



# AMES HOUSING PROJECT

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- ★ Popular
- ★ Zestimates
- ★ Check Price

# The Property Watch Of AMES, IA



- ❑ *What determines the price of a property?*
- ❑ *What property features are most important in accurately predicting sale price*
- ❑ *What kind of approach yield the most accurate prediction*

# Data Review

- 2 sets of Ames Housing datasets were provided dated from 2006-2010
- **Training data** : 2051 rows of observations with 81 columns
- **Test data**: 879 rows of observation with 80 columns
- The train dataset has 81 columns which includes 23 nominal, 23 ordinal, 14 discrete, and 20 continuous variables (and 2 additional observation identifiers).

# Procedure / Methodology

1. Data Cleaning
2. EDA
3. Feature Engineering
4. Model Prep
5. Cross Validation
6. Model Fitting (Linear Regression, Ridge, or Lasso)

Problem

Methodology

Key Visualisations

Primary Findings

Recommendations

# Data Cleaning

- Replacing the 'null' values with 'None'
- Imputing Missing Values
- Converting all ordinal variables to numeric values
- Dummying the categorical variables
- Identifying and removing the outliers

Problem

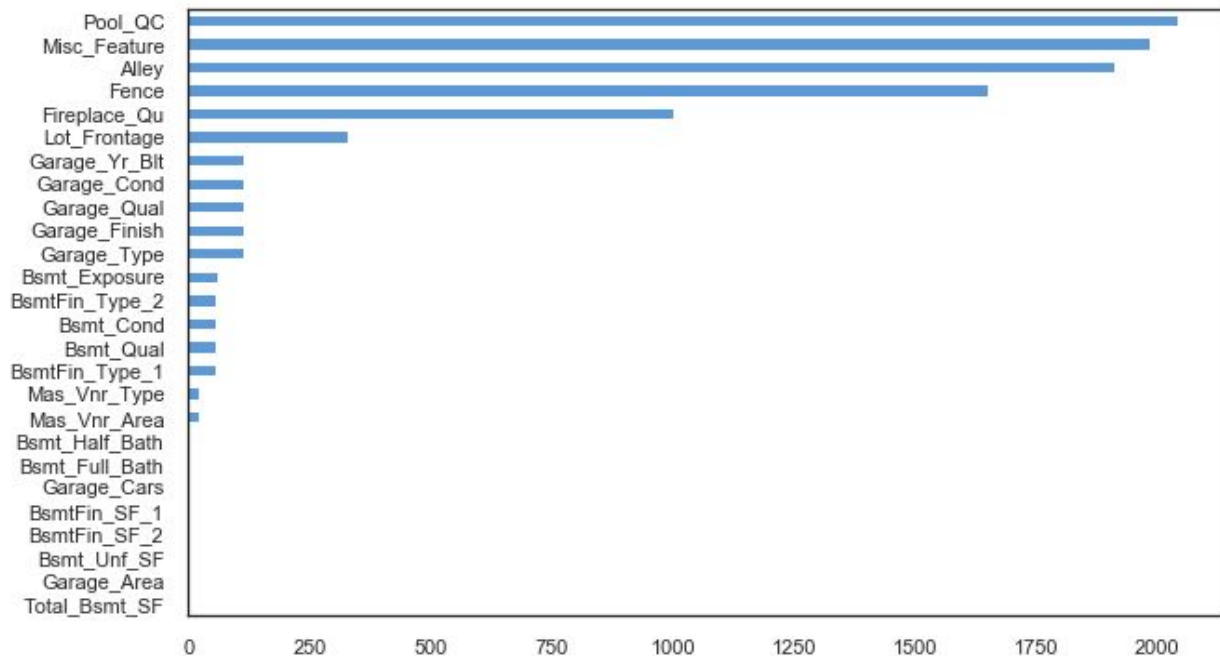
Methodology

Key Visualisations

Primary Findings

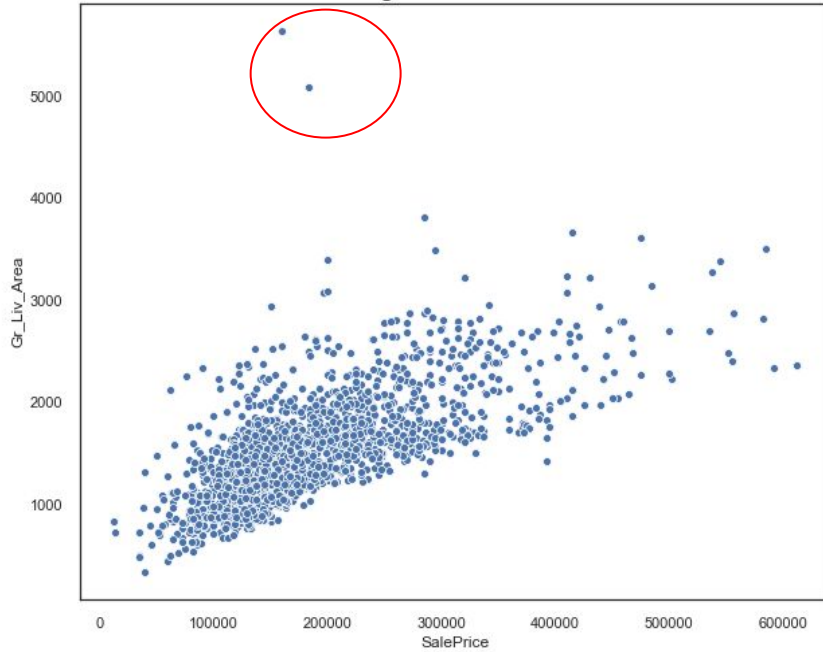
Recommendations

# Columns with the null values

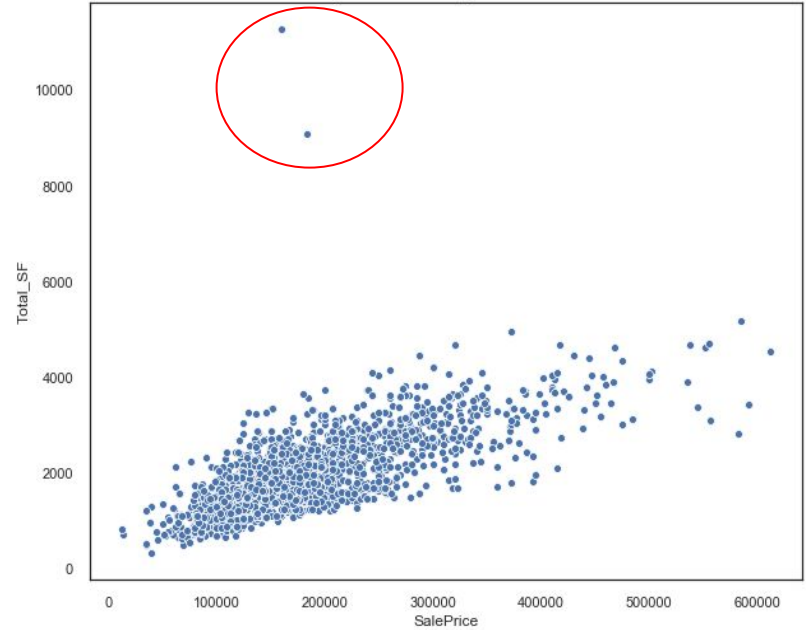


# Outliers

Gr Living Area vs Sale Price

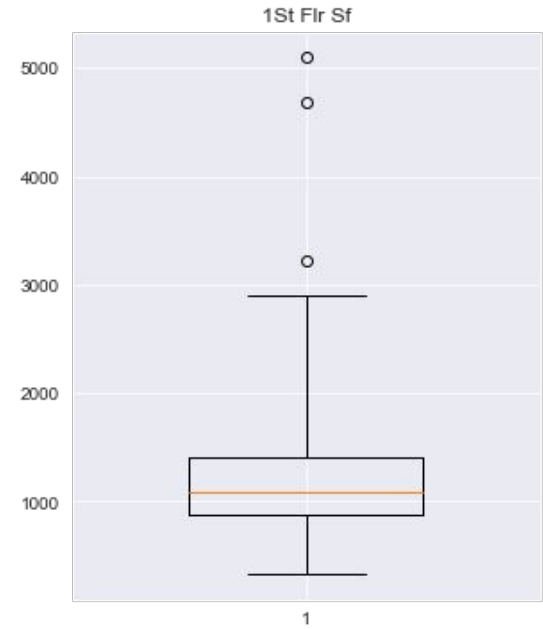
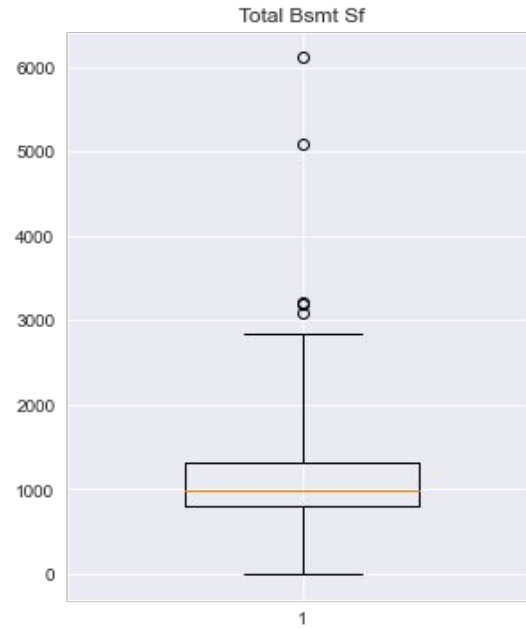
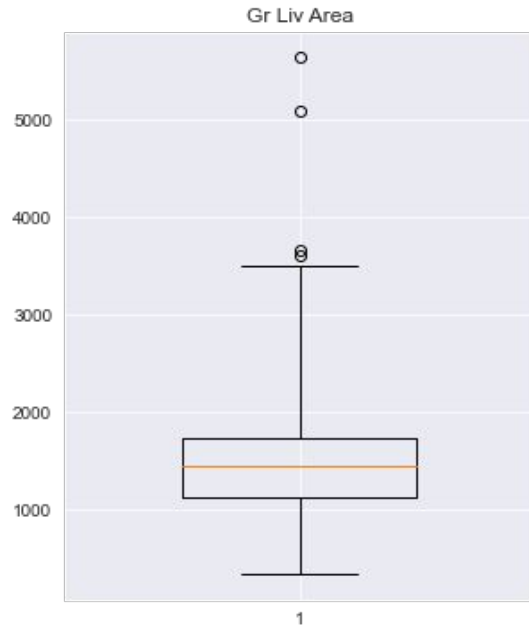


Total Square Footage vs Sale Price





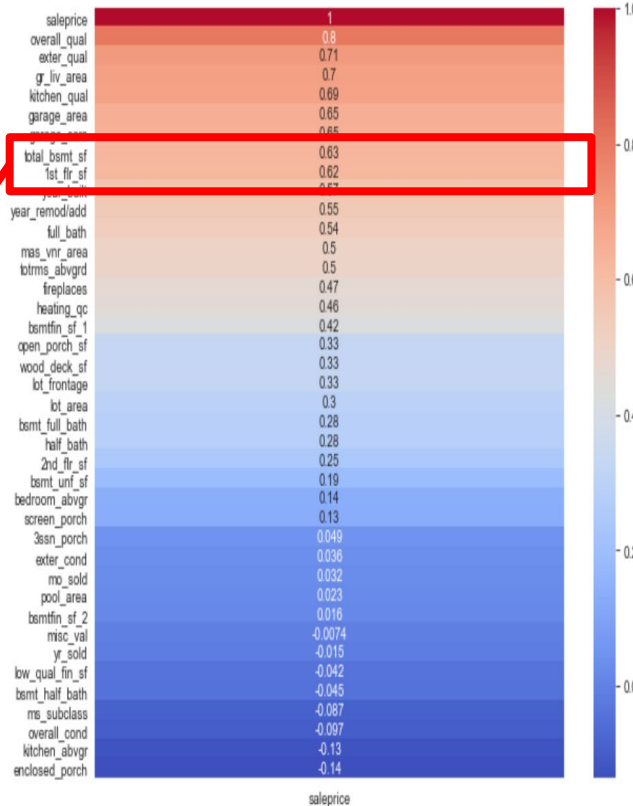
# Boxplot



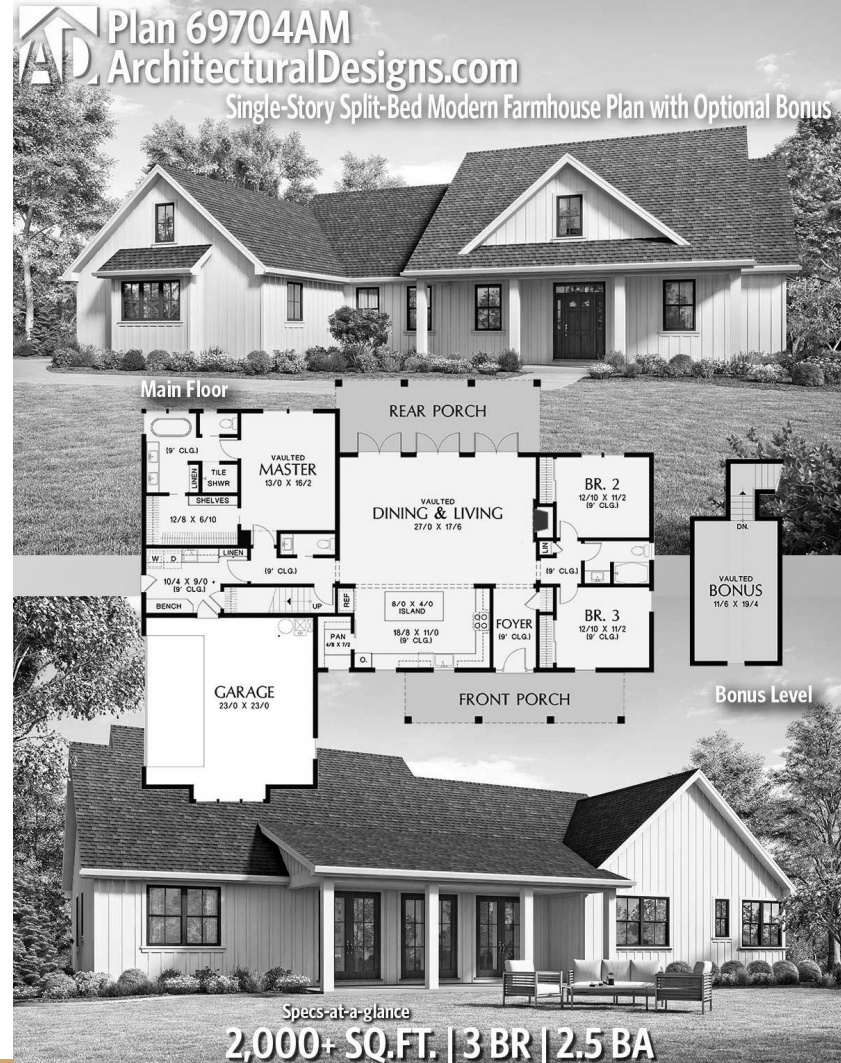
# Feature Engineering

With the Use  
Heatmap

- **Total Basement Sqft (Corr .63)**
- **1st Floor Sqft (Corr. 62)**



saleprice



# Feature Engineering

## OLD Vs NEW

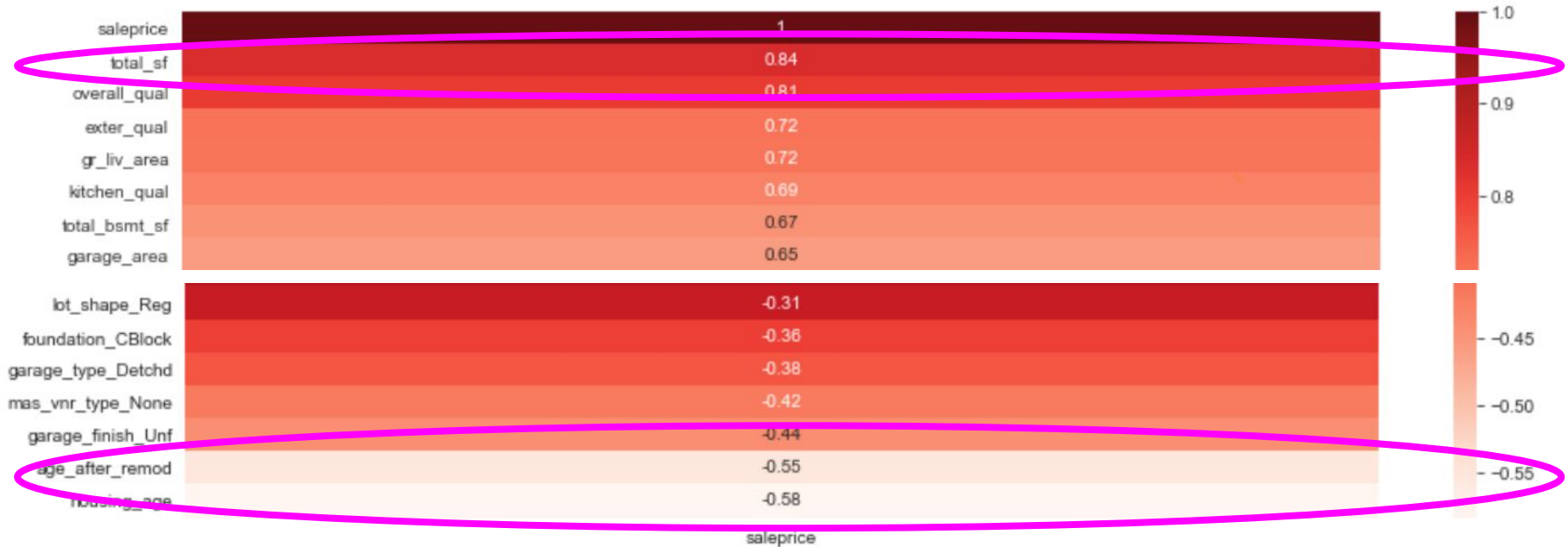
- Year Sold
- Year Built
- Year of Remodeling

## Dummies Variables

- Categorical
- Nominal



# Feature Engineering ( NEWLY IMPROVED)



Problem

Methodology


Key Visualisations

Primary Findings

Recommendations

# Model Selection

$$R^2 = \frac{\text{Explained variance}}{\text{Total variance}} = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

Model	R2 score	Selection
Linear regression	-1.3232	
Ridge	0.8994	
Lasso	0.9114	

# Model Selection

$$R^2 = \frac{\text{Explained variance}}{\text{Total variance}} = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

Model	R2 score
Train set	0.9310
Test set	0.9129

Goal: Get R2 as **close to 1** as possible.

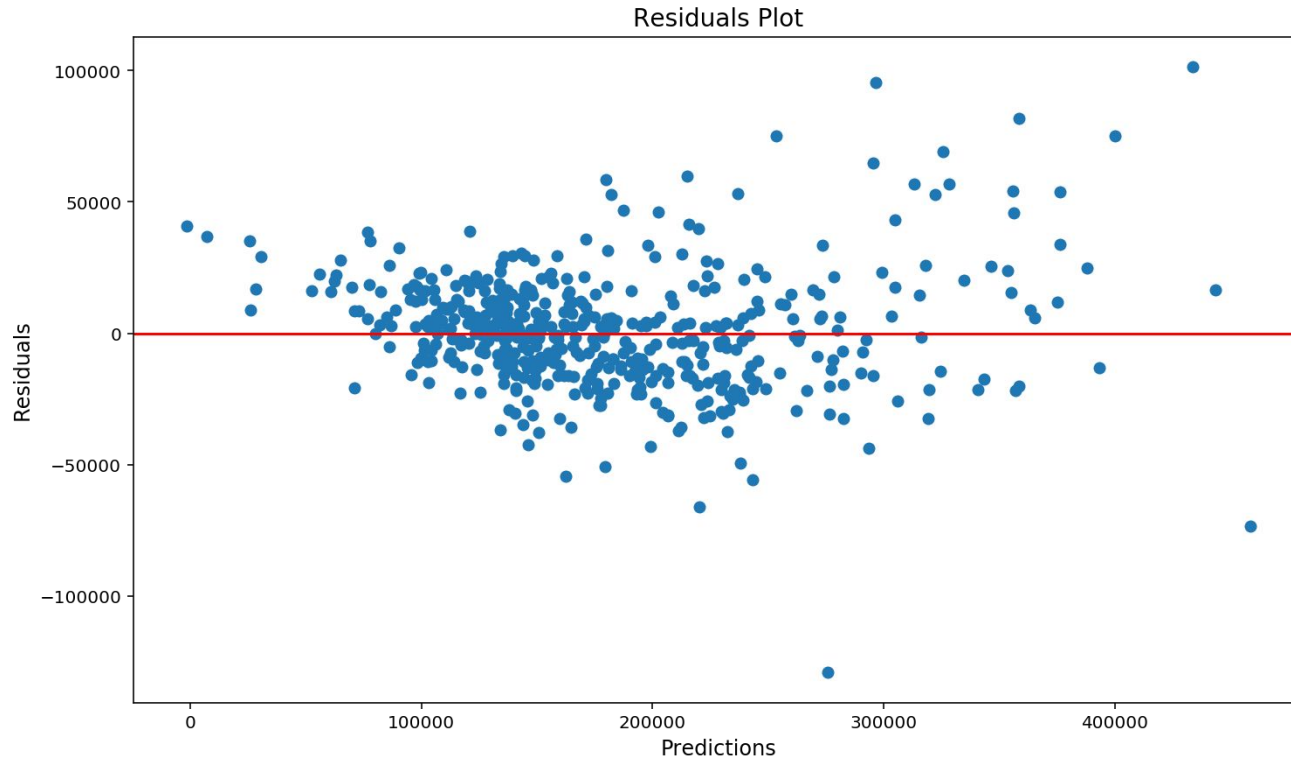
# Model Selection

$$RMSE(\mathbf{y}, \hat{\mathbf{y}}) = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

Model	RMSE
Baseline	78869.43
Test set	22298.09

Goal: Get RMSE as **close to 0** as possible.

# Model Selection





# Model Coefficients

	variable	coef	abs_coef
29	Gr Liv Area	16492.114	16492.114
58	total_sf	13025.572	13025.572
8	Overall Qual	12160.959	12160.959
19	BsmtFin SF 1	8910.810	8910.810
94	Neighborhood_NridgHt	7727.090	7727.090
10	Year Built	6695.917	6695.917
13	Exter Qual	6461.551	6461.551
12	Mas Vnr Area	5853.158	5853.158
100	Neighborhood_StoneBr	5481.017	5481.017
9	Overall Cond	5106.784	5106.784
17	Bsmt Exposure	4762.552	4762.552
36	Kitchen Qual	4192.917	4192.917
4	Lot Area	3975.733	3975.733
43	Garage Area	3610.511	3610.511

# Recommendations

	variable	coef	abs_coef
29	Gr Liv Area	16492.114	16492.114
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Features that appear to add the Most Value to a Home :

**Living Area, Total Sq feet, Overall Quality**

# Recommendations

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Features that could increase the value of the house:

**Overall Quality, Overall Condition**

**Masonry veneer area, Basement Exposure, Kitchen Quality**

# Recommendations

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Neighbourhoods Seem Like a Good Investment:

**Northridge Heights, Stone Brooke**

# Recommendations

	variable	coef	abs_coef
2	MS SubClass	-2823.937	2823.937
121	Bldg Type_TwnhsE	-1870.274	1870.274
132	Roof Style_Mansard	-1605.834	1605.834
120	Bldg Type_Twnhs	-1419.234	1419.234
16	Bsmt Cond	-1260.746	1260.746
34	Bedroom AbvGr	-1108.283	1108.283
119	Bldg Type_Duplex	-1107.471	1107.471
59	age	-1035.782	1035.782
166	Mas Vnr Type_BrkFace	-946.817	946.817
176	Heating_OthW	-778.322	778.322

Features that appears to hurt the home prices the most:

**Roof Style - Mansard, Unfinished Basement**

THANK YOU