

# **Ames Housing Price Prediction**

**Advanced Apex Project - Real Estate Price Modeling**

**Team: The Outliers**

**Institution: BITS Pilani - Digital Campus**

**Course: Advanced Apex Project 1**

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# 1. Executive Summary

The Ames Housing Price Prediction project builds data-driven valuation models using 2,930 residential property records and 82 raw features from the Ames, Iowa market. Through rigorous preprocessing, feature engineering, and comparative modeling, the final Ridge Regression model achieves an R-squared of 0.85 on the held-out test set, with an average error (RMSE) of \$34,713. The workflow supports buyers, sellers, investors, and lenders with objective pricing guidance and actionable insights.

- Complete handling of 15,749 missing values across 27 columns.
- Five engineered features capture holistic property characteristics (e.g., Total\_SF).
- Comparative modeling (Simple LR, Multiple LR, Ridge) ensures robustness.
- Visual storytelling translates analytical results into stakeholder-friendly insights.

## 2. Dataset Overview & Quality Assessment

### Dataset Summary

Metric	Value
Total Records	2,930
Original Features	82
Final Features Used	73
Price Range	\$12,789 - \$755,000
Mean Price	\$180,796
Median Price	\$160,000
Std Dev	\$79,887
Total Missing Values	15,749
Columns with Missing Data	27

Quality checks confirmed zero duplicate records and a complete SalePrice target. Features with more than 50% missingness were removed, while remaining gaps were resolved via semantic imputations (e.g., 'None' for missing basement qualities, 0 for non-existent garages) followed by median/mode filling.

### 3. Preprocessing & Feature Engineering

#### ***Missing Value Strategy***

A four-step pipeline addressed missing data: (1) drop high-missing features (>50%), (2) encode structural absence as 'None', (3) fill numerical amenities with 0 where applicable, and (4) median/mode imputation for residual gaps. This resulted in a 100% complete modeling dataset.

#### ***Engineered Features***

- $\text{Total\_Bathrooms} = \text{Full Bath} + 0.5 \times \text{Half} + \text{basement equivalents}$
- $\text{Total\_Porch\_SF} = \text{Sum of all porch square footage}$
- $\text{House\_Age} = \text{Yr Sold} - \text{Year Built}$
- $\text{Years\_Since\_Remod} = \text{Yr Sold} - \text{Year Remod/Add}$
- $\text{Total\_SF} = \text{Total Bsmt SF} + \text{Gr Liv Area}$

Total\_SF (sum of basement and above-grade living area) achieved the second-highest correlation with SalePrice ( $r = 0.79$ ), validating the domain-driven approach.

## 4. Modeling Strategy & Evaluation

Data was split 80/20 into training and testing sets with random\_state=42 for reproducibility. Simple Linear Regression established a baseline using Overall Quality alone. Multiple Linear Regression leveraged all 73 engineered and cleaned features, while Ridge Regression introduced L2 regularization to counter multicollinearity (VIF > 10 across size/quality attributes).

Model	Train R²	Test R²	RMSE	MAE	Overfit Gap
Simple Linear Regression	0.6325	0.6512	\$52,879	\$36,141	0.0187
Multiple Linear Regression	0.8612	0.8492	\$34,772	\$21,615	0.0120
Ridge Regression ( $\alpha=1.0$ )	0.8609	0.8497	\$34,713	\$21,551	0.0112

Ridge Regression (alpha = 1.0) provided the best balance of accuracy and generalization with R² = 0.8497 and RMSE = \$34,713 on the test set, while maintaining the lowest overfitting gap (0.0112).

## 5. Key Insights & Recommendations

- Overall Quality and Total\_SF dominate predictive power, aligning with real estate intuition.
- Quality upgrades (kitchen, bath, finishes) yield the highest ROI for sellers.
- Buyers should benchmark price-per-square-foot within the same neighborhood to capture location premiums.
- Investors can target properties where actual prices fall below model predictions for potential arbitrage.
- Ridge Regression's stability makes it suitable for deployment and underwriting support.

## 6. Visual Appendix

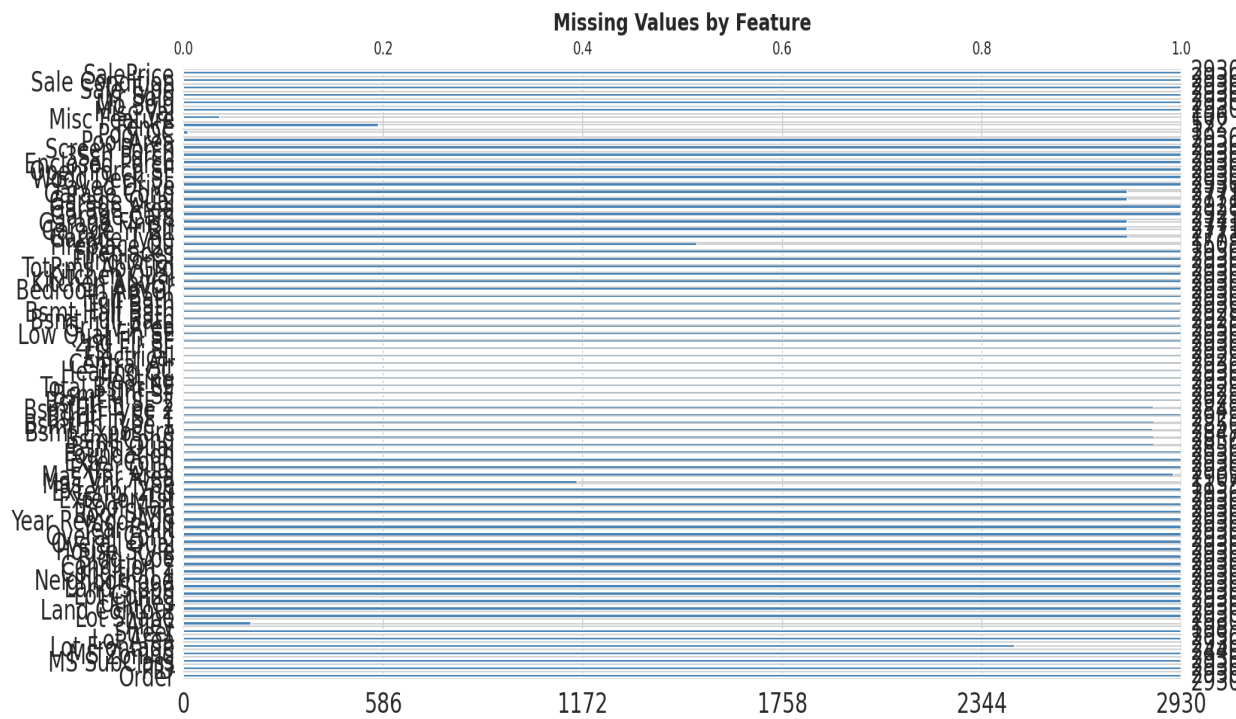


Figure 1: Missing Values by Feature



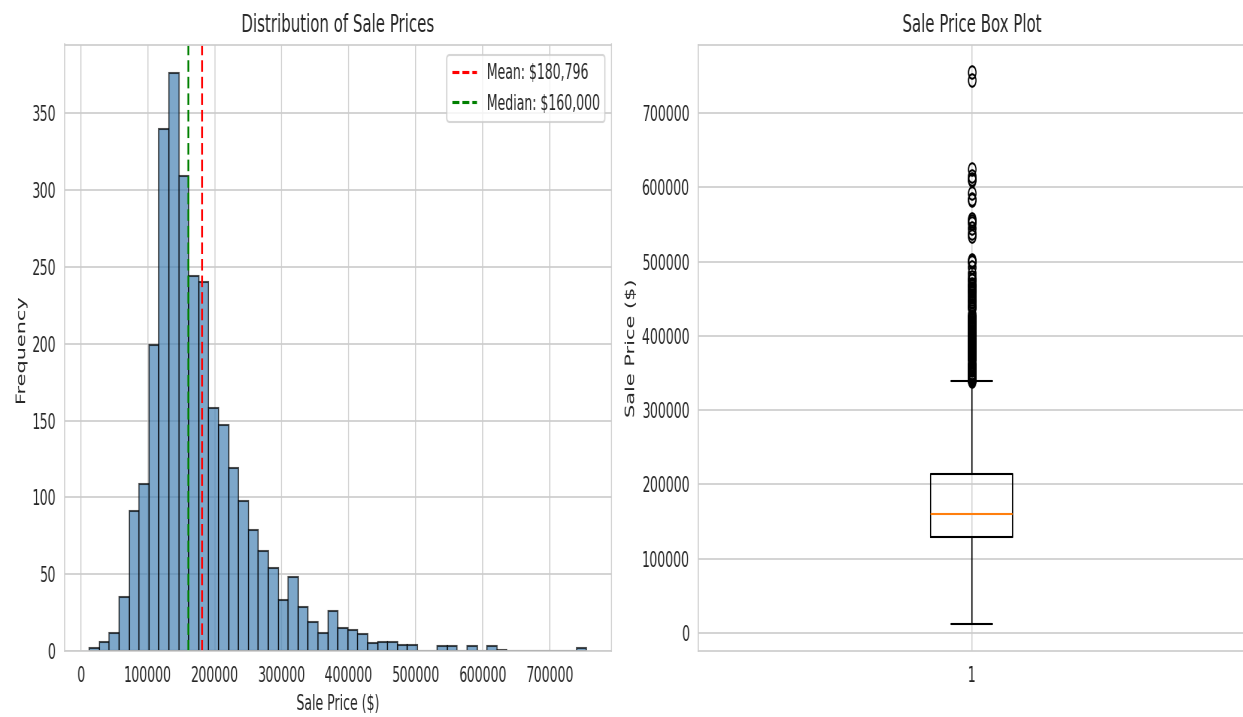


Figure 2: SalePrice Distribution

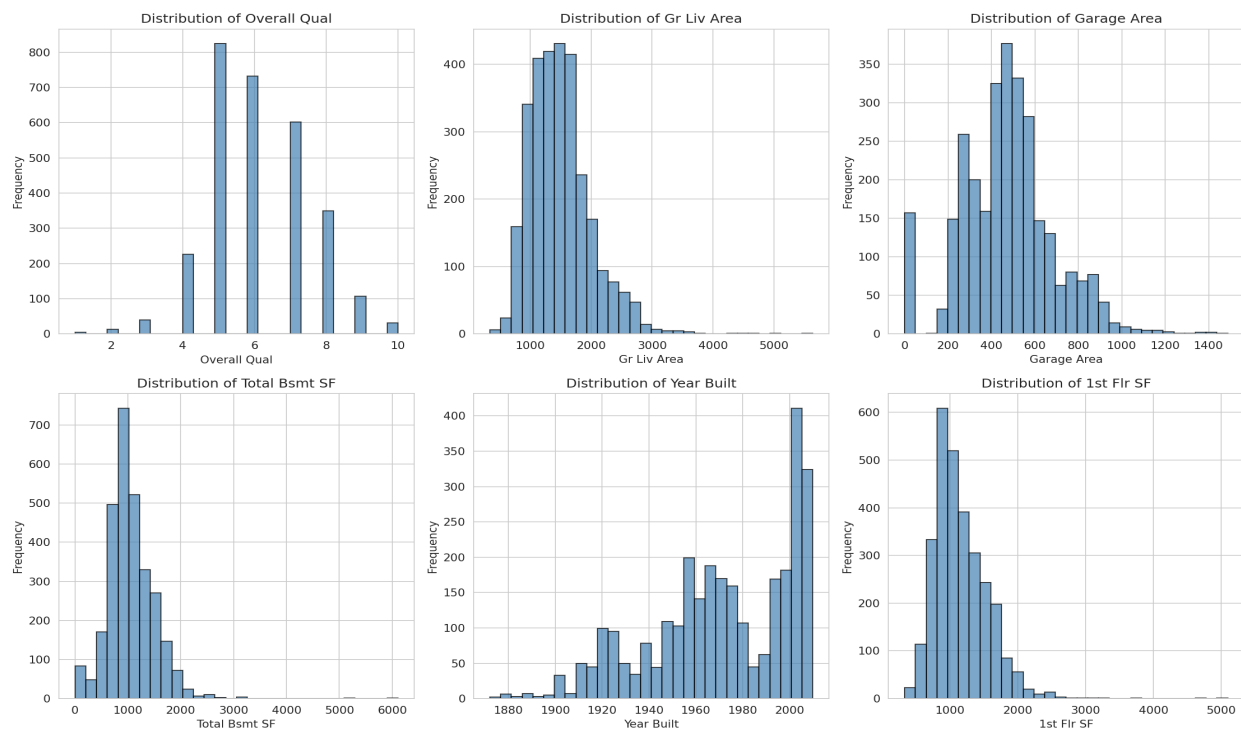


Figure 3: Key Feature Distributions

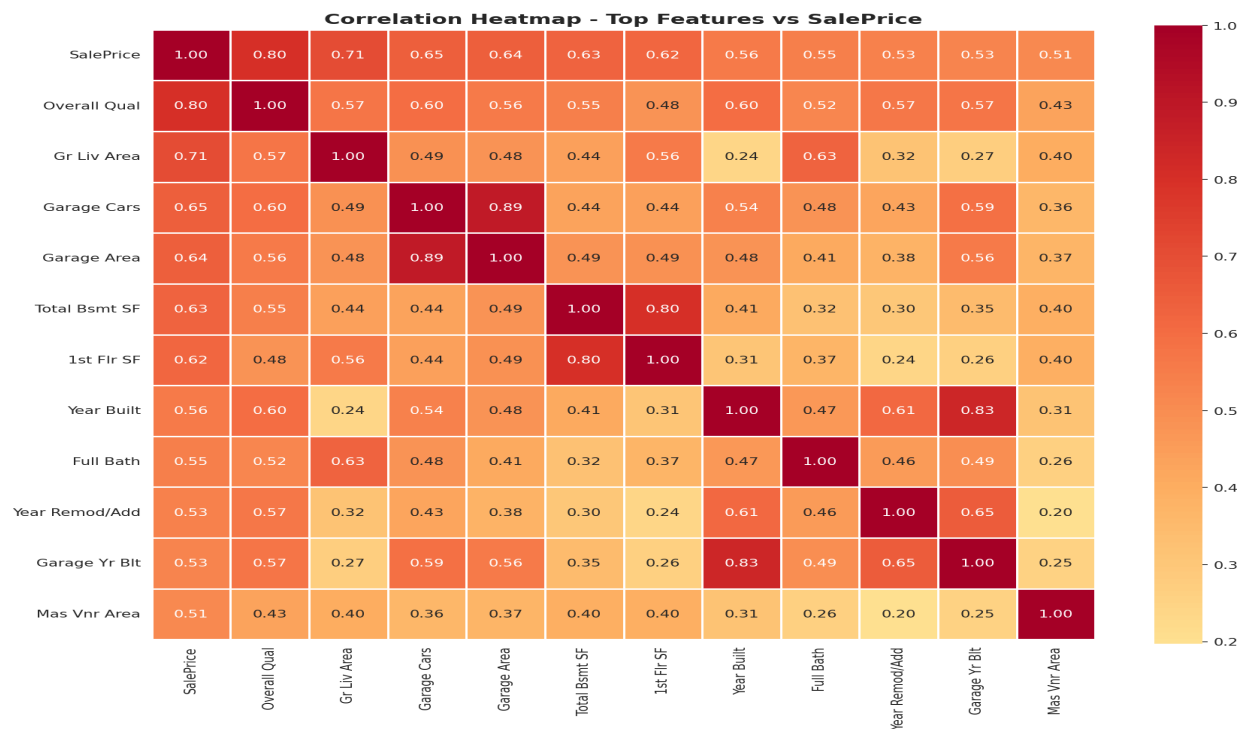


Figure 4: Top Feature Correlations

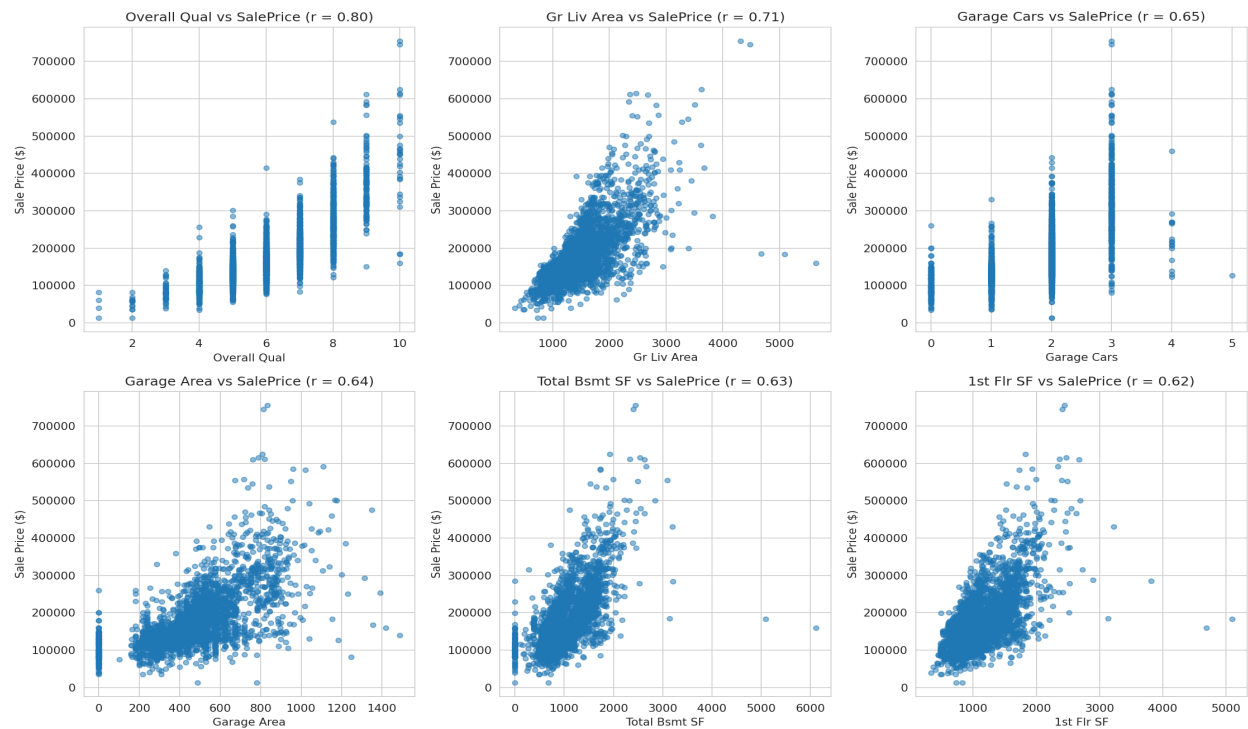


Figure 5: Top Predictors vs SalePrice

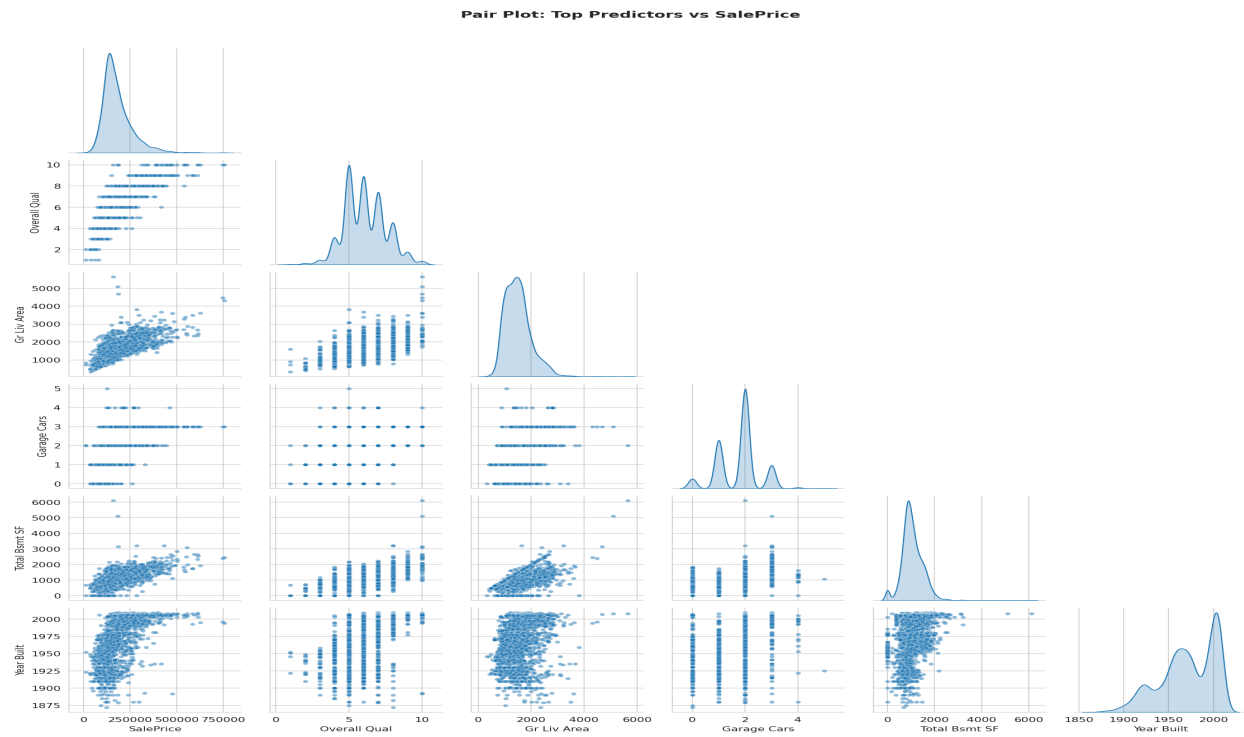


Figure 6: Pair Plot of Key Predictors

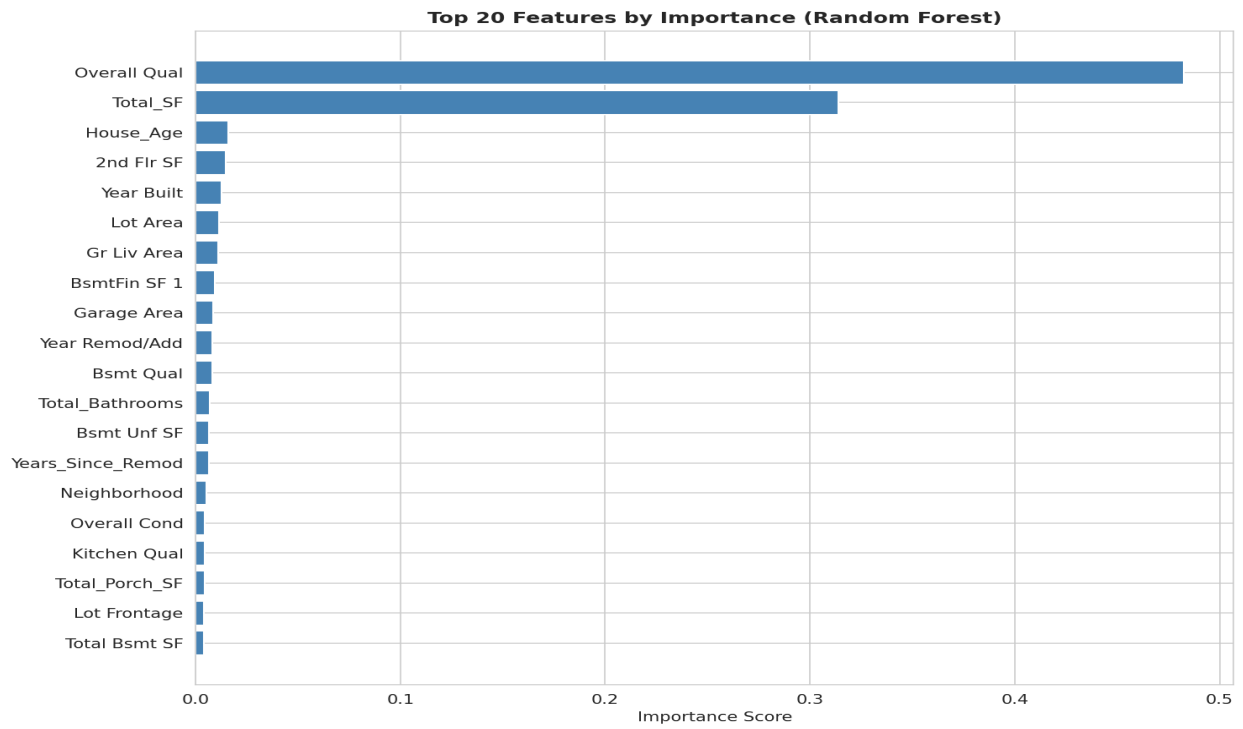


Figure 7: Top 20 Feature Importance

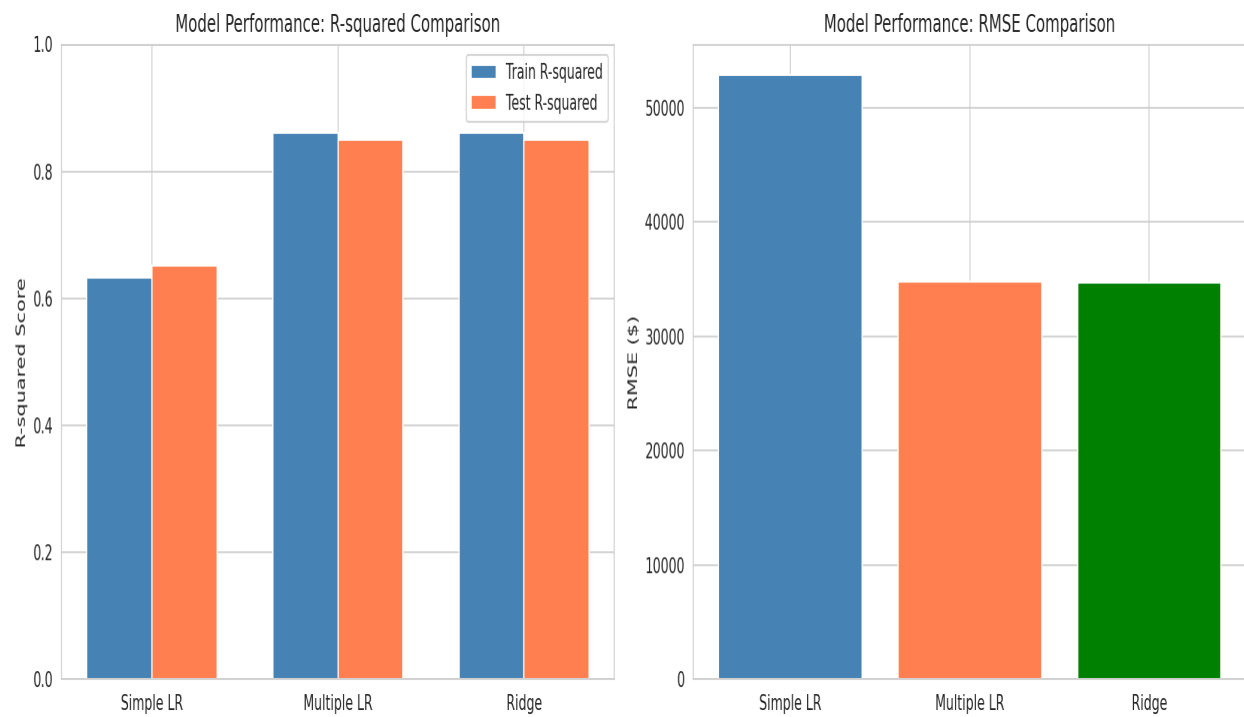


Figure 8: Model Comparison ( $R^2$  & RMSE)

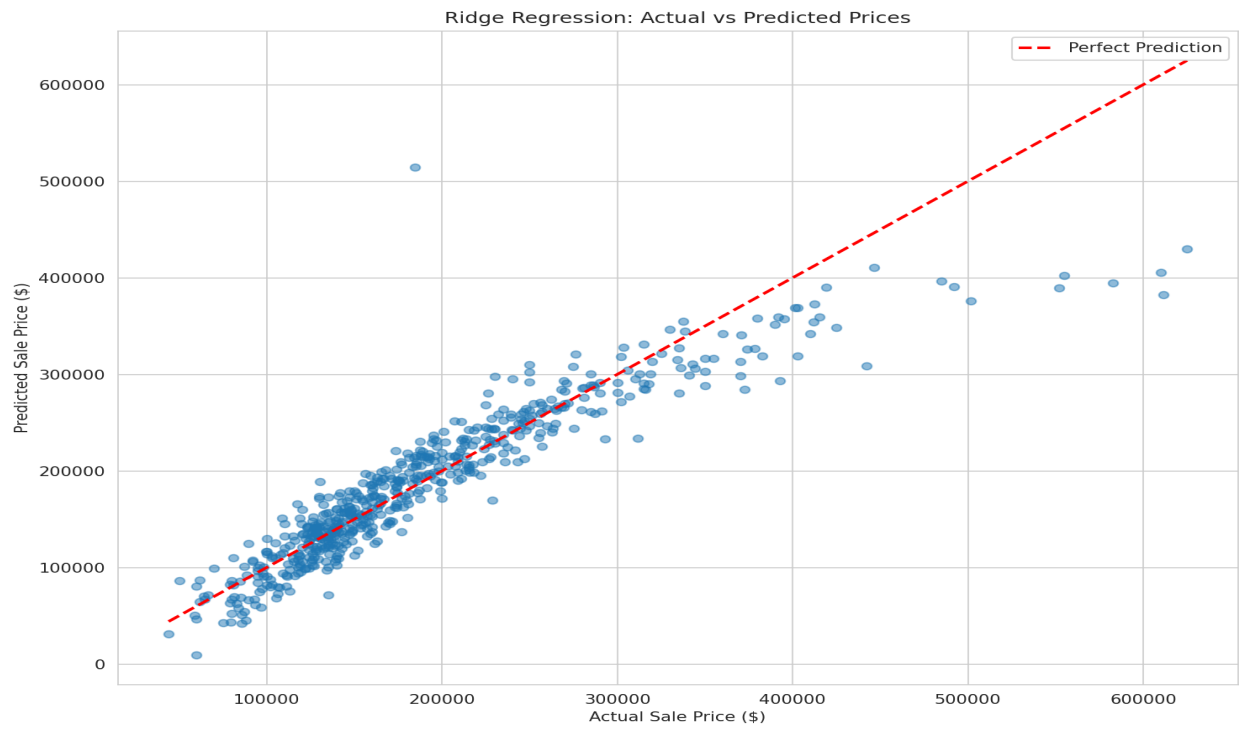


Figure 9: Ridge: Actual vs Predicted



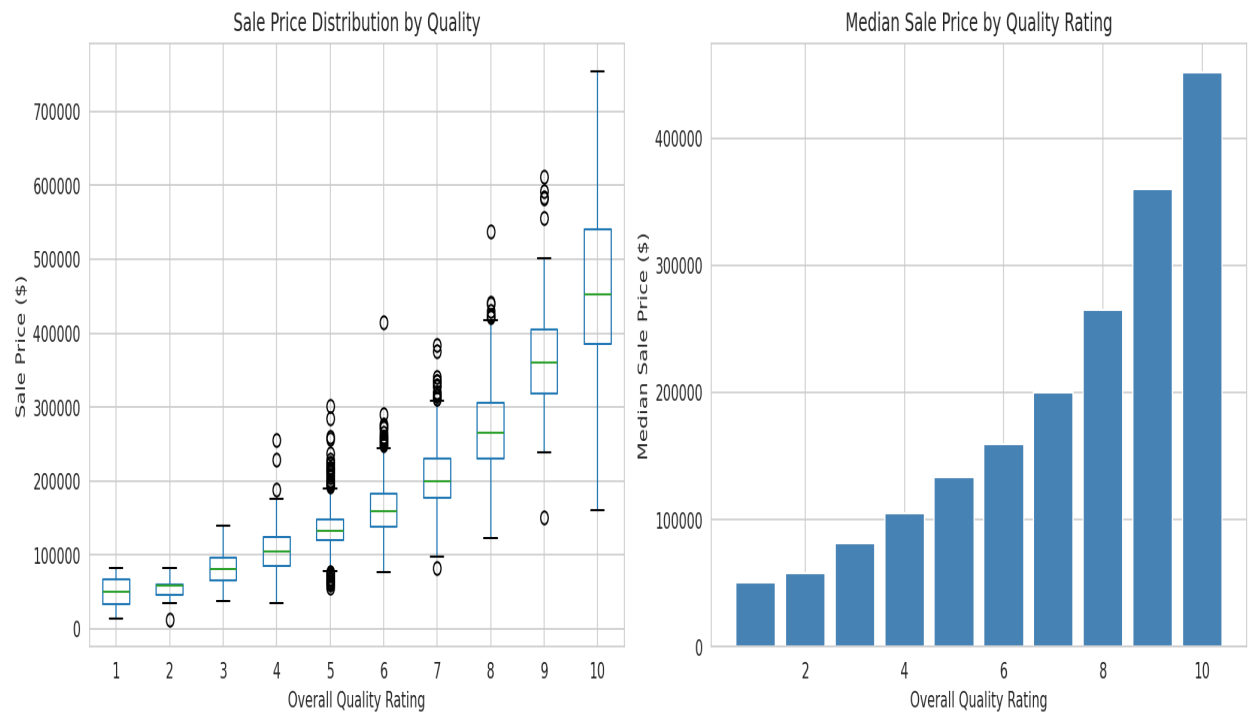


Figure 10: Price Distribution by Quality



Figure 11: Price vs Living Area by Neighborhood

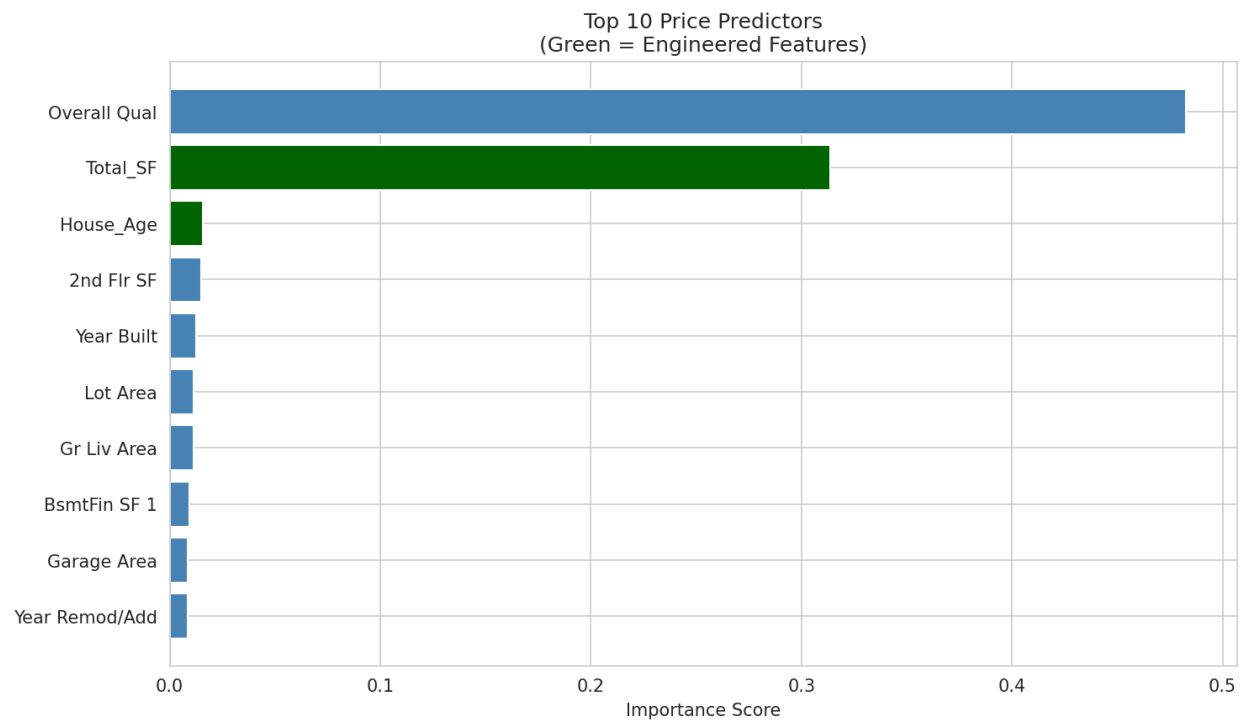


Figure 12: Top 10 Predictors (Engineered Highlighted)

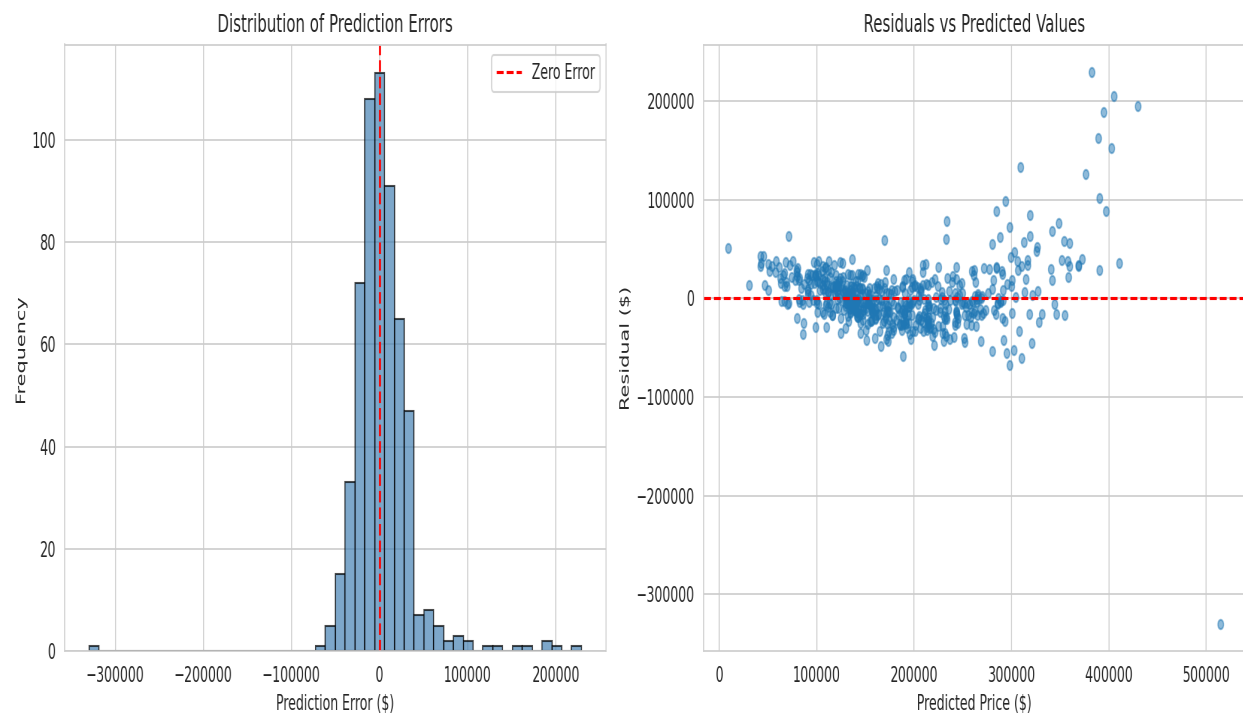


Figure 13: Residual Diagnostics

## Project Summary Dashboard

### AMES HOUSING PRICE PREDICTION - KEY METRICS

#### Dataset Overview

- Properties Analyzed: 2,930
- Features Used: 73
- Target: Sale Price (12,789 – 755,000)

#### Model Performance (Ridge Regression)

- R-squared: 84.97% of price variance explained
- RMSE: \$34,713 average error
- MAE: \$21,551 average absolute error

#### Top Predictors

1. Overall Quality ( $r = 0.80$ )
2. Total SF - Engineered ( $r = 0.79$ )
3. Living Area ( $r = 0.71$ )
4. Garage Cars ( $r = 0.65$ )
5. Total Basement SF ( $r = 0.63$ )

Key Finding: Quality and size are the primary drivers of home value.

Figure 14: Executive Summary Dashboard