CSE351 HW1

Name: Yuqing Wang SBU ID: 113923920

In [1]:
```
# all packages I will used in this project
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# use method in packet pandas to load the csv file about the New York City Airb
data = pd.read_csv('/Users/miku/AB_NYC_2019.csv')
```

Task 1 Clean the data

Before we clean the dataset, we need first observe the data and understand it. It will help us to know what data should be clean and better formatting.

In [3]:
```
# Show some statistics information about the data
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 16 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   id                              48895 non-null  int64
 1   name                            48879 non-null  object
 2   host_id                         48895 non-null  int64
 3   host_name                       48874 non-null  object
 4   neighbourhood_group             48895 non-null  object
 5   neighbourhood                   48895 non-null  object
 6   latitude                        48895 non-null  float64
 7   longitude                       48895 non-null  float64
 8   room_type                       48895 non-null  object
 9   price                           48895 non-null  int64
 10  minimum_nights                  48895 non-null  int64
 11  number_of_reviews               48895 non-null  int64
 12  last_review                     38843 non-null  object
 13  reviews_per_month               38843 non-null  float64
 14  calculated_host_listings_count  48895 non-null  int64
 15  availability_365                48895 non-null  int64
dtypes: float64(3), int64(7), object(6)
memory usage: 6.0+ MB
```

The information above tells us that there are 48895 observations and 16 factors in this dataset. We also acquire that the data type of each factor.

In [4]:
```
# We observe first five rows in this data set.
data.head(5)
```

Out[4]:

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude
0	2539	Clean & quiet apt home by the park	2787	John	Brooklyn	Kensington	40.64749
1	2595	Skylit Midtown Castle	2845	Jennifer	Manhattan	Midtown	40.75362
2	3647	THE VILLAGE OF HARLEM....NEW YORK !	4632	Elisabeth	Manhattan	Harlem	40.80902
3	3831	Cozy Entire Floor of Brownstone	4869	LisaRoxanne	Brooklyn	Clinton Hill	40.68514
4	5022	Entire Apt: Spacious Studio/Loft by central park	7192	Laura	Manhattan	East Harlem	40.79851

From first five rows, we could easily find that there are some NaN value in the dataset which are our next goal to handle those missing values.

1-1 Missing values

In [5]:

```
# show the number of missing value in each column in desending order.
data.isnull().sum().sort_values(ascending=False)
```

Out[5]:

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

From the output above we could find that the 'last_review' and 'reviews_per_month' get the most missing value. The last review indicates the date time of the latest time that a user reviews the website. There are also 21 missing values in the 'host_name' factor. But we could simply remove these two factors from our dataset because they are irrelevant and insignificant in our case. For the factor 'reviews_per_month', there are a lot of missing values but almost all of those values are missed because the value of reviews is 0. It is natural that the number of reviews per month is also 0. So, we need to impute the missing value in this column with 0. For the 16 missing values in the factor 'name', we could just use

' ' to replace the NaN. This is because we need reserve this factor to draw the word cloud of the name, but we do not want other replaced word to influence the original result of the word cloud.

In [6]:
```
# drop 'host_name' and 'last_review'
data.drop(['host_name','last_review'], axis=1, inplace=True)
# examing changes
data.head(3)
```

Out[6]:

	id	name	host_id	neighbourhood_group	neighbourhood	latitude	longitude
0	2539	Clean & quiet apt home by the park	2787	Brooklyn	Kensington	40.64749	-73.97237
1	2595	Skylit Midtown Castle	2845	Manhattan	Midtown	40.75362	-73.98377
2	3647	THE VILLAGE OF HARLEM....NEW YORK !	4632	Manhattan	Harlem	40.80902	-73.94190

In [7]:
```
# replacing all NaN values in 'reviews_per_month' with 0
data.fillna({'reviews_per_month':0}, inplace=True)
# examing changes
data.reviews_per_month.isnull().sum()
```

Out[7]: 0

In [8]:
```
# replacing all NaN values in 'name' with ' '
data.fillna({'name':' '}, inplace=True)
# examing changes
data.name.isnull().sum()
```

Out[8]: 0

1-2 Duplicate entries

The duplicate entries should be drop. In this case, there is not duplicate entry.

In [9]:
```
data.duplicated().sum()
```

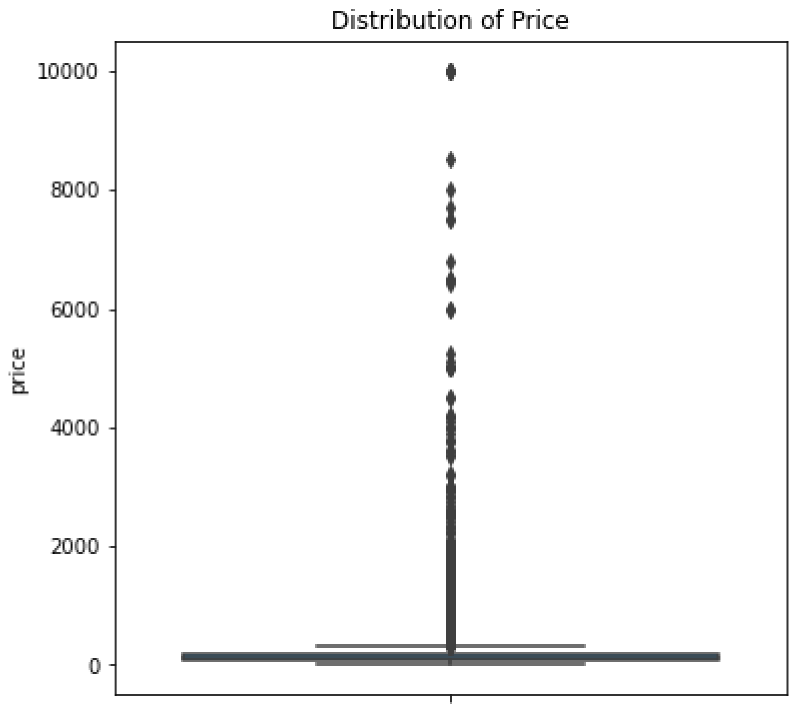
Out[9]: 0

The output above indicates that there are no duplicate entry in this dataset. Hence, we could keep to handle outliers.

1-3 Outliers

In this dataset, price is an important factor when concerning a room on Airbnb. So I draw the distribution of the price factor to check if there are outliers.

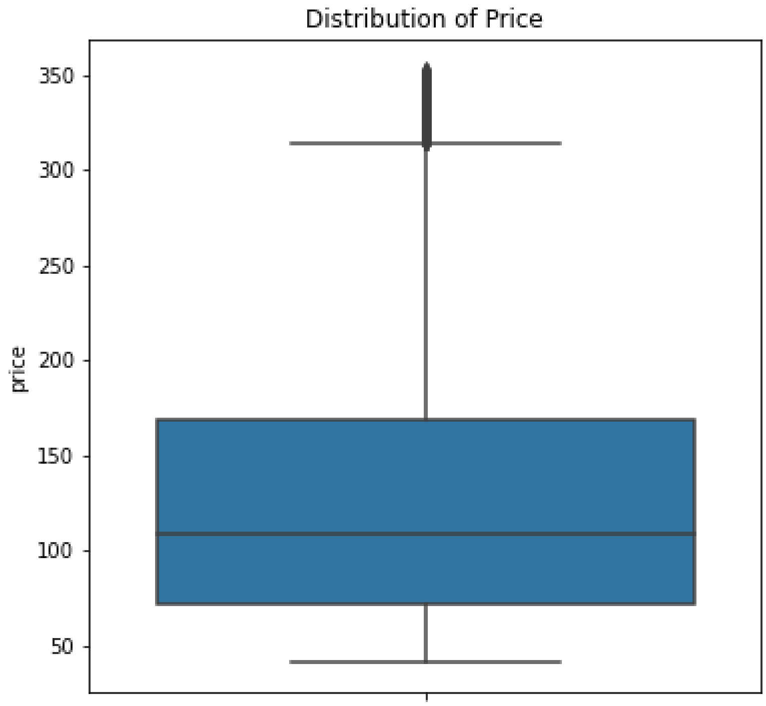
In [10]:
```
# show the distribution of price to check if there are outliers
plt.figure(figsize=(6,6))
sns.boxplot(y=data['price'])
plt.title("Distribution of Price before dropping outliers")
plt.show()
```



From the figure 'Distribution of Price', It shows that most of the price of rooms are under $2,000.However,thereareseveralroomwithapriceupto$10,000. It is obvious that there are a lot of outliers need to be dropped. So, I determined that the prices higher than 95% and lower than 5% are outliers.

In [11]:
```
# the highest thresold
max_thresold = data['price'].quantile(0.95)
# the lowest thresold
min_thresold = data['price'].quantile(0.05)
# only keep the data with price between the highest thresold and lowest thresol
data = data[(data['price']<max_thresold) & (data['price']>min_thresold)]
```

In [12]:
```
# figure of the distribution of price with data after dropping outliers
plt.figure(figsize=(6,6))
sns.boxplot(y=data['price'])
plt.title("Distribution of Price after dropping outliers")
plt.show()
```



From the figure 'Distribution of Price after dropping outliers', we could find that most of room at Airbnb are between $70 to$170. There are still some outliers displaying on the figure but they are acceptable.

task 2 Price and Neighborhood

2-a Top 5 and Bottom 5 Neighborhood

In [51]:
```
# count is the frequency of each neighbourhood
counts = data['neighbourhood'].value_counts()
# we only want the records with the neighborhoods with more than 5 listings.
task2 = data[~data['neighbourhood'].isin(counts[counts<5].index)]
counts
```

Out[51]:
```
Williamsburg          3716
Bedford-Stuyvesant    3296
Harlem                2483
Bushwick              2112
Upper West Side       1790
                      ...
Richmondtown             1
New Dorp                 1
Rossville                1
Willowbrook              1
Westerleigh              1
Name: neighbourhood, Length: 219, dtype: int64
```

This output indicates that Williamburg has the most Airbnb records, which has 3716 records. And there are also many neighborhood only have one record.

In [47]:
```
# I grouped rooms according to the neighborhood in which they were located and
a = task2.groupby('neighbourhood')['price'].mean().round(2).sort_values(ascendi
```

```
a = a.reset_index()
a
```

Out[47]:

	neighbourhood	price
0	Tribeca	221.95
1	NoHo	217.38
2	Flatiron District	199.05
3	West Village	197.53
4	Midtown	190.40

This table shows 5 neighborhoods with highest average price Airbnbs.

In [48]:
```
# bottom 5 neighborhood based on the price of the Airbnb in that neighborhood
b = task2.groupby('neighbourhood')['price'].mean().round(2).sort_values(ascendi
b = a.reset_index()
b
```

Out[48]:

	index	neighbourhood	price
0	0	Tribeca	221.95
1	1	NoHo	217.38
2	2	Flatiron District	199.05
3	3	West Village	197.53
4	4	Midtown	190.40

This table shows 5 neighborhoods with lowest average Airbnb price.

2-b Price and Neighborhood groups

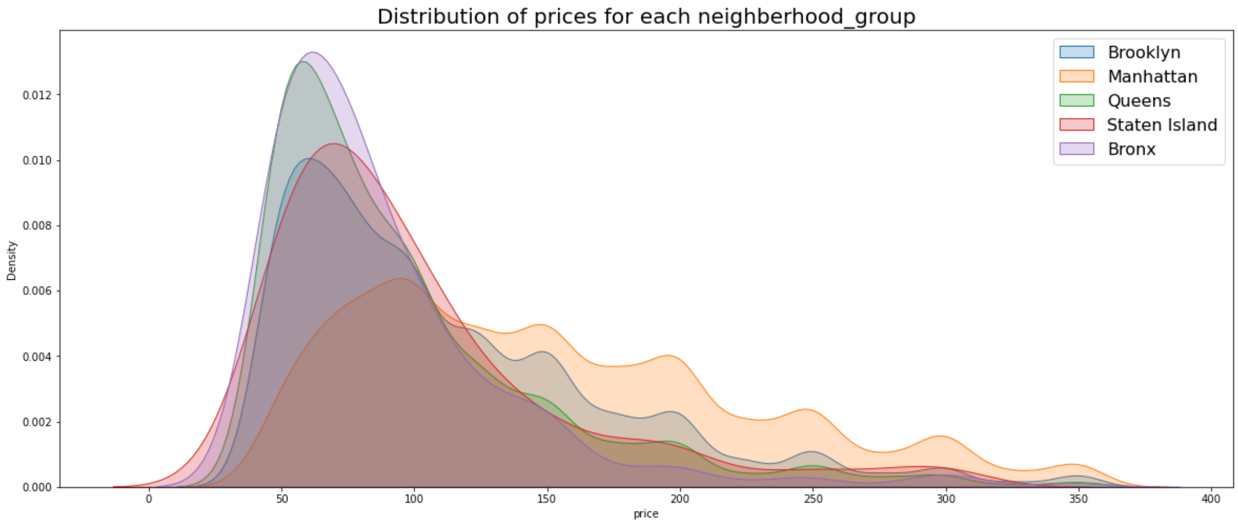
In [15]:
```
# I grouped the Airbnb by their different neighbourhood group.
sub_1=data.loc[data['neighbourhood_group'] == 'Brooklyn']
sub_2=data.loc[data['neighbourhood_group'] == 'Manhattan']
sub_3=data.loc[data['neighbourhood_group'] == 'Queens']
sub_4=data.loc[data['neighbourhood_group'] == 'Staten Island']
sub_5=data.loc[data['neighbourhood_group'] == 'Bronx']

# price_subx is the price variable for each neighborhood group
price_sub1=sub_1['price'] #Brooklyn
price_sub2=sub_2['price'] #Manhattan
price_sub3=sub_3['price'] #Queens
price_sub4=sub_4['price'] #Staten Island
price_sub5=sub_5['price'] #Bronx

# draw a plot to show the distribution of price for each neighborhood
plt.figure(figsize=(20,8))
sns.kdeplot(price_sub1[price_sub1<500],shade=True,label='Brooklyn')
sns.kdeplot(price_sub2[price_sub2<500],shade=True,label='Manhattan')
sns.kdeplot(price_sub3[price_sub3<500],shade=True,label='Queens')
sns.kdeplot(price_sub4[price_sub4<500],shade=True,label='Staten Island')
sns.kdeplot(price_sub5[price_sub5<500],shade=True,label='Bronx')
```

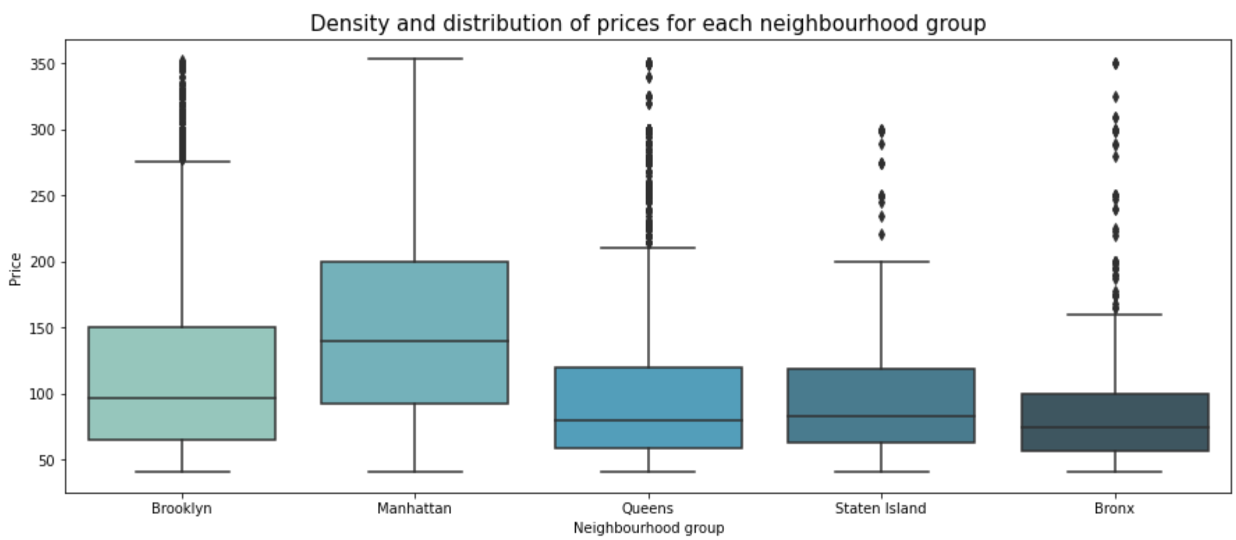
```python
plt.title('Distribution of prices for each neighborhood_group',size=20)
plt.legend(prop={'size':16})
```

Out[15]: <matplotlib.legend.Legend at 0x7f8700de6670>



In [16]:
```python
# Draw box plot for the density and distribution of prices for each neighborhoo
plt.figure(figsize=(15,6))
sns.boxplot(data=data, x='neighbourhood_group', y='price', palette='GnBu_d')
plt.title('Density and distribution of prices for each neighborhood group', for
plt.xlabel('Neighbourhood group')
plt.ylabel("Price")
```

Out[16]: Text(0, 0.5, 'Price')

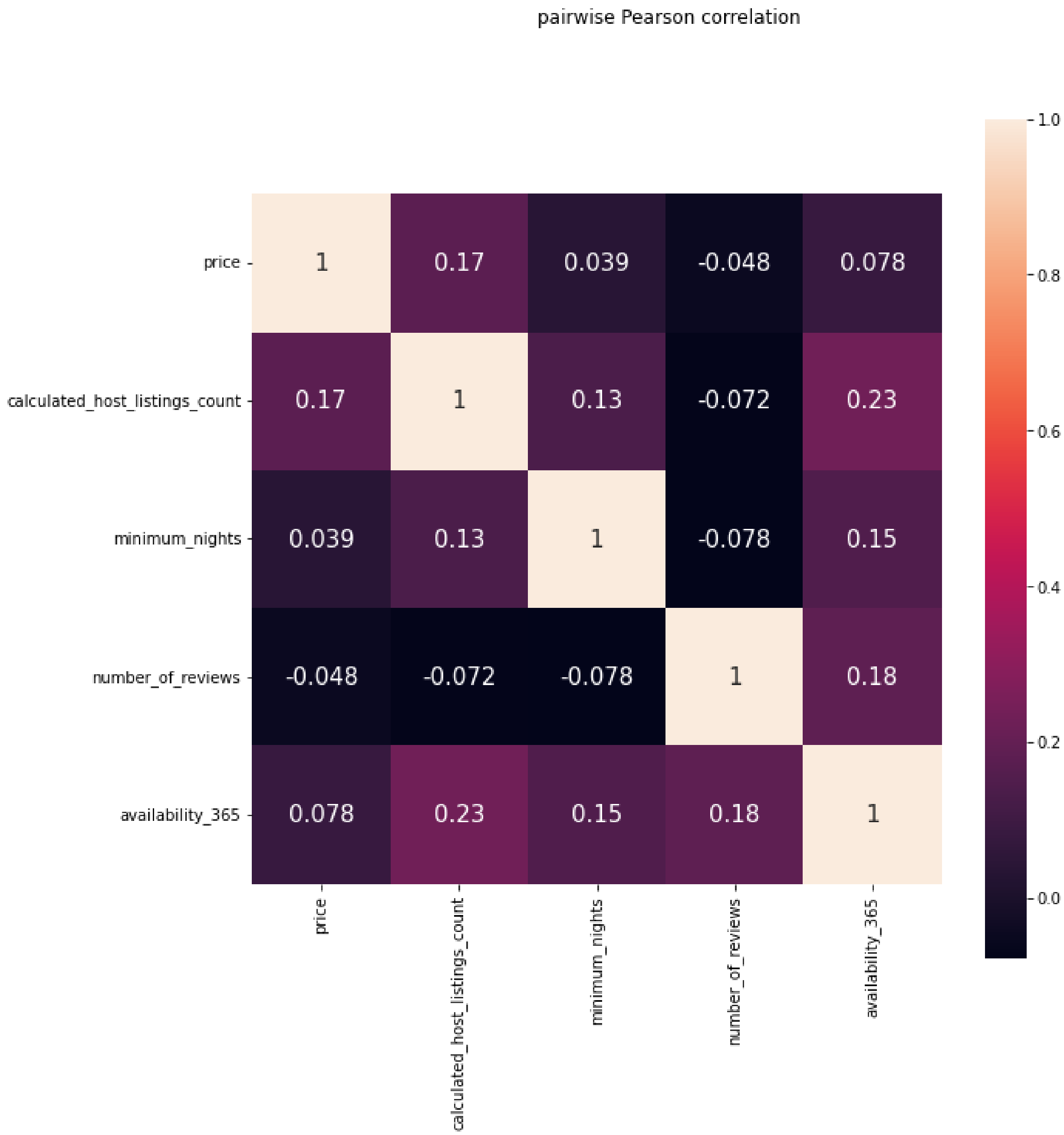


From two figures above, we can find that the Airbnb price above $150 is the highest density in Manhattan, while the density of Airbnb below ¥150 are all lowe$ $. This means that Manhattan has Airbnb at all price points, and overall is higher than theo$ $but still higher than the other three groups, and the Bronx has the most rooms around$ 50 and the fewest rooms in the higher price range of the five neighborhood groups. For Queens and Staten Island, Queens has more rooms in the \$50 price range, but both neighborhood groups have almost the same number of high-priced rooms.

task 3 Pearson correlation

In [53]:
```
# get the pearson correlation between the several numeric variables
df_corr = data[['price', 'calculated_host_listings_count','minimum_nights', 'nu

# draw the heatmap of the correlation
plt.figure(figsize=(10,10))
sns.heatmap(df_corr, annot=True, annot_kws={'size': 15}, square=True)
plt.suptitle('pairwise Pearson correlation')
plt.show()
```



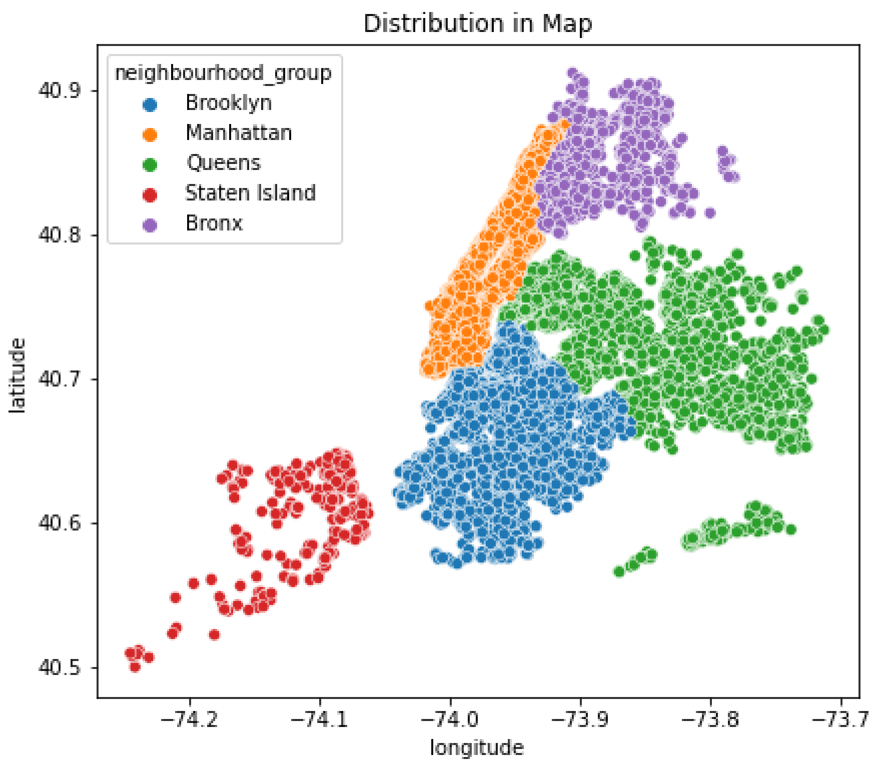
From the heatmap of the Pearson correlation, we could find that the availability_365 and price have the most positive correlation. It means that the higher the price is, the more days could the Airbnb is avilable in a year. The most negative correlation is between number of reviews and the minimum nights. It shows that the more reviews an Airbnb has, the higher the minimum nights is.

task 4 Distribution in Map

4-a location and neighborhood groups

In [18]:
```
fig = plt.figure(figsize=(15,6))
ax1 = fig.add_subplot(121)
# draw a scatter plot to show the Airbnbs' distribution in map with different c
sns.scatterplot(x=data['longitude'], y=data['latitude'], hue=data['neighbourhoo
ax1.set_title('Distribution in Map')
```

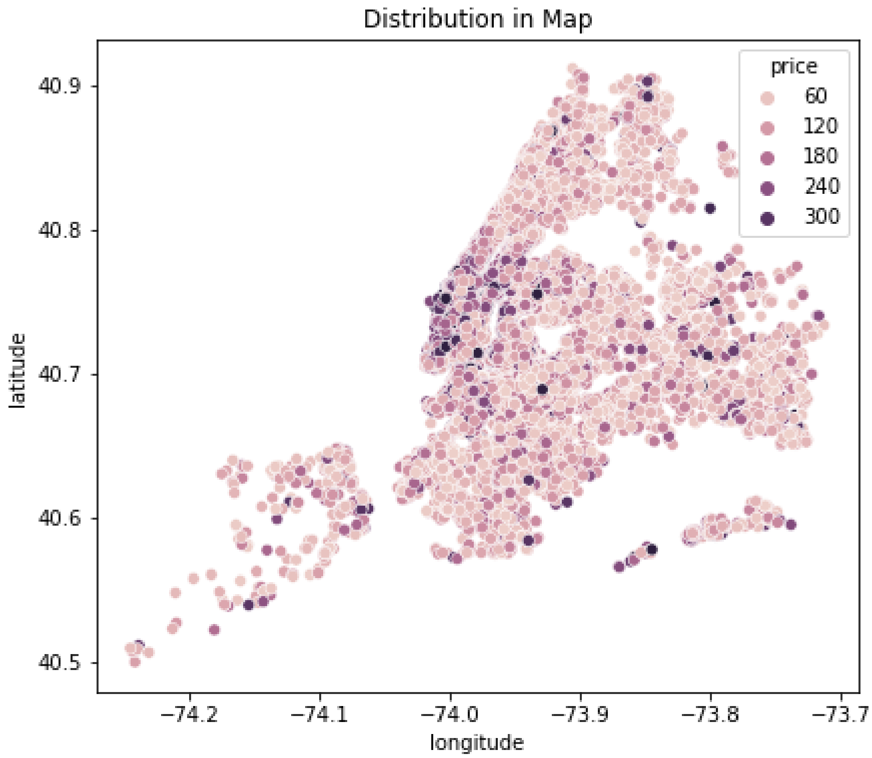
Out[18]:
```
Text(0.5, 1.0, 'Distribution in Map')
```



From the figure to show the distribution of Airbnb above, we could clearly to find the location of different neighborhood.

In [19]:
```
fig = plt.figure(figsize=(15,6))
ax1 = fig.add_subplot(121)
# draw a scatter plot to show the Airbnbs' distribution in map with different c
sns.scatterplot(x=data['longitude'], y=data['latitude'], hue=data['price'], ax=
ax1.set_title('Distribution in Map')
```

Out[19]:
```
Text(0.5, 1.0, 'Distribution in Map')
```

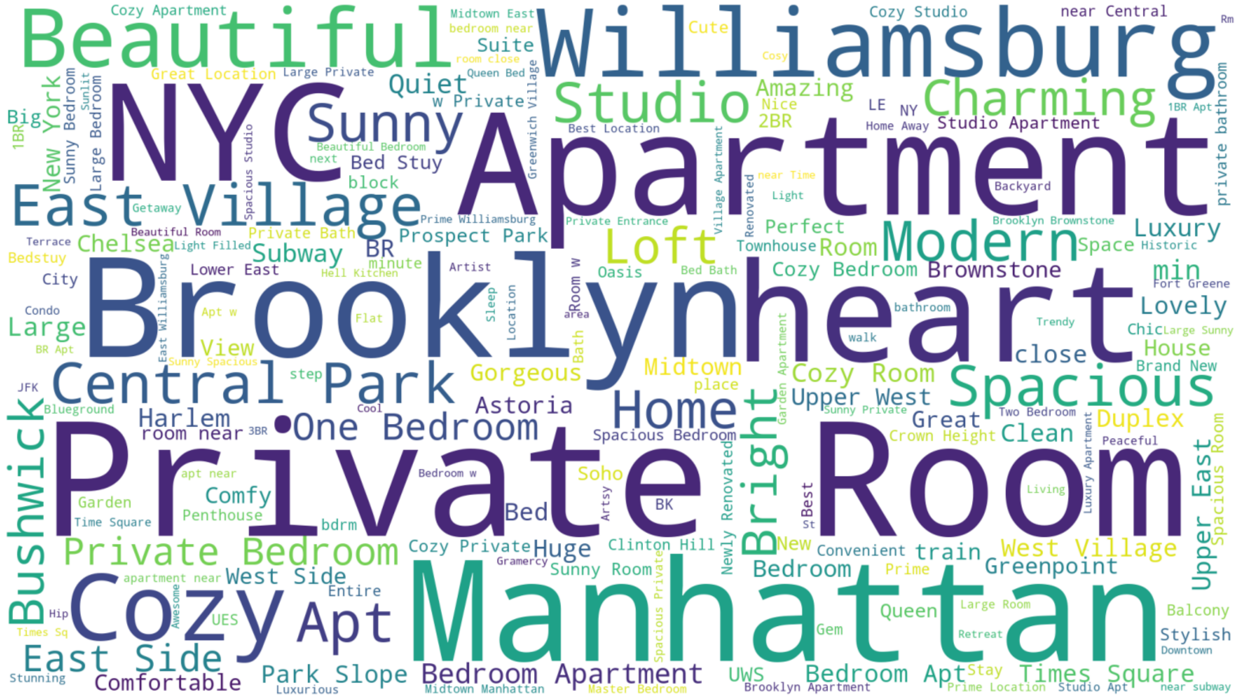


From the figure above, we could easily find that the Airbnbs with higher price and the Airbnbs with lower price.

task 5 Word Cloud

In [20]:
```
# import the package we will need to draw a world cloud
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator
```

In [21]:
```
# draw word cloud use the words in the factor 'name'
plt.subplots(figsize=(25,15))
wordcloud = WordCloud(
                          background_color='white',
                          width=1920,
                          height=1080
                         ).generate(" ".join(data.name))
plt.imshow(wordcloud)
plt.axis('off')
plt.savefig('nyc_airbnb.png')
plt.show()
```



From the word cloud above, we could easily find the words with highest frequency. The most frequency word is 'Private Room', 'Manhattan', 'Brooklyn' and 'Apartment'. These words may be used often because they are more appealing.

task 6 busiest area

In [22]:
```
# count the number of listings each host id in the cleaned dataset
busy_host=data.host_id.value_counts().head(10)
```

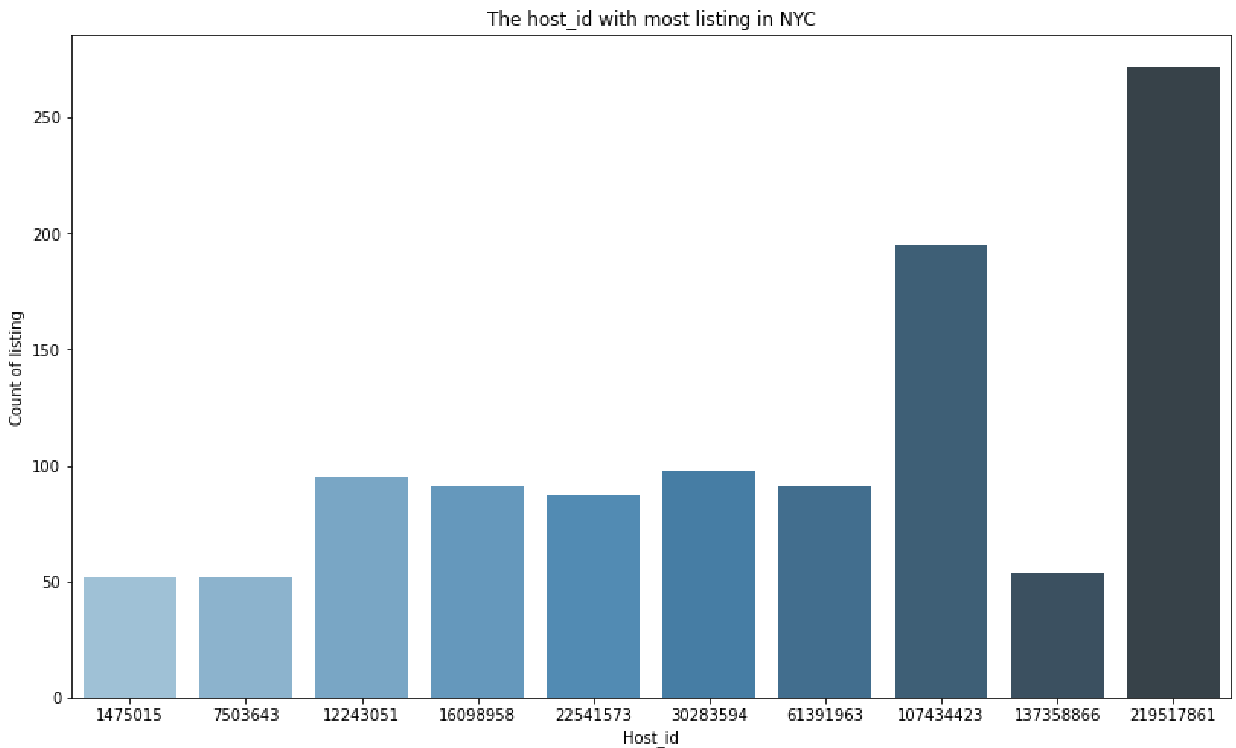
In [23]:
```
# create a data frame with host id and the number that how many listings do the
busy_host_df=pd.DataFrame(busy_host)
busy_host_df.reset_index(inplace=True)
busy_host_df.rename(columns={'index':'Host_ID', 'host_id':'Listing_num'}, inpla
busy_host_df
```

Out[23]:

	Host_ID	Listing_num
0	219517861	272
1	107434423	195
2	30283594	98
3	12243051	95
4	16098958	91
5	61391963	91
6	22541573	87
7	137358866	54
8	1475015	52
9	7503643	52

In [24]:
```
# draw a bar plot to show the top 10 host with most listings in NYC
fig = plt.figure(figsize=(30,8))
ax3 = fig.add_subplot(121)
sns.barplot(x="Host_ID", y="Listing_num", data=busy_host_df,
                 palette='Blues_d')
ax3.set_title('The host_id with most listing in NYC')
ax3.set_ylabel('Count of listing')
ax3.set_xlabel('Host_id')
```

Out[24]:
```
Text(0.5, 0, 'Host_id')
```



From the table and figure contain the information about the host with most listings in NYC, we could know the host with the most listing in NYC has 272 Airbnbs.

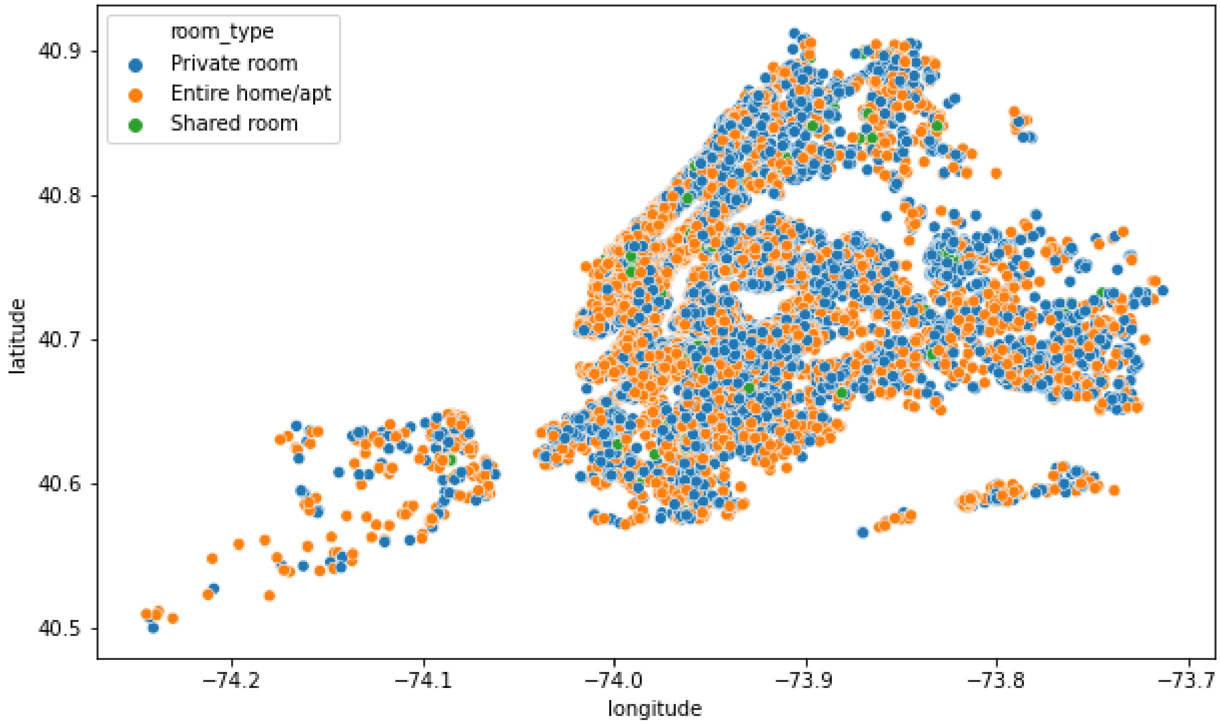
task 7 Others

7-1 location and room type

In this case, I draw a scatterplot of the distribution of Airbnbs in the map and use different colors to distinguish different room types. From the scatter plot below, I find that most of Airbnbs are private room or entire room. There are extremely less shared Airbnbs showed on the figure. It might because most people prefer to live in a private space. A private room or a entire apartment guarantees this requirement. So, there are less shared rooms showed on the map.

In [25]:
```
plt.figure(figsize=(10,6))
sns.scatterplot(x=data.longitude,y=data.latitude,hue=data.room_type)
plt.ioff()
```

Out[25]:
```
<matplotlib.pyplot._IoffContext at 0x7f8714399700>
```

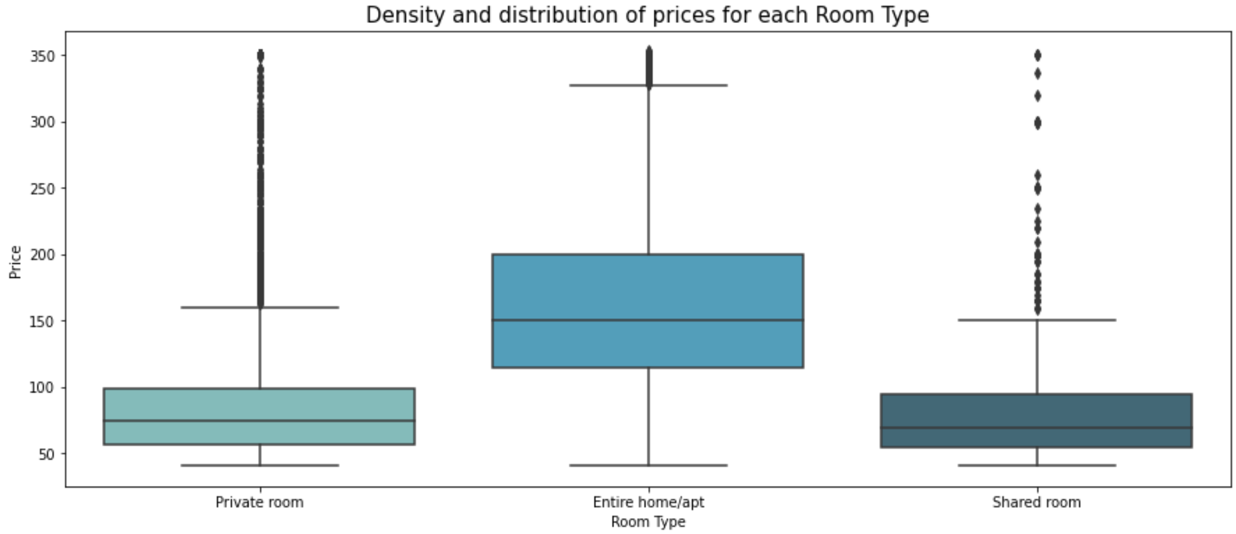


7-2

Then I was curious if the shared room with low demand and low supply had a lower price. Because people usually don't want to rent share a room with strangers. And they may compromise because of the low price. I think individual rooms are usually cheaper than the whole house because they are smaller in size. So I try to draw a box plot the check if my assumptions are right.

In [26]:
```
plt.figure(figsize=(15,6))
# draw box plot of the distribution of price for each room type
sns.boxplot(data=data, x='room_type', y='price', palette='GnBu_d')
plt.title('Density and distribution of prices for each Room Type', fontsize=15)
plt.xlabel('Room Type')
plt.ylabel("Price")
```

Out[26]:
```
Text(0, 0.5, 'Price')
```



With the box diagram I drew, I found that the shared room is indeed the least expensive of the three room types, but it is only a little bit lower than the private room. The whole house is really the most expensive as I guessed at the beginning. But what I didn't expect at first was that the range of prices for the whole house was also the largest. The lowest values for the three room types were actually close to the same.