







Optional Logistic Regression: Gradient

This is an optional reading where I explain gradient descent in more detail. Remember, previously I gave you the gradient update step, but did not explicitly explain what is going on behind the scenes.

The general form of gradient descent is defined as:

For all j. We can work out the derivative part using calculus to get:

$$egin{aligned} Repeat ~\{ \ heta_j := heta_j - rac{lpha}{m} \sum_{i=1}^m (h(x^{(i)}, heta) - y^{(i)}) x_j^{(i)} \ \} \end{aligned}$$

A vectorized implementation is:

$$heta := heta - rac{lpha}{m} X^T (H(X, heta) - Y)$$

Partial derivative of $J(\theta)$

First calculate derivative of sigmoid function (it will be useful while finding partial derivative of $J(\theta)$):

$$h(x)' = \left(rac{1}{1+e^{-x}}
ight)' = rac{-(1+e^{-x})'}{(1+e^{-x})^2} = rac{-1'-(e^{-x})'}{(1+e^{-x})^2} = rac{0-(-x)'(e^{-x})}{(1+e^{-x})^2} = rac{-(-1)(e^{-x})}{(1+e^{-x})^2} = rac{-(-1)(e^{-x})}{(1+e^{$$