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A novel approach to construct decision tree using quick C4.5 algorithm

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ABSTRACT

With the rapid growth in size and number of available databases in commercial, industrial, administrative and other applications, it is necessary and interesting to examine how to extract knowledge from huge amount of data. There are several mining algorithms available to solve diverse data mining problems. One of the knowledge and discovery in databases operations is the problem of inducing decision trees. C4.5 is one of the most important algorithms in Decision Tree Induction. In this paper the limitations of the existing C4.5 algorithm are discussed and an enhancement technique for improving its efficiency is proposed.

Key words: Data Mining, Decision Trees, C4.5 algorithm.

INTRODUCTION

Decision tree is probably the most widely used approach to represent classifiers. Originally it has been studied in the fields of decision theory and statistics. However, it was found to be effective in other disciplines such as data mining, machine learning, and pattern recognition. *Decision tree* is a classifier in the form of a tree structure (see Figure 2.4), where each node is either:

- a *leaf node* - indicates the value of the target attribute (class) of examples, or
- a *decision node* - specifies some test to be carried out on a single attribute-value, with one branch and sub-tree for each possible outcome of the test.

A decision tree can be used to classify an example by starting at the root of the tree and moving through it until a leaf node, which provides the classification of the instance.

Many decision-tree algorithms have been developed. One of the most famous is ID3 (Quinlan 1970's). The choice of split attribute in ID3 is based on information entropy.C4.5 is an extension of ID3 (Quinlan 1986). It improves computing efficiency, deals with continuous values, handles attributes with missing values, avoids over fitting, and performs other functions.

ID3 picks predictors and their splitting values based on the gain in information that the split or splits provide. Gain represents the difference between the amount of information that is needed to correctly make a prediction before a split is made and after the split has been made. If the amount of information required is much lower after the split is made then that split has decreased the disorder of the original single segment. Gain is defined as the difference between the entropy of the original segment and the accumulated entropies of the resulting split segments.

ID3 was later enhanced in the version called C4.5. C4.5 improves on ID3 in several important areas:

- predictors with missing values can still be used
- predictors with continuous values can be used

´ pruning is introduced
´ rule derivation

At each node of the tree, C4.5 chooses one attribute of the data that most effectively splits its set of samples into subsets enriched in one class or the other. Its criterion is the normalized information gain (difference in entropy) that results from choosing an attribute for splitting the data. The attribute with the highest normalized information gain is chosen to make the decision. The C4.5 algorithm then recourses on the smaller sub lists. This algorithm has a few base cases.

´ All the samples in the list belong to the same class. When this happens, it simply creates a leaf node for the decision tree saying to choose that class.
´ None of the features provide any information gain. In this case, C4.5 creates a decision node higher up the tree using the expected

Table 1: Decision Tree Induction: Training Dataset

age	income	student	credit_rating	buys_computer
<=30	high	no	fair	no
<=30	high	no	excellent	no
31…40	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
>40	low	yes	excellent	no
31…40	low	yes	excellent	yes
<=30	medium	no	fair	no
<=30	low	yes	fair	yes
>40	medium	yes	fair	yes
<=30	medium	yes	excellent	yes
31…40	medium	no	excellent	yes
31…40	high	yes	fair	yes
>40	medium	no	excellent	no

Table 2: Database after sorting

Age	Income	Student	Credit_rating	Buys_computer
<=30	High	No	Fair	No
<=30	High	No	Excellent	No
<=30	Medium	No	Fair	No
<=30	Low	Yes	Fair	Yes
<=30	Medium	Yes	Excellent	Yes
31…40	High	No	Fair	Yes
31…40	Low	Yes	Excellent	Yes
31…40	Medium	No	Excellent	Yes
31…40	High	Yes	Fair	Yes
>40	Medium	No	Fair	Yes
>40	Low	Yes	Fair	Yes
>40	Low	Yes	Excellent	No
>40	Medium	Yes	Fair	Yes
>40	medium	No	Excellent	No

value of the class.

´ Instance of previously-unseen class encountered. Again, C4.5 creates a decision node higher up the tree using the expected value.

In this paper, an algorithm that quickly induces a decision tree has been proposed. The paper has been organized as follows: Section 2 describes the related work in the area of C4.5 tree induction method; section 3 proposes a method that uses quick sort method in C4.5 algorithm to obtain a decision tree more efficiently; Section 5 draws the conclusion based on the comparison.

Related work

C4.5 is an algorithm used to generate a decision tree developed by Ross Quinlan. C4.5 is an extension of Quinlan's earlier ID3 algorithm. The decision trees generated by C4.5 can be used for classification, and for this reason, C4.5 is often referred to as a statistical classifier.

Input and Output

Input to C4.5 consists of a collection of training cases, each having a tuple of values for a fixed set of attributes (or independent variables) A = {A_1,A_2, ….. A_k} and a class attribute (or dependent variable). An attribute Aa is described as continuous or discrete according to whether its values are numeric or nominal. The class attribute C is discrete and has values C_1, C_2,……..,C_x. The goal is to learn from the training cases a function DOM(A_1) × DOM(A_2) ×……..× DOM(A_k) '! DOM(C) that maps from the attribute values to a predicted class.

Divide and Conquer

Decision tree learners use a method known as divide and conquer to construct a suitable tree from a training set S of cases:

´ If all the cases in S belong to the same class (Cj, say), the decision tree is a leaf labelled with Cj

´ Otherwise, let B be some test with outcomes b1, b2, ..., bt that produces a non-trivial partition of S, and denote by Si the set of cases in S that has outcome bi of B. The decision tree where Ti is the result of growing a decision tree for the cases in Si.

Analysis of Existing Algorithm

The algorithm is called with three parameters: D, *attribute_list*, and *Attribute_selection_method*. We refer to D as a data partition. Initially, it is the complete set of training tuples and their associated class labels. The parameter *attribute_list* is a list of attributes describing the tuples. *Attribute_selection_method* specifies a heuristic procedure for selecting the attribute that "best" discriminates the given tuples according to class. This procedure employs an attribute selection measure, such as information gain or the gini index. Whether the tree is strictly binary is generally driven by the attribute selection measure. Some attribute selection measures, such as the gini index, enforce the resulting tree to be binary. Others, like information gain, do not, therein allowing multiway splits.

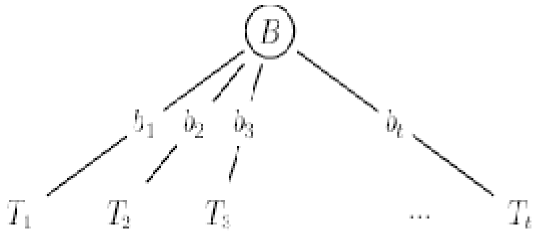


Fig. 2: Example of Divide and Conquer

Disadvantages of C4.5 Algorithm

´ The run-time complexity of the algorithm corresponds to the tree depth, which cannot be larger than the number of attributes. Tree depth is related to tree size, and thereby to the number of examples. So, the size of C4.5 trees increases linearly with the number of examples.

´ C4.5 rules slow for large and noisy datasets

´ Space complexity is very large as we have to store the values repeatedly in arrays.

Proposed system

Based on the disadvantages of Existing C4.5 Algorithm, an improved method is proposed: based on the application of the quick sort on the database. By applying quick sort on the database, after first splitting attribute is selected as the root, will reduce the complexity in finding the next splitting attribute, so that the efficiency is raised and the memory space is reduced.

The detailed steps of proposed modified algorithm are as follows:

Algorithm

Generate_decision_tree. Generate a decision tree from the training tuples of data partition D.

Input

´ Data partition, D, which is a set of training tuples and their associated class labels;

´ *attribute_list*, the set of candidate attributes;

´ *Attribute_selection_method*, a procedure to determine the splitting criterion that "best" partitions the data tuples into individual classes. This criterion consists of a *splitting_attribute* and, possibly, either a *split point* or *splitting subset*.

Output

A decision tree.

Method:

1. create a node N;
2. if tuples in D are all of the same class, C then
3. return N as a leaf node labeled with the class C and exit
4. If attribute_list is empty then, return N as a leaf node labeled with the majority class in D and exit.
5. If the tuples of the given class are not same, then, Calculate entropy (information gain) of the database by the given formula-Info(D) =
$$\sum_{i=1}^{c} - p_i \log_2 p_i$$
6. Calculate information required for each attribute, by the formula-
$$\text{Info}_A(D) = \sum_{j=1}^{v} \frac{|Dj|}{|D|} * \text{Info}(D)$$
7. Calculate gain of each attribute:
Gain(A) = Info(D) – Info_A(D)
8. Select the attribute with the maximum gain and store it in the 'max' variable, i.e.
max = Infogain(A)
9. Label node N with max.
10. After determining the possible outcomes(j) of the attribute A, we sort the database(D) on the basis of that attribute to form the database (Dj).
11. If the attribute A contains discrete value and multiway splits allowed then, attribute_list ß attribute_list – attribute(A)
12. For each outcome of the attribute A, if tuples in (Dj) are all of same class, then return as a leaf node, else goto step 4.
13. Return the decision tree.

The proposed algorithm has been tested on a set of data and the same is discussed through an example given below:

Step 1

First of all, we calculate the expected information gain needed to classify a tuple in database D, which is given by:

$$\text{Info}(D) = \sum_{i=1}^{c} - p_i \log_2 p_i \text{ no. of comparisons}$$

Cal Info(D) = I(9,5) = 0.940

Step 2

Now the amount of information still needed in order to arrive at the exact classification is measured -

Calculate Info_{age}(D) = 5/14 I(2,3) + 4/14 I(4,0) + 5/14 I(3,2) 14

Step 3

Calculate Info_{income}(D) = 4/14 I(2,2) + 6/14 I(4,2) + 4/14 I(3,1) 14

Step 4

Calculate $\text{Info}_{student}$(D) = 7/14 I(3,4) + 7/14 I(6,1) 14

Step 5

Calculate $\text{Info}_{credit\_rating}$(D) = 8/14 I(6,2) + 6/14 I(3,3) 14

Step 6

Calculate Information Gain, i.e., the difference between the original information requirement and the new requirement. That is,

Gain(A) = Info(D) – Info_A(D)

Gain(age) = 0.940 – 0.694 = 0.246

Gain(income) = 0.029

Gain(student) = 0.151

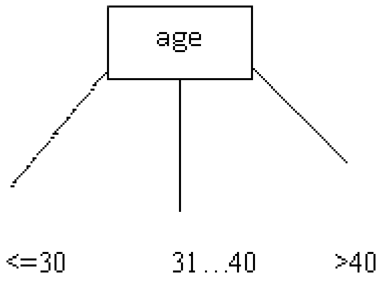
Gain(credit_rating) = 0.048

Step 7

On the basis of gain calculated, which is maximum of 'age', we select 'age' as the root. So, the tree till here becomes-

After applying quick sort method, on the basis of age, the new database will be:

In case of "<=30" and ">40", the output is both YES and NO. So, calculate further selection attribute on the basis of gain.



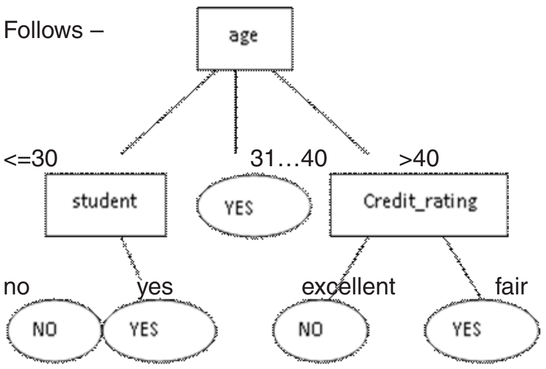
Step 8

The gain of student is maximum, followed by credit_rating. So, the tree is as

Complexity of quick sort = O(n log n)
= O(14 log 14)
= 14 * 1.14 = 15.96

Total no. of comparisons required are = complexity of quick sort + no. of iterations = 15.96 + 94 H" 110 , while it is 168 in the original algorithm.

Follows –



Advantages of Proposed System

The Proposed Algorithm has the following advantages

´ In this algorithm, we apply quick sort on the database after first splitting attribute is selected as the root. This will reduce the complexity in finding the next splitting attribute, so that the efficiency is raised.

´ Calculation of splitting attribute is much easy, once the root node has been decided.

´ It takes less time as compared to the previous C4.5 algorithm.

CONCLUSION

This paper presents an analytic evaluation of the runtime behavior of the C4.5 algorithm which highlights some efficiency improvements. Based on the analytic evaluation, I propose a more efficient version of the algorithm. It improves on C4.5 by minimizing the problem of space complexity and time complexity. This new algorithm is an improvement of C4.5 algorithm, which comprehensive utilized technologies of several improved C4.5 algorithm. This algorithm uses quick sort, so the database we get after the first split is sorted, due to which the no. of comparisons for searching the next splitting attribute is much less as compared to the previous C4.5 algorithm.

So it is a low-cost and efficient method as compared to existing algorithm.

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