Business Understanding

House market is a big yet complex market and is often affected by the overall economy, policies and neighborhood, making house prices difficult to predict. Besides, information asymmetry in the house market makes the prediction of future house prices more challenging.

Thus, the application of advanced data analysis and machine learning plays an important part in house prices prediction. The goal of this project is to apply machine-learning models to predict future house prices with accuracy and classify houses in order to provide a healthier house market by reducing information asymmetry with the application of data science.

Data Understanding

The first dataset is house prices in King County, WA, USA from 2014 to 2015.
The second dataset is King County median household income.
Dataset:

- https://www.kaggle.com/harlfoxem/housesalesprediction/data
- https://censusreporter.org/data/table/?table=B19013&geo_ids=05000US53033,860|05000US53033&primary_geo_id=05000US53033

Data Wrangling

The given dataset has no missing values and contains 21 variables.
However, there are 4 variables need to be converted into the correct data type.

- *date: the date when the house was sold*
- *zipcode: zip code where the house is located*
- *yr_built: the year when the house was built*
- *yr_renovated: the year when the house was renovated*

Variables	Data Type	Data Type(Corrected)
date	object	datetime64[ns]
zipcode	int64	object
yr_built	int64	object
yr_renovated	int64	object

Exploratory Data Analysis (EDA)

Distribution of Housing Prices in King County

First, look into the distribution of housing prices using distribution plot and Empirical Cumulative Distribution Function (ECDF).

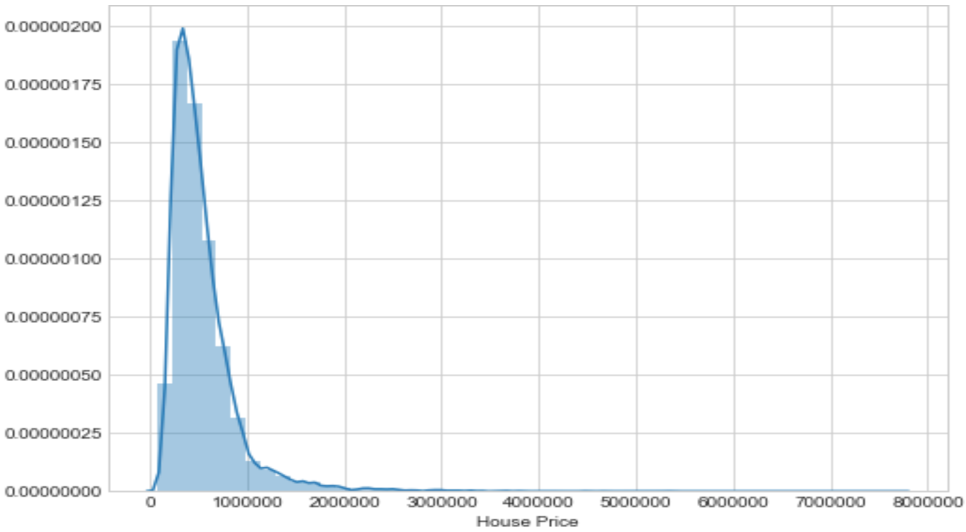


Figure1 Seaborn Distribution plot

The distribution of housing prices is deviated from normal distribution and is skewed to the right; we should take log of house price for further analysis.

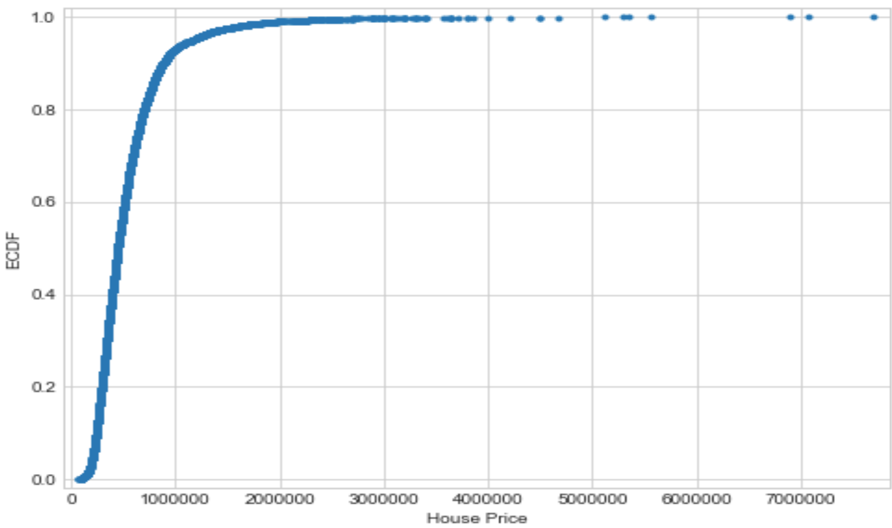


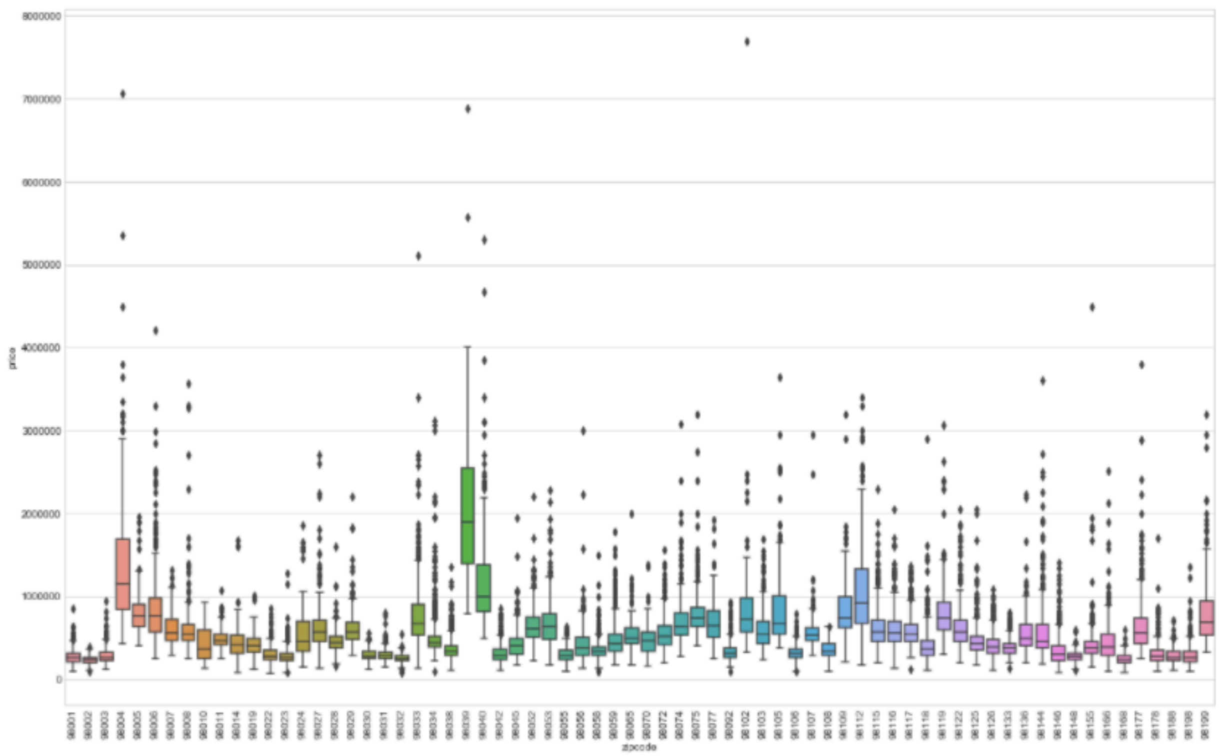
Figure2 ECDF Plot with x-axis “House Price” and y-axis “Probability”

From ECDF plot, we can see that there are 3 houses with prices over $6M, which deviate from normal price distribution.

Zip code and Housing Price

Location usually plays an important role when it comes to housing price. Therefore, used boxplot to visualize the distribution of housing price and median house price in each area based on zip code.

Figure3 Boxplot – House price



The plot above shows that areas with zip code 98039, 98004, 98040, 98112 and 98005 have higher median house price.

Figure4 Top5 median house price area

zipcode	median_price
98039	1892500.0
98004	1150000.0
98040	993750.0
98112	915000.0
98005	765475.0

Income and Housing Price

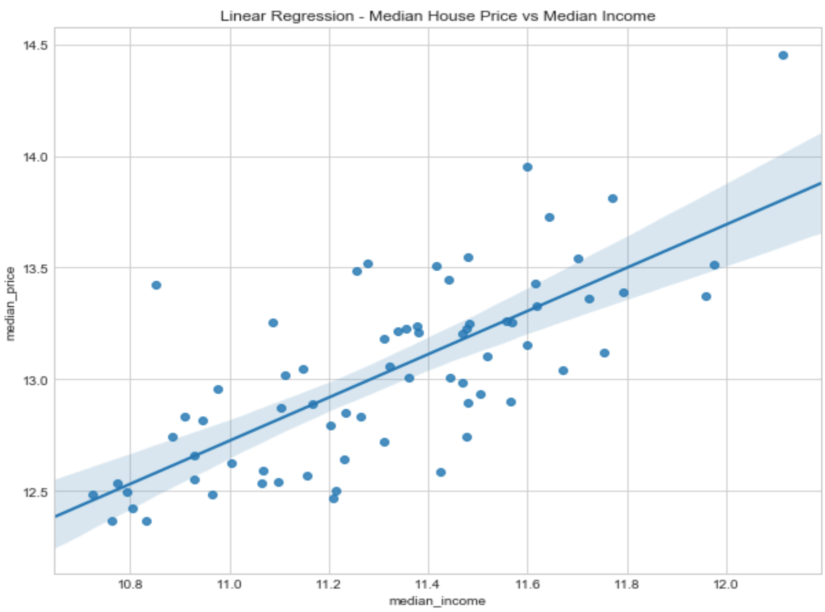
We also want to know if higher housing price areas also have higher income.

- Adding King County's median household income in the past 12 months.
- Performed Linear Regression (OLS) model with median household income as independent variable.
- From OLS regression results, the house price and income are statistical significant and the coefficient between house price and income is 0.967.
- From the regression plot, we can see that median house price and median income are positively correlated.

Figure5 OLS Regression Results

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     np.log(median_price)   R-squared:                       0.542
Model:                              OLS   Adj. R-squared:                  0.535
Method:                   Least Squares   F-statistic:                     80.39
Date:                  Sun, 11 Feb 2018   Prob (F-statistic):           3.89e-13
Time:                          16:43:32   Log-Likelihood:                -10.606
No. Observations:                    70   AIC:                             25.21
Df Residuals:                        68   BIC:                             29.71
Df Model:                             1
Covariance Type:              nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
Intercept                 2.0811      1.222      1.703      0.093      -0.357       4.519
np.log(median_income)     0.9677      0.108      8.966      0.000       0.752       1.183
==============================================================================
Omnibus:                        5.648   Durbin-Watson:                   1.366
Prob(Omnibus):                  0.059   Jarque-Bera (JB):                4.957
Skew:                           0.634   Prob(JB):                       0.0838
Kurtosis:                       3.301   Cond. No.                         408.
==============================================================================
```

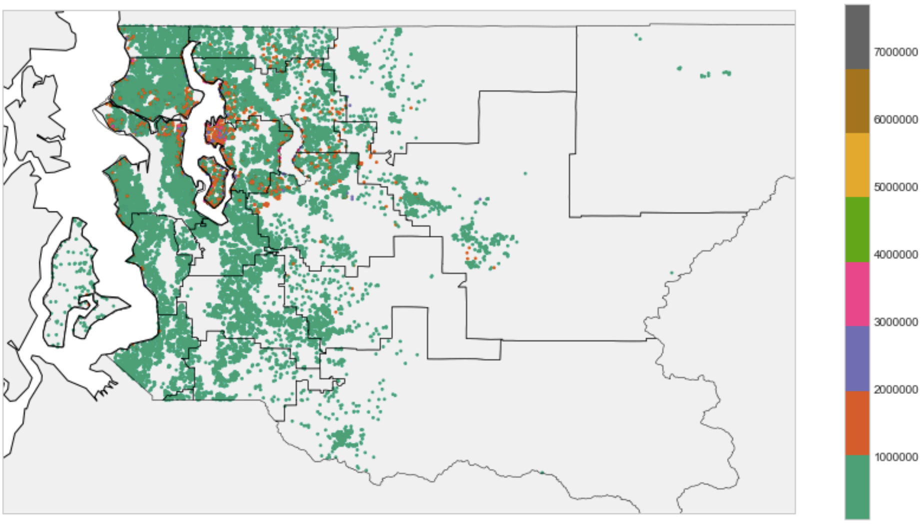
Figure6 Linear Regression – Median Housing Price vs Median Income



Where are those houses located in?

- Create a map of King County neighborhoods using Python Basemap.
- Each dot is a house with a price, and the bar at the right is price range.

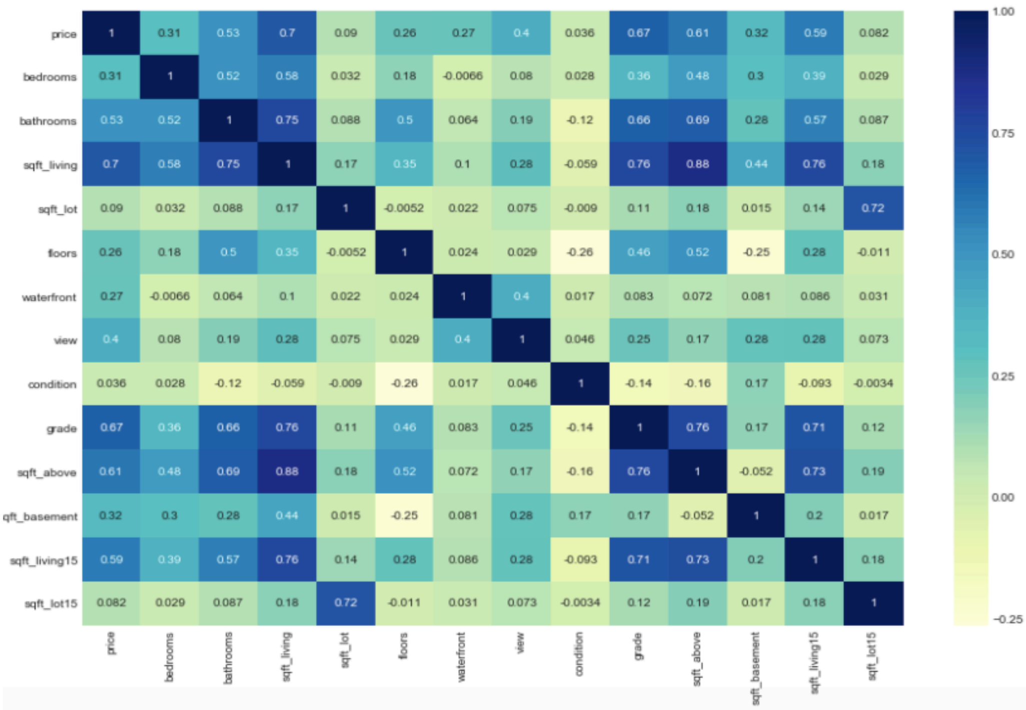
Figure7 Location of each house and its price



Correlation Heatmap

- Correlation heatmap to see if there's multicollinearity between variables.
- Usually, if two variables have over 90% correlation, we should consider variables have multicollinearity issue.

Figure8 Correlation Heatmap

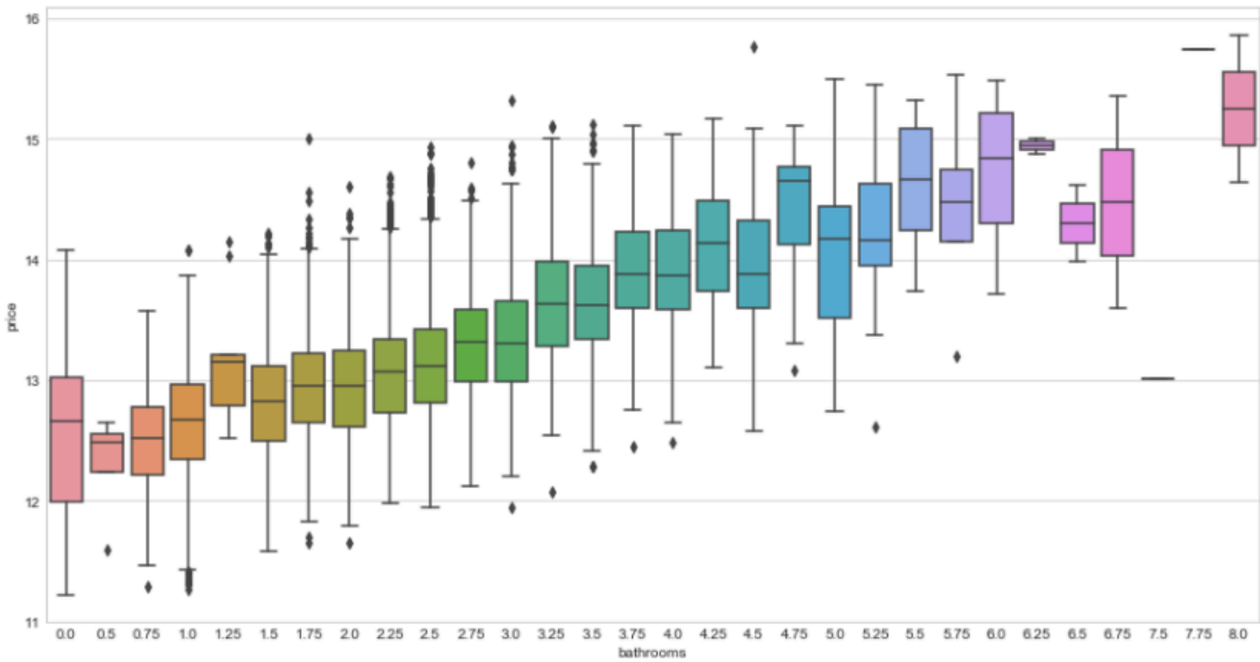


Based on the heatmap above, correlations between variables are < 90%, we can consider no multicollinearity issue.

Housing Price vs Bathroom

- From the boxplot, we can see that there are houses with 0 bathroom, which is not reasonable. Thus, drop out houses with 0 bathroom.

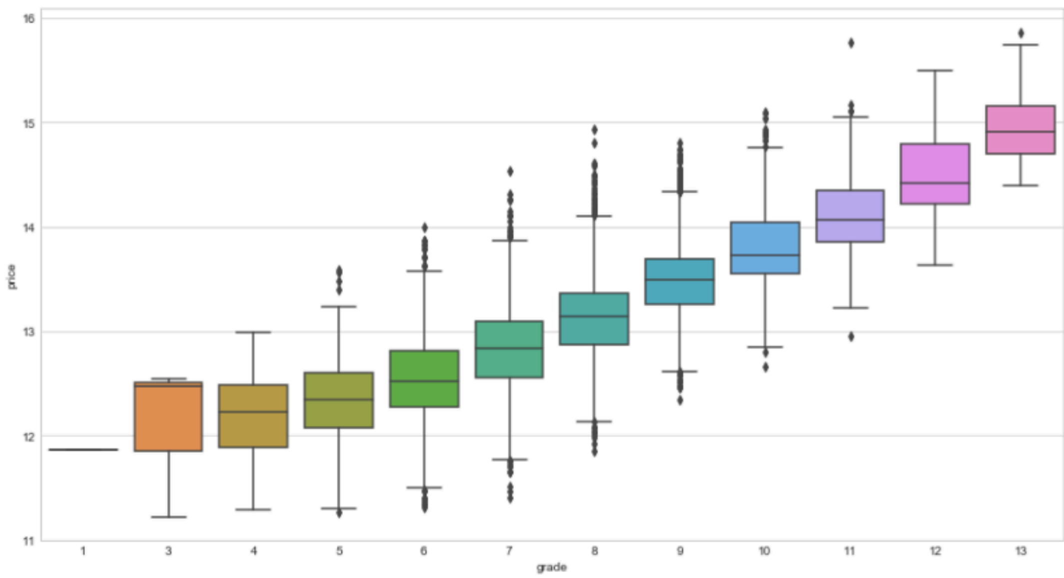
Figure9 House price vs #bathrooms



Housing Price vs Grade

- The boxplot shows that houses with higher grade tend to have higher prices.

Figure10 House price vs Grade



Feature Engineering

Dummy Variables

Convert categorical variables into dummy variables to find out if house prices are affected by variables w/wo basement, w/wo renovation and w/wo views.

Independent Categorical Variables:

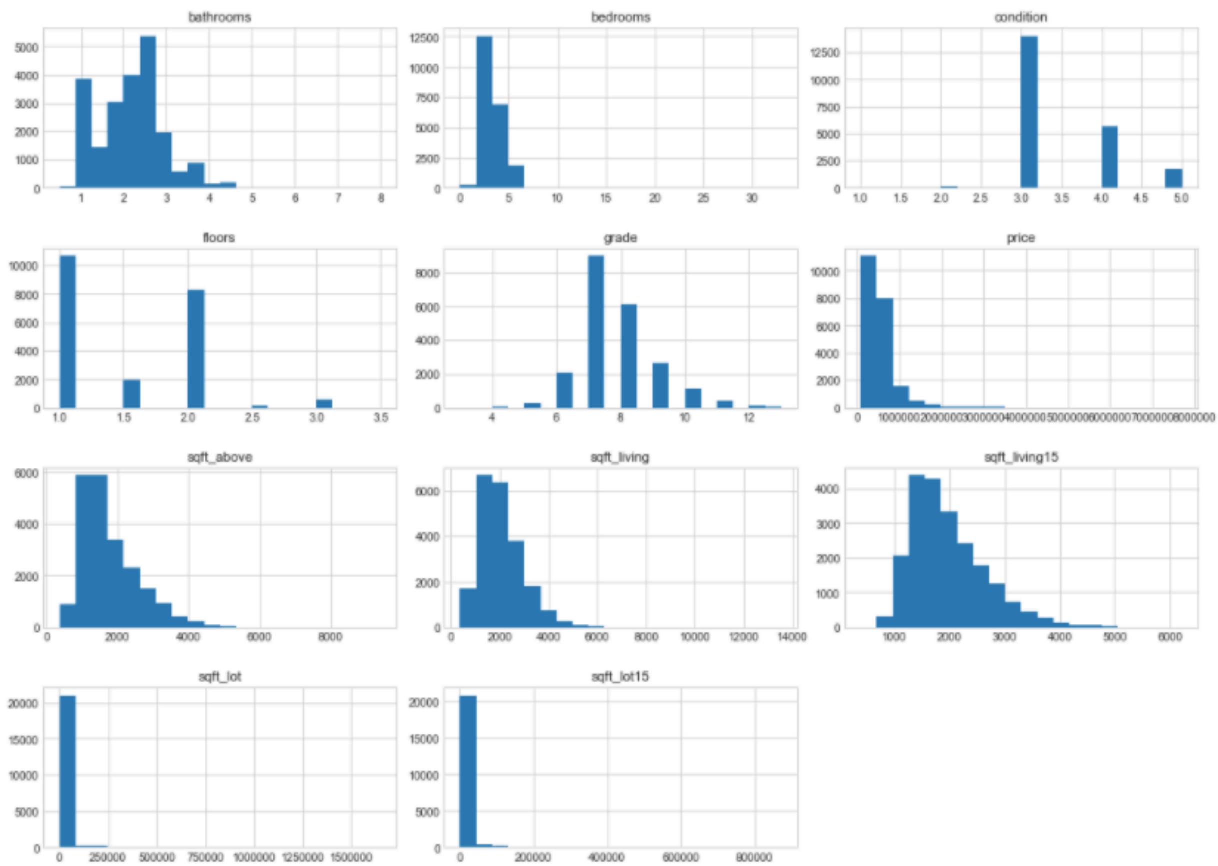
- *sqft_basement: square feet of basement*
- *yr_renovated: the year of the house renovated*
- *view: if the house has the water view or not*

Normality Test

Check whether variables are normally distributed before applying models.

- Plot out histograms to look into the distribution of each variable.
- Use skewness to check normality. Skewness close to 0 is normal distribution, with skewness > 0 means the left tail of the distribution is more weighted.

Figure11 Histogram- Most of the variables are skewed to the right



Skewness

The normality test results show variables are skewed to the right (skewness > 0) and thus need transformation to make data normally distributed.

```
               skewness
sqft_lot      13.057033
sqft_lot15     9.505720
price          4.025608
bedrooms       2.002336
sqft_living    1.472613
sqft_above     1.446937
sqft_living15  1.106906
condition      1.035838
grade          0.785404
floors         0.614549
bathrooms      0.519449
```

Box-Cox Transformation

First we apply Python Scipy's box-cox transformation to get transformed data then use probability plot to check if the transformed data is normally distributed.

Figure12 - Before box-cox transformation

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above
0	7129300520	2014-10-13	221900.0	3	1.00	1180	5650	1.0	0	0	...	7	1180
1	6414100192	2014-12-09	538000.0	3	2.25	2570	7242	2.0	0	0	...	7	2170
2	5631500400	2015-02-25	180000.0	2	1.00	770	10000	1.0	0	0	...	6	770
3	2487200875	2014-12-09	604000.0	4	3.00	1960	5000	1.0	0	0	...	7	1050
4	1954400510	2015-02-18	510000.0	3	2.00	1680	8080	1.0	0	0	...	8	1680

5 rows × 21 columns

Figure13 – After box-cox transformation

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sq
0	7129300520	2014-10-13	35.583909	1.540963	0.730463	12.597323	17.696152	0.730463	0	0	...	2.440268	12
1	6414100192	2014-12-09	41.586543	1.540963	1.289269	14.981646	18.620287	1.194318	0	0	...	2.440268	14
2	5631500400	2015-02-25	34.278249	1.194318	0.730463	11.403697	19.874209	0.730463	0	0	...	2.259674	11
3	2487200875	2014-12-09	42.431400	1.820334	1.540963	14.119786	17.253669	0.730463	0	0	...	2.440268	12
4	1954400510	2015-02-18	41.201236	1.540963	1.194318	13.644922	19.038978	0.730463	0	0	...	2.602594	13

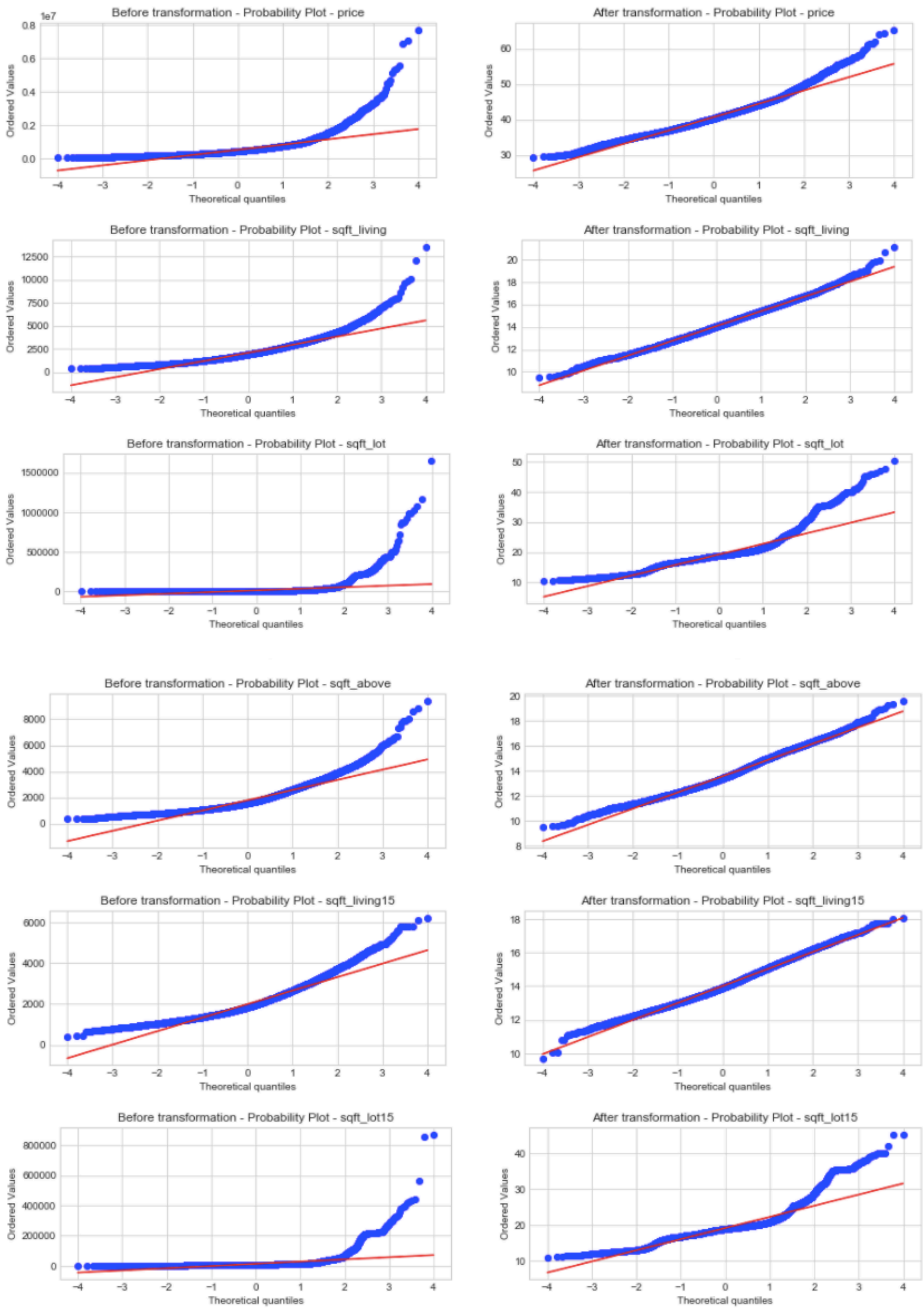
5 rows × 21 columns

Probability Plot

Use probability plot to check if the transformed data are normally distributed.

- Variables after transformation are closer to normal distribution even though some variables are still not normally distributed.

Figure14 – Probability plot



Modeling and Evaluation

Since the goal here is to predict housing price in King County, machine learning predictive models are top candidates. Using the following models for prediction.

Ridge Regression

Linear least squares with L2 regularization to reduce over-fitting issue.

- Ridge regression didn't perform very well, with 62.9% accuracy rate.

```
Test data score     :  0.629247618078
Training data score :  0.618334226155
```

Random Forest Regression

Random Forest makes the decision tree building process use different predictors to split at different times.

- Random Forest Regression performs better than Ridge Regression, the accuracy increased from 62.9% to 66.4%.

```
Test data score     :  0.664314490415
Training data score :  0.677593177162
```

Gradient Boosting Regression

In Gradient Boosting, the decision trees are generated in sequence. Each tree is generated using information from previously grown trees and the addition of a new tree improves upon the performance of the previous trees.

➢ **Grid Search with Cross Validation**

- Tuned parameter using Grid Search with cross validation
- Parameters we tuned:

  #criterion: friedman_mse, mse

  #max_depth: mean squared error with improvement score by Friedman

  #max_features: number of features to consider when looking for the best split

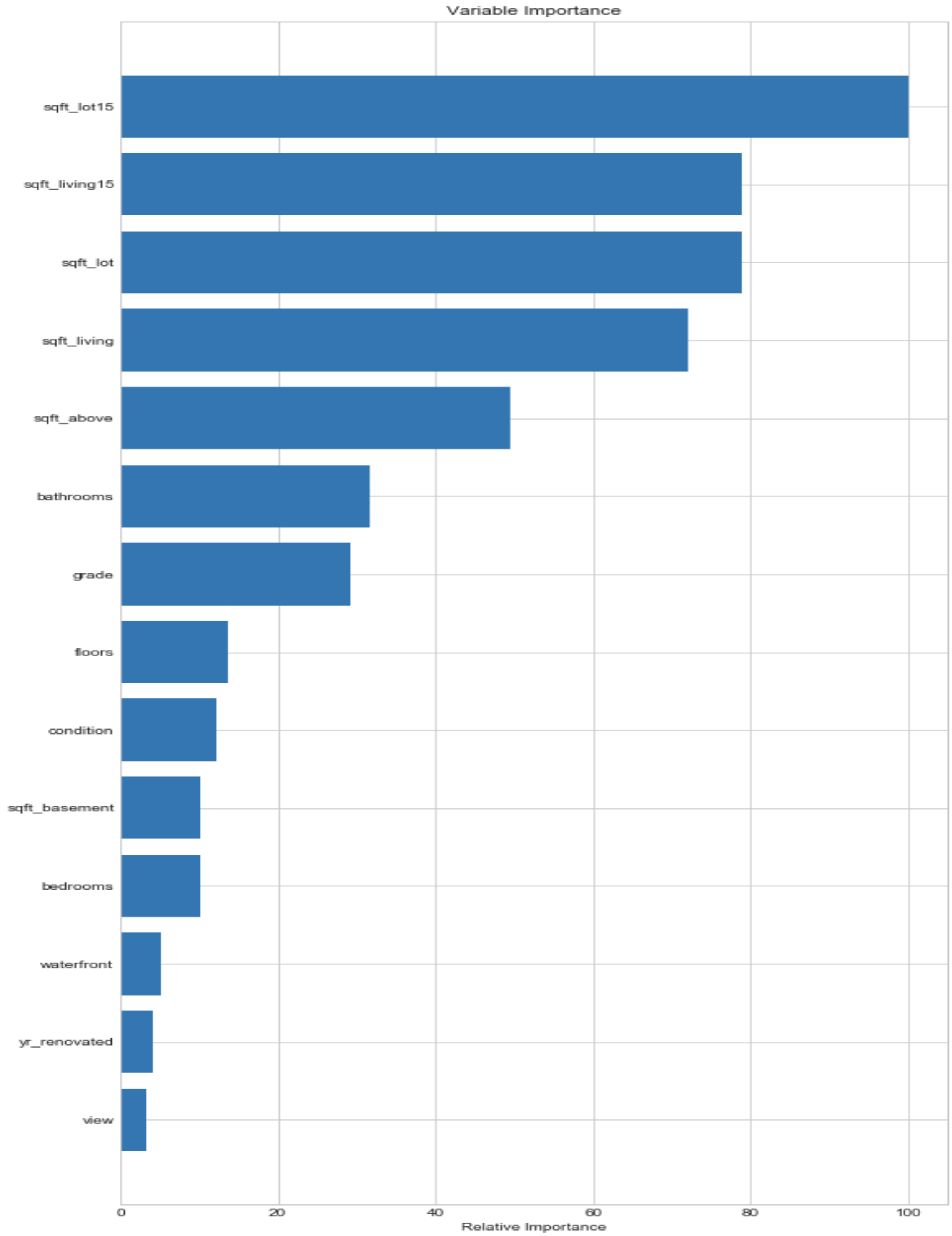
  #min_samples_split: min number of samples required to split an internal node
- Gradient Boosting Regression with grid search so far has better results than Ridge and Random Forest Regression. With 72% accuracy.

```
Best parameter     :  {'criterion': 'friedman_mse', 'max_depth': 4, 'max_features': 4, 'min_sample
s_split': 2, 'random_state': 42}
Test data score    :  0.721614432648
Training data score:  0.758956656955
```

Feature Importance

Plot out the important features based on gradient boosting.

- Top important features are features about square foot lot, square foot living and square foot above the ground.



Evaluation

Based on the predictive models above, Gradient Boosting Regression with Grid Search generates the best prediction result, because in boosting, the new decision tree is based on the residuals and is then added to the current decision tree, and the residuals are updated.

By fitting small trees to the residuals, we gradually improve the overall model in areas where it does not perform well. Therefore, Gradient Boosting outperforms than Ridge and Random Forest Regression, but Gradient Boosting costs more time to run in order to find the best parameters.