Università degli Studi di Milano
Master Degree in Computer Science

# Information Management course

Teacher: Alberto Ceselli

Lecture 15: 04/12/2012

# Data Mining:

# Concepts and Techniques

**(3rd ed.)**

**— Chapter 8 —**

Jiawei Han, Micheline Kamber, and Jian Pei

University of Illinois at Urbana-Champaign &

Simon Fraser University

©2011 Han, Kamber & Pei. All rights reserved.

# Classification methods

- Classification: Basic Concepts
- Decision Tree Induction
- Bayes Classification Methods
- Support Vector Machines
- Model Evaluation and Selection
- *Rule-Based Classification*
- *Techniques to Improve Classification Accuracy: Ensemble Methods*

# Supervised vs. Unsupervised Learning

- Supervised learning (classification)
  - Supervision: The training data (observations, measurements, etc.) are accompanied by **labels** indicating the class of the observations
  - New data is classified based on the training set
- Unsupervised learning (clustering)
  - The class labels of training data is unknown
  - Given a set of measurements, observations, etc. with the aim of establishing the existence of classes or clusters in the data

# Prediction Problems: Classification vs. Numeric Prediction

- Classification
  - predicts categorical class labels (discrete or nominal)
  - classifies data (constructs a model) based on the training set and the values (class labels) in a classifying attribute and uses it in classifying new data
- Numeric Prediction
  - models continuous-valued functions, i.e., predicts unknown or missing values
- Typical applications
  - Credit/loan approval:
  - Medical diagnosis: if a tumor is cancerous or benign
  - Fraud detection: if a transaction is fraudulent
  - Web page categorization: which category it is

# Classification—A Two-Step Process

- Model construction: describing a set of predetermined classes
  - Each tuple/sample is assumed to belong to a predefined class, as determined by the class label attribute
  - The set of tuples used for model construction is training set
  - The model is represented as classification rules, decision trees, or mathematical formulae
- Model usage: for classifying future or unknown objects
  - Estimate accuracy of the model
    - The known label of test sample is compared with the classified result from the model
    - Accuracy rate is the percentage of test set samples that are correctly classified by the model
    - Test set is independent of training set (otherwise overfitting)
  - If the accuracy is acceptable, use the model to classify data tuples whose class labels are not known

# Process (1): Model Construction (learning)

Training Data

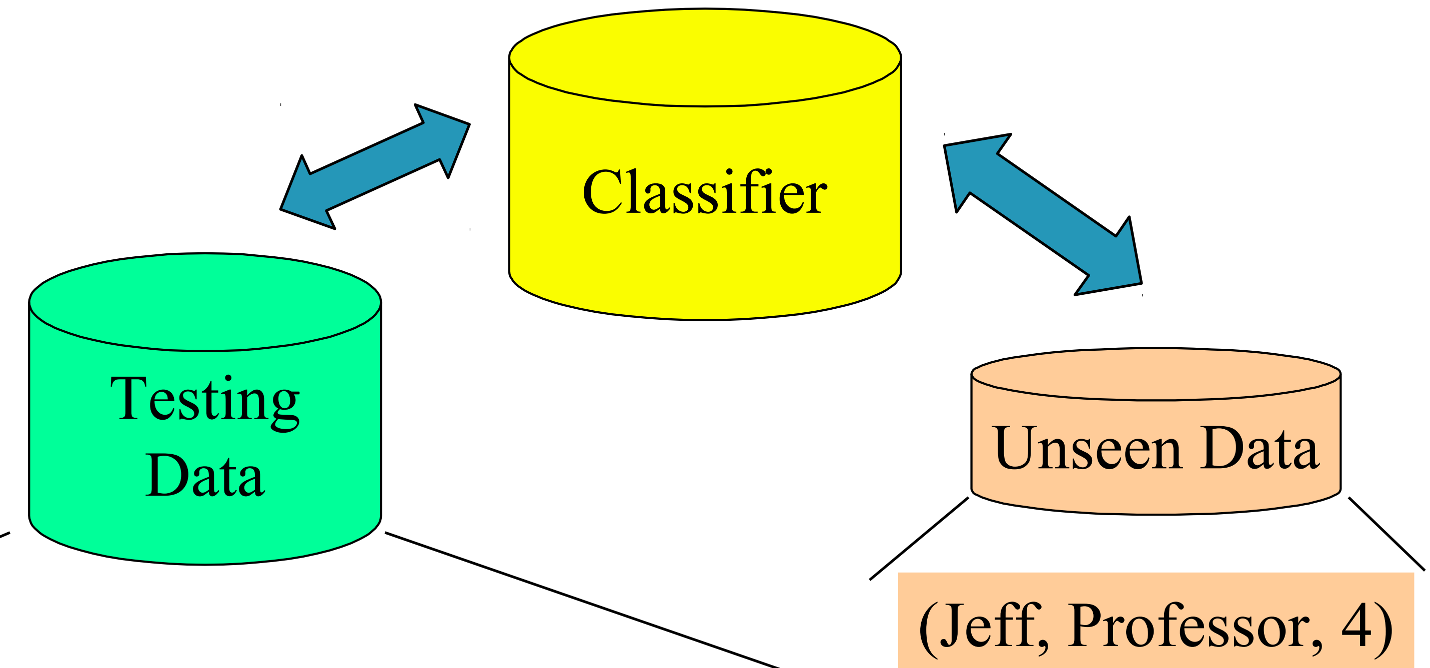
Classification Algorithms

Classifier (Model)

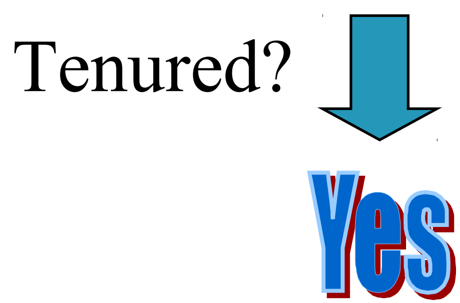
| NAME | RANK | YEARS | TENURED |
|---|---|---|---|
| Mike | Assistant Prof | 3 | no |
| Mary | Assistant Prof | 7 | yes |
| Bill | Professor | 2 | yes |
| Jim | Associate Prof | 7 | yes |
| Dave | Assistant Prof | 6 | no |
| Anne | Associate Prof | 3 | no |

IF rank = ‘professor’
OR years > 6
THEN tenured = ‘yes’

# Process (2): Using the Model in Prediction (classification)




| NAME | RANK | YEARS | TENURED |
|---|---|---|---|
| Tom | Assistant Prof | 2 | no |
| Merlisa | Associate Prof | 7 | no |
| George | Professor | 5 | yes |
| Joseph | Assistant Prof | 7 | yes |



# Classification techniques

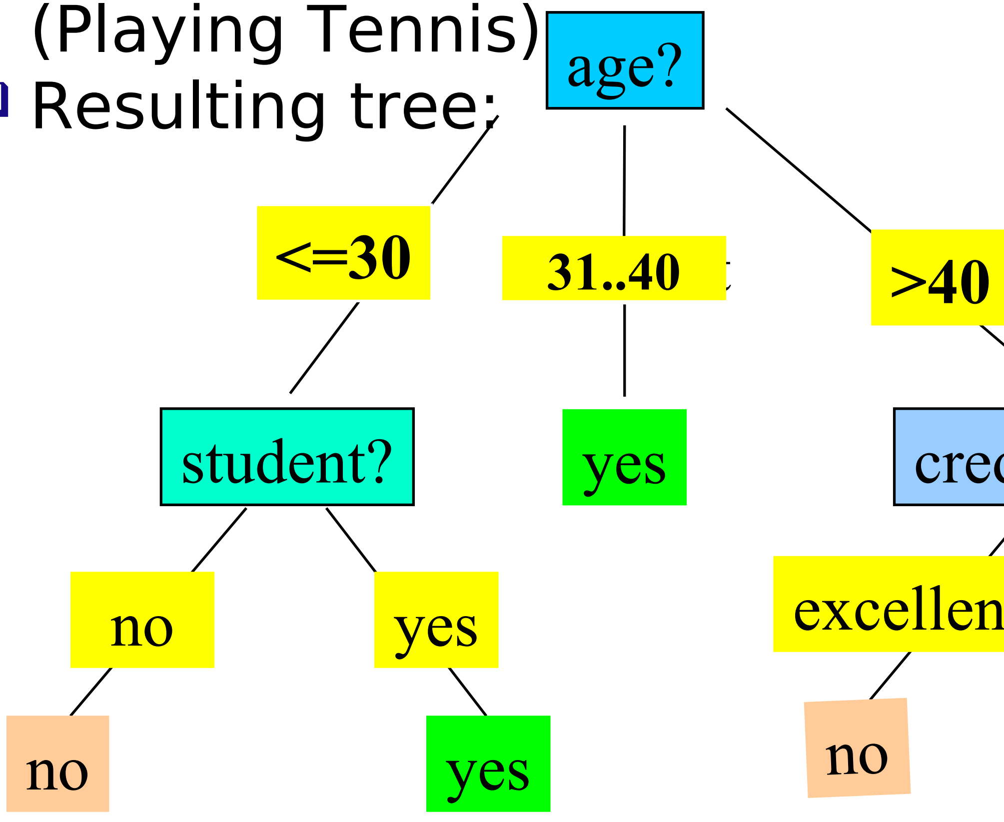
- Information-gain based methods
  → decision tree induction
- Classification probability based methods
  → Bayesian classification
- Geometry based methods
  → Support Vector Machines
- Other approaches (e.g. ANN)

# Classification methods

- Classification: Basic Concepts
- Decision Tree Induction
- Bayes Classification Methods
- Support Vector Machines
- Model Evaluation and Selection
- *Rule-Based Classification*
- *Techniques to Improve Classification Accuracy: Ensemble Methods*

# Decision Tree Induction: An Example

- Training data set: Buys_computer
- The data set follows an example of Quinlan's ID3 (Playing Tennis)
- Resulting tree:




# Algorithm for Decision Tree Induction

- Basic algorithm (a greedy algorithm)
  - Tree is constructed in a top-down recursive divide-and-conquer manner
  - At start, all the training examples are at the root
  - Attributes are categorical (if continuous-valued, they are discretized in advance)
  - Examples are partitioned recursively based on selected attributes
  - Test attributes are selected on the basis of a heuristic or statistical measure (e.g., information gain)

# Algorithm for Decision Tree Induction

- Conditions for stopping partitioning
  - All samples for a given node belong to the same class (pure partition)
  - There are no remaining attributes for further partitioning – majority voting is employed for classifying the leaf
  - There are no samples left
- Selection criteria:
  - Information gain (ID3)
  - Gain ratio (C4.5)
  - Gini index (CART)

# Attribute Selection Measure: Information Gain (ID3/C4.5)

- Let $p_i$ be the probability that an arbitrary tuple in D belongs to class $C_i$, estimated by $|C_{i,D}|/|D|$
- Recall: number of "binary tests" needed to find the class of a tuple in $C_i$ is $-\log_2(p_i)$
- Expected information (entropy) needed to classify a tuple in D:

$$Info(D) = -\sum_{i=1}^{m} p_i \log_2(p_i)$$

- Information needed (after using A to split D into v partitions) to classify D:

$$Info_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Info(D_j)$$

- Information gained by branching on attribute A

$$Gain(A) = Info(D) - Info_A(D)$$

# Attribute Selection: Information Gain

| ag |
| --- |
| <=30 |

# Attribute Selection: Information Gain

- Class P: buys_computer = “yes”
- Class N: buys_computer = “no”

$$Info(D) = I(9,5) = -\frac{9}{14}\log_2\left(\frac{9}{14}\right) - \frac{5}{14}\log_2\left(\frac{5}{14}\right) = 0.940$$

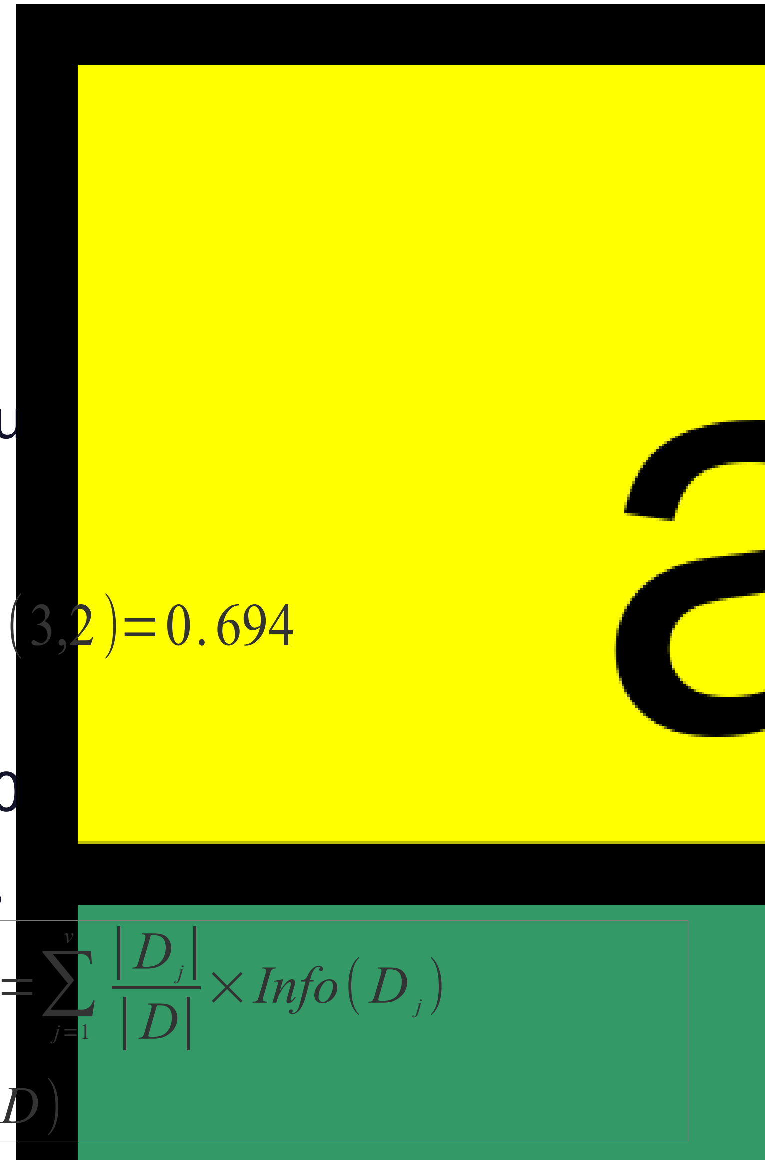
$\frac{5}{14} I(2,3)$ means “age <=30” has 5 ou

yes’es and 3 no’s. Hence

$$Info_{age}(D) = \frac{5}{14} I(2,3) + \frac{4}{14} I(4,0) + \frac{5}{14} I(3,2) = 0.694$$

and therefore Gain(age) = 0.940 – 0

Similarly Gain(income) = 0.029 bits



$$Info(D) = -\sum_{i=1}^{m} p_i \log_2(p_i) \qquad Info_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Info(D_j)$$

$$Gain(A) = Info(D) - Info_A(D)$$

# Computing Information-Gain for Continuous-Valued Attributes

- Let attribute A be a continuous-valued attribute
- Must determine the *best split point* for A
  - Sort the value A in increasing order
  - Typically, the midpoint between each pair of adjacent values is considered as a possible *split point:* $(a_i+a_{i+1})/2$
  - The point with the *minimum expected information requirement* for A is selected as the split-point for A
- Split:D1 is the set of tuples in D satisfying A ≤ split-point, and D2 is the set of tuples in D satisfying A > split-point

# Gain Ratio for Attribute Selection (C4.5)

- Information gain measure is biased towards attributes with a large number of values
- C4.5 (a successor of ID3) uses gain ratio to overcome the problem (normalization to information gain)

$$Info(D) = -\sum_{i=1}^{m} p_i \log_2(p_i)$$

$$Info_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Info(D_j)$$

$$Gain(A) = Info(D) - Info_A(D)$$

$$SplitInfo_A(D) = -\sum_{j=1}^{v} \frac{|D_j|}{|D|} \times \log_2\left(\frac{|D_j|}{|D|}\right)$$

  - GainRatio(A) = Gain(A) / SplitInfo(A)
- Ex.

$$SplitInfo_{income}(D) = -\frac{4}{14} \times \log_2\left(\frac{4}{14}\right) - \frac{6}{14} \times \log_2\left(\frac{6}{14}\right) - \frac{4}{14} \times \log_2\left(\frac{4}{14}\right) = 1.557$$

  - gain_ratio(income) = 0.029/1.557 = 0.019
- The attribute with the maximum gain ratio is selected as the splitting attribute

# Gini Index (CART, IBM IntelligentMiner)

- If a data set $D$ contains examples from $n$ classes, gini index, $gini(D)$ is defined as

$$gini(D) = 1 - \sum_{j=1}^{n} p_j^2$$

where $p_j$ is the relative frequency of class $j$ in $D$

- If a data set $D$ is split on A into two subsets $D_1$ and $D_2$, the *gini* index $gini(D)$ is defined as

$$gini_A(D) = \frac{|D_1|}{|D|} gini(D_1) + \frac{|D_2|}{|D|} gini(D_2)$$

- Reduction in Impurity:

$$\Delta gini(A) = gini(D) - gini_A(D)$$

- The attribute provides the smallest $gini_{split}(D)$ (or the largest reduction in impurity) is chosen to split the node (*need to enumerate all the possible splitting points for each attribute*)

# Computation of Gini Index

- Ex. D has 9 tuples in buys_computer = “yes” and 5 in “no”: 5/14 * I(2,3)

$$gini_{income \in \{low, medium\}}(D) = \left(\frac{10}{14}\right) Gini(D_1) + \left(\frac{4}{14}\right) Gini(D_1)$$

- Suppose the attribute income partitions D into 10 in $D_1$: {low, medium} and 4 in $D_2$

$$= \frac{10}{14}\left(1 - \left(\frac{7}{10}\right)^2 - \left(\frac{3}{10}\right)^2\right) + \frac{4}{14}\left(1 - \left(\frac{2}{4}\right)^2 - \left(\frac{2}{4}\right)^2\right)$$
$$= 0.443$$
$$= Gini_{income \in \{high\}}(D).$$

$Gini_{\{low,high\}}$ is 0.458; $Gini_{\{medium,high\}}$ is 0.450. Thus, split on the {low,medium} (and {high}) since it has the lowest Gini index

# Computation of Gini Index

- All attributes are assumed continuous-valued
- May need other tools, e.g., clustering, to get the possible split values
- Can be modified for categorical attributes

# Comparing Attribute Selection Measures

- The three measures, in general, return good results but
  - **Information gain**:
    - biased towards multivalued attributes
  - **Gain ratio**:
    - tends to prefer unbalanced splits in which one partition is much smaller than the others
  - **Gini index**:
    - biased to multivalued attributes
    - has difficulty when # of classes is large
    - tends to favor tests that result in equal-sized partitions and purity in both partitions

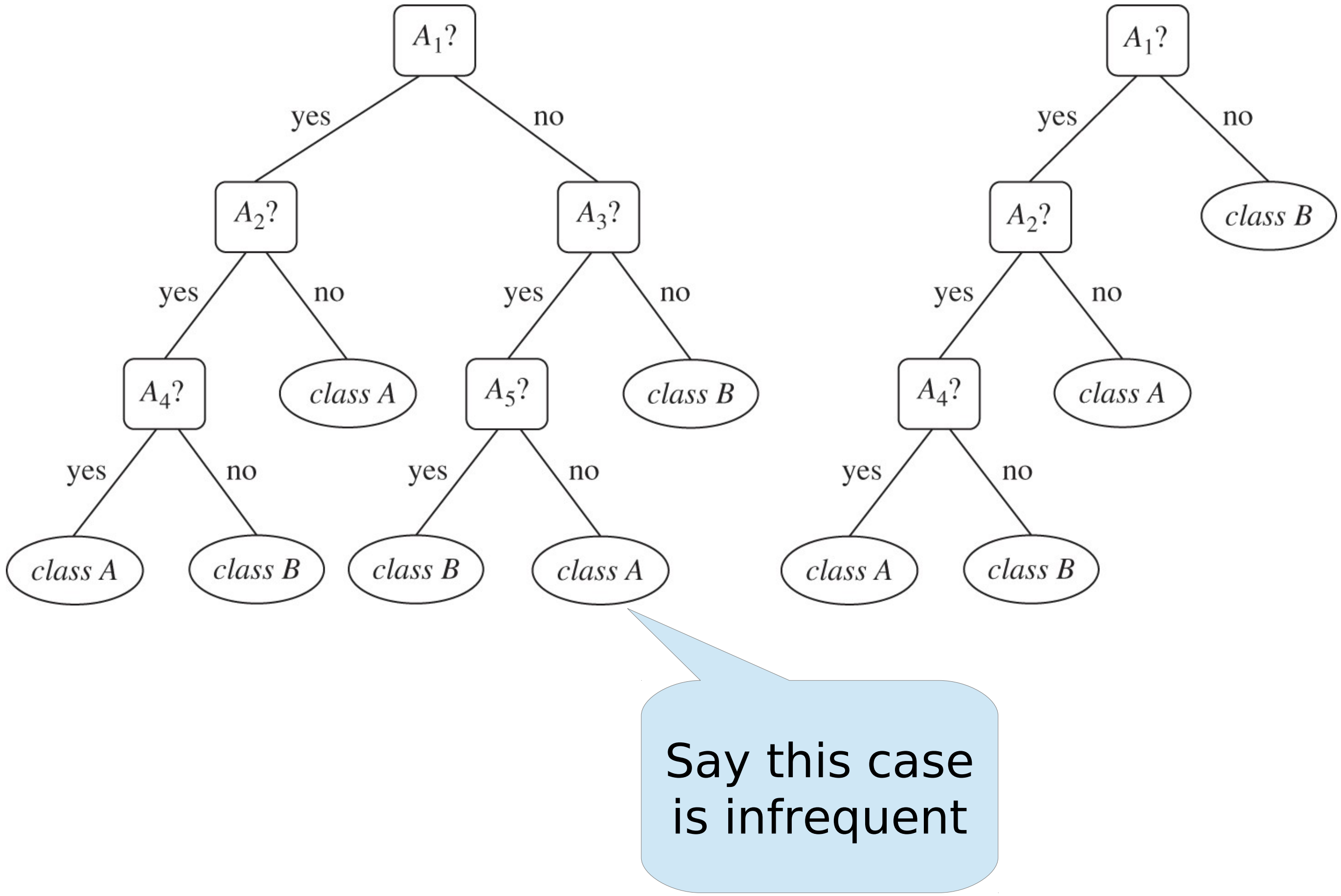
# Other Attribute Selection Measures

- CHAID: a popular decision tree algorithm, measure based on $\chi^2$ test for independence
- C-SEP: performs better than i. gain and gini index in certain cases
- G-statistic: has a close approximation to $\chi^2$ distribution
- MDL (Minimal Description Length) principle (i.e., the simplest solution is preferred): the best tree is one that requires the fewest # of bits to both (1) encode the tree, and (2) encode the exceptions (misclassifications)
- Multivariate splits (partition based on multiple variable combinations) → CART: finds multivariate splits based on a linear comb. of attrs. (*feature construction*)
- Which attribute selection measure is the best?
  - Most give good results, none is significantly superior

# Overfitting and Tree Pruning

- Overfitting: An induced tree may overfit the training data
  - Too many branches, some may reflect anomalies due to noise or outliers
  - Poor accuracy for unseen samples
  - Try to balance cost complexity and information gain
- Two approaches to avoid overfitting
  - Prepruning: *Halt tree construction early*- do not split a node if this would result in the goodness measure falling below a threshold
    - Difficult to choose an appropriate threshold
  - Postpruning: *Remove branches* from a “fully grown” tree—get a sequence of progressively pruned trees
    - Use a test set to decide which is “best pruning”

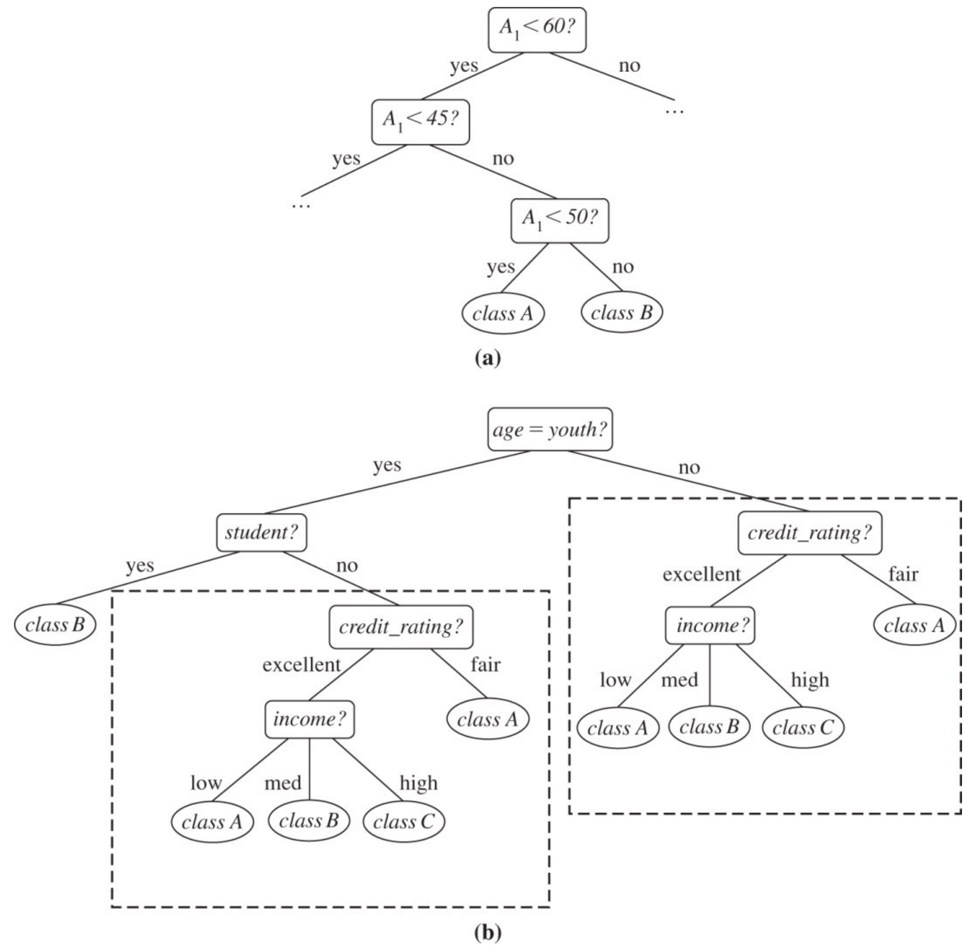
# Overfitting and Tree Pruning



# Repetition and Replication

(a) subtree **repetition**, where an attribute is repeatedly tested along a given branch of the tree (e.g., *age*)

(b) subtree **replication**, where duplicate subtrees exist within a tree (e.g., the subtree headed by the node “*credit_rating?*”)



# Classification in Big Data

- Classification—a classical problem extensively studied by statisticians and machine learning researchers
- Scalability: Classifying data sets with millions of examples and hundreds of attributes with reasonable speed
- Why is decision tree induction popular?
  - relatively faster learning speed (than other classification methods)
  - convertible to simple and easy to understand classification rules
  - can use SQL queries for accessing databases
  - comparable classification accuracy with other methods
- RainForest (VLDB'98 — Gehrke, Ramakrishnan & Ganti)
  - Builds an AVC-list (attribute, value, class label)

# Scalability Framework for RainForest

- Separates the scalability aspects from the criteria that determine the quality of the tree
- Builds an AVC-list: **AVC (Attribute, Value, Class_label)**
- **AVC-set** (of an attribute *X* )
  - Projection of training dataset onto the attribute *X* and class label where counts of individual class label are aggregated
- **AVC-group** (of a node *n* )
  - Set of AVC-sets of all predictor attributes at the node *n*

# Rainforest: Training Set and Its AVC Sets

Training Examples

AVC-set on *Age*

AVC-set on *income*

| | yes | n |
|---|---|---|
| high | 2 | |
| medium | 4 | |
| low | 3 | |

age

AVC-set on *Student*

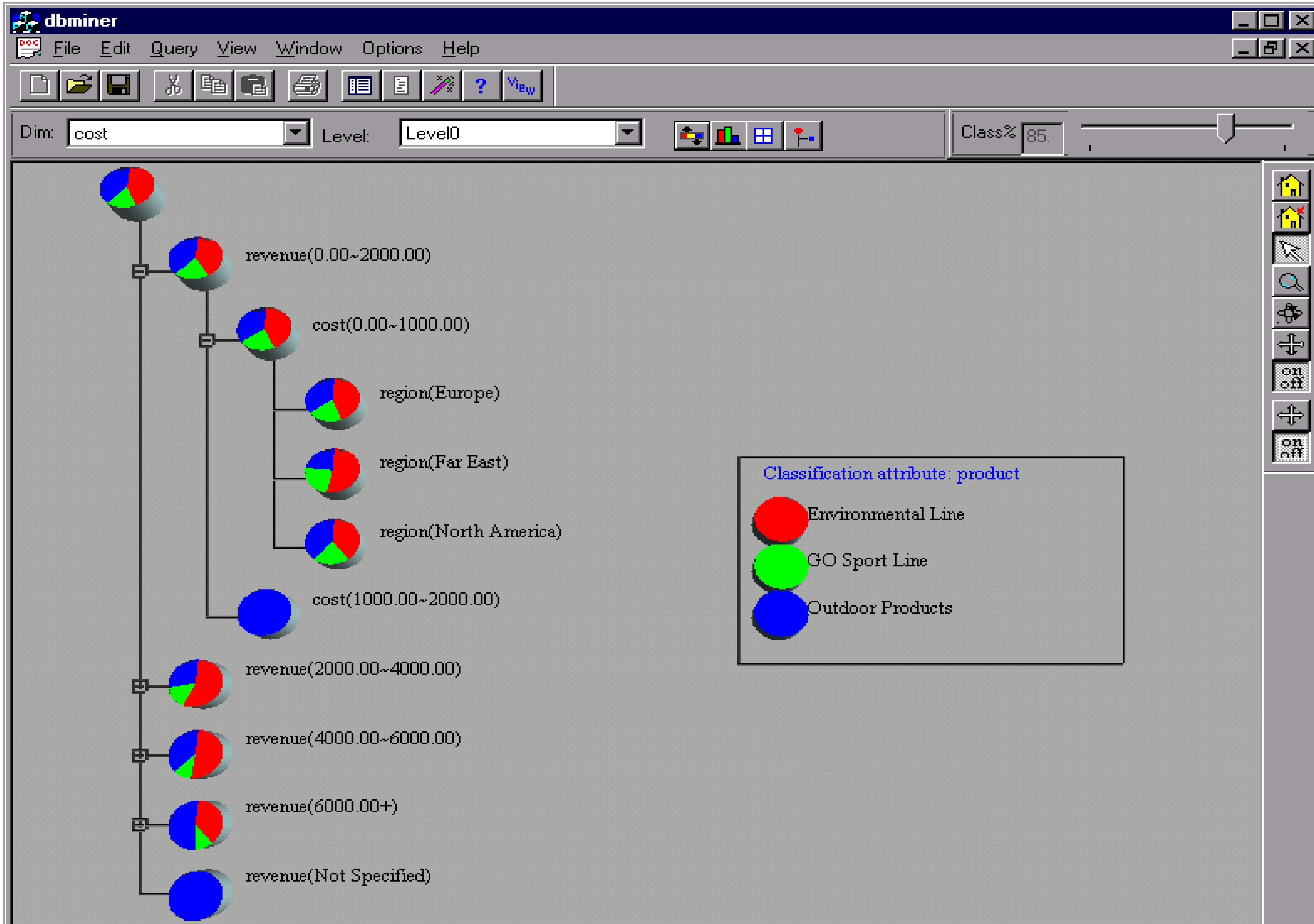
AVC-set on *credit_ratin*

<=30

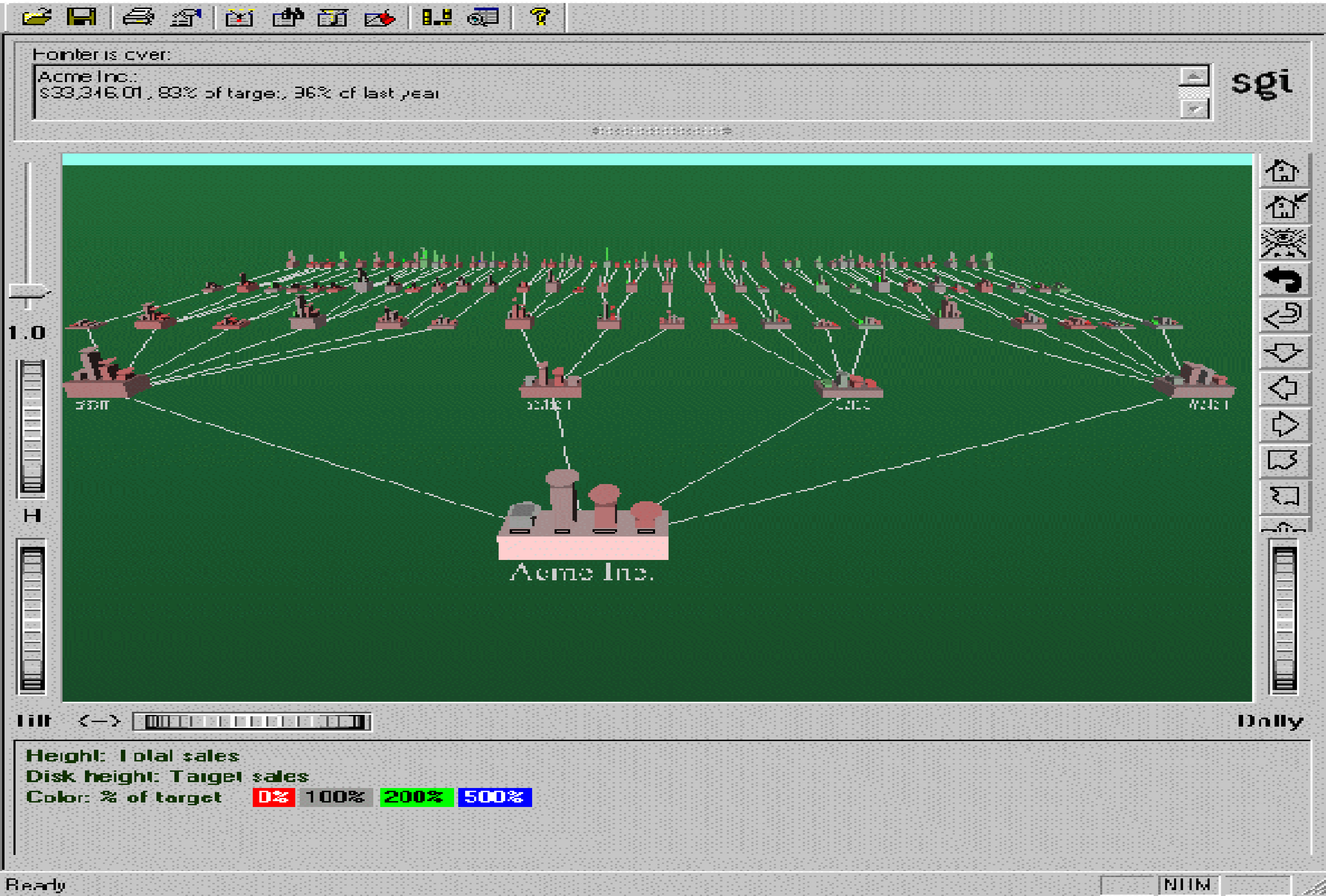
# BOAT (Bootstrapped Optimistic Algorithm for Tree Construction)

- Use a statistical technique called *bootstrapping* to create several smaller samples (subsets), each fits in memory
- Each subset is used to create a tree, resulting in several trees
- These trees are examined and used to construct a new tree *T'*
  - It turns out that *T'* is very close to the tree that would be generated using the whole data set together
- Adv: requires only two scans of DB, an incremental alg.

# Presentation of Classification Results



# Visualization of a Decision Tree in SGI/MineSet 3.0



# Interactive Visual Mining by Perception-Based Classification (PBC)