Ridge Regression

Introduction

Ridge Regression is a linear regression technique that is particularly useful when dealing with multicollinearity and overfitting in regression models. It is a regularization technique that adds a penalty term to the ordinary least squares (OLS) method to shrink the coefficients towards zero.

Key Features of Ridge Regression

- 1. Regularization: Ridge Regression adds a penalty term (L2 regularization) to the OLS loss function, which helps prevent overfitting by penalizing large coefficients.
- 2. Shrinkage: The penalty term in Ridge Regression forces the coefficients to be smaller compared to ordinary least squares, reducing the model's sensitivity to input variables.

- 3. Multicollinearity Handling: Ridge Regression is effective in handling multicollinearity, where predictor variables are highly correlated, by stabilizing the coefficients.
- 4. Bias-Variance Tradeoff: Ridge Regression helps in balancing the biasvariance tradeoff by introducing a regularization parameter that controls the amount of shrinkage applied to the coefficients.

Training a Ridge Regression Model

- 1. Optimization: The objective of Ridge Regression is to minimize the sum of squared errors of the predicted values and the actual values while penalizing large coefficients.
- 2. <u>Hyperparameter Tuning:</u> The key hyperparameter in Ridge Regression is the regularization strength parameter (alpha), which controls the impact of the penalty term on the coefficients.

Advantages of Ridge Regression

- 1. Reduced Overfitting: Ridge Regression addresses overfitting by adding a penalty term that discourages large coefficients, leading to a more generalizable model.
- 2. Stability: It provides stable and reliable results even in the presence of multicollinearity, making it a robust regression technique.
- 3. Feature Selection: Ridge Regression can also be used for feature selection by shrinking less relevant features towards zero coefficients.

Applications of Ridge Regression

Ridge Regression is commonly used in various fields such as finance, economics, biology, and social sciences for regression tasks where multicollinearity and overfitting are prevalent.

Limitations of Ridge Regression

1. Interpretability: The shrinkage effect in Ridge Regression can make it challenging to interpret the importance of individual features compared to traditional linear regression.

2. Not Suitable for Sparsity: Ridge Regression tends to keep all features in

the model as it only shrinks the coefficients towards zero without

enforcing exact zero values.

Conclusion

Ridge Regression is a valuable technique in regression analysis, particularly

when dealing with multicollinearity and overfitting issues. By introducing

regularization, it enhances model stability and generalization while balancing

the bias-variance tradeoff effectively.

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