Housing Data Analysis

Ames Iowa

Springboard - Second Capstone

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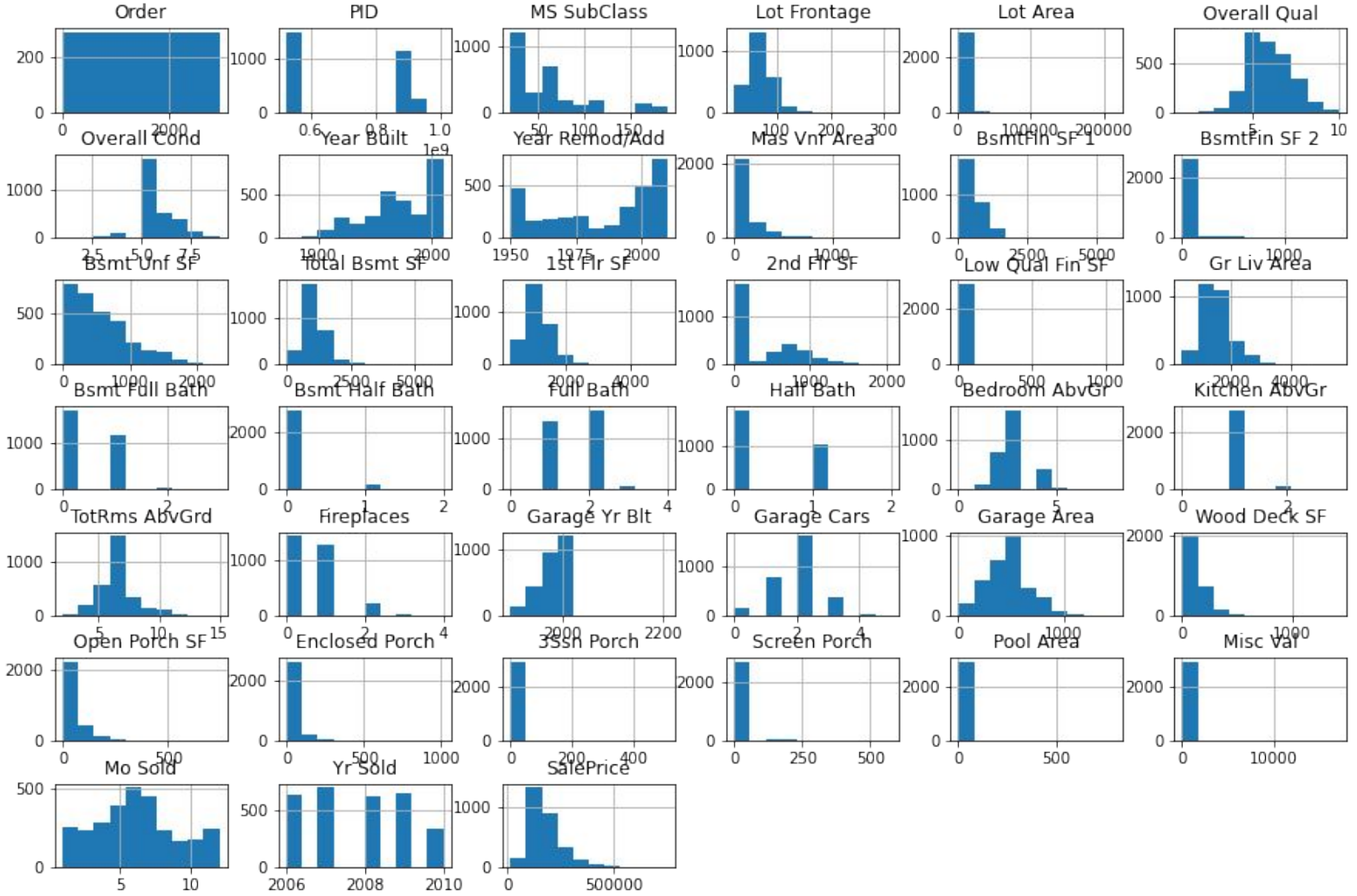
Dataset

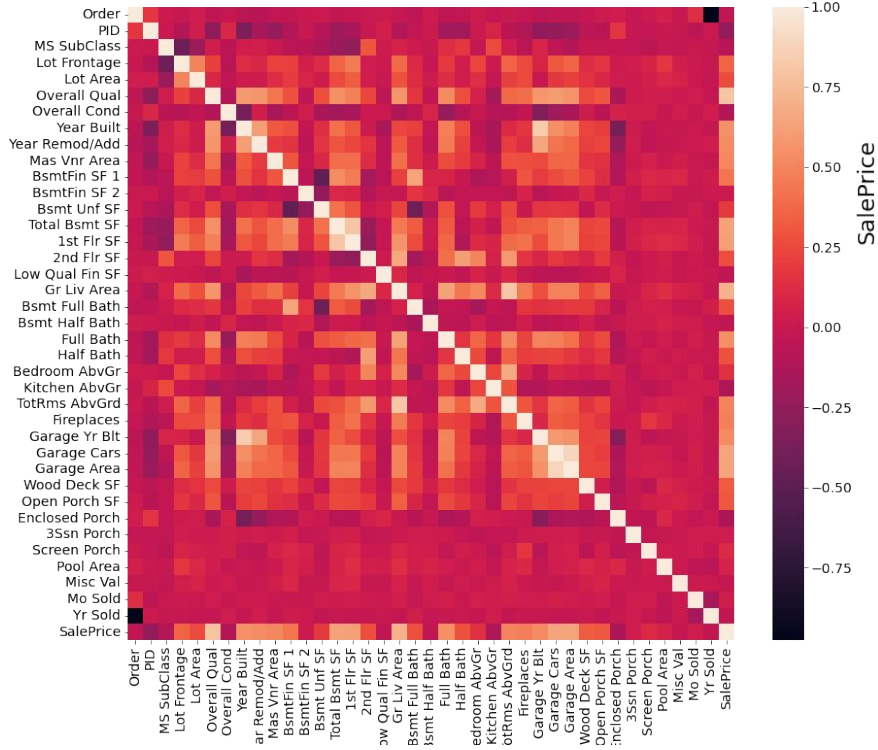
- Publicly available dataset with 2,930 unique sales between 2006 and 2010.
- 82 columns each representing a feature of the home.
- Includes categorical data:
  - Zoning
  - Neighborhood
  - Condition of the home…etc
- And numerical data:
  - Square footage
  - Lot size
  - Number of Bedrooms…etc

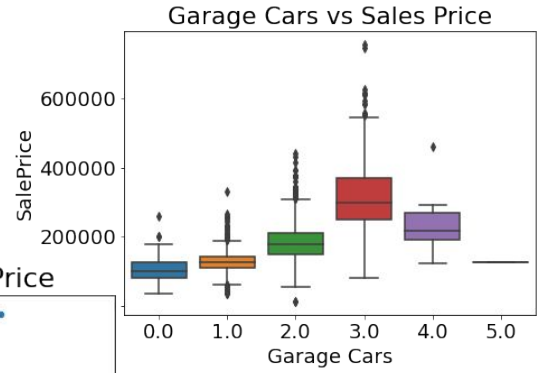

Order
PID
MS SubClass
Lot Frontage
Lot Area
Overall Qual
Overall Cond
Year Built
Year Remod/Add
Mas Vnr Area
BsmtFin SF 1
BsmtFin SF 2
Bsmt Unf SF
Total Bsmt SF
1st Flr SF
2nd Flr SF
Low Qual Fin SF
Gr Liv Area
Bsmt Full Bath
Bsmt Half Bath
Full Bath
Half Bath
Bedroom AbvGr
Kitchen AbvGr
TotRms AbvGrd
Fireplaces
Garage Yr Blt
Garage Cars
Garage Area
Wood Deck SF
Open Porch SF
Enclosed Porch
3Ssn Porch
Screen Porch
Pool Area
Misc Val
Mo Sold
Yr Sold
SalePrice

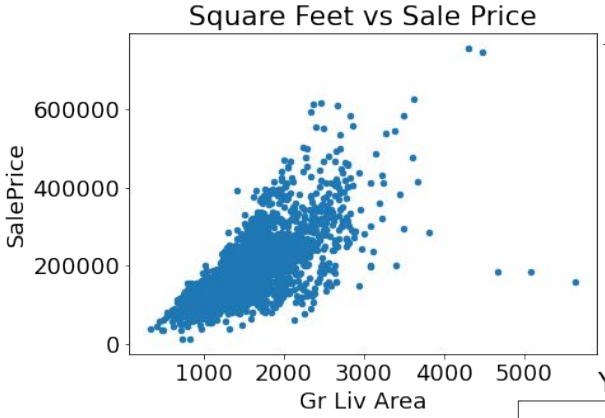
Data Cleaning and Data Wrangling

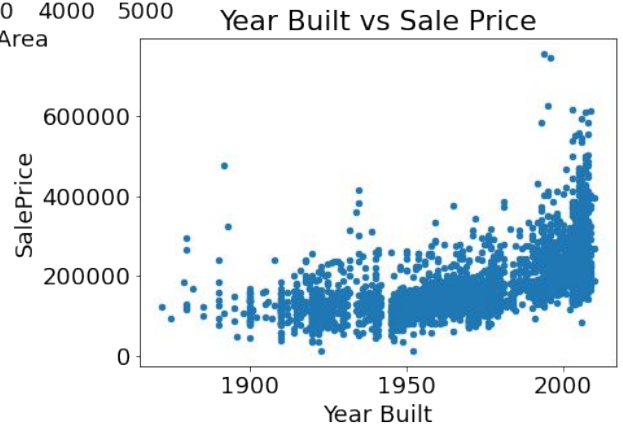
- Check for Duplicates (Parcel ID)
- Visually inspect histograms for outliers or errors (previous slide)
- Columns with mostly missing data
- Columns with mostly homogeneous data

Exploratory Data Analysis

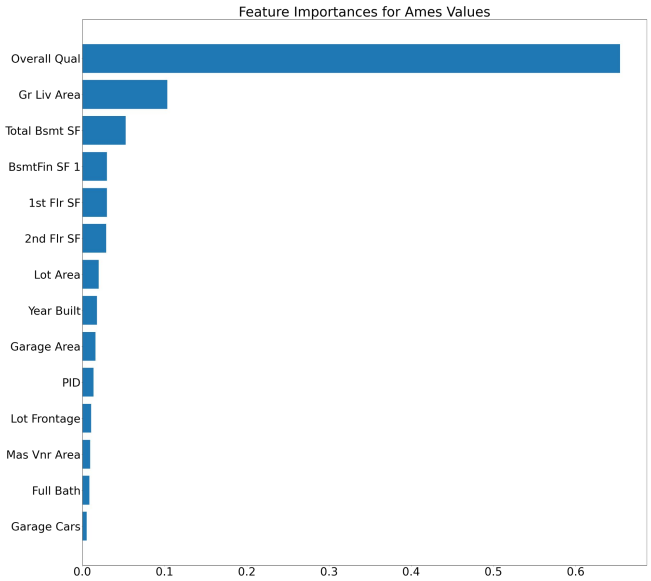




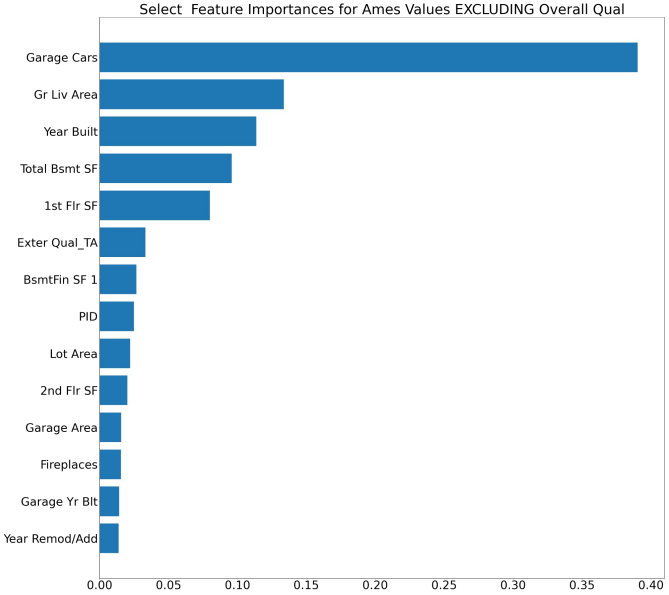




Exploratory Data Analysis Continued



- Random Forest Feature Importance
- Overall Qual had outsized importance
- Lack of information about what this variable is
- Ultimately Removed this Variable



Preprocessing and Training

- Imputing Values:
  - Imputed MEAN for Lot Frontage (490 sales were missing this data 16.7%)
  - DID NOT Impute data for Garage, Air Conditioning, 2nd floor and other features that may not be present in each home
- Create Dummy Variables
  - K-1 Variables to avoid unnecessary collinearity
- NOW Drop Missing Data – Results in 2,747 Rows and 244 Columns
- Address Multicollinearity – VIF Analysis AND Simple Collinearity

Feature Importance - OLS (Unscaled)

- Unscaled coefficients should correspond to $ impact on sales price.
- While a pool may detract from sales price, the magnitude of the impact is unreasonable.

```
coefs.sort_values(ascending=False).head(5)
```

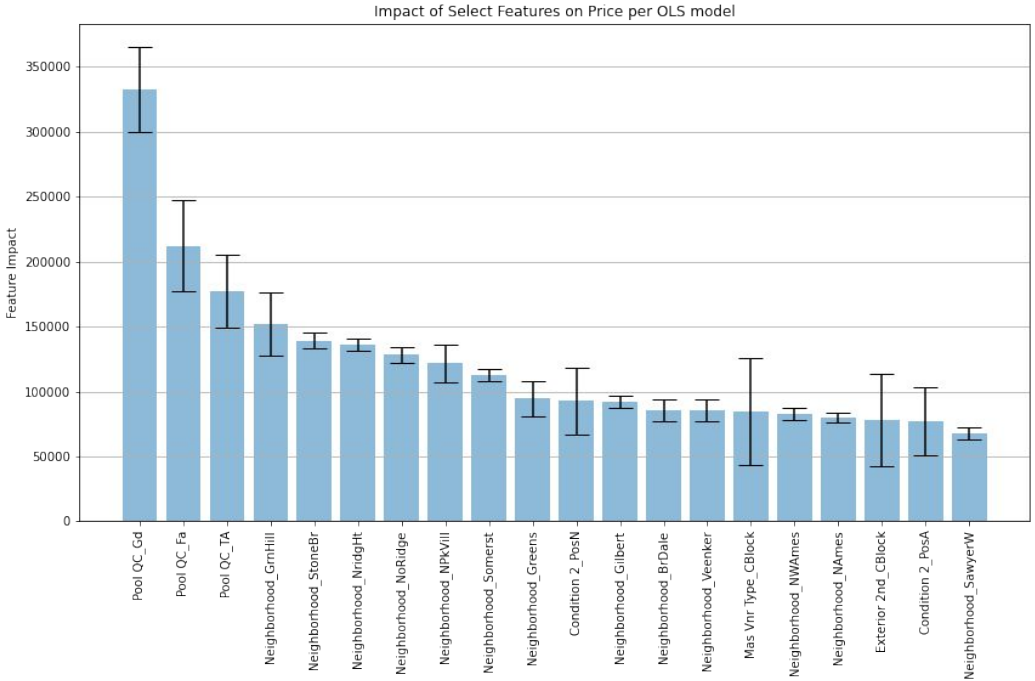
```
Neighborhood_GrnHill    136051.193859
Condition 2_PosA         90250.131444
Electrical_Mix           70502.849164
Neighborhood_StoneBr     68781.758793
Neighborhood_NridgHt     57973.372031
dtype: float64
```

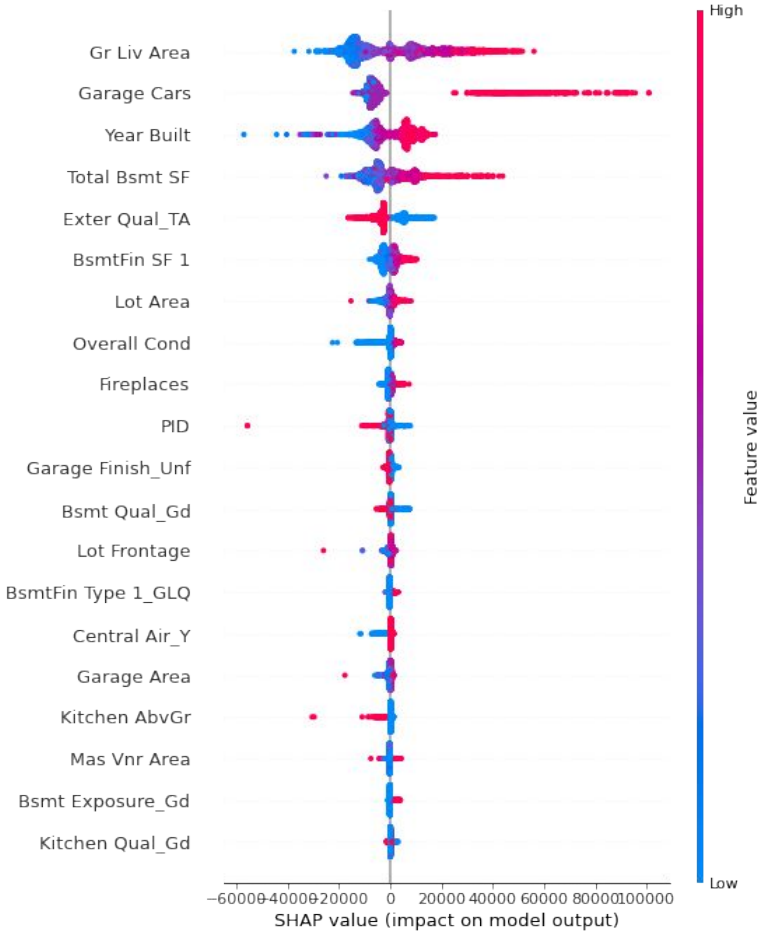
```
coefs.sort_values(ascending=False).tail(5)
```

```
Condition 2_PosN       -73622.193755
Mas Vnr Type_CBlock    -91966.406850
Pool QC_TA            -158684.213611
Pool QC_Fa            -188326.499476
Pool QC_Gd            -331994.124866
dtype: float64
```

Feature Importance

1. Coefficients from OLS Regression (standardized using Robust Scaler)
2. SHAP Feature Importance (right)



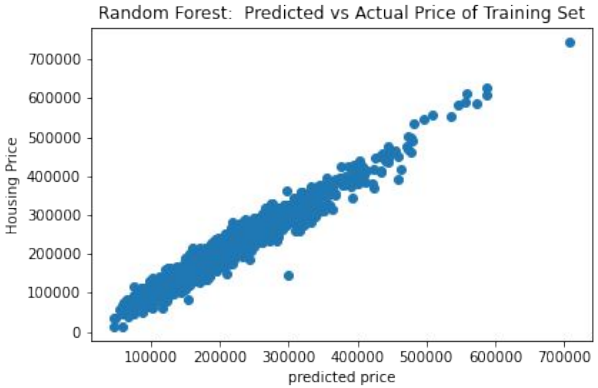


Train Test Split

- Training Set with 75% of the Sales
- Test Set with remaining 25% of the Data

Random Forest Model

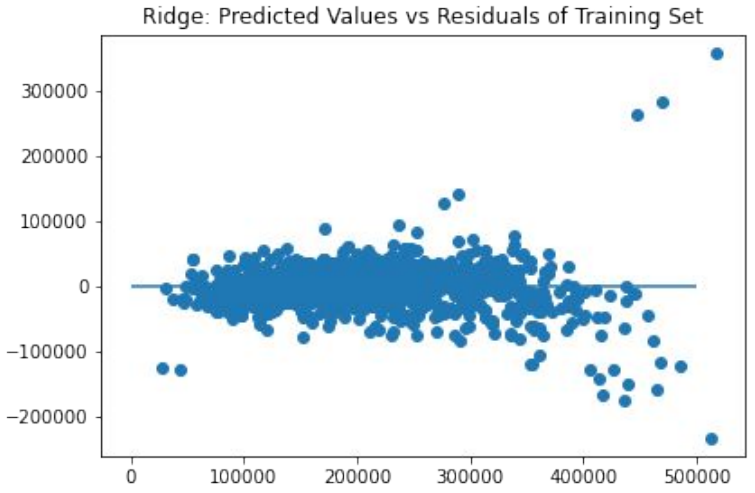
- Optimized Hyperparameters:
  - N_estimators
  - Max_depth
- Used Random Search for CV



Random Forest Evaluation Metrics	Model: All Features	Model: Top Twenty Features
r2 Score Train	0.983	0.983
r2 Score Test	0.862	0.856
Mean Absolute Error (MAE) Train	6189.75	6308.99
Mean Absolute Error(MAE) Test	17905.1	18336.8
Root Mean Square Error (RMSE) Train	10268.8	10250.1
Root Mean Square Error (RMSE) Test	29797.4	30411.4
Optimal n_estimtor	5308	10000
Optimal max_depth	20	110

Ridge Regression

- Useful when multicollinearity exists.
- Grid Search CV to optimize Alpha



Ridge Regression Evaluation Metrics	Model: All Features	Model: Top Twenty Features
r2 Score Train	0.88	0.789
r2 Score Test	0.883	0.829
Mean Absolute Error (MAE) Train	17309.2	22532
Mean Absolute Error(MAE) Test	18166.6	22350.1
Root Mean Square Error (RMSE) Train	27466.3	36415.1
Root Mean Square Error (RMSE) Test	27442.7	33171.5
Optimal Alpha	6	35

Gradient Boosting

- Grid Search Cv
- To optimize Learning Rate and Max Depth

Gradient Boosting Evaluation Metrics	Model: All Features	Model: Top Twenty Features
r2 Score Train	0.974	0.97
r2 Score Test	0.89	0.881
Mean Absolute Error (MAE) Train	9603.46	10340.5
Mean Absolute Error(MAE) Test	16981	17789.9
Root Mean Square Error (RMSE) Train	12869.2	13781.8
Root Mean Square Error (RMSE) Test	26604.8	27666.8
Optimal Learning Rate	0.1	0.1
Optimal Max Depth	4	4

Comparing The Models

- Random Forest performs best on Training Data
- Gradient Boosting has highest R-squared and Lowest RMSE on test data
- Expect Gradient Boosting to most precisely predict Sales Price

Model	r2 Score (Test-Data)	Root Mean Square Error (Test Data)	Hyperparameter 1	Hyperparameter 2
Random Forest (All Features)	0.862	29797.42	n_estimators = 5,308	max_depth = 20
Random Forest (Top 20 Features)	0.856	30411.44	n_estimators = 10,000	max_depth = 110
Ridge Regression (All Features)	0.883	27442.69	Alpha = 6	
Ridge Regression (Top 20 Features)	0.829	33171.55	Alpha = 35	
Gradient Boosting (All Features)	0.89	26604.81	Learning Rate = 0.1	max_depth = 4
Gradient Boosting (Top 20 Features)	0.881	27666.77	Learning Rate = 0.1	max_depth = 4

Gradient Boosting

- Selected as best model

Selected Model	Gradient Boosting (All Features)
Model	Gradient Boosting (All Features)
Hyperparameter 1	Max Depth = 4
Hyperparameter 2	Learning Rate = 0.1
r2 Score Train	0.974
r2 Score Test	0.89
Root Mean Square Error (RMSE) Train	12869.0
Root Mean Square Error (RMSE) Test	26605.0

Test Case

- Randomly Selected ONE property from our Test Data
- Applied Gradient Boosting Model (ALL Features) to predict Sales Price
- Model predicted Sales Price of $247,968
- Actual Sales Price of $226,000

Conclusion and Next Steps

Three models evaluated

- Random Forest, Ridge Regression, Gradient Boosting
- For all models looked at two feature sets

Compared models on R-Squared and RMSE to select best model

Best model was Gradient Boosting (All Features)

Next Steps:

- Further optimization of hyperparameters
- Additional feature sets
- Assess application for other real estate types (commercial , multifamily)