# Edx Capstone - Airbnb Analysis Report

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# 1 Executive Summary

Airbnb, Inc. is an online marketplace for offering lodging,homestays, or tourism experiences. The company does not own any of the real estate listings, nor does it host events; it acts as a broker, receiving commissions from each booking. This service has started in 2008 with 2 hosts and 3 travellers. Its number one concern is assuring safety of its customers while providing enjoyable experiences.

I performed a descriptive and exploratory analysis of the data, in order to understand how the phenomena of each variable behave individually and transversely. To perform this work, I will use statistical techniques very common in any type of analysis, simple or complex, such as classification of variables, frequency distribution tables, histograms, measures of central tendency and etc.

I have also done analysis on predicting the price of Airbnb listings as a suggestion for the hosts.

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

# 2 Dataset

There are 48895 observations which has data in 16 columns. Both categorical and quantitative data types could be observed. Each row represents details about lodgings 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

Descriptive analyzes are the first manipulations performed in a quantitative study and their main objective is to summarize and explore the behavior of the data involved in the study.

**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 |

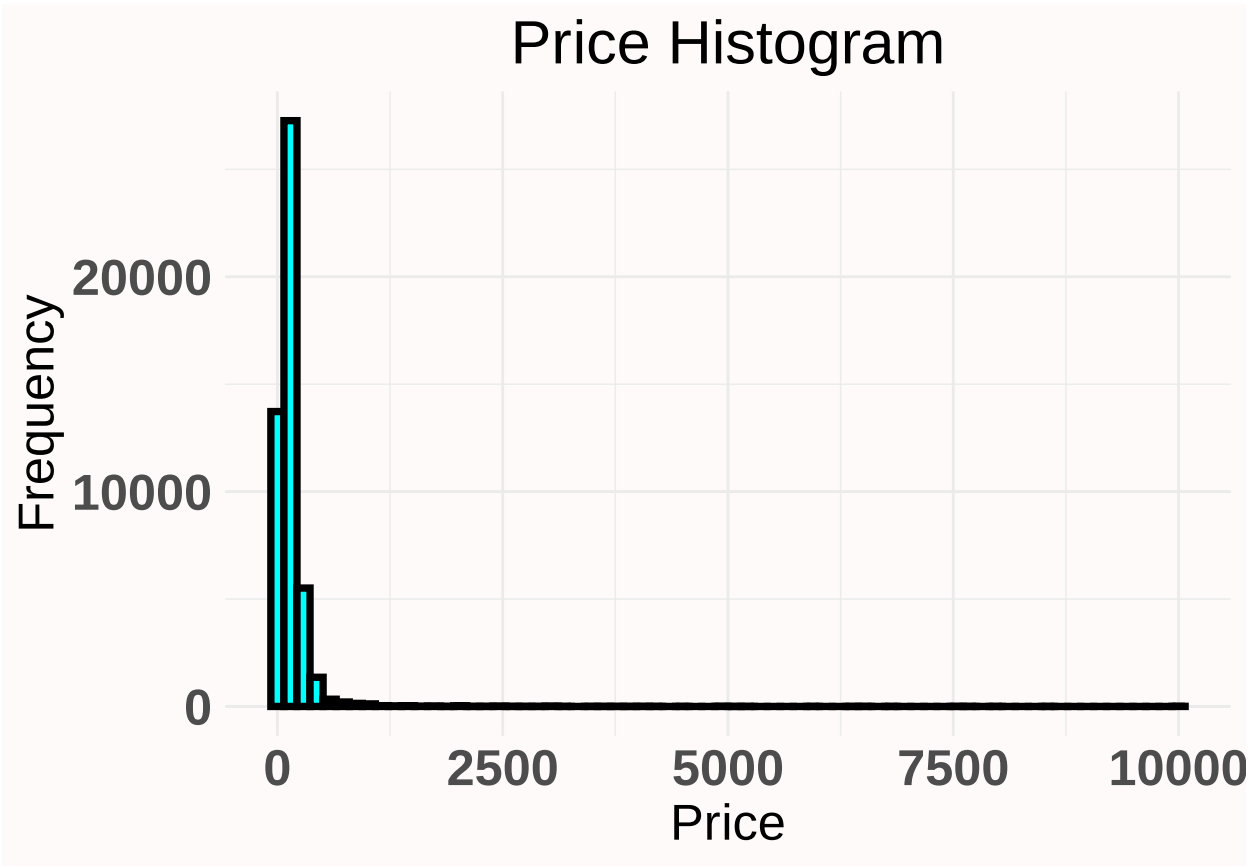
With the frequency tables created above, we can conclude that the frequency and the representative percentage of the most frequent categories of the categorical variables neighborhood_group, neighborhood and room_type are-

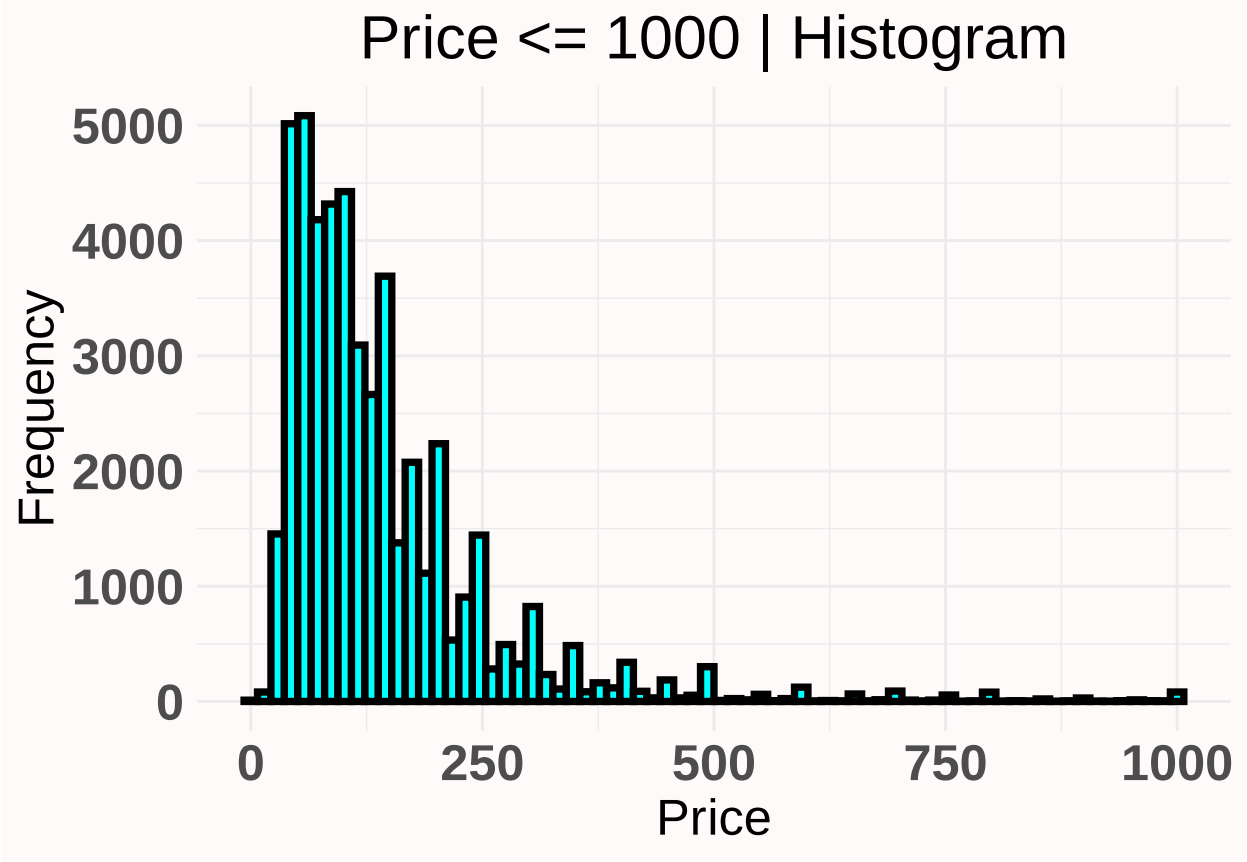
neighbourhood_group - Manhattan -> 21661(44.30%)

neighborhood - Williamsburg -> 3920(8.01%)

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

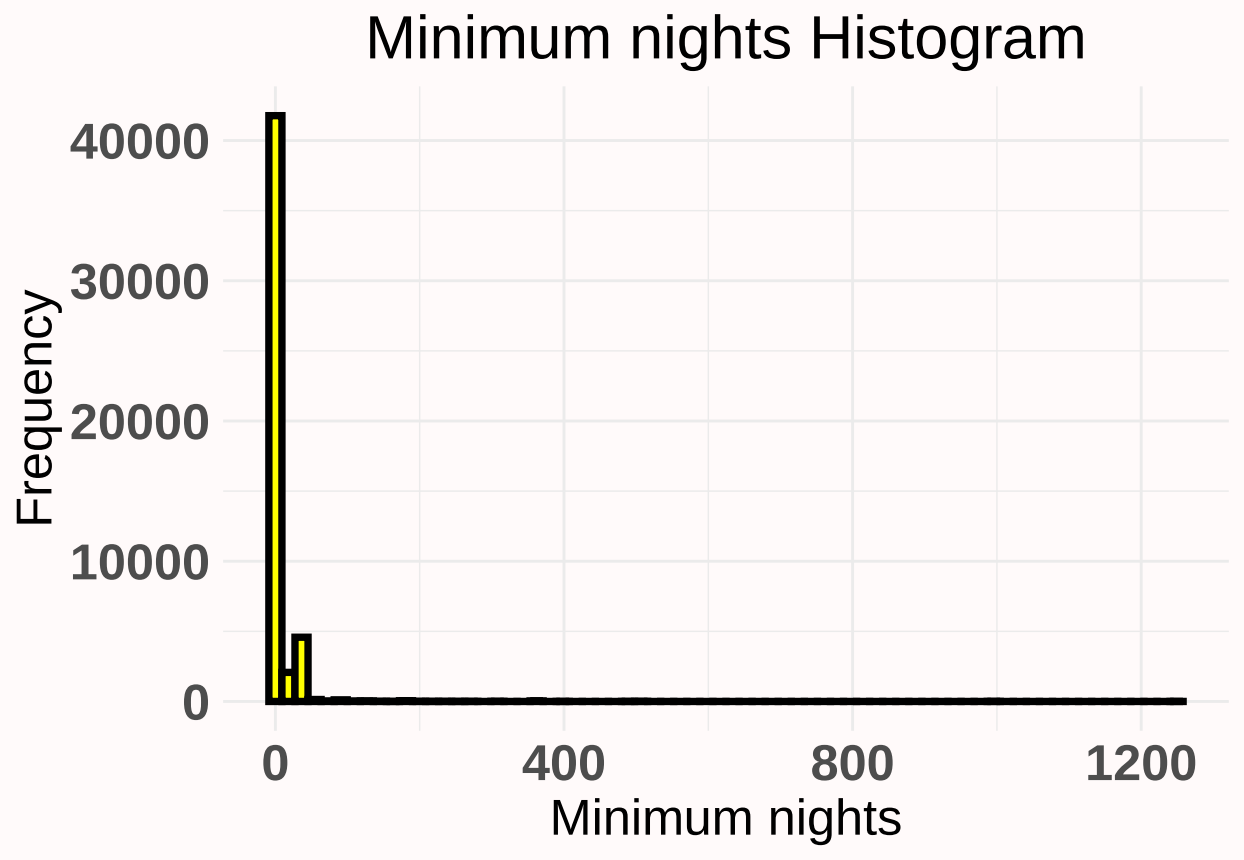
**Histogram for Price**

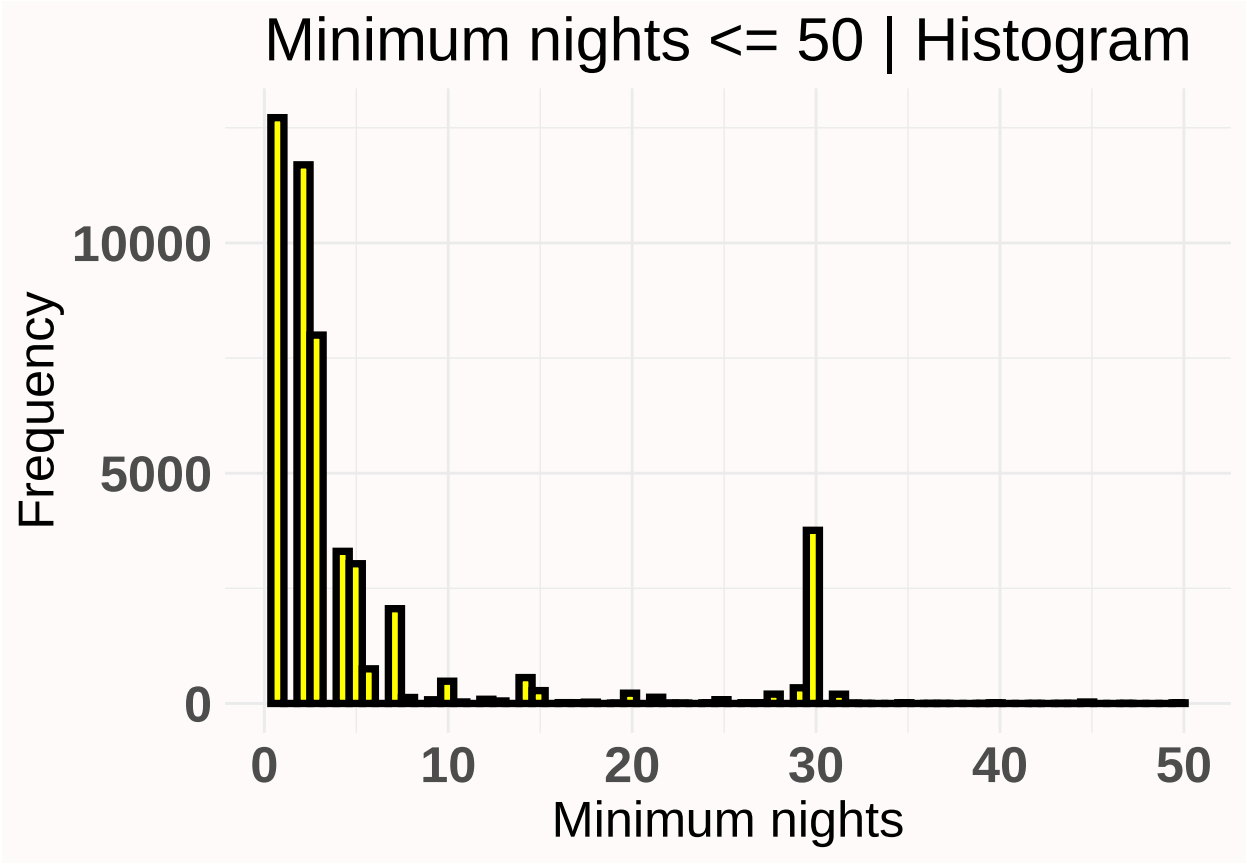

Price Histogram
Frequency
20000
10000
0
0
2500
5000
7500
10000
Price




We can see most of prices our under 1000

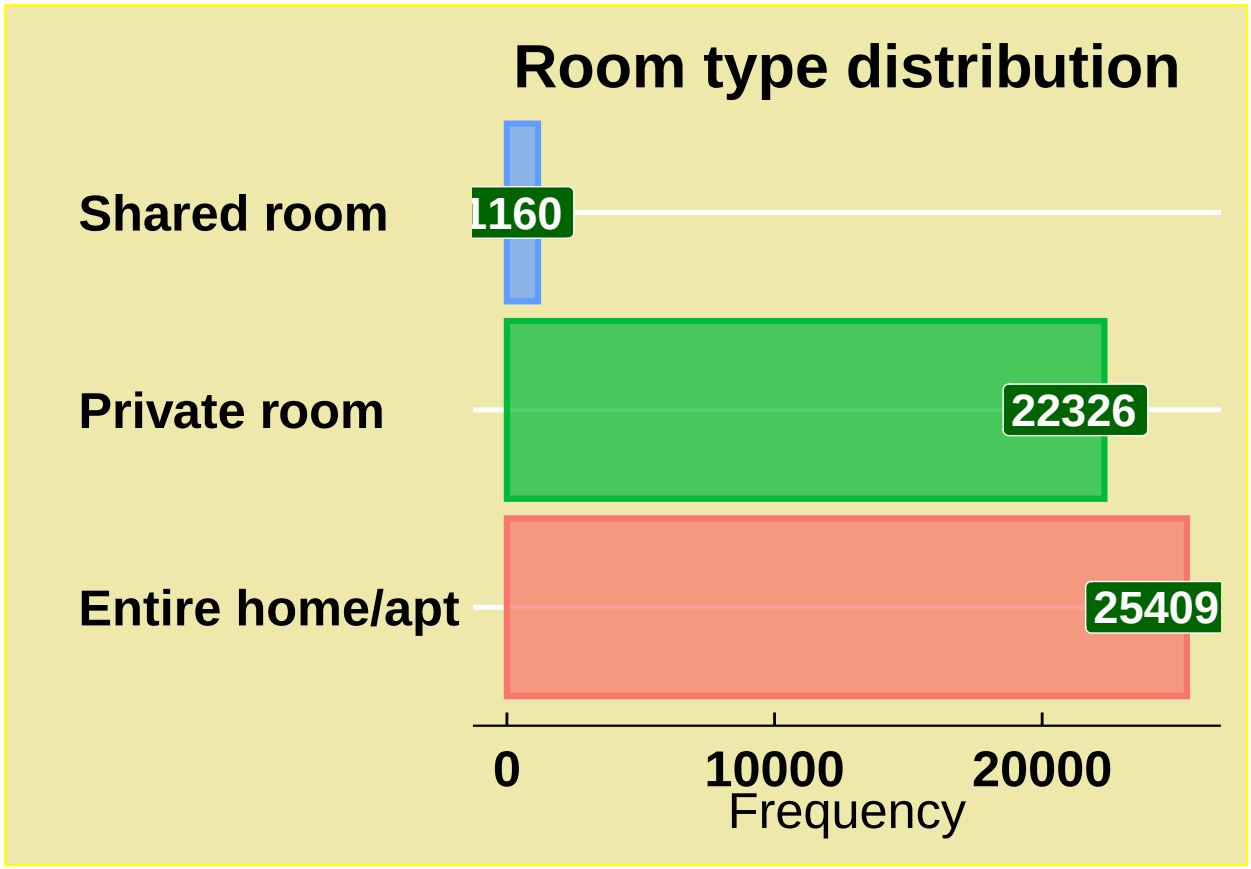
**Histogram For Minimum_Nights**


Minimum nights Histogram
Frequency
40000
30000
20000
10000
0
0
400
800
1200
Minimum nights



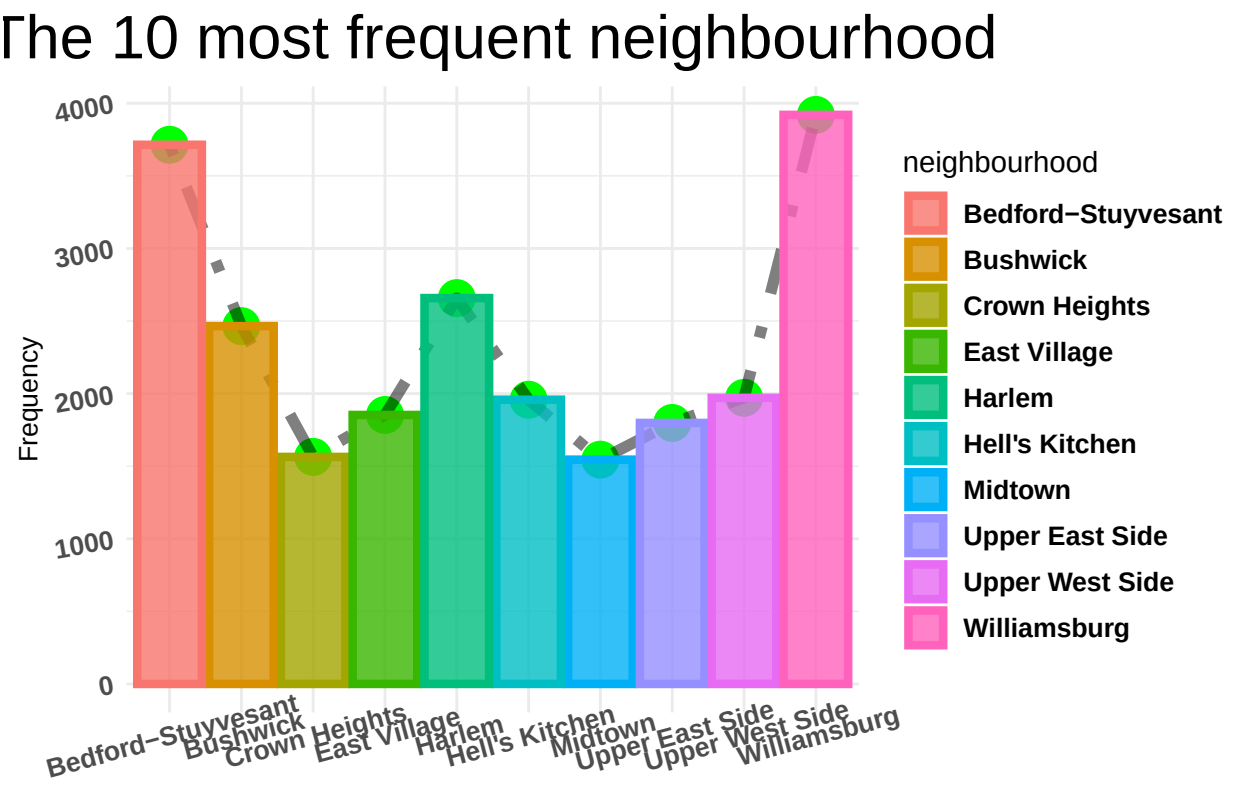

We can see that the minimum number of nights for all reservations made on airbnb are concentrated below 10 with a small peak at 30.

**Bar Graph for Room Type**



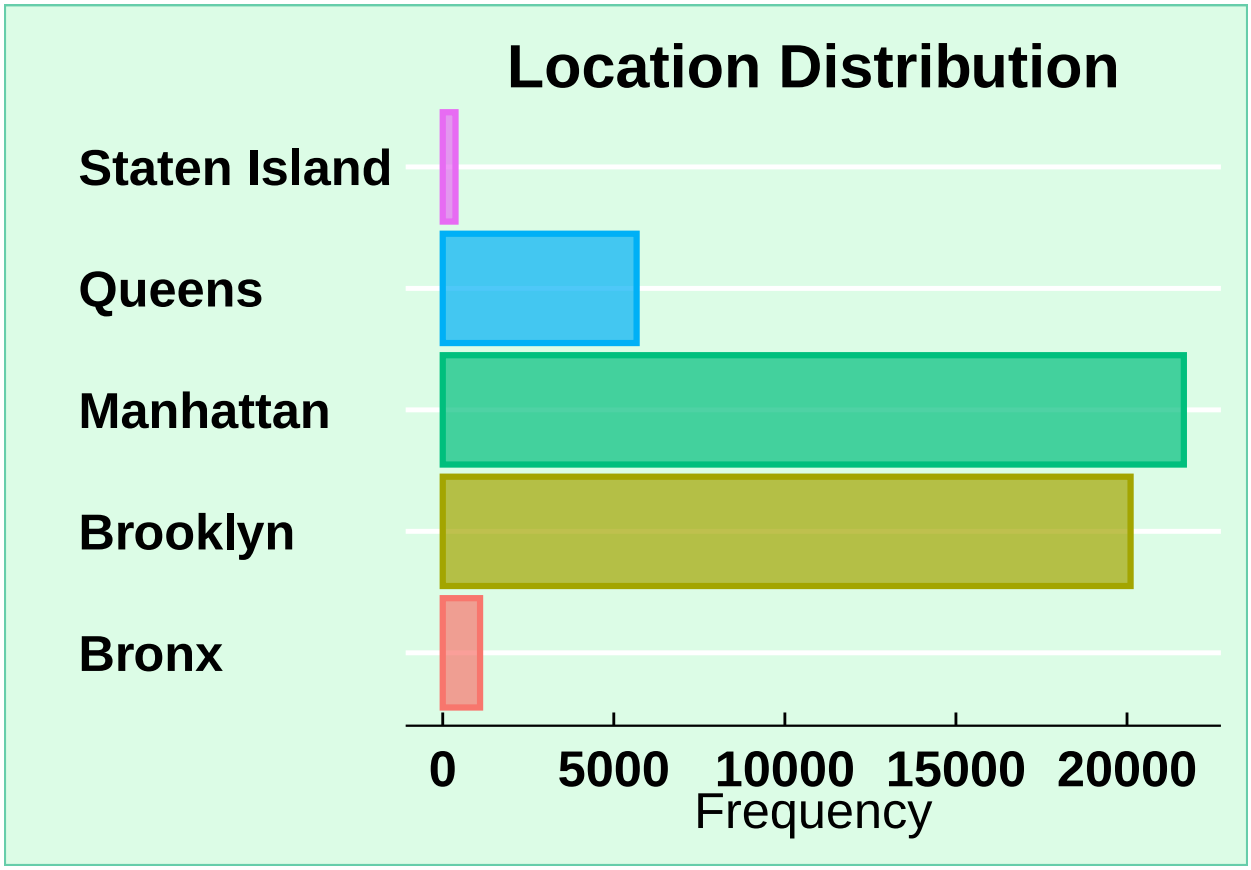

We can see most of the rooms belong private or entire apt/home category.

**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
```

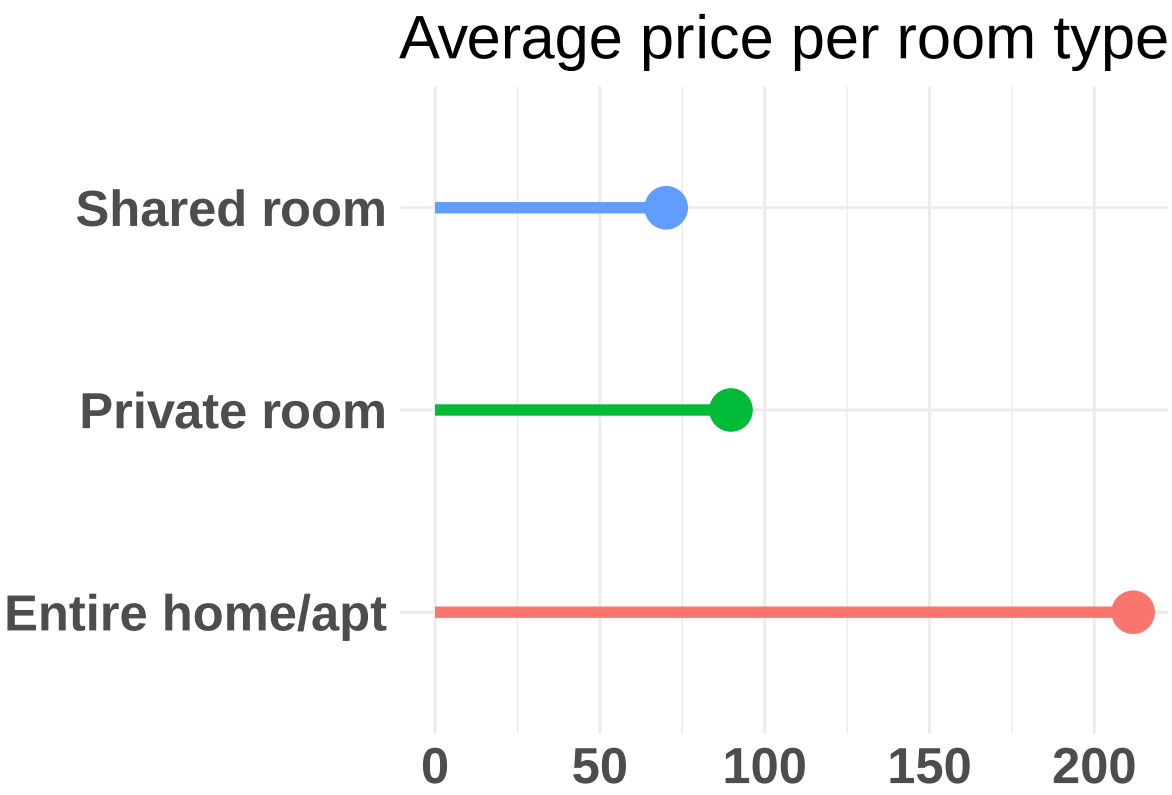
Some important points that you can describe in relation to the type of analysis are-

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

In statistics, exploratory data analysis is an approach to the analysis of data sets in order to summarize their main characteristics, often with visual methods. **Average price per room type**

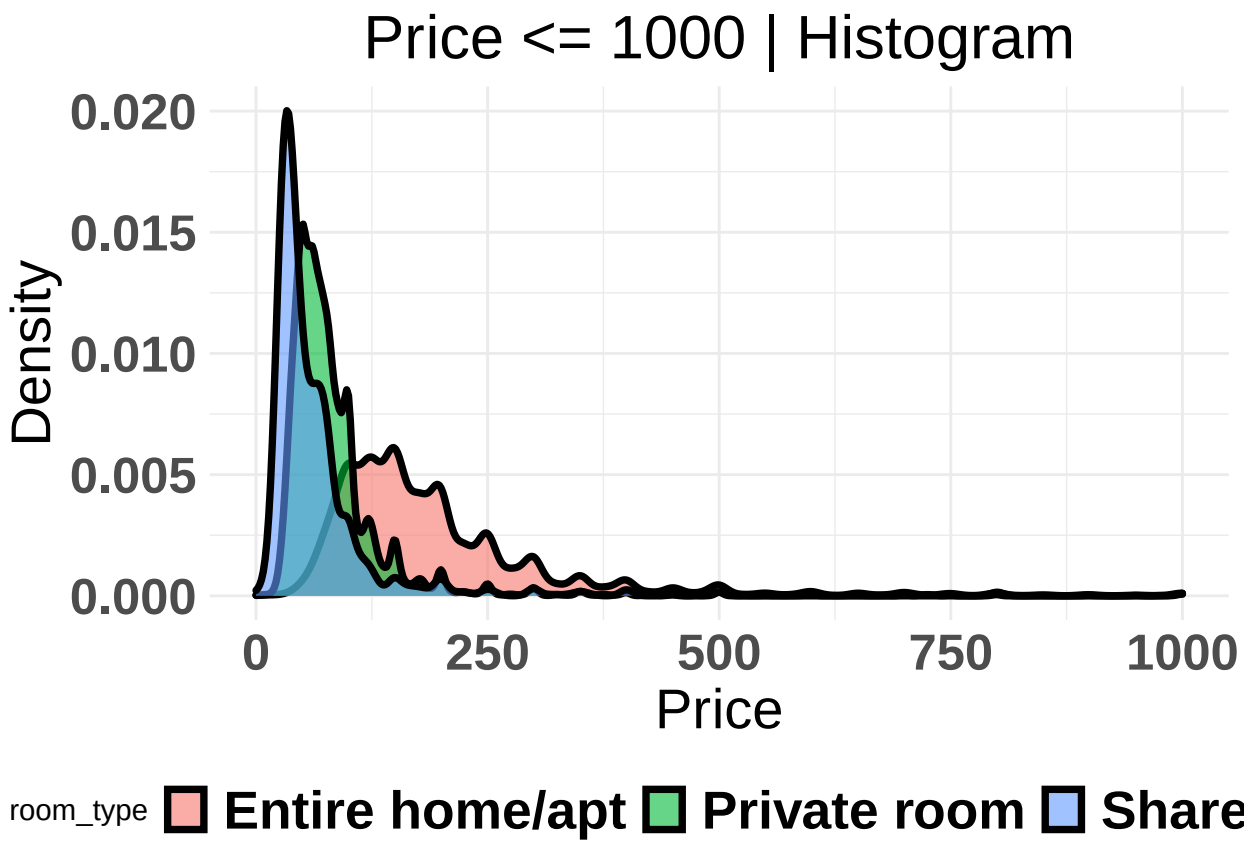
```
##         room_type average_price  Percent
## 1 Entire home/apt     211.79425 56.97946
## 2    Private room      89.78097 24.15397
## 3     Shared room      70.12759 18.86657
```




We can conclude that-

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 . We have that the Private room has an average price 32.82% less than Entire home / apt and 5.29% larger than the Shared room.
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**

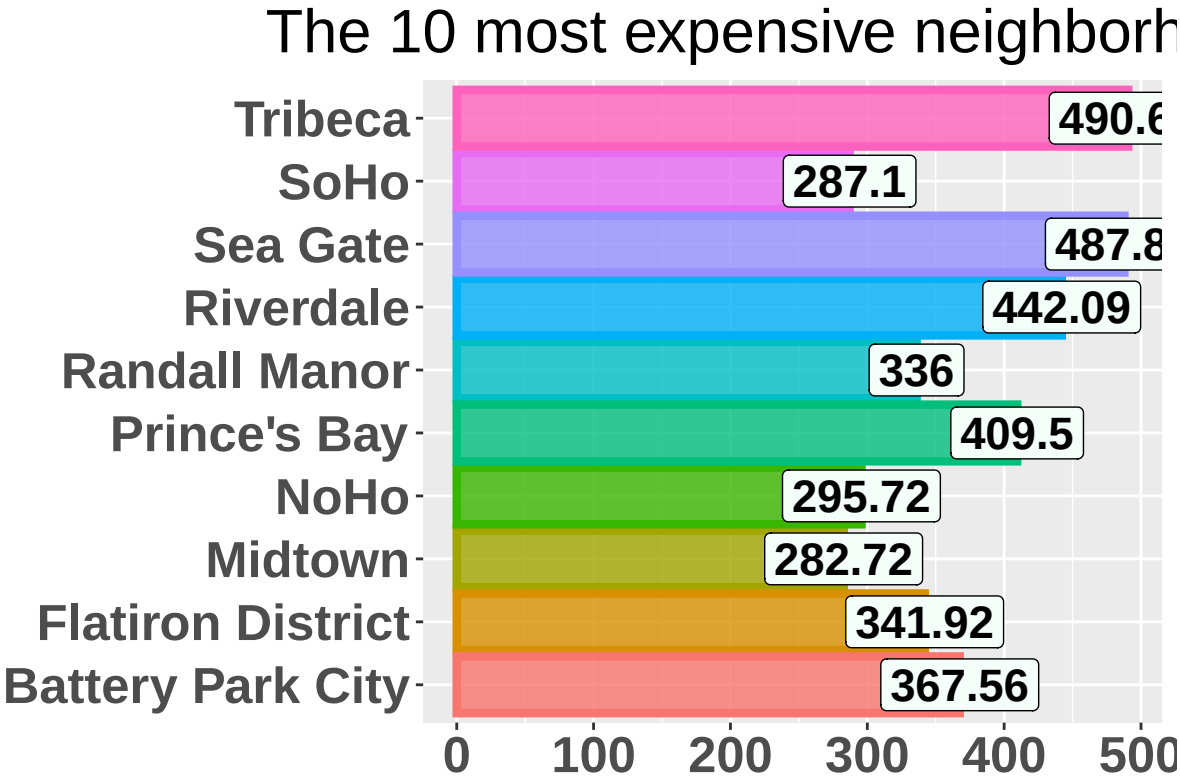



In addition to obtaining information such as the average price for reservations, it is interesting to know how these values that resulted in the average are distributed.

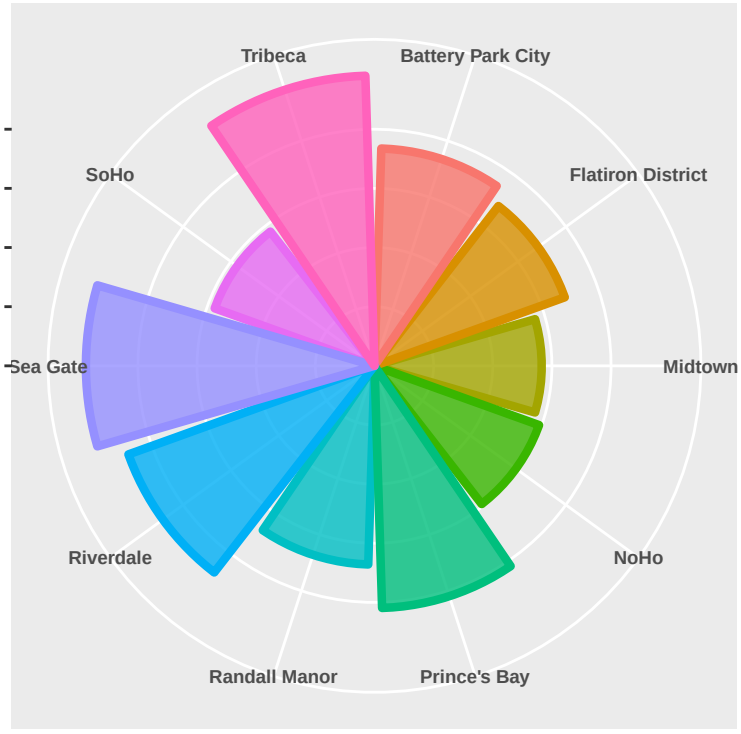
**Price in Relation to Neighborhood**

**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
```



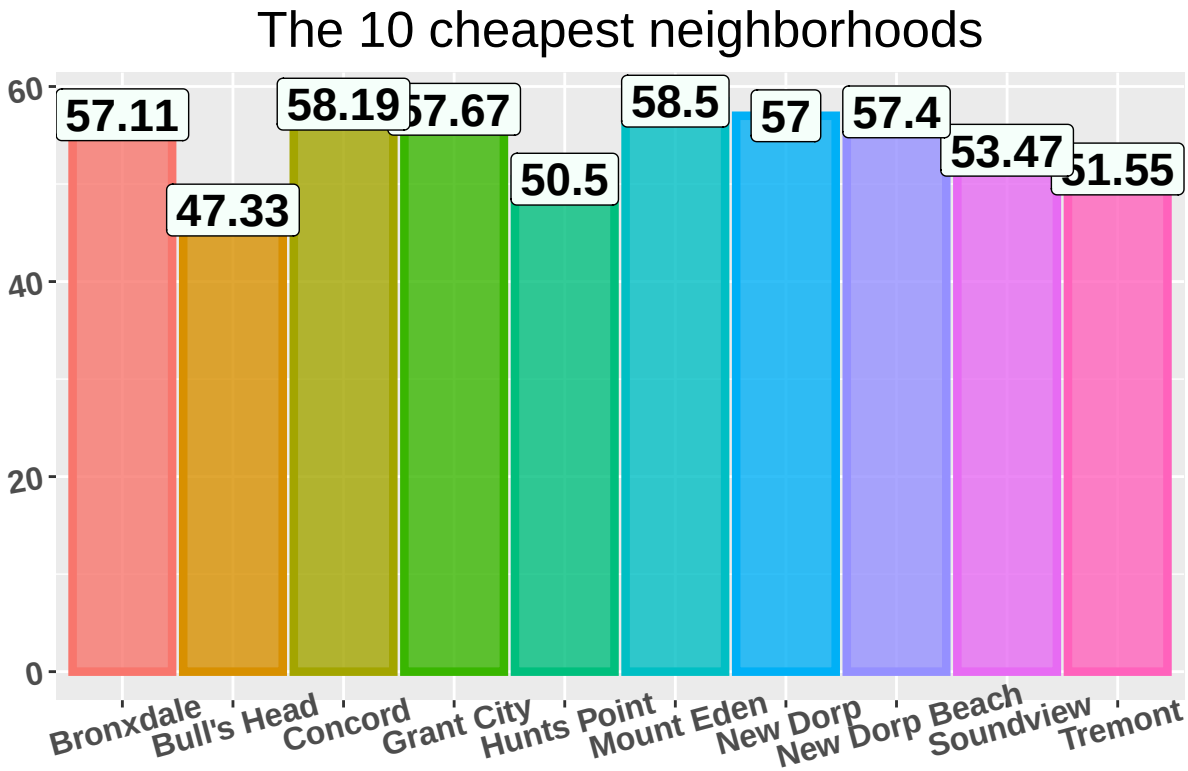

The 10 most expensive neighborhoods




**The 10 cheapest neighborhoods to book on airbnb**

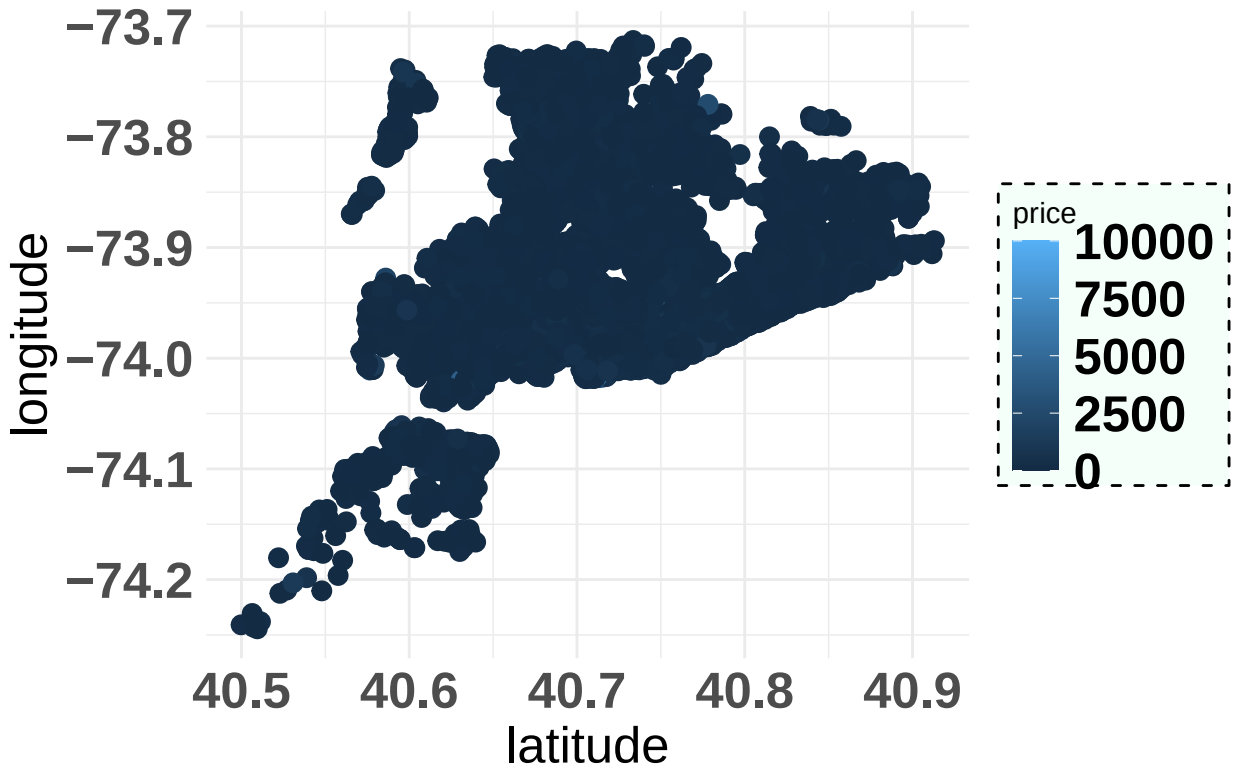
```
##     neighbourhood Average_price_per_neighborhood
## 1     Bull's Head                        47.33333
```

```
## 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
```

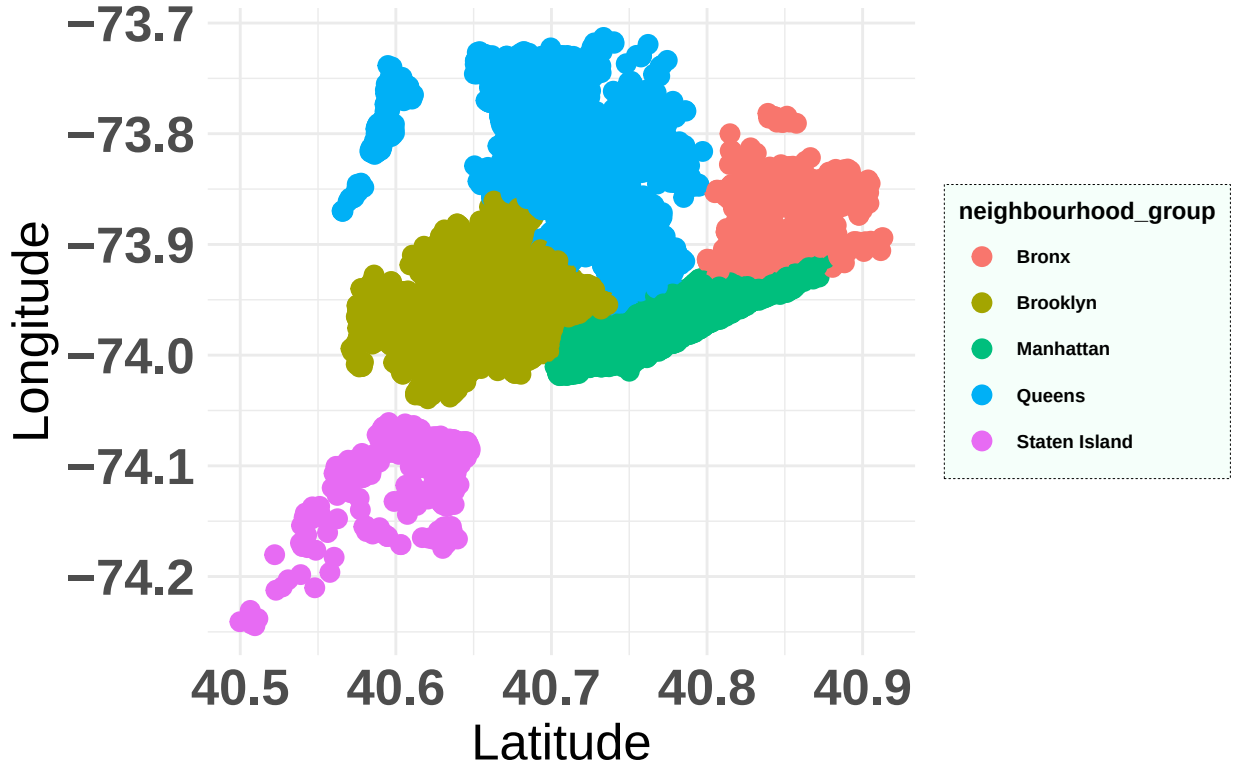


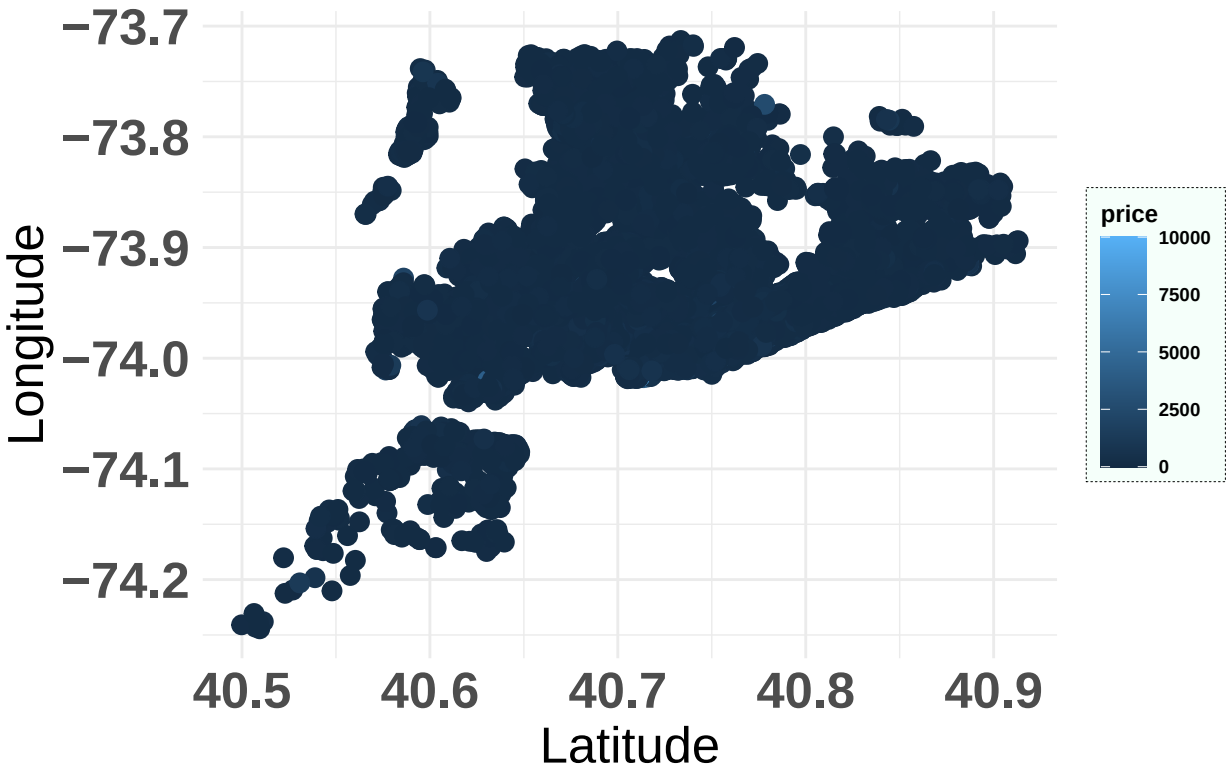

### 3.3 Geographic analysis

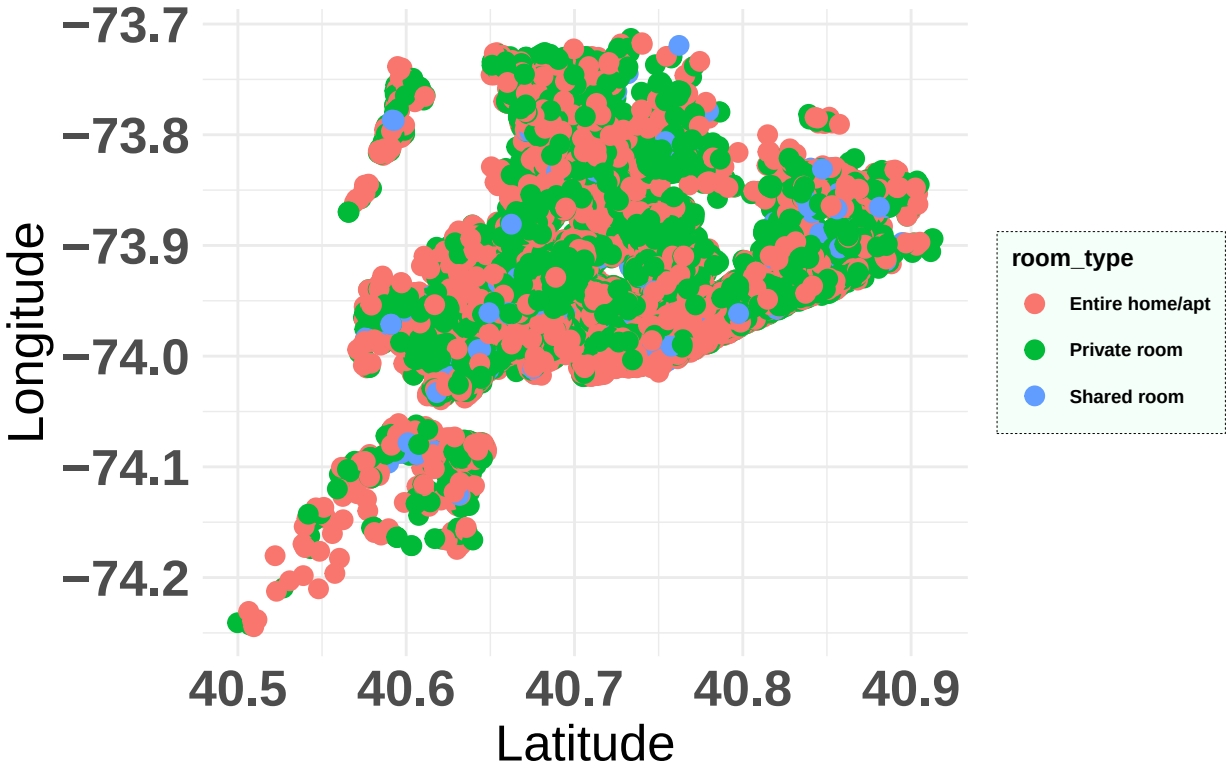
In this analysis I will explore the behavior of the price, neighborhood_group, minimum_nights and room_type through the coordinated latitude and longitude available in the airbnb data. This type of exploitation is extremely useful for understanding the behavior of the data on a geographic scale, consequently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

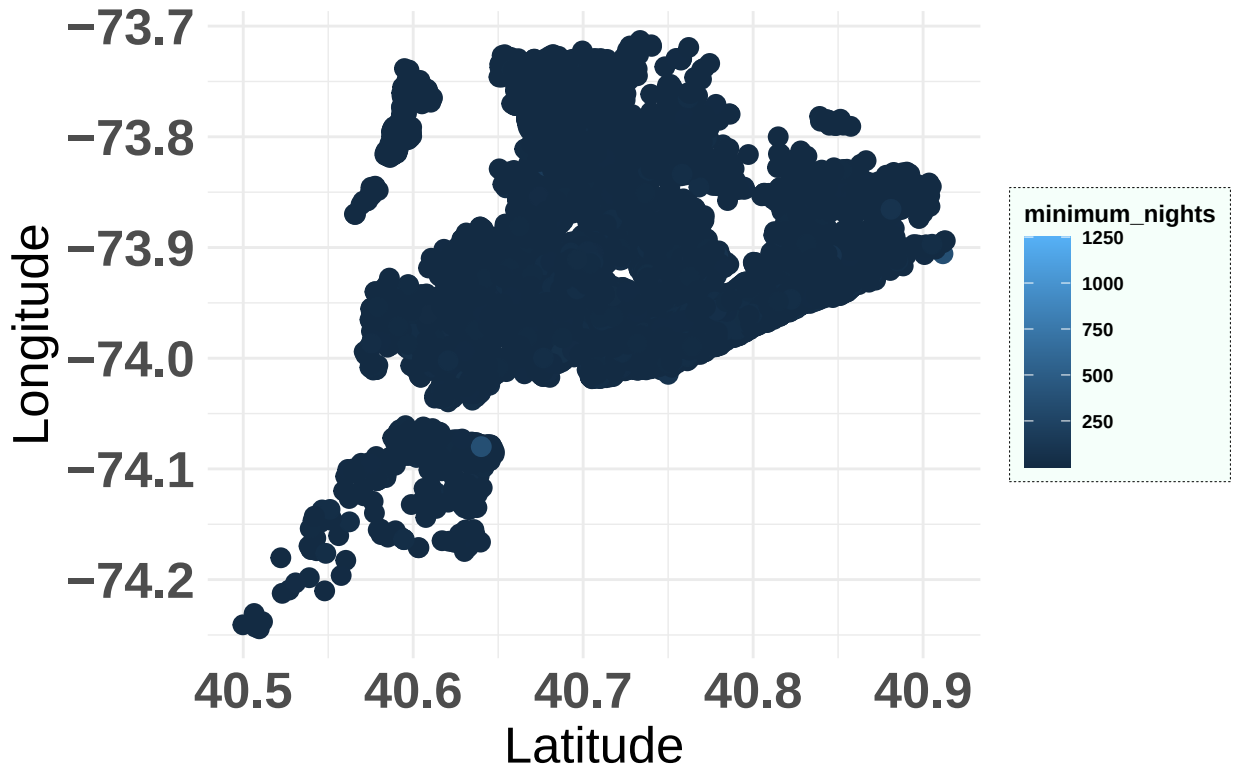



Further exploring in terms of neighbourhood_group, room_type and minimum nights.

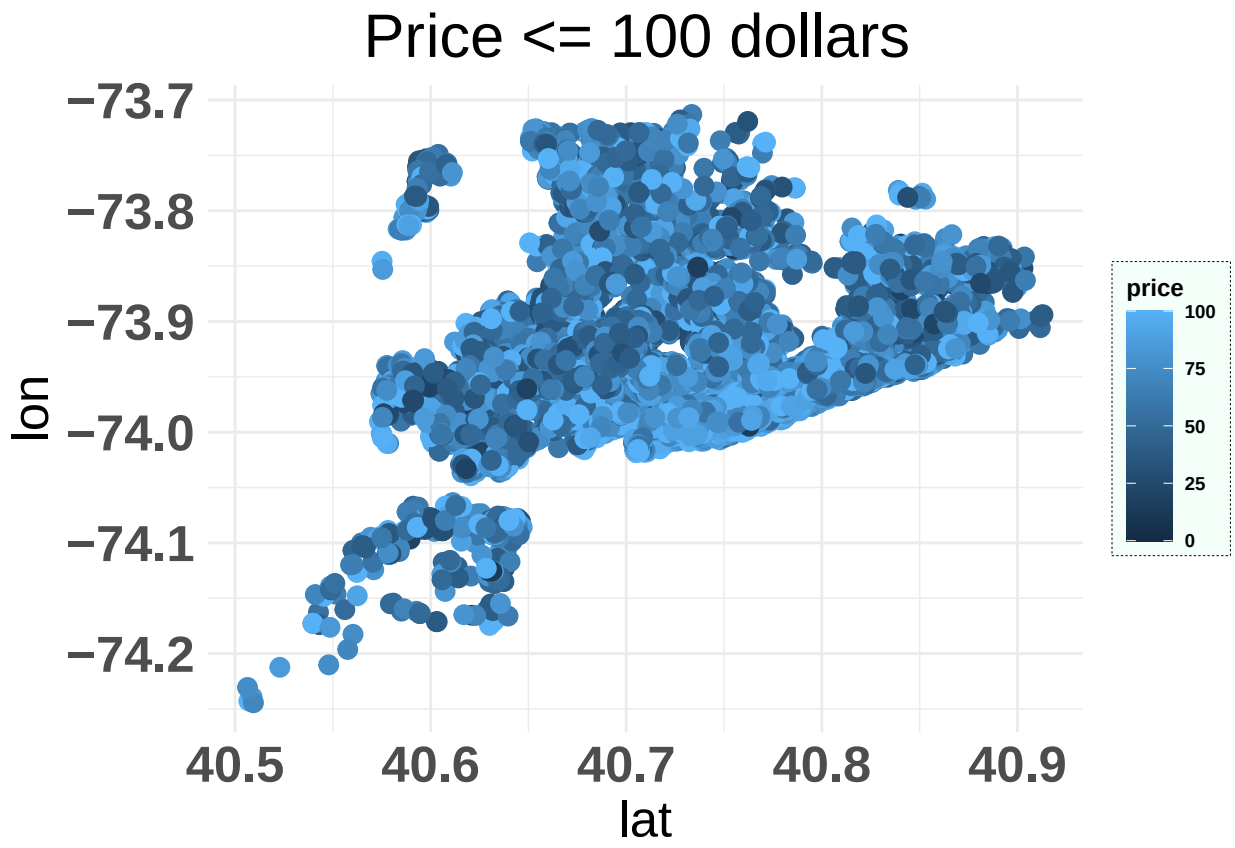



Longitude
−73.7
−73.8
−73.9
−74.0
−74.1
−74.2
40.5
40.6
40.7
40.8
40.9
Latitude
price
10000
7500
5000
2500
0

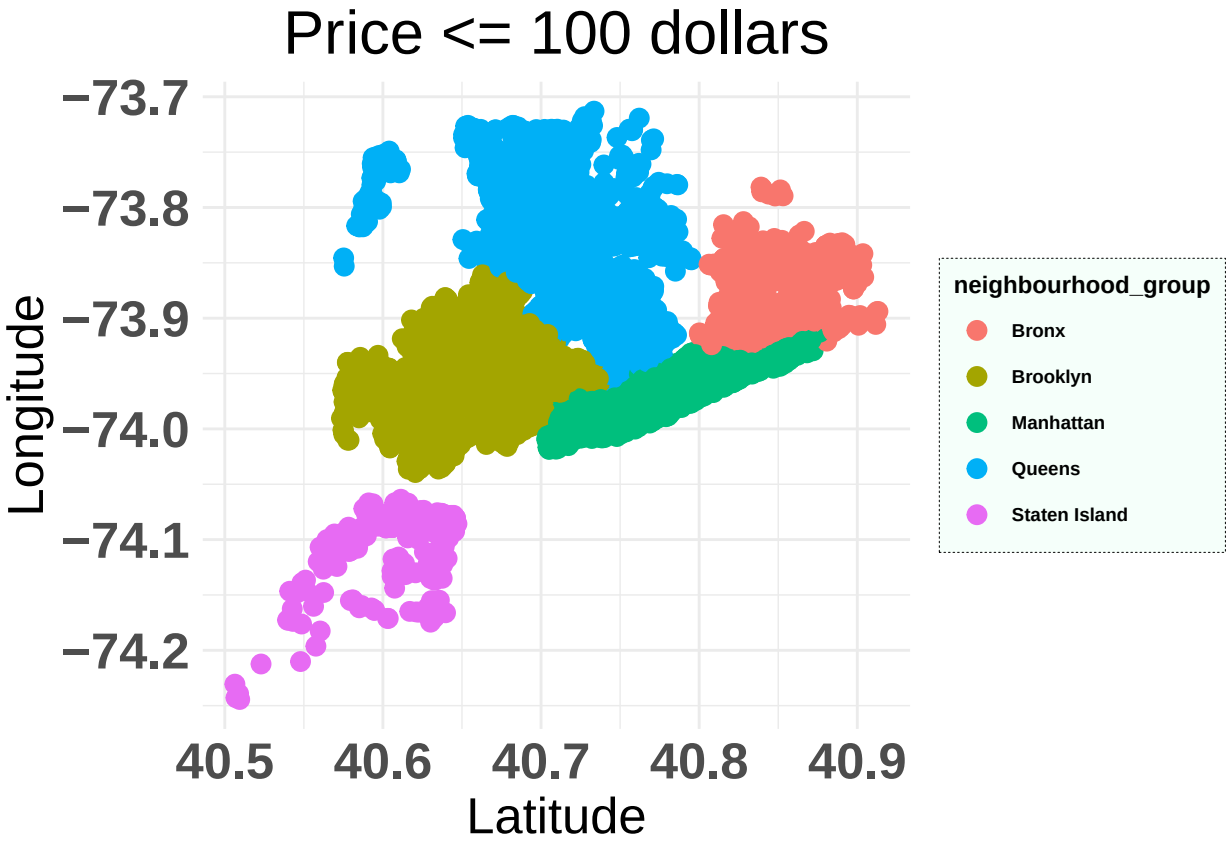

Longitude
−73.7
−73.8
−73.9
−74.0
−74.1
−74.2
40.5
40.6
40.7
40.8
40.9
Latitude
room_type
Entire home/apt
Private room
Shared room

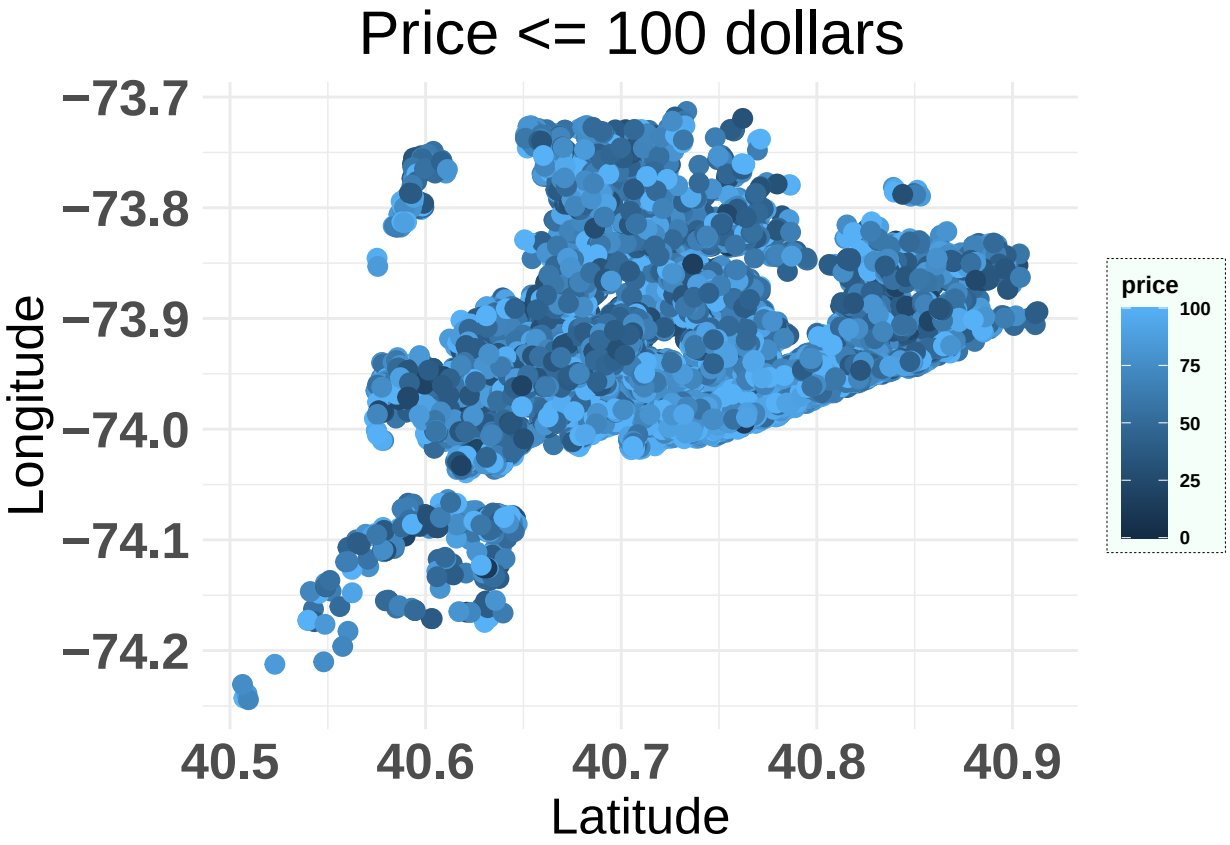


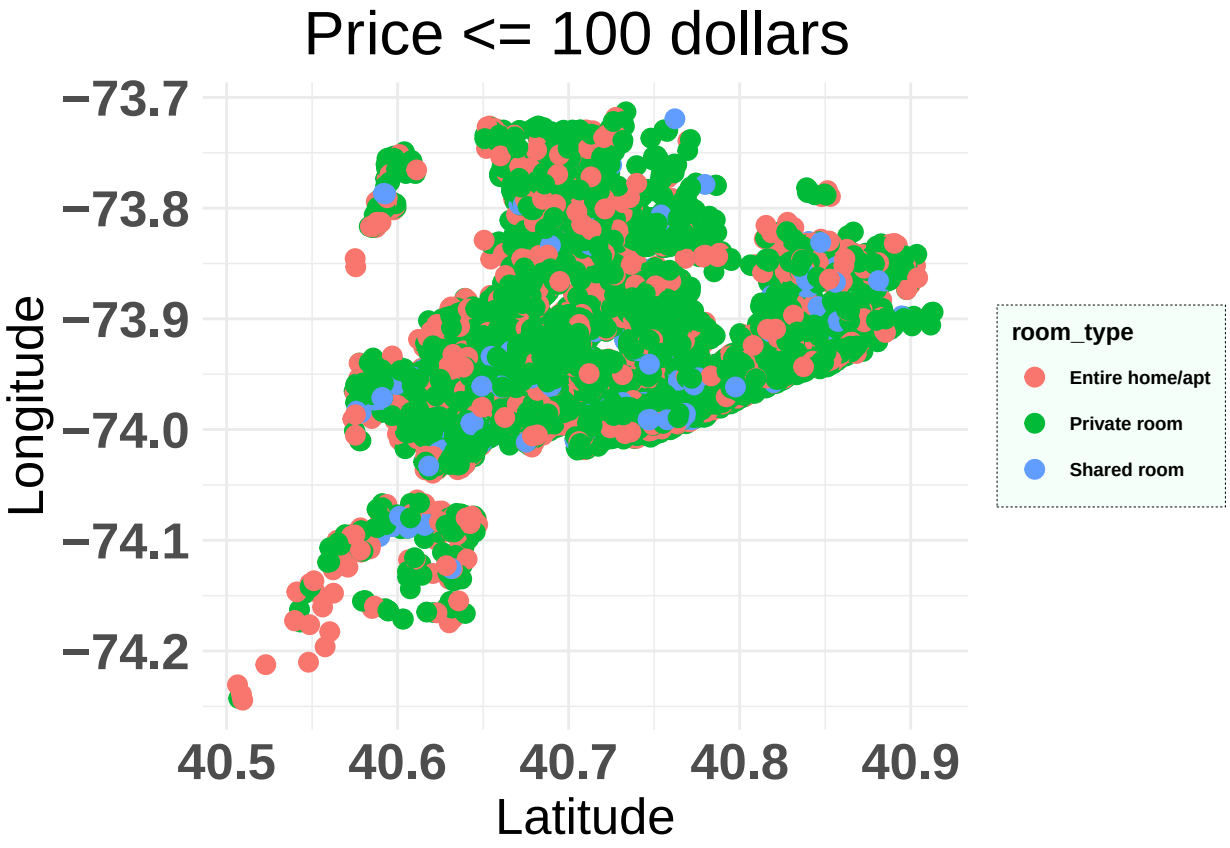

As our database prices are mostly below 100 dollars, we will filter the data to obtain only bookings below 100 dollars.

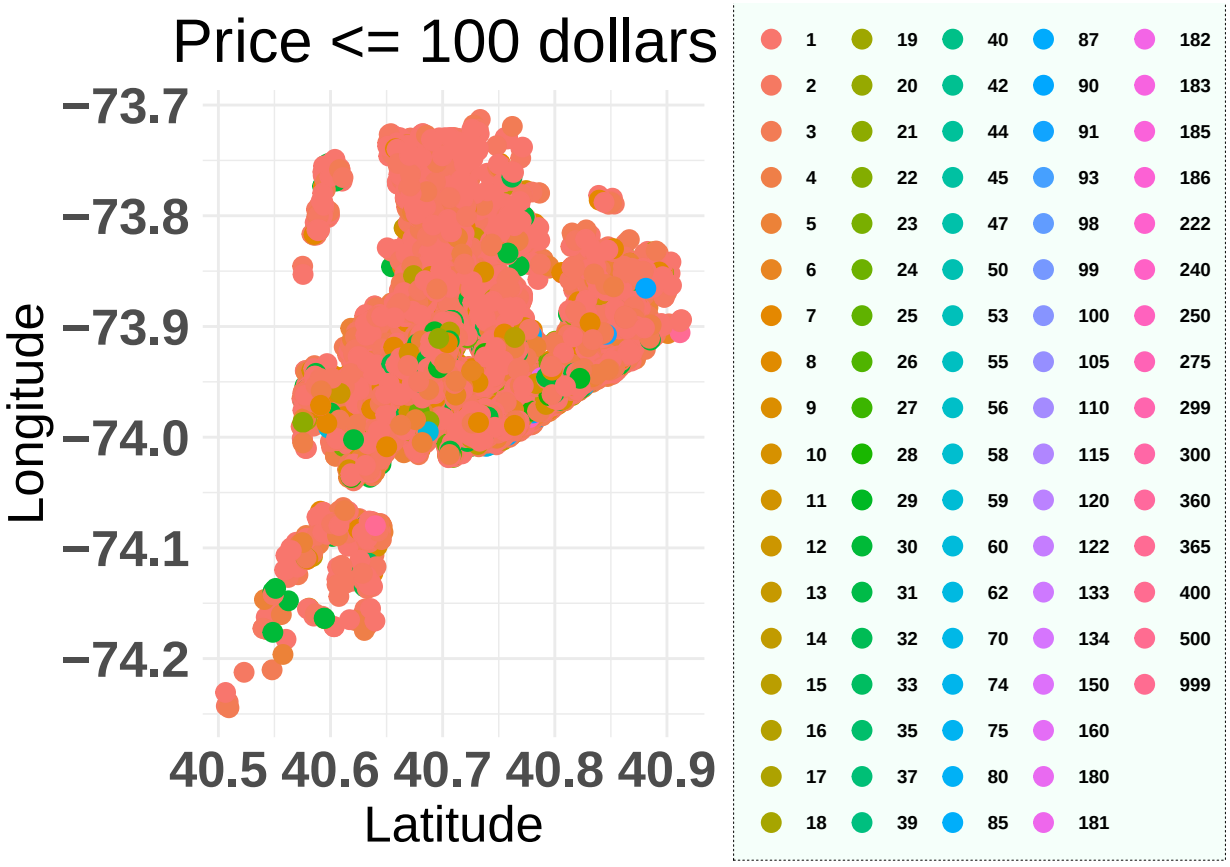


Understanding how this grouping behaves in relation to the coordinate.




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


Price <= 100 dollars
Longitude
−73.7
−73.8
−73.9
−74.0
−74.1
−74.2
40.5 40.6 40.7 40.8 40.9
Latitude
1 19 40 87 182
2 20 42 90 183
3 21 44 91 185
4 22 45 93 186
5 23 47 98 222
6 24 50 99 240
7 25 53 100 250
8 26 55 105 275
9 27 56 110 299
10 28 58 115 300
11 29 59 120 360
12 30 60 122 365
13 31 62 133 400
14 32 70 134 500
15 33 74 150 999
16 35 75 160
17 37 80 180
18 39 85 181

# 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 ...
```

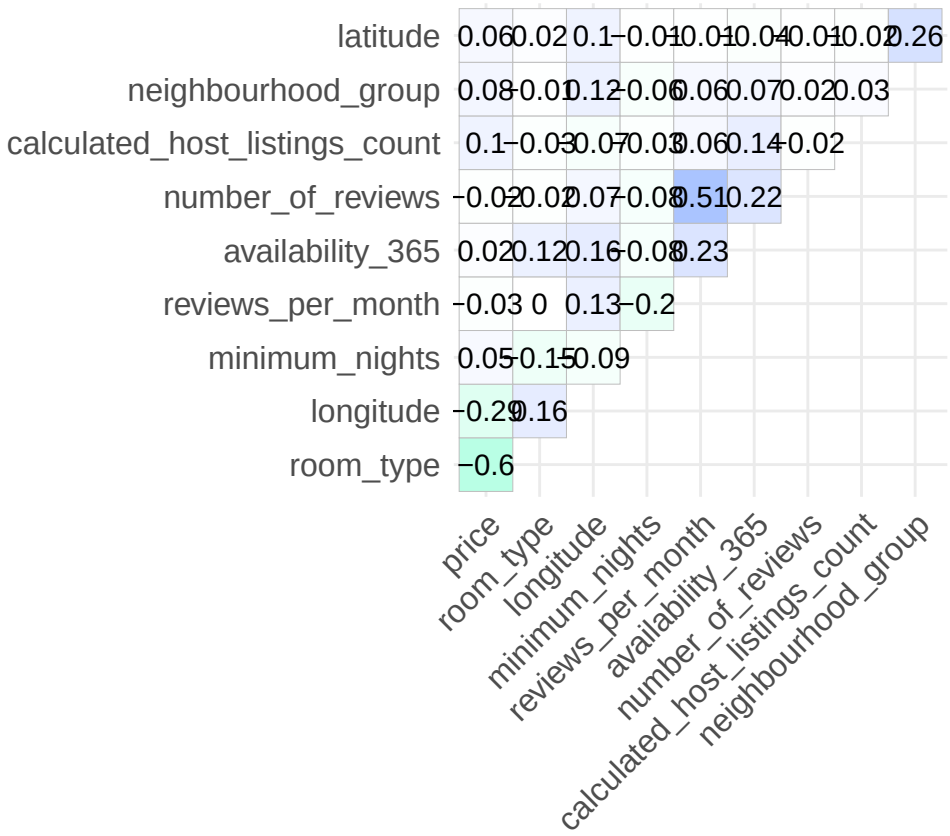
```
##   price neighbourhood_group latitude longitude       room_type minimum_nights
## 1   149            Brooklyn 40.64749 -73.97237    Private room              1
## 2   225           Manhattan 40.75362 -73.98377 Entire home/apt              1
## 3   150           Manhattan 40.80902 -73.94190    Private 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%

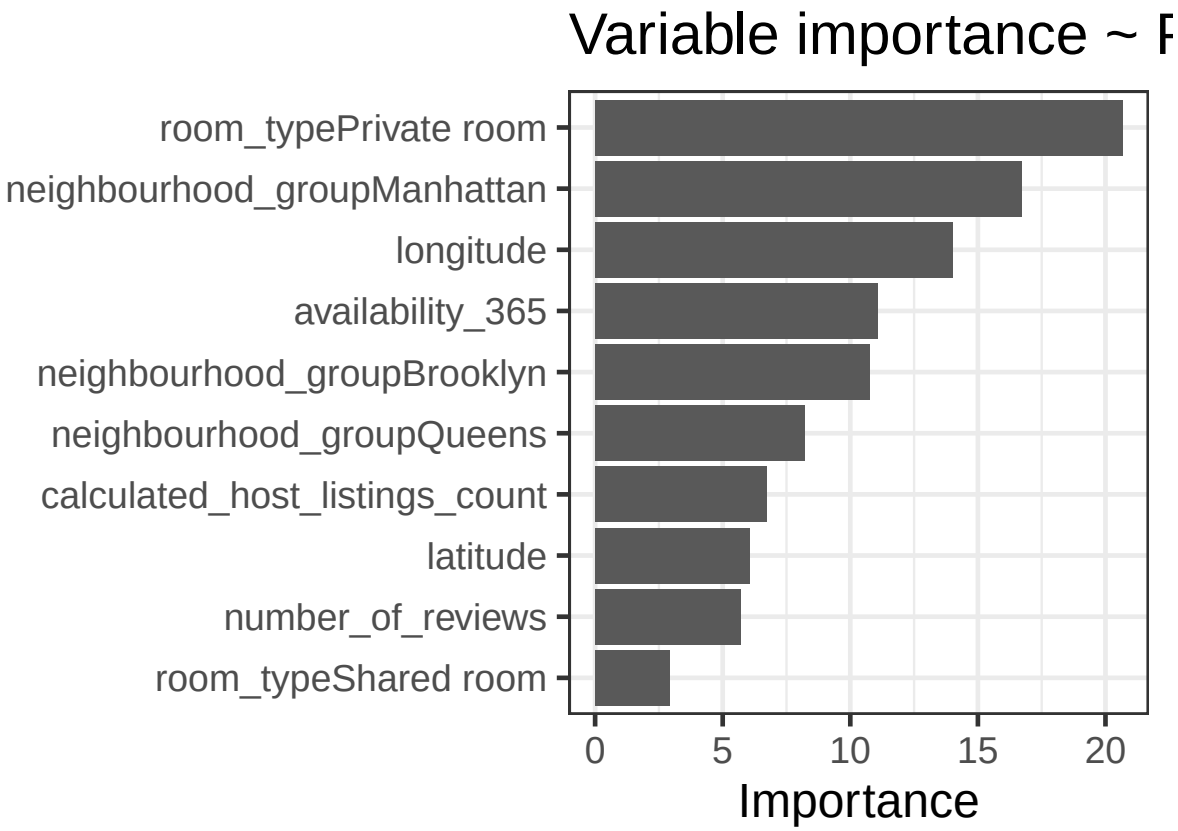
Trying Different Methods to Predict the price of Airbnb listings.

#### 4.0.1 Linear Regression - Math Model

Mean Absolute Error

```
## [1] 74.712
```

### 4.1 Partial Least-Squares Regression (PLS)




Mean Absolute Error

```
## [1] 72.805
```

### 4.2 Boosted Generalized Linear Model

Mean Absolute Error

```
## [1] 67.723
```

### 4.3 Pruned Tree Models

Mean Absolute Error Before Pruning

```
## [1] 70.853
```

Mean Absolute Error After Pruining

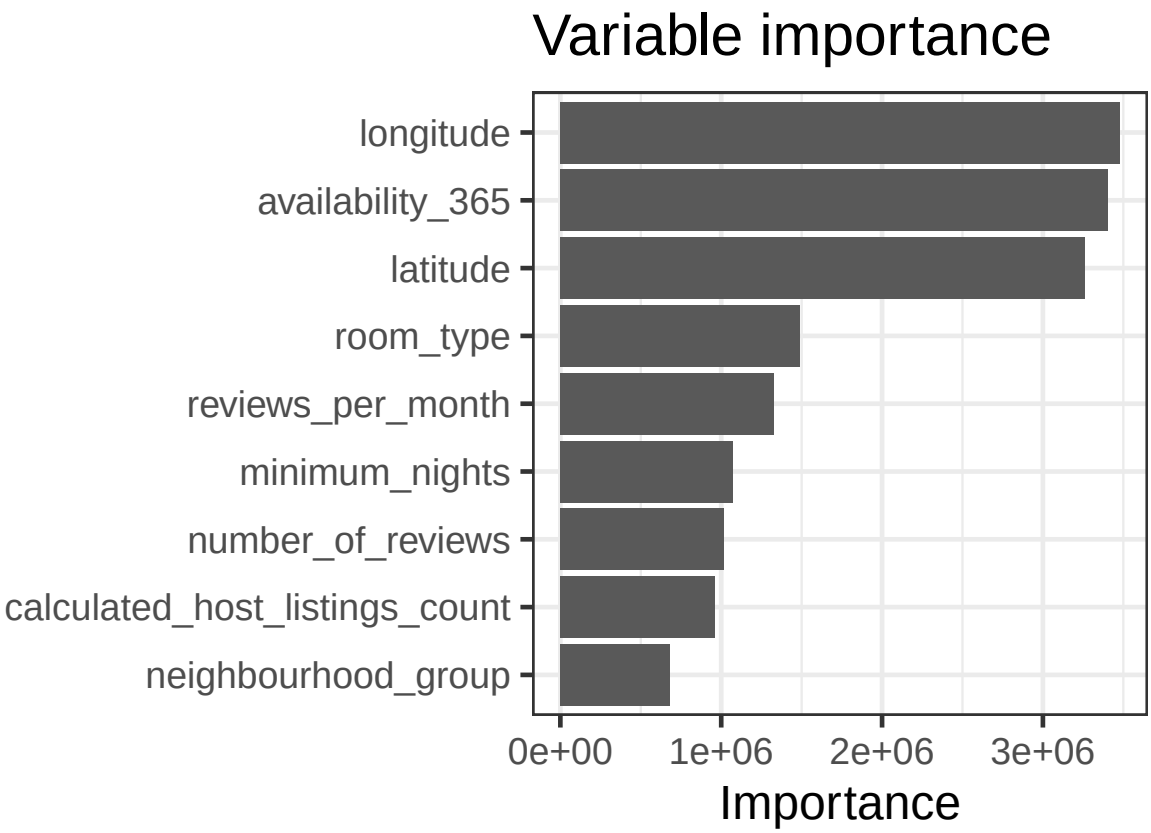
```
## [1] 89.682
```

### 4.4 Bagged CART

Mean Absolute Error

```
## [1] 67.478
```

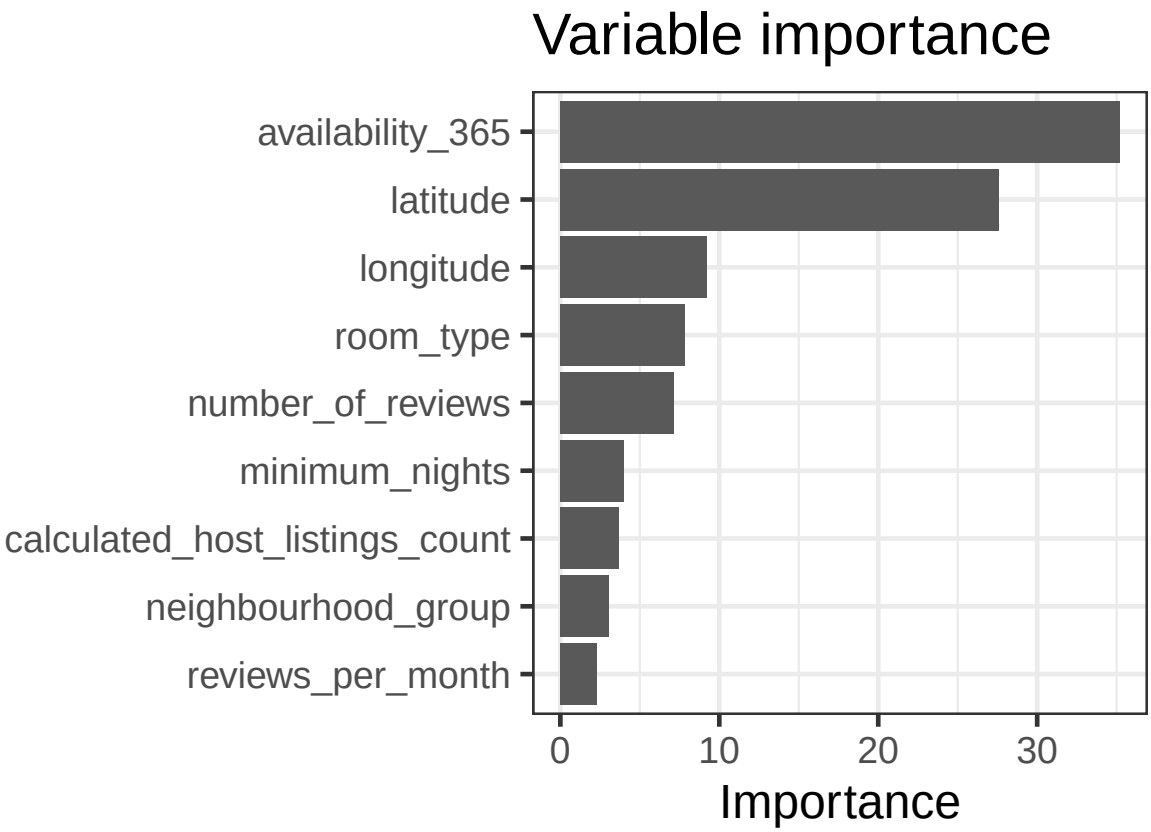
### 4.5 Random Forest




Mean Absolute Error

```
## [1] 55.438
```

### 4.6 Stochastic Gradient Boosting




Mean Absolute Error

```
## [1] 70.125
```

### 4.7 K-Nearest Neighbour

Mean Absolute Error

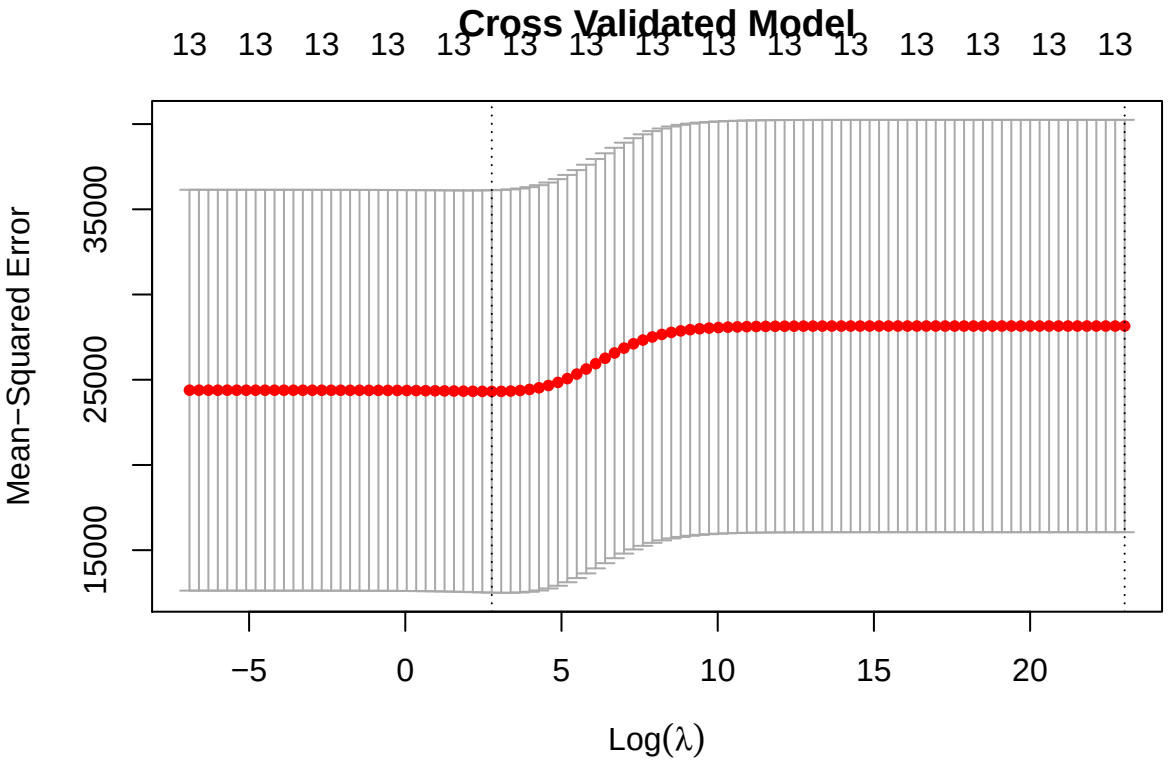
```
## [1] 67.286
```

### 4.8 Bagged Multivariate Adaptive Regression Spline

Mean Absolute Error

```
## [1] 65.161
```

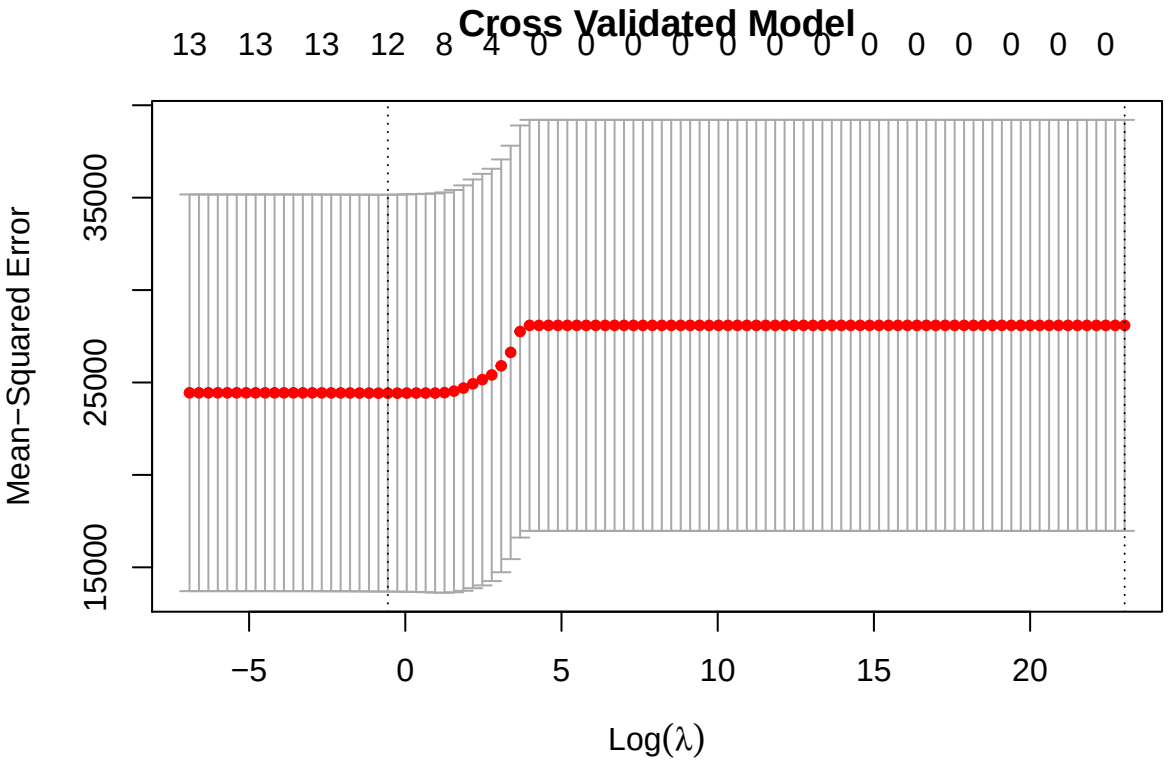
### 4.9 Ridge Regression




Mean Absolute Error

```
## [1] 72.459
```

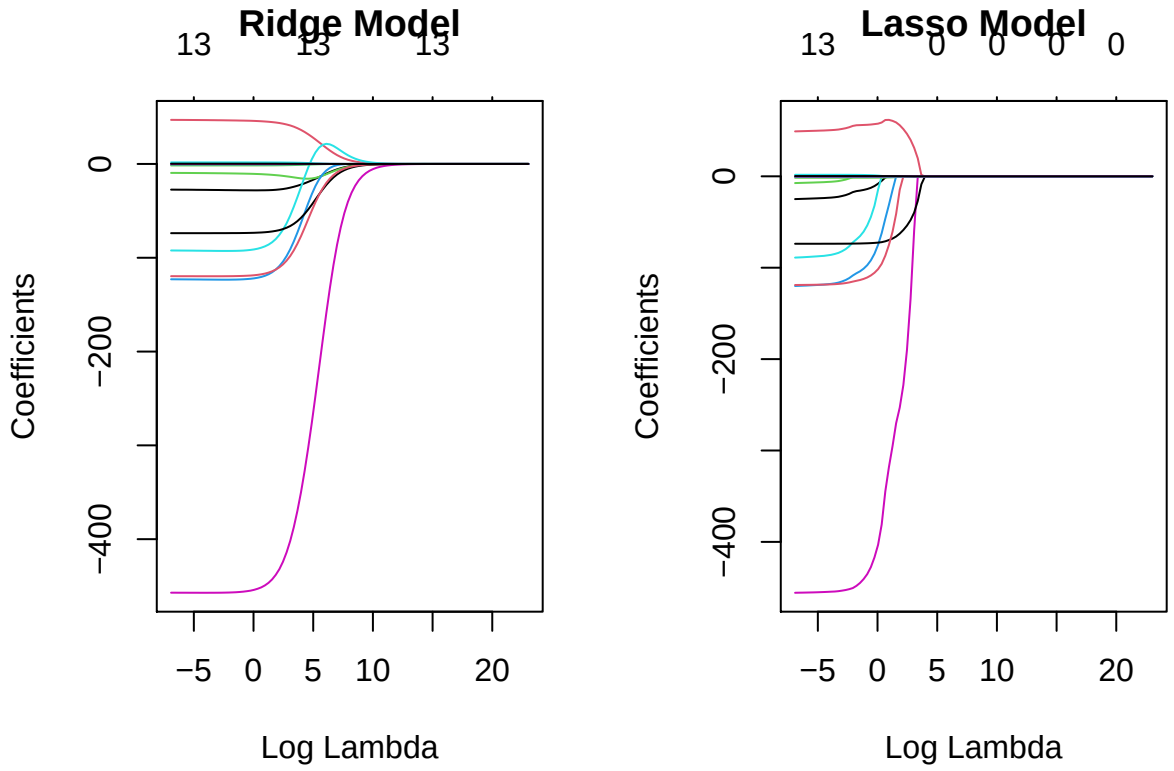
### 4.10 Lasso Regression




Mean Absolute Error

```
## [1] 73.492
```

### 4.11 Visualize the Ridge & Lasso Models




### 4.12 Support Vector Machines with Linear Kernel

Mean Absolute Error

```
## [1] 62.012
```

### 4.13 Support Vector Machines Radial Basis Function Kernel

Mean Absolute Error

```
## [1] 60.04
```

### 4.14 Support Vector Tuned Model 1

Mean Absolute Error

```
## [1] 57.715
```

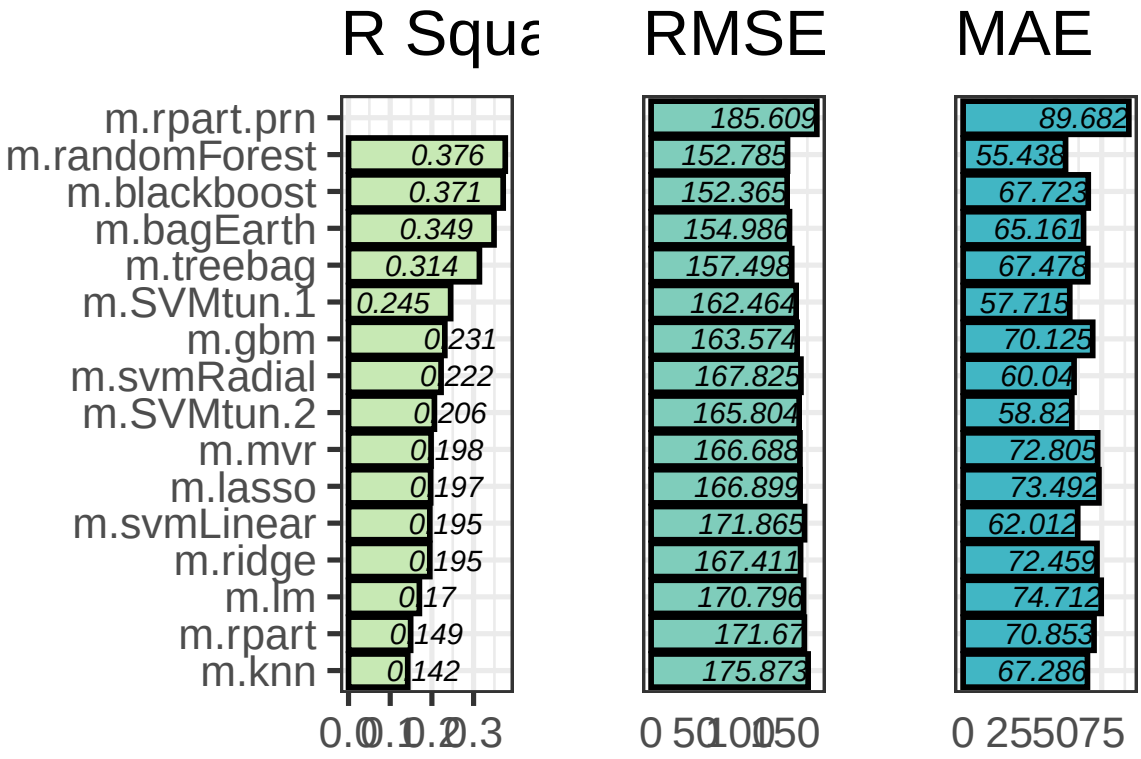
### 4.15 Support Vector Tuned Model 2

Mean Absolute Error

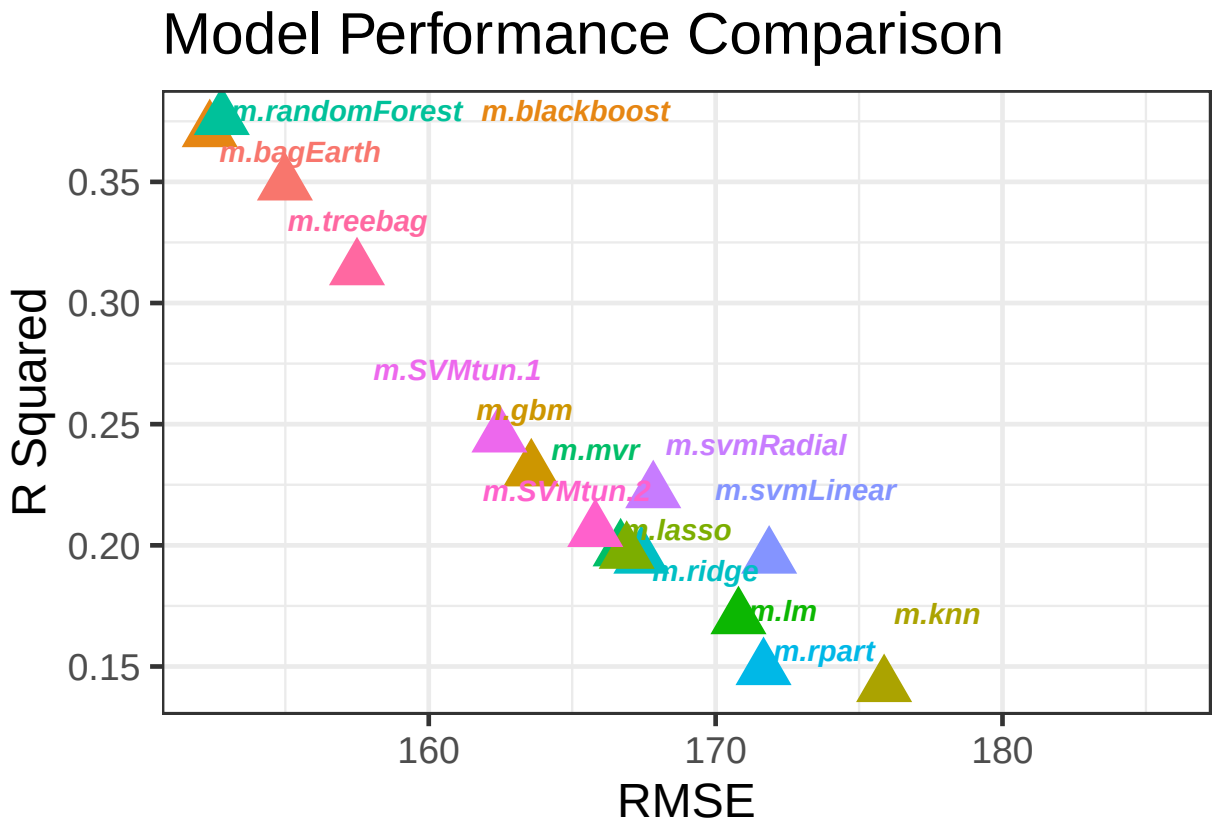
```
## [1] 58.82
```

# 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 |
|---|---|---|
| 55.438 | 152.785 | 0.376 |

## 6 Conclusion

The objective of this project was to use machine learning models to predict the Airbnb Prices and understand what features were important to explain the transit. In this report, we tried many models, created some new features, we selected Random Forest model betcause it has the best performance. The final model obtained an RMSE of 161.849 and MAE of 46.501. The most important feature to explain price is neighbourhood group .

## 7 References

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

https://medium.com/airbnb-engineering/categorizing-listing-photos-at-airbnb-f9483f3ab7e3

https://www.kaggle.com/chamodiperera/price-suggestion-for-airbnb-hosts-nyc-i

http://inseaddataanalytics.github.io/INSEADAnalytics/groupprojects/January2018FBL/Airbnb_Pricing_TeamR_MASTER.HTML