Predicting Airbnb Survival: A Bayesian Analysis of Supplier Persistence in Sharing Economy

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December 2019

Abstract

Sharing Economy has been one of the fastest growing business areas in recent years, with several new platforms revolutionizing the traditional markets, including Airbnb. This new type of economy has much lower barrier of entry, thus attractive many suppliers who would otherwise not participating in certain industries. However, this low barrier also mean that it is not likely for one to stay in the market in long term, and thus understanding the survival chance is pivotal. This paper looks at how we can model the survival probability of suppliers in a sharing economy, Airbnb to be specific, through both supplier-generated content, supplier and business characteristics, as well as user-generated content, using a combination of Machine Learning and Bayesian statistics.

1 Introduction

In recent years, the peer-to-peer business model has been experiencing a rapid growth in popularity, technology, and scale. These platforms, collectively known as the "sharing economy", which is projected to be $335 billion in 2025 [1], have become an ingrained

[1] Forbes, 2019. *The Sharing Economy Is Still Growing, And Businesses Should Take Note.*

part of modern society, enabling the general populace to make use of under-utilized assets through fee-based sharing. Consumers have so far enthusiastically adopted the services offered by firms such as Airbnb, Uber, or Lyft. Instead of spending hours of tedious planning and thousands of dollar in cost, one can now prepare for a trip effortlessly with just a few clicks on their phone. Inter-cities trips could be arranged with a stranger who has a spare seat on their car through BlaBlaCar, and accommodation could easily be found at someone's unused bedroom or apartment through home-sharing apps such as Airbnb or VRBO.

The emergence of these peer-to-peer platforms has arguably been enabled by two key factors: technological advancements and supply-side flexibility (Zervas et al., 2017). Innovations in technology help streamlining the process of market entry for aspiring suppliers, facilitated searchable listings for consumers, and reduced transaction overheads. Supply-side flexibility is another asset of these platforms: Uber drivers can add or remove themselves from the available supply with a swipe, and similarly other suppliers can readily list and delist the selection of goods or services they offer.

These newly found conveniences have offered entrepreneurial individuals a new source of income, which, for some, even supplants the traditional methods. However, the flexibility and simplicity also mean almost everyone can participate in this market, and this inevitably leads to over-supply. The laws of the market dictate that not everyone can be a winner in the sharing economy, and thus understanding what makes a peer-to-peer endeavor successful is essential to comprehensing this new kind of economy.

In order to achieve this, an intuitive starting point would be what these peer-to-peer platforms have been endowed with the most, thanks to technological advancement: ample user-generated, both the supplier and the user, as well as competition data. That is my main goal for this project, to investigate the relationship between an Airbnb listing's owner-provided data, reviews, competition landscape, and the probability of survival over time of these listings.

2 Literature Review

2.1 Sharing Economy

The sharing economy business models have gathered a significant, and growing, amount of attention from various academic disciplines, ranging from operation management, marketing and economics to information system and computer sciences.

The first stream of sharing economy literature concerns about the impact of sharing platforms to local, traditional economies. Zervas et al. (2014, 2017) demonstrate that each 10% increase in supply of Airbnb postings results in a .35% decrease in monthly hotel-room revenue, in a geographic region. Einav et al. (2016) discuss the design and regulation of peer-to-peer markets, with theoretical predictions of the effects of competition from these markets on incumbent firms. Martin et al. (2010) conclude that car sharing service availability reduces car ownership and gasoline consumption, and possibly alters consumer behaviors.

The second stream looks at behavioral models of agents within the sharing economy. As a new form of two-sided market, sharing economy inherits many important traits from the traditional model, including network externality. That is, each side of the market would benefit merely from the presence of the other (Farrell & Saloner 1985, and Katz & Shapiro 1985). This research stream formed later than the first one, but recent there has been several cursory researches into this, albeit mostly from a theoretical side. For example, Benjaafar et al. (2015) look at how collaborative consumption in rideshare model influences consumer's concept of product ownership. Li et al. (2016) find that supplier behaviors in Airbnb have certain anomalies between professional and beginner hosts, which leads to discrepancy in results. From the other direction, Zhang et al. (2015) assert the positive relationship between social engagement among customers and perceived service quality in a sharing education platform. Many studies also look at the motivation for participating in sharing economy, such as Hamari (2015) and Hawlitschek (2016) which find "Enjoyment in Sharing" to be the greatest factor for both supplier and consumer.

The third, and arguably fastest growing stream, researches the issue of reputation in sharing economy. Mittendorf (2016) show that consumer's trust influences business transaction in Airbnb. Similarly, Teubner et al. (2017) find that host's reputation has a positively relationship with price elasticity. On the other hand, Zervas et al. (2015) argue that online reputation of Airbnb is not a good differentiating feature, as most reviews are above average, with early 95% of Airbnb properties boast an average user-generated rating of either 4.5 or 5 stars.

My research in this paper contributes to both the second and the third streams above. Some researches in the second stream, as mentioned above, look at suppliers' motivation, and the anomalies in their behaviors. However, none of the existing literature investigate the survival of the suppliers and how does it relates to input from consumer side. This research also contribute to the third stream is that it investigate how features that influence a host reputation (their tenure, whether they are superhost, their rating, their generated content etc.) determines their survival.

2.2 User-Generated Content

While the study of user-generated content's influences on consumers' and firms' behaviors has become a huge inter-disciplinary area in recent years, most, especially in marketing, was devoted to either predicting rating behavior for recommender systems (Ghose, 2012), influences on other customer behaviors (Kumar et al., 2016) or market behavior (Tirunillai et al., 2012). Not many studies have investigated the link between user-generated content and a business survival. Luca (2016) looked at the relationship between Yelp reviews and restaurant revenue. However, none has look at the actual survival rate, since most analyses were concerned with traditional, established businesses, unlike the volatile status of the sharing market.

Recently, newer research have started to look into content generated by the supplier themselves, instead of just consumer-generated ones. For example, Proserpio

Zervas (2017) show that management responses have significant impact on consumer reviews, and Chevalier et al. (2018) show this effect is negative in long term. Perhaps closer to this research, Fagerstrøm (2017) show that facial expressions of the hosts in their profile photo influence consumers using Airbnb. This research contributes to this trend by investigating whether cover images, and listing description, created by the hosts, influence their survival chance.

2.3 Business Survival

The last branch of literature this research relates to is business survival literature. This is a somewhat sparse area, but existing literature could be divided to three main themes. The first theme is business characteristics, including whether it is independent or franchise (Bates 1995), institutional aspects such as legitimacy and innovation (Shane and Foo 1999, Mas-Verdú et al. 2015), or owner characteristics (Kalleberg 1991). The second theme is competitive landscape, especially for new entrants (Wagner 1994, Strotman 2007). The last theme is macroeconomic factors, including national circumstance (Audretsch and Mahmood 1995, Parsa et al. 2010), and local conditions (Haapanen and Tervo 2009, Kalnins and Lafontaine 2013). The model utilized in this paper involves all three themes through both host's characteristics and neighborhood characteristics. This paper also open up a theme for business survival research: through business-consumer dynamic.

3 Empirical Context and Data

3.1 Empirical Context: Airbnb Online Platform

Airbnb is a sharing-economy marketplace connecting hosts with empty rooms to potential renters. Airbnb describes itself as "a trusted community marketplace for people to list, discover, and book unique accommodations around the world," and it exemplifies a typical peer-to-peer platform in modern sharing economy. Prospective hosts (suppliers) list their spare rooms or apartments on the Airbnb platform; establish their own nightly, weekly or monthly price; and offer accommodation to guests. Guests (consumers) visit the Airbnb website or use their mobile application to search for desirable accommodations. Since its launch in 2008, the Airbnb online marketplace has experienced very rapid growth, with more than 6 million properties worldwide in more than 100 thousand destinations, and over 500 million guests who have used the service by September 2019. [2]

Similar to traditional two-sided markets such as phone directories, credit card companies etc., Airbnb earns revenues from both sides. In particular, guests have to pay a 9% to 12% service fee on average for each reservation, depending on the length of stay and the location, while hosts pay a 3% service fee to cover the cost of processing payments by Airbnb. Due to the novelty of Airbnb's model, currently there is little regulation in place to control this type of business. As a result, it becomes a major concern for some local governments such as New York City, that professional rental businesses use Airbnb to avoid taxes. [3]

At first look, hosting on Airbnb seems to be an easy and profitable endeavor for people with spared rooms or properties. However, there are many hidden costs prospective hosts may not aware of before signing up with the platform. Beside the 3% service fee above, hosts are usually not aware that if they rent out their property by more than 14 days per year, their Airbnb would be taxed as rental income, with limited possibilities for deduction. For each stay, there would additional costs incur as well, such as cost of clean supplies, seen the listings are expected to be cleaned and ready-to-go, and insurance, as some states require hosts to purchase insurance for Airbnb listings.

Even if insurance is not required, one may face significant costs if guests damage their properties without insurance to cover. These hidden costs make a significant share of new hosts drop out (disappear from Airbnb listings) only after a short stint with

[2] https://press.airbnb.com/fast-facts/

[3] "Airbnb, New York State Spar Over Legality Of Rentals." NPR. October 16, 2014.

the platform. For example, as Figure 1 demonstrates, in our data, 95 out of 673 new listings (14.11%) in September 2018 in Chicago area disappeared only after one month on the market, and the drop out rate after second month is even higher at 19.2%. The drop out rate only stabilise after 4-5 months, when perhaps only hosts who commit to Airbnb would stay. [4]

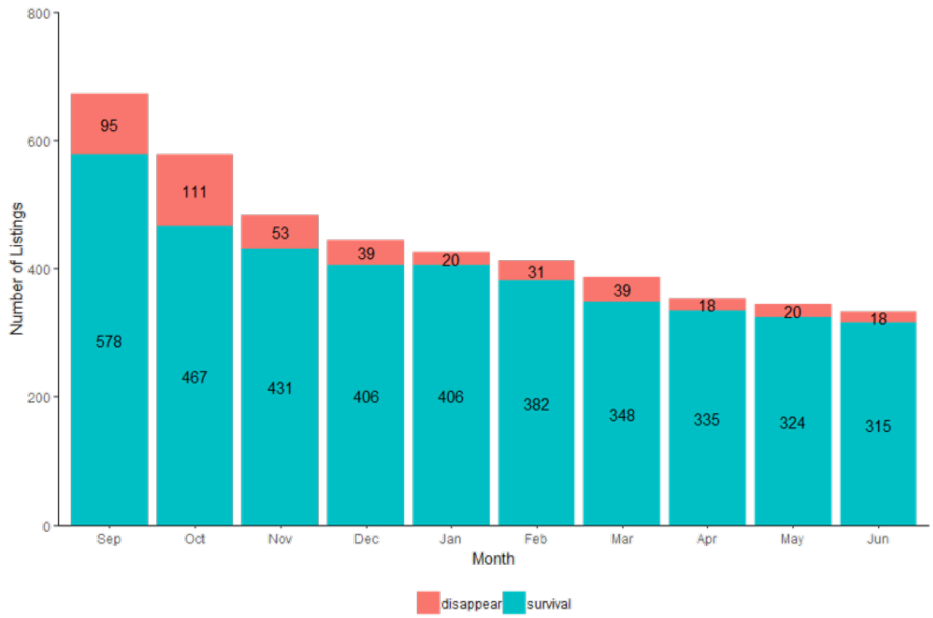

Figure 1: Survival and Disappearance of Airbnb Listings.

3.2 Data

For this study, I utilize the Airbnb listing dataset provided by Inside Airbnb project [5], which is comprised of publicly available data scraped from Airbnb website. Inside Airbnb Project provides monthly cleaned and aggregated Airbnb listings data of several key cities around the world, starting from April 2015. This data were scraped directly from Airbnb website interface using a permanently active web crawler which run every

[4]"Thinking of renting out your home on Airbnb? Consider these costs first.", Washington Post. July 27, 2015

[5]http://insideairbnb.com

15^{th} of each month. The process of how this work is as follow: (1) the crawler send request to Airbnb.com to search for available rooms in a city; (2) the crawler then follows the link to each listing and records the information about that listing, such as location, room type, images, descriptions, number of rooms, guest reviews, identify of the host, etc.; (3) for each listing, the crawler searches for availability and price of all stay dates during the one-year travel period.

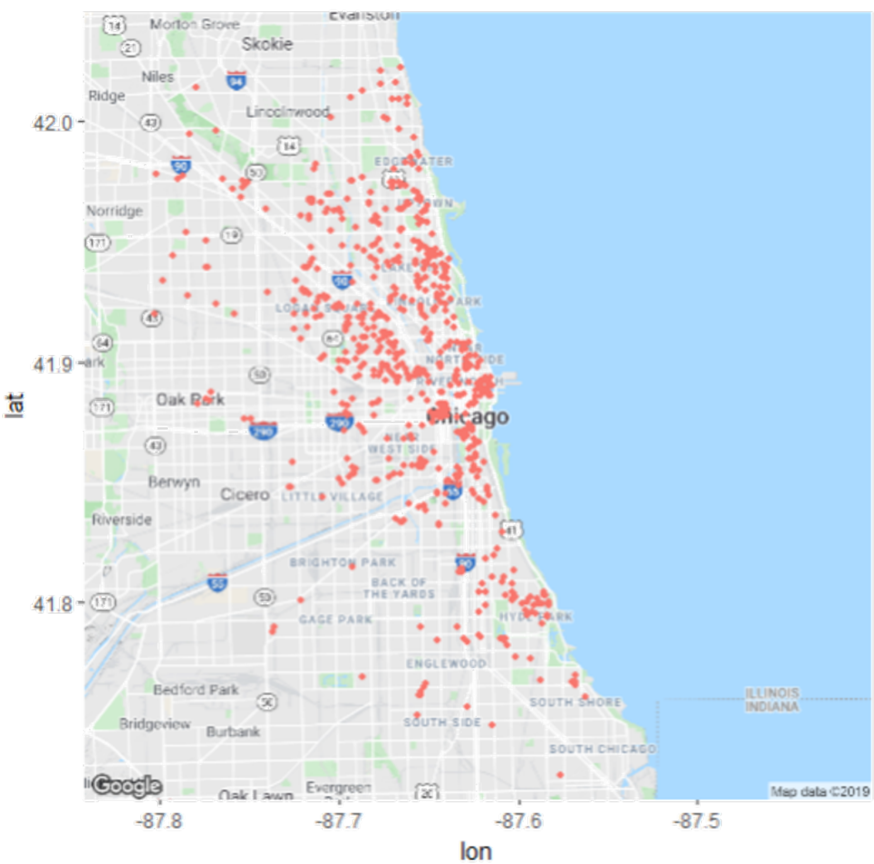

Figure 2: Airbnb Listings Distribution Map.

Due to the limited scope of this study, I focus on listings from only one city: Chicago, Illinois. The dataset for each city each month has 106 variables that represent all characteristics of a listing, including: Listing ID, name, location (neighborhood and coordinates), host-created description of the place, house rules, host information, price, number of rooms and amenities, number of reviews, and six dimensions of rating. Due

	N	Mean	Median	St. Dev	Min	Max
Price	4436	156.7	106.0	245.34	10	5000
Survival	4436	0.9	1	0.3	0	1
Number of Reviews	4436	14.97	6	24.93	0	243
Rating	3592	93.96	8.68	97	20	100
Accomodates	4436	3.9	3	2.59	1	16
Bed Rooms	4435	1.49	1.1	1	0	8
Availability 3 months	4436	53.62	64	31.49	0	90
Host Tenure	4436	31.93	31	23.65	0	107

Table 1: Summary Statistics of Airbnb Listings

to the limited scope of this study, I only look at some of these variables, which will be described below.

The dataset acquired through the InsideAirbnb crawler has more than 500,00 observations, covering a 12 month periods from August 2018 to July 2019. However, as the main focus of this paper is on survival of new listings, and to avoid potential bias from censored data (Cox, 2018), I select only the new listings first appeared in September 2018 (N = 673), and follow these listings over a period of 10 months. The listings covered three different types of room: Entire house/apartment, entire room, and share room. To reduce noise in the data, I also remove the niche property types which have less than 20 observations (Tree house, Snow truck, Cabins etc.). This results in a panel data of 4436 observations, which covers 56 neighborhoods in Chicago area. **Figure 2** shows the location of all listings used in this analysis, and **Table 1** shows some descriptive statistics of the listings.

Regarding the main dependent variable, since Airbnb does not reuse listing ID and host ID, a "delisting" could easily be identified through check whether a listing ID at month T occurs in the dataset of next month. This is showed in **Figure 1** above.

3.3 Host-Generated Contents

In order to investigate the effects of host-generated content on a listing survival, we can look at two main types of content: (1) The images a host used to showcase their listings to guests in their search, and (2) The description of the listings, written by the hosts to provide the guests with a general summary of their listing. Some research, such as Fagerstrøm (2017), looks at other properties such as host's profile photos or host's name and gender, but I want to focus of these two main features, as they are the first things a guest see when search for a listing (as illustrated by **Figure 3**). The next sections describe in detail the process of getting the features from these contents.

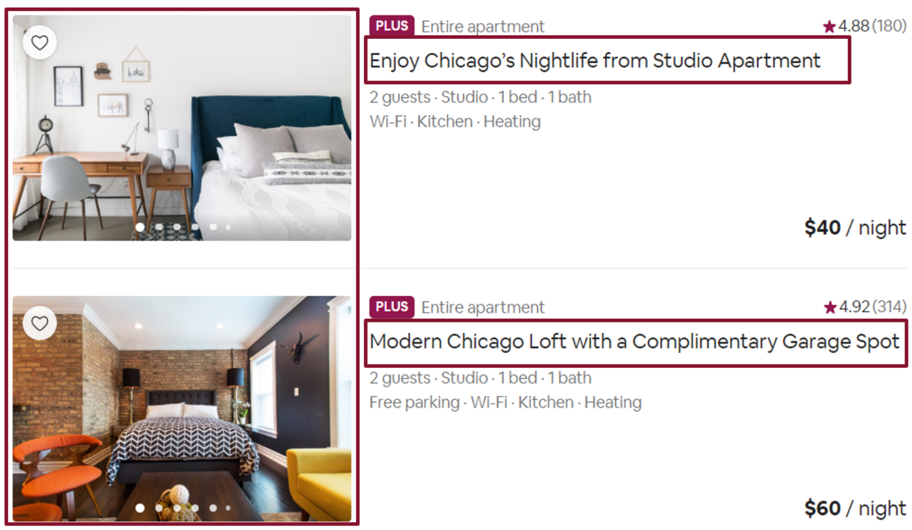

Figure 3: Airbnb Search Interface Example.

3.3.1 Text Description

For text description, in existing literature in Marketing as well as related fields, there are multiple approaches for feature extraction. For User-Generated contents, one popular approach is utilizing automated Sentiment Analysis algorithms, as demonstrated in papers such as Shin et al. (2010) or Ghose et al. (2012). This approach identifies whether a review or a comment is negative or positive in valance, and assign a score to represent the magnitude of valence. Sentiment analysis algorithm could also be used to see if the text displays any sign of anger, happiness or sadness. However, it is reasonable to argue that this approach will not be appropriate for our case, as the descriptions written by hosts would surely be either positive or neutral in sentiment.

The second approach is generated latent variables from the textual data. This could either through Principal Component Analysis of n-grams within the text (Ayeh 2013), or more recently, through topic modelling methods. Within the marketing literature, Latent Dirichlet Allocation - LDA (Blei et al., 2003), and its variants have increasingly become the standard practice for extracting topics from textual content (Büschken & Allenby, 2016). For example, Tirunillai and Tellis (2014) apply a variant of the LDA model to User-generated content to capture latent topics and valence, and analyze topic importance for various industries over time and utilize the emerging topics for brand positioning and market segmentation. In this paper, I follow this practice and apply a Sentence-Constrained LDA model to the ”summary” text provided by the host for each listing. The basic process of this model is described in **Figure 4** below.

A basic LDA model assumes the existence of a fixed number of latent topics that appear across multiple documents. Documents are represented as random mixtures over latent topics, (θ_d), and each topic is in turn characterized by a discrete probability distribution over words. Following normal practice, words with the highest probability are used to characterize the latent topics. The process is as follow for M documents:

1. Drawing $\theta_i \sim Dir(\alpha)$ with $i \in \{1, 2....M\}$.
2. Drawing $\varphi_k \sim Dir(\beta)$ with $k \in \{1, 2....K\}$, and K is the number of topics.
3. For each word in a document i of length J:
   (a) Choose a topic $z_{i,j} \sim Multinomial(\theta_i)$.
   (b) Choose a word $w_{i,j} \sim Multinomial(\varphi_{z_{i,j}})$.

For the Sentence-Constrained LDA model used in this paper, instead of have a topic $z_{i,j}$ for each word in a document, the topic distribution is constrained to be the same

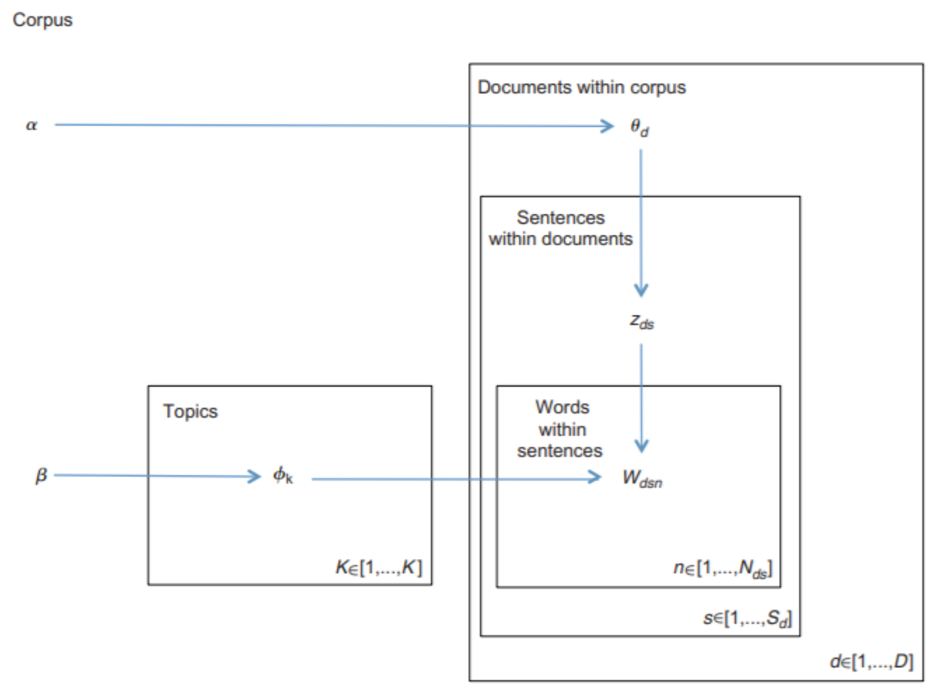

Figure 4: Sentence-Constrained LDA Model.

for each sentence within a document, to better reflect the natural data generating process. That is, instead of drawing $z_{i,j}$ for a document with J words, we draw $z_{i,n}$ for a document with N sentences.

For learning the distributions as outlined above, we can treat this as a hierarchical Bayes model, and infer using variational Bayes (as per the original paper by Blei et. al) or Gibbs Sampler. In this paper, I use Gibbs Sampler with 20,000 iterations. For selecting the approriate number of topics, the statistics proposed by Deveaud (2014) was used, and a choice of 6 topics maximize this statistics (See $Figure 5$). The φ score of each topic, which represent the distribution of that topic over the document, are used as variables for the model.

The resulting topics are depicted in the following graph by their top ten highest probability words. From the top words, we can characterize these topics as: (1) Living amenities; (2) Relaxing; (3) Rooms and Space, (4) Luggage & Check in information; (5) Generic description; (6) Transportation & getting around.

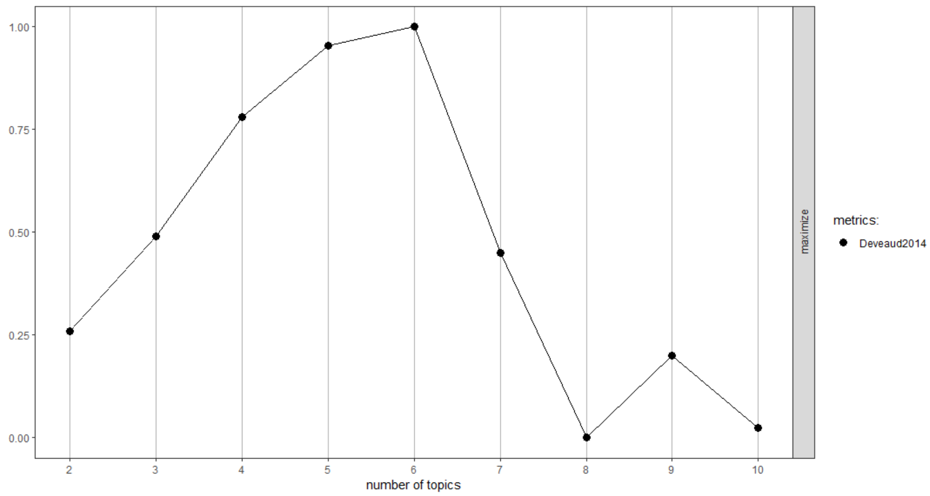

Figure 5: LDA Topic Selection.

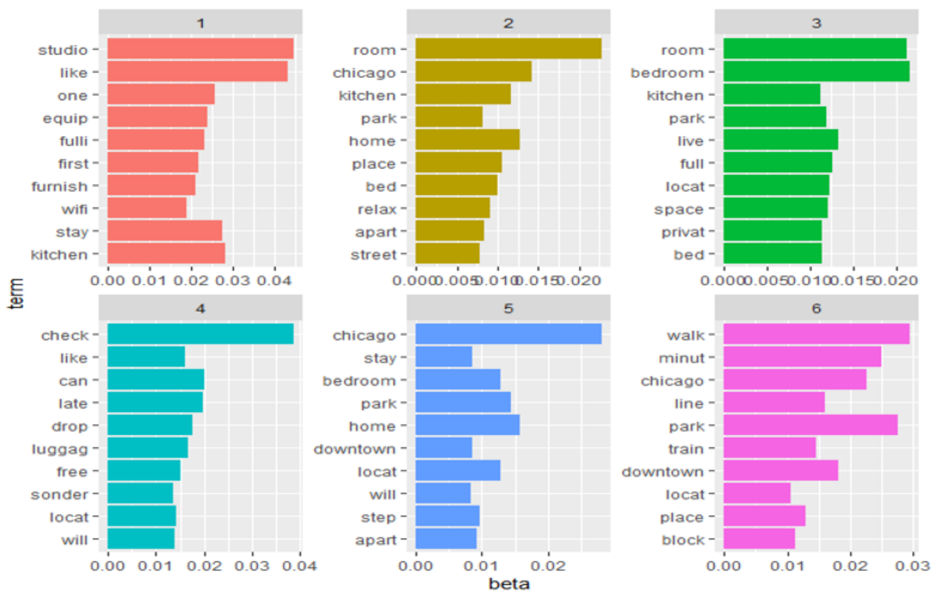

Figure 6: Top 10 Words of LDA topics.

3.3.2 Image Description

For the second type of host-generated content, there are fewer precedents on how to extract meaning variables in marketing literature. The most common approach is utilizing human grader to create labeled data on various properties of an image, for example attractiveness or recallability. These are usually gathered through crowdsourcing services such as Amazon MTurk. These labeled data are then used to train classification models to classify the remaining images. This approach is the best one for extracting subjective information such as the attractiveness or "emotion" of an image.

However, the above approach takes a large amount of time and resource to implement, and thus in this paper I follow a less subjective, yet still robush approach. My approach utilizes the method called Blind/Referenceless Image Spatial Quality Evaluator - BRISQUE (Mittal, 2011). This belongs to a type of image assessment called "No-reference image quality assessment", normally also referred to as "Blind methods". These are mostly comprised of two steps: The first step generates variables that represent the image's structure and the second step finds the latent patterns among the variables (in many ways similar to Principal Component Analysis) that could influence human opinion.

Among the blind methods, BRISQUE is unique as it only uses the image pixels to generate the latent variables (other methods are based on image transformation to other spaces like wavelet or DCT). It is demonstrated to be highly efficient as it does not need any transformation to calculate its variables. BRISQUE relies on spatial Natural Scene Statistics (NSS) model of locally normalized luminance coefficients in the spatial domain, as well as the model for pairwise products of these coefficients. The general process is depicted below:

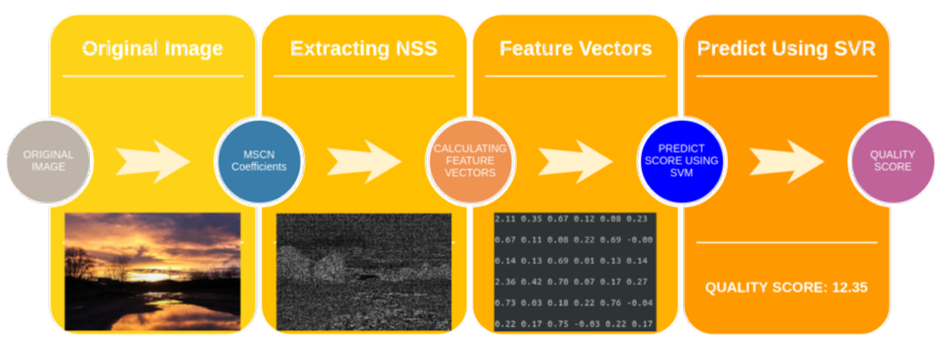

Figure 7: Blind/Referenceless Image Spatial Quality Evaluator.

For brevity's sake, reader could refer to Mittal (2011) for the details of the

BRISQUE model. In this paper, I generate the BRISQUE quality assessment score for each of the images used by the hosts to show their listings. This score is lower for higher quality images and higher for lower quality images. The scores are generated used the pre-trained SVR model provided in Mittal (2011), and then for each listings, the average score is calculated using weighted average, with the first image (which guests would see first), receiving a weight of 1, and each following image receiving a weight 0.8 times of the previous.

Beside the BRISQUE score, I also extract other basic properties of the image that are usually related to its quality, including Brightness, Saturation, and Hue. These are extracted by getting the Red, Green, and Blue color distributions of each image, and then calculating the indices using their mean and probability distributions.

3.3.3 Host Characteristics

In their research into host behaviors in Airbnb, Li et al. (2016) demonstrate that there are two main types of Airbnb hosts: the professional hosts, and the non-professional hosts, with the professional type accounts for around 20% of Airbnb hosts, and the rest is non-professional. Li et al. point out that professional hosts tend to stick with Airbnb much longer, and have higher resistance to negative shocks such as competition growth or lower customer rating. On the other hand, non-professional hosts tend to have anomalous behaviors and can suddenly delist their Airbnb listings.

In this analysis, the main characteristics of host I use to represent whether the host is professional or not are: The number of listings a host has; how long has the host been on Airbnb; and whether host is a super host. The number of listings of host and whether the host is super-host are scraped directly from Airbnb, while host tenure is calculated by the date of their first listing, and then converted to number of months. For this data, the host tenure is 31.93 (SD = 23.65) months on average, ranging from 0 to 107. Around 22% of the hosts are superhost, and the median number of listings owned by a host is 2, but could go up to more than 200. This shows that we can cover both the professional and non-professional hosts.

3.3.4 Listing Characteristics

For listing characteristics, I used the basic information scraped from Airbnb website, including: the average price in a 30 days period, the neighborhood of the listing, the number of people a listing can accommodates, the number of beds, and the number of bathrooms. All of these information are displayed to guests in their search screen, and thus would be the most impactful, as consumers do not have to incur any extra search cost for getting these data points in there decision making process. These information also represent the general scope of a listing, as we could reasonably assume that the more "impressive" a listing is, the higher commitment and investment a host has to invest in it, and the less likely it would be delisted. Time the host last updated the listing calendar is also used, as this is reflection of how much attention and care a host is paying to that particular listing.

3.3.5 Guest Generated Content

For guest generated content, I used the total number of reviews of a listing at time T, the number of reviews last month, as well as the average general rating and the rating in each of the six dimensions: accuracy, cleanliness, checkin, location, communication, and value. These are the rating asked by Airbnb after the guests stay at a listing. As many listings do not have rating, a rating indicator (1 = Has ratings, 0 = No rating) to account for this.

We could follow the same approach as described in the host-generated content section to analyze each of the reviews let by customers. However, as this topic is well-investigated in existing literature, and not the main concern of this paper, I assume that the rating scores can reflect most of guests attitude toward the listing. This is a reasonable assumption based on previous research (Zervas et al., 2017).

4 The Model

In order to model the survival of the listings, I employ a discrete time logit model with time variant variables. This type of model has been widely used in marketing literature for modeling inertia in customer behavior or lagged effects of market mix activities (Chintagunta, 1998; Dube et al., 2010). Hu and Van den Bulten (2014) consider this a hazard model for discrete time, and it has been used in other fields for discrete time survival analysis as well (Willet & Singer, 2004). The model could be specified generally as follow:

$$\begin{aligned} P_{it} = P(y_{it} = 1 | y_{it-1} = 1) = logit^{-1}(&\alpha + Host_{it}\beta_1 + Accom_i\beta_{2,r} + Price_{it}\beta_{3,n} \\ &+ ReviewNo_{it}\beta_4 + HasRating_{it}Rating_{it}\beta_5 + Text_i\beta_6 \\ &+ Image_i\beta_7 + Avail_{it}\beta_8 + Month_t + PropertyType_i + Neighborhood_i) \end{aligned}$$

Where P_{it} is the likelihood that the listing i will be listing in $t + 1$, given that it was listed in month t. The variables, along with their parameters and corresponding priors, are described below:

- For α, most literature usually just use a diffuse prior with normal distribution of mean 0 and standard deviation 100:

  $$\alpha \sim N(0, 10^2)$$

- The first variables are $\boldsymbol{Host_{it}}$, which is a vector of host characteristics of property i at time t, consisting of: host tenure - how long they have been hosting; total number of listings a host has; and whether they are superhost. It is reasonable to assume that the effects of these variables are positive, and correlated with each other. Therefore, we can use a multivariate normal prior:

  $$\beta_{1,j} \sim MVN(\mu_{1,j}, \Sigma_{1,j}); j = 1, 2, 3$$

  The mean could be assigned a reasonable weakly informative prior, and the co-variance matrix following an Inverse-Wishart distribution, with a scale factor of

1 and a shape of 4:

$$\mu_{1,j} \sim N(1,1)$$
$$\Sigma_{1,j} \sim InvWishart(\psi_1, 4)$$
$$\psi_1 = diag(1,1,1)$$

- The $Accom_i$ variable is a vector of accommodation characteristics, including: the number of people the listing can accommodates, the number of beds, number of bathroom. Since an Airbnb listing can be either entire house, an entire room, or shared room, the effect of accommodation size may be heterogeneous with regard to listing type. Therefore, we can allow for this effect to be different for each type, with diffuse normal priors:

$$\beta_{2i,r} \sim N(0, 10^2); r = 1,2,3, i = 1,2,3$$

- The $Price_{it}$ variable is the average price of listing i at time t. It could be the case that the higher the price, the more likely a listing would survive, as they are more high-end and require higher commitment from the hosts. The effect of price may also be different depending on the neighborhood of the listing, as price may be high in some neighborhoods and low in others. We can model the parameter $\beta_{3,n}$ for each neighborhood n through a linear function with the average price of that neighborhood, and a positive intercept prior:

$$\bar{\beta}_{3,n} = \gamma_0 + \gamma_1 AvgPrice_n$$
$$\beta_{3,n} \sim (\bar{\beta}_{3,n}, \sigma_p)$$
$$\gamma_0 \sim N(2,1)$$
$$\gamma_1 \sim N(0,1)$$
$$\sigma_p \sim N(0,1)$$

- Next, $ReviewNo$ and $Rating$ are both time-variant variables that measure number of lifetime aggregated reviews, and average rating, respectively. As mention, the $HasRating$ indicator is added to account for cases without any rating. The parameters for these can assume normally distributed priors with a positive mean:

$$\beta_i \sim N(2,1); i = 4,5$$

- The next one, $Text_i$ is a time-invariant vector of topics of text description of the listing, as mention above. The prior of the parameters of these topics are assumed to follow a multivariate normal distribution, similar to the host characteristics as above:

$$\begin{aligned} \beta_{6,j} \sim MVN(\mu_{6,j}, \Sigma_{6,j}); j = 1,2,...6 \\ \mu_{6,j} \sim N(1,1) \\ \Sigma_{6,j} \sim InvWishart(\psi_6, 7) \\ \psi_6 = diag(1,1,1,1,1,1) \end{aligned}$$

- Similarly, $Image_i$ is the vector of image features of the listing, including BRISQUE score, brightness, saturation, and hue, as mention above. The prior of the parameters saved for Brisque of these topics are assumed to follow a multivariate normal distribution, similar to the host characteristics and text description topics as above. For BRISQUE, following Fagerstrøm (2017), we can hypothesize that the importance of image quality evolves over time, so the effect is a function of age of the listing:

$$\begin{aligned} \beta_{7,j} \sim MVN(\mu_{7,j}, \Sigma_{7,j}); j = 1,2,...3 \\ \mu_{7,j} \sim N(1,1) \\ \Sigma_{7,j} \sim InvWishart(\psi_7, 4) \\ \psi_7 = diag(1,1,1,1) \end{aligned}$$

$$\bar{\beta}_{BRISQUE} = \gamma_0 + \gamma_1 Time_t$$
$$\beta_{BRISQUE} \sim (\bar{\beta}_{BRISQUE}, \sigma_p)$$
$$\gamma_0 \sim N(1,1)$$
$$\gamma_1 \sim N(0,1)$$
$$\sigma_p \sim N(0,1)$$

- $Avail_{it}$ is the availability of the listing in the next 90 days period. The parameter of this is assigned a diffuse prior:

$$\beta_{8,j} \sim N(0, 10^2)$$

- Lastly, I included fixed effect term for the month, as well as the property type (apartment, condo, or townhouse) and the neighborhood as covariates. The ffixed effects are assigned diffuse normal distribution priors:

$$month_t \sim N(0,10); t = 1, 2, ..10$$
$$property_p \sim N(0,10); p = 1, 2, ...9$$
$$Neighborhood_n \sim N(0,10); n = 1, 2, ...54$$

5 Results

The model above was estimated using Gibbs sampler with 100,000 iterations, including the first 20,000 as burn-ins. The model appears to converge well, with the Potential Scale Reduction Factor ($\hat{R}$) approximately 1 for all parameters. The mean estimates, as well as the 2.5% to 97.5% range and $\hat{R}$ are displayed in tables below.

The first table shows the parameters estimated for listing characteristics. We can see that Accommodation capacity is not really related to survival chance, saved for in Entire Room case, where more people likely leads to lower survival chance. This could

	Mean	St.Dev	Lower HDP	Upper HDP
Accom_Entirehouse	-.017	.03	-.075	.043
Accom_EntireRoom	-.111	.071	-.247	.031
Accom_SharedRoom	-.172	.0265	-.677	.358
Availability	.125	.059	.009	.242
Bath	-.226	.143	-.506	.056
Bed	-.07	.066	-.198	.064
γ_0^{price}	.404	.21	.015	.839
γ_1^{price}	.299	.153	.002	.607

Table 2: Parameters for Listing Characteristics

indicates a more crowded staying arrangement. Other estimates are contradictory to expectation. For example, availability has a positive relationship, which indicates that the more days available in a listing calendar, the more likely it is to survive. Normally, we would expect that lower availability means that the listings are fully booked, but it does not seem to be the case here. It is possible that lower availability comes mainly from the host's decision to make it unavailable, thus indicating an unwillingness to rent out the property, or an early sign of future delisting. Even more surprising, the number of beds and bathrooms are negatively related to survival (-0.226 and -0.07 respectively). It seems that the larger an accommodation is, the lower its survival chance. It is possible that hosts view the listings as sunk cost, so they do not care about smaller costs, but will withdraw higher investments if they think it is working out.

Regarding price, a positive γ_0^{price} shows that price is positively related to the survival chance, which is as expected, and the positive γ_1^{price} shows that this effect increase with neighborhood average price. That is, the more expensive a neighborhood is, the higher the differentiation effect of price on survival chance.

Next, we can look at the effects of Image variables. It seems that most image fea-

	Mean	St.Dev	Lower HDP	Upper HDP
$\gamma^0_{BRISQUE}$	0.1	0.209	-0.316	0.521
$\gamma^1_{BRISQUE}$	-.031	.027	-.105	-.04
Bright	.03	.059	-.086	.147
Saturation	-.012	.028	-0.072	.064
Hue	.023	.143	-.284	.293

Table 3: Image Variables Results

tures are not significantly related to survival chance. Interestingly, while initially, image quality, and represented by BRISQUE score, also is not related to survival chance, this effect does grow over time. The negative sign is expected, as lower BRISQUE score means higher quality of image.

	Mean	St.Dev	Lower HDP	Upper HDP
Topic 1	0.738	0.467	-0.08	1.755
Topic 2	0.588	0.323	-0.003	1.266
Topic 3	0.253	0.275	-0.259	0.818
Topic 4	0.365	0.36	-0.296	1.128
Topic 5	-0.475	0.268	-0.992	0.068
Topic 6	0.329	0.264	-0.166	0.879

Table 4: LDA Topic effects result.

The next table displays the effects of LDA generated topics from the text description of listings on survival chance. We can see that Topic 1, 2, and 5 has substantial effects, with the first two having positive effects and the later having negative effect. From our interpretation of the LDA topics above, we can see that descriptions that talk about ammenities and relaxing atmosphere results in higher chance of survival, while a generic description results in lower chance of survival. There are two potential explanation for this. First, it could be that the descriptions that talk about amenities and relaxing atmosphere lead to better results for the hosts. Second, it also could be the case that these descriptions represents a higher degree of commitment from the host, providing the place with amenities or spending time creating a good ambiance. It is also not surprising that Topic 5 results in negative effect, as this represents a lack of effort to make a unique description from the host.

	Mean	St.Dev	Lower HDP	Upper HDP
Host # Listings	0.613	0.196	0.282	1.051
Superhost	0.311	0.16	0.001	0.63
Host Tenure	0.124	0.065	-0.002	0.252
HasRating	-0.448	0.189	-0.822	-0.081
NumReview	0.016	0.075	-0.125	0.169
Rating	1.297	0.242	0.819	1.77

Table 5: Host Characteristics and User Rating effects

Table 5 displays the effects of Host characteristics and the guest-generated content. We can see that all three main characteristics that reflect the "professionalism" of a host have positive effects, with the number of listings having the largest effect at .613, following by Superhost at .311. This confirms the findings of Li et al. (2016), that the more professional a host is, the higher "stickiness" he or she is with the platform. These measures also represents the level of involvement a host is with Airbnb, and thus these results are to be expected. Interestingly, the HasRating indicator alone has a negative effect. This may be due to the fact that Airbnb listings without rating has not incurred any cost from having guests staying at the location or having negative reviews, thus still staying with the platform. In our last two variables, number of reviews does not have a substantial effect, while rating having very substantial positive effect. This reveals that Airbnb hosts may care only about their average rating rather than the number of reviews they receive. This differs from previous literature which shows that number of reviews has a positive relationship with business survival and growth.

It could be the case that this effect only materialize in long term, and not in this first phase.

6 Model Robustness Check

In order to check the performance of the full model, I estimated three other models, and compare those with the full model using Deviance Information Criterion. The alternative models are:

- Model 1: A model with fully pooled effects (single level model only, no multi level effects).
- Model 2: A Model without the text & image features.
- Model 3: A Model without the image features.
- Model 4: A Model with text features generated using Principal Component Analysis instead of Latent Dirichlet Allocation.
- Model 5: A model with linear effect of month (month is treated as a continuous variable, i.e. age of the listing), instead of fixed effect. A quadratic term is also added to reflect the observed survival rate.

The table below shows the comparison between these models using DIC sampled with 100,000 iterations:

As we can see, our full model performs better than the alternative ones, as it has the lowest DIC out of the six models. The model without image features (Model 3) has relatively similar performance, and this once again confirm that most image features used in this analysis do not have good predictive power of a listing survival chance.

The high DIC for model 1 shows that the imposed multi-level structure is a correct one, and similarly, the high DIC of model 2 shows the predictive power of the LDA topics used in the full model. It is surprising that the model with PCA instead of

Mode	**DIC**
Full Model	**2628.0**
Model 1	2681.3
Model 2	2676.8
Model 3	2630.1
Model 4	2680.8
Model 5	2660.2

Table 6: DIC Comparison

LDA has much higher DIC, and in this model, the PCA scores do not have substantial predictive powers. Generally, both approaches should be relatively similar to each other, both it seems that LDA is much more fitting for this case.

It is also worth noticing that in Model 5, the effect of month as linear predictor is substantial, with positive first order and negative second order polynomial. It may be the case that there are both listing's age effect and fixed effects of specific in play in this case, and that is why the fixed effects of month results in lower DIC than just the listing's age effects.

7 Contribution & Limitations

This research will contribute to the growing literature on peer-to-peer market, as Airbnb exemplifies a two-sided platform. Much of this literature has established the economic theory of two-sided markets—for example, through structural models that establish theories of price structure and usage (Rochet and Tirole 2003; Rysman 2009; Weyl 2010). However, empirical research into the interaction between suppliers and users, or between suppliers, is still nascent. An understanding of these relationships, especially through readily available data such as reviews, is important for both peer-to-peer platforms like Airbnb and to the general populace who want to take part in the burgeoning sharing economy. Knowing what influences an Airbnb listing survival rate would help hosts optimizing their content and platforms come up with innovations that improve experience for both sides.

From the results, we can conclude that there are substantial relationship between host-generated textual content, host characteristics, listing characteristics, user-generated content, and the survival probability of a host listing. Due the exploratory nature of this research, the underlying causal process is not investigated in detail, and this is something future studies could look into. For example, from Airbnb data, there are occasions where the host made change to the images and the description, and those could be a good opportunity to identify the true causal effects of those factors on survival rate.

The non-substantial effects of imagery content in this analysis could also come from the simplicity of feature extraction method. With more resources, researcher could implement better feature extraction using human-labeled data, or a more sophisticated method such as using Convoluted Neural Network for clustering images based on similarity. I advise against taking the results of this analysis at face value, and encourage future studies to try other methods, some of which may result in better and more accurate effect estimates of imagery content.

Lastly, a main limitation to this model is the imposed logit form. While this is a common approach in previous literature, the author believes that other approaches such as a latent state model (Hidden Markov or Kalman filter) would work better to represent the latent commitment of a host to Airbnb platform, and this could be a great extension to this paper.

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