Binary Classification:

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

<u>Examples:</u>

Email : Spam or not ?

Online Transactions : Fraud or not ?

Tumor : malignant or Benign ?

<u>**Threshold classifier output**</u> : 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 out 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.

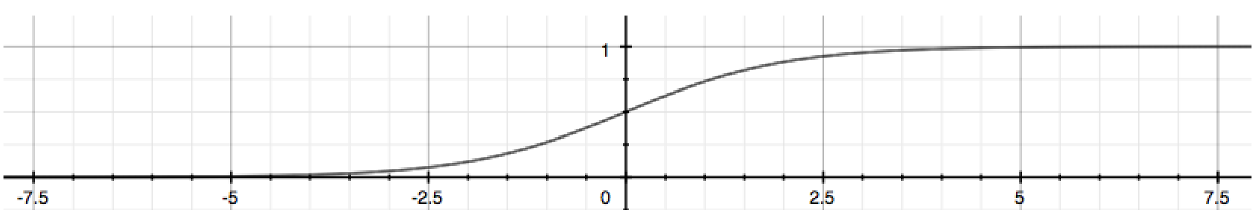
<u>**Logistic Regression**</u> :

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

θ

For Logistic regression we modify our hypothesis function as $h_\theta(x) = g(h_\theta(x))$, i.e. $h_\theta(\theta^T X) = \frac{1}{1+e^{-\theta^T X}}$

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



<u>Interpretation of Hypothesis Output</u>:

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

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

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

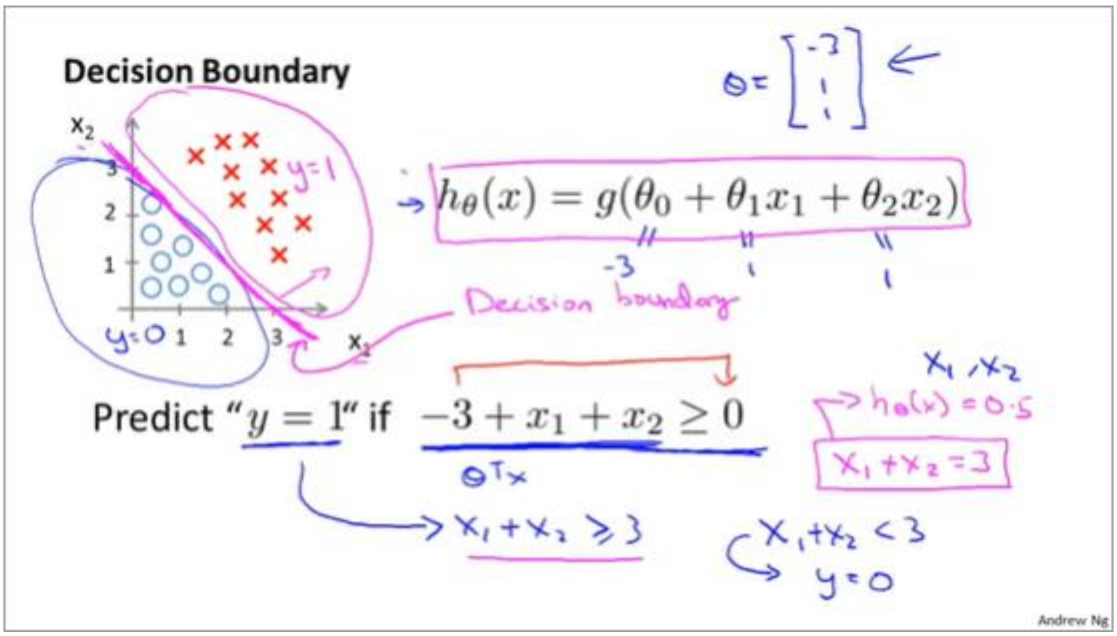
Also, P(y=1/x; θ) + P(y=0/x; θ) =1.

<u>Decision Boundary</u> :

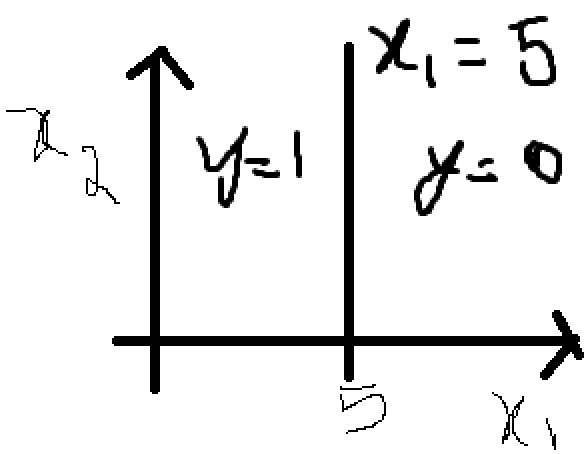
From sigmoid graph, we can say that g(z) >= 0.5 when z>=0, suppose if z=0 →g(z) =1/2

That is

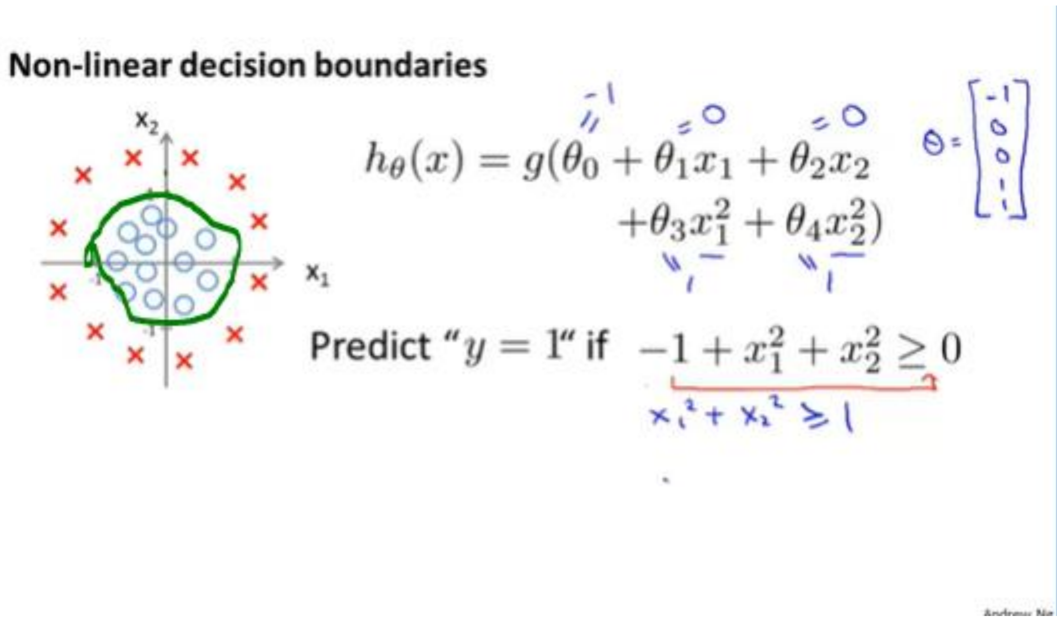
- for y=1, → g(θ^TX) >=0.5 i.e. (θ^TX) >= 0. Similarly
- for y = 0 → g(θ^TX) < 0.5 i.e. (θ^TX) < 0.



- Consider logistic regression with two features *x*1 and *x*2. Suppose theta_0 = 5 , theta_1 = -1 and theta_2=0, so that *hϑ*(*x*)=*g*(5−*x*1). Which of these shows the decision boundary of *hϑ*(*x*)?
- For y=1, θ^TX i.e. 5-x1 >= 0 → x1 <= 5 is the required decision Boundary equation.



- The decision boundaries might not always be linear, it can also be non-linear as well.



<u>Cost Function for Logistic Regression</u>:

Training set : $\{(x^1, y^1), (x^2, y^2), \ldots\ldots, (x^m, y^m)\}$, m examples and we have our X $\in \begin{vmatrix} x^0 \\ \vdots \\ x^n \end{vmatrix}$ i.e. a (n+1) dimensional vector and y $\in \{0,1\}$.

Our hypothesis/Objective function, $h_\theta(\theta^T X) = \dfrac{1}{1+e^{-\theta^T X}}$

Now how to choose parameters theta(θ) ?

Out Scope : Usage of 1x1 convolution ?

We can shrink the number of channels, based on the number of 1x1 convolutional filters.