UNLOCKING AIRBNB NYC

PRESENTATION - II

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OBJECTIVE

- Understand the Airbnb market in NYC and do a thorough analysis
- Identify key factors influencing occupancy and pricing
- Provide actionable insights to increase revenue

AGENDA

- Background
- Insights
  - Top 10 Hosts
  - % Listings basis Neighborhood Group
  - Guest Preferences
  - Effect of Minimum Nights on Reviews
- Conclusion & Recommendations
- Appendix
  - Data Sources/Methodology
  - Steps Performed during the Analysis

BACKGROUND

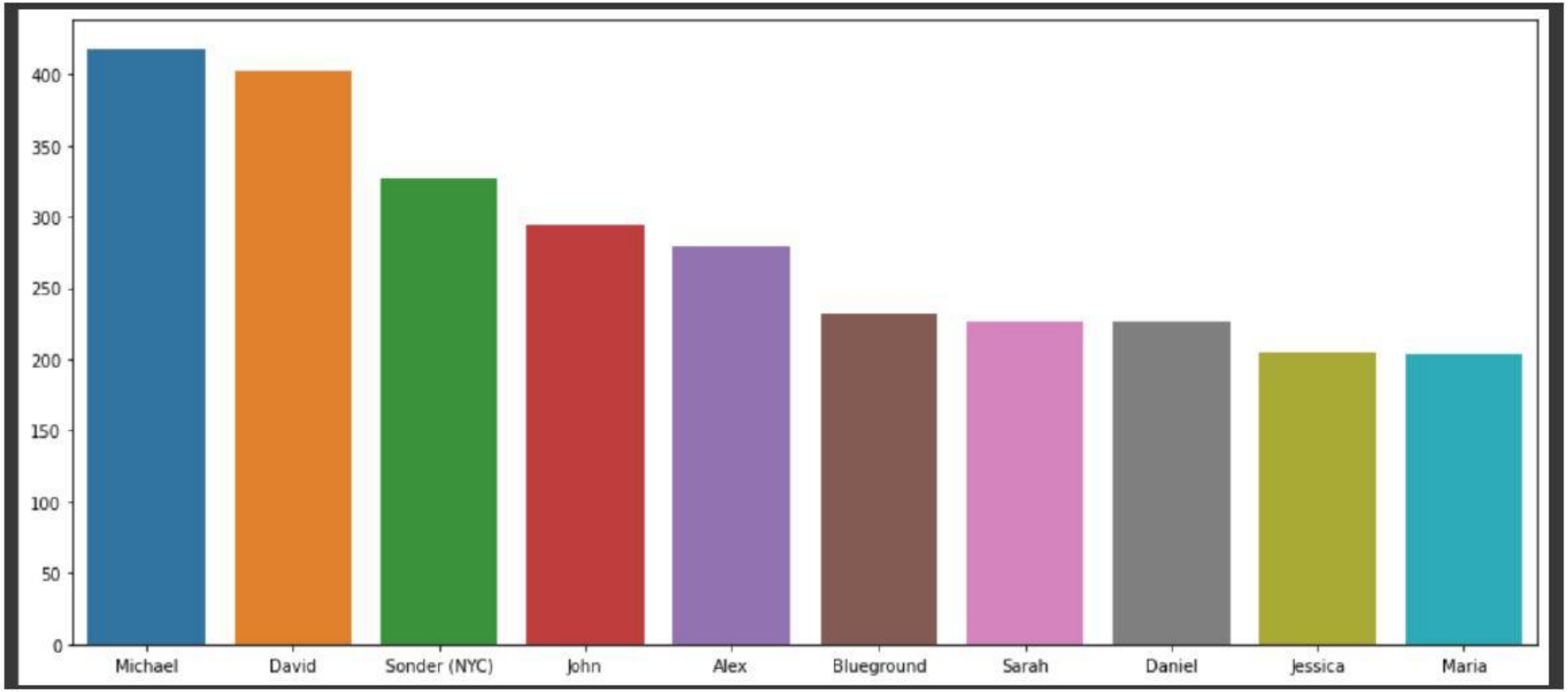
In recent months, Airbnb has experienced a significant decline in revenue.

Now that restrictions are lifting & people are starting to travel more.

Airbnb wants to ensure it is fully prepared for this shift.

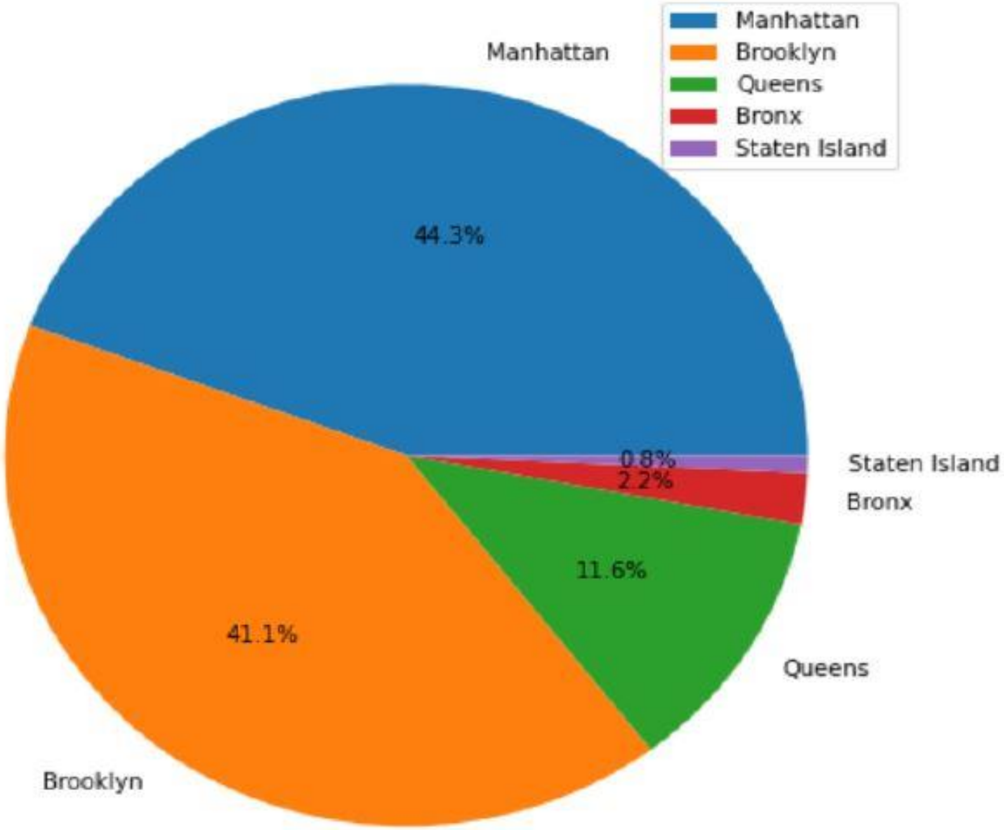
Top 10 Hosts

These top 10 hosts play a crucial role in shaping the Airbnb experience in New York City, offering a wide range of properties and catering to various customer preferences.



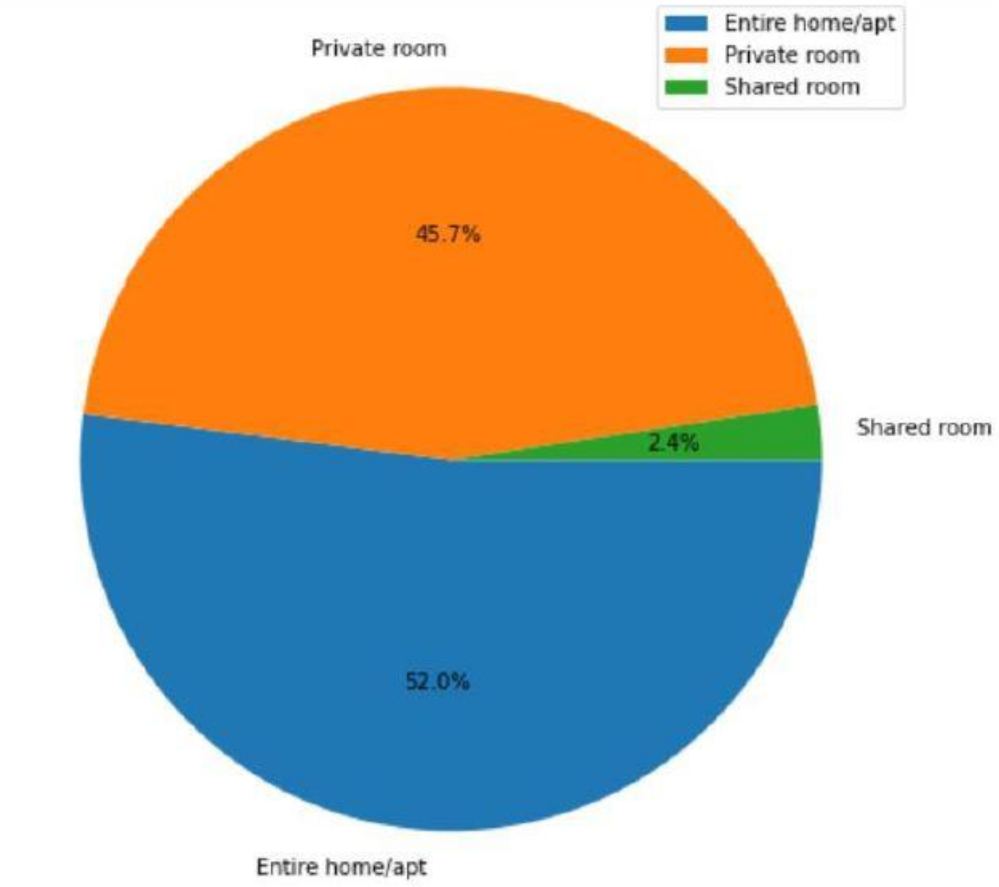
% of Listings with respect to Neighborhood Group

The image provides the percentages of listings in different neighborhood groups in NYC, with the highest percentages being Manhattan (44.3%) and Brooklyn (41.1%), which together account for 85.4% of the listings.

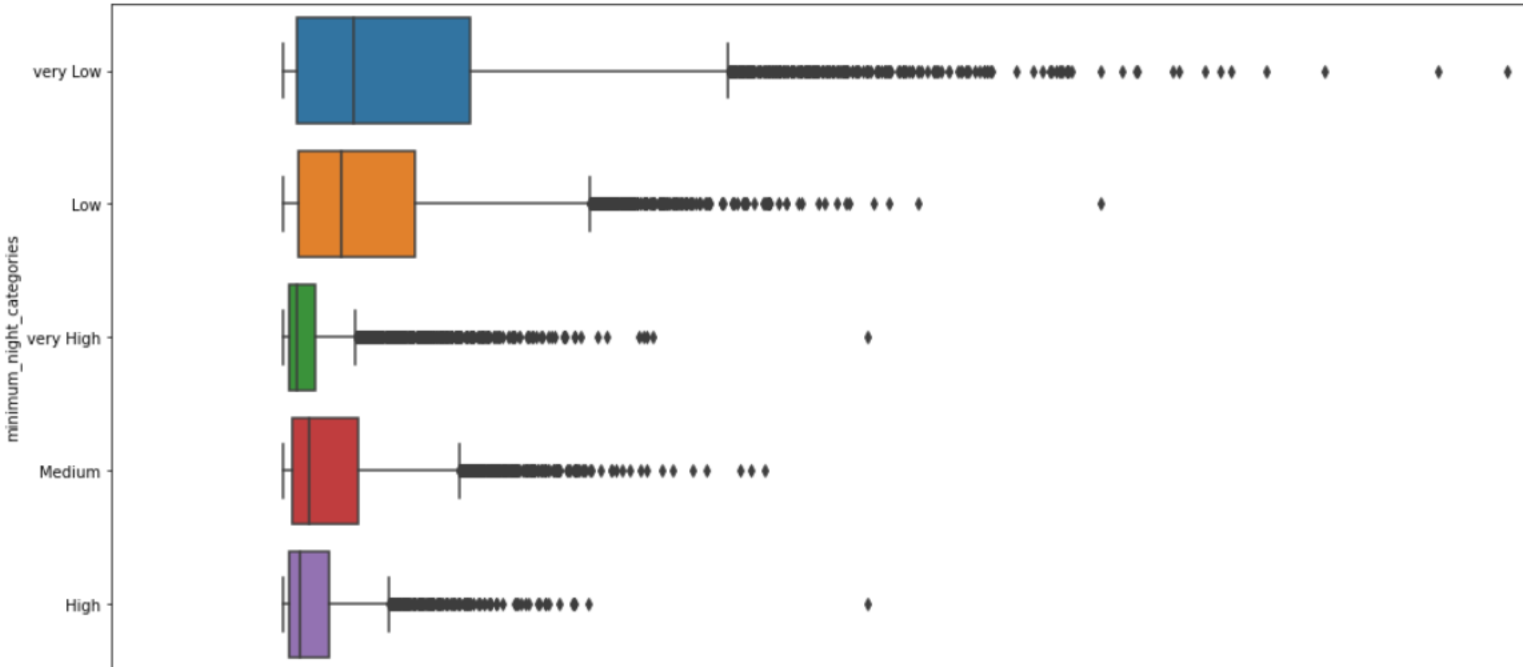


GUEST PREFERENCES

The pie chart shows the distribution of room types for Airbnb listings.



EFFECT OF MINIMUM NIGHT ON REVIEWS



- Customer's are more likely to leave reviews for low number of minimum nights.

- Adjustments in the existing properties to make it more customer-oriented?
  - minimum_nights should be on the lower side to make properties more customer-oriented.

CONCLUSION
&
RECOMMENDATIONS

- Focus on acquiring new hosts in high-demand neighborhoods to increase listings and revenue.
- Optimize property listings based on detailed analysis of customer preferences and feedback.
- The cumulative contribution of all hosts is better than a few hosts doing well.
- Shared rooms need to be inspected upon.
- More than 80 % of the listing are Manhattan & Brooklyn neighborhood group.
- Optimize property listings based on detailed analysis of customer preferences and feedback.
- Minimum nights Threshold should be on the lower side to make properties more customer-oriented.

APPENDIX

DATA SOURCES

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

METHODOLOGY

- Conduct a thorough analysis of New York Airbnb Dataset.
- Clean the data set using python.
- Derived necessary features.
- Used group aggregation & other statistical methods.
- Created charts and visualizations using univariate and bivariate analysis in Python.

Steps Performed during the Analysis

1. Importing Libraries & Reading The Data

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

```
airbnb = pd.read_csv("AB_NYC_2019.csv")
airbnb.head()
```

2. Data Exploration & Variable Identification

```
#checking what are the variables here:
airbnb.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'],
      dtype='object')
```

```
#basic information about the dataset
airbnb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 16 columns):
```

3. Creating Features

3.1 Categorizing The "availability_365" Column Into 5 Categories

```
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'
```

3.2 Categorizing The "minimum_nights" Column Into 5 Categories

```
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'
```

3.3 Categorizing The "number_of_reviews" Column Into 5 Categories

```
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'
```

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

4. Fixing Columns

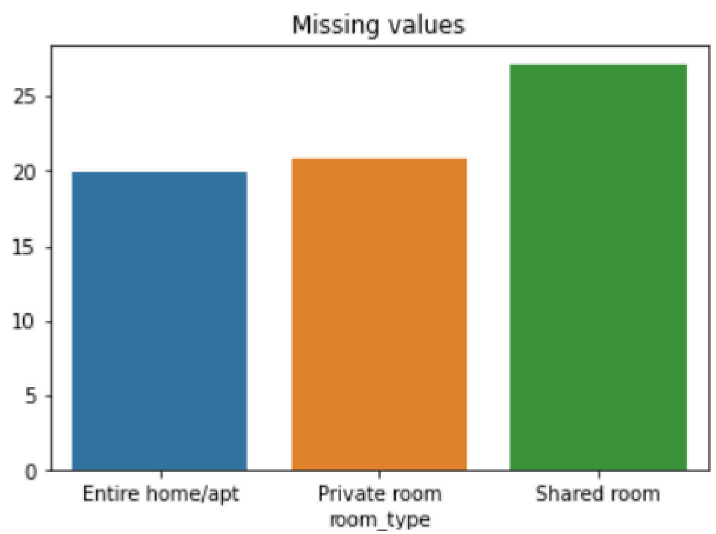
Fix: The **"reviews_per_month"** column is currently of object dtype ; changing it to **"datetime64"** would be more appropriate.

```
airbnb.last_review = pd.to_datetime(airbnb.last_review)
airbnb.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]
```

There are no more D-types to be fixed and data does not contain inconsistencies such as shifted columns, which is need to align correctly. The columns necessary for the further analysis are also derived.

5. Missing Values Analysis



Detailed Analysis of Missing Values:

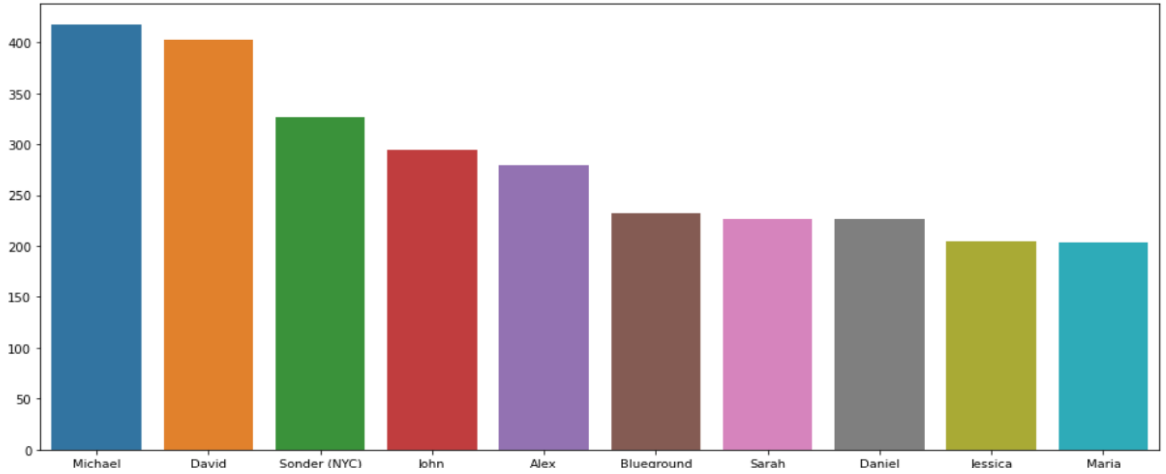
1) Higher Pricing with Missing 'last_review':
Observations indicate that listings without a 'last_review' tend to have higher prices.

2)Lower Review Frequency for Shared Rooms:
Shared rooms are less likely to receive reviews compared to other room types.

3)High Prices Correlate with Fewer Reviews:
Listings with higher prices tend to have fewer reviews, suggesting that guests may be less inclined to leave feedback for more expensive stays.

6. Univariate Analysis

```
# Top 10 host's
plt.figure(figsize=(16,7))
sns.barplot(x = airbnb.host_name.value_counts().index[:10] , y = airbnb.host_name.value_counts().values[:10])
plt.show()
```



7. Bivariate & Multivariate Analysis

Finding the correalations

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

' 'availability_365_categories', 'price_categories' and 'reviews_per_month'

```
pd.DataFrame(airbnb.groupby(['availability_365_categories','price_categories']).reviews_per_month.mean())
```