**To-Do List: Next Steps for Model Improvement**

1. **Interpret the MSE in Context**:
   * **Understand the Scale**: If your target variable (price) was scaled (standardized), interpret the MSE in terms of the original scale. If not scaled, compare it with the variance of the target variable to understand how well the model is performing.
   * **Baseline Comparison**: Compare the MSE with a baseline model (e.g., mean prediction) to see if your model is significantly better than a naive approach.
2. **Check for Model Improvement Opportunities**:
   * **Residual Analysis**: Plot residuals to check for patterns that suggest issues like non-linearity, heteroscedasticity, or the presence of outliers.
   * **Feature Importance**: Assess feature importance (if using tree-based models) or inspect coefficients (in linear models) to see which features contribute most to the prediction and whether any features can be added, removed, or transformed.
3. **Hyperparameter Tuning**:
   * **Grid Search / Random Search**: Use hyperparameter tuning techniques to find the optimal parameters for your model (e.g., Ridge/Lasso regression for linear models, or hyperparameters for tree-based models like Random Forest or Gradient Boosting).
   * **Cross-Validation**: Perform cross-validation to ensure your model generalizes well across different subsets of your data.
4. **Experiment with Other Models**:
   * **Non-Linear Models**: Consider trying non-linear models like Random Forest, Gradient Boosting, or XGBoost to capture more complex relationships that linear models might miss.
   * **Ensemble Methods**: Experiment with ensemble methods (e.g., combining predictions from multiple models) to reduce variance and improve predictive accuracy.
5. **Feature Engineering**:
   * **Create Interaction Features**: Consider adding interaction terms between features to capture more complex relationships.
   * **Polynomial Features**: Experiment with polynomial features if you suspect non-linearity in the relationship between features and the target variable.
   * **Dimensionality Reduction**: If your model has many features, consider using techniques like PCA (Principal Component Analysis) to reduce dimensionality while retaining most of the variance.
6. **Outlier Detection and Handling**:
   * **Identify Outliers**: Use residual plots, leverage, and Cook’s distance to identify potential outliers that may be unduly influencing your model.
   * **Handle Outliers**: Decide whether to remove, cap, or transform outliers based on their impact on the model.
7. **Try Regularization Techniques**:
   * **Ridge Regression**: Apply Ridge regression to address any remaining multicollinearity and stabilize the coefficient estimates.
   * **Lasso Regression**: Use Lasso regression for feature selection by shrinking some coefficients to zero.
8. **Reevaluate Model Performance**:
   * **Retrain with Adjustments**: After making any of the above adjustments, retrain your model and compare the new MSE with the previous one to assess improvement.
   * **Evaluate on Test Data**: If you haven’t already, split your data into training and test sets, and evaluate the final model on unseen test data to ensure it performs well outside of the training data.
9. **Document and Reflect**:
   * **Document Changes**: Keep track of the changes you make to the model, including feature selection, tuning, and model adjustments.
   * **Reflect on Impact**: After each change, consider the impact on the model’s performance and whether it aligns with your expectations.

**Summary**

1. **Understand the MSE**: Contextualize your MSE and compare it with a baseline.
2. **Refine the Model**: Perform residual analysis, tune hyperparameters, and explore other models.
3. **Feature Engineering**: Experiment with creating, transforming, or reducing features.
4. **Outlier Handling**: Detect and appropriately handle outliers.
5. **Regularization**: Consider Ridge or Lasso regression if necessary.
6. **Reevaluate**: Continuously retrain and evaluate your model to track improvements.