

Date.....

Maths behind Lasso Regression

As we know, → In Ridge as well as in Lasso also in normal Linear Regression the formula to calculate the "b" is same...

$$b = \bar{Y} - m \bar{X}$$

Calculating "m" for Lasso Regression...

$$\begin{array}{l} \text{Loss Function} \\ \Rightarrow \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 + \lambda |m| \end{array} \Rightarrow \sum_{i=1}^n (Y_i - m X_i - b)^2 + \lambda |m|$$

$$\Rightarrow \sum_{i=1}^n (Y_i - m X_i - \bar{Y} - m \bar{X})^2 + \lambda m \Rightarrow \frac{dL}{dm} \quad \text{Derivating in terms of "m"...}$$

[Assuming that the $m > 0$]

$$\frac{dL}{dm} \Rightarrow \sum_{i=1}^n (Y_i - m X_i - \bar{Y} - m \bar{X})(-X_i - \bar{X}) + \lambda m = 0 \quad [\text{Multiplying } 2 \text{ with } \lambda.]$$

$$\frac{dL}{dm} \Rightarrow \sum_{i=1}^n [(Y_i - \bar{Y}) - m(X_i - \bar{X})](X_i - \bar{X}) + \lambda m = 0$$

$$\Rightarrow -2 \sum_{i=1}^n [(Y_i - \bar{Y}) \cdot (X_i - \bar{X}) - m(X_i - \bar{X})^2] + \lambda m = 0$$

~~Dividing with 2~~ Dividing with 2 the complete equation...

$$\Rightarrow -\sum_{i=1}^n [(Y_i - \bar{Y}) \cdot (X_i - \bar{X}) + m(X_i - \bar{X})^2] + \lambda m = 0$$

$$\Rightarrow m(X_i - \bar{X})^2 + \lambda = \sum_{i=1}^n (Y_i - \bar{Y}) \cdot (X_i - \bar{X})$$

$$\Rightarrow m = \frac{\sum_{i=1}^n (Y_i - \bar{Y}) \cdot (X_i - \bar{X}) - \lambda}{(X_i - \bar{X})^2}$$

Date.....

As per the Lasso Regression is concerned, "m" can fall into 3 cases:-

Case-3

When $m > 0$ Case-1

$$m = \frac{\sum_{i=1}^n (Y_i - \bar{Y})(X_i - \bar{X}) - \lambda}{\sum_{i=1}^n (X_i - \bar{X})^2}$$

When $m = 0$ Case-2

$$m = \frac{\sum_{i=1}^n (Y_i - \bar{Y})(X_i - \bar{X})}{\sum_{i=1}^n (X_i - \bar{X})^2}$$

When $m < 0$

$$m = \frac{\sum_{i=1}^n (Y_i - \bar{Y})(X_i - \bar{X}) + \lambda}{\sum_{i=1}^n (X_i - \bar{X})^2}$$

Q Why there is Sparsity in the coefficient values in Lasso Regression??

A Meaning of Sparsity \Rightarrow Values of the coef- is equal to Zero '0'.

O Let's proof this with the help of example:-

As, per the formula where $m > 0$

let's say $\sum_{i=1}^n (Y_i - \bar{Y})(X_i - \bar{X}) = a$, $\sum_{i=1}^n (X_i - \bar{X})^2 = b$

$$a = 100, b = 50$$

$$m = 100 - \lambda$$

$$50$$

Case 1:- ' λ ' is equal to 0.

Case 2:- ' λ ' is equal to 50.

$$\Rightarrow m = \frac{100}{50} \Rightarrow 2 \quad \text{Case-1}$$

Case 3:- ' λ ' is equal to 100.

$$50$$

Case 4:- ' λ ' is equal to 100.

$$\Rightarrow m = \frac{100 - 50}{50} \Rightarrow 1 \quad \text{Case-2} \quad [\text{As ' λ ' increases, 'm' decreases...}]$$

$$\Rightarrow m = \frac{100 - 100}{50} \Rightarrow 0 \quad \text{Case-3}$$

This also leads to Feature Selection

$$\Rightarrow m = \frac{100 - 150}{50} \Rightarrow -1$$

If the Value of ' λ ' is increased to a level that it matches the value of 'a'. Then it leads to Sparsity in the values of coef-.

\therefore This is not acceptable because, here only positive values of "m" is included.

Date.....

So, if the value of ' λ ' increases too high and exceeds the value of '100' then automatically Case-3 is called..

$$m = \frac{\sum_{i=1}^n (Y_i - \bar{Y})(X_i - \bar{X}) + \lambda}{\sum_{i=1}^n (X_i - \bar{X})^2}$$

Case 4:- ' λ ' is equal to '150'.

$$m \Rightarrow \frac{100 + 150}{50} \Rightarrow [5]$$

"Therefore, we can conclude that, as the value of " λ " increases, the value of "m" decreases..."

"and the "m" value decreases to Zero '0', it can never be negative".