The web of host-guest connections on Airbnb— A social network perspective

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1. Introduction

Airbnb has emerged as the most important peer-based platform for accommodation sharing. It provides over 3 million listings in over 65,000 cities all across the world (Airbnb 2017). Airbnb's current market evaluation stands at $30bn, ranging in the league of many of the hospitality industry's incumbents such as the Hilton Group ($20bn) and Marriott ($34bn) (Forbes 2017). In contrast, Airbnb does not own hotels but operates a two-sided market place, bringing together hosts and guests. Evidently, the role of Airbnb as a platform and marketing channel is significant, as hosts on Airbnb generate an average additional income of $924 per month (Earnest 2017). Moreover, the variety offered through Airbnb is substantial, including everything from urban apartments, guest rooms, and vocational homes to more exotic listings such as tree houses, castles, igloos, and house boats (Forbes 2016). The platform addresses both private and business customers, and facilitates everything from day trips to stays of several months (Mittendorf and Ostermann 2017). Users on Airbnb can be classified as hosts and guests where, importantly, hosts may also be guests on Airbnb when they travel themselves.

A central and ongoing challenge for Airbnb is the creation and maintenance of trust between its users (Gebbia 2016; Hawlitschek et al. 2016). Besides common means of reputation management such as star ratings (Teubner et al. 2017; Zervas et al. 2015), mutual text reviews (Abramova et al. 2015; Bridges and Vásquez 2016), personal self-descriptions (Ma et al. 2017; Tussyadiah 2016), profile images (Ert et al. 2016; Fagerstrøm et al. 2017; Teubner et al. 2014), as well as identity verification and insurances (Teubner and Hawlitschek 2017), Airbnb has also attempted to make use of its users' underlying social network structure. The platform's *social connections feature* displays how users are "connected to others, either directly or through mutual friends" (Airbnb 2011). This includes their Facebook profile photo, recent locations visited, as well as Facebook friends (who also have an Airbnb account). However, only a minority (16%, see Table 2 in §3) in fact uses the "social connections" function. Interestingly, this relative practical irrelevance stands in contrast to first experimental results, indicating that the existence of a common ground between guest and host (e.g., having studied at the same university) is reflected in an increased willingness to engage in a transaction (Abramova et al. 2017). Since the encounters between hosts and guests on Airbnb represent interpersonal interactions (at times very substantial), it could be worthwhile to consider the social network structure *within Airbnb itself (Butts 2009)*. The main objective of this paper is hence to explore the inherent network structure emerging from the steadily growing body of Airbnb transactions between hosts and guests and to provide background information on the underlying data basis.

In doing so, this paper contributes to a better understanding of the types of relations on Airbnb and how the platform's users connect from a macroscopic perspective, with immediate implications for the design and operation of peer-based accommodation sharing. While – as illustrated in the next section – recent research has begun to explore data sets of listings and reviews on a large scale, none have done so for the emerging web of host-guest connections on Airbnb, that is, taking a social network perspective. The remainder of this paper is structured as follows. Section 2 reviews related work, focusing on quantitative studies on Airbnb's user and transaction base. Next, Section 3 presents and describes the employed data set, methods, and results. Last, Section 4 discusses findings and sketches out potential avenues for practical applications as well as future work in this regard.

2. Related Work

Over the past few years, several studies have dealt with Airbnb based on empirical data. Often, the basis for such investigation is a data snapshot, directly retrieved from the platform either manually or by means of web scraping techniques. Since 2014, community and data activist Murray Cox provides a large scale set of Airbnb data for (by now) 44 major cities worldwide, which is updated on a regular basis (Cox 2017; Wired 2017). In fact, for a Google search on "Airbnb data," Cox' website InsideAirbnb.com ranks higher than Airbnb's website itself. This data set appears to emerge as a common ground for researchers, enabling (more) reliable comparisons of results and conclusions, similar to the use of benchmark data sets in other disciplines such as operations research and machine learning.

Research based on Airbnb data can roughly be divided into three main categories. First, several scholars have considered the distribution of (star) ratings on Airbnb. It strikes the eye that the rating distribution is skewed. One property is that many listings do not have a rating at all. In this paper's data set, 24% do not have a rating. Moreover, most existing ratings lean towards the most positive values, that is, 4.5 or 5.0 stars (Fradkin et al. 2017; Gutt and Kundisch 2016; Ke 2017; Liang et al. 2017; Teubner et al. 2016, 2017; Wang and Nicolau 2017; Zervas et al. 2015). Interestingly, while Airbnb displays an aggregated review score (1 to 5 stars, steps of .5) only for listings with three or more reviews, the listing's HTML source code is more revealing. Indicated by the `review_score` variable, even for listings with only one or two reviews, a detailed score is provided. While the displayed star rating uses the 1-to-5-stars scale, the value in the HTML source code is on a scale from 20 to 100 (in steps of 1). The review score distribution of the listings in this paper's data set is depicted in Figure 1 (see also Table 2).

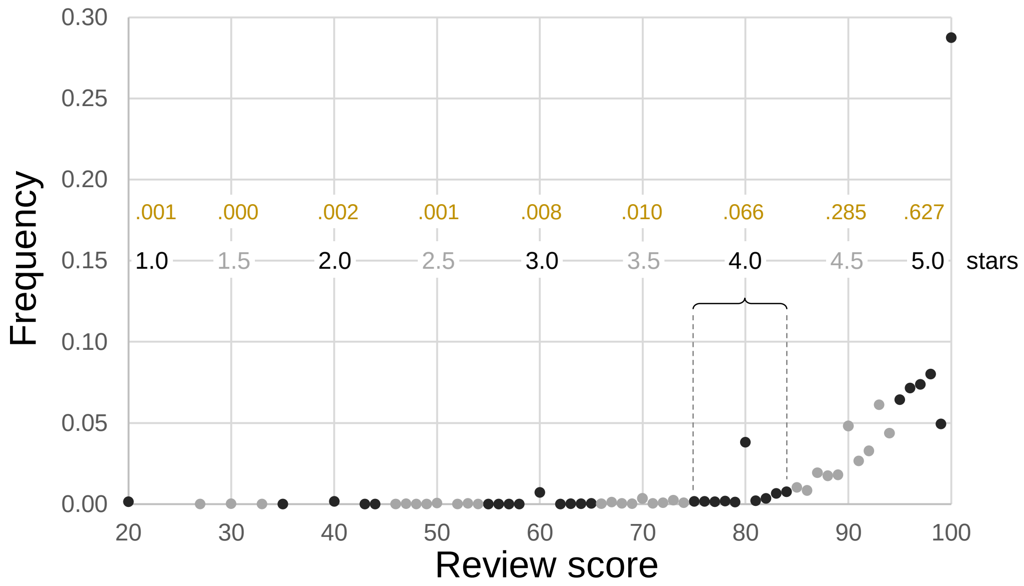

Figure 1: Distribution of review score values (hosts)

Second, several research papers have explored determinants of listing prices, usually based on hedonic pricing models, that is, the assumption that any valuable amenity (e.g., a whirl pool) or other competitive advantages (e.g., a favorable location) will – sooner or later – be reflected in price markups (Rosen 1974). While well-established for "brick-and-mortar" factors in the hospitality and tourism literature (Wang and Nicolau 2017), novel peer-based platforms such as Airbnb now pose the question of whether "soft" factors such as a host's reputation and personal branding yield tangible economic value. And indeed, based on interviews with hosts, Ikkala and Lampinen (2014) found that they in fact "divert their accumulated reputational capital into the rental price" (p. 173). And this stated intention is reflected by the data. Based on 13,884 Airbnb listings from Germany, Teubner et al. (2016, 2017) found host reputation to be associated with price premiums where, for instance, an additional star was reflected in a 20$ markup for a typical stay at a typical accommodation (2 persons, 2 nights; number of ratings: ~20). Similar results are found for other factors, data sets, and regions (Liang et al. 2017; Wang and Nicolau 2017). Moreover, Gutt and Herrmann (2015) illustrated the importance of reputational capital based on a longitudinal assessment of 14,871 listings from New York City. The authors found that once a listing's star rating became visible (i.e., for ≥ 3 ratings), its price was increased. Also based a differences-in-differences approach, listings with verified photos were found to be booked 9% more frequently (Zhang et al. 2016). In this regard, Edelman and Luca (2014) found an association of a host's skin color and listing price, where "non-black hosts charge approximately 12% more than black hosts for the equivalent rental" (p. 1), suggesting the occurrence of racial discrimination on the platform, unintendedly facilitated by the use of host profile images. In a follow-up field experiment, Edelman et al. (2017) found that that requests from users with distinctively African-American names (e.g., Tanisha Jackson, Tyrone Robinson) were 16% less likely to be accepted than when issued by users with distinctively White names (e.g., Laurie Ryan, Greg O'Brien).

Third, recent papers have applied text analysis and natural language processing to the context of Airbnb. Based on word co-occurrence in the textual *self-descriptions* of 12,785 hosts from New York City, Tussyadiah (2016) identified five clusters of hosts (global citizen, local expert, personable, established, creative), which differ in response behavior, pricing, and received ratings. Similarly, based on a series of studies, Ma et al. (2017) found hosts' self-descriptions refer to different themes (i.e., origin/residence 69%, work/education 60%, interests and tastes 58%, hospitality 53%, travel 48%, relationships 28%, personality 27%, life motto and values 8%) and that trustworthiness increased 1) with the amount of personal information revealed, and 2) particularly for information referring to origin/residence, work/education, interests and tastes, and hospitality. Bridges and Vásquez (2016) explored linguistic patterns in 400 *text reviews* (200 from each side), by and large reflecting the high proportion of positive numerical ratings also in the written evaluations (93% of the analyzed text reviews were classified as positive). Interestingly, 79.5% of all guest reviews mention the host by name (a similar proportion is reported by Alsudais 2017). From the 7% of not-entirely positive reviews, 3 out of 4 came from guests, typically referring to issues with comfort (48%), communication (21%), or cleanliness (15%). Interestingly, the authors suggest that less-than positive experiences may be communicated by means of subtle or "lukewarm" cues, for instance by *not* writing or emphasizing something. Analyzing word co-occurrence within text reviews, Tussyadiah and Zach (2016) identified five clusters of words (referring to service, facility, location, feeling welcome, and comfort). Linking cluster affiliation to a listing's overall rating, they found that the "location" and the "feel welcome" clusters were associated with higher, while signal words from the "service" cluster were associated with lower ratings. von Hoffen et al. (2017)

compared sentiment scores of Airbnb reviews with those of #airbnb-tweeds and found that overall, Airbnb reviews exhibit more positive sentiment. Last, Ke (2017) found that the positive-to-negative word ratio of 14 million English text reviews on Airbnb (classified using a dictionary approach; Warriner et al. 2013) was more than twice as high as compared to a benchmark set of Yelp reviews. Moreover, the author identified sets of over-represented words in the reviews of 5-star and 3.5-star-or-less profiles (e.g., wonderful, beautiful, amazing, comfortable, lovely, perfect – ok, dirty, small, noisy, broken, etc.).

In addition to the Airbnb-related quantitative studies, there exist few studies on other peer-to-peer platforms, employing transaction or network analysis. Livan et al. (2017), for instance, considered how users' reputation in different social media platforms is shaped by reciprocal endorsements and find that excess reciprocity plays a key role for reputation building (i.e., liking another user's post in order to provoke re-likes). In the same vein, based on 700,000 completed eBay transactions, Bolton et al. (2013) demonstrated that eBay's former mutual rating system evoked high degrees of (undesired) reciprocity between buyers and sellers. Based on ride sharing market data, Teubner and Flath (2015) considered the economic potential of combining ride offers from a ride sharing platform, suggesting that multi-hop ride sharing can increase the mobility network's connectedness by over a factor of two. These studies illustrate the potential of leveraging transaction data and network analysis to describe, understand, design, and possibly to improve peer-to-peer platforms. Yet, though recent research has begun to explore large scale data on Airbnb listings and reviews, the transactional web of host-guest connections has received no attention thus far.

3. Data Set and Analysis

This paper is based on transactional data from 16 major US cities (Asheville, Austin, Boston, Chicago, Denver, Los Angeles, Nashville, New Orleans, New York City, Oakland, Portland, San Diego, San Francisco, Santa Cruz, Seattle, and Washington D.C.), available at InsideAirbnb.com (Cox 2017; Wired 2017). The cities (including their metropolitan areas) account for 25% of the US population (81.3 million people). The data was retrieved in August 2017. Table 1 provides a city-wise overview on the number of distinct hosts, listings, transactions, guests, and information actuality (as indicated by InsideAirbnb). The data contains detailed information on listings and hosts (e.g., name, description, prices, location, apartment properties, reputation). A summary of all analyzed variables is provided in Table 2. Moreover, the data set contains a list of all publicly available reviews, indicating which guest has stayed at which accommodation, thus linking guests to listings (and hence to hosts). Note that for guests, no information beyond user id and name is provided. Also note that further information on guests (e.g., origin) can readily be retrieved (`airbnb.com/users/show/<userID>`). As a first step, entries (i.e., listings and associated transactions) with empty host name were removed. As can be seen from Table 1, New York City and Los Angeles alone account for roughly half of all hosts, listings, transactions, and guests. Taking a closer look at this data is quite informative. Overall, roughly 101k hosts maintain 135k listings, having engaged in 2.7m transactions with 2.1m distinct guests. Thus, hosts have roughly hosted 27 times on average, whereas each guest has stayed 2.7/2.1 = 1.3 times within the 16 considered cities. Interestingly, 18.6% of all hosts have also been active as guests (within the 16 cities). Since most of the considered hosts' trips are likely to involve other destinations, this number is likely to grossly underestimate the share of Airbnb hosts that also use the platform when travelling themselves. In contrast, only .89% of all considered guests are also hosting on Airbnb (within the 16 cities). Similarly, as the great majority of guests is likely to come from other cities, this number must also be understood as a lower bound for the share of Airbnb travelers that also host themselves.

Table 1: City-wise overview on hosts, listings, transactions, guests, and data actuality.

City	# Hosts		# Listings		# Transactions		# Guests		Date
Asheville	643	.006	864	.006	27,721	.010	25,669	.011	04/2016
Austin	7,490	.074	9,661	.071	134,545	.050	117,587	.050	03/2017
Boston	2,181	.022	3,585	.027	68,275	.025	63,789	.027	09/2016
Chicago	3,532	.035	5,207	.039	132,353	.049	121,572	.051	05/2017
Denver	1,971	.019	2,504	.019	46,454	.017	41,895	.018	05/2016
Los Angeles	20,796	.206	31,239	.231	651,816	.241	529,639	.223	05/2017
Nashville	2,278	.023	3,277	.024	83,383	.031	76,008	.032	09/2016
New Orleans	3,388	.034	5,303	.039	151,775	.056	140,724	.059	06/2017
New York City	34,108	.337	40,502	.300	661,320	.244	583,553	.246	05/2017
Oakland	1,426	.014	1,716	.013	26,715	.010	23,330	.010	05/2016
Portland	2,884	.029	3,548	.026	152,942	.057	134,257	.057	04/2017
San Diego	4,300	.043	6,608	.049	92,862	.034	85,263	.036	07/2016
San Francisco	6,912	.068	8,697	.064	215,602	.080	193,088	.081	04/2017
Santa Cruz	616	.006	814	.006	22,121	.008	20,455	.009	10/2015
Seattle	2,749	.027	3,816	.028	84,849	.031	75,730	.032	01/2016
Washington D.C.	5,818	.058	7,786	.058	152,546	.056	139,703	.059	05/2017
Sum	**101,092**	**1.00**	**135,127**	**1.00**	**2,705,279**	**1.00**	**2,372,262**	**1.00**	
Overall	**100,572**		**135,127**		**2,705,279**		**2,094,494**		

Note: The sums of all city-specific hosts (guests) add up to more than the overall number of distinct hosts (guests), since some hosts maintain listings in more than one city and some guests have stayed in more than one city. The data comprises a total of 100,572 distinct hosts. Of the 2,094,494 overall guests, 18,705 are also hosts. The total number of distinct "guest-only" users is hence 2,075,789. Consequently, the total number of users is 2,176,361.

Listings and hosts

Table 2 provides an overview on the main variables of the set of hosts and listings. By and large, these US-specific numbers are consistent with the numbers reported for 86 German cities (Teubner et al. 2017) and a global sample of 33 metropolises (Wang and Nicolau 2017). A typical host (median) has joined the platform in September 2014, writes 109 characters about him- or herself, and (alike 79.3% of all hosts) maintains one single listing. A typical host is called Michael (.95%), David (.89%), John (.66%), or Sarah (.60%). He or she answers all received requests, mostly within one hour. Moreover, 16% of all hosts hold Superhost status, 16% use the social connections feature (Facebook), 67% have conducted an identity verification, and 99.7% have uploaded a profile picture. A typical listing (median) accommodates a maximum of two persons, costs 113 US$ per night, has accumulated five reviews with an average score of 96 out of 100, which would be displayed as 5 out of 5 stars on the website. Overall, 59% of all listings fall into the entire home category and 23% are bookable instantly. Cancellation policies tend to be on the strict side. Of all listings, 53% do not require a security deposit (of those that do, the average value is 390$). Likewise, 28% do not charge cleaning fee (of those that do, the average value is 70$).

Table 2: Summary of main descriptive variables

	Variable	Mean	St. Dev.	Min	25%Q	Median	75%Q	Max
Host	Host since	2014-06	621 days	2008-03	2013-04	**2014-09**	2015-10	2017-05
	Host about (#chars)	239	368.64	0	0	**109**	358	10,880
	Response rate	.930	.19	0	1	**1**	1	1
	Response time[1]	1.735	.89	1	1	**1**	2	4
	# Listings	1.610	6.97	0	1	**1**	1	837
	Superhost	.162	-	-	-	**-**	-	-
	Facebook	.156	-	-	-	**-**	-	-
	Identity verified	.672	-	-	-	**-**	-	-
	Has profile pic	.997	-	-	-	**-**	-	-
Listing	Accommodates	3.42	2.36	1	2	**2**	4	21
	Price (US$)	155.9	136.61	0	75	**113**	189	999
	Number of reviews	20.04	36.98	0	1	**5**	22	735
	Review score	94.2	7.78	20	92	**96**	100	100
	Cancellation policy[2]	2.114	.85	1	1	**2**	3	3
	Security deposit	181.6	398.8	0	0	**0**	250	10,000
	Cleaning fee	50.4	61.1	0	0	**35**	75	1,073
	Minimum nights	3.303	11.08	1	1	**2**	3	1,250
	Entire home	.587	-	-	-	**-**	-	-
	Instant bookable	.232	-	-	-	**-**	-	-

[1] 1 = within an hour (53%), 2 = within a few hours (25%), 3 = within a day (19%), 4 = a few days or more (3%).
[2] 1 = flexible (31%), 2 = moderate (26%), 3 = strict (43%).

Network analysis

Figure 2 provides a schematic illustration of Airbnb's transaction network. Hosts are represented in blue, guests are represented in white. The network is directed; the arrows' directions indicate that the source vertex has stayed at the target vertex' accommodation. It is important to notice that hosts may also take on the role of guests (as h_4 in the sketch). Thus, even though there exist two types of vertices, the network does not represent a bipartite graph.

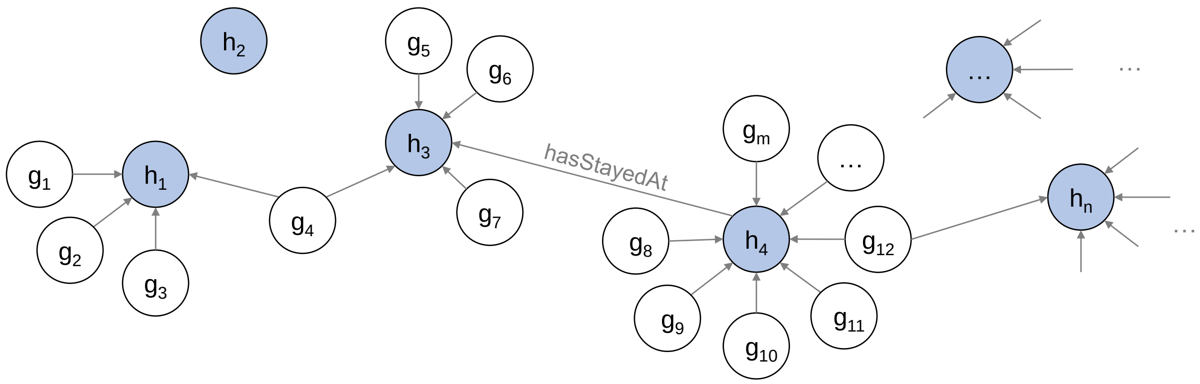

Figure 2: Schema of the Airbnb transactions network

Vertices and edges: Overall, the network comprises 2,176,361 vertices (n = 100,572 distinct hosts; m = 2,075,789 distinct "guest-only" guests). Thus, the number of guests is approximately m/n = 21 times larger than the number of hosts. Given that 18,705 hosts also take on the role of guests in at least one transaction (see h_4 in Figure 2), the total number of guests is 2,094,494 (see Table 1). Overall, the network has τ = 2,705,279 edges (i.e., transactions). Edge density is $\tau/((m+n)(m+n-1)) = 5.71\times10^{-7}$.

Degree distribution: The network's overall average degree is d_{all} = 2.49 with a standard deviation of 15.6. Host and guests, however, differ markedly with regard to degree distribution. Specifically, hosts exhibit an average degree of d_{host} = 27.21 (median = 6), whereas guests have an average degree of d_{guest} = 1.29 (median = 1). Importantly, the transactions concern only 77% of all hosts. Thus, 23% of all hosts have not hosted any guests (yet) and hence a degree of 0 (see h_2 in Figure 2). By design, all guests exhibit at least one transaction, otherwise they would not be included in the data set. The degree distribution for guests is even more skewed, with 80% of all guest vertices exhibiting a degree of 1, thus 20% with a degree of 2 or more (see g_4 and g_{12} in Figure 2). The proportion of guests with a degree of 20 or less is 99.6%, whereas the analogous proportion of hosts is only 71.1%. Figure 3 depicts the degree distributions differentiated for hosts and guests (log scale). Both distributions (zero-degree excluded) can be approximated by power law distributions very well (R^2_{hosts} = .984; R^2_{guests} = .993).

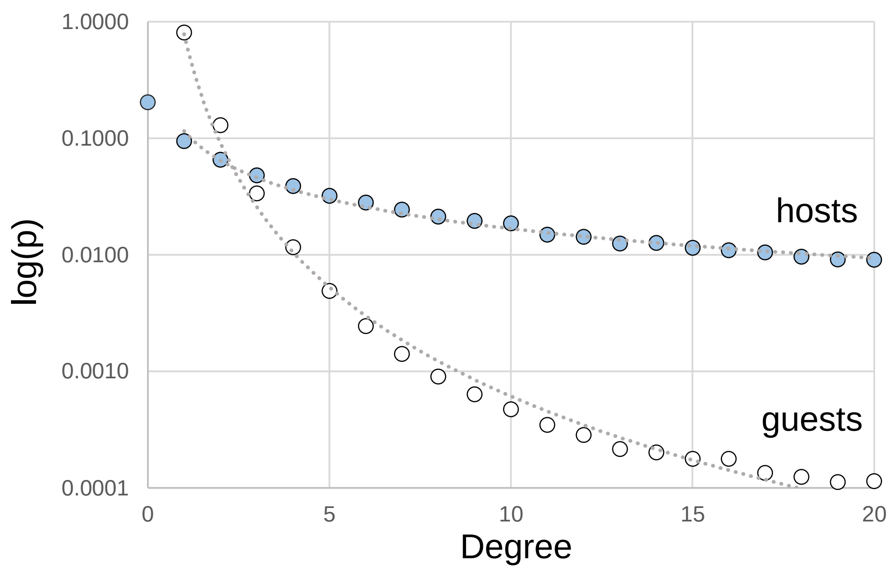

Figure 3: Degree distribution for host and guest vertices (log scale); power law estimations

Components: The network does not constitute a single connected component but more than 30,000 sub networks. However, there exists a giant component extending to 97.5% of all vertices (see Table 3).

Table 3: Component types in the network

Component type	Size	Count	Vertices	
Single host node	1	20,538	20,538	0.94%
Dyad (asymmetric/mutual)	2	5,101	10,202	0.47%
Small component	3 to 27	4,977	22,773	1.05%
Giant component	2,122,848	1	2,122,848	97.54%
$\sum$		30,617	**2,176,361**	**100%**

Network structure: Reciprocity is 1.14×10^{-4}. From a guest's perspective, a transaction always links it to a host. Vice versa, hosts transact with "guest only" vertices in 98.8% of all cases. Average clustering is 6.53×10^{-4}. Given this specific network structure, clustering can be expected to be close to zero since the most characteristic structure is a "star" where most of the outer nodes (guests) cannot form links among each other by design. There exist ca. 43k "repeated stay" relations in which a certain guest has stayed two or more times at a certain host's accommodation(s). Overall, however, 98% of all transactions represent first-time encounters, corroborating the paramount importance of reputation and initial trust in peer-to-peer sharing platforms (McKnight et al. 1998).

Average distance within the giant component is 6.91 (median = 6.89, min = 4.88, max = 11.06). These measures represent the inverse of closeness centrality, which is computationally expensive. The reported numbers are hence based on a random sample of 10,000 vertices. In order to obtain an estimate for the network's diameter, consider an Erdős-Rényi (ER) network, specified only by the number of nodes (n) and each edge having a fixed probability (p) of being present (Erdős and Rényi 1959). For large n and d ≥ (1+ε) *log*(n), average path length and diameter are approximately proportional to *log*(n) / *log*(d) in such networks, where d denotes average degree. This estimation yields a value of 15.7. Note that average distance and diameter are of the same magnitude in such networks since the majority of nodes is only reached with the last step when branching out from a given root node. For the Airbnb transaction network, however, the giant component's (GC) average degree is $d_{GC} = 2.53$, which is below $log(n_{GC}) = 6.33$. Also, the individual degree distributions seem to follow power law (see Figure 3) rather than binominal distributions (as are characteristic of ER networks) – the estimated value must hence be seen with caution.

Visual representation

Within the scope of this paper, the entire graph cannot be depicted in any reasonable way (>2.1 million vertices, >2.7 million edges). Also the largest component comprises 97.54% of all vertices and 99.14% of all edges. In order to illustrate some of the network's properties, Figures 4 to 6 represent different subgraphs, randomly selected through different sampling techniques. Each of these representations thus illustrates different characteristics of the overall network. As above, hosts are represented in blue, guests in white. An edge from *i* to *j* indicates that *i* has stayed at *j*'s accommodation. Note that edges from hosts to other hosts are possible. For all figures, the Fruchterman-Reingold layout was used (`igraph` library in R).

First, Figure 4 depicts a random sample of 500 of the 27,721 Asheville *transactions*. As can be seen, most depicted relations are dyads. Importantly, this does not mean that the depicted hosts do not have further links to other guests (see next figure). Moreover, several star-like structures are visible and also few interconnections between the host "hubs." Next, Figure 5 depicts a random sample 25 of 643 Asheville-based *hosts* and all associated guests. This graph exemplifies the hosts' degree distribution (Table 2). Again, several interconnections between the star-like host hubs are visible. Last, Figure 6 depicts a branched graph (3 steps), starting from *one random host*, where in each step, all connected users (hosts and guests) are included into the set. Depending on the arbitrarily selected root node, such graphs may become fairly large. This figure conveys the high degree of interconnectedness and complexity in the overall graph quite well, as it represents the full (but local) structure.

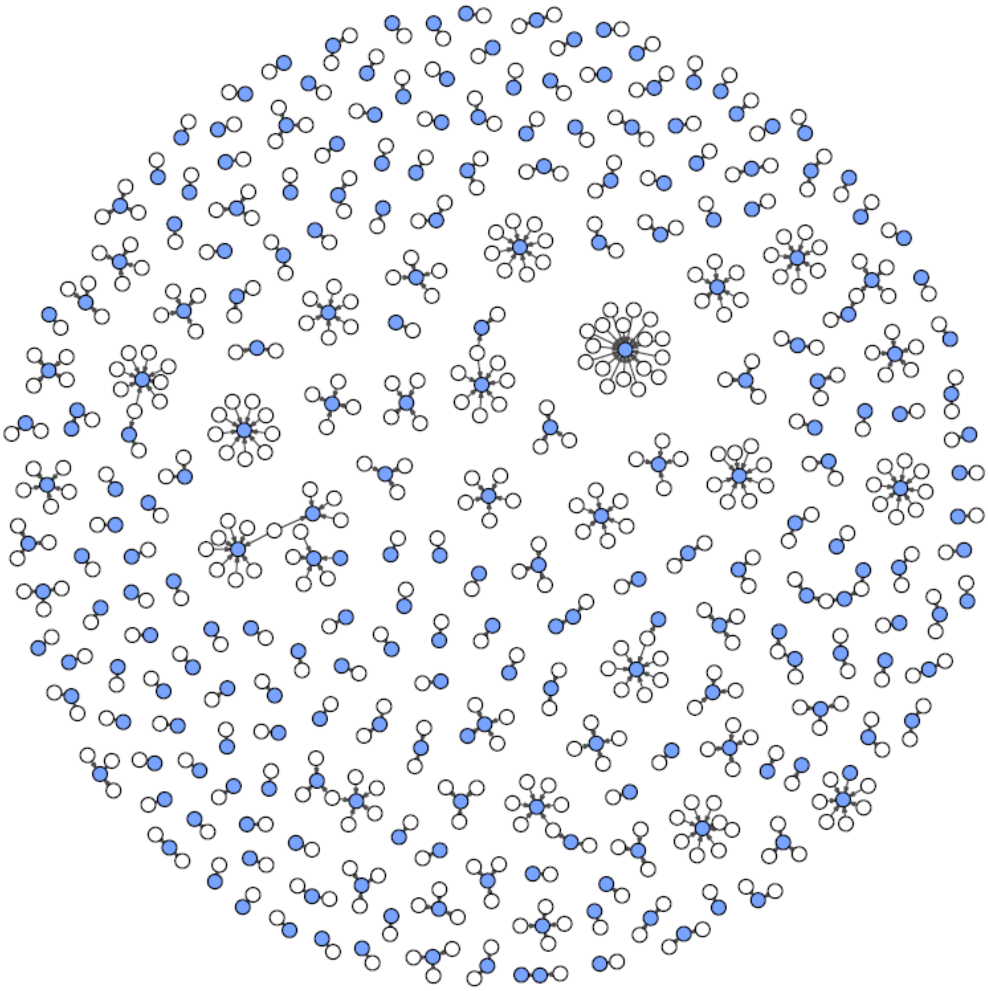

Figure 4: 500 randomly selected transactions (and associated hosts and guests)

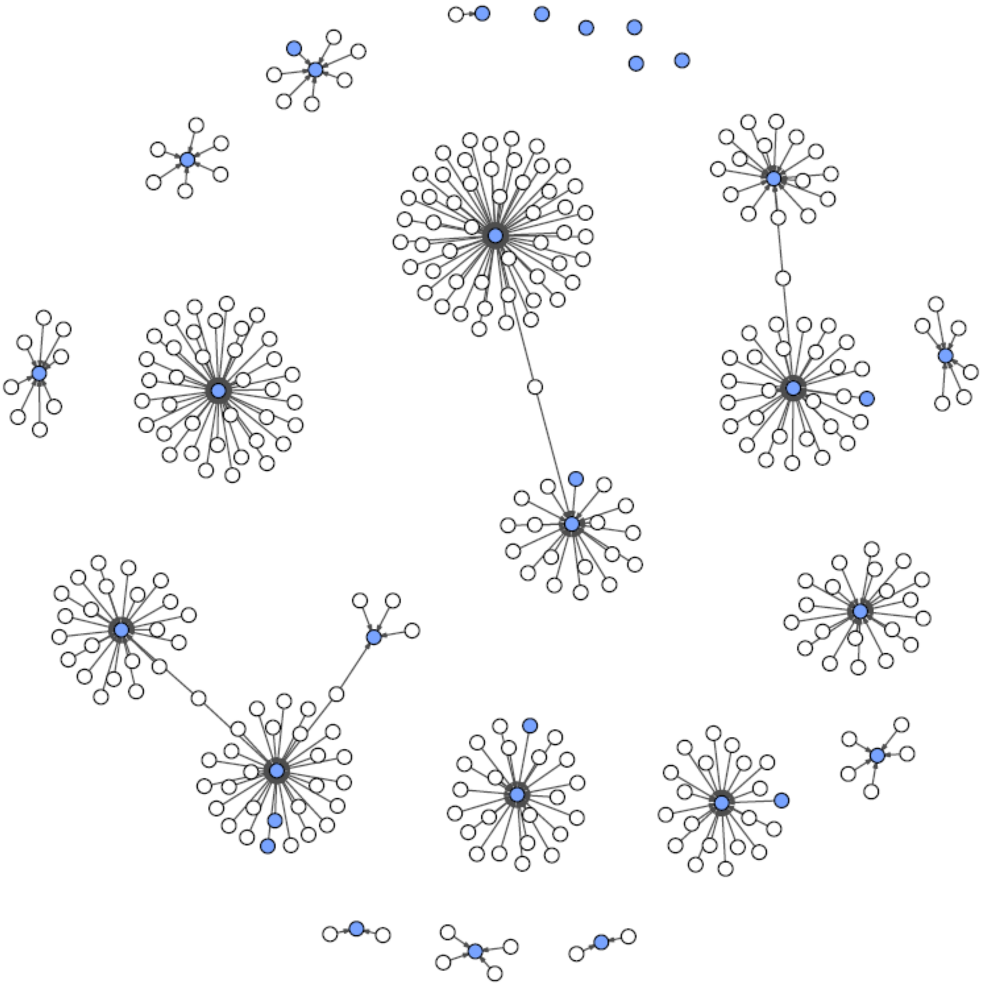

Figure 5: 25 randomly selected hosts (and associated guests and transactions)

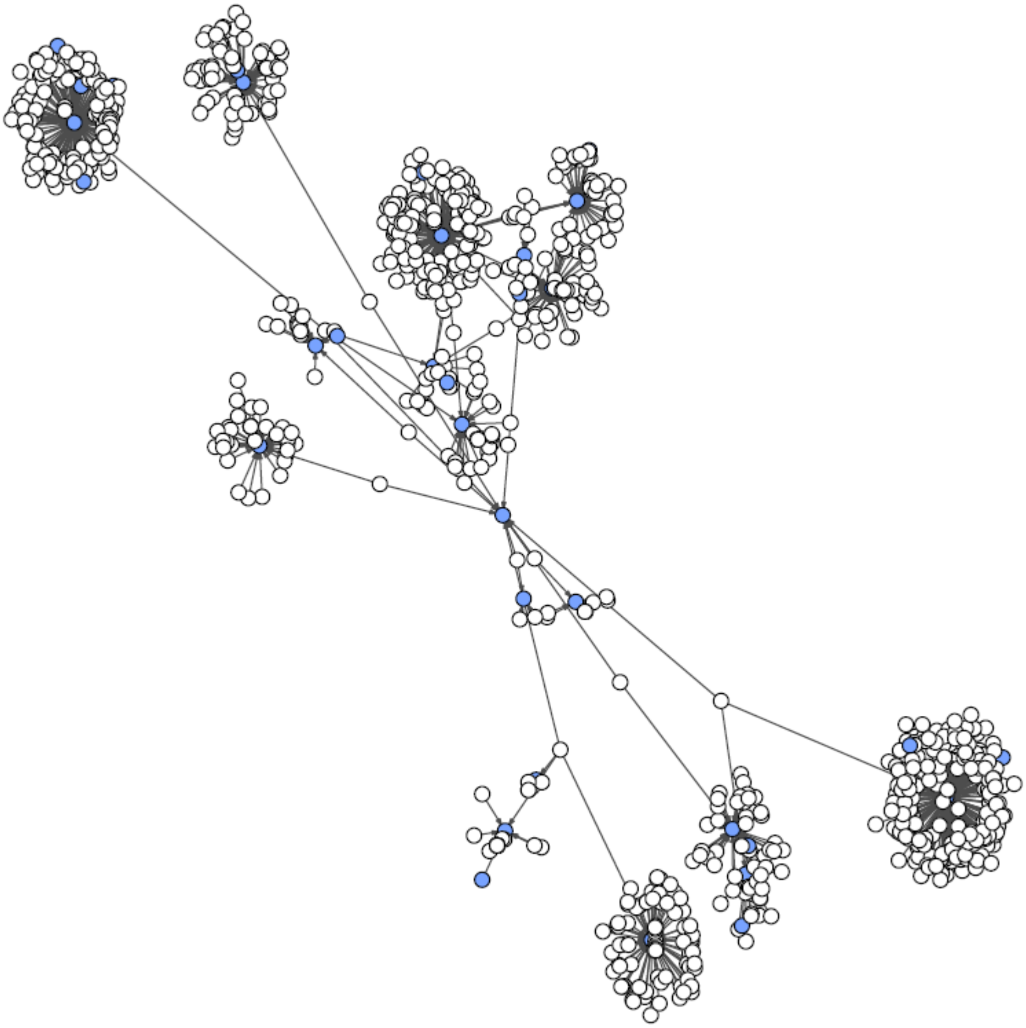

Figure 6: Iteratively emerged graph (1 random seed node, 3 iterations)

4. Discussion and Conclusion

The transaction-based perspective presented in this paper has several potential merits. First, the underlying data basis grows inherently and hence becomes more comprehensive and reliable over time. Also, it is based on context-specific data, rendering it relevant and applicable for the purposes of hosts, guests, and the platform itself. In view of privacy concerns related to linking one's social media profile to Airbnb, the transaction-based network also has the advantage of being built solely on publicly available data (Teubner and Flath 2016).

So what would Airbnb (and other platform operators) make out of this? Based on the analyses presented in this paper, three things come to mind. First, a transaction-based approach allows for an assessment of the user base, for instance, to identify determinants of hosts to use the platform when travelling themselves, which could, in turn be addressed by more effective marketing. A similar reasoning holds for guests. Second, in light of the high importance of preventing platform circumvention, one may specifically analyze repeated-stay transactions and the associated users in order to learn which factors let them to stick to the platform's processes (Bellotti et al. 2017). Last, the transactional network information may serve as a common ground for hosts and guests to relate to each other prior to booking (Abramova et al. 2017). As an illustrative example, consider Alice who has stayed at Bob and now thinks about booking a stay with Carol. Carol's overall rating is excellent, however, another guest who has stayed both at Bob's *and* Carol's place, has rated Bob just like Alice, but has really not liked Carol. Making use of this "users like you have also liked …" logic may improve the ratings' informativeness – especially in view of its skewness towards 5-star ratings (Zhong et al. 2016).

There exist several limitations, in particular concerning the conception of utilizing the inherent network data for collaborative filtering and trust building. Naturally, a transaction-based network (e.g., based on common prior interaction partners) to establish trust among strangers is certainly not as trust-effective as a relation-based social network (i.e., based on common friends). Also, the network is sparse, with few "connector" guests with multiple transactions, presumably impeding collaborative filtering. With regard to the underlying data, it must be said that this study is limited on 16 major US cities, putting a natural limit on the validity of some of the broached figures (e.g., fraction of hosts also travelling via Airbnb). Future work could use more comprehensive data, qualify host-guest relations (e.g., frequency, ratings, accommodation type), and make use of timestamps for dynamic network analysis. The latter could pave the way for empirical evaluations of theories of network formation (e.g., uniformly random growth, preferential attachment) within the context of peer-to-peer sharing.

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