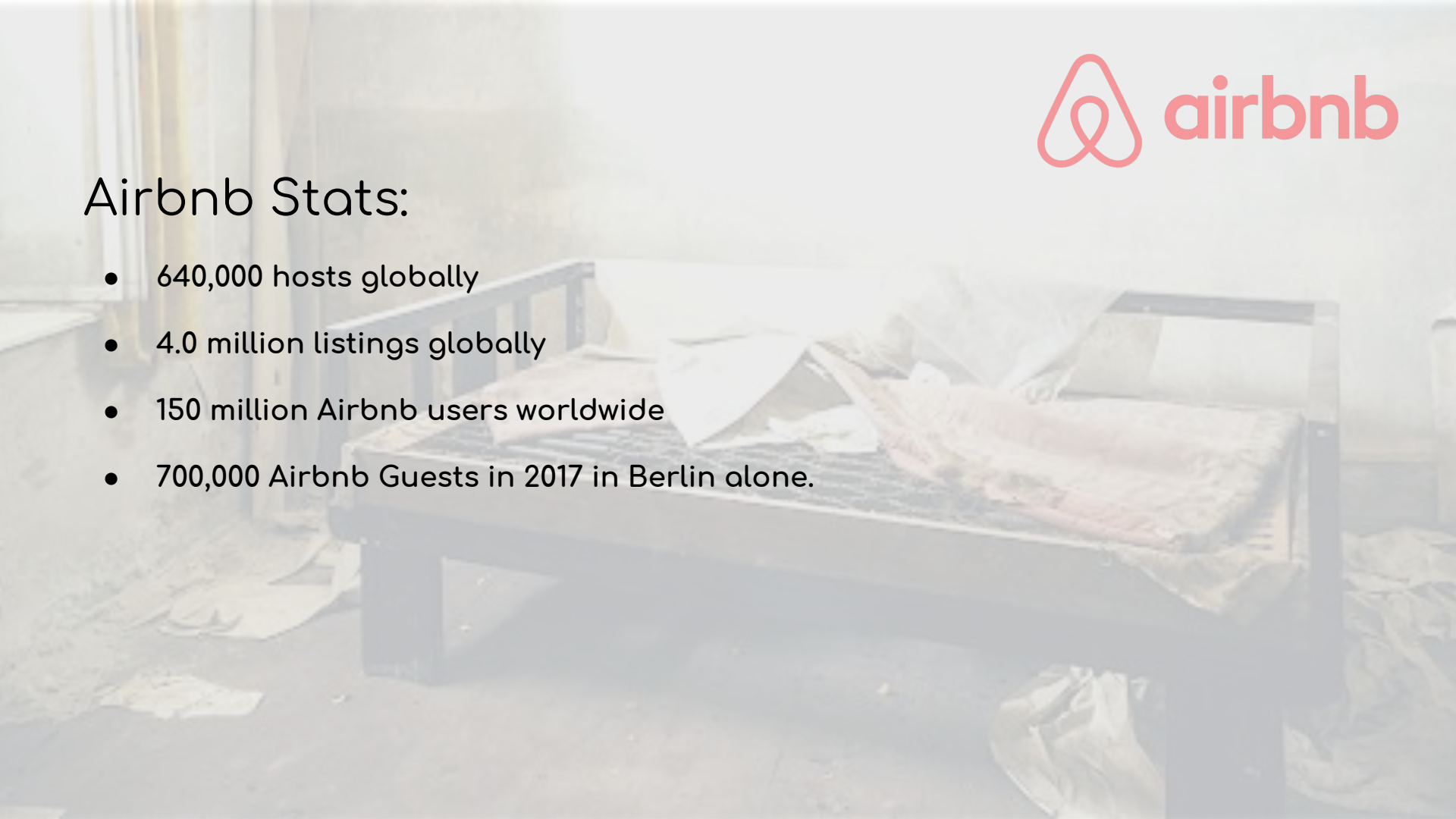
CAN MACHINE LEARNING IMPROVE MY AIRBNB?

Joseph Pearson | January 2019 | London DSI 7



Airbnb Stats:

- 640,000 hosts globally
- 4.0 million listings globally
- 150 million Airbnb users worldwide
- 700,000 Airbnb Guests in 2017 in Berlin alone.

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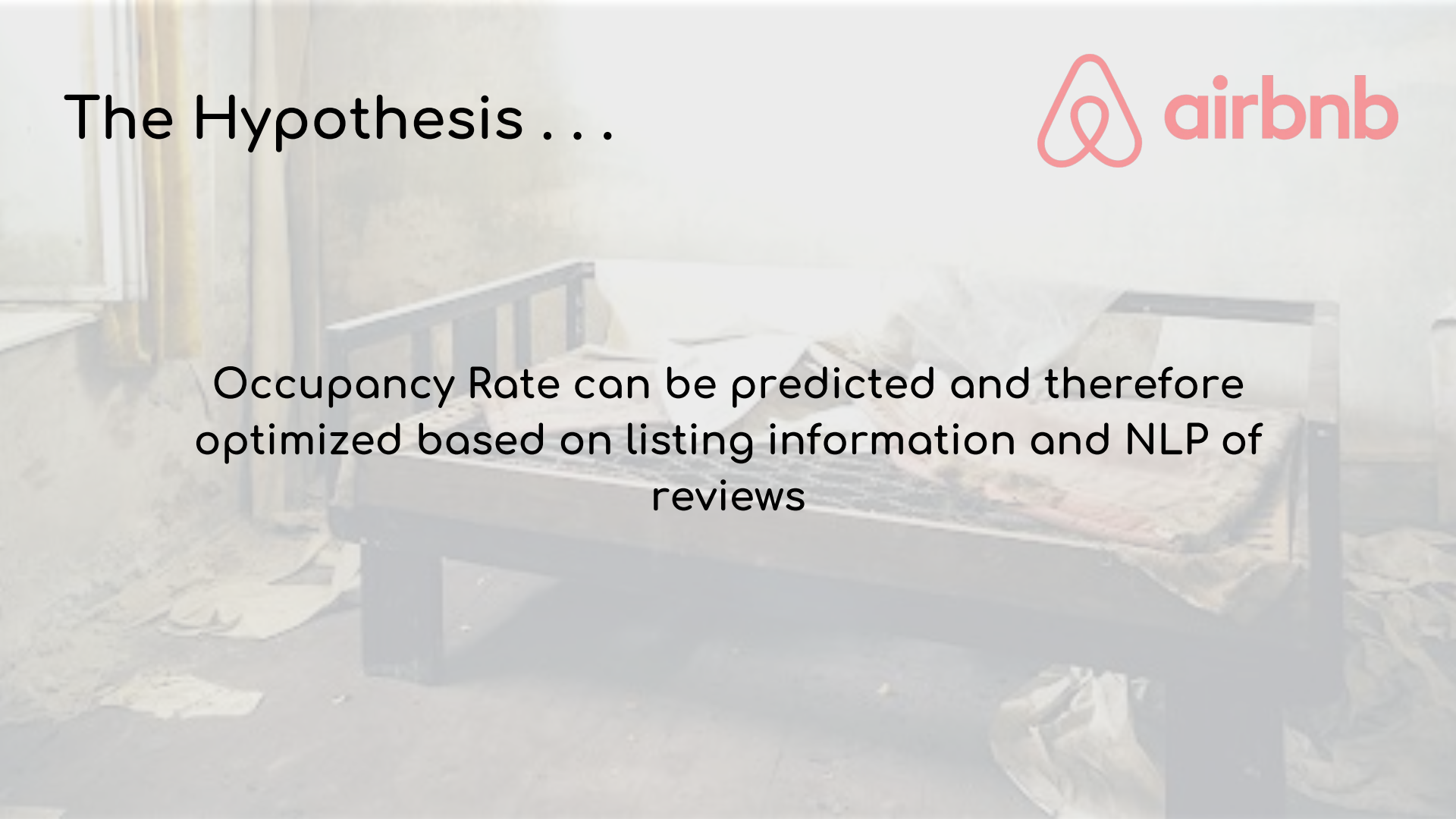
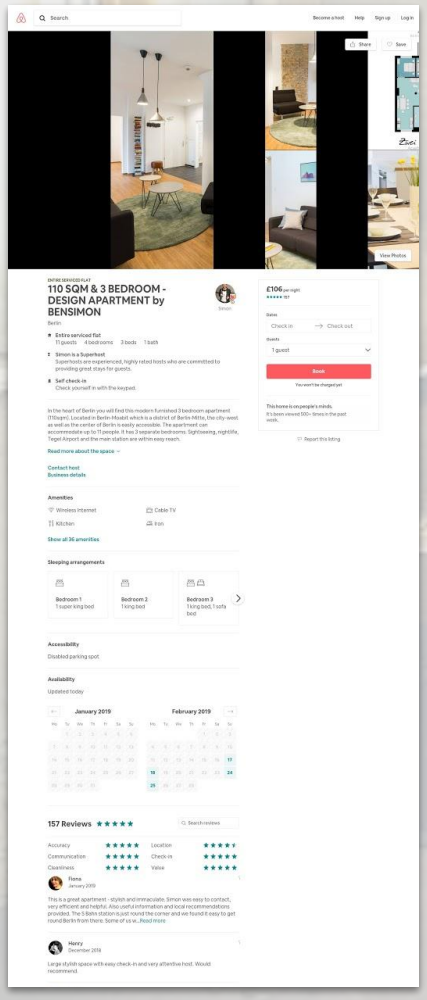
How do you make sure you capitalize on this?

Increase your Occupancy Rate

The Hypothesis . . .



Occupancy Rate can be predicted and therefore optimized based on listing information and NLP of reviews



The Data . . .

Data from http://insideairbnb.com/berlin/ in csv format scrapped from AirBnb

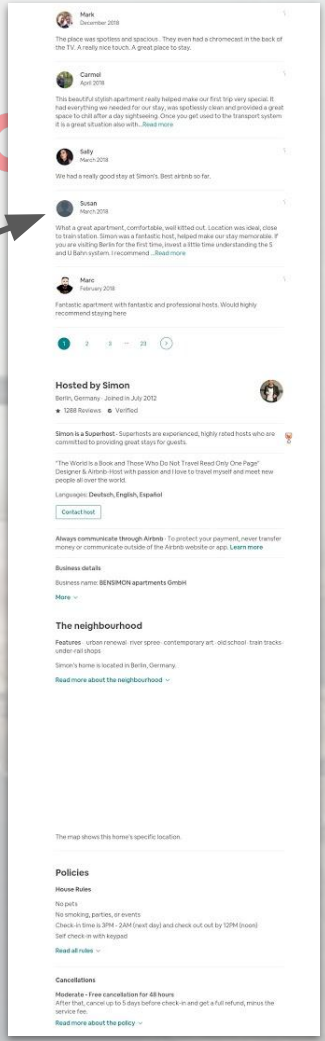
Reviews . . .

	listing_id	id	date	reviewer_id	reviewer_name	comments	length	language
0	2015	69544350	2016-04-11	7178145	Rahel	Mein Freund und ich hatten gute gemütliche vie...	88	de
1	2015	69990732	2016-04-15	41944715	Hannah	Jan was very friendly and welcoming host! The ...	29	en
2	2015	71605267	2016-04-26	30048708	Victor	Un appartement tres bien situé dans un quartie...	47	fr
3	2015	73819566	2016-05-10	63697857	Judy	It is really nice area, food, park, transport ...	10	en
4	2015	74293504	2016-05-14	10414887	Romina	Buena ubicación, el departamento no está orden...	53	es

- 401963 reviews from April 2017 to November 2018

Listings . . .

- All the rest of the Listing information
- 22500 unique listings



The Cleaning . . .

- Many columns contained mainly null values or very few non-zero values and were dropped.
- Listings with null values dropped
- Review lengths calculated and language of review each review determined and non-english reviews dropped
- Dropped reviews with < “50 days occupied/month” (I will explain this later)
- Dummified or Binarized many features

The Preprocessing . . .

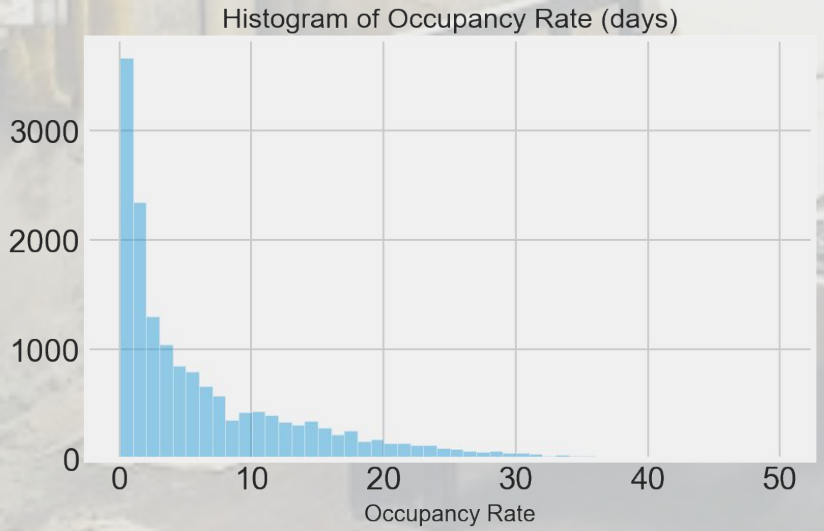
- Language of host determined and added as additional feature
- Vader Sentiment calculated for each review and then aggregated by listing
- CountVectorizer, TFiDF, Textacy doc_to_terms + Vectorizer, Textacy Topic Modeling
- Reviews and listing data-frames merged for modelling

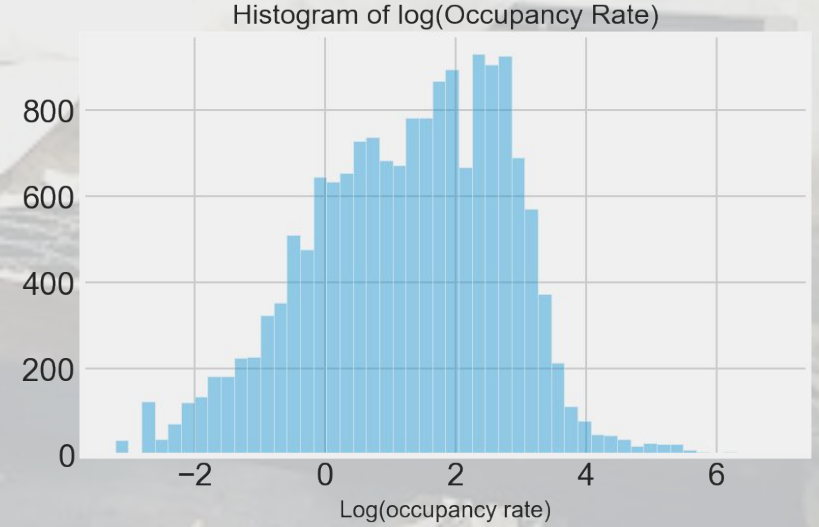
- Final Dataset:
  - 16,500 listings,
  - 244 features (not including word counts and topics)

The Target . . .

Occupancy Rate:

$$\frac{Reviews\_per\_Monthx2.4days}{0.5}$$





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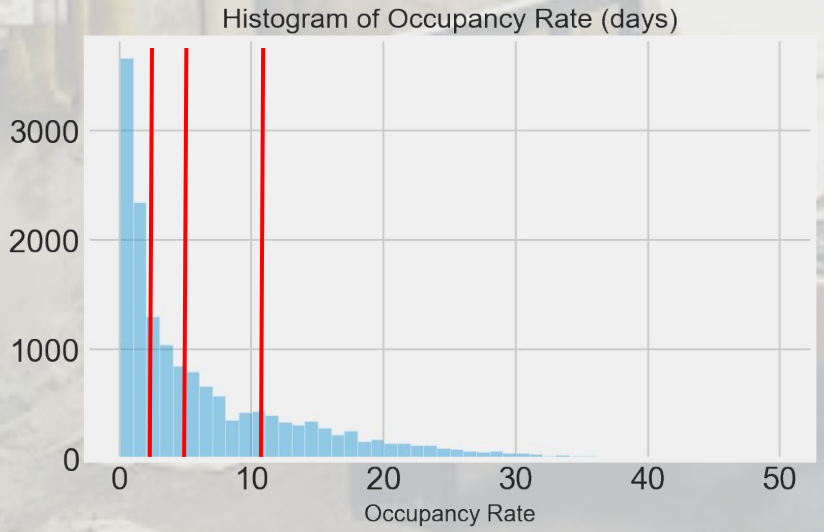
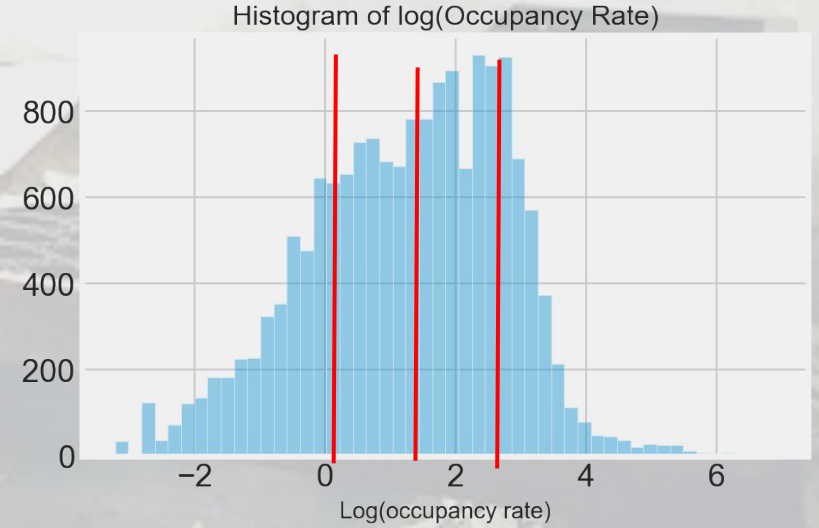


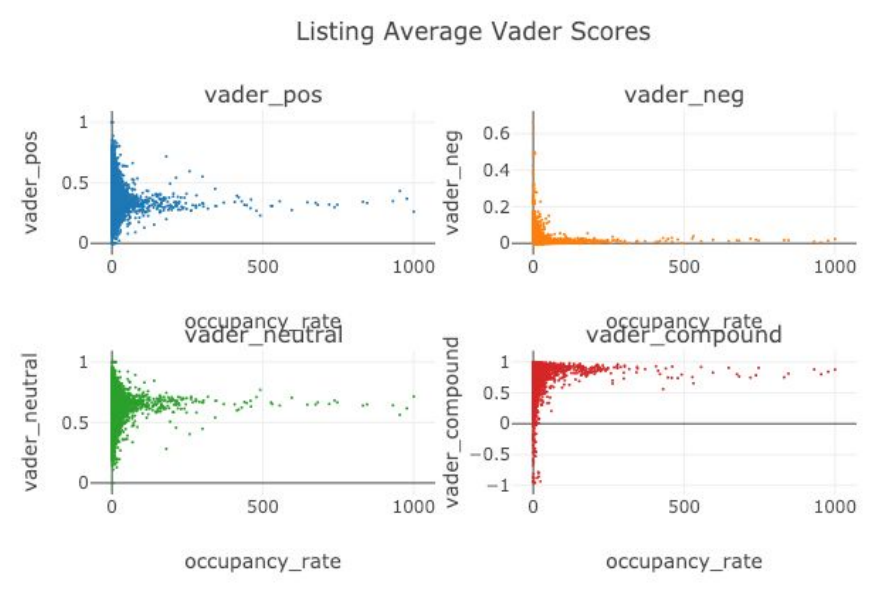


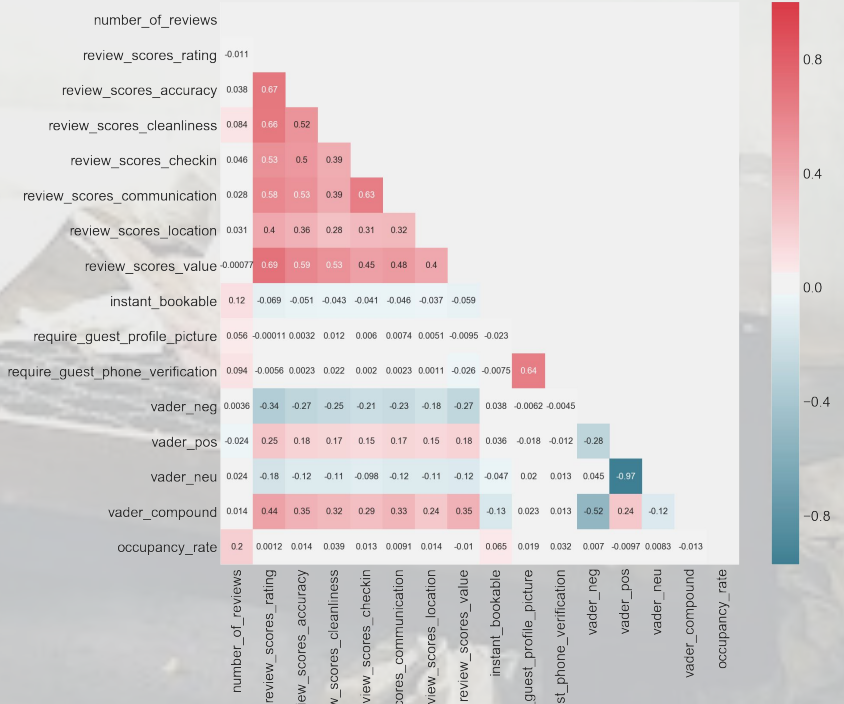
Classification target (quartiles):

Occupancy Rate = ['low' < 1.2days < 'med_low' < 3.96 days 'med_high' < 10.8 days < 'high']

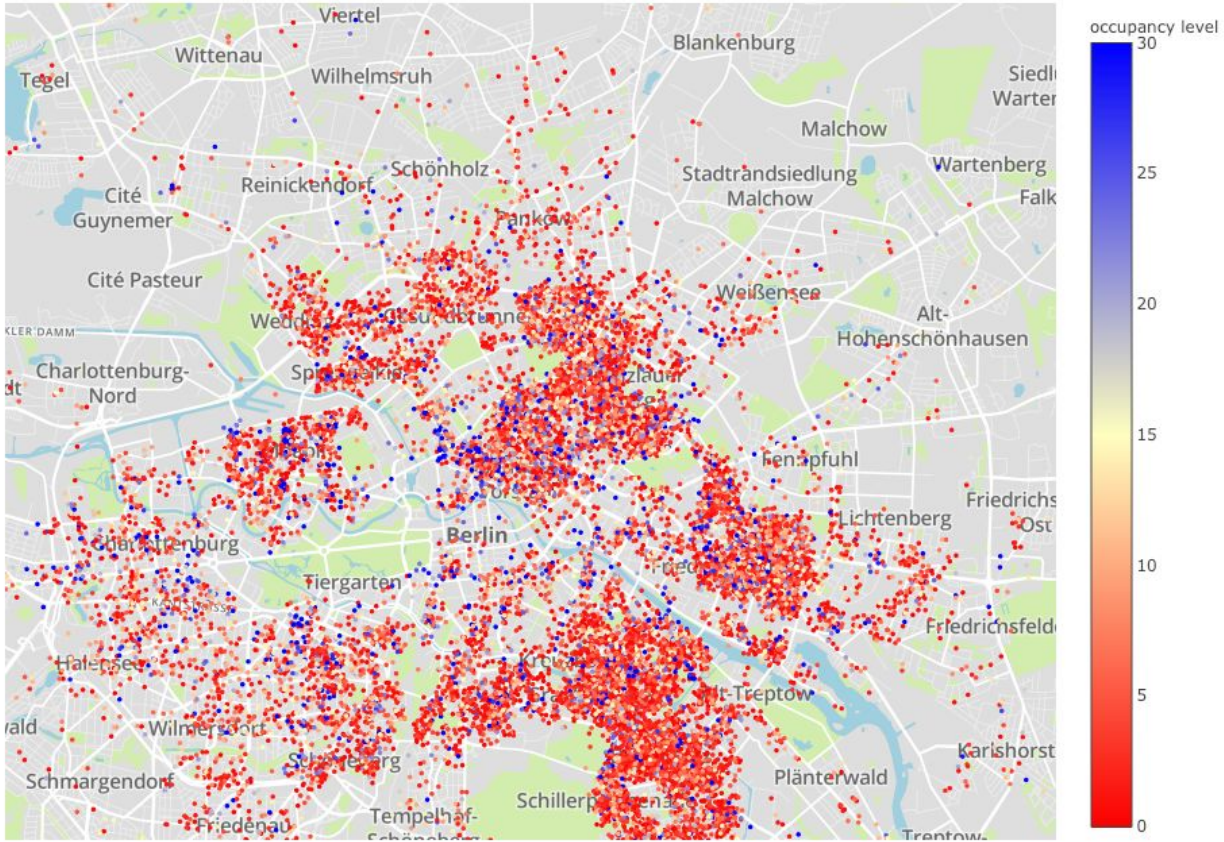
log(Occupancy Rate) = ['low' < 0.182 < 'med_low' < 1.376 'med_high' < 2.379 days < 'high']

The EDA . . .


Listing Average Vader Scores
vader_pos
vader_neg
vader_neutral
vader_compound
occupancy_rate
occupancy_rate
occupancy_rate
occupancy_rate


number_of_reviews
review_scores_rating
review_scores_accuracy
review_scores_cleanliness
review_scores_checkin
review_scores_communication
review_scores_location
review_scores_value
instant_bookable
require_guest_profile_picture
require_guest_phone_verification
vader_neg
vader_pos
vader_neu
vader_compound
occupancy_rate

AirBnbs in Berlin



airbnb

The EDA . . .

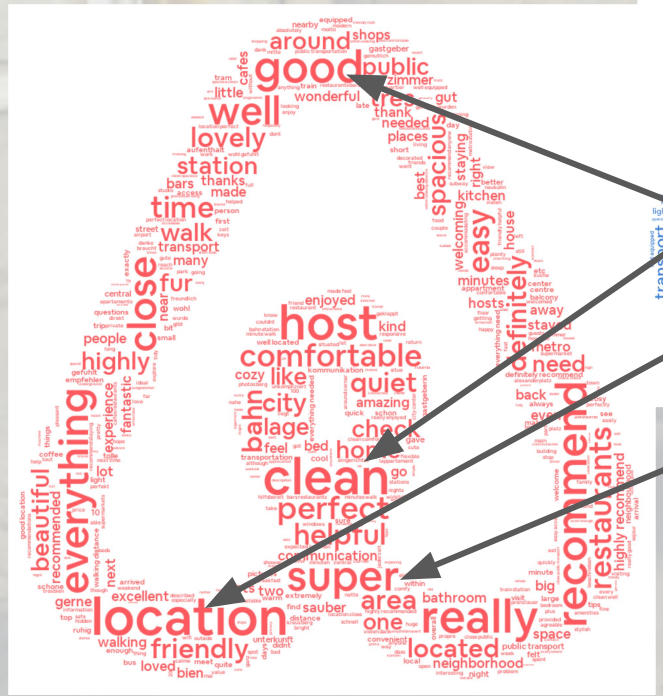
Positive Words

Negative Airbnb reviews word cloud

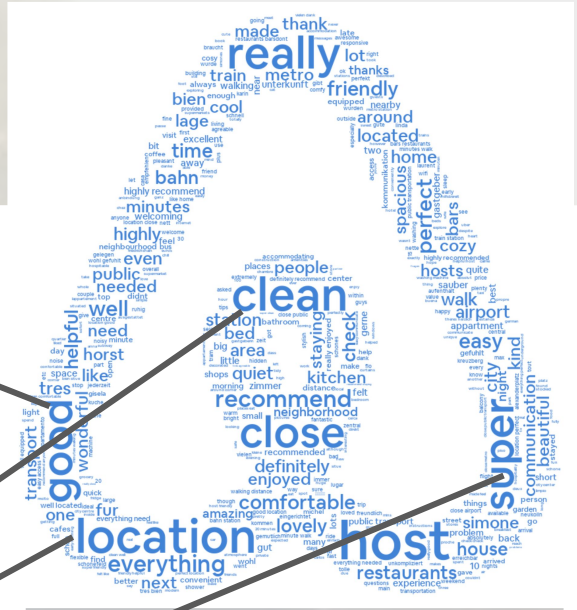
Positive n_grams (2 & 3)

The EDA . . .

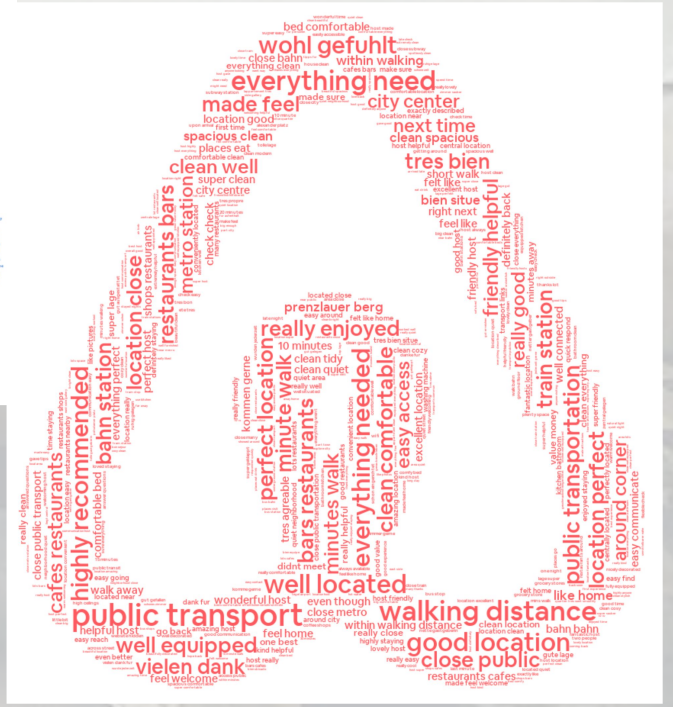
Positive Words



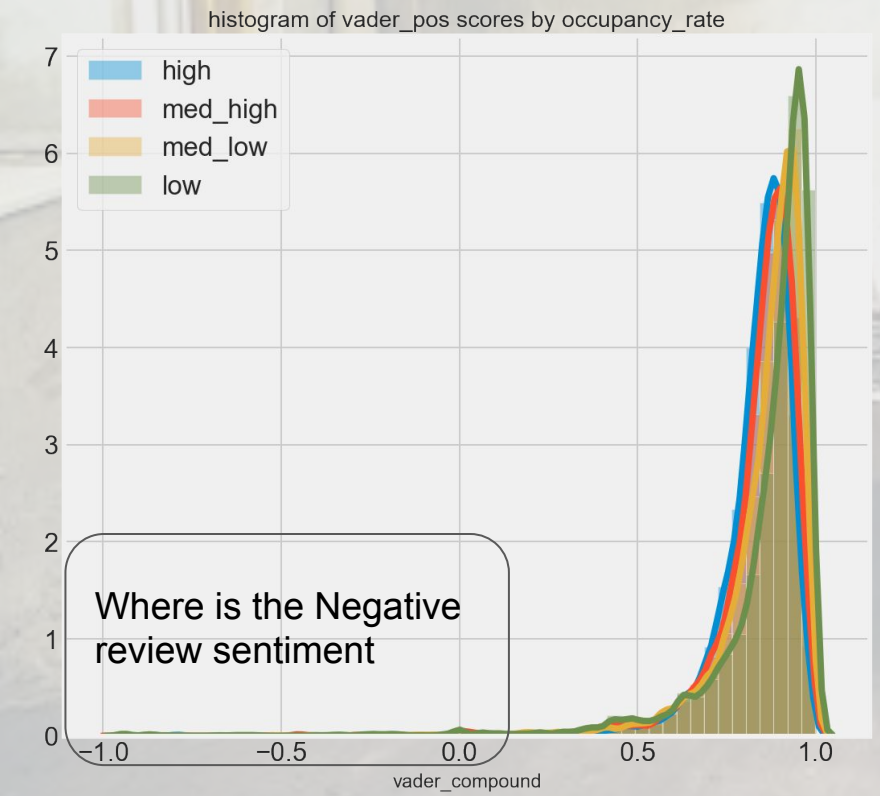
Negative Airbnb reviews word cloud



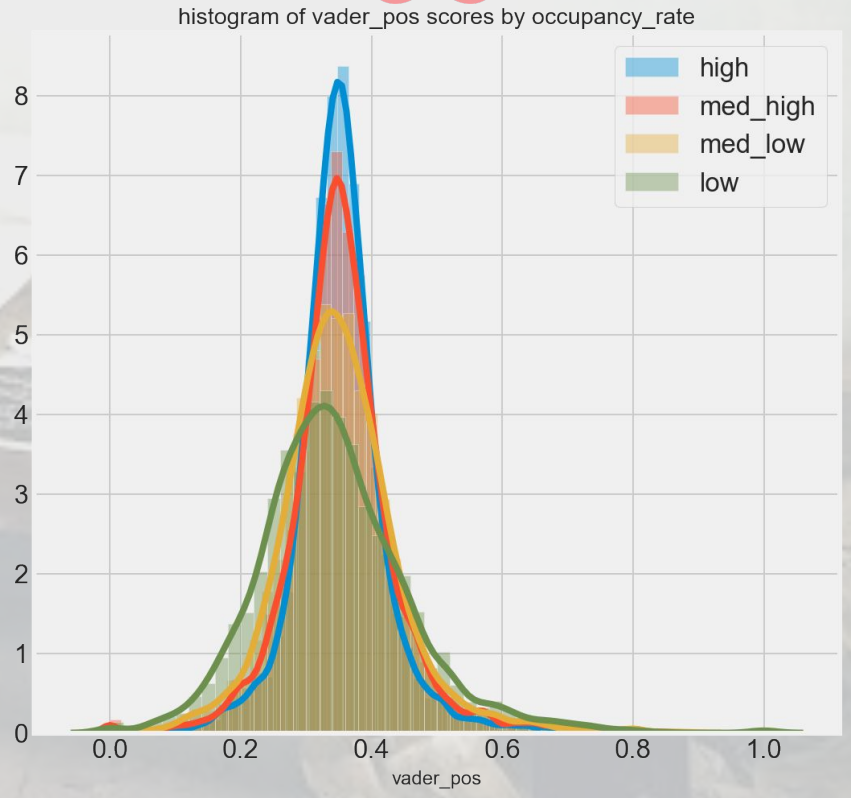
Positive n_grams (2 & 3)



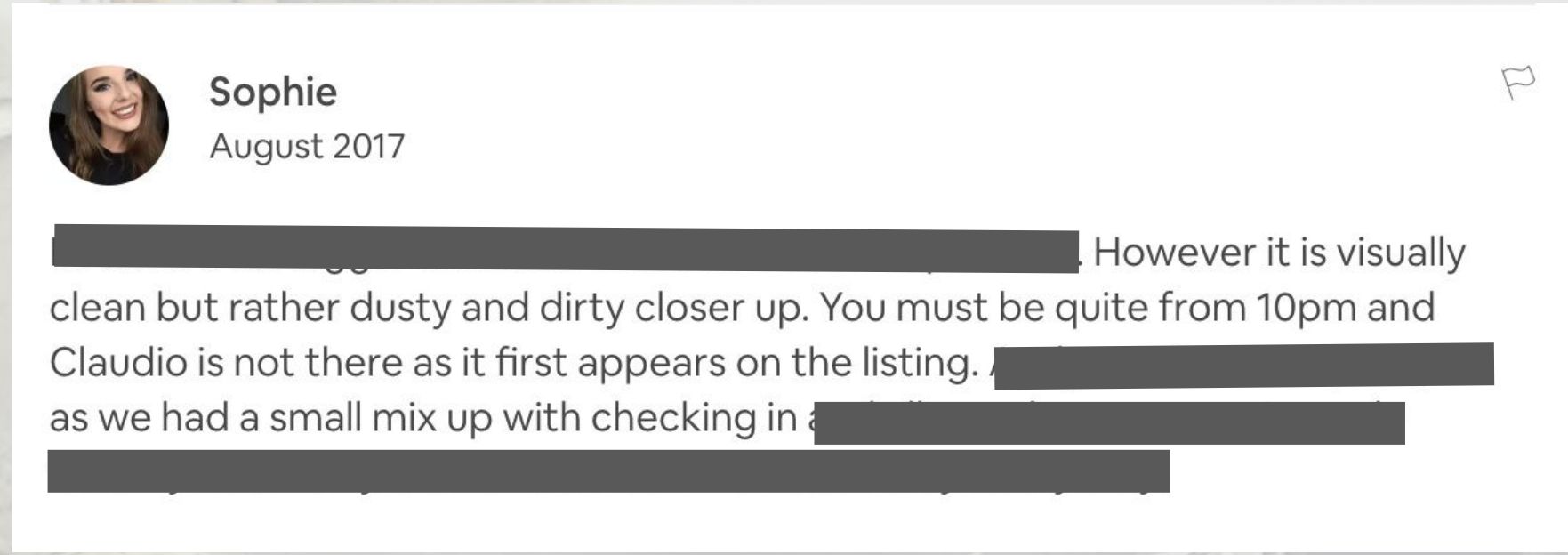
The Issue with NLP . . .



Where is the Negative review sentiment



The Issue with NLP . . .



Sophie
August 2017

[redacted]. However it is visually clean but rather dusty and dirty closer up. You must be quite from 10pm and Claudio is not there as it first appears on the listing. [redacted] as we had a small mix up with checking in [redacted]

Is this a Negative Review (?) . . .

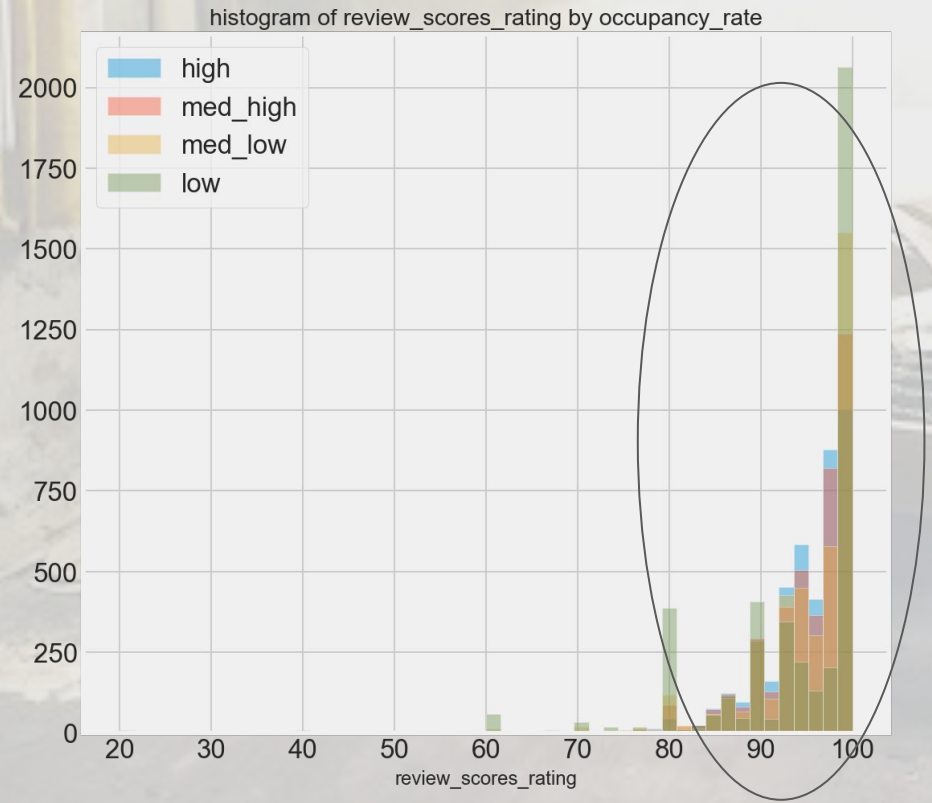
The Issue with NLP . . .

Sophie
August 2017

Room is a lot bigger and nicer in real life than on pictures. However it is visually clean but rather dusty and dirty closer up. You must be quite from 10pm and Claudio is not there as it first appears on the listing. Andy was incredibly helpful as we had a small mix up with checking in and all members were extremely friendly and lovely to meet. Overall we had a really lovely stay.

Is this a Negative Review . . . or a Positive review?

And Issue with AirBnb Reviews



The Models . . .

Regression

- Linear Regression
- LASSO Regression
- Ridge Regression
- Gradient Boosting
- Support Vector Machine
- Decision Tree
- Random Forest

Classification

- Logistic Regression
- Decision Tree
- Random Forest
- Gradient Boosting
- Support Vector Machine

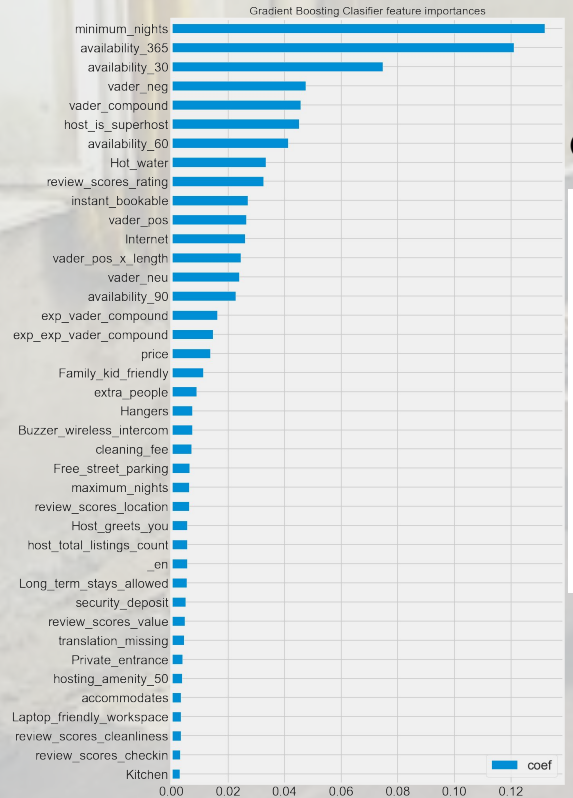
The Features . . .

Features tried:

- Listing Features only with Vader sentiment
- CountVectorisor & TFidF on review comments with and without listing features
- CountVectorisor & TFidF on Description column with and without listing features
- Textacy vectorisor on review comments with and without listing features
- Topics from Textacy topic models with Listing Features
- TruncatedSVD() on all above combinations

The Best Feature Combination : Listing Features with Vader Sentiment scores

The Classification Results . . .

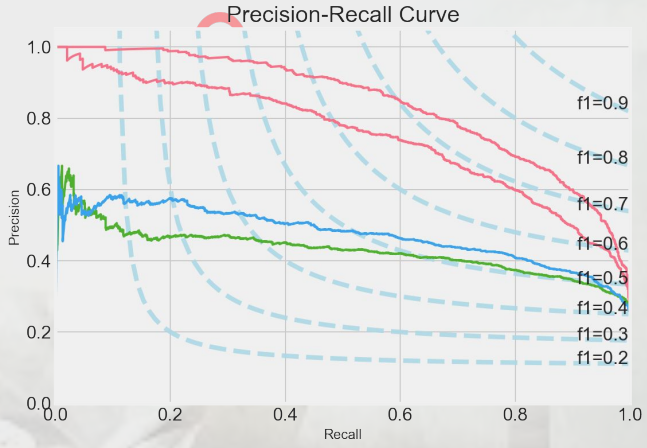


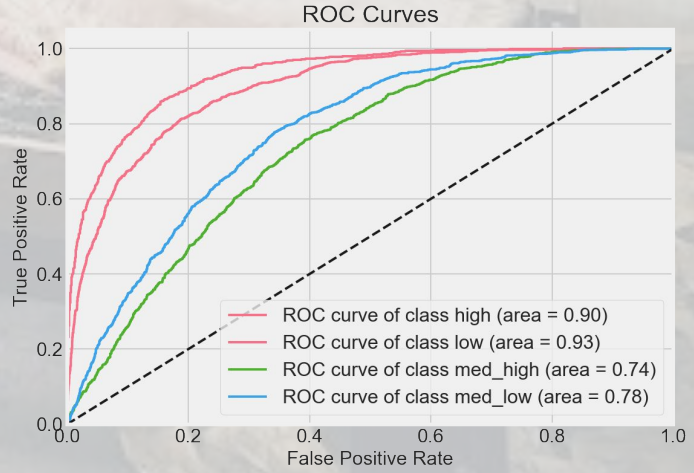
GradientBoostingClassifier()

Test score: 0.59882899252978

Predicted	high	low	med_high	med_low	All
Actual					
high	873	14	267	91	1245
low	17	957	62	224	1260
med_high	369	73	514	283	1239
med_low	93	233	261	622	1209
All	1352	1277	1104	1220	4953

	precision	recall	f1-score	support
high	0.65	0.70	0.67	1245
low	0.75	0.76	0.75	1260
med_high	0.47	0.41	0.44	1239
med_low	0.51	0.51	0.51	1209
micro avg	0.60	0.60	0.60	4953
macro avg	0.59	0.60	0.59	4953
weighted avg	0.59	0.60	0.60	4953

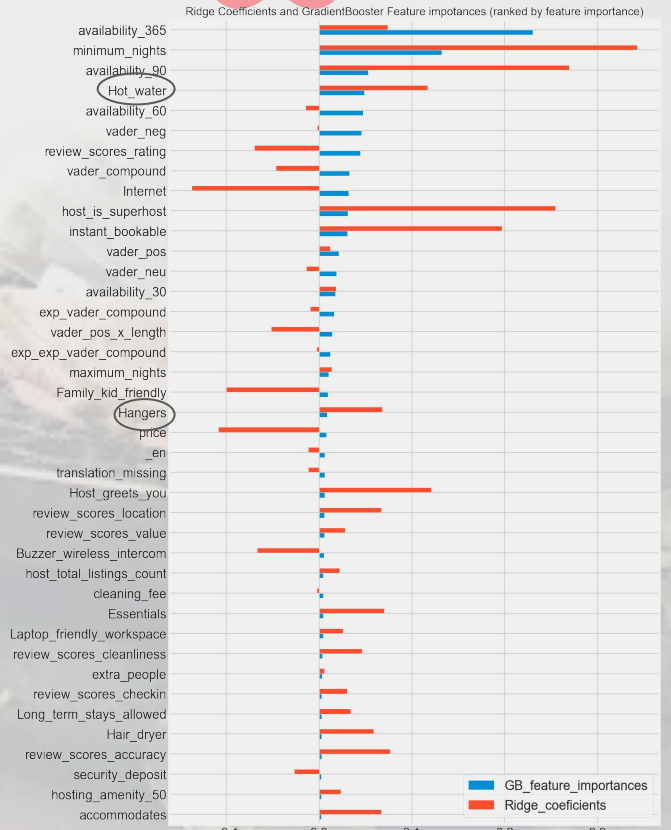




The Important Features . . .

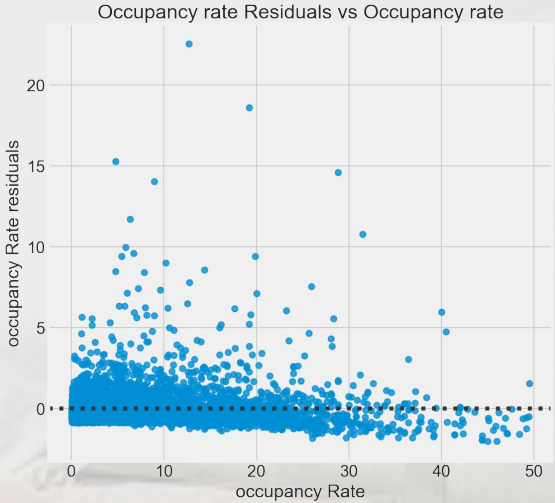
The Top 40 Features all pass the sense check

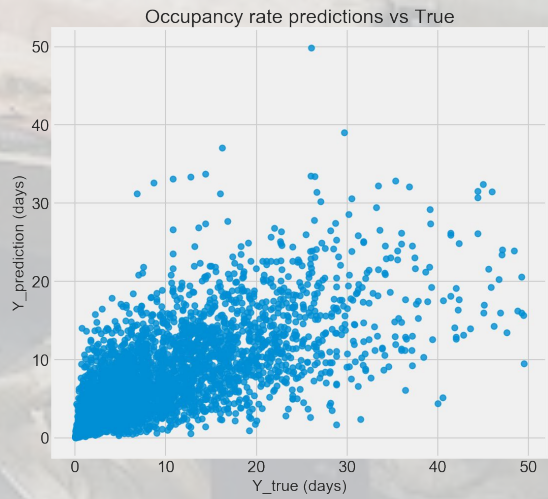
- **“Hangers”** stand out to me. Why are they important?
- “Hot_water” . . .?



The Regression Results . . .

Regression Model Results			
	Gradient Boosting Regressor	Support Vector Machine	Tuned Ridge Linear Regression
Cross-validated score on training set	0.715	0.554	0.470
RMSE (average error in log(days))	0.748	0.94	1.059
Score on unseen test set	0.734	0.582	0.469





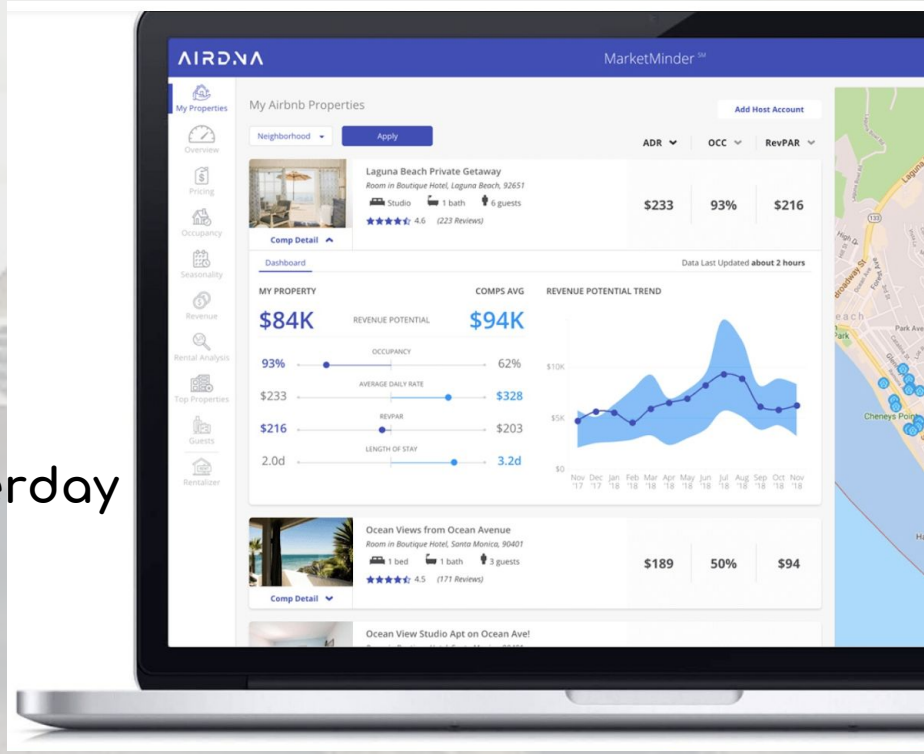
What could be improved?

- Better occupancy information
  - Actual nights booked vs Actual nights available
- Where are the negative reviews?
- Add listing descriptions and headlines and the Host descriptions into the models
- Additional factors such as distance to public transport and tourist attractions.

What Next? . . .

- Other cities

- Web app …
  - Like this one I “created” yesterday



Thankyou . . .

The Questions . . .