



Airbnb Case Study

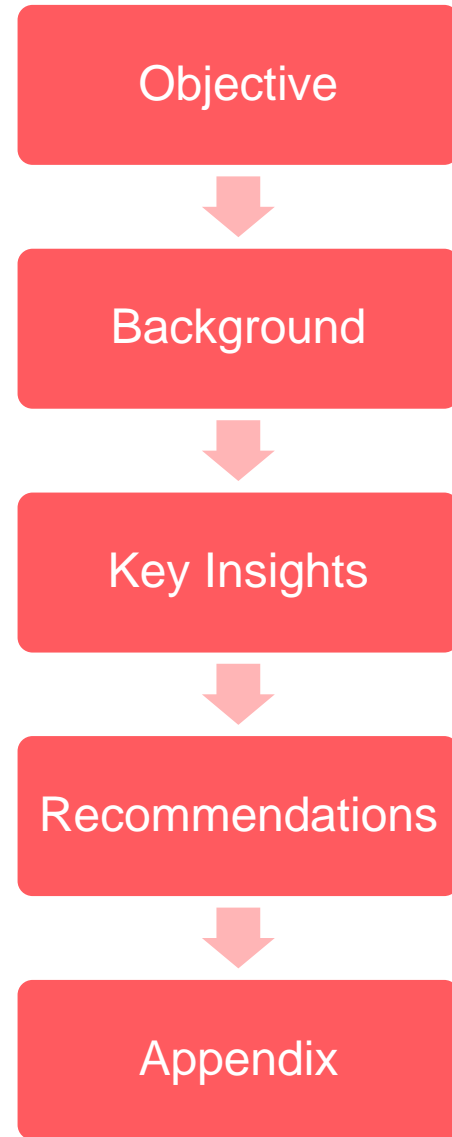
PPT-I

By:
Kunal Sadana





Agenda





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.



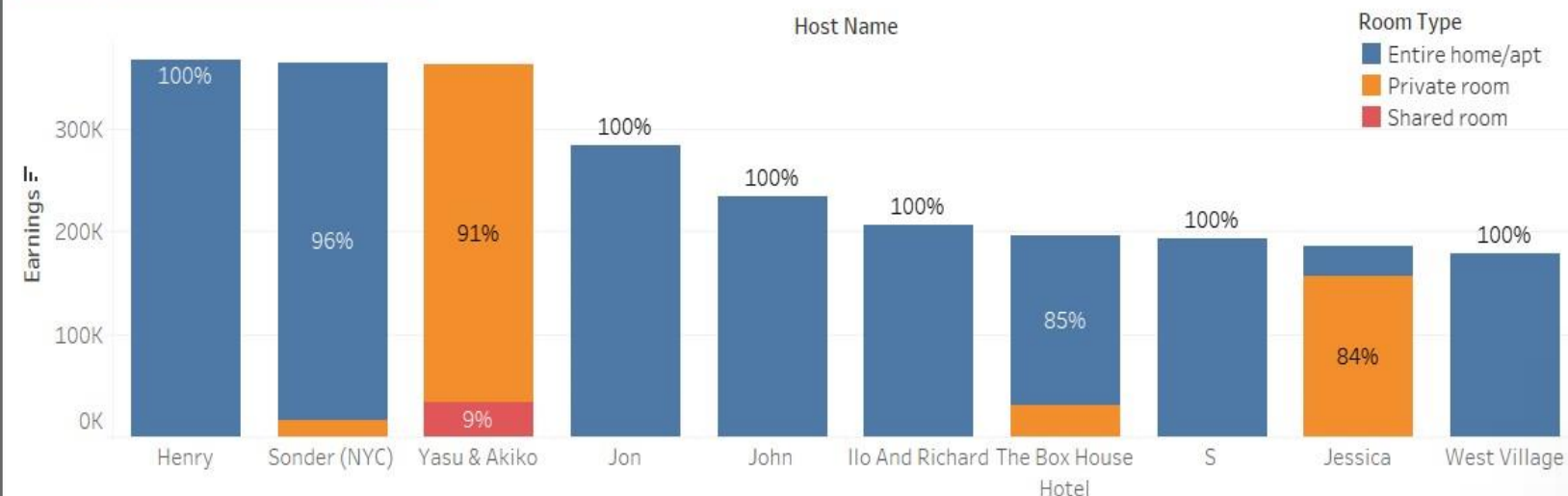
Background

- 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

Earnings for different room types



Minimum Nights for different Neighbourhood groups



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

NOTE: “Earnings” is a calculated feature derived by given formula.

Earnings

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

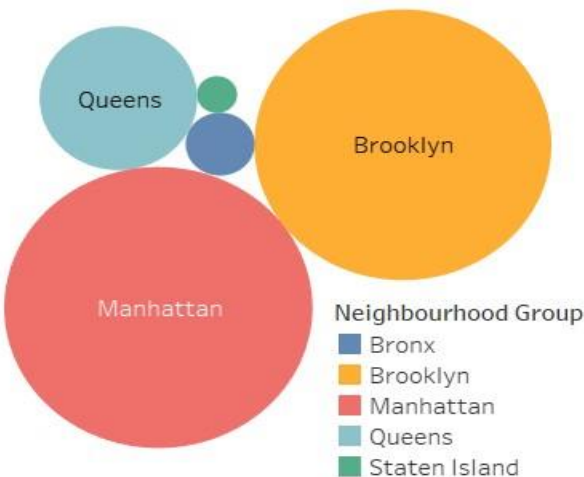
Formula

`[Number Of Reviews]*[Price]`

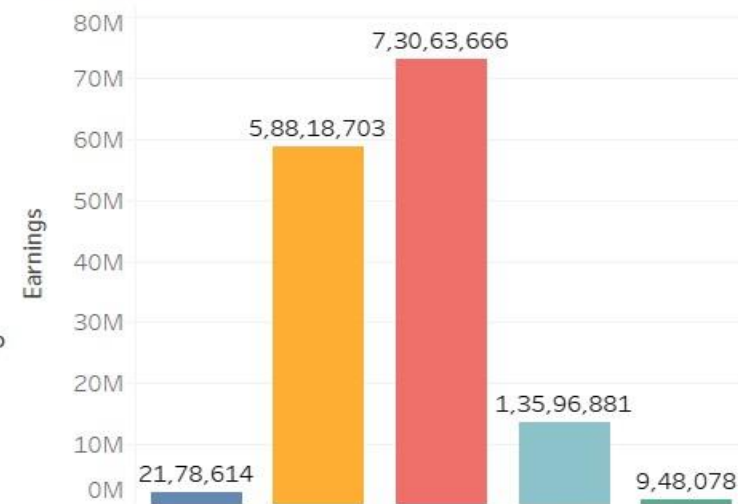


Neighbourhood Groups

Listings Count



Earnings

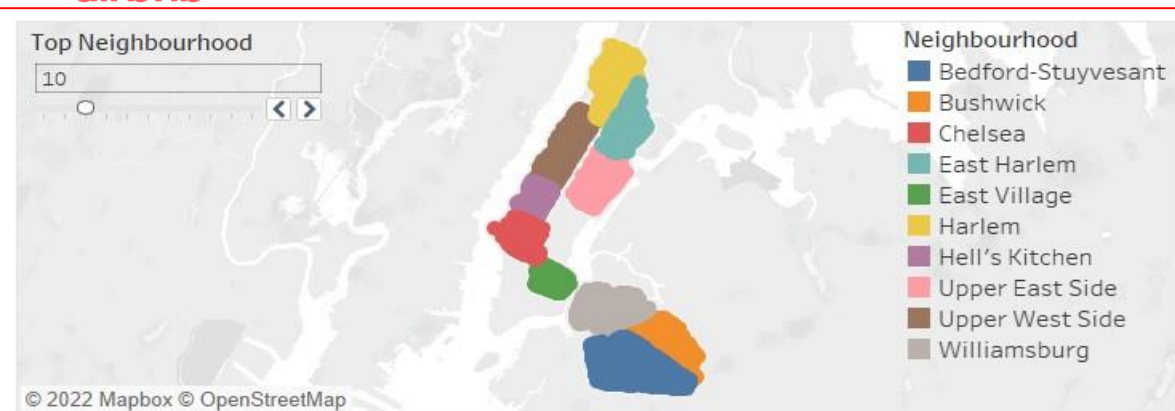


- The top New York City boroughs are Manhattan, Brooklyn, and Queens in this order.
- Manhattan has the most volume, highest Average Price and is the most popular destination for Airbnb.

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



Earnings and Average Price



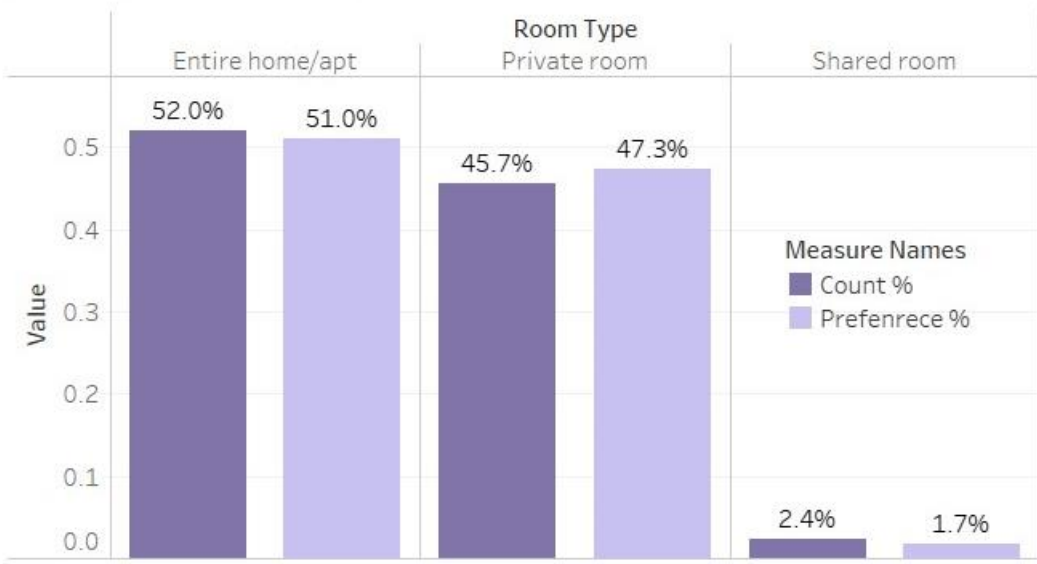
- Top 10 Neighbourhoods by earnings.
- Most of them lie in Manhattan followed by Brooklyn.
- Bushwick, Bedford-Stuyvesant and Harlem offer lowest Pricing.

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

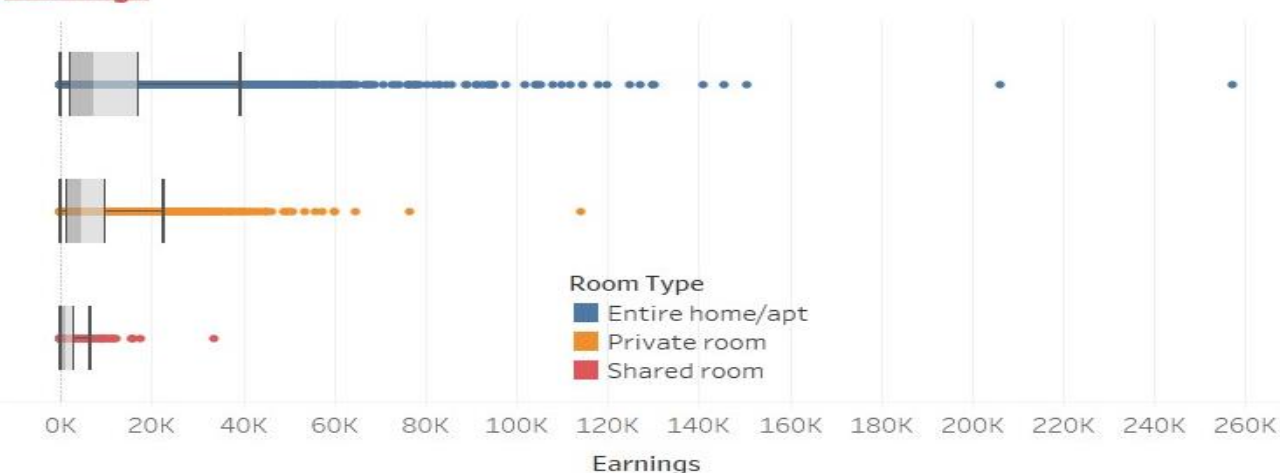
Count and Preference %



- 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.

NOTE: "Preference" is calculated based on "SUM(Number of Reviews)"

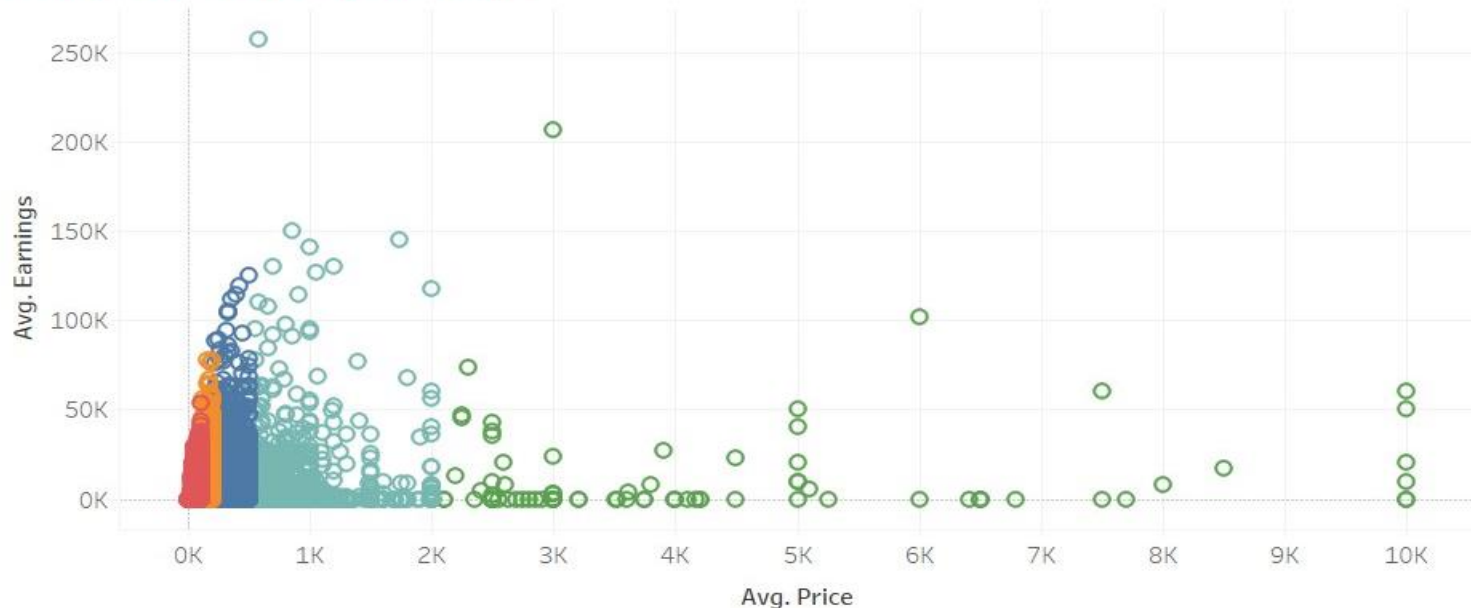
Earnings



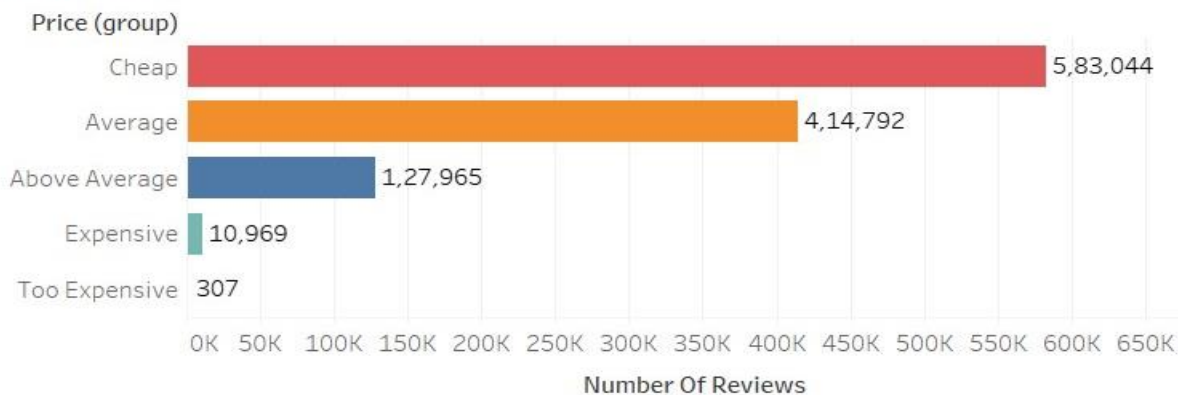


Pricing Ranges

Average Price vs Average Earnings



Preference



- Customers preference is inversely proportional to Pricing.
- Average and Above Average Pricing categories result in most Earnings.

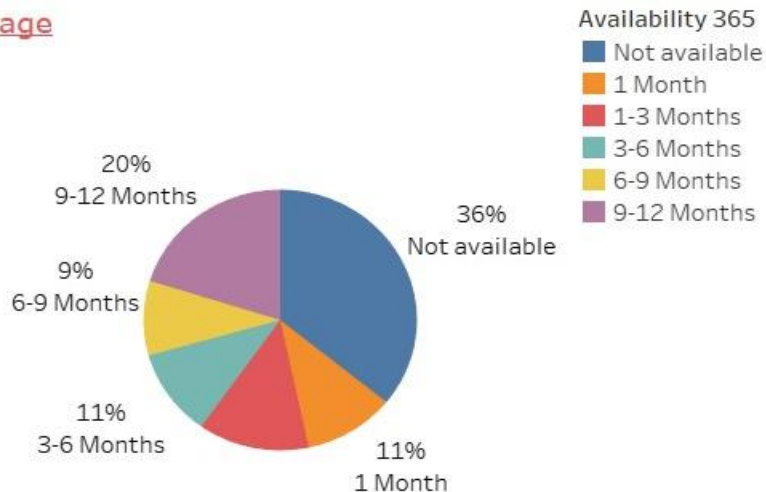
NOTE: “Price (groups)” is a calculated feature where Price has been binned into following categories:

Group	Range
Cheap	< 100\$
Average	100\$-200\$
Above Average	200\$-500\$
Expensive	500\$-2000\$
Too Expensive	> 2000\$



Availability for Booking

Count percentage



- 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.

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

Group	Range
Not Available	0
1 month	Up to 30 days
1-3 months	30-90 days
3-6 months	90-180 days
6-12 months	Above 180 days

Availability Prefence and Average Earnings





Recommendations



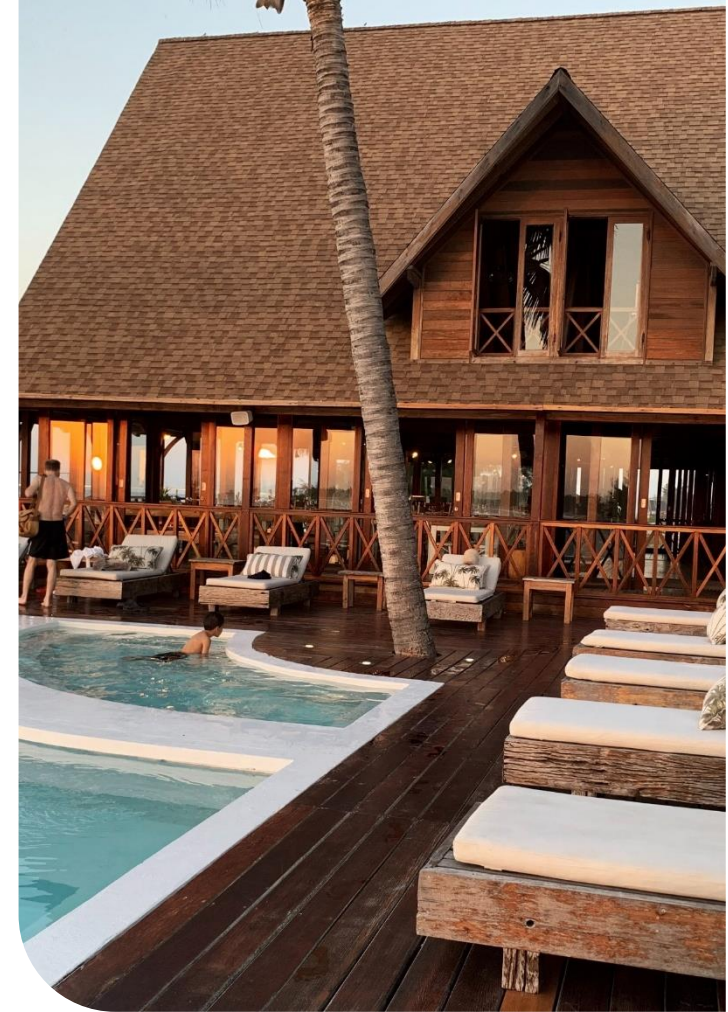
Following insights should be focused on for further development or investment:

- ✓ 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**.



Appendix

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





Appendix

Methodology

Data

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

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

Data Pre-processing

1. NULL values treatment

```
# percentage of NULL values
airbnb.isnull().sum()*100/len(airbnb)
```

id	0.000000
name	0.032723
host_id	0.000000
host_name	0.042949
neighbourhood_group	0.000000
neighbourhood	0.000000
latitude	0.000000
longitude	0.000000
room_type	0.000000
price	0.000000
minimum_nights	0.000000
number_of_reviews	0.000000
last_review	20.558339
reviews_per_month	20.558339
calculated_host_listings_count	0.000000
availability_365	0.000000
dtype: float64	

- 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 0 for 'reviews_per_month'
airbnb.reviews_per_month.fillna(0, inplace=True)
```

2. Conversion of datatype

- Converting "last_review" to datetime

```
# Converting 'last_review' to datetime
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

- Creation of new features/variables to help in better analysis via visualisation:

- Earnings:** "Earnings" is a calculated feature derived by given formula.

Role:	Continuous Measure
Type:	Calculated Field
Default aggregation:	Sum
Status:	Valid
Formula	
[Number Of Reviews]*[Price]	

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

Role:	Discrete Dimension
Type:	Ad-hoc group
Remote column:	[airbnb_treated.csv][availability_365]
Remote type:	Eight-byte, signed integer
Contains NULL:	Unknown
Locale:	
Sort flags:	Case-sensitive
Status:	Valid
Domain (6 members)	
1 Months	
1-3 Months	
2-6 Months	
6-9 Months	
9-12 Months	
Not available	

Group	Range
Not Available	0
1 month	Up to 30 days
1-3 months	30-90 days
3-6 months	90-180 days
6-12 months	Above 180 days

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

Role:	Discrete Dimension
Type:	Ad-hoc group
Remote column:	[airbnb_treated.csv][price]
Remote type:	Eight-byte, signed integer
Contains NULL:	Unknown
Locale:	
Sort flags:	Case-sensitive
Status:	Valid
Domain (5 members)	
Above Average	
Average	
Cheap	
Expensive	
Too Expensive	

Group	Range
Cheap	< 100\$
Average	100\$-200\$
Above Average	200\$-500\$
Expensive	500\$-2000\$
Too Expensive	> 2000\$

- "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