

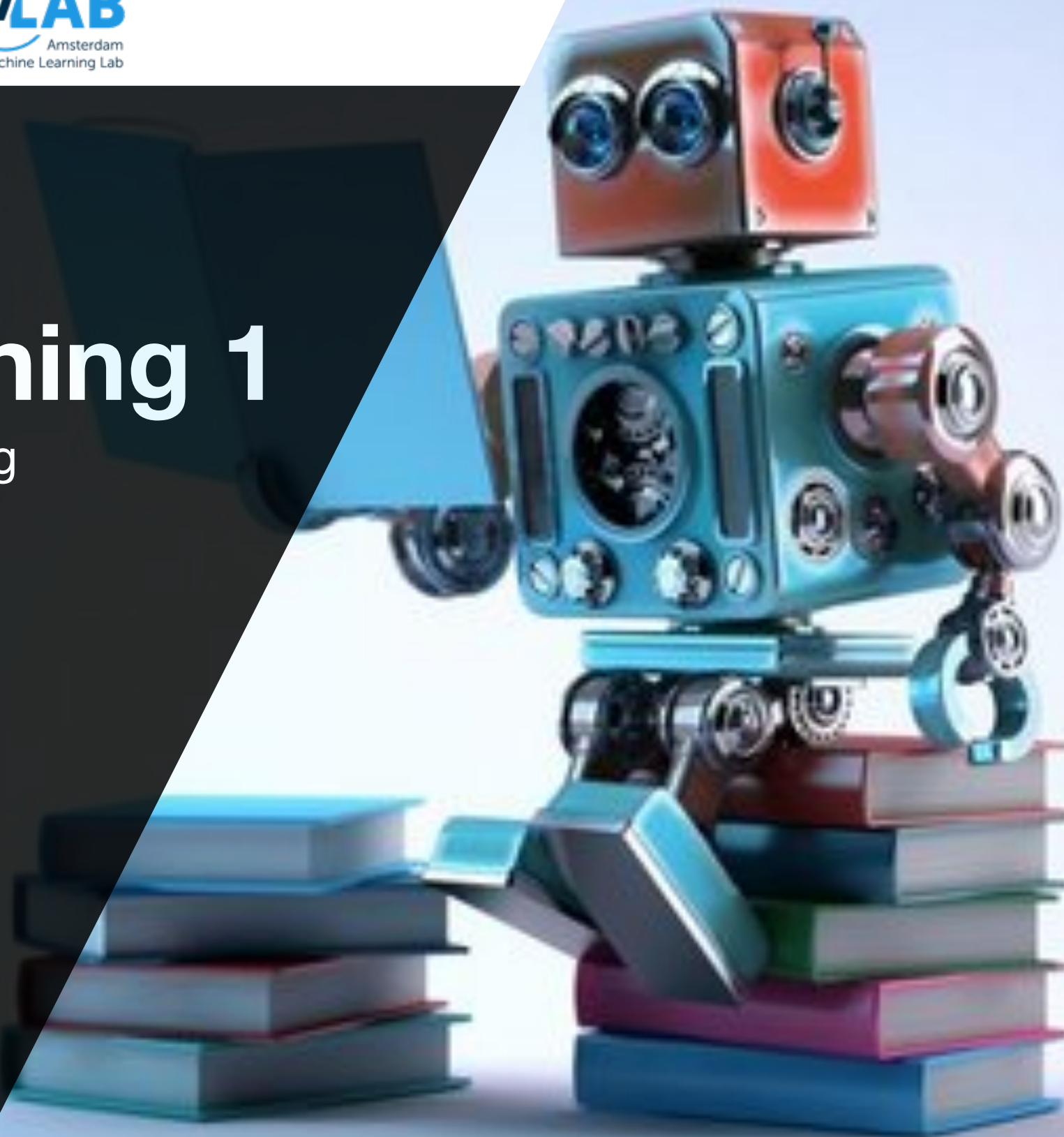


# Machine Learning 1

Lecture 5.3 - Supervised Learning  
Classification - Decision Regions

*Erik Bekkers*

*(Bishop 1.5, 4.1)*



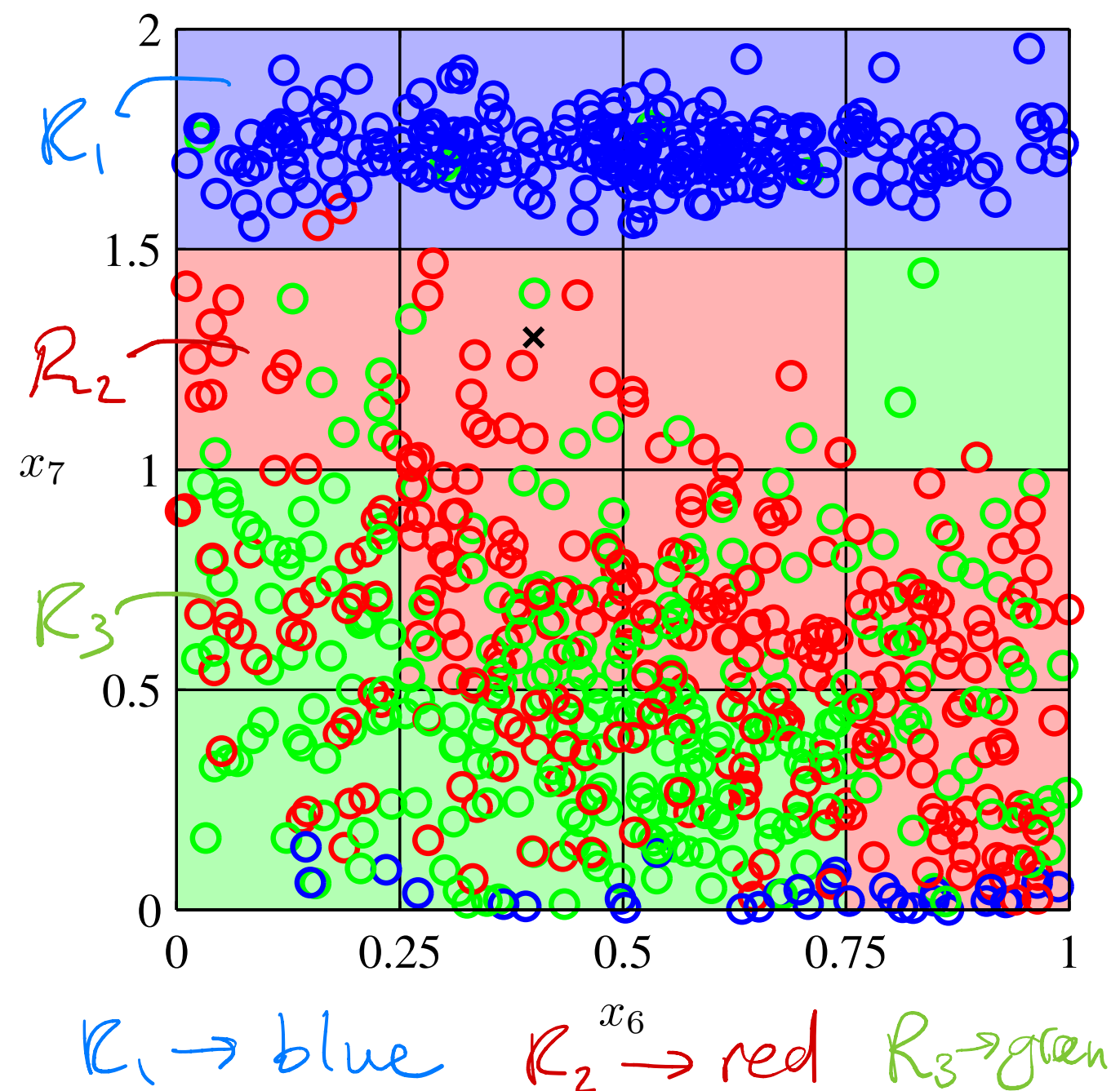
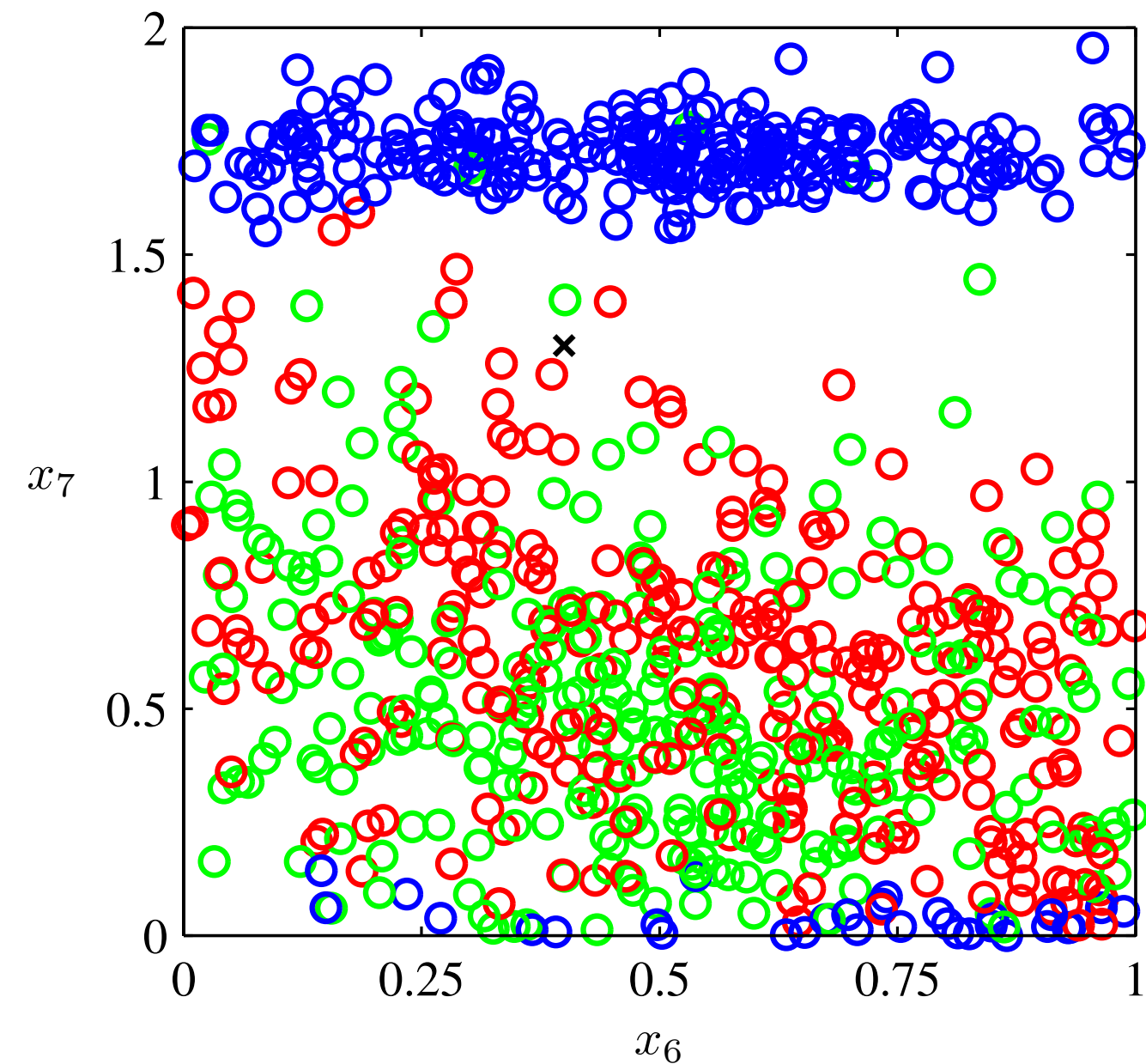
# Classification through decision regions

- Input:  $\mathbf{x} = (x_1, \dots, x_D)^T$
- Target:  $t \in \{C_1, C_2, \dots, C_k\}$ 
  - 2-class targets:  $t = C_1, t = C_2 \Leftrightarrow t = 0, t = 1$
  - Multi-class targets e.g.  $k=5, t = C_3 \Leftrightarrow$   $\begin{pmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{pmatrix}$   
one-hot encoding of class  $C_3$

## Strategy:

- Divide input space  $\mathbb{R}^D$  into  $K$  decision regions.  $R_k$
- Assign each decision region to a class  $C_k$
- Boundaries of decision regions are called *decision boundaries/surfaces*.

# Classification through Decision Regions

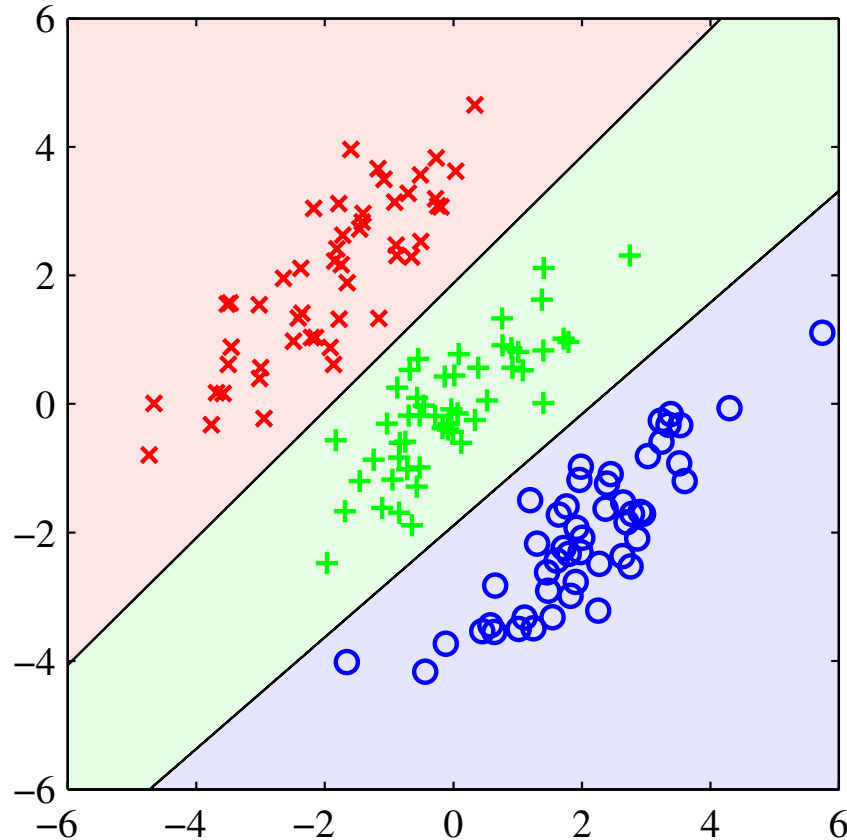


**Figures:** 3 class problem with decision boundaries. (Bishop 1.19 & 1.20)

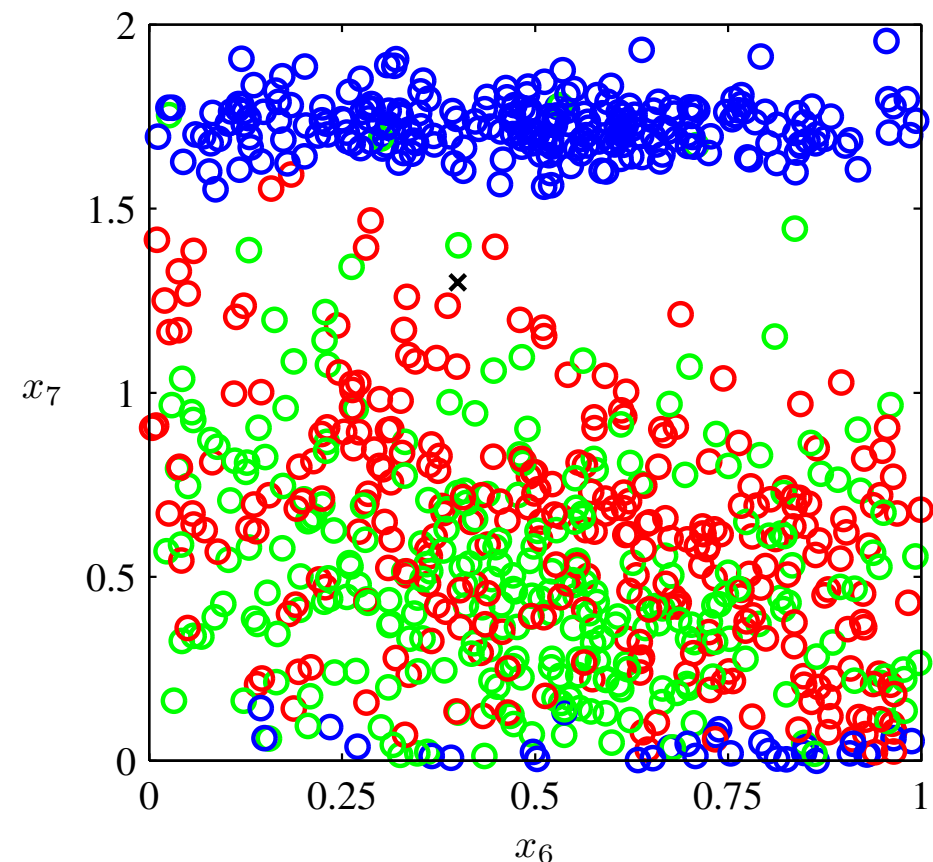
$K=3$

# Linear Classification

- ▶ **Linear Classification:** consider only *linear* decision boundaries
- ▶ For  $D$  - dimensional input space:  $\underline{x} \in \mathbb{R}^D$   
decision surface is a  $D-1$  dimensional hyperplane
- ▶ Datasets whose classes can be separated *exactly* by linear decision surfaces are called *linearly separable*



**Figure:** Linearly separable dataset (Bishop 4.5)



**Figure:** Not linearly separable dataset (Bishop 1.19)



# Multiple Classes ( $K > 2$ )

$t = C_1 \& C_2 ??$

- ▶  $K=2$  classes:

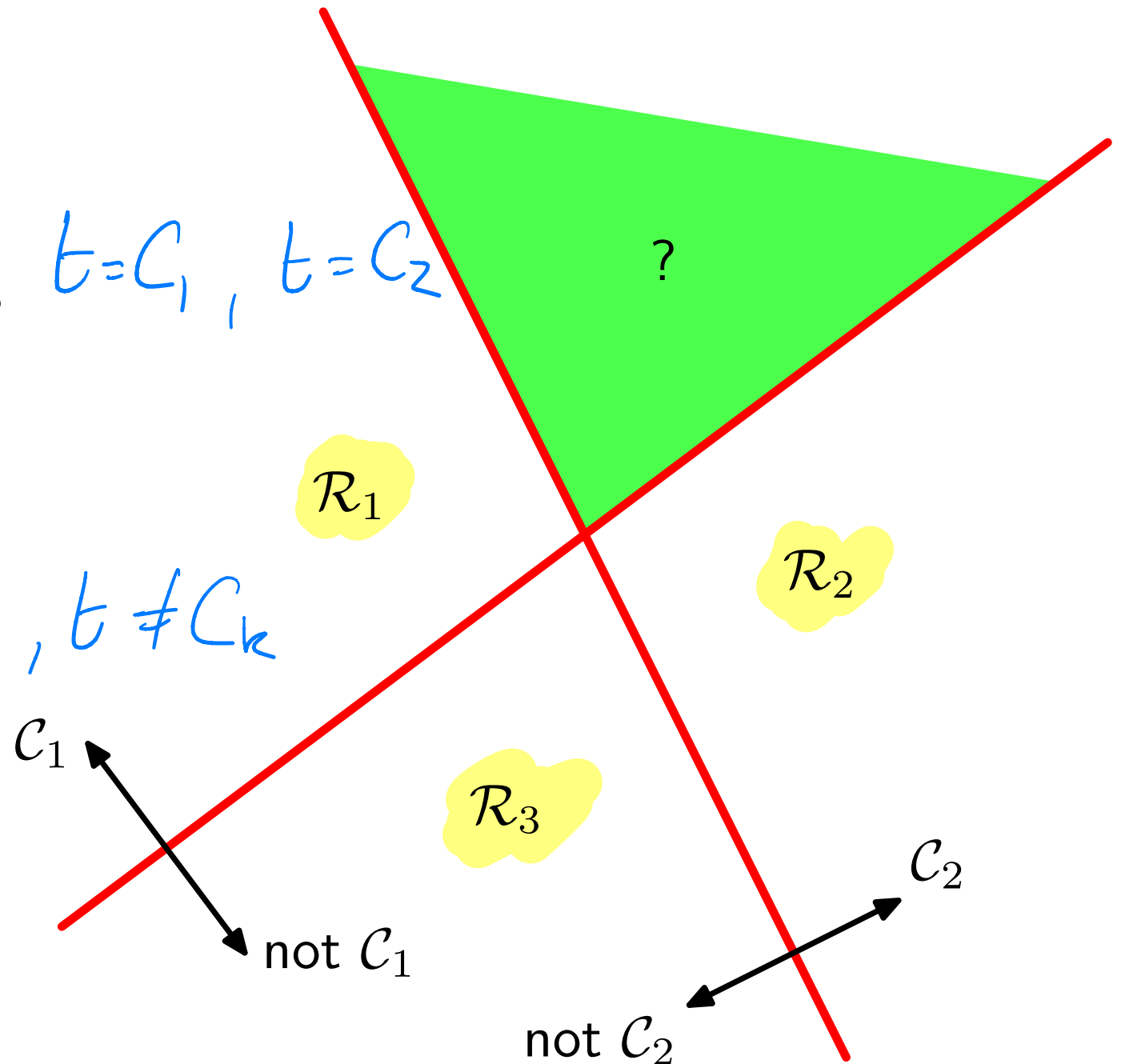
- ▶ 1 classifier determines

$t = C_1, t = C_2$

- ▶ Multiple classes:  $K > 2$

- ▶  $K-1$  classifiers:  $t = C_k, t \neq C_k$

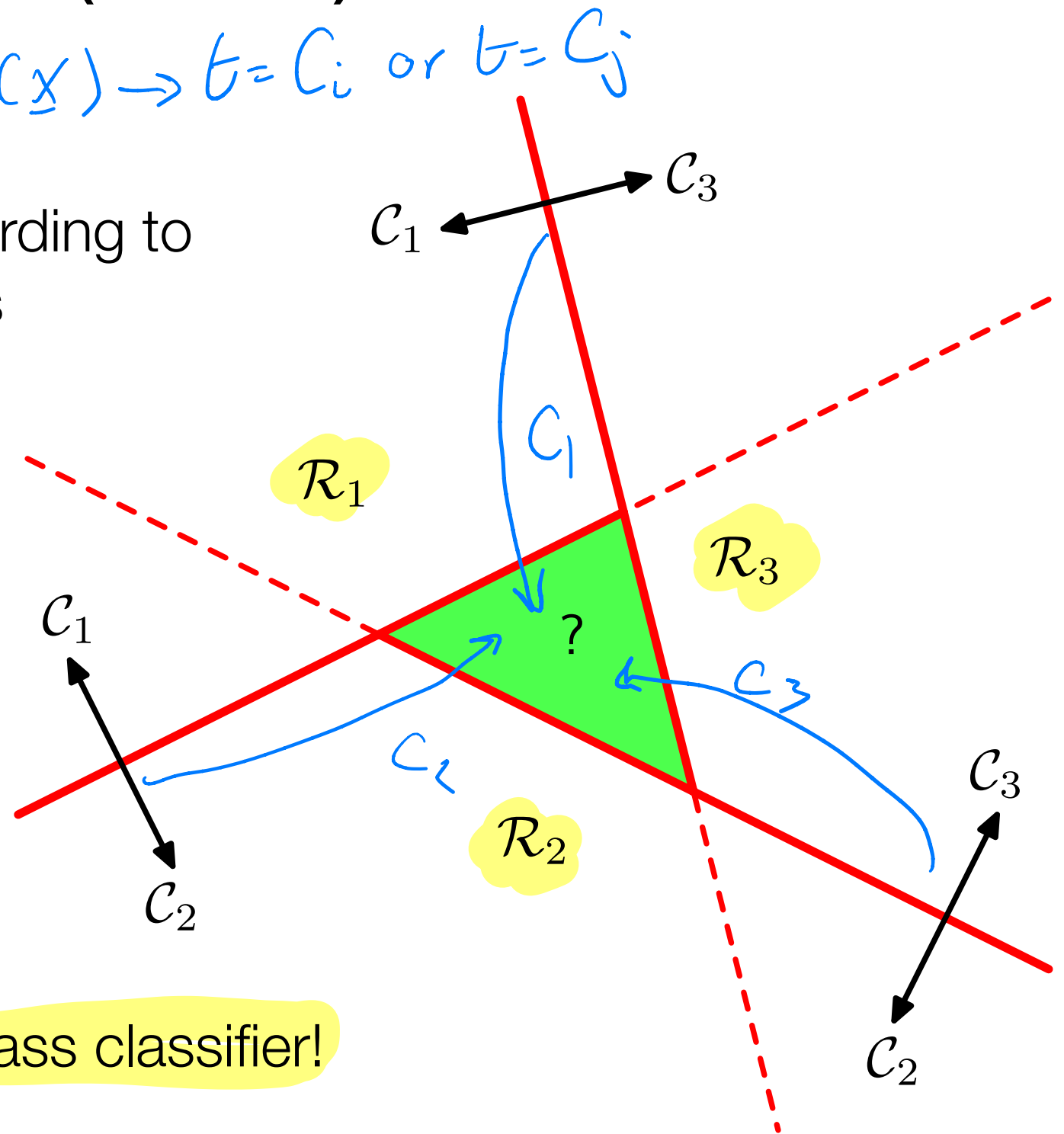
- ▶ One-versus-the-rest



**Figure:** one-versus-the-rest classifiers (Bishop 4.2)

# Multiple Classes ( $K > 2$ )

- ▶  $K(K-1)/2$  classifiers:  $\psi_{ij}(x) \rightarrow t = C_i \text{ or } t = C_j$
- ▶ Points are classified according to majority vote of classifiers
- ▶ one-versus-one



- ▶ **Solution:** Make one K-class classifier!  
(See later)

**Figure:** one-versus-one classifiers (Bishop 4.2)