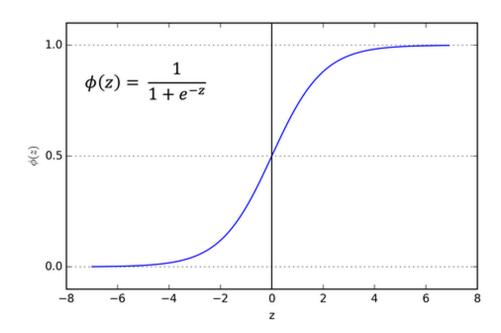
Logistic Regression

20 April 2018 22:12

Sigmoid Function

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



$$\widehat{y} = g\left(\sum w_i \cdot x_i\right) = g(z)$$

Derivative of sigmoid

$$\overline{g'(z) = g(z) *1(-g(z))}$$

Logistic Regression

$$P(Y|X) = \hat{y}^y (1 - \hat{y})^{(1-y)}$$

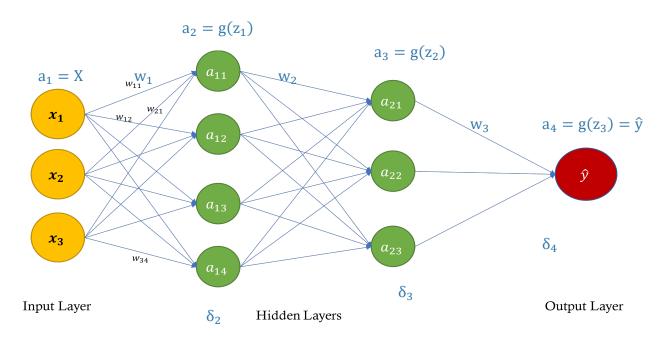
 $P(Y|X) = \hat{y}^y (1 - \hat{y})^{(1-y)}$ Probability of y given x

Cost Function for Logistic Regression

$$C = -\Sigma y \log(\hat{y}) + (1 - y)\log(1 - \hat{y})$$

$$\frac{\mathrm{dC}}{\mathrm{dw}} = (\hat{y} - y)x$$

Multilayer Neural Network and Back Propagation



Multilayer Perceptron

Forward Propagation

$$a_1 = x_i$$

$$z_1 = \sum w_{1*} x_i$$

$$a_2 = g(z_1)$$

$$z_2 = \sum w_2 * a_2$$

$$a_3 = g(z_2)$$

$$z_3 = \sum w_3 * a_3$$

$$a_4 = g(z_3) = \hat{y}$$

Backward Propagation

$$\delta_4 = (\hat{y} - y)$$

$$\frac{\partial c}{\partial \omega_3} = a_3 \delta_4$$

$$\delta_3 = (\mathbf{w}_3 \delta_4) * g'(z_3)$$

$$\frac{\partial c}{\partial \omega_2} = a_2 \delta_3$$

$$\delta_2 = (\mathbf{w}_2 \delta_3) * g'(z_2)$$

$$\frac{\partial c}{\partial \omega_1} = a_1 \delta_2$$

we know that

$$g'(z) = g(z) *1(-g(z))$$

And Finally

$$w_i = w_i - \lambda \frac{\partial C}{\partial w_i}$$

where λ is learning Rate.