```python
# This Python 3 environment comes with many helpful analytics
libraries installed
# It is defined by the kaggle/python Docker image:
https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import seaborn as sns
import matplotlib.pyplot as plt
from wordcloud import WordCloud
import warnings # I HAVE THIS TO SUPPRESS WARNINGS ON MISSING VALUES
(not errors)
warnings.simplefilter(action = "ignore", category = RuntimeWarning)

# Input data files are available in the read-only "../input/"
directory
# For example, running this (by clicking run or pressing Shift+Enter)
will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/)
that gets preserved as output when you create a version using "Save &
Run All"
# You can also write temporary files to /kaggle/temp/, but they won't
be saved outside of the current session
```

```
The history saving thread hit an unexpected error
(OperationalError('attempt to write a readonly database')).History
will not be written to the database.
/kaggle/input/new-york-city-airbnb-open-data/AB_NYC_2019.csv
/kaggle/input/new-york-city-airbnb-open-data/New_York_City_.png
```

```python
df =
pd.read_csv('/kaggle/input/new-york-city-airbnb-open-data/AB_NYC_2019.
csv')
df.head()
```

```
     id                                              name  host_id  \
0  2539                Clean & quiet apt home by the park     2787
1  2595                             Skylit Midtown Castle     2845
2  3647               THE VILLAGE OF HARLEM....NEW YORK !     4632
3  3831                   Cozy Entire Floor of Brownstone     4869
4  5022  Entire Apt: Spacious Studio/Loft by central park     7192

     host_name neighbourhood_group neighbourhood  latitude  longitude
```

```
\
0         John             Brooklyn    Kensington  40.64749  -73.97237

1     Jennifer            Manhattan       Midtown  40.75362  -73.98377

2    Elisabeth            Manhattan        Harlem  40.80902  -73.94190

3  LisaRoxanne             Brooklyn  Clinton Hill  40.68514  -73.95976

4        Laura            Manhattan   East Harlem  40.79851  -73.94399


         room_type  price  minimum_nights  number_of_reviews
last_review  \
0     Private room    149               1                  9  2018-10-
19
1  Entire home/apt    225               1                 45  2019-05-
21
2     Private room    150               3                  0
NaN
3  Entire home/apt     89               1                270  2019-07-
05
4  Entire home/apt     80              10                  9  2018-11-
19

   reviews_per_month  calculated_host_listings_count  availability_365

0               0.21                               6               365

1               0.38                               2               355

2                NaN                               1               365

3               4.64                               1               194

4               0.10                               1                 0
```

Question 1

There are several columns - id, name, host_id, host_name, neighbourhood_group, and so on with almost 49000 entries.

```
# mask = df.isna() # Figure out which entries are missing via True or
not (False)
mask = df.isna().sum() # Figure out number of missing values in
column, 16 missing in name, 21 in host_name, and 10052 for last_review
& reviews_permonth
print(mask)
```

```
id                                    0
name                                 16
host_id                               0
host_name                            21
neighbourhood_group                   0
neighbourhood                         0
latitude                              0
longitude                             0
room_type                             0
price                                 0
minimum_nights                        0
number_of_reviews                     0
last_review                       10052
reviews_per_month                 10052
calculated_host_listings_count        0
availability_365                      0
dtype: int64
```

After a close inspection of dataframe using df.head() and df.tail(), I found the two columns 'name' and 'host_name' to be not that important in general for the assignment. This is because there is only 16 and 21 missing values, respectively, from ~ 49k records. The significance of having accurate imputation is minimal in affecting the dataset.

As a result, I will impute the name field with a value of the form: "room_type" in "neighbourhood" columns to indicate relevant values. Additionally, as for host_name, I will impute "Anonymous".

```
mask = df['name'].isna() # Get which records are empty (true)
df.loc[mask, 'name'] = df['room_type'].fillna('') + ' ' +
df['neighbourhood'].fillna('') # Fill empty value of the format:
"Room_type in neighbourhood_name"
df['host_name'] = df['host_name'].fillna('Unknown') # As for hostname,
impute "Unknown"
print(df.isna().sum()) # Check status of missing values now
```

```
id                                    0
name                                  0
host_id                               0
host_name                             0
neighbourhood_group                   0
neighbourhood                         0
latitude                              0
longitude                             0
room_type                             0
price                                 0
minimum_nights                        0
number_of_reviews                     0
last_review                       10052
reviews_per_month                 10052
```

```
calculated_host_listings_count        0
availability_365                      0
dtype: int64
```

Now that the two columns have been taken care of, now I need to focus on last_review & reviews_per_month. Both of these have way too many values missing, almost 20% of the dataset for these columns respectively. An interesting point is that both are missing the exact same amount, which could be the rows are related. After further inspection of the data, I found they are indeed related to one another.

```
out = df[(df['last_review'].isna()) |
(df['reviews_per_month'].isna())] # Return all rows where either
last_review or reviews_per_month is missing
# out.describe()
# out.tail()
out.head()
```

```
       id                                               name  host_id
\
2    3647                THE VILLAGE OF HARLEM....NEW YORK !     4632

19   7750                    Huge 2 BR Upper East  Cental Park    17985

26   8700  Magnifique Suite au N de Manhattan - vue Cloitres    26394

36  11452                          Clean and Quiet in Brooklyn     7355

38  11943                            Country space in the city    45445


          host_name neighbourhood_group       neighbourhood  latitude
\
2         Elisabeth           Manhattan              Harlem  40.80902

19             Sing           Manhattan         East Harlem  40.79685

26  Claude & Sophie           Manhattan              Inwood  40.86754

36               Vt            Brooklyn  Bedford-Stuyvesant  40.68876

38          Harriet            Brooklyn            Flatbush  40.63702


    longitude        room_type  price  minimum_nights
number_of_reviews  \
2   -73.94190     Private room    150               3
0
19  -73.94872  Entire home/apt    190               7
0
26  -73.92639     Private room     80               4
```

```
0
36  -73.94312     Private room     35              60
0
38  -73.96327     Private room    150               1
0

   last_review  reviews_per_month  calculated_host_listings_count  \
2          NaN                NaN                               1
19         NaN                NaN                               2
26         NaN                NaN                               1
36         NaN                NaN                               1
38         NaN                NaN                               1

    availability_365 hostings_range reviews_range
2                365           0-10          0-50
19               249           0-10          0-50
26                 0           0-10          0-50
36               365           0-10          0-50
38               365           0-10          0-50
```

As it can be seen, the columns are indeed related as the average, min, and max for the number_of_reviews column is 0 and there are precisely 10,052 records indicating the relation of missing both values when this is the case. If there are 0 reviews for these, then I can impute 0 for "reviews_per_month" column, and a custom value like "Unreviewed" for "last_review" column.

```
df['reviews_per_month'] = df['reviews_per_month'].fillna(0) # Fill
missing values with "0" for reviews_per_month column
df['last_review'] = df['last_review'].fillna('Unreviewed') # Fill
missing values of last_review with "Unreviewed"
print(df.isna().sum())
```

```
id                                0
name                              0
host_id                           0
host_name                         0
neighbourhood_group               0
neighbourhood                     0
latitude                          0
longitude                         0
room_type                         0
price                             0
minimum_nights                    0
number_of_reviews                 0
last_review                       0
reviews_per_month                 0
calculated_host_listings_count    0
availability_365                  0
dtype: int64
```

```
df.describe()

                 id       host_id      latitude     longitude
price  \
count  4.889500e+04  4.889500e+04  48895.000000  48895.000000
48895.000000
mean   1.901714e+07  6.762001e+07     40.728949    -73.952170
152.720687
std    1.098311e+07  7.861097e+07      0.054530      0.046157
240.154170
min    2.539000e+03  2.438000e+03     40.499790    -74.244420
0.000000
25%    9.471945e+06  7.822033e+06     40.690100    -73.983070
69.000000
50%    1.967728e+07  3.079382e+07     40.723070    -73.955680
106.000000
75%    2.915218e+07  1.074344e+08     40.763115    -73.936275
175.000000
max    3.648724e+07  2.743213e+08     40.913060    -73.712990
10000.000000

       minimum_nights  number_of_reviews  reviews_per_month  \
count    48895.000000       48895.000000       48895.000000
mean         7.029962          23.274466           1.090910
std         20.510550          44.550582           1.597283
min          1.000000           0.000000           0.000000
25%          1.000000           1.000000           0.040000
50%          3.000000           5.000000           0.370000
75%          5.000000          24.000000           1.580000
max       1250.000000         629.000000          58.500000

       calculated_host_listings_count  availability_365
count                    48895.000000      48895.000000
mean                         7.143982        112.781327
std                         32.952519        131.622289
min                          1.000000          0.000000
25%                          1.000000          0.000000
50%                          1.000000         45.000000
75%                          2.000000        227.000000
max                        327.000000        365.000000
```

Even though missing values were fixed with imputation, there is a problem as can be seen above with outliers. For example, the max value for minimum_nights reads 1250 days, which is almost 4 years! And, there is a max of 10,000 dollars for daily price. This is unreasonable for a per-day basis as mean for price column is around 152 dollars, a reasonable average daily price for airbnbs. And, there is a problem where there is airbnb with price 0. For that, I will get a count to see how many have price 0

```python
out = df[df['price'] == 0] # Get only listings with price = 0
out.describe()
```

```
                 id       host_id   latitude  longitude  price  \
count  1.100000e+01  1.100000e+01  11.000000  11.000000   11.0
mean   2.057179e+07  5.862573e+07  40.712058 -73.925670    0.0
std    6.767257e+05  4.828458e+07   0.045317   0.025821    0.0
min    1.875060e+07  1.641537e+06  40.681730 -73.975970    0.0
25%    2.056598e+07  1.192073e+07  40.686510 -73.943585    0.0
50%    2.063963e+07  8.632710e+07  40.692110 -73.913420    0.0
75%    2.078688e+07  9.414883e+07  40.716500 -73.910490    0.0
max    2.130432e+07  1.316976e+08  40.832960 -73.886680    0.0

       minimum_nights  number_of_reviews  reviews_per_month  \
count       11.000000          11.000000          11.000000
mean         7.363636          34.272727           1.579091
std         11.262972          41.523706           1.906628
min          1.000000           0.000000           0.000000
25%          1.500000           2.500000           0.130000
50%          2.000000          12.000000           0.530000
75%          4.500000          74.000000           3.420000
max         30.000000          95.000000           4.370000

       calculated_host_listings_count  availability_365
count                       11.000000         11.000000
mean                         4.272727        120.909091
std                          2.053821        112.128011
min                          1.000000          0.000000
25%                          3.000000         14.000000
50%                          5.000000        127.000000
75%                          6.000000        199.000000
max                          6.000000        333.000000
```

Given that there are only 11 records with price = 0, I will remove these 11 records as the count is insignificant for the larger dataset.

```python
# Remove price = 0 columns, 11 only
df = df[df["price"] > 0] # Filter out such listings
df.describe() # Only 11 removed, 48895 --> 48884 (count)
```

```
                 id       host_id      latitude     longitude
price  \
count  4.888400e+04  4.888400e+04  48884.000000  48884.000000
48884.000000
mean   1.901679e+07  6.762203e+07     40.728953    -73.952176
152.755053
std    1.098432e+07  7.861666e+07      0.054532      0.046159
240.170260
min    2.539000e+03  2.438000e+03     40.499790    -74.244420
10.000000
```

```
25%    9.470548e+06  7.817310e+06     40.690100    -73.983080
69.000000
50%    1.967574e+07  3.079257e+07     40.723080    -73.955685
106.000000
75%    2.915297e+07  1.074344e+08     40.763120    -73.936290
175.000000
max    3.648724e+07  2.743213e+08     40.913060    -73.712990
10000.000000

       minimum_nights  number_of_reviews  reviews_per_month  \
count    48884.000000       48884.000000       48884.000000
mean         7.029887          23.271991           1.090800
std         20.512224          44.551331           1.597213
min          1.000000           0.000000           0.000000
25%          1.000000           1.000000           0.040000
50%          3.000000           5.000000           0.370000
75%          5.000000          24.000000           1.580000
max       1250.000000         629.000000          58.500000

       calculated_host_listings_count  availability_365
count                    48884.000000      48884.000000
mean                         7.144628        112.779498
std                         32.956185        131.627271
min                          1.000000          0.000000
25%                          1.000000          0.000000
50%                          1.000000         45.000000
75%                          2.000000        227.000000
max                        327.000000        365.000000
```

```
out = df[df["price"] < 20] # Current minimum airbnb listing in New
York is $ 20 (checked online on 03/28/2025)
out.head(n=10)
```

```
             id                                           name
host_id  \
2860    1620248  Large furnished 2 bedrooms- - 30 days Minimum
2196224
3950    2459916              $455 Cozy 1bd, BKLYN Sublet March
12577771
4647    3258197   Large 1br Duplex in Heart of Upper East Side
16477306
5542    4031809                  Prewar classic NYC apartment.
20902552
8169    6301965                             Beautiful SoHo Loft
655506
8270    6364324                                      The Oasis.
33106693
19922  15966074   Evergreen Upper Bed for Female Traveler 紐約民宿
101491116
20992  16620607        Spacious and Modern 2 Bedroom Apartment
```

```
109725962
21281  16927533                       Studio with amazing view
3737986
21700  17437106           Couch in Harlem Harvey Refugees only
33511962

      host_name neighbourhood_group       neighbourhood  latitude
longitude  \
2860      Sally           Manhattan        East Village  40.73051  -
73.98140
3950     Victor            Brooklyn  Bedford-Stuyvesant  40.68948  -
73.93528
4647       Jeff           Manhattan     Upper East Side  40.76866  -
73.95553
5542     Miquel           Manhattan  Washington Heights  40.83456  -
73.94344
8169     Silvia           Manhattan                SoHo  40.72340  -
73.99967
8270      Elena           Manhattan              Harlem  40.82159  -
73.95013
19922      Tong            Brooklyn       Cypress Hills  40.68313  -
73.87077
20992     Erika            Brooklyn            Bushwick  40.68994  -
73.91556
21281  Carolann           Manhattan  Financial District  40.70588  -
74.01590
21700    Morgan           Manhattan              Harlem  40.81302  -
73.95349

             room_type  price  minimum_nights  number_of_reviews
last_review  \
2860   Entire home/apt     10              30                  0
Unreviewed
3950      Private room     18               1                  0
Unreviewed
4647   Entire home/apt     16               2                 21
2019-06-30
5542      Private room     16              14                  0
Unreviewed
8169   Entire home/apt     16               3                  3
2018-01-08
8270      Private room     16               2                 43
2019-07-01
19922      Shared room     19               2                 76
2019-06-20
20992  Entire home/apt     11               2                113
2019-06-22
21281  Entire home/apt     12             300                  0
Unreviewed
```

```
21700      Shared room     10              1                  0
Unreviewed

       reviews_per_month  calculated_host_listings_count
availability_365
2860                0.00                               4
137
3950                0.00                               1
0
4647                1.69                               1
9
5542                0.00                               1
0
8169                0.16                               1
0
8270                1.66                               3
154
19922               2.40                               6
120
20992               3.86                               1
261
21281               0.00                               1
0
21700               0.00                               1
0
```

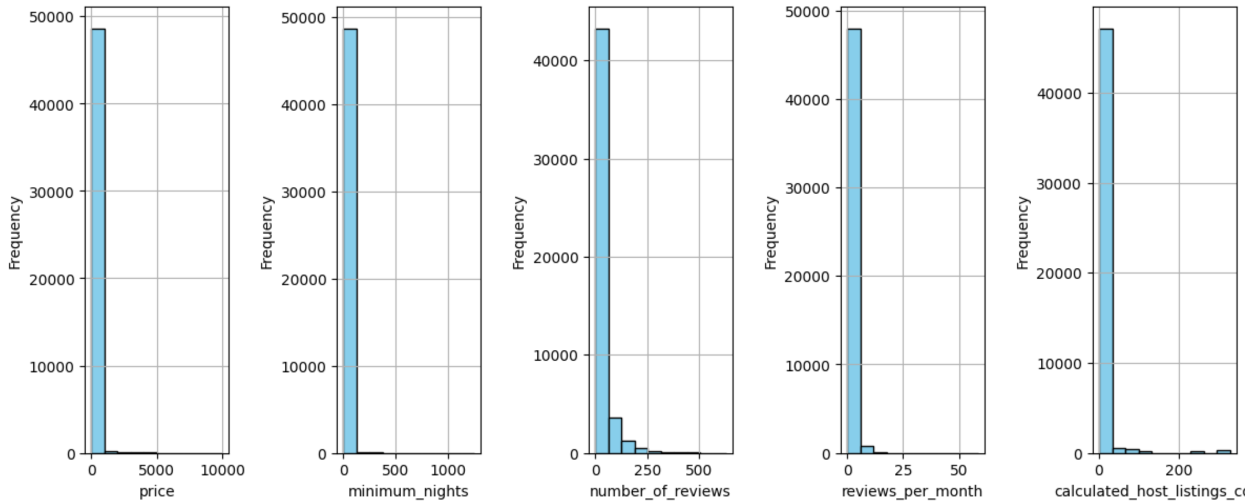
Furthermore, there are 0 listings below 10 dollars. The minimum is 10 dollars and that is fine because I can easily find 20 dollar listings currently, so this can be considered valid listings adjust for "reverse" inflation into the past. Now, I will focus on the outliers on other side. Likewise, I will repeat the case for the following columns: minimum_nights, number_of_reviews, reviews_per_month, and calculated_host_listings_count. I will use the 75% value to see how bad the outliers are.

```
# Only plot histograms for these columns
selected_columns = ['price', 'minimum_nights', 'number_of_reviews',
'reviews_per_month', 'calculated_host_listings_count']

# Plot histograms
fig, axes = plt.subplots(1, len(selected_columns), figsize=(12, 5))

for ax, col in zip(axes, selected_columns):
    df[col].plot(kind='hist', ax=ax, color='skyblue',
edgecolor='black')
    ax.set_xlabel(col)
    ax.grid(True)

plt.tight_layout() # minimize spacing between plots
plt.show()
```



As we can see, price above 5000 dollars is extremely unreasonable. But, I found most of these to be luxury apartments. Since price = 0 does not make sense, but price being 5000+ dollars could be reasonable for luxury apartments in an insanely expensive area. Additinally, these are few values, over a dataset of ~49k, they will have close to no influence on actual mean. Likewise, anything above 500 for minimum_nights, 500 for number_of_reviews, and 50 for reviews_per_month is suspicious, but they do not negatively affect the data as values like 0 minimum_nights would. The calculated_host_listings_count is fine as there are enough listings around that price. Now, I will move onto question 2.

Question 2

To find out the top 5 and bottom 5 neighbourhoods, I need to first group by neighbourhood and filter out the neighbourhoods with at most 5 listings. Then, I have to figure out average price of listings in neighbourhood. I group by neighbourhood_groups also to get average price of a neighbourhood as there may or may not be two neighbourhoods with exact same name in different neighbourhood groups. After, I sort the neighbourhoods by average price and via neighbourhood groups to finally be able to extract the top 5 and bottom 5 listings in each neighbourhood group as seen below.

```
out = df[['neighbourhood_group', 'neighbourhood', 'price']] # we don't need the rest of columns
out = out.groupby('neighbourhood').filter(lambda x: len(x) > 5) # we only need neighbourhoods with more than 5 listings
# average prices by neighbourhood
out = out.groupby(['neighbourhood_group', 'neighbourhood'])['price'].mean().reset_index() # We want to average for neighbourhoods and their groups (there can be 2 neighbourhoods with same name from different groups)
out.rename(columns={'price': 'average_price'}, inplace=True) # For readability
out = out.sort_values(by=["neighbourhood_group", "average_price"]) # sort so that we have it groups by neighbourhood_group with each
```

```
neighbourhood
print(out)
```

```
    neighbourhood_group   neighbourhood  average_price
16                Bronx     Hunts Point      50.500000
36                Bronx         Tremont      51.545455
34                Bronx       Soundview      53.466667
3                 Bronx       Bronxdale      57.105263
24                Bronx      Mount Eden      58.500000
..                  ...             ...            ...
185       Staten Island      St. George     118.145833
188       Staten Island     Tottenville     144.857143
183       Staten Island     Shore Acres     152.714286
176       Staten Island     Grymes Hill     159.142857
181       Staten Island   Randall Manor     336.000000

[190 rows x 3 columns]
```

Bottom 5 Listings for Each Neighbourhood Group:

```
# Bottom 5 Neighbourhoods based on average price for each
neighbourhood group
bottom_5 = out.groupby('neighbourhood_group').head(n=5) # It's in
ascending order
print(bottom_5)
```

```
    neighbourhood_group         neighbourhood  average_price
16                Bronx           Hunts Point      50.500000
36                Bronx               Tremont      51.545455
34                Bronx             Soundview      53.466667
3                 Bronx             Bronxdale      57.105263
24                Bronx            Mount Eden      58.500000
50             Brooklyn          Borough Park      63.066176
47             Brooklyn           Bensonhurst      75.786667
53             Brooklyn           Brownsville      76.459016
73             Brooklyn             Gravesend      79.014706
77             Brooklyn               Midwood      80.339450
102           Manhattan                Inwood      88.896825
106           Manhattan           Marble Hill      89.166667
120           Manhattan    Washington Heights      89.610679
112           Manhattan      Roosevelt Island     113.259740
108           Manhattan   Morningside Heights     114.783237
132              Queens                Corona      59.171875
167              Queens             Woodhaven      67.170455
161              Queens              Rosedale      76.694915
159              Queens             Ridgewood      77.184397
137              Queens              Elmhurst      80.459916
170       Staten Island           Bull's Head      47.333333
174       Staten Island            Grant City      57.666667
```

```
172       Staten Island            Concord      58.192308
179       Staten Island      New Springville    76.000000
187       Staten Island        Tompkinsville    76.190476
```

Top 5 Listings for Each Neighbourhood Group:

```
# TOP 5 Neighbourhoods based on average price for each neighbourhood
group
top_5 = out.groupby('neighbourhood_group').tail(n=5)
print(top_5)
```

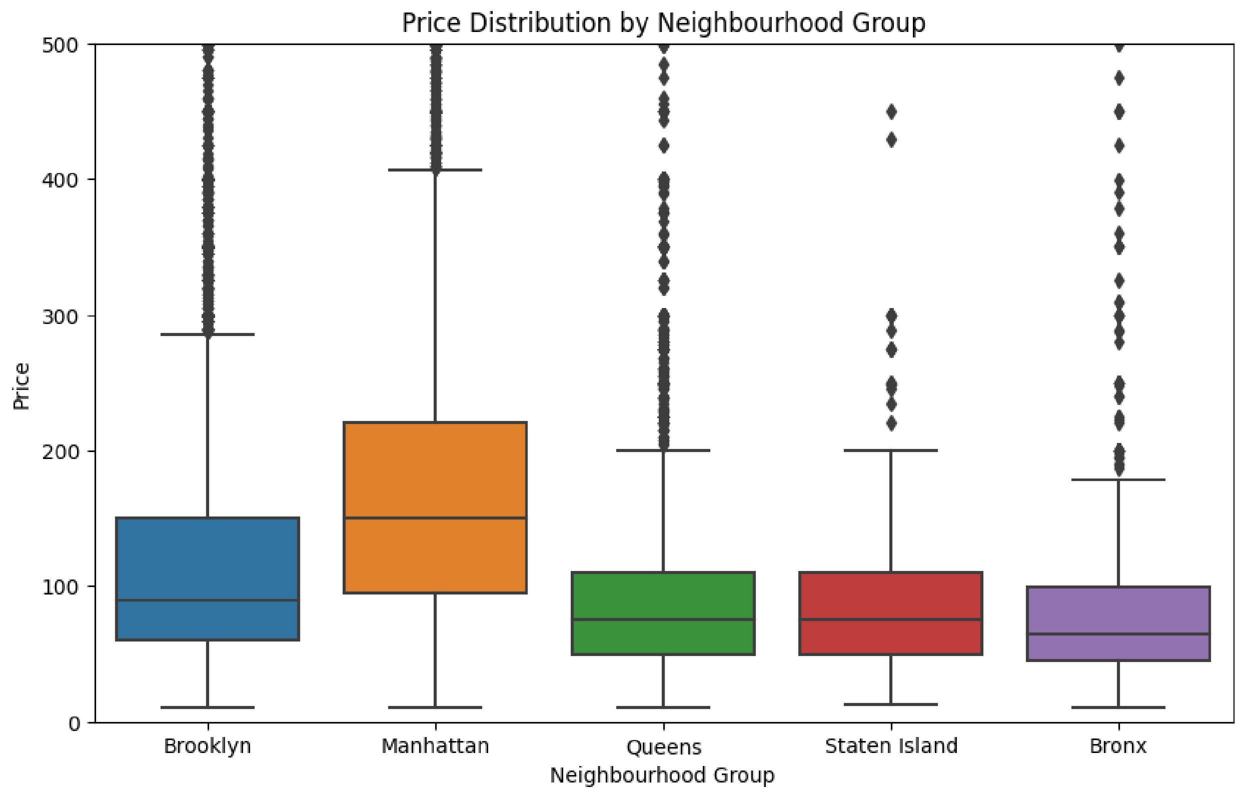
```
    neighbourhood_group       neighbourhood  average_price
41                Bronx  Westchester Square     122.200000
37                Bronx           Unionport     137.142857
11                Bronx         Eastchester     141.692308
5                 Bronx         City Island     173.000000
32                Bronx           Riverdale     442.090909
87             Brooklyn        Vinegar Hill     187.176471
63             Brooklyn               DUMBO     196.305556
52             Brooklyn   Brooklyn Heights      209.064935
58             Brooklyn         Cobble Hill     211.929293
83             Brooklyn            Sea Gate     487.857143
113           Manhattan                SoHo     287.103352
110           Manhattan                NoHo     295.717949
97            Manhattan   Flatiron District     341.925000
90            Manhattan   Battery Park City     367.557143
116           Manhattan             Tribeca     490.638418
125              Queens             Bayside     157.948718
138              Queens        Far Rockaway     165.862069
127              Queens        Belle Harbor     171.500000
122              Queens             Arverne     171.779221
147              Queens     Jamaica Estates     182.947368
185       Staten Island          St. George     118.145833
188       Staten Island         Tottenville     144.857143
183       Staten Island         Shore Acres     152.714286
176       Staten Island         Grymes Hill     159.142857
181       Staten Island       Randall Manor     336.000000
```

Now, to determine the extent of price variation, I will use the mean from previous example to plot a Histogram for each neighbourhood group. I use 500 as the limit for y-axis since the mean is around 100 for all neighbourhood groups, but so many outliers in price and beyond the upper quartile range. I think the limit 500 shows a good understanding of how these 'outliers' vary by each neighbourhood group too.

```
out = df[['neighbourhood_group', 'price']] # We don't need the other
columns
# out = out.groupby('neighbourhood_group')
['price'].mean().reset_index() # Group by neighbourhood group,
calculate the average.
```

```
plt.figure(figsize=(10, 6))
sns.boxplot(data=out, x='neighbourhood_group', y='price')

plt.title("Price Distribution by Neighbourhood Group")
plt.xlabel("Neighbourhood Group")
plt.ylabel("Price")
plt.ylim(0, 500) # limit upper end to avoid bad output
plt.show()
```



Question 3

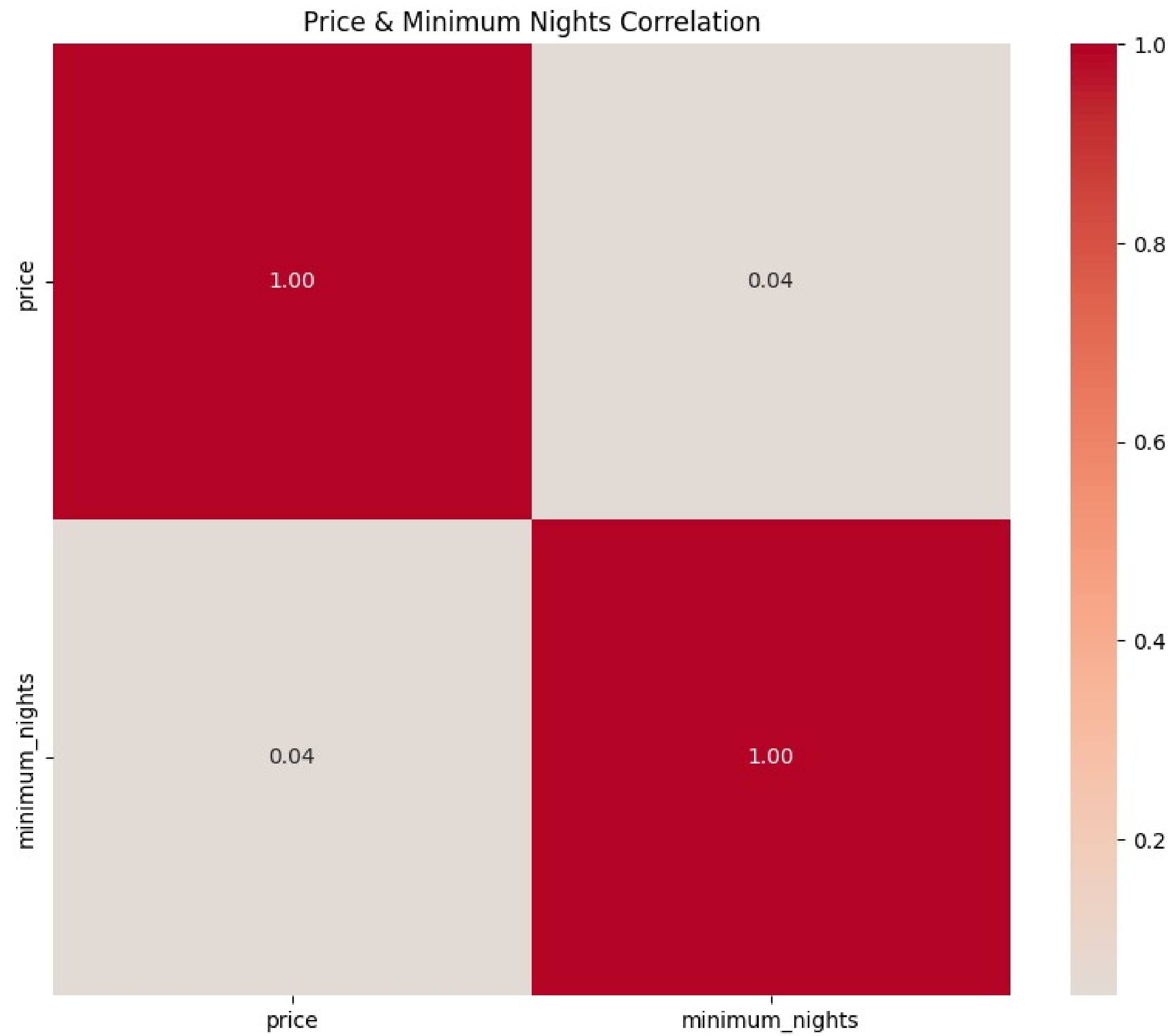
Set of interesting features: price, minimum_nights, number_of_reviews, calculated_host_listings

I will plot the following:

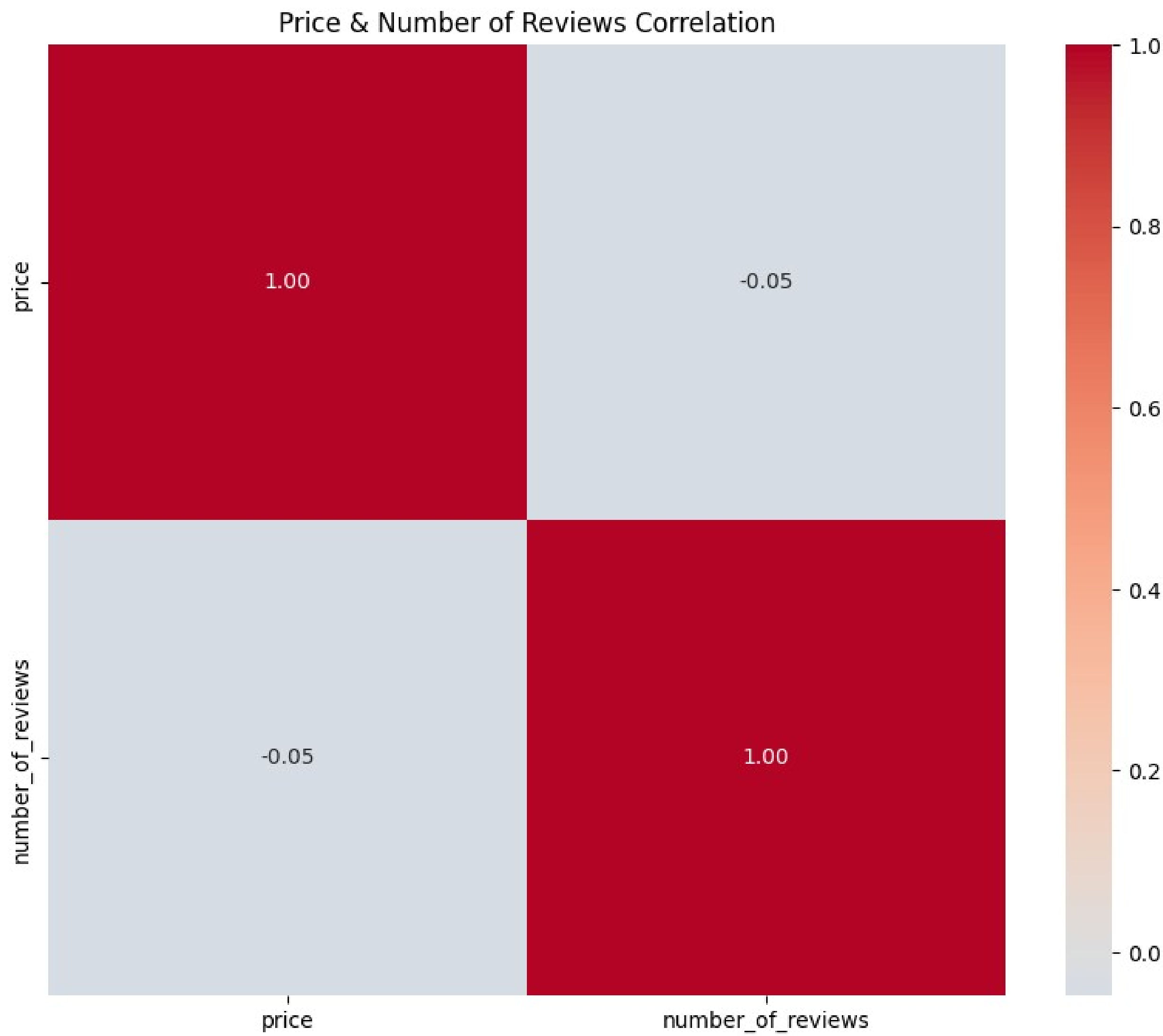
1. price vs minimum_nights correlation
2. price vs number_of_reviews correlation

```
columns = ['price', 'minimum_nights']
correlation_matrix = df[columns].corr(method='pearson')
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, fmt="0.2f",
```

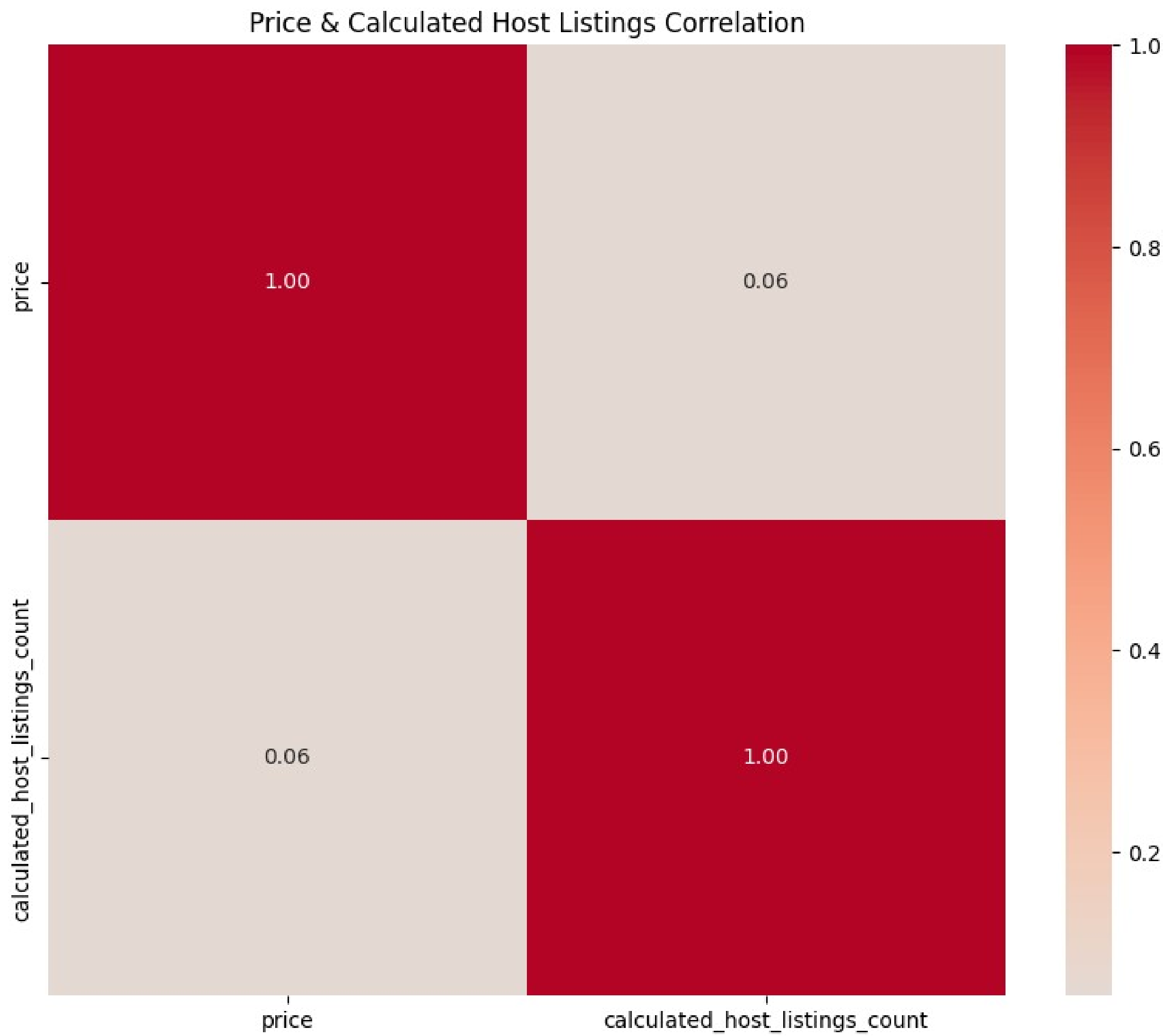
```
cmap="coolwarm", center=0)
plt.title("Price & Minimum Nights Correlation")
plt.show()
```



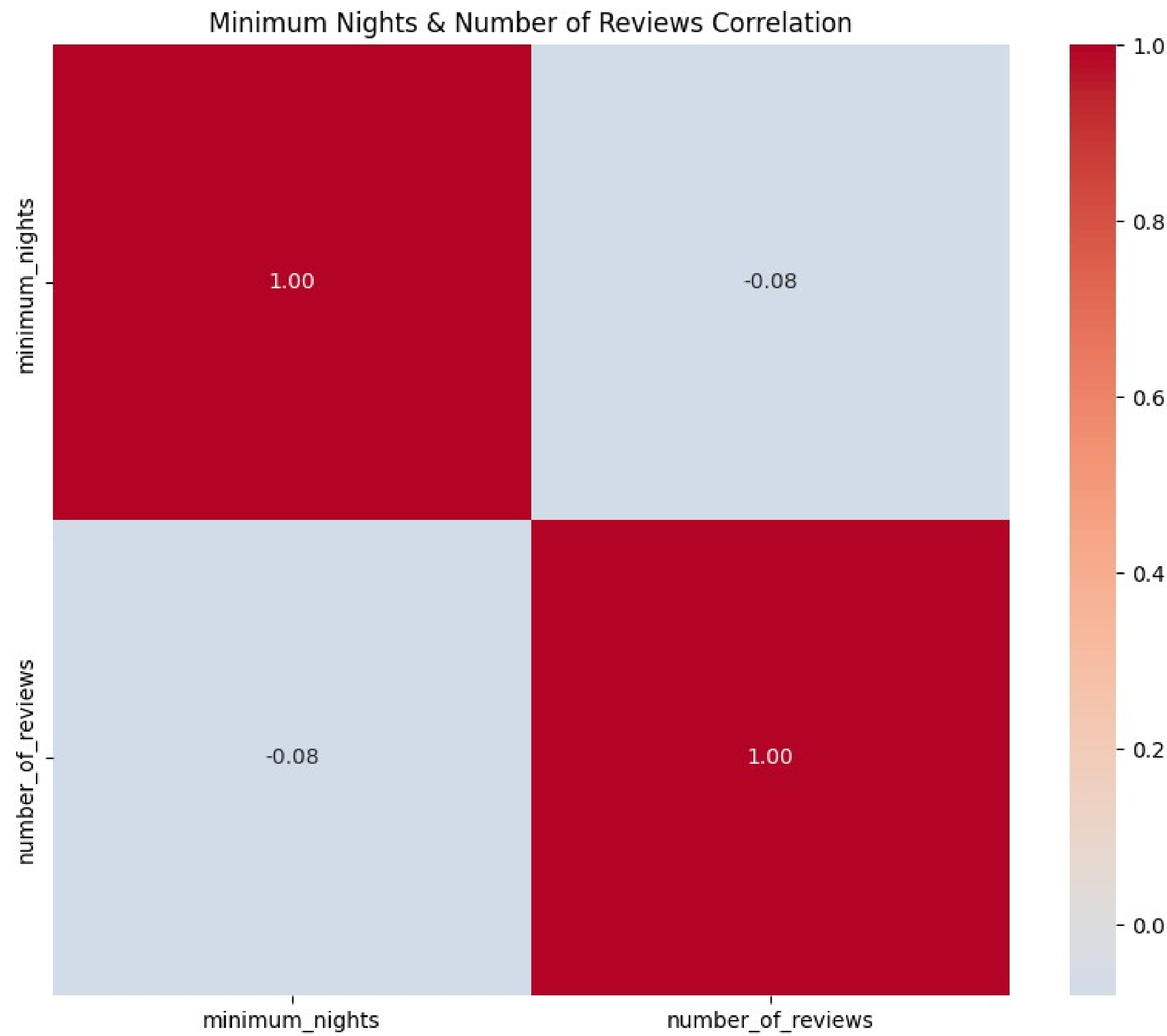

```
columns = ['price', 'number_of_reviews']
correlation_matrix = df[columns].corr(method='pearson')
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, fmt="0.2f",
cmap="coolwarm", center=0)
plt.title("Price & Number of Reviews Correlation")
plt.show()
```




```
columns = ['price', 'calculated_host_listings_count']
correlation_matrix = df[columns].corr(method='pearson')
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, fmt="0.2f",
cmap="coolwarm", center=0)
plt.title("Price & Calculated Host Listings Correlation")
plt.show()
```




```
columns = ['minimum_nights', 'number_of_reviews']
correlation_matrix = df[columns].corr(method='pearson')
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, fmt="0.2f",
cmap="coolwarm", center=0)
plt.title("Minimum Nights & Number of Reviews Correlation")
plt.show()
```



Strongest positive correlation 0.06 between price & calculated host listings

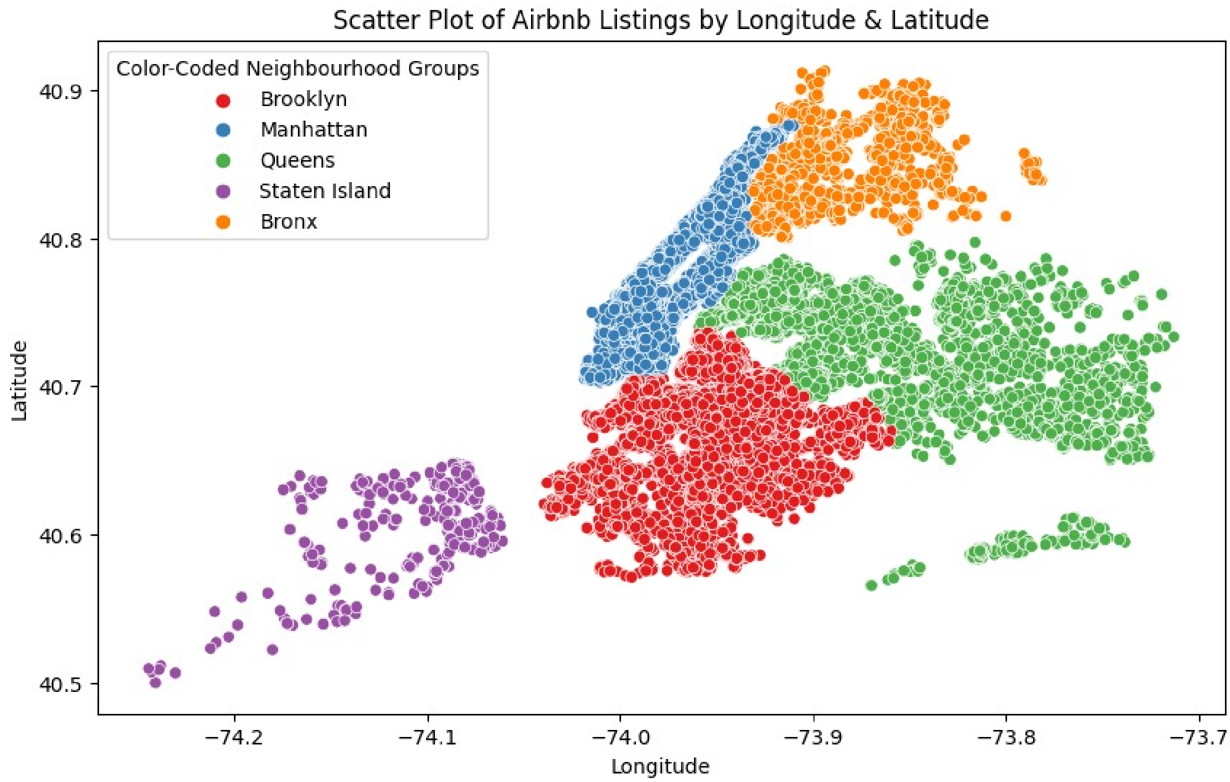
Strongest anti correlation -0.08 between minimum nights and the number of reviews

Question 4

I use seaborn with matplotlib to plot a scatterplot using longitude for x-axis, latitude for y-axis, and neighbourhood_group as hue for color coding. I stick to default "Set1" for the actual coloring, which is nice enough visually to differentiate the different boroughs of New York City.

```
plt.figure(figsize=(10,6))
sns.scatterplot(data=df, x='longitude', y='latitude',
hue='neighbourhood_group', palette='Set1')
plt.title('Scatter Plot of Airbnb Listings by Longitude & Latitude')
plt.xlabel('Longitude')
```

```
plt.ylabel('Latitude')
plt.legend(title='Color-Coded Neighbourhood Groups')
plt.show()
```



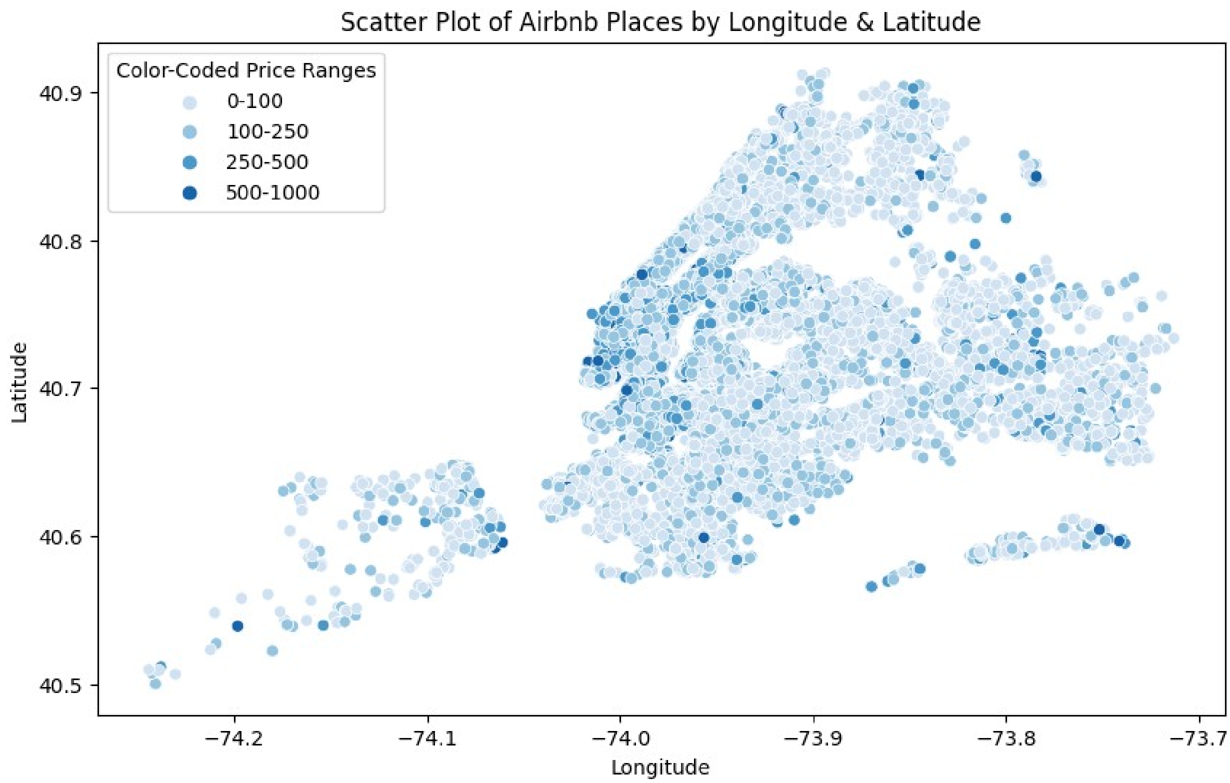
First, I filter for Airbnb listings that are at most 1000 dollars. Then, I make a copy to avoid the SettingWithCopyWarning. Then, I create bins for ranges 0-100, 100-250, 250-500, 500-1000 alongside labels to use with the scatter plot. Then, I create a price_range column which labels different listings with the labels within the ranges described for bins for easily plotting a scatter plot. Now, I use these unequal ranges because the motivation is that a rich person will not care if a listing is 800 dollars or 900 dollars, whereas the poor person will certainly care about a difference between 50 and 80 dollar listing. Additionally, this is just me trying to show the essence of wealth distribution - a power law based phenomena.

```
out = df[df['price'] < 1000] # Filter for only listings below $ 1,000
out = out.copy() # Avoid SettingWithCopyWarning warning

bins = [0, 100, 250, 500, 1000]
labels = ['0-100', '100-250', '250-500', '500-1000']
out.loc[:, 'price_range'] = pd.cut(out['price'], bins=bins,
labels=labels, right=False) # Create a price_range column using the
bins & labels

plt.figure(figsize=(10,6))
sns.scatterplot(data=out, x='longitude', y='latitude',
hue='price_range', palette='Blues') # Choose palette Blues for cleaner
```

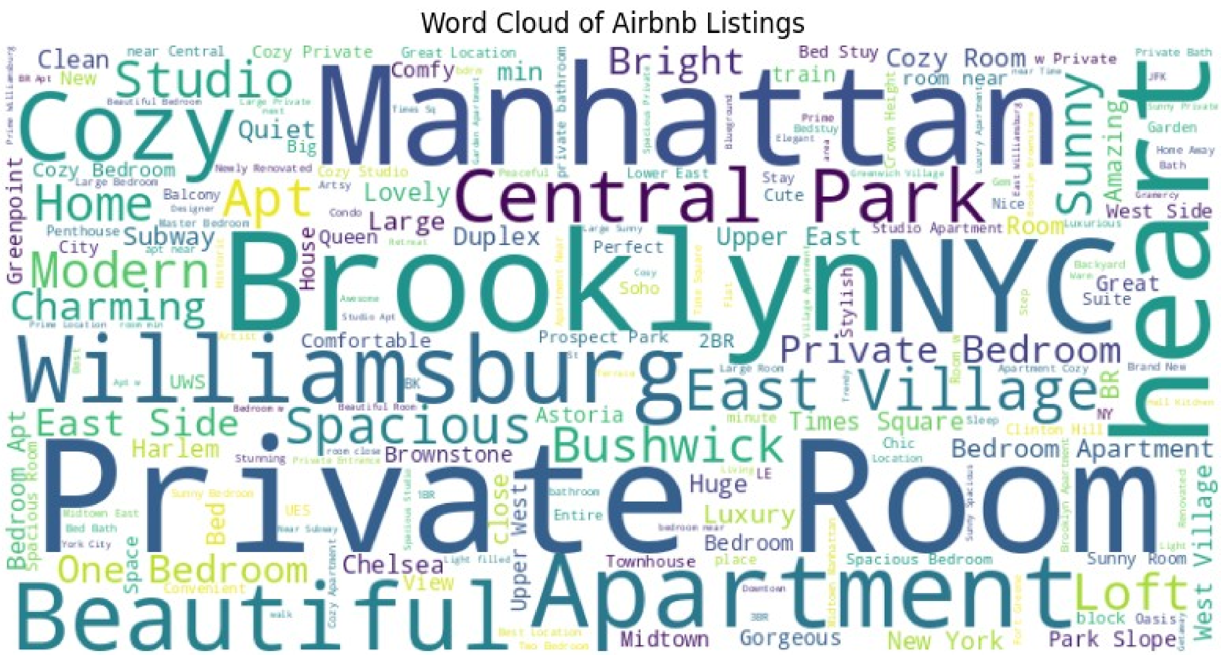
```
shading of which area is more expensive
plt.title('Scatter Plot of Airbnb Places by Longitude & Latitude')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.legend(title='Color-Coded Price Ranges')
plt.show()
```



Question 5

I used wordcloud library as it was allowed by professor on piazza

```
text = " ".join(df['name'].dropna()) # Join all name values into one
single string
wordcloud = WordCloud(width=800, height=400,
background_color='white').generate(text) # create wordcloud
plt.figure(figsize=(10,6))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud of Airbnb Listings')
plt.show()
```

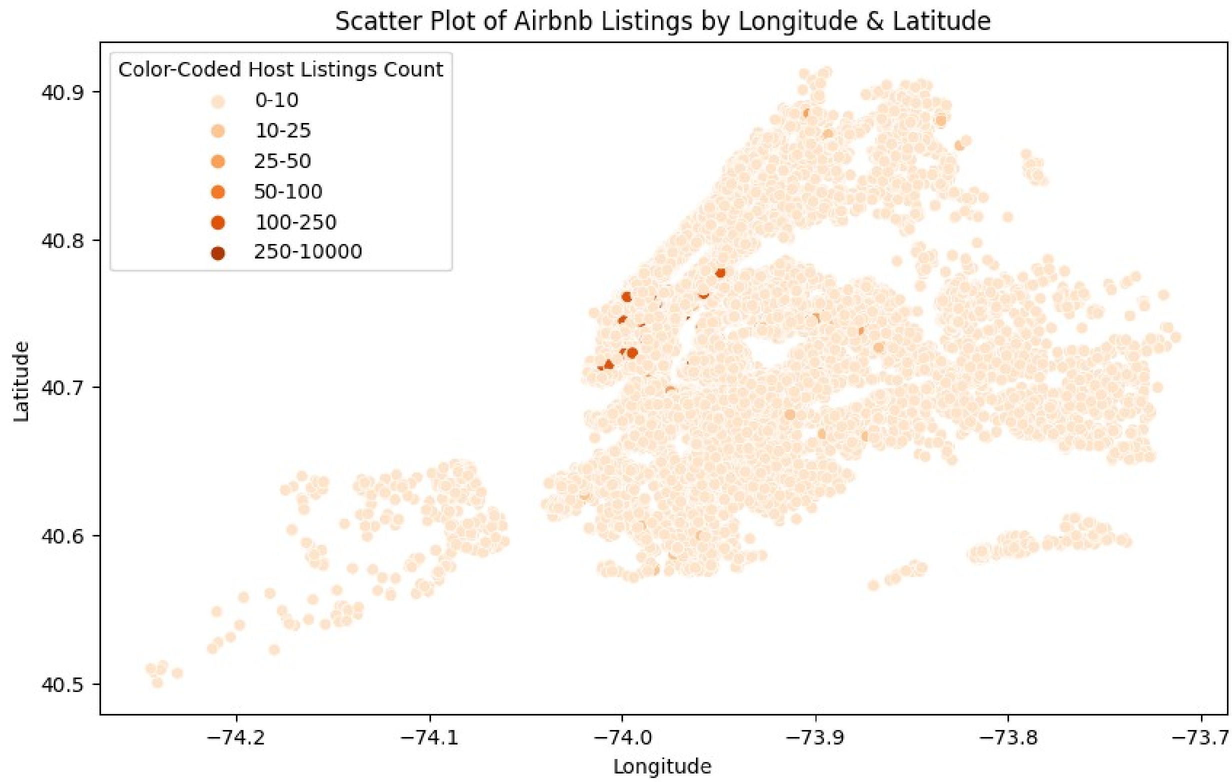


Question 6

First, I create bins and labels just like previous scatter plots of color-coding by Host Listings Count value. Then, I create the column that labels using the provided bins and labels list. Then, I use orange palette to show which areas were more busy as ornage indicates "hot" in a heatmap type map - in this case the color-coded scatter plot acts a lot like a heatmap. As it can be seen, the majority of listings are in Manhattan or more accurately, the majority of high listing hosts are in Manhattan.

```
out = df
bins = [0, 10, 25, 50, 100, 250, 10000]
labels = ['0-10', '10-25', '25-50', '50-100', '100-250', '250-10000']
out.loc[:, 'hostings_range'] =
pd.cut(df['calculated_host_listings_count'], bins=bins, labels=labels,
right=False) # Create a price_range column using the bins & labels

plt.figure(figsize=(10,6))
sns.scatterplot(data=out, x='longitude', y='latitude',
hue='hostings_range', palette='Oranges') # Choose palette Oranges to
stress busy areas
plt.title('Scatter Plot of Airbnb Listings by Longitude & Latitude')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.legend(title='Color-Coded Host Listings Count')
plt.show()
```



To put a number to each neighbourhood group, I did the average of calculated host listings and as it can be seen, Manhattan far surpasses in host listings than other boroughs.

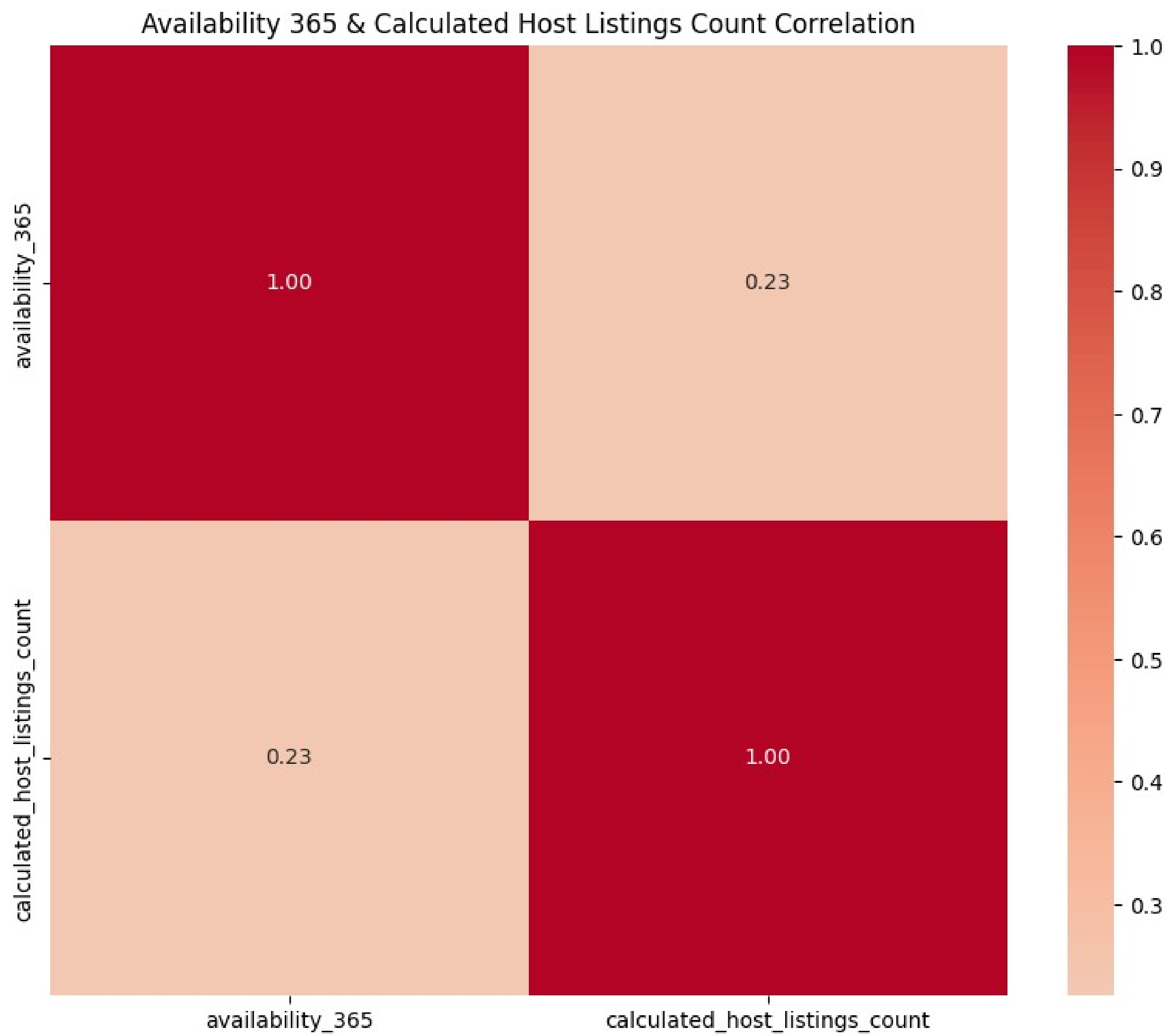
```
out = df[["neighbourhood_group", "calculated_host_listings_count"]]
out = out.groupby('neighbourhood_group')
['calculated_host_listings_count'].mean().reset_index()
out.head() # There are only 5 neighbourhood groups aka boroughs
```

	neighbourhood_group	calculated_host_listings_count
0	Bronx	2.233731
1	Brooklyn	2.284371
2	Manhattan	12.791330
3	Queens	4.060184
4	Staten Island	2.319035

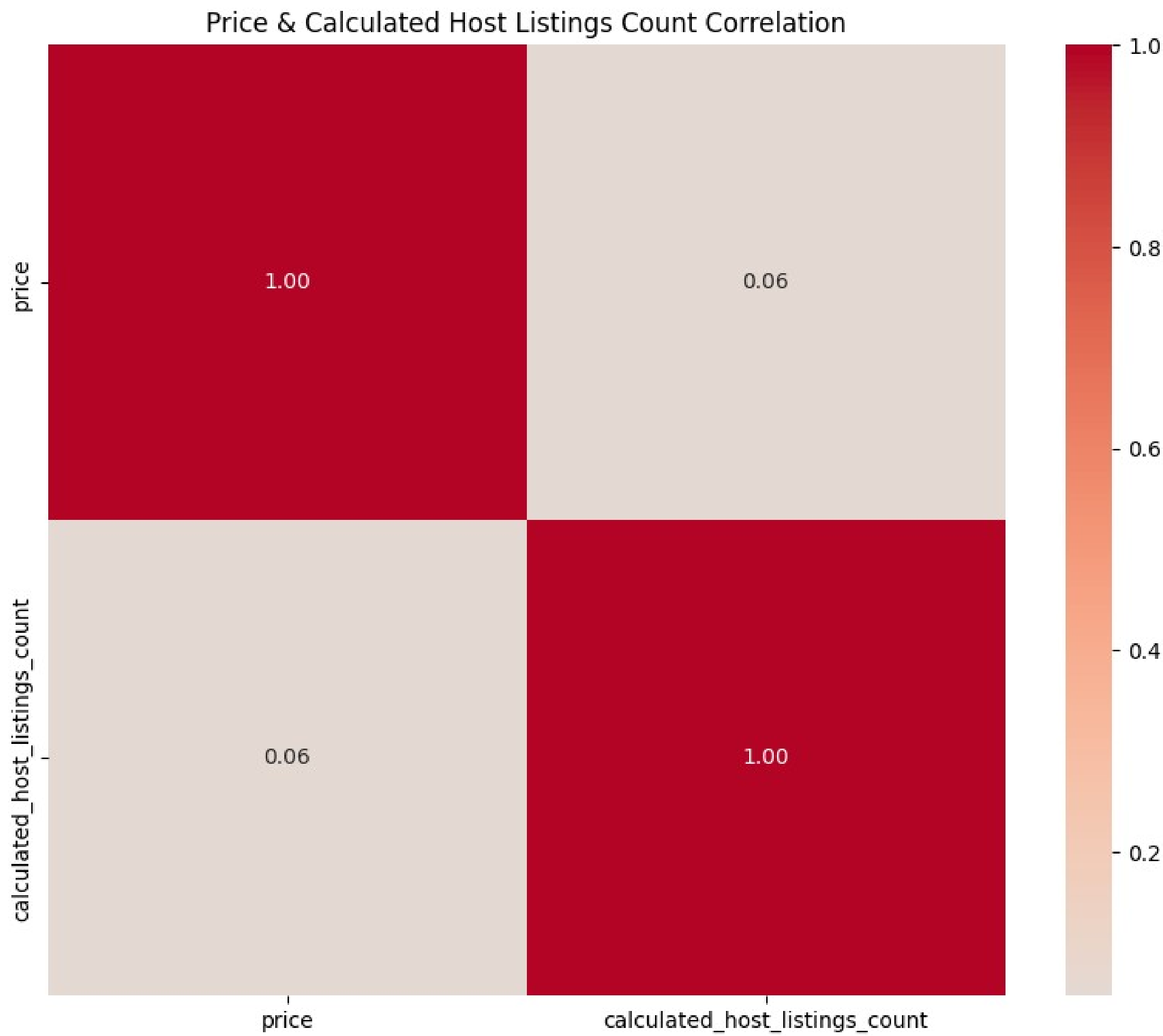
Now, I plot a bunch of correlations to further examine the claim and as it can be seen from the following correlations plus the ones from Question 3, the strongest correlation is between availability 365 and calculated host listings. This gives us a natural insight - many of Manhattan properties for Airbnb are readily available because they exist to make money from Airbnb. Additionally, another strong correlation was between Calculated Host Listings and Minimum Nights of r = 0.13. Other correlations were not as strong such as the one between price & calculated host listings correlation of around 0.06

```
columns = ['availability_365', 'calculated_host_listings_count']
correlation_matrix = df[columns].corr(method='pearson')
```

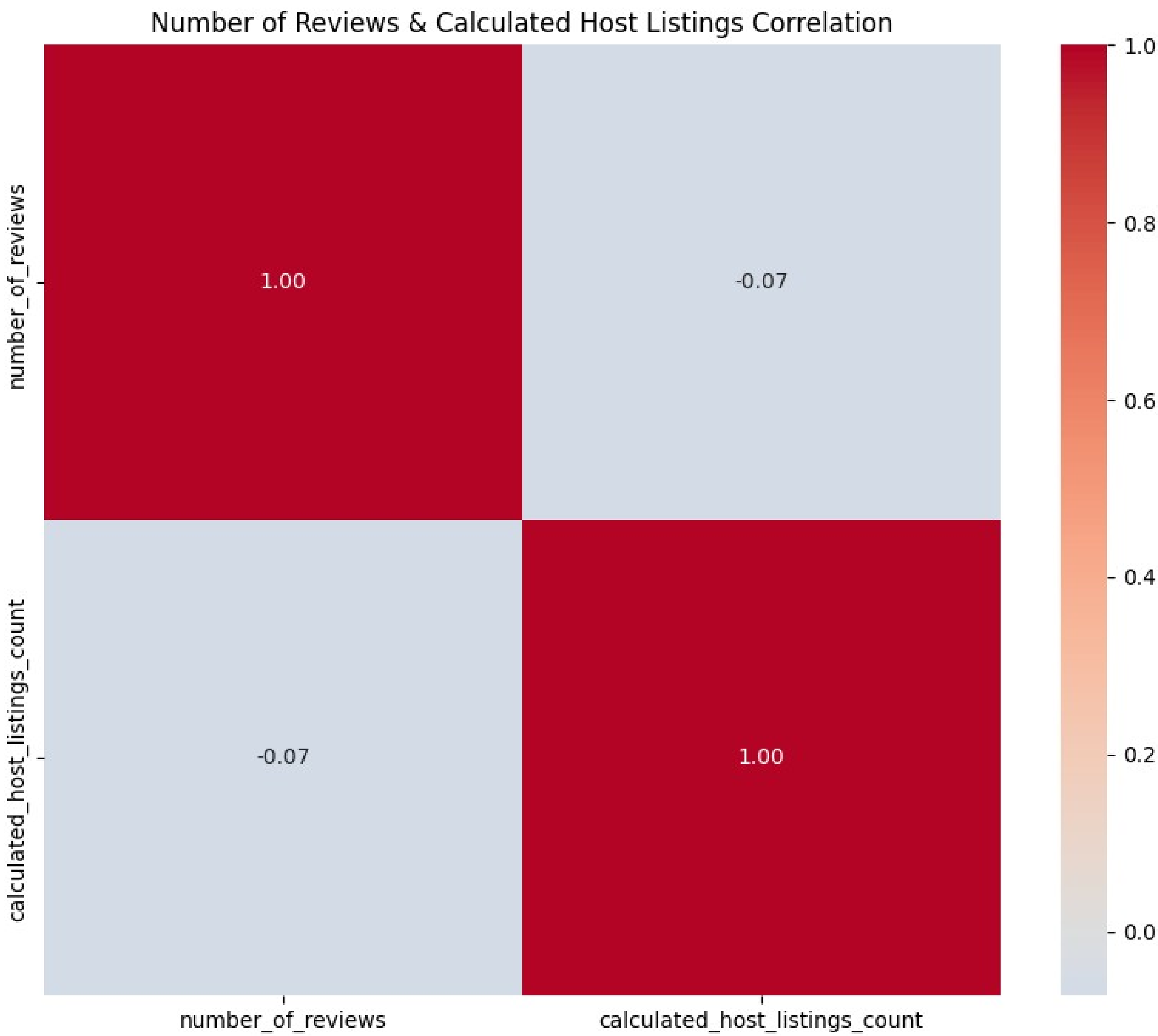
```
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, fmt="0.2f",
cmap="coolwarm", center=0)
plt.title("Availability 365 & Calculated Host Listings Count
Correlation")
plt.show()
```



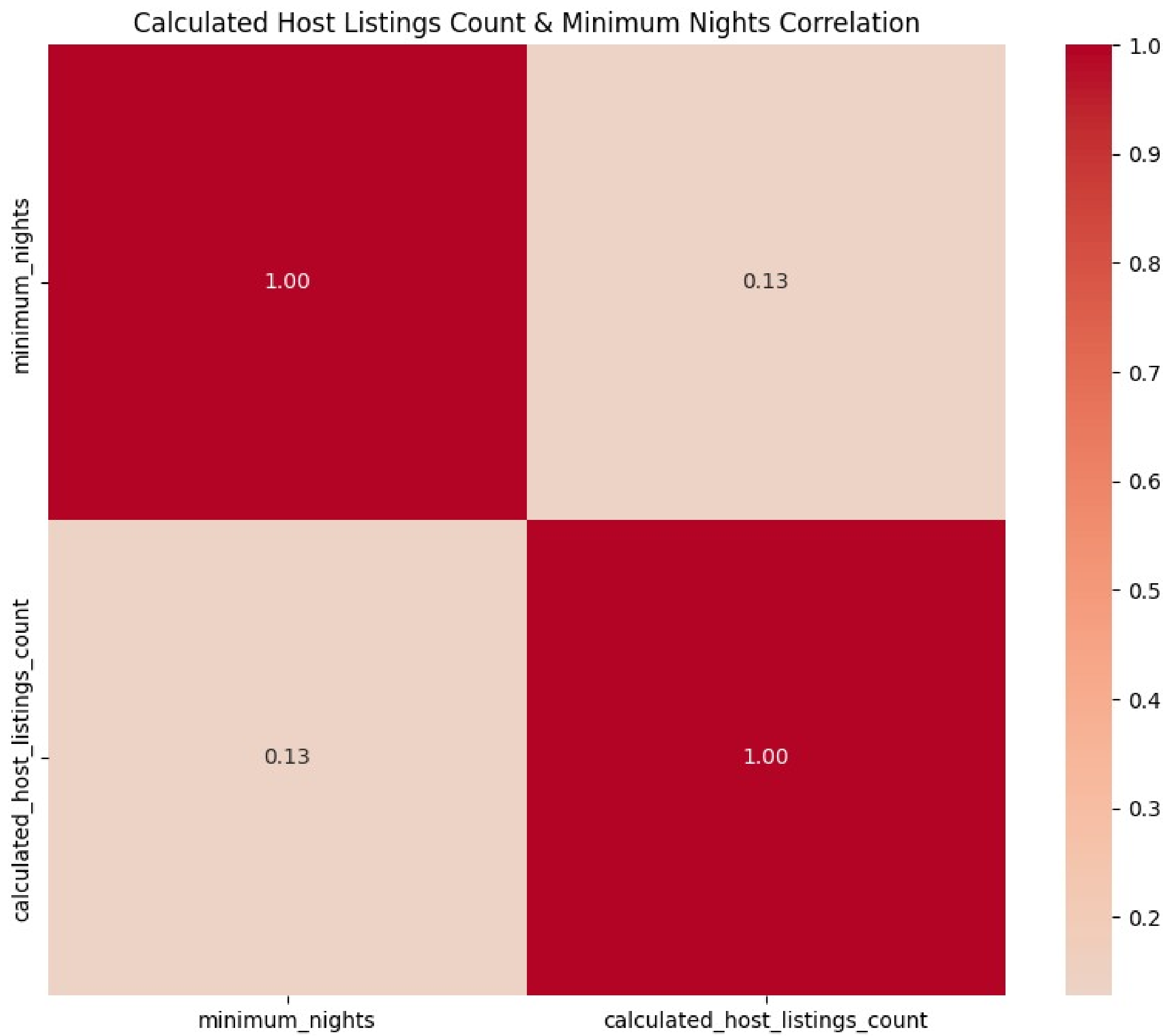

```
columns = ['price', 'calculated_host_listings_count']
correlation_matrix = df[columns].corr(method='pearson')
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, fmt="0.2f",
cmap="coolwarm", center=0)
plt.title("Price & Calculated Host Listings Count Correlation")
plt.show()
```




```
columns = ['number_of_reviews', 'calculated_host_listings_count']
correlation_matrix = df[columns].corr(method='pearson')
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, fmt="0.2f",
cmap="coolwarm", center=0)
plt.title("Number of Reviews & Calculated Host Listings Correlation")
plt.show()
```




```
columns = ['minimum_nights', 'calculated_host_listings_count']
correlation_matrix = df[columns].corr(method='pearson')
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, fmt="0.2f",
cmap="coolwarm", center=0)
plt.title("Calculated Host Listings Count & Minimum Nights
Correlation")
plt.show()
```



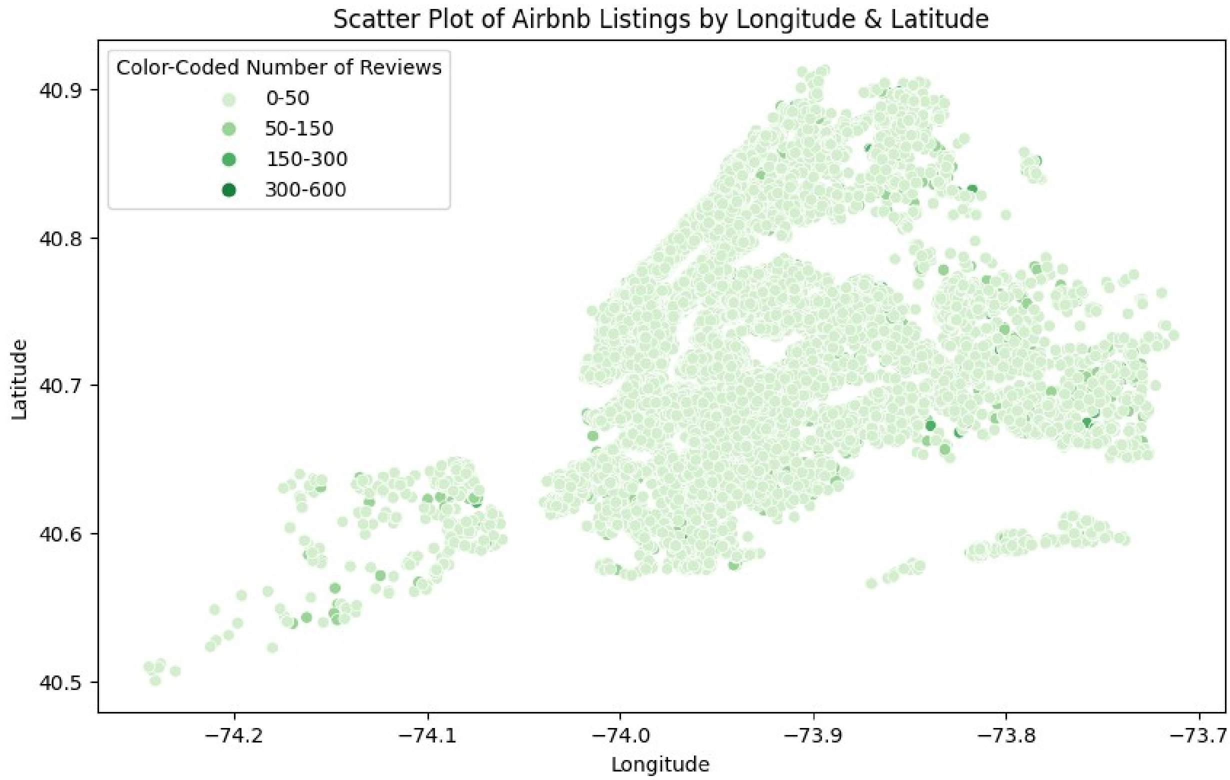
Question 7

Unique Plot 1 - Scatterplot of longitude/latitude, color-coding for number of reviews

I consider this interesting because it could be considered in terms of finding locations that are heavily discussed, or perhaps have the most number of negative reviews driving up traffic, or even for algorithmic updates based on number of reviews of given locations.

```
out = df # reset out variable to dataframe
bins = [0, 50, 150, 300, 600]
labels = ['0-50', '50-150', '150-300', '300-600']
out.loc[:, 'reviews_range'] = pd.cut(out['number_of_reviews'],
bins=bins, labels=labels, right=False) # Create a price_range column
using the bins & labels
```

```
plt.figure(figsize=(10,6))
sns.scatterplot(data=out, x='longitude', y='latitude',
hue='reviews_range', palette='Greens') # Choose palette Oranges to
stress busy areas
plt.title('Scatter Plot of Airbnb Listings by Longitude & Latitude')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.legend(title='Color-Coded Number of Reviews')
plt.show()
```



The below is an average on number of reviews to further corrobarate which areas were picked on the scatter plot.

```
out = df # reset out variable to dataframe
out = out.groupby(['neighbourhood', 'neighbourhood_group'])
['number_of_reviews'].mean().reset_index()
out.rename(columns={'number_of_reviews': 'average_number_of_reviews'},
inplace=True) # For readability
out = out.sort_values(by=["average_number_of_reviews"],
ascending=False) # sort so that we have it groups by
neighbourhood_group with each neighbourhood
out.head(n=20)

           neighbourhood neighbourhood_group
average_number_of_reviews
```

```
177          Silver Lake       Staten Island
118.500000
59         East Elmhurst              Queens
81.659459
165         Richmondtown       Staten Island
79.000000
69           Eltingville       Staten Island
76.000000
135           Mount Eden               Bronx
70.000000
183  Springfield Gardens              Queens
69.094118
194        Tompkinsville       Staten Island
57.142857
101             Huguenot       Staten Island
55.666667
120      Manhattan Beach            Brooklyn
50.625000
96            Highbridge               Bronx
48.814815
181     South Ozone Park              Queens
48.675000
62       East Morrisania               Bronx
48.000000
40               Clifton       Staten Island
47.200000
10            Baychester               Bronx
44.285714
218             Woodlawn               Bronx
44.000000
0               Allerton               Bronx
42.928571
105              Jamaica              Queens
42.900433
134           Mott Haven               Bronx
42.366667
36           City Island               Bronx
42.166667
8            Bay Terrace              Queens
41.500000
```

Unique Plot 2 - Piechart of Each Neighbourhood Group's Share of Listings

I consider this also an important chart because we need to know which neighbourhood groups dominate majority of the listings. As we can see, mainly two - Brooklyn and Manhattan dominate the Airbnb listings. This is important as it can be useful information on further understanding the nature of the dataset, and for making predictions based on some model.

```
plt.figure(figsize=(10, 10))
out = df

neighbourhood_counts = out['neighbourhood_group'].value_counts() #
Count up each neighbourhood group
wedges, texts, autotexts = plt.pie(neighbourhood_counts,
autopct='%1.1f%%', startangle=140, colors=sns.color_palette('muted',
len(neighbourhood_counts)), wedgeprops={'edgecolor': 'black'}) # plot
the chart
plt.legend(wedges, neighbourhood_counts.index, title="Neighbourhood
Group", loc="center left", bbox_to_anchor=(1, 0.5)) # Add legends

plt.title('Distribution of Properties by Neighbourhood Group')
plt.show()
```