Lasso Regression

About Lasso Regression:

1. Supervised Learning Model
2. Regression model
3. **L**east **A**bsolute **S**hrinkage and **S**election **O**perator
4. Implements Regularization (L1) to avoid Overfitting

it is built upon linear regression. It avoid overfitting by regularization.

Regularization

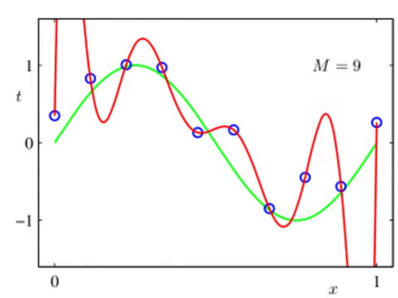
Regularization is used to reduce the overfitting of the model by adding a penalty term (λ) to the model. Lasso Regression uses L1 regularization technique.

The "penalty" term reduces the value of the coefficients or eliminate few coefficients, so that the model has fewer coefficients. As a result, overfitting can be avoided.

3^{rd} order Polynomial equation : $y = ax^3 + bx^2 + cx + d$

This Process is called as Shrinkage.

LASSO --> Least **A**bsolute **S**hrinkage and **S**election **O**perator



Math behind LASSO Regression

Cost Function for Lasso Regression :

$$J = \frac{1}{m}\left[\sum_{i=1}^{m}\left(y^{(i)} - \hat{y}^{(i)}\right)^2 + \lambda \sum_{j=1}^{n} w_j\right]$$

m --> Total number of Data Points

n --> Total number of input features

$y^{(i)}$ --> True Value

$\hat{y}^{(i)}$ --> Predicted Value

λ --> Penalty Term

w --> Parameter of the model

here n is the number of parameters(number of columns) and m is the number of rows.
lambda is also called regularization parameter.

Gradient Descent

Gradients for Lasso Regularization

if $(w_j > 0)$:	***else*** $(w_j \leq 0)$:
$\frac{dJ}{dw} = \frac{-2}{m}\left[\left[\sum_{i=1}^{m} x_j \cdot \left(y^{(i)} - \hat{y}^{(i)}\right)\right] + \lambda\right]$	$\frac{dJ}{dw} = \frac{-2}{m}\left[\left[\sum_{i=1}^{m} x_j \cdot \left(y^{(i)} - \hat{y}^{(i)}\right)\right] - \lambda\right]$

$$\frac{dJ}{db} = \frac{-2}{m}\left[\sum_{i=1}^{m}\left(y^{(i)} - \hat{y}^{(i)}\right)\right]$$

$$w_2 = w_1 - L^* \frac{dJ}{dw}$$

$$b_2 = b_1 - L^* \frac{dJ}{db}$$

$$y = w.x + b$$

dj/db is same for both.