

Makine Öğrenmesi

2020

Perceptron Gradyenli Alçalma

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GRADYENLİ ALÇALMA

- Gradyenli (Dereceli) Alçalma ✓
- Çok Etiketli Sınıflandırma / Regresyon ✓
- Lojistik vs Perceptron – Neden Perceptron ? ✓



Perceptron

Gradyenli (Dereceli) Alçalma

Genelleştirilmiş Lineer Modeller (GLM)

$$w := w - \alpha \frac{\partial J(w, b)}{\partial w} = w + \alpha \frac{1}{n} \sum_{i=1}^n x_{(i)} (y^{(i)} - a^{(i)}), \quad \frac{\partial J(w, b)}{\partial w} = dw = - \frac{1}{n} \sum_{i=1}^n x_{(i)} (y^{(i)} - a^{(i)}) = \frac{1}{n} \sum_{i=1}^n -dw_{(i)}$$

$$b := b - \alpha \frac{\partial J(w, b)}{\partial b} = b + \alpha \frac{1}{n} \sum_{i=1}^n (y^{(i)} - a^{(i)}), \quad \frac{\partial J(w, b)}{\partial b} = db = - \frac{1}{n} \sum_{i=1}^n (y^{(i)} - a^{(i)}) = \frac{1}{n} \sum_{i=1}^n -db_{(i)}$$

$$dw_{(i)} = -x_{(i)} (y^{(i)} - a^{(i)}) \longrightarrow [n \times 1] \text{ kolon vektörü}$$

$$dw = -\frac{1}{n} X(y-a) = -\frac{1}{n} X^T (y-a)$$

$$db_{(i)} = -(y^{(i)} - a^{(i)}) \longrightarrow [1 \times 1] \text{ skaler}$$

$$db = -\frac{1}{n} \text{np.sum}(y-a)$$

$$dw_{(i)} = x_{(i)} (a^{(i)} - y^{(i)}) = x_{(i)} (h_w(x^{(i)}) - y^{(i)})$$

$$w := w - \alpha dw = w + \alpha \frac{1}{n} X(y-a) = w + \alpha \frac{1}{n} X^T (y-a)$$

$$db_{(i)} = a^{(i)} - y^{(i)} = h_w(x^{(i)}) - y^{(i)}$$

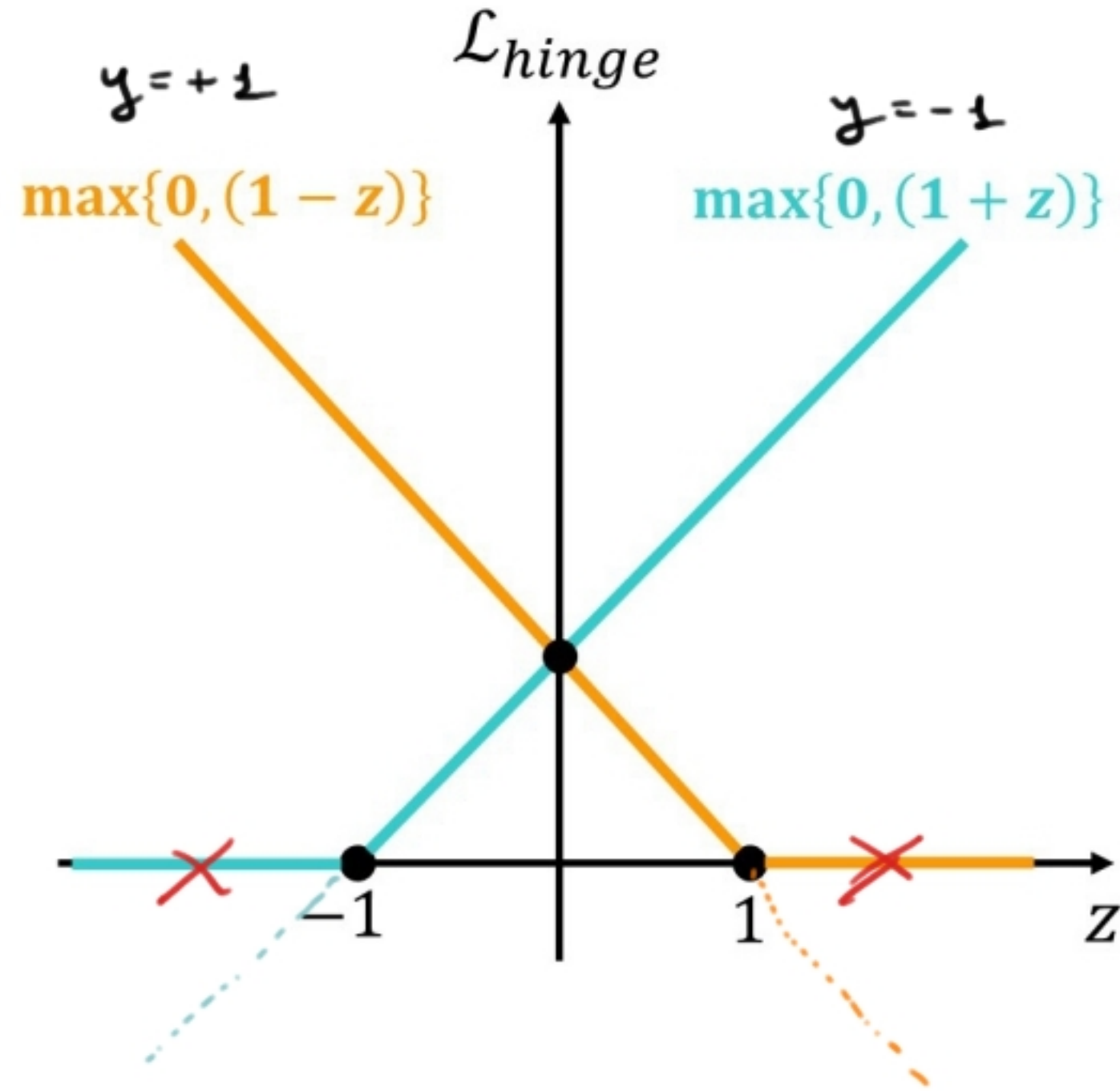
$$b := b - \alpha db = b + \alpha \frac{1}{n} \text{np.sum}(y-a)$$

$$a = \hat{y} = g(z) = h_w(x) = h(x)$$

$$z = Xw + b \rightarrow [n \times 1], \quad w^T x + b \rightarrow [1 \times n]$$

Gradyenli (Dereceli) Alçalma

-1 ve 1 durumu için : Tek örnekli $\rightarrow X \rightarrow [1 \times n] \rightarrow x \rightarrow [n \times 1]$



$$L(w, b) = \left(\frac{1+y}{2}\right)(1-z) + \left(\frac{1-y}{2}\right)(1+z)$$

$$= \frac{1+y}{2} - z \frac{1+y}{2} + \frac{1-y}{2} + z \frac{1-y}{2}$$

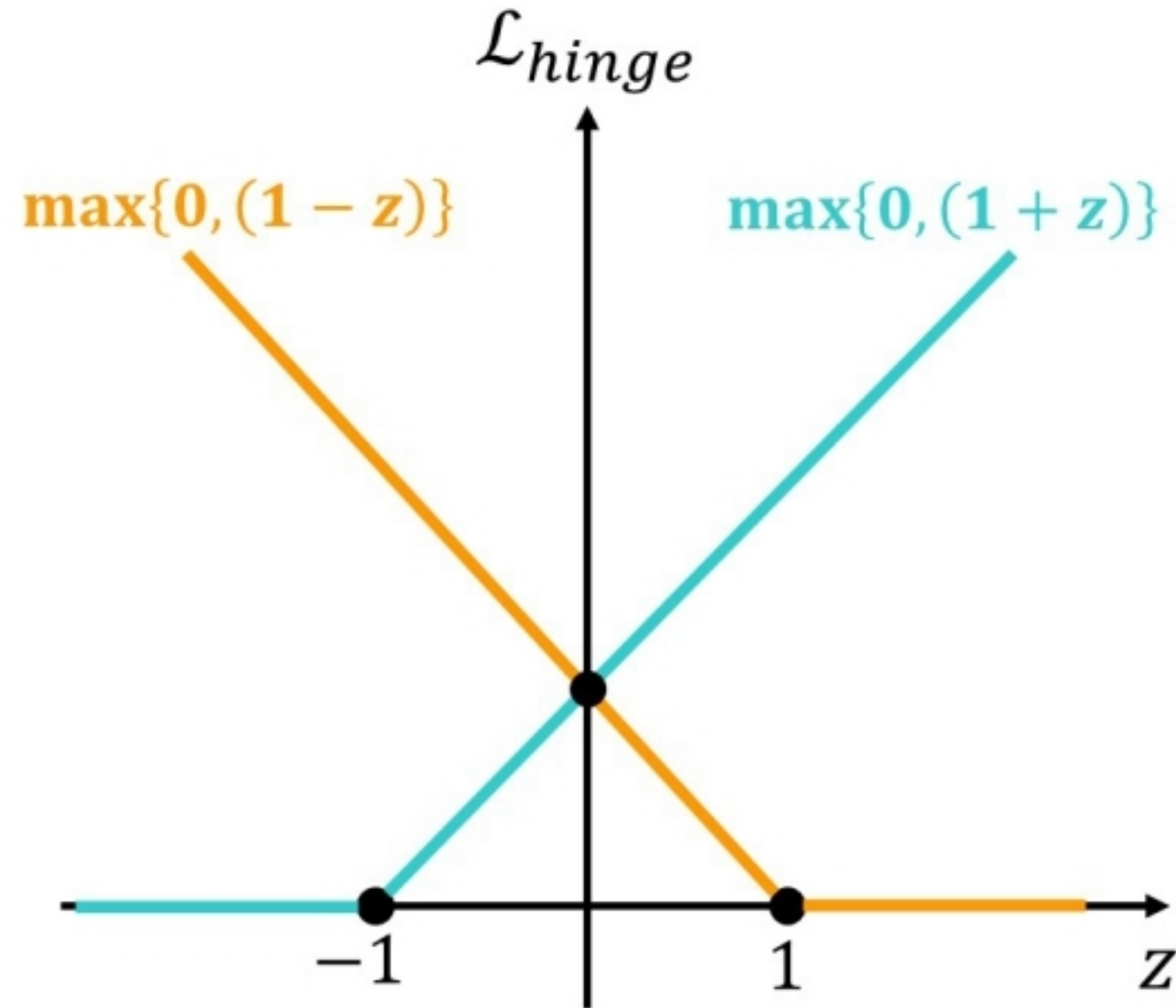
$$= 1 + z(-y) = 1 - yz = 1 - y(\omega^T x + b)$$

$$\frac{\partial L(w, b)}{\partial w} = -y x$$

$$\frac{\partial L(w, b)}{\partial b} = -y$$

Gradyenli (Dereceli) Alçalma

-I ve I durumu için : Tek örnekli $\rightarrow X \rightarrow [1 \times n] \rightarrow x \rightarrow [n \times 1]$



$$\hat{y} = a$$

$$\frac{\partial L(w, b)}{\partial w} = -y x, \quad \frac{\partial L(w, b)}{\partial b} = -y$$

Eğer $y \neq a$ ise;

$$w := w - \alpha \frac{\partial L(w, b)}{\partial w} = w + \alpha y x \begin{cases} y = -1 \rightarrow w := w - \alpha x \\ y = +1 \rightarrow w := w + \alpha x \end{cases}$$

$$b := b - \alpha \frac{\partial L(w, b)}{\partial b} = b + \alpha y \begin{cases} y = -1 \rightarrow b := b - \alpha \\ y = +1 \rightarrow b := b + \alpha \end{cases}$$

Gradyenli (Dereceli) Alçalma

-I ve I durumu için : Çok örnekli $\rightarrow X \rightarrow [m \times n] \rightarrow x \rightarrow [n \times m]$

$$w := w - \alpha \frac{\partial J(w, b)}{\partial w}$$

$$\frac{\partial J(w, b)}{\partial w} = dw = -\frac{1}{m} \sum_{i=1}^m x_{(i)} (y^{(i)} - a^{(i)})$$

$$w := w + \alpha \frac{1}{m} \sum_{i=1}^m x_{(i)} (y^{(i)} - a^{(i)})$$

$$b := b - \alpha \frac{\partial J(w, b)}{\partial b}$$

$$\frac{\partial J(w, b)}{\partial b} = db = -\frac{1}{m} \sum_{i=1}^m (y^{(i)} - a^{(i)})$$

$$b := b + \alpha \frac{1}{m} \sum_{i=1}^m (y^{(i)} - a^{(i)})$$

$dw_{(i)} = -x_{(i)} (y^{(i)} - a^{(i)}) \rightarrow [n \times 1]$ kolon vektörü

$db_{(i)} = -(y^{(i)} - a^{(i)}) \rightarrow$ skaler

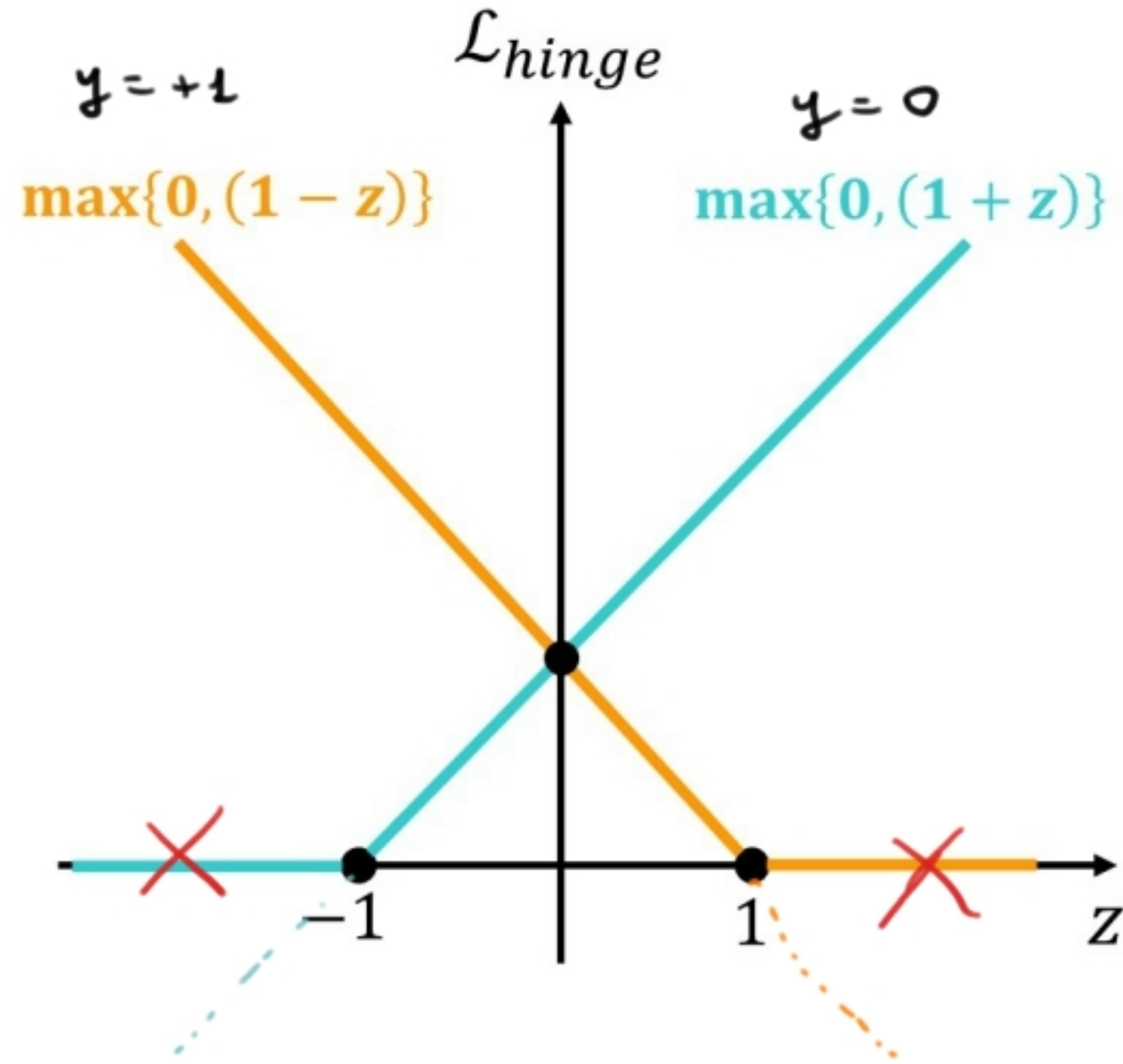
$$w := w - \alpha dw_{(i)} = w + \alpha x_{(i)} (y^{(i)} - a^{(i)})$$

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$y^{(i)} = a^{(i)} \rightarrow w := w$
 $y^{(i)} = -1, a^{(i)} = +1 \rightarrow w := w - \alpha 2x_{(i)}$
 $y^{(i)} = +1, a^{(i)} = -1 \rightarrow w := w + \alpha 2x_{(i)}$

Gradyenli (Dereceli) Alçalma

0 ve 1 durumu için : Tek örnekli $\rightarrow X \rightarrow [1 \times n] \rightarrow x \rightarrow [n \times 1]$



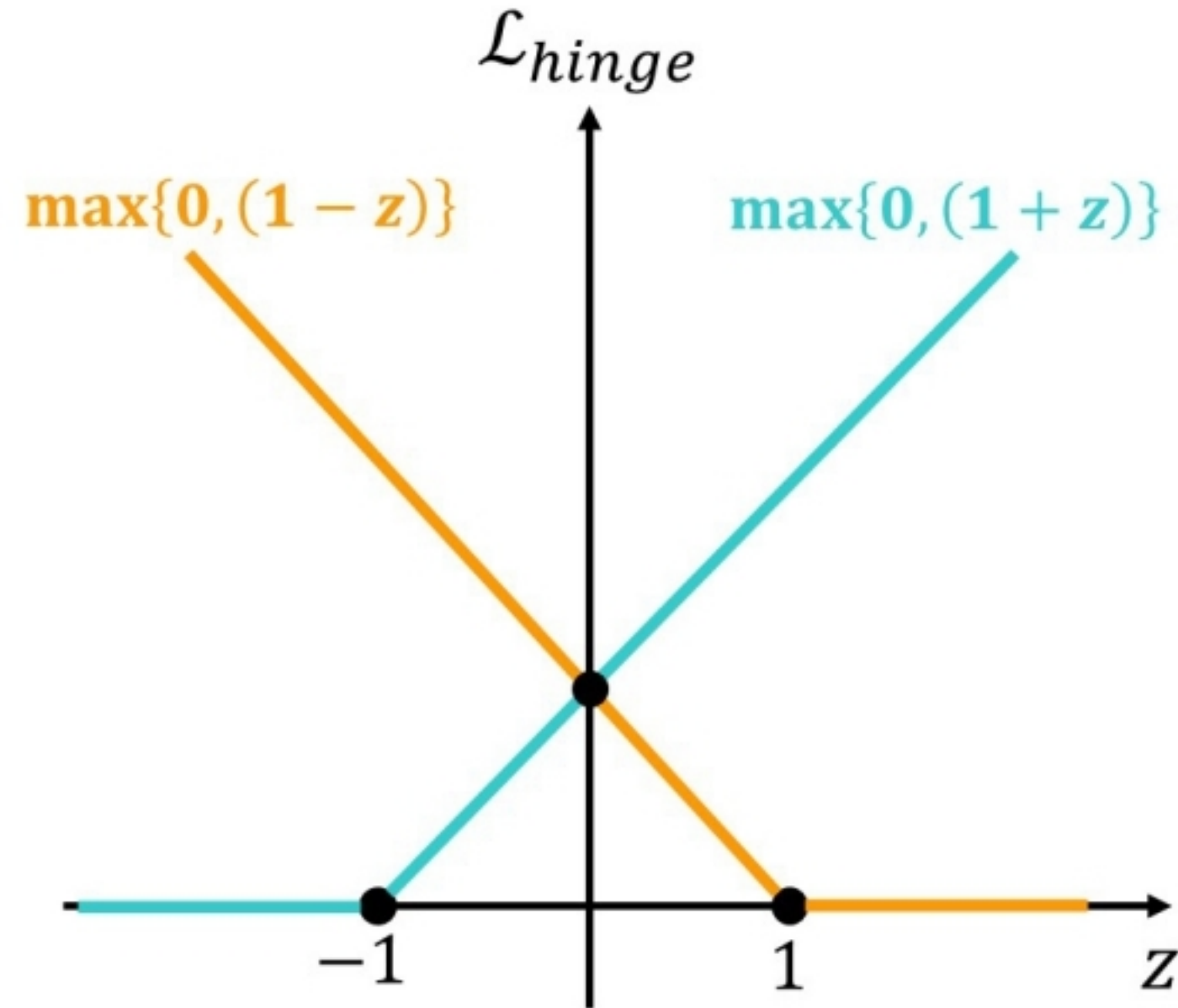
$$\begin{aligned} L(w, b) &= y(1-z) + (1-y)(1+z) \\ &= \cancel{y} - yz + 1 + z - \cancel{y} - yz = 1 + z - 2yz = 1 + z(1-2y) \\ &= 1 + (w^T x + b)(1-2y) \end{aligned}$$

$$\frac{\partial L(w, b)}{\partial w} = x(1-2y)$$

$$\frac{\partial L(w, b)}{\partial b} = 1-2y$$

Gradyenli (Dereceli) Alçalma

0 ve 1 durumu için : Tek örnekli $\rightarrow X \rightarrow [1 \times n] \rightarrow x \rightarrow [n \times 1]$



$$\hat{y} = a$$

Eğer $y \neq a$ ise;

$$w := w - \alpha x(1 - 2y) \begin{cases} y = 0 \rightarrow w := w - \alpha x \\ y = 1 \rightarrow w := w + \alpha x \end{cases}$$

$$b := b - \alpha(1 - 2y) \begin{cases} y = 0 \rightarrow b := b - \alpha \\ y = 1 \rightarrow b := b + \alpha \end{cases}$$

Gradyenli (Dereceli) Alçalma

0 ve 1 durumu için : Çok örnekli $\rightarrow X \rightarrow [m \times n] \rightarrow x \rightarrow [n \times m]$

$$w := w - \alpha \frac{\partial J(w, b)}{\partial w}$$

$$\frac{\partial J(w, b)}{\partial w} = dw = -\frac{1}{m} \sum_{i=1}^m x_{(i)} (y^{(i)} - a^{(i)})$$

$$w := w + \alpha \frac{1}{m} \sum_{i=1}^m x_{(i)} (y^{(i)} - a^{(i)})$$

$$b := b - \alpha \frac{\partial J(w, b)}{\partial b}$$

$$\frac{\partial J(w, b)}{\partial b} = db = -\frac{1}{m} \sum_{i=1}^m (y^{(i)} - a^{(i)})$$

$$b := b + \alpha \frac{1}{m} \sum_{i=1}^m (y^{(i)} - a^{(i)})$$

$dw_{(i)} = -x_{(i)} (y^{(i)} - a^{(i)}) \rightarrow [n \times 1]$ kolon vektörü

$db_{(i)} = -(y^{(i)} - a^{(i)}) \rightarrow$ skaler

$$w := w - \alpha dw_{(i)} = w + \alpha x_{(i)} (y^{(i)} - a^{(i)})$$

The diagram shows three cases branching from the general update rule:

- Case 1: $y^{(i)} = a^{(i)} \rightarrow w := w$
- Case 2: $y^{(i)} = 0, a^{(i)} = 1 \rightarrow w := w - \alpha x_{(i)}$
- Case 3: $y^{(i)} = 1, a^{(i)} = 0 \rightarrow w := w + \alpha x_{(i)}$

Gradyenli (Dereceli) Alçalma

Kodlama için $\{0, 1\}$ ve $\{-1, 1\}$ farketmeksizin genel prensip :

$w := np.zeros(n, 1), b = np.zeros(1)$

for epoch in epochs:

$$dw := -\frac{1}{m} x(y-a) = -\frac{1}{m} X^T(y-a)$$

$$db := -\frac{1}{m} np.sum(y-a)$$

$$w := w - \alpha dw$$

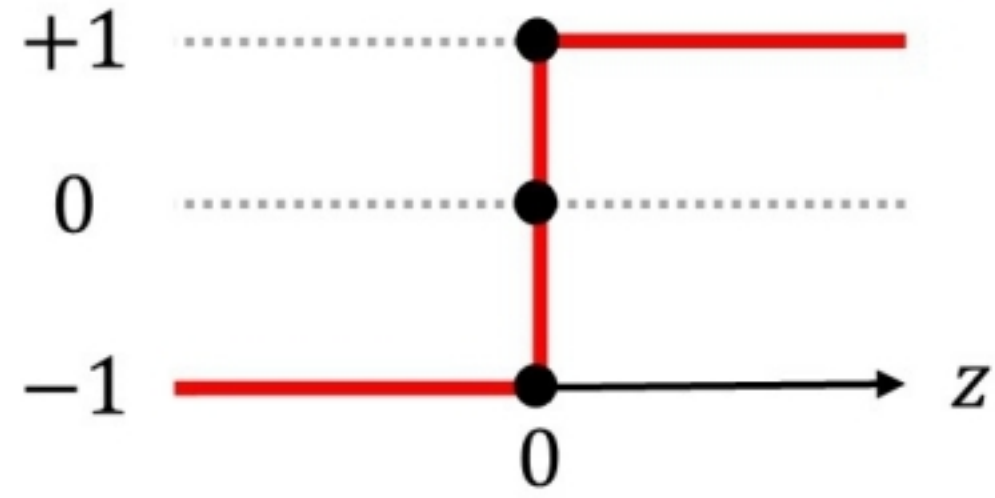
$$b := b - \alpha db$$

GLM

(Genelleştirilmiş Linear Modeller)

(Generalized linear models)

Gradyenli (Dereceli) Alçalma



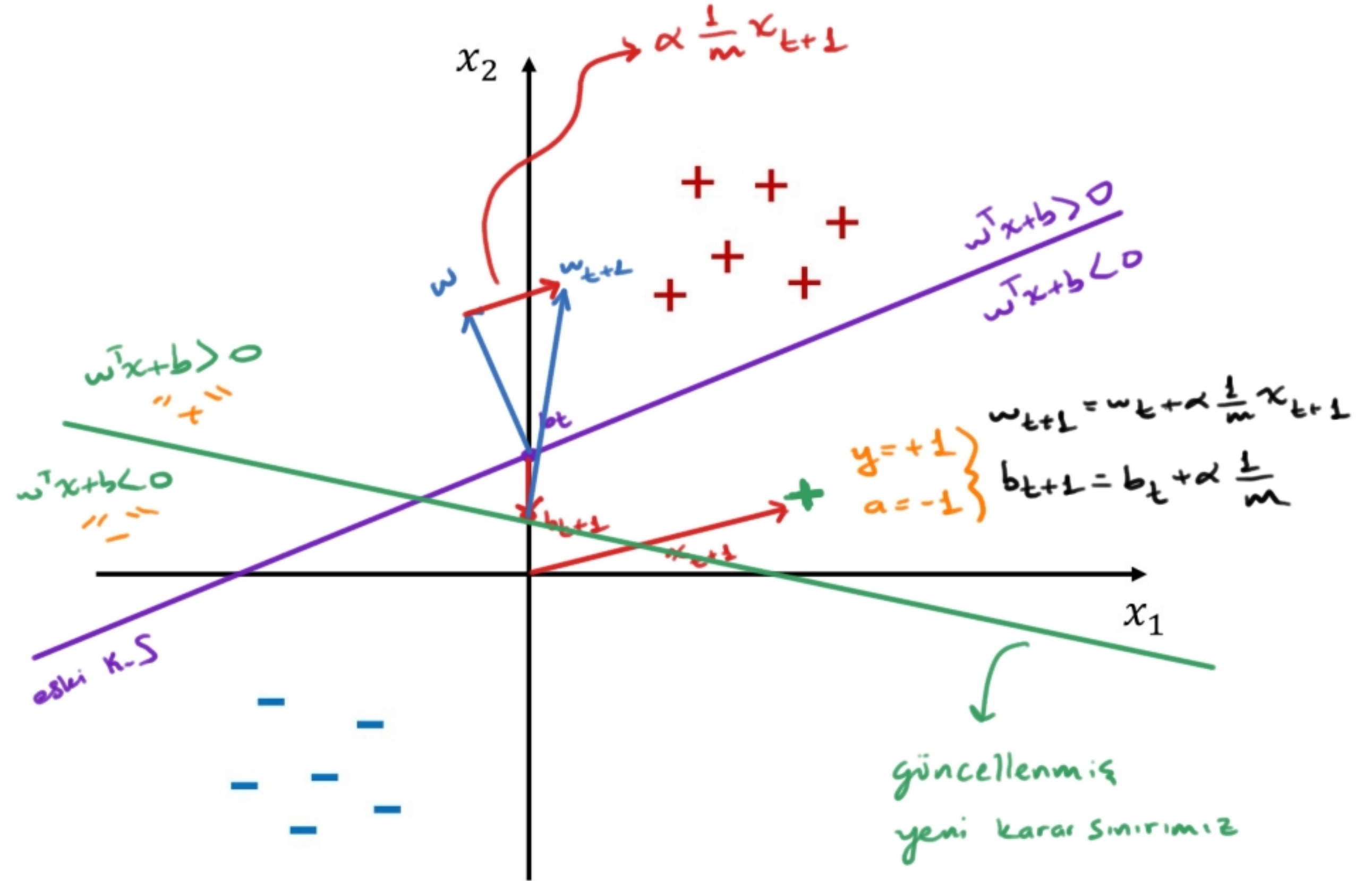
$$s(z) = \begin{cases} +1, & z \geq 0 \\ -1, & z < 0 \end{cases}$$

$$h_w(x) = \hat{y} = a = s(w^T x + b) \sim s(xw + b)$$

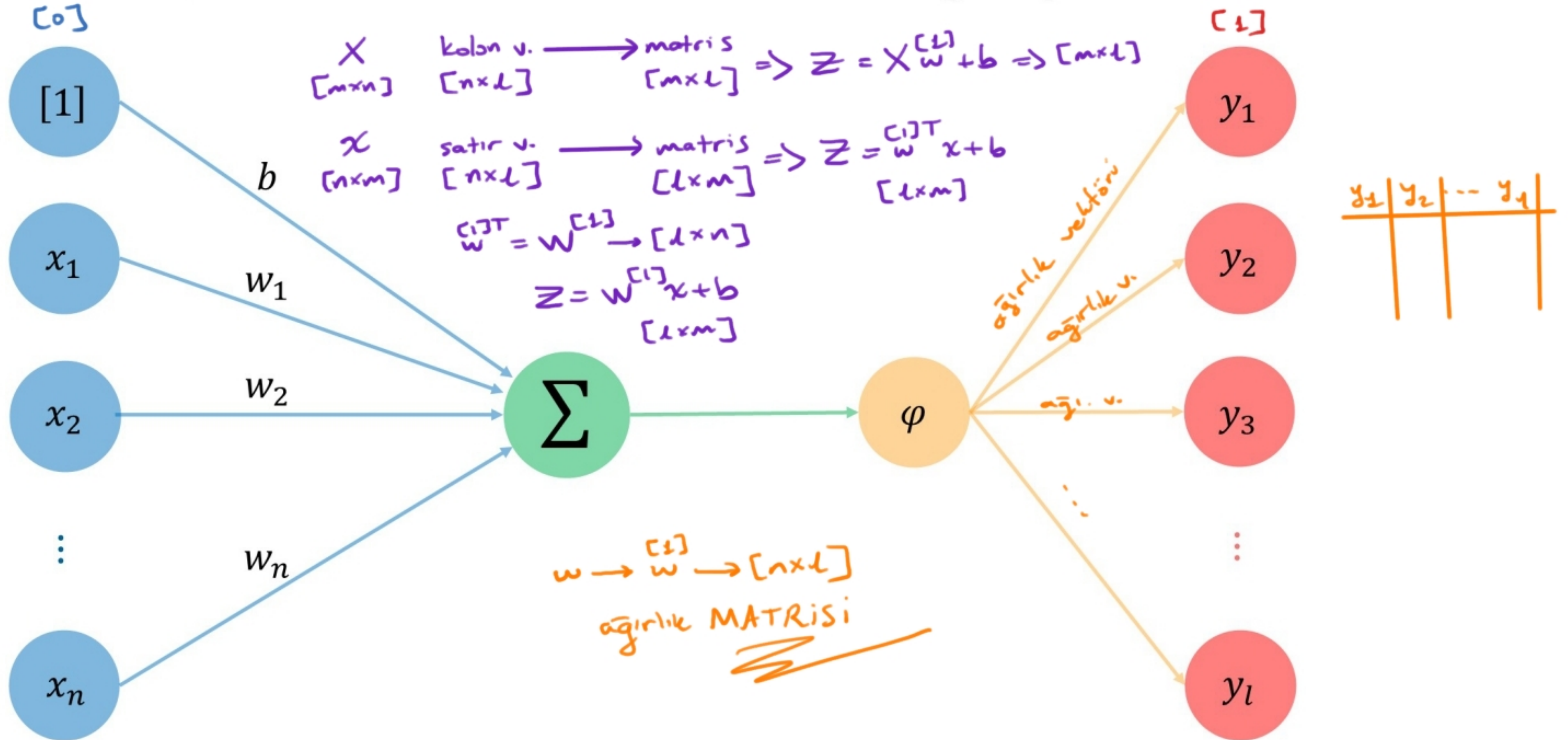
$$dw = -\frac{1}{m} x(y - a), \quad db = -\frac{1}{m} n p \cdot \text{sum}(y - a)$$

$$w := w - \alpha dw$$

$$b := b - \alpha db$$

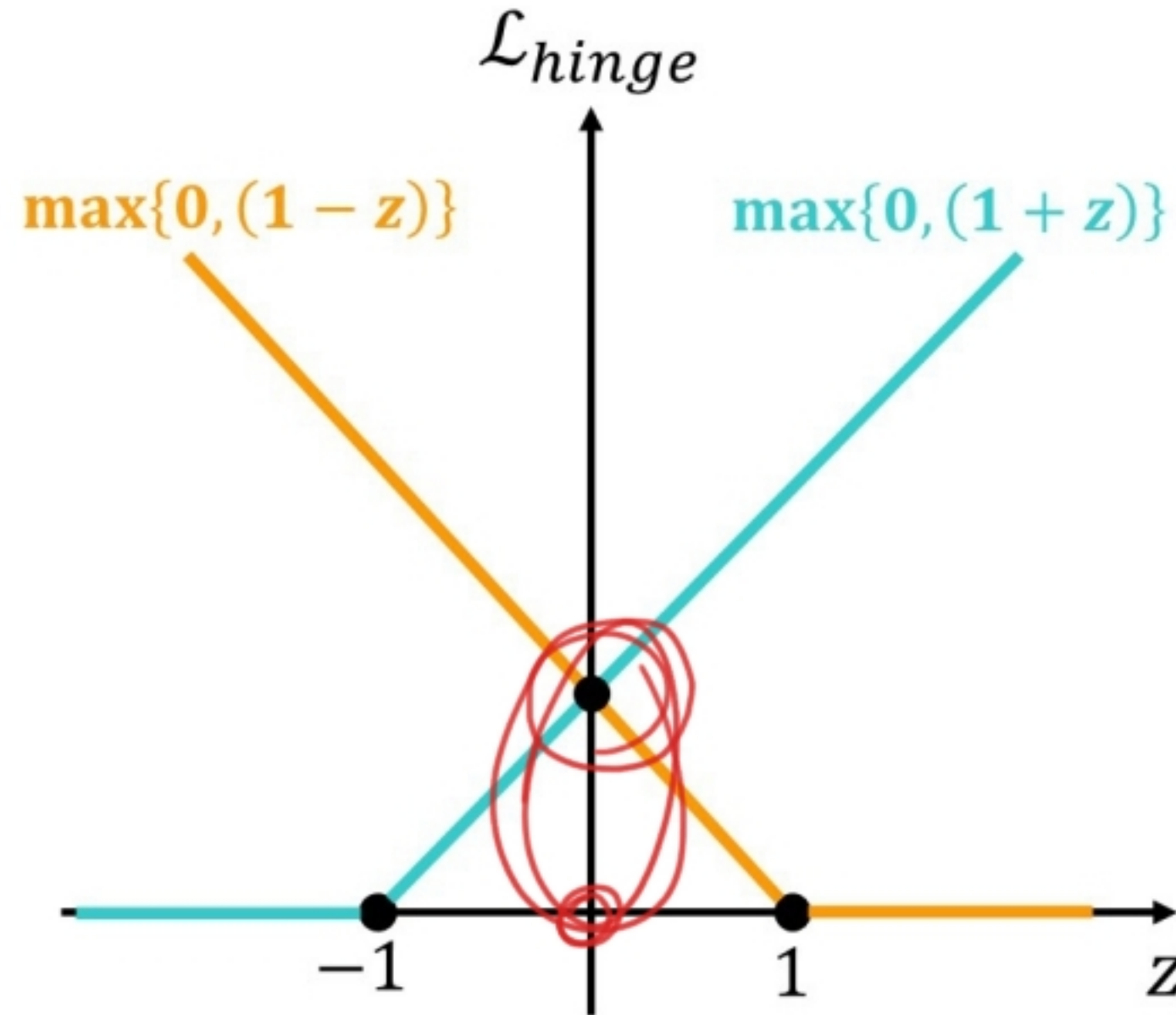


Çok Etiketli Sınıflandırma / Regresyon



Lojistik vs Perceptron - Neden Perceptron ?

Menteşe Kaybı (Hinge Loss)



lojistik
perceptron \rightarrow
 $w := w - \alpha dw$
 $b := b - \alpha db$

$$z = Xw + b \text{ \& } z = w^T x + b$$

$$\text{Sigmoid} = g(z) = \frac{1}{1 + e^{-z}} = a = h(x)$$

$$w := w + \alpha \frac{1}{n} x^T (y - a)$$

$$b := b + \alpha \frac{1}{n} \text{np.sum}(y - a)$$

Lojistik daha iyi $\checkmark \rightarrow$ YSA (ANN) \Rightarrow Son Katman: "sigmoid"

Perceptron \rightarrow DVM (Destek Vektör Makineleri) \sim SVM

$$w^T x + b > 0 \rightarrow w^T x + b > +1 \rightarrow \text{pozitif marjin sınırı}$$

$$w^T x + b < 0 \rightarrow w^T x + b < -1 \rightarrow \text{negatif marjin sınırı}$$

