New York City Airbnb Exploratory Data Analysis

A) Background

Context

Since 2008, guests and hosts have used Airbnb to expand on traveling possibilities and present more unique, personalized way of experiencing the world. This dataset describes the listing activity and metrics in NYC, NY for 2019.

Content

This data file includes all needed information to find out more about hosts, geographical availability, necessary metrics to make predictions and draw conclusions.

Acknowledgements

This public dataset is part of Airbnb, I pulled this data from Kaggle https://www.kaggle.com/dgomonov/new-york-city-airbnb-open-data

Some Questions to answer :

1) What can we learn about different hosts and areas?

2) What can we learn from predictions? (ex: locations, prices, reviews, etc)

3) Which hosts are the busiest and why?

4) Is there any noticeable difference of traffic among different areas and what could be the reason for it?

B) Import the Libraries :

In [123]:

```
import pandas as pd
import numpy as np
import seaborn as sns

import matplotlib.pyplot as plt
from matplotlib import rcParams

import warnings
warnings.filterwarnings('ignore')
```

C) Get the Data (Read the .csv file) :

In [40]:

```
data = pd.read_csv('/content/AB_NYC_2019.csv')
```

D) Let's explore the data :

```
i.   Data Overview
ii.  No. of Records & Features
iii. Summary & info
iv. Conclusion
```

i. Data Overview :

In [41]:

```
# Top 5 records :

data.head(5)
```

Out[41]:

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

ii. No. of Records & Features :

In [42]:

```
# Let's know our features:
```

```python
print('SHAPE OF OUR DATASET :',data.shape)

print('\n WHAT ARE OUR FEATURES ? : \n',data.columns)
```

```
SHAPE OF OUR DATASET : (48895, 16)

 WHAT ARE OUR FEATURES ? :
 Index(['id', 'name', 'host_id', 'host_name', 'neighbourhood_group',
       'neighbourhood', 'latitude', 'longitude', 'room_type', 'price',
       'minimum_nights', 'number_of_reviews', 'last_review',
       'reviews_per_month', 'calculated_host_listings_count',
       'availability_365'],
      dtype='object')
```

OBSERVATION :

1) There are around 48895 records in our dataset.

2) We have 16 features :

```
id, name, host_id, host_name, neighbourhood_group, neighbourhood, latitude, longitu
de, room_type, price, minimum_nights, number_of_reviews, last_review, reviews_per_m
onth, calculated_host_listings_count, availability_365
```

iii. Descriptive Summary

In [43]:

```python
data.describe()
```

Out[43]:

	id	host_id	latitude	longitude	price	minimum_nights	number_of_reviews	reviews_
count	4.889500e+04	4.889500e+04	48895.000000	48895.000000	48895.000000	48895.000000	48895.000000	388
mean	1.901714e+07	6.762001e+07	40.728949	-73.952170	152.720687	7.029962	23.274466	
std	1.098311e+07	7.861097e+07	0.054530	0.046157	240.154170	20.510550	44.550582	
min	2.539000e+03	2.438000e+03	40.499790	-74.244420	0.000000	1.000000	0.000000	
25%	9.471945e+06	7.822033e+06	40.690100	-73.983070	69.000000	1.000000	1.000000	
50%	1.967728e+07	3.079382e+07	40.723070	-73.955680	106.000000	3.000000	5.000000	
75%	2.915218e+07	1.074344e+08	40.763115	-73.936275	175.000000	5.000000	24.000000	
max	3.648724e+07	2.743213e+08	40.913060	-73.712990	10000.000000	1250.000000	629.000000	

In [44]:

```python
# INFO

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
```

iv. Conclusion :

- **We have total 16 features, out of which "*last_review*", "*name*","*host_name*" are least important in my opinion. (So we'll ignore it)**
- **Factors/Metrics to look into**

```
  a) price   b) number_of_reviews   c) reviews_per_month  d) availability_365
e) calculated_host_listings_count
```

- **We can group the data based on**

```
  a) host_id, host_name   b) neighbourhood_group   c) neighbourhood   d) room_t
ype
```

- **We can utilise Longitude & Latitude values for geospatial visualization**
- **We have some features with *null* values.**

E) Data Wrangling :

```
i. Duplicate Values
ii. Missing Values
```

i. Duplicate Values :

In [45]:

```
# For [id] :

print("Total no. of id values :", data['id'].count())
print("No. of unique id values :",len(data['id'].unique()))

# For [name] :

print("\nTotal no. of name values : ",data['name'].count())
print("No. of unique name values : ",len(data['name'].unique()))

# For [host_id] :

print("\nTotal no. of host_id values :", data['host_id'].count())
print("No. of unique host_id values :",len(data['host_id'].unique()))

# For [host_name] :

print("\nTotal no. of host_name values : ",data['host_name'].count())
print("No. of unique host_name values : ",len(data['host_name'].unique()))
```

```
Total no. of id values : 48895
No. of unique id values : 48895

Total no. of name values :  48879
No. of unique name values :  47906

Total no. of host_id values : 48895
No. of unique host_id values : 37457
```

```
Total no. of host_name values :  48874
No. of unique host_name values :  11453
```

Observation :

- **As we can see, we have some duplicate records when it comes to ' *name*' & ' *host_name*'**
- **We don't need these 3 features:**

```
a) name    b) host_name    c) last_review

So, we'll drop these features.
```

- **Also, we even have null values in this features & they don't seem really helpful. So, let's drop them.**

 # Drop these 3 features in our DataFrame

In [46]:

```python
# Drop the features from the dataframe

cleaned_data = data.drop(['name','host_name','last_review'], axis=1)

cleaned_data
```

Out[46]:

	id	host_id	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	nu
0	2539	2787	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	1	
1	2595	2845	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	1	
2	3647	4632	Manhattan	Harlem	40.80902	-73.94190	Private room	150	3	
3	3831	4869	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	1	
4	5022	7192	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	10	
...	...	...	...	...	...	...	...	...	...	
48890	36484665	8232441	Brooklyn	Bedford-Stuyvesant	40.67853	-73.94995	Private room	70	2	
48891	36485057	6570630	Brooklyn	Bushwick	40.70184	-73.93317	Private room	40	4	
48892	36485431	23492952	Manhattan	Harlem	40.81475	-73.94867	Entire home/apt	115	10	
48893	36485609	30985759	Manhattan	Hell's Kitchen	40.75751	-73.99112	Shared room	55	1	
48894	36487245	68119814	Manhattan	Hell's Kitchen	40.76404	-73.98933	Private room	90	7	

48895 rows × 13 columns

ii. Missing Values :

In [48]:

```python
# Find the missing / NaN values :

print(cleaned_data.isnull().sum())
```

```
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
reviews_per_month                  10052
calculated_host_listings_count         0
availability_365                       0
dtype: int64
```

Observation :

- **There's just 1 feature with huge no. of missing values i.e.** ***reviews_per_month***
- **Let's replace this missing values with '0'**

In [49]:

```python
# Fill the missing values :

cleaned_data.fillna(value = 0,inplace = True)
```

In [50]:

```python
# New Cleaned Data

cleaned_data
```

Out[50]:

	id	host_id	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	nu
0	2539	2787	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	1	
1	2595	2845	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	1	
2	3647	4632	Manhattan	Harlem	40.80902	-73.94190	Private room	150	3	
3	3831	4869	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	1	
4	5022	7192	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	10	
...	...	...	...	...	...	...	...	...	...	
48890	36484665	8232441	Brooklyn	Bedford-Stuyvesant	40.67853	-73.94995	Private room	70	2	
48891	36485057	6570630	Brooklyn	Bushwick	40.70184	-73.93317	Private room	40	4	
48892	36485431	23492952	Manhattan	Harlem	40.81475	-73.94867	Entire home/apt	115	10	
48893	36485609	30985759	Manhattan	Hell's Kitchen	40.75751	-73.99112	Shared room	55	1	
48894	36487245	68119814	Manhattan	Hell's Kitchen	40.76404	-73.98933	Private room	90	7	

48895 rows × 13 columns

F) Exploratory Data Analysis :

i. Host
ii. price
iii. room_type
iv. Area (neighborhood, neighborhood_group)
v. availability_365

i. Host

- **Who are the busiest hosts?**
- **Which areas do these hosts cater to ?**

In [69]:

```
cleaned_data['host_id'].value_counts()
```

Out[69]:

```
219517861    327
107434423    232
30283594     121
137358866    103
12243051      96
            ...
1641589        1
4070519        1
208106618      1
235939247      1
1288080        1
Name: host_id, Length: 37457, dtype: int64
```

Q1 . Who is the most busiest host in New York City?

In [70]:

```
cleaned_data['host_id'].mode()
```

Out[70]:

```
0    219517861
dtype: int64
```

Observation :

- ***'219517861'* is the most busiest host**
- ***'107434423', '30283594', '137358866', '12243051'* are the other top hosts**

In [71]:

```
top_hosts = [219517861,107434423,30283594,137358866,12243051]

top_hosts
```

Out[71]:

```
[219517861, 107434423, 30283594, 137358866, 12243051]
```

In [132]:

```
print('Top Hosts Name : \n')

for i in top_hosts:
    print(data[data['host_id'] == i].host_name.unique())
```

```
Top Hosts Name :

['Sonder (NYC)']
['Blueground']
```

```
['Blueground']
['Kara']
['Kazuya']
['Sonder']
```

Q2. What are the areas these busiest hosts belong to ?

In [72]:

```
features = ['host_id','neighbourhood_group']

busiest_hosts = cleaned_data[cleaned_data['host_id'].isin(top_hosts)]

busiest_hosts_areas = busiest_hosts.loc[:,['host_id','neighbourhood_group']]
busiest_hosts_areas.drop_duplicates(inplace = True)

busiest_hosts_areas
```

Out[72]:

	host_id	neighbourhood_group
9740	30283594	Manhattan
26137	107434423	Manhattan
30637	12243051	Manhattan
32718	137358866	Manhattan
33268	137358866	Queens
36698	137358866	Brooklyn
38293	219517861	Manhattan
39275	107434423	Brooklyn

Observation :

- ***'Sonder (NYC) ',' Blueground ',' Kara ',' Kazuya ',' Sonder '*** **are the busiest hosts.**
- **These busiest hosts mostly belong to *Manhattan, Brooklyn & Queens*.**

ii. Price

- **Price distribution**
- **Median Price in $**
- **Price Statistic**
- **At what price do the busiest/top hosts offer their services?**
- **Prices across different regions**

In [28]:

```
prices_df = cleaned_data.loc[:,['id','host_id','neighbourhood_group','price']]

prices_df
```

Out[28]:

	id	host_id	neighbourhood_group	price
0	2539	2787	Brooklyn	149
1	2595	2845	Manhattan	225
2	3647	4632	Manhattan	150
3	3831	4869	Brooklyn	89

	id	host_id	neighbourhood_group	price
4	5022	7192	Manhattan	80
...	...	...	...	...
48890	36484665	8232441	Brooklyn	70
48891	36485057	6570630	Brooklyn	40
48892	36485431	23492952	Manhattan	115
48893	36485609	30985759	Manhattan	55
48894	36487245	68119814	Manhattan	90

48895 rows × 4 columns

 # Price Distribution :

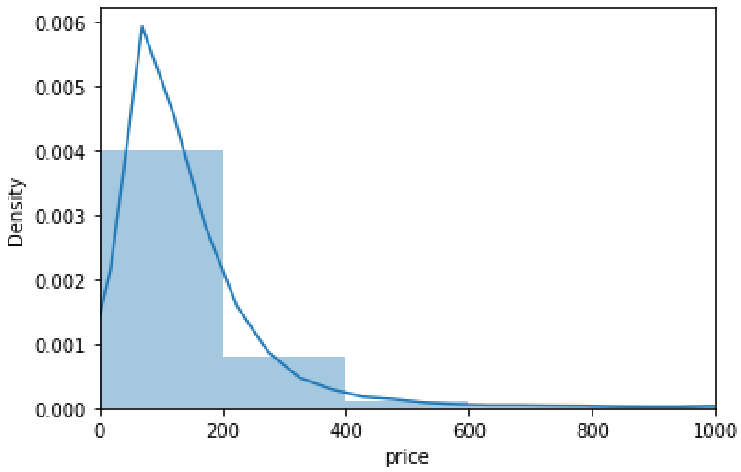
In [36]:

```
sns.distplot(prices_df['price'])

plt.xlim(0, 1000)
```

Out[36]:

```
(0.0, 1000.0)
```



 # Median Price in $:

In [51]:

```
print('Median Price ',prices_df['price'].median())
```

```
Median Price  106.0
```

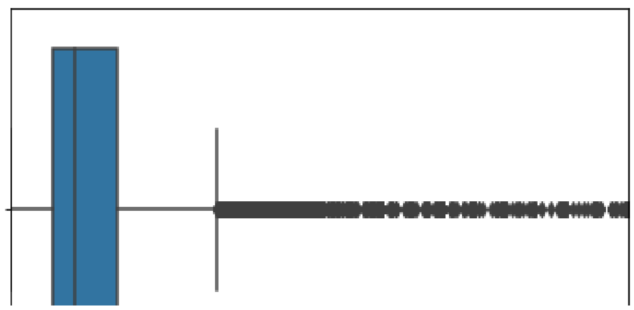
 # Price Statistic :

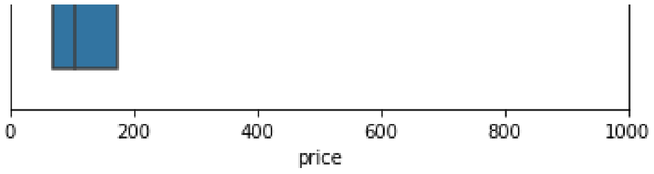
In [62]:

```
sns.boxplot(x = prices_df['price'])
plt.xlim(0,1000)
```

Out[62]:

```
(0.0, 1000.0)
```





In [63]:

```
# Percentile values :

print('\n25th percentile :',prices_df['price'].quantile(q=0.25))
print('\n50th percentile :',prices_df['price'].quantile(q=0.5))
print('\n75th percentile :',prices_df['price'].quantile(q=0.75))
print('\n99th percentile :',prices_df['price'].quantile(q=0.99))
```

```
25th percentile : 69.0

50th percentile : 106.0

75th percentile : 175.0

99th percentile : 799.0
```

Observation :

- **Mostly the prices lies between $ 69 & $ 175**
- **Median price across all of New York City is $ 106**
- **Also, our price data contains huge amount of outliers (which is why we used Median in place of Averages/Mean value)**

 # At what price do the busiest/top hosts offer their services?

In [56]:

```
busiest_hosts_prices = busiest_hosts.loc[:,['host_id','price']]

busiest_hosts_prices
```

Out[56]:

	host_id	price
9740	30283594	169
10075	30283594	135
10335	30283594	369
10398	30283594	335
10490	30283594	129
...	...	...
48723	107434423	316
48724	107434423	385
48725	107434423	267
48726	107434423	278
48727	107434423	365

879 rows × 2 columns

In [57]:

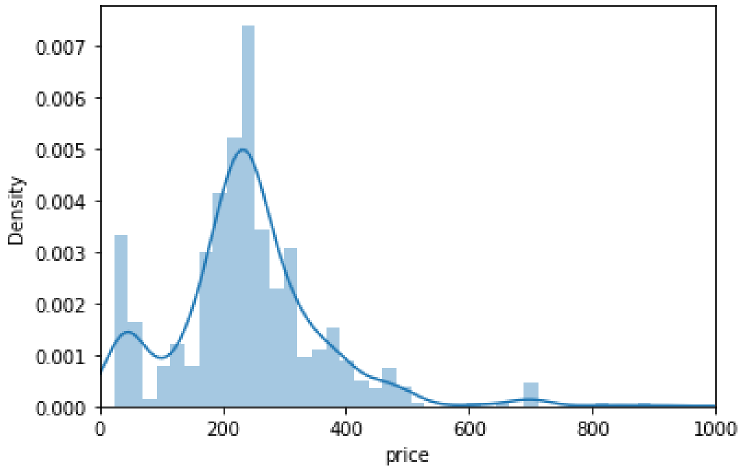
```
sns.distplot(busiest_hosts_prices['price'])

plt.xlim(0, 1000)
```

Out[57]:

Out[57]:

(0.0, 1000.0)

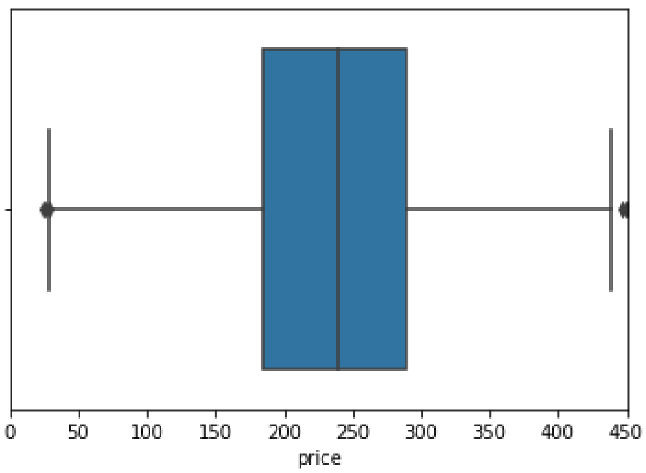


In [67]:

```
sns.boxplot(x = busiest_hosts_prices['price'])
plt.xlim(0,450)
```

Out[67]:

(0.0, 450.0)



In [68]:

```
# Percentile values :

print('\n25th percentile :',busiest_hosts_prices['price'].quantile(q=0.25))
print('\n50th percentile :',busiest_hosts_prices['price'].quantile(q=0.5))
print('\n75th percentile :',busiest_hosts_prices['price'].quantile(q=0.75))
print('\n99th percentile :',busiest_hosts_prices['price'].quantile(q=0.99))
```

```
25th percentile : 185.0

50th percentile : 239.0

75th percentile : 289.0

99th percentile : 699.0
```

Observation :

- **Turns out that the Busiest host's in New York City cost a little more expensive than others. i.e. between $ *185* & $ *289***

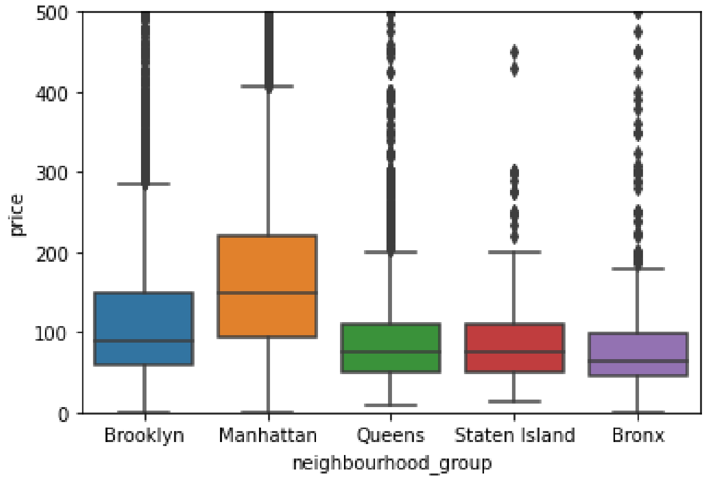
 # Prices across different regions :

In [64]:

```
sns.boxplot(x="neighbourhood_group", y="price", data = prices_df)
plt.ylim(0,500)
```

Out[64]:

```
(0.0, 500.0)
```



Observation :

- **Manhattan is the most expensive area. (highest price)**
- **Manhattan & Brooklyn turns out to be the most expensive areas.**
- **Rest, { Queens, Staten Island, Bronx } have similar prices and are cheaper than Manhattan & Brooklyn.**

iii. Room Type :

- **Which room types are more popular?**
- **Which room types are more cheaper than others?**

In [73]:

```
roomtype_df = cleaned_data.loc[:,['id','room_type','price']]

roomtype_df
```

Out[73]:

	id	room_type	price
0	2539	Private room	149
1	2595	Entire home/apt	225
2	3647	Private room	150
3	3831	Entire home/apt	89
4	5022	Entire home/apt	80
...	...	...	...
48890	36484665	Private room	70
48891	36485057	Private room	40
48892	36485431	Entire home/apt	115
48893	36485609	Shared room	55
48894	36487245	Private room	90

48895 rows × 3 columns

Popularity of different room_types :

In [82]:

```
print('Distribution of Room Types : \n\n',roomtype_df['room_type'].value_counts())
```

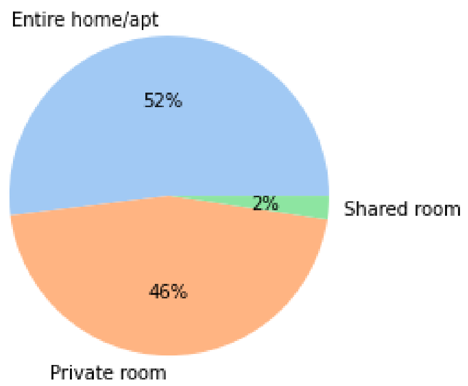
```
Distribution of Room Types :

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

In [85]:

```
# Visualize the above result in form of pie-chart :

count = [25409,22326,1160]
labels = ['Entire home/apt','Private room','Shared room']
colors = sns.color_palette('pastel')
plt.pie(count, labels=labels,colors = colors, autopct = '%0.0f%%')
plt.show()
```



Observation :

- **As we can clearly see, '** ***Entire home/apt*** **' and '** ***Private room*** **' are the more popular room types.**
- **Shared room is the least preffered room type contributing to just 2 % of all bookings.**

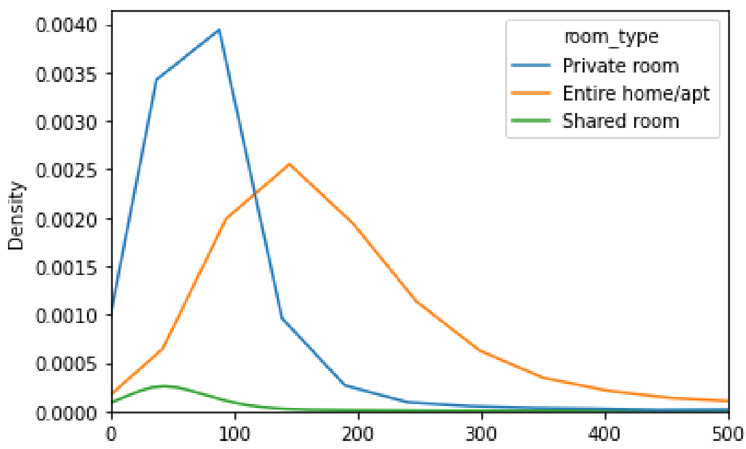
Price of different room_types

In [75]:

```
sns.kdeplot(data = roomtype_df, x="price", hue="room_type")
plt.xlim(0,500)
```

Out[75]:

```
(0.0, 500.0)
```



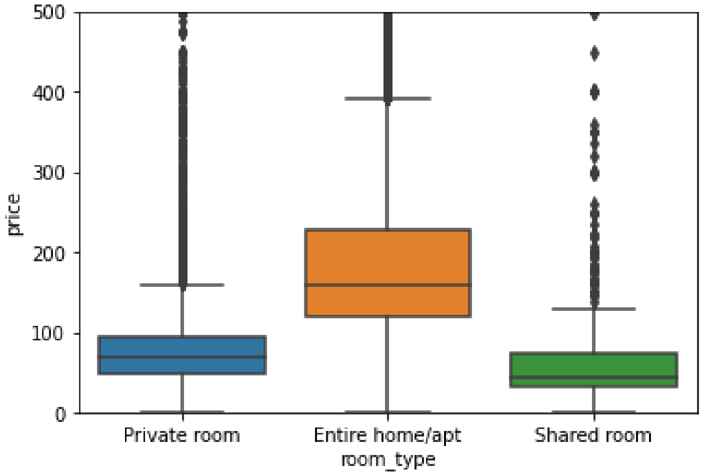
price

In [77]:

```
sns.boxplot(x="room_type", y="price", data = roomtype_df)
plt.ylim(0,500)
```

Out[77]:

```
(0.0, 500.0)
```



Observation :

- **"Entire Home/Apt" is the most expensive room type.**
- **"Private Room" & "Shared Room" are almost comparable in terms of Price.**
- **"Shared Room" is the cheapest room type.**

iv. Area (neighbourhood_group, neighbourhood):

- **Which are the most busiest/popular areas in New York City?**

In [86]:

```
neighbour_group = cleaned_data.groupby(by='neighbourhood_group')

neighbour_group
```

Out[86]:

```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x7fcfce117f50>
```

In [90]:

```
neighbour_group.describe()
```

Out[90]:

	id								host_
	count	mean	std	min	25%	50%	75%	max	coun
neighbourhood_group									
Bronx	1091.0	2.273492e+07	1.023402e+07	44096.0	16174880.50	23879304.0	31899087.00	36442252.0	109
Brooklyn	20104.0	1.825685e+07	1.083320e+07	2539.0	8704323.75	18876042.5	27843948.75	36485057.0	2010
Manhattan	21661.0	1.877494e+07	1.116793e+07	2595.0	9162161.00	19116844.0	29541214.00	36487245.0	2166
Queens	5666.0	2.175500e+07	1.037687e+07	12937.0	13960418.25	22564596.0	30768797.25	36484363.0	566

	id								host_
	count	mean	std	min	25%	50%	75%	max	coun
Staten Island	373.0	2.159747e+07	1.039310e+07	42882.0	15532430.00	22977021.0	30082958.00	36438336.0	37

In [91]:

```
neighbour_group['id'].count()
```

Out[91]:

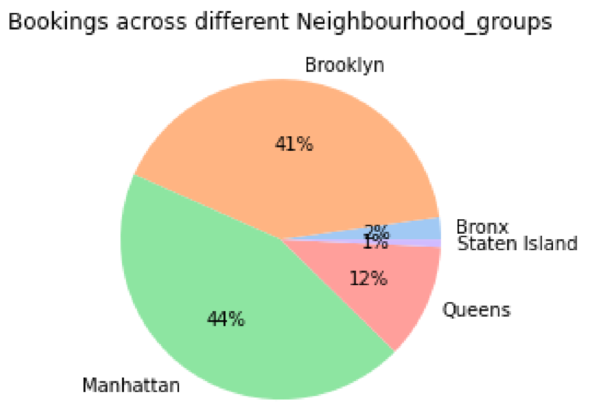
```
neighbourhood_group
Bronx             1091
Brooklyn         20104
Manhattan        21661
Queens            5666
Staten Island      373
Name: id, dtype: int64
```

In [99]:

```
g = dict(neighbour_group['id'].count())

keys = list(g.keys())
values = list(g.values())

plt.title('Bookings across different Neighbourhood_groups')
colors = sns.color_palette('pastel')
plt.pie(values, labels=keys, colors = colors, autopct = '%0.0f%%')
plt.show()
```



Observation :

- **Manhattan & Brooklyn are the busiest areas (neighbourhood_group). These two contributes to around 85 % of the total traffic**

vi. Availability_365 :

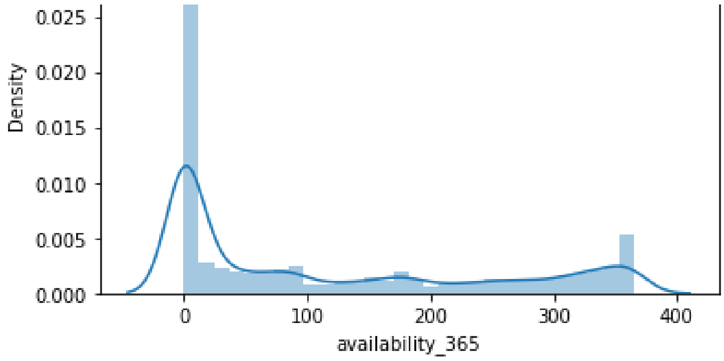
Availability across all hosts :

In [109]:

```
sns.distplot(cleaned_data['availability_365'])
```

Out[109]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcfca71ded0>
```

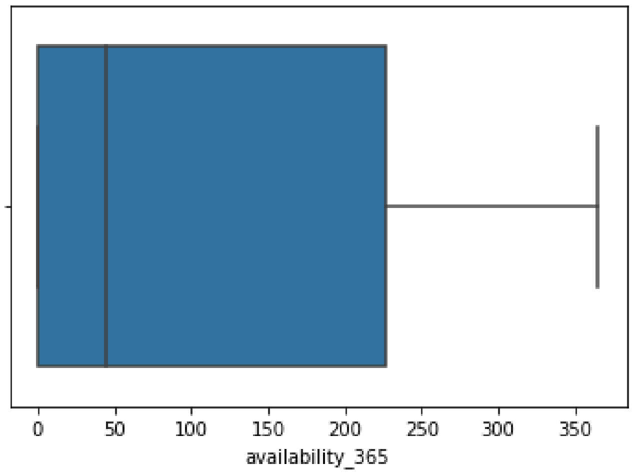


In [110]:

```
sns.boxplot(x=cleaned_data['availability_365'])
```

Out[110]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcfcd275690>
```



In [111]:

```
# Percentile values :

print('\n25th percentile :',cleaned_data['availability_365'].quantile(q=0.25))
print('\n50th percentile :',cleaned_data['availability_365'].quantile(q=0.5))
print('\n75th percentile :',cleaned_data['availability_365'].quantile(q=0.75))
print('\n99th percentile :',cleaned_data['availability_365'].quantile(q=0.99))
```

```
25th percentile : 0.0

50th percentile : 45.0

75th percentile : 227.0

99th percentile : 365.0
```

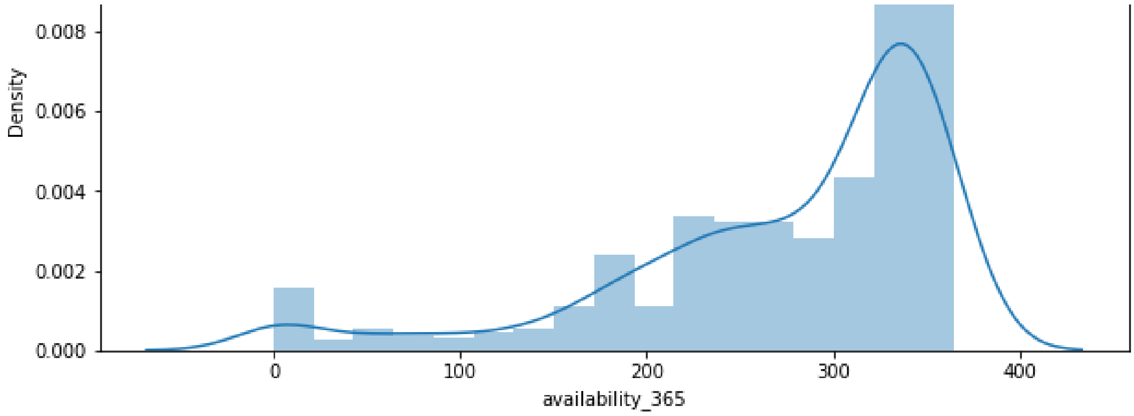
Observation :

- **Most of the Airbnb host's offer their services for over 0 to 227 days in a year.**

 # Availability across the busiest hosts :

In [135]:

```
sns.distplot(busiest_hosts['availability_365'])
rcParams['figure.figsize'] = 7,5
```

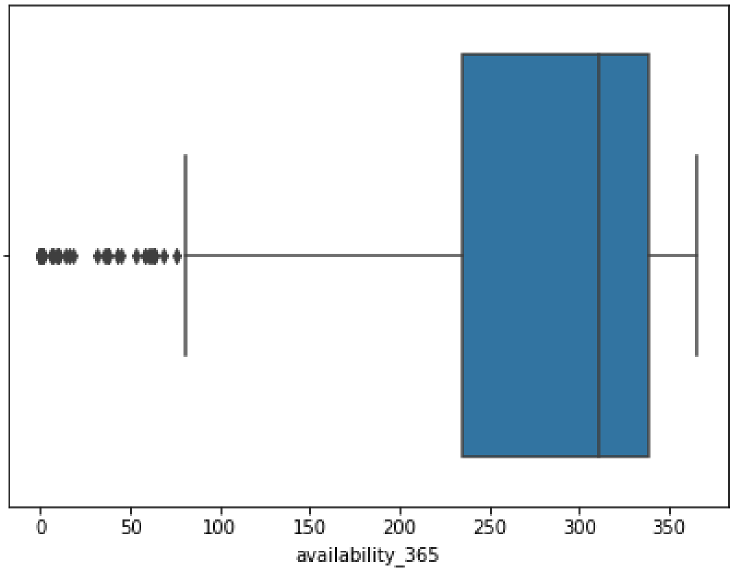


In [136]:

```
sns.boxplot(x=busiest_hosts['availability_365'])
```

Out[136]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcfcb003d10>
```



In [137]:

```
# Percentile values :

print('\n25th percentile :',busiest_hosts['availability_365'].quantile(q=0.25))
print('\n50th percentile :',busiest_hosts['availability_365'].quantile(q=0.5))
print('\n75th percentile :',busiest_hosts['availability_365'].quantile(q=0.75))
print('\n99th percentile :',busiest_hosts['availability_365'].quantile(q=0.99))
```

```
25th percentile : 235.0

50th percentile : 311.0

75th percentile : 339.0

99th percentile : 365.0
```

Observation :

- **The busiest Airbnb host's offer their services for over 235 to 339 days in a year.**

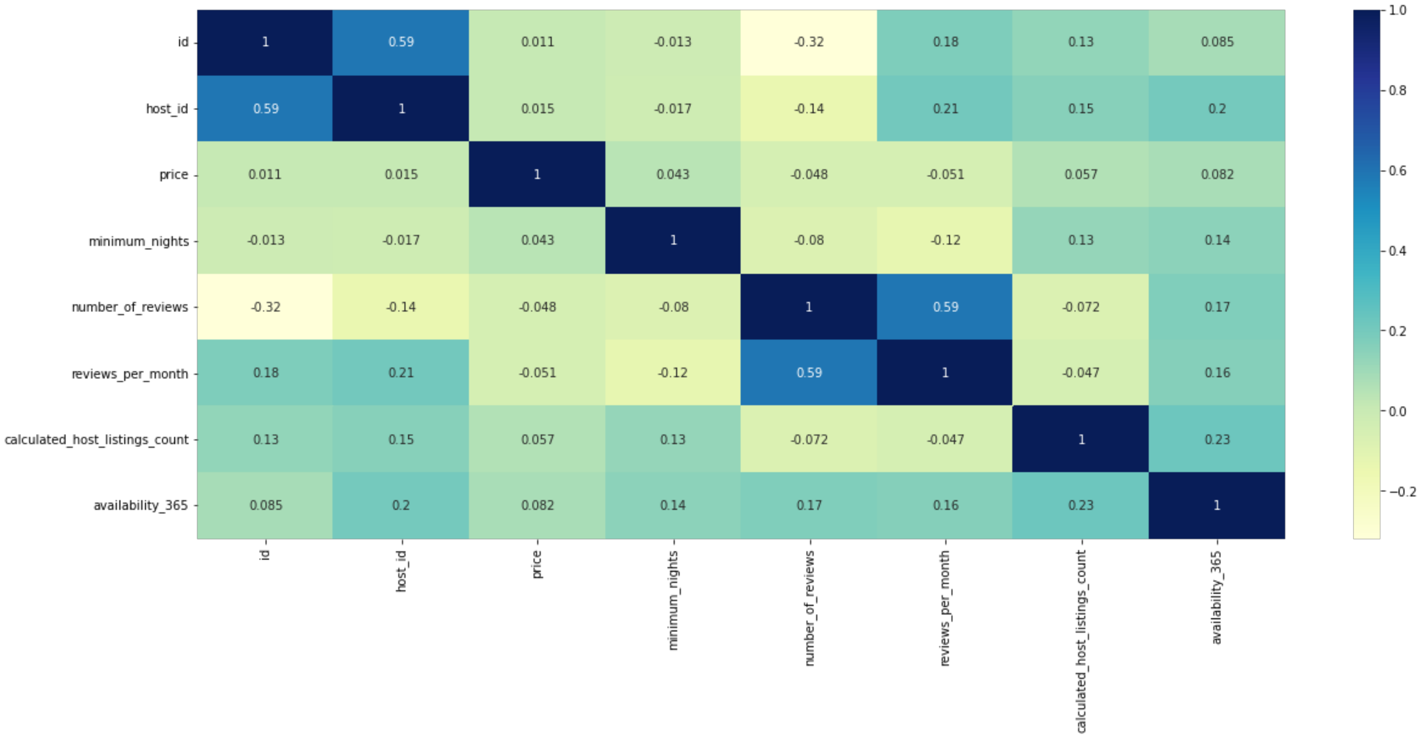
G) Correlation between Features :

In [127]:

```
new_df = cleaned_data.drop(['longitude','latitude'], axis=1)
```

```
corr_df = new_df.corr()

sns.heatmap(corr_df, cmap="YlGnBu", annot=True)
rcParams['figure.figsize'] = 18,8
plt.show()
```



H) Conclusion :

- **Our Dataset contained 48,895 Airbnb booking records around New York City for the year of 2019.**
- **We were provided with 16 features, out of which we used some of the features for the purpose of analysis.**
- ***'Sonder (NYC) ',' Blueground ',' Kara ',' Kazuya ',' Sonder '* are the busiest hosts. These hosts cater around *Manhattan* & *Brooklyn* areas.**
- **Manhattan & Brooklyn are the most popular areas in New York City with the busiest traffic. These areas are also the most expensive ones. (contributing to 85% of the total traffic)**
- **Manhattan is the most expensive area.**
- **'Entire home/Apt' and 'Private room' are the most preffered room categories.**
- **'Entire home/Apt' is the most expensive room category.**
- **'Shared rooms' are hardly booked(only 2% out of total bookings), even though it is the cheapest room category.**
- **While most of the Airbnb host's offer their services for over 0 to 227 days in a year. The busiest Airbnb hosts offer their services from 235 to 339 days in a year. (which is so much more than other hosts)**

I) Recommendation :

- Customers surely seems to value **'quality experience'** over **'money'**. So, Airbnb should advise their hosts to prioitize on providing a high quality experience & then later align their prices.
- **Manhattan**, **Brooklyn** and **Queens** receives the best traffic among all the neighbourhood areas. So, Airbnb should find more hosts catering to these areas.
- **'Shared Rooms'** don't get much customer traffic. So it would be a wise idea to remove this room category from the Airbnb services.