

Ridge & Lasso Regression.

Ridge Regression

→ Cost function in case of Ridge Regression.

$$CF = \underbrace{\sum_{i=1}^n (y_i - \sum_j x_{ij} \beta_j)^2}_{\text{From Linear Regression.}} + \underbrace{\lambda \sum_{j=1}^p \beta_j^2}_{L_2 \text{ Regularization.}}$$

- This reduces variance in Linear Regression Model.
- This increases bias in Linear Regression Model.
- This prevents overfitting.
- λ learned through cross-validation / hyperparameter tuning.
- This reduces model complexity & over-fitting.
- ⇒ This puts constraints on the coefficients (w)
- λ (penalty term) reduces overall slope
- So, Ridge Regression shrinks coefficients and helps to reduce model complexity & multi-collinearity.

Lasso Regression

→ Cost function in case of Lasso Regression.

$$CF = \underbrace{\sum_{i=1}^n (y_i - \sum_j x_{ij} \beta_j)^2}_{\text{From Linear Regression}} + \underbrace{\lambda \sum_{j=1}^p |\beta_j|}_{L_1 \text{ Regularization.}}$$

- Reduces variance, Increases bias, Reduces overfitting & complexity
- λ (penalty term) reduces overall slope and is learnt through cross-validation / hyperparameter tuning.
- constraints β
- Reduces multi-collinearity