

## Some Important Topics for ML Basics for the Model

### ① - Interpretation of Coefficients -

\* A linear regression model with two predictor variables results in the following equation:

$$\hat{y}_i = b_0 + b_1 x_1 + b_2 x_2 + e_i$$

The variables in the model are -

$\hat{y}_i$  = the response variable

$x_1$  = the first predictor variable

$x_2$  = the second predictor variable

$e$  = the residual error.

The parameters in the model are -

$B_0 (b_0)$  = The  $y$ -intercept

$B_1 (b_1)$  = the first regression coefficient

$B_2 (b_2)$  = the second regression coefficient.

### \*\* Interpreting the Intercept -

\*  $B_0 (b_0)$  = the  $y$  intercept can be interpreted as the value you would predict for  $y$  if both  $x_1 = 0$  and

$$x_2 = 0.$$

$$b_0 = b_0 + b_1 x_1$$

### \*\* Interpreting Coefficients -

\*  $x_1$  is a first predictor variable,  $B_1 (b_1)$  represents the difference in the predicted value of  $y$  for each one unit difference in  $x_1$ , if  $x_2$  remain constant.



\* That means that if  $x_1$  differed by one unit ( $x_2$  did not differ)  $\hat{y}$  will differ by  $B_1(b_1)$  units on average.

\*  $B_2(b_2)$  is interpreted as the difference in the predicted value in  $\hat{y}$  for each one unit difference in  $x_2$  if  $x_1$  remain constant. However, since  $x_2$  is a categorical variable coded as 0 or 1; one unit difference represent switching from one category to the other.

## ② RSE (Residual Standard Error) —

\* It is also known as residual standard deviation.

$$\Rightarrow \text{Standard Error} = \frac{\sigma}{\sqrt{n}} = \frac{\text{std deviation}}{\sqrt{n}}$$

$$\Rightarrow \sqrt{\frac{\sigma^2}{n}} = \sqrt{\frac{\text{variance}}{n}}$$

$$\Rightarrow \text{Residual Standard Error} = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - \hat{y}_{pi})^2}{n}}$$

$$\Rightarrow \text{Residual Standard Error} = \sqrt{\frac{\text{Residual sum of square (RSS)}}{n}}$$

Here =  $\sigma$  = standard deviation

$n$  = total no. of sample

$\hat{y}_i$  = Individual actual output

$\hat{y}_{pi}$  = Predicted output

### ③ R-Square -

\* R-square will provide, how much target variable explained by input variables.

\* Formula -

$$\Rightarrow [SS_{\text{Total}} = SS_{\text{Residual}} + SS_{\text{Explained}}]$$

$SS_{\text{Total}}$  = Total sum of square

$SS_{\text{Residual}}$  = Residual sum of square

$SS_{\text{Explained}}$  = Explained sum of square

$$\Rightarrow \left[ \sum_{i=1}^n (y_i - \bar{y})^2 = \sum_{i=1}^n (y_i - \hat{y}_i)^2 + \sum_{i=1}^n (\hat{y}_i - \bar{y})^2 \right]$$

$\hat{y}_i$  = Prediction

$y_i$  = actual output

$\bar{y}$  = average output

$$\Rightarrow R\text{-Square} = 1 - \frac{SS_{\text{residual}}}{SS_{\text{Total}}}$$

$$\left[ R\text{-Square} = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \right]$$

R = Coefficient of determination, will tell about explainability of  $y$ .