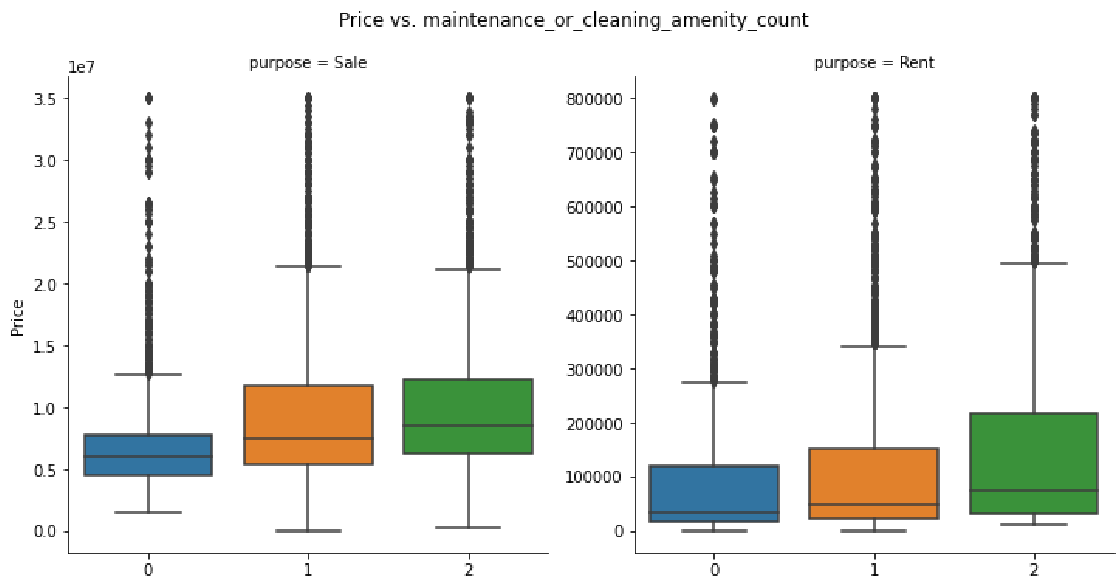
```
Price percentile range for 'Rent'

count    2.315600e+04
mean     1.092878e+07
std      8.266022e+08
min      0.000000e+00
2%       0.000000e+00
30%      1.800000e+04
50%      3.200000e+04
60%      5.000000e+04
90%      4.500000e+05
95%      8.000000e+05
99%      2.500000e+06
max      1.000000e+11
Name: price, dtype: float64


Price percentile range for 'Sale'

count    1.731000e+04
mean     2.077500e+09
std      1.839185e+11
min      0.000000e+00
```

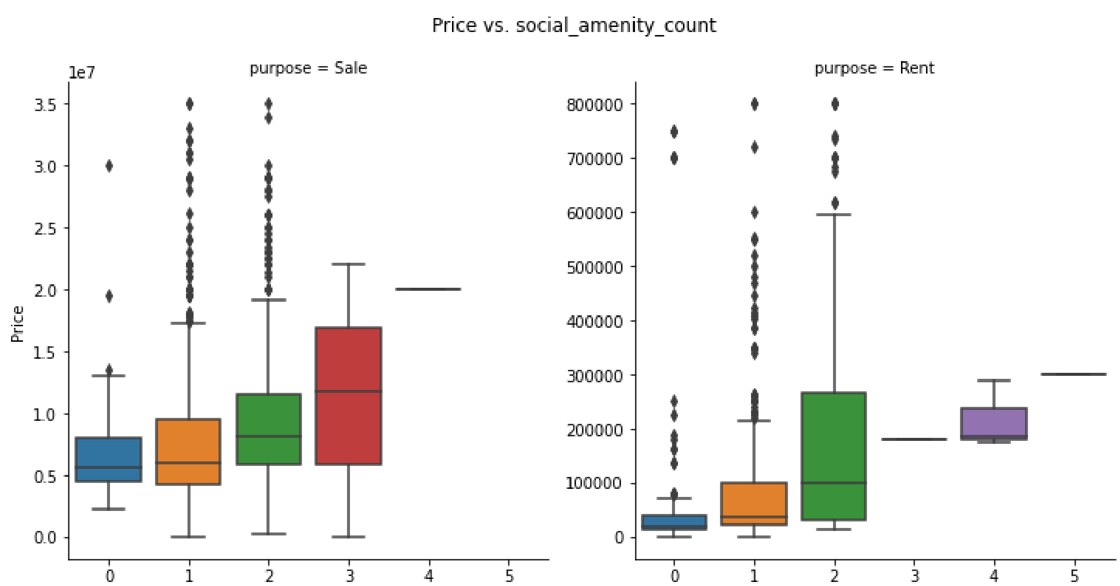
```
2%       4.500000e+05
30%      5.337000e+06
50%      7.200000e+06
60%      8.220000e+06
90%      2.000000e+07
95%      3.500000e+07
99%      6.500000e+08
max      2.400000e+13
Name: price, dtype: float64
```

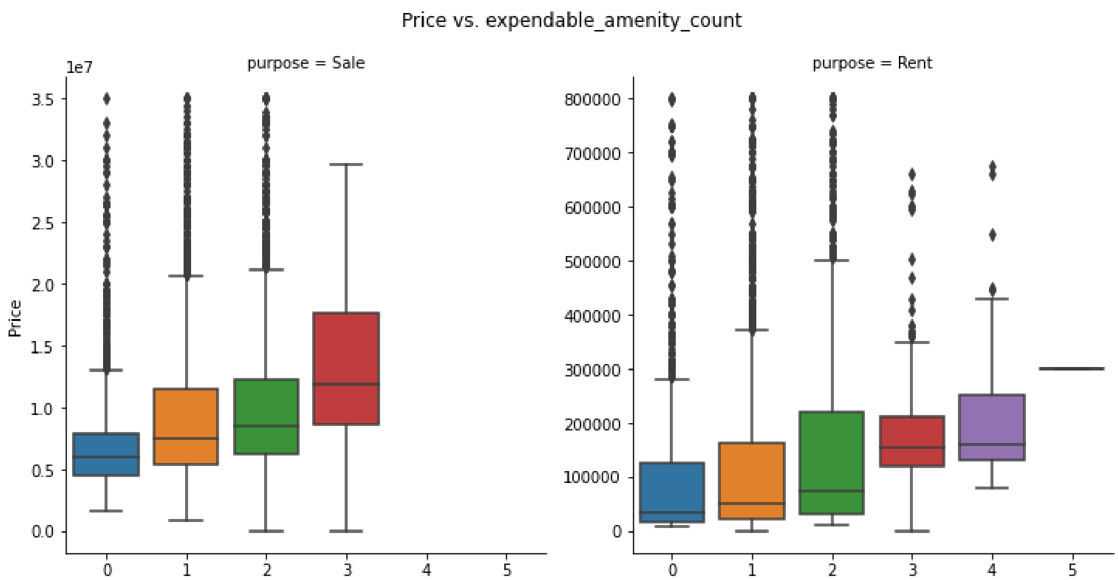
[1181]:
```
# Take a subset of data such that properties with very hight values (upper␣
↪5%tile) are excluded
df_sub = df_merged[(((df_merged.purpose == 'Rent') & (df_merged.price <=␣
↪percl_price_Rent['95%'])) |
                    ((df_merged.purpose == 'Sale') & (df_merged.price <=␣
↪percl_price_Sale['95%']))
                   )]

for amenity_name in amenities:
    g = sns.catplot(y="price", x="security_amenity_count",
                    data = df_sub[df_sub[amenity_name] > 0],
                    kind="box",
                    col= "purpose",
                    sharey = False
                   )

    g.set_axis_labels('', 'Price')

    # Add row title
    fig = g.fig
    fig.suptitle(f"Price vs. {amenity_name}", y=1.05)

    plt.plot()
```

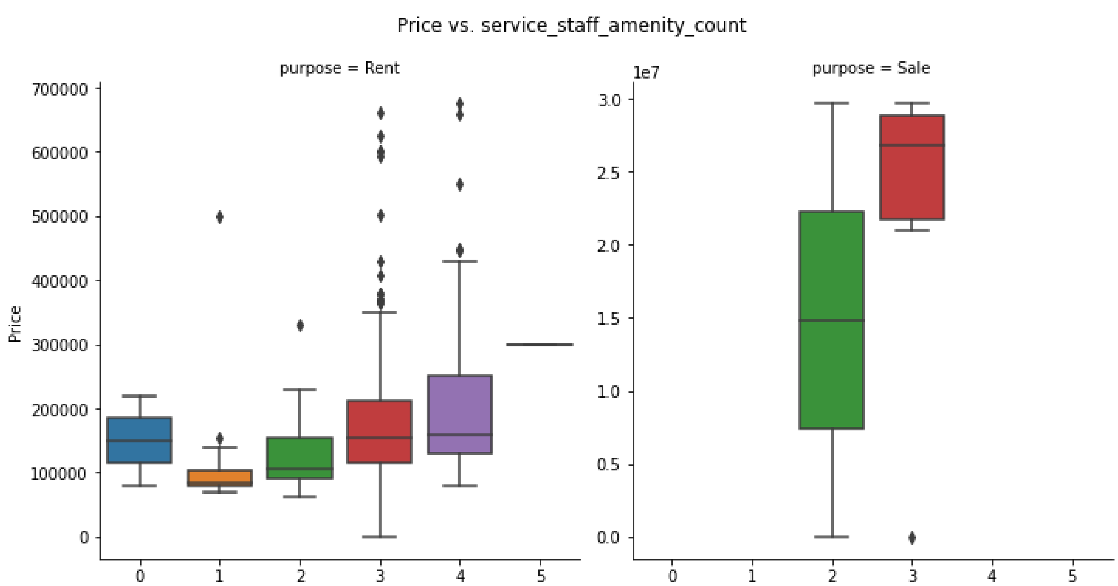

Price vs. relaxation_amenity_count
purpose = Sale
purpose = Rent
1e7
Price
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
800000
700000
600000
500000
400000
300000
200000
100000
0
0
1
2
3
4
5

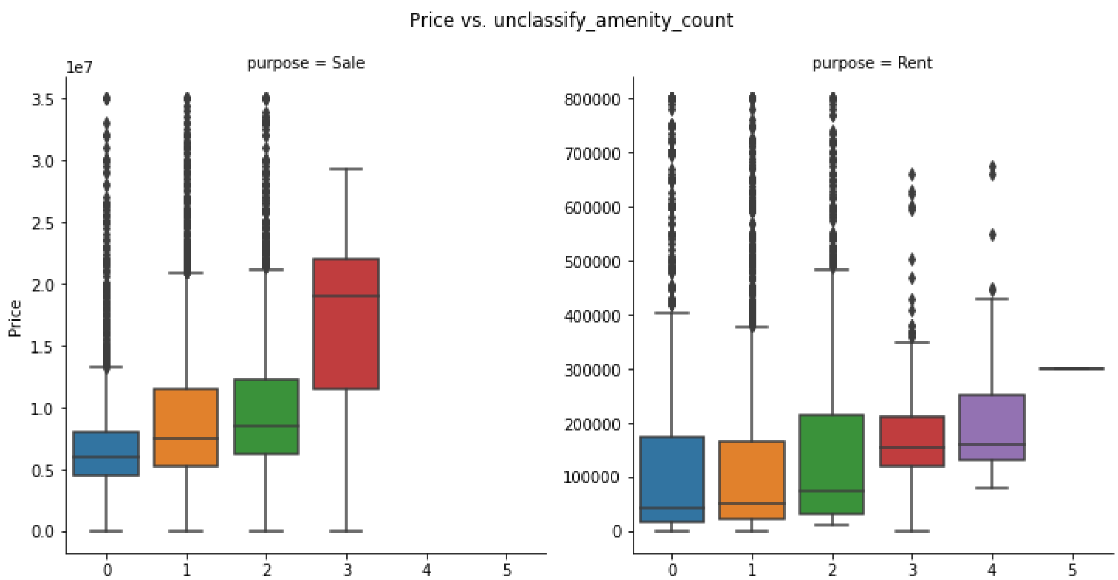

Price vs. security_amenity_count
purpose = Sale
purpose = Rent
1e7
Price
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
800000
700000
600000
500000
400000
300000
200000
100000
0
1
2
3
4
5


Price vs. maintenance_or_cleaning_amenity_count
purpose = Sale
purpose = Rent
1e7
Price
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
800000
700000
600000
500000
400000
300000
200000
100000
0
0
1
2


Price vs. social_amenity_count
purpose = Sale
purpose = Rent
1e7
Price
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
800000
700000
600000
500000
400000
300000
200000
100000
0
0
1
2
3
4
5


Price vs. expendable_amenity_count
purpose = Sale
purpose = Rent
Price
1e7
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
800000
700000
600000
500000
400000
300000
200000
100000
0
0
1
2
3
4
5


Price vs. service_staff_amenity_count
purpose = Rent
purpose = Sale
Price
700000
600000
500000
400000
300000
200000
100000
0
1e7
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0
1
2
3
4
5



2.1 (d) How do they influence the price: linearly / non-linearly / stepwise?

This question is answered by looking at plots for question 2(a) and 2(c) above.

3 Question: 8

- Mean prices per building_type (apartment/shop/…); the goal is to understand if it is worth it to have such an attribute, or if building_nature (commercial/residential) is enough.

[1182]:
```
# Calculate 'Sale' and 'Rent' means separately and merge
df_mean_price = pd.merge(df_merged[df_merged['purpose'] == 'Sale'].
 ↪groupby('building_type_comb', as_index=False)['price'].mean(),
        df_merged[df_merged['purpose'] == 'Rent'].groupby('building_type_comb',␣
 ↪as_index=False)['price'].mean(),
         on='building_type_comb', how='outer', suffixes = ['_sale', '_rent']).
 ↪fillna(0)
```

[1183]:
```
df_mean_price
```

[1183]:

	building_type_comb	price_sale	price_rent
0	Apartment	2.100880e+09	5.843884e+06
1	Building	7.466818e+07	1.136901e+08
2	Commercial Space	4.570320e+07	0.000000e+00
3	Duplex	4.516184e+07	4.089677e+05
4	Floor	4.999938e+07	4.800843e+05

```
5                House  1.168833e+11  2.964626e+05
6                 Land  1.042472e+07  0.000000e+00
7               Office  3.833758e+07  3.580366e+05
8                 Plot  2.765887e+07  2.708750e+05
9     Residential Plot  2.866166e+06  4.300400e+04
10                Shop  4.825875e+06  2.764426e+05
11               other  1.144293e+07  1.759479e+05
12              Garage  0.000000e+00  2.784603e+03
```

[1184]:

```python
fig, ax = plt.subplots(1,2)

# First plot
ax[0].barh(df_mean_price['building_type_comb'], df_mean_price['price_sale'])
ax[0].set_title('For Sale')
ax[0].set_xscale('log')
ax[0].set_xlabel('Mean price in BDT (log scale)')


# # Second plot
ax[1].barh(df_mean_price['building_type_comb'], df_mean_price['price_rent'])
ax[1].set_title('For Rent')
ax[1].set_xscale('log')
ax[1].set_xlabel('Mean price in BDT (log scale)')

# Adjust the size of the figure
fig.set_size_inches([20,8])

plt.show()
```