

$x \in \mathbb{R}^d$
 $y \in [C]$
 $f: \mathbb{R}^d \rightarrow [C]$
 $C = \{1, 2, \dots, C\}$
Step 1
 $\{\pm 1\}$
 $\{1, 2\}$

$$f(x) = \begin{cases} 1 & \text{if } w_1^T x > w_2^T x \\ 2 & \text{otherwise} \end{cases}$$

$$f(x) = \begin{cases} 1 & \text{if } w_1^T x > w_2^T x \\ 2 & \text{if } w_1^T x < w_2^T x \\ k & \text{if } w_k^T x > w_j^T x \text{ for } k \neq j \end{cases}$$

w_1, w_2
 $w_1^T x$
 $w_2^T x$
score

Step 2

$$f(x) = \begin{cases} 1 & \text{if } w_1^T x > w_2^T x \\ 2 & \text{if } w_2^T x > w_1^T x \\ k & \text{if } w_k^T x > w_j^T x \text{ for } k \neq j \end{cases}$$

Step 3

$$\mathcal{F} = \{f(x) = \arg \max_k w_k^T x : w_k \in \mathbb{R}^d\} = \{f(x) = \arg \max_k (Wx)_k : W \in \mathbb{R}^{C \times d}\}.$$

w_1, w_2

$$P(y = 1 | x; w) = \sigma(w^T x) = \frac{1}{1 + e^{-w^T x}} = \frac{e^{w_1^T x}}{e^{w_1^T x} + e^{w_2^T x}} \propto e^{w_1^T x}.$$

$$P(y = 2 | x; w) \propto e^{w_2^T x}.$$

w_k

$$P(Y = k | x; W) = \frac{\exp(w_k^T x)}{\sum_{j \in [C]} \exp(w_j^T x)} \propto \exp(w_k^T x).$$

$w_k^T x \mapsto$

$P(y =$

$k |$

$x; w)$

softmax function

y_1, \dots, y_n
 x_1, \dots, x_n

$$P(W) = \prod_{i=1}^n P(y_i | x_i; W) = \prod_{i=1}^n \frac{\exp(w_{y_i}^T x_i)}{\sum_{k \in [C]} \exp(w_k^T x_i)}.$$

negative
 multi-class
 logistic
 loss

$$F(W) = \sum_{i=1}^n \log \left(\frac{\exp(w_{y_i}^T x_i)}{\sum_{k \in [C]} \exp(w_k^T x_i)} \right) = \sum_{i=1}^n \log \left(1 + \sum_{k \neq y_i} \exp((w_k - w_{y_i})^T x_i) \right).$$

0-
 1-
 mis-
 clas-
 si-
 fi-
 ca-