Predicting Housing Prices in King County, WA

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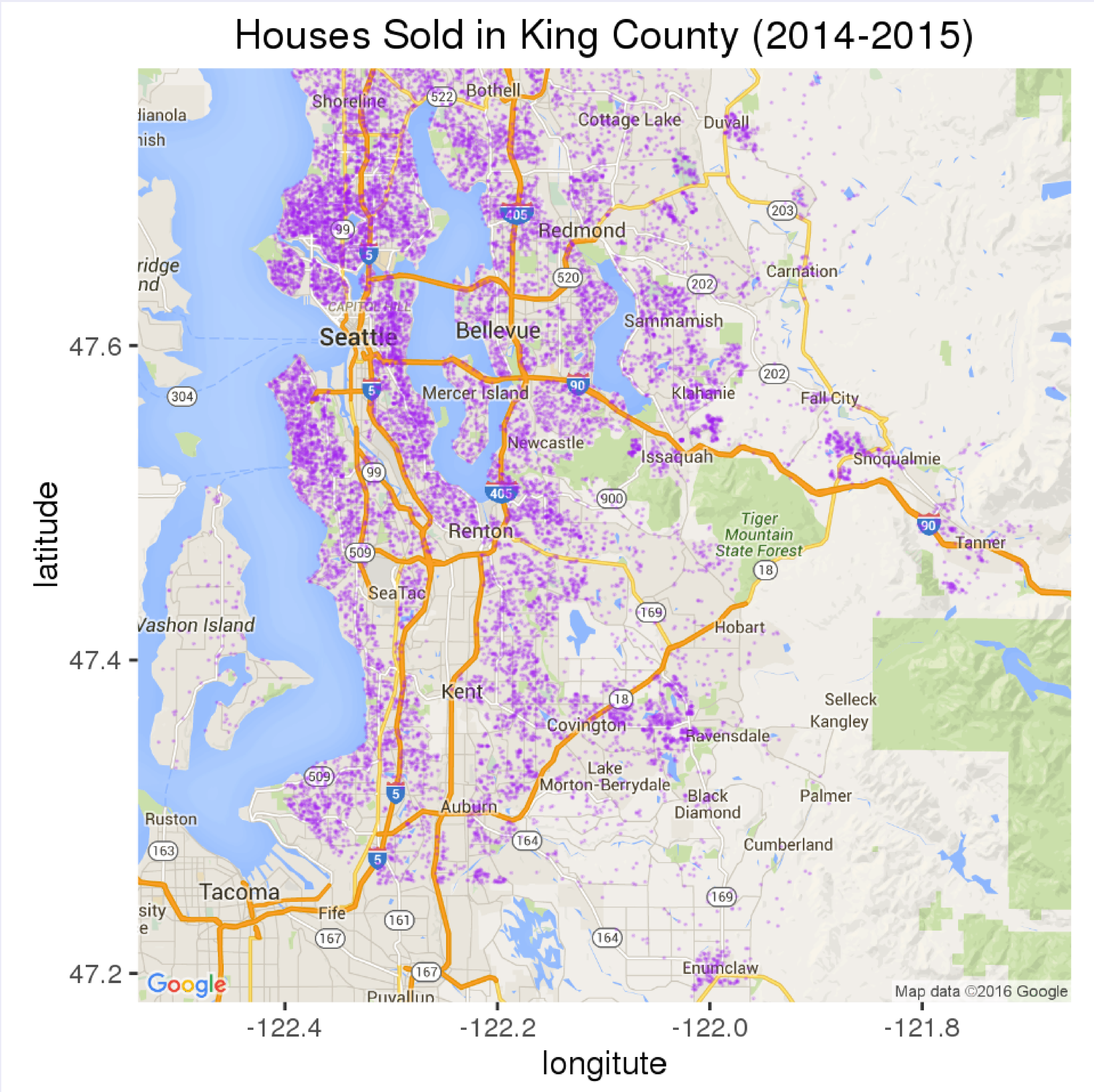
Overview

- The goal of this project was to predict prices for houses in King County, Washington.
- Data was examined from 17384 houses sold in the county between 2014 and 2015 in order to construct a pricing model.
- Models were constructed through exploratory analysis and forward AIC selection, and then tested using K-fold cross-validation.
- All computations and graphs are created with the open source software R [5].

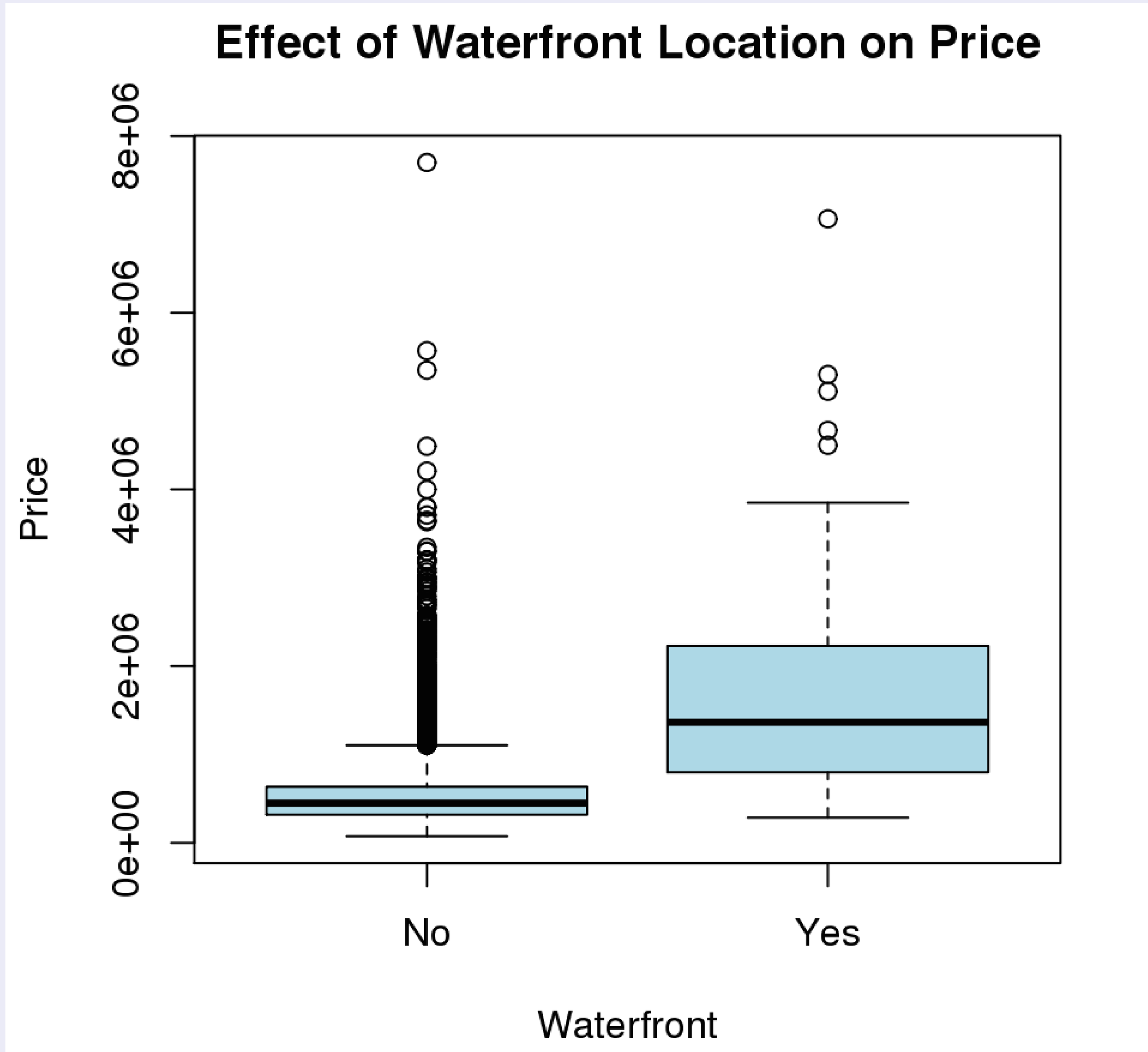


Data Formatting

- The variables *Waterfront*, *Condition*, *Grade*, and *Zipcode* were converted from numeric values to factors.
- The variable *YearRenovated* was set to the corresponding *YearBuilt* for any houses that were missing *YearRenovated* values - that is, any houses that had not been renovated had their renovation dates re-set to the dates they were originally built.
- The variables *Grade* and *Condition* were collapsed to account for limited observations and limited distinct effect in their lower categories.
- Finally, a new variable, *LotSize*, was introduced based on established realtor lot categories [4].

Exploratory Analysis

- Exploratory analysis was performed by examining plots and single-variable regressions for various variables on to *Price*, as well as variable interactions which were assumed to be significant (such as the interaction between *Bedrooms* and *Bathrooms* on to *Price*) [3].
- Variables and interactions which looked to have strong correlation were later added to the model and tested for significance.
- The boxplot below shows the effect of waterfront location on house price:



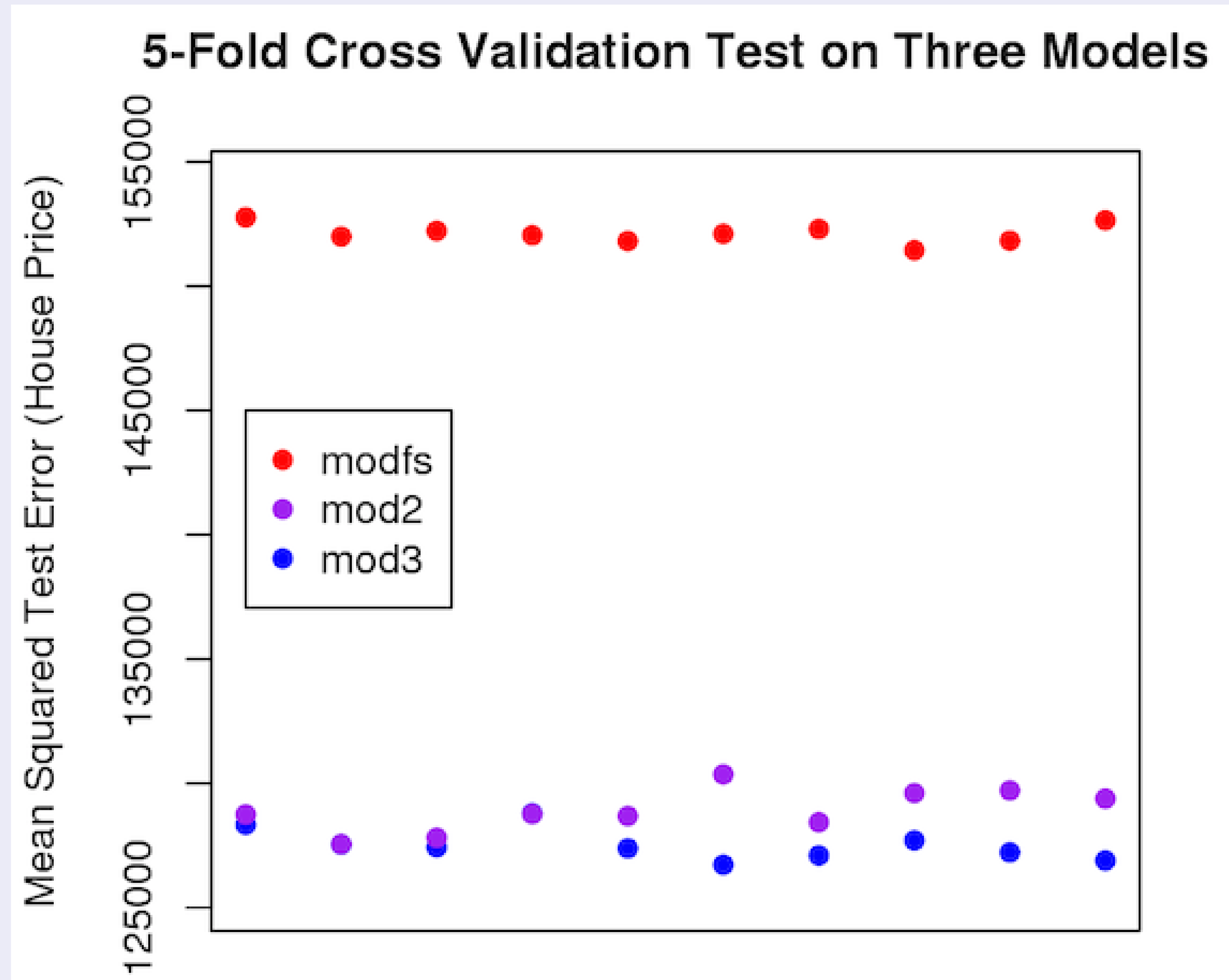
Model Creation

- The first model was created by comparing AIC in a forward stepwise algorithm [6].
- The second model included polynomials based on residual plots of the forward-selected model [2], and interaction terms based on exploratory analysis.
- The final model was a simplified version of the second, dropping features with low significance. It included these features and interactions:

$$E(price) = b_0 + b_1 Grade + b_2 Zipcode + b_3 SqftLiving^2 + b_4 Waterfront + b_5 View + b_6 LotSize + b_7 Condition + b_7 SqftAbove^2 + b_8 YearBuilt + b_9 YearRenovated + b_1 0 Floors + b_1 1 SqftLiving15 + b_1 2 SqftLot15 + b_1 3(SqftLiving : SqftLot) + b_1 5(Bedrooms : Bathrooms) + b_1 6(Waterfront : SqftLiving) + b_1 7(Waterfront : SqftLot) + b_1 8(Lat : Long) + b_1 9(Zipcode : SqftLiving)$$

Model Selection

- We used 5-fold cross-validation to select the best model [1]. The simplified final model consistently performed the best, having the lowest mean squared test error.
- Results of ten repetitions of cross-validation on all three models are plotted below:



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