How does San Francisco fit with sharing economy? Empirical analysis of Airbnb listing rental prices.

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July 23, 2022

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Abstract

Using data on Airbnb listings, this study evaluates the influence of conventional economic model on the sharing economy in the city of San Francisco. This paper finds that the model of listing price in this market highly follows the traditional economy models. Better neighbourhood, individual room and higher review scores inevitably result to a higher price. The key feature of peer-to-peer accommodation, availability of the listings, has no importance to the price. In order to quantify the impact of conventional capital power, this research uses non-supervised learning and finds out over one third of the listings belong to the commercial hosts on San Francisco Airbnb platform. The results which are consistent across all models, shows that Airbnb's sharing economy depends greatly on conventional economy model in San Francisco.

1 Introduction

In the 2000s, a significant technology breakthrough took place in the city of San Francisco. The city gradually becomes much more open and welcome to internet-based companies. The growing power of those new e-commence business enterprise changed and transformed the Bay Area. The emergence and development of new-form of economy, majorly ”sharing economy” in which firms were capitalizing in peer-to-peer sharing, in areas such as accommodation, car-pooling, and trading. In an earlier article, Belk (2007) defines sharing as follows:

”Sharing is an alternative to the private ownership that is emphasized in both marketplace exchange and gift giving. In sharing, two or more people may enjoy the benefits (or costs) that flow from possessing a thing. Rather than distinguishing what is mine and yours, sharing defines something as ours.”(- Belk, 2007, p. 127)[3]

San Francisco, with many “early adopters” of these technologies under ”sharing economy”, thus became a hub for launching new services and products for them. Peer-to-peer accommodation platforms are typically considered as examples of the sharing economy or collaborative consumption, one leading platform is Airbnb.[4]

Airbnb was founded in San Francisco in 2008 as a for-profit peer-to-peer accommodation platform for listing and renting private residences while Airbnb charging service fees to both hosts and guests.[2]

San Francisco is a complex city with rich humanity culture and new-born technology. Employing Airbnb listings data could explore deeper into this city and take a glimpse of the local life. Airbnb market in San Francisco has a considerable size. As one of the representative platform of the new shared economy, Airbnb brings strong pressure to the ”old money” in the city, such as the major hotel chains. Building a model of the rental price of listings is a way to better understand the reason behind the transform of San Francisco economy system. Further, know more about the city itself.

This paper mainly focused on the price in the exploration of the data. Addressing the behavior of price with various features like room types, neighbourhood regions, availability, allowed nights, bed number and the review values helps understanding the market of Aribnb under the sharing economy in San Francisco quantitatively. It also gives a prospect to view the city of San Francisco differently from the coastal scenic views.

This research finds that the model of listing price in this market highly follows the traditional economy models. Better neighbourhood, individual room and higher review scores inevitably result to a higher price. The key feature of peer-to-peer accommodation, availability of the listings, has no importance to the price. Further, using non-supervised learning ones find out over one third of the listings belong to the commercial hosts on San Francisco Airbnb platform. Thus it is reasonable to conclude Airbnb's "sharing economy" depends greatly on conventional economy model in San Francisco.

2 Literature Review

Although "sharing economy" is a new term for the rental market in San Francisco because of the recent improvement in information and communication technology at a global scale, there are some authors who take investigation and notice that this new form of economy in San Francisco is not that different from the "old money" when it comes to the leading companies in the industries. The changes brought by the peer-to-peer accommodations do exist while they are still under the significant influence of the local government, policies and market in San Francisco.

Because of the monetary nature of Airbnb, the use of term "sharing economy" might not be the precise term to describe its economic behavior. In fact, Airbnb is a for-profit and market-dominating peer-to-peer accommodation platform. Ulrich Gunter then claims that relationship between peers registered to the Airbnb is not necessary symmetric. Gunter notices that Commercial Airbnb providers are not minority in the Airbnb listing market.[2] Furthermore, neither all commercial nor all non-commercial (local residence) Airbnb provides are equally taking competition in the market, while some of those are super hosts, conferred many benefits from Airbnb. Such none-symmetric feature of Airbnb is also reflected on the super host status. Gunter doubts that status is awarded automatically, as claimed by Airbnb. Instead, the awarding is actually a steered process, especially considering the huge impact of being commercial Airbnb providers easier to obtain and maintain the super host status. Gunter claims that there may not even be any super host automatism in the Airbnb platform.

Further, Airbnb's preference regarding the super host criteria can clearly be ranked, followed by a reliable cancellation behavior of the host, host responsiveness and sufficient Airbnb demand. Gunter concludes that Airbnb is not indifferent between their type when awarding the super host status.[2] The positive effects of low price, proximity to Downtown San Francisco, a high rating and high responsiveness on Airbnb demand largely agrees with the ex-ante expectation from the economic theory. While building a quantitative model to understand the listing price could support Gunter point by showing how different is the rental market in San Francisco under the sharing economy than in the pre-existing economic theory.

One must admit the technology investment capital does bring major impact to San Francisco urban economy and results technology-driven socioeconomic changes in this area. As Donald McNeill claims, those changes are the subject of significant public debate, such as the free San Francisco Bay Guardian, argued that the gentrification process in mid-2000s was replayed with greater intensity.[1]

Airbnb, as a global leader in the rental housing, inevitably is in the controversies surrounding the local regulation of shared accommodation. McNeill defines the behavior of Airbnb is monetizing the sharing economy. In 2015, the US $25 billion valuation of Airbnb [5] enabled Mayor Lee want to exempt Airbnb from paying 15% tourism tax that the traditional hotels need to pay. This was quickly over-ruled City Comptroller as being potentially illegal.[6] McNeill further points that the Airbnb in the rapidly growing San Francisco economy was being used an an excuse by a number of property owners to withdraw their properties from highly regulated rental market, as deregulation was a key goal for Airbnb's venture investors; while in many other cities the service was seen as relatively unproblematic. Mc-

Neill points that due to San Francisco's political subcultures: liberal, environmentalists and populists, the city's municipal politics has mostly dominated by shifting and surprising coalitions of interest.[1]

San Francisco is an important city for considering the dilemmas that tech-friendly city governments face in handing high-growth and high-risk companies. Exploring the data of Airbnb listings, one could see how the reshaping of capital fractions taken place in the property rental filed while aggressively challenged the municipal regulations.

3 Data Description and Visualization

3.1 Data and Variables

The data used to explore San Francisco short-term rental market is provided by Inside Airbnb, a non-commercial set of tools and data collected from Airbnb platform with aim of better understand short-term rental market on local cities. Inside Airbnb provides information covers different characteristics of each listings on the Airbnb. It used no private information; it only collect the data as it displayed on Airbnb.

This platform updates with latest data from Airbnb. This paper focus on the data compiled in November, 2021, for the city San Francisco, California, United States. Combine the listings data and review data, total there are 6552 different listings collected. Each of these 6552 listings is an object that is displayed on Airbnb website, with availability for short-term rentals. What need to be noticed is that the impact of COVID (Coronavirus disease) on short-term rental market is not in the scope of this paper. Because the data used in the analyzing is the latest data, the obtained results are inevitably effected by the severe contemporary situation of global tourism. While ones shall not forget the impact of COVID.

There are total 74 variables in the raw data set. 29 features are chosen to understand and visualize the data respectively, and 7 features to build the models. Some variables that will be referring to later could be seen in the table 1.

3.2 Visualization

In order to better understand the short-term rental market on Airbnb in San Francisco, ones could first get to know the distribution of selected features. There are mainly two groups of visualization, one associates with the distribution of the feature itself; another one relates the features with price. The later type of visualization give the direction in building the quantitative model.

3.2.1 Features only

The most common seen room type in San Francisco is *Entire home/apt* and followed by *Private room*. As shown in the plot 1., those two types occupied the absolute majority of the market. Listings covers all neighbours in San Francisco 2. The neighbourhood with most listings is *Downtown/Civic center*, with more than 700 listings 3. Each of the top 5 neighbourhoods has more then 330 listings 3 and they agree with the tourists spots in San Francisco greatly.

The statistics towards the hosts in Airbnb shows that there are more than half of the listings (3397 out of 6552) does not belong to single host. What's more, there are 64 hosts have more than 10 listings and 9 hosts have over 40 listings, as shown in the graph 4. Particularly, one host id *107434423* has 150 listings 4. These are strong evidence that commercial hosts are major parts in San Francisco Airbnb market.

Airbnb website gives 6 review scores which allow the renters to evaluate the listings from six aspects: 1) how well it match the description, 2) check-in condition, 3)how well the communication with hosts, 4) how well the location, 5) how is the rating, 6) how is the value compared with its price. Average those 6 score, ones could get a mean review score for each of the listings. The average review score for all 6552 listings in San Francisco is 4.768 out of 5. Most mean review scores are above 4, as shown in the graph 5.

3.2.2 Relate to Price

Price distribution does vary a lot from different room types. As shown in the plot 6, for a *shared room*, it has a relative low price range, peaks at $40 per night. For *Private room*, it has a wider price range while peaks at $50 per night. However, for the most popular *Entire home/apt* room type, it is relative more expensive and the number of choice are overall the same from $80 to $200. Consider that *Entire home/apt* is the dominate room type, it is reasonable to show that there are evidently two very different markets which could identified by the room type. One is the type of *Entire home/apt* and the other is the rest.

There are total 36 neighbourhood, for the clarity of presenting, plots for the price distribution for top 5 7, middle 5 8 and end 5 9 neighbourhood (according to the number of appearance in the all 6552 listings) are shown. It can be seen that the price peaks in the top 5 neighbourhood are in the same range, from $80 to $120, while the price peaks for the rest two groups varies differently. Thus ones could divide the neighbourhoods into two large groups: ones in the top 5 neighbourhood (according to number of appearance in all 6552 listings) and the ones are not.

The relationship between *Availability* and *Price* is not obvious if ones keep *Availability* as numerical values. Instead, ones can classify the *Availability* into *high ava* if the *Availability* is larger than 90 days a year and *low ava* if *Availability* is smaller than 90 days a year [7]. From the plot 10, it shows that the price distribution density for *high ava* and *low ava* cases are not very much the same. Thus one can use *high ava* and *low ava* as two different classes in later building the model towards the price. Further, the plot showing the counts of *low ava* and *high ava* for top 11, middle 12 and end 5 13 neighbourhood tells that this binary classes still hold true across the *Neighbourhood* variable; since *high ava* class is more than *low ava* for a neighbourhood for most cases.

Besides the previous three binary classes, the other three numerical variables analyzed are *nights total*, *beds* and *mean review score*. The plot of *nights total* 14 and *beds* 15 indicate that there are general inverse linear relationships to the *price*. While the plot of *mean review score* 16 shows that there might be an exponential relationship to the *price*.

Overall, ones could use those variables are potential candidates in building the *price* model later since they do show some relationship with the change of *price*.

4 Model

To understand the short-term rental market in San Francisco, employed some machine learning algorithm is helpful. In this paper, there are two types of model on the price. One is a regression model, which returns a predict numerical value of *price*. Another is a classification model. After scaling the numerical *price* variable, this research sets the non-negative scaled *price* as *expensive*. Further this paper sets the negative scaled *price* as *cheap*. The regression model could help to understand how each features contribute to the *price* quantitatively, while the classification model gives a more clearly way to present and understand the position (or the group) of each listing belong to. The goal of two models is to show that short-term rental market on Airbnb in San Francisco under "sharing economy" is not a distinct different economic ecology. In stead, this market could be largely explained with traditional economic systems after nearly a decade of invasion of commercial power.

The data used in building both regression model and classification model has been cleaned so that the outliers have minimum impact on the models. Further, as mentioned before, the scaling of *price* and *total nights* variables minimizes the distance influence, center those two variables with mean value 0 and standard deviation 1. This scaling process leads to a faster training process and removes the restrictions on getting local optimum outcomes.

Binary label encoding with three variables is used regression model, while binary label encoding with four variables is used for classification model, as shown in the table 2

For all the models, the processes use the cross validation with 10 k-folds and iterate four times.

4.1 Regression Model

The math model chosen in regression model is a general linear model (glm).

$$\begin{aligned} price = \beta_0 &+ \beta_1 * Neighbourhood + \beta_2 * Room\ type + \beta_3 * Availability\ label \\ &+ \beta_4 * Nights\ total + \beta_5 * Beds + \beta_6 * Mean\ review\ score \\ &+ \beta_7 * Nightstotal * Beds + \beta_8 * Nights\ total * Mean\ review\ score \\ &+ \beta_9 * Beds * Mean\ review\ score \\ &+ \beta_{10} * Beds * Mean\ review\ score * Nights\ total \end{aligned} \tag{1}$$

Where β_i is a constant belongs to real number range.

The choice of this model is after the comparison to the low-degree polynomial regression model, since the glm model gives better RMSE and R^2 values. The summary of the coefficient and the evaluation is shown below in the table 3 and table 4 respectively.

The calculated R^2 for glm is approximate 0.2. Although the value is relative low, the model itself still gives a decent direction of how each feature varies with the price. The detailed analyze will be shown in the later analysis part.

4.2 Classification Model

4.2.1 Supervised learning: Random forest

The first classification model used here is the Random Forest to test the select features. Random Forest is a classifier that is formed with many Decision Tree models for classification.

For a well constructed single Decision Tree, each question will cut the number of options by approximately half. Thus it could quickly narrows the options.

6552 samples, 6 predictors and 2 classes (*cheap* and *expensive*) are used in Random Forest model. The final value used for the model was mtry = 2. The value of mtry indicates the number of variables randomly sampled as candidates at each split is 2.

The confusion matrix for this model and the evaluation is shown in the tables 5 and table 6 respectively.

Another candidate for classification model is KNN model with k = 9 gives best result. While KNN model has a lower accuracy(0.792) compared with Random Forest accuracy (0.80194).

The accuracy obtained from Random Forest model with mtry = 2 is high (close to 0.8), that suggests that the selected features could well explained the price in the short-term rental market in San Francisco.

With support form this Random Forest model, ones select *neighbourhood*, *room type*, *bed*, *mean review score* and *price* as features that has close relationship to the price. Thus the rest features *nights total* and *availability label* has relative less dependency on *price*.

4.2.2 Unsupervised learning: K-means

The second classification model is using K-means to do an unsupervised learning to determine the impact of commercial power on the market quantitatively. K-means is a classification model minimizes the distances of the data points to the clusters' centroids over iterations until the algorithm finds the optimum centroids for each clusters. The result is shown in table 7 with average value of each cluster.

5 Empirical Analysis

The new term "sharing economy" might shows that short-term rental market formed by Airbnb in the city of San Francisco is a distinct peer-to-peer market, ones should not take such a statement for granted. From the data exploration and the models, all of them show that a large part of this market has been occupied by commercial power and has high similarity to traditional hotel industry.

Start with the listings themselves. Total 6552 listings of objects on the Airbnb are not composed with 6552 ordinary hosts/families in San Francisco. In stead, over half of the hosts have more than one object posted. There are 167 hosts have more than 5 listings posted and 64 hosts have more then 10 listings posted. From this, ones could tell that the San Francisco market is as simple as just posted the spare room in people's house on Airbnb. The hosts are not peers as the tourists who travel to San Francisco. Commercial hosts play great part in this market.

If we take a deeper look at each of the features in the glm model, we could see that the market for San Francisco Airbnb is a developed commercial short-term rental market. The first three binary labeled encoding variables all have positive coefficient. That shows that if the this listing is in the top 5 popular neighbourhood, is a entire home/apt and its availability is more than 90 days over the year, then this property is more expensive than others. Particularly, the coefficient for the *Room type label* is 0.211 3, which is large, while with small p-value 4. Consider the target *price* variable in the model has been scaled, so we could reject null hypothesis for this feature. That suggests that if the object is an entire home/apt, it could cost much more than a shared room in the popular neighbourhood. *Room type* thus is a variable that determines the price in a great extend.

Also, the magnitudes of coefficient for *Nights total* and *Beds* are very large (0.51998 and -0.40607) 3. That implies that longer the nights per renter could rent the property per order, the property will be more expensive. More beds, on the contrary, could decrease the price of the property. The interesting point of the San Francisco model is that the *nights total* is a scaled variable while *Beds* is not. Thus the increase in the number of beds will lead to a much more severe decrease in the listing price. Combine with the information from the bed plot 17 and the room type plot 1, this shows one special aspect of the San Francisco Airbnb market: a market that mostly filled with expensive one-bed room. If it is a one-bed apartment then it is going to be even more expensive.

Another variable, the *mean review score*, also affects the price to some extent, but not as great as *room type* or*beds*. Higher scores could give a higher price. While people should keep in mind that the review scores are very much concentrated from 4.0 to 5.0 16. Besides, the cross term tell that the dominant feature is still *beds*, supported by small p-value of the cross term 3.

The p-value for the *Availability label* is high (0.29948) 3, this means we could accept the null-hypothesis for this feature. As shown before, the number of listings with high availability are always much more than the ones with low availability regardless of neighbourhoods or other variables. Thus, the availability time period has no significant influence towards the price of the listings. However, availability is the key to separate the peer-to-peer accommodation from traditional hotels. The hotel industry is always open for business throughout the year, so its annual availability could be interpret as 365 days. The annual availability for houses from peer hosts, on the other hand, ideally should be low. If ones don't have to consider the availability feature for the object while giving it price on Airbnb, it deprives the very fundamental characteristic of the peer-to-peer accommodation. In such cases, choosing between listings with different availability has no influence on the price, just like the choosing between hotels, which availability also has no influence on the price.

In the Random Forest classification model testing the *cheap* and *expensive* ones, those features from the glm model behave really well with high accuracy of 0.8 6. That suggests that the major features are *neighbourhood*, *room type*, *bed* and *mean review score* in determining the price of the listings since we reject null hypothesis for those. In other words, those features have high dependency over the price and will overweight the contribution of *price* if keep them in the classification model together with *price*. So later when doing the unsupervised learning to separate commercial hosts and peer hosts, I select the rest two variables *nights total* and *availability label* to compensate the information loss by *price* with maximum scale.

Using K-means cluster with those three features ones can separate all the listings into two clusters18. The are approximate 36.3% of listings that can be clustered as under commercial listings and 63.7% as peer listings 7. More than one third of the listings on the market could be clusters as commercial listings, with obvious longer nights total (1.27 over -0.78) 7 and long availability (0.744 over 0.633) compared with peer hosts. The commercial hosts could provide longer nights total per order and longer annual availability because those hosts don't live in those listings. Those listings are their personal hotels business. Thus naturally they could provide cheaper price (-0.017 over -0.0084) 7 as they have larger scale of business than peer-hosts do.

6 Conclusion

Airbnb was born as a peer-to-peer accommodation platform in the 2008s. With its for-profit nature, after a decade of growing under capital power in San Francisco, the short-term rental market on Airbnb no longer looks the same as before. The newly formed "sharing economy" represented by Airbnb is not an exception from the long-established economy models. The commercial power takes great proportion in this market over the years.

The model of listing price in this market highly follows the traditional economy models. Better neighbourhood, individual room and higher review scores inevitably result to a higher price. The key feature of peer-to-peer accommodation, availability of the listings, has no importance to the price.

Further, using non-supervised learning ones find out over one third of the listings belong to the commercial listings on San Francisco Airbnb platform. Thus it is reasonable to conclude Airbnb's "sharing economy" depends greatly on conventional economy model in San Francisco.

Ones could also take a glimpse of the complexity of San Francisco. Indeed this is the area gives birth to numerous internet-based companies and e-commence businesses, and it is the place that witnesses the significant breakthrough brought by those technology companies. The round of globalization in San Francisco brings the new policies and allowing companies like Airbnb set their goals as deregulation from established regulated markets. But the "old money" and the urban political and public culture in San Francisco interfere greatly with the formation of the ideal sharing economy.

With obvious interference of commercial power, Airbnb affects the value of neighbourhoods in San Francisco by displaying residents and attracting wealthier ones (usually travellers). Such process is highly similar to the gentrification and companies like Airbnb need to rethink how individuals (or peers) consume (and produce) services under the challenges from political and public cultures while constructing a new type of economy of their own.

7 Appendix

7.1 Tables

Variable Name	Interpretation
Room type	The type of room that Airbnb hosts list their property as
Neighbourhood	Geographically separated communities within city of San Francisco
Host id	The id for Airbnb hosts. Not necessary appear just once
Mean review score	Calculated average of review scores
Price	Listed price for the property, one night, in USD
Availability	Days that hosts list their property as available to rent within a year
nights total	Days that per renter could rent the property per order
beds	Number of beds in the property

Table 1: Interpretation of some variables referred to in this paper

Variable Name	Label as 0	Label as 1	Applied Model
Availability label	High availability	Low availability	Regression & Classification
Neighbourhood label	Top 5 neighbourhood	The rest neighbourhood	Regression & Classification
Room type label	Entire home/apt	The rest room types	Regression & Classification
Price label	Expensive	Cheap	Classification

Table 2: Binary label encoding for four variables

β_i Constant Coefficient	Estimate	Std. Error	t value	$Pr(>\|t\|)$
β_0	0.10556	0.23862	0.442	0.65824
β_1	0.08017	0.02602	3.081	0.00208
β_2	0.21163	0.02683	7.887	3.76e-15
β_3	-0.02772	0.02672	-1.038	0.29948
β_4	0.51988	0.24760	2.100	0.03580
β_5	-0.40607	0.12893	-3.150	0.00164
β_6	-0.14825	0.04937	-3.003	0.00269
β_7	-0.37673	0.14635	-2.574	0.01007
β_8	-0.10126	0.05173	-1.958	0.05034
β_9	0.13723	0.02681	5.118	3.21e-07
β_{10}	0.07238	0.03042	2.380	0.01737

Table 3: General linear model (glm) coefficients

RMSE	R^2
0.08327	0.19314

Table 4: Evaluation of glm model

		Actual Class		
		Cheap	Expensive	Total
Prediction Class	Cheap	%65.8	%14.6	%80.4
	Expensive	%5.2	%14.4	%19.6
	Total	%70.0	%30.0	%100.0

Table 5: Confusion matrix for Random Forest model on price

Accuracy	Kappa
0.80194	0.46858

Table 6: Evaluation of Random Forest

cluster name	percent	price	nights total	availability label
Commercial Listings	36.3%	-0.01767306	1.2736271	0.7445099
Peer Listings	63.7%	-0.00839774	-0.7816904	0.6327029

Table 7: Clustering with k-means on Airbnb San Francisco data

7.2 Graphs

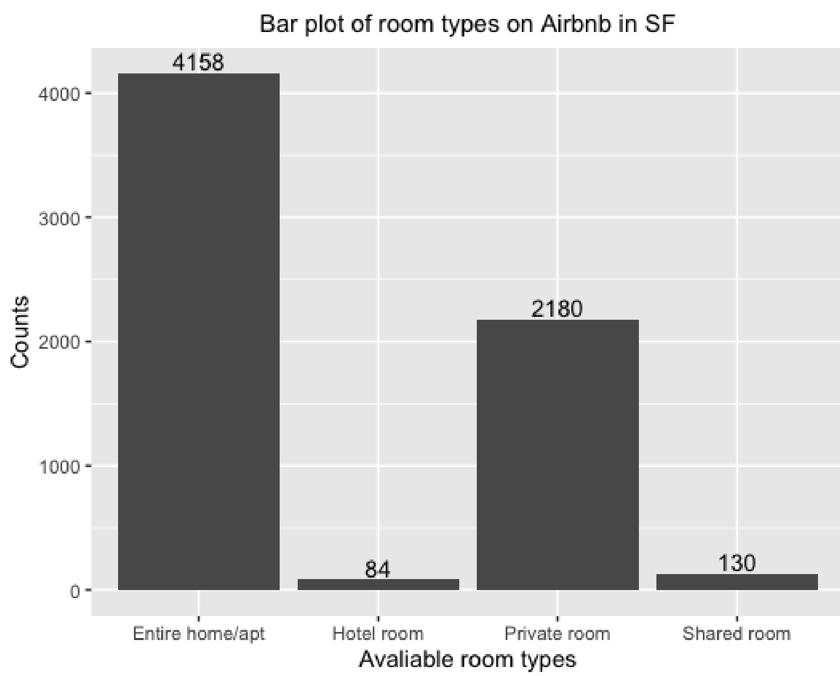

Figure 1: Room types counts in San Francisco

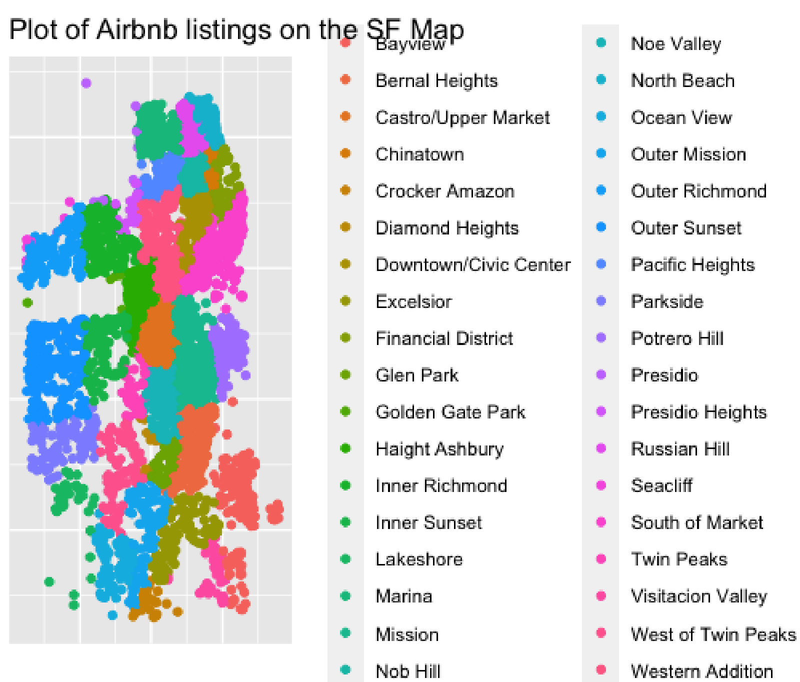

Figure 2: Listings over San Francisco area

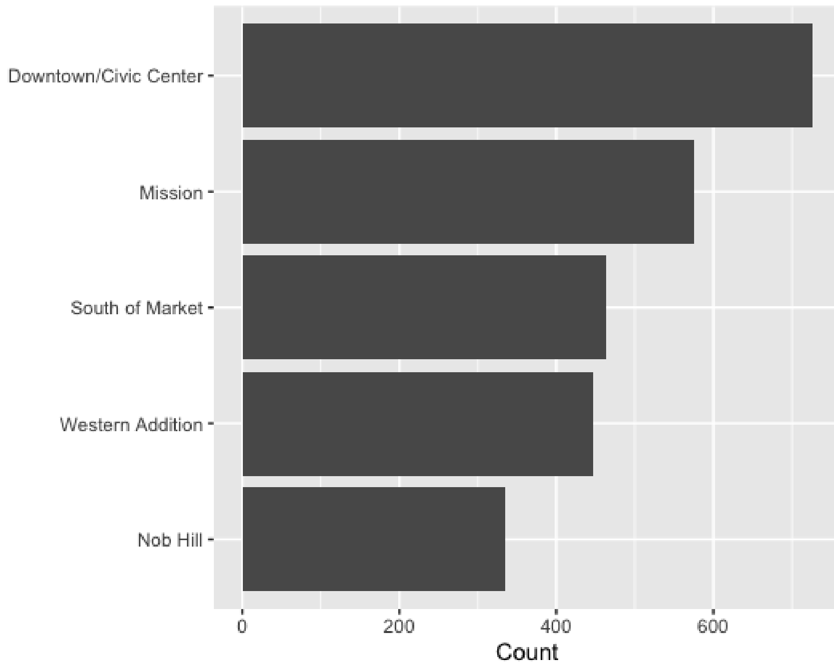

Figure 3: Neighbourhoods with over 330 listing

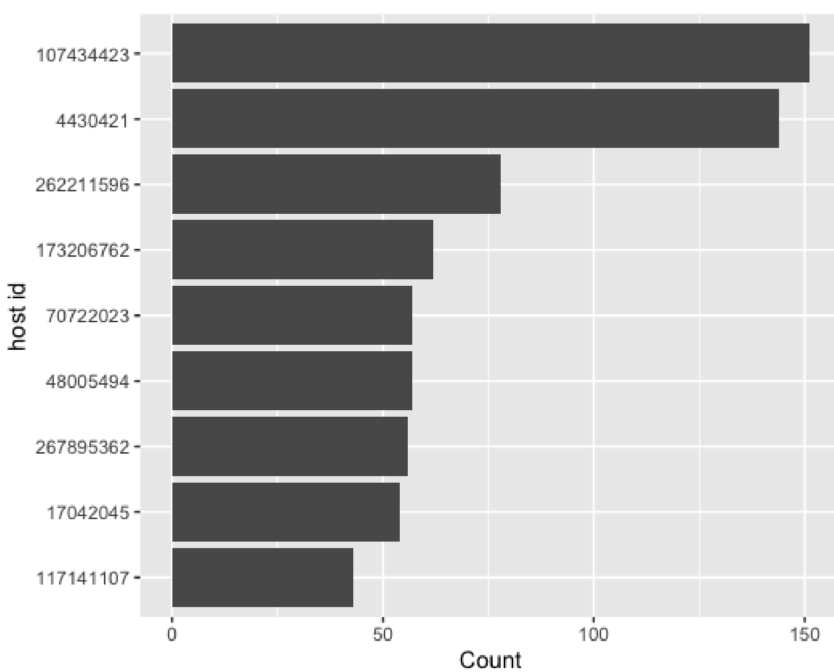

Figure 4: Hosts with more than 40 listings

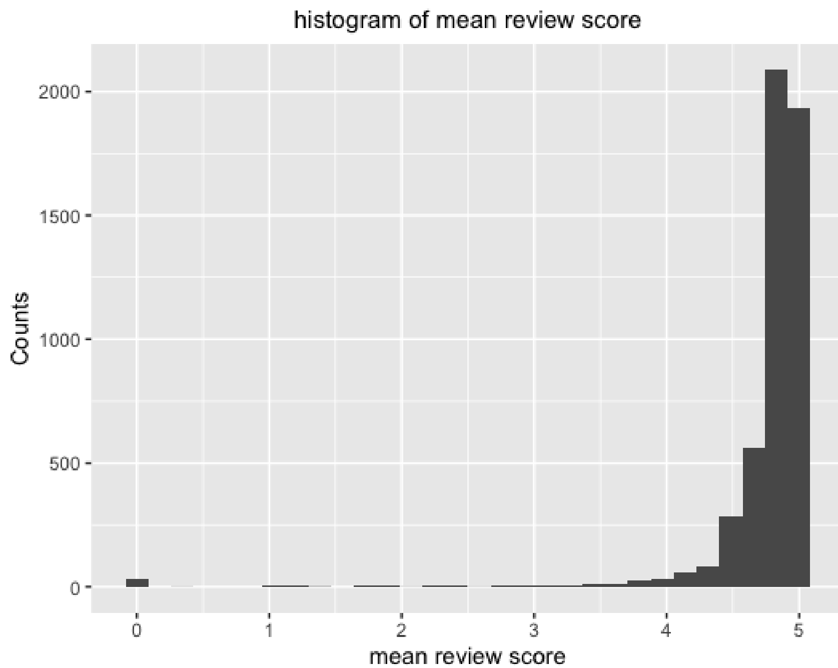

Figure 5: Distribution of mean review scores

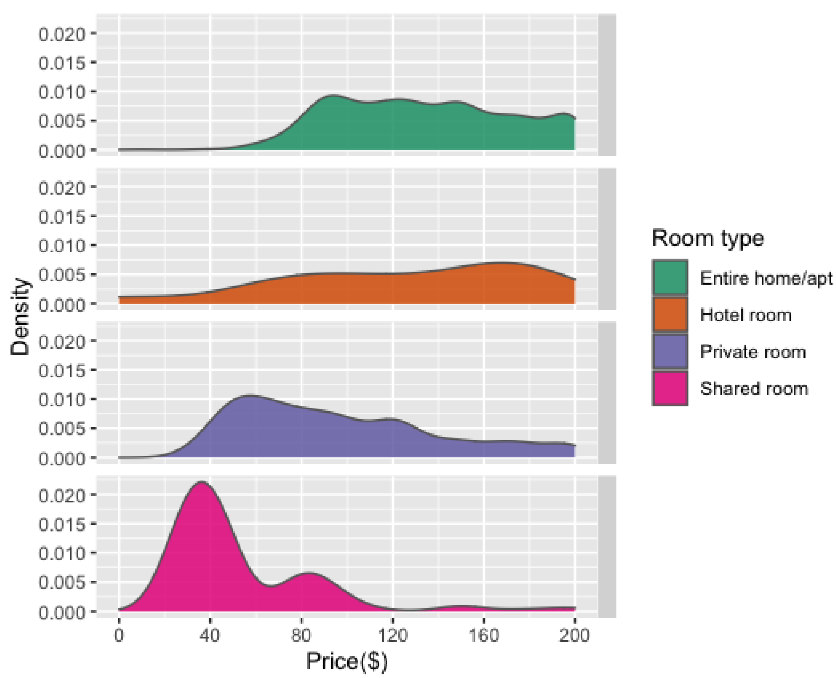

Figure 6: Price distribution of different room types

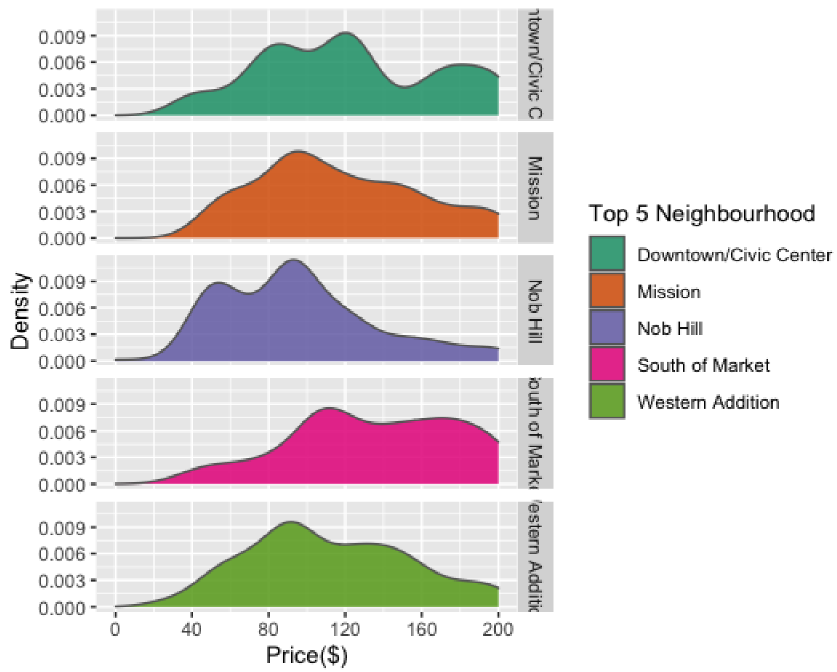

Figure 7: Price distribution for top 5 neighbourhoods

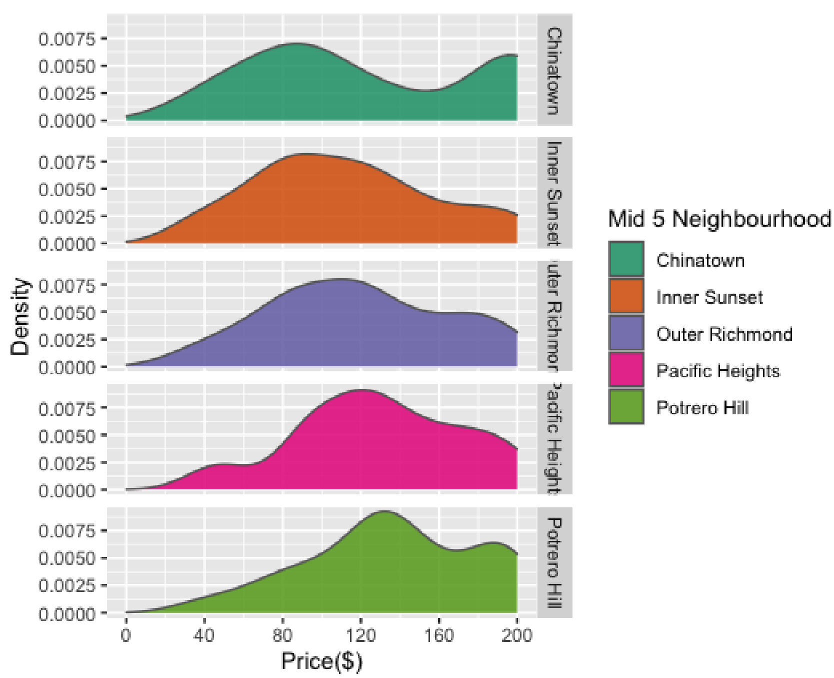

Figure 8: Price distribution for middle 5 neighbourhoods

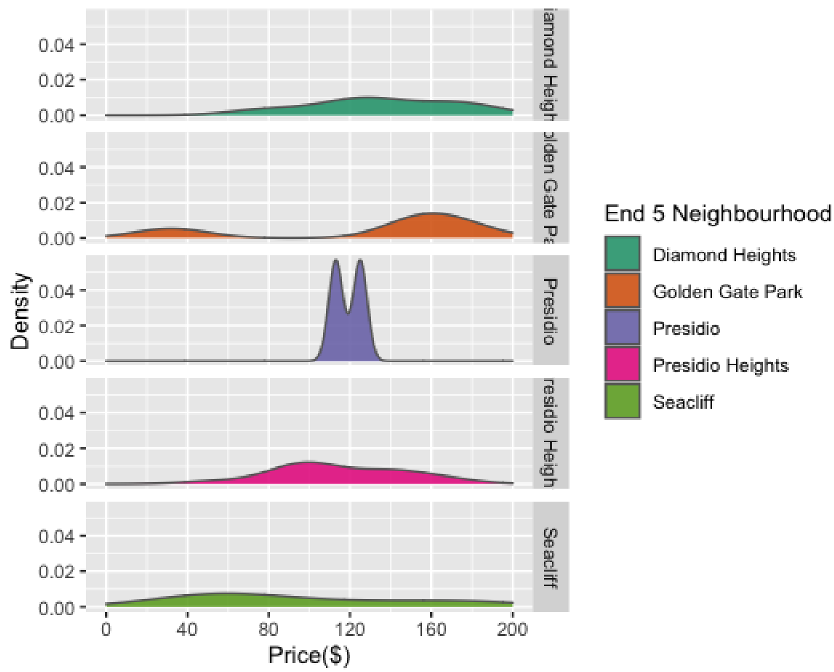

Figure 9: Price distribution for end 5 neighbourhoods

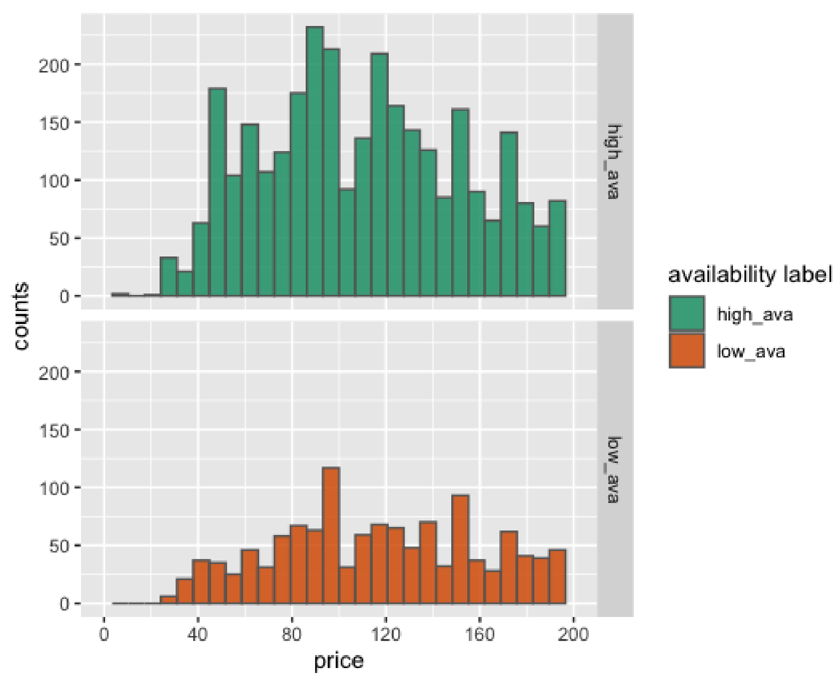

Figure 10: Distribution of price for high (larger than 90 days availability for a year) and low availability

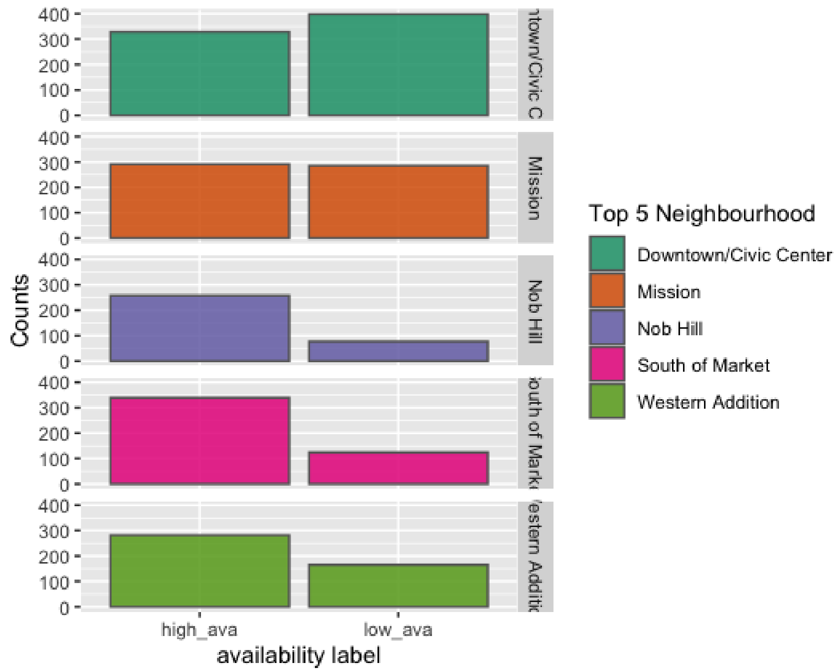

Figure 11: Counts of availability label for top 5 neighbourhoods

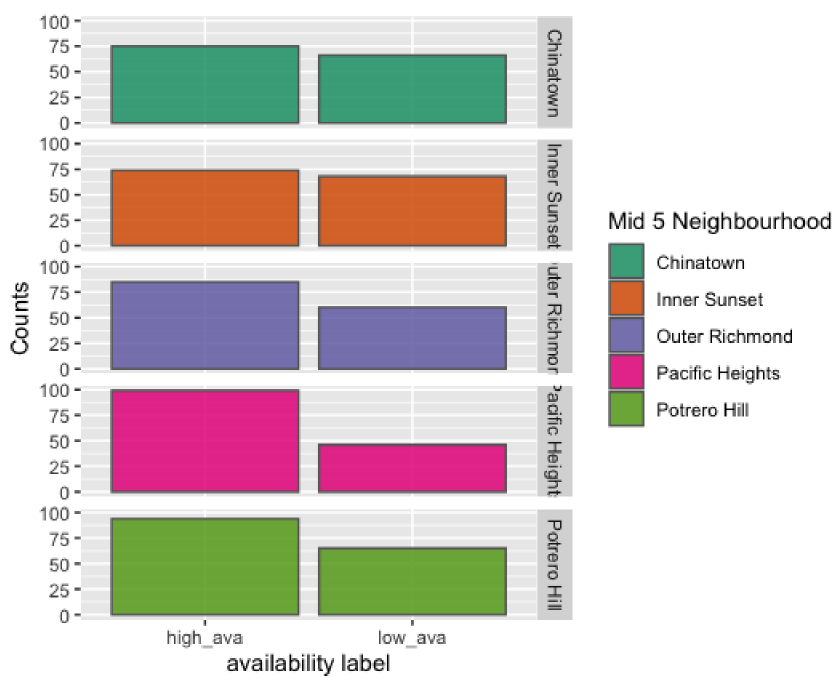

Figure 12: Counts of availability label for middle 5 neighbourhoods

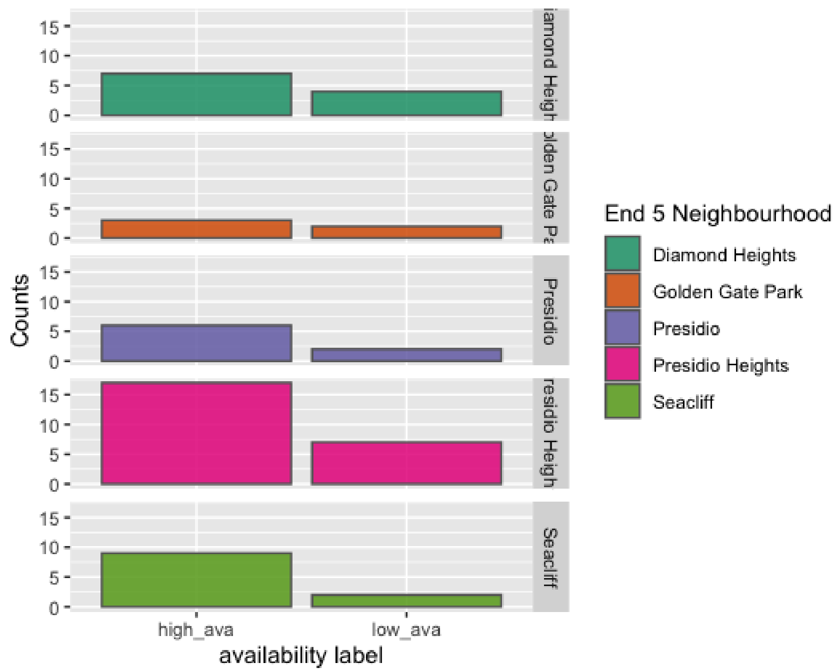

Figure 13: Counts of availability label for end 5 neighbourhoods

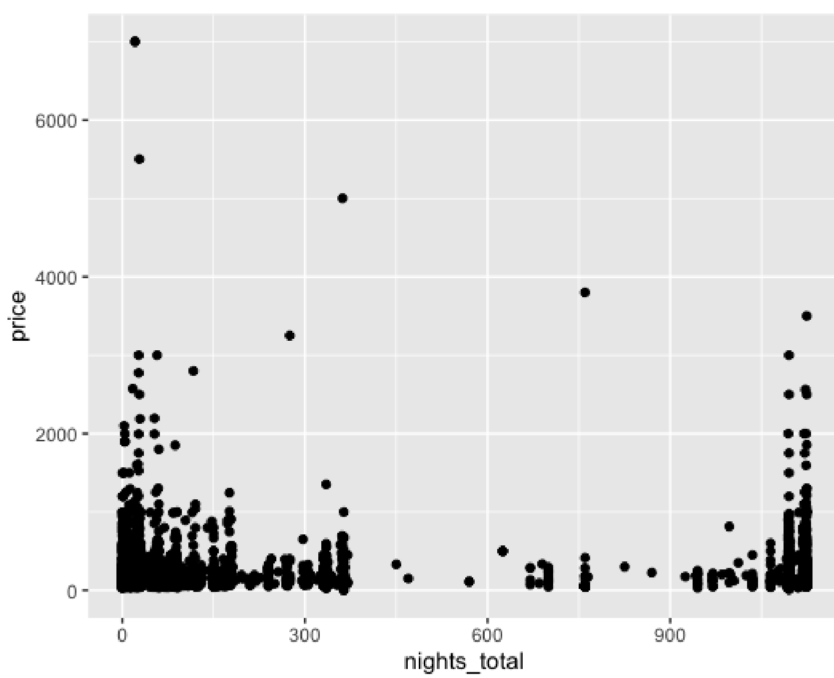

Figure 14: Plot of nights total vs price

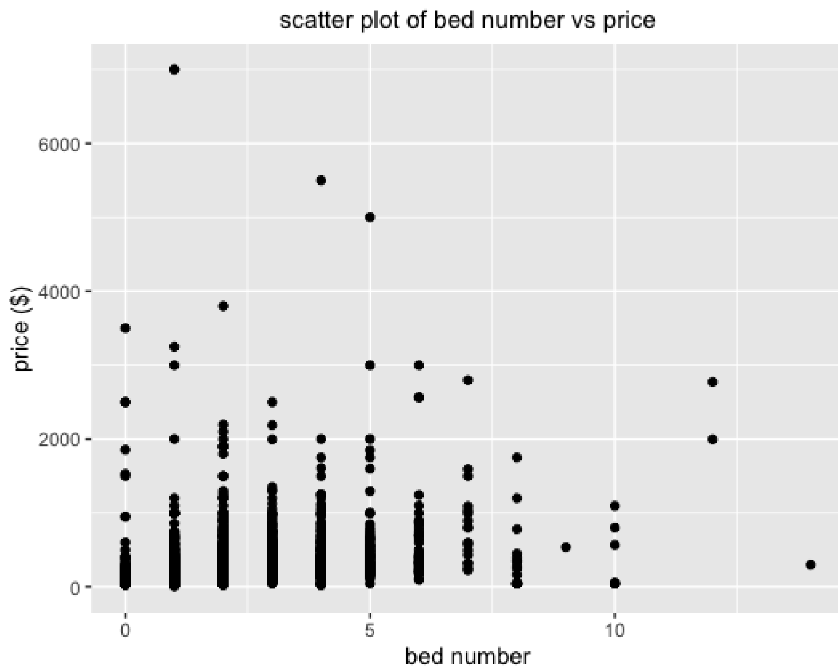

Figure 15: Plot of beds number vs price

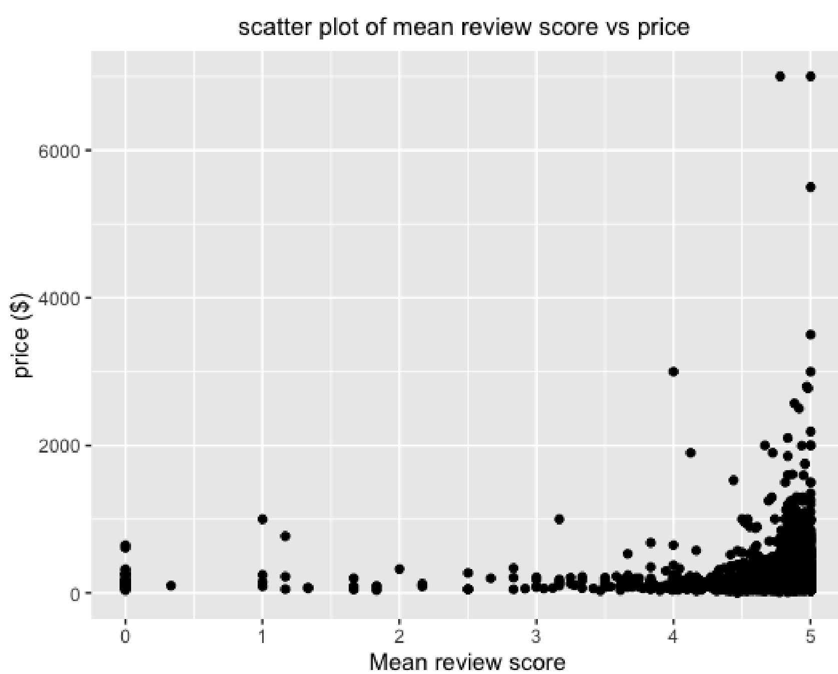

Figure 16: Plot of mean review scores vs price

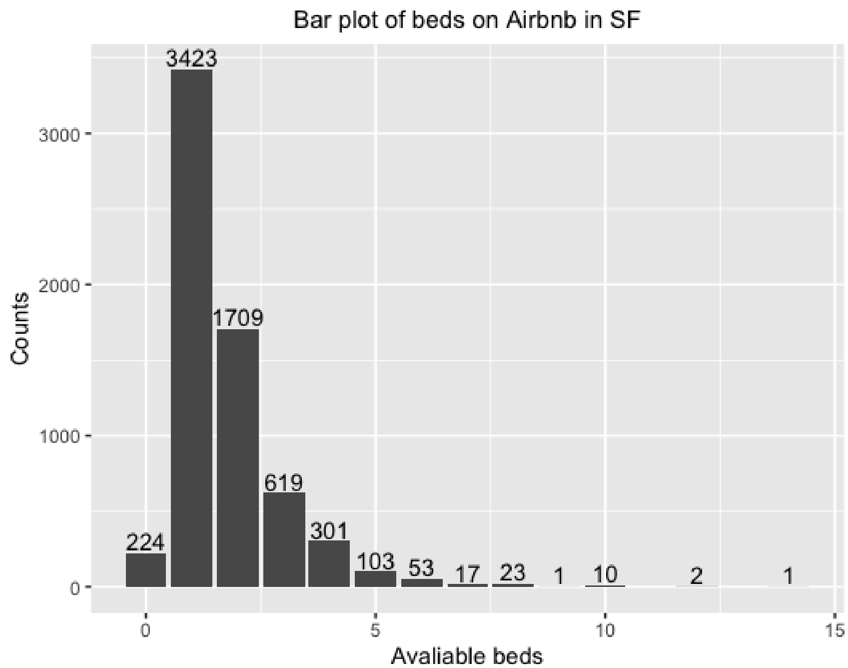

Figure 17: Histogram of number os beds in the listings

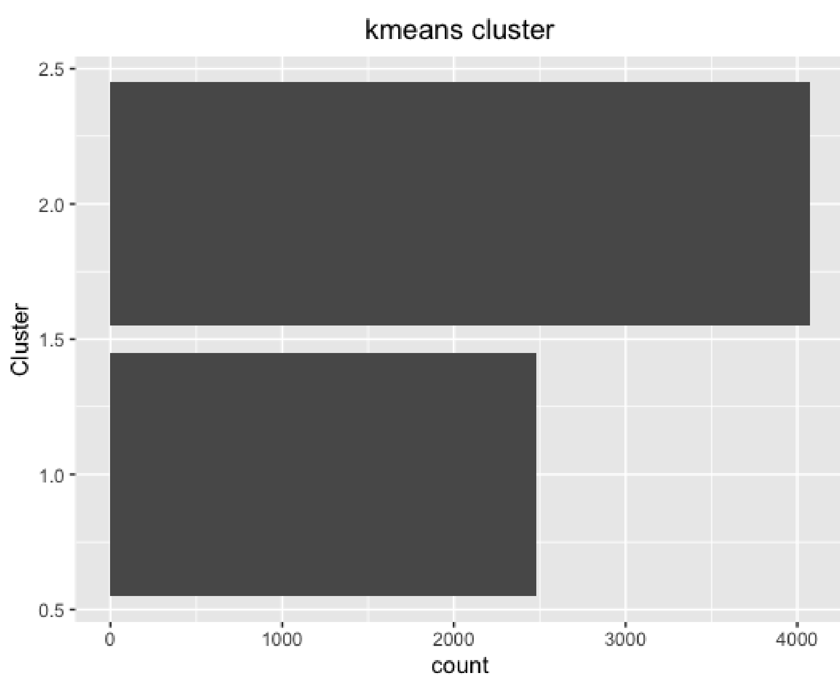

Figure 18: Clustering of listings to commercial and peer listings

7.3 Code

The programming language used for this paper's analyse is R. The code could be accessed in `https://github.com/yyang44/airbnb_sf_2021/blob/main/airbnb_sf_2021.R`.

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