

# Lecture 5 – unannotated slides

# Minimax criteria

- Sometimes we must design our classifier to perform well over a range of prior probabilities.
- For instance, the likelihood may remain same, but the prior may completely change in a new setup. Or we want to use a classifier in a new setup and prior is unavailable.
- Approach – minimize maximum possible overall risk

- In order to understand this, we let  $R_1$  denote that (as yet unknown) region in feature space where the classifier decides  $\omega_1$  and likewise for  $R_2$  and  $\omega_2$ , and then write our overall risk

$$R = \int_{R_1} [\lambda_{11}P(\omega_1) p(x|\omega_1) + \lambda_{12}P(\omega_2) p(x|\omega_2)] dx + \\ \int_{R_2} [\lambda_{21}P(\omega_1) p(x|\omega_1) + \lambda_{22}P(\omega_2) p(x|\omega_2)] dx .$$

- We use the fact that  $P(\omega_2) = 1 - P(\omega_1)$  and that

$$\int_{R_1} p(x|\omega_1) dx + \int_{R_2} p(x|\omega_1) dx = 1$$

Minimax risk

$$R(P(\omega_1)) = \underbrace{\lambda_{22} + (\lambda_{12} - \lambda_{22}) \int_{R_2} p(x|\omega_2) dx}_{\text{Minimax risk}} +$$

$$P(\omega_1) \underbrace{[(\lambda_{11} - \lambda_{22}) - (\lambda_{21} - \lambda_{11}) \int_{R_2} p(x|\omega_1) dx - (\lambda_{12} - \lambda_{22}) \int_{R_1} p(x|\omega_2) dx]_{\text{Minimax risk}}}_{\text{Minimax risk}}$$

0 for minimax sol

# Classifiers, Discriminant Functions and Decision Surfaces

- The multi-category case (consider zero-one loss only)
  - Set of discriminant functions  $g_i(x)$ ,  $i = 1, \dots, c$
  - The classifier assigns a feature vector  $x$  to class  $\omega_i$  if:

$$g_i(x) > g_j(x) \quad \forall j \neq i$$

- Let  $g_i(x) = -R(\alpha_i | x) = P(\omega_i | x) - 1$   
(max. discriminant corresponds to min. risk!)

- For the minimum error rate, we take

$$g_i(x) = P(\omega_i | x)$$

(max. discrimination corresponds to max. posterior!)

$$g_i(x) \equiv P(x | \omega_i) P(\omega_i)$$

$$g_i(x) = \ln P(x | \omega_i) + \ln P(\omega_i)$$

(ln: natural logarithm!)