

Exploratory Analysis of Data for Airbnb Listings in NYC

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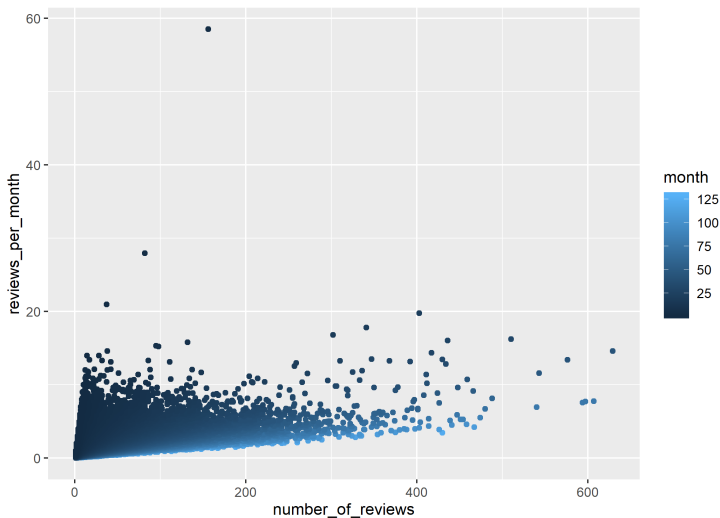
Introduction

- ▶ 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?

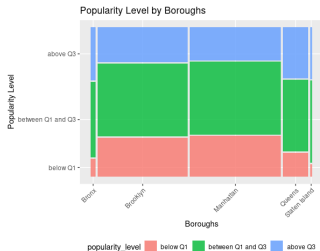
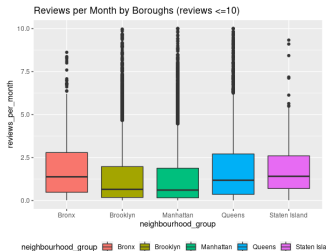
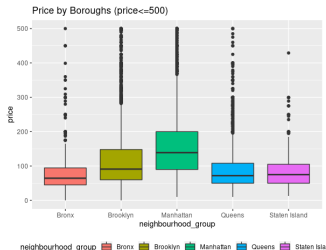


- **Monthly reviews** adjusts for the history of a listing (albeit not perfectly)

Heterogeneity of Price / Popularity across Boroughs

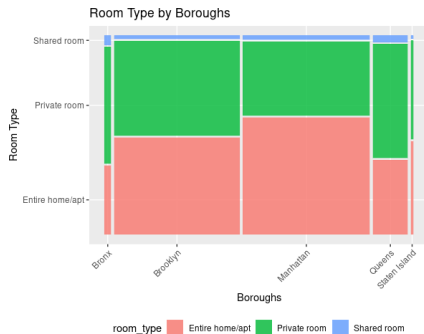
- ▶ Create new variables “Price Level” and “Popularity Level”:
 - ▶ “Below Q1” for values $< 25\text{th Percentile}$
 - ▶ “Between Q1 and Q3” for values from 25th to 75th Percentile
 - ▶ “Above Q3” for values $> 75\text{th Percentile}$
- ▶ Create contingency table and conduct Chi-squared Test for Homogeneity

Heterogeneity of Price / Popularity across Boroughs



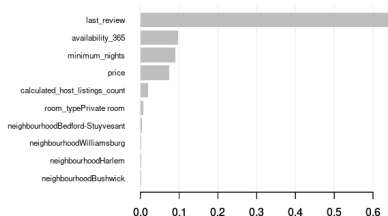
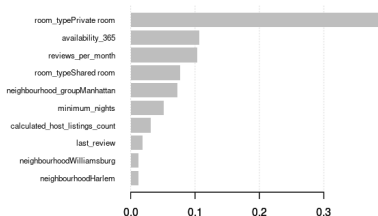
► Small p-value suggests heterogeneity across boroughs.

Heterogeneity of Room type across Boroughs



- Small p-value suggests heterogeneity across boroughs.

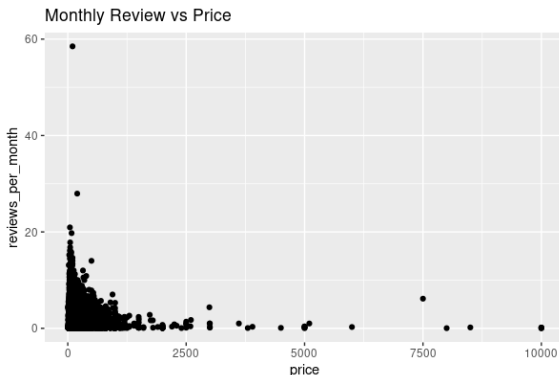
XGBoost for Important Variables



- The most influential factors for price include: room type, availability, monthly reviews, boroughs, etc.

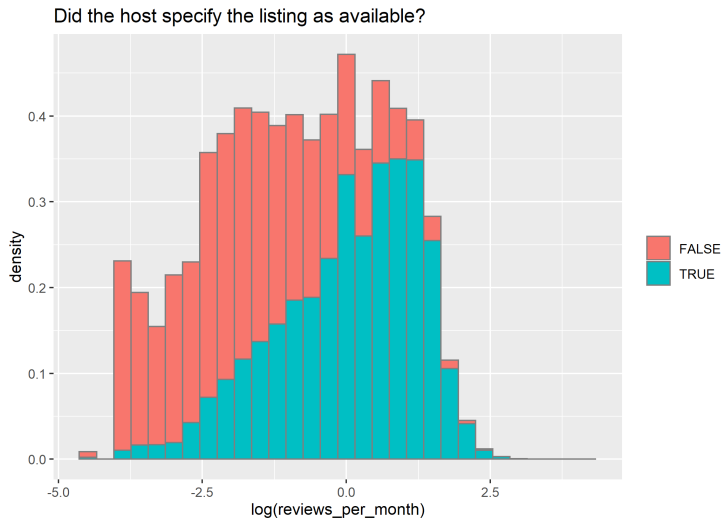
EDA - Price and Popularity

- ▶ 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:



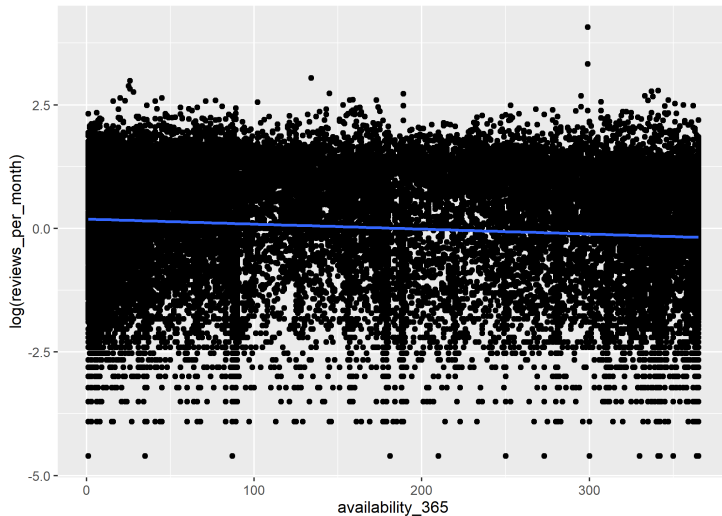
- ▶ We may consider model them as bivariate response.

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

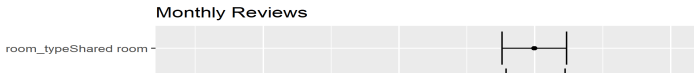
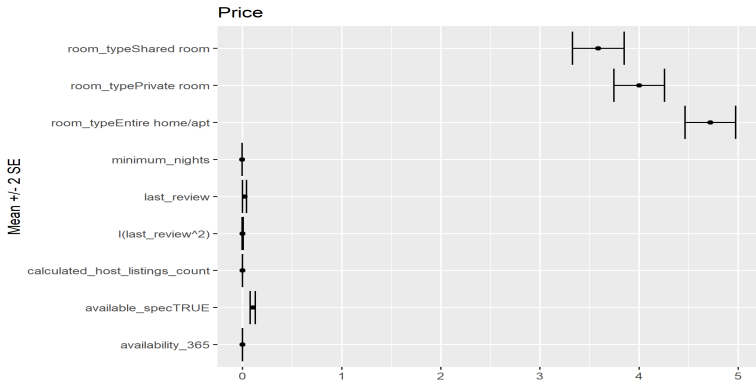
- Varying intercept model: For the i -th listing in neighborhood j , within borough k ,

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

- 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

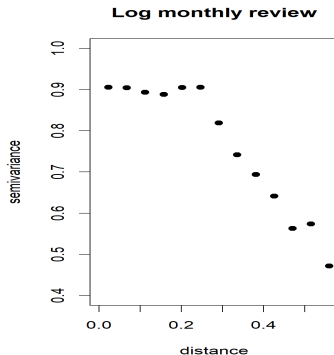
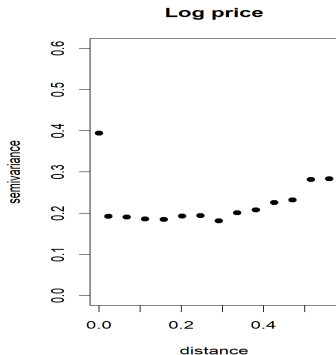
variableprice	variablereviews_per_month
0.03	-0.01
-0.01	0.04

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 $\text{Var}(Y(\mathbf{s}_i + d) - Y(\mathbf{s}_i))$ 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