Project code

October 19, 2022

0.0.1 Airbnb Data Preparation

- EDA
- Splitting
- Preprocessing

0.0.2 Import Data and Library

[1]:
```
### Import library
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
%matplotlib inline
import seaborn as sns
import pandas as pd
import matplotlib.pyplot as plt
from wordcloud import WordCloud
import statsmodels
import statsmodels.api as sm
import scipy.stats as stats
import verstack
verstack.__version__
from verstack.stratified_continuous_split import scsplit
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder,␣
↪OrdinalEncoder, MinMaxScaler

### Import Dataset
Airbnb = pd.read_csv("Data/AB_NYC_2019.csv")
```

```
/Users/hanjunwei/Desktop/DATA_1030/1030_venv/lib/python3.10/site-
packages/xgboost/compat.py:36: FutureWarning: pandas.Int64Index is deprecated
and will be removed from pandas in a future version. Use pandas.Index with the
appropriate dtype instead.
  from pandas import MultiIndex, Int64Index
```

0.1 ## 1. EDA

0.1.1 Overall

a. Shape

[2]:
```
### Inspect shape
print("Number of Observations: ", str(Airbnb.shape[0]))
print("Number of Features: ", str(Airbnb.shape[1]))
### Examing head
#Airbnb.head(5)
```

```
Number of Observations:  48895
Number of Features:  16
```

b. Data Type

[3]:
```
Airbnb.dtypes
```

[3]:
```
id                                 int64
name                              object
host_id                            int64
host_name                         object
neighbourhood_group               object
neighbourhood                     object
latitude                         float64
longitude                        float64
room_type                         object
price                              int64
minimum_nights                     int64
number_of_reviews                  int64
last_review                       object
reviews_per_month                float64
calculated_host_listings_count     int64
availability_365                   int64
dtype: object
```

From the data table, we know variable last_view is date, Hence we will convert it to type date.

[4]:
```
Airbnb['last_review'] = pd.
↪to_datetime(Airbnb['last_review'],infer_datetime_format=True)
```

[5]:
```
Airbnb.dtypes
```

[5]:
```
id                                 int64
name                              object
host_id                            int64
host_name                         object
neighbourhood_group               object
neighbourhood                     object
latitude                         float64
longitude                        float64
room_type                         object
```

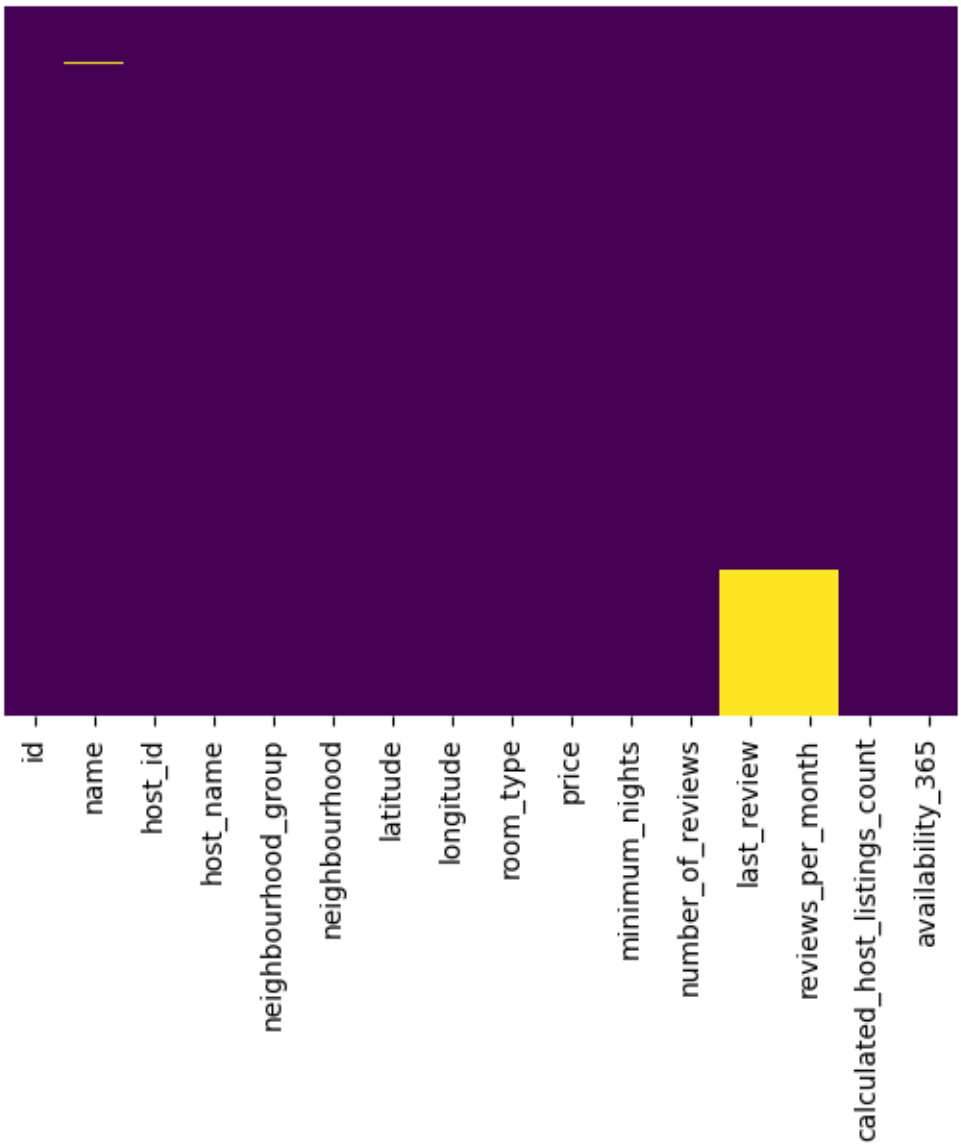
```
price                                 int64
minimum_nights                        int64
number_of_reviews                     int64
last_review                  datetime64[ns]
reviews_per_month                   float64
calculated_host_listings_count        int64
availability_365                      int64
dtype: object
```

c. Missing Data

[6]:
```
total = Airbnb.isnull().sum().sort_values(ascending = False)
percent = Airbnb.isnull().sum()/Airbnb.shape[0]
missing_data = pd.concat([total, percent], axis=1,
                         keys=['Total number of missing values','Percent'],
                         sort=False).sort_values('Total number of missing␣
 ↪values', ascending=False)
sns.heatmap(Airbnb.sort_values("reviews_per_month").isnull(),yticklabels =␣
 ↪False,
            cbar = False, cmap = "viridis")
missing_data[missing_data["Total number of missing values"]>0]
```

[6]:

	Total number of missing values	Percent
last_review	10052	0.205583
reviews_per_month	10052	0.205583
host_name	21	0.000429
name	16	0.000327



4 out of **16** variables contain missing values and they are: - **Categorical** - `name` (Airbnb name) - `host_name` (Airbnb owner's name) - **Continuous** - `last_review` (The date of the latest review recieved) - `reviews_per_month` (number of review a Airbnb recieved in a month) - Potential explaination: `Nan` indicates the Airbnb have not received any reviews.

0.1.2 0. Price (target)

- Summary statistics

[7]:
```
value = Airbnb['price'].describe()
Summary = pd.concat([value], axis=1,
                          keys=['value'],
```

```
                          sort=False)
Summary
```

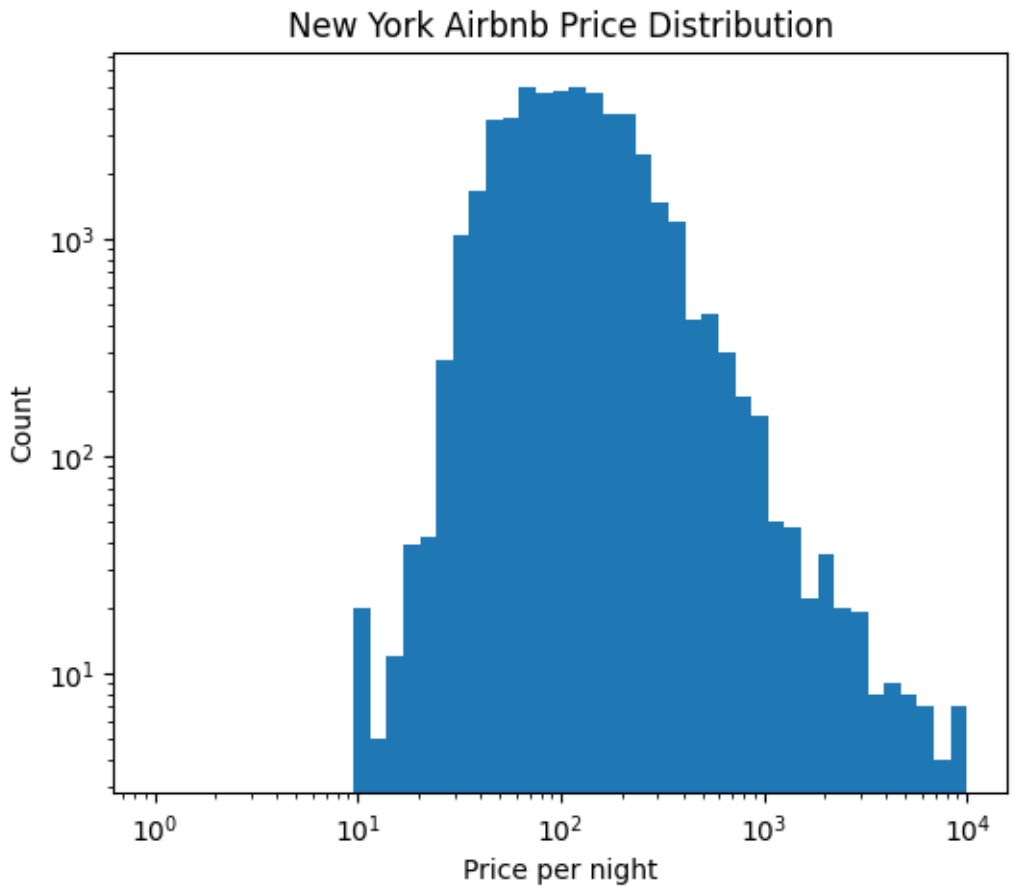
[7]:
```
              value
count  48895.000000
mean     152.720687
std      240.154170
min        0.000000
25%       69.000000
50%      106.000000
75%      175.000000
max    10000.000000
```

[8]:
```
print("the mode is:", str(Airbnb['price'].mode()[0]))
```

```
the mode is: 100
```

- Plot

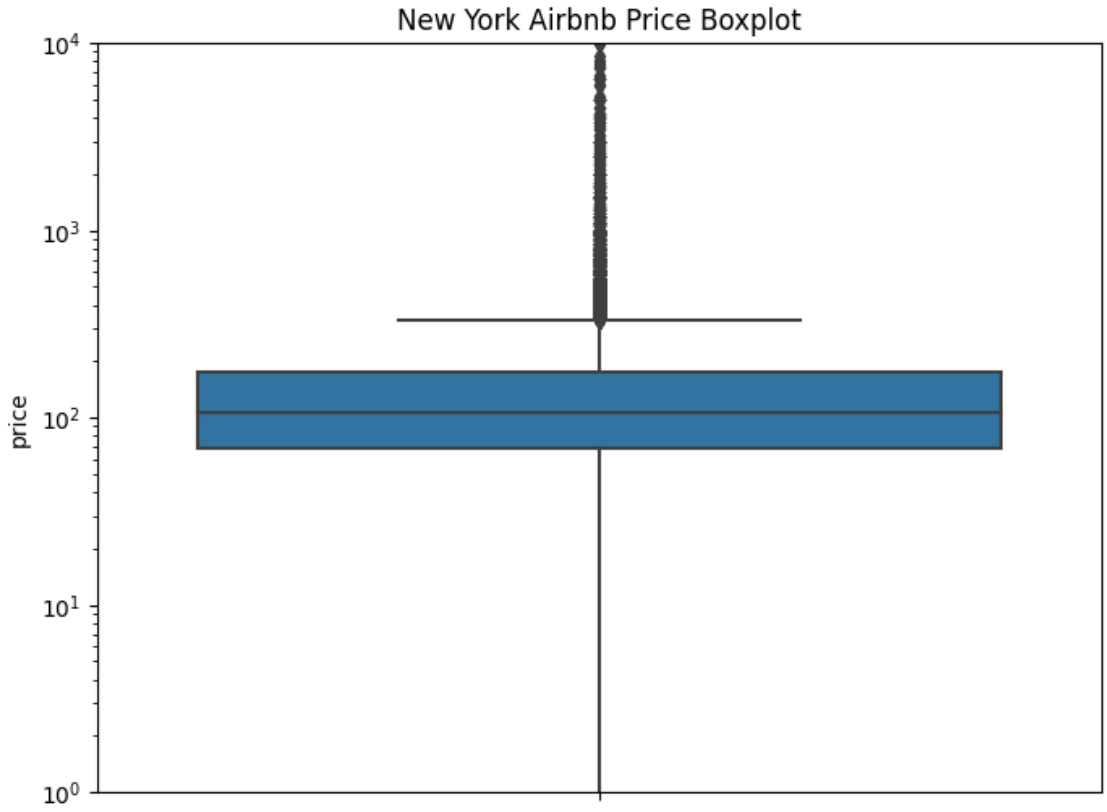
[9]:
```
plt.figure(figsize = (6,5))
Airbnb['price'].plot.hist(log=True, bins = np.logspace(np.log10(1),np.log10(np.
 ↪max(Airbnb['price'])),50))
plt.semilogy()
plt.semilogx()
plt.xlabel('Price per night')
plt.ylabel('Count')
plt.title('New York Airbnb Price Distribution')
plt.show()
plt.savefig('price.png')
```




```
<Figure size 640x480 with 0 Axes>
```

- Boxplot

[10]:
```
sns.boxplot(data=Airbnb, y="price")
plt.yscale('log')
plt.ylim(1,10000)
fig = plt.gcf()
fig.set_size_inches(8, 6)
plt.title('New York Airbnb Price Boxplot')
plt.savefig('price_box.png')
```



- Calculate Extreme Outlier

[11]:
```
### Outlier
IQ = Airbnb['price'].describe()["75%"] - Airbnb['price'].describe()["25%"]
### upper outer fence
uof = Airbnb['price'].describe()["75%"] + 3*IQ
### lower outer fence
lof = Airbnb['price'].describe()["25%"] - 3*IQ

print("precentage of extreme outlier in this data:
 ↪",str((sum(Airbnb['price']>=uof)/len(Airbnb['price']))*100),"%")
```

```
precentage of extreme outlier in this data: 2.716024133346968 %
```

Where price is 0

[12]:
```
len(Airbnb[Airbnb['price']==min(Airbnb['price'])])
```

[12]:
```
11
```

[13]:
```
Airbnb = Airbnb.loc[Airbnb["price"]!= 0].reset_index(drop=True)
```

Comment * According to the statistics, Y is continuous variable * Strong right skewed * we should

satrify while spliting the dataset

There is no missing value in target variable.

0.1.3 Split target and predictor

[14]:
```
X = Airbnb.loc[:,Airbnb.columns!="price"]
y = Airbnb["price"]
```

0.1.4 1. id

[15]:
```
## check unique
len(X["id"].unique())
sum(X["id"].value_counts()!=1)
```

[15]:
```
0
```

[16]:
```
X.drop(['id'], axis=1, inplace=True)
```

- categorical variable
- No duplicated values, function as identifier of each observations (airbnb)

0.1.5 2. name

[17]:
```
X["name"].head()
```

[17]:
```
0                  Clean & quiet apt home by the park
1                               Skylit Midtown Castle
2                 THE VILLAGE OF HARLEM…NEW YORK !
3                     Cozy Entire Floor of Brownstone
4    Entire Apt: Spacious Studio/Loft by central park
Name: name, dtype: object
```

[18]:
```
X.drop(['name'], axis=1, inplace=True)
```

- Text data
- Not important in our senorial
- contain 0.000327 missing value
- We should drop this entire column

0.1.6 3. host_id

- Summary Statistics

[19]:
```
print(len(X["host_id"].unique()))
value = X["host_id"].value_counts().describe()
Summary = pd.concat([value], axis=1,
                        keys=['value'],
                        sort=False)
Summary
```

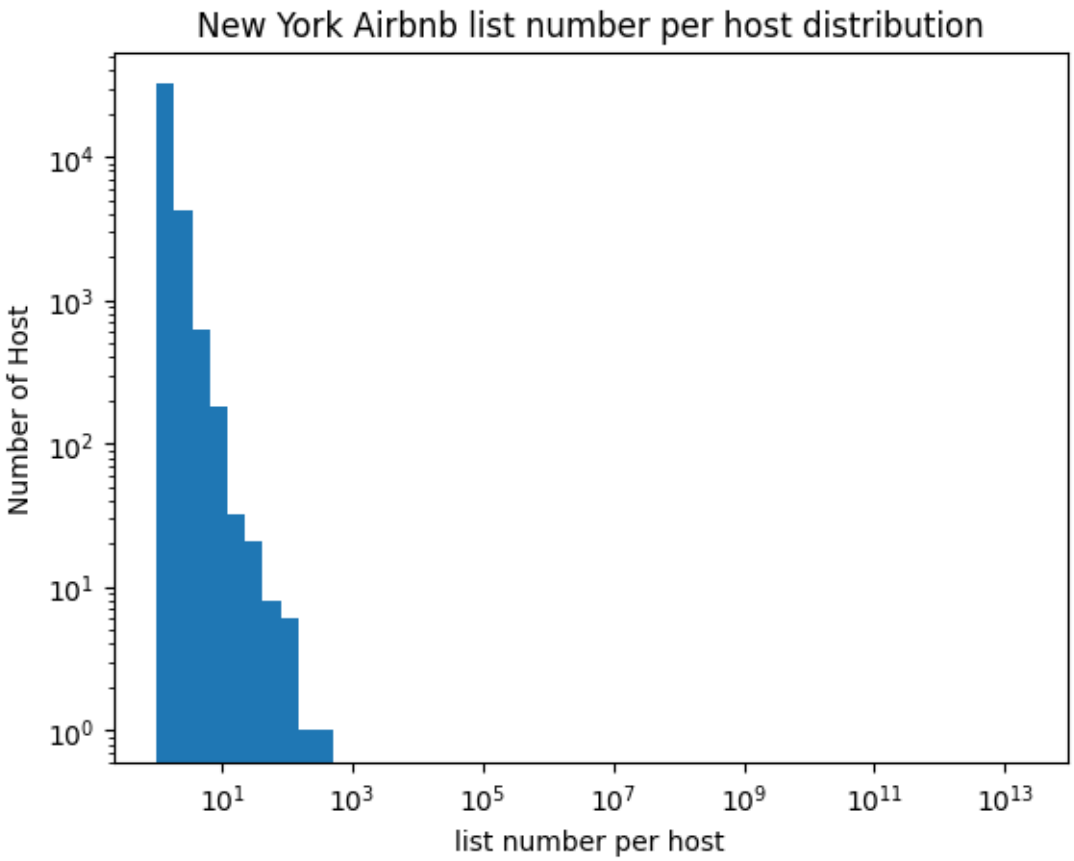
```
37455
```

[19]:
```
              value
count  37455.00000
mean       1.30514
std        2.76058
min        1.00000
25%        1.00000
50%        1.00000
75%        1.00000
max      327.00000
```

[20]:
```
number_of_airbnb = X["host_id"].value_counts()
list_per_owner = pd.concat([number_of_airbnb], axis=1,
                           keys=['number_of_airbnb'],
                           sort=False)
list_per_owner
```

[20]:
```
            number_of_airbnb
219517861                327
107434423                232
30283594                 121
137358866                103
12243051                  96
…                        …
1722054                    1
33363604                   1
69507287                   1
20892338                   1
68119814                   1

[37455 rows x 1 columns]
```

[21]:
```
list_per_owner["number_of_airbnb"].plot.hist(log=True,
                                             bins = np.logspace(np.log2(1),
                                                                np.log2(np.
 ↪max(Airbnb['price'])),50))
plt.semilogy()
plt.semilogx()
plt.xlabel('list number per host')
plt.ylabel('Number of Host')
plt.title('New York Airbnb list number per host distribution')
plt.savefig('Number_per_host_distribution.png')
```



[22]:
```
X.drop(['host_id'], axis=1, inplace=True)
```

- Categorical
- The id number of the host.
- There is duplication, one host can have multiple properties.
- There are 37457 host recorded
- The average number of properties managed by host are 1.3
- The minimum number of properties managed by host is 1
- The maximum number of properties managed by host are 327

0.1.7 4. host_name

[23]:
```
X["host_name"].head()
```

[23]:
```
0           John
1       Jennifer
2      Elisabeth
3    LisaRoxanne
4          Laura
Name: host_name, dtype: object
```

[24]:
```
X.drop(['host_name'], axis=1, inplace=True)
```

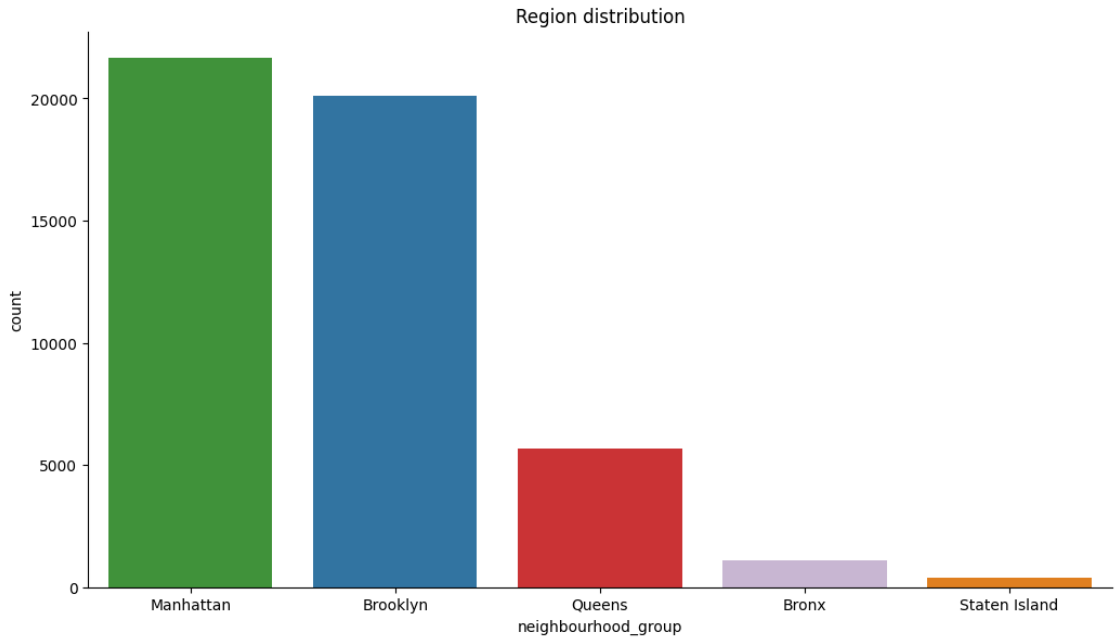
- Text dataset
- the name of the host
- Missing proportion is 0.000429
- We can use the host_id as the host identifier
- Not important and drop

0.1.8 5. neighbourhood_group

[25]:
```
for region in Airbnb['neighbourhood_group'].unique():
    print(region)
```

```
Brooklyn
Manhattan
Queens
Staten Island
Bronx
```

[26]:
```
custom_palette = sns.color_palette("Paired", 9)
my_pal = {"Brooklyn": custom_palette[1],
          "Manhattan": custom_palette[3],
          "Queens":custom_palette[5],
          "Staten Island": custom_palette[7],
          "Bronx": custom_palette[8]}


sns.catplot(x='neighbourhood_group', kind='count' ,data=Airbnb, order =␣
 ↪["Manhattan", "Brooklyn",
                                                                      ␣
 ↪"Queens", "Bronx", "Staten Island"], palette=my_pal)
plt.title('Region distribution')

fig = plt.gcf()
fig.set_size_inches(12, 6)
plt.savefig('Region_distribution.png')
```



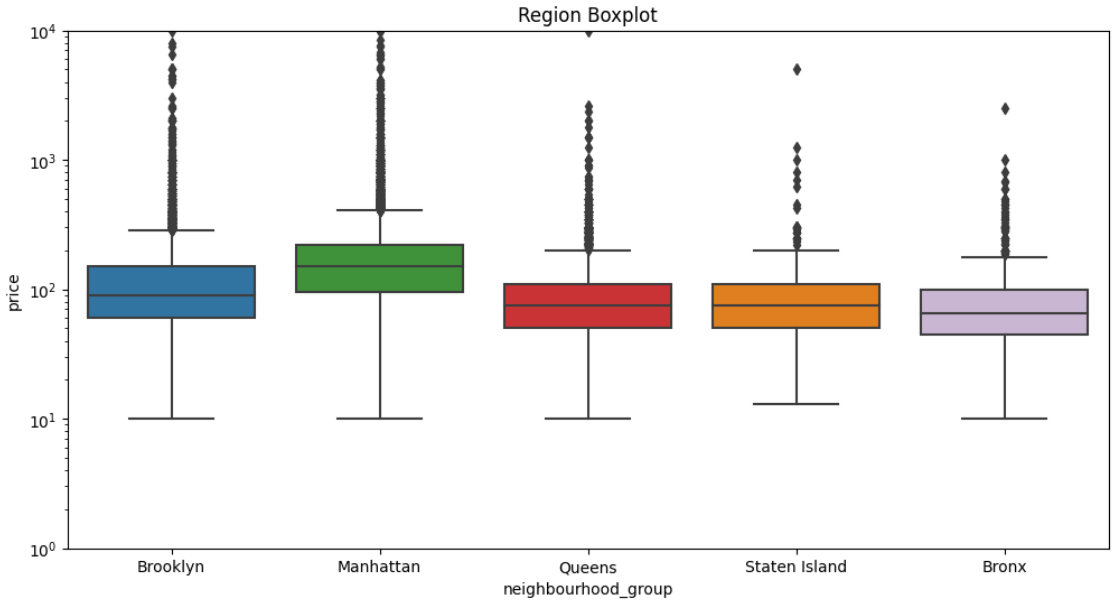
[27]:
```
sum(Airbnb["neighbourhood_group"]=="Manhattan")/
  ↪len(Airbnb["neighbourhood_group"])
```

[27]: 0.44308976352180673

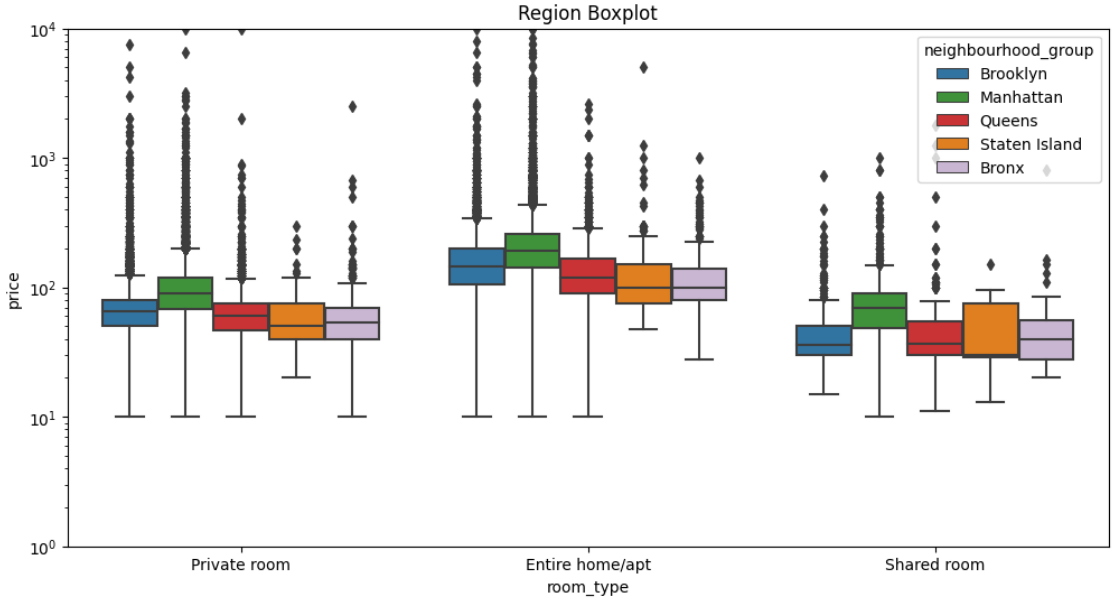
[28]:
```
min(Airbnb[(Airbnb["neighbourhood_group"]== "Staten Island")]["price"])
```

[28]: 13

[29]:
```
sns.boxplot(data=Airbnb, x="neighbourhood_group", y="price", palette=my_pal)
plt.yscale('log')
plt.ylim(1,10000)
fig = plt.gcf()
fig.set_size_inches(12, 6)
plt.title('Region Boxplot')
plt.savefig('Region_boxplot.png')
```



[30]:
```
sns.boxplot(data=Airbnb, x="room_type", y="price", hue = "neighbourhood_group",␣
↪palette=my_pal)
plt.yscale('log')
plt.ylim(1,10000)
fig = plt.gcf()
fig.set_size_inches(12, 6)
plt.title('Region Boxplot')
plt.savefig('Region_boxplot_2.png')
```

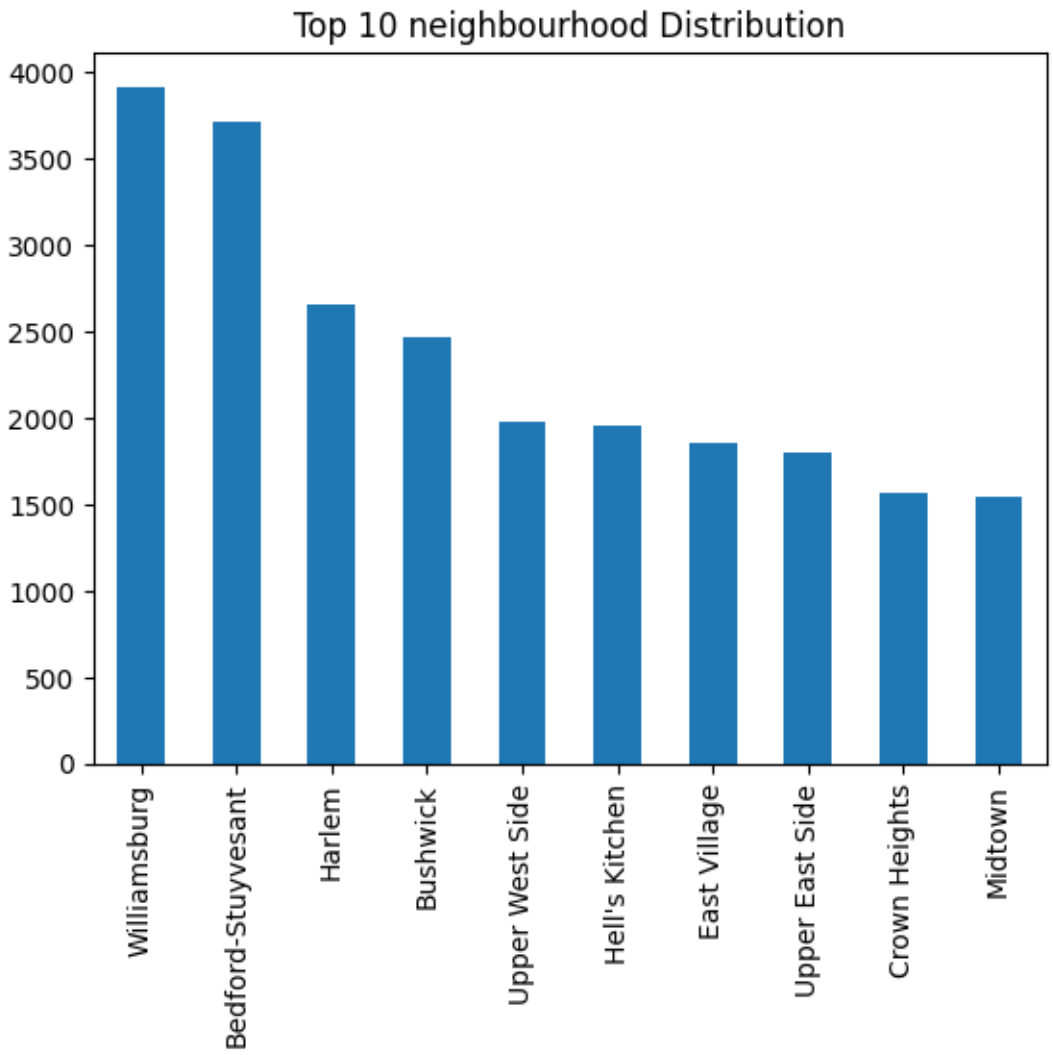


- Categorical variable
- 5 categories
- Manhattan have the most number of airbnb
- Staten Island have the less number of airbnb
- Check population in each region

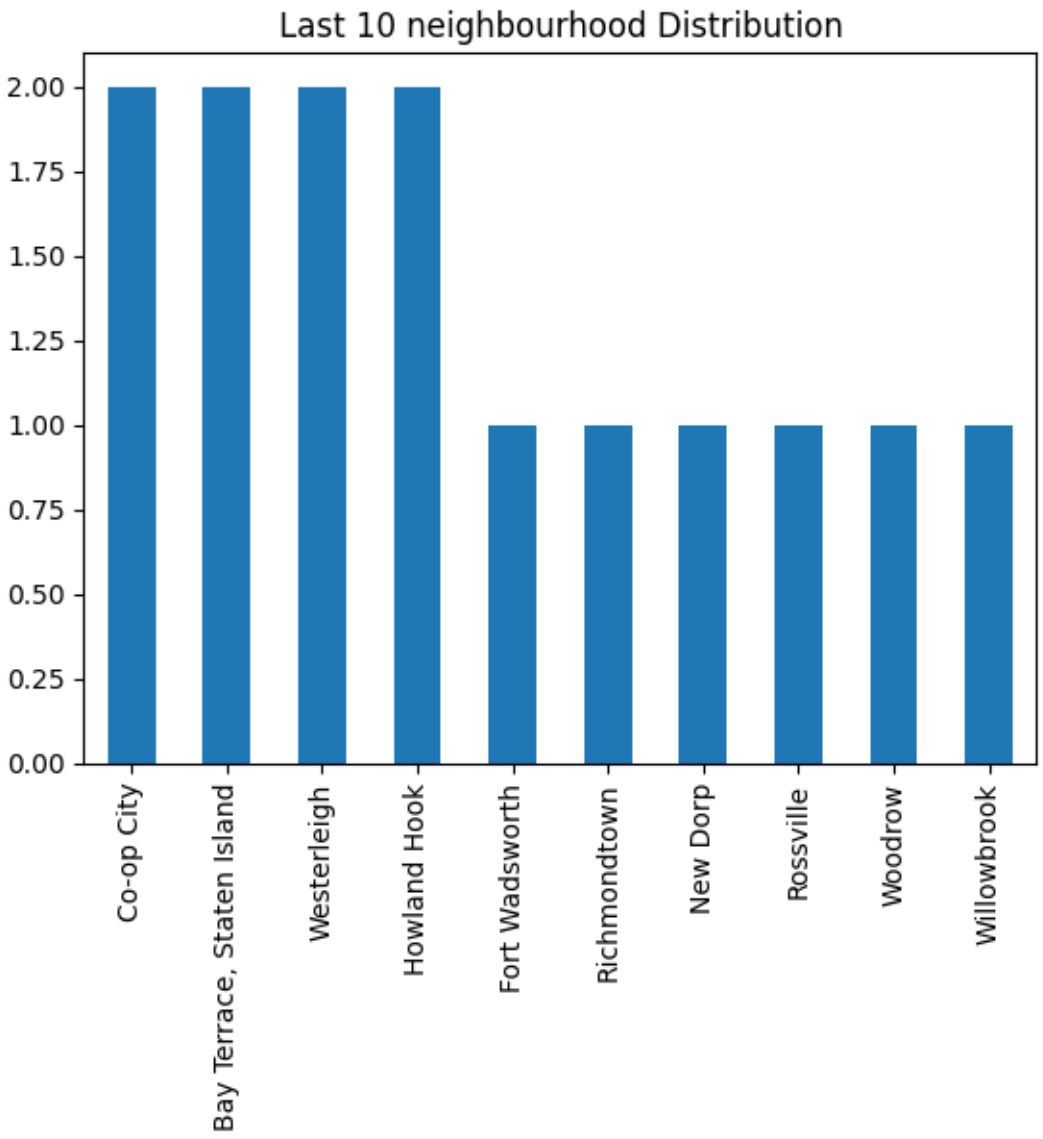
0.1.9 6. neighbourhood

[31]:
```
print(X["neighbourhood"].nunique())
print(X["neighbourhood"].value_counts().head())
### Top 10, 221 total
pd.value_counts(X['neighbourhood']).sort_values(ascending = False)[:10].plot.
  ↪bar()
plt.title('Top 10 neighbourhood Distribution')
plt.savefig('Top_10_neighbourhood.png')
```

```
221
Williamsburg          3919
Bedford-Stuyvesant    3710
Harlem                2658
Bushwick              2462
Upper West Side       1971
Name: neighbourhood, dtype: int64
```



[32]:
```
### Least 10
pd.value_counts(X['neighbourhood']).sort_values(ascending = False)[-10:].plot.
  ↪bar()
plt.title('Last 10 neighbourhood Distribution')
plt.savefig('Last_10_neighbourhood.png')
```



- Categorical Variable, name of the naborhood
- 221 categories
- More specify than neighbourhood_group

0.1.10 7. latitude and longitude

[33]:
```
X[["latitude","longitude"]]
```

[33]:

	latitude	longitude
0	40.64749	-73.97237
1	40.75362	-73.98377
2	40.80902	-73.94190

```
3      40.68514  -73.95976
4      40.79851  -73.94399
…         …         …
48879  40.67853  -73.94995
48880  40.70184  -73.93317
48881  40.81475  -73.94867
48882  40.75751  -73.99112
48883  40.76404  -73.98933

[48884 rows x 2 columns]
```

[34]:
```
import plotly
import plotly.express as px
import pandas as pd
#size = "price",
px.set_mapbox_access_token(open("access.mapbox_token").read())
df = Airbnb[Airbnb['price']<=uof]
fig = px.scatter_mapbox(df, lat="latitude", lon="longitude",␣
 ↪color="price",opacity=0.2,
                 color_continuous_scale=px.colors.sequential.Blugrn,␣
 ↪size_max=15, height=900, zoom=10, title = "New York City Airbnb Price")
fig.show()
plt.savefig('price_geo.png')
```

```
<Figure size 640x480 with 0 Axes>
```

[35]:
```
import plotly
import plotly.express as px
import pandas as pd
#size = "price",
px.set_mapbox_access_token(open("access.mapbox_token").read())
df = Airbnb
fig = px.scatter_mapbox(df, lat="latitude", lon="longitude",␣
 ↪color="neighbourhood_group", opacity=1,
                 color_continuous_scale=px.colors.sequential.Blugrn,␣
 ↪size_max=15, height=900, zoom=10)
fig.show()
```

[36]:
```
import plotly
import plotly.express as px
import pandas as pd
#size = "price",
px.set_mapbox_access_token(open("access.mapbox_token").read())
df = Airbnb
fig = px.scatter_mapbox(df, lat="latitude", lon="longitude",␣
 ↪color="neighbourhood", opacity=0.2,
```

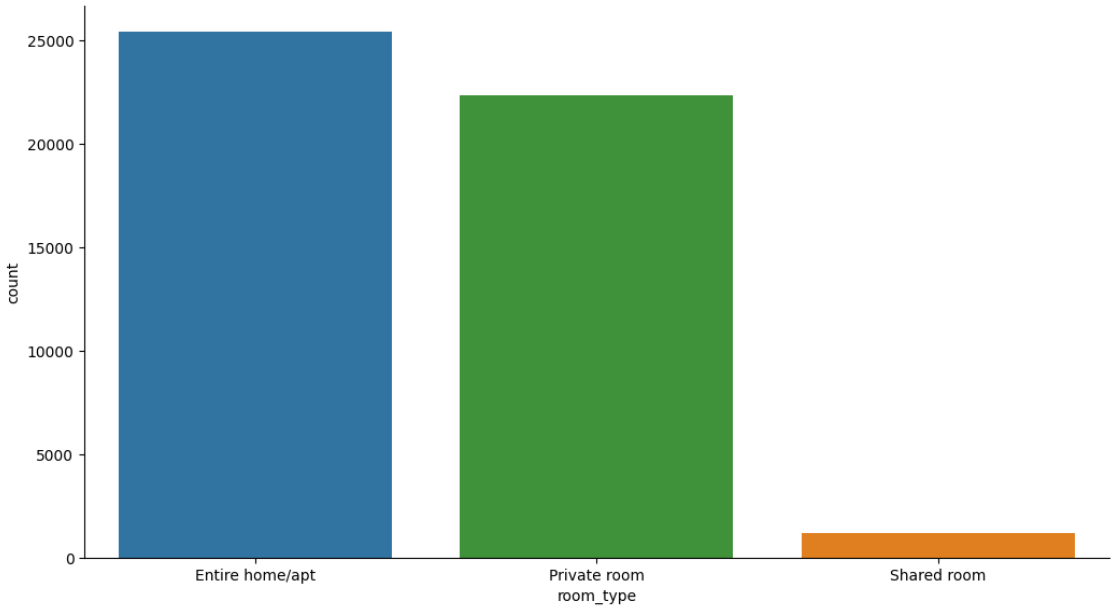
```
                    color_continuous_scale=px.colors.sequential.Blugrn,␣
 ↪size_max=15, height=900, zoom=10)
fig.show()
```

[37]:
```
#reviews_per_month
import plotly
import plotly.express as px
import pandas as pd
#size = "price",
px.set_mapbox_access_token(open("access.mapbox_token").read())
df = Airbnb
fig = px.scatter_mapbox(df, lat="latitude", lon="longitude",␣
 ↪color="reviews_per_month",opacity=0.5,
                    color_continuous_scale=px.colors.sequential.Blugrn,␣
 ↪size_max=15, height=900, zoom=10)
fig.show()
```

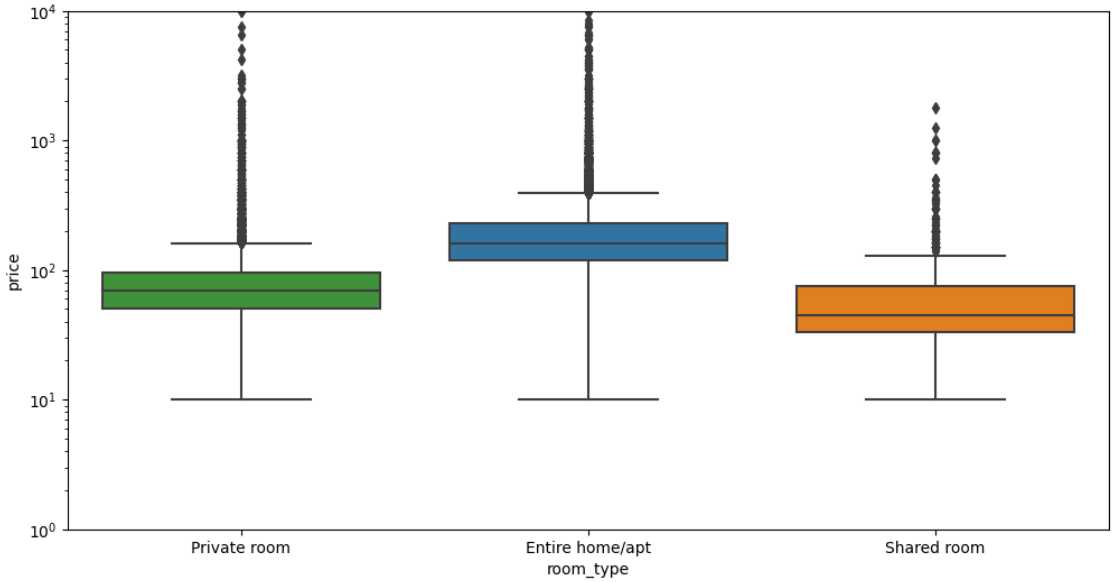
[38]:
```
# number_of_reviews
px.set_mapbox_access_token(open("access.mapbox_token").read())
df = Airbnb
fig = px.scatter_mapbox(df, lat="latitude", lon="longitude",␣
 ↪color="number_of_reviews",opacity=0.5,
                    color_continuous_scale=px.colors.sequential.Blugrn,␣
 ↪size_max=15, height=900, zoom=10)
fig.show()
```

8. room_type

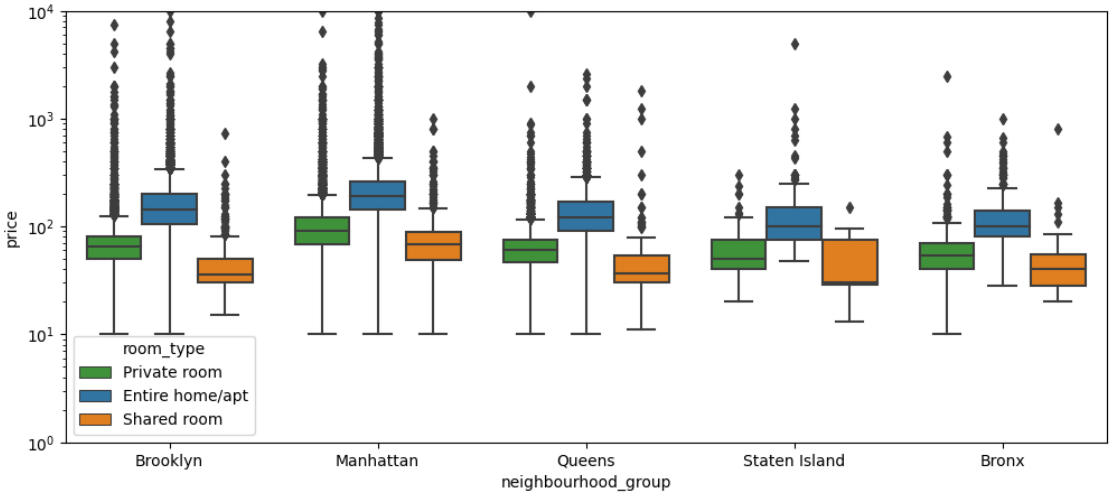
[39]:
```
custom_palette = sns.color_palette("Paired", 9)
my_pal = {"Entire home/apt": custom_palette[1], "Private room":␣
 ↪custom_palette[3], "Shared room":custom_palette[7]}
sns.catplot(x='room_type', kind='count' ,data=Airbnb, order = ["Entire home/
 ↪apt", 'Private room', 'Shared room'], palette=my_pal)
fig = plt.gcf()
fig.set_size_inches(12, 6)
```



[40]:
```
sns.boxplot(data=Airbnb, x="room_type", y="price", palette=my_pal)
plt.yscale('log')
plt.ylim(1,10000)
fig = plt.gcf()
fig.set_size_inches(12, 6)
```

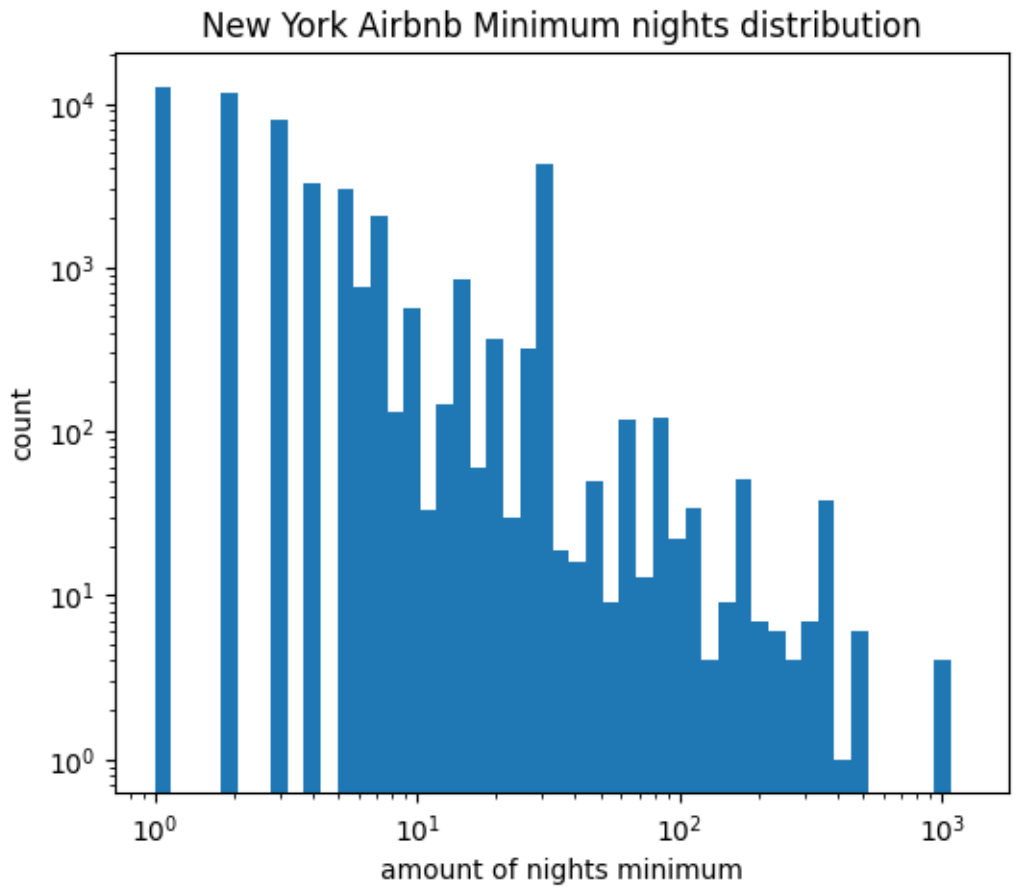


[41]:
```
sns.boxplot(data=Airbnb, x="neighbourhood_group", y="price", hue = "room_type",␣
 ↪palette=my_pal)
plt.yscale('log')
plt.ylim(1,10000)
fig = plt.gcf()
fig.set_size_inches(12, 5)
```



9. minimum_nights

[42]:
```
plt.figure(figsize = (6,5))
X["minimum_nights"].plot.hist(log=True, bins = np.logspace(np.log10(1),np.
 ↪log10(np.max(X["minimum_nights"])),50))
plt.semilogy()
plt.semilogx()
plt.xlabel('amount of nights minimum')
plt.ylabel('count')
plt.title('New York Airbnb Minimum nights distribution')
plt.show()
```



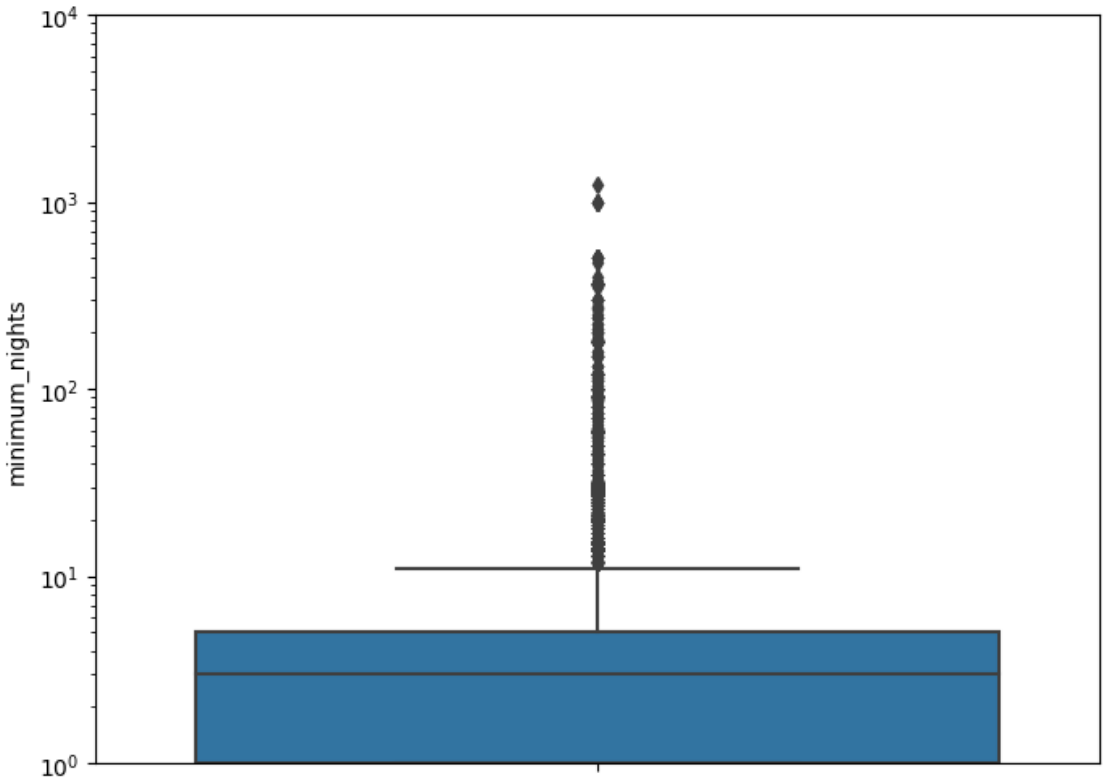
[43]:
```
value = X["minimum_nights"].describe()
Summary = pd.concat([value], axis=1,
                    keys=['value'],
                    sort=False)
Summary
```

[43]:

	value
count	48884.000000
mean	7.029887
std	20.512224
min	1.000000
25%	1.000000
50%	3.000000
75%	5.000000
max	1250.000000

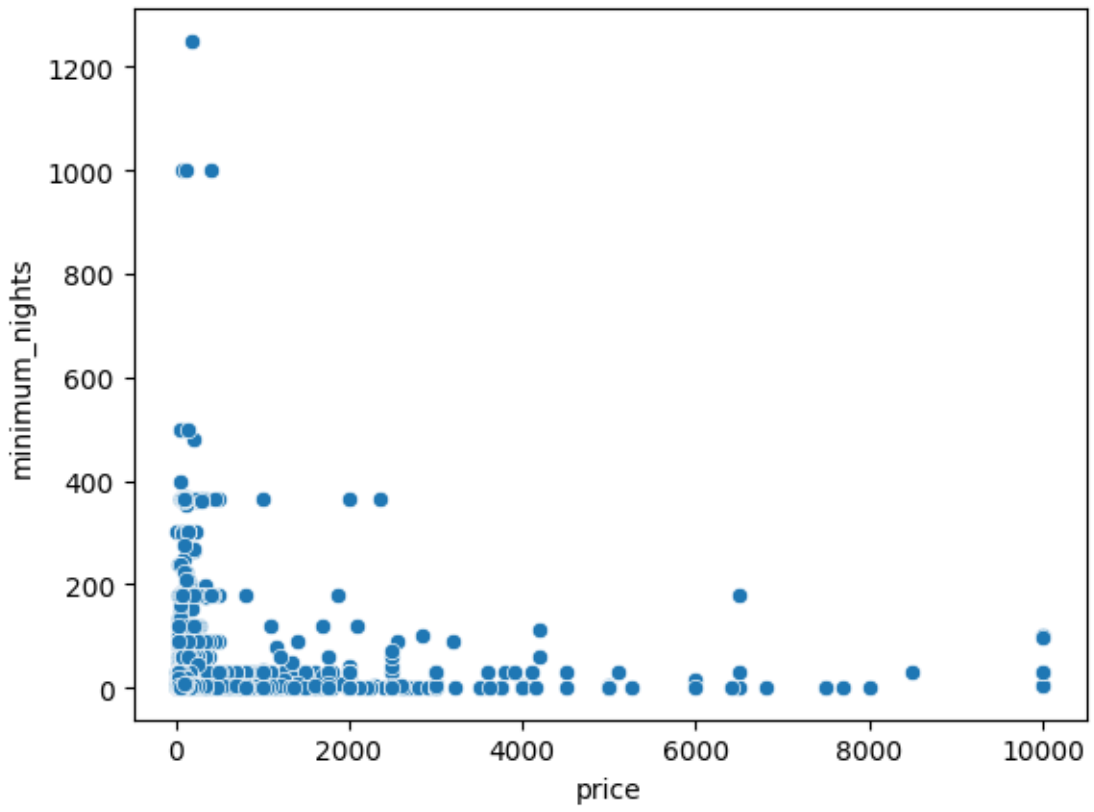
[44]:
```
sns.boxplot(data=Airbnb, y="minimum_nights")
plt.yscale('log')
plt.ylim(1,10000)
```

```
fig = plt.gcf()
fig.set_size_inches(8, 6)
```



[45]:
```
sns.scatterplot(data=Airbnb, x="price", y="minimum_nights")
```

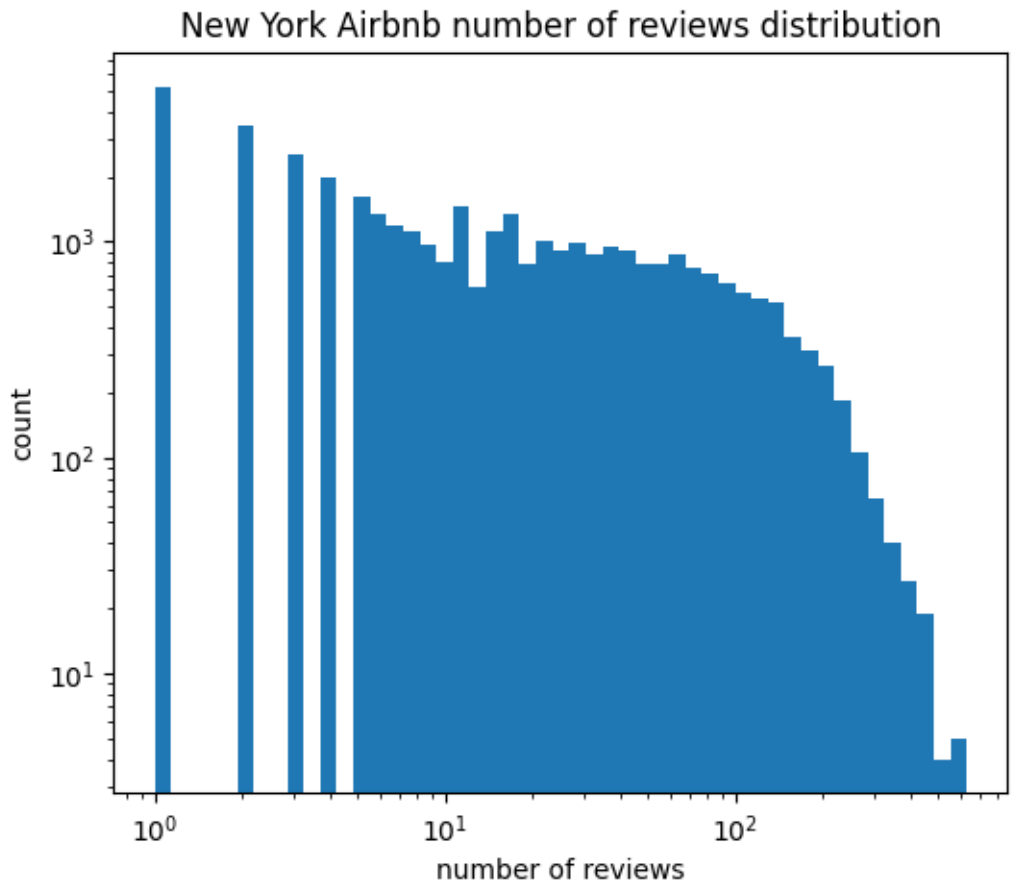
[45]: <AxesSubplot:xlabel='price', ylabel='minimum_nights'>



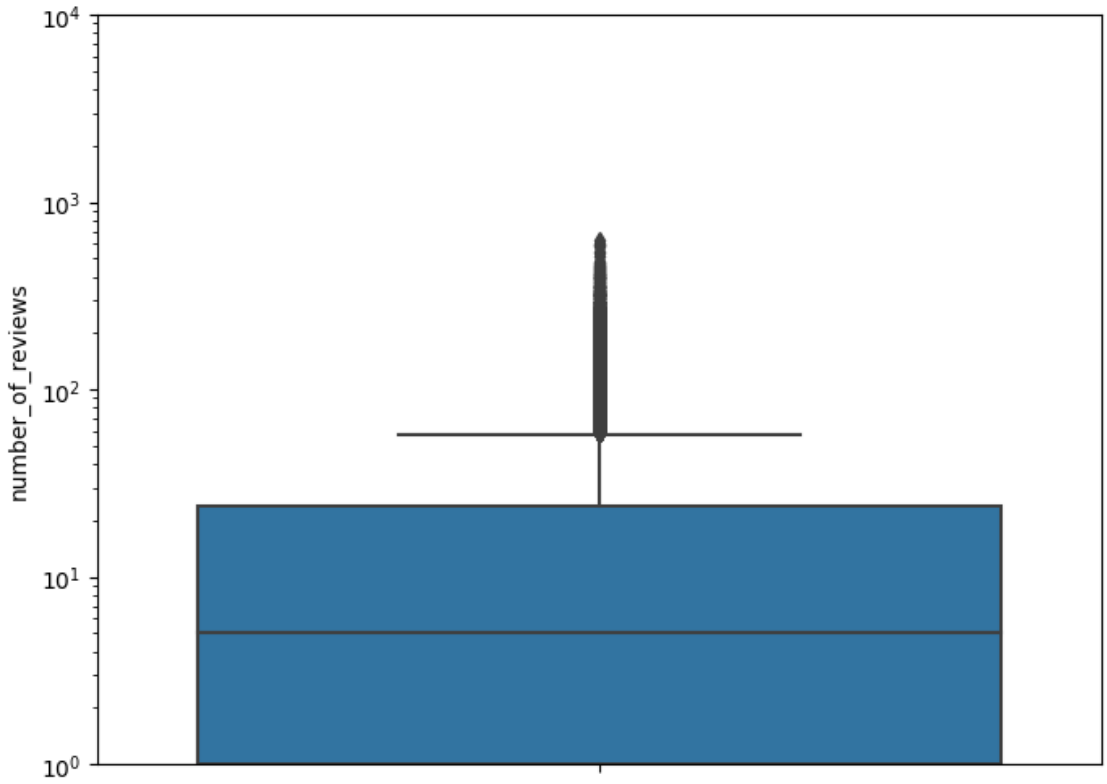
- Maximum mini night 1250 three and a half years.
- Average mini night is 7
- Median mini night is 3

0.1.11 10. number_of_reviews

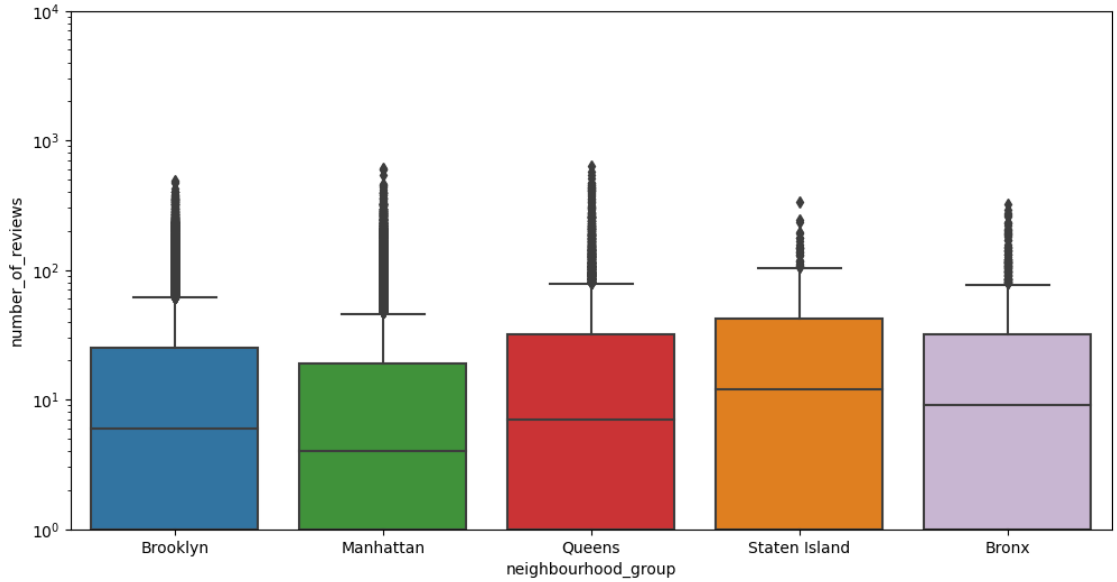
[46]:
```
plt.figure(figsize = (6,5))
X["number_of_reviews"].plot.hist(log=True, bins = np.logspace(np.log10(1),np.
↪log10(np.max(X["number_of_reviews"])),50))
plt.semilogy()
plt.semilogx()
plt.xlabel('number of reviews')
plt.ylabel('count')
plt.title('New York Airbnb number of reviews distribution')
plt.show()
```



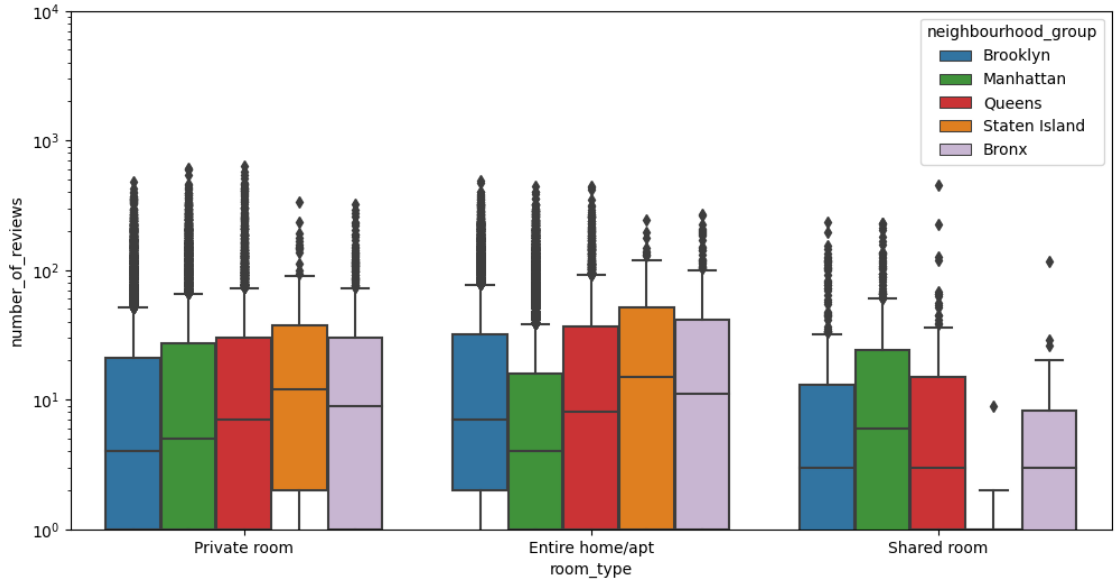
[47]:
```
sns.boxplot(data=Airbnb, y="number_of_reviews")
plt.yscale('log')
plt.ylim(1,10000)
fig = plt.gcf()
fig.set_size_inches(8, 6)
```



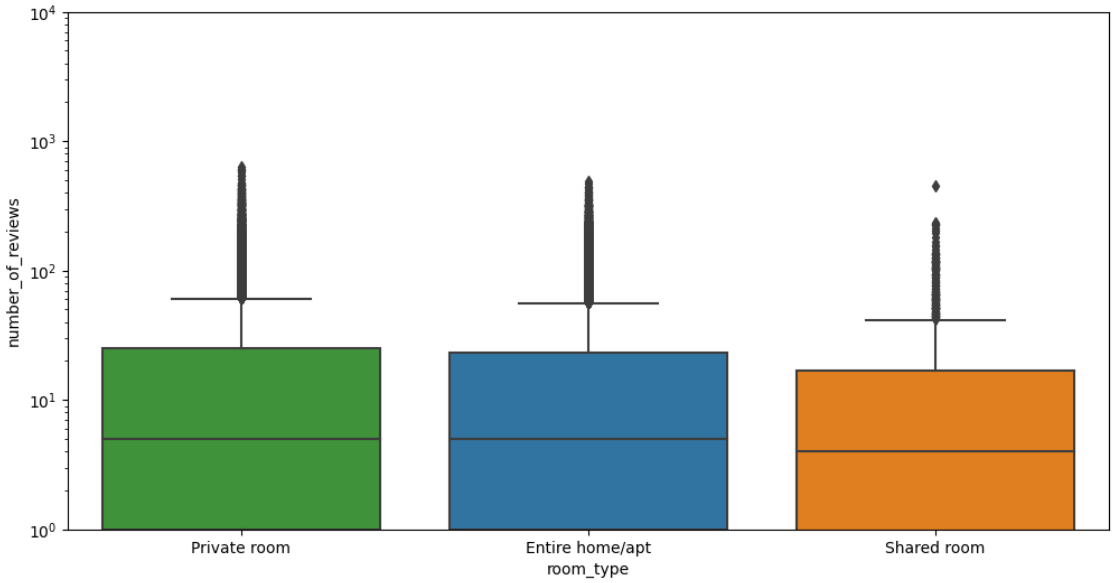
[48]:
```
custom_palette = sns.color_palette("Paired", 9)
my_pal = {"Brooklyn": custom_palette[1],
          "Manhattan": custom_palette[3],
          "Queens":custom_palette[5],
          "Staten Island": custom_palette[7],
          "Bronx": custom_palette[8]}


sns.boxplot(data=Airbnb, x="neighbourhood_group", y="number_of_reviews",␣
 ↪palette=my_pal)
plt.yscale('log')
plt.ylim(1,10000)
fig = plt.gcf()
fig.set_size_inches(12, 6)
```



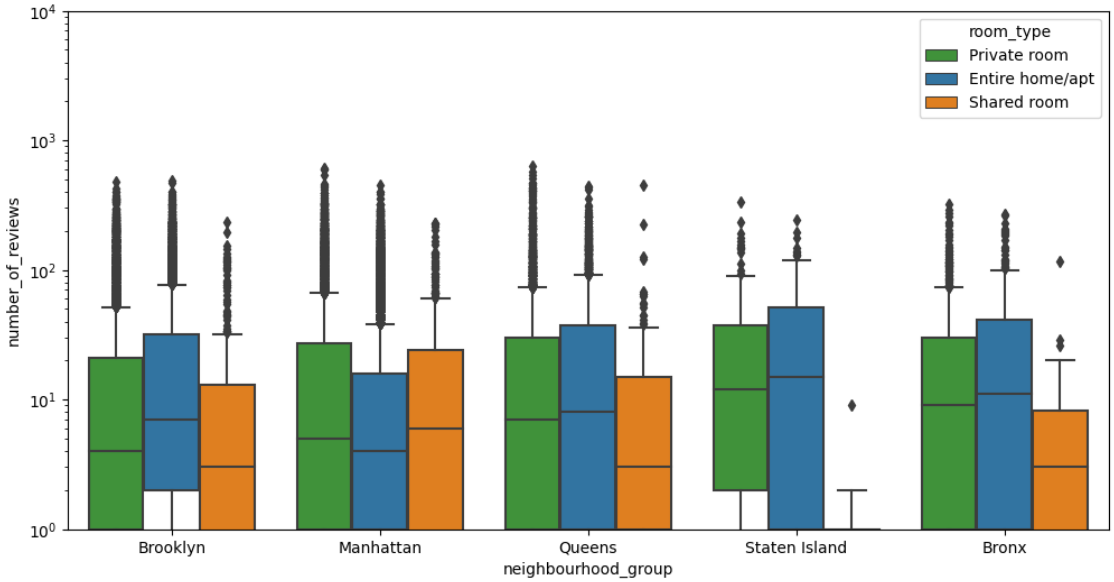
[49]:
```
sns.boxplot(data=Airbnb, x="room_type", y="number_of_reviews", hue =␣
 ↪"neighbourhood_group", palette=my_pal)
plt.yscale('log')
plt.ylim(1,10000)
fig = plt.gcf()
fig.set_size_inches(12, 6)
```



[50]:
```
my_pal = {"Entire home/apt": custom_palette[1], "Private room":␣
↪custom_palette[3], "Shared room":custom_palette[7]}
sns.boxplot(data=Airbnb, x="room_type", y="number_of_reviews", palette=my_pal)
plt.yscale('log')
plt.ylim(1,10000)
fig = plt.gcf()
fig.set_size_inches(12, 6)
```

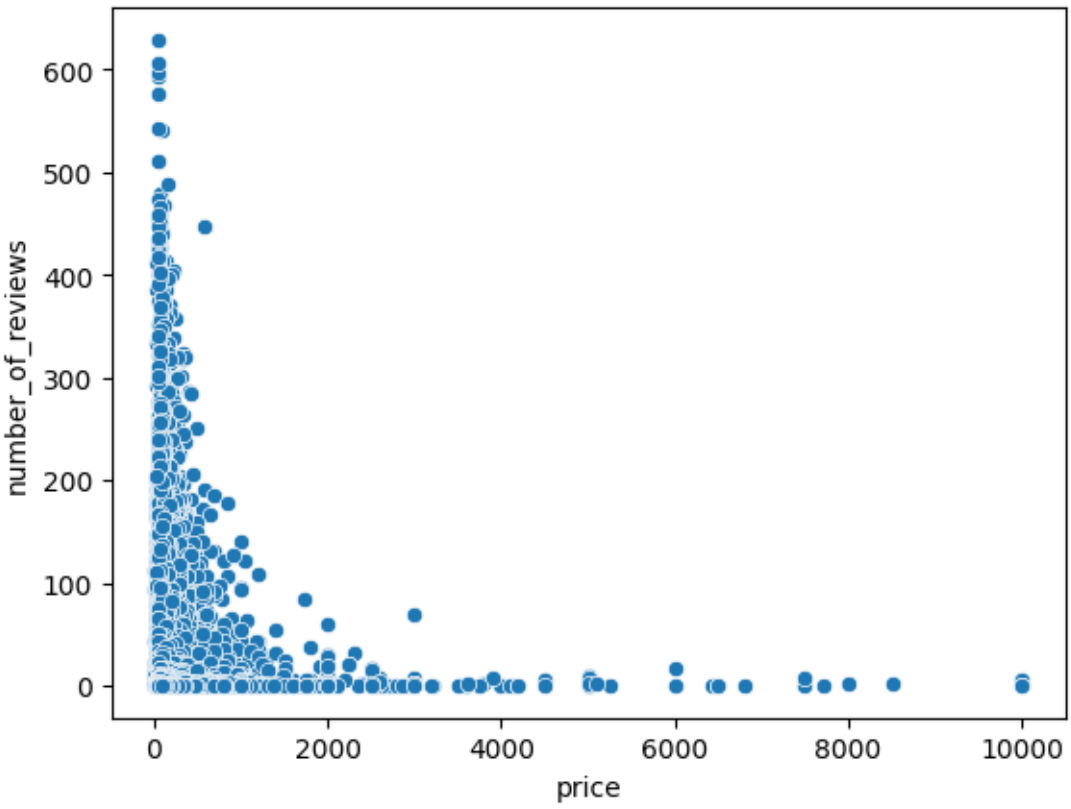


[51]:
```
sns.boxplot(data=Airbnb, x="neighbourhood_group", y="number_of_reviews", hue =␣
↪"room_type", palette=my_pal)
plt.yscale('log')
plt.ylim(1,10000)
fig = plt.gcf()
fig.set_size_inches(12, 6)
```



[52]:
```
sns.scatterplot(data=Airbnb, x="price", y="number_of_reviews")
```

[52]: <AxesSubplot:xlabel='price', ylabel='number_of_reviews'>



- The average number of review is 23
- Median is 5
- min is 0
- max is 629

0.1.12 11. last_review

[53]:
```
X["last_review"].value_counts()
```

[53]:
```
2019-06-23    1412
2019-07-01    1359
2019-06-30    1341
2019-06-24     874
2019-07-07     718
              …
2015-02-28       1
2014-08-01       1
2012-08-25       1
2013-12-25       1
2018-03-29       1
Name: last_review, Length: 1764, dtype: int64
```

12. New variable

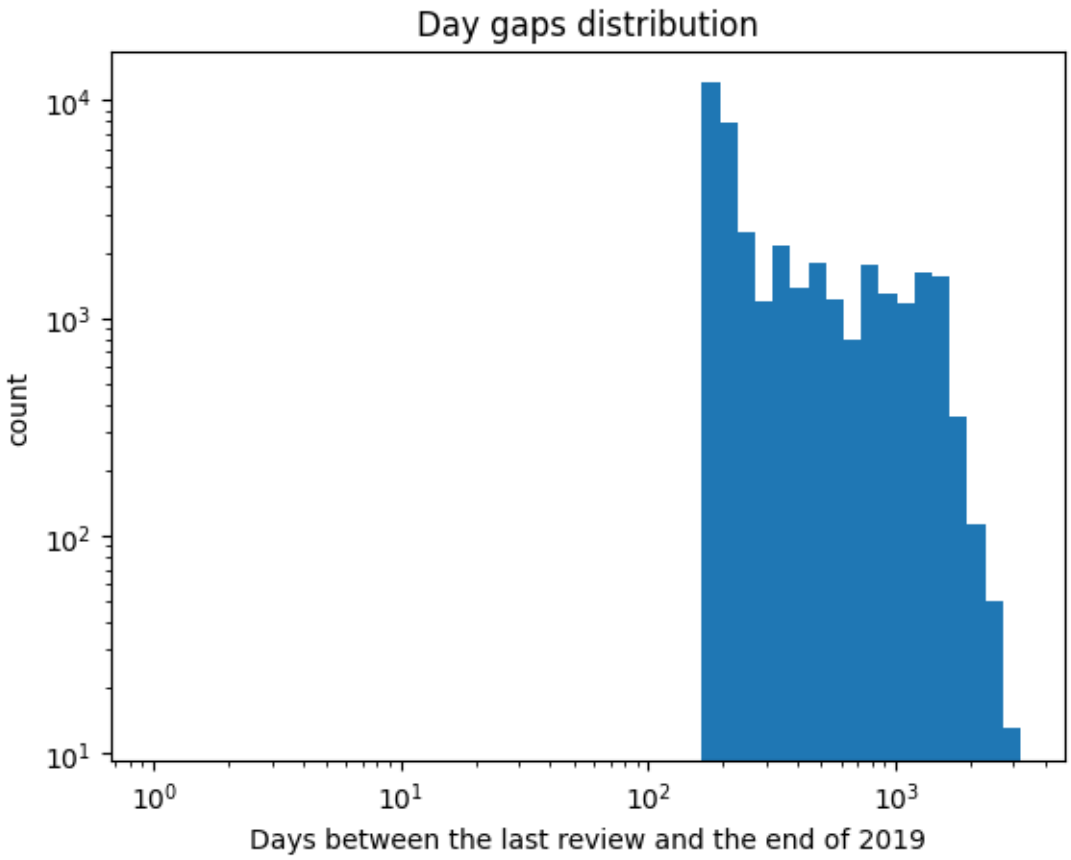
[54]:
```
X["gap_between_last_review_and_end_of_2019"] = [i.days for i in pd.
 ↪to_datetime("2019-12-31", infer_datetime_format=True) - X["last_review"]]
Airbnb["gap_between_last_review_and_end_of_2019"] =␣
 ↪X["gap_between_last_review_and_end_of_2019"]
```

[55]:
```
value = X["gap_between_last_review_and_end_of_2019"].describe()
Summary = pd.concat([value], axis=1,
                        keys=['value'],
                        sort=False)
Summary
```

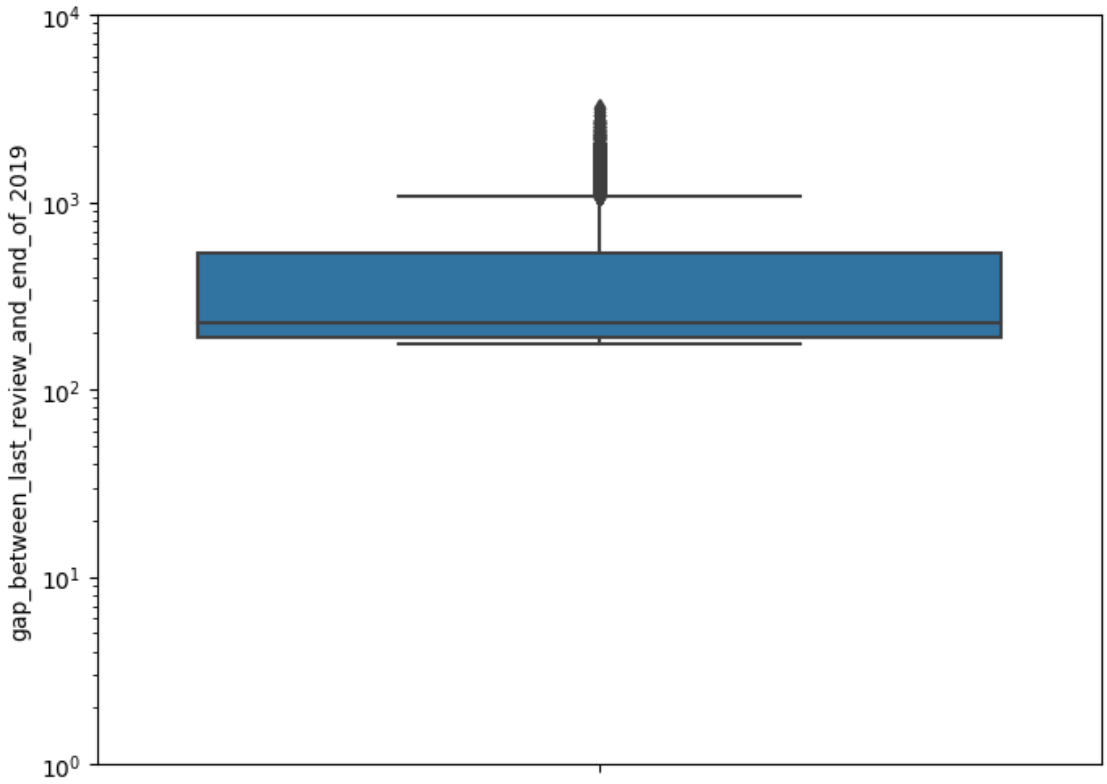
[55]:
```
              value
count  38833.000000
mean     452.947802
std      413.948228
min      176.000000
25%      191.000000
50%      226.000000
75%      541.000000
max     3200.000000
```

[56]:
```
X.drop(['last_review'], axis=1, inplace=True)
```

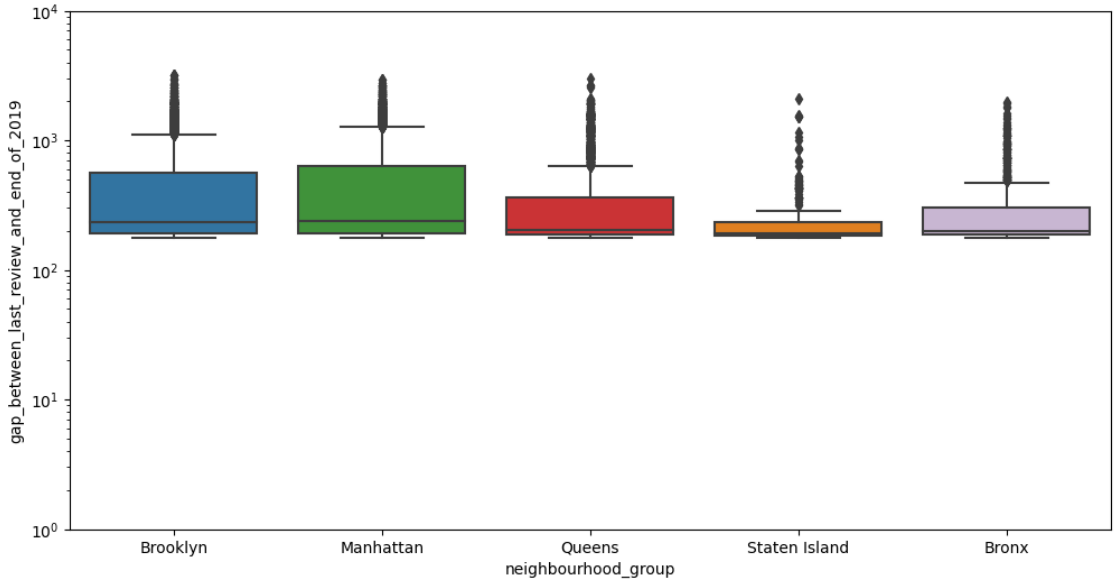
[57]:
```
X["gap_between_last_review_and_end_of_2019"].plot.hist(log=True, bins = np.
↪logspace(np.log10(1),np.log10(np.
↪max(X["gap_between_last_review_and_end_of_2019"])),50))
plt.semilogy()
plt.semilogx()
plt.xlabel('Days between the last review and the end of 2019')
plt.ylabel('count')
plt.title('Day gaps distribution')
plt.show()
```



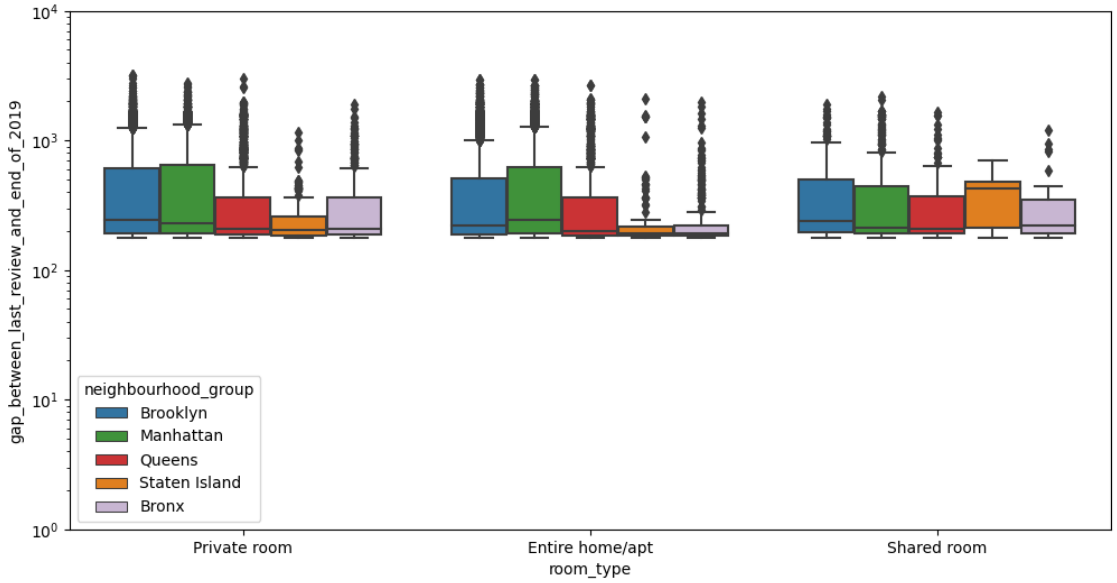
[58]:
```
sns.boxplot(data=X, y="gap_between_last_review_and_end_of_2019")
plt.yscale('log')
plt.ylim(1,10000)
fig = plt.gcf()
fig.set_size_inches(8, 6)
```



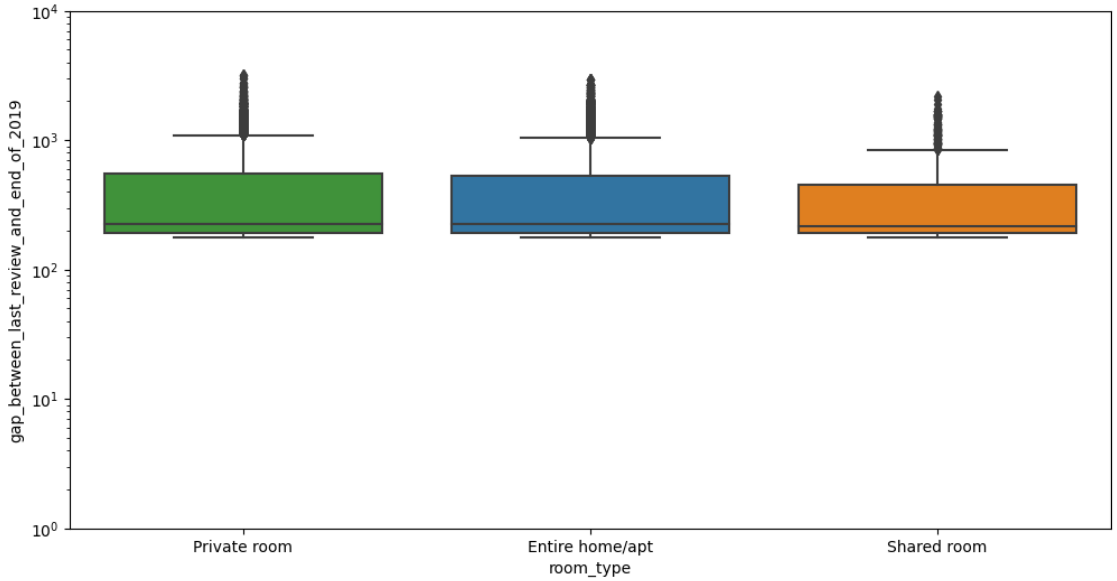
[59]:
```
custom_palette = sns.color_palette("Paired", 9)
my_pal = {"Brooklyn": custom_palette[1],
          "Manhattan": custom_palette[3],
          "Queens":custom_palette[5],
          "Staten Island": custom_palette[7],
          "Bronx": custom_palette[8]}


sns.boxplot(data=Airbnb, x="neighbourhood_group",␣
 ↪y="gap_between_last_review_and_end_of_2019", palette=my_pal)
plt.yscale('log')
plt.ylim(1,10000)
fig = plt.gcf()
fig.set_size_inches(12, 6)
```



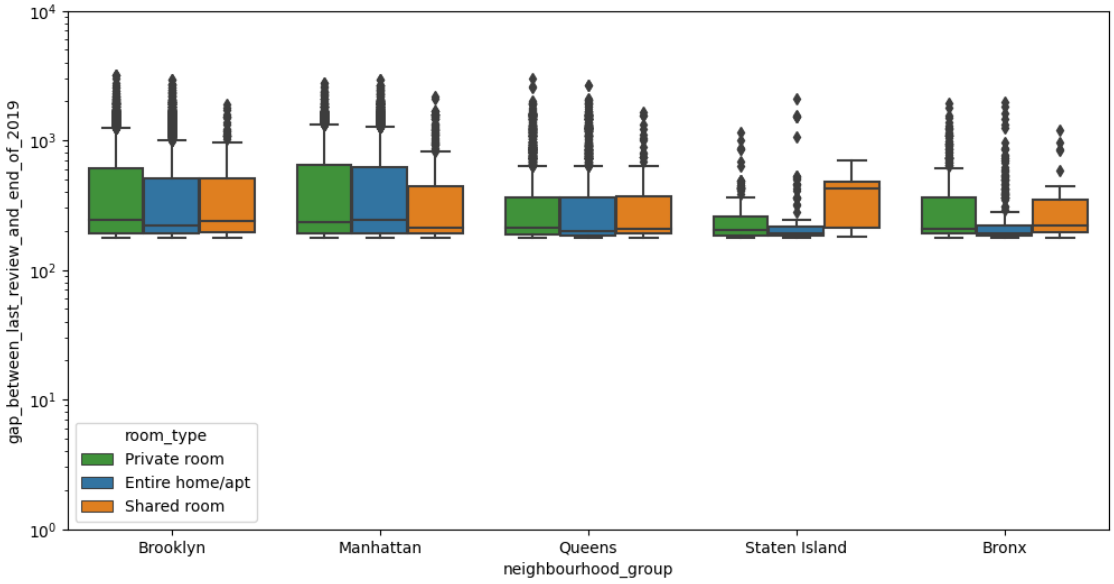
[60]:
```
sns.boxplot(data=Airbnb, x="room_type",␣
 ↪y="gap_between_last_review_and_end_of_2019", hue = "neighbourhood_group",␣
 ↪palette=my_pal)
plt.yscale('log')
plt.ylim(1,10000)
fig = plt.gcf()
fig.set_size_inches(12, 6)
```



[61]:
```
my_pal = {"Entire home/apt": custom_palette[1], "Private room":␣
 ↪custom_palette[3], "Shared room":custom_palette[7]}
sns.boxplot(data=Airbnb, x="room_type",␣
 ↪y="gap_between_last_review_and_end_of_2019", palette=my_pal)
plt.yscale('log')
plt.ylim(1,10000)
fig = plt.gcf()
fig.set_size_inches(12, 6)
```

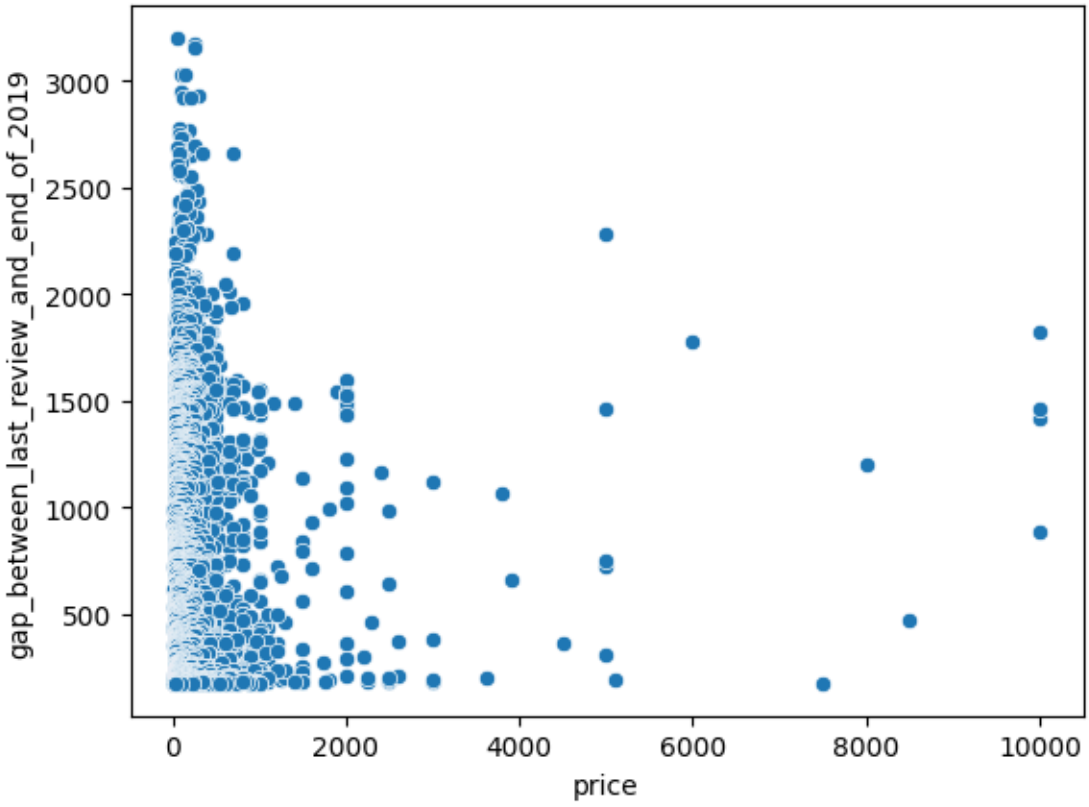


[62]:
```
sns.boxplot(data=Airbnb, x="neighbourhood_group",␣
 ↪y="gap_between_last_review_and_end_of_2019", hue = "room_type",␣
 ↪palette=my_pal)
plt.yscale('log')
plt.ylim(1,10000)
fig = plt.gcf()
fig.set_size_inches(12, 6)
```



[63]:
```
sns.scatterplot(data=Airbnb, x="price",␣
↪y="gap_between_last_review_and_end_of_2019")
```

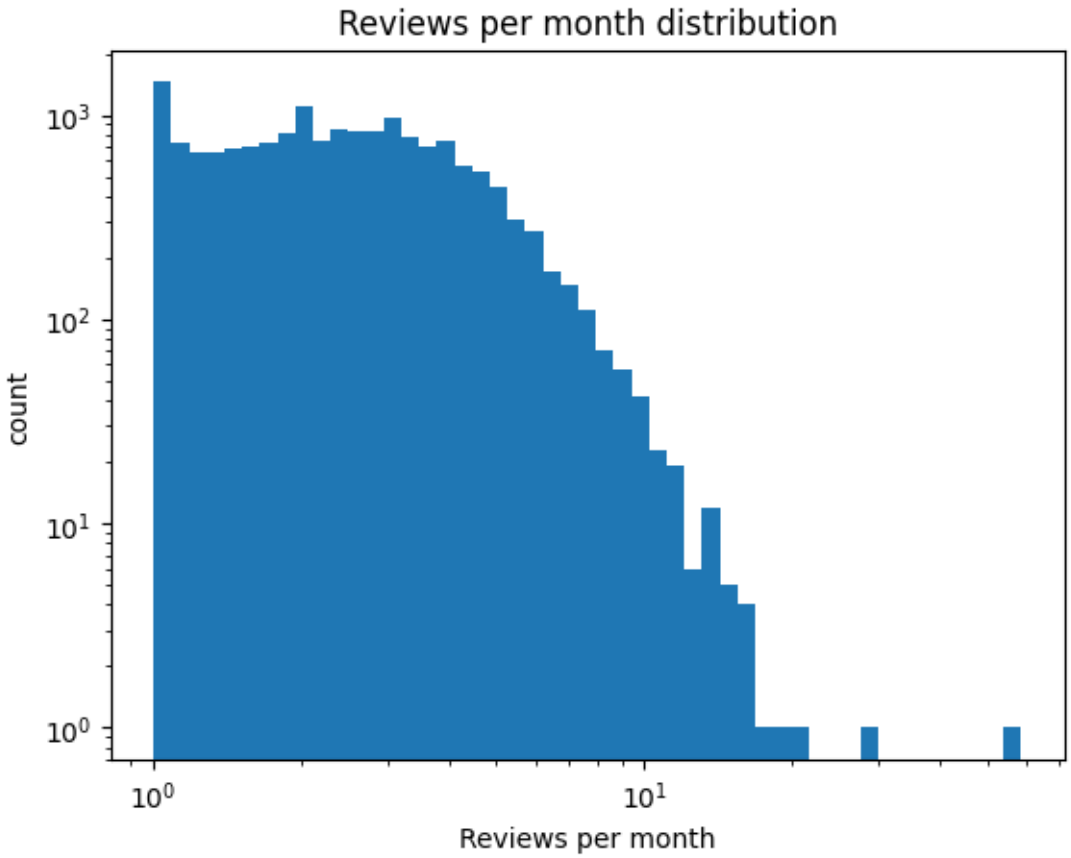
[63]: <AxesSubplot:xlabel='price', ylabel='gap_between_last_review_and_end_of_2019'>



- Not important
- drop

13. reviews_per_month

[64]:
```
X["reviews_per_month"].plot.hist(log=True, bins = np.logspace(np.log10(1),np.
↪log10(np.max(X["reviews_per_month"])),50))
plt.semilogy()
plt.semilogx()
plt.xlabel('Reviews per month')
plt.ylabel('count')
plt.title('Reviews per month distribution')
plt.show()
```

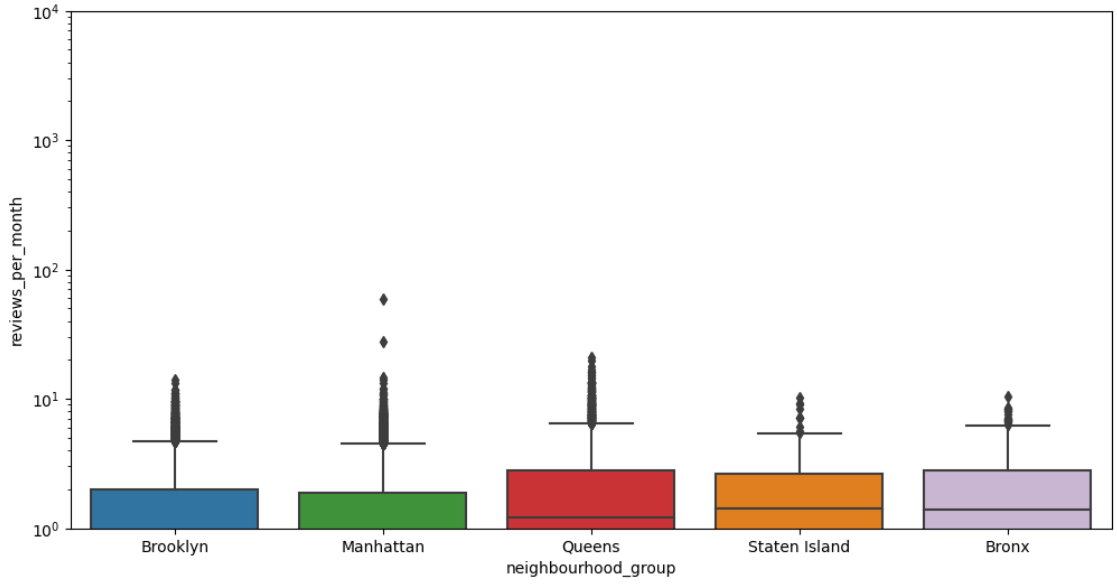


[65]:
```
value = X["reviews_per_month"].describe()
Summary = pd.concat([value], axis=1,
                    keys=['value'],
                    sort=False)
```

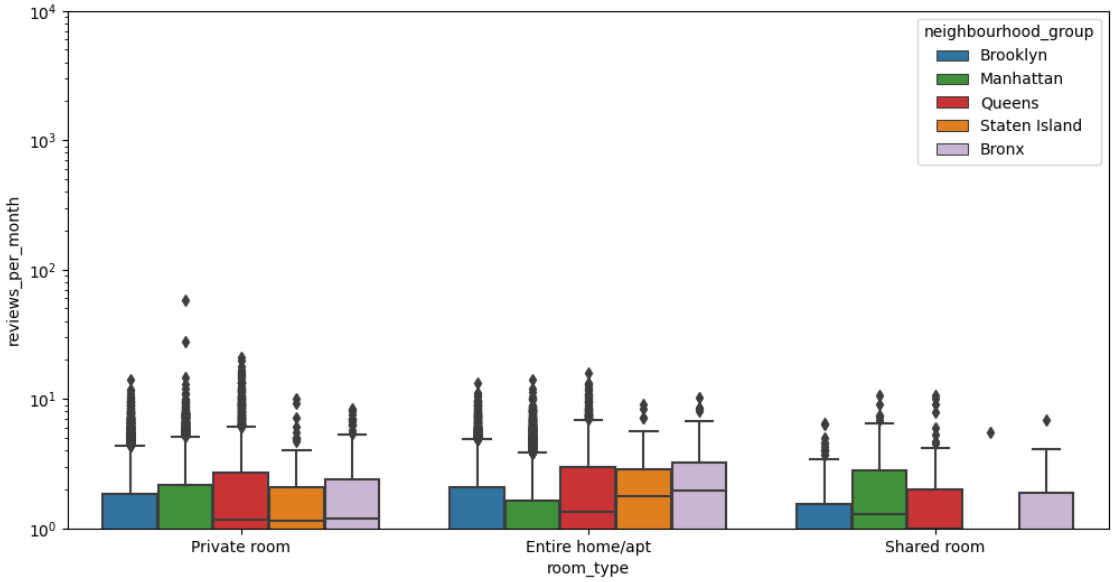
```
Summary
```

[65]:
```
              value
count  38833.000000
mean       1.373128
std        1.680391
min        0.010000
25%        0.190000
50%        0.720000
75%        2.020000
max       58.500000
```

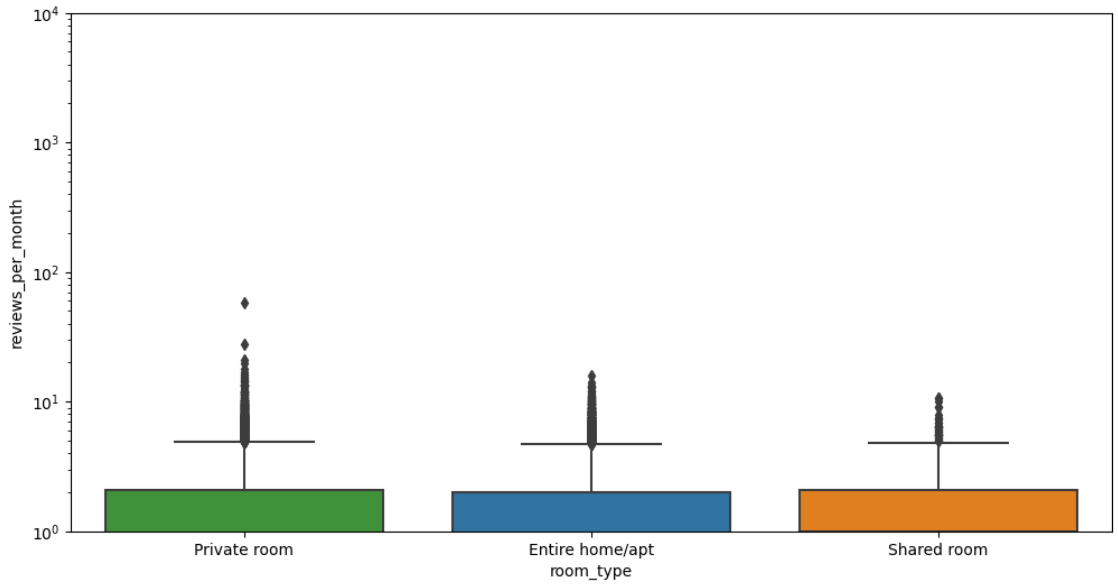
[66]:
```
custom_palette = sns.color_palette("Paired", 9)
my_pal = {"Brooklyn": custom_palette[1],
          "Manhattan": custom_palette[3],
          "Queens":custom_palette[5],
          "Staten Island": custom_palette[7],
          "Bronx": custom_palette[8]}


sns.boxplot(data=Airbnb, x="neighbourhood_group", y="reviews_per_month",␣
 ↪palette=my_pal)
plt.yscale('log')
plt.ylim(1,10000)
fig = plt.gcf()
fig.set_size_inches(12, 6)
```



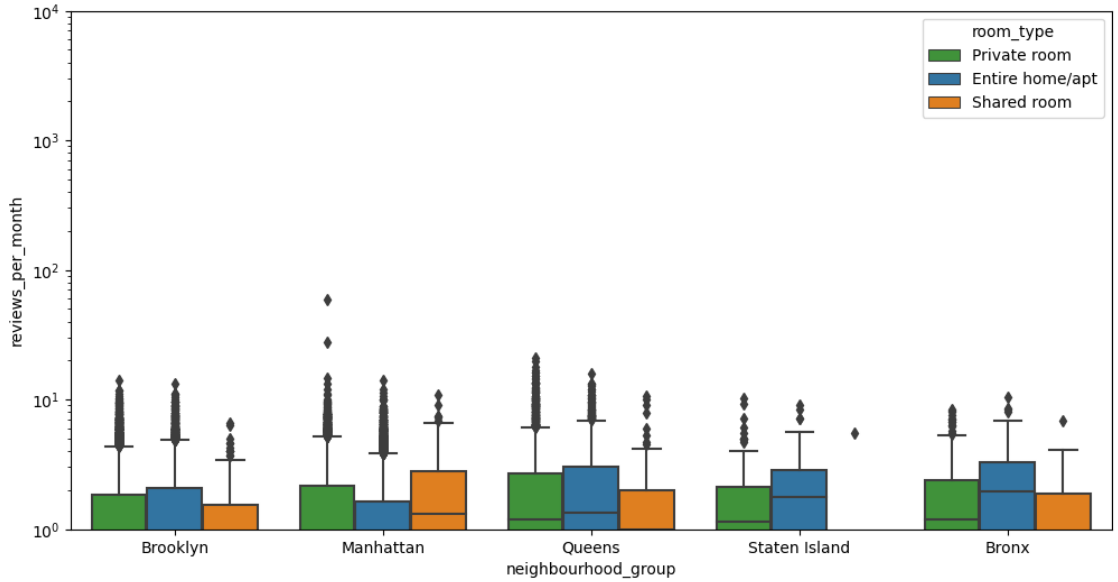
[67]:
```
sns.boxplot(data=Airbnb, x="room_type", y="reviews_per_month", hue =␣
 ↪"neighbourhood_group", palette=my_pal)
plt.yscale('log')
plt.ylim(1,10000)
fig = plt.gcf()
fig.set_size_inches(12, 6)
```



[68]:
```
my_pal = {"Entire home/apt": custom_palette[1], "Private room":␣
 ↪custom_palette[3], "Shared room":custom_palette[7]}
sns.boxplot(data=Airbnb, x="room_type", y="reviews_per_month", palette=my_pal)
plt.yscale('log')
plt.ylim(1,10000)
fig = plt.gcf()
fig.set_size_inches(12, 6)
```

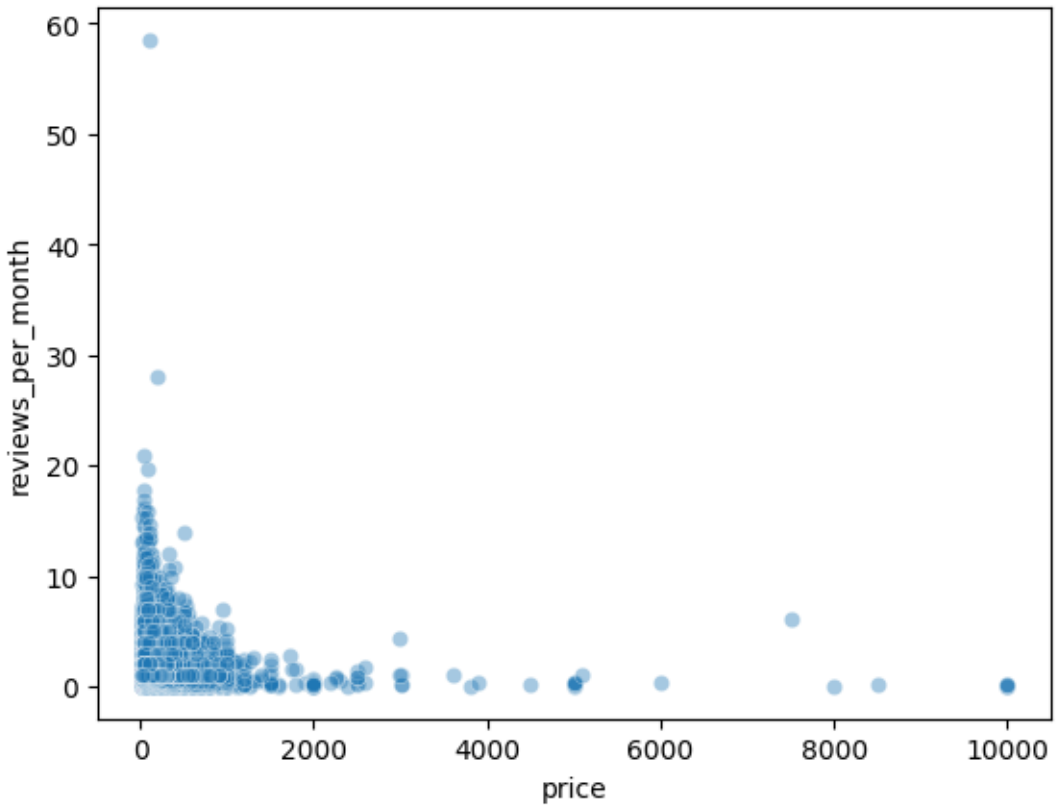


[69]:
```
sns.boxplot(data=Airbnb, x="neighbourhood_group", y="reviews_per_month", hue =␣
↪"room_type", palette=my_pal)
plt.yscale('log')
plt.ylim(1,10000)
fig = plt.gcf()
fig.set_size_inches(12, 6)
```



[70]:
```
sns.scatterplot(data=Airbnb, x="price", y="reviews_per_month", alpha = 0.4)
```

[70]:
```
<AxesSubplot:xlabel='price', ylabel='reviews_per_month'>
```



0.1.13 14. calculated_host_listings_count

[71]:
```
value = X["calculated_host_listings_count"].describe()
Summary = pd.concat([value], axis=1,
                    keys=['value'],
                    sort=False)
Summary
```

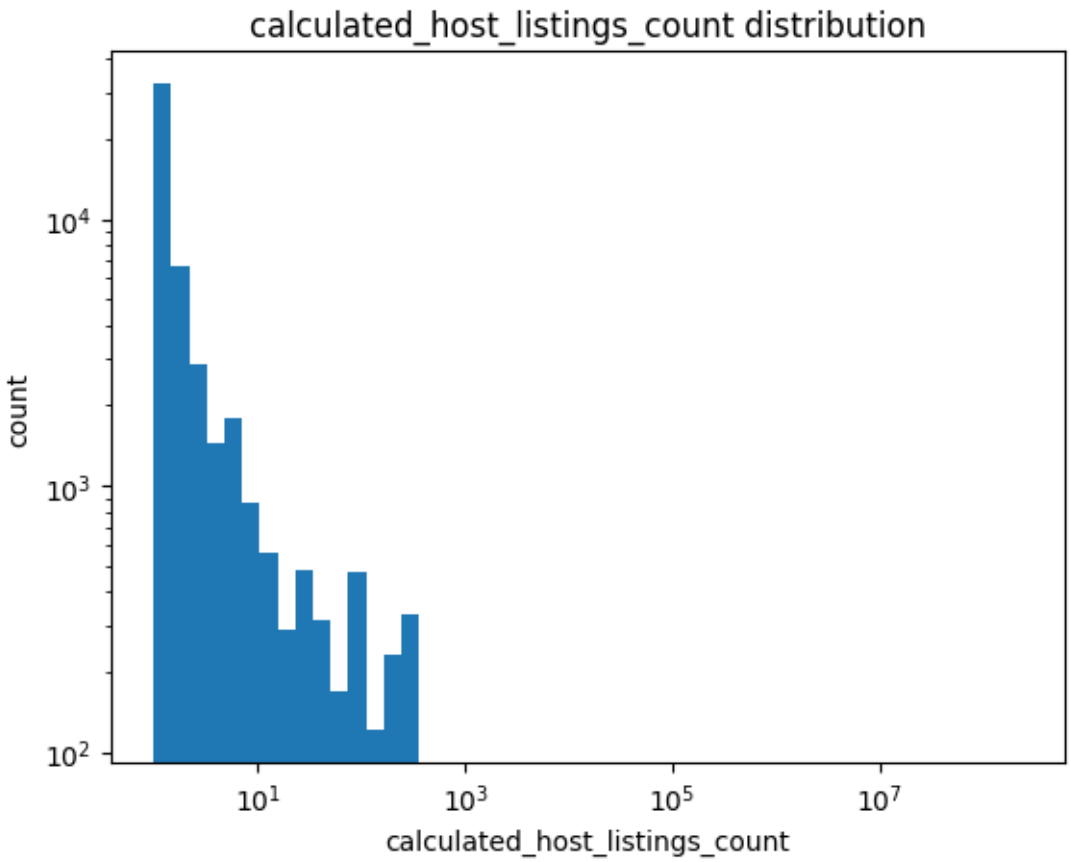
[71]:

	value
count	48884.000000
mean	7.144628
std	32.956185
min	1.000000
25%	1.000000
50%	1.000000
75%	2.000000
max	327.000000

[72]:
```
sum(X["calculated_host_listings_count"]>1)/
  ↪len(X["calculated_host_listings_count"])
```

[72]:
```
0.33923165043777104
```

[73]:
```
X["calculated_host_listings_count"].plot.hist(log=True, bins = np.logspace(np.
  ↪log2(1),np.log2(np.max(X["calculated_host_listings_count"])),50))
plt.semilogy()
plt.semilogx()
plt.xlabel('calculated_host_listings_count')
plt.ylabel('count')
plt.title('calculated_host_listings_count distribution')
plt.show()
```

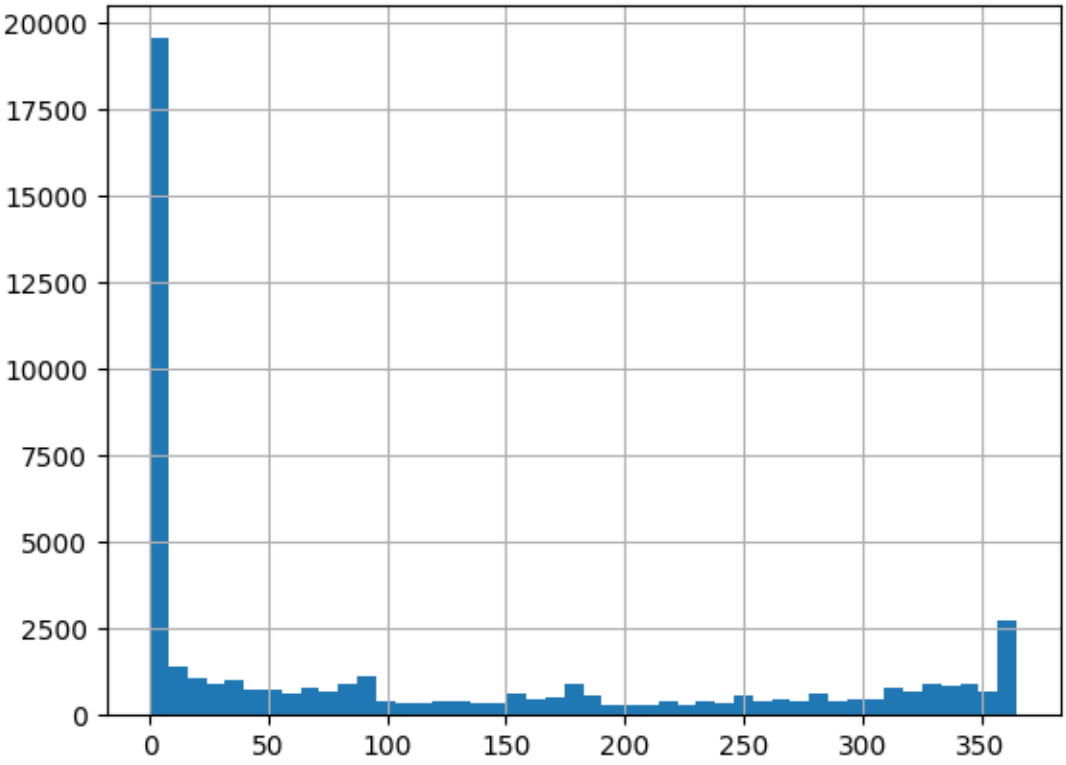


- The number of total properties the host have

15. availability_365

[74]:
```
X["availability_365"].hist(bins = X["availability_365"].nunique()-320)
```

[74]: <AxesSubplot:>

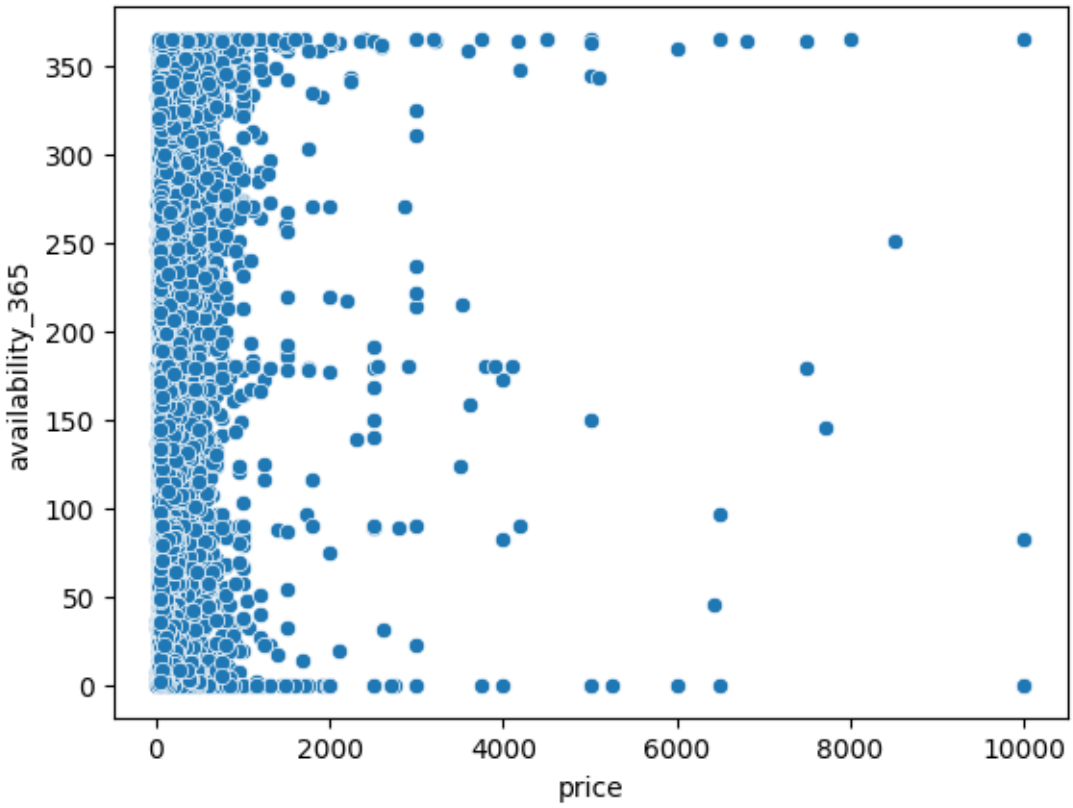


[75]:
```
X["availability_365"].describe()
```

[75]:
```
count    48884.000000
mean       112.779498
std        131.627271
min          0.000000
25%          0.000000
50%         45.000000
75%        227.000000
max        365.000000
Name: availability_365, dtype: float64
```

[76]:
```
sns.scatterplot(data=Airbnb, x="price", y="availability_365")
```

[76]:
```
<AxesSubplot:xlabel='price', ylabel='availability_365'>
```



0.2 # Spliting

0.2.1 Stratified Based Spliting

[77]:
```
## Basic Split
X_train, X_other, y_train, y_other = scsplit(X,
                                             y,
                                             stratify = y,
                                             train_size = 0.7,
                                             random_state = 130)

X_val, X_test, y_val, y_test = scsplit(X_other.reset_index(drop=True),
                                       y_other.reset_index(drop=True),
                                       stratify = y_other.
  ↪reset_index(drop=True),
                                       train_size = 0.7,
                                       random_state = 130)
print("sum of sets:",str(len(y_train)/len(Airbnb)+len(y_val)/
  ↪len(Airbnb)+len(y_test)/len(Airbnb)))
print("Train Set:",str(len(y_train)/len(Airbnb)))
print("Validation Set:", str(len(y_val)/len(Airbnb)))
```

```
print("Test Set:", str(len(y_test)/len(Airbnb)))
```

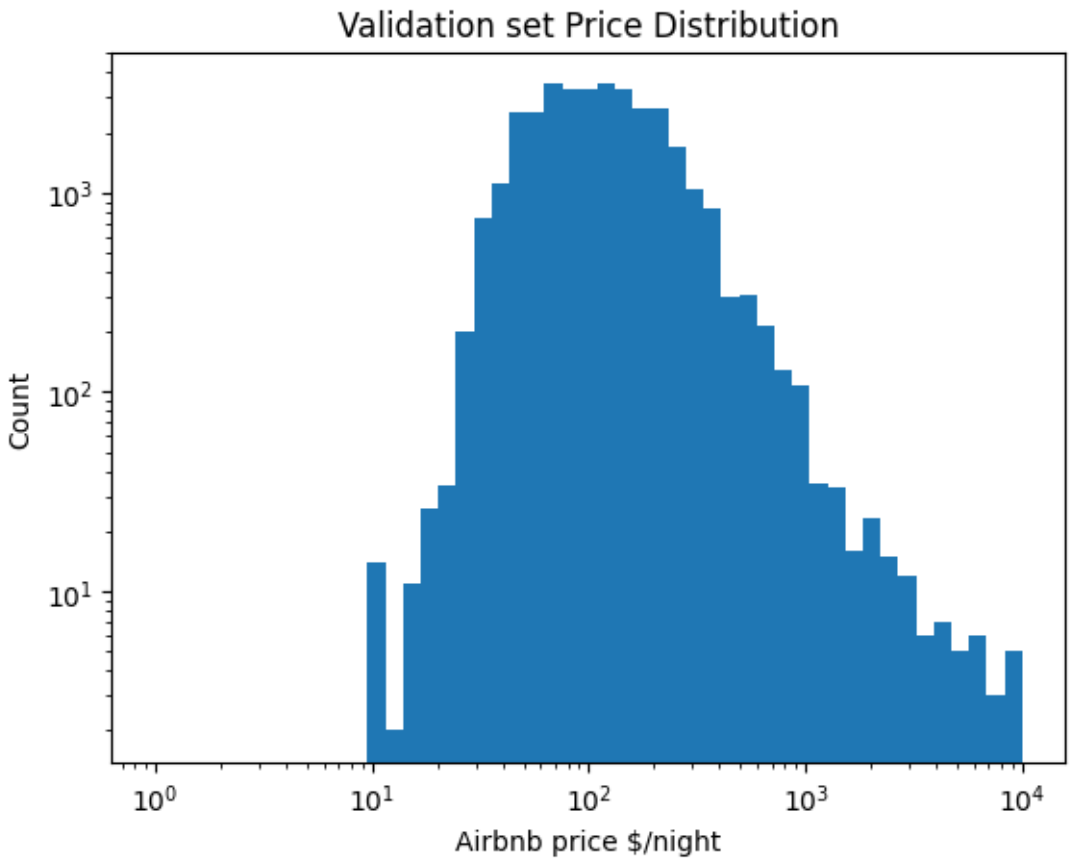
```
sum of sets: 1.0
Train Set: 0.6999836347271091
Validation Set: 0.2100073643728009
Test Set: 0.09000900090009001
```

0.2.2 Stratified Kfold Spliting

[78]:
```
### K fold
#X_other, X_fold1, y_other, y_fold1 = scsplit(X,
#                                             y,
#                                             stratify = y,
#                                             train_size = 0.8,
#                                             random_state = 130)
#
#X_other, X_fold2, y_other, y_fold2 = scsplit(X_other.reset_index(drop=True),
#                                          y_other.reset_index(drop=True),
#                                          stratify = y_other.
 ↪reset_index(drop=True),
#                                          train_size = 0.7,
#                                          random_state = 130)
#X_other, X_fold3, y_other, y_fold3 = scsplit(X_other.reset_index(drop=True),
#                                          y_other.reset_index(drop=True),
#                                          stratify = y_other.
 ↪reset_index(drop=True),
#                                          train_size = 0.7,
#                                          random_state = 130)
#X_fold5, X_fold4, y_fold5, y_fold4 = scsplit(X_other.reset_index(drop=True),
#                                          y_other.reset_index(drop=True),
#                                          stratify = y_other.
 ↪reset_index(drop=True),
#                                          train_size = 0.7,
#                                          random_state = 130)
#
```

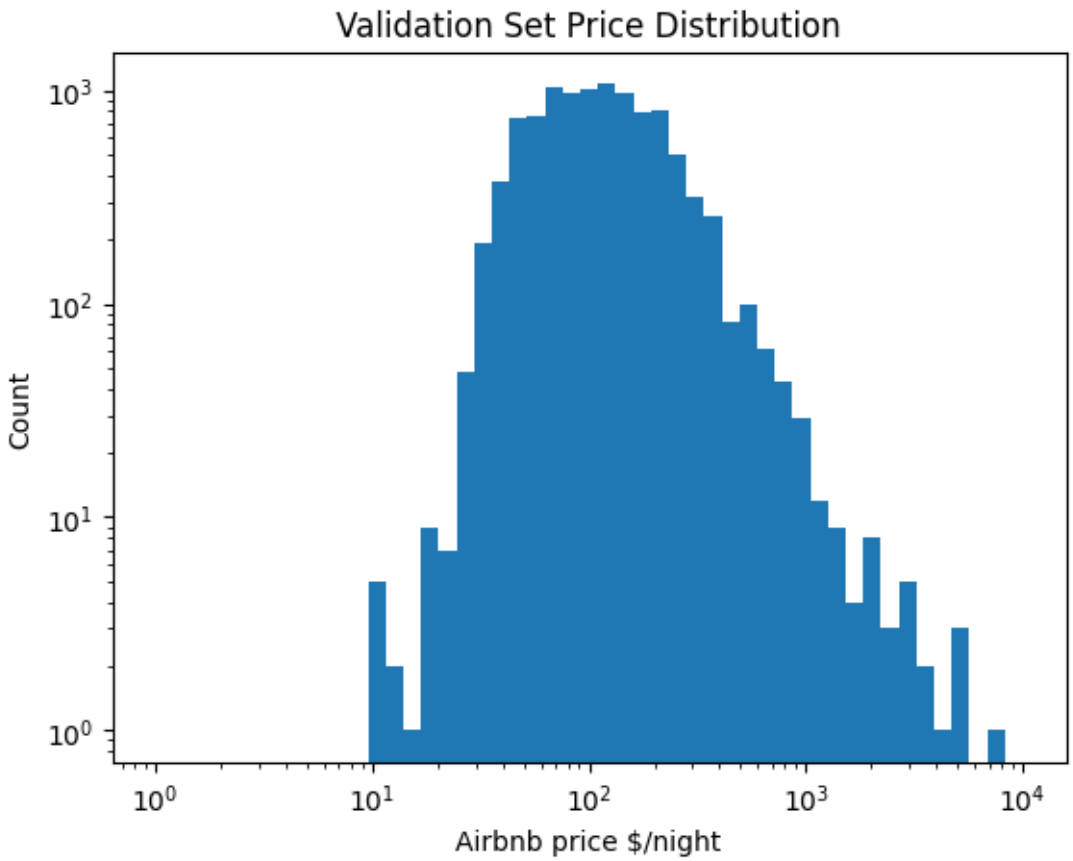
0.2.3 Train set

[79]:
```
y_train.plot.hist(log=True, bins = np.logspace(np.log10(1),np.log10(np.
 ↪max(y_train)),50))
plt.semilogy()
plt.semilogx()
plt.xlabel('Airbnb price $/night')
plt.ylabel('Count')
plt.title('Validation set Price Distribution')
plt.show()
```



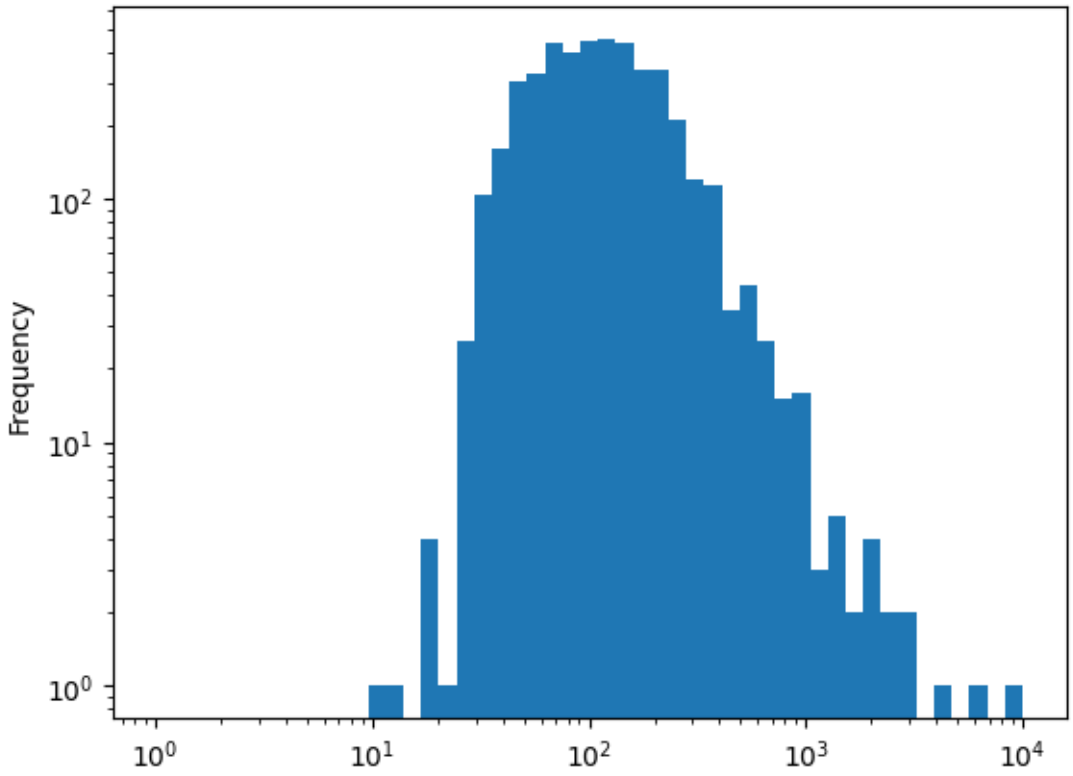
0.2.4 Validation Set

[80]:
```
y_val.plot.hist(log=True, bins = np.logspace(np.log10(1),np.log10(np.
↪max(y_val)),50))
plt.semilogy()
plt.semilogx()
plt.xlabel('Airbnb price $/night')
plt.ylabel('Count')
plt.title('Validation Set Price Distribution')
plt.show()
```



0.2.5 Test Set

[81]:
```
y_test.plot.hist(log=True, bins = np.logspace(np.log10(1),np.log10(np.
  ↪max(y_test)),50))
plt.semilogy()
plt.semilogx()
#plt.xlabel('Airbnb price $/night')
#plt.ylabel('Count')
#plt.title('Training Set Price Distribution')
plt.show()
```



0.3 ## Preprocessing

0.3.1 Check Type

[82]:
```
X.dtypes
```

[82]:
```
neighbourhood_group                            object
neighbourhood                                  object
latitude                                      float64
longitude                                     float64
room_type                                      object
minimum_nights                                  int64
number_of_reviews                               int64
reviews_per_month                             float64
calculated_host_listings_count                  int64
availability_365                                int64
gap_between_last_review_and_end_of_2019       float64
dtype: object
```

0.3.2 Define Preprocessor

[83]:
```
ordinal_ftrs= ["room_type"]
ordinal_cats = [["Shared room", "Private room", "Entire home/apt"]]
onehot_ftrs = ["neighbourhood_group", "neighbourhood"]
minmax_ftrs = ["availability_365"]
std_ftrs = ["minimum_nights", "number_of_reviews", "longitude", "latitude",␣
 ↪"gap_between_last_review_and_end_of_2019","reviews_per_month",␣
 ↪"calculated_host_listings_count"]
```

0.3.3 Preprocess

[84]:
```
# collect all the encoders
preprocessor = ColumnTransformer(
    transformers=[
        ('ord', OrdinalEncoder(categories = ordinal_cats), ordinal_ftrs),
        ('onehot', OneHotEncoder(sparse=False,handle_unknown='ignore'),␣
 ↪onehot_ftrs),
        ('minmax', MinMaxScaler(), minmax_ftrs),
        ('std', StandardScaler(), std_ftrs)])

clf = Pipeline(steps=[('preprocessor', preprocessor)]) # for now we only␣
 ↪preprocess
                                                       # later on we will add␣
 ↪other steps here

X_train_prep = clf.fit_transform(X_train)
X_val_prep = clf.transform(X_val)
X_test_prep = clf.transform(X_test)
```

0.3.4 Check Shape

[85]:
```
X_train_prep.shape
```

[85]: (34218, 234)

[86]:
```
Airbnb.shape
```

[86]: (48884, 17)

[87]:
```
48895-11
```

[87]: 48884