

Rule Induction



Rule Induction



- **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  $S = \emptyset$ 
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 $\text{Ancestor}(x,y)$, x_i is $\text{Parent}(x,y)$
- 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.: $\text{Ancestor}(x,z) \wedge \text{Parent}(z,y) \Rightarrow \text{Ancestor}(x,y)$
- $\text{Eval}(r)$ 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