Data Visualization Final Group Project Process Book

Group P members: Gerald Lee, Joellyn Heng, Kyung Suk Lee

Project Title

Airbnb PriceR: Airbnb Analytics

Data Description

Airbnb: The dataset that we are using consists of data regarding Airbnb listings and reviews from 2009 to 2019. The dataset was obtained from InsideAirbnb.com (http://insideairbnb.com/london/) but a pre-processed version can be found on Kaggle. It comprises over 90 columns (e.g., customer ratings, room price, location etc.) and approximately 85,000 host listings in London, UK from 2009 to 2019. For the reviews dataset, which comprises plain-text reviews from Airbnb, we have applied text cleaning and preprocessing steps to the plain-text reviews. These steps include removing punctuations, removing numbers, making all text lowercase, removing stop words and stemming the words.

Tube (London Metro System): For the data that we have used for metro information, we obtained from "Transport For London" (https://tfl.gov.uk/). The London Underground is a public rapid transit system serving the London region. The dataset comprises approximately 470 stations with geographic locations.

Purpose of Website

We decided to create this website as a tool that can be used by Airbnb hosts to better understand their potential competitors and customers. Although there are numerous analyses that are targeted towards Airbnb users, we thought information that aids existing hosts is rare. Thus, for hosts with established listings, by giving sense of how the price differs across various dimensions (e.g. location, room types, number of guests etc.), we hope that hosts can use this website for a pulse-check on whether they remain well-positioned for competition. Furthermore, for anyone who wishes to become a host and list their property for the first time, this tool would be very useful for a first-cut understanding of the competitive landscape for market entry and pricing strategy.

Our visualizations are broken down into the sections below, keeping in mind the needs of our target audience. Apart from being able to visualize their competitors' locations and pricing at a quick glance, they will also be able to visualize analytics on supply, prices, ratings etc. at the selected neighbourhood- and listing-specific levels. We also analysed

cleaning fees as a component of total listing price, in order to better inform pricing strategy of hosts. Finally, we also provide some sentiment analysis through ratings and reviews of customers in the neighbourhood, in order for hosts to have a sense of how they are faring vis-à-vis their nearest competitors. Airbnb users and travellers are also welcome to use the website for the same information.

Section 1: Listings

Here, we have an interactive map that allows users to view the available listings across London. Users can adjust the slider on the left to filter based on their neighborhood, number of guests, and type of lodging in order to produce matching results. Users can also choose to overlay subway stations on the map to find out how far the nearest subway station is to specific listings. By hovering on the dots, users will be able to see the price of each listing, and when they click on them, more details including rating and direct links to the listing are provided.

Section 2: Explore Listings

This section provides an alternative view of the listings based on the same filters that the user has chosen. Instead of a map, it contains a data table that allows users to observe the price, property type, review scores and the direct link to the listing.

Section 3: Neighborhood Analytics

In this section, users are able to see two sets of visualizations, one on the selected neighborhood and another on comparable listings within the neighborhood.

The first set comprises two graphs that take into account all the input filters chosen by the host, and provide analyses of close comparables within the neighborhood. The first graph is scatterplot that maps the ratings and prices of comparable listings. With the median of both axes in dotted lines, hosts are able to visualize and place themselves among their competitors, and inform them on price and rating strategies. Next, we chose to use a histogram as the second graph to provide a clear distribution of prices of closest comparables.

The next two graphs are aimed at providing hosts an overview of the current supply and price range across lodging types and sizes (i.e. bedrooms and maximum pax). We chose a stacked bar graph, so that hosts are able to see the total units per lodging size, as well as the proportions of types within each size. This would enable them to understand the supply situation within the neighborhood, and assess market gaps and saturation across listing types. Next, we chose to use boxplots to visualize prices, as it could efficiently show the median, quantiles as well as outliers. On the x-axis, we similarly used lodging size, and we

faceted it by lodging type. Hosts are then able to have a sense of the price differentials across these two dimensions.

Section 4: Cleaning Fees

In this section, users can analyze the breakdown between cleaning and room fee. We have chosen to visualize this, as cleaning fee is one other substantial component of total fees. Based on all the input filters, users can observe the breakdown between cleaning and the room fee per bed, and hosts can also be better informed on the average amounts that they should charge as room fee vs. cleaning fee. The second graph is a heat map that shows cleaning fees based on the number of guests, but compared across room types and all neighborhoods. This would provide hosts with an idea of the spread of cleaning fees across room types and all of London.

Section 5: Guest Ratings

Here, users can observe the distribution of customer ratings and polarity scores of reviews derived from sentiment analysis. In the first chart, a histogram highlights the distribution of numerical ratings. For the second chart, the distribution of sentiment scores is displayed. Both charts can be toggled and adjusted based on the neighbourhoods. The polarity scores were derived using the AFINN lexicon and uni-grams from the plain-text reviews. The final 2 charts show word clouds for the top 80 words from the positive and negative reviews. These visualizations can be important for hosts because it highlights where they stand in comparison to others and what are positive or negative attributes, especially from the word clouds they should account for.

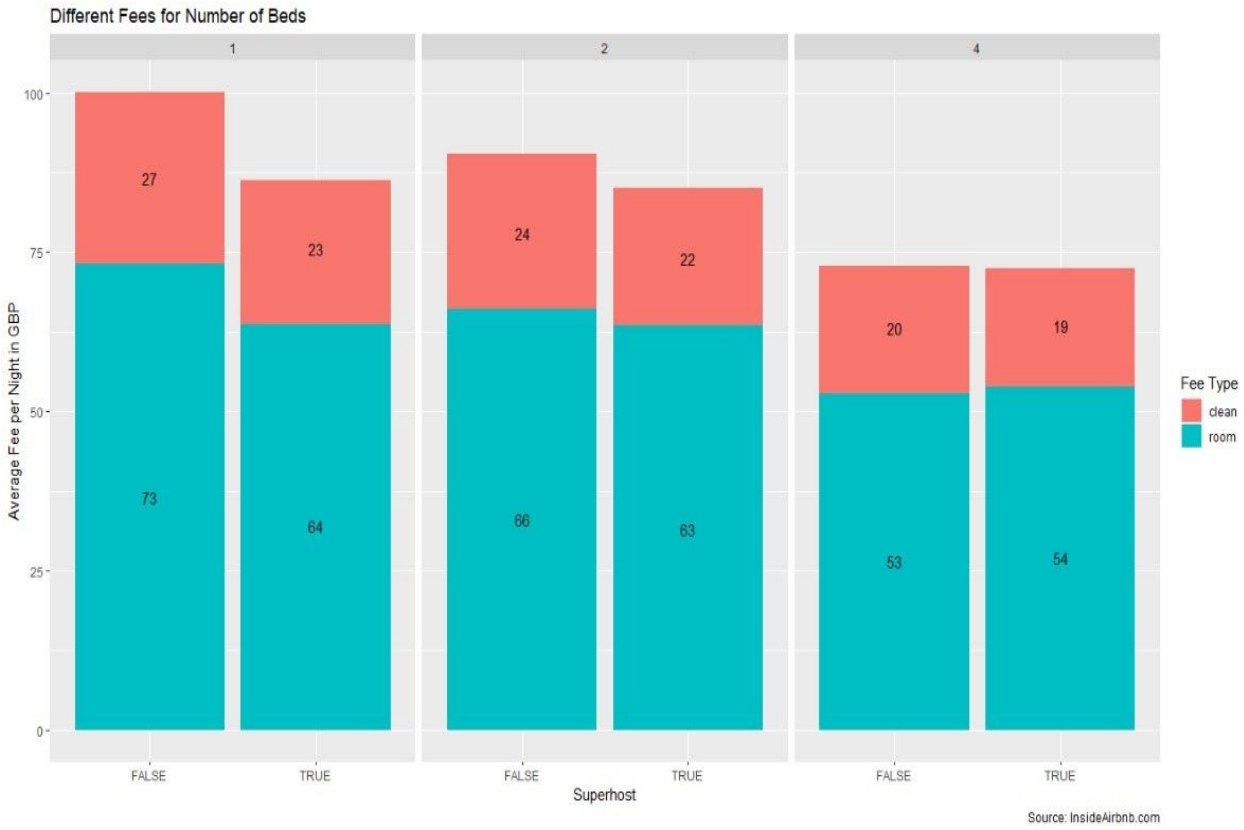
Initial ideas and Refinements

One of the questions we were interested to explore was how a new Airbnb host can gain credibility as a newcomer. As an extension, we thought we could explore the behaviour and best practices of Airbnb hosts across multiple segments beyond newcomers, including listings that are popular and established, listings that are consistently rated badly, and listings that have been around but are unable to obtain sufficient reviews. Without the date that the listing was established, we used the date of first review as a proxy. However, we realized we were unable to capture certain important groups of interest, such as those with none or few ratings given the proxy we were using.

Another area we thought to explore was the importance of host indications (e.g. superhost, response rate, response time) on listing prices. The hypothesis was that positive host indications allowed them to price a premium on their listings, as it provided a sense of security to Airbnb travellers. One way we tested this was to plot price against stays per month (using reviews per month as a proxy) across superhost and non-superhosts. If the

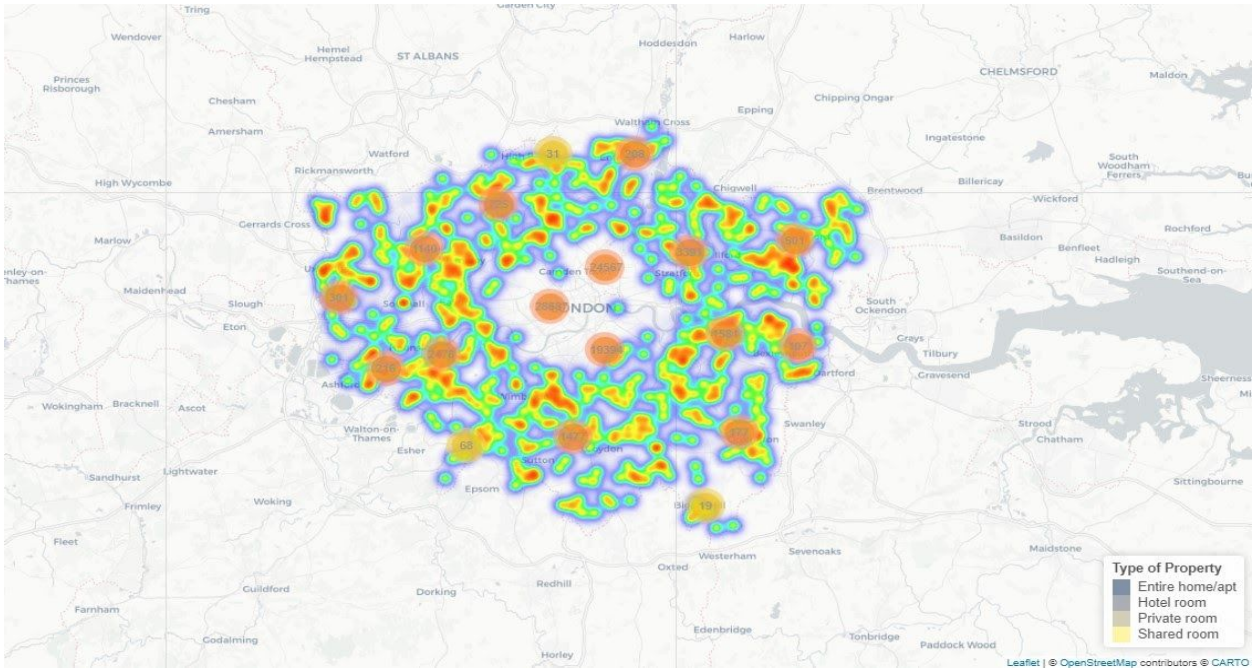
negative correlation was weaker in the former, it would mean that prices did not deter stays as much among superhost listings. However, the negative correlation was stronger among superhosts, though not too significantly.

Another analysis we did to test for the price premium for super hosts was a bar chart that compares average fee across superhost and non-superhost (faceted by number of beds).



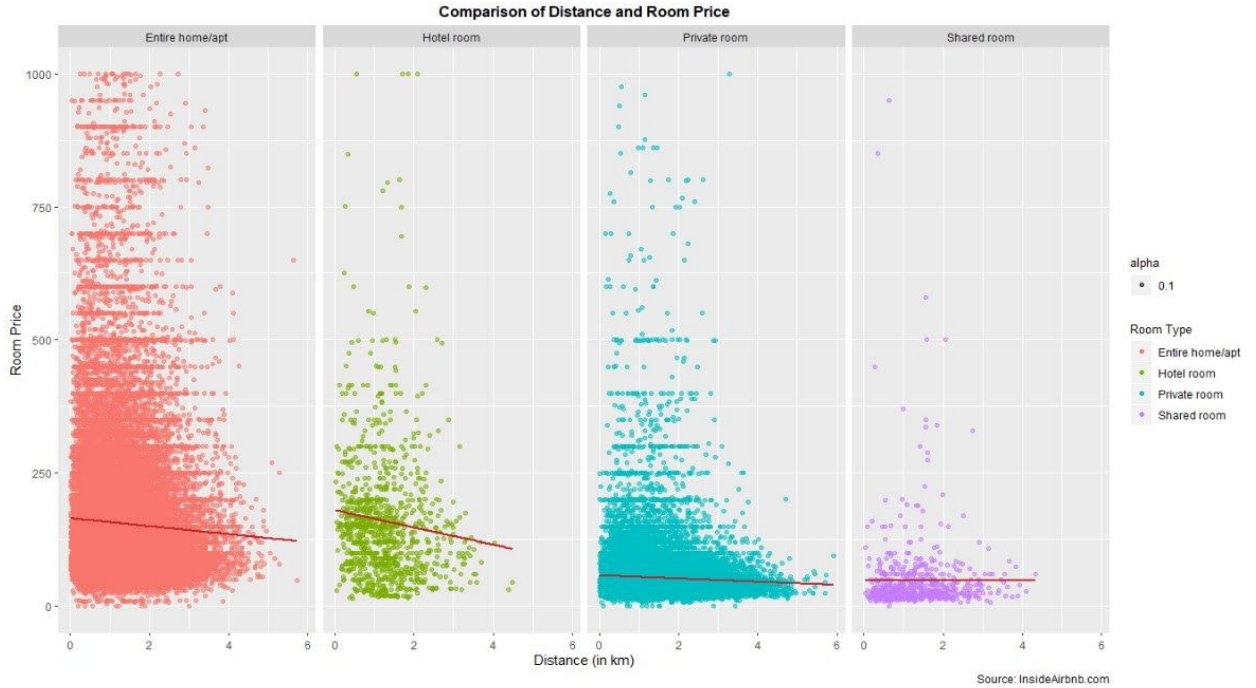
As seen from above, instead of pricing a premium, the average fee for superhosts were rather discounted. We however decided to exclude this in our final results, as we realized the graph did not take into account other features of the listings, such as property type (e.g. loft vs.) and room type (e.g. shared room vs. entire apartment), which may affect prices more. Once we subset the data accordingly in order to compare price premiums, the dataset becomes too small to be representative.

As part of pricing analytics, one visualization that we attempted but decided to discard is a heatmap of London that shows the average price differences.



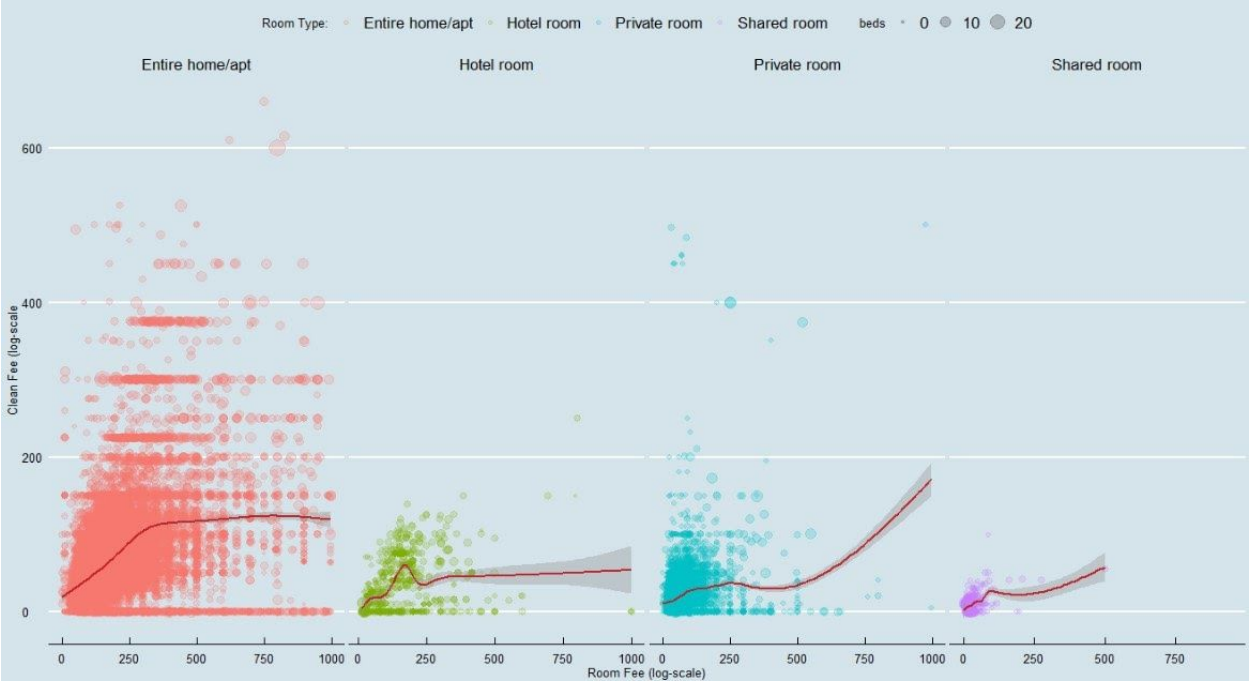
However, as the plots were scattered across the London region, there was no significant pattern observed. Thus, we decided to remove this analysis from the final output.

Also in line with pricing, we wanted to observe how the distance between the listings and the nearest tube station (London Metro System) affects the price of listings.

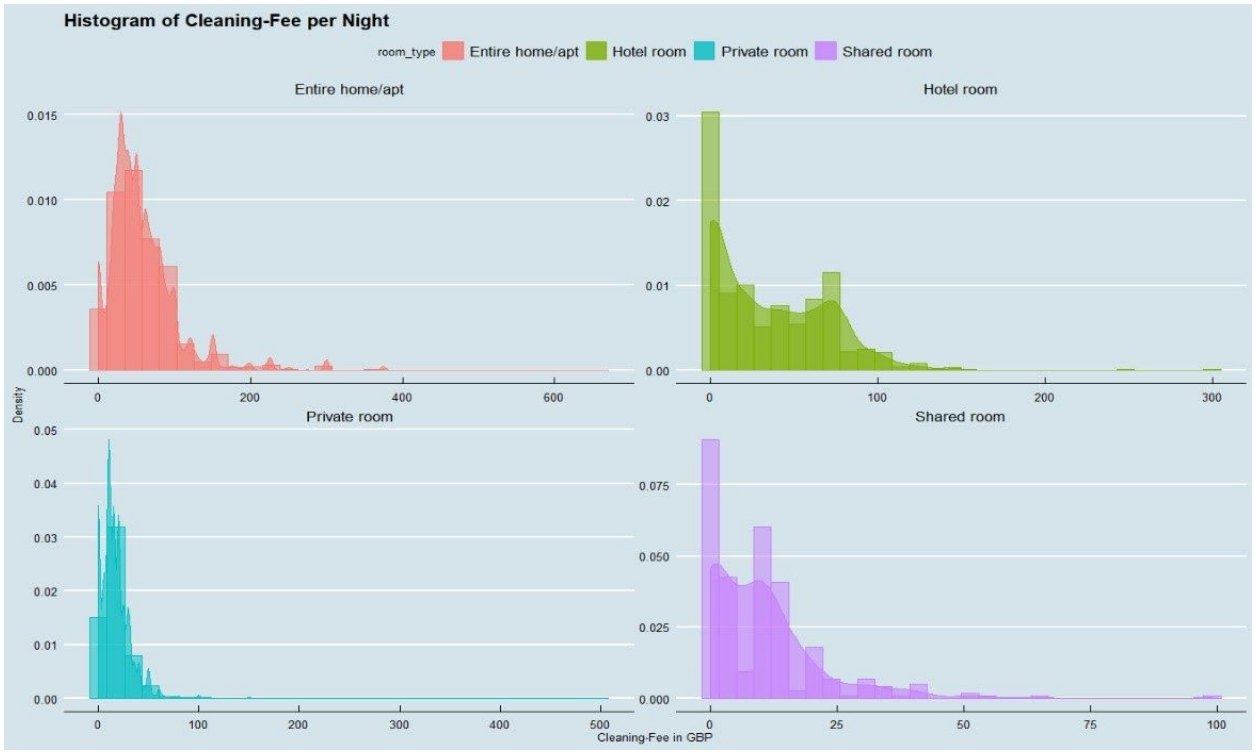


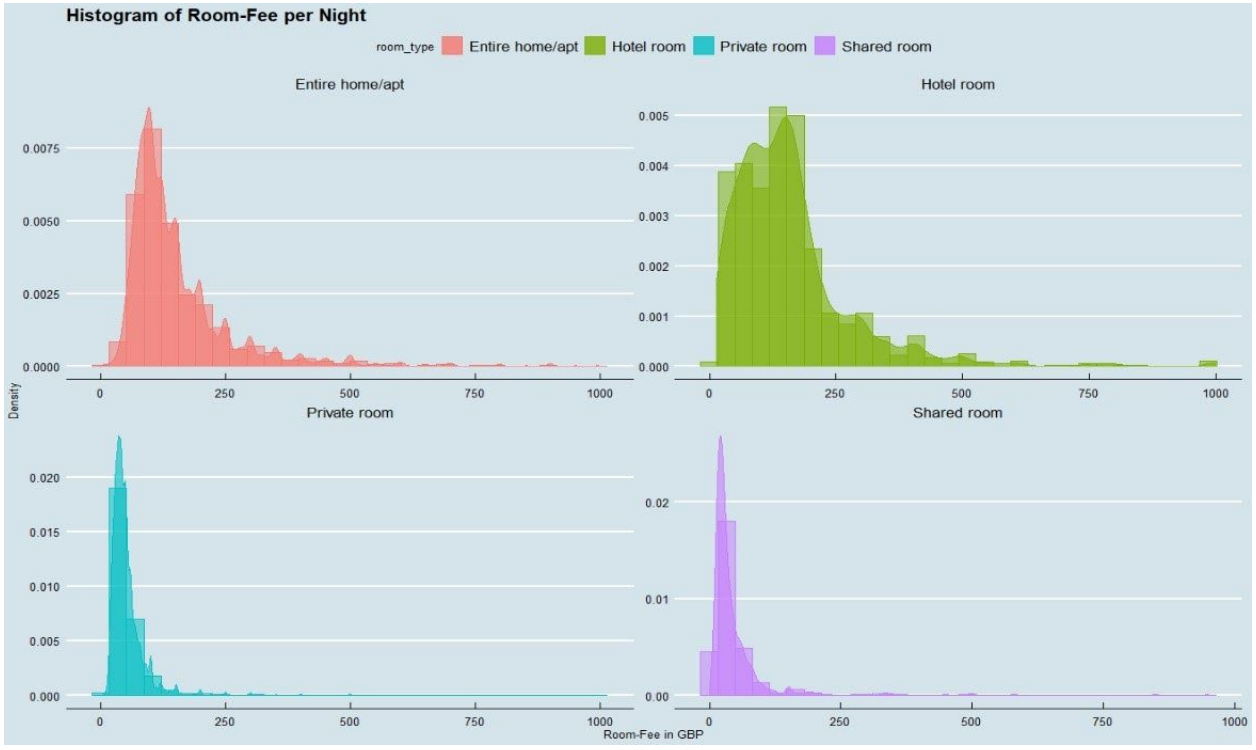
Above shows the average price difference with distance where the tube station is located, faceted by room types. However, the results were not significant nor coherent across different neighborhoods in London. While this insight was interesting to us, we have decided not to include it as it turned out not to be a significant price determinant.

In line with our interest on cleaning fee as a component, we also tried to have observed whether there is a pattern between room fee and cleaning fee.



As you can see above, we were not able to find meaningful correlation among different room types. Furthermore, as discussed above, varying by different parameters also produced various results. Thus, we have decided not to include it in the final visuzlatioan. Lastly, we have made a density-barplot where it shows how the room-fee and cleaning-fee was distributed among total listings.





Nonetheless, this result also varied by the different parameters and we believed that just showing the density of how the different fees are outlined did not really make any

contribution towards our purpose of the project. Hence, we have removed these visualizations from the final submission also.

Final Remarks

Above mentioned visualizations are just a few among various analyses we have covered using the data we have gathered. Most challenging issues we have confronted while preparing our final project was the inconsistency of and to match the results by various parameters. This makes sense since different environments of the listings lead to varying results. Nevertheless, by focusing on aspects that, what we believe, are meaningful towards hosts of Airbnb, we have visualized crucial aspects that could determine the decision making of both existing and potential hosts. With these visualizations in the website, we hope to equip Airbnb hosts with more information to make data-driven decisions on their pricing and other potential marketing strategies.