

A Decade of NYC's Airbnb: Data-Driven Perspectives on Hosting Patterns and Market Dynamics

Dr. Sameer Jain

OSD to President and Chancellor, National Institute of Construction Management and Research (NICMAR) University,
Pune, India

Email: sameerjain@nicmar.ac.in

Abstract—This research paper conducts a comprehensive data analysis of New York City (NYC) Airbnb listings spanning from 2011 to 2023, encompassing over 40 thousand listings. Employing Python for data cleaning, type handling, and extensive visualization, the study addresses data integrity issues, delving into critical aspects of the NYC Airbnb market. Visualizations cover topics such as hosting listings distribution by room types and neighbourhood's, price dynamics by room type and borough, spatial distribution via heatmap and geographical maps, average pricing trends, guest satisfaction based on reviews, room availability, and pricing trends over time, host activities, and frequently occurring host names in a Word Cloud. These insights serve property hosts and potential guests, promoting data-driven decisions in the dynamic NYC Airbnb market while contributing to a broader understanding of short-term rental landscape evolution over more than a decade.

Keywords— Airbnb, New York City; Data Analysis; Data Visualization; Short-term Rentals, Pricing Trends; Geospatial Analysis; Word Cloud.

I. INTRODUCTION

The emergence of the sharing economy has ushered in a transformative era in the travel and hospitality industry. Airbnb, founded in 2008, has rapidly grown to become a global platform connecting travellers with unique accommodation options. With its user-friendly interface and an ever-expanding portfolio of listings, Airbnb has not only changed the way people travel but also disrupted the traditional hotel industry (Cheng, 2016).

As one of the most iconic cities in the world, New York City serves as an ideal backdrop for the study of Airbnb's impact on urban accommodations. The "City that Never Sleeps" has consistently been one of Airbnb's most popular destinations, attracting a diverse array of travellers seeking authentic and cost-effective lodging experiences. The exponential growth of Airbnb listings in New York City has raised important questions about the platform's implications for local neighbourhood's, housing availability, and pricing dynamics (Zervas, Proserpio, & Byers, 2017). This paper embarks on a comprehensive analysis of Airbnb data in New York City, spanning a period from 2011 to 2023. Drawing from a dataset encompassing over 40 thousand listings, our research aims to unravel the multifaceted landscape of short-term rentals in this bustling metropolis. Utilizing Python for data pre-processing, cleaning, and visualization, we delve into various aspects of Airbnb's presence in New York City.

Our investigation encompasses a wide range of topics, including but not limited to pricing trends, room type distribution, neighbourhood preferences, host engagement, and guest satisfaction.

Through rigorous data analysis and visualization techniques, we seek to provide valuable insights for both hosts and guests in navigating the dynamic Airbnb marketplace in New York City. Zhang et.al (2020) framework underscored the significance of employing text analytics techniques to decipher the subtleties of host self-description. Through the analysis of substantial textual data, their research extracted insights illuminating the interplay between linguistic elements, trust perception, and consumer behavior within the Airbnb ecosystem. It emphasized the need for hosts to craft persuasive and informative self-descriptions, recognizing their influence on trust-building and subsequent guest behavior. The research by Zhang et al. (2023) underscored the importance of positive sentiment expressions in shaping guests' booking decisions. Their research showed that good evaluations from guests not only boosted the possibility of reservations but also improved host reputation and platform success as a whole. On the other hand, displays of negative attitude might discourage reservations and affect hosts' ratings. This demonstrates how important user-generated material is to the popularity of P2P renting systems. The current study article, which explores data analytics of Airbnb listings in New York City, is especially pertinent to the mixed-method methodology used. In the context of the hotel sector, Xu and Li (2016) acknowledged the complexity of consumer pleasure and discontent. In their study, text mining was used to analyse customer reviews and comments in order to get insights into the elements that influence consumer sentiment. The research provided a comprehensive knowledge of the sources of pleasure and discontent, providing light on the varied experiences of hotel visitors through the categorization and quantification of textual data. Airbnb Superhosts, a title designated for highly-rated and knowledgeable hosts, are acknowledged by Scerri and Presbury (2020) as having a significant impact on the visitor experience and booking decisions. Their research centered on the discourse and communication techniques utilized by Superhosts in business contexts. The research gave insights into how these hosts interact with visitors, look after their properties, and contribute to Airbnb's overall success by analysing the discourse of Superhosts. The research by Qiu et al. (2022) emphasizes the relevance of affinity-seeking methods as crucial elements of effective hosting on Airbnb. Their research provided light on host behaviours that contribute to satisfying visitor experiences and eventually have an influence on host success, including customized communication, local suggestions, and guest involvement. This body of work adds to our knowledge of the sharing economy by highlighting the role that host-guest interactions play in the popularity of peer-to-peer housing websites like Airbnb. The study by Cheung and Yiu (2022) highlights the intricacy of the link between Airbnb, crime rates, and home values. Their study emphasizes that Airbnb's impacts depend on context, are impacted by a variety of urban characteristics, and may call for careful governmental responses. This body of work highlights the necessity for thorough and context-specific assessments and advances our knowledge of the effects of the sharing economy on urban dynamics. The influence of social media brand communities in influencing customer behaviour was acknowledged by Goh et al. (2013). Their study aimed to measure the relative influence of material produced by marketers (brands) and users (consumers) inside these online communities. The study used quantitative analytics to determine the degree to which marketer- and user-generated content affects customer engagement and behaviour. Online hotel reviews are regarded by Cherapanukorn and Charoenkwan (2018) as important sources of guest feedback. Their study used cutting-edge methods like word cloud visualizations to extract the feelings and phrases that were most commonly used in these evaluations. The study aims to offer insights into the facets of hotel experiences that have the most impact on determining customer happiness by utilizing these visualizations. In the age of online reviews and social media, Huang, Liang, and Choi (2022) noticed the developing nature of consumer feedback. They used a sophisticated text-mining technique in their study to examine and contextualize instances of hotel service failures. The research sought to identify the complex components and situations that lead to service failures in hotel environments by parsing and analysing textual data.

II. RESEARCH METHODOLOGY

An organized technique or a methodical plan of action is known as research methodology, and it is what researchers employ to carry out their studies or investigations. The research approach would include the following crucial elements in the context of your study, which uses Python to analyse Airbnb data in New York City and carry out numerous data-related activities and visualizations:

A. Data Collection

Find and get the New York City Airbnb dataset from Kaggle, which contains information like the 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 listing count, availability 365, and number of reviews items.

B. Data Cleaning

Use data cleaning techniques to fix issues with the dataset, such as missing numbers, outliers, and inconsistencies. Handle duplicate values to ensure data integrity. Convert data types as needed to facilitate analysis.

C. Data Visualization

Utilize Python libraries such as Matplotlib, Seaborn, and Plotly to create various visualizations based on research objectives. Generate visualizations such as bar charts for hosting listing counts, price distribution plots, heatmaps, geographical maps, and word clouds.

D. Descriptive Statistics

Calculate summary statistics, such as mean, median, standard deviation, and percentiles, for relevant attributes. Analyze the distribution of prices, reviews, and availability over time.

E. Exploratory Data Analysis (EDA)

Conduct EDA to gain insights into the relationships between variables. Explore the distribution of room types and neighbourhood locations in the dataset. Examine trends in pricing by room type and neighbourhood group.

F. Time-Series Analysis

Analyze price trends over the years, potentially using time-series decomposition or trend analysis. Investigate the number of listings by hosts over time.

G. Host Analysis

Identify the top five hosts based on various criteria such as the number of listings. Create word clouds to visualize frequently occurring host names.

H. Spatial Analysis

Utilize geographical data (latitude and longitude) to create maps, including heatmaps and geographical distribution maps. Explore the mean price distribution by neighbourhood groups and room types spatially.

I. Room Type and Neighbourhood Analysis

Analyze the number of reviews, availability of rooms, and pricing by room type and neighbourhood locations.

J. Interpretation and Reporting

Interpret the findings from the analysis, draw conclusions, and discuss their implications. Present the results in a clear and organized manner through visualizations and written explanations.

Step 1: Obtain the dataset and load the data using 'Python' tool.

Step 2: Explore, clean and pre-process the data.

Attributes Name and their Description

The provided information describes a dataset related to Airbnb listings in New York City. Here are the definitions of the key attributes in the dataset:

- id: This is the unique identifier for each hosted house or apartment.
- name: The name or title of the hosted house or apartment.
- host_id: This is the unique identifier for the host who owns the property.
- host_name: The name of the host who owns and manages the property.
- neighbourhood group: This attribute represents the boroughs of New York City where the property is located.
- neighbourhood: It details the borough's neighbourhood in which the property is located.
- latitude: The location of the property's latitude coordinates.
- longitude: The location of the property's longitude coordinates.
- room_type: This specifies the kind of lodging the host is providing, such as "Entire home/apt," "Private room," or other options.
- price: The prices involved in only short-term renting out the home.
- minimum_nights: While reserving a property, the required minimum number of nights.
- number_of_reviews: The total number of reviews that the property has received.
- last_review: The date of the most recent review posted for the property.

- reviews_per_month: The average number of reviews received per month for the property.
- calculated_host_listings_count: The number of accommodations that the same host has provided
- availability_365: The amount of days that can be reserved throughout the following 365 days.
- number_of_reviews_ltm: The number of reviews that have been received in the last 'n' months, where 'n' represents a certain amount of time.
- license: A statement stating if the lodging has the necessary permit or license.

This dataset's information, which covers hosts, locations, costs, and reviews, appears to be helpful for analysing Airbnb listings in New York City. Researchers and analysts can use this data to find out more about the short-term rental market in the city.

Final Datatype is

```

name                object
host_name            object
neighbourhood_group  object
neighbourhood        object
latitude             float64
longitude             float64
room_type            object
price                int64
minimum_nights        int64
number_of_reviews     int64
last_review          datetime64[ns]
reviews_per_month     float64
calculated_host_listings_count  int64
availability_365      int64
number_of_reviews_ltm  int64
year                 float64
dtype: object

```

Figure 1: Datatype for Airbnb attributes

The dataset comprises 42,931 rows and 18 columns, encompassing a total of 772,758 records. To facilitate data analysis, we will eliminate the "license and Id" column, which primarily functions as an identifier. Additionally, it's noteworthy that the License Column contains the highest number of NaN (missing) values, hence, we will proceed to drop this particular column.

Step 3: Data Visualization

Hosting Listings Count by Room Types

- The "room_type" attribute describes the different types of accommodations available in the dataset. Here is a breakdown of the available room types and the corresponding counts:
- Entire home/apt: There are a total of 555,985 records with this room type. This category represents properties where guests can rent the entire home or apartment for their exclusive use.
- Hotel room: There are 2,809 records categorized as "Hotel room." This type typically refers to a room in a hotel or similar lodging establishment.
- Private room: There are a substantial 471,145 records labelled as "Private room." This indicates properties where guests can book a private room within a shared living space.
- Shared room: There are 2,615 records classified as "Shared room." This room type suggests that guests will share the living space with others, such as in a hostel or shared accommodation setting.

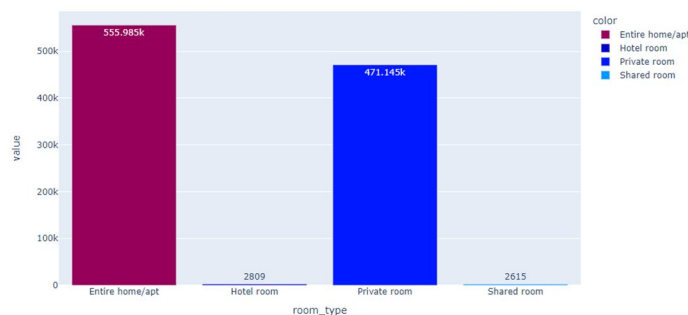


Figure 2: Bar Chart for House Listings count by Room Types

Hosting Listings Count by Neighbourhood Locations

The dataset offers details on the number of hosting listings in various New York City neighbourhoods. The quantity of hosting listings in each borough is described as follows:

- Bronx: In the Bronx, there are 5,103 listings for hosts. This shows how many houses are available in this borough for short-term rentals.
- Brooklyn: Brooklyn has 229,209 homes listed as hosts, which is a sizable quantity. This shows that it's a well-liked Airbnb rental place with a variety of lodging options.
- Manhattan: With a total of 645,602 homes accessible for short-term rental, Manhattan has the most hosting listings of any borough. Given that Manhattan is a significant commercial and tourism destination in New York City, this is not shocking.
- Queens: There are 151,472 hosting listings in Queens, making it another significant location for short-term rentals. Queens offers a diverse range of accommodation options.
- Staten Island: Staten Island has 1,168 properties up for short-term rental, which is a comparatively lesser amount of hosting listings. The fact that it has the fewest residents among the five boroughs may account for the lack of postings.

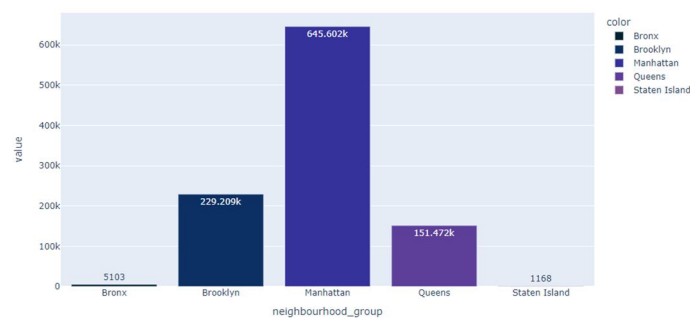


Figure 3: Bar Chart for Hosting Listings Count by Neighbourhood Locations

Price plot by Room Type

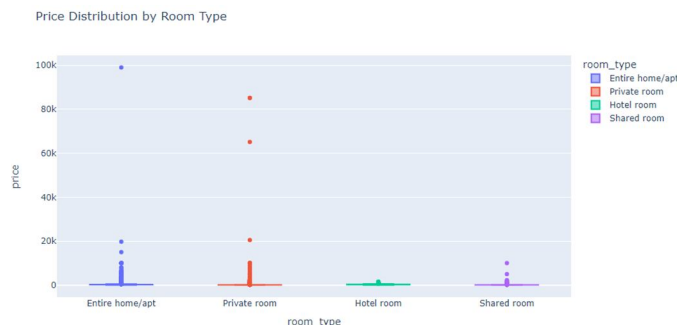


Figure 4: Price plot by Room Type

Price plot by Neighbourhood Groups

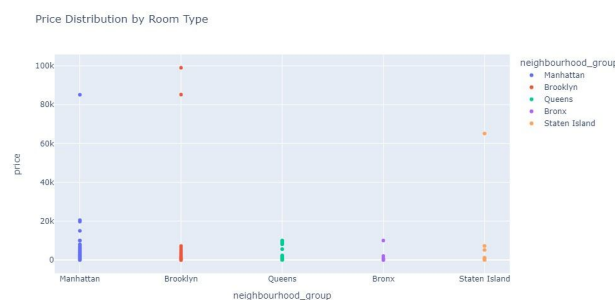


Figure 5: Price Distribution by Neighbourhood Groups

Heat Map

The associations between various variables in a dataset are often depicted as numerical values in a heatmap or correlation matrix. The matrix in this instance shows the relationships between several characteristics associated with Airbnb listings, such as:

- price: The price of the hosted properties.
- minimum_nights: The minimum number of nights that visitors must book.
- number_of_reviews: the overall amount of evaluations for the properties.
- reviews_per_month: The average number of reviews received per month.
- calculated_host_listings_count: The count of accommodations hosted by the same host.
- availability_365: The number of available days for booking within the next 365 days.
- number_of_reviews_ltm: The number of reviews received in the last certain number of months (possibly a specific period).

Each cell in the matrix contains a numerical value that represents the correlation between two variables. Correlation measures the strength and direction of a linear relationship between two variables:

A value of 1 indicates a perfect positive correlation, meaning that as one variable increases, the other also increases linearly.

A value of -1 indicates a perfect negative correlation, meaning that as one variable increases, the other decreases linearly.

A value close to 0 indicates a weak or no linear correlation between the variables.

For example, in this matrix, you can observe that "reviews_per_month" and "number_of_reviews_ltm" have a relatively high positive correlation of 0.858727, suggesting that as the average monthly number of reviews increases, the number of reviews received in the last few months also tends to increase. On the other hand, "minimum_nights" and "number_of_reviews" have a negative correlation of -0.138867, indicating that a longer minimum stay requirement is associated with fewer total reviews.

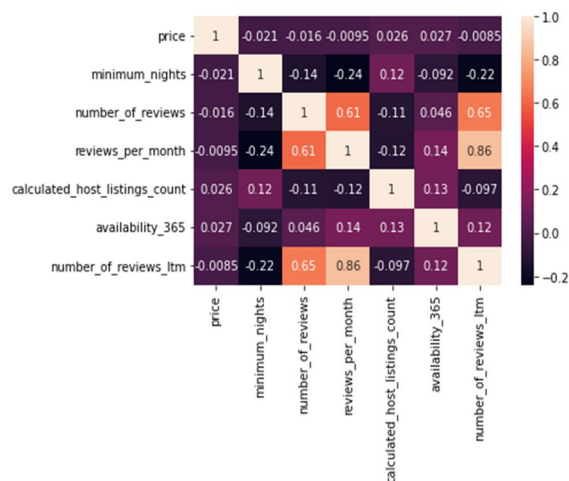


Figure 6: Heat Map

Geographical Map



Figure 7: Geographical Map

Mean Price Distribution by Neighbourhood Groups and Room Types

The "mean price by room types" represents the average or mean price associated with different types of accommodations (room types) in a given dataset. Here's the mean price for each room type:

- Entire home/apt: The average price for renting an entire home or apartment is approximately \$249.26.
- Hotel room: The average cost to reserve a hotel room is about \$309.96.
- Private room: The typical cost for a private room in a shared residence is about \$134.70.
- Shared room: The average price for a shared room, where guests share the living space with others, is approximately \$126.25.

When booking or selling homes on websites like Airbnb, these mean prices give both hosts and visitors information about the normal cost associated with various types of lodging.

The term "mean price by neighbourhood group types" describes the average or mean cost of lodging across various neighbourhood groups in a given area or city. For each neighbourhood group, the mean price is computed in this context. The average rates for each neighbourhood category are listed below:

- Bronx: The average price for accommodations in the Bronx neighbourhood group is approximately \$117.51.
- Brooklyn: The average price for accommodations in the Brooklyn neighbourhood group is around \$162.77.
- Manhattan: Accommodations in Manhattan have the highest average price, which is approximately \$268.12.
- Queens: Accommodations in Queens typically cost around \$128.17 per night.
- Staten Island: The second-highest average price is found in Staten Island, where hotel stays typically cost \$309.04 per night.

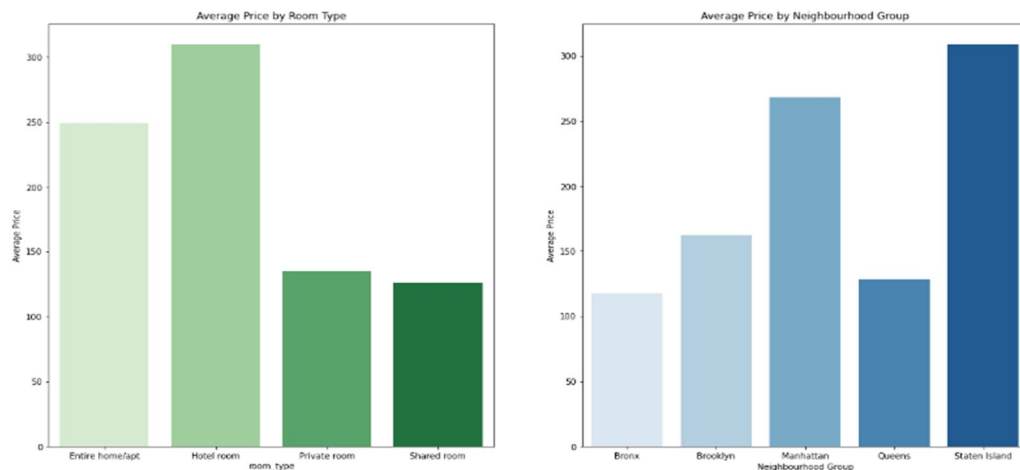


Figure 8: Bar Chart for Mean Price Distribution by Neighbourhood Groups and Room Types

Number of reviews by Room Type and Neighbourhood Locations

The total number of reviews that were submitted for various room kinds of accommodations are shown as "Number of reviews by Room Type" in a particular dataset. Here's the breakdown of the number of reviews for each room type:

- Entire home/apt: Accommodations categorized as "Entire home/apt" have received a total of 645,605 reviews. This indicates the cumulative number of reviews for properties where guests can rent the entire home or apartment for their exclusive use.
- Hotel room: Accommodations listed as "Hotel room" have accumulated 10,292 reviews in total. These reviews pertain to properties that offer hotel-style rooms.
- Private room: For accommodations labelled as "Private room," there are a total of 442,186 reviews. These reviews are associated with properties where guests can book a private room within a shared living space.
- Shared room: Accommodations categorized as "Shared room" have received a total of 11,940 reviews. This represents the number of reviews for properties where guests share the living space with others, such as in a hostel or shared accommodation setting.

"Number of reviews by neighbourhood group" refers to the total count of reviews received for accommodations located in different neighbourhood groups within a specific city or region. Here's the breakdown of the number of reviews for each neighbourhood group:

- Bronx: Accommodations situated in the Bronx neighbourhood group have accumulated a total of 43,047 reviews. This represents the overall number of reviews for properties located in the Bronx area.

- Brooklyn: In the Brooklyn neighbourhood group, accommodations have received a substantial total of 466,643 reviews. This indicates the cumulative number of reviews for properties in the borough of Brooklyn.
- Manhattan: Accommodations in the Manhattan neighbourhood group have garnered a total of 376,780 reviews. This reflects the number of reviews for properties located in the borough of Manhattan.
- Queens: The neighbourhood group of Queens has accumulated a total of 208,344 reviews. This represents the combined number of reviews for accommodations in Queens.
- Staten Island: Accommodations in Staten Island's neighbourhood group have received a total of 15,209 reviews. This reflects the number of reviews for properties located in Staten Island.

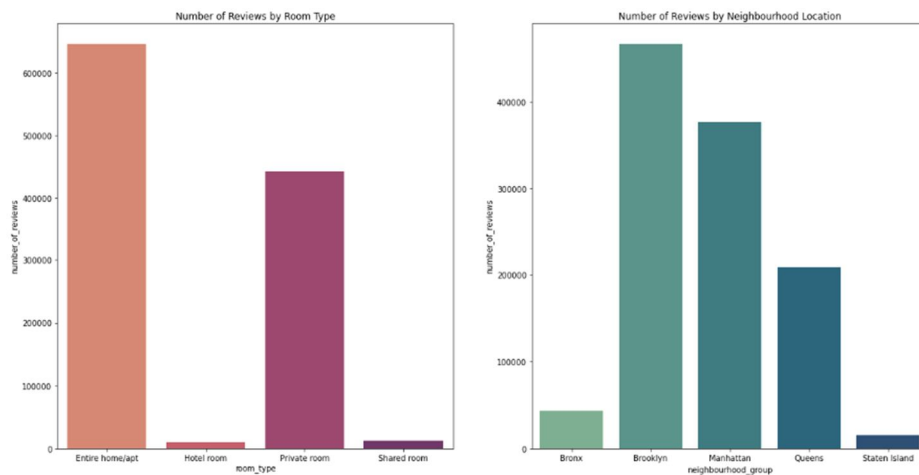


Figure 9: Number of reviews by Room Type and Neighbourhood Locations

Availability of Rooms

"Availability of Rooms" refers to the total number of room listings available for booking within different room types in a specific context, typically within a specific dataset or platform. Here's the availability breakdown for each room type:

- Entire home/apt: There are 3,468,510 entire home/apartment listings available. This indicates the total number of properties where guests can book and have the entire home or apartment to themselves during their stay.
- Hotel room: There are 40,942 hotel room listings available. This represents the number of hotel-style rooms that guests can book within the given dataset or platform.
- Private room: There are 2,417,111 private room listings available. Accommodations in this category allow visitors to reserve a private room inside a communal living area.
- Shared room: There are now 93,359 listings for shared rooms. These are establishments where visitors live in residences with other people, such in a hostel or other type of shared lodging.

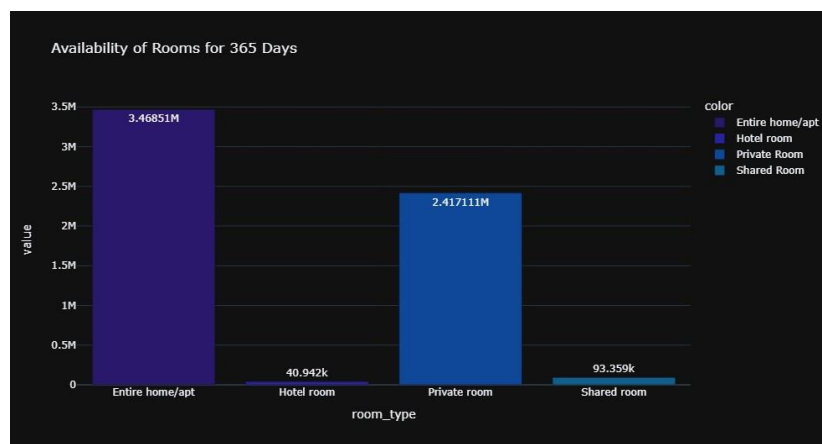


Figure 10: Availability of Rooms for 365 Days

Price by Year

Within a given dataset, "Price by Year" shows the average or overall cost of a specific item or service across each year. In this situation, the dataset offers details on a product's pricing over a period of years. The price information for each year is broken down as follows:

- Year 2011: The cost was \$844 in 2011.
- Year 2012: The cost rose to \$1,696 in that year.
- Year 2013: In 2013, the cost increased further and topped \$6,430.
- Year 2014: The cost climbed to \$16,068 in 2014.
- Year 2015: The cost significantly increased to \$127,204 in 2015.
- Year 2016: The cost increased to \$191,224 in 2016.
- Year 2017: The cost was \$155,581 in 2017.
- Year 2018: The cost grew to \$204,155 in the following year, 2018.
- Year 2019: The cost surpassed \$338,396 in the year 2019.
- Year 2020: \$380,013 was the cost in 2020.
- Year 2021: The price fell to \$288,765 in the following year, 2021.
- Year 2022: The price increased significantly in 2022, reaching \$1,963,554 overall.
- Year 2023: The dataset has a total cost of \$2,217,188 and covers the year 2023.

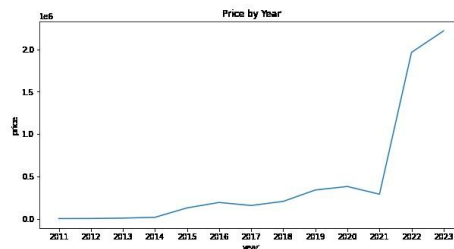


Figure 11: Line Plot Price by Year

Host Listings by Year

The data in "Host Listings by Year" shows how many hosts or properties there were on a certain platform or in a particular dataset across a number of years. The breakdown of the host listings information by year is as follows:

- Year 2011: In 2011, there were 32 host listings available.
- Year 2012: The number of host listings decreased to 16 in 2012.
- Year 2013: In 2013, the number of host listings increased to 33.
- Year 2014: The number of host listings further increased to 112 in 2014.
- Year 2015: In 2015, there was a significant jump in host listings, reaching 898.
- Year 2016: The number of host listings continued to grow to 1,764 in 2016.
- Year 2017: In 2017, there were 2,238 host listings available.
- Year 2018: The number of host listings increased to 2,855 in 2018.
- Year 2019: In 2019, there was a substantial increase in host listings, reaching 12,653.
- Year 2020: The number of host listings further increased to 19,224 in 2020.
- Year 2021: In 2021, there was a significant surge in host listings, totalling 49,855.
- Year 2022: In 2022, the number of host listings saw a substantial increase to 140,638.
- Year 2023: The dataset extends to 2023, with a total of 96,291 host listings.

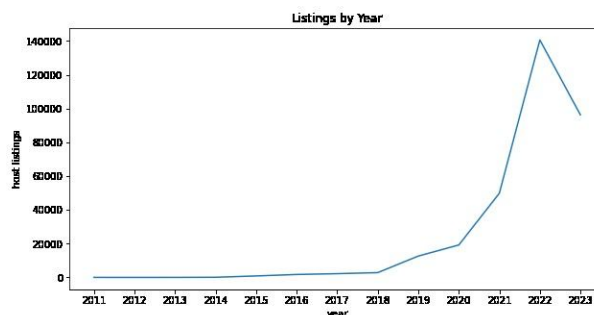
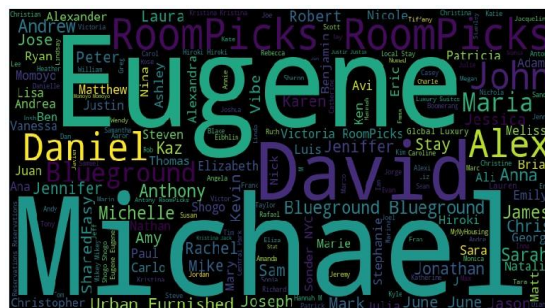


Figure 12: Line Plot Host Listings by Year

"Top Five Listings by Host Names" displays a list of the top five hosts in a given dataset or context in terms of the quantity of listings. The top five hosts are shown here, along with the number of listings that each has.:

-
- Top Five Listings by Host names
- | host_name | value |
|------------|-------|
| Blueground | ~260k |
| Eugene | ~150k |
| RoomPicks | ~125k |
| June | ~50k |
| Hiroki | ~40k |

Word Cloud for Hostnames: In the context of Airbnb, a "Word Cloud for Hostnames" is a visual depiction of the most frequent words or keywords found in the hostnames of Airbnb property listings. The names or titles that hosts provide to specific Airbnb listings are often represented by hostnames. By processing the text data from these hostnames and graphically showing the words in various sizes, these word clouds are created, with bigger text size signifying more frequency.



1233

III. RESULTS AND DISCUSSION

In conclusion, the examination of the New York City Airbnb dataset shows a number of noteworthy trends and insights: With a substantial number of listings, Manhattan appears as the most popular neighbourhood for Airbnb rentals, perhaps as a result of its prominence as a major tourist and commercial hub. Staten Island stands out among the boroughs for having the most expensive average pricing, with Airbnb accommodations costing on average \$309 per night. This could be due to its unique appeal and offerings. There was a remarkable surge in both the number of Airbnb listings and their prices in the year 2022. This suggests a potential shift or peak in the short-term rental market during that year. The analysis indicates that renting an entire house or apartment is the most expensive option, with an average cost of around \$10,000. This likely reflects the premium associated with having the entire space to oneself. A word cloud, which visually represents the most frequently occurring words in the dataset, has been generated and can be found in the repository. This word cloud can provide additional insights into the key terms or descriptors associated with Airbnb listings in New York City.

REFERENCES

- [1] Cheng, M. (2016). The sharing economy: A contemporary review. *International Journal of Hospitality Management*, 57, 60-70.
- [2] Cheung, K. S., & Yiu, C. Y. (2022). The paradox of Airbnb, crime and house prices: A reconciliation. *Tourism Economics*. Advance online publication. doi:10.1177/13548166221102808.
- [3] Cherapanukorn, V., & Charoenkwan, P. (2018). Word cloud of online hotel reviews in Thailand for customers' satisfaction analysis. *JP Journal of Heat and Mass Transfer*, SV2018(2), 213–220. doi:10.17654/hmsi218213.
- [4] Goh, K.-Y., Heng, C.-S., & Lin, Z. (2013). Social media brand community and consumer behavior: Quantifying the relative impact of user- and marketer-generated content. *Information Systems Research: ISR*, 24(1), 88–107. doi:10.1287/isre.1120.0469.
- [5] Huang, S., Liang, L. J., & Choi, H. C. (2022). How we failed in context: A text-mining approach to understanding hotel service failures. *Sustainability*, 14(5), 2675. doi:10.3390/su14052675.
- [6] Scerri, M. A., & Presbury, R. (2020). Airbnb Superhosts' talk in commercial homes. *Annals of Tourism Research*, 80(102827), 102827. doi:10.1016/j.annals.2019.102827.
- [7] Qiu, H., Chen, D., Bi, J.-W., Lyu, J., & Li, Q. (2022). The construction of the affinity-seeking strategies of Airbnb homestay hosts. *International Journal of Contemporary Hospitality Management*, 34(3), 861–884. doi:10.1108/ijchm-10-2020-1157.
- [8] Xu, X., & Li, Y. (2016). The antecedents of customer satisfaction and dissatisfaction toward various types of hotels: A text mining approach. *International Journal of Hospitality Management*, 55, 57–69. doi:10.1016/j.ijhm.2016.03.003.
- [9] Zhang, L., Yan, Q., & Zhang, L. (2020). A text analytics framework for understanding the relationships among host self-description, trust perception and purchase behavior on Airbnb. *Decision Support Systems*, 133, 113288. doi:10.1016/j.dss.2020.113288.
- [10] Zhang, X., Wei, X., Zhang, T., Liang, S., Ma, Y., & Law, R. (2023). Power of sentiment expressions on peer-to-peer rental platforms: A mixed-method approach. *Journal of Travel Research*, 00472875231158598. doi:10.1177/00472875231158598.
- [11] Zervas, G., Proserpio, D., & Byers, J. W. (2017). The rise of the sharing economy: Estimating the impact of Airbnb on the hotel industry. *Journal of Marketing Research*, 54(5), 687-705.