

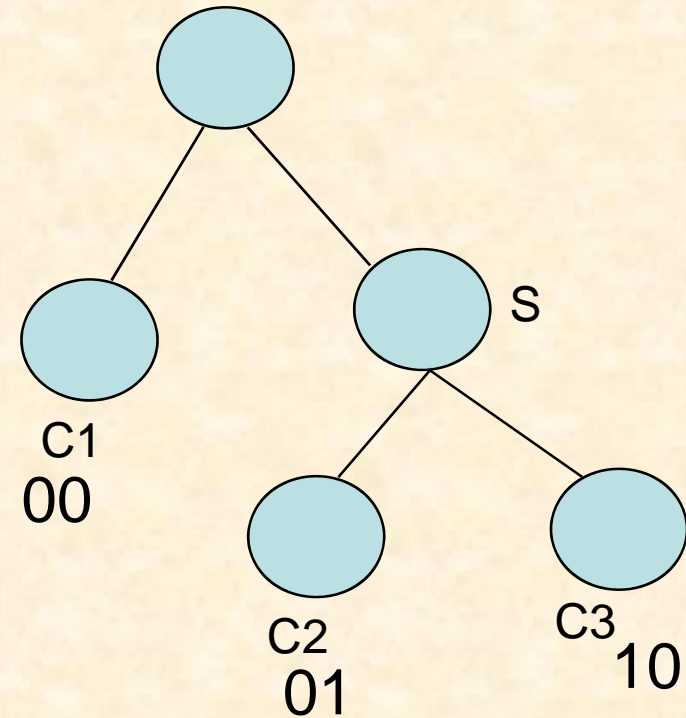
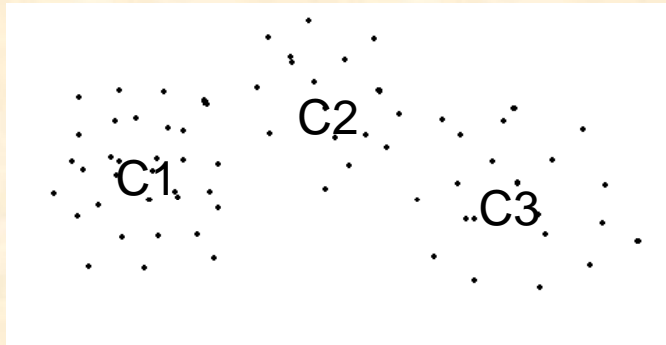
# Variable-Branch Decision Tree based on Genetic Algorithm

楊雄彬

# Contents

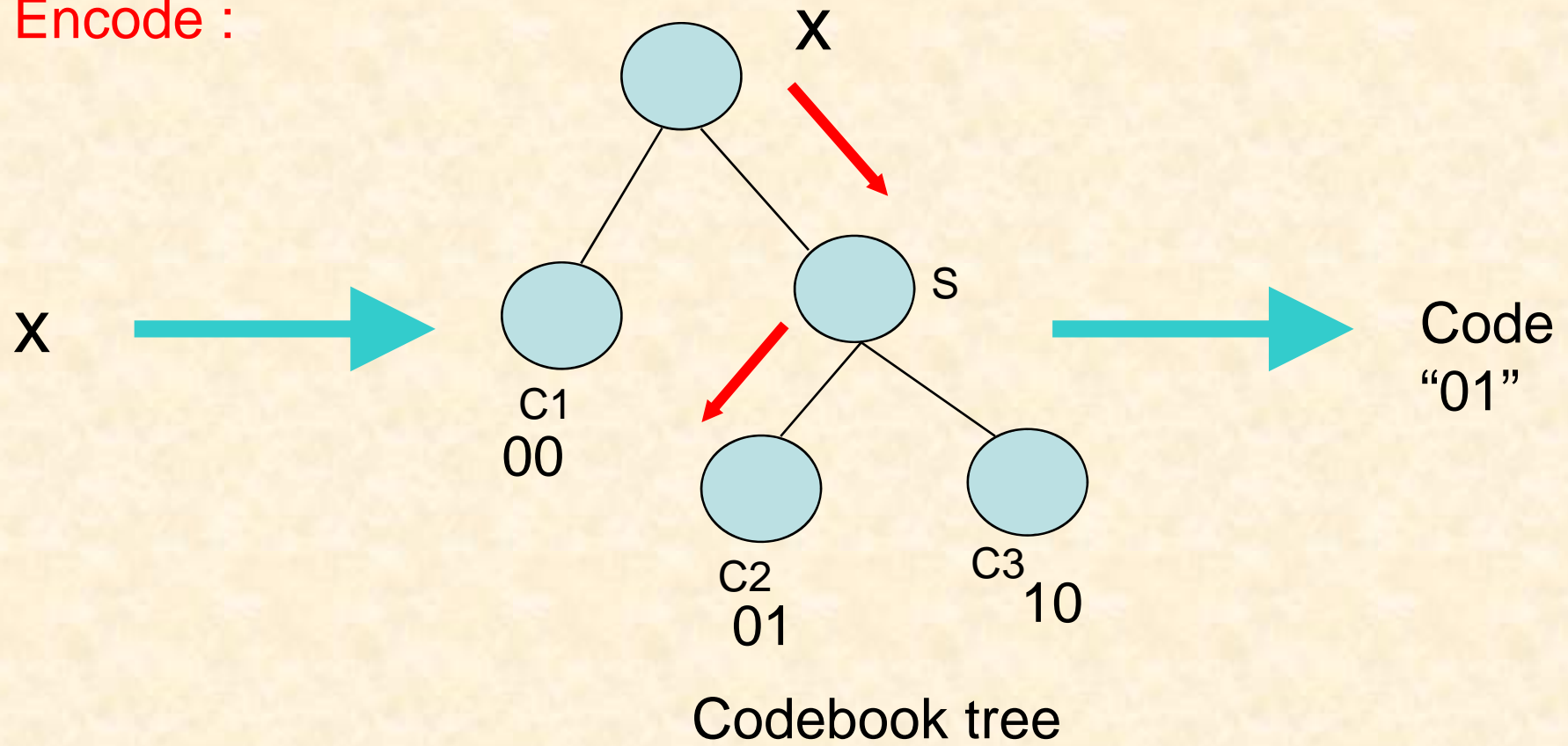
- Decision tree for compression and recognition
- K-means algorithm
- Binary decision tree
- Greedy decision tree
- Two problems of greedy decision tree
- **Genetic algorithm** for solving problem 1.
- **Classification points** for solving problem 2.
- Conclusions

# Decision tree-compression

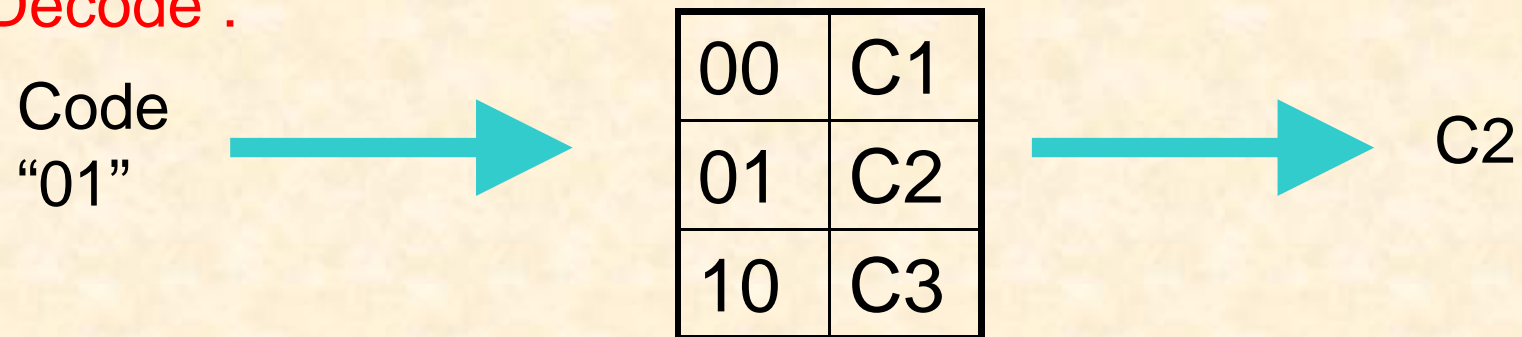


Codebook tree

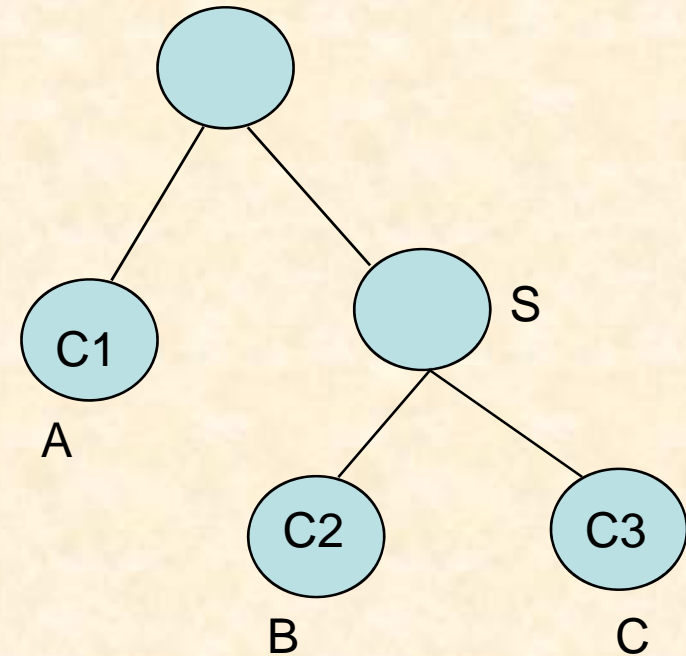
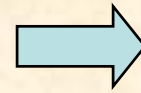
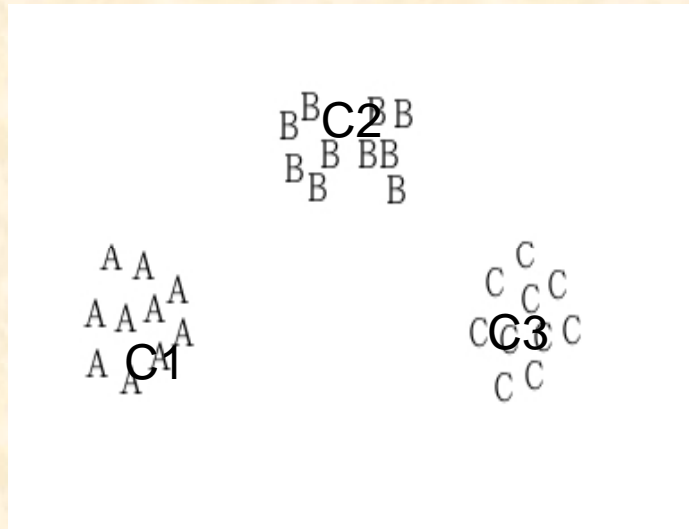
Encode :



Decode :

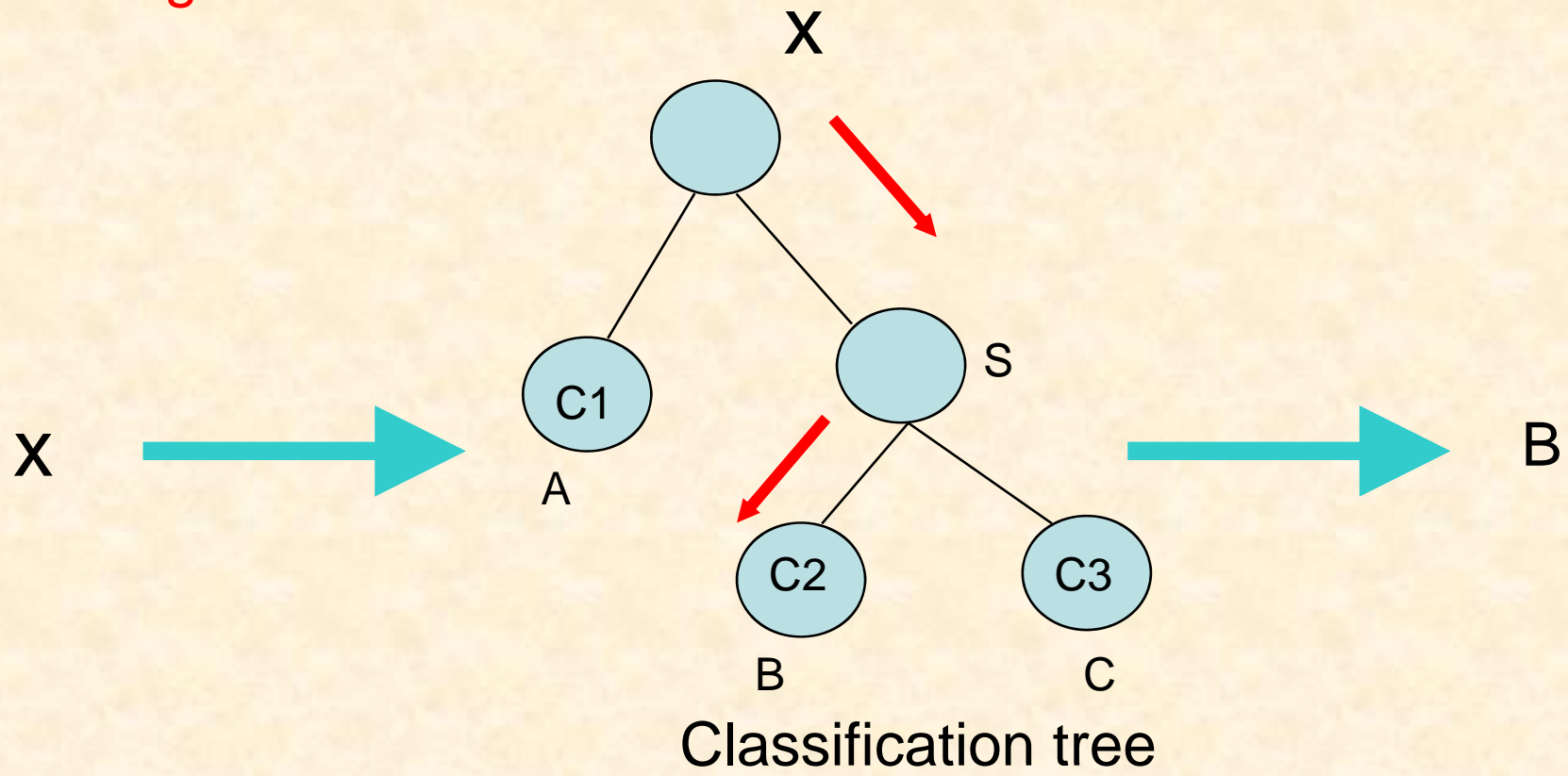


# Decision tree-Recognition

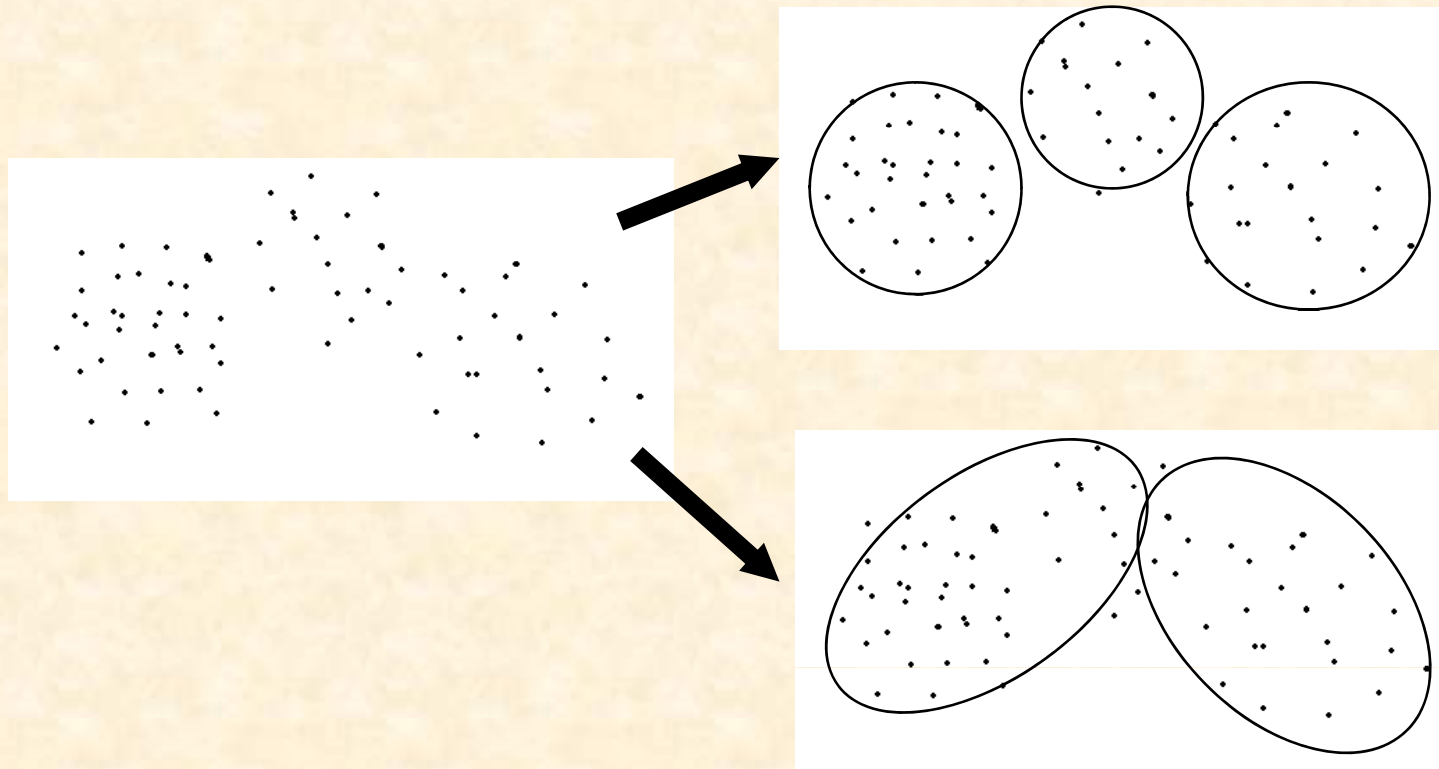


Classification tree

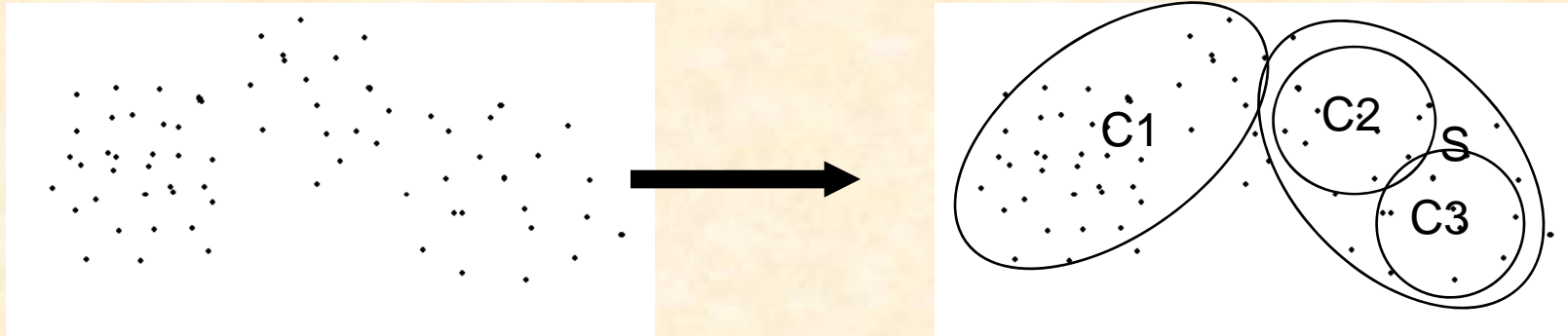
# Recognition:



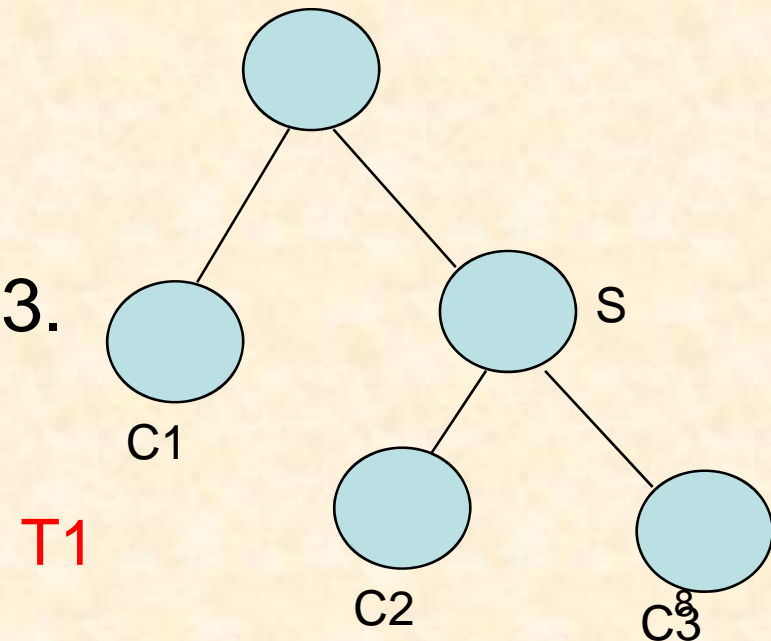
- K-means (C-means) algorithm
  - Divide the data set into k clusters.



- Decision tree ----- **Compression**
  - Binary decision tree (k=2)

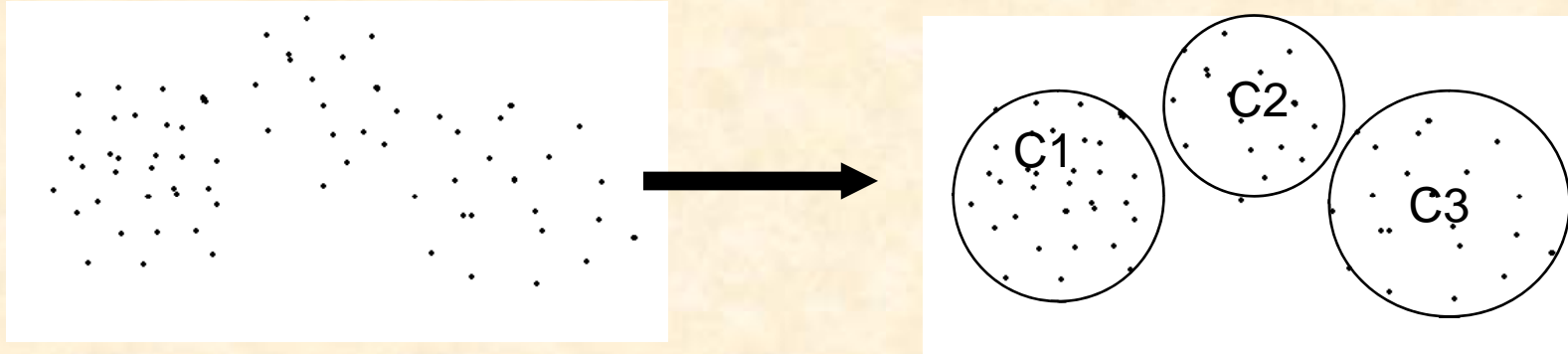


- Input X is encoded in T1.  
X is compared with three codewords, C1, C2 and C3.

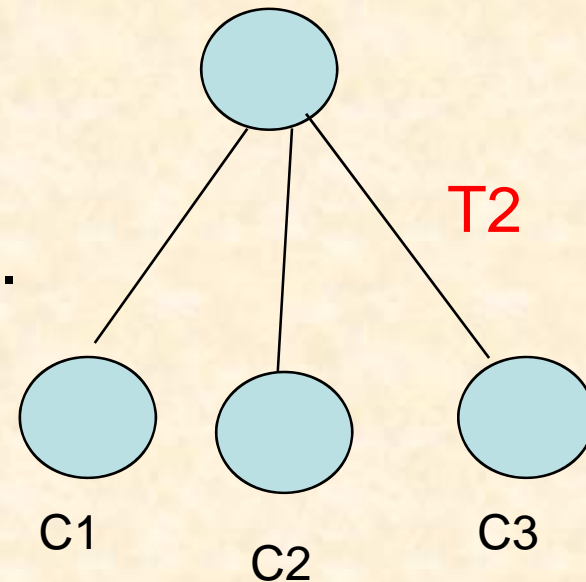




- Decision tree ----- **Compression**
  - 3-ary decision tree ( $k=3$ )



- Input  $X$  is encoded in  $T2$ .  
 $X$  is compared with three codewords,  $C1, C2$  and  $C3$ .



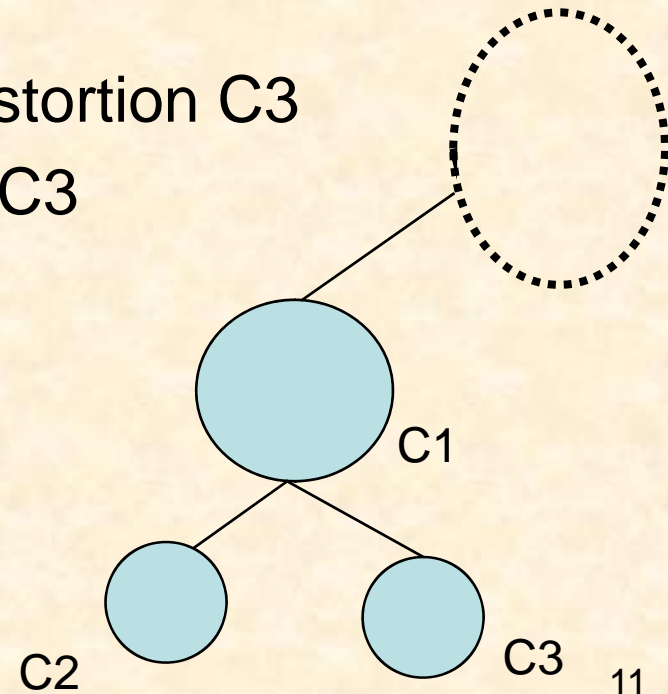
- T1 and T2, which one is better ? Optimal?
  - It is hard for the users to determine which one is better.
  - The users usually have no ideal about the value of  $k$ . Thus, T1 and T2 are not optimal.
  - Compression performance is depended on the **coding quality** and **bit rate**. The coding quality is as **high** as possible. The bit rate is as **low** as possible.

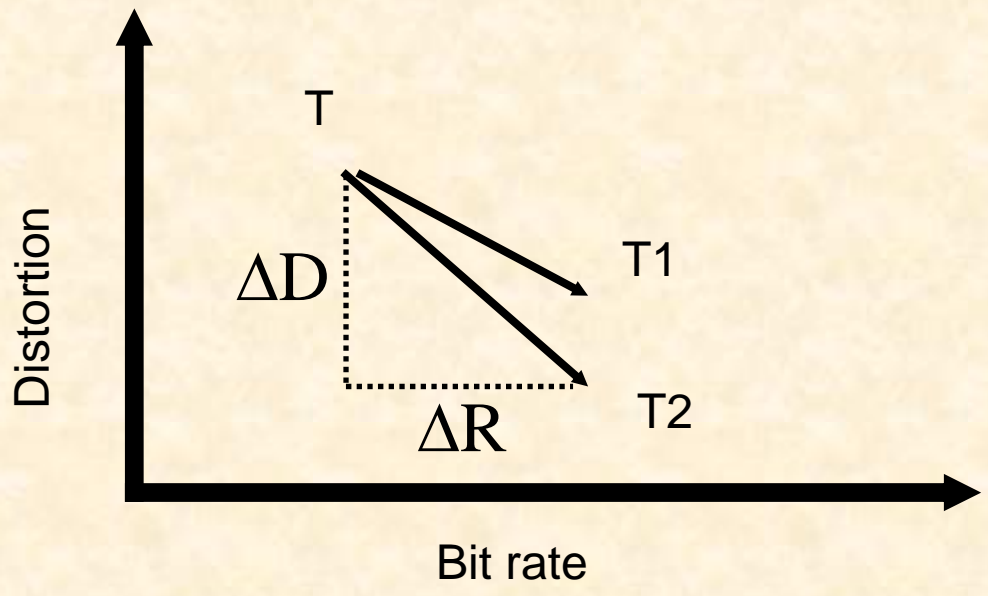
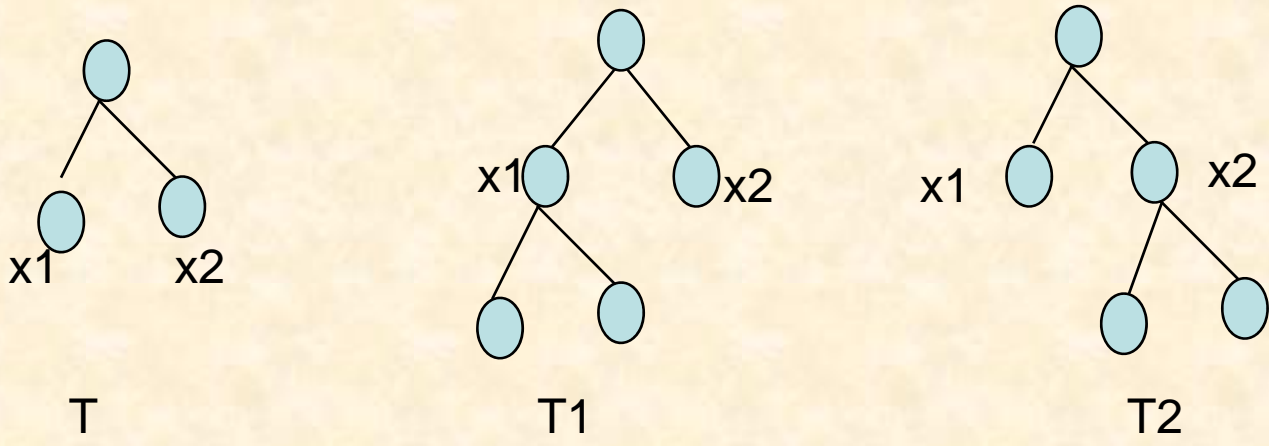
- Greedy decision tree (K=2)

- The growing method selects nodes with the maximum value of  $\lambda$  to split during the design of decision tree.

$$\lambda = \frac{\Delta \text{Distortion}}{\Delta \text{Bit rate}} = \left| \frac{\Delta D}{\Delta R} \right|$$

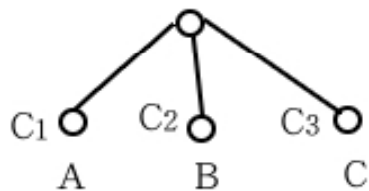
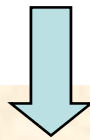
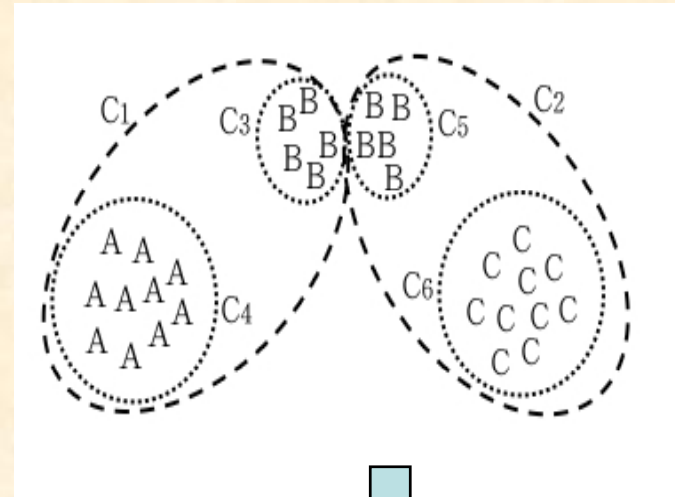
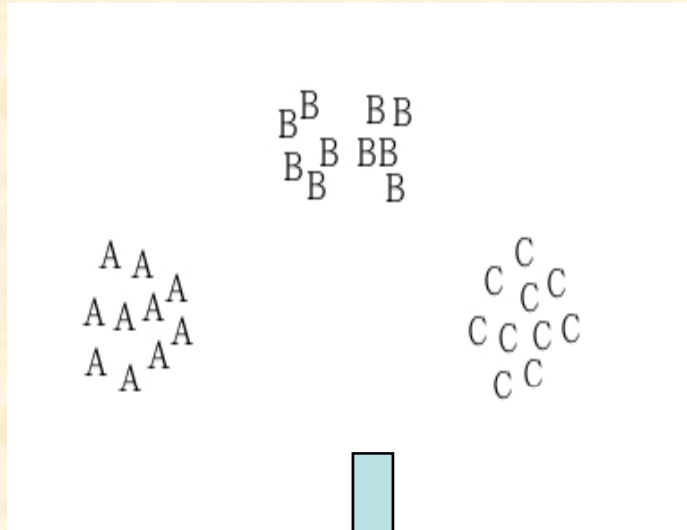
- Distortion  $C1 > \text{Distortion } C2 + \text{Distortion } C3$
- Bit rate  $C1 < \text{Bit rate } C2 + \text{Bit rate } C3$



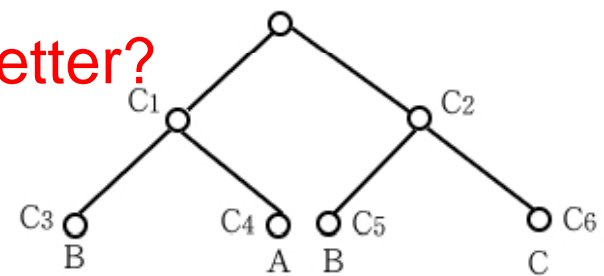
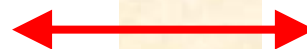


T2 is better than T1.

- Problem1: The greedy decision tree is a fixed-branch decision tree. It is still not an optimal decision tree.

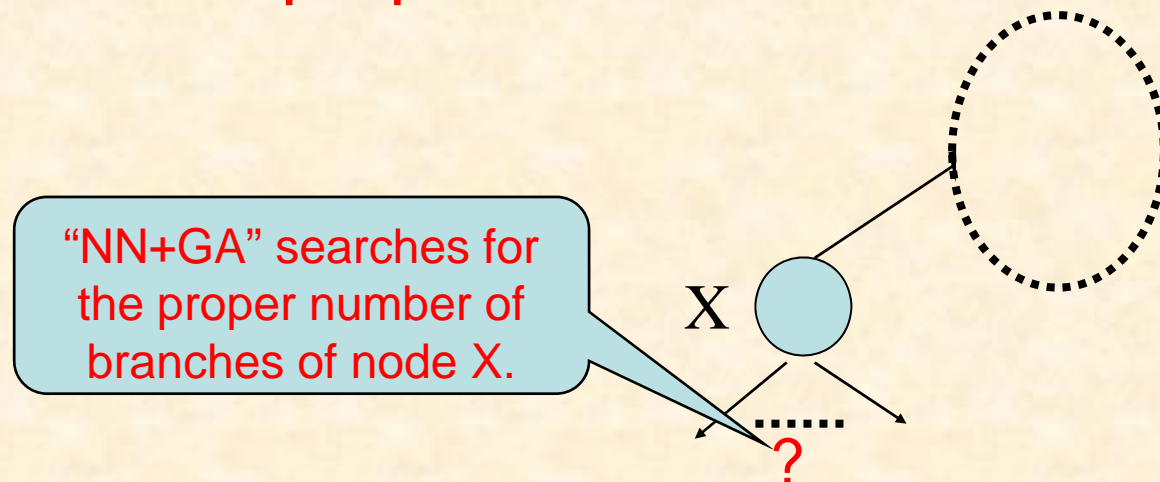


Which one is better?

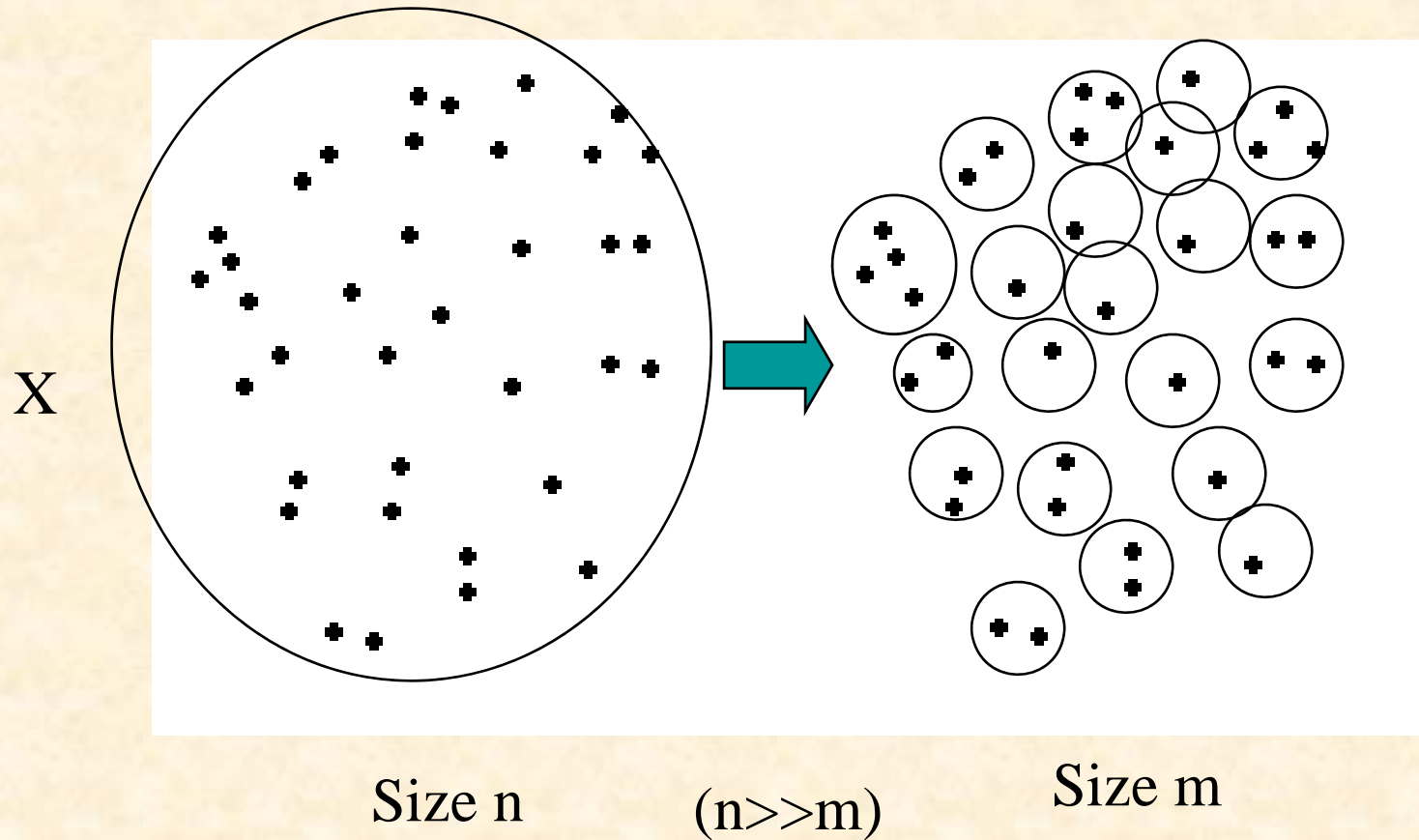
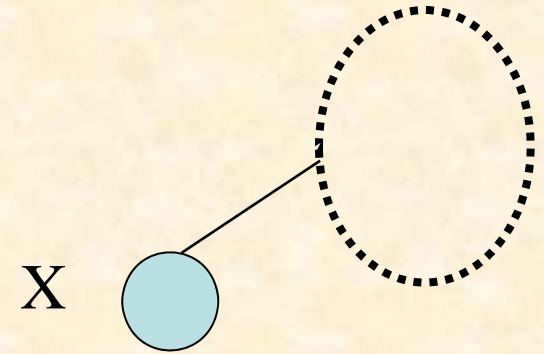


- **Solution** for Problem1

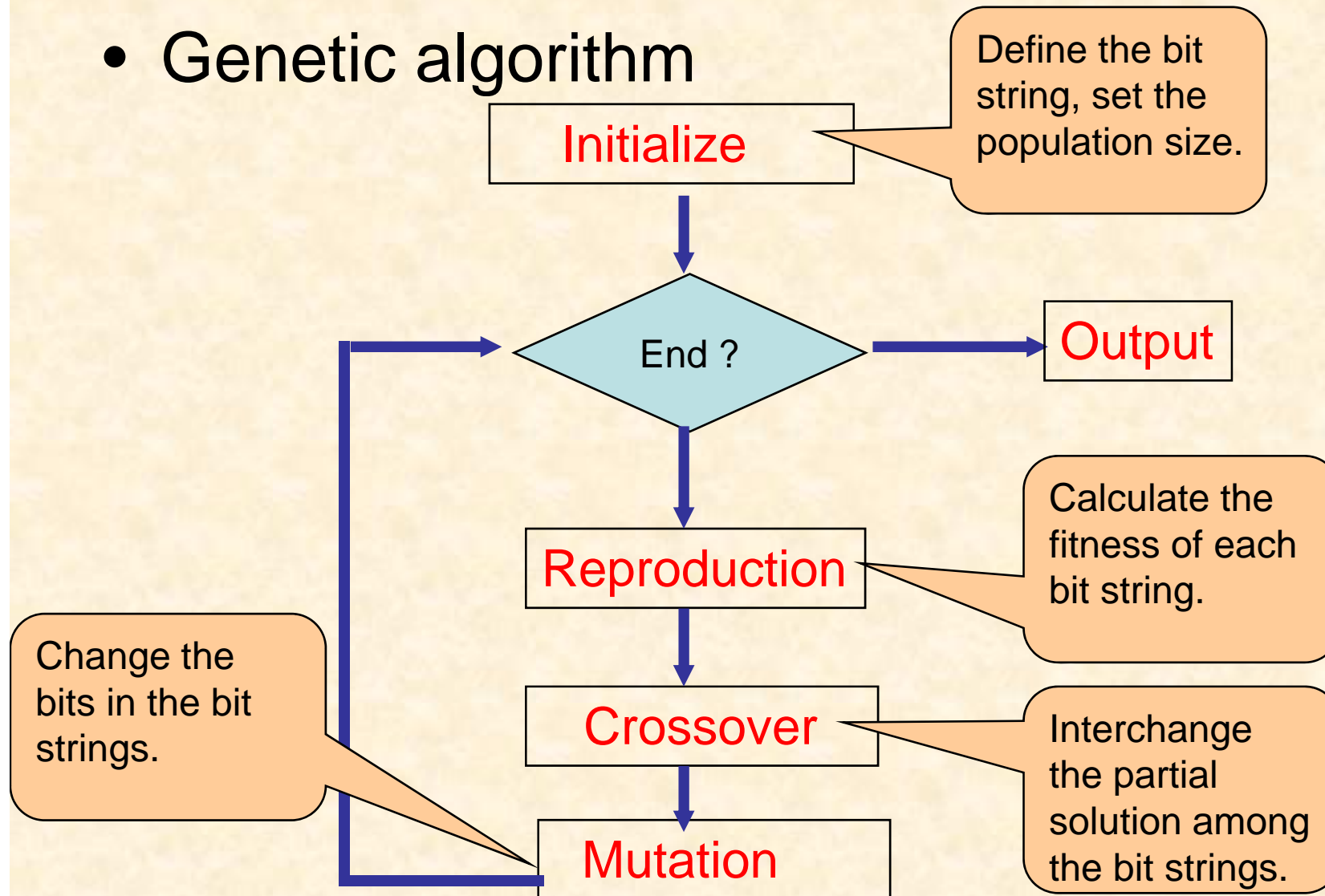
- **Variable-branch decision tree** is proposed to replace the **fixed-branch decision tree**.
- How to determine the proper number of branches of a node?
- **“Nearest-neighbor algorithm + Genetic clustering algorithm”** automatically determines the **proper number of branches** in a node.



- Reduce the training data set using the nearest-neighbor algorithm.

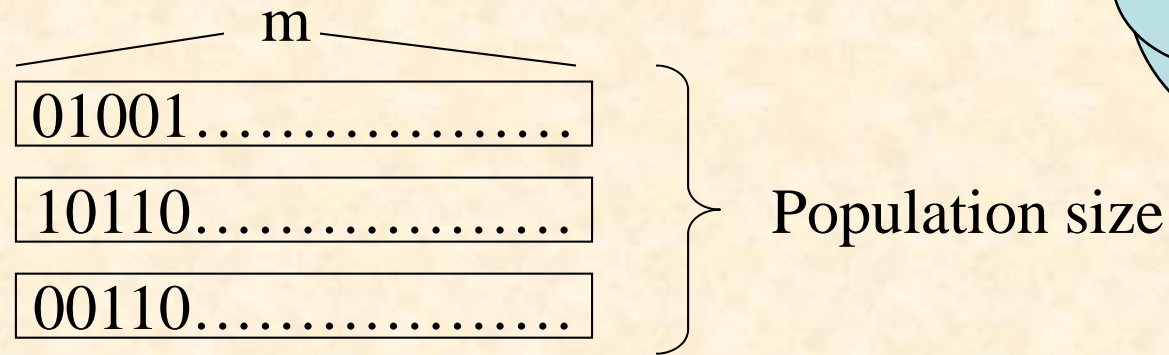


- Genetic algorithm

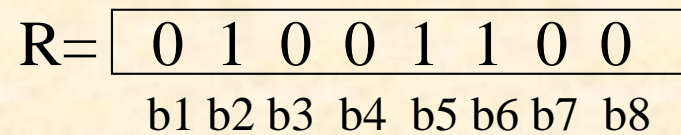




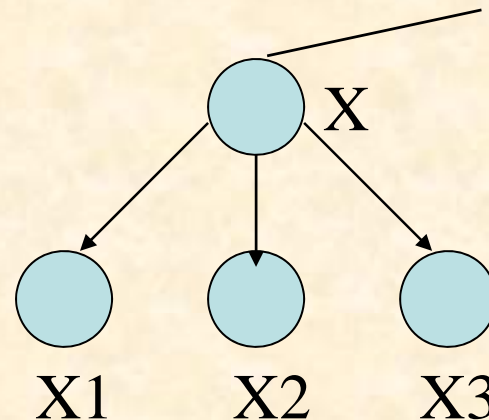
- Initialize



Ex:  $m=8$

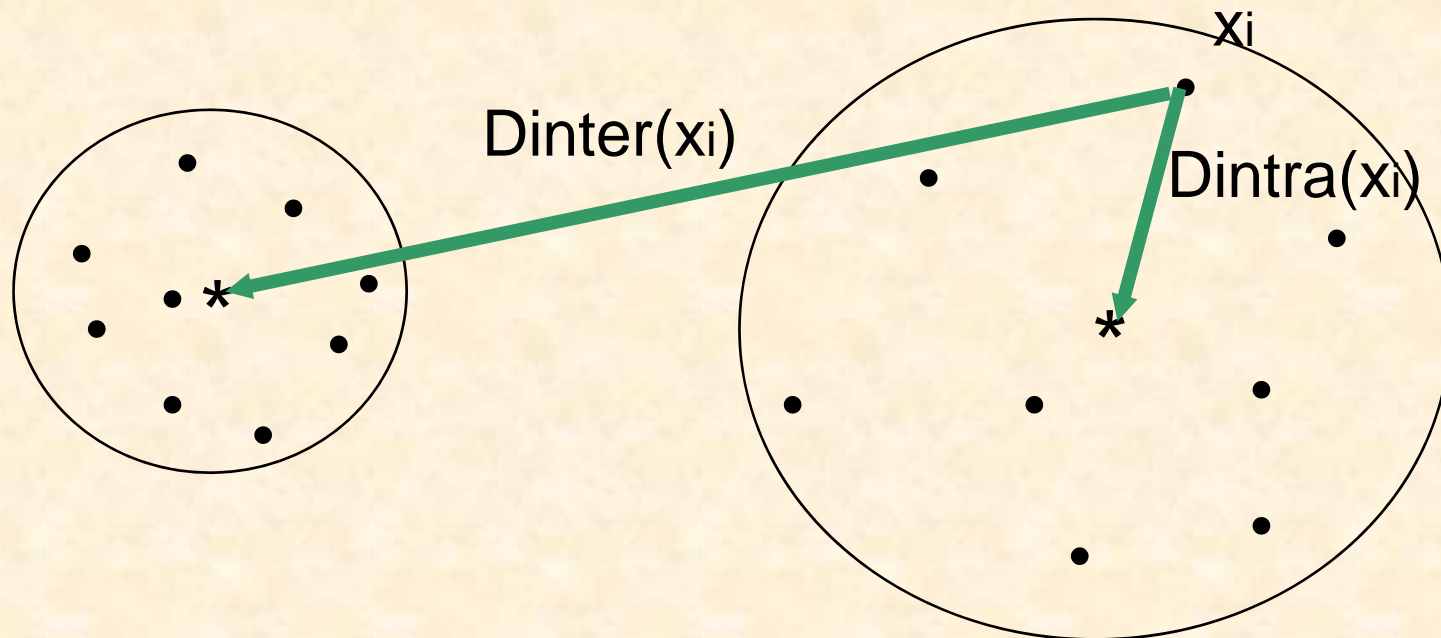


Three initial seeds, b2, b5 and b6, generate three clusters, X1, X2 and X3.

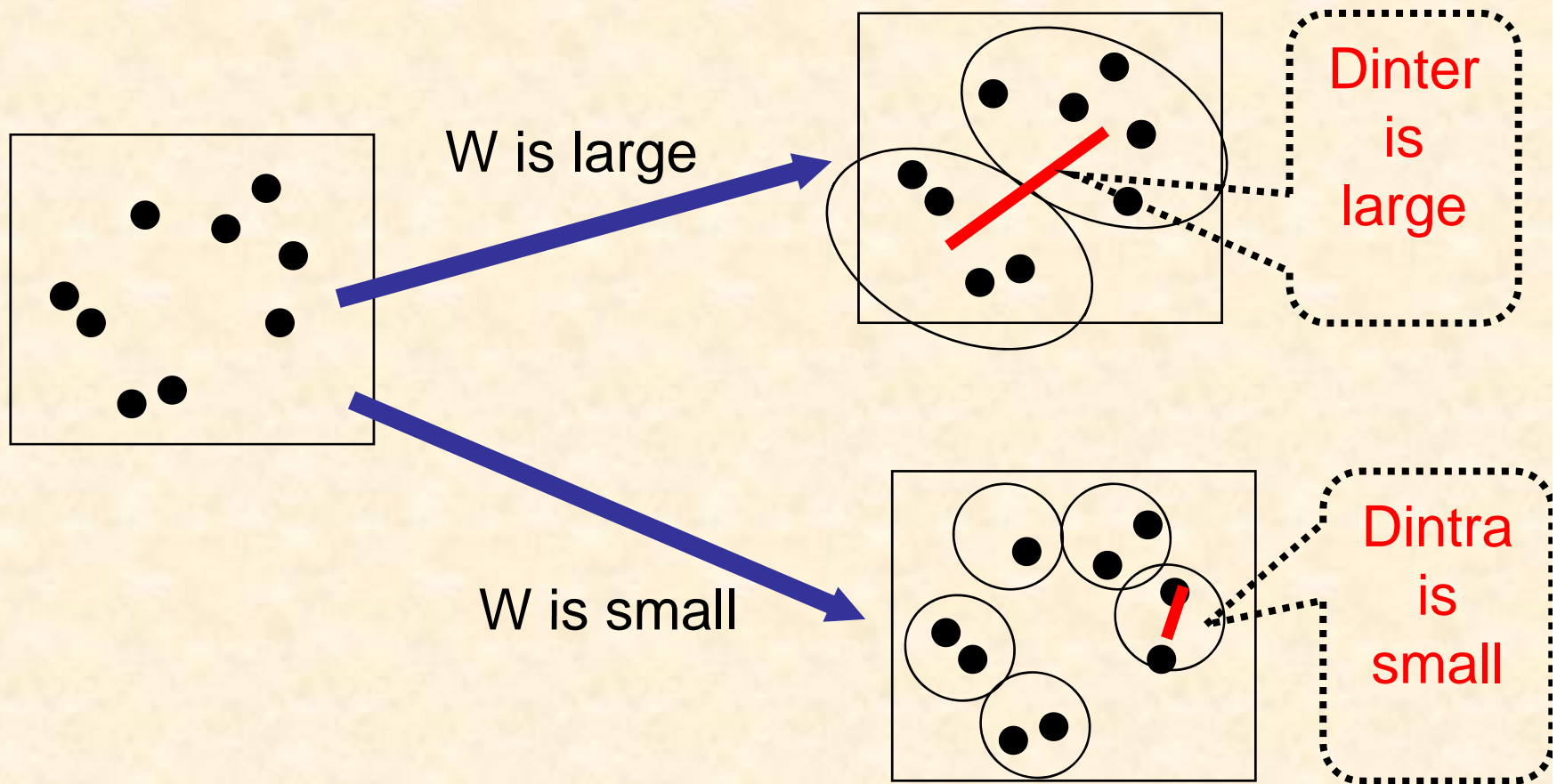


## • Reproduction(1)

- $Fitness(R) = \sum_{x_i \in \text{Data set}} [D_{inter}(x_i) * w - D_{intra}(x_i)]$
- $D_{inter}(x_i)$  denotes the minimal distance between the sample  $x_i$  and its nearest cluster.
- $D_{intra}(x_i)$  denotes the distance between the sample  $x_i$  and its center.



- If  $w$  is large, Fitness is determined by  $D_{inter}$ .
- If  $w$  is small, Fitness is determined by  $D_{intra}$ .



• Ex:

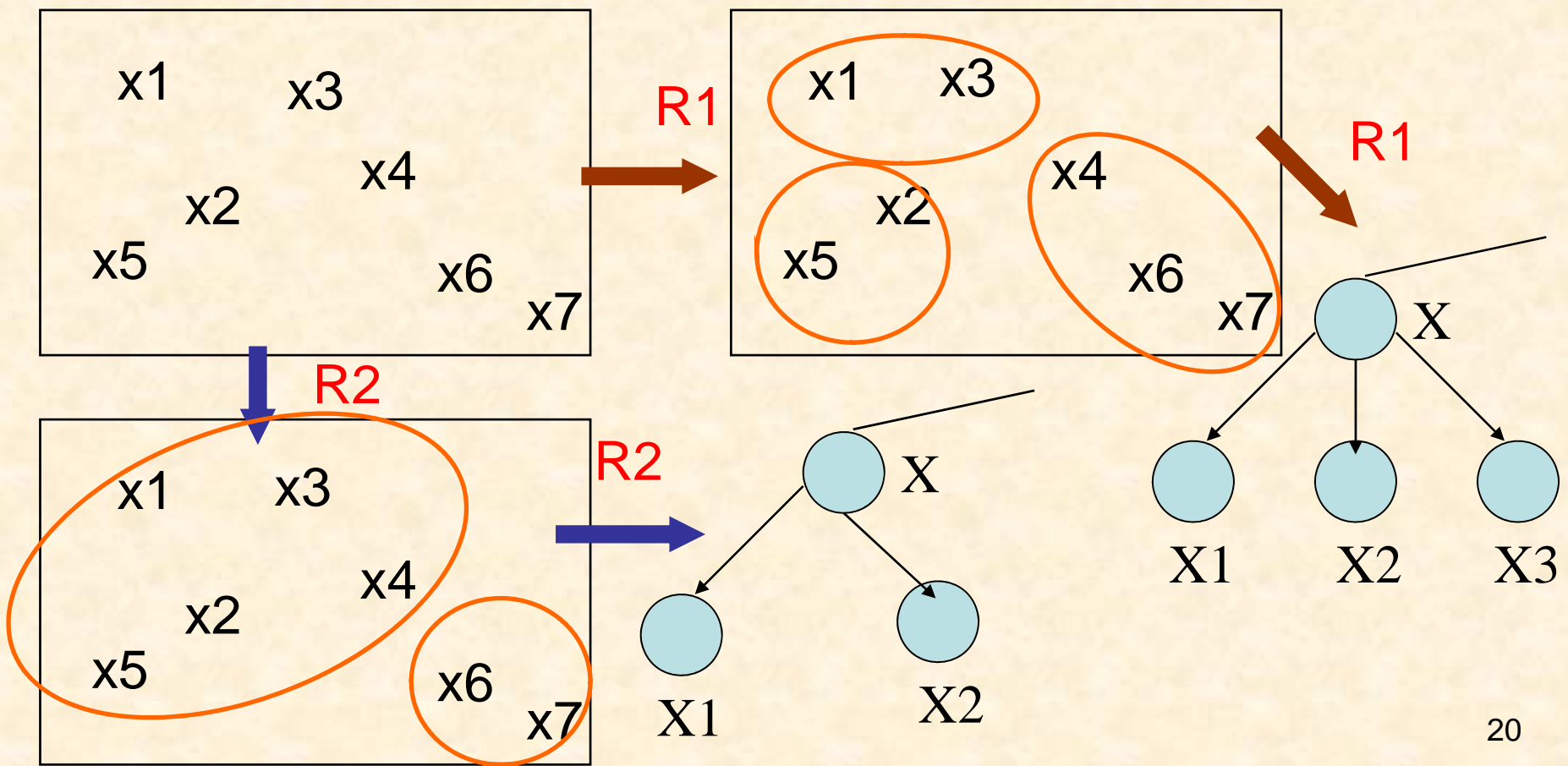
$$R1 = \begin{bmatrix} 1 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \end{bmatrix}$$

b1 b2 b3 b4 b5 b6 b7 b8

(3 clusters)

$$R2 = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

(2 clusters)



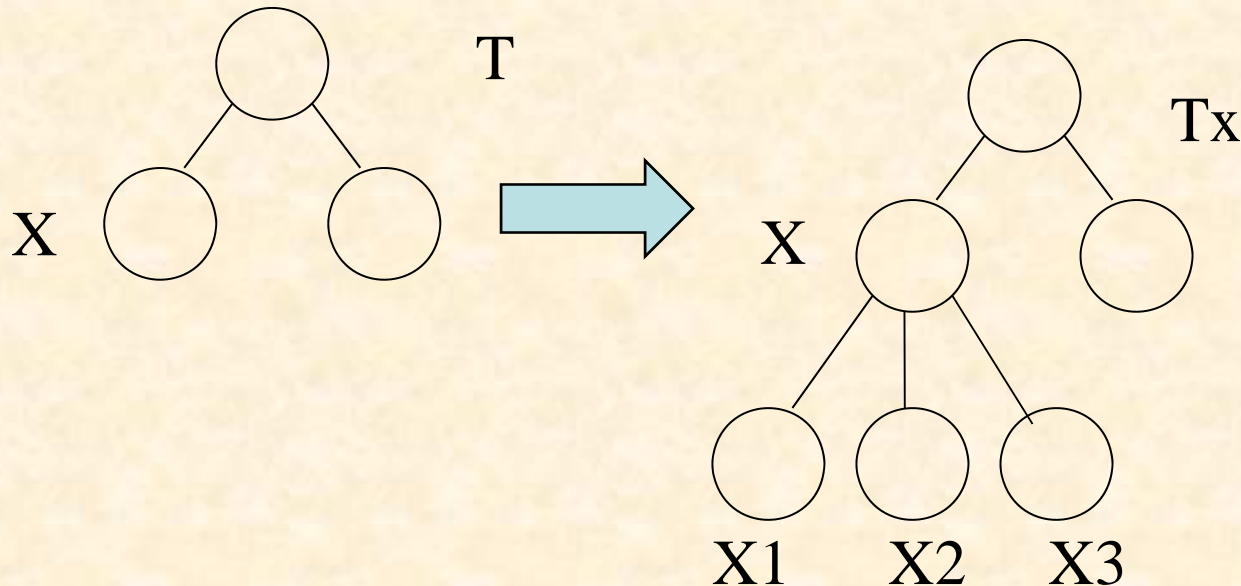
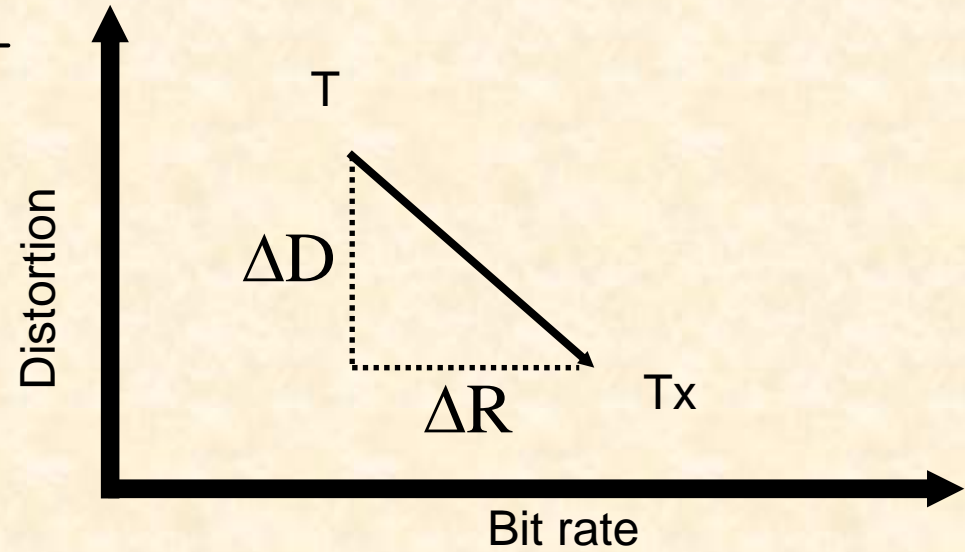
A good clustering result

?=?

A good decision tree for  
compression

- **Reproduction(2)**

$$- \textit{Fitness}(R) = \lambda = \frac{\Delta D}{\Delta R}$$



- Ex:

R1= 

0	1	0	0	1	1	0	0
---	---	---	---	---	---	---	---

 (3 branches)  
b1 b2 b3 b4 b5 b6 b7 b8

R2= 

0	0	1	0	0	1	0	0
---	---	---	---	---	---	---	---

 (2 branches)

R3= 

1	1	1	0	0	1	0	0
---	---	---	---	---	---	---	---

 (4 branches)

R4= 

0	0	0	0	1	1	1	1
---	---	---	---	---	---	---	---

 (4 branches)

R5= 

0	1	0	0	1	0	0	0
---	---	---	---	---	---	---	---

 (2 branches)

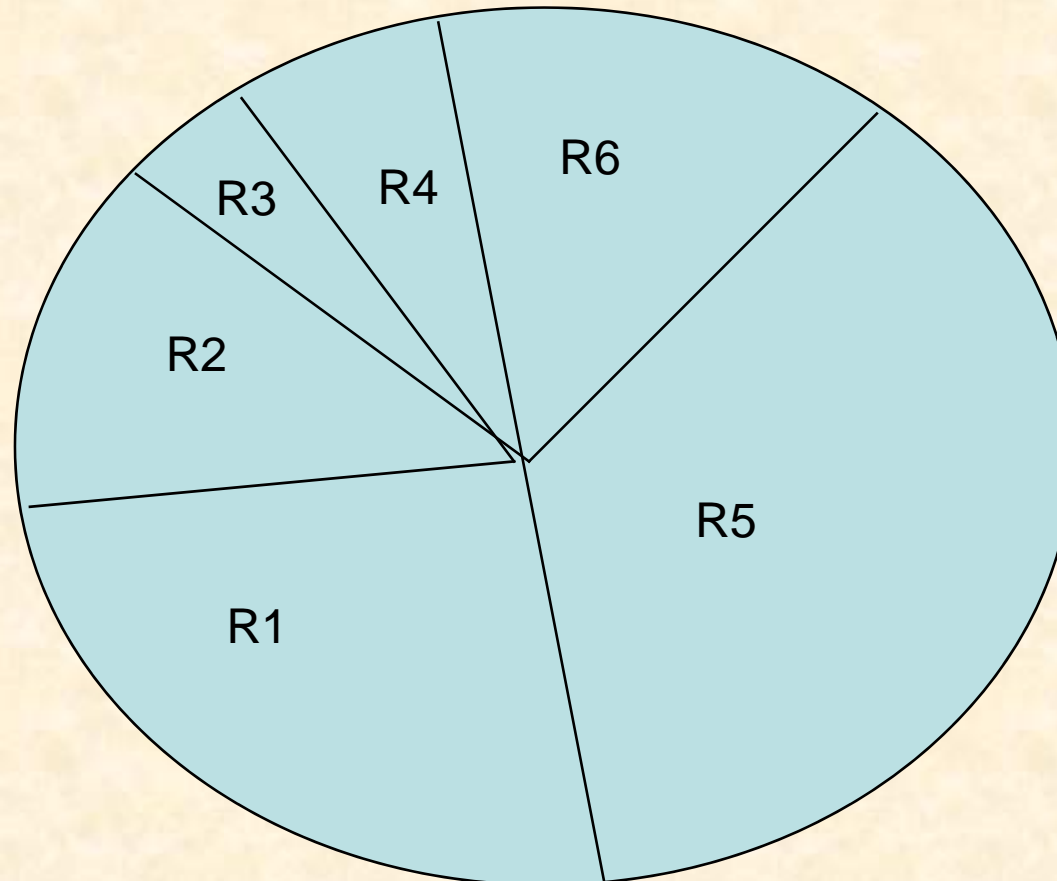
R6= 

0	1	0	1	0	1	0	0
---	---	---	---	---	---	---	---

 (3 branches)

• Fitness(R5) > Fitness(R1) > Fitness(R6) > Fitness(R2) > Fitness(R4) > Fitness(R3)

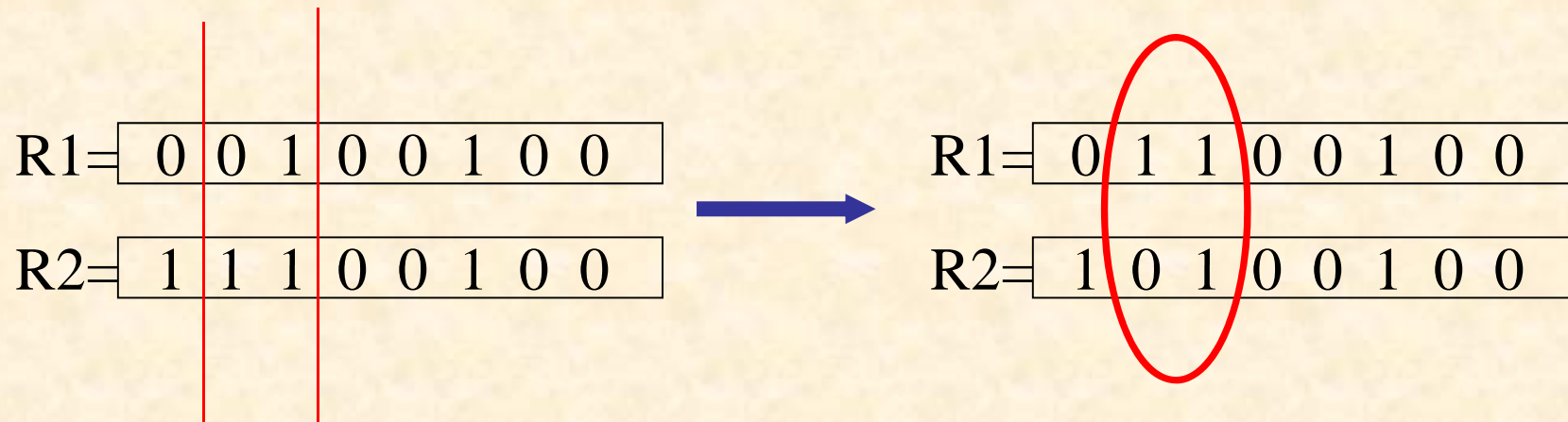
- $\text{Prob}(R5) > \text{Prob}(R1) > \text{Prob}(R6) > \text{Prob}(R2) > \text{Prob}(R4) > \text{Prob}(R3)$



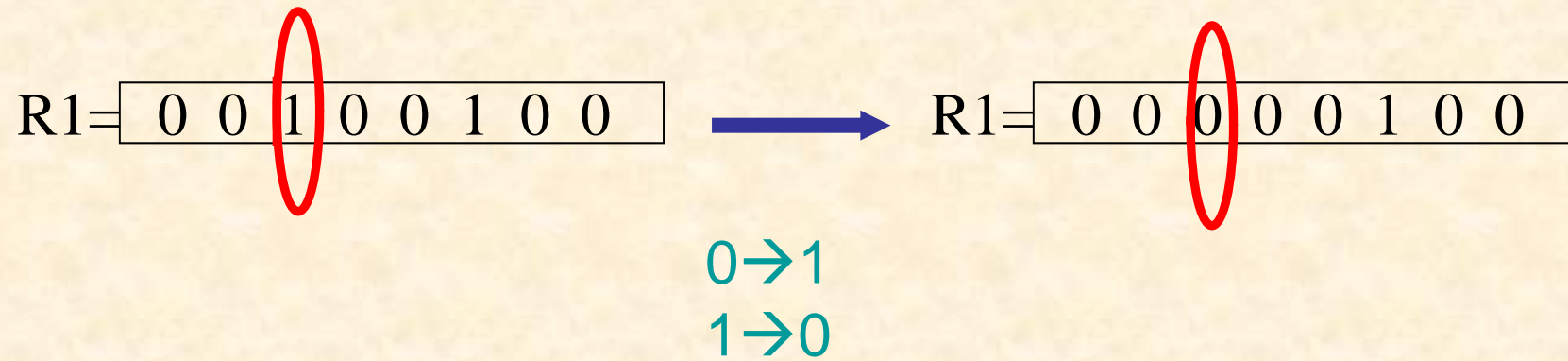
- Ex: R5, R1, R5, R6, R5, R4 are selected to be the next population.



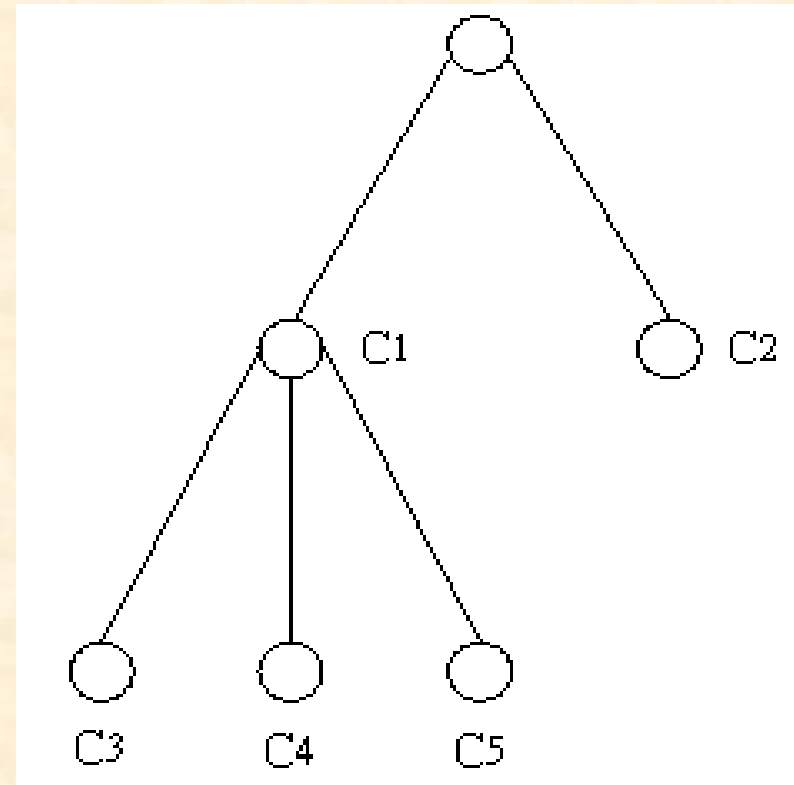
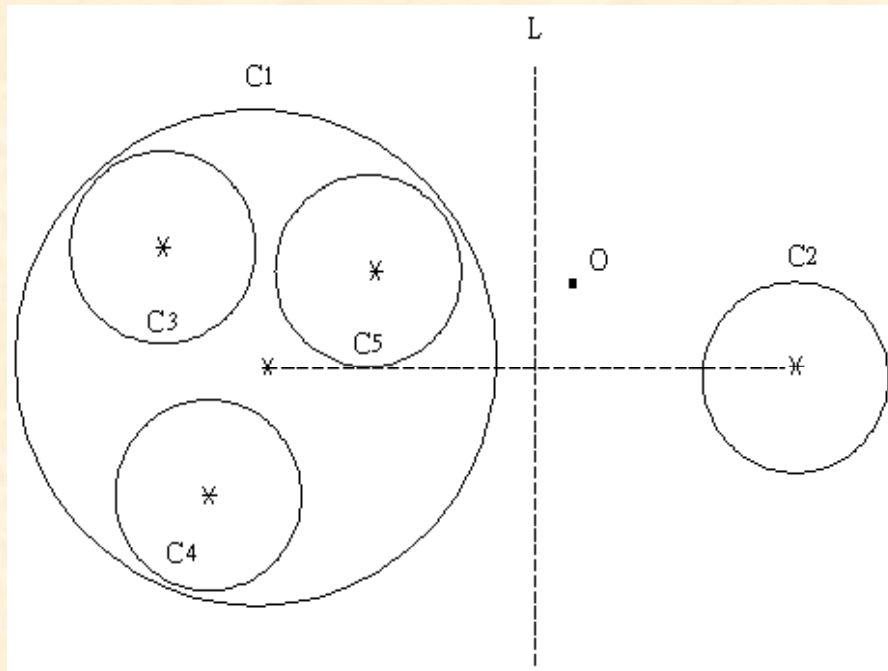
- Crossover



- Mutation

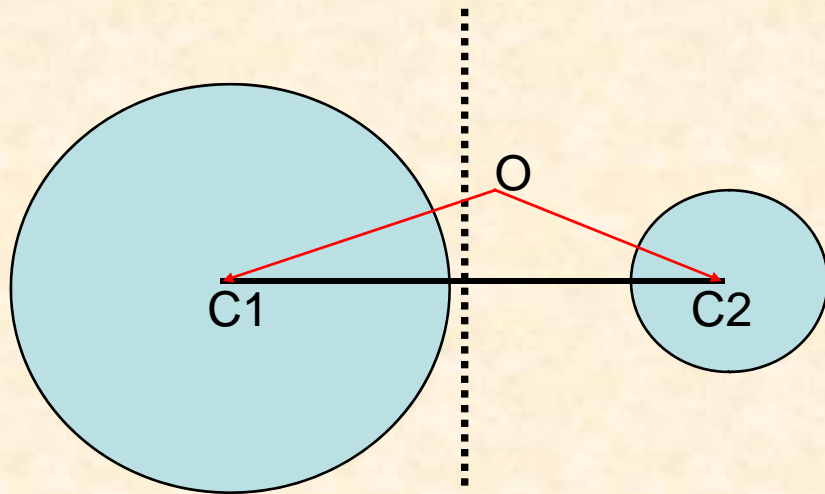


- Problem 2: The encoding codeword is not the closest codeword to the input  $X$ .



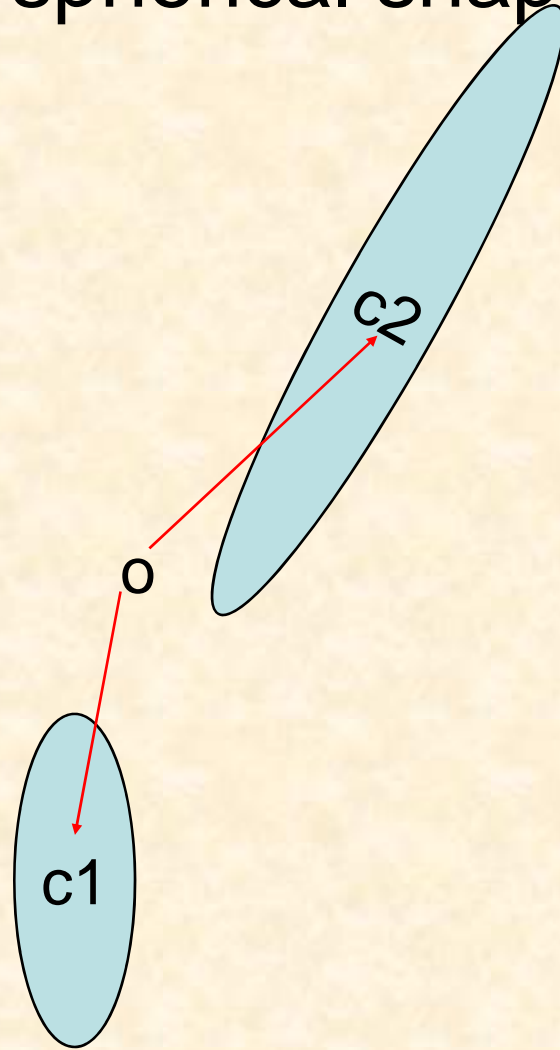
- Input  $O$  is encoded by **C2** in the decision tree. However,  $O$  is closer to **C5**.

- **Solution** for Problem 2
  - The **cluster center** is **not** proper to classify the input vector in the decision tree.
  - Ex:
    - (1) Large cluster

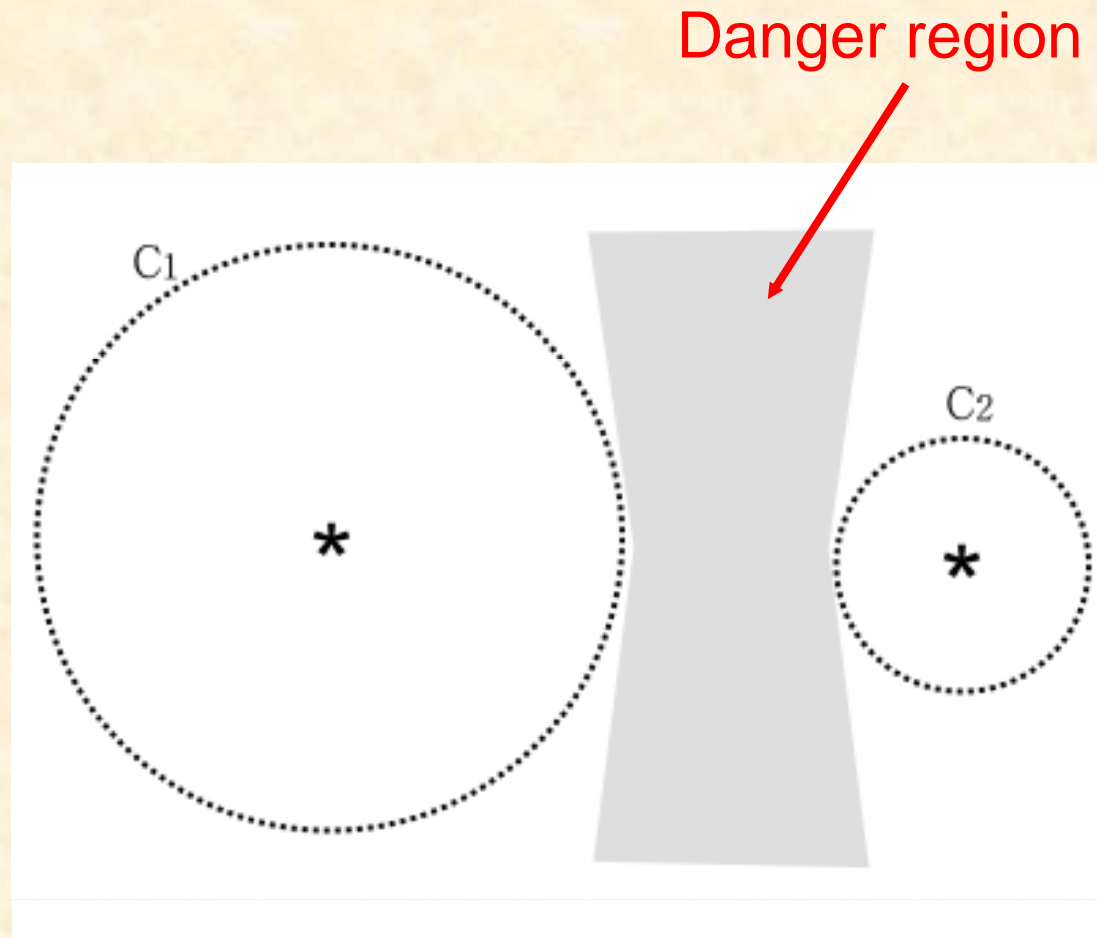


– Ex:

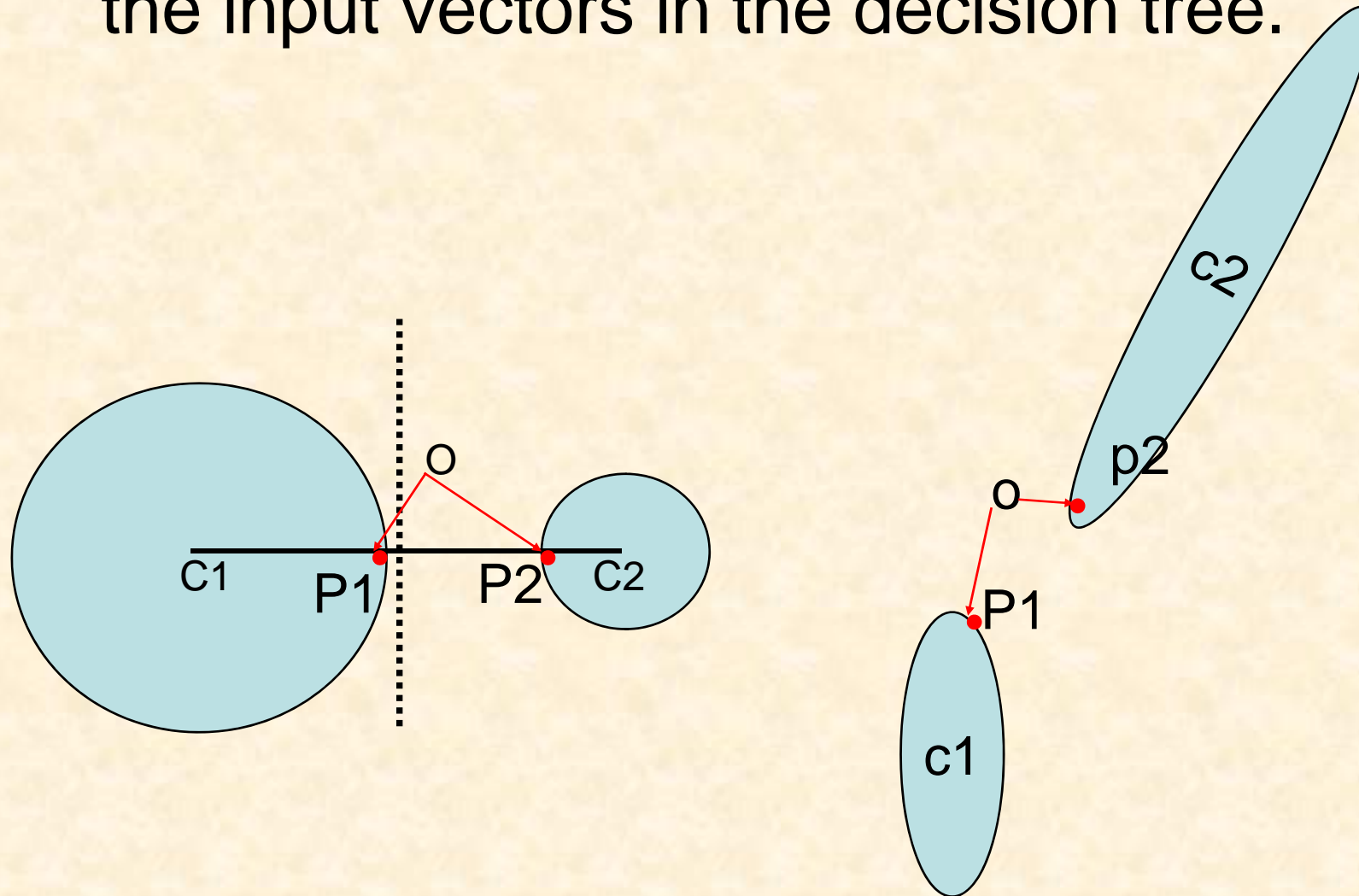
(2) Non-spherical shape of clusters



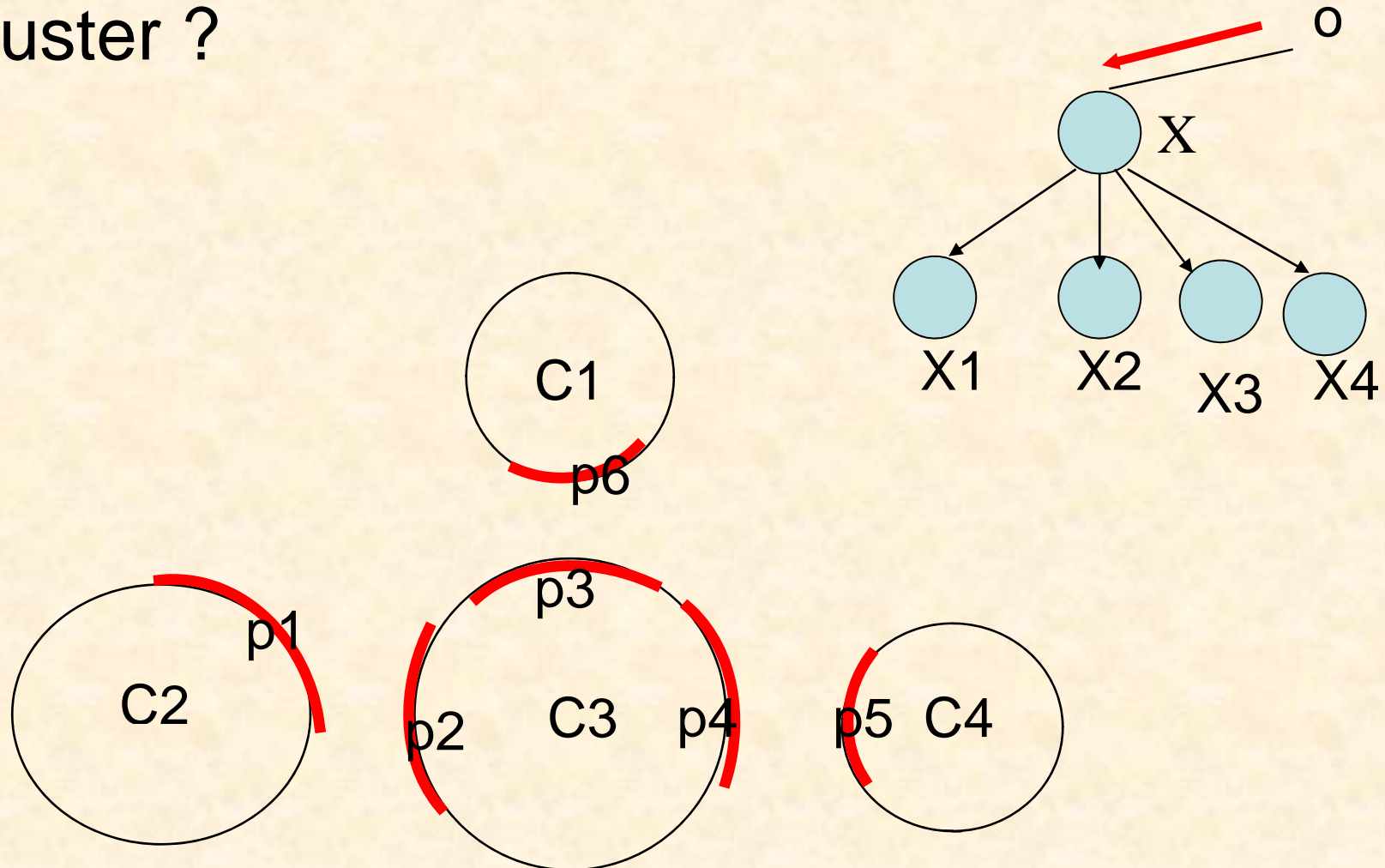
- **Danger region** among the clusters



- Classification point is defined to classify the input vectors in the decision tree.



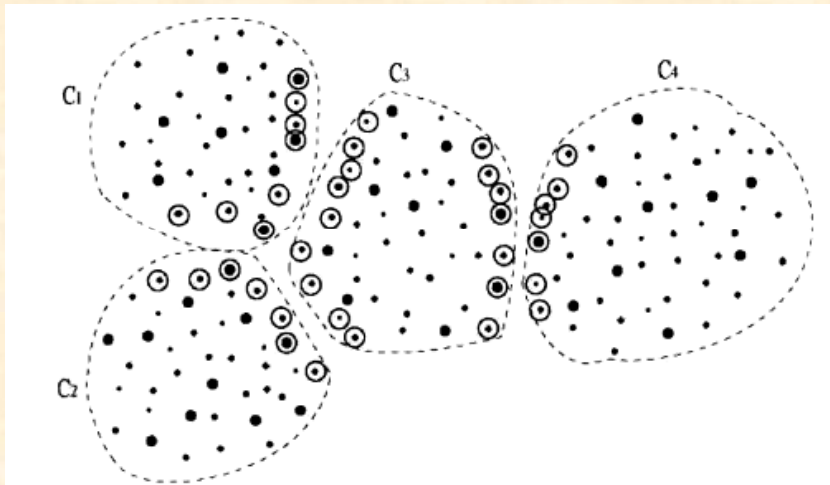
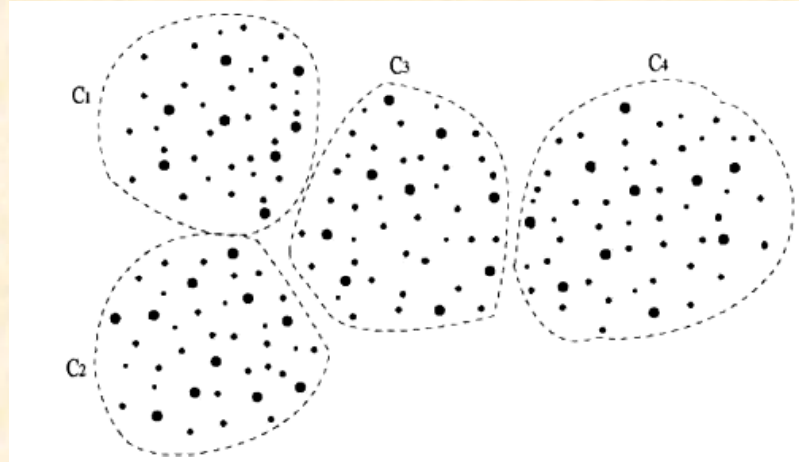
- How to find the classification points in a cluster ?



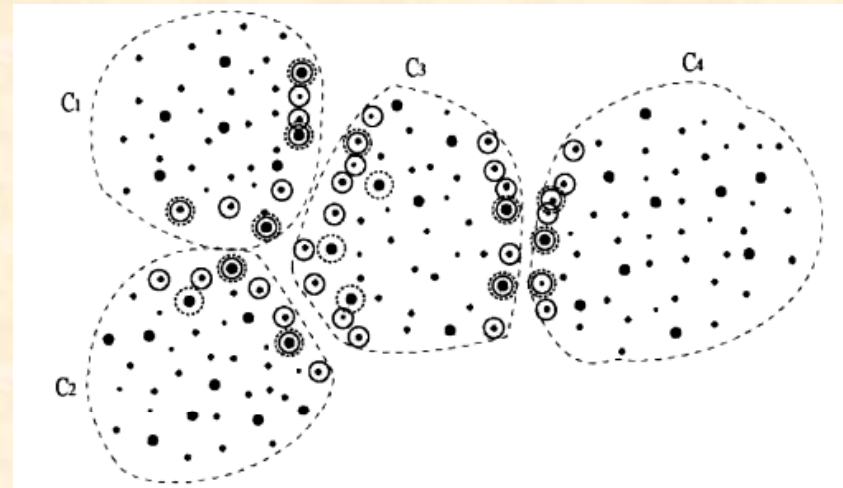
– O is compared with p1, p2, p3, p4, p5 and p6.



(1)



(2)



(3)

# Conclusions

- Variable-branch decision tree can also be applied to recognition applications.
- Traditional NCUT tree can be improved by genetic algorithm.
- Adaptive variable-branch decision tree can be proposed in the further.

感謝