

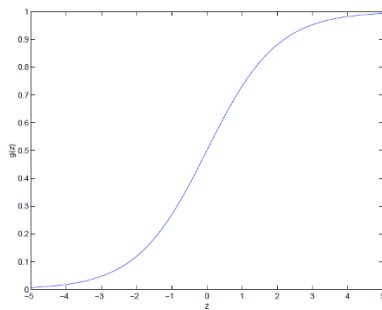
Hypothesis

$$h_{\theta}(x) = g(\theta^T x) = \frac{1}{1 + e^{-\theta^T x}}$$

where

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

$g(z)$ is called the logistic function or the sigmoid function and looks like this:



The derivative the sigmoid function is

$$\begin{aligned}\frac{d}{dx} \sigma(x) &= \frac{d}{dx} \left[\frac{1}{1 + e^{-x}} \right] \\&= \frac{d}{dx} (1 + e^{-x})^{-1} \\&= -(1 + e^{-x})^{-2} (-e^{-x}) \\&= \frac{e^{-x}}{(1 + e^{-x})^2} \\&= \frac{1}{1 + e^{-x}} \cdot \frac{e^{-x}}{1 + e^{-x}} \\&= \frac{1}{1 + e^{-x}} \cdot \frac{(1 + e^{-x}) - 1}{1 + e^{-x}} \\&= \frac{1}{1 + e^{-x}} \cdot \left(\frac{1 + e^{-x}}{1 + e^{-x}} - \frac{1}{1 + e^{-x}} \right) \\&= \frac{1}{1 + e^{-x}} \cdot \left(1 - \frac{1}{1 + e^{-x}} \right) \\&= \sigma(x) \cdot (1 - \sigma(x))\end{aligned}$$

Cost Function J

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

Gradient Descent

Remember that the general form of gradient descent is:

$$\text{Repeat } \left\{ \begin{array}{l} \theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta) \end{array} \right\}$$

We can work out the derivative part using calculus to get:

$$\text{Repeat } \left\{ \begin{array}{l} \theta_j := \theta_j - \frac{\alpha}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x_j^{(i)} \end{array} \right\}$$

How do we obtain this?

In what follows, the superscript *(i)* denotes individual measurements or training examples.

$$\begin{aligned} \frac{\partial J(\theta)}{\partial \theta_j} &= \frac{\partial}{\partial \theta_j} \frac{-1}{m} \sum_{i=1}^m \left[y^{(i)} \left(\log(h_{\theta}(x^{(i)})) \right) + (1 - y^{(i)}) \left(\log(1 - h_{\theta}(x^{(i)})) \right) \right] \\ &\stackrel{\text{linearity}}{=} \frac{-1}{m} \sum_{i=1}^m \left[y^{(i)} \frac{\partial}{\partial \theta_j} \log(h_{\theta}(x^{(i)})) + (1 - y^{(i)}) \frac{\partial}{\partial \theta_j} \left(\log(1 - h_{\theta}(x^{(i)})) \right) \right] \\ &\stackrel{\text{chain rule}}{=} \frac{-1}{m} \sum_{i=1}^m \left[y^{(i)} \frac{\frac{\partial}{\partial \theta_j} (h_{\theta}(x^{(i)}))}{h_{\theta}(x^{(i)})} + (1 - y^{(i)}) \frac{\frac{\partial}{\partial \theta_j} (1 - h_{\theta}(x^{(i)}))}{1 - h_{\theta}(x^{(i)})} \right] \\ &\stackrel{h_{\theta}(x) = \sigma(\theta^T x)}{=} \frac{-1}{m} \sum_{i=1}^m \left[y^{(i)} \frac{\frac{\partial}{\partial \theta_j} \sigma(\theta^T x^{(i)})}{h_{\theta}(x^{(i)})} + (1 - y^{(i)}) \frac{\frac{\partial}{\partial \theta_j} (1 - \sigma(\theta^T x^{(i)}))}{1 - h_{\theta}(x^{(i)})} \right] \end{aligned}$$

$$\stackrel{\sigma'}{=} \frac{-1}{m} \sum_{i=1}^m \left[y^{(i)} \frac{\sigma(\theta^T x^{(i)}) (1 - \sigma(\theta^T x^{(i)})) \frac{\partial}{\partial \theta_j} (\theta^T x^{(i)})}{h_{\theta}(x^{(i)})} - (1 - y^{(i)}) \frac{\sigma(\theta^T x^{(i)}) (1 - \sigma(\theta^T x^{(i)})) \frac{\partial}{\partial \theta_j} (\theta^T x^{(i)})}{1 - h_{\theta}(x^{(i)})} \right]$$

$$\stackrel{\sigma(\theta^T x) = h_{\theta}(x)}{=} \frac{-1}{m} \sum_{i=1}^m \left[y^{(i)} \frac{h_{\theta}(x^{(i)}) (1 - h_{\theta}(x^{(i)})) \frac{\partial}{\partial \theta_j} (\theta^T x^{(i)})}{h_{\theta}(x^{(i)})} - (1 - y^{(i)}) \frac{h_{\theta}(x^{(i)}) (1 - h_{\theta}(x^{(i)})) \frac{\partial}{\partial \theta_j} (\theta^T x^{(i)})}{1 - h_{\theta}(x^{(i)})} \right]$$

$$\frac{\partial}{\partial \theta_j} (\theta^\top x^{(i)}) = x_j^{(i)} \quad \frac{-1}{m} \sum_{i=1}^m \left[y^{(i)} \left(1 - h_\theta \left(x^{(i)} \right) \right) x_j^{(i)} - \left(1 - y^{(i)} \right) h_\theta \left(x^{(i)} \right) x_j^{(i)} \right]$$

$$\stackrel{\text{distribute}}{=} \frac{-1}{m} \sum_{i=1}^m \left[y^{(i)} - y^{(i)} h_\theta \left(x^{(i)} \right) - h_\theta \left(x^{(i)} \right) + y^{(i)} h_\theta \left(x^{(i)} \right) \right] x_j^{(i)}$$

$$\stackrel{\text{cancel}}{=} \frac{-1}{m} \sum_{i=1}^m \left[y^{(i)} - h_\theta \left(x^{(i)} \right) \right] x_j^{(i)}$$

$$= \frac{1}{m} \sum_{i=1}^m \left[h_\theta \left(x^{(i)} \right) - y^{(i)} \right] x_j^{(i)}$$