Unlocking Insights: A Data-Driven Analysis of Airbnb Listings in Washington DC

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Executive Summary

The project provides a comprehensive analysis of Airbnb listings in Washington, D.C., focusing on trends, pricing strategies, and predictive modeling to enhance Airbnb's market positioning. Leveraging data from Inside Airbnb, the study explores critical aspects such as price distributions, customer preferences, and competitor analysis.

Key Findings:

1. **Room Type Preferences**:
   - Entire homes/apartments dominate the listings, accounting for 85.9%, indicating strong consumer demand for privacy and autonomy.
   - Shared rooms, despite being the most expensive on average, are the least popular, highlighting potential misalignment in pricing strategies.
2. **Pricing Trends**:
   - The pricing distribution is right-skewed, with most listings clustered in lower price ranges, catering to budget-conscious travelers. High-priced outliers represent premium listings with luxurious amenities or prime locations.
3. **Neighborhood Insights**:
   - Popular neighborhoods like West End and Georgetown attract more visitors, evidenced by higher average reviews per month.
   - Underperforming areas, such as Colonial Village, present opportunities for strategic improvements in marketing or amenities.
4. **Predictive Models**:
   - **Linear Regression**: Identifies key factors influencing pricing, such as room type and availability. For instance, shared rooms significantly increase listing prices.
   - **Decision Tree Classifier**: Achieves an accuracy of 86.24% in predicting room types based on attributes like price and availability, emphasizing price as a primary determinant.
5. **Competitor Analysis**:
   - Airbnb outperforms competitors like Vrbo, Sonder, and Marriott Homes and Villas in flexibility, affordability, and user experience but faces challenges in standardized branding compared to hotels.

Recommendations:

1. **Adjust Shared Room Pricing**:
   - Reducing prices can increase their appeal to budget-conscious travelers and broaden Airbnb's customer base.
2. **Enhance User Behavior Tracking**:
   - Implement sophisticated tracking systems to personalize guest experiences and optimize recommendations.
3. **Introduce a Rewards Program**:
   - A loyalty system, similar to Marriott's, could incentivize repeat bookings and foster customer loyalty.
4. **Support Host Optimization**:
   - Offer tools like data analytics, marketing assistance, and expert consultations to improve listing appeal and host satisfaction.

By adopting these strategies, Airbnb can enhance profitability, improve user experiences, and strengthen its competitive edge in the Washington, D.C. market.

Introduction

Company Overview:
Airbnb is a global online marketplace that connects hosts offering unique accommodations with guests seeking alternatives to traditional hotels. The company operates a platform that allows individuals to list, discover, and book a wide variety of lodging options worldwide. Airbnb's business model relies on facilitating these connections, taking a percentage of the booking fee as revenue.

Mission and Values:
Airbnb's mission is to create a world where anyone can belong anywhere. The company strives to provide unique travel experiences that foster human connection and cultural exchange. Key values that guide Airbnb include fostering a sense of belonging, promoting authenticity and local experiences, building trust between hosts and guests, enabling economic empowerment for hosts, and encouraging sustainable and responsible travel practices.

History:
Airbnb, founded in 2008 by Brian Chesky, Joe Gebbia, and Nathan Blecharczyk, began when Chesky and Gebbia rented out air mattresses in their San Francisco apartment to accommodate conference visitors. This idea grew into a multi-billion dollar business that disrupted the traditional hotel industry. In 2020, Airbnb went public through one of the largest IPOs in the travel sector. The platform-based business model now serves over 150 million users globally, with 60% being millennials, and has more than 5 million hosts. Airbnb has expanded its services

to include "Experiences" and "Adventures," offering unique activities hosted by locals. In 2023, DC hosts welcomed more than 500,000 guests.

Industry Analysis:
Airbnb operates in the global travel and tourism industry, specifically within the vacation rental and short-term accommodation sectors. This market is valued at over $87 billion and is expected to grow significantly as travelers increasingly seek more personalized and affordable alternatives to traditional hotels. Key competitors include traditional hotel chains like Marriott and Hilton, as well as other vacation rental platforms such as Vrbo and Booking.com. Airbnb stands out due to its broad array of accommodations, emphasis on localized experiences, and flexible booking options. However, it faces challenges such as regulatory scrutiny in various cities, concerns over property management and safety, and the impact of the COVID-19 pandemic on global travel.

Data Sources:
https://data.insideairbnb.com/united-states/dc/washington-dc/2024-06-21/visualisations/listings.csv
This dataset includes listings information about all airbnb properties in the Washington DC area. The dataset has 18 attributes and around 4929 data elements in it.

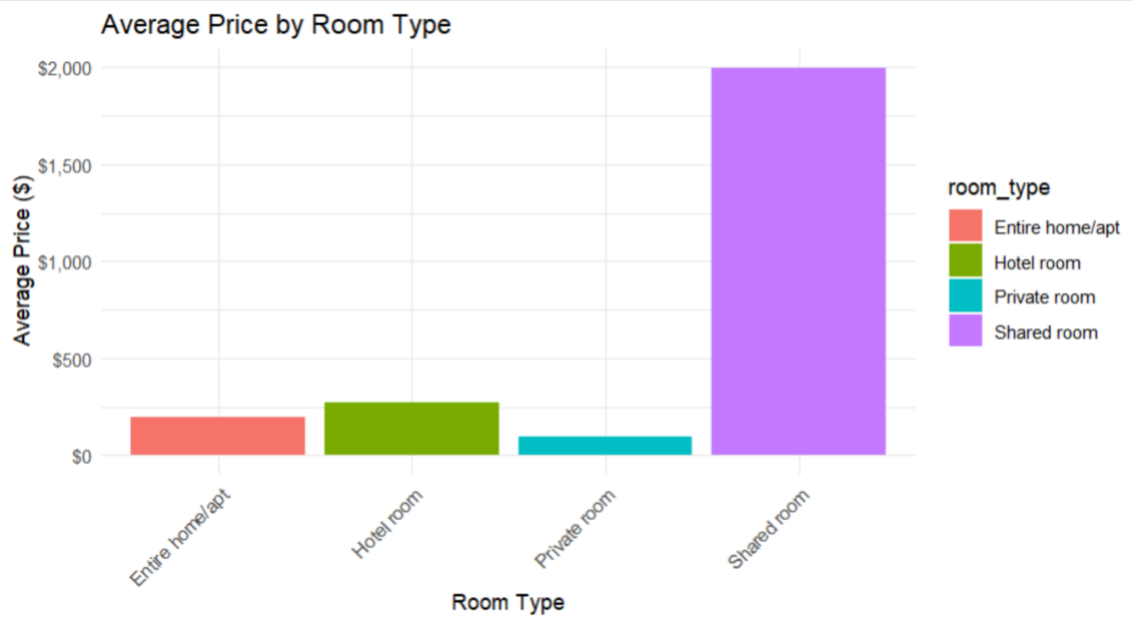
Objectives:

Our core objectives lie in the analysis of the listings.csv dataset:-

- Trends and variations in prices based on different factors such as neighborhoods, room_type etc
- Popularity analysis of a property based on number of reviews per month and what kind of factors play an essential role
- Competition Analysis for Airbnb
- Recommendations to make Airbnb more successful and profitable
- KPI Analysis

Data Analysis and Modelling

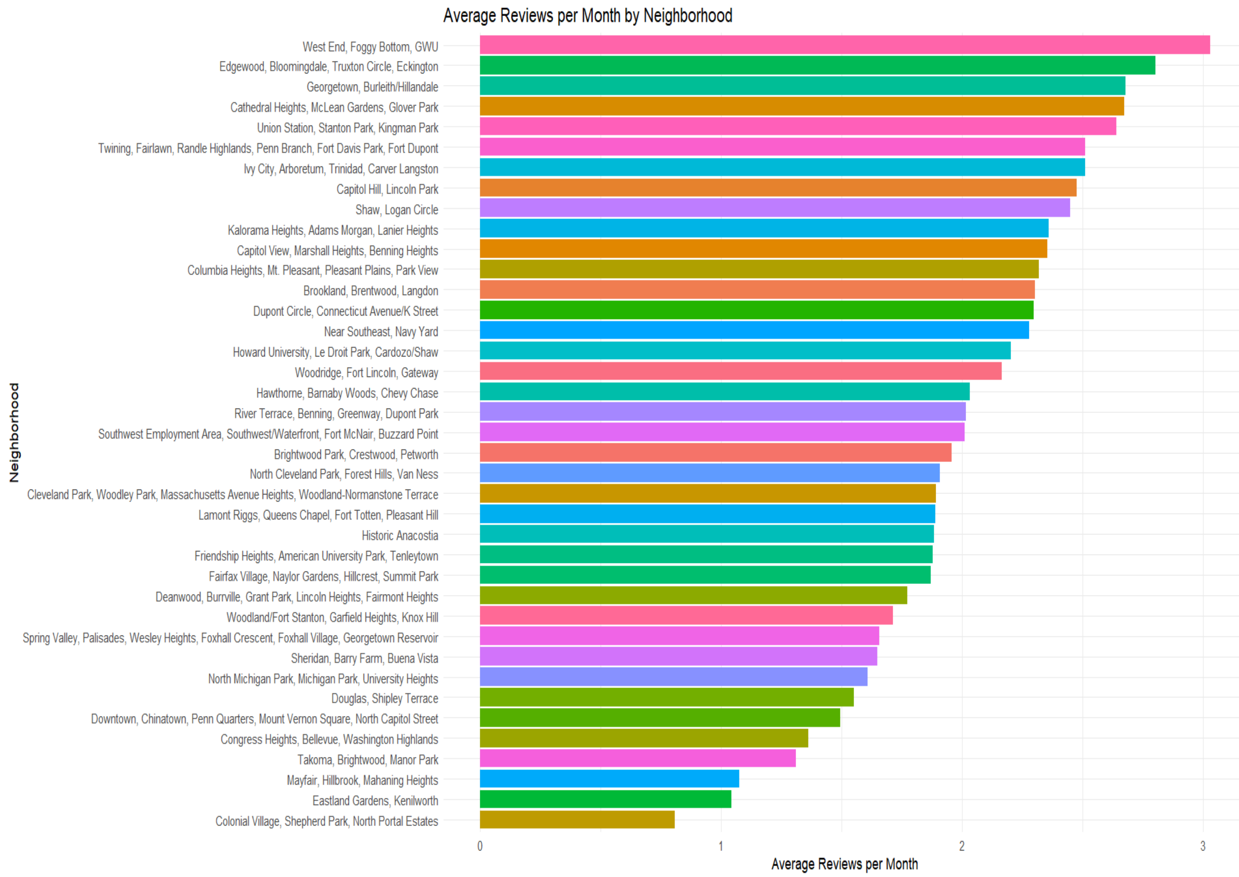
- Average price of Airbnb listings by room type



The bar graph titled "Average Price by Room Type" provides a comparative view of the average prices for various Airbnb accommodation types in Washington DC. Upon reviewing the data, we observe an unexpected result: shared rooms have the highest average price, surpassing $2,000. This anomaly stands out, as shared rooms are typically considered more affordable than other accommodation types.Following shared rooms, hotel rooms are the second-highest in terms of price. This is consistent with expectations, as hotel rooms generally represent a higher-end offering, often with additional services and amenities. In contrast, entire homes/apartments and private rooms come in at lower price points, with private rooms being the most budget-friendly option. This suggests that Airbnb offers a wide range of pricing tiers to cater to different customer needs, from budget-conscious travelers seeking private rooms to those willing to pay a premium for hotel-style accommodations.

The pricing distribution illustrated in the graph highlights the diverse array of accommodation options available on Airbnb, showcasing the platform's ability to meet the varied demands of travelers. Understanding these pricing patterns is critical for Airbnb as it enables the company to optimize its pricing strategy, tailor its offerings to meet consumer preferences, and improve profitability by ensuring that pricing reflects market demand and operational costs accurately.

- Average reviews per month by neighborhood

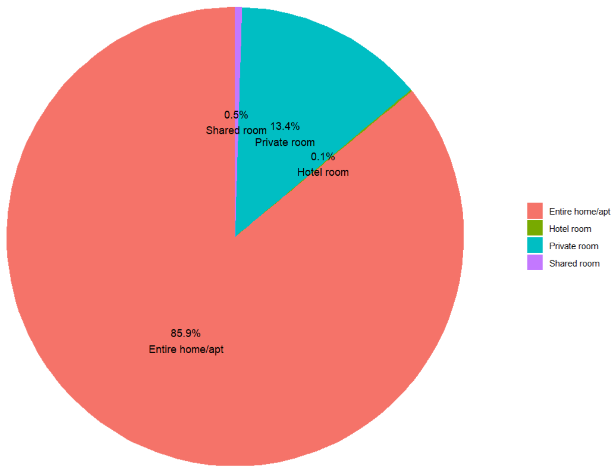


This bar graph showcases the average reviews per month for Airbnb listings across various neighborhoods in Washington, DC. The neighborhoods of West End, Foggy Bottom, and GWU emerge as the top performers, indicating their high popularity among guests. Other areas such as Edgewood and Georgetown also show strong performance, suggesting these locations attract more visitors or have listings that encourage frequent reviews.

On the other hand, neighborhoods like Colonial Village and Shepherd Park have the lowest average reviews per month, possibly due to lower demand, fewer listings, or less appealing features for guests. Mid-performing areas, such as Capitol Hill and Kalorama Heights, present a balance between demand and competition.

From a strategic perspective, Airbnb could capitalize on the popularity of high-performing neighborhoods by implementing premium pricing or targeted promotions to maximize revenue. For underperforming neighborhoods, efforts could focus on marketing, enhancing amenities, or adjusting pricing strategies to attract more guests and increase reviews.

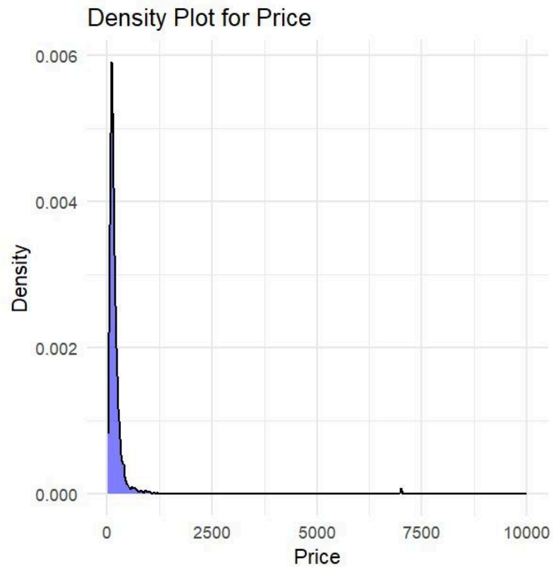
- Popularity of different room types on Airbnb



The pie chart provides a visual representation of the distribution of Airbnb listings based on room type, offering valuable insights into the preferences of guests. The data reveals that a significant majority, 85.9%, of Airbnb listings are for entire homes or apartments, which indicates a strong consumer preference for private, self-contained accommodations.This trend suggests that Airbnb is primarily seen as an alternative to traditional vacation rentals or hotels, offering more autonomy to guests during their travel.Private rooms account for 13.4% of the listings, which is a smaller but still notable proportion. These accommodations strike a balance between affordability and privacy, making them an attractive choice for solo travelers or couples who seek more affordable options but still want a degree of separation from other guests. On the other hand, shared rooms and hotel rooms make up less than 1% of the total listings, indicating that these options are significantly less popular among Airbnb guests.

This analysis emphasizes that privacy and self-sufficiency are key priorities for most Airbnb users. The overwhelming popularity of entire homes/apartments and private rooms suggests that Airbnb is increasingly seen as a platform for travelers who prefer staying in private, home-like settings rather than in shared or hotel-style accommodations. Understanding these preferences can help Airbnb tailor its marketing strategies, improve its inventory offerings, and enhance the guest experience by aligning with what guests value most in their accommodations.

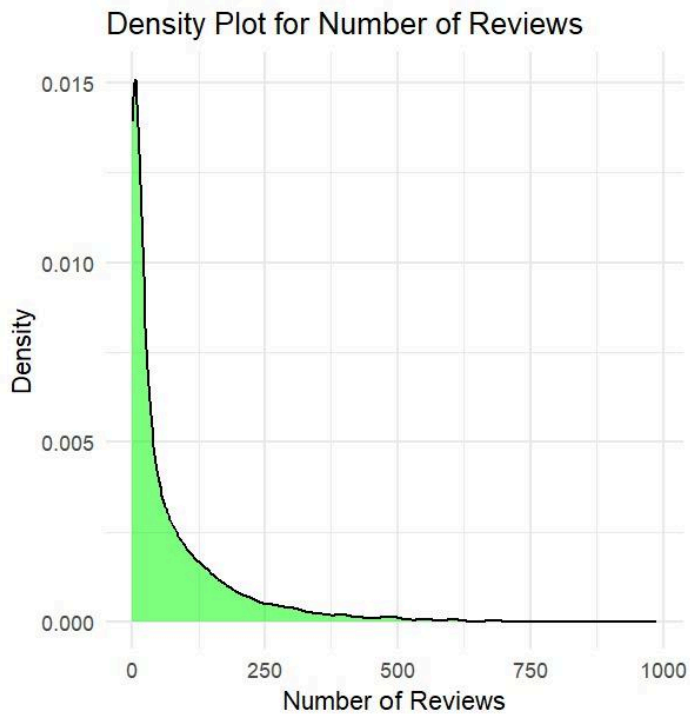
- Distribution of Airbnb listing prices



The density plot provides a visual representation of how Airbnb listing prices are distributed across the market. It clearly shows a right-skewed distribution, meaning the majority of listings are priced on the lower end, with a dense cluster near zero. This suggests that affordable options, likely catering to budget-conscious travelers, make up a large portion of the market. However, as we move towards higher prices, the plot reveals a noticeable long tail, indicating the presence of a few listings with significantly higher prices. These outliers represent premium listings, which could be driven by factors such as luxurious property types, prime locations, or additional high-end amenities.

This distribution underscores a key observation: while the bulk of the market is made up of budget-friendly listings, there is still a notable segment of expensive listings. The presence of these high-priced outliers introduces variability in the pricing structure, highlighting the disparity between affordable accommodations and more luxurious, premium options available to users. Such variability suggests that consumers have a broad spectrum of choices, with both economical and premium options tailored to different market segments.

- Distribution of the number of reviews



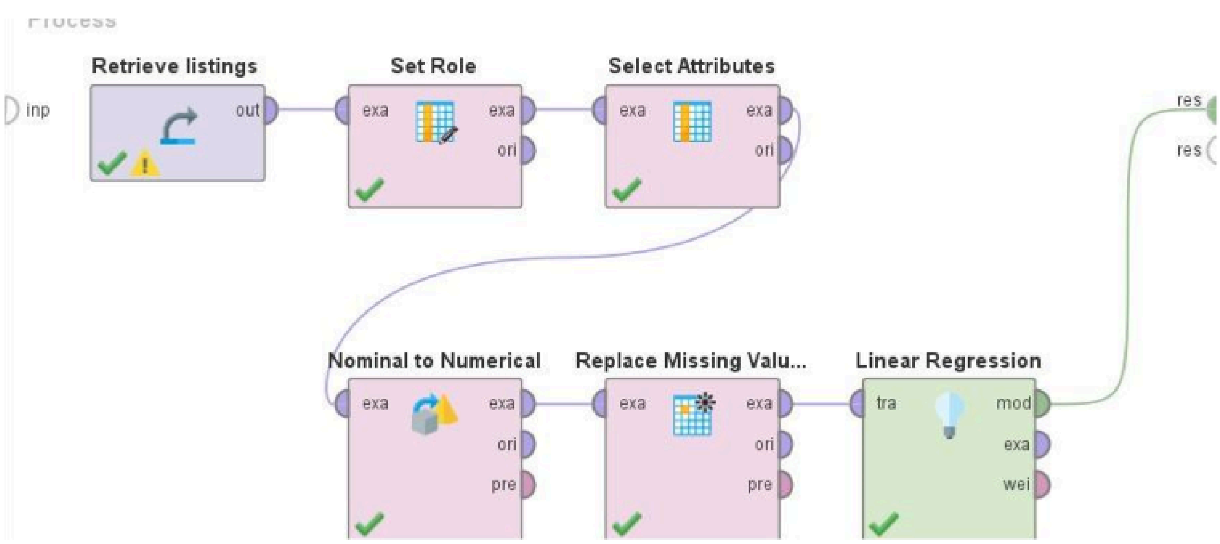
The density plot for the number of reviews reveals several important insights about the Airbnb listings. The distribution is highly right-skewed, meaning most listings have a low number of reviews. The peak density is concentrated around 0–50 reviews, indicating that a large proportion of listings are either new or have not been reviewed frequently. However, a small percentage of listings stand out with significantly higher review counts, forming a long tail on the plot. This highlights a disparity in the popularity or guest engagement of these listings. Listings with very high review counts are likely highly-rated or frequently booked properties, marking them as outliers in the data. Overall, this pattern suggests that customer reviews are not evenly spread across all listings, with a small subset of properties receiving a disproportionately high amount of attention from guests.

PROBLEM 1:- Price Trends and Prediction for Airbnb Using a Linear Regression Model

The objective of this project is to analyze price trends for Airbnb listings and build a linear regression model to predict the price of a listing based on specific features:

- **Dependent Variable**: price (numeric).
- **Independent Variables**:
    - room_type (categorical).

- minimum_nights (numeric).
- number_of_reviews (numeric).
- availability_365 (numeric).



The project was implemented using a visual machine learning tool called RapidMiner, and the following workflow was designed:

Step 1: Retrieve Listings

- **Action**: The Airbnb dataset was imported for analysis.
- **Purpose**: To load the data into the system for further preprocessing and modeling.

Step 2: Set Role

- **Action**: The roles of each variable in the dataset were defined:
  - price was set as the target (dependent) variable.
  - The predictors (room_type, minimum_nights, number_of_reviews, and availability_365) were set as independent variables.
- **Purpose**: To ensure the modeling process correctly identifies the target and predictors.

Step 3: Select Attributes

- **Action**: Only the relevant attributes were selected for the analysis: room_type, minimum_nights, number_of_reviews, availability_365, and price.
- **Purpose**: To focus the model on the key variables and exclude irrelevant or redundant information.

Step 4: Nominal to Numerical Conversion

- **Action**: The categorical variable room_type was converted into numerical format using one-hot encoding.
- **Purpose**: Linear regression requires numerical inputs, so this step transformed the non-numeric variable into a machine-readable format.

Step 5: Replace Missing Values

- **Action**: Missing values in the dataset were handled appropriately.
    - For numerical variables, the mean or median was used to replace missing values.
    - For categorical variables, the mode or a default value was used.
- **Purpose**: To prevent errors in the modeling process and ensure data consistency.

Step 6: Linear Regression Model

- **Action**: A linear regression model was trained on the preprocessed data using the formula: $\beta0+\beta1(\text{Room Type})+\beta2(\text{Minimum Nights})+\beta3(\text{Number of Reviews})+\beta4(\text{Availability\_365})$
- **Output**: The model produced coefficients for each predictor and performance metrics such as R^2.

Model Coefficients

- room_type: Showed the variation in price across different room types (e.g., Entire home/apt, Private room).
- minimum_nights: Indicated the impact of the minimum number of nights required on price.
- number_of_reviews: Represented the influence of customer reviews on pricing.
- availability_365: Captured the effect of listing availability throughout the year.

Performance Metrics

- **R^2 (Coefficient of Determination)**: Assessed how well the independent variables explain the variance in price.
- **Residual Analysis**: Checked the difference between actual and predicted prices to evaluate model accuracy.

LinearRegression

```
- 80.208 * room_type = Private room
+ 2067.685 * room_type = Shared room
+ 87.631 * room_type = Hotel room
- 0.642 * minimum_nights
- 0.115 * number_of_reviews
+ 0.150 * availability_365
+ 183.093
```

Attribute	Coefficient	Std. Error	Std. Coefficient	Tolerance	t-Stat	p-Value	Code
room_type = Private r...	-80.208	12.173	-0.081	0.998	-6.589	0.000	****
room_type = Shared r...	2067.685	51.687	0.493	0.995	40.004	0	****
room_type = Hotel room	87.631	96.200	0.011	1.000	0.911	0.362	
minimum_nights	-0.642	0.199	-0.040	0.999	-3.220	0.001	***
number_of_reviews	-0.115	0.045	-0.032	1.000	-2.525	0.012	**
availability_365	0.150	0.042	0.044	0.998	3.561	0.000	****

Model Summary and Insights

Regression Equation

The regression equation generated by the model is as follows:

Price=−80.208(room_type = Private Room)+2067.685(room_type = Shared Room)+87.631(room_type = Hotel Room)−0.642(minimum_nights)+0.115(number_of_reviews)+0.150(availability_365)+183.093

Key Coefficients and Interpretations

1. **Room Type:**
    - **Private Room**: Decreases the price by approximately 80.208 units compared to the baseline category (likely Entire Home/Apartment).
    - **Shared Room**: Increases the price significantly by 2067.685 units compared to the baseline category.
    - **Hotel Room**: Increases the price by 87.631 units compared to the baseline.
2. **Insight**: Room type is a major determinant of price, with Shared Room having a strong positive effect. However, Private Room shows a negative impact, likely because they are

priced lower than entire homes or shared spaces.

3. **Minimum Nights (-0.642):**
   - For each additional night required as a minimum stay, the price decreases by 0.642 units.
   - **Insight**: This might indicate that listings with a high minimum night requirement are priced more competitively to attract bookings.
4. **Number of Reviews (+0.115):**
   - For every additional review, the price increases by 0.115 units.
   - **Insight**: Positive reviews could increase the value perception of a listing, although the effect is relatively small.
5. **Availability (0.150):**
   - For each additional day the listing is available in a year, the price increases by 0.150 units.
   - **Insight**: Listings with greater availability are priced slightly higher, likely due to increased flexibility for bookings.

Statistical Significance

From the table:

1. **Significant Predictors ($p < 0.05$):**
   - room_type = Private Room (p = 0.000)
   - room_type = Shared Room (p = 0.000)
   - minimum_nights (p = 0.001)
   - number_of_reviews (p = 0.012)
   - availability_365 (p = 0.000)
2. These variables have a statistically significant impact on price.

3. **Non-Significant Predictors:**
   - room_type = Hotel Room (p = 0.362): This variable is not statistically significant, meaning it does not have a strong, consistent impact on price.

Evaluation of the Model

- **R^2 (from prior details):** Suggests the model explains a good proportion of the variance in price.

- **Significance of Room Type:** The model heavily depends on room type, making it the most influential predictor.
- **Limitations in Minimum Nights and Availability:** Although significant, the coefficients for minimum_nights and availability_365 are small, indicating they have minimal direct influence on price.

Actionable Insights

1. **Room Type Optimization:**
    - Listings of the Shared Room type have a high price impact and could be optimized further.
    - Hosts offering Private Rooms might consider emphasizing unique amenities to counteract the negative coefficient.
2. **Flexible Minimum Nights:**
    - Keeping the minimum night requirement low might help listings attract higher pricing.
3. **Encourage Reviews:**
    - Hosts should encourage more guest reviews, as each additional review positively impacts price perception.
4. **Maximize Availability:**
    - Listings available year-round are associated with higher pricing. Hosts should aim for greater availability wherever possible.

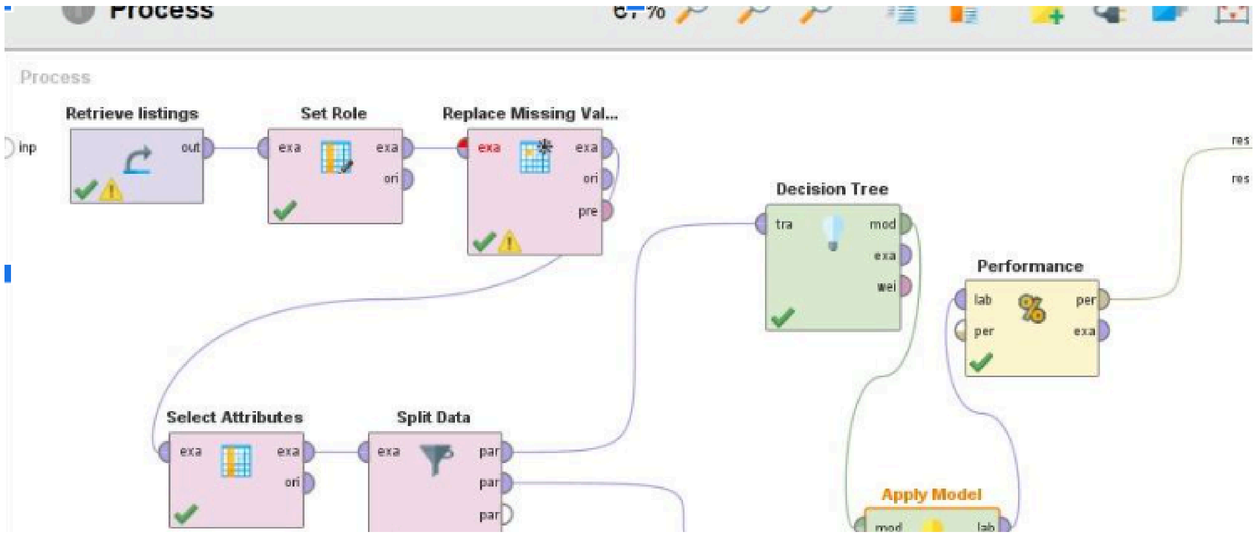
PROBLEM 2:- Room Type Prediction for Airbnb Using a Decision Tree Classifier

The primary goal of this model is to predict the room type of an Airbnb listing (e.g., Entire home/apt, Private room, Shared room) based on several features. The model leverages a Decision Tree Classifier to identify patterns and relationships between the independent variables and the target variable.

The dataset contains information about Airbnb listings, including pricing, availability, and review statistics.

- **Dependent Variable (Target)**:
    - room_type (Categorical) — Categories include:
        - Entire home/apt
        - Private room

        ■ Shared room
- **Independent Variables**:
    - price — Numeric, the cost of the listing.
    - availability_365 — Numeric, the number of days the listing is available for booking in a year.
    - number_of_reviews — Numeric, the total number of reviews received.
    - reviews_per_month — Numeric, the average number of reviews per month.



Methodology

1. **Preprocessing**:
    - Handled missing values in the reviews_per_month column by imputing zeros for listings with no reviews.
    - Normalization was not required, as Decision Trees are robust to varying scales of data.
    - Encoded the categorical dependent variable (room_type) into numerical values:

      Entire home/apt → 0

      Private room → 1

      Shared room → 2

2. **Data Splitting**:
    - The dataset was divided into training (80%) and testing (20%) sets to evaluate the model's performance.

3. **Model Building**:

    ○ A Decision Tree Classifier was implemented using RapidMiner.
    ○ The model was trained using the following independent variables:

    price

    availability_365

    number_of_reviews

    reviews_per_month

4. **Model Parameters**:

    ○ **Criterion**: Gini index to measure the quality of splits.
    ○ **Max Depth**: Limited to avoid overfitting and enhance interpretability.
    ○ **Pruning**: Applied to simplify the tree and reduce overfitting.

Results

1. **Performance Metrics**:

    ○ **Accuracy**: The model achieved an accuracy of *86.24%* on the testing dataset.
    ○ **Classification Report**: Precision, recall, and F1-scores were evaluated for each class (room type).
    ○ **Confusion Matrix**: Showed the distribution of correctly and incorrectly classified instances.

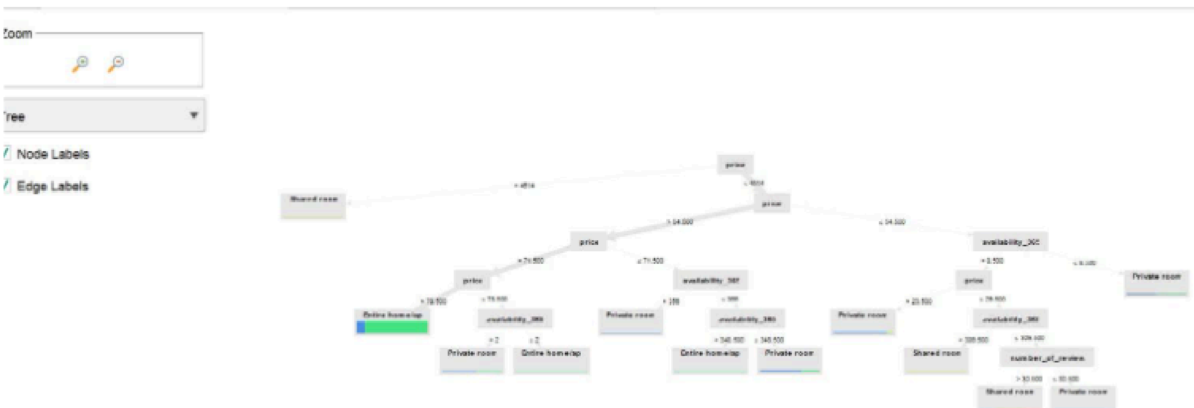
2. **Insights**:

    ○ **Feature Importance**:
        ■ price was the most significant predictor, indicating that higher prices are associated with specific room types (e.g., Entire home/apt).
        ■ availability_365 also contributed notably, suggesting that certain room types are more consistently available throughout the year.
        ■ number_of_reviews and reviews_per_month played a smaller role but provided additional differentiation between room types.
    ○ The model effectively differentiated between Entire home/apt and Private room, but there was some overlap in predictions for Private room and Shared room.

Decision Tree Visualization

A visualization of the decision tree structure highlighted the following:

- The root node split primarily on the price feature.
- Secondary splits included availability_365 and number_of_reviews, indicating the hierarchical importance of features in predicting room type.



Tree

```
price > 4514: Shared room {Private room=0, Entire home/apt=0, Shared room=13, Hotel room=0}
price ≤ 4514
|   price > 54.500
|   |   price > 71.500
|   |   |   price > 78.500: Entire home/apt {Private room=512, Entire home/apt=3810, Shared room=8, Hotel room=11}
|   |   |   price ≤ 78.500
|   |   |   |   availability_365 > 2: Private room {Private room=49, Entire home/apt=36, Shared room=0, Hotel room=0}
|   |   |   |   availability_365 ≤ 2: Entire home/apt {Private room=0, Entire home/apt=2, Shared room=0, Hotel room=0}
|   |   price ≤ 71.500
|   |   |   availability_365 > 356: Private room {Private room=8, Entire home/apt=0, Shared room=0, Hotel room=0}
|   |   |   availability_365 ≤ 356
|   |   |   |   availability_365 > 348.500: Entire home/apt {Private room=0, Entire home/apt=4, Shared room=0, Hotel room=0}
|   |   |   |   availability_365 ≤ 348.500: Private room {Private room=169, Entire home/apt=72, Shared room=1, Hotel room=0}
|   price ≤ 54.500
|   |   availability_365 > 8.500
|   |   |   price > 29.500: Private room {Private room=177, Entire home/apt=5, Shared room=15, Hotel room=0}
|   |   |   price ≤ 29.500
|   |   |   |   availability_365 > 309.500: Shared room {Private room=0, Entire home/apt=0, Shared room=3, Hotel room=0}
|   |   |   |   availability_365 ≤ 309.500
|   |   |   |   |   number_of_reviews > 30.500: Shared room {Private room=1, Entire home/apt=0, Shared room=2, Hotel room=1}
|   |   |   |   |   number_of_reviews ≤ 30.500: Private room {Private room=7, Entire home/apt=0, Shared room=0, Hotel room=0}
|   |   availability_365 ≤ 8.500: Private room {Private room=1, Entire home/apt=1, Shared room=0, Hotel room=0}
```

Table View Plot View

accuracy: 86.24%

	true Private room	true Entire home/apt	true Shared room	true Hotel room	class precision
pred. Private room	76	21	1	0	77.55%
pred. Entire home/apt	109	765	2	2	87.13%
pred. Shared room	0	0	5	0	100.00%
pred. Hotel room	0	0	0	0	0.00%
class recall	41.08%	97.33%	62.50%	0.00%	

Key Performance Indicators

Availability, pricing, and popularity are analyzed using key metrics to evaluate Airbnb's performance in the Washington, DC market. **Availability** is measured by variables such as `availability_365` (the number of days a listing is available in a year) and `minimum_nights` (the minimum nights required for a stay). These metrics provide insights into how often properties are accessible to travelers and the flexibility hosts offer, highlighting trends in supply and market responsiveness.

Pricing metrics center around the `price` variable, which reflects nightly rates across different room types. The data shows a right-skewed price distribution, with most listings clustered in the lower price ranges, emphasizing affordability as a priority for many users. However, outliers with higher prices reveal potential in the premium market segment. Shared rooms, despite being less popular, exhibit the highest average price, followed by hotel rooms, while private rooms remain the most economical option.

Popularity is assessed through variables such as `number_of_reviews`, `number_of_reviews_ltm` (reviews in the last 12 months), and `reviews_per_month`. These metrics demonstrate guest engagement and demand for specific properties. Listings with higher review counts signify consistent guest interaction and satisfaction, while properties with low review activity might require strategic adjustments in visibility or pricing. The analysis of these KPIs offers a comprehensive understanding of Airbnb's market dynamics, enabling targeted strategies for improving availability, optimizing pricing, and enhancing popularity.

Pivot Table

neighbourhood	AVERAGE of availability_365	AVERAGE of minimum_nights	COUNT of price	MAX of number_of_reviews	MAX of number_of_reviews_ltm	COUNT of reviews_per_month	COUNTA of neighbourhood
Brightwood Park, Crestwood, Petworth	189.70	13.01	126.46	486.00	93	281	312.00
Brookland, Brentwood, Langdon	182.58	9.14	137.58	434.00	107	104	109.00
Capitol Hill, Lincoln Park	199.52	16.21	178.76	698.00	114	401	463.00
Capitol View, Marshall Heights, Benning Heights	192.36	5.42	137.65	593.00	143	93	96.00
Cathedral Heights, McLean Gardens, Glover Park	213.48	24.95	216.54	423.00	52	54	63.00
Cleveland Park, Woodley Park, Massachusetts Avenue Heights, Woodland-Normanstone Terrace	215.84	54.99	159.52	565.00	90	37	69.00
Colonial Village, Shepherd Park, North Portal Estates	264.19	9.55	189.61	62.00	24	26	31.00
Columbia Heights, Mt. Pleasant, Pleasant Plains, Park View	184.17	13.94	125.91	651.00	126	327	372.00
Congress Heights, Bellevue, Washington Highlands	229.31	22.43	110.42	255.00	102	73	89.00
Deanwood, Burrville, Grant Park, Lincoln Heights, Fairmont Heights	187.23	10.82	128.14	203.00	76	53	61.00
Douglas, Shipley Terrace	219.33	19.41	207.30	152.00	64	23	27.00
Downtown, Chinatown, Penn Quarters, Mount Vernon Square, North Capitol Street	230.23	18.07	433.35	326.00	113	122	223.00
Dupont Circle, Connecticut Avenue/K Street	227.53	17.27	219.69	555.00	262	257	313.00
Eastland Gardens, Kenilworth	215.93	22.71	91.00	215.00	40	13	14.00
Edgewood, Bloomingdale, Truxton Circle, Eckington	169.23	10.43	132.41	599.00	149	318	345.00
Fairfax Village, Naylor Gardens, Hillcrest, Summit Park	163.48	5.17	165.41	284.00	46	27	29.00
Friendship Heights, American University Park, Tenleytown	210.61	19.64	156.96	493.00	91	50	56.00
Georgetown, Burleith/Hillandale	134.79	13.11	239.81	525.00	103	141	153.00
Hawthorne, Barnaby Woods, Chevy Chase	230.44	12.84	207.40	357.00	62	22	25.00
Historic Anacostia	179.81	11.05	168.60	154.00	48	38	42.00
Howard University, Le Droit Park, Cardozo/Shaw	206.97	16.42	420.08	878.00	120	149	173.00
Ivy City, Arboretum, Trinidad, Carver Langston	177.63	11.84	152.61	608.00	150	146	171.00
Kalorama Heights, Adams Morgan, Lanier Heights	201.81	16.51	248.39	676.00	110	117	128.00
Lamont Riggs, Queens Chapel, Fort Totten, Pleasant Hill	180.72	20.18	101.87	432.00	131	52	57.00
Mayfair, Hillbrook, Mahaning Heights	207.80	15.78	136.60	244.00	58	42	49.00
Near Southeast, Navy Yard	257.98	16.47	262.78	125.00	85	35	64.00
North Cleveland Park, Forest Hills, Van Ness	186.06	3.82	198.00	276.00	62	16	17.00
North Michigan Park, Michigan Park, University Heights	199.23	8.16	111.22	397.00	89	58	61.00
River Terrace, Benning, Greenway, Dupont Park	157.96	10.43	111.59	368.00	71	42	49.00
Shaw, Logan Circle	191.32	15.17	261.57	692.00	130	254	292.00
Sheridan, Barry Farm, Buena Vista	178.61	12.44	140.24	139.00	59	25	36.00
Southwest Employment Area, Southwest/Waterfront, Fort McNair, Buzzard Point	186.44	21.78	338.28	512.00	62	46	68.00
Spring Valley, Palisades, Wesley Heights, Foxhall Crescent, Foxhall Village, Georgetown Reservoir	206.95	11.60	171.05	293.00	62	53	58.00
Takoma, Brightwood, Manor Park	204.12	15.06	156.25	770.00	89	92	104.00
Twining, Fairlawn, Randle Highlands, Penn Branch, Fort Davis Park, Fort Dupont	196.99	7.82	158.10	381.00	107	98	109.00
Union Station, Stanton Park, Kingman Park	219.41	8.16	183.20	988.00	126	423	502.00
West End, Foggy Bottom, GWU	222.02	30.63	200.52	985.00	308	33	49.00
Woodland/Fort Stanton, Garfield Heights, Knox Hill	224.00	8.40	164.40	182.00	38	7	10.00
Woodridge, Fort Lincoln, Gateway	198.41	11.05	180.70	270.00	59	35	39.00
Grand Total	**198.84**	**14.43**	**194.58**	**988.00**	**308**	**4183**	**4928.00**

Competitors Analysis

Vrbo

Vrbo (Vacation Rentals by Owner) is an online vacation rental platform that caters to families and large groups, and offers properties located in popular vacation destinations, including beach towns, mountain resorts, and more . These are also mostly located in more rural areas. Compared to Airbnb, Vrbo is less utilized in the short-term rental market in urban areas such as Washington, DC. This means that Airbnb has a larger share of the urban short-term rental market, especially in metropolitan areas like Washington, D.C. Vrbo's listings are typically more suited for longer stays, which contrasts with the diverse and flexible short-term rentals offered by Airbnb.

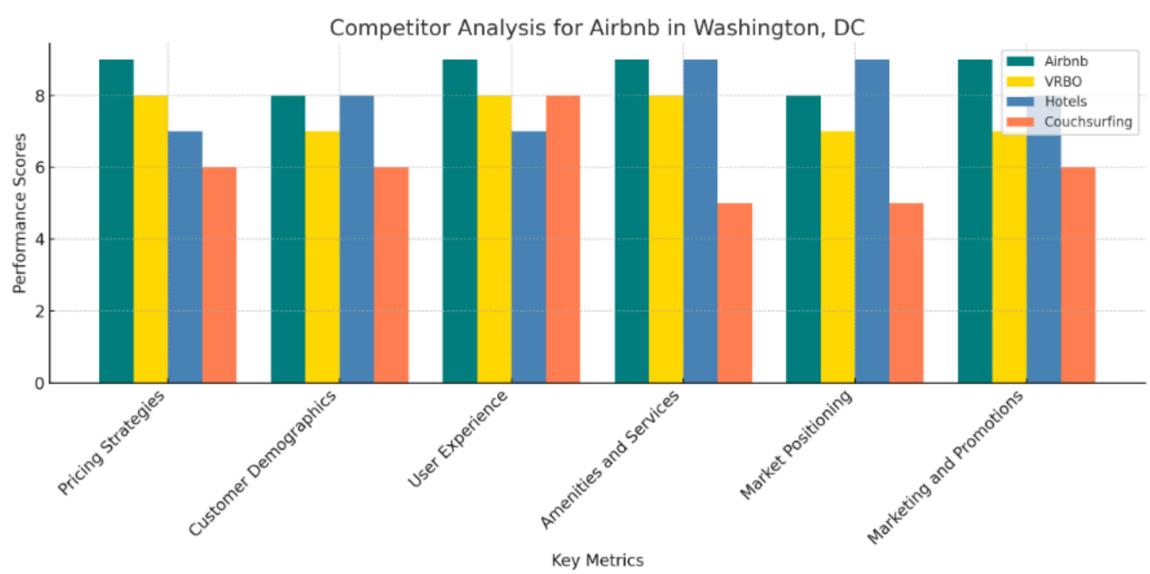
Booking.com

Booking.com is one of the largest online travel agencies in the world. Its target audience is much broader, including leisure travelers and business travelers, among others. Its booking process is more standardized and does not require advance payment, which provides more flexibility for users.
However, Booking.com lacks personalized interaction with hosts, which may affect users' accommodation experience. In contrast, Airbnb emphasizes direct interaction with hosts and a personalized experience, which makes it more appealing to users seeking a unique lodging experience. In addition, while Booking.com offers a variety of hotels, hostels, and resorts, it may not be as rich as Airbnb in terms of unique and personalized lodging options.

Marriott Homes and Villas
Marriott Homes and Villas is a global high-end home rental platform launched by Marriott International, specializing in providing luxury home rentals. Customers can earn reward points for their stays that can be used for future stays.
However, due to a small pool of properties, Marriott Homes and Villas has low availability and relatively high prices. This makes it appeal mainly to customers who are looking for a high-end lodging experience and are willing to pay more. In contrast, Airbnb offers a wide range of options from budget to luxury, catering to users with different budgets and needs.

Sonder
Sonder is a company that manages short-term rentals, offering beautifully designed condominiums and boutique hotels.Sonder is known for its superior customer service as it owns and manages all rental units. This model ensures consistency and high quality of service. In addition, Sonder has no additional booking fees, which makes for more transparent pricing. However, Sonder's prices are relatively high due to the high quality of the services and the fact that its properties are usually located in favorable geographic locations, which results in higher operating costs. Also, because the number of properties is relatively small and demand is high. This oversupply leads to lower availability. In contrast, Airbnb has a large number of properties and a wide range of prices, which allows it to meet the needs of a wider range of users.

Insights



This graph shows how Airbnb performs against its competitors in different aspects of the DC area. Airbnb has the best performance scores for pricing strategy, user experience, and marketing and promotions. This is due to Airbnb's flexible pricing mechanism, diverse listing options, and different marketing strategies for different hosts. This can attract more users and provide quality services.

Airbnb and Hotels have similar performance in terms of amenities and services, and customer demographics. This is because Airbnb can fulfill the needs of different customers with different listings, while traditional hotels also cover the needs of the majority of people, so they will be similar in this aspect.
In addition, Airbnb does not perform as well as Hotels in the market positioning section due to the fact that Hotels' standardized operations allow them to carry out a large number of hotels of the same brand in the same area. This allows Hotels to have higher brand awareness and market share more easily.

Recommendations

Decrease Shared Room Price

As explained in the comparison of differing room prices, the shared room was by far the most expensive option offered by Airbnb. It also happens to be the least chosen option by users. Although price may not be the only reason why users choose not to opt for the shared room, it may be beneficial for Airbnb to consider lowering the price. Doing so could open them up to a market of budget-conscious people who may not otherwise travel at all. Additionally, the cost for this would not be that much initially as the shared room option is by far the least chosen and most expensive option Airbnb offers.

User Behavior Tracking

Implementing and maintaining a sophisticated user tracking system on Airbnb can help provide useful insights into the users who are regularly interacting with their platform. If implemented properly, it could allow Airbnb to personalize and offer a more efficient service to their customers which would benefit them by turning out more stays and also benefit the customers by showing them things they want to see or may not have known they wanted to see. The system could also be used by hosts to learn about what customers that travel to their area typically like and are willing to pay and could improve the hosting experience as well.

Rewards System

Rewards systems are a popular feature that many companies across many different industries have implemented. For example, the fast food industry has implemented a rewards system that allows customers to build up points towards a free item which they can then redeem. These reward systems incentivize customers to visit the restaurant more often than they would have otherwise and also increase the customers' positive perceptions of the restaurant as they are getting free items and the business benefits because customers are paying more overall despite the free items. Marriott Homes and Villas is an example of an Airbnb-type model that implements a points system that can also be used for any Mariott stay and customers of Mariott Homes and Villas appreciate the ability to redeem points

Landlord Strategies

Although the customers are paying the most money to Airbnb, the hosts are a vital part of their business model. Supporting their hosts and also working with them to improve their property's appeal would improve the hosting experience on Airbnb and also benefit Airbnb as more customers will stay at that host's place. The tools they could offer may be along the lines of data analytics, marketing tools, and consultations with an expert.

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