"Revealing the Hidden Insights of Airbnb in NYC”

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AGENDA

Objective

Data life cycle

Analysis methods

Recommendations

Appendix:

- *Data sources*
- *Data methodology*
- *Data model assumptions*

OBJECTIVE

- *To Conduct a thorough analysis of New York Airbnb Dataset.*
- *Ask ef ective questions that can lead to data insights*
- *process,analyze and share findings by data visualization And statistical techniques*

DATA LIFE CYCLE

In the first phase the data captured and loaded into various envirnoment.

Once data is cleaned, EDA is done and new features are created.

Then Meaningful insights are derived using various analytical methods.

1. Importing libraries and reading the data

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```python
inp0 = pd.read_csv('AB_NYC_2019.csv')
inp0.head(5)
```

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

2. Creating features

2.1 categorizing the "availability_365" column into 5 categories

```python
def availability_365_categories_function(row):
    """
    Categorizes the "minimum_nights" column into 5 categories
    """
    if row <= 1:
        return 'very Low'
    elif row <= 100:
        return 'Low'
    elif row <= 200 :
        return 'Medium'
    elif (row <= 300):
        return 'High'
    else:
        return 'very High'
```

2.2 categorizing the "minimum_nights" column into 5 categories

```python
def minimum_night_categories_function(row):
    """
    Categorizes the "minimum_nights" column into 5 categories
    """
    if row <= 1:
        return 'very Low'
    elif row <= 3:
        return 'Low'
    elif row <= 5 :
        return 'Medium'
    elif (row <= 7):
        return 'High'
    else:
        return 'very High'
```

2.3 categorizing the "number_of_reviews" column into 5 categories

```python
def number_of_reviews_categories_function(row):
    """
    Categorizes the "number_of_reviews" column into 5 categories
    """
    if row <= 1:
        return 'very Low'
    elif row <= 5:
        return 'Low'
    elif row <= 10 :
        return 'Medium'
    elif (row <= 30):
        return 'High'
    else:
        return 'very High'
```

Note: By categorizing, we are able to better understand relationships and connections between things and better communicate our findings.

3. Fixing columns

Fix: reviews_per_month is of object Dtype. datetime64 is a better Dtype for this column.

```
inp0.last_review = pd.to_datetime(inp0.last_review)
inp0.last_review
```

```
0        2018-10-19
1        2019-05-21
2               NaT
3        2019-05-07
4        2018-11-19
            ...
48890           NaT
48891           NaT
48892           NaT
48893           NaT
48894           NaT
Name: last_review, Length: 48895, dtype: datetime64[ns]
```

```
inp0.columns
```

```
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', 'availability_365_categories',
       'minimum_night_categories', 'number_of_reviews_categories',
       'price_categories'],
      dtype='object')
```

There are no more Dtypes to be fixed and data does not contain inconsistencies such as shifted columns, which is need to align correctly.The columns necessery for the futher analysis are also derived.

4. Data types

4.1 Categorical

```
1  inp0.columns
```

```
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', 'availability_365_categories',
       'minimum_night_categories', 'number_of_reviews_categories',
       'price_categories'],
      dtype='object')
```

```
1  # Categorical nominal
2  categorical_columns = inp0.columns[[0,1,3,4,5,8,16,17,18,19]]
3  categorical_columns
```

```
Index(['id', 'name', 'host_name', 'neighbourhood_group', 'neighbourhood',
       'room_type', 'availability_365_categories', 'minimum_night_categories',
       'number_of_reviews_categories', 'price_categories'],
      dtype='object')
```

4.2 Numerical

```
1  numerical_columns = inp0.columns[[9,10,11,13,14,15]]
2  numerical_columns
```

```
Index(['price', 'minimum_nights', 'number_of_reviews', 'reviews_per_month',
       'calculated_host_listings_count', 'availability_365'],
      dtype='object')
```

```
1  inp0[numerical_columns].describe()
```

	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availability_365
count	48895.000000	48895.000000	48895.000000	38843.000000	48895.000000	48895.000000
mean	152.720687	7.029962	23.274466	1.373221	7.143982	112.781327
std	240.154170	20.510550	44.550582	1.680442	32.952519	131.622289
min	0.000000	1.000000	0.000000	0.010000	1.000000	0.000000
25%	69.000000	1.000000	1.000000	0.190000	1.000000	0.000000
50%	106.000000	3.000000	5.000000	0.720000	1.000000	45.000000
75%	175.000000	5.000000	24.000000	2.020000	2.000000	227.000000
max	10000.000000	1250.000000	629.000000	58.500000	327.000000	365.000000

4.3 Coordinates and date

```
1  coordinates = inp0.columns[[5,6,12]]
2  inp0[coordinates]
```

	neighbourhood	latitude	last_review
0	Kensington	40.64749	2018-10-19
1	Midtown	40.75362	2019-05-21
2	Harlem	40.80902	NaT
3	Clinton Hill	40.68514	2019-05-07
4	East Harlem	40.79851	2018-11-19
...	...	...	...
48890	Bedford-Stuyvesant	40.67853	NaT
48891	Bushwick	40.70184	NaT
48892	Harlem	40.81475	NaT
48893	Hell's Kitchen	40.75751	NaT
48894	Hell's Kitchen	40.76404	NaT

48895 rows × 3 columns

5. Missing values

```
# Percentage of missing values
round((inp0.isnull().sum()/len(inp0))*100,2)
```

```
id                                 0.00
name                               0.03
host_id                            0.00
host_name                          0.04
neighbourhood_group                0.00
neighbourhood                      0.00
latitude                           0.00
longitude                          0.00
room_type                          0.00
price                              0.00
minimum_nights                     0.00
number_of_reviews                  0.00
last_review                       20.56
reviews_per_month                 20.56
calculated_host_listings_count     0.00
availability_365                   0.00
availability_365_categories        0.00
minimum_night_categories           0.00
number_of_reviews_categories       0.00
price_categories                   0.00
dtype: float64
```

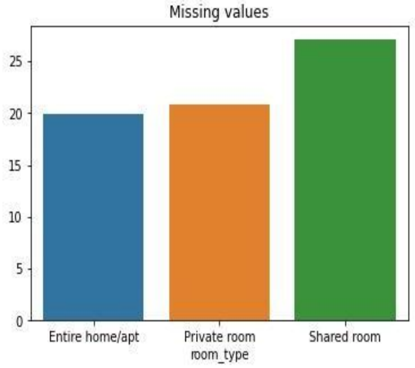
- Two columns (last_review , reviews_per_month) has around 20.56% missing values. name and host_name has 0.3% and 0.4 % missing values

- We need to see if the values are, MCAR: It stands for Missing completely at random.

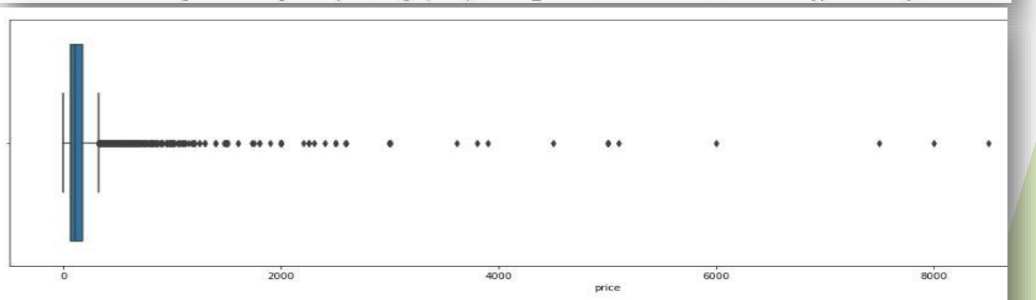
The reason behind the missing value is not dependent on any other features or if it is MNAR: It stands for Missing not at random. There is a specific reason behind the missing value.

- There is no dropping or imputation of columns as we are just analyzing the dataset and not making a model.Also most of the features are important for our analysis.

5.1 Missing value analysis



'Shared room' has the highest missing value percentage (27 %) for 'last_review' feature while to other room types has only about 20 %.



- The pricing is higher when 'last_review' feature is missing .
- reviews are less likely to be given for shared rooms
- When the prices are high reviews are less likely to be given
- The above analysis seems to show that the missing values here are not MCAR (missing completely at random)

6. Analysis

6.6 room_type

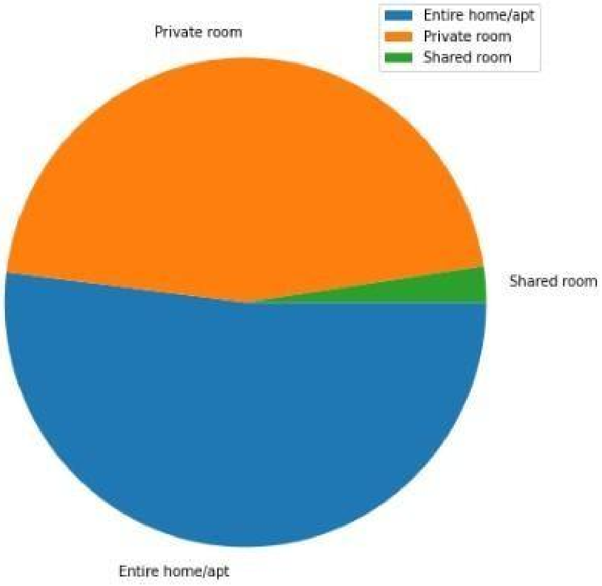
```
inp0.room_type.value_counts()
```

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

```
inp0.room_type.value_counts(normalize=True)*100
```

```
Entire home/apt    51.966459
Private room       45.661111
Shared room         2.372431
Name: room_type, dtype: float64
```

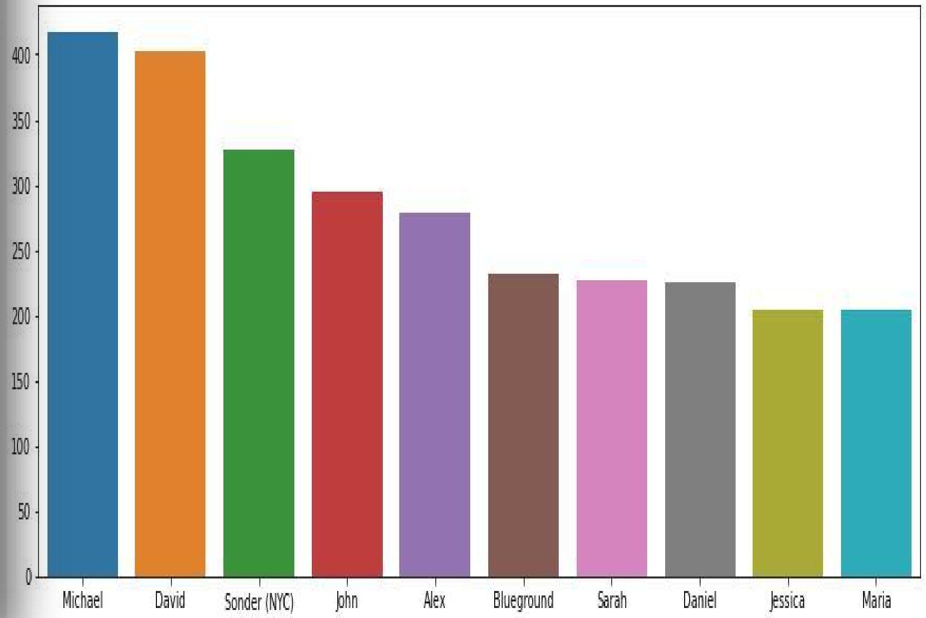
```
plt.figure(figsize=(8,8))
plt.pie(x = inp0.room_type.value_counts(normalize= True) * 100,labels = inp0.room_type.value_counts(normalize= True).
plt.legend()
plt.show()
```



6.3 host_name

```
inp0.host_name.value_counts()
```

```
Michael              417
David                403
Sonder (NYC)         327
John                 294
Alex                 279
                    ...
Rhonycs                1
Brandy-Courtney        1
Shanthony              1
Aurore And Jamila      1
Ilgar & Aysel          1
Name: host_name, Length: 11452, dtype: int64
```



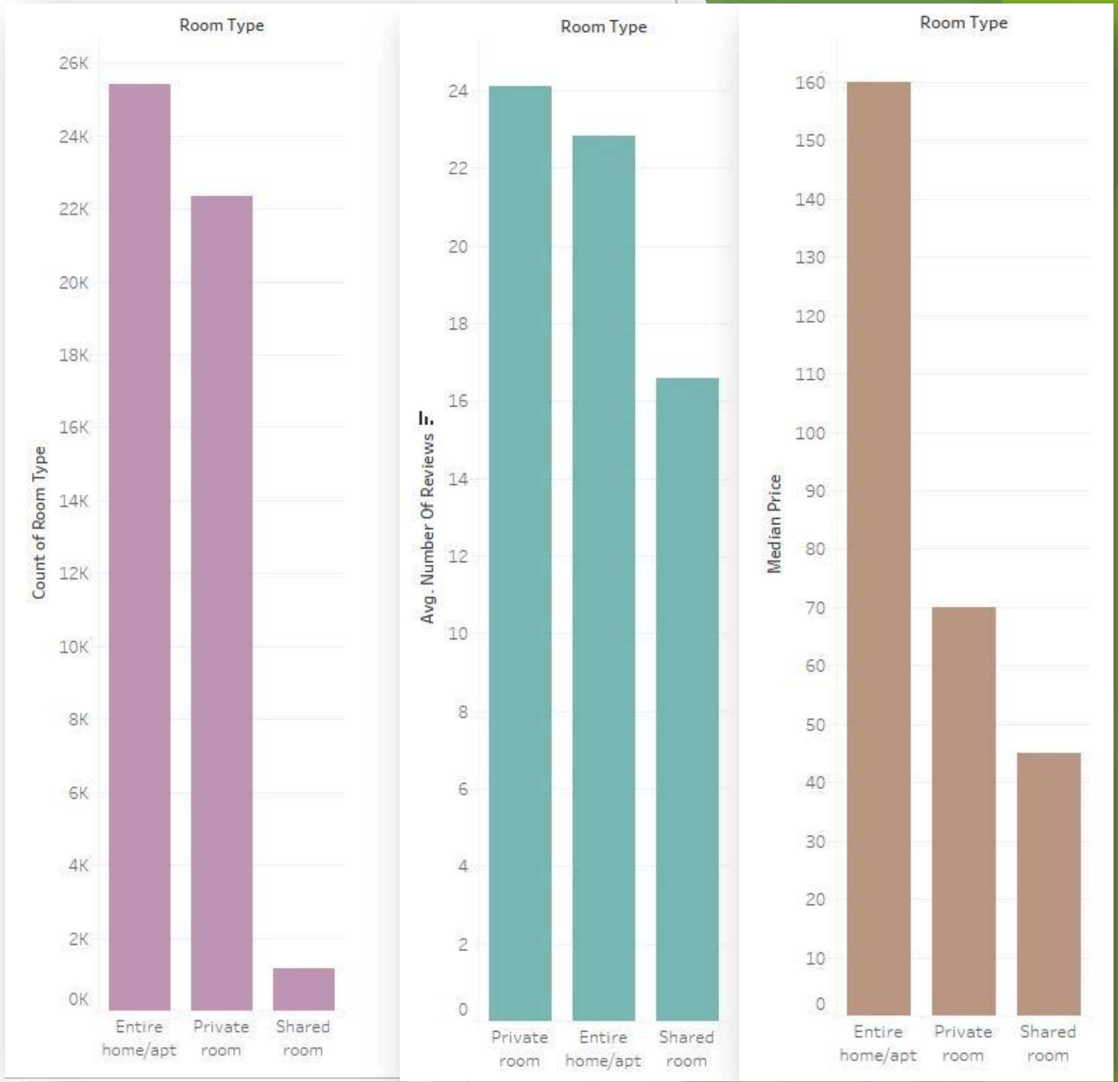
THE PROBLEMS WITH SHARED ROOMS

Shared rooms only account for 2 % of the

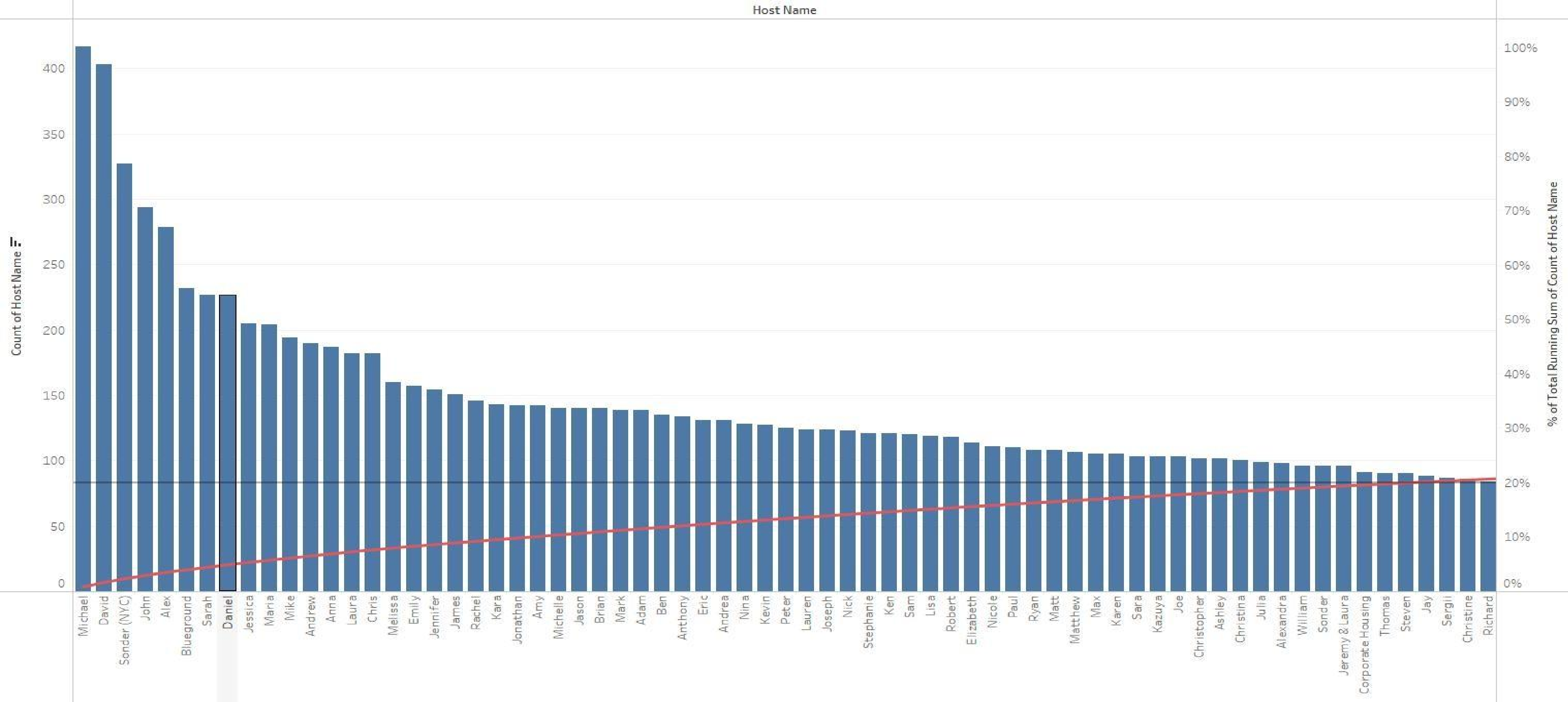
total types of rooms.

They are less likely to be reviewed.

Median rates for shared rooms are significantly lower.

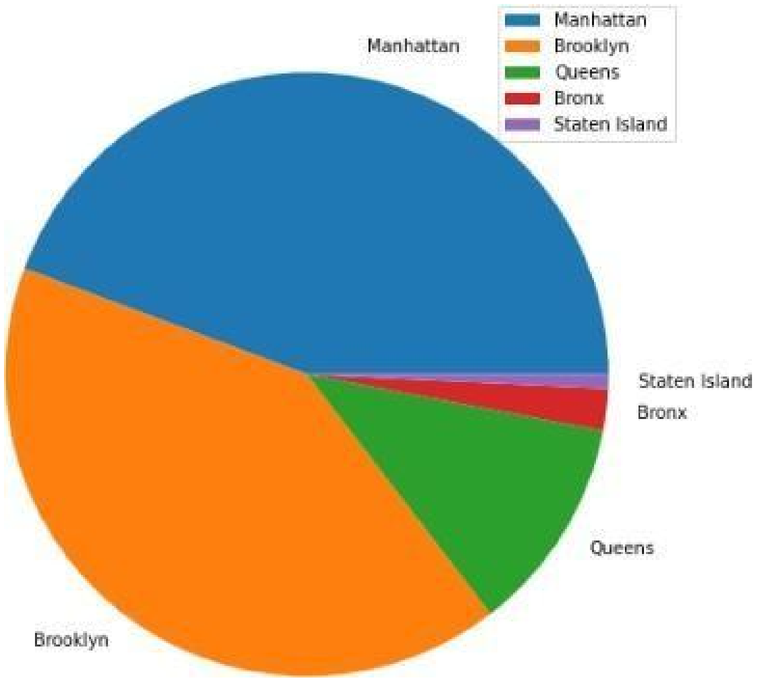


EVERY HOST



- ***The top 60 hosts only make up 20% of the total host count!***

MOST CONTRIBUTING NEIGHBORHOODS

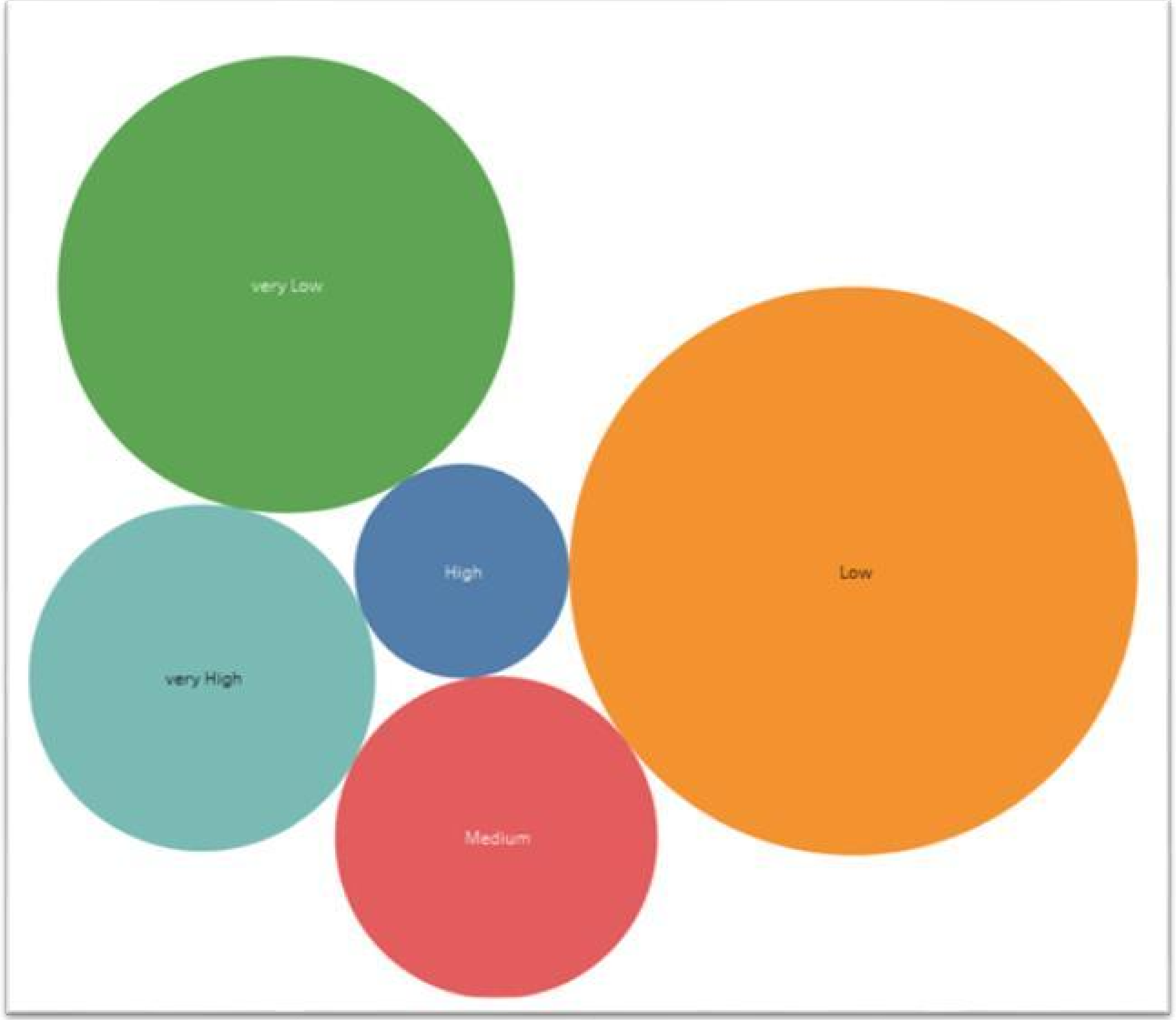


Neighborhood group percentages

Manhattan	44.301053
Brooklyn	41.116679
Queens	11.588097
Bronx	2.231312
Staten Island	0.762859

- ***81 % of the listing are Manhattan and Brooklyn neighborhood group***
- ***Staten Island has the lowest contribution.***

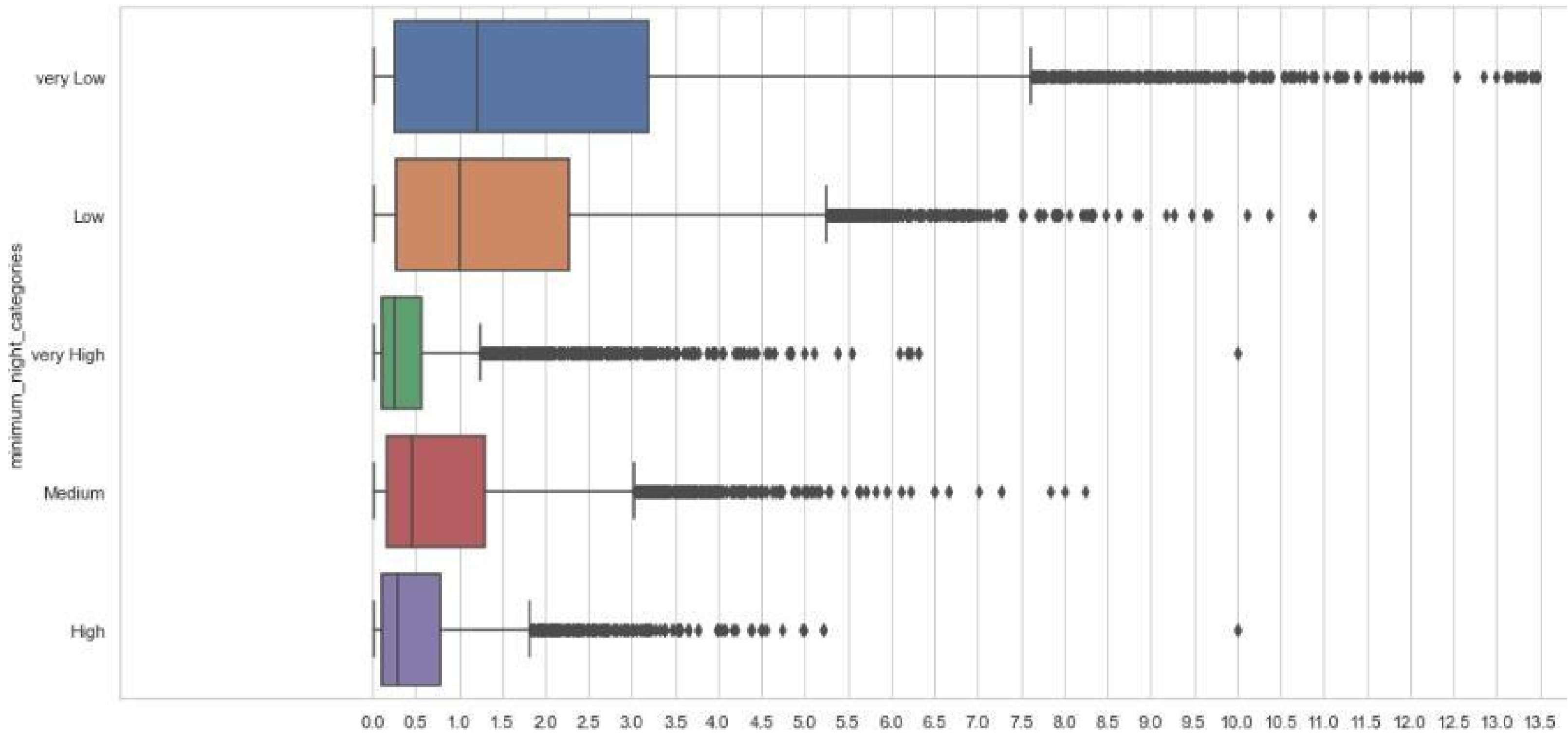
MINIMUM NIGHT CATEGORIES



Minimum night category percentages

Low	40.280192
very Low	26.014930
very High	14.997444
Medium	12.960425
High	5.747009

- *Low category in minimum night feature contributes 40 %*



EFFECT OFMINIMUM NIGHT ON REVIEWS

Customers are more likely to leave reviews for lower number of minimum nights.

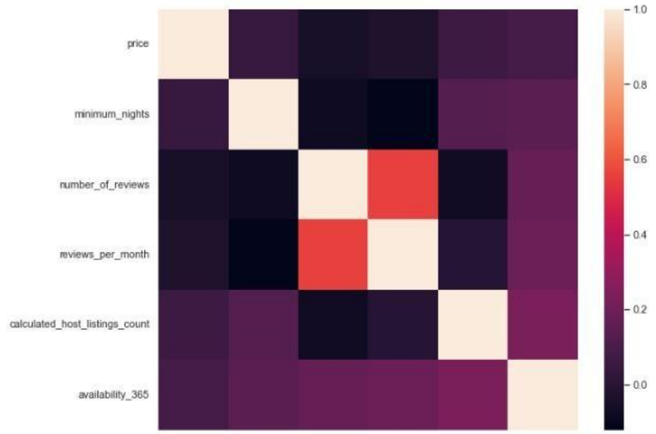
7. Bivariate and Multivariate Analysis

7.1 Finding the correalations

```
inp0[numerical_columns].corr()
```

	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availability_365
price	1.000000	0.042799	-0.047954	-0.030608	0.057472	0.081829
minimum_nights	0.042799	1.000000	-0.080116	-0.121702	0.127960	0.144303
number_of_reviews	-0.047954	-0.080116	1.000000	0.549868	-0.072376	0.172028
reviews_per_month	-0.030608	-0.121702	0.549868	1.000000	-0.009421	0.185791
calculated_host_listings_count	0.057472	0.127960	-0.072376	-0.009421	1.000000	0.225701
availability_365	0.081829	0.144303	0.172028	0.185791	0.225701	1.000000

```
plt.figure(figsize=(10,8))
sns.heatmap(data = inp0[numerical_columns].corr())
plt.show()
```



CONCLUSION

Strong significant insights are derived based on various attributes in the dataset.

Ample amount and variety of visuals have can used in the presentations for the stake-holders.

Data collection team should collect data about review scores so that it can strengthen the later analysis

A clustering machine learning model to identify groups of similar objects in datasets with two or more variable quantities can be made

APPENDIX - DATA SOURCES

- *The columns in the dataset are self-explanatory. You can refer to the diagram given below to get a better idea of what each column signifies.*

Column	Description
id	listing ID
name	name of the listing
host_id	host ID
host_name	name of the host
neighbourhood_group	location
neighbourhood	area
latitude	latitude coordinates
longitude	longitude coordinates
room_type	listing space type
price	
minimum_nights	amount of nights minimum
number_of_reviews	number of reviews
last_review	latest review
reviews_per_month	number of reviews per month
calculated_host_listings_count	amount of listing per host
availability_365	number of days when listing is available for booking

APPENDIX –DATA METHODOLOGY

- *Conducted a thorough analysis of NewYork Airbnbs Dataset.*
- *Cleaned the data set using python.*
- *Derived the necessary features.*
- *Used group aggregation, pivot table and other statistical methods.*
- *Created charts and visualizations using Tableau.*

APPENDIX - DATA ASSUMPTIONS

```
Categorical Variables:
      - room_type
      - neighbourhood_group
      - neighbourhood

Continous Variables(Numerical):
      - Price
      - minimum_nights
      - number_of_reviews
      - reviews_per_month
      - calculated_host_listings_count
      - availability_365
- Continous Variables could be binned in to groups too

Location Varibles:
      - latitude
      - longitude

Time Varibale:
      - last_review
```