

Exploratory Analysis of Data for Airbnb Listings in NYC

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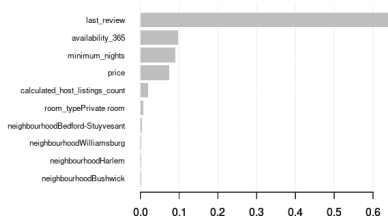
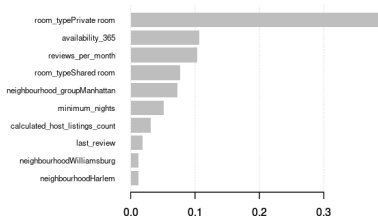
Data Processing

- ▶ Remove 14 observations with *minimum_nights* > 365
- ▶ *Price*: the lowest non-zero value is 10, change 0 to 5
- ▶ *Reviews per Month*: missing values are set to 0 (there is no review for these listings)
- ▶ *Last Review*: group by years from 2019 (e.g. 2019 -> 0; 2018 -> 1, etc.)

Response Variables - Price and Popularity

- ▶ Metric for price: **price**
- ▶ Metric for popularity: **monthly reviews** adjusts for the history of a listing (albeit not perfectly)
- ▶ Price and popularity seem to be negatively correlated (in log scale)

XGBoost for Important Variables

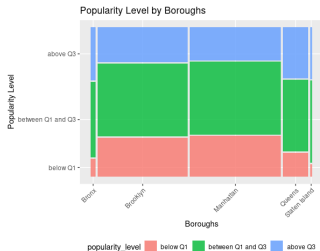
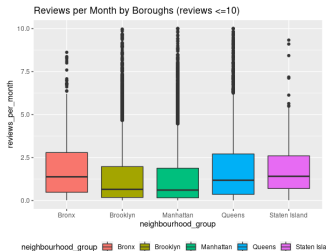
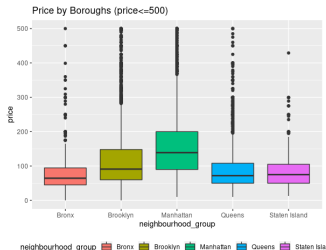


- Most important variable for price: *Room Type*.

Heterogeneity of Price / Popularity across Boroughs

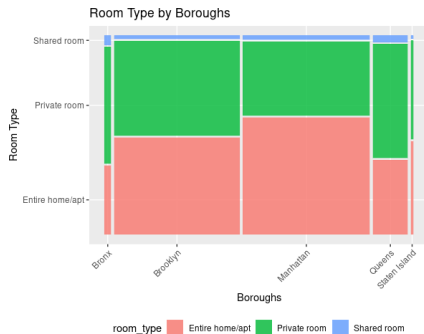
- ▶ Create new variables “Price Level” and “Popularity Level”:
 - ▶ “Low” for values < 25 th Percentile
 - ▶ “Medium” for values between 25th and 75th Percentile
 - ▶ “High” for values > 75 th Percentile
- ▶ Create contingency table and conduct Chi-squared Test for Homogeneity

Heterogeneity of Price / Popularity across Boroughs



► Small p-value suggests heterogeneity across boroughs.

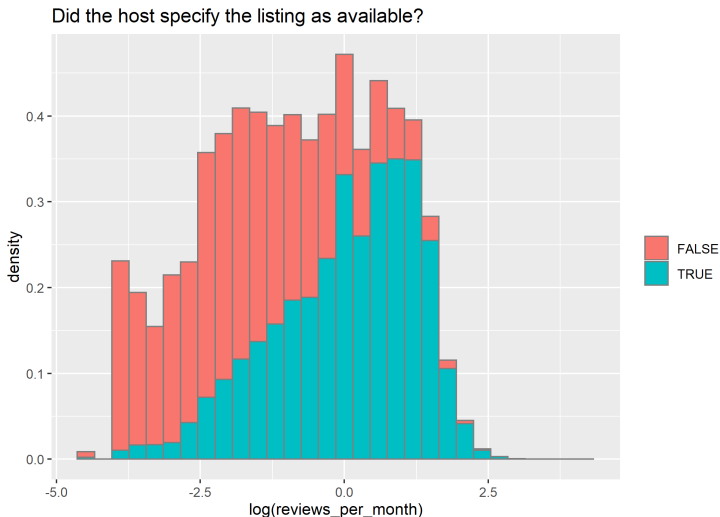
Heterogeneity of Room type across Boroughs



- Small p-value suggests heterogeneity across boroughs.

Unreliability of Availability Feature

- ▶ `availability_365`: Only important info. seems to come from whether it is zero or not



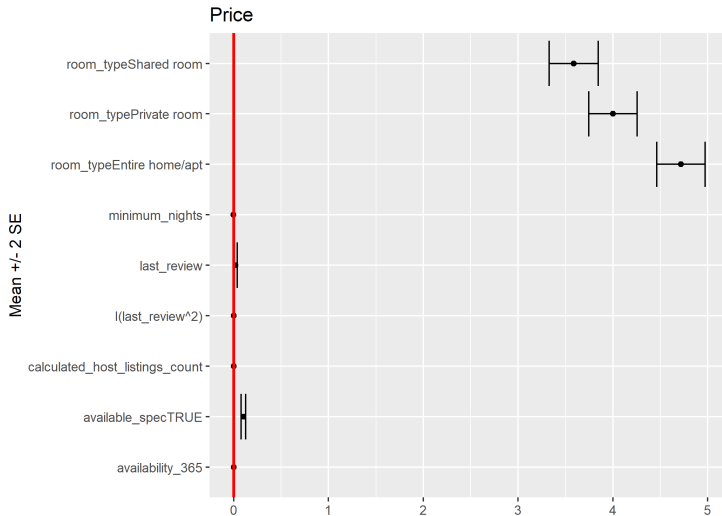
Modeling: Bivariate Mixed Effects Regression

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

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

- ▶ Availability is included both as a non-zero indicator and numeric variables
- ▶ 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?



► Apartment > Pvt room > Shared room in price

What Are the Important Predictors for Popularity?



- To have reviews, a listing on average should be young and actually on business

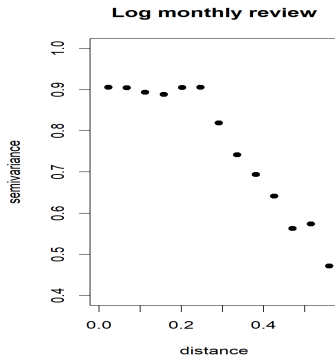
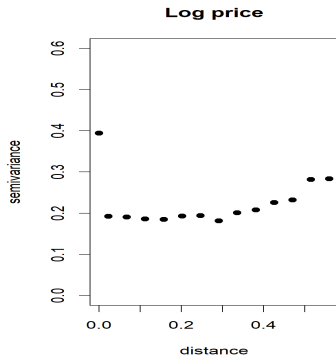
Random Intercepts for Groups

| | variableprice | variablereviews_per_month |
|---------------|---------------|---------------------------|
| Bronx | -0.21 | 0.05 |
| Brooklyn | 0.07 | -0.12 |
| Manhattan | 0.45 | -0.11 |
| Queens | -0.10 | 0.11 |
| Staten Island | -0.22 | 0.06 |

- ▶ Manhattan most expensive, Queens most popular
- ▶ Strong negative correlation between two random intercepts between boroughs (-0.76)
- ▶ Neighborhood-level variation is relatively minute

Examining Spatial Correlation of the Residuals

- ▶ Plotting semivariogram as evidence of within-neighborhood spatial structure

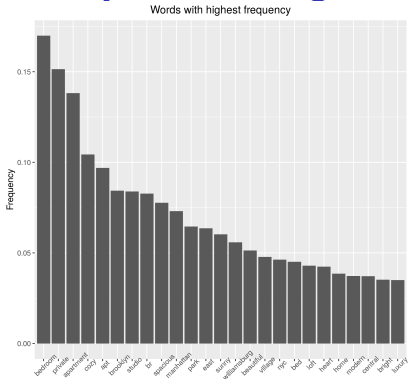


- ▶ We observe large semivariogram for price when listings are extremely close, and **negative spatial correlation** for monthly review rates

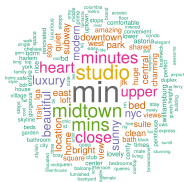
Possible Insights

- ▶ 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



Text Analysis for Listing Names



Foreign language, Special Characters, and Misspelling

*"WilliamsburgBrooklynPrivateBedroom" "NiceRoom-
NiceNeighborhoodCloseMaimonidesHospital"*

Conclusions

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