Decision tree algorithm short Weka tutorial

Croce Danilo, Roberto Basili

Machine leanring for *Web Mining*
a.a. 2009-2010

Machine Learning: brief summary

Example

You need to write a program that:

- given a Level Hierarchy of a company
- given an employe described trough some *attributes* (the number of attributes can be very high)
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Solution

Learn the *function* to link each employe to the correct level.

Supervised Learning process: two steps

Learning (Training)

Learn a *model* using the training data

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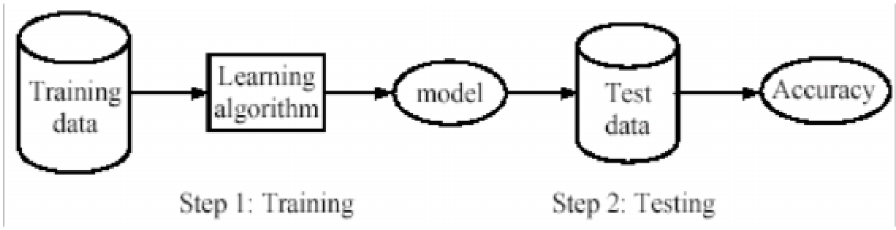

Learning Algorithms

- Probabilistic Functions (Bayesian Classifier)
- Functions to partitioning Vector Space
  - Non-Linear: KNN, Neural Networks, ...
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- Boolean Functions (Decision Trees)

Decision Tree: Domain Example

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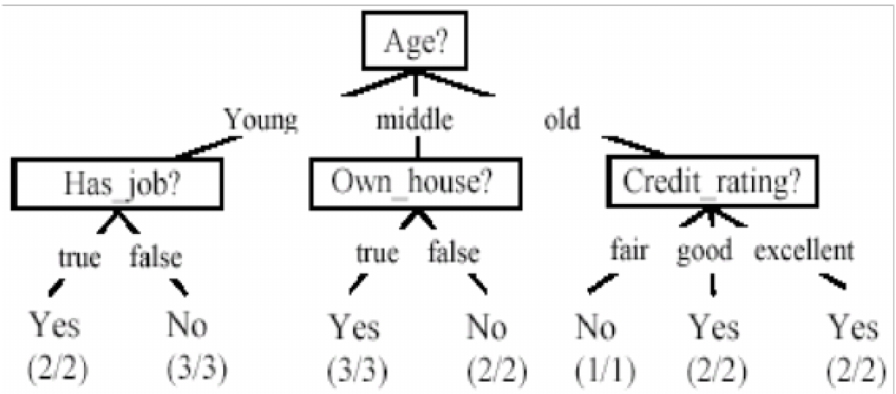
Decision Tree



Decision Tree example for the loan problem

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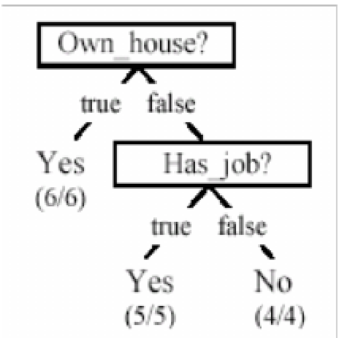

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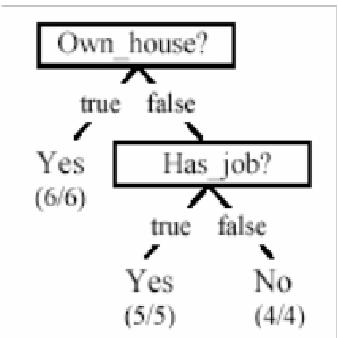

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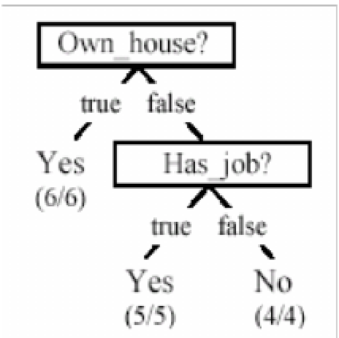

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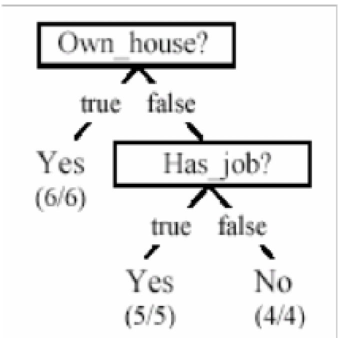

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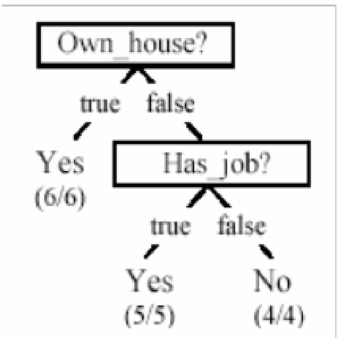
- A decision tree can be converted to a set of rules .

From a decision tree to a set of rules



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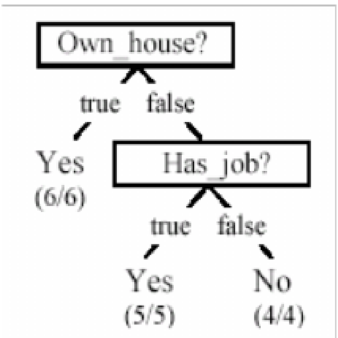

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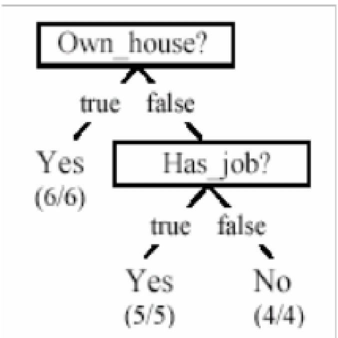

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Rules

Own_house = true → Class = yes
Own_house = false , Has_job = true → Class = yes
Own_house = false , Has_job = false → Class = no

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The heuristic is to choose the attribute with the maximum *Information Gain* or *Gain Ratio* based on information theory.

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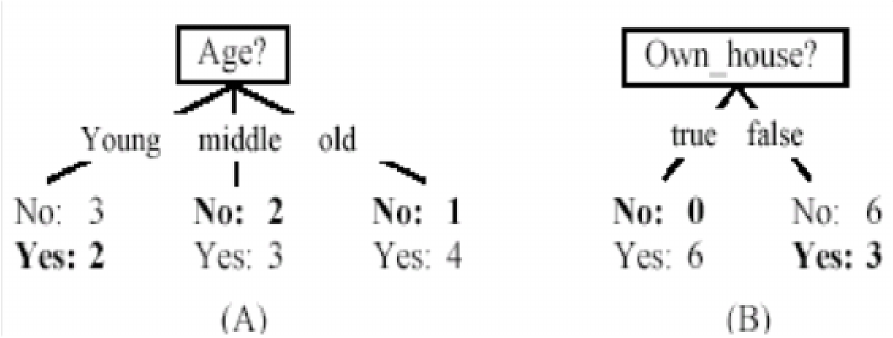

Information Gain

Entropy of D

- Entropy is a measure of the uncertainty associated with a random variable.
- Given a set of examples D is possible to compute the original entropy of the dataset such as:

$$H[D] = -\sum_{j=1}^{|C|} P(c_j) log_2 P(c_j)$$

where C is the set of desired class.

Entropy

1. The data set D has 50% positive examples ($\Pr(positive) = 0.5$) and 50% negative examples ($\Pr(negative) = 0.5$).

$$entropy(D) = -0.5 \times \log_2 0.5 - 0.5 \times \log_2 0.5 = 1$$

2. The data set D has 20% positive examples ($\Pr(positive) = 0.2$) and 80% negative examples ($\Pr(negative) = 0.8$).

$$entropy(D) = -0.2 \times \log_2 0.2 - 0.8 \times \log_2 0.8 = 0.722$$

3. The data set D has 100% positive examples ($\Pr(positive) = 1$) and no negative examples, ($\Pr(negative) = 0$).

$$entropy(D) = -1 \times \log_2 1 - 0 \times \log_2 0 = 0$$

As the data become purer and purer, the entropy value becomes smaller and smaller.

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Entropy of an attribute A_i

If we make attribute A_i, with v values, the root of the current tree, this will partition D into v subsets $D_1, D_2, \ldots, D_v$. The expected entropy if A_i is used as the current root:

$$H_{A_i}[D] = \sum_{j=1}^{v} \frac{|D_j|}{|D|} H[D_j]$$

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Information gained by selecting attribute A_i to branch or to partition the data is given by the difference of *prior* entropy and the entropy of selected branch

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$$gain(D, A_i) = H[D] - H_{A_i}[D]$$

We choose the attribute with the *highest gain* to branch/split the current tree.

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Back to the example

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Example

9 examples belong to "YES" category and 6 to "NO". Exploiting prior knowledge we have:

$$H[D] = -\sum_{j=1}^{|C|} P(c_j) log_2 P(c_j)$$

$$H[D] = -\frac{6}{15} log_2 \frac{6}{15} - \frac{9}{15} log_2 \frac{9}{15} = 0.971$$

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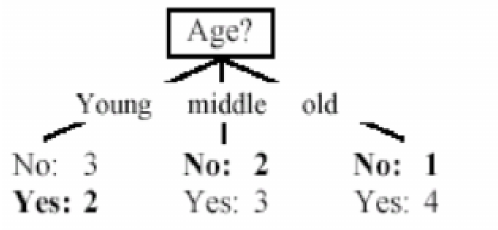

(A)

while partitioning through the Age feature:

$$H_{Age}[D] = -\frac{5}{15} H[D_1] - \frac{5}{15} H[D_2] - \frac{5}{15} H[D_3] = 0.888$$

where

$$H[D_1] = -\frac{3}{3+2} \cdot log_2(\frac{3}{3+2}) - \frac{2}{3+2} \cdot log_2(\frac{2}{3+2}) = 0.971$$
$$H[D_2] = -\frac{2}{2+3} \cdot log_2(\frac{2}{2+3}) - \frac{3}{2+3} \cdot log_2(\frac{3}{2+3}) = 0.971$$
$$H[D_3] = -\frac{1}{1+4} \cdot log_2(\frac{1}{1+4}) - \frac{4}{1+4} \cdot log_2(\frac{4}{1+4}) = 0.722$$

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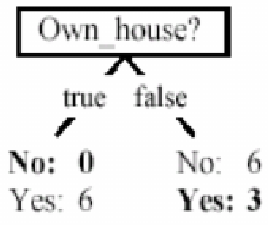
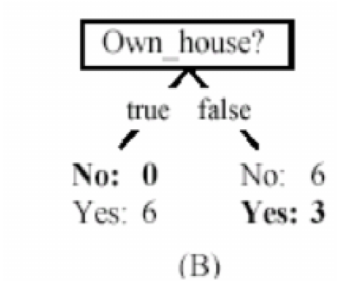


(B)

Example



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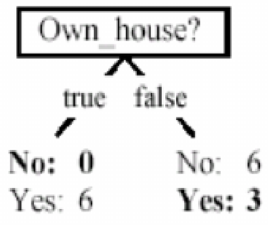

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$gain(D, Age) = 0.971 - 0.888 = 0.083$
$gain(D, Own\_House) = 0.971 - 0.551 = 0.420$
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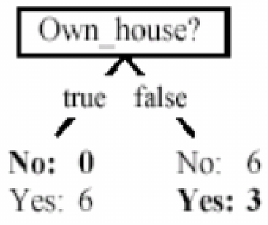

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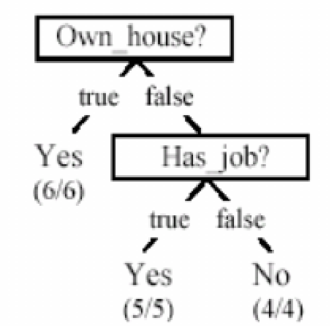

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Basic algorithm (a greedy divide-and-conquer algorithm)

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```
Algorithm decisionTree(D, A, T)
if D contains only training examples of the same class c_j ∈ C then
    make T a leaf node labeled with class c_j;
elseif A = ∅ then
    make T a leaf node labeled with c_j, which is the most frequent class in D
else  // D contains examples belonging to a mixture of classes. We select a single
      // attribute to partition D into subsets so that each subset is purer
    p_0 = impurityEval-1(D);
    for each attribute A_i ∈ {A_1, A_2, …, A_k} do
        p_i = impurityEval-2(A_i, D)
    end
    Select A_g ∈ {A_1, A_2, …, A_k} that gives the biggest impurity reduction,
        computed using p_0 – p_i;
    if p_0 – p_g < threshold then     // A_g does not significantly reduce impurity p_0
        make T a leaf node labeled with c_j, the most frequent class in D.
    else                              // A_g is able to reduce impurity p_0
        Make T a decision node on A_g;
        Let the possible values of A_g be v_1, v_2, …, v_m. Partition D into m
            disjoint subsets D_1, D_2, …, D_m based on the m values of A_g.
        for each D_j in {D_1, D_2, …, D_m} do
            if D_j ≠ ∅ then
                create a branch (edge) node T_j for v_j as a child node of T;
                decisionTree(D_j, A-{A_g}, T_j)// A_g is removed
            end
        end
    end
end
```

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- For classification, Weka allows train/test split or Cross-fold validation
- Schemes for clustering:
  - EM and Cobweb

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1.4, 0.2, Setosa
1.4, ?, Versicolor
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- Note that the omitted values in a sparse instance are 0, they **are not** *missing* values! If a value is unknown, you must explicitly represent it with a question mark (?)

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- Example learner classes:
  - Decision Tree: `weka.classifiers.trees.J48`
  - Naive Bayes: `weka.classifiers.bayes.NaiveBayes`
  - k-NN: `weka.classifiers.lazy.IBk`
- Important generic options:
  - `-t <training file>` Specify training file
  - `-T <test files>` Specify Test file. If none testing is performed on training data
  - `-x <number of folds>` Number of folds for cross-validation
  - `-l <input file>` Use saved model
  - `-d <output file>` Output model to file
  - `-split-percentage <train size>` Size of training set
  - `-c <class index>` Index of attribute to use as class (NB: the index start from 1)
  - `-p <attribute index>` Only output the predictions and one attribute (0 for none) for all test instances.