

Final Report

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Contents

1	Introduction	1
2	Exploration	2
2.1	Regression Model Selection	3
2.2	Classification Model Selection	5
3	Analysis of Results	5

1 Introduction

The main dataset we are working with in this project has data on Airbnb listings in Seattle. Through analyzing this data, we are trying to fulfill two main objectives. First, we are trying to determine whether several host and housing quality measurements have an effect on the price of a given listing. Second, we are attempting to determine whether these same measurements have an effect on the review score of the given listing. The first task is a regression based task and the second is a classification based solution. Our tasks have two different datasets, of which the price dataset has 5200 observations and 25 variables, including our response variable *price*. Our review dataset has 4043 observations and 26 variables, including our response variable *review_scores_rating*. Initially, there were 48 NA values in the price dataset and 34 NA values in the review dataset. These NA variables were entirely contained in 2 columns, *price* and *cleaning_fee*. We treated the NA values by converting them to 0, meaning that there was no price or cleaning fee for a given listing.

2 Exploration

We begin by taking a look at the different neighborhoods in Seattle. The table below summarizes the top and bottom five average prices of listings in each neighborhood and its proportion over both datasets. We see that about 18% of the listings alone are located in Downtown Seattle. On average, the price per listing there is about 60 dollars more expensive than the overall average of about 147 dollars. Note that in Queen Anne, a notoriously expensive area of Seattle, the average price is about 30 dollars more expensive than the overall average. This difference in price hints at the importance of location for an Airbnb listing.

	mean price	proportion
Downtown	204.23477	17.616961
Queen Anne	184.88353	6.954582
Cascade	173.61775	4.260357
Magnolia	153.17117	1.946791
Capitol Hill	144.67793	11.398992
University District	114.34861	2.839785
Northgate	105.79103	2.220165
Beacon Hill	104.43276	4.169707
Lake City	102.29285	1.678889
Delridge	89.65243	2.940082

Each listing in the dataset included its unique latitude and longitude coordinates. To make the latitude and longitude measurements more useful and to improve the feature set, we tabulated the latitude/longitude coordinates of five Seattle places of interest: downtown, the Space Needle, the Gum Wall, Pike Place Market, and the Great Wheel. We wrote a script that calculated, for each listing, the distance between the listing and each of the five important locations in Seattle. This provided context to our task because it established how well-located certain listings were in comparison to others.

More specifically, for both the regression and classification task, predicting *price* and classifying *review_scores_rating* in the best way required first looking at the data and evaluating the feature set. Both datasets contained the same feature set with the review dataset containing an extra variable - our response *review_scores_rating* for the classification task.

We continued by looking for potentially problematic features in the dataset. In the price dataset, there were

two: *amenities* and *room_type*. The *amenities* variable, for each listing, lists the specific amenities that the listing has such as wifi access, TV availability and air conditioning. The *room_type* variable lists the type of the room offered by a given listing. These two features presented problematic due to the number of levels of the factor variables.

Each index in the *amenities* column contained a dictionary containing that specific listing’s amenities. Logically, we decided to test if the number of amenities for a given listing would affect its price instead of the amenities themselves. We parsed the *amenities* column and produced a new feature *num_amenities* that reported the total number of amenities for each listing. We dropped the original amenities column from our analysis, and dropped the room type column as well from our analysis, as the ordering of its levels presented problems in the model creation process. We kept all other variables that were initially in the dataset in some form in our analysis.

Finally, multiple features in the dataset required recoding. For instance, we refactored the *host_is_superhost*, *host_identity_verified*, and *instant_bookable* variables that were originally true/false variables coded as “t” and “f” into 0/1 variables with 1 coded as true. `## maybe line of code here and below ##` The *host_response_rate* variable was a percentage in the original dataset, and was changed into a proportion. Two variables: *host_response_time* and *cancellation_policy* were refactored into categorical variables with numbers representing levels of factors instead of words. Our response variable *price* and the *cleaning_fee* variable contained the “\$” character before their values - this character was removed and the predictors were converted to numeric variables.

2.1 Regression Model Selection

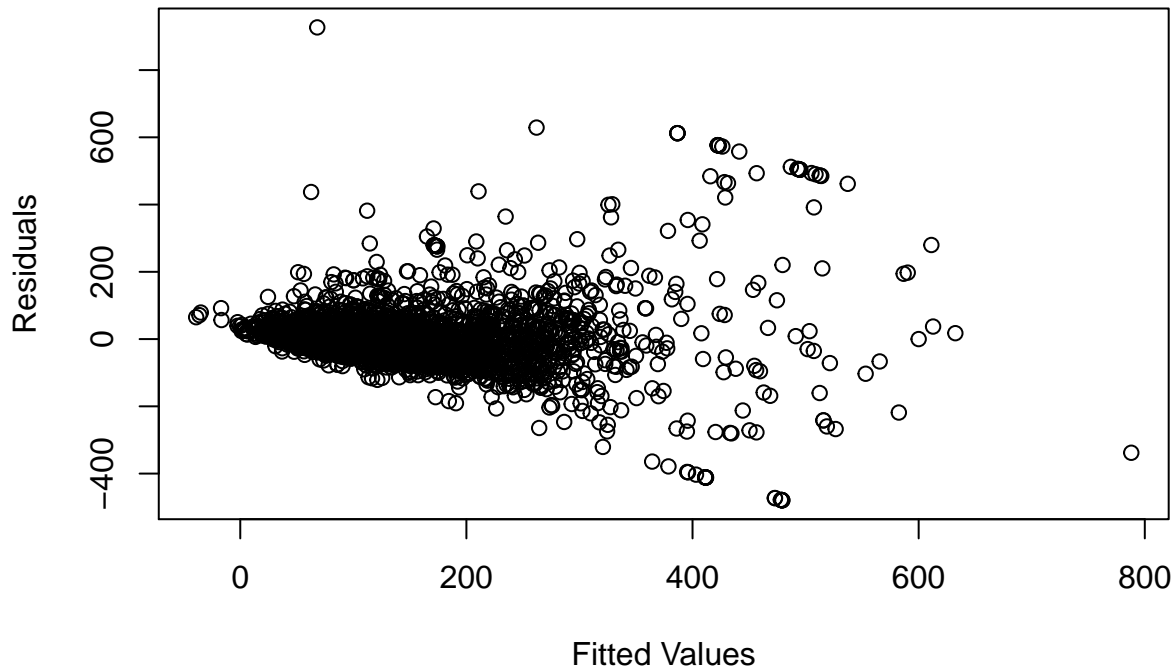
At this point, after processing and cleaning the data, we had a feature set that we felt good about. To move forward with the regression task, we knew that some variables had linear correlation with our response variable *price*, namely *cleaning_fee* and *beds*. It seemed that fitting a multiple linear regression model was a logical place to start as a baseline technique for prediction.

To begin, we split our price dataset into a training and test set with 75% of data in the price dataset allocated to training and 25% allocated to a validation test set. We fit a multiple linear regression model, regressing price against all the variables in our final, processed training set.

$$lm(price \sim ., data = price.train) \tag{1}$$

The goodness of the fit was evaluated in two ways: against our regression assumptions and with cross-validated mean squared error. The residuals vs fitted values plot of the fitted regression object, found below, showed a cluster of points around 0 with high outliers, potential influential points, and an uneven distribution. Our baseline linear model was not optimal for the dataset, and we inferred another technique could produce a better fit. The cross-validated error for the linear model using k-fold cross validation was around 11,000. ## check this number ##

Residuals vs Fitted Values



With our baseline in hand, we logically assumed that it's possible the fit could be improved by improving the bias-variance tradeoff we were dealing with. To make the model more generalizable and get a sense for which predictors were important, we fit a ridge and lasso model on our training set, where equations 2 and 3 represent ridge and lasso respectively.

$$cv.glmnet(model.matrix(price \sim ., data = price.train), price.train.price, alpha = 0) \quad (2)$$

$$cv.glmnet(model.matrix(price \sim ., data = price.train), price.train.price, alpha = 1) \quad (3)$$

We used cross validation techniques to establish the optimal lambda penalty value for both the ridge and lasso regression models above. Our cross-validated mean squared errors for both ridge and lasso were around 8,000 which was an improvement on our baseline model. ## check this number ## We further explored trees and random forests. Given the data had a mix of categorical and numeric predictors, with some outliers

in the data, trees and random forests provide a robust measure that does not lose predictive power to high outliers and non-linearity. We also fit a normal decision tree, and a pruned version of the tree, shown below.

$$tree = rpart(price \sim ., data = price.train) \quad (4)$$

$$pruned.tree = prune(tree, cp = 0.019) \quad (5)$$

From the plot of the decision tree we chose a cp parameter that minimized relative error. The cross validated mean squared errors both the normal decision tree and pruned tree improved upon ridge/lasso and were around 6,000.

Random forests are an algorithmic improvement on decision trees, due to their greedy search on a subset of features for the best split to make rather than evaluating all features in a decision tree. In addition, random forests retain the strengths of decision trees in working with numeric and categorical predictors and generally produce low bias, moderate variance models.

We fit a random forest with 500 trees as a baseline on our training set.

$$randomForest(price \sim ., data = price.train, ntree = 500) \quad (6)$$

Random forests had the lowest cross-validated mean squared error around 4000. The predictions that the random forest produced were the closest to the price of the listings in our training set. ## TuneRF here? ##

2.2 Classification Model Selection

3 Analysis of Results