Exploratory Analysis of Data for Airbnb Listings in NYC

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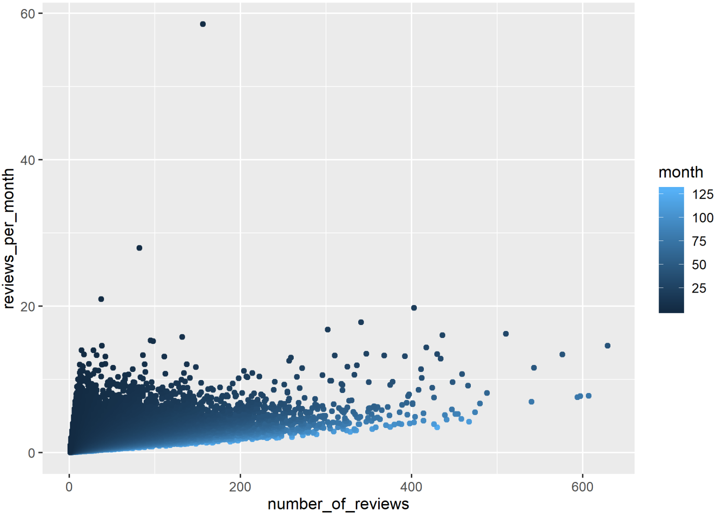
Introduction

- 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

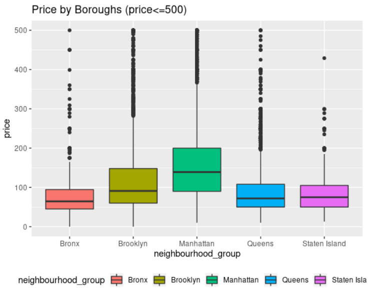
- Remove 14 observations with *minimum_nights* > 365
- *Price*: the lowest non-zero value is 10, added 5 to 0's
- *Reviews per Month*: missing values are set to 0 (last review dates are missing and total number of reviews are 0)
- *Last Review*: group by years from 2019 (e.g. 2019 -$>$ 0; 2018 -$>$ 1,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

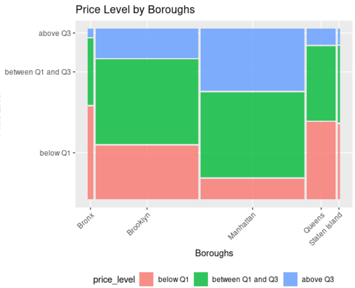
What is a Valid Metric for Popularity?



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

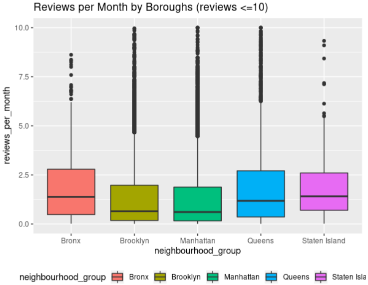
Heterogeneity of Price across Boroughs

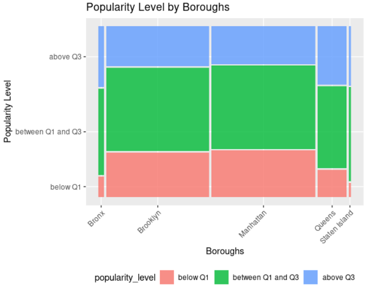




- Generate 3 price levels:
  "below Q1", "between Q1 and Q3", "above Q3"
- Pearson's Chi-squared test: p-value $< 2.2e\text{-}16$

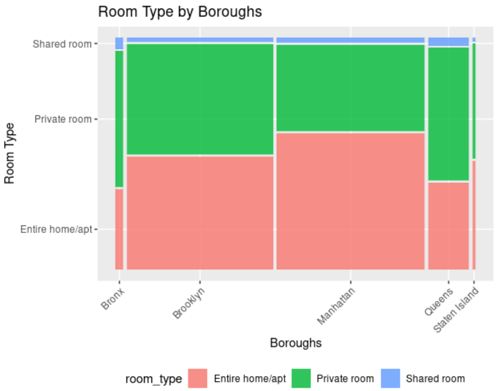
Heterogeneity of Popularity across Boroughs





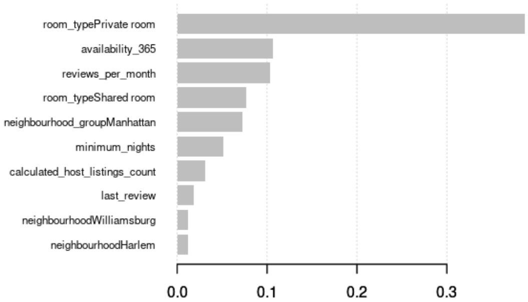
- Generate 3 popularity levels:
  "below Q1", "between Q1 and Q3", "above Q3"
- Pearson's Chi-squared test: p-value $< 2.2e\text{-}16$

Heterogeneity of Room type across Boroughs



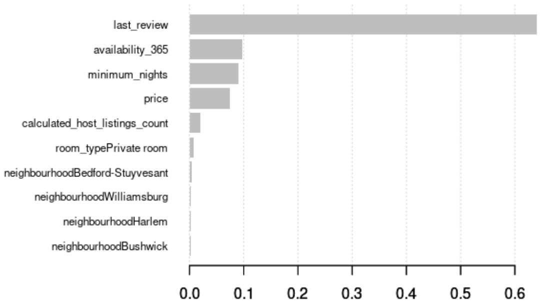
- Pearson's Chi-squared test: p-value $< 2.2\text{e-}16$

Price: XGBoost for Important Variables



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

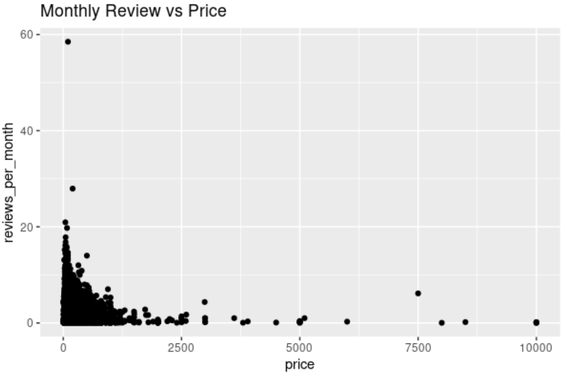
Popularity: XGBoost for Important Variables



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

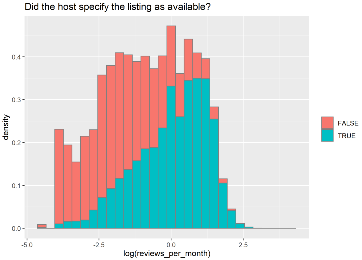
EDA - Price and Popularity

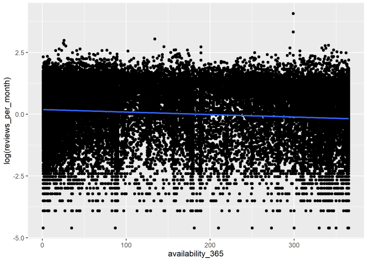
- From XGBoost outputs, price and popularity are closely related, both being an important variable of the other.
- The plot below shows a negative correlation between them on *log-scale*:



- We may consider model them as bivariate reponse.

Possibly Unreliable Predictors





Modeling: Bivariate Mixed Effects Regression

- Varying intercept model: Random effects for each neighbourhood, and each borough

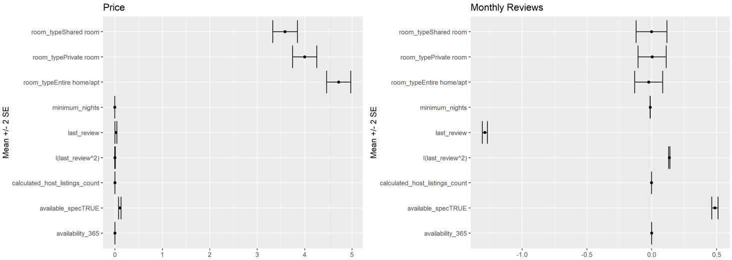
For the $i-$th observation in neighbourhood j, in borough k,

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

$$\boldsymbol{\epsilon} \sim N(\mathbf{0}, \sigma^2 I_2).$$

- Quadratic term for how “old” a listing 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

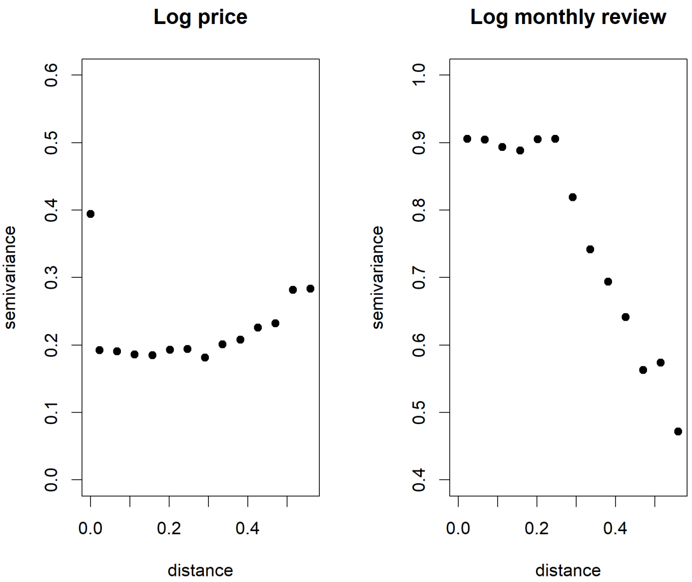
Estimates for Group Heterogeneities

	variableprice	variablereviews_per_month
variableprice	0.0285713	-0.0073314
variablereviews_per_month	-0.0073314	0.0369951

	variableprice	variablereviews_per_month
variableprice	0.0795922	-0.0238308
variablereviews_per_month	-0.0238308	0.0124831

- Many coefficients for significant predictors (adjusted for other variables) are swamped by the variability within/between different neighborhoods and boroughs
- Negative correlation between coefficients for price and popularity

Examining Spatial Correlation of the Residuals



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 for price).

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