House Prices Analysis Report

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This report has 4 sections: **README, Understanding the Problem, Data Exploration, Machine Learning**.

README

The code for this report is well-documented in the form of python files, where,
`./lib/1.geo_recovering.py` reads the original data and impute streets, neighborhoods, cities, counties, states, countries information to the data, and search & count the number of clinics, schools, restaurants, supermarkets, transportations around the location by Google Geocoding API.
`./lib/2.prepare_data.py` transforms/adds features by analysis specified in this report. `./lib/3.split_train_val_test.py` prepares the training/validation/testing data used for machine learning model.
`./lib/4.feature_engineering.py` defines experiment criteria used for training/testing different model iteratively for the purpose of feature engineering.

All experiments conditions and results are stored in `./experiments/exp_logs.xlsx`

`./visualize/visualize.py` is code for visualizations.

`./tmp` stores the intermediate data.

`./logs` stores the logs of model training.

`./data` stores the original data used for this project, which can be easily changed to data with a similar format.

Understanding the Problem

Essentially, the price changes can be divided into two parts: changes from the vehicle of the housing market and the quality of the house itself.

The market-level analysis is hard to be done since the window of House Prices Data is only 2 years. You can skip to the next paragraph if you are more interested in this specific data problem. Here I list the potential market-level analysis that can be done given more data and longer time:
1) **Substitutes Analysis**, e.g. trends of House Renting market can influence the House Buying market prices. 2) **Rivalry Analysis**, e.g. competitors' new products can change the rivalry dynamic and influence the prices on the market. 3) **New Entrants Analysis**, e.g. newcomers can bring new technology that changes the game or consume more raw materials that influence costs and prices. 4) **Bargaining Power of Buyers Analysis**, e.g. demographical changes over the area (growth of population, etc.) may change supplier/buyer ratio; also, customer's personal background, for example, her banking credit histories sometimes can influence the prices she gets.

We can do a product-level analysis for this single data set, which focuses on the **Bargaining Power of Suppliers**. The deal-breaking factors for house buyers are: 1. **Property**: Amenity, Age, structure, area size, decoration, luxury. 2. **Policy**: tax rate, interest rate, economic conditions. 3. **Location**: Neighborhood Safety, Transportation, Commercials (groceries, markets, restaurants), Schools (benefit for new parents), Hospitals (benefit for the old). (More details can be found in this quora answer.)

Our dataset has rich information for **property**, such as: - overall score: 'grade';
- structures: 'bedrooms', 'bathrooms', 'floors', 'waterfront', 'view';
- area size: 'sqft_living','sqft_lot','sqft_above', 'sqft_basement', 'sqft_living15', 'sqft_lot15';
- age: 'condition','date', 'yr_built', 'yr_renovated';

Policies seem a complicated & hard question, but actually, they are the same in one state, therefore, adding a categorical state name variable can roughly carry this information. However, since sales records in our data are only in Washington, this can be ignored.

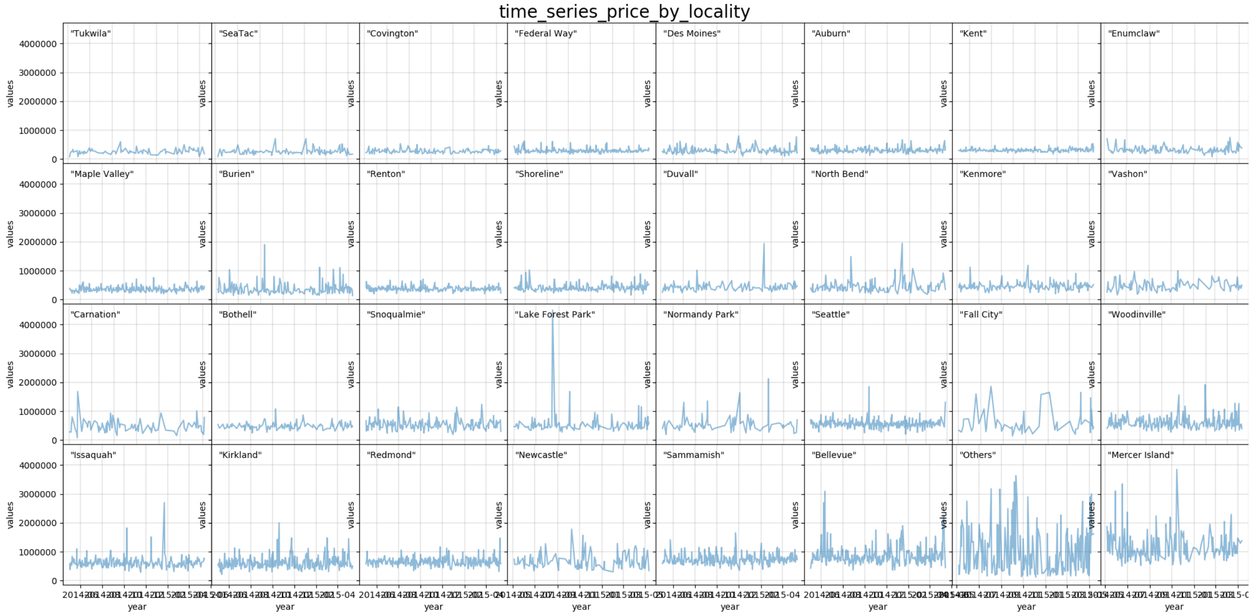
Location carries rich deal-breaking information and we get the latitude and longitude, it is promising to spend sometime recover it.
I use Google Reverse Geocoding API to recover **Street, Neighborhood, County, State, Country** information from longitude and altitude.
I then use Google Place API to search & count **Transportation, Supermarkets, Restaurants** in 10 minutes walking distance and *Schools and Hospitals** in 30 minutes walking distance.

The imputed data can be found in `./tmp/data_imputed.csv`.
The API query code can be found in `./lib/geo_recovering.py`.

Data Exploration

1. How prices flow with time (Time Series Analysis)

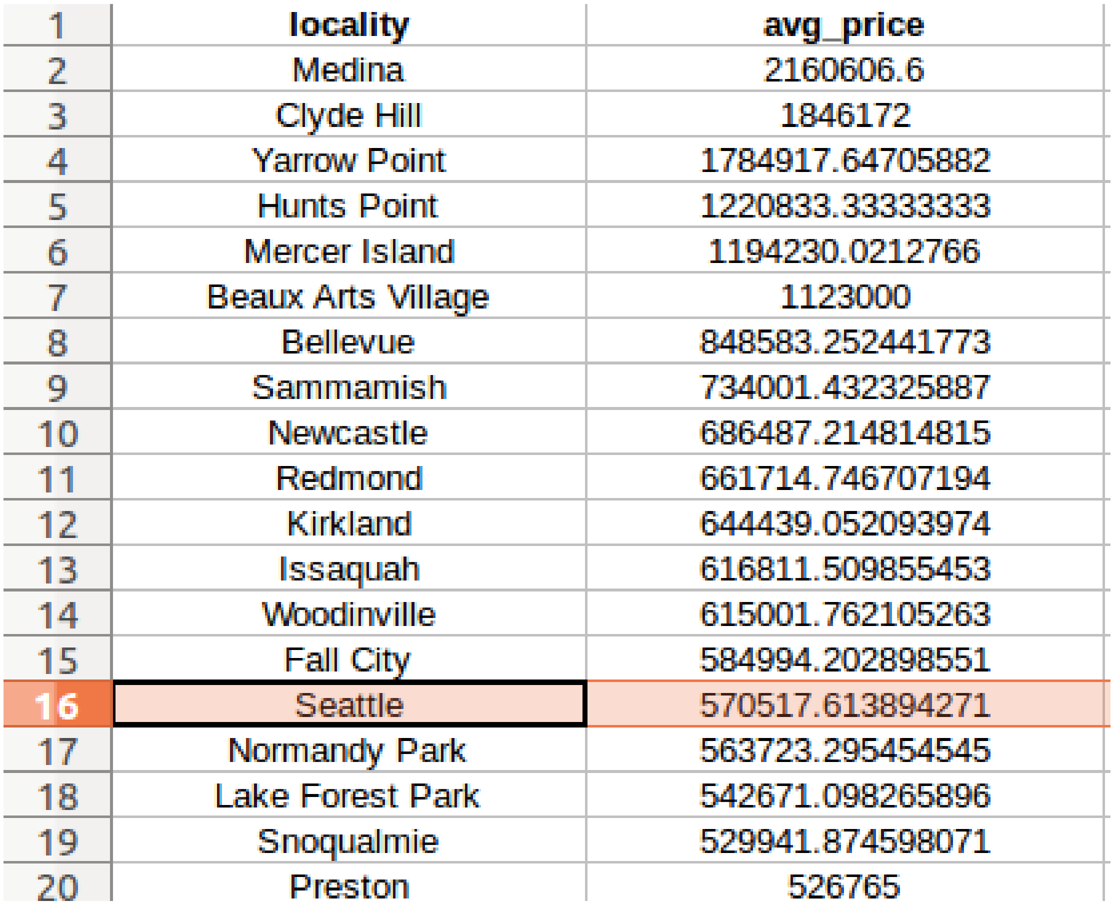
Whether it is reasonable to predict future by model depends on whether the price pattern is constant over time. I plot the daily mean price for each city (locality in the plot):



Peaks can be found in 8/32 cities we have (Seattle, Carnation, Lake Forest Park, Burien, Issaquah, Normandy Park, Bellevue, Mercer Island), not too many, and we can say the price is stable/stationary in the 2-year window. It means we can create a model ignoring absolute time, which means we can transform columns like yr_built/yr_renovated to relative time, e.g. age/age_renovated or simply delete them.

2. How prices stretch by values (Distribution Analysis)

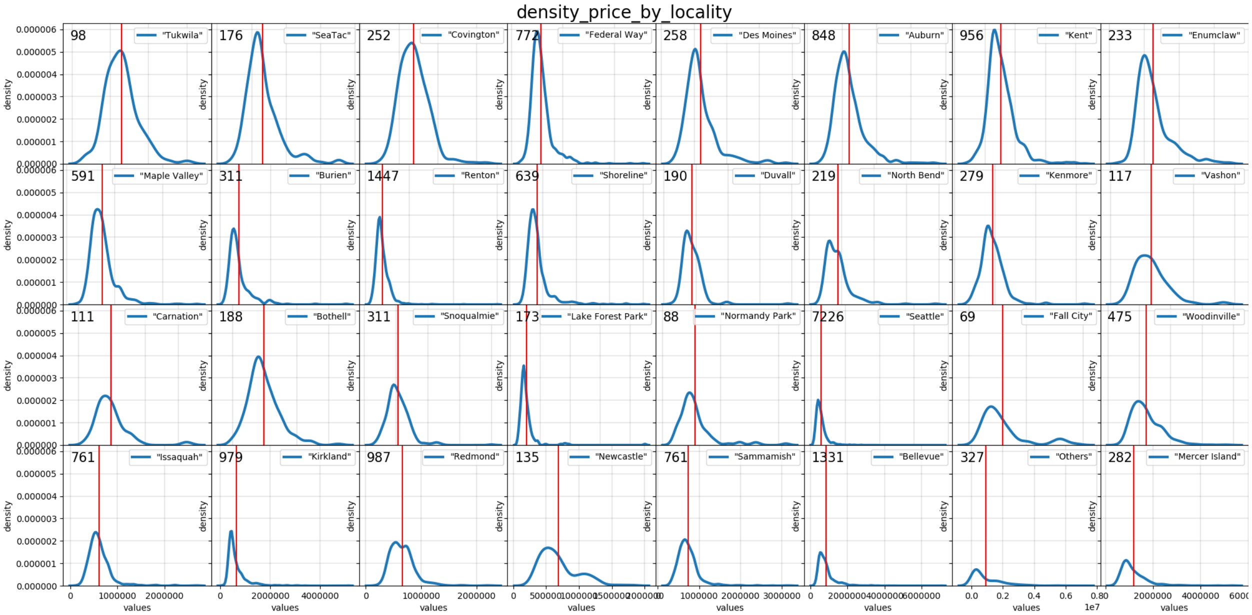
I print the mean price for different cities in Washington.



1	locality	avg_price
2	Medina	2160606.6
3	Clyde Hill	1846172
4	Yarrow Point	1784917.64705882
5	Hunts Point	1220833.33333333
6	Mercer Island	1194230.0212766
7	Beaux Arts Village	1123000
8	Bellevue	848583.252441773
9	Sammamish	734001.432325887
10	Newcastle	686487.214814815
11	Redmond	661714.746707194
12	Kirkland	644439.052093974
13	Issaquah	616811.509855453
14	Woodinville	615001.762105263
15	Fall City	584994.202898551
16	Seattle	570517.613894271
17	Normandy Park	563723.295454545
18	Lake Forest Park	542671.098265896
19	Snoqualmie	529941.874598071
20	Preston	526765

Seattle, the only city I ever heard of in Washington, whose house average prices rank 16. And Medina, the most expensive city in Washington has itself surrounding by the pretty Lake Washington.

More details can be found in the following density plot:

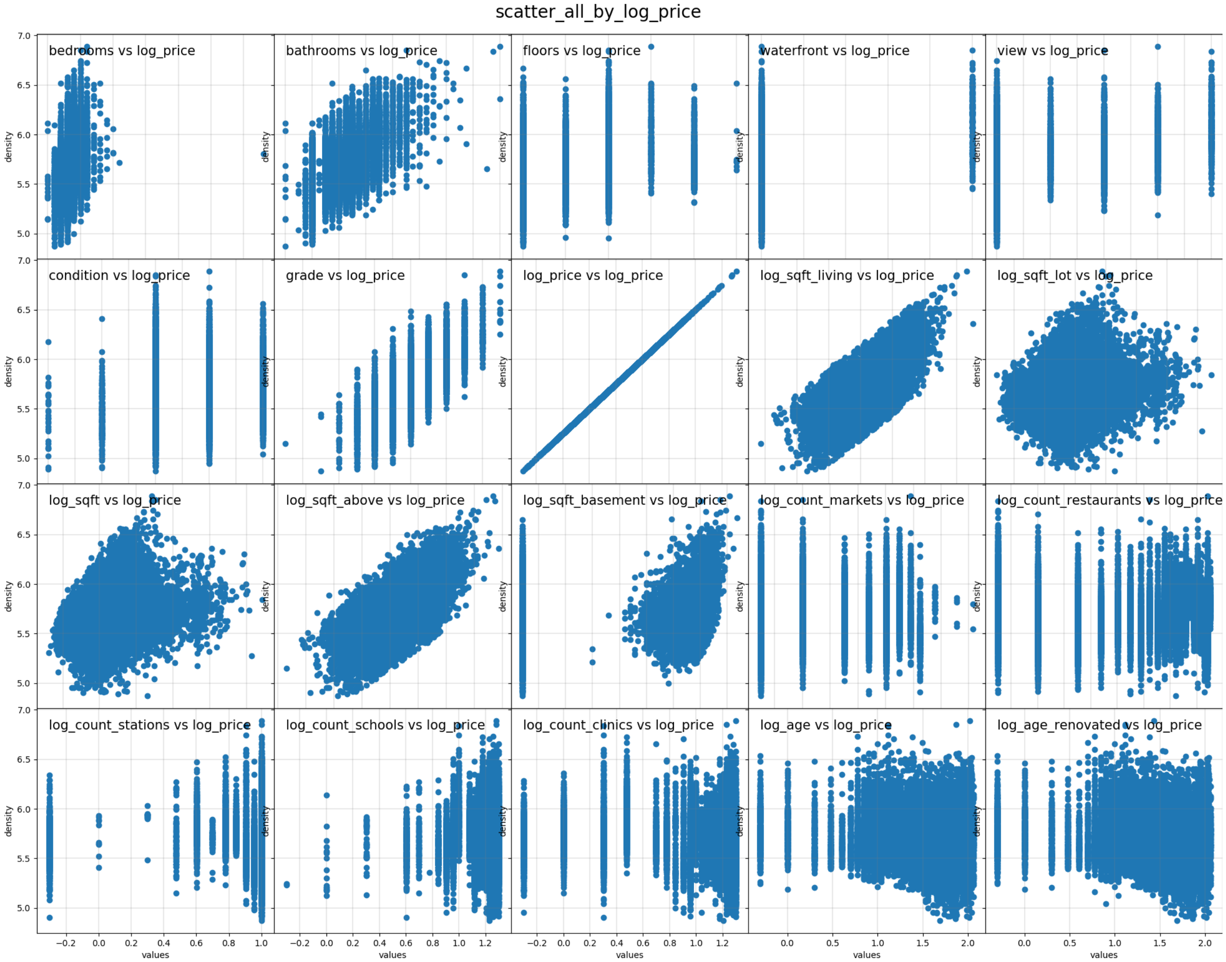


The number on the plot indicate the count of data in that region. It is clear to see that most of the sales

(7226/21590) go to Seattle. Another point is that a majority of the regional prices have long tails. Normally, if the long tails take up big proportion in a variable, we may benefit from logarithm transformation of the variable since it rebalances the data by reducing the skewness.

3. How price correlates to indicators (Correlation Analysis)

To show this I made the scatter plots between each indicator to the logarithm of price:



Out of all columns, the grade, size of the living room (sqft_living), waterfront, size of the above (sqft_above) have the strongest correlation on the plot (this is further shown in importance analysis).

Code of visualizing can be found in `./visualize/visualize.py`.

Machine Learning

1. Data preparation

I take Issaquah, a city with 761 records whose average price is 644439.05 to be the test set.

I split the rest data into 8/2, where the training set has 16663 records and validation set has 4166 records.

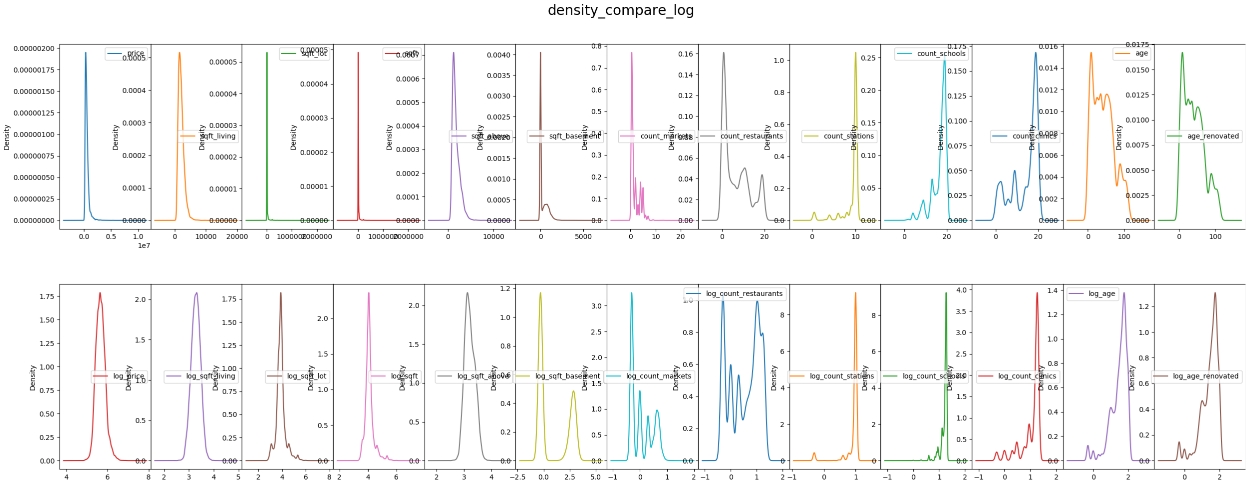
Code of preparing training/validation/testing dataset is in `./lib/split_train_val_test.py`.

2. Feature Engineering

I extract the following columns out of the original data:

- **age**: age of the house, age = date - yr_built.
- **age_renovated**: time since last renovate, age_renovated = date - yr_renovated.
- **sqft** = sqft_above+sqft_basement+sqft_living+sqft_lot.
- **count_markets**: the count of supermarkets in a radius of 800.
- **count_restaurants**: the count of restaurants in a radius of 800.
- **count_stations**: the count of transition stations in a radius of 800.
- **count_schools**: the count of schools in a radius of 2400.
- **count_clinics**: the count of clinics in a radius of 2400.
- **logarithm form** for selective variables.

I compare the **logarithm form** and original form of a selected list of variables:



We have recovered/transformed enough features, next, we need to reduce redundancies/noises for modeling. At feature-level, highly correlated features can confuse the model, for example, the presence of both **age** (age = date - yr_built) and **yr_built** not only increase computation but also can reduce coefficients of each one of them; at record-level, outliers that share significant different values may bias the model. To find which features/outliers to delete/transform, I will use a trained model validation performance as criteria.

Code of preparing data can be found in `./lib/prepare_data.py`.

3. Model Setup

When a human customer goes to buy a house it can be thought as a combination of decisions over different perspectives, a decision tree, which is born to mimic human decision-making process seems a good fit for such task. Since the perspectives to be considered are many, the house price patterns vary geographically and property-wisely, therefore, I use a bootstrap-upgraded decision called Random Forest to ensure robustness.

The best part for using Random Forest is that it doesn't have any assumptions like those of Linear Regressions: **Multivariate normality, Linear relationship, No multicollinearity, No auto-correlation**, etc. Although this should be checked to help approach better performance or robustness, these are not required here.

A bonus for Random Forest is that we can check feature (node) importance like we do for P-Values Check in Linear Regression, which helps us to find the best features.

4. Loss function and metrics

I choose **Mean Squared Error** as loss function for machine learning since it is faster than Mean Absolute Error. Doing so causes a potential problem of bias over the outliers to have bigger values, two solutions to this: - Delete outliers by a threshold.
- Transform the skewed data with logarithm.

On evaluating results, I didn't use MSE directly but use proportional MAE, which is Mean Absolute Error divided by mean of true labels.

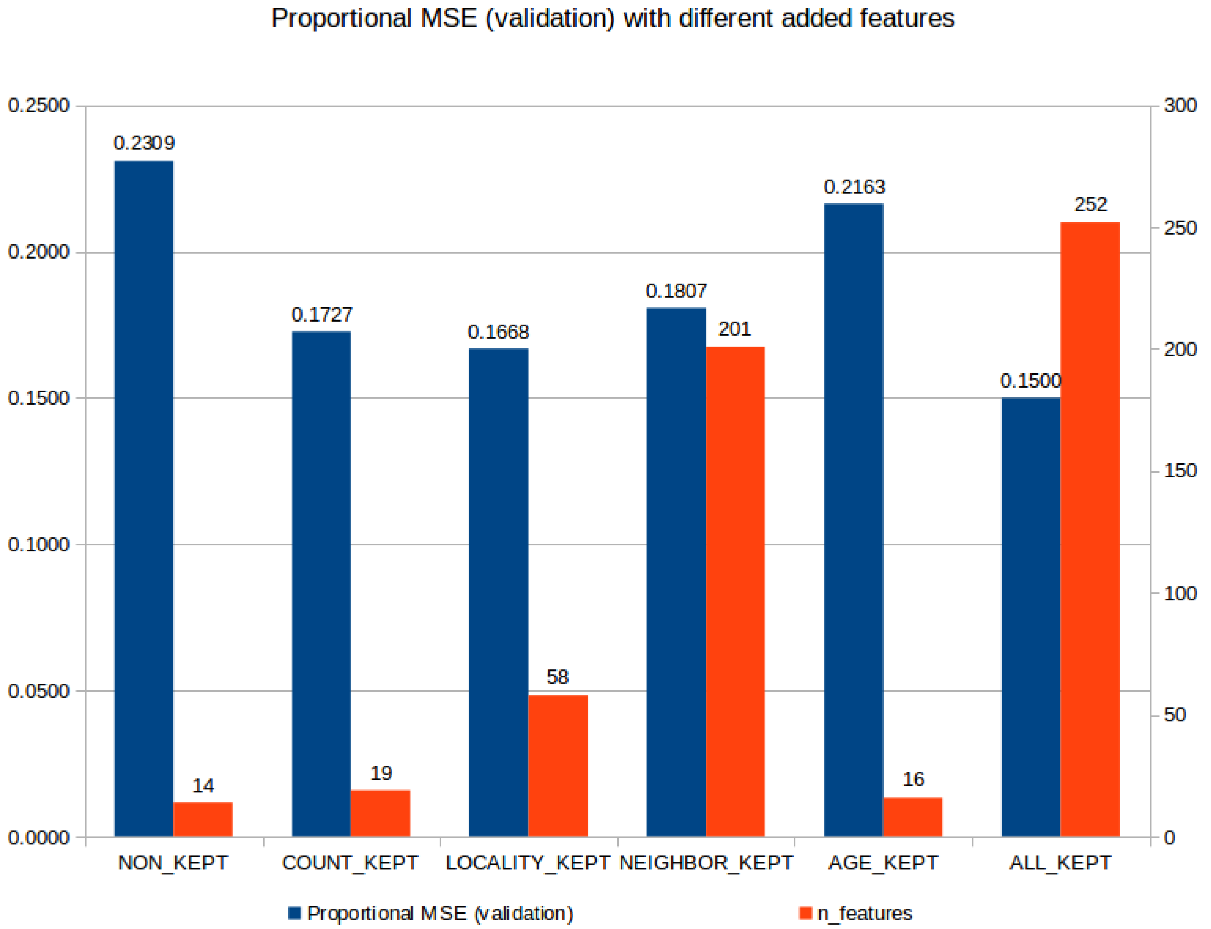
$$MAE_i^{prop} = \frac{MAE_i}{\frac{1}{N}\sum_N Y_i^{true}}$$

where N is the size of the test batch, Y_i^{true} is the true values of prices, MAE are the Mean Absolute Error.

5. Experiments

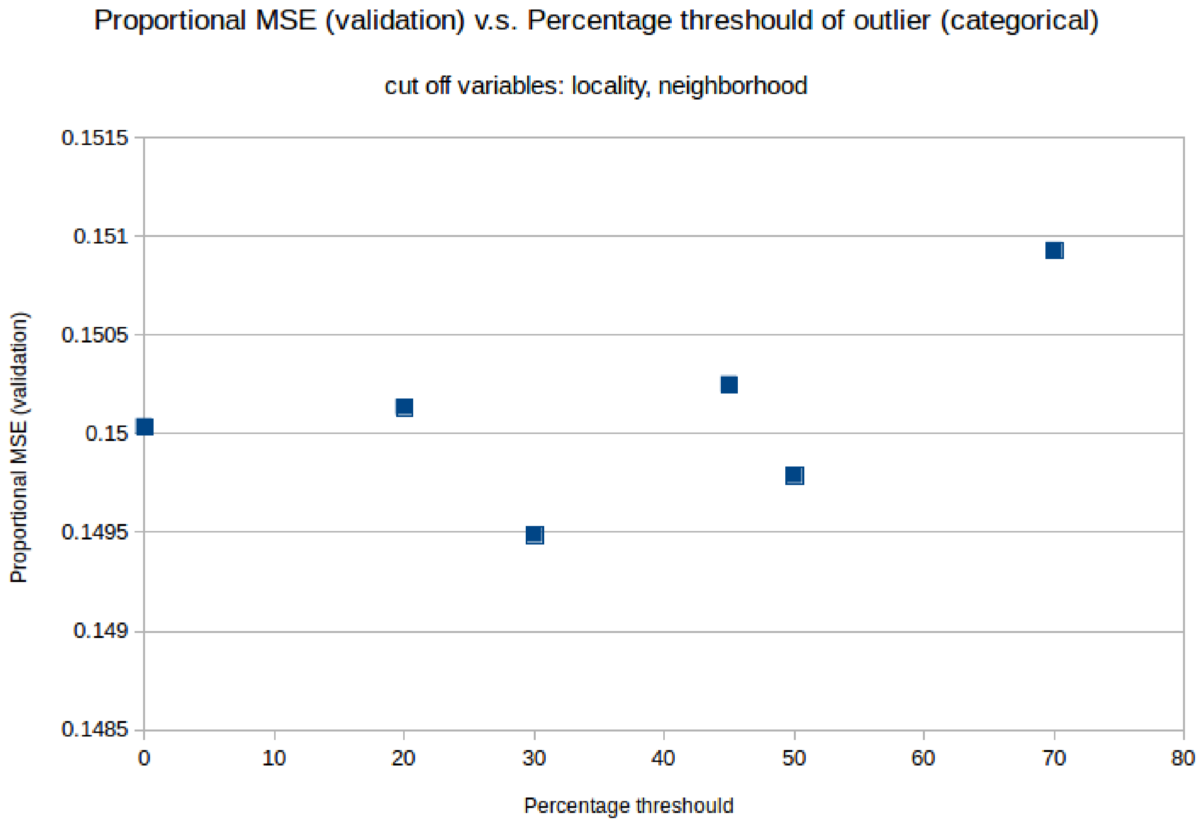
5.1. Do added features make sense?

I show the effects of added features in the following plot:



Comparing to the baseline (NON_KEPT, where we use all 14 original features came with the dataset), all added features improve the validating Proportional MAE to different extents. Among them, COUNT_KEPT and LOCALITY_KEPT significantly improve the prediction.

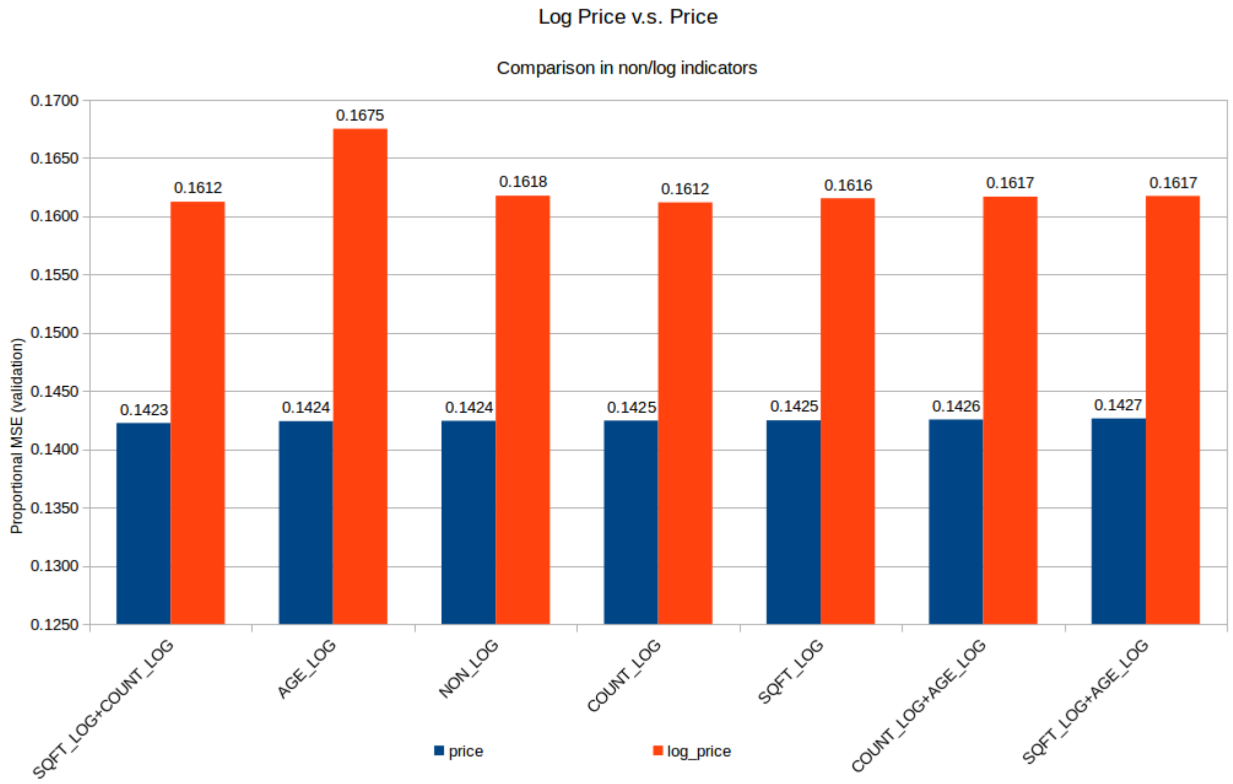
Though not shown in the plot, testing Proportional MAE indicates the direct uses of features of locality and neighborhood lead to overfitting. To improve, I merged small-sized categories (e.g. under locality we have some cities getting only 1 record) under locality/neighborhood to a category called “Others” (which is also the category for unobserved locality/neighborhood in training dataset). The following plot indicates that the quantile of 30% is a good threshold for deciding “small categories”.



Alternative ways to deal with a large number of feature reduction automatically are LASSO, or stepwise AIC, BIC, however, given limited time I only tried AIC, but my first try wasn’t good enough for selecting categories under locality/neighborhood, I will continue this effort given more time.

5.2. Does logarithm transformation help to rebalance skewness?

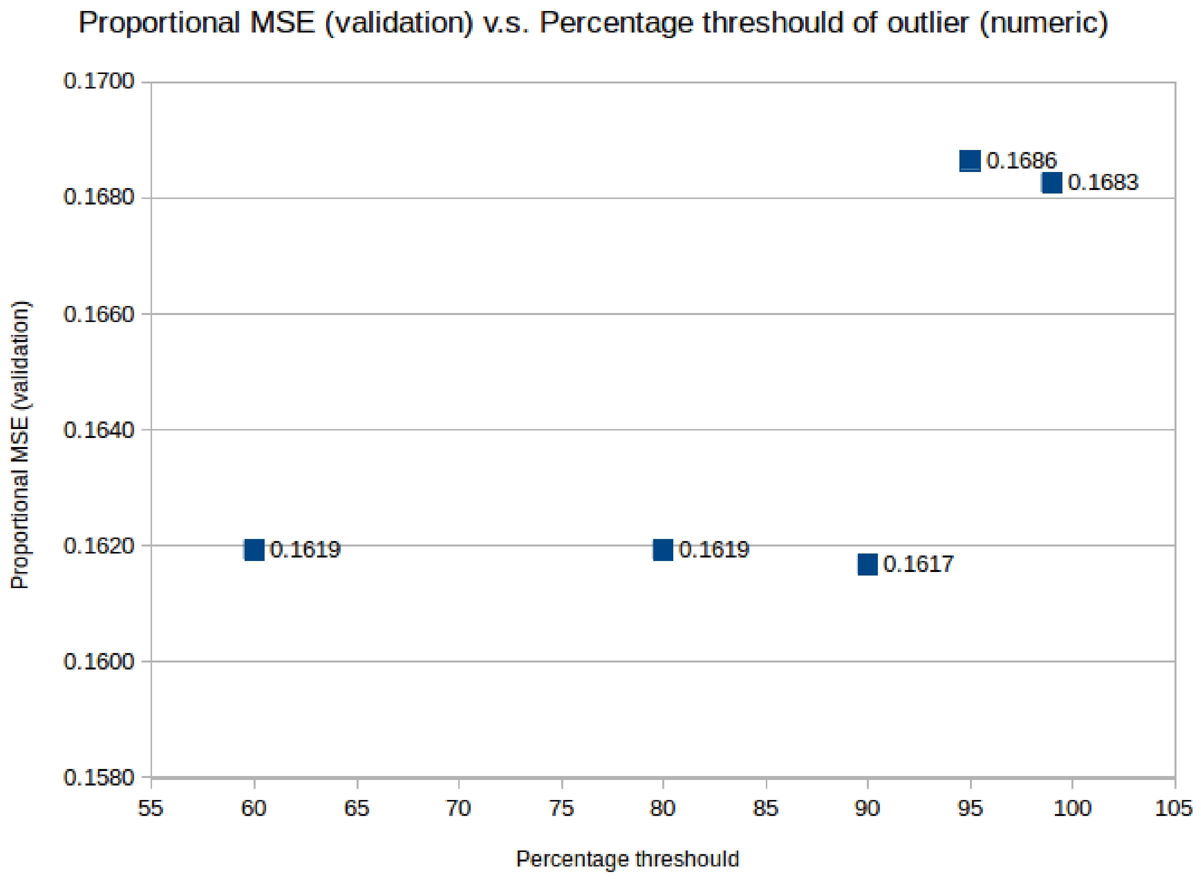
As stated in section 4, we use logarithm transformation to deal with skewed data issue. We first try to implement it on price:



Results show that it harms the validating Proportional MAE, though a further check shows that it helps increase robustness (differences between validating Proportional MAE and testing Proportional MAE). I haven't got enough time to analyze whether the incorrect predictions are for the smaller/bigger-value prices.

5.3. Does Threshold help to cutoff outliers?

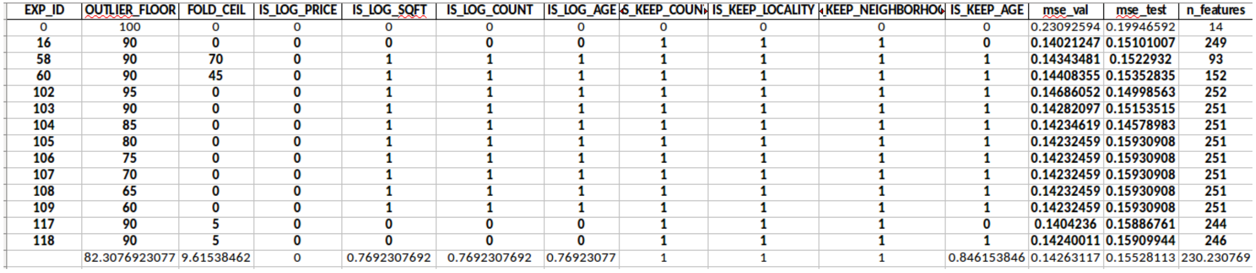
To cutoff outliers bigger than a threshold of 90, which means for all numeric indicators, any values bigger than 90% quantile of for this indicator will be deleted. The experiment shows it helps to decrease validating Proportional MAE:



Given limited time, I only show the points, a better way of doing this is to cutoff by clustering or by assumed distribution like multivariate Gaussian.

5.4. Current Results

Based on insights from 5.1~5.3, I zoom in on 10 different experiment factors and set up 127 experiments. By the criteria of validating Proportional MAE and testing Proportional MAE, I found the best models and list them here, this table also shows the 10 experimental factors:



EXP_ID	OUTLIER_FLOOR	FOLD_CEIL	IS_LOG_PRICE	IS_LOG_SQFT	IS_LOG_COUNT	IS_LOG_AGE	S_KEEP_COUN	IS_KEEP_LOCALITY	KEEP_NEIGHBORHO	IS_KEEP_AGE	mse_val	mse_test	n_features
0	100	0	0	0	0	0	0	0	0	0	0.23092594	0.19946592	14
16	90	0	0	0	0	0	1	1	1	0	0.14021247	0.15101007	249
58	90	70	0	1	1	1	1	1	1	1	0.14343481	0.1522932	93
60	90	45	0	1	1	1	1	1	1	1	0.14408355	0.15352835	152
102	95	0	0	1	1	1	1	1	1	1	0.14686052	0.14998563	252
103	90	0	0	1	1	1	1	1	1	1	0.14282097	0.15153515	251
104	85	0	0	1	1	1	1	1	1	1	0.14234619	0.14578983	251
105	80	0	0	1	1	1	1	1	1	1	0.14232459	0.15930908	251
106	75	0	0	1	1	1	1	1	1	1	0.14232459	0.15930908	251
107	70	0	0	1	1	1	1	1	1	1	0.14232459	0.15930908	251
108	65	0	0	1	1	1	1	1	1	1	0.14232459	0.15930908	251
109	60	0	0	1	1	1	1	1	1	1	0.14232459	0.15930908	251
117	90	5	0	0	0	0	1	1	1	0	0.1404236	0.15886761	244
118	90	5	0	0	0	0	1	1	1	1	0.14240011	0.15909944	246
	82.3076923077	9.61538462	0	0.7692307692	0.7692307692	0.76923077	1	1	1	0.846153846	0.14263117	0.15528113	230.230769

The 127 experiments can be found in `./experiments/exp_logs.xlsx`.

The best models have an average validating Proportional MAE of 0.1426 and a testing Proportional MAE of 0.1553, whereas the baseline models have a validating Proportional MAE of 0.2310 and an average testing Proportional MAE of 0.1995. **An average of 62% improvement** has been seen on the dataset! The feature engineering efforts are quite rewarding.

The code of feature engineering can be found in `./lib/feature_engineering.py`.

6. Error Analysis (haven't done)

Plot the error and check its distribution (expected to be normally distributed), if there are any significant patterns in error distribution, Gradient Boost Random Forest can be implemented to improve the prediction.

7. Node Importance Analysis (haven't done)

Identify the most important nodes of the optimal model.

8. Conclusions

1. Replacing prices with logged prices increase robustness but hurt model fitting, it can be improved by replacing logarithm with Box-Cox transformation.
2. Logged count, logged age, and logged sqft didn't improve much than their original forms, but they should be kept since they help to moderate robustness issue caused by taking MSE loss, which is biased for outliers. In another word, the log-transformed features may keep the model prediction consistently accurate even when encountering outliers in the future batches of testing data.
3. Count and locality provide the biggest improvement for prediction (minimizing validating Proportional MAE). But a lower testing performance comparing to validating performance suggests overfitting. Additionally, since locality and neighborhood cover only information in Washington, whether to keep them or not depends on what kind/size of future data we will be given in the real implementation of this problem.
4. Given more time to collect data, the market-level analysis is expected to improve the models.