

Airbnb Listings Dashboard Documentation

Overview:

This project centers on examining Airbnb listing data from two prominent U.S. cities—Chicago and New Orleans—to uncover valuable insights about market dynamics, host behavior, pricing trends, and property distribution. Using Power BI, the initiative transforms raw data into an engaging, interactive dashboard that allows users to compare and explore Airbnb activity across these urban landscapes.

The primary objective is to perform Exploratory Data Analysis (EDA) and translate the findings into a structured, visually appealing dashboard. This dashboard serves as a decision-making tool for stakeholders, hosts, and analysts—helping them understand neighborhood-level performance, price fluctuations, dominant property types, and the connection between host experience, reviews, and pricing.

The dataset includes extensive details such as room type, neighborhood, price, host profile, availability, and review count. By combining data preprocessing and transformation in Python with visual analytics in Power BI, the project produces a comprehensive dashboard organized into four major analytical sections, each highlighting distinct aspects of Airbnb market insights. They are:

- 1. Overview of Airbnb**
- 2. Property Analysis**
- 3. Pricing Analysis**
- 4. Host Analysis**

The dashboard offers interactive filters for city, room type, and price range, allowing users to explore data dynamically and intuitively. It functions as a decision-making aid, helping stakeholders pinpoint top-performing neighborhoods, craft effective pricing strategies, and assess how a host's experience influences guest engagement and satisfaction.

Data Source:

The data was sourced from open Airbnb datasets and consists of individual CSV files for each city:

- Chicago.csv
- New Orleans.csv

These datasets contain information such as:

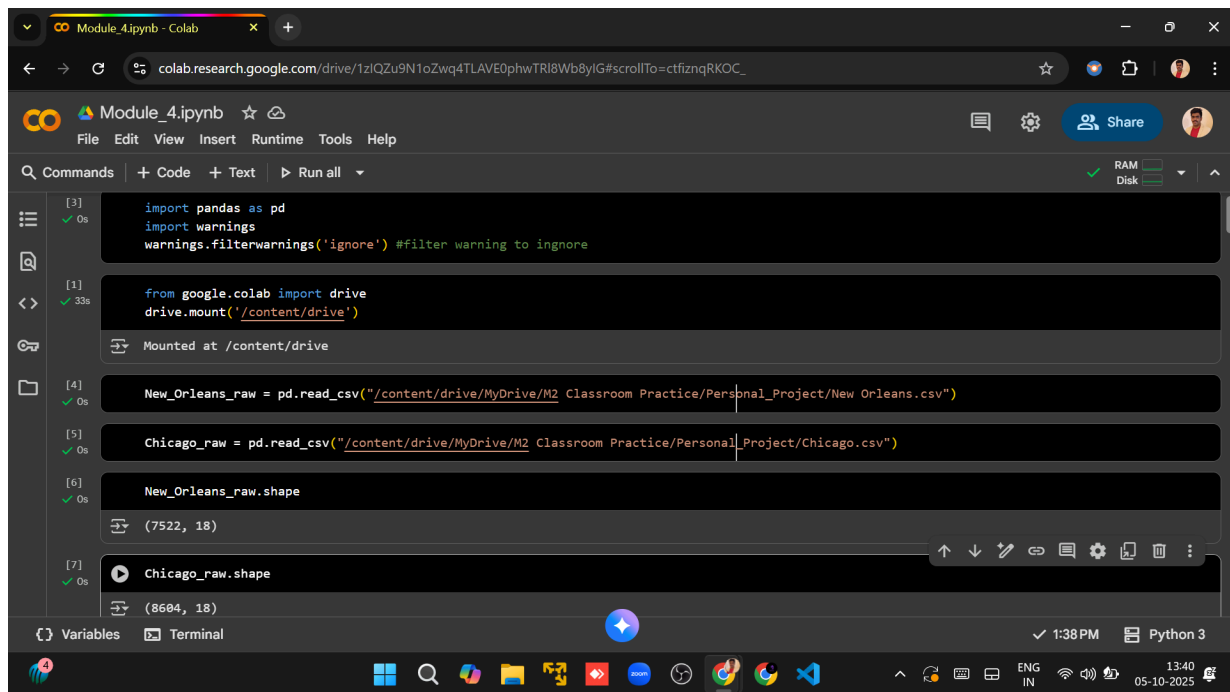
- Listing ID, property and room types
- Host details and review metrics
- Availability and pricing
- Neighbourhood information

Why Airbnb:

Airbnb is a global platform that enables users to book diverse types of accommodations worldwide. Its appeal lies in its **cost-effectiveness** and the **authentic local experiences** it offers. Operating across **more than 191 countries**, Airbnb hosts over **4 million listings** and serves **around 150 million users**. Valued at **approximately \$32 billion**, the company has experienced an impressive **153% growth** globally since its inception in 2009.

Methodology:

1. Data Cleaning and Transformation:



The screenshot displays a Google Colab notebook titled 'Module_4.ipynb'. The interface includes a menu bar (File, Edit, View, Insert, Runtime, Tools, Help), a toolbar with icons for commands, code, text, and running all cells, and a status bar at the bottom showing 'Python 3' and the time '1:38 PM'. The notebook content consists of several code cells with their outputs:

- Cell [3]: Imports pandas as pd, warnings, and filters warnings to ignore. Output: [3] ✓ 0s
- Cell [1]: Imports drive from google.colab and mounts the content drive. Output: [1] ✓ 33s Mounted at /content/drive
- Cell [4]: Reads the 'New Orleans.csv' file into 'New_Orleans_raw'. Output: [4] ✓ 0s
- Cell [5]: Reads the 'Chicago.csv' file into 'Chicago_raw'. Output: [5] ✓ 0s
- Cell [6]: Prints the shape of 'New_Orleans_raw'. Output: [6] ✓ 0s (7522, 18)
- Cell [7]: Prints the shape of 'Chicago_raw'. Output: [7] ✓ 0s (8604, 18)

The bottom status bar also shows system icons for Windows, search, and network, along with the date '05-10-2025'.

The screenshot shows a Google Colab notebook with two code cells. The first cell contains Python code for cleaning the 'New Orleans' dataset. It drops irrelevant columns, handles missing values, and filters out rows with missing prices or last reviews. The second cell shows the shape of the cleaned 'New Orleans' dataset as (4064, 18). The third cell contains similar Python code for cleaning the 'Chicago' dataset, applying the same logic to drop irrelevant columns, handle missing values, and filter out rows with missing prices or last reviews.

```
# 1. Drop irrelevant columns
if "neighbourhood_group" in New_Orleans_raw.columns:
    New_Orleans_raw.drop(columns=["neighbourhood_group"], inplace=True)
# 2. Handle missing values
New_Orleans_raw = New_Orleans_raw[New_Orleans_raw["price"].notnull() & (Chicago_raw["price"] > 0)] # remove rows without price or invalid price
New_Orleans_raw["last_review"] = pd.to_datetime(New_Orleans_raw["last_review"], errors="coerce") # convert to datetime
New_Orleans_raw.dropna(subset=["last_review"], inplace=True) # remove rows with missing last_review
New_Orleans_raw["last_review"] = New_Orleans_raw["last_review"].dt.date # keep only the date (remove time)
New_Orleans_raw["reviews_per_month"].fillna(0, inplace=True) # missing reviews_per_month + 0
New_Orleans_raw["license"] = New_Orleans_raw["license"].fillna("Not Registered")
New_Orleans_raw["city"] = "New Orleans"

New_Orleans_raw.shape

(4064, 18)

# 1. Drop irrelevant columns
if "neighbourhood_group" in Chicago_raw.columns:
    Chicago_raw.drop(columns=["neighbourhood_group"], inplace=True)
# 2. Handle missing values
Chicago_raw = Chicago_raw[Chicago_raw["price"].notnull() & (Chicago_raw["price"] > 0)] # remove rows without price or invalid price
Chicago_raw["last_review"] = pd.to_datetime(Chicago_raw["last_review"], errors="coerce") # convert to datetime
Chicago_raw.dropna(subset=["last_review"], inplace=True) # remove rows with missing last_review
Chicago_raw["last_review"] = Chicago_raw["last_review"].dt.date # keep only the date (remove time)
Chicago_raw["reviews_per_month"].fillna(0, inplace=True) # missing reviews_per_month + 0
Chicago_raw["license"] = Chicago_raw["license"].fillna("Not Registered")
Chicago_raw["city"] = "Chicago"
```

The screenshot shows a Google Colab notebook with two code cells. The first cell concatenates the cleaned 'New Orleans' and 'Chicago' datasets into a single 'Final_DataSet'. The second cell saves the 'Final_DataSet' as a CSV file named 'Airbnb_Final.csv' in the specified directory.

```
(6113, 18)

Final_DataSet = pd.concat([New_Orleans_raw, Chicago_raw], ignore_index=True)

Airbnb_Final = Final_DataSet.to_csv("/content/drive/MyDrive/M2 Classroom Practice/Personal_Project/Airbnb_Combined.csv", index=False)
```

2. DAX Calculated Columns in Power BI

- Host Category

```
1 Host_Category =
2 IF('Airbnb_Combined csv'[number_of_reviews] > 50, "Experienced",
3   IF('Airbnb_Combined csv'[number_of_reviews] > 10, "Moderate", "New"))
```

- Price Category

```
1 Price_Category = SWITCH(TRUE(),
2   'Airbnb_Combined csv'[price] <= 100, "Low",
3   'Airbnb_Combined csv'[price] <= 200, "Medium",
4   "High"
5 )
```

- Latitude Round

```
1 Lat_Rounded =
2 ROUND ( 'Airbnb_Combined csv'[latitude], 2 )
```

- Longitude Round

```
1 Lon_Rounded =
2 ROUND ( 'Airbnb_Combined csv'[longitude], 2 )
```

Dashboard Visualizations

Airbnb Listings Overview: Comparative Analysis of Chicago and New Orleans

KPI Card: Total Listings

- Metric Displayed: Total number of Airbnb listings across both cities.
- Value: 16,617 listings.
- This provides a quick snapshot of the total supply of Airbnb properties in Chicago and New Orleans combined.

Slicers

1. City
 2. Room Type
 3. Price Category
- Functionality: These interactive filters allow users to explore the data by selecting specific cities (Chicago or New Orleans), room types (e.g., Entire home/apt, Private room), and price categories (e.g., Low, Medium, High).
 - This enables focused analysis by refining the data view based on selected parameters.

City-wise Breakdown – Pie chart

- Visualization: A Pie chart is used to compare the distribution of total Airbnb listings between Chicago and New Orleans.

- Insight:
 1. Chicago accounts for 60% of the total listings, which is approximately 6113 listings.
 2. New Orleans contributes the remaining 39%, approximately 4064 listings.

Property Analysis:

Top 10 Neighbourhoods by Price – Clustered bar chart

- Visualization: Clustered bar chart listing the Top 10 neighbourhoods with the highest average listing prices.
- Insight:
 1. Highlights premium locations where Airbnb listings command higher rates - eg., neighborhoods like Freret in Chicago or Near North Side in New Orleans have the highest rates.
 2. May include upscale neighborhoods, tourist hotspots, or waterfront locations.
- Purpose:
 1. Supports strategic pricing analysis and helps in identifying high-value localities.
 2. Useful for investors, property managers, and tourism analysts targeting premium segments.

Listings by Neighbourhood – Stacked bar chart

- Visualization: Bar chart displaying the Top 10 Neighbourhoods ranked by the number of Airbnb listings.
- Insight: Reveals hotspots within the cities where listings are concentrated — e.g., neighborhoods like the Central business district in Chicago or Near North Side in New Orleans have the highest number of listings.
- Purpose: Assists in location-based analysis, such as identifying:
 1. High-demand areas
 2. Opportunities for market expansion
 3. Neighborhood-wise performance

Room Type Distribution – Donut Chart

- Visualization: Donut chart displaying the proportion of each room type available in Airbnb listings.
- Common Categories:
 1. Entire home/apt
 2. Private room
 3. Shared room
 4. Hotel room
- Insight: Shows the dominant room type in the dataset is the entire home or an apartment. It indicates that most hosts offer fully private properties.
- This helps stakeholders understand guest preferences and market trends in accommodation types across both cities or filtered selections.

Pricing Analysis:

Avg Price by Location – Map Chart

- Visualization: Bubbles size to represent Average Price.
- Insight:
 1. The prices in the Chicago area are much higher than in the New Orleans area.
- Purpose:
 1. Helps understand pricing strategy by room type.
 2. Useful for both hosts and analysts to evaluate which room types yield higher returns.

Avg Price vs Room Type – Clustered column chart

- Visualization: Clustered column chart showing the average price for each room type.
- Insight:
 1. Allows comparison of how pricing varies between categories like Entire home/apt, Private room, Shared room, etc.
 2. Hotel rooms have the highest average price, while shared rooms tend to be the cheapest.
- Purpose:
 1. Helps understand pricing strategy by room type.
 2. Useful for both hosts and analysts to evaluate which room types yield higher returns.

Host Analysis:

Host Category vs Avg Reviews & Pricing – Stacked Bar Chart

- Visualization: A stacked bar chart where each bar represents a host category:
 1. Experienced
 2. Moderate
 3. New
- Insight:
 1. Experienced hosts have the highest average number of reviews, indicating strong guest engagement and consistent performance.
 2. Average pricing may also be higher for experienced hosts, showing their ability to charge a premium due to trust and reputation.
 3. New hosts have fewer reviews and lower average pricing, which may reflect their strategy to attract bookings and build credibility.

Insights:

1. Popular Neighbourhoods:

- **Pricing Hotspot:** The **French Quarter in New Orleans** commands the highest average pricing at **\$2,576.08**.
- **Inventory Hotspot:** The **Central Business District (CBD) in New Orleans** has the maximum number of listings, with **673 properties** listed, indicating it is the most saturated neighborhood.

2. Room/Property Type Share:

- **Dominant Type:** **Entire home/apartment** overwhelmingly dominates the market in both cities, accounting for **8,408 listings** in total.
- **Price and Type Correlation:** **Private rooms** are significantly more common in the **lower price ranges** (1,169 listings) compared to the medium (334 listings) and higher (152 listings) price ranges, suggesting private rooms are the primary budget-friendly option.

3. Location Patterns:

- **City-Level Focus:** The overall analysis shows that the primary locations for high pricing and high listing volume are the major metropolitan areas of **Chicago** and **New Orleans**.
- **Neighborhood Divergence:** In New Orleans, there is a clear distinction between the **premium, high-price tourist destination** (French Quarter) and the **high-volume, central business-oriented area** (CBD), highlighting different operational strategies based on neighborhood type.

4. Price Variation:

- **General City Comparison:** Property in **New Orleans** generally had **lower pricing** compared to Chicago.
- **Premium Drivers:** Higher pricing trends are specifically observed for **hotel rooms** and properties within **highly desirable, iconic neighborhoods** (like the French Quarter).

5. Host Patterns:

- **Experience Premium:** **Experienced hosts** generally achieve higher pricing and accumulate more reviews.
- **Pricing Anomaly:** Hosts in the **"Moderate review category"** exhibit an unexpected trend by having **higher pricing** compared to experienced hosts (this is an important, non-obvious data point).
- **Market Entry Strategy:** **New hosts** strategically **charge competitively** to quickly attract bookings and build their initial review base.