Exploratory Analysis of Data for Airbnb Listings in NYC

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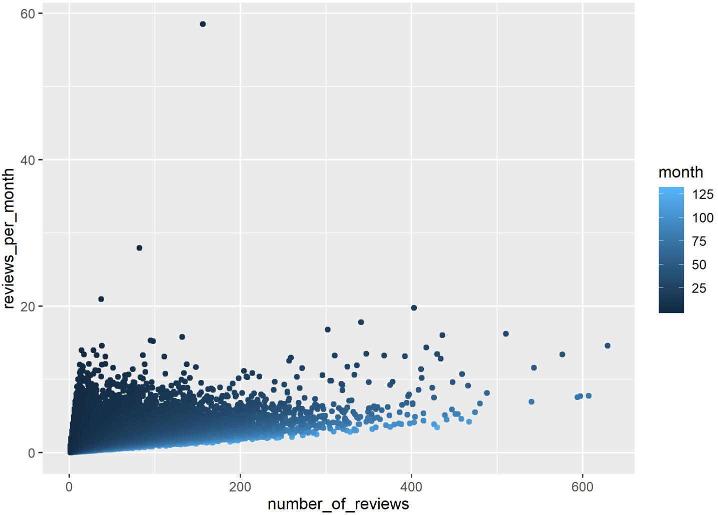
Introduction

- Data: Airbnb New York City open data collected from 2019, with 48,895 listings and 16 variables.
- Goals:
  - Identify most influential factors for price/popularity
  - Examine heterogeneity across boroughs and neighbourhoods
  - Recommend best location and name for airbnb

Data Processing

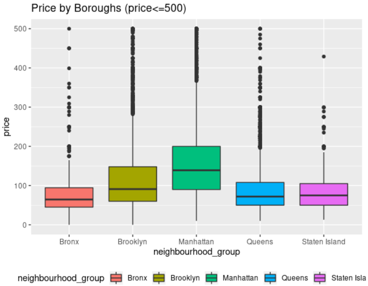
- Remove 14 observations with *minimum_nights* > 365
- *Price*: the lowest non-zero value is 10, added 5 to 0's
- *Reviews per Month*: missing values are set to 0 (last review dates are missing and total number of reviews are 0)
- *Last Review*: group by years from 2019 (e.g. 2019 -$>$ 0; 2018 -$>$ 1, etc.)
- *availability_365*: create a new variable *available_spec* to indicate whether the value is 0

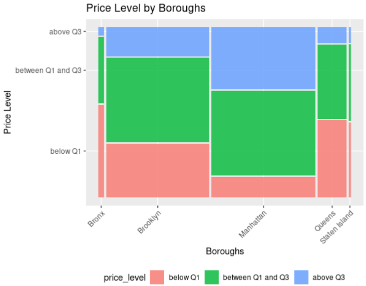
What is a Valid Metric for Popularity?



- **Monthly reviews** adjusts for the history of a listing (albeit not perfectly)

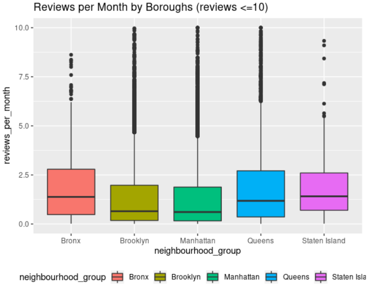
Heterogeneity of Price across Boroughs

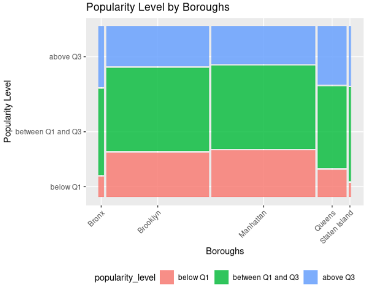




- Generate 3 price levels:
  "below Q1", "between Q1 and Q3", "above Q3"
- Pearson's Chi-squared test: p-value $< 2.2e\text{-}16$

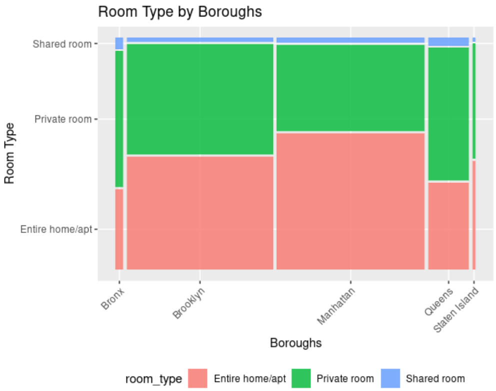
Heterogeneity of Popularity across Boroughs





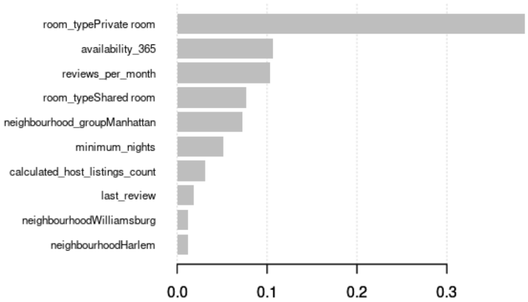
- Generate 3 popularity levels:
  "below Q1", "between Q1 and Q3", "above Q3"
- Pearson's Chi-squared test: p-value $<$ 2.2e-16

Heterogeneity of Room type across Boroughs



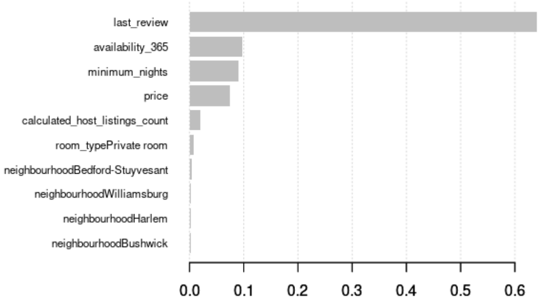
- Pearson's Chi-squared test: p-value $< 2.2e\text{-}16$

Price: XGBoost for Important Variables



- The most influential factors for price of airbnb include: room type (private room), availability, monthly reviews, boroughs (Manhattan), etc.

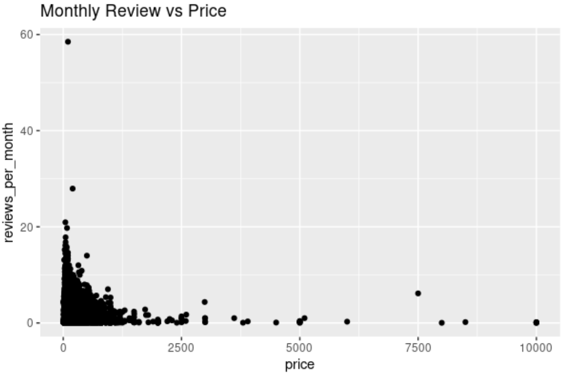
Popularity: XGBoost for Important Variables



- The most influential factors for popularity of airbnb include: last review (in years from 2019), availability, minimum nights, price, etc.

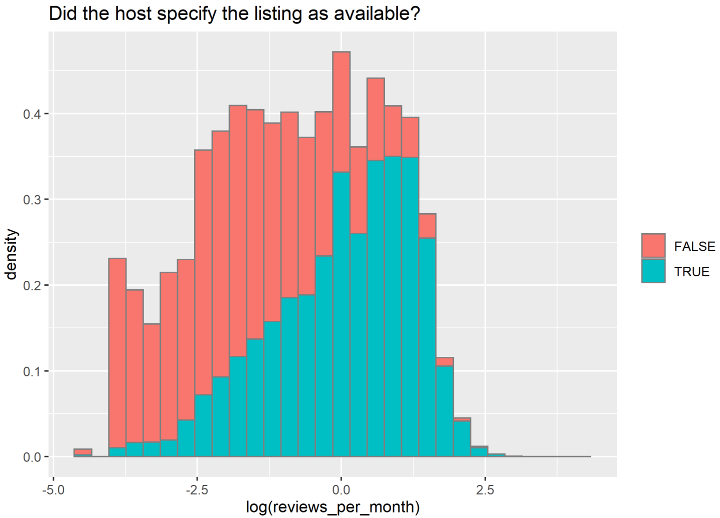
EDA - Price and Popularity

- From XGBoost outputs, price and popularity are closely related, both being an important variable of the other.
- The plot below shows a negative correlation between them on *log-scale*:



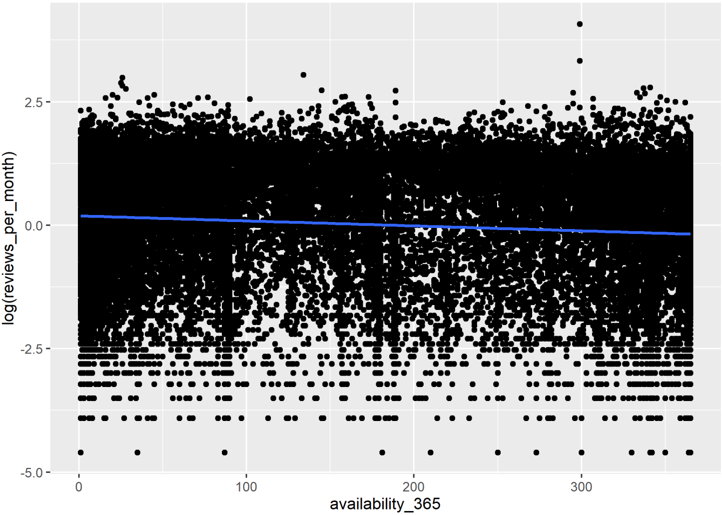
- We may consider model them as bivariate reponse.

Unreliability of Availability Feature



On average, it seems the listings that are "temporarily unavailable" (zero availability) have lower monthly review rate...

Unreliability of Availability Feature



. . . but *conditioned on* non-zero availability, the association is less obvious (can be negative?).

Modeling: Bivariate Mixed Effects Regression

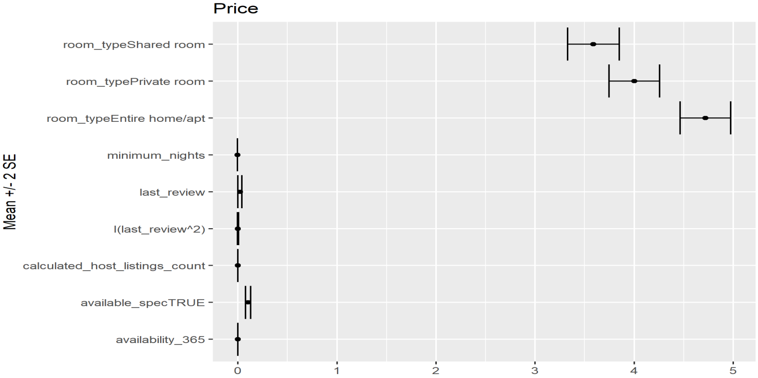
- Varying intercept model: For the i-th listing in neighborhood j, within borough k,

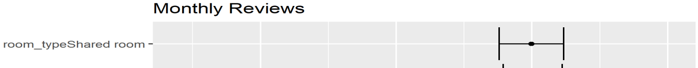
$$\begin{pmatrix} \text{Price}_{k[j[i]]} \\ \text{Monthly review}_{k[j[i]]} \end{pmatrix} = \begin{pmatrix} \beta_1^T \mathbf{X}_i \\ \beta_2^T \mathbf{X}_i \end{pmatrix} + \boldsymbol{\eta}_{k[j]} + \boldsymbol{\theta}_j + \boldsymbol{\epsilon}_{k[j[i]]}.$$

- Quadratic term of the listing's age is included
- Observations with no reviews excluded (21% of the data)

What Are the Important Predictors for Price/Popularity?

- In terms of magnitude, not significance, **room type** for price, and **last review** for popularity
- Apartments > Pvt room > Shared room for price, and more popular if the listing is young





Estimates for Group Heterogeneities

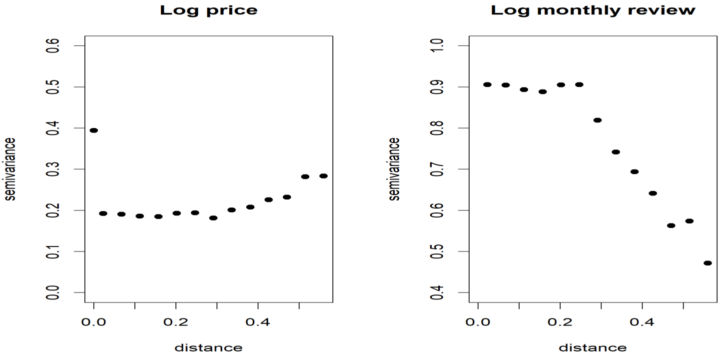
variableprice	variablereviews_per_month
0.03	-0.01
-0.01	0.04

variableprice	variablereviews_per_month
0.08	-0.02
-0.02	0.01

- Many significant coefficients can be swamped by the variability within/between different neighborhoods and boroughs
- Strong negative correlation between two random intercepts between boroughs (-0.76)

Examining Spatial Correlation of the Residuals

- Semivariograms: For location $\mathbf{s}_i$, estimate $\mathrm{Var}(Y(\mathbf{s}_i + d) - Y(\mathbf{s}_i))$ in increasing distance d.



- We observe large semivariogram for price when listings are extremely close, and **negative spatial correlation** for monthly review rates

Possible Insights

- When two listings are very close (identical coordinates), the market effect takes sway over all others. One potential customer is being sapped away from one listing to another.
- As a result, closer things have more dissimilar popularity measures. As distance increases, however, the effect becomes less severe and association between a listing's features and sales becomes noticeable.
- However, price is relatively "inelastic"; unless two listings are extremely close to each other, the hosts' pricing policy remains relatively indifferent to their neighbors, adjusted for other features of a listing.
- Hence, we observe no evidence of spatial correlation, conditional on what neighborhood a listing belongs to, except in extreme proximity (high semivariogram).

Text Analysis for Listing Names

(. . . Phuc's analysis. . .)

Limitations and Further Work

- Including varying slopes calls for strong shrinkage
- Care is needed for spatial covariance models: "soft" adjacency matrix for neighborhoods/boroughs, negative autocorrelation, etc.
- Missing data/latent space model for `availability_365`
- Nonparametric approach for bivariate model