# DevelopmentTeamProject

July 27, 2023

[1]:
```
##Research Question:What types of properties are most commonly listed in New␣
↪York City Airbnb Dataset and how the property type affect the price and␣
↪availability for booking?
```

[1]:
```
import pandas as pd
import seaborn  as sns
from matplotlib import pyplot as plt
```

[2]:
```
Dataset=pd.read_csv('AB_NYC_2019.csv')
```

[3]:
```
#The display.max_columns option controls the number of columns to be printed␣
↪(none represent all the columns included in the dataset)
pd.set_option('display.max_columns', None)
#You can change the width of the column with the option max_colwidth (none␣
↪represent the maximum characters included in a cell within the dataset)
pd.set_option('max_colwidth', None)
```

[5]:
```
Dataset
```

[5]:
```
             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
…           …                                                  …        …
48890  36484665    Charming one bedroom - newly renovated rowhouse   8232441
48891  36485057      Affordable room in Bushwick/East Williamsburg   6570630
48892  36485431            Sunny Studio at Historical Neighborhood  23492952
48893  36485609               43rd St. Time Square-cozy single bed  30985759
48894  36487245  Trendy duplex in the very heart of Hell's Kitchen  68119814

          host_name neighbourhood_group       neighbourhood  latitude  \
0              John            Brooklyn          Kensington  40.64749
1          Jennifer           Manhattan             Midtown  40.75362
2         Elisabeth           Manhattan              Harlem  40.80902
3       LisaRoxanne            Brooklyn        Clinton Hill  40.68514
4             Laura           Manhattan         East Harlem  40.79851
```

```
…              …                …                   …       …
48890       Sabrina          Brooklyn  Bedford-Stuyvesant  40.67853
48891       Marisol          Brooklyn            Bushwick  40.70184
48892  Ilgar & Aysel        Manhattan              Harlem  40.81475
48893            Taz        Manhattan      Hell's Kitchen  40.75751
48894     Christophe        Manhattan      Hell's Kitchen  40.76404

       longitude        room_type  price  minimum_nights  number_of_reviews  \
0      -73.97237     Private room    149               1                  9
1      -73.98377  Entire home/apt    225               1                 45
2      -73.94190     Private room    150               3                  0
3      -73.95976  Entire home/apt     89               1                270
4      -73.94399  Entire home/apt     80              10                  9
…            …                …    …               …                  …
48890  -73.94995     Private room     70               2                  0
48891  -73.93317     Private room     40               4                  0
48892  -73.94867  Entire home/apt    115              10                  0
48893  -73.99112      Shared room     55               1                  0
48894  -73.98933     Private room     90               7                  0

      last_review  reviews_per_month  calculated_host_listings_count  \
0      2018-10-19               0.21                               6
1      2019-05-21               0.38                               2
2             NaN                NaN                               1
3      2019-07-05               4.64                               1
4      2018-11-19               0.10                               1
…             …                  …                               …
48890         NaN                NaN                               2
48891         NaN                NaN                               2
48892         NaN                NaN                               1
48893         NaN                NaN                               6
48894         NaN                NaN                               1

       availability_365
0                   365
1                   355
2                   365
3                   194
4                     0
…                   …
48890                 9
48891                36
48892                27
48893                 2
48894                23

[48895 rows x 16 columns]
```

[6]:
```
#The dataset involves 48895 rows and 16 columns
Dataset.shape
```

[6]: (48895, 16)

[7]:
```
#Check the data type of the variables within the dataset
Dataset.dtypes
```

[7]:
```
id                                 int64
name                              object
host_id                            int64
host_name                         object
neighbourhood_group               object
neighbourhood                     object
latitude                         float64
longitude                        float64
room_type                         object
price                              int64
minimum_nights                     int64
number_of_reviews                  int64
last_review                       object
reviews_per_month                float64
calculated_host_listings_count     int64
availability_365                   int64
dtype: object
```

[8]:
```
#Transform the variables 'id' and 'host_id' from numerical variable into␣
↪objects(we desrire these variables to be treated as objects and not numbers)
#For example it doesnt make sense to find the mean or median of the 'id'␣
↪variable
Dataset = Dataset.astype({'id': object,'host_id':object})
```

[9]:
```
Dataset.dtypes
```

[9]:
```
id                                object
name                              object
host_id                           object
host_name                         object
neighbourhood_group               object
neighbourhood                     object
latitude                         float64
longitude                        float64
room_type                         object
price                              int64
minimum_nights                     int64
number_of_reviews                  int64
last_review                       object
```

```
reviews_per_month                   float64
calculated_host_listings_count        int64
availability_365                      int64
dtype: object
```

[10]:
```
#I have divided the last review_variabel into␣
↪last_review_year,last_review_month and last_review_day for better␣
↪exploration
Dataset[['last_review_year','last_review_month','last_review_day']]=Dataset['last_review'].
↪str.split('-',expand=True)
```

[11]:
```
#Drop the last_review variable which we already divided in the previous step
Dataset=Dataset.drop(['last_review'], axis=1)
```

[12]:
```
Dataset.dtypes
```

[12]:
```
id                                   object
name                                 object
host_id                              object
host_name                            object
neighbourhood_group                  object
neighbourhood                        object
latitude                            float64
longitude                           float64
room_type                            object
price                                 int64
minimum_nights                        int64
number_of_reviews                     int64
reviews_per_month                   float64
calculated_host_listings_count        int64
availability_365                      int64
last_review_year                     object
last_review_month                    object
last_review_day                      object
dtype: object
```

[13]:
```
Dataset
```

[13]:
```
             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
…           …                                                …        …
48890  36484665   Charming one bedroom - newly renovated rowhouse   8232441
48891  36485057     Affordable room in Bushwick/East Williamsburg   6570630
```

```
48892  36485431          Sunny Studio at Historical Neighborhood  23492952
48893  36485609             43rd St. Time Square-cozy single bed  30985759
48894  36487245  Trendy duplex in the very heart of Hell's Kitchen  68119814

          host_name neighbourhood_group       neighbourhood  latitude  \
0              John            Brooklyn          Kensington  40.64749
1          Jennifer           Manhattan             Midtown  40.75362
2         Elisabeth           Manhattan              Harlem  40.80902
3       LisaRoxanne            Brooklyn        Clinton Hill  40.68514
4             Laura           Manhattan         East Harlem  40.79851
…               …                   …                   …         …
48890       Sabrina            Brooklyn  Bedford-Stuyvesant  40.67853
48891       Marisol            Brooklyn            Bushwick  40.70184
48892  Ilgar & Aysel           Manhattan              Harlem  40.81475
48893           Taz           Manhattan      Hell's Kitchen  40.75751
48894    Christophe           Manhattan      Hell's Kitchen  40.76404

       longitude        room_type  price  minimum_nights  number_of_reviews  \
0      -73.97237     Private room    149               1                  9
1      -73.98377  Entire home/apt    225               1                 45
2      -73.94190     Private room    150               3                  0
3      -73.95976  Entire home/apt     89               1                270
4      -73.94399  Entire home/apt     80              10                  9
…            …                …      …               …                  …
48890  -73.94995     Private room     70               2                  0
48891  -73.93317     Private room     40               4                  0
48892  -73.94867  Entire home/apt    115              10                  0
48893  -73.99112      Shared room     55               1                  0
48894  -73.98933     Private room     90               7                  0

       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
…                    …                               …                 …
48890                NaN                               2                 9
48891                NaN                               2                36
48892                NaN                               1                27
48893                NaN                               6                 2
48894                NaN                               1                23

      last_review_year last_review_month last_review_day
0                 2018                10              19
1                 2019                05              21
2                  NaN               NaN             NaN
```

```
3                  2019              07              05
4                  2018              11              19
…                  …                 …               …
48890               NaN               NaN             NaN
48891               NaN               NaN             NaN
48892               NaN               NaN             NaN
48893               NaN               NaN             NaN
48894               NaN               NaN             NaN

[48895 rows x 18 columns]
```

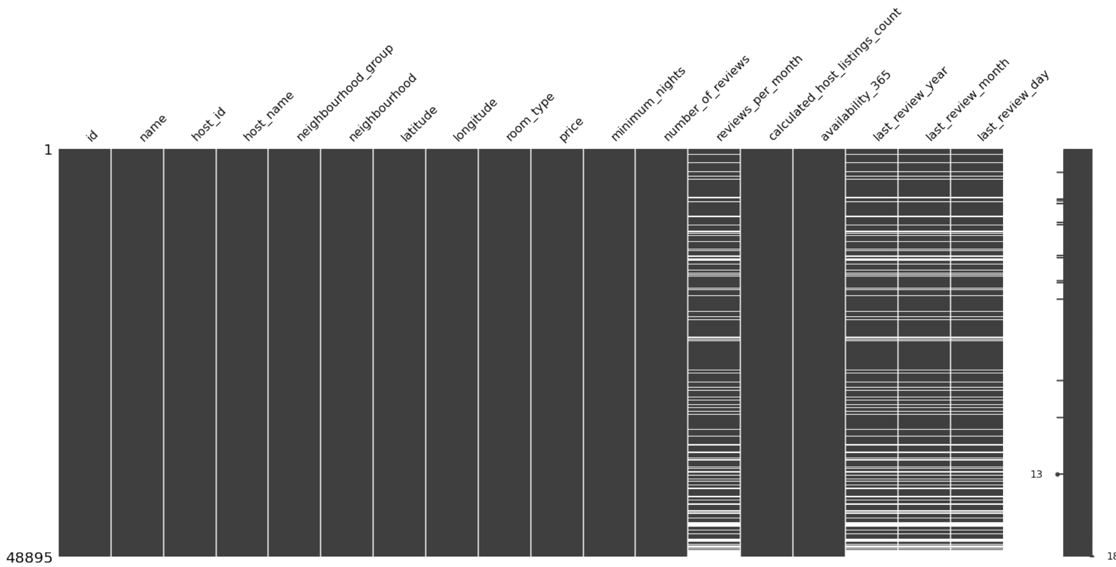
[14]:
```python
import missingno as msno
```

[15]:
```python
#We can observe that the most important variables we should take into␣
 ↪cosideration have no missing values
#Therefore we should just ignore the the missing values and continue the␣
 ↪exploration
Dataset.isna().sum()
```

[15]:
```
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
reviews_per_month                 10052
calculated_host_listings_count        0
availability_365                      0
last_review_year                  10052
last_review_month                 10052
last_review_day                   10052
dtype: int64
```

[16]:
```python
#This step helps us to understand where are the missing values located within␣
 ↪our dataset
msno.matrix(Dataset)
```

[16]: <AxesSubplot:>




[17]:
```
#For the machine learning models we will take place we dont really need the␣
↪variable with the missing values so we should just remove these variables
Dataset=Dataset.
↪drop(['name','host_name','reviews_per_month','last_review_year','last_review_month','last_r
```

[18]:
```
#Observe the relevant details of each object variable within the dataset
Dataset[['id','host_id','neighbourhood_group','neighbourhood','room_type']].
↪describe()
```

[18]:

| | id | host_id | neighbourhood_group | neighbourhood | room_type |
|---|---|---|---|---|---|
| count | 48895 | 48895 | 48895 | 48895 | 48895 |
| unique | 48895 | 37457 | 5 | 221 | 3 |
| top | 2539 | 219517861 | Manhattan | Williamsburg | Entire home/apt |
| freq | 1 | 327 | 21661 | 3920 | 25409 |

[19]:
```
#The object variables within the dataset seem correct since:
#The 'id' variable which represents listing ID is unique as should be
#Some hosts have in their property more than one residence which makes sense as␣
↪well
#My only concern is that the host with number '219517861' has too many␣
↪residences in his possession so that seems a little strange to me
#We have 5 unique locations in which the properties exist which makes sense
#We have 221 unique areas(neighbourhoud) in which the properties exist which␣
↪makes sense
#We have 3 unique room types which makes sense as well
```

[20]:
```
#Below we can observe the summary statistics of the numerical variables of our␣
↪dataset
```

```
Dataset[['latitude','longitude','price','minimum_nights','number_of_reviews','calculated_host_
↪describe()
```

[20]:

```
                latitude     longitude         price  minimum_nights  \
count  48895.000000  48895.000000  48895.000000    48895.000000
mean      40.728949    -73.952170    152.720687        7.029962
std        0.054530      0.046157    240.154170       20.510550
min       40.499790    -74.244420      0.000000        1.000000
25%       40.690100    -73.983070     69.000000        1.000000
50%       40.723070    -73.955680    106.000000        3.000000
75%       40.763115    -73.936275    175.000000        5.000000
max       40.913060    -73.712990  10000.000000     1250.000000

       number_of_reviews  calculated_host_listings_count  availability_365
count       48895.000000                    48895.000000      48895.000000
mean           23.274466                        7.143982        112.781327
std            44.550582                       32.952519        131.622289
min             0.000000                        1.000000          0.000000
25%             1.000000                        1.000000          0.000000
50%             5.000000                        1.000000         45.000000
75%            24.000000                        2.000000        227.000000
max           629.000000                      327.000000        365.000000
```

[21]:

```
#We can observe that the latitude and longitude variable have a very small␣
↪standard deviation and thus data are clustered around the mean values(This␣
↪indicates that the properties are located close by to each other)
#The unusual measure in relevance to the price is that the min value is 0.00.
↪These are propably records which habe been written incorrectly so we should␣
↪drop these records.In addition there are too many outliers within this␣
↪variable that makes me a little concerned as regards the validity of the␣
↪records
```

[22]:

```
Dataset[Dataset.price==0]
```

[22]:

```
             id    host_id neighbourhood_group       neighbourhood  latitude  \
23161  18750597    8993084            Brooklyn  Bedford-Stuyvesant  40.69023
25433  20333471  131697576               Bronx     East Morrisania  40.83296
25634  20523843   15787004            Brooklyn            Bushwick  40.69467
25753  20608117    1641537            Brooklyn          Greenpoint  40.72462
25778  20624541   10132166            Brooklyn        Williamsburg  40.70838
25794  20639628   86327101            Brooklyn  Bedford-Stuyvesant  40.68173
25795  20639792   86327101            Brooklyn  Bedford-Stuyvesant  40.68279
25796  20639914   86327101            Brooklyn  Bedford-Stuyvesant  40.68258
26259  20933849   13709292           Manhattan         Murray Hill  40.75091
26841  21291569  101970559            Brooklyn            Bushwick  40.69211
26866  21304320  101970559            Brooklyn            Bushwick  40.69166
```

```
       longitude        room_type  price  minimum_nights  number_of_reviews  \
23161  -73.95428     Private room      0               4                  1
25433  -73.88668     Private room      0               2                 55
25634  -73.92433     Private room      0               2                 16
25753  -73.94072     Private room      0               2                 12
25778  -73.94645  Entire home/apt      0               5                  3
25794  -73.91342     Private room      0               1                 93
25795  -73.91170     Private room      0               1                 95
25796  -73.91284     Private room      0               1                 95
26259  -73.97597  Entire home/apt      0               3                  0
26841  -73.90670      Shared room      0              30                  2
26866  -73.90928      Shared room      0              30                  5

       calculated_host_listings_count  availability_365
23161                               4                28
25433                               4               127
25634                               5                 0
25753                               2                 0
25778                               1                73
25794                               6               176
25795                               6               232
25796                               6               222
26259                               1                 0
26841                               6               333
26866                               6               139
```

[23]:
```
#Drop the records where the price value is '0'
Dataset=Dataset.
↪drop([23161,25433,25634,25753,25778,25794,25795,25796,26259,26841,26866])
```

[24]:
```
#The summary statistics within the variable minimum_nights seems logical.
↪However we should examine the following:
```

[25]:
```
#Delete records in which minimum_nights(amount of nights minimum) is less than␣
↪availability_365
Dataset=Dataset[Dataset.availability_365>Dataset.minimum_nights]
```

[26]:
```
#There is not anything strange with the number_of_reviews variable
```

[27]:
```
#The minimum value of the variable number_of_reviews is 0.00.However the␣
↪minimum value of reviews_per_months is 0.01 rather than 0.00
#The explanation for that is the fact that all the records with values 0.00␣
↪within the number_of_reviews contain an NaN value within the corresponding␣
↪reviews_per_month variable as shown below and thus they are not included in␣
↪the summary statistics.
```

[28]:
```
Dataset[Dataset.number_of_reviews==0]
```

[28]:
```
          id   host_id neighbourhood_group       neighbourhood  latitude  \
2       3647      4632           Manhattan              Harlem  40.80902
19      7750     17985           Manhattan         East Harlem  40.79685
36     11452      7355            Brooklyn  Bedford-Stuyvesant  40.68876
38     11943     45445            Brooklyn            Flatbush  40.63702
204    54466    253385           Manhattan              Harlem  40.80234
…        …        …                  …                …        …
48890  36484665   8232441            Brooklyn  Bedford-Stuyvesant  40.67853
48891  36485057   6570630            Brooklyn            Bushwick  40.70184
48892  36485431  23492952           Manhattan              Harlem  40.81475
48893  36485609  30985759           Manhattan      Hell's Kitchen  40.75751
48894  36487245  68119814           Manhattan      Hell's Kitchen  40.76404

       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
36     -73.94312     Private room     35              60                  0
38     -73.96327     Private room    150               1                  0
204    -73.95603     Private room    200              30                  0
…          …             …    …            …                …
48890  -73.94995     Private room     70               2                  0
48891  -73.93317     Private room     40               4                  0
48892  -73.94867  Entire home/apt    115              10                  0
48893  -73.99112      Shared room     55               1                  0
48894  -73.98933     Private room     90               7                  0

       calculated_host_listings_count  availability_365
2                                   1               365
19                                  2               249
36                                  1               365
38                                  1               365
204                                 1               365
…                               …               …
48890                               2                 9
48891                               2                36
48892                               1                27
48893                               6                 2
48894                               1                23

[5034 rows x 12 columns]
```

[29]:
```
#There are some outliers within the variable calculated_host_listings_count(amount of listing per host).However we can not be certain if the corresponding records are incorrect.
#Propably some hosts are very rich they own a large number of properties
```

[30]:
```
#We should exlude all the properties which are not available anymore
Dataset=Dataset[Dataset.availability_365!=0]
```

[31]:
```
Dataset
```

[31]:
```
             id   host_id neighbourhood_group       neighbourhood  latitude  \
0          2539      2787            Brooklyn          Kensington  40.64749
1          2595      2845           Manhattan             Midtown  40.75362
2          3647      4632           Manhattan              Harlem  40.80902
3          3831      4869            Brooklyn        Clinton Hill  40.68514
5          5099      7322           Manhattan         Murray Hill  40.74767
…           …        …                   …                 …       …
48890  36484665   8232441            Brooklyn  Bedford-Stuyvesant  40.67853
48891  36485057   6570630            Brooklyn            Bushwick  40.70184
48892  36485431  23492952           Manhattan              Harlem  40.81475
48893  36485609  30985759           Manhattan      Hell's Kitchen  40.75751
48894  36487245  68119814           Manhattan      Hell's Kitchen  40.76404

       longitude        room_type  price  minimum_nights  number_of_reviews  \
0      -73.97237     Private room    149               1                  9
1      -73.98377  Entire home/apt    225               1                 45
2      -73.94190     Private room    150               3                  0
3      -73.95976  Entire home/apt     89               1                270
5      -73.97500  Entire home/apt    200               3                 74
…          …              …    …             …                 …
48890  -73.94995     Private room     70               2                  0
48891  -73.93317     Private room     40               4                  0
48892  -73.94867  Entire home/apt    115              10                  0
48893  -73.99112      Shared room     55               1                  0
48894  -73.98933     Private room     90               7                  0

       calculated_host_listings_count  availability_365
0                                   6               365
1                                   2               355
2                                   1               365
3                                   1               194
5                                   1               129
…                               …                …
48890                               2                 9
48891                               2                36
48892                               1                27
48893                               6                 2
48894                               1                23

[30171 rows x 12 columns]
```

[32]:
```
#We should explore the value counts of the room type variable(this is usefule␣
↪to answer the question given)
print(Dataset[['room_type']].value_counts())
```

```
room_type
Entire home/apt    15754
Private room       13568
Shared room          849
dtype: int64
```

[33]:
```
#As we can see there very very few properties with prices more than 1000␣
↪dollars
#We assume that this is propably a mistake of the dataset and we drop the␣
↪relevant records
Dataset=Dataset[Dataset.price<=1000]
```

[34]:
```
#Calculation of the skewness and kurtosis of the price variable(we should give␣
↪more attention to this variable since it is mentioned in the question)
skewness_of_price=Dataset['price'].skew()
kurtosis_of_price=Dataset['price'].kurt()
```

[35]:
```
#Skewness is a measure of symmetry of the distribution
#The price variable is positively skewed(the tail of the distribution is more␣
↪pronounced on the right side than it is on the left)
skewness_of_price
```

[35]: 2.782595510288187

[36]:
```
#The value of kyrtosis is aproximately 11 which indicates that the distribution␣
↪is too peaked
kurtosis_of_price
```

[36]: 10.990149383963127

[37]:
```
#Calculation of the skewness and kurtosis of the availability_365 variable(we␣
↪should give more attention to this variable since it is mentioned in the␣
↪question)
skewness_of_availability=Dataset['availability_365'].skew()
kurtosis_of_availability=Dataset['availability_365'].kurt()
```

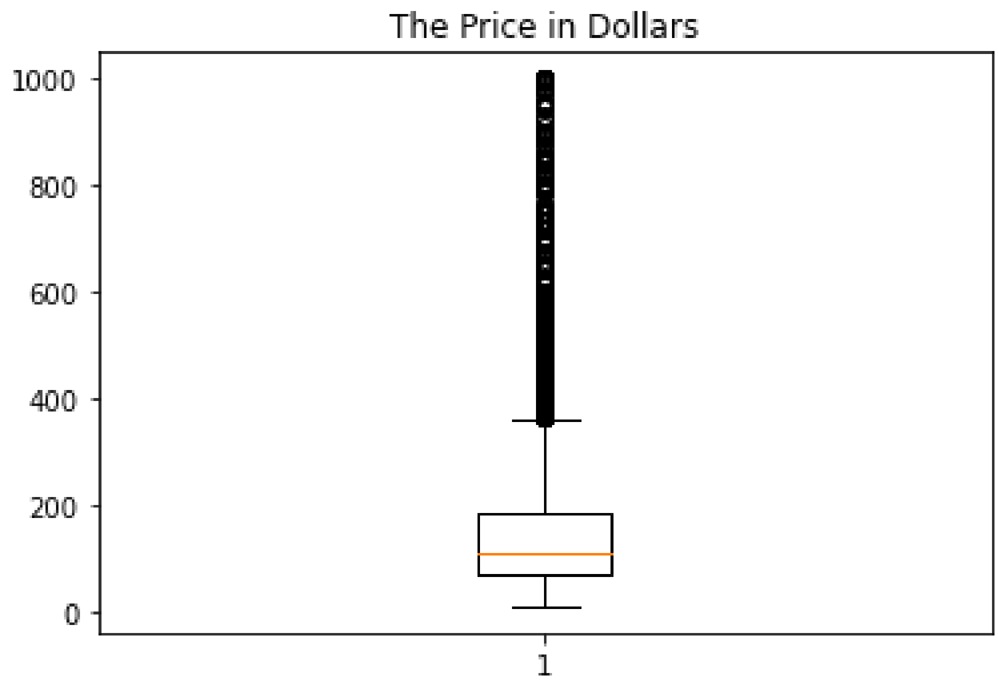
[38]:
```
#The value of skewness of the variable indicates that this variable is nearly␣
↪symmetrical
skewness_of_availability
```

[38]: 0.08528724137360862

[39]:
```
#The value os kurtosis of the variable indicates that the distribution has␣
↪light tails
kurtosis_of_availability
```

[39]: -1.472077753946266

[40]:
```
#Create the boxplot of the variables 'availability_365' and 'price'
import matplotlib.pyplot as plt
import numpy as np
# Creating plot
plt.boxplot(Dataset.price)
plt.title("The Price in Dollars")
# show plot
plt.show()
```

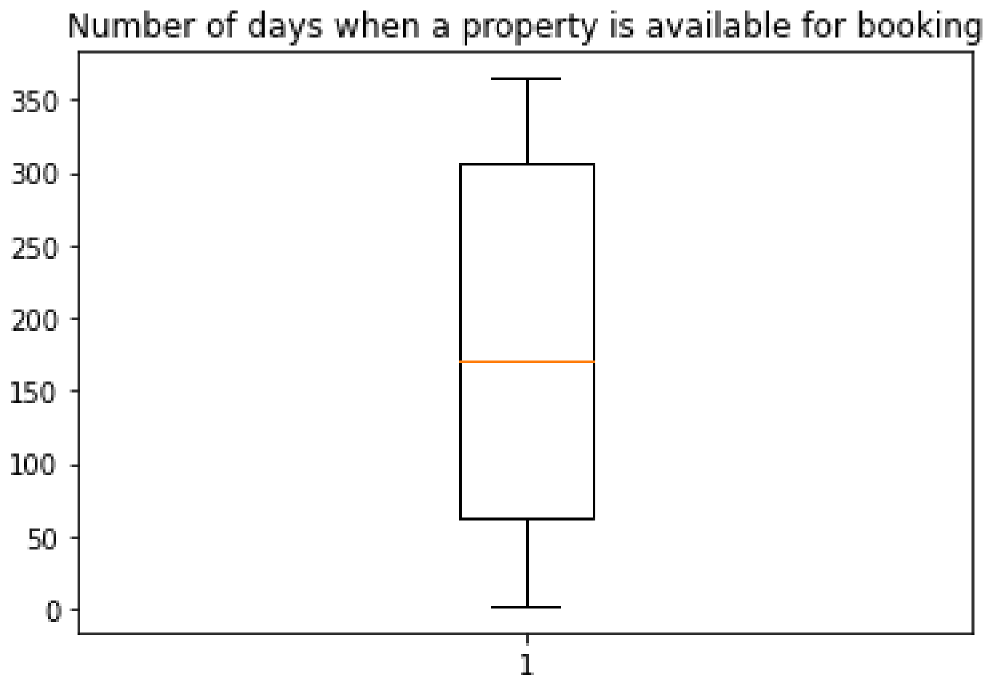



[41]:
```
#Delete all the records with the outliers in price
Dataset=Dataset[Dataset.price<=301]
```

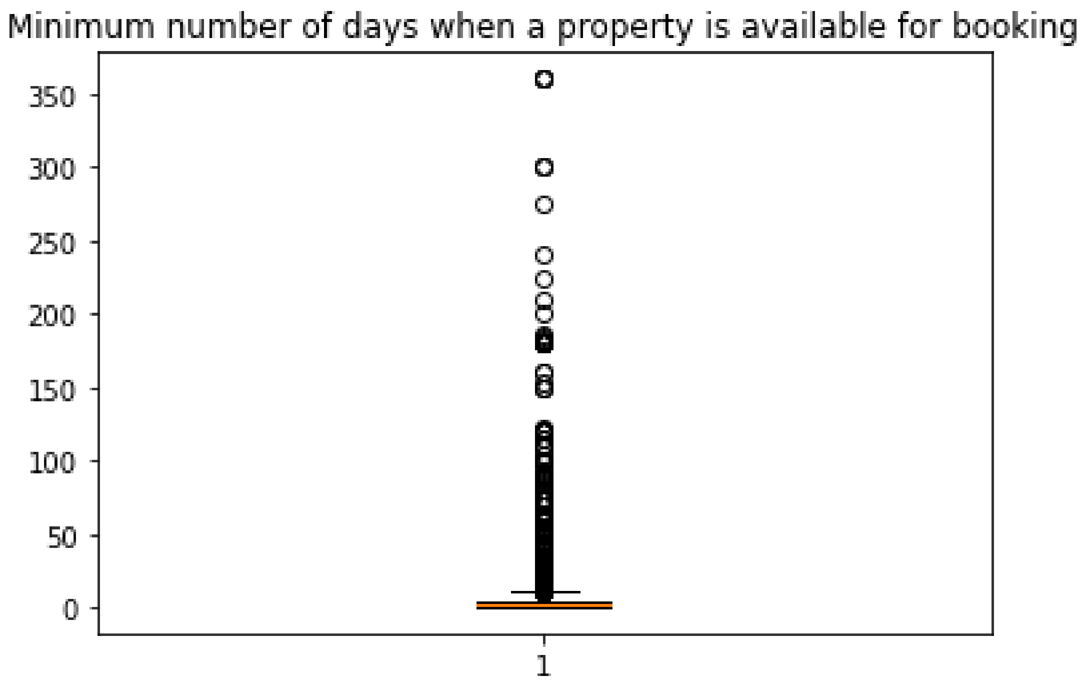
[42]:
```
#We can observe that there are some outliers above the value of 400 dollars␣
↪price as indicated from its skewness and kurtois as well
```

[43]:
```
#Creating plot
plt.boxplot(Dataset.availability_365)
plt.title("Number of days when a property is available for booking")
```

```
#Show plot
plt.show()
#We can observe that there are no outliers within this variable as indicated␣
↪from its skewness and kurotis as well
```




[44]:
```
#Creating plot
plt.boxplot(Dataset.minimum_nights)
plt.title("Minimum number of days when a property is available for booking")
#Show plot
plt.show()
```




[45]:
```python
#Delete all the records with the outliers in minimum nights
Dataset=Dataset[Dataset.minimum_nights<7]
```

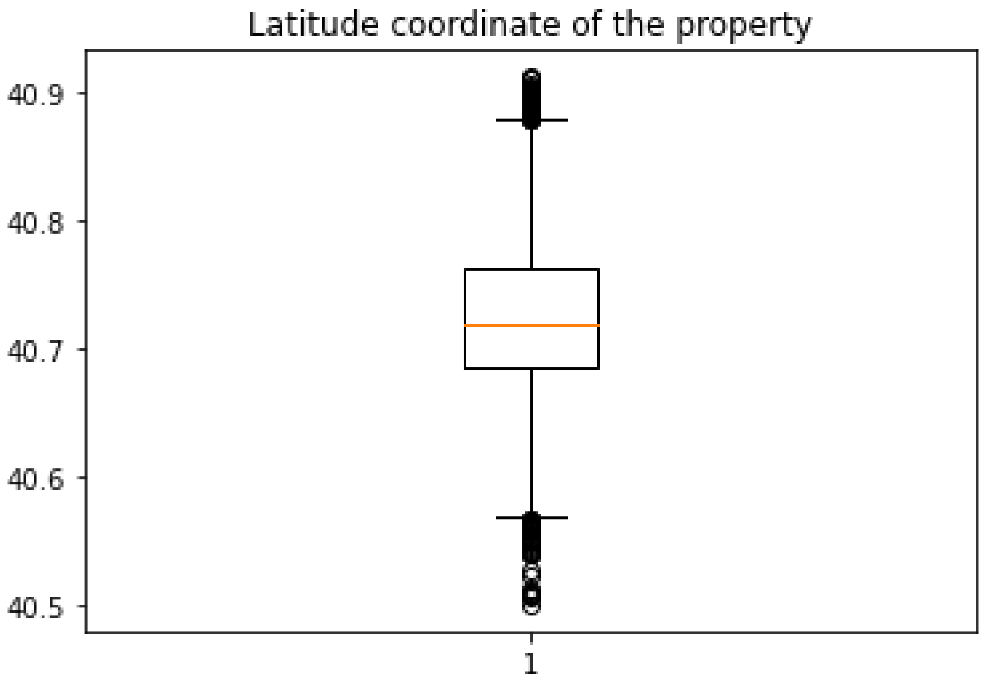
[46]:
```python
Dataset
```

[46]:
```
             id    host_id neighbourhood_group       neighbourhood  latitude  \
0          2539       2787            Brooklyn          Kensington  40.64749
1          2595       2845           Manhattan             Midtown  40.75362
2          3647       4632           Manhattan              Harlem  40.80902
3          3831       4869            Brooklyn        Clinton Hill  40.68514
5          5099       7322           Manhattan         Murray Hill  40.74767
…             …          …                   …                   …         …
48888  36484087  274321313           Manhattan      Hell's Kitchen  40.76392
48889  36484363  107716952              Queens             Jamaica  40.69137
48890  36484665    8232441            Brooklyn  Bedford-Stuyvesant  40.67853
48891  36485057    6570630            Brooklyn            Bushwick  40.70184
48893  36485609   30985759           Manhattan      Hell's Kitchen  40.75751

       longitude        room_type  price  minimum_nights  number_of_reviews  \
0      -73.97237     Private room    149               1                  9
1      -73.98377  Entire home/apt    225               1                 45
2      -73.94190     Private room    150               3                  0
3      -73.95976  Entire home/apt     89               1                270
5      -73.97500  Entire home/apt    200               3                 74
```

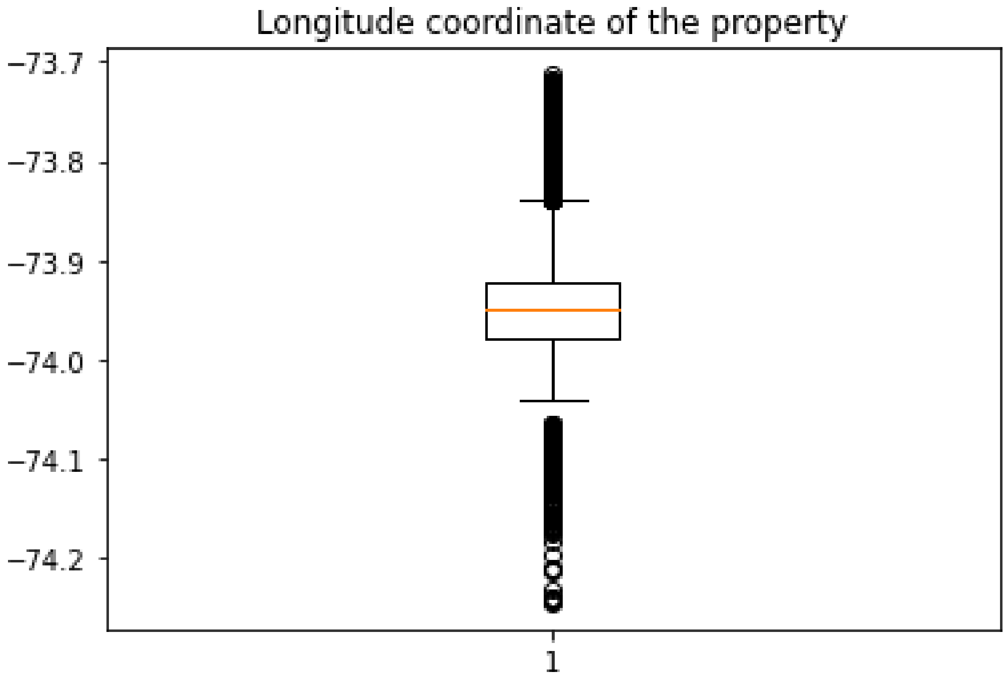
```
…           …              …    …             …                …
48888  -73.99183     Private room    125             4                 0
48889  -73.80844     Private room     65             1                 0
48890  -73.94995     Private room     70             2                 0
48891  -73.93317     Private room     40             4                 0
48893  -73.99112      Shared room     55             1                 0

       calculated_host_listings_count  availability_365
0                                   6               365
1                                   2               355
2                                   1               365
3                                   1               194
5                                   1               129
…                                 …               …
48888                               1                31
48889                               2               163
48890                               2                 9
48891                               2                36
48893                               6                 2

[21780 rows x 12 columns]
```

[47]:

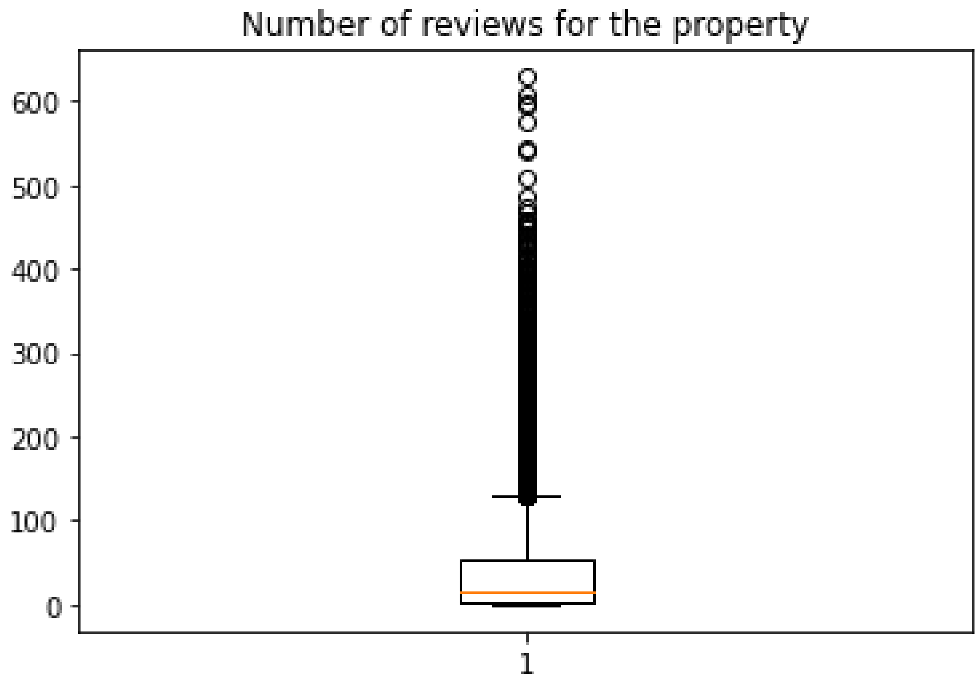
```python
#Creating plot
plt.boxplot(Dataset.latitude)
plt.title("Latitude coordinate of the property")
#Show plot
plt.show()
#In this situation we preseve the outliers since they are too close to the␣
 ↪upper and lower boundaries
```



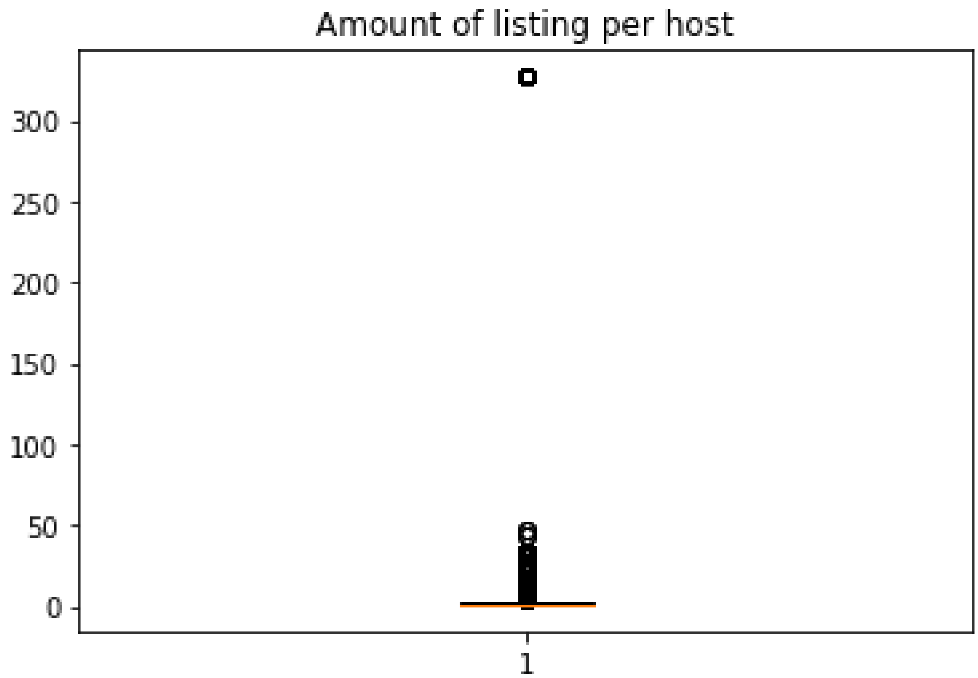

[48]:
```
#Creating plot
plt.boxplot(Dataset.longitude)
plt.title("Longitude coordinate of the property")
#Show plot
plt.show()
#In this situation we presevre the outliers since they are too close to the␣
 ↪upper and lower boundaries
```




[49]:
```
#Creating plot
plt.boxplot(Dataset.number_of_reviews)
plt.title("Number of reviews for the property")
#Show plot
plt.show()
#We will preseve the outliers since this boxplot corresponds to reality(for␣
↪some properties theere are too many reviews)
```

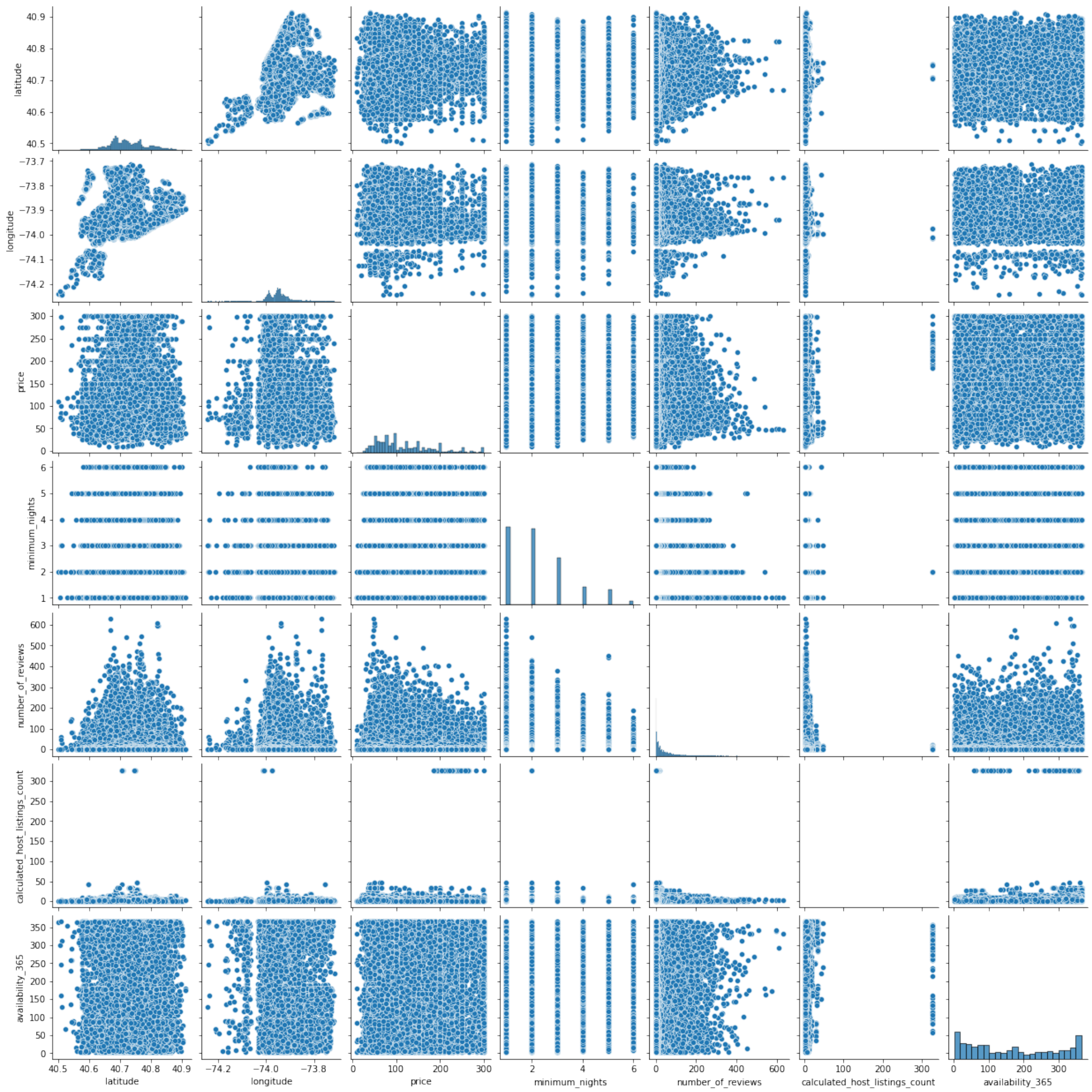



[50]:
```
#Creating plot
plt.boxplot(Dataset.calculated_host_listings_count)
plt.title("Amount of listing per host")
#Show plot
plt.show()
#We are not in a position to tell that the outliers are due to errors since␣
↪there are reach people who belong too many properties
```




[51]:
```
#Perfom the scatterplot between the numerical variables to confirm the above␣
↪correlations
sns.
↪pairplot(Dataset[['latitude','longitude','price','minimum_nights','number_of_reviews','calc
```

[51]: <seaborn.axisgrid.PairGrid at 0x16d4c56e340>

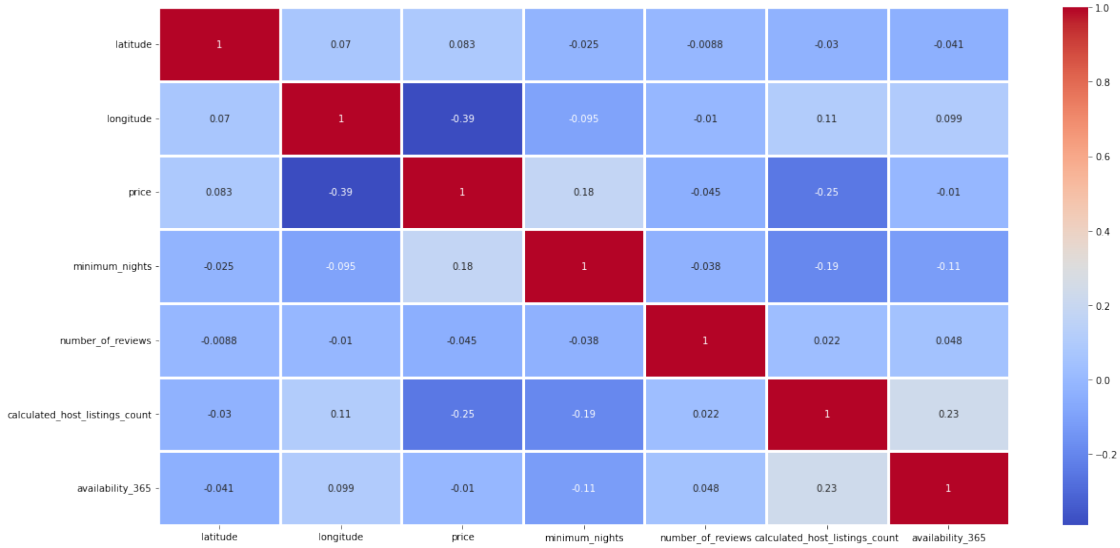



```
[52]: #Calculation of the correlation among the numerical variables of our dataset␣
      ↪with the spearman method since this is more accorate method than pearson,␣
      ↪when we dont deal with variables where exist linear relationship (as␣
      ↪indicated in the pairwise-scatter plots above there is no demonstration that␣
      ↪linear relationship exists among the numerical variables of our dataset)
      Correlation=Dataset[['latitude','longitude','price','minimum_nights','number_of_reviews','calc
      ↪corr(method='spearman')
```

```
[53]: #Display the heatmap in which we can observe the value of the correlation among␣
      ↪the numerical variables
      plt.figure(figsize=(20,10))
```

```
sns.
↪heatmap(Correlation,annot=True,cmap='coolwarm',linecolor='white',linewidths=3)
```

[53]: <AxesSubplot:>




[54]:
```
Dataset
```

[54]:
```
          id    host_id neighbourhood_group       neighbourhood  latitude  \
0       2539       2787            Brooklyn          Kensington  40.64749
1       2595       2845           Manhattan             Midtown  40.75362
2       3647       4632           Manhattan              Harlem  40.80902
3       3831       4869            Brooklyn        Clinton Hill  40.68514
5       5099       7322           Manhattan         Murray Hill  40.74767
…          …          …                   …                   …         …
48888  36484087  274321313          Manhattan      Hell's Kitchen  40.76392
48889  36484363  107716952             Queens             Jamaica  40.69137
48890  36484665    8232441           Brooklyn  Bedford-Stuyvesant  40.67853
48891  36485057    6570630           Brooklyn            Bushwick  40.70184
48893  36485609   30985759          Manhattan      Hell's Kitchen  40.75751

       longitude        room_type  price  minimum_nights  number_of_reviews  \
0      -73.97237     Private room    149               1                  9
1      -73.98377  Entire home/apt    225               1                 45
2      -73.94190     Private room    150               3                  0
3      -73.95976  Entire home/apt     89               1                270
5      -73.97500  Entire home/apt    200               3                 74
…            …               …    …               …                  …
48888  -73.99183     Private room    125               4                  0
48889  -73.80844     Private room     65               1                  0
```

```
48890  -73.94995     Private room     70              2                 0
48891  -73.93317     Private room     40              4                 0
48893  -73.99112      Shared room     55              1                 0

       calculated_host_listings_count  availability_365
0                                   6               365
1                                   2               355
2                                   1               365
3                                   1               194
5                                   1               129
…                               …               …
48888                               1                31
48889                               2               163
48890                               2                 9
48891                               2                36
48893                               6                 2

[21780 rows x 12 columns]
```

[55]:
```
#Display the updated statistical summary of the new dataset created(after
 ↪deleting some varibales and records as shown above) for the numerical
 ↪variables
Dataset[['latitude','longitude','price','minimum_nights','number_of_reviews','calculated_host_
 ↪describe()
```

[55]:
```
           latitude     longitude         price  minimum_nights  \
count  21780.000000  21780.000000  21780.000000    21780.000000
mean      40.725880    -73.942475    119.255464        2.270983
std        0.059818      0.055147     66.551522        1.250312
min       40.499790    -74.244420     10.000000        1.000000
25%       40.685080    -73.978950     67.000000        1.000000
50%       40.718365    -73.948985    100.000000        2.000000
75%       40.763220    -73.923340    158.000000        3.000000
max       40.913060    -73.712990    301.000000        6.000000

       number_of_reviews  calculated_host_listings_count  availability_365
count       21780.000000                    21780.000000      21780.000000
mean           40.145317                        4.429293        166.025115
std            57.061100                       26.327039        122.668684
min             0.000000                        1.000000          2.000000
25%             4.000000                        1.000000         53.000000
50%            17.000000                        1.000000        150.500000
75%            54.000000                        2.000000        284.000000
max           629.000000                      327.000000        365.000000
```

[56]:

```
#Display the updated statistical summary of the new dataset created(after␣
 ↪deleting some varibales and records as shown above) for the categorical␣
 ↪variables
Dataset[['id','host_id','neighbourhood_group','neighbourhood','room_type']].
 ↪describe()
```

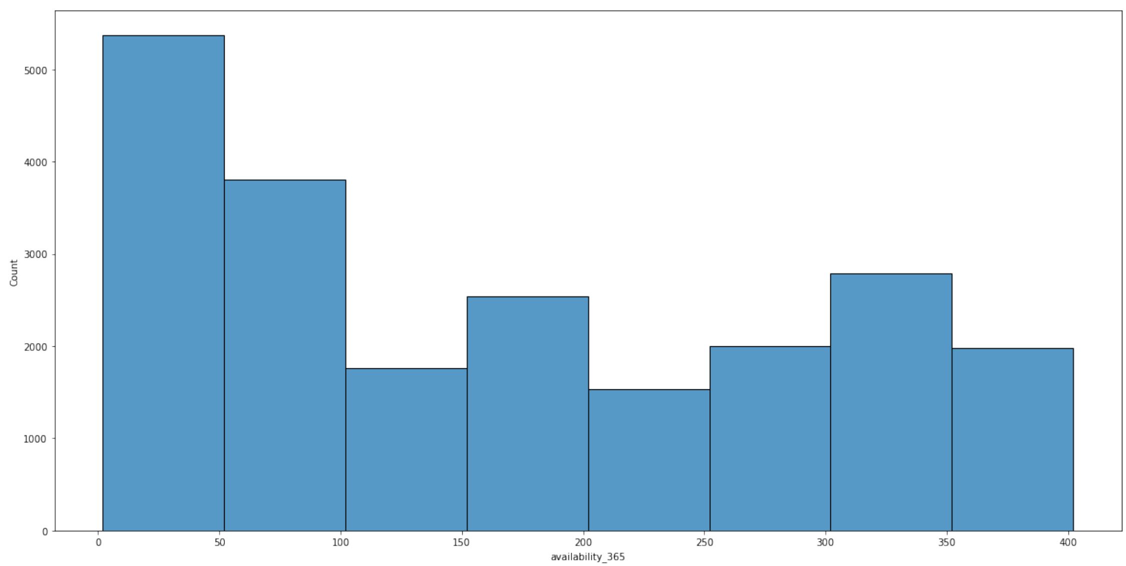
[56]:

| | id | host_id | neighbourhood_group | neighbourhood | room_type |
|---|---|---|---|---|---|
| count | 21780 | 21780 | 21780 | 21780 | 21780 |
| unique | 21780 | 16364 | 5 | 217 | 3 |
| top | 2539 | 219517861 | Brooklyn | Bedford-Stuyvesant | Private room |
| freq | 1 | 142 | 9239 | 1958 | 11250 |

[57]:
```
#Plot the data distribution of the price(price in dollars) and␣
 ↪availability_365(number of days when listing is available for booking)
```

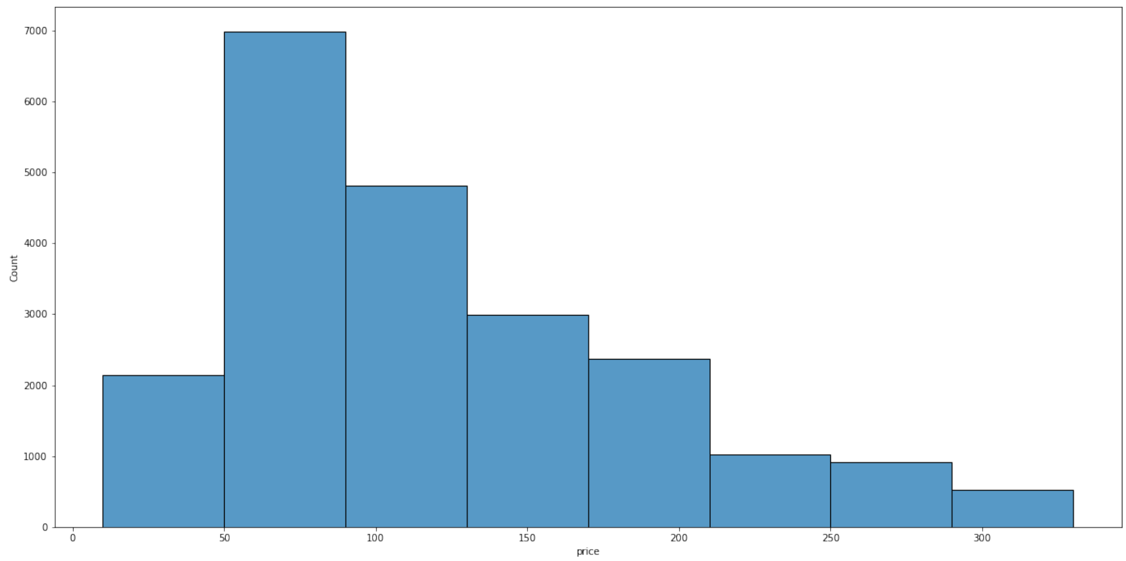
[58]:
```
#Plot the histogram of the 'availability_365'(number of days when listing is␣
 ↪available for booking) and get a general idea of the distribution
plt.figure(figsize=(20,10))
sns.histplot(data=Dataset,x='availability_365',binwidth=50)
```

[58]: <AxesSubplot:xlabel='availability_365', ylabel='Count'>



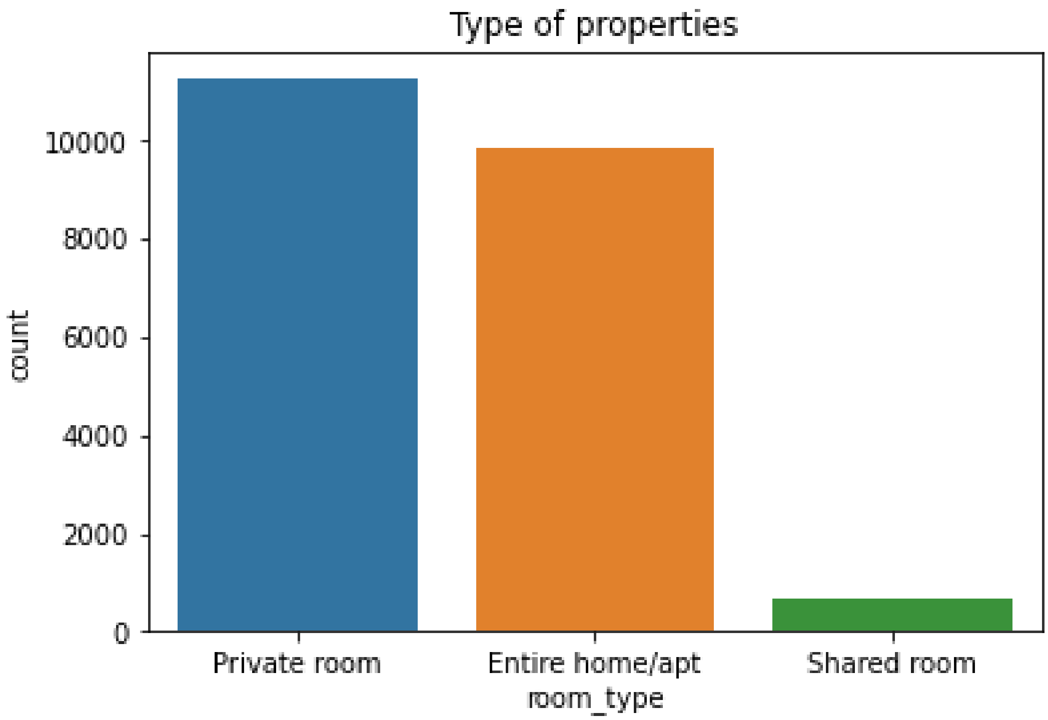

[59]:
```
#Plot the histogram of the price variable and get a general idea of the␣
 ↪distribution
plt.figure(figsize=(20,10))
sns.histplot(data=Dataset,x='price',binwidth=40)
```

[59]: <AxesSubplot:xlabel='price', ylabel='Count'>



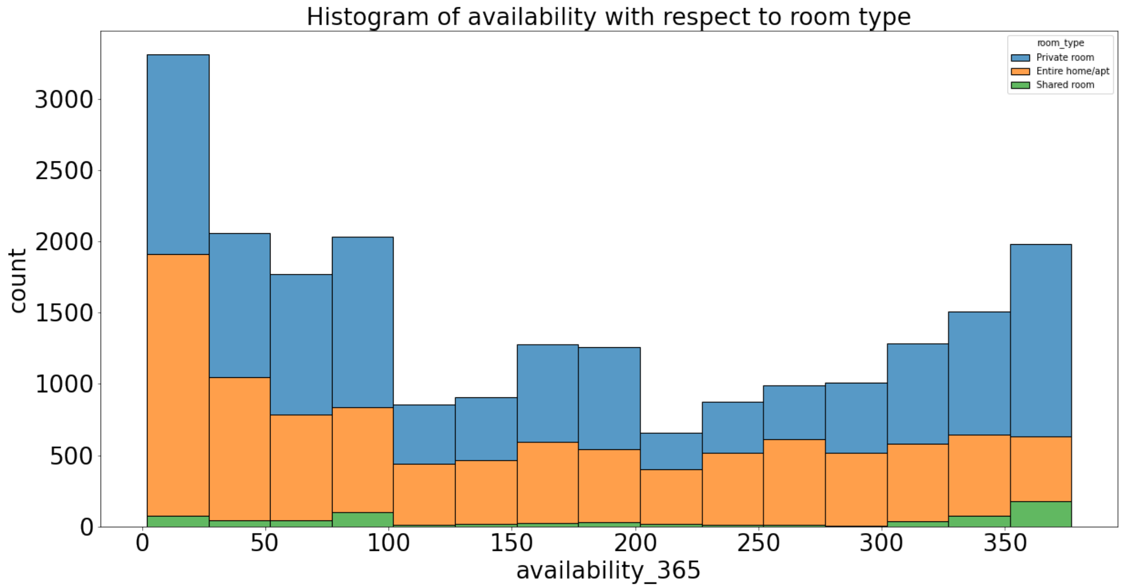

[60]:
```
#What type of properties are most commonly listed on New York City Airbnb Open
 ↪Data
#We can observe that private rooms are the most commonly listed followed by
 ↪entire home/apt room types with a small difference
#We can also observe that the minority is the shared room type with a big
 ↪difference from the rest categories
from matplotlib import pyplot as plt
sns.countplot(data=Dataset,x='room_type')
plt.title("Type of properties")
```

[60]:
```
Text(0.5, 1.0, 'Type of properties')
```



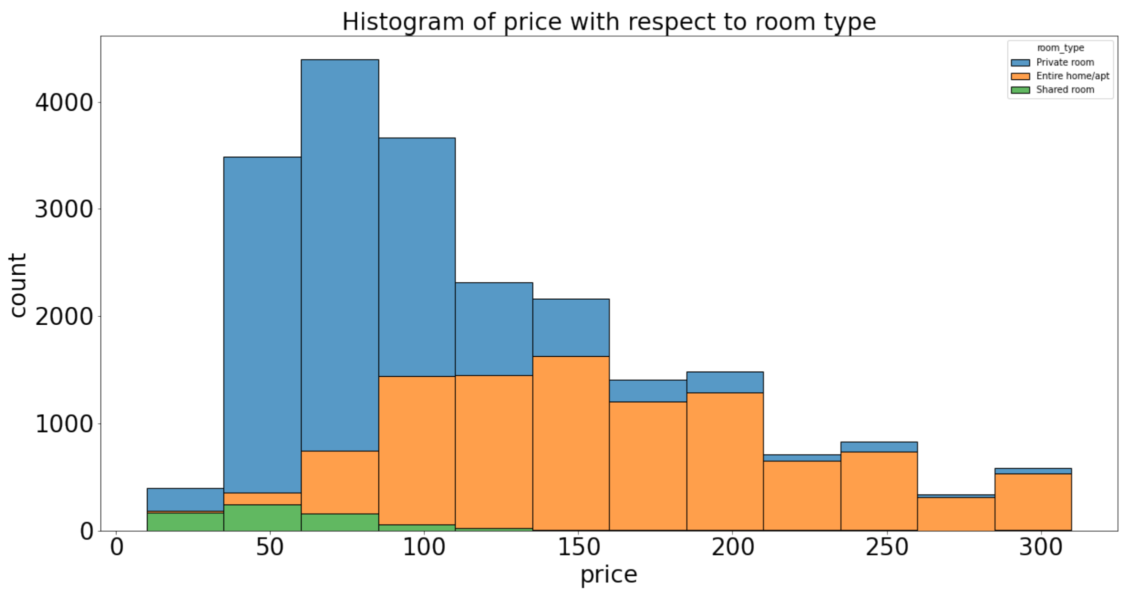

[88]:
```
#How does the property type affect the price?
#Plot the histogram of the 'availability_365'(number of days when listing is␣
↪available for booking)
#There is not a significant pattern here in relevance to the room_types(they␣
↪are almost equally spread)
#However we can opbserve that most of the properties are available between␣
↪10-100 days or 300-365 days
plt.figure(figsize=(20,10))
sns.
↪histplot(data=Dataset,binwidth=25,x='availability_365',hue='room_type',multiple="stack")
sns.histplot()
plt.yticks(fontsize=26)
plt.xticks(fontsize=26)
plt.xlabel('availability_365', fontsize=26)
plt.ylabel('count', fontsize=26)

plt.title('Histogram of availability with respect to room type',size=26)
```

[88]:
```
Text(0.5, 1.0, 'Histogram of availability with respect to room type')
```




[90]:
```
#Plot the histogram of the 'availability_365'(number of days when listing is␣
↪available for booking)
#We can observe that Entire home/apt are more expensive than private rooms.Also␣
↪shared rooms are the cheapest properties
#we can observe that there is a pattern as regards the room types and␣
↪prices(entire home/apt seems to be the most expensive room type)
plt.figure(figsize=(20,10))
sns.
↪histplot(data=Dataset,x='price',binwidth=25,hue='room_type',multiple='stack')
plt.yticks(fontsize=26)
plt.xticks(fontsize=26)
plt.xlabel('price', fontsize=26)
plt.ylabel('count', fontsize=26)
plt.title('Histogram of price with respect to room type',size=26)
```

[90]: Text(0.5, 1.0, 'Histogram of price with respect to room type')



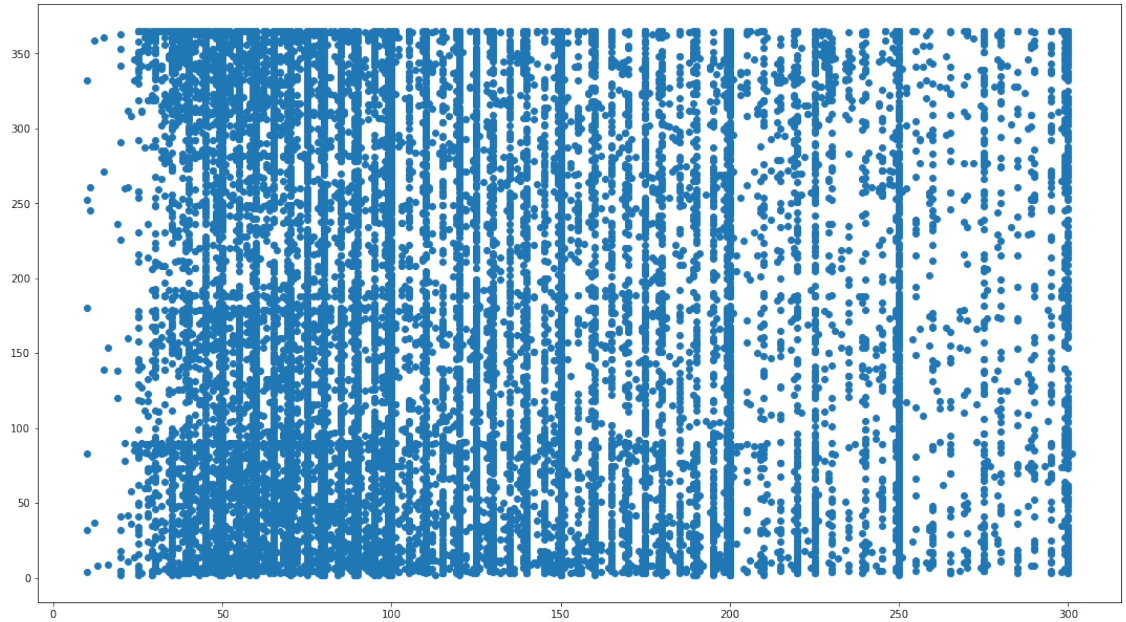

[91]:
```
#We should try to explain the above graphs with the following contigency table␣
↪and our personal experience(criticality)
#Maybe some areas are more expensive than others and some areas are only␣
↪approachable only a limited number of days within a year
data_crosstab = pd.crosstab(Dataset['room_type'],
                            Dataset['neighbourhood_group'],
                                margins = False)
print(data_crosstab)
```

```
neighbourhood_group  Bronx  Brooklyn  Manhattan  Queens  Staten Island
room_type
Entire home/apt        259      4307       3882    1260            135
Private room           501      4719       3705    2170            155
Shared room             43       213        278     145              8
```

[92]:
```
#Machine Learning algorithms
```

[93]:
```
#Create the scatter plot between the 'price' and 'availability' variables which␣
↪I am going to perform a clustering algorithm(get an initial perception of␣
↪the variables)
fig = plt.gcf()
fig.set_size_inches(18.5, 10.5)
plt.scatter(Dataset.price,Dataset.availability_365)
```

[93]: <matplotlib.collections.PathCollection at 0x16d5b12a3d0>




[94]:
```python
from sklearn.cluster import KMeans
```

[95]:
```python
#Perform clustering using 5 clusters
#We use k-means++ centroid initialization for the algorithm(this is a good␣
 ↪method of spearding out the initial centroids and thus speeds up the␣
 ↪algorithm's convergence)
#I choose randomly number of clusters to be 5
#n_init represent the times which the algorithm will run with different␣
 ↪centroids chosen.Eventually the chosen centroids will be those which␣
 ↪decrease inertia at the final stage
#Define max iterations to be 300
km=KMeans(n_clusters=5,init= "k-means++",n_init= 15,max_iter=300)
km
```

[95]:
```
KMeans(n_clusters=5, n_init=15)
```

[96]:
```python
#Assign each record into one cluster of the 5 clusters created previously
y_predicted=km.fit_predict(Dataset[['price','availability_365']])
print(y_predicted)
```

```
[0 4 0 … 1 1 1]
```

[97]:
```python
#Append on the current dataset another one column which shows the clustering of␣
 ↪each record
Dataset['clusters']=y_predicted
Dataset
```

[97]:

```
          id    host_id neighbourhood_group       neighbourhood  latitude  \
0       2539       2787            Brooklyn          Kensington  40.64749
1       2595       2845           Manhattan             Midtown  40.75362
2       3647       4632           Manhattan              Harlem  40.80902
3       3831       4869            Brooklyn        Clinton Hill  40.68514
5       5099       7322           Manhattan         Murray Hill  40.74767
…          …          …                   …                   …         …
48888  36484087  274321313           Manhattan      Hell's Kitchen  40.76392
48889  36484363  107716952              Queens             Jamaica  40.69137
48890  36484665    8232441            Brooklyn  Bedford-Stuyvesant  40.67853
48891  36485057    6570630            Brooklyn            Bushwick  40.70184
48893  36485609   30985759           Manhattan      Hell's Kitchen  40.75751

       longitude        room_type  price  minimum_nights  number_of_reviews  \
0      -73.97237     Private room    149               1                  9
1      -73.98377  Entire home/apt    225               1                 45
2      -73.94190     Private room    150               3                  0
3      -73.95976  Entire home/apt     89               1                270
5      -73.97500  Entire home/apt    200               3                 74
…            …              …     …               …                  …
48888  -73.99183     Private room    125               4                  0
48889  -73.80844     Private room     65               1                  0
48890  -73.94995     Private room     70               2                  0
48891  -73.93317     Private room     40               4                  0
48893  -73.99112      Shared room     55               1                  0

       calculated_host_listings_count  availability_365  clusters
0                                   6               365         0
1                                   2               355         4
2                                   1               365         0
3                                   1               194         2
5                                   1               129         3
…                                  …                …        …
48888                               1                31         1
48889                               2               163         2
48890                               2                 9         1
48891                               2                36         1
48893                               6                 2         1

[21780 rows x 13 columns]
```

[98]:

```
#Seperate the initial Dataset into 5 subdatasets each one including records of the same cluster
Dataset1=Dataset[Dataset.clusters==0]
Dataset2=Dataset[Dataset.clusters==1]
Dataset3=Dataset[Dataset.clusters==2]
Dataset4=Dataset[Dataset.clusters==3]
```

```
Dataset5=Dataset[Dataset.clusters==4]
```

[103]:
```
#Plot the scatter plot of the variables of interest(different colors represent␣
↪different clusters)
fig = plt.gcf()
fig.set_size_inches(18.5, 10.5)
plt.scatter(Dataset1.price,Dataset1.availability_365,color='green')
plt.scatter(Dataset2.price,Dataset2.availability_365,color='red')
plt.scatter(Dataset3.price,Dataset3.availability_365,color='black')
plt.scatter(Dataset4.price,Dataset4.availability_365,color='purple')
plt.scatter(Dataset5.price,Dataset5.availability_365,color='orange')
plt.xlabel('Price($)')
plt.ylabel('Availability(days)')

plt.yticks(fontsize=26)
plt.xticks(fontsize=26)
plt.xlabel('Price($)', fontsize=26)
plt.ylabel('Availability(days)', fontsize=26)
plt.title('The scatterplot of the price and availability',size=26)
```

[103]:
```
Text(0.5, 1.0, 'The scatterplot of the price and availability')
```


[100]:
```
import numpy as np
def NormalizeData(data):
    return (data - np.min(data)) / (np.max(data) - np.min(data))
```

[101]:

```
#Convert the scaling of the variables 'price' and 'availability_365' into the
↪interval [0,1] so that there is no difference in the range of the axes which
↪can affect the algorithm
Dataset['price']=NormalizeData(Dataset['price'])
Dataset['availability_365']=NormalizeData(Dataset['availability_365'])
Dataset
```

[101]:

```
             id    host_id neighbourhood_group       neighbourhood  latitude  \
0          2539       2787            Brooklyn          Kensington  40.64749
1          2595       2845           Manhattan             Midtown  40.75362
2          3647       4632           Manhattan              Harlem  40.80902
3          3831       4869            Brooklyn        Clinton Hill  40.68514
5          5099       7322           Manhattan         Murray Hill  40.74767
…             …          …                   …                   …       …
48888  36484087  274321313           Manhattan      Hell's Kitchen  40.76392
48889  36484363  107716952              Queens             Jamaica  40.69137
48890  36484665    8232441            Brooklyn  Bedford-Stuyvesant  40.67853
48891  36485057    6570630            Brooklyn            Bushwick  40.70184
48893  36485609   30985759           Manhattan      Hell's Kitchen  40.75751

       longitude        room_type     price  minimum_nights  \
0      -73.97237     Private room  0.477663               1
1      -73.98377  Entire home/apt  0.738832               1
2      -73.94190     Private room  0.481100               3
3      -73.95976  Entire home/apt  0.271478               1
5      -73.97500  Entire home/apt  0.652921               3
…            …                …         …              …
48888  -73.99183     Private room  0.395189               4
48889  -73.80844     Private room  0.189003               1
48890  -73.94995     Private room  0.206186               2
48891  -73.93317     Private room  0.103093               4
48893  -73.99112      Shared room  0.154639               1

       number_of_reviews  calculated_host_listings_count  availability_365  \
0                      9                               6          1.000000
1                     45                               2          0.972452
2                      0                               1          1.000000
3                    270                               1          0.528926
5                     74                               1          0.349862
…                      …                               …                 …
48888                  0                               1          0.079890
48889                  0                               2          0.443526
48890                  0                               2          0.019284
48891                  0                               2          0.093664
48893                  0                               6          0.000000

       clusters
```

```
0              0
1              4
2              0
3              2
5              3
…         …
48888          1
48889          2
48890          1
48891          1
48893          1

[21780 rows x 13 columns]
```

[102]:
```
#Perform once again the clustering algorithm to observe if there are any␣
↪differences in relevance to the perfomance of the scaled variables
km=KMeans(n_clusters=5,init= "k-means++",n_init= 15,max_iter=300)
y_predicted=km.fit_predict(Dataset[['price','availability_365']])
y_predicted
```

[102]:
```
array([1, 2, 1, …, 0, 0, 0])
```

[75]:
```
#Replace on the current dataset the updated clusters which shows the updated␣
↪clustering of each record
Dataset['clusters']=y_predicted
Dataset
```

[75]:
```
             id    host_id neighbourhood_group       neighbourhood  latitude  \
0          2539       2787            Brooklyn          Kensington  40.64749
1          2595       2845           Manhattan             Midtown  40.75362
2          3647       4632           Manhattan              Harlem  40.80902
3          3831       4869            Brooklyn        Clinton Hill  40.68514
5          5099       7322           Manhattan         Murray Hill  40.74767
…           …        …                   …                 …       …
48888  36484087  274321313           Manhattan      Hell's Kitchen  40.76392
48889  36484363  107716952              Queens             Jamaica  40.69137
48890  36484665    8232441            Brooklyn  Bedford-Stuyvesant  40.67853
48891  36485057    6570630            Brooklyn            Bushwick  40.70184
48893  36485609   30985759           Manhattan      Hell's Kitchen  40.75751

       longitude        room_type     price  minimum_nights  \
0      -73.97237     Private room  0.477663               1
1      -73.98377  Entire home/apt  0.738832               1
2      -73.94190     Private room  0.481100               3
3      -73.95976  Entire home/apt  0.271478               1
5      -73.97500  Entire home/apt  0.652921               3
…          …               …       …             …
```

```
48888  -73.99183     Private room  0.395189                4
48889  -73.80844     Private room  0.189003                1
48890  -73.94995     Private room  0.206186                2
48891  -73.93317     Private room  0.103093                4
48893  -73.99112      Shared room  0.154639                1

       number_of_reviews  calculated_host_listings_count  availability_365  \
0                      9                               6          1.000000
1                     45                               2          0.972452
2                      0                               1          1.000000
3                    270                               1          0.528926
5                     74                               1          0.349862
…                    …                               …                …
48888                  0                               1          0.079890
48889                  0                               2          0.443526
48890                  0                               2          0.019284
48891                  0                               2          0.093664
48893                  0                               6          0.000000

       clusters
0             3
1             2
2             3
3             0
5             1
…           …
48888         4
48889         0
48890         4
48891         4
48893         4

[21780 rows x 13 columns]
```

[76]:
```
#Seperate the initial Dataset into 5 subdatasets each one including records of
 ↪the same cluster
Dataset1=Dataset[Dataset.clusters==0]
Dataset2=Dataset[Dataset.clusters==1]
Dataset3=Dataset[Dataset.clusters==2]
Dataset4=Dataset[Dataset.clusters==3]
Dataset5=Dataset[Dataset.clusters==4]
```

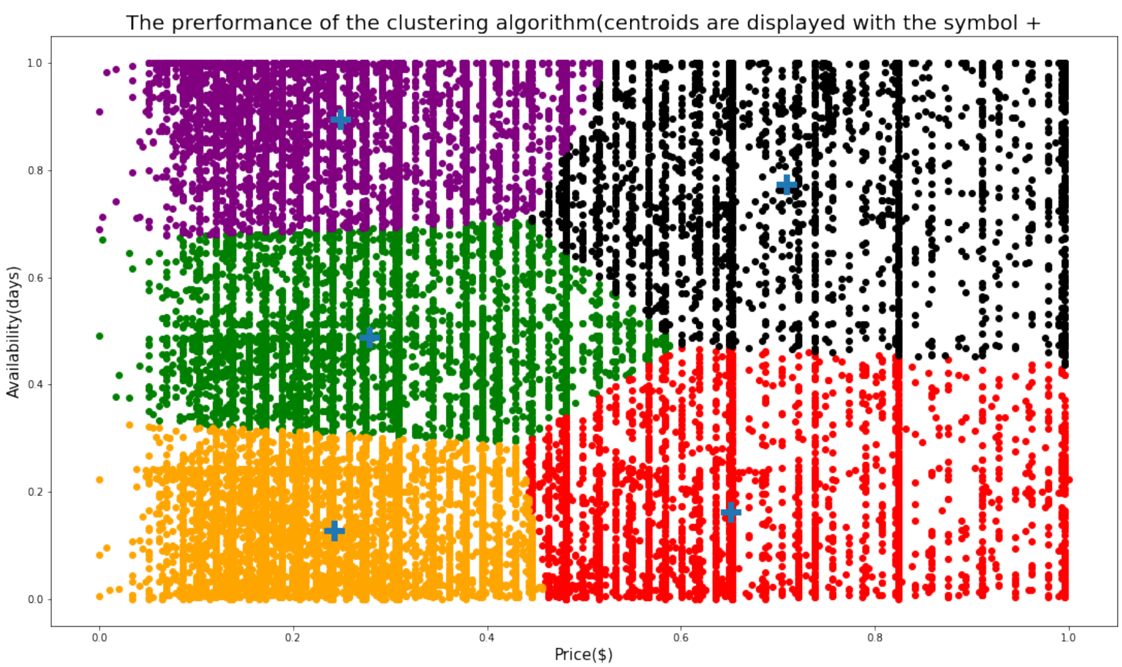
[77]:
```
#Display the 5 centroids of the clustering algorithm
km.cluster_centers_
```

[77]:
```
array([[0.27920081, 0.48696339],
       [0.6523255 , 0.16179599],
```

```
[0.70977053, 0.77167075],
[0.24912601, 0.89483721],
[0.24279846, 0.12661249]])
```

[78]:
```
#Plot the scatter plot of the variables of interest(different colors represent␣
↪different clusters)
fig = plt.gcf()
fig.set_size_inches(18.5, 10.5)
plt.scatter(Dataset1.price,Dataset1.availability_365,color='green')
plt.scatter(Dataset2.price,Dataset2.availability_365,color='red')
plt.scatter(Dataset3.price,Dataset3.availability_365,color='black')
plt.scatter(Dataset4.price,Dataset4.availability_365,color='purple')
plt.scatter(Dataset5.price,Dataset5.availability_365,color='orange')
plt.scatter(km.cluster_centers_[:,0],km.cluster_centers_[:
↪,1],marker='+',label='centorid',linewidths=20)
plt.xlabel('Price($)',size=15)
plt.ylabel('Availability(days)',size=15)
plt.title('The prerformance of the clustering algorithm(centroids are displayed␣
↪with the symbol +',size=20)
```

[78]:
```
Text(0.5, 1.0, 'The prerformance of the clustering algorithm(centroids are
displayed with the symbol +')
```




[79]:
```
#Calculate the Sum of Squares Error value for different number of clusters
k_range=range(1,10)
```

```
Sum_of_Squares_Error=[]
for k in k_range:
    km=KMeans(n_clusters=k,init= "k-means++",n_init= 15,max_iter=300)
    km.fit(Dataset[['price','availability_365']])
    Sum_of_Squares_Error.append(km.inertia_)
```

[80]:
```
#We can observe that while increasing the number of clusters the Sum of Squares␣
↪Error is decreasing(howver the error is still to large since there exist too␣
↪many records within our dataset)
Sum_of_Squares_Error
```

[80]:
```
[3626.2093829469577,
 1638.087114522479,
 1147.079219863167,
 812.4920886803034,
 591.9885357421293,
 505.09800431631146,
 434.2812582004155,
 380.4774143235378,
 338.71770179656943]
```

[81]:
```
#Using the elbow rule we can observe that the best choice for number of␣
↪clusters to perfom our algorithm is 5.
plt.style.use("fivethirtyeight")
plt.xlabel('Number of Clusters')
plt.ylabel('Sum of Squared Error(SSE)')
plt.plot(k_range,Sum_of_Squares_Error)
```

[81]:
```
[<matplotlib.lines.Line2D at 0x26b5e20d370>]
```


[82]:
```
#Silhouette coefficients is a measure of cluster cohesion and seperation(It␣
↪quantifies how well a data point fits into its assigned cluster based on two␣
↪factors:

#1.How close the data point is to other points in the cluster
#2.How far away the data point is from points in other clusters

#Calculate the silhouette coefficients
from sklearn.metrics import silhouette_score, silhouette_samples
silhouette_coefficients = []

# Notice you start at 2 clusters for silhouette coefficient
for k in range(2, 10):
    kmeans = KMeans(n_clusters=k, init= "k-means++",n_init= 12,max_iter= 300)
    kmeans.fit(Dataset[['price','availability_365']])
    score = silhouette_score(Dataset[['price','availability_365']], kmeans.
↪labels_)
    silhouette_coefficients.append(score)
    print('Choosing the number of clusters to be equal to',k,'the corresponding␣
↪silhouette coefficient is',silhouette_coefficients[k-2])

#As we can see below the best choices of number of clusters is 2,3 and 5 since␣
↪the value of the silhouette coefficients in these situations have the␣
↪maximum scores
```

```
Choosing the number of clusters to be equal to 2 the corresponding silhouette
coefficient is 0.4928128435722896
Choosing the number of clusters to be equal to 3 the corresponding silhouette
coefficient is 0.4539714870673677
Choosing the number of clusters to be equal to 4 the corresponding silhouette
coefficient is 0.43221477759789995
Choosing the number of clusters to be equal to 5 the corresponding silhouette
coefficient is 0.44642733410852337
Choosing the number of clusters to be equal to 6 the corresponding silhouette
coefficient is 0.42421968581715536
Choosing the number of clusters to be equal to 7 the corresponding silhouette
coefficient is 0.427417064102737
Choosing the number of clusters to be equal to 8 the corresponding silhouette
coefficient is 0.39959462939780416
Choosing the number of clusters to be equal to 9 the corresponding silhouette
coefficient is 0.38214001875620457
```

[83]:
```
#Calculate the count,mean,std,min,25%,median,75% and max for each numerical␣
↪variable within our dataset, seperately for each group of records assigned␣
↪to a different cluster.
#In this way we can distinguish some differences for each cluster in relevance␣
↪to the numerical variables of our dataset
Dataset.groupby('clusters').describe()
```

[83]:

| | latitude | | | | | | \ |
|---|---|---|---|---|---|---|---|
| | count | mean | std | min | 25% | 50% | |
| clusters | | | | | | | |
| 0 | 4092.0 | 40.725466 | 0.063923 | 40.50873 | 40.68200 | 40.713910 | |
| 1 | 3500.0 | 40.730056 | 0.045021 | 40.53871 | 40.70205 | 40.728090 | |
| 2 | 2727.0 | 40.727545 | 0.049922 | 40.50868 | 40.69172 | 40.724970 | |
| 3 | 4854.0 | 40.721559 | 0.066944 | 40.49979 | 40.67824 | 40.709095 | |
| 4 | 6607.0 | 40.726410 | 0.062028 | 40.52293 | 40.68464 | 40.713990 | |

| | | | longitude | | | | \ |
|---|---|---|---|---|---|---|---|
| | 75% | max | count | mean | std | min | |
| clusters | | | | | | | |
| 0 | 40.766420 | 40.91306 | 4092.0 | -73.933644 | 0.057946 | -74.24442 | |
| 1 | 40.760638 | 40.88238 | 3500.0 | -73.964280 | 0.039492 | -74.16966 | |
| 2 | 40.759325 | 40.90260 | 2727.0 | -73.961875 | 0.045745 | -74.23986 | |
| 3 | 40.762982 | 40.90804 | 4854.0 | -73.929386 | 0.063564 | -74.24285 | |
| 4 | 40.765745 | 40.90406 | 6607.0 | -73.938002 | 0.051841 | -74.21238 | |

| | | | | | price | | \ |
|---|---|---|---|---|---|---|---|
| | 25% | 50% | 75% | max | count | mean | |
| clusters | | | | | | | |
| 0 | -73.964337 | -73.942665 | -73.913820 | -73.71299 | 4092.0 | 0.279562 | |
| 1 | -73.990190 | -73.970925 | -73.949095 | -73.71690 | 3500.0 | 0.652723 | |

```
2        -73.990610 -73.967240 -73.943565 -73.71829  2727.0  0.709683
3        -73.960030 -73.939340 -73.907130 -73.72173  4854.0  0.249013
4        -73.963070 -73.944650 -73.921285 -73.71928  6607.0  0.242886

                                                                      \
               std       min       25%       50%       75%       max
clusters
0         0.123686  0.000000  0.175258  0.261168  0.378007  0.587629
1         0.154275  0.439863  0.515464  0.635739  0.749141  1.000000
2         0.154476  0.446735  0.584192  0.652921  0.824742  0.996564
3         0.111467  0.000000  0.161512  0.230241  0.309278  0.515464
4         0.097547  0.000000  0.168385  0.237113  0.309278  0.457045

         minimum_nights                                               \
                  count      mean       std  min  25%  50%  75%  max
clusters
0                4092.0  2.187195  1.236870  1.0  1.0  2.0  3.0  6.0
1                3500.0  2.645143  1.282956  1.0  2.0  2.0  3.0  6.0
2                2727.0  2.378071  1.205759  1.0  1.0  2.0  3.0  6.0
3                4854.0  2.029254  1.190996  1.0  1.0  2.0  3.0  6.0
4                6607.0  2.258060  1.251521  1.0  1.0  2.0  3.0  6.0

         number_of_reviews                                                     \
                     count       mean        std  min  25%   50%   75%    max
clusters
0                   4092.0  49.185239  65.819731  0.0  6.0  23.0  68.0  576.0
1                   3500.0  27.377429  40.700091  0.0  2.0  11.0  35.0  396.0
2                   2727.0  45.481848  60.797340  0.0  4.0  19.0  66.0  488.0
3                   4854.0  43.635352  62.062286  0.0  4.0  19.0  59.0  629.0
4                   6607.0  36.543514  51.464227  0.0  4.0  16.0  49.0  451.0

         calculated_host_listings_count                                       \
                                  count       mean        std  min  25%  50%
clusters
0                                4092.0   2.361437   2.959122  1.0  1.0  1.0
1                                3500.0   3.470857  24.673368  1.0  1.0  1.0
2                                2727.0  16.887422  67.234618  1.0  1.0  1.0
3                                4854.0   3.304491   4.372939  1.0  1.0  2.0
4                                6607.0   1.902074   1.800597  1.0  1.0  1.0

                     availability_365                                          \
          75%    max            count      mean       std       min       25%
clusters
0         3.0   47.0           4092.0  0.486577  0.101323  0.294766  0.413223
1         1.0  327.0           3500.0  0.161838  0.125133  0.000000  0.046832
2         2.0  327.0           2727.0  0.772012  0.158948  0.438017  0.652893
3         4.0   47.0           4854.0  0.894576  0.092111  0.677686  0.826446
```

```
4          2.0   18.0           6607.0  0.126602  0.087933  0.000000  0.044077

                50%       75%       max
clusters
0          0.482094  0.556474  0.702479
1          0.143251  0.239669  0.468320
2          0.771350  0.914601  1.000000
3          0.914601  0.980716  1.000000
4          0.115702  0.209366  0.325069
```

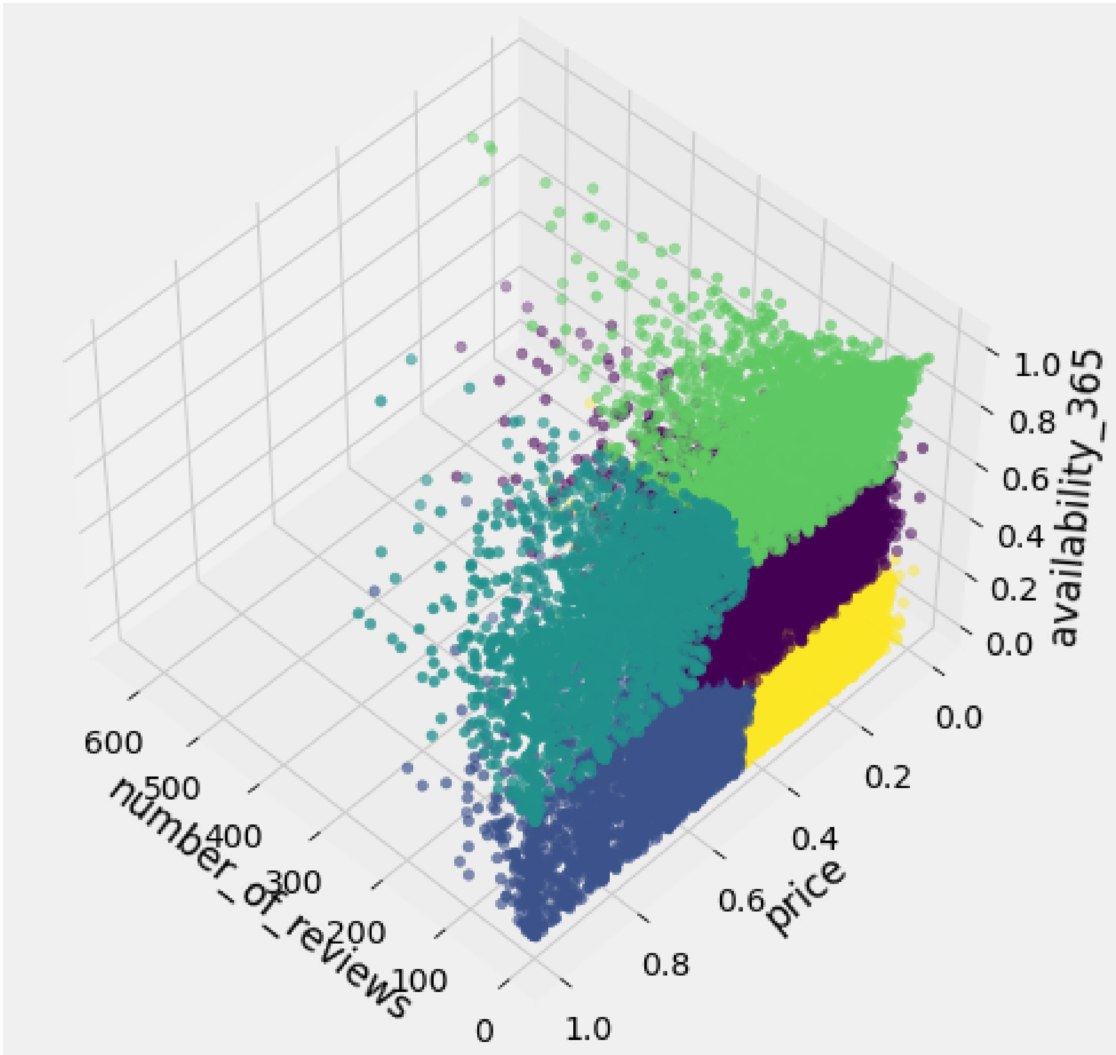
[84]:

```python
from mpl_toolkits.mplot3d import Axes3D
fig = plt.figure(figsize=(8,6))
ax = Axes3D(fig, rect=[0, 0, 0.95, 1], elev=48, azim=134)
ax.set_xlabel('number_of_reviews')
ax.set_ylabel('price')
ax.set_zlabel('availability_365')
ax.scatter(Dataset['number_of_reviews'], Dataset['price'],␣
 ↪Dataset['availability_365'], c= Dataset['clusters'])
```

```
C:\Users\stell\AppData\Local\Temp/ipykernel_820/3148523095.py:3:
MatplotlibDeprecationWarning: Axes3D(fig) adding itself to the figure is
deprecated since 3.4. Pass the keyword argument auto_add_to_figure=False and use
fig.add_axes(ax) to suppress this warning. The default value of
auto_add_to_figure will change to False in mpl3.5 and True values will no longer
work in 3.6.  This is consistent with other Axes classes.
  ax = Axes3D(fig, rect=[0, 0, 0.95, 1], elev=48, azim=134)
```

[84]:

```
<mpl_toolkits.mplot3d.art3d.Path3DCollection at 0x26b600221f0>
```


availability_365
1.0
0.8
0.6
0.4
0.2
0.0
number_of_reviews
600
500
400
300
200
100
0
price
0.0
0.2
0.4
0.6
0.8
1.0

```
[ ]:
```