

# LS FOR CLASSIFICATION (CH. 4.1.3)

(4)

CLASS  $C_k$ :  $y_k(x) = \underline{w}_k^T \underline{x} + w_{k0}$   $k=1 \dots K$

WHERE

$y_k = \underline{\tilde{w}}_k^T \underline{\tilde{x}}$  IS THE LARGEST

$y(x) = \underline{\tilde{w}}^T \underline{\tilde{x}}$

$(1, \underline{x}^T)^T$

$\underline{\tilde{w}} = [\dots \underline{\tilde{w}}_k \dots]$

$(w_{k0}, \underline{w}_k^T)^T$

TRAINING SET:  $\{\underline{x}_n, t_n\}$   $n=1 \dots N$

K-CLASS CODING

(ERROR: EVERY  $k$  EVERY  $n$ )

$\underline{T} = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix}$   $\underline{\tilde{X}} = \begin{bmatrix} \underline{\tilde{x}}_1^T \\ \vdots \\ \underline{\tilde{x}}_N^T \end{bmatrix}$

$E_D(\underline{\tilde{w}}) = \frac{1}{2} \text{Tr} \{ (\underline{\tilde{X}} \underline{\tilde{w}} - \underline{T})^T (\underline{\tilde{X}} \underline{\tilde{w}} - \underline{T}) \}$   $\frac{\partial}{\partial \underline{\tilde{w}}} = 0 !$

$\underline{\tilde{w}} = (\underline{\tilde{X}}^T \underline{\tilde{X}})^{-1} \underline{\tilde{X}}^T \underline{T} = \underline{\tilde{X}}^+ \underline{T}$

$y(x) = \underline{\tilde{w}}^T \underline{\tilde{x}} = \underline{T}^T (\underline{\tilde{X}}^+)^T \underline{\tilde{x}}$

DISCRIMINANT FUNCTION

~~$\frac{\partial}{\partial \underline{\tilde{w}}} = 0 !$~~   
( $\det(A^T X) = \det(A(X))$ )  
ETC.

- LIKE LS REGRESSION

- SENSITIVE TO OUTLIERS (HERE "SURE" DATA  $\rightarrow$  FIG. 4.4)

## FISHER'S LINEAR DISCRIMINANT (CH. 4.1.4)

(FIG. 4.6)

$C_1, C_2$  PROJECTION TO 1 DIM

EVEN IF LINEARLY SEPARABLE  
L OVERLAPPING POSSIBLE

COMPARE PROJECTIONS

$P_1, P_2, P_3$

