AMES HOUSING PRICE PREDICTION

Presented by,
-Abirami Rajamanickam

Project Overview

Objective:

- Predict the sale price of residential homes in Ames, Iowa using features like the number of rooms, neighborhood, and house condition.
- Goal: Build an accurate predictive model to estimate sale prices for real estate decisions.

Goal of the Model:

• Develop a model that generalizes well to unseen data and can provide accurate price predictions for homes of various price ranges.

Data Science Approach:

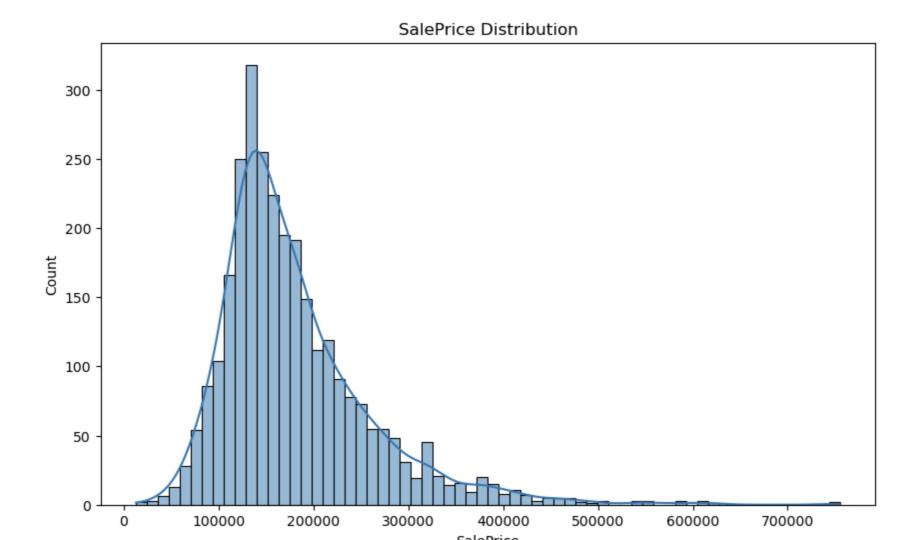
- **Preprocessing**: Handle missing values, scale numerical features, and encode categorical variables.
- **Modeling**: Apply **Ridge regression** to capture relationships between features and target price while preventing overfitting through regularization.
- Evaluation: Use metrics like RMSE and R² to assess model performance and make improvements.

Exploratory Data Analysis (EDA)

Identified missing data and handled it through imputation.

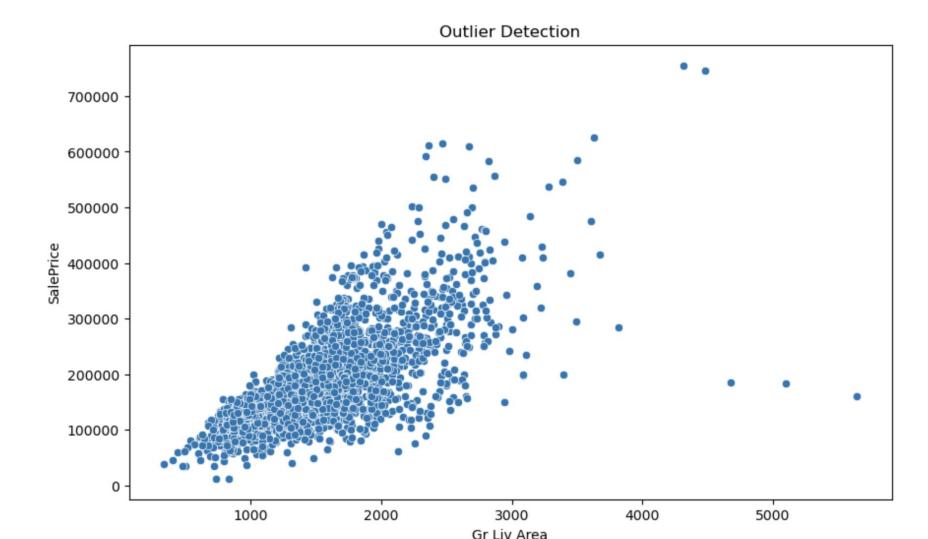
Visualized relationships between features like Gr Liv Area, Overall Qual, TotRms AbvGrd, etc., with the target SalePrice.

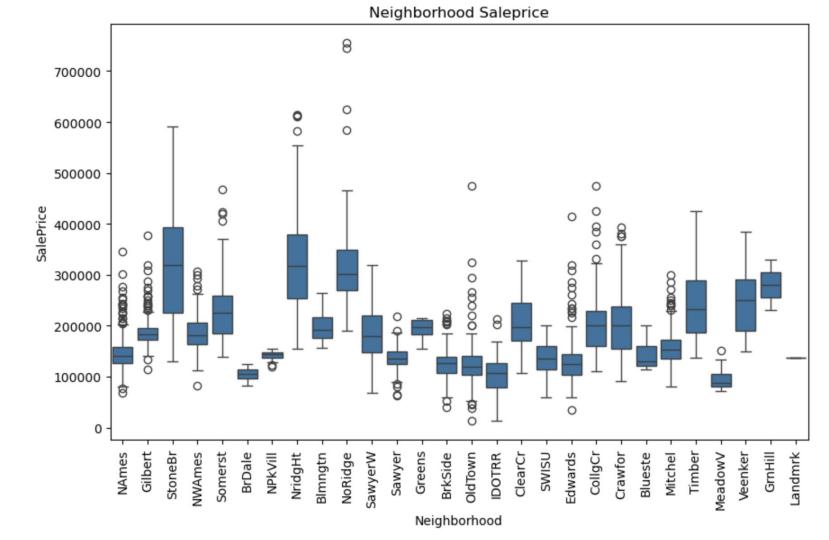
Used correlation heatmap to identify key features influencing sale prices.



Gr Liv Area Sales Price SalePrice

Gr Liv Area





Year Built - 0.6 0.240.540.480.410.31 1 0.470.610.790.310.110.170.280.110.23 0.2 0.270.210.01 Full Bath -0.520.630.480.410.320.370.47 1 0.460.480.250.530.230.0780.170.180.260.160.0230.4 Year Remod/Add -0.570.320.430.38 0.3 0.240.610.46 1 0.630.19 0.2 0.130.150.0860.220.240.210.130.16 Garage Yr Blt -0.540.260.480.470.330.250.790.480.63 1 0.240.150.0860.190.0690.220.220.220.140.084

1st Flr SF -0.480.560.440.49 0.8 1 0.310.370.240.250.390.390.410.460.420.230.24 -0.1 0.26-0.25

Top 20 Features Correlated with SalePrice **1** 0.57 0.6 0.560.550.48 0.6 0.520.570.540.420.380.390.28 0.2 0.26 0.3 0.270.170.24

- 0.8

- 0.6

- 0.4

Bsmt Full

Mas Vnr Area -0.42 0.4 0.360.370.390.390.310.250.190.24 1 0.280.27 0.3 0.2 0.170.140.190.140.12 TotRms AbvGrd -0.38 0.81 0.36 0.33 0.28 0.39 0.11 0.53 0.2 0.15 0.28 1 0.30 0.48 0.32 0.15 0.24 0.35 0.04 0.59 Fireplaces -0.390.450.320.290.330.410.170.230.130.0860.27 0.3 1 0.3 0.230.230.16 0.2 0.170.17 - 0.2 BsmtFin SF 1 -0.280.210.260.310.540.460.280.0780.150.19 0.30.0480.3 1 0.2 0.220.12 .0080.64 0.16 Lot Frontage - 0.2 0.350.290.340.330.420.110.170.086.0690.2 0.320.23 0.2 1 0.1 0.150.030.097.02 1 0.0350.120.190.089 Wood Deck SF -0.260.250.240.240.230.230.230.180.220.220.170.150.230.22 0.1 0.0

Open Porch SF - 0.3 0.34 0.2 0.230.250.24 0.2 0.260.240.220.140.240.160.120.150.039 1 0.180.0810.18 Half Bath -0.270.430.230.180.0550.1 0.270.160.210.220.190.35 0.20.008403 0.120.18 1 -0.030.61 Bsmt Full Bath -0.170.0570.160.180.330.260.210.020.130.140.140.040.170.640.0970.190.080.035 1 -0.16

-0.22nd Flr SF -0.240.660.180.13-0.210.250.0170.4 0.160.0840.120.590.17-0.160.020.0890.180.61-0.16 1

SF SF **TotRms AbvGrd** Lot Frontage Half Bath Total Bsmt

Feature Engineering and Model Selections

Transformations:

- Handled categorical features with OneHotEncoding.
- Standardized numerical features using StandardScaler.
- Split dataset into training and testing sets to validate model performance.

Model Choice:

- Selected Ridge regression for its regularization properties to avoid overfitting.
- Also tested Lasso regression to compare performance with Ridge.

Model Training and Evaluation

Model Training

Modeling Pipeline:

- Used Pipeline for streamlined preprocessing and model fitting.
- Ridge and Lasso models were trained on the dataset with the features and targets.

Model Evaluation (Ridge)

Performance:

• Ridge RMSE: 28,909.72

Ridge R²: 0.8958

Lasso RMSE: 29,230.17

Lasso R²: 0.8934

Demonstrated that Ridge regression is slightly better in performance compared to Lasso.

Prediction Accuracy

Top 5 Most Accurate Predictions:

- Small errors between actual and predicted prices.
- Examples:
 - Actual: \$390,000 | Predicted: \$389,873.61 | Error: \$126.39
 - o Actual: \$175,900 | Predicted: \$176,045.30 | Error: \$145.30

Bottom 5 Predictions:

- Larger discrepancies in predicted vs actual prices.
- Example:
 - Actual: \$611,657 | Predicted: \$436,617.86 | Error: \$175,039.14

Model Insights, Conclusion & Next Steps

Summary:

- Ridge model is effective for mid-range properties, showing high accuracy with smaller errors.
- Struggles with high-value properties, suggesting potential improvements with advanced models for outlier prediction.

Key Takeaways:

- The Ridge model performs well on most properties but faces challenges with high-value homes.
- Potential to explore more complex models (e.g., Random Forest, Gradient Boosting) to improve predictions for outliers.
- Further tuning and feature engineering could enhance model performance.

Next Steps:

- Experiment with different algorithms.
- Hyperparameter tuning and model ensembling.

Thank you