

CS370



Symbolic Programming Declarative Programming

LECTURE 17: Machine Learning

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Machine Learning

- ⊙ Introduction
- ⊙ Learning concepts from examples
- ⊙ Learning relational descriptions
- ⊙ Learning simple if-then rules
- ⊙ Induction of decision trees
- ⊙ Learning from noisy data and tree pruning
- ⊙ Success of learning

Introduction

◎ Forms of Learning

- ◆ learning by being told
- ◆ learning by discovery
- ◆ learning from examples (inductive learning)

◎ Types of task

- ◆ diagnosing a patient or a plant disease
- ◆ predicting a weather or the biological activity of a new chemical compound
- ◆ determining the biological degradability of chemicals

Learning concepts from examples

© Concepts as sets

- ◆ U : the universal set of objects
- ◆ Concept C : a subset of objects in U
- ◆ To learn concept C means to learn to recognize objects in C .

Learning concepts from examples

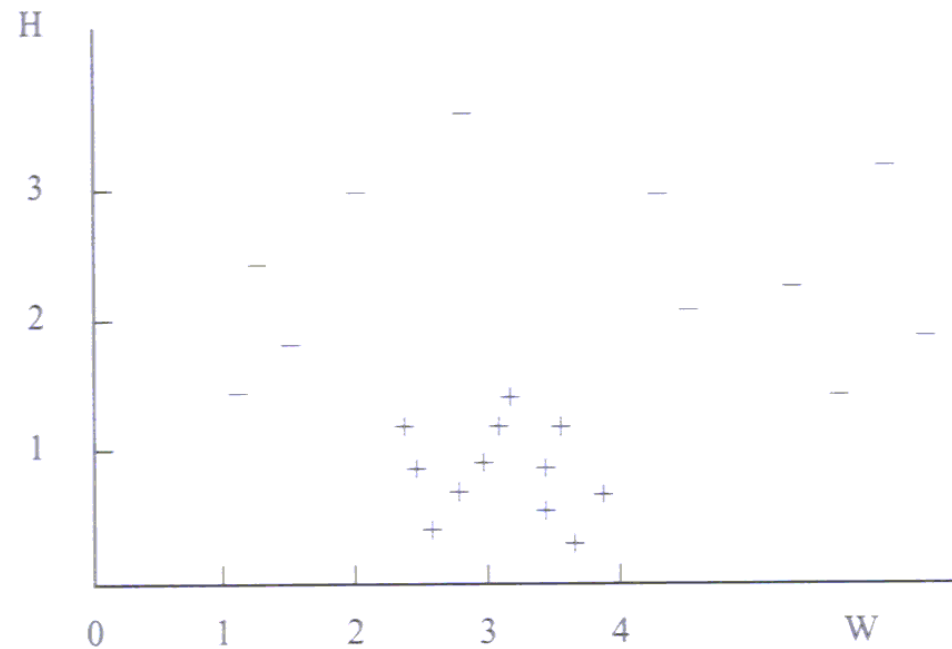
◎ Examples

- ◆ the concept of being poisonous
- ◆ the concept of an arch
- ◆ the concept of multiplication
- ◆ the concept of a certain disease

Learning concepts from examples

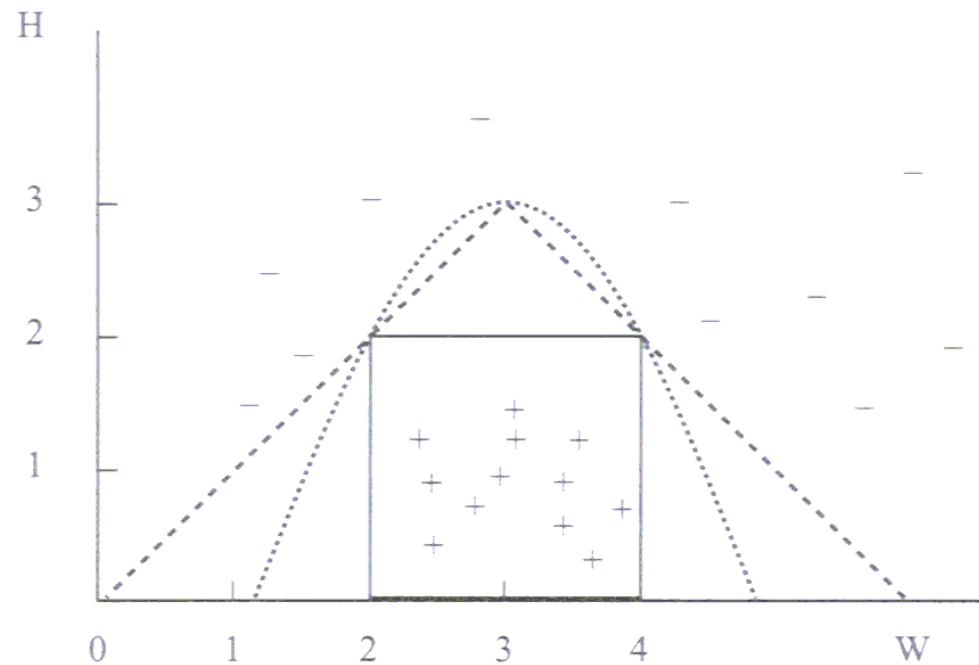
© Examples and hypotheses

- ◆ Pluses for edible, minuses for poisonous



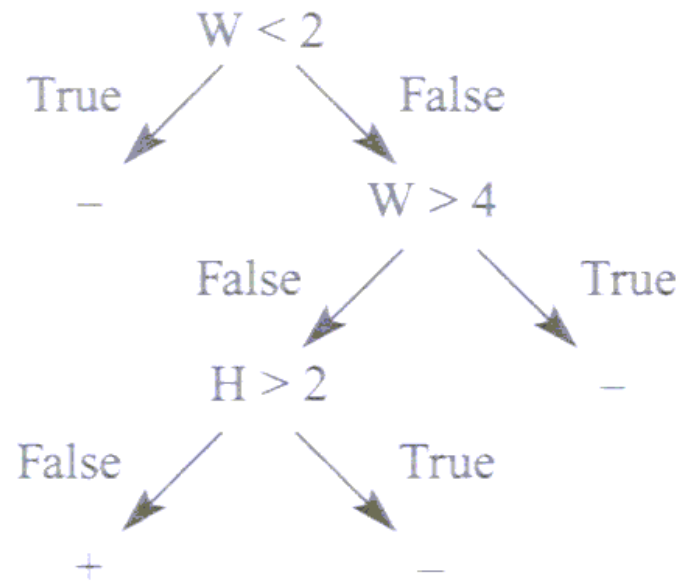
Learning concepts from examples

© Examples and hypotheses



Learning concepts from examples

© Examples and hypotheses



Learning concepts from examples

© Description languages for objects and concepts

- ◆ relational (structural) descriptions
 - an object is defined in terms of its components and the relations between them
- ◆ attribute-value descriptions
 - an object is defined in terms of its global features, or a vector of attribute values

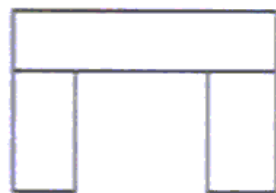
Learning concepts from examples

◎ Accuracy of hypotheses

- ◆ C: target concept
- ◆ L: hypothesis language
- ◆ S: a set of classified examples (Obj, Class)
- ◆ Goal: Find a formula H in L such that H corresponds to C

Learning relational descriptions

©the program ARCHES



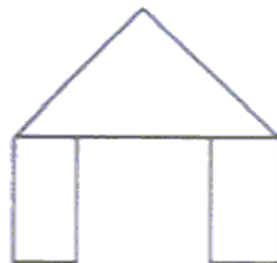
An arch



Not an arch



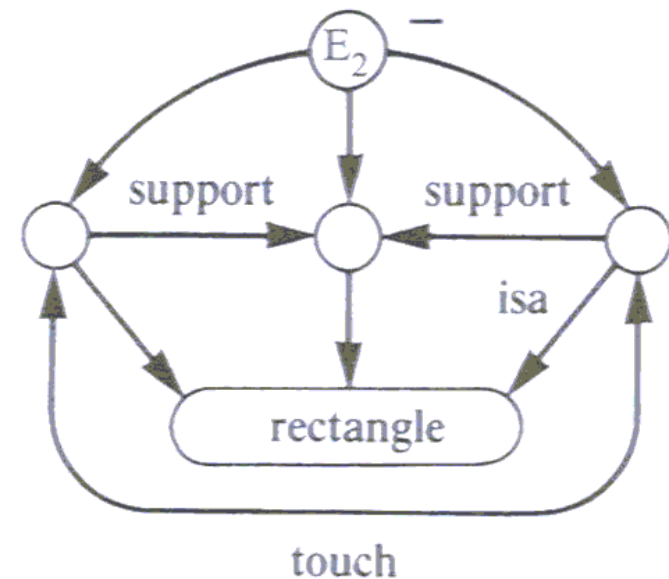
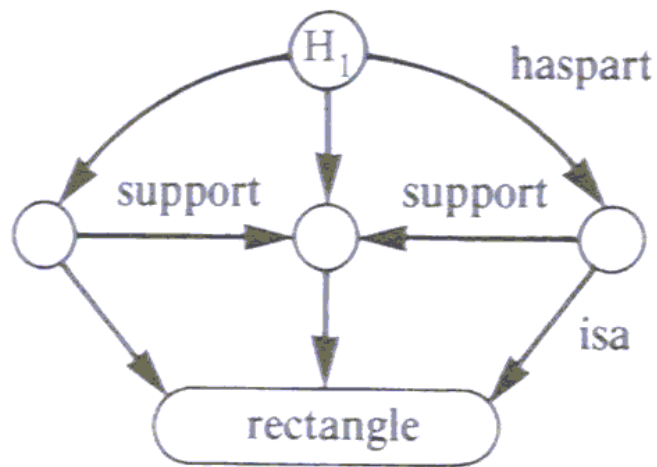
Not an arch



An arch

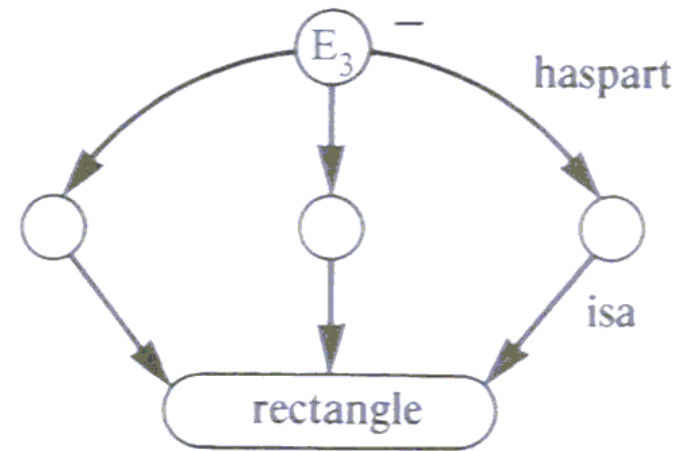
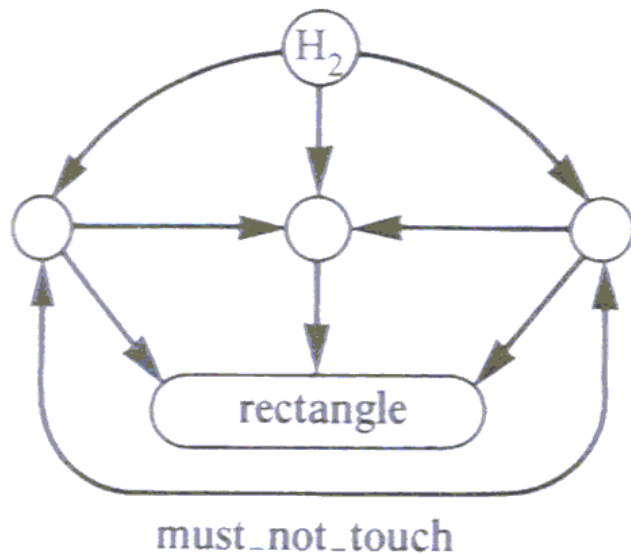
Learning relational descriptions

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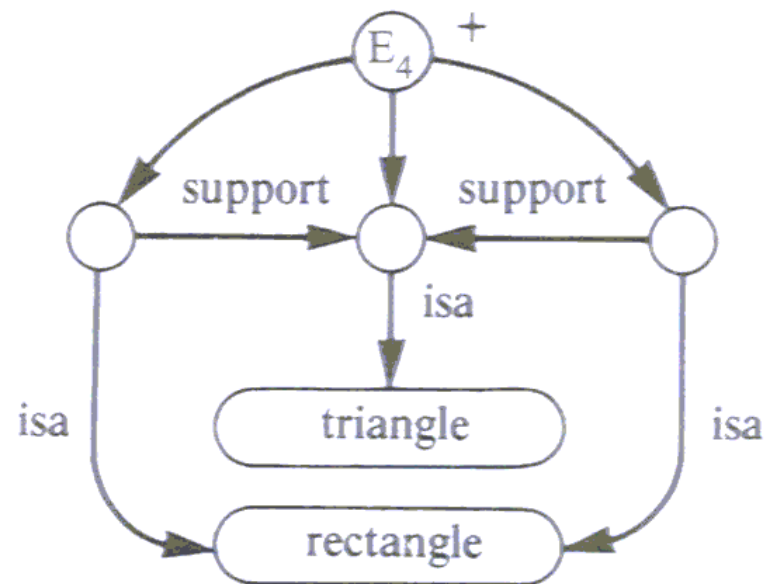
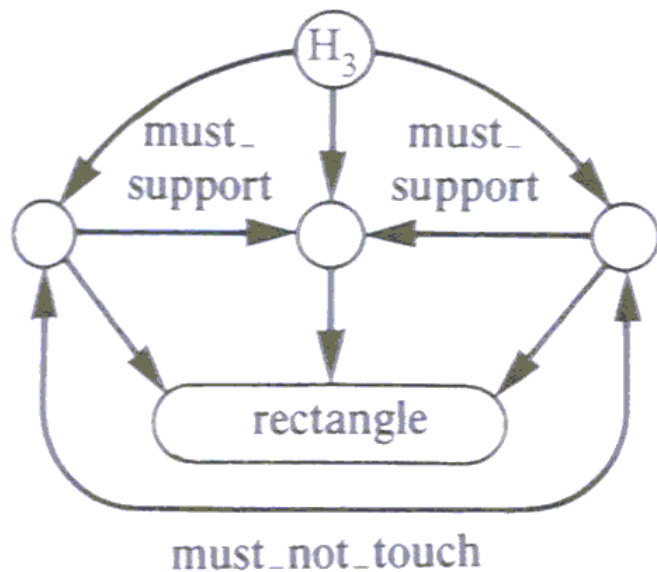
Learning relational descriptions

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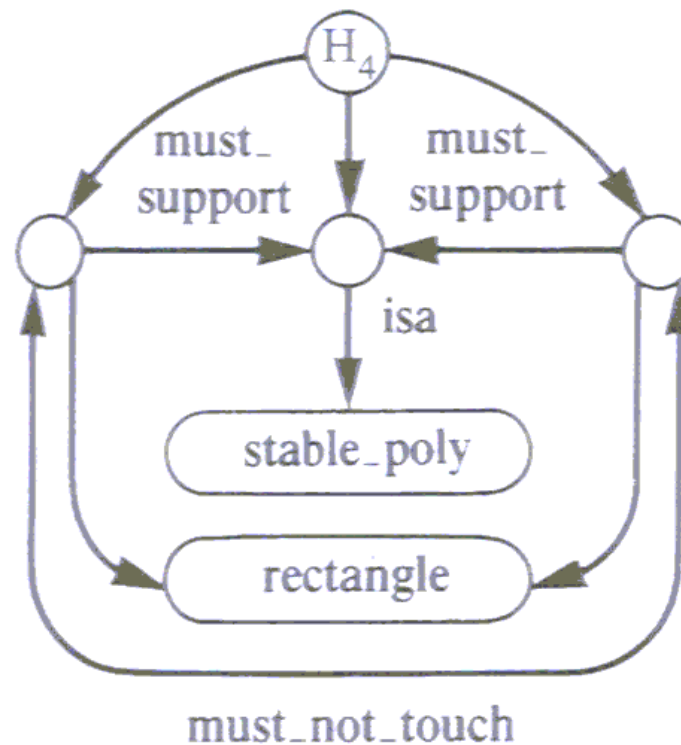
Learning relational descriptions

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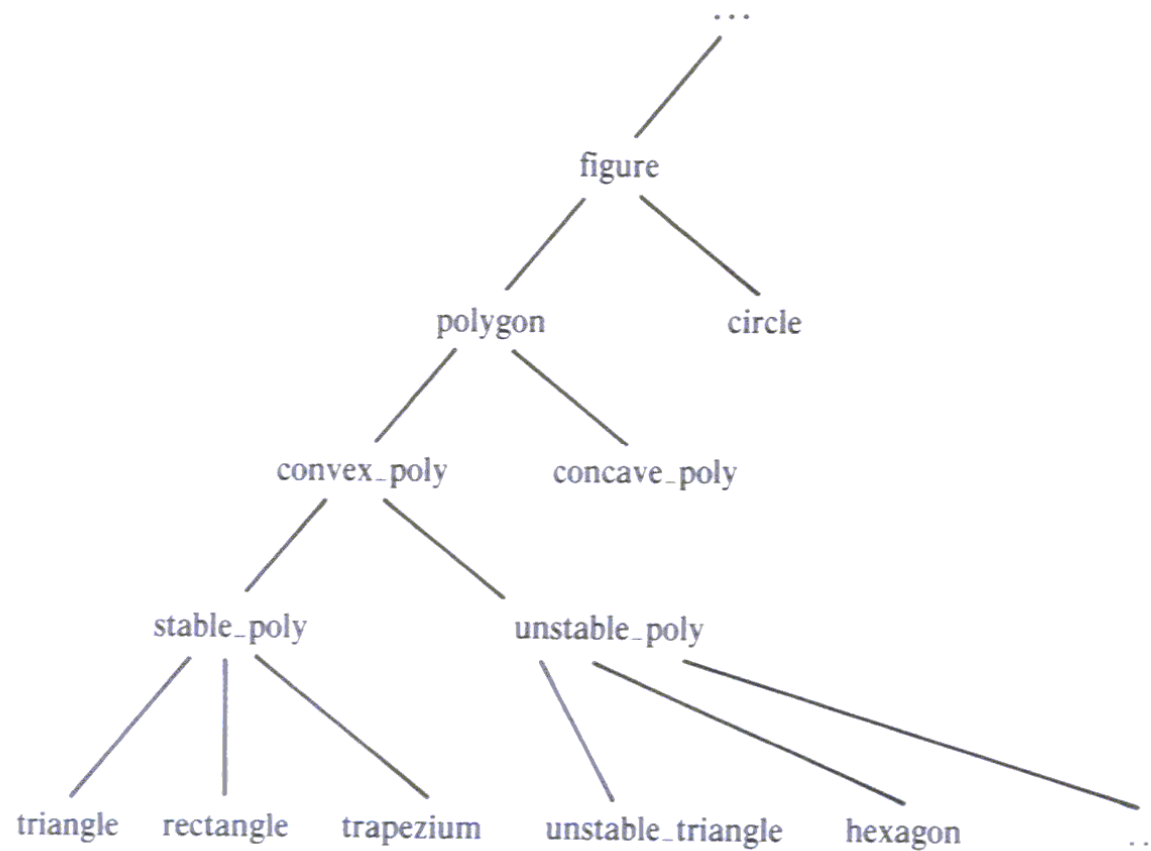


Learning relational descriptions

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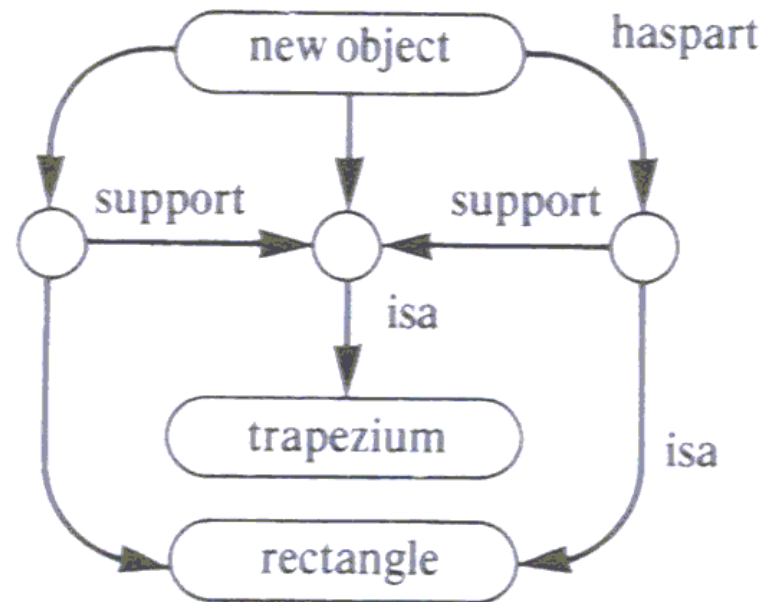
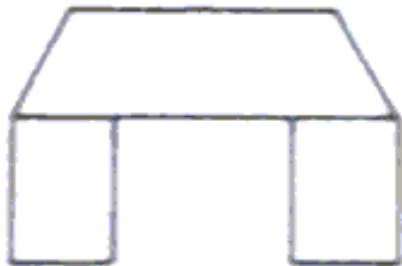


Learning relational descriptions



Learning relational descriptions

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Learning simple if-then rules

© Describing objects and concepts by attributes



Learning simple if-then rules

⊙ Describing objects and concepts by attributes

- ◆ An object is described by a vector of attribute values.
 - size: small, large
 - shape: long, compact, other
 - holes: none, 1, 2, 3, many

Learning simple if-then rules

⊙ Describing objects and concepts by attributes

attribute(size, [small, large]).

attribute(shape, [long, compact, other]).

attribute(holes, [none, 1, 2, 3, many]).

...

example(nut, [size=small, shape=compact, holes=1]).

...

Learning simple if-then rules

© Matching an object and a concept description in Prolog

```
match(Object,Description) :-  
    member(Conjunction,Description),  
    satisfy(Object,Conjunction).  
satisfy(Object,Conjunction) :-  
    not ( member(Att = Val,Conjunction),  
          member(Att = ValX,Object),  
          ValX \== Val ).
```

Learning simple if-then rules

◎ Inducing rules from examples

- ◆ batch learning (vs incremental learning)
- ◆ covering algorithm (Figure 18.11)

```
learn(Class) :-
```

```
    bagof(example(ClassX,Obj),  
          example(ClassX,Obj),  
          Examples),
```

```
    learn(Examples,Class,Description),
```

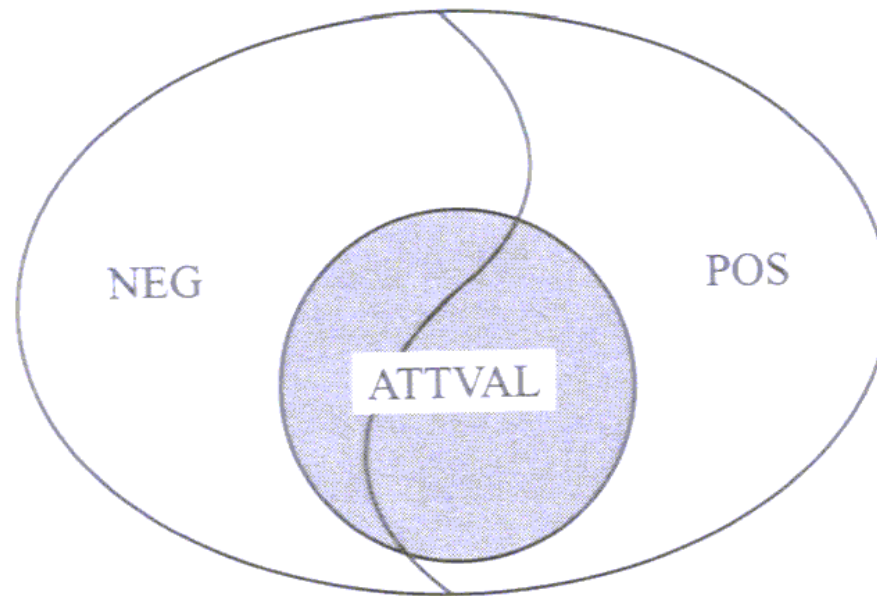
```
    nl, write(Class), write(' < == '), nl,
```

```
    writelist(Description),
```

```
    assert(Class < == Description).
```

Learning simple if-then rules

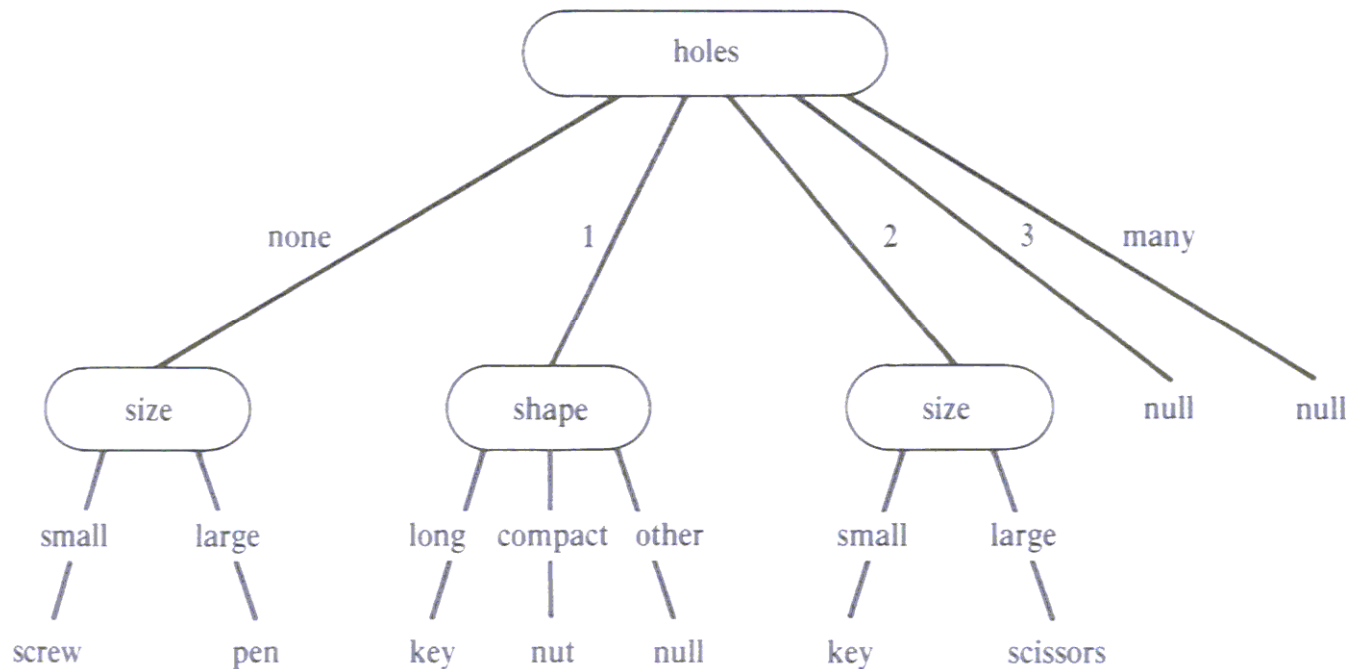
⊙ Heuristic scoring of an attribute value
score(Examples, Class, AttributeValue, Score)



The heuristic score of the attribute value is the # of positive examples in ATTVAL minus the # of negative examples in ATTVAL.

Induction of decision trees

© Induced decision tree: An example



Learning from noisy data and tree pruning

⊙noise in learning

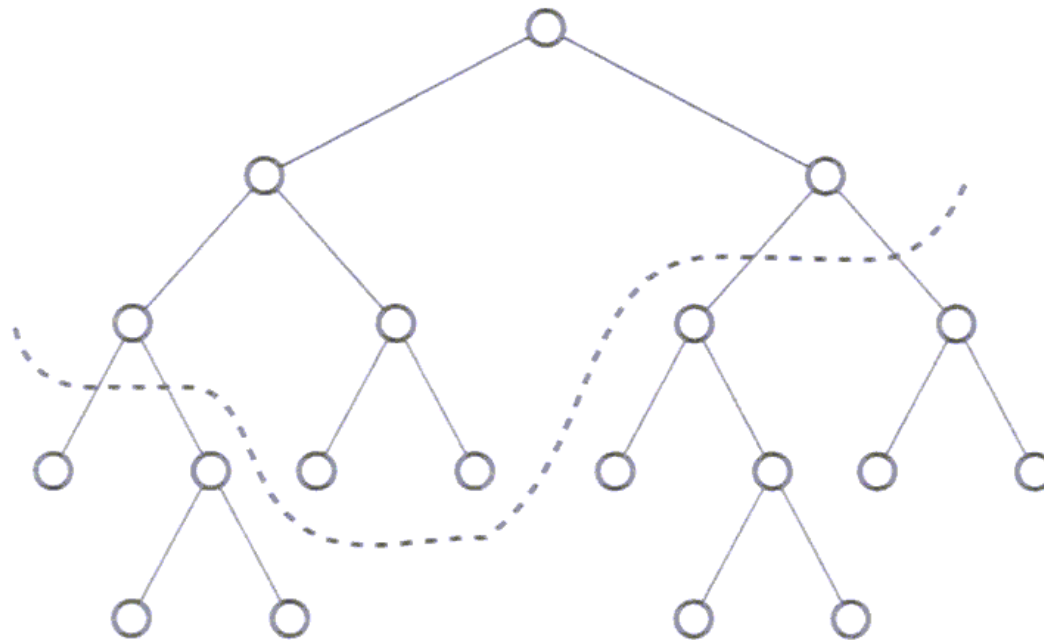
- ◆ errors in attribute values and class values

⊙tree pruning

- ◆ take into account
 - the number of examples in the node
 - the prevalence of the majority class at the node
 - to what extent an additional attribute selected at this node would reduce the impurity of the example set
- ◆ to decide whether to stop expanding the tree or not
- ◆ forward pruning and post-pruning

Learning from noisy data and tree pruning

© Pruning of decision trees



Success of learning

© Criteria for success of learning

- ◆ classification accuracy
 - accuracy on new objects
 - accuracy on the objects in S
- ◆ comprehensibility (understandability)
- ◆ computational complexity
 - generation complexity
 - execution complexity

Summary

- ⊙ Learning concepts from examples
- ⊙ Learning relational descriptions
- ⊙ Learning simple if-then rules
- ⊙ Induction of decision trees
- ⊙ Learning from noisy data and tree pruning
- ⊙ Success of learning