Airbnb in NYC (2019)

Exploratory Data Analysis
&
Smart Price Prediction

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Data Overview

- 48,895 observations, 16 variables (before cleaning)
- 47,709 observations, 12 variables
- Numerical Variables:

  latitude: latitude coordinates, **longitude:** longitude coordinates, **price:** price in dollars, **minimum_nights:** amount of nights minimum, **number_of_reviews:** number of reviews, **reviews_per_month:** number of reviews per month, **calculated_host_listings_count:** amount of listing per host, **availability_365:** number of days when listing is available for booking

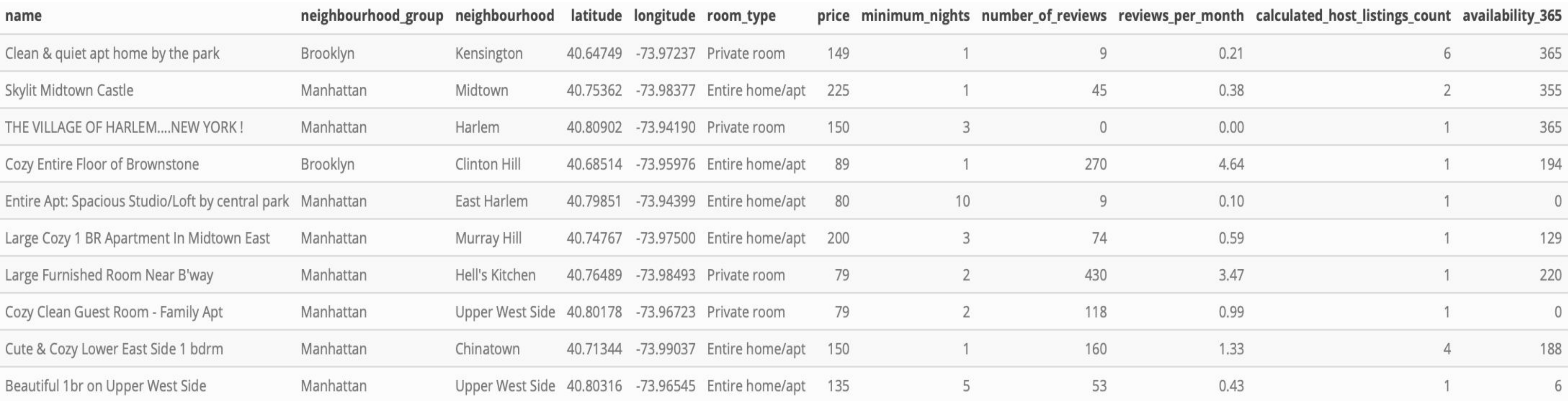
- Categorical Variables:

  name: name of the listing, **neighbourhood_group:** location, **neighbourhood:** area, **room_type:** listing space type

Data Cleaning

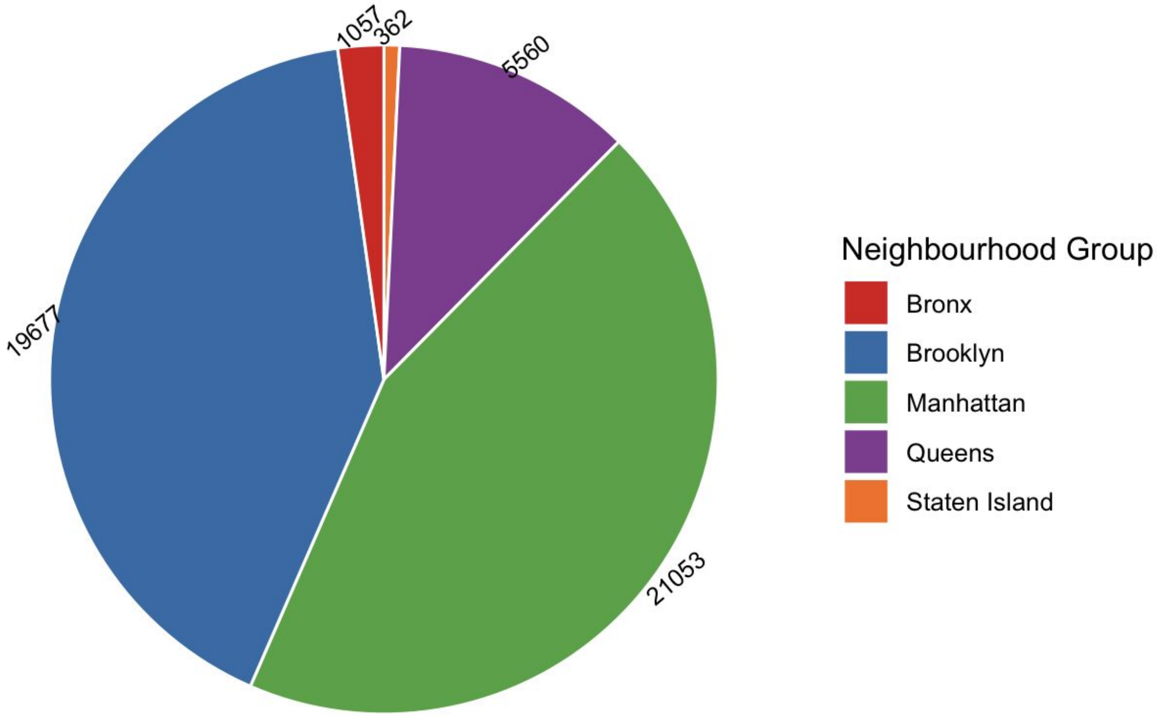
- 48,895 observations, 16 variables
- Procedures:
  - Deal with missing variables (replace or delete the observation)
  - Remove uninformative variables (id, host_id, host_name)
  - Remove outliers (price out of 99.5% interval)
  - Change categorical variables into factors

Data Overview

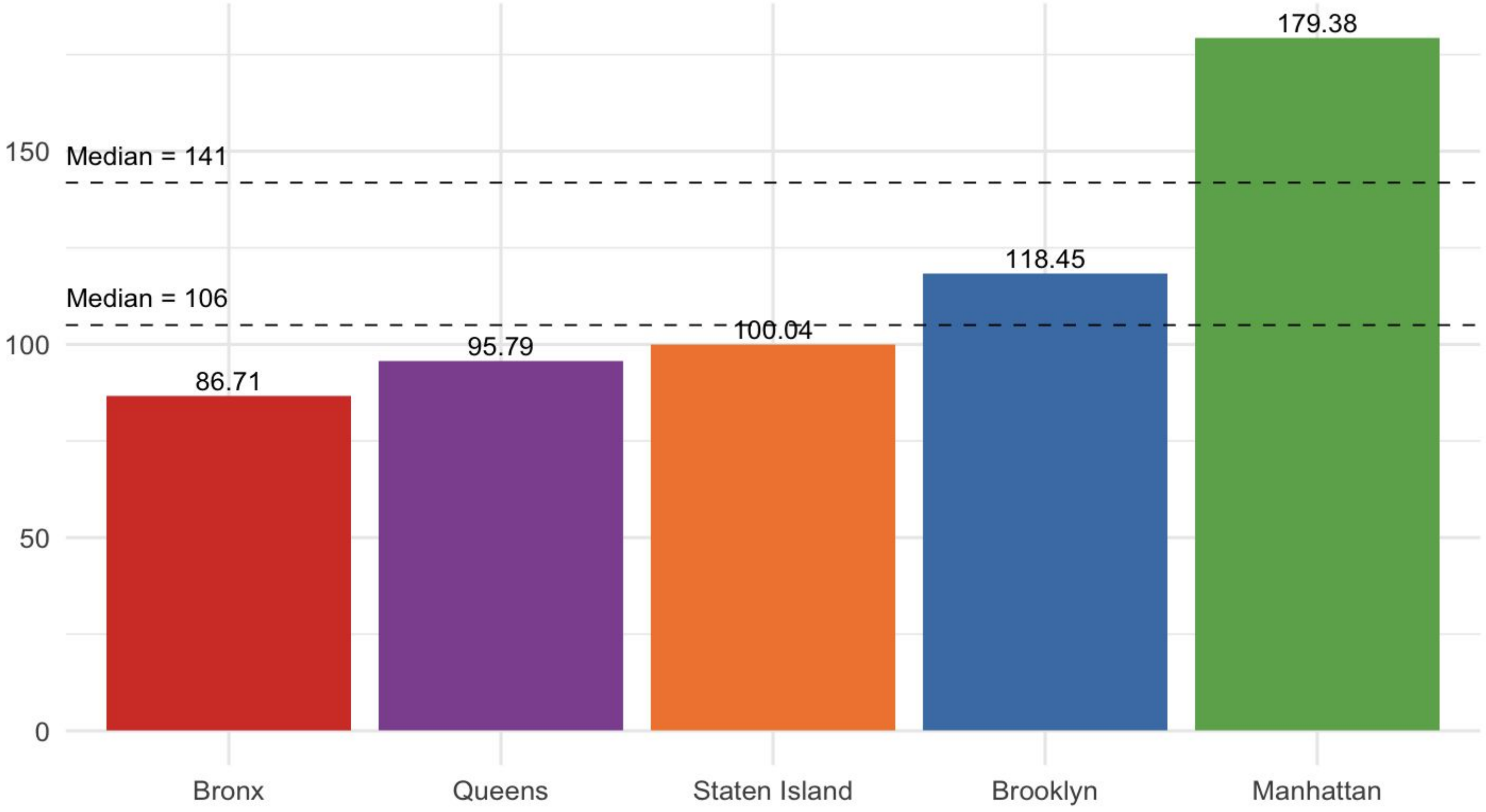


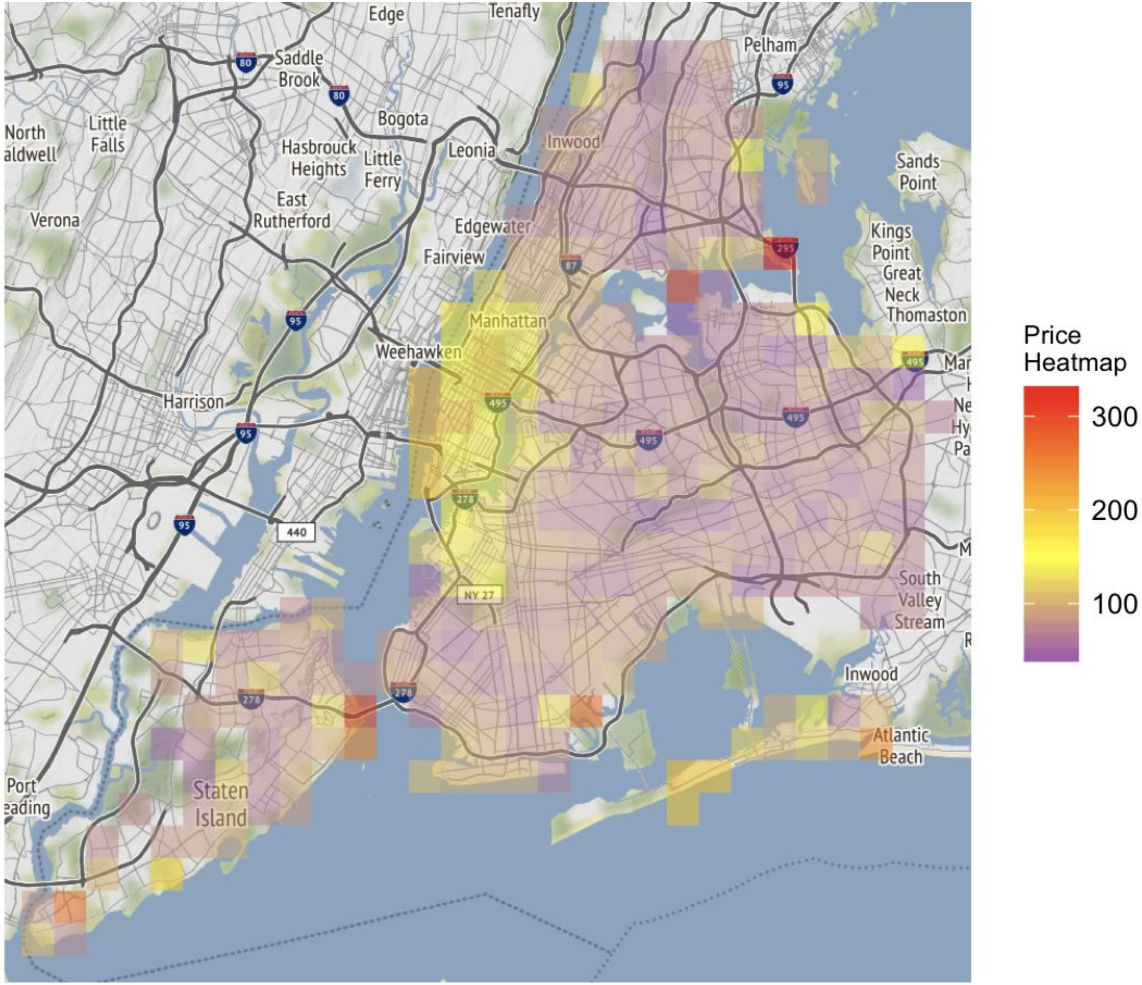
name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availability_365
Clean & quiet apt home by the park	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	1	9	0.21	6	365
Skylit Midtown Castle	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	1	45	0.38	2	355
THE VILLAGE OF HARLEM....NEW YORK !	Manhattan	Harlem	40.80902	-73.94190	Private room	150	3	0	0.00	1	365
Cozy Entire Floor of Brownstone	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	1	270	4.64	1	194
Entire Apt: Spacious Studio/Loft by central park	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	10	9	0.10	1	0
Large Cozy 1 BR Apartment In Midtown East	Manhattan	Murray Hill	40.74767	-73.97500	Entire home/apt	200	3	74	0.59	1	129
Large Furnished Room Near B'way	Manhattan	Hell's Kitchen	40.76489	-73.98493	Private room	79	2	430	3.47	1	220
Cozy Clean Guest Room - Family Apt	Manhattan	Upper West Side	40.80178	-73.96723	Private room	79	2	118	0.99	1	0
Cute & Cozy Lower East Side 1 bdrm	Manhattan	Chinatown	40.71344	-73.99037	Entire home/apt	150	1	160	1.33	4	188
Beautiful 1br on Upper West Side	Manhattan	Upper West Side	40.80316	-73.96545	Entire home/apt	135	5	53	0.43	1	6

Number of Listings in 5 Neighbourhood Groups



Average Price Per Night by Neighbourhood Group

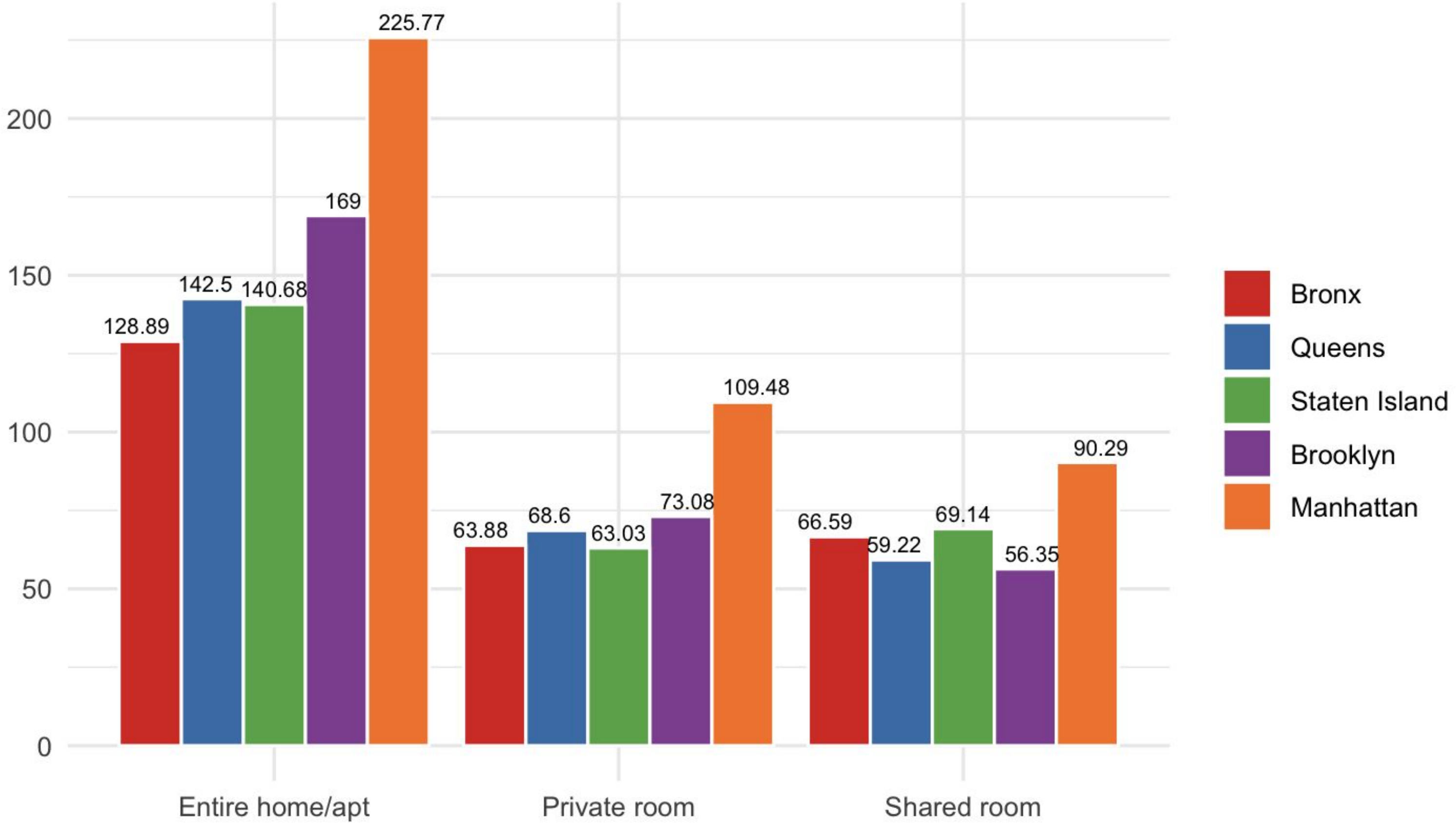




- Listings near Manhattan Midtown, west village area tend to be more expensive.

- Other areas have some stays more expensive than usual price, and most of them are near the gulf area

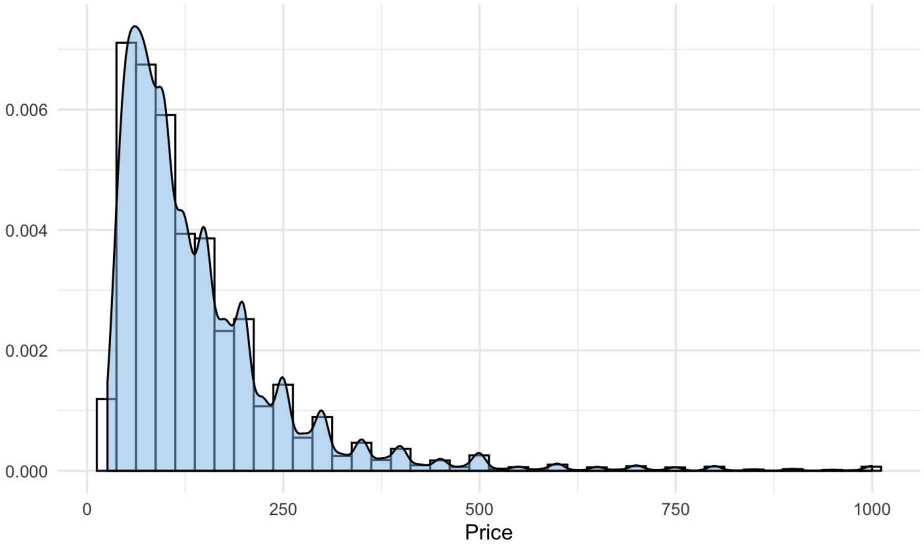
Average Price by Neighbourhood and Room Type



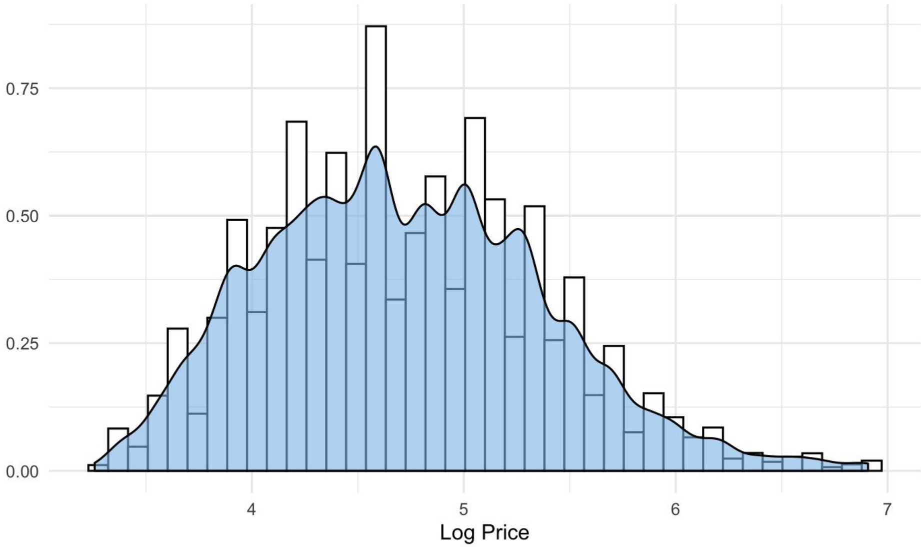
Multiple Linear Regression for Price Prediction

- Log transformation on predicted variable (price)

Density Plot of Price



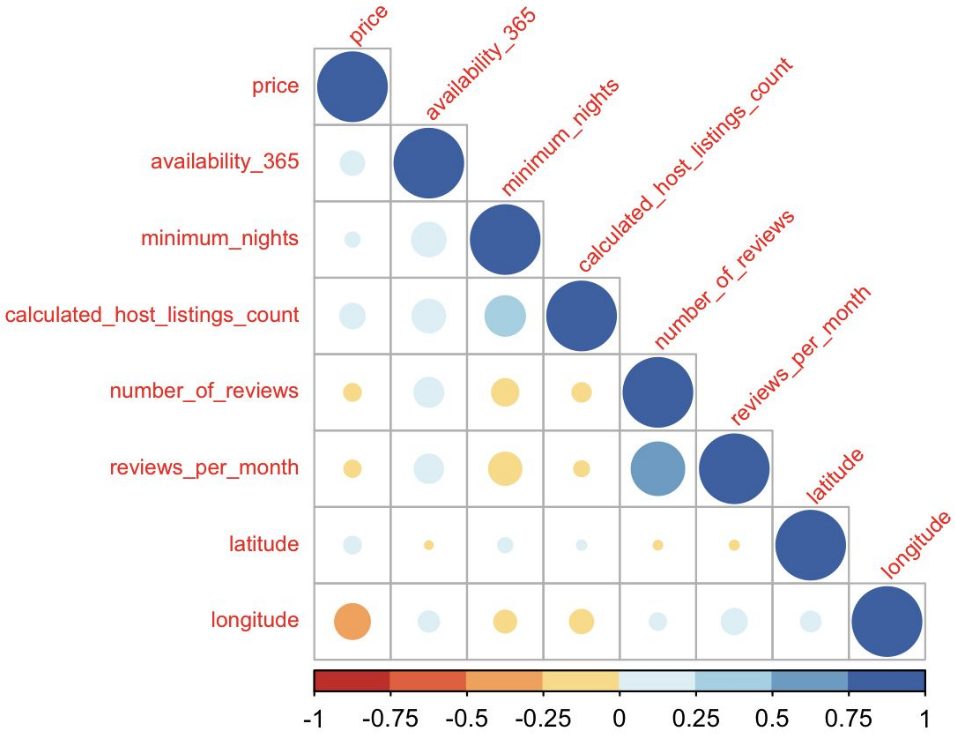
Density Plot of Price after Transformation



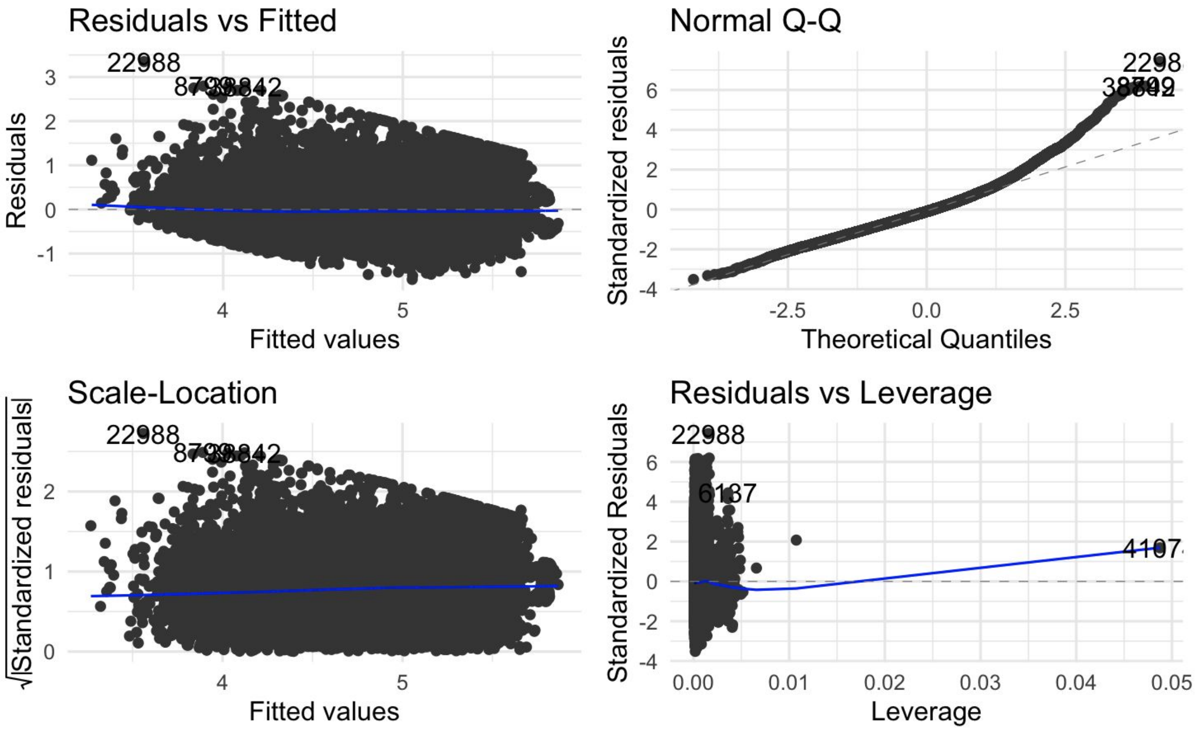
Multiple Linear Regression for Price Prediction

- Model building & variables selection

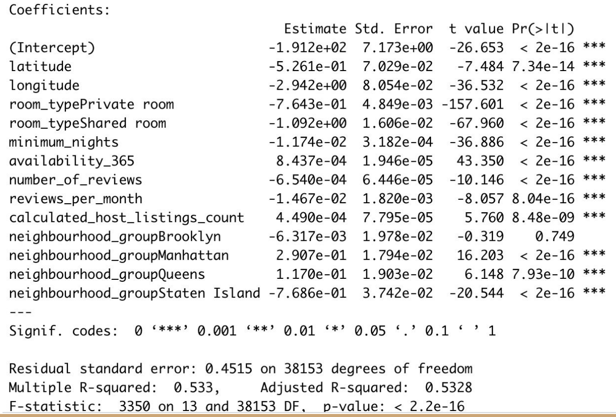
1. Split data into training (80%) and testing (20%)
2. Build a full model with training data: lm(log_price ~ latitude + longitude + room_type + minimum_nights + availability_365 + number_of_reviews + reviews_per_month + calculated_host_listings_count + neighbourhood_group, data = train)
3. Stepwise model selection from both directions, the result gives back the full model



Diagnostic Plots and Model Prediction Result



1. Diagnostic plots look fine
2. Adjusted R² of training data is 0.5328
3. Adjusted R² of testing data is 0.5316
4. All predictors are significant expect neighbourhood_groupBrooklyn



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Coefficients:
                              Estimate Std. Error  t value Pr(>|t|)    
(Intercept)                 -1.912e+02  7.173e+00  -26.653  < 2e-16 ***
latitude                    -5.261e-01  7.029e-02   -7.484 7.34e-14 ***
longitude                   -2.942e+00  8.054e-02  -36.532  < 2e-16 ***
room_typePrivate room       -7.643e-01  4.849e-03 -157.601  < 2e-16 ***
room_typeShared room        -1.092e+00  1.606e-02  -67.960  < 2e-16 ***
minimum_nights              -1.174e-02  3.182e-04  -36.886  < 2e-16 ***
availability_365             8.437e-04  1.946e-05   43.350  < 2e-16 ***
number_of_reviews           -6.540e-04  6.446e-05  -10.146  < 2e-16 ***
reviews_per_month           -1.467e-02  1.820e-03   -8.057 8.04e-16 ***
calculated_host_listings_count  4.490e-04  7.795e-05    5.760 8.48e-09 ***
neighbourhood_groupBrooklyn -6.317e-03  1.978e-02   -0.319    0.749    
neighbourhood_groupManhattan  2.907e-01  1.794e-02   16.203  < 2e-16 ***
neighbourhood_groupQueens    1.170e-01  1.903e-02    6.148 7.93e-10 ***
neighbourhood_groupStaten Island -7.686e-01  3.742e-02  -20.544  < 2e-16 ***
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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4515 on 38153 degrees of freedom
Multiple R-squared:  0.533,	Adjusted R-squared:  0.5328 
F-statistic:  3350 on 13 and 38153 DF,  p-value: < 2.2e-16
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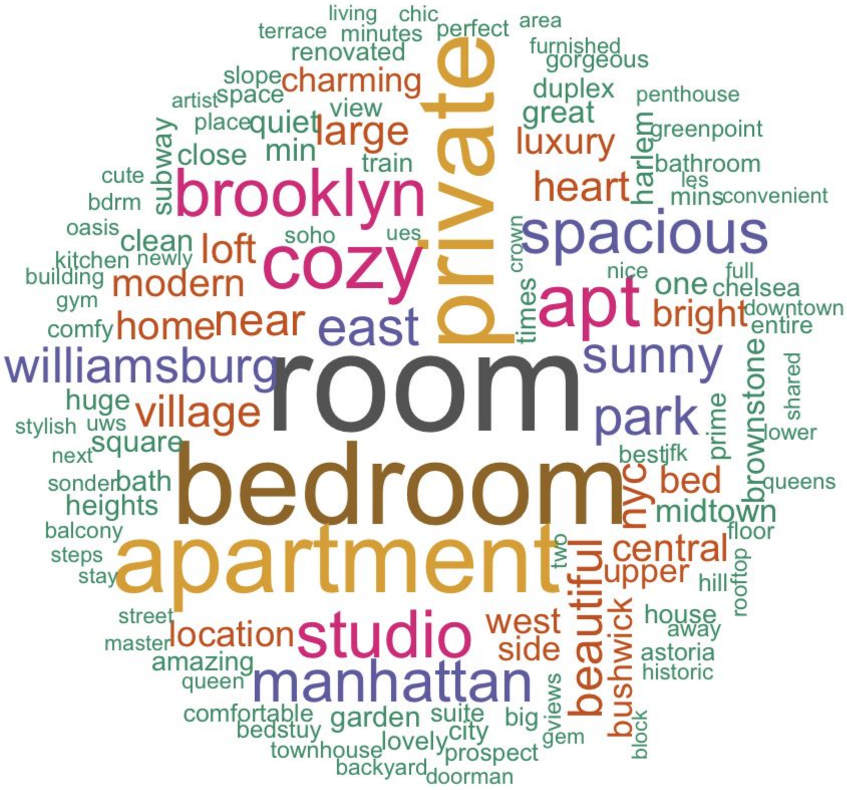
Limitations and Future Work

1. Consider interaction terms
2. Try more models (ridge, lasso, knn, etc.)
3. Try dimension reduction
4. Cross validation
5. Can do a time series analysis with more data from more years
6. Can do a text mining analysis (for example, topic modeling to create new predictors)
7. Can access external data (area criminal rates, transportation, etc.) to better estimate the price



Thank you!
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Happy Wednesday!