Multiple Regression

Saturday, November 5, 2022 8:39 PM

*MULTIPLE REGRESSION :-

* More than one independent feature.

- NO multicollinearity
- Normality
- Independent features should be linearly associated with dependent feature (Individually).
- NO Autocorrelation.

x_1	x_2	. . . .	x_n	Y
–	–		–	–
–	–		–	–

$$\boxed{\hat{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \ldots \beta_n X_n}$$

> Learn Best Values of $\beta_0, \beta_1, \beta_2 \ldots \beta_n$.

$$J(Y, \hat{Y}) = \frac{1}{m} \Sigma (Y - \hat{Y})^2$$

i) Initialise the parameters.

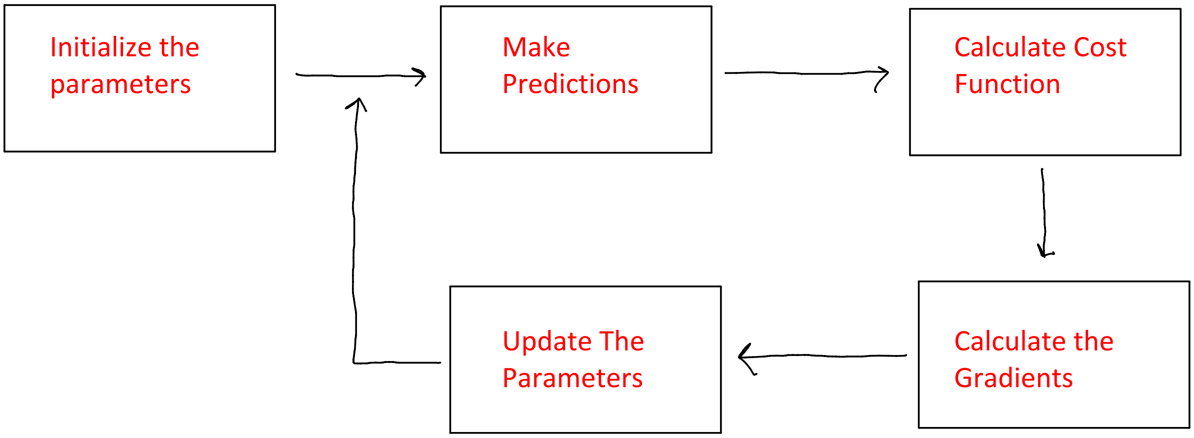
ii) Make Predictions

(iii) Calculate Cost function

(iv) Calculate Gradients

(v) Update the parameters

(v) Update the parameters
(vi) Go back to step 2.



Ex: $\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$

i) Initialize the parameters.
ii) make predictions :

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$$

iii) Calculate Cost :-

$$J(y, \hat{y}) = \frac{1}{n} \Sigma (y - \hat{y})^2$$

$$= \frac{1}{n} \Sigma \left(y - (\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3) \right)^2$$

(iv) Calculate Gradients :-

$$\frac{dJ}{d\beta_0} = \frac{2}{n} \Sigma (y - \hat{y}) \cdot (-1)$$

$$\frac{dJ}{} = \frac{2}{} \Sigma (y - \hat{y}) \; (-x_1)$$

$$\frac{dJ}{d\beta_1} = \frac{2}{n}\Sigma(y-\hat{y}).(-x_1)$$

$$\frac{dJ}{d\beta_2} = \frac{2}{n}\Sigma(y-\hat{y}).(-x_2)$$

$$\frac{dJ}{d\beta_3} = \frac{2}{n}\Sigma(y-\hat{y}).(-x_3)$$

V) Update the parameters :-

$$\beta_0 = \beta_0 - \alpha \frac{dJ}{d\beta_0}$$

$$\beta_1 = \beta_1 - \alpha \frac{dJ}{d\beta_1}$$

$$\beta_2 = \beta_2 - \alpha \frac{dJ}{d\beta_2}$$

$$\beta_3 = \beta_3 - \alpha \frac{dJ}{d\beta_3}$$

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* POLYNOMIAL :-

$$f(x) = a_0 x^0 + a_1 x^1 + a_2 x^2 \cdots a_n x^n$$

> DEGREE :- Highest power of variable in the polynomial

> Linear Polynomial : Degree 1

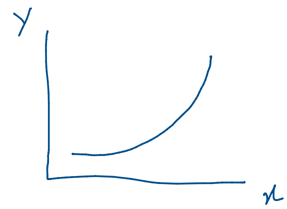
> Non Linear Polynomial : Degree ≥ 2

> Non Linear Polynomial: Degree ≥ 2

* POLYNOMIAL REGRESSION:-

> Used when the relationship b/w independent and dependent feature is non linear.

x	Y
-	-
-	-



$$\boxed{\hat{Y} = \beta_0 + \beta_1 x + \beta_2 x^2 \ldots \ldots \beta_n x^n}$$

$$x = x_1$$
$$x^2 = x_2$$
$$\vdots$$
$$x^n = x_n$$

$$\boxed{\hat{Y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \ldots \beta_n x_n}$$