

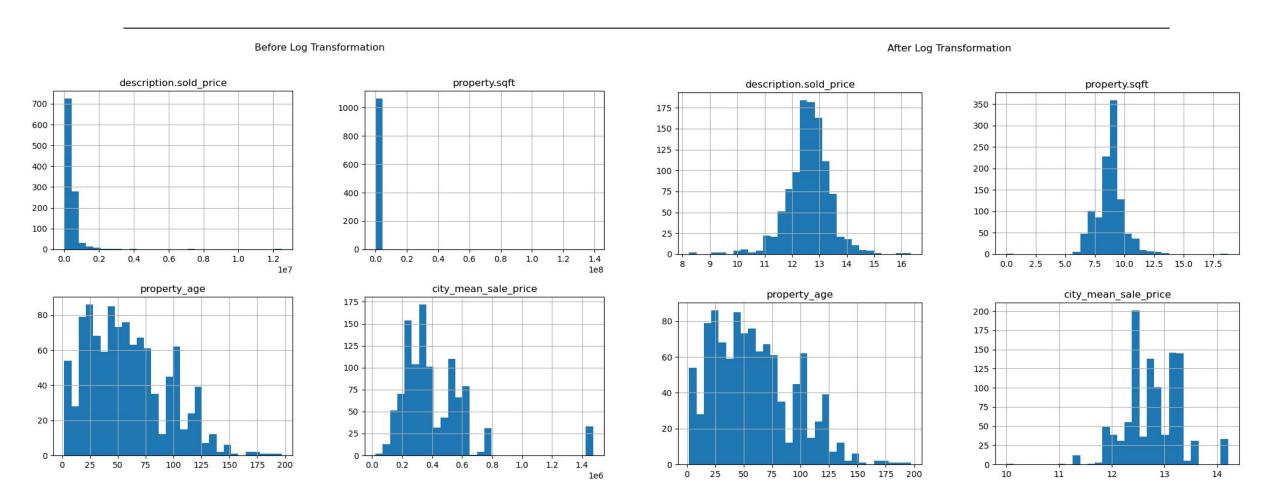
Project/Goals

- 1. Load, preprocess, and explore housing sales data.
- 2. Train, evaluate, and optimize supervised learning models.
- 3. Fine-tune the best model and implement a prediction pipeline.

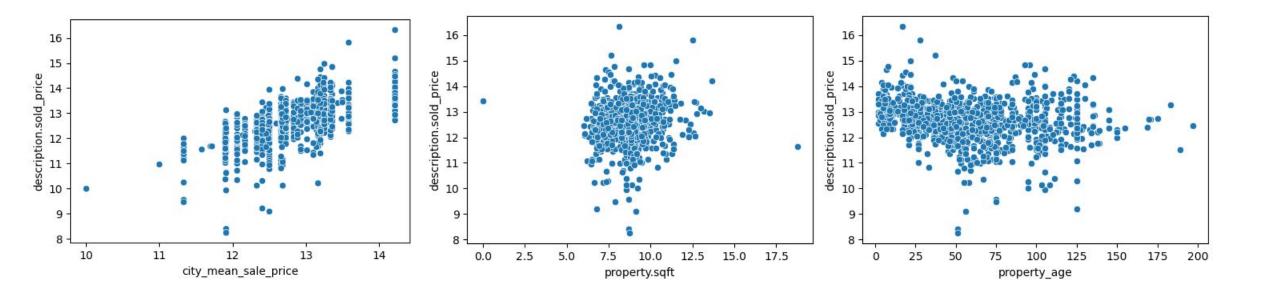
Process

- I. Data Cleaning, Exploration and Visualization
- II. Model Selection
- III. Finetuning
- IV. Model Evaluation & Results

I. Data Cleaning, Exploration and Visualization



I. Data Cleaning, Exploration and Visualization

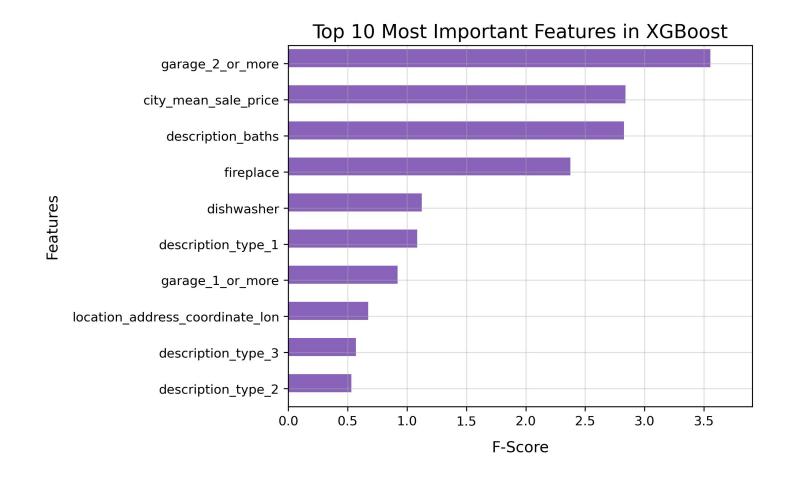


II. Model Selection: XGBoost

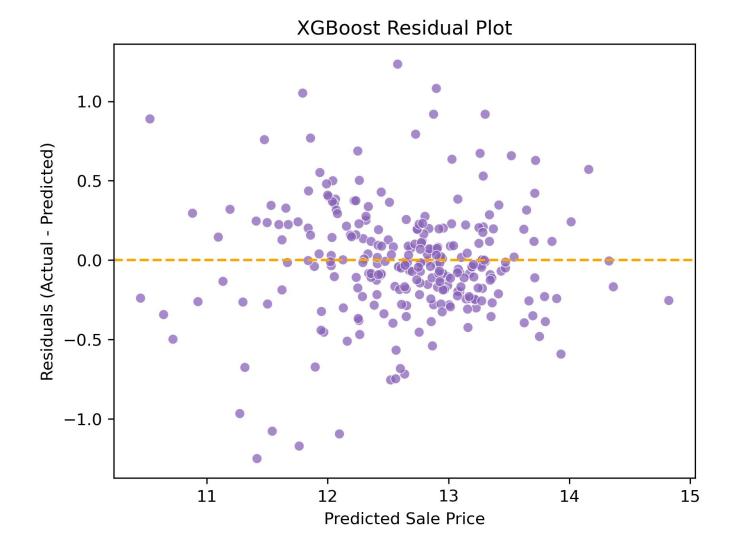
Model	Train MAE	Test MAE	Train RMSE	Test RMSE	Train R^2	Test R^2
Linear Regression	0.30	0.30	0.43	0.39	0.6905	0.7447
SVR	0.15	0.26	0.31	0.37	0.8466	0.7683
Random Forest	0.21	0.28	0.33	0.40	0.8169	0.7293
XGBoost	0.20	0.27	0.30	0.37	0.8494	0.7758

III. Fine-Tuned XGBoost's Performance:

Metric	Before (XGBoost)	After (Fine-Tuning)	Change
Test MAE	0.2700	0.2536	-6.1%
Test RMSE	0.3700	0.3525	-4.7%
Test R ² Score	0.7758	0.7945	+1.9%



IV. Model Evaluation & Results



IV. Model Evaluation Na Results



IV. Model Evaluation Na Results

Conclusion

- Our project successfully explored housing sales data, implementing data cleaning, visualization, and machine learning techniques to build a predictive model.
- After evaluating multiple models, XGBoost was chosen for its strong performance.
- Through fine-tuning, we optimized its predictive accuracy, demonstrating its effectiveness in forecasting housing prices.
- Our findings emphasize the importance of robust preprocessing, model selection, and hyperparameter tuning in predictive modeling. With additional refinements, our approach can contribute to more accurate and reliable real estate price predictions.

Challenges

- 1. Iterative Data Cleaning & Wrangling
- 2. Handling List-Type Tags in String Format

Future Goals

- 1. More advanced feature selection
- 2. Train separate models for high vs low priced homes
- 3. Address potential multicollinearity
- 4. Incorporate more location-based features