

Sep 24, 2024

x_1	y_1	\hat{y}_1
\vdots	\vdots	\vdots
x_N	y_N	\hat{y}_N
ground truth		prediction

goal: \hat{y}_i the same as y_i

$$\hat{y}_i = f(x_i)$$

linear regression $\hat{y}_i = w^T x_i$

logistic regression $\hat{y}_i = \sigma(w^T x_i)$

loss function

linear regression $J(w) = \sum_{i=1}^N (y_i - \hat{y}_i)^2$ Squared loss

logistic regression

$$J(w) = \sum_{i=1}^N -y_i \log \hat{y}_i - (1-y_i) \log (1-\hat{y}_i)$$

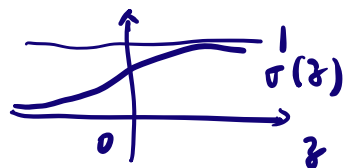
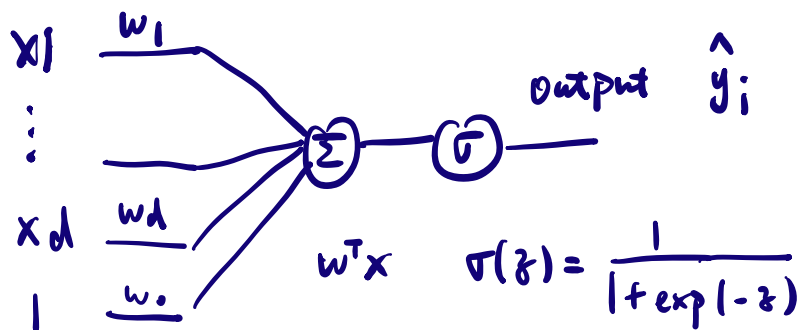
Cross entropy / log loss

$$J(w) = \sum_{i=1}^N |y_i - \hat{y}_i| + \frac{1}{2} \lambda w^T w$$

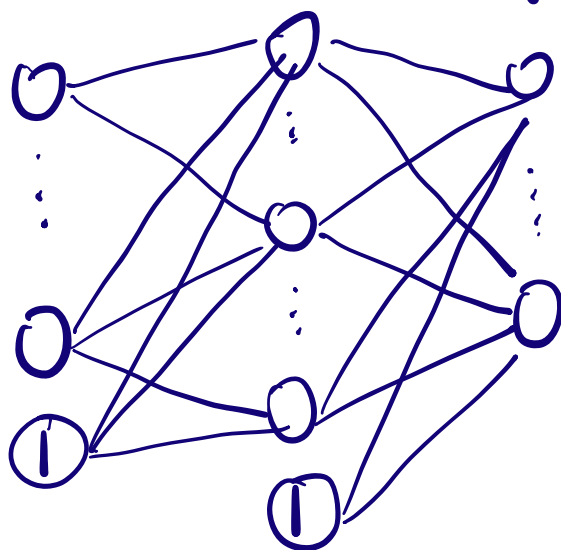
Gradient Descent

$$\min J(w)$$

$$w_k = w_{k-1} - \eta \frac{\partial J(w)}{\partial w}$$



$$\frac{\partial \sigma(z)}{\partial z} = \sigma(1 - \sigma)$$



input x

hidden

output

$$h = w_h^T x$$

$$h = \sigma(w_h^T x)$$

$$o = w_o^T h = \underbrace{w_o^T (w_h^T x)}_{\text{linear function}}$$

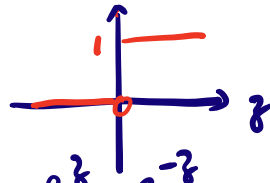
$$o = \sigma(w_o^T h)$$

non-linear activation function

Sigmoid $\sigma(z)$

$$\text{relu}(z) = \max(0, z)$$

$$\frac{\partial \text{relu}(z)}{\partial z}$$



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

