Classifying Airbnb Reviews With Natural Language Processing

Brenner Heintz

Data

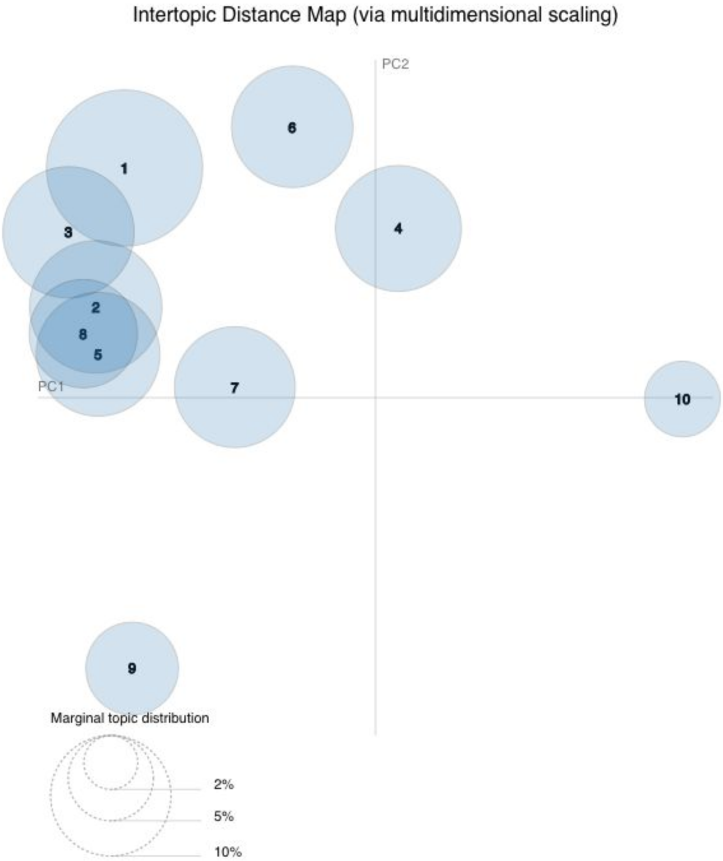
- InsideAirbnb.com
- Portland, Oregon
- 4,911 listed rental properties
- 318,262 reviews

Goals

- **Classify customers into groups using NLP** to analyze their reviews.
- Use those groups (along with listing data) to **predict the price of Airbnb rentals.**

Methodology

- Data munging & preprocessing
  - Punctuation, etc.
  - Stop words
- Topic modeling: Latent Dirichlet Allocation (10 topics)
  - Stemming
  - Bi-grams



Topic Modeling

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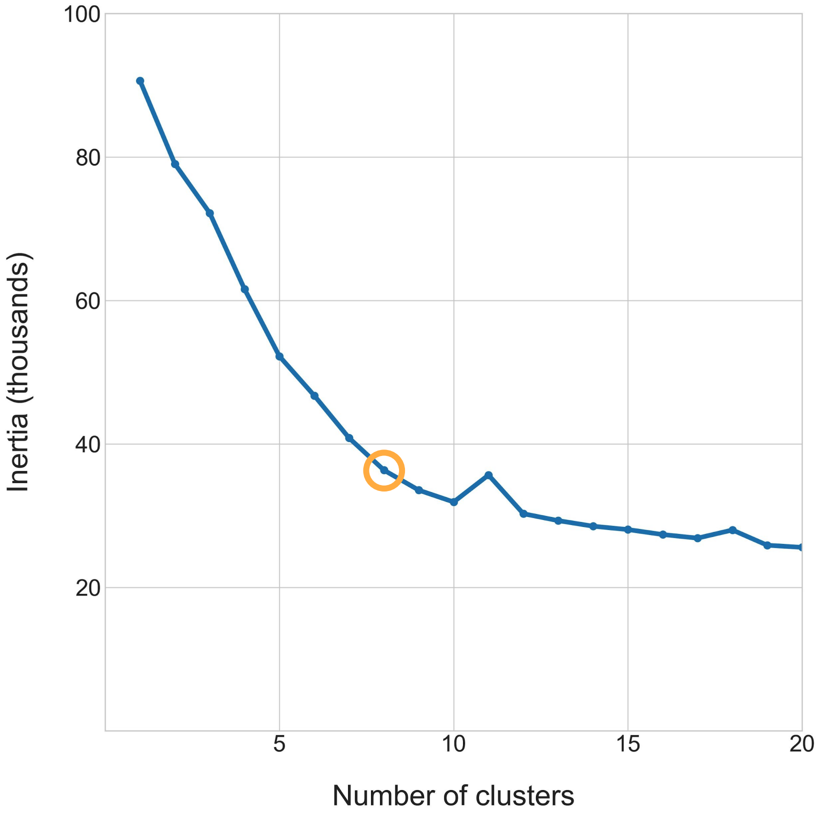
Topic	**“Close to Everything”**	**“Feels Cozy”**	**“Host with the Most”**	**“Holistic Experiences”**
Words	**great location** **downtown** **walking distance** **neighborhood** **restaurants** **food**	**feels (like) home** **perfect** **cottage** **space** **comfortable**	**host** **gracious** **wonderful host** **easy (to) communicate** **loved**	**great experience** **really nice** **exactly (as) described** **best** **good** **time**
Example Quote	“...the apartment is really close to bus lines...we took public transportation to go everywhere…” “It's a great location, close to restaurants and bars.” “Peninsula Park, New Seasons Market and access to I-5 are also really close to the apartment”	“Very comfortable and felt like home.' “...this was a magical, cozy space that made us dream of creating a similar converted-attic space for our kids some day…” “In fact, it didn't feel like a basement at all!...cohesive design sense that is modern yet cozy”	“Thank you for hosting and I appreciate the good communication…” “Leslie was super accommodating...They were super attentive and responded really quickly....	“Excellent first experience with Airbnb, exactly as described...“ “Overall, we had a great experience and couldn’t be happier with Sara’s condo.”

K-Means Clustering

- Used K-Means to create 8 clusters based upon LDA probabilities
- Fed into supervised learning algorithm to predict rental prices

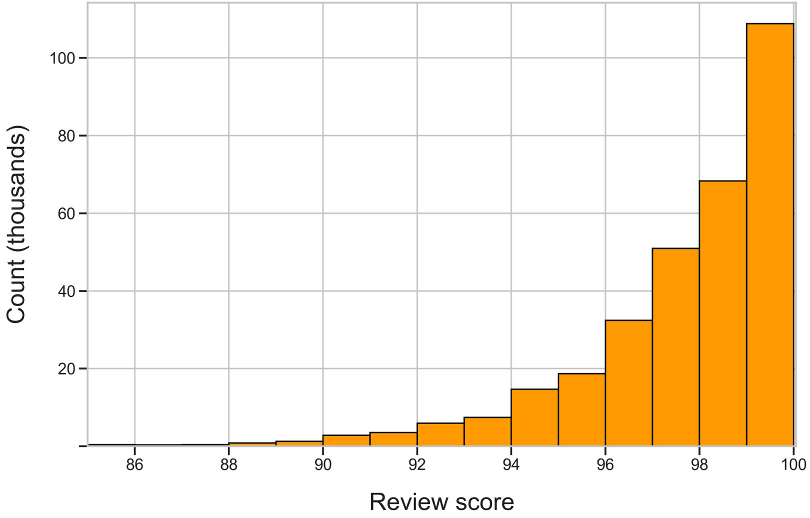


Regression Presented Challenges

- Best R^2 score = Random Forests (0.14)
- Failure to reject null hypothesis → cannot accurately predict rental prices based upon current features
- Still, topic modeling may provide some insight

Lessons Learned

- Reviews on Airbnb carry very little information, and are *extremely* skewed
  - May be biased by “quid pro quo”
  - Company may ferret out bad reviews or intervene with unhappy customers
- Topic modeling is difficult for reviews, since they are inherently limited in terms of topic scope



Future Work

- Look at markets outside of Portland with wider price ranges
- Bring in features from property descriptions
- Focus analysis on bad reviews, and the factors that are most likely to cause them
    - Likely to produce more robust topic modeling results

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Thank You

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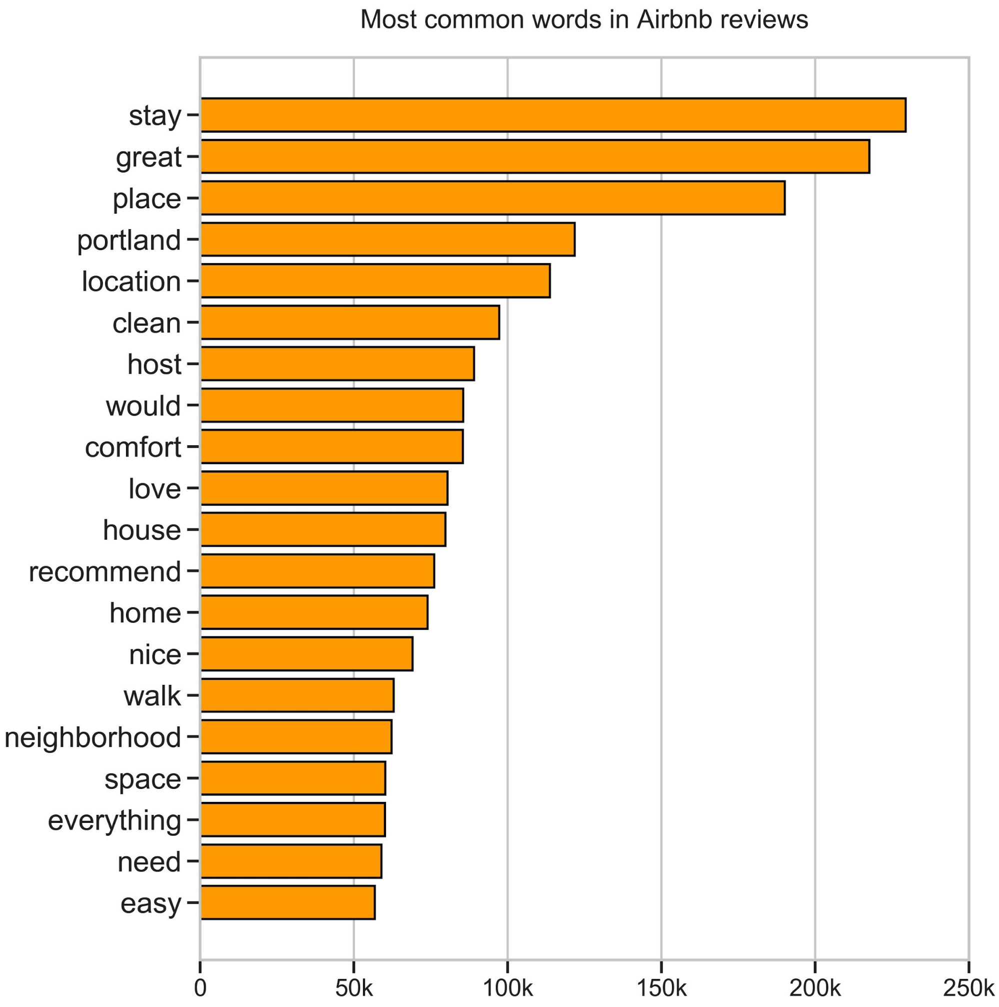
Most common words in Airbnb reviews
stay
great
place
portland
location
clean
host
would
comfort
love
house
recommend
home
nice
walk
neighborhood
space
everything
need
easy
0
50k
100k
150k
200k
250k

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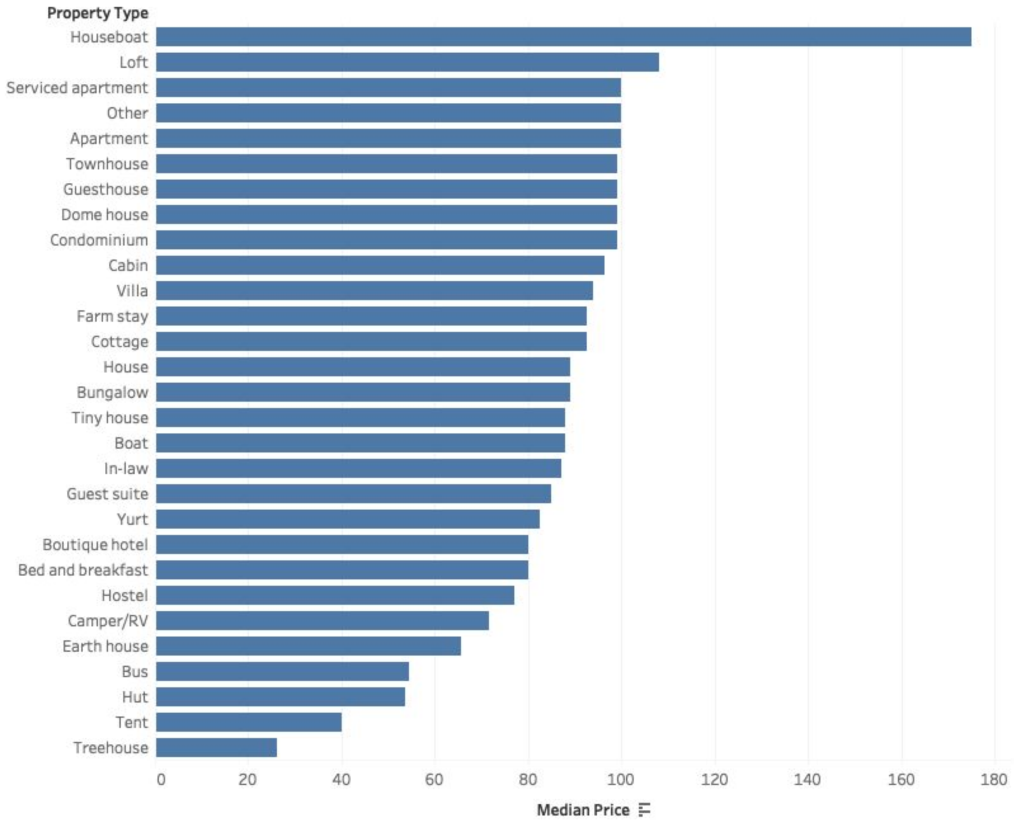
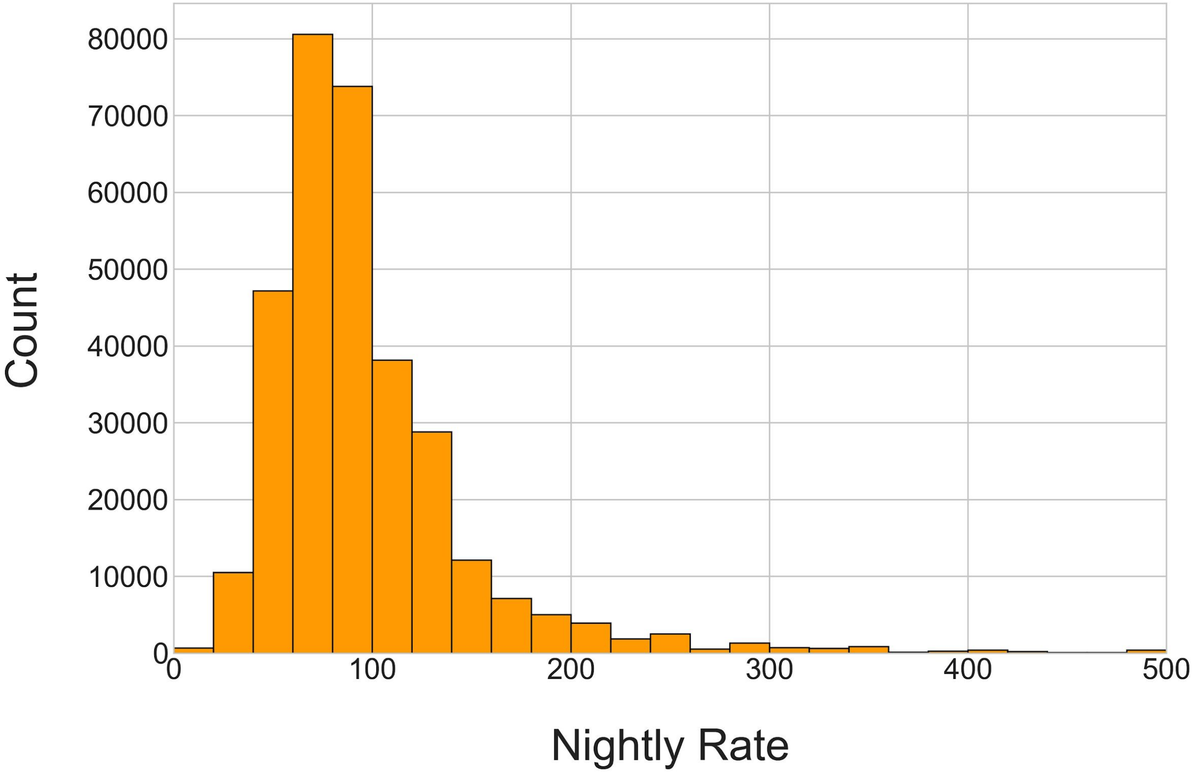
Average Cost by Property Type



Average Portland Airbnb Nightly Rate



Review Sentiment (Polarity)

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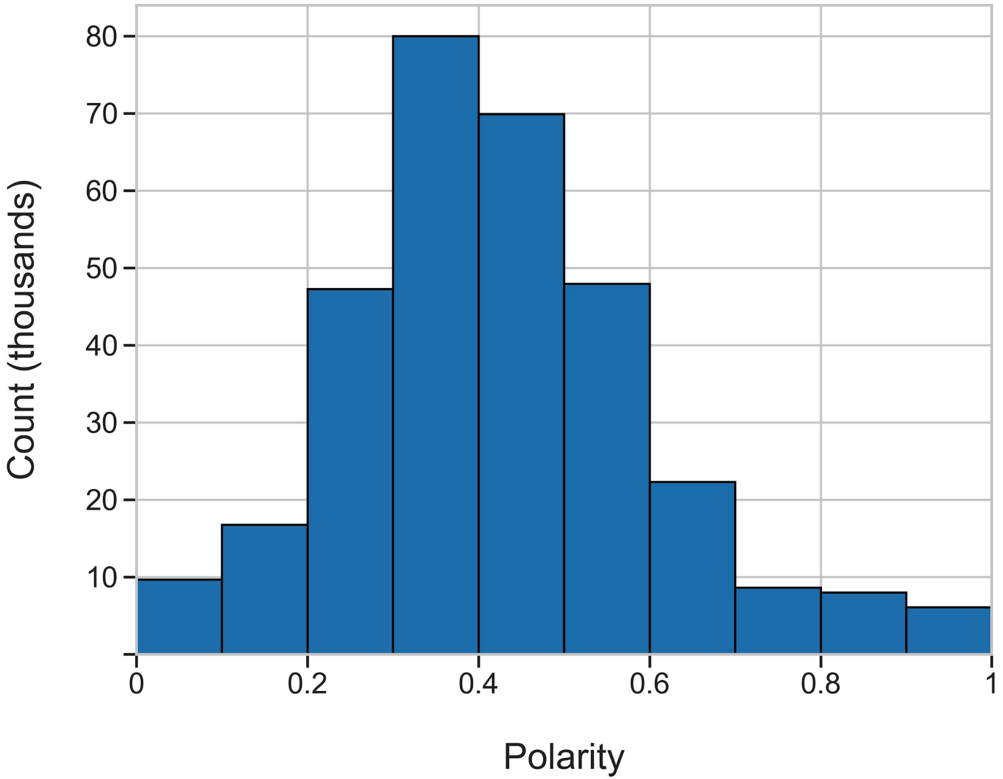
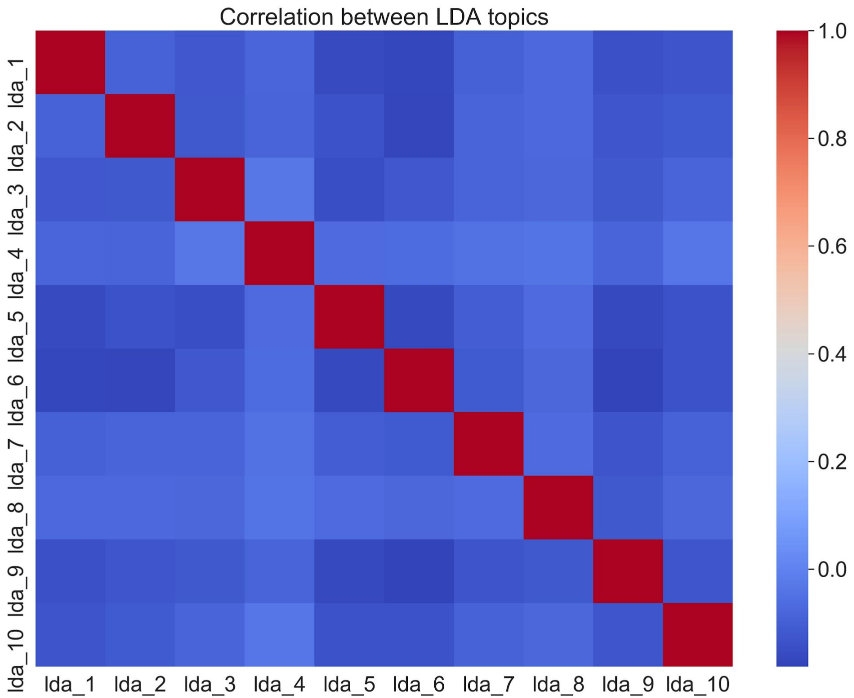
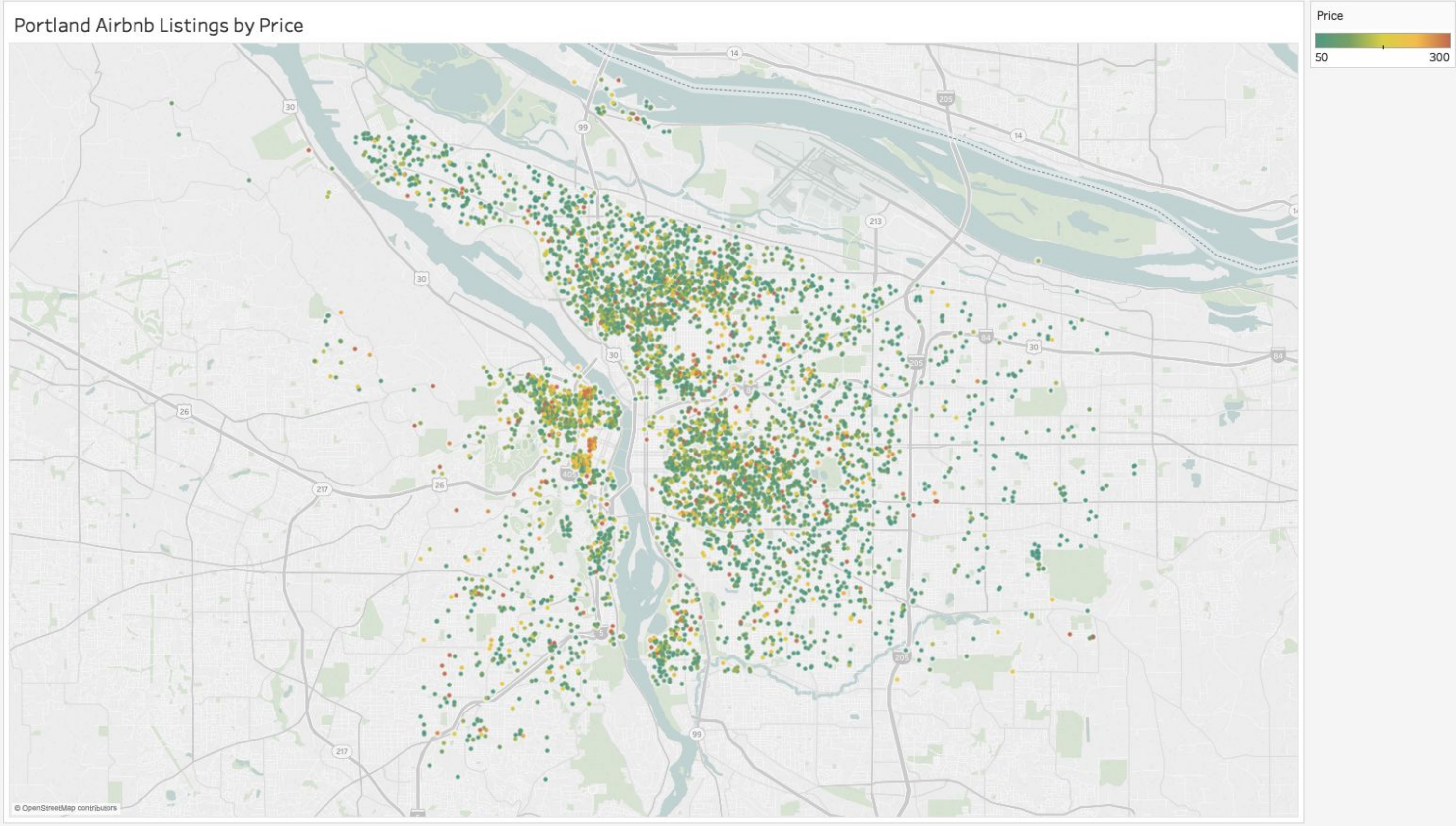


Correlation between LDA topics

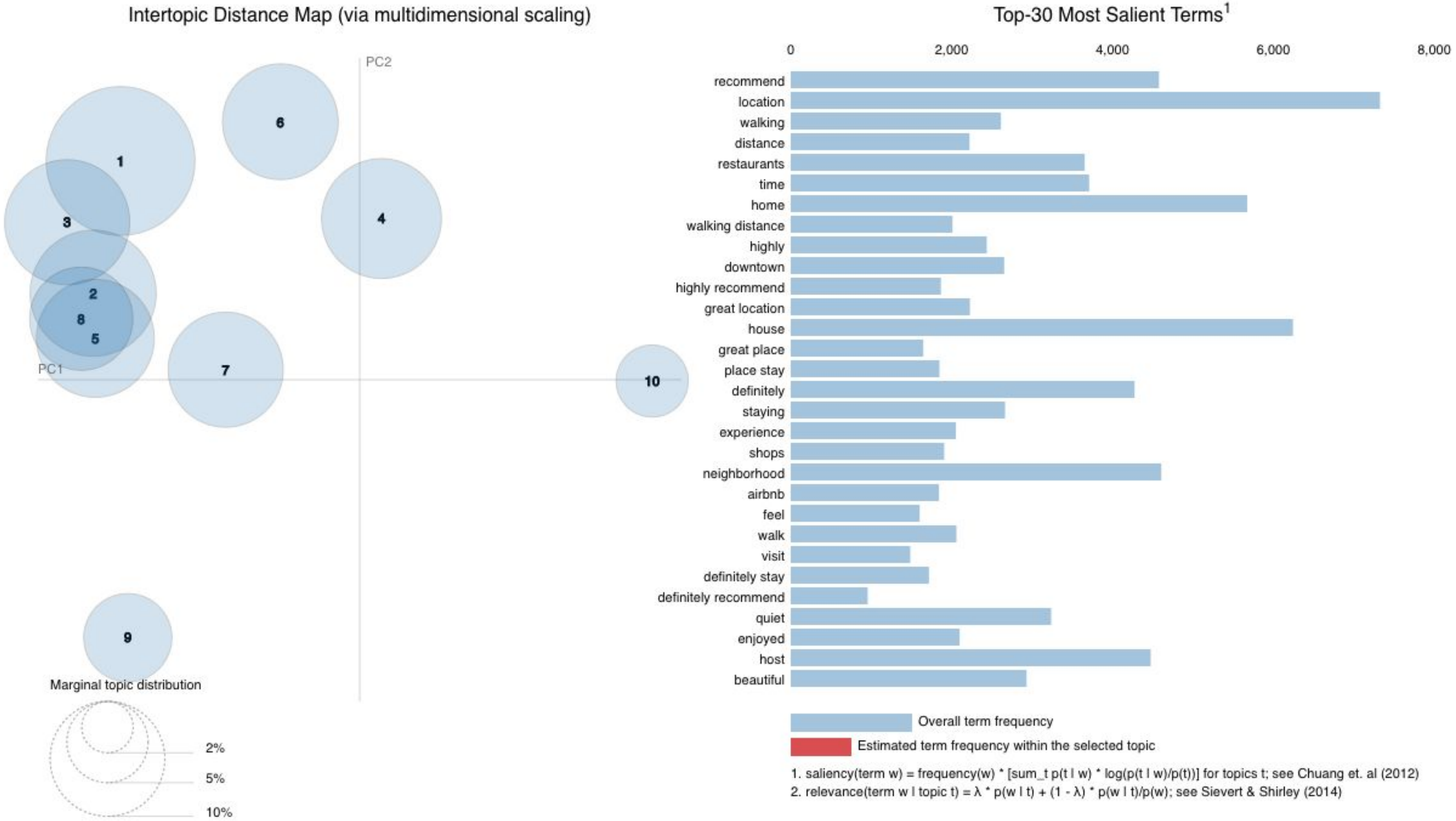


Airbnb Listings Mapped by Price



Portland Airbnb Listings by Price

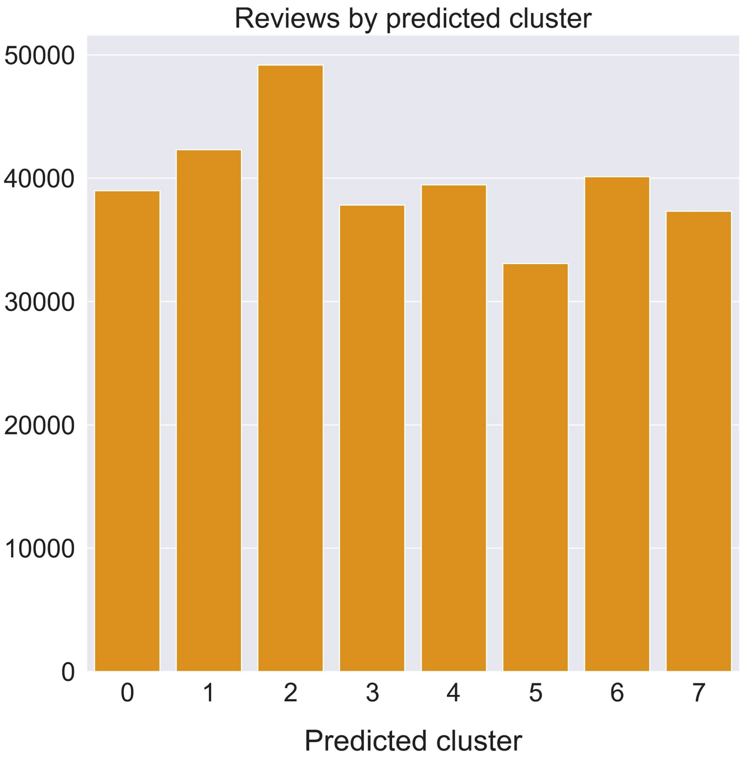
Latent Dirichlet Allocation

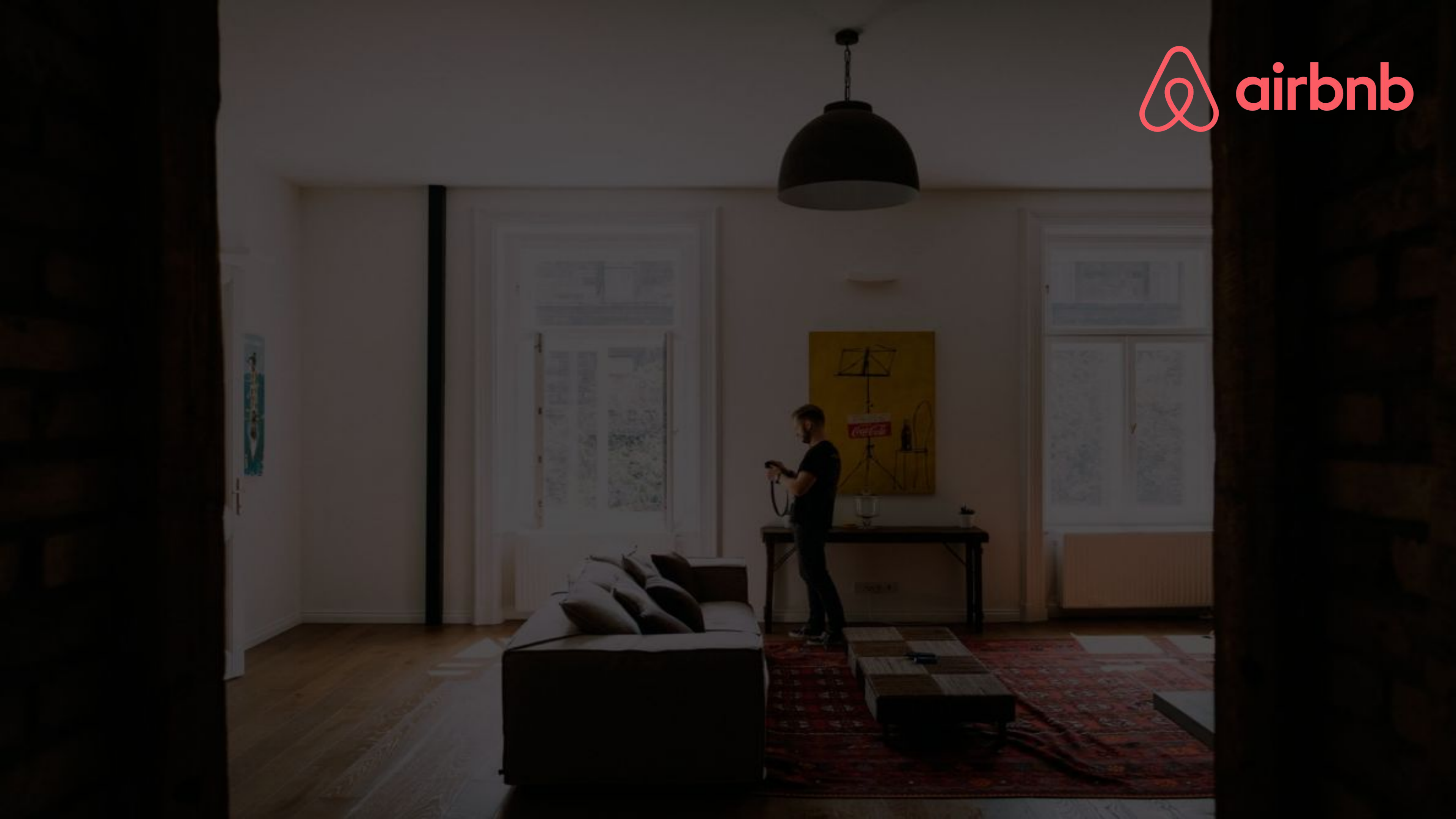

Intertopic Distance Map (via multidimensional scaling)

Top-30 Most Salient Terms[1]

1. saliency(term w) = frequency(w) * [sum_t p(t | w) * log(p(t | w)/p(t))] for topics t; see Chuang et. al (2012)
2. relevance(term w | topic t) = λ * p(w | t) + (1 - λ) * p(w | t)/p(w); see Sievert & Shirley (2014)

Reviews Per K-Means Cluster

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