

# How to Succeed as an Airbnb Host ——Evidence from Machine Learning and Text Analysis Approaches

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Cleanliness,

Conclusion

communication, location

and verification of super

factors for the rating score

Three localities display

debate (Cheng & Jin, 2019))

**London:** property

New York: host

Tokyo: location

significant differences in

Successful hosts should

Limitations

cultural regions, adding to the

convergence/divergence of

experiences (Brochado et al.,

References

• Cheng, M., & Jin, X. (2019). What

The need to analyze more

different, or even cross-

literature regarding the

Airbnb guests' traveling

2017).

strategically arouse

resonance in guests

terms of factors framing the

results("amenities, host and location"

host are the main influencing

### Research Question

### Q1: What factors are the driving forces behind Airbnb review ratings?

Review scores are metric for the satisfactionlevel of the guests.

Q2: Are there any geospatial differences?

- Hosts can condition their property/self attributes
- Airbnb can incentivize their hosts to change

### Data Collection and Pre-processing

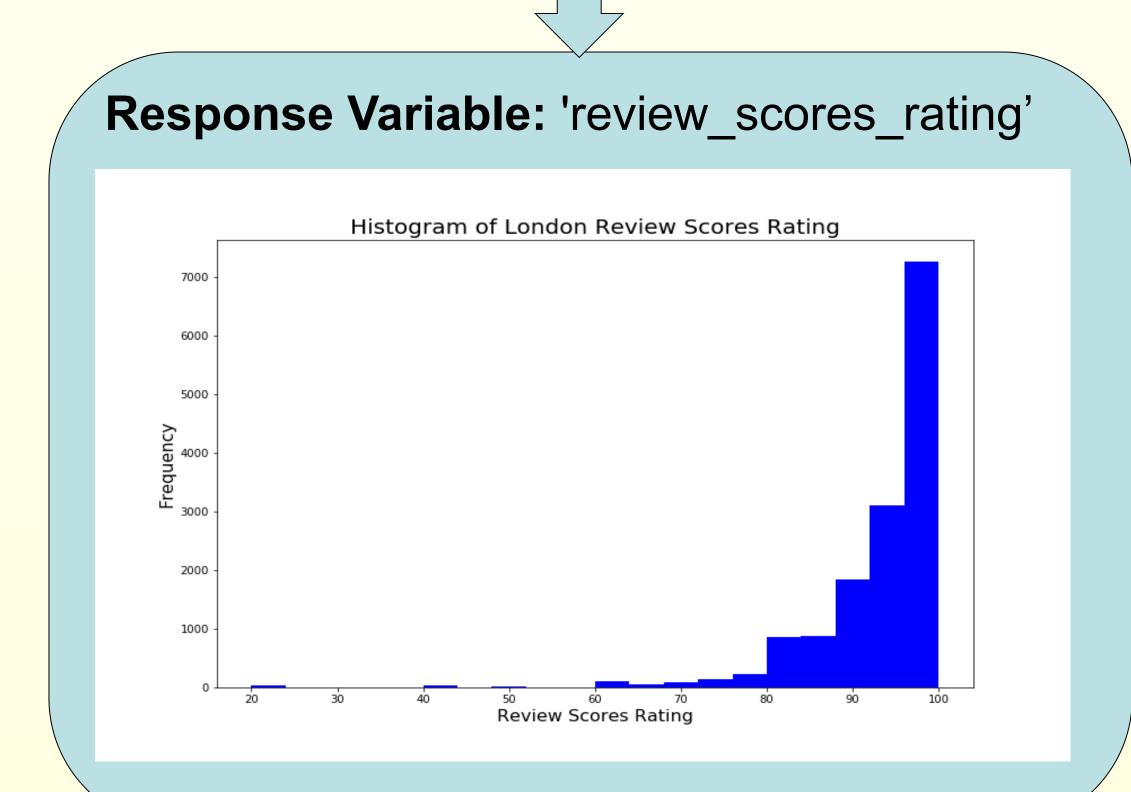
http://insideairbnb.com/get-the-data.html (April 2020)

#### 1. Drop/Create/Modify attributes

Numerical: 'beds', 'bedrooms', 'guests included', 'bathrooms', 'review scores communication', etc.

Categorical: 'host\_has\_profile\_pic', 'TV' 'host\_identity\_verified', 'property\_type', etc.

Text: 'house description', 'self about'



#### 2. Heatmaps---No feature removed

#### 3. Data normalization + Text: uni-/bi-gram

City	Sample	Feature Number	
London	14676	10051	
New York	8427	10052	
Tokyo	5288	10049	

#### 4. Pipeline Construction

- Pipeline1: (numerical, categorical, text(bag of words))
- Pipeline2: (numerical, categorical, text(TF-IDF))

### Machine Learning Approach and the Results

# <u>London</u> **Training R2** Test R2 Ridge1 29.1

<b>D</b> : 1					
Model Name	Training R2	Test R2	MSE	MAE	
New-York					
Gradient Boosting	0.84	0.69	23.1	2.93	
Random Forest	0.9	0.68	24.02	2.94	
Lasso2	0.67	0.65	25.86	3.24	
Lasso1	0.68	0.66	25.33	3.2	
Ridge2	0.81	0.66	25.55	3.3	

New-York							
Model Name	Training R2	Test R2	MSE	MAE			
Ridge1	0.74	0.68	12.56	2.39			
Ridge2	0.69	0.67	12.73	2.37			
Lasso1	0.66	0.65	13.4	2.43			
Lasso2	0.65	0.64	14.02	2.47			
Random Forest	0.87	0.62	14.78	2.38			
Gradient Boosting	0.86	0.65	13.49	2.31			

Tokyo					
Model Name	Training R2	Test R2	MSE	MAE	
Ridge1	0.74	0.71	14.05	2.63	
Ridge2	0.7	0.71	14.24	2.68	
Lasso1	0.67	0.7	14.72	2.72	
Lasso2	0.67	0.7	14.85	2.73	
Random Forest	0.87	0.68	15.52	2.54	
Gradient Boosting	0.86	0.7	14.51	2.59	

## Top five features

Review scores for cleanliness(+) Review scores for communication(+) Review scores for location(+) Number of reviews(+) Verification as super host(+)

#### **Top five features** Review scores for cleanliness(+) Review scores for communication(+) Review scores for location(+) Verification as super host(+) Flat(unigram)(-)

#### **Top five features** Review scores for cleanliness(+)

Review scores for communication(+) Review scores for location(+) Verification as super host(+) Meter(unigram)(-)

#### **London-specific features** Property/neighborhood attributes

bathrooms, beds, bedrooms, guest capacity, beautiful kitchen

### **New York-specific features Host attributes**

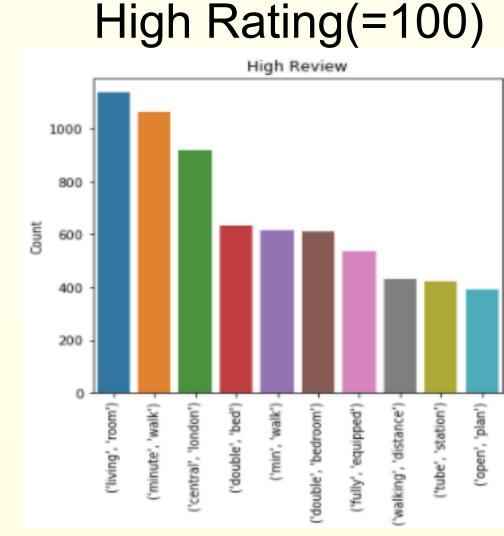
Time as host, host acceptance rate (almost in every model)

## **Tokyo-specific features**

Location

Asakusa/Ueno(-), Narita(-), Shibuya (+),Ginza(+)

### Text Analysis(Bigram analysis) Approach and the Results



Models:

pipelines)

pipelines)

pipeline)

pipeline)

**Optimization:** 

Ridge regression (both

Lasso regression (both

Random forest (the first

Gradient boosting(the first

Hyperparameter tuning:

**Performance metric:** 

r2 (Main metric)

randomized search method

5-fold cross-validation with

10 iterations on the training

Mean squared error (MSE)

Mean absolute error (MAE)

### **House Description**

London

- Amenities: double bed Location: central London Neighborhood: min walk
  - Transportation: tube

**New York** 

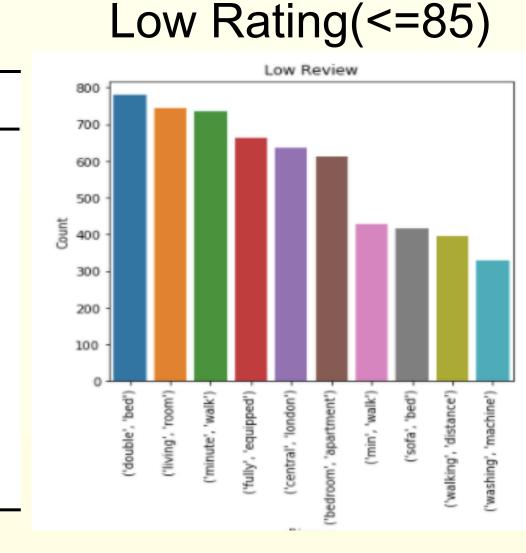
Amenities: living room,

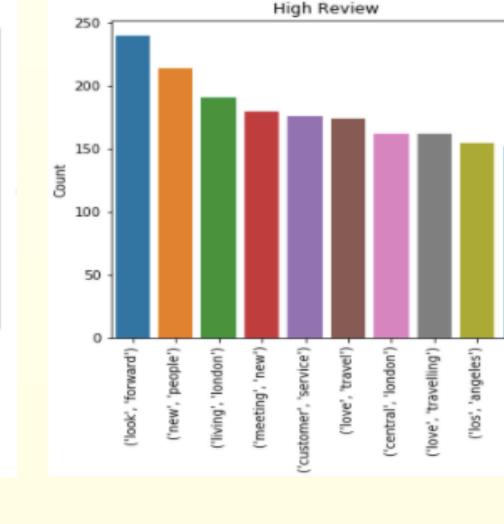
newly renovated (high)

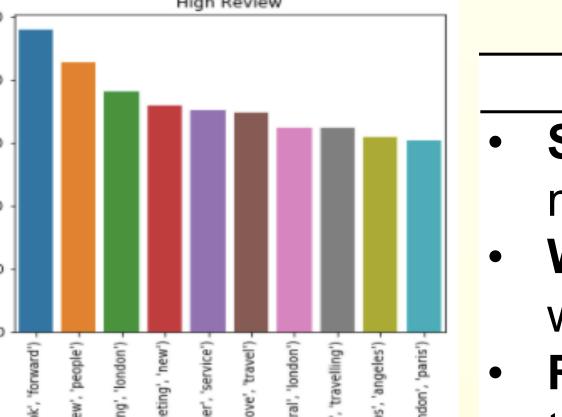
Neighborhood: min walk

Location: New York

station







High Rating(=100)

### London Self-background:

**Host Description** 

- management company Welcome message: would happy
- Resonance (high):love travel

York, time square

(high): feel free

travel

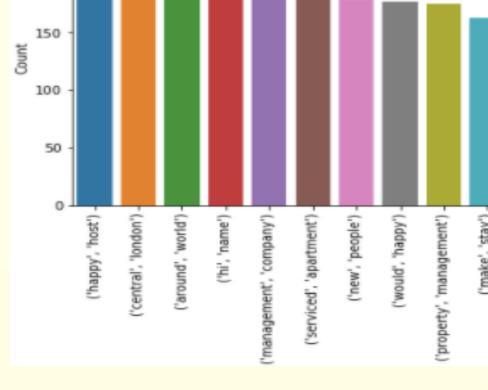
Welcome message

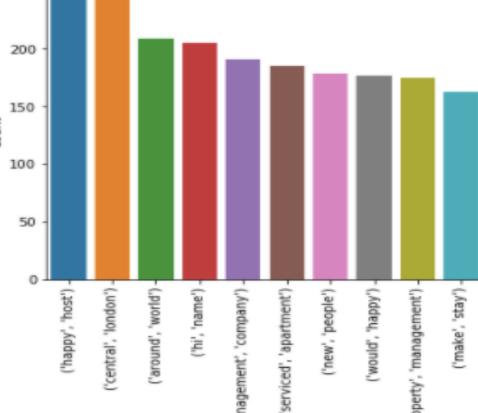
Resonance (high):love

Tokyo

**New York** 

Surroundings (low):New





Low Rating(<=85)

do Airbnb users care about? An analysis of online review comments. International Journal of Hospitality Management, 76, 58-70. Brochado, A., Troilo, M., &

Aditya, S. (2017). Airbnb customer experience: evidence of convergence across three countries. Annals of Tourism Research, 63, 210-212.



I sincerely thank Dr. Evans and all classmates in MACS 30250-Perspectives on Computational Research in Economics for your helpful comments and suggestions.



- Amenities: double bed Location: Ikebukuro station (low), Shinjuku station (high)
- Neighborhood: min walk

