It’s all about location, right?

PREDICTING HOUSING PRICES, MACHINE LEARNING

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A G E N D A

- **Project Overview**
- Project Objectives
- Processing Methodology
- Predictive Modelling
- Descriptive Modelling
- Conclusion
- Appendix

PROJECT OVERVIEW

This project uses the AMES Iowa housing dataset to study the housing market, develop predictive models for pricing, and produces an easy to use online quiz, for realtors and homeowners to quickly calculate house prices.

This dataset was initially hosted on Kaggle.

Full codework for this presentation can be found on Katie Kwan's Github.

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PROJECT OBJECTIVES

develop

Predictive Modelling

Develop a clear methodology and process for modeling.

Test various models, linear regression, penalized models, and tree based models and boosting.

produce

User friendly model

Develop a V.1 user friendly model with under 15 features. Features should be easy to measure -- a ruler should be used minimally!

explain

Descriptive Modelling

Examine features , relevance, narratives, and storylines that explain SalesPrice behavior.

enrich

User model

Finalized V1 Model using insights from descriptive modeling.

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    - Tree Based Models

PROCESSING METHODOLOGY

1

Load and clean

- Data cleaning and reconciling.
- Output, clean master doc.

2

Basic EDA

- Research
- Y transformations
- Basic visualization - variance.

3

Correlations

- Heatmaps
- Anovas
- SalePrice x Feature plotting

4

Build Pipeline

- Build pipeline functions: load, split, encode, preprocess, run regressor.

5

Predictive and Descriptive Modeling

- Comparative Modeling, Recursive Feature Elimination.
- Feature engineering and descriptive research.

DATA CARD

FEATURE DICTIONARY

Hosted on Kaggle.

Cleaned Data Set

2559 records.
5 added Features.

FEATURES

Land: 'PID', 'MSZoning', 'LotFrontage', 'LotArea', 'Street', 'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlope', 'Neighborhood', 'PavedDrive',

Type: 'MSSubClass', 'BldgType', 'HouseStyle','YearBuilt', 'YearRemodAdd','GarageYrBlt',

Finishes: 'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType','ExterCond', 'Foundation', 'BsmtExposure', 'BsmtFinType1', 'GarageFinish',

Quality: 'Condition1', 'Condition2', 'OverallQual', 'OverallCond', 'BsmtQual', 'BsmtCond', 'KitchenQual', 'FireplaceQu', 'Functional', 'GarageQual', 'GarageCond', 'ExterQual',

FEATURES, GROUPED

Size: 'GrLivArea', 'MasVnrArea','BsmtFinSF1', 'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr','TotRmsAbvGrd', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea',

Amenities: 'Fireplaces','GarageType', 'GarageCars', 'PoolQC', 'Fence', 'MiscFeature', 'MiscVal', 'HeatingQC', 'CentralAir', 'Electrical', 'Heating',

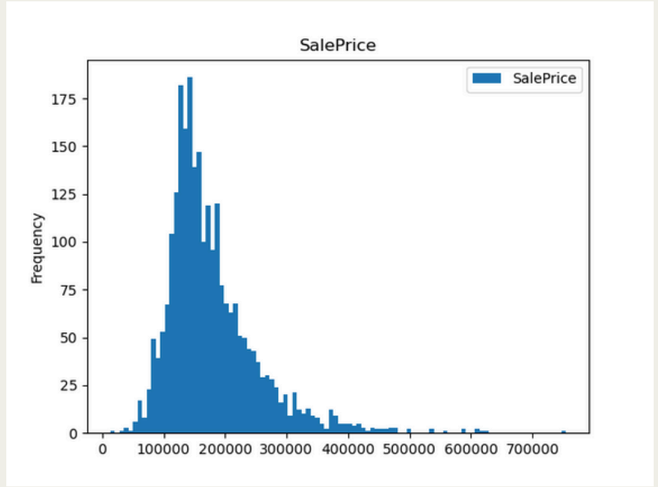
Sales Terms: 'MoSold', 'YrSold', 'SaleType', 'SaleCondition'

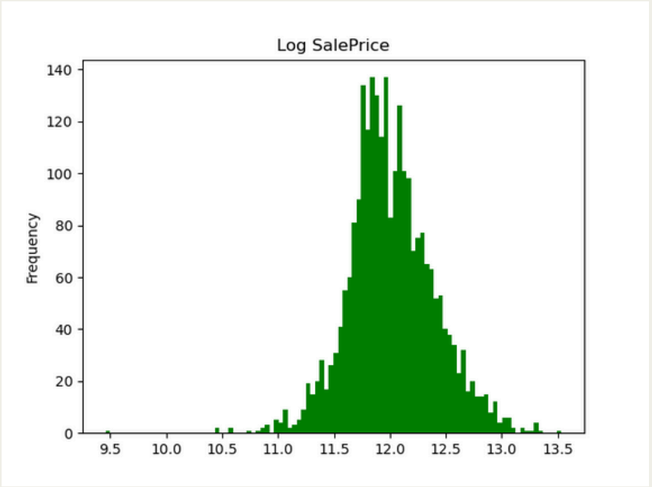
KEY DECISIONS DURING DATA PREP

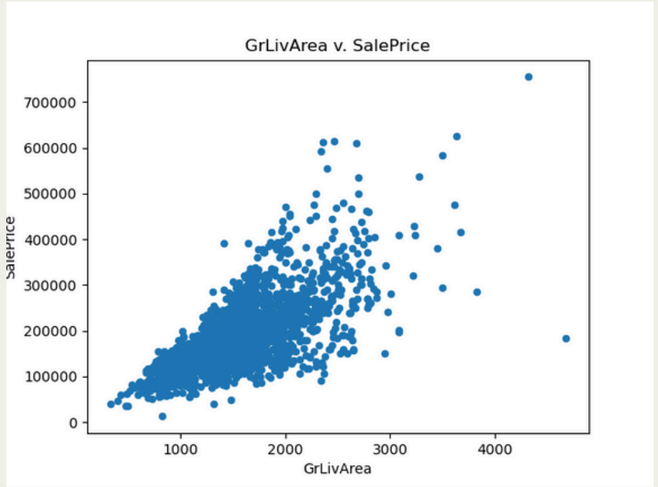
Y Transformation

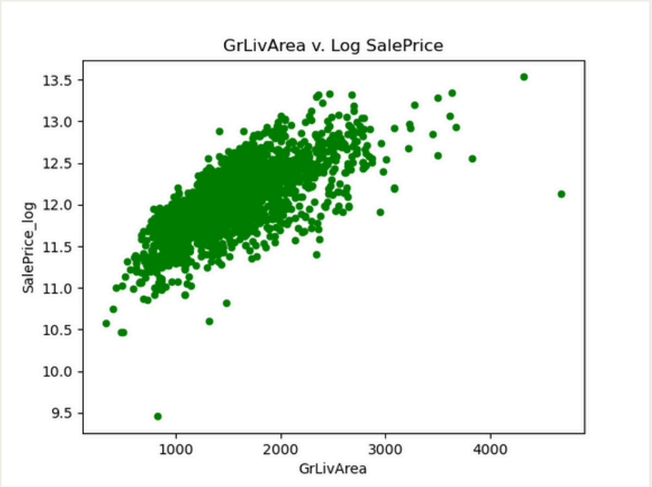
SalePrice distribution not Gaussian curve.

Scatterplots of continuous variables v SalePrice need to be corrected to proceed with linear regression.









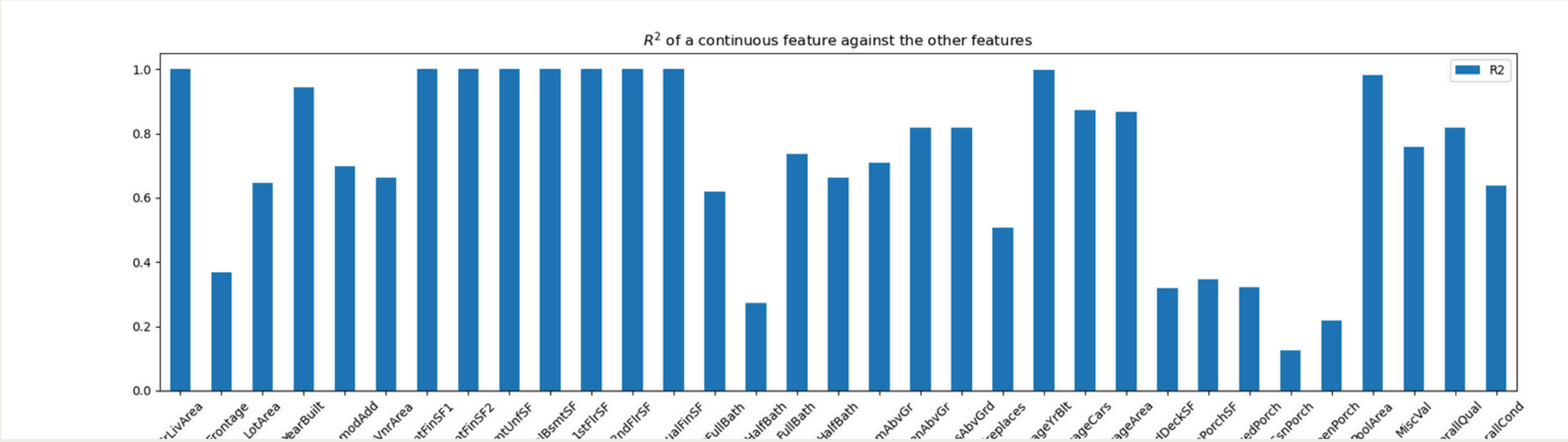
KEY DECISIONS DURING DATA PREP

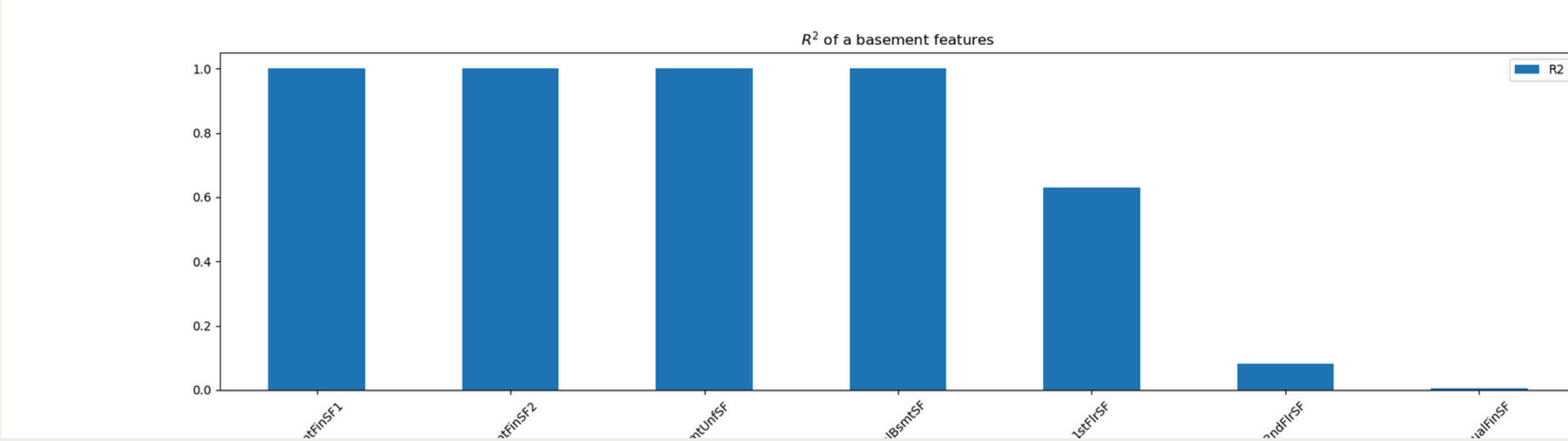
Features within groups need to be eliminated

R Squared values of linear regression models where:

- Each feature is the dependent variable
- All other features are independents

R2 = 0, exhibits no signs of multicollinearity.
R2 = 1, is multicolinear with features.

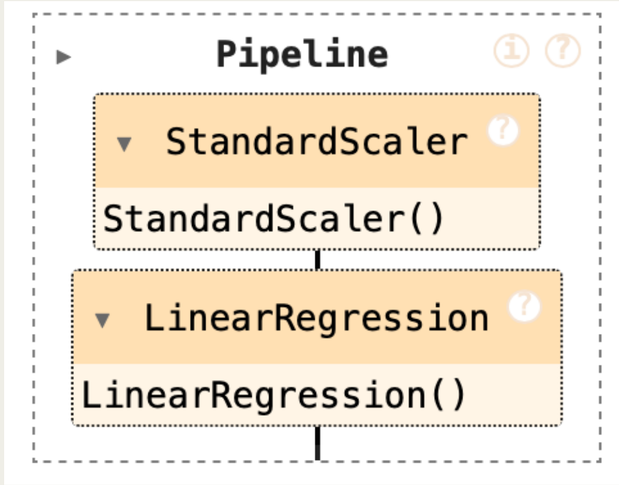




KEY DECISIONS DURING DATA PREP

Preprocessing Process

1. One Hot Encoder to dummify all categorical features
2. Test SalesPrice and log of SalePrice as dependent variable for each model to determine best outcome.
3. Train Test Split (80/20)
4. Transform continuous features
    a. Use Normalizer to transform when dealing with the saturated model. All features scaled from 0 to 1. Enable feature selection based on coefficient values.
    b. Use StandardScaler on all features for models with fewer features.
5. Fit training data to regressor.
6. Use to test data to produce and R squared and Adjusted R squared.
    a. Use Adjusted R Squared to compare models.



LOG MODEL INTERPRETATION

Every Feature Produces is a Multiplier

SalePrice is now the product of a multiples each (e^beta*x), where beta is the coefficient returned by the model and x is the features.

- If <1, reduces house price
- If >1, increase house price.

a. Base Price: e^intercept
b. For a dummified feature,
    i. if x = 0, e^0 = 1.
        1. no change on outcome.
    ii. if x = 1, e^beta*1
        1. Multiplier = e^beta.
c. For a continuous feature,
    i. Multiplier = e^beta*x, this can range from (0,infinity).

$$Y = \beta_0 + \beta_1 \cdot features$$

$$Y = log(price)$$

$$log(price) = \beta_0 + \beta_1 \cdot features$$

$$price = e^{\beta_0} \cdot e^{\beta_1 * x_1} \cdot e^{\beta_2 * x_2} \cdot e^{\beta_n * x_n}.$$

$$price = e^{inter} \cdot e^{\beta_1 * x_1} \cdot e^{\beta_2 * x_2} \cdot e^{\beta_n * x_n}.$$

$$price = \prod_{i=o}^{n} e^{\beta_i * x_i}$$

*e ≈ 2.72.

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  - **Linear Models**
  - Tree Based Models
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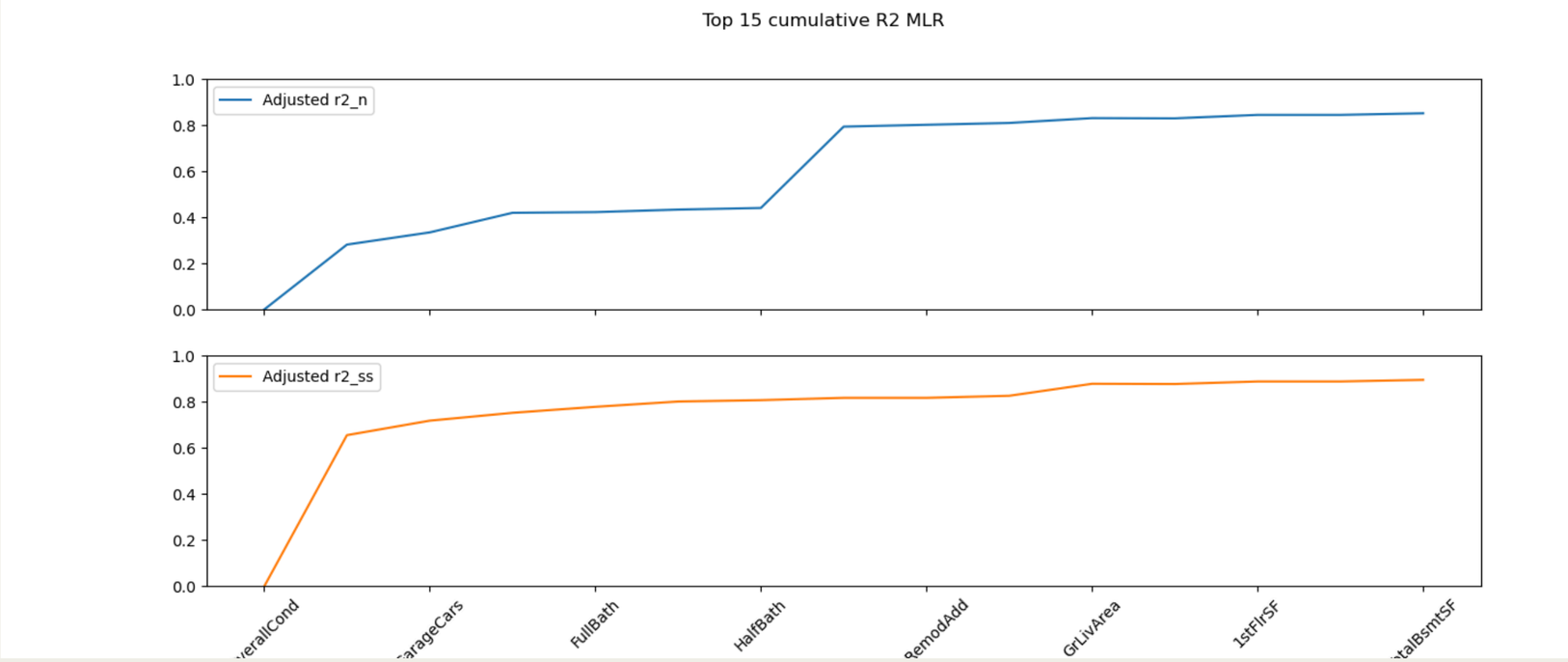
PREDICTIVE MODELLING

Feature Selection Process

1. Run saturated models.
2. Extract top 15 features.
3. Run through other models to compare Adjusted R2.
4. Find best top 15 and best model.



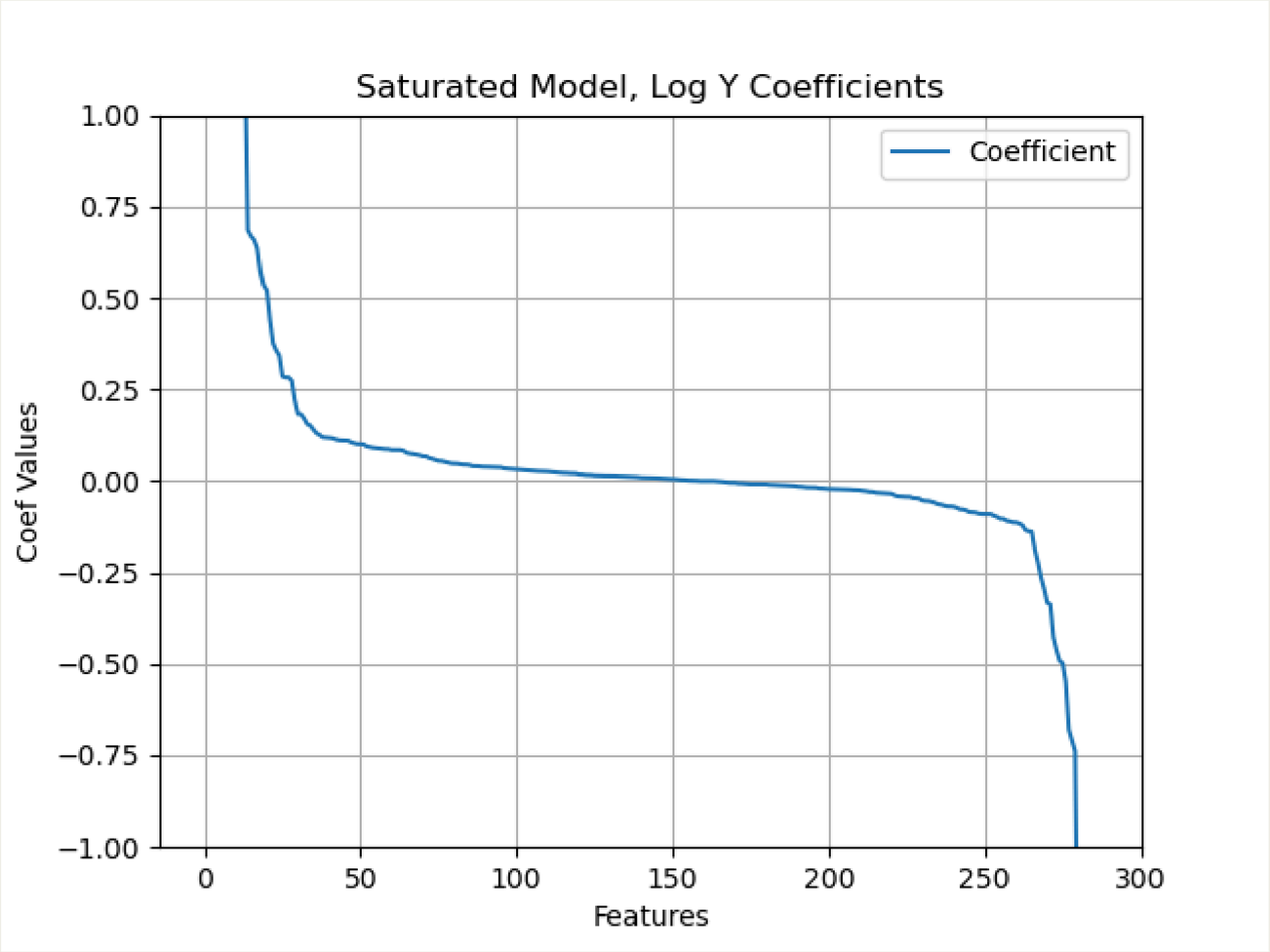
The graph above shows adjusted R squared values for models, each with increasing number of the Linear Regression Top 15 features.

- With StandardScaler in preprocessing, the R squared gores to ~.9 quicker than Normalizer.
- Beyond 15 features, there is marginal improvement to scoring.

PREDICTIVE: COEFS AT A GLANCE

Coefficient Significance

- At coef = .1,
  - e^.1*x ranges between [1.1,1] as a multiplier. The most it can shift the model is 10%.
- At coef = 0,
  - e^.1*0 = 1 and has no impact on the model
- At coef = -1,
  - e^-1*x ranges between [.36,1] as a multiplier. The most it can shift the model is 10%.



PREDICTIVE: LINEAR RESULTS (SATURATED)

Saturated Model Results

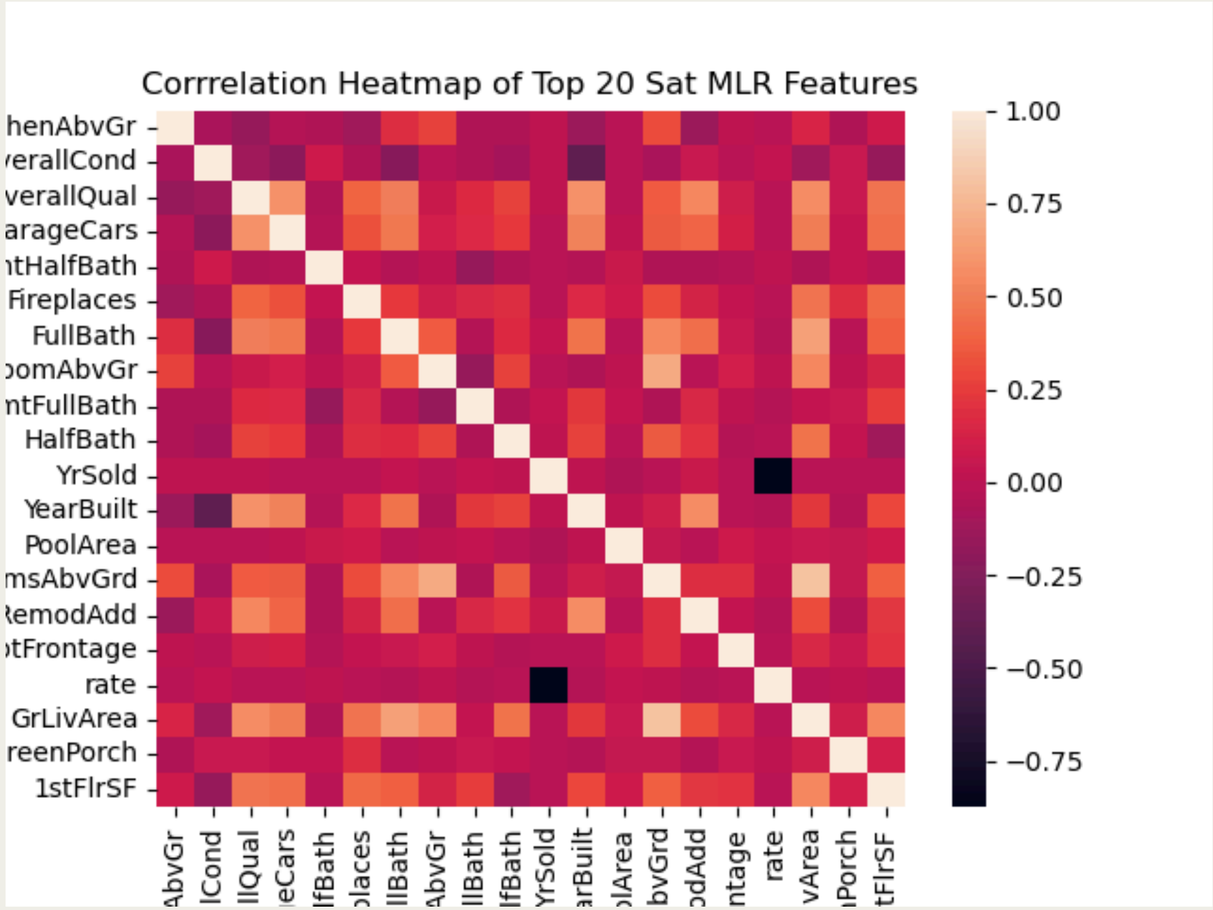
- Model resutls are similiar, differnet MSE units
- Train and Test do not display obvious signs of overfitting.
- Large difference between R2 and Adjusted R2.
- Stability of model is compromised with having colinear features.

Model	Test R Squared	Test Adj R Squared	Train R Squared	MSE	RMSE
Linear Regression Normalized, Log Y	.910	.796	.934	.014	.118
Lasso Standard Scaler, Y (alpha = 4500)	.916	.809	.94	5.33* 10^8	23.090
Ridge Standard Scaler, Log Y alpha = undetermined	.930	.841	.964	.011	.105
Elastic Net Standard Scaler Y alpha = .028, l1-ratio = .11	.901	.755	.912	6.32 * 10^8	25,156
LassoCV Standard Scaler, Log Y alpha = .0029	.925	.833	.934	.012	.11

PREDICTIVE: LINEAR TOP 15

Top 15 Correlation

1. Plot absolute value of coefficients.
    a. Extract top 20.
2. Plot heatmap to indentify highly correlated features. Strip out one or all of features that show multicollinearity and add them back in through iterative loops.
3. Find Feature set that optimizes either accuracy or accuracy and simplicity for adjusted r2.



PREDICTIVE: LINEAR TOP 15

Accuracy Based Feature Set

Top Features

Top MLR Features

- **MLR 15 = OverallCond, OverallQual, GarageCars, Fireplaces, FullBath, BsmtFullBath, HalfBath, YearBuilt, YearRemodAdd, LotFrontage, GrLivArea, ScreenPorch, 1stFlrSF, 3SsnPorch, TotalBsmtSF**

Adjusted r2 = .894

r2	Adjusted r2	train r2	MSE	Abs Error	RMSE	0	Dropped Features
0.897000	0.894000	0.885000	0.016000	skip	0.126000	30	[]
0.897000	0.894000	0.885000	0.016000	skip	0.126000	4	['HalfBath']
0.896000	0.893000	0.885000	0.016000	skip	0.126000	8	['1stFlrSF', 'HalfBath']
0.896000	0.893000	0.885000	0.016000	skip	0.126000	0	['1stFlrSF']
0.890000	0.887000	0.880000	0.017000	skip	0.130000	3	['Fireplaces']
0.890000	0.887000	0.880000	0.017000	skip	0.130000	14	['Fireplaces', 'HalfBath']
0.890000	0.887000	0.879000	0.017000	skip	0.130000	11	['TotalBsmtSF', 'HalfBath']
0.890000	0.887000	0.879000	0.017000	skip	0.130000	1	['TotalBsmtSF']
0.888000	0.886000	0.879000	0.017000	skip	0.130000	20	['1stFlrSF', 'Fireplaces', 'HalfBath']
0.888000	0.885000	0.879000	0.017000	skip	0.130000	7	['1stFlrSF', 'Fireplaces']
0.884000	0.881000	0.874000	0.018000	skip	0.134000	23	['TotalBsmtSF', 'Fireplaces', 'HalfBath']
0.884000	0.881000	0.874000	0.018000	skip	0.134000	10	['TotalBsmtSF', 'Fireplaces']
0.880000	0.877000	0.871000	0.019000	skip	0.138000	5	['1stFlrSF', 'TotalBsmtSF']

Table of linear model scores.
Top 15 Features = []. Features Dropped shows th model[] without specified feature.
Goal is to drop features and maintain accuracy.

PREDICTIVE: LASSO TOP 15

Feature Selection

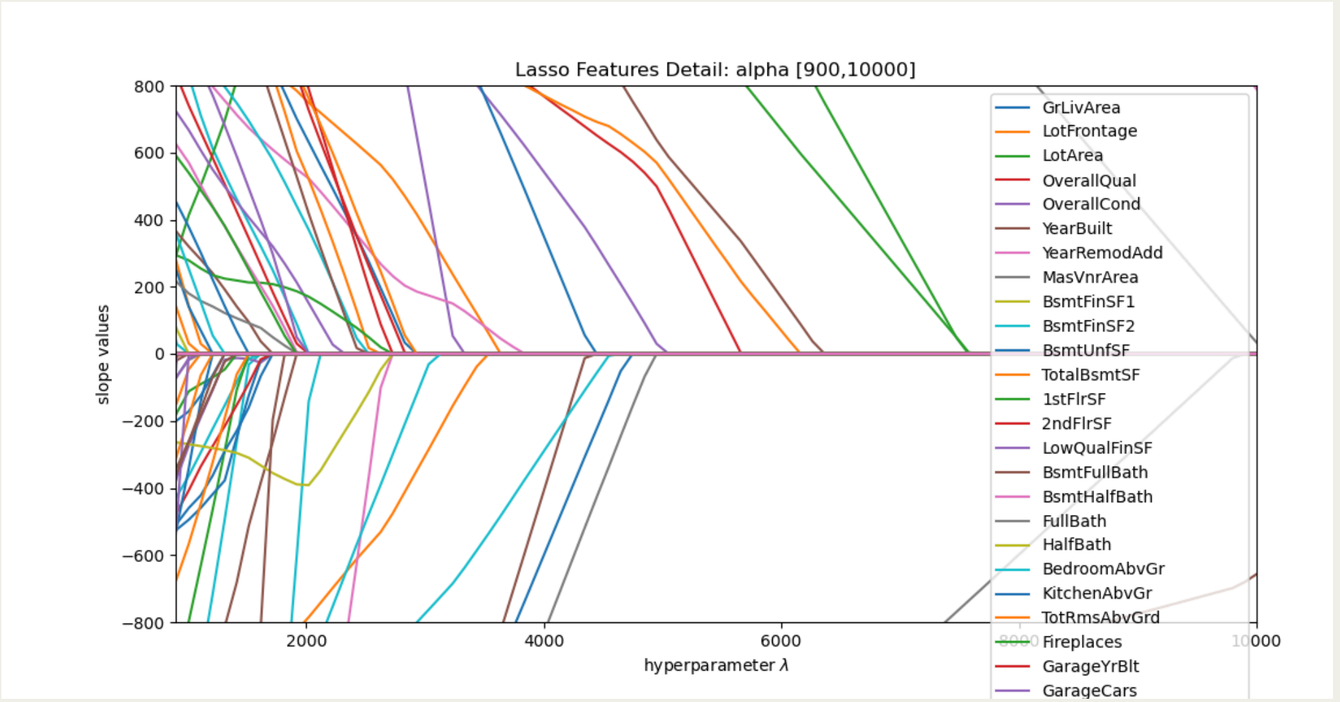
1. Maximize penalization (alpha) to find all features that are not equal to zero.

a. **Lasso 15 = OverallQual*, GrLivArea*, TotalBsmtSF*, BsmtFinSF1, GarageArea, 1stFlrSF*, YearBuilt*, GarageCars*, BsmtExposure_Gd, YearRemodAdd*, MasVnrArea, ExterQual_TA**

Top Lasso Features

Adjusted R Squared = .871

**Shares the the same features with MLR Top feature.*



As alpha (or lambda here) goes to 10000, features go to zero. At 10,000, there are only a select few features that are non-zero. These are the top features. Alpha tuning visualization.

PREDICTIVE: LASSOCV TOP 15

Feature Selection

1. LassoCV provides cross validation and auto alpha tuning, returns feature set.

   a. **Lasso CV Top 15 = GrLivArea*, OverallQual*, YearBuilt*, OverallCond*, TotalBsmtSF*, BsmtFinSF1**, GarageCars*, Neighborhood_Somerst, Neighborhood_Crawfor, YearRemodAdd**, Fireplaces*, LotArea, SaleCondition_Normal, Neighborhood_NridgHt, MSZoning_RL**

Top Lasso CV Features

Adjusted R2 = .907

**seen in MLR and Lasso Top Features*

***seen Lasso Top Features*

	r2	Adjusted r2	train r2	MSE	Abs Error	RMSE
Lassocv Top 15	0.910000	0.907000	0.900000	0.014000	skip	0.118000
MLR 15	0.897000	0.894000	0.885000	0.016000	skip	0.126000
Lasso Top 15 coef	0.881000	0.878000	0.871000	0.019000	skip	0.138000

LassoCV best score is usign its own returned features. It is worth exploring if these features - neighborhood and zoning - can be explored in a more orgnaized fashion in descriptive analysis.

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PREDICTIVE: TREE FAMILY RESULTS

Saturated Model Results

1. Run saturated models with default settings.
2. Run saturated models with some tuning techniques:
    a. Grid Search
    b. Custom tuning function.
3. Record best r2.

SalePrice used instead of log SalePrice.

With tuning, smaller difference between test and train r squared.

	train r2	test r2	hyperparameters
Decision Tree *Default Params*	.666	.666	criterion = mse min_samples_split= 325
Decision Tree	.892	.813	criterion = abs error min_samples_leaf = 8
Random Forest *Default params*	.981	.876	criterion = mse min_samples_split = 2 ooh score = .86
Random Forest	.907	.885	criterion = friedman_mse min_samples_leaf = 2 n_estimators = 100
Boosting	.981	.933	learning rate = .001 max_depth = 4

PREDICTIVE: TREE SCORES FOR FEATURE SETS

	MLR train r2	MLR test r2	Lasso train r2	Lasso test r2	hyperparameters
Decision Tree	.678 tree in appendix	.678	.661 tree in appendix	.669	criterion = mse, min_samples_split= 325
Random Forest	.984	.904	.982	.865	criterion = mse, min_samples_split = 2, ooh score = .86
Random Forest	.907	.885	.965	.906	criterion = friedman_mse min_samples_leaf = 2 n_estimators = 100
Boosting w tuning	.963	.910	.939	.86	learning rate = .001, max_depth = 4

MLR Features = OverallCond, OverallQual, GarageCars, Fireplaces, FullBath, BsmtFullBath, HalfBath, YearBuilt, YearRemodAdd, LotFrontage, GrLivArea, ScreenPorch, 1stFlrSF, 3SsnPorch, TotalBsmtSF

Lasso Features = OverallQual, GrLivArea, TotalBsmtSF, BsmtFinSF1, GarageArea, 1stFlrSF, YearBuilt, GarageCars, BsmtExposure_Gd, YearRemodAdd, MasVnrArea, ExterQual_TA

EASY FEATURE MODEL V1

Objective: Build a simple model with few inputs and high impact. Users are real estate agents, and buyers and sellers that want a quick answer on house prices.

Through an iterative process of removing collinear features from the MLR 15 features and taking their acurracy scores, pared the listed down to 9 features that are easy to measure and user friendly.

Easy Features = GarageCars ,Fireplaces, FullBath, BsmtFullBath, YearBuilt, OverallCond, OverallQual, GrLivArea, Remodeled (bool, added feature)

Adjust R2:

- Linear Regression: .871
- LassoCV: .871
- Random Forest: .866
- Boosting: .892

In the next section we will perform some descriptive analysis. From our descriptive analysis, we will revisit this model and see how we can trade in features for better results.

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APPROACH

This half of the study focuses on the macro features impacting SalePrice -- those features beyond the four walls of the house.

To kickstart this inquiry, I asked people in San Francisco, what they thought drove pricing in the housing market. I list the following assumptions and analyses to strengthen our understanding of the market and hopefully the model.

ASSUMPTION #1

“Location, location, location!”

N E I G H B O R H O O D S

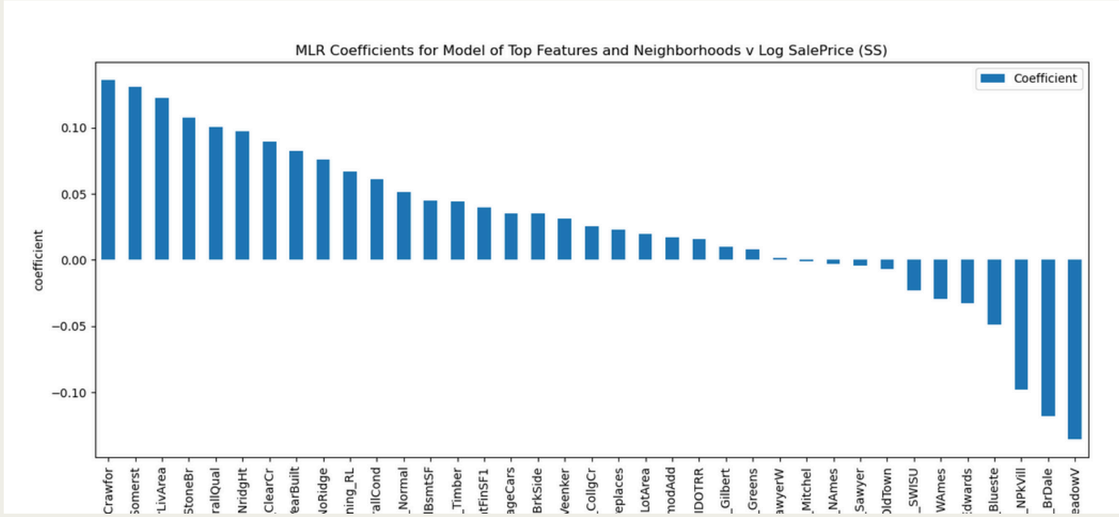
Using Linear Regression to assign values to Neighborhoods

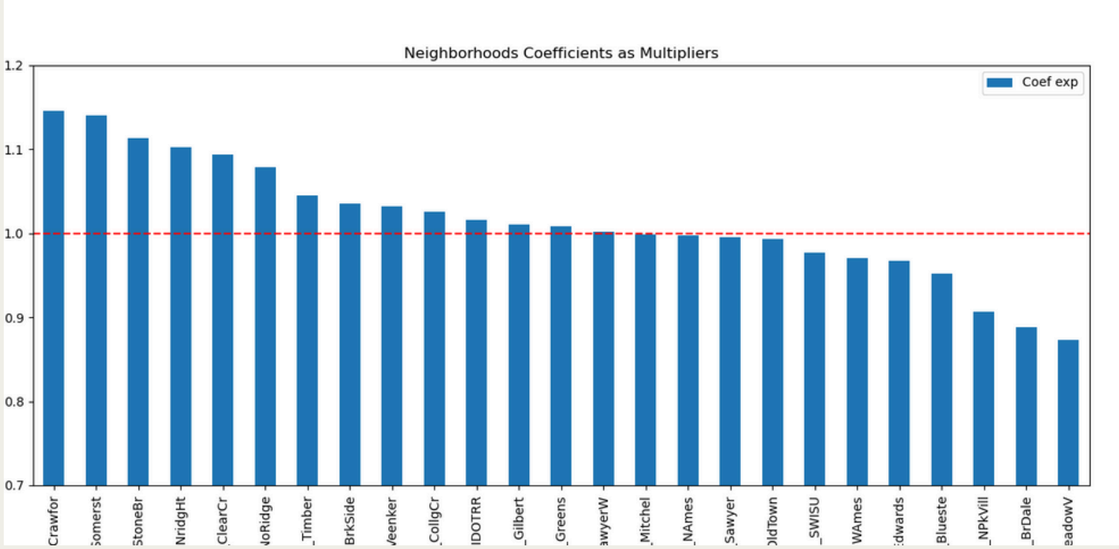
1. Use Top MLR Features + Neighborhood feature.
2. Plot Coef Values.
3. Sort and divide by dummified neighborhoods by quantile.
4. Assign a new feature: Neighborhood quantile (aka New_quant): Low, LowMed, MedHigh, High.

Y axis aka ‘Multiplers’ on second graph = e^beta*x. Remember,

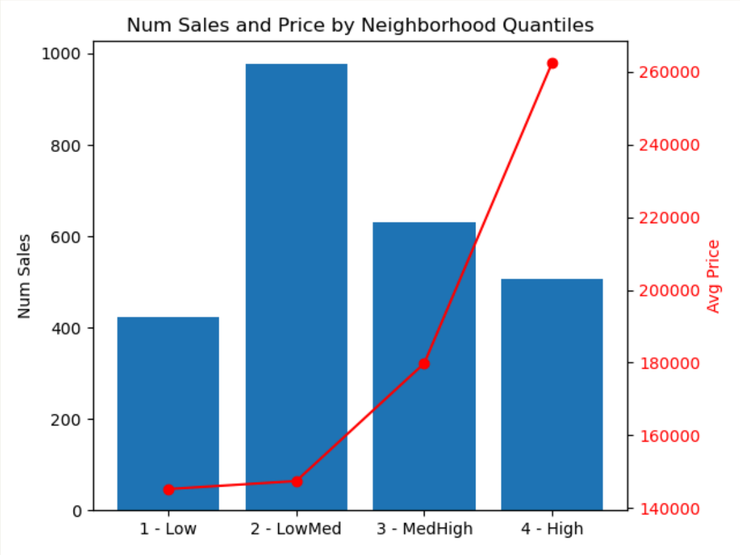
$$price = e^{inter} \cdot e^{\beta_1 * x_1} \cdot e^{\beta_2 * x_2} \cdot e^{\beta_n * x_n}.$$

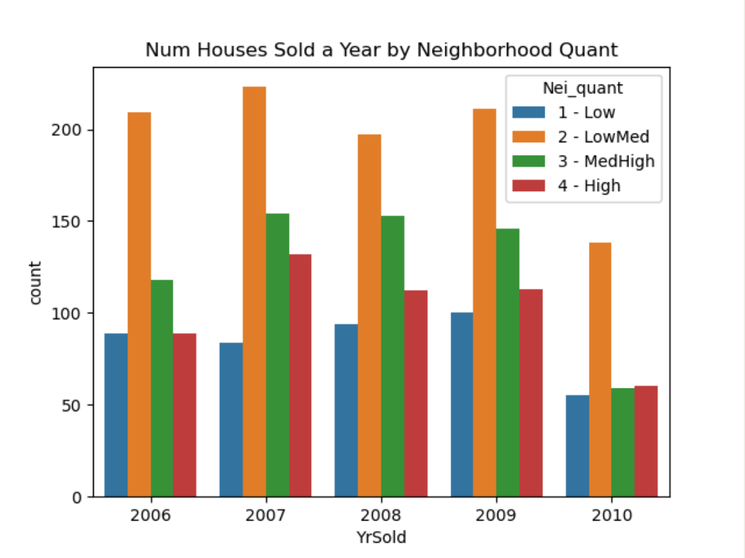
Each neighborhood either increases or decrease overall value by a percentage. Crawford increases SalePrice by 1.14 aka 14%.

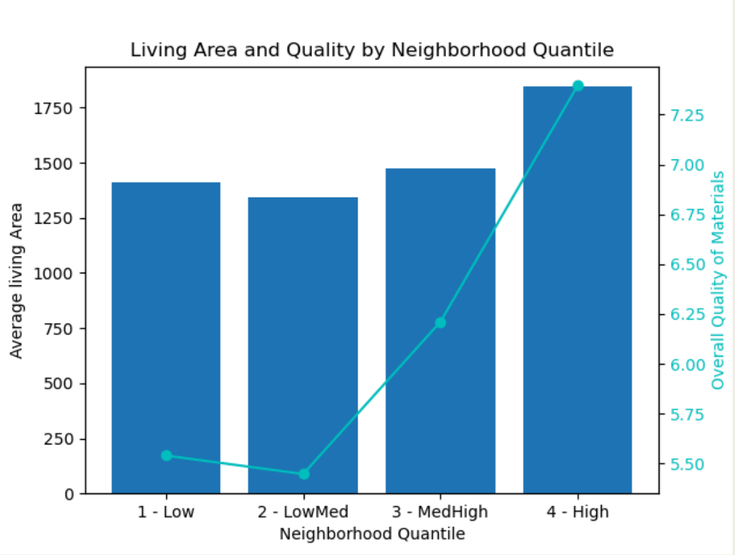




NEIGHBORHOODS







Observations

By assigning Neighborhood Quantiles, we can visualize these neighborhoods and how they look:

- High Neighborhoods: Largest, with avg SalePrice is 180% of Low Neighborhoods. The houses themselves are made of higher quality materials.
- LowMed Neighborhoods show the most activity, with the must number of sales occurring in these areas.
- Low Neighborhoods have the fewest sales.

ASSUMPTION #2

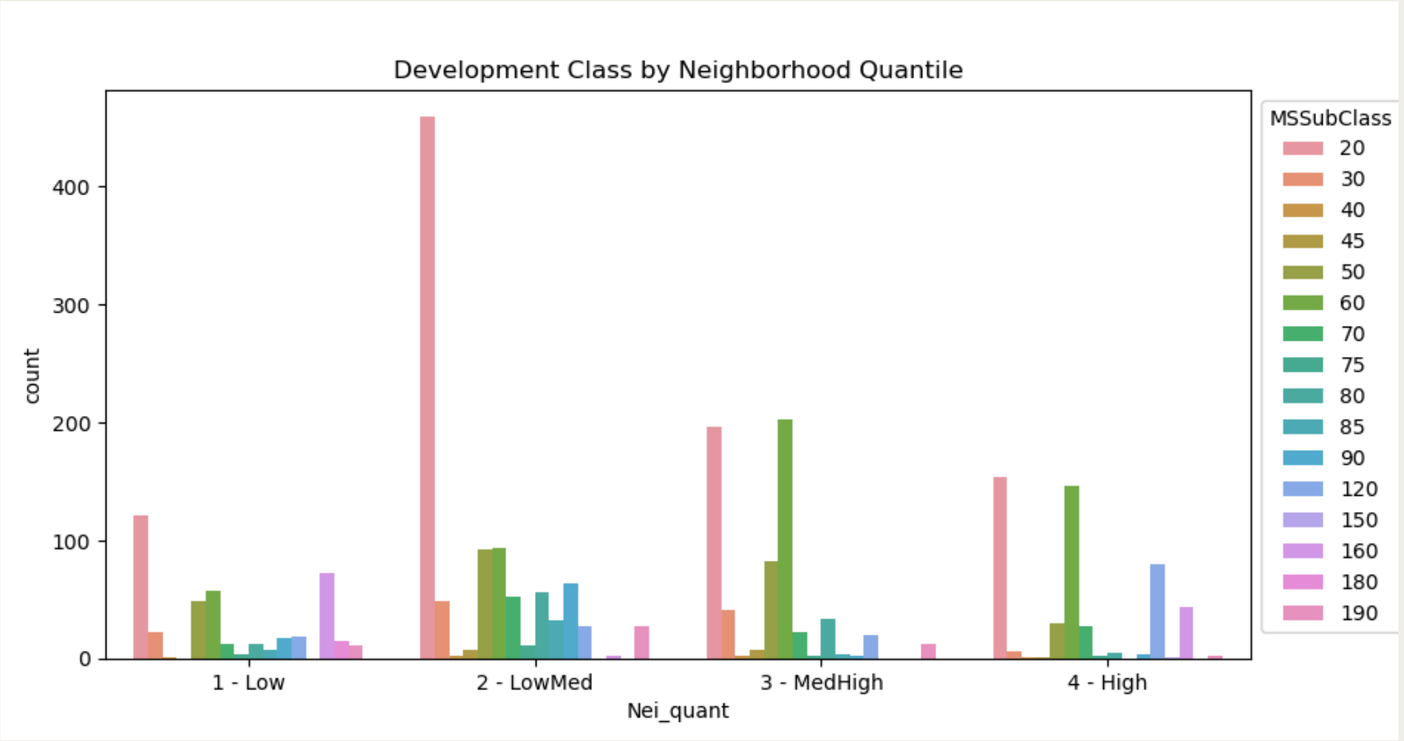
“How old is the city?

People like old historic houses.”

DWELLING TYPE

MSSubClass: Type of dwelling

20* 1-STORY 1946 & NEWER ALL STYLES
30* 1-STORY 1945 & OLDER
40 1-STORY W/FINISHED ATTIC ALL AGES
45 1-1/2 STORY - UNFINISHED ALL AGES
50* 1-1/2 STORY FINISHED ALL AGES
60* 2-STORY 1946 & NEWER
70 2-STORY 1945 & OLDER
75 2-1/2 STORY ALL AGES
80 SPLIT OR MULTI-LEVEL
85 SPLIT FOYER
90 DUPLEX - ALL STYLES AND AGES
120* 1-STORY PUD (Planned Unit Development) - 1946 & NEWER
150 1-1/2 STORY PUD - ALL AGES
160* 2-STORY PUD - 1946 & NEWER
180 PUD - MULTILEVEL - INCL SPLIT LEV/FOYER
190 2 FAMILY CONVERSION - ALL STYLES AND AGES



- Single Houses built after 1946 are most common sale.
  - There are very few houses being sold that are built before 1946.
- MedHigh and High neighborhoods have more two story houses.
- High Neighborhood higher incidence of PUD's, track homes/housing developments.

ASSUMPTION #3

“It's all about Supply and Demand.

How many houses are for sale?”

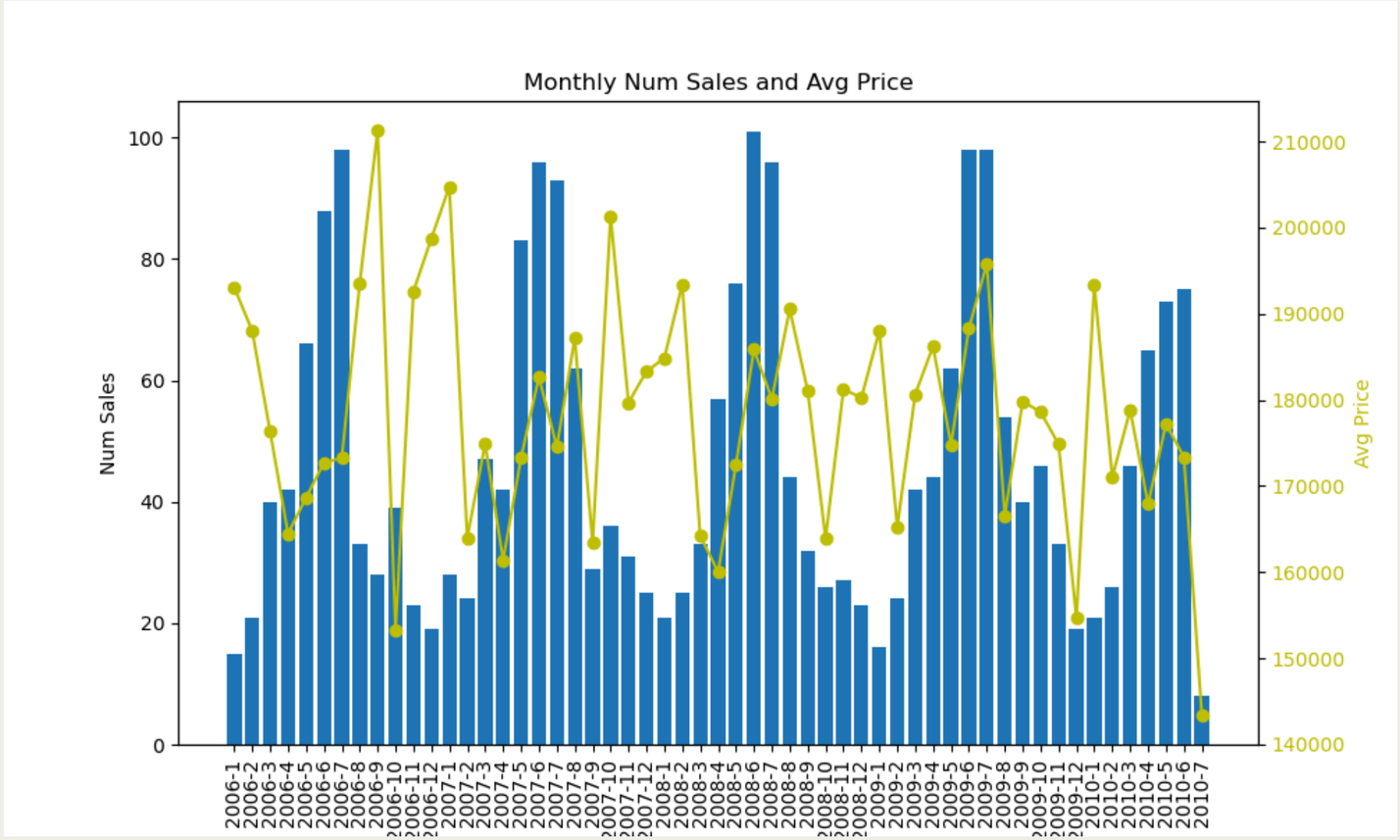
MONTHLY NUM SALES V AVG PRICE

Supply and Demand and seasonality.

- Number of sales steady by year.
  - Sales per month peak in June.
  - Second peak in September

- 2006, 2007, 2008 Prices are highest when sales are lowest.

- 2009 and 2010 Price and number of sales are in step, peaking at the same time.
  - This change demonstrates a disruption in the marketplace
  - This may be a result of the 2008 housing crisis.



ASSUMPTION #4

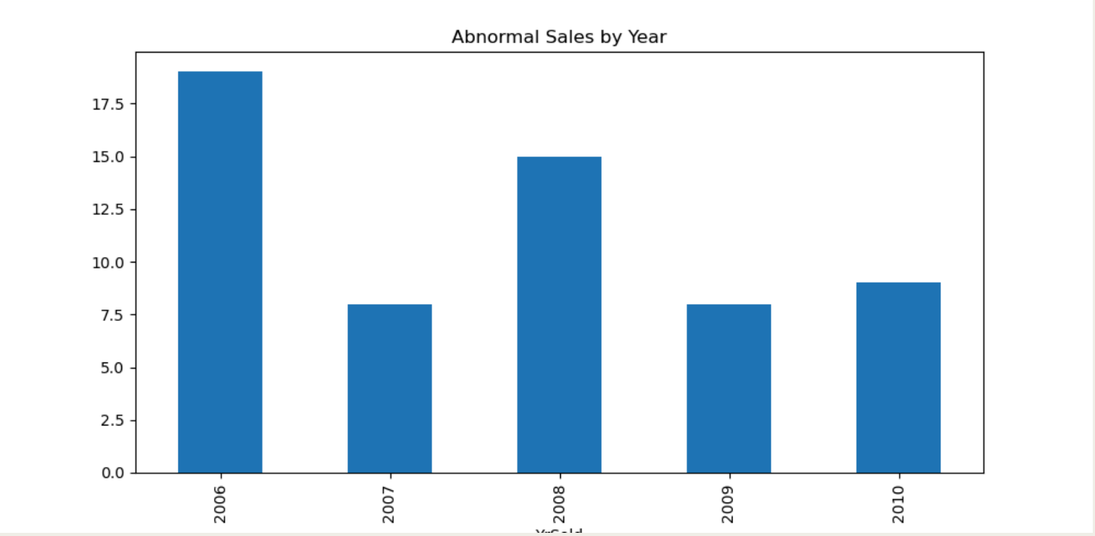
“The market tanked in 2008. It can’t be good.”

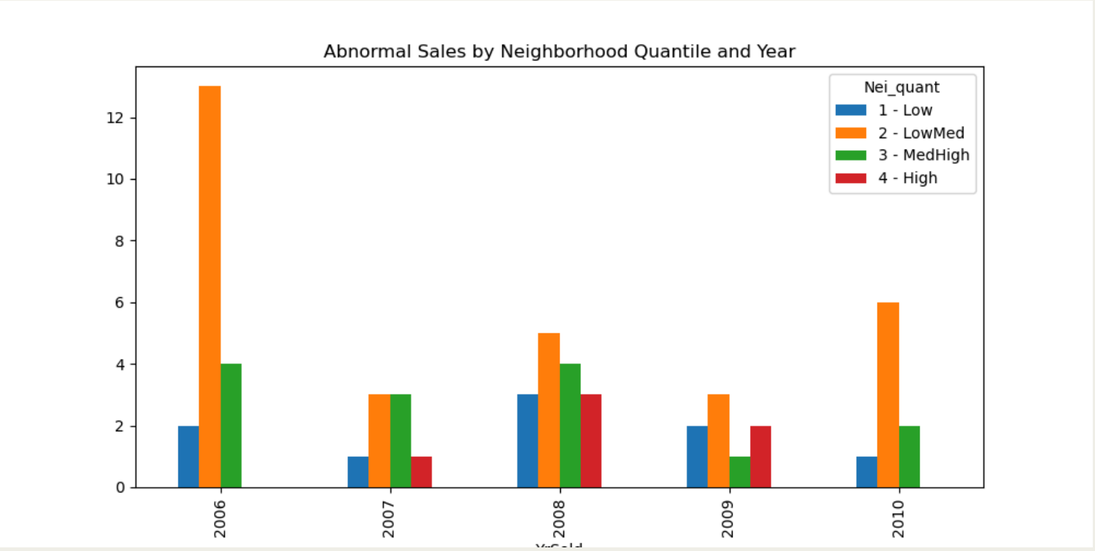
ABNORMAL SALES BY YEAR

Trade, foreclosure, short sale

- Abnormal sales ~ 1-2% of all sales in the dataset.
- Number of Abnormal Sales are highest in 2006 and 2008, and most common in LowMed neighborhoods.
  - In the years leading up to the housing crisis, banks were approving subprime mortgages to less qualified people resulting in higher volume of house sales, higher demand, and at times, foreclosure (when people were not able to afford their monthly premiums).
  - One would expect foreclosures to increase in 2008 and after, but rates stayed low. This may be a result of Congress (1) encouraging banks to restructure mortgages to avoid foreclosures, and (2) increasing mortgage amount the Federal Housing Administration would insure. This was done in an effort to stabilize the housing market, and prevent housing prices from falling.
  - In fact, housing sales and prices remain constant throughout 2008-2010.

Source: federalreservehistory.org





ASSUMPTION #5

“Mortgage rates are down, you better hurry up and buy!”

ADDED FEATURE: MORTGAGE RATES

Added Feature

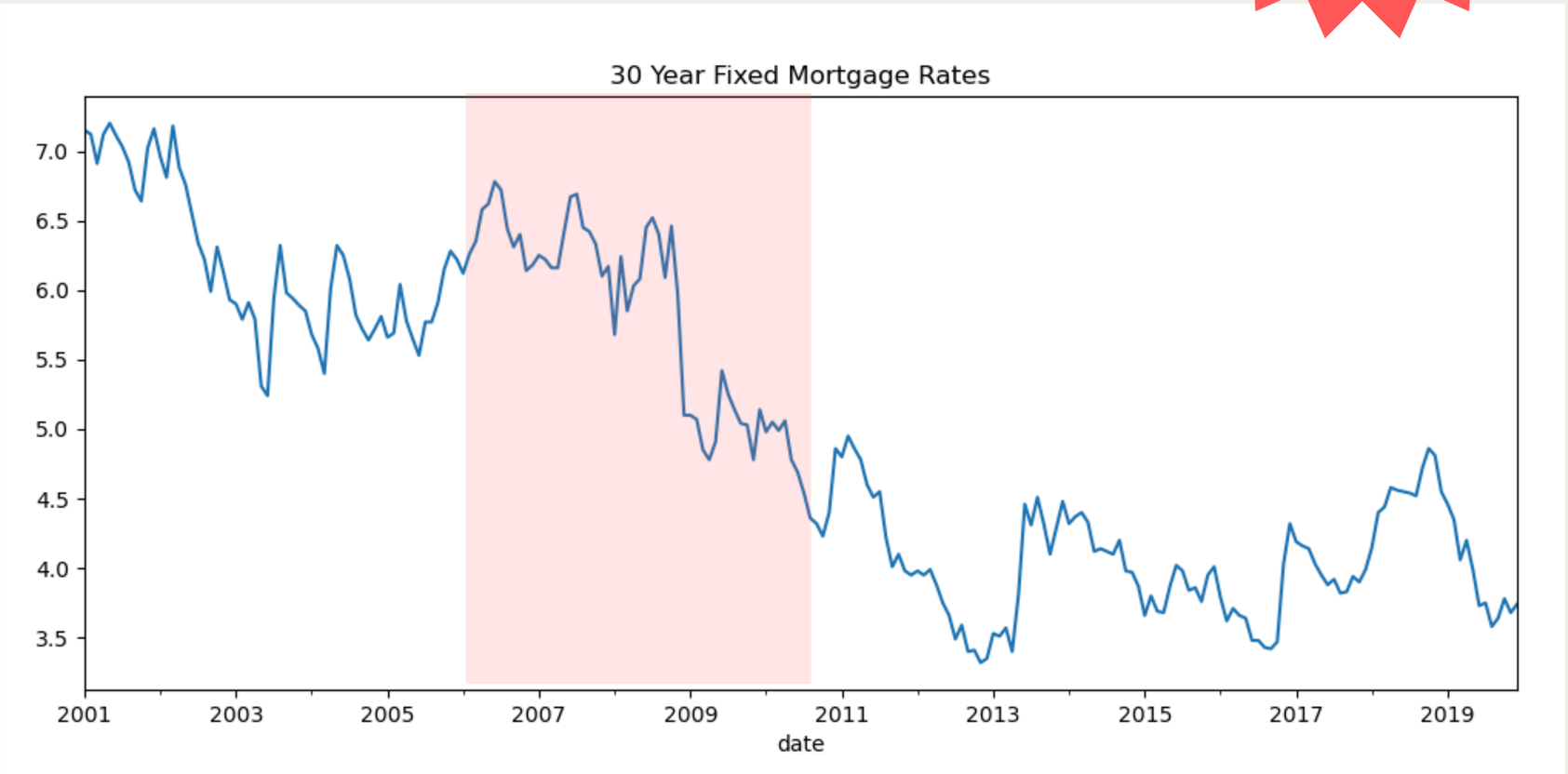
30 year Fixed Rate

A monthly average of the 30 year Fixed Mortgage Rate was added to the data set.

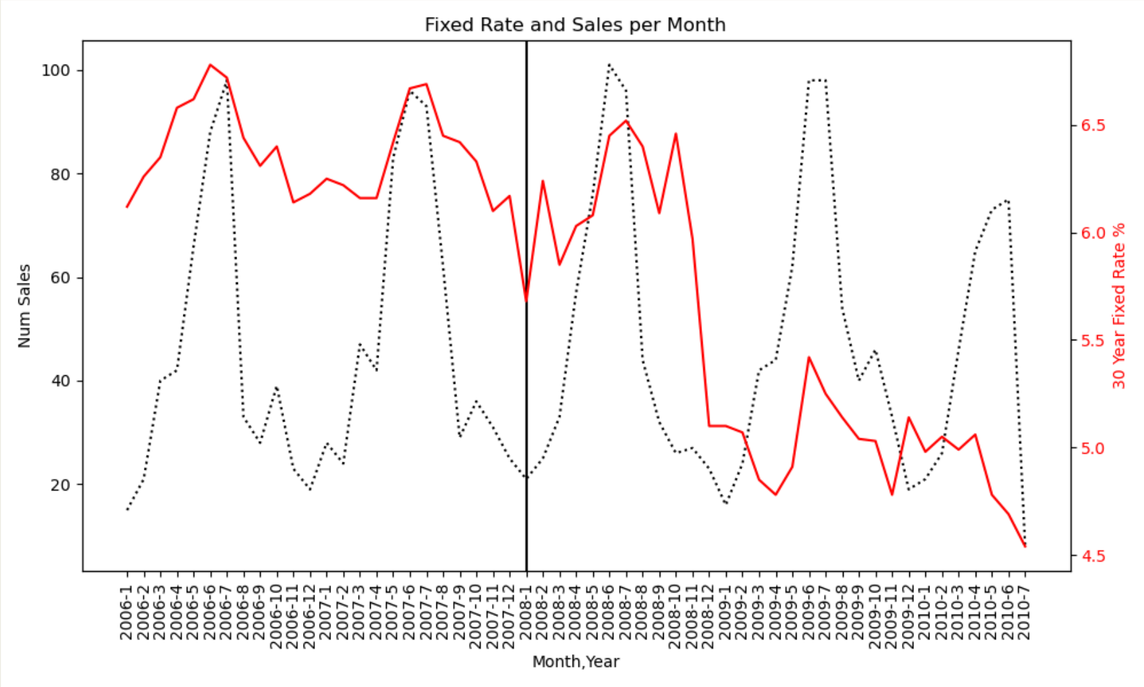
2006-2008 follow a similiar pattern and amount.

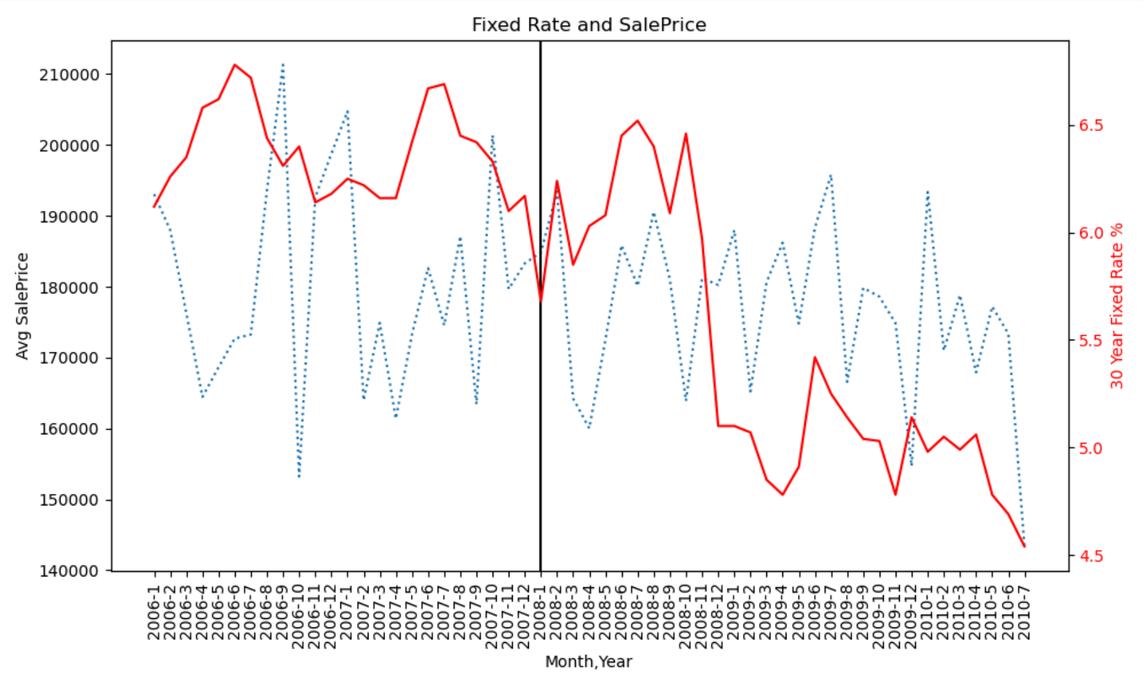
In 2009, the Mortgage Rate drops by a point plus when The Federal Reserve decided to lower rates.

At the beginning of the millennium, rates are at 7% and hit a low during 2013 at < 3.5%.



PLOTTING FIXED RATE AGAINST SALES





- Num Sales and Fixed Rate seem to follow the same shape and cadence with peaks in the middle of the year. In the 2009, Fixed Rate falls, but Num Sales does not and the peaks are less in line.
- Fixed Rate and SalePrice seem to be inverse in 2006 and 2007. When mortgage rates are higher, one has less to spend on the premium, and house prices are lower.
- In 2008, 2009, and 2010, this pattern is less consistent.

RATE, SALES, AND PRICE CORRELATIONS

Correlation Matrix of Sales Per Month, AveragePrice, and Fixed Rate , by Year

	2006			2007			2008			2009			2010		
	Sales Month	Avg Price	Fixed Rate	Sales Month	Avg Price	Fixed Rate	Sales Month	Avg Price	Fixed Rate	Sales Month	Avg Price	Fixed Rate	Sales Month	Avg Price	Fixed Rate
Sales Month	1.00	-0.46	0.93	1.00	-0.06	0.77	1.00	0.03	0.58	1.00	0.54	0.56	1.00	0.71	0.18
Avg Price	-0.46	1.00	-0.51	-0.06	1.00	-0.05	0.03	1.00	0.12	0.54	1.00	0.05	0.71	1.00	0.59
Fixed Rate	0.93	-0.51	1.00	0.77	-0.05	1.00	0.58	0.12	1.00	0.56	0.05	1.00	0.18	0.59	1.00

- In 2006, Sales per Month and Fixed Rate are highly correlated at .93. This value decrease by year, but remains over .5 through 2009. In 2010, this value falls to .18
- In 2006, Fixed Rate shows some correlation to Avg Price, but this drops off in the subsequent years.
- In non-recession and non-crisis years, trends between Sales per Month, Avg Price, and Fixed Rate are more correlated. However government intervention alters this relationship.
- When included as a feature in the model, these features did not improve scoring. MoSold performed slightly better but none improved accuracy of the model.

SYNTHESIS

“So, what happened?”

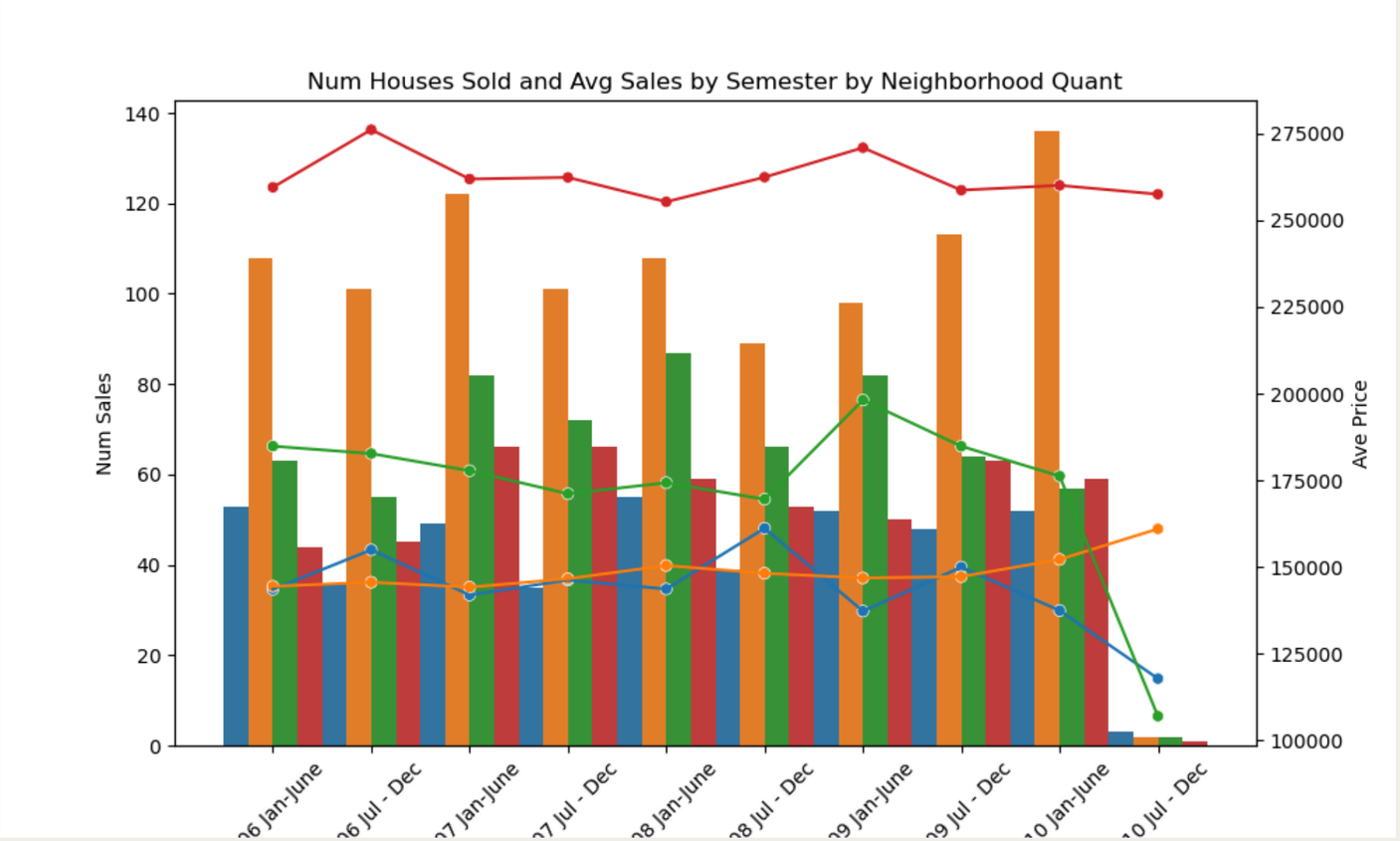
PRICE AND VOLUME BY SEMESTER

LowMed Sales Trend Upward

Number of Sales and Price by semester shows us:

- Low, MedHigh, and High Sales remain relatively constant, with a dip in number of sales in Jan-June 2010. Low and High Sales follow a Sales per Month and SalePrice inverse relationship.

- LowMed Sales Continues to increase through Jan-June of 2010 while price is constant.
  - Those selling may be motivated to recoup costs.
  - Those buying have undergone a more rigorous approval process and purchase at lower mortgages rates. Although prices have not lowered, their premium amounts are less bc fixed rate is less.



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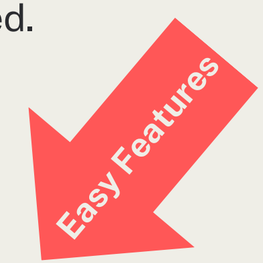
- Processing Methodology
- Predictive Modelling
- Descriptive Modelling
    - **Easy Feature Model V2**
- Conclusion
- Appendix

EASY FEATURES FINAL MODEL

Objective: Build a simple model with few inputs and high impact. Users are real estate agents, and buyers and sellers that want a quick answer on house prices.

1. Recall Easy Features = GarageCars ,Fireplaces, FullBath, BsmtFullBath, YearBuilt, OverallCond, OverallQual, GrLivArea, Remodeled (bool, added feature) from initial Linear Regression Exploration.
2. Iterate through, adding and subtracting features to find optimal balance between adjusted R squared and train R squared.
    a. To add in: 'MSSubClass', 'Nei_quant', 'rate' (fixed rate mortgage), 'YrSold', 'MoSold'
    b. To subtract: Full Bath, 'remodeled', 'YearBuilt'.
3. Run through LassoCV, Random Forest.



Final Features: GarageCars, Fireplaces, BsmtFullBath, YearBuilt, OverallCond, OverallQual, GrLivArea, MSSubClass, Nei_quant

Model	Adjusted R2	Train R2	Hyperparameters
MLR (log saleprice, SS)	.902	.897	(log saleprice, SS)
LassoCV	.901	.897	(log saleprice, SS, cv = 5, aplha = 0.00035)
Random Forest w Grid Search tree visual	.899	.966	{'criterion': 'squared_error', 'min_samples_leaf': 2, 'n_estimators': 100}

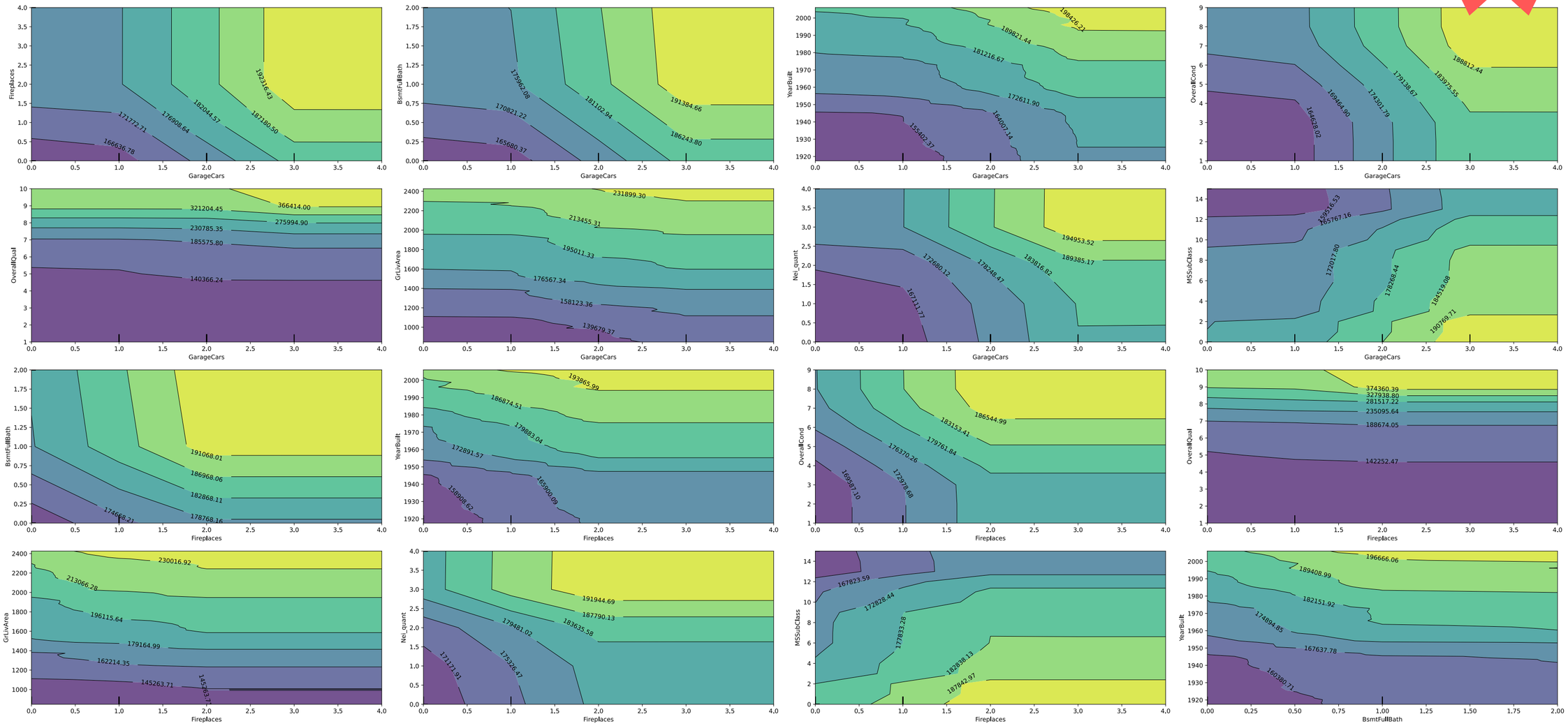
RANDOM FOREST FEATURE IMPORTANCE

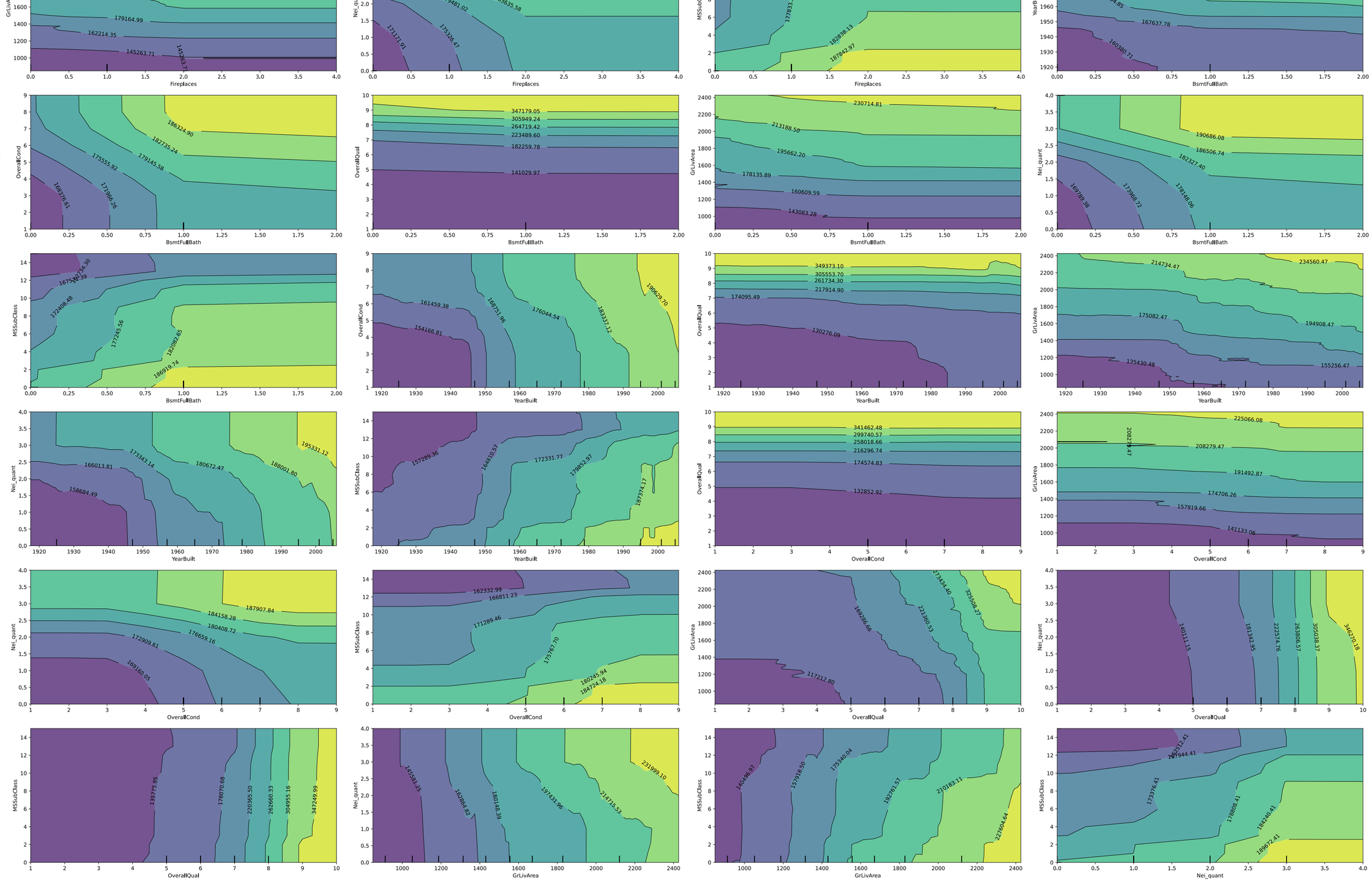
```
[(0.593, 'OverallQual'),
 (0.217, 'GrLivArea'),
 (0.054, 'YearBuilt'),
 (0.047, 'GarageCars'),
 (0.021, 'Fireplaces'),
 (0.021, 'MSSubClass'),
 (0.019, 'BsmtFullBath')
 (0.018, 'Nei_quant'),
 (0.009, 'OverallCond')]
```

EASY FEATURE DEPENDENCE PLOTS

OverallQuality Dominates

Partial Dependence Plots of Easy Features




GrLivArea
Fireplaces
179164.99
162214.35
145263.71
Nei_quant
Fireplaces
179481.02
153835.58
175326.47
171171.91
MSSubClass
Fireplaces
178331.13
182898.13
187842.97
YearBuilt
BsmtFullBath
167637.78
160380.71
OverallCond
BsmtFullBath
186324.90
182735.24
179145.58
175555.92
173986.26
168376.61
OverallQual
BsmtFullBath
347179.05
305949.24
264719.42
223489.60
182259.78
141029.97
GrLivArea
BsmtFullBath
230714.81
213188.50
195662.20
178135.89
160609.59
143083.28
Nei_quant
BsmtFullBath
190686.08
186506.74
182327.40
178148.06
173968.72
169789.38
MSSubClass
BsmtFullBath
175734.30
172408.48
177245.56
182082.65
186919.74
OverallCond
YearBuilt
161459.38
168731.96
176044.54
183337.12
190629.70
154166.81
OverallQual
YearBuilt
349373.10
305553.70
261734.30
217914.90
174095.49
130276.09
GrLivArea
YearBuilt
234560.47
214734.47
194908.47
175082.47
155256.47
135430.48
Nei_quant
YearBuilt
195331.12
173343.14
180672.47
188001.80
166013.81
158684.49
MSSubClass
YearBuilt
157289.36
164810.57
172331.77
179852.97
187374.17
OverallQual
OverallCond
341462.48
299740.57
258018.66
216296.74
174574.83
132852.92
GrLivArea
OverallCond
225066.08
208279.47
191492.87
174706.26
157919.66
141133.06
Nei_quant
OverallCond
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184158.28
180408.72
176659.16
172909.61
169160.05
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OverallCond
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175767.70
180245.94
184724.18
GrLivArea
OverallQual
173434.40
325508.27
221360.53
169286.66
117212.80
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OverallQual
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OverallQual
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197431.96
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145581.25
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192761.57
175340.04
157918.50
140496.97
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MSSubClass
Nei_quant
189672.41
184240.41
178808.41
173376.41
167944.41
162512.41

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L E A R N I N G S

Predictive Model Selection is an iterative process complemented by research and Descriptive Analysis.

Be willing to be disproven. Anecdotal vs quantitative evidence may differ.

This model may not work for all locations. Models are specific.

Define business object and set attainable goalposts.

There is always more to do. Know when to stop.

FINDINGS & FUTURE WORK

Biggest surprise: SalePrice was impervious to the 2008 Housing Crisis.

Many things happened under the hood. Within this dataset and outside.

However, the SalePrice was not impacted. What degree of government intervention resulted in no change in the marketplace?

Quality, Quality, Quality!

More than Location, housing value is tied closely to Overall Quality, the overall material and finish of the house.

For those who want to remodel, quality drives prices more than square footage. Good news for those who don't want to increase the envelope of their house.

Investing in good quality materials is closely tied to increasing the value of a house.

Future Work

- Investigate how SalePrice Increase when improving the quality of certain aspects of the home.
  - Used to inform how to remodel in order to increase the value of the home.
  - Ex. Kitchen Quality vs Exterior Masonry, which increases SalePrice the most?

- If Low and LowMed neighborhoods are similar in size and OverallQuality, what is it about Low Neighborhoods that decrease SalePrice?

- Use Recursive Feature Elimination to improve feature set.
- Run Feature set through more models, XGBoost, and SVG to get to a better outcome.

Thank you!

For more, see Appendix

Katie Kwan, Data Scientist

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  - **Lasso, Ridge, Elastic Net and Visuals**
  - **Tree Models, Ice Plots and Visuals**

PREDICTIVE: RIDGE AND ELASTIC NET RESUTLS

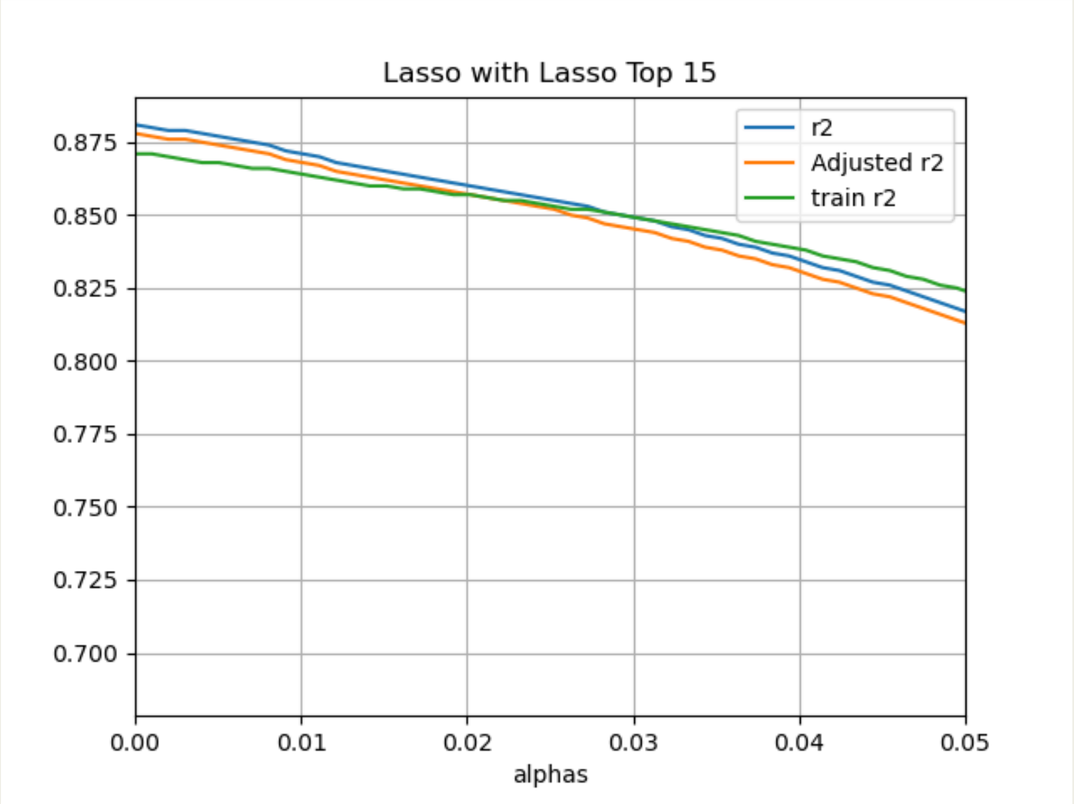
Reduced Feature Set Results

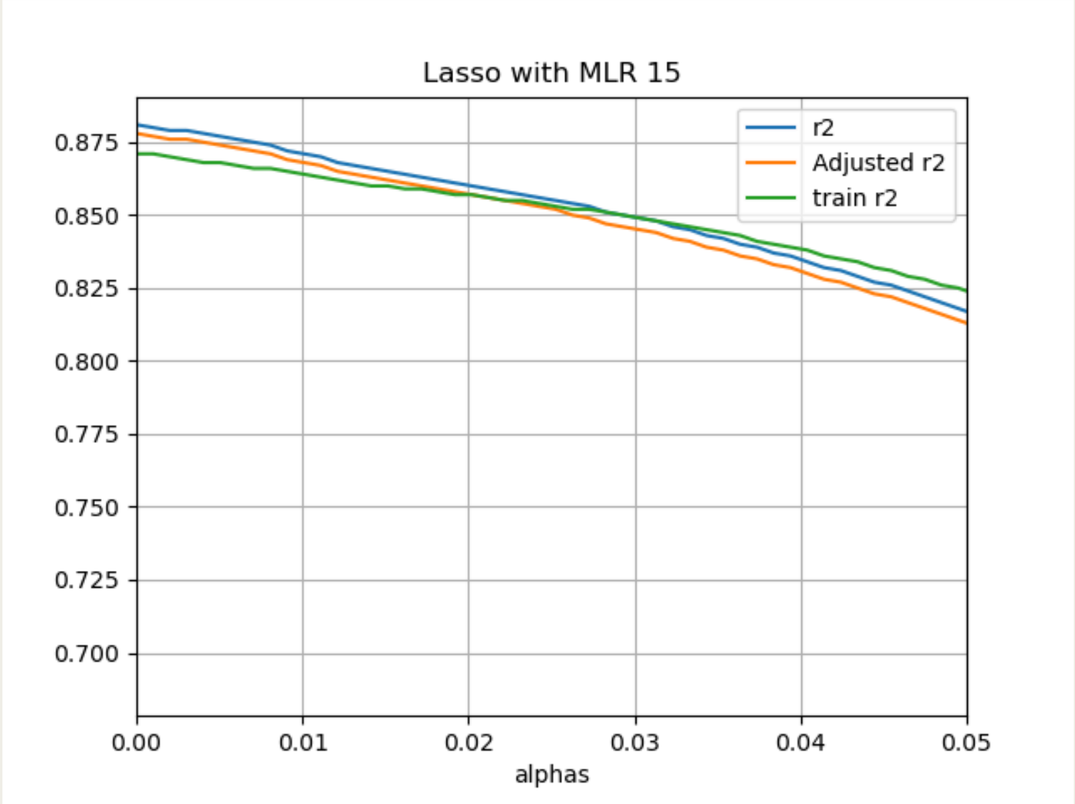
1. Ridge
    a. A loop on a range of alphas was run (similar to Lasso). Alpha was determined where training R squared cross testing R squared
2. Elastic Net
    a. A grid search was run on the feature options. Best alpha and l1_ratio were returned

	MLR Top 15	**Lasso Top 15**
Ridge	.846 alpha = 1666	.858 alpha = 707
Elastic Net	.872 alpha = .0006 l1_ratio = .666 cross validation = 5 scoring = r2	.885 alpha = .01 l1_ratio = 0.0 cross validation = 5 scoring = r2

Elastic Net, a hybrid Ridge and Lasso model performs best better than Ridge.

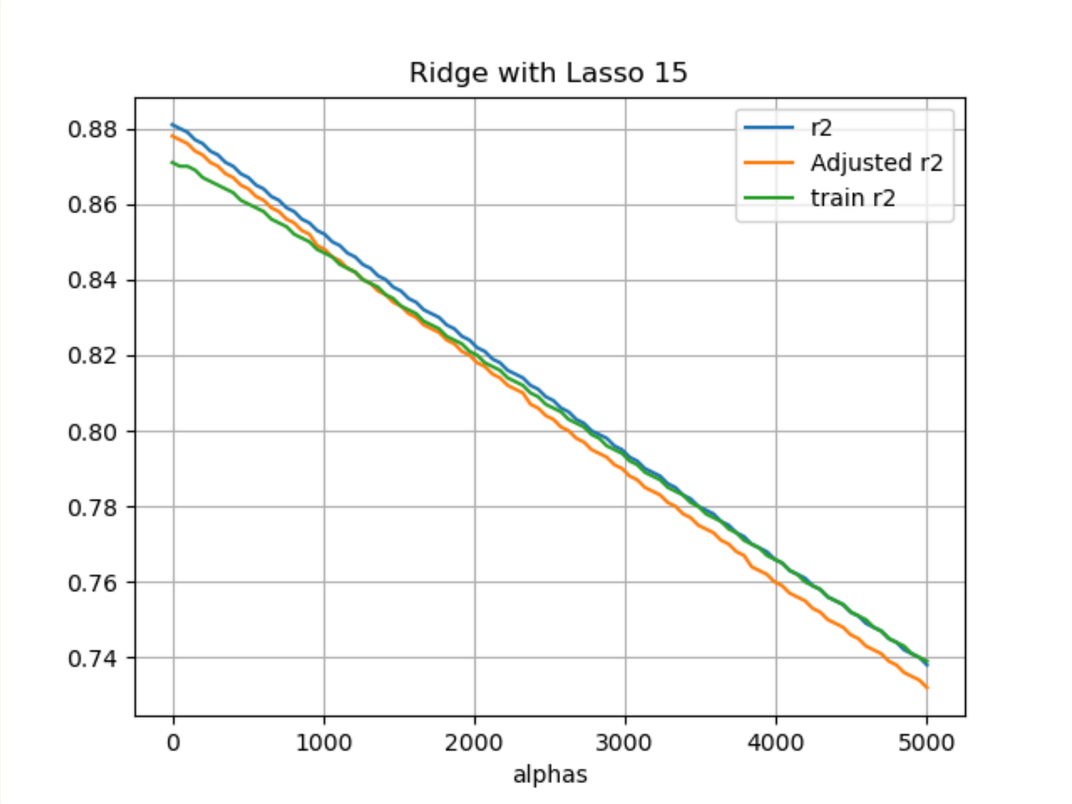
PREDICTIVE: PLOTTING ALPHA FOR LASSO

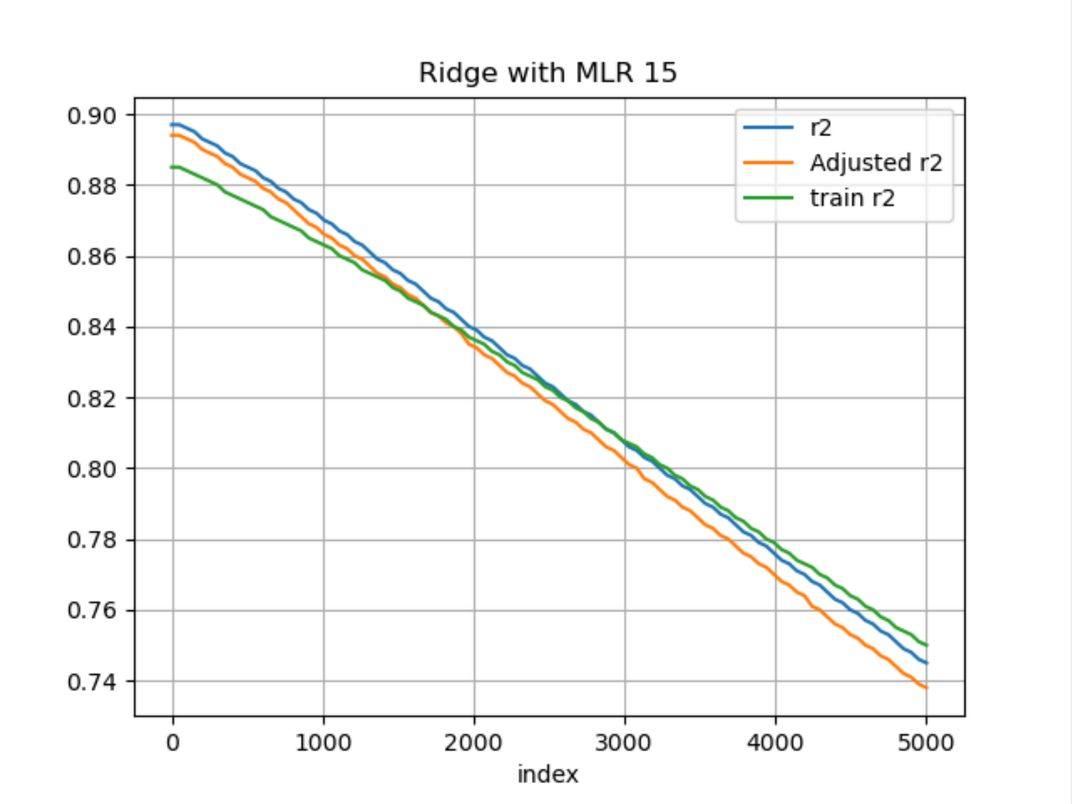




Adjusted R2 and train r2 cross at the optimal alpha.

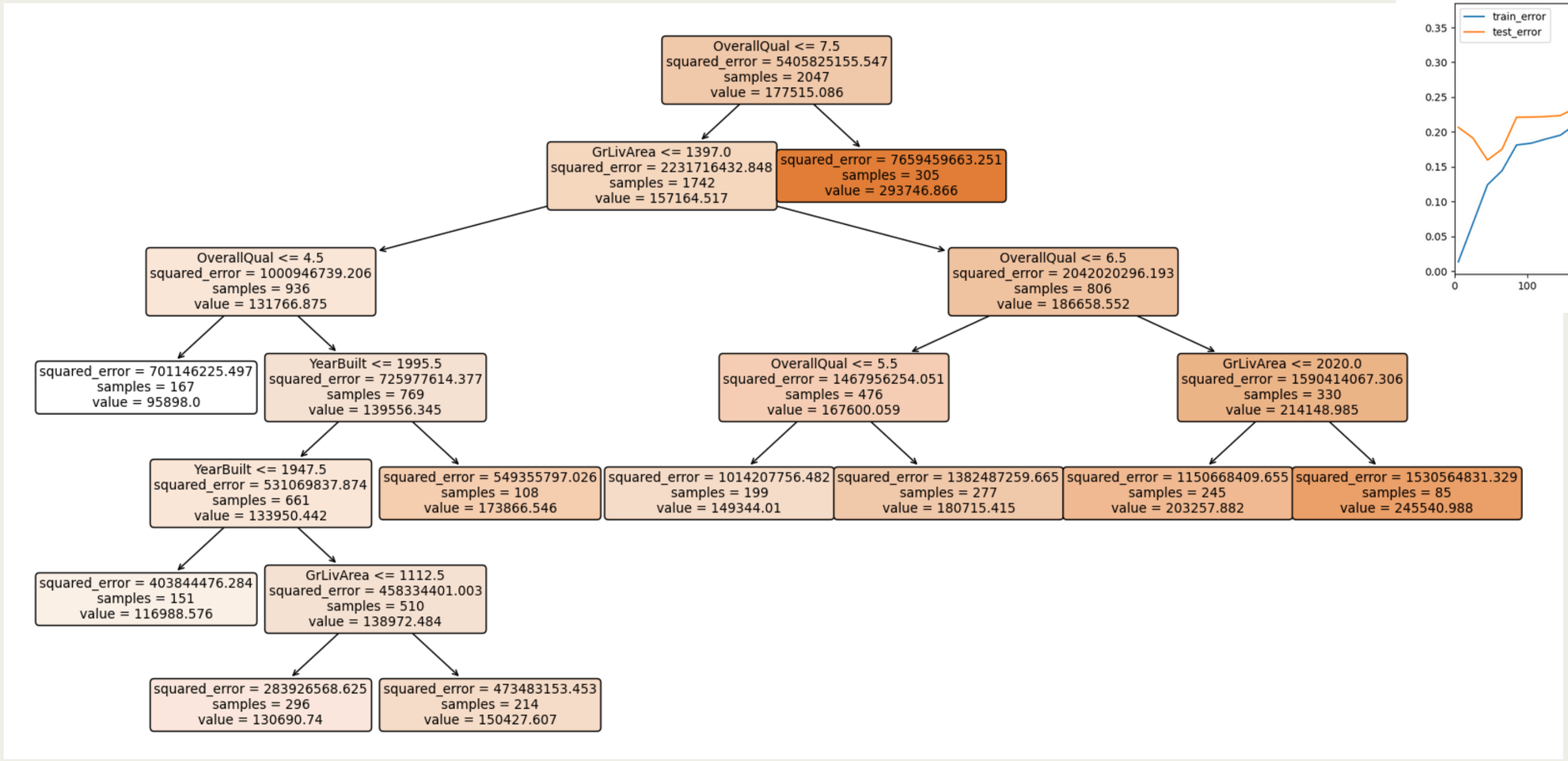
PREDICTIVE: PLOTTING ALPHA FOR RIDGE

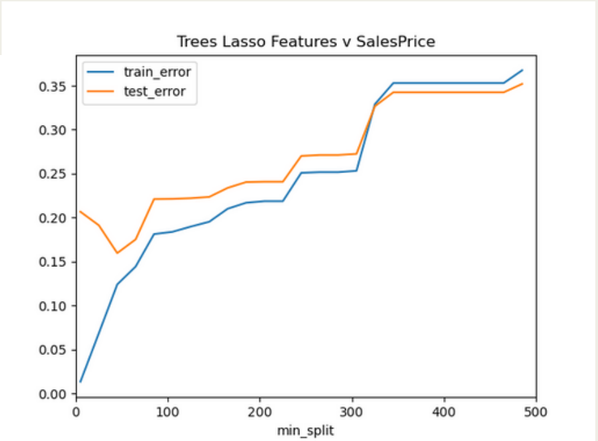




Adjusted R2 and train r2 cross at the optimal alpha. Accuracy v alpha appear linear.

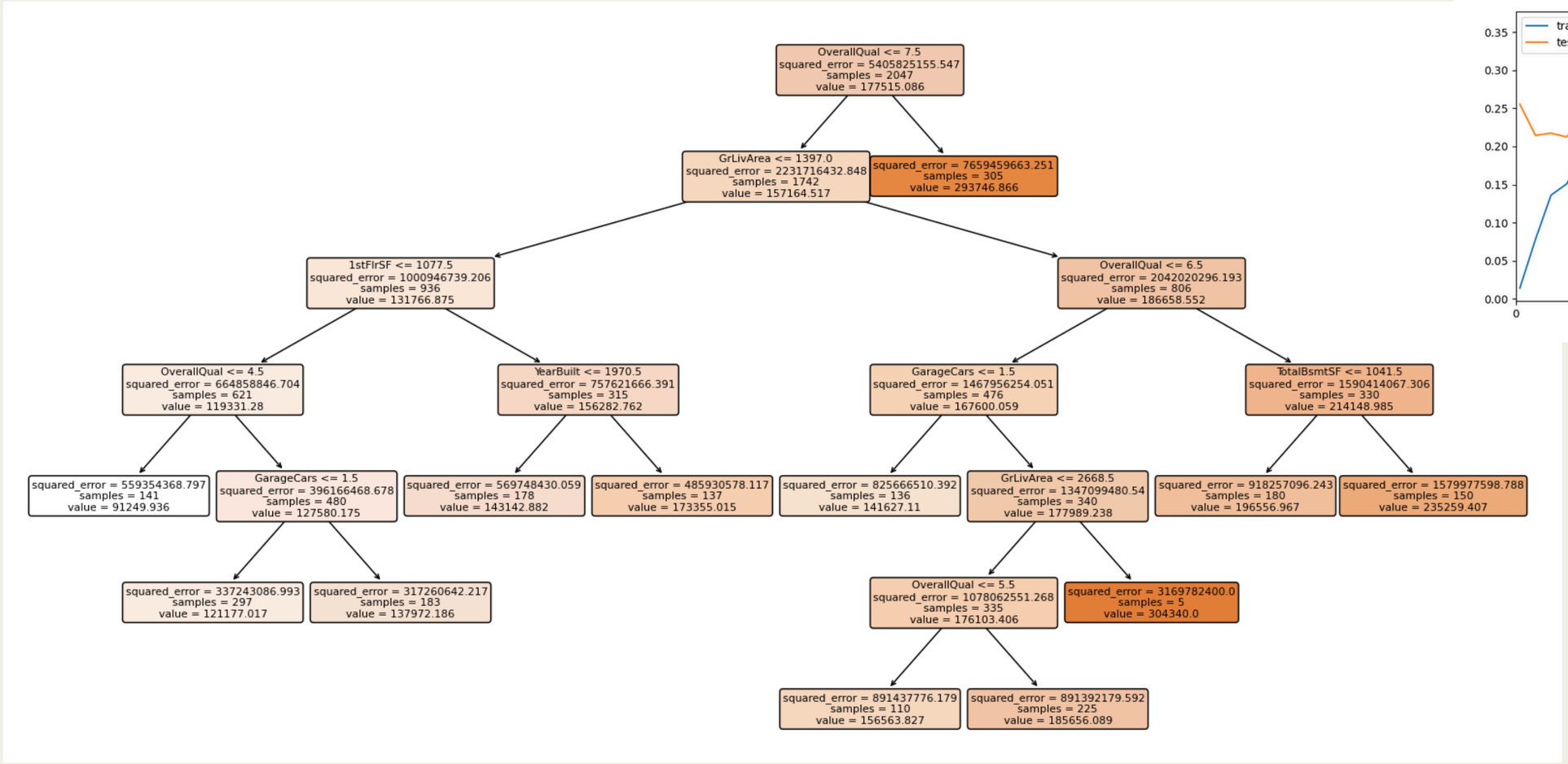
PREDICTIVE: TREE OF LASSO FEATURES R2 .667





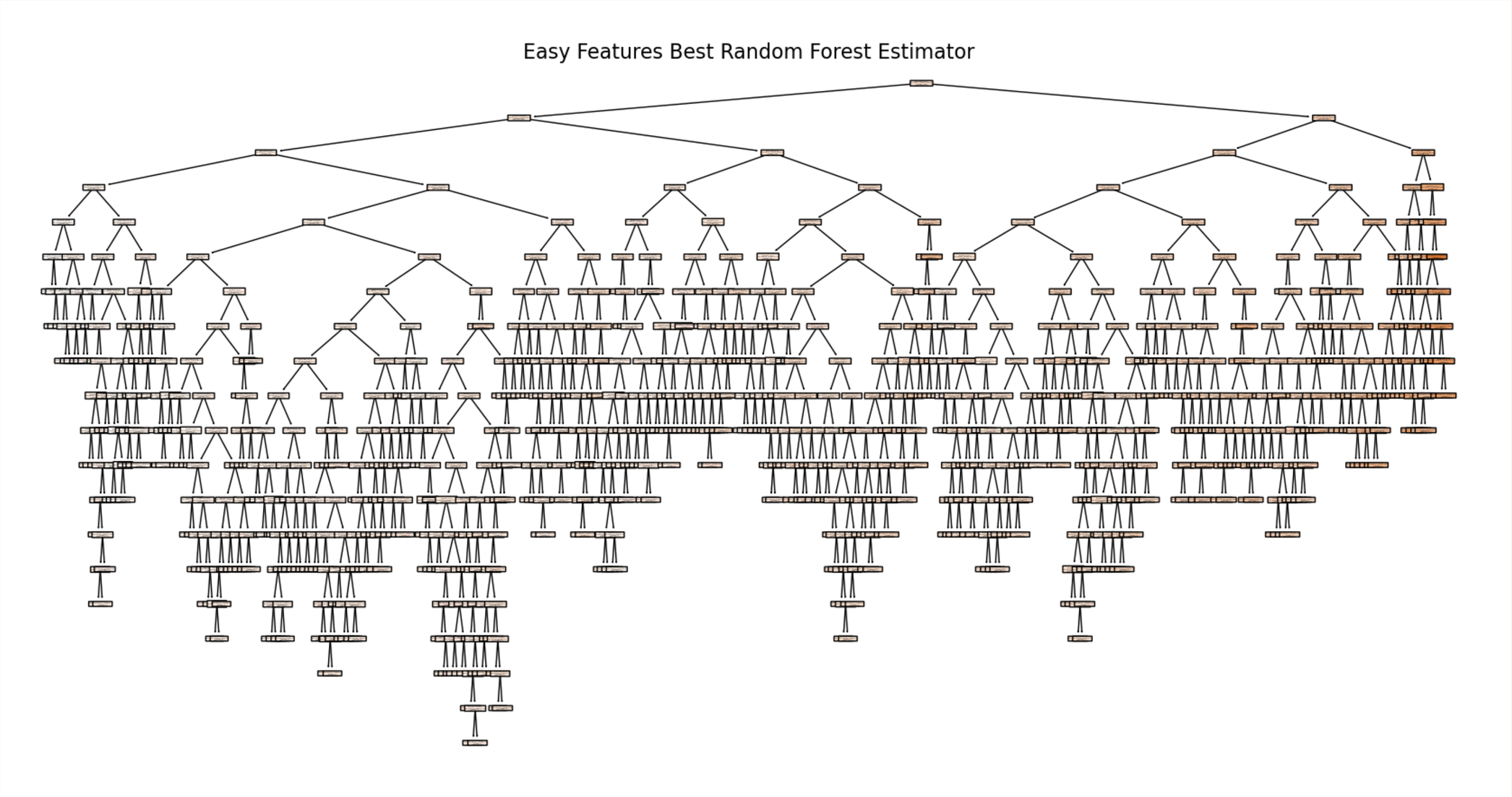
Only 3 features used: Overall Qual, GrLivArea, YearBuilt, 9 were fed to model

PREDICTIVE: TREE OF MLR FEATURES R2 .678



Only 3 features used: Overall Qual, GrLivArea, 1st FlrSF, GarageCars, TotalBsmtSF, YearBuilt. 15 were fed to the model

EASY FEATURE FOREST AND FEATURES



EASY FEATURE RANDOM FOREST ICE PLOTS