COMP3420: Advanced Databases and Data Mining

Classification and prediction: Introduction and Decision Tree Induction

Lecture outline

- Classification versus prediction
- Classification – A two step process
- Supervised versus un-supervised learning
- Evaluating classification methods
- Decision tree induction
- Attribute selection measures
  - Information gain, Gain ratio, and Gini index
- Overfitting and tree pruning
- Enhancements to basic decision tree induction
- Classification in large databases

Classification versus prediction

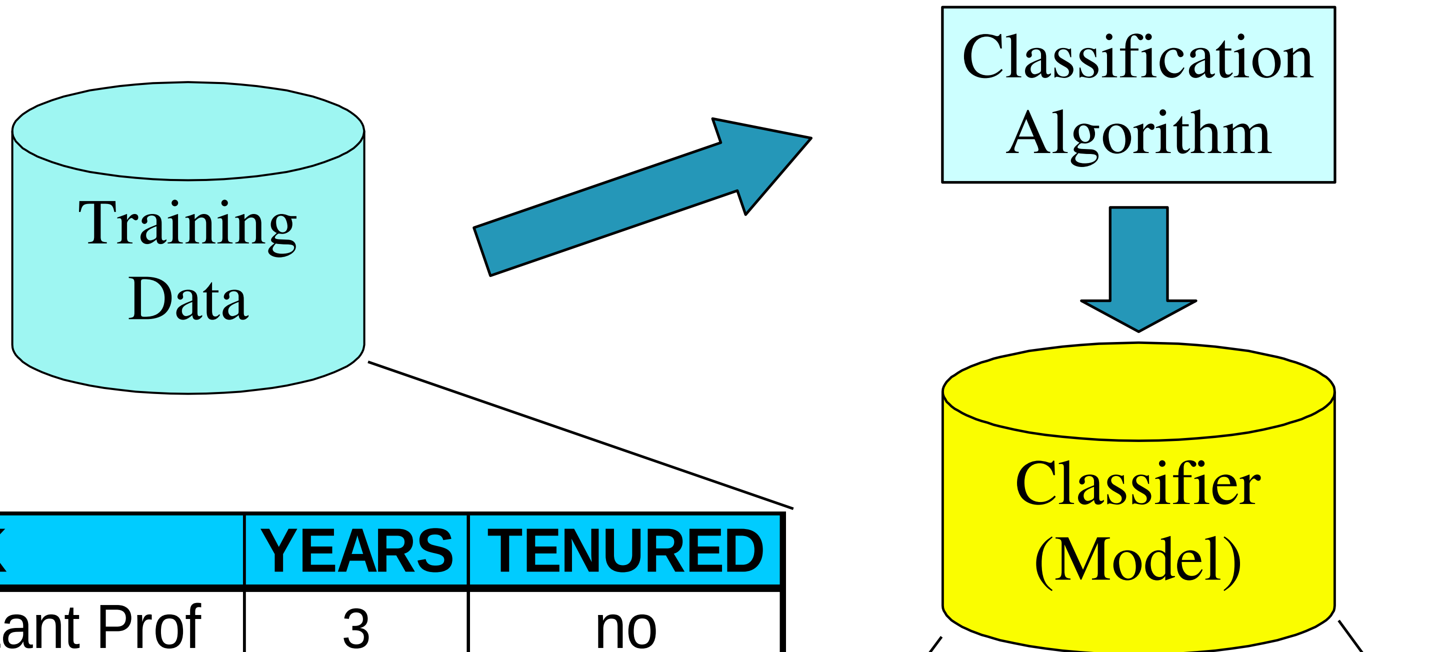
- Classification
  - Predicts categorical class labels (discrete or nominal)
  - Classifies data (constructs a model) based on the training set and the values (class labels) in a classifying attribute and uses it in classifying new data
- Prediction
  - Models continuous-valued functions, (predicts unknown or missing values)
- Typical applications
  - Credit approval
  - Target marketing
  - Medical diagnosis
  - Fraud detection

Classification – A two step process

- *Model construction:* Describing a set of predetermined classes
  - Each tuple/sample/record is assumed to belong to a predefined class, as determined by the *class label attribute*
  - The set of tuples used for model construction is the *training set*
  - The model is represented as classification rules, decision trees, or mathematical formulas

- *Model usage:* For classifying future or unknown objects
  - Need to estimate the *accuracy* of the model
  - The known label of a test sample is compared with the classified results from the model
  - *Accuracy rate* is the percentage of test set samples that are correctly classified by the model
  - The test set is independent of the training set, otherwise *over-fitting* will occur
  - If the accuracy is acceptable, use the model to *classify* data objects whose class labels are not known

Example: Model construction

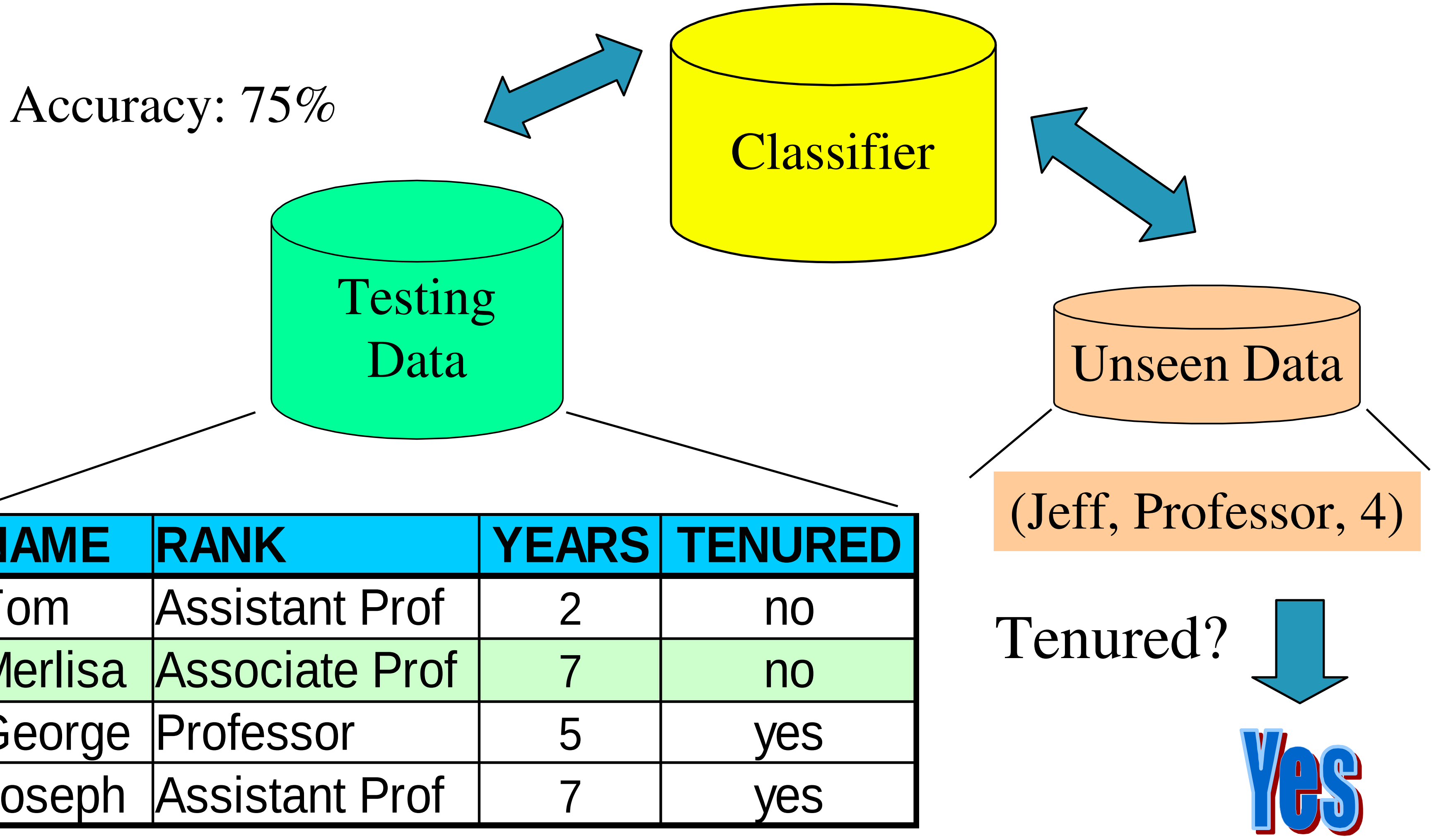


NAME	RANK	YEARS	TENURED
Mike	Assistant Prof	3	no
Mary	Assistant Prof	7	yes
Bill	Professor	2	yes
Jim	Associate Prof	7	yes
Dave	Assistant Prof	6	no
Anne	Associate Prof	3	no

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

Source: Han and Kamber, DM Book, 2nd Ed. (Copyright © 2006 Elsevier Inc.)

Example: Using the model in classification



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

Source: Han and Kamber, DM Book, 2nd Ed. (Copyright © 2006 Elsevier Inc.)

Supervised versus un-supervised learning

- Supervised learning (classification and prediction)
  - Supervision: The training data (observations, measurements, etc.) are accompanied by labels indicating the class of the observations (in previous example: attribute 'Tenured' with classes `yes' and `no')
  - New data is classified based on the training set
- Un-supervised learning (clustering and associations)
  - The class label 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

Evaluating classification methods

- Accuracy (or other quality measures)
  - Classifier accuracy: Predicting class label
  - Predictor accuracy: Guessing value of predicted attributes
- Speed and complexity
  - Time to construct the model (training time)
  - Time to use the model (classification/prediction time)
  - Scalability: Efficiency in handling disk-based databases
- Robustness: Handling noise and outliers
- Interpretability: Understanding and insight provided by the model
- Other measures (for example goodness of rules)
  - Such as decision tree size or compactness of classification rules

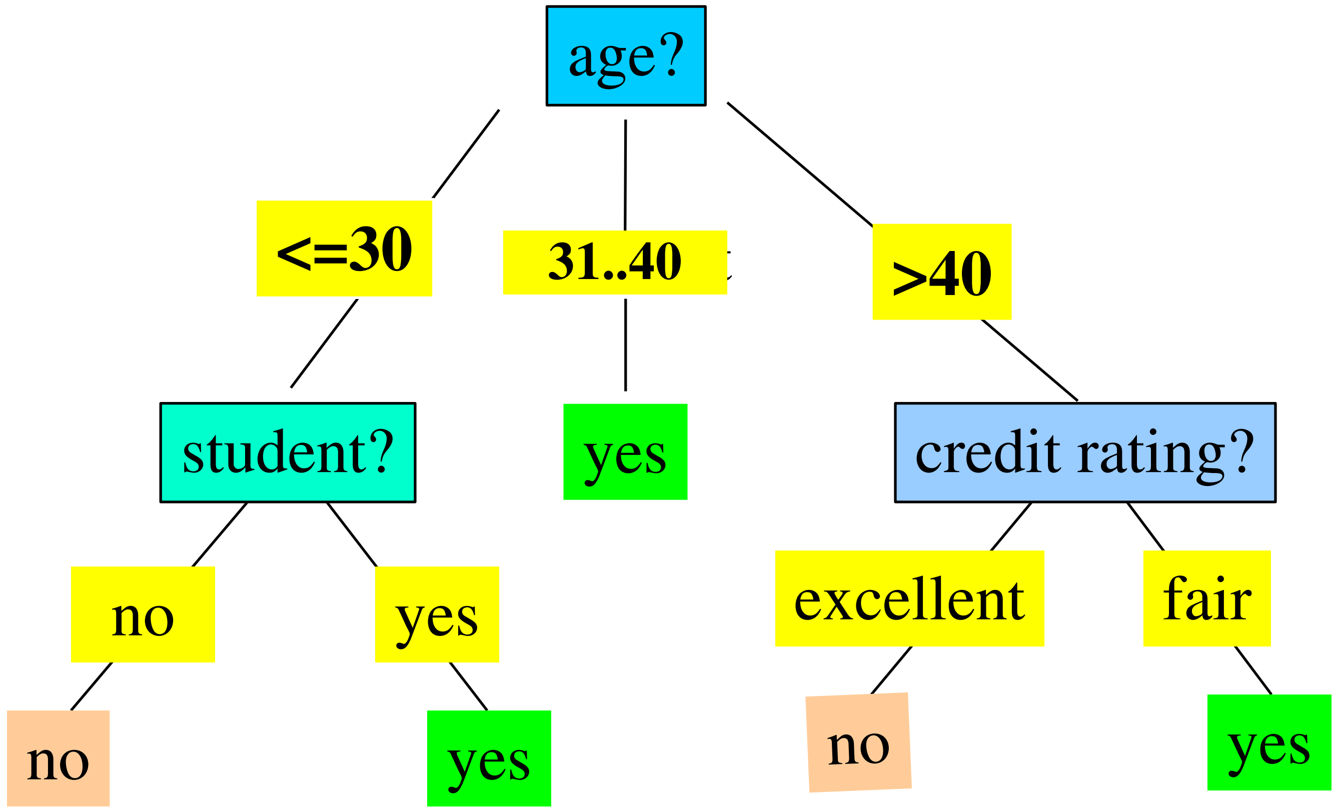
Decision tree induction: Example training data set

What rule would you learn to identify who buys a computer?

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

Source: Han and Kamber, DM Book, 2nd Ed. (Copyright © 2006 Elsevier Inc.)

Example output: A decision tree for *"Buys computer"*



Source: Han and Kamber, DM Book, 2nd Ed. (Copyright © 2006 Elsevier Inc.)

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 training examples are at the root
  - Take the best immediate (local) decision while building the tree
  - Data is partitioned recursively based on selected attributes
  - Attributes are categorical (if continuous-valued, they need to be discretised in advance)
  - Attributes are selected on the basis of a heuristic or statistical measure (for example, *information gain, gain ratio,* or *Gini index)*

- Conditions for stopping partitioning
  - 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

Attribute selection measure: Information gain

- Used in popular decision tree algorithm *ID3*
- In each step, select the attribute with the highest *information gain*
- Let p_i be the probability that an arbitrary record in data set D belongs to class C_i, estimated as $|C_i|/|D|$ *(| | = number of...)*
- *Expected information* (information entropy) needed to classify a record in D is (m being the number of classes):

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

- *Information required* (after using attribute A to split D into v partitions) to classify D is:

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

- The smaller $Info_A(D)$ is, the purer the partitions are
- *Information gained* by using attribute A for branching:

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

Information gain example

Class P: *"Buys computer"* = "yes"

Class N: *"Buys computer"* = "no"

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

$$Info_{age}(D) = \frac{5}{14}Info(D_1) + \frac{4}{14}Info(D_2) + \frac{5}{14}Info(D_3) = 0.694$$

Age	p_i	n_i	*Partition j*
<=30	2	3	*1*
31…40	4	0	*2*
>40	3	2	*3*

From this follows:

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

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

And similar:

$$Gain(Income) = 0.029$$

$$Gain(Student) = 0.151$$

$$Gain(Credit\ rating) = 0.048$$

Calculate information gain for continuous-value attributes

- Let *A* be an attribute with continuous values (e.g. income)
- We have to determine the best *split-point* for *A*
  - Sort the values of A in increasing order
  - Typically, the mid-point 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}
  - The point with the *minimum expected information requirement* for *A*, $Info_A(D)$, *is* selected as the split-point for *A*
- Split:
  - D_1 is the set of records in *D* satisfying $A \leq$ split-point, and D_2 is the set of tuples in *D* satisfying $A >$ split-point

Attribute selection measure: Gain ratio

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

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

- *GainRatio(A) = Gain(A) / SplitInfo(A)*
- The attribute with the maximum gain ratio is selected as the splitting attribute
- Example: Gain ratio on attribute *income*

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

GainRatio(income) = 0.029 / 0.926 = 0.031

Attribute selection measure: Gini index

- Used in *CART*, *IBM Intelligent Miner*
- If a data set D contains records from m classes, the Gini index, $gini(D)$, is defined as:

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

  - p_j is the relative frequency of class j in D
- If D is split on attribute A into two sub-sets D_1 and D_2, the Gini index, $gini_A(D)$, is defined as:

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

- Reduction in impurity: $gini(A) = gini(D) - gini_A(D)$
- The attribute that provides the smallest $gini_A(D)$ (or the largest reduction in impurity) is chosen to split a node
  - Need to enumerate all possible splitting points for each attribute

Gini index example

- Example data set D has 9 records in class *"Buys computers"* = "yes" and 5 in *"Buys computers"* = "no"

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

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

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

$$= \left(\frac{10}{14}\right)\left(1 - \left(\frac{7}{10}\right)^2 - \left(\frac{3}{10}\right)^2\right) + \left(\frac{4}{14}\right)\left(1 - \left(\frac{2}{4}\right)^2 - \left(\frac{2}{4}\right)^2\right) = 0.443$$

- Split on {"low","high"} and {"medium"} gives a Gini index of 0.458, and on {"medium", "high"} and {"low"} gives 0.450
  - Best split for attribute *income* is on {"low","medium"} and {"high"} because it minimises the Gini index

Comparing attribute selection measures

- The three measures, in general, return good results, but...
- Information gain
  - Is biased towards multivalued attributes
- Gain ratio
  - Tends to prefer unbalanced splits in which one partition is much smaller than the others
- Gini index
  - Is biased to multivalued attributes
  - Has difficulty when the number of classes is large
  - Tends to favor tests that result in equal-sized partitions and purity in both partitions
- There are many other selection measures!

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
  - Classify training records very well, but poor accuracy for unseen records

- Two approaches to avoid overfitting
  - *Prepruning:* Halt tree construction early: do not split a node if this would result in a 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 set of data different from the training data to decide which is the “best pruned tree”)

Enhancements to basic decision tree induction

- Allow for continuous-valued attributes
  - Dynamically define new discrete-valued attributes that partition the continuous attribute value into a discrete set of intervals
- Handle missing attribute values
  - Assign the most common value of the attribute
  - Assign probability to each of the possible values
- Attribute (feature) construction
  - Create new attributes based on existing ones that are sparsely represented

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 fast learning speed (compared to 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