Analyzing and Predicting Airbnb Listing Price and Host Type in New York City

Presented by Team 3B

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About Us

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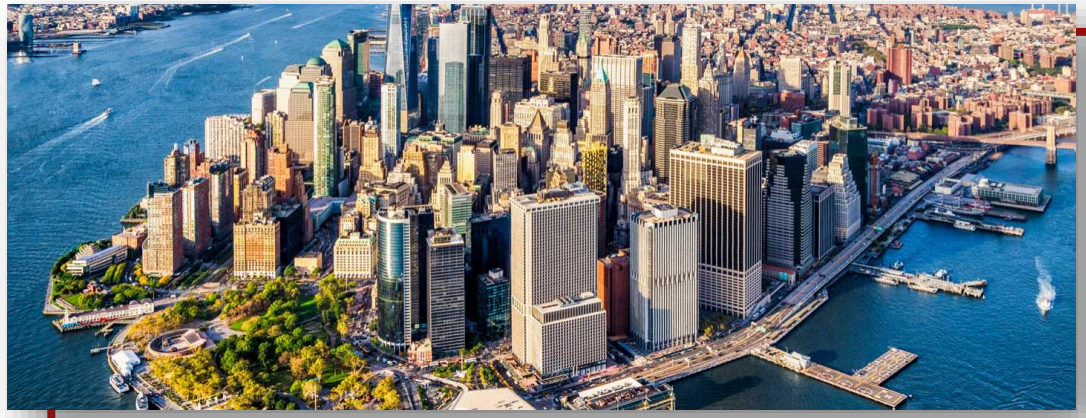
AGENDA

- Project Overview
- About the Dataset
- Data Cleaning
- Exploratory Data Analysis
- Machine Learning:
  Classification & Regression
- Conclusion & Future Work

Project Overview

Objectives

- Analyzing neighborhood popularity for superhosts and non-superhosts
- Comparing the pre- and post-COVID listing prices
- Predicting the type of host and understanding what attributes contribute to the classification of a superhost
- Predicting the price for Airbnb listings in New York City and understanding what features contribute to profitable business opportunities for Airbnb



Data Source

The datasets have been taken from InsideAirbnb and were last updated in October 2020.

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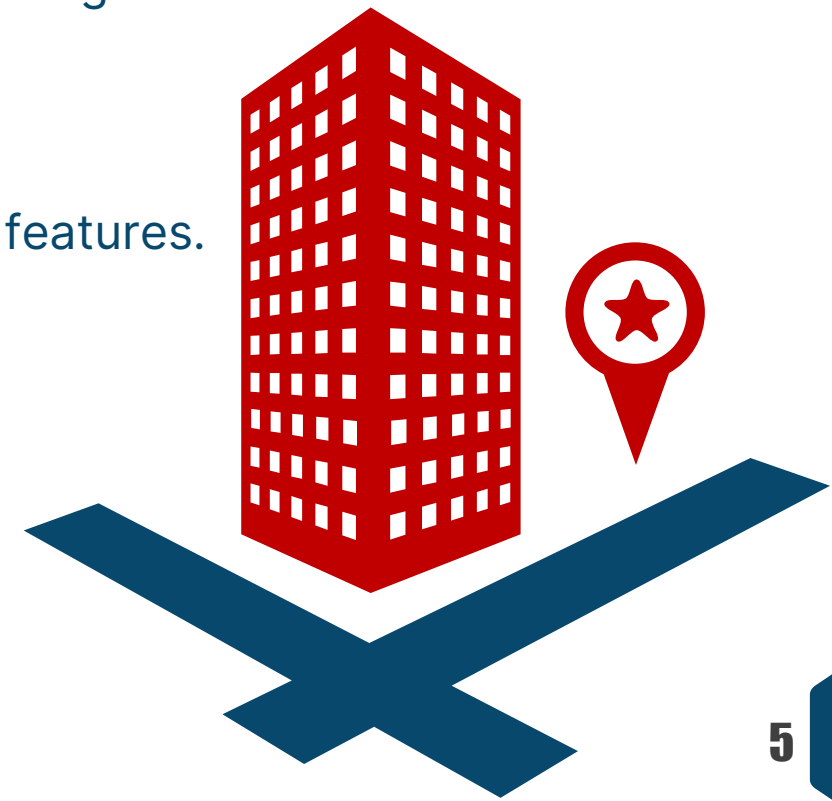
About the Dataset

Listings
There are 44666 unique observations (listings) and 74 features.

Neighborhoods
There are 230 unique observations (neighborhoods) in 5 boroughs.

Reviews
There are 1003064 unique observations (comments) and 6 features.

Calendar
There are 18747307 observations and 7 features.



Data Cleaning

Listings

- **Step 1: Unifying Formats and Data Types**
  - Converted each column to the correct format and data type

- **Step 2: Dealing with Missing Values**
  - Dropped empty columns (E.g., "bathrooms“)
  - Dropped 25 listings had price as $0 and 1595 listings had no beds

- **Step 3: Analyzing Outliers**
  - Some listing prices are greater than 5,000 USD
  - The maximum number of beds is 40 and it hosts 16 people

After cleaning, we now have **31880** unique observations.

Data Cleaning - Outlier Examples

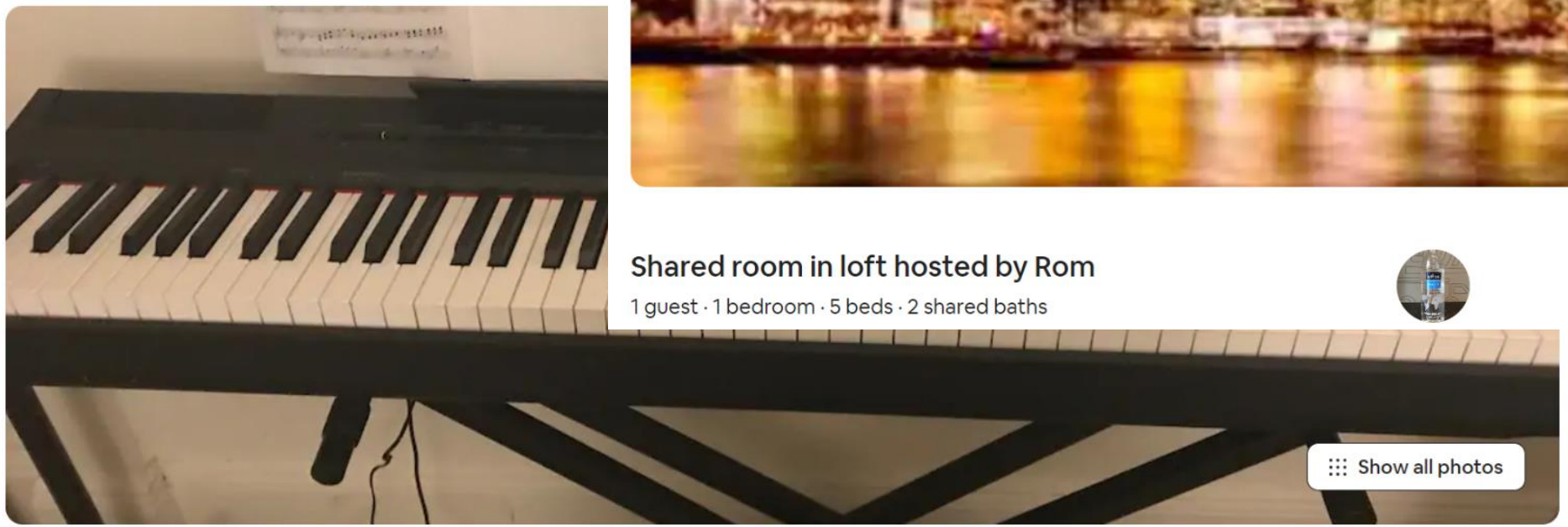
~New jersey loft

★ 4.50 (11) · New York, United States

Share Save

the best you can find

New York, United States



Shared room in loft hosted by Rom

1 guest · 1 bedroom · 5 beds · 2 shared baths

$10,000 / night ★ 4.50 (11)

Entire apartment hosted by Qiuchi

1 guest · Studio · 1 bed · 1 bath

$0 / night

Data Cleaning

Reviews

- Dropped comments with missing values and those that have less than 3 characters, after which we have **1002383** comments for **34142** listings.

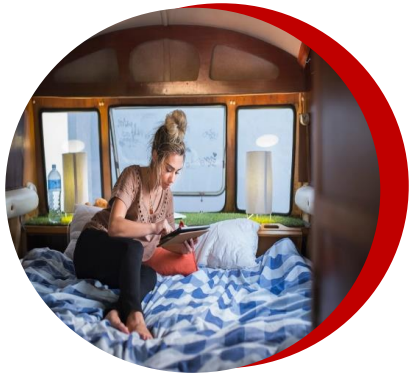
Calendar

- Converted “price” and “date” columns to float and datetime data types
- Brought in archived datasets to compare price fluctuations between 2019 and 2020

Exploratory Data Analysis

Neighborhood

Hosts



Reviews

Price

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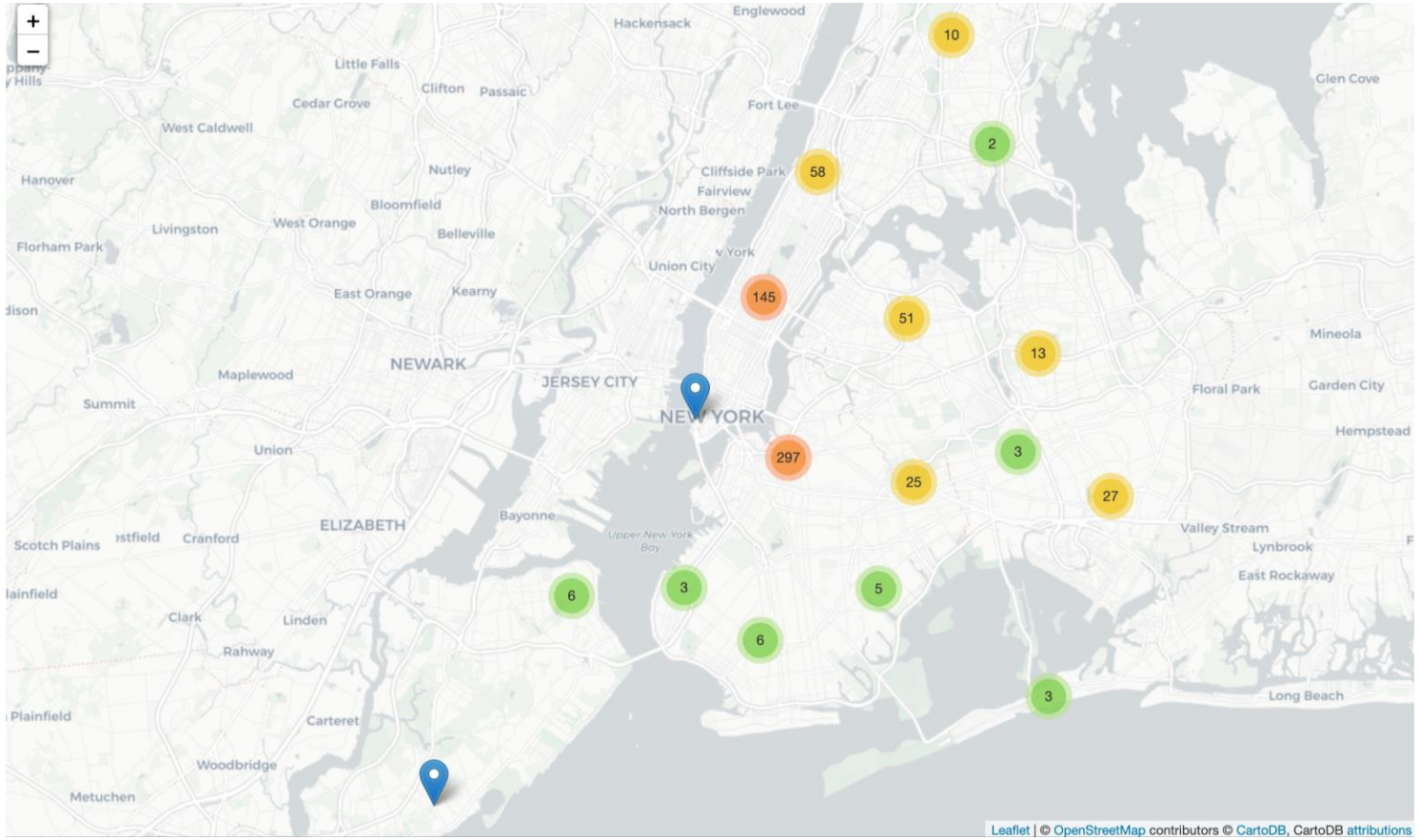
Exploratory Data Analysis for Neighborhoods

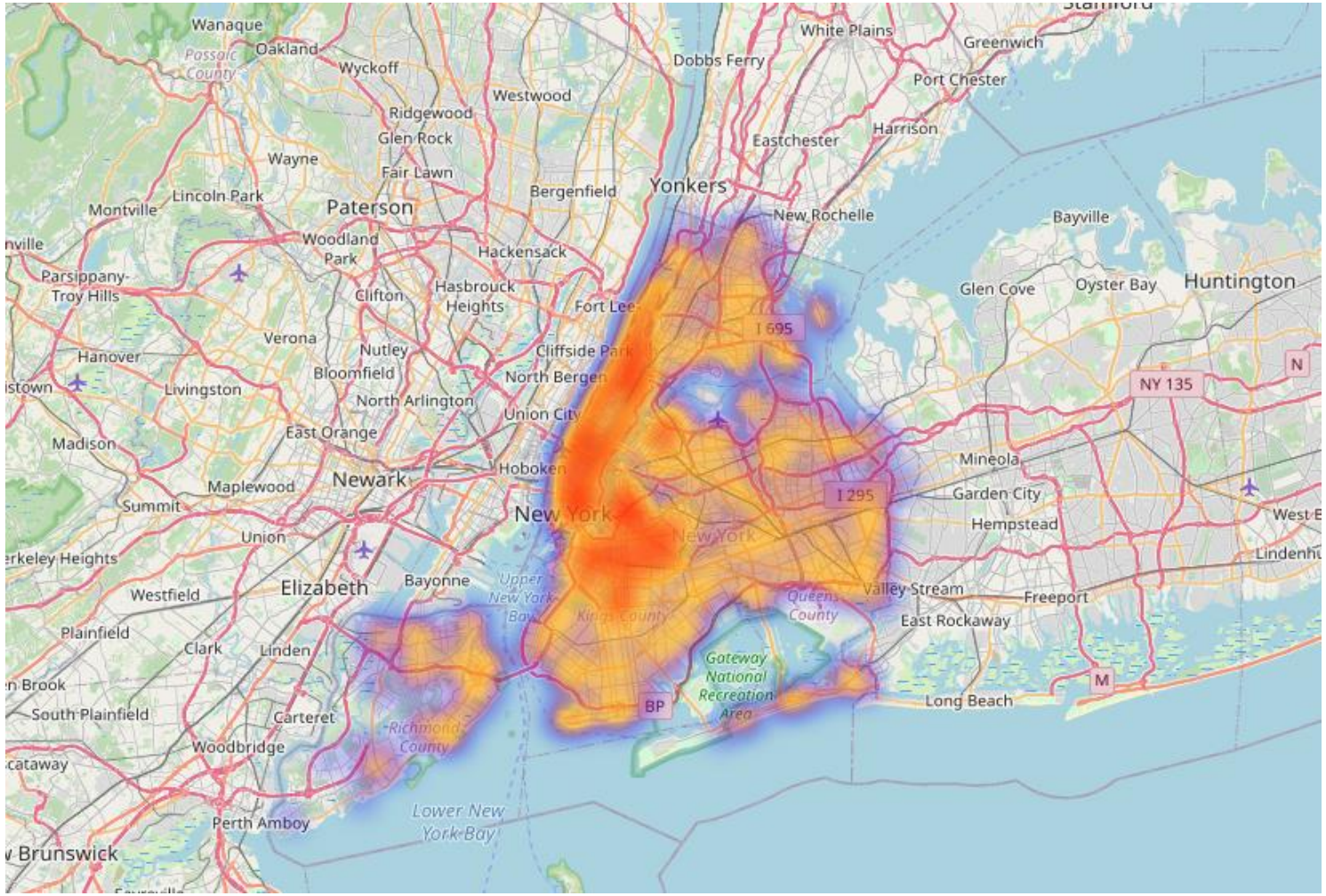
Most Reviewed Listings (Interactive Map)

- There are 657 apartments with more than 200 reviews, out of which 336 apartments are from Brooklyn, 204 are from Manhattan, followed by 97 in Queens.



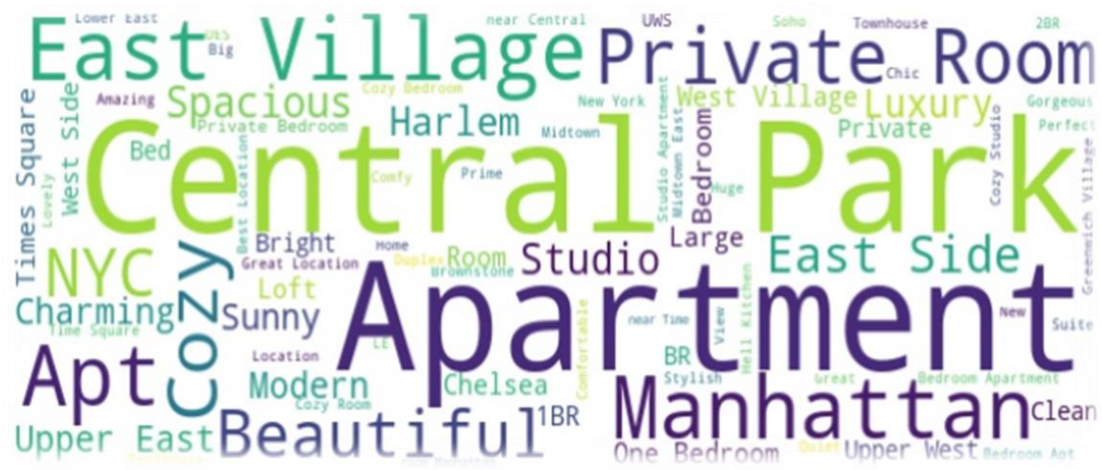
Exploratory Data Analysis for Neighborhoods

Interactive Heatmap of NYC Listings



Exploratory Data Analysis for Neighborhoods

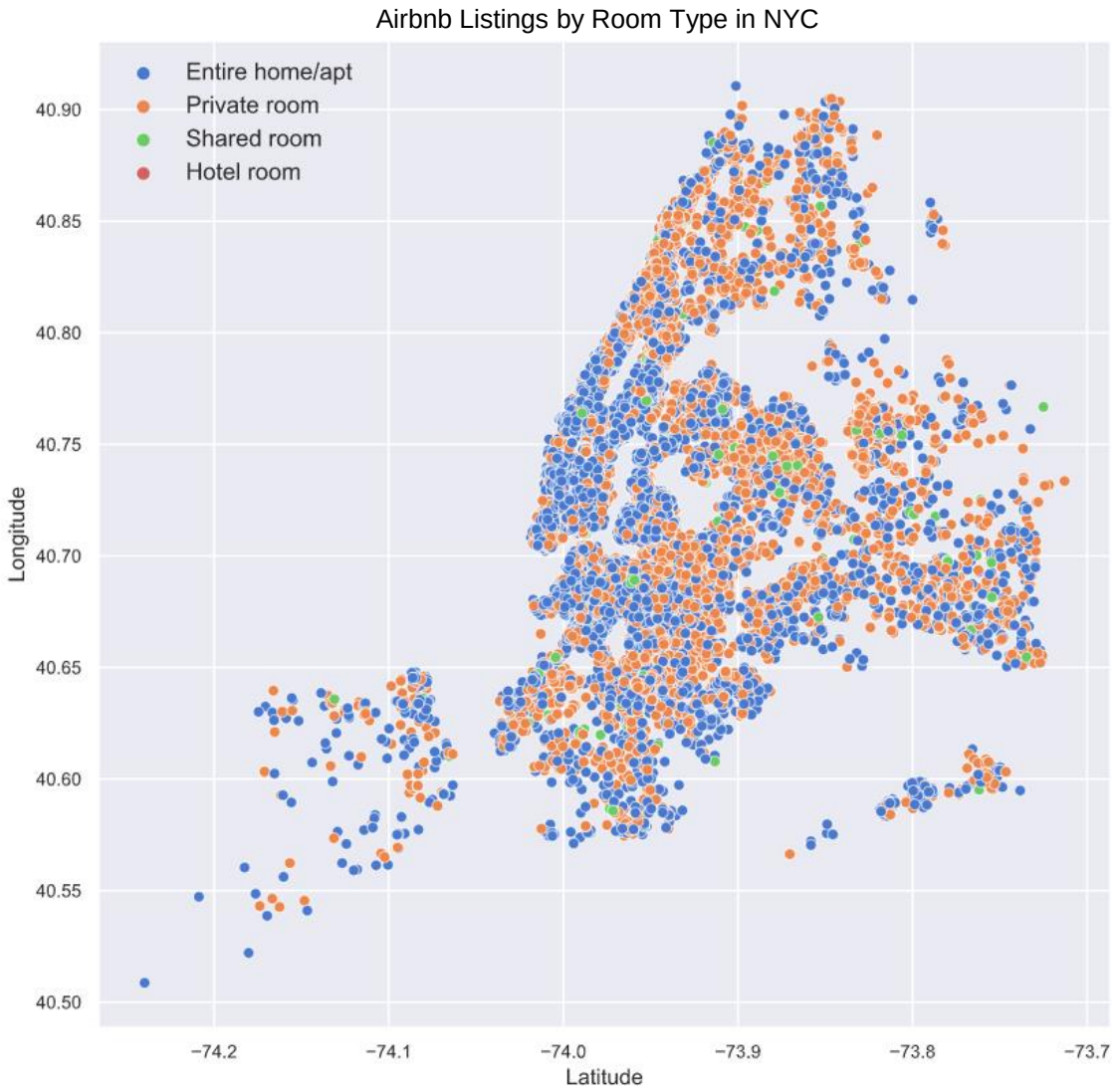
Keywords in Manhattan

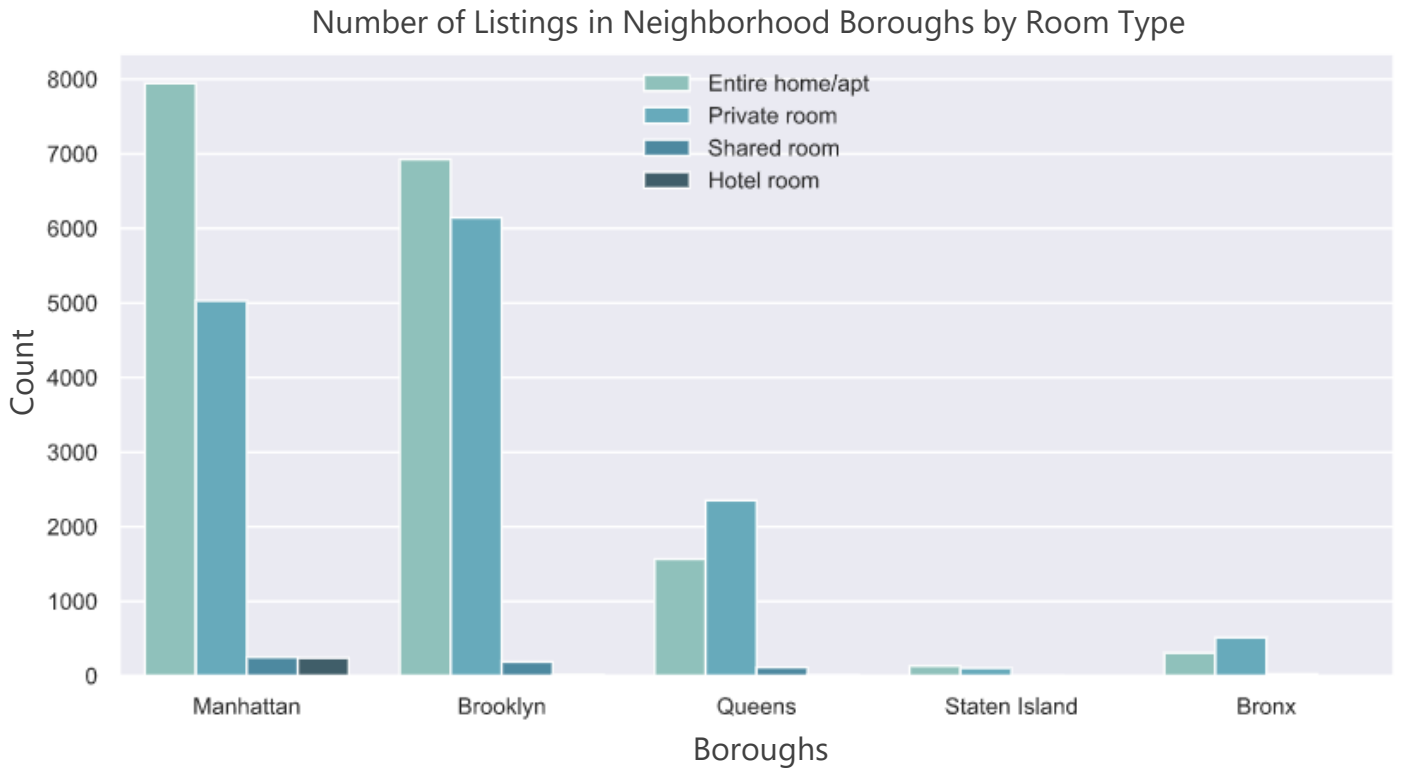


Keywords in Brooklyn

Exploratory Data Analysis for Neighborhoods

Analyzing Listings by Room Type

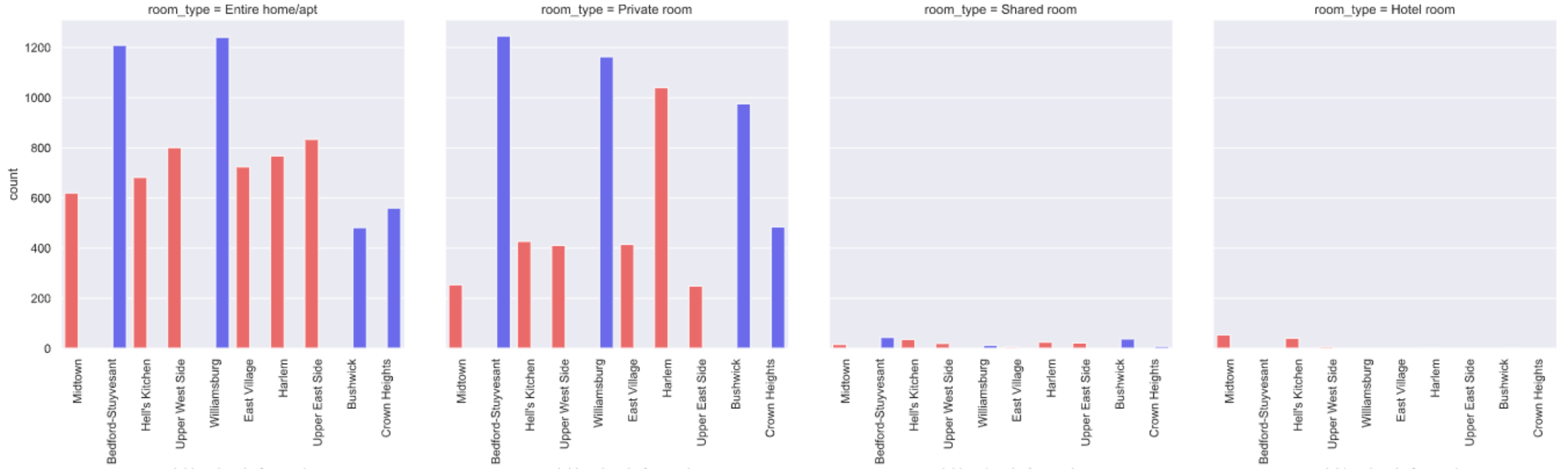




Exploratory Data Analysis for Neighborhoods

Top 10 Hottest Neighborhoods by Room Type

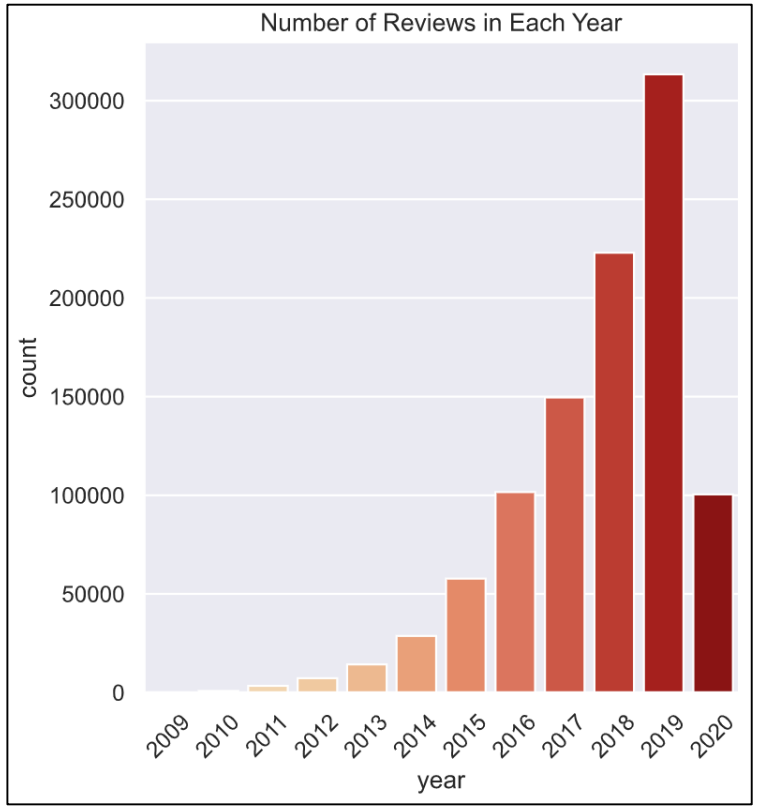
1. Bedford-Stuyvesant
2. Williamsburg
3. Harlem
4. Bushwick
5. Upper West Side
6. Hell's Kitchen
7. East Village
8. Upper East Side
9. Crown Heights
10. Midtown

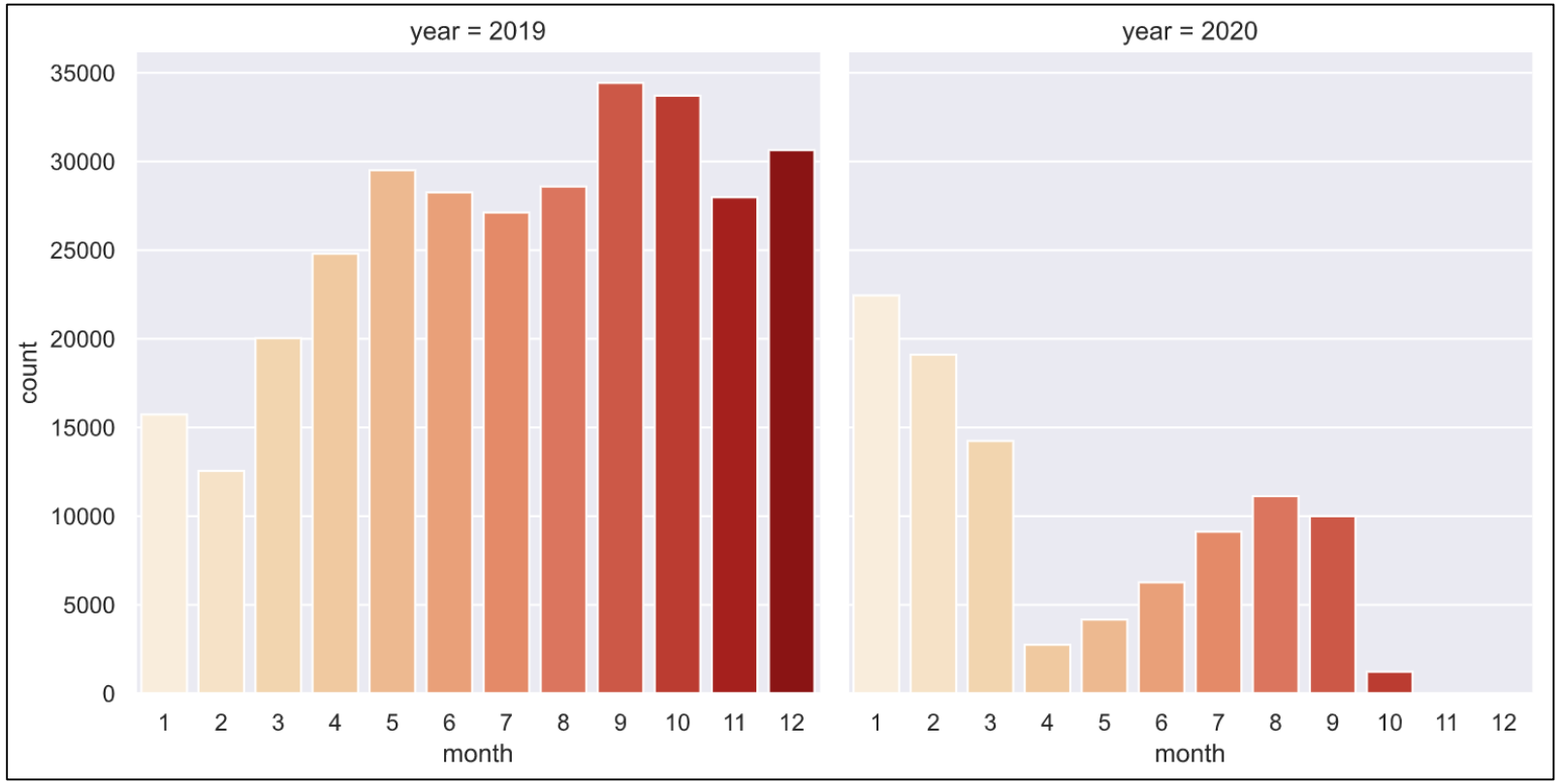


Exploratory Data Analysis for Reviews

Impact of COVID-19 on the Number of Reviews

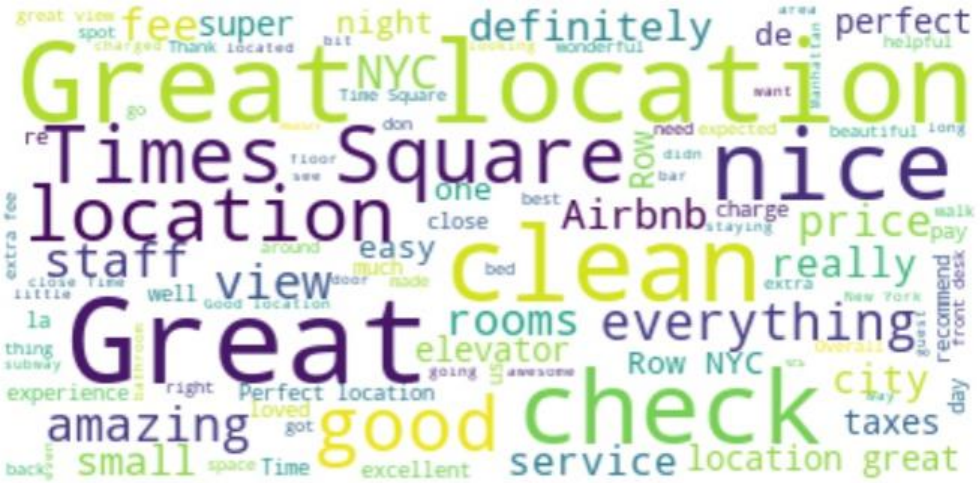
- The number of reviews drastically reduces approximately 66% in 2020.





Exploratory Data Analysis for Reviews

Comments for the Top-Rated Listing



Comments for the Lowest-Rated Listing

Exploratory Data Analysis for Hosts

Superhost is a host who consistently receives good reviews and provides guests with extraordinary experiences over at least a year.

4.8+ overall rating

10+ stays in the past year

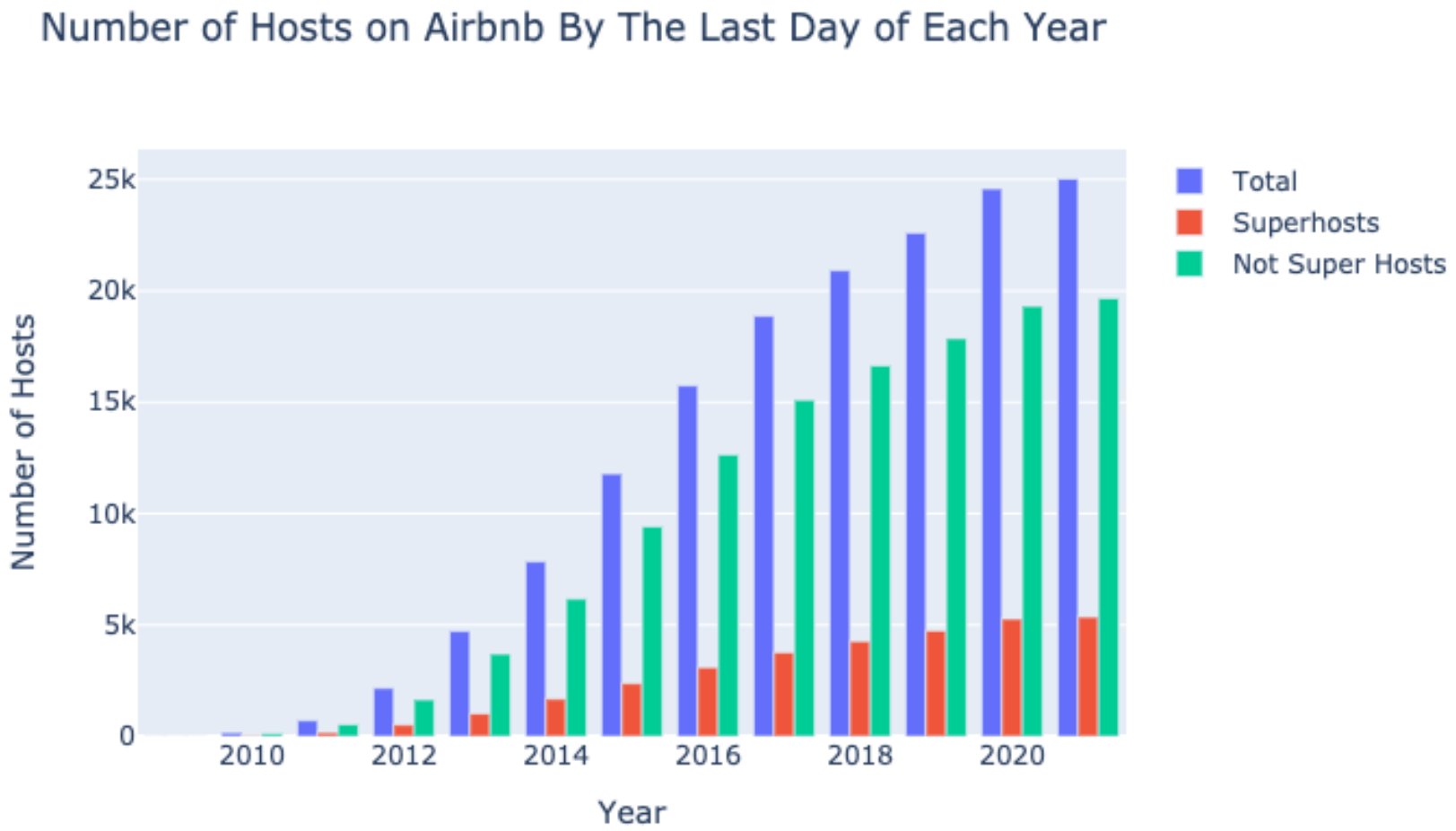
90% response rate

<1% cancellation rate

Exploratory Data Analysis for Hosts

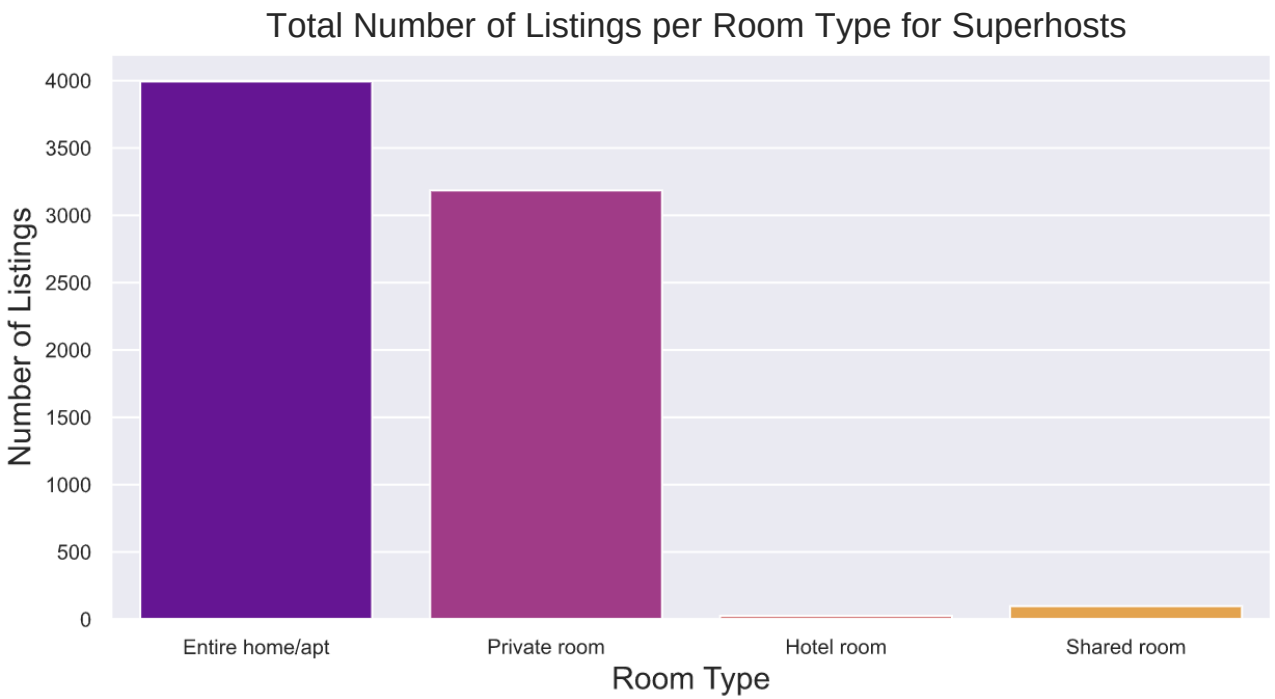
Breakdown on Number of Hosts by Type (Superhosts/Non-Superhosts)

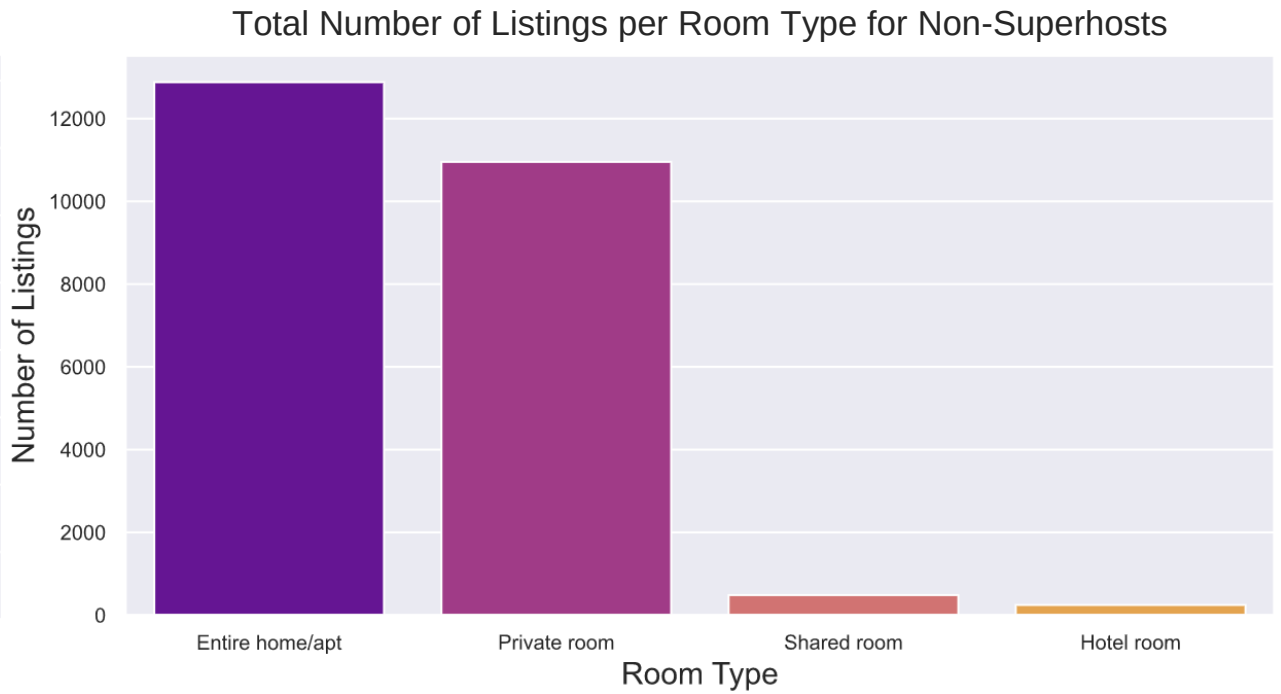
- There is an upward trend in the number of superhosts and non-superhosts.
- The number of non-superhosts is higher for each year.



Exploratory Data Analysis for Hosts

Comparison of Superhost and Non-Superhost by Room Type

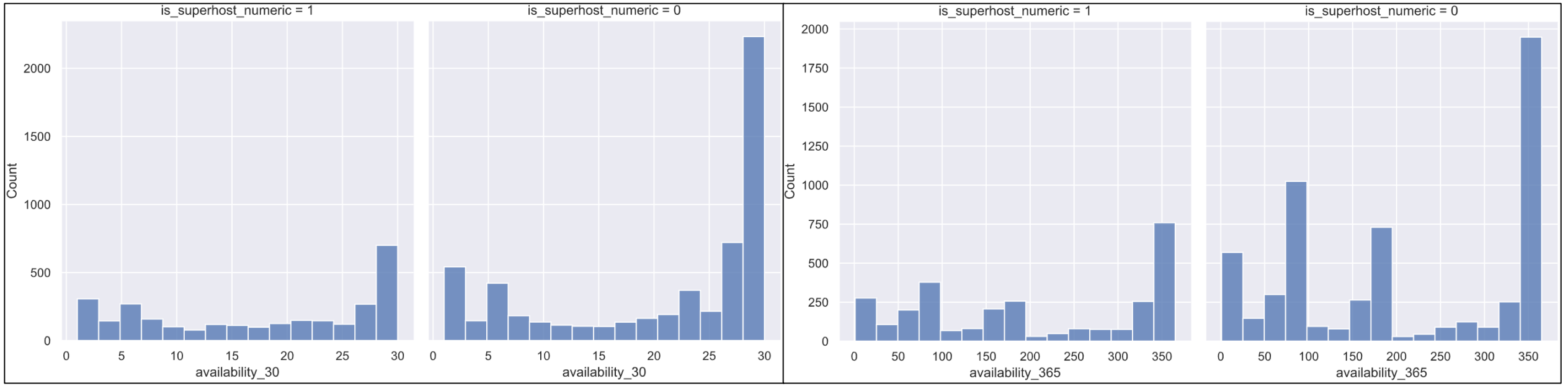




- The most prolific room type is an entire home/apartment, and the least prolific appears to be the hotel room.
- A critical observation is that non-superhosts have 68% more listings that are entire homes/apartments than superhosts, and 75% more listings that are private rooms.

Exploratory Data Analysis for Hosts

Superhosts and Non-Superhosts Availability (Over 30 days and 365 days)

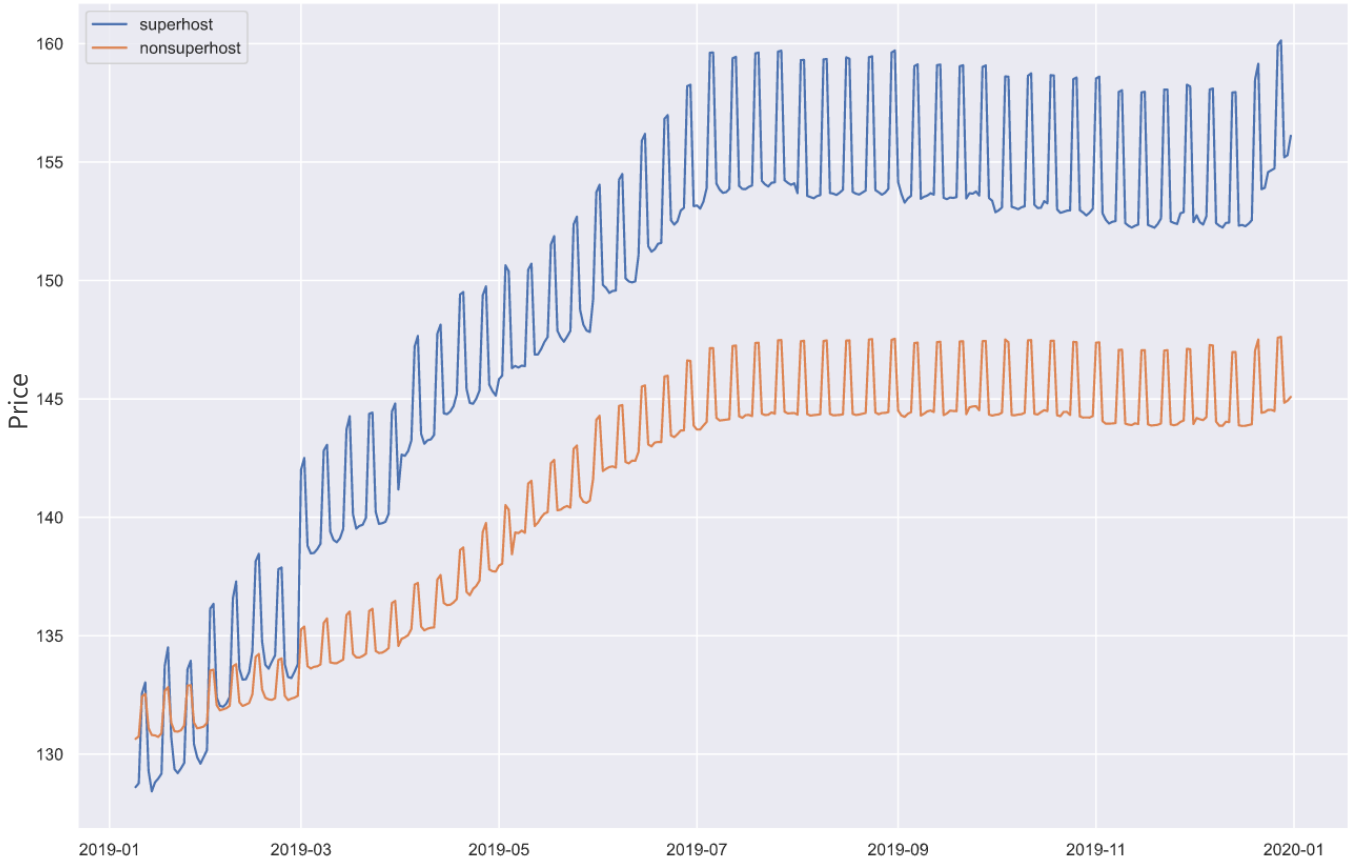


- Generally, non-superhosts have higher number of listings available over a period of 30 and 365 days.

Exploratory Data Analysis for Price

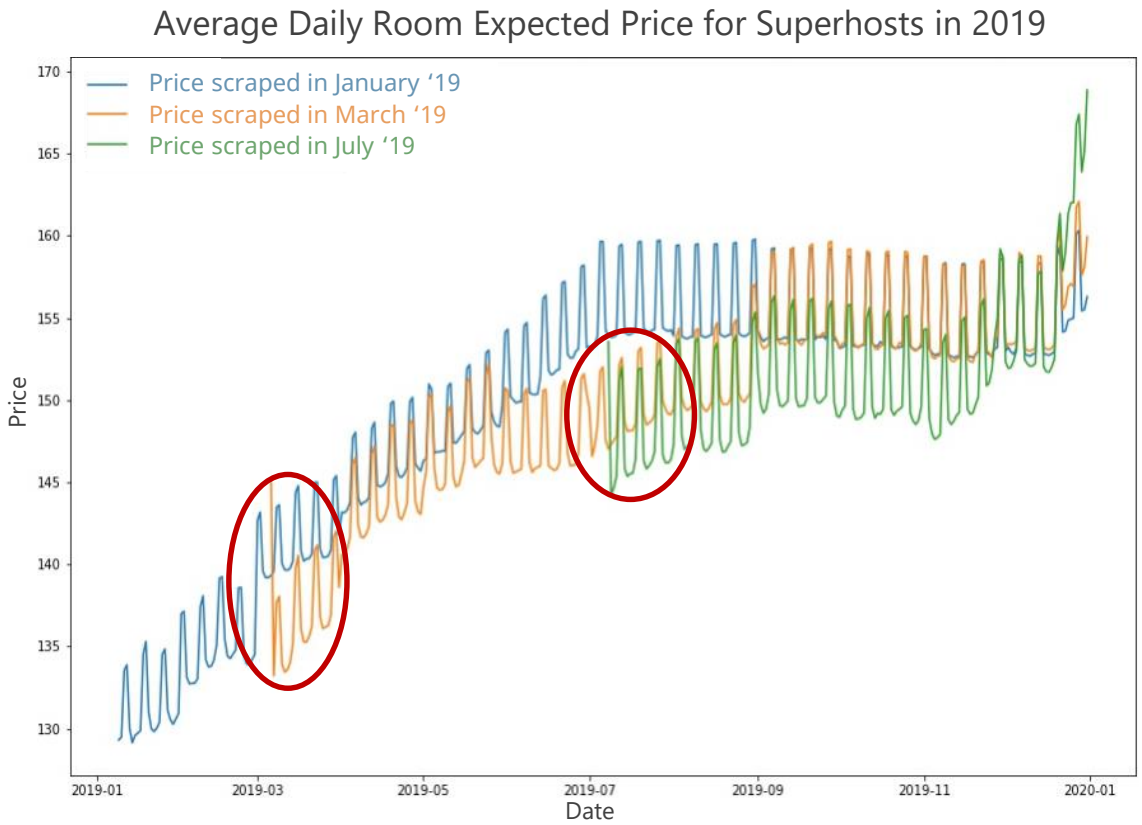
Average Daily Room Price for Superhosts and Non-Superhosts in 2019

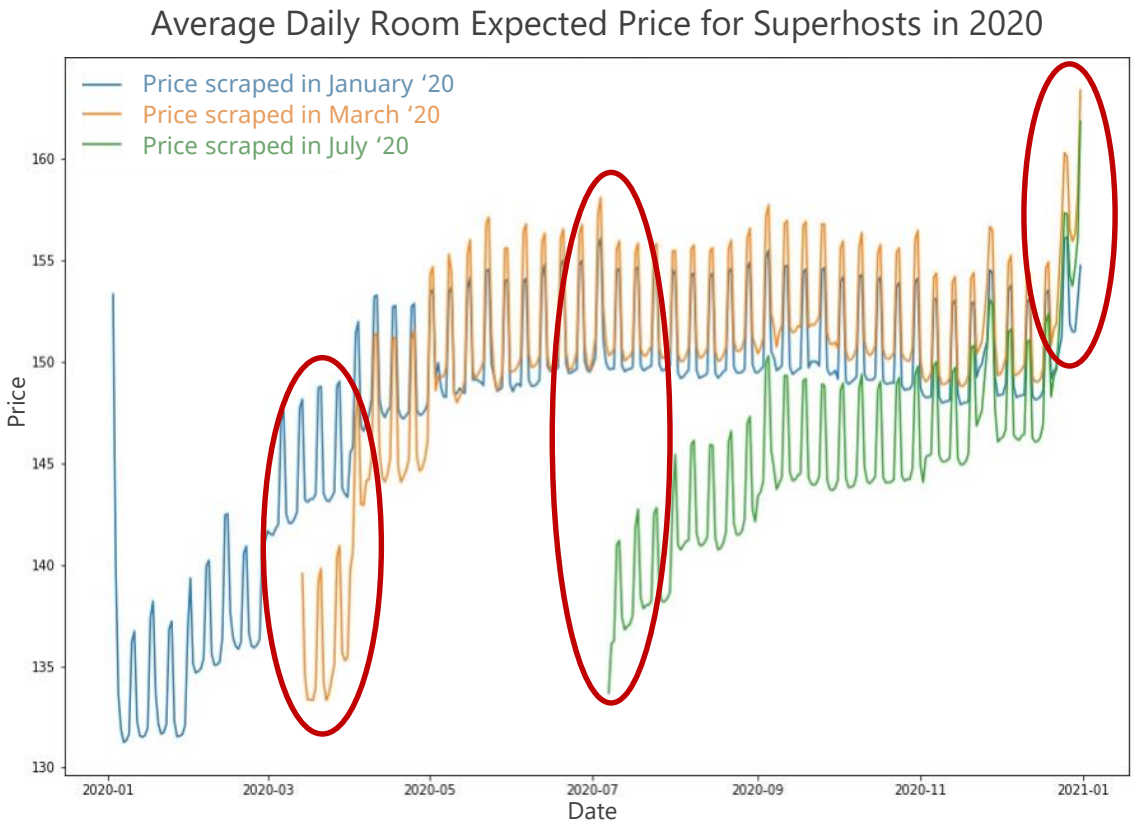
- During a year, the price rises between Jan. and Jul., and fluctuates between Jul. and Dec.
- For each week, the price on weekends is higher than that of weekdays.
- The average daily room price for super hosts tends to be higher than that of non-super hosts.



Exploratory Data Analysis for Price

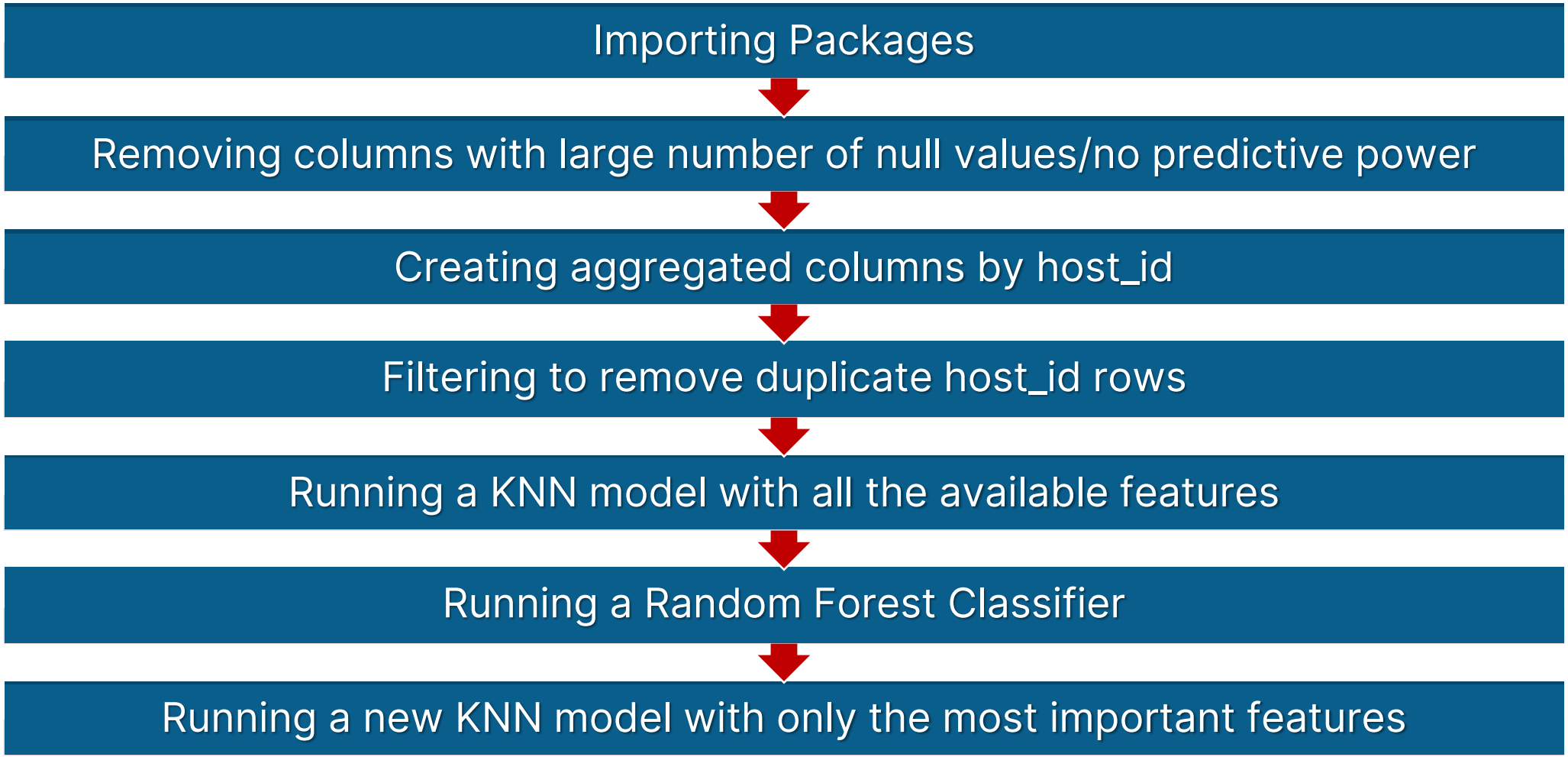
Impact of COVID-19 on Average Daily Room Price for Superhosts





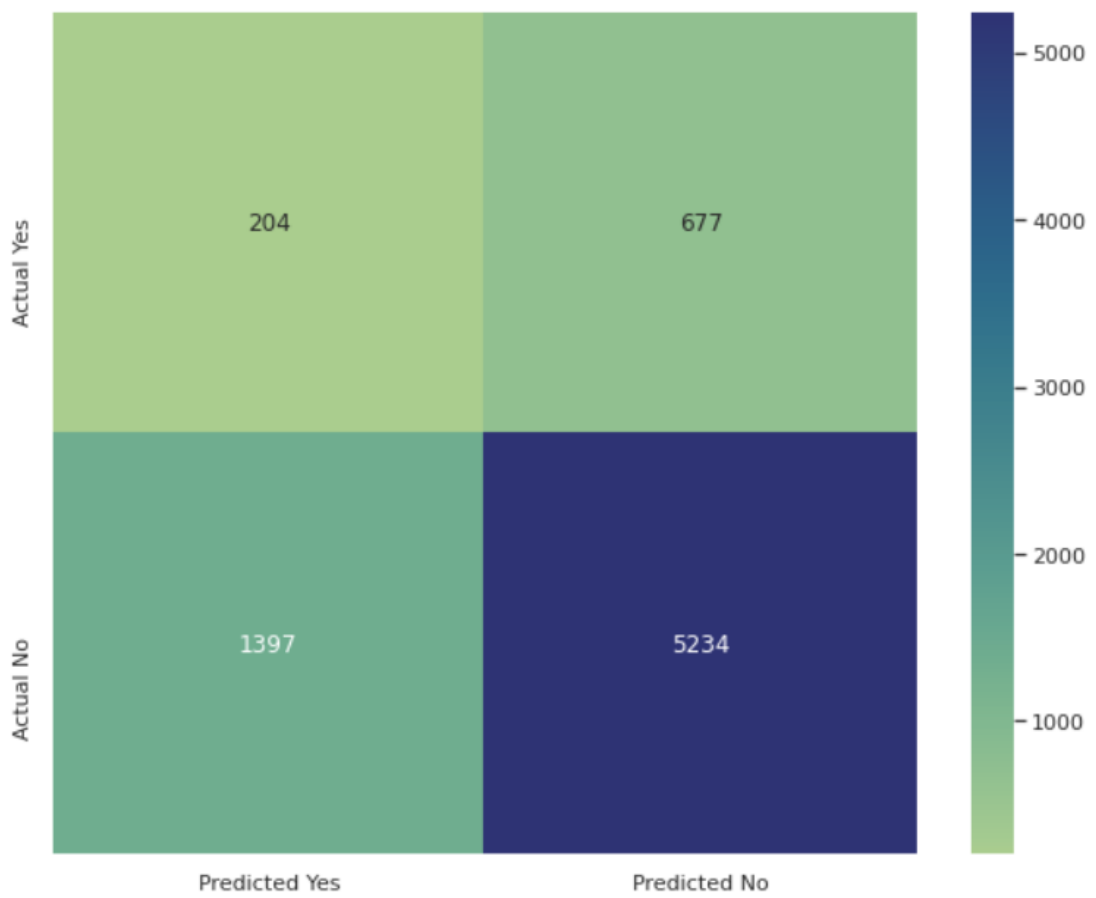
Machine Learning – Classification Model

Steps implemented to build the model to predict if the host is a superhost/non-superhost



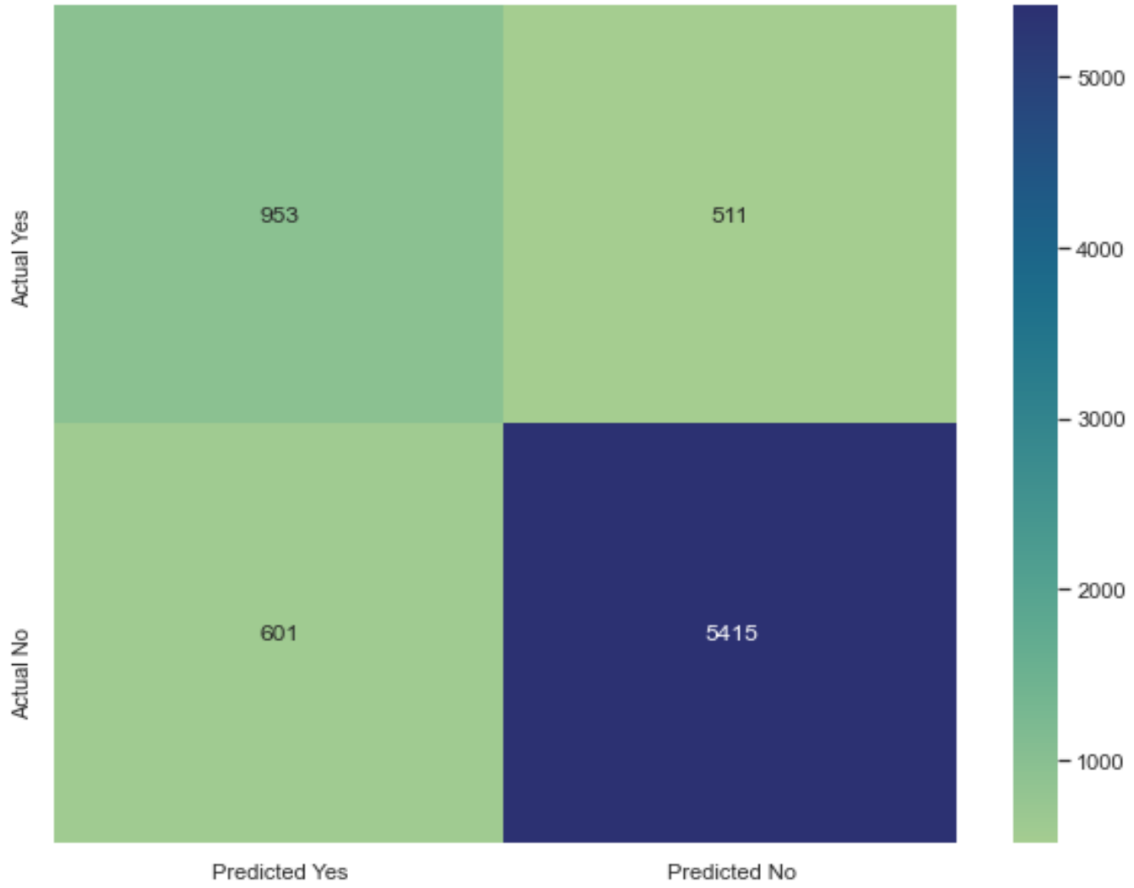
Machine Learning – Classification Model

Confusion Matrix for Prediction of Superhosts Using All Features



True Positive Rate: 12.74%
False Positive Rate: 21%
Accuracy Score: 72.39%

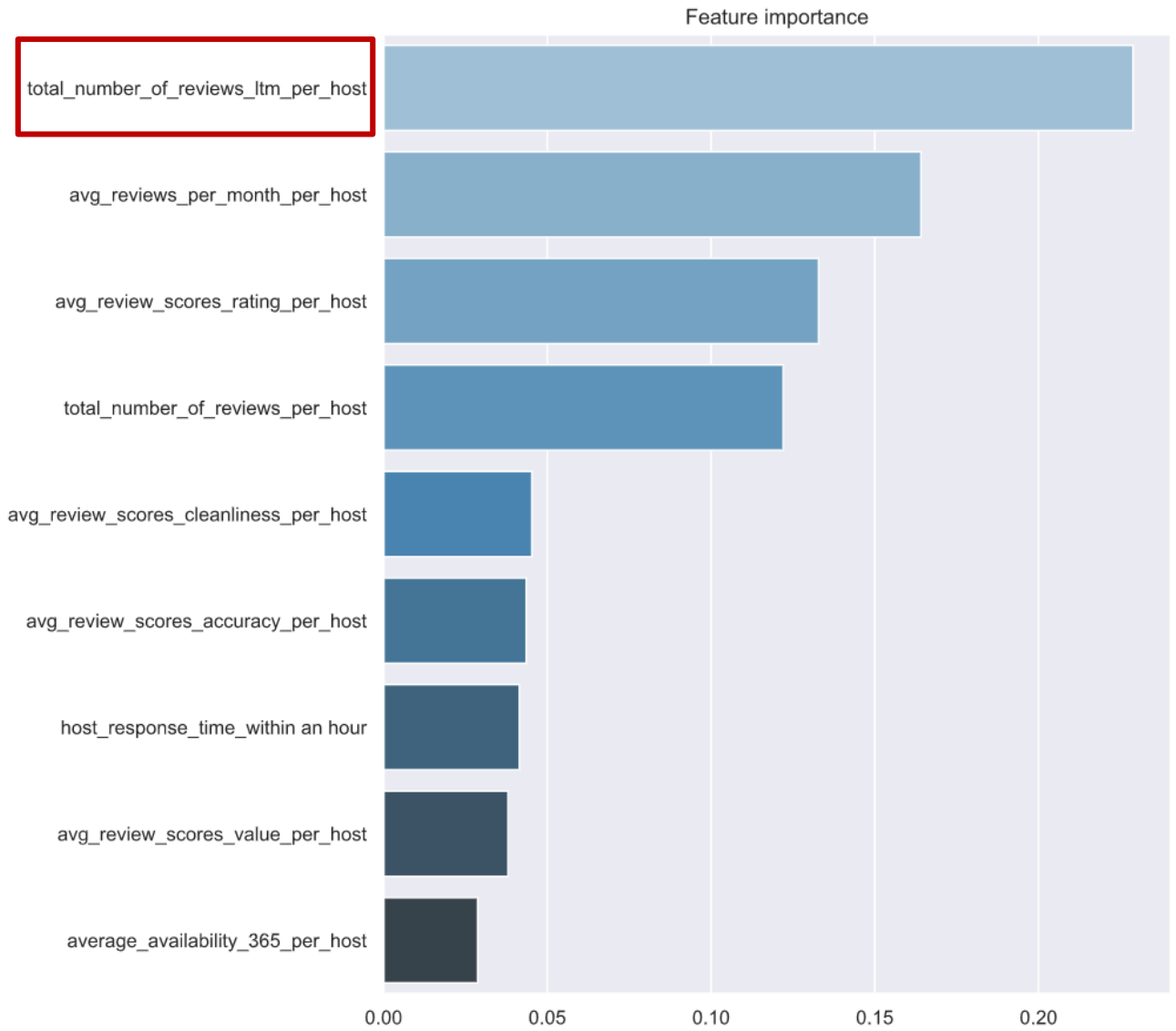
Confusion Matrix for Prediction of Superhosts Using Top Features



True Positive Rate: **62.96%**
False Positive Rate: **8.94%**
Accuracy Score: 85%

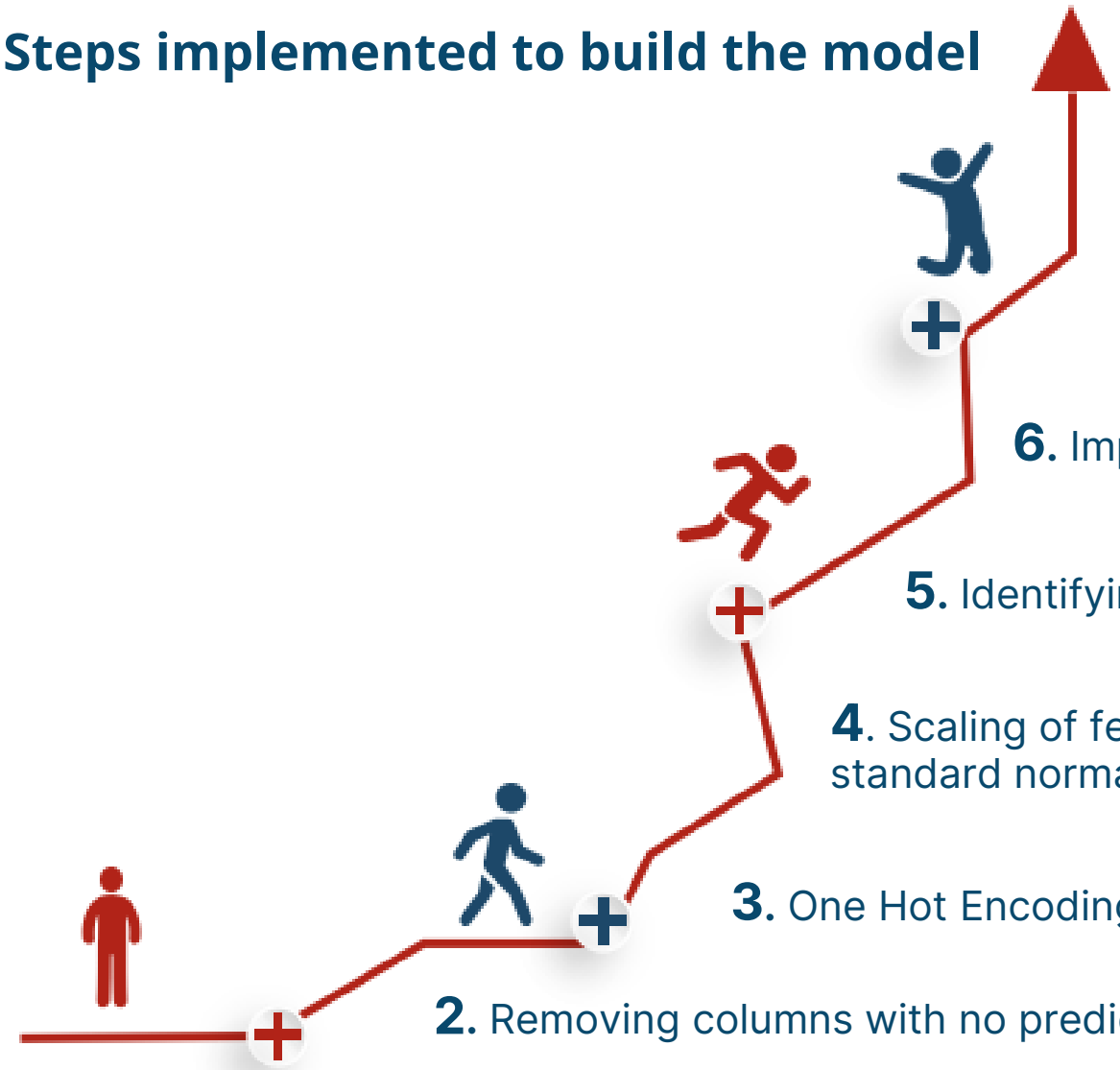
Machine Learning – Classification Model

Random Forest Classifier with Top Features



Machine Learning – Linear Regression Model

Steps implemented to build the model



1. Import Packages

2. Removing columns with no predictive power/redundant columns

3. One Hot Encoding of Categorical Variables

4. Scaling of features (through standardization) to achieve data in a standard normal structure

5. Identifying correlation of all features with the dependent variable

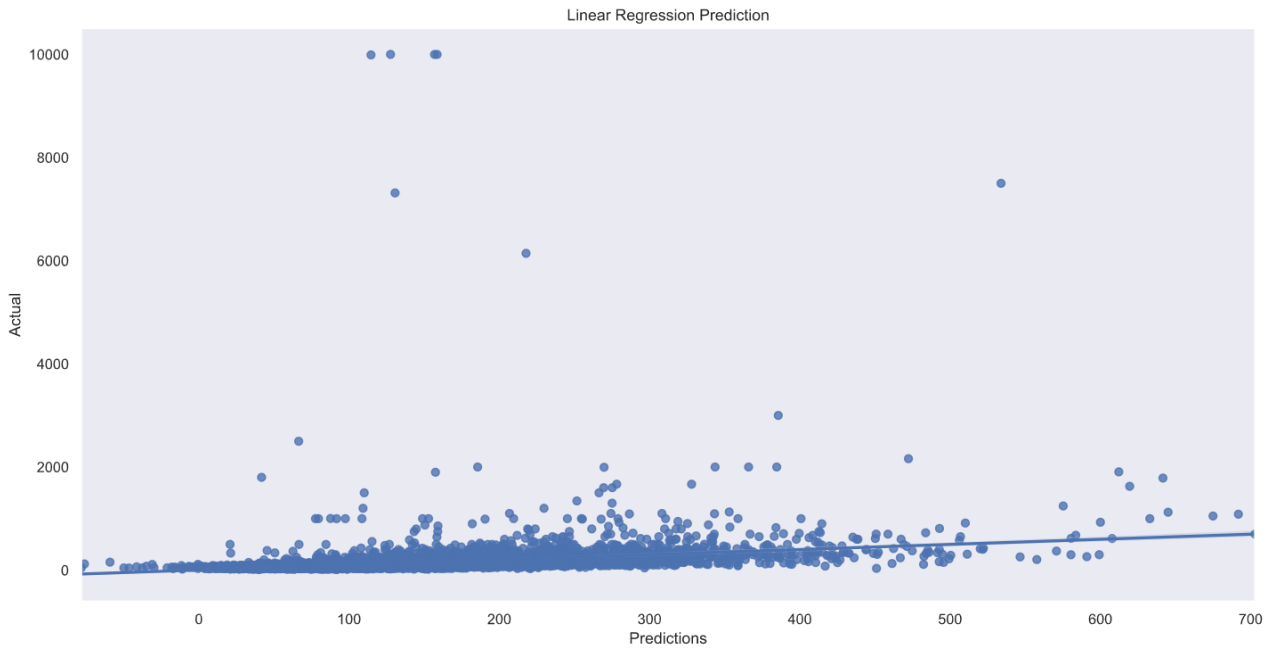
6. Implementing linear regression models for the entire dataset

7. Filtering the dataset to remove outliers (price < $500) and running the model

8. Taking the log of price to account for outliers and re-implementing the model

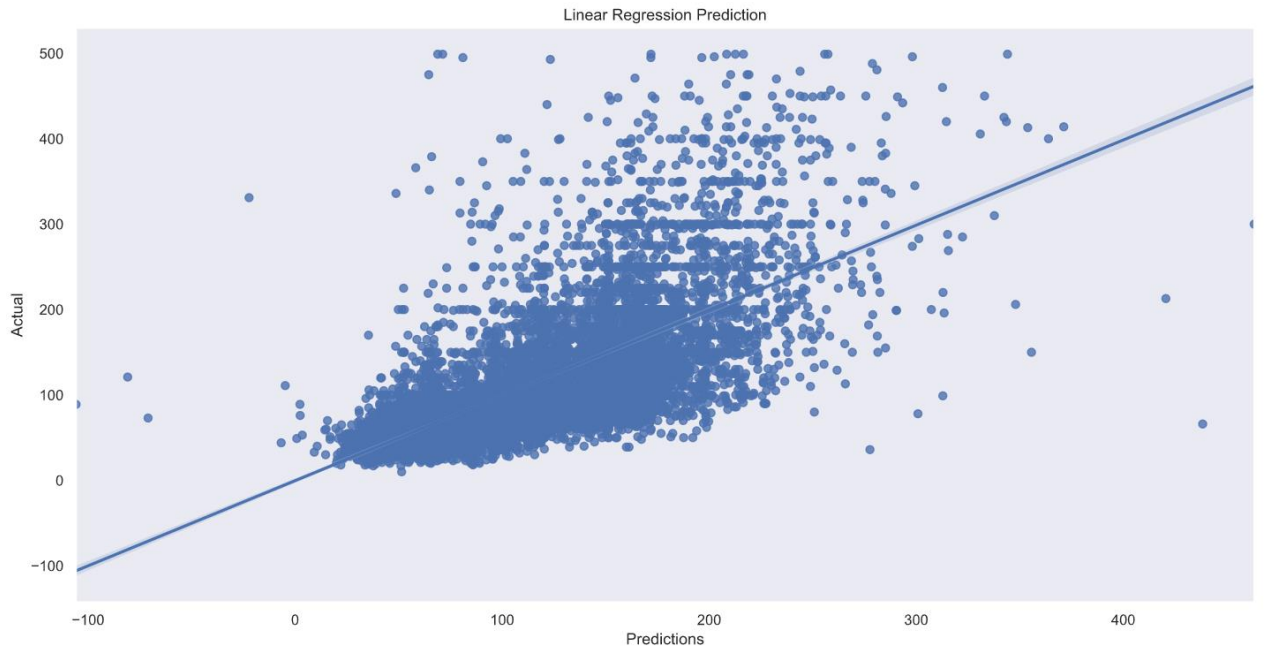
Machine Learning – Linear Regression Model

Linear Regression Model with Total Price



- MAE: 61.83
- MSE: 49282.50
- RMSE: 221.99
- R-Squared: 0.1228

Linear Regression Model with Price < $500



- MAE: 39.40
- MSE: 3265.60
- RMSE: 57.14
- R-Squared: 0.47

Machine Learning – Linear Regression Model

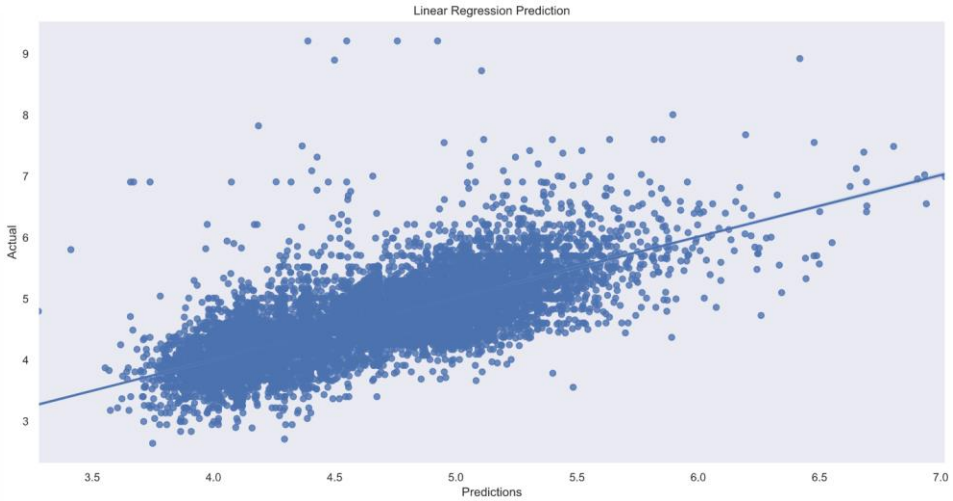
OLS Regression Results

Dep. Variable:	price	R-squared:	0.534
Model:	OLS	Adj. R-squared:	0.534
Method:	Least Squares	F-statistic:	1828.
Date:	Sat, 28 Nov 2020	Prob (F-statistic):	0.00
Time:	16:54:11	Log-Likelihood:	-20708.
No. Observations:	31880	AIC:	4.146e+04
Df Residuals:	31859	BIC:	4.163e+04
Df Model:	20		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	4.6056	0.017	277.020	0.000	4.573	4.638
accommodates	0.1743	0.005	36.997	0.000	0.165	0.184
bedrooms	0.1088	0.004	26.263	0.000	0.101	0.117
beds	-0.0260	0.004	-5.831	0.000	-0.035	-0.017
availability_30	0.1705	0.011	15.725	0.000	0.149	0.192
availability_60	-0.1020	0.025	-4.142	0.000	-0.150	-0.054
availability_90	-0.0015	0.019	-0.080	0.937	-0.038	0.035
availability_365	-0.0070	0.004	-1.663	0.096	-0.015	0.001
number_of_reviews	0.0035	0.004	0.855	0.392	-0.004	0.011
number_of_reviews_ltm	-0.0232	0.005	-4.502	0.000	-0.033	-0.013
number_of_reviews_l30d	-0.0184	0.003	-5.442	0.000	-0.025	-0.012
reviews_per_month	-0.0221	0.006	-3.547	0.000	-0.034	-0.010
is_superhost_numeric	0.0674	0.007	10.113	0.000	0.054	0.080
neighbourhood_group_cleansed_Brooklyn	0.1886	0.017	11.414	0.000	0.156	0.221
neighbourhood_group_cleansed_Manhattan	0.4666	0.017	28.194	0.000	0.434	0.499
neighbourhood_group_cleansed_Queens	0.0745	0.018	4.259	0.000	0.040	0.109
neighbourhood_group_cleansed_Staten Island	-0.0662	0.034	-1.955	0.051	-0.133	0.000
room_type_Hotel room	0.4463	0.029	15.377	0.000	0.389	0.503
room_type_Private room	-0.5633	0.006	-90.531	0.000	-0.576	-0.551
room_type_Shared room	-0.7556	0.020	-37.598	0.000	-0.795	-0.716
instant_bookable_t	-0.0122	0.006	-2.159	0.031	-0.023	-0.001

Omnibus:	9770.630	Durbin-Watson:	1.853
Prob(Omnibus):	0.000	Jarque-Bera (JB):	81763.289
Skew:	1.238	Prob(JB):	0.00
Kurtosis:	10.445	Cond. No.	31.1

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.



Number of reviews as well as features related to availability for 90 and 365 days and Staten Island are not statistically significant in predicting price (p-value > 0.05).

Conclusion

- Higher competition for Airbnb hosts in Manhattan and the most expensive neighborhoods (Flatiron District and Tribeca) are in downtown Manhattan
- Hosts in Manhattan might look at Airbnb listings as a business opportunity, viz-av-z hosts in Brooklyn, who would be looking to save rent/money by renting out private rooms
- COVID-19 impacted the price and number of reviews of the listings which decreased
- The number of reviews plays a significant role in determining the prediction of host types, but is not significant in predicting price of listings
- Features related to accommodation, room type and neighborhoods in Manhattan, Queens and Brooklyn play an important role in determining future price of the listings

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Recommendations for Prospective Hosts

- Regular updates of listing images and descriptions as accuracy ratings are based on these features
- Adjustment of listing prices based on the availability of competing listings within the neighborhood, especially during special circumstances such as COVID-19
- More emphasis in increasing exposure of the listing and the number of positive reviews
- Penetrating markets/boroughs with popular neighborhood locations where listings are in higher demand

Future Work

- Exploring other models to predict price
- Finding new alternatives to deal with outliers and missing values
- Gaining more insight on the lack of number of listings for shared room types in NYC

THANK YOU!

Any questions?