Importing Libraries

In [12]:
```
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
import plotly.express as px
```

Reading Dataset

In [13]:
```
#Reading the dataset.
data = pd.read_csv("AB_NYC_2019.csv")
```

In [14]:
```
data.head()
```

Out[14]:

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_reviews
0	2539	Clean & quiet apt home by the park	2787	John	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	1	9
1	2595	Skylit Midtown Castle	2845	Jennifer	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	1	45
2	3647	THE VILLAGE OF HARLEM....NEW YORK !	4632	Elisabeth	Manhattan	Harlem	40.80902	-73.94190	Private room	150	3	0
3	3831	Cozy Entire Floor of Brownstone	4869	LisaRoxanne	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	1	270
4	5022	Entire Apt: Spacious Studio/Loft by central park	7192	Laura	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	10	9

In [15]:
```
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
```

In [16]:
```
data.describe()
```

Out[16]:

	id	host_id	latitude	longitude	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_cou
count	4.889500e+04	4.889500e+04	48895.000000	48895.000000	48895.000000	48895.000000	48895.000000	38843.000000	48895.0000
mean	1.901714e+07	6.762001e+07	40.728949	-73.952170	152.720687	7.029962	23.274466	1.373221	7.1439
std	1.098311e+07	7.861097e+07	0.054530	0.046157	240.154170	20.510550	44.550582	1.680442	32.9525
min	2.539000e+03	2.438000e+03	40.499790	-74.244420	0.000000	1.000000	0.000000	0.010000	1.0000
25%	9.471945e+06	7.822033e+06	40.690100	-73.983070	69.000000	1.000000	1.000000	0.190000	1.0000
50%	1.967728e+07	3.079382e+07	40.723070	-73.955680	106.000000	3.000000	5.000000	0.720000	1.0000
75%	2.915218e+07	1.074344e+08	40.763115	-73.936275	175.000000	5.000000	24.000000	2.020000	2.0000
max	3.648724e+07	2.743213e+08	40.913060	-73.712990	10000.000000	1250.000000	629.000000	58.500000	327.0000

In [17]:
```
data.shape
```

Out[17]:
```
(48895, 16)
```

In [18]:
```
data.nunique()
```

Out[18]:
```
id                                48895
name                              47896
host_id                           37457
host_name                         11452
neighbourhood_group                   5
neighbourhood                       221
latitude                          19048
longitude                         14718
room_type                             3
price                               674
minimum_nights                      109
number_of_reviews                   394
last_review                        1764
reviews_per_month                   937
calculated_host_listings_count       47
availability_365                    366
dtype: int64
```

In [19]:
```
data.duplicated().sum()
```

Out[19]:
```
0
```

In [ ]:
```
```

Handling missing values

In [20]:
```
#null or missing values in the dataset.
data.isnull().sum()
```

Out[20]:
```
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
```

1. Missing values are present in the name, host_name, last_reviews and reviews_per_month columns.
2. In the above exploration part we can see that if the null value count in number_of_reviews column is 0, NaN in last_review and reviews_per_month doesn't add any information.

In [21]:
```
data[['number_of_reviews','reviews_per_month']][data['reviews_per_month'].isnull()].head()
```

Out[21]:

	number_of_reviews	reviews_per_month
2	0	NaN
19	0	NaN
26	0	NaN
36	0	NaN
38	0	NaN

We can see thats when thw number_of_reviews is 0, the last_review and review_per_month is NaN.

In [22]:
```
assumption_test.shape
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-22-b4fc5afe8193> in <module>
----> 1 assumption_test.shape

NameError: name 'assumption_test' is not defined
```

The exact amount of null values present in both the columns. We will substitute 0 for the missing values present in reviews_per_month column.

As for the last_review column we know that it is a datetime object of the pandas and substituting 0 is not possible.

In [23]:
```
#filling the missing values in reviews_per_month with 0.
data.reviews_per_month.fillna(0, inplace=True)
```

In [24]:
```
#Checking if the changes made are reflected.
data.isnull().sum()
```

Out[24]:
```
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                   0
calculated_host_listings_count      0
availability_365                    0
dtype: int64
```

In [25]:
```
data.last_review.fillna(method="ffill",inplace=True)
data.last_review.isnull().sum()
```

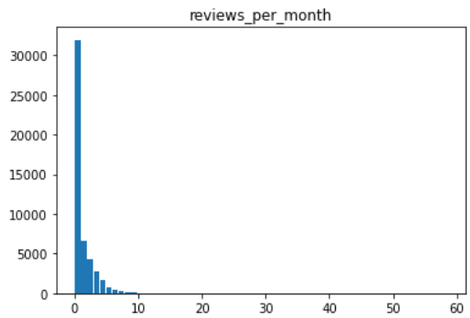
Out[25]:
```
0
```

In [26]:
```
data.isnull().sum()
```

Out[26]:
```
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                         0
reviews_per_month                   0
calculated_host_listings_count      0
availability_365                    0
dtype: int64
```

In [27]:
```
data.hist(column='reviews_per_month',bins=60,grid=False,rwidth=0.9)
```

Out[27]:
```
array([[<AxesSubplot:title={'center':'reviews_per_month'}>]], dtype=object)
```

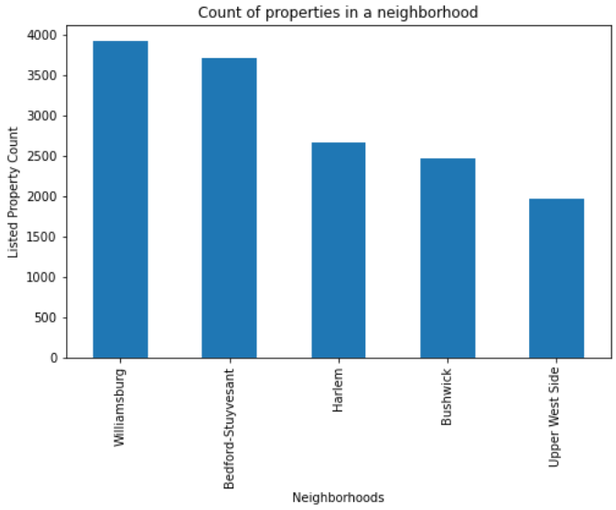


Exploratory Data Analysis (EDA)

Categorical Variables

In [28]:
```
#checking the to 5 neighborhood where the properties are listed most.
top_5_neighborhoods = data.neighbourhood.value_counts().head(5)
print(top_5_neighborhoods)

#plotting
plt.figure(figsize=(8,5))
top_5_neighborhoods.plot.bar()
plt.xlabel('Neighborhoods')
plt.ylabel('Listed Property Count')
plt.title('Count of properties in a neighborhood')
plt.show() #optional
```

```
Williamsburg          3920
Bedford-Stuyvesant    3714
Harlem                2658
Bushwick              2465
Upper West Side       1971
Name: neighbourhood, dtype: int64
```



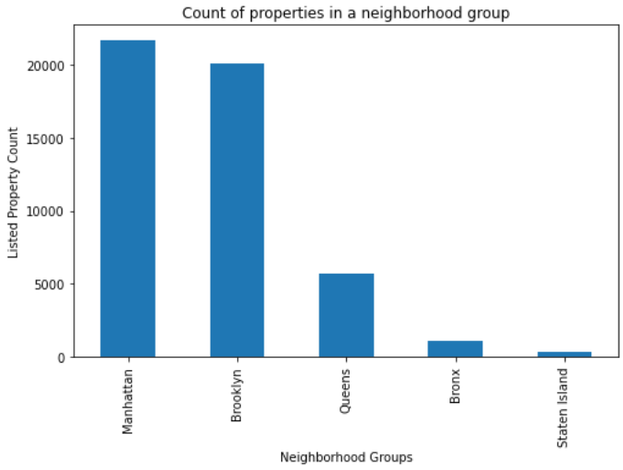
The top 5 neighborhoods whcih have the highest number of properties listed are shown above. We can see that Williamsburg has the highest number of properties listed (3920) followed by Bedford-Stuyvesant (3714).

As Williamsburg has the highest number of properties listed then the Brooklyn neighborhood group must also have the highest number of properties listed as williamburg comes under brooklyn neighborhood group.

Lets check if this is correct or not.

In [29]:
```
#checking the to 5 neighborhood groups where the properties are listed most.
top_5_neighborhood_group = data.neighbourhood_group.value_counts()
print(top_5_neighborhood_group)

#plotting
plt.figure(figsize=(8,5))
top_5_neighborhood_group.plot.bar()
plt.xlabel('Neighborhood Groups')
plt.ylabel('Listed Property Count')
plt.title('Count of properties in a neighborhood group')
plt.show() #optional
```

```
Manhattan        21661
Brooklyn         20104
Queens            5666
Bronx             1091
Staten Island      373
Name: neighbourhood_group, dtype: int64
```



Our assumption was wrong. As it turned out that Manhattan has the higghest number of properties listed although Williamsburg town in Brooklyn had the highest number of properties amongh the neighbor towns.

This infers that there are many other towns in Manhattan that have properties listed and that is why Manhattan neighborhood as a whole has the highest number of properties.

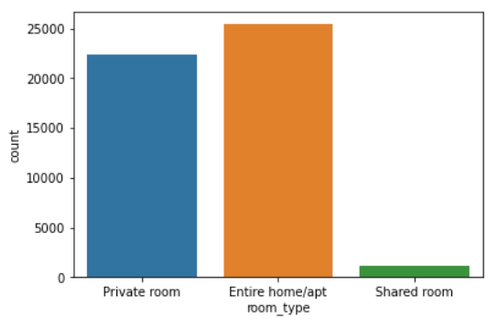
We can also see that other neighborhood groups such as Queens, Bronx and Staten Island contribute less compared to Manhattan and Brooklyn.

In [30]:
```
#number of rooms_type provided by the hosts
print(data.room_type.value_counts())
sns.countplot(data.room_type)
```

```
Entire home/apt    25409
Private room       22326
Shared room         1160
Name: room_type, dtype: int64
```

```
/Users/sukeerthig/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[30]:
```
<AxesSubplot:xlabel='room_type', ylabel='count'>
```



There are 3 room type provided by the host. Most of the rooms provided are private rooms and Entire home or apartments type.

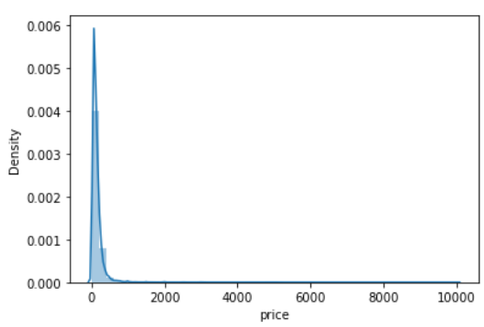
Share rooms are listed very few, as it make sense that people travelling with family will prefer the top 2 room types rather than sharing.

For the Room Type, ther are 3 types of values which are private room, entire home/ apt and shared room. Entire home/apt leads the column with 25000, followed by private room then shared room. There are 5 types of neighbourhood group which are Brooklyn, Manhattan, Queens, Staten Island, and Bronx. Manhattan leads, followed by Brooklyn and Queens. For the neighborhoud variable, there are too many unique values in the variable, thus it is not possible to plot a graph on the values, and it will not be readable as well.

In [31]:
```
#Lets check the distribution of the price of the properties.
sns.distplot(data.price, bins=50)
```

```
/Users/sukeerthig/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[31]:
```
<AxesSubplot:xlabel='price', ylabel='Density'>
```



The distribution of price is heavily left skewed. Meaning the most of the properties price are between 0 - 2000 and some minority of the properties are having prices grator than that making the data to be skewed.

Also we saw that some properties have a price as 0 and that could not be possible here as no one will be giving their property on rent for free! That will be absurd.

In [32]:
```
#Looking into the properties having 0 Price
free_properties = data.loc[data.price <= 0]
print('Shape of the data:', free_properties.shape)
free_properties.head()
```

```
Shape of the data: (11, 16)
```

Out[32]:

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of
23161	18750597	Huge Brooklyn Brownstone Living, Close to it all.	8993084	Kimberly	Brooklyn	Bedford-Stuyvesant	40.69023	-73.95428	Private room	0	4	
25433	20333471	★Hostel Style Room | Ideal Traveling Buddies★	131697576	Anisha	Bronx	East Morrisania	40.83296	-73.88668	Private room	0	2	
25634	20523843	MARTIAL LOFT 3: REDEMPTION (upstairs, 2nd room)	15787004	Martial Loft	Brooklyn	Bushwick	40.69467	-73.92433	Private room	0	2	
25753	20608117	Sunny, Quiet Room in Greenpoint	1641537	Lauren	Brooklyn	Greenpoint	40.72462	-73.94072	Private room	0	2	
25778	20624541	Modern apartment in the heart of Williamsburg	10132166	Aymeric	Brooklyn	Williamsburg	40.70838	-73.94645	Entire home/apt	0	5	

11 properties have are having 0 price. Assuming this to be a mistake or error from the Airbnb side, we will have to impute the prices according.

One way to impute will be by taking the mean, but as we saw earlier the price distribution is highly skewed and hence that will affect the mean of the price.

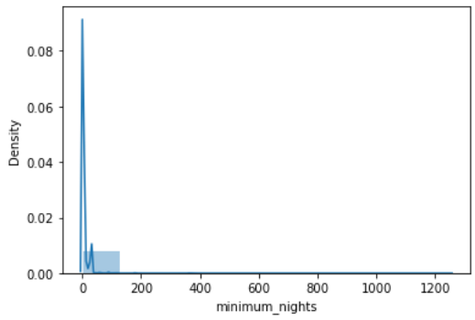
Presence of outliers or extreme values in the dataset effect the mean of the data and is not a good option to impute. Other method is to impute the data with mediian as median is less affected by outliers/extreme values.

The other effective way will be to see the affect of price or the relation of price on various other factors in the dataset and come up with a formula or a model that will do the imputation for us. We will look into this later.

In [33]:
```
#minimum number of nights allowed by the host.
sns.distplot(data.minimum_nights, bins=10)
```

```
/Users/sukeerthig/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[33]:
```
<AxesSubplot:xlabel='minimum_nights', ylabel='Density'>
```



The minimum nights goes from 1 to 1200+. Only 1 host provide minimum_nights to be 1200+. We come to know from the distribution that the data is skewed.

Now let's check which top 5 properties have recieved the highest number of reviewes.

In [34]:
```
#properties recieving highest reviews.
highest_reviews = data.sort_values(by='number_of_reviews', ascending=False)
highest_reviews.head()
```

Out[34]:

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_rev
11759	9145202	Room near JFK Queen Bed	47621202	Dona	Queens	Jamaica	40.66730	-73.76831	Private room	47	1	
2031	903972	Great Bedroom in Manhattan	4734398	Jj	Manhattan	Harlem	40.82085	-73.94025	Private room	49	1	
2030	903947	Beautiful Bedroom in Manhattan	4734398	Jj	Manhattan	Harlem	40.82124	-73.93838	Private room	49	1	
2015	891117	Private Bedroom in Manhattan	4734398	Jj	Manhattan	Harlem	40.82264	-73.94041	Private room	49	1	
13495	10101135	Room Near JFK Twin Beds	47621202	Dona	Queens	Jamaica	40.66939	-73.76975	Private room	47	1	

The above table shows the top 5 properties which have recieved the highest number of reviews. Out of the 5, three properties are from the Manhattan neighborhood group in Harlem.

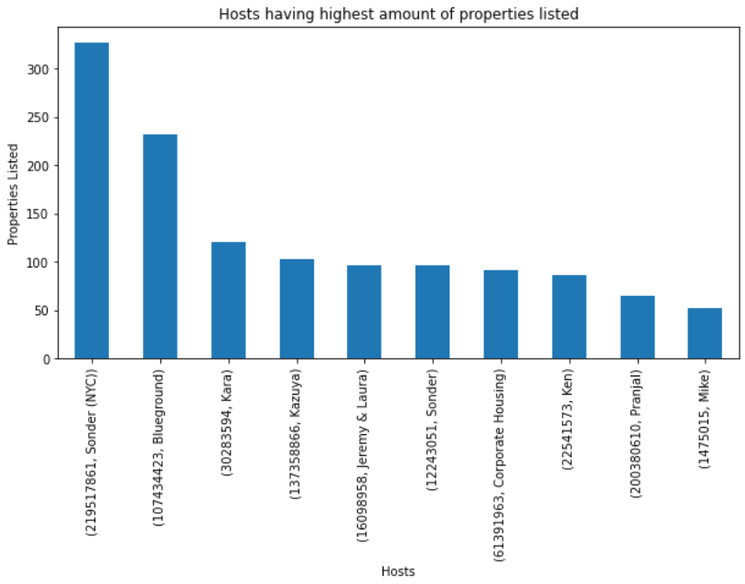
The top property which has recieved the most reviews is from Queens in the neighborhood of Jamica. The property having 5th highest review is also from Queens.

Let us look at these properties and try to come up with some hypothesis on why these properties have the highest reviews.

These properties are the most popular properties among the others and that is why they may be getting more bookings and hence more reviews. They come from the same host i.e Dona and JJ. May be they are a good and popular hosts that is why are recieving good amount of bookings and reviews. The

Dona host has her room near the JFK i.e nearer to the international airport and that's why the high amount of bookings. All of them share the similar room type, i.e Private rooms. So we can assume that the private rooms are more popular than any other rooms. The price is also almost similar of all the properties approx 50. They all offer minimum 1 night stay which most of the people prefer as it is very flexible. The availability of the rooms is also high with the top 4 having an availability rate of approx 300 days and +.

In [35]:
```
#host having highest amount of properties listed.
highest_props_host = data.groupby(['host_id', 'host_name'])['host_id'].count().sort_values(ascending=False)[:10]
highest_props_host.plot.bar(figsize=(10,5))
plt.xlabel('Hosts')
plt.ylabel('Properties Listed')
plt.title('Hosts having highest amount of properties listed');
```



We can see that Sonder(NYC) has the highest number of properties that are listed but his property was not in the top 5 highest reviews table we saw earlier.

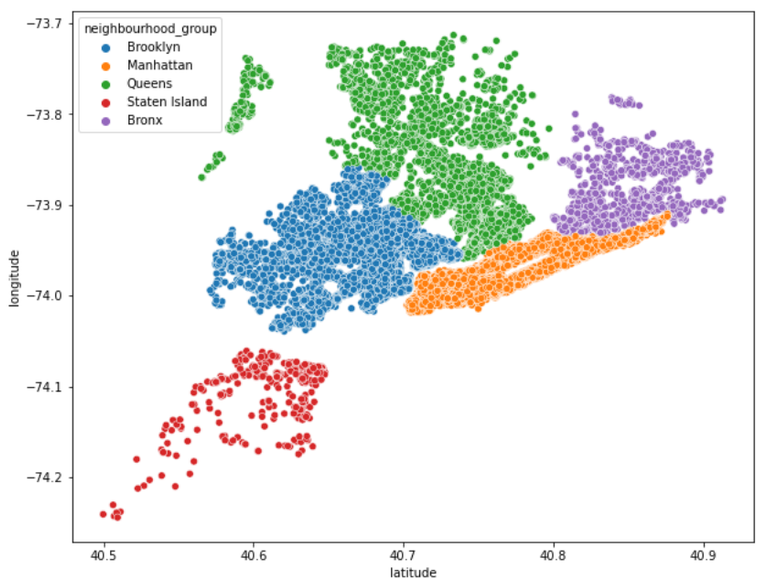
This means that the number of properties listed on the Airbnb does not mean that the number of customers you will have will be more.

Bivariate analysis

In [36]:
```
#neighborhood group based on the latitude and longitude
plt.figure(figsize=(10,8))
sns.scatterplot(data.latitude,data.longitude, hue='neighbourhood_group', data=data)
```

```
/Users/sukeerthig/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as key
word args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit ke
yword will result in an error or misinterpretation.
  warnings.warn(
```

Out[36]:
```
<AxesSubplot:xlabel='latitude', ylabel='longitude'>
```

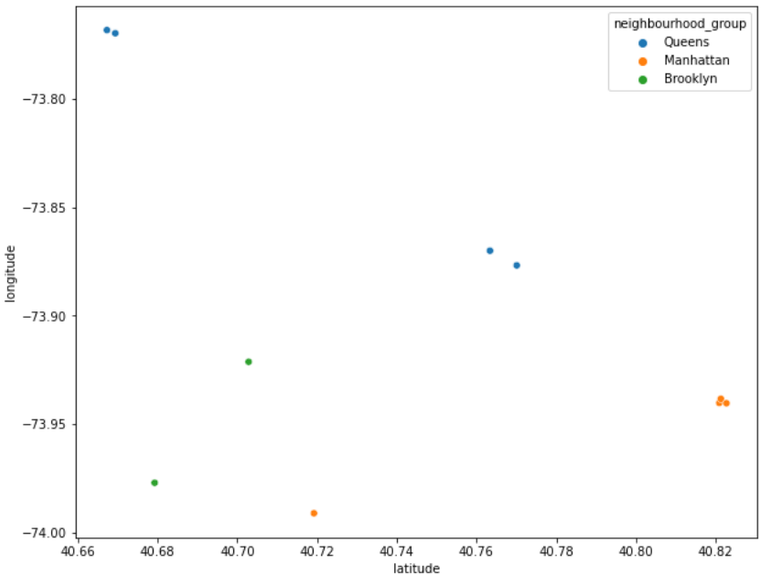


The above resemble the map of NYC and shows the various neighbourhoods and the properties listed in each neighbourhood.

In [37]:
```
# #Properties in the neighbourhood with most reviews.
plt.figure(figsize=(10,8))
sns.scatterplot('latitude', 'longitude', hue='neighbourhood_group', data=highest_reviews.head(10))
```

```
/Users/sukeerthig/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as key
word args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit ke
yword will result in an error or misinterpretation.
  warnings.warn(
```

Out[37]:
```
<AxesSubplot:xlabel='latitude', ylabel='longitude'>
```

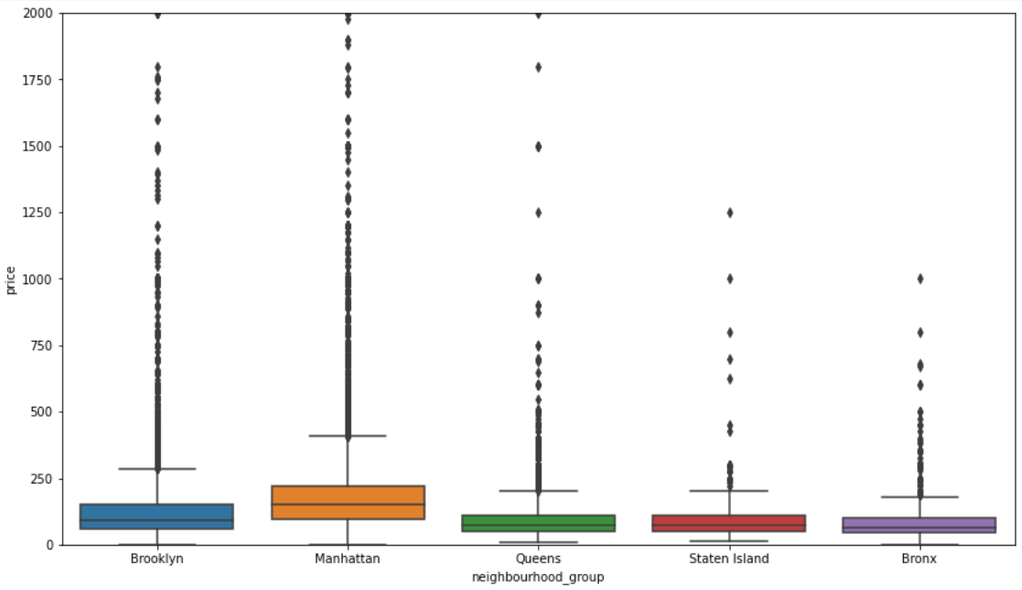


So far we have done some basic exploring of the dataset and have gain few insights from it such as:

Came to know that the price column had some irregularities such as the minimum price was 0$ which is not possible. Missing values in the last_review column and reviews_per_month column were following a pattern. If number_of_reviews was 0 then these two columns had null values. From the univariate analysis we came to know the top 5 neighbourhood whcih had the highest number of properties listed. We also came to know the top neighbourhood groups which had the highest number of properties listed. We came to know the top 5 properties which had the highest review and factors contibuting to their reviews. We came to know that properties closer to the airport had a good number of reviews. We saw the host which had the highest number of properties listed on Airbnb. We saw the distribution of the properties based on the neighbourhood_group on a scatter plot.

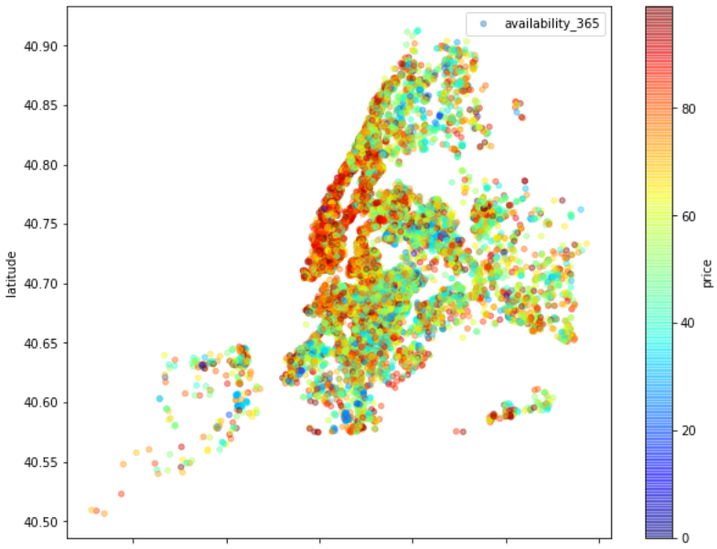
In [38]:
```
# Neighbourhood group and price
plt.figure(figsize=(14,8))
sns.boxplot(data.neighbourhood_group,data.price)
# sns.swarmplot(data.neighbourhood_group,data.price)
plt.ylim(0,2000)
plt.show()
```

```
/Users/sukeerthig/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as key
word args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit ke
yword will result in an error or misinterpretation.
  warnings.warn(
```



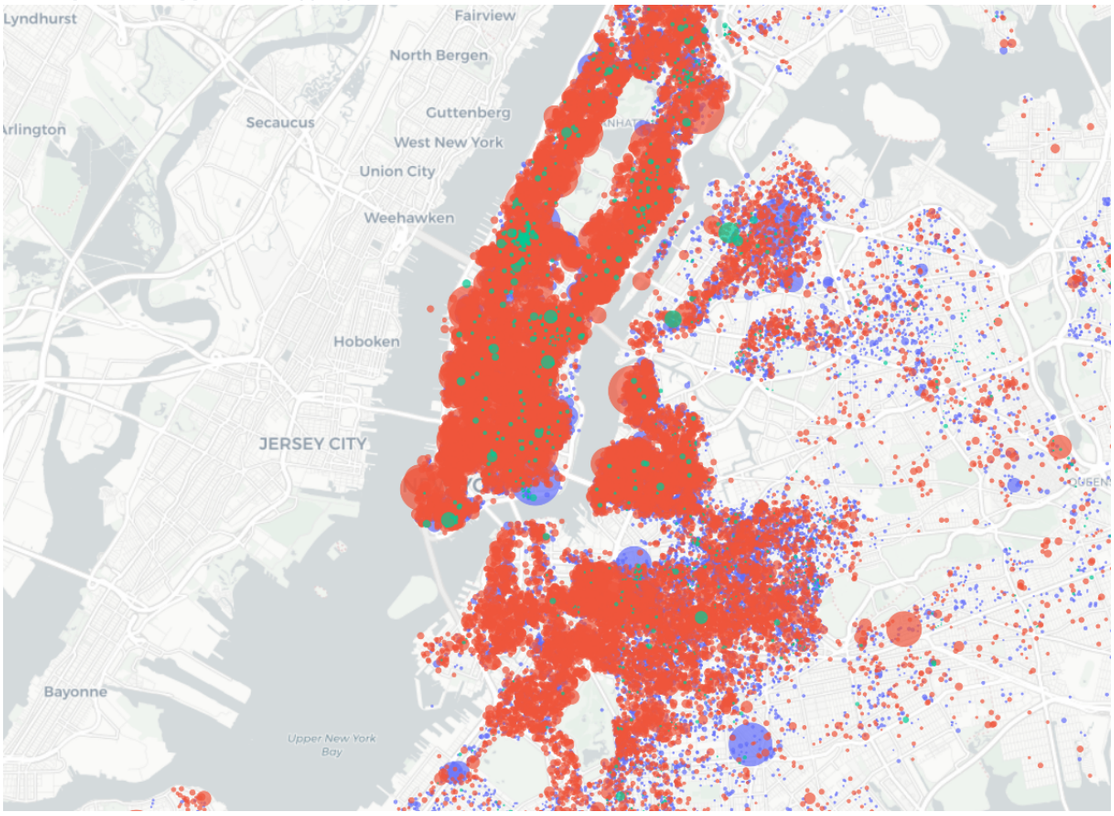
In [39]:
```
#Neighbourhood groups with price less than 100
sub_6=data[data.price < 100]
viz_4=sub_6.plot(kind='scatter', x='longitude', y='latitude', label='availability_365', c='price',
                 cmap=plt.get_cmap('jet'), colorbar=True, alpha=0.4, figsize=(10,8))
viz_4.legend()
```

Out[39]:
```
<matplotlib.legend.Legend at 0x7f873a2e9bb0>
```



In [40]:
```
#Room types and associated prices(Size of bubbles)
fig = px.scatter_mapbox(data,
                        lat="latitude",
                        lon="longitude",
                        color="room_type",
                        size="price",
                        color_continuous_scale=px.colors.cyclical.IceFire,
                        size_max=30,
                        opacity = .70,
                        zoom=11,
                       )
fig.layout.mapbox.style = 'carto-positron'
fig.update_layout(title_text = 'Room types and prices<br>(Click legend to toggle room types)', height = 800)

fig.show()
```

Room types and prices
(Click legend to toggle room types)



In [41]:
```
data.quantile([0.7,0.75,0.8,0.85,0.9,0.95,0.995,1])
```

Out[41]:

	id	host_id	latitude	longitude	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availabilit
0.700	27140739.60	8.082452e+07	40.756030	-73.941290	155.0	4.0	17.00	1.18	2.0	
0.750	29152178.50	1.074344e+08	40.763115	-73.936275	175.0	5.0	24.00	1.58	2.0	
0.800	30530272.40	1.371296e+08	40.770982	-73.927698	200.0	6.0	33.00	2.00	3.0	
0.850	32306597.20	1.695347e+08	40.787490	-73.919130	225.0	7.0	48.00	2.58	3.0	
0.900	33990939.60	2.128114e+08	40.804890	-73.907810	269.0	28.0	70.00	3.25	5.0	
0.950	35259101.20	2.417646e+08	40.825643	-73.865771	355.0	30.0	114.00	4.31	15.0	
0.995	36355802.18	2.703085e+08	40.873219	-73.754920	1000.0	90.0	256.53	7.97	327.0	
1.000	36487245.00	2.743213e+08	40.913060	-73.712990	10000.0	1250.0	629.00	58.50	327.0	

In [42]:
```
# Understanding the numerical variable

df_num = data[['price','minimum_nights','number_of_reviews','reviews_per_month','calculated_host_listings_count','availability_365']]
df_num.describe().transpose()
```

Out[42]:

	count	mean	std	min	25%	50%	75%	max
price	48895.0	152.720687	240.154170	0.0	69.00	106.00	175.00	10000.0
minimum_nights	48895.0	7.029962	20.510550	1.0	1.00	3.00	5.00	1250.0
number_of_reviews	48895.0	23.274466	44.550582	0.0	1.00	5.00	24.00	629.0
reviews_per_month	48895.0	1.090910	1.597283	0.0	0.04	0.37	1.58	58.5
calculated_host_listings_count	48895.0	7.143982	32.952519	1.0	1.00	1.00	2.00	327.0
availability_365	48895.0	112.781327	131.622289	0.0	0.00	45.00	227.00	365.0

Price: The mean value for price column is 152.72usd, median is at 106usd and the maximum price is 10000.00 which is clearly an outliers.

Minimum nights: The mean value for the minimum night is 7.03 days, while there are customers whom even stayed for 1250.00 days which is in this case, is an outliers.

Number of Reviews: For the number of reviews, the mean values lies in 23.27 reviews, median is at 5.00.

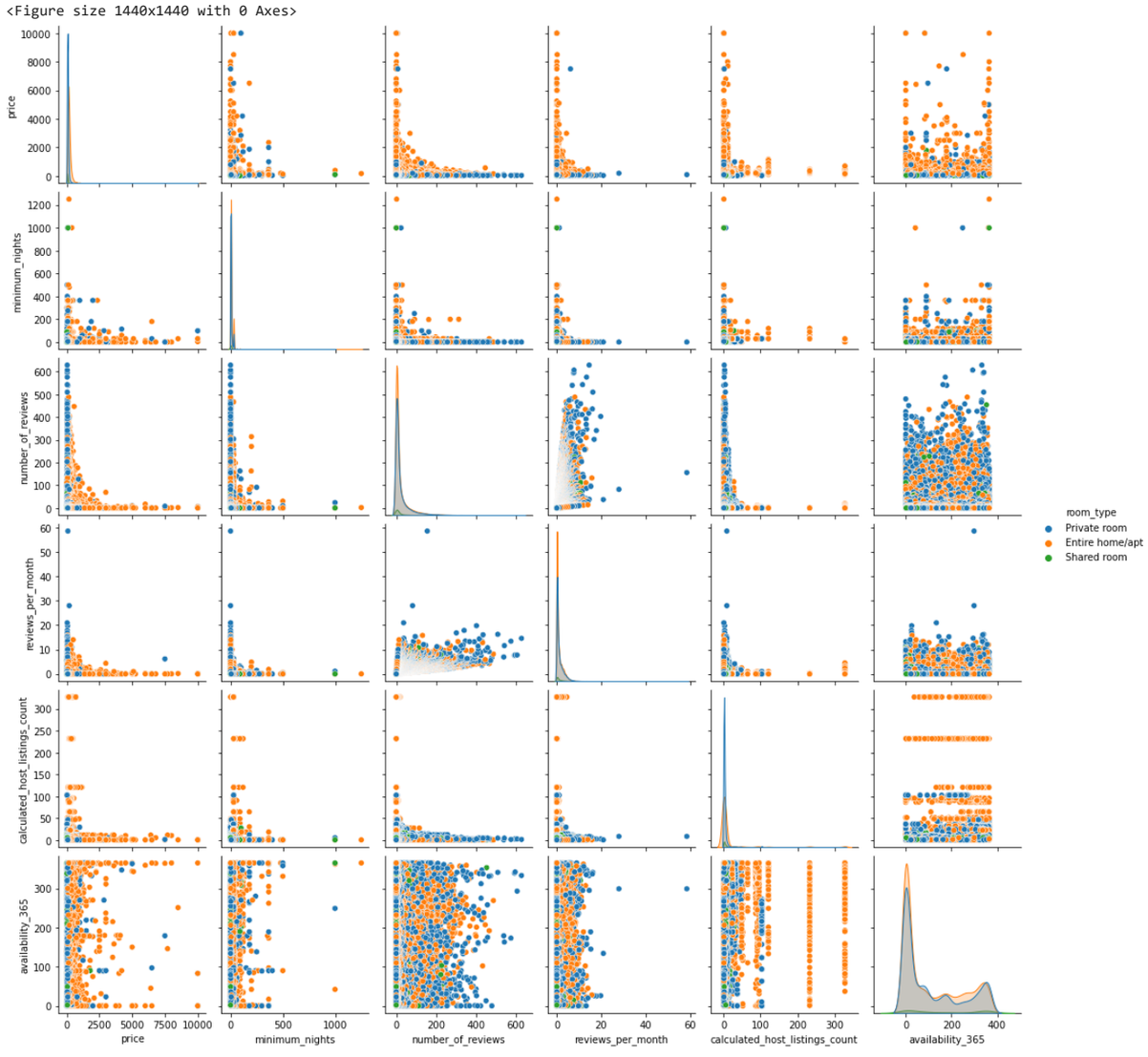
Reviews per Month: For the number of reviews per months, the mean of the variable is at 1.09 reviews, median is at 0.37 and max number of reviews is at 58.5.

Calculated host listing account: This is an amount of listing per host, in this variable, 7.14 listing is the mean value, and the mximum listing up to per host.

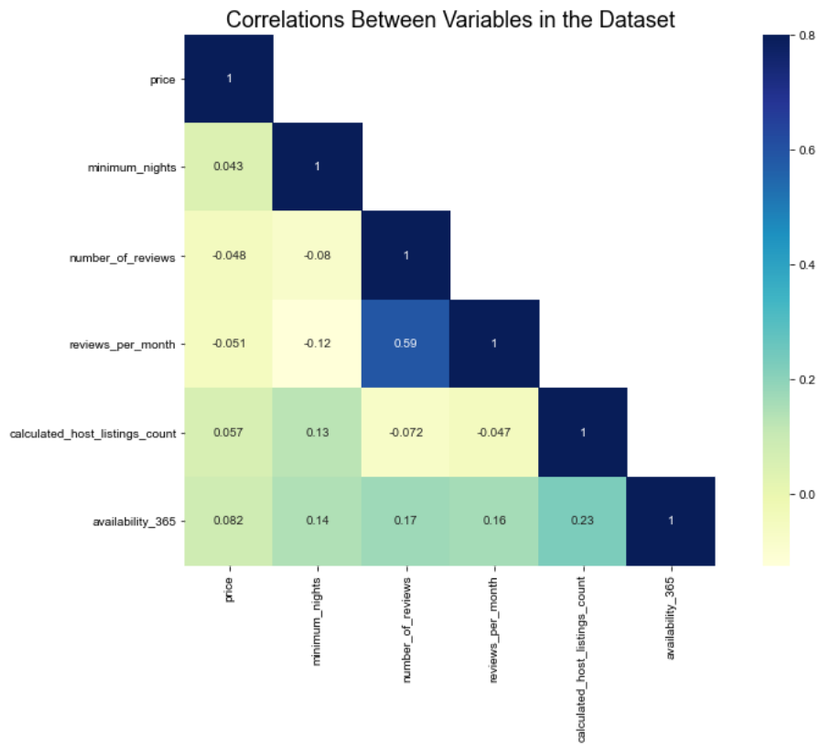
Availability 365: For the number of days when listing is available, the mean value is at 112.78 days, median is at 45 days and maximum days is 365.0 days.

In [43]:
```
plt.figure(figsize=(20,20))
sns.pairplot(data[['price','minimum_nights','number_of_reviews','reviews_per_month',
                   'calculated_host_listings_count','availability_365','room_type']], hue="room_type")
```

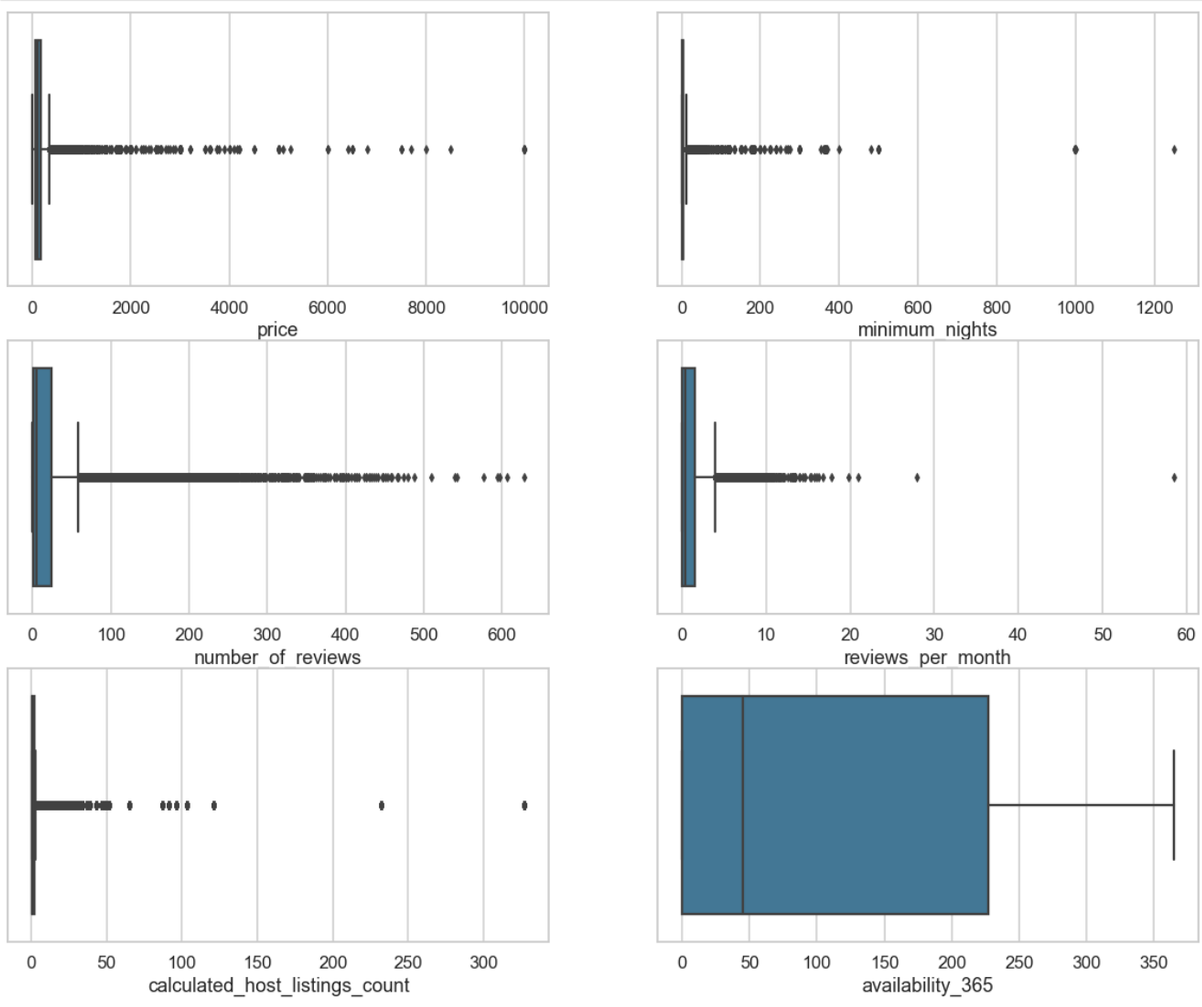
Out[43]:
```
<seaborn.axisgrid.PairGrid at 0x7f873a83eee0>

<Figure size 1440x1440 with 0 Axes>
```



In [44]:
```
# Checking the correlation between variables

plt.figure(figsize=(14,8))
mask = np.array(df_num.corr())
mask[np.tril_indices_from(mask)] = False
sns.heatmap(df_num.corr(), mask = mask, vmax = .8, square =  True, annot=True, cmap='YlGnBu')

sns.set_style('whitegrid')
sns.set_context('talk')
plt.title('Correlations Between Variables in the Dataset')
plt.show()
```



In [45]:
```
# Analysing outliers for numerical columms

plt.figure(figsize=(20,16))

for i in enumerate(df_num):
    plt.subplot(3,2, i[0]+1)
    sns.boxplot(x = i[1], data = data, palette='mako')
```



Analyzing and treating outliers

Price column

In [46]:
```
# Analysing the description

data['price'].describe()
```

Out[46]:
```
count    48895.000000
mean       152.720687
std        240.154170
min          0.000000
25%         69.000000
50%        106.000000
75%        175.000000
max      10000.000000
Name: price, dtype: float64
```

In [47]:
```
# Plotting boxplot to see the distribution of the data in the column

data.boxplot(column = 'price')

plt.xlabel('Price')
plt.title('Distribution of the Price')

plt.show()
```

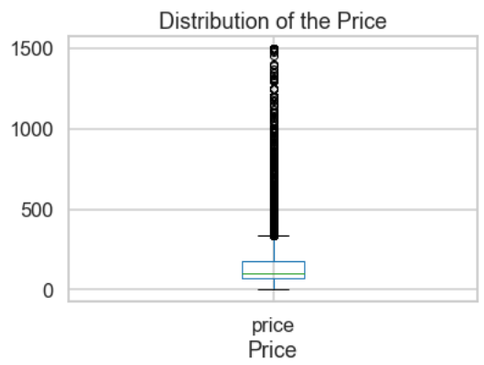
In [48]:
```
# Binning the price column

data['price'].quantile([0,0.25,0.50,0.75,0.90,0.95,0.99,0.997])
```

Out[48]:
```
0.000       0.0
0.250      69.0
0.500     106.0
0.750     175.0
0.900     269.0
0.950     355.0
0.990     799.0
0.997    1500.0
Name: price, dtype: float64
```

We will consider the values above 99.7% as an outliers, thus we will drop the values above 99.7% as per the rule of normal distribution.

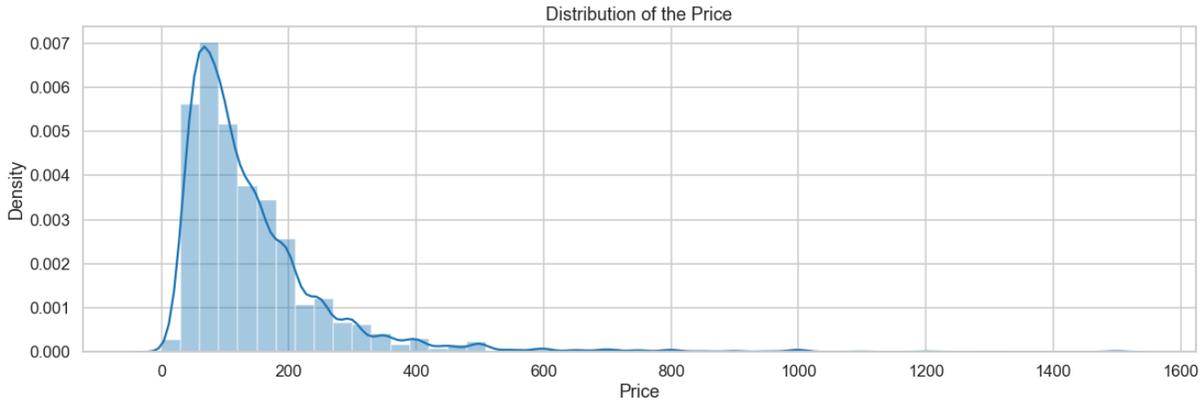
In [49]:
```
# Dropping the value above 99.7 quantile.

data.drop(data[data['price'] > data['price'].quantile(0.997)].index, axis=0, inplace=True)
```

In [50]:
```
# Replotting the boxplot after the outlier treatments

data.boxplot(column = 'price')

plt.xlabel('Price')
plt.title('Distribution of the Price')

plt.show()
```



In [51]:
```
# Plotting the displot to see the distributions

plt.figure(figsize=(20,6))
sns.distplot(data['price'])

plt.xlabel('Price')
plt.title('Distribution of the Price')
plt.show()
```

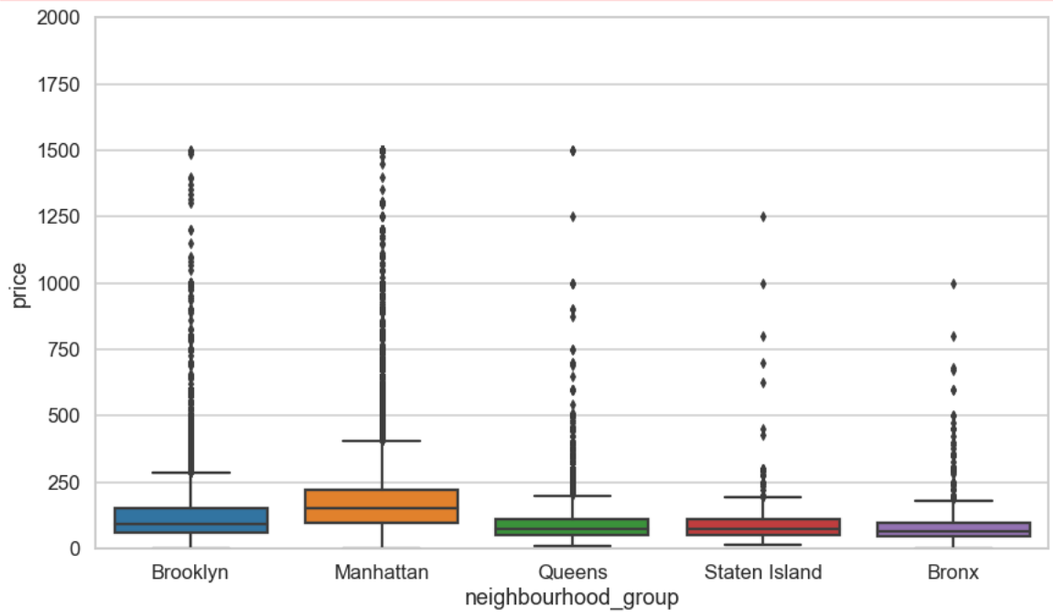
```
/Users/sukeerthig/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:2557: FutureWarning:

`distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-lev
el function with similar flexibility) or `histplot` (an axes-level function for histograms).
```



After treating the outliers, based from the above graph, the price has been capped at the value of 1500usd as compared with 10000usd before the outlier treatments.

In [52]:
```
# Neighbourhood group and price
plt.figure(figsize=(14,8))
sns.boxplot(data.neighbourhood_group,data.price)
# sns.swarmplot(data.neighbourhood_group,data.price)
plt.ylim(0,2000)
plt.show()
```

```
/Users/sukeerthig/opt/anaconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning:

Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing oth
er arguments without an explicit keyword will result in an error or misinterpretation.
```

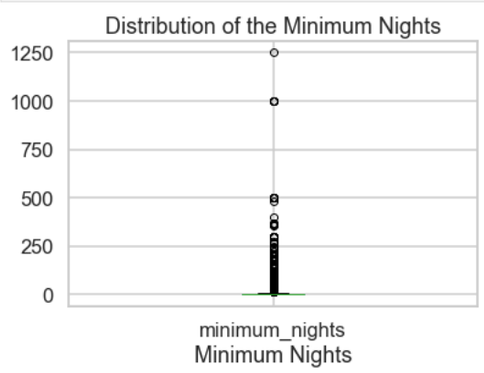


Minumum Nights

In [53]:
```
# Analysing the description

data['minimum_nights'].describe()
```

Out[53]:
```
count    48756.000000
mean         6.983612
std         20.327452
min          1.000000
25%          1.000000
50%          3.000000
75%          5.000000
max       1250.000000
Name: minimum_nights, dtype: float64
```

In [54]:
```
# Plotting boxplot to see the distribution of the data in the column

data.boxplot(column = 'minimum_nights')

plt.xlabel('Minimum Nights')
plt.title('Distribution of the Minimum Nights')

plt.show()
```



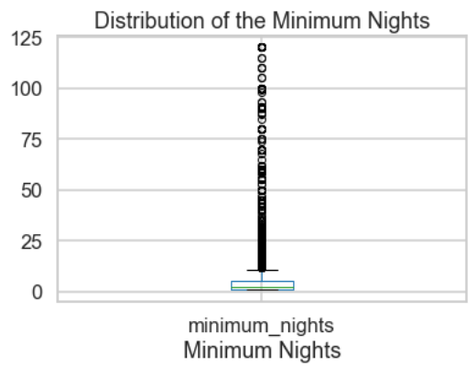
In [55]:
```
# Binning the Minimum Nights column

data['minimum_nights'].quantile([0,0.25,0.50,0.75,0.90,0.95,0.99,0.997])
```

Out[55]:
```
0.000      1.00
0.250      1.00
0.500      3.00
0.750      5.00
0.900     28.00
0.950     30.00
0.990     42.45
0.997    120.00
Name: minimum_nights, dtype: float64
```

We will consider the values above 99.7% as an outliers, thus we will drop the values above 99.7% as per the rule of normal distribution.

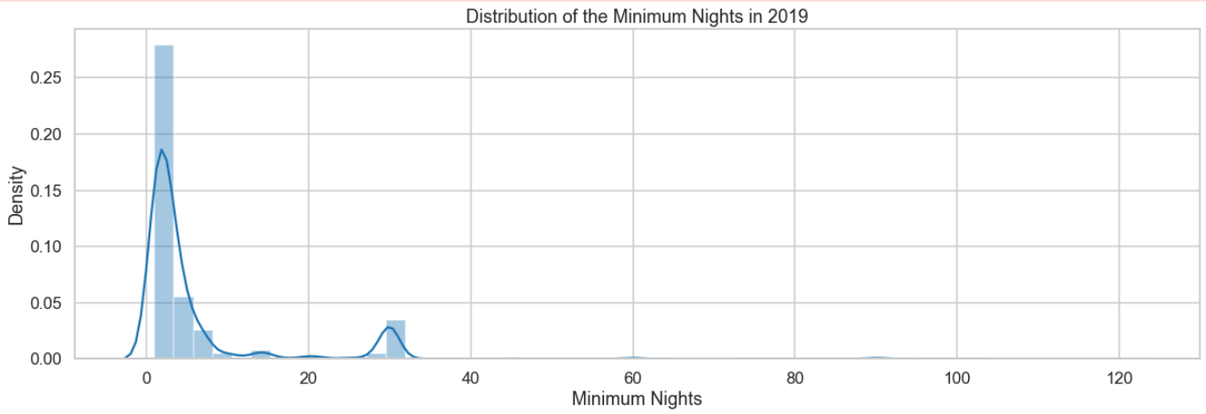
In [56]:
```
# Dropping the value above 99.7 quantile.

data.drop(data[data['minimum_nights'] > data['minimum_nights'].quantile(0.997)].index, axis=0, inplace=True)
```

In [57]:
```
# Replotting the boxplot after the outlier treatments

data.boxplot(column = 'minimum_nights')

plt.xlabel('Minimum Nights')
plt.title('Distribution of the Minimum Nights')

plt.show()
```



In [58]:
```
# Plotting the displot to see the distributions

plt.figure(figsize=(20,6))
sns.distplot(data['minimum_nights'])

plt.xlabel('Minimum Nights')
plt.title('Distribution of the Minimum Nights in 2019')
plt.show()
```

```
/Users/sukeerthig/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributions.py:2557: FutureWarning:

`distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-lev
el function with similar flexibility) or `histplot` (an axes-level function for histograms).
```



After replotting the boxplot and distribution plot, we can see that the value is being capped at 120 days, and the distribution can be clearly seen from the above graph.

In [59]:
```
data.to_csv("AB_NYC_2019_updated.csv", index=False)
print('DataFrame is written to Excel File successfully.')
```

```
DataFrame is written to Excel File successfully.
```

In [ ]:

In [ ]: