MULTISTRATEGY LEARNING

Instructors
Ryszard S. Michalski
and Gheorghe Tecuci
A TUTORIAL ON MULTISTRATEGIC LEARNING

SUMMARY

Michalski@ic.emory.edu
and Knowledge Academy
George Mason University

R. S. Michalski

A TUTORIAL ON MULTISTRATEGIC LEARNING
Tutorial T15

MULTISTRATEGY LEARNING
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R. S. Michalski
George Mason University
Fairfax, VA

G. Tecuci
George Mason University
and Romanian Academy

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1. INTRODUCTION

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

1. Introduction
2. Learning strategies and methodologies
3. Theoretical framework for multi-strategy learning
4. Multi-strategy concept learning: methods
5. Multi-strategy knowledge base improvement
6. Summary, current trends and frontier research
7. References
Major Areas of Application

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

- Constructing learning systems and applying them to practical problems
- Developing computational theories and methods of learning
<table>
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<th>OTHERS</th>
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<td>1993</td>
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- University of Massachusetts
- University of Michigan
- University of California, Irvine
- Rutgers University
- University of Illinois at Urbana-Champaign
- Carnegie-Mellon University

### Machine Learning Workshops/Conferences

MAJOR EVENTS

IN USA:
A HISTORICAL SKETCH

- Emphasis on practical applications
- Integrated and multi-institutional systems
- Computational learning theory
- Reversal of non-symbolic methods
- Experimental comparisons

End of Innocence (1988-...)

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

Renaissance (1976-1988)

- Symbolic concept acquisition
- To acquire knowledge one needs knowledge

Dark Ages (1962-1976)

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

Early Enthusiasm or Tabula Rasa Crase (1955-1965)
Applications
Implementation of learning systems for specific engineering

Building computer models of human or animal learning

Modeling of natural learning systems

Possible methods
Theoretical analyses and an exploration of the space of science of learning

Research Orientations
<table>
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<td>Coroenna, Belgium</td>
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<td>Ceske, Germany</td>
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<td>Italy</td>
<td>1993</td>
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<td>Les Arcs, France</td>
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<td>Bressans, France</td>
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**Summer Schools and Special Meetings**

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<td>Vienna</td>
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<td>Porto</td>
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<td>Montpellier</td>
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<td>Glasgow</td>
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<td>Bled</td>
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<td>Oresay</td>
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**Working Sessions on Learning (EWIS)**

IN EUROPE:
observation and experimentation
Discovery of new facts or theories through
representations
Organization of knowledge into new more effective
instruction and practice
Development of motor and cognitive skills through
acquisition of declarative knowledge

PHENOMENON COMPRISINC:
LEARNING IS A MULTI-FACETED
What is Learning?

A system learns if it makes changes in itself that enable changing behavior due to experience. Improving performance with practice and acquiring new knowledge might make it perform better on a given task.
The learning goal can vary from very specific to very general.

The constructed knowledge can be in many different forms.

The initial knowledge can vary from very limited to quite rich.

The inputs can vary from raw observations to refined knowledge.

Learning is a complex process because...
The learner's experience
of knowledge structures representing
A goal-oriented creation or improvement
or, more precisely,
Self-construction of knowledge structures

**THE ESSENCE OF LEARNING**
Prior knowledge: Limited (Empirical), Rich (Knowledge-intensive)

Input acquisition: Passive, Active

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

Input type: Examples, Facts, Generalizations

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

CLASSIFICATION CRITERIA
Multicriterion classification of methods

Basic paradigms

Computational strategies

Inferential strategies

Classification criteria

METHODOLOGIES

2. LEARNING STRATEGIES AND
Method

Representation

Computational strategy (The underlying form of knowledge)

Interpersonal strategy (The underlying type of inference)

Classification criteria

Backpropagation, General Programming, etc.
Execution, Generate & Test, Genetic algorithm,
Equation solving, Search & Select, Rule-

Artificial neural net, Programming language
Tions, Semantic nets, Frames, Classifier system,
Rules, Hierarchies, Grammars, Relational databases
Parameters, Equations, Decision trees, Decision

Creating or modifying this representation

No inference, Deduction, Analogy, Induction
Conceps are representd by single units

Local connectionist networks

(Hinton, McClelland, Rumelhart, 1985)

Pattern of a collection of units

Conceps are representd by an activation

Parallel distribute models

Two types of models:

1. Activation sent to other units

2. Each unit sending excitatory or inhibitory signals

In a network of neuron-like elements (units),

Learning is done by setting the proper weights.

ARTIFICIAL NEURAL NETS
Concept Learning from Examples

Symbolic Empirical Learning

Decision Rules (AQ-based methods)

Decision Trees (ID3-based methods)
The total input $y_i'$ received by the $i$th unit from other units, $x_i'$ is usually defined as

$$y_i' = \text{SUM} (w_{ii}' \cdot x_i')$$

The activation functions

UNIT ACTIVATION FUNCTIONS
THREE LAYER NEURAL NET

Input units
Hidden units
Output units
brought together
were far apart may be
of the rules (elements that
Reordering the components

a local optimum
system from getting stuck at
rules. This may prevent the
Making random changes in
exchange ("rule matching")
Chunks of two rules are

INVERSION

MUTATION

CROSSOVER

BASIC GENETIC OPERATORS
Evolutionary Learning Strategies

GENETIC ALGORITHMS
BY DIFFERENT METHODS
THE SAME CONCEPT LEARNED
description that covers the example

An effective (operational) concept

Determine:

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

Given:

(EBL)

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

strategies
two or more interpretative and/or computational
developing learning systems that integrate
• Multi-strategy Learning is concerned with

LEARNING
WHAT IS MULTI-STRATEGY
A comparison of strategies

Analysis of knowledge operators

Analysis of types of inference

Learning as search in a knowledge space

What is multi-strategy learning

FOR MULTI-STRATEGY LEARNING

3. Theoretical Framework
MTL (Michailiski & Teague, 1992; D'Ih-1993)

AG-GA (Bola, K. Delong & Rachowicz, 1991)

KBANN (Towell & Shavlik, 1991)

EITHER (Mooney & Quron, 1991)

CLINT (De Rieudi & Bruynooghe, 1991)

KBL (Whitwell, 1990)

PRODIGY (Carbonell, Knoblock & Mintos, 1989)

WYF (Flan & Dietrich, 1989)

ENIGMA (Bergeradno, Girardino & Saito, 1988)

OCAM (Pazzani, 1988)

Gemini (Danylik, 1987)

DISCIPLE (Kohdari & Teague, 1987)

Odysseus (Willkms. Clancy & Buchanam, 1986)

Unicorn (Lobdowicz, 1986)

EXAMPLES OF MSL SYSTEMS
- neural net and genetic algorithm
- symbolic method and genetic algorithm
- symbolic method and neural net
- Computational strategies, e.g.

Multi-paradigm -- system that combine different

(constructive induction)
- empirical generalization, deduction and/or abduction
- induction, analogy and deduction
- empirical induction and explanation-based learning
- different inferential strategies, e.g.

Multi-inferential -- systems that combine

TYPES OF MSL SYSTEMS
"Biais" – any information that limits the choice of a hypotheses

Consistent and complete
All possible expressions

Pr(error rate ≤ ε) ≥ 1 - 8 (Vollant)

Probably approximately correct (PAC):

{0, 1}^n → {0, 1}^n

An approximation of a function f

An expression that provides a good

Determine:

A set of pairs {x, f(x)}

Given:

Computational Theory of Learning

Learning as Function Reconstruction
Multistrategy Learning Processes

Memory

- Background Knowledge

| Goals |

- Deduction
- Analogy
- Induction

Inference Mechanism

External Input

Internal Input

Output

External Input
Given: Interential Theory of Learning

Learning as Search in a Knowledge Space

\[
\begin{align*}
\{ \text{l!} \} & = 1 & \text{Transmutations} \\
\{ \text{G!} \} & = G & \text{Goal Specification} \\
\{ \text{K!} \} & = K & \text{Initial Knowledge} \\
\{ \text{I!} \} & = I & \text{Input Information} \\
\end{align*}
\]

Determine:

1. To K and I.
2. By applying knowledge transmutations, new knowledge K' that satisfies goal.
Information about the set
- abstraction & concretion (change the amount of entities being described, called the reference set)
- generalization & specialization (change the set of

For example
- change or derive various aspects of knowledge
- can employ any type of inference
- generic patterns of knowledge transformation

KNOWLEDGE TRANSMUTATIONS
transformation or change
of knowledge derivation,
where by "Interencing" is meant any type
Learning = Interencing + Memorizing

AN "EQUATION" FOR LEARNING
MAJOR TYPES OF INFERENCE

INDUCTION

CONCLUSION

DEDUCTION

CONCLUSION

CONTINGENT

Domain-dependent rules

Domain-independent rules

P ↔ BK ⊃ C

Truth-preserving

Falsity-preserving

Analogy
Given C and BK hypothesis P

Induction

Given P and BK derive C

Deduction

A rule, a set of rules, etc.

Where P, BK and C can be a single fact,

Premise with Background Knowledge Entails Consequent

P ∩ BK = C

The Fundamental Equation of Inference

Basic Forms of Inference
An example of empirical generalization

Hypothesis:

For all e, p(e) \Rightarrow p(e')

Input: Grey(e), Grey(e), Grey(e), Grey(e), Grey(e), Grey(e), Grey(e)

Output: BK

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

Test of inductive condition:

For all e from B, Grey(e)

\( c = \) Grey(e1), Grey(e2), Grey(e3),...
and the hypotheses selection criterion.

$$P \text{ and } \neg B \text{ and } \neg K \Rightarrow C$$

The fundamental equation

A hypothesis, $P$ ("Premise"), that satisfies the hypothesis:

**Hypothesis:**
\[
\text{consists of ("bias", }
\text{ (bias,
\text{ criterion reflecting learner's goals and inference rules, and a hypotheses selection domain independent and/or dependent }
\text{ background knowledge (BK), which includes }
\text{ an input, C ("Consequent"))}
\text{ Given: }
\text{Inductive Inference}}
\]
For all $e$ from $B$, $\text{grey}(e)$

$\Rightarrow$

For all $e$, made-of($e$, steel) $\Rightarrow$ $\text{grey}(e)$

For all $e$ from $B$, made-of($e$, steel) $\&$

Test of inductive condition:

For all $e$ from $B$, made-of($e$, steel)

Hypothesize:

For all $e$, made-of($e$, steel) $\Rightarrow$ $\text{grey}(e)$

For all $e$, $\text{p}(e) = \Rightarrow \text{p}(e)$

$B_k$: Balls $e_1$, $e_2$, $e_3$...are from box $B$

Example of constructive generalization

Input: $\text{grey}(e_1), \text{grey}(e_2), \text{grey}(e_3)$...
Greym(e) =

\[ \text{For all e, Made-of(e, Steel) \implies Grey(e)} \]

Test of Inductive Condition:

<table>
<thead>
<tr>
<th>Made-of(e, Steel)</th>
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Hypothesis:

\[ \text{For all e, Made-of(e, Steel) \implies Grey(e)} \]

Input:

\[ \text{BK: Grey(e)} \]

An Example of Abduction
Knowledge Generation Transmutations

A Selection

Induction

Analogy

Deduction

Inference Type

Deduction

Abstraction

Concentration

Explanation

Prediction

Similarization

Selection

Generalization

Abstraction

Specialization

Generalization

Characterization

Discrimination

Association

Dissociation

Transmutation
Abstraction (concretion) decreases •

Generalization (specificization) increases •

described by a set of sentences

Reference set -- the set of entities being

Definition:

GENERALIZATION VS. ABSTRACTION
Generalization

Explanation-based

Example

Domain Rules + Operational CD

Example

Given:

I. INPUT

II. CONCEPTS

An operational concept description:

 Learned:

To create an operational description of the concept of cup:

3. GOAL

made-of(x, hard-material) & has-handle(x)

Other relevant knowledge

made-of(x, glass)

Domain rules

open-vessel(x)

Complete

Abstract CD

...
A COMPARISON OF STRATEGIES
By combining several learning strategies and consistent with the DT characterizing the example(s) Goal: learn a concept description or complete domain theory (DT) a weak, incomplete, partially incorrect examples of a concept

BK: INPUT: one or more positive and/or negative

The class of learning tasks

4.1 Multi-strategy concept learning
and symbolic empirical inductive learning

4.2 Integration of genetic algorithm-based learning

4.3 Integration of empirical inductive learning, analogy

4.2 Explanation-based learning

4.1 The class of learning tasks

METHODS, SYSTEMS AND APPLICATIONS

4. MULTISTRATEGY CONCEPT LEARNING:
4.2 Integration of Empirical Inductive Learning and Explanation-Based Learning (EBL)

- Exploratory Inference Learning (EIL)
- Complementary nature of EIL and EBL
- Types of Integration of EIL and EBL
GOAL: Learn an operational concept description of CUP

1. cup(x) ⇒ (stable(x) ∧ graspsable(x)).
2. cup(x) ⇒ (stable(x) ∧ graspsable(x)).
3. cup(x) ⇒ (stable(x) ∧ graspsable(x)).
4. cup(x) ⇒ (stable(x) ∧ graspsable(x)).

Bk: a theory of vessels (domain rules)

INPUT: Examples of the cup concept

Illustration of a Learning Task
Explaination-based learning

Needs only one example

Is Knowledge Intensive (Requires a Complete DT)

Proves that the training example is an instance of the target concept and generalizes the proof

Proves that 01 is a cup:

Generalize the proof:

Prove that 01 is a cup:

made-from(p1, plastic)

has-handle(01)

graspable(01)

stable(01)

cup(01)

The material the cup is made

from need not be "plastic"

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

Negative examples of cups:
P1

Positive examples of cups:
P2

Performs well in knowledge-weak domains

Is data-intensive (requires many examples)

Generates descriptions of the similarities and differences, and creates a set of examples in terms of their

EMPIRICAL INDUCTIVE LEARNING
Guiding Induction by domain theories
Induction over unexplained
Combining EBL with version spaces
Induction over explanations
Explanation before induction
MSL METHODS INTEGRATING EBL AND EBL
<table>
<thead>
<tr>
<th>Domain</th>
<th>Examples</th>
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<tr>
<td>Theory</td>
<td>weak need to be complete or partially incomplete</td>
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<tr>
<th>MSL</th>
<th>EBL</th>
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<tr>
<td>(EIL+EBL)</td>
<td>one</td>
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**EIL and EBL**

**Complementary Nature of**
Integration of EBL and EIL in OCCAM
A learned economic sanctions schema:

outcome of hypothetical events.

OCCAM is a schema-based system that learns to

OCCAM (Razzaq, 1988, 1990)

Explanation Before Induction
- Introduce equality constraints (e.g. \( v_1 = v_2 \))
- Specialize ICD to reflect the similarities between the training examples
- Apply EBL to generalize the subtree and retain the leaves as an intermediate concept description (ICD)
- Find the largest common subtree
- Build an explanation tree for each example
explained by the DT (i.e. Incomplete DT)

May discover concept features that are not
learns from a set of positive examples

IOE

Requires a complete DT

because it is a generalization of a single example

The learned concept might be too specific

Limitations of EBL

WYI (Flann and Dietrich, 1989)

Induction over Explanations (IOE)
Learned concept:

\[
\begin{align*}
\text{in ICD:} & \quad (y = \text{plastic}) \\
\text{in example1:} & \quad (y = \text{plastic}) \\
\text{in example2:} & \quad (y = \text{plastic})
\end{align*}
\]

Generalization of the common subtree:

ICD

\text{has-flat-bottom}(x), \text{up-concave}(x), \text{cup}(x) \Rightarrow \text{made-from}(x, \text{plastic}), \text{light-matt}(\text{plastic}), \text{graspable}(x)

\text{stable}(x), \text{open-vein}(x)

\text{generalization of the common subtree}:
The EBL-VS Method

- Apply the EBL to generalize the positive 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
from knowledge-rich to knowledge-free

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

EBL-VS

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

Limitations of IOE

(Hirsch, 1989, 1990)

COMBINING EBL WITH VERSION SPACES (EBL-VS)
The learned concept is $C_e \cup C_n$

- Apply EIL to determine a generalization of the reduced set of simplified examples (this is the nonexplanatory component $C_n$)

- Disregard negative examples not satisfying $C_e$ and remove the features mentioned in $C_e$ from all the examples

- Apply EBL to generalize each positive example (this is the explanatory component $C_e$)

The IOU Method
and conventional aspects

- Learns concepts with both explainable
- The DT may explain negative examples
- Of an example may be incomplete
- The explanation-based generalization
- DT could be incomplete but correct

IOU

- Assumes that at least one generalization
- Limitations of EBL-VS

Mooney and Ohrstrom, 1989

Induction over Unexplained (IOU)
Examples may be noisy

ENIGMA

Examples have to be noise-free

DT rules could be partially incorrect

Limitations of IOU

The ENIGMA System

GUIDING INDUCTION BY DOMAIN THEORY

BERGADANO, GIORDANO, SAPIA ET AL. 1988, 1990
C = C ∈ Cn
C covers Cup1, Cup2 but not Short-Glass1, Mug1
Cn = Volume(x, small)
C covers Cup1, Cup2, Short-Glass1, Mug1 but not Can-

{width(x, small), has-insulating(x), has-handle(x)}
C = has-flat-bottom(x) & has-flat-top(x) & concave(x)

drinking vessels but no definition of cups

Domain Theory: Incomplete (contains a definition of

Illustration
Operational predicates start with a lowercase letter

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

**DT:**

- Open-versed(x) ⇒ up-concave(x).
- Stable(x) ⇒ body(x, y), support(x, z), above(y, z).
- Stable(x) ⇒ has-flat-bottom(x).
- Liable(x) ⇒ high(x), has-handle(x).
- Cup(x) ⇒ liable(x), stable(x), open-versed(x).

**Domain Theory**

- above(a, b), up-concave(o4).
- Cup(o4) ⇒ high(o4), support(o4, b), body(o4, a).

Positive examples (p4):

- Examples (4 pos, 4 neg)
The learned concept is a disjunction of leaves.

- An example-based inductive specialization of D
- A DT-based deuctive specialization of D

Decide between performing:

- To identify the covered and the uncovered ones
- Whenever a specialization of the definition D contains operational predicates, compare it with the examples

Successfully specialize the abstract definition D of the

(method 1) trades off the use of DT rules against the coverage of examples

The Learning Method
Covers p₂, p₄
above(y, z), up-concave(x),
Cup(x) \Rightarrow \text{light}(x), \text{body}(x, y), \text{support}(x, z),

Covers p₃, p₃
has-small-bottom(x),
Cup(x) \Rightarrow \text{light}(x), \text{has-flat-bottom}(x),

The Learned Concept
<table>
<thead>
<tr>
<th>Time Development</th>
<th>Recognition Rate</th>
<th>Rules of Ambiguity</th>
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<tr>
<td>18 months</td>
<td>0.95</td>
<td>1.46</td>
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<tr>
<td>4 months</td>
<td>0.95</td>
<td>1.21</td>
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**MEPS**

**ENIGMA**

the hand-coded KB of the Expert System MEPS

the KB learned by ENIGMA and

Comparison between
A learned rule:

• In different points and conditions of the device
• Typical examples: 20 to 60 noisy measurements taken
• 209 examples and 6 classes
• Through an analysis of their vibrations
• Diagnosis of faults in electro-mechanical devices

(Bergadano et al., 1990)

Application of Enigma
Acquiring Rules for Loop: Speaker Manufacturing
4.3 INTEGRATION OF EMPIRICAL INDUCTIVE LEARNING, EXPLA NATION-BASED LEARNING, AND LEARNING BY ANALOGY

DISCIPLE (Tecuci, 1988; Tecuci and Kodratoff, 1990)
18 initial features, 9 final features.

Application: Texture recognition

Training examples

(FEL based)

Evaluation function

Subset feature

Goodness of recognition

Algorithm Genetic

Subset feature

Best feature

Subset feature

GA-AG (Yartie and K. Dejong, 1991)

AND SYMBOLIC INDUCTION LEARNING

4.4 INTEGRATION OF GENETIC ALGORITHMS
Press X ON Y
Apply Z ON X
by solving the subproblems
Attach X TO Y
solve the problem

Then

(material n)
(material m)
(clue n)
(clue m)

(adhesive Z (type fluid)
(something Y (made-from m)
(something X (made-from m)

If

Acquired Rule
5.5 Applying different computational strategies

5.4 Applying learning modules in a problem solving environment

5.3 Integrating elementary inferences

5.2 Cooperating learning modules

5.1 The class of learning tasks

METHODS, SYSTEMS AND APPLICATIONS

IMPROVEMENT (THEORY REVISION): MULTISTRATEGY KNOWLEDGE BASE
GA improves the weakest concept description

Application: Texture Recognition

GA description improved with GA

12 concepts

Examples

Training

Descriptions

Concepts

Final

Learning

Based

Algorithm

Genetic

Intermediate

Empirical

Inductive

Symbolic

AQ-GA (Bala, K. Dejong and Rachowicz, 1991)
Types of Theory Errors (in a rule-based system)
The class of learning tasks
Improvement (Theory Revision)
5.1 Multi-strategy Knowledge Base
Imperfect Theory of Vessels

Positive and negative examples of cups
5.2 Cooperating Learning Modules

Either (Mooney and Quinlan, 1991) (Abduction, Abduction and Empirical Induction)
Different types of input

Different types of information (e.g., facts, examples, problems, solving episodes)

Different types of knowledge and the learning goal

Determine the relationship between the input information, the background knowledge, and the type of the integrated strategies depends on the order and the type of the integrated strategies involved.

Dynamic integration of learning strategies

Generative, analogical, and empirical strategies

MLR-JT (Tečuci, 1993)

5.3 Integrating elementary inferences
II. Plant Pathology: Diagnosing soybean diseases

Correctness on test data

Training examples

0 20 40 60 80

1D3

0 20 40 60 80

0 100

Neither

Neither

Neither

Applications of either

I. Molecular Biology: Recognizing Promoters

and Splice-Junctions in DNA Sequences
Plausible Justification Tree (PJT):

climate(Tropical, Thailand),
temperature(Tropical, Thailand, SE-Asia),
rainfall(Tropical, Thailand, heavy),
soil(Tropical, Red-soil),
⇒ grows(Thailand, rice)

Positive example (P1):

Question-Answering in Geography
HIGH-LEVEL ROBOTIC PLANNING

Applications

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

LEARNING STRATEGIES

Planner based on state space search

PERFORMANCE ENGINE

PRODIGY (Carpaneto, Knapick, and Minion, 1989)

A PROBLEM SOLVING ENVIRONMENT

5.4 APPLYING LEARNING MODULES IN
Grows(x, rice)

Operational and abstract definitions of the concept

water-in-soil(x, z) \Rightarrow rainfall(x, y), terrain(x, flat).

Specialized plausible determination

soil(x, fertile-soil) \Rightarrow soil(x, red-soil).

New Rule:

water-in-soil(Pakistan, high).

water-in-soil(Thailand, high).

New Facts:

Improved KB
Common Interface

NEVId
MOBAl
KBE
APR (Disciple)

(for communication)
representation language

- a common knowledge
- a consultant
- a common interface

loosely integrated through: 10 independent ML systems

Turing Institute, GMD, Siemens, Coimbra, FortH
MLT (LR1, I2S0T, CCE-LDM, INRIA, BAE, Aberdeen, etc.)

in a uniform environment

Independent Learning Systems
The PRODIGY Architecture
Rules to Network Translator
COMPUTATIONAL STRATEGIES
5.5 APPLYING DIFFERENT

(Keunnam (Towell and Shavlik, 1991))
(Symbolic rules and neural networks)

KB ANN
(Trained Network)

Training Network

Network to Rules

KB
Symbolic
Improved

Rules to Network

KB
Symbolic
Imperfect

Examples

Initial Network

Translator

Network to Rules

Translator

KB
Symbolic
Improved
39% Splice-Junction Domain
49% Promoter Domain

3.1 4.6
N of M

1.9 4.9
KBANN

0.0 0.4
N of M

0.6 4.7
KBANN

Error Rates

Initial KB: Testing set

Training set

Error rate
$Z \rightarrow [\{A, C, F\}]$ 

(N of M rules)

Network to Rules Translator

$\text{bias} = 10.9$

$6.2 \rightarrow 10.9$

$6.1 \rightarrow 10.9$
SCALEDURING: machine-shop scheduling (PRODIGY)

PREDICTION: econometric sanctions (OCCAM)

PLANNING: high-level robot planning (PRODIGY)

MANUFACTURING: Loudspeakers (DISCIPLE)

PLANT PATHOLOGY (ETHERE)

DIAGNOSIS: mechanical trouble-shooting (ENIGMA)

TEXTURE RECOGNITION (AG-CRA, GA-AG)

CLASSIFICATION: DNA concepts (ETHERE, KBANN)

SUMMARY OF APPLICATION DOMAINS
Areas of Frontier Research

Multistrategy Task-adaptive Learning

Current Trends in Multistrategy Learning

Learning Method

Issues in Selecting a Multistrategy

Summary of Application Domains

AND FRONTIER RESEARCH

6. SUMMARY, CURRENT TRENDS
More comprehensive theories of learning

Applications of MSL systems

Integration of MSL and problem solving

Integration of MSL and knowledge acquisition

General frameworks for MSL

Dealing with incomplete or noisy examples

New ways of integrating learning strategies

Comparisons of learning strategies

CURRENT TRENDS IN MSL
Partially incorrect
- Incomplete
- Complete

Domain theory: Weak

Noisy examples
- Positive and negative examples

Input data: Positive examples only

Theory revision

Learning problem: Concept learning

MULTISTRATEGY LEARNING METHOD

SOME ISSUES IN SELECTING A
Relationship to achieve the learning goal

- Modifications DlH structures accordingly to the

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

Determines the strategy on the basis of type

MTL-DH
multitype interference

interrelated hierarchies (that facilitate)
of knowledge representation (dynamic)

• The MTL-DIH approach employs a new type

( the learning goal)

strategies to the learning task (input, BK, and
adapts the strategy or a combination of
multistrategy task-adaptive learner (MTL)

• A multistrategy task-adaptive learner (MTL)

Michalski & Hleb)

LEARNING: MTL-DIH
MULTISTRATEGY TASK-ADAPTIVE

One of new ways of integrating learning strategies
Combining computational theory of learning with inferential theory

Investigations of human learning as MSL

different forms of plausible reasoning
certainty of the learned knowledge using
development of methods for evaluating the
use learning goals in MSL
better understanding of how to represent and
learning strategies
synergistic integration of a wide range of

AREAS OF FRONTIER RESEARCH
Some power plants in New York have mechanical failures.

Special Issue on Multistrategy Learning, Machine Learning, Morgan Kaufmann, San Mateo, 1993.


References


