Boston Airbnb Fair Pricing Tool and Recommender

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Agenda

- Introduction / Problem Statement / Data Sources / Architecture
- Exploratory Data Analysis
- Feature Engineering
- Feature Selection
- Modeling
- Recommender
- Conclusions / Next Steps

Intro | Problem Statement | Data Sources | Architecture

Introduction

Airbnb General:

- Hosts allow guests to stay at their property for a fee
- Alternative to traditional hotel / hostel
- Passive (or main) income for hosts

Airbnb Listing Prices:

- Pricing very subjective
- Vary wildly
- Finding best deals - time consuming
- Setting listing price - time consuming

Problem Statement at a Glance

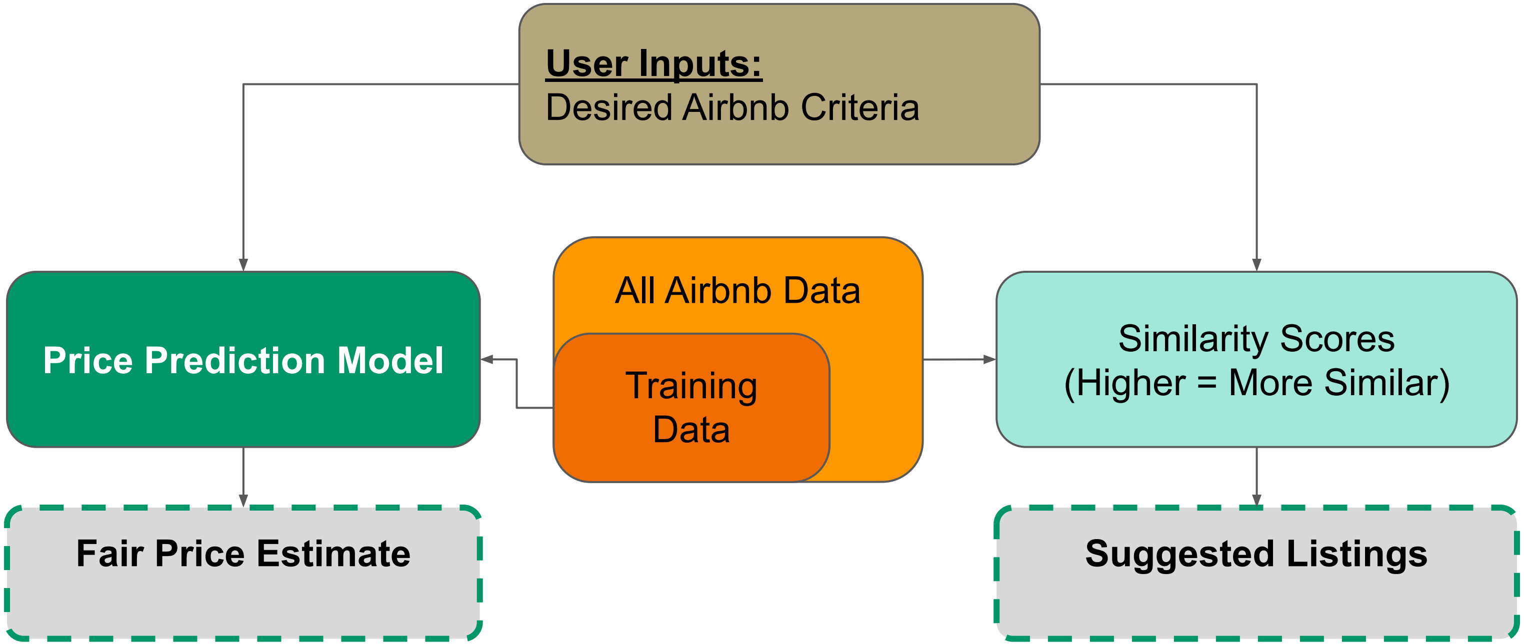
- Be the ***Kelly Blue Book*** of Airbnb's
- Estimate fair prices for
  - Guests
  - Hosts
  - Developers
- Goal: RMSE of $20
- Recommend criteria-based listings
  - Criteria in ⇒ Fair Price / Recommended Listings out
- Fast, easy, quick

Data Sources

- Airbnb Data - *Inside Airbnb* [1]
    - Includes: 75 numerical and categorical variables

- Geographic Data: Listing locations to Subway Stations
    - *MBTA Stations* [2] - 132 total Stations
    - Google Geocoding API [3]
        - T-stop addresses ⇒ latitude / longitude

Product Architecture



Exploratory Data Analysis (EDA)

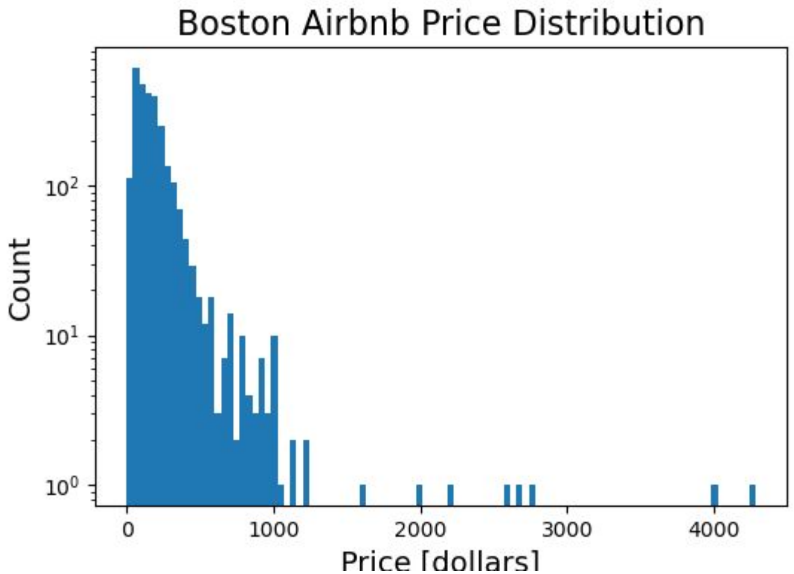
NOTE: All Subsequent EDA Performed on Training Data

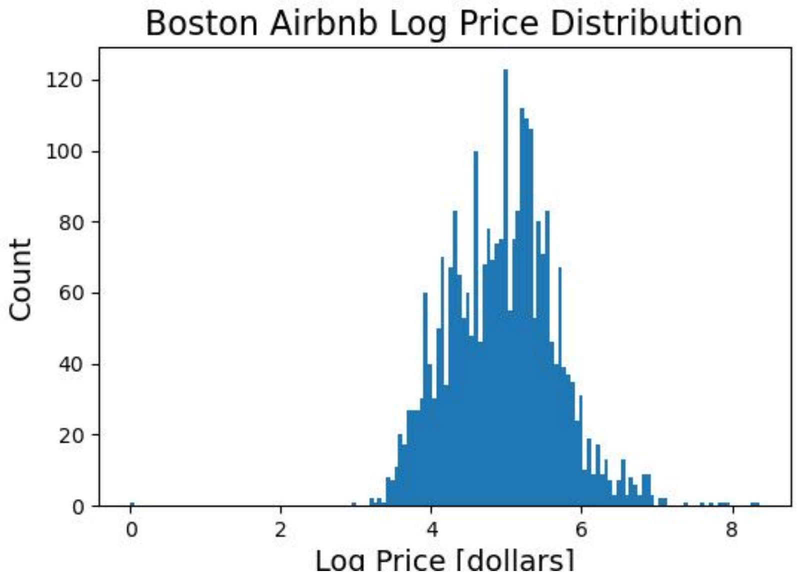
Exploratory Data Analysis – Basic Stats

	Mean	Min	25th Pcntl	50th Pcntl	75th Pcntl	Max
Guests Accommodated	3.17	1	2	2	**4**	16
No. Bedrooms	1.75	1	1	1	**2**	13
No. Beds	1.79	1	1	1	**2**	22
Price	$188.39	$0	$83	$146	**$225**	$4283
Number of Reviews	41.09	0	0	7	44	821

Most Airbnb's are not extravagant

Exploratory Data Analysis – Price





<u>Log transformations help normalize price data ⇒ better modeling</u>

Feature Engineering

Feature Engineering - Descriptive Columns (Tokenizing)

Airbnb Data:

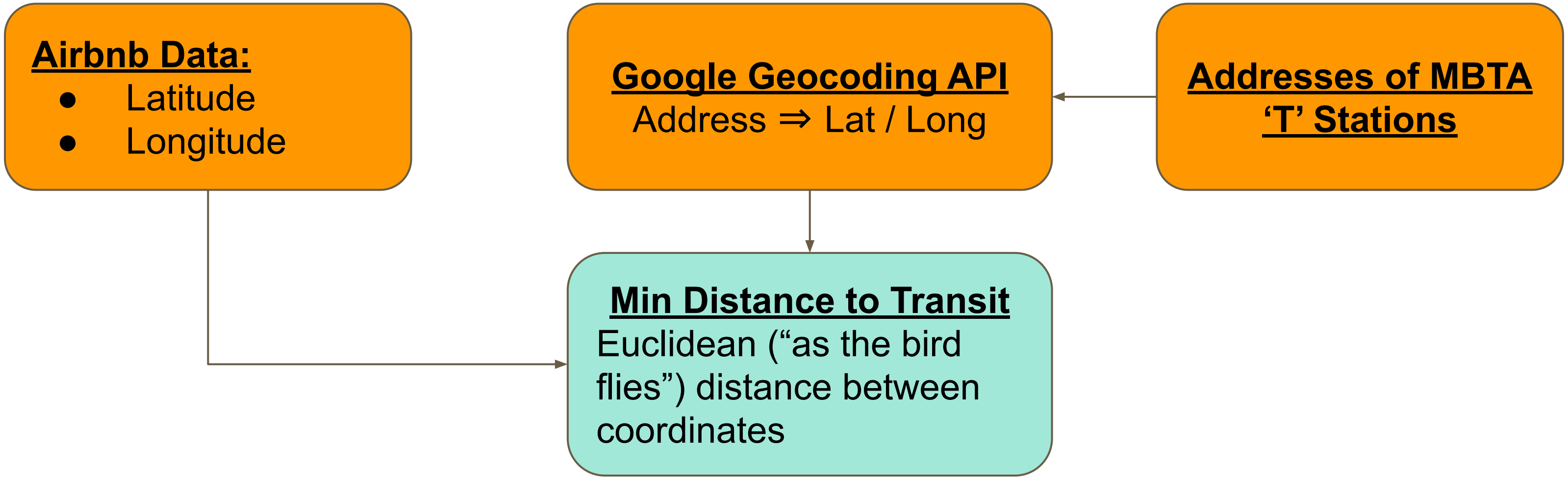
- Amenities
- Name
- Description
- Neighborhood Description
- Host About Information

For Each Category Find:

- Common Words
- Common phrases up to 4 word strings (n-grams)
- In at least 10% of listings

	Amn. word_1	**Amn. word_2**	**…**	**Name word_1**	**…**	**Descr. word_1**	**…**	**Nbhd word_1**		**Hst. Abt. word_1**	**etc…**
Listing 1	yes	no	…		…	yes	…	no	…	yes	…
LIsting 2	yes	yes	…		…	no	…	no	…	yes	…
etc…	…	…	…		…	…	…		…		…

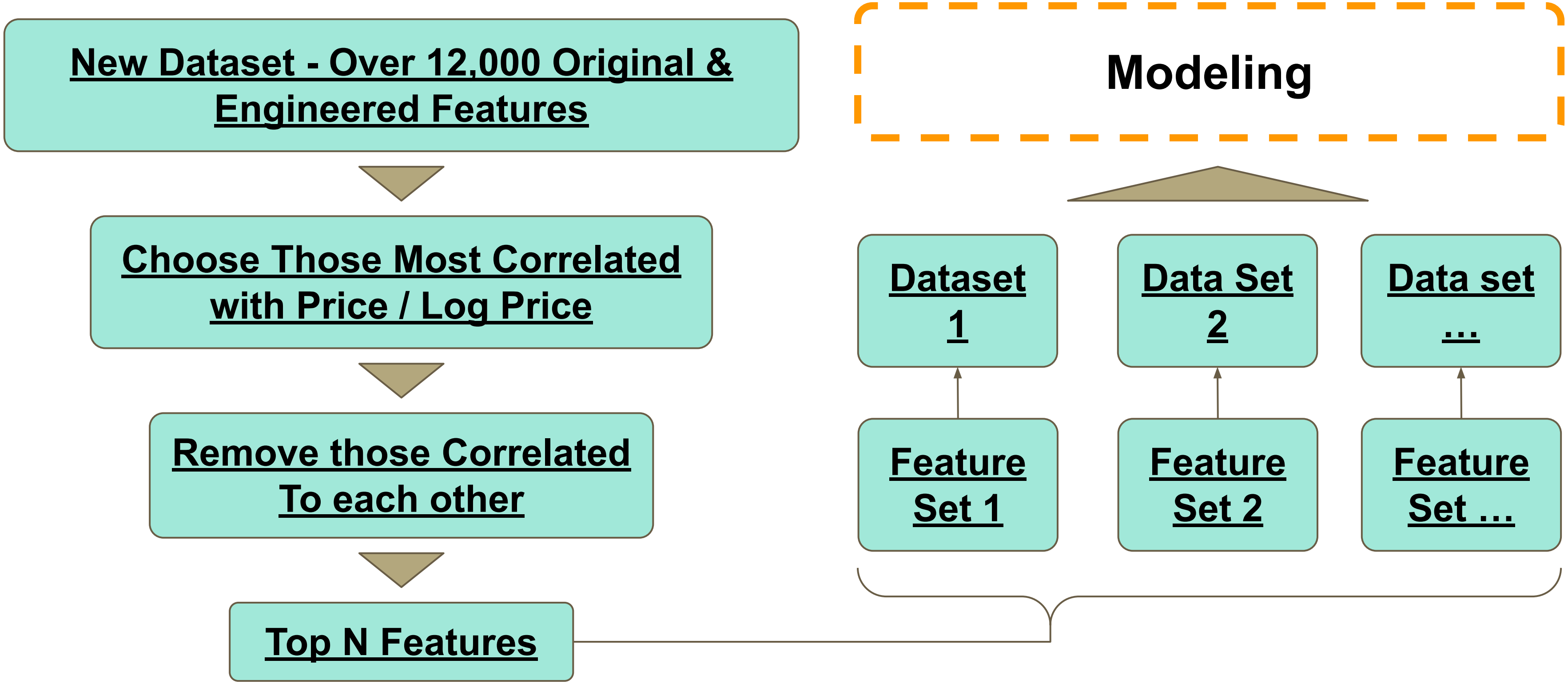
Feature Engineering – Proximity to Public Transit



Other features were engineered but won't be discussed

Feature Selection

Correlations - Quantitative Feature Selection Process



Modeling

Modeling

Primary Metric: Root Mean Squared Error

- Standard Deviation of Errors
    - ~67% of values within +/- RMSE
- R-squared - secondary metric

Modeling Steps Taken

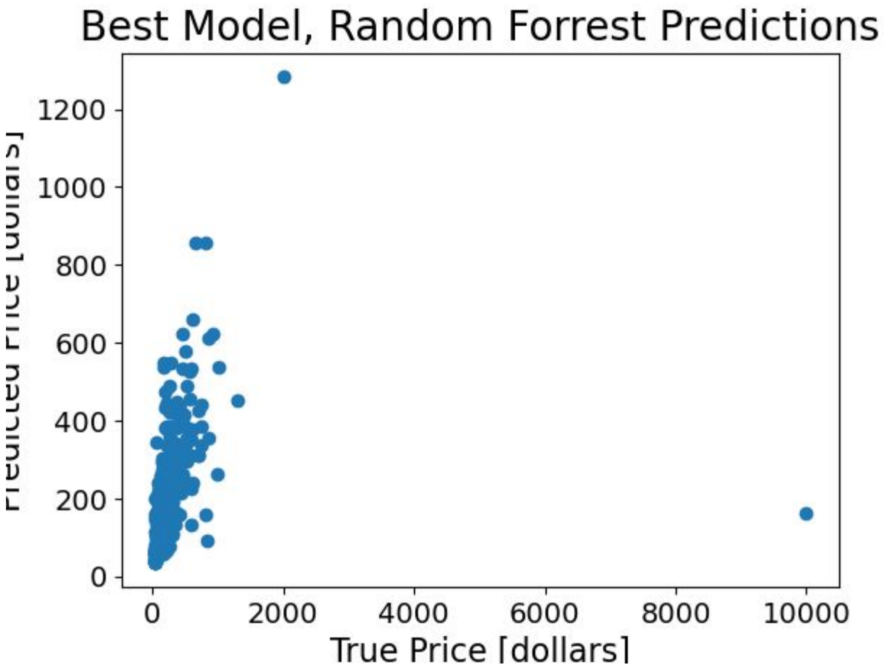
- Seven different regression model varieties
- Ran models on different feature sets
- Optimized models
- Dimensionality reduction

Models:

- Linear Regression
- Random Forest Regressor
- Decision Tree Regressor
- Gradient Boosting Regressor
- AdaBoost Regressor
- Extra Trees Regressor
- Bagging Regressor

Modeling Results

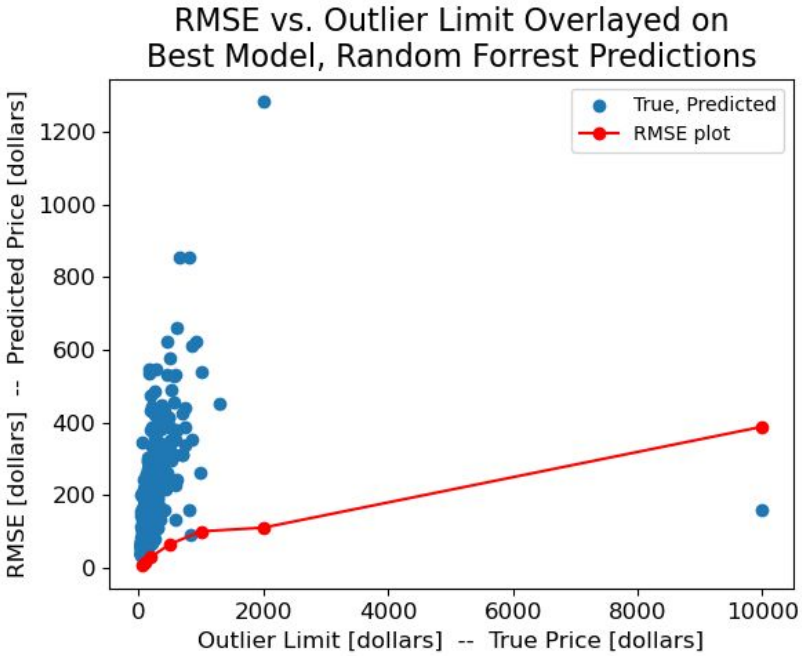
- All results: poor
- RMSEs High $300s - High $400s
- Best model:
  - Random Forest Regressor
  - Default Parameters
  - Feature set - 10 Features
- Metrics:
  - RMSE Training Data: $138.88
  - ***RMSE Validation Data: $388.90***
  - R2 Training Data: 0.56
  - R2 Validation Data: 0.09



Outliers

- Data start to become very scattered after $500
- Need better features need for higher-priced listings
- $10,000 listing more than doubles RMSE

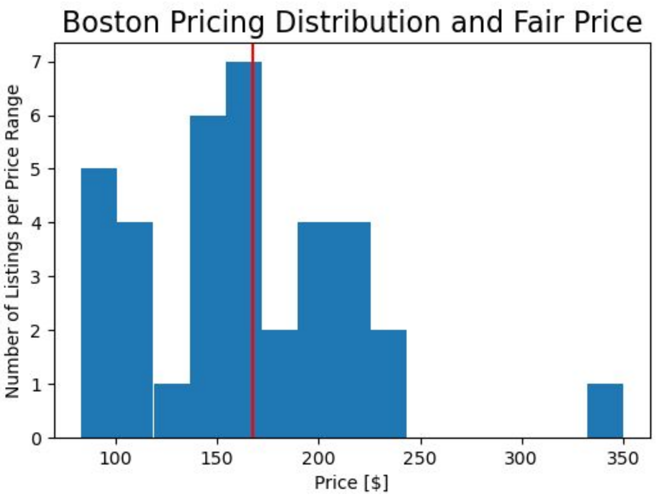
<u>Including higher-priced listings in training data increases RMSE</u>



Recommender

Recommender Tool Outputs

- Provides listing prices as distribution
- Fair price - red line
- Suggested listings: similarity ⇒ price



Suggested Listings			

Conclusions & Next Steps

Conclusions

- Poorly performing Fair price predictor created
    - RMSE way above $20
    - Appropriate for recommender pricing distribution
- Outliers affected model
- Data somewhat unpredictable
- Additional features or data may improve performance
- Recommender performed as envisioned

Next Steps

- In-depth exploration of outliers
- Create additional features not tackled in this phase
- Attempt clustering ⇒ new features
- Refine dimensionality reduction methods
- Train a neural network
- Streamlit app

Sources

[1] - Inside Airbnb: http://insideairbnb.com/get-the-data/

[2] - MBTA Stations: https://www.mbta.com/stops/subway

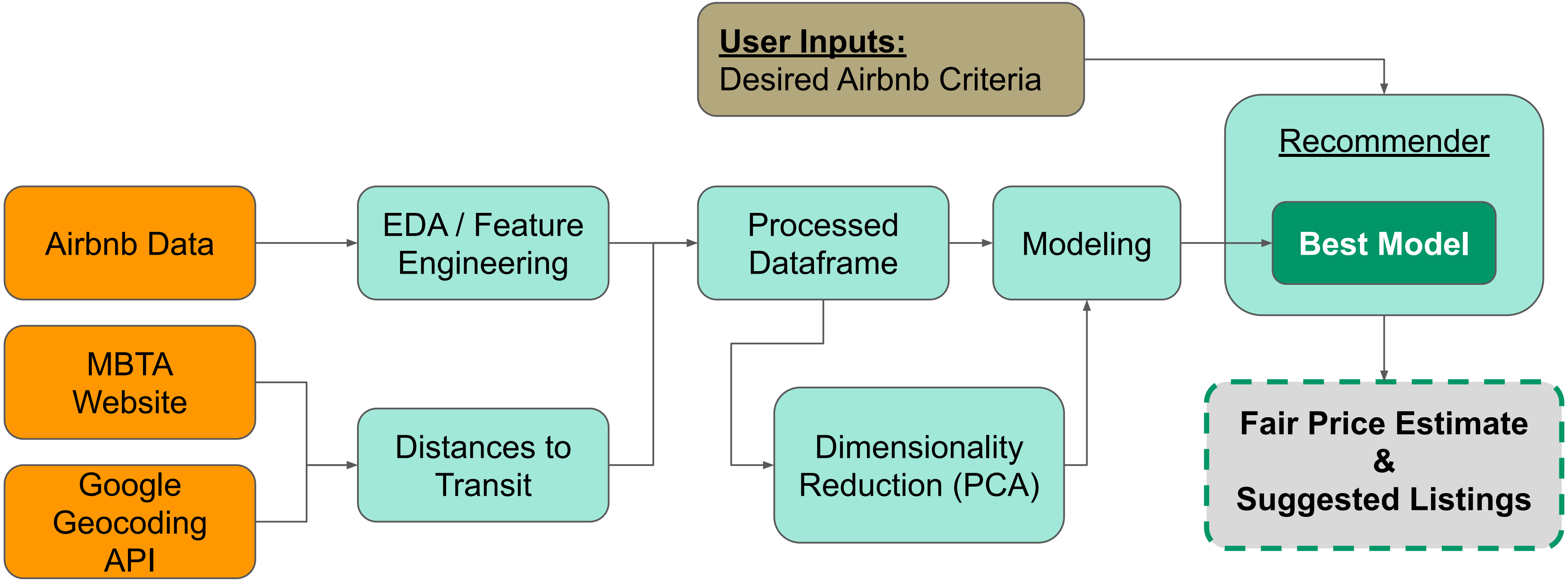
[3] - Google Geocoding API: https://developers.google.com/maps/documentation/geocoding

Other:

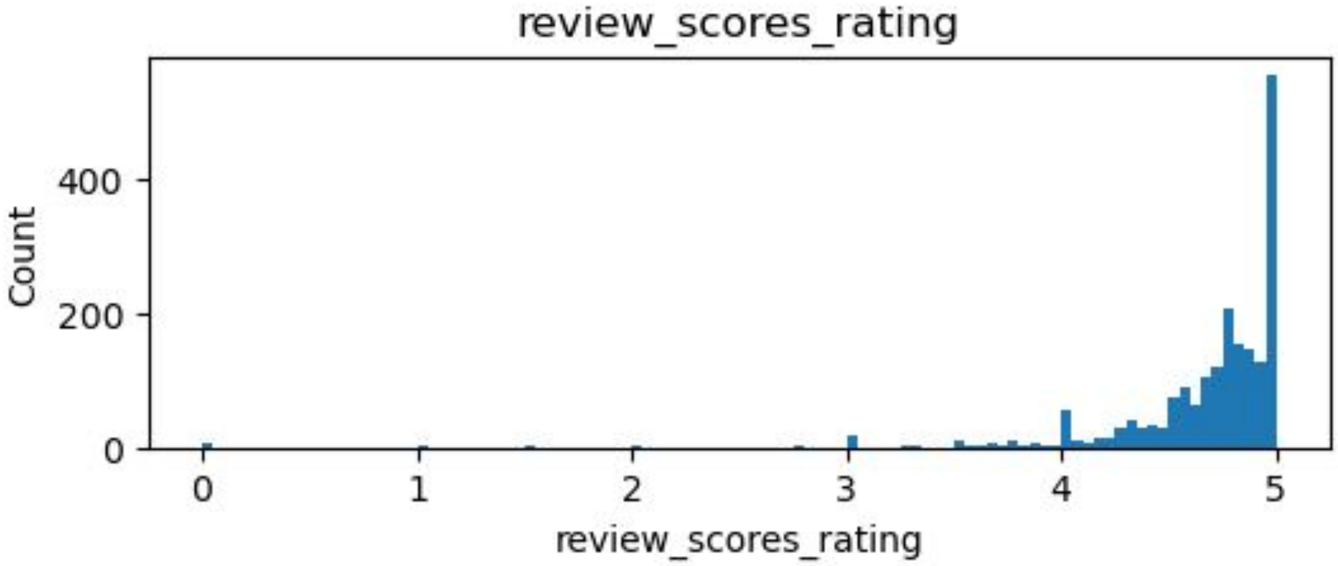
Inside Airbnb Data Dictionary: https://docs.google.com/spreadsheets/d/1iWCNJcSutYqpULSQHlNyGInUvHg2BoUGoNRIGa6Szc4/edit#gid=1322284596

Additional Materials

Project Architecture



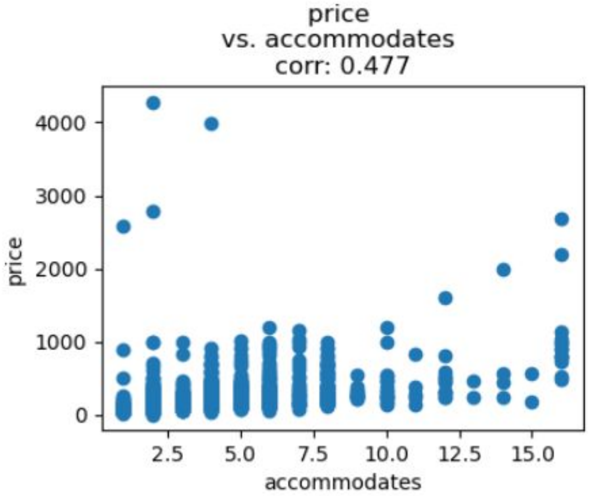
Exploratory Data Analysis – Review Scores

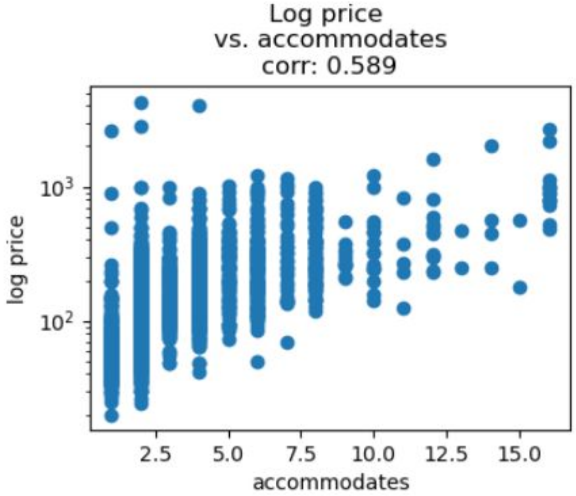


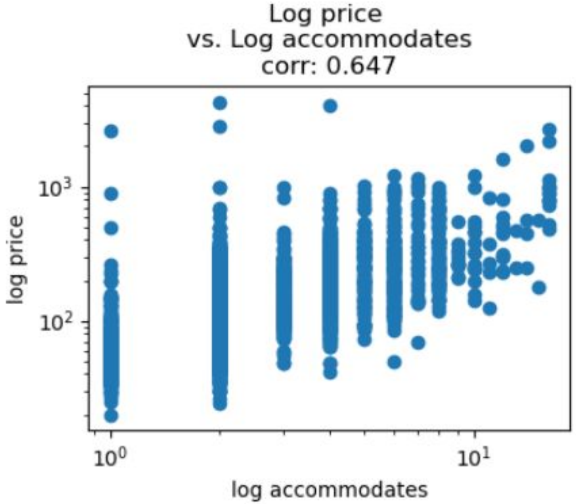
Exponential Distribution

Very few listings score below 4.5 (average of all ratings)

Exploratory Data Analysis – Accommodates vs. Price

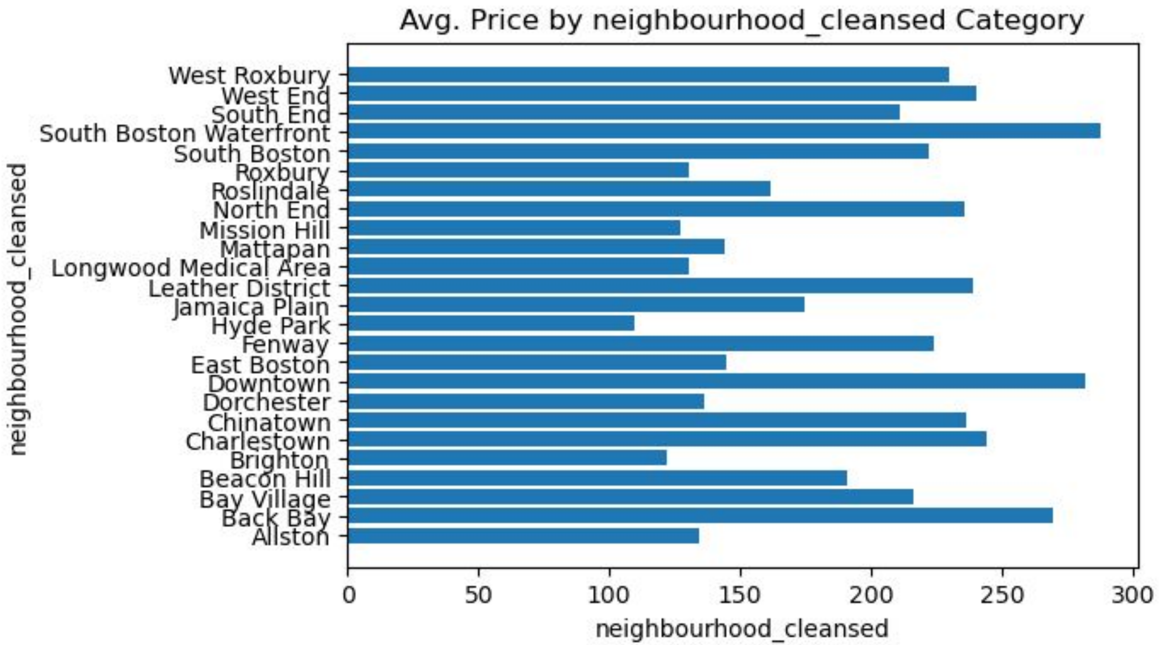






<u>No. of People Accommodated Moderately Correlates to Price / Log Price</u>

Exploratory Data Analysis – Neighborhoods



Average Prices Change by Boston Neighborhood

Feature Engineering – Amenities (Tokenizing)

Airbnb Data - Amenities:

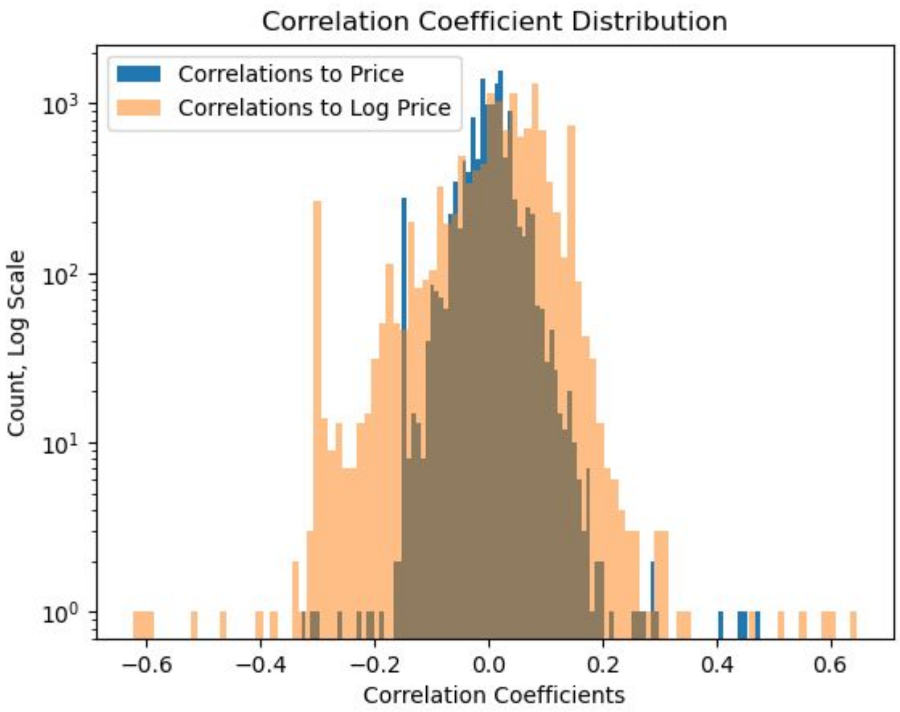
- [‘wi-fi’, ‘oven’, ‘full kitchen’ …]
- [‘wi-fi’, ‘Disney+’, ‘baby stroller’ …]
- …

wi-fi **Disney+** **oven**

full kitchen **baby stroller** **etc…**

	wi-fi	Disney+	full kitchen	oven	baby stroller	etc…
Listing 1	yes	no	yes	yes	no	…
LIsting 2	yes	yes	no	no	yes	…
etc…	…	…	…	…	…	…

Correlations – Very Few Highly Correlated Features



- Ideally: *<u>magnitude</u>* over 0.6 - 0.7
- Correlations to log price stronger

<u>Poorly correlated features usually not helpful when modeling</u>