

Predicting Housing Prices (Ames, USA)

Modeling and Analysis



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Problem Statement

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Using the available data to build an optimum model that can predict the sale price of homes in Ames, Iowa for real estates agents to use as a reference. To analyze and study the important features, allowing the agents to advice their client (homesellers) on ways to increase their homes' value.

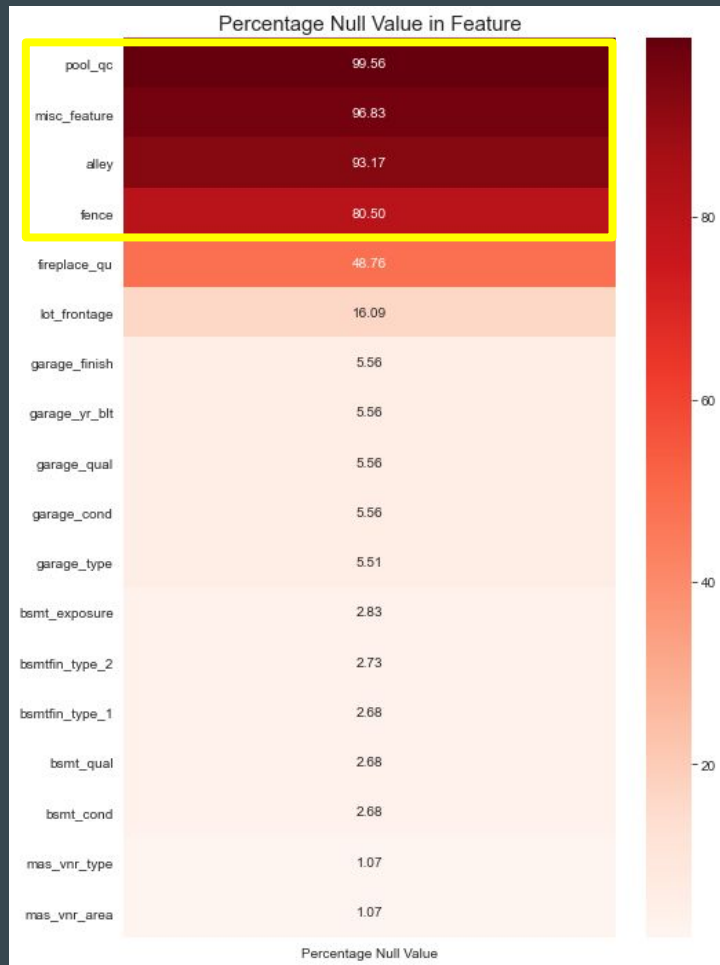
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Exploratory Data Analysis (EDA) & Data Cleaning

- Features with Missing Values
 - Null Values
 - Zero Values
- Features with High Percentage of Single Value
- Features with High Pairwise Collinearity
- Features with Low Correlation to Sale Price
- Other Preprocessing:
 - Removing Outliers
 - Handling Categorical Data

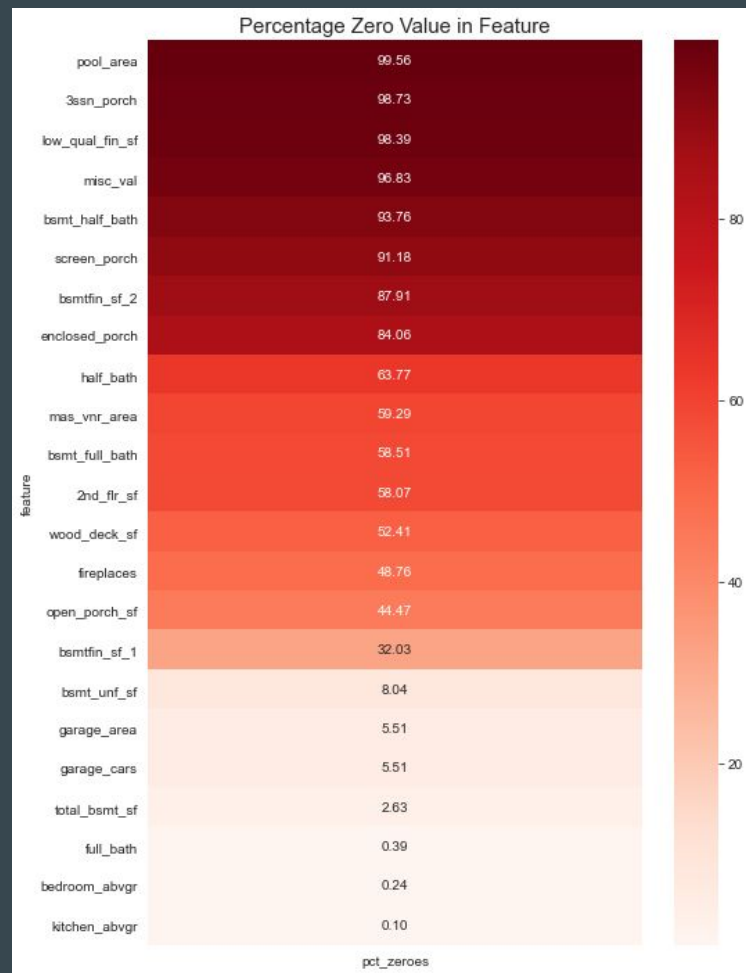
Dealing with missing values

- Dropped 4 features with **over 80% null values**.
(Pool QC, Alley, Misc Feature, Fence)
- **Systematically assign values to missing data** via inference.
(e.g. Impute Garage type with 'None', if all the other garage variables are null or 0)



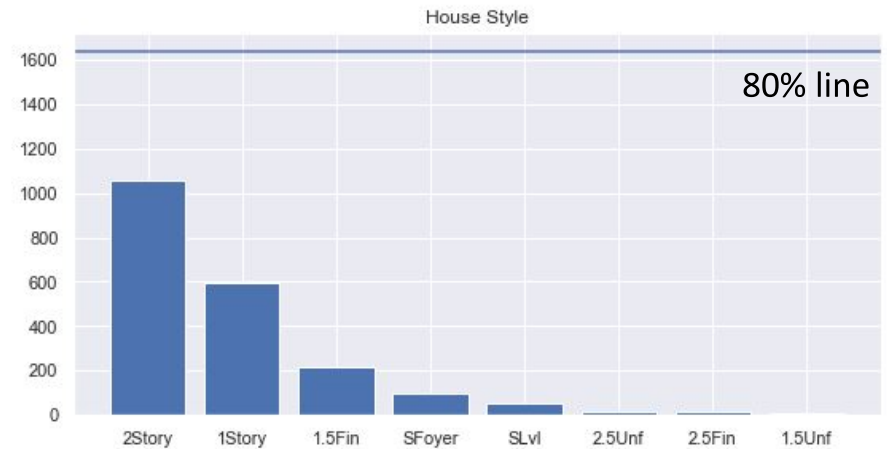
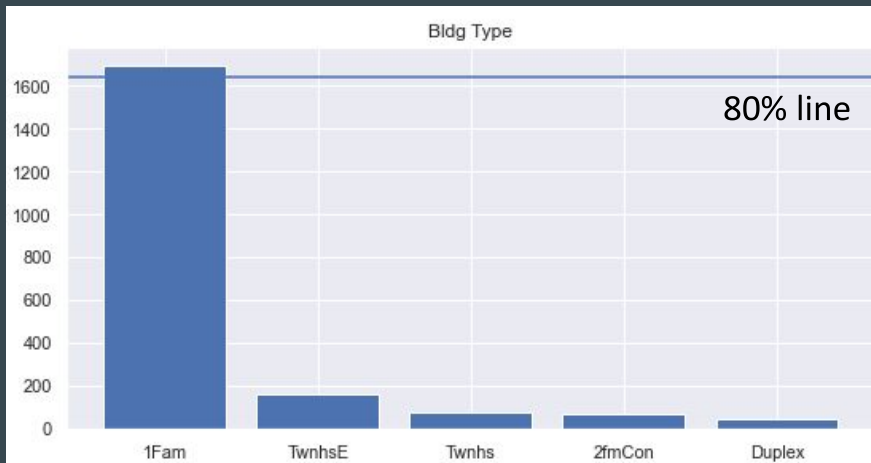
Dealing with Zero Values

- Features such as Pool Area, 3 Season Porch, Screen Porch, Low Quality Finish Surface Area have very **significant percentage of zero values**.
- Dropped numerical features with **more than 80% zero values**.



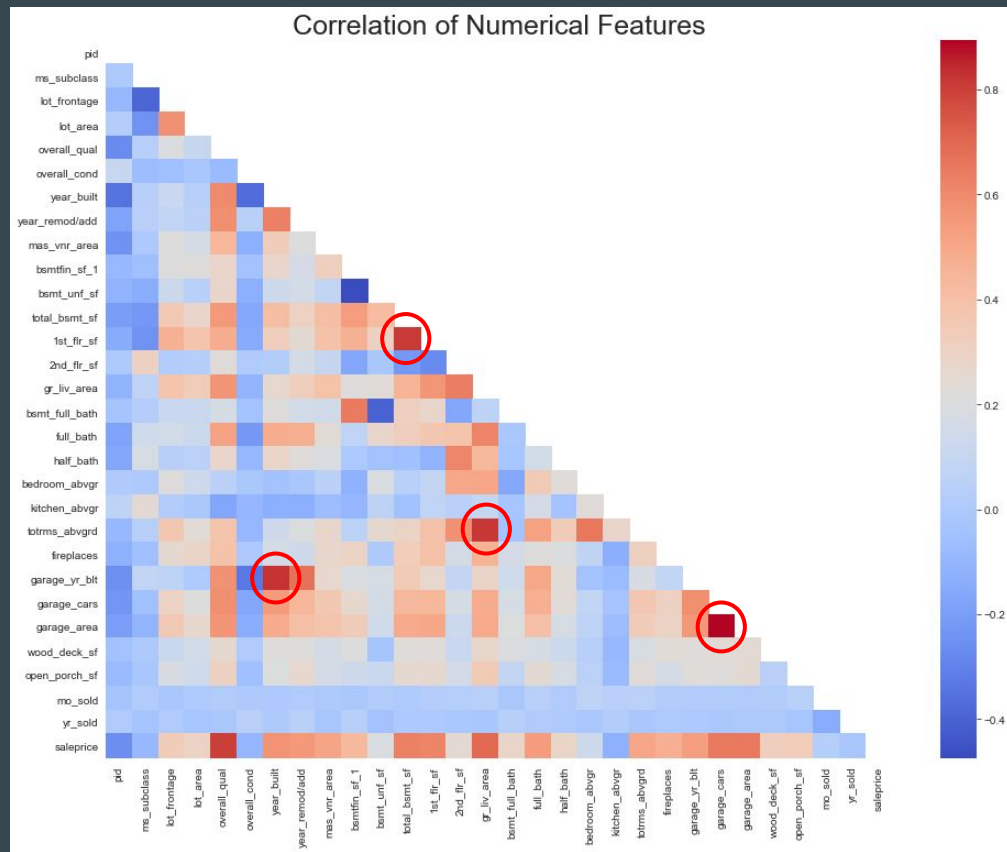
Features with High Percentage of Single Value

- Bar chart was plotted for categorical features.
- Any feature with a class **exceeding the 80%** was removed as they have **insufficient variance** and does not contribute to understanding of sale price.



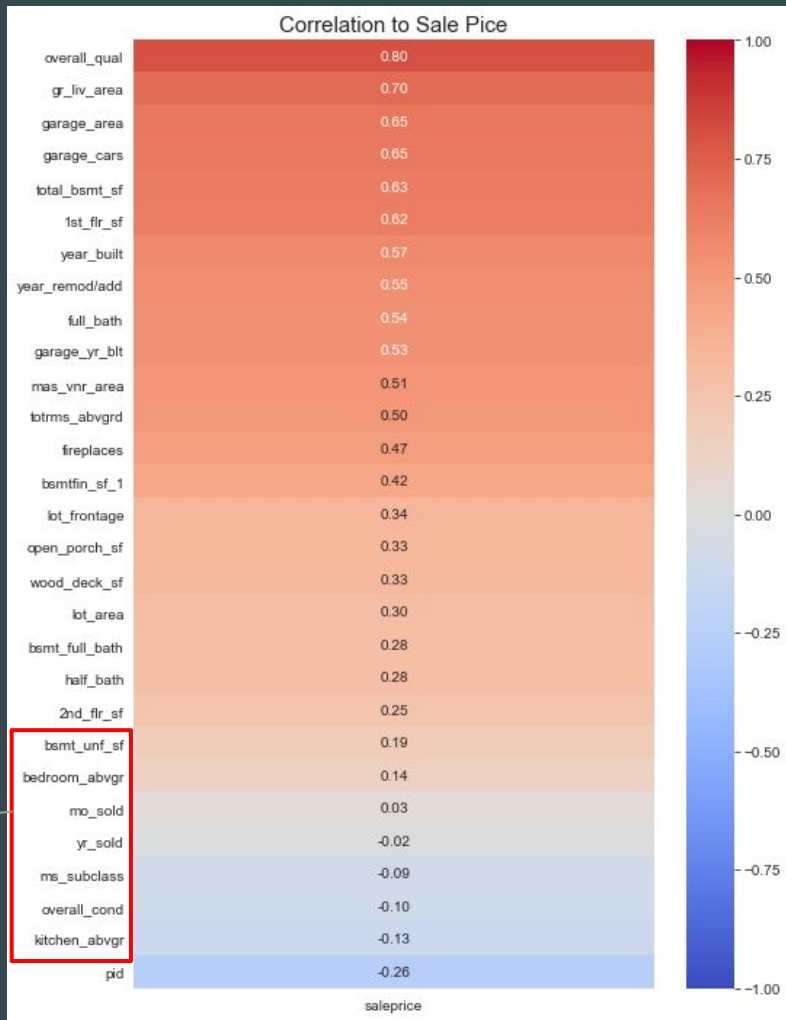
Features with High Pairwise Collinearity

- 4 Pairs of features had **high pairwise collinearity** (correlation > 0.8).
- The pairs were explored, and **only one feature was retained** (with better correlation with sale price).



Features with Low Correlation to Sale Price

- Explored features with **low correlation to sale price**.
- Removed features whose distribution showed that it does not contribute to the understanding of sale price.



Feature Engineering

Interaction Terms

Code Snippet:

1.8 Using Interaction Terms to combine features

```
def interaction_terms(ames_train):  
    ames_train['House Age']=ames_train['Yr Sold']-ames_train['Year Built']  
    ames_train['Years since Remod/Add']=ames_train['Yr Sold']-ames_train['Year Remod/Add']  
    ames_train['Garage Age']=ames_train['Yr Sold']-ames_train['Garage Yr Blt']  
    ames_train.drop('Yr Sold', axis=1, inplace=True)  
    ames_train.drop('Year Built', axis=1, inplace=True)  
    ames_train.drop('Year Remod/Add', axis=1, inplace=True)  
    ames_train.drop('Garage Yr Blt', axis=1, inplace=True)
```

executed in 4ms, finished 18:53:26 2020-11-22

```
interaction_terms(ames_train);
```

executed in 9ms, finished 18:53:26 2020-11-22

Dropping “Unnecessary” Features

Code Snippet:

```
1 train_num[['1stflrsf', '2ndflrsf', 'lowqualfinsf', 'grlivarea']].sum()  
  
1stflrsf      2378578  
2ndflrsf      674504  
lowqualfinsf    11307  
grlivarea     3064389  
dtype: int64
```

- Sum of square feet of 1st floor, 2nd floor and low quality finish were almost equal to square feet of general living (above ground)

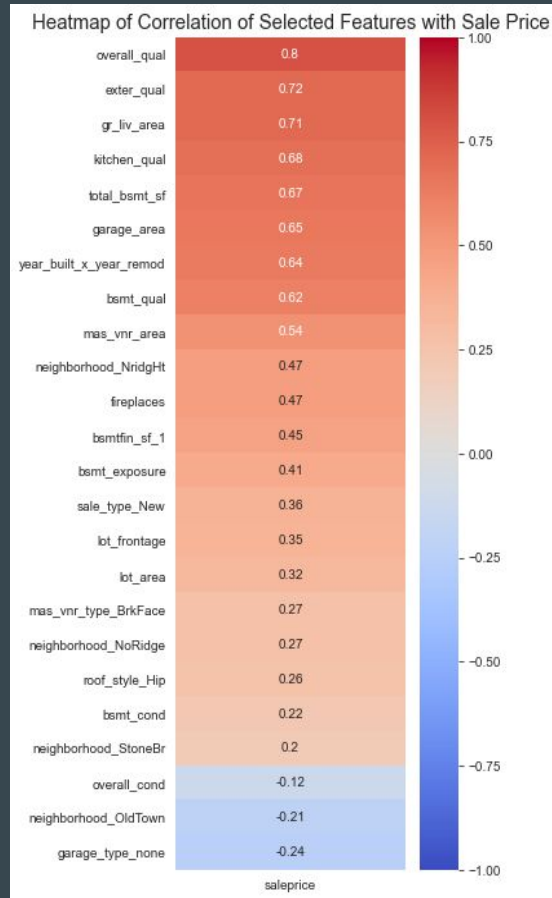
Feature Selection

Recursive Feature Elimination

1. Using the RFE function, **selected 30 features**
2. Modeling the dataset with the **chosen 30 features using Lasso and Ridge** produced the results below:
 - Lasso: $R^2(\text{Test}) - 0.898$
 - Lasso: $\text{RMSE}(\text{Test}) - 26\text{k}$
 - Ridge: $R^2(\text{Test}) - 0.899$
 - Ridge: $\text{RMSE}(\text{Test}) - 27\text{k}$

LassoCV and RidgeCV Coefficient

1. Ran LassoCV and RidgeCV on **all features**
2. Generate two lists of **30 features** with the **highest absolute coefficient** from LassoCV and RidgeCV
3. Among the two lists, there are **39 features in total** (21 features overlapped)
4. **24 features** with the **highest correlation to sale price** were selected for final model building



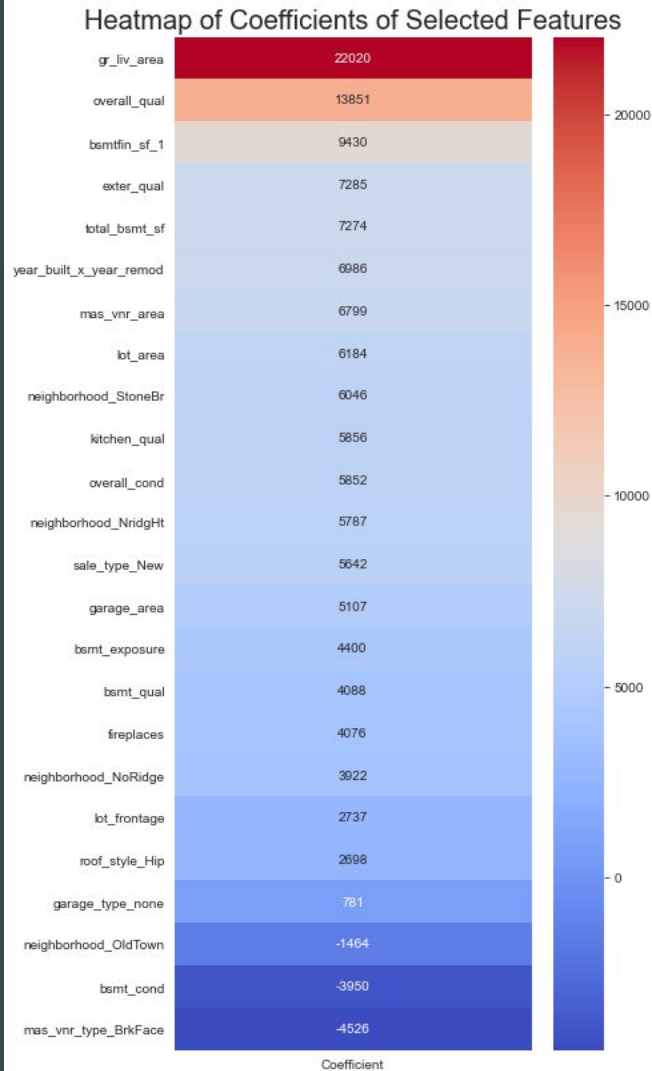
Results

		R2 (Train)	R2 (Test)	RMSE (Test)	Improvement over Baseline (%)
Features Used	Model				
All Features (191)	Linear Regression	0.928982	-1.25069e+26	9.02279e+17	-1.11822e+15
	Lasso	0.926415	0.905644	24782.9	69.29
	Ridge	0.927557	0.905264	24832.7	69.22
	ElasticNet	0.927158	0.905484	24803.7	69.26
Selected Features (24)	Linear Regression	0.904043	0.90003	25509.4	68.39
	Lasso	0.904043	0.90003	25509.4	68.39
	Ridge	0.903969	0.900032	25509.1	68.39
	ElasticNet	0.903928	0.900009	25512.1	68.38

- Linear Regression with all features performed very badly → Highly overfitted
- With all features, the Lasso model performed the best
- With selected feature, the Ridge model performed the best
- With selected feature, the Lasso model had the same result as Linear Regression → Features selected were all useful
-

Business Insights / Conclusions

- Number of features was trimmed for better interpretability and to reduce the data collection cost/effort
 - Having more features would have led to better predictions.
- Area, quality (and condition), age and neighborhood were the best predictors of sale price.
- Home owners wishing to sell their properties can increase the home value by:
 - Repair any defects in the house, Repaint the house → Improve the overall material and finish quality
 - Pursue expansion projects or re-purpose parts of the house to → Increase living area
 - Repairing / Renovate kitchen → Improve kitchen quality
 - Add a fireplace (if there is none)



Limitations

1. As mentioned previously, the sale price predicted by the model should only be **used as a reference**.
2. The data used is between 2006 to 2010 and **may not fit well to present-day data**.
3. Might not fit well to **other locations**.

Potential Improvements

1. **Location specific features** should be removed. (i.e. feature such as neighborhood)
2. Use **data from a longer period of time**. Allow the sale price to be better generalized.
3. **New model** for target location with **different local culture**.



A modern two-story house with a dark grey shingled roof and light blue horizontal siding. The house features a large two-car garage with grey doors and a small dormer window above it. To the right of the garage is a front entrance with a teal door and a small porch. The house is set on a wet, reflective driveway and lawn, with a small tree and shrubs in the front yard. The sky is a mix of blue and pink, suggesting a sunset or sunrise. The text "Thank you!" is overlaid in white on the garage door.

Thank you!