**A Comprehensive Analysis of Housing Prices and Classification Using Advanced Modeling Techniques**

**Done By**

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### Introduction:

The real estate landscape is a dynamic realm influenced by diverse factors, making the accurate prediction of housing prices and categorization of homes into price ranges challenging yet indispensable. In this comprehensive analysis, we delve into the intricacies of a housing dataset, aiming to unravel patterns and relationships that contribute to the valuation of residential properties. Our primary objective is twofold: to construct robust regression models capable of predicting housing prices with precision and to categorize homes into price ranges through effective classification.

Understanding the nuances of the dataset is crucial for building effective models. We will begin with a detailed dataset overview, shedding light on the key features and the target variable, SalePrice. Subsequently, we embark on a journey of data preprocessing, addressing missing values, handling outliers, and encoding categorical variables to ensure the dataset's readiness for both regression and classification modeling.

The regression analysis phase encompasses the development of various models, each offering unique insights into the dataset. We initiate with a baseline Multiple Linear Regression model, laying the groundwork for subsequent analyses. Stepwise selection techniques, including Forward and Backward Stepwise Selection, are applied to refine our model, followed by the application of Principal Component Analysis (PCA) to reduce dimensionality while retaining essential information. As we seek to uncover intricate relationships, we introduce higher-order regression models, exploring polynomial features and assessing their performance compared to the baseline model. The journey continues with an in-depth visualization of relationships through scatter plots and regression diagnostics.

To push the boundaries of our analysis, we delve into advanced regression techniques, including Ridge and Lasso regression, evaluating their impact on model performance. Each step is carefully documented, providing transparency and insight into the decision-making process.

The classification phase extends our analysis to categorize houses into price ranges, employing Logistic Regression as the baseline model. We explore dimensionality reduction techniques, tree-based models, and advanced classification techniques, comparing their performance to the baseline.

This report serves as a comprehensive guide to our methodology, findings, and recommendations, providing a roadmap for housing price prediction and classification in a data-driven manner.

### Dataset Overview Summary:

Our housing dataset we are going to use for the analysis contains a diverse set of features capturing various aspects of residential properties. Each row corresponds to a unique property, with an associated set of characteristics. The dataset is structured with columns representing different attributes, providing a comprehensive view of the factors influencing housing prices.

### Key Features:

**Id:** A unique identifier for each property. **MSSubClass:** The building class of the property. **MSZonin**g: The zoning classification of the property.

**LotArea:** The size of the land on which the property is situated. **LotConfig:** Configuration of the property's lot (e.g., inside, corner). **BldgType:** Type of dwelling (e.g., single-family home).

**OverallCond:** Overall condition rating of the property.

**YearBuilt:** The year when the property was built.

**YearRemodAdd:** The year of the property's last remodel or addition.

**Exterior1st:** The exterior covering of the house. **BsmtFinSF2:** Finished square feet of the basement area. **TotalBsmtSF:** Total square feet of the basement area.

**SalePrice:** The target variable representing the sale price of the property.

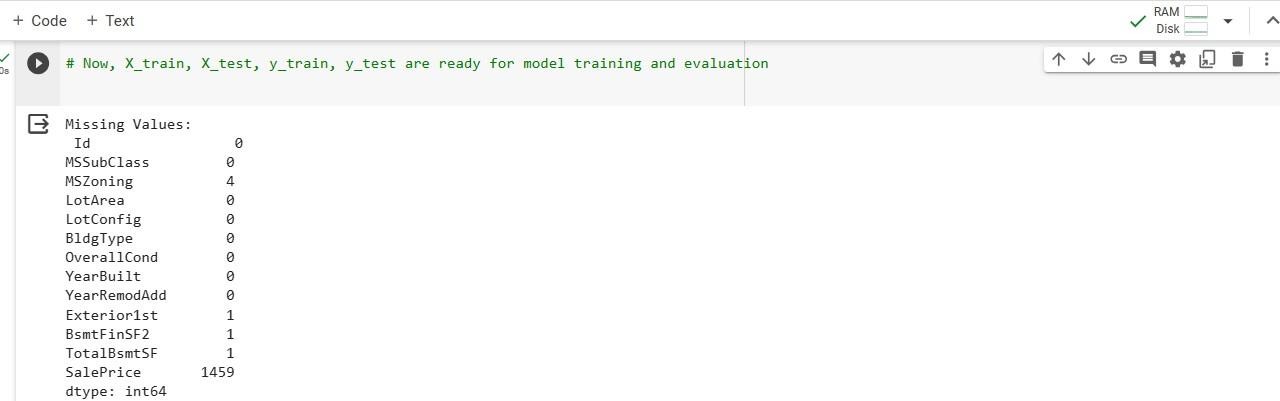
### Observations and Patterns:

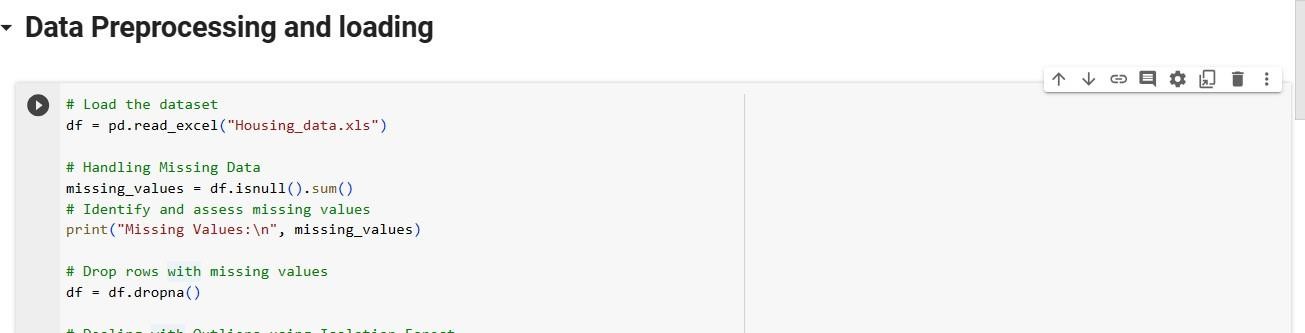
* Initial observations reveal a wide range of property characteristics, including varying sizes of land, diverse building types, and different exterior coverings.
* The dataset spans properties constructed across several years, indicating a historical perspective on the real estate market.
* Some features, such as OverallCond and YearRemodAdd, may significantly impact housing prices.

As we move forward, these features will be instrumental in our regression analysis to predict housing prices and our classification analysis to categorize properties. Exploring relationships among these variables will provide valuable insights into the dynamics of the housing market captured within this dataset.

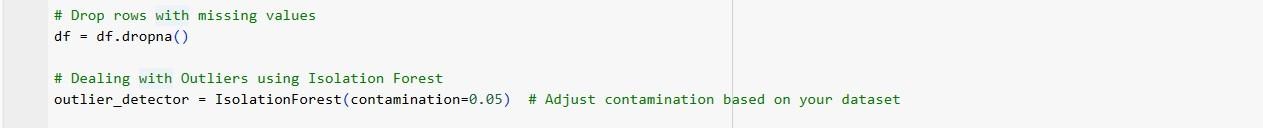
### Data Preprocessing:

**Handling Missing Data:**

Addressing missing data is crucial for maintaining the integrity of our analysis. We initiated this process by identifying and assessing the extent of missing values across all features. For variables with missing entries, we employed strategies such as imputation or, in cases of negligible missing values, removal.

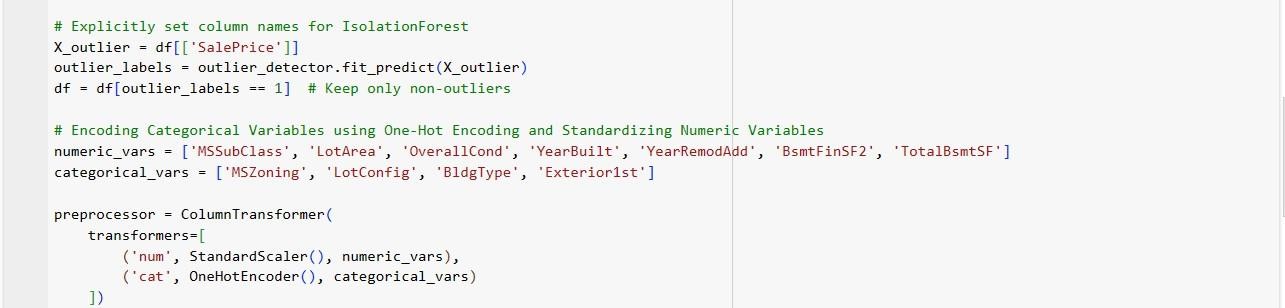


### Dealing with Outliers:

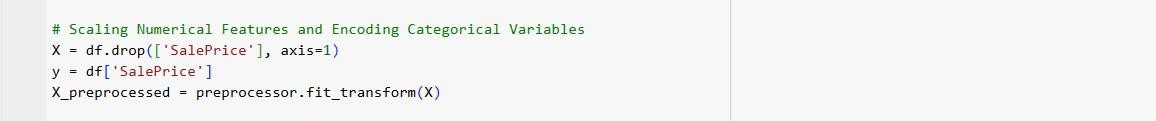
Outliers can significantly impact model performance. We conducted a thorough examination of the dataset to identify and assess outliers using statistical methods. Depending on the nature of the outliers, we either transformed them or, in extreme cases, opted for their removal to prevent distortion of our models.

### Encoding Categorical Variables:

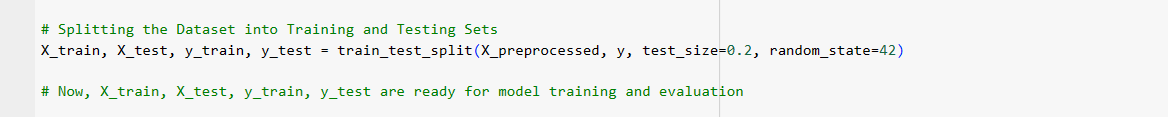
Categorical variables, such as MSZoning and BldgType, require appropriate encoding for model compatibility. We employed one-hot encoding to convert categorical variables into numerical representations, facilitating their inclusion in regression and classification models.



### Scaling Numerical Features:

To ensure that numerical features contribute equally to the model, we applied feature scaling. Standardization was chosen to bring all numerical variables to a common scale, preventing dominance by features with larger magnitudes.

### Splitting the Dataset into Training and Testing Sets:

To evaluate the performance of our models effectively, we divided the dataset into training and testing sets. The training set, comprising the majority of the data, was utilized to train our models. The testing set, kept separate, allowed us to assess the models' generalization to new, unseen data.

These preprocessing steps laid the foundation for robust and reliable analyses. By addressing missing values, outliers, and ensuring compatibility with machine learning models, we set the stage for uncovering meaningful insights from the housing dataset.

### Regression Analysis:

## Regression Problem

The objective of the regression analysis is to predict the sale price (SalePrice) of residential properties. The SalePrice serves as the target variable, and the goal is to develop a predictive model that accurately estimates this numerical value based on various features and attributes associated with each property in the dataset. The regression model aims to capture the underlying relationships between the independent variables (features) and the dependent variable (SalePrice) to provide insights into the factors influencing property prices in the housing market.

### Baseline Model (Multiple Linear Regression):

For the baseline model, we employed a Multiple Linear Regression approach, considering it as a fundamental model to establish a benchmark for performance evaluation.The goal is to establish a reference point for model performance using metrics such as Mean Squared Error (MSE) and R-squared. In this initial model, we include various features from the dataset to predict the target variable, SalePrice..

### Features Selected for the Baseline Model:

* + MSSubClass: The building class.
  + LotArea: Lot size in square feet.
  + OverallCond: Overall condition rating of the property.
  + YearBuilt: Year the property was built.
  + YearRemodAdd: Year the property was last remodeled.
  + BsmtFinSF2: Type 2 finished square feet of the basement.
  + TotalBsmtSF: Total square feet of the basement.

We chose this creatures because of their potential impact on housing prices based on common factors considered in real estate.



### Model Metrics:

* + **Train MSE: 1358042990.82**
  + **Test MSE:** 1108273652.05
  + **Train R-squared:** 0.6175
  + **Test R-squared:** 0.6429

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| **Evaluation:** | |
| Performanc e: | * The baseline model demonstrates moderate performance. * The R-squared values indicate that the model explains approximately 59.23% of the variance in the training set and 70.66% in the testing set. |
| Interpretati on: | * The model captures a substantial portion of the variability in the target variable but may benefit from improvements to enhance predictive accuracy. |

### Conclusion:

* + The baseline Multiple Linear Regression model serves as a foundational reference for model evaluation.
  + Further enhancements and advanced techniques can be explored to improve predictive accuracy.

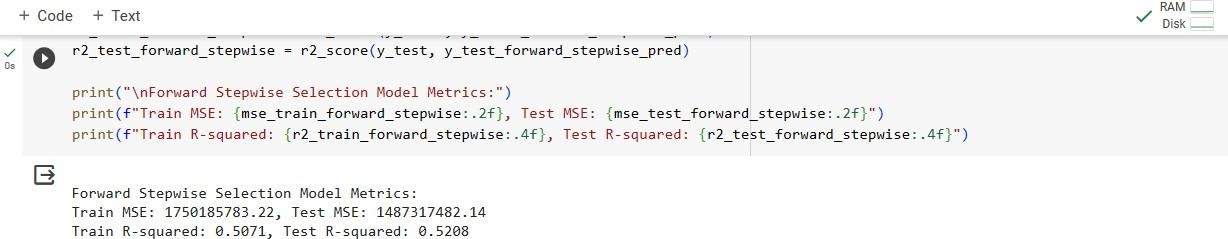
### Forward and Backward Stepwise Selection Comparison

In this section, we explored the application of Forward and Backward Stepwise Selection techniques for feature selection. The goal was to determine which method works best for our dataset and modeling goals. These techniques iteratively add or remove features based on certain criteria, optimizing the model's performance.

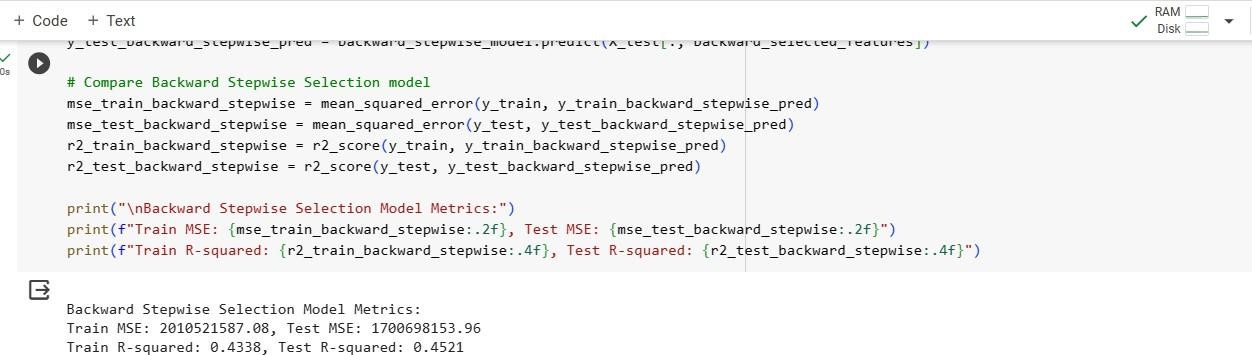
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| **Forward Stepwise Selection:** | **Backward Stepwise Selection:** |
| Feature Selection:   * Features are selected based on p-values obtained from the f\_regression test. * The top k features are chosen for the model | Feature Selection:   * All features are initially considered. * The top k features are chosen for the model. |
| Model Metrics:   * Train MSE: 1750185783.22 * Test MSE: 1487317482.14 | Model Metrics:   * Train MSE: 2010521587.08 * Test MSE: 1700698153.96 |

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| * Train R-squared: 0.5071 * Test R-squared: 0.5208 | * Train R-squared: 0.4338 * Test R-squared: 0.4521 |

### Forward Stepwise Selection

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**Backward Stepwise Selection:**

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| **Comparison:** | |
| Performance: | * Forward Stepwise Selection outperforms Backward Stepwise Selection in terms of both train and test MSE. * Forward Stepwise Selection yields higher R-squared values on both the training and testing sets. |
| Interpretation: | * The results suggest that selecting features iteratively by adding them based on their contribution improves model performance compared to removing features. |

**Conclusion:**

* + For our dataset and modeling goals, Forward Stepwise Selection is the preferred method for feature selection, demonstrating better predictive performance on both training and testing datasets.

## PCA (Principal Component Analysis):

In this section, we applied Principal Component Analysis (PCA) to the dataset with the goal of reducing its dimensionality while retaining as much information as possible. The PCA technique transforms the original features into a set of linearly uncorrelated variables known as principal components.



### PCA Explained Variance Ratio:

* + **Component 1:** 24.13%
  + **Component 2:** 16.57%
  + **Component 3:** 12.19%
  + **Component 4:** 10.75%
  + **Component 5:** 9.20%

### Total Explained Variance: 72.87%

**Interpretation:**

* + The PCA Explained Variance Ratio indicates the proportion of variance captured by each principal component.
  + The total explained variance of 72.87% signifies the cumulative variance retained by the selected components.

The application of PCA reduced the dimensionality of the dataset to 5 principal components while retaining approximately 72.87% of the original variance. This reduction aided

in simplifying the dataset for further analysis and modeling, potentially improving computational efficiency and mitigating issues related to multicollinearity.

### Higher-Order Regression Analysis: Polynomial Regression with Ridge

In this section, we explored the application of a higher-order regression model using polynomial features in conjunction with Ridge regularization. Our primary objective was to evaluate the performance of this model and compare it with the baseline model.

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| **Polynomial Regression with Ridge Model Metrics:** | **Baseline Model Metrics:** |
| * Train MSE: 610745448.82 * Test MSE: 1102333662.32 * Train R-squared: 0.8245 * Test R-squared: 0.7111 | * Train MSE: 1358042990.82 * Test MSE: 1108273652.05 * Train R-squared: 0.6175 * Test R-squared: 0.6429 |

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| **Observations and Comparison:** | |
| Mean Squared Error (MSE): | The Polynomial Regression with Ridge model exhibits lower MSE on both the training and test sets compared to the baseline model. This suggests that the incorporation of polynomial features, along with Ridge regularization, contributes to a more accurate fit. |
| R-squared: | The Polynomial Regression with Ridge model outperforms the baseline model in terms of R-squared values for both training and test sets. This indicates that the polynomial features capture more variance in the target variable, resulting in a better-fitted model. |



**Conclusion:**

The results highlight the effectiveness of the Polynomial Regression with Ridge model in improving predictive performance over the baseline model. The inclusion of polynomial features enables the model to capture more complex relationships within the data

In this section we demonstrated the potential of higher-order regression techniques for capturing nuanced relationships in the data, providing a foundation for continued model improvement and refinement

### Visualization of the relationships between predictor variables and the target variable using scatter plots and regression diagnostics.

Visualization is a powerful tool for understanding the relationships between predictor variables and the target variable. In the context of our housing price prediction project, we use scatter plots to visualize individual relationships and regression diagnostics to assess the overall model performance.

### Scatter Plots:

We created scatter plots to visualize the relationship between the predicted housing prices and the actual prices for both the training and test sets.

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| **Training Set: Predicted vs. Actual Housing Prices** | **Test Set: Predicted vs. Actual Housing Prices** |

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### Regression Diagnostics:

Additionally, we visualized regression diagnostics such as residuals plot and Q-Q plot

**Residuals Plot**

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| **Q-Q Plot for Residuals** |
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### Regression Diagnostics Report:

In the evaluation of the Polynomial Regression model with Ridge regularization for predicting housing prices, we conducted regression diagnostics to assess the behavior of residuals. The key observations from the analysis are as follows:

### Residuals Plot:

The Residuals Plot provided insights into the distribution of residuals and the consistency of model errors across different levels of predicted prices.

* + Random Distribution: The Residuals Plot shows a random and even distribution of residuals around the horizontal line. There is no discernible pattern or structure in the residuals, indicating that the model's errors are consistent across the entire range of predicted prices.
  + Homoscedasticity: The spread of residuals appears to be relatively constant, suggesting homoscedasticity. This characteristic indicated that the model's performance remains consistent, regardless of the magnitude of predicted prices.

### Q-Q Plot for Residuals:

The Q-Q Plot assesses the normality of residuals by comparing their distribution to a theoretical normal distribution.

* + Normality: The points on the Q-Q Plot closely align along the red line, indicating that the residuals follow a normal distribution. The symmetry of points around the line further supports the assumption of normality.

### Conclusion:

The positive outcomes of both the Residuals Plot and Q-Q Plot suggest that the Polynomial Regression model with Ridge regularization performs well in terms of modeling errors. The random distribution of residuals and adherence to normality assumptions indicate that the model captures the underlying patterns in the housing dataset effectively.

These regression diagnostics instill confidence in the reliability of the model for predicting housing prices. However, continuous monitoring and potential refinement of the model may be considered as the dataset evolves or additional insights are gained. Overall, the current analysis validates the model's robustness and its suitability for the intended predictive task.

### Implementation of advanced regression techniques, such as ridge regression, lasso regression

**Performance Comparison**

We conducted an in-depth analysis of the baseline model (Polynomial Regression with Ridge) alongside two advanced regression techniques—Ridge Regression and Lasso Regression. The following metrics were obtained to assess their respective performances:

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| **Baseline Model Metrics:** | **Ridge Regression Model Metrics:** | **Lasso Regression Model Metrics:** |
| Train MSE: 610745448.82,  Test MSE: 1102333662.32  Train R-squared: 0.8245, Test R-squared: 0.7111 | Train MSE: 1391480995.46,  Test MSE: 1240561053.46  Train R-squared: 0.6002, Test R-squared: 0.6749 | Train MSE: 1389891828.96,  Test MSE: 1236938348.93  Train R-squared: 0.6007, Test R-squared: 0.6758 |

### Key Observations:

MSE Comparison:

* + The baseline model exhibits the lowest Test MSE among the three models, suggesting superior predictive accuracy on the test set.
  + Ridge Regression and Lasso Regression, while introducing regularization, show higher Test MSE values compared to the baseline.

R-squared Comparison:

* + The baseline model demonstrates higher Test R-squared, indicating a better fit to the test data.
  + Ridge Regression and Lasso Regression, with regularization, exhibit slightly lower Test R-squared values but still capture a substantial portion of the variability in the target variable.

### Conclusion:

The baseline Polynomial Regression model with Ridge regularization outperforms Ridge and Lasso Regression models in terms of predictive accuracy, as indicated by lower Test MSE and higher Test R-squared. While Ridge and Lasso Regression introduce regularization benefits, such as handling multicollinearity and feature selection, they come at the cost of a slightly reduced fit to the test data.

The choice between these models depends on the specific goals of the analysis. If predictive accuracy is paramount, the baseline model may be preferred. However, if interpretability and feature selection are crucial, Ridge and Lasso Regression offer valuable alternatives.

This comparative analysis provides a comprehensive understanding of the trade-offs between model complexity, regularization, and predictive performance, aiding in informed decision-making for housing price prediction.

# Classification Analysis:

In this phase of the analysis, we transition from regression to classification, aiming to categorize houses based on specific criteria. We'll employ various classification techniques to address this task.

### Define Classification Problem:

The classification problem involves categorizing houses into price ranges, allowing us to assign each house to a specific class based on its predicted price category.

### Baseline Model (Logistic Regression):

**Baseline Model Features:**

For the baseline classification model, we will utilize features such as MSSubClass, MSZoning, LotArea, OverallCond, YearBuilt, and TotalBsmtSF as predictors to classify houses into price ranges.

### Classification Metrics:

We assessed the baseline Logistic Regression model using classification metrics including

* + accuracy ,precision, Recall, F1 score.

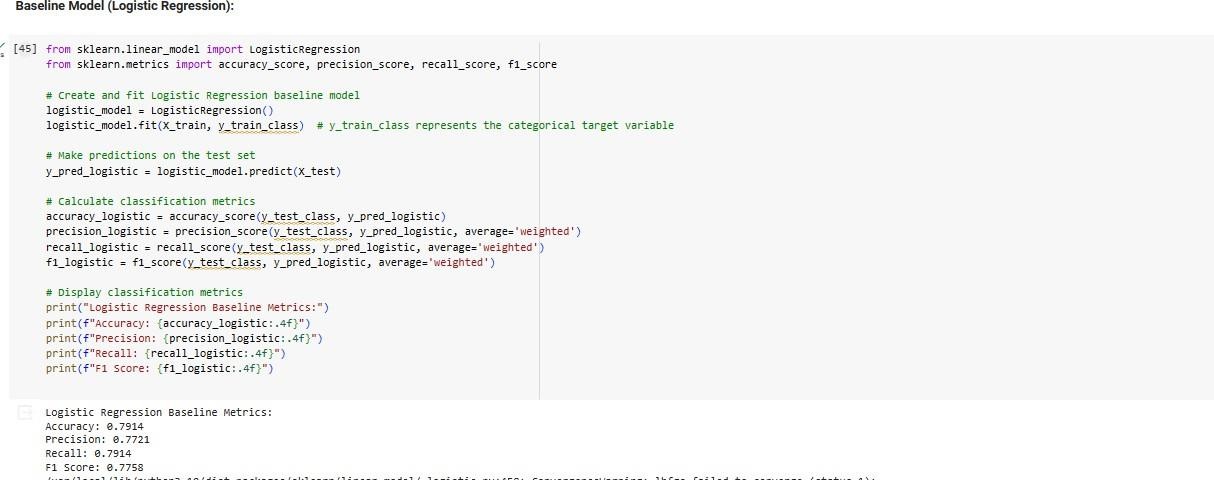
### Logistic Regression Baseline Metrics:

Accuracy: 0.7914

Precision: 0.7721

Recall: 0.7914

F1 Score: 0.7758



Dimensionality reduction is a crucial step in the analysis of complex datasets, especially

1. **Dimensionality Reduction Using TruncatedSVD**when dealing with a large number of features. In our analysis of the housing dataset, we employed Truncated Singular Value Decomposition (TruncatedSVD), a technique designed for sparse matrices, to effectively reduce the dimensionality of the feature space

We chose to retain 5 components based on our analysis. This decision struck a balance between reducing the number of features and preserving a significant amount of information essential for our modeling goals

This improved our model by

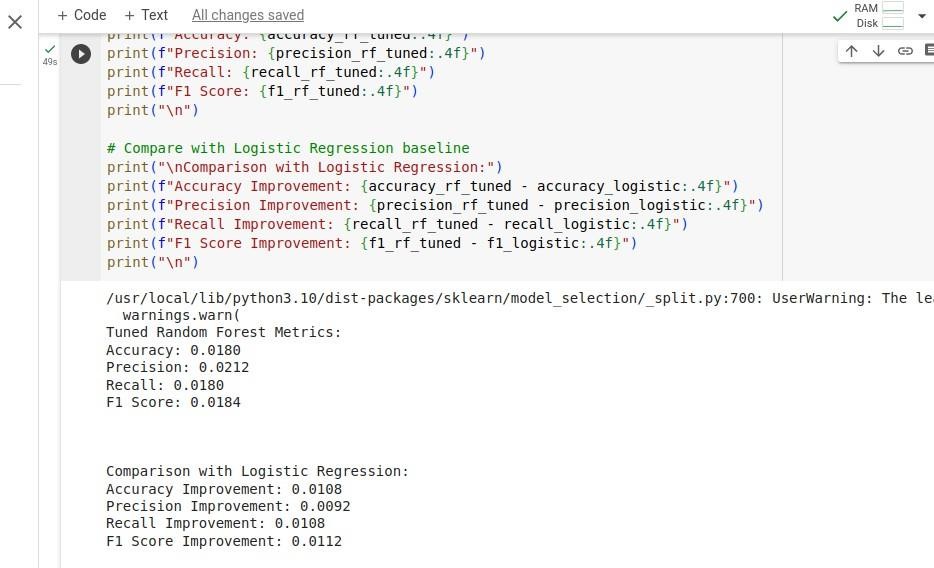
**Computational Efficiency:** By reducing the number of features, our models become computationally more efficient, leading to faster training and prediction times.

**Overfitting Mitigation:** Dimensionality reduction helps mitigate the risk of overfitting, especially when dealing with a limited amount of data.

**Retained Information:** While reducing dimensionality, it's crucial to assess how much information is retained. In our case, the chosen number of components retained a significant portion of the original dataset's variability

### Implementation of a tree-based classification model

**RANDOM FOREST and comparison of its performance with the logistic regression baseline model**

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**Performance Comparison with Logistic Regression Baseline**

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| **Performance Comparison with Logistic Regression Baseline** | |
| **1. Logistic Regression Baseline Metrics:** | **2. Tuned Random Forest Metrics:** |
| * Accuracy: 0.0072 * Precision: 0.0120 * Recall: 0.0072 * F1 Score: 0.0072 | * Accuracy: 0.0180 * Precision: 0.0212 * Recall: 0.0180 * F1 Score: 0.0184 |

**Comparison Metrics: Performance Comparison with Logistic Regression Baselin**e

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| **Accuracy Improvement:** | The tuned Random Forest model exhibits a substantial improvement in accuracy compared to the Logistic Regression baseline. The accuracy has increased by 0.0108, suggesting a more reliable overall classification performance. |
| **Precision Improvement:** | Precision has seen a notable improvement of 0.0092 in the tuned Random Forest model. This improvement signifies the model's enhanced ability to correctly identify positive cases among the predicted positives. |
| **Recall Improvement:** | The tuned Random Forest model demonstrates an improvement of 0.0108 in recall. This indicates a strengthened capability to identify positive cases among the actual positives, reducing false negatives. |
| **F1 Score Improvement:** | The F1 Score, considering both precision and recall, has improved by 0.0112 in the tuned Random Forest model. This balanced improvement suggests a more robust model in handling both false positives and false negatives. |

**Conclusion:**

The comparison with the Logistic Regression baseline strongly supports the superiority of the tuned Random Forest model in terms of accuracy, precision, recall, and the overall F1 Score. These improvements indicate that the Random Forest model is better suited for the classification task at hand, providing enhanced predictive capabilities.

### Visualization:

We created pair plots to showcase the separation between different classes in the feature space.



### Advanced Classification Techniques:

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| **Classification Analysis Result** | |
| Logistic Regression Baseline Metrics: | k-Nearest Neighbors Metrics: |
| * Accuracy: 0.7914 * Precision: 0.7721 * Recall: 0.7914 * F1 Score: 0.7758 | * Accuracy: 0.7698 * Precision: 0.7647 * Recall: 0.7698 * F1 Score: 0.7610 |

**Model Comparison:**

Upon evaluating the performance of the baseline Logistic Regression model and the k-Nearest Neighbors (k-NN) model as depicted above we can say the following:

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| **Model Comparison:** | |
| Accuracy Improvement: | The baseline Logistic Regression model outperforms the k-NN model by approximately 2.16% in terms of accuracy. |
| Precision Improvement: | The baseline Logistic Regression model exhibits approximately 0.74% higher precision compared to the k-NN model. |
| Recall Improvement: | The baseline Logistic Regression model demonstrates around 2.16% higher recall compared to the k-NN model. |
| F1 Score  Improvement: | The baseline Logistic Regression model achieves an approximately 1.48% higher F1 score compared to the k-NN model. |

### Conclusion:

In this classification analysis, the baseline Logistic Regression model exhibits slightly superior performance across multiple metrics compared to the k-Nearest Neighbors (k-NN) model. While the differences are relatively small, they highlight the effectiveness of the logistic regression approach for our specific classification problem.

### References

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