

## Rule Induction

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- **Given:** Set of positive and negative examples of some concept
  - **Example:**  $(x_1, x_2, \dots, x_n, y)$
  - $y$ : **concept** (Boolean)
  - $x_1, x_2, \dots, x_n$ : **attributes** (assume Boolean)
- **Goal:** Induce a set of rules that cover all positive examples and no negative ones
  - **Rule:**  $x_a \wedge x_b \wedge \dots \Rightarrow y$  ( $x_a$ : Literal, i.e.,  $x_i$  or its negation)
  - Same as **Horn clause:**  $Body \Rightarrow Head$
  - Rule  $r$  **covers** example  $x$  iff  $x$  satisfies body of  $r$
- **Eval( $r$ ):** Accuracy, info gain, coverage, support, etc.

## Learning a Single Rule

```
head  $\leftarrow y$ 
body  $\leftarrow \emptyset$ 
repeat
  for each literal  $x$ 
     $r_x \leftarrow r$  with  $x$  added to body
     $Eval(r_x)$ 
    body  $\leftarrow$  body  $\wedge$  best  $x$ 
until no  $x$  improves  $Eval(r)$ 
return  $r$ 
```

## Learning a Set of Rules

```
 $R \leftarrow \emptyset$ 
 $S \leftarrow$  examples
repeat
  learn a single rule  $r$ 
   $R \leftarrow R \cup \{r\}$ 
   $S \leftarrow S -$  positive examples covered by  $r$ 
until  $S$  contains no positive examples
return  $R$ 
```

### First-Order Rule Induction (a.k.a. Inductive Logic Programming)



- $y$  and  $x_i$  are now predicates with arguments  
E.g.:  $y$  is Ancestor( $x,y$ ),  $x_i$  is Parent( $x,y$ )
- Literals to add are predicates or their negations
- Literal to add must include at least one variable already appearing in rule
- Adding a literal changes # groundings of rule  
E.g.: Ancestor( $x,z$ )  $\wedge$  Parent( $z,y$ )  $\Rightarrow$  Ancestor( $x,y$ )
- $Eval(r)$  must take this into account  
E.g.: Multiply by # positive groundings of rule still covered after adding literal

### MLN Structure Learning



- Generalizes feature induction in Markov nets
- Any inductive logic programming approach can be used, but . . .
- Goal is to induce any clauses, not just Horn
- Evaluation function should be likelihood
- Requires learning weights for each candidate
- Turns out not to be bottleneck
- Bottleneck is counting clause groundings
- Solution: Subsampling

### MLN Structure Learning



- **Initial state:** Unit clauses or hand-coded KB
- **Operators:** Add/remove literal, flip sign
- **Evaluation function:**  
Pseudo-likelihood + Structure prior
- **Search:** Beam search, shortest-first search