House Price Prediction Model, Group 119

Introduction/Background

Predicting house prices is critical to the real estate industry, as it provides valuable insight for buyers, sellers, and even investors. Since we have access to housing data, we want to build a model that takes into account various home characteristics, such as square footage and home type, for accurate and reliable home price predictions.

Studies such as by Kok et al. (2017) utilized a linear regression model to predict home prices with features including house size, number of rooms, and location. The model was proven accurate based on the given training dataset, and the results were easy to interpret.

We will be using the Ames Housing Dataset, an alternative to the popular Boston Dataset found in James et al. (2018), but with more features and observations. This dataset can be found at the following link: Ames Housing Dataset on Kaggle

Problem Definition

Problem

The problem we are addressing is the challenge of accurately predicting house prices located in Ames, Iowa. Traditional methods often rely on simple models or manual predictions which don't capture the more complex relationships between predictive variables. This leads buyers, sellers, and investors to make suboptimal decisions because of a lack of accurate information.

Motivation

By accurately automating house price prediction, it would help homebuyers, sellers, real estate agents, and investors make informed decisions.

Methods

Data Preprocessing Methods:

- Imputation:
  - Numeric Columns: Median imputation to handle skewed distributions.
  - Categorical Columns: Mode imputation for missing values, filling based on grouping (e.g., median for neighborhood).
- Encoding: One-hot encoding for categorical variables to ensure compatibility with regression models.
- Target Transformation: Log-transform of the target variable (SalePrice) to handle skewness.
- Feature Scaling: StandardScaler applied to numeric columns for uniformity in model fitting.
- Dimensionality Reduction: PCA applied to retain 95% of the variance while reducing feature dimensions.

Machine Learning Models:

- **Lasso Regression:**
  - Uses L1 regularization for automatic feature selection and reducing overfitting.
  - Hyperparameter tuning performed on alpha values ranging from 0.0001 to 1.0 using grid search.
- **Ridge Regression:**
  - Employs L2 regularization to manage multicollinearity and provide robust predictions.
  - Hyperparameter tuning on alpha values similar to Lasso for optimal regularization strength.
- **Random Forest:**
  - An ensemble learning method with multiple decision trees for robust predictions and feature importance ranking.
  - Hyperparameters included 100 estimators and a maximum depth of 15 to balance accuracy and overfitting.
- **Stacked Residual Model:**
  - Combines Lasso Regression and Random Forest, with Lasso addressing linear relationships and Random Forest handling residuals.

- Hyperparameter tuning performed on Lasso alpha and Random Forest parameters for optimal stacking.

The preprocessing pipeline ensured data quality, consistency, and compatibility with the selected models. Lasso and Ridge Regression were chosen for their ability to regularize and manage high-dimensional data, with Ridge offering robust predictions and Lasso aiding feature selection. Random Forest provided flexibility to capture nonlinear patterns, while the Stacked Model combined these strengths to deliver the best overall performance. Hyperparameter tuning and cross-validation ensured that the models generalized well across unseen data.

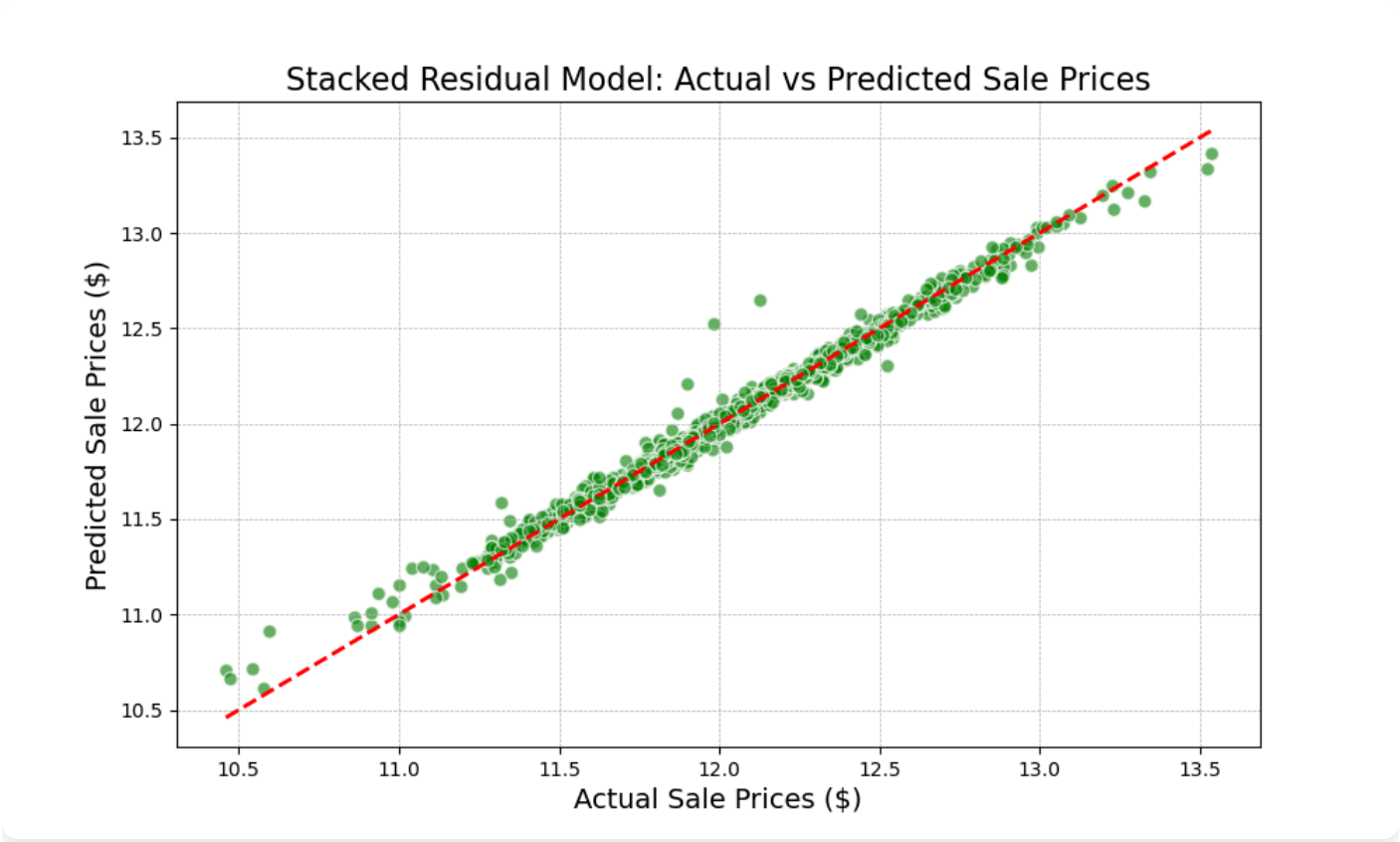
Results and Expectations

Model-Specific Visualizations and metrics:

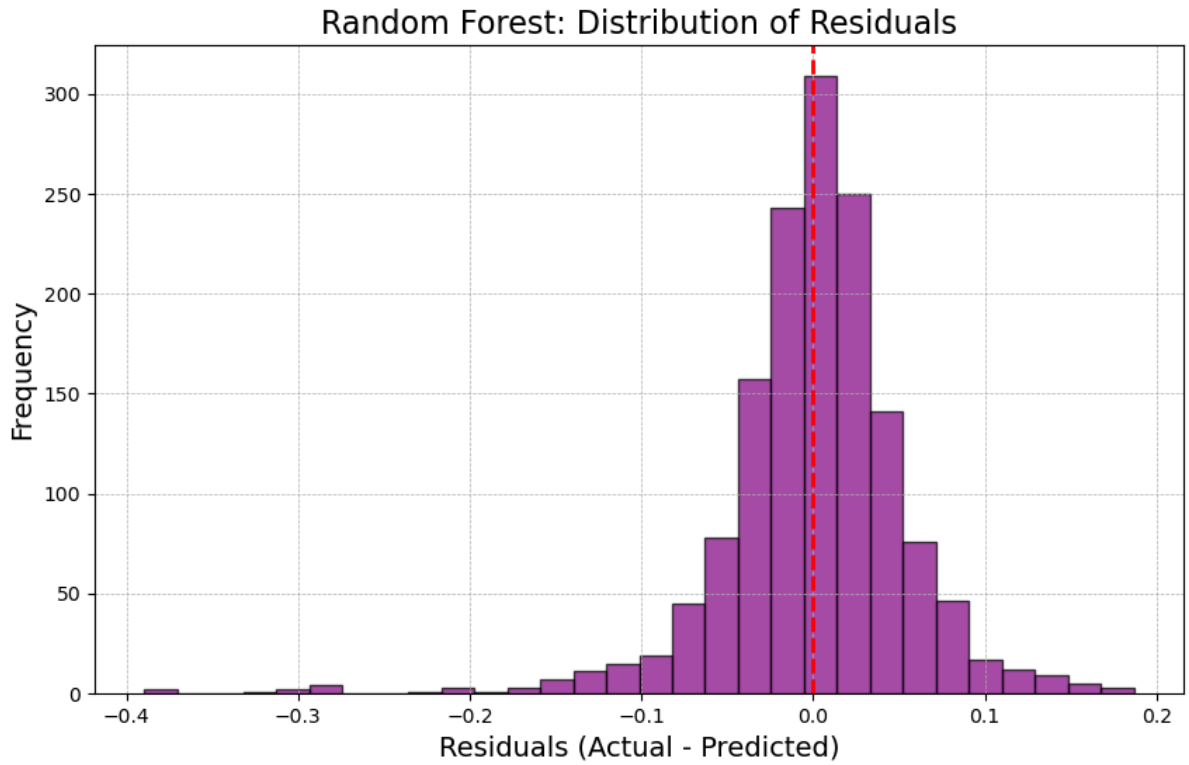
Click to expand to view each model's visualizations and performance metrics.

- ▶ Legacy (Midterm LASSO)
- ▶ Lasso Regression
- ▶ Ridge Regression
- ▶ Random Forest
- ▶ Stacked Model

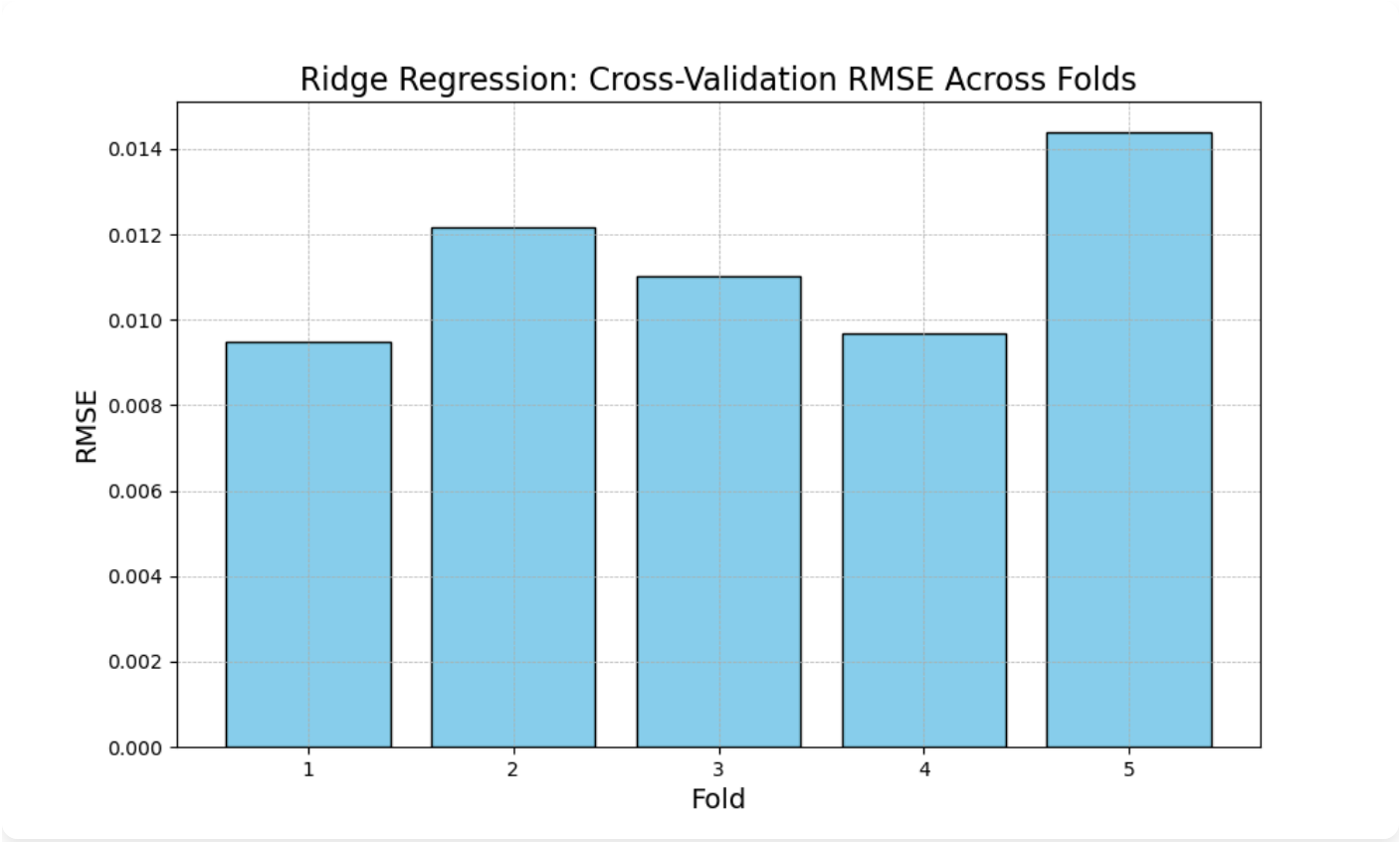
Visualization Comparisons:



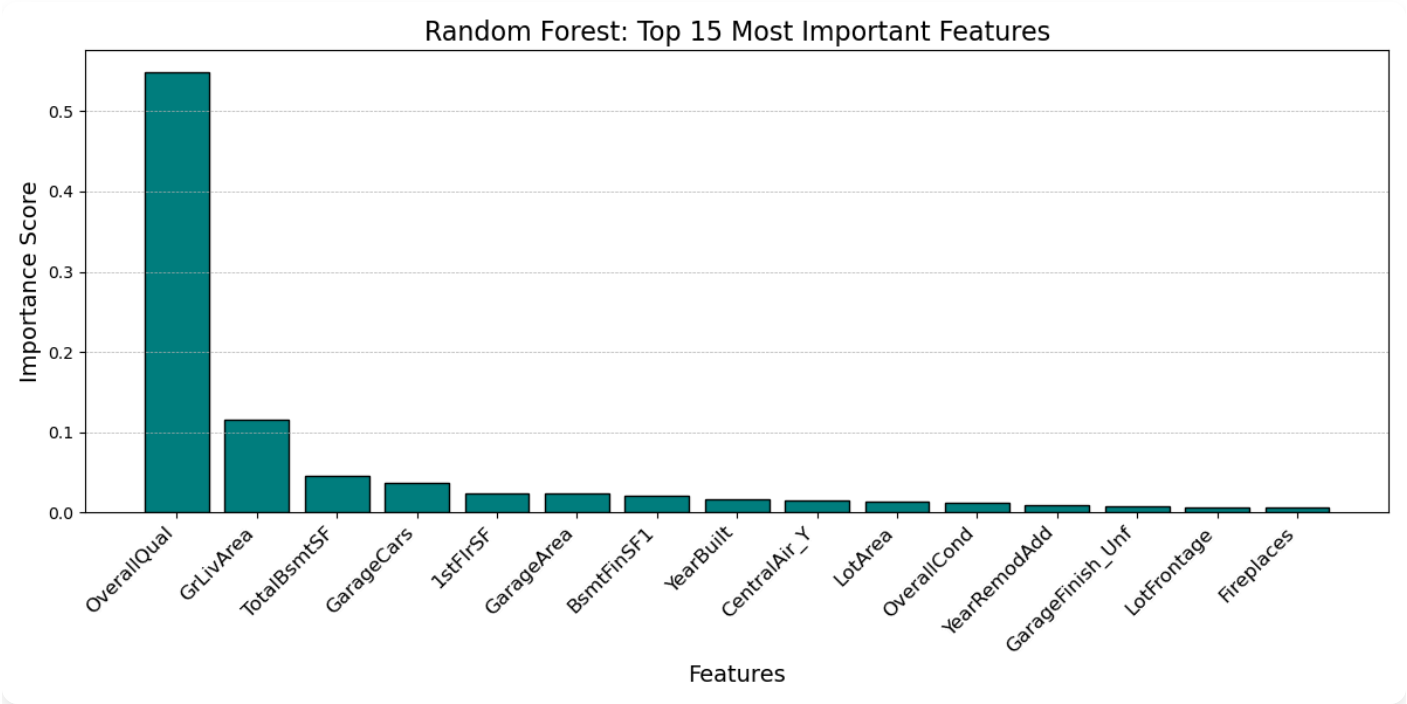
Best Actual vs Predicted: The Stacked Residual Model delivers the most accurate alignment with the red dashed line, broadcasting reliable predictions for all houses at all price ranges. Deviations are minimal compared to other models, even for higher-priced homes. This is further proven by the RMSE being 0.9866, presenting the model's accuracy.



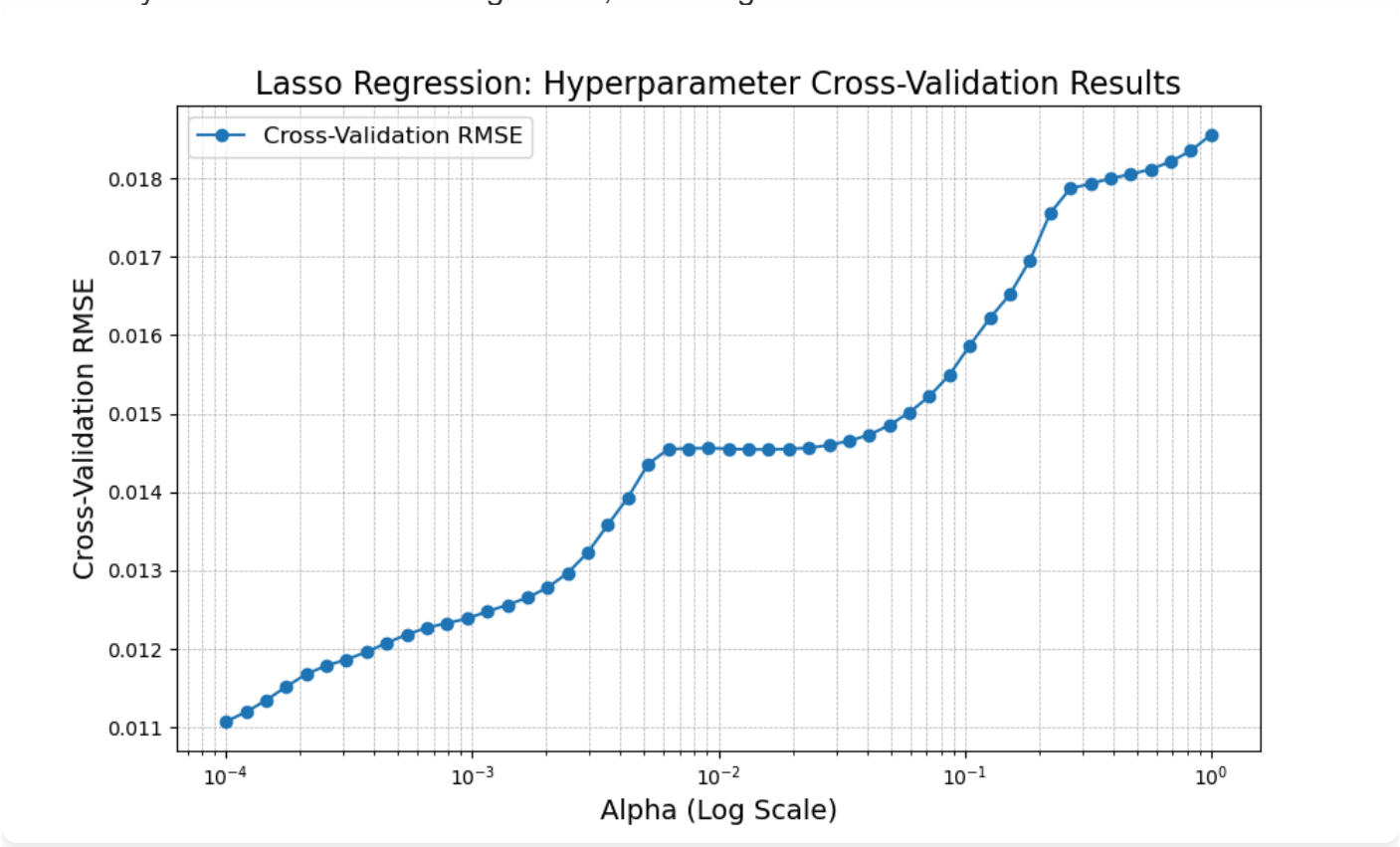
Best Residual Distribution: The Random Forest Model has the tightest residual distribution centering, showcasing its ability to minimize errors effectively. The symmetrical and narrow spread indicates both precise predictions with low variance.



Best Cross-Validation RMSE: Ridge Regression demonstrates the most consistent RMSE across folds, as shown in the bar plot. This consistency indicates stable performance and robustness across different data splits.



Best Feature Importance: The Random Forest Model provides a clear and interpretable bar plot, highlighting "Overall Quality" and "GrLivArea" as dominant features. Further, the features are dominantly found to be the most siginifican, indicating confidence from the model.



Best Hyperparameter Tuning Visualization: The Lasso Regression plot clearly illustrates the relationship between alpha values (on a log scale) and RMSE, highlighting the optimal alpha value. The smooth curve provides an intuitive understanding of the regularization trade-offs.

Statistic Comparisions:

- **Best Training RMSE:** 0.05 (Achieved by both Random Forest and Stacked Residual Model)
- **Highest Training R^2 Score:** 0.9866 (Achieved by Stacked Residual Model)
- **Lowest Cross-Validation RMSE:** 0.01 (Achieved by Ridge, Lasso, and Stacked Residual Models)
- **Most Consistent Model:** Ridge Regression (High R^2 and stable RMSE across folds)
- **Most Influential Feature:** "Overall Quality" (Identified as the most important feature across all models)

Results:

From the midterm, we had noticed heteroskedasticity; decreased accuracy at higher values (evident in the legacy model.) To imrpove on this we used a log transformation on the target variable, SalePrice, to reduce the skewness and heteroskedasticity. This transformation improved the model's performance significantly, as seen in the Lasso regression model. The lasso regression model was strong in the feature selection, as its feature importance plot revealed the key variable of “overall quality”. The Alpha vs RMSE plot also provided an ntuitive visualization of the tradeoffs of regularization, showing the best alpha value that balances accuracy and simplicity in the model. The residuals, while centered around zero, were wider than the ride and random forest models that we used, suggesting higher predictions errors. This model’s ability to shrink coefficients to zero made it very strong in finding the most impactful variables, particularly in high dimensional datasets. However, the tradeoff with this is the excessive regularization that can lead to underfitting, when some features are penalized unnecessarily and shrunk to become insignificant. Similarly to the ridge model, lasso assumes linearity and ends up struggling to model the complex relationships between multidimensional datasets. The weaker performance compared to the ensemble models we used can be attributed to these two major limitations. Computational efficiency and simplicity make it a very strong choice for quick feature selection and light modeling, but one of the ensemble models would be best for anything beyond that.

The ridge regression model had its strengths lie in its consistency and stability, as demonstrated by the cross validation RMSE plot showing minimal variability across folds. The robustness it displays also makes it reliable when using it with unseen data. The Actual vs Predicted plot shows good correlation for most of the values but falls apart when it deals with extreme prices, its residuals being wider than those of random forest, indicating higher errors. Ridge regression also effectively handles the multicollinearity by penalizing large coefficients which prevents overfitting but introduces the problem of underfitting similarly to lasso regression. The nature of ridge regression is in a linear relationship; therefore, it struggles a lot with complex relationships with lots of data. The model’s reliance on feature scaling and regularization also means that small hyperparameter errors can lead to underfitting. Its performance reflects the limitations stated with regularization preventing overfitting and maintaining stability.

The random forest model had a very strong and robust performance, with the Actual vs Predicted plot showing a strong alignment with the diagonal line, indicating high accuracy predictions across the entire range of prices. Its residual distribution was the tightest and most symmetrical centered around zero, showing the model’s strength in minimizing errors effectively. The model also identified “overall quality” and “GrLivArea” as the most critical features, aligning with our knowledge and highlighting the ability to capture complex and nonlinear relationships between many variables. We can attribute these strengths to the nature of Random Forest, which combines decision trees to reduce overfitting and variance. The high-quality performance of this model has the downside of being very computationally expensive, especially with larger datasets due to the need to train and

combine multiple decision trees. Another weakness is the inability to account for feature interactions explicitly, differentiating it from the intuitive nature of the feature importance plot. The model performed well because of the model's robustness towards overfitting and noise, using ensemble learning to produce stable and accurate predictions.

The stacked residual model was the best performing model overall. Its Actual vs Predicted plot showed the closest alignment to the red dashed line, even for high-priced homes, something that several model underperformed in. This model also achieved the highest training R2 score of 0.9866 and tied with Random Forest for the best training RMSE of 0.05, showing its ability to explain much of the variance in the target variable. The stacked residual model combines the strengths of linear models, such as the ridge regression model, with the residual error reduction capability of the random forest one, making it highly effective at handling both linear and nonlinear patterns. However, due to the complexity of this process, the model introduces some tradeoffs: higher sensitivity to hyperparameter tuning and increased computational complexity, making it less practical for larger and updating datasets that would be used for a more volatile housing market. The model is excellent for this dataset due to its hybrid approach that leverages the strengths of its components to reduce the residual error and increase the accuracy of the predictions. The model's performance is a testament to the effectiveness of ensemble learning and the power of combining different models to create a more robust and accurate prediction system.

Some next steps would be to create more visualizations for the stacked model, and perhaps explore other ensemble models such as gradient boosting or XGBoost to see if they can improve the model's performance. Furthermore, we could also try different models in the stack, such as a neural network, to see if it can improve the model's performance. We could also try to improve the model's performance by using different feature selection techniques, such as recursive feature elimination, to see if we can improve the model's performance.

References

- Kok, N., Monkkonen, P., & Quigley, J. M. (2014). Land use regulations and the value of land and housing: An intra-metropolitan analysis. *Journal of Urban Economics, 81*, 136–148.
- Manning, W. G. (1998). The logged dependent variable, heteroscedasticity, and the retransformation problem. *Journal of Health Economics, 17*(3), 283–295.
- James, G., et al. (2018). *Introduction to Statistical Learning*. Springer.

Contribution Table

Name	Contribution to the Midterm Review
Lohith Dasari	Presentation
Kushal Dudipala	Wrote code for lasso regression, organized codebase and github, wrote code for website, updated the visualization/statistics/methods write up section, edited the results write up section, created visualizations, trained models for visualization and quantitative data, README.md/ Statistics.md, Gantt chart
Axel Diaz	-
Ben DiPrete	Wrote code for ridge regression, random forest, and stacked model
Miguel Cruz	Updated the Result write up section

Gantt Chart

Download the Gantt chart file by clicking the link below:

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