

CS522 Advanced Database Systems  
Classification: Rule-based Classifiers

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## Rule-based Classification Example ...

### The Vertebrate dataset

Name	Blood Type	Give Birth	Can Fly	Live in Water	Class
human	warm	yes	no	no	mammals
python	cold	no	no	no	reptiles
salmon	cold	no	no	yes	fishes
whale	warm	yes	no	yes	mammals
frog	cold	no	no	sometimes	amphibians
komodo	cold	no	no	no	reptiles
bat	warm	yes	yes	no	mammals
pigeon	warm	no	yes	no	birds
cat	warm	yes	no	no	mammals
leopard shark	cold	yes	no	yes	fishes
turtle	cold	no	no	sometimes	reptiles
penguin	warm	no	no	sometimes	birds
porcupine	warm	yes	no	no	mammals
eel	cold	no	no	yes	fishes
salamander	cold	no	no	sometimes	amphibians
gila monster	cold	no	no	no	reptiles
platypus	warm	no	no	no	mammals
owl	warm	no	yes	no	birds
dolphin	warm	yes	no	yes	mammals
eagle	warm	no	yes	no	birds

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## ... Rule-based Classification Example

### The Rules

- r1: (Give Birth = no)  $\wedge$  (Can Fly = yes)  $\rightarrow$  Birds
- r2: (Give Birth = no)  $\wedge$  (Live in Water = yes)  $\rightarrow$  Fishes
- r3: (Give Birth = yes)  $\wedge$  (Blood Type = warm)  $\rightarrow$  Mammals
- r4: (Give Birth = no)  $\wedge$  (Can Fly = no)  $\rightarrow$  Reptiles
- r5: (Live in Water = sometimes)  $\rightarrow$  Amphibians

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## Terminology

Rule set:  $R = (r_1 \vee r_2 \vee \dots \vee r_k)$

Rule:  $r_i: (\text{Condition}_i) \rightarrow c_i$

- ◆  $\text{Condition}_i = (A_1 \text{ op } v_1) \wedge (A_2 \text{ op } v_2) \wedge \dots \wedge (A_k \text{ op } v_k)$ 
  - Rule antecedent, precondition
  - **Conjunct:**  $(A_i \text{ op } v_i), \text{op} \in \{=, \neq, <, >, \leq, \geq\}$
- ◆  $c_i$ 
  - Class label
  - Rule consequent

## Coverage and Accuracy

- ◆ A rule  $r$  covers a record  $x$  if the precondition of  $r$  matches the attributes of  $x$ 
  - A.K.A.  $r$  is *fired/triggered* by  $x$
- ◆  $\text{Coverage}(r) = |A| / |D|$ 
  - $|A|$ : # of records covered by  $r$
- ◆  $\text{Accuracy}(r) = |A \cap y| / |A|$ 
  - $|A \cap y|$ : # of records that satisfy both the antecedent and consequent of  $r$
- ◆ Example
  - coverage and accuracy of  $r3$ ??

## How a Rule-based Classifier Works

Name	Blood Type	Give Birth	Can Fly	Live in Water	Class
lemur	warm	yes	no	no	?
turtle	cold	no	no	sometimes	?
dogfish shark	cold	yes	no	yes	?

- ◆ Lemur: ??
- ◆ Turtle: ??
- ◆ Dogfish shark: ??

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## Two Properties of a Rule-based Classifier

- ◆ Exhaustive Rules
  - Every combination of the attribute values is covered by at least one rule
- ◆ Mutually Exclusive Rules
  - No two rules are triggered by the same record

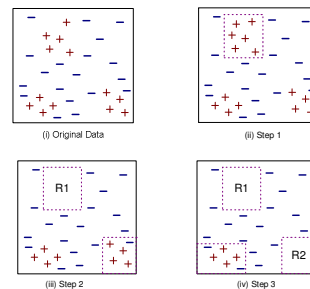
## Make a Rule Set Exhaustive/Mutually Exclusive

- ◆ Default rule:  $() \rightarrow c_d$
- ◆ Ordered rules
  - Quality-based ordering
  - Class-based ordering
- ◆ Unordered rules
  - Majority votes
    - ◆ Weighted by the rule's accuracy

## Sequential Covering Algorithms

- ◆ Order the classes  $\{c_1, c_2, \dots, c_k\}$
- ◆ For each class  $c_i, i < k$ 
  - Find the best rule  $r$  for  $c_i$
  - Remove the records covered by  $r$
  - Add  $r$  to the rule list
  - Repeat until the stop condition is met
- ◆ Add a default rule  $() \rightarrow c_k$

## Sequential Covering Example



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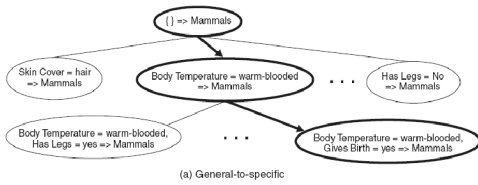
## Ordering Classes and Rules

- ◆ Class ordering
  - Based on frequency
- ◆ Rule ordering
  - Based on classes
  - Based on quality of the rules

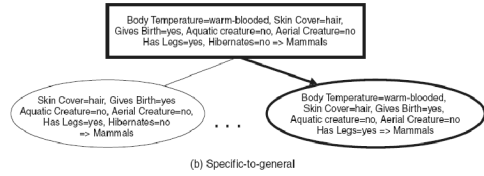
## Rule Growing

- ◆ From general to specific
  - Start with  $() \rightarrow c_i$
  - *Greedily* add one conjunct at a time
- ◆ From specific to general
  - Start with any positive record
  - *Greedily* remove one conjunct at a time
- ◆ Augmented by *beam search* with  $k$  best candidates

## Rule Growing Example (a)



## Rule Growing Example (b)



## Rule Evaluation

- ◆ Decide which conjunct should be added (or removed)

## Rule Evaluation Example

- ◆ A training set contains 60 records in class  $c_1$  and 100 records in class  $c_2$
- ◆ Compare two rules
  - $r_1$ : covers 50  $c_1$  and 5  $c_2$
  - $r_2$ : covers 2  $c_1$  and 0  $c_2$

## Rule Evaluation Measure (a)

Likelihood Ratio:

$$R(r) = 2 \sum_{i=1}^k f_i \log(f_i / e_i)$$

$f_i$ : observed # of class  $i$  records covered by  $r$   
 $e_i$ : expected # of class  $i$  records covered by  $r$

## Rule Evaluation Measure (b)

FOIL's information gain:

$$FGain(r) = n'_c \times (\log_2 \frac{n'_c}{n'} - \log_2 \frac{n_c}{n})$$

	# of records covered by $r$	# of correct records covered by $r$
Before rule growth	$n$	$n_c$
After rule growth	$n'$	$n'_c$

## Stop Conditions

- ◆ Stop growing a rule
- ◆ Stop adding a rule for class  $c_i$ 
  - Minimum Description Length (MDL)

## Rule Pruning

- ◆ Similar to post-pruning of decision trees
- ◆ Remove a conjunct if the accuracy rate improves based on a validation set

## Indirect Rule Extraction

- ◆ Using decision tree
  - Rule generation
  - *Exhaustive?? Mutually Exclusive??*
- ◆ Using association rule mining
  - Find association rules in the form of  $A \rightarrow c_i$
  - Select a subset of the rules to form a classifier
    - Sort the rules based on confidence, support, and length
    - Add to a rule list one at a time
    - Add a default rule

## Readings

- ◆ Textbook Chapter 6.5