Machine Learning



Machine Learning

Decision trees

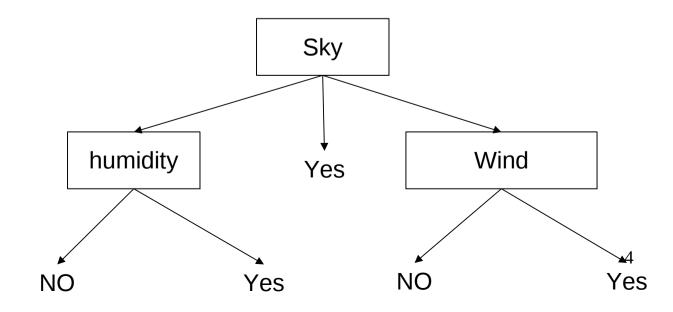
The perceptron and neural networks

Unsupervised learning

Decision Trees

Introduction

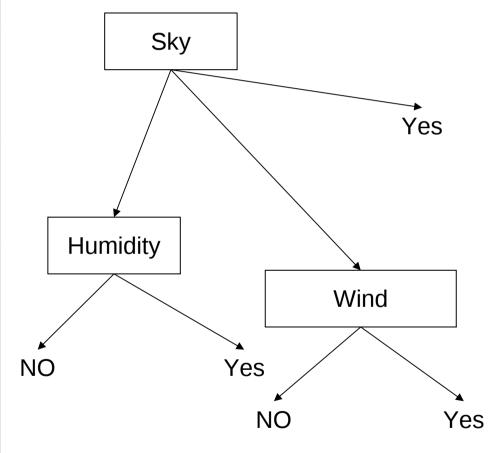
- Usage: Classification.
- Tree representation
 - Not terminal nodes: represent a question on an attribute.
 - Leaf nodes: answers or classes.
- Examples: Medical diagnostic, loan availability, ¿is today a good day to play tennis?



Learning

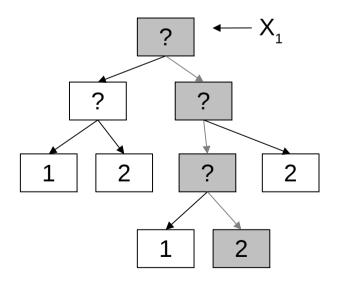
• To construct the tree from a data set:

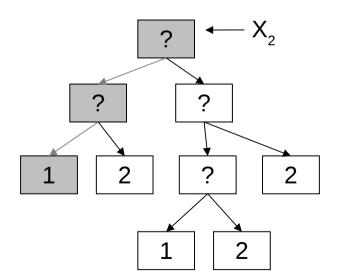
| da y | sky | temperature | humidity | wind | play- tennis? |
|---------|--------|-------------|----------|--------|------------------|
| d1 | sunny | hot | high | weak | no |
| d2 | sunny | hot | high | strong | no |
| d3 | cloudy | hot | high | weak | yes |
| d4 | rain | warm | high | weak | yes |
| d5 | rain | cold | normal | weak | yes |
| d6 | rain | cold | normal | strong | no |
| d7 | cloudy | cold | normal | strong | yes |
| d8 | sunny | warm | high | weak | no |
| d9 | sunny | cold | normal | weak | yes |
| d10 | rain | warm | normal | weak | yes |
| d11 | sunny | warm | normal | strong | yes |
| d12 | cloudy | warm | high | strong | yes |
| d13 | cloudy | hot | normal | weak | yes |
| d14 | rain | warm | high | strong | no |



Classification

 Given a pattern X, to obtain its class, regardless the learning set. For each no terminal node, to answer the question according to the attributes of X.





Automatic construction: ID3

- It is based on reducing the entropy
- It obtains good trees, although they are not optimal
- It is a greedy algorithm
- It requires the number of patterns to be highly superior to the number of classes.
- Applications: discrete attributes and finite set of classes

Entropy

- Def: "Magnitude that measures the information in a dataflow, i.
 e., how much new information is given." Wikipedia (Spanish)
 March 3, 2006.
- Def2: "It is a measure of the randomness of elements in a system".
- Example1: "Suppose a family with 4 members. It is three o'clock and all of them have lunch. All them decide to see the news on TVE". In this example, the entropy on the TV preferences is 0. The reason is that there is no diversity, every member prefers the same.
 - If three members prefer a channel and the another one, other channel, the entropy increases.
 - If two members prefer a channel and the another two, other channel, the entropy increases.
 - If every member prefer a different channel, the entropy is maximal.

ID3: Execution

- It starts from a set of patterns
- While there are sets with patterns of different classes
 - For each attribute, yet chosen, classify the patterns of the set.
 - Compute the profit of classifying by means of each attribute (it is based on the entropy).
 - Choose the attribute that produces the highest profit.
 - Repeat the procedure for every subset.

Formulae

Probability for an attribute K to be set to a value v in the set S

$$P(K=v,S) = \frac{|S_{K=v}|}{|S|} P(play=yes,Total) = \frac{9}{14} P(play=no,Total) = \frac{5}{14}$$

Entropy of the set S

$$E\left(P\left(res=v_{I},S\right),\ldots,P\left(res=v_{n},S\right)\right) = \sum_{i=1}^{n} -P\left(res=v_{i},S\right) \cdot \log_{2}\left(P\left(res=v_{i},S\right)\right)$$

$$E\left(\frac{9}{14},\frac{5}{14}\right) = \frac{-9}{14} \cdot \log_{2}\left(\frac{9}{14}\right) + \frac{-5}{14} \cdot \log_{2}\left(\frac{5}{14}\right) = 0,94$$

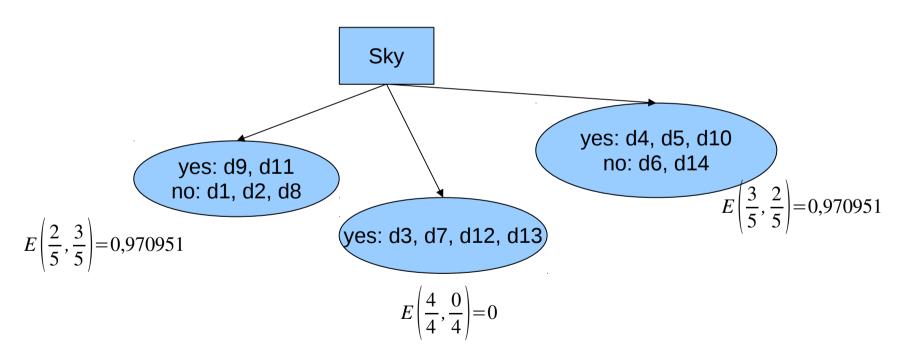
Profit of classifying by means of the attribute K

$$Profit(S,K) = E(S) - \sum_{value \in K} P(K=value,S) \cdot E(S_v)$$

Example

Yes: d3, d4, d5, d7, d9, d10, d11, d12, d13 no: d1, d2, d6, d8, d14

$$E(S) = 0.94$$

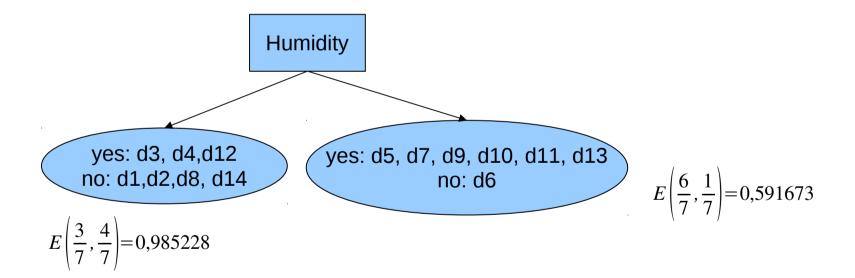


$$Profit \left(Sky, S \right) = E\left(S \right) - P\left(C = sunny, S \right) \cdot E\left(S_{C = sunny} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(C = cloudy, S \right) \cdot E\left(S_{C = cloudy} \right) - P\left(S_{$$

Ejemplo(2)

yes: d3, d4, d5, d7, d9, d10, d11, d12, d13 no: d1, d2, d6, d8, d14

$$E(S) = 0.94$$



$$Profit \left(Humidity, S \right) = E\left(S \right) - P\left(H = high, S \right) \cdot E\left(S_{H = high} \right) - P\left(H = normal, S \right) \cdot E\left(S_{H = normal} \right) = 0.94 - \frac{7}{14} \cdot 0,985228 - \frac{7}{14} \cdot 0,591673 = 0,15183544$$

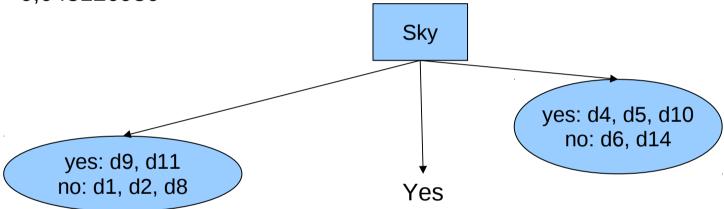
Choose attribute and repeat

Profit(Sky,S) = 0,24674976

Profit(Humidity,S) = 0,15183544

Profit(Temperature,S) = 0.029222548

Profit(Wind,S) = 0.048126936



Profit(Temperature, $S_{c=sunny}$) = 0,5709506

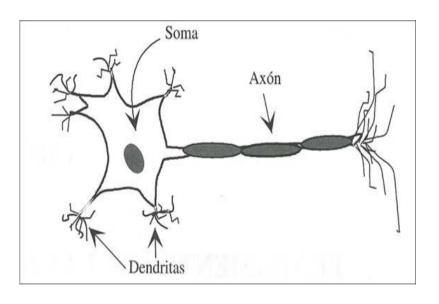
Profit(Humidity, $S_{c=sunnv}$) = 0,9709506

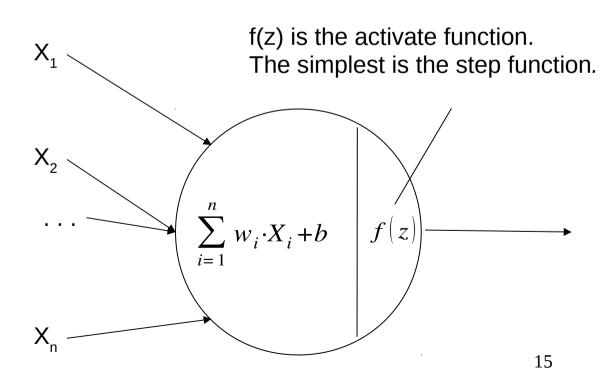
 $Profit(Wind,S_{c=sunnv}) = 0.01997304$

The Perceptron and the neural networks

Introduction

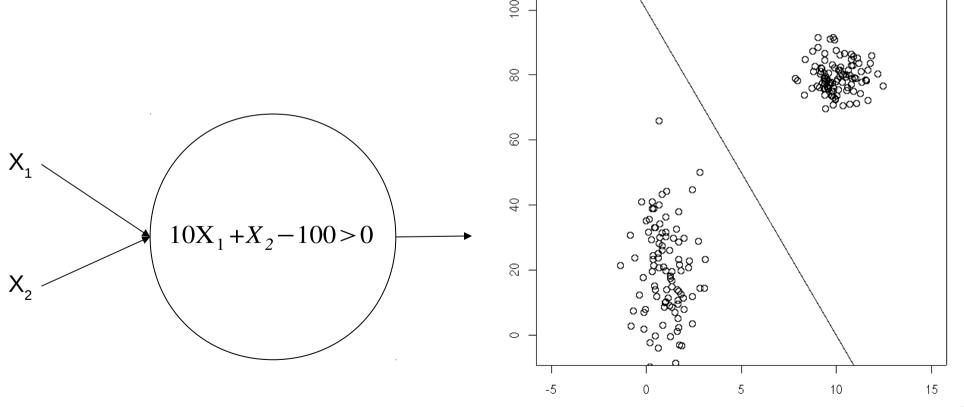
They are inspired in the neural connections of our brain.
 In particular, in the multipolar neurons.





Utility

• It is only able to solve hyperplane functions (they perform a simple cut)



Training: Delta rule

- The data is presented to the perceptron and the weights are updated if the output is not right:
 - α is the learning rate, and it should be small

$$w_i = w_i + \alpha \left(Y_{expected} - Y_{obtained} \right) \cdot X_i$$

$$b=b+\alpha (Y_{expected}-Y_{obtained})$$

Exercise

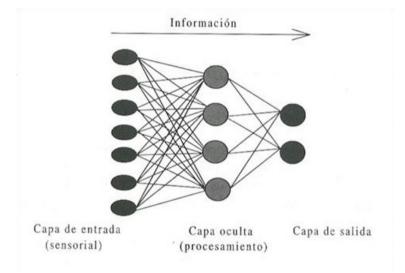
| patrón | x1 | <i>x</i> 2 | y |
|--------|----|------------|---|
| 1 | 2 | 1 | 0 |
| 2 | 1 | 1 | 0 |
| 3 | 3 | 2 | 1 |
| 4 | 3 | 3 | 1 |

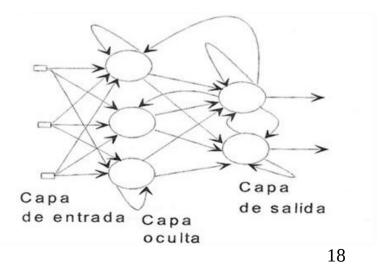
$$w_1 = 0, \quad w_2 = 0, \quad b = 0, \quad f(z) = \begin{cases} 1, & z > 0 \\ 0, & z \le 0 \end{cases}$$

 $\alpha = 0.01$

Comments

- Neural networks presents several layers to tackle complex problems:
 - to obtain the past tense of English verbs
 - to predict a temporal series.
 - artificial vision
- Feedforward networks are trained by means of an algorithm derived from the delta rule: backpropagation.
- Recurrent networks are trained by means of evolutionary algorithms.





Unsupervised learning

Introduction

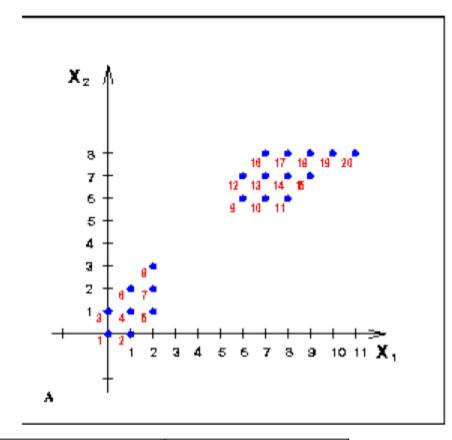
- Unsupervised learning: to classify a data set without labels.
- Clustering techniques identify groups of data.
- Each group should be homogeneous and different to the other groups.
 - Distance: the distance between elements of the same group should be small, and large between elements of different groups.
- The clustering algorithms require parameters that affect the results.
- Usually, each group is characterized by means of its mean and variance.

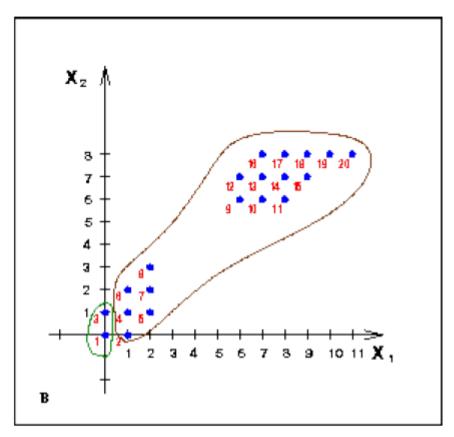
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KMeans

- **1. Initialize** randomly the centres of *K* groups (parameter)
- 2. Assignation and update of the centres.
 - Each pattern is assigned to its nearest centre.
 - Compute the new centres according to the mean of the assigned patterns
- 3. Repeat step 2 until convergence.
 - When updating the centres, some patterns change to another nearest centre.

Example

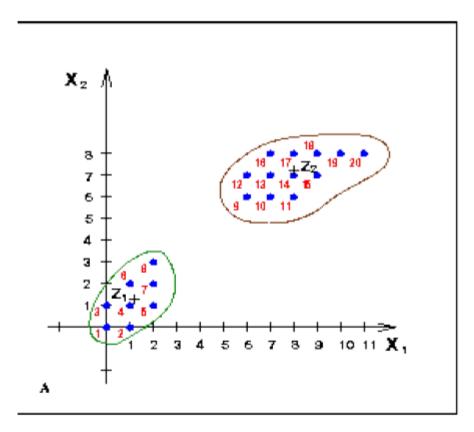


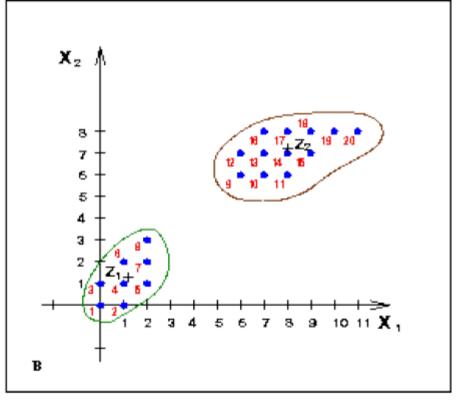


| $S_1(0) = \{X_1\}$ | $Z_1(0) = (0, 0)$ |
|--------------------|-------------------|
| $S_2(0) = \{X_2\}$ | $Z_2(0) = (1, 0)$ |

| $S_1(1) = \{X_1, X_3\}$ | $Z_1(1) = (0, 0.5)$ |
|---------------------------------------|-----------------------|
| $S_2(1) = \{X_2, X_4, X_5,, X_{20}\}$ | $Z_2(1) = (5.8, 5.3)$ |

Example (2)





| $S_1(2) = \{X_1, X_2,, X_8\}$ | $Z_1(2) = (1.1, 1.3)$ |
|-------------------------------------|-----------------------|
| $S_2(2) = \{X_9, X_{10},, X_{20}\}$ | $Z_2(2) = (8.0, 7.2)$ |

| $S_1(3) = \{X_1, X_2,, X_8\}$ | $Z_1(3) = (1.1, 1.3)$ | |
|-------------------------------------|-----------------------|--|
| $S_2(3) = \{X_9, X_{10},, X_{20}\}$ | $Z_2(3) = (8.0, 7.2)$ | |