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The Data

- 15.2 thousand house records from Zillow home listings
- 47 features including:
 - Tax rates, garage spaces, cooling, heating
 - o appliances, lot size, living area size
 - o number of schools, bathrooms, bedrooms, and stories
- Dataset found on Kaggle
 - https://www.kaggle.com/datasets/ericpierce/austinhousingprices



The Goal

- Creating regression models
 - Selecting the best one for predicting housing prices in Austin, Texas



Conclusions: Best Model

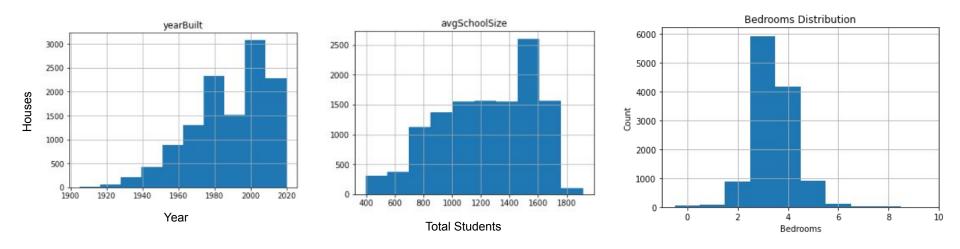
- Linear Regression
 - o 31 Features that remained after Backwards Elimination
 - Train set R-squared = 0.46
 - Test set R-squared = 0.43



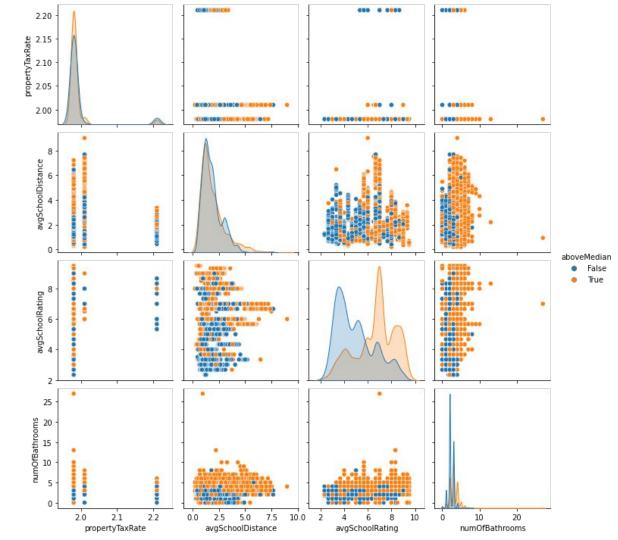
Conclusions: Other Models

- What improved prediction
 - Backwards elimination
 - Reduced the number of features, and the R-squared remained the same.
- What didn't improve prediction
 - Dimensionality Reduction (PCA)
 - The dimensionality reduction worked, but the model's predictive power decreased:
 - (Without PCA) Train set R-squared = 0.46
 - (With PCA) Train set R-squared = 0.39
 - Ridge optimized with GridSearchCV
 - Train set R-squared = 0.41
 - Lasso optimized with GridSearchCV
 - Train set R-squared = 0.24

Other Findings: YearBuilt, SchoolSize, Bedrooms



Other Findings: SchoolRatings & Bathrooms



Other Findings: Two Best Predictors

- Lasso
 - Just two features helped explain about 24% of the variability in the test set's housing prices
 - Living Area Square Feet
 - Number of Bathrooms





Other Findings: Two Best Predictors

- The best Linear Regression model (31 Features)
 - livingAreaSqFt coefficient = \$106,300
 - numOfBathrooms coefficient = \$224,300
 - For every 1 unit increase for each feature, the house's price will increase by the coefficient.
 - The features are standardized, a shift of 1 standard deviation to the right of the distribution.

