Cairo University

Faculty of Engineering Credit Hours System

Data Mining, Big Data Analysis

CMPS451

Airbnb Data Analytics Project

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Contents

I. Problem definition

The project aims to analyze a comprehensive dataset of Airbnb accommodations across various U.S. cities. The objective is to extract insights that can guide property owners and business stakeholders in making informed decisions regarding property investments, pricing strategies, and market understanding within the Airbnb ecosystem.

The rise of Airbnb as a popular platform for short-term rental accommodations has created a dynamic and competitive market landscape across various cities in the United States. For property owners and business stakeholders, understanding the intricacies of this market is crucial for making strategic decisions regarding property investments, pricing strategies, and market positioning.

Challenges in the Airbnb Market:

- **Property Selection**: Property owners need to identify optimal locations and property types that are likely to attract guests and yield high returns.
- **Pricing Strategies**: Determining competitive and profitable pricing strategies based on location, property features, and market demand is essential for maximizing occupancy rates and revenue.
- **Market Insight**: A comprehensive understanding of the Airbnb ecosystem, including guest preferences, amenities, and regional trends, is vital for making informed investment decisions.

Project Objectives

The primary goal of this project is to leverage big data analytics techniques to extract actionable insights from a comprehensive Airbnb dataset. These insights will empower property owners and business stakeholders by providing:

1. **Market Understanding**:
    - Identify lucrative regions and property types based on historical Airbnb data.
    - Analyze the impact of various attributes (e.g., property type, amenities, location) on rental success metrics (e.g., occupancy rates, guest satisfaction).
2. **Decision Support**:
    - Enable data-driven property investment decisions by recommending optimal property types and locations.
    - Offer pricing recommendations based on market dynamics and competitive analysis within specific regions.
3. **Competitive Advantage**:
    - Equip property owners with the knowledge to position their listings strategically to maximize market competitiveness and guest satisfaction.

Dataset Overview

The Airbnb dataset comprises over 70,000 entries encompassing diverse attributes related to accommodations, hosts, pricing, and guest reviews across multiple U.S. cities. Key dataset features include:

- **Property Attributes**: Property type, room type, amenities, and listing descriptions.
- **Host Characteristics**: Host profile and hosting history.
- **Geographical Details**: Location coordinates, neighborhood information, and city.
- **Guest Reviews**: Ratings, comments, and feedback from previous guests.

Significance of Analysis

The insights derived from this analysis will have profound implications for:

- **Property Owners**: Optimize property investments and improve rental performance based on data-driven strategies.
- **Business Owners**: Enhance revenue generation through informed pricing decisions and market positioning strategies.
- **Industry Stakeholders**: Gain a deeper understanding of the evolving Airbnb market landscape and emerging trends.

By conducting a comprehensive analysis of the Airbnb dataset, this project aims to bridge the gap between data analytics and real-world decision-making in the dynamic short-term rental market, ultimately fostering success and competitiveness for property owners and stakeholders.

II. Project pipeline

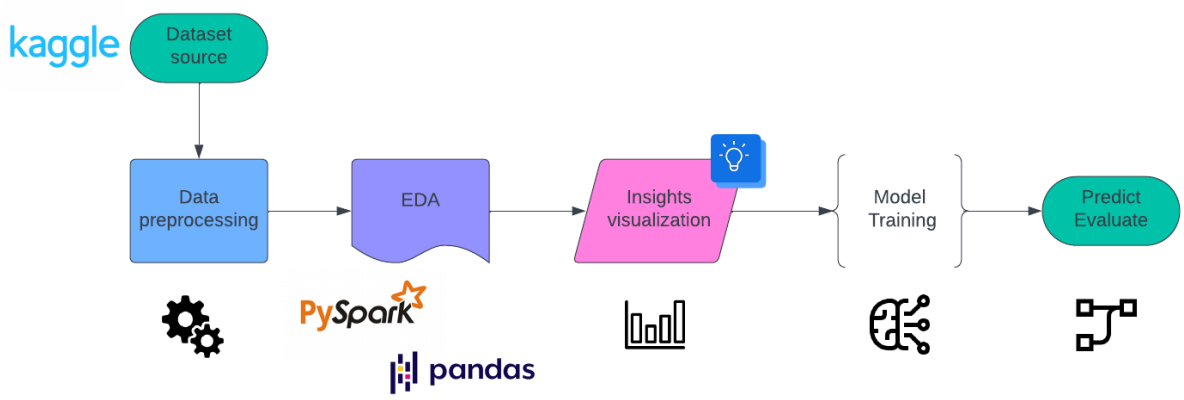


Figure 1: Project pipeline.

Data Preprocessing: Cleanse and preprocess the dataset to handle missing values, outliers, and ensure uniform data formatting for analysis.

Exploratory Data Analysis (EDA):

- **Visualization**: Utilize visualization techniques to understand data distributions, correlations, and trends.
- **Insights Extraction**: Identify key patterns and insights from the dataset to inform property investment strategies and pricing decisions.

Model Training:

- Develop predictive models (Polynomial regression, Random Forest) to forecast prices
- Develop a city prediction model using SVM

III. Analysis and solution of the problem

1) Data preprocessing

- Convert the log_price column to price by taking the exponent of each value
- Categorize the price column to ease the analysis
- Remove useless columns
- Remove null values

2) Analysis, Visualization, and Insights

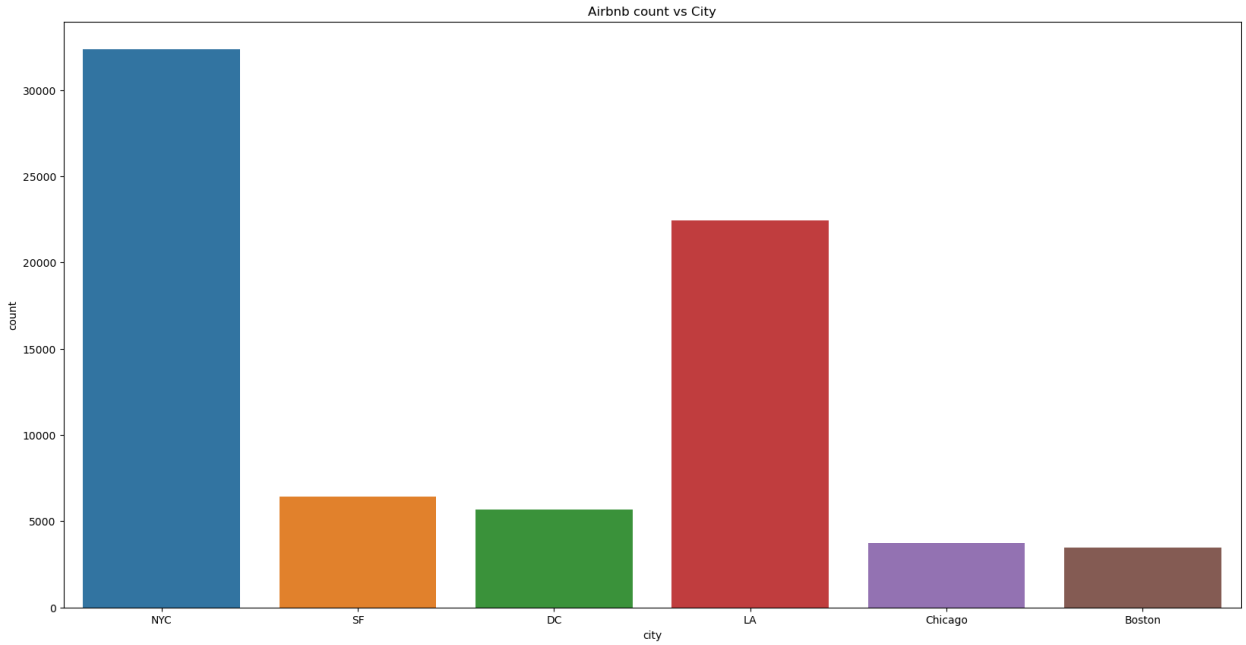
The Following section shows the EDA done and insights found in the data

Cities

Unique cities

- San Fransisco - SF
- New York - NYC
- Washington - DC
- Los Angeles - LA
- Boston
- Chicago

Distribution of Airbnb listings per city



- **NYC** is the city with the most Airbnb offerings with over 32,300 Airbnb listings.
- **Boston** has the minimum Airbnb offerings with count of 3,468 Airbnb listings.

Distribution of average price vs the city

- **San Francisco SF** is the city with highest average price which is equal to 227.37 USD.
- **Chicago** is the city with the lowest average price, with avg of 132.47 USD.

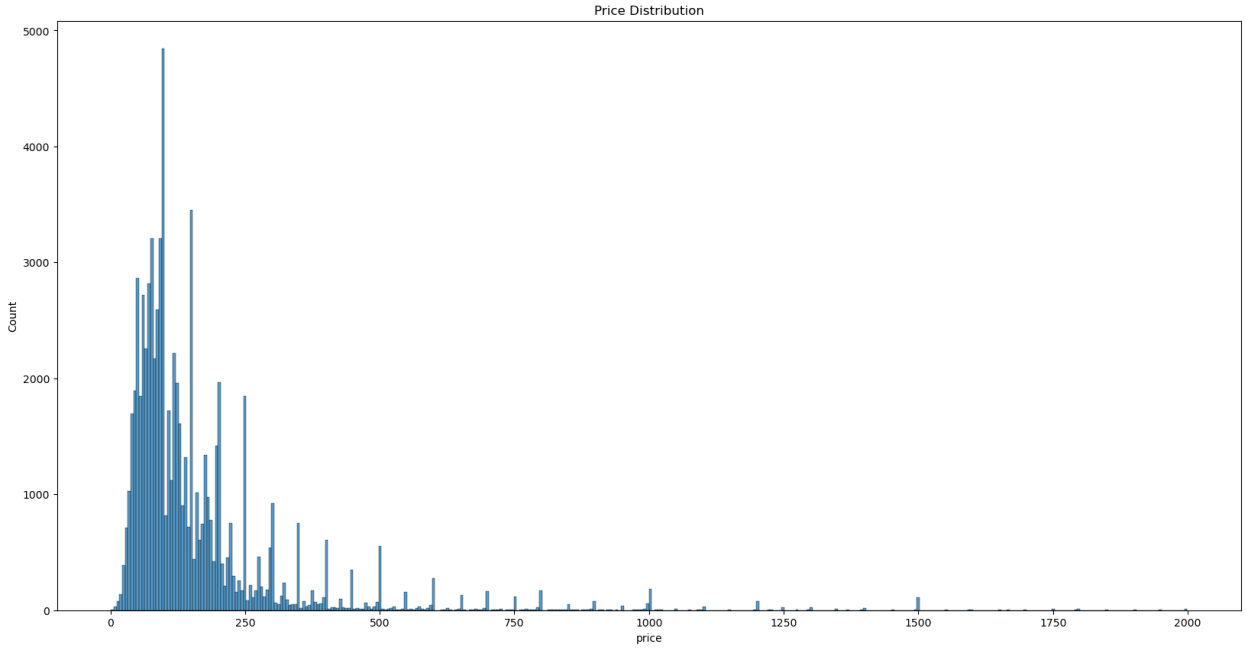
Prices

The mean value: 160.37 usd

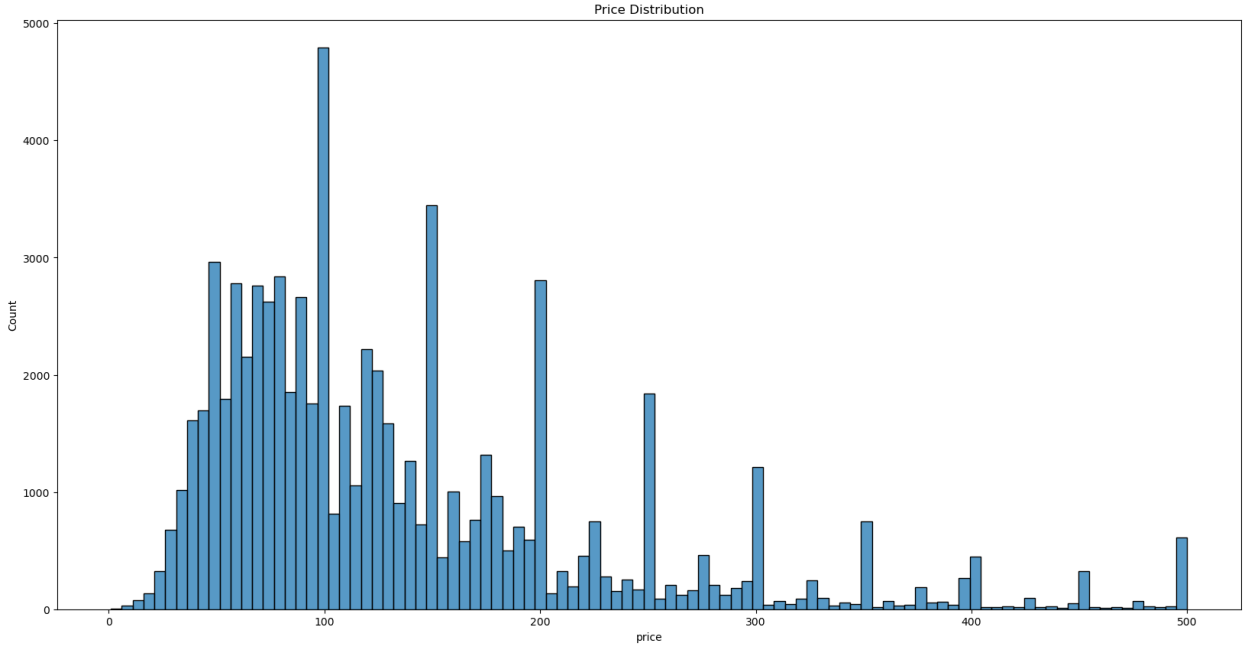
25%	75.0	50%	111.0	75%	185.0

Maximum price: 1999.0 usd Minimum price: 1.0 usd

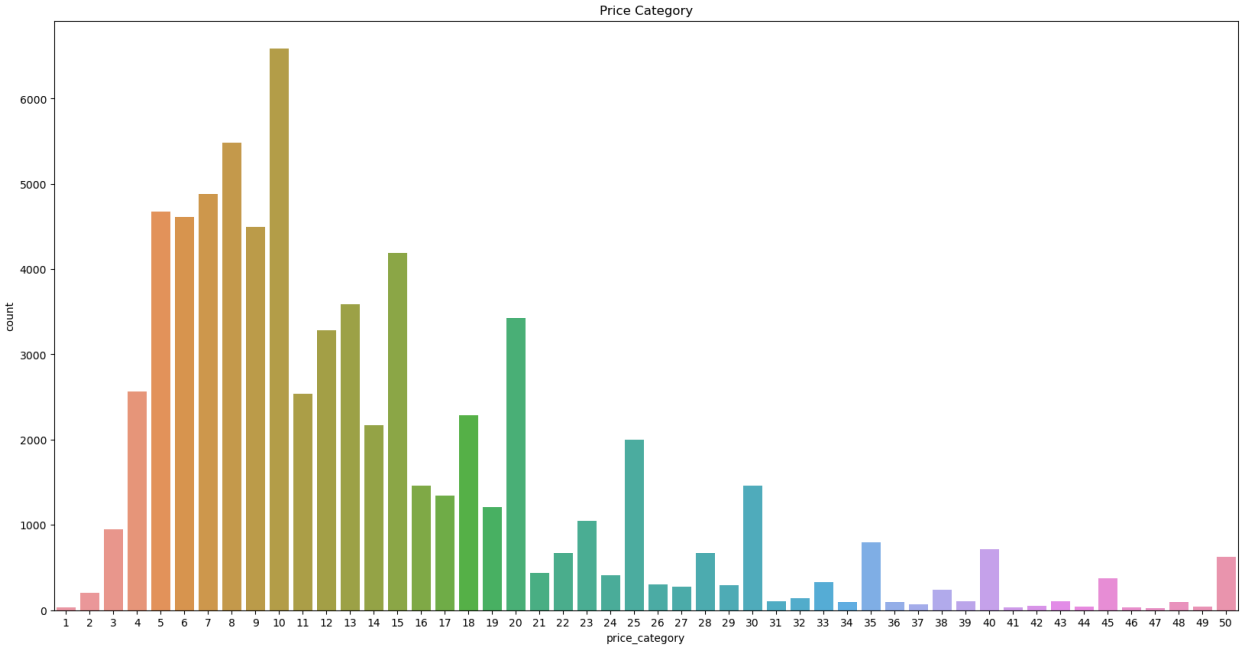
The std: 168.580415



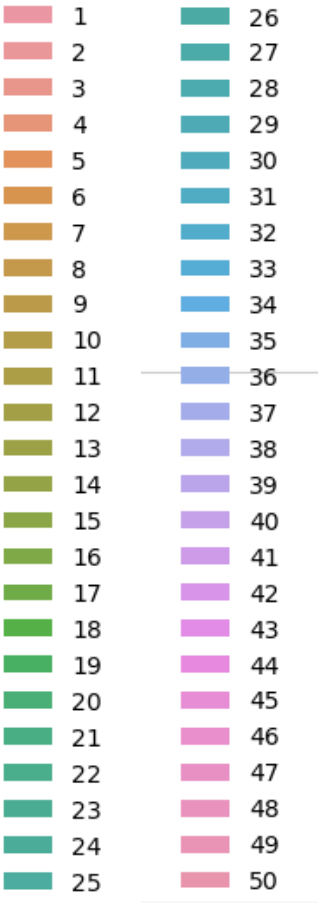
After removing the Airbnb listings with price > 500 USD.



We decided to categorize the prices ranges to ease collecting insights.



N.B: each category spans an incremental range of 10 USD, Color code of price categories:



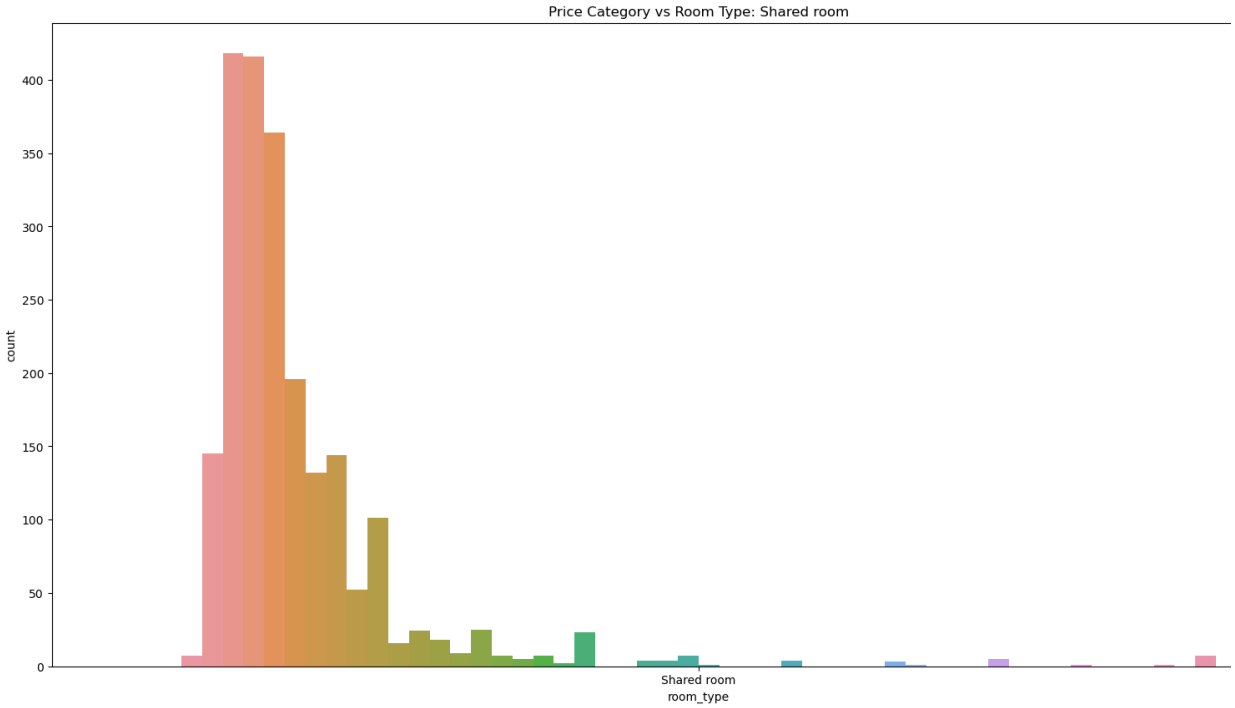
Room Type

Unique room types are:

- Shared Room
- Private Room
- Entire Home/Apt

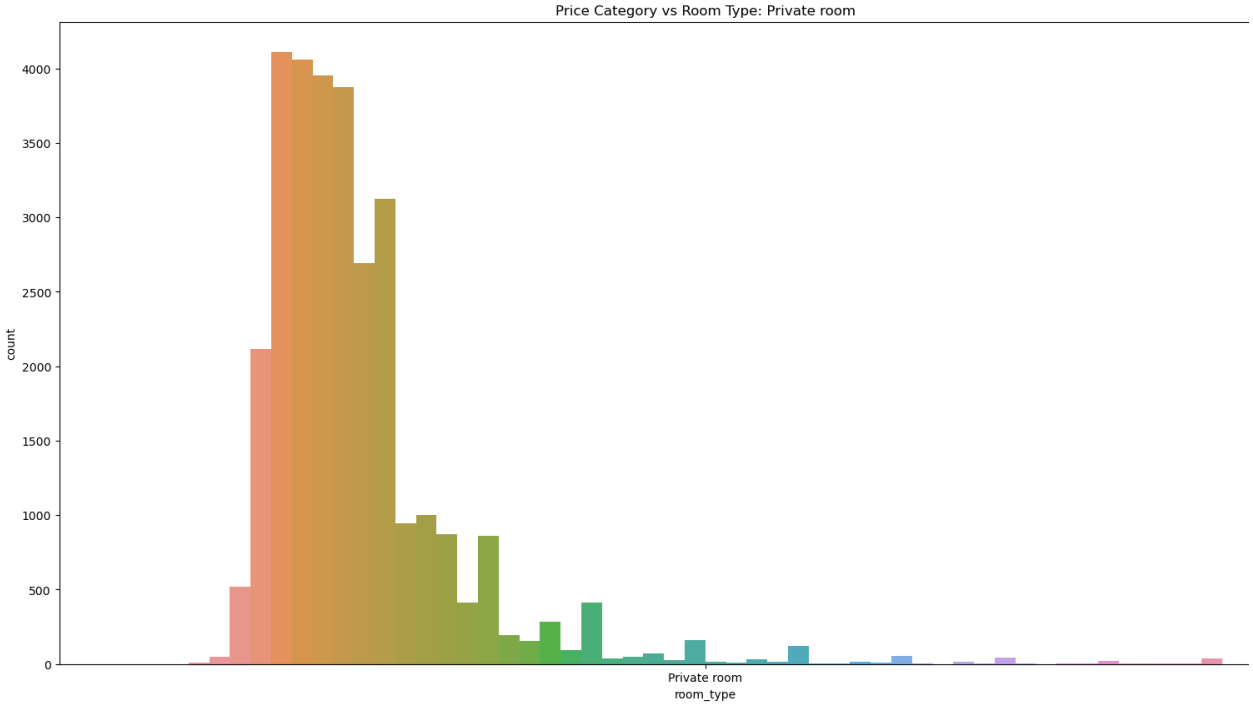
Price categories vs Room Type (*)

Shared Room



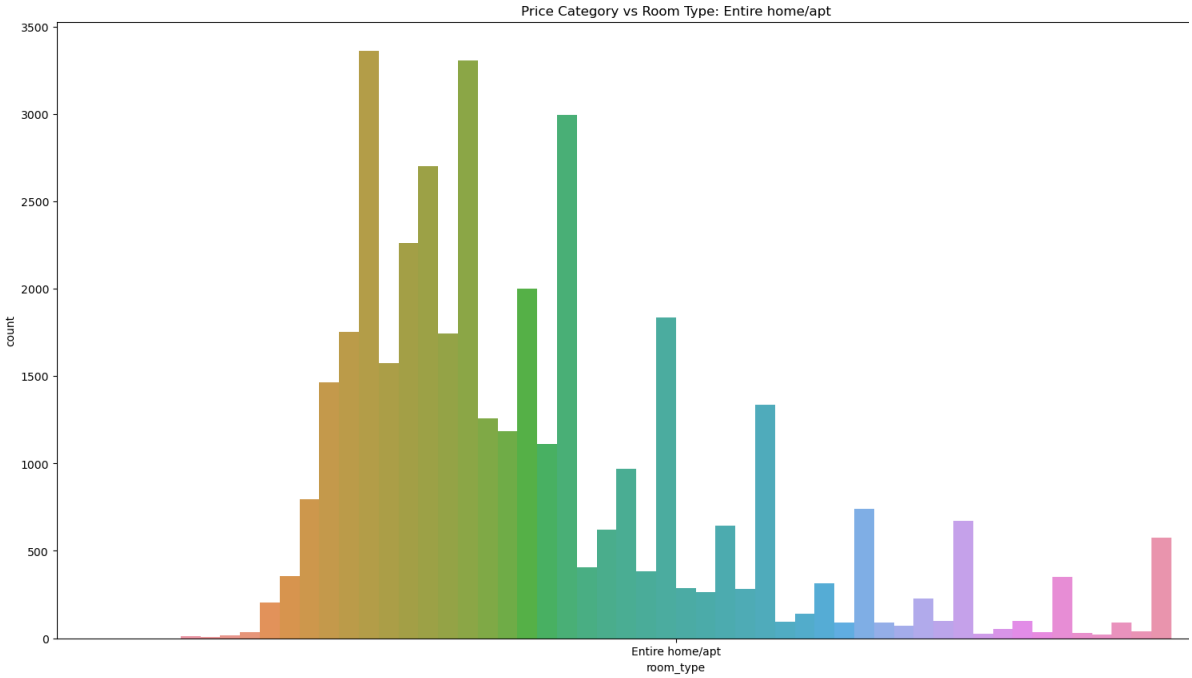
- We could see that the most listings with shared room type are concentrated in low budget end of the price categories

Private Room



- The price distribution for private room is larger than the price distribution of shared room,

Entire home/apt



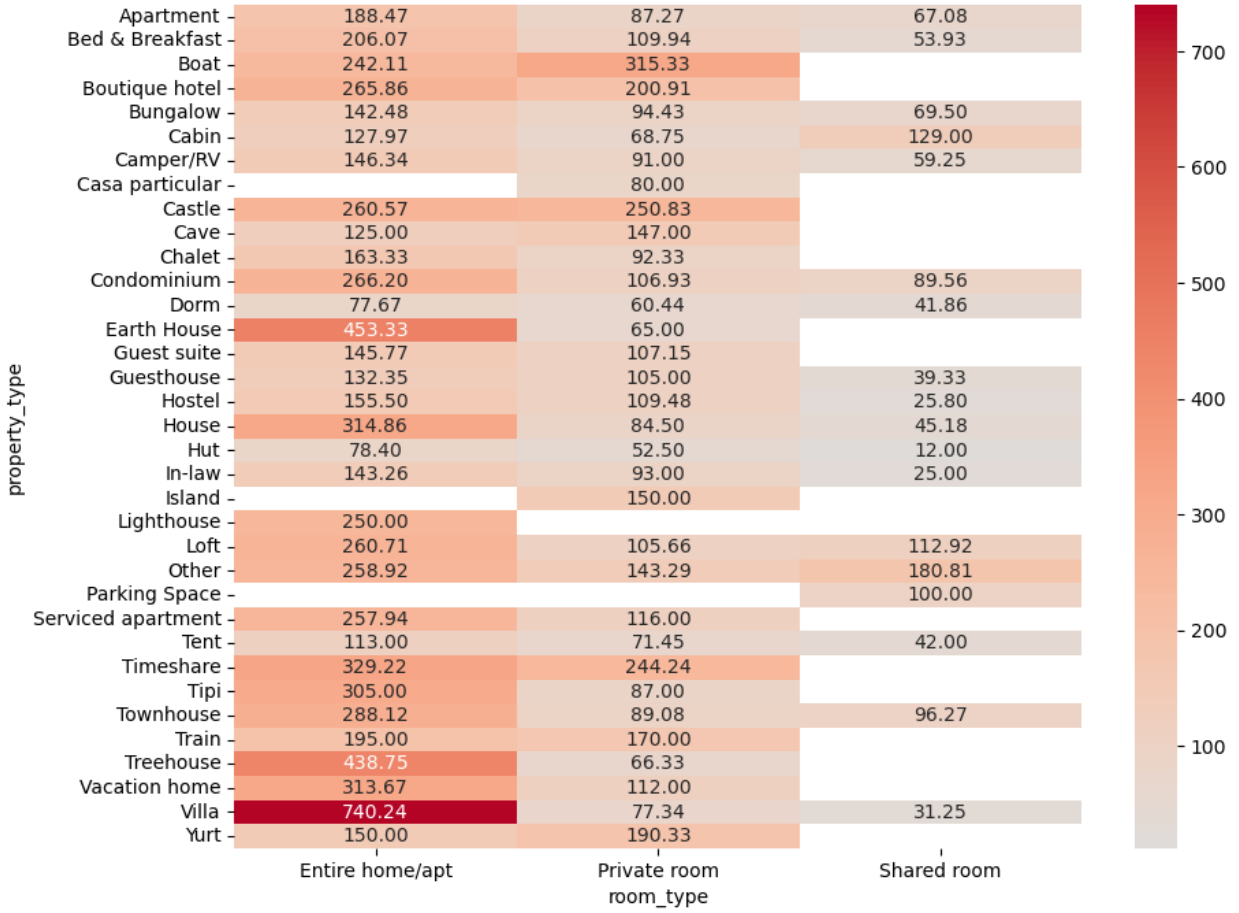
- The price distribution for entire home/apt spans more expensive categories.

Property Type

Examples of property types

Apartment, House, Condominium, Hostel, Dorm, Camper/RV, Villa, Boutique hotel, Timeshare, Boat, Castle, Treehouse, Tipi,..

The correlation between property type, room type and average price (color code column)

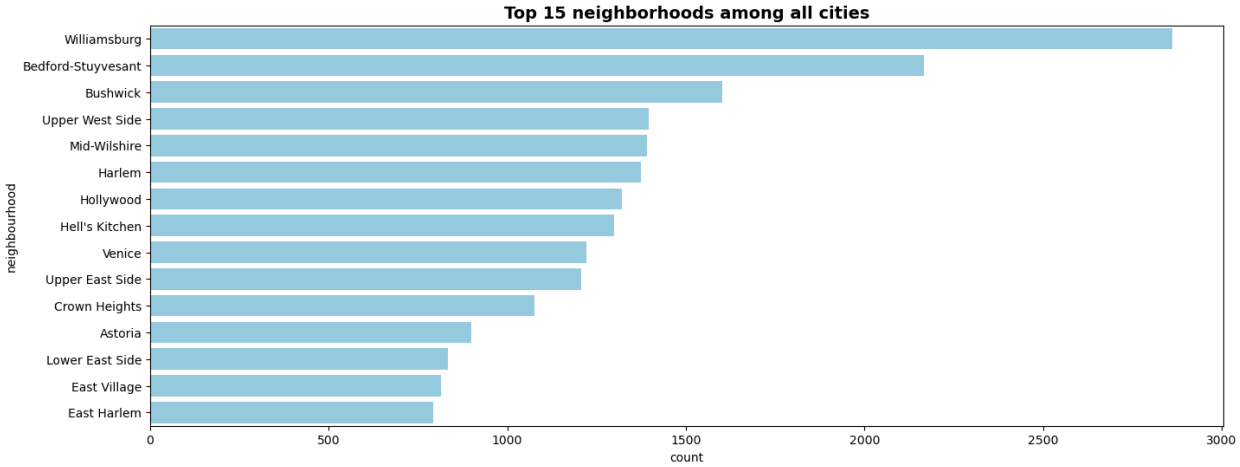


- If we look at shared room column, we could see that the **avg price** is very low (31 - 180) usd, Which shows that shared rooms offerings have low budget price.
- For the private room

Neighborhood

Each city has a number of neighborhoods, the count and avg price of airbnbs in each neighborhood differ.

The neighborhoods that have the most Airbnb listings



The top 3 neighborhoods in avg price in each city

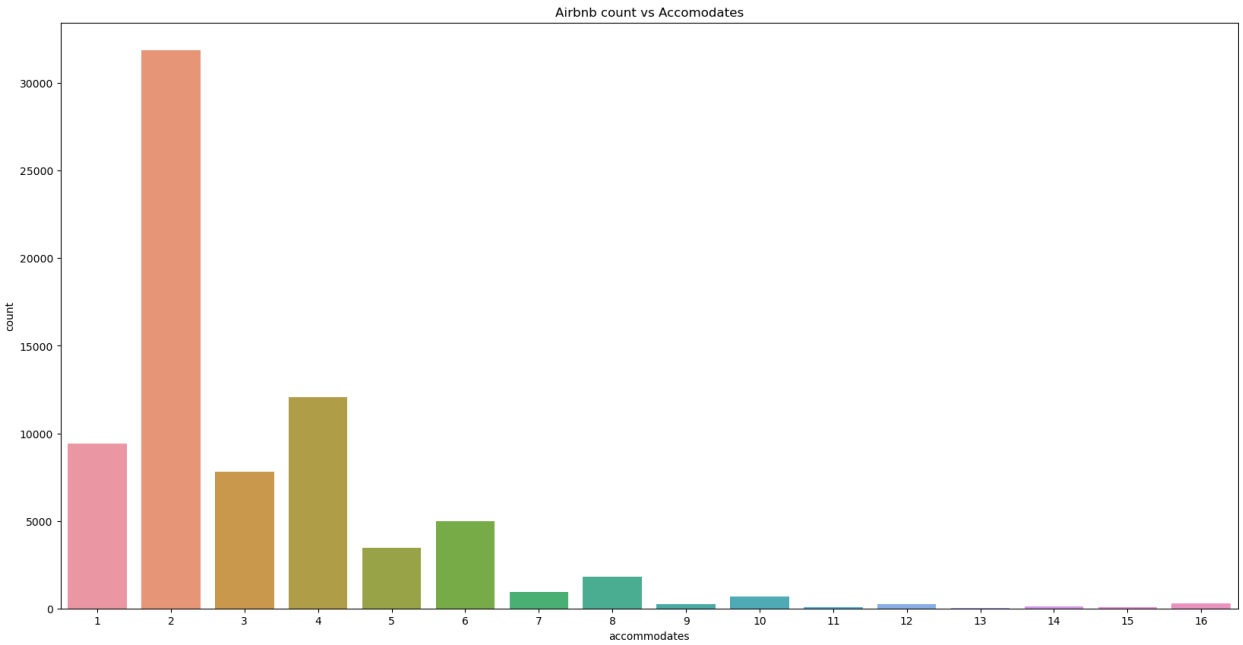
	city	neighbourhood	price
0	Boston	Cambridge	324.500000
1	Boston	Downtown	289.764706
2	Boston	Chinatown	268.021505
3	Chicago	Old Town	214.694444
4	Chicago	Wrigleyville	213.452381
5	Chicago	River West	202.058824
6	DC	Chevy Chase, MD	1250.000000
7	DC	Observatory Circle	825.000000
8	DC	Bellevue	671.666667
9	LA	Wilmington	1300.000000
10	LA	Bel Air/Beverly Crest	527.809160
11	LA	Malibu	522.708108
12	NYC	Mill Basin	500.000000
13	NYC	Emerson Hill	464.500000
14	NYC	Huguenot	372.500000
15	SF	Sea Cliff	797.000000

- Chicago city
    - Neighborhood of highest avg price: Old Town – 214.7usd
    - Neighborhood of lowest avg price: South Chicago – 25 usd
- NYC city
    - Neighborhood of highest avg price: Mill Basin – 500 usd
    - Neighborhood of lowest avg price: Morris Park – 43.6 usd
- Boston city
    - Neighborhood of highest avg price: Cambridge – 324.5 usd
    - Neighborhood of lowest avg price: Somerville – 54 usd
- SF city
    - Neighborhood of highest avg price: Sea Cliff – 797 usd
    - Neighborhood of lowest avg price: West Portal – 125 usd
- DC city
    - Neighborhood of highest avg price: Chevy Chase, MD – 1250 usd
    - Neighborhood of lowest avg price: Suitland-Silver Hill, MD – 37 usd
- LA city
    - Neighborhood of highest avg price: Wilmington – 1300 usd
    - Neighborhood of lowest avg price: La Puente – 40 usd

Number of accommodates

The number of accommodates is the maximum number of people a listing can accommodate.

Distribution of Airbnb listings vs number of accommodates



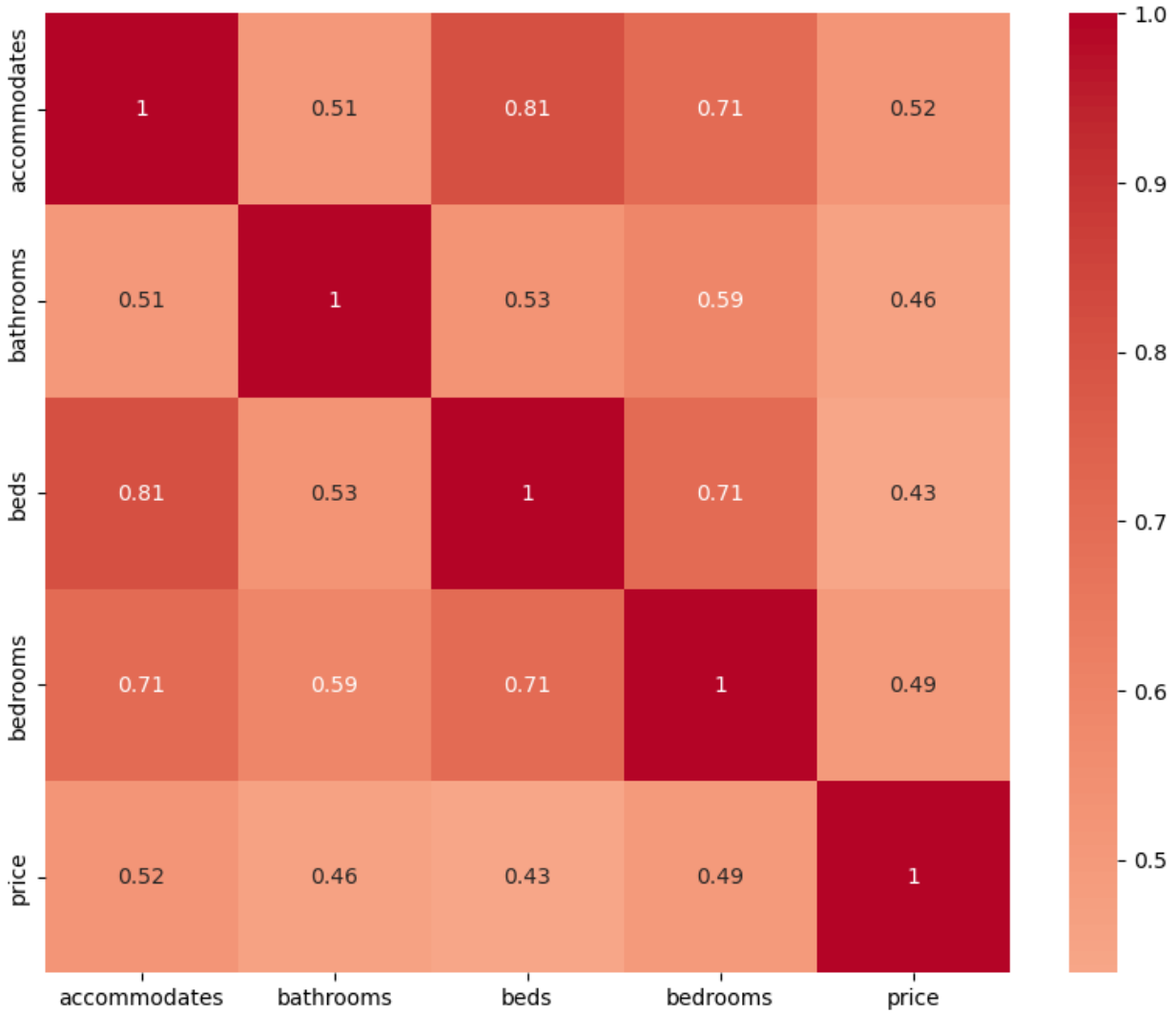
- The most common Airbnb offerings are for places that allow up to **2 accommodates**.
- The mean is 3.155 accommodates.

Amenities

The most frequent amenities using **word cloud**

- Wireless Internet, Smoke detector, Air conditioning are the most frequent amenities in airbnb listings.
- Few Airbnb allow pets.

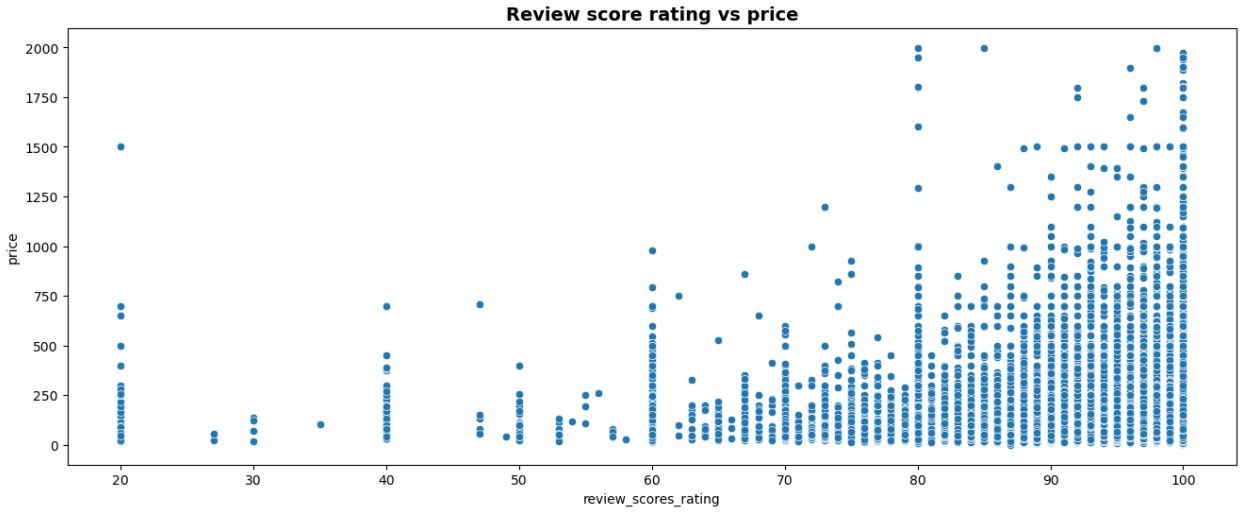
The correlation between multiple features



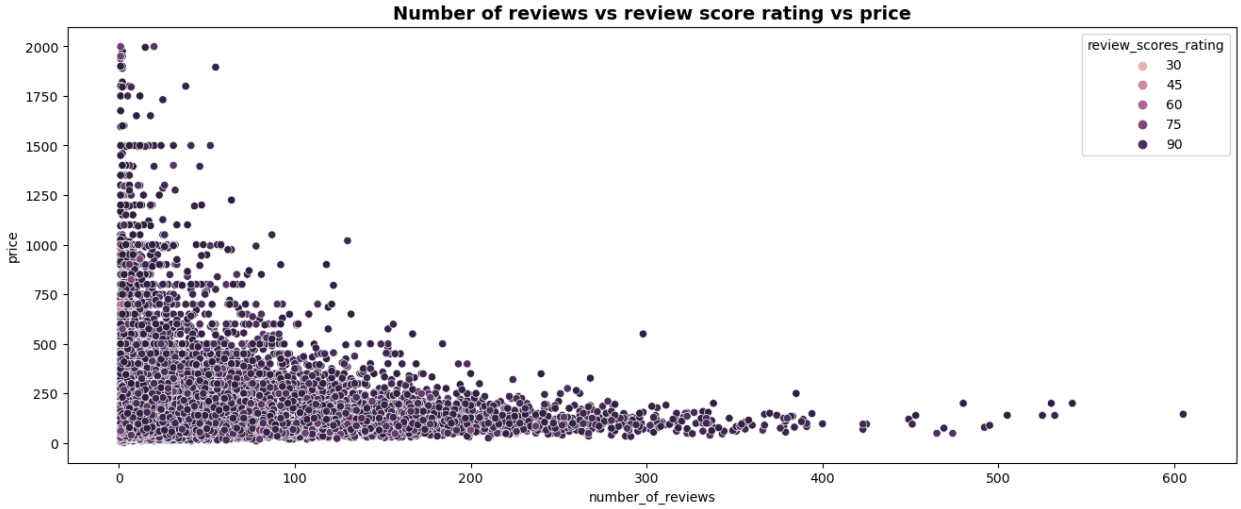
From this heat map we can conclude that,

- The correlation between the number of accommodates and the number of beds is very high (0.81)
- The correlation between the number of accommodates and the number of bedrooms is very high (0.71)
- The correlation between the number of accommodates and the number of bathrooms is not high.

Reviews

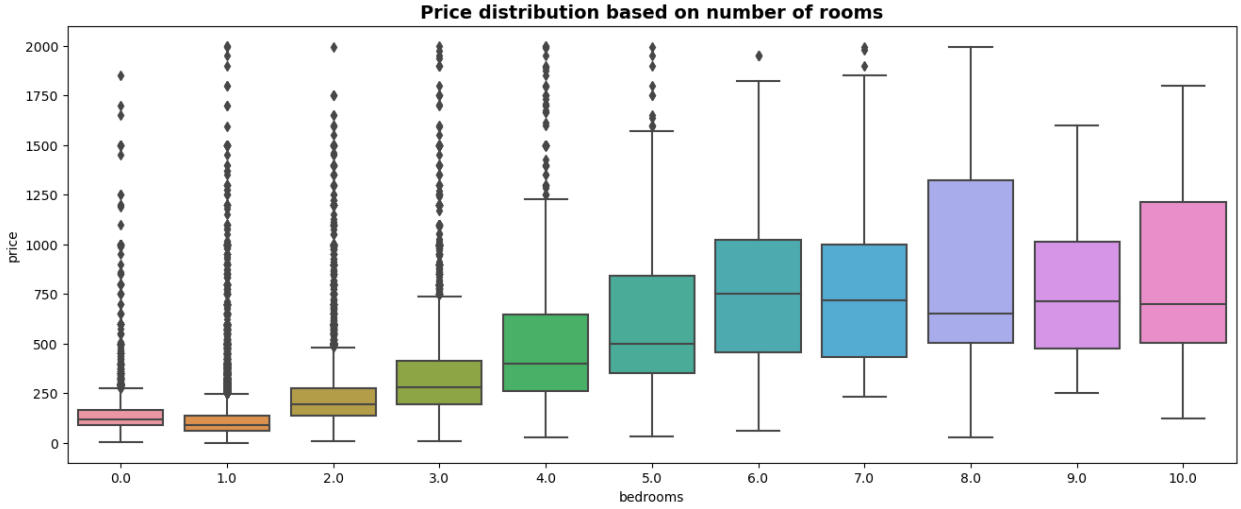


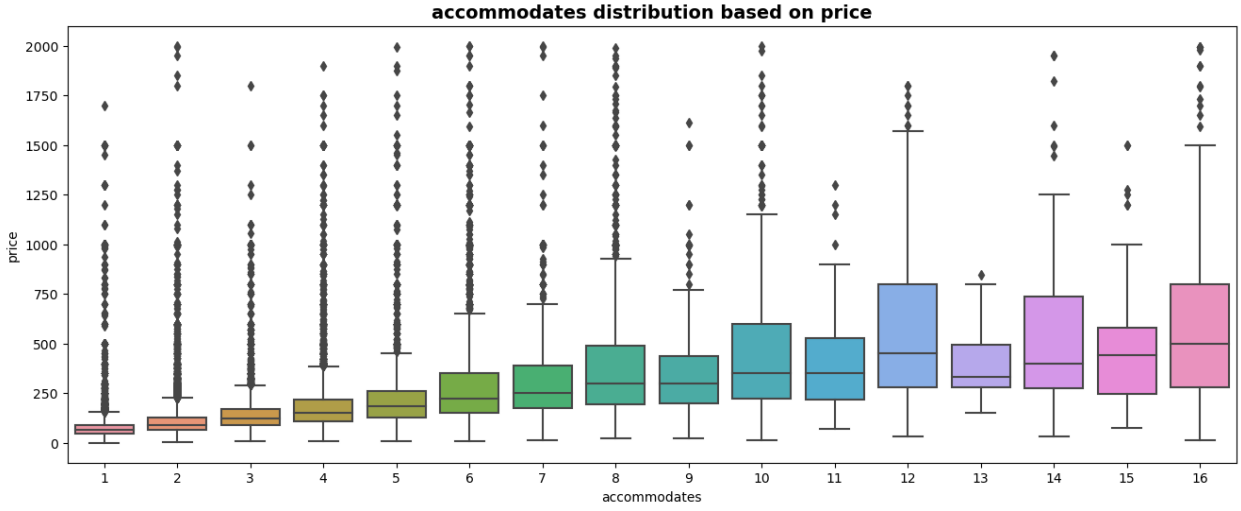
- We could conclude that most of the reviews are for positive sentiment (70 – 100)%
- As we said it is not correlated with the price
- Few reviews are less than 60%



- From this graph, it is clear that the number of reviews does not depend on the price.

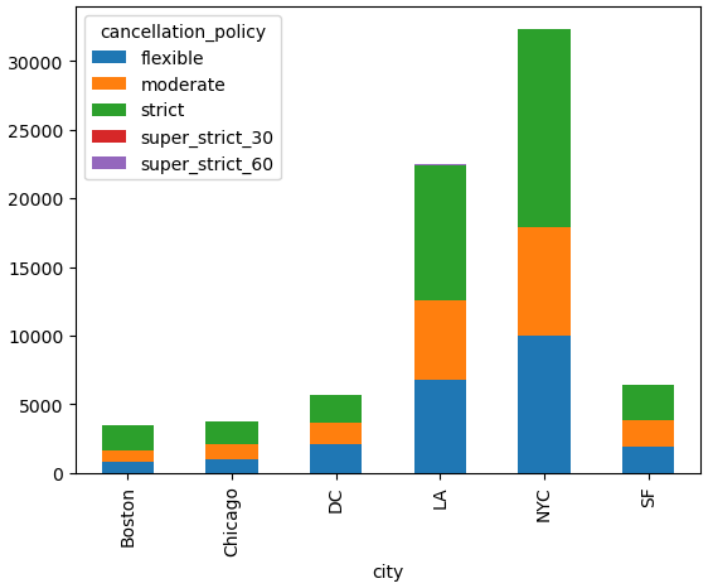
Price correlated features



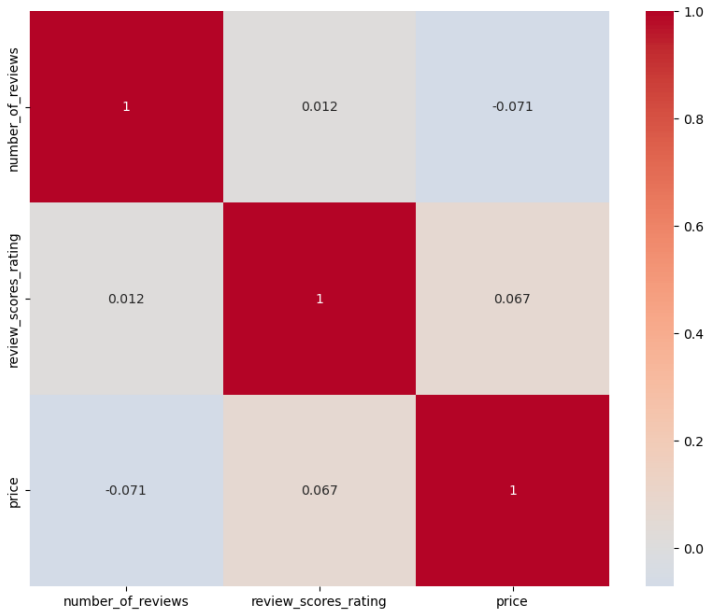


Uncorrelated features

Correlation between city and cancellation policy



We conclude that the cancellation policy does not vary from a city to another, and it has almost the same distribution among all cities.



The number of reviews, reviews scores and price are not correlated

Model and Ai:

First: Price Prediction model

We used 80% of the dataset for training and 20% for testing

We developed 2 model to predict the price, we dropped the null enteries, and used the following features: ['beds', 'bedrooms', 'city', 'number_of_reviews', 'cancellation_policy', 'review_scores_rating', 'room_type', 'property_type', 'neighbourhood', 'cleaning_fee', 'instant_bookable', 'accommodates', 'amenities', 'latitude', 'longitude']

For the categorial features we factorized them in order to use them in the training

First model was Polynomial Regression model it gave accuracy equal to 0.67463935

Second model was a Random Forest which gave a better performance and accuracy equal to 0.71992

Second: City prediction model

We developed an SVM model that takes ['price','bathrooms', 'cleaning_fee', 'bedrooms', 'number_of_reviews', 'cancellation_policy', 'review_scores_rating', 'latitude', 'longitude'] as features

And predicts the city

It gave an accuracy of 99.89% and F1 score of 0.9985209

Failed Trials: before getting those results, we tried decision tree and logistic regression models for the price, they both gave very low accuracies, we tried using SVM and Random forest but it still didn't improve much, it was fixed by using the log(price) instead of the price in training.

Future Work:

If we can get more data from different Airbnbs around the world we can find relations between the features that our models and analysis found uncorrelated such as price and cancellation policy and review score vs cleaning fee, as those insights have a very high chance of affecting each other.

Also having more diverse data can help business owners decide where to start their business no only within the US major cities but also around the world