

Regularization

It is a technique used to reduce the errors by fitting the function appropriately on the given training set & avoid overfitting.

Types -

- i) L_1 / Lasso regularization
 - ii) L_2 / Ridge regression
 - iii) Elastic Net
- ii) Ridge Regression (L_2) - It modifies the overfitted or underfitted model by adding the penalties equivalent to the sum of the squares of the magnitude of coefficients.

$$L_2 = \frac{1}{2m} \sum_{i=1}^m (y_i - \hat{y}_i)^2 + \lambda (\text{Slope})^2$$

$$= \sum_{i=1}^m (y_i - \hat{y}_i)^2 + \lambda m^2$$

$$\Rightarrow \text{RSS} + \lambda m^2$$

- iii) Lasso regularization (L_1) - The regularization technique performs L1
- It modifies the RSS by adding the penalties equivalent to the sum of absolute value of coefficients.

$$L_1 = \sum_i (y_i(\hat{y}_i) - y_i)^2 + \lambda |\text{slope}|$$

or

$$L_2 = \frac{1}{2n} + \lambda \sum_i w_i^2$$

Lasso (L_1) is helping Overfitting prevent & helps do Feature Selection,

Ridge (L_2) helps in Overfitting.

$$\cdot \bar{y} = y_{\text{hat}} \quad | \quad \lambda = \text{lambday} \quad | \quad \alpha = \text{alpha} \quad | \quad \epsilon = \text{Subtraction}$$

$$\cdot \lambda \rightarrow \text{lambday} \quad | \quad \beta = \text{beta}$$

Elastic Net - This method used to perform Variable Selection & regularization Simultaneously.

It is hybrid of Lasso & Ridge

$$\rightarrow \frac{(y_i - \hat{y}_i)^2}{2n} + \lambda \left(\frac{1-\alpha}{2} \right) \sum \beta_j^2 + \alpha \sum |\beta_j|$$

[here $\beta = w$]

Q How you will able to build a robust model

Ans - I will try to use regularization model

(Feature Scaling) Standardization / Normalization

i) Standardization / Z-score Normalization - It typically means rescales data to have a mean of 0 & standard deviation (σ) of 1. It is often called z-score.

\rightarrow Score

$$z = \frac{x - \text{mean}}{\text{s.d.}} \quad \text{zscore} = \frac{x - \text{mean}}{\text{s.d.}}$$

If the mean = 0 & $s.d. = 1$ then the output will consider us z-score.

\rightarrow It is used when the feature distribution is normally or Gaussian distribution.

ii) Normalization / Min-Max Scaling - It is the process in machine learning of translating data into the range $[0, 1]$ or $[-1, 1]$

$$x_{\text{new}} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}$$

Difference between

Normalization (Min-Max)

(Z-score) Standardization

- i) Scale value between $[0, 1]$ or $[-1, 1]$. It is not bounded to a certain range.
- ii) It is really affected by outlier. Not affected or less affected by outliers.
- iii) It is useful when we don't know the distribution. It is useful when the feature distribution is normal/Gaussian.
- iv) It is used when features are of different scales. It is used when we want to assume zero mean and unit standard deviation.

Actual data	After Normalization	After Standardization
$\begin{matrix} 1 & 2 & 3 & 4 & 5 \\ 6 & 7 & 8 & 9 & 10 \end{matrix}$	$\begin{matrix} 0 & 0.5 & 1 & 1.5 & 2 \\ 2.5 & 3 & 3.5 & 4 & 4.5 \end{matrix}$	$\begin{matrix} -3 & -2 & -1 & 0 & 1 \\ 1 & 0 & -1 & -2 & -3 \end{matrix}$

min X_i = x_{min} max X_i = x_{max} N

Why to use Standard Scaler -

If my data dispersion is varying a lot / lot of Variances. So in that case my model is not going to understand a relation with respect to independence to dependence Variable in a better way. So to give a better relation among Feature & Label Variable we use Standard Scaler.

Standardization vs Normalization -

Most oftenly Standardization use for clustering analysis, PCA.

Normalization proper for Image processing because pixel intensity between 0 to 255, neural network algorithm require data in Scale 0-1, i.e. N .