Modeling Price and Popularity of AirBnB listings in New-York

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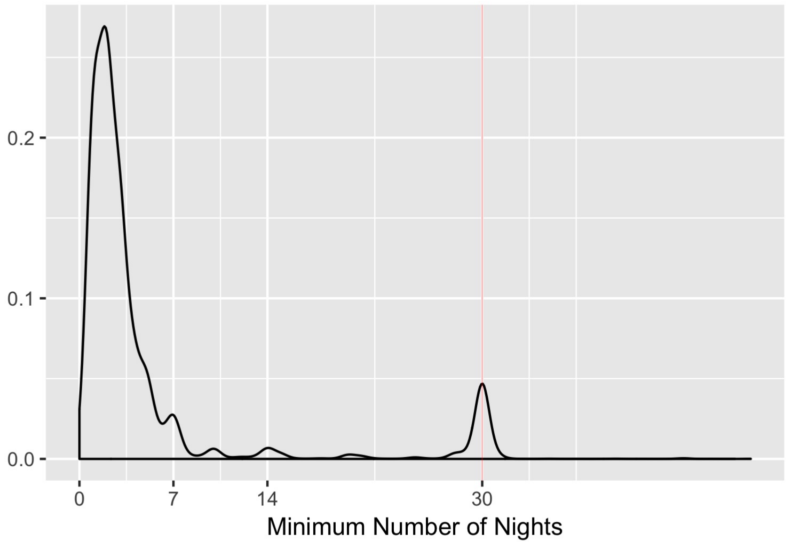
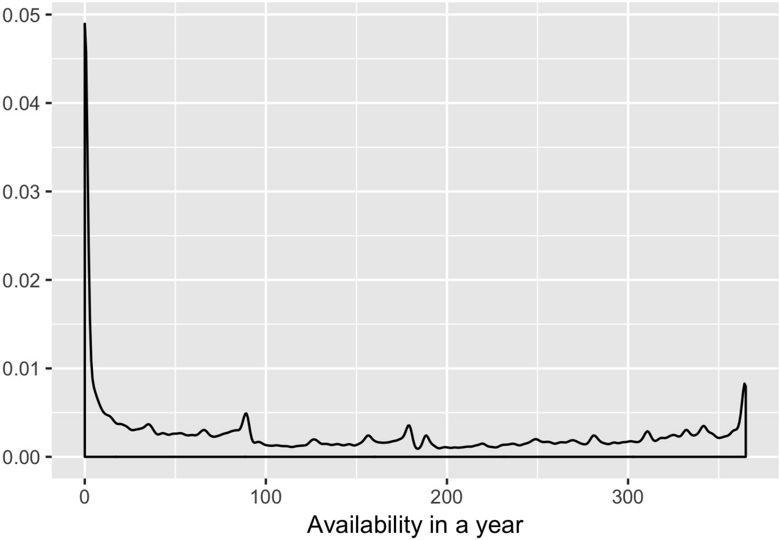
EDA - A city of two tales

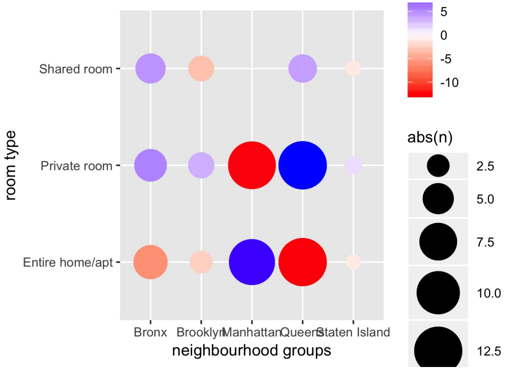


EDA - Are you available?

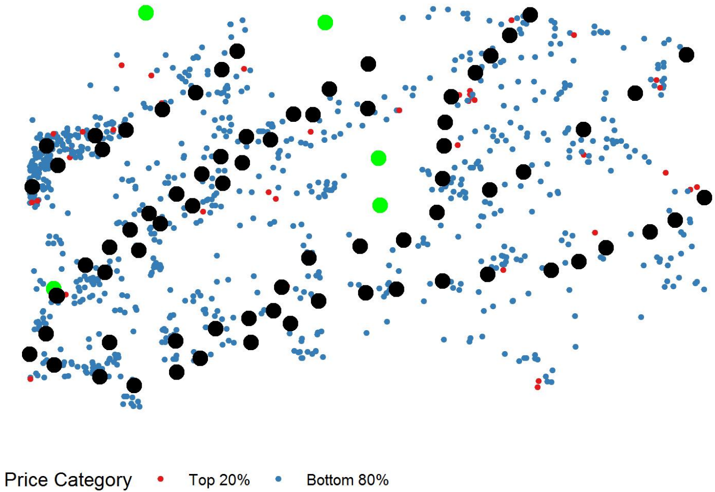


EDA - Room type

- $p < 1e-16$



EDA - Attractions



Data Cleaning

Since the data quality is questionable, we narrow down our focus to *active* listing for *short term* stays that are *private*:

- last review is less than 12 months old
- min number of days inferior to to 29
- less than 5 listings per owner

We also incorporate external data:

- Location of metro stations
- Location of main attractions

Feature Engineering - Proximity to Metro and Attractions

EDA suggests spatial modeling:

- Proximity to closest metro stations

$$dist_{Manhattan}(x, y) = |lat_x - lat_y| + |long_x - long_y|$$

- Average proximity to (36) attractions

$$proximity(X) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{dist(X, attraction_i)}$$

Feature Engineering - Textual Data

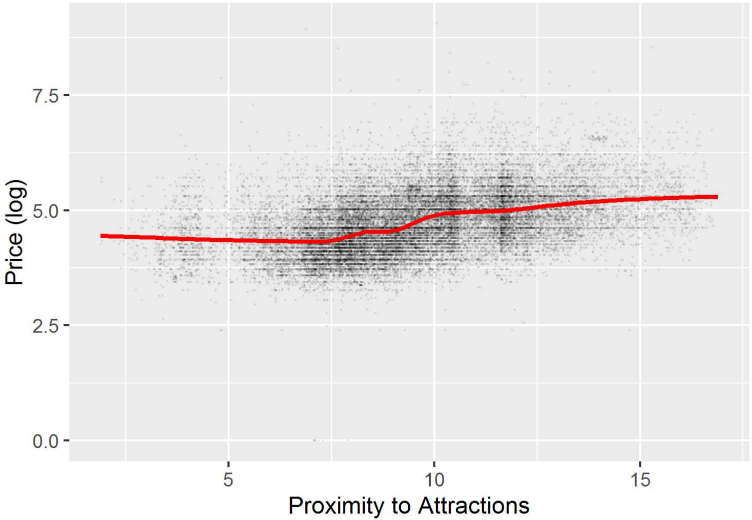
Textual data always invites creativity:

- Sentiment analysis of listing name

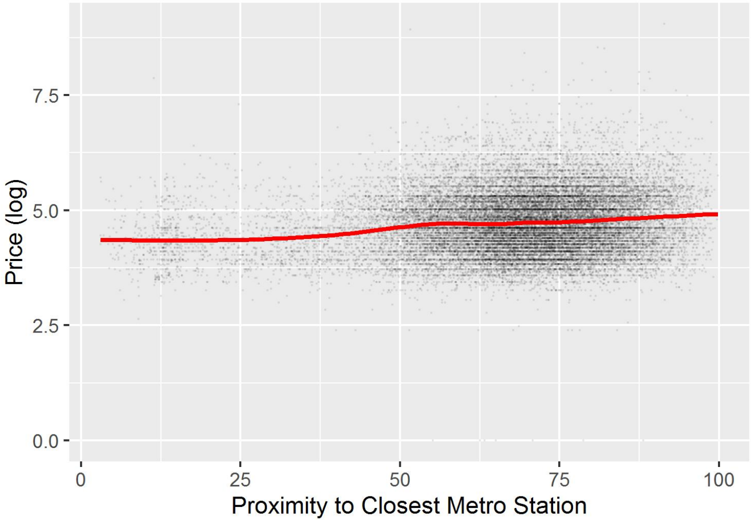
$$Sentiment(W) = \frac{1}{n}\sum_{i=1}^{n} dictionary(w_i)$$

  where $dictionary_{Affin}(w) \in \{-5, -4, \ldots, 5\}$
- Origin of host $\Rightarrow$ frequency of name

Feature Engineering - Attractions



Feature Engineering - Metro



Models

Two regression models

- Regression Model
  - Outcome: price, popularity
    - popularity $= \frac{\text{reviews per month}}{\text{availability}}$
  - Predictors: listing sentiment, name frequency, proximity metro, proximity attraction, room type, etc.
  - $n = 25,000$, $p = 14$
- Random Forest
  - $1,900$ trees, subsamples $19,000$
  - $m = \frac{p}{3} = 4$ variables at each split, $n_{leaf} \geq 5$.
- BMA
  - Linear combination of predictors
  - Prior: Cauchy
  - N.Models: 2^{15}
  - MCMC.iterations: 10^{16}
  - initprobs = "marg-eplogp"

Models - continued

- Important Predictors
  - RF: variable importance
  - BMA: PIP
- Sensitivity Analysis
  - RF: vary m and minimum n_{leaf}.
  - BMA: consider different priors (Cauchy prior, g prior for $g = 1, 5, 8, 100, 500, 1000$)

Results - Random Forest Price

	Predictors	Variable.Importance
1	longitude	978.10
2	proximity_metro	231.64
3	reviews_per_month	107.88
4	listing_sentiment	101.15
5	number_of_reviews	100.73
6	neighbourhood_group	95.16
7	latitude	94.24
8	room_type	90.71
9	name_listing_length	89.26
10	minimum_nights	88.53
11	popularity_log	61.00
12	name_host_special	53.69
13	proximity_attraction	47.78
14	name_host_freq	39.16
15	listing_count	16.42

Results - Random Forest Popularity

	Predictors	Variable.Importance
1	latitude	62.77
2	listing_sentiment	59.50
3	minimum_nights	57.85
4	neighbourhood_group	54.93
5	room_type	50.03
6	reviews_per_month	49.69
7	longitude	45.87
8	name_listing_length	41.50
9	name_host_special	35.34
10	popularity_log	33.77
11	proximity_attraction	20.73
12	listing_count	8.76
13	name_host_freq	8.72
14	proximity_metro	0.42

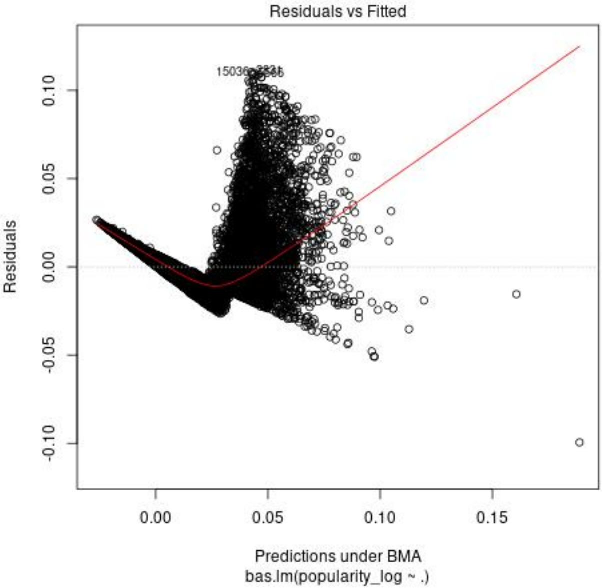
Results - BMA Price

	Predictors	PIP	Estimate	Lower.Confint	Upper.Confint	Significance
1	Intercept	1.00	4.70	4.70	4.71	*
2	name_host_freq	1.00	0.07	0.07	0.07	*
3	Neighbourhood_group:Manhattan	1.00	0.17	0.15	0.18	*
4	number of reviews	1.00	-0.01	-0.02	-0.01	*
5	Room_type:Entire home/apt	1.00	0.74	0.73	0.75	*
6	availability_365	1.00	0.00	0.00	0.00	*
7	name_listing_sentiment	1.00	0.00	0.00	0.00	*
8	last_review	1.00	-0.00	-0.00	-0.00	*
9	Neighbourhood_group:Queens	1.00	-0.11	-0.13	-0.10	*
10	name_host_special:True	1.00	10.42	7.38	13.55	*
11	Room_type:Shared room	1.00	-0.51	-0.54	-0.47	*
12	calculated_host_listings_count	1.00	-0.01	-0.02	-0.01	*
13	type_stay:Long	1.00	0.00	0.00	0.00	*
14	Neighbourhood_group:Bronx	1.00	-0.17	-0.20	-0.14	*
15	name_listing_length	1.00	0.06	0.04	0.08	*
16	proximity_metro	0.89	-0.00	-0.00	0.00	
17	proximity_attraction	0.50	-0.01	-0.04	0.00	
18	reviews_per_month	0.07	-0.00	-0.00	0.00	
19	Neighbourhood_group:Staten Island	0.02	-0.00	0.00	0.00	

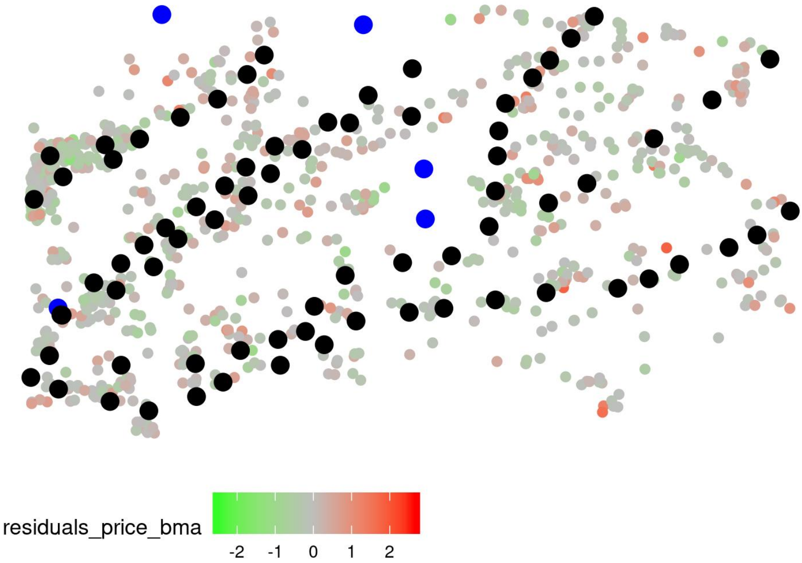
Results - BMA Popularity

	Predictors	PIP	Estimate	Lower.Confint	Upper.Confint	Significance
1	Intercept	1.00	0.02	0.02	0.02	*
2	calculated_host_listings_count	1.00	0.01	0.01	0.01	*
3	reviews_per_month	1.00	0.00	0.00	0.00	*
4	name_listing_sentiment	1.00	-0.00	-0.00	-0.00	*
5	Room_type:Entire home/apt	1.00	-0.00	-0.00	-0.00	*
6	number of reviews	0.95	-0.00	-0.00	0.00	
7	last_review	0.74	-0.00	-0.00	0.00	
8	proximity_metro	0.62	0.00	0.00	0.00	
9	Room_type:Shared room	0.23	0.00	0.00	0.00	
10	Neighbourhood_group:Queens	0.14	-0.00	-0.00	0.00	
11	name_listing_length	0.05	-0.00	0.00	0.00	
12	name_host_freq	0.03	0.00	0.00	0.00	
13	Neighbourhood_group:Bronx	0.02	0.00	0.00	0.00	
14	Neighbourhood_group:Staten Island	0.01	0.00	0.00	0.00	
15	name_host_special:True	0.01	-0.00	0.00	0.00	
16	availability_365	0.01	0.00	0.00	0.00	
17	Neighbourhood_group:Manhattan	0.01	-0.00	0.00	0.00	
18	type_stay:Long	0.01	-0.00	0.00	0.00	
19	proximity_attraction	0.01	-0.00	0.00	0.00	

Diagnostic Plots - BMA - Popularity



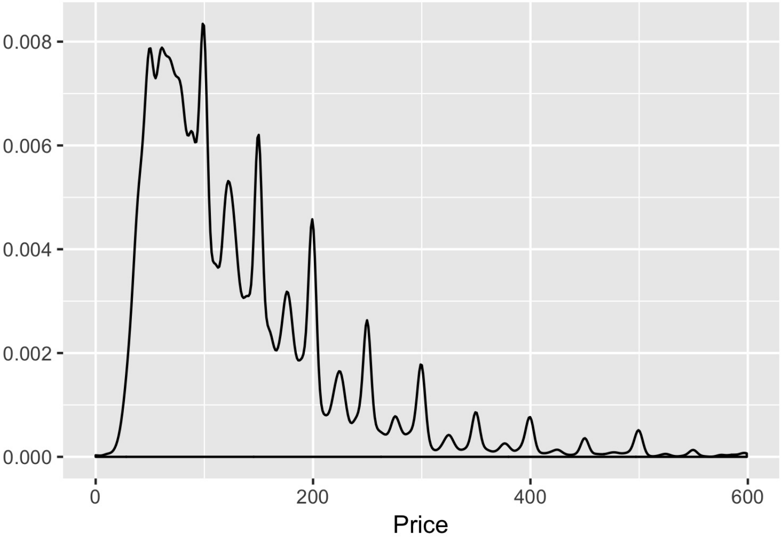
Residuals - BMA



Discussions - Future Directions

- Data collection
  - One row per booking
- Spatial modeling
  - Incusion of boroughs does not work well. Spatial modeling that addresses relationship between houses (Valente, 2005).
- Domain-specific knowledge
  - Submarkets influence pricing. Finite mixture model by Belasco1, 2012.
  - Knowledge in marketing. E.g. consider form of pricing as an influencer of popularity (99 vs 100).

Discussions



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