# Analyzing New York City Airbnb Data with Machine Learning and Geospatial Modeling

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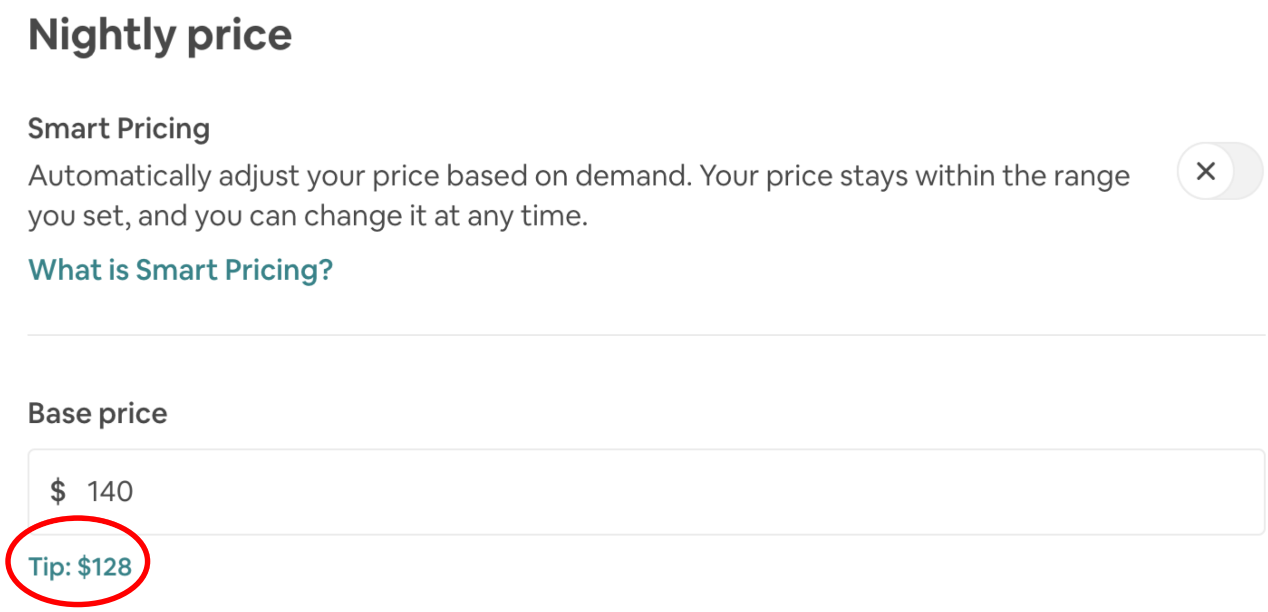
# Outline

- Motivation and background information
- The data
- Data Analysis via visualization and geospatial modeling
- Model training and prediction via machine learning
- Concluding remarks

# Introduction

- Airbnb generates revenue by charging its guests and host fees for arranging stays (hosts are charged 3% of the value of the booking; guests are charged 6-12% depending on the nature of the booking)
- As an ecosystem, Airbnb transactions generate a lot of data: density of rentals across cities and neighborhoods; price variations across rentals and cities; host-guest interactions in the form of reviews (mainly guest experiences).
- A "smart pricing" algorithm recommends hosts a price to set when posting



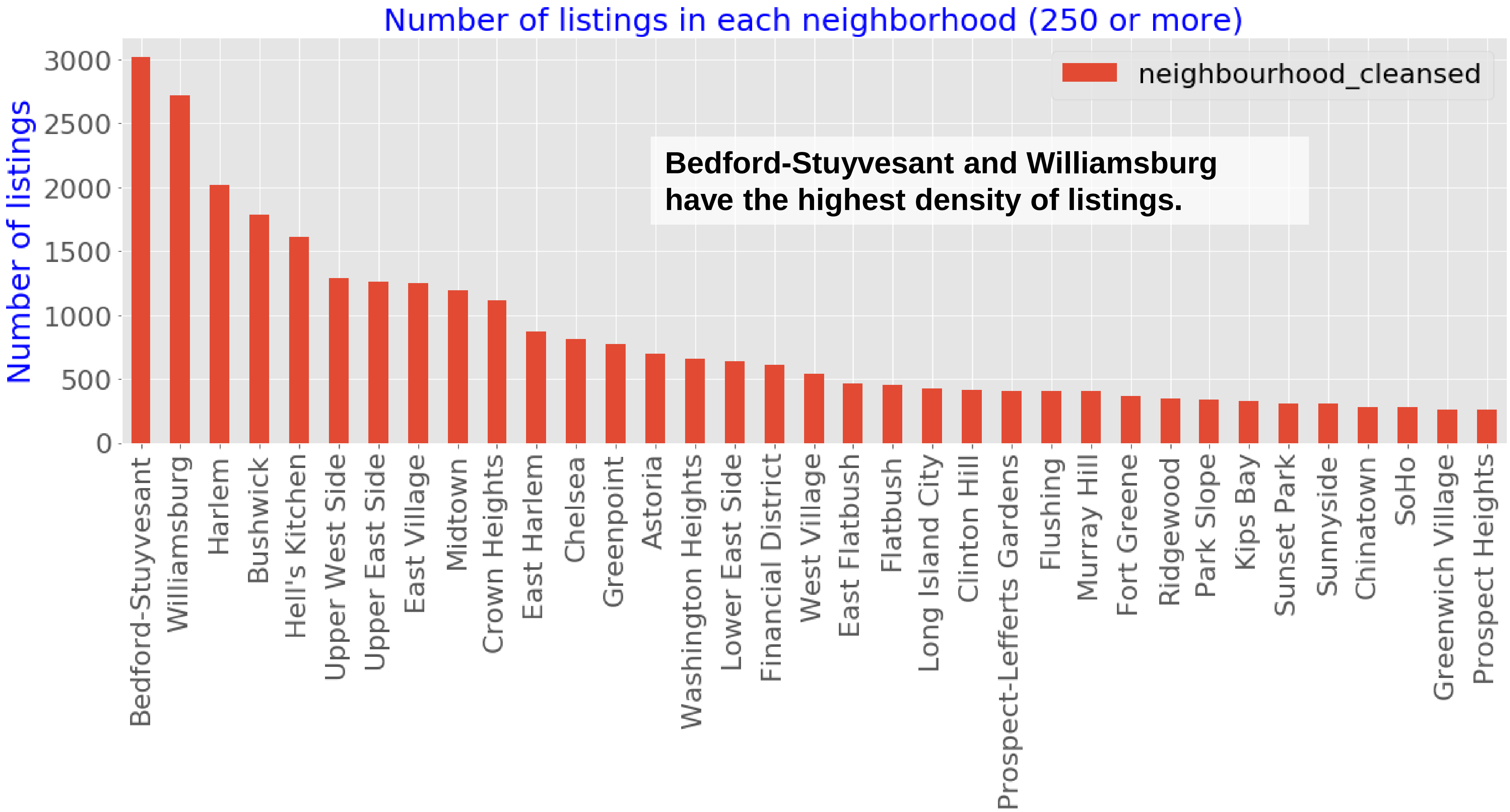
# Motivation

- Airbnb's goal is to book as many properties as possible
- Question: Is the algorithm a smart move for hosts, or is it only "smart" with regard to Airbnb's objectives?
- What further information can be gleaned from Airbnb transactions in New York city?
    - How are the rental properties geographically distributed across the city?
    - How do prices vary across properties, neighborhoods and rental amenities?
    - How well can the rental prices be predicted using machine learning methods?

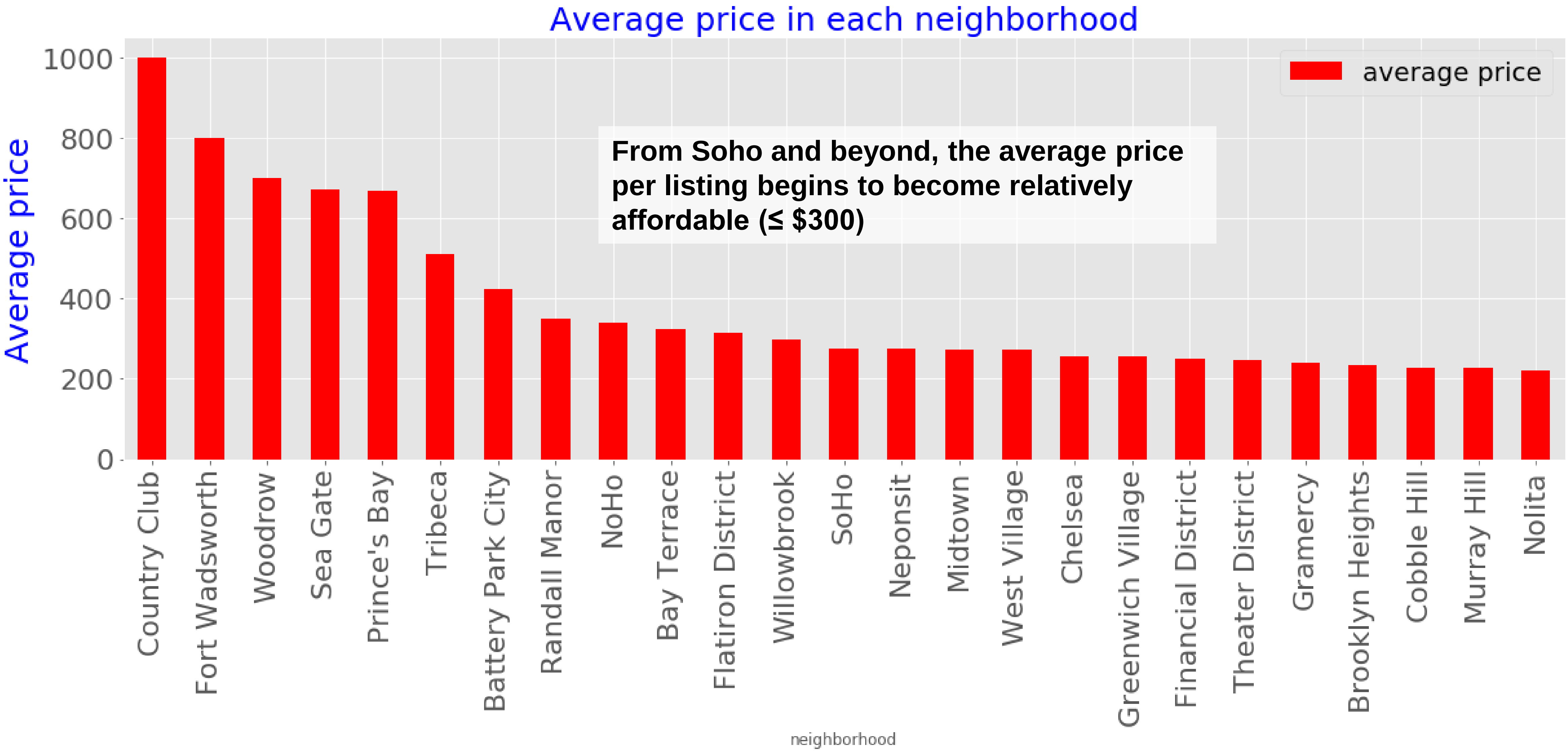
# The data

- The data set is broken into three key groups:
  - Listings: a detailed list of rental listings with 106 attributes from Inside Airbnb (independent of Airbnb). A few of the attributes are price, number of beds, property type, neighborhood, cleaning fee, etc.
  - Mapping shapefiles: Inside Airbnb's map of neighborhood boundaries for mapping; US Census shapefiles of census tracts and blocks
  - Property taxes: Primary Land Use Tax Lot Output (PLUTO) – Public register of NYC property values and taxes assessed. Values are based on estimates for 1 year worth of rental income

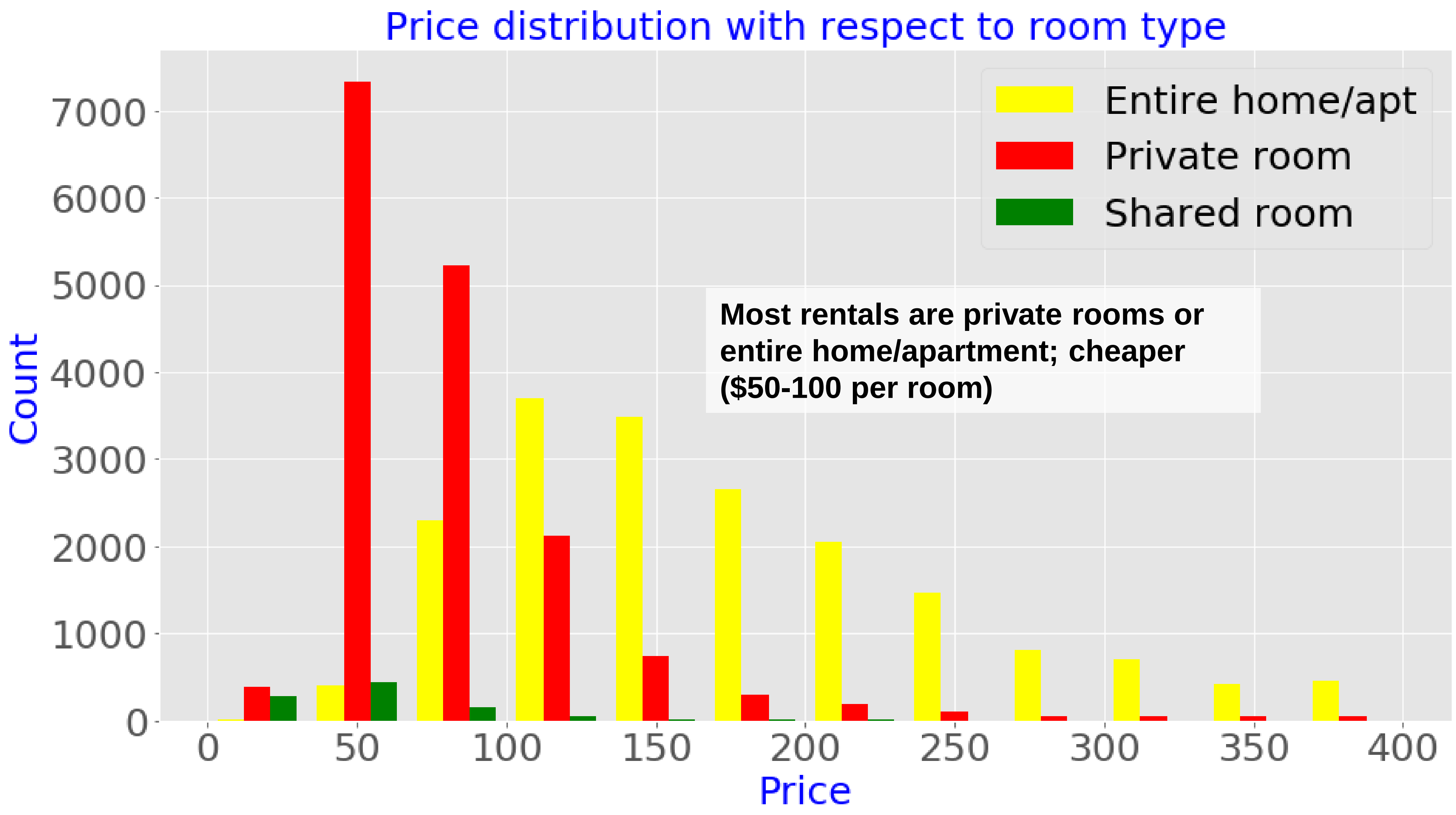
# Exploring the data: listings per neighborhood



# Exploring the data: price per neighborhood

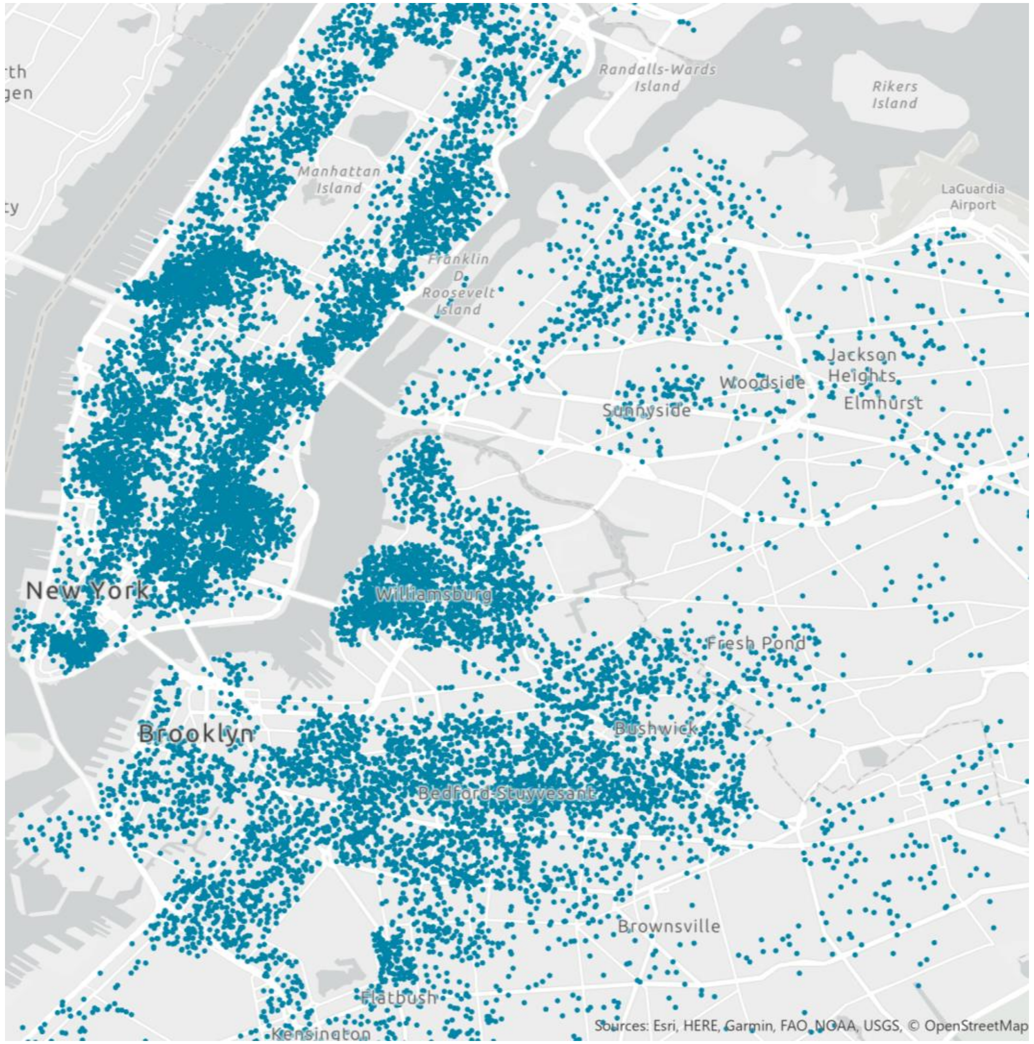


# Exploring the data: price distributions



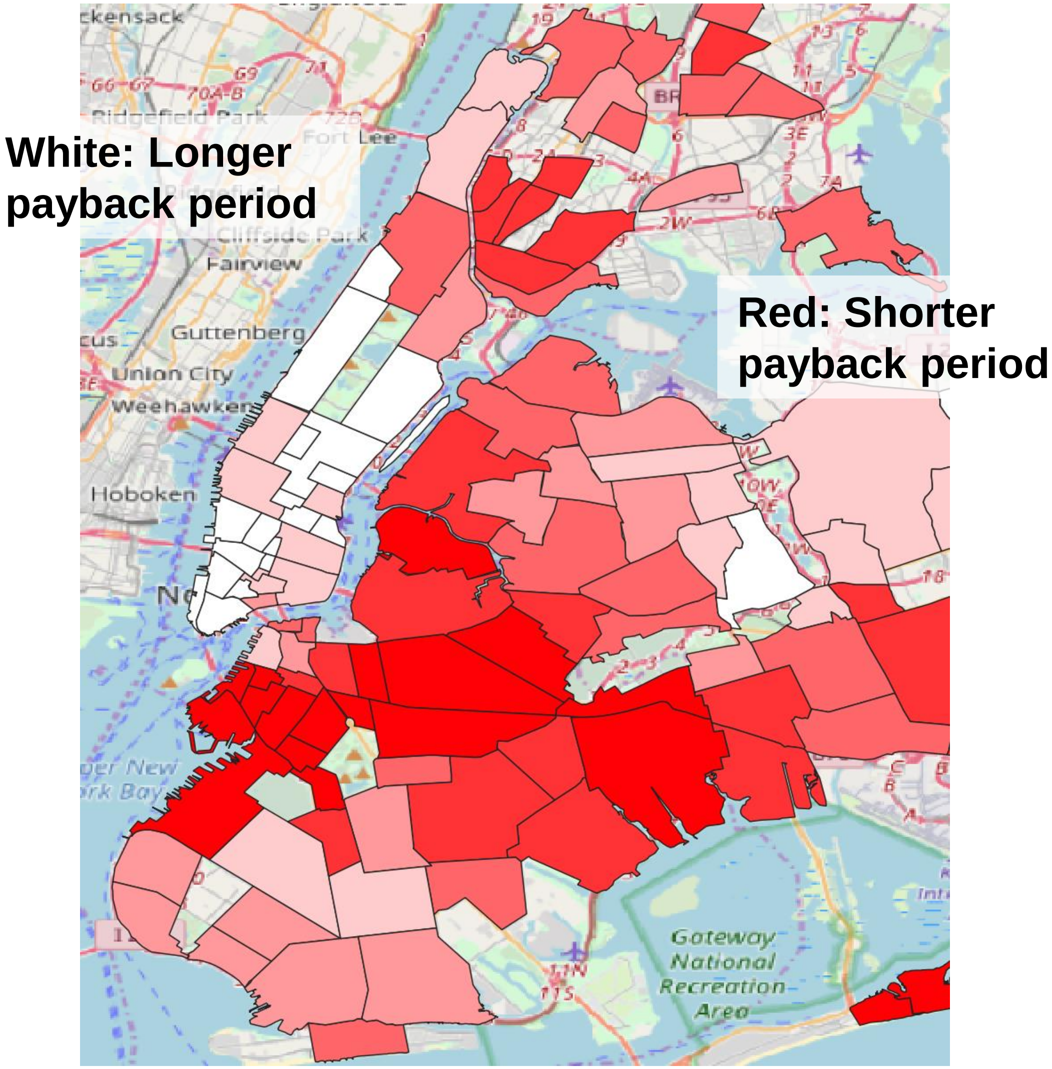
# Geospatial modeling

- There are ~19,000 Airbnbs (entire apartments) in New York
- Questions:
  - Are there any geographic patterns in the data?
  - Where to buy property for the best return on Airbnb?
- Methodology:
  - Divide the city and geospatially join sections with Airbnb coordinates (ArcGIS)
  - Compare Airbnb prices to property values to determine where to buy
- Problem: How to subdivide the city?



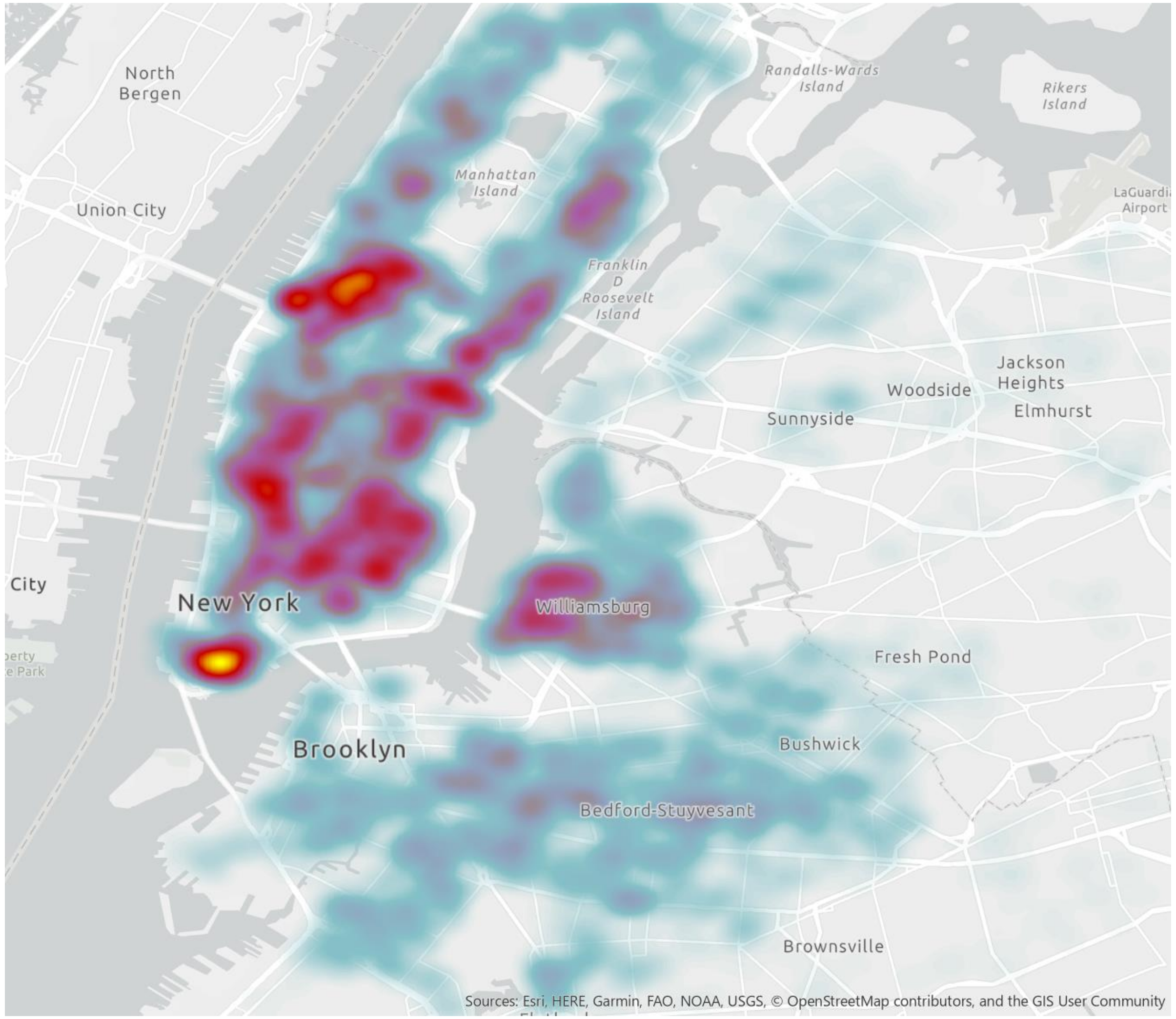
# Geospatial modeling

- Problem: The neighborhoods provided by Airbnb give a highly generalized overview
- In reality these neighborhoods are extremely diverse, with luxury high-rises a few blocks away from low-income housing



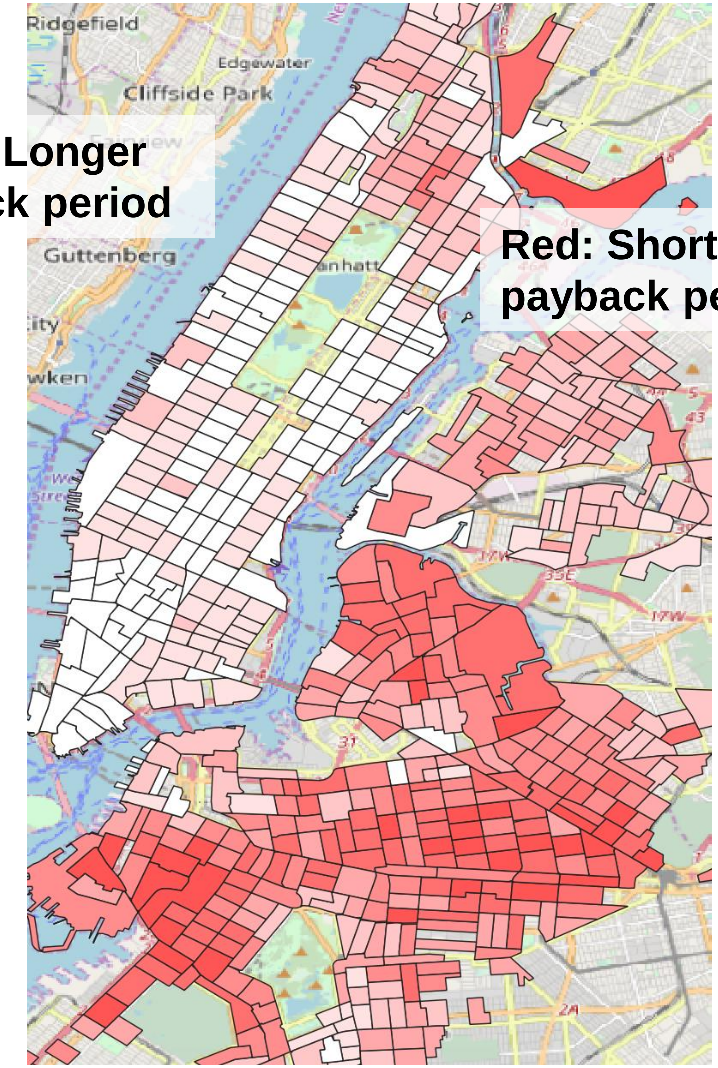
# Geospatial modeling

- Idea 1: Show Airbnb prices with a heatmap
- Pros:
  - Easy to build
  - Does not depend on arbitrary boundaries
- Cons:
  - Does not take property values into account
  - Difficult to analyze against other data (tax, census)
  - Too easy



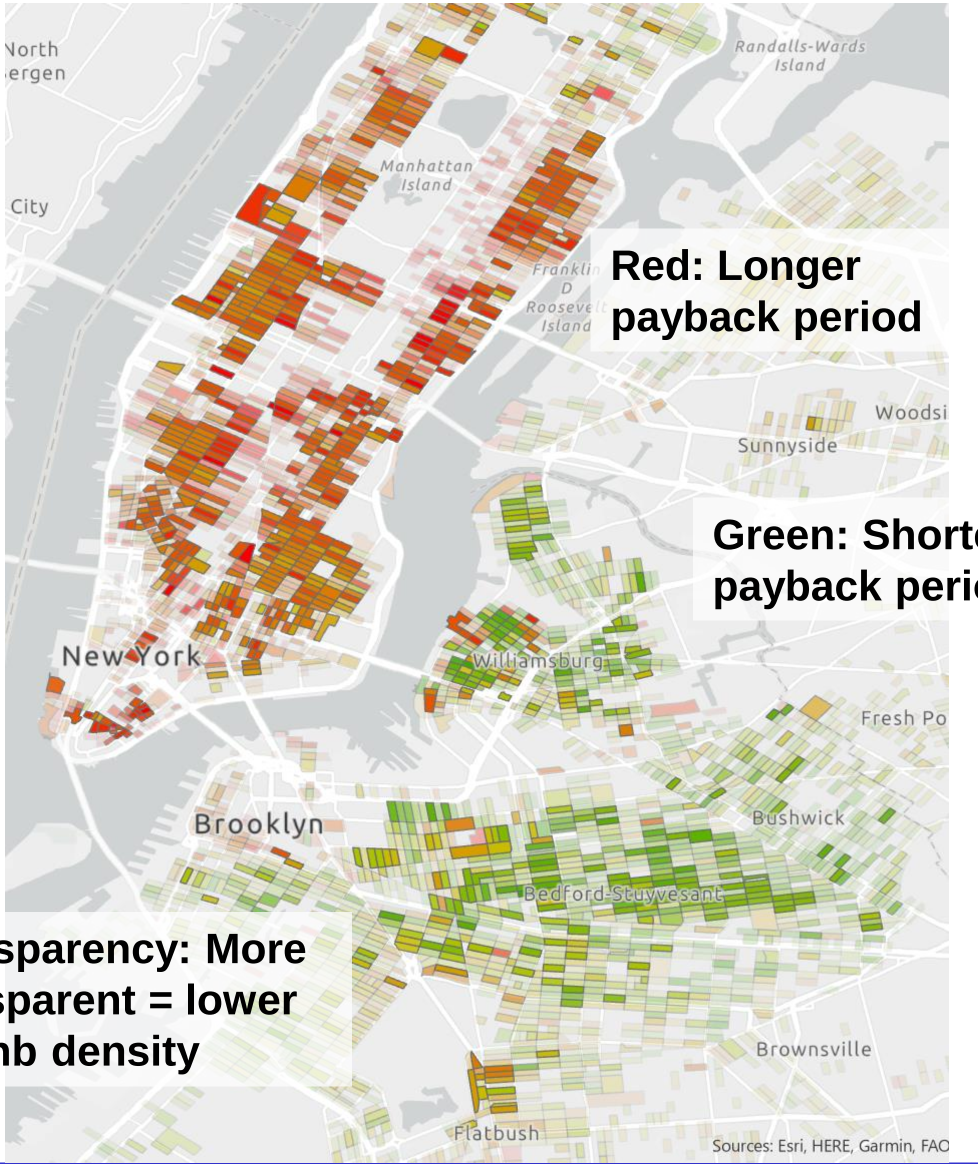
# Geospatial modeling

- Idea 2: Divide the city by census tracts
- Pros:
  - Smaller than neighborhoods
  - Easy to define
  - Well documented, easy to digest
- Cons:
  - Too much price variation
  - Housing values fluctuate wildly within tracts



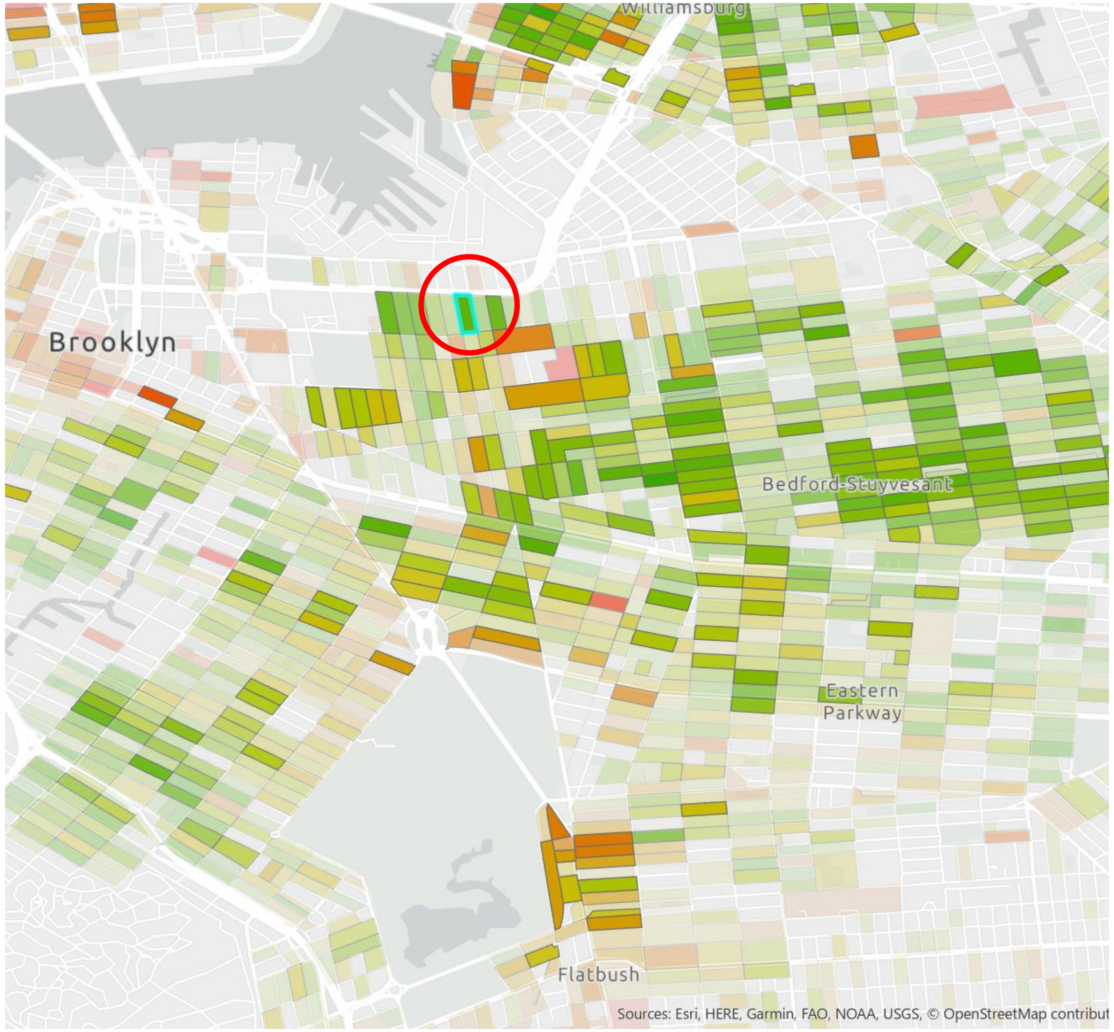
# Geospatial modeling

- Idea 3: Divide the city by census blocks
- Pros:
  - Much more granular than tracts
  - Less price variation
  - Can be joined with property tax and and census data
- Cons:
  - Computationally intensive



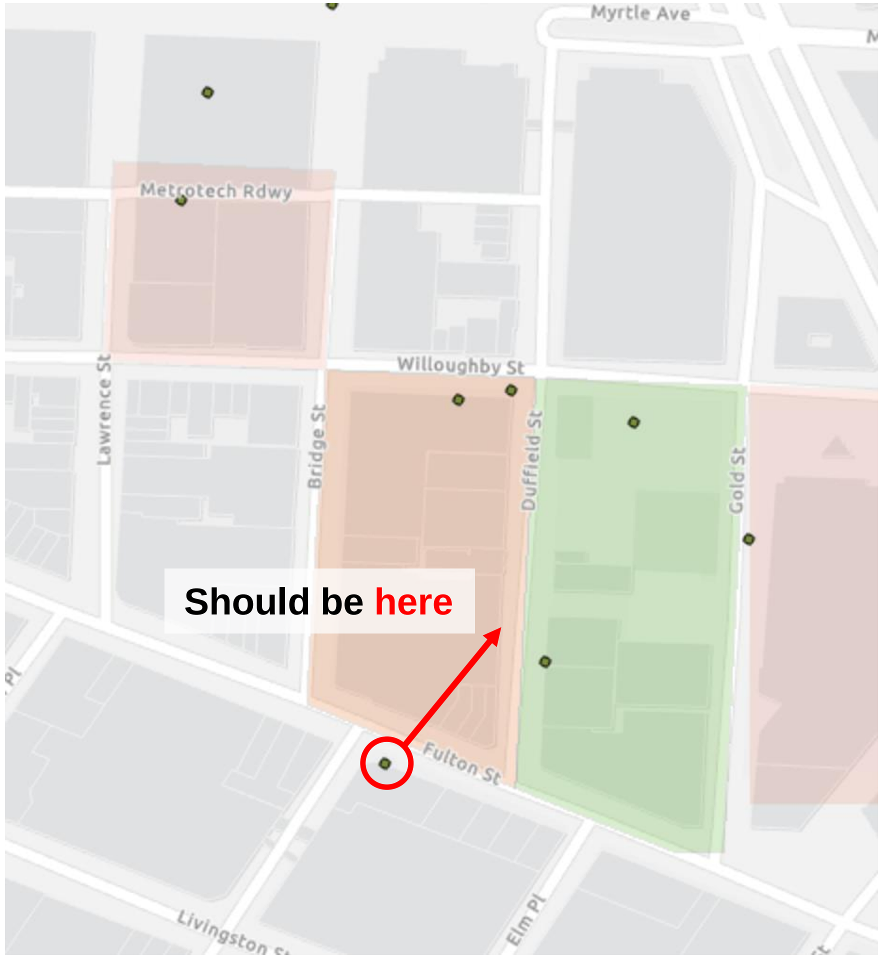
# Geospatial modeling

- Example: Fort Greene
- Median rent: $3300 (approx.)
- Median nightly rate: $224
- Median payback period: 176 nights



# Geospatial modeling

- Caveats:
  - Property taxes do not always coincide with rents
  - Airbnbs are not necessarily a perfect cross-section of rentals
  - For privacy reasons, Airbnb coordinates are not 100% accurate



# Machine learning models for price prediction

- The number one factor that affects a customer's choice of rental is price (followed by the rental property type and the quality of the neighborhood, and other factors).
- Can accurate models be built to reliably predict the price of a rental given features such as: neighborhood, rental type, amenities, etc.?
- To answer this question, we resort to machine learning methodologies.

# Data splitting

- Before any preprocessing was done, the data was split in a 80%:20% ratio with 80% comprising the training data and 20% comprising the validation/test data.
- The division between training and test set is an attempt to replicate the situation where you have past information and are building a model which you will test on future as-yet unknown information.
- More specifically,  anything done on the training data should not be informed by the test data (the philosophy here is that the future should not affect the past).

# Feature selection

- Price was the response/dependent variable; there were 105 features (or predictors) of 63 were categorical and 42 were numerical.

- **Feature selection:** The features were selected with the customer in mind. Features like host picture verification, description of rental property were dropped as they virtually have no effect on price.

- We ended up selecting two sets of features: a small set of 26 features and a large set with 51 features.

- The discussions to follow will be focused on the data with the large set of features.

# Feature selection

- Example: small feature set of size 26

11 categorical features=['amenities', 'bed_type', 'cancellation_policy', 'host_has_profile_pic', 'host_identity_verified', 'host_is_superhost', 'instant_bookable', 'neighbourhood_cleansed', 'property_type', 'require_guest_profile_picture', 'room_type’]

15 numerical features=['accommodates', 'bathrooms', 'bedrooms', 'beds', 'cleaning_fee', 'extra_people', 'guests_included', 'latitude', 'longitude', 'maximum_nights', 'minimum_nights', 'number_of_reviews', 'price', 'security_deposit', 'square_feet']

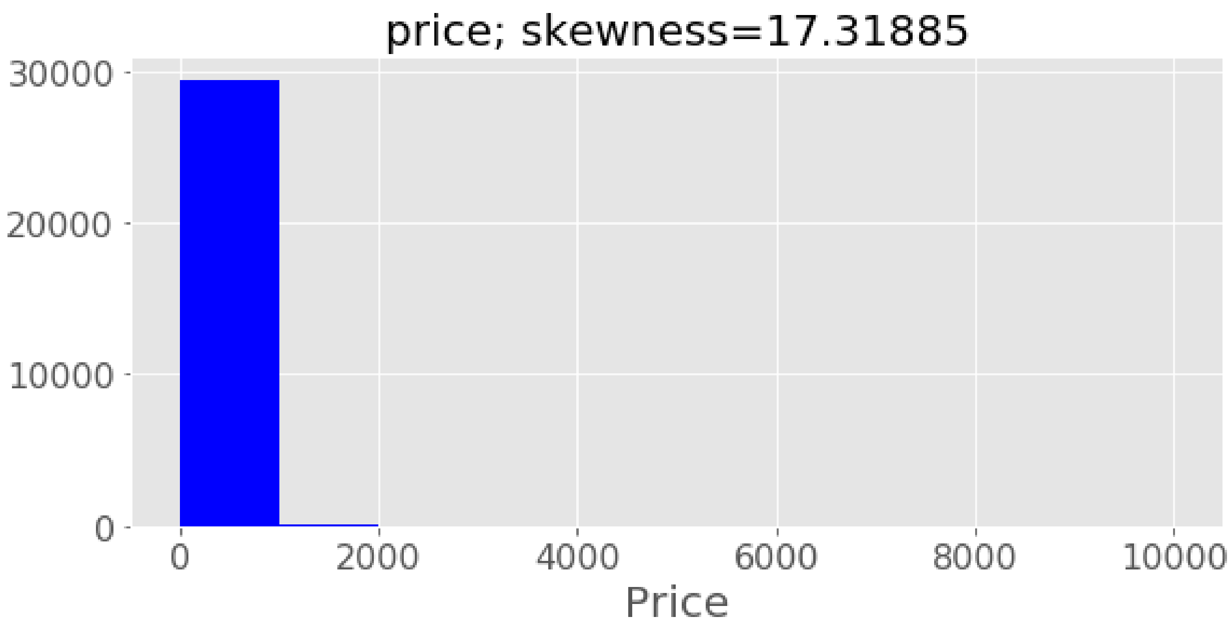
# Cleaning the data

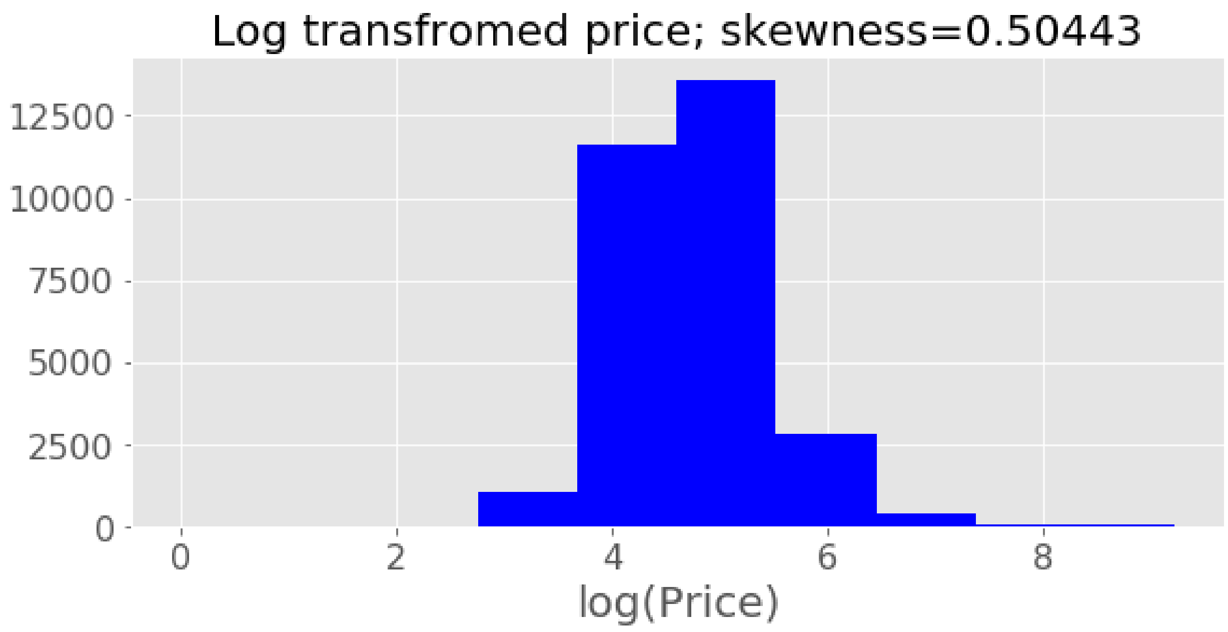
- Missing numerical values were imputed the with zero or the mean value of the feature; missing categorical values were imputed with the mode of the feature.

| | Feature | Missing values | Feature type | Percentage missing | First 5 values |
|---|---|---|---|---|---|
| 0 | security_deposit | 8479 | numerical | 28.347431 | (0.0, 0.0, 0.0, 600.0, 0.0) |
| 1 | cleaning_fee | 4613 | numerical | 15.422420 | (10.0, nan, 20.0, 80.0, 15.0) |
| 2 | zipcode | 265 | categorical | 0.885962 | (10453, 10451, 10002, 10010, 11211) |
| 3 | amenities | 46 | categorical | 0.153790 | (TV,TV,Internet,Wifi,Air conditioning,Free str... |
| 4 | city | 44 | categorical | 0.147103 | (Bronx, The Bronx, New York, New York, Brooklyn) |
| 5 | bathrooms | 27 | numerical | 0.090268 | (1.0, 1.0, 1.0, 1.0, 1.0) |
| 6 | bedrooms | 16 | numerical | 0.053492 | (1.0, 1.0, 1.0, 1.0, 1.0) |
| 7 | beds | 15 | numerical | 0.050149 | (1.0, 1.0, 1.0, 1.0, 1.0) |
| 8 | host_is_superhost | 5 | categorical | 0.016716 | (f, f, f, t, t) |
| 9 | host_total_listings_count | 5 | numerical | 0.016716 | (8.0, 1.0, 5.0, 1.0, 1.0) |
| 10 | host_has_profile_pic | 5 | categorical | 0.016716 | (t, t, t, t, t) |
| 11 | host_identity_verified | 5 | categorical | 0.016716 | (t, f, t, t, f) |

# Response variable transformation

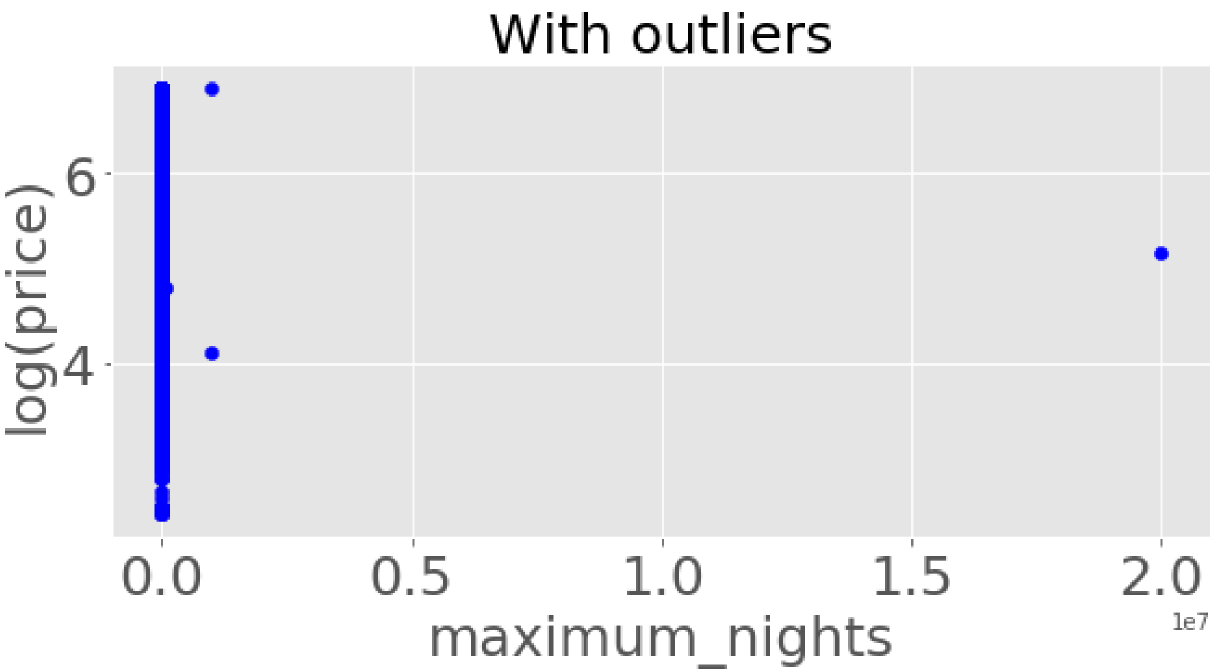
The skewness of the response variable (price) was corrected using a logarithm transformation

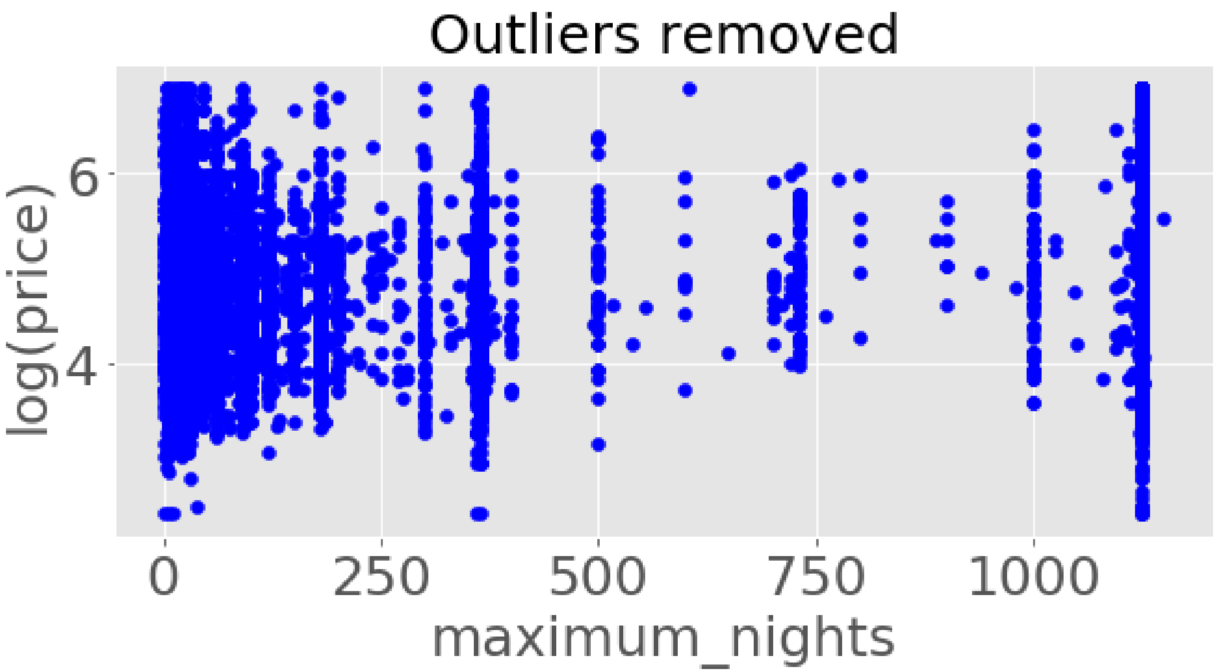


# Removal of outliers

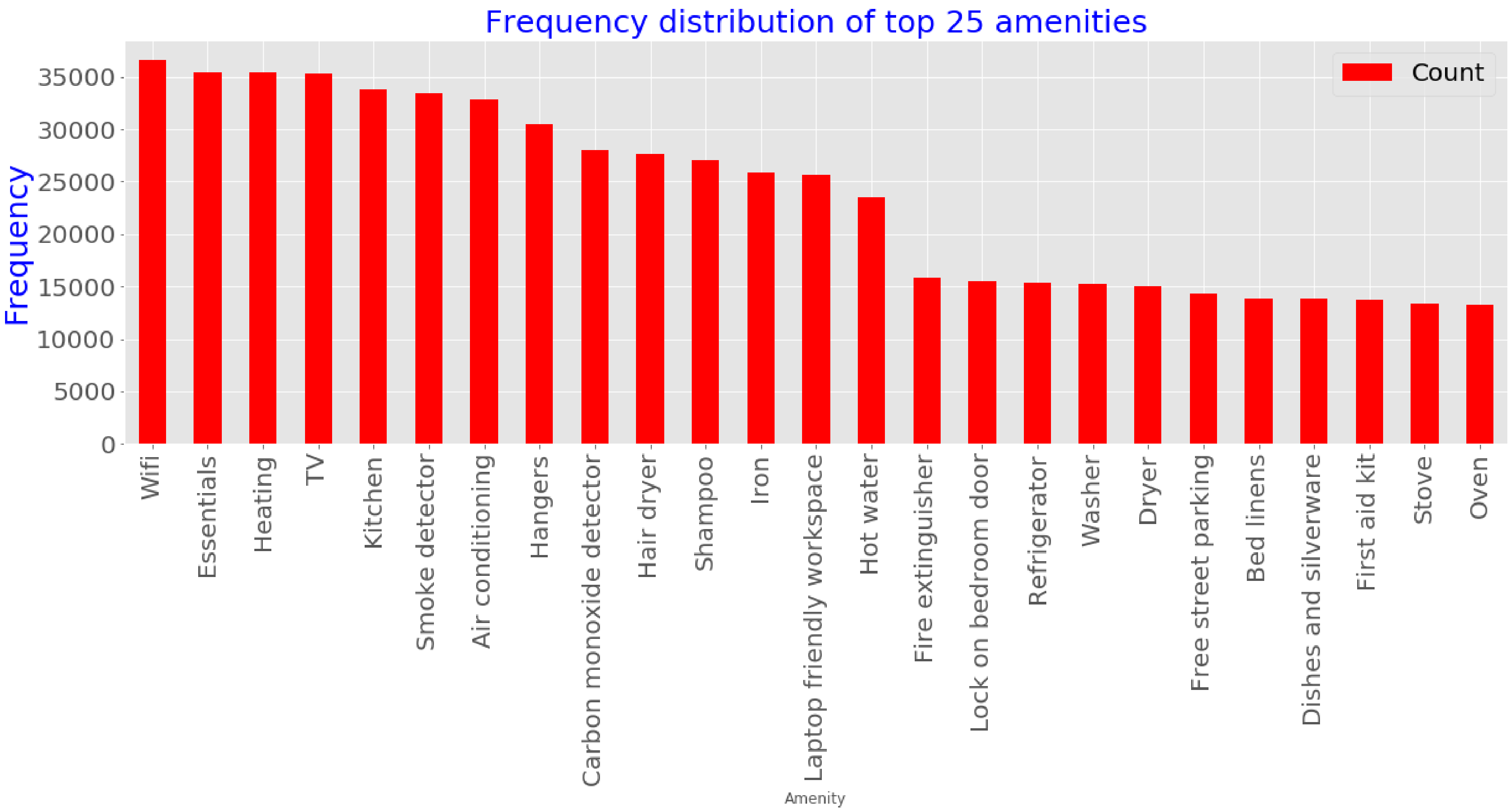
Outliers in the numerical features were removed via visual/graphical inspection. Below is an example of outlier removal in the feature maximum_nights:



# Feature engineering

The amenities feature comprises several sub-features such as Wifi, TV, Heating, etc (128 of in total). Some were more frequent that others.



# Feature engineering

The amenities feature was engineered as follows:

(i) Each sub-feature $i \in \{\mathbf{Wifi, TV, heating, pool, \ldots .}\}$ was assigned weight *w*(*i*) given by:

$$w(i) = \frac{f(i)}{f_{max}}$$

where $f(i)$ is the frequency of $i$ in the data set and $f_{max}$ is the maximum frequency.

(ii) The sum of the weights $\mathbf{s}$ is used to represent the value of each row of amenities column:

$$s = \sum w(i)$$

# Feature engineering

```
train['amenities'].head()

0    TV,TV,Internet,Wifi,Air conditioning,Free stre...
1    Wifi,Air conditioning,Kitchen,Heating,Smoke de...
2    Wifi,Air conditioning,Kitchen,Heating,Smoke de...
3    TV,TV,Internet,Wifi,Air conditioning,Kitchen,P...
4    Wifi,Pets allowed,Heating,Smoke detector,Carbo...
Name: amenities, dtype: object
```

```
train['amenities'].head()

0    13.464043
1    10.242527
2    10.817777
3    17.599993
4     7.089850
Name: amenities, dtype: float64
```

- The remaining categorical variables were one-hot encoded (binary categorical variables) or label-encoded.

# Regression models

We employed the following models as implemented in scikit-learn machine learning module in Python:

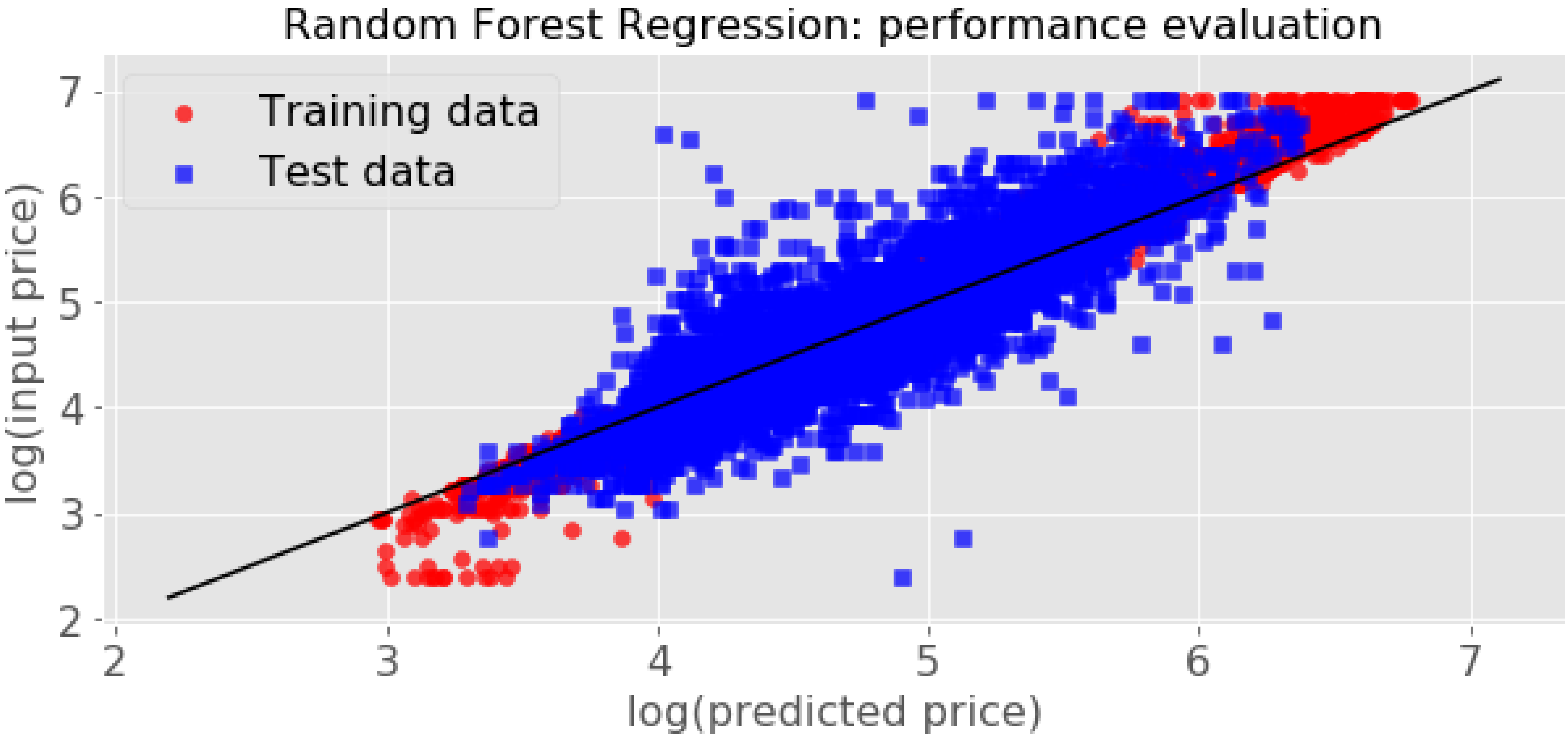
- Lasso regression
- Gradient boosting regression
- Extreme gradient boosting regression
- Random forest regression

Each regression method was hyperparameter-tuned using a grid search and a 10-fold cross-validation (CV). The CV scoring method was “negative root mean squared error.”

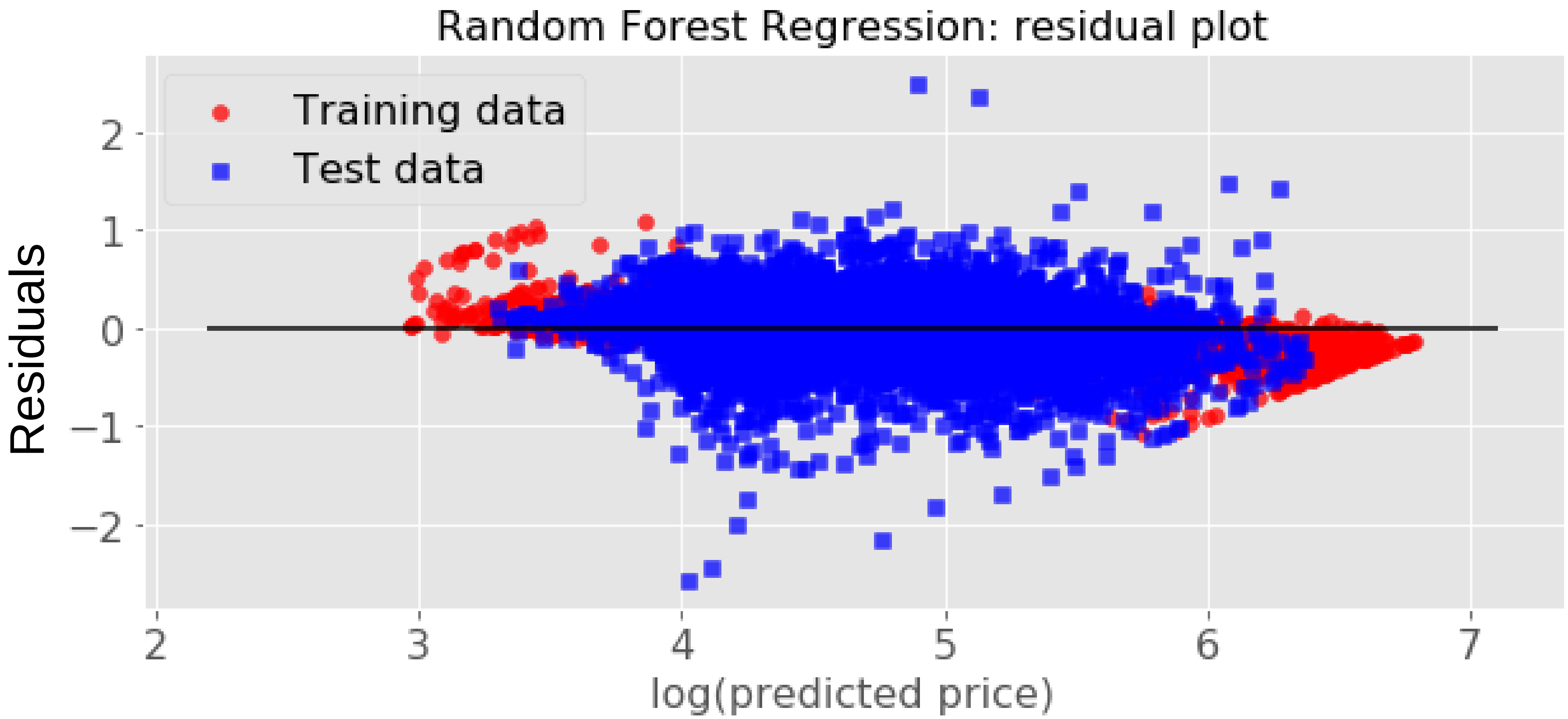
# Results

| Model | Training Score | Training RMSE | Test RMSE | Training $R^2$ | Test $R^2$ | Training Accuracy | Test Accuracy |
|---|---|---|---|---|---|---|---|
| Lasso | 0.1563 | $82 | $79 | 65% | 64% | 69% | 69% |
| GBR | 0.0904 | $40 | $61 | 92% | 79% | 86% | 77% |
| XGBR | 0.0918 | $35 | $62 | 93% | 78% | 86% | 77% |
| RF | 0.0990 | $32 | $67 | 97% | 77% | 91.6% | 76% |

# Results

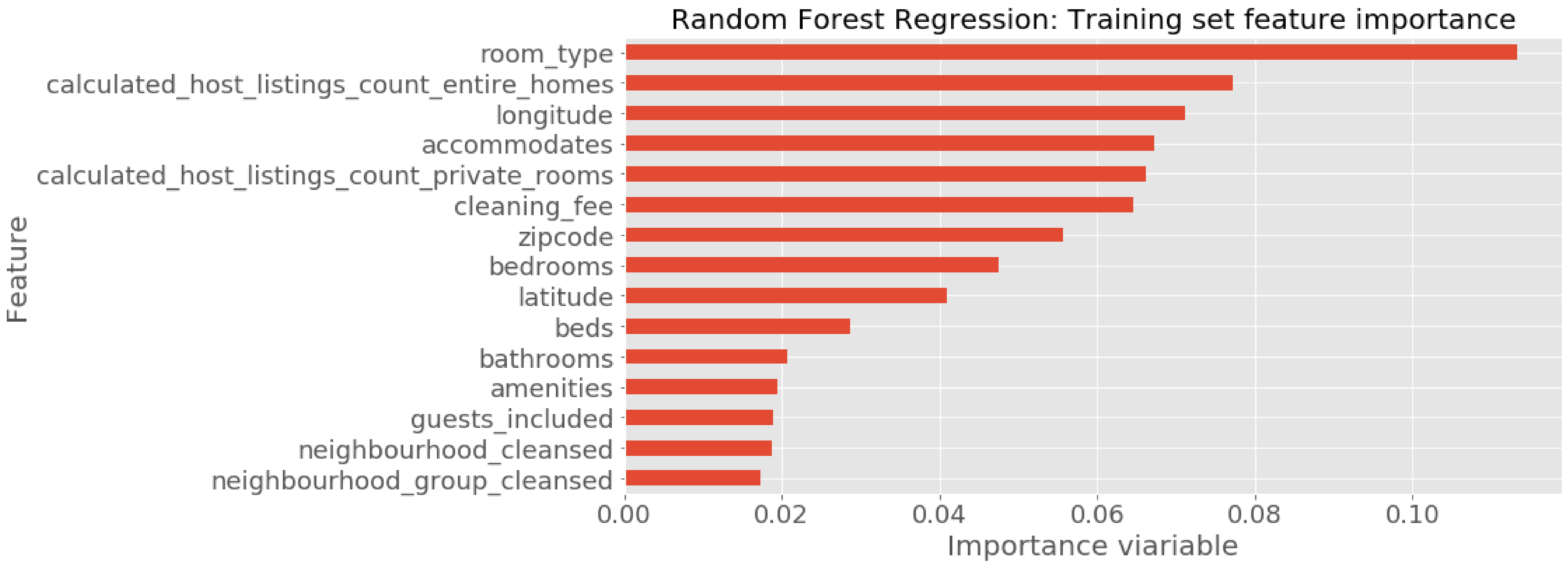

Random Forest Regression: performance evaluation
Training data
Test data
log(input price)
log(predicted price)
2
3
4
5
6
7
2
3
4
5
6
7

# Results


Random Forest Regression: residual plot
Training data
Test data
Residuals
2
1
0
−1
−2
2
3
4
5
6
7
log(predicted price)

# Results

- Random forest “room_type” was the feature with the most importance



# Conclusions

- When it comes to Airbnb pricing, there are definitive numeric and geospatial patterns in pricing
- Understanding these patterns can benefit guests and hosts alike (but not Airbnb!)
- Next steps:
  - Join with census data to extrapolate key attributes of profitable blocks for clustering
  - Integrate better real estate pricing data to identify properties for sale
  - Explore other cities
  - Turn into a product (Flask web app)