Ridge Regression

A Statistical Approach for Predicting Outcomes

@DataByteSun

What is Ridge Regression?

- **Definition:** Ridge Regression is a type of linear regression that adds an L2 penalty (the square of the coefficients) to the model, helping to prevent overfitting by shrinking the coefficients.
- **Goal:** The goal is to improve model stability and accuracy by limiting the size of the coefficients, using the L2 regularization term.

Key Concepts in Ridge Regression

- **L2 Regularization:** Ridge regression adds a penalty proportional to the sum of the squared coefficients to the cost function.
- **Multicollinearity Handling:** Ridge regression is particularly useful when the features are highly correlated (multicollinearity), as it reduces the impact of correlated predictors by shrinking their coefficients.
- **Shrinkage:** Ridge regression reduces the magnitude of coefficients, but unlike Lasso Regression, it does not set them to zero. This means all features remain in the model, but with smaller values.
- **Tuning Hyperparameter (Alpha):** The strength of the regularization is controlled by the hyperparameter alpha. A higher alpha increases regularization, leading to more coefficients being near to zero.

Assumptions of Ridge Regression

- **Linearity:** Relationship between x and y is linear.
- **Independence:** The residuals (errors) should be independent of each other.
- **Homoscedasticity:** Constant variance of errors.
- **Normality:** Errors are normally distributed.
- **Multicollinearity (optional):** requires that independent variables have no or low to moderate correlations with one another.
- **Sufficient Data:** Ensure that you have enough data for reliable coefficient estimation.
- **Tuning the Regularization Parameter:** α should be appropriately chosen using cross-validation.

Ridge Regression Equation

The objective of lasso regression is to minimize the following cost function:

$$\text{Cost Function} = \text{RSS} + \lambda\ (\beta i)^2$$

Where,

- RSS (Residual Sum of Squares) is the sum of squared errors (the usual loss function for linear regression).

$$RSS = \sum_{i=1}^{n} (\mathrm{y}_i - \hat{y}_i)^2$$

Where,
- y_i is the true value for the i-th observation.
- $\hat{y}_i$ is the predicted value for the i-th observation.

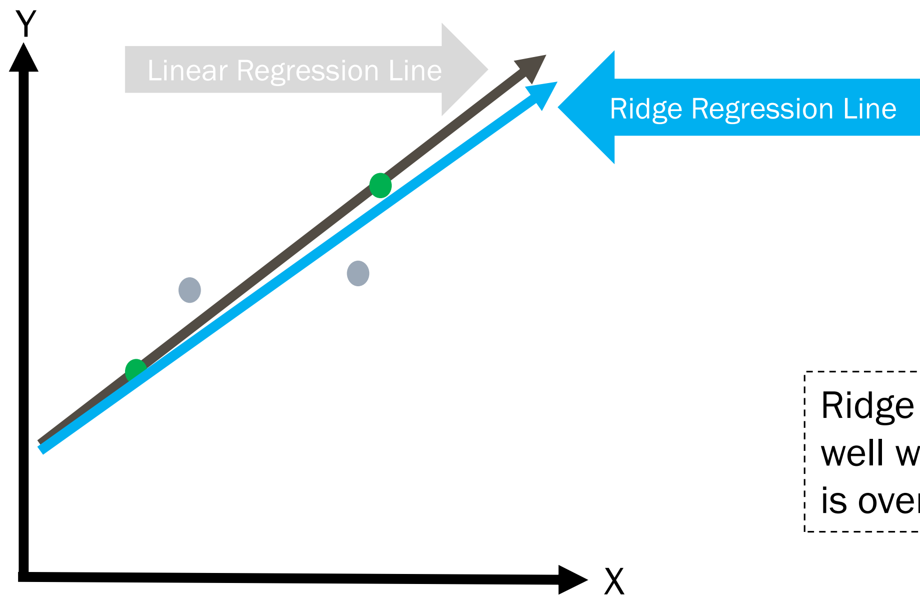
- λ (lambda) is the regularization parameter (also called the **penalty term**).

- βi represents the coefficients of the predictors.

How Ridge Regression Works

- **Linear Model:** Lasso fits a linear model to the data by finding the line (or hyperplane in higher dimensions) that minimizes the error between the predicted and actual values.
- **Penalty:** The regularization term (penalty) prevents the model from fitting too closely to the data (which would lead to overfitting).
- **Shrinkage:** Some feature coefficients will be shrunk near to zero, effectively handling those features for the model.

Ridge Regression



- train dataset
- test dataset

Ridge Regression line generalize well where, Linear Regression line is overfitting.

@DataByteSun

When to Use Ridge Regression

- **Many Features, All Important:** Use Ridge when you believe all features contribute to the model and don't need feature selection.
- **Multicollinearity:** Use Ridge if features are highly correlated to stabilize the model.
- **Predictive Power:** Use Ridge for better predictive accuracy when you don't want to remove features.
- **Feature Selection Not Needed:** Use Ridge if you don't need to remove irrelevant features.
- **Avoid Overfitting, Keep All Features:** Ridge helps reduce overfitting by shrinking coefficients but retains all features.
- **More Features than Data Points:** Ridge works well when more features than data points.

Lasso Regression
VS
Ridge Regression

Lasso Regression

- **Lasso** uses the **L1 regularization** (absolute value of coefficients), which can shrink some coefficients to zero, thus performing **feature selection.**
- Use when only some of features are important.
- Lasso Regression can shrink the slope **all the way to 0.**

Cost Function = RSS +λ $|\beta i|$

Ridge Regression

- **Ridge** uses **L2 regularization** (square of coefficients), which tends to shrink coefficients but doesn't set them exactly to zero. Ridge regularization **doesn't perform feature selection** in the same way lasso does.
- Use when most or all features are useful.
- Ridge Regression can only shrink the slope asymptotically **close to 0.**

Cost Function = RSS +λ $(\beta i)^2$

@DataByteSun

Thank You

\- @DataByteSun