American University of Armenia

Airbnb market analysis: Case study of Armenia

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Abstract

Insufficient attention has given to rental price setting mechanism in rental market of Armenia. This paper studies how different characteristics affects the housing prices in forty-six urban areas. The paper raises important questions about pricing in the sharing economy and generates hedonic price model and different machine learning algorithms to predict the prices. Some conclusions and recommendations are done based on the estimated results.

Keywords: Airbnb, hedonic pricing, Armenia, sharing economy, prediction models

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1. Introduction

With the appeal of the term 'sharing economy,' new businesses started to develop, which put the traditional bartering into new levels with easier share-based transactions. Belk (2007) was one of the pioneers who proposed the sharing concept as "the act and process of distributing what is ours to others for their use and/or the act and process of receiving or taking something from others for our use." Gradually, the sharing economy model entered all possible industries such as transportation, consumer goods, professional and personal services, healthcare, and travel and hospitality. In the travel and hospitality industry, collaborative economy shaped successful companies that offer peer-to-peer (P2P) services such as Airbnb, founded in 2008, which is one of today's most relevant accommodation collaborative services with more than 5 million homes across more than 81,000 cities and 191 countries as of August 2018("10 Years of Community," 2018). Airbnb is a disruptive innovation in the sharing economy whose business model focuses on tourist accommodation, and this accommodation has a unique appeal to tourists(Gibbs et al., 2018). Nowadays, there are lots of reasons that people chose Airbnb services over hotels, such as website trust, facility attributes, and host's personal photos, consumers' reviews and opinions, etc. (Perez-Sanchez et al., 2018). However, the economic benefit—better value for money—and the quality of accommodation at a lower cost are among the most relevant ones(Stors & Kagermeier, 2015).

Based on Airbnb listings in all Armenian urban market, we used the hedonic price method to examine if and how different features reflect the price in this paper. The features include not only amenities such as number of bedrooms, availability of parking, etc., but many other characteristics as well, such as reviews, number of years as a host, etc. With log-linear regression model two machine learning algorithms were also used to make housing price prediction. The data used in the paper were collected by the mean of scraping from the Airbnb homepage. Our paper is based on existing literature, which examines the topic based on country cases. However, the market is not researched in Armenia, and our paper aims to fill the exiting gap.

2. Literature review

To study the price dynamic and price determinants for Airbnb listings and conduct a comprehensive analysis, we look through several articles regarding the topic. Dan Wanga and Juan L. Nicolau (2017) used linear QR(Quantile Regression) and OLS regression models to find the relationships between a dependent variable(price) and explanatory variables(such as availability of different kinds of amenities, review scores, type of home, etc.), which they divided into five categories: site-specific characteristics, quality-signaling factors, hotel services and amenities, accommodation specification, and external market factors. QR model was used to get a more comprehensive description of the conditional distribution.

V. Raul Perez-Sanchez, Leticia Serrano-Estrada end others(2018) used OLS to determine and quantify the relation between accommodation attributes and price. Overall, they generated twenty-five explanatory variables and classified them into the following groups: Accommodation characteristics (property type, number of bathrooms), advertisement and host features (number of property photos displayed, rating), environmental characteristics (accommodation location), and location characteristics (the distance from both the coastal fringe and the touristic area). Although, in terms of OLS, as Sirmans et al (2008). highlight that the results obtained with these models are specific to the case study and cannot be generalized to other locations. So, the authors also developed the QR model (see explanation above).

In their research Chunwei Chang and Shengli Li(2021) also used OLS to explore the effects of different variables on the prices. Besides the first model, they built a second model with interaction terms to identify interaction effects if they exist. The variables are also classified into five main groups (listing attributes, listing location, host attributes, rental rules, and listing reputation).

Chris Gibbs, Daniel Guttentag, and others(2018) did their analysis again based on OLS, although the uniqueness of their research is that they took into account the one-time cleaning fee that many listings require. Airbnb has indicated that its guests stay an average of 4.5 nights(Guttentag et al., 2018), so it rounded to five, and one-fifth of each listings' cleaning fee was added to the base price.

Other authors, such as Yuan Cai and Yongbo Zhou(2019) evaluated eight separate log-linear hedonic price models to estimate the effects of five groups of explanatory variables on price using OLS. The hedonic price model is a model where the price is determined both by internal characteristics of goods and external factors affecting them). They identified the following five groups of independent variables; listing attributes, host attributes, listing reputation, rental policies, and listing location.

Troy Lordea, Jadon Jacoba, and Quinn Weekes(2018) also employed a hedonic price approach to assessing how prices are being generated in Airbnb. Here the predictors are categories in the following way: site, reputation, convenience, personal, amenities, and country. They added country attributes such as GDP per capita, population size, etc., to catch country differences that may result in the cross-country pricing variation. OLS and QR methods were used to estimate the hedonic price equation.

Zhihua Zhang, Rachel J. C. Chen and others(2017)used two different models to investigate the connection between dependent and independent variables. Firstly, they evaluated general linear model (GLM) to explore price determinants affecting prices. Afterward, they developed the geographically weighted regression (GWR) to understand how the relationships can be affected by location details and see how local factors affect the listing price.

3. Methodology and research data

3.1. Research data

The market chosen for this research is Armenia. We used software to scrape data from the listings of all 46 Armenian cities posted on Airbnb.com to do the research. The scrape was set up to collect publicly available data such as listing names, amenities, property types, reviews, locations, etc. In the research, these groups of variables are used as independent variables. The variables are conditionally divided into four groups: geographic features, home properties, home characteristics, and host characteristics. The dependent variable of this study is log of listing price which is also owned by the mean of scraping. After the scraping, some variables were generated; for example, city population, distance from Yerevan, number of years that home is posted, etc., (for a more detailed explanation for variables, see Appendix Table 2). Initially, two thousand two hundred fourteen listings were scrapped, which then reduced to 738 observations with 95 variables[1]. After the cleaning, the number of cities that had a listing on Airbnb also declined, and the actual numbers of the city available on data sets became 22. The spatial distribution of sample listings is shown in Figure 1. The sample price distribution for entire home and room depicted in Figure 1.

[1] The initial data was modified while generating three regression models

Figure 1: Distribution of sample listings among cities

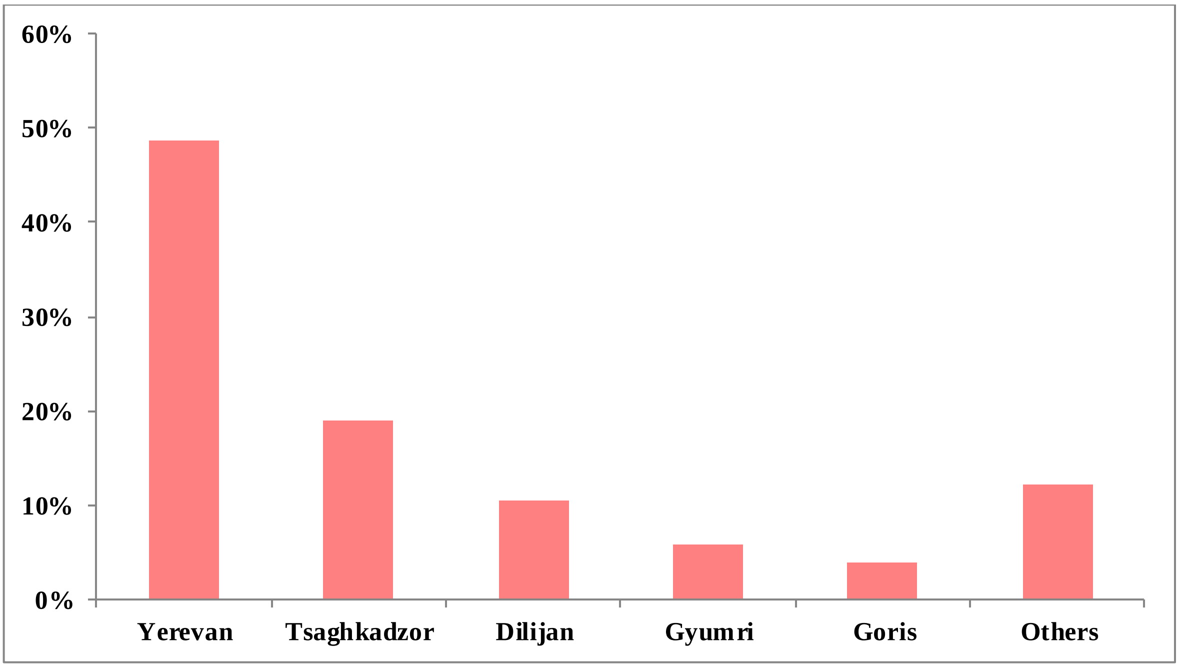
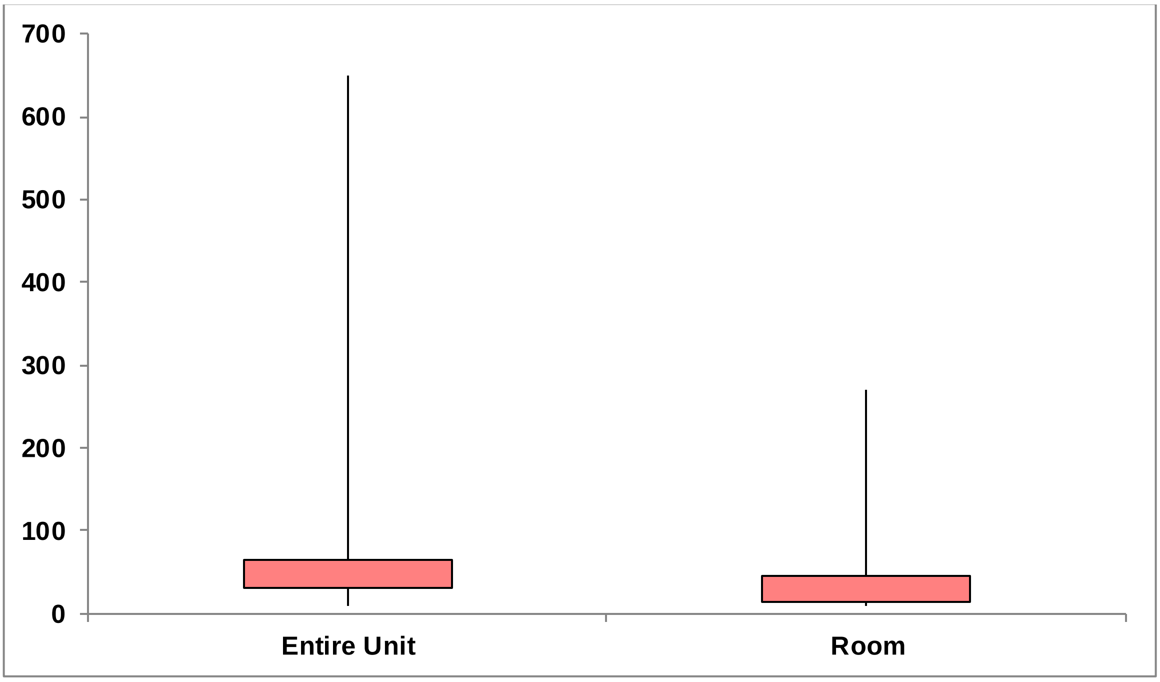


Figure 2: Price distribution for entire units and rooms



Data contained some outliers (see Appendix Figure 8, and Figure 9), which were detected and removed from the data set by using Q3 + 1.5 * IQR formula for models' consistency perspectives.

3.2. Methodology

As mentioned above, hedonic pricing theory states that a good or service price is a function of characteristics affecting the utility of a price or service. According to hedonic pricing theory, Airbnb listings' characteristics are a bundle of variables that affect the price. Hedonic pricing models are usually multivariable regressions taken in a log-linear form which can be generally specified as

$$LnP = \beta_0 + \sum \beta_i X_i + \varepsilon$$

Also, the model can estimate marginal effects of characteristics that have a significant effect on price. Price is taken in logarithm form to escape the heteroskedasticity problem of the data. The original distribution of the price and the logarithmic distribution are shown in figure 4 and figure 5, respectively.

Figure 3: The original distribution of price

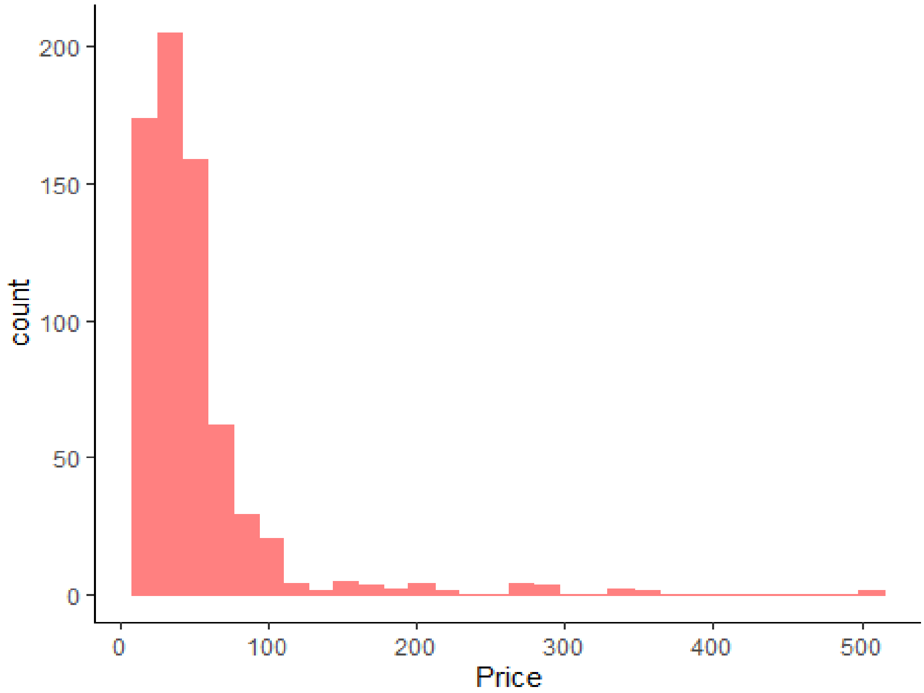
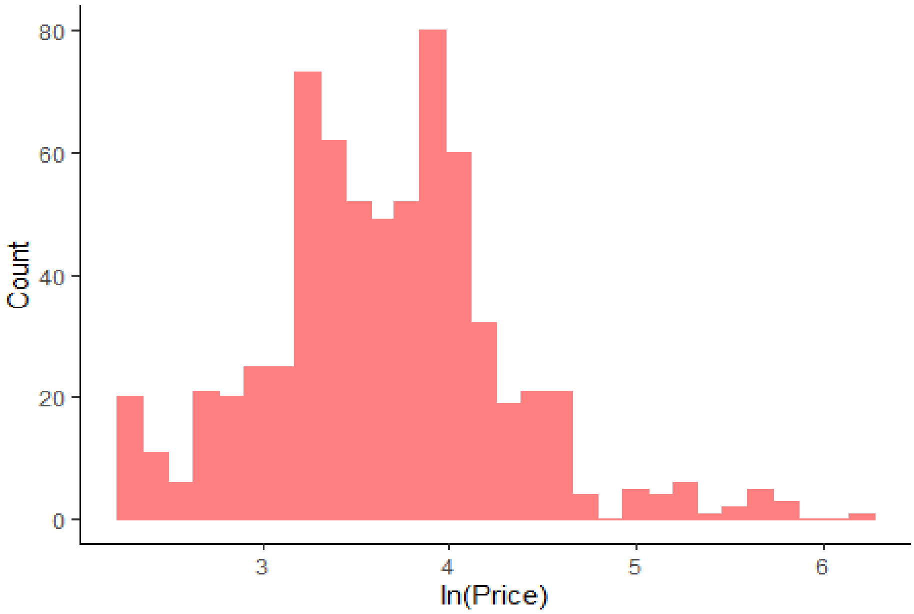


Figure 4: The logarithmic distribution of price



Independent variables of the model are divided into four groups. The first group of variables is used to control the effects of geographical location on price. We have created nine dummy variables for each of the regions of Armenia except Ararat region[2] to capture the price disparities between Yerevan and the regions. The second group of variables represents home characteristics. The third group of variables captures host characteristics. Finally, the fourth group of variables is used to control home amenities. There are more than 80 home amenities listed on the Airbnb website. To get appropriate data, we excluded the amenities that were either available in 90 percent of the listings or were absent from more than 90 percent of them. Then; we conducted individual t-tests for the remaining amenities to find out which of them has a significant effect on price (detailed information is provided in Appendix). In the final model are included only the amenities that had a significant effect on the price. The final model has the following specification.

$$LnP = \beta_0 + \sum \beta_i Region_i + \sum \beta_i HomeCharacteristic_i + \sum \beta_i HostCharacteristic_i + \sum \beta_i Amenity_i + \varepsilon$$

We also examine the features that influence Armenian home prices and use two machine learning algorithms to make housing price predictions: K-Nearest Neighbor (KNN) and Random Forest for regression. We identify the optimal value for the hyperparameter in KNN by using 10-fold cross-validation and Grid Search methods. In Random Forest for regression, we define the value of mtry to be equal to one-third of the number of predictors. The optimal number of trees is defined by using the Elbow method. We use the population of cities, their distance from Yerevan, number of accommodates, bathrooms, bedrooms, beds, and reviews as independent variables for these two algorithms. We use an 80/20 ratio to divide our data set into training and testing sets and then test the models by making predictions against the test set. By Random Forest for regression algorithm, we represent the importance of features as well. Finally, we evaluate the findings to discover the most accurate model for predicting Armenian home prices on the Airbnb website.

3.3. Limitations

The Airbnb data has several limitations. The website's popularity is not equally distributed throughout Armenia; The number of announcements made by Yerevan exceeds the number of announcements of regions. Except for a few cities in the regions, a minimal number of listings are available; moreover, the announcements are absent in some cities. This is since the hosts mostly use the list.am platform for renting houses in the regions. Because of this problem,

[2] There was no listing from Ararat region after data cleaning.

we could not analyze the pricing in the regional cities in depth. The other problem is the incompatibility of the characteristics of the announcements of the houses operating in different price segments. Lower price segment homes are described more detailed rather than the rentals in the high price segment. For example, the presence of shampoo has a significant negative impact on house prices, but this does not mean that the shampoo has a negative impact on the price, but simply that the presence of shampoo is more often mentioned for homes in the lower price segment. Such incompatibility produced spurious results during the modeling phase, which is why in our regression analysis, we refrained from discussing the marginal effects of individual amenities instead of focusing on building a model for predicting the announcement price.

4. Estimations and results

Table 1: Log-linear multivariate regression

	(1)
VARIABLES	lnprice
Syuniq	0.212*
	(0.111)
Vayk	-0.113
	(0.108)
Shirak	0.0465
	(0.0783)
Lori	-0.126
	(0.116)
Tavush	0.186***
	(0.0678)
Aragacotn	-0.0874
	(0.286)
Kotayq	0.963***
	(0.0834)
Gexarquniq	-0.277**
	(0.111)
Armavir	0.0478
	(0.193)
Backyard	-0.107*
	(0.0586)
Breakfast	0.110*
	(0.0616)
Cooking_basics	-0.0523
	(0.0568)
Dishes_and_silverware	-0.0191
	(0.0707)
Extra_pillows_and_blankets	0.0418
	(0.0510)
Fire_extinguisher	0.177***
	(0.0490)

Freestreetparking	-0.0853*
	(0.0502)
Hangers	0.0181
	(0.0516)
Hotwater	0.0428
	(0.0546)
Indoorfireplace	0.323***
	(0.0680)
Privateentrance	0.00723
	(0.0422)
Refrigerator	-0.0982
	(0.0753)
Shampoo	-0.183***
	(0.0461)
Smokealarm	0.00614
	(0.0420)
Smokingallowed	-0.0571
	(0.0418)
Stove	0.0278
	(0.0645)
Suitableforevents	0.0577
	(0.0506)
TV	0.266***
	(0.0672)
Host_Years	-0.0258**
	(0.0101)
HostIdentityVerifiedDummy	0.194***
	(0.0496)
SuperhostDummy	0.172***
	(0.0582)
RoomDummyRoom1EntireUnit0	-0.383***
	(0.0599)
accomodates	0.0331**
	(0.0129)
number_bathroom	0.00661
	(0.0295)
number_bedroom	0.00349
	(0.0289)
number_beds	-0.0401***
	(0.0107)
review	0.000617**
	(0.000246)
Constant	3.325***
	(0.106)
Observations	680
Adjusted R-squared	0.457
Root MSE	0.478

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Regression model results show that prices in Syuniq, Tavush, and Kotayq regions on average are higher than Yerevan prices by 21.2, 18.6, and 96.6 percent, respectively. Prices in Gexarquniq region, on average, were lower by 27.7 percent. We think that this is a result of small samples of listings in regions. Also, these samples are not representative because most of the hosts in the regions use list.am as the main platform for listings. Most of the listings in the regions were from the high price segment of the market. This feature is very well reflected by the 96.6 percent disparity between prices in the Kotayk region and Yerevan. Most of the listings in the Kotayk region are luxury apartments and Cottages located in Tsagkadzor. Results also show that the older the host, the lower the price of its listing, with each additional year of hosting price decreases by 2.58 percent. Prices of identity verified hosts are on average higher by 19.4 percent from unverified hosts. Prices of super hosts are, on average higher by 17.2 percent. Prices of rooms are on average lower by 38.3 percent than the prices of entire apartments. The more guests the apartment accommodates, the higher its price. With each additional guest, the price is higher by 3.3 percent. The number of reviews is also significant, but it has a very low marginal effect on price. With each additional review price increases only by 0.02 percent.

KNN regression

The prediction that **KNN regression** made provides an average for the nearest neighbors. For **KNN regression**, we select the population of cities, cities' distance from Yerevan, the number of accommodates, bathrooms, bedrooms, beds, and reviews.

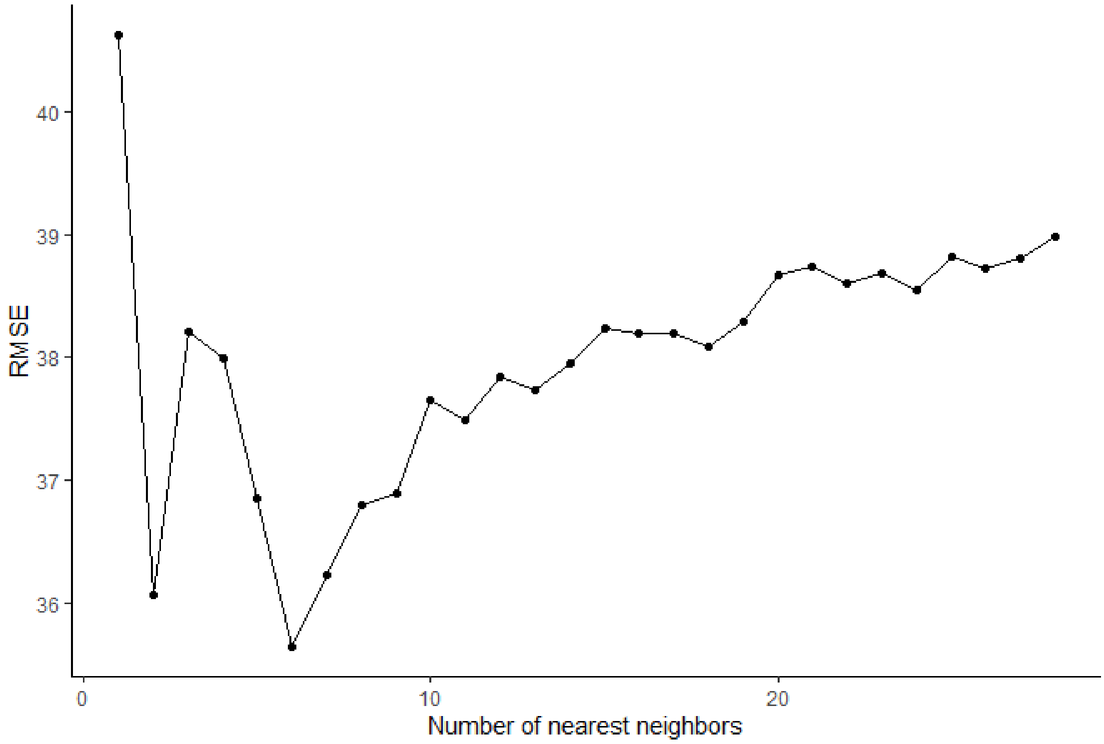
We normalize the range of the variables using **Z-score normalization** as the range of the variables varies on a large scale. We normalize the data in order to decrease the influence of the arbitrary variable on the model.

$$\frac{value - \mu}{\sigma}$$

We divide the data set into training and testing sets by using an 80/20 ratio.

As the square root of the number of observations is equal to 26.07681, we calculate the **RMSE** for different values of **k** starting from one to the square root of the number of observations.

Figure 5: RMSE vs Number of nearest neighbors



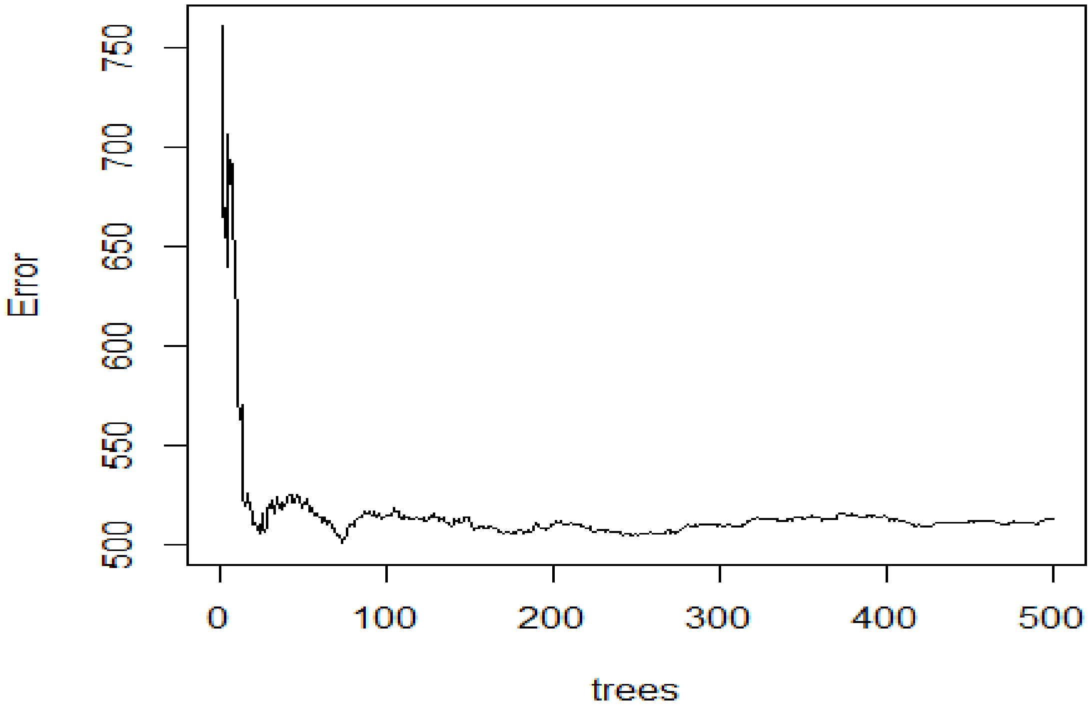
The **optimal value** of **k** (number of nearest neighbors) is equal to **six**.

The root mean squared error for the test data set is equal to 43.43162. The closer the root mean squared error is to zero, the more accurate the model is.

Random Forest for regression

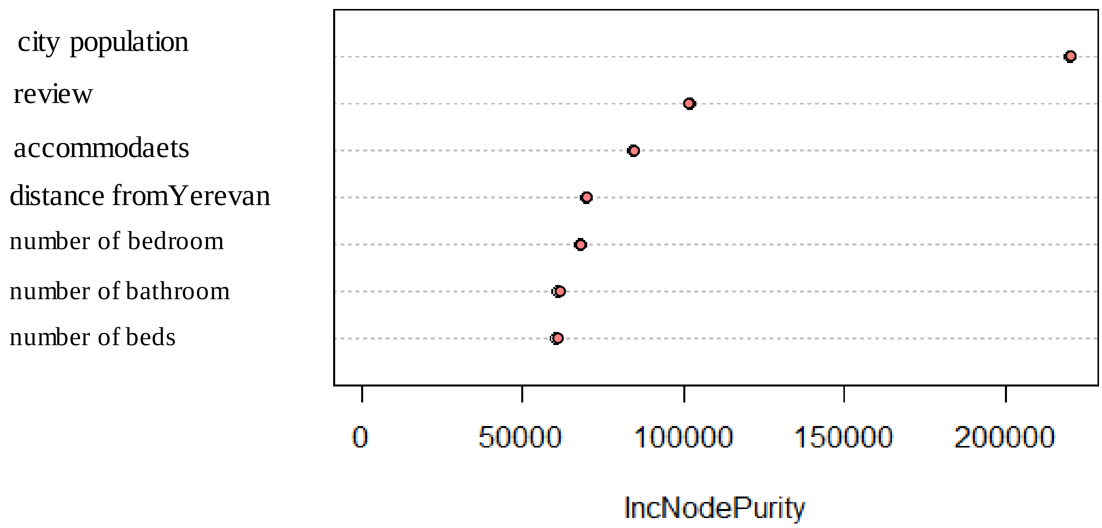
In a Random Forest for regression algorithm, we select those variables that have been used to predict the price in **the KNN** algorithm. We define the value of **mtry** to be equal to p/3 where p is the number of predictors.

Figure 6: Error vs number of trees



According to the graph, the error is decreasing by adding more and more trees and average them. The optimal number of trees is equal to seventy-four.

Figure 7: Importance of features



IncNodePurity measures variable importance based on the Gini impurity index used for calculating the splits in trees. It measures the total decrease in node impurity that results from splits over that variable, averaged over all trees. The higher the value of the mean decrease Gini score, the higher the importance of the variable to the model. For the Mean Decrease Gini (IncNodePurity), the most important variable is the city population.

The root mean squared error (RMSE) is equal to 22.71323. The closer the root mean squared error is to zero, the more accurate the model is.

5. Recommendations and conclusion

The data set study revealed the under-representation of the regional cities on the Airbnb website. This creates serious obstacles for the study of the B&B market of the regional cities. In addition, in our opinion, the under-representation of regional cities prevents the attraction of foreign tourists to regional cities, as this platform is much more popular among foreign tourists. Hence, the increase of representation of the regional cities on the site may increase the popularity of regions among visitors.

In the next stage of the research, we plan to scrape the listings of Tbilisi and make a comparative analysis with Yerevan based on it. This will allow us to understand the peculiarities of pricing in Yerevan and Tbilisi and to evaluate the B&B market in the cities.

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Appendices

Table 2: Summary statistics

Variables	N	Mean	SD	Min	Max
Price	680	48.96	45.99	10	500
Syuniq	680	0.0426	0.202	0	1
Vayk	680	0.0456	0.209	0	1
Shirak	680	0.0824	0.275	0	1
Lori	680	0.0353	0.185	0	1
Tavush	680	0.122	0.328	0	1
Aragacotn	680	0.00441	0.0663	0	1
Kotayq	680	0.0779	0.268	0	1
Gexarquniq	680	0.0338	0.181	0	1
Ararat	680	0	0	0	0
Armavir	680	0.0103	0.101	0	1
City_Population	680	589,104	509,782	1,281	1.055e+06
Distance_from_Yerevan	680	50.24	65.34	0	238
Air_conditioning	680	0.584	0.493	0	1
BBQ_grill	680	0.128	0.334	0	1
Backyard	680	0.171	0.376	0	1
Bed_linens	680	0.481	0.500	0	1
Breakfast	680	0.243	0.429	0	1
Carbon_monoxide_alarm	680	0.615	0.487	0	1
Clothing_storage	680	0.113	0.317	0	1
Coffee	680	0.313	0.464	0	1
Coffee_maker	680	0.309	0.462	0	1
Cooking_basics	680	0.524	0.500	0	1
Crib	680	0.135	0.342	0	1
Dedicated_workspace	680	0.722	0.448	0	1
Dishes_and_silverware	680	0.524	0.500	0	1
Dryer	680	0.203	0.402	0	1
Elevator	680	0.241	0.428	0	1
Extra_pillows_and_blankets	680	0.287	0.453	0	1
Fire_extinguisher	680	0.262	0.440	0	1
First_aid_kit	680	0.376	0.485	0	1
Freestreetparking	680	0.459	0.499	0	1
Hairdryer	680	0.872	0.334	0	1
Hangers	680	0.781	0.414	0	1
Hotwater	680	0.715	0.452	0	1
Hotwaterkettle	680	0.113	0.317	0	1
Indoorfireplace	680	0.100	0.300	0	1
Iron	680	0.851	0.356	0	1
Lockbox	680	0.196	0.397	0	1
Luggagedropoffallowed	680	0.331	0.471	0	1
Microwave	680	0.315	0.465	0	1
Oven	680	0.232	0.423	0	1
Patioorbalcony	680	0.287	0.453	0	1
Privateentrance	680	0.396	0.489	0	1
Refrigerator	680	0.515	0.500	0	1

Roomdarkeningshades	680	0.166	0.373	0	1
Selfcheckin	680	0.324	0.468	0	1
Shampoo	680	0.703	0.457	0	1
Showergel	680	0.106	0.308	0	1
Singlelevelhome	680	0.122	0.328	0	1
Smokealarm	680	0.457	0.499	0	1
Smokingallowed	680	0.374	0.484	0	1
Stove	680	0.419	0.494	0	1
Suitableforevents	680	0.290	0.454	0	1
TV	680	0.897	0.304	0	1
Washer	680	0.813	0.390	0	1
Host_Years	680	3.581	2.063	0	11
HostIdentityVerifiedDummy	680	0.750	0.433	0	1
SuperhostDummy	680	0.368	0.483	0	1
RoomDummyRoom1EntireUnit0	680	0.284	0.451	0	1
accomodates	680	4.569	2.998	1	16
number_bathroom	680	1.376	1.036	0	11
number_bedroom	680	1.669	1.439	0	11
number_beds	680	2.950	3.017	0	25
review	680	67.58	108.9	0	536

Figure 8: Price distribution for room of Armenian cities

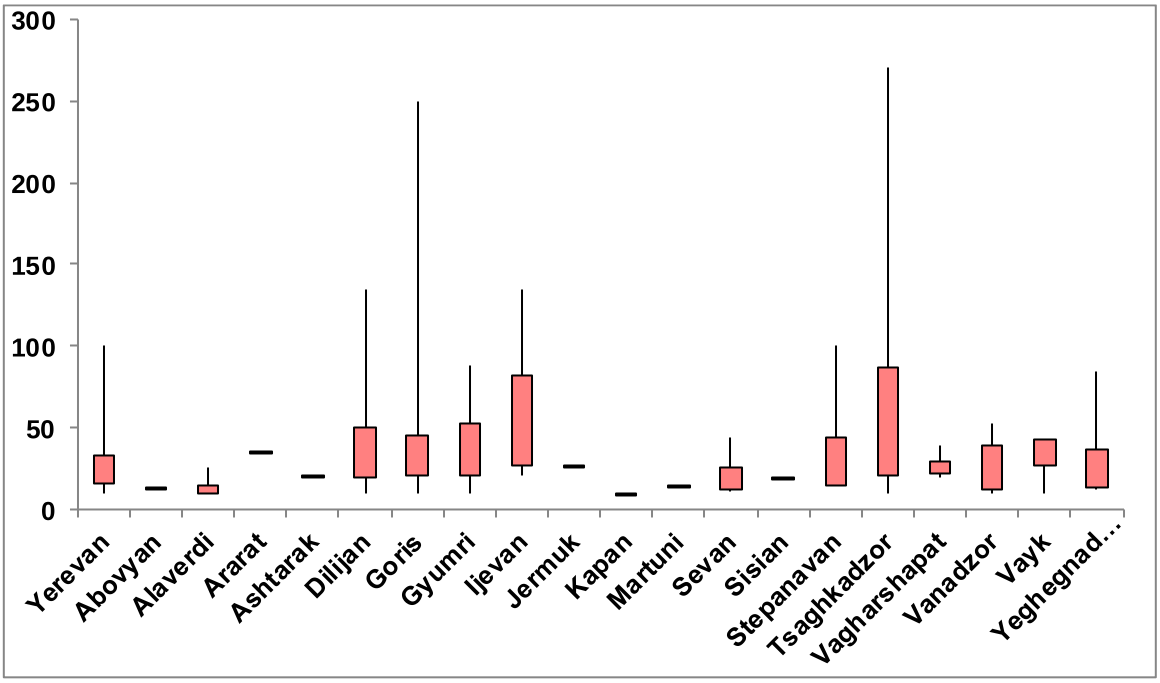

Figure 9: Price distribution for entire home of Armenian cities

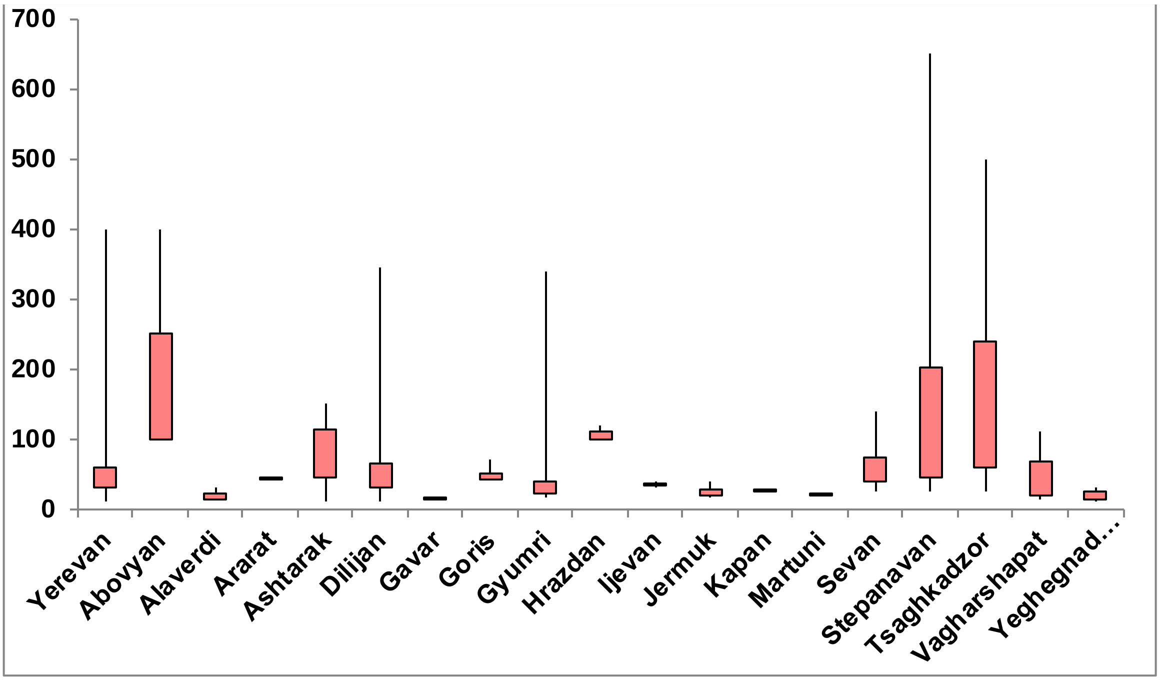

Table 3. t-tests results of independent variables

Air Conditioning				
Group	Obs	Mean	t value	P value
0	283	48.07	-0.43	0.67
1	397	49.59		
BBQ_grill				
Group	Obs	Mean	t value	P value
0	593	48.89	-0.10	0.92
1	87	49.43		
Backyard				
Group	Obs	Mean	t value	P value
0	564	50.23	1.59	0.11
1	116	42.78		
Bed_linens				
Group	Obs	Mean	t value	P value
0	353	50.48	0.90	0.37
1	327	47.32		
Breakfast				
Group	Obs	Mean	t value	P value
0	515	52.81	3.90	0.00
1	165	36.93		
Carbon_monoxide_alarm				

Group	Obs	Mean	t value	P value
0	262	46.67	-1.03	0.30
1	418	50.39		
Clothing_storage				
Group	Obs	Mean	t value	P value
0	603	48.38	-0.91	0.36
1	77	53.47		
Coffee				
Group	Obs	Mean	t value	P value
0	467	48.95	-0.01	0.99
1	213	48.98		
Coffee_maker				
Group	Obs	Mean	t value	P value
0	470	48.92	-0.04	0.97
1	210	49.06		
Cooking_basics				
Group	Obs	Mean	t value	P value
0	324	52.97	2.17	0.03
1	356	45.31		
Crib				
Group	Obs	Mean	t value	P value
0	588	48.88	-0.11	0.91
1	92	49.45		
Dedicated_workspace				
Group	Obs	Mean	t value	P value
0	189	49.59	0.22	0.83
1	491	48.72		
Dishes_and_silverware				
Group	Obs	Mean	t value	P value
0	324	53.40	2.41	0.02
1	356	44.92		
Dryer				
Group	Obs	Mean	t value	P value
0	542	48.40	-0.63	0.53
1	138	51.15		
Elevator				
Group	Obs	Mean	t value	P value
0	516	48.58	-0.38	0.70
1	164	50.15		
Extra_pillows_and_blankets				
Group	Obs	Mean	t value	P value

0	485	51.62	2.39	0.02
1	195	42.33		
		Fire_extinguisher		
Group	Obs	Mean	t value	P value
0	502	45.85	-2.97	0.00
1	178	57.72		
		First_aid_kit		
Group	Obs	Mean	t value	P value
0	424	48.58	-0.28	0.78
1	256	49.59		
		Freestreetparking		
Group	Obs	Mean	t value	P value
0	368	54.55	3.47	0.00
1	312	42.37		
		Hairdryer		
Group	Obs	Mean	t value	P value
0	87	53.55	1.00	0.32
1	593	48.29		
		Hangers		
Group	Obs	Mean	t value	P value
0	149	55.25	1.89	0.06
1	531	47.20		
		Hotwater		
Group	Obs	Mean	t value	P value
0	194	57.97	3.25	0.00
1	486	45.36		
		Hotwaterkettle		
Group	Obs	Mean	t value	P value
0	603	48.44	-0.82	0.41
1	77	53.01		
		Indoorfireplace		
Group	Obs	Mean	t value	P value
0	612	44.76	-7.42	0.00
1	68	86.75		
		Iron		
Group	Obs	Mean	t value	P value
0	101	56.80	1.86	0.06
1	579	47.59		
		Lockbox		
Group	Obs	Mean	t value	P value
0	547	48.29	-0.77	0.44

1	133	51.71		
Luggagedropoffallowed				
Group	Obs	Mean	t value	P value
0	455	50.50	1.28	0.20
1	225	45.75		
Microwave				
Group	Obs	Mean	t value	P value
0	466	48.52	-0.37	0.71
1	214	49.92		
Oven				
Group	Obs	Mean	t value	P value
0	522	48.67	-0.30	0.76
1	158	49.92		
Patioorbalcony				
Group	Obs	Mean	t value	P value
0	485	49.28	0.28	0.78
1	195	48.17		
Privateentrance				
Group	Obs	Mean	t value	P value
0	411	46.94	-1.41	0.16
1	269	52.04		
Refrigerator				
Group	Obs	Mean	t value	P value
0	330	53.86	2.72	0.01
1	350	44.33		
Roomdarkeningshades				
Group	Obs	Mean	t value	P value
0	567	48.81	-0.19	0.85
1	113	49.71		
Selfcheckin				
Group	Obs	Mean	t value	P value
0	460	48.69	-0.22	0.82
1	220	49.53		
Shampoo				
Group	Obs	Mean	t value	P value
0	202	63.84	5.61	0.00
1	478	42.67		
Showergel				
Group	Obs	Mean	t value	P value
0	608	48.74	-0.37	0.71
1	72	50.85		

Singlelevelhome				
Group	Obs	Mean	t value	P value
0	597	48.61	-0.54	0.59
1	83	51.51		
Smokealarm				
Group	Obs	Mean	t value	P value
0	369	44.58	-2.86	0.00
1	311	54.42		
Smokingallowed				
Group	Obs	Mean	t value	P value
0	426	46.05	-2.15	0.03
1	254	53.85		
Stove				
Group	Obs	Mean	t value	P value
0	395	52.02	2.05	0.04
1	285	44.72		
Suitableforevents				
Group	Obs	Mean	t value	P value
0	483	44.14	-4.34	0.00
1	197	60.78		
TV				
Group	Obs	Mean	t value	P value
0	70	33.57	-2.97	0.00
1	610	50.73		
Washer				
Group	Obs	Mean	t value	P value
0	127	46.90	-0.56	0.58
1	553	49.43		