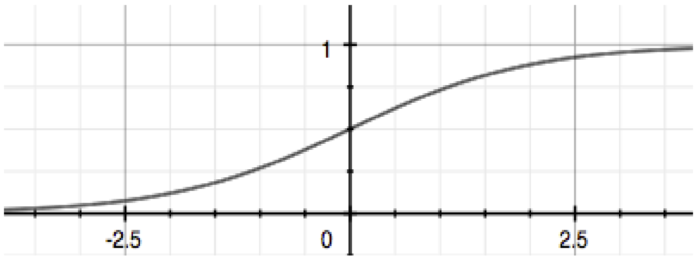
Logistic Regression

Logistic Regression: is named that way for historical reasons and is actually an approach to classification problems, not regression problems.

Binary Classification - Sigmoid

$$g(z) = \frac{1}{1+e^{-z}}$$



hypothesis should satisfy: $0 \leq h_\theta(x) \leq 1$

Decision Boundary

$h_\theta(x) \geq 0.5 \rightarrow y = 1$

$h_\theta(x) < 0.5 \rightarrow y = 0$

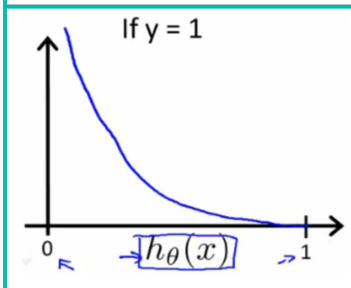
translate the output of the hypothesis function

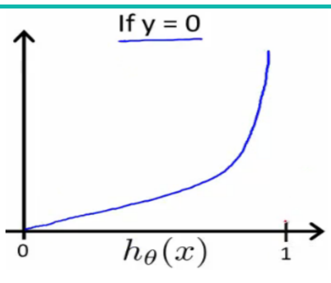
Cost Function

$$J(\Theta) = \frac{1}{m}\sum_{i=1}^{m}(Cost(h_\theta(x_{(i)}), y_{(i)}))$$

$\mathrm{Cost}(h_\theta(x), y) = -\log(h_\theta(x))$ if y = 1

$\mathrm{Cost}(h_\theta(x), y) = -\log(1 - h_\theta(x))$ if y = 0





$\mathrm{Cost}(h_\theta(x), y) = 0$ if $h_\theta(x) = y$

$\mathrm{Cost}(h_\theta(x), y) \rightarrow \infty$ if $y = 0 \mathrm{and} h_\theta(x) \rightarrow 1$

$\mathrm{Cost}(h_\theta(x), y) \rightarrow \infty$ if $y = 1 \mathrm{and} h_\theta(x) \rightarrow 0$

Gradient Descent

$Repeat$ {

$\theta_j := \theta_j - \frac{\alpha}{m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})x_j^{(i)}$

}

Simplified Cost Function

$$J(\Theta) = \frac{1}{m}\sum_{i=1}^{m}[y^{(i)}log(h_\theta(x^{(i)})) + (1 - y^{(i)})log(1 - h_\theta(x^{(i)}))]$$