How can the effectiveness of marketing be improved ‘Airbnb Seattle’?

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Overview

Background

Start of an equally simple business

"Brian thought of a way to make a few bucks - turning our place into *designers bed and breakfast* - offering young designers who come to town a place to cra during the 4 day event, complete with wireless Internet, a small desk space, sleeping mat, and breakfast each morning. Ha! joe"

Basics

Airbnb is a model based on share economy. Everyone who owns an apartment can rent it out for travelers as a resting place, where it feels like home. There is a Mobile app/website: online platform to match demand and supply Listings (check in and check out: demand for short period rent apartment) .

Procedural Method

General Methology

Using data analysis and show how it can be used to improve the marketing of Airbnb in Seattle according to each policy of the marketing-mix.

Marketing

The 4 P's of the Marketing-Mix

1. Product
2. Price
3. Promotion
4. Place

Definition Marketing

Marketing is about the firm's effort to address customer needs and expectations, which influences the demands made by the customers on the product and need to be fulfilled by the product.

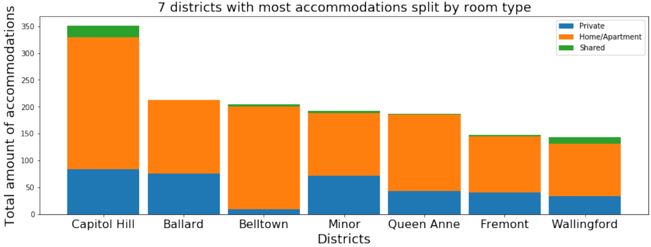
How to use Data Analysis to improve the Airbnb Marketing?

- **Descriptive analysis:** Reviews, locations, review and price correlation, details of listings and price correlation
- **Descriptive analysis:** Predict the number of customer
- **Optimization:** Optimize the booking of listings
- **Adaptive learning:** Learn from the results generated and combine results to give out suggestion in marketing campaigns may hold by Airbnb

Data Description

Listings

- Consist of 92 columns, with attributes describing different characteristics of the rented apartments
- Contains 3818 apartments distributed in 79 Neighborhood

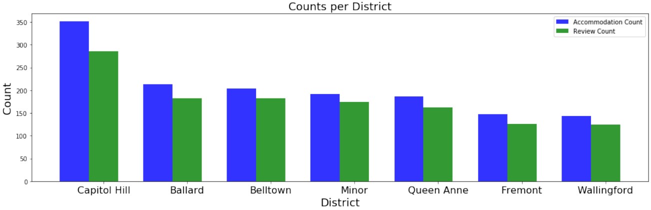


Preprocessing Steps

- Drop rows with too much sparse data (nan-values)
- Replace nan-values with default values
- Replace categorical with numerical features
- Select features as input values (x) and the price as output value (y)
- Split into training and test data (80/20)

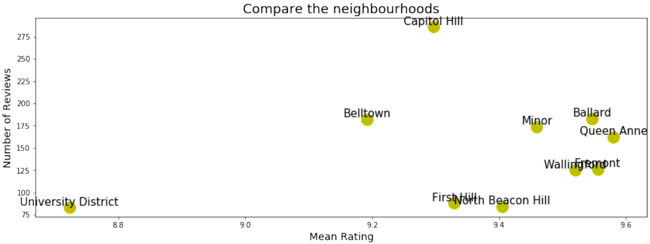
Reviews comparison

We can see a correlation between the amount of reviews and the accommodation counts.



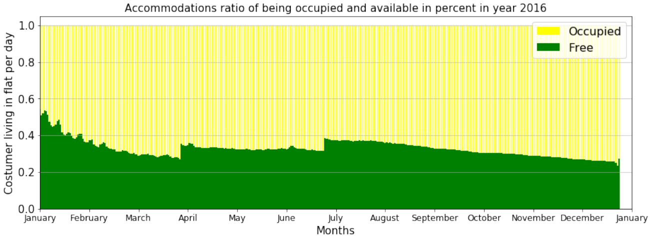
Reviews

- Apartments in total got 50 to 100 review scores and a mean rating of about 9.2 to 9.7
- The same mean rating is also achieved by each district where the apartments are rated between 125 and 300 times
- The mean rating for every district is relatively high (too positive phenomenon)



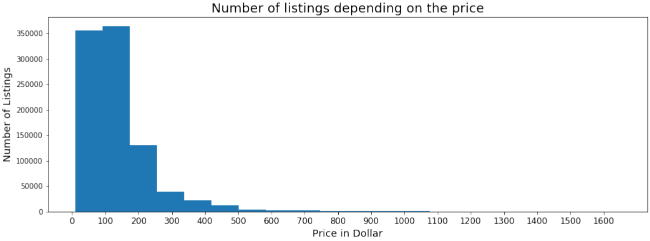
Calendar

- In January, only half of the apartments have been occupied
- The number of rented apartments were raised until April when a sudden drop of rented apartments appeared
- The occupationrate raised to July and decrease again
- The number of rented apartments have increased till December



Accumulated Listig prices

- Minimum price is 10$
- Maximum price is 1650$
- Average price is 137.94$
- We have 669 unique values for the price among Seattle



Models

Natural Language Processing

- Regular Expression Tokenizer
- Stop Words for English + Seattle + Neighbourhood
- Lowercase
- WordNetLemmatizer

Linear Regression

- Use a Linear function and estimate its parameters
- There are different approaches to estimate the parameters
- The accuracy of a model can be compared with different loss functions

The fitted line can mathematically described as:

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i \quad (1)$$

Elastic Net CV

A general summary would be that the elastic net is a convex sum of ridge and lasso penalties, so the objective function for a Gaussian error model looks like:

Mathematically defined

$$\text{Residual MSE} + \alpha \cdot \text{Ridge Penalty} + (1 - \alpha) \cdot \text{LASSO Penalty} \quad (2)$$

$$1 - \alpha) \cdot \text{LASSO Penalty} \quad (3)$$

for $\alpha \in [0, 1]$.

Multinomial Naive Bayes

- Assumes conditionally independent classes
- Probability of observing features f_1 through f_n , given some class c

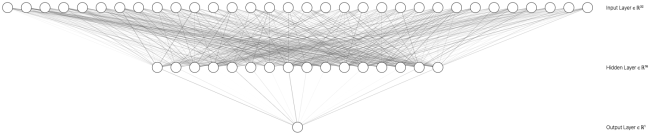
$$p(f_1, ..., f_n|c) = \prod_{i=1}^{n} p(f_i|c) \tag{4}$$

This means that when I want to use a Naive Bayes model to classify a new example, the posterior probability is much simpler to work with:

$$p(c|f_1, ..., f_n) \propto p(c)p(f_1|c)...p(f_n|c) \tag{5}$$

LSTM Neural Network

- Long Short Term Memory Neural Network is based on the Recurrent Neural Network
- It is very well suited for timeseries analysis like the prediction of price
- Futher explanation exceeds this presentation



Analysis

The team around Josh Keating reached a mean absolute error between 32$ to 35$

- Our network design was way to simple
- We didn't include the important neighbourhood feature
- Our result with our LSTM neural network was 64.04$ (MSA)
- Nevertheless, our best model was the linear regression with a MAE of 43.89$

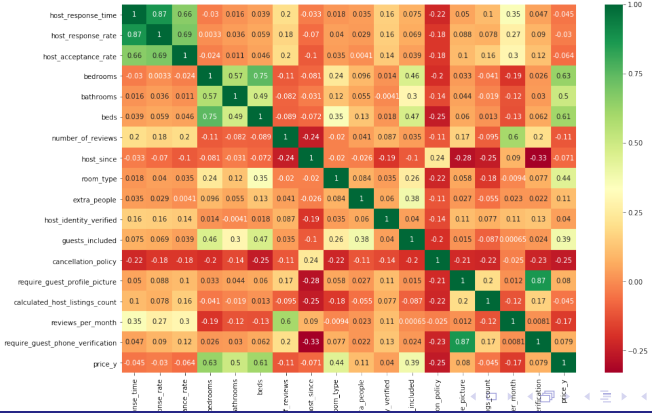
Which facts lessors need to address in their description to raise the interest of potential customer, who ‘fit’ the vibe of the neighborhood and set their focus on the same aspects as former customers of these apartments?

As shown in the word cloud:

- The six most reviewed cities are Capitol Hill, Ballard, Queen Anne, Belltown, Minor, Wallingford
- All cities have the words walk, park and restaurant written in big
- The word “downtown” is also used often
- For Minor, the word “lake” is very important
- Interestingly, the word “Washington” is important for the cities Minor and Capitol Hill

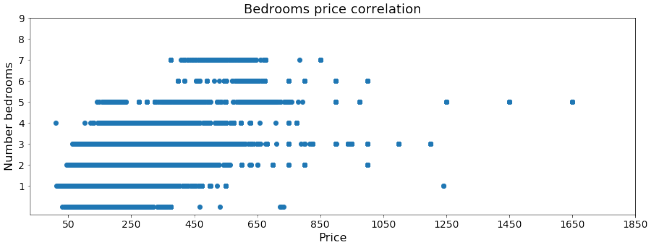
Which price can be charged for an apartment with certain characteristics?

Heatmap: Correlation between features and price



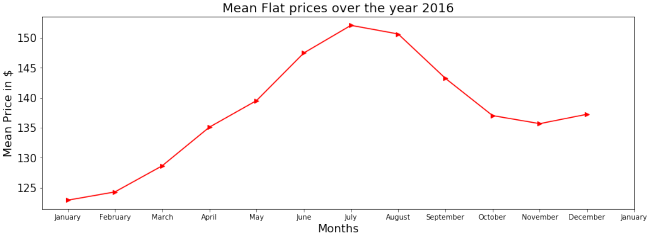
Which price can be charged for an apartment with certain characteristics?

As shown in the heatmap from the previous slide, there is a clear correlation between number of bedrooms and price.
More features with correlate with the price are the beds, bathrooms, room type and guests included.



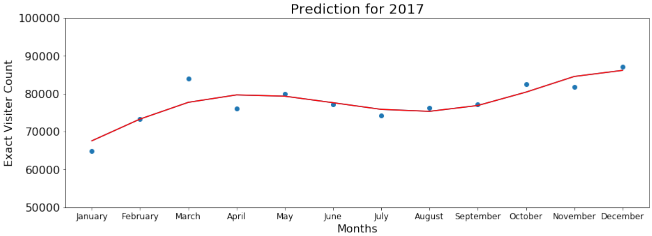
Which price can be charged for an apartment with certain characteristics?

Another big indicatior is the **season**. As shown in the figure below there is a strong fluctuation between the prices and the seasons. So, we need to adapt our price on the current month.



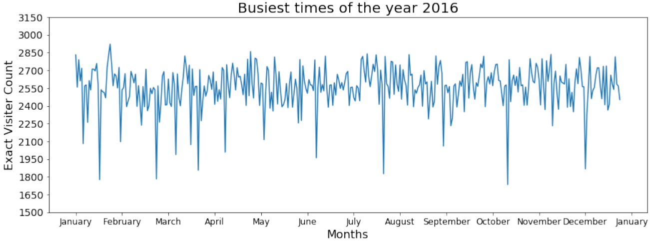
When can lessors increase the price per night for their apartment and when should they lower it?

- Price increase from January and July from 120$ to 150$
- Price decrease until November to 135$
- We can detect an increasing demand for flats in summer time and Christmas with a correlation of an increasing price



What is a good point in time to start a marketing campaign?

We can see clearly the high fluctuation of visitors on a weekly basis, but it is also obvious that it correlates with the picture before.
It could be explained by people are more likely to travel on weekends than on weekdays



Impacts

Our Findings and Impacts

- The reviews are the most important factor of the costumers decision
- Lessors should ask their guests to leave a review after staying at the
- Lessors should consider to update their description with attractive places nearby. For example a lake, park or restaurants.

Our Findings and Impacts

- Another big factor is how long the host has been acted and how many listings the host has
- Hosts should try to increase their response time
- Obviously providing more bathrooms or bedrooms leads to rent the flat for a higher price

Conclusion

Conclusion

- We made some suggestions how to apply marketing-mix strategies effectively. The focus was on the Product, Price and Promotion policy which is known from the marketing definition
- Lessors could experiment with new trendy words in their description
- The number of bedrooms has to be exceeded to five before the entry price increased

Conclusion

- From January until July lessor should increase their price but decrease again until November
- On Christmas they can Increase their price
- It make sense to start the marketing campaign in February to be noticed before the rising customer counts

References

For references pleace look in the origin report "How can the effectivness of marketing 'Airbnb Seattle' be improved? - dataset of 2016

– The End –