

## Binary Classification:

In this our dependent variable ( $y$ ) is a discrete variable where it takes two values i.e.  $y \in \{0,1\}$  where 0 represents negative class and 1 represents a positive class.

### Examples:

Email : Spam or not ?

Online Transactions : Fraud or not ?

Tumor : malignant or Benign ?

**Threshold classifier output** : We use linear regression and map all predictions greater than 0.5 as a 1 and all less than 0.5 as a 0. However, this method doesn't work well because classification is not actually a linear function.

What if we use linear reg for classification problem ?

If we use linear regression model then our predicted output might be  $<0$  or sometimes it might be  $>1$ , both the cases are not suitable for classification problem.

We can use classification algorithms such as **logistic Regression** for the binary classification.

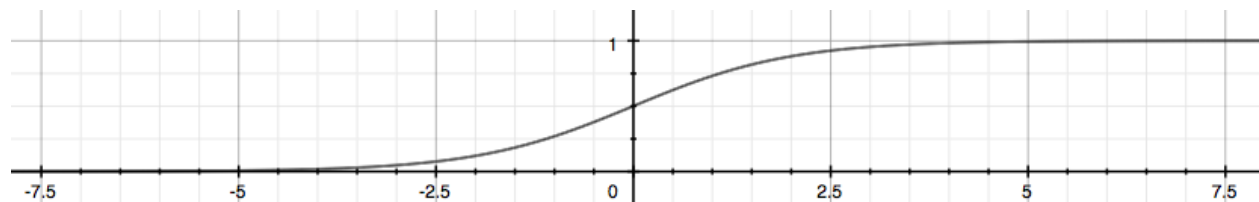
### Logistic Regression :

Our goal is to have our hypothesis function between 0 to 1, i.e.  $0 \leq h_{\theta}(x) \leq 1$ .

$\theta$

For Logistic regression we modify our hypothesis function as  $h_{\theta}(x) = g(h_{\theta}(x))$ , where  $g(z)$  is a

logistic/sigmoid function, where  $g(z) = \frac{1}{1+e^{-z}}$ , the graph looks like below.



### Interpretation of Hypothesis Output:

$h_{\theta}(x)$  = estimated probability that  $y=1$  on input  $x$ .

Example of cancer prediction :  $h_{\theta}(x) = 0.7 \rightarrow$  it tells that 70% chance of tumor being malignant tumor.

Another way of notation is  $h_{\theta}(x) = P(y=1/x; \theta) \rightarrow$  "probability that  $y=1$ , given  $x$ , parameterized by  $\theta$ "

Also,  $P(y=1/x; \theta) + P(y=0/x; \theta) = 1$ .

