The Development of Discrete Decision Tree Induction for Categorical Data

Nittaya Kerdprasop and Kittisak Kerdprasop

***Abstract*—**In decision analysis, decision trees are commonly used as a visual support tool for identifying the best strategy that is most likely to reach a desired goal. A decision tree is a hierarchical structure normally represented as a tree-like graph model. The tree consists of decision nodes, splitting paths based on the values of a decision node, and sink nodes representing final decisions. In data mining and machine learning, decision tree induction is one of the most popular classification algorithms. The popularity of decision tree induction over other data mining techniques are its simple structure, ease of comprehension, and the ability to handle both numerical and categorical data. For numerical data with continuous values, the tree building algorithm simply compares the values to some constant. If the attribute has value smaller than or equal to the constant, then proceeds to the left branch; otherwise, takes the right branch. Tree branching process is much more complex on categorical data. The algorithm has to calculate the optimal branching decision based on the proportion of each individual value of categorical attribute to the target attribute. A categorical attribute with a lot of distinct values can lead to the *overfitting* problem. Overfitting occurs when a model is overly complex from the attempt to describe too many small samples which are the results categorical attributes with large quantities. A model that overfits the training data has poor predictive performance on unseen test data. We thus propose novel techniques based on data grouping and heuristic-based selection to deal with overfitting problem on categorical data. Our intuition is on the basis of appropriate selection of data samples to remove random error or noise before building the model. Heuristics play their role on pruning strategy during the model building phase. The implementation of our proposed method is based on the logic programming paradigm and some major functions are presented in the paper. We observe from the experimental results that our techniques work well on high dimensional categorical data in which attributes contain distinct values less than ten. For large quantities of categorical values, discretization technique is necessary.

***Keywords*—** Overfitting problem, Categorical data, Data mining, Decision tree induction, Prolog language.

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N. Kerdprasop is an associate professor and the director of Data Engineering Research Unit, School of Computer Engineering, Suranaree University of Technology, 111 University Avenue, Muang District, Nakhon Ratchasima 30000, Thailand (phone: +66-44-224-432; fax: +66-44-224-602; e-mail: nittaya@sut.ac.th).

K. Kerdprasop is with the School of Computer Engineering and Data Engineering Research Unit, Suranaree University of Technology, 111 University Avenue, Muang District, Nakhon Ratchasima 30000, Thailand (e-mail: KittisakThailand@gmail.com).

I. Introduction

DECISION tree induction is a popular method for mining knowledge from data by means of decision tree building and then representing the end result as a classifier tree. Popularity of this method is due to the fact that mining result in a form of decision tree is interpretability, which is more concern among casual users than a sophisticated method but lacking of understandability such as support vector machine or neural network [6], [7], [8], [9], [12], [18], [19].

A decision tree is a hierarchical structure with each internal node containing a decision attribute, each node branch corresponding to a distinct attribute value of the decision node, and the class of decision appears at the leaf node [3]. The goal of building a decision tree is to partition data with mixing classes down the tree until each leaf node contains data instances with pure class**.**

When a decision tree is built, many branches may be overly expanded due to noise or random error in the training data set. Noisy data contain incorrect attribute values caused by many possible reasons, for instance, faulty data collected from instruments, human errors at data entry, errors in data transmission [1]. If noise occurs in the training data, it can lower the performance of the learning algorithm [20]. The serious effect of noise is that it can confuse the learning algorithm to produce too specific model because the algorithm tries to classify all records in the training set including noisy ones. This situation leads to the *overfitting* problem [4], [11], [17].

Even if training data do not contain any noise, but they instead contain categorical data with excessive number of distinct values. The tree induction results also lead to the same problem because with large quantities of categorical values, the algorithm has to divide data into a lot of small groups. The extreme example is a group of one data instance. That introduces a lot of noise into the model.

General solution to this problem is a tree pruning method to remove the least reliable branches, resulting in a simplified tree that can perform faster classification and more accurate prediction about the class of unknown data class labels [4], [11], [14].

Most decision tree learning algorithms are design with the awareness of noisy data. The ID3 algorithm [13] uses the pre-pruning technique to avoid growing a decision tree too deep down to cover the noisy training data. Some algorithms adopt the technique of post-pruning to reduce the complexity of the learning results. Post-pruning techniques include the cost-complexity pruning, reduced error pruning, and pessimistic pruning [10], [15]. Other tree pruning methods also exist in the literature such as the method based on minimum descriptive length principle [16], and dynamic programming based mechanism [2].

A tree pruning operation, either pre-pruning or post-pruning, involves modifying a tree structure during the model building phase. Our proposed method is different from most existing mechanism in that we deal with noisy data prior to the tree induction phase. Its loosely coupled framework is intended to save memory space during the tree building phase and to ease the future extension on dealing with streaming data.

We present the framework and the detail of our methodology in Section 2. The prototype of our implementation based on the logic programming paradigm is illustrated in Section 3, whereas the Prolog source code of our prototype is provided in Appendix. Efficiency of our implementation on categorical data is demonstrated in Section 4. Conclusion and discussion appear as the last section of this paper.

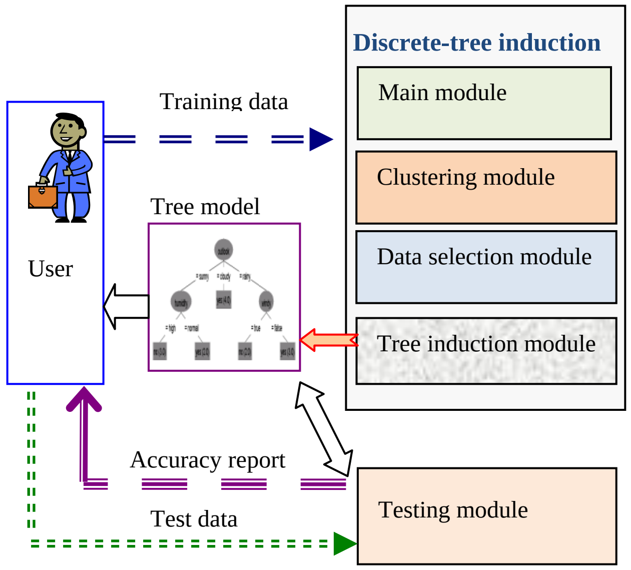


Fig. 1 a decision tree induction framework

II. A Method for Building Decision Tree to Handle Categorical Data

Our proposed system has been named *discrete-tree induction* to enunciate our intention to design a decision tree induction method to handle categorical data containing numerous discrete values. The framework as shown in Figure1 is composed of the discrete-tree component, which is the main decision tree induction part, and the testing component responsible for evaluating the accuracy of the decision tree model as well as reporting some statistics such as tree size and running time.

Categorical value handling of our discrete-tree induction method can be achieved through the selection of the representative data, instead of learning from each and every training data. These selected data are used further in the tree building phase. Training data are first clustered by clustering module to find the mean point of each data group. The data selection module then uses these mean points as a criterion to select the training data representatives. It is a set of data representatives that to be used as input of the tree induction phase.

Heuristics have to be applied as a threshold in the selection step and as a stopping criterion in the tree building phase. The algorithms of a main module as well as the clustering, data selection, and tree induction modules are presented in Figures 2-5, respectively.

Input: Data D with class label
Output: A tree model M

Steps:

```
1. Read D and extract class label to check distinctive
   values K
2. Cluster D to group data into K groups
3. In each group
   3.1  Get mean attribute values
   3.2. Compute similarity of each member compared to
        its mean
   3.3  Compute average similarity and variance
   3.4  Set threshold T = 2*Variance
   3.5  Select only data with similarity > T
4. Set stopping criteria S for tree building as
   S = K – log [ (number of removed data + K) / |D| ]
5. Send selected data and criteria S into tree-induction
   module
6. Return a tree model
```

Fig. 2 discrete-tree induction main algorithm

```
Steps:
1. Initialize K means  /* Create temporary mean
       points for all K clusters.  */
2. Call find_clusters(K, Instances, Means) /* assign
       each data to the closest cluster; reference point
       is the mean of cluster */
3. Call find_means(K, Instances, NewMeans) /*
       compute new mean of each cluster; this
       computation is based on current members of
       each cluster */
4. If Means ≠ NewMeans Then repeat step 2
5. Output mean values and instances in each clusters
```

Fig. 3 categorical data clustering algorithm

```
Steps:
1. For each data cluster
2.     Compute similarity of each member compared to
        cluster mean
3.     Computer average similarity score of a cluster
4.     Computer variance on similarity of a cluster
5.     Threshold = 2* variance
6.     Remove member with
           similarity score  < Threshold
7. Return K clusters with selected data
```

Fig. 4 data selection algorithm

```
Steps:
1.  If data set is empty
2.      Then Assert(node(leaf,[Class/0], ParentNode)
3.           Exit
     /* insert a leaf node in a database, then exit */

4.  If number of data instances < MinInstances
5.      Then Compute distribution of each class
6.           Assert(node(leaf, ClassDistribution,
                                        ParentNode)

7.  If all data instances have the same class label
8.      Then  Assert(node(leaf, ClassDistribution,
                                        ParentNode)

9.  If data  > MinInstances and data have mixing class
                        labels
10.     Then BuildSubtree

11. If data attributes conflict with the existing attribute
                values of a tree
12.     Then stop growing and create a leaf node with
                  mixing class labels
13. Return a decision tree
```

Fig. 5 tree building algorithm

III. A Logic-Based Implementation

We implement the *discrete-tree induction* method based on the logic programming paradigm using SWI-Prolog (www.swi-prolog.org). Program and data set are in the same format, that is Horn clauses. Example of data set is shown in Figure 6.

```
% attribute detail
attribute(size,   [small, large]).
attribute(color,  [red, blue]).
attribute(shape, [circle, triangle]).
attribute(class,  [positive, negative]).
%  data
instance(1, class=positive, [size=small, color=red,
                                   shape=circle]).
instance(2, class=positive, [size=large, color=red,
                                   shape=circle]).
instance(3, class=negative, [size=small, color=red,
                                   shape=triangle]).
instance(4, class=negative, [size=large, color=blue,
                                   shape=circle]).
```

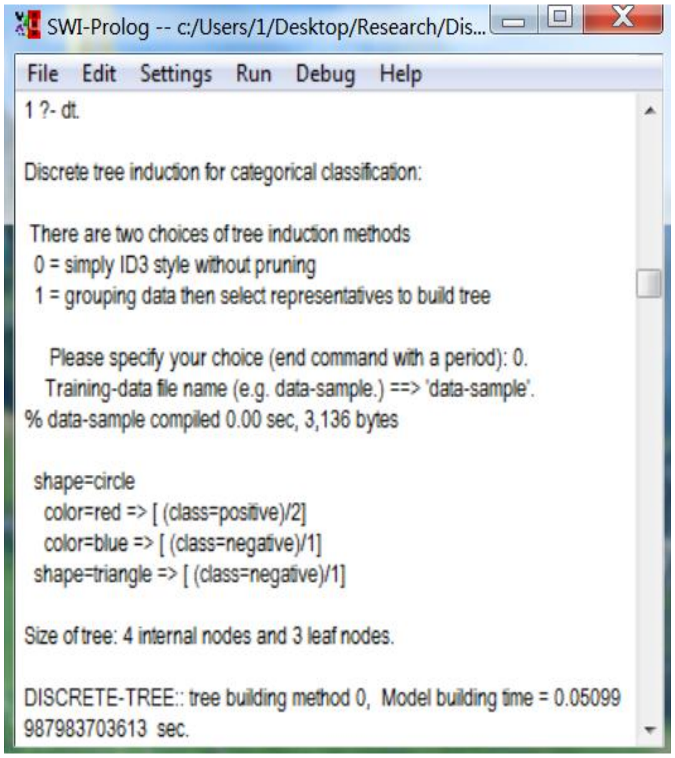
Fig. 6 sample data set in a Horn clause format

Discrete-tree induction program provides two schemes of tree building: 0 and 1. Scheme 0 corresponds to ordinary ID3 style [9] without additional noise handling mechanism. Scheme 1 is a tree induction with a heuristic-based mechanism to deal with noisy and categorical data. Prolog coding of both schemes are as follows.

```
%% Main module:  dt
%% ==========
  dt :-
    write('   Training-data file name ==> '),
    read(D),          % get data file
    consult(D),       % data is also a prolog program
    get_time(StartTime),
         % clear all nodes and node-ID counter in the DB
     retractall(node(_, _, _)),
     retractall(counter(_)),
         % make list Attr of all predictive attribute names
    findall(A, (attribute(A, _), A \= class), Attr),
    dtree(L,Attr),      % call discrete tree induction module
    get_time(FinishTime),
    Time is FinishTime-StartTime.

% -------------------------------------
%  start traditional tree-induction with ID3 algorithm

  dtree(0,Attr) :-  !,
          % make a list Ins = [1,2,...,n] of all instance ID
     findall(N, instance(N, _, _), Ins),
          % create decision tree, start with the root node
          % set MinInstance in leaf nodes = 1
          % then show model as decision tree once finish
          % building phase
     induce_tree(root, Ins, Attr, 1),
     print_tree_model.

%-------------------------------------------
```

```
% start tree-induction by clustering before induce tree

   dtree(1,Attr) :-  !,
       attribute(class, ClassList),
       length(ClassList, K),
       findall(N, instance(N,_,_),Ins),
       clustering(Ins, K, Clusters, Means),
       select_DataSample(Clusters,K,Means,[],Sample),
       removed_Data(Sample, Ins, Removed),
       length(Removed, R),
       length(Ins, I),
                              % a heuristic to prune tree
       MinInstance is K-log((R+K)/I),
       induce_tree(root,Sample,Attr,MinInstance),
       print_tree_model.
%% ----------------------------------------
%% Module induce_tree(+ParentNode, +InstanceIDlist,
                  +AttributeList, +MinInstance)
%% ===============
%% Special case: empty data set, do nothing
       induce_tree(ParentNode,[],_,_) :-
                 instance(_,Class,_),
                 assertz(node(leaf,[Class/0],ParentNode)), !.

%%   Case 1: Number of instances =< MinInstance.
%% Thus, create a leaf node labelled with class distribution.

   induce_tree(ParentNode, InstanceIDlist, _, MinInstance) :-
          length(InstanceIDlist, NumInstances),
          NumInstances =< MinInstance,
                      % a constraint to satisfy case1
                      % count distinctive of current classes
          classDistribution(InstanceIDlist, Dist),
                % insert a leaf node into the DB
          assertz(node(leaf, Dist, ParentNode)), !.

%%  Case 2: Number of instances > MinInstance,
%%    but instances are the same class, create a leaf node
%%
  induce_tree(ParentNode, InstanceIDlist, _, _) :-
          classDistribution(InstanceIDlist, Dist),
          length(Dist, 1),  % constraint: case of single class
          assertz(node(leaf, Dist, ParentNode)), !.

%%   Case 3:  Number of instances > MinInstance.
%%   Data contain a mixture of classes, then grow tree.

  induce_tree(ParentNode, InstanceIDlist, AttrList, MinInstance) :-
         choose_attribute(InstanceIDlist, AttrList, A, Values,
                RestAttr),      % choose the best attribute
                            % then build a subtree with
         build_subtree(Values,A,InstanceIDlist,ParentNode,
                RestAttr,MinInstance), !.

%%    Case 4:  Cannot inducing tree, inconsistent data
%%         thus, stop growing tree and create a leaf node

  induce_tree(ParentNode, InstanceIDlist, _, _) :-
        node(ParentNode, TestAttribute, _),
        classDistribution(InstanceIDlist, Dist),
        assertz(node(leaf, Dist, ParentNode)), !.
                  % insert a leaf node into the DB
%% -----------------------------------------
```

Program running on sample data set start with a command 'dt' as shown in Figure 7. Users have two choices of tree induction method: conventional decision tree induction (response with 0), and a discrete-tree induction with facilities to handle categorical data (response with 1).



```
1 ?- dt.

Discrete tree induction for categorical classification:

 There are two choices of tree induction methods
  0 = simply ID3 style without pruning
  1 = grouping data then select representatives to build tree

    Please specify your choice (end command with a period): 0.
   Training-data file name (e.g. data-sample.) ==> 'data-sample'.
% data-sample compiled 0.00 sec, 3,136 bytes

 shape=circle
   color=red => [ (class=positive)/2]
   color=blue => [ (class=negative)/1]
 shape=triangle => [ (class=negative)/1]

Size of tree: 4 internal nodes and 3 leaf nodes.

DISCRETE-TREE:: tree building method 0,  Model building time = 0.05099
987983703613  sec.
```

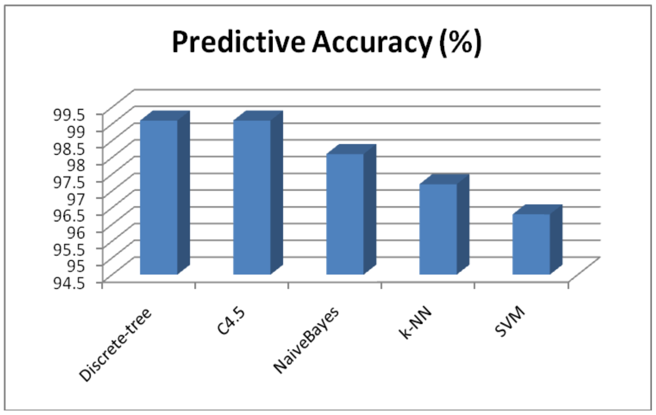
Fig. 7 a screenshot of running a discrete-tree program on sample data set of four instances

IV. Experimentation and Results

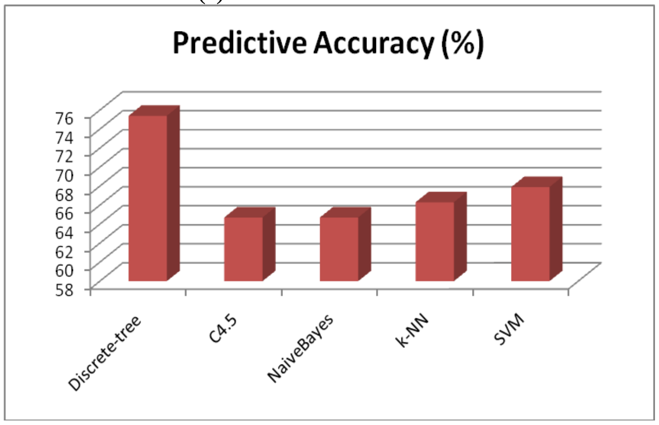
To test the accuracy of the proposed discrete-tree induction system, we use the standard UCI data repository [5] including the Wisconsin breast cancer, SPECT heart, DNA splice-junction, and audiology data sets. Each data set is composed of two separate subsets of training and test data. We then run the discrete-tree program and observe the results comparing to other learning algorithms, namely C4.5, Naive Bayes, k-Nearest Neighbor, and support vector machine. The comparison results are graphically shown in Figure 8.

It can be noticed from the results that the discrete-tree induction method shows considerably accurate prediction on SPECT heart data set. On Wisconsin breast cancer and DNA splice-junction data sets, our algorithm is as good as the other learning algorithms. But the discrete-tree induction performs poorly on audiology dataset. The poor performance may be due to the fact that such data set contains a single value on many attributes causing our data selection scheme making a poor set of samples.

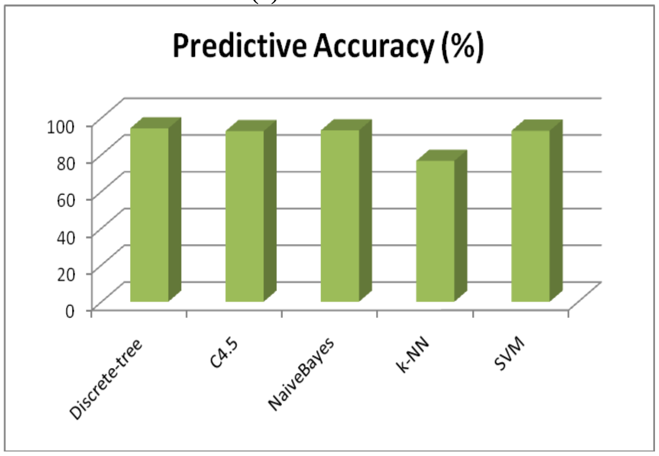
For a SPECT heart data set, we provide tree model obtained from our algorithm to compare against the model obtained from the C4.5 algorithm. The two models are presented in Figure 9.



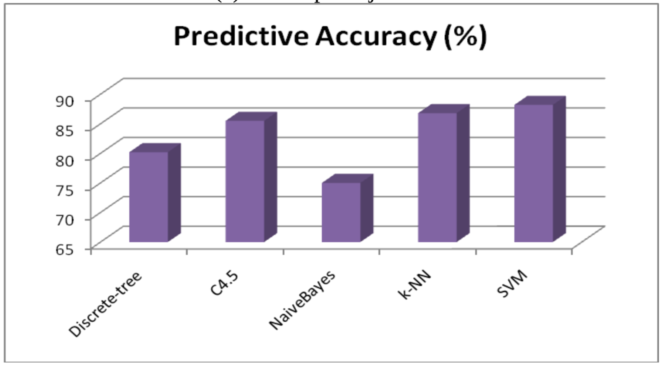
(a) Wisconsin breast cancer



(b) SPECT heart



(c) DNA splice-junction



(d) Audiology

Fig. 8 comparison results of prediction accuracy

C4.5 model:

```
F18 = 0
|  F21 = 0: 0 (59.0/12.0)
|  F21 = 1
|  |  F9 = 0
|  |  |  OVERALL_DIAGNOSIS = 0: 0 (3.0/1.0)
|  |  |  OVERALL_DIAGNOSIS = 1: 1 (7.0/1.0)
|  |  F9 = 1: 0 (5.0/1.0)
   F18 = 1: 1 (6.0)
```

Discrete-tree model:

```
 f13=0
    f2=0
   f1=0 => [ (class=0)/12, (class=1)/2]
   f1=1 => [ (class=1)/0]
 f2=1 => [ (class=1)/0]
          f4=1 => [ (class=0)/1]
          f6=1 => [ (class=0)/1]
         f22=1 => [ (class=0)/3, (class=1)/1]
        f5=1 => [ (class=0)/4]
       f19=1 => [ (class=0)/1, (class=1)/1]
      f20=1 => [ (class=0)/2, (class=1)/1]
     f8=1 => [ (class=0)/2]
    f9=1 => [ (class=0)/3]
   f7=1 => [ (class=0)/3, (class=1)/2]
  f16=1 => [ (class=1)/2]
 f11=1
  f16=0
   f19=0 => [ (class=0)/2, (class=1)/3]
   f19=1 => [ (class=1)/5]
  f16=1 => [ (class=0)/1]
 f13=1
f16=0
  f8=0
   f10=0 => [ (class=0)/4, (class=1)/1]
   f10=1 => [ (class=1)/2]
  f8=1
   f21=0 => [ (class=1)/5]
   f21=1 => [ (class=0)/1, (class=1)/4]
 f16=1 => [ (class=1)/11]
```

Fig. 9 a tree model of C4.5 comparing to a tree model of discrete-tree induction algorithm on a SPECT heart data set

V. Conclusion

Categorical data can cause serious problem to many tree learning algorithms in terms of distorted results and the decrease in predicting performance of the learning results. In this paper, we propose a methodology to deal with categorical values in a decision tree induction algorithm. Our intuitive idea is to select only potential representatives, rather than applying the whole training data that some values are highly dispersed, to the tree induction algorithm.

Data selection process starts with clustering in order to obtain the mean point of each data group. For each data group, the heuristic *T = 2 * Variance-of-cluster-similarity* will be used as a threshold to select only data around mean point within this *T* distance. Data that lie far away from the mean point are considered prone to noise and outliers; we thus remove them.

The removed data still play their role as one factor of a tree building stopping criterion, which can be formulated as $S = K - \log[(\text{number of removed data instances} + K) / |D|]$, where *K* is the number of clusters, which has been set to be equal to the number of class labels, and *D* is the number of training data.

From experimental results, it turns out that our heuristic-based decision tree induction method produces a good predictive model on categorical data set. It also produces a compact tree model. With such promising results, we thus plan to improve our methodology to be incremental such that it can learn model from steaming data.

Appendix

A source code of discrete decision tree, implemented with Prolog programming language.

```
%% Program   Discrete-Tree Induction
%%
%%   by Nittaya Kerdprasop
%%   date 1 August 2011
%%
%%   A decision tree induction program that can handle
%%       categorical and noisy data.
%%   The effect of noise is to be decreased by clustering
%%       and data around means are selected for further
%%       classification by decision-tree induction.
%%
%%   Data format:
%%
%%  attribute(size, [small, large]).
%%  attribute(color, [red, blue]).
%%  attribute(shape, [circle, triangle]).
%%  attribute(class, [positive, negative]).
%
%%  instance(1, class=positive, [size=small, color=red,
%%                                    shape=circle]).
%%  instance(2, class=positive, [size=large, color=red,
%%                                    shape=circle]).
%%  instance(3, class=negative, [size=small, color=red,
%%                                    shape=triangle]).
%%  instance(4, class=negative, [size=large, color=blue,
%%                                    shape=circle]).
%
%% Node format:         node(NodeID, NodeLabel, ParentNode)
%%     where
%%              NodeID = 1, 2, 3, ..., root, leaf
%%              NodeLabel = "attribute=value / number_of_instances"
%%              ParentNode = 1, 2, 3, ..., root
%%  e.g.
%%        node(1, shape=triangle, root).
%%        node(2, shape=circle, root).
%%        node(3, color=blue, 2).
%%        node(4, color=red, 2).
%%        node(leaf, [(class=negative/1)], 1).
%%        node(leaf, [(class=negative/1)], 3).
%%        node(leaf, [(class=positive/2)], 4).
%
%% Start program with the query
%%                    ?- dt.        % for discrete-tree induction
%%
%%    then specify parameter:
%%     0 = no addition of pruning technique; traditional ID3
%%     1 = extract data around centroids as representatives for
%%               tree building
%%                (number of clusters = number of classes,
%%                  clustering technique is K-medoids)
%%
%%  Input data with the following format:
%%          data-sample.
%%
%%  To test model accuracy, call          ?-test.
%%  Then input test data, e.g.,
%%          data-sample-test.
%
% ==================================
%% Program source code start here:
%%
%%   Note that  each module will be explained with the following
%%   format:
%%           an input argument is prefixed with a plus sign (+),
%%           the output argument is prefixed with a minus sign (-).

%% Main module:  dt
%% ==========
  dt :-
     writeln('Discrete tree induction for categorical classification:'),nl,
     writeln(' There are two choices of tree induction methods'),
     writeln('  0 = simply ID3 style without pruning'),
     writeln('  1 = grouping data then select representatives to
               build tree'),
     nl,
     write('     Please specify your choice (and end command with
               a period): '),
     read(L),
     write('    Training-data file name (e.g. data-sample.) ==> '),
      read(D),                    % get data file
      consult(D),                 % data is also a prolog program
      get_time(StartTime),
            % clear all nodes and node-ID counter in the DB
            % node and counter are two global values of this program
      retractall(node(_, _, _)),
      retractall(counter(_)),
          % make list Attr of all attribute names except attribute class
     findall(A, (attribute(A, _), A \= class), Attr),
     dtree(L, Attr),
     get_time(FinishTime),
     Time is FinishTime-StartTime,
      nl,write('DISCRETE-TREE:: tree building method '),
      write(L),write(',  '),
      write('Model building time = '),
      write(Time), writeln('  sec.').

% -------------------------------------
%  start traditional tree-induction with ID3 algorithm

  dtree(0, Attr) :-  !,
            % make a list Ins = [1,2,...,n] of all instance ID
      findall(N, instance(N, _, _), Ins),
          % create decision tree, start with the root node
          % set MinInstance in leaf nodes = 1
          % then show model as decision tree once finish
          % building phase
      induce_tree(root, Ins, Attr, 1),
      print_tree_model.

%---------------------------------------------
% start clustering before induce tree

   dtree(1, Attr) :-  !,
      attribute(class, ClassList),
      length(ClassList, K),
      findall(N, instance(N,_,_),Ins),
      clustering(Ins, K, Clusters, Means),
      select_DataSample(Clusters,K,Means,[],Sample),
      removed_Data(Sample, Ins, Removed),
      length(Removed, R),
      length(Ins, I),
      MinInstance is K-log((R+K)/I),       % a heuristic to prune tree
      induce_tree(root,Sample,Attr,MinInstance),
      print_tree_model,
     write('Min instances in each branch = '), writeln(MinInstance),
     nl,write('Initial Data = '),write(I),writeln(' instances'),
      write('Removed Data = '), writeln(Removed),
      write('    removed = '),write(R), writeln('   instances'),nl .

%% --------------------------------------------------------
%% Module induce_tree(+ParentNode, +InstanceIDlist,
%%  ===============   +AttributeList, +MinInstance)
%%
%% This module induces each node of decision tree.
%% There are four possible cases of tree induction based on
%% current data characteristics.
%%

%% Special case: empty data set, do nothing
        induce_tree(ParentNode,[],_,_) :-
                    instance(_,Class,_),
                    assertz(node(leaf,[Class/0],ParentNode)), !.

%%   Case 1: Number of instances =< the specified MinInstance.
%%         Thus, create a leaf node labelled with class distribution.

   induce_tree(ParentNode, InstanceIDlist, _, MinInstance) :-
          length(InstanceIDlist, NumInstances),
                 % a constraint to satisfy case1
          NumInstances =< MinInstance,
                 % count distinctive classes of current InstanceIDlist
                 % e.g. Dist = [class=negative/1, class=positive/2]
          classDistribution(InstanceIDlist, Dist),
                 % insert a leaf node into the DB, don't try other cases
          assertz(node(leaf, Dist, ParentNode)), !.

%%  Case 2: Number of instances > the specified MinInstance,
%%        but all instances are in the same class.
%%       Therefore, create a leaf node labelled with a class
%%       distribution.

  induce_tree(ParentNode, InstanceIDlist, _, _) :-
           classDistribution(InstanceIDlist, Dist),
           length(Dist, 1),
                 % a constraint to assert the case of single class
           assertz(node(leaf, Dist, ParentNode)), !.

%%   Case 3:  Number of instances > the specified MinInstance.
%%          Data contain a mixture of several classes, then grow tree.

  induce_tree(ParentNode, InstanceIDlist, AttrList, MinInstance) :-
       choose_attribute(InstanceIDlist, AttrList, A, Values, RestAttr),
                      % choose the best attribute A from the AttrList
                      % then build a subtree with A as a root node
      build_subtree(Values, A, InstanceIDlist, ParentNode,
                        RestAttr, MinInstance),
      !.

%%     Case 4:  Cannot inducing tree due to inconsistent data
%%                 thus, stop growing tree and create a leaf node with
%%                 heterogenous classes, e.g., [(class=positive/2),
%%                 (class=negative/1)]

  induce_tree(ParentNode, InstanceIDlist, _, _) :-
       node(ParentNode, TestAttribute, _),
              % locate the error point
       write(' Inconsistent data: '), write(InstanceIDlist),
       write('     Cannot split at node: '), writeln(TestAttribute),
       classDistribution(InstanceIDlist, Dist),
       assertz(node(leaf, Dist, ParentNode)), !.
              % insert a leaf node into the DB
%% ---------------------------------------------------------------

%% Module classDistribution(+InstanceIDlist, -ClassDistribution)
%% ===================
%%  e.g.  InstanceIDlist = [1,2,3,4]
%%         ClassDistribution = [class=positive/2, class=negative=2]

   classDistribution(InstanceIDlist, ClassDistribution) :-
          setof(Class, I^AttrList^(member(I, InstanceIDlist),
                                     instance(I, Class, AttrList)), C),
            % make a set C of distinctive classes from InstanceIDlist
            % e.g. C = [class=positive, class=negative]
          countClassMember(C, InstanceIDlist, ClassDistribution).
            % count number of instances in each class and return
            % a class distribution, e.g., [class=positive/2,
            % class=negative/2]

    countClassMember([], _, []) :- !.
    countClassMember([C|L], I, [C/N | T]) :-
            findall(X, (member(X, I), instance(X, C, _)), W),
                   % make a list W of instanceID in each class
                   % e.g. W = [1,2] for class positive
            length(W, N),
                   % output N = number of instances in class C
            countClassMember(L, I, T).    % count remaining classes
%% --------------------------------------------------------------

%% Module choose_attribute(+InstanceIDlist, +AttrList, -A, -Values,
-RestAttr)
%% ===================
%%    e.g., InstanceIDlist = [1,2,3,4],  AttrList = [size, color, shape]
%%     A = shape,  Values = [triangle, circle], RestAttr = [size, color]

   choose_attribute(InstanceIDlist, AttrList, A, Values, RestAttr) :-
           length(InstanceIDlist, InsLen),
           compute_info(InstanceIDlist, InsLen, I), !,
                  %  I  is expected number of information needed
                  %    to encode class of the given InstanceIDlist
           findall( A/Gain,    % find gain value of each attribute
             %  with the following pattern of computation
           ( member(A, AttrList),  attribute(A, Values),
                split_instances(Values, InstanceIDlist, A, InsSubset),
                subset_info(InsSubset, InsLen, R),
                Gain is I - R ),
              % extract attribute name A from AttrList one at a time,
              % and get all possible values of attribute A
              % then split instances based on the value of A
              % compute info of data subset
              % then compute gain value of A
          AttributeGainList),
              % output is a list of attribute/gain
              % e.g. [size/0, color/0.311278, shape/0.311278]
          maximum(AttributeGainList, A/_),
               %  find attribute A with the maximum gain
          attribute(A, Values),
               % extract valuelist of this attribute
               %  and return the list of remaining attributes
          remainAttr(A, AttrList, RestAttr), !.
```

```
%% supporting module to compute info I of given instances
%    e.g., info([positive/2, negative/1]
%              = -2/3 log 2/3 - 1/3 log 1/3 = 0.918
compute_info(InstanceIDlist, InsLen, I) :-
       attribute(class, CList),          % get a list of class values
       sum_info(CList, InstanceIDlist, InsLen, I).

sum_info(_,_,0,0) :- !.          % zero instance has info = 0
sum_info([], _, _, 0) :- !.     % an empty class has info = 0
sum_info([C | Cs], InsIDlist, InsLen, Info) :-
    findall(Ins, ( member(Ins, InsIDlist),
                   instance(Ins, class=C, _) ), ClassInstance),
                  % create a list to contain instances of each class
    length(ClassInstance, N),
                  % then count the instance number
    sum_info(Cs, InsIDlist, InsLen, I),
                  % do the same with other classes
    InsLen > 0,
    P is N / InsLen,
                  % if (N/InsLen) = 0,
                  %   set Info = 0 to avoid calculate log(0)
    ( P=0, Info = 0;
      Info is I - (P) * (log( P ) / log(2) ) ).

% supporting module
% split_instances(+Values,+InstanceIDlist, +A, - InsSubset)
%             e.g.,Values=[large, small],
%             InstanceIDlist=[1,2,3,4], A=size
%             the module will return InsSubset = [ [2,4], [1,3]]
 split_instances([], _, _, []) :- !.
 split_instances([V | Vs], InstanceIDlist, A, [InsIDlist | Rest]) :-
    findall( InsID, ( member(InsID, InstanceIDlist),
                      instance(InsID, _, L),
                      member( A=V, L) ), InsIDlist),
          % split instances into subset InsIDlist based on
          % the attribute value V
          % then, do the same for other attribute values Vs
    split_instances(Vs, InstanceIDlist, A, Rest).

%% supporting module subset_info
%%
subset_info([], _, 0) :- !.
subset_info([InsGroup | OtherGroups], Len, Res) :-
    length(InsGroup, LenInsGroup),
    compute_info(InsGroup, LenInsGroup, I), !,
    subset_info(OtherGroups, Len, R),
    Len > 0,
    Res is R + I * LenInsGroup / Len.

%% supporting module maximum to search for attribute with
%% maximum gain
%%
maximum([A], A) :- !.             % base case: list of one attribute
maximum([A/GainA | Rest], Attribute/Gain) :-
                                  % recursively shorten the list
    maximum(Rest, Att/G),
    (GainA > G, Attribute/Gain = A/GainA ;
               Attribute/Gain = Att/G ), !.

%% supporting module remainAttr
%%
  remainAttr(A, [A | T], T) :- !.
  remainAttr(A, [X | T], [X | Rest] ) :- remainAttr(A, T, Rest).
%% -----------------------------------------------------------------

%% Module build_subtree(+AttrValues, +A, +InstanceIDlist,
%%  ===============    +ParentNode, +RestAttr,+MinInstance)
%%    This module recursively create subtree start from the
%%       chosen attribute A.
%%    Branches of A are stored in a list AttrValues.
%%  e.g., A= shape, AttrValues = [triangle, circle],
%%         InstanceIDlist = [1,2,3,4],
%%         ParentNode = root
%%    the module builds subtree extended from the root node
%%  with two branceses:
%%       shape = triangle   and  shape = circle
%%   The build_subtree process continues until
%%       the stopping criteria MinInstance has been reached.
%%

   build_subtree([], _, _, _, _, _) :- !.
             % base case: there is no more attribute left
             % to create subtree

   build_subtree([ V|Vs], A, InsIDlist, ParentNode,
                       RestAttr, MinInstance) :-
              % create root of subtree
              % get subset of instances with attribute A=V
    findall(InsID, (member(InsID, InsIDlist), instance(InsID, _, L),
            member(A=V, L) ), Inslist),
    getNodeID(NodeID),
    assertz(node(NodeID, A=V, ParentNode)),
           % recursively build left subtree
    induce_tree(NodeID, Inslist, RestAttr, MinInstance), !,
           % build  right subtree based on Vs
    build_subtree(Vs, A, InsIDlist, ParentNode,
                       RestAttr, MinInstance).

%% supporting module getNodeID(-NodeID)
%%
getNodeID(M) :-
    retract(counter(N)),     % check current counter N
    M is N + 1,     % increment N by 1
    assert(counter(M)), !.  % then record the new counter

 getNodeID(1) :- assert(counter(1)).
                    % if counter does not exist, then create one

%% ------------------------------------------------------------------
%% Module print_tree_model:
%% =============
  print_tree_model :-
           print_tree_model(root, 0),
                   % start from root node at position zero
           nl, nl, write('Size of tree: '),
           retract(counter(N)), write(N), write(' internal nodes and '),
           findall(Node, node(leaf, _,Node), NL),
           length(NL, M),
           write(M), writeln(' leaf nodes.').

  print_tree_model(ParentNode, _) :-
                   % the case for printing leaf node
        node(leaf, Class, ParentNode), !,
        write(' => '), write(Class).

  print_tree_model(ParentNode, Position) :-
        findall(Son, node(Son, _, ParentNode), L),
        Position1 is Position+2,
        childList(L, Position1), !.

  childList([], _) :- !.
  childList([N|Child], Pos) :-
          node(N, NodeLabel, _),
          nl, tab(Pos), write(NodeLabel),
          print_tree_model(N, Pos),
          childList(Child, Pos).

%============END BUILD DISCRETE-TREE==========
%
%==== Test Tree Accuracy ========
%
test :-
     write('Test-data file name (e.g. data-sample-test.) ==> '),
     read(D),      consult(D),
     get_time(Start),
                   % get all instance ID of test data
     findall(TestIns, instance(TestIns, _, _), TestInsList),
     length(TestInsList, NumTestCase),
                    % send all test cases to test_accuracy module
                    %      with initial correct case = 0
    test_accuracy(TestInsList, 0, Totalcorrect), !,
    Accuracy is Totalcorrect / NumTestCase,
    nl,write('Predicting correctly: '), write(Totalcorrect),
    write(' from '), write(NumTestCase), write(' cases ==> '),
    write('Accuracy = '), writeln(Accuracy),
    get_time(Finish),
    Time is Finish- Start,
    nl, tab(5),write('Model Test Time = '),write(Time),writeln('  sec.').

 %% Module test_accuracy
 %%  get all test cases, and
 %%    start evaluating correctness of prediction one case at a time,
 %%    stop when the lest of test cases is empty,
 %%    then report the total number of cases predicted correctly

test_accuracy([], C, C) :- !.

test_accuracy([Case| Rest], Correct, NextCorrect) :-
      instance(Case, Trueclass, AttList), % get current test case
            % search tree for predicted class start from root node
      search_decision(root, AttList, Prediction),
            % compare Trueclass and PredictedClass
            % and count correct prediction
      evaluate(Case, Trueclass, Prediction, Correct, NewCorrect),
            % recursively do the same for other cases
      test_accuracy(Rest, NewCorrect, NextCorrect).

search_decision(StartNode, _, Prediction) :-
       node(leaf, Prediction, StartNode), !.
                  % return Prediction once leaf node has been found

search_decision(StartNode, AttList, Prediction) :-
       node(NextNode, TestAtt, StartNode),
       member(TestAtt, AttList), !,
       search_decision(NextNode, AttList, Prediction).

evaluate(_, Trueclass, Prediction, Correct, NewCorrect) :-
           % Prediction might be a mixture such as
           %         [(class=positive)/2, (class=negative)/1]
           % thus, PredictedClass should be the majority class
       maximum(Prediction, PredictedClass/_),
      (Trueclass == PredictedClass,  NewCorrect is Correct +1;
       NewCorrect = Correct).

%% ======== END Test-Tree=====================
%%
%%  Module Clustering
%%  =============
clustering(Ins, K, Clusters, Means) :-
    length(Ins, N),
    initialized_means(N, K, [], MeanPoints),
                        % e.g. MeanPoints = [2/1, 3/2]
                         % get attributes of initial MeansPoints
    findall(MeanAttr/Cluster, (member(P/Cluster, MeanPoints),
                instance(P, _, MeanAttr)), MeansAttrList),
                  % e.g. [(size=small,color=red,shape=circle)/1,
                  %        (size=large,color=blue,shape=circle)/2]
    assign_clusters(MeansAttrList, Ins, K, Clusters,Means).

assign_clusters(MeansAttr, Ins, K, Clusters,Means) :-
    find_clusters(MeansAttr, Ins, [], InsClusterList),
    find_means(InsClusterList, K, [], TempMeans),
    getRepresentatives(TempMeans,Ins,[],RepList),
    getMeans(RepList,[],NewMeans),
    find_clusters(NewMeans, Ins, [], NewInsClusterList),
    entropy(InsClusterList, K, PreEntropy),
    entropy(NewInsClusterList, K, PostEntropy),
    average(PreEntropy, PreEn),
    average(PostEntropy, PostEn),
    (PostEn >= PreEn, Clusters = InsClusterList,
                        Means = NewMeans, ! ;
      assign_clusters(NewMeans, Ins, K, Clusters,Means),!).

initialized_means(_, 0, Means, Means) :- !.

initialized_means(N, K, Means, NewMeans) :-
      MeanIns is random(N-1)+1,
      NewK is K-1,
      initialized_means(N, NewK, [MeanIns/K|Means], NewMeans).

find_clusters(_, [], List, List) :- !.

find_clusters(MeanAttrList, [Ins|Rest], CurrentList, NewList) :-
       findall(Cluster/Score, (instance(Ins,_, InsAtt),
             member(MAtt/Cluster, MeanAttrList),
             similarity(MAtt, InsAtt, 0, Score) ),
             ClusterScoreList),
       maximum(ClusterScoreList, Cluster/_),
       find_clusters(MeanAttrList, Rest, [Ins/Cluster|CurrentList],
             NewList).

similarity([],[],S,S) :- !.

similarity([A | RestA1], [A | RestA2], Score, NewS) :-
              NewScore is Score + 1, !,
              similarity(RestA1, RestA2, NewScore, NewS).

similarity([A1| RestA1], [A2|RestA2], Score, NewS) :-
               A1 \= A2,
               similarity(RestA1, RestA2, Score, NewS).

minimum([ClusterScore], ClusterScore) :- !.

minimum([C/S | Rest], Cluster/Score) :-
         minimum(Rest, Clus/Sc),
         ( Sc > S, Cluster/Score = C/S ;
                   Cluster/Score = Clus/Sc), !.

find_means(_, 0, List, List) :- !.

find_means(InsClusterList, K, CurrentList, NewList) :-
        findall(Ins, member(Ins/K, InsClusterList), InsList),
        findall(Name=Vlist, (attribute(Name,Values),
              Name \= class,
               findall(V/0, member(V,Values), Vlist)),
               AttValueList),
        common_attributes(InsList, AttValueList, AttrList),
        NewK is K - 1,
        find_means(InsClusterList, NewK, [AttrList/K | CurrentList],
              NewList).

common_attributes([], AttValueList, AttList) :- !,
         findall(A=V, (member(A=VList, AttValueList),
                     maximum(VList, V/_)  ),   AttList).

common_attributes([Ins|Rest], AttValueList, AttList) :-
        instance(Ins,_, AttValue),
        count_value(AttValue, AttValueList, NewAttValueList),
        common_attributes(Rest, NewAttValueList, AttList).

count_value([], AVList, AVList) :- !.

count_value([A=V|Rest], AttValueList, NewAttValueList) :-
        member(A=VList, AttValueList),
        delete(AttValueList, A=VList, TempAttValueList),
        member(V/Count, VList),
        delete(VList, V/Count, TempVList),
        NewCount is Count + 1,
        append([V/NewCount], TempVList, NewVList),
        append([A=NewVList], TempAttValueList, NewAVList),
        count_value(Rest, NewAVList, NewAttValueList).

entropy(_, 0, []) :- !.

entropy(InsCluster, K, Entropy) :-
        K>0,
        findall(Ins, member(Ins/K, InsCluster), InsList),
          length(InsList, InsLen),
          (InsLen >0,
                compute_info(InsList, InsLen, Info),
                Entropy = [K/Info | RestEntropy];
          Entropy = [K/1 | RestEntropy]),
          NewK is K-1,
          entropy(InsCluster, NewK, RestEntropy).

sum_list([], 0) :- !.
sum_list([H|T], Value) :-
           sum_list(T, NewValue),
           Value is H + NewValue.

getRepresentatives([],_, List, List) :- !.
getRepresentatives([Mean/Cluster | Rest], InsList, Current,
                          NewList) :-
          findall(Ins/Score, (member(Ins, InsList),
                    instance(Ins,_,InsAtt),
                    similarity(InsAtt, Mean, 0, Score)),
                    InsScoreList),
          maximum(InsScoreList, Instance/_),
          delete(InsList, Instance, NewIns),
          getRepresentatives(Rest,NewIns,
                    [Instance/Cluster | Current], NewList).

getMeans([], List, List) :- !.
getMeans([Ins/Cluster | Rest], Current, NewMeans) :-
          instance(Ins,_, InsAtt),
          getMeans(Rest, [InsAtt/Cluster | Current], NewMeans).

removed_Data(DataSample, InstList ,RemovedData  ) :-
           findall( D, (member(D, InstList),
                          not(member(D, DataSample))),
                          RemovedData).

select_DataSample(_, 0, _, DataSample, DataSample) :- !.

select_DataSample(Clusters, K, Means, TempData, DataSample) :-
           findall(Ins, member(Ins/K, Clusters), InsKList),
           length(InsKList, Len), Len > 0,
           findall(I/Score, (member(I, InsKList),
                    instance(I, _, InsAtt), member(MAtt/K, Means),
                    similarity(InsAtt, MAtt, 0,Score)),
                    IScoreList),
          average(IScoreList, Average),
          variance(IScoreList, Average,Variance),
          Threshold is (2 * Variance),
          findall(Inst, (member(Inst/Sc, IScoreList),
                          Sc >= Threshold),
                          InstList),
          append(InstList, TempData, NewData),
          NewK is K-1,
          select_DataSample(Clusters, NewK, Means,
                                NewData, DataSample).

 average(ValueList, E) :-
          findall(S, member(_/S, ValueList), SList),
          sum_list(SList, SValue),
          length(SList, Len),
          (Len=0, E = 0; E is SValue / Len).

variance(ValueList, Avg, Var) :-
          findall(Diff, (member(_/S, ValueList),
                          Diff is abs(S-Avg)),
                          DiffList),
          sum_list(DiffList, DValue),
          length(DiffList, DLen),
          D is DLen-1,
          (D=0, Var = 0; Var is DValue / D).

% ===== End Clustering =============
```

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Nittaya Kerdprasop is an associate professor and the director of Data Engineering research unit, school of computer engineering, Suranaree University of Technology, Thailand. She received her B.S. in radiation techniques from Mahidol University, Thailand, in 1985, M.S. in computer science from the Prince of Songkla University, Thailand, in 1991 and Ph.D. in computer science from Nova Southeastern University, U.S.A., in 1999. She is a member of IAENG, ACM, and IEEE Computer Society. Her research of interest includes Knowledge Discovery in Databases, Data Mining, Artificial Intelligence, Logic and Constraint Programming, Deductive and Active Databases.

Kittisak Kerdprasop is an associate professor at the school of computer engineering and one of the principal researchers of Data Engineering research unit, Suranaree University of Technology, Thailand. He received his bachelor degree in Mathematics from Srinakarinwirot University, Thailand, in 1986, master degree in computer science from the Prince of Songkla University, Thailand, in 1991 and doctoral degree in computer science from Nova Southeastern University, USA, in 1999. His current research includes Data mining, Machine Learning, Artificial Intelligence, Logic and Functional Programming, Probabilistic Databases and Knowledge Bases.