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# Decision Trees with Minimal Costs

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## Abstract

We propose a simple, novel and yet effective method for building and testing decision trees that minimizes the sum of the misclassification and test costs. More specifically, we first put forward an original and simple splitting criterion for attribute selection in tree building. Our tree-building algorithm has many desirable properties for a cost-sensitive learning system that must account for both types of costs. Then, assuming that the test cases may have a large number of missing values, we design several intelligent test strategies that can suggest ways of obtaining the missing values at a cost in order to minimize the total cost. We experimentally compare these strategies and C4.5, and demonstrate that our new algorithms significantly outperform C4.5 and its variations. In addition, our algorithm's complexity is similar to that of C4.5, and is much lower than that of previous work. Our work is useful for many diagnostic tasks which must factor in the misclassification and test costs for obtaining missing information.

## 1. Introduction

Inductive learning techniques have had great success in building models that assign test cases to classes (Quinlan 1993; Mitchell 1997). However, much previous inductive learning research has focused on minimizing classification errors which are useful in deciding whether a learned model tends to make correct decisions when assigning class labels to new cases; thus, they are an important factor to consider. There are, however, different types of classification errors, and their costs are often very

different. For example, in a binary classification task in the medical domain, the cost of false positive (FP) and the cost of false negative (FN) are often very different. In addition, misclassification costs are not the only costs to consider when applying the model to new cases; we also consider the "test cost" which is as important as the misclassification cost when test cases do not provide all the values for their attributes that may be necessary for classification. That is, the test strategies may suggest obtaining more information, at additional cost, for the missing values.

Inductive learning methods that consider a variety of costs are often referred to as cost-sensitive learning (Turney 2002), and tasks that incur both misclassification and test costs abound in practice. As an example, consider again the task of a medical practice that examines incoming patients based on previous experiences. Suppose that these experiences have been compiled into a model such as a decision tree (Quinlan 1993). When dealing with a new patient, certain information about this patient may be unknown; for example, the blood tests or the X-ray test may not have been done yet.

One obvious approach to solving this type of problem is to use C4.5's strategy (Quinlan 1993) in dealing with missing values. When a test case is classified by the decision tree, and is stopped at an attribute whose value is unknown, no test will be performed to obtain its value; instead, the test case is distributed along attribute branches and the classification results are weighted on all of the branches. But this approach ignores the possibility of obtaining the missing value at a cost to further reduce the misclassification cost, and thus the total cost. One of our test methods (the third method discussed in Section 4) uses the C4.5's strategy, and it is shown to be inferior to the new method proposed in this paper (see Sections 4 and 5). Another obvious approach is to perform all tests for unknown values. This is clearly not optimal either as the tests can be very expensive. A third obvious approach is to utilize the decision tree built by C4.5 to guide which tests should be performed. Again when a test case is

classified by the decision tree, and is stopped at an attribute whose value is unknown, the tree naturally suggests that this test should be done at a cost, and the test case will follow the appropriate branch, until it can be classified in a leaf. The problem with this approach is that when building the decision tree, the costs of obtaining these test results are completely ignored. As a consequence, tests that incur heavy costs may be placed on top of the tree, requiring all future patients to complete these tests. This may greatly increase the total test cost, and thus, the total cost. We compare this approach with our new methods, and show that the former is again inferior to the best method we propose (Sections 4 and 5).

In this paper, we study a tree-building strategy that minimizes the misclassification and test costs. Also, we study a set of test strategies that may suggest additional tests at a cost to minimize the total cost on test cases. Our tree-building algorithm has a number of very desirable properties for cost-sensitive learning systems, including important properties as pointed out by (Turney, 2000; Turney 1995). For example, if all test costs are larger than the misclassification cost, then no test should be performed and a one-node decision tree will be returned. As important as building a tree with minimal total cost, we formulate several strategies to deal with unknown values by taking into account both the misclassification and the test costs. These strategies are compared with each other and the best strategy is selected.

The rest of the paper is organized as follows. We first review the related work in Section 2. Then we present our new tree-building algorithm, and show it has many desirable properties (Section 3). After that, we consider several test strategies and analyze their relative merits (Section 4). Finally, we present our experimental results (Section 5) and conclude the work with a discussion of future work (Section 6).

## 2. Review of Previous Work

Much work has been done in machine learning on minimizing the classification errors. This is equivalent to assigning the same cost to each type of classification error (for example, FP and FN), and then minimizing the total misclassification costs. In his survey article, (Turney 2000) analyzes a variety of costs in machine learning, and the test cost is singled out as one of the least considered areas in machine learning. In particular, (Turney 2000) considered the following types of costs in machine learning:

- Misclassification costs: costs incurred by misclassification errors. Works such as (Domingos 1999, Elkan 2001 and Kai 1998) considered machine learning with non-uniform misclassification costs
- Test costs: costs incurred for obtaining attribute values. Previous work such as (Nunez, 1991; Tan

1993) considered the test cost alone without incorporating misclassification cost. As pointed out by (Turney 2000) it is obviously an oversight. As far as we know, the only work considering both misclassification and test costs includes (Turney 1995; Zubek and Dietterich 2002; Greiner et al. 2002). We discuss these works in detail below.

In (Zubek and Dieterrich 2002), the cost-sensitive learning problem is cast as a Markov Decision Process (MDP), and an optimal solution is given as a search in a state space for optimal policies. For a given new case, depending on the values obtained thus far, the optimal policy can suggest a best action to perform to minimize both the misclassification and the test costs. While related to our work, their research adopts an optimal strategy, which may incur very high computational cost to conduct the search. In contrast, we adopt the local search algorithm of (Quinlan 1993) using a polynomial time algorithm to build a model, which returns a new decision tree. Then, when performing the test, our strategy (see later) together with the decision tree will suggest whether to conduct a test or not effectively.

(Greiner et al. 2002) studied the theoretical aspects of active learning with test costs using a PAC learning framework. (Turney 1995) presented a system called ICET, which uses a genetic algorithm to build a decision tree to minimize the cost of tests and misclassification. Our work also considers the decision tree model, where we additionally consider both the minimization of misclassification cost on training data and the formulation of a test strategy for minimizing the test costs on the test data. As mentioned above, because our algorithm essentially adopts the same decision-tree building framework as in (Quinlan 1993), our algorithm is expected to be more efficient than Turney's genetic algorithm based approach.

## 3. Building Decision Tree With Minimal Costs

We assume that the training data may consist of missing values (whose values cannot be obtained). We also assume a static cost structure where the cost is not a function of time or cases. Further, we assume that the test cost and the misclassification cost have been defined on the same cost scale, such as the dollar cost incurred in a medical diagnosis.

Our new decision-tree learning algorithm is quite simple. We consider discrete attribute and binary class labels; extensions to other cases can also be made. We assume that  $FP$  is the cost of one false positive example, and  $FN$  is the cost of one false negative example. Our algorithm uses a new splitting criterion of *minimal total cost* on training data, instead of minimal entropy, to build decision trees. This cost measure is equivalent to the expected total cost measure used in the works of (Turney 1995; Zubek and Dietterich 2002; Greiner et al. 2002). At

each step, rather than choosing an attribute that minimizes the entropy (as in C4.5), our algorithm chooses an attribute that reduces and minimizes the total cost, the sum of the test cost and the misclassification cost, for the split. Then, similar to C4.5, our algorithm chooses a locally optimal attribute without backtracking. Thus the resulting tree may not be globally optimal. However, the efficiency of the tree-building algorithm is generally high. A concrete example is given later in this section.

A fine point of our new algorithm is the way it deals with attributes with unknown values in the training set. In many variations of decision tree algorithms, the unknown value is treated as an ordinary value. However, in our work, the strategy is that all unknown values (we use “?”) are treated as a special “value”: no leaf or sub-tree will be built for examples with the “?” value. This is because it is unrealistic to assume the unknown values would be as useful for classification as the known values. In addition, when a test example is stopped at an attribute whose value is unknown, if the attribute has a “?” branch, it is impossible to decide whether the test should be performed by the tree. Therefore, the examples with unknown attribute values are not grouped together as a leaf, or built into a sub-tree; instead, they are “gathered” inside the node that represents that attribute. We then calculate the ratio of the positive and negative examples in the internal node. See the example given later for more details. Our second test algorithm (see Section 4) will incorporate such ratios in making predictions.

Another important point is how the leaves are labeled. In traditional decision tree algorithms, the majority class is used to label the leaf node. In our case, as the decision tree is used to make predictions to minimize the total cost, the leaves are labeled also to minimize the total cost. That is, at each leaf, the algorithm labels the leaf as either positive or negative (in a binary decision case) by minimizing the misclassification cost. Suppose that the leaf has  $P$  positive examples, and  $N$  negative examples. If  $P \times FN > N \times FP$  (i.e., the cost of predicting negative is greater than the cost of predicting positive), then the leaf is labeled as positive; otherwise it is labeled as negative. Therefore, the label of a leaf does not just depend on the majority class of the leaf, but also on the cost of misclassification.

Let us look at a concrete example. Assume that during the tree building process, there is a set of  $P$  and  $N$  positive and negative examples respectively to be further classified by possibly building a sub-tree. If we assume that  $P \times FN > N \times FP$ , then, if no sub-tree is built, the set would be labeled as positive, and thus, the total misclassification cost is  $T = N \times FP$ . Suppose that an attribute  $A$  with a test cost  $C$  is considered for a potential splitting attribute. Assume that  $A$  has two values, and there are  $P1$  and  $N1$  positive and negative examples with the first value,  $P2$  and  $N2$  positive and negative examples with the second value, and  $P0$  and  $N0$  positive and negative examples with  $A$ 's value unknown. Then the

total test cost would be  $(P1+N1+P2+N2) \times C$  (i.e., cases with unknown attribute values do not incur test costs). Assume that the first branch is labeled positive (as  $P1 \times FN > N1 \times FP$ ), and the second branch is labeled negative, then the total misclassification cost of the two branches is  $N1 \times FP + P2 \times FN$ . As we have discussed earlier in this section, examples with the unknown value of  $A$  stay with the attribute  $A$ , and we have assumed that the original set of examples is labeled as positive. Thus, the misclassification cost of the unknowns is  $N0 \times FP$ . The total cost of choosing  $A$  as a splitting attribute would be:

$$T_A = (P1+N1+P2+N2) \times C + N1 \times FP + P2 \times FN + N0 \times FP$$

If  $T_A < T$ , where  $T = N \times FP$ , then splitting on  $A$  would reduce the total cost of the original set, and we would then choose an attribute with the minimal total cost as a splitting attribute. We then apply this process recursively on examples falling into branches of this attribute. If  $T_A \geq T$  for all remaining attributes, then no further sub-tree will be built, and the set would become a leaf, with a positive label.

Finally, as our tree attempts to minimize the total cost, it may also overfit the training dataset. Traditional decision tree algorithms such as C4.5 incorporate a post-tree pruning procedure to simplify the tree. The current version of our algorithm, however, does not yet incorporate tree pruning. As all of our tree building algorithms (see Section 3) build unpruned trees, our experiment comparisons (Section 5) are still fair and valid. It remains our future work to include pruning in our tree-building algorithm with a minimal total cost.

Aimed at minimizing the total cost of test and misclassification, our new decision-tree algorithm has several desirable features. We will discuss these features below, using the dataset “Ecoli” as an example (Blake & Merz 1998). This dataset, after pre-processing, has 332 labelled examples, which are described by six attributes. The numerical attributes are first discretized using the minimal entropy method (Fayyad & Irani 1993), as our tree building algorithm can only accept discrete attributes (but it is straightforward to extend our algorithm to accept continuous attributes as C4.5 does). The attribute values are renamed as 1, 2, 3, and so on. More details on this and other datasets used in experiments can be found in Section 5.

The first property, as discussed in the Introduction, is that the relative difference between misclassification and test costs can affect the tree dramatically. If the former is less than the latter, then no test should be performed, and the decision tree would be simply a one-node leaf. On the other hand, if the former is much larger than the latter, then all tests should be done, as long as they are relevant; i.e., they can improve the predictive accuracy. This can be seen clearly from the “Ecoli” dataset. Indeed, if the misclassification cost is set to 200 for both FP and FN, and all test cost is set to 300, then the algorithm returns a one-leaf node as shown in Figure 1 (a). On the other hand,

when all test costs are set to zero, then the tree is the “largest”; in this case, the tree has 13 nodes in total, and can be seen in Figure 1 (c). As an “intermediate” case, if all test costs are set to 20, then the decision tree with the minimal cost has six nodes in total, and the tree can be seen in Figure 1 (b).

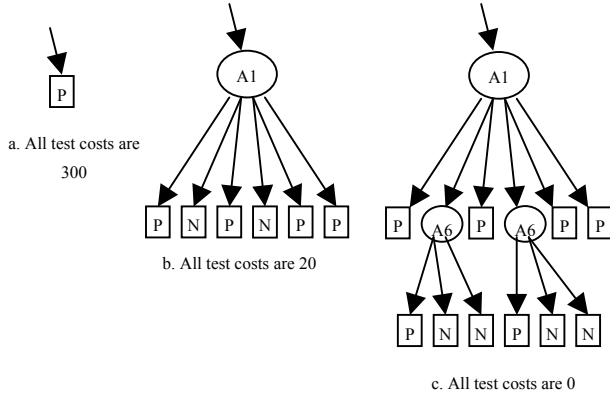


Figure 1. Three different decision trees built with different test costs.

The second important and desirable property is that for attributes with different test costs, our new algorithm is likely to choose an attribute with zero or the smallest cost at the top (or root) of the tree. This is because the attribute at the root will be tested by all examples, and thus the total attribute cost would be relatively high. Choosing an attribute with zero or the smallest cost helps reduce the total cost. Of course attribute selection also depends on the distribution of attribute values and class labels of the training examples.

Table 1. Three different sets of attribute costs.

COST	A1	A2	A3	A4	A5	A6
Tree # 1	20	20	20	20	20	20
Tree # 2	200	20	100	100	200	200
Tree # 3	200	100	100	100	20	200

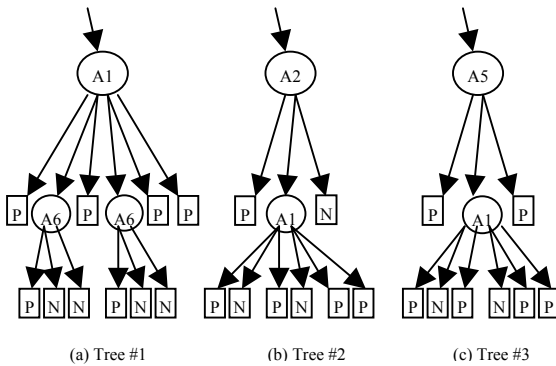


Figure 2. Three different decision trees built with three different test costs as in Table 1.

Table 1 shows three cases in which attribute costs are different. In the first case (the baseline), all attribute costs are set to 20. In the second and third cases attribute costs are set differently. The misclassification cost is set at 800 for both FP and FN. As we can see, in the second case, the attribute A2 has the smallest test cost, and it is indeed chosen as the root of the tree as shown in Figure 2(b). In the third case, attribute A5 has the smallest test cost, and it is chosen as the root (Figure 2(c)).

The third property, related to the second one, is that when the test cost of an attribute is increased, that test attribute will be “pushed” down in the tree, until it “falls out” of the tree (when the test cost becomes too large). If the test cost of A1 is set to 20, 50, and 80, respectively, while other costs are fixed, we obtain trees (not shown here) with A1 at the root (similar to Figure 2(a)), in the middle of the tree (similar to Figure 2(b)), and not in the tree, respectively.

#### 4. Performing Tests on Test Examples

After the minimal-cost decision tree is built, the next interesting question is how this tree can be used to deal with test examples with many missing values, in order to predict the class of the test examples with the minimal total cost for this case. Deciding which tests should be performed is a part of the test strategy.

We will study four test strategies. We use the decision tree in Figure 3, built with the test cost in Table 2, and a test example in Table 3 to illustrate the four strategies described below. Bear in mind that this is only for one particular test case. The overall performance of these strategies will be compared in the next section with a large number of test examples.

The first strategy, called Optimal Sequential Test (OST), is very simple and intuitive. It uses the tree built with the minimal cost to decide what tests must be performed in sequence. More specifically, each test example goes down the tree until an attribute whose value is unknown is met in the test example. As the tree was built to minimize the total cost, this tree would suggest that this test should be performed at the cost, and its value would decide which branch to go down the tree further. For example, when the test example in Table 3 goes down the tree in Figure 3, it will stop at the node A6. Then the test is done at a cost 20, and it reveals the value 3. Then the example goes down to node A1, and a test on A1 is performed at a cost 50, with the value 6. Thus, it falls into the rightmost leaf under A1, which predicts the class P. The prediction is the same as the true class of the test case, so there is no misclassification cost. Thus the total cost is 20 + 50 = 70.

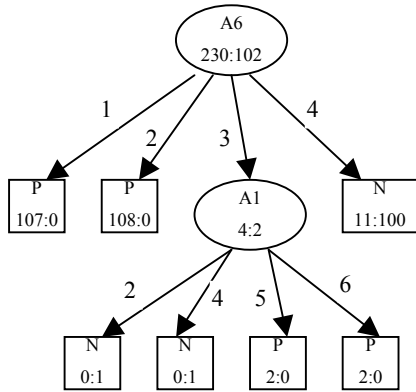


Figure 3. A decision tree built from the Ecoli dataset (costs are set as in Table 2).

Table 2. Test and misclassification costs set for Ecoli dataset.

A1	A2	A3	A4	A5	A6	FP/FN
50	50	50	50	50	20	800/800

Table 3. An example test case with several unknown values. The true values are in parenthesis and can be obtained by performing the tests (with costs list in Table 2).

A1	A2	A3	A4	A5	A6	Class
? (6)	2	? (1)	2	2	? (3)	P

This strategy, while optimal based on the minimal cost of the training set, is sequential. That is, one must wait for the result of the first test before the next test can be determined. In medical diagnoses, doctors often cannot wait for the result of the first test before other tests can be done; they normally order a set of tests to be done at once. A “Batch Test” strategy can be modeled easily into our decision tree. When a test case is stopped at the first attribute whose value is unknown, all unknown values under that attribute must be obtained. Clearly this strategy will return the same prediction as OST (i.e., same misclassification cost), but it would incur a higher test cost.

The second strategy uses the same decision to make prediction, but it stipulates that no further tests should be done. More specifically, when a test example is stopped at an attribute whose value is unknown, it stops right there, and uses the ratio of positive and negative examples in that (internal) node to predict the test example (recall that these ratios are calculated based on training cases which also have unknown values at this node). Using the same example, when the test example stops at the node A6, it would predict that the test example is of class for the node A6 (which is positive by  $P \times FN > N \times FP$  i.e.  $230 \times 800 > 102 \times 800$ ). As no test is done, there is no test cost. The total cost is thus 0 here.

The third strategy is a variation of the second strategy. Instead of stopping at the node whose attribute value is unknown in the test case, this strategy will “split” the test case into fractions according to the training examples, and go down all branches simultaneously. The final class is a weighted sum of the class in each branch. Note that this is essentially C4.5’s strategy in dealing with missing values. Using the same example to illustrate this strategy, the test case will not stop at node A6 this time; instead, it will distribute into four branches with a ratio  $107/108/6/111$ . The first two branches make a correct prediction with no misclassification cost. The last branch makes a wrong prediction, with a misclassification cost of 800. The third branch encounters another unknown value, so it is distributed further down in the tree, with a ratio of  $1/1/2/2$ . The first two branches make a wrong prediction (costing 800), while the next two branches make a correct prediction. With the total number of 332 ( $230+102$ ) training examples in the tree building, the weighted cost for this test example is thus:  $800 \times (1+1+111)/332 = 272.3$ .

The fourth and final strategy also stipulates that no further tests should be done, but it utilizes the existing attribute values to the full extent. For each test example, a new (and different) decision tree is built dynamically from all of the training examples with only those attributes whose values are known in the test example. In this way, the new decision tree only uses attributes with known values in the test example, and thus, no new test is needed. As an example, as A2, A4, and A5 are the only known attributes, a new decision tree (not shown here) using the training examples with A2, A4, and A5 as attributes will be built. From this tree, we obtain that the total cost is 800.

This final strategy in itself is interesting, and it is a kind of lazy learning algorithm where the learning model is built only during test and can be affected by the test examples (see, for example, LazyDT by (Friedman et al 1996)). Here, as test examples may have a different set of known attributes, the trees from different test examples can be different, too.

We expect that our first test strategy, the Optimal Sequential Test, would be the best with the overall lowest total cost, as it is based on minimizing the total cost in the training set. The fourth method, building different trees for different test cases, would be second, as it utilizes fully the training data, and like lazy learning, it explores the search space in the local region. The second and third methods would probably perform the worst. In the next section, we will perform extensive experiments to compare and evaluate these methods with real-world datasets.

## 5. Experiments

We conduct experiments on five real-world datasets and compare the four test strategies against the baseline C4.5. In C4.5, we use the information gain to build a decision

tree (without pruning). Missing values are ignored in training examples as done in C4.5. Then the tree is used to predict the test examples with a process similar to our first test strategy (Optimal Sequential Test). That is, when the test example is classified by the tree, and if an attribute value is unknown, a test is done at a cost. The test example then goes down further according to the value obtained, until it reaches the leaf, where a prediction is made.

We use five datasets in our experiments. These datasets are chosen because they have at least some discrete attributes, binary class, and a good number of examples. The numerical attributes in datasets are discretized first using minimal entropy method (Fayyad & Irani 1993) as our algorithm can currently only deal with discrete attributes. The datasets are listed in Table 4.

Table 4. Datasets used in the experiments.

	No. of attributes	No. of examples	Class distribution (P/N)
Ecoli	6	332	230/102
Breast	9	683	444/239
Heart	8	161	98/163
Thyroid	24	2000	1762/238
Australia	15	653	296/357

For the experiments, each dataset is split into two parts: the training set (60%) and the test set (40%). A decision tree is built from the training set using our new algorithm that minimizes the total cost (Section 3). For our fourth lazy-style test method, a different tree is built for each test case. The decision tree is then used to predict the test examples, and to decide what tests, if any, should be performed to minimize the total cost. This process is repeated five times, and results, in consequent figures, are averages of the five runs.

As we discussed in the Introduction section, test examples would often have more unknown values, as it is part of the test process to decide what tests need to be performed. Therefore, a certain percentage of attributes are randomly selected and marked as unknown. If the test algorithm decides to perform a test on an unknown attribute, then its real value is revealed and a cost is incurred.

Figure 4 shows different algorithms in terms of the different percentages of unknown attribute values in the test examples. This figure shows the graph for the Ecoli dataset, whereas the other figures for other datasets are similar and thus are omitted. The scales on the x-axis (20%, 40%, and so on) represent the percentage of unknown attributes in the test sets. The curve represents the average total cost of a test case of five different test strategies, averaged over five runs. In this set of experiments, the misclassification cost is set as 400/400

(400 for FN and 400 for FP), and the test costs are set randomly between zero and 100.

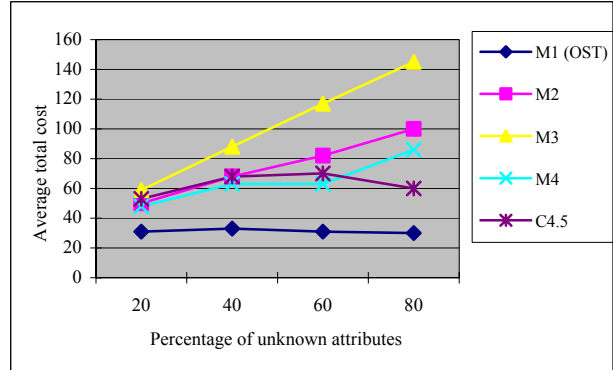


Figure 4. Comparing the total cost under different unknowns.

From this experiment, we can draw several interesting conclusions. First, our first method (M1), Optimal Sequential Test (OST), is clearly the winner. The total cost is always the lowest, and it does not increase much when the percentage of unknown values increases. This is mainly because the test costs are relatively cheap, and with the suggestions of tests performed by OST, the final prediction is quite accurate (resulting in a small misclassification cost). Second, our fourth method (M4), a lazy-style decision tree algorithm, is the second best when the percentage of unknown attributes is less than 60% because it utilizes fully the known attributes by building a new decision tree for each test example. However, when there are too many unknown attributes (such as 80%), the decision tree built from only 20% of the known attributes is obviously inaccurate, thus the misclassification cost increases dramatically, increasing the total cost as well. Third, C4.5 performs the third best overall, and as with OST, the total cost does not increase with more missing values in test cases. This shows that doing tests (as in Optimal Sequential Test and C4.5) is better than not doing tests (as in Methods 2, 3 and 4) when the test cost is not too large. However, C4.5 is not as good as OST because test costs are not taken into consideration when the decision tree is built. Fourth, the second and third methods (M2 and M3) are worse, because they use a single decision tree built from the training set, and it does not perform tests to improve predictive accuracy. Here we can see that their performance degrades as the unknown values increase. Fifth, it is clear from the graphs that the more unknown attribute values, the higher the total cost for test strategies without doing the test, and the more advantageous our first method Optimal Sequential Test and C4.5 would be compared to other methods.

Recall that M3 is essentially C4.5's strategy in dealing with unknown values. It is surprising to see that in this and later experiments M3 (the C4.5 strategy) seems to be

worse than the naïve strategy M2. We think that the main reason is that distribution into branches of the tree due to unknown values accumulates a large misclassification cost overall. It would be interesting to see if C4.5 would be better off using the naïve strategy, as in M2, in dealing with missing values.

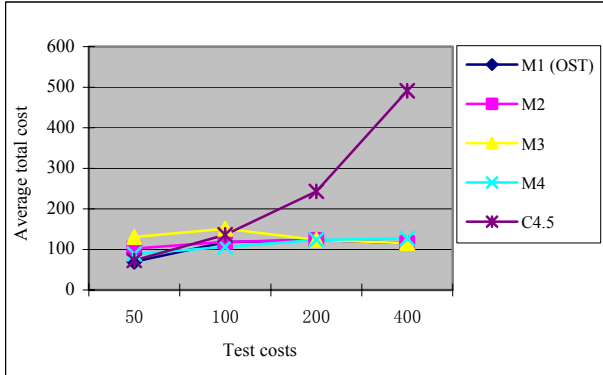


Figure 5. Comparison under different test costs.

The next set of experiments compares different algorithms in terms of their test cost magnitudes while the misclassification cost is fixed at 400/400. In Figure 5, which plots the result on the Ecoli dataset, the costs of the tests (attributes) range from 50 to 400. The percentage of unknown attribute values is set to 60%. Again we can make many interesting conclusions, some of which are similar to what we stated earlier, but some are quite different. First, our first method (M1), Optimal Sequential Test (OST), is still clearly the winner. But other test strategies we proposed (M2, M3, and M4) become very similar to OST when the test cost increases. This is expected as the test costs increase, our tree-building algorithm will prefer not to build a tree (or only to build a one-node tree) to save the total cost which may end up with lower total costs. When this happens, the four test strategies we proposed may become the same. Second, C4.5 performs much worse when the test cost increases. This is also expected as C4.5 builds the same decision tree independent of the test cost, and thus the total costs become much larger when the test costs increase. Third, when the test cost is still relatively small (from 50 to 100), our fourth method (M4), a lazy-style decision tree algorithm, is still next in ranking because, again, it utilizes fully the known attributes by building a new decision tree for each test example. Fourth, it is clear from the graphs that the test strategies' total test cost does not increase much when the test cost increases because our tree-building algorithm and test strategies aim at minimizing the total cost of misclassifications and tests.

Our last set of experiments is similar to the one above, but with more unbalanced misclassification costs. The FP and FN costs are set to 400/1500, and the percentage of unknown attribute values is 60%. In this case, we confirm our expectation that C4.5 would not perform well as it

does not distinguish between the two types of misclassification costs while our methods do. Our test algorithms M1, M2, and M4 perform similarly and better than C4.5, as they are based on the decision tree with minimal total cost. The result is presented in Figure 6.

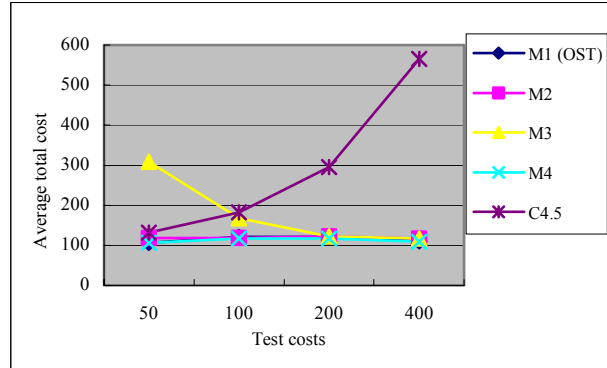


Figure 6. Comparing unbalanced misclassification costs.

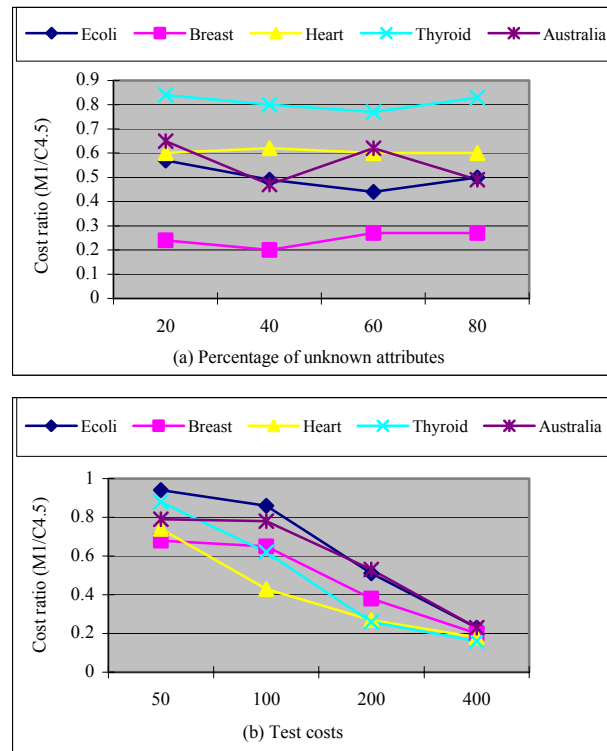


Figure 7. Comparing M1 and C4.5 for different datasets with varying unknowns as in (a), and test costs as in (b)

One of our significant results is that the best performance as demonstrated by the method M1 on the Ecoli dataset is repeatable throughout all datasets that we consider (see Table 4). Figures 7 (a) and (b) compare the performance of M1 and C4.5 for different datasets. As the percentage

of unknowns and the test costs change, the ratio of the average total cost by M1 over C4.5 is always lower than one across different datasets. We can conclude that the superiority of M1 is a general phenomenon.

## 6. Conclusions and Future Work

In this paper, we present a simple and novel method for effectively building decision trees that minimizes the sum of the misclassification cost and the test cost. Our method utilizes a new cost-based splitting criterion for attribute selection, and incorporates several intelligent test strategies that can suggest how to obtain missing values with new tests. Our experiments show that our new decision-tree-building algorithm, together with the best test strategy, Optimal Sequential Test, can dramatically outperform a number of other competing algorithms, including C4.5. In addition, compared to other related works, our algorithm has a much lower computational complexity, and is thus more practical.

In the future, we plan to consider methods of minimizing the total cost when all new tests must be decided together, rather than in a sequential manner. We did extend our Optimal Sequential Test to the Batch Test in Section 4, but it would be interesting to find more effective methods. Also pruning can be introduced in our tree-building algorithm to avoid overfitting the data. Finally, we plan to study ways to incorporate other types of costs in our decision tree learning and test algorithms.

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