DECISION TREE PRUNING USING EXPERT KNOWLEDGE

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DECISION TREE PRUNING USING EXPERT KNOWLEDGE

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Dissertation

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ABSTRACT

Decision tree technology has proven to be a valuable way of capturing human decision making within a computer. It has long been a popular artificial intelligence(AI) technique. During the 1980s, it was one of the primary ways for creating an AI system. During the early part of the 1990s, it somewhat fell out of favor, as did the entire AI field in general. However, during the later 1990s, with the emergence of data mining technology, the technique has resurfaced as a powerful method for creating a decision-making program.

How to prune the decision tree is one of the research directions of the decision tree technique, but the idea of cost-sensitive pruning has received much less attention than other pruning techniques even though additional flexibility and increased performance can be obtained from this method. This dissertation reports on a study of cost-sensitive methods for decision tree pruning. A decision tree pruning algorithm called KBP1.0, which includes four cost-sensitive methods, is developed. The intelligent inexact classification is used for first time in KBP1.0 to prune the decision tree. Using expert knowledge in decision tree pruning is discussed for the first time. By comparing the cost-sensitive pruning methods in KBP1.0 with other traditional pruning methods, such as reduced error pruning, pessimistic error pruning, cost complexity pruning, and C4.5, on benchmark data sets, the advantage and disadvantage of cost-sensitive methods in KBP1.0 have been summarized. This research will enhance our understanding of the theory, design and implementation of decision tree pruning using expert knowledge. In the future, the cost-sensitive pruning methods can be integrated into other pruning methods, such as minimum error pruning and critical value pruning, and include new

pruning methods in KBP. Using KBP to prune the decision tree and getting the rules from the pruned tree to help us build the expert system is another direction of our future work.

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CHAPTER I

INTRODUCTION

1. Motivation

"An expert system is a computer system which emulates the decision-making ability of a human expert." [101] The power behind an expert system is its knowledge. However, obtaining the knowledge from an expert can be a very difficult task in real-world problems. The knowledge engineer must be versed in the techniques of eliciting knowledge, which requires good communication skills and some understanding of the psychology of human interaction. Acquiring these skills, and being able to practice them effectively, can be difficult [1]. Another challenge with extracting knowledge occurs when the expert is not consciously aware of the knowledge used [1]. The third difficulty occurs for expert system applications where no real experts exist [1]. Though knowledgeable individuals exist who can predict some event, they usually rely upon past events to aid their prediction. Therefore, the domain knowledge rests in past examples, and not with human expertise. In these applications, the knowledge engineer must again use some techniques that can uncover the knowledge contained within the examples. Induction technique can be used to acquire knowledge from a set of examples. There are many such induction techniques and the decision tree is only one of them. Every induction technique has its advantages and disadvantage [97]. For example, a neural network is better than a decision tree in accuracy [120], while a decision tree is more robust than a neural network [121]. No single technique has been found to be superior over all others for all data sets.

Decision tree technology has proven to be a valuable way of capturing human decision making within a computer. But it often suffers the disadvantage of developing very large trees making them incomprehensible to experts. To solve this problem, researchers in the field have much interest in decision tree pruning. Decision tree pruning methods transform a large tree into a smaller one, making it easily understood. Many decision tree pruning algorithms have been shown to yield simpler or smaller trees.

One main problem for many traditional decision tree pruning methods is that when they are used to prune a decision tree, it is always assumed that all the classes are equally probable and equally important. However, in real-world classification problems, there is also a cost associated with misclassifying examples from each class. For example, granting a credit to an unreliable applicant may be more expensive for a bank than refusing it to a good applicant. This is the reason that a cost-sensitive pruning method is needed to prune the decision tree. Unfortunately, the idea of cost-sensitive pruning has received much less attention than other pruning techniques even though additional flexibility and increased performance can be obtained from this method. The research in this dissertation focuses on cost-sensitive pruning. In the dissertation, expert knowledge is used to improve the performance of cost-sensitive pruning. Cost is domain-specific and is quantified in arbitrary units [46]. In this sense, an expert is needed.

The Merriam-Webster dictionary defines cost as "loss or penalty incurred especially in gaining something". Although there are many types of costs in the real world, such as cost of time and cost of memory, only misclassification cost is considered in this dissertation. Almost every error will cause cost. For example, in decision trees, there are misclassification errors. If this misclassification is used in applications, it will certainly cause cost. A matrix is used to define the misclassifications cost in decision tree pruning. In this matrix, the element in row i and column j specifies the cost of assigning a case to class i when it actually belongs

to class j. When i equals to j, the cost is zero which means there is no misclassification for this class. The cost matrix will be discussed in more detail later. There are not only misclassification errors but also other kinds of errors. For example, nuclear power stations might not be safe, i.e., a nuclear leak will threaten our life. However, in this dissertation, error only refers to misclassification error in decision tree. Hereinafter, unless specified otherwise, cost of a pruning algorithm means the misclassification cost.

2. Contributions of Research

This research focuses on decision tree pruning. The main contributions of this dissertation, in the author's opinion, are the following:

(1) The major contribution of the research is the use of expert knowledge in cost-sensitive pruning. In the cost-sensitive pruning, the misclassification cost is provided by domain experts and represented as a cost matrix. An example is used to explain how expert knowledge is used to help define the cost matrix. To the best of the author's knowledge, the use of expert knowledge in cost-sensitive pruning of decision trees has not been reported in the literature.

(2) There are many decision tree pruning methods, but most of them only consider error rate or cost during pruning. Another contribution of the research is that two ways to integrate error rate and cost in the pruning method are proposed. One method uses intelligent inexact classification (IIC) and the other uses a threshold to integrate error rate and cost. To the best of the author's knowledge, IIC and threshold value in decision tree pruning have not been used thus far in this context. Moreover, the proposed pruning method is more general than other non-cost sensitive pruning methods. For example, the cost weight can be set to value 0 and the cost-sensitive pruning can be changed to an error based non-sensitive pruning.

(3) A decision tree pruning algorithm called KBP1.0, which includes four cost-sensitive pruning methods, was developed and its framework was introduced. KBP1.0 and some well-known traditional pruning methods, such as reduced error pruning, pessimistic error pruning, and C4.5, are compared on data sets from the UCI Machine Learning Repository and the results are reported and discussed.

(4) The framework for knowledge-base pruning method was introduced. Then, the strategies under the framework were discussed.

(5) There is a preliminary discussion on the sensitivity of the pruning method to the cost matrix. To the best of the author's knowledge, it is the first time that this kind of sensitivity is analyzed.

The decision tree pruning algorithm KBP1.0 provides us more options to prune the decision tree, especially when cost is too important to be ignored. Its potential application includes most problems which should take into account misclassification cost, such as medical diagnosis, stock prediction, credit grant, and so on. Another value of the cost-sensitive pruning methods is that designers can form a balance between error and cost in decision tree pruning by defining the weights of cost and error under the guidance of experts.

Most of this dissertation is from the point of view of machine learning and has an experimental flavor. Experiments are carefully designed and controlled from the basis of observations and conclusions. An experimental analysis is given in the dissertation.

3. Dissertation Outline

This dissertation is organized as follows. Chapter 2 is devoted to an overview of decision tree classifier methodology. Chapter 3 introduces new methods for cost-sensitive decision tree pruning under the program name KBP1.0. An example of KBP 1.0 is also provided in Chapter 3. Comparative analysis of KBP1.0 and other traditional methods for pruning a decision tree is described and the sensitivity of the pruning method to the cost matrix is investigated in

Chapter 4. Chapter 5 introduces the framework for KBP1.0. Finally, a summary of the research is given in Chapter 6, which discusses some concerns of the research and answers some questions. It also discusses the future work of the research.

CHAPTER II

OVERVIEW OF DECISION TREE TECHNOLOGY

This chapter is an overview of decision tree technology which is not author's original contribution.

1. Definition of Terminology

To avoid possible confusion with the textual description in this dissertation, the following definitions are provided(these definitions are cited from some dictionaries, websites, and books):

Tree: "A tree is a connected acyclic graph." [102] In this dissertation, every tree is a decision tree. "The decision tree is a tree diagram which is used for making decisions in business or computer programming and in which the branches represent choices with associated risks, costs, results, or probabilities." [103]

Class: "The class is a group or set sharing common attributes. In a decision tree, classes are the categories to which cases are to be assigned." [104]

Object: "The object is something material that may be perceived by the senses." [105]

Set: "a number of things of the same kind that belong or are used together." [106]

Path: "A path in a graph is an ordered list of distinct vertices v_1,...,v_n such that $v_{i-1}v_i$ is an edge for all $2 <= i <= n$." [98]

Subtree: "A tree structure created by arbitrarily denoting a node to be the root node in a tree. A subtree is always part of a whole tree." [98]

Node: “In a tree structure, a node is a point at which subordinate items of data originate.” [98]

Leaf: “In a tree, a leaf is a node without children.” [98]

Root: “In a decision tree, a root is a node that has no parent. All other nodes of a tree are descendants of the root.” [98]

Attribute: “An inherent characteristic.” [122]

Subset: “A set each of whose elements is an element of an inclusive set.” [123]

Entropy: “The degree of disorder or uncertainty in a system.” [124]

2. What is Decision Tree

A decision tree gets its name because it is shaped like a tree and can be used to make decisions. “Technically, a tree is a set of nodes and branches and each branch descends from a node to a another node. The nodes represent the attributes considered in the decision process and the branches represent the different attribute values. To reach a decision using the tree for a given case, we take the attribute values of the case and traverse the tree from the root node down to the leaf node that contains the decision.” [109]

A critical issue in artificial intelligence(AI) research is to overcome the so-called “knowledge-acquisition bottleneck” in the construction of knowledge-based systems. Decision tree can be used to solve this problem. Decision trees can acquire knowledge from concrete examples rather than from experts [1]. In addition, for knowledge-based systems, decision trees have the advantage of being comprehensible by human experts and of being directly convertible into production rules [13]. A decision tree not only provides the solution for a given case, but also provides the reasons behind its decision. So the real benefit of decision tree technology is that it avoids the need for human expert. Because of the above advantages, there are many successes in applying decision tree learning to solve real-world problems.

Durkin, J. summarized that decision tree technology has several advantages and disadvantages [60][118]. The advantages include:

(1) Discovers rules from examples,

(2) Avoids knowledge elicitation problems,

(3) Can discover new knowledge,

(4) Can uncover critical decision factors,

(5) Can eliminate irrelevant decision factors,

(6) Robust to noisy data.

The disadvantages of the technology are:

(1) Often difficult to choose good decision factors,

(2) Difficult to understand rules generated from large trees,

(3) Often leads to an overfitting problem when decision tree is big or there is not much training data.

Decision tree technology has proven to be a valuable way of capturing human decision making within a computer. Unfortunately, as AI fell out of favor, so did decision tree technology. Fortunately, with the emergence of the relatively new field of data mining, which includes decision tree technology as one of the primary ways of capturing human decision making, there is renewed interest in the technology.

3. Decision Tree Construction

Several algorithms have been developed to create a decision tree. Some of the more popular ones are ID3 (Quinlan 1986), C4.5 (Quinlan 1993), CART(Brieman et al., 1984) and CHAID(Kass 1980). While they all differ in some way, they all share the common idea of building the tree using a technique based on information theory. In this section, only Quinlan's ID3 algorithm for constructing a decision tree is introduced. In decision tree construction, the

set of cases with known classes from which a decision tree is constructed is called the training set and other collections of cases not seen while the tree was being developed are known as test sets.

A decision tree building algorithm determines the classification of objects by testing the values of their attributes. The tree is built in a top down direction. An attribute is tested at each node of the tree and the results is used to partition the object set. This process is recursively done till the set in a given subtree only contains objects belonging to the same category or class- in other words it becomes a leaf node [110].

ID3 consists of the following steps [111]:

(1) Select the attribute with the most gain

(2) Create the subsets for each value of the attribute

(3) For each subset

1) if not all the elements of the subset belongs to same class repeat the steps 1-3 for the subset

2) if all the elements of the subset belongs to same class end

Entropy in information gain is used to measure which attribute is most informative. Entropy is a measure from information theory. It characterizes the impurity or homogeneity, of an arbitrary collection of examples [127]. Mathematicians know that information is maximized when entropy is minimized. Entropy determines the extent of randomness or chaos in data. The development of the idea of entropy of random variables and processes by Shannon provided the beginning of information theory and of the modern age of ergodic theory [56]. This concept is key to decision tree construction, as is shown in the following.

The process of building a decision tree starts with the selection of an attribute A as the root node of the tree that does the best job of dividing the set of samples S into subsets s_1,s_2,...,s_n, in which many samples belong to the same class C.

To measure the total disorder, or inhomogeneity in the subsets, the entropy of attribute A can be calculated as follows [41]

$$Average\ Entropy(A) = \sum(\frac{n_b}{n_t}) * \sum -(\frac{n_{bc}}{n_b}) \log_2(\frac{n_{bc}}{n_b}) \tag{1}$$

where:

n_b is the number of samples in branch b,

n_t is the number of samples in all branches,

n_{bc} is the total number of samples in branch b of class c.

After calculating the entropy of each attribute, the one which has minimal entropy is chosen because minimal entropy means largest information gain.

To understand how the average entropy equation can be used to generated the decision tree, let us start by considering the set of samples at the end of branch b. We want an equation containing n_b and n_{bc} that gives us a high number when the set is highly inhomogeneous and a low number when the set is highly homogeneous. Fortunately, the following entropy equation borrowed from information theory can be used to accomplish this:

$$Entropy = \sum -(\frac{n_{bc}}{n_b}) \log_2(\frac{n_{bc}}{n_b}) \tag{2}$$

To get a feel on how this equation works, let's look at some examples. First suppose we have only two classes: C_1 and C_2 in a sample set. Further assume that the sample set contains an equal number of samples from both classes. It then follows that the entropy is 1, the maximum possible value:

$$
\begin{aligned}
Entropy &= \sum -(\frac{n_{bc}}{n_b}) \log_2(\frac{n_{bc}}{n_b}) \\
&= -\frac{1}{2} \log_2(\frac{1}{2}) - \frac{1}{2} \log_2(\frac{1}{2}) \\
&= \frac{1}{2} + \frac{1}{2} \\
&= 1
\end{aligned}
\tag{3}
$$

For the next example, let's assume that the sample set contains only samples from C_1 or C_2. In this case, the set is perfectly homogeneous and it follows that the entropy is 0, the minimum possible value:

$$
\begin{aligned}
Entropy &= \sum -(\frac{n_{bc}}{n_b}) \log_2(\frac{n_{bc}}{n_b}) \\
&= -1 \log_2(1) - 0 \log_2(0) \\
&= -0 - 0 \\
&= 0
\end{aligned}
\tag{4}
$$

It is clear that entropy varies smoothly between zero and one when the sample set moves from perfect balance to perfect homogeneity [41].

The prior discussion shows how to measure the entropy in one set. We next need to obtain the average entropy of the sets at the ends of the branches under the attribute A. To obtain this measure, the entropy in each branch's set is weighted by the size of the set relative to the total size of all the branches' sets. Therefore, given that n_b is the number of samples in branch b and n_t is the total number of samples in all branches, it follows that

$$
Average\ Entropy(A) = \sum -(\frac{n_b}{n_t}) * (Entropy\ in\ the\ branch\ b\ set) \tag{5}
$$

which is the same as equation (1).

Using this idea we take each attribute and compute its average entropy, and then select the one for the root node that has the minimum entropy value. As the tree is further developed, the same idea is followed in node selection.

The use of entropy for attribute selection is just one of several methods employed in building a decision tree. A good review of available methods can be found in Breimann et al., (1984) and in Mingers (1989).

Once a decision tree is constructed, it is easy to convert it into a set of equivalent rules. We just trace each path in the decision tree, from root node to leaf node, recording the test outcomes as antecedents and the leaf-node classification as the consequent. However, if the tree is large, then the rules created are likewise large and difficult to understand. This is where pruning becomes important.

4. Pruning a Decision Tree

Although the decision trees generated by methods such as ID3 and C4.5 are accurate and efficient, they often suffer the disadvantage of providing very large trees that make them incomprehensible to experts [12]. To solve this problem, researchers in the field have considerable interest in tree pruning. Tree pruning methods convert a large tree into a small tree, making it easier to understand. Such methods "typically use statistical measures to remove the least reliable branches, generally resulting in faster classification and an improvement in the ability of the tree to correctly classify independent test data." [107] It is necessary for us to know the advantage and disadvantage of every decision tree pruning method before it is decided that which pruning method will be selected. The following are some main methods to simplify decision trees.

(1) Reduced Error Pruning

This method was proposed by Quinlan [12]. It is the simplest and most understandable method in decision tree pruning. For every non-leaf subtree S of the original

decision tree, the change in misclassification over the test set is examined. The misclassification would occur if this subtree were replaced by the best possible leaf which is the majority of leaf. If the error rate of the new tree would be equal to or smaller than that of the original tree and that subtree S contains no subtree with the same property, S is replaced by the leaf. Otherwise, stop the process. The constraint that the subtree S contains no subtree with the same property guarantees reduced error pruning in bottom-up induction [11].

Since each node is visited only once to evaluate the opportunity of pruning it, the advantage of this method is its linear computational complexity [11]. However, this method requires a test set separate from the cases in the training set from which the tree was constructed [12]. When the test set is much smaller than the training set, this method may lead to overpruning. Many researchers found that Reduced Error Pruning performed as well as most of the other pruning methods in terms of accuracy and better than most in terms of tree size [11].

(2) Pessimistic Error Pruning

This method was also proposed by Quinlan [12] and was developed in the context of ID3. Quinlan found that it is too optimistic for us to use a training set to test the error rate of a decision tree, because decision trees have been tailored to the training set. In this case, the error rate can be 0. But some data other than the training set is used, the error rate will increase dramatically. To solve this problem, Quinlan used continuity correction for the binomial distribution to get an error rate which is more realistic. In statistics, continuity correction is a useful method in the application of the normal distribution to the computation of binomial probabilities. "When the normal distribution (a continuous distribution) is used to find approximate answers to problems arising from the binomial distributions (discrete distribution),

an adjustment is made for the mismatch of types of distribution. This is called the continuity correction." [108]

Quinlan uses the following equations to obtain the number of misclassifications:

$$n^{'}(t) = e(t) + (\frac{1}{2}) \tag{6}$$

$$n^{'}(T_t) = e(T_t) + (\frac{N_T}{2}) \tag{7}$$

Equation(6) is the number of misclassifications for node t and equation(7) is the number of misclassifications for subtree T.

where:

N_T is the number of leaves for subtree T,

$e(t)$ is the number of misclassifications at node t,

$e(T_t)$ is the number of misclassifications for subtree T.

The 1/2 in the equation (6) and (7) is a constant which indicates the contribution of a leaf to the complexity of the tree. This pruning method only keeps the subtree if its corrected figure (from equation 7) is more than one standard error better than the figure for the node (from equation 6).

This method is much faster than Reduced Error Pruning and also provides higher accuracies. Its disadvantage is that, in the worst case, when the tree does not need pruning at all, each node will still be visited once [11].

(3) Cost-Complexity Pruning

This method was proposed by Breiman et al., [7]. It takes account of both the number of errors and the complexity of the tree. The size of the tree is used to

represent the complexity of the tree. It is also known as the CART pruning method and Floriana Esposito, et al, describe it in two steps [11]:

1) Selection of a parametric family of subtrees of $\{ T_0, T_1, \ldots, T_L \}$, according to some heuristics. T_0 is the original decision tree and each T_{i+1} is obtained by replacing one or more subtrees of T_i with leaves by pruning those branches that show the lowest increase in apparent error rate per pruned leaf until the final tree T_L is just a leaf.

2) Choice of the best tree according to an estimate of the true error rates of the trees in the parametric family.

For example, consider subtree T used to classify each of the N cases in the training set and E of N examples are wrongly classified if subtree T is replaced by the best leaf. Let N_T be the number of leaves in subtree T. the following equation is used to define the total cost-complexity of subtree T:

$$cos - complexity = (\frac{E}{N}) + \alpha * N_T \tag{8}$$

where α is the cost of one extra leaf in the tree and gives the reduction in error per leaf.

If the subtree is pruned, the new tree would misclassify M more of the cases in the training set but would contain $N_T - 1$ fewer leaves. the same cost-complexity will be obtained when

$$\alpha = (\frac{M}{N * (N_T - 1)}) \tag{9}$$

From the above equation, α can be calculated for each subtree and the subtree(s) with the smallest value of α is selected for pruning. Continue to process this until the

leaf is obtained. The next job is to select one of the trees. The standard error (SE) of the misclassification rate is

$$SE = (\frac{R * (100 - R)}{N}) \tag{10}$$

where:

R=misclassification rate of the pruned tree,

N=number of examples in the test data.

The smallest tree whose observed number of errors on the test set does not exceed $R + SE$ is selected.

This method requires a pruning set distinct from the original training set. Its disadvantage is that it can only choose a tree in the set $\{ T_0, T_1, \ldots, T_L \}$,which is obtained in the first step, instead of the set of all possible subtrees [11]. It also seems anomalous that the cost-complexity model used to generate the sequence of subtrees is abandoned when the best tree is selected [12].

(4) Minimum Error Pruning

This method was developed by Niblett and Brotko [48]. It is a bottom-up approach which seeks a single tree that minimizes the expected error rate on an independent data set.

Assume that there are k classes for a set of data which number is n and n_c is the class c with the greatest number of data. If it is predicted that all future examples will be in class c, the following equation is used to predict the expected error rate:

$$E_k = (\frac{n - n_c + k - 1}{n + k}) \tag{11}$$

where:

k is the number of classes for all data,

E_k is the expected error rate if we predict that all future examples will be in class c.

The method consist of three steps [112]:

1) At each non-leaf node in the decision tree, use equation(11) to calculate the expected error rate if that subtree is pruned.

2) Calculate the expected error rate if the node is not pruned, combined by weighting according to the proportion of observations along each branch [11][48].

3) If pruning the node leads to a greater expected error rate, then keep the subtree; otherwise, prune it.

J. Mingers [8] points out that there are several disadvantages in this method. First, it is seldom true in practice that all the classes are equally likely. Second, this method produces only a single tree. This is a disadvantage in the context of expert systems, where it will be more helpful if several trees, pruned to different degrees, are available. Third, the number of classes strongly affects the degree of pruning, leading to unstable results.

Minimum error pruning was improved by Cestnik and Bratko [48] and the most recent version of minimum error pruning overcomes two problems of original method: optimistic bias and dependence of the expected error rate on the number of classes.

(5) Critical Value Pruning

This method was proposed by Mingers [43]. In this method, a threshold, named the critical value, is set to estimate the importance or strength of a node. When the node does not reach the critical value, it will be pruned. But when a node meets the pruning condition but its children do not all meet the pruning condition, this branch

should be kept because it contains relevant nodes. If a larger critical value is selected, a smaller resulting tree will be obtained because of the more drastic pruning.

Mingers describes the critical value pruning as two main steps [43]:

1) Prune subtree for increasing critical values,

2) Measure the significance of the pruned trees as a whole and their predictive ability and choose the best tree among them.

The disadvantage of this method is its strong tendency to underprune and this method selects trees with comparatively low predictive accuracy [42].

(6) Optimal Pruning

Breiman et al., introduce a convenient terminology used to state and verify the mathematical properties of optimal pruning [7]. They also introduce an algorithm to select a particular optimally pruned subtree from among the k candidates [7]. Bratko and Bohanec [73] and Almuallim [74] address the issue of finding optimal pruning in another way. Bohanes et al., [73] introduced an algorithm guaranteeing optimal pruning (OPT), and Almuallim [74] further improved OPT in terms of the computational complexity. Their motivation for simplifying decision trees is different from the typical motivation for pruning decision trees when learning from noisy data. Both [73] and [74] assume that the initial, unpruned decision trees are completely correct. However, in learning from noisy data, which is our case, it is assumed that the initial, unpruned decision tree is inaccurate and appropriate pruning would improve its accuracy.

5. Other Work on Decision Tree Technology

Currently, the research in decision tree technology mainly focuses on the following directions:

(1) Integrating decision trees with other AI techniques

How to integrate the decision tree technique with other new techniques is one of the hottest topics in decision tree research. this work is summarized as follows:

(a) Integrating decision trees with neural networks

Neural networks offer a exciting computational paradigm for cognitive machines and are successful in acquiring hidden knowledge in data sets. But the knowledge which they acquire is represented in a form not understandable to humans. O. Boz dealt with this shortcoming by extracting decision trees from trained neural networks [17]. A new decision tree extraction technique (DecText) is developed to extract classical decision trees from trained neural networks and the tree is pruned in a way to maximize the fidelity between the tree and the Neural Network. I. Sethi [18] did this research in another way: a decision tree is restructured as a three-layer neural network, called an entropy network. A mapping method is used to map a decision tree into a multilayer neural network structure. An entropy network architecture has many advantages, such as fewer neural connections and faster progressive training procedure.

(b) Integrating decision trees with fuzzy logic

"Decision trees have already shown to be interpretable, efficient, problem-independent and able to treat large scale applications. But they are also recognized as highly unstable classifiers with respect to minor perturbations in the training data, in other words, methods presenting high variance" [113]. Fuzzy logic brings an improvement due to the elasticity of fuzzy sets formalism. C. Olaru, et al., propose a new method of fuzzy decision trees called soft decision trees(SDT) [20]. SDT is a variant of classical

decision tree inductive learning using fuzzy set theory. M. Dong and R. Kothari presented a computationally efficient way of incorporating look-ahead into fuzzy decision tree induction which leads to smaller decision trees and better performance [19].

(c) Integrating decision trees with evolutionary algorithms, genetic algorithms and genetic programming

Evolutionary algorithms(EA) are stochastic search methods based on the mechanics of natural selection and genetics. E. Cautu-Paz and C. Kalles substituted the greedy search technique in traditional decision tree technology with two evolutionary algorithms [21]. This EA-based tree inducer resulted in faster training time. EAs can also find oblique trees with a similar or higher accuracy than existing algorithms. EAs are a promising technique to build oblique trees for the following reasons [21]:

(1) Scalability to high dimensional spaces,

(2) Tolerance to noise,

(3) Parallel implementations,

(4) More sophisticated optimizers,

(5) Use of problem-specific knowledge such as seeding the initial population of the Evolutionary Algorithm (EA) with "good" solutions.

Genetic algorithms(GA) have been used for classification. A. Papagelis and D. Kalles used GAs to directly evolve classification decision trees [22][23]. Their method shows the potential advantages of GAs over other greedy heuristics, especially when there are irrelevant or strongly dependent attributes. D. Carvalho and A. Freitas proposed a hybrid decision tree/genetic algorithm method to deal with the problem of small disjuncts [24]. In this method, when examples belong to large disjuncts, they are classified by rules produced by a decision tree, otherwise, they are classified by rules produced by a specifically designed genetic algorithm. The quality of the rules

discovered by this hybrid algorithm is much better than that of the rules discovered by C4.5 alone. The disadvantage of the hybrid decision tree/genetic algorithm is that it is much more computationally expensive.

Genetic programming(GP) is a method of adaptive automatic program induction. The difference between GP and GA is that, for GP, individuals are no longer strings but parse trees of the programs [128]. GP is a effective way of overcoming the limitations of the standard greedy decision tree induction algorithms. Each individual of the population in GP can be a decision tree. The functions to be used in the GP are the attributes of the decision tree and classes form the terminal set. G. Tur and H. A. Guvenir did some work in this respect [25]. They found that decision trees created using genetic programming can find the optimum solution for a small sized data set.

(d) Integrating decision trees with a multiagent system

Mutiagent System(MAS) has emerged as an active subfield of Artificial Intelligence in recent years. MAS aims to provide both principles for construction of complex systems involving multiple agents and mechanisms for coordination of independent agents behaviors [114]. Because machine learning has the potential to provide robust mechanisms that leverage upon experience to equip agents with a large spectrum of behavior, machine learning is a promising area to merge with multiagent systems [27]. P. Stone and M. Veloso published some papers on this research [27][28][29]. They proposed a novel technique for agent control in a complex multiagent domain based on the confidence factors provided by the C4.5 decision tree algorithm. It was realized in robotic soccer [28].

There are some other research directions for decision tree technology as follows:

(2) Looking for better methods to construct decision trees

Several algorithms have been developed to create a decision tree. Some of the more popular ones are ID3, C4.5, CART and CHAID. While they all differ in some way, they all share the common idea of building the tree using a technique based on information theory. M. Ankerst, et al., introduced a fully interactive method based on a multidimensional visualization technique and appropriate interaction capabilities [31]. In this construction method, domain knowledge of an expert can be effectively included in the tree construction phase to reduce the tree size and improve the understandability of the resulting decision tree.

(3) Looking for better methods to simplify decision trees

There are mainly two research directions in decision tree pruning. One is comparing the different methods for decision tree pruning. The other is looking for better methods to simplify decision trees. For the first area, J. Mingers and F. Esposito, et al., published some important papers [11][43]. For the second area, many researchers are trying to use new techniques to help simplify decision trees. For example, D. Fournier and B. Cremilleux found a new pruning method called DI pruning that takes into account the complexity of subtrees [30]. Even some subtrees created using this method do not increase the classification efficiency. DI pruning can assess the quality of the data used for the knowledge discovery task.

(4) Doing research on the impact of data size and quality on decision tree performances

Different from the previous research directions, this direction focus is on the impact of data size and data quality on decision tree performances. It is clear that increasing the training set size often results in a linear increase in tree size even without a significant increase in classification accuracy [15]. In this sense, a data reduction technique, which is different from a pruning technique, is very important for a decision

tree's quality. On the other hand, improving the quality of the training data results in an increasing classification accuracy. M. Sebban [14], T. Oates [15] and C. E. Brodley [16] performed research in this area.

(5) Decision trees in an uncertain environment

Although the decision tree technique is one of the most popular and efficient supervised learning approaches, a major problem faced in the standard decision tree algorithms results from the uncertainty encountered in the data [44]. This uncertainty can appear either in the construction or in the classification phase. In many cases, the uncertainty may affect the classification results and may even result in erroneous decisions, therefore it can't be ignored. There are mainly two ways to deal with the uncertainty: one is probabilistic decision trees and the other is fuzzy decision trees. Z. Elouedi, et al., developed a belief decision tree which integrates the advantages of both the decision tree technique and the belief function theory to deal with the uncertainty [44]. B. Crmilleux, et al., also did some work in uncertain domains and decision trees [45].

(6) Computational Complexity of Decision trees

Algorithms based on the decision tree technique can reach a high computational complexity. Catlett [83] and Fifield [92] proposed some methods to reduce the computational complexity. However, their methods all require that all data will be loaded into main memory before induction. Chan and Stolfo's method [93] reduces the computational complexity, but the classification accuracy decreases. There are some other important researches in reducing computational complexity of decision trees. For example, Mehta et al. [94] proposed SLIQ, Shafer [95] et al. presented SPRINT, and Gehrke [96] et al. introduced RainForest to deal with the computational complexity.

(7) Cost-Sensitive Decision Tree Pruning

One main problem for many decision tree pruning methods is that when a decision tree is pruned, it is always assumed that all the classes are equally probable and equally important. However, in real-world classification problems, there is also a cost associated with misclassifying examples from each class. Unfortunately, the method of cost-sensitive pruning has received much less attention even though additional flexibility and increased performances have been obtained from this method. Currently, the most common method for cost-sensitive pruning method is to use techniques in statistics to deal with the problem. Because the research in the dissertation focuses on cost-sensitive pruning, the statistical method for cost-sensitive pruning is discussed here.

The use of probability models and statistical methods for analyzing data has become common practice in virtually all scientific disciplines. For example, M. Jordan used a statistical approach to build a decision tree model [53]. A parameter can be estimated from sample data either by a single number (a point estimate) or an entire interval of plausible values (a confidence interval). Frequently, however, the objective of an investigation is not to estimate a parameter but to decide which of two contradictory claims about the parameter is correct (some cost-sensitive pruning method makes use of this [10]). Methods for accomplishing this comprise the part of statistical inference called hypothesis testing. The null hypothesis, denoted by H_0, is the claim about one or more population characteristics that is initially assumed to be true. The alternative hypothesis, denoted by H_a, is the assertion that is contradictory to H_0. The null hypothesis will be rejected in favor of the alternative hypothesis only if sample evidence suggests that H_0 is false. If the sample does not strongly contradict H_0, we will continue to believe in the truth of the null hypothesis. The two possible

conclusions from a hypothesis-testing analysis are then rejecting H_0 or fail to reject H_0. A test of hypothesis is a method for using sample data to decide whether the null hypothesis should be rejected. For example, we might test $H_0 : R = 0.75$ against the alternative $H_a : R \neq 0.75$. Only if sample data strongly suggests that R is something other than 0.75 should the null hypothesis be rejected. In the absence of such evidence, H_0 should not be rejected, since it is still quite plausible. Sometimes an investigator does not want to accept a particular assertion unless and until data can provide strong support for the assertion. As an example, suppose a bank is considering whether to grant a credit to an unreliable applicant. The bank would not want to grant a credit to this applicant unless evidence strongly suggested that this applicant is a good applicant because granting a credit to an unreliable applicant may be more expensive for a bank than refusing it to a good applicant. The conclusion that the applicant is not a good applicant is identified with H_0, while that the applicant is a good applicant is identified with H_a. It would take conclusive evidence to justify rejecting H_0 and granting a credit to the applicant. Of course, it is also possible to take conclusive evidence to not reject H_0 and deny granting a credit to the applicant.

A test procedure is specified by the following [33]:

(a) A test statistic, a function of the sample data on which the decision (reject H_0 or do not reject H_0) is to be based.

(b) A rejection region, the set of all test statistic values for which H_0 will be rejected.

The null hypothesis will then be rejected if and only if the observed or computed test statistic value falls in the rejection region.

The basis for choosing a particular rejection region lies in an understanding of the errors that one might be faced with in drawing a conclusion. It is possible that H_0

may be rejected when it is true or that H_0 may not be rejected when it is false. There are definitions for these two errors [33]:

A type I error consists of rejecting the null hypothesis H_0 when it is true.

A type II error involves not rejecting H_0, when H_0 is false.

Instead of demanding error-free procedures, we must look for procedures for which either type of error is unlikely to occur. A good procedure is one for which the probability of making either type of error is small. The choice of a particular rejection region cutoff value fixes the probability of type I and type II errors [33]. These error probabilities are traditionally referred to as α and β, respectively. There is a proposition in statistics: Suppose an experiment and a sample size are fixed, and a test statistic is chosen. Then decrease the size of the region to obtain a smaller value of α results in a larger value of β for any particular parameter value consistent with H_a [115]. So a region must be chosen to affect a compromise between α and β. How to choose α and β in decision tree pruning is very important. Conclusively, in this method, we will construct our test procedure in the following three steps [115]:

(a) Specify a test statistic.

(b) Decide on the general form of the rejection region.

(c) Select the specific numerical critical value or values that will separate the rejection region from the acceptance region.

There are many ways to choose α and β. For example, A. Bradley and B. Lovell used the ROC (receiver operating characteristic) to choose α and β in cost-sensitive decision tree pruning [10].

6. Decision Tree Applications

The decision tree technique has been used in many applications. Here are several successful applications of the technology across multiple disciplines.

(1) Soybean Diagnosis

Michalski and others [50] developed a program called AQ11 for diagnosing soybean diseases. From 630 examples of diseased soybean plants, the system was built using 290 of the examples along with 35 decision factors. The remaining 340 examples were used for testing. AQ11 formulated a set of rules for classifying a new example into one of 15 different disease categories.

In a parallel effort, the designers of AQ11 developed a rule-based system on the same problem. Knowledge for this system came from a plant pathologist. A study was then performed to compare the performance of the rule-based and the induction systems. The 340 examples not used in the formulation of the induction system were used for the comparative testing. The rule-based system gave the correct result 71.8% of the time, while AQ11 scored 97.6%.

(2) Thunderstorm Prediction

Severe thunderstorms in the United States annually cause loss of lives and millions of dollars in property damage. Forecasting thunderstorms is done by expert meteorologists with the National Severe Storms Forecast Center(NSSFC). This task is time consuming and involves the continuous analysis of vast amount of data. A decision tree program called WILLARD was developed to aid this task [51].

WILLARD was developed using 140 examples of thunderstorm weather data. The system uses a hierarchy of 30 modules, each with a single decision tree. It queries the user about pertinent weather conditions for the area and then produces a complete forecast with supporting justification. The system characterizes the certainty of a severe thunderstorm occurrence as: none, approaching, slight, moderate or high, with each prediction given with a numerical probability range.

WILLARD was tested over a one-week period in late spring of 1984, in a region including west and central Texas, Oklahoma and Colorado. During this period, five severe thunderstorms passed through this region. WILLARD's forecasts were found to compare favorably with those made by a meteorologist expert from NSSFC.

(3) Customer Support

NORCOM, a software company located in Juneau, Alaska, markets a software product called SCREENIO [116]. SCREENIO allows the users to design IBM PC screens for their Realia COBOL programs. NORCOM has over 500 customers for this product who will often contact NORCOM for product support. To help alleviate the workload associated with their customer support, NORCOM developed a decision tree program to aid their support personnel.

NORCOM had nine months of data on typical customer problems and associated solutions. The examples contained nine decision factors. Using this information, the decision tree program was developed in one day.

In operation, the system is used by support personnel who ask the customer for values for each of the decision factors. According to NORCOM general partner John Anderson, the system has "made a major improvement in our customer support responsiveness and efficiency." Another value of the system is that entry-level personnel can use the system effectively since it leads them through consultation.

(4) Predicting Stock Market Behavior

Predicting stock market behavior is a difficult challenge. Analysts use techniques such as trend analysis, cycle analysis, charting techniques or other types of historical data analysis. Each of these techniques provides the analyst with information that can be used for predicting future trends. However, each technique provides a degree of uncertainty that may make it unreliable.

Braun [52] developed a decision tree program to improve the reliability of stock market prediction. An investment analyst was used as the expert for the study. The problem chosen focused on predicting intermediate fluctuations in the movement of the market for nonconservative investors.

Twenty decision factors were chosen for producing the system. Values for these factors were determined over a time period between March 20, 1981 to April 9, 1983. Most of the information was obtained from the Wall Street Journal, while some data was found from interpretations of trend-charting techniques. Three different results were used to categorize the prediction: Bullish(forecasting an upward trend), bearish(forecasting a downward trend), and neural(indicating that either call was too risky). These predictions were interpreted for each of the 108 weeks of the study. Data was collected on the actual market movement during this period and the movement predicted by the expert analyst. In tests, the system correctly predicted the actual market movement 64.4 percent of the time while the expert analyst was correct 60.2 percent.

7. Intelligent Inexact Classification in Expert System

We confront uncertainty every day. Uncertainty is a problem because it may prevent us from making the best decision and may even cause a bad decision. In medicine, uncertainty may prevent the best treatment for a patient or contribute to an incorrect therapy. In business, uncertainty may mean financial loss instead of profit. Uncertainty in decision tree pruning may develop a decision tree with high misclassification error.

A number of theories have been devised to deal with uncertainty which include classical probability, Bayesian probability, Hartley theory based on classical sets [56], Shannon theory based on probability [57], Dempster-Shafer theory [58] and Zadeh's fuzzy theory [59].

A number of different methods have been proposed for dealing with uncertainty to aid in picking the best conclusion. It is the responsibility of the expert system designer to pick the most appropriate method depending on the application. There are many expert systems applications, such as MYCIN [54] for medical diagnosis and PROSPECTOR [55] for mineral exploration, that use inexact reasoning involving uncertain facts.

John Durkin proposed an intelligent inexact classification method in 1991 [60]. This approach can be used of in cost-sensitive pruning. We often encounter problems where the task is to decide which of several categories a given object best belongs. By "best" we mean the category in which the object appears to best fit, even it appears to also fit into other categories.

To get the best category, Durkin developed an inexact classification technique that forms "belief" values for category matches. One method is to use an expert system approach along with an evaluation function that performs the matching task in an intelligent fashion. To illustrate the method, he considered the problem of selecting a product best suited to the needs of a customer.

Assume we have N different products and I different factors for each product. Our task is to determine how well a given product matches a buyer's needs. Durkin accomplish this by forming an evaluation function F that returns a value F_n for product n representing a degree of match between the buyer and the product. The greater the value of F_n the better the match.

this evaluation can be calculated from

$$F_n = \frac{\sum_{i=1}^{I} \alpha_i \beta_{in}}{\sum_{i=1}^{n} \alpha_i} \tag{12}$$

where:

α_i is the importance of factor i,

β_{in} is a measure of the user's desire for factor-value i of product n,

We assume that both α and β are bound by 0 and 1, so F_n is also bound by 0 and 1.

$$0 \leq \alpha \leq 1, 0 \leq \beta \leq 1, 0 \leq F_n \leq 1 \tag{13}$$

where, when:

$\alpha = 0$ priority is definitely not important

$\alpha = 1$ priority is definitely important

$\beta = 0$ match is definitely not true

$\beta = 1$ match is definitely true

We will recommend the product with the largest F value. Durkin described that there are three types of factor values for β, i.e., numeric, symbolic and boolean. He also explored ways of determining this belief value.

It is clear the decision which we make from equation 12 is context-based. α_i and β_{in} can reflect the context because for different customers, the importance of a specific factor and the measure of the desire for that factor value will change. Even for the same customer these two parameters can change under different conditions.

Now, an example is given to demonstrate this intelligent inexact classification technique. Assume we want to buy a used car and we have two cars to select from and two factors to consider: price and color. Further assume we know the importance of each factor, as given by

$\alpha_1 = 0.8$ importance of car's price

$\alpha_2 = 0.6$ importance of car's color

Next, assume we are able to determine the closeness of match between the user's desire of a product's factor value, as given by

$\beta_{11} = 0.4$ belief that price of car1 matches buyer's desire price

$\beta_{12} = 0.6$ belief that price of car2 matches buyer's desire price

$\beta_{21} = 0.8$ belief that color of car1 matches buyer's desire color

$\beta_{22} = 0.3$ belief that color of car2 matches buyer's desire color

From equation(12) we obtain

$F_1 = (\alpha_1\beta_{11} + \alpha_2\beta_{21})/(\alpha_1 + \alpha_2) = 0.57$, belief that car1 matches buyer's desires

$F_2 = (\alpha_1\beta_{12} + \alpha_2\beta_{22})/(\alpha_1 + \alpha_2) = 0.47$, belief that car2 matches buyer's desires

Since $F_1 > F_2$, we would then recommend car1.

In the same way, equation (12) can be used when the task is to decide which of several errors of a given object are the least cost.

CHAPTER III

KBP1.0: A NEW DECISION TREE PRUNING METHOD

This chapter focuses on developing practical algorithms to deal with the cost-sensitive classification problem when there are costs for making misclassification errors. Many traditional pruning methods assume that all the classes are equally probable and equally important, so they only consider the error rate during pruning. However, in real-world classification problems, there is also a cost associated with misclassifying examples from each class and only considering error rate during pruning tends to generate a decision tree with a large misclassification cost. A new algorithm called KBP1.0 is proposed to solve this dilemma. Another key motivation of the cost-sensitive pruning in the dissertation is "trading error and cost". When both cost and error rate should be considered, the cost-sensitive pruning methods are useful. Two ways are proposed to integrate error rate and cost in the pruning method. One method uses intelligent inexact classification (IIC) and the other uses threshold to integrate error rate and cost. An example is also used to explain how expert knowledge helps define the cost matrix. An experiment is designed to investigate the sensitivity of the pruning method to the cost matrix. It is the first time that the use of expert knowledge in cost-sensitive pruning of decision trees and the sensitivity of the pruning method to the cost matrix are discussed.

1. Using Intelligent Inexact Classification in Cost-sensitive Pruning

Just as intelligent inexact classification is used in an expert system, it can be used when the task is to decide which of several errors of a given object are the least cost. The only difference for the intelligent inexact classification used in an expert system and that used in

cost-sensitive pruning is that expert system needs the importance of the factors, while cost-sensitive technique needs the seriousness of the errors. As mentioned earlier, there are two kinds of errors in decision tree pruning. One is the null hypothesis H_0 may be rejected when it is true, the other is H_0 may not be rejected when it is false. Assume i is the kind of classes in the data set and j is the kind of classes that the decision tree classifies. $error(ij)$ is defined as the error that the decision tree misclassifies class i as class j. Then for decision tree pruning the error cost can be evaluated from

$$C = \frac{\sum_{i,j=1}^{n} \alpha_{ij} p_{ij}}{\sum_{i,j=1}^{n} \alpha_{ij}} \tag{14}$$

where:

α_{ij} is the seriousness of $error(ij)$

p_{ij} is a measure of the error possibility of $error(ij)$ if tree is pruned

where, when,

$\alpha_{ij} = 0$ $error(ij)$ is definitely not serious

$\alpha_{ij} = 1$ $error(ij)$ is definitely serious

$p_{ij} = 0$ there is no error if we prune node n

$p_{ij} = 1$ it's absolutely wrong if we prune node n

When $i = j$, $\alpha_{ij} = 0$. The following cost matrix is used to define the α_{ij} for different $error(ij)$.

Cost Matrix:

Classified As

1 2 3 ..... j ..... n $<-$classified as

$--$ $--$ $--$ $--$ $--$

α_{11} α_{12} α_{13} ..... α_{1j}.....α_{1n} 1

α_{21} α_{22} α_{23} ..... α_{2j}.....α_{2n} 2

α_{31} α_{32} α_{33} ..... α_{3j}.....α_{3n} 3 Actual Class

.....

α_{i1} α_{i2} α_{i3} ..... α_{ij}.....α_{in} i

.....

α_{n1} α_{n2} α_{n3} ..... α_{nj}.....α_{nn} n

Now, how $error(ij)$ and p_{ij} are calculated is illustrated as follows:

For example, assume a dataset has two classes: class 1 and class 2. Also assume the number of the instances is 50 and the decision tree correctly classifies 40 instances. Further assume for the misclassification, three class 1 instances are misclassified as class 2 and seven class 2 instances are misclassified as class 1. Therefore, error(1, 2)=3, error(2, 1)=7, $p_{12} = 3/50$, and $p_{21} = 7/50$.

The cost evaluation function in equation 14 can be used to replace the error rate in reduced error pruning. For every non-leaf subtree S of the original decision tree, the change in misclassification cost over the test set, which would occur if this subtree were replaced by the best possible leaf or its most frequently used branch, is examined. If the cost of the new tree would be equal to or be smaller than that of original tree and that subtree S contains no subtree with the same property, S is replaced by the leaf or branch. Otherwise, stop the process [9]. This method is called " Reduce Cost Pruning (RCP)". The difference between

reduced error pruning and reduce cost pruning is that reduced error pruning considers error change with it prunes the decision tree, but reduce cost pruning considers cost change with it prunes the decision tree.

Another method is provided to deal with cost-sensitive decision tree pruning. In this method, for every non-leaf subtree S of the original decision tree, the change in misclassification cost over the test set, which would occur if this subtree were replaced by every possible leaf or its every branch, is examined. If the cost of the new tree would be equal to or be smaller than that of the original tree and that subtree S contains no subtree with the same property, S is replaced by the leaf or branch. Otherwise, stop the process. If more than one leaf or branch can replace the subtree, we select the one with least cost (Pruning a decision tree to lower cost or reducing tree size can be done. We prefer to get the cost as low as possible in KBP1.0-1, so KBP1.0-1 selects the one with least cost. This does not deny that selecting the smallest size is also acceptable. It can be applied in another pruning method). If there are more than one subtree with the same least cost, we select the one with smallest size. This method is called KBP1.0-1. In this method, the expert is relied upon to set the values of α_{ij} in the cost matrix. KBP1.0-1 can get a simpler tree than does reduce cost pruning method. Reduce cost pruning only tries to replace the subtree with majorities of leaf or branch. When majorities of leaf or branch can not replace the subtree, reduce cost pruning will stop pruning. However, KBP1.0-1 tries to replace the subtree with any leaf and branch (not only majorities of leaf or branch), so even when the majorities of leaf or branch can not replace the subtree, other leaves and branches still have chance to replace it. Therefore, KBP1.0-1 tends to get a simpler tree than does reduce cost pruning method.

The difference between reduced cost pruning and KBP1.0-1 is that reduce cost pruning only tries to replace the subtree with majorities of leaf or branch, while KBP1.0-1 tries to replace the subtree with any leaf and branch (not only majorities of leaf or branch).

The cost of a certain type of error may be conditional on the circumstances. Turney [34] summarized four types of conditional error cost, i.e., error cost conditional on individual case, on time of classification, on classification of other cases and on feature value. In this sense, the error cost is context-based.

2. How to Determine α_{ij}

It is very easy for us to calculate p_{ij} in equation 14. But how can we get the α_{ij} value? How to determine the α_{ij} values appears to very important for us. α_{ij} is defined as the seriousness of a given error when pruning a node. It can be determined in the following ways:

(1) User determines α_{ij} values.

In some applications, we rely on the user to specify the seriousness of a given error when deciding whether to prune or not. In this situation, we can directly ask the user for the α_{ij} value.

EXAMPLE

QUESTION: In the range of 0 to 1, how serious is it if you misdiagnose disease A as disease B?

α_{ij}= 0.9

(2) Expert determines α_{ij} values.

In other applications, we rely upon the expert to set the α_{ij} value. That is, we rely upon the expert's judgement with setting the seriousness of the various errors when pruning a node.

EXAMPLE

EXPERT: If a bank grants a credit to an unreliable applicant, it is a very serious mistake.

α_{ij}=0.9

(3) Expert system determines α_{ij} value.

In some cases we may need to rely upon an expert system to establish the α_{ij} value.

EXAMPLE

IF Patient is old than 60

AND Patient's health is very bad

THEN The seriousness of misdiagnosis is high

AND α_{ij}=0.9

Else IF Patient is young than 60

AND Patient's health is good

THEN The seriousness of misdiagnosis is low

AND α_{ij}=0.3

3. Using Cost and Error Rate in Decision Tree Pruning

Most pruning techniques only consider the error rate while cost-sensitive pruning only considers the cost. But it is not a good system if only its cost is low but its error rate is too high, or its error rate is low but its cost is too high. So some other pruning methods are proposed to deal with this. These pruning methodes use intelligent inexact classification to prune decision tree and are based on not only considering the error rate but also considering the cost of the error. Two methods are proposed to deal with it:

(1) Using the following equation to calculate the evaluation of pruning

$$F = I_1 * C + I_2 * E \tag{15}$$

where:

F is the evaluation value used in decision tree pruning,

I_1 is the importance of cost,

I_2 is the importance of error rate,

C is the cost which we get from equation (14),

E is the error rate.

The decision tree is selected to be pruned if the result of equation (15) is decreased after pruning, otherwise it is not pruned. If more than one leaf or branch can replace the subtree, the one with least cost is select. If there are more than one subtree with the same least cost, the one with smallest size is selected. This pruning method is called KBP1.0-2. The assignment of I_1 and I_2 is problem dependent and needs domain knowledge. In some cases, for example, in medical diagnosis, misclassification, i.e., misdiagnosis, can critically damage the patient, so I_1 should be high. In some cases, for example, when different cost misclassifications are roughly the same, C is not very critical, so I_1 can be set to a low value. Therefore, this pruning method is more general than other non-cost sensitive pruning methods. For example, I_1 can be set to value 0 and get an error based non-sensitive pruning. Notice that KBP1.0-1 is the specific case of KBP1.0-2, because I_1 can be set to value 1 and I_2 can be set to value 0 which transfers KBP1.0-2 to KBP1.0-1.

The KBP1.0-2 algorithm is expressed as follows:

Algorithm 1 KBP1.0-2

$PruneATree(Tree\ T)$
read the pruning data;
calculate the size, error, and cost of T before pruning;
$Prune2(T, T)$;
calculate the size, error, and cost of T after pruning;

$Prune2(Tree\ T,\ Tree\ St)$ {St is the subtree to be pruned in T}
if (St is a leaf) **then**
return;
end if
for each branch v of St /*a branch v of St is a subtree rooted at a child of St*/
$prune2(T, v)$;
endfor
calculate $TreeCost$ and $TreeError$, the cost and error before pruning respectively;
$Tree\_WeightedCost = Cost\ weight\ I_1 * TreeCost + Error\ weight\ I_2 * TreeError$;
for each class c
calculate $leaf\_costs[c]$ and $leaf\_errors[c]$, the cost and error if the subtree St is replaced by a leaf of class c;
$leaf\_WeightedCost[c] = Cost\ weight\ I_1 * leaf\_costs[c] + Error\ weight\ I_2 * leaf\_errors[c]$;
endfor
select the best class c_{best} such that $leaf\_WeightedCosts[c_{best}] \leq Tree\_WeightedCost$, and $leaf\_WeightedCosts[c_{best}]$ is minimized;
for each branch v of St
calculate $branch\_costs[v]$ and $branch\_errors[v]$, the cost and error if the subtree St is replaced by a branch v;
$branch\_WeightedCost[v] = Cost\ weight\ I_1 * branch\_costs[v] + Error\ weight\ I_2 * branch\_errors[v]$;
endfor
select the best branch v_{best} such that $branch\_WeightedCosts[v_{best}] \leq Tree\_WeightedCost$, and $branch\_WeightedCosts[v_{best}]$ is minimized;
if both c_{best} and v_{best} exist **then**
if ($leaf\_WeightedCosts[c_{best}] \leq branch\_WeightedCosts[v_{best}]$) **then**
replace the subtree St with class c_{best};
else
replace the subtree St with branch v_{best};
end if
else if c_{best} exists but v_{best} does not exist **then**
replace the subtree St with class c_{best};
else if v_{best} exists but c_{best} does not exist **then**
replace the subtree St with branch v_{best};
else
do not prune the subtree St;
end if

(2) Setting the threshold value to make the pruning decision

In this method, threshold means the point at which a subtree can be pruned. Advice can be obtained from experts to set the threshold value for the cost defined in equation (14) and another threshold value for the error rate. Let c represent the threshold value for cost and e represent the threshold value for error rate. The following rules are used to make the pruning decision:

(1) IF both the error rate E and error cost C decreases THEN prune

(2) IF both the error rate E and error cost C increases THEN do not prune

(3) IF error rate E decreases and error cost C increases THEN:

(a) IF the error cost C is equal to or less than c THEN prune

(b) IF the error cost C is larger than c THEN do not prune

(4) IF the error rate E increases and error cost C decreases THEN:

(a) IF the error rate E is equal to or less than e THEN prune

(b) IF the error rate E is larger than e THEN do not prune

This method is called KBP1.0-3 and rely upon the expert to set the threshold values. There are some methods to set the threshold values. For example, traditional pruning methods, such as reduced error pruning or pessimistic pruning, can be used to prune the decision tree and test the pruned decision tree to get it error rate e_1. Then the threshold value for error e can be set as e_1. In the same way, KBP1.0-1 can be used to prune the decision tree and test the pruned decision tree to get its cost c_1. Then the threshold value for cost c can be set as c_1.

The KBP1.0-3 algorithm is expressed as follows:

Algorithm 2 KBP1.0-3

$PruneATree(Tree\ T)$
read the pruning data;
calculate the size, error, and cost of T before pruning;
$Prune3(T, T)$;
calculate the size, error, and cost of T after pruning;

$Prune3(Tree\ T,\ Tree\ St)$ {St is the subtree to be pruned in T}
if (St is a leaf) **then**
return;
end if
for each branch v of St /*a branch v of St is a subtree rooted at a child of St*/
$prune3(T, v)$;
endfor
calculate $TreeCost$ and $TreeError$, the cost and error before pruning respectively;
for each branch v of St
calculate $branch\_costs[v]$ and $branch\_errors[v]$, the cost and error if the subtree St is replaced by the branch v;
endfor
for each branch v of St
if (($branch\_costs[v] \leq TreeCost$) and ($branch\_errors[v] \leq TreeError$)) or (($branch\_costs[v] \leq TreeCost$) and ($branch\_errors[v] > TreeError$) and ($branch\_errors[v] \leq ErrorThreshold * TreeError$)) or (($branch\_costs[v] > TreeCost$) and ($branch\_errors[v] \leq TreeError$) and ($branch\_costs[v] \leq CostThreshold * TreeCost$)) **then**
set $branchPrune\_Flag[v]$ to be true, i.e., the subtree can be replaced by the branch v;
else
set $branchPrune\_Flag[v]$ to be false;
end if
endfor
select the branch v_{best} such that $branchPrune\_Flag[v_{best}] = true$ and $branch\_costs[v_{best}]$ is minimized;
for each class c
calculate $leaf\_costs[c]$ and $leaf\_errors[c]$, the cost and error if the subtree St is replaced by a leaf of class c;
endfor
for each class c
if (($leaf\_costs[c] \leq TreeCost$) and ($leaf\_errors[c] \leq TreeError$)) or (($leaf\_costs[c] \leq TreeCost$) and ($leaf\_errors[c] > TreeError$) and ($leaf\_errors[c] \leq ErrorThreshold * TreeError$)) or (($leaf\_costs[c] > TreeCost$) and ($leaf\_errors[c] \leq TreeError$) and ($leaf\_costs[c] \leq CostThreshold * TreeCost$)) **then**
set $leafPrune\_Flag[c]$ to be true, i.e., the subtree can be replaced by class c;
else
set $leafPrune\_Flag[c]$ to be false;
end if
endfor
select the best class c_{best} such that $leafPrune\_Flag[c_{best}] = true$ and $leaf\_costs[c_{best}]$ is minimized;

```
if both c_best and v_best exist then
  if (leaf_costs[c_best] ≤ branch_costs[v_best]) then
    replace the subtree St with class c_best;
  else
    replace the subtree St with branch v_best;
  end if
else if c_best exists but v_best does not exist then
  replace the subtree St with class c_best;
else if v_best exists but c_best does not exist then
  replace the subtree St with branch v_best;
else
  do not prune the subtree St;
end if
```

4. Pessimistic Cost Pruning

In Chapter 2, pessimistic error pruning(PEP) which was proposed by Quinlan and developed in the context of ID3 is introduced. Compared with other traditional pruning methods, PEP has a better performance in respect to cost. Sometimes, it is even better than KBP1.0-1, KBP 1.0-2, and KBP1.0-3 (The comparison will be discussed in detail in Chapter 5). Learning from PEP, a new pruning method called Pessimistic Cost Pruning(PCP) is proposed. The difference between PEP and PCP is that the error in PEP is replaced by the cost in PCP.

When the original tree T is used to classify the N cases in the training set from which it was generated, let some leaf account for K of these cases with J of them misclassified. The equation(14) is used to calculate the misclassification cost C. Same as in PEP, a more realistic cost might be obtained using the continuity correction for the binomial distribution in which C is replaced by $C + 1/2$.

Let S be a subtree of T containing $L(S)$ leaves. If S were replaced by the best leaf, let C' be the misclassification cost from the training set. The pessimistic cost pruning method replaces S by the best leaf whenever $C' + 1/2$ is within one standard error of $C + \frac{L(S)}{2}$. All non-leaf subtrees are examined just once to see whether they should be pruned but sub-subtrees of pruned subtrees need not be examined at all.

This method can keep the advantages of PEP such as faster and high accuracies. Unlike other pruning methods in KBP1.0, it does not require a pruning set separate from the cases

in the training set from which the tree was constructed. It has the same disadvantage with PEP, i.e., in the worst case, when the tree does not need pruning at all, each node will still be visited once [11]. This method is called KBP1.0-4.

The KBP1.0-4 algorithm is expressed as follows:

Algorithm 3 KBP1.0-4

$PruneATree(Tree\ T)$
read the pruning data;
calculate the size, error, and cost of T before pruning;
$Prune4(T, T)$;
calculate the size, error, and cost of T after pruning;

$Prune4(Tree\ T,\ Tree\ St)$ {St is the subtree to be pruned in T}
if (St is a leaf) **then**
return;
end if
for each branch v of St /*a branch v of St is a subtree rooted at a child of St*/
$prune4(T, v)$;
endfor
calculate $TreeCost$, the cost before pruning;
for each class c
calculate $leaf\_costs[c]$, the cost if the subtree St is replaced by a leaf of class c;
endfor
select the best class c_{best} such that $leaf\_costs[c_{best}] - TreeCost \leq \frac{number\ of\ leaves\ in\ St\ -\ 1}{2} + \sqrt{TreeCost + \frac{number\ of\ leaves\ in\ St}{2}}$, and $leaf\_costs[c_{best}]$ is minimized;
if c_{best} exists **then**
replace the subtree St with class c_{best};
else
do not prune the subtree St;
end if

5. Expert Knowledge used in Decision Tree Pruning

In Section 3.4, how to determine α is discussed and one of methods is using an expert system to determine which cost matrix we should use. The cost matrix is different in different applications. Therefore, the expert is relied upon to set the values of α_{ij} in the cost matrix according to the different applications.

Experts use their knowledge to define the cost matrix. For example, when a doctor diagnoses whether a patient has hepatitis or not, the doctor considers the following items when he/she defines the cost matrix:

(1) Will the misdiagnosis hurt the patient's health? How serious?

(2) Will the patient spend more money if the misdiagnosis happens? How much?

(3) Will the patient spend more time to treat his/her illness? How much?

EXAMPLE

IF misdiagnosis will badly hurt the patient's health

THEN the α_{ij} is 0.9

Else

IF misdiagnosis will make patient spend much more money

THEN the α_{ij} is 0.5

Else

IF misdiagnosis will make patient spend much more time

THEN the α_{ij} is 0.6

6. Difference between KBP1.0 and C4.5

C4.5 is a software extension of the basic ID3 algorithm designed by Quinlan [41]. It is one of the most successful decision tree generators. Generally, it can construct decision trees, prune decision trees and generalize rules from decision trees.

C4.5 can be freely downloaded and freely used for research. You can get C4.5 from Quinlan's homepage:http://www.rulequest.com/Personal/.

KBP1.0, is a cost-sensitive decision tree pruning algorithm based on C4.5. KBP1.0 integrates intelligent inexact classification to deal with cost-sensitive pruning.

KBP1.0 uses the same method as that of C4.5 to construct the original decision tree. But its pruning method is different from that of C4.5. KBP1.0-1, KBP1.0-2, and KBP1.0-3, which use separate pruning sets to prune the original tree, while KBP1.0-4 does not use a separate pruning set to prune the original tree. KBP1.0 considers cost during pruning. When a decision tree has been constructed, the rules can be obtained from the tree, as does C4.5.

KBP1.0 has one more files than C4.5. This file is used to define the cost matrix. The training data, pruning data, and testing data are saved in three files respectively. KBP1.0 can split the data set into training set and pruning set.

Since KBP1.0 originated from C4.5, they have some similarities. For example, KBP1.0 uses the same methods as C4.5 to construct decision trees and obtain rules from the trees. KBP1.0 also uses the same methods as C4.5 on dealing with missing attribute values. But KBP1.0 is a cost-sensitive decision tree pruning algorithm and has many differences with C4.5, especially in tree pruning. Their differences is summarized as follows:

(1) In C4.5, the number of predicted errors of leaves and subtrees is calculated and compared to decide whether to prune the tree or not. In KBP1.0, not only the errors but also the misclassification cost of the original trees and pruned trees are compared to decide whether to prune the tree or not.

(2) C4.5 does not require a pruning set separated from the cases in the training set from which the tree was constructed. In KBP1.0, some pruning methods such as KBP1.0-1, KBP1.0-2, and KBP 1.0-3 use a pruning set to simplify the decision tree, but KBP 1.0-4(PCP) doesn't use a pruning set separate from the training set.

(3) KBP1.0 can randomly split the data set into three subsets: training set, pruning set, and testing set. There is a small program called convert which can randomly divide the data. It is much more convenient for users when they need to divide the data set. In KBP1.0, you have to split the data set by yourself.

(4) There are four pruning methods in KBP1.0 and the user can select one of them to prune decision tree.

KBP1.0 uses the same method as that of C4.5 to construct the original decision tree, with slight code modifications to support the KBP1.0 pruning technique.

The pruning code in C4.5 has been modified to realize the pruning methods in KBP1.0. The big difference between KBP1.0's pruning code and C4.5's pruning code is that the pruning method in C4.5's is based on error, while the pruning method in KBP1.0 is based on cost, or on both error and cost. In addition, C4.5's pruning code can only calculate the misclassification error during pruning, while KBP1.0's pruning code can calculate both the misclassification error and misclassification cost during pruning.

7. AN EXAMPLE OF KBP1.0

In this chapter an example is shown to illustrate how KBP1.0 works. The pruning method used in this example is KBP1.0-2.

(1) KBP1.0-2

Because the pruning method used in this example is KBP1.0-2, we review the KBP1.0-2 which has been introduced in Chapter 3.

KBP1.0-2 uses the following equation to calculate the evaluation of pruning.

$$F = I_1 * C + I_2 * E \tag{16}$$

where:

F is the evaluation value used in decision tree pruning,

I_1 is the weight of cost,

I_2 is the weight of error rate,

C is the cost which we get from equation (17),

E is the error rate.

The decision tree is select to be pruned if the result of equation (16) is decreased after pruning, otherwise it is not select to be pruned. If more than one subtree satisfies the pruning requirement, the one with the smallest size is selected.

$error(ij)$ is defined as the error that the decision tree classifies class i as class j. Then for decision tree pruning the cost can be obtained from

$$C = \frac{\sum_{i,j=1}^{n} \alpha_{ij} p_{ij}}{\sum_{i,j=1}^{n} \alpha_{ij}} \tag{17}$$

where:

α_{ij} is the seriousness of $error(ij)$,

p_{ij} is a measure of the error possibility of $error(ij)$ if tree is pruned.

(2) The Data Set Used in this Example

In this example, the goal is to predict the result of a vote. The data set used in this example is from the 1984 United States congressional voting records database [38]. This data set includes votes for each of the U.S. House of representatives congressmen on the 16 key votes identified by the Congressional Quarterly Almanac(CQA). The CQA lists nine different types of votes: voted for, paired for, and announced for (these three are simplified to y that represents a yes vote), voted against, paired against, and announced against (these three are simplified to n that represents a no vote), voted present, voted present to avoid conflict of interest, and did not vote or otherwise make a position known (these three are simplified to u). The number of instances in the data set is 435 (267 democrats, 168 republicans) and the number of attributes is 16 and the number of classes is 2 (Democrat and Republican). There are 392 missing values in the data set. The main attributes which are used in the decision tree are shown in Table 1. Ten attributes are not used in the decision tree because they are irrelevant for predicting the final result.

TABLE 1. Attribute Information.

Attributes	Values of Attribute
handicapped infants	y, n, u
water project cost sharing	y, n, u
adoption of the budget resolution	y, n, u
physician fee freeze	y, n, u
education spending	y, n, u
synfuels corporation cutback	y, n, u

(3) The Cost Matrix and Weights

The cost weight is defined as 0.7 (I_1 in equation 16) and error weight as 0.3 (I_2 in equation 16). The cost matrix is also defined as follows.

Cost Matrix:

Classified As		
(democrat)	(republican)	$<-$classified as
$--$	$--$	
0.0	0.2	(democrat): class democrat
0.8	0.0	(republican): class republican

In the matrix, "democrat" and "republican" in the first row represent the classes that the decision tree classifies, "democrat" and "republican" in the last column represent the classes in fact. For the numbers in the matrix, 0.2 is the seriousness if the decision tree misclassifies class "democrat" as class "republican", 0.8 is the seriousness if the decision tree misclassifies class "republican" as class "democrat". How this cost matrix is gotten is not discussed here and just used in the example.

(4) Dividing the Data Set

A program called "convert" is used to randomly divide the data set into three parts: training set (150 cases), pruning set (150 cases), and testing set (135 cases).

(5) Constructing the Original Decision Tree

KBP1.0 uses the same method as C4.5 to create the original decision tree. The following tree was constructed using the 150 cases in the training set. The (N) or (N/E) appearing after a leaf indicates that the leaf covers N training cases among which E cases are misclassified.

Original Decision Tree

physician fee freeze = n:

| adoption of the budget resolution = y: democrat(77.0)

| adoption of the budget resolution = u: democrat (1.0)

| adoption of the budget resolution = n:

| | education spending = n: democrat (3.0)

| | education spending = y: democrat (5.0)

| | education spending = u: republican (1.0)

physician fee freeze = y:

| synfuels corporation cutback = n: republican (48.0)

| synfuels corporation cutback = u: republican (2.0)

| synfuels corporation cutback = y:

| | handicapped infants = y: republican (2.0)

| | handicapped infants = u: republican (0.0)

| | handicapped infants = n:

| | | adoption of the budget resolution = n: republican (5.0/1.0)

| | | adoption of the budget resolution = y: democrat (2.0)

| | | adoption of the budget resolution = u: republican (0.0)

physician fee freeze = u:

| water project cost sharing = n: democrat (0.0)

| water project cost sharing = y: democrat (2.0)

| water project cost sharing = u: republican (2.0)

In this tree, the first "physician fee freeze = n:" is the root of the tree. The other attributes in the tree are the nodes of the tree. "|" represents the branch of the tree. The "democrat" and "republican" which followed by the numbers in parentheses are the leaves of the tree.

(6) Pruning the Decision Tree

After the original decision tree is constructed, it is pruned. In this example, the KBP1.0-2 is used to prune the decision tree. In the pruning procedure, 150 cases is placed in the pruning data set to the original tree and the following tree can be obtained.

physician fee freeze = n:

| adoption of the budget resolution = y: democrat (74.0)

| adoption of the budget resolution = u: democrat (0.0)

| adoption of the budget resolution = n:

| | education spending = n: democrat (3.0)

| | education spending = y: democrat (4.0)

| | education spending = u: republican (0.0)

physician fee freeze = y:

| synfuels corporation cutback = n: republican (49.0/3.0)

| synfuels corporation cutback = u: republican (2.0)

| synfuels corporation cutback = y:

| | handicapped infants = y: republican (6.0/3.0)

| | handicapped infants = u: republican (0.0)

| | handicapped infants = n:

| | | adoption of the budget resolution = n: republican (6.0/2.0)

| | | adoption of the budget resolution = y: democrat (1.0/1.0)

| | | adoption of the budget resolution = u: republican (0.0)

physician fee freeze = u:

| water project cost sharing = n: democrat (0.0)

| water project cost sharing = y: democrat (2.0)

| water project cost sharing = u: republican (3.0/2.0)

Again, the (N) or (N/E) appearing after a leaf indicates that the leaf covers N pruning cases among which E cases are misclassified. From the original tree, KBP1.0 uses the cost matrix, the equation 16 and 17, and cost weight and error weight to calculate the evaluation value as follows

$$C = 0.8 * (1/150) + 0.2 * (10/150) = 0.018667 \tag{18}$$

$$F = I_1 * C + I_2 * E = 0.7 * 0.018667 + 0.3 * (1 + 10)/150 = 0.035067 \tag{19}$$

Then KBP1.0 replaces the subtree

| | education spending = n: democrat (3.0)

| | education spending = y: democrat (4.0)

| | education spending = u: republican (0.0)

with its three leaves separately. Now, KBP1.0 calculates the new evaluation value if the replacement happens. From equation 16, KBP 1.0 can calculate their evaluation value, i.e.,

0.035067(democrat), 0.035067(democrat) and 0.0556(republican). Because when leaf democrat replaces the above subtree, the number and distribution of misclassification will not change, the evaluation value will not change. But when the leaf republican replaces the above tree, the number of misclassification of considering democrat as republican will increase 7, so the evaluation value will change as follows

$$C = 0.8 * (1/150) + 0.2 * (10 + 7/150) = 0.028 \tag{20}$$

$$F = I_1 * C + I_2 * E = 0.7 * 0.028 + 0.3 * (1 + 17)/150 = 0.556 \tag{21}$$

KBP1.0 will select to prune the decision tree unless the result of evaluation value does not increase after pruning. Because only the leaf democrat can satisfy this requirement, the above subtree is replaced by the leaf democrat and I get the following pruned tree:

physician fee freeze = n:

| adoption of the budget resolution = y: democrat (74.0)

| adoption of the budget resolution = u: democrat (0.0)

| adoption of the budget resolution = n: democrat (7.0)

physician fee freeze = y:

| synfuels corporation cutback = n: republican (49.0/3.0)

| synfuels corporation cutback = u: republican (2.0)

| synfuels corporation cutback = y:

| | handicapped infants = y: republican (6.0/3.0)

| | handicapped infants = u: republican (0.0)

| | handicapped infants = n:

| | | adoption of the budget resolution = n: republican (6.0/2.0)

| | | adoption of the budget resolution = y: democrat (1.0/1.0)

| | | adoption of the budget resolution = u: republican (0.0)

physician fee freeze = u:

| water project cost sharing = n: democrat (0.0)

| water project cost sharing = y: democrat (2.0)

| water project cost sharing = u: republican (3.0/2.0)

KBP1.0 will continue to prune the above decision tree in the same way until it gets the following simplest tree:

Pruned Decision Tree

physician fee freeze = n: democrat (81.0)

physician fee freeze = y: republican (64.0/8.0)

physician fee freeze = u: democrat (5.0/1.0)

(7) Testing the Decision Tree

Finally, the 135 cases in the test data set is used to test the original and pruned decision tree. KBP1.0 shows the following results which include the original decision tree, the pruned decision tree, the cost of the original decision tree and pruned tree, the error of the original decision tree and pruned tree, the size of the original tree and pruned tree.

Original Decision Tree:

physician fee freeze = n:

| adoption of the budget resolution = y: democrat (68.0)

| adoption of the budget resolution = u: democrat (2.0)

| adoption of the budget resolution = n:

| | education spending = n: democrat (8.0/1.0)

| | education spending = y: democrat (1.0)

| | education spending = u: republican (0.0)

physician fee freeze = y:

| synfuels corporation cutback = n: republican (41.0)

| synfuels corporation cutback = u: republican (3.0)

| synfuels corporation cutback = y:

| | handicapped infants = y: republican (3.0/1.0)

| | handicapped infants = u: republican (0.0)

| | handicapped infants = n:

| | | adoption of the budget resolution = n: republican (5.0)

| | | adoption of the budget resolution = y: democrat (2.0/2.0)

| | | adoption of the budget resolution = u: republican (0.0)

physician fee freeze = u:

| water project cost sharing = n: democrat (0.0)

| water project cost sharing = y: democrat (1.0)

| water project cost sharing = u: republican (1.0/1.0)

Cost before pruning for testing data: 0.02074

Pruned Tree:

physician fee freeze = n: democrat (79.0/1.0)

physician fee freeze = y: republican (54.0/1.0)

physician fee freeze = u: democrat (2.0)

Cost after pruning for testing data: 0.00741

Evaluation on test data (135 items):

Before Pruning After Pruning

− − − − − − − − − − − − − − − − −

Size Errors Size Errors

22 5(3.7%) 4 2(1.48%) <<

Class distribution for test data in original tree

Classified As

(democrat) (republican) < −classified as

−− −−

79 2 (democrat): class democrat Actual Class

3 51 (republican): class republican

Class distribution for test data in pruned tree

Classified As

(democrat) (republican) < −classified as

−− −−

80 1 (democrat): class democrat Actual Class

1 53 (republican): class republican

From the class distribution for the test data in the original tree, it is clear that 2 classes "democrat" are misclassified as "republican" and 3 classes "republican" are misclassified as "democrat". The class distribution for the test data in the pruned tree tells us that 1 class

"democrat" is misclassified as "republican" and 1 class "republican" is misclassified as "democrat".

In the next chapter, the results from KBP1.0 and C4.5 is compared.

CHAPTER IV

COMPARATIVE ANALYSIS

Comparing the different methods for pruning a decision tree and summarizing the advantage of the knowledge-based pruning technique is one of the most important tasks in this dissertation. In this chapter, an experiment is designed to make a comparative study between some of the well known decision tree pruning techniques and the cost-sensitive pruning methods in KBP1.0. From the comparison, the strengths and weaknesses of KBP1.0 can be identified.

The C4.5's pruning code is modified to get the KBP1.0's pruning code and other traditional pruning methods' codes.

1. The Design of the Experiment

The main characteristics of the data sets used in this experiments are reported in Table 2. All these data sets are available from the UCI Machine Learning Repository [38]. They are also very common in decision tree pruning experiments [11][47]. The data sets chosen are Pima, Hepatitis, Cleveland, Vote, Iris, and Glass. Almost the same data sets as used [11][47] are selected, because it is very convenient to make use of the results from [11] and [47] and compare them with ones in our experiment. Table 2 shows the main characteristics of the databases used for the experimentation. In Table 2, the columns headed "real" and "multi" concern the number of attributes that are treated as real-value and multi-value discrete attributes, respectively. The column "Base error" means the percentage error obtained if the most frequent class is always predicted. The column "Null Values" means whether there are

miss values or not. The last column "Uniform Distrib" states whether the distribution of examples per class is uniform or not.

TABLE 2. Major properties of the data sets considered in the experimentation

data set	No. Classes	No. Attributes	Real	Multi	Null Values	Base error	Uniform Distrib
Glass	7	9	9	0	no	64.49	yes
Cleveland	2	14	5	5	yes	45.21	approx.
Hepatitis	2	19	6	0	yes	10.65	no
Hypo	4	29	7	1	yes	7.7	no
Iris	3	4	4	0	no	66.67	yes
Pima	2	8	8	0	no	34.9	no
Vote	2	16	0	16	yes	45.2	no

The six data sets is described in detail as follows. All the information is from the UCI Machine Learning Repository [38].

(1) Glass

This is a glass identification database which is used to classify the type of glass. The study of classification of glass types was motivated by criminological investigation [38]. At the scene of the crime, the glass left can be used as evidence, if it is correctly identified. Number of instances in the data set is 214, number of attributes is 9, and number of classes is 7 including 163 Window glass (building windows and vehicle windows), 87 float processed, 70 building windows, 17 vehicle windows, 76 non-float processed, 76 building windows, 0 vehicle windows, 51 Non-window glass, 13 containers, 9 tableware, and 29 headlamps. There are no missing values in this data set.

(2) Heart Disease Domain(Cleveland)

This data set is used to diagnose whether a patient has heart disease or not. It is one of the 4 databases(Cleveland, Hungarian, Switzerland, and Long Beach) concerning heart disease diagnosis. Number of instances in the data set is 303, number

of attributes is 76, and number of classes is 5 classes from value 0 to value 4. To create a 2-class problem, I grouped values 1, 2, 3, 4 together as class 1(sich=presence of heart disease), and retained value 0(absence of heart disease). 160 of the examples are healthy and the others have heart disease. There are 6 missing values in this data set.

(3) Hepatitis

This data set is used to diagnose whether a hepatitis patient will die or live. Number of instances in the data set is 155, number of attributes is 20, and number of classes is 2 including DIE and LIVE. There are 123 LIVE instances and 32 DIE instances. There are 168 missing values in this data set.

(4) Hypothyroid

This thyroid disease data set comes from the Garavan Institute of Medical Research, Sydney. This data set is used to diagnose whether a patient has thyroid disease or not. There are six data sets in this database and I only selected one of them, hypothyroid, in my experiment. Number of instances in the data set is 3163, number of attributes is 25, and number of class is 2 including 151 hypothyroid and 3012 negative. There are many missing values in this data set.

(5) Iris

This is perhaps the best known data set to be found in the pattern recognition literature. The data set is used to predict the class of an iris plant. Number of instances in the data set is 50, number of attributes is 4, and the number of classes is 3. There is no missing values in this data set.

(6) Pima Indians Diabetes Domain (pima)

This data set is used to diagnose whether a patient has diabetes or not. All patients in the data set are females, at least 21 years old, and of Pima Indian heritage. Number

of instances in the data set is 768, number of attributes is 8, and number of classes is 2 (0=health, 1=tested positive for diabetes). There are 500 of the examples which are healthy and the others are tested positive for diabetes. There is no missing attribute values.

(7) Vote

This data set is used to predict the result of a vote. It is from 1984 united states congressional voting records database. This data set includes votes for each of the U.S. House of representatives congressmen on the 16 key votes identified by the Congressional Quarterly Almanac(CQA). The CQA lists nine different types of votes: voted for, paired for, and announced for (these three simplified to yea), voted against, paired against, and announced against (these three simplified to nay), voted present, voted present to avoid conflict of interest, and did not vote or otherwise make a position known (these three simplified to an unknown disposition). Number of instances is 435 (267 democrats, 168 republicans), number of attributes is 16, and number of classes is 2. There are 392 missing values in this data set.

2. Criteria and Data Set Partition

Ideally, the pruned decision tree should be much more comprehensible than the original decision tree but should not be significantly less accurate when classifying unseen cases [12]. These are two important criterions, which are size and accuracy, to test how well a pruning method works [11]. The cost is added as the third criterion to test the pruning methods. The behavior of the new cost-sensitive pruning methods was analyzed in a series of experiments. The data set is randomly split into three subsets. The three subsets are the training set (49 percent), the pruning set (21 percent), and the testing set (30 percent). The reason that the data set was partitioned in this way is that a decision tree is created in two phases: tree building phase, i.e., repeatedly partitioning the training data until all the examples in each

partition belong to one class [94] or the partition is sufficiently small, and tree pruning phase, i.e., removing dependency on statistical noise or variation that may be particular only to the training set [125]. Both the training set and the pruning set are used to build decision trees, i.e., the training set is used to create the original decision trees and the pruning set is used to prune the original decision tree and obtain the pruned trees. But some pruning methods, such as cost-complexity pruning, do not need the independent pruning set to obtain the pruned decision tree. F. Esposito also calls the original tree the grown tree and the pruned tree the trained tree [11]. The test set is used to test the decision tree.

3. Cost Matrix

Through discussions with domain experts, the cost matrices, cost weights and error weights are defined as follows:

GLASS

(1)	(2)	(3)	(4)	(5)	(6)	
−−	−−	−−	−−	−−	−−	
0.0	0.3	0.3	0.6	0.6	0.9	(1)
0.3	0.0	0.9	0.7	0.7	0.8	(2)
0.5	0.7	0.0	0.4	0.6	0.6	(3)
0.6	0.6	0.4	0.0	0.5	0.5	(4)
0.7	0.5	0.5	0.6	0.0	0.6	(5)
0.9	0.7	0.5	0.6	0.7	0.0	(6)

CLEVELAND

(heart disease)	(no heart disease)	
−−	−−	
0.0	0.8	(heart disease)
0.3	0.0	(no heart disease)

$I_1 = 0.8, I_2 = 0.2$

HEPATITIS

(LIVE)	(DIE)	
−−	−−	
0.0	0.9	(LIVE)
0.4	0.0	(DIE)

HYPOTHYROID

(thyroid)	(no thyroid)	
−−	−−	
0.0	0.8	(thyroid)
0.3	0.0	(no thyroid)

IRIS

(Setosa)	(Versicolour)	(Virginica)	
−−	−−	−−	
0.0	0.3	0.9	(Setosa)
0.3	0.0	0.9	(Versicolour)
0.7	0.7	0.0	(Virginica)

PIMA

(diabetes)	(no diabetes)	
−−	−−	
0.0	0.9	(diabetes)
0.3	0.0	(no diabetes)

VOTE

(democrat)	(republican)	
−−	−−	
0.0	0.2	(democrat)
0.8	0.0	(republican)

4. Cost and Error Weights, Cost and Error Threshold Values

Cost weight I_1, error weight I_2, cost threshold C_{th} and error threshold E_{th} are set as follows:

TABLE 3. Values for I_1, I_2, C_{th} & E_{th}

Pruning method	I_1	I_2	C_{th}	E_{th}
GLASS	0.6	0.4	0.14	0.16
CLEVELAND	0.8	0.2	0.12	0.15
HEPATITIS	0.8	0.2	0.08	0.13
HYPOTHYROID	0.9	0.1	0.02	0.003
IRIS	0.6	0.4	0.013	0.02
PIMA	0.9	0.1	0.6	0.95
VOTE	0.6	0.4	0.03	0.03

Reduced error pruning was used to pruned the decision tree and set its error rate as error threshold and KBP1.0-1 was used to pruned the decision tree and set its misclassification cost as cost threshold for KBP1.0-3.

5. Experimental Results

5.1. Comparative Analysis Based on Cost.

In this section, The results of the comparative analysis based on cost between the cost-sensitive pruning methods and other traditional non-cost sensitive pruning methods are shown. Also, the comparative analysis based on cost between KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP1.0-4 are shown in this section. In the experiments, each data set was run by each pruning method 10 times and the results are summarized in Table 4 and in Figure 1 to Figure 4. In this table, REP represents reduced error pruning, CCP represents cost-complexity pruning, and PEP represents pessimistic pruning. The reason that these three traditional pruning methods are selected is that they are among the most popular pruning methods and many researchers used them in comparative analysis for pruning decision trees [8][11][12].

The equation(14) is used to calculate the cost and the results are shown in Table 4. Table 4 shows that most of the KBP1.0 cost-sensitive pruning methods provide a lower cost than

the other non cost-sensitive pruning methods; PEP, CCP, and REP. This conclusion is easier to see from Figure 1 to Figure 4. The cost-sensitive pruning method KBP1.0-1, which only considers the cost and not the error rate during pruning, achieves the lowest cost. From the results of these experiments, it also noticed that the pessimistic pruning method (PEP) sometimes has a very good performance in cost (especially for the Hypo and Vote data sets). One reason may be that pessimistic pruning does not require a pruning set separated from the cases in the training set from which the tree was constructed. This is why KBP1.0-4 which integrates the advantages of PEP and cost-sensitive pruning is proposed, while KBP1.0-1, KBP1.0-2, and KBP1.0-3 require pruning sets separated from the cases in the training set from which the tree was constructed. From Table 4 and Figure 1 to Figure 4, we can also find that, when we compare the cost-sensitive pruning methods in KBP1.0, KBP1.0-4 provides the biggest cost.

TABLE 4. Test results on cost between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP1.0-4, and the other non-cost sensitive pruning methods

data set	KBP1.0-1	KBP1.0-2	KBP1.0-3	KBP1.0-4	PEP	CCP	REP
Glass	0.1367	0.1410	0.1413	0.1548	0.1625	0.1631	0.1609
Cleveland	0.1162	0.1380	0.1398	0.1516	0.1613	0.1644	0.1542
Hepatitis	0.0817	0.0978	0.1239	0.1048	0.1039	0.1574	0.1246
Hypo	0.0019	0.0022	0.0021	0.0017	0.0011	0.0024	0.0026
Iris	0.0130	0.0139	0.0120	0.0156	0.0180	0.0163	0.0166
Pima	0.6087	0.6144	0.6105	0.7939	0.8478	0.9751	0.9288
Vote	0.0259	0.0205	0.0205	0.0253	0.0187	0.0295	0.0263

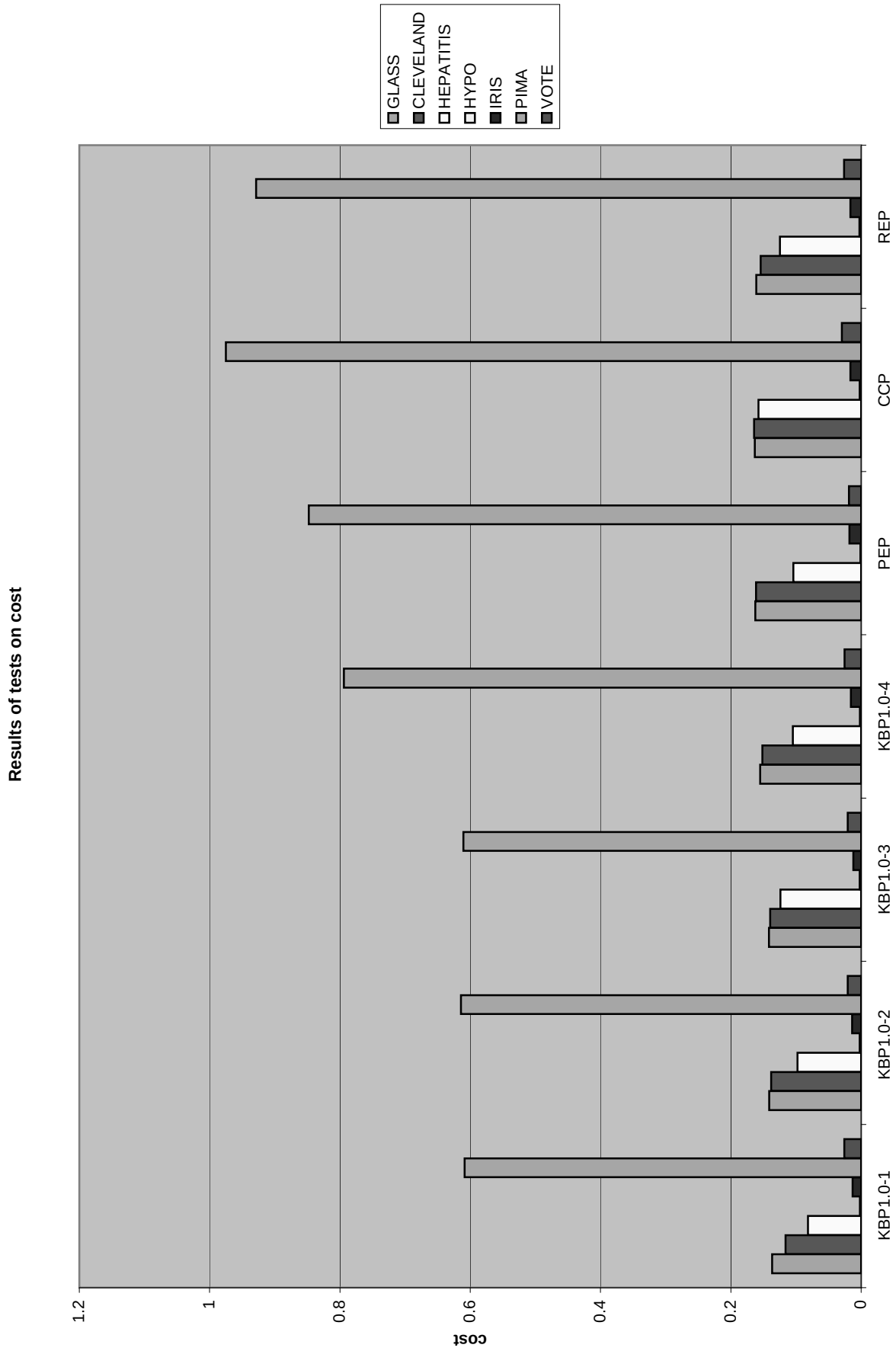

FIGURE 1. Test results on cost between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP1.0-4, and the other non-cost sensitive pruning methods for all the data sets

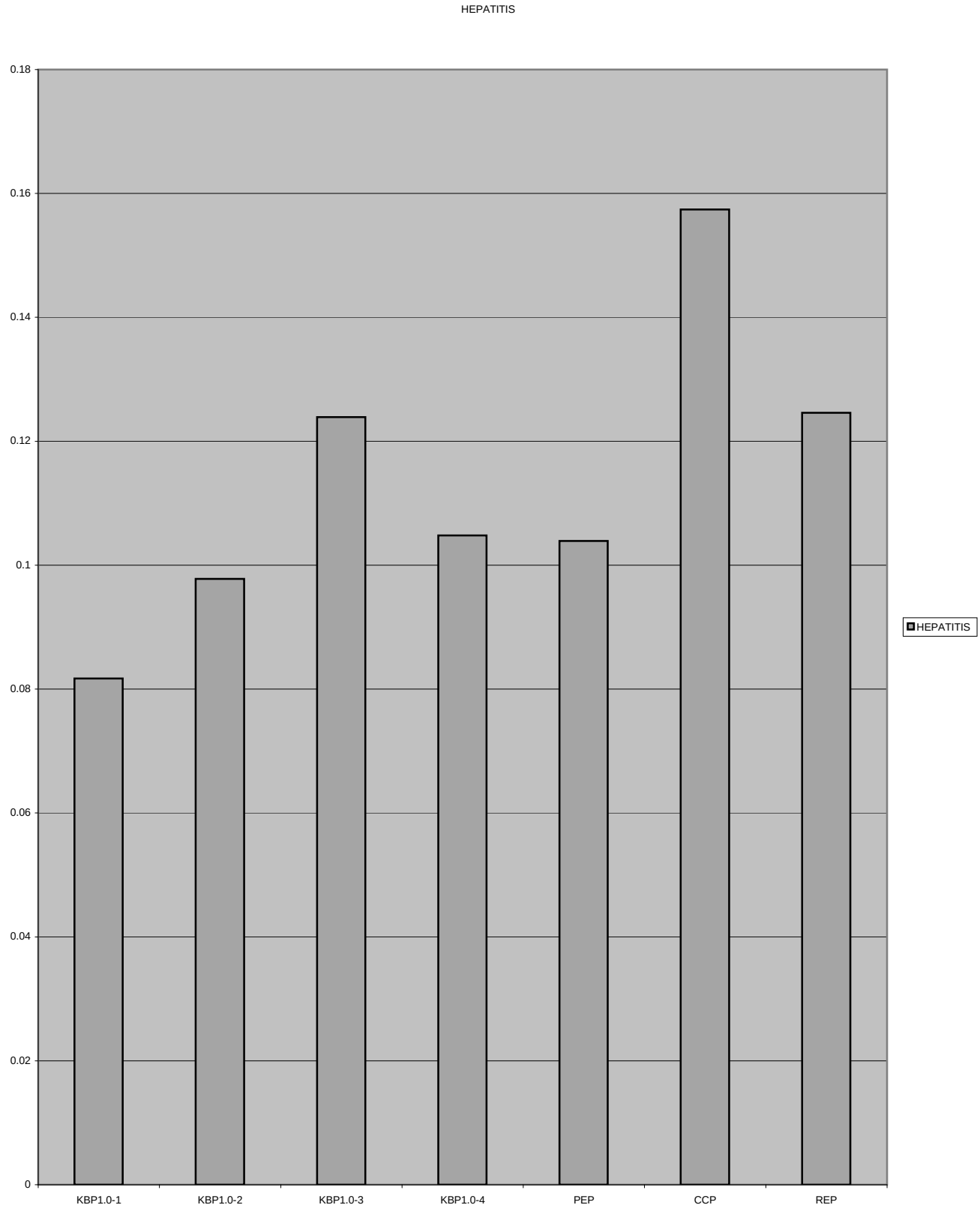

FIGURE 2. Test results on cost between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP1.0-4 and the other non-cost sensitive pruning methods for the Hepatitis data set

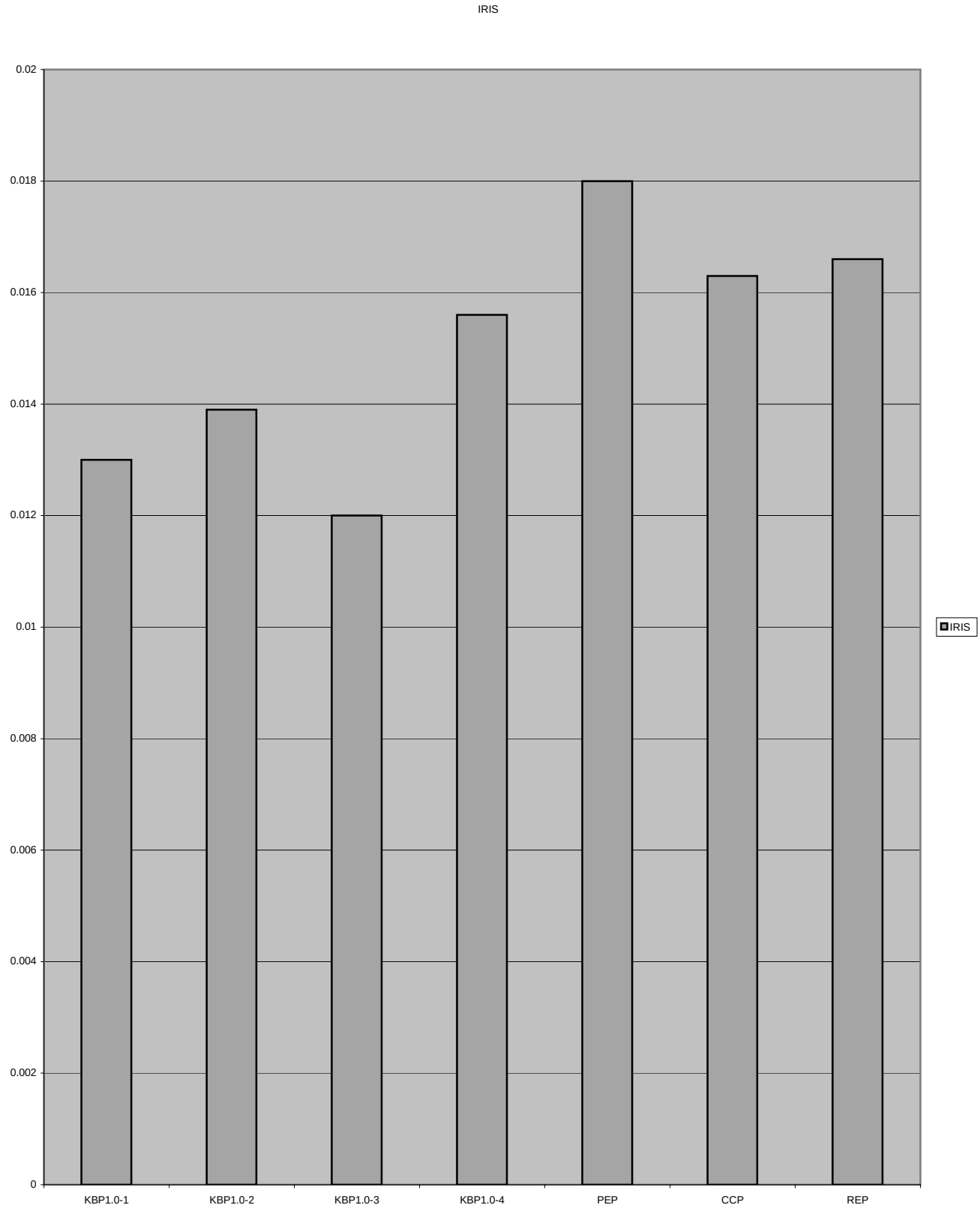

FIGURE 3. Test results on cost between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP1.0-4, and the other non-cost sensitive pruning methods for the Iris data set

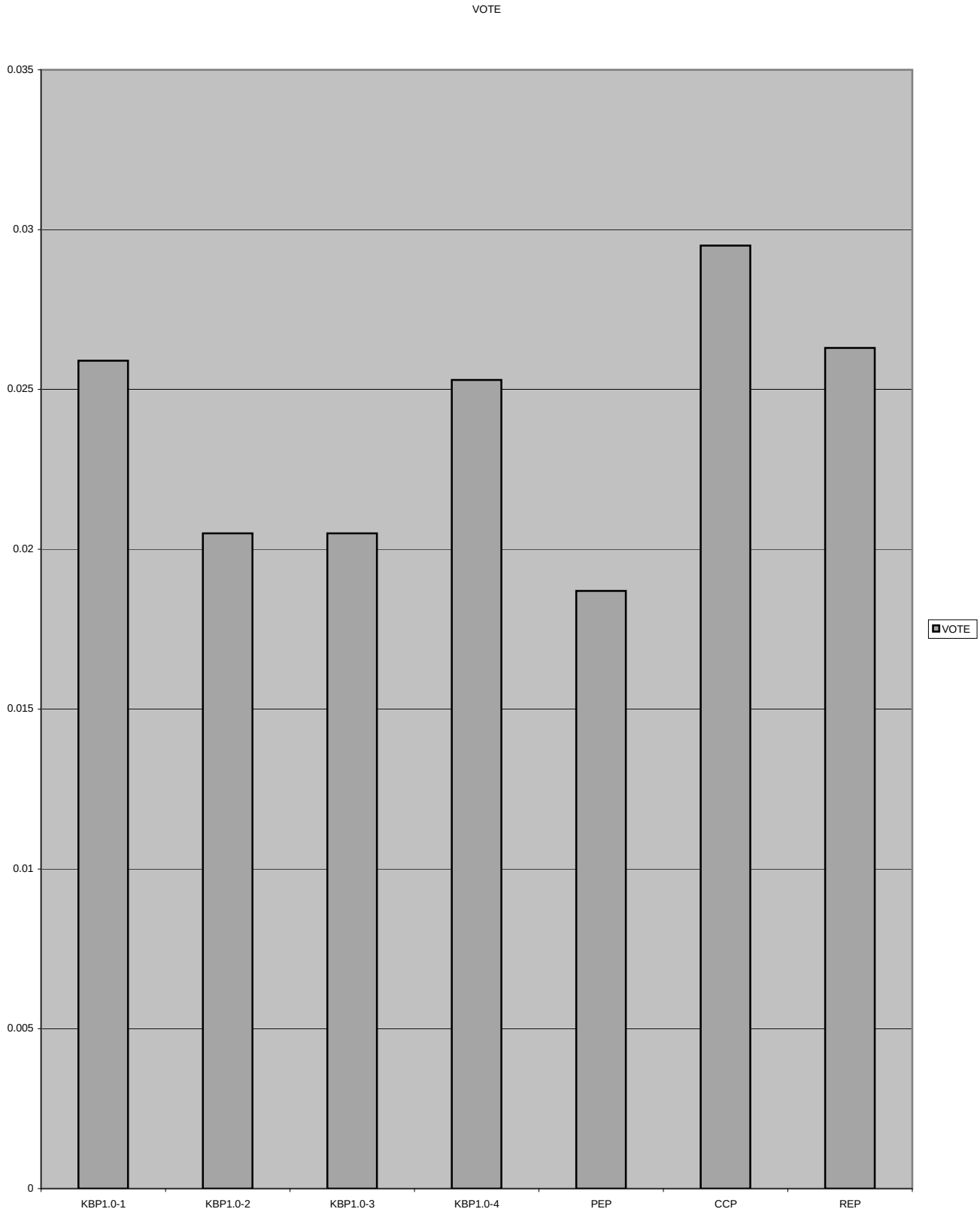

FIGURE 4. Test results on cost between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP1.0-4, and the other non-cost sensitive pruning methods for the Vote data set

5.2. Comparative Analysis Based on Error Rate.

In this section, the result of the comparative analysis based on error rate between the cost-sensitive pruning methods and other traditional non-cost sensitive pruning methods is shown. Also, the comparative analysis based on error rate between KBP1.0-1, KBP 1.0-2, KBP1.0-3, and KBP1.0-4 are shown in this section. In the experiments, each data set was run by each pruning method 10 times and the results are summarized in Table 5 and in Figure 5 to Figure 6. In this table, REP represents reduced error pruning, CCP represents cost-complexity pruning, and PEP represents pessimistic pruning.

From Table 5 and Figure 5 to Figure 6, it is noticed that KBP1.0-1, which only considers cost and not the error rate in pruning, shows a larger error rate than KBP1.0-2, KBP1.0-3, and KBP1.0-4, which consider both cost and error rate in pruning. In most cases, the other well-known non-cost sensitive pruning methods are of superior accuracy to the KBP1.0 cost-sensitive pruning methods. This is reasonable because the non-cost sensitive pruning methods only consider error rate during pruning. But, as shown in the prior section, we obtain lower cost from cost-sensitive pruning. From this, it is clear that we should find a balance between error rate and cost. We can change the cost matrix, the cost weight, or the error weight to adjust the error rate and cost.

From Table 5 and Figure 5 to Figure 6, it is noticed that, compared with the other cost-sensitive pruning methods in KBP1.0, KBP1.0-4 achieves the lowest error, while KBP1.0-1 gets the highest error rate.

TABLE 5. Test results on error rate (percent) between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP 1.0-4 and the other non-cost sensitive pruning methods

data set	KBP1.0-1	KBP1.0-2	KBP1.0-3	KBP1.0-4	PEP	CCP	REP
Glass	49.2	39.85	36.46	36.25	33.74	37.17	38.91
Cleveland	30.11	30.76	27.66	26.02	26.91	24.89	25.57
Hepatitis	45.22	20.23	20.77	19.56	20.22	20.43	21.09
Hypo	0.82	0.76	0.72	0.49	0.33	0.83	0.74
Iris	5.67	6.35	4.33	5.78	7.34	7.36	7.62
Pima	38.52	36.46	37.12	25.82	27.41	27.46	27.01
Vote	6.13	5.22	4.72	4.65	4.67	6.58	4.98

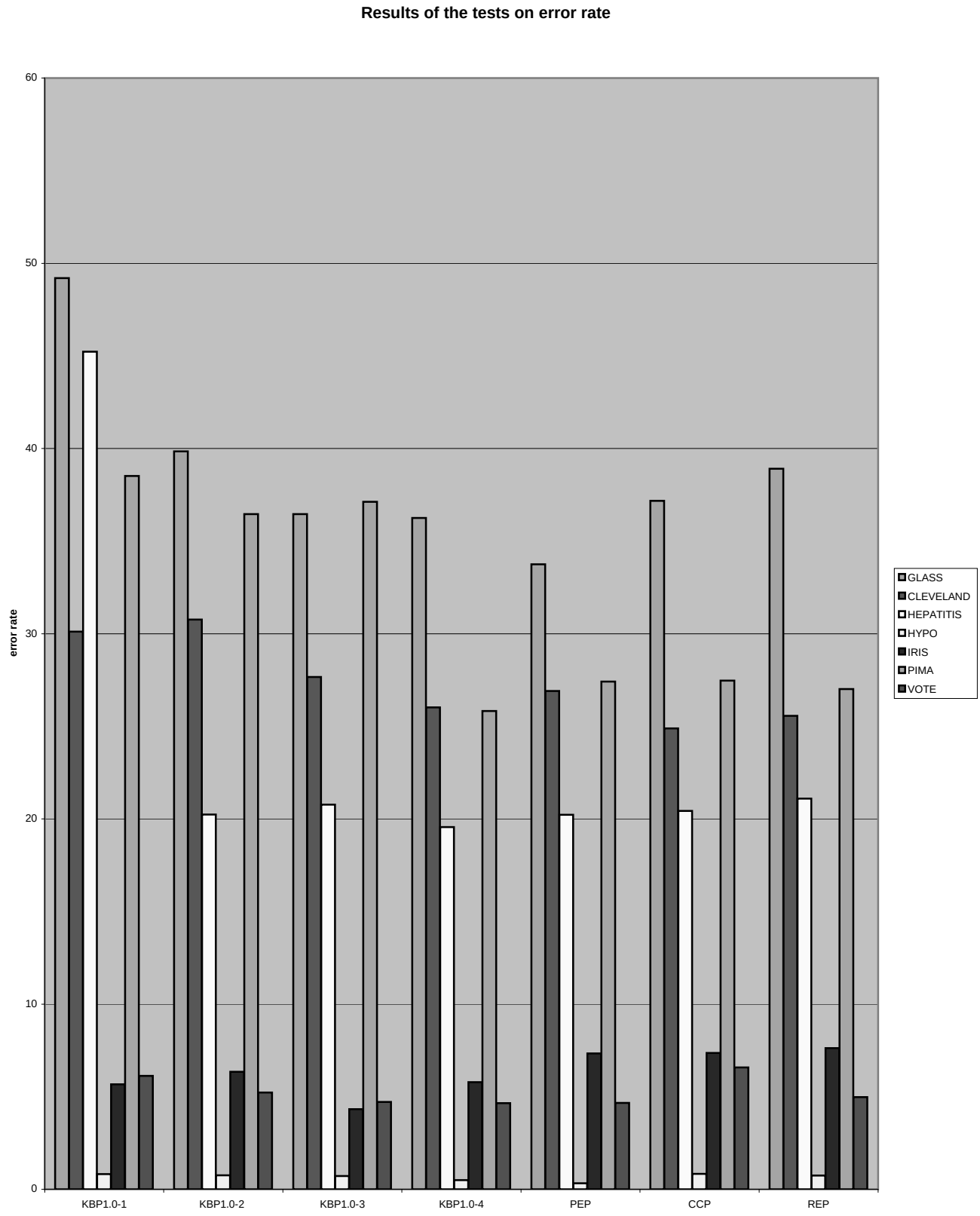

FIGURE 5. Test results on error rate (percent) between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP1.0-4, and the other non-cost sensitive pruning methods for all the data sets

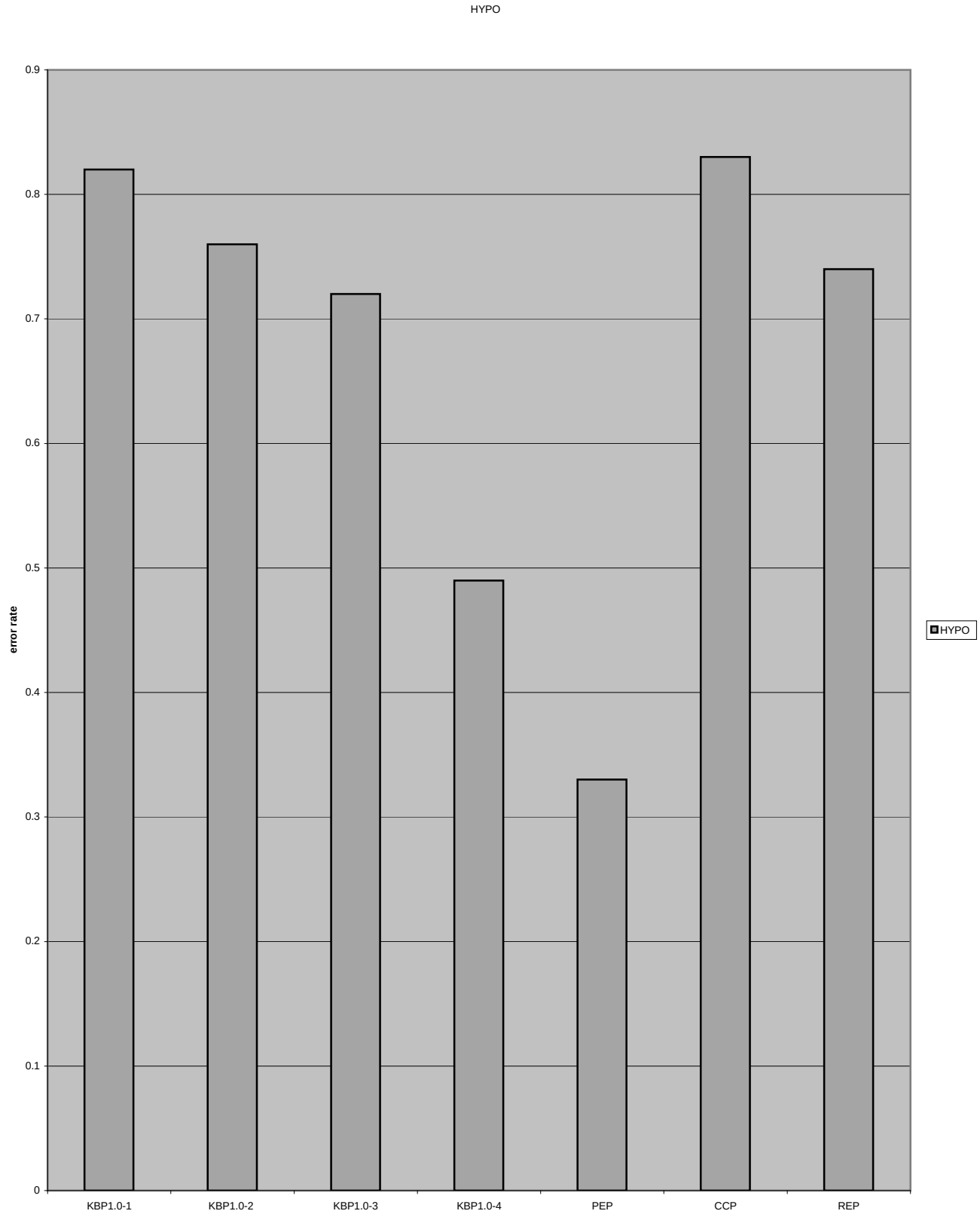

FIGURE 6. Test results on error rate (percent) between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP1.0-4, and the other non-cost sensitive pruning methods for the Hypothyroid data set

5.3. Comparative Analysis Based on Size.

In this section, the result of the comparative analysis based on size between the cost-sensitive pruning methods and other traditional non-cost sensitive pruning methods is shown. The number of leaves and nodes is used to represent the size of decision tree. Also, the comparative analysis based on size between KBP1.0-1, KBP1.0-2, KBP 1.0-3, and KBP1.0-4 are shown in this section. In the experiments, each data set was run by each pruning method 10 times and the results are summarized in Table 6 and in Figure 7. In this table, REP represents reduced error pruning, CCP represents cost-complexity pruning, and PEP represents pessimistic pruning.

The number of leaves together with the number of nodes is used to represent the size of decision tree. From the results shown in Table 5, it is clear that most cost-sensitive pruning methods tend to produce a larger decision tree than the other well-known non-cost sensitive pruning methods which are selected. It is reasonable because most pruning methods in KBP1.0 need to consider both cost and error when deciding whether to prune subtrees or not. But the other traditional non-cost sensitive pruning methods only consider the error when deciding to prune. For example, for most non-cost sensitive pruning methods, when error rate decreases, they can prune the decision tree, but for most cost-sensitive pruning methods, only when both error rate and cost decrease, they can prune the decision tree. It is noticed that the size difference between cost-sensitive pruning methods and non-cost sensitive pruning methods is not very big, the size of the decision trees which are pruned by the cost-sensitive pruning methods is acceptable for us. In many cases, a small decision tree with high cost or error is unacceptable.

From Table 6 and Figure 7, it is noticed that, compared with the other cost-sensitive pruning methods in KBP1.0, KBP1.0-1 gets the smallest decision tree. It is because that,

among the new cost-sensitive pruning methods, KBP1.0-1 is the only one which only considers cost when deciding whether to prune subtree or not.

TABLE 6. Test results on size between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP1.0-4, and the other non-cost sensitive pruning methods

data set	KBP1.0-1	KBP1.0-2	KBP1.0-3	KBP1.0-4	PEP	CCP	REP
Glass	13.6	17.2	16	10.8	10.2	11	14.2
Cleveland	16.2	20.5	20.5	7.1	9	8.1	21.7
Hepatitis	5	8.2	6.8	7.4	4.6	1.4	5.8
Hypo	9.4	10	10	13.4	13.4	9.8	8.8
Iris	5	5.8	10	5.8	5.6	5	5
Pima	11.6	10	12	8	8.2	6.4	15.2
Vote	4	4	4.9	4	4	4	4.3

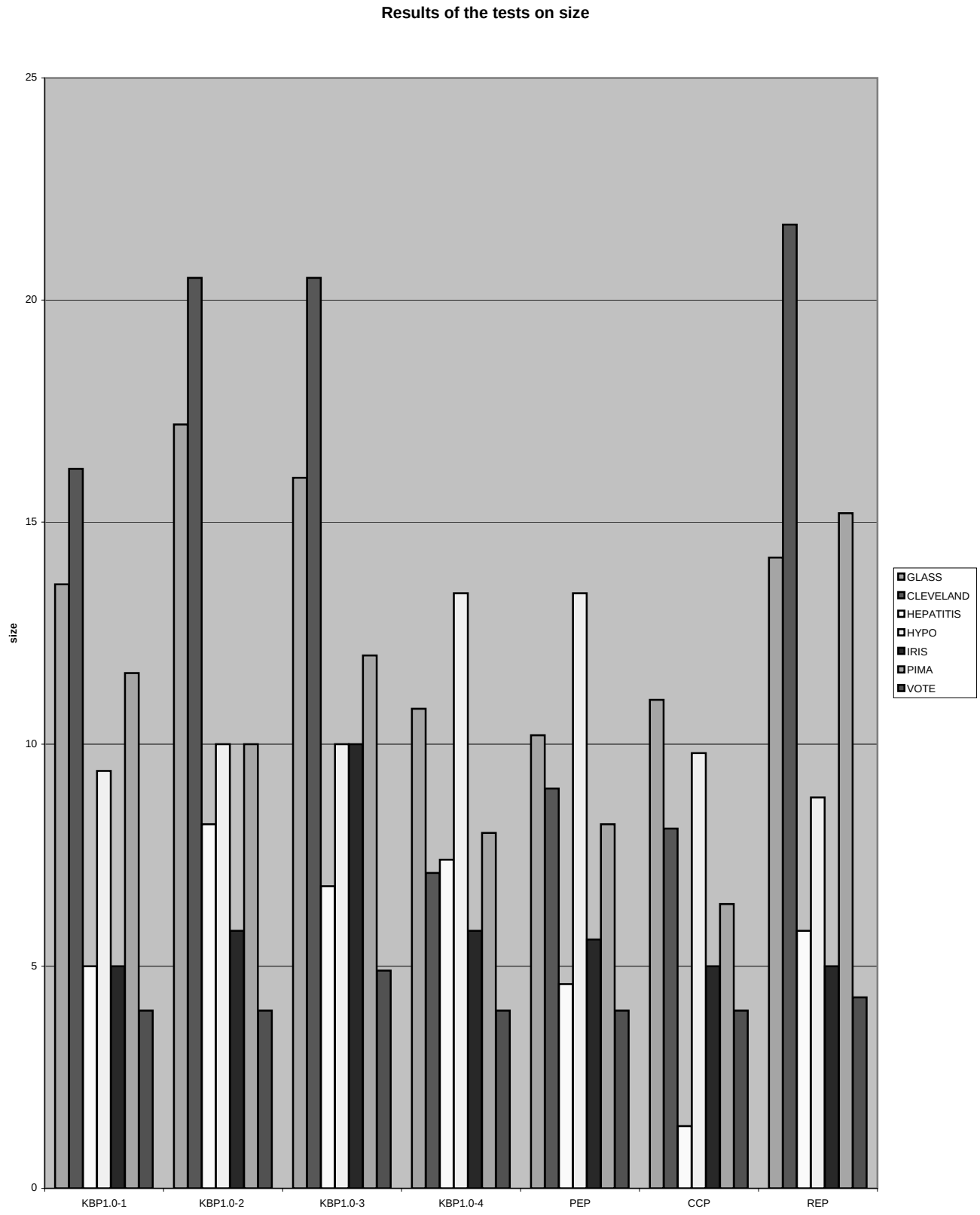

FIGURE 7. Test results on size between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP1.0-4, and the other non-cost sensitive pruning methods for all the data sets

5.4. Comparison of KBP1.0 Pruning with C4.5 Pruning.

C4.5 is the most popular decision tree algorithm. It is often used as a test benchmark for decision tree algorithms [90][91]. In this section, the results of the comparative analysis based on size, error rate, and cost of the pruned decision trees created by KBP1.0 cost-sensitive pruning methods and C4.5 pruning methods are shown.

It is known that Pessimistic Error Pruning (PEP) increases the number of errors observed at each leaf by 0.5 [12]. C4.5 employs a far more pessimistic estimate than PEP. In C4.5, when N training cases are covered by a leaf and E of them are misclassified, the number of predicted errors of that leaf will be $N * U_{CF}(E, N)$ [13]. CF is the confidence level (C4.5's default confidence level is 25%). U_{CF} is the upper limit on the E/N for a given confidence level CF. C4.5 calculates the change of the number of predicted errors when deciding to prune or not. The detailed information about how C4.5 prunes the decision tree can be found in [13].

The equation(14) is used to calculate the cost and compared the results with what is obtained from each pruning method. C4.5 was executed in a default setting environment, in which the filename is specified and the tree evaluation on the test set is enable. The results are shown in Table 7 and in Figure 8 to Figure 10. The results show that every KBP1.0 cost-sensitive pruning method obtained a lower cost than C4.5. Even compared with other well-known non-cost sensitive pruning methods, C4.5 has the worse performance in cost.

TABLE 7. Test results on cost between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP1.0-4, and the C4.5 pruning method

database	KBP1.0-1	KBP1.0-2	KBP1.0-3	KBP1.0-4	C4.5
Glass	0.1367	0.1410	0.1413	0.1548	0.1762
Cleveland	0.1162	0.1380	0.1398	0.1516	0.18716
Hepatitis	0.0817	0.0978	0.1239	0.1048	0.15717
Hypo	0.0019	0.0022	0.0021	0.0017	0.0032
Iris	0.0130	0.0139	0.0120	0.0156	0.0326
Pima	0.6087	0.6144	0.6105	0.7939	0.6955
Vote	0.0259	0.0205	0.0205	0.0253	0.0357

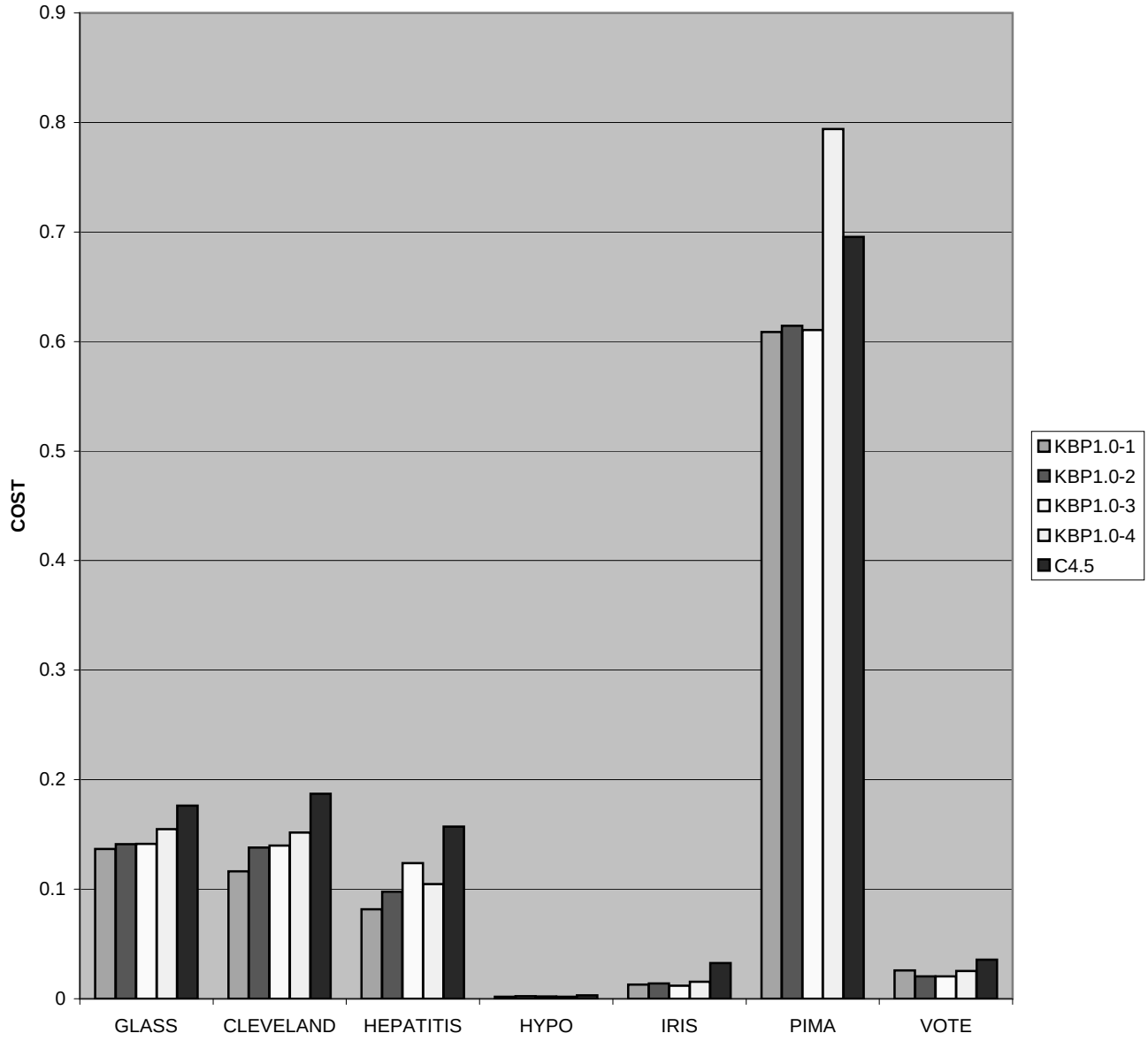

FIGURE 8. Test results on cost between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP1.0-4, and the C4.5 pruning method for all the data sets

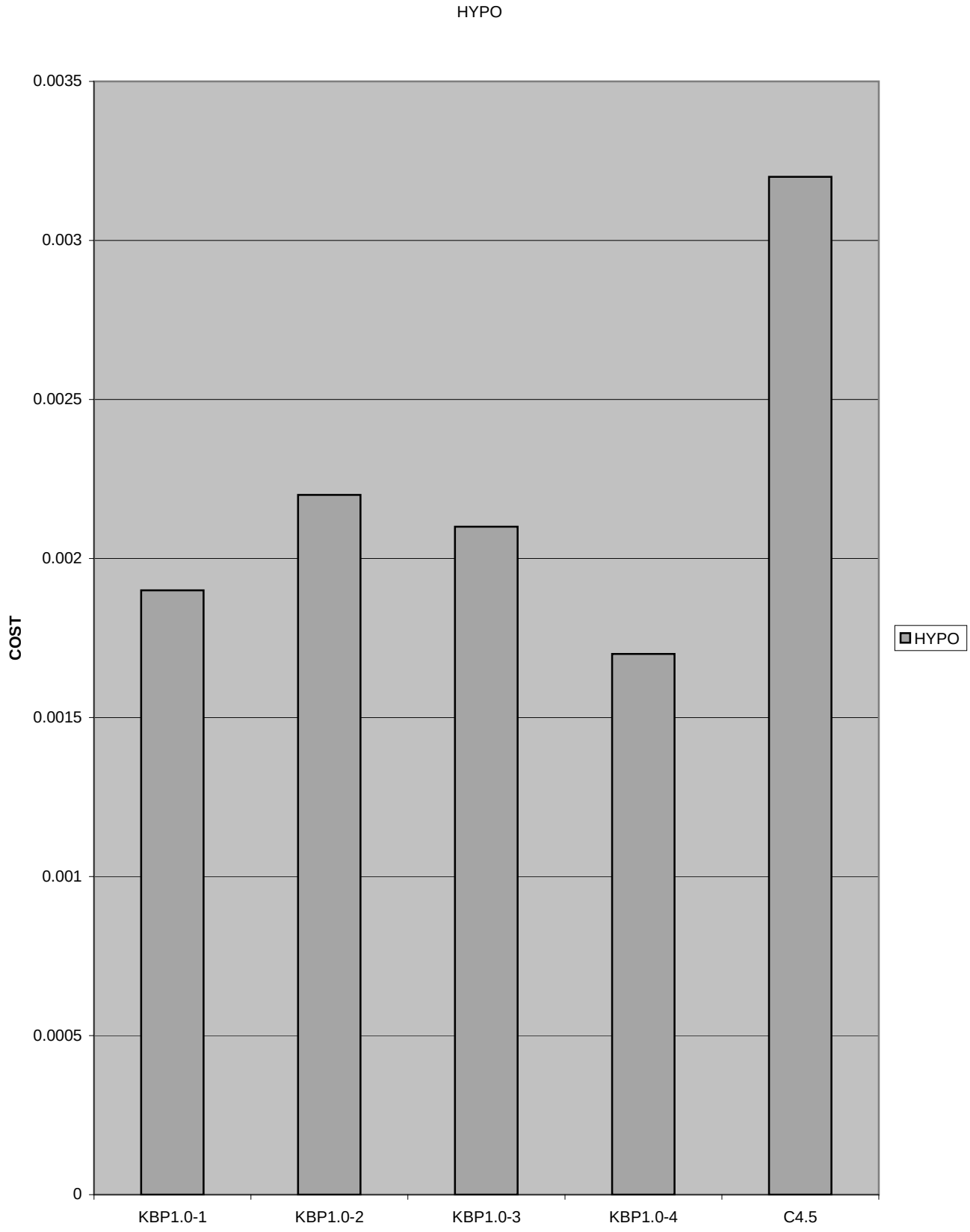

FIGURE 9. Test results on cost between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP1.0-4, and the C4.5 pruning method for the Hypothyroid data set

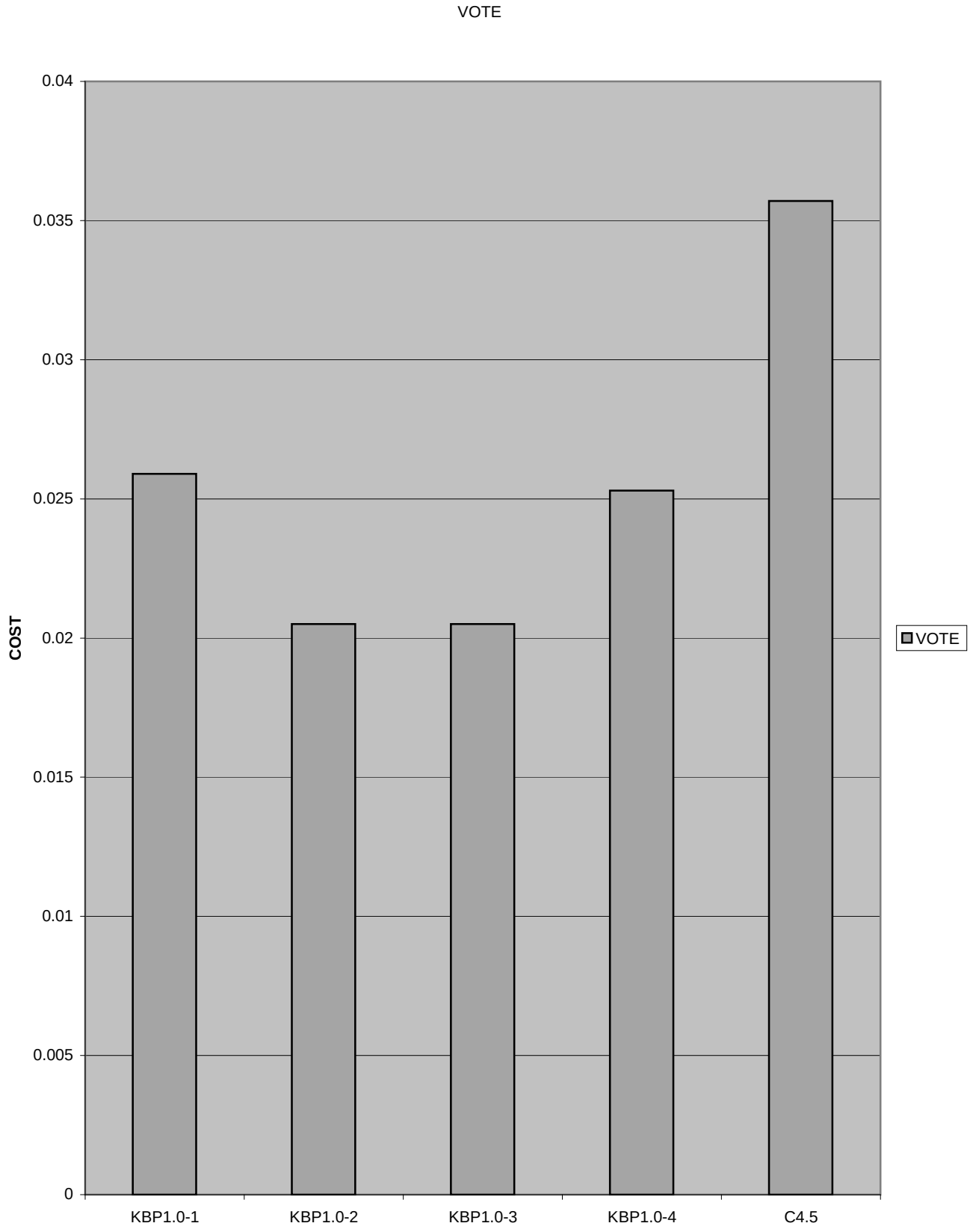

FIGURE 10. Test results on cost between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, and KBP1.0-3, and the C4.5 pruning method for the Vote data set

The results of the tests on error rate between KBP1.0 cost-sensitive pruning methods and C4.5 are compared. The results are shown in Table 8 and in Figure 11 to Figure 13. From Table 6, it is noticed that, in most cases, C4.5 is of superior accuracy to the cost-sensitive pruning. C4.5 has good performance in reducing error as well as other traditional non-cost sensitive pruning methods.

TABLE 8. Test results on error rate (percent) between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP 1.0-4, and the C4.5 pruning method

data set	KBP1.0-1	KBP1.0-2	KBP1.0-3	KBP1.0-4	C4.5
Glass	49.2	39.85	36.46	36.25	32.82
Cleveland	30.11	30.76	27.66	26.02	25
Hepatitis	45.22	20.23	20.77	19.56	23.48
Hypo	0.82	0.76	0.72	0.49	0.6
Iris	5.67	6.35	4.33	5.78	6.87
Pima	38.52	36.46	37.12	25.82	27.9
Vote	6.13	5.22	4.72	4.65	5.77

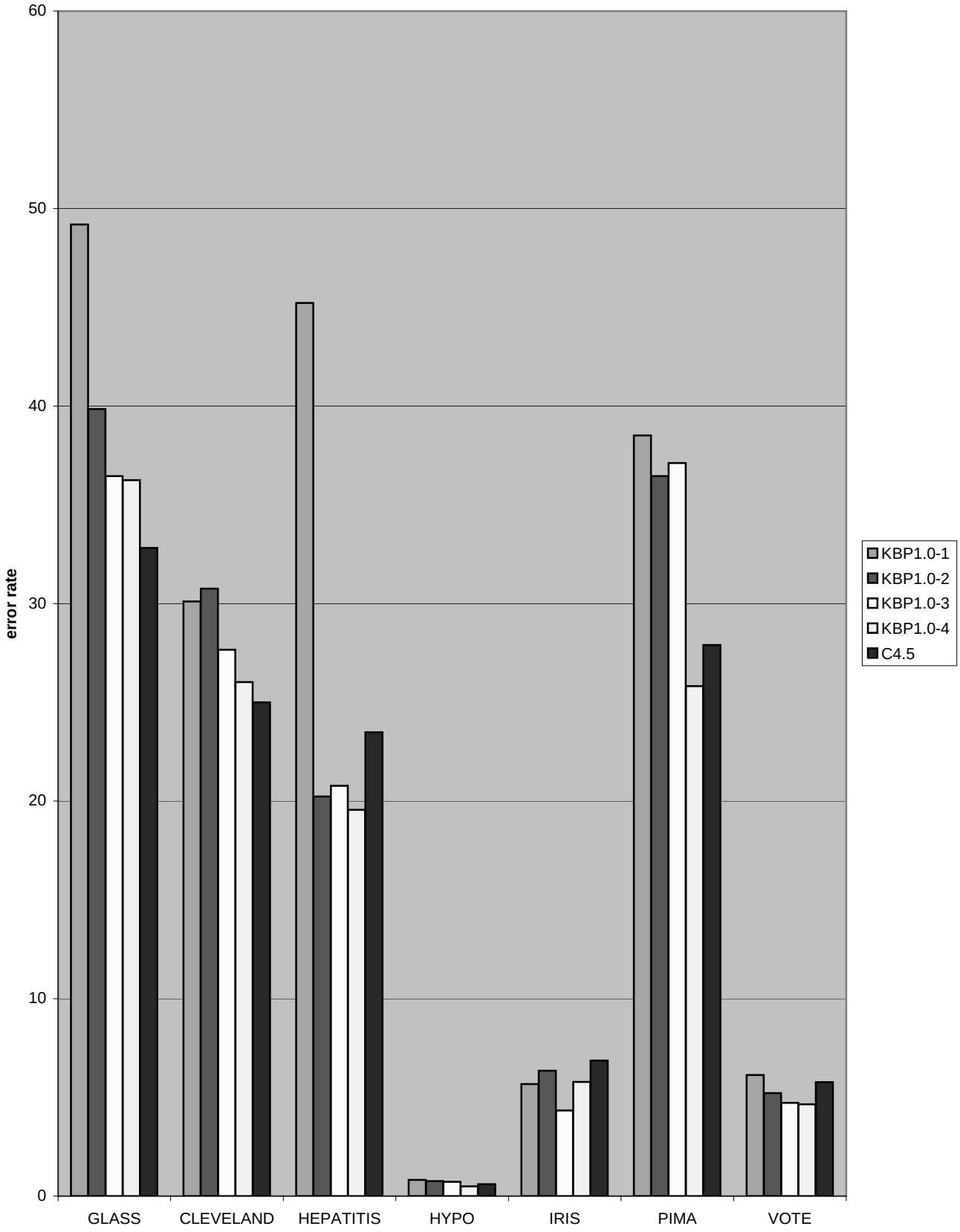

FIGURE 11. Test results on error rate between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP1.0-3, and the C4.5 pruning method for all the data sets

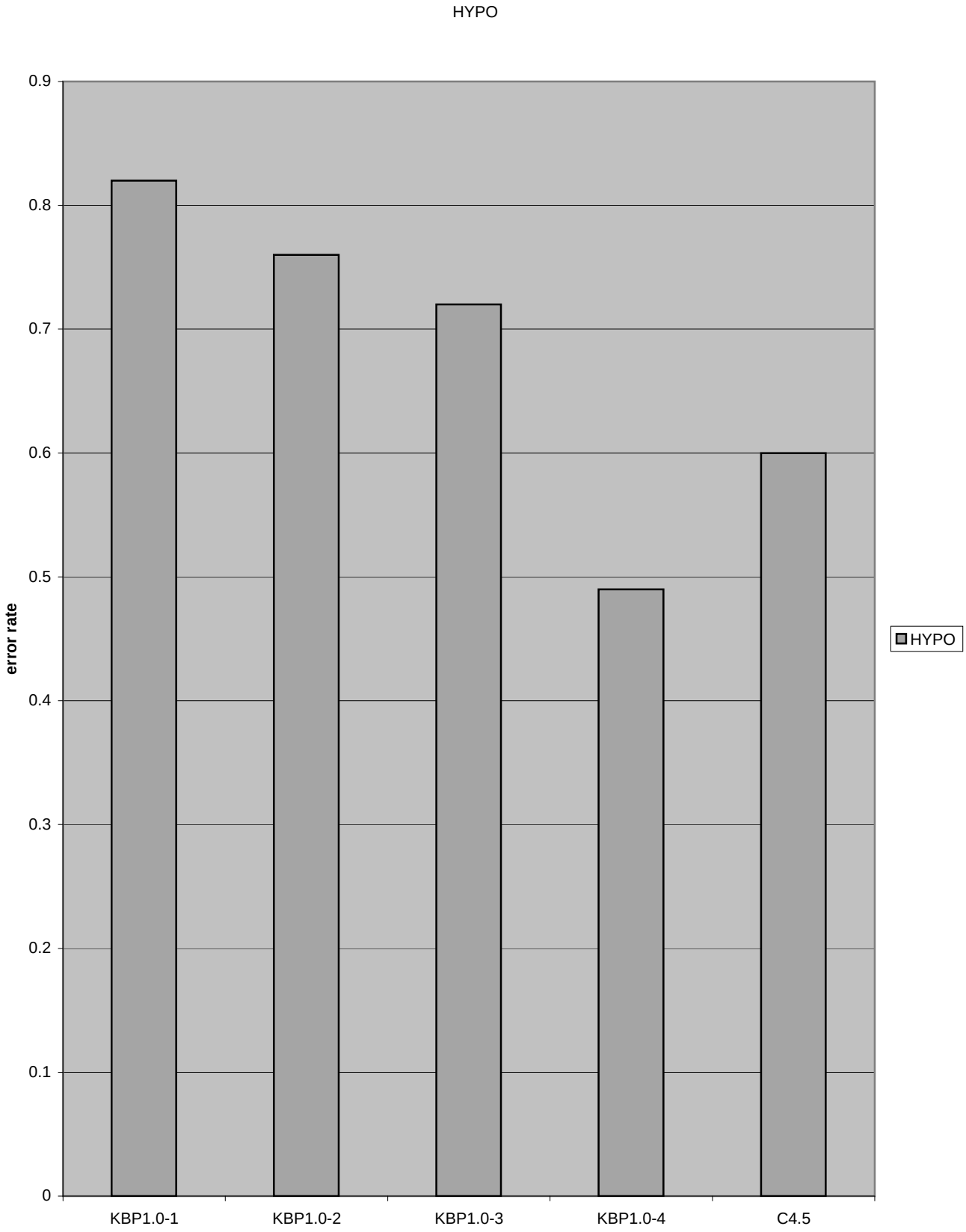

FIGURE 12. Test results on error rate between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP1.0-4, and the C4.5 pruning method for Hypothyroid data set

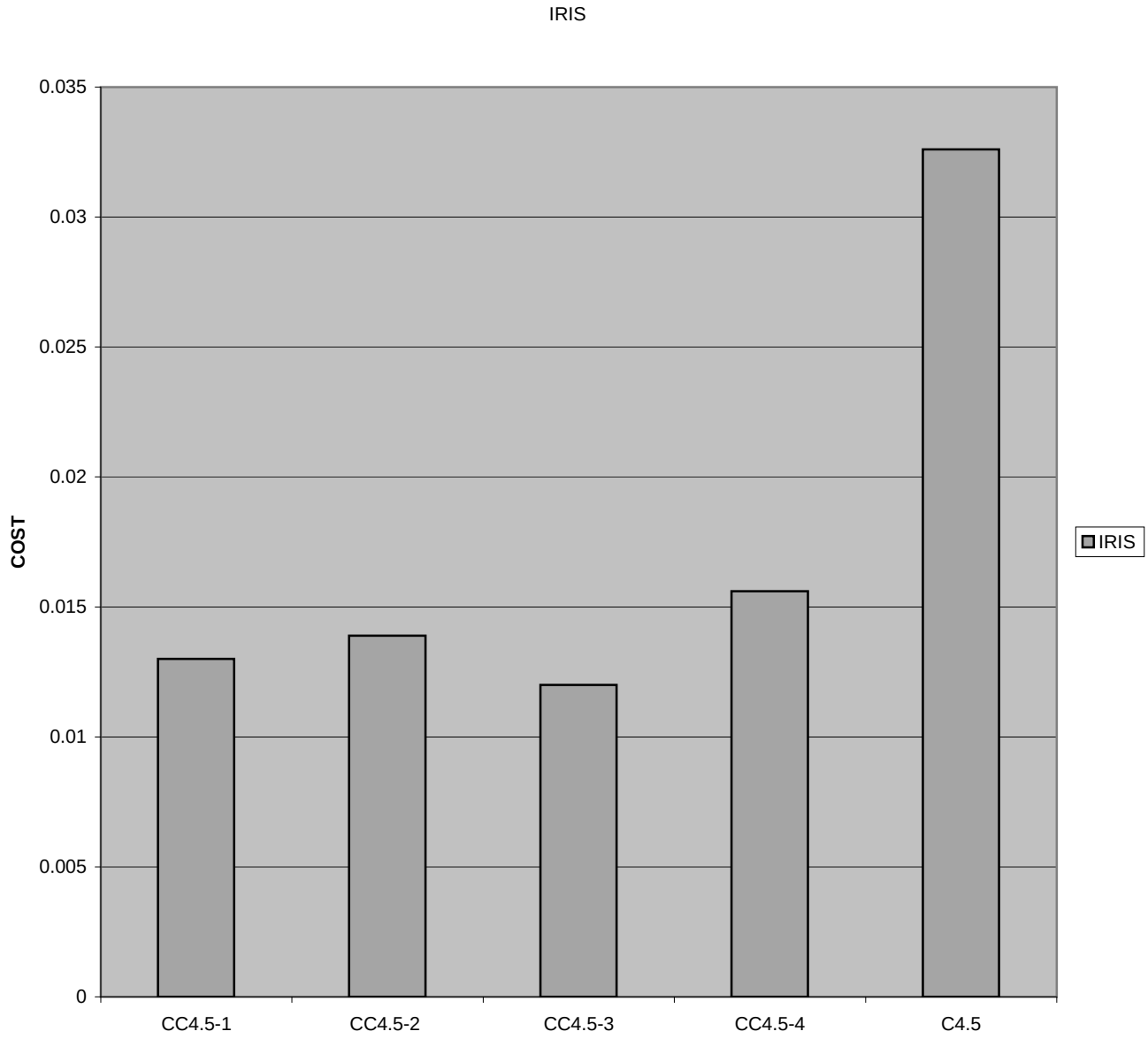

FIGURE 13. Test results on error rate between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP1.0-4, and the C4.5 pruning method for the Iris data set

The results of the tests on size are reported in Table 9 and Figure 14. The number of leaves and nodes is used to represent the size of the decision tree. It is clear that, compared with KBP1.0 pruning methods, C4.5 tends to produce a smaller decision tree. It is reasonable because most pruning methods in KBP1.0 need to consider both cost and error when deciding whether to prune subtrees or not. But the C4.5 only considers the error when deciding to prune. It is noticed that the size difference is not very big and the size of the decision tree pruned by KBP1.0 pruning methods is acceptable. Among the pruning methods in KBP1.0, KBP1.0-1 has the same advantage in getting a small tree size as C4.5.

TABLE 9. Test results on size between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP1.0-4, and the C4.5 pruning method

data set	KBP1.0-1	KBP1.0-2	KBP1.0-3	KBP1.0-4	C4.5
Glass	13.6	17.2	16	10.8	14
Cleveland	16.2	20.5	20.5	7.1	15.3
Hepatitis	5	8.2	6.8	7.4	5.1
Hypo	9.4	10	10	13.4	9.1
Iris	5	5.8	10	5.8	7
Pima	11.6	10	12	8	9.7
Vote	4	4	4.9	4	4.1

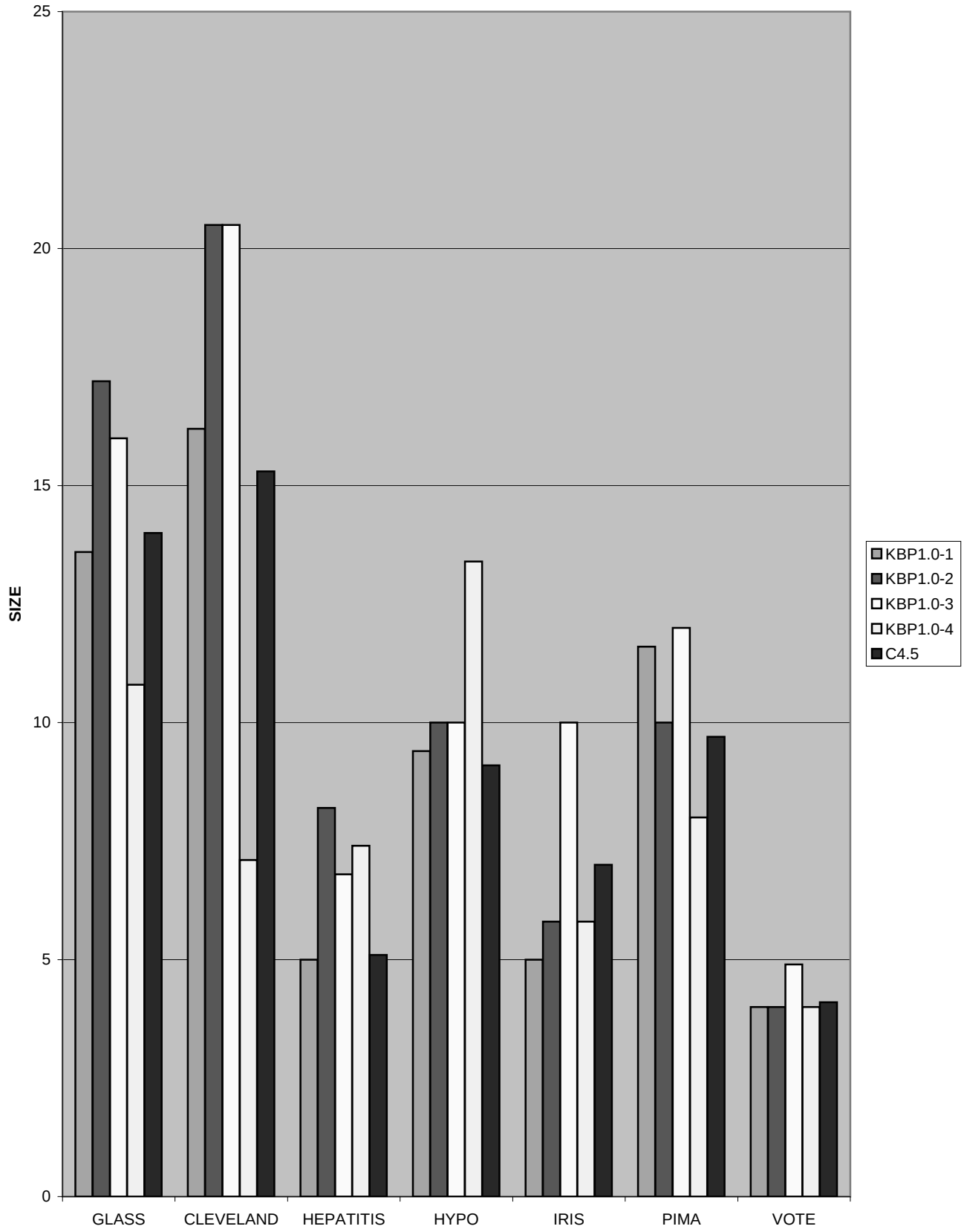

FIGURE 14. Test results on size between the cost-sensitive pruning methods KBP1.0-1, KBP1.0-2, KBP1.0-3, and KBP1.0-4, and the C4.5 pruning method for all the data sets

6. Statistical Measures

In previous sections in this chapter, the different results between KBP1.0 and other traditional pruning methods are compared. But the comparison methods used are not enough to conclude that KBP1.0 has a higher performance than other traditional non-cost sensitive pruning methods. The problem is that we can only make a finite number of measurements on the real world, called a sample, as we seek to gain information about it. It is possible that the sample may not actually represent what is typical in the real world. We would like to be able to get an idea of what level of confidence can be placed on the ability of the measurements to represent what is really going on in the world. That is why statistical measures are needed. When there are more than two groups, the ANOVA can be used to test the hypothesis that the means among two or more groups are equal, under the assumption that the sampled populations are normally distributed.

To complete the analysis of cost, the significance of differences among the cost-sensitive methods in KBP1.0 and the non-cost sensitive pruning methods in REP, PEP, CCP, and C4.5 is investigated. ANOVA is used to do this comparison.

(1) ANOVA

ANOVA is a general technique that can be used to test the hypothesis that the means among two or more groups are equal, under the assumption that the sampled populations are normally distributed [33].

(2) ANOVA results

A statistical tool called Minitab is used to do the ANOVA work. The significance level is 0.05. The ANOVA results can be found in Appendix B. From the ANOVA results, it is noticed that the cost obtained from KBP1.0 is statistically different from the cost obtained from the traditional pruning methods. Most of the KBP1.0 cost-sensitive pruning methods provide a lower cost than the other non cost-sensitive pruning methods: i.e., PEP, CCP, REP,

and C4.5. The cost-sensitive pruning method in KBP1.0-1, which only considers the cost and not the error rate during pruning, achieves the lowest cost. It is also noticed that the pessimistic pruning method (PEP) sometimes has a very good performance in cost (especially for the Hypo and Vote data sets). One reason may be that pessimistic pruning does not require a pruning set separated from the cases in the training set from which the tree was constructed. When we compare the cost-sensitive pruning methods in KBP1.0, KBP1.0-4 provides the biggest cost.

7. The Cost Matrix Sensitivity

In this section, preliminary experiments and discussion is given on the cost matrix sensitivity in the pruning methods in KBP1.0.

The experiment settings are as follows: two data sets, i.e., Hepatitis and Pima, are used, and the same cost matrices in the previous experiments are used as the base cost matrix. Meanwhile, a random matrix generation program was designed to generate random matrices with some deviation from a base matrix. Several random matrices were generated within a factor of ϵ of the base matrices. Then, these random matrices were fed to the four cost-sensitive pruning methods in KBP1.0 for $\epsilon = 0.05$ and 0.1. All cost-sensitive pruning methods in KBP1.0 was run 10 times with the random cost matrices to get the average cost. The difference of cost of the pruned tree between using these random matrices and using the base matrices is observed and the results are shown in Table 10.

TABLE 10. Experimental results on cost according to different cost matrices

data set	KBP1.0-1	KBP1.0-2	KBP1.0-3	KBP1.0-4
Hepatitis (base)	0.0817	0.0978	0.1239	0.1048
Hepatitis ($\epsilon = 0.05$)	0.0708	0.1212	0.11387	0.1117
Hepatitis ($\epsilon = 0.1$)	0.0799	0.0815	0.09927	0.11743
Pima (base)	0.6087	0.6144	0.6105	0.7939
Pima ($\epsilon = 0.05$)	0.3644	0.3348	0.4343	0.8018
Pima ($\epsilon = 0.1$)	0.3309	0.324	0.3828	0.8894

From Table 10, equation (22) is used to calculate the percentage of cost changes when random matrices are used, and the results are shown in Table 11.

$$Percentage\ of\ cost\ change = \frac{|C_{base} - C_{random}|}{C_{base}} \tag{22}$$

where:

C_{base} is the cost based on the base matrices,

C_{random} is the cost based on the random matrices

TABLE 11. Experimental results on the percentage of cost changes

data set	KBP1.0-1	KBP1.0-2	KBP1.0-3	KBP1.0-4
Hepatitis ($\epsilon = 0.05$)	13	23	8	6.58
Hepatitis ($\epsilon = 0.1$)	2	16.7	19.88	12.1
Pima ($\epsilon = 0.05$)	40.1	45.5	28.9	10
Pima ($\epsilon = 0.1$)	45.6	47.3	37.3	12

From Table 10 and Table 11, it is found that the cost matrix sensitivity in the pruning methods is problem dependent. For example, the percentage of cost changes is much bigger in the Pima data set than in the Hepatitis data set. In most cases, except for the Hepatitis data set in KBP1.0-1 and KBP1.0-2, the percentage of cost changes for a random cost matrix with $\epsilon = 0.1$ is bigger than that for a random cost matrix with $\epsilon = 0.05$ of the base matrices to the cost based on the base matrices. Further research on the cost matrix sensitivity in the pruning methods, such as the strict definition of sensitivity and the underlying reason for the experiment results, may be done in future work.

CHAPTER V

The Framework for Knowledge-base Pruning

This chapter introduces the framework for knowledge-base pruning. Then, the strategies for KBP1.0 are given. Finally, some future researches are discussed.

1. Definitions

This section contains the definitions needed for later sections.

Definition: Let α_{ij} be the cost of misclassifying a class i object as a class j object and satisfies

$$\alpha_{ij} \begin{cases} > 0, & \text{if } i \neq j; \\ = 0, & \text{if } i = j. \end{cases}$$

$\alpha_{ij} \in [0, +\infty)$.

The probability that a sample in node t falls into class i can be given as follows:

$$p(i|t) = \frac{p(i,t)}{p(t)} \tag{23}$$

where $\sum_i p(i|t) = 1$,

$p(i,t)$ is the probability that a sample will both be in class i and fall into node t,

$p(t)$ is the probability that any sample falls into node t and can be defined as follows:

$$p(t) = \sum_i p(i,t) \tag{24}$$

During the pruning procedure, let node be replaced by the class j which minimizes the misclassification cost. Therefore, given the samples under node t, the total misclassification cost for node t can be defined as follows:

$$r(t) = \min_j \sum_i \alpha_{ij} p(i|t) \tag{25}$$

Let $\sum_j \alpha_{ij} = k_i$ and $\sum_i k_i = K$, equation(25) can be normalized as

$$r(t) = \frac{1}{K}(\min_j \{\sum_i \alpha_{ij} p(i|t)\}) \tag{26}$$

Definition: Let $R(t)$ be the misclassification cost for node t given as

$$R(t) = r(t)p(t) \tag{27}$$

Then, let $R(T)$ be the total misclassification cost for tree T given as

$$R(T) = \sum_{t \in T} R(t) \tag{28}$$

Definition: When $\alpha_{ij} = 1$ $(i \neq j)$, let $E(t)$ be the error rate for node t given as

$$E(t) = K * R(t) \tag{29}$$

Furthermore, let $E(T)$ be the total error rate for tree T given as

$$E(T) = K * R(T) = K * \sum_{t \in T} R(t) \tag{30}$$

Most pruning techniques only consider the error rate while cost-sensitive pruning only considers the cost. But it may lead to a poor system performance if only its cost is low but its error rate is too high, or its error rate is low but its cost is too high. So some other

pruning methods are proposed to deal with this. The pruning method in this dissertation uses intelligent inexact classification to prune decision tree and is based on not only considering the error rate but also considering the cost of the error. The following equation is used to deal with it:

$$F(T) = I_1 * R(T) + I_2 * E(T) \tag{31}$$

where:

$F(T)$ is the evaluation value for tree T used in decision tree pruning;

I_1 is the weight of cost, $I_1 \in [0, 1]$;

I_2 is the weight of error rate, $I_2 \in [0, 1]$;

$I_1 + I_2 = 1$;

$R(T)$ is the misclassification cost of the tree T;

$E(T)$ is the total error rate by tree T.

The assignment of I_1 and I_2 is problem dependent and needs domain knowledge. In some cases, for example in medical diagnosis, misclassification, i.e., misdiagnosis, can critically damage the patient, so I_1 should be high. In some other cases, for example when different cost misclassifications are roughly the same, cost is not very critical, so I_1 can be set to a low value. Therefore, this pruning method is more general than other non-cost sensitive pruning methods. For example, I_1 can be set to value 0 and get an error based non-sensitive pruning. It is clear that I_1 and I_2 can be changed to adjust the error rate and cost.

KBP1.0 uses equation(31) in the pruning procedure. It is discussed in more detailed in the next section.

Definition: Let $F(t)$ be the evaluation value for node t given as

$$F(t) = I_1 * R(t) + I_2 * E(t) \tag{32}$$

It is clear that

$$F(T) = \sum_{t \in T} F(t) \tag{33}$$

2. Strategies for KBP1.0

In this section the strategy for KBP1.0 is introduced. The definitions in the previous sections have been used in this section to make the description clear.

The main strategy for KBP1.0 is that $F(T)$ in equation(31) is used in the pruning procedure. I_1 and I_2 have different values for different pruning methods in KBP1.0 as shown in table 12.

TABLE 12. Values for I_1 & I_2 in KBP1.0

Pruning method	$F(t) = I_1 * R(t) + I_2 * E(t)$
KBP1.0-1	$I_1 = 1$, $I_2 = 0$
KBP1.0-2	$I_1 \in [0, 1]$, $I_2 \in [0, 1]$
KBP1.0-4	$I_1 = 1$, $I_2 = 0$

Let T_{max} be the initial tree without being pruned. For an initial tree T_{max}, KBP1.0 computes $F(t)$ for each node t ($t \in T_{max}$) in a bottom-up fashion. Therefore, T_{max} is progressively pruned upward to its root node. For KBP1.0-1 and KBP1.0-2, tree T will be pruned if $F(T') < F(T)$ (T' is the pruned tree of T and is obtained from T by successively pruning off branches).

Let $R_{th}(T)$ be the threshold value for misclassification cost and $E_{th}(T)$ be the threshold value for error rate.

The idea behind KBP1.0-3 is as follows:

For each stage of the pruning process, KBP1.0-3 computes $R(T)$ and $E(T)$. The following rules are used to make the pruning decision:

(1) Tree T will be pruned when $R(T') < R(T)$ and $E(T') < E(T)$.

(2) Tree T will not be pruned when $R(T') > R(T)$ and $E(T') > E(T)$.

(3) When $R(T^{'}) > R(T)$ and $E(T^{'}) < E(T)$, tree T will be pruned only when $R(T^{'}) < R_{th}(T)$.

(4) When $R(T^{'}) < R(T)$ and $E(T^{'}) > E(T)$, tree T will be pruned only when $E(T^{'}) < E_{th}(T)$.

There are different ways to set the values of $R_{th}(T)$ and $E_{th}(T)$. For example, traditional pruning methods, such as reduced error pruning or pessimistic pruning, can be used to prune the decision tree and get its error rate e_1. Then $E_{th}(T)$ can be set as e_1. In the same way, KBP1.0-1 can be used to prune the decision tree and get its cost c_1. Then $R_{th}(T)$ can be set as c_1.

KBP1.0-4's pruning procedure is similar to that of the pessimistic error pruning(PEP). The only difference between KBP1.0-4 and PEP is that: $F(t)$ replaces $E(t)$ in each stage of pruning, i.e., PEP calculates the error rate, while KBP1.0-4 calculates the misclassification cost during pruning. Note that in the unit misclassification cost case(i.e., $\alpha_{ij} = 1$ when $i \neq j$), KBP1.0-4 is equivalent to PEP.

Definition: For any subtree T, Let $|T|$ be the number of terminal nodes in T which represent the complexity of subtree T. The *cost-complexity measure* is defined as

$$R^{'}(T) = R(T) + \frac{|T|}{2} \tag{34}$$

Definition: Let t be the node of subtree T, if subtree T is replaced by the node t, let the misclassification cost obtained be R_t. The pessimistic misclassification measure is defined as

$$R_t^{'} = R_t + \frac{1}{2} \tag{35}$$

For each subtree, KBP1.0-4 computes $R^{'}(T)$ and $R_t^{'}(t \text{ is node of subtree } T)$. Then, KBP1.0-4 tests whether the following equation is satisfied

$$R_t^{'} \leq R^{'}(T) + [R^{'}(T)]^{1/2} \tag{36}$$

When equation(36) is satisfied, subtree T is replaced by node t.

3. Discussion

KBP1.0 uses $F(T)$ as the criterion to prune the decision tree. From equation (31), it is clear that I_1 and I_2 need to be set before pruning. Through discussions with the experts, I find that it is hard for experts to give the exact values for I_1 and I_2. The experts can only set the fuzzy value for I_1 and I_2. Although the experiments for KBP1.0 have good results, how to set more reasonable values for I_1 and I_2 can be for future research.

Threshold values $R_{th}(T)$ and $E_{th}(T)$ need to be set in KBP1.0-3. In experiments, reduced error pruning was used to help us set $E_{th}(T)$ and KBP1.0-1 was used to help us set $R_{th}(T)$. How to get some other better methods to set more reasonable values for $R_{th}(T)$ and $E_{th}(T)$ can be for future research.

Breiman, et al., concluded that the right sized tree T_{k_0} can be selected by the following rule [7]:

$$R(T_{k_0}) = \min_k R(T_k) \tag{37}$$

where T_k is the sequence of trees.

In KBP1.0, the best subtree T_{k_0} could be defined as the subtree that minimizes $F(T_k)$ as follows

$$R(T_{k_0}) = \min_k F(T_k) \tag{38}$$

Because $F(T_k) = I_1 * R(T_k) + I_2 * E(T_k)$ and $E(T_k)$ is the special case of $R(T_k)$, equation(38) is determined by I_1, I_2 and $R(T_k)$. The analysis of optimal pruning based on expert knowledge can be for future research.

CHAPTER VI

SUMMARY

1. Summary

The idea of cost-sensitive pruning has received much less attention than other pruning techniques even though additional flexibility and increased performance can be obtained from this method. In this dissertation, a cost-sensitive decision tree pruning algorithm called KBP1.0, which includes four cost-sensitive pruning methods, has been introduced. In these four cost-sensitive pruning methods, two ways are proposed to integrate error rate and cost in the pruning methods. One method uses intelligent inexact classification (IIC) and the other uses threshold to integrate error rate and cost. It is the first time that IIC and threshold are used in this way in pruning the decision tree. By comparing the cost-sensitive pruning methods in KBP1.0 with other traditional pruning methods, such as reduced error pruning, pessimistic error pruning, cost complexity pruning, and C4.5, on benchmark data sets, the advantage and disadvantage of cost-sensitive methods in KBP1.0 have been summarized. The sensitivity of the pruning method to the cost matrix is first discussed in this dissertation. The central problem investigated in this dissertation is the problem of minimizing the cost of misclassification or balancing the error and the cost of misclassification when the cost is too important to be ignored.

In particular, KBP1.0's performance has been compared with those of several well-known pruning methods including Reduced Error Pruning, Pessimistic Error Pruning, Cost-Complexity Pruning, and C4.5. The strengths and weaknesses of KBP1.0 have also been pointed out.

From the comparative analysis based on cost between the cost-sensitive pruning methods and non-cost sensitive pruning methods, it is clear that most of the KBP1.0 cost-sensitive pruning methods provide a lower cost than the other non cost-sensitive pruning methods. The cost-sensitive pruning method KBP1.0-1, which only considers the cost and not the error rate during pruning, achieves the lowest cost. Compared with the other cost-sensitive pruning methods in KBP1.0, KBP1.0-4 provides the biggest cost.

From the comparative analysis based on error rate between the cost-sensitive pruning methods and other traditional non-cost sensitive pruning methods, it is noticed that KBP1.0-1, which only considers cost and not the error rate in pruning, shows a larger error rate than KBP1.0-2, KBP1.0-3, and KBP1.0-4, which consider both cost and error rate in pruning. In most cases, the other well-known non-cost sensitive pruning methods are of superior accuracy to the KBP1.0 cost-sensitive pruning methods. Compared with the other cost-sensitive pruning methods in KBP1.0, KBP1.0-4 achieves the lowest error, while KBP1.0-1 gives the highest error rate.

From the comparative analysis based on size between the cost-sensitive pruning methods and other traditional non-cost sensitive pruning methods, it is clear that most cost-sensitive pruning methods tend to produce a larger decision tree than the other well-known non-cost sensitive pruning methods selected. But the size difference between cost-sensitive pruning methods and non-cost sensitive pruning methods is not that large, the size of the decision trees which are pruned by the cost-sensitive pruning methods is acceptable to the author. In many cases, a small decision tree with high cost or error is unacceptable. When comparing the cost-sensitive pruning methods in KBP1.0, KBP1.0-1 gives the smallest decision tree.

From the comparative analysis based on size, error rate, and cost of the pruned decision trees created by KBP1.0 cost-sensitive pruning methods and C4.5 pruning methods, it is clear that every KBP1.0 cost-sensitive pruning method obtained a lower cost than C4.5. It is also

found that, in most cases, C4.5 is of superior accuracy to the cost-sensitive pruning. C4.5 has good performance in reducing error as well as other traditional non-cost sensitive pruning methods. Compared with KBP1.0 pruning methods, C4.5 tends to produce a smaller decision tree. But the size difference is not that large and the size of the decision tree pruned by KBP1.0 pruning methods is acceptable. Among the pruning methods in KBP1.0, KBP1.0-1 has the same advantage in getting a small tree size as C4.5.

The statistical measures are also used to test that cost-sensitive pruning methods in KBP1.0 tend to provide lower cost than the other non-cost sensitive pruning methods. The results confirm the above conclusions.

It is clear that some of the new cost-sensitive pruning methods (KBP1.0-1, KBP1.0-2, and KBP1.0-3) require pruning sets separate from the training sets from which the tree was constructed. But KBP1.0-4 does not require the separated pruning set because it integrates PEP with cost-sensitive pruning method.

The decision tree pruning algorithm KBP1.0 provides more options to prune the decision tree, especially when cost is too important to be ignored. It is believed that many real-world classification problems involve more than merely maximizing accuracy. In certain applications, a decision tree that merely maximizes accuracy (e.g., trees generated by C4.5) may be far from the performance that is possible with an algorithm that considers such realistic constraints as misclassification cost [46]. KBP1.0 can be applied to solve real-world data mining problems and its potential application includes almost all applications of the decision tree, especially some problems which should take into account misclassification cost, such as medical diagnosis, stock prediction, credit-risk analysis, and so on. KBP1.0 can also be applied to some applications in which the accuracy of a classification or prediction is the only thing that matters, because it is convenient to set I_1 in KBP1.0-2 to value 0 and get an error-based non-sensitive pruning. In the future, a decision tree pruned by KBP1.0 can be converted to

rules and these rules can be used to build an expert system. Generally, future applications of KBP1.0 include banking (e.g., predictive and risk assessment models for the financial services industry), fraud detection (e.g., uncovering network intrusions), health care (e.g., data warehousing solutions for health care industry), and stock and investment analysis and prediction (e.g., predicting stock price changes).

2. Discussions

This section discusses some concerns of the research in this dissertation.

(1) The expert knowledge used in cost matrix

To the best of the author's knowledge, the use of expert knowledge in cost-sensitive pruning of decision trees has not been discussed before in the literature. In this work, the cost matrices are defined through discussions with domain experts. It may be a concern for this research to place a burden on domain experts. Actually, expert system design relies upon domain experts much more heavily than this work [1]. Furthermore, expert system can determine α values.

Most experts are skillful at solving problems within their narrow area of expertise, but have limited ability outside this area. Therefore, finding the right experts to help define the cost matrices is important for this work.

(2) Experimental results

In this dissertation, KBP1.0's performance has been compared with those of several well-known pruning methods including Reduced Error Pruning, Pessimistic Error Pruning, Cost-Complexity Pruning, and C4.5. From the results, it is clear that most of the KBP1.0 cost-sensitive pruning methods provide a lower cost than the other non cost-sensitive pruning methods. However, there are some exceptions. For example, in Hepatitis data set, KBP1.0-3 gets a higher cost than PEP and REP. This is not

unusual because there is no overall best algorithm. One can improve KBP1.0's performance in several ways, i.e., adjusting the cost matrix by changing the threshold values which were set. Another concern for the comparison presented here is that the datasets selected in the experiment are not very large datasets. Will KBP1.0 have a good performance in a very large dataset? This will be future work of the author's research.

(3) ANOVA results

The ANOVA is used to investigate the significance of differences among the cost-sensitive methods in KBP1.0 and non-cost sensitive pruning methods in REP, PEP, CCP, and C4.5. From ANOVA results, it can be found that there are statistical differences between the performance of the cost-sensitive methods in KBP1.0 and that of non-cost sensitive pruning methods in REP, PEP, CCP, and C4.5. The ANOVA, other than the t-test, is selected to analyze the experimental results because the major difference between ANOVA and t-test is that, where the t-test measures the difference between the means of two groups, an ANOVA tests the difference between the means of two or more groups [126]. The advantage of using ANOVA rather than multiple t-tests is that it reduces the probability of a type-I error [126]. However, one potential drawback to an ANOVA is that specificity is lost: all an ANOVA tells you is that there is a significant difference between groups, not which groups are significantly different from each other [117]. In future work, the t-test may be used to find out where the differences are, i.e., which groups are significantly different from each other and which are not.

(4) Cost matrix sensitivity in the pruning methods

To the best of our knowledge, the cost matrix sensitivity in the pruning methods is first discussed in this dissertation. An experiment is designed to test the cost

matrix sensitivity. However, the results obtained are preliminary in the sense that the definition of sensitivity is not well-defined. In the experiment, when the cost matrix is changed, the pruned tree is also changed because the pruning methods in KBP1.0 are guided by the cost matrix. Another concern for the sensitivity of the pruning methods to the cost matrix is whether or not the sensitivity is relevant to the size of the cost matrix. In future work, a clear definition for the sensitivity of the pruning method to the cost matrix may be given and further research on sensitivity to the cost matrix with different sizes may be done.

3. Future work

Some of future work is mentioned in above discussion section. For example, the KBP1.0 will be used in some very large data set and analyze its performance, and a clear definition for the sensitivity of the pruning method to the cost matrix may be given. There are also other directions for future work. Future work will also focus on the integration of cost-sensitive pruning methods in other pruning methods, such as Minimum Error Pruning and Critical Value Pruning and compare KBP1.0 pruning methods to other pruning methods. It will also include the Ontology and why an Ontology would aid us in obtaining reasonable cost matrices in the future. A prototype expert system to define the cost matrix will be developed. Using KBP1.0 to prune the decision tree and getting the rules from the pruned trees to help us build the real-world expert system is another important direction for future work.

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APPENDIX

APPENDIX A

PUBLICATIONS DURING PhD STUDY

Book Chapters

- J. Cai, Chapter 5 Computational Intelligence (2): Evolutionary and Artificial Life in "Artificial Intelligence: Principles and Applications(undergraduate edition)" Z. Cai, G. Xu, (ed.), Tsinghua University Press, China, 2004. Pages 128-148.
- J. Cai, Section 4.2 Neural Computation, Section 4.3 Fuzzy Computation in "Artificial Intelligence: Principles and Applications(graduate edition)" Z. Cai, G. Xu, (ed.), Tsinghua University Press, China, 2003. Pages: 126-148.

Journals

- J. Durkin, J. Cai, Z. Cai, Decision Tree Technique and Its Current Research, Journal of Control Engineering of China, 2005, 12(1):15-18, 21.
- J. Cai, J. Durkin, Q. Cai. Opportunities, Applications and Suggestions for Data Mining. Journal of Computer Science of China, 2002, 29(9):225-228.

Conferences

- J. Cai, J. Durkin, Use of Expert Knowledge for Decision Tree Pruning, AAAI 2005 Conference, Pittsburgh, Pennsylvania, July 9-13, 2005. Pages 1600-1601.
- J. Cai, J. Durkin, Q. Cai CC4.5: Cost-Sensitive Decision Tree Pruning, Data Mining 2005 Conference, Skiathos, Greece, May 25 - 27, 2005. Pages 239-245.
- Z. Cai, Z. Duan, J. Cai, X. Zou, J. Yu, A Multiple Particle Filters Method for Fault Diagnosis of Mobile Robot Dead-Reckoning System, 2005 IEEE/RSJ International Conference on Intelligent Robots and Systems, Edmonton, Alberta, Canada, August 2 - 6, 2005. Pages 480-485

- T. Gong, J. Cai, Z. Cai, A Coding and Control Mechanism of Natural Computation. Proceedings of 2003 IEEE 18th International Symposium on Intelligent Control(ISIC), Houston, Texas, October 5-8, 2003. Pages 727-732.

APPENDIX B

PRUNING PROGRAM for KBP1.0-1 and KBP1.0-2

C4.5 can be freely downloaded and freely used for research.
You can get C4.5 from Quinlan's homepage:
http://www.rulequest.com/Personal/.

KBP1.0 uses the same method as that of C4.5 to construct
the original decision tree, with slight code modifications
to support the KBP1.0 pruning technique.

The pruning code in C4.5 was modified to realize the pruning
methods in KBP1.0. The big difference between KBP1.0's
pruning code and C4.5's pruning code is that the pruning
method in C4.5's is based on error, while the pruning method
in KBP1.0 is based on cost, or on both error and cost. In
addition, C4.5's pruning code can only calculate the
misclassification error during pruning, while KBP1.0's
pruning code can calculate both the misclassification error
and misclassification cost during pruning.

In Appendix A, B, and C, the source codes are not complete because
of the license and rules for redestribution for C4.5.

```
/*****************************************************************/
/*        */
/* KBP1.0-1,2 pruning method  */
/* ------------------------------------------       */
/*        */
/*****************************************************************/




void TestPruned(T, raw)
/*      -----  */
    Tree T;
    Tree raw;
{
    float CalculateCostTest(), ComputeCostAndError();
    void  ClearTree();


    printf("Tree before pruning:\n");
    /*ClearTree(raw);
    InitialiseWeights();
    showPruningDistr(raw, 0, MaxItem, 0, true);*/
    printf("\n Cost before pruning for testing data: %f \n",
    CalculateCostTest(raw, true));
    //PrintTree(raw);
```

```
    printf("Tree after pruning:\n");
    /*ClearTree(T);
    InitialiseWeights();
    showPruningDistr(T, 0, MaxItem, 0, true);*/
    printf("\n Cost after pruning for testing data: %f \n",
    CalculateCostTest(T, true));
    //PrintTree(T);
}



/*****************************************************************************/
/*  */
/* Compute the costs and errors of pruning a given subtree ST  */
/*  */
/*****************************************************************************/


float ComputeCostAndError(T, ST, Fp, Lp, Sh, UpdateTree)
/*    --------------  */
    Tree T;
    Tree ST; //subtree
    ItemNo Fp, Lp;
    short Sh;
    Boolean UpdateTree;
{
```

```
    ItemNo i, Kp, Ep, Group(); //Group defined in build.c
    ItemCount Cases, KnownCases, *LocalClassDist, LeafErrors,
    CountItems(), Factor;
    DiscrValue v, MaxBr, tmpBest, tmpBestLeaf;
    ClassNo c, BestClass, tmpLeaf;
    Boolean PrevAllKnown;
    float cost = 0, *classDist, *fork_costs, CalculateCost(),
    TreeCost, BranchCost,
*leaf_costs, tmpCost, LeafCost;
    Tree *tmpBranch, *tmpST;
    short tmpNodeType;

    if ( ! ST->NodeType ) /*  leaf  */
    {   //LocalVerbosity(1)
{ printf("Leaf node! Items: %f\n", ST->Items);
}

if ( UpdateTree )
{
    LocalVerbosity(1)
    {
Intab(Sh);
     printf("%s (%.2f:%.2f/%.2f)\n", ClassName[ST->Leaf],
     ST->Items, LeafErrors, ST->Errors);
    }
```

```
}


return 0;
    }


    //LocalVerbosity(1)
    { printf("Node type: %d, Items: %f, Forks: %hd \n",
              ST->NodeType, ST->Items, ST->Forks);
    }


    Kp = Group(0, Fp, Lp, ST) + 1;
    KnownCases = CountItems(Kp, Lp);


    PrevAllKnown = AllKnown;
    if ( Kp != Fp ) AllKnown = false;


    fork_costs = (float *) calloc (ST->Forks + 1, sizeof(float));
    leaf_costs = (float *) calloc (MaxClass + 2, sizeof(float));
    tmpBranch = (char *) calloc (ST->Forks, sizeof (Tree*));
    memcpy((char *)tmpBranch, (char *)ST->Branch, ST->Forks * sizeof(Tree*));


/*Here, unknown data are disregarded.*/
/*   ForEach(v, 1, ST->Forks)
    {
Ep = Group(v, Kp, Lp, ST);
```

```
if ( Kp <= Ep )
{
    ComputeCostAndError(T, ST->Branch[v], Fp, Ep, Sh+1, UpdateTree);
}
    }*/


/*Unknown data are taken into account*/
    ForEach(v, 1, ST->Forks)
    {
Ep = Group(v, Kp, Lp, ST);

if ( Kp <= Ep )
{
    Factor = CountItems(Kp, Ep) / KnownCases;

    ForEach(i, Fp, Kp-1)
    {
Weight[i] *= Factor;
    }

    ComputeCostAndError(T, ST->Branch[v], Fp, Ep, Sh+1, UpdateTree);

    Group(0, Fp, Ep, ST);
```

```
    ForEach(i, Fp, Kp-1)
    {
Weight[i] /= Factor;
    }
}
    }



    TreeCost = CalculateCost(T, false);  //calculate cost before pruning.
    printf("Tree Cost: %f  \t", TreeCost);
    tmpNodeType = ST->NodeType;
    tmpLeaf = ST->Leaf;
    ST->NodeType = 0;
    //ST->Forks = 0;
    //cost improvement by replace ST with a leaf
    ForEach(c, 0, MaxClass)
    {
ST->Leaf = c;
     leaf_costs[c] = CalculateCost(T, true) - TreeCost;
printf("***leaf_costs[%hd]: %f***", c, leaf_costs[c]);
    }
    ST->NodeType = tmpNodeType;
    ST->Leaf = tmpLeaf;
    tmpBestLeaf = 0;
    LeafCost = leaf_costs[tmpBestLeaf];
```

```
    ForEach(c, 0, MaxClass)
    {
if (leaf_costs[c] < LeafCost)
{   LeafCost = leaf_costs[c];
    tmpBestLeaf = c;
}
    }
    printf("Leaf Class: %hd, Items: %f, Forks: %hd, Leaf Cost - Tree Cost: %f  \n",
           T->Leaf, ST->Items, ST->Forks, LeafCost);

    tmpST = (Tree*) calloc(1, sizeof(TreeRec));
    memcpy((char *)tmpST, (char *) ST, sizeof(TreeRec));

    ForEach(v, 1, ST->Forks)
    {   printf("\n# of branches %d: \n", v);
Ep = Group(v, Kp, Lp, ST);
fork_costs[v] = 32768;
//if ( Kp <= Ep )
//{
    memcpy((char *) ST, (char *) ST->Branch[v], sizeof(TreeRec));
        BranchCost = CalculateCost (T, false);
    printf("Tree Cost: %f \n", TreeCost);
    printf("Branch Cost: %f \t Branch items: %f\t Branch Forks: %hd ",
                BranchCost, ST->Items, ST->Forks);
    fork_costs[v] = BranchCost - TreeCost;
```

```
    memcpy((char *) ST, (char *) tmpST, sizeof(TreeRec));
//}


Group(0, Fp, Ep, ST);
    }


    tmpBest = 1;
    tmpCost = fork_costs[tmpBest];
    ForEach(v, 1, ST->Forks)
    {
if (fork_costs[v] < tmpCost)
{   tmpCost = fork_costs[v];
    tmpBest = v;
}
    }
    if ( (LeafCost <= 0) && (LeafCost <= tmpCost) )
    {
LocalVerbosity(1)
{
    Intab(Sh);
    printf("Replaced with leaf %s\n", ClassName[tmpBestLeaf]);
}
printf("---------Replaced with leaf %s, LeafCost: %f\n",
               ClassName[tmpBestLeaf], LeafCost);
ST->NodeType = 0;
```

```
   ST->Leaf = tmpBestLeaf;
ST->Forks = 0;
Changed = true;
    }
    else if ((tmpCost <= 0) && (LeafCost > tmpCost))
    { LocalVerbosity(1)
{
    Intab(Sh);
    printf("Replaced with branch %d\n", tmpBest);
}

AllKnown = PrevAllKnown;
memcpy((char *) ST, (char *) ST->Branch[tmpBest], sizeof(TreeRec));
   printf("---------------Replaced with branch %d, BranchCost: %f\n",
               tmpBest, fork_costs[tmpBest]);
Changed = true;
    }
    else
Changed = false;

    AllKnown = PrevAllKnown;

    if ( ! UpdateTree )
    {
//free(LocalClassDist);
```

```
//free(classDist);
if (fork_costs != NULL) free(fork_costs);

return TreeCost;
    }

    AllKnown = PrevAllKnown;
   if (fork_costs) free(fork_costs);
   if (leaf_costs) free(leaf_costs);
   if (tmpST) free(tmpST);

    return 0;
}

/************************************************************************/
/*  */
/* Calculate the costs in a given subtree  */
/*  */
/************************************************************************/

float    CalculateCost(T, print)
    Tree T;
    Boolean print;
{
```

```
    ClassNo RealClass, PrunedClass, Category();
    float cost = 0;
    ItemNo *ConfusionMat, i, j, PrunedErrors;
    void PrintConfusionMatrix();

    ConfusionMat = (ItemNo *) calloc((MaxClass+1)*(MaxClass+1), sizeof(ItemNo));

    PrunedErrors = 0;

    ForEach(i, 0, MaxItem)
    {
RealClass = Class(Item[i]);
PrunedClass = Category(Item[i], T);

if ( PrunedClass != RealClass )
{
    PrunedErrors++;
}
ConfusionMat[RealClass*(MaxClass+1)+PrunedClass]++;
    }

    ForEach(i, 0, MaxClass)
ForEach(j, 0, MaxClass)
    {
cost += Cost[ i * (MaxClass + 1) + j] * ConfusionMat[i * (MaxClass+1) + j] ;
```

```
    }
    cost /= (float) (MaxItem + 1);  //normalization
    printf("Errors: %d \t", PrunedErrors);
    if (print)
PrintConfusionMatrix(ConfusionMat);
    cost=Cost_Weight * cost + Error_Weight * PrunedErrors / (float) (MaxItem + 1);

    free(ConfusionMat);
    return cost;
}


/*************************************************************************/
/*  */
/* Calculate the costs in a given subtree  */
/*  */
/*************************************************************************/

float    CalculateCostTest(T, print)
    Tree T;
    Boolean print;
{
    ClassNo RealClass, PrunedClass, Category();
    float cost = 0;
    ItemNo *ConfusionMat, i, j, PrunedErrors;
```

```
    void PrintConfusionMatrix();


    ConfusionMat = (ItemNo *) calloc((MaxClass+1)*(MaxClass+1), sizeof(ItemNo));


    PrunedErrors = 0;


    ForEach(i, 0, MaxItem)
    {
RealClass = Class(Item[i]);
PrunedClass = Category(Item[i], T);


if ( PrunedClass != RealClass )
{
    PrunedErrors++;
}
ConfusionMat[RealClass*(MaxClass+1)+PrunedClass]++;
    }


    ForEach(i, 0, MaxClass)
ForEach(j, 0, MaxClass)
    {
cost += Cost[ i * (MaxClass + 1) + j] * ConfusionMat[i * (MaxClass+1) + j] ;
    }
    cost /= (float) (MaxItem + 1);  //normalization
    printf("Errors: %d \t", PrunedErrors);
```

```
    if (print)
PrintConfusionMatrix(ConfusionMat);



    free(ConfusionMat);
    return cost;
}


/*************************************************************************/
/*  */
/* Initialize pruning data distribution in a decision tree.  */
/*  */
/*************************************************************************/


void ClearTree(T)
    Tree T;
{
    int v;


    T->Items = 0;
    T->Errors = 0;
    ForEach(v, 0, MaxClass)
     T->ClassDist[v] = 0;


    if (T->NodeType != 0)
```

```
      ForEach(v, 1, T->Forks)
ClearTree(T->Branch[v]);
    else T->Forks = 0;
    return;
}



/*************************************************************************/
/*  */
/* Show pruning data distribution in a decision tree. comparable to */
/* classify in classify.c    */
/*  */
/*************************************************************************/


showPruningDistr(T, Fp, Lp, Sh, UpdateTree)
    Tree T;
    ItemNo Fp, Lp;
    short Sh;
    Boolean UpdateTree;
{
    DiscrValue v, dv;
    float Cv;
    Attribute a;
    ClassNo c, BestClass;
    ItemNo i, Kp, Ep, Group();
```

```
    ItemCount Cases, KnownCases, count, LeafErrors,
              *LocalClassDist, CountItems(), Factor;
    Boolean PrevAllKnown;

   /*  Generate the class frequency distribution  */
    Cases = CountItems(Fp, Lp);
    LocalClassDist = (ItemCount *) calloc(MaxClass+1, sizeof(ItemCount));
    ForEach(i, Fp, Lp)
    {
LocalClassDist[ Class(Item[i]) ] += Weight[i];
    }

    /*  Find the most frequent class and update the tree  */

    BestClass = 0;
    ForEach(c, 0, MaxClass)
    {
if ( LocalClassDist[c] > LocalClassDist[BestClass] )
{
    BestClass = c;
}
    }
    LeafErrors = Cases - LocalClassDist[BestClass];

    if ( UpdateTree )
```

```
    {
T->Items = Cases;
T->Leaf  = BestClass;
memcpy(T->ClassDist, LocalClassDist, (MaxClass + 1) * sizeof(ItemCount));
    }


    if ( ! T->NodeType ) /*  leaf  */
    { T->Errors = LeafErrors;
if ( UpdateTree )
{
    LocalVerbosity(1)
    {
Intab(Sh);
     printf("%s (%.2f:%.2f/%.2f)\n", ClassName[T->Leaf],
     T->Items, LeafErrors, T->Errors);
    }
}
free(LocalClassDist);
return;
    }


    Kp = Group(0, Fp, Lp, T) + 1;
    KnownCases = CountItems(Kp, Lp);


    PrevAllKnown = AllKnown;
```

```
    if ( Kp != Fp ) AllKnown = false;


    ForEach(v, 1, T->Forks)
    {
Ep = Group(v, Kp, Lp, T);

if ( Kp <= Ep )
{
    Factor = CountItems(Kp, Ep) / KnownCases;

    ForEach(i, Fp, Kp-1)
    {
Weight[i] *= Factor;
    }

    showPruningDistr(T->Branch[v], Fp, Ep, Sh+1, UpdateTree);

    Group(0, Fp, Ep, T);
    ForEach(i, Fp, Kp-1)
    {
Weight[i] /= Factor;
    }
}
    }
```

```
    AllKnown = PrevAllKnown;


    free(LocalClassDist);

    return;

}
```

APPENDIX C

PRUNING PROGRAM for KBP1.0-3

C4.5 can be freely downloaded and freely used for research.
You can get C4.5 from Quinlan's homepage:
http://www.rulequest.com/Personal/.

KBP1.0 uses the same method as that of C4.5 to construct
the original decision tree, with slight code modifications
to support the KBP1.0 pruning technique.

The pruning code in C4.5 was modified to realize the pruning
methods in KBP1.0. The big difference between KBP1.0's
pruning code and C4.5's pruning code is that the pruning
method in C4.5's is based on error, while the pruning method
in KBP1.0 is based on cost, or on both error and cost. In
addition, C4.5's pruning code can only calculate the
misclassification error during pruning, while KBP1.0's
pruning code can calculate both the misclassification error
and misclassification cost during pruning.

In Appendix A, B, and C, the source codes are not complete because
of the license and rules for redestribution for C4.5.

```
/*********************************************************/
/*  */
/* KBP1.0-3(threshold) pruning method  */
/* ------------------------------------------- */
/*  */
/*********************************************************/




/*****************************************************************/
/*  */
/*  Test tree T  */
/*  */
/*****************************************************************/



void TestPruned(T, raw)
/*      -----  */
    Tree T;
    Tree raw;
{
    float CalculateCost_Test(), CalculateError();
    void  ClearTree();
```

```
    printf("Testing data for the tree before pruning:\n");
    /*ClearTree(raw);
    InitialiseWeights();
    showPruningDistr(raw, 0, MaxItem, 0, true);*/
    printf("\n Cost before pruning for testing data: %f \n",
CalculateCost_Test(raw, true));
    printf("\n Error before pruning for testing data: %f \n",
CalculateError(raw, false));
    //PrintTree(raw);

    printf("Testing data for the tree after pruning:\n");
    /*ClearTree(T);
    InitialiseWeights();
    showPruningDistr(T, 0, MaxItem, 0, true);*/
    printf("\n Cost after pruning for testing data: %f \n",
CalculateCost_Test(T, true));
    printf("\n Error after pruning for testing data: %f \n",
CalculateError(T, false));
    //PrintTree(T);
}

/*****************************************************************************/
/* */
/* Compute the costs and errors of pruning a given subtree ST */
```

```
/* */

/*************************************************************************/


float ComputeCostAndError(T, ST, Fp, Lp, Sh, UpdateTree)

/*    --------------  */

    Tree T;

    Tree ST; //subtree

    ItemNo Fp, Lp;

    short Sh;

    Boolean UpdateTree;

{

    ItemNo i, Kp, Ep, Group();  //Group defined in build.c

    ItemCount Cases, KnownCases, *LocalClassDist, LeafErrors,

CountItems(), Factor;

    DiscrValue v, BestLeaf, BestBranch;

    ClassNo c, c1, BestClass, tmpLeaf;

    Boolean PrevAllKnown, *LeafPrune_Flag, *BranchPrune_Flag;

    float cost = 0, *fork_costs, *fork_errors, CalculateError(),

CalculateCost(), TreeCost,

BranchCost, TreeError, BranchError, *leaf_costs, *leaf_errors,

LeafCost, LeafError;

    Tree *tmpBranch, *tmpST;

    short tmpNodeType;


    if ( ! ST->NodeType ) /*  leaf  */
```

```
    {   printf("Leaf node! Items: %f\n", ST->Items);
/*LocalVerbosity(1)
{ printf("Leaf node! Items: %f\n", ST->Items);
}*/

if ( UpdateTree )
{
    LocalVerbosity(1)
    {
Intab(Sh);
     printf("%s (%.2f:%.2f/%.2f)\n", ClassName[ST->Leaf],
     ST->Items, LeafErrors, ST->Errors);
    }
}

return 0;
    }

    printf("Node type: %d, Items: %f, Forks: %hd \n",
ST->NodeType, ST->Items, ST->Forks);

    Kp = Group(0, Fp, Lp, ST) + 1;
    KnownCases = CountItems(Kp, Lp);

    PrevAllKnown = AllKnown;
```

```
    if ( Kp != Fp ) AllKnown = false;


/*Unknown data are taken into account*/

    ForEach(v, 1, ST->Forks)

    {

Ep = Group(v, Kp, Lp, ST);


if ( Kp <= Ep )

{

    Factor = CountItems(Kp, Ep) / KnownCases;


    ForEach(i, Fp, Kp-1)

    {

Weight[i] *= Factor;

    }


    ComputeCostAndError(T, ST->Branch[v], Fp,

Ep, Sh+1, UpdateTree);


    Group(0, Fp, Ep, ST);

    ForEach(i, Fp, Kp-1)

    {

Weight[i] /= Factor;

    }

}
```

```
    }

    fork_costs = (float *) calloc (ST->Forks + 1, sizeof(float));
    fork_errors = (float *) calloc (ST->Forks + 1, sizeof(float));
    leaf_costs = (float *) calloc (MaxClass + 2, sizeof(float));
    leaf_errors = (float *) calloc (MaxClass + 2, sizeof(float));
    tmpBranch = (Tree *) calloc (ST->Forks, sizeof (Tree*));
    memcpy((char *)tmpBranch, (char *)ST->Branch, ST->Forks * sizeof(Tree*));

    TreeCost = CalculateCost(T, false);  //calculate cost before pruning.
    TreeError = CalculateError(T, false);  //calculate error before pruning.
    printf("Tree Cost before pruning: %f  \t", TreeCost);
    printf("Tree Error before pruning: %f  \t", TreeError);
    tmpNodeType = ST->NodeType;
    tmpLeaf = ST->Leaf;

    //cost improvement by replace ST with a leaf
    LeafPrune_Flag = (Boolean *) calloc (MaxClass + 2, sizeof(Boolean));
    ST->NodeType = 0;
    ForEach(c, 0, MaxClass)
    {
ST->Leaf = c;
printf("Leaf Class: %hd\n", ST->Leaf);
     leaf_costs[c] = CalculateCost(T, true) - TreeCost;
  leaf_errors[c] = CalculateError(T, false) - TreeError;
```

```
//get the leaves that is good for pruning
        if ((leaf_costs[c] <= 0) && (leaf_errors[c] <= 0))
LeafPrune_Flag[c] = true;
else if ((leaf_costs[c] <= 0) && (leaf_errors[c] > 0) &&
(leaf_errors[c] <= Error_Thres * TreeError))
LeafPrune_Flag[c] = true;
else if ((leaf_costs[c] > 0) && (leaf_errors[c] <= 0) &&
(leaf_costs[c] <= Cost_Thres * TreeCost))
LeafPrune_Flag[c] = true;
else LeafPrune_Flag[c] = false;
printf("***leaf_costs[%hd]: %f***", c, leaf_costs[c]);
printf("***leaf_errors[%hd]: %f***; LeafPrune_Flag: %s.\n", c,
leaf_errors[c], LeafPrune_Flag[c]== true?"true":"false");
    }
    ST->NodeType = tmpNodeType;
    ST->Leaf = tmpLeaf;

    //pruning conditions for leaves
    c = 0;
    while ((LeafPrune_Flag[c] == false) && (c <= MaxClass))
c++;
    if (LeafPrune_Flag[c] == true)
    { BestLeaf = c;
     LeafCost = leaf_costs[BestLeaf];
        ForEach(c, 0, MaxClass)
```

```
     {
if ((leaf_costs[c] < LeafCost) && (LeafPrune_Flag[c] == true))
{   LeafCost = leaf_costs[c];
    BestLeaf = c;
}
     }
     //printf("Leaf Class: %hd, Items: %f, Forks: %hd,
Leaf Cost - Tree Cost: %f  \n",
ST->Leaf, ST->Items, ST->Forks, LeafCost);
    }
    else BestLeaf = -1;
    printf("BestLeaf after comparing all leaves: %hd\n", BestLeaf);

    tmpST = (Tree*) calloc(1, sizeof(TreeRec));
    memcpy((char *)tmpST, (char *) ST, sizeof(TreeRec));

    BranchPrune_Flag = (Boolean *) calloc (ST->Forks + 1, sizeof(Boolean));
    ForEach(v, 1, ST->Forks)
    {   printf("\n# of branches %d: \n", v);
fork_costs[v] = 32768;
memcpy((char *) ST, (char *) ST->Branch[v], sizeof(TreeRec));
    fork_costs[v] = CalculateCost (T, false) - TreeCost;
fork_errors[v] = CalculateError(T, false) - TreeError;
//get the branches that is good for pruning
if ((fork_costs[v] <= 0) && (fork_errors[v] <= 0))
```

```
BranchPrune_Flag[v] = true;
else if ( (fork_costs[v] <= 0) && (fork_errors[v] > 0) &&
(fork_errors[v] <= Error_Thres * TreeError) )
BranchPrune_Flag[v] = true;
else if ( (fork_costs[v] > 0) && (fork_errors[v] <= 0) &&
(fork_costs[v] <= Cost_Thres * TreeCost) )
BranchPrune_Flag[v] = true;
else BranchPrune_Flag[v] = false;
//printf("Tree Cost: %f ; Tree Errors: %f \n", TreeCost, TreeError);
printf("Branch Cost: %f \t Branch errors: %f\t Branch items:
%f\t Branch Forks: %hd \n",
fork_costs[v], fork_errors[v], ST->Items, ST->Forks);
memcpy((char *) ST, (char *) tmpST, sizeof(TreeRec));
    }


    //pruning conditions for branches
    v = 1;
    while ((BranchPrune_Flag[v] == false) && (v <= ST->Forks))
v++;
    if (BranchPrune_Flag[v] == true)
    { BestBranch = v;
     BranchCost = fork_costs[BestBranch];
        ForEach(v, 1, ST->Forks)
     {
if ((fork_costs[v] < BranchCost) && (BranchPrune_Flag[v] == true))
```

```
{   BranchCost = fork_costs[v];
    BestBranch = v;
}
     }
     printf("Branch Class: %hd, Items: %f, Forks: %hd,
Branch Cost - Tree Cost: %f  \n",
ST->Leaf, ST->Items, ST->Forks, BranchCost);
    }
    else BestBranch = -1;
    printf("BestBranch after comparing all leaves: %hd\n", BestBranch);

    if ( ((BestLeaf >= 0) && (BestBranch == -1)) || ((BestLeaf >= 0) &&
(BestBranch >= 0) && (leaf_costs[BestLeaf] <= fork_costs[BestBranch])) )
    {
LocalVerbosity(1)
{
    Intab(Sh);
    printf("Replaced with leaf %s\n", ClassName[BestLeaf]);
}
printf("----Replaced with leaf %s, LeafCost: %f\n", ClassName[BestLeaf],
leaf_costs[BestLeaf]);
ST->NodeType = 0;
   ST->Leaf = BestLeaf;
ST->Forks = 0;
Changed = true;
```

```
    }
    else if ( ((BestLeaf == -1) && (BestBranch >= 0)) || ((BestLeaf >= 0) &&
(BestBranch >= 0) && (leaf_costs[BestLeaf] > fork_costs[BestBranch])) )
    { LocalVerbosity(1)
{
    Intab(Sh);
    printf("Replaced with branch %d\n", BestBranch);
}

AllKnown = PrevAllKnown;
memcpy((char *) ST, (char *) ST->Branch[BestBranch], sizeof(TreeRec));
   printf("-------------------------Replaced with branch %d, BranchCost: %f\n",
BestBranch, fork_costs[BestBranch]);
Changed = true;
    }
    else
     Changed = false;

    AllKnown = PrevAllKnown;

    if ( ! UpdateTree )
    {
//free(LocalClassDist);
if (fork_costs != NULL) free(fork_costs);
return 0;
```

```
    }


    AllKnown = PrevAllKnown;
    if (fork_costs) free(fork_costs);
    if (leaf_costs) free(leaf_costs);
    if (leaf_errors) free(leaf_errors);
    if (fork_errors) free(fork_errors);
    if (LeafPrune_Flag) free(LeafPrune_Flag);
    if (BranchPrune_Flag) free(BranchPrune_Flag);
    if (tmpST) free(tmpST);
    if (tmpBranch) free (tmpBranch);
    return 0;
}



/*****************************************************************/
/*  */
/* Calculate the cost of a given subtree  */
/*  */
/*****************************************************************/


float    CalculateCost(T, print)
    Tree T;
    Boolean print;
{
```

```
    ClassNo RealClass, PrunedClass, Category();
    float cost = 0;
    ItemNo *ConfusionMat, i, j, PrunedErrors;
    void PrintConfusionMatrix(), PrintDescription();

    ConfusionMat = (ItemNo *) calloc((MaxClass+1)*(MaxClass+1), sizeof(ItemNo));

    PrunedErrors = 0;

    ForEach(i, 0, MaxItem)
    {
RealClass = Class(Item[i]);
PrunedClass = Category(Item[i], T);
    //PrintDescription(Item[i]);
  //printf("Real Class: %hd, PrunedClass %hd\n", RealClass, PrunedClass);

if ( PrunedClass != RealClass )
{   if (print) {}
    PrunedErrors++;
}
ConfusionMat[RealClass*(MaxClass+1)+PrunedClass]++;
    }

    ForEach(i, 0, MaxClass)
ForEach(j, 0, MaxClass)
```

```
    {
cost += Cost[ i * (MaxClass + 1) + j] * ConfusionMat[i * (MaxClass+1) + j] ;
    }
    cost /= (float) (MaxItem + 1);  //normalization
    if (print)
PrintConfusionMatrix(ConfusionMat);
    cost = Cost_Weight*cost+Error_Weight*PrunedErrors/(float)(MaxItem + 1);

    free(ConfusionMat);
    //printf("cost returned from CalculateCost: %f\n", cost);
    return cost;
}

/*****************************************************************/
/*  */
/* Calculate the cost of a given subtree for testing data  */
/*  */
/*****************************************************************/

float    CalculateCost_Test(T, print)
    Tree T;
    Boolean print;
{
    ClassNo RealClass, PrunedClass, Category();
    float cost = 0;
```

```
    ItemNo *ConfusionMat, i, j, PrunedErrors;
    void PrintConfusionMatrix(), PrintDescription();

    ConfusionMat = (ItemNo *) calloc((MaxClass+1)*(MaxClass+1), sizeof(ItemNo));

    PrunedErrors = 0;

    ForEach(i, 0, MaxItem)
    {
RealClass = Class(Item[i]);
PrunedClass = Category(Item[i], T);
    //PrintDescription(Item[i]);
  //printf("Real Class: %hd, PrunedClass %hd\n", RealClass, PrunedClass);

if ( PrunedClass != RealClass )
{   if (print) {}
    PrunedErrors++;
}
ConfusionMat[RealClass*(MaxClass+1)+PrunedClass]++;
    }

    ForEach(i, 0, MaxClass)
ForEach(j, 0, MaxClass)
    {
cost += Cost[ i * (MaxClass + 1) + j] * ConfusionMat[i * (MaxClass+1) + j] ;
```

```
    }
    cost /= (float) (MaxItem + 1);  //normalization
    if (print)
PrintConfusionMatrix(ConfusionMat);
    //cost=Cost_Weight*cost+Error_Weight*PrunedErrors/(float)(MaxItem+1);

    free(ConfusionMat);
    //printf("cost returned from CalculateCost: %f\n", cost);
    return cost;
}

/*********************************************************/
/*  */
/* Calculate errors of a given subtree  */
/*  */
/*********************************************************/

float    CalculateError(T, print)
    Tree T;
    Boolean print;
{
    ClassNo RealClass, PrunedClass, Category();
    float error = 0;
    ItemNo *ConfusionMat, i, j, PrunedErrors;
```

```
    void PrintConfusionMatrix();


    ConfusionMat = (ItemNo *) calloc((MaxClass+1)*(MaxClass+1), sizeof(ItemNo));


    PrunedErrors = 0;


    ForEach(i, 0, MaxItem)
    {
RealClass = Class(Item[i]);
PrunedClass = Category(Item[i], T);


if ( PrunedClass != RealClass )
{
    PrunedErrors++;
}
ConfusionMat[RealClass*(MaxClass+1)+PrunedClass]++;
    }


    ForEach(i, 0, MaxClass)
ForEach(j, 0, MaxClass)
    {   if (i != j)
error += ConfusionMat[i * (MaxClass+1) + j] ;
    }


    if (print)
```

```
PrintConfusionMatrix(ConfusionMat);


    free(ConfusionMat);
    //printf("error returned from CalculateError: %f\n", error);
    return error;
}



/*****************************************************************/
/*  */
/* Initialize pruning data distribution in a decision tree. */
/*  */
/*****************************************************************/


void ClearTree(T)
    Tree T;
{
    int v;


    T->Items = 0;
    T->Errors = 0;
    ForEach(v, 0, MaxClass)
     T->ClassDist[v] = 0;


    if (T->NodeType != 0)
```

```
      ForEach(v, 1, T->Forks)
ClearTree(T->Branch[v]);
    else T->Forks = 0;
    return;
}



/*************************************************************************/
/*  */
/* Show pruning data distribution in a decision tree. comparable to */
/* classify in classify.c    */
/*  */
/*************************************************************************/


showPruningDistr(T, Fp, Lp, Sh, UpdateTree)
    Tree T;
    ItemNo Fp, Lp;
    short Sh;
    Boolean UpdateTree;
{
    DiscrValue v, dv;
    float Cv;
    Attribute a;
    ClassNo c, BestClass;
    ItemNo i, Kp, Ep, Group();
```

```
    ItemCount Cases, KnownCases, count, LeafErrors,
*LocalClassDist, CountItems(), Factor;
    Boolean PrevAllKnown;

   //  Generate the class frequency distribution
    Cases = CountItems(Fp, Lp);
    LocalClassDist = (ItemCount *) calloc(MaxClass+1, sizeof(ItemCount));
    ForEach(i, Fp, Lp)
    {
LocalClassDist[ Class(Item[i]) ] += Weight[i];
    }

    /*  Find the most frequent class and update the tree  */

    BestClass = 0;
    ForEach(c, 0, MaxClass)
    {
if ( LocalClassDist[c] > LocalClassDist[BestClass] )
{
    BestClass = c;
}
    }
    LeafErrors = Cases - LocalClassDist[BestClass];

    if ( UpdateTree )
```

```
    {
T->Items = Cases;
T->Leaf  = BestClass;
memcpy(T->ClassDist, LocalClassDist, (MaxClass + 1) * sizeof(ItemCount));
    }


    if ( ! T->NodeType ) /*  leaf  */
    { T->Errors = LeafErrors;
if ( UpdateTree )
{
    LocalVerbosity(1)
    {
Intab(Sh);
     printf("%s (%.2f:%.2f/%.2f)\n", ClassName[T->Leaf],
     T->Items, LeafErrors, T->Errors);
    }
}
free(LocalClassDist);
return;
    }


    Kp = Group(0, Fp, Lp, T) + 1;
    KnownCases = CountItems(Kp, Lp);


    PrevAllKnown = AllKnown;
```

```
    if ( Kp != Fp ) AllKnown = false;


    ForEach(v, 1, T->Forks)
    {
Ep = Group(v, Kp, Lp, T);

if ( Kp <= Ep )
{
    Factor = CountItems(Kp, Ep) / KnownCases;

    ForEach(i, Fp, Kp-1)
    {
Weight[i] *= Factor;
    }

    showPruningDistr(T->Branch[v], Fp, Ep, Sh+1, UpdateTree);

    Group(0, Fp, Ep, T);
    ForEach(i, Fp, Kp-1)
    {
Weight[i] /= Factor;
    }
}
    }
```

```
    AllKnown = PrevAllKnown;


    free(LocalClassDist);

    return;


}



void PrintDescription(CaseDesc)

    Description CaseDesc;

{   int i;

    String name, CopyString();

    short Dv;

    float Cv;


    ForEach(i, 0, MaxAtt)

    {

if ( MaxAttVal[i] || SpecialStatus[i] == DISCRETE )

    {

/*  Discrete value  */

Dv = DVal(CaseDesc,i);

        if ( Dv == 0)

{

    printf ("%s", "?,");

}
```

```
        else
        {
    name = CopyString(AttValName[i][Dv]);
    printf ("%s,", name);
        }
    }
    else
    {
/*  Continuous value  */
Cv = CVal(CaseDesc,i);
        if ( Cv == Unknown )
    printf ("%s", "?,");
        else
    printf ("%g,", Cv);
    }
    }

    Dv = Class(CaseDesc);
    printf("%s.\n", ClassName[Dv]);
    return;
}
```

APPENDIX D

APPENDIX C: PRUNING PROGRAM for KBP1.0-4

C4.5 can be freely downloaded and freely used for research.
You can get C4.5 from Quinlan's homepage:
http://www.rulequest.com/Personal/.

KBP1.0 uses the same method as that of C4.5 to construct
the original decision tree, with slight code modifications
to support the KBP1.0 pruning technique.

The pruning code in C4.5 was modified to realize the pruning
methods in KBP1.0. The big difference between KBP1.0's
pruning code and C4.5's pruning code is that the pruning
method in C4.5's is based on error, while the pruning method
in KBP1.0 is based on cost, or on both error and cost. In
addition, C4.5's pruning code can only calculate the
misclassification error during pruning, while KBP1.0's
pruning code can calculate both the misclassification error
and misclassification cost during pruning.

In Appendix A, B, and C, the source codes are not complete because
of the license and rules for redestribution for C4.5.

```
/*****************************************************************/
/*  */
/* KBP1.0-4(pessimistic cost pruning) pruning method  */
/* ---------------------------------------------- */
/*  */
/*****************************************************************/




/*************************************************************************/
/*  */
/*  Test tree T  */
/*  */
/*************************************************************************/


void TestPruned(T, raw)
/*      -----  */
    Tree T;
    Tree raw;
{
    float CalculateCostTest();
```

```
    printf("Tree before pruning on testing data:\n");
    printf("\n Cost before pruning for testing data: %f \n",
CalculateCostTest(raw, Cost, true));

    printf("Tree after pruning on testing data:\n");
    printf("\n Cost after pruning for testing data: %f \n",
CalculateCostTest(T, Cost, true));
}

/*************************************************************************/
/*  */
/*  Calculate number of leaves in subtree T  */
/*  */
/*************************************************************************/

int LeafCount(T)
    Tree T;
{   int v, n=0;

    if ( ! T->NodeType ) /*  leaf  */
return 1;
    else
    { ForEach(v, 1, T->Forks)
n += LeafCount(T->Branch[v]);
return n;
```

```
    }
}


/*************************************************************************/
/*  */
/* Compute errors of pruning a given subtree ST      */
/*  */
/*************************************************************************/


float ComputeCostAndError(T, ST, Fp, Lp, Sh, UpdateTree)
/*    --------------  */
    Tree T;
    Tree ST; //subtree
    ItemNo Fp, Lp;
    short Sh;
    Boolean UpdateTree;
{
    ItemNo i, Kp, Ep, Group(); //Group defined in build.c
    ItemCount Cases, KnownCases, *LocalClassDist, LeafError,
CountItems(), Factor;
    DiscrValue v, MaxBr, tmpBest, tmpBestLeaf;
    ClassNo c, BestClass, tmpLeaf;
    Boolean PrevAllKnown, firstLeaf;
    float cost = 0, *classDist, *fork_errors, CalculateCost(),
```

```
TreeError, TreeCost, BranchCost,
*leaf_errors, *leaf_costs, tmpCost, LeafCost, CalculateError();
    Tree *tmpBranch, *tmpST;
    short tmpNodeType;

    if ( ! ST->NodeType ) /*  leaf  */
    {   //LocalVerbosity(1)
{ printf("Leaf node! Items: %f\n", ST->Items);
}

if ( UpdateTree )
{
    LocalVerbosity(1)
    {
Intab(Sh);
     printf("%s (%.2f:%.2f/%.2f)\n", ClassName[ST->Leaf],
     ST->Items, LeafError, ST->Errors);
    }
}

return 0;
    }

    //LocalVerbosity(1)
    { printf("Node type: %d, Items: %f, Forks: %hd \n", ST->NodeType,
```

```
ST->Items, ST->Forks);
    }

    Kp = Group(0, Fp, Lp, ST) + 1;
    KnownCases = CountItems(Kp, Lp);

    PrevAllKnown = AllKnown;
    if ( Kp != Fp ) AllKnown = false;

    //fork_errors = (float *) calloc (ST->Forks + 1, sizeof(float));
    leaf_errors = (float *) calloc (MaxClass + 2, sizeof(float));
    leaf_costs = (float *) calloc (MaxClass + 2, sizeof(float));

    //tmpBranch = (char *) calloc (ST->Forks, sizeof (Tree*));
    //memcpy((char *)tmpBranch, (char *)ST->Branch, ST->Forks *
sizeof(Tree*));

/*Unknown data are taken into account*/
    ForEach(v, 1, ST->Forks)
    {
Ep = Group(v, Kp, Lp, ST);

if ( Kp <= Ep )
{
    Factor = CountItems(Kp, Ep) / KnownCases;
```

```
    ForEach(i, Fp, Kp-1)
    {
Weight[i] *= Factor;
    }

    ComputeCostAndError(T, ST->Branch[v], Fp, Ep, Sh+1, UpdateTree);

    Group(0, Fp, Ep, ST);
    ForEach(i, Fp, Kp-1)
    {
Weight[i] /= Factor;
    }
}
    }



    TreeCost = CalculateCost(T, false);
    printf("Tree Error: %f  \t Tree Cost: %f \t", TreeError, TreeCost);
    tmpNodeType = ST->NodeType;
    tmpLeaf = ST->Leaf;
    ST->NodeType = 0;

    //error improvement by replace ST with a leaf
    ForEach(c, 0, MaxClass)
```

```
    {
ST->Leaf = c;
leaf_costs[c] = CalculateCost(T, true) - TreeCost;
printf("***leaf_errors[%hd]: %f;\t leaf_costs[%hd]: %f ***\n", c,
leaf_errors[c], c, leaf_costs[c]);
    }
    ST->NodeType = tmpNodeType;
    ST->Leaf = tmpLeaf;
    tmpBestLeaf = 0;
    firstLeaf = true;
    ForEach(c, 0, MaxClass)
    {
if ((firstLeaf == true)
    && (leaf_costs[c] <= (LeafCount(ST) - 1)/2.0 + sqrt(TreeCost +
LeafCount(ST) /2.0)) )
{   firstLeaf = false;
    tmpBestLeaf = c;
}
else if ((firstLeaf == false)
 && (leaf_costs[c] <= (LeafCount(ST) - 1)/2.0 + sqrt(TreeCost +
LeafCount(ST) /2.0))
 && (leaf_costs[c] <= leaf_costs[tmpBestLeaf]) )
{    tmpBestLeaf = c;
}
    }
```

```
    if (firstLeaf == true)
LeafError = -1;
    else
LeafError = leaf_errors[tmpBestLeaf];
    printf("Leaf Class: %hd, Items: %f, Forks: %hd, Leaf Error - Tree
Error: %f  \n", ST->Leaf, ST->Items, ST->Forks, LeafError);


    printf("(LeafCount(ST) - 1)/2  : %f\n",(LeafCount(ST) - 1)/2.0);
    if (leaf_costs[tmpBestLeaf] <= (LeafCount(ST) - 1)/2.0 + sqrt(TreeCost
+ LeafCount(ST) /2.0))
    {
LocalVerbosity(1)
{
    Intab(Sh);
    printf("Replaced with leaf %s\n", ClassName[tmpBestLeaf]);
}
printf("-------------------------Replaced with leaf %s, LeafError:
%f\n", ClassName[tmpBestLeaf], LeafError);
ST->NodeType = 0;
   ST->Leaf = tmpBestLeaf;
ST->Forks = 0;
Changed = true;
    }
    else
Changed = false;
```

```
    AllKnown = PrevAllKnown;


    if ( ! UpdateTree )
    {
//free(LocalClassDist);
//free(classDist);
if (fork_errors != NULL) free(fork_errors);


return TreeError;
    }


    AllKnown = PrevAllKnown;
   //if (fork_errors) free(fork_errors);
   if (leaf_errors) free(leaf_errors);
   //if (tmpST) free(tmpST);


    return 0;
}



/*************************************************************************/
/*  */
/* Calculate errors for each of the trials    */
/*  */
```

```
/*************************************************************************/

float    CalculateError(T, print)
    Tree T;
    Boolean print;
{
    ClassNo RealClass, PrunedClass, Category();
    ItemNo *ConfusionMat, i, j, PrunedErrors;
    void PrintConfusionMatrix();

    ConfusionMat = (ItemNo *) calloc((MaxClass+1)*(MaxClass+1),
sizeof(ItemNo));

    PrunedErrors = 0;

    ForEach(i, 0, MaxItem)
    {
RealClass = Class(Item[i]);
PrunedClass = Category(Item[i], T);

if ( PrunedClass != RealClass )
{
    PrunedErrors++;
}
ConfusionMat[RealClass*(MaxClass+1)+PrunedClass]++;
```

```
    }


    //printf("Errors: %d \t", PrunedErrors);
    if (print)
PrintConfusionMatrix(ConfusionMat);

    free(ConfusionMat);
    return PrunedErrors;
}



/*************************************************************************/
/*  */
/* Calculate the costs in a given subtree  */
/*  */
/*************************************************************************/

float    CalculateCost(T, print)
    Tree T;
    Boolean print;
{
    ClassNo RealClass, PrunedClass, Category();
    float cost = 0;
    ItemNo *ConfusionMat, i, j, PrunedErrors;
    void PrintConfusionMatrix();
```

```
    ConfusionMat = (ItemNo *) calloc((MaxClass+1)*(MaxClass+1),
sizeof(ItemNo));

    PrunedErrors = 0;

    ForEach(i, 0, MaxItem)
    {
RealClass = Class(Item[i]);
PrunedClass = Category(Item[i], T);

if ( PrunedClass != RealClass )
{
    PrunedErrors++;
}
ConfusionMat[RealClass*(MaxClass+1)+PrunedClass]++;
    }

    ForEach(i, 0, MaxClass)
ForEach(j, 0, MaxClass)
    {
cost += Cost[ i * (MaxClass + 1) + j] * ConfusionMat[i * (MaxClass+1)
+ j] ;
    }
    cost /= (float) (MaxItem + 1);  //normalization
```

```
    printf("Errors: %d \t", PrunedErrors);
    if (print)
PrintConfusionMatrix(ConfusionMat);
    cost = Cost_Weight * cost + Error_Weight * PrunedErrors / (float)
(MaxItem + 1);

    free(ConfusionMat);
    return cost;
}



/*************************************************************************/
/*  */
/* Calculate the costs in a given subtree in the test  */
/*  */
/*************************************************************************/

float    CalculateCostTest(T, print)
    Tree T;
    Boolean print;
{
    ClassNo RealClass, PrunedClass, Category();
    float cost = 0;
    ItemNo *ConfusionMat, i, j, PrunedErrors;
    void PrintConfusionMatrix();
```

```
    ConfusionMat = (ItemNo *) calloc((MaxClass+1)*(MaxClass+1),
sizeof(ItemNo));

    PrunedErrors = 0;

    ForEach(i, 0, MaxItem)
    {
RealClass = Class(Item[i]);
PrunedClass = Category(Item[i], T);

if ( PrunedClass != RealClass )
{
    PrunedErrors++;
}
ConfusionMat[RealClass*(MaxClass+1)+PrunedClass]++;
    }

    ForEach(i, 0, MaxClass)
ForEach(j, 0, MaxClass)
    {
cost += Cost[ i * (MaxClass + 1) + j] * ConfusionMat[i * (MaxClass+1)
+ j] ;
    }
    cost /= (float) (MaxItem + 1);  //normalization
```

```
    printf("Errors: %d \t", PrunedErrors);
    if (print)
PrintConfusionMatrix(ConfusionMat);
    //cost = Cost_Weight * cost + Error_Weight * PrunedErrors / (float)
(MaxItem + 1);

    free(ConfusionMat);
    return cost;
}
```

APPENDIX F: ANOVA RESULTS

GLASS:

One-way ANOVA: CC4.5-1, CC4.5-2, CC4.5-3, CC4.5-4, C4.5, PESSIMISTIC, ...

Source	DF	SS	MS	F	P
Factor	7	0.01325	0.00189	1.20	0.314
Error	72	0.11362	0.00158		
Total	79	0.12687			

S = 0.03972 R-Sq = 10.44% R-Sq(adj) = 1.74%

Level	N	Mean	StDev	Individual 95% CIs For Mean Based on Pooled StDev
CC4.5-1	10	0.13672	0.01999	(---------*---------)
CC4.5-2	10	0.14100	0.05681	(---------*---------)
CC4.5-3	10	0.14125	0.03683	(----------*---------)
CC4.5-4	10	0.15484	0.03960	(---------*---------)
C4.5	10	0.17620	0.04044	(---------*---------)
PESSIMISTIC	10	0.16250	0.04092	(---------*---------)
COST-COMPLEXITY	10	0.16313	0.03649	(---------*---------)
ERROR_REDUCE	10	0.16094	0.03784	(---------*---------)

```
                                        -----+---------+---------+---------+----
                                           0.125     0.150     0.175     0.200
```

Pooled StDev = 0.03972

Fisher 95% Individual Confidence Intervals

All Pairwise Comparisons

Simultaneous confidence level = 50.66%

CC4.5-1 subtracted from:

	Lower	Center	Upper
CC4.5-2	-0.03113	0.00428	0.03970
CC4.5-3	-0.03088	0.00453	0.03995
CC4.5-4	-0.01729	0.01813	0.05354
C4.5	0.00407	0.03948	0.07490
PESSIMISTIC	-0.00963	0.02578	0.06120
COST-COMPLEXITY	-0.00901	0.02641	0.06182
ERROR_REDUCE	-0.01120	0.02422	0.05963

```
                --------+---------+---------+---------+-
CC4.5-2                    (--------*--------)
```

```
CC4.5-3                    (--------*--------)
CC4.5-4                        (--------*-------)
C4.5                               (--------*--------)
PESSIMISTIC                     (-------*--------)
COST-COMPLEXITY                 (--------*-------)
ERROR_REDUCE                    (--------*--------)
                 --------+---------+---------+---------+-
                      -0.040     0.000     0.040     0.080
```

CC4.5-2 subtracted from:

	Lower	Center	Upper
CC4.5-3	-0.03516	0.00025	0.03566
CC4.5-4	-0.02157	0.01384	0.04926
C4.5	-0.00021	0.03520	0.07062
PESSIMISTIC	-0.01391	0.02150	0.05691
COST-COMPLEXITY	-0.01329	0.02213	0.05754
ERROR_REDUCE	-0.01548	0.01994	0.05535

```
                 --------+---------+---------+---------+-
CC4.5-3                    (--------*--------)
CC4.5-4                        (-------*--------)
C4.5                               (--------*--------)
PESSIMISTIC                     (-------*--------)
```

```
COST-COMPLEXITY                 (--------*-------)
ERROR_REDUCE                    (--------*--------)
                  --------+---------+---------+---------+-
                       -0.040     0.000     0.040     0.080
```

CC4.5-3 subtracted from:

	Lower	Center	Upper
CC4.5-4	-0.02182	0.01359	0.04901
C4.5	-0.00046	0.03495	0.07037
PESSIMISTIC	-0.01416	0.02125	0.05666
COST-COMPLEXITY	-0.01354	0.02188	0.05729
ERROR_REDUCE	-0.01573	0.01969	0.05510

```
                  --------+---------+---------+---------+-
CC4.5-4                        (-------*--------)
C4.5                               (--------*--------)
PESSIMISTIC                    (--------*--------)
COST-COMPLEXITY                 (-------*--------)
ERROR_REDUCE                   (--------*--------)
                  --------+---------+---------+---------+-
                       -0.040     0.000     0.040     0.080
```

```
CC4.5-4 subtracted from:

                    Lower   Center    Upper
C4.5             -0.01406  0.02136  0.05677
PESSIMISTIC      -0.02776  0.00766  0.04307
COST-COMPLEXITY  -0.02713  0.00828  0.04370
ERROR_REDUCE     -0.02932  0.00609  0.04151

                 --------+---------+---------+---------+-
C4.5                          (--------*--------)
PESSIMISTIC                (--------*--------)
COST-COMPLEXITY            (--------*--------)
ERROR_REDUCE               (--------*-------)
                 --------+---------+---------+---------+-
                      -0.040     0.000     0.040     0.080


C4.5 subtracted from:

                    Lower    Center    Upper
PESSIMISTIC      -0.04912  -0.01370  0.02171
COST-COMPLEXITY  -0.04849  -0.01308  0.02234
ERROR_REDUCE     -0.05068  -0.01527  0.02015

                 --------+---------+---------+---------+-
```

```
PESSIMISTIC            (--------*-------)
COST-COMPLEXITY        (--------*--------)
ERROR_REDUCE           (--------*--------)
                 --------+---------+---------+---------+-
                      -0.040     0.000     0.040     0.080
```

PESSIMISTIC subtracted from:

	Lower	Center	Upper
COST-COMPLEXITY	-0.03479	0.00062	0.03604
ERROR_REDUCE	-0.03698	-0.00156	0.03385

```
                 --------+---------+---------+---------+-
COST-COMPLEXITY            (--------*--------)
ERROR_REDUCE               (--------*-------)
                 --------+---------+---------+---------+-
                      -0.040     0.000     0.040     0.080
```

COST-COMPLEXITY subtracted from:

	Lower	Center	Upper
ERROR_REDUCE	-0.03760	-0.00219	0.03323

```
                --------+---------+---------+---------+-
ERROR_REDUCE            (-------*--------)
                --------+---------+---------+---------+-
                     -0.040     0.000     0.040     0.080
```

CLEVELAND

One-way ANOVA: CC4.5-1, CC4.5-2, CC4.5-3, CC4.5-4, C4.5, PESSIMISTIC, ...

Source	DF	SS	MS	F	P
Factor	7	0.03107	0.00444	2.96	0.009
Error	72	0.10786	0.00150		
Total	79	0.13894			

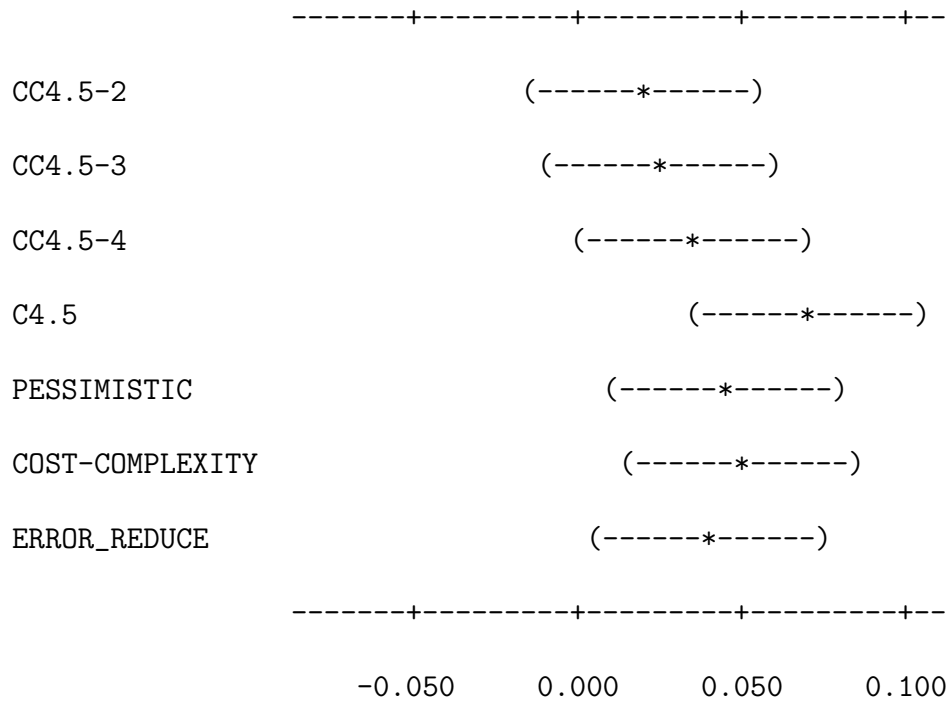
S = 0.03871 R-Sq = 22.36% R-Sq(adj) = 14.82%

Level	N	Mean	StDev
CC4.5-1	10	0.11622	0.01883
CC4.5-2	10	0.13800	0.03297
CC4.5-3	10	0.13978	0.02753
CC4.5-4	10	0.15156	0.05178
C4.5	10	0.18716	0.03568

```
PESSIMISTIC      10  0.16133  0.03750

COST-COMPLEXITY  10  0.16444  0.05437

ERROR_REDUCE     10  0.15422  0.03834


                 Individual 95% CIs For Mean Based on

                 Pooled StDev

Level            ---------+---------+---------+---------+

CC4.5-1          (-------*-------)

CC4.5-2                 (-------*-------)

CC4.5-3                 (--------*-------)

CC4.5-4                     (--------*-------)

C4.5                                (-------*--------)

PESSIMISTIC                     (-------*-------)

COST-COMPLEXITY                  (-------*-------)

ERROR_REDUCE                 (-------*--------)

                 ---------+---------+---------+---------+

                        0.120     0.150     0.180     0.210


Pooled StDev = 0.03871



Fisher 95% Individual Confidence Intervals

All Pairwise Comparisons


Simultaneous confidence level = 50.66%
```

CC4.5-1 subtracted from:

	Lower	Center	Upper
CC4.5-2	-0.01273	0.02178	0.05628
CC4.5-3	-0.01095	0.02356	0.05806
CC4.5-4	0.00083	0.03533	0.06984
C4.5	0.03643	0.07093	0.10544
PESSIMISTIC	0.01060	0.04511	0.07962
COST-COMPLEXITY	0.01372	0.04822	0.08273
ERROR_REDUCE	0.00349	0.03800	0.07251



```
CC4.5-2 subtracted from:

                   Lower   Center    Upper
CC4.5-3          -0.03273  0.00178  0.03628
CC4.5-4          -0.02095  0.01356  0.04806
C4.5              0.01465  0.04916  0.08366
PESSIMISTIC      -0.01117  0.02333  0.05784
COST-COMPLEXITY  -0.00806  0.02644  0.06095
ERROR_REDUCE     -0.01828  0.01622  0.05073

                -------+---------+---------+---------+--
CC4.5-3                    (------*------)
CC4.5-4                       (------*------)
C4.5                                (------*------)
PESSIMISTIC                   (------*------)
COST-COMPLEXITY               (------*------)
ERROR_REDUCE                  (------*------)
                -------+---------+---------+---------+--
                    -0.050     0.000     0.050     0.100


CC4.5-3 subtracted from:

                   Lower   Center    Upper
CC4.5-4          -0.02273  0.01178  0.04628
```

```
C4.5              0.01287  0.04738  0.08188
PESSIMISTIC      -0.01295  0.02156  0.05606
COST-COMPLEXITY  -0.00984  0.02467  0.05917
ERROR_REDUCE     -0.02006  0.01444  0.04895


                 -------+---------+---------+---------+--
CC4.5-4                       (------*------)
C4.5                                (-----*------)
PESSIMISTIC                   (------*------)
COST-COMPLEXITY                (------*------)
ERROR_REDUCE                  (------*------)
                 -------+---------+---------+---------+--
                     -0.050     0.000     0.050     0.100


CC4.5-4 subtracted from:


                    Lower   Center    Upper
C4.5              0.00109  0.03560  0.07011
PESSIMISTIC      -0.02473  0.00978  0.04428
COST-COMPLEXITY  -0.02162  0.01289  0.04740
ERROR_REDUCE     -0.03184  0.00267  0.03717


                 -------+---------+---------+---------+--
C4.5                           (------*------)
```

```
PESSIMISTIC                  (------*------)

COST-COMPLEXITY               (------*-----)

ERROR_REDUCE                 (------*-----)

                 -------+---------+---------+---------+--

                     -0.050     0.000     0.050     0.100
```

C4.5 subtracted from:

```
                    Lower    Center    Upper

PESSIMISTIC      -0.06033  -0.02582  0.00868

COST-COMPLEXITY  -0.05722  -0.02271  0.01180

ERROR_REDUCE     -0.06744  -0.03293  0.00157

                 -------+---------+---------+---------+--

PESSIMISTIC           (------*------)

COST-COMPLEXITY        (-----*------)

ERROR_REDUCE          (-----*------)

                 -------+---------+---------+---------+--

                     -0.050     0.000     0.050     0.100
```

PESSIMISTIC subtracted from:

```
                    Lower    Center    Upper
```

```
COST-COMPLEXITY  -0.03140   0.00311  0.03762
ERROR_REDUCE     -0.04162  -0.00711  0.02739

                 -------+---------+---------+---------+--
COST-COMPLEXITY             (------*------)
ERROR_REDUCE              (------*-----)
                 -------+---------+---------+---------+--
                     -0.050     0.000     0.050     0.100
```

COST-COMPLEXITY subtracted from:

```
                Lower    Center    Upper
ERROR_REDUCE  -0.04473  -0.01022  0.02428

              -------+---------+---------+---------+--
ERROR_REDUCE          (------*------)
              -------+---------+---------+---------+--
                  -0.050     0.000     0.050     0.100
```

HEPATITIS

One-way ANOVA: CC4.5-1, CC4.5-2, CC4.5-3, CC4.5-4, C4.5, PESSIMISTIC, ...

```
Source  DF       SS       MS     F      P
```

```
Factor   7  0.05253  0.00750  3.94  0.001
Error   72  0.13710  0.00190
Total   79  0.18962

S = 0.04364   R-Sq = 27.70%   R-Sq(adj) = 20.67%

                                          Individual 95% CIs For Mean Based on
                                          Pooled StDev
Level             N     Mean    StDev  -----+---------+---------+---------+----
CC4.5-1          10  0.08174  0.03321  (-------*-------)
CC4.5-2          10  0.09783  0.03466       (-------*-------)
CC4.5-3          10  0.12391  0.04642               (------*-------)
CC4.5-4          10  0.10478  0.03621         (-------*-------)
C4.5              10  0.15717  0.03766                       (-------*-------)
PESSIMISTIC      10  0.10391  0.03989         (-------*-------)
COST-COMPLEXITY  10  0.15739  0.02466                       (-------*-------)
ERROR_REDUCE     10  0.12456  0.07645               (-------*------)
                                          -----+---------+---------+---------+----
                                             0.070     0.105     0.140     0.175

Pooled StDev = 0.04364

Fisher 95% Individual Confidence Intervals
```

```
All Pairwise Comparisons

Simultaneous confidence level = 50.66%


CC4.5-1 subtracted from:

                    Lower   Center    Upper
CC4.5-2          -0.02281  0.01609  0.05499
CC4.5-3           0.00327  0.04217  0.08108
CC4.5-4          -0.01586  0.02304  0.06195
C4.5              0.03653  0.07543  0.11434
PESSIMISTIC      -0.01673  0.02217  0.06108
COST-COMPLEXITY   0.03675  0.07565  0.11455
ERROR_REDUCE      0.00392  0.04282  0.08173

                ------+---------+---------+---------+---
CC4.5-2                     (------*-----)
CC4.5-3                          (-----*------)
CC4.5-4                      (------*-----)
C4.5                                (------*-----)
PESSIMISTIC                  (------*-----)
COST-COMPLEXITY                     (------*-----)
ERROR_REDUCE                     (-----*------)
                ------+---------+---------+---------+---
```

```
                   -0.060     0.000     0.060     0.120
```

CC4.5-2 subtracted from:

```
                    Lower   Center    Upper
CC4.5-3          -0.01281  0.02609  0.06499
CC4.5-4          -0.03195  0.00696  0.04586
C4.5              0.02045  0.05935  0.09825
PESSIMISTIC      -0.03281  0.00609  0.04499
COST-COMPLEXITY   0.02066  0.05957  0.09847
ERROR_REDUCE     -0.01216  0.02674  0.06564

                 ------+---------+---------+---------+---
CC4.5-3                      (-----*------)
CC4.5-4                    (-----*------)
C4.5                              (------*-----)
PESSIMISTIC                (-----*-----)
COST-COMPLEXITY                   (------*-----)
ERROR_REDUCE                 (-----*------)
                 ------+---------+---------+---------+---
                    -0.060     0.000     0.060     0.120
```

CC4.5-3 subtracted from:

```
                    Lower    Center    Upper
CC4.5-4          -0.05803  -0.01913  0.01977
C4.5             -0.00564   0.03326  0.07216
PESSIMISTIC      -0.05890  -0.02000  0.01890
COST-COMPLEXITY  -0.00542   0.03348  0.07238
ERROR_REDUCE     -0.03825   0.00065  0.03955


                  ------+---------+---------+---------+---
CC4.5-4                 (------*-----)
C4.5                              (------*-----)
PESSIMISTIC             (------*-----)
COST-COMPLEXITY                   (------*-----)
ERROR_REDUCE                (-----*------)
                  ------+---------+---------+---------+---
                     -0.060     0.000     0.060     0.120



CC4.5-4 subtracted from:

                    Lower    Center    Upper
C4.5              0.01349   0.05239  0.09129
PESSIMISTIC      -0.03977  -0.00087  0.03803
COST-COMPLEXITY   0.01371   0.05261  0.09151
ERROR_REDUCE     -0.01912   0.01978  0.05868
```

```
                 ------+---------+---------+---------+---
C4.5                               (------*-----)
PESSIMISTIC                (------*-----)
COST-COMPLEXITY                    (------*-----)
ERROR_REDUCE                  (-----*------)
                 ------+---------+---------+---------+---
                    -0.060     0.000     0.060     0.120
```

C4.5 subtracted from:

```
                      Lower    Center     Upper
PESSIMISTIC       -0.09216  -0.05326  -0.01436
COST-COMPLEXITY   -0.03868   0.00022   0.03912
ERROR_REDUCE      -0.07151  -0.03261   0.00629

                 ------+---------+---------+---------+---
PESSIMISTIC       (-----*------)
COST-COMPLEXITY            (-----*------)
ERROR_REDUCE         (------*-----)
                 ------+---------+---------+---------+---
                    -0.060     0.000     0.060     0.120
```

```
PESSIMISTIC subtracted from:

                    Lower   Center    Upper
COST-COMPLEXITY   0.01458  0.05348  0.09238
ERROR_REDUCE     -0.01825  0.02065  0.05955

                  ------+---------+---------+---------+---
COST-COMPLEXITY                     (------*-----)
ERROR_REDUCE                  (-----*------)
                  ------+---------+---------+---------+---
                     -0.060     0.000     0.060     0.120


COST-COMPLEXITY subtracted from:

                   Lower    Center    Upper
ERROR_REDUCE  -0.07173  -0.03283  0.00607

                ------+---------+---------+---------+---
ERROR_REDUCE       (------*-----)
                ------+---------+---------+---------+---
                   -0.060     0.000     0.060     0.120
```

HYPO:

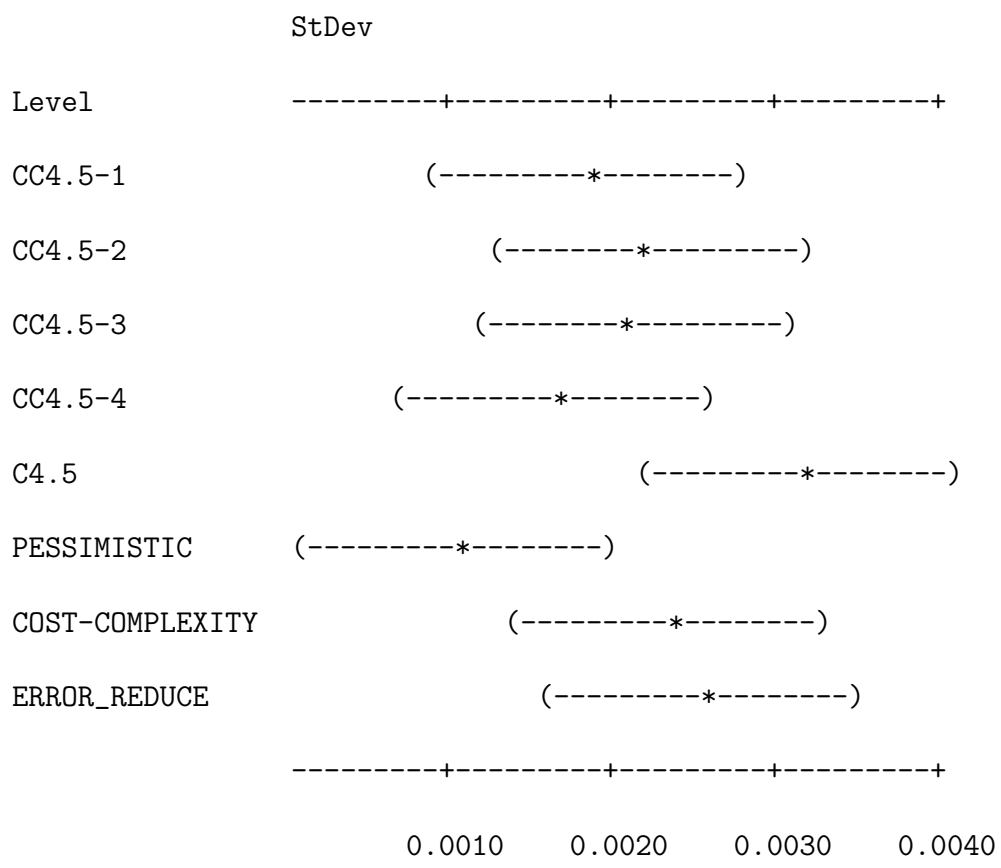
One-way ANOVA: CC4.5-1, CC4.5-2, CC4.5-3, CC4.5-4, C4.5, PESSIMISTIC, ...

Source	DF	SS	MS	F	P
Factor	7	0.0000268	0.0000038	1.69	0.126
Error	72	0.0001631	0.0000023		
Total	79	0.0001899			

S = 0.001505 R-Sq = 14.09% R-Sq(adj) = 5.74%

Level	N	Mean	StDev
CC4.5-1	10	0.001857	0.000927
CC4.5-2	10	0.002228	0.001527
CC4.5-3	10	0.002149	0.001149
CC4.5-4	10	0.001698	0.001127
C4.5	10	0.003152	0.001830
PESSIMISTIC	10	0.001072	0.001079
COST-COMPLEXITY	10	0.002361	0.001534
ERROR_REDUCE	10	0.002563	0.002341

Individual 95% CIs For Mean Based on Pooled



Pooled StDev = 0.001505

Fisher 95% Individual Confidence Intervals

All Pairwise Comparisons

Simultaneous confidence level = 50.66%

CC4.5-1 subtracted from:

	Lower	Center	Upper

```
CC4.5-2          -0.000971   0.000371  0.001713
CC4.5-3          -0.001050   0.000292  0.001634
CC4.5-4          -0.001501  -0.000159  0.001183
C4.5             -0.000047   0.001295  0.002637
PESSIMISTIC      -0.002127  -0.000785  0.000557
COST-COMPLEXITY  -0.000838   0.000504  0.001846
ERROR_REDUCE     -0.000636   0.000706  0.002048


                 -------+---------+---------+---------+--
CC4.5-2                      (------*------)
CC4.5-3                      (-----*------)
CC4.5-4                   (------*------)
C4.5                            (-----*------)
PESSIMISTIC            (------*------)
COST-COMPLEXITY              (------*-----)
ERROR_REDUCE                 (------*-----)
                 -------+---------+---------+---------+--
                     -0.0020    0.0000    0.0020    0.0040



CC4.5-2 subtracted from:

                     Lower     Center     Upper
CC4.5-3          -0.001422  -0.000080  0.001262
CC4.5-4          -0.001872  -0.000530  0.000811
```

```
C4.5             -0.000419   0.000923  0.002265
PESSIMISTIC      -0.002498  -0.001156  0.000185
COST-COMPLEXITY  -0.001209   0.000133  0.001475
ERROR_REDUCE     -0.001007   0.000335  0.001677


                 -------+---------+---------+---------+--
CC4.5-3                     (------*-----)
CC4.5-4                   (-----*------)
C4.5                            (------*-----)
PESSIMISTIC             (-----*------)
COST-COMPLEXITY               (------*-----)
ERROR_REDUCE                   (------*-----)
                 -------+---------+---------+---------+--
                     -0.0020    0.0000    0.0020    0.0040


CC4.5-3 subtracted from:

                     Lower     Center     Upper
CC4.5-4          -0.001793  -0.000451  0.000891
C4.5             -0.000339   0.001003  0.002345
PESSIMISTIC      -0.002419  -0.001077  0.000265
COST-COMPLEXITY  -0.001130   0.000212  0.001554
ERROR_REDUCE     -0.000927   0.000415  0.001756
```

```
                  -------+---------+---------+---------+--
CC4.5-4                      (------*-----)
C4.5                                (------*------)
PESSIMISTIC                (------*-----)
COST-COMPLEXITY                  (------*------)
ERROR_REDUCE                      (------*------)
                  -------+---------+---------+---------+--
                      -0.0020    0.0000    0.0020    0.0040
```

CC4.5-4 subtracted from:

	Lower	Center	Upper
C4.5	0.000112	0.001454	0.002796
PESSIMISTIC	-0.001968	-0.000626	0.000716
COST-COMPLEXITY	-0.000679	0.000663	0.002005
ERROR_REDUCE	-0.000477	0.000865	0.002207

```
                  -------+---------+---------+---------+--
C4.5                                  (-----*------)
PESSIMISTIC                  (------*------)
COST-COMPLEXITY                    (-----*------)
ERROR_REDUCE                        (-----*------)
                  -------+---------+---------+---------+--
                      -0.0020    0.0000    0.0020    0.0040
```

```
C4.5 subtracted from:

                    Lower     Center      Upper
PESSIMISTIC      -0.003422  -0.002080  -0.000738
COST-COMPLEXITY  -0.002133  -0.000791   0.000551
ERROR_REDUCE     -0.001931  -0.000589   0.000753

                 -------+---------+---------+---------+--
PESSIMISTIC      (------*-----)
COST-COMPLEXITY        (------*------)
ERROR_REDUCE            (------*------)
                 -------+---------+---------+---------+--
                     -0.0020    0.0000    0.0020    0.0040


PESSIMISTIC subtracted from:

                    Lower    Center     Upper
COST-COMPLEXITY  -0.000053  0.001289  0.002631
ERROR_REDUCE      0.000149  0.001491  0.002833

                 -------+---------+---------+---------+--
COST-COMPLEXITY                  (-----*------)
```

```
ERROR_REDUCE                        (-----*------)

                 -------+---------+---------+---------+--

                     -0.0020    0.0000    0.0020    0.0040
```

COST-COMPLEXITY subtracted from:

	Lower	Center	Upper
ERROR_REDUCE	-0.001140	0.000202	0.001544

```
              -------+---------+---------+---------+--

ERROR_REDUCE             (------*------)

              -------+---------+---------+---------+--

                  -0.0020    0.0000    0.0020    0.0040
```

IRIS:

One-way ANOVA: CC4.5-1, CC4.5-2, CC4.5-3, CC4.5-4, C4.5, PESSIMISTIC, ...

Source	DF	SS	MS	F	P
Factor	7	0.0029873	0.0004268	5.87	0.000
Error	72	0.0052325	0.0000727		
Total	79	0.0082198			

S = 0.008525 R-Sq = 36.34% R-Sq(adj) = 30.15%

```
Level             N      Mean     StDev
CC4.5-1          10  0.012955  0.005144
CC4.5-2          10  0.013864  0.004476
CC4.5-3          10  0.012046  0.010335
CC4.5-4          10  0.015555  0.003920
C4.5             10  0.032644  0.018221
PESSIMISTIC      10  0.018000  0.006411
COST-COMPLEXITY  10  0.016318  0.004963
ERROR_REDUCE     10  0.016591  0.003870


                 Individual 95% CIs For Mean Based on
                 Pooled StDev
Level            --+---------+---------+---------+-------
CC4.5-1           (------*------)
CC4.5-2             (-----*------)
CC4.5-3          (------*------)
CC4.5-4               (-----*------)
C4.5                                    (------*------)
PESSIMISTIC             (------*-----)
COST-COMPLEXITY        (-----*------)
ERROR_REDUCE            (------*-----)
                 --+---------+---------+---------+-------
```

```
                0.0080    0.0160    0.0240    0.0320

Pooled StDev = 0.008525


Fisher 95% Individual Confidence Intervals

All Pairwise Comparisons


Simultaneous confidence level = 50.66%


CC4.5-1 subtracted from:

                    Lower     Center     Upper

CC4.5-2          -0.006691   0.000909  0.008509

CC4.5-3          -0.008509  -0.000909  0.006691

CC4.5-4          -0.004999   0.002601  0.010201

C4.5              0.012090   0.019690  0.027290

PESSIMISTIC      -0.002554   0.005046  0.012646

COST-COMPLEXITY  -0.004236   0.003364  0.010964

ERROR_REDUCE     -0.003963   0.003637  0.011237

                ---------+---------+---------+---------+

CC4.5-2                        (----*----)

CC4.5-3                      (----*----)
```

```
CC4.5-4                          (----*----)

C4.5                                        (----*----)

PESSIMISTIC                       (----*----)

COST-COMPLEXITY                  (----*----)

ERROR_REDUCE                     (----*----)

                 ---------+---------+---------+---------+

                       -0.015     0.000     0.015     0.030
```

CC4.5-2 subtracted from:

	Lower	Center	Upper
CC4.5-3	-0.009418	-0.001818	0.005782
CC4.5-4	-0.005908	0.001692	0.009292
C4.5	0.011181	0.018781	0.026381
PESSIMISTIC	-0.003463	0.004137	0.011737
COST-COMPLEXITY	-0.005145	0.002455	0.010054
ERROR_REDUCE	-0.004872	0.002728	0.010327

```
                 ---------+---------+---------+---------+

CC4.5-3                     (----*----)

CC4.5-4                       (----*----)

C4.5                                    (-----*----)

PESSIMISTIC                     (----*----)

COST-COMPLEXITY                  (----*----)
```

```
ERROR_REDUCE                    (----*----)

                ---------+---------+---------+---------+

                      -0.015     0.000     0.015     0.030
```

CC4.5-3 subtracted from:

	Lower	Center	Upper
CC4.5-4	-0.004090	0.003510	0.011110
C4.5	0.012999	0.020599	0.028199
PESSIMISTIC	-0.001645	0.005955	0.013555
COST-COMPLEXITY	-0.003327	0.004273	0.011873
ERROR_REDUCE	-0.003054	0.004546	0.012146

```
                ---------+---------+---------+---------+
CC4.5-4                         (----*----)
C4.5                                      (----*----)
PESSIMISTIC                       (----*----)
COST-COMPLEXITY                   (----*----)
ERROR_REDUCE                      (----*----)
                ---------+---------+---------+---------+
                      -0.015     0.000     0.015     0.030
```

CC4.5-4 subtracted from:

```
                    Lower    Center     Upper
C4.5              0.009489  0.017089  0.024689
PESSIMISTIC      -0.005155  0.002445  0.010045
COST-COMPLEXITY  -0.006837  0.000763  0.008363
ERROR_REDUCE     -0.006564  0.001036  0.008636


                 ---------+---------+---------+---------+
C4.5                                    (----*----)
PESSIMISTIC                        (----*----)
COST-COMPLEXITY                  (-----*----)
ERROR_REDUCE                       (----*----)
                 ---------+---------+---------+---------+
                       -0.015     0.000     0.015     0.030


C4.5 subtracted from:

                    Lower     Center      Upper
PESSIMISTIC      -0.022244  -0.014644  -0.007044
COST-COMPLEXITY  -0.023926  -0.016326  -0.008726
ERROR_REDUCE     -0.023653  -0.016053  -0.008453


                 ---------+---------+---------+---------+
PESSIMISTIC           (----*----)
```

```
COST-COMPLEXITY     (----*----)
ERROR_REDUCE        (----*----)
                 ---------+---------+---------+---------+
                       -0.015     0.000     0.015     0.030
```

PESSIMISTIC subtracted from:

```
                     Lower     Center     Upper
COST-COMPLEXITY  -0.009282  -0.001682  0.005918
ERROR_REDUCE     -0.009009  -0.001409  0.006191

                 ---------+---------+---------+---------+
COST-COMPLEXITY               (----*----)
ERROR_REDUCE                  (----*----)
                 ---------+---------+---------+---------+
                       -0.015     0.000     0.015     0.030
```

COST-COMPLEXITY subtracted from:

```
                   Lower    Center     Upper
ERROR_REDUCE  -0.007327  0.000273  0.007873

              ---------+---------+---------+---------+
```

```
ERROR_REDUCE                (----*----)

             ---------+---------+---------+---------+

                   -0.015     0.000     0.015     0.030
```

PIMA:

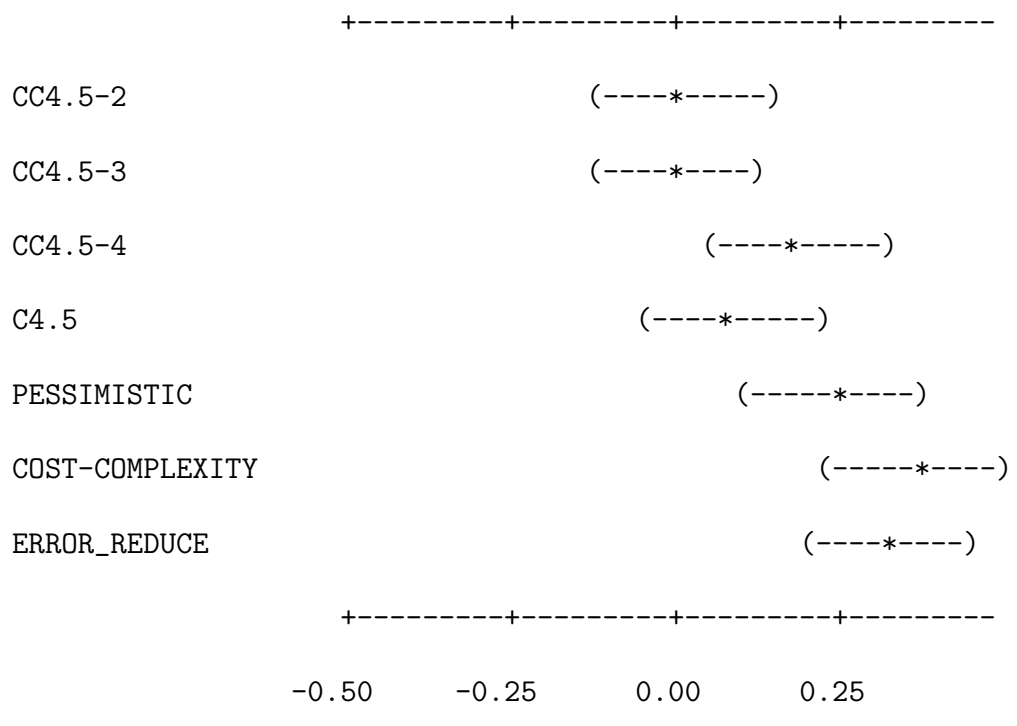
One-way ANOVA: CC4.5-1, CC4.5-2, CC4.5-3, CC4.5-4, C4.5, PESSIMISTIC, ...

Source	DF	SS	MS	F	P
Factor	7	1.5423	0.2203	10.01	0.000
Error	72	1.5842	0.0220		
Total	79	3.1265			

S = 0.1483 R-Sq = 49.33% R-Sq(adj) = 44.40%

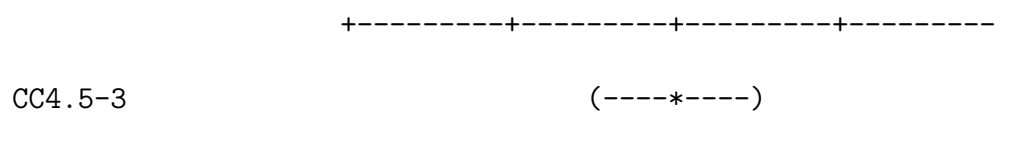
Level	N	Mean	StDev	Individual 95% CIs For Mean Based on Pooled StDev
CC4.5-1	10	0.6087	0.0435	(------*-----)
CC4.5-2	10	0.6144	0.0997	(-----*-----)
CC4.5-3	10	0.6105	0.1180	(------*-----)
CC4.5-4	10	0.7939	0.0831	(-----*-----)
C4.5	10	0.6955	0.1024	(-----*------)

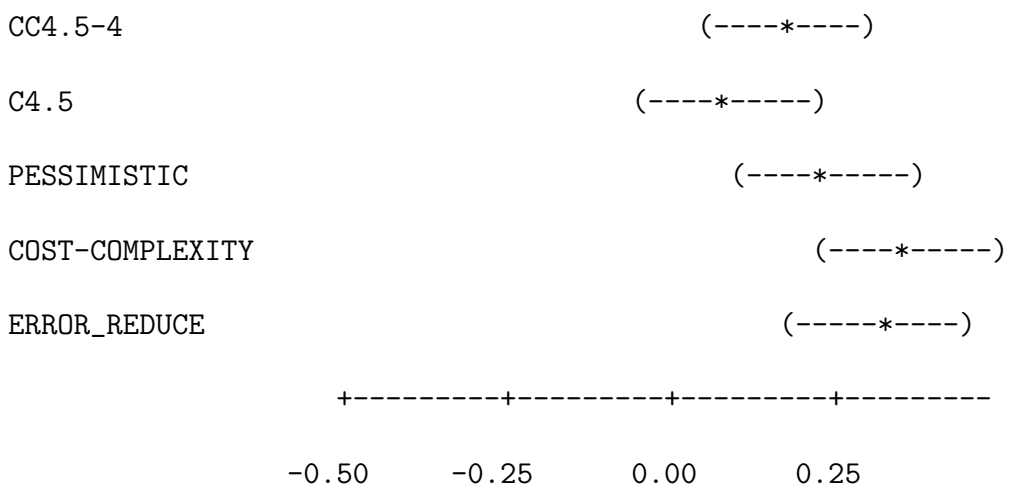
```
PESSIMISTIC      10  0.8478  0.1509                  (------*-----)
COST-COMPLEXITY  10  0.9751  0.2704                        (-----*-----)
ERROR_REDUCE     10  0.9288  0.1924                     (-----*-----)
                                      ------+---------+---------+---------+---
                                          0.60      0.75      0.90      1.05

Pooled StDev = 0.1483


Fisher 95% Individual Confidence Intervals
All Pairwise Comparisons

Simultaneous confidence level = 50.66%


CC4.5-1 subtracted from:

                   Lower  Center   Upper
CC4.5-2          -0.1266  0.0057  0.1379
CC4.5-3          -0.1305  0.0017  0.1340
CC4.5-4           0.0529  0.1852  0.3174
C4.5             -0.0455  0.0867  0.2190
PESSIMISTIC       0.1069  0.2391  0.3713
COST-COMPLEXITY   0.2341  0.3664  0.4986
ERROR_REDUCE      0.1878  0.3201  0.4523
```



CC4.5-2 subtracted from:

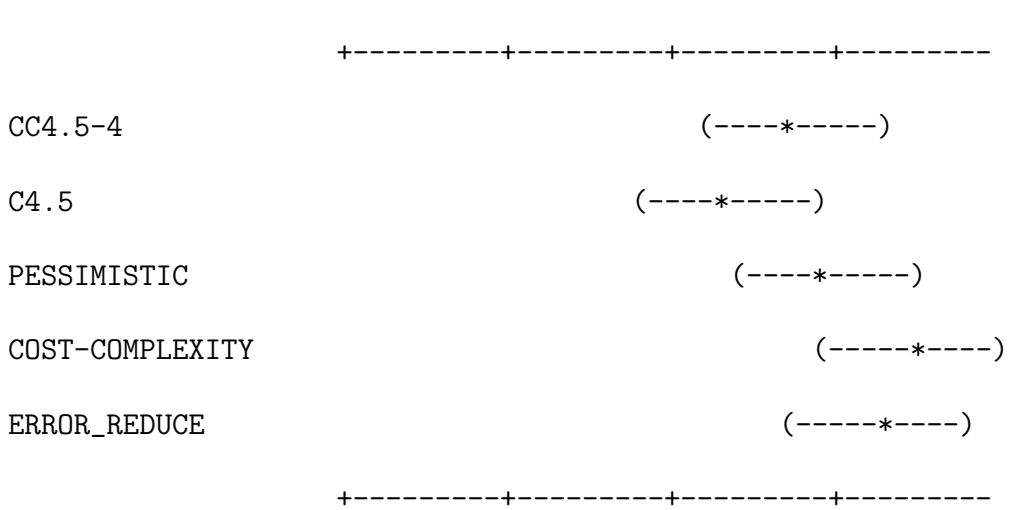
	Lower	Center	Upper
CC4.5-3	-0.1362	-0.0039	0.1283
CC4.5-4	0.0473	0.1795	0.3117
C4.5	-0.0512	0.0811	0.2133
PESSIMISTIC	0.1012	0.2334	0.3657
COST-COMPLEXITY	0.2285	0.3607	0.4929
ERROR_REDUCE	0.1822	0.3144	0.4467





CC4.5-3 subtracted from:

	Lower	Center	Upper
CC4.5-4	0.0512	0.1834	0.3157
C4.5	-0.0472	0.0850	0.2172
PESSIMISTIC	0.1051	0.2373	0.3696
COST-COMPLEXITY	0.2324	0.3646	0.4969
ERROR_REDUCE	0.1861	0.3183	0.4506



```
                -0.50     -0.25      0.00      0.25
```

CC4.5-4 subtracted from:

```
                   Lower   Center   Upper
C4.5             -0.2307  -0.0984  0.0338
PESSIMISTIC      -0.0783   0.0539  0.1862
COST-COMPLEXITY   0.0490   0.1812  0.3134
ERROR_REDUCE      0.0027   0.1349  0.2671

                   +---------+---------+---------+---------
C4.5                          (----*----)
PESSIMISTIC                        (----*----)
COST-COMPLEXITY                         (----*-----)
ERROR_REDUCE                       (----*-----)
                   +---------+---------+---------+---------
                -0.50     -0.25      0.00      0.25
```

C4.5 subtracted from:

```
                  Lower  Center   Upper
PESSIMISTIC      0.0201  0.1523  0.2846
COST-COMPLEXITY  0.1474  0.2796  0.4119
```

```
ERROR_REDUCE     0.1011  0.2333  0.3656


                    +---------+---------+---------+---------
PESSIMISTIC                               (----*----)
COST-COMPLEXITY                                (----*----)
ERROR_REDUCE                                (----*-----)
                    +---------+---------+---------+---------
                  -0.50     -0.25      0.00      0.25



PESSIMISTIC subtracted from:

                   Lower  Center   Upper
COST-COMPLEXITY  -0.0050  0.1273  0.2595
ERROR_REDUCE     -0.0512  0.0810  0.2132


                    +---------+---------+---------+---------
COST-COMPLEXITY                          (----*----)
ERROR_REDUCE                            (----*-----)
                    +---------+---------+---------+---------
                  -0.50     -0.25      0.00      0.25



COST-COMPLEXITY subtracted from:
```

```
                Lower   Center   Upper
ERROR_REDUCE  -0.1785  -0.0463  0.0860


                  +---------+---------+---------+---------
ERROR_REDUCE                    (----*----)
                  +---------+---------+---------+---------
               -0.50     -0.25      0.00      0.25
```

VOTE:

One-way ANOVA: CC4.5-1, CC4.5-2, CC4.5-3, CC4.5-4, C4.5, PESSIMISTIC, ...

Source	DF	SS	MS	F	P
Factor	7	0.002184	0.000312	1.26	0.280
Error	72	0.017773	0.000247		
Total	79	0.019957			

S = 0.01571   R-Sq = 10.94%   R-Sq(adj) = 2.29%

Level	N	Mean	StDev
CC4.5-1	10	0.02591	0.01618

```
CC4.5-2          10  0.02045  0.01055

CC4.5-3          10  0.02045  0.01441

CC4.5-4          10  0.02533  0.01391

C4.5             10  0.03569  0.02028

PESSIMISTIC      10  0.01867  0.01418

COST-COMPLEXITY  10  0.02955  0.01473

ERROR_REDUCE     10  0.02636  0.01926


                 Individual 95% CIs For Mean Based on

                 Pooled StDev

Level             -+---------+---------+---------+--------

CC4.5-1                 (---------*---------)

CC4.5-2               (--------*---------)

CC4.5-3               (--------*---------)

CC4.5-4                   (---------*---------)

C4.5                                (---------*---------)

PESSIMISTIC        (---------*---------)

COST-COMPLEXITY                (---------*--------)

ERROR_REDUCE                (---------*---------)

                  -+---------+---------+---------+--------

                 0.010     0.020     0.030     0.040


Pooled StDev = 0.01571
```

```
Fisher 95% Individual Confidence Intervals

All Pairwise Comparisons


Simultaneous confidence level = 50.66%



CC4.5-1 subtracted from:


                    Lower    Center    Upper

CC4.5-2          -0.01946  -0.00545  0.00855

CC4.5-3          -0.01946  -0.00545  0.00855

CC4.5-4          -0.01458  -0.00058  0.01343

C4.5             -0.00423   0.00978  0.02379

PESSIMISTIC      -0.02125  -0.00724  0.00676

COST-COMPLEXITY  -0.01037   0.00364  0.01764

ERROR_REDUCE     -0.01355   0.00045  0.01446


                 ---------+---------+---------+---------+

CC4.5-2                  (--------*-------)

CC4.5-3                  (--------*-------)

CC4.5-4                     (--------*-------)

C4.5                              (--------*--------)

PESSIMISTIC              (-------*--------)

COST-COMPLEXITY                (-------*--------)

ERROR_REDUCE                (-------*--------)
```

```
                  ---------+---------+---------+---------+
                        -0.016     0.000     0.016     0.032
```

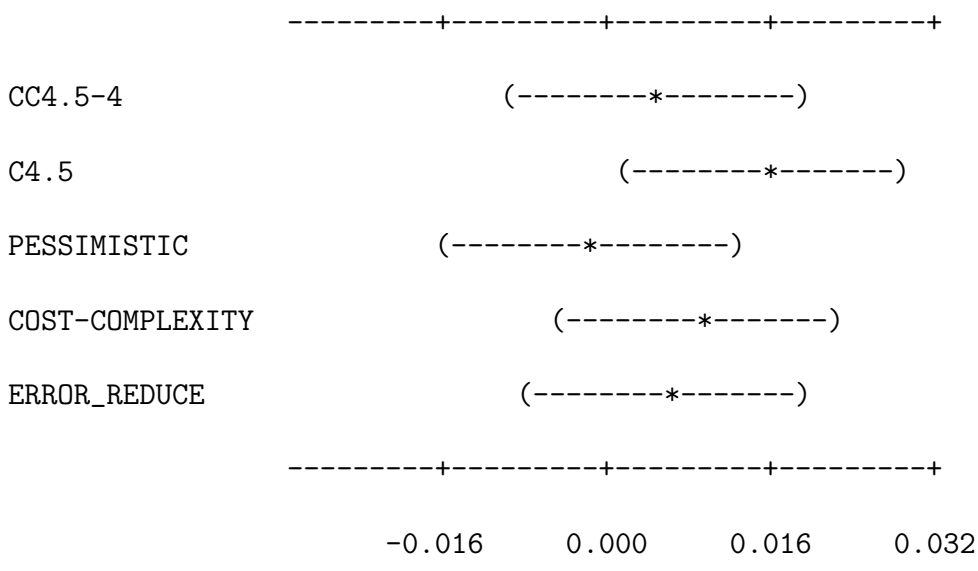
CC4.5-2 subtracted from:

	Lower	Center	Upper
CC4.5-3	-0.01401	-0.00000	0.01401
CC4.5-4	-0.00913	0.00488	0.01889
C4.5	0.00123	0.01523	0.02924
PESSIMISTIC	-0.01579	-0.00179	0.01222
COST-COMPLEXITY	-0.00492	0.00909	0.02310
ERROR_REDUCE	-0.00810	0.00591	0.01992

```
                  ---------+---------+---------+---------+
CC4.5-3                     (--------*--------)
CC4.5-4                        (--------*--------)
C4.5                                (--------*-------)
PESSIMISTIC                  (--------*--------)
COST-COMPLEXITY                    (--------*-------)
ERROR_REDUCE                    (--------*-------)
                  ---------+---------+---------+---------+
                        -0.016     0.000     0.016     0.032
```

CC4.5-3 subtracted from:

	Lower	Center	Upper
CC4.5-4	-0.00913	0.00488	0.01889
C4.5	0.00123	0.01523	0.02924
PESSIMISTIC	-0.01579	-0.00179	0.01222
COST-COMPLEXITY	-0.00492	0.00909	0.02310
ERROR_REDUCE	-0.00810	0.00591	0.01992



CC4.5-4 subtracted from:

	Lower	Center	Upper
C4.5	-0.00365	0.01036	0.02436
PESSIMISTIC	-0.02067	-0.00667	0.00734
COST-COMPLEXITY	-0.00979	0.00421	0.01822

```
ERROR_REDUCE     -0.01298   0.00103  0.01504


                 ---------+---------+---------+---------+
C4.5                              (-------*--------)
PESSIMISTIC             (--------*--------)
COST-COMPLEXITY                (--------*-------)
ERROR_REDUCE                (--------*-------)
                 ---------+---------+---------+---------+
                       -0.016     0.000     0.016     0.032



C4.5 subtracted from:

                    Lower    Center     Upper
PESSIMISTIC      -0.03103  -0.01702  -0.00302
COST-COMPLEXITY  -0.02015  -0.00614   0.00786
ERROR_REDUCE     -0.02333  -0.00933   0.00468


                 ---------+---------+---------+---------+
PESSIMISTIC      (-------*--------)
COST-COMPLEXITY        (--------*--------)
ERROR_REDUCE         (--------*--------)
                 ---------+---------+---------+---------+
                       -0.016     0.000     0.016     0.032
```

```
PESSIMISTIC subtracted from:

                    Lower   Center    Upper
COST-COMPLEXITY  -0.00313  0.01088  0.02489
ERROR_REDUCE     -0.00631  0.00770  0.02170

                  ---------+---------+---------+---------+
COST-COMPLEXITY                    (--------*--------)
ERROR_REDUCE                     (--------*--------)
                  ---------+---------+---------+---------+
                        -0.016     0.000     0.016     0.032


COST-COMPLEXITY subtracted from:

                   Lower    Center    Upper
ERROR_REDUCE  -0.01719  -0.00318  0.01082

                ---------+---------+---------+---------+
ERROR_REDUCE           (--------*--------)
                ---------+---------+---------+---------+
                      -0.016     0.000     0.016     0.032
```