MULTISTRATEGY LEARNING

⇛ T15

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MULTISTRATEGY LEARNING

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A TUTORIAL ON MULTISTRATEGY LEARNING

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SUMMARY

This tutorial presents an overview of methods, systems and applications of multistrategy learning. Multistrategy learning is concerned with developing learning systems that integrate two or more inferential and/or computational strategies. For example, a multistrategy system may combine empirical induction with explanation-based learning, symbolic and neural net learning, deduction with abduction and analogy, quantitative and qualitative discovery, symbolic and genetic algorithm-based learning. Due to the complementary nature of various strategies, multistrategy learning systems have a potential for a wide range of applications. This tutorial describes basic learning strategies, a conceptual framework for their analysis and integration, representative multistrategy learning systems, and their applications in areas such as automated knowledge acquisition, planning, scheduling, manufacturing, technical and medical decision making, and computer vision.

Tutorial T15

MULTISTRATEGY LEARNING

(IJCAI-93)

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1. INTRODUCTION

- Goals and applications of machine learning
- Historical outline of the field
- Research orientations and definitions

OUTLINE

1. Introduction
2. Learning strategies and methodologies
3. Theoretical framework for multistrategy learning
4. Multistrategy concept learning: methods, systems and applications
5. Multistrategy knowledge base improvement: methods, systems and applications
6. Summary, current trends and frontier research
7. References

MAJOR AREAS OF APPLICATION

- Pattern classification and recognition
- Knowledge discovery in databases
- Adaptive control systems
- Expert and advisory systems
- Sensory systems (vision, speech, ...)
- Planning systems
- Intelligent tutoring systems
- Autonomous robots

GOALS OF MACHINE LEARNING

- Developing computational theories and methods of learning
- Constructing learning systems and applying them to practical problems

MAJOR EVENTS

IN USA:

Machine Learning Workshops/Conferences

1980 - Carnegie-Mellon University
1983 - University of Illinois at Urbana-Champaign
1985 - Rutgers University
1987 - University of California at Irvine
1988 - University of Michigan
1989 - Cornell University
1990 - University of Texas
1991 - Northwestern University
1992 - Aberdeen (UK) - USA+Europe
1993 - University of Massachusetts

1991 - 1st Int. Workshop on Multistrategy Learning, George Mason Univ.
1993 - 2nd Int.Workshop on Multistrategy Learning, George Mason Univ.

OTHER: COLT meetings (since 88 annualy), EBL (88), Knowledge Discovery in Databases workshops, ANN conferences

A HISTORICAL SKETCH

Early Enthusiasm or Tabula Rasa Craze (1955-1965)

- Learning without knowledge
- Neural modeling (self-organizing systems & decision space techniques)
- Evolutionary learning

Dark Ages (1962-1976)

- To acquire knowledge one needs knowledge
- Symbolic concept acquisition

Renaissance (1976-1988)

- Exploration of different strategies
- Knowledge-intensive learning
- Successful applications
- Machine Learning conferences/Workshops worldwide

End of Innocence (1988- ...)

- Experimental comparisons
- Revival of non-symbolic methods
- Computational learning theory
- Integrated and multistrategy systems
- Emphasis on practical applications

RESEARCH ORIENTATIONS

- **Science of learning**

  Theoretical analysis and an exploration of the space of possible methods

- **Modeling of natural learning systems**

  Building computer models of human or animal learning

- **Engineering**

  Implementation of learning systems for specific applications

IN EUROPE:

Working Sessions on Learning (EWSL)

1986	-	Orsay	(France)
1987	-	Bled	(Yugoslavia)
1988	-	Glasgow	(UK)
1989	-	Montpellier	(France)
1991	-	Porto	(Portugal)
1993	-	Vienna	(Austria)

Summer Schools and Special Meetings

1974	-	Int. Meeting	(Bonas, France)
1986	-	IMAL	(Les Arcs, France)
1987	-	ISSEK	(Italy)
1987	-	KROML	(Geseke, Germany)
1988	-	MLML	(Sesimbra, Portugal)
1988	-	Sum. School	(Les Arcs, France)
1989	-	Sum. School	(Urbino, Italy)
1989	-	ISSEK	(Bled, Yug)
1991	-	Sum. School	(Corsendonk, Belgium)
1993	-	ACAI	(Capri, Italy)

LEARNING IS A MULTI-FACETED PHENOMENON COMPRISING:

- Acquisition of declarative knowledge
- Development of motor and cognitive skills through instruction and practice
- Organization of knowledge into new more effective representations
- Discovery of new facts or theories through observation and experimentation

WHAT IS LEARNING?

<u>Common views:</u>

Acquiring new knowledge

Improving performance with practice

Changing bevavior due to experience

A system learns if it makes changes in itself that enable it to perform better a given task

LEARNING IS A COMPLEX PROCESS BECAUSE

- The inputs can vary from raw observations to refined knowledge
- The initial knowledge can vary from very limited to quite rich
- The constructed knowledge can be in many different forms
- The learning goal can vary from very specific to very general

THE ESSENCE OF LEARNING

Self-construction of knowledge structures

or, more precisely,

A goal-oriented creation or improvement of knowledge structures representing the learner's experience

CLASSIFICATION CRITERIA

Goal of learning: Knowledge reformulation (*Analytic learning*)
Knowledge creation (*Synthetic learning*)

Input type: Examples, Facts, Generalizations

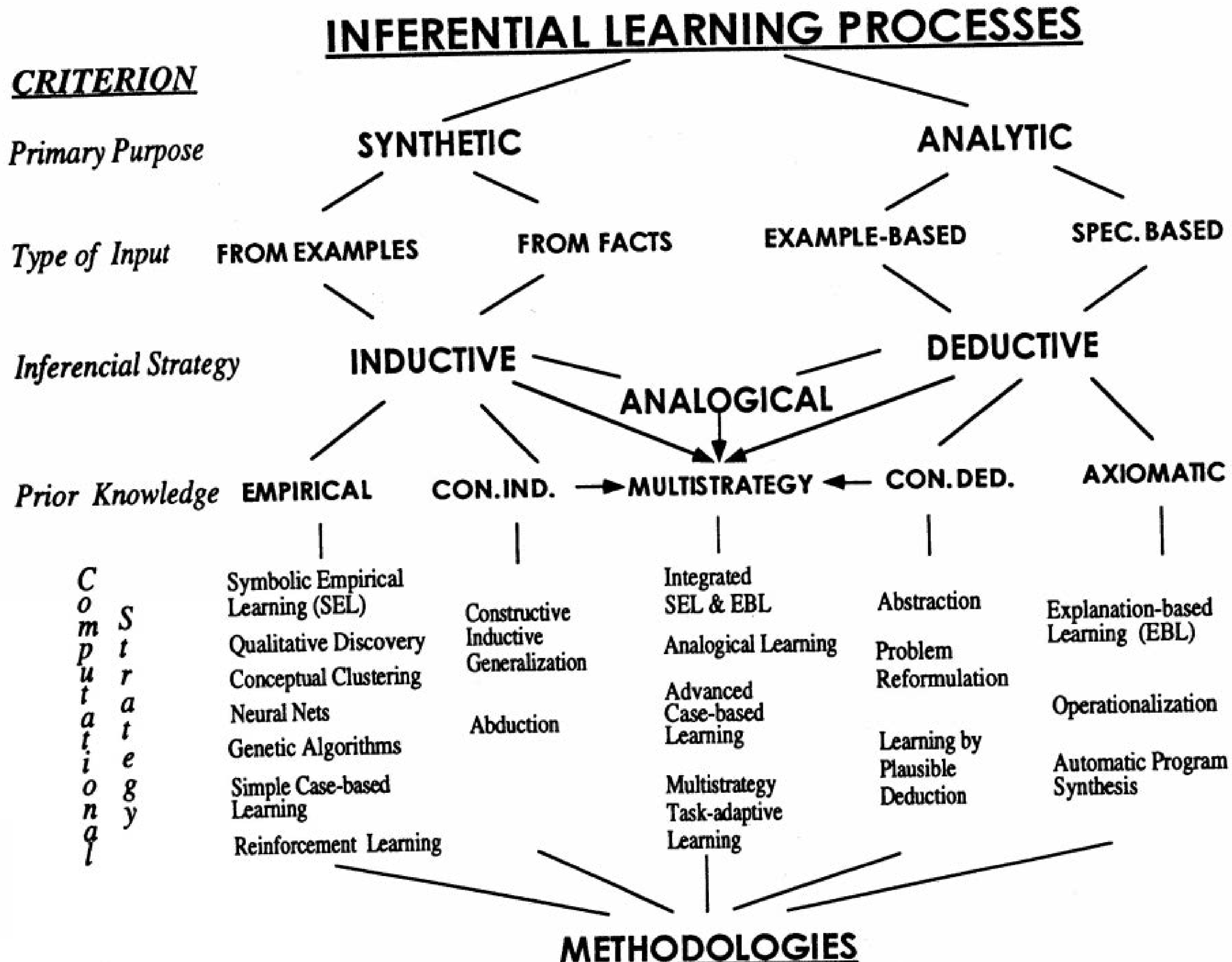
Input mode: All in one (*Batch*), In portions (*Incremental*)

Input acquisition: Passive, Active

Prior knowledge: Limited (*Empirical*), Rich(*Knowledge-intensive*)

2. LEARNING STRATEGIES AND METHODOLOGIES

- Classification criteria
- Inferential strategies
- Computational strategies
- Basic paradigms
- Multicriterion classification of methods



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CLASSIFICATION CRITERIA

Inferential strategy (The underlying type of inference):

No inference, Deduction, Analogy, Induction

Computational strategy (The underlying form of knowledge representation and the computational method for creating or modifying this representation):

Representation Parameters, Equations, Decision trees, Decision rules, Hierarchies, Grammars, Relational descriptions, Semantic nets, Frames, Classifier system, Artificial neural net, Programming language

Method Equation solving, Search & select, Rule-execution, Generate & test, Genetic algorithm, Backpropagation, General programming, etc.

ARTIFICIAL NEURAL NETS

- Learning is done by setting the proper weights in a network of neuron-like elements (units), each sending excitatory or inhibitory signals to other units
- Two types of models:

Parallel distributive models

Concepts are represented by an activation pattern of a collection of units

(Hinton, McClelland, Rumelhart, 1985)

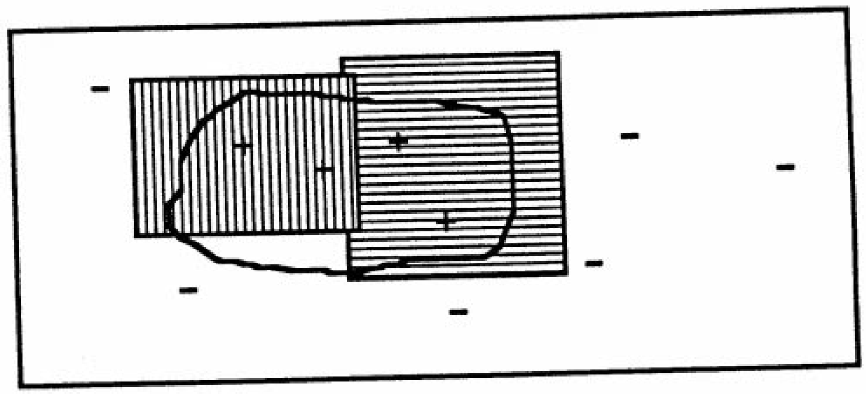
Local connectionist networks

Concepts are represented by single units

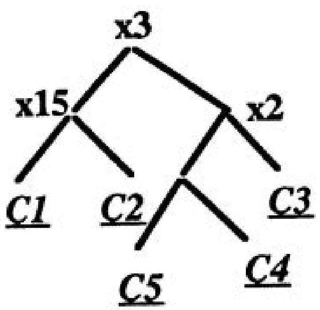
(Barlow, 1972; Feldman, 1986)

SYMBOLIC EMPIRICAL LEARNING

Concept learning from examples



Decision trees (ID3 -based methods)



(Hunt, 1962; Quinlan, 1979)

Decision rules (AQ-based methods)

[x3 = 1] & [x15 > 6] &... => *C1*
[x2 = 0] & [x7 = 2..7] & => *C1*

[x8 <6] & [x9 = A] &.. => *C2*

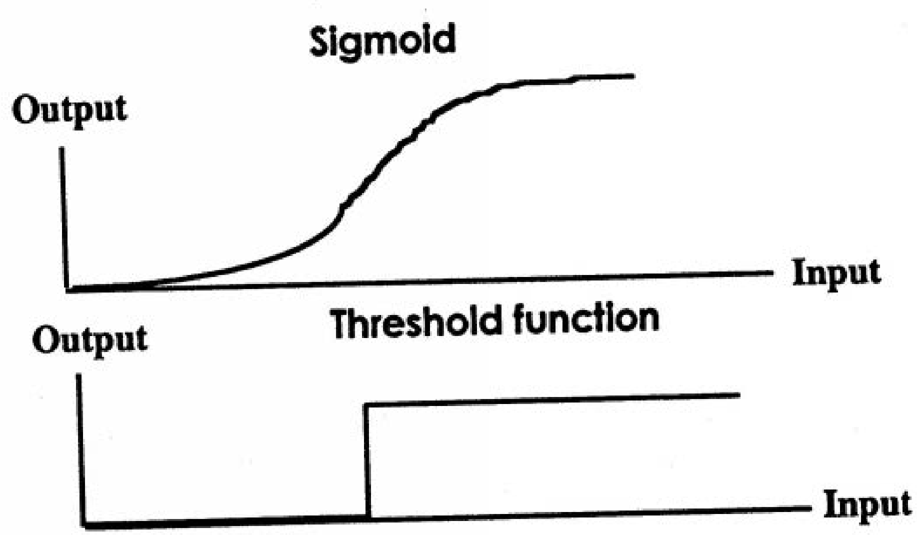
(Michalski, 1972)

UNIT ACTIVATION FUNCTIONS

The total input y_i received by the jth unit from other units, x_j, is usually defined as

$$y_i = \text{SUM}(w_{ij} \cdot x_j)$$

Unit output:

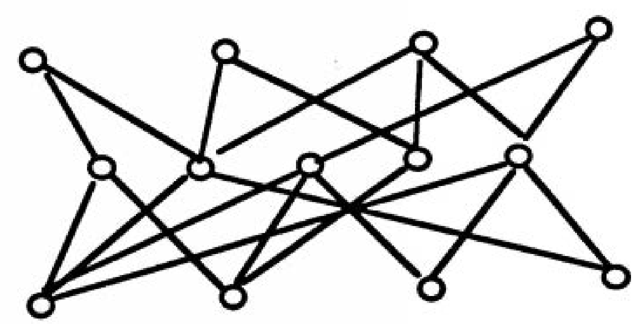


THREE LAYER NEURAL NET

Output units

Hidden units

Input units



BASIC GENETIC OPERATORS

- **CROSSOVER** — Chunks of two rules are exchanged ("rule mating")
- **MUTATION** — Making random changes in rules. This may prevent the system from getting stuck at a local optimum
- **INVERSION** — Reordering the components of the rules (elements that were far apart may be brought together)

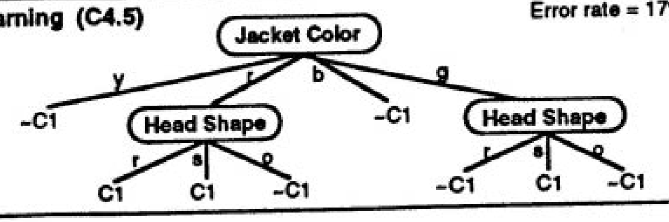
GENETIC ALGORITHMS
Evolutionary Learning Strategies

- Explore an analogy with evolution as a model of learning
- A set of rules (a parallel production system) can be viewed as a population of pseudo-organisms
- Rules are modified by pseudo-random or random genetic operators
- The performance of the modified rules affects the likelyhood of their "breeding"
- The process stops when a satisfactory performance has been achieved or computational resources exhausted

(Holland, 1975)

THE SAME CONCEPT LEARNED BY DIFFERENT METHODS

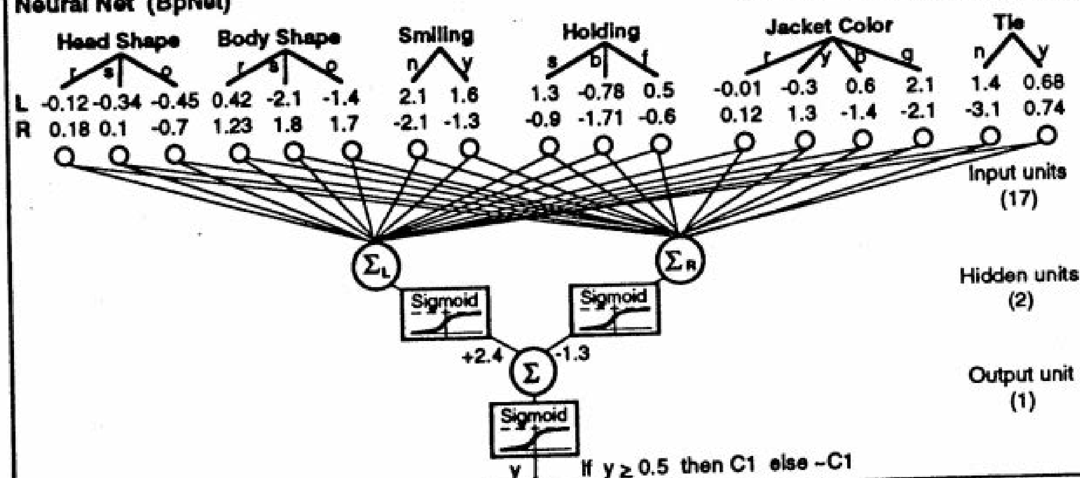
A **Decision Tree Learning (C4.5)** Error rate = 17% R-complexity = 3



B **Rule Learning (AQ17 - HCI)** Error rate = 0% R-complexity = 2

If (**Head Shape** = round & **Jacket Color** = red) or
(**Head Shape** = square & **Holding** = balloon) then C1

C **Neural Net (BpNet)** Error rate = 21% R-complexity = 23



D **Classifier System (CFS)** Error rate = 21% R-complexity = 38

```
                     HS BS SM HO JC TI
No Id    Condition1                     Condition2                     Action                     Strength  BidRatio
1  1227 m000000  01 0#  1  10 #1  1, m00#00# 01 00 1 10 #1 # / 10 1101100#0000 0#    222    0.81
2  1236 m000000  01 0#  1  10 #1  1, m00#00# 01 00 1 10 #1 # / 10 1101100#0000 0#    219    0.81
3  1217 m0#0000  00 10  1  00 0#  0, m##0000 #0 10 1 00 #0 # / 10 0#1101101100 11    208    0.78
...
60 0017 m000000  01 01  1  10 01  1, m00000# 01 00 1 10 11 1 / 10 1101100#0000 0#     34    0.25

                              HS BS SM HO JC TI
Effector 1: If   m10 0 ##1  0#  11  0  10  01 1   then C1
Effector 2: If   m10 1 ###  11  01  1  00  #0 0   then ~C1
```

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EXPLANATION-BASED LEARNING (EBL)

Given:

- An abstract concept description
- An example of the concept
- Domain theory
- Operationality criterion

Determine:

- An effective (operational) concept description that covers the example

WHAT IS MULTISTRATEGY LEARNING

- Multistrategy learning is concerned with developing learning systems that integrate two of more inferential and/or computational strategies

- In order to develop foundations for building such systems, one needs to understand the role and the applicability conditions of different strategies

3. THEORETICAL FRAMEWORK FOR MULTISTRATEGY LEARNING

- What is multistrategy learning
- Learning as search in a knowledge space
- Analysis of types of inference
- Analysis of knowledge operators
- A comparison of strategies

EXAMPLES OF MSL SYSTEMS

- Unimem (Lebowitz, 1986)
- Odysseus (Wilkins, Clancey & Buchanan, 1986)
- DISCIPLE (Kodratoff & Tecuci, 1987)*
- Gemini (Danyluk, 1987)
- OCCAM (Pazzani, 1988)*
- ENIGMA (Bergadano, Giordana & Saitta, 1988)*
- WYL (Flann &Dietterich, 1989)*
- PRODIGY (Carbonell, Knoblock & Minton, 1989)*
- KBL (Whitehall, 1990)
- CLINT (De Raedt & Bruynooghe, 1991)
- EITHER (Mooney & Ourston, 1991)*
- KBANN (Towel & Shavlik, 1991)*
- AQ-GA (Bala, K. DeJong & Pachowicz, 1991)*
- MTL (Michalski & Tecuci &Hieb, JT-1991, DIH-1993)*

TYPES OF MSL SYSTEMS

- Multi-inferential -- systems that combine different inferential strategies, e.g.,
  - empirical induction and explanation-based learning
  - induction, analogy and deduction
  - empirical generalization, deduction and/or abduction (constructive induction)
- Multi-paradigm -- system that combine different computational strategies, e.g.,
  - symbolic method and neural net
  - symbolic method and genetic algorithm
  - neural net and genetic algorithm

LEARNING AS FUNCTION RECONSTRUCTION

Computational Theory of Learning

Given: A set of pairs $\{x, f(x)\}$

Determine: An expression that provides a good approximation of a function f

$$f: \{0,1\}^n \dashrightarrow \{0,1\}$$

Probably approximately correct (PAC):

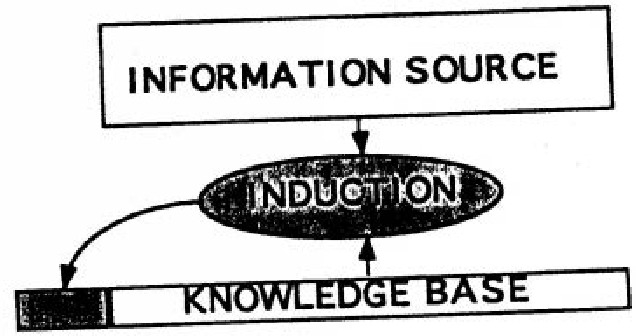
$\Pr(\text{error rate} \leq \varepsilon) \geq 1 - \delta$ (Valiant)

All possible expressions

Consistent and complete (C&C)

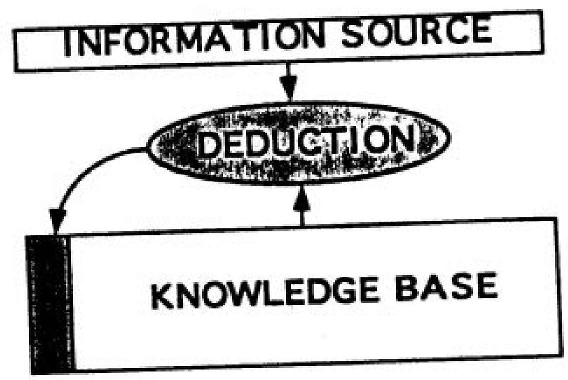
"Bias"- any information that limits the choice of a hypothesis

Synthetic Learning



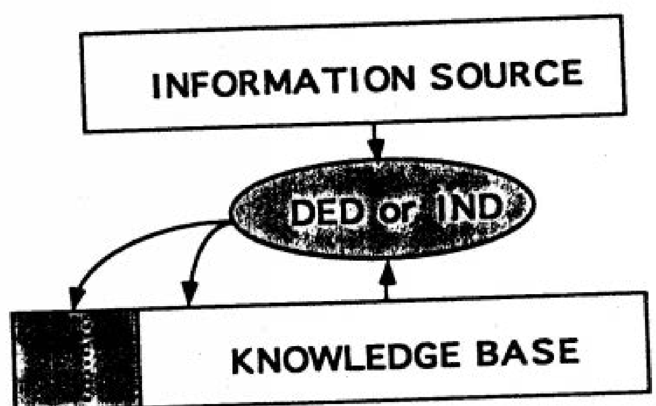
NEW KNOWLEDGE

Analytical Learning



MORE EFFECTIVE KNOWLEDGE

Multistrategy Learning



NEW KNOWLEDGE
or
MORE EFFECTIVE KNOWLEDGE

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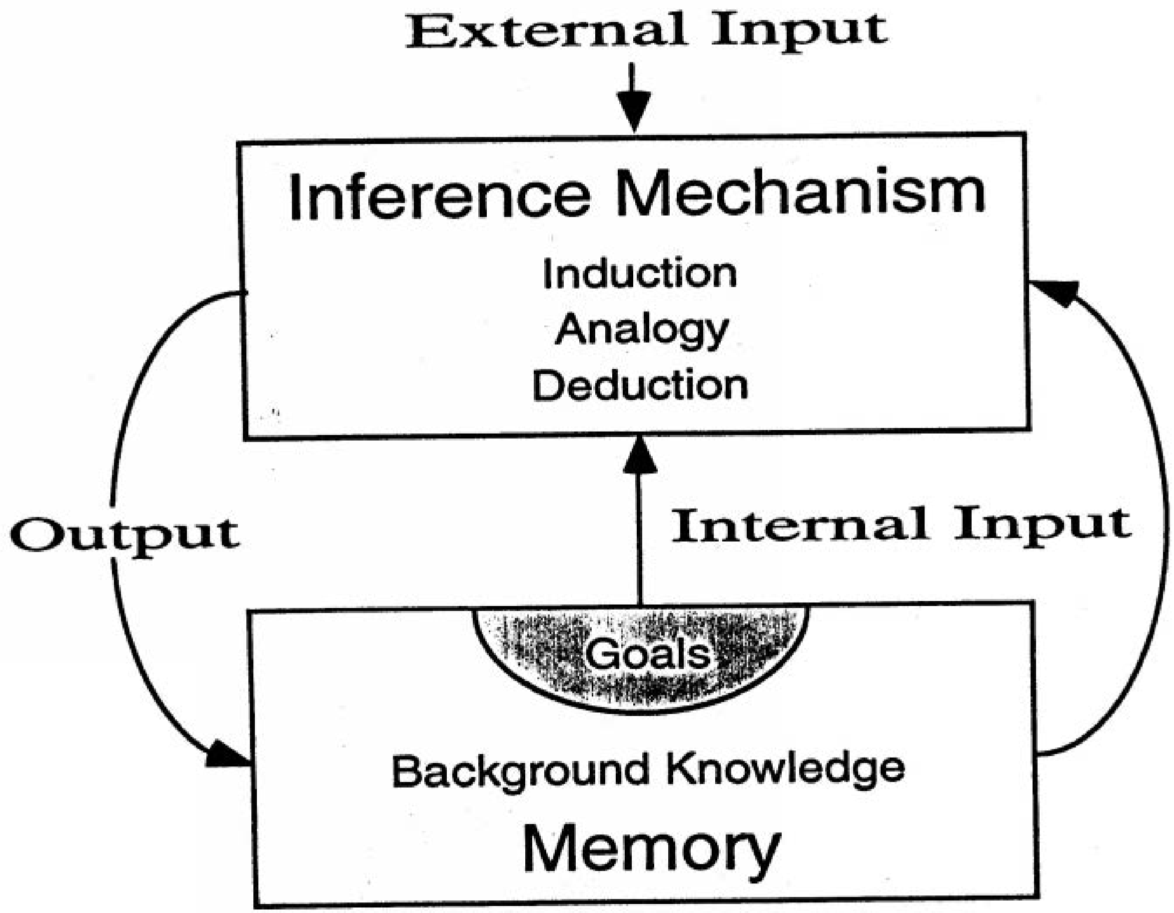


Multistrategy Learning Processes

LEARNING AS SEARCH IN A KNOWLEDGE SPACE

Inferential Theory of Learning

Given:

- **Input information** $I = \{I_i\}$
- **Initial knowledge** $K = \{K_i\}$
- **Goal specification** $G = \{G_i\}$
- **Transmutations** $T = \{T_i\}$

Determine:

- **New knowledge, K', that satisfies goal G, by applying knowledge transmutations, T, to K and I.**

KNOWLEDGE TRANSMUTATIONS

- **Generic patterns of knowledge transformation**
- **Can employ any type of inference**
- **Change or derive various aspects of knowledge**

For example

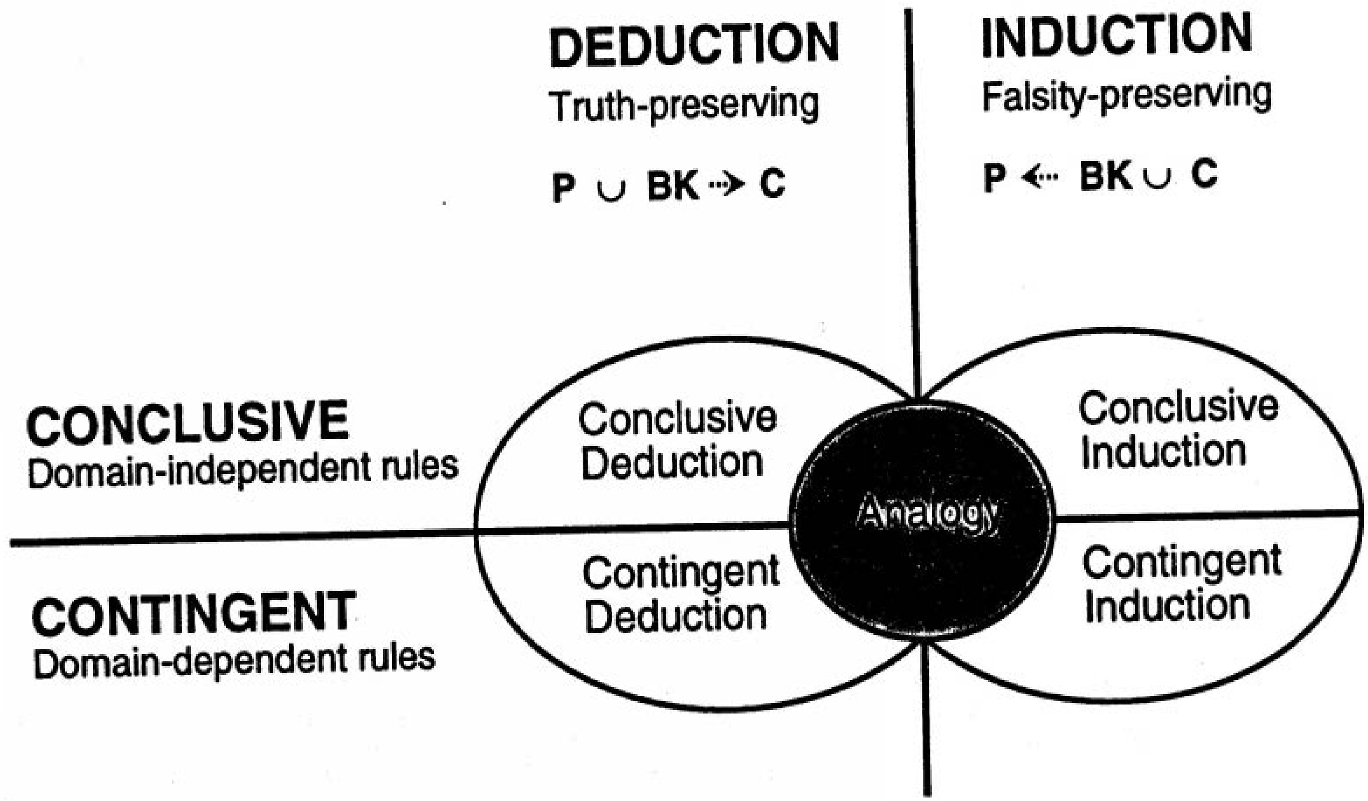
- *generalization & specialization* (change the set of entities being described, called the reference set)
- *abstraction & concretion* (change the amount of information about the set)

AN "EQUATION" FOR LEARNING

Learning = Inferencing + Memorizing

where by "inferencing" is meant any type of knowledge derivation, transformation or change

MAJOR TYPES OF INFERENCE



BASIC FORMS OF INFERENCE

The Fundamental Equation of Inference

$$\mathbf{P} \cup \mathbf{BK} \models \mathbf{C}$$

Premise	with	Background Knowledge	Entails	Consequent

where P, BK and C can be a single fact, a rule, a set of rules, etc.

Deduction

Given P and BK derive C

Induction

Given C and BK hypothesize P

An Example of Empirical Generalization

Input: Grey(e_1), Grey(e_2), Grey(e_3)...

BK: Balls e_1, e_2, e_3,...are from box B

For all e, P(e) => P(e_i)

Hypothesize:

For all e from B, Grey(e)

Test of inductive condition:

For all e from B, Grey(e) (P)

Balls e1, e2, e3...are from box B

(For all e from B, P(e)) => P(e_i) (BK)

$\models$

Grey(e1), Grey(e2), Grey(e3)... (C)

INDUCTIVE INFERENCE

Given:

- An input, C ("Consequent")
- Background knowledge (BK), which includes domain independent and/or dependent inference rules, and a hypothesis selection criterion reflecting learner's goals and constraints ("bias")

Hypothesize:

A hypothesis, P ("Premise") that satisifies the relation (the "fundamental equation")

$$P \,\&\, BK \models C$$

and the hypothesis selection criterion.

An Example of Constructive Generalization

Input: Grey(e_1), Grey(e_2), Grey(e_3)...

BK: Balls e_1, e_2, e_3,...are from box B

For all e, P(e) => P(e_i)

For all e, Made-of(e,steel) => Grey(e)

Hypothesize:

For all e from B, Made=of(e, steel)

Test of inductive condition:

For all e from B, Made-of(e, steel) & (P)

For all e, Made-of(e,steel) => Grey(e) (BK)

$\models$

For all e from B, Grey(e) (C)

An Example of Abduction

Input: Grey(e_1)

BK: For all e, Made-of(e,steel) =>Grey(e)

Hypothesize:

Made-of(e_1, Steel)

Test of inductive condition:

Made-of(e_1, Steel) (P)

For all e, Made-of(e,steel) => Grey(e) (BK)

$\models$

Grey(e_1) (C)

Knowledge Generation Transmutations

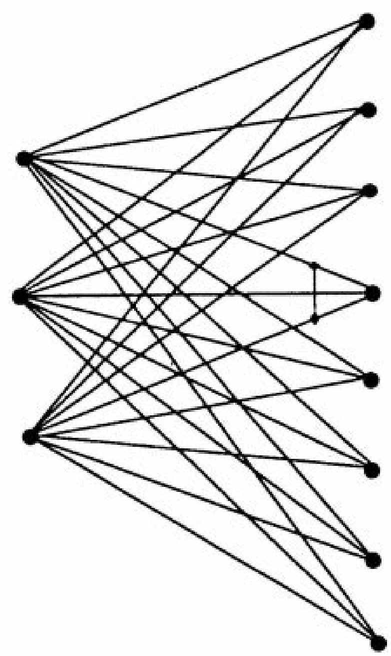
A Selection

Inference Type

DEDUCTION

ANALOGY

INDUCTION



Transmutation

Generalization
Specialization

Abstraction
Concretion

Explanation
Prediction

Similization
Dissimilization

Selection
Generation

Agglomeration
Decomposition

Characterization
Discrimination

Association
Disassociation

GENERALIZATION VS. ABSTRACTION

Definition:

Reference set ---the set of entities being described by a set of sentences

- *Generalization* (*specialization*) increases (decreases) the reference set
- *Abstraction* (*concretion*) decreases (increases) the amount of detail specified in the description of the reference set

Explanation-based Generalization

Abstract CD
Domain rules ⊨ **Operational CD**
Example

Given:

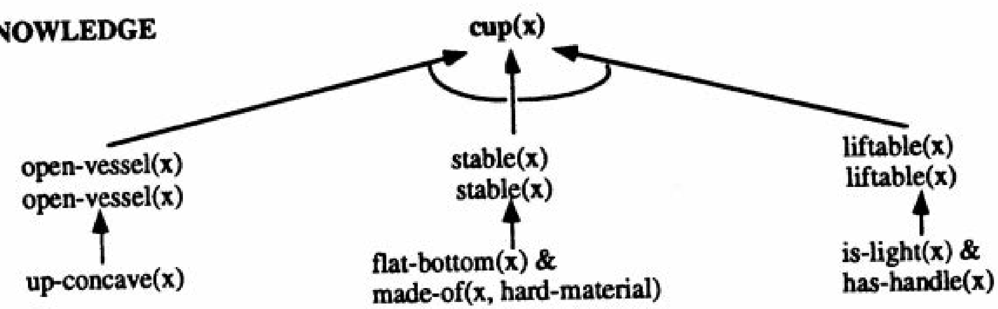
1. INPUT *Example*:

cup(O1) <= up-concave(O1) & is-light(O1) & has-handle(O1) & made-of(O1,glass) & has-flat-bottom(O1) & ...

2. BACKGROUND KNOWLEDGE

Complete Abstract CD

Domain rules



Other relevant knowledge
made-of(x)=hard_material <= made-of(x, glass)

3. GOAL

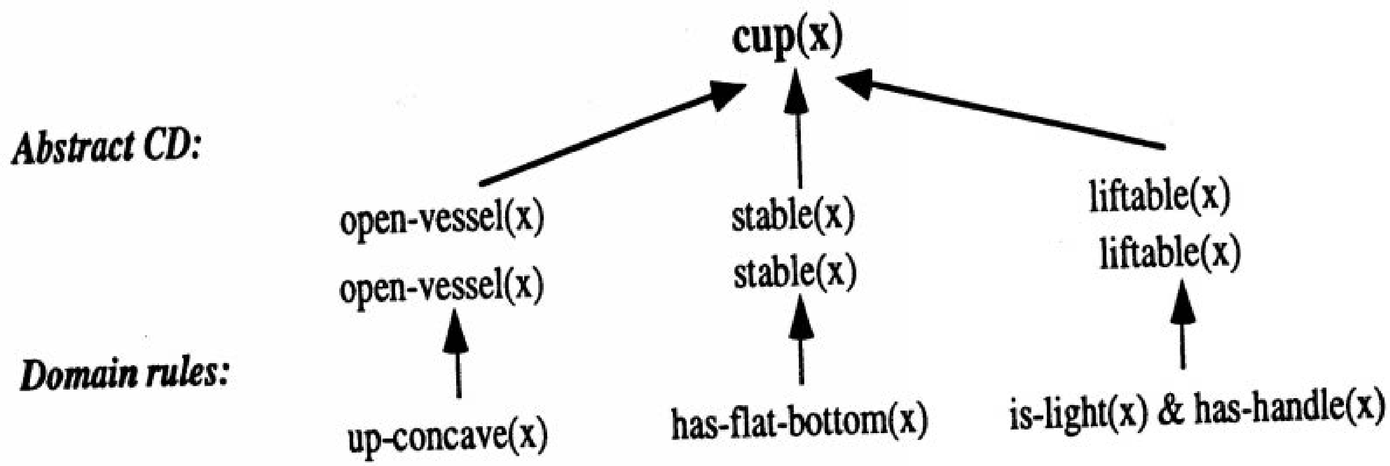
To create an operational description of the concept of cup.

Learned:

An operational concept description:

cup(x) <= up-concave(x) & flat-bottom(x) & is-light(x) & made-of(x, hard-material) & has-handle(x)

CUP EXAMPLE



Example (Specific OD):

cup(O1) <= up-concave(O1) & has-flat-bottom(O1) &
& color(O1, red) & owner(CUP1, RSM) & made-of(O1, glass) &...

Abstract OD:

cup(O1) <=open-vessel(O1) & stable(O1) & liftable(O1) & ...

Operational CD:

cup(x) <= up-concave(x) & has-flat-bottom(x) & is-light(x) & has-handle(x)

A COMPARISON of STRATEGIES

	Given:		To be learned:
Explanation-based Learning	Abstract CD Domain rules Example	$\models$	Operational CD
Constructive Deduction (Abstraction)	Example Domain rules	$\models$	Abstract OD
Empirical Induction	Examples Partial BK'	$\Lsh$	Operational CD
Constructive Induction (Generalization)	Domain rules Example(s)	$\Lsh$	Abstract CD
Constructive Induction (Abduction)	Example(s) Abstract CD	$\Lsh$	Domain rules
Multistrategy Learning	Any of the above and other combinations, depending on what is the input, what the learner knows already, and what is to be learned		

Constructive Induction Example(s) Domain rules ⊨ Abstract CD

(Abduction + generalization)

Given:

1. INPUT *Examples::*

Cup(O1) <= up-concave(O1) & is-light(O1) & has-handle(O1) & made-of(O1,glass) & has-flat-bottom(O1)...

Jar(O2) <= up-concave(O2) & Is-heavy(OBJ2) & has-handle(O2) & made-of(O2)=wood & has-flat-bottom(O2)....

Jar(O3) <= up-concave(O3) & is-light(O3) & made-of(O3,glass) & has-flat-bottom(O3) & no-handle(O3)...........

2. BACKGROUND KNOWLEDGE

Incomplete Abstract CD

cup(x)

open-vessel(x) stable(x) liftable(obj)

Domain rules

open-vessel(x) ← up-concave(x)

stable(x) ← has-flat-bottom(obj) & made-of(obj, hard-material)

liftable(obj) ← is-light(obj) & has-handle(obj)

Other relevant knowledge

Made-of(obj)=hard_material <= made-of(x, glass) made-of(x, hard_material) <= made-of(x, wood)

is-light(x) =/= is-heavy(x)

3. GOAL

To create a complete abstract description of the concept of cup

Learned:

A complete abstract concept description:

cup(x) <= open-vessel(x) & stable(x) & liftable(x)

4.1 MULTISTRATEGY CONCEPT LEARNING
The Class of Learning Tasks

INPUT: one or more positive and/or negative examples of a concept

BK: a weak, incomplete, partially incorrect, or complete domain theory (DT)

GOAL: learn a concept description
characterizing the example(s)
and consistent with the DT
by combining several learning strategies

4. MULTISTRATEGY CONCEPT LEARNING: METHODS, SYSTEMS AND APPLICATIONS

4.1 The class of learning tasks

4.2 Integration of empirical inductive learning and explanation-based learning

4.3 Integration of empirical inductive learning, explanation-based learning, and learning by analogy

4.2 Integration of genetic algorithm-based learning and symbolic empirical inductive learning

4.2 INTEGRATION OF EMPIRICAL INDUCTIVE LEARNING AND EXPLANATION-BASED LEARNING

- Empirical Inductive Learning (EIL)
- Explanation-Based Learning (EBL)
- Complementary nature of EIL and EBL
- Types of integration of EIL and EBL

Illustration of a Learning Task

INPUT: examples of the CUP concept

cup(o1) ⇐ color(o1, white), shape(o1, cyl), volume(o1, 8),
made-from(o1, plastic), light-mat(plastic),
has-handle(o1), has-flat-bottom(o1),
up-concave(o1).

BK: a theory of vessels (domain rules)

cup(x) ⇐ liftable(x), stable(x), open-vessel(x).
liftable(x) ⇐ light(x), graspable(x).
stable(x) ⇐ has-flat-bottom(x).

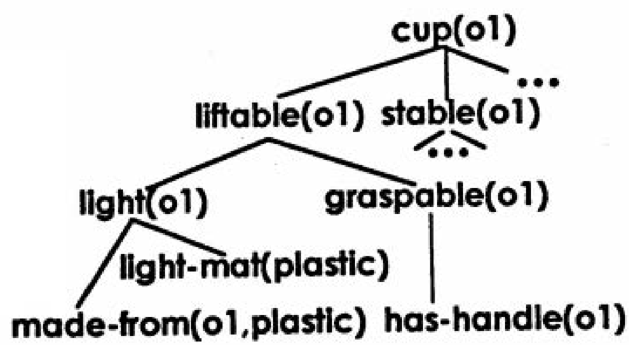
GOAL: learn an operational concept description of CUP

cup(x) ⇐ made-from(x, plastic), light-mat(plastic),
graspable(x), has-flat-bottom(x), up-concave(o1).

EXPLANATION-BASED LEARNING

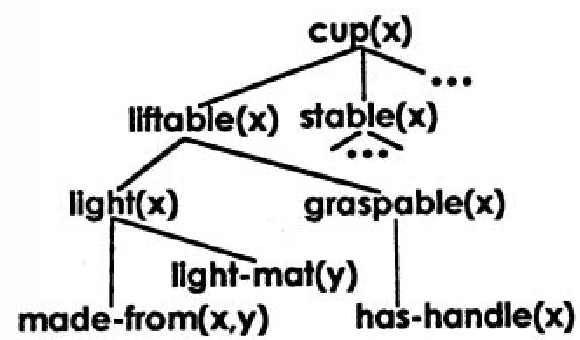
- Proves that the training example is an instance of the target concept and generalizes the proof
- Is knowledge intensive (requires a complete DT)
- Needs only one example

Prove that o1 is a CUP:



- "has-handle(o1)" is needed to prove "cup(o1)"
- "color(o1,white)" is not needed to prove "cup(o1)"

Generalize the proof:



- the material the cup is made from need not be "plastic"

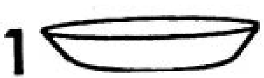
EMPIRICAL INDUCTIVE LEARNING

- Compares the examples in terms of their similarities and differences, and creates a generalized description of the similarities of the positive examples

- Is data intensive (requires many examples)

- Performs well in knowledge-weak domains

Positive examples of cups: P1  P2  ...

Negative examples of cups: N1  ...

Description of the cup concept: has-handle(x),...

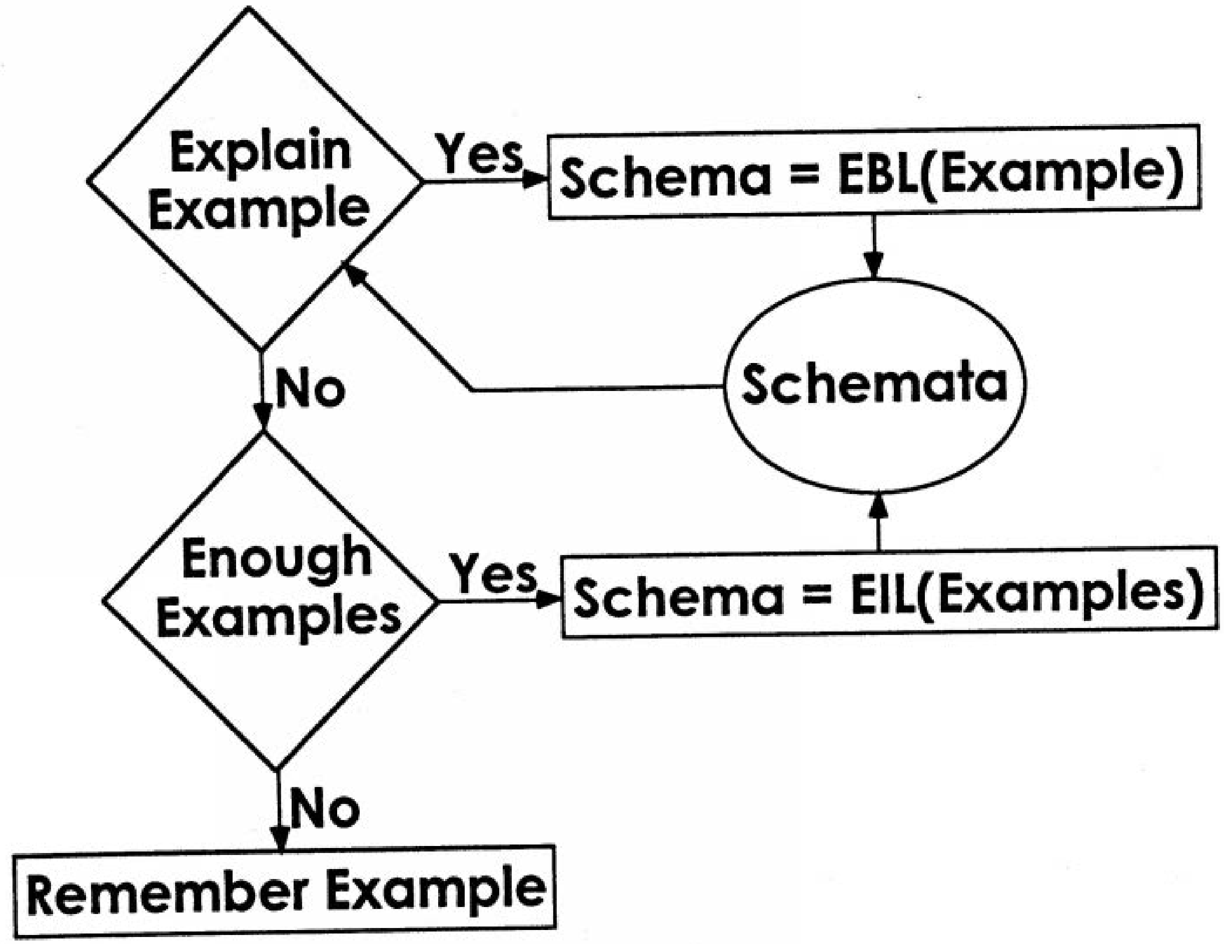
MSL METHODS INTEGRATING EIL AND EBL

- Explanation before induction
- Induction over explanations
- Combining EBL with Version Spaces
- Induction over unexplained
- Guiding induction by domain theories

COMPLEMENTARY NATURE OF EIL AND EBL

	EIL	EBL	MSL (EIL+EBL)
Examples	many	one	several
Domain Theory	weak is enough	need to be complete	incomplete or partially incorrect

Integration of EBL and EIL in OCCAM



EXPLANATION BEFORE INDUCTION
OCCAM (Pazzani, 1988, 1990)

OCCAM is a schema-based system that learns to predict the outcome of events by applying EBL or EIL, depending on the available background knowledge and examples. It may answer questions about the outcome of hypothetical events.

A learned economic *sanctions* schema:

When a country threatens a wealthy country by refusing to sell a commodity, then the sanctions will fail because an alternative supplier will want to make a large profit by selling the commodity at a premium.

The IOE Method

- Build an explanation tree for each example
- Find the largest common subtree
- Apply EBL to generalize the subtree and retain the leaves as an intermediate concept description (ICD)
- Specialize ICD to reflect the similarities between the training examples:
  - replace variables with constants (e.g. $v = c$)
  - introduce equality constraints (e.g. $v1 = v2$)

INDUCTION OVER EXPLANATIONS (IOE)
WYL (Flann and Dietterich, 1989)

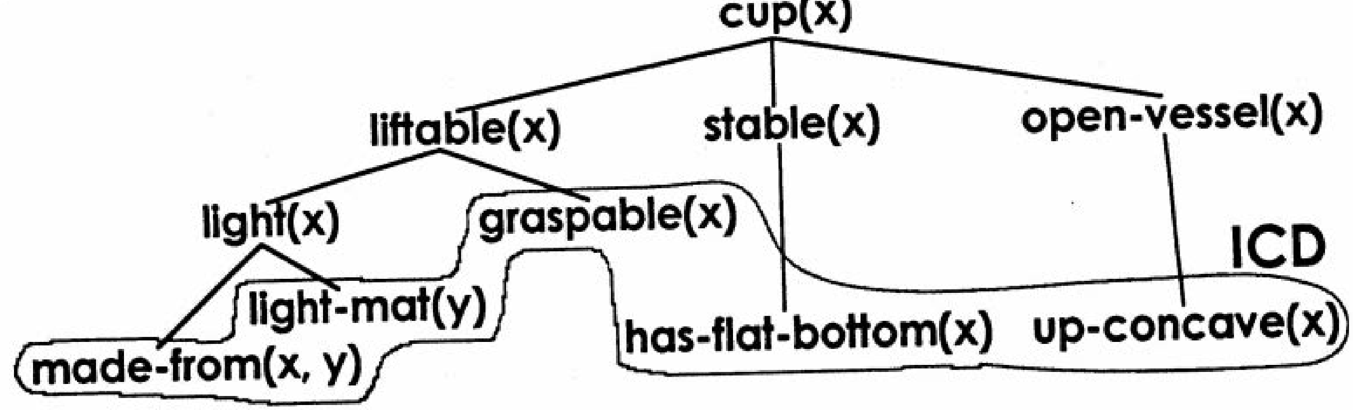
Limitations of EBL

- The learned concept might be too specific because it is a generalization of a single example
- Requires a complete DT

IOE

- Learns from a set of positive examples
- May discover concept features that are not explained by the DT (i.e. incomplete DT)

Generalization of the common subtree:



Specialization of ICD:

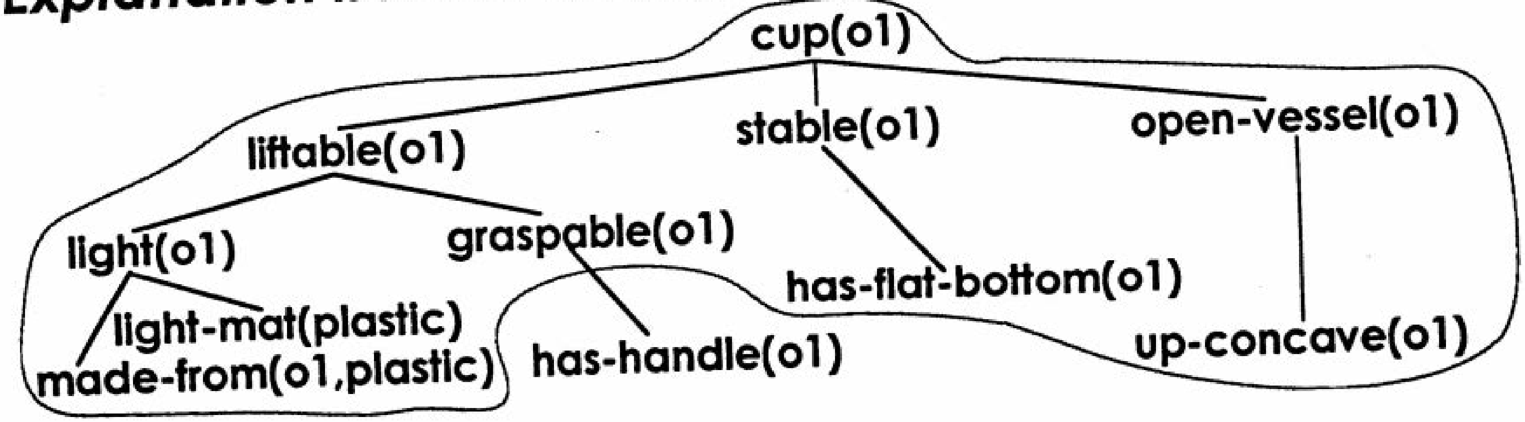
in example1: (y = plastic)
in example2: (y = plastic)
in ICD: (y = plastic)

Learned concept:

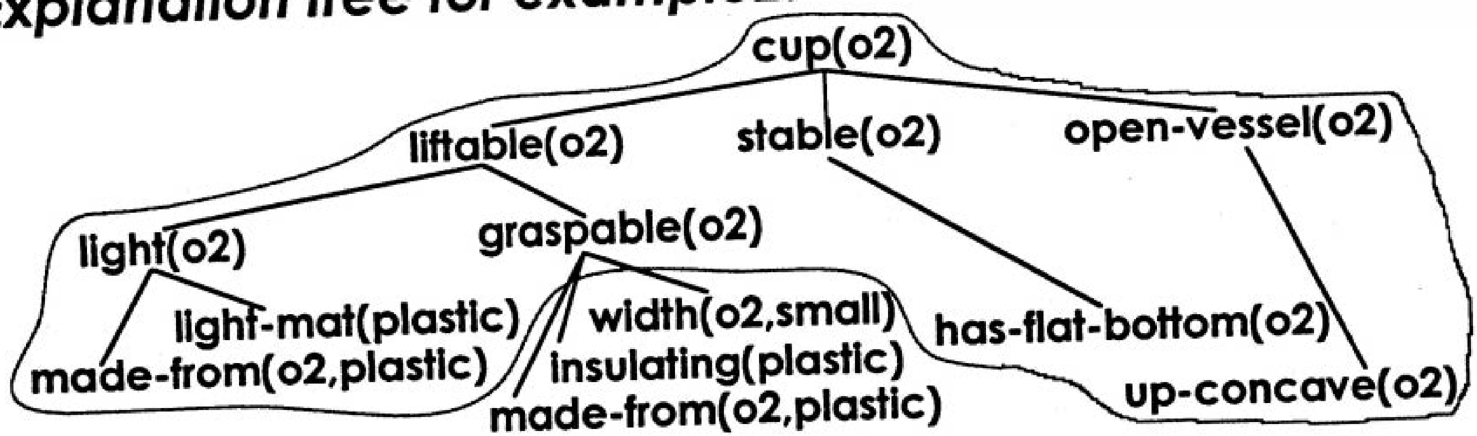
cup(x) ⇐ made-from(x, plastic), light-mat(plastic), graspable(x),
has-flat-bottom(x), up-concave(x).

Illustration

Explanation tree for example1:



Explanation tree for example2:



The EBL-VS Method

- Apply EBL to generalize the positive and the negative examples
- Replace each example that has been generalized with its generalization
- Apply the version space method (or the incremental version space merging method) to the new set of examples

COMBINING EBL WITH VERSION SPACES (EBL-VS)
(Hirsh, 1989, 1990)

Limitations of IOE

- Learns only from positive examples
- Needs an "almost" complete domain theory (DT)

EBL-VS

- Learns from positive and negative examples
- Can learn with an incomplete DT
- Can learn with a special type of incorrect DT
- Can learn with different amounts of knowledge, from knowledge-free to knowledge-rich

The IOU Method

- Apply EBL to generalize each positive example
- Disjunctively combine these generalizations (this is the explanatory component C_e)
- Disregard negative examples not satisfying C_e and remove the features mentioned in C_e from all the examples
- Apply EIL to determine a generalization of the reduced set of simplified examples (this is the nonexplanatory component C_n)

The learned concept is C_e & C_n

INDUCTION OVER UNEXPLAINED (IOU)

(Mooney and Ourston, 1989)

Limitations of EBL-VS

- Assumes that at least one generalization of an example is correct and complete

IOU

- DT could be incomplete but correct
  - the explanation-based generalization of an example may be incomplete
  - the DT may explain negative examples
- Learns concepts with both explainable and conventional aspects

GUIDING INDUCTION BY DOMAIN THEORY

The ENIGMA System

(Bergadano, Giordana, Saitta et al. 1988, 1990)

Limitations of IOU

- DT rules have to be correct
- Examples have to be noise-free

ENIGMA

- DT rules could be partially incorrect
- Examples may be noisy

Illustration

Positive examples of cups: Cup1, Cup2

Negative examples: Shot-Glass1, Mug1, Can1

Domain Theory: incomplete (contains a definition of drinking vessels but no definition of cups)

C_e = has-flat-bottom(x) & light(x) & up-concave(x) & {[width(x,small) & insulating(x)] $\vee$ has-handle(x)}

C_e covers Cup1, Cup2, Shot-Glass1, Mug1 but not Can1

C_n = volume(x,small)

C_n covers Cup1, Cup2 but not Shot-Glass1, Mug1

$C = C_e$ & C_n

Examples (4 pos, 4 neg)*

Positive example4 (p4):

Cup(o4) ⇐ light(o4), support(o4, b), body(o4, a),
above(a, b), up-concave(o4).

Domain Theory

Cup(x) ⇐ Liftable(x), Stable(x), Open-vessel(x).
Liftable(x) ⇐ light(x), has-handle(x).
Stable(x) ⇐ has-flat-bottom(x).
Stable(x) ⇐ body(x, y), support(x, z), above(y, z).
Open-vessel(x) ⇐ up-concave(x).

DT: - overly specific (explains only p1 and p2)
- overly general (explains n3)

---

* Operational predicates start with a lower-case letter

The Learning Method

(trades-off the use of DT rules against the coverage of examples)

- Successively specialize the abstract definition *D* of the concept to be learned by applying DT rules
- Whenever a specialization of the definition *D* contains operational predicates, compare it with the examples to identify the covered and the uncovered ones
- Decide between performing:
  - a DT-based deductive specialization of *D*
  - an example-based inductive modification of *D*

The learned concept is a disjunction of leaves of the specialization tree built.

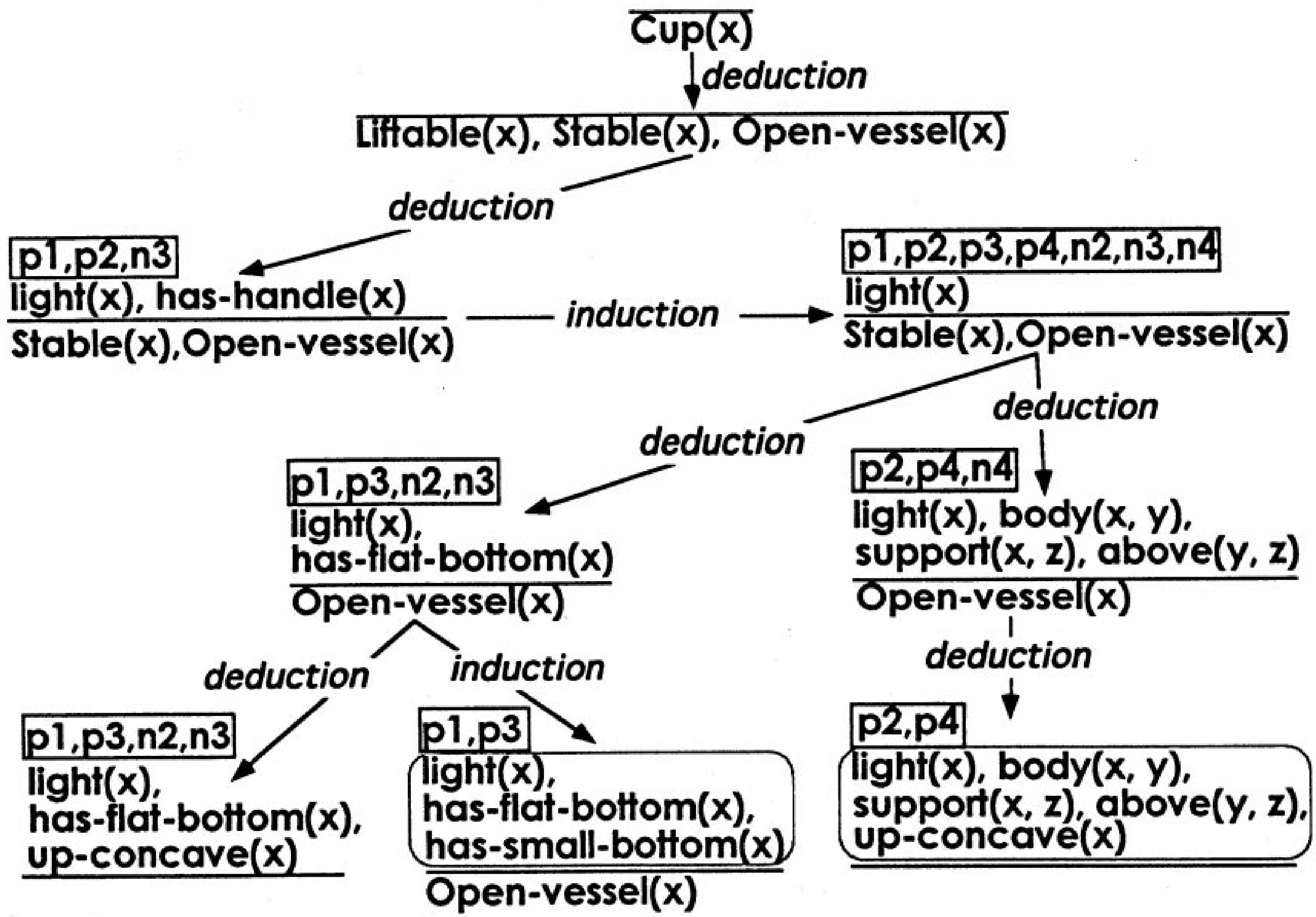
The Learned Concept

Cup(x) ⇐ light(x), has-flat-bottom(x),
has-small-bottom(x).

Covers p1, p3

Cup(x) ⇐ light(x), body(x, y), support(x, z),
above(y, z), up-concave(x).

Covers p2, p4


Cup(x)
deduction
Liftable(x), Stable(x), Open-vessel(x)
deduction
p1,p2,n3
light(x), has-handle(x)
Stable(x),Open-vessel(x)
induction
p1,p2,p3,p4,n2,n3,n4
light(x)
Stable(x),Open-vessel(x)
deduction
deduction
p1,p3,n2,n3
light(x),
has-flat-bottom(x)
Open-vessel(x)
p2,p4,n4
light(x), body(x, y),
support(x, z), above(y, z)
Open-vessel(x)
deduction
induction
deduction
p1,p3,n2,n3
light(x),
has-flat-bottom(x),
up-concave(x)
p1,p3
light(x),
has-flat-bottom(x),
has-small-bottom(x)
Open-vessel(x)
p2,p4
light(x), body(x, y),
support(x, z), above(y, z),
up-concave(x)

Comparison Between the KB Learned by ENIGMA and the Hand-coded KB of the Expert System MEPS

	Ambiguity of rules	Recognition rate	Development time
ENIGMA	1.21	0.95	4 months
MEPS	1.46	0.95	18 months

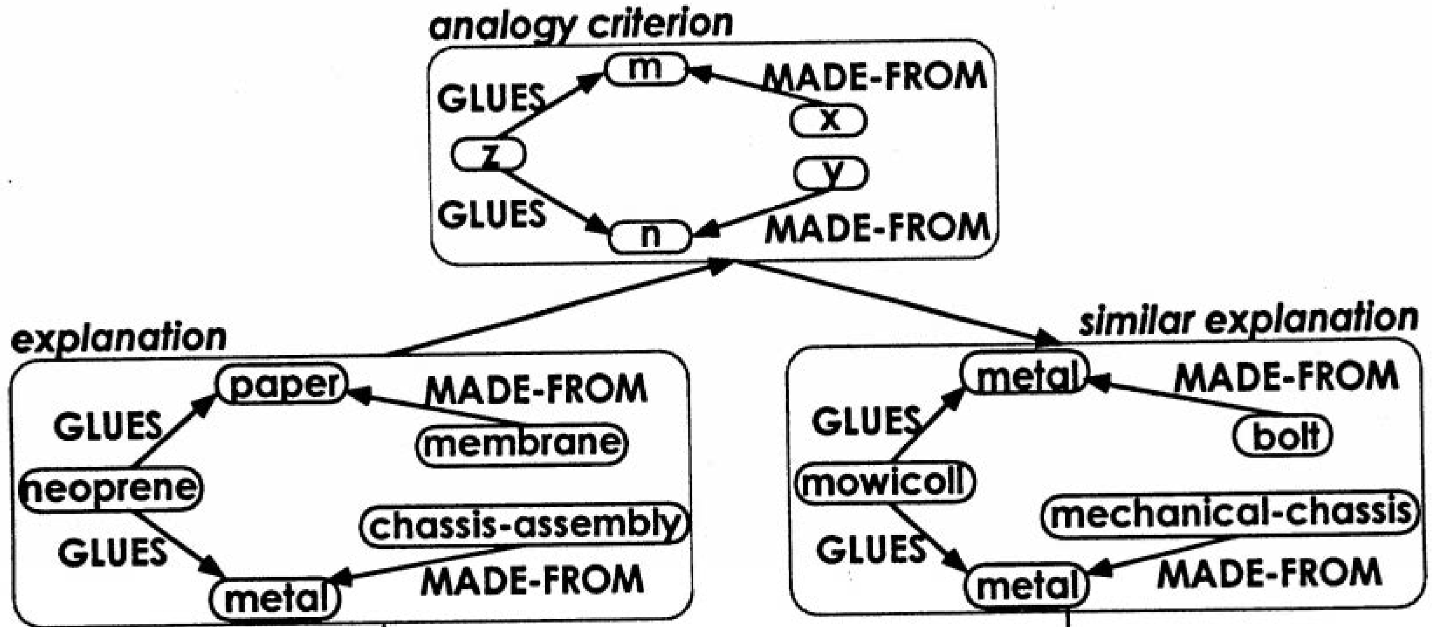
Application of ENIGMA
(Bergadano et al. 1990)

- Diagnosis of faults in electro-mechanical devices through an analysis of their vibrations
- 209 examples and 6 classes
- Typical example: 20 to 60 noisy measurements taken in different points and conditions of the device
- A learned rule:

IF the shaft rotating frequency is w_0 and the harmonic at w_0 has high intensity and the harmonic at $2w_0$ has high intensity in at least two measurements

THEN the example is an instance of C_1 (problems in the joint), C_4 (basement distortion) or C_5 (unbalance)

Acquiring Rules for Loudspeaker Manufacturing



initial example

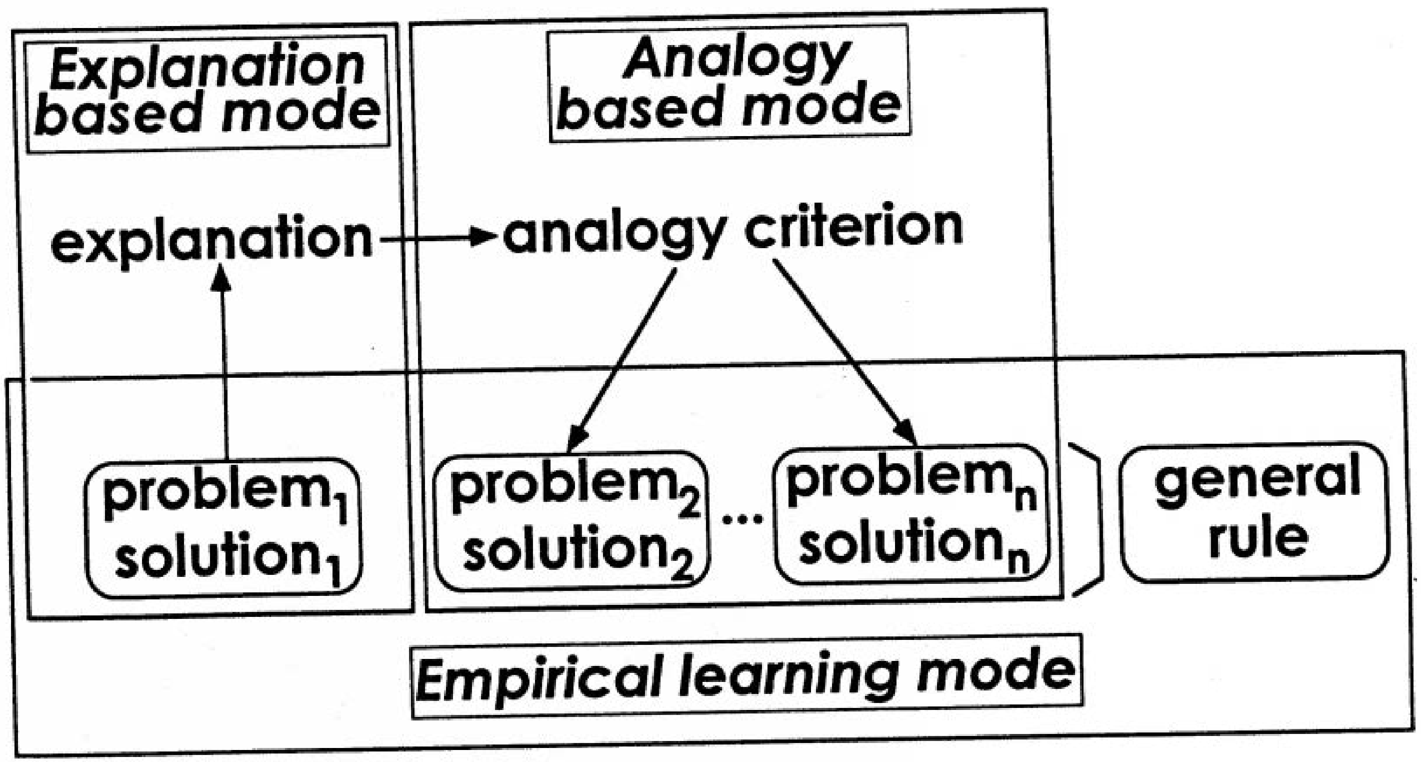
Solve the problem
ATTACH membrane TO chassis-assembly
by solving the subproblems
APPLY neoprene ON membrane
PRESS membrane ON chassis-assembly

generated example

May I solve the problem
ATTACH bolt TO mechanical-chassis
by solving the subproblems
APPLY mowicoll ON bolt
PRESS bolt ON mechanical-chassis ?

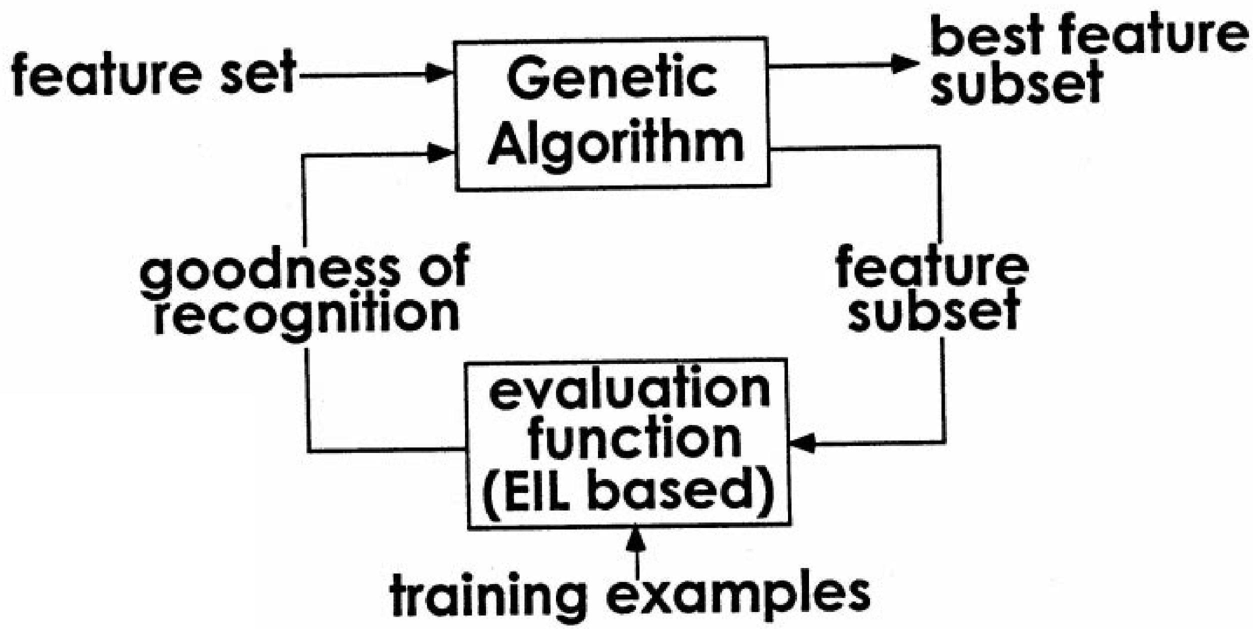
4.3 INTEGRATION OF EMPIRICAL INDUCTIVE LEARNING, EXPLANATION-BASED LEARNING, AND LEARNING BY ANALOGY

DISCIPLE (Tecuci, 1988; Tecuci and Kodratoff, 1990)



4.4 INTEGRATION OF GENETIC ALGORITHMS AND SYMBOLIC INDUCTIVE LEARNING

GA-AQ (Vafaie and K.DeJong, 1991)



Application: Texture recognition
18 initial features, 9 final features

Acquired Rule

```
IF
    (something  x  (MADE-FROM m))
    (something  y  (MADE-FROM n))
    (adhesive   z  (TYPE fluid)
                   (GLUES m)
                   (GLUES n))
    (material m)
    (material n)
THEN
solve the problem
    ATTACH x TO y
by solving the subproblems
    APPLY  z  ON x
    PRESS  x  ON y
```

5. MULTISTRATEGY KNOWLEDGE BASE IMPROVEMENT (THEORY REVISION): METHODS, SYSTEMS AND APPLICATIONS

5.1 The class of learning tasks

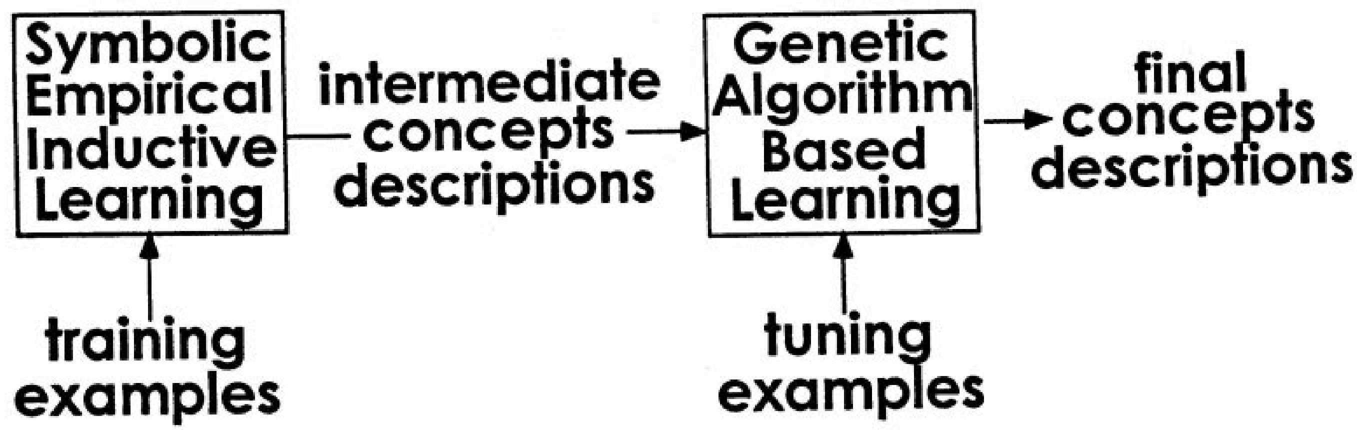
5.2 Cooperating learning modules

5.3 Integrating elementary inferences

5.4 Applying learning modules in a problem solving environment

5.5 Applying different computational strategies

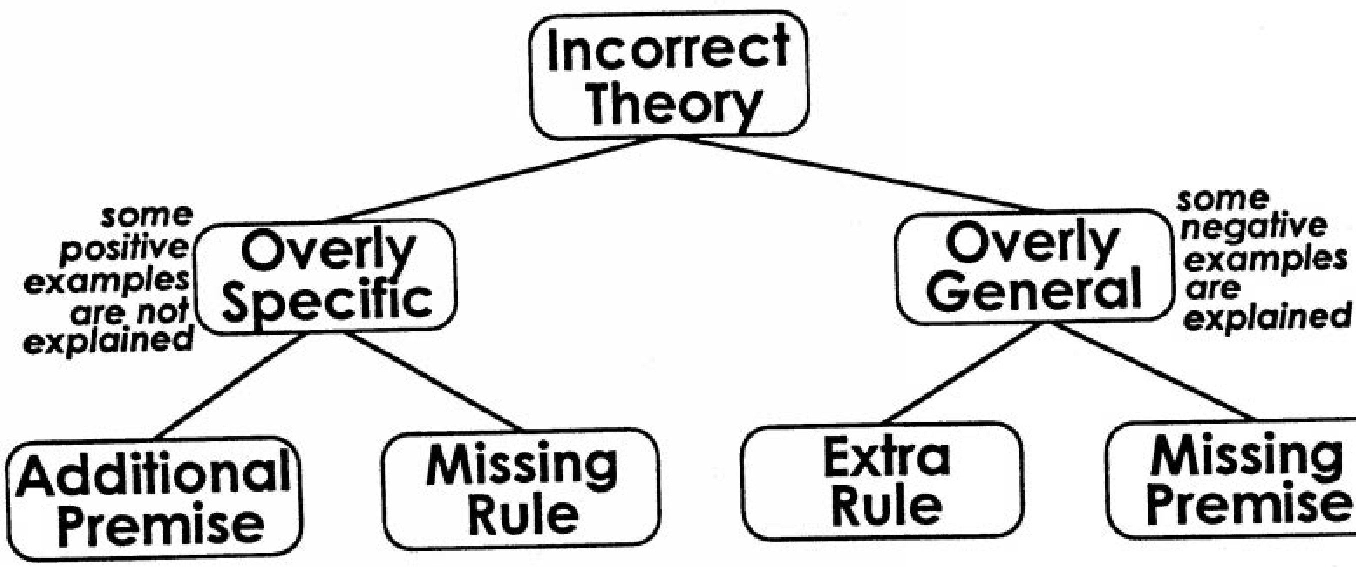
AQ-GA (Bala, K.DeJong and Pachowicz, 1991)



GA improves the weakest concept description

Application: Texture recognition
12 concepts
1 description improved with GA

Types of Theory Errors
(in a rule based system)



graspable(x) ⇐
width(x, small),
insulating(x),
<u>shape(x, round).</u>

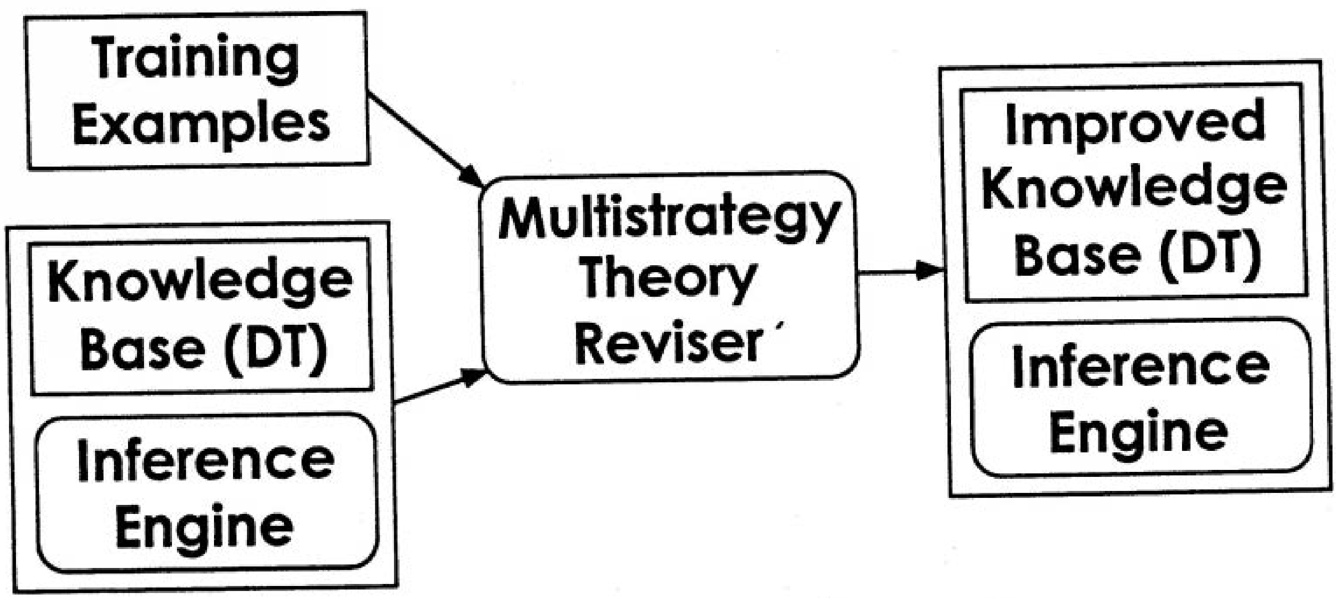
graspable(x) ⇐
has-handle(x).

graspable(x) ⇐
shape(x, round).

graspable(x) ⇐
insulating(x).

5.1 MULTISTRATEGY KNOWLEDGE BASE IMPROVEMENT (THEORY REVISION)

The class of learning tasks



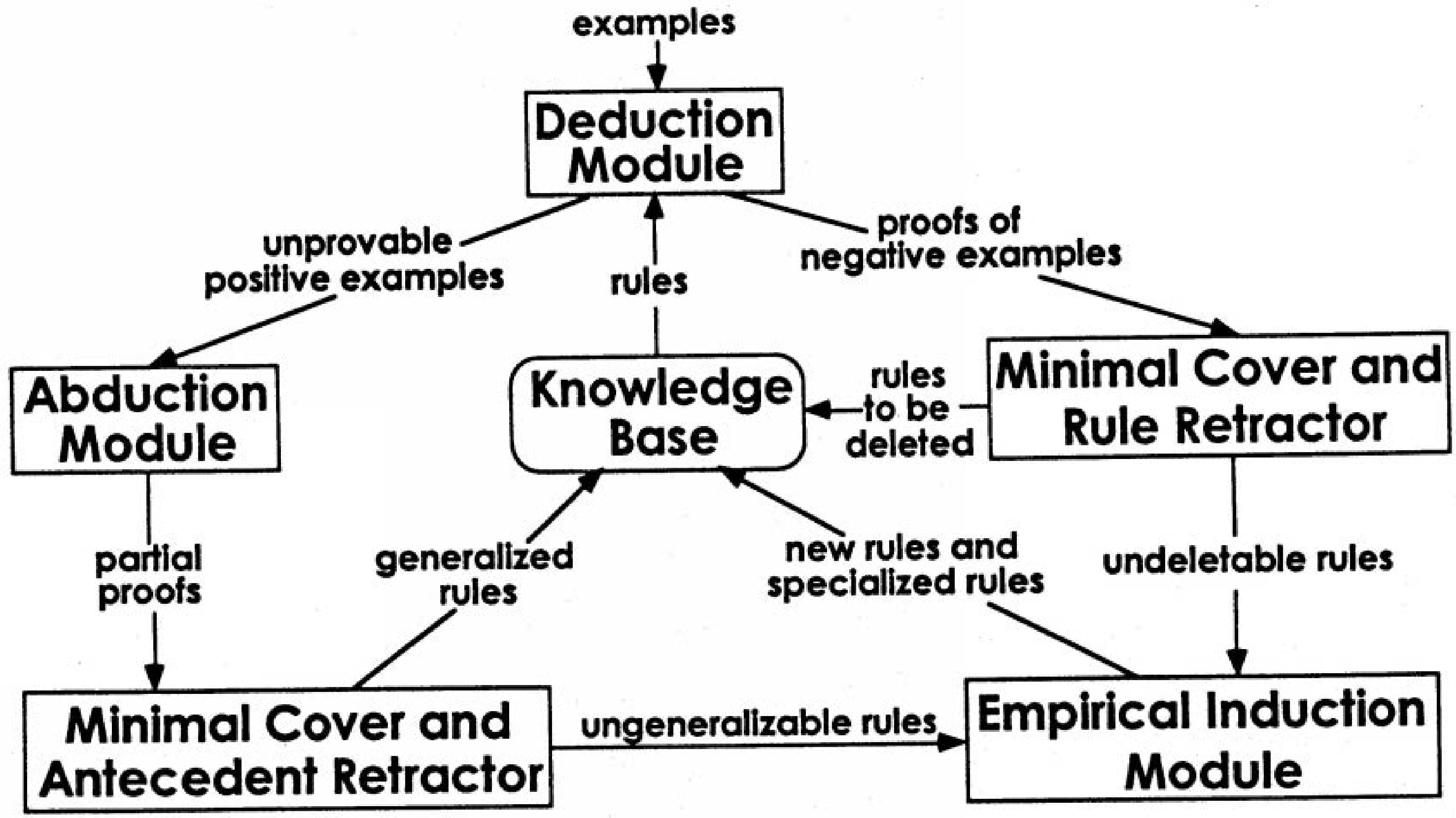
Positive and negative examples of cups

cup(o1) ⇐ width(o1, small), light(o1), color(o1, red),
styrofoam(o1), shape(o1, hem), has-flat-bottom(o1),
up-concave(o1), volume(o1,8).

Imperfect Theory of Vessels

cup(x) ⇐ stable(x), liftable(x), open-vessel(x).
stable(x) ⇐ has-flat-bottom(x).
liftable(x) ⇐ light(x), graspable(x).
graspable(x)⇐ has-handle(x).
graspable(x) ⇐ *width(x, small)*, insulating(x).
insulating(x) ⇐ styrofoam(x).
insulating(x) ⇐ ceramic(x).
open-vessel(x) ⇐ up-concave(x).

5.2 COOPERATING LEARNING MODULES
(deduction, abduction and empirical induction)
EITHER (Mooney and Ourston, 1991)



5.3 INTEGRATING ELEMENTARY INFERENCES

MTL-JT (Tecuci, 1993)

- **Deep integration of learning strategies**

  integration of the elementary inferences that are employed by the single-strategy learning methods (e.g. deduction, analogy, empirical inductive prediction, abduction, deductive generalization, inductive generalization, inductive specialization, analogy-based generalization)

- **Dynamic integration of learning strategies**

  the order and the type of the integrated strategies depend of the relationship between the input information, the background knowledge and the learning goal

- **Different types of input**

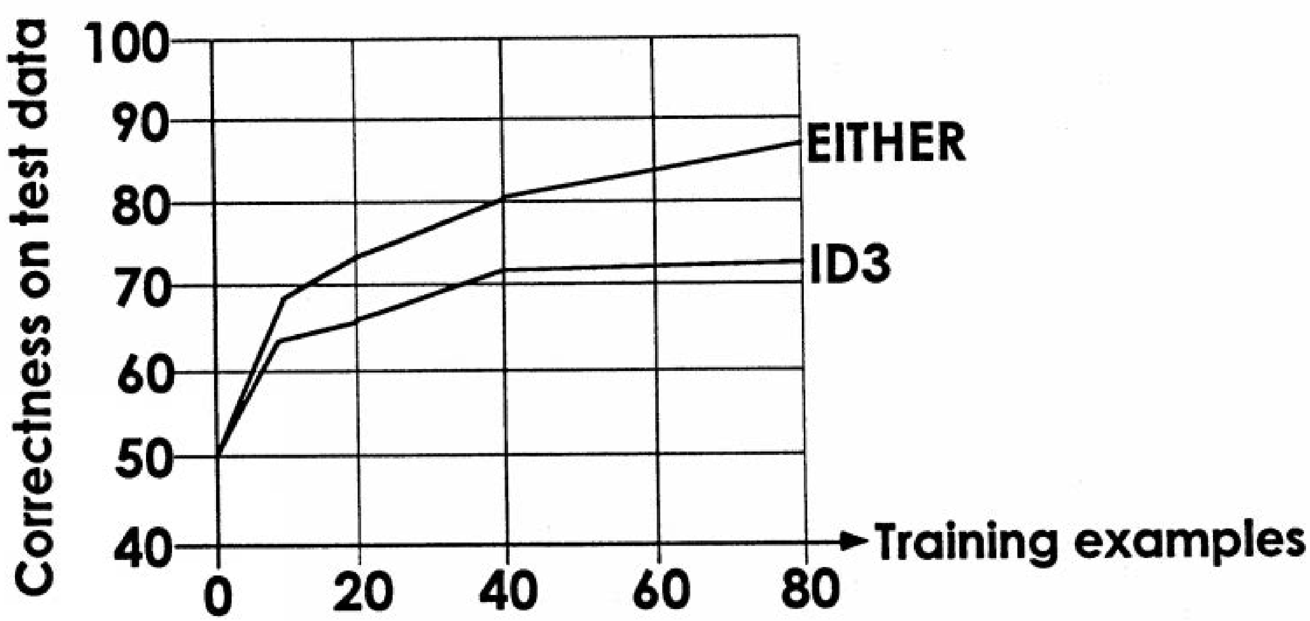
  (e.g. facts, concept examples, problem solving episodes)

- **Different types of DT knowledge pieces**

  (e.g.facts, examples, implicative relationships, plausible determinations)

Applications of EITHER

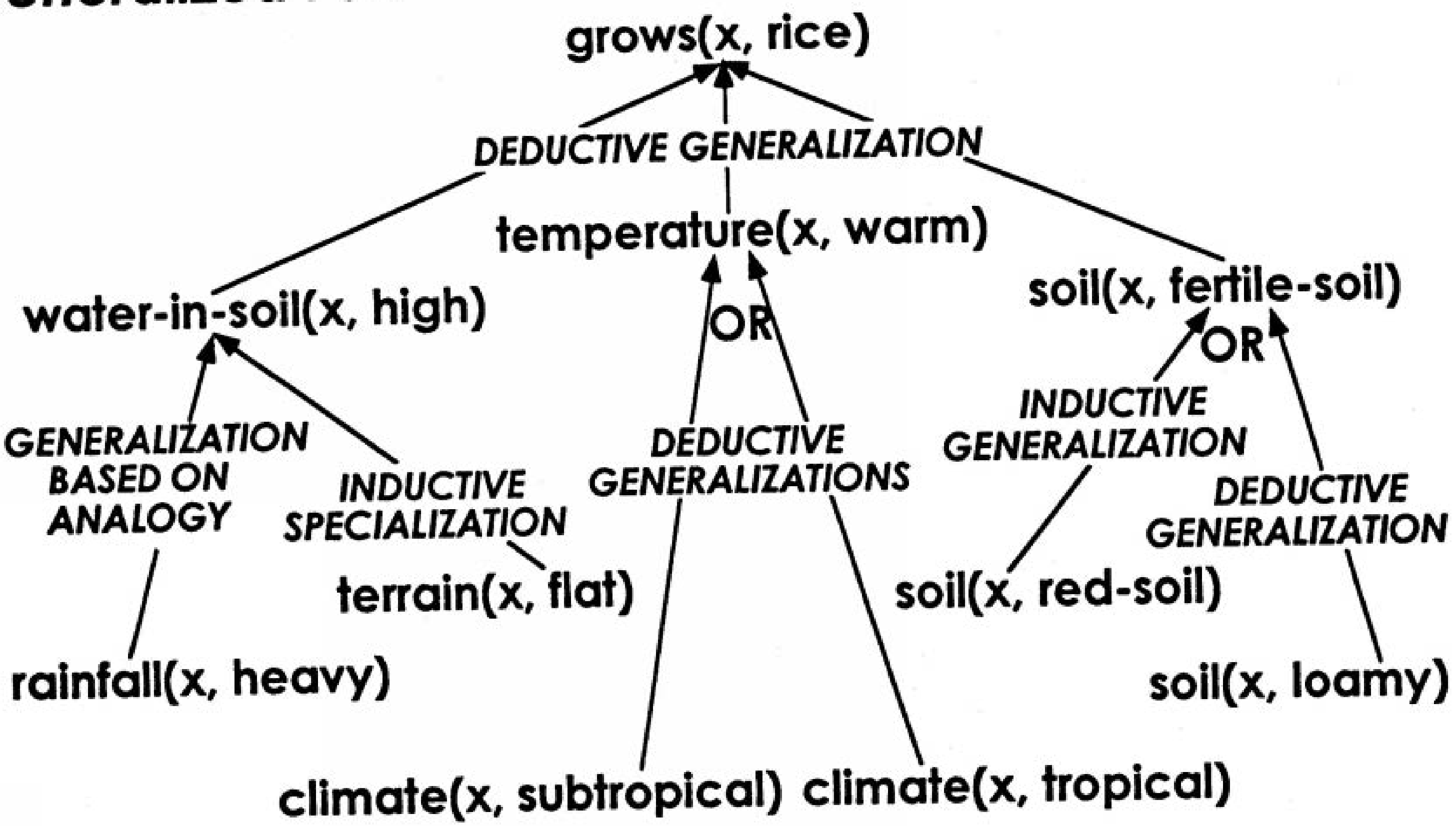
I. Molecular Biology: recognizing promoters and splice-junctions in DNA sequences



II. Plant Pathology: diagnosing soybean diseases

Examples: P1, P2, N1

Generalized PJT:

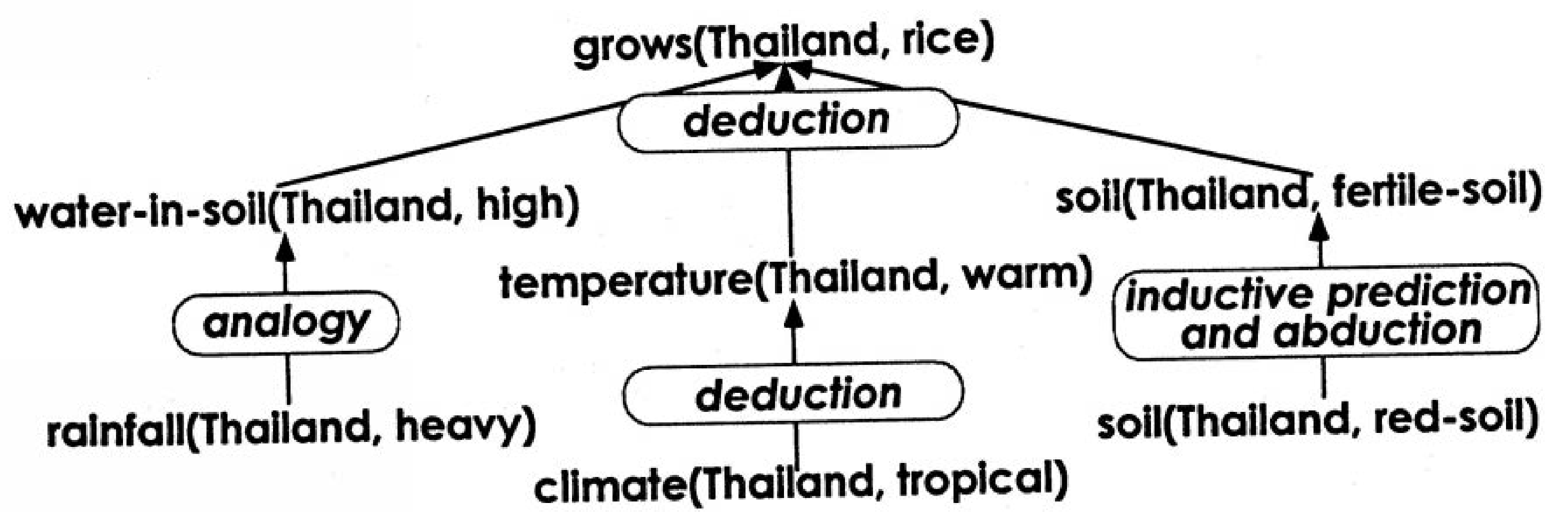


Question-Answering in Geography

Positive example1 (P1):

grows(Thailand, rice) ⇐
rainfall(Thailand, heavy), soil(Thailand, red-soil),
terrain(Thailand, flat), location(Thailand, SE-Asia),
climate(Thailand, tropical).

Plausible Justification Tree (PJT):



5.4 APPLYING LEARNING MODULES IN A PROBLEM SOLVING ENVIRONMENT

PRODIGY (Carbonell, Knoblock and Minton, 1989)

- Performance engine

  Planner based on state space search

- Learning strategies

  Explanation-based learning
  Learning by analogy
  Learning by abstraction
  Learning by experimentation

- Applications

  Machine-shop scheduling
  High-level robotic planning

Improved KB

- New facts:

  <u>*water-in-soil(Thailand, high).*</u>

  <u>*water-in-soil(Pakistan, high).*</u>

- New rule:

  <u>*soil(x, fertile-soil) ⇐ soil(x, red-soil).*</u>

- Specialized plausible determination

  water-in-soil(x, z) <≈ rainfall(x, y), <u>*terrain(x, flat).*</u>

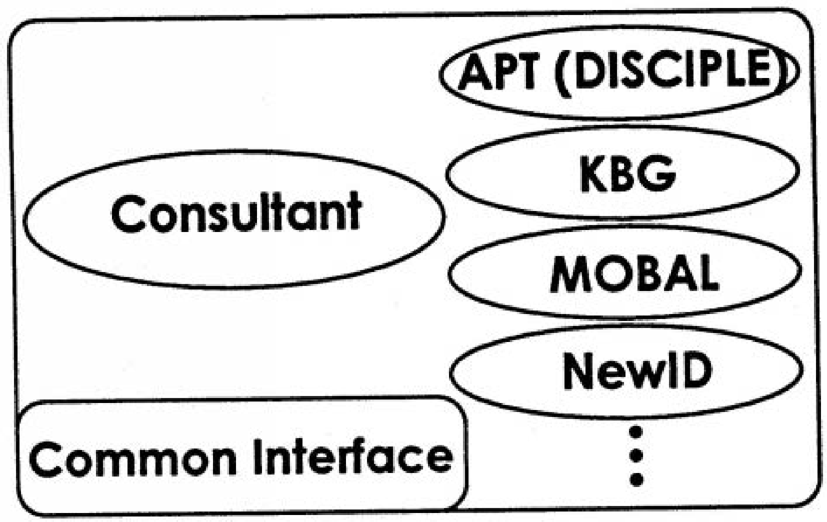
- Operational and abstract definitions of the concept "grows(x, rice)"

Independent Learning Systems in a Uniform Environment

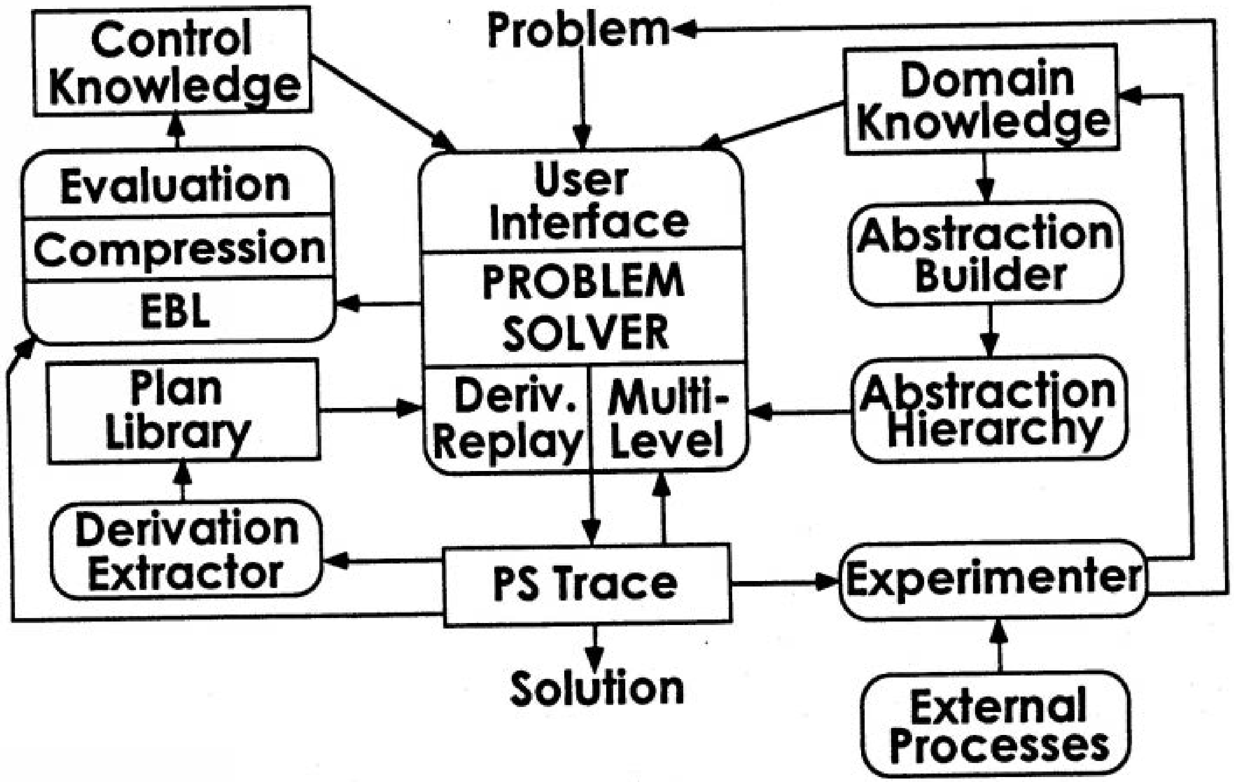
MLT (LRI, ISoft, CGE-LdM, INRIA, BAe, Aberdeen, Turing Institute, GMD, Siemens, Coimbra, Forth)

10 independent ML systems loosely integrated through:

- a common interface;
- a consultant;
- a common knowledge representation language (for communication)



The PRODIGY Architecture



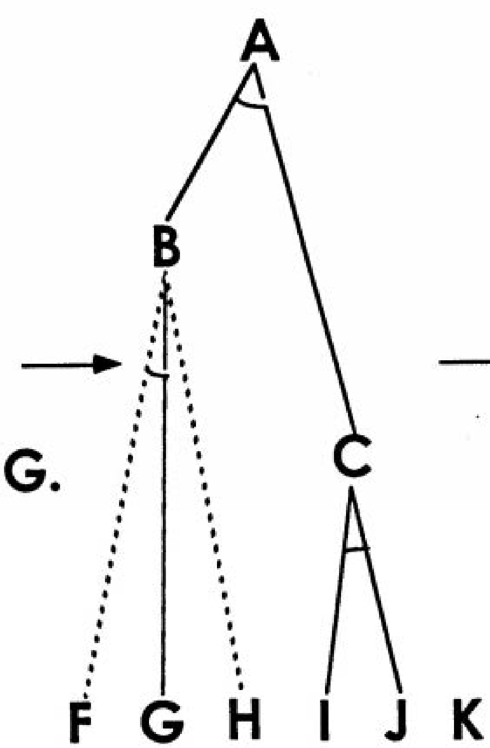
Rules to Network Translator

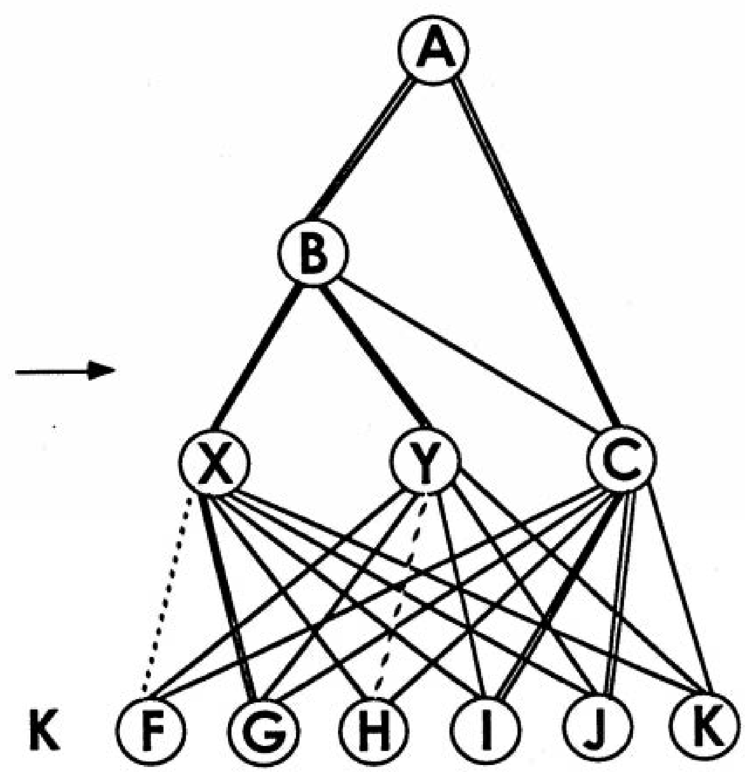
$A \Leftarrow B, C.$

$B \Leftarrow \text{not } H.$

$B \Leftarrow \text{not } F, G.$

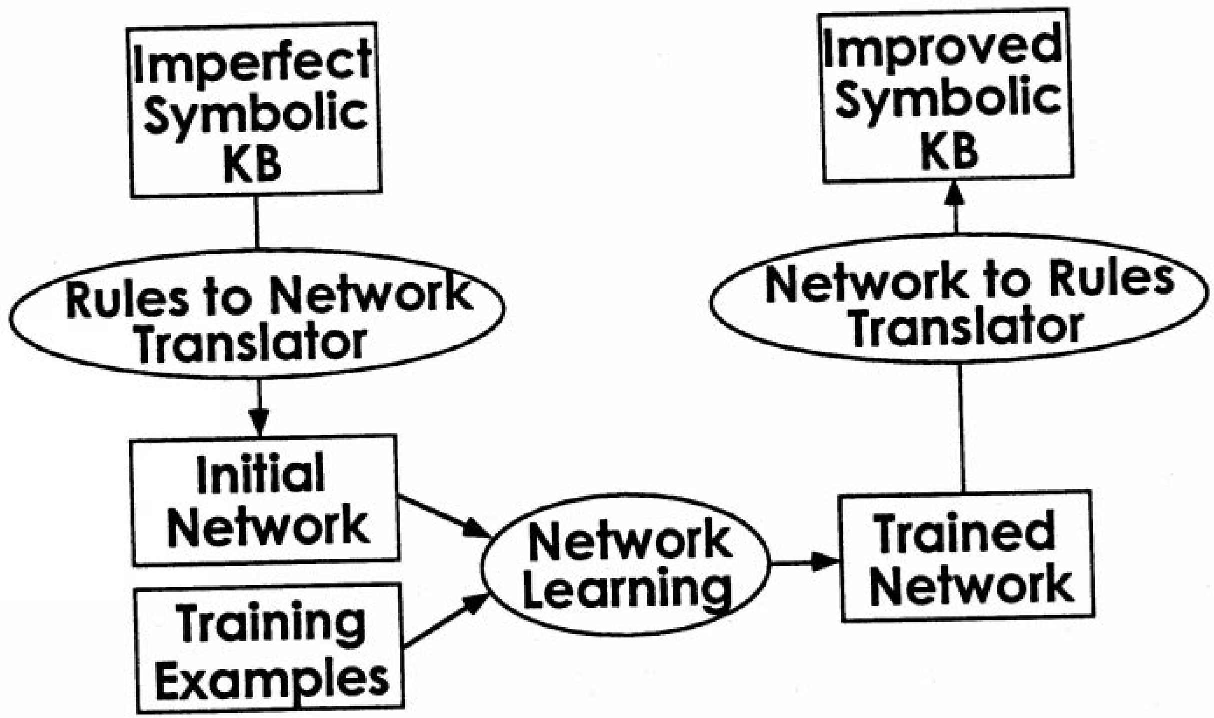
$C \Leftarrow I, J.$





5.5 APPLYING DIFFERENT COMPUTATIONAL STRATEGIES

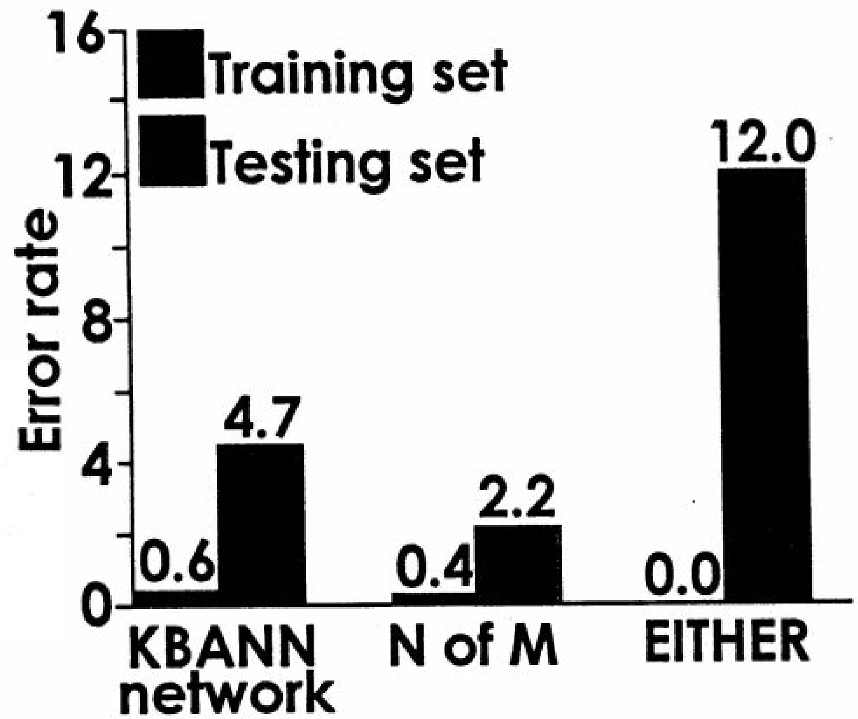
(symbolic rules and neural networks) KBANN (Towell and Shavlik, 1991)

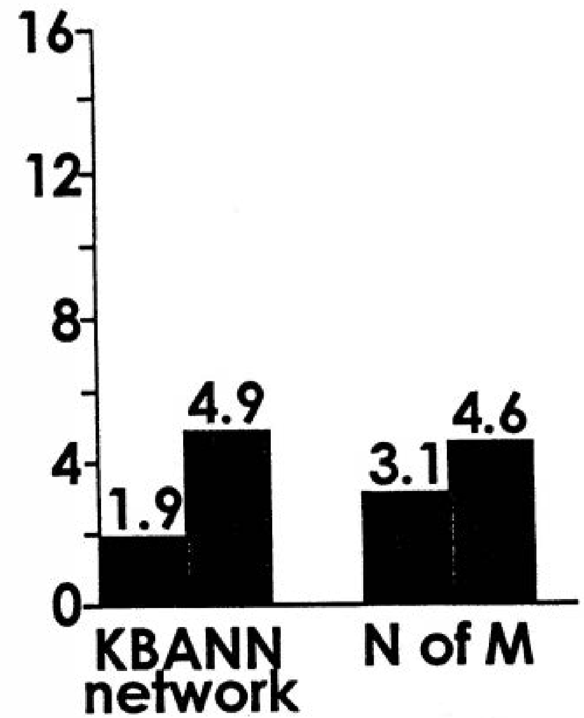


Error Rates

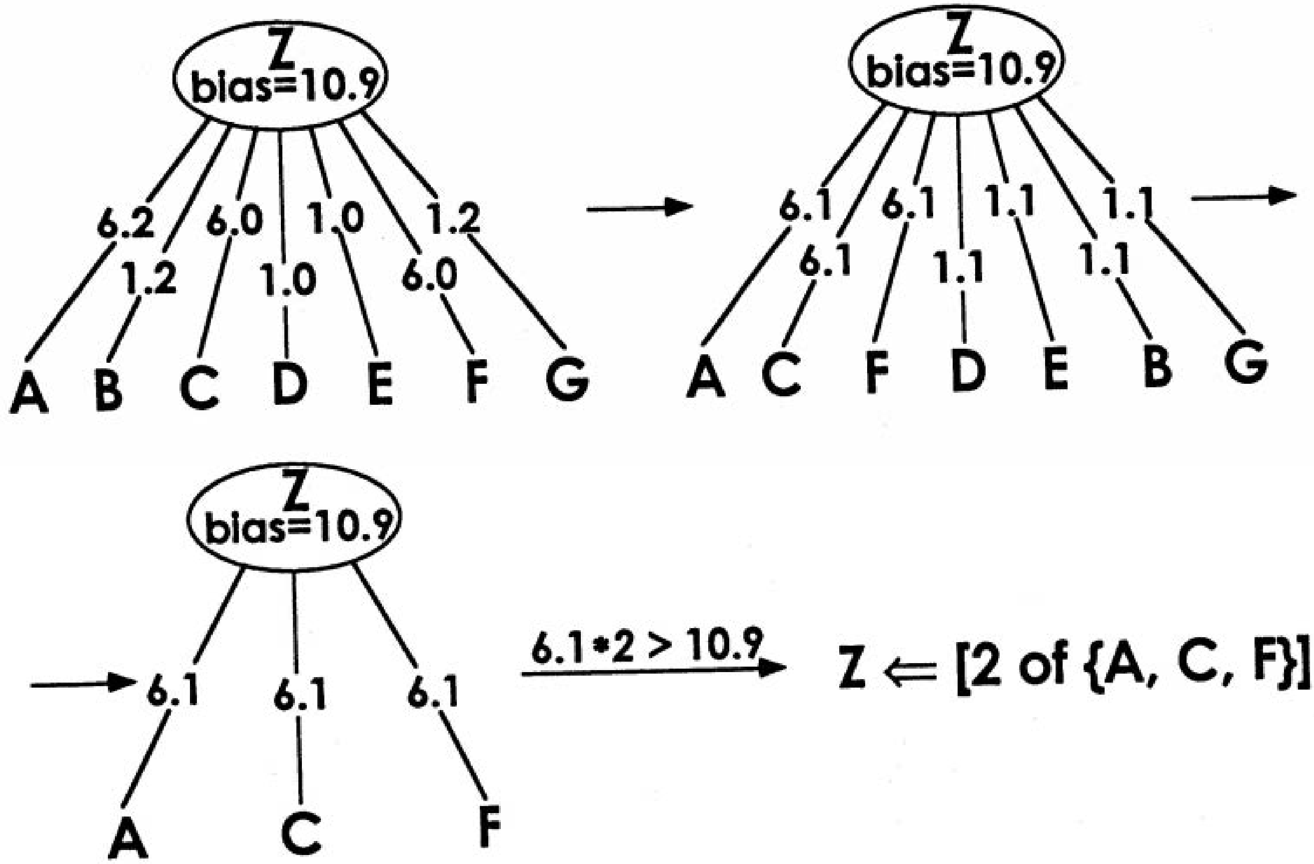
Promoter Domain — Splice-Junction Domain

Initial KB: 50% — 39%





Network to Rules Translator
(N of M rules)



SUMMARY OF APPLICATION DOMAINS

- Classification: DNA concepts (EITHER, KBANN)
  texture recognition (AQ-GA, GA-AQ)
- Diagnosis: mechanical trouble-shooting (ENIGMA)
  plant pathology (EITHER)
- Manufacturing: loudspeakers (DISCIPLE)
- Planning: high-level robot planning (PRODIGY)
- Prediction: economic sanctions (OCCAM)
- Scheduling: machine-shop scheduling (PRODIGY)

6. SUMMARY, CURRENT TRENDS AND FRONTIER RESEARCH

- Summary of application domains
- Issues in selecting a multistrategy learning method
- Current trends in multistrategy learning
- Multistrategy task-adaptive learning
- Areas of frontier research

CURRENT TRENDS IN MSL

- Comparisons of learning strategies
- New ways of integrating learning strategies
- Dealing with incomplete or noisy examples
- General frameworks for MSL
- Integration of MSL and knowledge acquisition
- Integration of MSL and problem solving
- Applications of MSL systems
- More comprehensive theories of learning

SOME ISSUES IN SELECTING A MULTISTRATEGY LEARNING METHOD

- Learning problem: - concept learning
  - theory revision
- Input data: - positive examples only
  - positive and negative examples
  - noisy examples
- Domain theory: - weak
  - complete
  - incomplete
  - partially incorrect

MTL-DIH

- **Determines the strategy on the basis of type of relationship between the input and BK:**

  A. The input is pragmatically new information
  B. The input contradicts some part of BK
  C. The input is implied by, or implies a part of BK
  D. The input evokes an analogy to a part of BK
  E. The input is already known to the learner

- **Modifies DIH structures accordingly to the relationship to achieve the learning goal**

One of new ways of integrating learning strategies

MULTISTRATEGY TASK-ADAPTIVE LEARNING: MTL-DHI

(Michalski & Hieb)

- A Multistrategy Task-adaptive Learner (MTL) adapts the strategy or a combination of strategies to the learning task (Input, BK, and the learning goal)

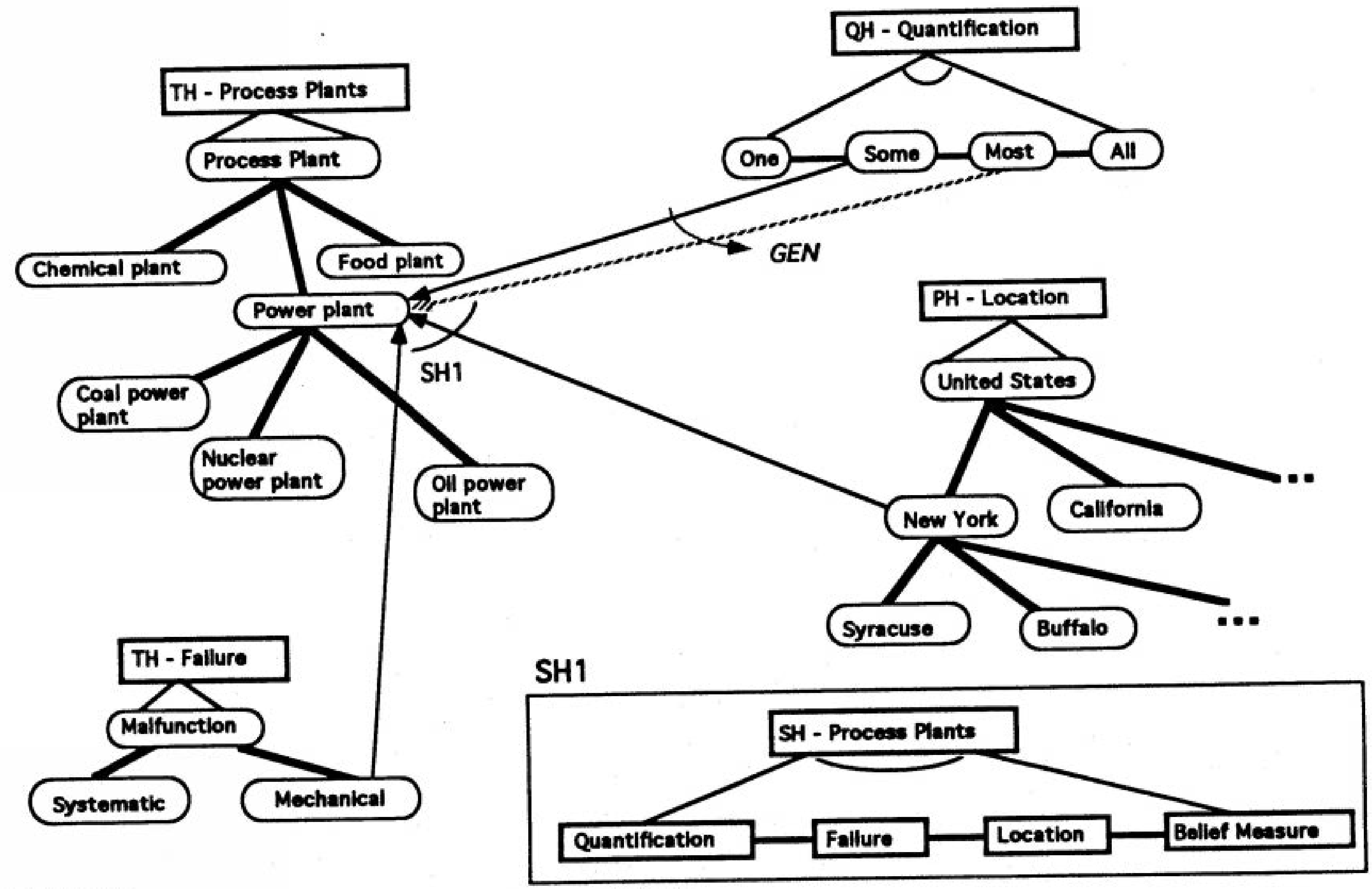
- The *MTL-DIH approach* employs a new type of knowledge representation *(Dynamic Interlaced Hierarchies)* that facilitates multitype inference

AREAS OF FRONTIER RESEARCH

- Synergistic integration of a wide range of learning strategies
- Better understanding of how to represent and use learning goals in MSL
- Development of methods for evaluating the certainty of the learned knowledge using different forms of plausible reasoning
- Investigations of human learning as MSL
- Combining computational theory of learning with inferential theory

DIH: Performing Inference by Perturbing Knowledge Traces

"Some power plans in New York have machanical failures"



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T15-103

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