# Cribs

## Regression modeling for home price

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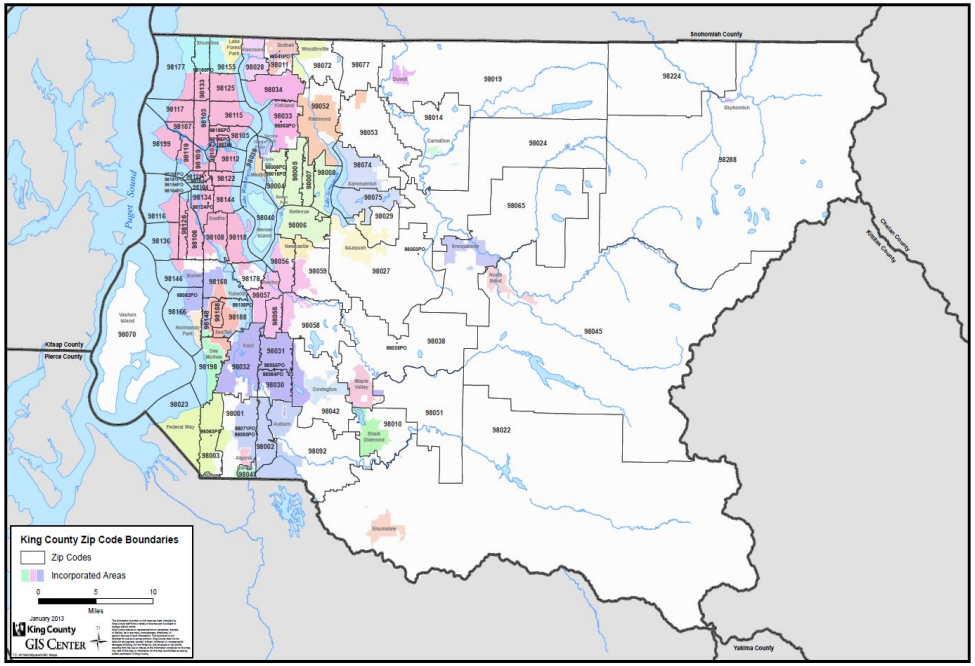
# Describe data and goal

- Downloaded from Kaggle.com
- 21,613 records of home sales in King County, WA. from May 2014 to May 2015.



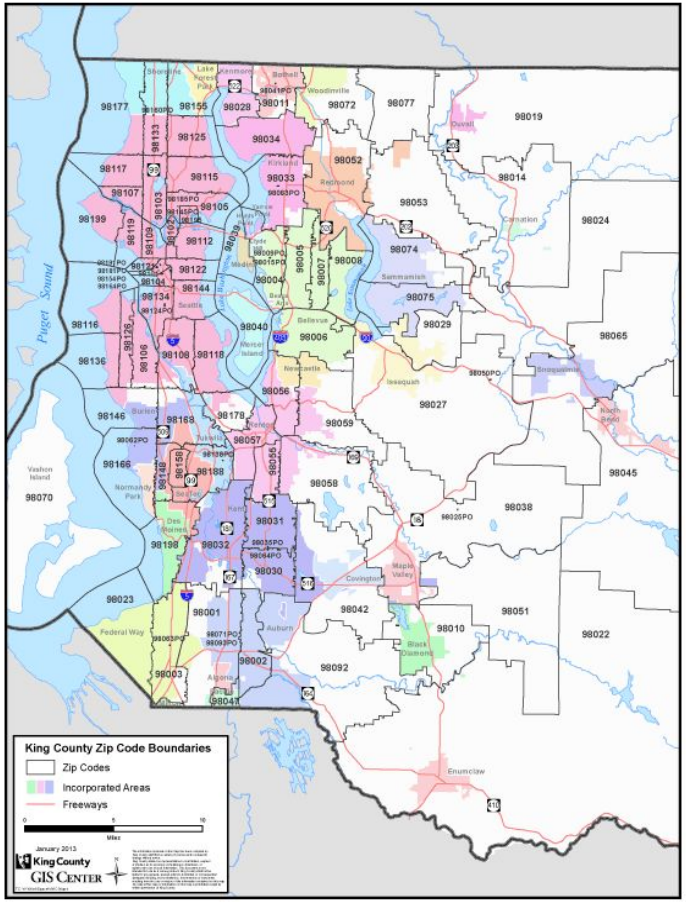

**The goal of the analysis**

- Generate the best fitted regression model for predicting home sale price in King county.

# Houses in the West

- All the data was about houses located in the west side of King County.

- There were no houses in the data which were located at the east side of King County.



# Features in the Dataset

- ID
- Date
- Price
- Bedrooms
- Bathrooms
- Sqft_living
- Sqft_lot
- Floors
- Waterfront
- View
- Condition
- Grade
- Sqft_above
- Sqft_basement
- yr_built
- yr_renovation
- zipcode
- lat
- long
- Sqft_living15
- Sqft_lot15

**21 Variables**

Features used in the analysis

- Date
- Price
- Bedrooms
- Bathrooms
- Sqft_living
- Sqft_lot
- Floors
- Waterfront
- View
- Condition
- Grade
- Sqft_above
- Sqft_basement
- yr_renovation
- lat
- long

**16 Variables**

# Explaining Variables

- Price = house price
- Bedrooms = # of bedrooms
- Bathrooms = # of bathrooms
- Sqft_living = square footage of the interior living space
- Sqft_lot = square footage of the land space
- Sqft_above = Sqft_living - Sqft_basement
- Floors = # of floors
- Waterfront = value is 1 if there is waterfront otherwise, 0 (binary)
- Condition = value is 1 if the condition is reasonable otherwise, 0 (binary)

We used the above variables as they were.

# Explaining Variables

- sqft_basement: The square footage of the interior housing space that is below ground level

  Created a dummy variable, basement, for sqft_basement.

  basement = 1 when sqft_basement > 0 otherwise, basement = 0,

- yr_renovation: The year of the house's last renovation

  Created a dummy variable, renovated, for yr_renovation

  renovated = 1 when yr_renovation is given otherwise, renovated = 0

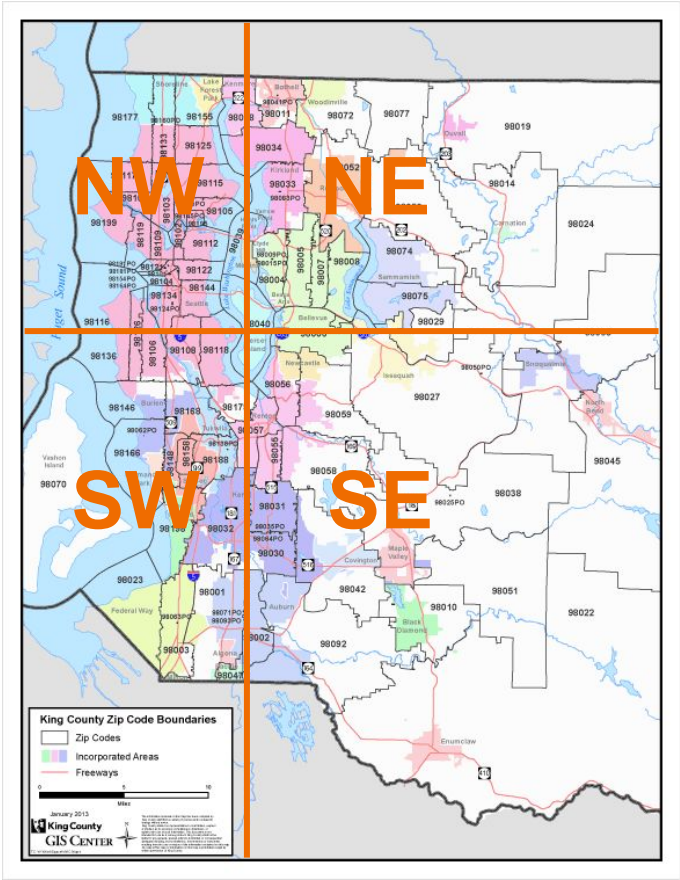
# Explaining Variables

## Date: Date of the house sale

- Original Format YYYYMMDDT000000
- Read in first 8 digits YYYYMMDD
- Assign each date to one of the four quarters in a year
- Make Q1 the base level
- Create Q2, Q3 and Q4 as dummy variables

## Location: Given in latitudes and longitudes

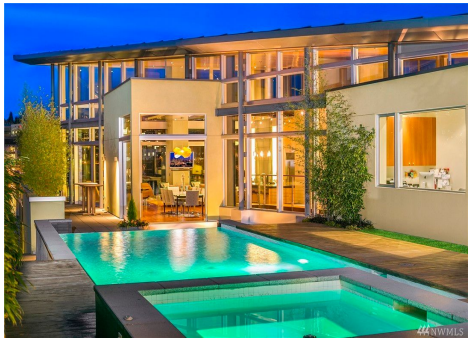
- Find the median longitude and latitude.
- Assign houses to North West, South West, North East or South East.
- Make North West (NW) the base level
- Create NE, SW, SE as dummy variables



# Explaining Variables

Grade: An index from 1 to 13, where 1-3 falls short of building construction and design, 7 has an average level of construction and design, and 11-13 have a high-quality level of construction and design

Grade = 1



Grade = 13

Assign grade to four divisions

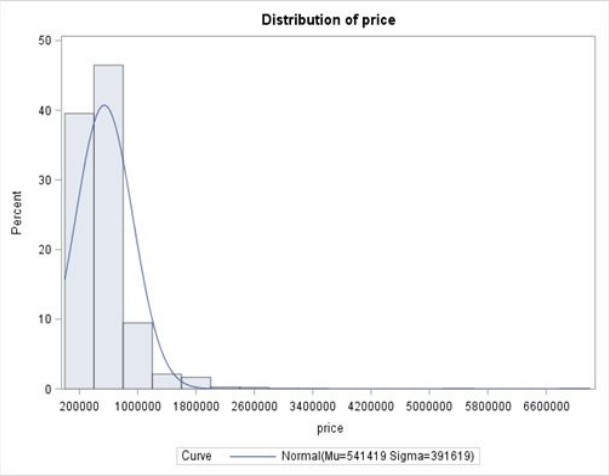
Make the first division the base level

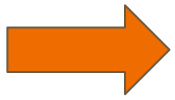
Make grade_b, grade_a and grade_h as dummy variables

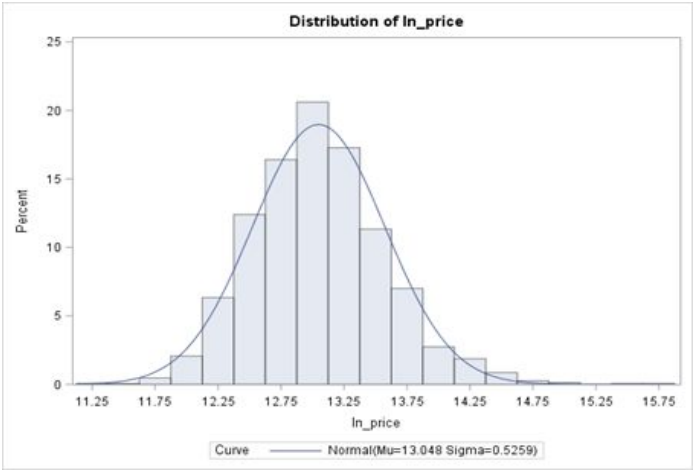
| grade_b | grade_a | grade_h |
|---|---|---|
| grade = 4 - 6 | grade = 7 - 10 | grade = 11 - 13 |

# Transformation of Dependent Variable

We transformed the response variable, price, with log transformation because it was positively skewed and used ln_price as our dependent variable.

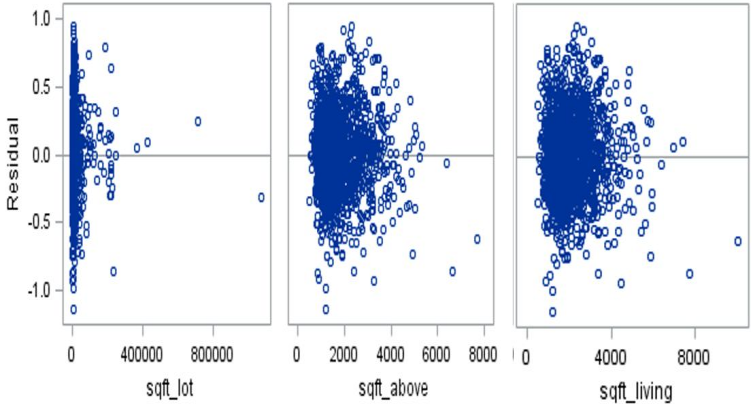


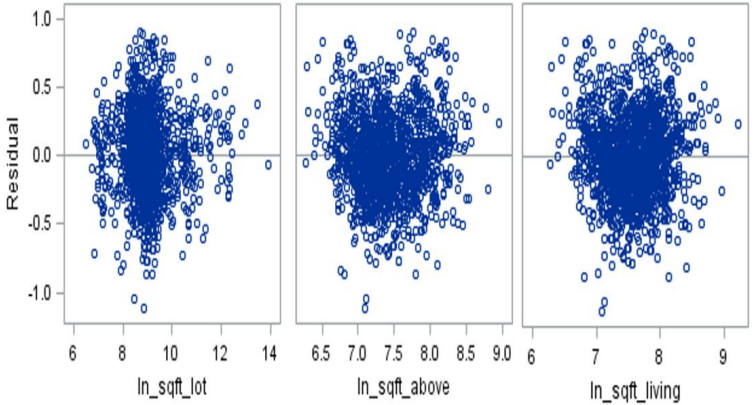





# Transformation of Independent variables

We transformed the sqft_living, sqft_above and sqft_lot because their residuals did not have constant variance and independence.



# Methodology

- **STEP1: Each member selected a sample of 1500 rows randomly from the dataset.**
- STEP2: Preprocessed the sample by creating dummy variables.
- STEP3: Transformed the response and three quantitative variables.
- **STEP4: Checked the sample for multicollinear predictors and removed them.**
- **STEP5: Created interactive variables, however, they exhibited multicollinearity.**
- **STEP6: To fix the multicollinearity we centered the quantitative variables in the interactive terms and created new centered interactive variables.**

# Methodology

- **STEP7: Afterwards, we identify outliers and influence points in our respective samples and take all or some of them out of the sample.**
- **STEP8: Then, we splitted the data into a training set and testing set.**
- **STEP9: Each member used two different selection method to find the best set of predictors using the training data set.**

# JUN'S PART

# Methodology

- STEP10: Validity test on training set and Performance test on Testing set
- STEP11: Choosing the final model
- STEP12: Interpretation of the important parameters

# After model selection

**Model 1** (Jun): ln_price = 13.3336 - 0.0746*bedrooms - 0.6983*ln_sqft_above_c + 0.7534*waterfront + 0.3226*view_good +0.1536*condition_good - 0.1123*grade_b + 0.4532*grade_h + 0.3768*basement - 0.5468*SW - 0.3844*SE - 0.1054*Q4 - 0.2190*above_NE_c + 0.2811*above_SW_c - 0.2688*above_SE_c

**Model 2** (Omer): ln_price = 13.6272 - 0.6689*ln_sqft_living_c + 0.3597*view_good + 0.15775*condition_good - 0.5265*grade_b - 0.4731*grade_a + 0.1918*renovated - 0.4127*SW - 0.3761*SE - 0.2520*ln_sqft_living_SE_c

**Model 3** (Yusheng): ln_price = 13.16315 - 0.6982*ln_sqft_living_c + 0.6044*waterfront + 0.4120*view_good - 0.4693*SW - 0.4133*SE - 0.0906*bb_c +0.2633*bathliving_c + 0.1038*bedliving_c - 0.2716*living_SE_c

# Model Validity test on Training set

| | *M1* | *M2* | *M3* |
|---|---|---|---|
| *The number of predictors* | 14 | 9 | 9 |
| *Goodness of Fit* | p<0.001 | p<0.001 | p<0.001 |
| *RMSE* | 0.23755 | 0.29616 | 0.30424 |
| *R square* | 0.7301 | 0.6762 | 0.6637 |
| *Adjusted R square* | 0.7263 | 0.6743 | 0.6610 |

# Predictive Performance on Testing set

| | *M1* | *M2* | *M3* |
|---|---|---|---|
| *RMSE* | 0.2410 | 0.2993 | 0.2722 |
| *MAE* | 0.1962 | 0.2436 | 0.2209 |
| *R square* | 0.7665 | 0.6933 | 0.7179 |
| *Adjusted R square* | 0.7563 | 0.6857 | 0.7109 |
| *Cross-validated R square* | 0.0262 (<0.3) | 0.0153 (<0.3) | 0.0494 (<0.3) |

# Interpretation of Regression Coefficients

***Parameter Estimates***

| *Variable* | DF | Parameter Estimate | Standard Error | t Value | Pr > \|t\| | Standardized Estimate |
|---|---|---|---|---|---|---|
| *ln_sqft_above_c* | 1 | -0.69832 | 0.07163 | -9.75 | <.0001 | **-0.58981** |
| *basement* | 1 | 0.37681 | 0.03111 | 12.11 | <.0001 | **0.37483** |

# Effect of basement on Price

Parameter estimate =0.3768

100*(e^0.3768 -1) = 45.76%

Assuming all other variables constant, home sale price increases by 45.76% if the property has a basement.

# Effect of sqft_above on Price

## sqft_above... too complicated predictor

1. Log transformation on Y and X
2. Interaction variable (NW NE SW SE)
3. Centered

Base = NW

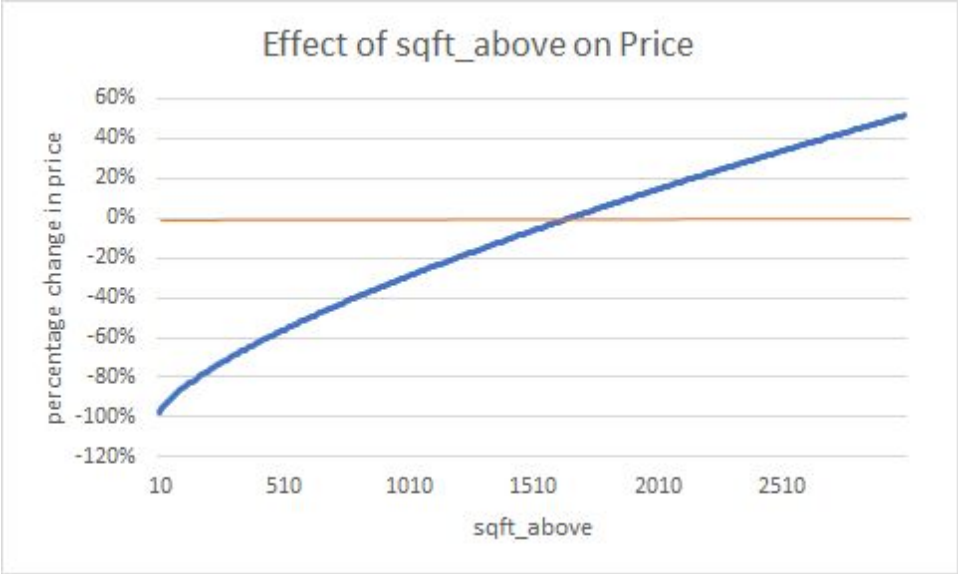
ln_PRICE

ln_ sqft_above_c

# Effect of sqft_above on Price

100*(e^(-0.6983*(7.4107-ln(1)))-1)
= -99.43%

100*(e^(-0.6983*(7.4107-ln(1654)))-1)
= 0.01%



# Effect of sqft_above on Price

Home Sale Price will start to increase

IF the property is larger than 1,654 sqft

IF the property is located in NW

# Yusheng's Part

# Model Predictions

| Obs | Dependent Variable | Predicted Value | Std Error Mean Predict | 95% CL Mean | | 95% CL Predict | | Residual |
|---|---|---|---|---|---|---|---|---|
| 1 | 12.1495 | 12.5380 | 0.0522 | 12.4353 | 12.6407 | 12.0624 | 13.0136 | -0.3885 |
| 2 | 12.7038 | 13.1537 | 0.0454 | 13.0643 | 13.2430 | 12.6808 | 13.6266 | -0.4499 |

ln_price: 0.3885

| Obs | Dependent Variable | Predicted Value | Std Error Mean Predict | 95% CL Mean | | 95% CL Predict | | Residual |
|---|---|---|---|---|---|---|---|---|
| 1 | $188,999.57 | $278,730.32 | | | $173,234.25 | $448,471.31 | | |
| 2 | $328,995.71 | $515,916.39 | | | $321,515.17 | $827,860.55 | | |

House Price: $89,730.75

# Limitations

- Transformation Method may cause inaccurate prediction results
- Lack of domain knowledge
- Odd revelations on certain predictors' impact on house prices

# Future Work

- Try different transformation method: Box-Cox
- Try on large dataset
- Hedonic Pricing Model--internal factors

--external factors

# Summary

- 14 predictors
- Adjusted R square: 0.7563
- RMSE:0.2410
- Cross validated R square:  0.0262 <0.3
- Most important predictors: size of a house and whether there is a basement or not.
- If we had more variables like property taxes, neighbouring public schools, air quality, and interest rates we could come up with a more accurate model.

# Q&A