BABEŞ-BOLYAI UNIVERSITY
Faculty of Computer Science and Mathematics

# ARTIFICIAL INTELLIGENCE

**Intelligent systems**

Machine learning

Support Vector Machines

K-means

# Topics

A. Short introduction in Artificial Intelligence (AI)

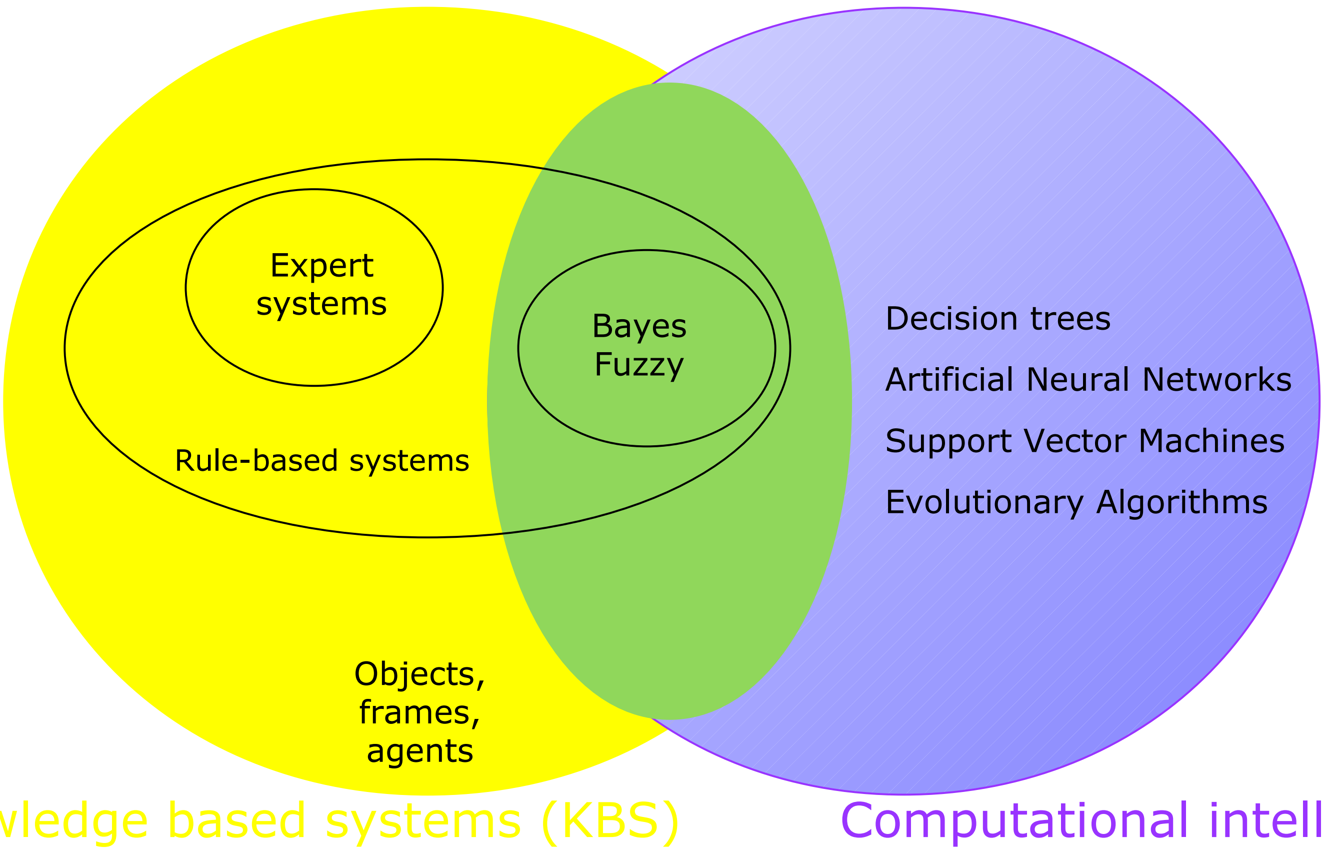
A. Solving search problems
   A. Definition of search problems
   B. Search strategies
      A. Uninformed search strategies
      B. Informed search strategies
      C. Local search strategies (Hill Climbing, Simulated Annealing, Tabu Search, Evolutionary algorithms, PSO, ACO)
      D. Adversarial search strategies

C. **Intelligent systems**
   A. Rule-based systems in certain environments
   B. Rule-based systems in uncertain environments (Bayes, Fuzzy)
   C. **Learning systems**
      A. Decision Trees
      B. Artificial Neural Networks
      C. Evolutionary algorithms
      D. **Support Vector Machines**
      E. **K-means**
   D. Hybrid systems

# Useful information

- Chapter 15 of *C. Groşan, A. Abraham, Intelligent Systems: A Modern Approach, Springer, 2011*
- Chapter 9 of *T. M. Mitchell, Machine Learning, McGraw-Hill Science, 1997*
- Documents from *svm* folder

# Intelligent systems



# Intelligent systems – Machine Learning

- Typology

  - Experience criteria:
    - Supervised learning
    - Unsupervised learning
    - Active learning
    - Reinforcement learning

  - Algorithm criteria
    - Decision trees
    - Artificial Neural Networks
    - Evolutionary Algorithms
    - **Support Vector Machines**
    - Hidden Markov Models
    - K-means

# Intelligent Systems – Support Vector Machines

- Support Vector Machines (SVMs)
  - Definition
  - Solved problems
  - Advantages
  - Difficulties
  - Tools

# Intelligent Systems – Support Vector Machines

- Definition
  - Developed by Vapnik in 1970
  - Popularised after 1992
  - Linear classifiers that identify the hyper-plane that separates the positive and negative classes
  - Have a theoretical foundation
  - Work very well for large data (text mining, image analysis)

  - **Remember**
    - Supervised learning problem – a data set:
      - $(x^d, t^d)$, with:
      - $x^d \in \mathbf{R}^m \Rightarrow x^d=(x^d_1, x^d_2,\ldots, x^d_m)$
      - $t^d \in \mathbf{R} \Rightarrow t^d \in \{1, -1\}$, $1 \rightarrow$ positive class, $-1 \rightarrow$ negative class
      - where $d = 1,2,\ldots,n,n+1,n+2,\ldots,N$
    - First n data ($x^d$ and $t^d$ are known) are used as training data
    - Last N-n data ($x^d$ is known, $t^d$ is unknown) are used as testing data

# Intelligent Systems – Support Vector Machines

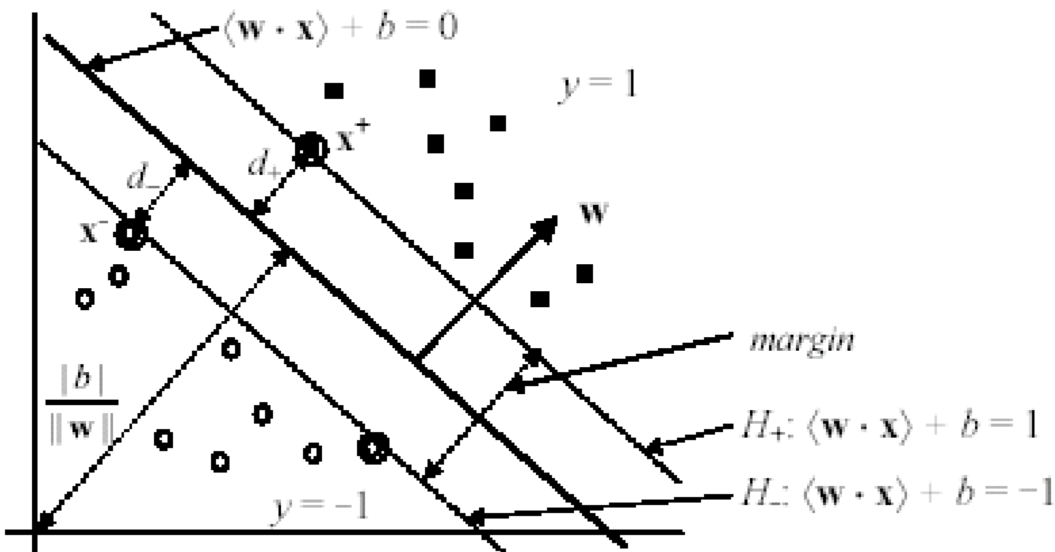
- Definition
  - SVM finds a linear function $f(\mathbf{x}) = \langle \mathbf{w} \cdot \mathbf{x} \rangle + b$, ($\mathbf{w}$ –weight vector) such as

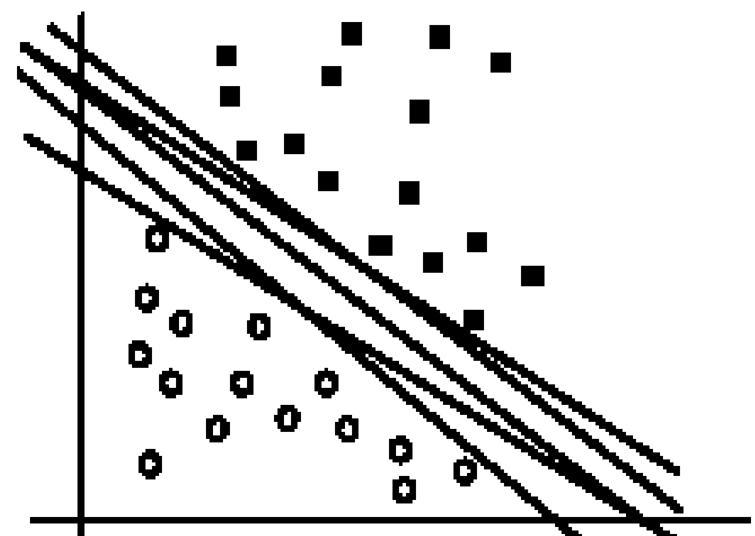
$$y_i = \begin{cases} 1 & \text{if } \langle \mathbf{w} \cdot \mathbf{x}_i \rangle + b \geq 0 \\ -1 & \text{if } \langle \mathbf{w} \cdot \mathbf{x}_i \rangle + b < 0 \end{cases}$$

  - $\langle \mathbf{w} \cdot \mathbf{x} \rangle + b = 0$ → decision hyper-plane that separates the two classes

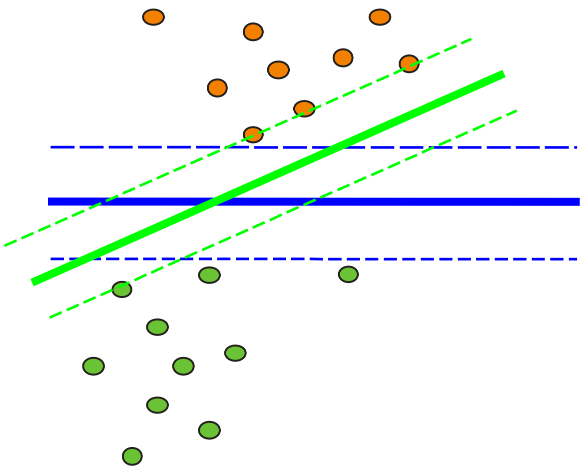
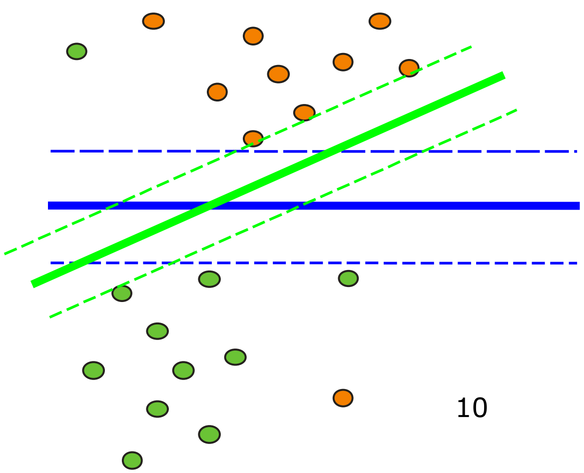
# Intelligent Systems – Support Vector Machines

- Definition
  - There are more hyper-planes
    - Which is the best hyper-plane?
  - SVM searches the hyper-plane with the largest margin (that minimises the generalisation error)
    - SMO (*Sequential minimal optimization*) algorithm



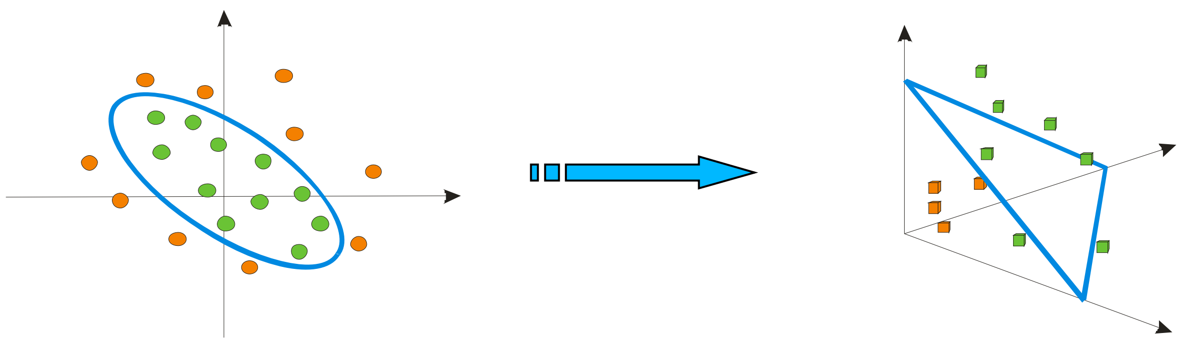



# Intelligent Systems – Support Vector Machines

- Solved problems
  - Classification problems → more cases (based on the data type):
    - Linear separable
      
      - Separable
        - Error = 0
      
      - Non-separable
        - Constrains are relaxed → some error are allowed
        - C – penalisation coefficient

# Intelligent Systems – Support Vector Machines

- Solved problems → classification problems → data cases:
  - Non-linear separable
    - Input space is transformed (mapped) into a space of more dimensions (feature space) by using kernel function – in this new space the data becomes linear separable
    - In SVMs the kernel function computes the distance among 2 points
      - → kernel ~ similarity function



# Intelligent Systems – Support Vector Machines

- Solved problems → classification problems → data cases:
  - Non-linear separable → possible kernels
    - Classic kernels
      - Polynomial kernel: $K(\boldsymbol{x}^{d1}, \boldsymbol{x}^{d2}) = (\boldsymbol{x}^{d1}, \boldsymbol{x}^{d2} + 1)^p$
      - RBF kernel: $K(\boldsymbol{x}^{d1}, \boldsymbol{x}^{d2}) = exp(- ||\boldsymbol{x}^{d1} - \boldsymbol{x}^{d2}||^2/2\sigma^2)$
    - Multiple Kernels
      - Linear : $K(\boldsymbol{x}^{d1}, \boldsymbol{x}^{d2}) = \sum w_i K_i (\boldsymbol{x}^{d1}, \boldsymbol{x}^{d2})$
      - Non-linear
        - Without coefficients: $K(\boldsymbol{x}^{d1}, \boldsymbol{x}^{d2}) = K_1(\boldsymbol{x}^{d1}, \boldsymbol{x}^{d2}) + K_2(\boldsymbol{x}^{d1}, \boldsymbol{x}^{d2}) * exp(K_3(\boldsymbol{x}^{d1}, \boldsymbol{x}^{d2}))$
        - With coefficients: $K(\boldsymbol{x}^{d1}, \boldsymbol{x}^{d2}) = K_1 (\boldsymbol{x}^{d1}, \boldsymbol{x}^{d2}) + c_1 * K_2 *(\boldsymbol{x}^{d1}, \boldsymbol{x}^{d2}) \ exp(c_2 + K_3(\boldsymbol{x}^{d1}, \boldsymbol{x}^{d2}))$
    - Kernels for strings
    - Kernels for images
    - Kernels for graphs

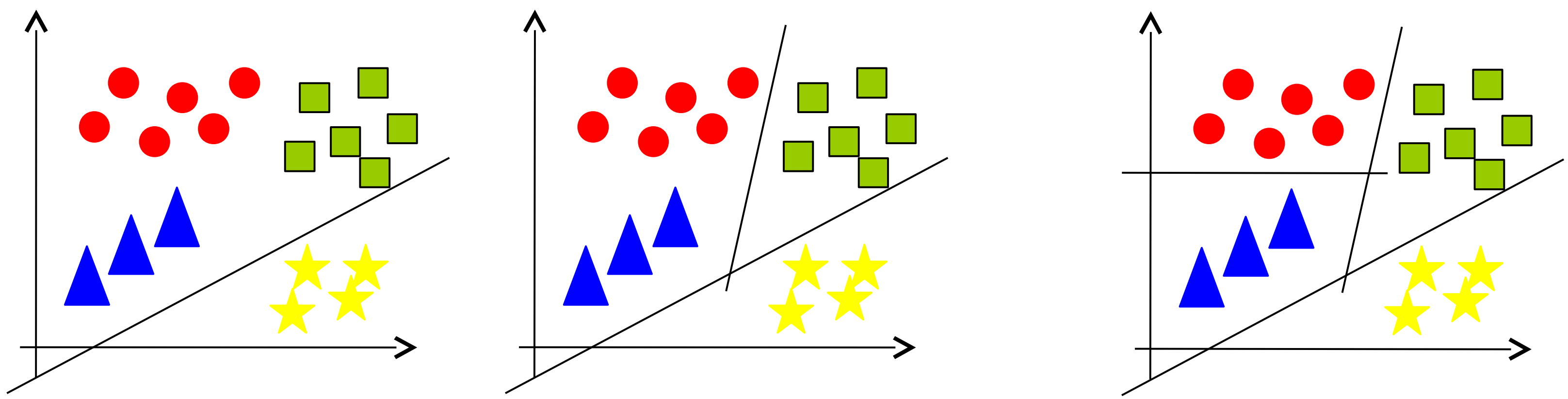
# Intelligent Systems – Support Vector Machines

- SVM setting
  - SVM's parameters
    - Penalisation coefficient C
      - C- small → slowly convergence
      - C – large → fast convergence

    - Kernel parameters (what kernel and what parameters)
      - If m (# of attributes) is larger than n (# of data)
        - SVM by a linear kernel (SVM without kernel) → $K(\boldsymbol{x}^{d1}, \boldsymbol{x}^{d2}) = \boldsymbol{x}^{d1} \cdot \boldsymbol{x}^{d2}$
      - If m (# of attributes) is large and n (# of data) is medium
        - SVM with Gaussian kernel $K(\boldsymbol{x}^{d1}, \boldsymbol{x}^{d2}) = \exp(-||\boldsymbol{x}^{d1} - \boldsymbol{x}^{d2}||^2/2\sigma^2)$
        - σ – dispersion of training data
        - Attributes must be normalised (scalled to (0,1))
      - If m (# of attributes) is small and n (# of data) is large
        - Ad new attributes and than SVM with linear kernel

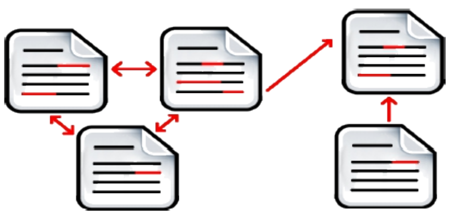
# Intelligent Systems – Support Vector Machines

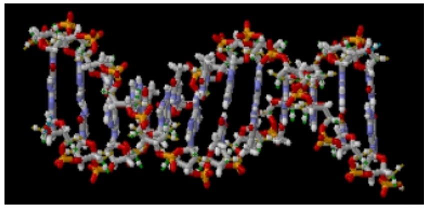
- SVM for multi-class classification problems (more than 2 classes)
  - one *vs.* all



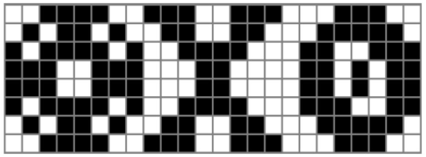
# Intelligent Systems – Support Vector Machines

- Structured SVMs
  - Machine Learning
    - Simple SVM $f: X \rightarrow R$
      - Any type of inputs
      - Numerical outputs (natural numbers, integers, real numbers)
    - Structured SVM: $X \rightarrow Y$
      - Any type of inputs
      - Any type of outputs (numerical or structured outputs)





  - Structured information
    - Texts and hyper-texts
    - Molecules and molecular structures
    - Images



# Intelligent Systems – Support Vector Machines

- Structured SVMs
  - Applications
    - Natural Language Processing
      - Automatic translation (outputs → sentences)
      - Syntactic and/or morphologic analysis of sentences (outputs → syntactic and/or morphologic tree)
    - Bioinformatic
      - Prediction of secondary structures (outputs → bi=partite graphs)
      - Prediction of enzyme function (outputs → paths in trees)
    - Speech processing
      - Automatic transcriptions (outputs → sentences)
      - Transformation of texts in voice (outputs → audio signal)
    - Robotics
      - Planning (outputs → sequences of actions)

# Intelligent Systems – Support Vector Machines

- Advantages
  - Can work with any type of data (linear or non-linear separable, uniform distributed or not, with known or unknown distribution)
    - Kernel function that creates new attributes (features) → hidden layers of an ANN
  - If the problem is convex SVM finds a unique solution → global optima
    - ANNs can associates more solutions → local optima
  - Automatic selection of the learnt model (by support vectors)
    - In ANNs hidden layers have to be configured a priori
  - Avoid over fitting
    - ANNs have over fitting problems even the cross-validation is involved

- Difficulties
  - Real attributes only
  - Binary classification problems only
  - Difficult mathematical background

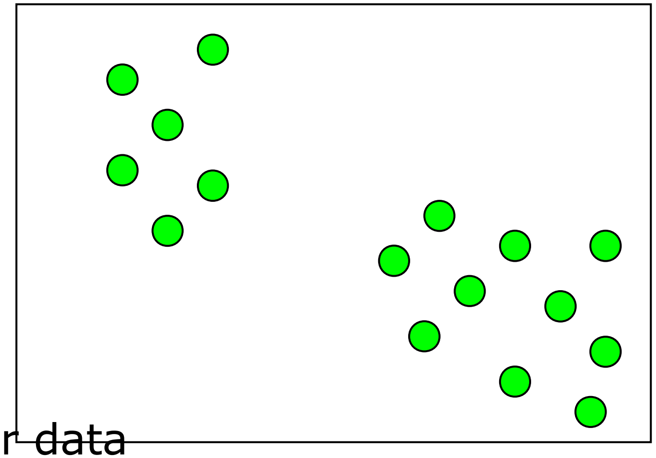
- Tools
  - LibSVM → http://www.csie.ntu.edu.tw/~cjlin/libsvm/
  - Weka → SMO
  - SVMLight → http://svmlight.joachims.org/
  - SVMTorch → http://www.torch.ch/
  - http://www.support-vector-machines.org/

# Intelligent systems – Machine Learning

- Typology
  - Experience criteria:
    - Supervised learning
    - Unsupervised learning
    - Active learning
    - Reinforcement learning
  - Algorithm criteria
    - Decision trees
    - Artificial Neural Networks
    - Evolutionary Algorithms
    - Support Vector Machines
    - Hidden Markov Models
    - **K-means**

# Unsupervised learning

- Aim
  - Finds a model or a structure of data
- Solved problems
  - Identification of groups (clusters)
    - Analysis of genes
    - Image processing
    - Analysis of social networks
    - Market segmentation
    - Analysis of astronomic data
    - Clusters of computers
  - Dimension reduction
  - Identification of causes (explanations) for data
  - Modelling the data densities



- Specific
  - Data are not annotated (labelled)

# Unsupervised learning – definition

Separates the un- labeled examples in disjoint sub-sets (clusters) such as:

- Examples of the same cluster are similar
- Examples of different clusters are different

Definition

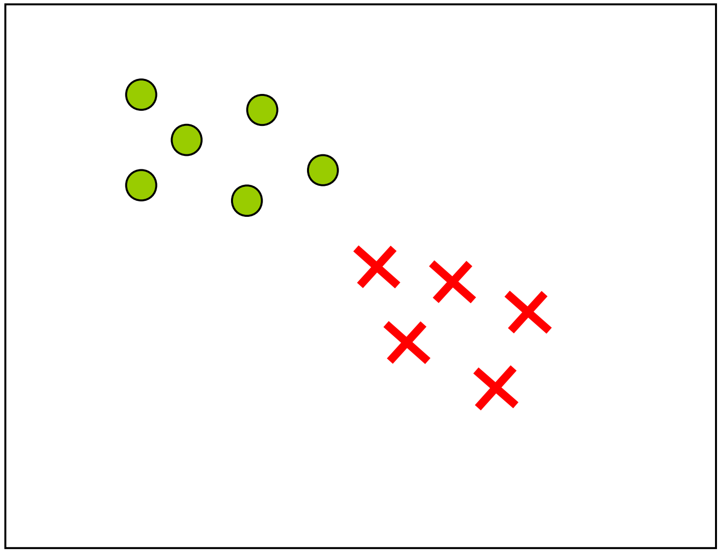
- Given
  - A set of data (examples, instances, cases)
    - Training data
      - As ***atribute_data**$_i$*, where
        - $i = 1,N$ ($N$ = # of training data
        - ***atribute_data**$_i$*= ($atr_{i1}$, $atr_{i2}$, ..., $atr_{im}$), $m$ – # of attributes (characteristics, properties) of data
    - Testing data
      - As (***atribute_data**$_i$*), $i = 1,n$ ($n$ = # of testing data)
- Determine
  - An unknown function that groups the training data in more classes
    - # of classes can be pre-defined (k) or un-known
    - Data of the same class are similar
  - The class of a new testing data by using the learnt grouping (on training data)

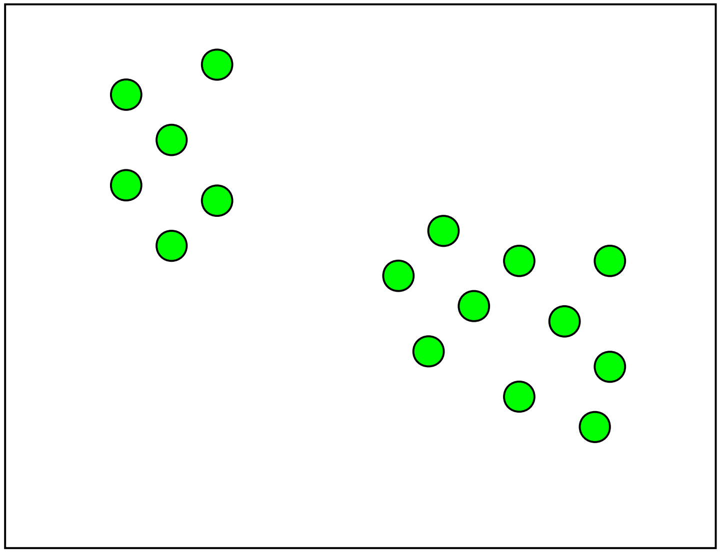
Other names

- Clustering

# Unsupervised learning – definition

- Supervised *vs.* un-supervised





# Unsupervised learning – definition

- Distance between 2 elements $\boldsymbol{p}$ and $\boldsymbol{q} \in R^m$
  - Euclid distance
    - $d(\boldsymbol{p},\boldsymbol{q})=sqrt(\sum_{j=1,2,\dots,m}(p_j-q_j)^2)$
  - Manhattan distance
    - $d(\boldsymbol{p},\boldsymbol{q})=\sum_{j=1,2,\dots,m}|p_j-q_j|$
  - Mahalanobis distance
    - $d(\boldsymbol{p},\boldsymbol{q})=sqrt(\boldsymbol{p}-\boldsymbol{q})S^{-1}(\boldsymbol{p}-\boldsymbol{q})),$
      - Where S is the covariance matrix ($S= E[(\boldsymbol{p}-E[\boldsymbol{p}])(\boldsymbol{q}-E[\boldsymbol{q}])]$)
  - Internal product
    - $d(\boldsymbol{p},\boldsymbol{q})=\sum_{j=1,2,\dots,m}p_jq_j$
  - Cosine distance
    - $d(\boldsymbol{p},\boldsymbol{q})=\sum_{j=1,2,\dots,m}p_jq_j / (sqrt(\sum_{j=1,2,\dots,m}p_j^2) * sqrt(\sum_{j=1,2,\dots,m}q_j^2))$
  - Hamming distance
    - # of differences between ***p*** and ***q***
  - Levenshtein distance
    - Minimal # of operations required for transforming ***p*** in ***q***

- Distance *vs.* similarity
  - Distance → minimisation
  - Similarity → maximisation

# Unsupervised learning – definition

Application

- Gene clustering
- Market segmentation (for client clustering)
- news.google.com

# Unsupervised learning – process

Process

- 2 steps:
  - Learning
    - Determine (learn), by using an algorithm, the existing clusters
  - Testing
    - Include a new data in one of the identified (during training) clusters

Learning quality (clustering validation)

- Internal criteria
  - Large similarity inside the cluster and reduce similarity between clusters
- External criteria
  - Using benchmarks composed of *apriori* grouped data

# Unsupervised learning – evaluation

Performance measures

- Internal criteria
  - Distance inside the cluster
  - Distance between clusters
  - Davies-Bouldin index
  - Dunn index

- External criteria
  - Comparison with known data – impossible in real-world applications
  - Precision
  - Recall
  - F-measure

# Unsupervised learning – evaluation

## Performance measures

- Internal criteria
  - Distance inside cluster $c_j$ that contains $n_j$ instances
    - Average distance (among instances)
      - $D_a(c_j) = \sum_{xi1,xi2 \epsilon cj} ||x_{i1} - x_{i2}|| / (n_j(n_j-1))$
    - Nearest neighbour distance
      - $D_{nn}(c_j) = \sum_{xi1 \epsilon cj} min_{\ xi2 \epsilon cj} ||x_{i1} - x_{i2}|| / n_j$
    - Distance between centroids
      - $D_c(c_j) = \sum_{xi, \epsilon cj} ||x_i - \mu_j|| / n_j$, $unde\ \mu_j = 1/ n_j \sum_{xi \epsilon cj} x_i$

# Unsupervised learning – evaluation

Performance measure

- Internal criteria
  - Distance between 2 clusters $c_{j1}$ and $c_{j2}$
    - Simple link
      - $d_s(c_{j1}, c_{j2}) = min_{\ xi1\epsilon cj1,\ xi2\epsilon cj2} \{||x_{i1} - x_{i2}||\}$
    - Complete link
      - $d_{co}(c_{j1}, c_{j2}) = max_{\ xi1\epsilon cj1,\ xi2\epsilon cj2} \{||x_{i1} - x_{i2}||\}$
    - Average link
      - $d_a(c_{j1}, c_{j2}) = \sum_{\ xi1\epsilon cj1,\ xi2\epsilon cj2} \{||x_{i1} - x_{i2}||\} / (n_{j1} * n_{j2})$
    - Link between centroids
      - $d_{ce}(c_{j1}, c_{j2}) = ||\mu_{j1} - \mu_{j2}||$

# Unsupervised learning – evaluation

Performance measures

- Internal criteria
  - Davies-Bouldin index → min ➔ compact clusters
    - $DB = 1/nc*\sum_{i=1,2,...,nc} max_{j=1, 2, ..., nc, j \neq i}((\sigma_i + \sigma_j)/d(\mu_i, \mu_j))$
    - where:
      - $nc$ – # of clusters
      - $\mu_i$ – centroid of cluster *i*
      - $\sigma_i$ – average of distances between elements form cluster *i* and the centroid $\mu_i$
      - $d(\mu_i, \mu_j)$ – distance between centroid $\mu_i$ and centroid $\mu_j$
  - Dunn index
    - Identifies the dense clusters and well separated
    - $D=d_{min}/d_{max}$
    - where:
      - $d_{min}$ – minimal distance between 2 elements from different clusters - intra-cluster distance
      - $d_{max}$ – maximal distance between 2 elements from the same cluster - inter-cluster distance

# Unsupervised learning – typology

- How the clusters are forming
  - Hierarchic clustering
  - Non-hierarchic (partitioned) clustering
  - Clustering based on data density
  - Clustering based on a grid

# Unsupervised learning – typology

- How the clusters are forming
  - Hierarchic clustering
    - Creates a dendogram (taxonomic tree)
      - Creates the clusters (recursively)
      - k (# of clusters) is un-known
    - Aglomerativ clustering (bottom-up) → small clusters to large clusters
    - Divisiv clustering (top-down) → large clusters to small clusters
    - Eg.
      - Clustering ierarhic aglomerativ

# Unsupervised learning – typology

- How the clusters are formed
  - Non-hierarchic
    - Partitional → determine a data separation → all the clusters in the same time
    - Optimises an objective function defined
      - Locally – by using some features only
      - Globally – by using all attributes

      that can be:

      - squared error – sum of squared distances between data and the cluster's centroid → min
        - Ex. *K-means*
      - Graph-based
        - Ex. Clustering based in minimum spanning tree
      - Based on probabilistic models
        - Ex. Identify the data distribution → expectation maximisation
      - Based on the nearest neighbour
    - Required to fix k apriori → fix the initial clusters
      - Algorithm is run more times with different parameters and the most efficient version is selected
    - Ex. *K-means, ACO*

# Unsupervised learning – typology

- How the clusters are forming
  - Based on data densities
    - Data density and data connectivity
      - Cluster formation is based on data density from a given region
      - Cluster formation is based on data connectivity from a given region
    - Function of data density
      - Tries to model the data distribution
    - Advantage:
      - Modeling of clusters of any shape

# Unsupervised learning – typology

- How the cluster are forming
  - Based on a grid
    - Is not a distinct approach
      - Can be hierarchic, partitional or density-based
    - Involves data space segmentation in regular areas
    - Objects are placed on a multi-dimensional grid
    - Eg. ACO

# Unsupervised learning – typology

- How the algorithms work
  - Agglomerativ clustering
    1. Initially, each instance form a cluster
    2. Compute the distance between any 2 clusters
    3. Reunion the closest 2 clusters
    4. Repeat steps 3 and 4 until a single cluster is obtained or other stop criterion is satisfied
  - Divisive clustering
    1. Establish the number of clusters ($k$)
    2. Initialise the centre of each cluster
    3. Determine a data separation
    4. Re-compute the centre of each cluster
    5. Repeat steps 3 and 4 until the partition is unchanged (algorithm converges)

- How the algorithm takes into account the attributes (features)
  - Monotonic – attributes are taken into account one-by-one
  - Polytonic – attributes are simultaneous taken into

# Unsupervised learning – typology

- How the data belong to clusters
  - Exact clustering (hard clustering)
    - Each instance $x_i$ has associated a label (class) $c_j$
  - Fuzzy clustering
    - Each instance has associated a membership degree (probability) $f_{ij}$ to a given class $c_j$ → an instance xi can belongs to more clusters
    - Asociază fiecarei intrări $\boldsymbol{x_i}$ un grad (probabilitate) de apartenenţă $f_{ij}$ la o anumită clasă $c_j$ ➔ o instanţă $\boldsymbol{x_i}$ poate aparţine mai multor clusteri

# Unsupervised learning – algorithms

- Agglomerative hierarchical clustering
- K-means
- AMA
- Probabilistic models
- Nearest neighbour
- Fuzzy
- Artificial Neural Network
- Evolutionary algorithms
- ACO

# Unsupervised learning – algorithms

Agglomerative hierarchical clustering

- Consider a distance between 2 instances $d(x_{i1}, x_{i2})$

- Form $N$ clusters, each of them containing an instance

- Repeat
  - Determine the closest 2 clusters
  - Reunion the 2 clusters → a cluster
- Until a single cluster is obtained (that contains all the instances)

# Unsupervised learning – algorithms

Agglomerative hierarchical clustering

- Distance between 2 clusters $c_i$ and $c_j$:
  - Simple link → minimal distance between the objects of 2 clusters
    - $d(c_i, c_j) = max_{xi1\epsilon ci,\ xi2\epsilon cj}\ sim(\mathbf{x}_{i1}, \mathbf{x}_{i2})$
  - Complete link → maximal distance between the objects of 2 clusters
    - $d(c_i, c_j) = min_{xi1\epsilon ci,\ xi2\epsilon cj}\ sim(\mathbf{x}_{i1}, \mathbf{x}_{i2})$
  - Average link → mean of distances between the objects of 2 clusters
    - $d(c_i, c_j) = 1 / (n_i * n_j)\ \Sigma_{xi1\epsilon ci}\ \Sigma_{xi2\epsilon cj}\ d(\mathbf{x}_{i1}, \mathbf{x}_{i2})$
  - Average link over group → distance between the means (centroids) of 2 clusters
    - $d(c_i, c_j) = \rho(\boldsymbol{\mu}_i, \boldsymbol{\mu}_j)$, $\rho$ – distance, $\boldsymbol{\mu}_j = 1/n_j \sum_{xi\epsilon cj} \mathbf{x}_i$

# Unsupervised learning – algorithms

K-means (Lloyd algorithm / Voronoi iteration)

- Suppose that k clusters will form

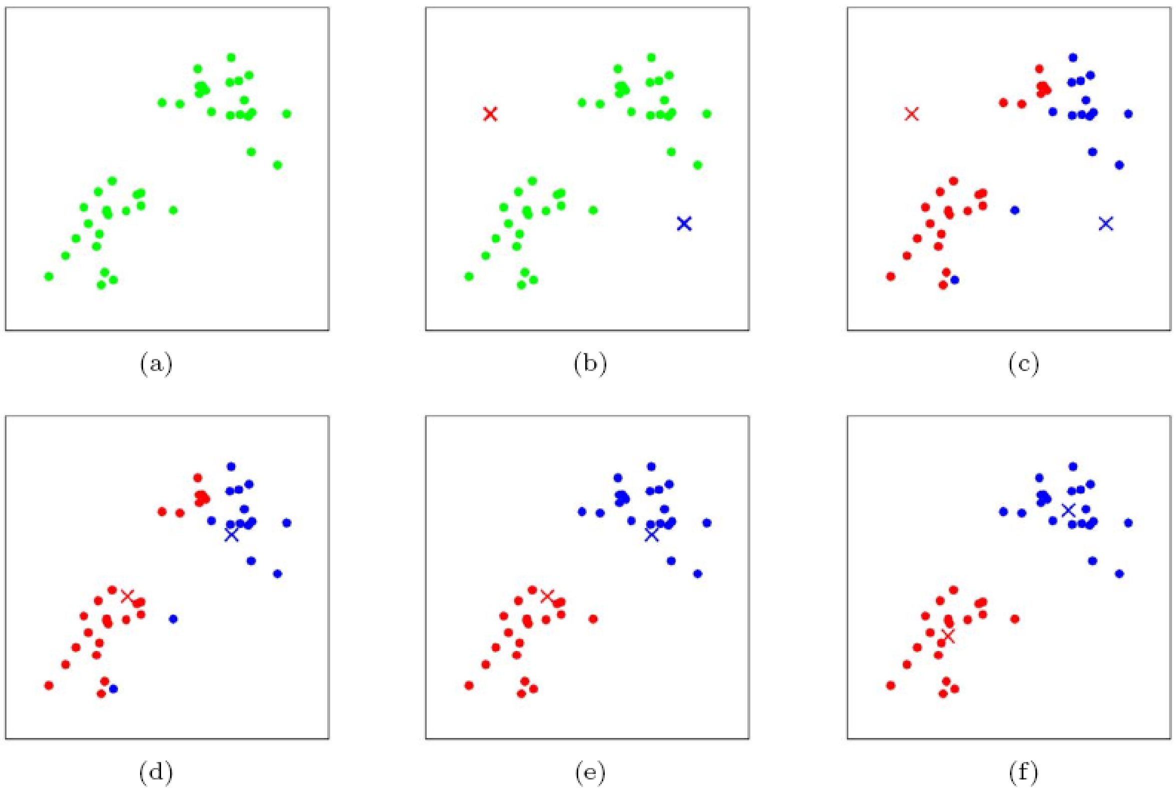
- Initialise *k* centroids $\boldsymbol{\mu}_1, \boldsymbol{\mu}_2, \ldots, \boldsymbol{\mu}_k$
  - A centroid $\boldsymbol{\mu}_j$ ($i=1,2, \ldots, k$) is a vector of *m* values (*m* - # of features)

- Repeat until convergence
  - Associated to each instance the nearest centroid → for each instance $\boldsymbol{x}_i$, $i = 1, 2, \ldots, N$
    - $c_i = arg\ min_{j = 1, 2, \ldots, k} ||\boldsymbol{x}_i - \boldsymbol{\mu}_j||^2$

  - Re-compute the centroids by moving them in the mean of instances associated to it → for each cluster $c_j$, $j = 1, 2, \ldots, k$
    - $\boldsymbol{\mu}_j = \sum_{i=1,2, \ldots N} 1_{ci=j}\ \boldsymbol{x}_i / \sum_{i=1,2, \ldots N} 1_{ci=j}$

# Unsupervised learning – algorithms

- K-means



# Unsupervised learning – algorithms

K-means

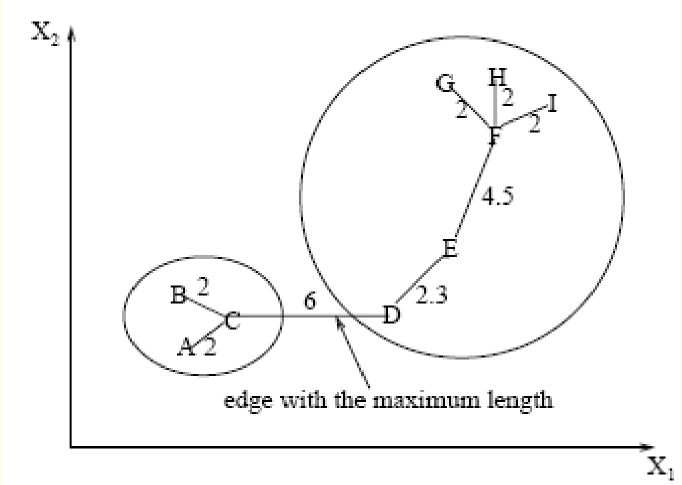
- Initialisation of *k* centroids $\boldsymbol{\mu}_1, \boldsymbol{\mu}_2, \ldots, \boldsymbol{\mu}_k$
  - With random values (in the definition domain of the problem)
  - With *k* instances of *N* (randomly selected)

- Does algorithm converge always?
  - Yes, because of distortion function J
    - $J(c, \mu) = \sum_{i=1,2,\ldots,N} ||\boldsymbol{x}_i - \boldsymbol{\mu}_{cj}||^2$

    which is decreasing
  - Converges in a local optima
  - Finding the global optima → NP-difficult problem

# Clustering based on minimum spanning tree

- Construct the minimum spanning tree of data
- Eliminate from the tree the longest edges and form clusters



# Învăţare ne-supervizată – algoritmi
## Modele probabilistice

- http://www.gatsby.ucl.ac.uk/~zoubin/course0
- http://learning.eng.cam.ac.uk/zoubin/nipstut.

# Învăţare ne-supervizată – algoritmi Cel mai apropiat vecin

- Se etichetează câteva dintre instanţe
- Se repetă până la etichetarea tuturor instanţelor
  - O instanţă ne-etichetată va fi inclusă în clusterul instanţei cele mai apropiate
    - dacă distanţa între instanţa neetichetată şi cea etichetată este mai mică decât un prag

# Învăţare ne-supervizată – algoritmi
## Clusterizare fuzzy

- Se stabileşte o partiţionare fuzzy iniţială
  - Se construieşte matricea gradelor de apartenenţă U, unde $u_{ij}$ – gradul de apartenenţă al instanţei $\boldsymbol{x}_i$ ($i=1,2, ..., N$) la clusterul $c_j$ ($j = 1, 2, ..., k$) ($u_{ij} \in [0,1]$)
    - Cu cât $u_{ij}$ e mai mare, cu atât e mai mare încrederea că instanţa $\boldsymbol{x}_i$ face parte din clusterul $c_j$

- Se stabileşte o funcţie obiectiv
  - $E^2(U) = \sum_{i=1,2, ..., N}\sum_{j=1,2,...,k}u_{ij}||\boldsymbol{x}_i - \boldsymbol{\mu}_j||^2$,
    - unde $\boldsymbol{\mu}_j = \sum_{i=1,2, ..., N}u_{ij}\boldsymbol{x}_i$ – centrul celui de-al $j$-lea fuzzy cluster
  - care se optimizează (min) prin re-atribuirea instanţelor (în clusteri noi)

- Clusering fuzzy ➔ clusterizare *hard* (fixă)
  - impunerea unui prag funcţiei de apartenenţă $u_{ij}$

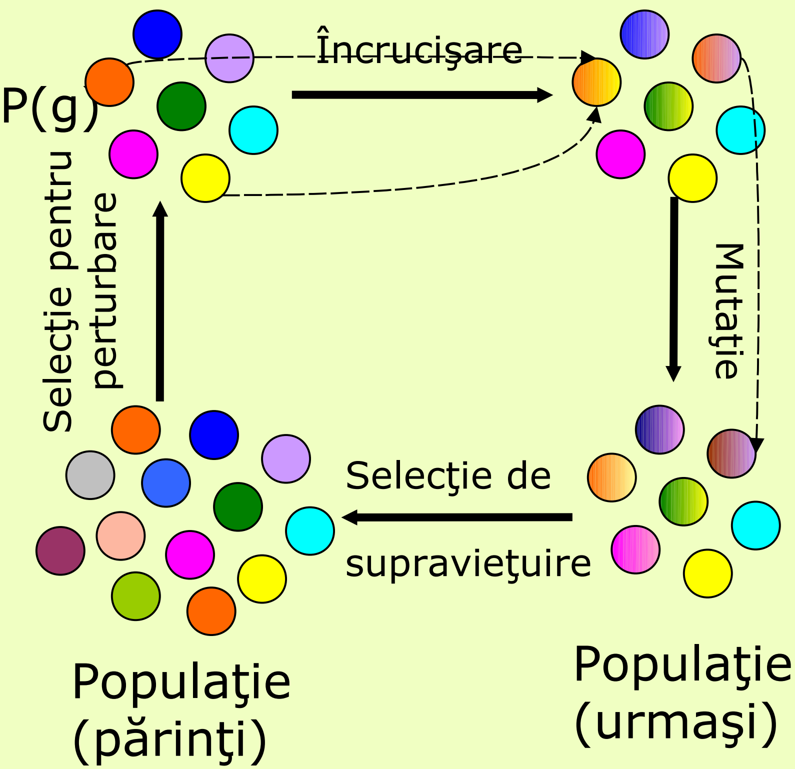
# Învăţare ne-supervizată – algoritmi
# Algoritmi evolutivi

- Algoritmi
  - Inspiraţi din natură (biologie)
  - Iterativi
  - Bazaţi pe
    - populaţii de potenţiale soluţii
    - căutare aleatoare ghidată de
      - Operaţii de selecţie naturală
      - Operaţii de încrucişare şi mutaţie
  - Care procesează în paralel mai multe soluţii
- Metafora evolutivă

| Evoluţie naturală | Rezolvarea problemelor |
|---|---|
| Individ | Soluţie potenţială (candidat) |
| Populaţie | Mulţime de soluţii |
| Cromozom | Codarea (reprezentarea) unei soluţii |
| Genă | Parte a reprezentării |
| Fitness (măsură de adaptare) | Calitate |
| Încrucişare şi mutaţie | Operatori de căutare |
| Mediu | Spaţiul de căutare al problemei |

# Învăţare ne-supervizată – algoritmi
## Algoritmi evolutivi

```
Initializare populaţie P(0)
Evaluare P(0)
g := 0; //generaţia
CâtTimp (not condiţie_stop) execută
    Repetă
        Selectează 2 părinţi p1 şi p2 din P(g)
        Încrucişare(p1,p2) =>o1 şi o2
        Mutaţie(o1) => o1*
        Mutaţie(o2) => o2*
        Evaluare(o1*)
        Evaluare(o2*)
        adăugare o1* şi o* în P(g+1)
    Până când P(g+1) este completă
    g := g + 1
Sf CâtTimp
```

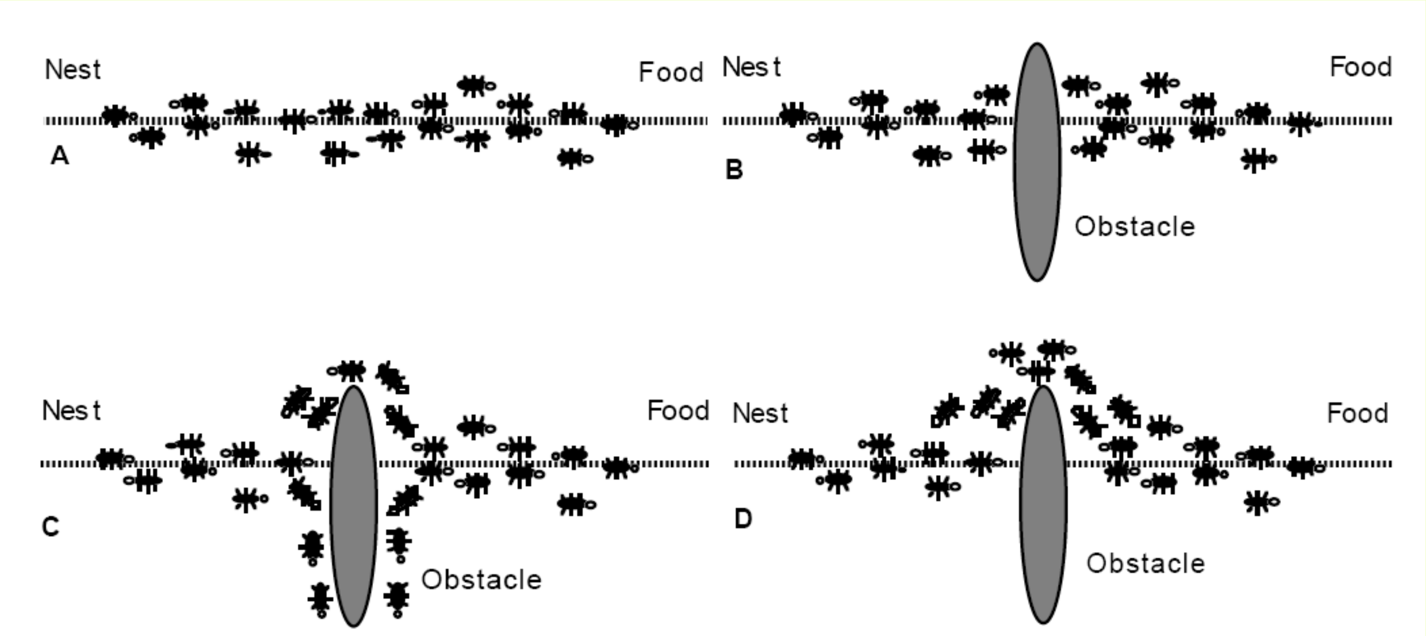


# Învăţare ne-supervizată – algoritmi
# Algoritmi evolutivi

- Reprezentare
  - Cromozomul = o partiţionare a datelor
    - Ex. 2 clusteri ➔ cromozom = vector binar
    - Ex. *K* clusteri ➔ cromozom = vector cu valori din {*1,2,…,k*}
- Fitness
  - Calitatea partiţionării
- Iniţializare
  - Aleatoare
- Încrucişare
  - Punct de tăietură
- Mutaţie
  - Schimbarea unui element din cromozom

# Învăţare ne-supervizată – algoritmi ACO

- Preferinţa pentru drumuri cu nivel ridicat de feromon
- Pe drumurile scurte feromonul se înmulţeşte
- Furnicile comunică pe baza urmelor de feromon



# Învăţare ne-supervizată – algoritmi ACO

- Algoritm de clusterizare bazat pe un grid
- Obiectele se plasează aleator pe acest grid, urmând ca furnicuţele să le grupeze în funcţie de asemănarea lor
- 2 reguli pentru furnicuţe
  - Furnica "ridică" un obiect-obstacol
    - Probabilitatea de a-l ridica e cu atât mai mare cu cât obiectul este mai izolat (în apropierea lui nu se află obiecte similare)
    - $p(ridica)=(k^+/(k^++f))^2$
  - Furnica "depune" un obiect (anterior ridicat) într-o locaţie nouă
    - Probabilitatea de a-l depune e cu atât mai mare cu cât în vecinătatea locului de plasare se afla mai multe obiecte asemănătoare
    - $p(depune)=(f/(k^-+f))^2$
  - $k^+$, $k^-$ - constante
  - *f* – procentul de obiecte similare cu obiectul curent din memoria furnicuţei
- Furnicuţele
  - au memorie
    - reţin obiectele din vecinătatea poziţiei curente
  - se mişcă ortogonal (N, S, E, V) pe grid pe căsuţele neocupate de alte furnici

# Recapitulare

- Sisteme care învaţă singure (SIS)
  - Maşini cu suport vectorial (MSV)
    - Modele computaţionale care
      - rezolvă (în special) probleme de învăţare supervizată
      - prin identificarea celui mai bun hyper-plan de separare a datelor
  - K-means
    - Modele computaţionale care
      - rezolvă probleme de clusterizare
        - → nu se cunosc etichetele claselor
      - prin
        - minimizarea diferenţelor între elementele aceleaşi calse
        - maximizarea diferenţelor între elementele claselor diferite

# Cursul următor

A. Scurtă introducere în Inteligenţa Artificială (IA)

B. Rezolvarea problemelor prin căutare
   - Definirea problemelor de căutare
   - Strategii de căutare
     - Strategii de căutare neinformate
     - Strategii de căutare informate
     - Strategii de căutare locale (Hill Climbing, Simulated Annealing, Tabu Search, Algoritmi evolutivi, PSO, ACO)
     - Strategii de căutare adversială

C. Sisteme inteligente
   - Sisteme bazate pe reguli în medii certe
   - Sisteme bazate pe reguli în medii incerte (Bayes, factori de certitudine, Fuzzy)
   - Sisteme care învaţă singure
     - Arbori de decizie
     - A. Reţele neuronale artificiale
     - B. Maşini cu suport vectorial
     - B. Algoritmi evolutivi
   - B. Sisteme hibride

- Informaţiile prezentate au fost colectate din diferite surse de pe internet, precum şi din cursurile de inteligenţă artificială ţinute în anii anteriori de către:
  - Conf. Dr. Mihai Oltean – www.cs.ubbcluj.ro/~moltean
  - Lect. Dr. Crina Groşan - www.cs.ubbcluj.ro/~cgrosan
  - Prof. Dr. Horia F. Pop - www.cs.ubbcluj.ro/~hfpop