The ID3 Algorithm

Abstract

This paper details the ID3 classification algorithm. Very simply, ID3 builds a decision tree from a fixed set of examples. The resulting tree is used to classify future samples. The example has several attributes and belongs to a class (like yes or no). The leaf nodes of the decision tree contain the class name whereas a non-leaf node is a decision node. The decision node is an attribute test with each branch (to another decision tree) being a possible value of the attribute. ID3 uses information gain to help it decide which attribute goes into a decision node. The advantage of learning a decision tree is that a program, rather than a knowledge engineer, elicits knowledge from an expert.

Introduction

J. Ross Quinlan originally developed ID3 at the University of Sydney. He first presented ID3 in 1975 in a book, *Machine Learning*, vol. 1, no. 1. ID3 is based off the Concept Learning System (CLS) algorithm. The basic CLS algorithm over a set of training instances C:

Step 1: If all instances in C are positive, then create YES node and halt.

If all instances in C are negative, create a NO node and halt.

Otherwise select a feature, F with values v1, ..., vn and create a decision node.

Step 2: Partition the training instances in C into subsets C1, C2, ..., Cn according to the values of V.

Step 3: apply the algorithm recursively to each of the sets Ci.

Note, the trainer (the expert) decides which feature to select.

ID3 improves on CLS by adding a feature selection heuristic. ID3 searches through the attributes of the training instances and extracts the attribute that best separates the given examples. If the attribute perfectly classifies the training sets then ID3 stops; otherwise it recursively operates on the n (where n = number of possible values of an attribute) partitioned subsets to get their "best" attribute. The algorithm uses a greedy search, that is, it picks the best attribute and never looks back to reconsider earlier choices.

Discussion

ID3 is a nonincremental algorithm, meaning it derives its classes from a fixed set of training instances. An incremental algorithm revises the current concept definition, if necessary, with a new sample. The classes created by ID3 are inductive, that is, given a small set of training instances, the specific classes created by ID3 are expected to work for all future instances. The distribution of the unknowns must be the same as the test cases. Induction classes cannot be proven to work in every case since they may classify an infinite number of instances. Note that ID3 (or any inductive algorithm) may misclassify data.

Data Description

The sample data used by ID3 has certain requirements, which are:

- Attribute-value description - the same attributes must describe each example and have a fixed number of values.
- Predefined classes - an example's attributes must already be defined, that is, they are not learned by ID3.
- Discrete classes - classes must be sharply delineated. Continuous classes broken up into vague categories such as a metal being "hard, quite hard, flexible, soft, quite soft" are suspect.
- Sufficient examples - since inductive generalization is used (i.e. not provable) there must be enough test cases to distinguish valid patterns from chance occurrences.

Attribute Selection

How does ID3 decide which attribute is the best? A statistical property, called information gain, is used. Gain measures how well a given attribute separates training examples into targeted classes. The one with the highest information (information being the most useful for classification) is selected. In order to define gain, we first borrow an idea from information theory called entropy. Entropy measures the amount of information in an attribute.

Given a collection S of c outcomes

$$\text{Entropy}(S) = S\ {-p(I)} \log2\ p(I)$$

where p(I) is the proportion of S belonging to class I. S is over c. Log2 is log base 2.

Note that S is not an attribute but the entire sample set.

Example 1

If S is a collection of 14 examples with 9 YES and 5 NO examples then

$$\text{Entropy}(S) = - (9/14)\ \text{Log2}\ (9/14) - (5/14)\ \text{Log2}\ (5/14) = 0.940$$

Notice entropy is 0 if all members of S belong to the same class (the data is perfectly classified). The range of entropy is 0 ("perfectly classified") to 1 ("totally random").

Gain(S, A) is information gain of example set S on attribute A is defined as

$$\text{Gain}(S, A) = \text{Entropy}(S) - S\ ((|S_v| / |S|) * \text{Entropy}(S_v))$$

Where:

S is each value v of all possible values of attribute A

S_v = subset of S for which attribute A has value v

$|S_v|$ = number of elements in S_v

|S| = number of elements in S

Example 2

Suppose S is a set of 14 examples in which one of the attributes is wind speed. The values of Wind can be *Weak* or *Strong*. The classification of these 14 examples are 9 YES and 5 NO. For attribute Wind, suppose there are 8 occurrences of Wind = Weak and 6 occurrences of Wind = Strong. For Wind = Weak, 6 of the examples are YES and 2 are NO. For Wind = Strong, 3 are YES and 3 are NO. Therefore

$$Gain(S,Wind)=Entropy(S)-(8/14)*Entropy(S_{weak})-(6/14)*Entropy(S_{strong})$$

$= 0.940 - (8/14)*0.811 - (6/14)*1.00$

$= 0.048$

$Entropy(S_{weak}) = - (6/8)*log2(6/8) - (2/8)*log2(2/8) = 0.811$

$Entropy(S_{strong}) = - (3/6)*log2(3/6) - (3/6)*log2(3/6) = 1.00$

For each attribute, the gain is calculated and the highest gain is used in the decision node.

Example of ID3

Suppose we want ID3 to decide whether the weather is amenable to playing baseball. Over the course of 2 weeks, data is collected to help ID3 build a decision tree (see table 1).

The target classification is "should we play baseball?" which can be yes or no.

The weather attributes are outlook, temperature, humidity, and wind speed. They can have the following values:

outlook = { sunny, overcast, rain }

temperature = {hot, mild, cool }

humidity = { high, normal }

wind = {weak, strong }

Examples of set S are:

Day	Outlook	Temperature	Humidity	Wind	Play ball
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
D3	Overcast	Hot	High	Weak	Yes
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes

D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D8	Sunny	Mild	High	Weak	No
D9	Sunny	Cool	Normal	Weak	Yes
D10	Rain	Mild	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes
D12	Overcast	Mild	High	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes
D14	Rain	Mild	High	Strong	No

Table 1

We need to find which attribute will be the root node in our decision tree. The gain is calculated for all four attributes:

Gain(S, Outlook) = 0.246

Gain(S, Temperature) = 0.029

Gain(S, Humidity) = 0.151

Gain(S, Wind) = 0.048 (calculated in example 2)

Outlook attribute has the highest gain, therefore it is used as the decision attribute in the root node.

Since Outlook has three possible values, the root node has three branches (sunny, overcast, rain). The next question is "what attribute should be tested at the Sunny branch node?" Since we=92ve used Outlook at the root, we only decide on the remaining three attributes: Humidity, Temperature, or Wind.

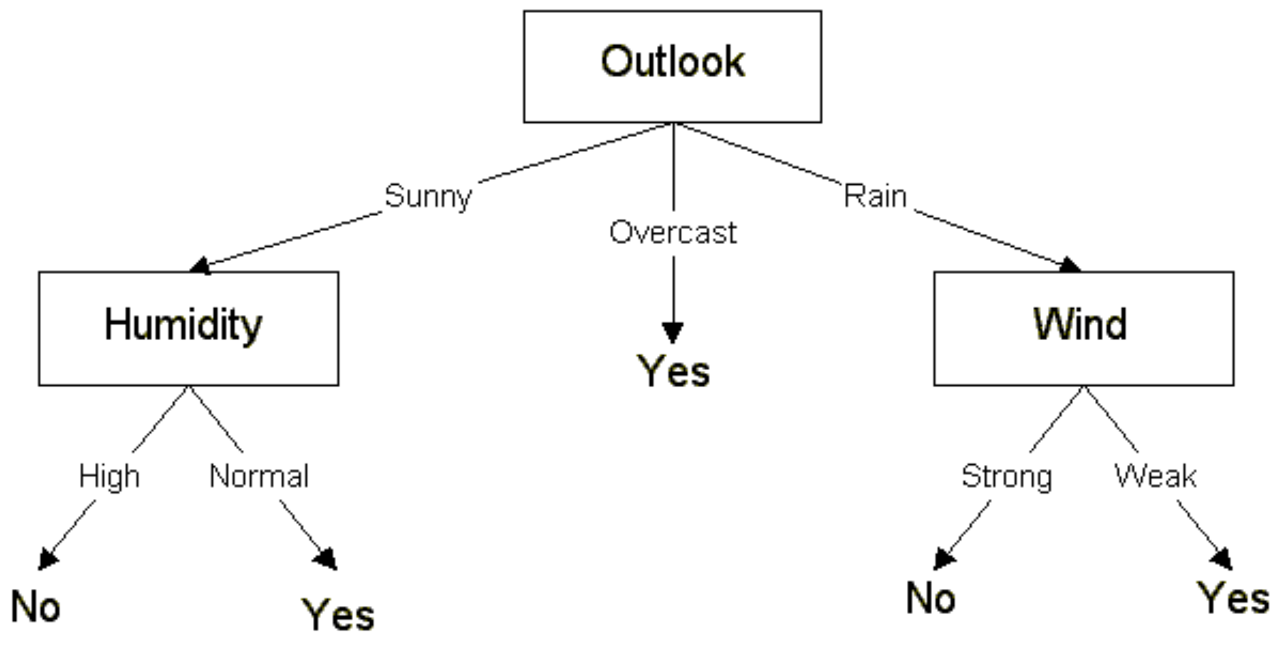
S_{sunny} = {D1, D2, D8, D9, D11} = 5 examples from table 1 with outlook = sunny

Gain(S_{sunny}, Humidity) = 0.970

Gain(S_{sunny}, Temperature) = 0.570

Gain(S_{sunny}, Wind) = 0.019

Humidity has the highest gain; therefore, it is used as the decision node. This process goes on until all data is classified perfectly or we run out of attributes.



The final decision = tree

The decision tree can also be expressed in rule format:

IF outlook = sunny AND humidity = high THEN playball = no

IF outlook = rain AND humidity = high THEN playball = no

IF outlook = rain AND wind = strong THEN playball = yes

IF outlook = overcast THEN playball = yes

IF outlook = rain AND wind = weak THEN playball = yes

ID3 has been incorporated in a number of commercial rule-induction packages. Some specific applications include medical diagnosis, credit risk assessment of loan applications, equipment malfunctions by their cause, classification of soybean diseases, and web search classification.

Conclusion

The discussion and examples given show that ID3 is easy to use. Its primary use is replacing the expert who would normally build a classification tree by hand. As industry has shown, ID3 has been effective.

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