

King County House Sales Study

Flatiron School

Kamile Yagci 12/13/2021

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Overview

- This project is the analysis of the King County House Sales.
- The Multiple Linear Regression is used to model the data and predict the house sale price.

Project Details:

- GitHub: <https://github.com/kamileyagci/dsc-phase-2-project>

Business Problem

The Windermere Real Estate Agency request an analysis on House Sale Prices in King County. They will use the results of the study to advise their customers.

Questions:

1. What are the main predictors for House Sale Price?
2. Create a model to predict the House Sale Price.
3. Do house renovation affects the Sale Price?

Method

1. Data
 - * Load
 - * Explore
 - * Clean
 - * Check correlation
3. Model - Apply multiple regression and do validation
 - * Baseline model with one best predictor
 - * Second and Third models (Search for the next best predictors)
 - * Final Model with five best predictors
3. Interpret
 - * Interpret Final Model
 - * Check multiple regression assumptions
4. Future work

OSEMN Model

Obtain

Scrub

Explore

Model

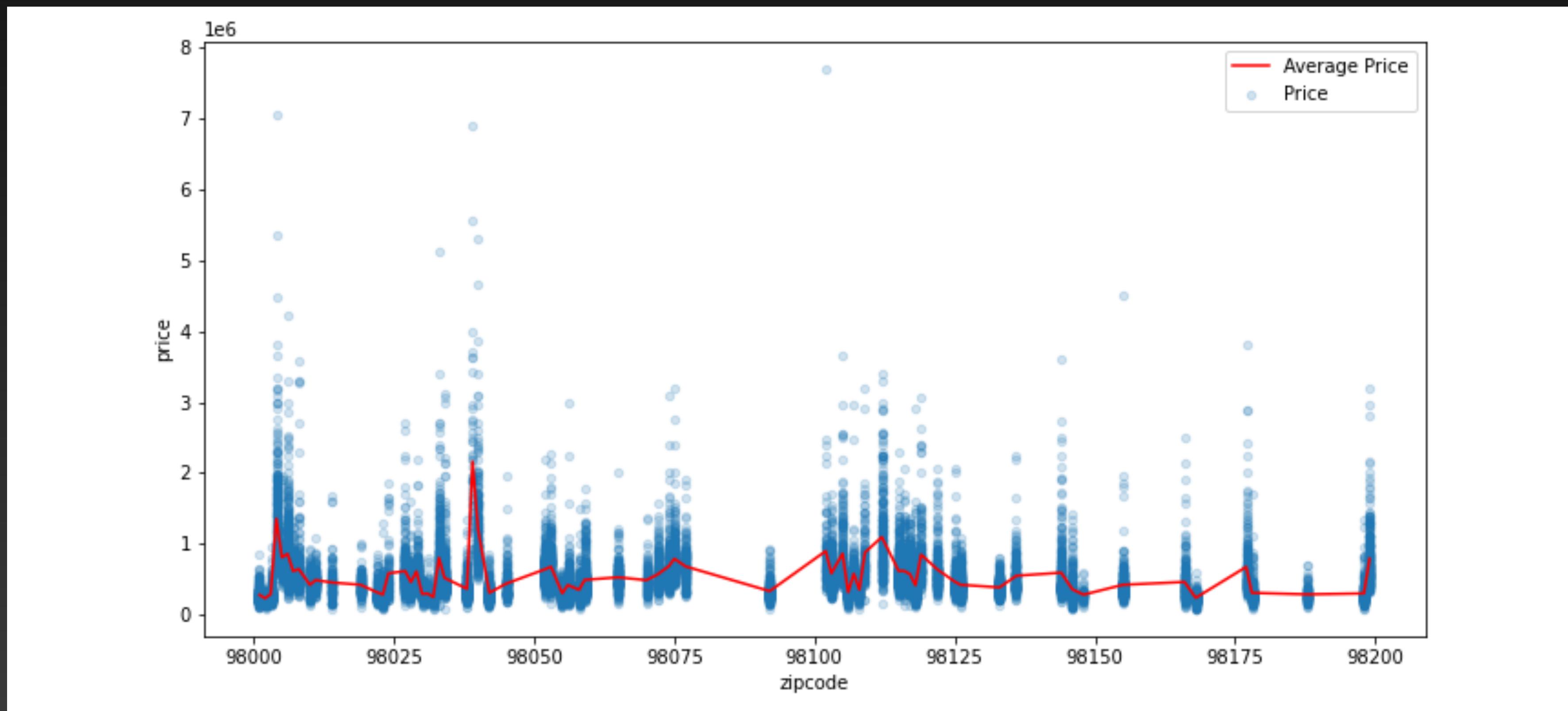
Interpret

Data: Load & Explore & Clean

- King County House Sales Data 'kc_house_data.csv'
- 21597 houses sold between May 2014 - May 2015
- 21 columns in unprocessed data
- 8 columns to be removed
- The columns left: 'id', 'price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'waterfront', 'condition', 'grade', 'yr_built', 'yr_renovated', 'zipcode'
- The missing values in 'waterfront' and 'yr_renovated' are handled

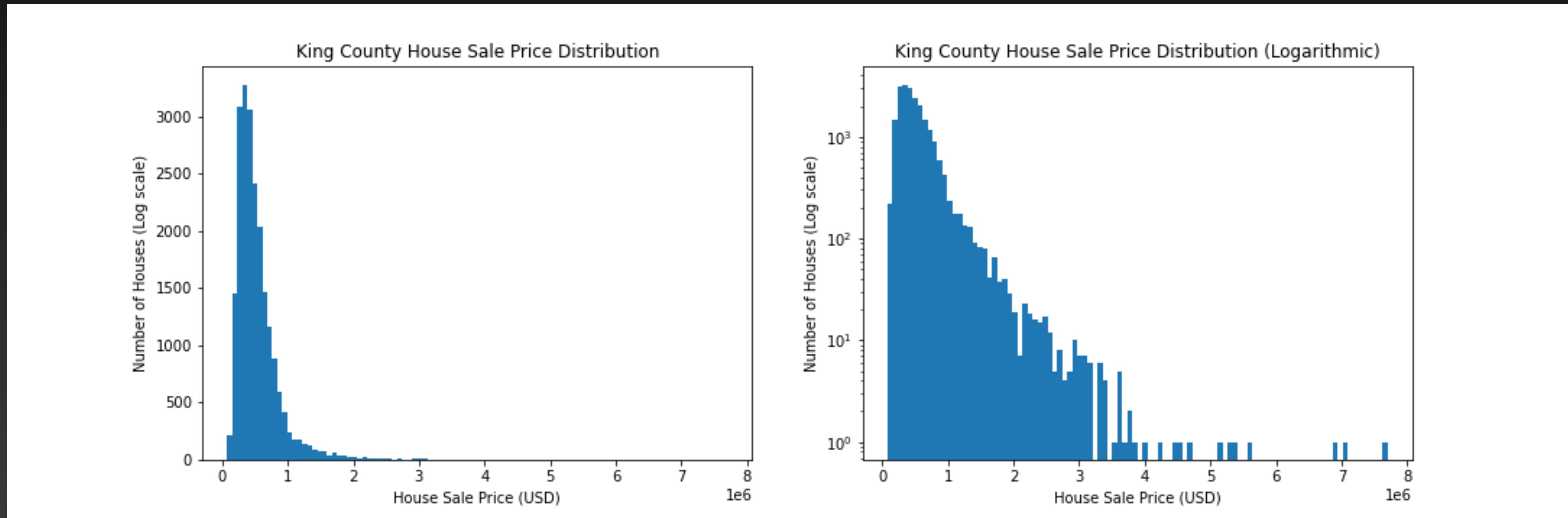
Data: 'zipcode'

- The 'zipcode' is a categorical variable, and there are 69 zip codes in data
- The location is an important predictor in house sale price
- Hot-encoding is applied and dummy zipcodes columns are created

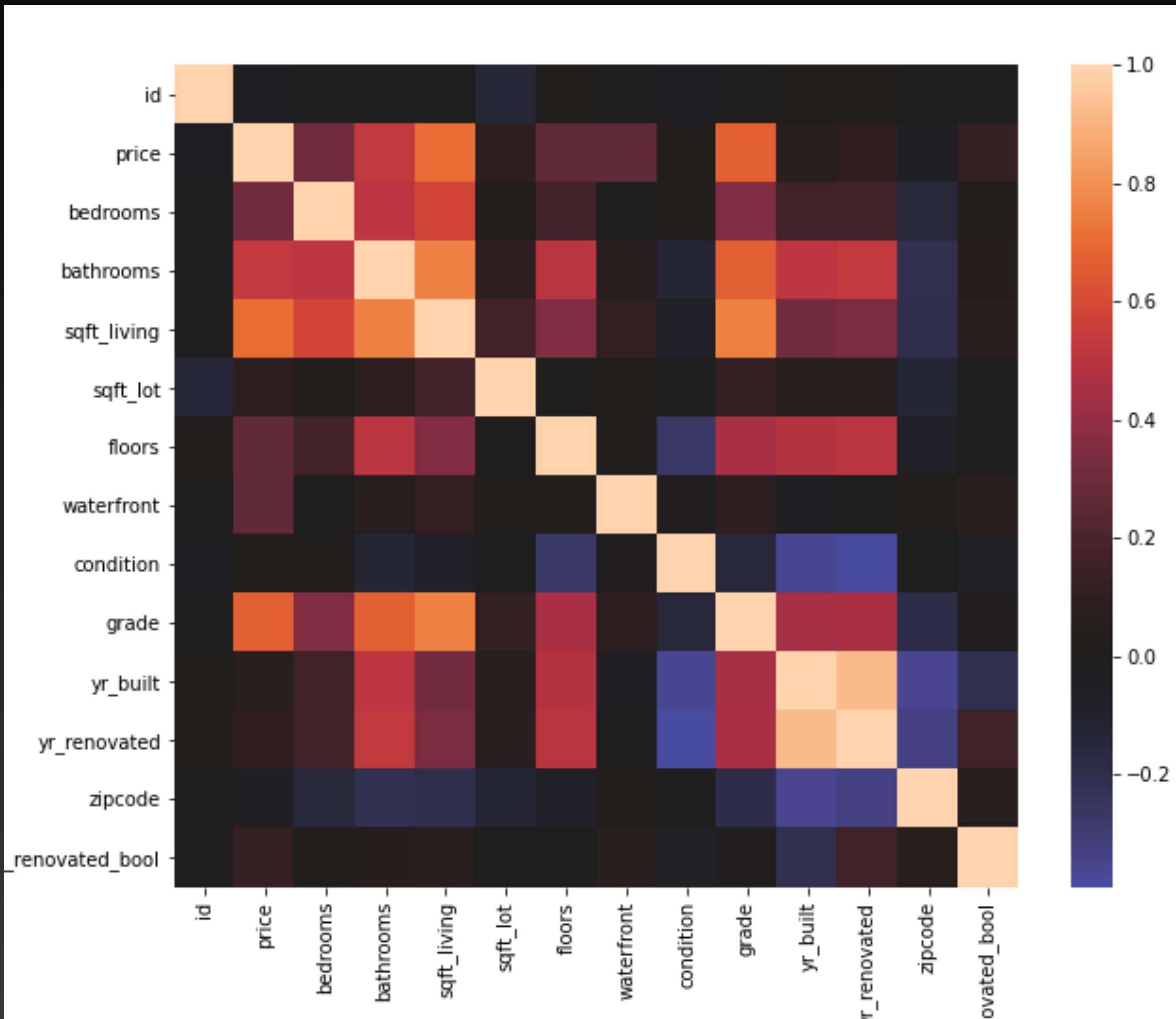


Data: 'price'

- House sale 'price' is the target variable
- It is left-skewed normal distribution
- The outliers are observed in high sale prices



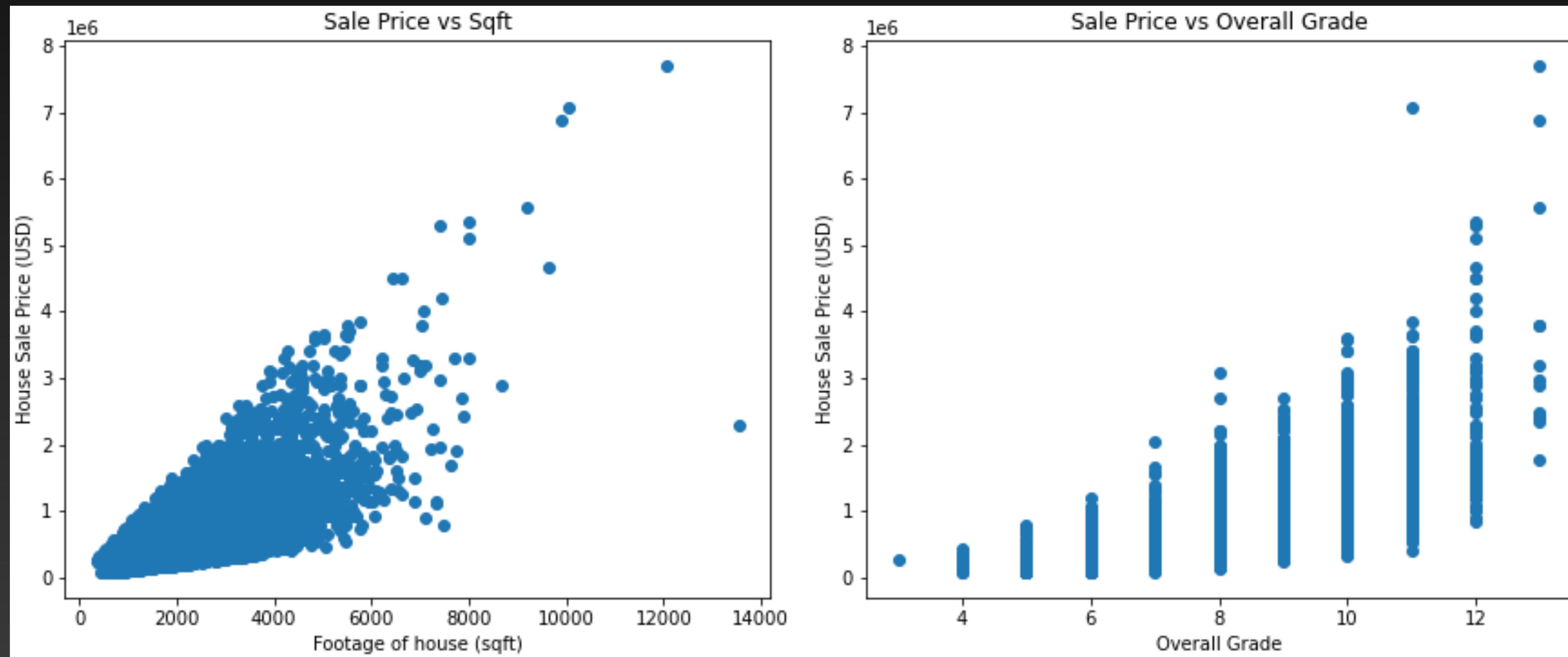
Data: Correlation



- good correlation between Price and (bedrooms, bathrooms, sqft_living, grade)
- good correlation among bedrooms, bathrooms, sqft_living, grade (multicollinearity)
- high correlation between yr_renovated and yr_built (multicollinearity)
- **highest correlation with Sale Price: 'sqft_living' and 'grade'**

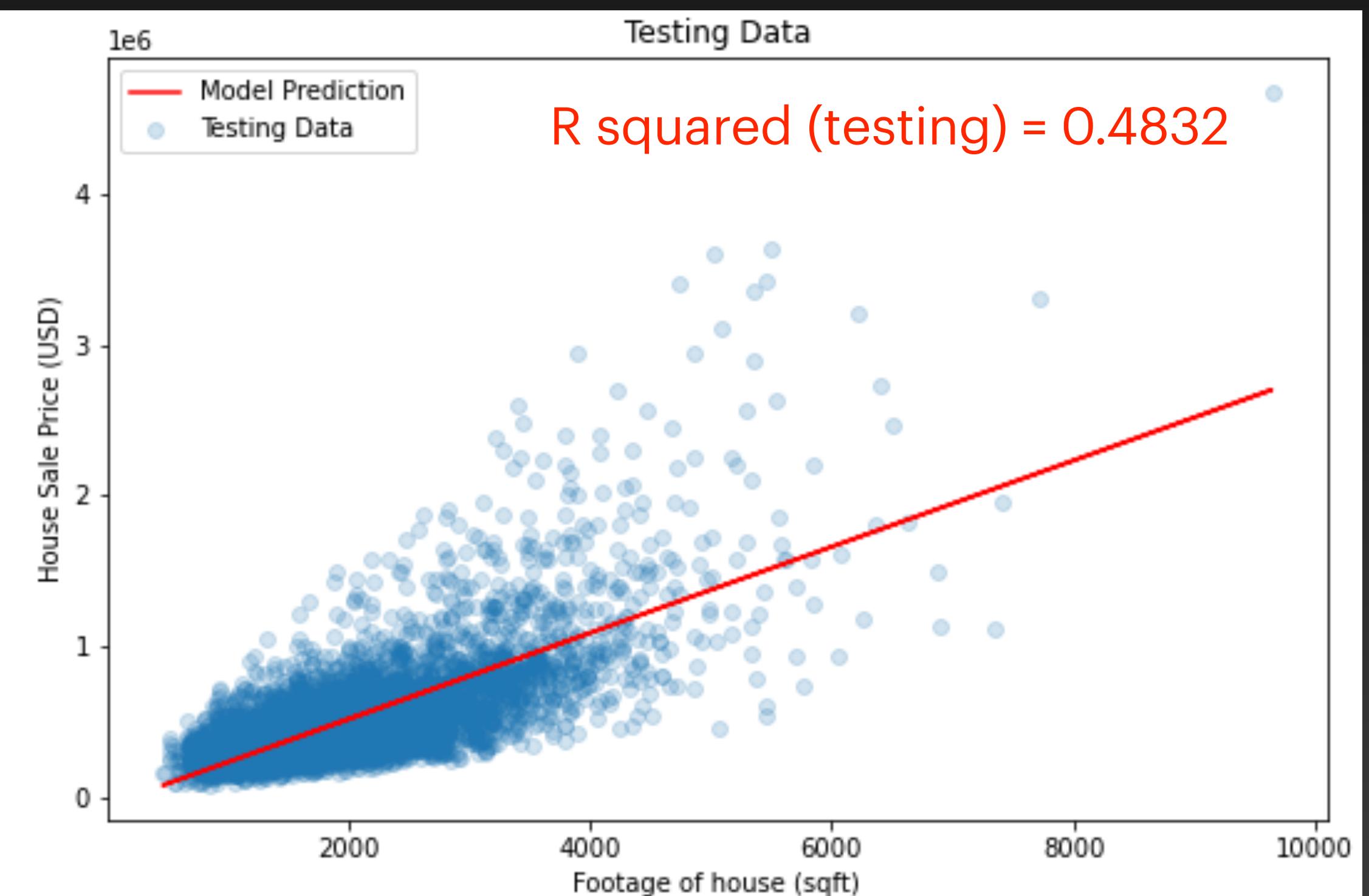
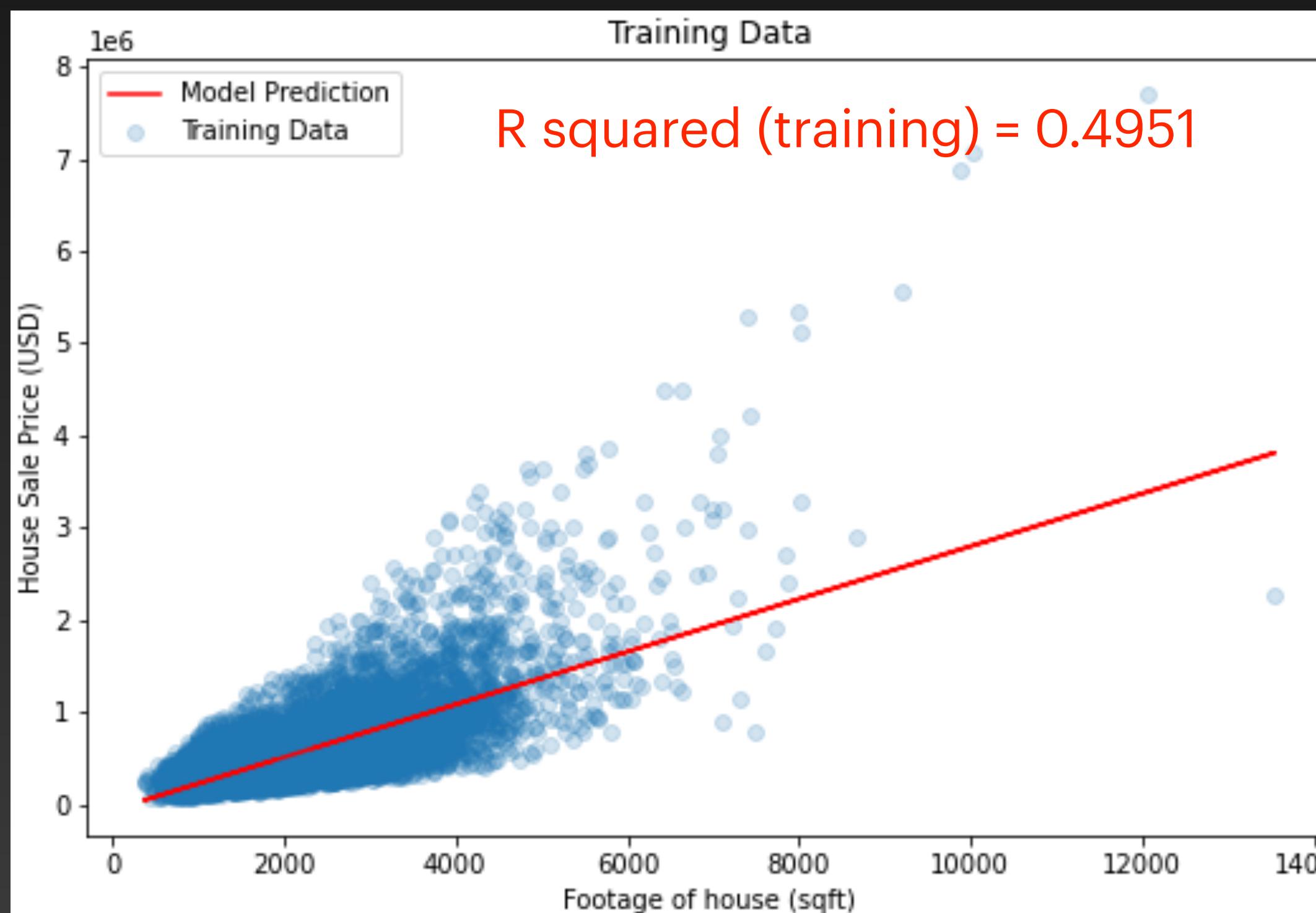
Data: 'sqft_living' and 'grade'

- sqft_living: square footage of the home (continuous variable)
- grade: overall grade given to the housing unit, based on King County grading system (categorical variable)



Model: baseline model

- Three steps in modeling:
 - Separate data into train and test splits
 - Apply Linear Regression Fit to training data and make predictions
 - Validate predictions
- Target: 'price' & Predictor: 'sqft_living'
 - Linear Regression fit results:
 - Slope: 285.58
 - y-intercept: -53321.49



Model: Second and Third models

Second model with two predictors:

	two_predictors	R_squared_train	R_squared_test
0	[sqft_living, zip_98004]	0.533440	0.520127
1	[sqft_living, waterfront]	0.529563	0.528285
2	[sqft_living, yr_builtin]	0.526124	0.518243
3	[sqft_living, zip_98039]	0.517281	0.506499
4	[sqft_living, yr_renovated]	0.516954	0.507128
5	[sqft_living, zip_98112]	0.511713	0.506115
6	[sqft_living, zip_98040]	0.508561	0.496405
7	[sqft_living, zip_98023]	0.504133	0.492635
8	[sqft_living, zip_98038]	0.502710	0.491157
9	[sqft_living, zip_98042]	0.502537	0.492249
10	[sqft_living, zip_98105]	0.502214	0.491189
11	[sqft_living, zip_98092]	0.501713	0.491271
12	[sqft_living, yr_renovated_bool]	0.501480	0.491107
13	[sqft_living, zip_98119]	0.501165	0.493318
14	[sqft_living, condition]	0.501093	0.489588

Third model with three predictors:

	three_predictors	R_squared_train	R_squared_test
0	[sqft_living, zip_98004, waterfront]	0.569135	0.566727
1	[sqft_living, yr_builtin, zip_98004]	0.562154	0.552604
2	[sqft_living, yr_builtin, waterfront]	0.556858	0.558546
3	[sqft_living, zip_98039, zip_98004]	0.556583	0.544304
4	[sqft_living, zip_98004, yr_renovated]	0.553657	0.543087
5	[sqft_living, zip_98039, waterfront]	0.551630	0.552382
6	[sqft_living, zip_98112, zip_98004]	0.551043	0.544249
7	[sqft_living, waterfront, yr_renovated]	0.549054	0.549292
8	[sqft_living, zip_98040, zip_98004]	0.548339	0.534251
9	[sqft_living, yr_builtin, zip_98039]	0.546934	0.539806
10	[sqft_living, zip_98112, waterfront]	0.546886	0.552160
11	[sqft_living, zip_98040, waterfront]	0.541900	0.539191
12	[sqft_living, zip_98023, zip_98004]	0.541846	0.528913
13	[sqft_living, zip_98105, zip_98004]	0.541012	0.528563
14	[sqft_living, zip_98038, zip_98004]	0.540323	0.527330

Best five predictors:

- sqft_living,
- waterfront,
- yr_builtin,
- zip_98004,
- zip_98039

Model: Final Model

- Multiple Linear Regression is applied on data
 - Five Final model predictors:
 - 'sqft_living',
 - 'waterfront',
 - 'yr_built',
 - 'zip_98004',
 - 'zip_98039'
 - R squared:
 - Training: 0.6159
 - Testing: 0.6179
 - MSE = 4.549e+10 & RMSE = 2.133e+05
- Results:
- Intercept: 4014990.7576159136
 - Coefficients:
 - sqft_living: 2.844667e+02
 - waterfront: 8.040627e+05
 - yr_built: -2.071868e+03
 - zip_98004: 6.201505e+05
 - zip_98039: 1.162237e+06

Model: 'yr_renovated'

Linear Regression Results:

- predictor: 'yr_renovated'
 - R squared for Training: 0.0102
 - R squared for Testing: 0.0061
- predictors: 'sqft_living', 'waterfront', 'yr_built', 'zip_98004', 'zip_98039', 'yr_renovated' (final model predictors + 'yr_renovated')
 - R squared for Training: 0.617
 - R squared for Testing: 0.618

House Renovation doesn't have significant effect on House Sale Price.

Interpret: House Sale Price Prediction

$$y = b + m_1x_1 + m_2x_2 + m_3x_3 + m_4x_4 + m_5x_5$$

$$\text{House Sale Price} = 4014990.7576159136 + (2.844667e+02 * \text{sqft_living}) + (8.040627e+05 * \text{waterfront}) + (-2.071868e+03 * \text{yr_built}) + (6.201505e+05 * \text{zip_98004}) + (1.162237e+06 * \text{zip_98039})$$

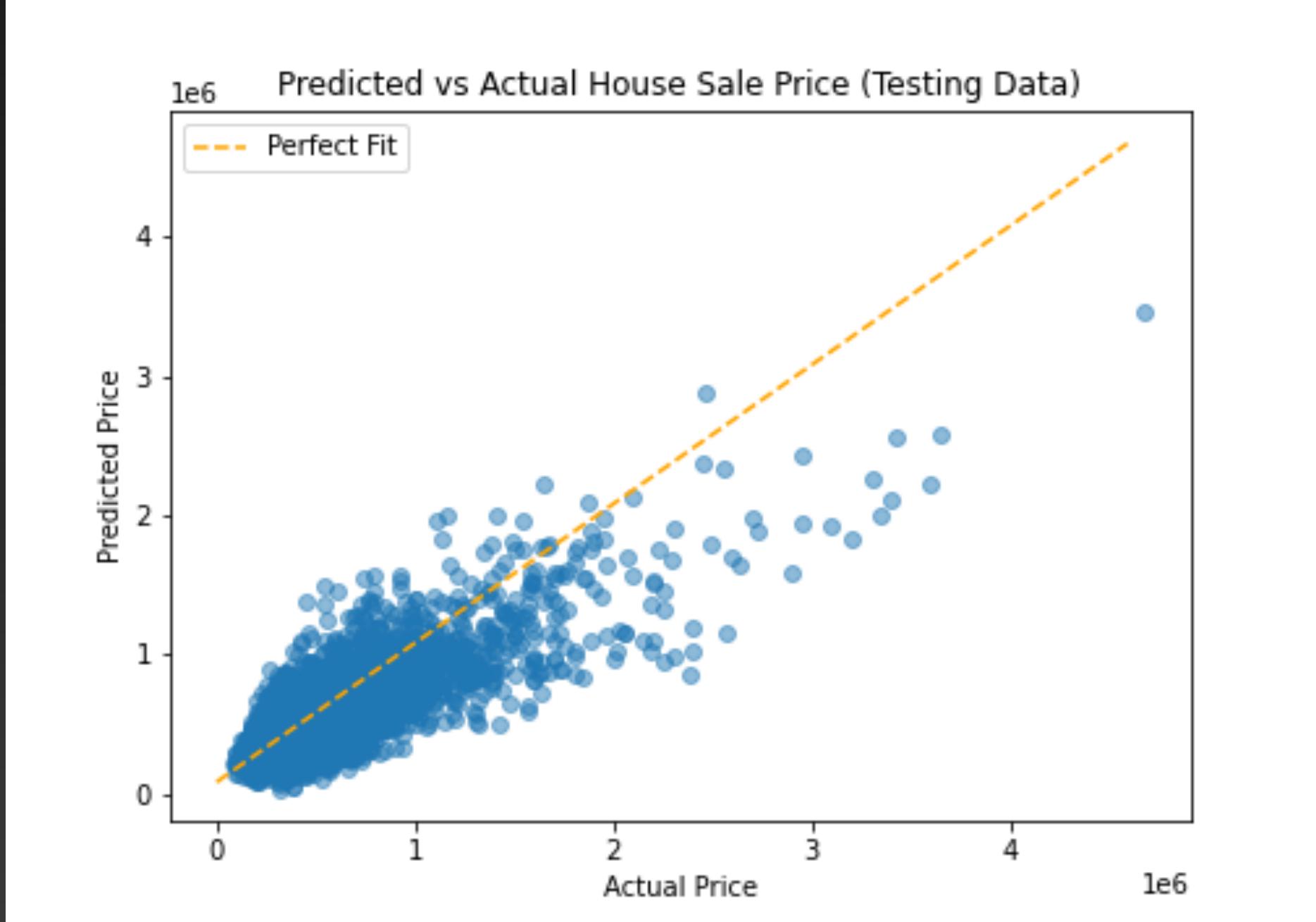
House Sale price prediction examples:

1. sqft_living=2800, waterfront=0, year_built=1978, zipcode_98004=0, zipcode_98039=0 => price = \$713,342
2. sqft_living=4200, waterfront=0, year_built=1978, zipcode_98004=0, zipcode_98039=0 => price = \$1,111,595
3. sqft_living=2800, waterfront=1, year_built=1978, zipcode_98004=0, zipcode_98039=0 => price = \$1,517,405
4. sqft_living=2800, waterfront=0, year_built=2015, zipcode_98004=0, zipcode_98039=0 => price = \$636,683
5. sqft_living=2800, waterfront=0, year_built=1978, zipcode_98004=1, zipcode_98039=0 => price = \$1,333,493
6. sqft_living=2800, waterfront=0, year_built=1978, zipcode_98004=0, zipcode_98039=1 => price = \$1,875,579

Interpret: Assumptions

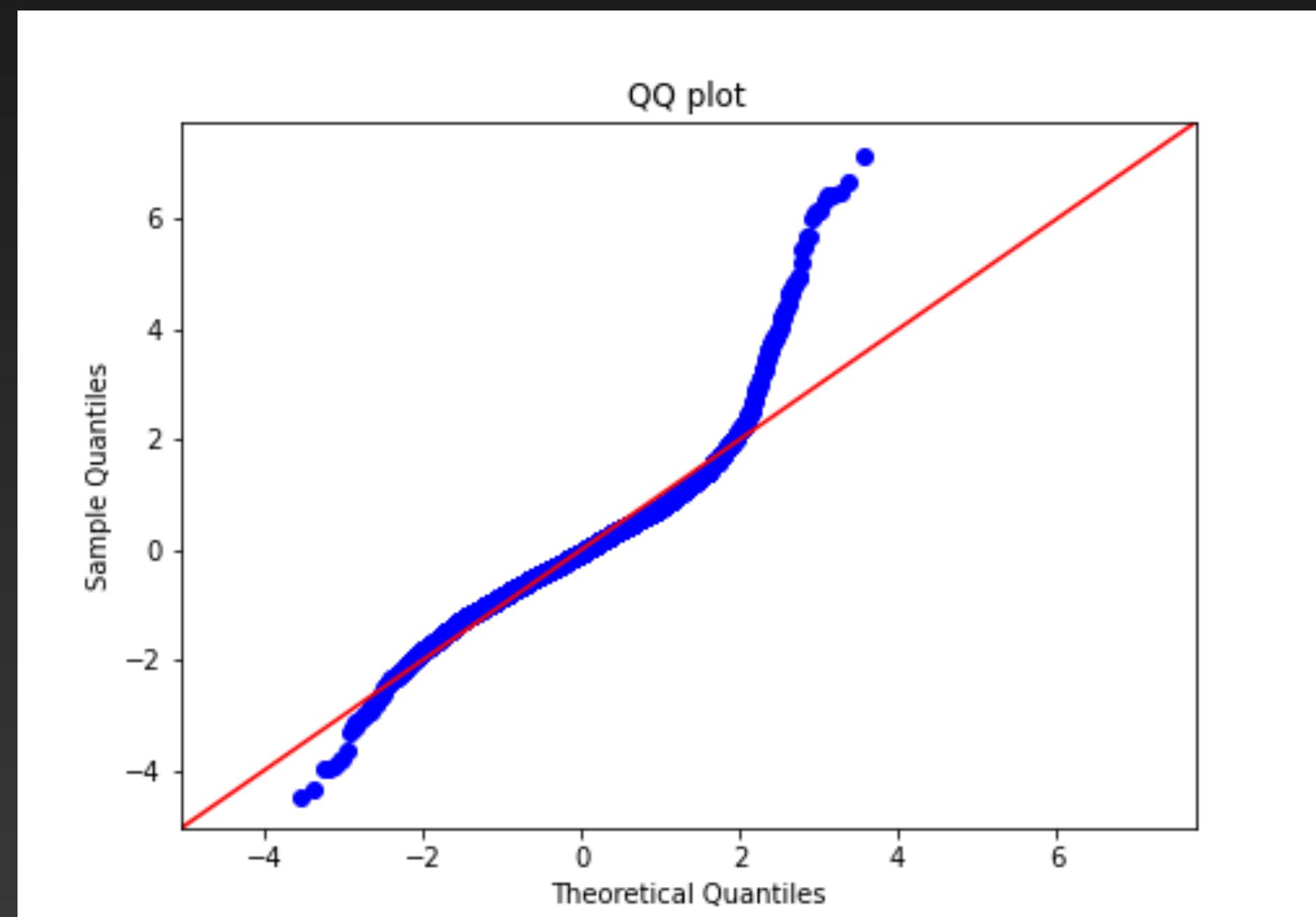
Linearity

- Linearity assumption holds for the majority of the data, except outliers at high sale prices
- At high sale prices, the predicted value is deflecting away from the perfect fit: outliers



Normality

- Normality assumption holds for the majority of the data, except outliers at high sale prices.
- Skewness on tails/edges is caused by the outliers at the high sale prices.



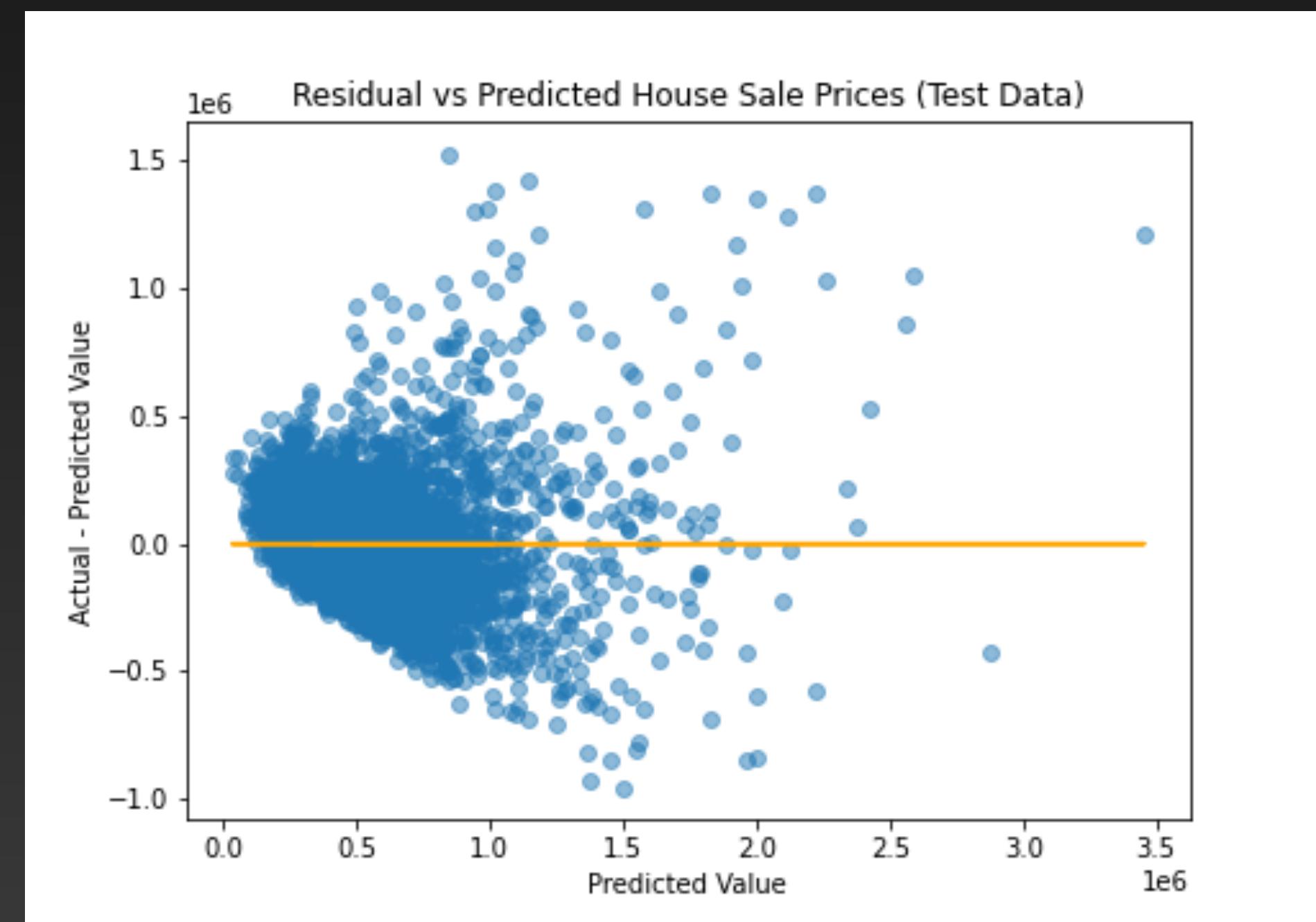
Interpret: Assumptions

Multicollinearity (Independence)

- Independence Assumption is violated since significant multicollinearity is observed
- Multicollinearity scores:
 - sqft_living: 6.460982
 - waterfront: 1.019214
 - yr_built: 6.320784
 - zip_98004: 1.029405
 - zip_98039: 1.010471
- sqft_living and yr_built are correlated!

Homoscedasticity

- Homoscedasticity assumption is violated
- The cone/funnel shape is observed on data.



Future Work

- Two of four linear regression assumptions failed. The others two also fail at high sale prices. I guess one of the main causes for the violations is outliers. For future work, I need to study outliers, and maybe remove from data?
- The correlation between sqft_living and yr_built is interesting. The multicollinearity caused by their correlation affects the model. Should 'yr_built' be removed from model? Advantages and disadvantages?
- Apparently residual increases as the sale price increases. Homoscedasticity even observed at low house sale prices. How can we avoid it?

Questions?