Edx Capstone - Airbnb Analysis Report

Eshna Airon

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Contents

1 Executive Summary

Airbnb, Inc. is an online marketplace that offers accommodation and entertainment. The company does not have a real estate list, and does not host events; acts as a reseller, earning commissions from each booking. The service was launched in 2008 with 2 hosts and 3 guests. Its number one concern ensures the safety of its customers while providing an enjoyable experience.

I have performed descriptive and critical data analysis, in order to understand how each of the variables behaves individually and dynamically. To do this task, I will use the most common mathematical techniques for any type of analysis, simple or complex, such as variable variables, frequency distribution tables, histograms, intermediate inclination measures and more.

I also did an analysis by predicting the price of the Airbnb list as a suggestion for experts.

The models I have used here are Linear Regression, Partial Least-Squares Regression (PLS), Enhanced Normal Line Model, Repeated Trees and Reversal Trees, Shaved Tree Models, Bound Carriage, Random Forest, Stochastic Gradient Boosting Strength, KNN, Ridge Regression, Lasso Regression and Support Vector Regression.

2 Dataset

There are 48895 views with data in 16 columns. Both separate and multiple types of data can be detected. Each line represents details about inclusion in NYC.

Source https://www.kaggle.com/dgomonov/new-york-city-airbnb-open-data

3 Analysis

I will perform a descriptive ,geographic and exploratory analysis of the data, in order to understand how the phenomena of each variable behave individually and transversely, in addition to to generate hypotheses useful for future decision-making.

3.1 Descriptive Analysis

Dimensions

```
## [1] 48895    16
```

Summary

```
##        id               name              host_id           host_name
##  Min.   :    2539   Length:48895       Min.   :      2438   Length:48895
##  1st Qu.: 9471945   Class :character   1st Qu.:   7822033   Class :character
##  Median :19677284   Mode  :character   Median : 30793816   Mode  :character
##  Mean   :19017143                      Mean   : 67620011
##  3rd Qu.:29152178                      3rd Qu.:107434423
##  Max.   :36487245                      Max.   :274321313
##
##  neighbourhood_group neighbourhood         latitude       longitude
##  Length:48895        Length:48895       Min.   :40.50   Min.   :-74.24
##  Class :character    Class :character   1st Qu.:40.69   1st Qu.:-73.98
##  Mode  :character    Mode  :character   Median :40.72   Median :-73.96
##                                         Mean   :40.73   Mean   :-73.95
```

```
##                                         3rd Qu.:40.76   3rd Qu.:-73.94
##                                         Max.   :40.91   Max.   :-73.71
##
##   room_type             price         minimum_nights    number_of_reviews
##  Length:48895       Min.   :    0.0   Min.   :   1.00   Min.   :  0.00
##  Class :character   1st Qu.:   69.0   1st Qu.:   1.00   1st Qu.:  1.00
##  Mode  :character   Median :  106.0   Median :   3.00   Median :  5.00
##                     Mean   :  152.7   Mean   :   7.03   Mean   : 23.27
##                     3rd Qu.:  175.0   3rd Qu.:   5.00   3rd Qu.: 24.00
##                     Max.   :10000.0   Max.   :1250.00   Max.   :629.00
##
##  last_review        reviews_per_month calculated_host_listings_count
##  Length:48895       Min.   : 0.010    Min.   :  1.000
##  Class :character   1st Qu.: 0.190    1st Qu.:  1.000
##  Mode  :character   Median : 0.720    Median :  1.000
##                     Mean   : 1.373    Mean   :  7.144
##                     3rd Qu.: 2.020    3rd Qu.:  2.000
##                     Max.   :58.500    Max.   :327.000
##                     NA's   :10052
##  availability_365
##  Min.   :  0.0
##  1st Qu.:  0.0
##  Median : 45.0
##  Mean   :112.8
##  3rd Qu.:227.0
##  Max.   :365.0
##
```

Unique Neighbourhood Groups

```
## $neighbourhood_group
## [1] "Brooklyn"      "Manhattan"     "Queens"        "Staten Island"
## [5] "Bronx"
```

Unique Neighbourhoods

```
## $neighbourhood
##   [1] "Kensington"                "Midtown"
##   [3] "Harlem"                    "Clinton Hill"
##   [5] "East Harlem"               "Murray Hill"
##   [7] "Bedford-Stuyvesant"        "Hell's Kitchen"
##   [9] "Upper West Side"           "Chinatown"
##  [11] "South Slope"               "West Village"
##  [13] "Williamsburg"              "Fort Greene"
##  [15] "Chelsea"                   "Crown Heights"
##  [17] "Park Slope"                "Windsor Terrace"
##  [19] "Inwood"                    "East Village"
##  [21] "Greenpoint"                "Bushwick"
##  [23] "Flatbush"                  "Lower East Side"
##  [25] "Prospect-Lefferts Gardens" "Long Island City"
##  [27] "Kips Bay"                  "SoHo"
##  [29] "Upper East Side"           "Prospect Heights"
##  [31] "Washington Heights"        "Woodside"
##  [33] "Brooklyn Heights"          "Carroll Gardens"
##  [35] "Gowanus"                   "Flatlands"
##  [37] "Cobble Hill"               "Flushing"
```

```
##  [39] "Boerum Hill"                "Sunnyside"
##  [41] "DUMBO"                      "St. George"
##  [43] "Highbridge"                 "Financial District"
##  [45] "Ridgewood"                  "Morningside Heights"
##  [47] "Jamaica"                    "Middle Village"
##  [49] "NoHo"                       "Ditmars Steinway"
##  [51] "Flatiron District"          "Roosevelt Island"
##  [53] "Greenwich Village"          "Little Italy"
##  [55] "East Flatbush"              "Tompkinsville"
##  [57] "Astoria"                    "Clason Point"
##  [59] "Eastchester"                "Kingsbridge"
##  [61] "Two Bridges"                "Queens Village"
##  [63] "Rockaway Beach"             "Forest Hills"
##  [65] "Nolita"                     "Woodlawn"
##  [67] "University Heights"         "Gravesend"
##  [69] "Gramercy"                   "Allerton"
##  [71] "East New York"              "Theater District"
##  [73] "Concourse Village"          "Sheepshead Bay"
##  [75] "Emerson Hill"               "Fort Hamilton"
##  [77] "Bensonhurst"                "Tribeca"
##  [79] "Shore Acres"                "Sunset Park"
##  [81] "Concourse"                  "Elmhurst"
##  [83] "Brighton Beach"             "Jackson Heights"
##  [85] "Cypress Hills"              "St. Albans"
##  [87] "Arrochar"                   "Rego Park"
##  [89] "Wakefield"                  "Clifton"
##  [91] "Bay Ridge"                  "Graniteville"
##  [93] "Spuyten Duyvil"             "Stapleton"
##  [95] "Briarwood"                  "Ozone Park"
##  [97] "Columbia St"                "Vinegar Hill"
##  [99] "Mott Haven"                 "Longwood"
## [101] "Canarsie"                   "Battery Park City"
## [103] "Civic Center"               "East Elmhurst"
## [105] "New Springville"            "Morris Heights"
## [107] "Arverne"                    "Cambria Heights"
## [109] "Tottenville"                "Mariners Harbor"
## [111] "Concord"                    "Borough Park"
## [113] "Bayside"                    "Downtown Brooklyn"
## [115] "Port Morris"                "Fieldston"
## [117] "Kew Gardens"                "Midwood"
## [119] "College Point"              "Mount Eden"
## [121] "City Island"                "Glendale"
## [123] "Port Richmond"              "Red Hook"
## [125] "Richmond Hill"              "Bellerose"
## [127] "Maspeth"                    "Williamsbridge"
## [129] "Soundview"                  "Woodhaven"
## [131] "Woodrow"                    "Co-op City"
## [133] "Stuyvesant Town"            "Parkchester"
## [135] "North Riverdale"            "Dyker Heights"
## [137] "Bronxdale"                  "Sea Gate"
## [139] "Riverdale"                  "Kew Gardens Hills"
## [141] "Bay Terrace"                "Norwood"
## [143] "Claremont Village"          "Whitestone"
## [145] "Fordham"                    "Bayswater"
```

```
## [147] "Navy Yard"                  "Brownsville"
## [149] "Eltingville"                "Fresh Meadows"
## [151] "Mount Hope"                 "Lighthouse Hill"
## [153] "Springfield Gardens"        "Howard Beach"
## [155] "Belle Harbor"               "Jamaica Estates"
## [157] "Van Nest"                   "Morris Park"
## [159] "West Brighton"              "Far Rockaway"
## [161] "South Ozone Park"           "Tremont"
## [163] "Corona"                     "Great Kills"
## [165] "Manhattan Beach"            "Marble Hill"
## [167] "Dongan Hills"               "Castleton Corners"
## [169] "East Morrisania"            "Hunts Point"
## [171] "Neponsit"                   "Pelham Bay"
## [173] "Randall Manor"              "Throgs Neck"
## [175] "Todt Hill"                  "West Farms"
## [177] "Silver Lake"                "Morrisania"
## [179] "Laurelton"                  "Grymes Hill"
## [181] "Holliswood"                 "Pelham Gardens"
## [183] "Belmont"                    "Rosedale"
## [185] "Edgemere"                   "New Brighton"
## [187] "Midland Beach"              "Baychester"
## [189] "Melrose"                    "Bergen Beach"
## [191] "Richmondtown"               "Howland Hook"
## [193] "Schuylerville"              "Coney Island"
## [195] "New Dorp Beach"             "Prince's Bay"
## [197] "South Beach"                "Bath Beach"
## [199] "Jamaica Hills"              "Oakwood"
## [201] "Castle Hill"                "Hollis"
## [203] "Douglaston"                 "Huguenot"
## [205] "Olinville"                  "Edenwald"
## [207] "Grant City"                 "Westerleigh"
## [209] "Bay Terrace, Staten Island" "Westchester Square"
## [211] "Little Neck"                "Fort Wadsworth"
## [213] "Rosebank"                   "Unionport"
## [215] "Mill Basin"                 "Arden Heights"
## [217] "Bull's Head"                "New Dorp"
## [219] "Rossville"                  "Breezy Point"
## [221] "Willowbrook"
```

Unique Room types

```
## $room_type
## [1] "Private room"    "Entire home/apt" "Shared room"
```

Range of Prices

```
## Minimum Price: 0 | Maximum Price: 10000
```

Range of Longitude

```
## Minimum Longitude : -74.24442 | Maximum Longitude: -73.71299
```

Range of Latitude

```
## Minimum Latitude : 40.49979 | Maximum Latitude: 40.91306
```

The first step in an analysis work is the knowledge of the behavior of the variables involved in the study. Using statistical techniques such as frequency distribution tables, histograms and bar graphs we can better understand how the phenomena under study are distributed.

Neighbourhood_group/Location Freq table

	Frequency	Percent
Staten Island	373	0.7628592
Bronx	1091	2.2313120
Queens	5666	11.5880969
Brooklyn	20104	41.1166786
Manhattan	21661	44.3010533

Neighbourhood/Area Freq table (Displaying only top 10 rows)

	Frequency	Percent
Fort Wadsworth	1	0.0020452
New Dorp	1	0.0020452
Richmondtown	1	0.0020452
Rossville	1	0.0020452
Willowbrook	1	0.0020452
Woodrow	1	0.0020452
Bay Terrace, Staten Island	2	0.0040904
Co-op City	2	0.0040904
Howland Hook	2	0.0040904
Lighthouse Hill	2	0.0040904

Room Type Freq table

	Frequency	Percent
Shared room	1160	2.372431
Private room	22326	45.661110
Entire home/apt	25409	51.966459

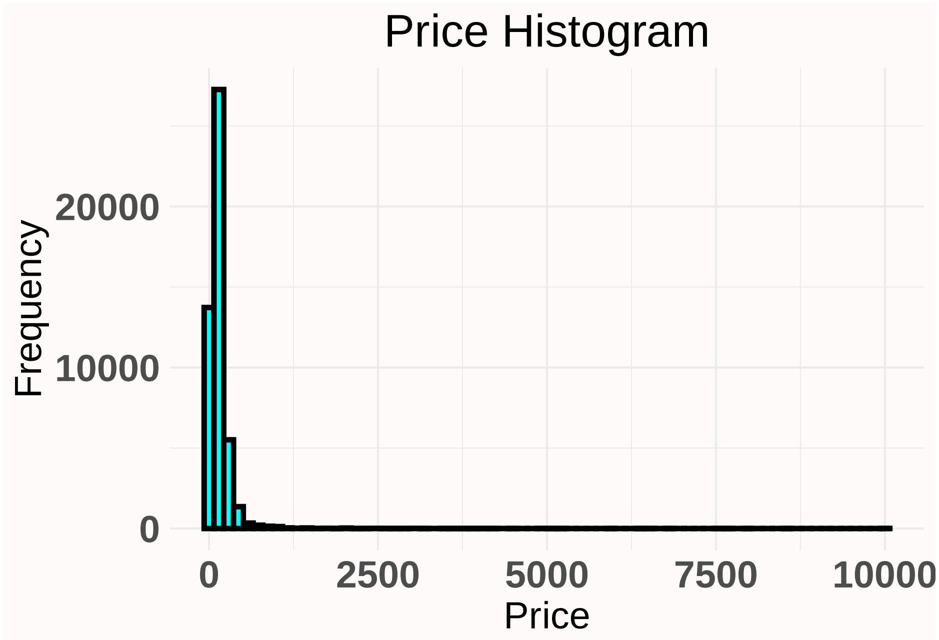
With the frequency tables created above, we can conclude that the frequency and the representative percentage of the most frequent categories of the categorical variables neighborhood_group, neighborhood and room_type are-

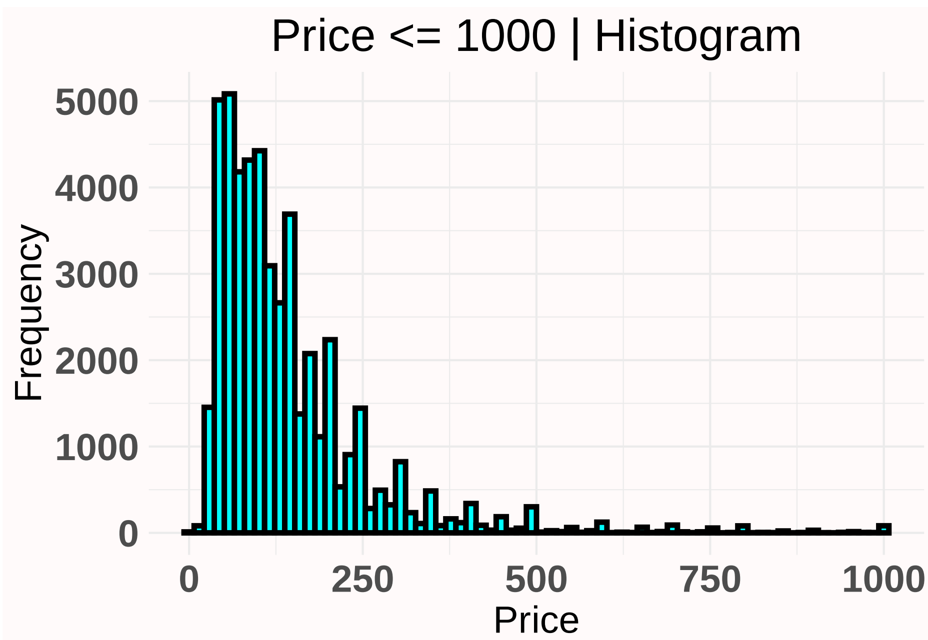
neighbourhood_group - Manhattan -> 21661(44.30%)

neighborhood - Williamsburg -> 3920(8.01%)

room_type - Entire home/apt -> 25409(51.96%)

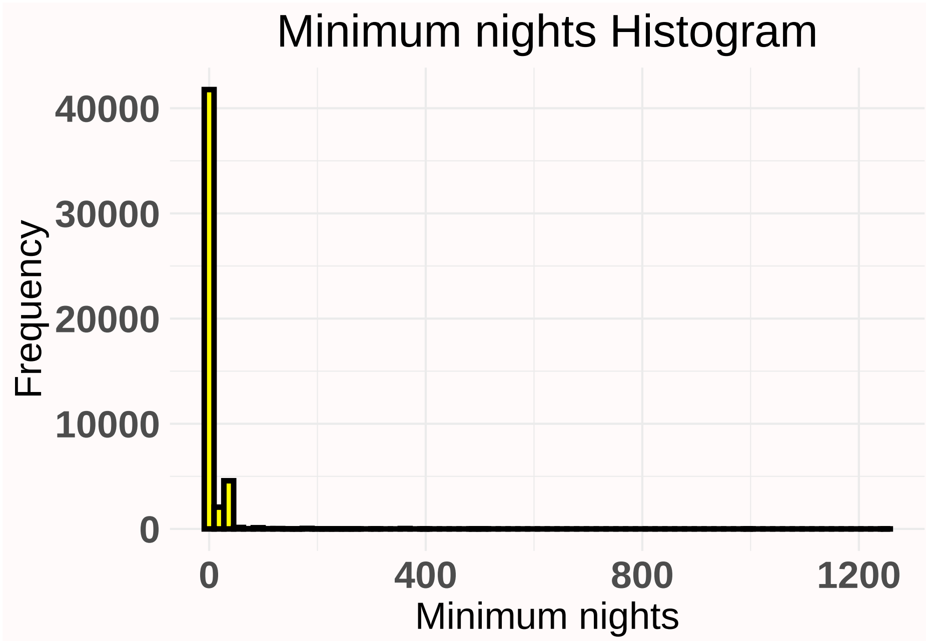
Histogram for Price

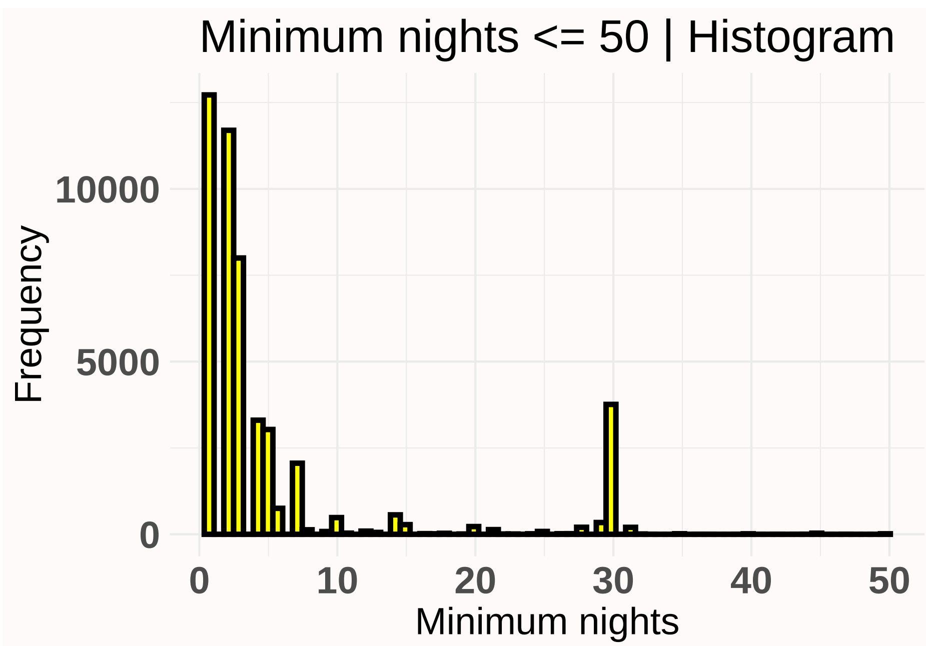




We can see most of prices our under 1000

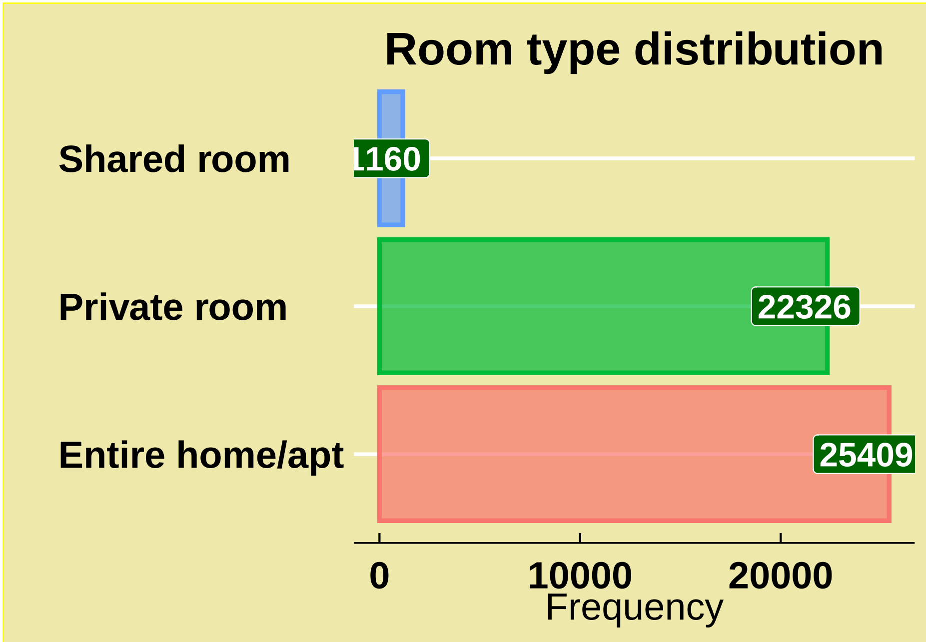
Histogram For Minimum__Nights





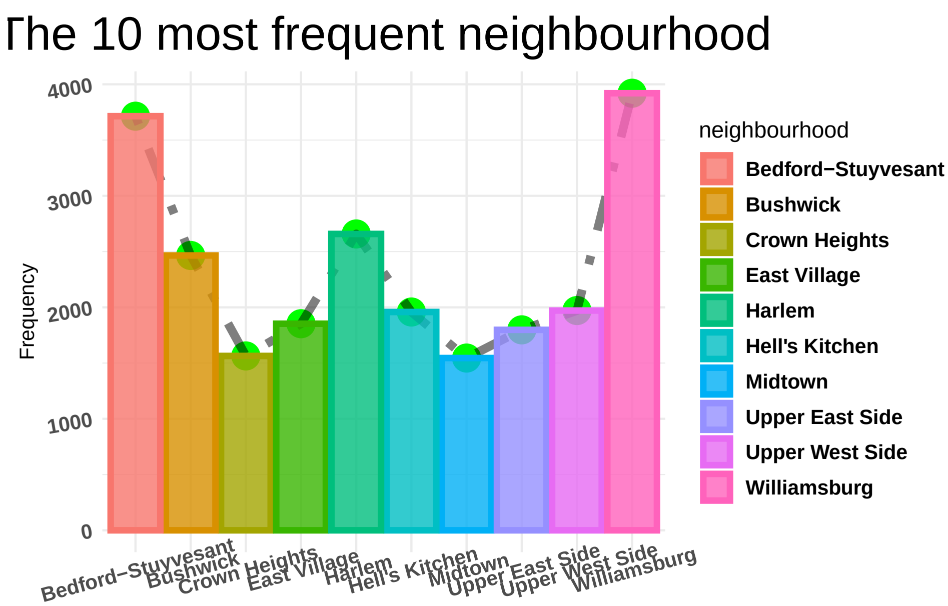
We can see that the minimum number of nights for all reservations made on airbnb are concentrated below 10 with a small peak at 30.

Bar Graph for Room Type



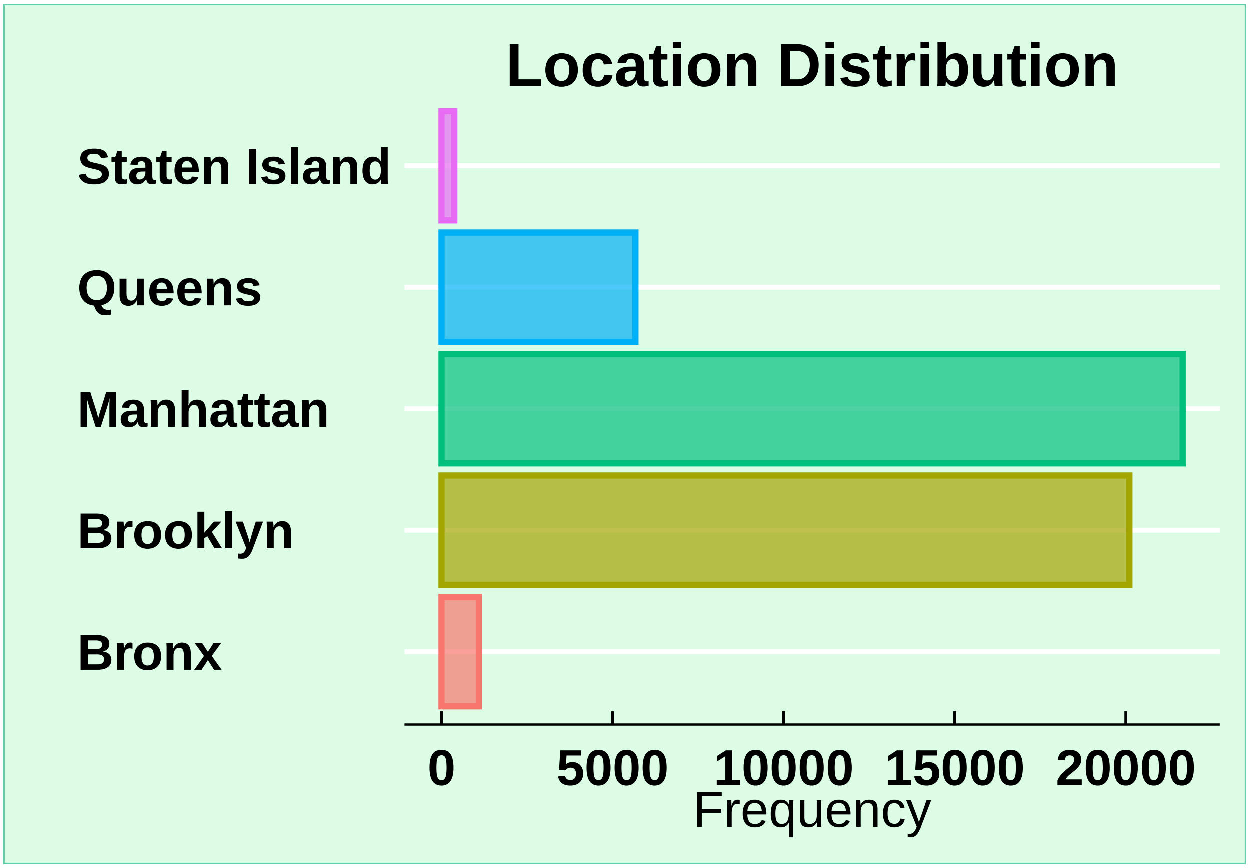
We can see most of the rooms belong private or entire apt/home category.

Bar Graph of The 10 most frequent neighbourhood



Of all 221 neighbourhoods ,these are the top 10 neighborhoods, which are most requested by customers for advertisements and accommodation reservations on the airbnb website.

Bar Graph for neighbourhood_group



Manhattan is the most famous neighbouring group folllowed by Brooklyn, Queens, Bronx and Staten Island

Seprating Measures

```
##      Price minimum_nights
## 1%      30              1
## 2%      35              1
## 3%      36              1
## 4%      39              1
## 5%      40              1
## 6%      42              1
## 7%      45              1
## 8%      45              1
## 9%      47              1
## 10%     49              1
## 11%     50              1
## 12%     50              1
## 13%     50              1
## 14%     53              1
## 15%     55              1
## 16%     55              1
## 17%     59              1
## 18%     60              1
## 19%     60              1
## 20%     60              1
```

```
## 21%    63                 1
## 22%    65                 1
## 23%    65                 1
## 24%    67                 1
## 25%    69                 1
## 26%    70                 1
## 27%    70                 2
## 28%    72                 2
## 29%    75                 2
## 30%    75                 2
## 31%    75                 2
## 32%    79                 2
## 33%    80                 2
## 34%    80                 2
## 35%    81                 2
## 36%    85                 2
## 37%    85                 2
## 38%    89                 2
## 39%    90                 2
## 40%    90                 2
## 41%    93                 2
## 42%    95                 2
## 43%    98                 2
## 44%    99                 2
## 45%   100                 2
## 46%   100                 2
## 47%   100                 2
## 48%   100                 2
## 49%   101                 2
## 50%   106                 3
## 51%   110                 3
## 52%   110                 3
## 53%   115                 3
## 54%   119                 3
## 55%   120                 3
## 56%   120                 3
## 57%   125                 3
## 58%   125                 3
## 59%   128                 3
## 60%   130                 3
## 61%   134                 3
## 62%   137                 3
## 63%   140                 3
## 64%   145                 3
## 65%   149                 3
## 66%   150                 3
## 67%   150                 4
## 68%   150                 4
## 69%   150                 4
## 70%   155                 4
## 71%   160                 4
## 72%   165                 4
## 73%   170                 4
## 74%   175                 5
```

```
## 75%    175              5
## 76%    180              5
## 77%    185              5
## 78%    190              5
## 79%    197              5
## 80%    200              6
## 81%    200              7
## 82%    200              7
## 83%    205              7
## 84%    220              7
## 85%    225              7
## 86%    233             10
## 87%    249             14
## 88%    250             15
## 89%    250             20
## 90%    269             28
## 91%    285             30
## 92%    300             30
## 93%    300             30
## 94%    340             30
## 95%    355             30
## 96%    400             30
## 97%    450             30
## 98%    550             30
## 99%    799             45
```

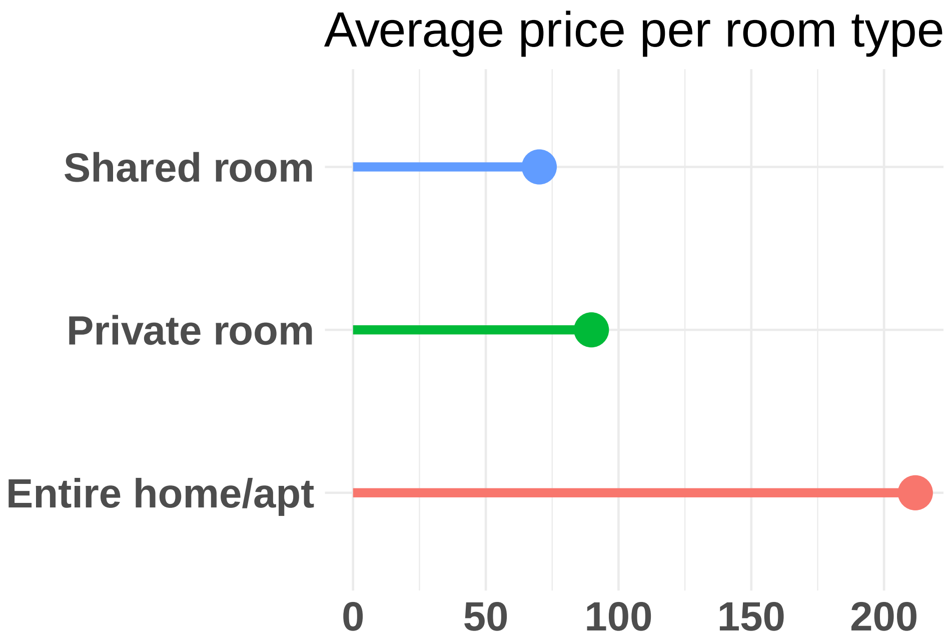
Observations-

1) 25.00% of bookings made on airbnb are of values equal to or less than 69 dollars and 1 minimum night.
2) 50.00% of bookings made on airbnb are of values equal to or less than 106 dollars and 3 minimum nights.
3) 75.00% of bookings made on airbnb are of values equal to or less than 175 dollars and 5 minimum nights.
4) 99.00% of bookings made on airbnb are of values equal to or less than 799 dollars and 45 minimum nights, meaning only 1.0% of bookings are of values above 799 dollars with a maximum value of 10000 dollars and 1250 minimum nights.

3.2 Exploratory Data Anaylsis

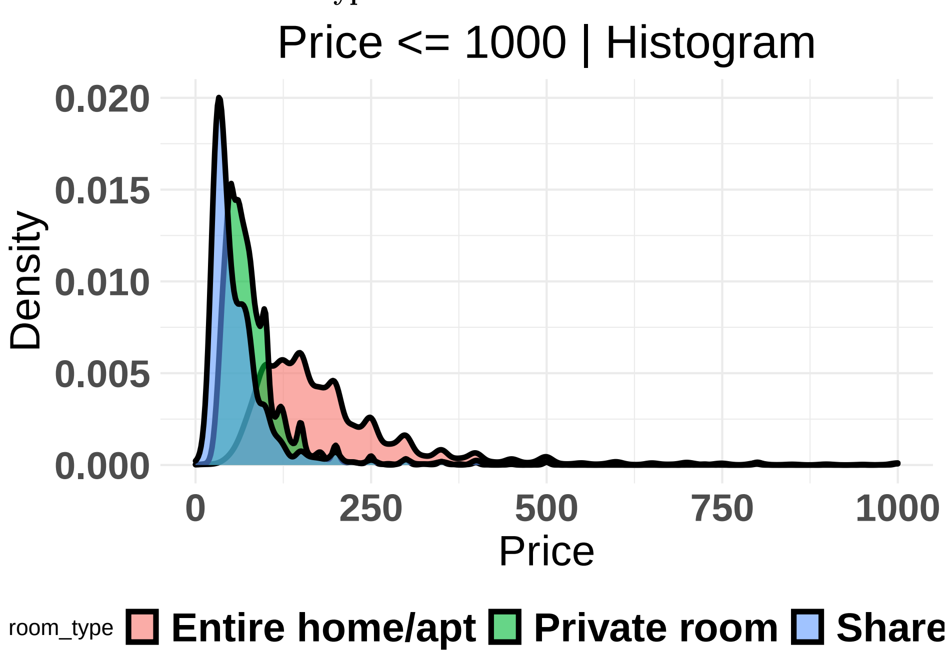
Average price per room type

```
##         room_type average_price  Percent
## 1 Entire home/apt     211.79425 56.97946
## 2    Private room      89.78097 24.15397
## 3     Shared room      70.12759 18.86657
```



1) The Entire home / apt type has an average price for reservations around 211.79 dollars , which represents 56.97 % of all types of rooms . We have the Entire home / apt has an average price of 32.82% more expensive than the Private room and 38.11% more expensive than the Shared room .
2) The Private room which has an average booking price of around 89.78 dollar, which represents 24.15% of all types of rooms .
3) The Shared room which has an average booking price of around 70.12 dollars , which represents 18.86% of all types of rooms . We have that the Shared room has an average price 38.1% less than Entire home / apt and 5.29% smaller than the Private room.

Price behavior in relation to room types

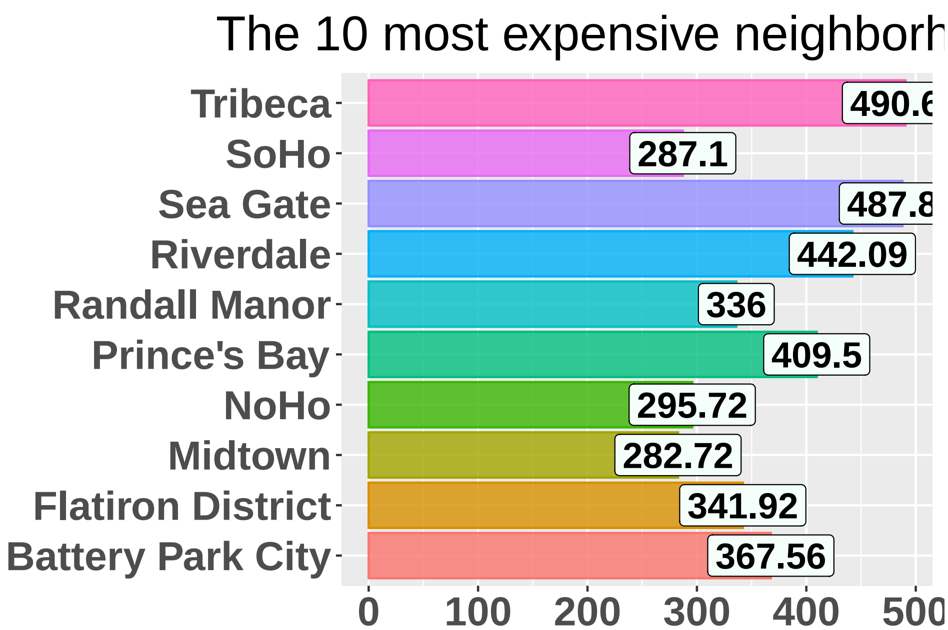


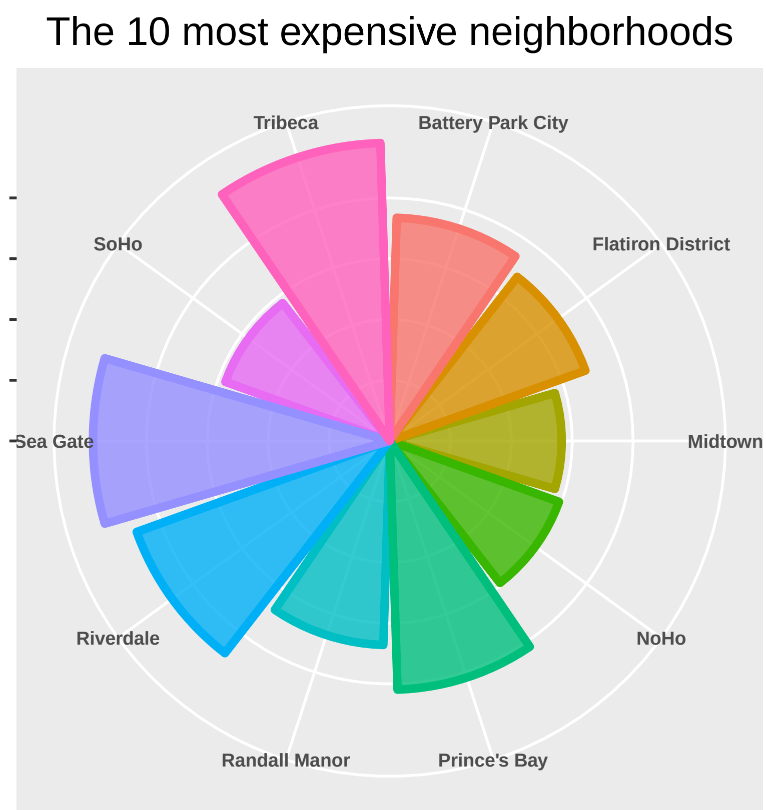
In addition to obtaining information such as the average price for reservations, it is interesting to know how these values that resulted in the average are distributed.

Price in Relation to Neighborhood

The 10 most expensive neighborhoods to book on airbnb

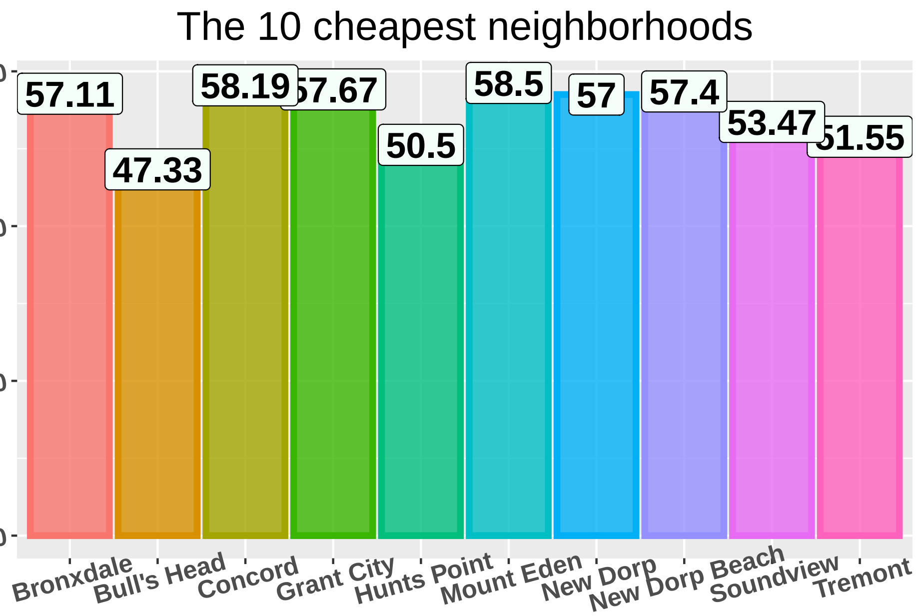
```
##          neighbourhood Average_price_per_neighborhood
## 10             Midtown                       282.7191
## 9                 SoHo                       287.1034
## 8                 NoHo                       295.7179
## 7        Randall Manor                       336.0000
## 6   Flatiron District                       341.9250
## 5   Battery Park City                       367.5571
## 4          Prince's Bay                      409.5000
## 3            Riverdale                       442.0909
## 2             Sea Gate                       487.8571
## 1              Tribeca                       490.6384
```





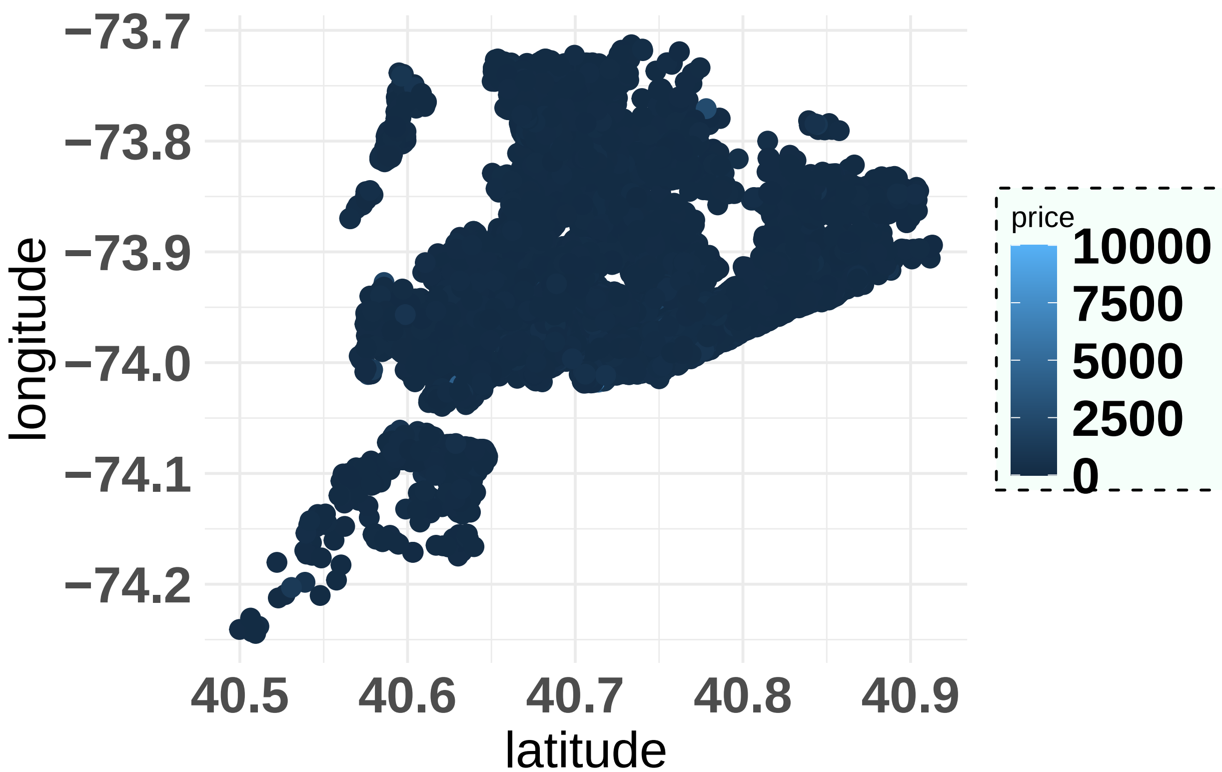
The 10 cheapest neighborhoods to book on airbnb

```
##      neighbourhood Average_price_per_neighborhood
## 1      Bull's Head                       47.33333
## 2      Hunts Point                       50.50000
## 3          Tremont                       51.54545
## 4        Soundview                       53.46667
## 5         New Dorp                       57.00000
## 6        Bronxdale                       57.10526
## 7   New Dorp Beach                       57.40000
## 8       Grant City                       57.66667
## 9          Concord                       58.19231
## 10      Mount Eden                       58.50000
```

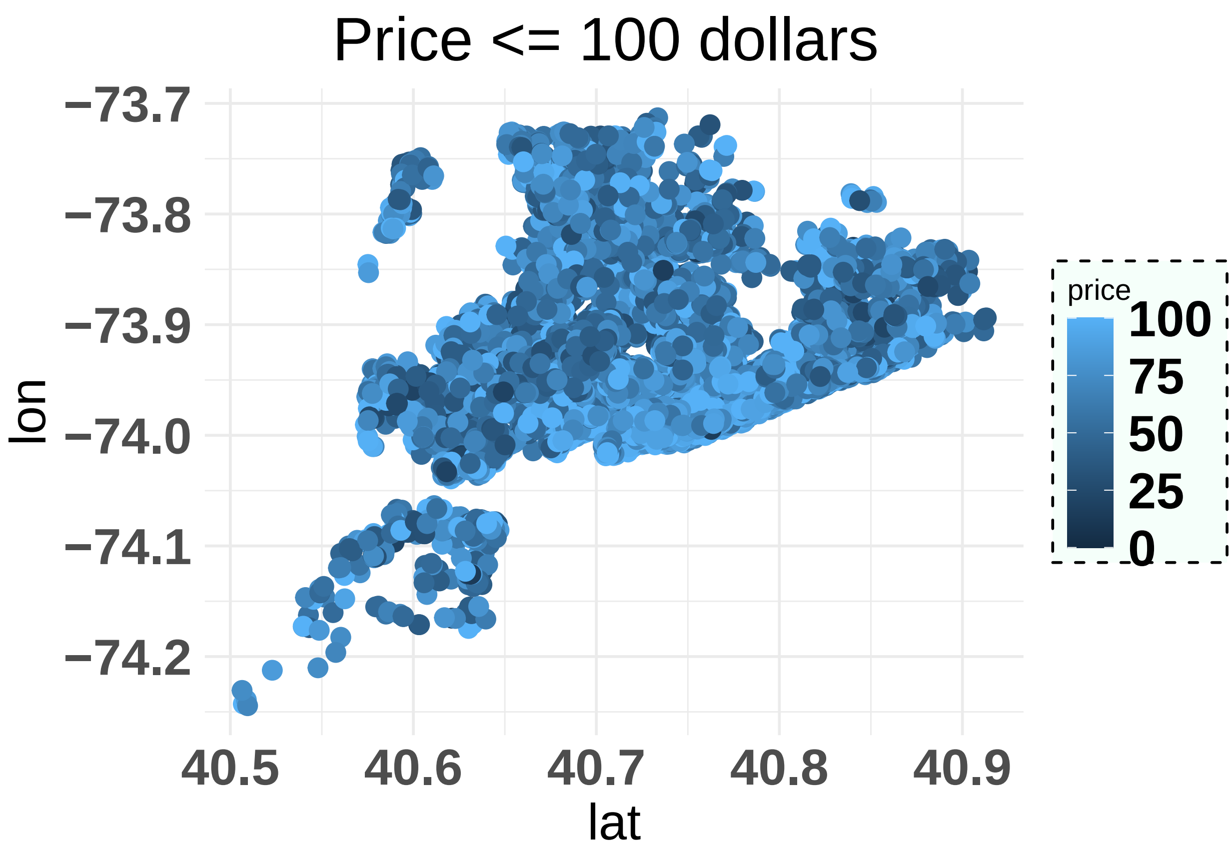


3.3 Geographic analysis

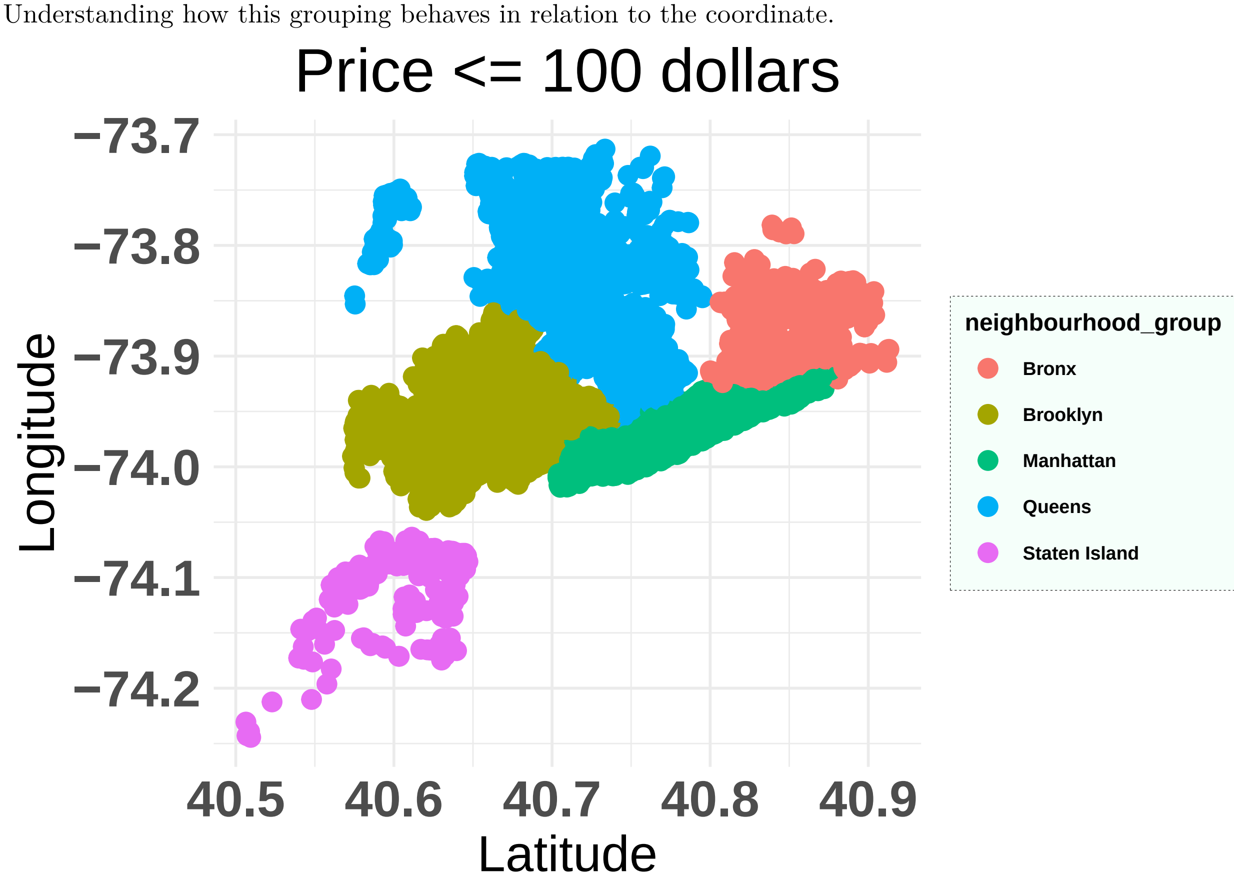
In this analysis I will explore the behavior of the price, neighborhood_group, minimum_nights and room_type through the coordinated latitude and longitude available in the airbnb data. This type of exploitation is extremely useful for understanding the behavior of the data on a geographic scale, consequently helping in decision making.

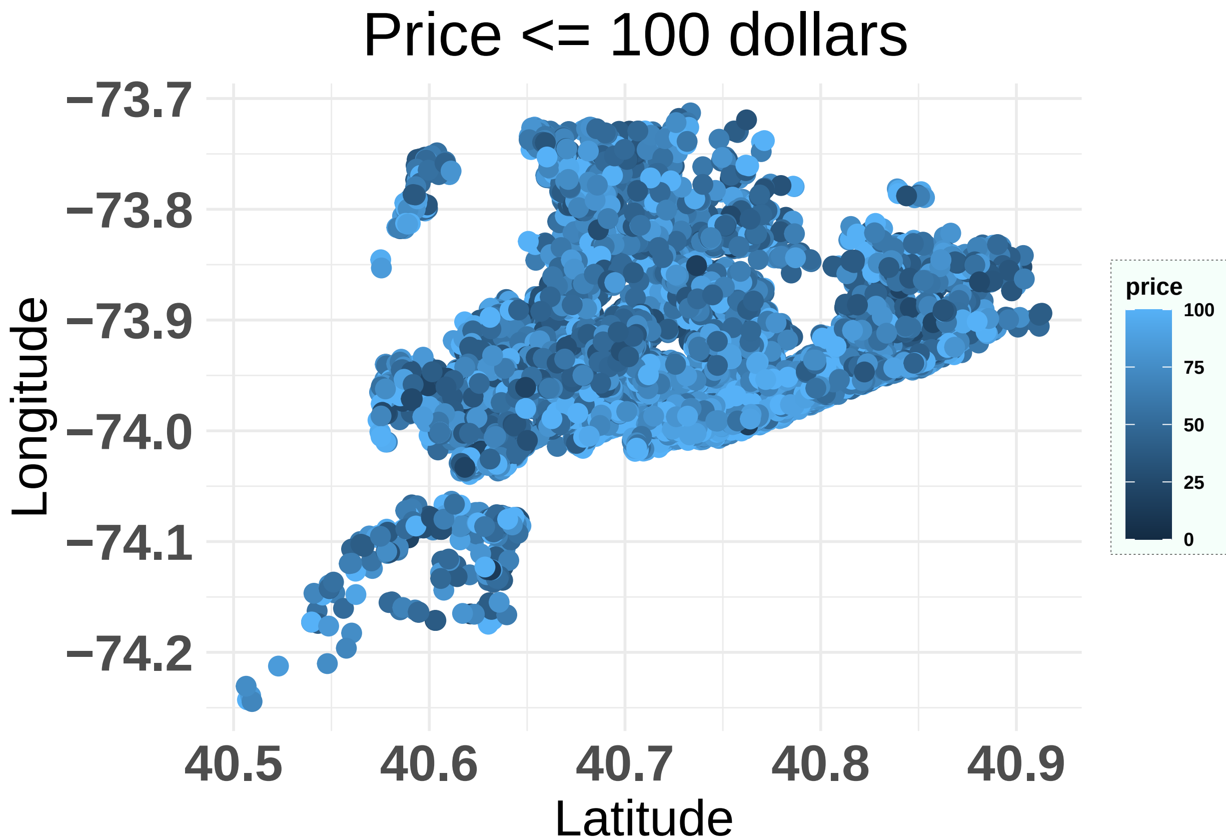


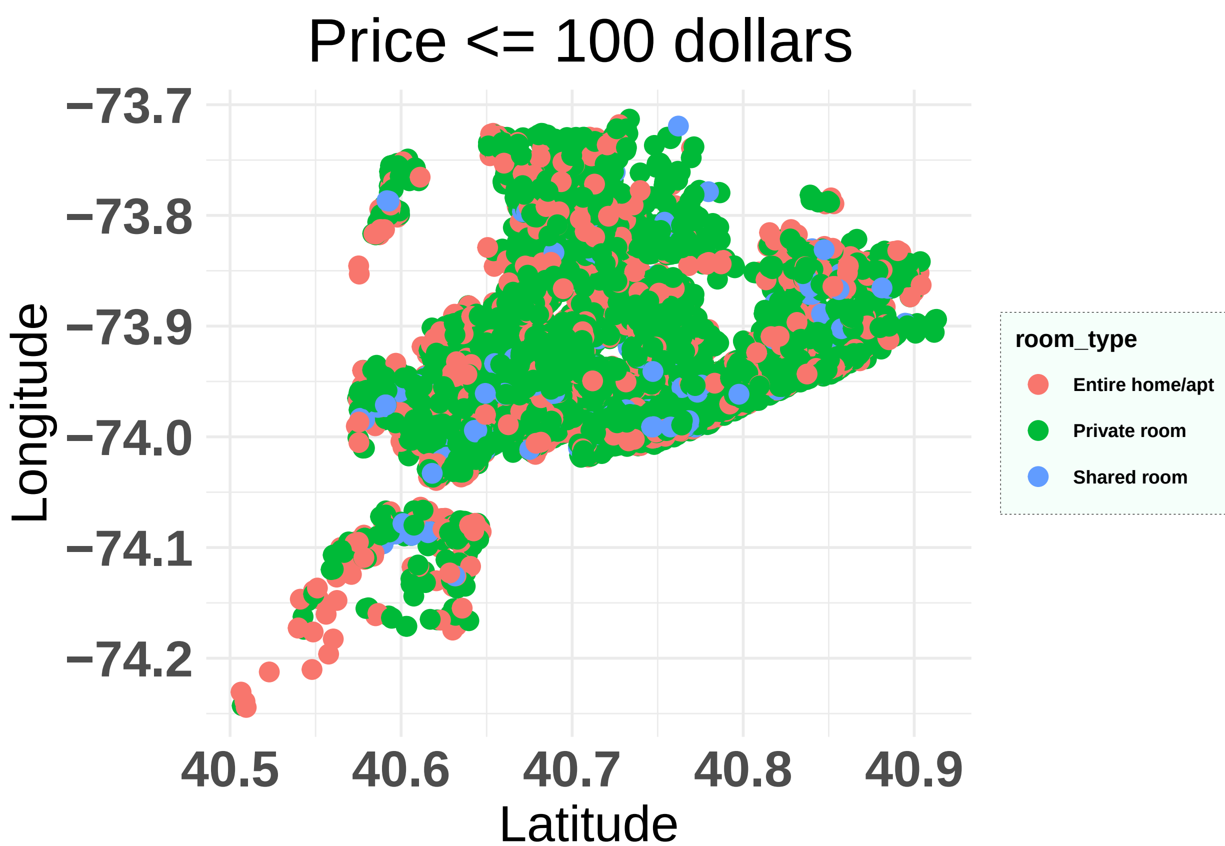
As our database prices are mostly below 100 dollars, we will filter the data to obtain only bookings below 100 dollars.

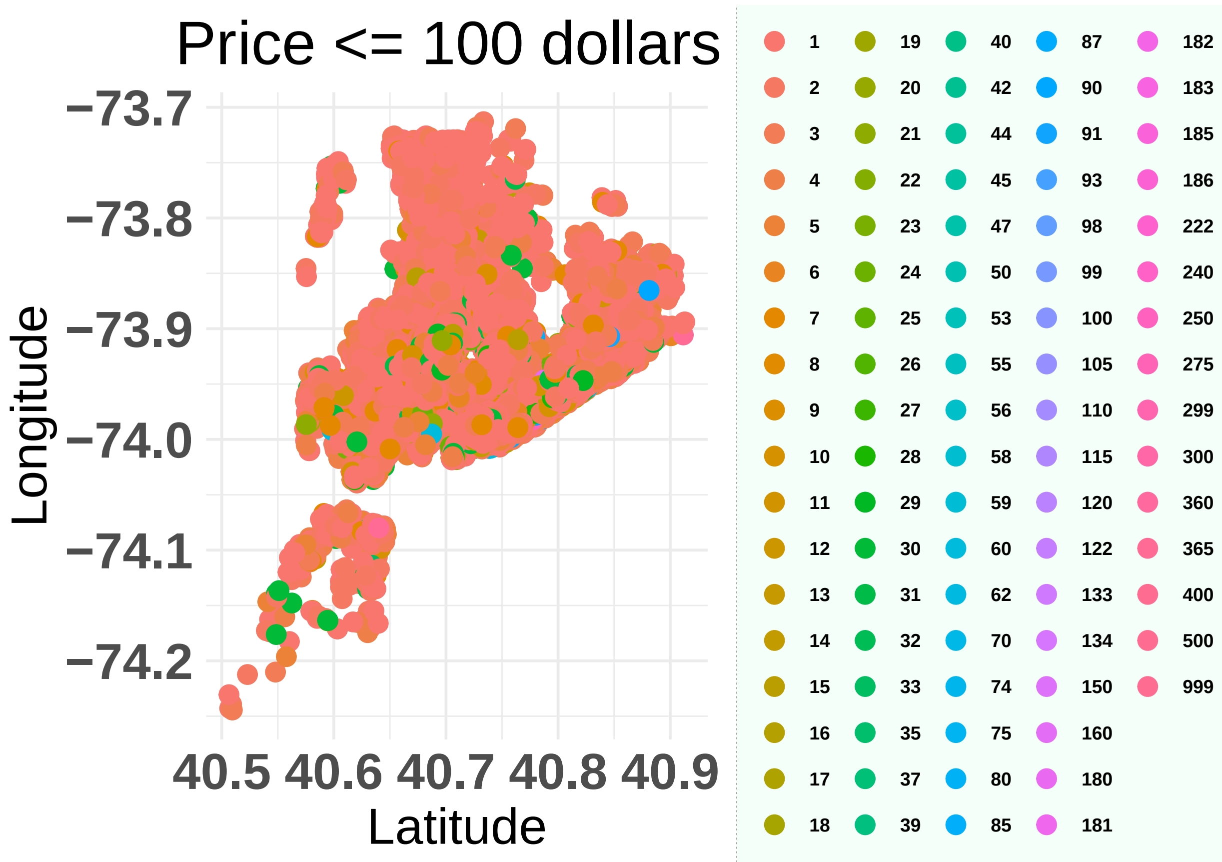


Understanding how this grouping behaves in relation to the coordinate.




Price <= 100 dollars
Longitude
Latitude
−73.7
−73.8
−73.9
−74.0
−74.1
−74.2
40.5
40.6
40.7
40.8
40.9
price
100
75
50
25
0


Price <= 100 dollars
Longitude
Latitude
−73.7
−73.8
−73.9
−74.0
−74.1
−74.2
40.5
40.6
40.7
40.8
40.9
room_type
Entire home/apt
Private room
Shared room



4 Modeling

In this i have tried different methods to predict the price of Airbnb listings.

The models I have applied here are Linear Regression , Partial Least-Squares Regression (PLS), Boosted Generalized Linear Model ,Recursive Partitioning and Regression Trees, Pruned Tree Models, Bagged CART ,Random Forest ,Stochastic Gradient Boosting ,KNN ,Ridge Regression ,Lasso Regression and Support Vector Regression. ## Data prepartion

Removing Unwanted Columns

Some of the variables have been removed from the dataset due to several reasons.

1) id,name,host_id : We know that logically, we don't look at these variables when we select a place to stay during vacation.
2) neighbourhood : This variable consisted of a large number of factor levels and this complicates the models and also some neighbourhoods have very less information and eventually will result in misleading results.
3) last_review : This was a date variable and we have extracted sufficient information from this variable and these information is recorded in the variable year_cat.

Converting string to Factors

```
## 'data.frame':    48895 obs. of  2 variables:
##  $ neighbourhood_group: Factor w/ 5 levels "Bronx","Brooklyn",..: 2 3 3 2 3 3 2 3 3 3 ...
##  $ room_type          : Factor w/ 3 levels "Entire home/apt",..: 2 1 2 1 1 1 2 2 2 1 ...
```

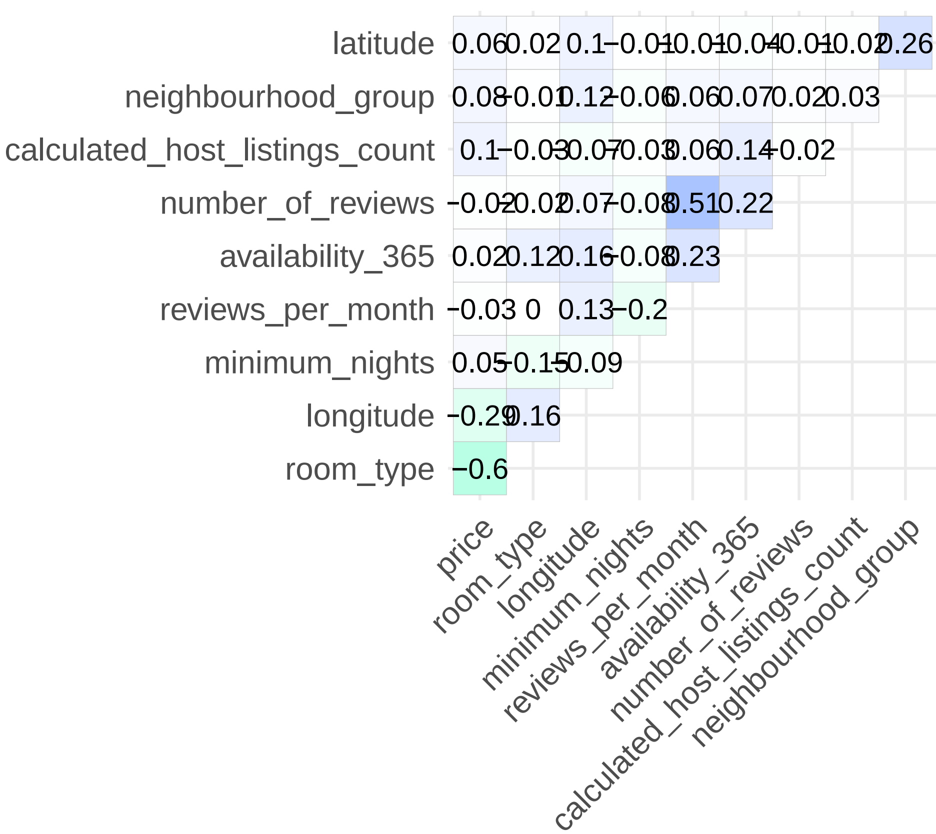
```
##   price neighbourhood_group latitude longitude       room_type minimum_nights
## 1   149            Brooklyn 40.64749 -73.97237    Private room              1
## 2   225           Manhattan 40.75362 -73.98377 Entire home/apt              1
## 3   150           Manhattan 40.80902 -73.94190    Private room              3
## 4    89            Brooklyn 40.68514 -73.95976 Entire home/apt              1
## 5    80           Manhattan 40.79851 -73.94399 Entire home/apt             10
##   number_of_reviews reviews_per_month calculated_host_listings_count
## 1                 9              0.21                              6
## 2                45              0.38                              2
## 3                 0              0.00                              1
## 4               270              4.64                              1
## 5                 9              0.10                              1
##   availability_365
## 1              365
## 2              355
## 3              365
## 4              194
## 5                0
```

Other Alterations-.

1)All the missing values of reviews_per_month were replaced by 0.

2)Removing Outliners for Price,Minimum nights and number of reviews.

Finding Correlations



Multicollinearity

```
##            neighbourhood_group                            latitude
```

```
##                       1.093851                        1.083564
##                      longitude                       room_type
##                       1.087609                        1.065210
##                 minimum_nights               number_of_reviews
##                       1.073376                        1.378366
##              reviews_per_month calculated_host_listings_count
##                       1.434202                        1.039998
##               availability_365
##                       1.141387
```

Splitting into training and test sets

Training Set=75%

Testing Set=25%

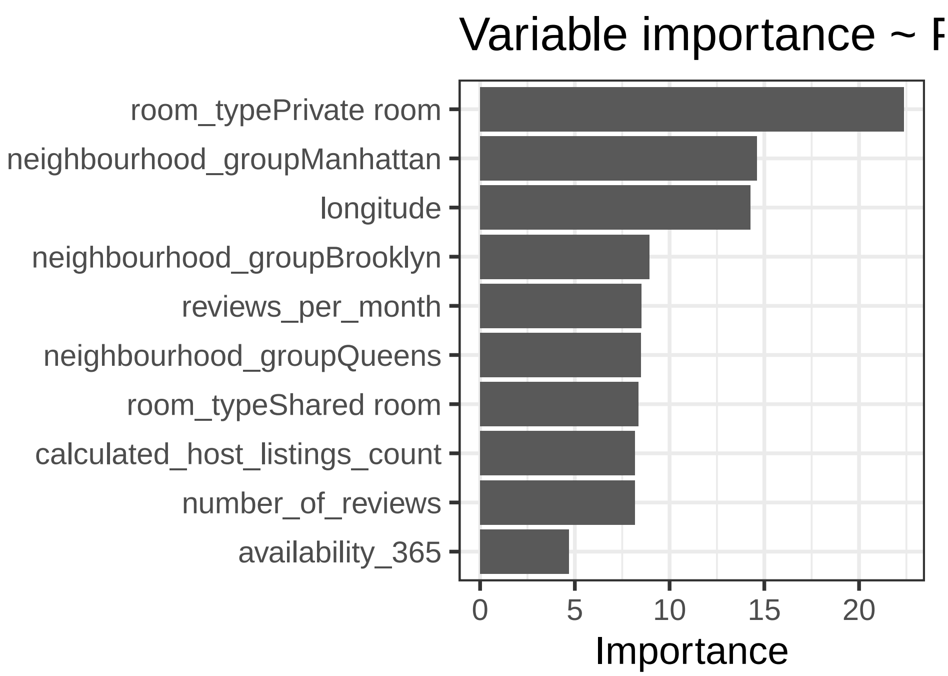
Trying Different Methods to Predict the price of Airbnb listings.

4.0.1 Linear Regression - Math Model

Mean Absolute Error

```
## [1] 75.194
```

4.1 Partial Least-Squares Regression (PLS)



Mean Absolute Error

```
## [1] 70.148
```

4.2 Boosted Generalized Linear Model

Mean Absolute Error

```
## [1] 68.107
```

4.3 Pruned Tree Models

Mean Absolute Error Before Pruning

```
## [1] 78.788
```

Mean Absolute Error After Pruining

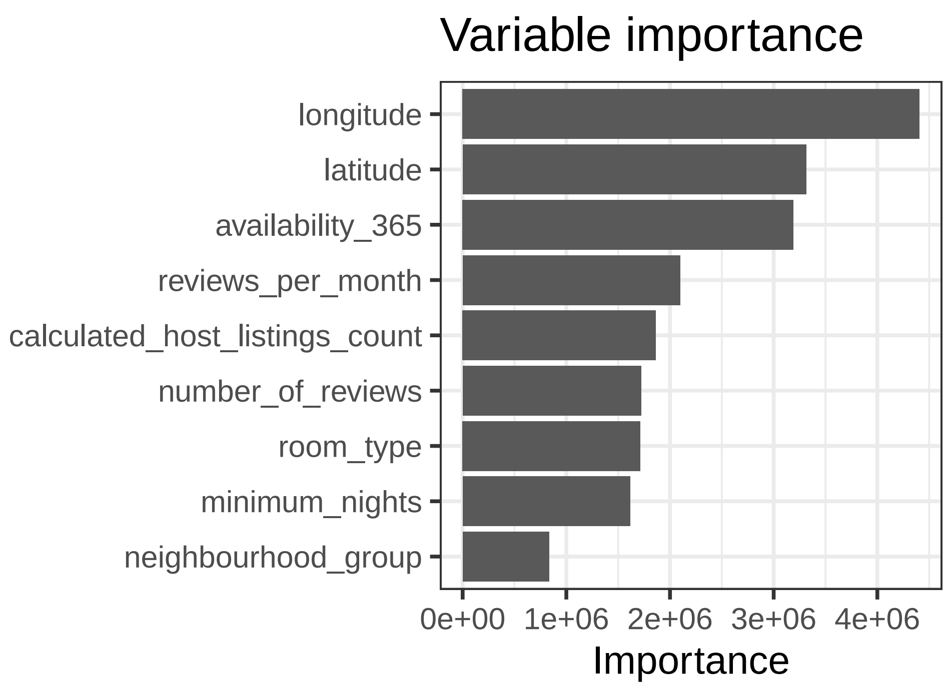
```
## [1] 69.769
```

4.4 Bagged CART

Mean Absolute Error

```
## [1] 69.938
```

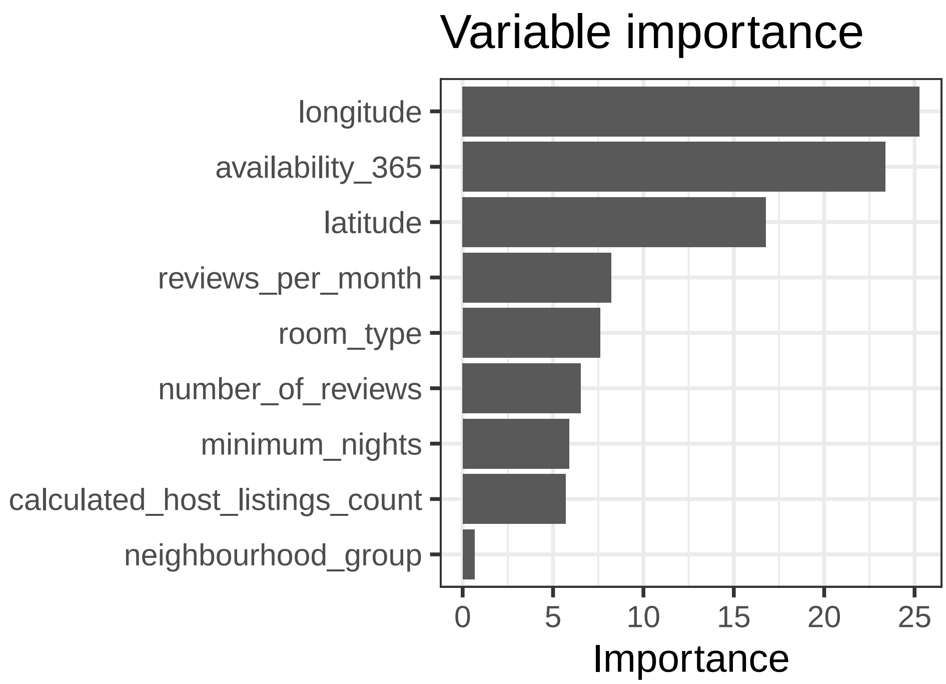
4.5 Random Forest



Mean Absolute Error

```
## [1] 51.366
```

4.6 Stochastic Gradient Boosting



Mean Absolute Error

```
## [1] 66.863
```

4.7 K-Nearest Neighbour

Mean Absolute Error

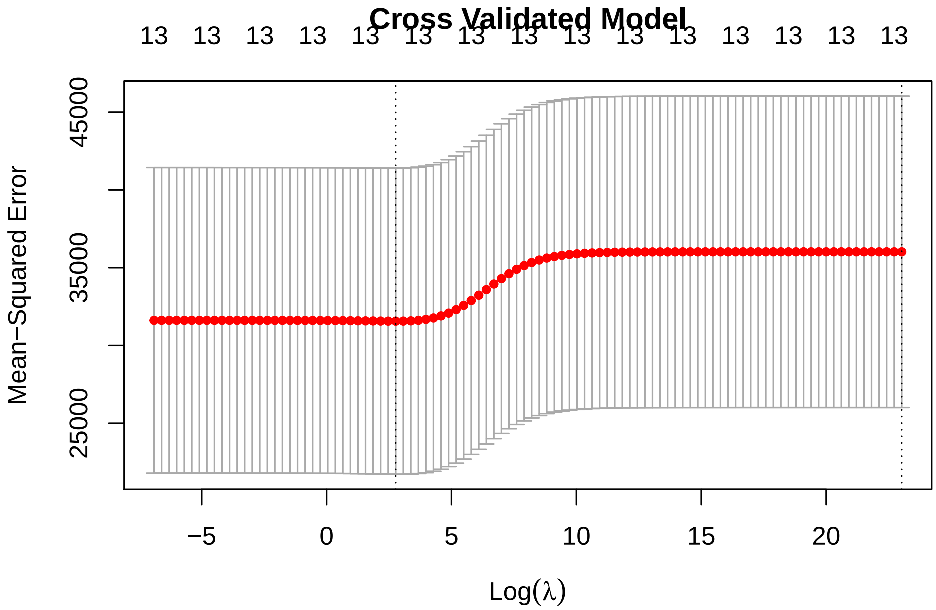
```
## [1] 65.345
```

4.8 Bagged Multivariate Adaptive Regression Spline

Mean Absolute Error

```
## [1] 71.999
```

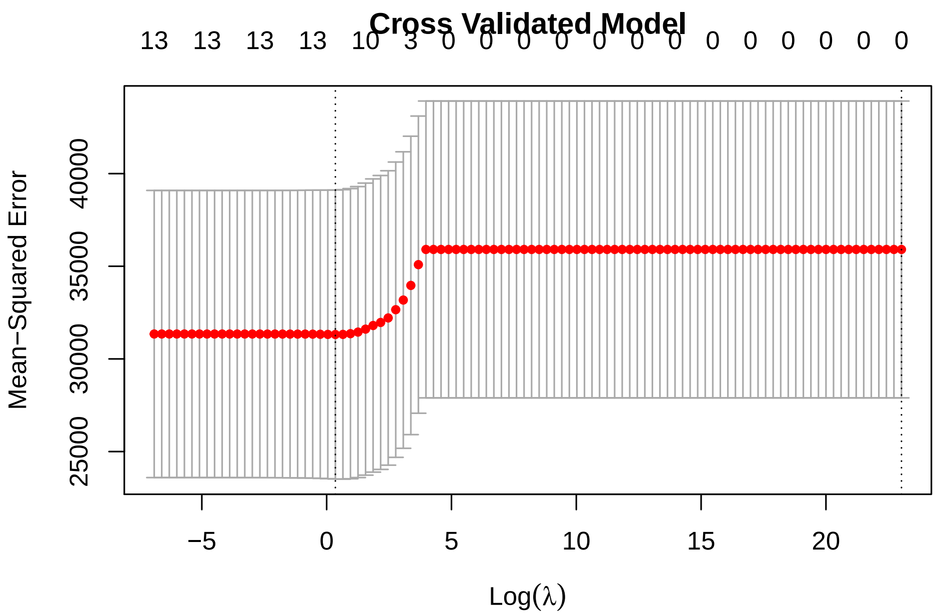
4.9 Ridge Regression



Mean Absolute Error

```
## [1] 70.205
```

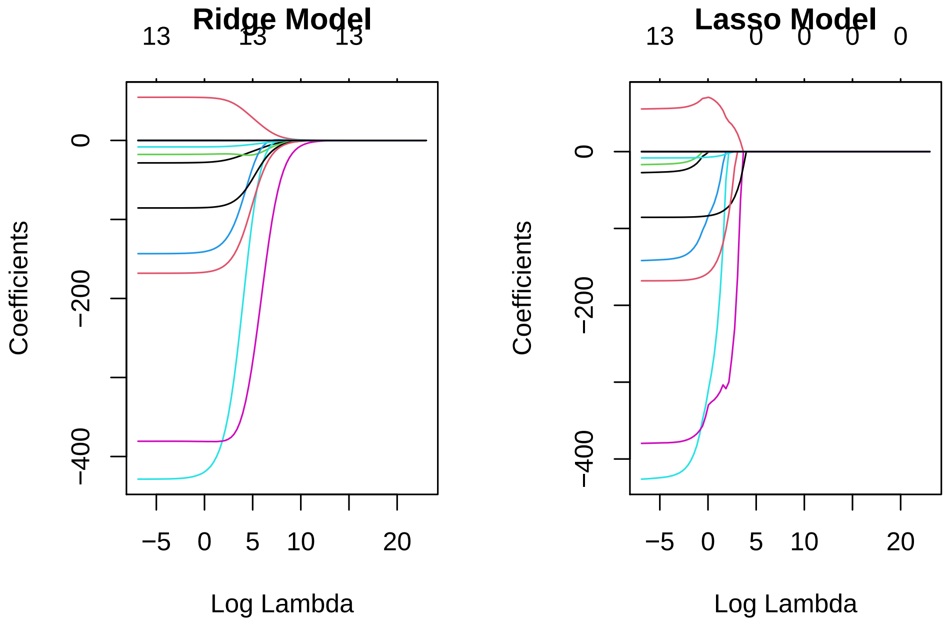
4.10 Lasso Regression



Mean Absolute Error

```
## [1] 70.011
```

4.11 Visualize the Ridge & Lasso Models



4.12 Support Vector Machines with Linear Kernel

Mean Absolute Error

```
## [1] 59.764
```

4.13 Support Vector Machines Radial Basis Function Kernel

Mean Absolute Error

```
## [1] 54.565
```

4.14 Support Vector Tuned Model 1

Mean Absolute Error

```
## [1] 53.815
```

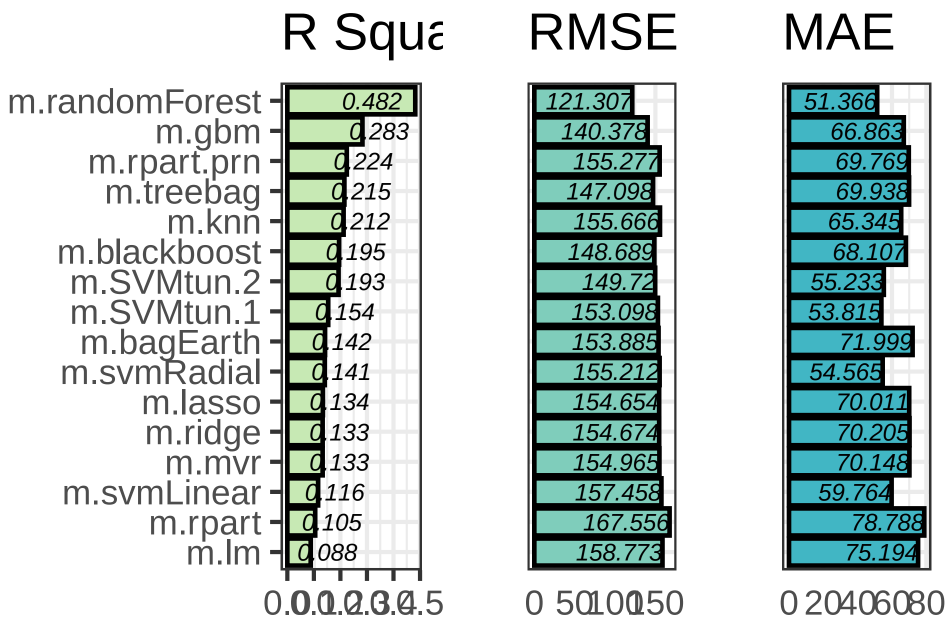
4.15 Support Vector Tuned Model 2

Mean Absolute Error

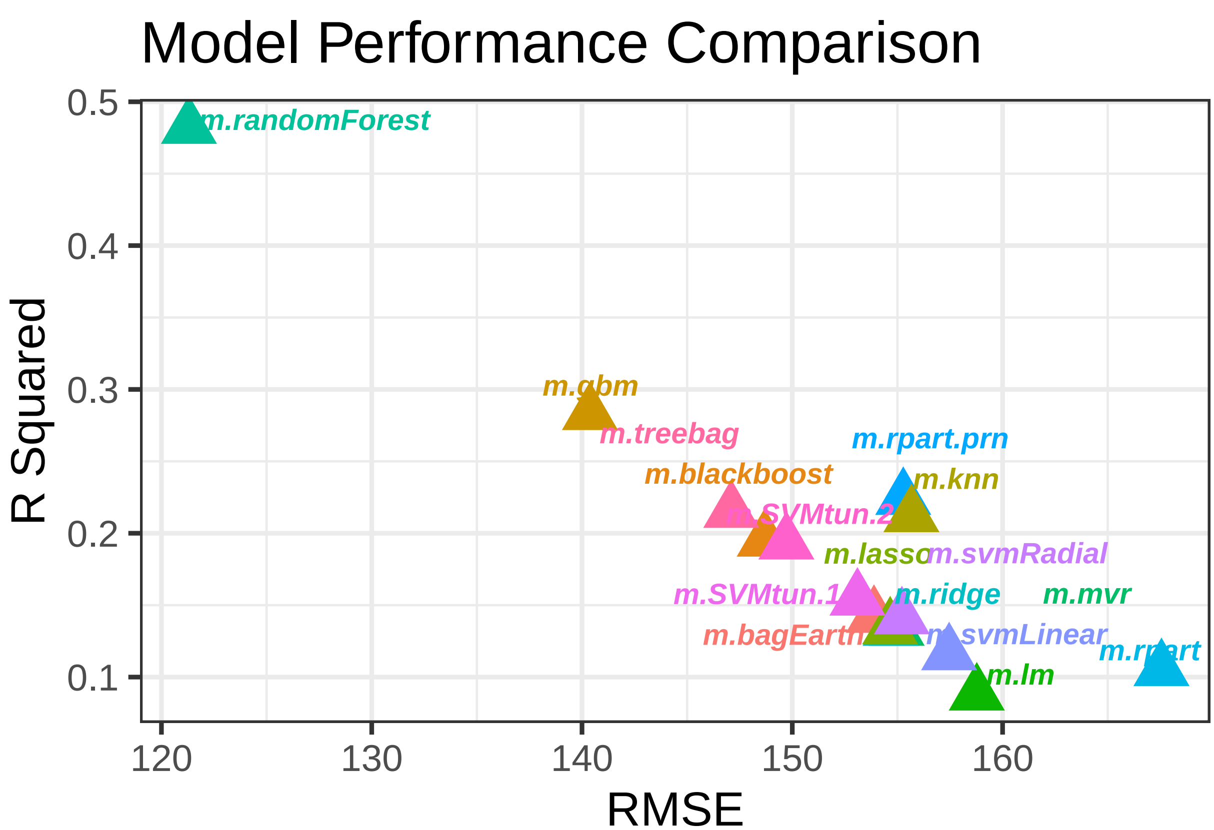
```
## [1] 55.233
```

5 Result

Final Model Comparisons



Scatter plot of Model Performance



By comparing the values obtained above, it is clear that the best model is Random Forest.

Model Performance

MAE	RMSE	R.Squared
51.366	121.307	0.482

6 Conclusion

I performed Expolatory analysis on the data and used various machine learning models to predict Airbnb prices and to understand what factors are important to define it. In this report, I tried various models like Partial Least-Squares Regression (PLS), Boosted Generalized Linear Model ,Recursive Partitioning and Regression Trees, Pruned Tree Models etc.and chose the Random Forest model because it works really well. The final model recieved an RMSE of 121.307 and MAE of 51.366.

7 References

https://towardsdatascience.com/predicting-airbnb-prices-with-machine-learning-and-deep-learning-f46d44afb8a6

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