Pure Induction – Decision Trees

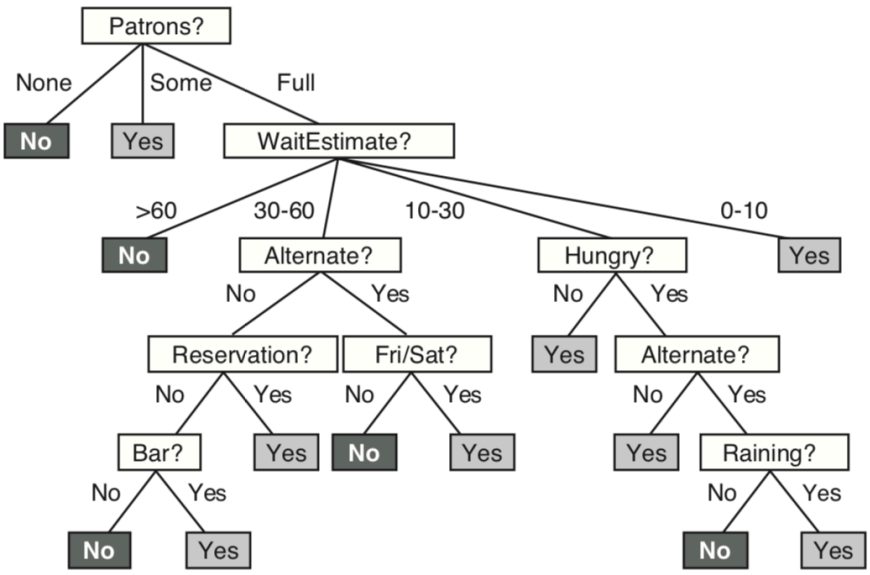


Figure 18.2 **FILES: figures/restaurant-tree.eps (Tue Nov 3 16:23:29 2009).** A decision tree for deciding whether to wait for a table.

Constructing an Intensional Description from an Extensional One

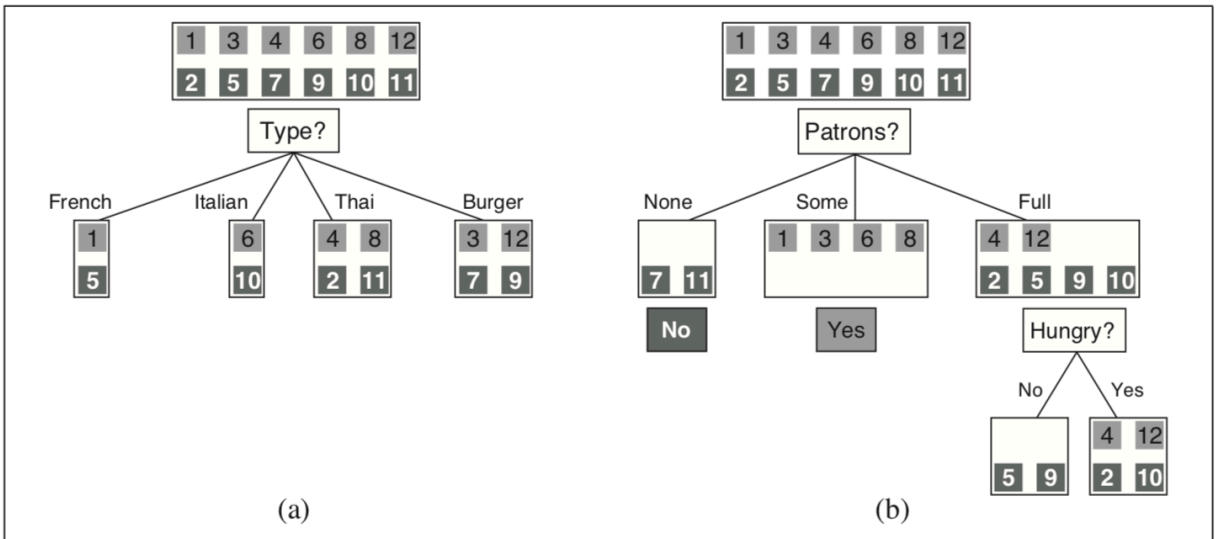


Figure 18.4 **FILES: figures/restaurant-stub.eps (Tue Nov 3 16:23:28 2009).** Splitting the examples by testing on attributes. At each node we show the positive (light boxes) and negative (dark boxes) examples remaining. (a) Splitting on *Type* brings us no nearer to distinguishing between positive and negative examples. (b) Splitting on *Patrons* does a good job of separating positive and negative examples. After splitting on *Patrons*, *Hungry* is a fairly good second test.

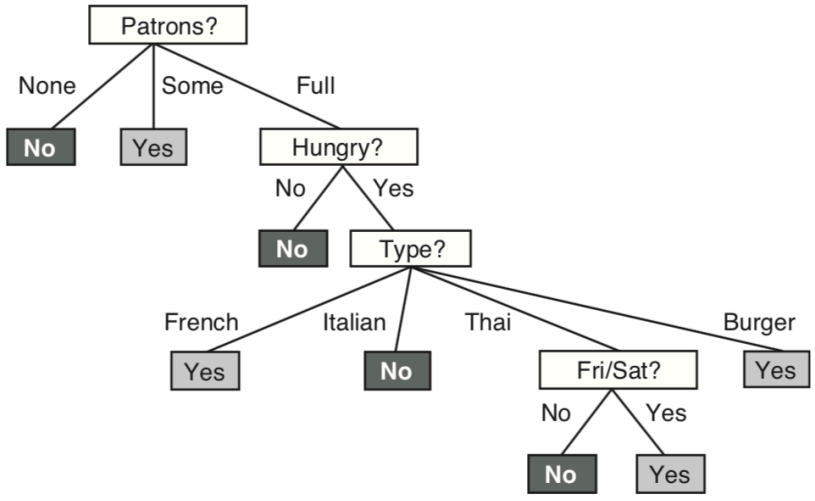


Figure 18.6 FILES: figures/induced-restaurant-tree.eps (Tue Nov 3 16:23:04 2009). The decision tree induced from the 12-example training set.

Chapter 19

Generalization / Specialization

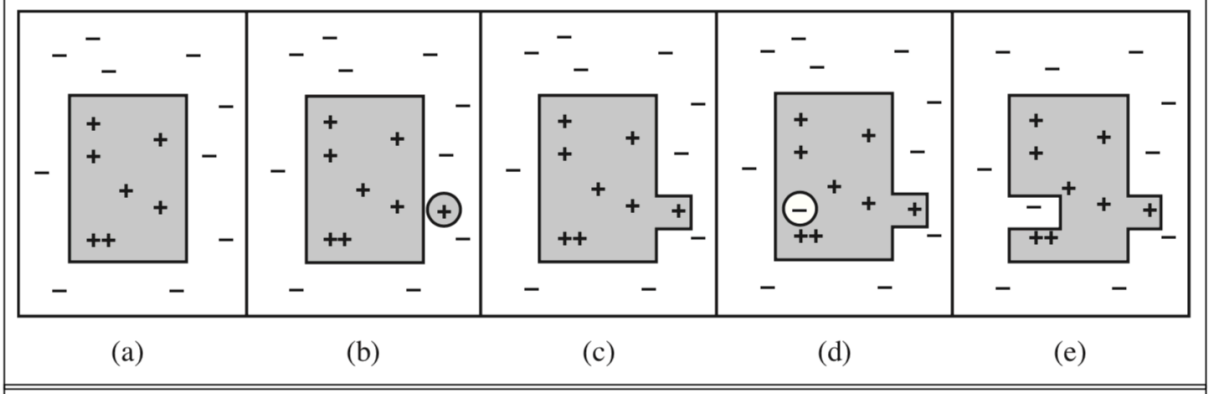


Figure 19.1 FILES: figures/cbh.eps (Tue Nov 3 16:22:32 2009). (a) A consistent hypothesis. (b) A false negative. (c) The hypothesis is generalized. (d) A false positive. (e) The hypothesis is specialized.

$$\forall x \;\; C_2(x) \;\Rightarrow\; C_1(x)$$

Version Space

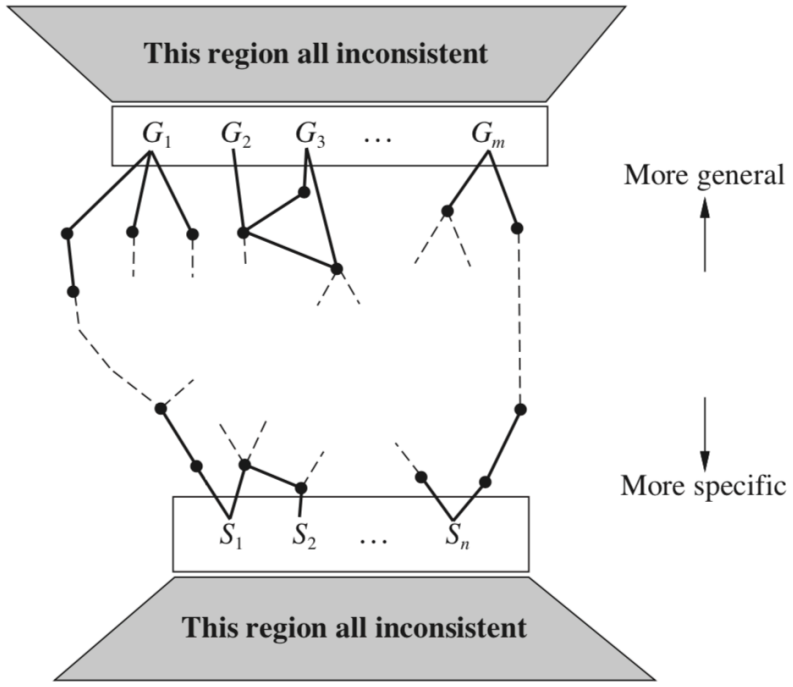


Figure 19.4 FILES: figures/version-space.eps (Tue Nov 3 16:24:02 2009). The version space contains all hypotheses consistent with the examples.

Hypothesis space is hyperexponential.

Candidate elimination Example:

Example	*Sky*	*AirTemp*	*Humidity*	*Wind*	*Water*	*Forecast*	*EnjoySport*
1	Sunny	Warm	Normal	Strong	Warm	Same	Yes
2	Sunny	Warm	High	Strong	Warm	Same	Yes
3	Rainy	Cold	High	Strong	Warm	Change	No
4	Sunny	Warm	High	Strong	Cool	Change	Yes

Table of examples for EnjoySport

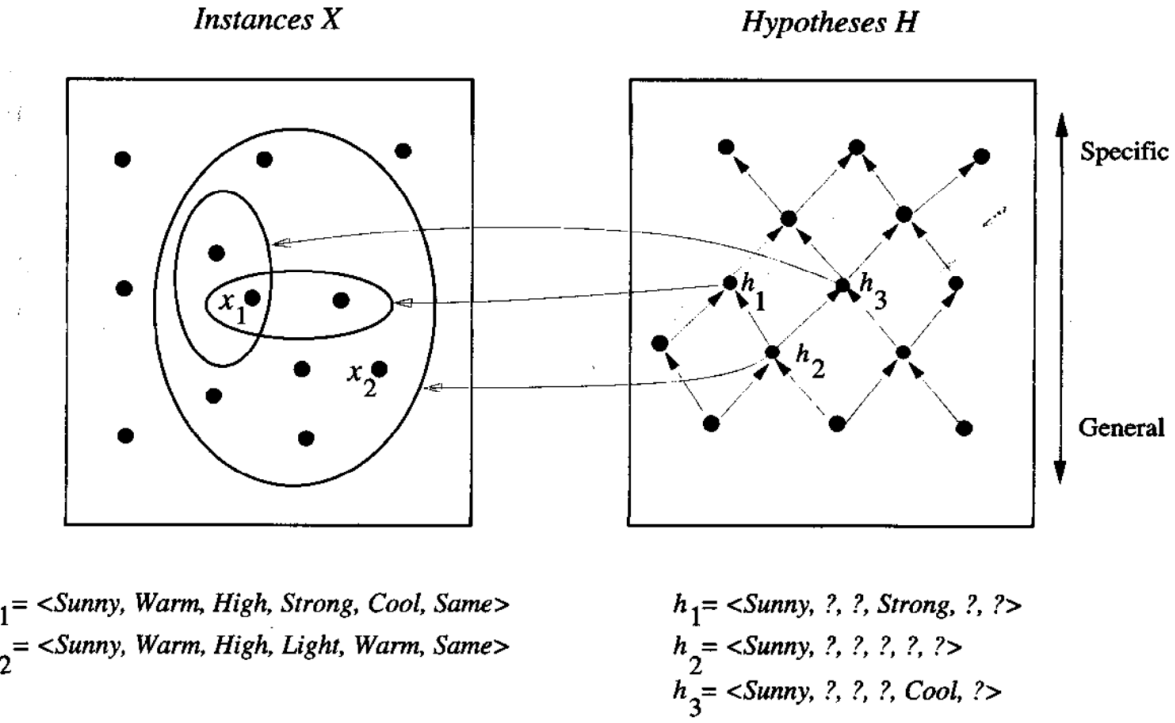
Possible hypotheses for EnjoySport:

$\langle ?, Cold, High, ?, ?, ? \rangle$ only on cold days with high humidity

$\langle ?, ?, ?, ?, ?, ? \rangle$ the most general hypothesis - always

$\langle \emptyset, \emptyset, \emptyset, \emptyset, \emptyset, \emptyset \rangle$ the most specific hypothesis – never

General-to-specific ordering of hypotheses:

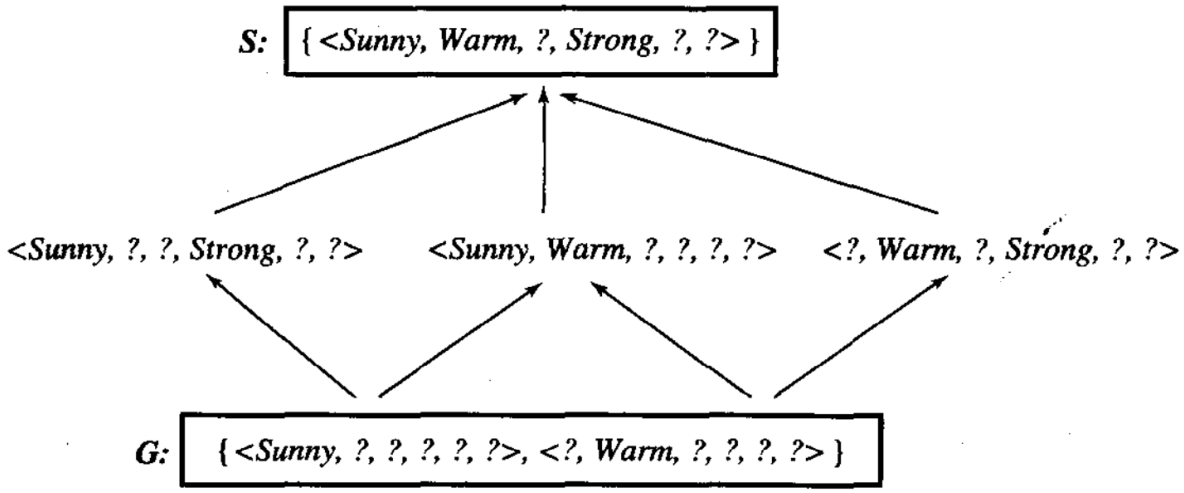


x_1= <Sunny, Warm, High, Strong, Cool, Same>
x_2= <Sunny, Warm, High, Light, Warm, Same>

h_1= <Sunny, ?, ?, Strong, ?, ?>
h_2= <Sunny, ?, ?, ?, ?, ?>
h_3= <Sunny, ?, ?, ?, Cool, ?>

Each hypothesis corresponds to a subset of instances. h2 is more general than h1 and h3.

A version space for this task:



The version space is represented as S and G, and contains the 6 hypotheses that are consistent with all four training examples.

Let us construct this version space step by step from the four examples.

The initial version space is:

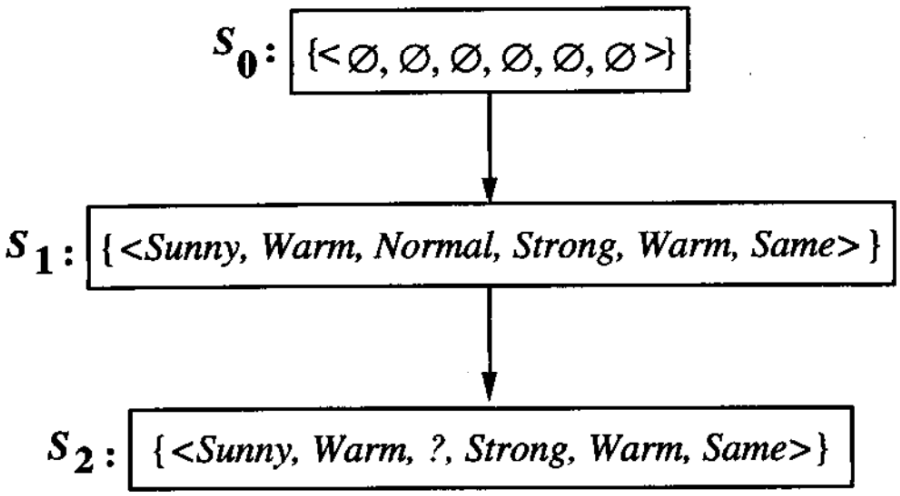
$$G_0 \leftarrow \{\langle ?, ?, ?, ?, ?, ? \rangle\}$$

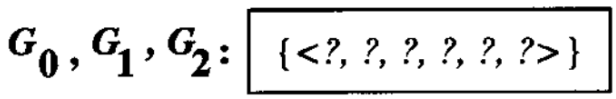
$$S_0 \leftarrow \{\langle \emptyset, \emptyset, \emptyset, \emptyset, \emptyset, \emptyset \rangle\}$$

The examples are:

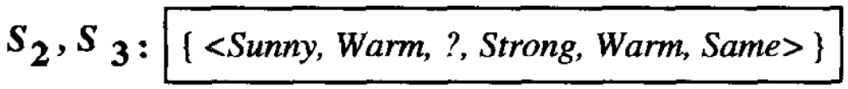
Example	*Sky*	*AirTemp*	*Humidity*	*Wind*	*Water*	*Forecast*	*EnjoySport*
1	Sunny	Warm	Normal	Strong	Warm	Same	Yes
2	Sunny	Warm	High	Strong	Warm	Same	Yes
3	Rainy	Cold	High	Strong	Warm	Change	No
4	Sunny	Warm	High	Strong	Cool	Change	Yes

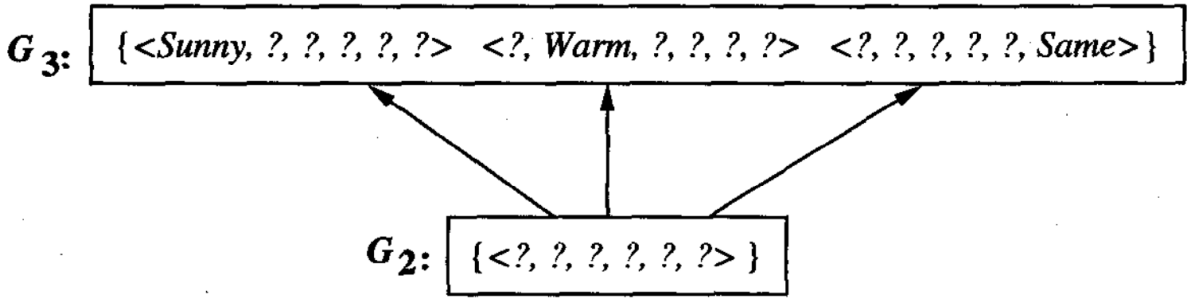
Examples 1 and 2 are positive examples, and the specific boundary changes:





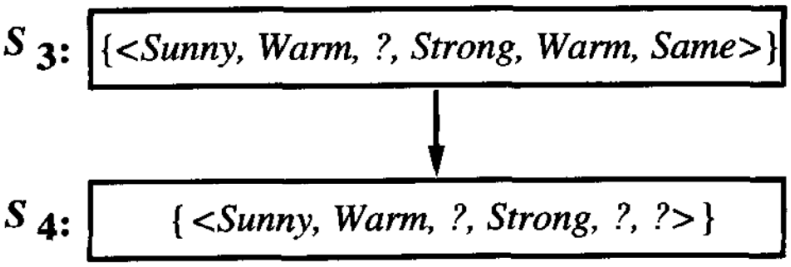
The third example is a negative example that changes G:

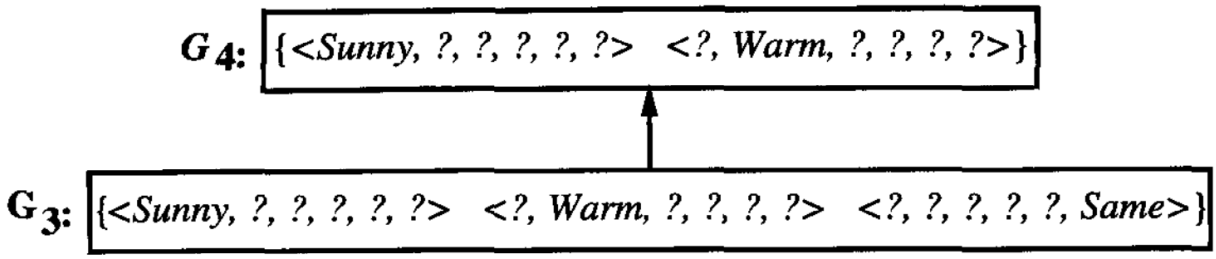




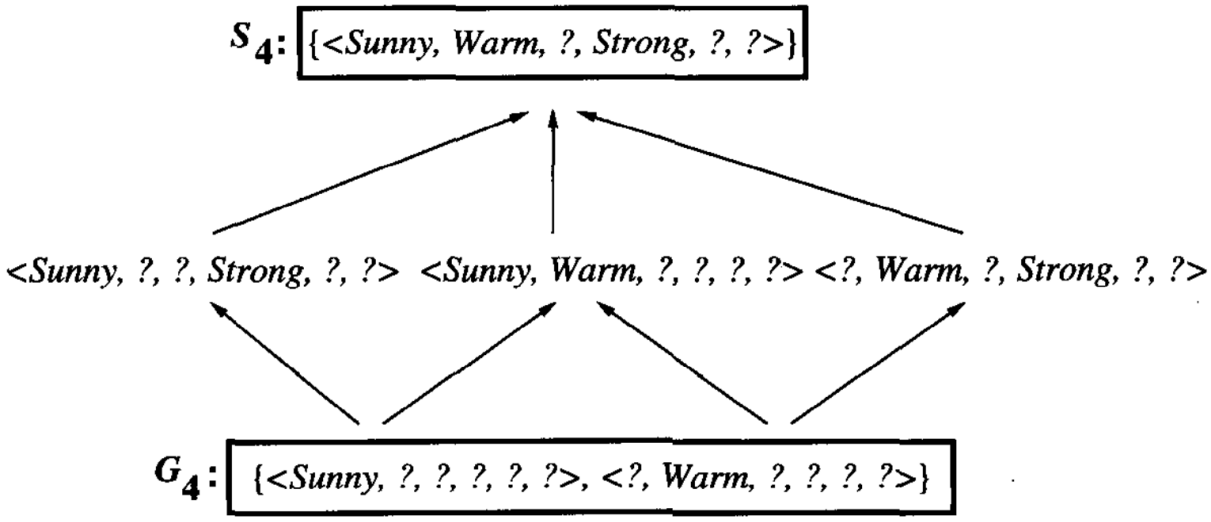
Notice that the new G hypotheses must also correctly classify the previous positive examples, so that [?, ?, Normal, ?, ?, ?] is not included in G.

Finally, the fourth training example is used, and produces:





The final version space:



Here are some new instances to classify. Some will require voting.

Instance	*Sky*	*AirTemp*	*Humidity*	*Wind*	*Water*	*Forecast*	*EnjoySport*
A	Sunny	Warm	Normal	Strong	Cool	Change	?
B	Rainy	Cold	Normal	Light	Warm	Same	?
C	Sunny	Warm	Normal	Light	Warm	Same	?
D	Sunny	Cold	Normal	Strong	Warm	Same	?

Knowledge in learning:

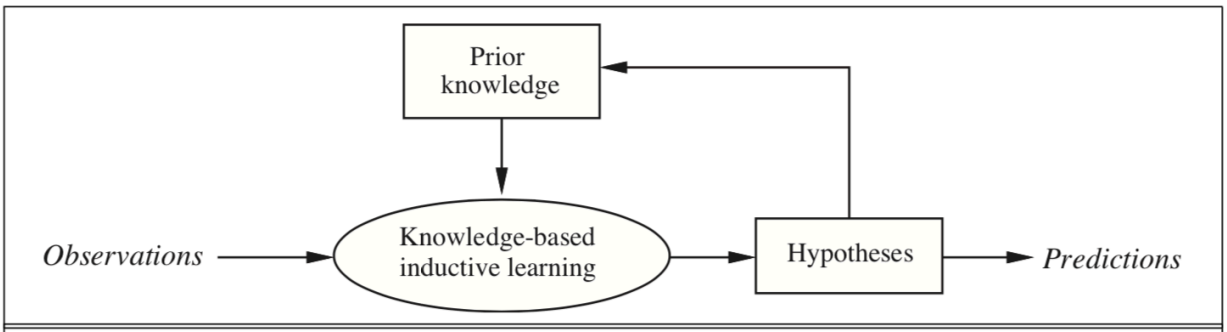


Figure 19.6 FILES: figures/cumulative-learning.eps (Tue Nov 3 16:22:36 2009). A cumulative learning process uses, and adds to, its stock of background knowledge over time.

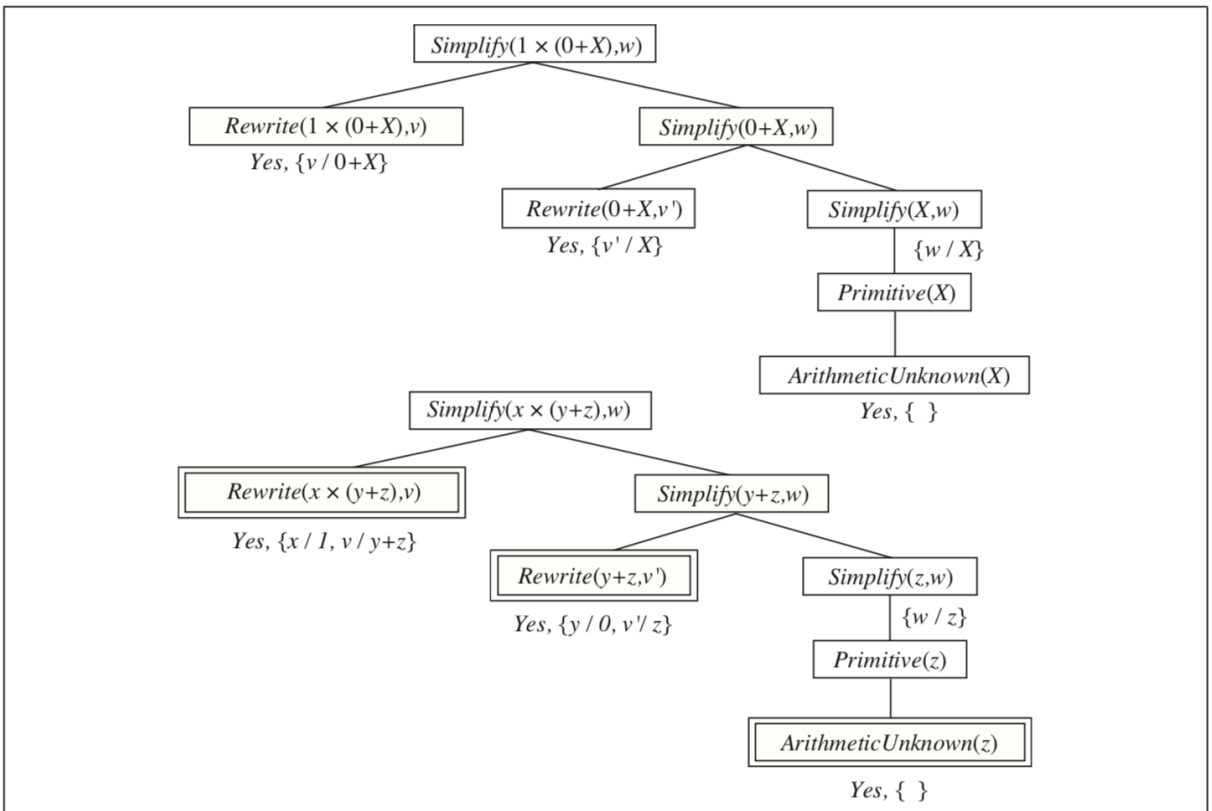


Figure 19.7 FILES: figures/simplify-proof2.eps (Tue Nov 3 16:23:44 2009). Proof trees for the simplification problem. The first tree shows the proof for the original problem instance, from which we can derive

$$ArithmeticUnknown(z) \Rightarrow Simplify(1 \times (0 + z), z) .$$

The second tree shows the proof for a problem instance with all constants replaced by variables, from which we can derive a variety of other rules.

What is means for an hypothesis to explain the classifications:

$$Hypothesis \wedge Descriptions \models Classifications$$

Explanation-based learning converts general knowledge into useful special routines.

Examples:

Physics

https://webhome.phy.duke.edu/~rgb/Class/intro_physics_1/intro_physics_1.pdf

Algebra

http://www.doe.virginia.gov/instruction/mathematics/resources/va_algebraic_properties.pdf

Background knowledge and the hypothesis explain the classifications of the examples:

$$Background \wedge Hypothesis \wedge Descriptions \models Classifications$$