Canadian Real Estate Rental Market – Artificial Hype or Reality? Airbnb vs Traditional Rental Market

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ABSTRACT

Through this report we are presenting a comparative analysis of short and long-term rental market in major Canadian cities. We relied on the most comprehensive dataset provided by inside Airbnb [32] for Airbnb activity from 2015 to 2019 and Canada Mortgage and Housing Corporation [31] for data on rental market from 1990 to 2018.The scheme evaluated how short term and seasonal housing sooq are affecting Canadian real estate market. A big portion of residential units are being used by Toronto Airbnb with a 1.6% increase in 2019 of Toronto Housing stock. However, Airbnb Vancouver has observed a huge decrement in whole Airbnb market. For a rational mathematical chronological investigation of market, we used hypothesis testing, forecasting and predictive learning approach for comparing these two markets' price, seasonality, neighbourhood and demand effects. Besides, we explored how the income varies for the two type of owners along with the effect of rating and review on Airbnb Market.

KEYWORDS

Prediction, Airbnb, Determinants, Analytics, Visualization, Forecast, Investment, Vacancy, Availability, Income, Seasonality, Airbnb, Tourism, Airbnb, Sharing, NLTK

1 Introduction

Short-term rentals are expanding rapidly across Canadian cities. In May 2016, there were approximately 50,000 Airbnb listings in the Montreal, Toronto and Vancouver regions, which had been active at some point in the previous 12 months. A year later, there were over 81,000. In the same time, the number of entire homes rented more than 60 days a year has increased from 8,900 to 13,700 across the three cities. Meanwhile, Airbnb revenue has become concentrated among a small set of large-scale operators. Hosts with multiple full-time, entire-home listings now earn more than a third of all platform revenue, despite only controlling eight percent of active listings. This growth poses a number of questions for policymakers and communities.

Short-term rentals often operate in legal grey zones, able to avoid existing accommodation regulations and taxes, and are now being targeted with specific regulations. The Province of Quebec was the first major Canadian jurisdiction to legalize short-term rentals, implementing a regime focused on recovering tax revenues. Toronto and Vancouver acknowledging the wide range of impacts from short-term rentals have both proposed more stringent regulations, including limiting short-term rentals to principal residences. "The City of Vancouver announced on Wednesday that it is moving to ban all Airbnb and short-term rentals in secondary homes in the city. Mayor Gregor Robertson says they expect about 1,000 rental units to get returned to the market" [33]. In continuing efforts to crack down upon short-term rental loom through Airbnb, Toronto passes strict Airbnb rules aimed at preserving long-term rental supply [34].

Toronto's long-term market (over 3 months) is now at a concerned level because of the historic low vacancy rate (0.5%) and highest average rent for a one-bedroom apartment ($2,360) leaving thousands on waiting lists. Affordability has reached crisis levels due to lower number of new housing construction, higher housing price index, high migration rate to Toronto, lower labor participation rate, high unemployment rate and so on. On the other hand, Airbnb is booming with three different categories of housing for rentals; entire homes where the guest has access to the entire housing unit and the host is generally not present, Private rooms where the host is often present in or around the house, and shared rooms, where hosts or others guests may sleep in the same room. Figure 1 represents map of Airbnb listings of all three categories in Toronto.

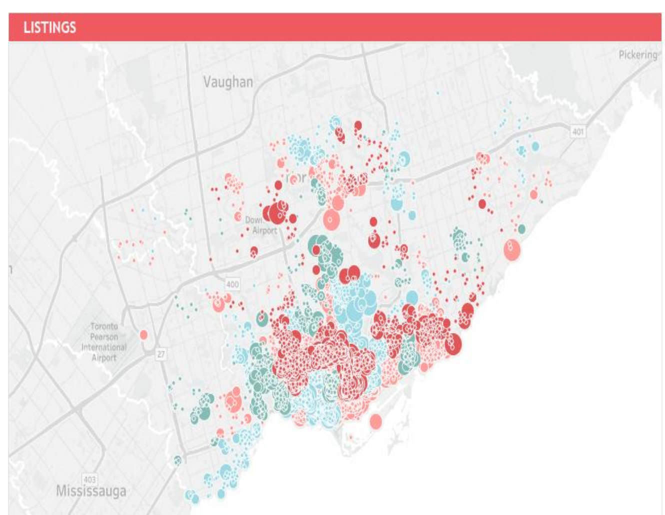

Figure 1. Map for Toronto Airbnb Active Listings July 2016 – December 2018.

2 Problem Statement and Methodology

With a goal of investigating Airbnb service's impact on long-term rental shortage in vacancies, we assumed that it has inflated the rental market hype somehow. Thus, we projected an in-depth exploratory and diagnostic analysis of that datasets to gain insight and justify whether our assumption is true by combining data analytics and visualization along with predictive analysis.

We focused mainly on Airbnb Market in Toronto and a small analysis on Vancouver and Montreal. The rationale to choose these is large number of the listings on Airbnb. For long term rental Toronto's low vacancy rates could have something to do with the city's large quantity of Airbnb listings. As many as 19,255 Toronto homes are listed on Airbnb a number that has almost tripled since 2015. From CMHC we collected data for Toronto long-term rental vacancy rates (10Mb), availability rate (10Mb), average rent (10Mb), number of houses (10Mb) by different neighborhood and property types from 1990-2018 and merged them together to run the final analysis. Analysis result has been submitted in midterm report. For Toronto Airbnb we merged listings data from 2015 to 2019 March which was in total 250 MB, and calendar.csv.gz 150 Mb that contains day wise listing demand and price. The merges data from review.csv.gz was a size of 320 Mb and for neighborhood.csv the size was 100 Mb. All of the archived data was merged to get a large amount of data so that we can have a good prediction result.

In first step we ran exploratory data analysis to see how the features of each market are related with one other. The realization was submitted in midterm report, and then we forwarded towards their active and passive impact on the market. Active means how a feature drives its own market and passive is how it influence the contemporary market. We took hypothesis testing, predictive analysis, forecasting models as the key tools here to answer the following questions: how one market is influencing other, what will be the price and demand of the markets in the next few years, what is the effect of neighborhood on the market, how the market demand changes weekly and monthly, what effects the price and the reviews on the market and who are the top earners in the market. For data analysis we first cleaned and extracted features from our data using python. For different files cleaning and feature extraction were different and the respective description is added in each analysis section. Then we used forecasting and predictive models from python and to show the results we mostly used python seaborn, bokeh libraries, D3, Tableau and Amcharts [30].

3. Data Cleaning and Management

We performed following data cleansing to perform trend and seasonality analysis of Airbnb and long-term rental market; our data source contained listings.csv, neighborhood csv, calendar csv and review csv for Toronto over the years 2015-2019. The calendar data was in a specific date, month, weekdays format, the daily prices transformed from string to float data and categorical feature: 'availability' was shaped into logical value. Major cleaning operations performed to bring the features of "listing.csv" to specific format for fitting them into specific predictive models. The file contained 52 features, but for per night price prediction most important 20 predictors are selected by running random forest and gradient boosting models. The missing values were imputed and outliers were removed using scikit learning, currency data was formatted into float values and review score range, amenities, response time and other 7 categorical values were encoded differently. For the Review Rating Predictions 'comments' from the 'review.csv' was processed with Natural Language Processing library of python. 'neighbourhood.csv' was used for neighborhood modeling by processing the "Zip code" and "Neighborhood" attributes to latitude and longitude.

4. Results and Discussions

The key analysis results and visualizations are described in the following sections.

This part of our research is a focused research is to investigate how Airbnb is draining houses from Toronto and Vancouver housing stock and to shrink the real estate market. Our focus is on three major cities in Ontario, Canada; with total population 37,193,795. The selected cities Toronto and Vancouver, [4]

	2011	**2016**	**Percent Growth**
Toronto	2,615,060	2,731,571	6.2%
Montreal	1,704,694	1,649,519	4.2%
Vancouver	603,502	631,486	6.5%

Table 1. Population of cities under study

According to Statistics Canada [5] "The majority of occupied private dwellings in Canada in 2016 were single-detached houses. Single-detached houses represented 53.6% of all dwelling types in 2016. This share has been declining over the past three decades. The share of dwellings that were apartments was highest in The Census Metropolitan Areas (CMAs) of Montréal, Vancouver."

While determining any possible effect of Airbnb it may have on housing market of Toronto, an important factor is the scale of Airbnb. According to the Canadian census data in 2016 (Table 2), total number of houses in Toronto 1,179,057 and total number of entire houses on Airbnb is 12,374 in year 2018 which represents only 1.04% of Toronto housing units. In Year 2011, total number of listings in Toronto Airbnb [6] was 12,801 and total number of housing units was 1,107,851 that represents only 1.3% only. According to the numbers in Table 3, during the period of two years from 2016 – 2018, total number of listings including entire house, shared room and private room as on Airbnb; that was 12,801 houses in 2016 has increased to 19,255 in 2018 that indicates the number of listings increased by 50% in two years. Figure 4 indicates the major increase was observed in listing type "Private Room" and "Shared Room" that increased by 1200% and 298% in these two years, respectively.

In Vancouver city, total number of houses is 309,418 in year 2016 and the total number of listings on Airbnb [6] is 5483 that includes entire house/apt, private room and shared room. Table 4, reveals the statistics in year 2016, Figure 4 demonstrates a visible decrease of

22% in total number of listings was observed. Similarly, the decrease of 18% ruled the Vancouver short-term rental market for entire houses. However, in other categories of listing, e.g. private room is decreased to 12% and shared room has observed huge decrement of 75% in year 2018.

Toronto	2017	2018	
Total Housing Units	1,179,057	1,179,057	
Airbnb	12,714	19,255	1.6 %

Table 2. Toronto City House Stock in Year 2017-2018

	2016	2018	Increase
Airbnb Listings	12,801	19,255	150%
Entire House/Apt	8,294	12,374	49%
Private Room	545	6,526	1097%
Shared Room	119	355	198%

Table 3. Toronto Airbnb Listings Comparison in Year 2016-2018

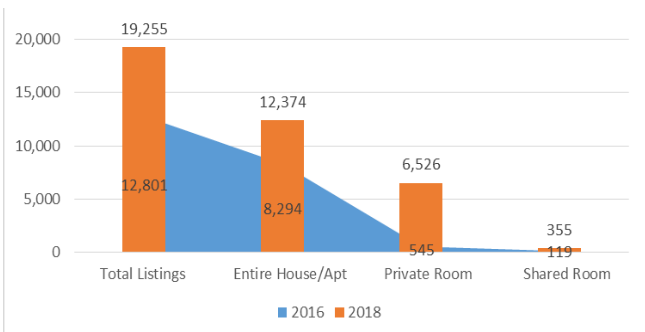

Figure 2. Toronto Airbnb Listings Comparison in Year 2016-2018.

	2016	2018	Decrease
Airbnb Listings	5483	4278	-22%
Entire House/Apt	4025	3283	-18 %
Private Room	1667	1473	-12 %
Shared Room	151	38	-75 %

Table 4. Vancouver Airbnb Listings Comparison 2016-2018

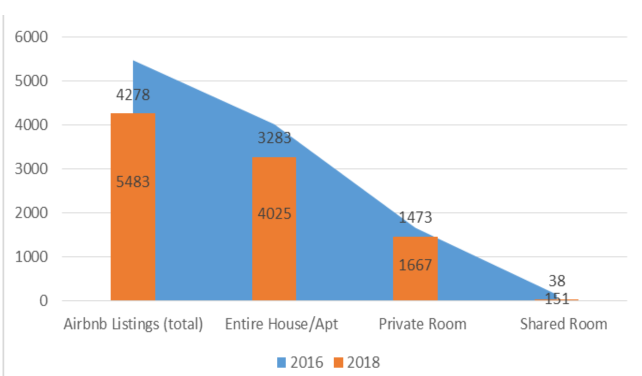

Figure 3. Vancouver Airbnb Listings Comparison 2016-2018

We have explored Airbnb listing and review data for Toronto Only We were interested in understanding how Airbnb operated around the world, specifically what factors determined the pricing and how visitors appraise their experience with host, listing and surroundings. Our research hypotheses question is how prices of Airbnb and Long-term Market are determined. We ran this test for Airbnb Toronto dataset and the results (Figure 4); According to the decision tree model, "room type", "review rating" does a good job in deciding the price level.

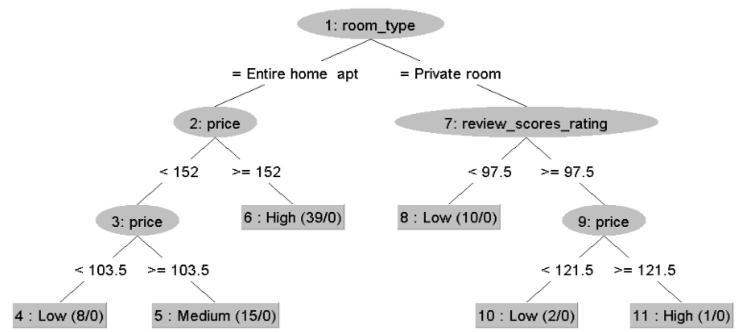

Figure 4. Decision Tree: Toronto Airbnb

We ran pruned C4.5 decision tree, using confidence factor 0.25 and batch size is 10 for both of the market along with reduced error pruning, Laplace correction. We used the host_listings_count, neighbourhood, property_type, room_type, price_level (low, medium, high), review_scores_rating attributes to test the determinant factors for Airbnb price hype with 10-fold cross-validation with 77%. For permanent market we used the attributes property type, vacancy rate, neighborhood, unemployment rate, migration rate, housing index for taking decision and achieved a classification accuracy of 73.44%. But as we limited our tree up to depth 4, most of the features may not be present in the figure 4 and 5.

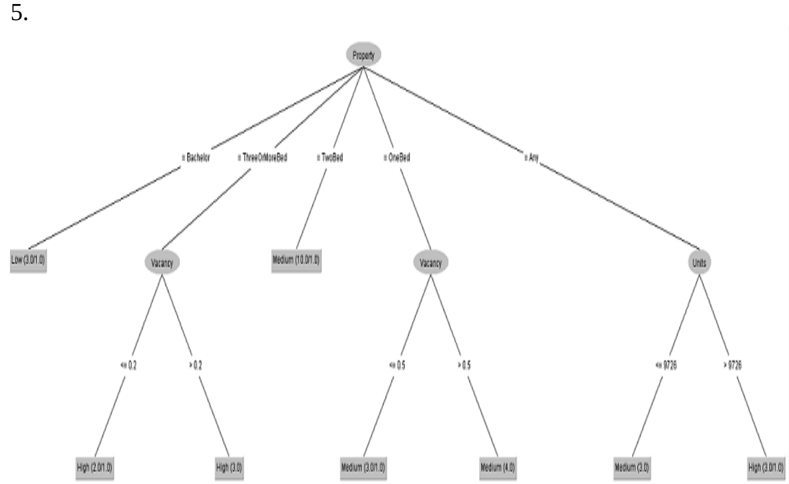

Figure 5. Decision Tree: Rental Market

For long term rental, most important factors for taking decisions are vacancy rate, room type, number of units in the market. We applied two other popular classification model Naïve Bayes and K-nearest neighbor to justify that our decision tree is not overestimation the accuracy. For Naive Bayes with estimator classes, 10 batch size, and supervised discretization, kernel estimator we got even higher accuracy up to 80.1%, 89.9329% for long and short-term market respectively. Our K-NN classifier 3 neighbors, 10 batch size and distance weighting and achieved 78% and 77.777% accuracy for the mentioned markets. In a word, the factors that are responsible for price hype are different in both of the market.

Another measurable dimension is rent gap; accoding to Neil Smith's concept of the Rent Gap is that over time, as a neighborhood's properties deteriorate, the actual revenue landowners are able to earn from their properties also tends to decline, but the possible revenue (were the properties to be redeveloped or renovated) tends to increase. If this "gap" between actual and potential revenue gets large enough, eventually it becomes likely that redevelopment capital arrives to take advantage of the profit-making opportunity. The result is renovations, new construction, displacement of existing tenants, and the arrival of more affluent tenants and homeowners—gentrification.

To measure the "unfilled" rent gap, we compared Airbnb host revenues with what those hosts likely could have earned on the traditional rental market. The intuition here is that, in the absence of strong policies to prevent property owners from converting long-term rentals to short-term rentals, a rough revenue equilibrium should emerge between the two. If you are a landlord earning \$1800/month in rent for an apartment, but you could be earning \$3700/month if you put that same apartment on Airbnb, you will have a strong incentive to get rid of your current tenant and do just that. This, of course, is the rent gap. If enough landlords take advantage of these opportunities, we should expect yearly rent bins to increase so if they cannot put their house on Airbnb they can try to match level of earning from traditional rent market to short term rents market. In order to measure the size of this outstanding rent gap, we compared the average revenue earned by full-time, whole-unit Airbnb listings in a given census tract with the median contract rent in that

4.2. Trend Analysis of Airbnb and Long-Term Rental Market

After performing the data preprocessing and feature extraction we implemented forecasting models[19] on two datasets. For long term data we cleared the unusual prices and availability rates and brought it to proper csv formats after merging by property types. On the processed files, we ran trend analysis and plotted in figure 6 the Autocorrelation Factor plot of long-term market price change. We can find out clear spikes in the autocorrelation at every 9 year. It means that the time series is correlated with itself by 9 years shifting, in other word seasonality of 9 years.

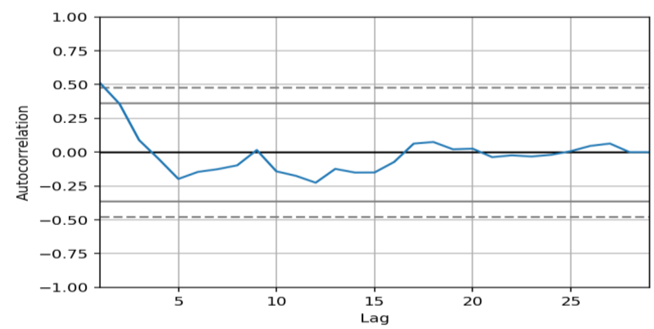

Figure 6. ACF of Permanent Rental Market

Then we applied Autoregressive Integrated Moving Average (ARIMA) forecasting model over our two data sets. With ARIMA analytics we forecasted the market price over next few months and compared it to the real price of Airbnb and permanent rental time series. In figure 7, we set forecasts to start at 2018–02–01 to the end of the data for long-term market, as we didn't have data after June 2018. The Mean Squared Error of that forecast is 1.16.

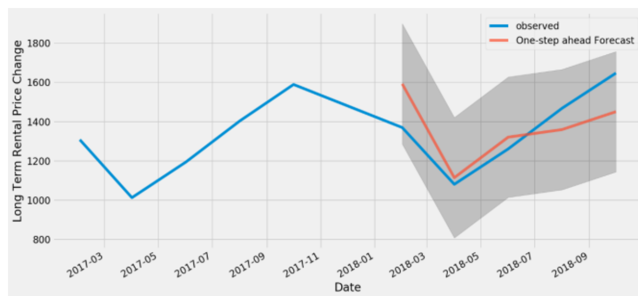

Figure 7. Permanent Rental Price Forecasting from 2017 March to 2018 March Toronto

We applied Dickey-Fuller test and found out that Airbnb and Permanent rental price is not stationary. We applied SARIMA through python SARIMAX package and uncovered the optimum model parameters (p, d, q) x (P, D, Q, s) through Akaike Information Criterion (AIC) function lowest value. From the figure 8 we can realize that our model fitting is acceptable as the residual is following normal distribution and the residual is showing a seasonality of 7 days in the Correlogram. We fitted SARIMA with order (1, 1, 1) and seasonal_order (1, 1, 1, 12) parameters which has a lowest AIC of 1554.35.

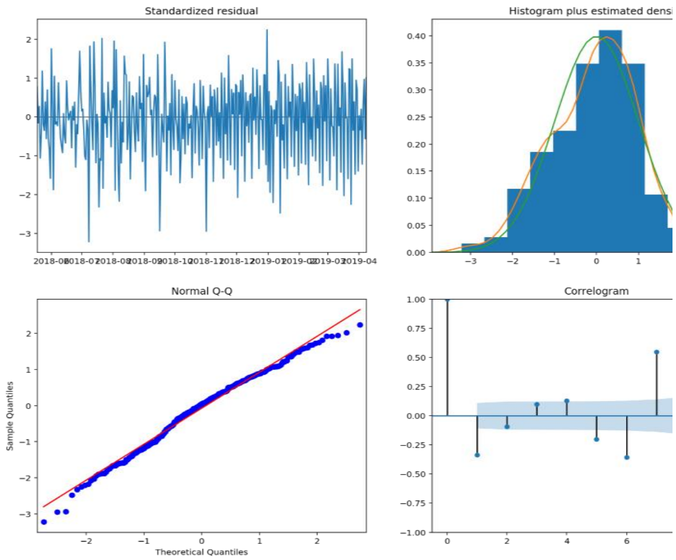

Figure 8. Residual Plot and ACF of Airbnb Market Price Trend.

4.2. Seasonality in Demand and Pricing of Airbnb Calendar

This analysis will show hypothetical seasonal pattern of Airbnb listings price and demand. We have 1619 days and 34255 unique listings in the calendar data and Timestamp starts expands between '2015-06-07' and '2020-03-10'. Our reorganized calendar data covers six-year periods with price and availability every day. Therefore, first we want to analyze the most popular times of the year for rentals of Toronto Airbnb. For a Toronto homeowner considering renting out a home on Airbnb, it would be useful to know the most popular times of the year to enable them to plan the timing for any preparation of the home for the peak season, as well as planning maintenance or upkeep work for less popular months. Among the total listings, over six years 13591002 were not available and 10106623 were available. If we look at it by year segmentation-

Start Date	**End date**	**Available**	**Not Available**	**Availability**
2015-06-07	2016-06-05	1487547	622883	70.5%
2016-07-05	2017-07-04	1973857	1751698	52.9%
2017-06-03	2018-06-02	1988684	2651926	42.8%
2018-07-06	2019-07-06	2007029	4040656	33.2%
2019-01-13	2020-01-12	1487547	622883	70%
2015-06-07	2020-01-12	10106623	13591002	42.6%

Table 5 . Airbnb Market Demand From 2015 to 2020.

Next to find out weekly, monthly price and demand fluctuations we have converted the 'available' column formatting to 0 if available and 1 if not busy. Besides, we needed to remove "$" symbol in price column and convert it to numeric, and convert date to date and time.

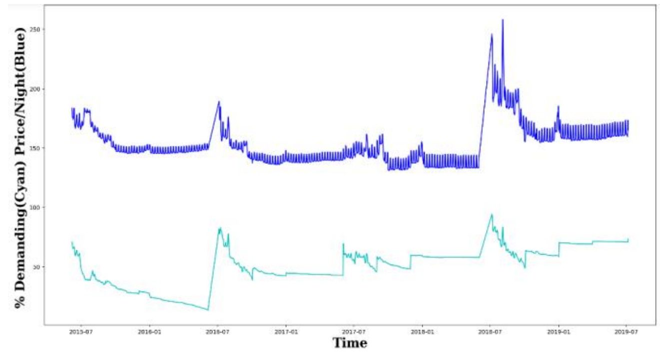

Figure 9. Clear spikes of number of listings availability and prices from 2015 to 2019

Figure 9 demonstrates that Airbnb availability is not stable all year round and it increases in the first few months of the year. Price is increasing from 2018 July as home availability decreases after that time. We broke down the 'date' feature, made two new feature 'weekday' and 'month' to see that effect of months, and weekends on the Airbnb market.

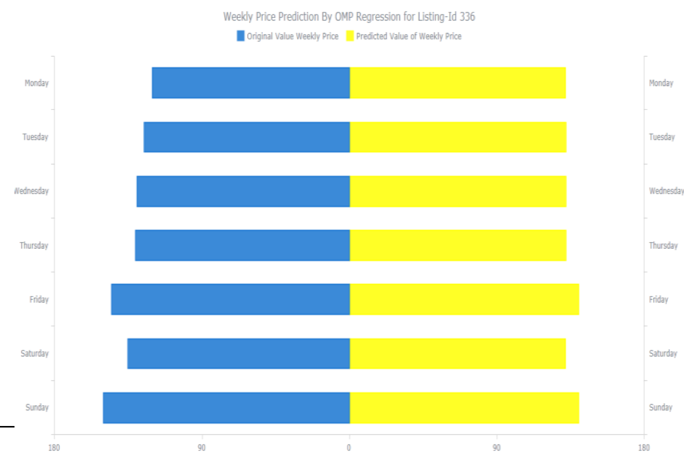

Figure 10. Weekdays price variation of Airbnb by listing ID.

We have used our OMP pricing model to predict this weekly price and showed the result in Figure 10. It is clear that price start rising one day before the weekend and one Sunday price is the highest among the week. There is a mark able periodical price-moving circle corresponding to months in Figure 11, D3 radial column graph. It shows the percentage of listings that become unavailable in Toronto per month, through 2015 to 2019 with spikes from May to September at Summer times. Moreover, the highest unavailability is of listings occurs near June then September. The busy months in Toronto seems after April and extend to the summer. So, first four months of the year the best months visiting Toronto as accommodation is more available at that time at an affordable price.

Figure 11. Airbnb Market Demand throughout the Year

4.3. Neighborhood effect on Airbnb and Long-Term Rental Market

For Airbnb, neighborhood variable influences the monthly market demand and price more than the long-term market. To determine neighborhood effect, we processed the 'neighborhood.csv' file and merged it with the 'listing.csv' file based on listing_id to determine how fast an id is getting booked after posting depending on places. Figure 12, we see that each of the areas has price and demand fluctuation throughout 12 months although in the summer the price along with demand seems to be higher. We found that the Sunnybrook, Forest Hill neighborhood generated the highest overall revenues, due to higher average price.

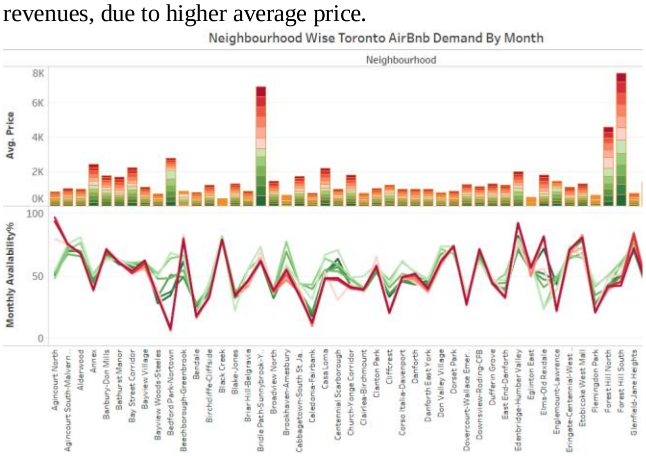

Figure 12. Demand and Price Per Night Variation Throughout Months of the Year According to Area

Next, we move to determine the importance of location in rental market. Both Airbnb and long-term rental show area wise demand and price variation. In Figure 13, bubble chart shows that York, Brampton, Markham, Etobicoke, Mississauga have higher rental demand that other areas.

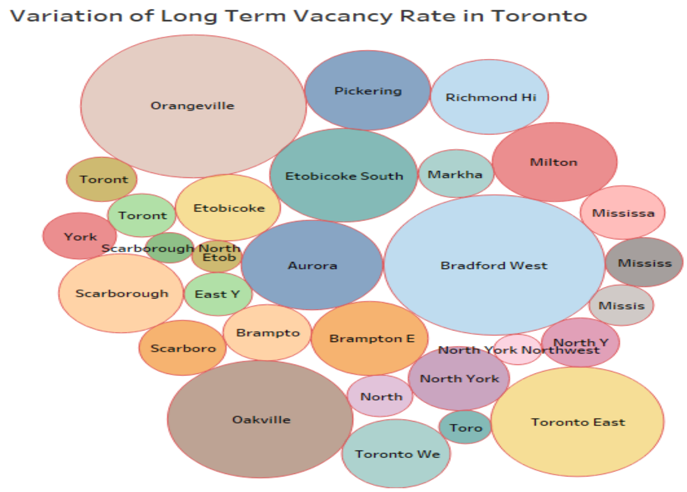

Figure 13. Area wise demand variation of long-term rental.

The area wise Airbnb market demand depends on the comfortability and the nearby attractive places. Figure 14, shows most of the areas are trying to provide amenities such as ready to use kitchen, dryer, washer, Wi-Fi, internet, toiletries and so on. If the neighborhood is instantly bookable with all other facilities then the place is always on high demand.

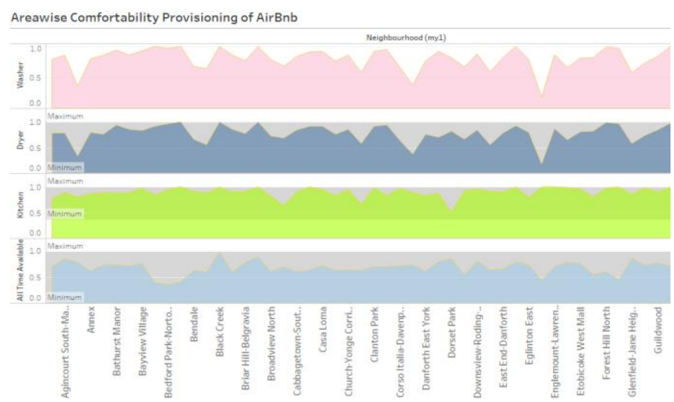

Figure 14. Area wise Comfortability of Airbnb

4.4. Rating and Review effects on Airbnb Market Only

Airbnb homeowners should try to maximize their revenues through the offering the guests a great experience to ensure a good rating. For that we predicted the main factors for getting higher ratings because homes with a higher rating would tend to attract other guests to stay there, ensuring that a home continues generating rentals. In Toronto 'review_csv' dataset, 11000 listings get review score in between 90 to 100 and 7712 listings have no review_scores_rating values. So, majority of the listings possess overall favorable ratings. We replace any NaN values that have no review with 'No Reviews' and we remove any remaining inconsistent NaN values that have a number_of_reviews greater that zero. We will also convert the review_scores_ratings into buckets. Figure 15 tells us that listings with prices that range around 0 to 500 get the most reviews, probably because they are in the most reasonable price range. The number quickly declines as the price goes up. This indicates that more people book listings that are around $0 - 500 in prices. This shows that it is not necessary for an expensive listing to have large number of reviews. So, there is no exact relation between prices and number of reviews for a listing.

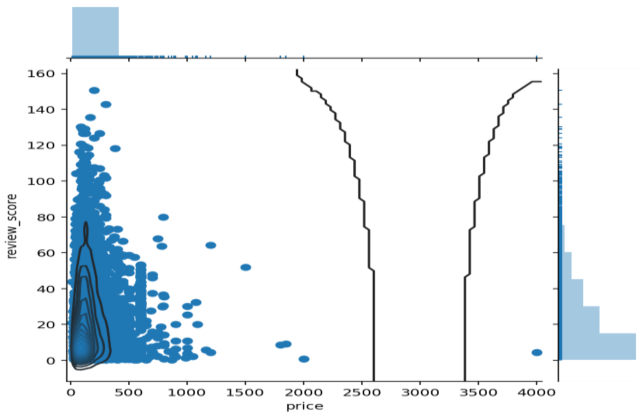

Figure 15. Review Score Dependence of Airbnb Price

In order to identify other drivers of higher ratings, we have used Random Forest and Gradient Boosting Regression Models to determine the dominating features that have larger effects on the rating of the listing.

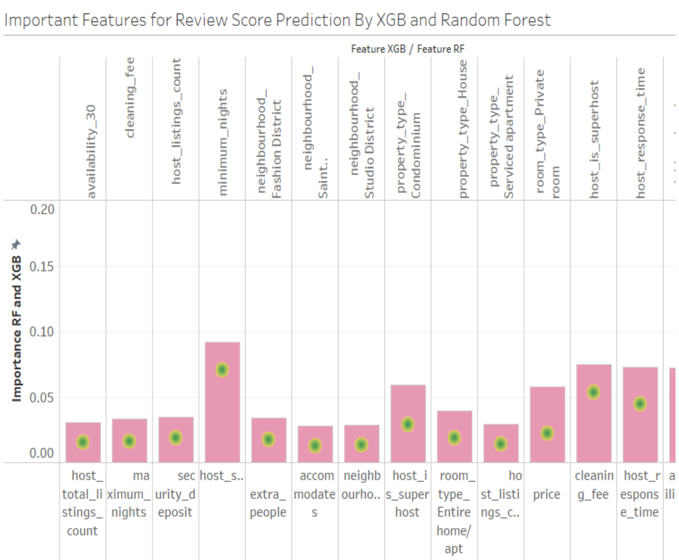

Figure 16. Factors that influence review score of Airbnb Market according to Boosting and Random Forest Model.

In Figure 16, we have showed the top 15 found from the two models among the total 80 features. Minimum_number_of_nights, host_is_superhost, cleanliness, host¬_response_time, accommodates, property_type, neighborhood, room_type- these features exerts the most influence on review ratings. Depending on the review, the owner needs to reduce the price if the previous score is bad or add additional amenities or extra services. To predict and see the review rating, we constructed a new variable review_score by multiplying review_rating and number_of_review_per_month. We ran investigation on reviewers' sentiment to determine how it effects Airbnb market. We used publicly available pre-trained Vader Sentiment Model based on NLTK to check what the reviewers' sentiment about the listings.

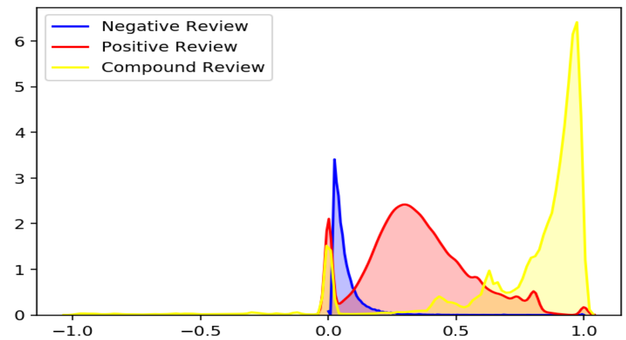

Figure 17. Distribution of Review Sentiment

The overwhelming majority of reviews (>80%) according to density plot in figure 17 appears to be positive. Negative and compound reviews have multi-peaked structure due to some model misclassification. 15% of the reviews are strongly negative, and 50% can be termed as a mixture of positive and negative. Number of unique reviews for particular id is a pretty big range from 1 to 677. As review number is very large, we only considered listings having at least 100 reviews for applying LSTM neural network model. The LSTM model forecasts reviewer's sentiment against the `listing_id` and compare against the actual rating. Figure 18 is a comparison of different optimizers of LSTM model, we see that SGD applies best to our case.

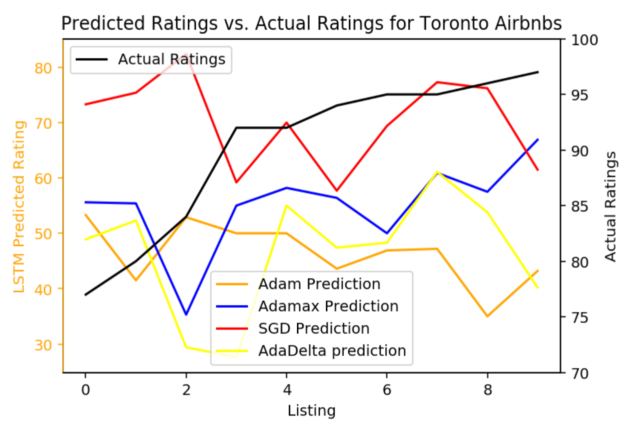

Figure 18. Predicted versus actual rating found after applying LSTM model on reviewers' comments.

4.5. Predictive Model Analysis on Long-Term and Short-Term Rental Market

We have tried to predict what the main causes behind Airbnb price difference are. We performed target variable examination through gradient boosting and random forest to gain an understanding of their possible influences on Airbnb per night price [14][15][16]. Target variable 'Price' has a lot of variation, so we took both the original price and its natural logarithm to build models. We preprocessed the 'listings.csv' and among 80 (categorical, numeric, boolean, text) features we chose the most important 20. Among

19255 rows of information, and log price fluctuates between 3 to 7.7 and found out that Space, description, experiences offered, neighborhood_overview, notes, thumbnail_url, medium_url, xl_picture_url,host_acceptance_rate, license, jurisdiction names neighbourhood_group_cleansed, are the biggest culprits for missing values. Besides them scrape_id, last scraped, picture_url, host_picture_url, neighbourhood_group_cleansed, square feet, monthly price, weekly price weekly were removed since we are focusing on single day listings. Rows with nan and inconsistent values were removed and finally we got rows of 13782.

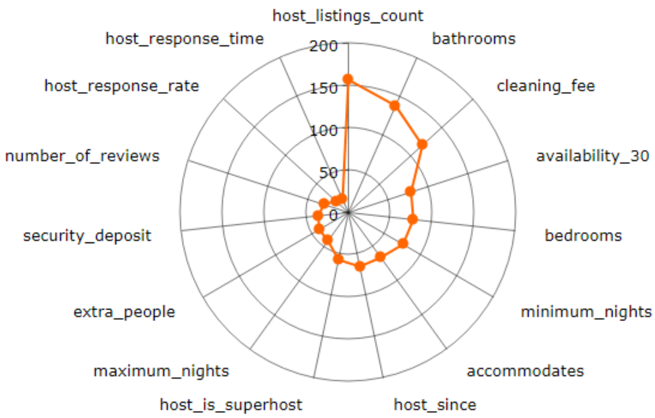

Figure 19. Scores of important features for price prediction according to XGB model.

Figure 19 shows us the most important 15 features found from XGB (gradient boosting) model for Toronto Airbnb target features. We multiplied the score by 100 to make them visible the d3 polar chart. We ran 15 Regression Models with python scikit learn library and found out that support vector, KNN and neural net are not suitable for this data set rather simple models suit better with smaller Mean Absolute Error. The models' MAE (Mean Absolute Error) performance parameters are plotted in the figure 20 D3 pyramid chart. As we see, our MAE values are very small, specifying our models' best accuracy. The topmost models perform the best.

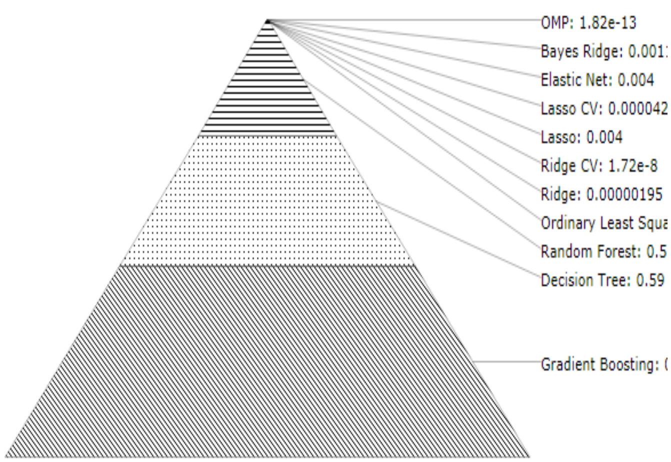

Figure 20. Pyramid Chart showing the MAE value of different regression model for predicting price

4.6. How the Income is different In Airbnb Market Earner and Permanent Rental Owners, who is the top earner

From unstructured text features such as summary, description analysis made word cloud to get a sense of the typical content of that feature. For a successful Airbnb advertisement, the sellers mainly focus their neighborhood zones. The following word cloud in figure 21 gives us an interesting insight into the area. We looked at the differences between the words used in listings for Airbnb locations in different Toronto neighborhoods by merging the features name, space, description, neighborhood description, neighborhood cleaned and build SGD Classifier to dug through 15130 words with log n scale and displayed most cited 400 words. It can be seen that unique words like cozy, Toronto, Car, Walking, Restaurant, close, city, min are very commonly words used when hosts are describing their homes. Word cloud satisfies the conclusion that the primary purpose of Airbnb is not to deliver extravagance accommodation facilities but to serve as an affordable and apposite place so that the tenant can easily stay and travel to the nearest center. When the hosts understand these purposes and their posting has these feature words focusing on location and amenities, they can charm many travelers and boost their income. According to Figure 21, most repetitive words are "great', "center", "bar", "walking" and "cozy" that plays an important role in attracting more tenants.

Figure 21. Word Cloud Recommendations for Describing Airbnb Location

While we want to compare the income from Airbnb to long-term market [20], we can look in the figure 22. We see that 85% of the Airbnb rent is between $10-$250 CAD per night and they are available throughout the month. If the listing gets booked 50% the time, then the income becomes $3750 CAD per month. While the maximum income possible from long-term rental in this case is $1500 CAD per month (Figure 23). Therefore, the Airbnb seller in having more than double income than the long-term rental.

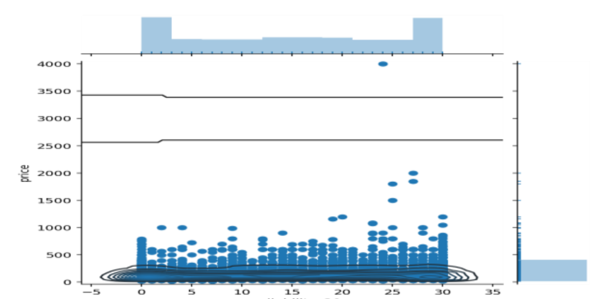

Figure 22. Airbnb Earning

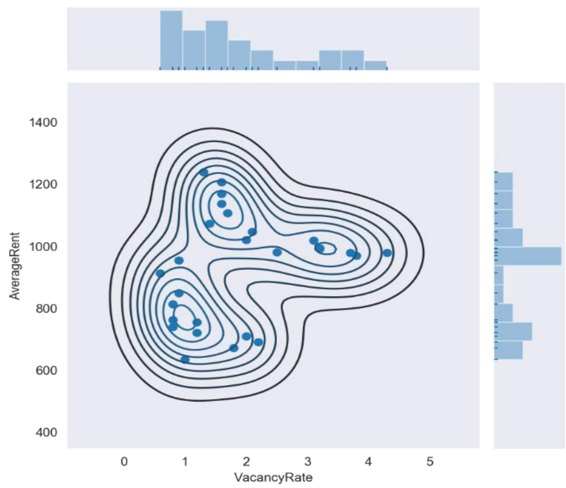

Figure 23. Long Term Rental Earning

Airbnb supply traveler cheaper places to stay for short durations of time without any monthly commitment. But this market includes some listings with a high pricing as well for the hosts who require more comfortability and bigger house. In Airbnb all are not earning in a similar pattern, some hosts are low and some are high earners. In figure 24, we are showing the comparison between Airbnb high earners and low earners.

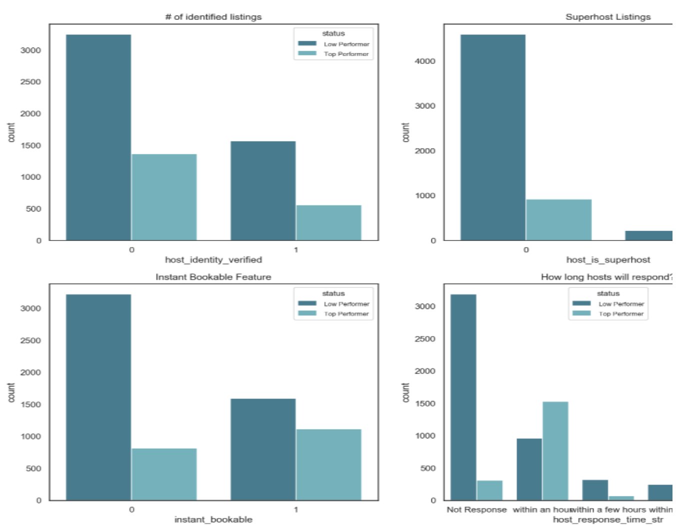

Figure 24. Top earners in Toronto Airbnb

We see in figure 24 that for top performer, almost 90% of the host's listings has been identified by Airbnb and for the low earner 38% of host's listings hasn't been identified by Airbnb. 40% Top earner is Super host Predicate while most of the low performers are not super-host. Instant bookable feature is very important but 62% of the top listings do not activate their instant_booking by ~62% and in low earner group, more than 90% has not the instant bookable system. ~78% of top listings' hosts always response conversations immediately but many of host of low performer listings respond the conversation longer than top-performer listings. Therefore, we can say if the host on Airbnb is very responsive and its property is instantly bookable with other convenient features, this can help hosts to be among high earners.

6. Related Work

To Best of our knowledge, Canadian Airbnb market is not explored to its potential. Airbnb booked "entire home" listings represent a tiny fraction (0.85%) of Toronto housing units. Frequently booked entire home listings represent 0.20% of Toronto's housing units.1 Frequently booked entire home listings that out-compete the long-term market represent 0.07% of Toronto housing units[6]

Cities should regulate short-term rentals according to three simple principles: 1) one host, one rental; 2) no full-time, entire-home rentals; 3) platforms responsible for enforcement. The City of Amsterdam provides an encouraging example of these principles in practice, while Fairbnb.ca's recent regulatory proposals for Toronto offers a closer-to-home.

In recent years, multiple strands of scientific literature on the sharing economy have evolved across several IS-related fields, covering subjects such as consumption practice, innovation, lifestyle and social movement, the sharing paradigm, and trust (Cheng, 2016). Trust is considered to be of particular importance for the sharing economy and especially for P2P markets (Belk,56 2010; Botsman and Rogers, 2010; Ert et al., 2016; Hawlitschek, Teubner, and Gimpel 2016; Strader and Ramaswami 2002). Consequently, P2P platform operators have implemented mechanisms and signals to facilitate the formation of trust between providers and consumers (Resnick and Zeckhauser, 2002; Zervas et al., 2015), including identity verification, mutual rating and review schemes, insurances, and specific web design techniques
(Gebbia, 2016; Teubner, 2014). Reputation and electronic word of mouth thereby help to assess the trustworthiness of peers in electronic communities (Xiong and Liu, 2004).

7. Conclusion

On concluding note, Airbnb is not affecting Toronto real estate market as it is capturing a very minimal <2% housing stock out of Toronto housing stock. However, in Vancouver, Airbnb as decreased its scale by reducing its listing stock in comparison to 2016. We found out the best time and place for Toronto homeowners' highest revenue-generation. Homeowner rents out their home is to earn revenue from either long or short-term rentals. We already know the highest revenue-generating season of the year for Airbnb but long-term rental cannot exhibit seasonal price fluctuation. Therefore, short-term business aims to maximize revenues from renting out their property then. Pulling out the specific average prices in the month of March in 2018, we can see that the price ranged from $138–$140. Meanwhile, to identify the areas, which would generate the most revenue for a Toronto homeowner, we performed neighborhood analysis the analysis for short and long-term market. Areas with the highest price may not be popular with guests or renter. Therefore, we cannot say that costly areas would give the most revenue to long or short-term business. The most popular areas can be identified with the highest number of listing number, it was observed that in the year 2016, the Broadway neighborhood was the clear top revenue-generating neighborhood for Seattle homeowners, while Bell town is a distant second. Meanwhile, the other neighborhoods are about 60% less revenue generating compared to Broadway. Hence, an actionable next step for the prospective Airbnb homeowner is to check which neighborhood their home is in and see what is the competitive prices for their home in that time of year, while checking how popular their neighborhoods is. That being said, an important caveat for this analysis is that the data is only for one year's worth of house listings. The trends might be different for 2018.

References

[1] David Wachsmuth, Danielle Kerrigan, David Chaney, Andrea Shillolo.2017. Short-term Cities: Airbnb's Impact on Canadian Housing Markets. UPGo, the Urban Politics and Governance research group at McGill University.

[2] Barron, K., Kung, E., & Proserpio, D. (2017). The Sharing Economy and Housing Affordability: Evidence from Airbnb. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3006832

[3] BJH Advisors. (2016). Short Changing New York City: The Impact of Airbnb on New York City's Housing Market. Policy report prepared for Housing Conservation Coordinators and MFY Legal Services.

[4] CTV Montreal (2017). "Plateau Mont Royal taking action against excessive Airbnb rentals." Retrieved May 10, 2017 from http://montreal.ctvnews.ca/rising-number-of-complaints-about-airbnbrentalsin-plateau-1.3530677

[5] Knight, B. (2017). Airbnb dominated by professional landlords. Deutsche Welle. Retrieved August 4, 2017 from http://www.dw.com/en/airbnb-dominatedby-professional-landlords/a-39972379

[6] Peter Coles, Head Economist, Airbnb, Vanessa Lauf, Policy Researcher, Airbnb. 2016. Housing, and the City of Toronto.

[7] Richard Martinez, Anthony Carrington, Tiffany Kuo, Lena Tarhuni, Nour Adel Zaki Abdel-Motaal.2017. The Impact of an AirBnB Host's Listing Description 'Sentiment' and Length On Occupancy Rates, https://arxiv.org/abs/1711.09196

[8] Botsman, R., and R. Rogers (2010). What's Mine Is Yours: How Collaborative Consumption Is Changing the Way We Live. New York: Harper Collins.

[9] Cheng, M. (2016). "Sharing Economy: A Review and Agenda for Future Research," International Journal of Hospitality Management 57: 60–70.

[10] Hawlitschek, F., T. Teubner, and H. Gimpel (2016). "Understanding the Sharing Economy – Drivers and Impediments for Participation in Peer-to-Peer Rental," in HICSS 2016 Proceedings, 4782–4791.

[11] Teubner, Timm, Florian Hawlitschek, and David Dann (2017), "Price Determinants on Airbnb: How Reputation Pays Off in the Sharing Economy," Journal of Self-Governance and Management Economics 5(4): 53–80

[12] Lee, D. (2016). How Airbnb Short-Term Rentals Exacerbate Los Angeles's Affordable Housing Crisis: Analysis and Policy Recommendations. Harvard Law & Policy Review 10: 229-253.

[13] Knight, B. (2017). Airbnb dominated by professional landlords. Deutsche Welle. Retrieved August 4, 2017 from http://www.dw.com/en/airbnb-dominatedby-professional-landlords/a-39972379

[14] https://towardsdatascience.com/statistical-overview-of-barcelonas-airbnb-market-83dc7d6be648

[15] https://www.kaggle.com/jeremywickman/sleeping-in-seattle-predicting-airbnb-ratings

[16] Retrieved from https://www.kaggle.com/aleksandradeis/airbnb-seattle-reservation-prices-analysis

[17] https://infogram.com/app/#/edit/86ab02ec-a7ea-4f05-aa26-db3e87ef4524

[18] https://davidwachsmuth.com/2017/03/17/how-do-we-measure-airbnbs-impact-on-housing-and-gentrification/

[19] https://www.kaggle.com/firdausprabowo/price-forecasting-using-sarima#

[20] https://www.kaggle.com/yogi045/how-to-become-top-earner-in-airbnb

[21] https://www.kaggle.com/ibjohnsson/predicting-listing-prices

[22] https://www.kaggle.com/aleksandradeis/airbnb-seattle-reservation-pricesanalysis

[23] https://www.dataquest.io/blog/understanding-regression-error-metric

[24] https://www.jasondavies.com/wordcloud/

[25] https://bl.ocks.org/kerryrodden/766f8f6d31f645c39f488a0befa1e3c8

[26] https://towardsdatascience.com/exploring-machine-learning-for-airbnb-listings-in-toronto-efdbdeba2644

[27] https://bl.ocks.org/kerryrodden/7090426

[28] https://datavizcatalogue.com/methods/radial_bar_chart.html

[29]https://github.com/ruchigupta19/Boston-Airbnb-data analysis/tree/master/Analysis

[30] https://live.amcharts.com/new/edit/

[31] Rental Data Tables for Research. https://www.cmhc-schl.gc.ca/en/rental-housing

[32] Toronto and Vancouver Airbnb Data. insideairbnb.com/get-the-data.html

[33] City of Vancouver moves to ban Airbnb in secondary homes. https://globalnews.ca/news/4137803/city-vancouver-airbnb-ban-second-homes/

[34] Toronto passes strict Airbnb rules aimed at preserving long-term rental supply https://www.theglobeandmail.com/news/toronto/toronto-passes-strict-airbnb-rules-aimed-at-preserving-long-term-rental supply/article37265435/