

Airbnb Case Study

PPT-II

By: Kunal Sadana





Objective

Background



Recommendations

Appendix





Objective

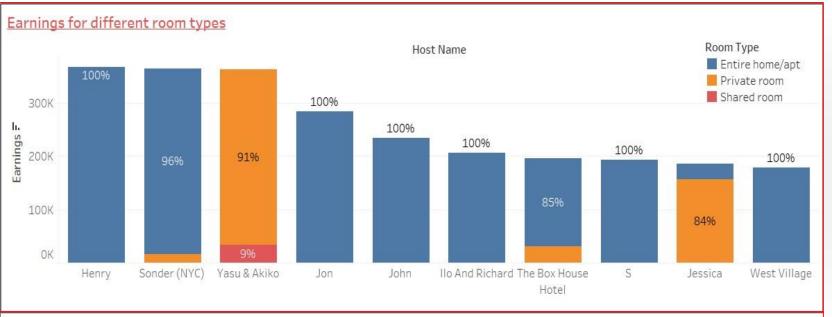
- Analyse the dataset consisting of various Airbnb listings in New York.
- Understand some important insights based on various attributes in the dataset so as to increase the revenue.



Background

- For the past few months, Airbnb has seen a major decline in revenue.
- Now that the restrictions have started lifting and people have started to travel more, Airbnb wants
 to make sure that it is fully prepared for this change.

Top Hosts



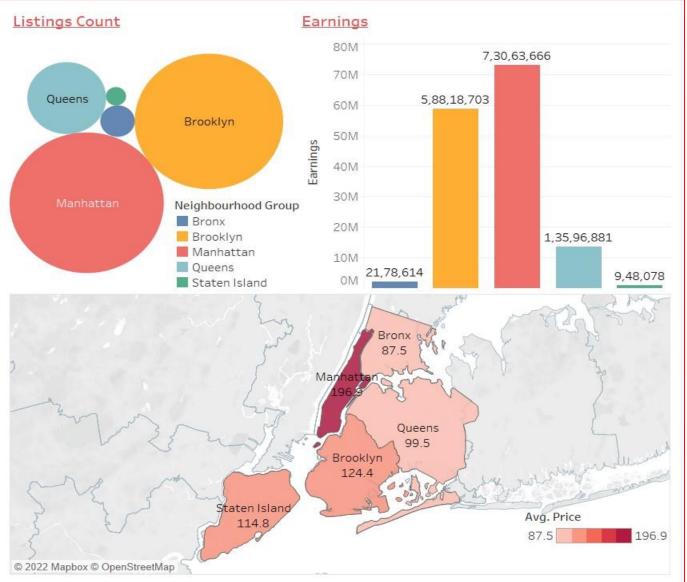


- Top 10 hosts by earnings.
- Most of them have Entire Home/apartment as room type.
- All have listings in Manhattan and Brooklyn area.

Host Listings Count			
Host Name ₣			
Sonder (NYC)	327.0		
The Box House Hotel	28.0		
Henry	11.0		
Jessica	11.0		
Yasu & Akiko	11.0		
West Village	4.0		
Jon	3.0		
John	2.0		
S	2.0		
Ilo And Richard	1.0		



Neighbourhood Groups

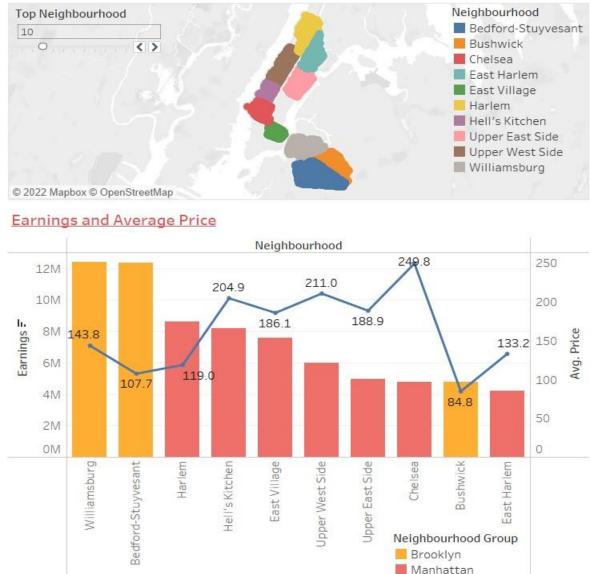


- The top New York City boroughs are Manhattan, Brooklyn, and Queens in this order.
- Manhattan has the most volume, highest Average Price and is the most popular destination for Airbnb.

As one of the quietest boroughs, Staten Island is ideal for a peaceful stay from the hustle and bustle of the city and can be promoted more.



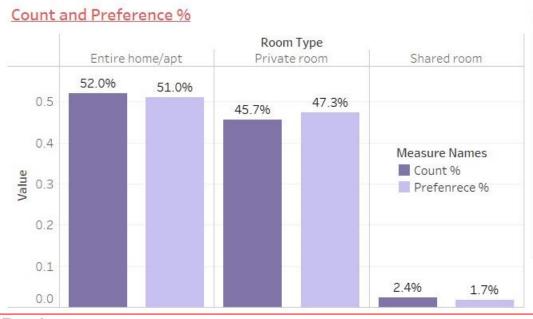
Top Neighbourhoods

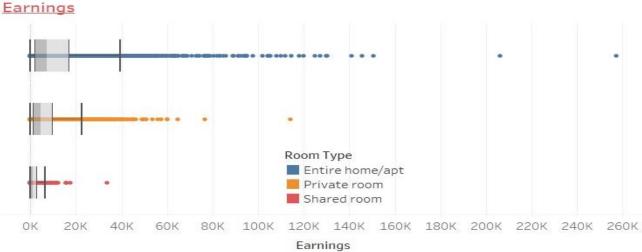


- Top 10 Neighbourhoods by earnings.
- Most of them lie in Manhattan followed by Brooklyn.
- Bushwik, Bedford-Stuyvesant and Harlem offer lowest Pricing.

Proximity to city attractions, the subway, and hip places are all factors that contribute to making these neighborhood famous and ideal for more investment.

Property Types





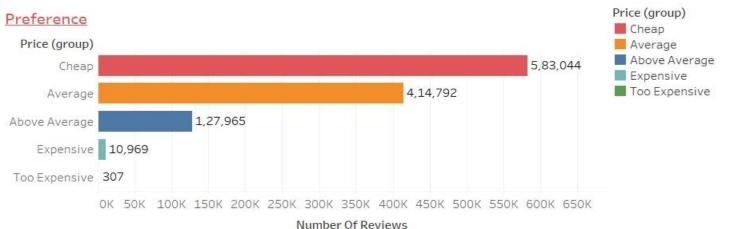
- Entire home/apartments have highest share of listing counts followed closely by Private rooms.
- Most of the customers prefer Entire home/apartments and Private rooms with very few preferring Shared rooms.

Earnings via Entire home/apt is quite high making them ideal for more investments.



Pricing Ranges





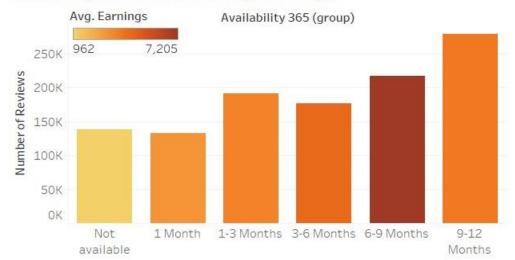
- Customers prefer properties having cheaper rates and very few have booked properties which are Expensive and too Expensive.
- Average and Above Average Pricing categories result in most Earnings.



Availability for Booking



Availability Prefence and Average Earnings



- A lot of properties have been listed as "Not Available". Low Earning being one of the reason.
- People have preferred properties which are available for booking for more days in an year.
- Properties available for 6-9 months top in Average Earnings.



Recommendations



Following insights should be focused on for further development or investment:

- Hosts who have less number of properties listed and have Entire home/apartments as property type.
- Manhattan and Brooklyn are the top New York city boroughs.
- Harlem in Manhattan and Bedford-Stuyvesant in Brooklyn offer unique investment opportunity with less Average Price and high Earnings.
- Listings having Average or Above Average Price range.
- Listings available for booking for 6-9 months.





- A thorough analysis of the given dataset was conducted.
- Data Methodology document has been attached with the file.





Methodology

Data

- PYTHON (JUPYTER) used for initial Data understanding and processing.
- · Here is a snapshot of data dictionary:

Column	Description	
ld	listing ID	
name	name of the listing	
host_ld	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	

Data Pre-processing

1. NULL values treatment

<pre># percentage of MRL values airbnb.isnull().sum()*i00/len(airbnb)</pre>		
id	0.000000	
name	0.032723	
ost_id	0.000000	
ost name	0.042949	
eighbourhood group	0.000000	
eighbourhood	0.000000	
atitude	0.000000	
ongitude	0.000000	
oom type	8.000000	
rice	0.000000	
inimum nights	0.000000	
umber of reviews	0.000000	
ast review	20.558339	
reviews per month	20.558339	
alculated host listings_count	0.000000	
wailability_365 htype: float64	0.000000	

Deleting all rows where either "name" or "host_name" is missing

Deleting all rows where either 'name' or 'host_name' is NULL
airbnb.dropna(subset=['name','host_name'], inplace=True)

Filling NULL values with 0 for "reviews, per month" since the same rows which
had NULL values for this column had 0 for "number of reviews".

Filling NULL values with θ for `reviews_per_month` airbnb.reviews_per_month.fillna(θ, inplace=True)

- 2. Conversion of datatype
 - Converting "last, review" to datetime

Converting `last_review` to datetype
airbnb.last_review = pd.to_datetime(airbnb.last_review)

- 3. Saving the file
 - · Saving the pre-processed file to be used in TABLEAU for visualisation

creating a new file to be used for visualisation in TABLEAU airbnb.to_csv('airbnb_treated.csv', index=False)

Data Visualisation

TABLEAU used for the Data Visualisation purposes

- o Creation of new features/variables to help in better analysis via visualisation:
 - a. Earnings: "Earnings" is a calculated feature derived by given formula.

Earnings

Role: Continuous Measure
Type: Calculated Field
Default aggregation: Sum
Status: Valid

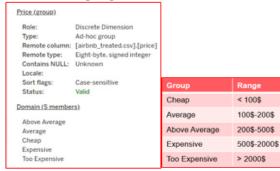
Formula

[Number Of Reviewa]*[Price]

 Availability 365 (groups): "Availability 365 (groups)" is a calculated feature where Availability has been binned into following categories:



 Price (groups): "Price (groups)" is a calculated feature where Price has been binned into following categories:



- o "Preference" of customers is based on "SUM (number_of_reviews)".
- Various types of plots used:
 - Bar graphs
 - Stacked Bar charts
 - Scatter plots
 - Bubble charts
 - Maps
 - Box plots
 - Pie Charts