Decision tree algorithm
Weka tutorial

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Web Mining e *Retrieval*
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Machine Learning: brief summary

Example

You need to write a program that:

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- 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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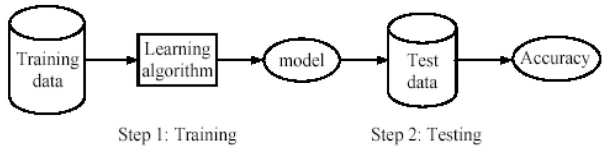

Learning Algorithms

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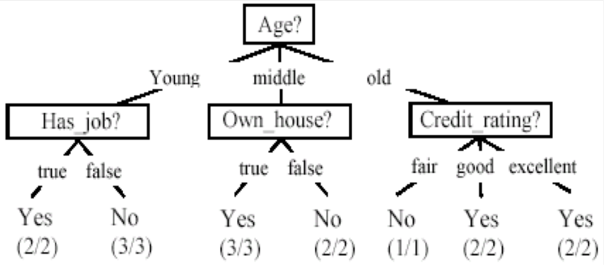
- Boolean Functions (Decision Trees)

Decision Tree: Domain Example

The class to learn is: approve a loan

ID	Age	Has_Job	Own_House	Credit_Rating	Class
1	young	false	false	fair	No
2	young	false	false	good	No
3	young	true	false	good	Yes
4	young	true	true	fair	Yes
5	young	false	false	fair	No
6	middle	false	false	fair	No
7	middle	false	false	good	No
8	middle	true	true	good	Yes
9	middle	false	true	excellent	Yes
10	middle	false	true	excellent	Yes
11	old	false	true	excellent	Yes
12	old	false	true	good	Yes
13	old	true	false	good	Yes
14	old	true	false	excellent	Yes
15	old	false	false	fair	No

Decision Tree



Decision Tree example for the loan problem

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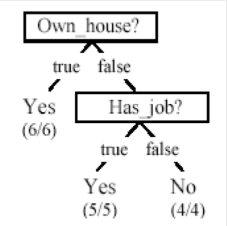

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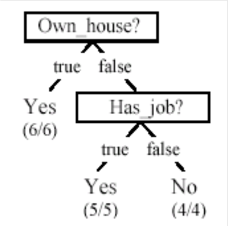

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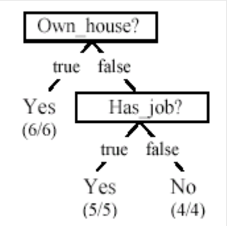

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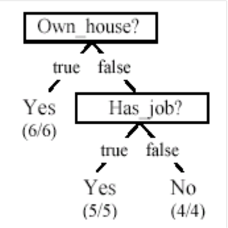

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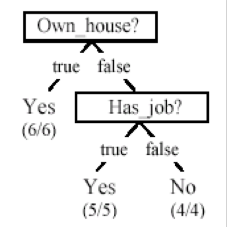
- A decision tree can be converted to a set of rules .

From a decision tree to a set of rules



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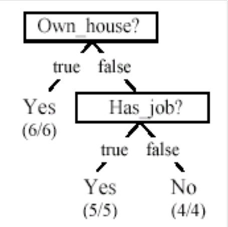

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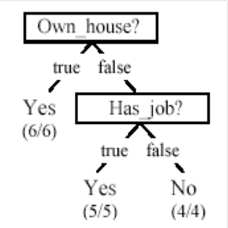

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Rules

Own_house = true $\rightarrow$ Class = yes
Own_house = false , Has_job = true $\rightarrow$ Class = yes
Own_house = false , Has_job = false $\rightarrow$ Class = no

Choose an attribute to partition data

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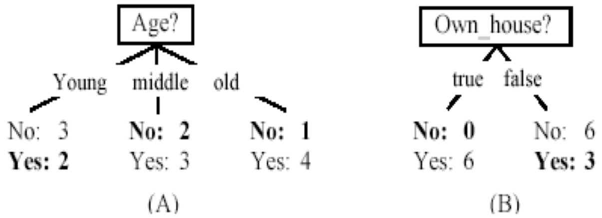

Information Gain

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.

Information Gain

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where C is the set of desired class.

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:

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

Information Gain

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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

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

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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.

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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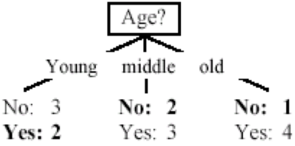


(A)

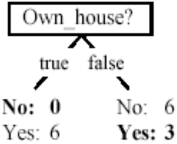
while partitioning through the *Age* feature:

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

where

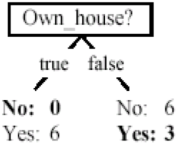
$$H[D_1] = -\frac{3}{3+2} \cdot log_2(\frac{3}{3+2}) - \frac{2}{3+2} \cdot log_2(\frac{2}{3+2}) = 0.971$$
$$H[D_2] = -\frac{2}{2+3} \cdot log_2(\frac{2}{2+3}) - \frac{3}{2+3} \cdot log_2(\frac{3}{2+3}) = 0.971$$
$$H[D_3] = -\frac{1}{1+4} \cdot log_2(\frac{1}{1+4}) - \frac{4}{1+4} \cdot log_2(\frac{4}{1+4})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

Example



(B)

Example



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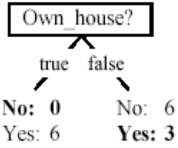

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$$gain(D, Age) = 0.971 - 0.888 = 0.083$$
$$gain(D, Own\_House) = 0.971 - 0.551 = 0.420$$
$$gain(D, Has\_Job) = 0.971 - 0.647 = 0.324$$
$$gain(D, Credit) = 0.971 - 0.608 = 0.363$$

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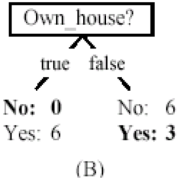

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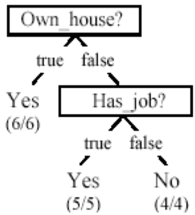

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Basic algorithm (a greedy divide-and-conquer algorithm)

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Algorithm for decision tree learning

. **Algorithm** decisionTree(D, A, T)

    if D contains only training examples of the same class $c_j \in C$ **then**
        make T a leaf node labeled with class c_j;
    elseif $A = \emptyset$ **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 $A_i \in \{A_1, A_2, \ldots, A_k\}$ **do**
            p_i = impurityEval-2(A_i, D)
        end
        Select $A_g \in \{A_1, A_2, \ldots, A_k\}$ 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 $v_1, v_2, \ldots, v_m$. Partition D into m disjoint subsets $D_1, D_2, \ldots, D_m$ based on the m values of A_g.
            for each D_j in $\{D_1, D_2, \ldots, D_m\}$ **do**
                if $D_j \neq \emptyset$ **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 (?)

Running Learning Schemes

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- 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.