Predicting Housing Sale Prices

A Machine Learning Approach

Andrea Pena
03/06/2025

Why predict home prices?

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- Buyers
- Sellers
- Investors
- Real estate agents

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Image Source: Topp_Yimgrimm/Getty Images

Data Overview

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- Size: 1,460 rows, 80 columns
- Data Cleaning
- Exploratory Data Analysis
- Preprocessing

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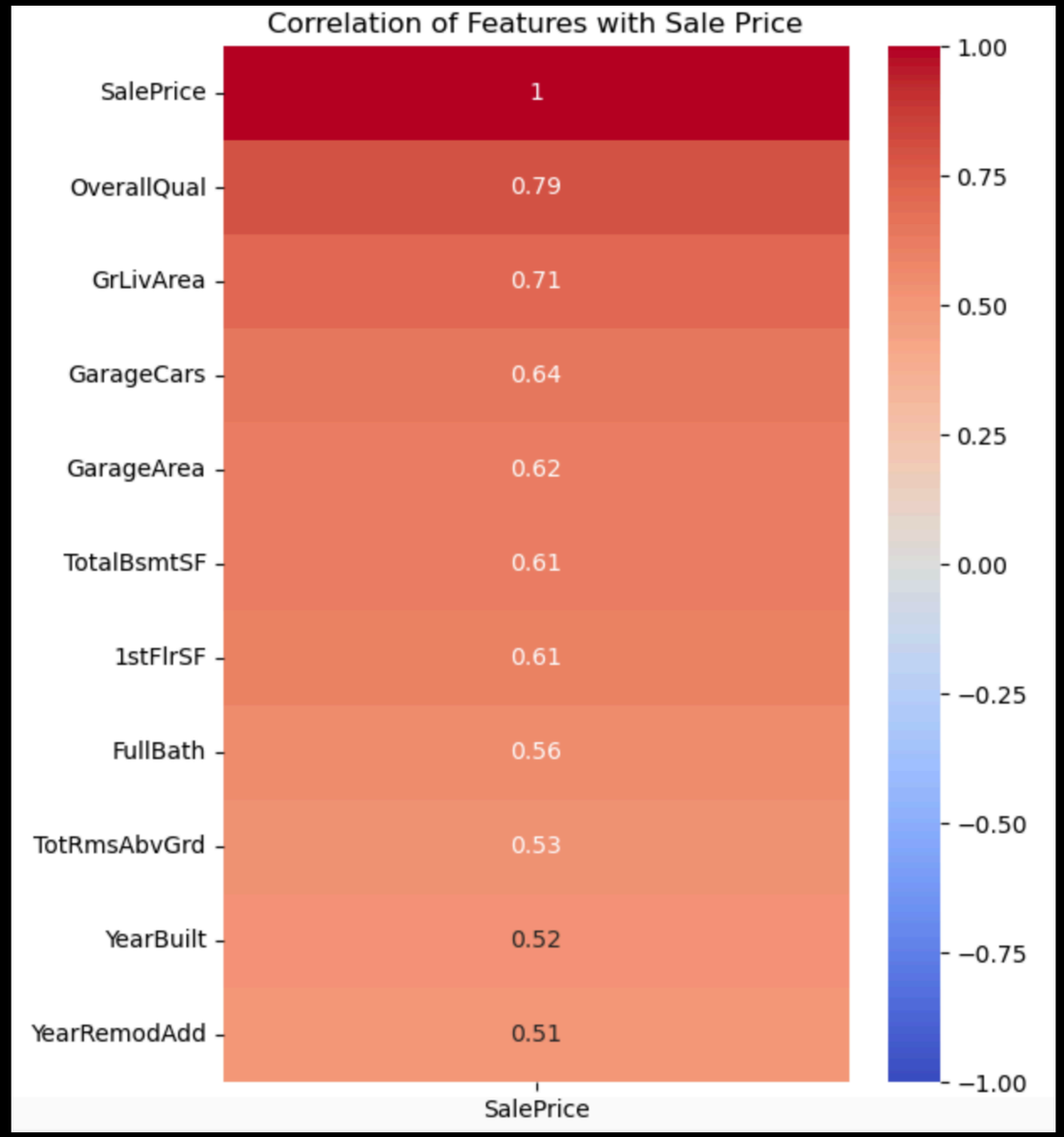

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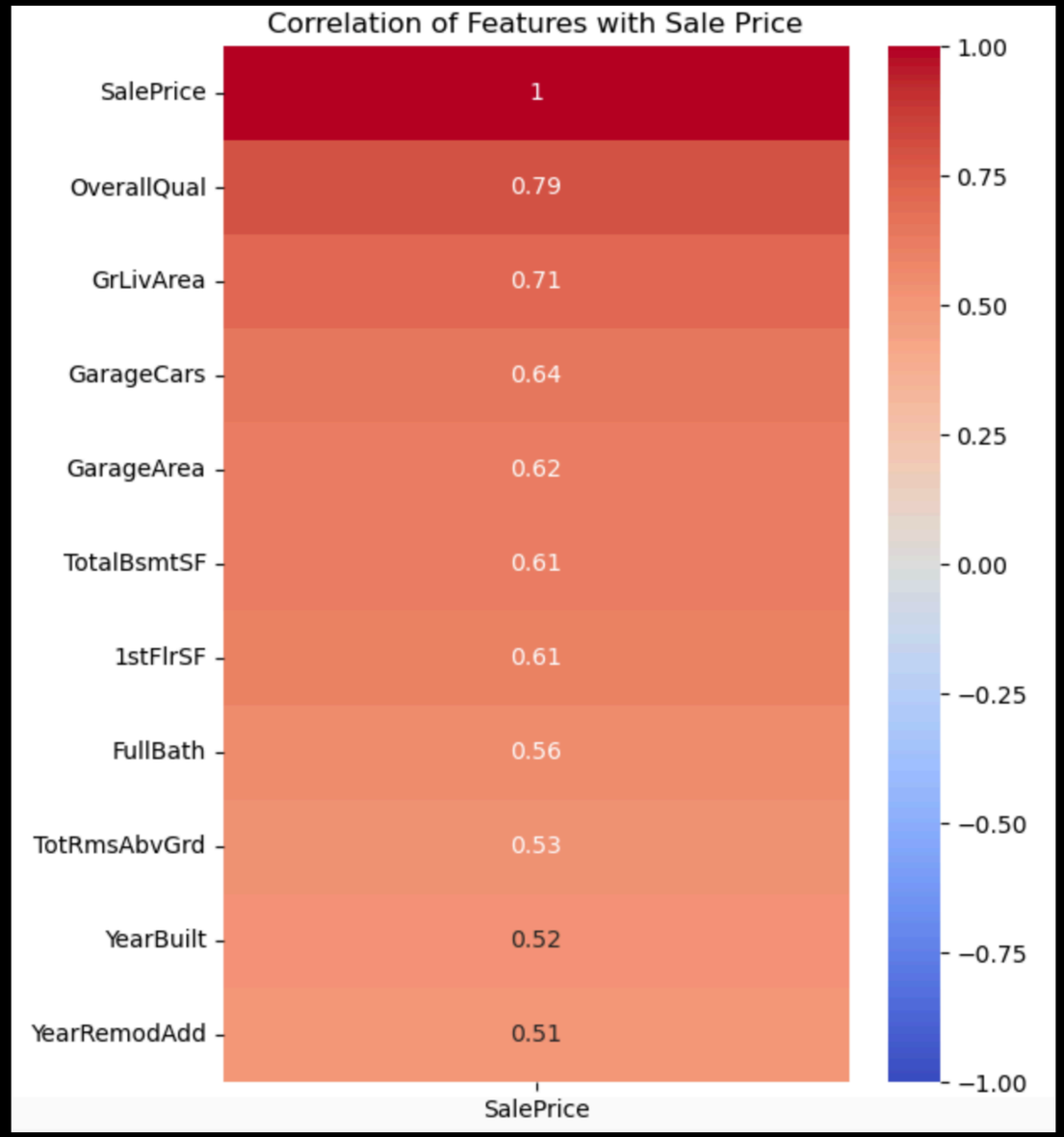

Since the dataset was small, all missing values were imputed to median for numerical values and mode for categorical. In EDA, histograms, scatterplots and bar plots were used for visualization. There was a one-hot encoded to prepare for modeling.

Model Selection

Linear Models Tested

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- Ridge
- OLS
- Lasso

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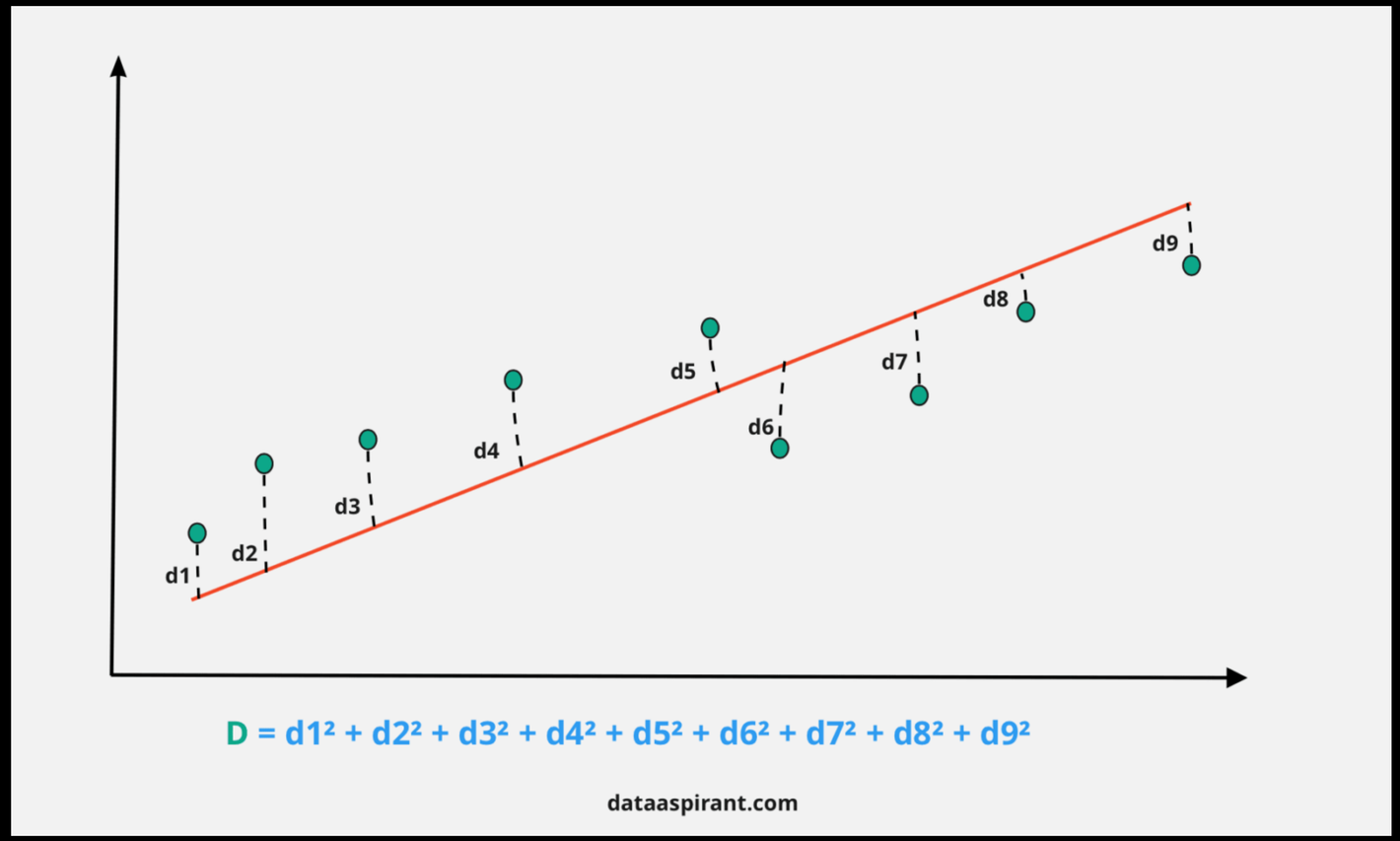
Lasso Residual Plot



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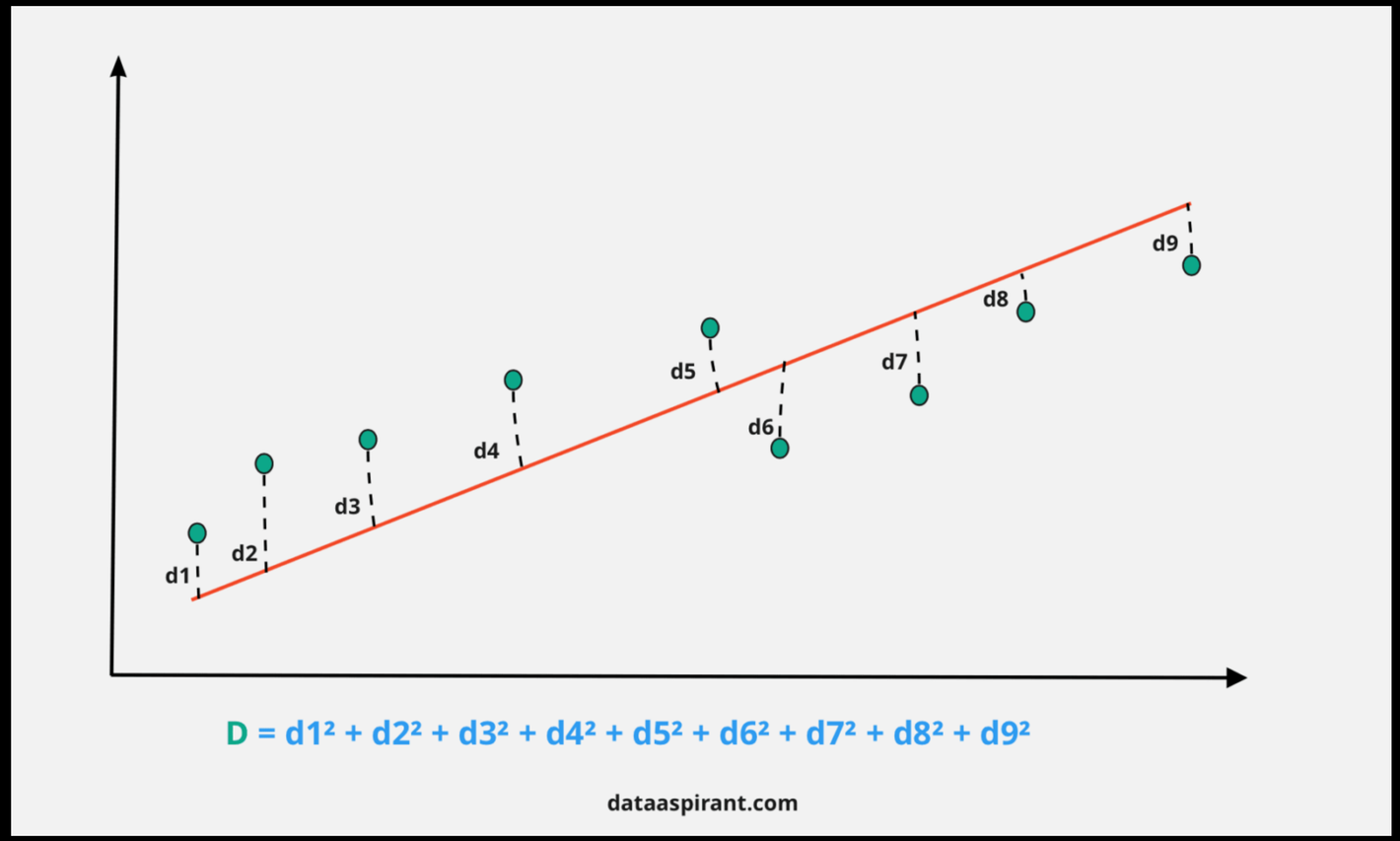

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Three linear models were evaluated, with Lasso having the lowest score. This may be because Lasso performs well when dealing with many features by applying regularization, which helps prevent overfitting.

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Nonlinear models

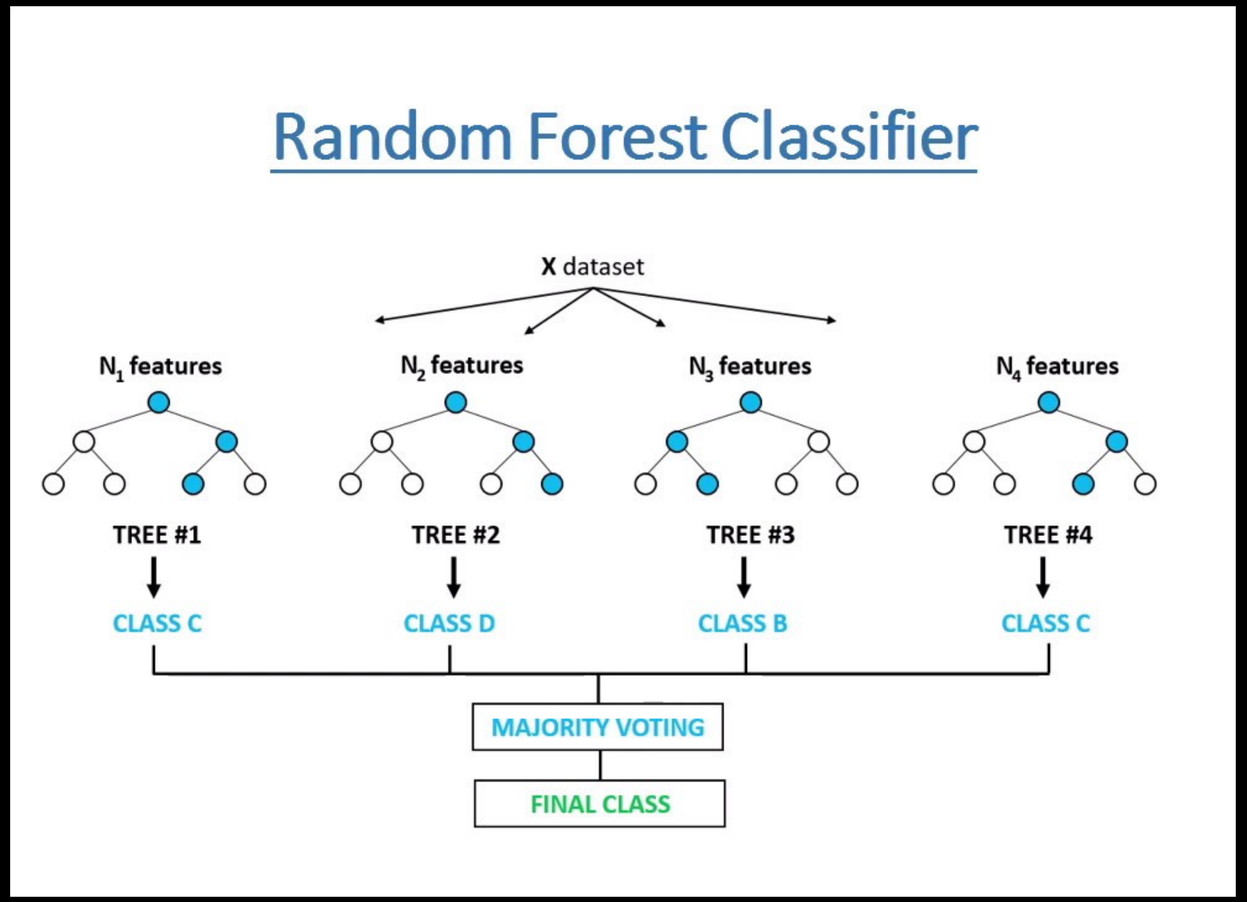
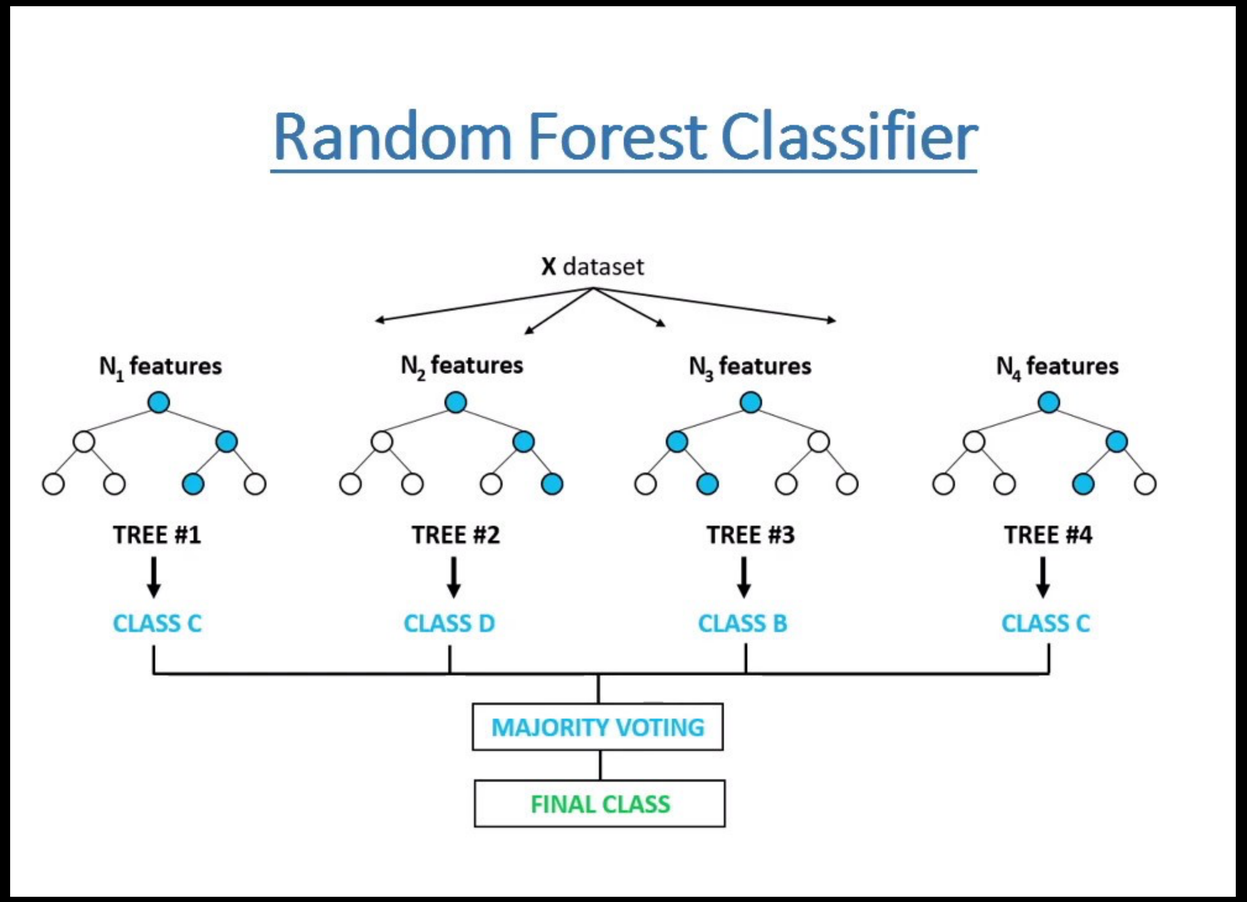


Image Source: Kaggle (Prashant Banerjee)

Model Selection

Nonlinear models

- Random Forest
- Gradient Boosting
- SVR



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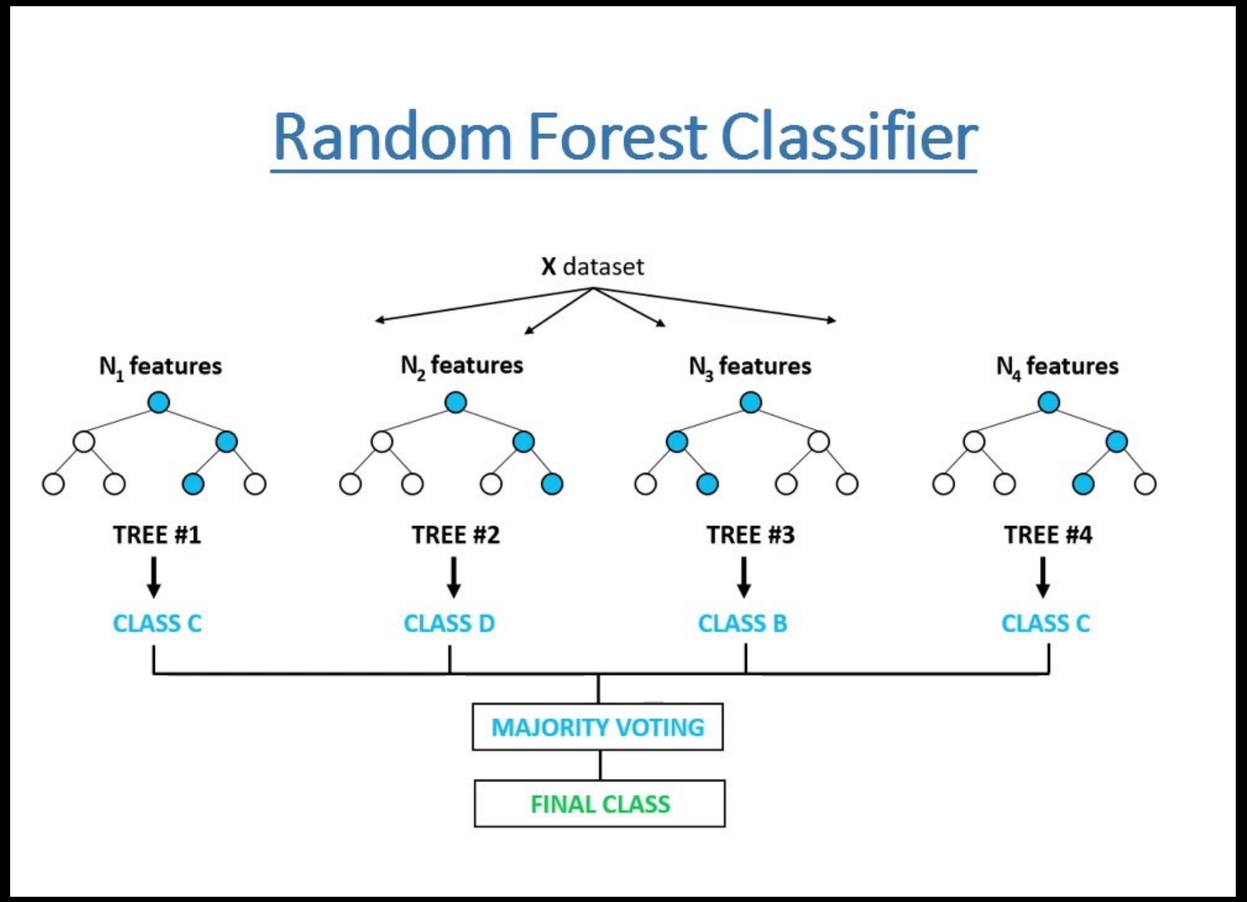

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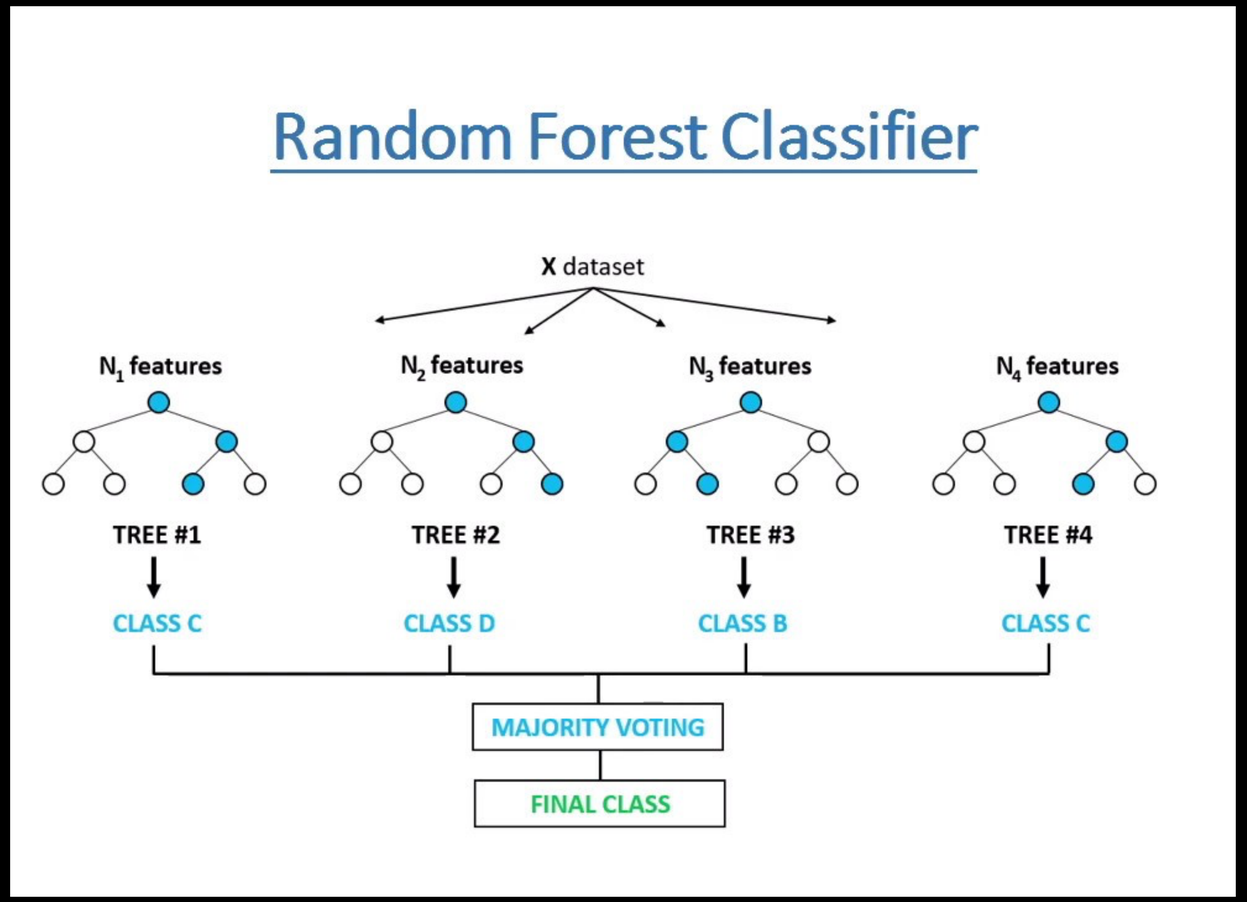

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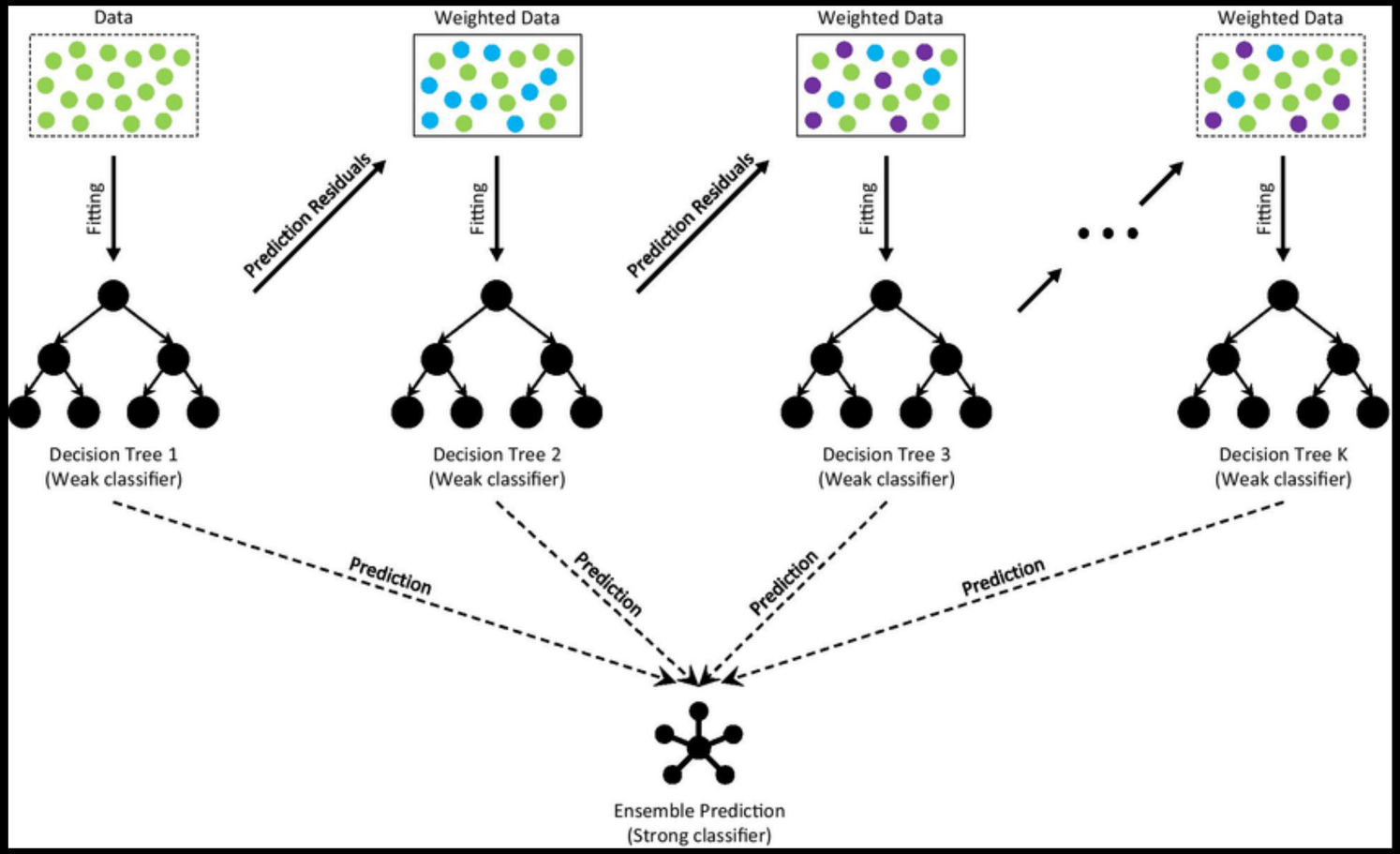
The Random Forest (RF) model was compared to Lasso and performed better, likely because RF can handle complex features and the dataset exhibits nonlinearity. RF was then compared to other non-linear models, and Gradient Boosting (GB) achieved a lower error score.

Winner: Gradient Boosting!



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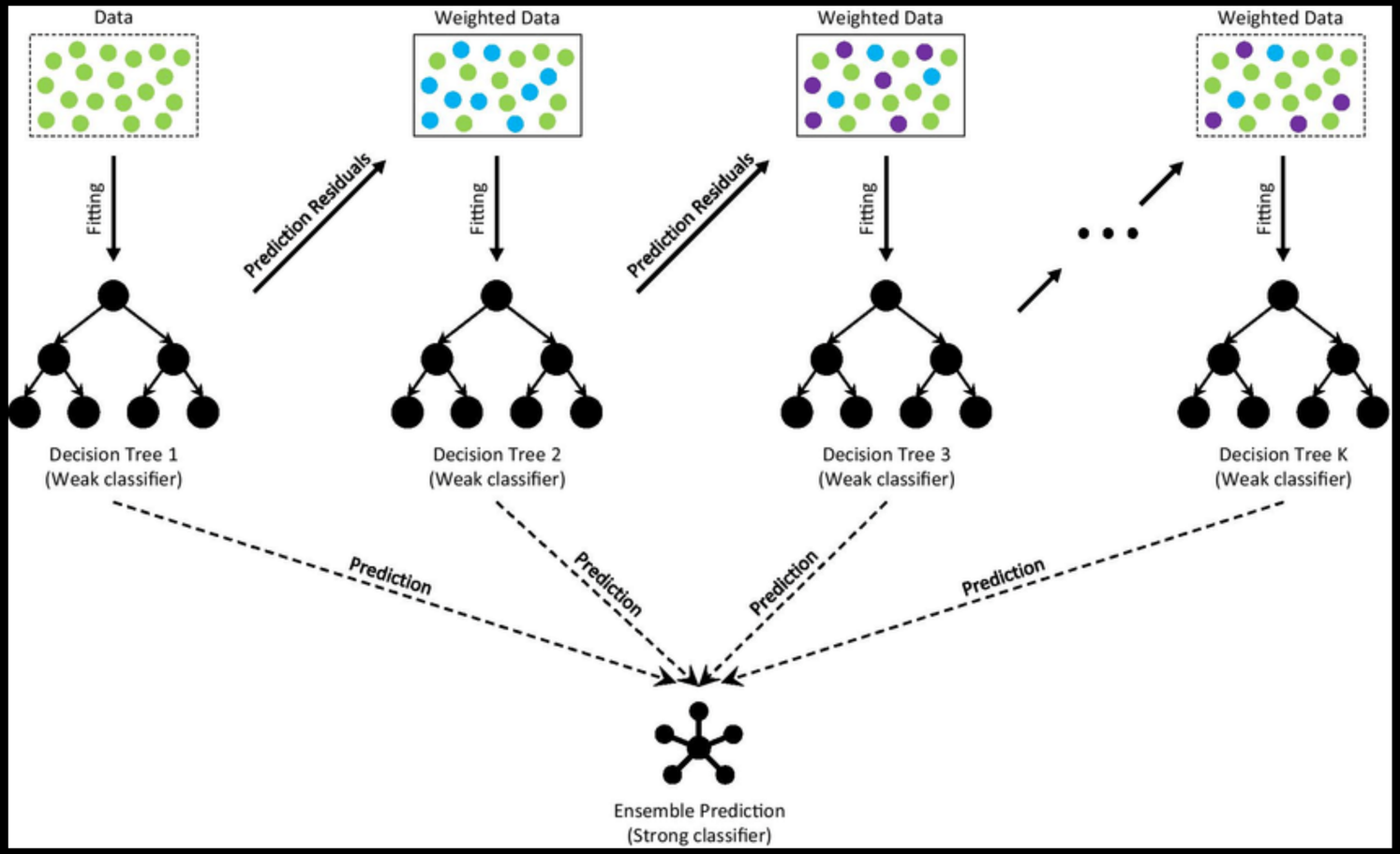

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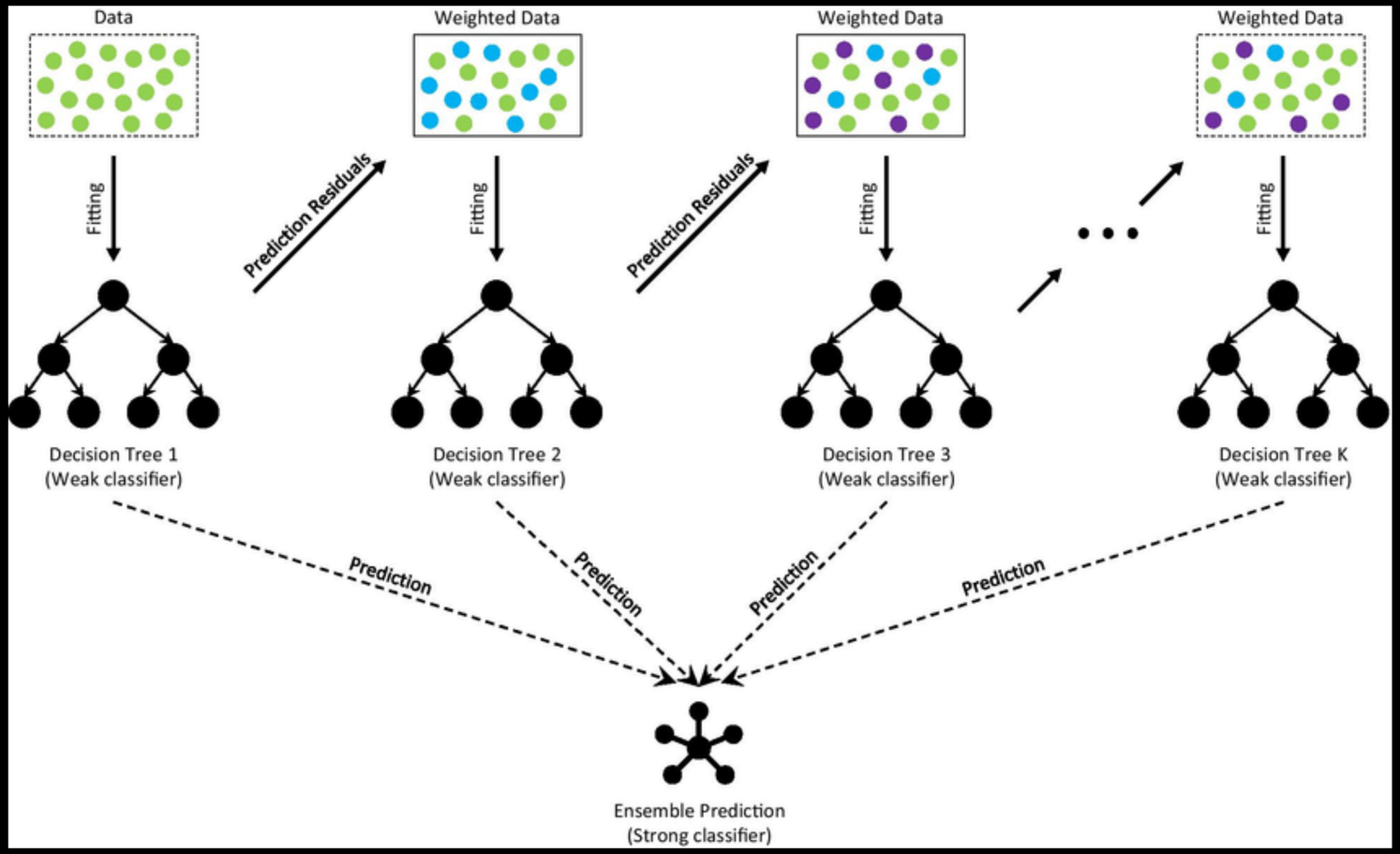

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GB model corrects mistakes over many iterations.

Model Performance

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Model	Train	Test
Lasso Regression	--	34, 262.05
Random Forest	--	27,245.97
Tuned RF	11,054.71	27,173.45
Modified Tuned RF	26,085.00	28,653.73
Gradient Boosting	4,143.35	25,844.64
Tuned GB	8,782.17	24, 327.50
Tuned GB	17, 055.26	25,405.89
Tuned GB	**20,307.08**	**25,492.86**
GB(with outlier removal)		26,930.21

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This figure shows the train and test scores of each model. After RF outperformed the linear models, hyperparameter tuning was performed, improving its performance. However, after GB achieved a better score, it was further optimized, ultimately yielding the lowest test error

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- Ground Living Area
- Garage Cars
- Total Basement (sq footage)
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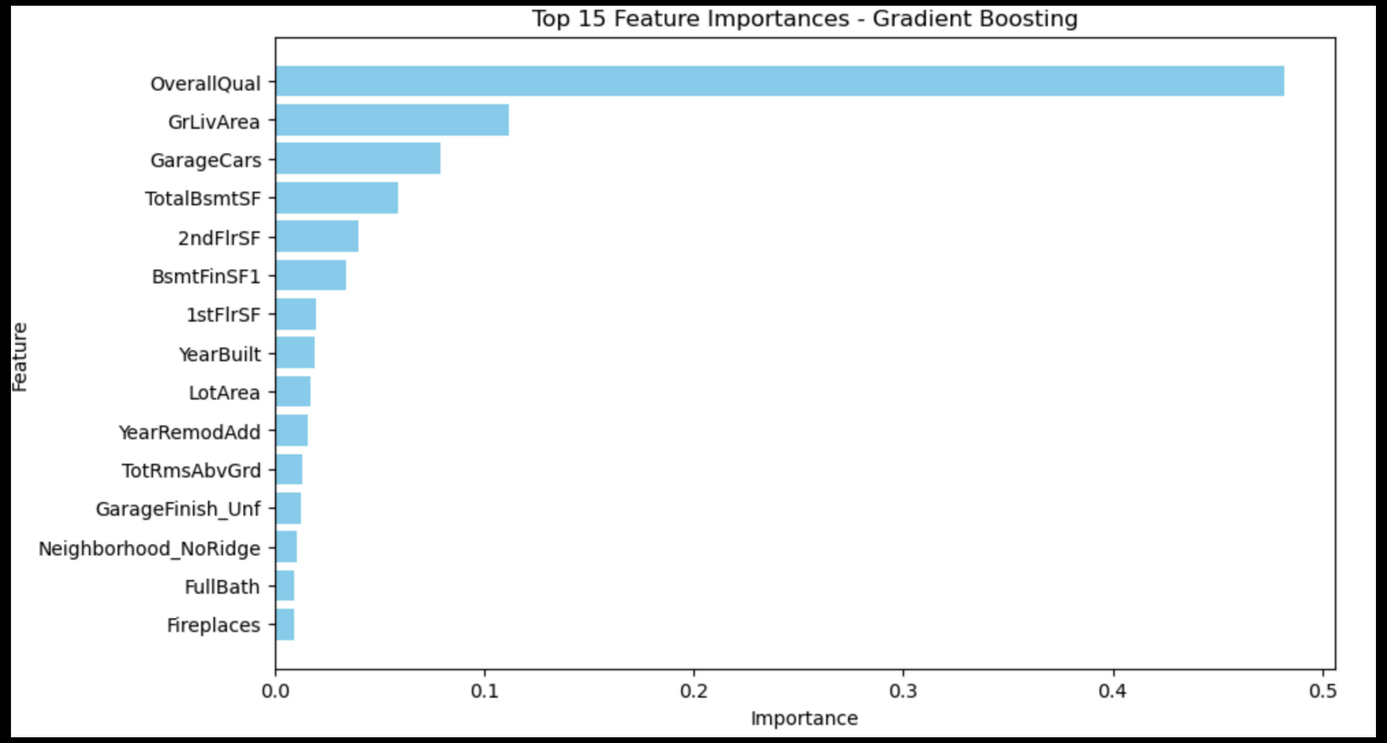

Business Impact

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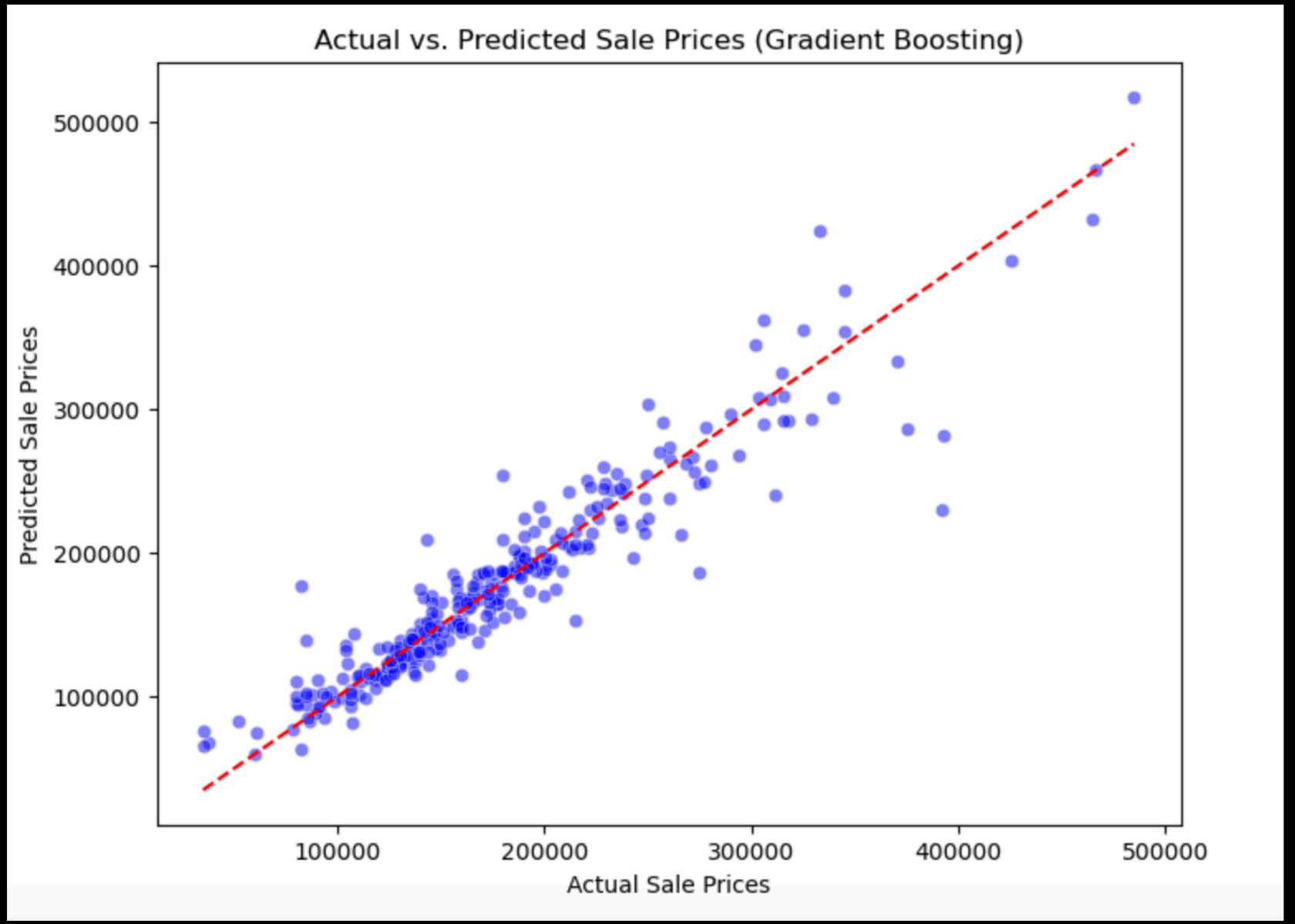
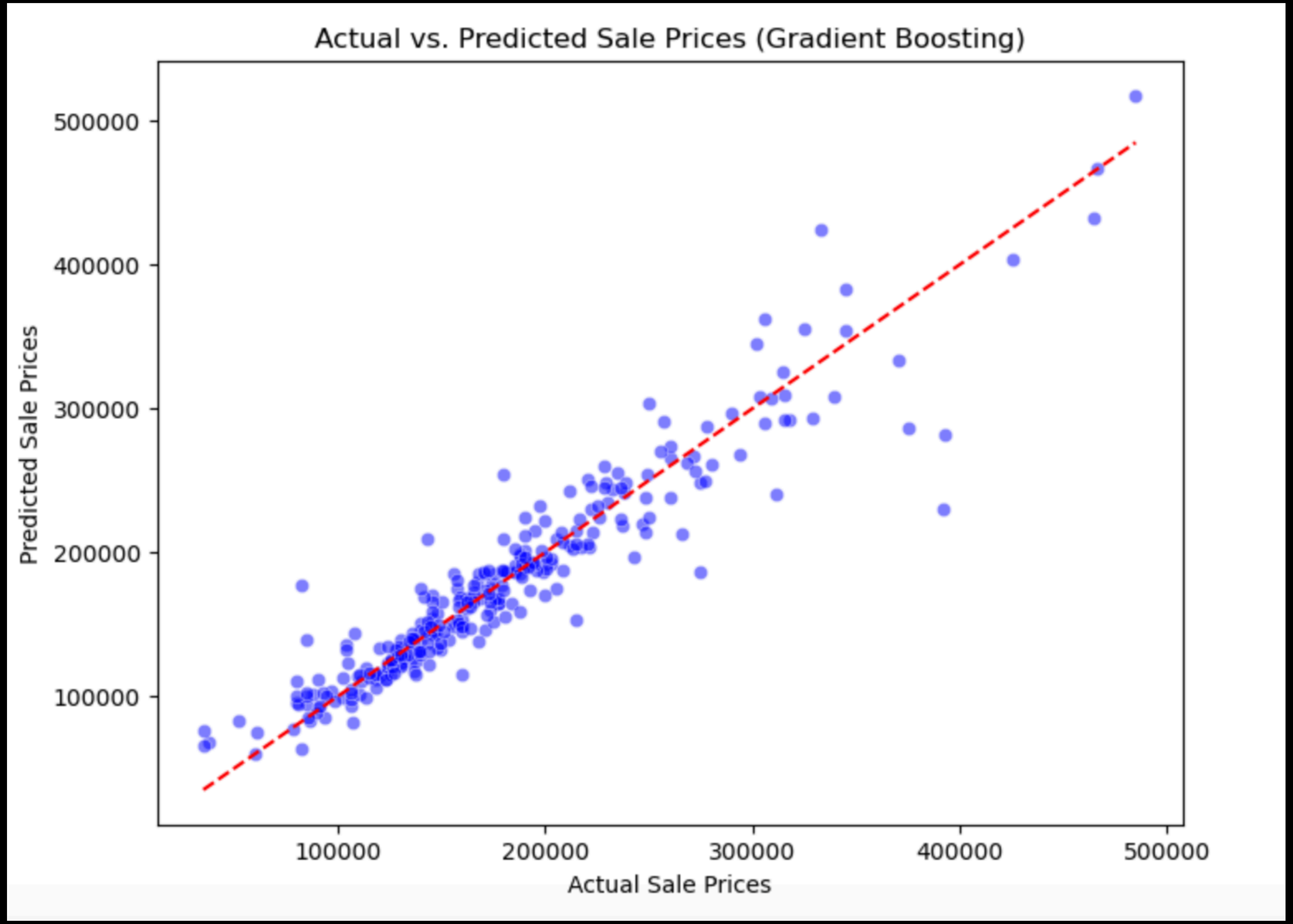
Sellers can use model insights to set competitive prices, while buyers ensure they aren't overpaying. For real estate agents, understanding key property features that drive sale prices can help guide clients in their buying and selling decisions. Lastly, identifying undervalued properties based on predictive modeling can help investors make data-driven purchasing decisions to maximize returns.

Conclusion

Key Takeaways:

- Final Model: Gradient Boosting
- Predicting home prices is possible with strong feature selection.
- Property characteristics (like size, quality and garage space) matter most.


Actual vs. Predicted Sale Prices (Gradient Boosting)
Predicted Sale Prices
Actual Sale Prices
100000
200000
300000
400000
500000



Most predictions align well, but some high-value homes are harder to predict.

Future Steps

- Fine-tuning hyperparameters.
- Trying different ensemble models.
- Testing additional datasets.
- Incorporating real-time market trends.

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