You have built a decision tree learner. How can you use it to make classifications? How does its performance scale with training data set size?

Background

The starter code for this assignment also contains these files you copied from the MathLAN directory

~weinman/courses/CSC261/code/dtree

analysis.scm Routines for helping you perform some analysis. Namely, splitting the example data into train/test subsets and selecting a (smaller) random subset of examples for training.

classify.scm Documentation for the procedure you will write.

Given a decision tree, how do you classify an instance? Now that you know the recursive structure of a decision tree, classification is straightforward. If the decision tree starts with a cons cell (which you can test using the predicate pair?), then you know you need to apply an attribute test. You will need to

- get the attribute test specified in the decision tree,
- get the value of that attribute in the instance (using assoc),
- follow the branch of the decision tree having that value to get the next decision tree (again using assoc), and then
- recursively apply the classification routine on the next decision (sub)tree.

Otherwise, the decision tree is simply a classification value, which may be directly returned. For example:

```
> (load "restaurant.scm")
> (load "dtree.scm")
> (load "learning.scm")
> (load "classify.scm")
> (define restaurant-tree (decision-tree-learning restaurant-examples

restaurant-attributes #t)

> (cdr restaurant-examples)

(("Alt" . #t) ("Bar" . #f) ("Fri" . #t) ("Hun" . #t) ("Pat" . "Some")

("Price" . "$$") ("Rain" . #f) ("Res" . #t) ("Type" . "French")

("Est" . "0-10")

> (decision-tree-classify restaurant-tree (cdr restaurant-examples))

#t
```

Assignment

Problem 1: decision-tree-classify

Implement the decision-tree-classify procedure documented in classify.scm. Note the structure of the procedure outlined above and consult Exercise D.2 of Lab: Decision Trees.
Problem 2: Analysis

You now have everything you need to train \textit{and} test your supervised learning classifier. Note that \texttt{dtree.scm} includes the procedure \texttt{(decision-tree-accuracy decision-tree examples)}, which allows you to test the accuracy (a number between 0 and 1) on some examples. Of course, the examples need not be the same ones used to train the given decision tree.

Compiled implementations (which you copied with the starter code) of \texttt{decision-tree-learning} and \texttt{decision-tree-classify} are optionally available. To use them, add the following to your analysis program before loading \texttt{analysis.scm} or \texttt{dtree.scm}:

\begin{verbatim}
(require "weinman-dtree.scm")
\end{verbatim}

Part A

On the last assignment you built a tree from the entire mushroom data set. What is the accuracy of the resulting decision tree on the same data?

Part B

Here you will apply the methodology for assessing a learning algorithm using the mushroom data. Namely, this requires us to:\footnote{Adapted from “Assessing the performance of the learning algorithm,” AIMA 2/e pp. 660-661.}

1. Collect a large set of examples (which we have already done).
2. Divide the examples into two disjoint sets, one for training and another for testing.
3. Apply \texttt{decision-tree-learning} to a training set, generating a hypothesis “function” \texttt{h}.
4. Measure the accuracy on the test set made by \texttt{h}.
5. Repeat steps 2 to 4 for different sizes of training sets and different randomly selected sets of each size.

Note that this process empirically assesses the “generalizability” of the learned hypothesis function (i.e., decision tree) by measuring the accuracy on testing data that was not used to train the classifier.

The procedure \texttt{(run-trials examples attributes default num-trials)} in \texttt{analysis.scm} does precisely this sort of assessment, measuring the \textbf{error rate} (not accuracy) on a \textit{single} test set with randomly selected training subsets of lengths 0,5,10,15,20,25,...,85,90,95,100. It reports the average error rate over several trials for each length.

Use this procedure and display your learning curve in a graph, much like Figure 18.7 (p. 703). Title your graph, clearly label your axes, and include a caption briefly explaining the data (noting its source), evaluation procedure, and any relevant learning and evaluation parameters.

What to turn in

Your submission should include the following

- Your completed \texttt{classify.scm}
- The driver program generating the data for Problem 2
- A single PDF containing (merged)
  - Your Scheme files
  - A transcript of your driver program’s output
  - Your answer to Problem 2(A) and your graph (etc.) of Problem 2(B)

Submissions missing the PDF or files in any other formats will not be graded.

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