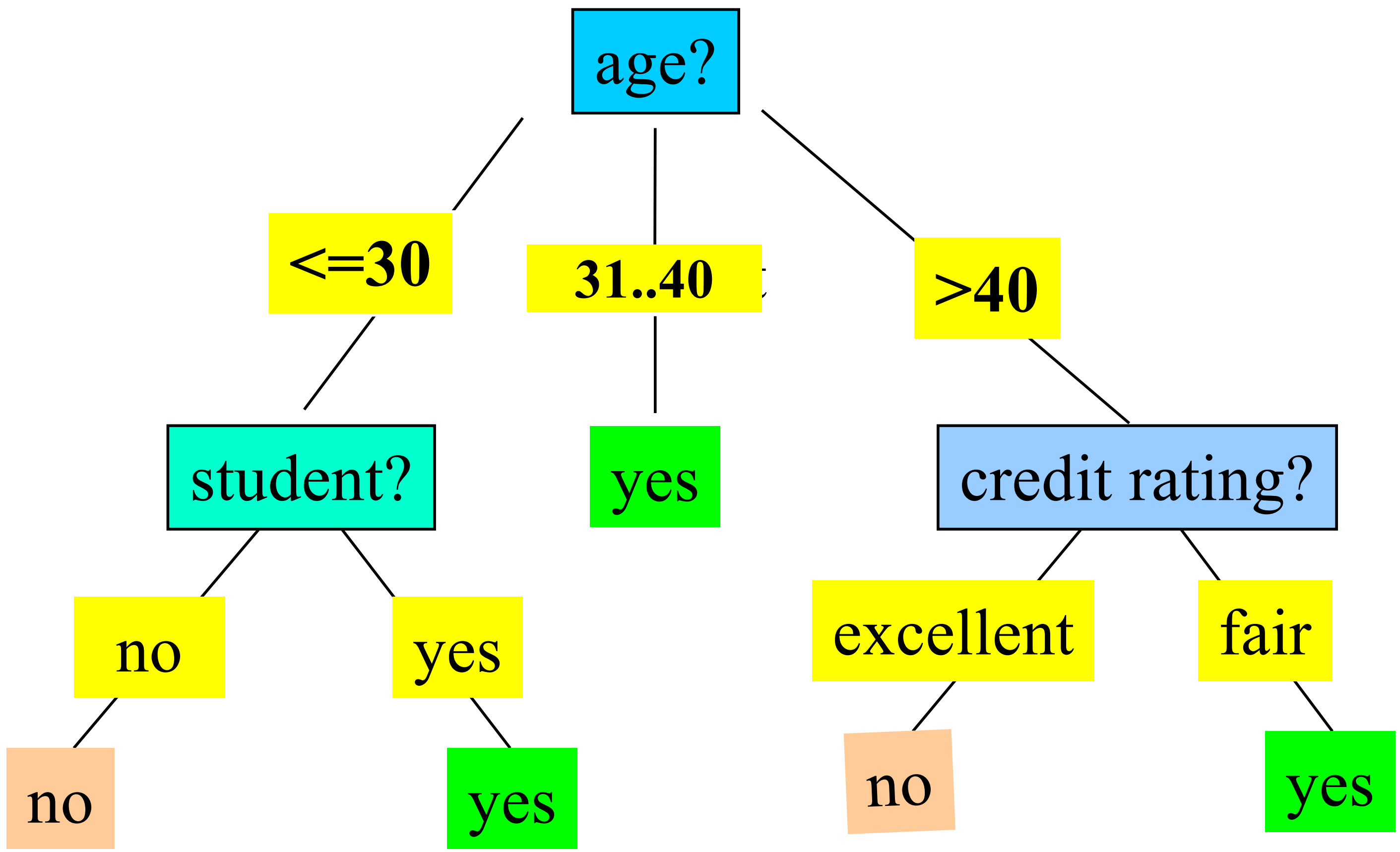
Algorithm for Decision Tree Induction

- Basic algorithm
  - A greedy algorithm that constructs a decision tree in a top-down recursive divide-and-conquer manner
  - At start, all the training examples are at the root
  - Attributes are assumed to be categorical
    - If continuous-valued, they are discretized in advance
  - Examples are partitioned recursively based on the selected test attributes
  - Test attributes are selected on the basis of a heuristic or statistical measure (e.g., information gain)

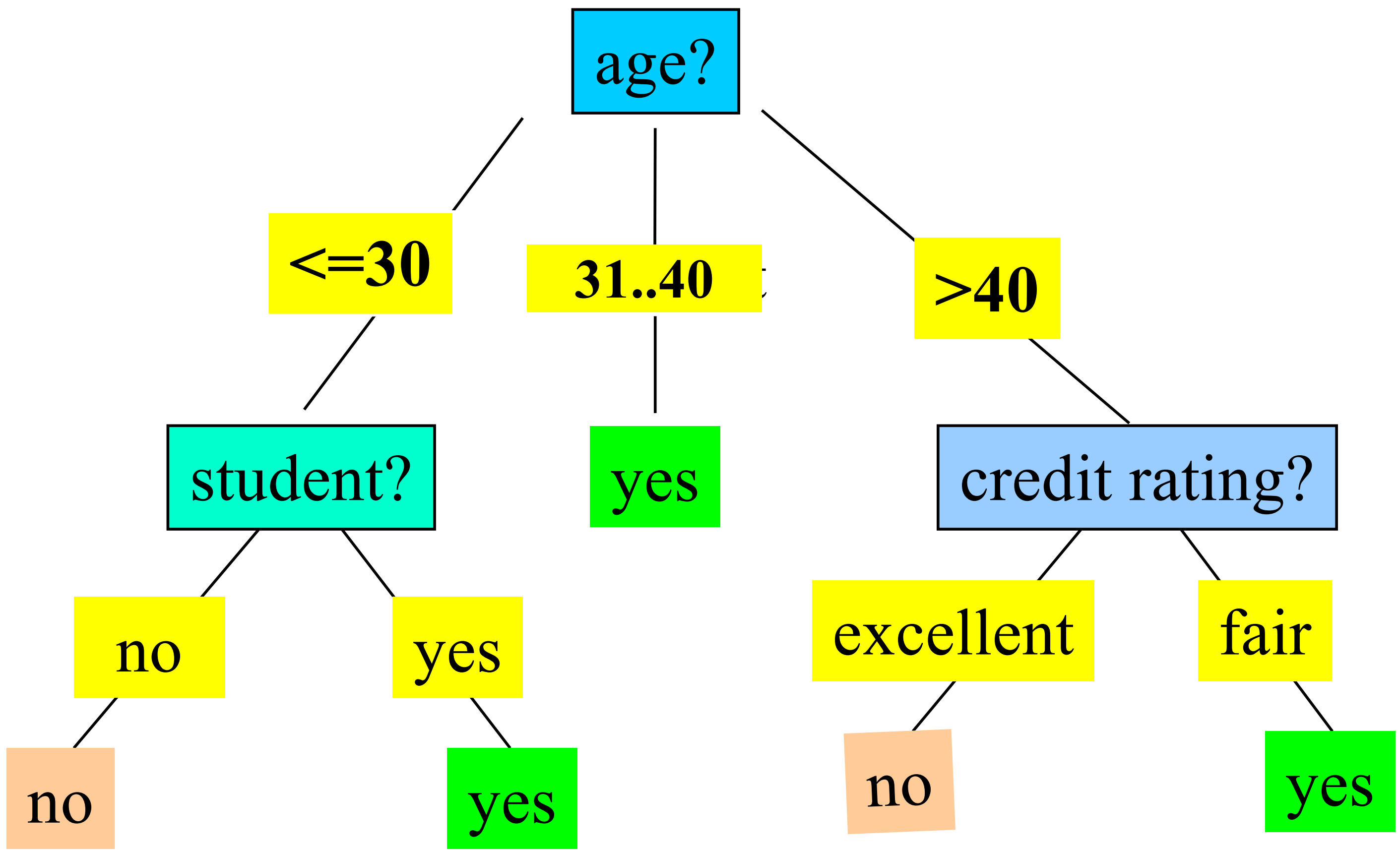
Output: A Decision Tree for "*buys_computer*"



Algorithm for Decision Tree Induction

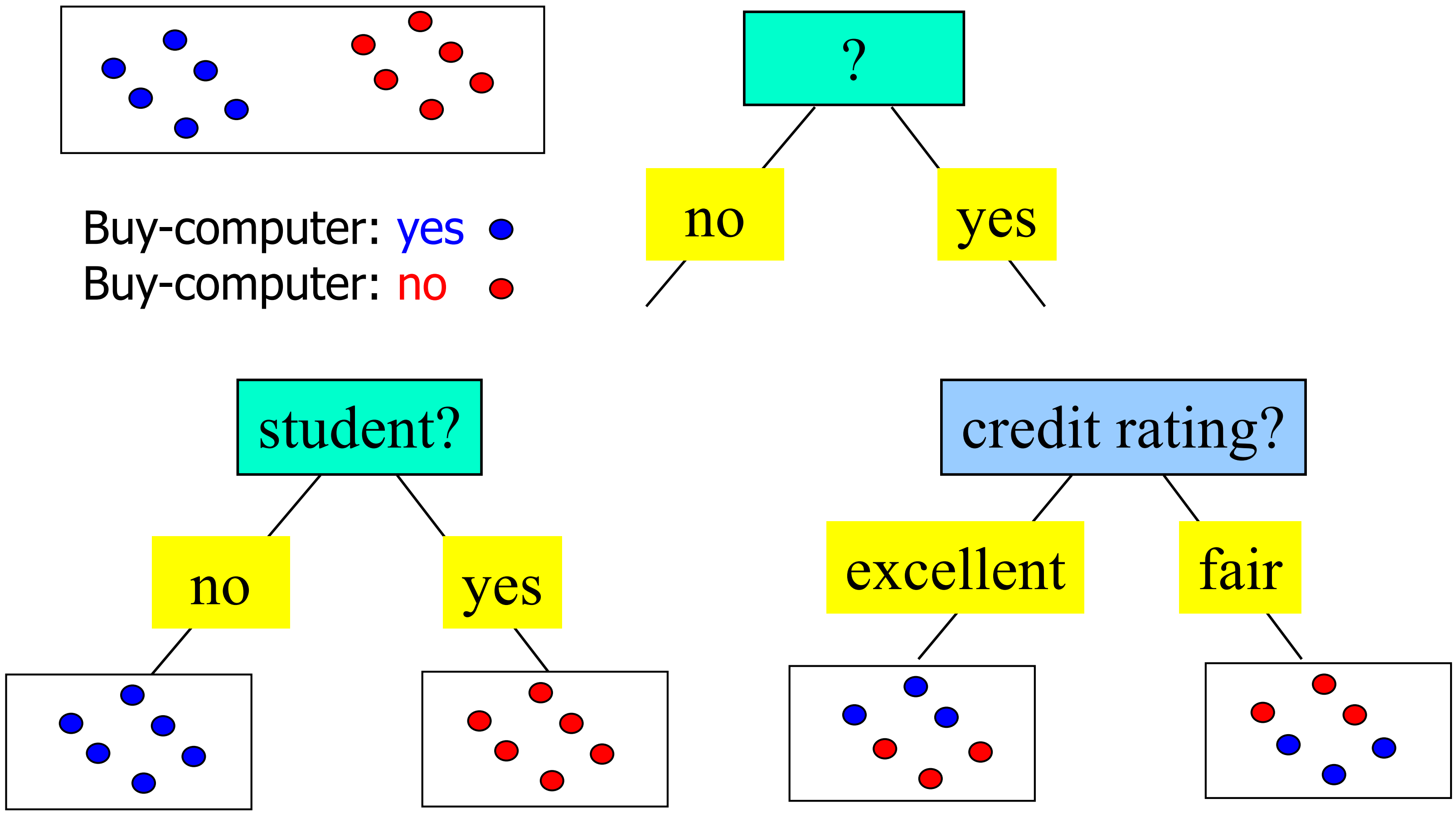
- Conditions for stopping the partitioning process
  - All samples for a given node belong to the same class
  - There are no remaining attributes for further partitioning – majority voting is employed for classifying the leaf
  - There are no samples left

Output: A Decision Tree for "*buys_computer*"



Test Attribute Selection

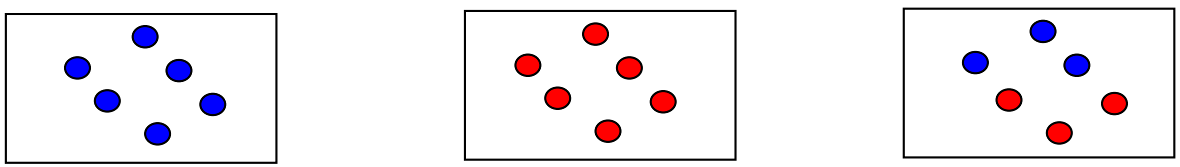
- Which is better as a test attribute?
  - Partitions a group into more homogeneous ones



Attribute Selection Measure: Information Gain

- Select the test attribute having the highest information gain
- Let p_i be the probability that an arbitrary tuple in D belongs to class C_i, estimated by $|C_{i,D}|/|D|$
- Entropy (expected information) to classify a tuple in D:
  - $$Info(D) = -\sum_{i=1}^{m} p_i \log_2(p_i)$$
  - The more heterogeneous the higher

0 0 < Info(D)



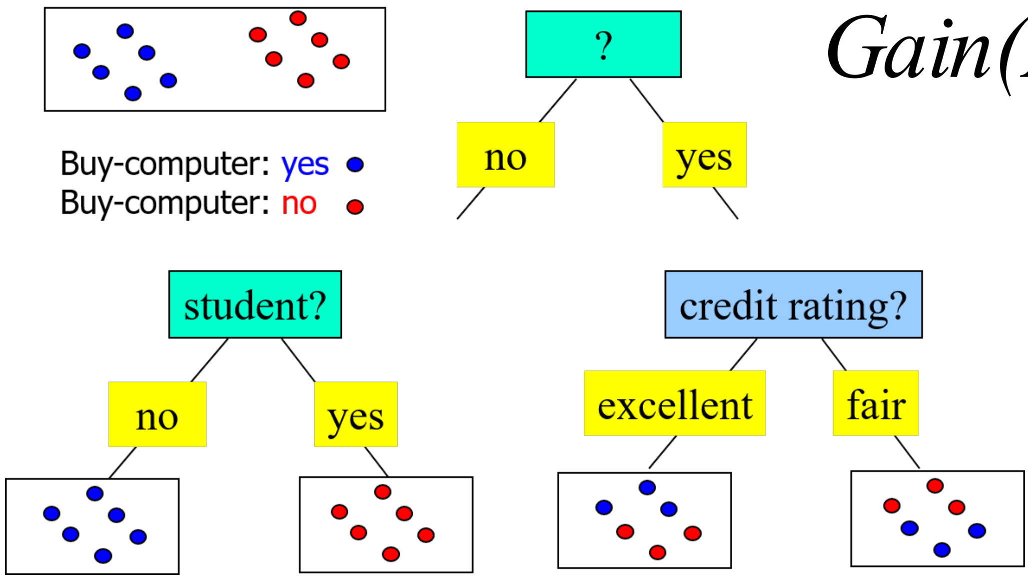
Attribute Selection Measure: Information Gain

- Expected 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

- Class P: buys_computer = "yes"
- Class N: buys_computer = "no"

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

age	p_i	n_i	$I(p_i, n_i)$
<=30	2	3	0.971
31…40	4	0	0
>40	3	2	0.971

age	income	student	credit_rating	buys_computer
<=30	high	no	fair	no
<=30	high	no	excellent	no
31…40	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
>40	low	yes	excellent	no
31…40	low	yes	excellent	yes
<=30	medium	no	fair	no
<=30	low	yes	fair	yes
>40	medium	yes	fair	yes
<=30	medium	yes	excellent	yes
31…40	medium	no	excellent	yes
31…40	high	yes	fair	yes
>40	medium	no	excellent	no

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

$\frac{5}{14}I(2,3)$ means "age <=30" has 5 out of 14 samples, with 2 yes'es and 3 no's. Hence

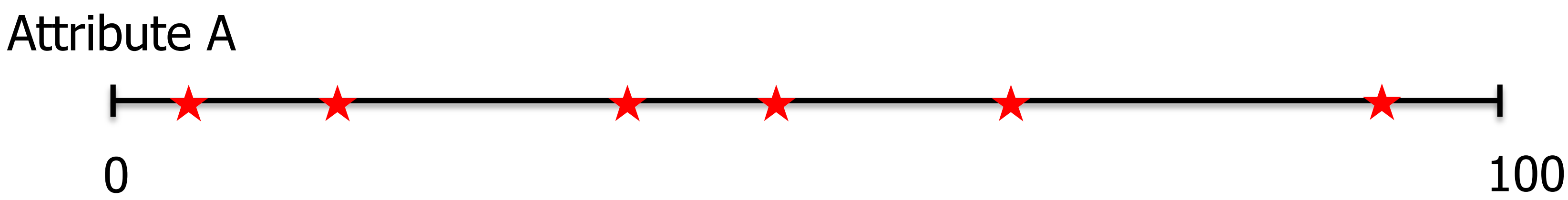
$$Gain(age) = Info(D) - Info_{age}(D) = 0.246$$

Similarly,

$$Gain(income) = 0.029$$
$$Gain(student) = 0.151$$
$$Gain(credit\_rating) = 0.048$$

Computing Information-Gain for Continuous-Value Attributes

- Let attribute A be a continuous-valued attribute
- Make attribute A discrete by deciding the *split points* for A
  - Sort the existing values for A in increasing order
  - Typically, the midpoint between each pair of adjacent values is considered as a possible *split point*
    - $(a_i+a_{i+1})/2$ is the midpoint between the values of a_i and a_{i+1}



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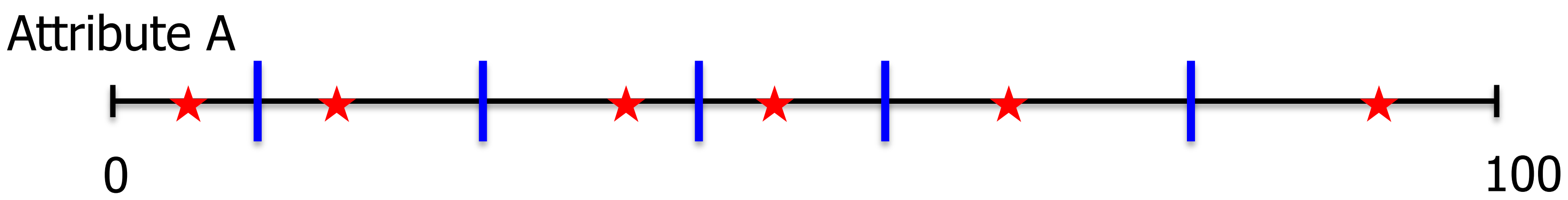
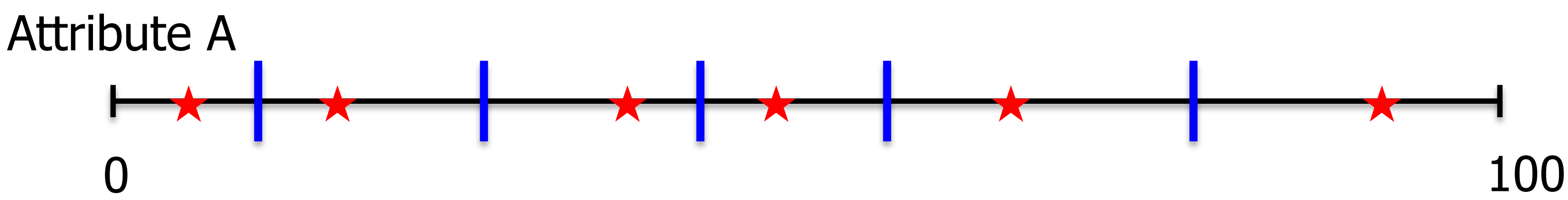


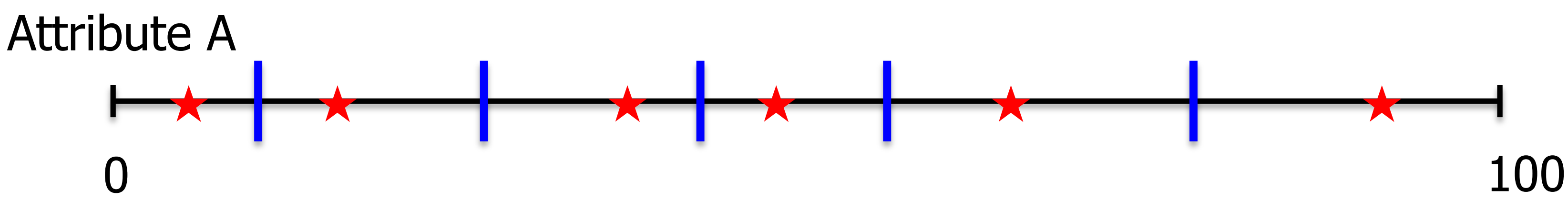
Computing Information-Gain for Continuous-Value Attributes

- Compute the entropy for each split point:
  - D1 is the set of tuples in D satisfying A ≤ split-point
  - D2 is the set of tuples in D satisfying A > split-point
- Determine the *best split point* for A
  - The point giving the *minimum entropy* (i.e., *maximum information gain*) for A is selected



Computing Information-Gain for Continuous-Value Attributes

- Question
  - While a binary partition is assumed currently, an n-ary partition could be considered
  - What is the problem with this case?



Gain Ratio for Attribute Selection (C4.5)

- Information gain measure is biased towards attributes with a large number of values
  - If A has 5 values and B has 2 values,
  - A tends to have higher information gain than B
- C4.5 (a successor of ID3) uses gain ratio to overcome the problem (normalization to information gain)
  - GainRatio(A) = Gain(A) / SplitInfo(A)

Gain Ratio for Attribute Selection (C4.5)

- GainRatio(A) = Gain(A) / SplitInfo_A(D)

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

- Example
  - gain_ratio(income) = 0.029/0.926 = 0.031

$$SplitInfo_A(D) = -\frac{4}{14} \times \log_2(\frac{4}{14}) - \frac{6}{14} \times \log_2(\frac{6}{14}) - \frac{4}{14} \times \log_2(\frac{4}{14}) = 0.926$$

- The attribute with the maximum gain ratio is selected as the splitting attribute

Gini index (CART, IBM IntelligentMiner)

- If a data set *D* contains tuples 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 probability 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 (impurity) *gini*(*D*) is defined as

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

  - where D_1 is a set of tuples having some values for A while D_2 is a set of tuples having the other values for A

Gini index (CART, IBM IntelligentMiner)

- Reduction in impurity:

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

- The attribute providing the largest reduction in impurity (i.e., the smallest $gini_A(D)$) is chosen to as the test attribute to split the node
  - *Binary partition: need to enumerate all the possible splitting points for each attribute*

Gini index (CART, IBM IntelligentMiner)

- Example: D has 9 tuples in buys_computer = "yes" and 5 tuples in buys_computer = "no"

$$gini(D) = 1 - \left(\frac{9}{14}\right)^2 - \left(\frac{5}{14}\right)^2 = 0.459$$

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

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

$$= \frac{10}{14}(1 - (\frac{6}{10})^2 - (\frac{4}{10})^2) + \frac{4}{14}(1 - (\frac{1}{4})^2 - (\frac{3}{4})^2)$$

$$= 0.450$$

$$= Gini_{income \in \{high\}}(D)$$

- If $gini_{\{medium,high\}}$ is 0.30, it will be better since it is the lower

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:
    - has difficulty when # of classes is large
    - tends to favor tests that result in equal-sized partitions and purity in both partitions

Overfitting

- Overfitting
  - An induced tree may overfit the training data
  - Extreme case
    - Every tuple has its own branch in the tree
- Problem
  - Too many branches, some may reflect anomalies due to noise or outliers
  - Poor accuracy for unseen samples

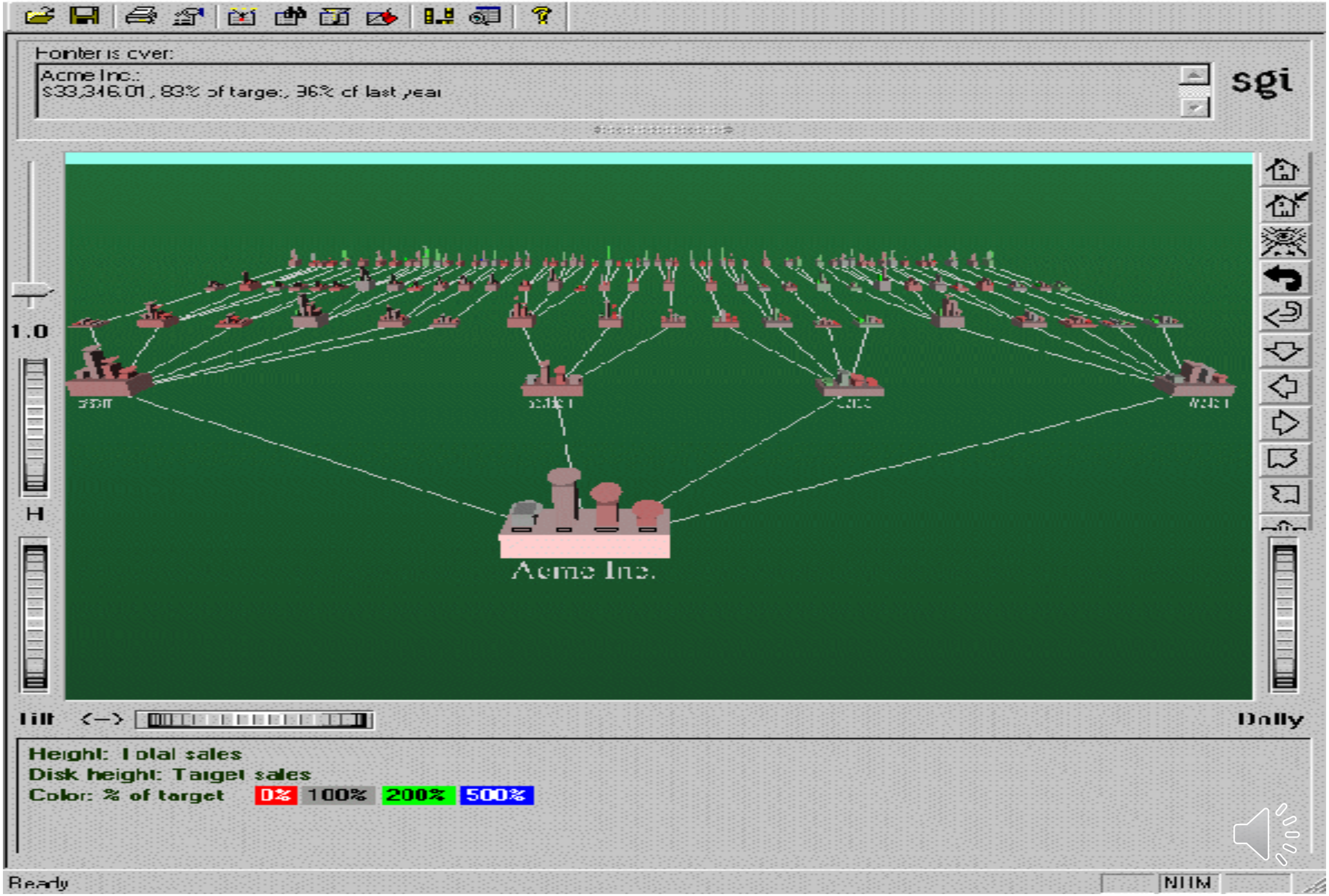
Overfitting and Tree Pruning

- 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 (see Fig. 6.6 in text)
    - Use a set of data different from the training data to decide which is the “best pruned tree”

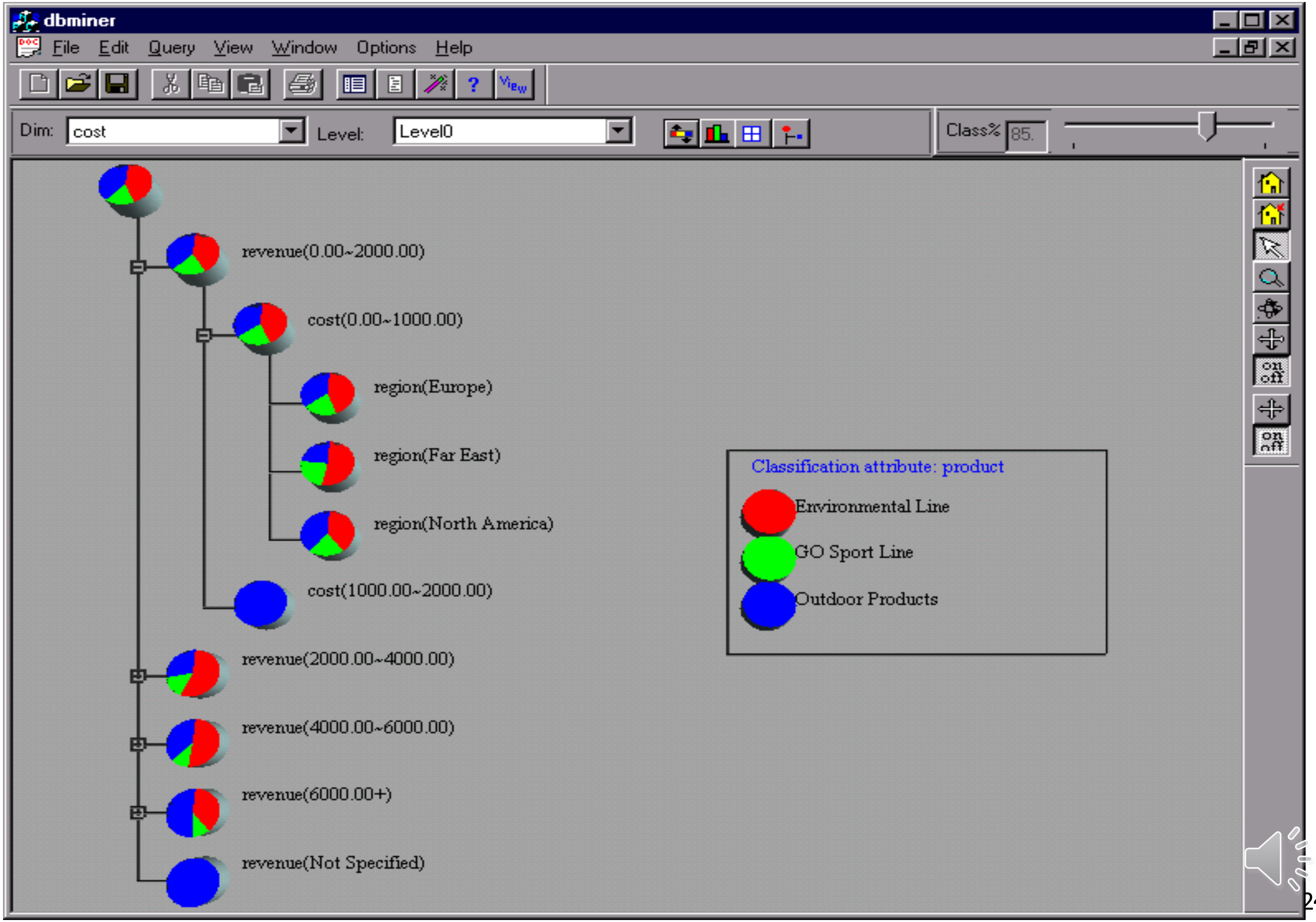
Classification in Large Databases

- 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 decision tree induction in data mining?
  - 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

Visualization of a Decision Tree in SGI/MineSet 3.0



Presentation of Classification Results



Chapter 6. Classification and Prediction

- What is classification? What is prediction?
- Issues regarding classification and prediction
- Classification by decision tree induction
- Bayesian classification
- Rule-based classification
- Classification by back propagation
- Support Vector Machines (SVM)
- Associative classification
- Lazy learners (or learning from your neighbors)
- Other classification methods
- Prediction
- Accuracy and error measures
- Ensemble methods
- Model selection
- Summary