AirBnB Listings: An in depth dive into the world of short-term sublets

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2021-12-07

Motivation

This dataset is interesting to us because it combines our love for statistics with our love for vacation planning. Statistical analysis of this data will provide insights while comparing prices and booking accommodations.

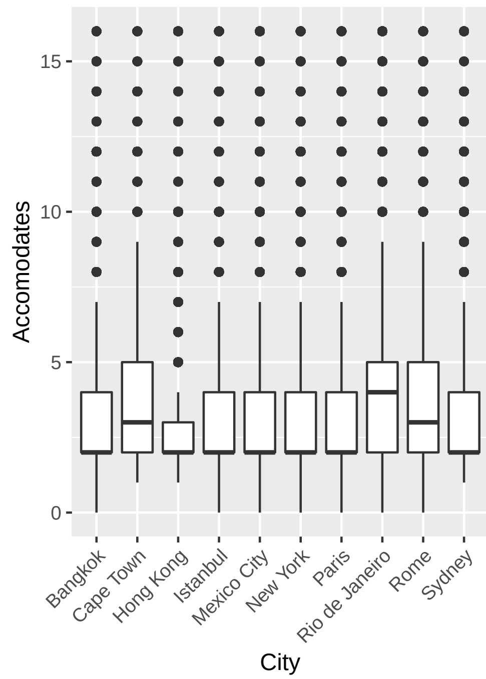
Introduction

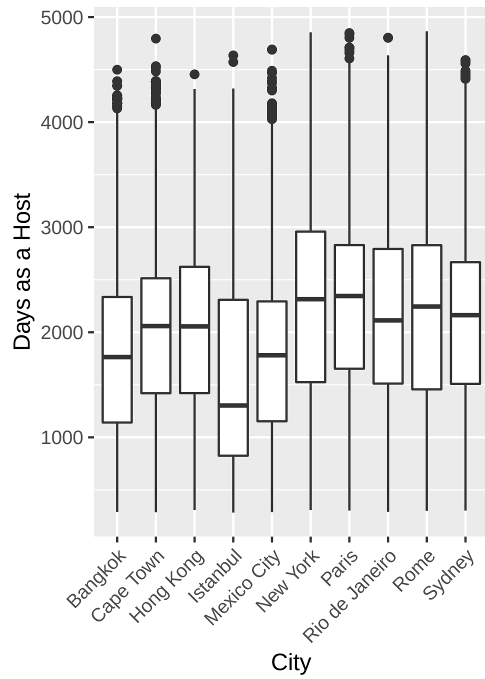
This project aims to investigate AirBnb listings and obtain insights into the most important features of short-term sublets. More specifically, the goal of this project is to classify the cities based on different attributes. The dataset, which was obtained from Kaggle, contains 10 cities from very distinct parts of the world: Bangkok, Cape Town, Hong Kong, Istambul, Mexico City, New York, Paris, Rio de Janeiro, Rome, and Sydney. The Airbnb data contains 280 000 listings including, but not limited to: host info, geographical data, price, number of bedrooms, amenities, and review scores.

The analysis can then reveal important aspects regarding how different attributes may characterize each city, for example:
- Which amenities are more important for each city when selecting a property?
- Does the host profile differ among different cities?
- Which types of accommodation are more common depending on the city?
- Can we predict the city based on different preferences related to the place to stay?

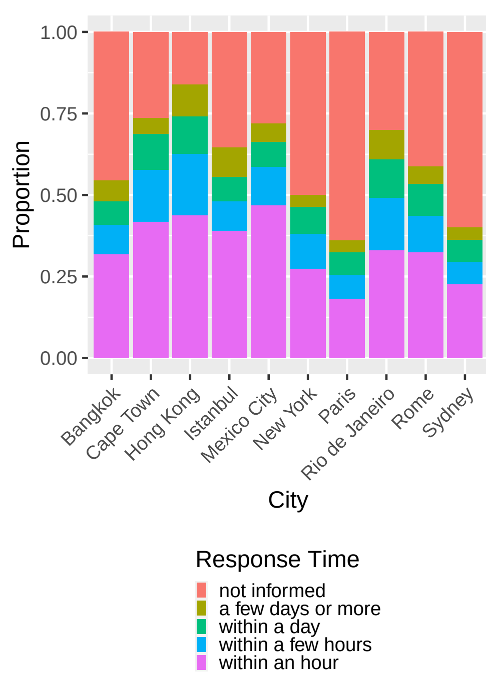
Exploratory Analysis

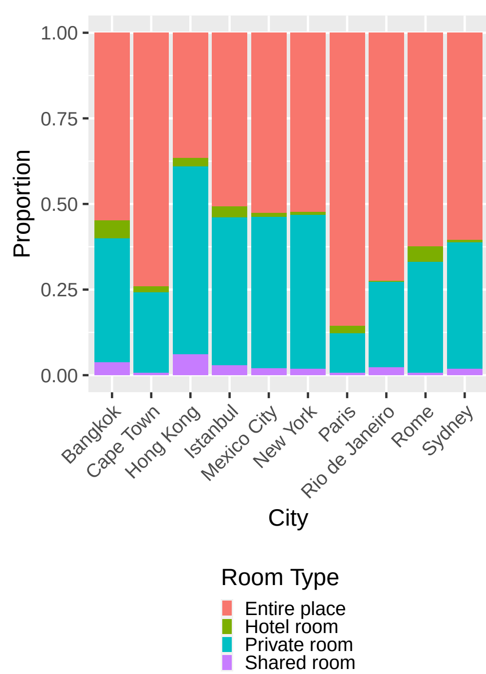
Several insights can be obtained by plotting different variables against the cities. For example, the next figure shows boxplots that present (1) the number of guests the listing accommodates and (2) for how long the host has been renting properties in AirBnB. The first boxplot indicates that cities such as Cape Town, Rio de Janeiro, and Rome tend to offer listings with more guests, which might be suitable for group or family trips. For Hong Kong, however, the accommodations tend to be for fewer guests, which shows that listings might be tiny and that the city is more appropriate for business trips. In addition, the second boxplot shows that AirBnb has been used in some cities for more time than in others. For example, New York and Paris have an average for the number of days as a host variable that is considerably higher than the average for Istambul. It might show that AirBnB has only been widely used in Istambul for a shorter amount of time.





The next plot shows the proportion per city of (1) response time and (2) room type for different categories. The first plot shows that hosts in Mexico City and Hong Long tend to have the highest response times, whereas hosts in Paris and New York have the lowest response times. The second plot shows that most of the accommodations in Paris and Cape Town are for the entire place, and most of the accommodations in Hong Kong are for private rooms. This room type analysis for Hong Kong is consistent with the previous plots (i.e., the number of guests a property can accommodate). The room type variable can also provide information regarding the trip purpose (e.g., business, family, group). Cities such as Paris are preferred for group trips, whereas Hong Kong is more appropriate for business trips.



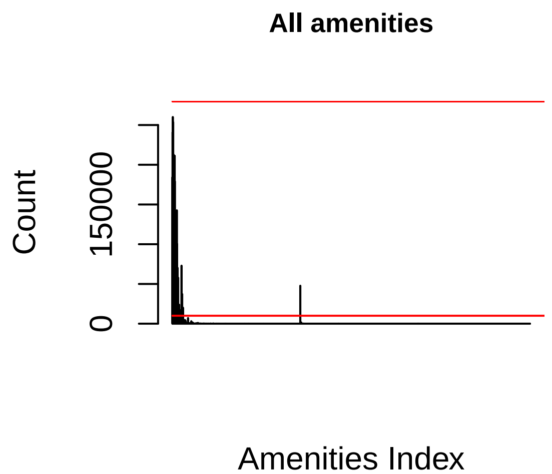


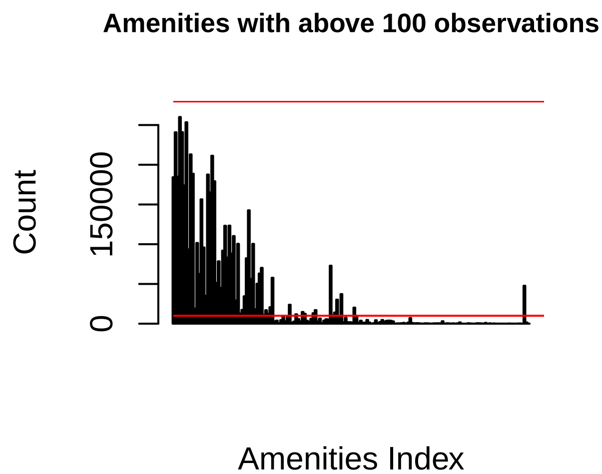
Exploring Amenities

In the original dataset, there is a column with a list of string of possible amenities a listing has. Here we explored these lists to extract useful information for our predictions. For example:

[“Heating”, “Kitchen”, “Washer”, “Wifi”, “Long term stays allowed”]

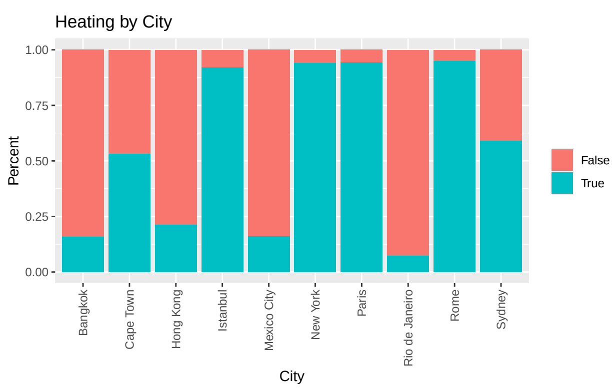
We found the list of all amenities and graphically determined which to include in the updated dataset.

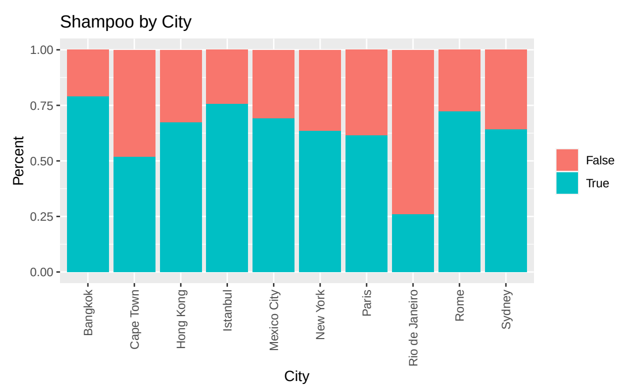




There were 2865 different amenities and a lot of them only have a count of 1. So, to better view the distribution, we removed all amenities that had below 100 observations in the second graph above. The red lines are at total observation and cut-off for amenities inclusion (10,000).

All observations were updated with new columns: 1 for has amenity and 0 for not. Below are graphs of the percent TRUE/FALSE values of 2 of the 60 included amenities in the updated dataset.





Exploring Interactions

The addition of interaction terms is a form of basis expansion. Interaction terms model the change in response variables against the change in a product or quotient of two or more predictor variables. They help in the case where the added effects of two predictor variables do not stack linearly, rather, they compound on each other. The right interaction terms can improve a model, but adding too many terms, or the wrong terms, increase variance and can actually worsen out of sample performance.

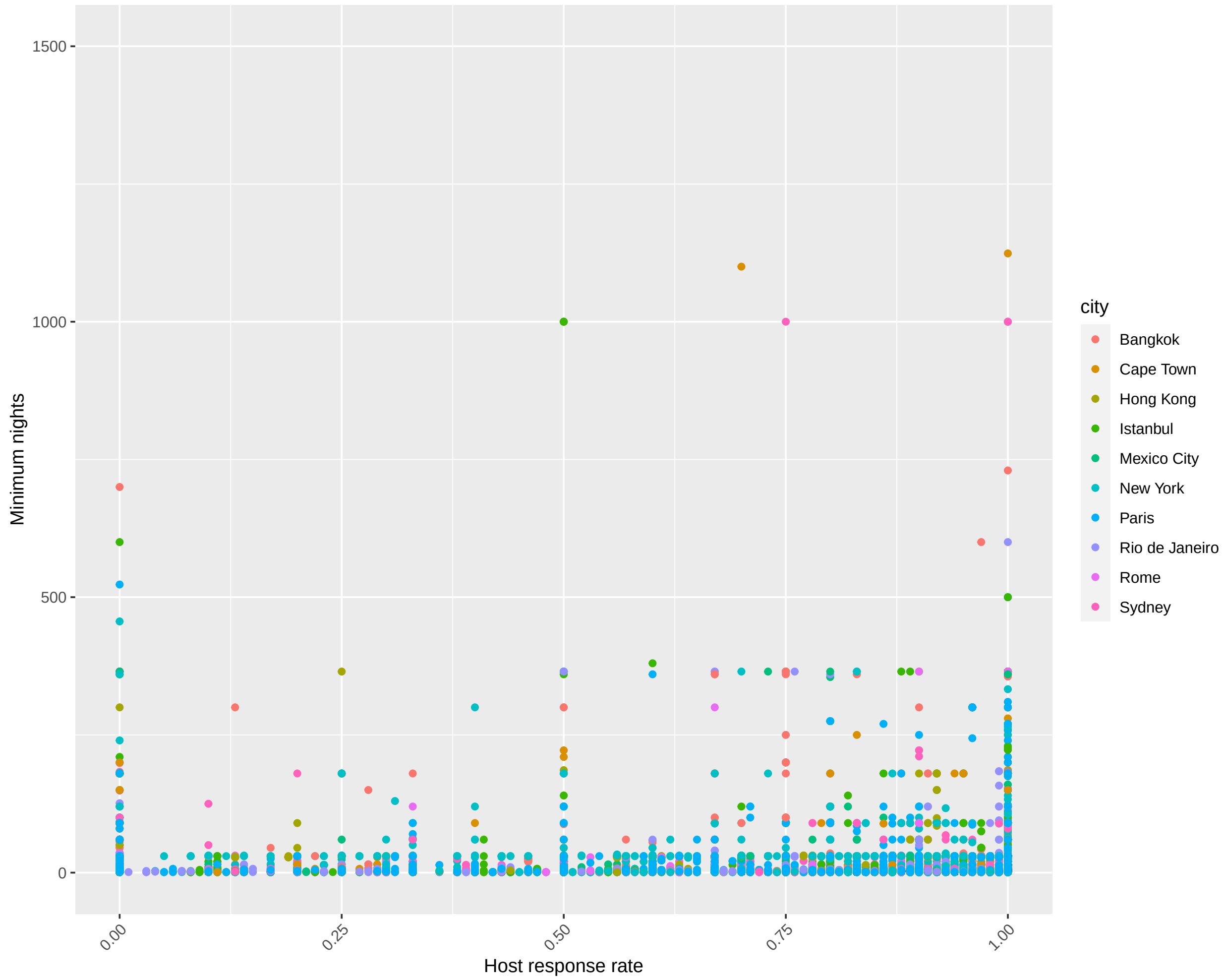
Method

The method was to systematically fit a separate model for each interaction term. The interaction terms used were products of pairs of predictor variables. As such, the categorical variables were not included in the analysis of interactions. The true/false variables were converted into binary 0/1. Some data cleaning had to be done: ListingID and name were removed as they uniquely identify the corresponding observation, geographical information, such as neighbourhood, longitude, latitude, district, and location were removed as they also eliminate the challenge of predicting the city. Amenities were also removed for this analysis as they provided too much trouble. Each combination of amenities is considered a unique categorical variable. Overcoming this challenge is covered within this report, but it was not necessary for this particular analysis. The data set was cut down from ~300k observations to 1k observations, blocked by city and randomized, with 100 observations for each one. This was done to expedite the process of fitting so many models. The model used was a basic LDA model over all variables, minus the aforementioned removals. For each model, one unique product of two numeric variables was added to the predictor space, and the misclassification rate was recorded.

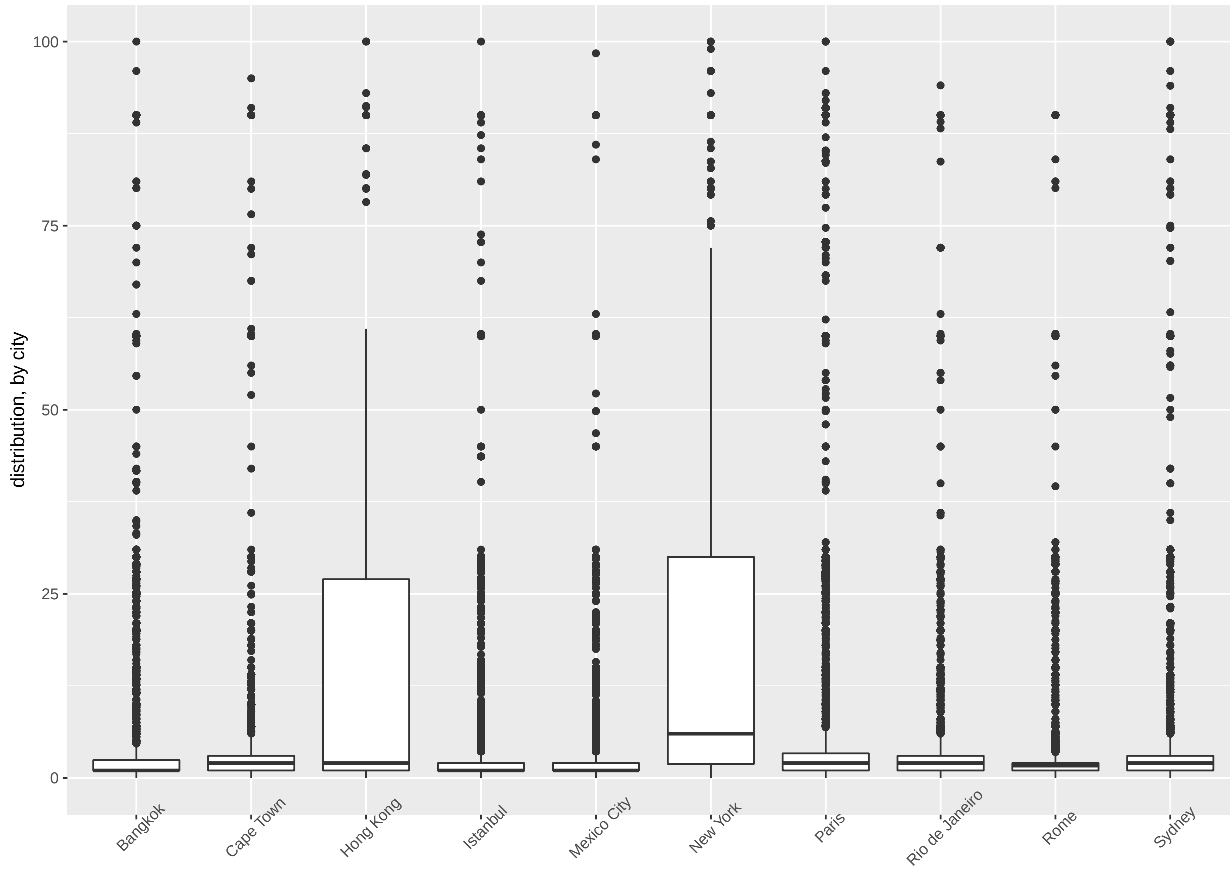
Results

The best performing models are seen in the table below. The default (no interaction terms added) misclassification rate was 0.013. There were two interaction terms that provided a rate of 0.008. The first was host_response_rate * minimum_nights, and the second was host_identity_verified * review_scores_communication. Five interaction terms gave a misclassification rate of 0.009, three of which contained the variable host_is_superhost, and the other two contained the variable bedrooms. Of these seven interaction terms, four contained a binary 0/1 variable, essentially meaning that the other term in the interaction had a different effect on the city depending on some binary condition.

```
##      [,1]
## [1,] "misclass error"
## [2,] "0.008"
## [3,] "0.008"
## [4,] "0.009"
## [5,] "0.009"
## [6,] "0.009"
## [7,] "0.009"
## [8,] "0.009"
##      [,2]
## [1,] "model formula"
## [2,] "city ~ . + host_response_rate * minimum_nights"
## [3,] "city ~ . + host_identity_verified * review_scores_communication"
## [4,] "city ~ . + host_is_superhost * host_total_listings_count"
## [5,] "city ~ . + host_is_superhost * price"
## [6,] "city ~ . + host_is_superhost * review_scores_location"
## [7,] "city ~ . + bedrooms * maximum_nights"
## [8,] "city ~ . + bedrooms * review_scores_location"
```

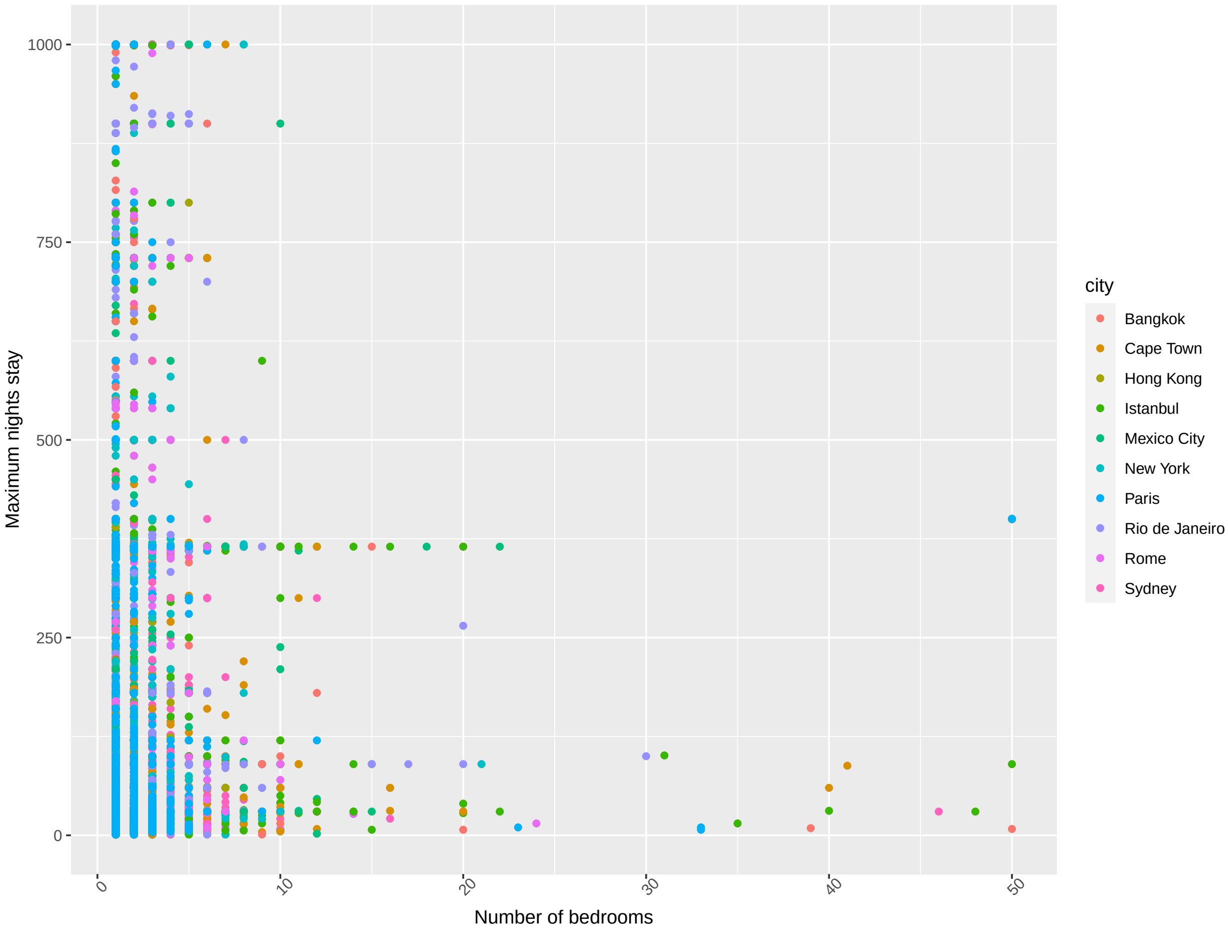


1500
1000
500
0
Minimum nights
0.00
0.25
0.50
0.75
1.00
Host response rate
city
Bangkok
Cape Town
Hong Kong
Istanbul
Mexico City
New York
Paris
Rio de Janeiro
Rome
Sydney

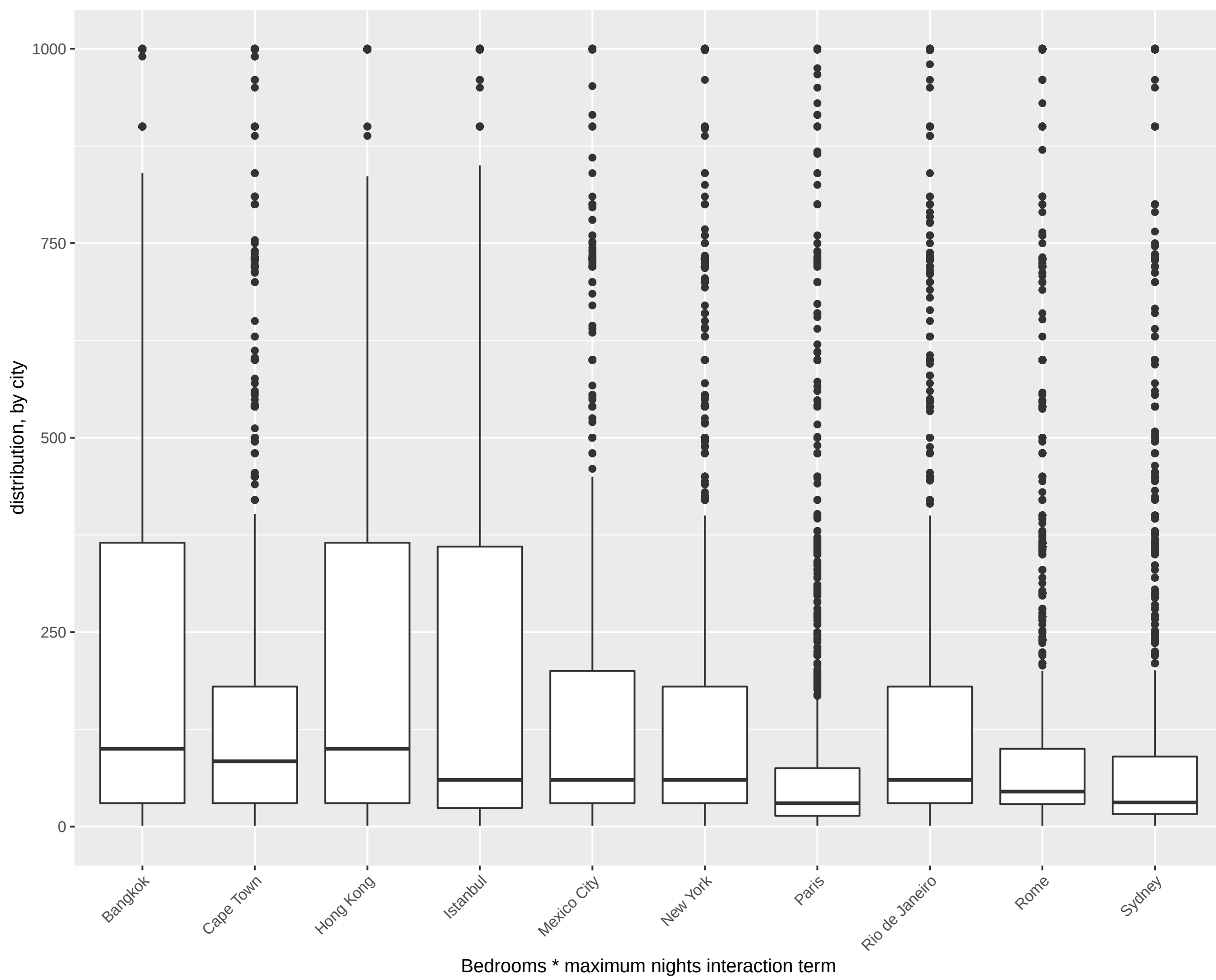


Host response rate * minimum nights interaction term

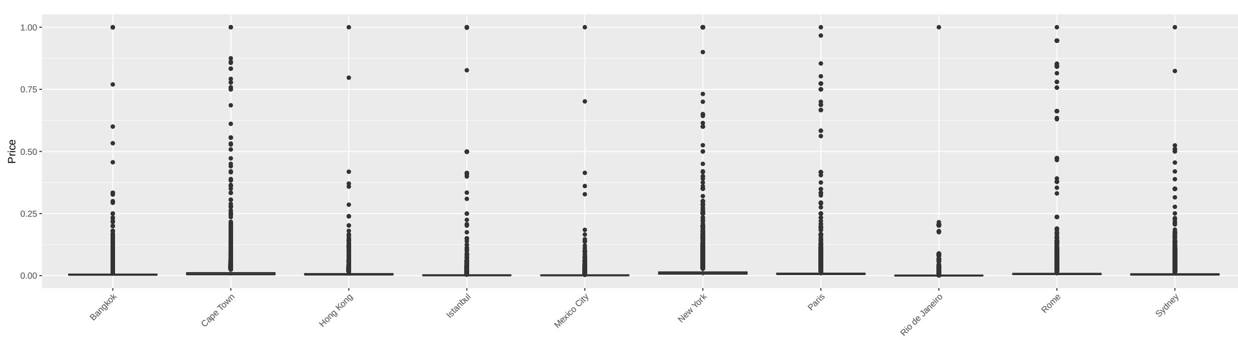
As we can see, this interaction term helps to identify observations as New York or Hong Kong Airbnbs because their distributions are much higher than the other cities in the dataset. Adding this interaction term to the model may improve the model's ability to correctly identify these two cities, as well as deter it from misidentifying other cities as New York or Hong Kong.



We can see that the observations' cluster along the axes of the plot, resulting on low product interaction terms. We see a cluster of observations coloured 'Paris' in the bottom corner, implying that Parisian Airbnbs have low values for their interaction terms. Looking at the next plot, a boxplot of the interaction term by city, we see this is confirmed.

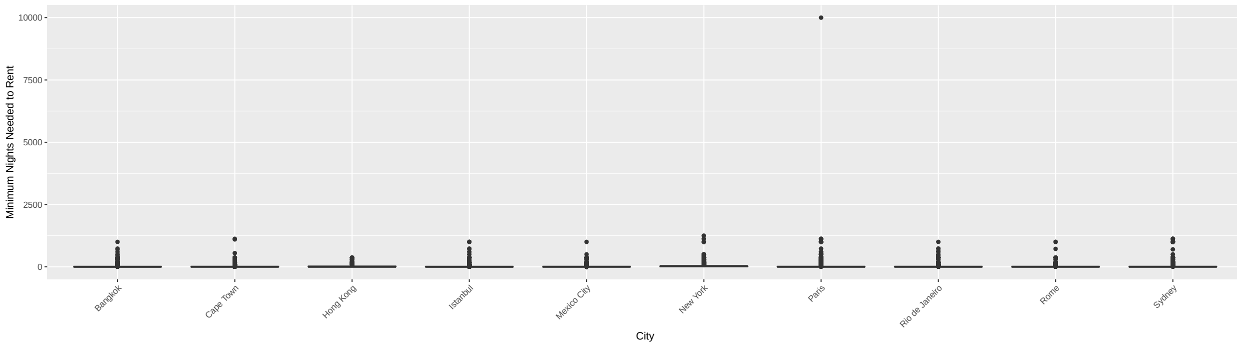


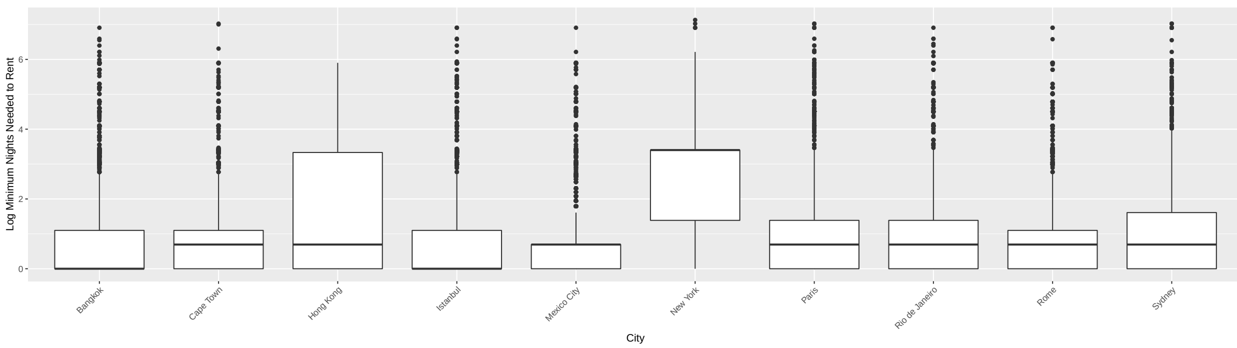
Exploring Price



Since prices of Airbnb's are recorded in each city's country's own currency, to make the prices comparable, it makes sense to standardize the variable. The best way to make all listings' prices comparable is to divide each observation's price by its city's costliest Airbnb. That way, the spreads of the data separated by city are preserved while making the price variable unitless to allow for comparison of observations between cities.

Exploring Minimum Nights





Since no other observations have anywhere near 10000 minimum nights required to rent, which no person would realistically want to rent anyway, it is reasonable to remove this observation from the data set. Furthermore, there are still many outliers, i.e., values above the whiskers, preventing the spread from being reasonably assessed, so we apply a log transformation to minimum_nights to make it more readable.

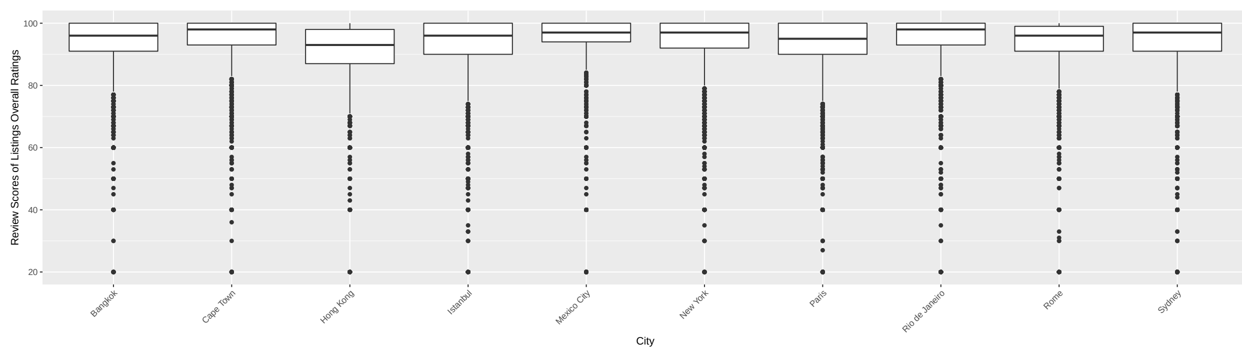
Upon transforming the data, it is clear that most cities have many listings with very few minimum nights required to rent, as many of their boxes show Q1's hovering right at 0. New York is the only exception, with a Q1 value of about 1.5 log days, or about 4.5 days, and a median of about 12 days. Conversely, Istanbul and Bangkok have medians hovering just above 0. These distinct spreads of values of minimum days may make Istanbul, Bangkok, and especially New York much easier to predict if this variable is significant in our model.

Exploring Review Score of Overall Rating

Many observations had to be removed from the data to accommodate the large amount of NANs in the review_score_ratings variable.

The high medians of and Q1 values of Cape Town and Rio suggest that these cities may be easier to predict than the rest. Hong Kong also seems to have a significantly lower rating spread of ratings than the rest of the cities, suggesting it may also be easier to predict than the rest.

However, unless the model used is sensitive to subtle differences in the values of these ratings, it likely won't be very useful for classification. This is because the spreads of the data for these reviews are all very similar, with almost all quantiles above a score of 90. This contradicts what we originally thought, as we predicted that overall reviews may differ significantly from city to city. Generally, it seems Airbnb customers seem to give high reviews.



Exploring Review Scores of Location

Similar to overall review scores, many observations had to be removed to analyze review_scores_location due to the high volume of NANs. Some cities, such as Hong Kong, were significantly effected, as they have far fewer location reviews than, say, Paris.

The largest proportion of high reviews, i.e., 9s and 10s, belong to Paris at 24.99% and 26.09% respectively. Also, Istanbul has large shares of low reviews, with 23.15%, 28.57%, and 22.22% of 2s, 3s, and 4s respectively, compared to the other cities. These heavy tails may make it easier to classify these two cities if review scores based on location are a significant predictor in our model.

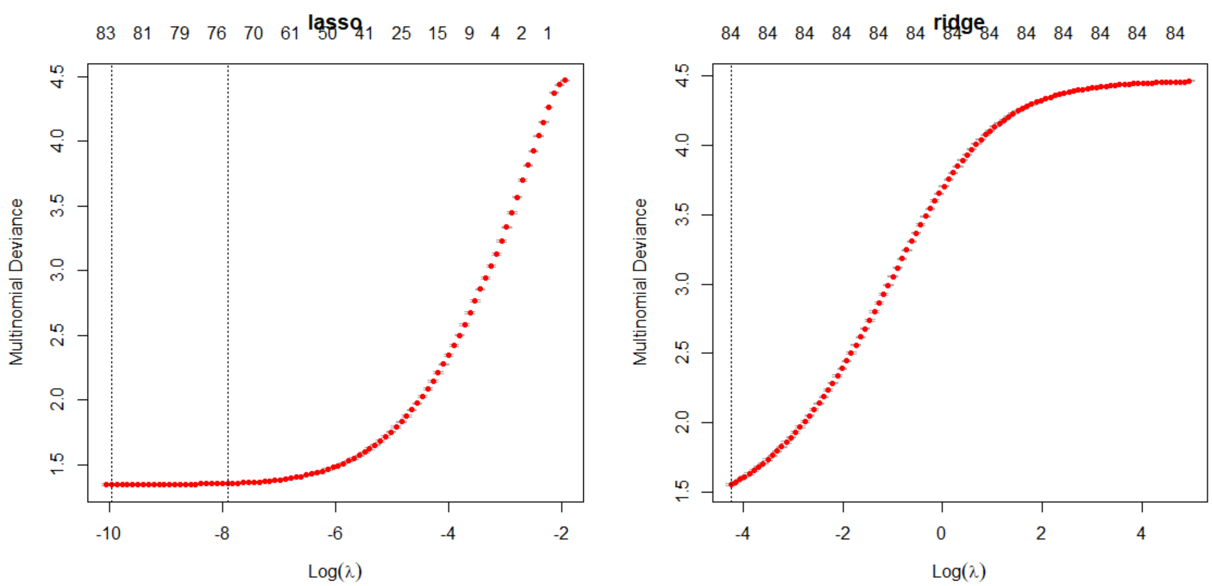
```
##            city    10   2 3  4  5   6   7    8    9
##         Bangkok  5598  62 0 33 15 181 217 1230 3832
##       Cape Town 10900  50 1 10  9  94  59  426 1847
##       Hong Kong  2698  29 0 12  4  33  24  175  804
##        Istanbul  7886 147 2 52 28 212 137  713 2042
##     Mexico City 12674  70 0  8  2  78  42  233 1336
##        New York 18819  64 0 27 14 200 151 1245 6220
##           Paris 36662  76 1 22 12 243 239 1882 8833
##  Rio de Janeiro 13657  46 1 20  7 114  63  497 1701
##            Rome 13842  29 1 27 21 138 130 1076 5548
##          Sydney 17759  62 1 23  8 187  89  988 3186
```

```
##            city     10      2      3      4      5      6      7      8      9
##         Bangkok  3.98%  9.76%  0.00% 14.10% 12.50% 12.23% 18.85% 14.53% 10.84%
##       Cape Town  7.76%  7.87% 14.29%  4.27%  7.50%  6.35%  5.13%  5.03%  5.23%
##       Hong Kong  1.92%  4.57%  0.00%  5.13%  3.33%  2.23%  2.09%  2.07%  2.27%
##        Istanbul  5.61% 23.15% 28.57% 22.22% 23.33% 14.32% 11.90%  8.42%  5.78%
##     Mexico City  9.02% 11.02%  0.00%  3.42%  1.67%  5.27%  3.65%  2.75%  3.78%
##        New York 13.39% 10.08%  0.00% 11.54% 11.67% 13.51% 13.12% 14.71% 17.60%
##           Paris 26.09% 11.97% 14.29%  9.40% 10.00% 16.42% 20.76% 22.23% 24.99%
##  Rio de Janeiro  9.72%  7.24% 14.29%  8.55%  5.83%  7.70%  5.47%  5.87%  4.81%
##            Rome  9.85%  4.57% 14.29% 11.54% 17.50%  9.32% 11.29% 12.71% 15.69%
##          Sydney 12.64%  9.76% 14.29%  9.83%  6.67% 12.64%  7.73% 11.67%  9.01%
```

Model Analysis

Since determining city is a classifier problem we could eliminate all models that do not fit well with classifiers. At first glance, on the table below, are some of these models we chose to try using on this dataset. Of the seven models tried here, lasso regression with cross validation performed the best.

```
##       Lasso.Logit.cv Lasso.Logit Ridge.Logit.cv Ridge.Logit    LDA  QDA
## Error         0.2342      0.3219          0.244      0.5506 0.2619 0.31
##       multinom
## Error    0.532
```



Using he graphs above we can compare the lasso vs ridge and the number of predictors used. The reason lasso performs better is because it uses a subset of the predictors. Some of the predictors were not useful in the final model and that is the final accuracy of lasso outperformed ridge.

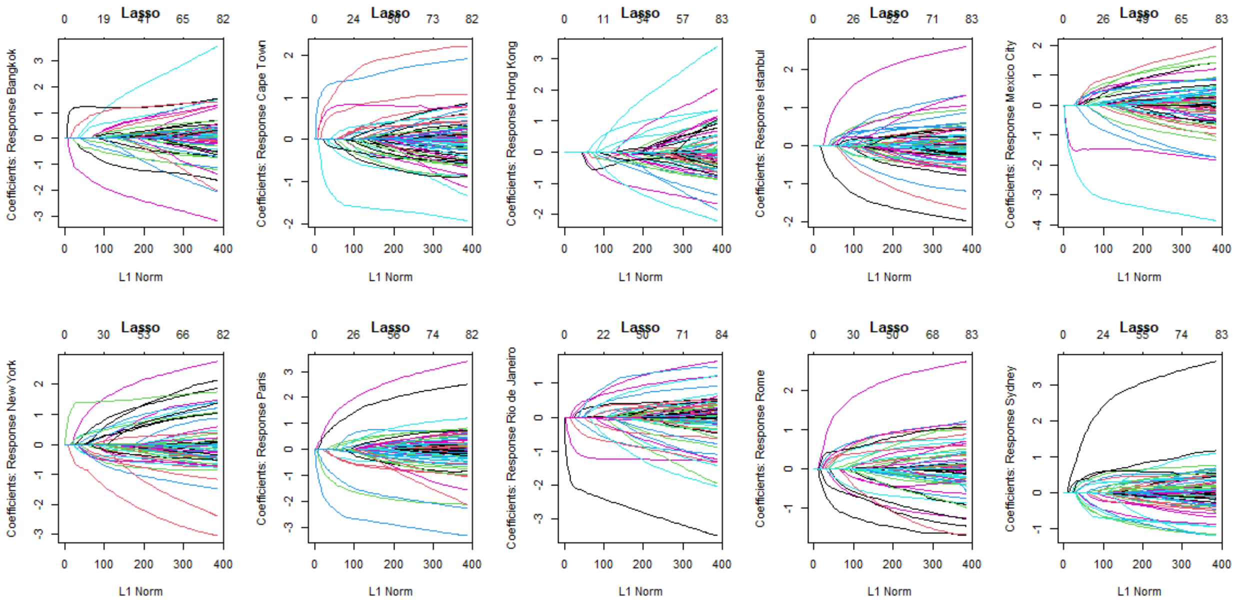
Another attempt to incrase accuracy was preprocessing; however, by default glmnet does standardize data. Looking at the table below we can see that accuracy with different preprocessing. Feature Scaling/ Normalization has a significant different on the accuracy, which makes sense as regression does require scaling otherwise some betas maybe be so large as to outweight certain predictors.

```
##       Lasso.Without Lasso.With.Standardization Lasso.With.Min.Max.Scaling
## Error        0.8566                     0.2342                     0.7842
```

The two tables below give a better idea of the accuracy of the model by city. The first table is a confusion and the second in the accuracy by city. Rio de Janeiro had the highest accuracy of all the citys at 82.97% accuracy.

```
##                 Reference
## Prediction       Bangkok Cape Town Hong Kong Istanbul Mexico City New York
##   Bangkok           5041        84       267      117          59       21
##   Cape Town           57      6707        15      281         461       73
##   Hong Kong          170         6      1182       39          11       43
##   Istanbul           147       241       101     4516         198      353
##   Mexico City         53       735        17      204        8826       50
##   New York            46       139       128      561          95    10123
##   Paris               10       124        68      649         321      448
##   Rio de Janeiro     387       342       210      120         420       64
##   Rome                75       247       194     1069         160      276
##   Sydney             121       632        70      346         211      425
##                 Reference
## Prediction       Paris Rio de Janeiro  Rome Sydney
##   Bangkok           23            366    47    144
##   Cape Town         85            264   207    535
##   Hong Kong         30             80    57     59
##   Istanbul         398             93   787    350
##   Mexico City      169            642   115    334
##   New York         491             85   455    550
##   Paris          11624             53   639    574
##   Rio de Janeiro    68           9147   143    123
##   Rome             505            184  9158    195
##   Sydney           297             81   114   5897

##        Bangkok      Cape Town      Hong Kong       Istanbul    Mexico City
##      0.8171503      0.7722510      0.7048301      0.6286192      0.7919246
##       New York          Paris Rio de Janeiro           Rome         Sydney
##      0.7987848      0.8011027      0.8297351      0.7591810      0.7196729
```


Lasso
Coefficients: Response Bangkok
Coefficients: Response Cape Town
Coefficients: Response Hong Kong
Coefficients: Response Istanbul
Coefficients: Response Mexico City
Coefficients: Response New York
Coefficients: Response Paris
Coefficients: Response Rio de Janeiro
Coefficients: Response Rome
Coefficients: Response Sydney
L1 Norm