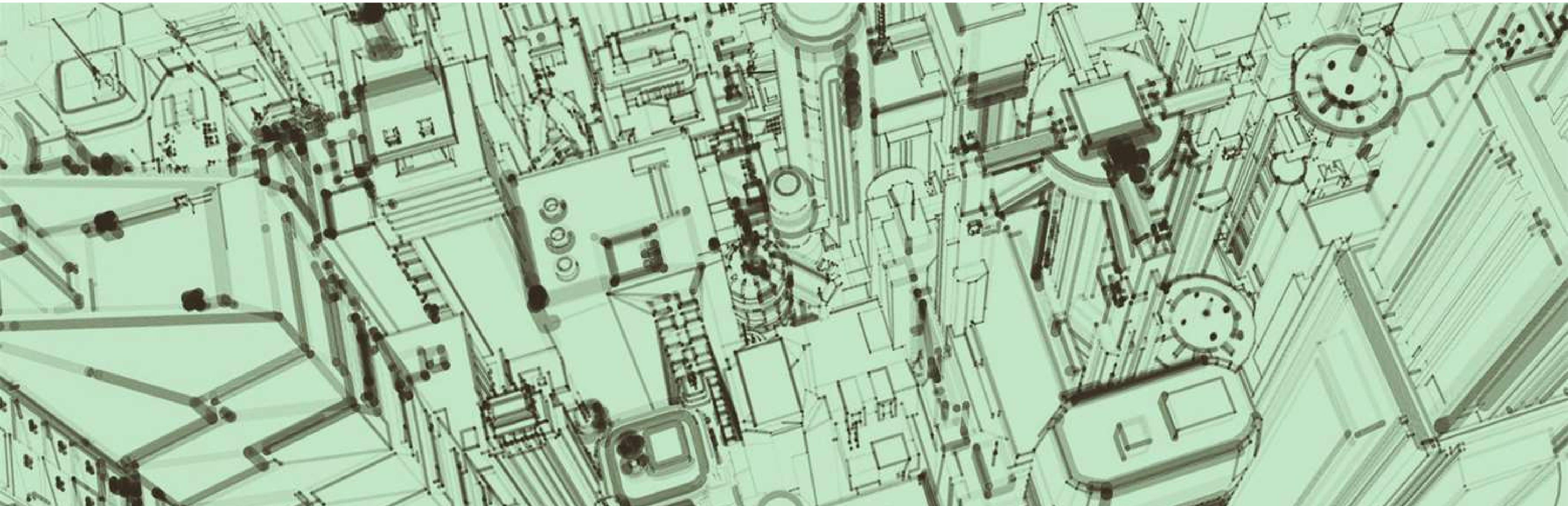

Finding Undervalued Homes is the AMES

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June 2, 2023

Introduction

Purchasing a home is one of the biggest financial decisions in a person's life.

Searching for a new home in an unfamiliar area can be overwhelming.

Hiring consultants eases the stress and uncertainty of finding an affordable home, which would enable clients to focus on other important matters.

Today's Objective

Compare a wide range of machine learning models to identify the most effective model to predict sales prices based on key features.

Discover undervalued homes for clients so they get the best bang for their buck and can purchase property that appreciates in value.

Benefits:

1. Clients can obtain the best value for their money.
2. Increase the likelihood of long-term property value appreciation.

Housing Dataset Overview

2,580 records of residential homes in Ames, Iowa

79 features

Time Range: 2006-2010

Data Preprocessing Techniques

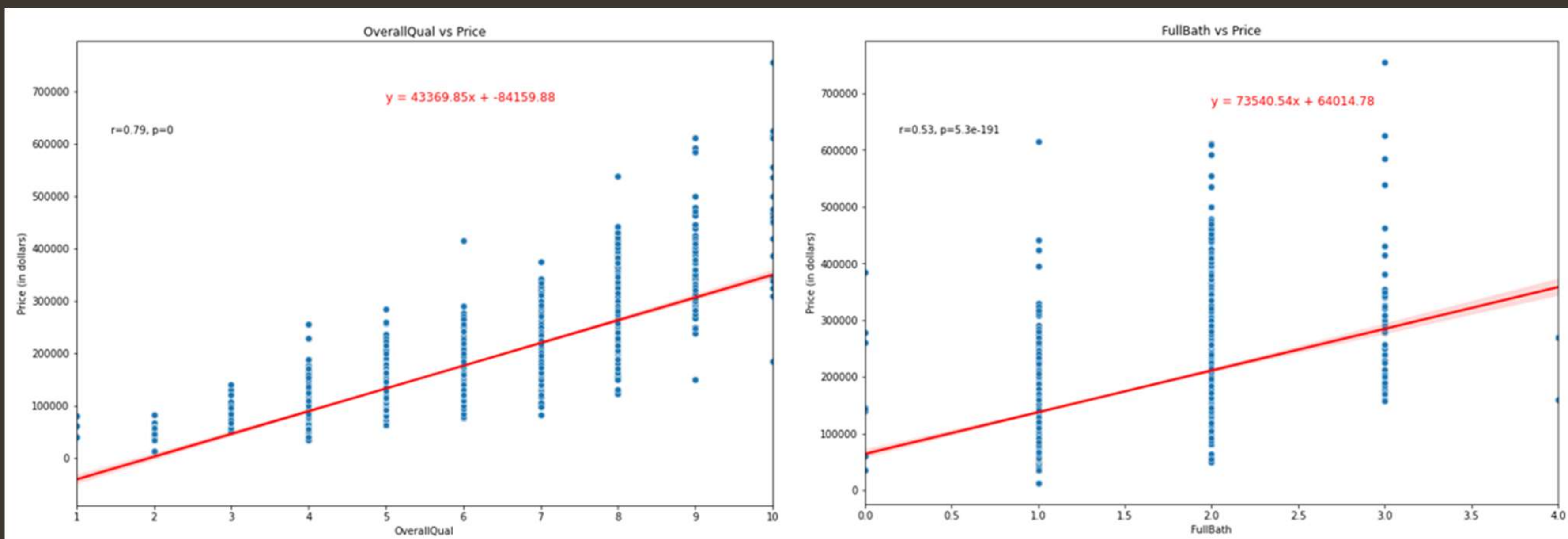
Numerical Variables:

- StandardScaler used to scale the original data.
- KNNImputer employed for imputing missing values.
- Rescaled back to the original scale using inverse_transform.

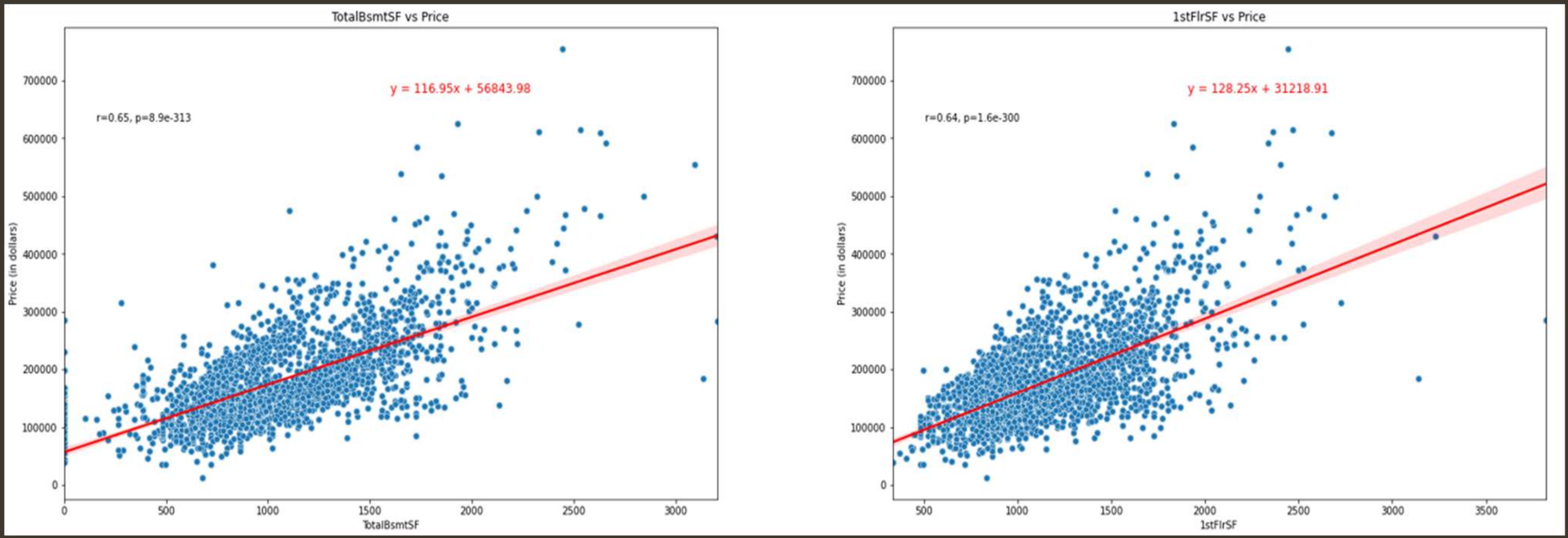
Categorical Variables:

- Missing values imputed with "Unknown".
- Categorical variables encoded using one-hot encoding.

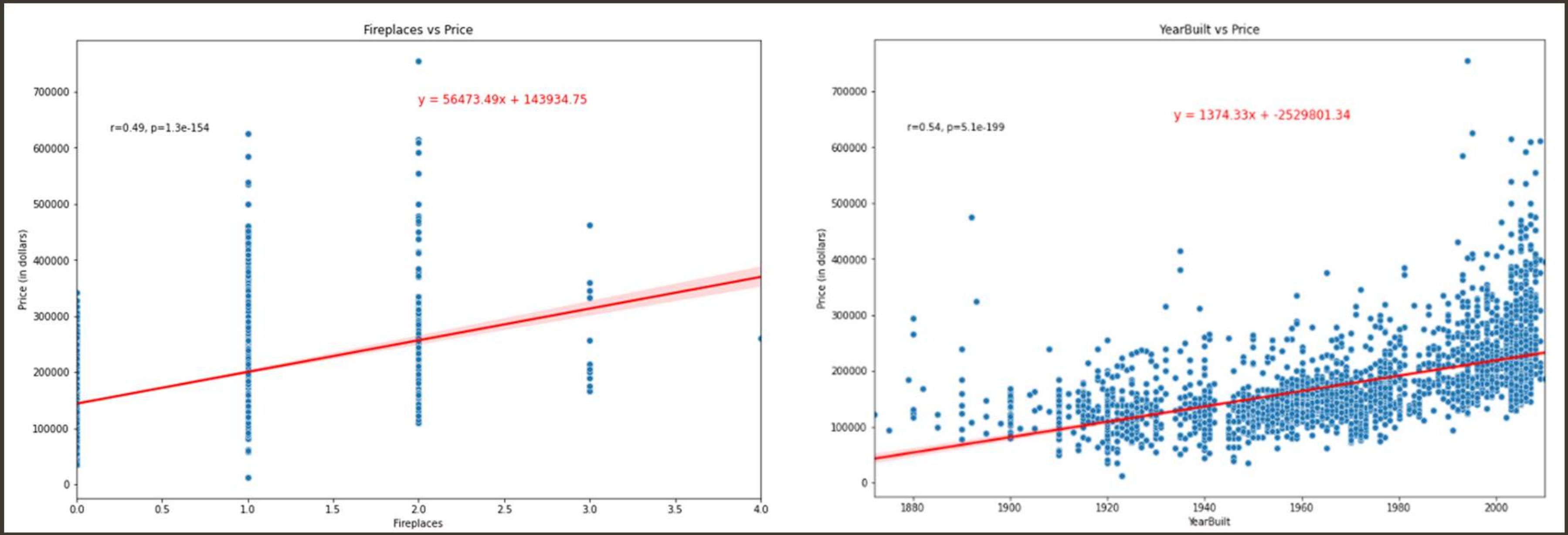
EDA – Univariate Analysis – I



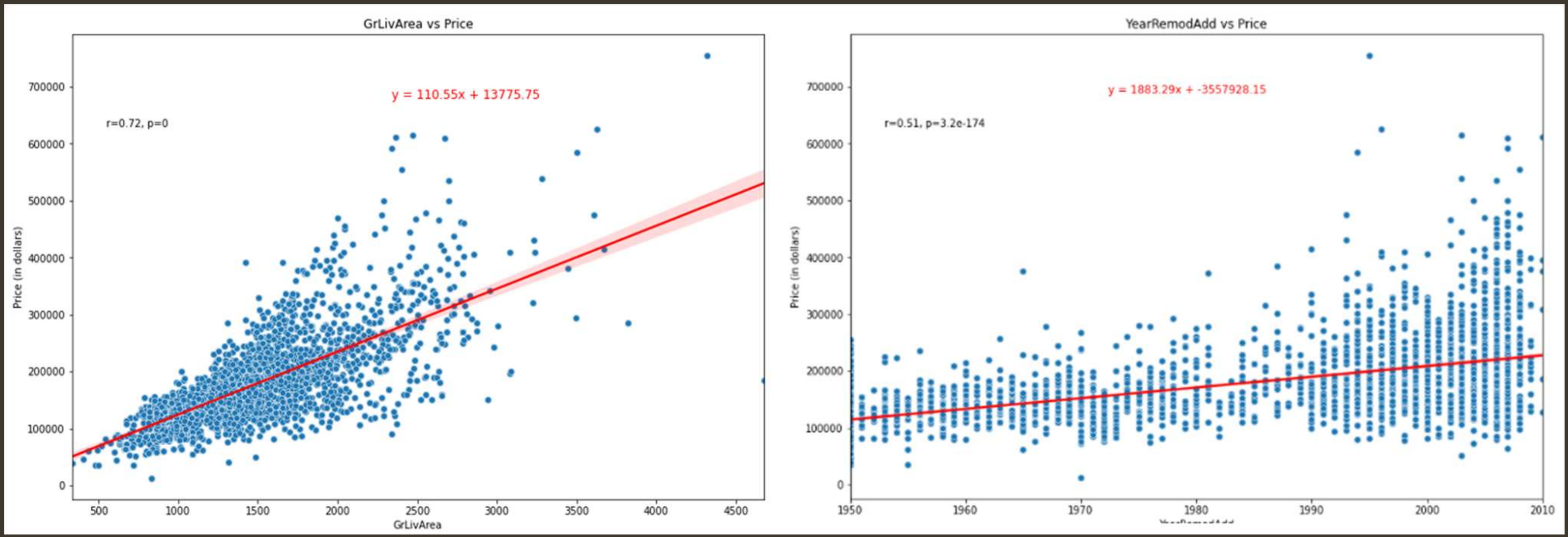
EDA – Univariate Analysis – II



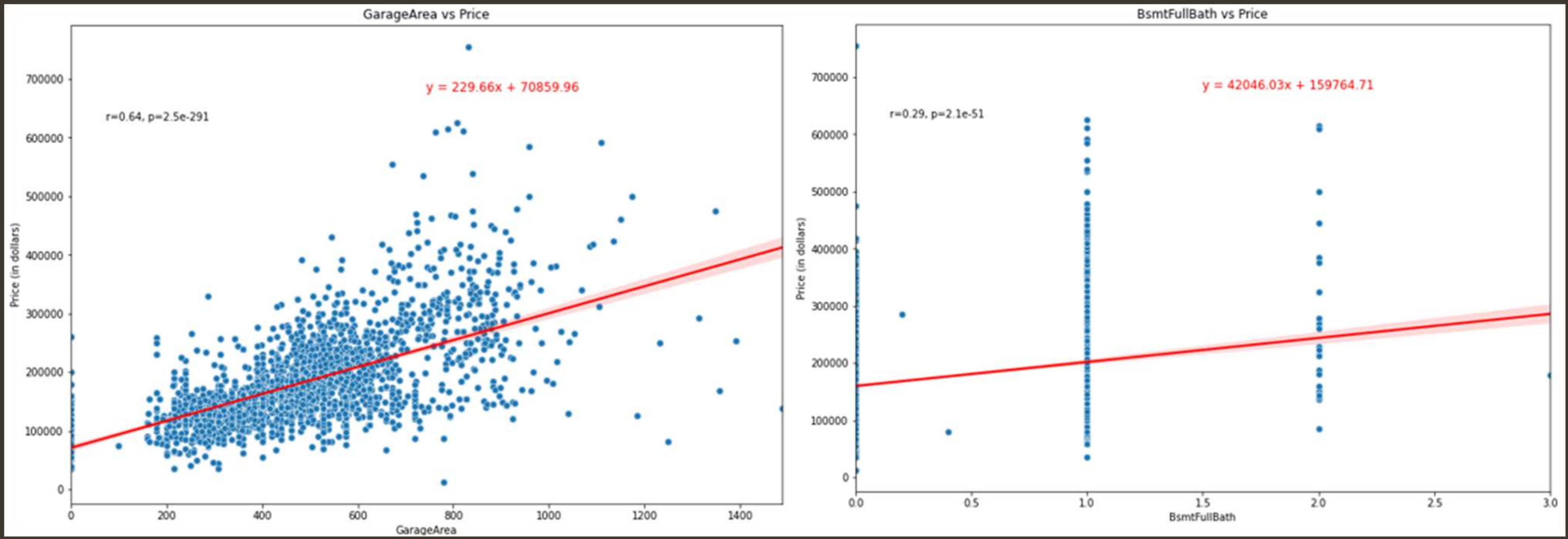
EDA – Univariate Analysis – III



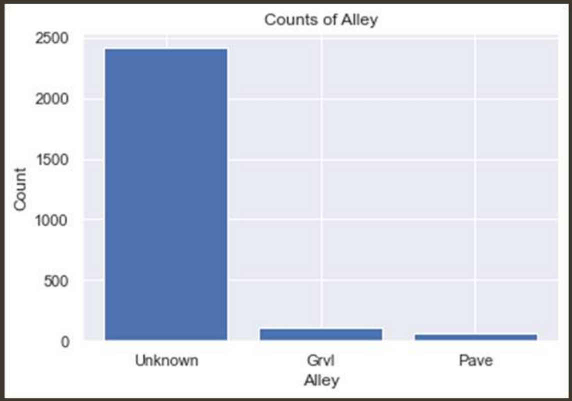
EDA – Univariate Analysis – IV

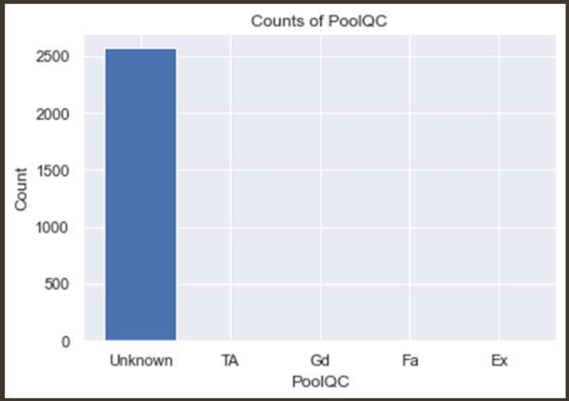


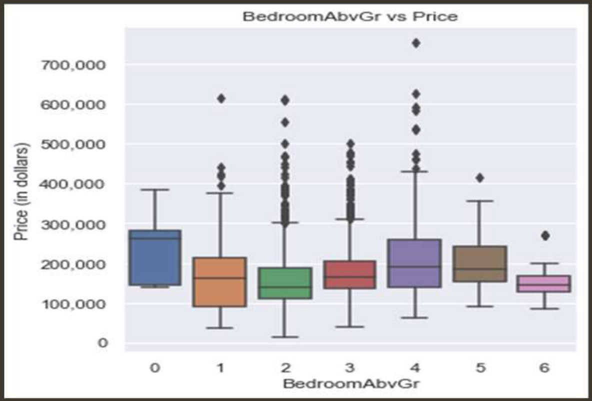
EDA – Univariate Analysis – V

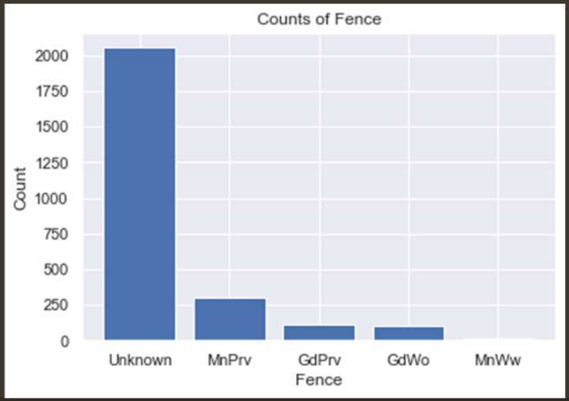


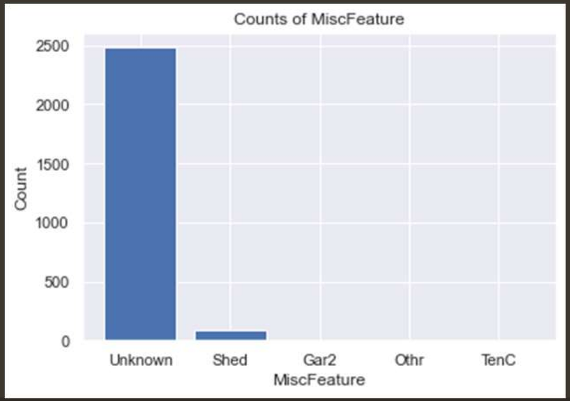
EDA – Dropped Features – Many Nulls or Indistinct Trend

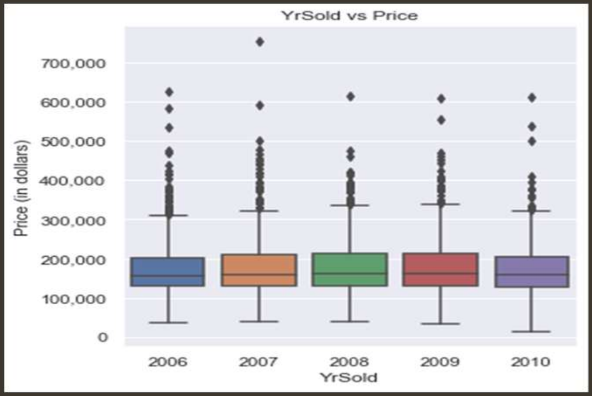




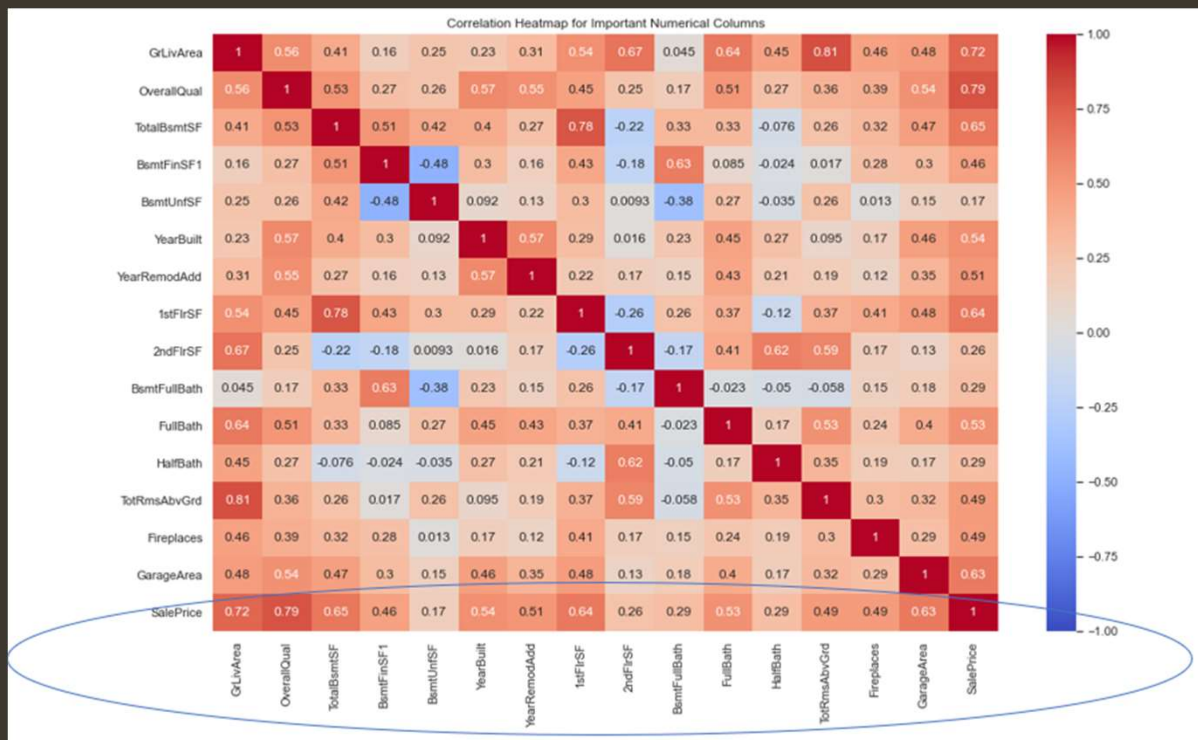








Heatmap – Correlation between Features and Target



Feature Selection Techniques

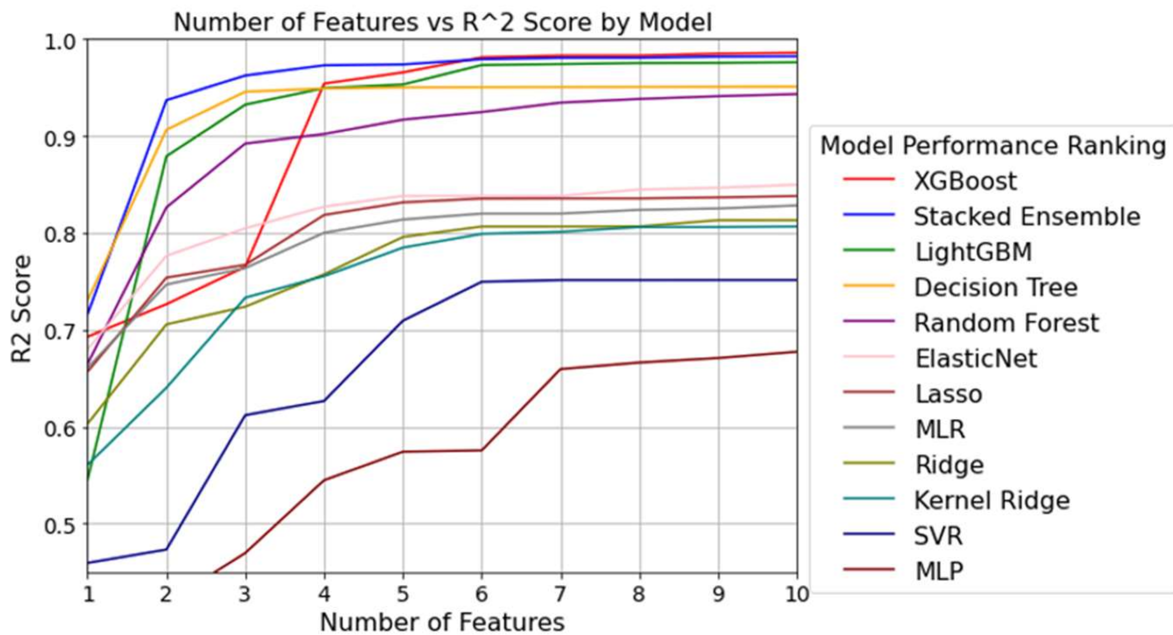
Original Technique: RFE (Recursive Feature Elimination)

- Optimal Number of Features: 10
- Selected Features:
  - 'GrLivArea', 'LotArea', 'OverallQual', 'YearBuilt', 'BsmtFinSF1', 'TotalBsmtSF', '1stFlrSF', 'Fireplaces', 'GarageArea’

Chosen Technique: Forward Feature Across All Models

- Less computationally expensive
- Improved overall efficiency

Number of Features vs R^2 Performance by Model



This is a line graph illustrating the performance of each model with their respective unique set of top 10 selected features.

Model Performance Evaluation

Model Performance Ranking (Highest to Lowest)	Test R^2 of 10 Best Features (KFold CV=5, Shuffle=True)	Preprocessing and EDA	Feature Selection	Hyperparameter Tuning (Used GridsearchCV or RandomsearchCV)
XGBoost	0.986	1. Used StandardScalar to impute Numerical Nulls with KNN imputer, and rescaled back to original scale. 2. Imputed categorical nulls with "Unknown". 3. One hot encoded categorical variables, using drop_first=True to reduce multicollinearity. 4. Used VIF to detect and remove some multicollinear features. 5. In univariate analysis, used scatterplots and boxplots to identify features that had a strong correlation with the target variable (SalePrice) and dropped some features that did not have a clear relationship with SalePrice. 6. Used same preprocessed dataset across models.	Forward Feature Selection of 10 best features to improve R^2 using KFold CV=5, Shuffle=True. For tree based models, used feature importance. For SVR & MLP, used SelectFromModel.	n_estimators': 400, 'max_depth': 10, 'learning_rate': 0.1, 'min_child_weight': 10, 'colsample_bytree': 0.5, subsample': 0.75, 'gamma': 0
Stacked Ensemble	0.982			XGBoost, Random Forest, Decision Tree
LightGBM	0.976			n_estimators': 271, 'learning_rate': 0.1, 'max_depth': 6, 'num_leaves': 30, 'min_child_samples': 8, 'reg_alpha': 0.1, 'reg_lambda': 0.5
Decision Tree	0.951			max_depth': 15, 'min_samples_split': 4, 'min_samples_leaf': 1, 'max_features': None
Random Forest	0.943			n_estimators': 500, 'max_depth': 10, 'min_samples_split': 10, 'min_samples_leaf': 2
ElasticNet	0.85			Default
Lasso	0.838			
Multiple Linear Regression	0.828			
Ridge	0.813			
Kernel Ridge	0.806			
Support Vector Machine	0.751			
Multi-Layer Perceptron	0.678			

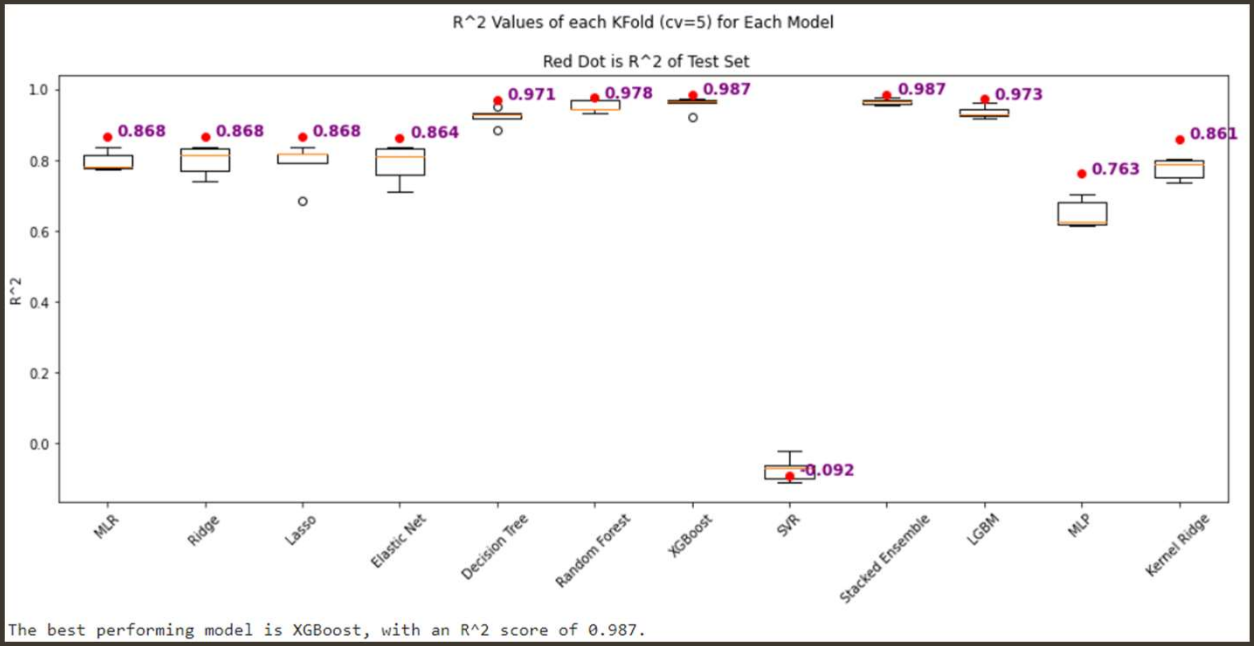
Top 10 Frequently Selected Features across Top 5 models

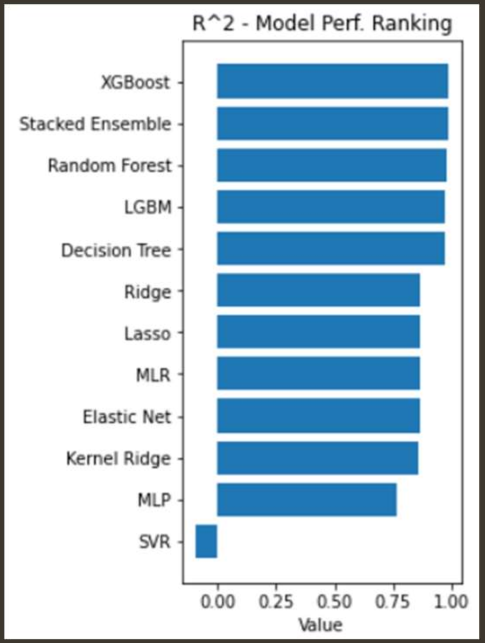
Using tree-based models (including stacked ensemble) in forward feature selection, this is the tally of how often certain features were selected across the Top 5 models: Decision Tree, Random Forest, LightGBM, Stacked Ensemble, and XGBoost.

Features	Frequency of Selection
OverallQual	3 times
GrLivArea	3 times
TotalBsmtSF	3 times
1stFlrSF	3 times
GarageArea	2 times
YearBuilt	2 times
YearRemodAdd	2 times
BsmtFinSF1	2 times
BsmtUnfSF	2 times
Fireplaces	2 times

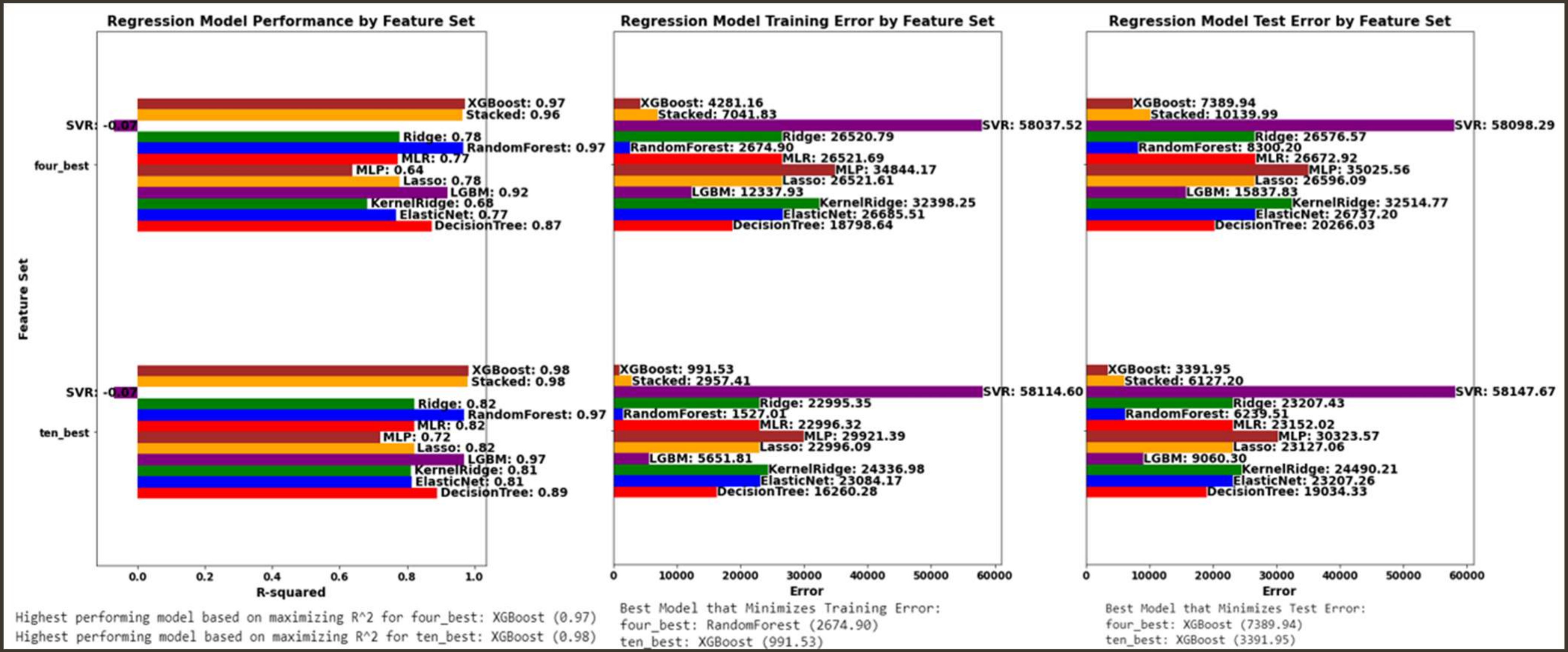
I used these specific features to automate model selection of 4 best and 10 best features with the goal of optimizing R^2.

Model Comparisons using Top 10 Frequently Selected Features + Neighborhoods





Model Comparisons using Top 4 and Top 10 Frequently Selected Features



Hyperparameter Tuning Winner Model: XGBoost

Used Top 10 Features

Best Hyperparameters:

Estimators: 300,

Learning Rate: 0.1,

Max Depth: 5

Test R^2 (cv=5, shuffle=True): .97

Top 10 Undervalued Properties			
Neighborhood	Actual Sale Price	Predicted Sale Price	Residual
Veenker	$ 150,000.00	$ 380,131.75	$ 230,131.75
NAmes	$ 84,900.00	$ 222,556.94	$ 137,656.94
NAmes	$ 167,000.00	$ 271,021.34	$ 104,021.34
MeadowV	$ 151,400.00	$ 247,910.06	$ 96,510.06
OldTown	$ 122,000.00	$ 216,369.02	$ 94,369.02
NWAmes	$ 278,000.00	$ 362,180.97	$ 84,180.97
NridgHt	$ 386,250.00	$ 470,245.03	$ 83,995.03
CollgCr	$ 239,000.00	$ 312,992.75	$ 73,992.75
CollgCr	$ 185,000.00	$ 255,453.08	$ 70,453.08
SWISU	$ 197,000.00	$ 265,626.69	$ 68,626.69

Looked for undervalued properties using residuals

where the Actual Sale Price < Predicted Sale Price.

Summary & Actionable Insights

Top features for predicting the target variable: OverallQual, GrLivArea, TotalBsmtSF, 1stFlrSF, GarageArea, YearBuilt, YearRemodAdd, BsmtFinSF1, BsmtUnfSF, Fireplaces.

To increase the value of undervalued property in the long term, prioritize investments that expand living space and feature high-quality materials, superior craftsmanship, and an elegant appearance.

Visit undervalued properties and consult with real estate brokers and appraisers to gain insights into factors not captured by the model.

Explore the impact of proximity to amenities like schools, parks, Starbucks, and shopping centers on house prices for potential price appreciation.

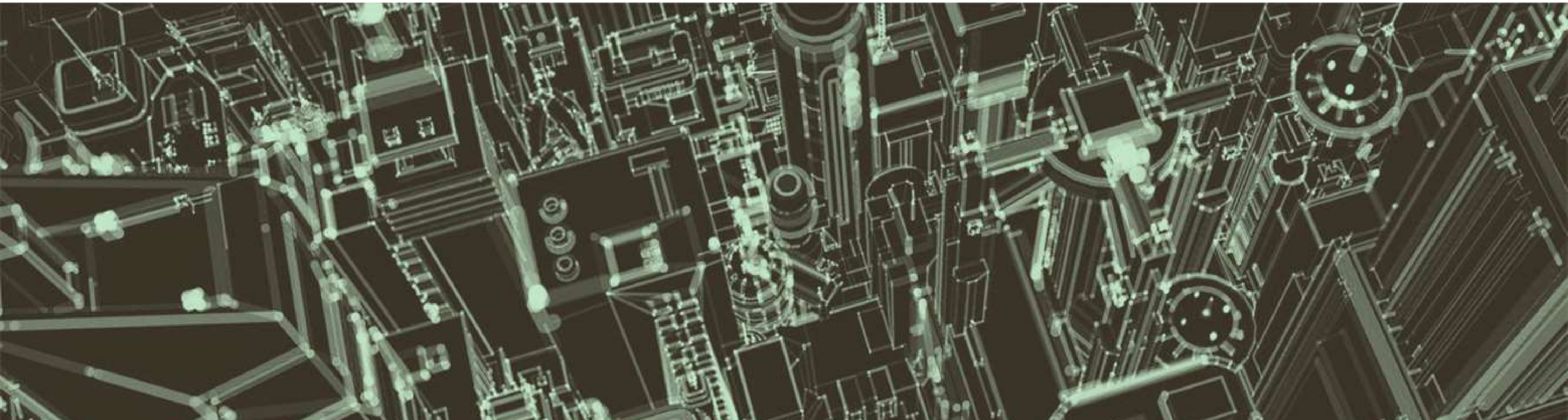
Further Approaches to Enhance Project

During feature selection, elected for least computationally intensive methods. With more time, explore other methods like backward stepwise selection that may select features that may perform well across models.

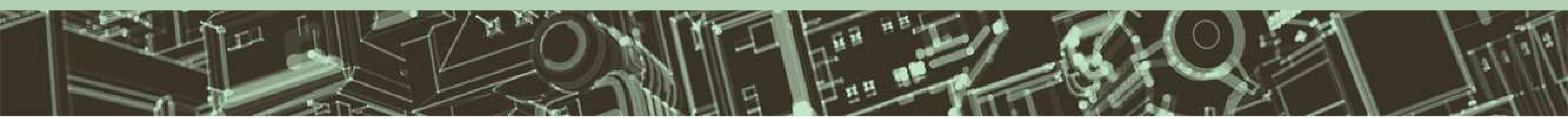
Perform feature engineering such as cut YearBuilt into bins that would have improved the performance of linear models.

Consider how to handle outliers that may affect housing pricing prediction.

To validate the predictions of an updated model for predicting house prices in Ames based on recent data and key features, compare the model's outputs with the actual prices listed on live platforms like Redfin.



Appendix



Models Compared & Descriptions

Multiple Linear Regression (MLR) is a statistical technique used to analyze the relationship between a dependent variable and one or more independent variables by fitting a linear equation to the observed data.

Ridge Regression: A tool that helps make predictions more accurate by balancing the importance of different factors.

Lasso Regression: A tool that helps make predictions more accurate by focusing only on the most important factors.

ElasticNet Regression: A tool that combines the benefits of Ridge and Lasso regression to make more flexible and accurate predictions.

Decision Tree: predicts the value of a target variable by dividing the data into smaller / simpler subsets using a tree-like model.

Random Forest: A group of decision trees that work together to make a prediction.

Models Compared & Descriptions

Extreme Gradient Boosting (XGBoost): Combining many decision trees that are good at different things, to make better predictions.

Support Vector Regression (SVR): A way of predicting something by finding the best boundary between different possibilities.

Stacked Ensemble: A way of combining many different prediction methods, to get the best of all worlds.

Light Gradient Boosting Machine (LGBM): build models that make predictions based on combining many simple decision trees.

Multilayer Perceptron (MLP) is a type of machine learning algorithm modeled after the structure of the human brain that is particularly good at identifying complex patterns and relationships between variables.

Kernel Ridge is a machine learning algorithm that uses a kernel function to map input data into a high-dimensional feature space and then performs ridge regression on this transformed data to predict outcomes. It is commonly used for regression tasks and can handle nonlinear relationships between input variables and the target variable.

Models Strengths and Weaknesses

1. MLR Regression

- Strengths:
  - Easy to understand and interpret the coefficients of the model
  - Can handle both categorical and continuous predictor variables
- Weaknesses:
  - Assumes a linear relationship between the predictors and the response, which may not always hold true
  - May not work well with high-dimensional data or correlated predictors

2. Ridge Regression

- Strengths:
  - Reduces the effect of multicollinearity in the data
  - Can handle a large number of predictors even when the sample size is small
- Weaknesses:
  - Requires tuning of the regularization parameter, which can be challenging
  - Can introduce bias in the estimates of the coefficients

Models Strengths and Weaknesses

3. Lasso Regression

- Strengths:
  - Performs feature selection by shrinking the coefficients of less important predictors to zero
  - Can work well with high-dimensional data and correlated predictors
- Weaknesses:
  - May not work well with a small sample size
  - Can be unstable in the presence of highly correlated predictors

4. Elastic Net

- Strengths:
  - Combines the strengths of Ridge and Lasso Regression by balancing between the two methods
  - Works well with high-dimensional data and correlated predictors
- Weaknesses:
  - Requires tuning of the regularization parameter, which can be challenging
  - Can be computationally expensive for large datasets

Models Strengths and Weaknesses

5. Decision Tree

- Strengths:
  - Can capture non-linear relationships between the predictors and the response
  - Easy to interpret and visualize
- Weaknesses:
  - Prone to overfitting, especially when the tree is deep
  - Can be sensitive to the choice of hyperparameters

6. Random Forest

- Strengths:
  - Reduces the overfitting of a decision tree by aggregating multiple trees
  - Can handle high-dimensional data and correlated predictors
- Weaknesses:
  - Can be computationally expensive, especially for large datasets
  - May produce biased predictions for imbalanced data

Models Strengths and Weaknesses

7. XGBoost

- Strengths:
  - Can improve on the performance of Random Forest by optimizing a specific objective function
  - Handles missing data and imbalanced data well
- Weaknesses:
  - Requires tuning of many hyperparameters, which can be challenging
  - Can be computationally expensive for large datasets

8. SVR

- Strengths:
  - Can capture non-linear relationships between the predictors and the response
  - Works well with small sample sizes
- Weaknesses:
  - Requires tuning of the regularization parameter and kernel function, which can be challenging
  - Can be sensitive to outliers in the data

Models Strengths and Weaknesses

9. Stacked Ensemble

- Strengths:
  - Can combine the strengths of multiple models to improve the overall predictive performance
  - Can handle different types of predictors and non-linear relationships
- Weaknesses:
  - Can be computationally expensive, especially for large datasets
  - Requires tuning of many hyperparameters, which can be challenging

10. LGBM:

- Strengths: Fast, handles large datasets, good for many features.
- Weaknesses: Prone to overfitting, difficult to interpret.

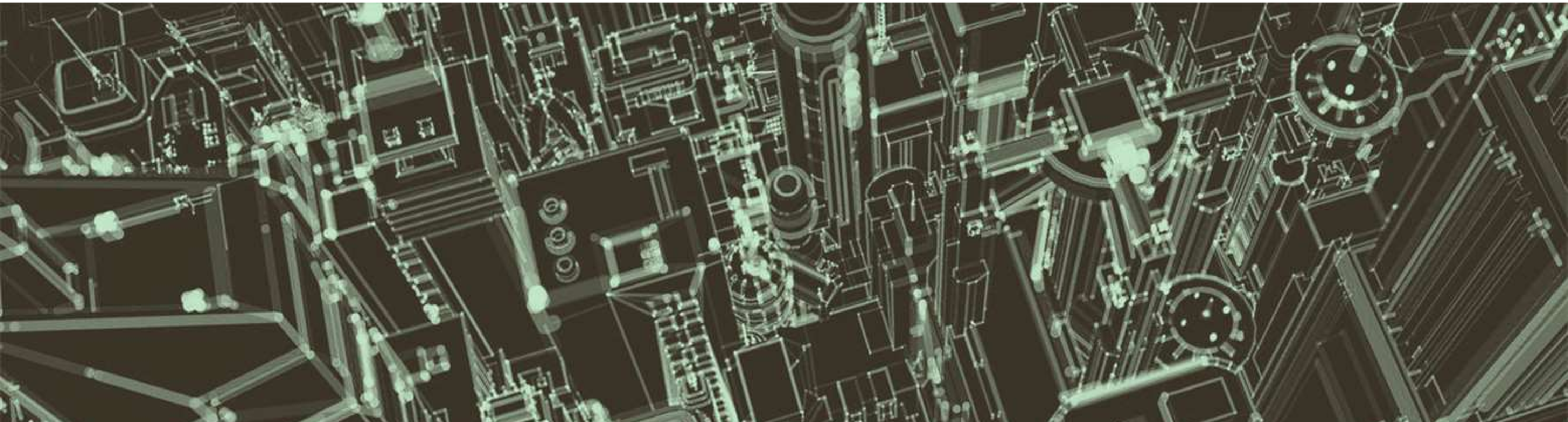
Models Strengths and Weaknesses

11. MLP:

- Strengths: Learns complex patterns, handles different data types, can be fine-tuned.
- Weaknesses: Prone to overfitting, computationally expensive, difficult to interpret.

12. Kernel Ridge:

- Strengths:
  - Kernel ridge is able to handle non-linear relationships between variables.
  - It provides a solution to overfitting by balancing the weights of the regression coefficients.
- Weaknesses:
  - The choice of kernel function can significantly affect the performance of the algorithm.
  - It is computationally intensive and can be slow for large datasets.



Thank You

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January 2023 Cohort