

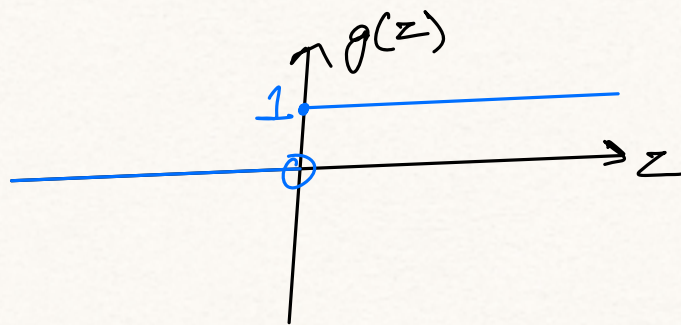
# Classification

## Perceptron Algorithm

$$x^{(i)} \in \mathbb{R}^{d+1} \quad y^{(i)} \in \{0, 1\}$$

$$h_{\theta}(x) = g(\theta^T x)$$

$$g(z) = \begin{cases} 1 & ; z \geq 0 \\ 0 & ; z < 0 \end{cases}$$

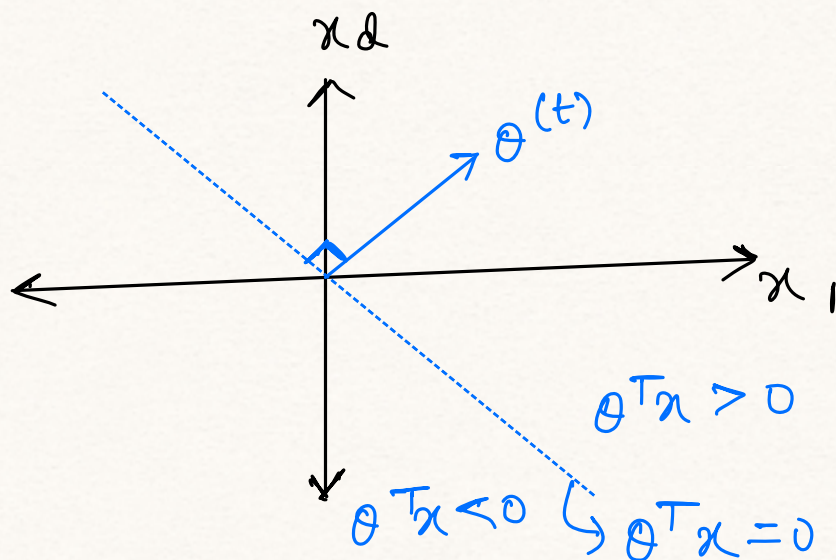


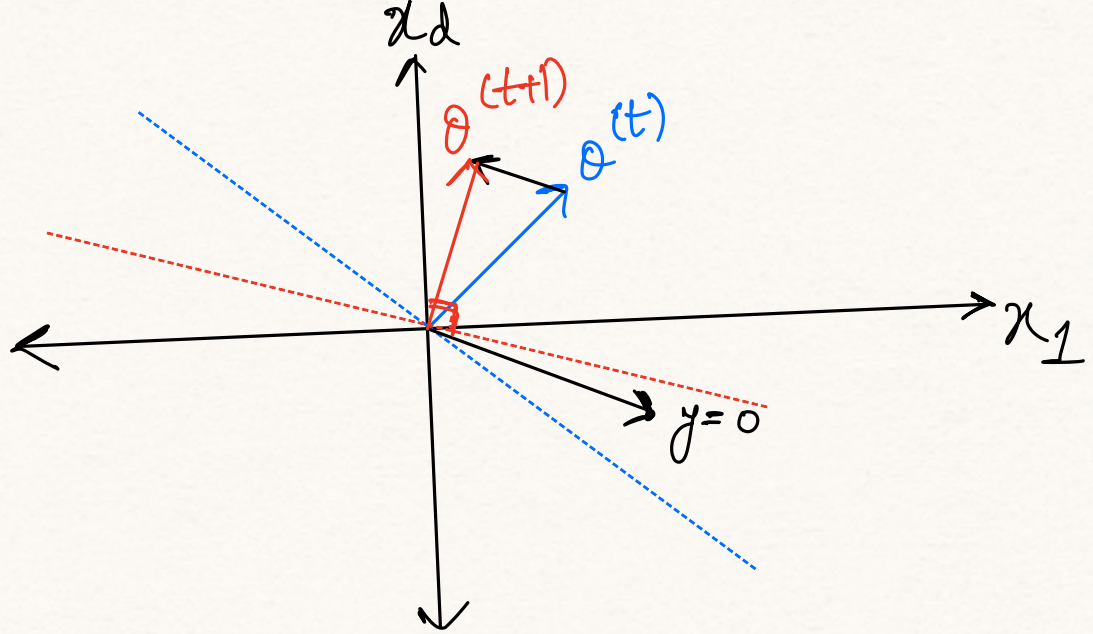
Algo:

$$\vec{\theta} := \text{Init. } (\vec{0})$$

For  $i$  in  $1, 2, \dots$

$$\theta := \theta + \alpha (y^{(i)} - h_{\theta}(x^{(i)})) \cdot x^{(i)}$$





## Logistic Regression

$$x^{(i)} \in \mathbb{R}^d ; y^{(i)} \in \{0, 1\}$$

$y^{(i)} = 1$  : positive example

$y^{(i)} = 0$  : negative example

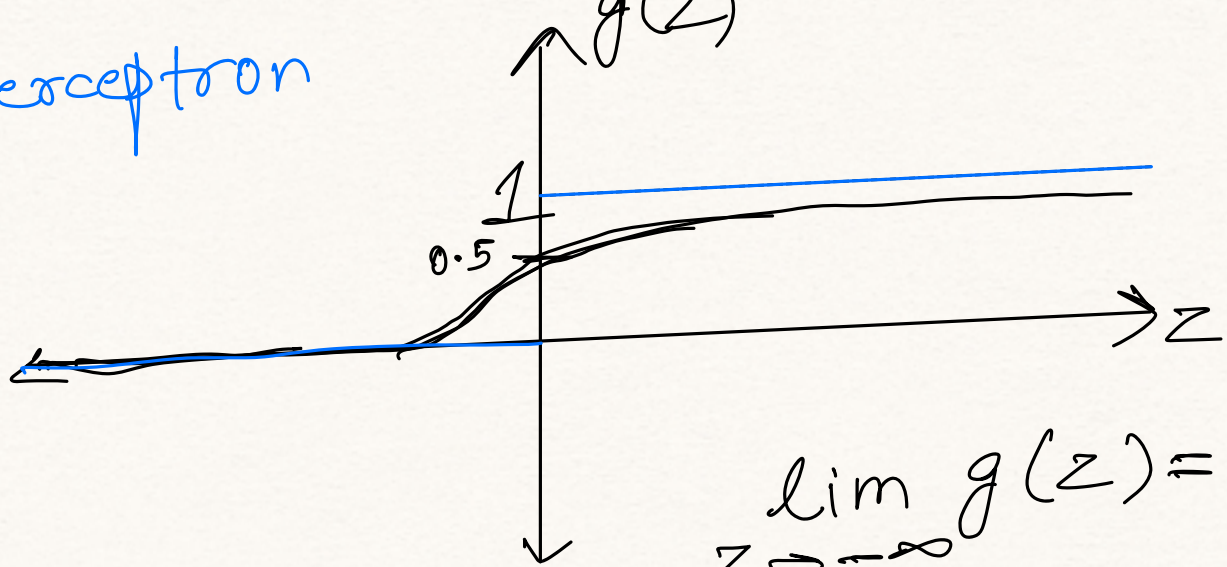
$$h_{\theta}(x) = g(\theta^T x)$$

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

$$g(z)$$



• → perceptron



$$\lim_{z \rightarrow -\infty} g(z) = 0$$

$$\lim_{z \rightarrow +\infty} g(z) = 1$$

$$P(y^{(i)} = 1 | x^{(i)}; \theta) = h_{\theta}(x)$$

$$P(y^{(i)} = 0 | x^{(i)}; \theta) = 1 - h_{\theta}(x)$$

→ probability machine rather than classifier. outputs probability that example is positive or negative. It is on us what we take the threshold probability to be. (Generally taken to be 0.5)

$$p(y|x; \theta) = [h_\theta(x)]^y \times [1 - h_\theta(x)]^{1-y}$$

$$L(\theta) = \prod_{i=1}^n p(y^{(i)} | x^{(i)}; \theta)$$

[I.I.D]

$$\log L(\theta) = \ell(\theta) = \sum_{i=1}^n y^{(i)} \log h_\theta(x^{(i)}) + (1 - y^{(i)}) \log (1 - h_\theta(x^{(i)}))$$

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

$$\begin{aligned} g'(z) &= \frac{-1}{(1 + e^{-z})^2} \times -e^{-z} = \left( \frac{1}{1 + e^{-z}} \right) \left( \frac{e^{-z}}{1 + e^{-z}} \right) \\ &= \left( \frac{1}{1 + e^{-z}} \right) \left( \frac{1 + e^{-z} - 1}{1 + e^{-z}} \right) \\ &= \left( \frac{1}{1 + e^{-z}} \right) \left( 1 - \frac{1}{1 + e^{-z}} \right) \\ &= g(z) (1 - g(z)) \end{aligned}$$



$$l(\theta) = y \log(g(\theta^T x)) + (1-y) \log(1-g(\theta^T x))$$

$$\nabla_{\theta} l(\theta) = y \cdot \frac{1}{g(\theta^T x)} g'(\theta^T x) \cdot x + (1-y) \cdot \frac{1}{1-g(\theta^T x)} \cdot (-1) g'(\theta^T x) \cdot x$$

$$= y \cdot (1-g(\theta^T x)) \cdot x - (1-y) g(\theta^T x) x$$

$$= [y - g(\theta^T x)] x$$

$$\nabla_{\theta} l(\theta) = [y - h_{\theta}(x)] x$$

$$\theta := \theta + \alpha [y - h_{\theta}(x)] x$$

↳ same as perceptron & G.D.

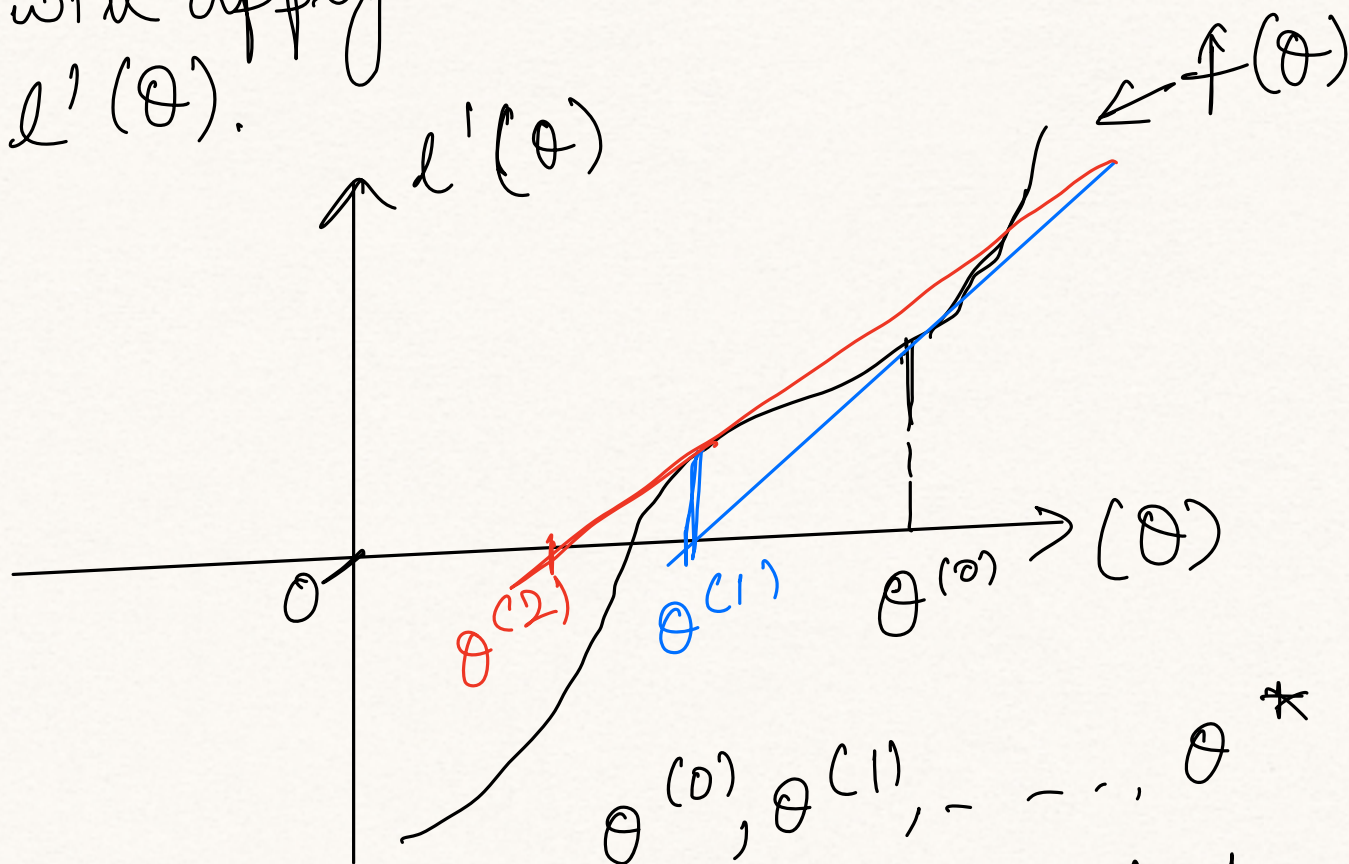
## Newton's Method

(Alternative to G.D)

→ Root finding method.

Finds  $x$  for which  $f(x) = 0$

We will apply Newton's method on  $l'(\theta)$ .



converges way faster than G.D.

linearly approximate & then jump to that point.

$$\theta^{(t+1)} = \theta^{(t)} - \frac{f(\theta^{(t)})}{f'(\theta^{(t)})}$$



$$\theta^{(t+1)} = \theta^{(t)} - \frac{l'(\theta^{(t)})}{l''(\theta^{(t)})}$$

Scalar  
 $\theta$ .

Vector  $\theta$  :

$$\theta^{(t+1)} = \theta^{(t)} - \alpha \cdot H^{-1} \nabla_{\theta} l(\theta^{(t)})$$

$H$  = Hessian of loss  $l(\theta)$

Newton's method  $\rightarrow O(d^3)$

Gr.D  $\rightarrow O(d)$