Oct 7. 2017

How to get better review

Improve lodging experience and host profits

Team 1
Cheng Cheng, Liyuan Liu, Jingbo Shang, Xiaoming Zhao

How to get better review in Airbnb?

Improving the guest lodging experience and host profit

Team 1 - Jingbo Shang, Liyuan Liu, Xiaoming Zhao, Cheng Cheng

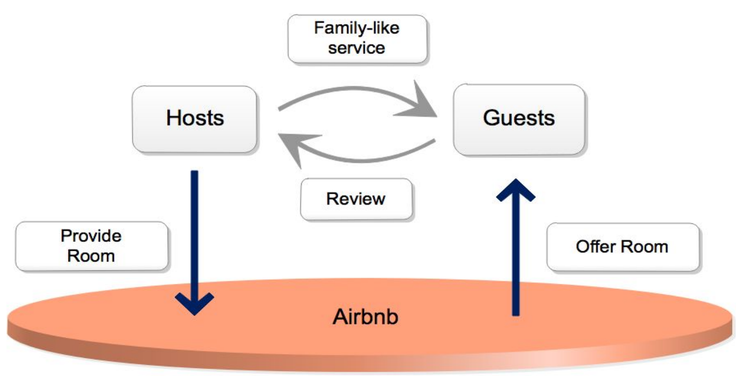
Topic Question

Airbnb is an online platform for people to lease or rent short-term lodging, such as vacation rentals, apartment rentals, homestays, hostel beds, and hotel rooms [1]. It provides more reasonable price and exposure to local people for travellers, and has attracted 150 million of users (i.e., guests and hosts) all over the world.

However, unlike traditional hotel vendors, Airbnb does not own the properties on its platform. Consequently, the lodging experience at Airbnb properties is hard to guarantee, and blames arose [2]. Given the challenges Airbnb is facing, our team works on **strategies to improve both guest lodging experience and host profit at Airbnb properties**. Specifically, based on the provided data, we focus on **how to help hosts get higher review scores, and thus harvesting more profit**.

We believe our research can help improve future guests lodging experience and help hosts get higher profit. As an overall measurement, review score ratings reflect guests lodging experience during their stays. Intuitively, when two properties have similar locations and prices, guests tend to book the one with a higher rating, even if its price is a little higher.

Since we focus on the rating scores, *listings* is our major dataset. Besides, we explored the *calendar* and *econ_state*.



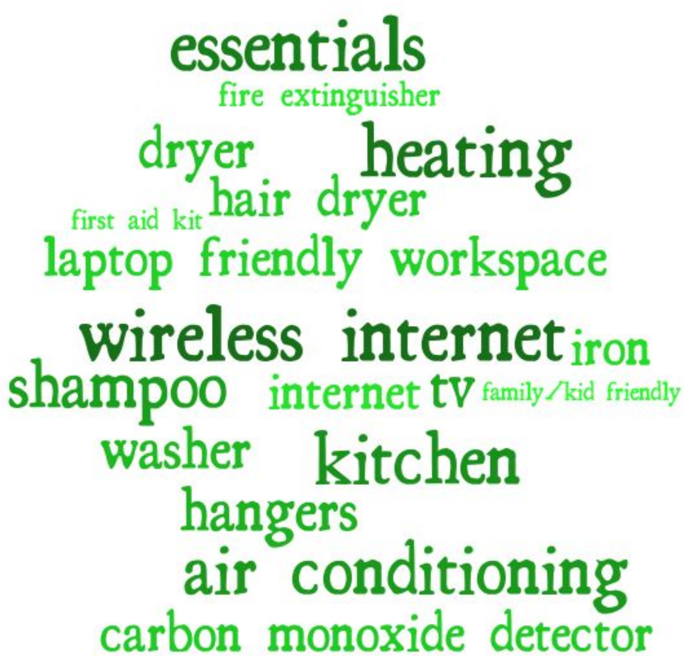
Non-Technical Executive Summary

We first analyzed the statistics of review scores, such as distributions of review scores and correlation between different fields in the dataset. Then, we proceeded to find key factors affecting the review scores from multiple points of view.

Constructive Suggestions Through Discrminative Amenity Mining

By leveraging techniques like discriminative phrase mining [3], we extracted the most discriminative amenities from the listings dataset, based on which we proposed some constructive suggestions.

- **Shampoo & Hanger: spend little, earn more.** Among the properties with shampoo and other essentials, around 76.69% received overall review scores over 95. For properties with overall review scores below 95, only 57.30% provided shampoo and other essentials. Among the properties with hangers, around 76.50% received overall review scores over 95. For properties with overall review scores below 95, only 53.61% provided shampoos. From this fact, we conclude that supply of shampoo and hanger is a key factor to improve guest lodging experience. Since price of hangers and disposable essentials are not high, providing it will very likely increase the profit of hosts.
- **Washer & Dryer: worthwhile investments:** Doing laundry is a common need of travellers that cannot be neglected by Airbnb hosts. While most hotels have laundry service, Airbnb properties with washer & dryer are more capable of competing with traditional hotel vendors. We found that among the properties with washers, around 73.81% received overall review scores over 95. For properties with overall review scores below 95, only 39.94% provided washers. Among the properties with dryers, around 78.89% received overall review scores over 95. For properties with overall review scores below 95, only 39.88% provided washers. Although washers and dryers can be expensive for an Airbnb host's budget, it is a wise investment to buy them for profits in the long run.



Which are the most crucial factors from the guest view?

After training a logistic classifier with focus on the review scores in the "*listings.csv*" dataset, our team finds **Rental Value (Price)** and **Cleanliness** play the most important roles among all five aspect in the guest's journey experience. The other three aspects are Check-in, Communication and Location.

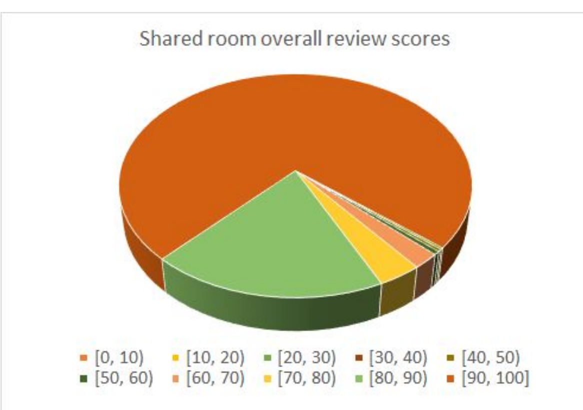
From host's side, based on this insight, while maintaining the convenience of check-in and warm communication with guests, if hosts pay more attention to the cleanliness of the room, they may make more profit. However, hosts should not increase the rent price too high. Drastic increase of price may cause low rating of Rental Value, making a bad overall experience. From guest's point, a reasonable rental price and neat room make up a great memory of journey.

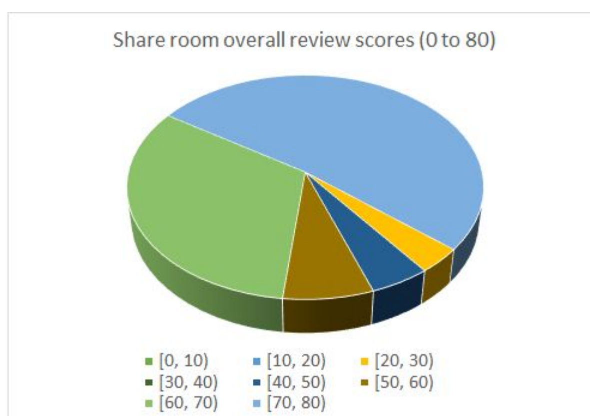
After first getting this result, it is a little surprising to us that Location does not rank first. However, after thinking over it, we find this is reasonable. Before booking on Airbnb, guests already have strong passion about the destination they will go. Location is not the factor they care most.

Distributions of review scores

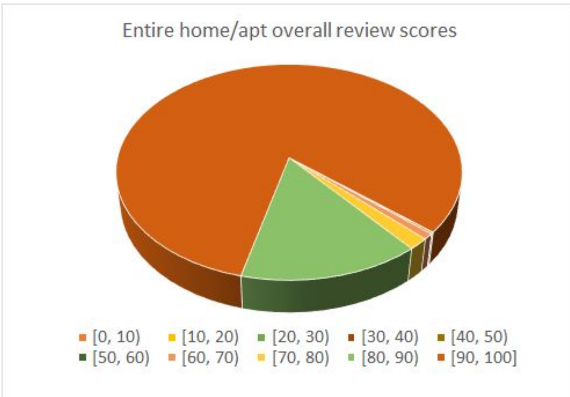
In the Airbnb listings, there are three types of rooms available, namely, shared room, entire home/apt, and private room. In all the listings, 45,110 have valid feature fields. We plotted pie charts of overall customer review scores for each type of property to give the readers a sense of the distributions of the overall review scores.

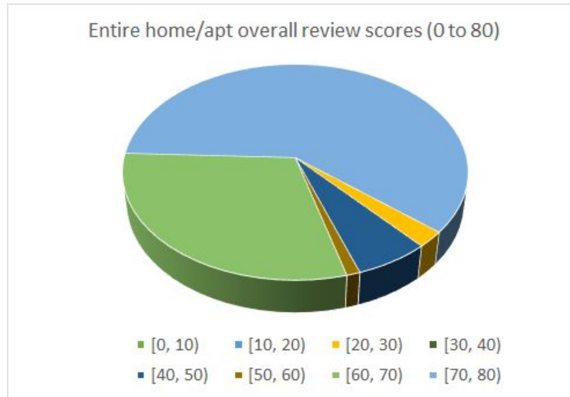
For the 1,222 shared rooms, the distributions of overall review scores are shown in the pie charts below. In the left pie chart, we can see that 74.06% guests rated scores over 90, while 6.79% guests gave scores less than 80. The right pie chart shows the distribution of scores less than 80.



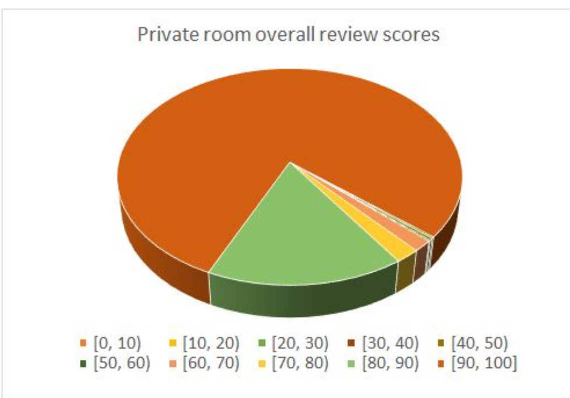


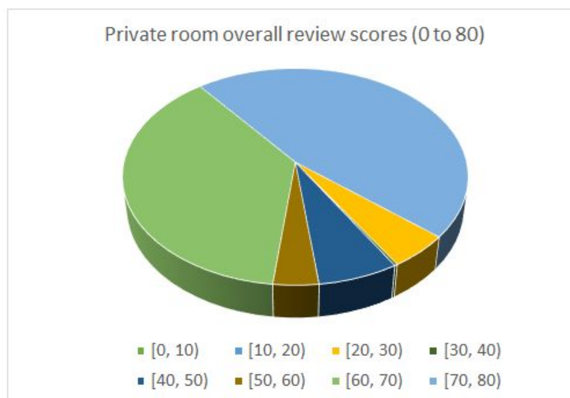
For the 24967 entire homes or apartments, the overall review scores distributions are reflected in the following pie charts. 82.18% guests rated scores over 90, while 2.86% guests gave scores less than 80.





For the 18921 private rooms, the overall review scores distributions are reflected in the following pie charts. 79.28% guests rated scores over 90, while 4.37% guests gave scores less than 80.





The above distributions show that the overall review scores are concentrated in the range above 80, but low scores are not scarce. A few (62 out of the total 45110) guests rated extremely low scores (in the range of 20 to 30). After removing list entries without valid review scores, we believe the overall review scores is an objective evaluation of guest lodging experience.

Technical Executive Summary

Data Preprocessing

As we are interested in the review scores, we focus on the "*listings.csv*" dataset. There are 6 kinds of review scores, namely

1. Check-in (*review_scores_checkin*)
2. Cleanliness (*review_scores_cleanliness*)
3. Communication (*review_scores_communication*)
4. Location (*review_scores_location*)
5. Rent Value (*review_scores_value*)
6. Overall Rating (*review_scores_rating*)

where, *'review_scores_rating'* is the overall score guests give for the entire experience of the journey. Other 5 scores are the scores of fine-grained aspects that Airbnb thinks are important.

In total, we have 59,824 properties in '*listings.csv*'. After exploration, there are 14,397 data which may contain NULL in any one of the 6 review score fields. We assume this means there's no guest review available for this property. Therefore, we simply remove them and there are 45,427 left.

In the original dataset, overall review score is an integer from 0 to 100. Based on our analysis, the score distribution is rather skewed. For example, about 27% of the overall rating is 100 and there are a very limited number of low scores (i.e., < 50). Therefore, we choose 95 as an splitting point, because there are 50% data with overall ratings more than 95. Therefore, we treat the properties with an overall rating more than 95 as **good properties**. The other properties **need to be improved**.

Which are the most crucial factors from the guest view?

Airbnb has pointed 5 important aspects including check-in, cleanliness, communication, location, and rent value. However, guests may have different preferences on these aspects.

In order to understand which are the most crucial factors from the guest view, we studied the relationship between the overall rating and those fine-grained aspects. Specifically, we adopt a logistic classifier to analyze the weight of each aspect that contributes to the overall rating.

Since there is no training and test splitting available, we applied a 5-fold cross validation. We select the 5 columns of aspect review score and store it in a matrix D of a shape [45427, 5]. Then we store the overall rating label into a matrix l of a shape [45427, 1]. The mathematical formula for logistic classifier is $p = \frac{1}{1+e^{-t}}$, $t = aX + b$. Here X is the training data, which contains $\frac{4}{5}$ data in D. p is the probability the model calculates. We assign label

$y = 1 \; iff \; p > 0.5$. After the **two round 5-fold cross validation**, we have results showing below.

		Coefficients for subfield review scores ($\times 10^{-4}$)				
	Test Accuracy	Check-in	Cleanliness	Communication	Location	Rent Value
Mean	81.5%	0.5791	1.1477	0.864	0.5408	1.5388
Variance	1.456 $\times 10^{-5}$	1.76	1.833	2.004	1.781	1.397

From this table, one can easily identify the importance of the aspects in the guest view is ranked as follows:

Rent Value > Cleanliness > Communication > Check-in > Location

What are the most effective amenities to get a higher rating?

As same as the logistic regression model, we treat the properties with an overall rating more than 95 as good properties. The other properties need to be improved.

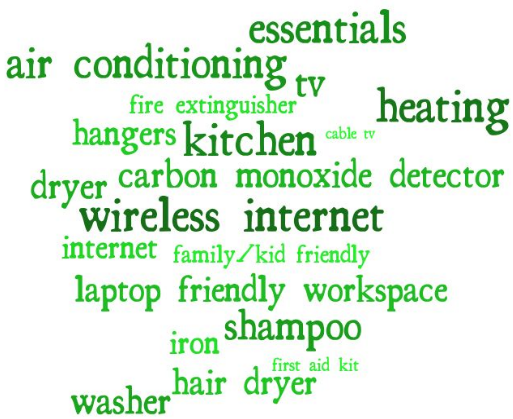
For each property p, we extract all its amenities to a list, which is denoted $amentities(p)$. Then, we compute the $discrminativeness$ as follows

$$discrminativeness(e) = P(p \; has \; e \mid p \; is \; good) * log \frac{P(p \; has \; e \mid p \; is \; good)}{P(p \; has \; e \mid p \; needs \; improvement)}$$

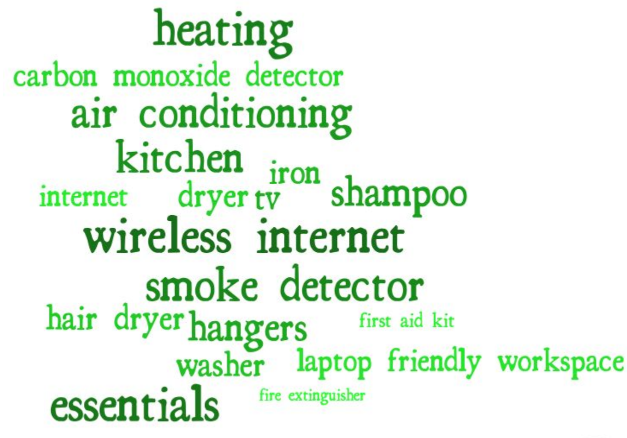
The idea is similar to the pointwise KL divergence by treating an amenity as a word, all good properties as the major corpora, and all bad properties as the reference corpora.

Since properties of different room types may have different features, we also partition the data into 3 groups based on the room types. After that, we apply the $discriminativeness$ scores to rank the amenities. The results can be found in the following figures. The overall discriminative amenities are shown in the previous section. The room-type specific word clouds are listed as below.

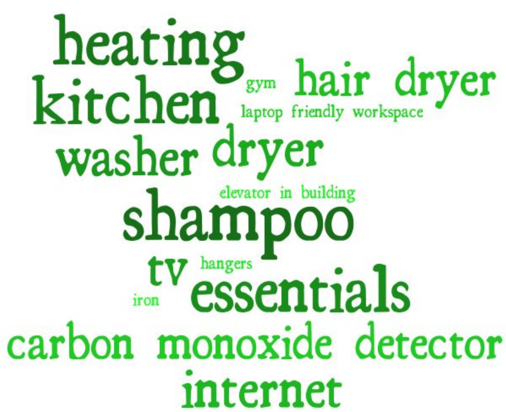
Entire room



Private room



Shared room



References

[1] https://en.wikipedia.org/wiki/Airbnb
[2] https://www.airbnbhell.com/
[3] Liu, Jialu, et al. "Mining quality phrases from massive text corpora." *Proceedings of the 2015 ACM SIGMOD International Conference on Management of Data*. ACM, 2015.