



AN OVERVIEW OF RESEARCH ACTIVITIES
IN THE MACHINE LEARNING AND INFERENCE
LABORATORY: 1997-1998

Edited by

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Reports

Machine Learning and Inference Laboratory

**An Overview of Research Activities in
the Machine Learning and Inference
Laboratory: 1997-1998**

(Based on the MLI Laboratory
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School of Information Technology and Engineering

George Mason University

**An Overview of Research Activities in
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Ryszard S. Michalski and Qi Zhang (Eds.)

January 5, 1998

Machine Learning and Inference Laboratory

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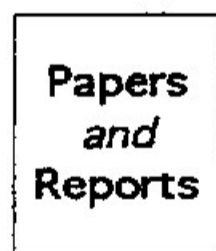
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Mission

Machine Learning and Inference (MLI) Laboratory conducts fundamental and experimental research on the development of intelligent systems capable of advanced forms of learning and inference, and applies them to real-world problems. Major research areas include the development of theories and models of learning and inference, data mining and knowledge discovery, task-adaptive intelligent agents, self-customizing tutoring system, software systems with learning capabilities, knowledge acquisition, morphogenetic systems, machine vision through learning, and integrating learning with perception. The developed systems are experimentally applied in cooperation with industry to a wide spectrum of practical problems. Application areas of special interest include engineering design, information systems, communication networks, intelligent net surfing, geographic information systems, world economy, computer vision, education and software engineering. The Laboratory supports education, scholarship and research in these areas. It has a highly international team of researchers and the state-of-the-art computer facilities.

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Major Research Projects

Research Areas

- Theories of Learning, Inference and Discovery
 - Machine Learning Systems
 - Data Mining and Knowledge Discovery in Databases
 - Machine Vision through Learning
 - Education
-

Theories of Learning, and Inference and Discovery

- Inferential Theory of Learning (Michalski, Wnek, Sklar, Alkharouf, Bloedorn, Kaufman, Utz)
 - Multistrategy Task-Adaptive Learning: MTL (Michalski, Wnek, Kaufman, Utz, Vafaie, Zhang)
 - Knowledge Representation Using Dynamically Interlaced Hierarchies (Michalski, Alkharouf, Utz)
 - Cognitive Models of Plausible Reasoning (Michalski and Sklar)
 - Learning Goals in Multistrategy Learning (Michalski and Utz)
 - Inferential Theory of Design (Arciszewski, Michalski, Wnek)
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Machine Learning Systems

- AQ18-MOR and Natural Induction (Michalski, Zhang)
- Data-driven Constructive Induction: AQ17-DCI (Michalski, Bloedorn)
- Hypothesis-driven Constructive Induction: AQ17-HCI (Michalski, Wnek)

- Multistrategy Constructive Induction: AQ17-MCI (Michalski, Bloedorn, Wnek)
 - Constructive Induction in Engineering Design (Arciszewski, Michalski, Wnek, Bloedorn)
 - Constructive Induction Approach to Growing Neural Networks (Wnek)
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Data Mining and Knowledge Discovery in Databases

- Knowledge Discovery in Databases: INLEN (Michalski, Kaufman, Ternstedt, Bloedorn, Kerschberg, Wnek, Imam, Ribeiro, Wozniak)
 - Learning Problem-Optimized Decision Trees from Decision Rules (Michalski, Imam)
 - Expert Systems with Learning Capabilities (Michalski, Kaufman, Imam, Ribeiro)
 - Significance Vector Approach to Analysis of Ultra-Large Databases (Michalski, Goshorn)
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Machine Vision through Learning

- Multi-Level Image Sampling and Interpretation: MIST Methodology (Michalski, Duric, Zhang, Maloof)
 - Machine Vision and Learning (Michalski, Duric, Maloof, Zhang, Wnek, Bloedorn) (with Computer Vision Laboratory of the University of Maryland at College Park, Rosenfeld, Aloimonos, Davis)
 - Multistrategy Learning Vision Tasks by Integrating Symbolic and Neural Net Learning for Vision Tasks (Michalski, Zhang)
 - Natural Scene Interpretation (Michalski, Zhang)
 - Target Detection in SAR Images (Michalski, Duric, Zhang)
 - Learning to Recognize Shapes (Michalski, Duric, Maloof)
 - Dynamic Recognition (Michalski, Bloedorn)
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Education

- Integrated Learning Systems for Education and Research: Emerald (Michalski, Kaufman, Lee, Wnek,

Bloedorn, De Jong, Schultz)

● Diagrammatic Visualization of Learning Processes (KV) (Michalski, Zhang, Wnek)

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Inferential Theory of Learning

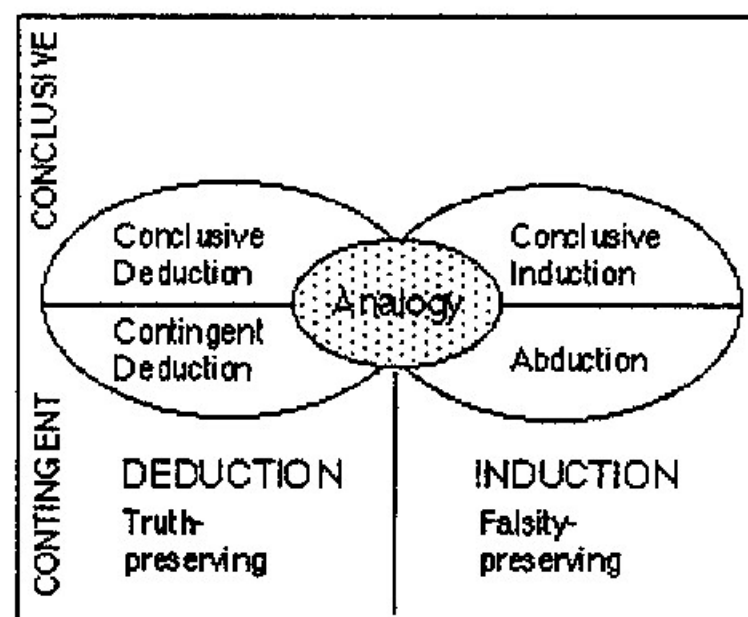
(Michalski, Wnek, Alkharouf, Bloedorn, Kaufman, Sklar, Utz)

This project aims at the development of the Inferential Theory of Learning (ITL) that views learning as a goal-oriented process of improving the learner's knowledge by exploring the learner's experience. The theory aims at understanding the competence aspects of learning processes, in contrast to the Computational Learning Theory that concerns their computational complexity. ITL addresses such questions as what types of inference and knowledge transformations underlie learning processes and strategies; what types of knowledge the learner is able to learn from a given input and from a given prior knowledge; what logical relationships exist among the learned knowledge, possible inputs and prior knowledge, etc.

The theory analyzes learning processes in terms of high level inference patterns called knowledge transmutations. Among basic transmutations are generalization, abstraction, similization, generation, insertion and replication. The central aspect of any transmutation is the type of underlying inference. If results of inference are found useful, then they are memorized. Thus, we have an "equation":

$$\text{Learning} = \text{Inferencing} + \text{Memorizing}$$

Since learning processes may involve any possible type of inference, the ITL postulates that a complete learning theory has to encompass a theory of inference. To this end, we have attempted to identify and classify all major types of inference.



A Classification of Major Types of Inference

The figure above illustrates the proposed classification. The first criterion divides inferences into deductive and inductive. To explain them in a general way, consider the fundamental equation for inference: $P \dot{\cup} BK \models C$, where P stands for premise, BK for reasoner's background knowledge, \models for entailment, and C for consequent. Deductive inference is deriving C, given P and BK, and is truth-preserving. Inductive inference is hypothesizing P, given C and BK, and is falsity-preserving.

The second classification divides inferences into conclusive (strong) and contingent (weak). Conclusive inferences involve domain-independent inference rules, while contingent inferences involve domain-

dependent rules. Contingent deduction produces likely consequences of given causes, and contingent induction produces likely causes of given consequences. Analogy can be characterized as induction and deduction combined, and therefore occupies the central area in the diagram. Using this approach, we have clarified several basic knowledge transmutations, such as inductive and deductive generalization, inductive and deductive specialization, and abstraction and concretion. Generalization and specialization transmutations change the reference set of a description, and abstraction and concretion change its level-of-detail.

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For more references, see Publication section.

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Multistrategy Task-Adaptive Learning:MTL

(*Michalski, Wnek, Kaufman, Utz, Vafaie, J. Zhang*)

This project is concerned with developing a novel methodology for multistrategy learning, based on the Inferential Theory of Learning. The proposed methodology, called multistrategy task-adaptive learning (MTL) integrates a range of learning strategies, in particular, two basic and mutually complementary learning paradigms: empirical learning and analytical learning (see Figure beside). Empirical learning assumes that the learner does not have much prior knowledge relevant to the task of learning, while analytic learning assumes that the learner has sufficient knowledge to solve the problem in principle, but that knowledge is not directly applicable or efficient. Empirical learning is based primarily on inductive inference from facts, while analytical learning is based primarily on deductive inference from prior knowledge.

Other major learning strategies that are integrated in MTL include constructive induction, analogical learning, and abstraction. Constructive induction employs background knowledge to generate problem-relevant descriptive concepts, and through them derives the most plausible inductive hypotheses. Analogical learning transfers knowledge from one problem domain to another through an analysis of similarities between concepts or problem solving methods. Abstraction transfers a description from a high-detail level to a low-detail and more goal-oriented level.

MTL postulates that the learning strategy, or a combination thereof, should be based on the analysis of the learning task at hand. A learning task is defined by the input, learner's prior knowledge and the learner's goal(s). The learning goal(s) are viewed as a central factor in controlling a learning process. This research provides foundations for building advanced learning systems, and applying them to such tasks as knowledge acquisition, planning, problem solving, intelligent robots and knowledge extraction from databases.

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For more references, see Publication section.

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Knowledge Representation Using Dynamically Interlaced Hierarchies

(Michalski, Alkharouf, Utz)

This project concerns a development of a new type of knowledge representation that facilitates all kinds of inferences and is thus particularly relevant to the development of multistrategy task-adaptive learning. Dynamic Interlaced Hierarchies (DIH) is based on psychological research into human semantic memory structure and utilizes hierarchies as its basic organizational principle. By storing new knowledge as links between hierarchically organized concepts, a conceptual framework is constructed that can represent very diverse and complex forms of knowledge as well as various knowledge transformations.

DIH uses type and part hierarchies of concepts as background knowledge, or knowledge considered to be relatively stable and unchanging. Statements or facts are stored as links between concepts and are considered dynamic knowledge, as these links are constantly being created and modified, strengthened or weakened. These links have numeric factors (or 'merit parameters') attached that affect the strength of the relationship between the various concepts. Rules and dependencies are bi-directional, each with a separate forward and backward 'strength'.

Inference patterns such as generalization/specialization, abstraction/ concretion, and similarity are easily visualized in DIH. Also these inferences are facilitated, since the procedure consists of manipulating links between hierarchies. Creating new links between concepts represents learning. In this way learning builds upon the background knowledge of the hierarchies and the dynamic knowledge already in place.

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Cognitive Models of Plausible Reasoning

(Michalski, Sklar)

The ability to reason plausibly, that is to derive useful conclusions from imperfect premises, is one of the most remarkable properties of the human mind, and a key to understanding intelligent behavior. In plausible reasoning, the premises may be incomplete, uncertain, imprecise or only partially relevant to the task. Yet, people are able to make useful conclusions from premises. The initial core theory of human plausible reasoning was developed by Collins and Michalski (1990--see see MLI publications). The goals of this research are to develop a computational theory and models of plausible reasoning, to validate the theory by experiments involving the models and human subjects, and to apply it to developing a new approach to knowledge representation, filling gaps in databases, and dynamic recognition.

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Learning Goals in Multistrategy Learning

(Michalski, Utz)

Learning arises from an intelligent individual's inability to reason and comprehend with its current knowledge. From prior research, every learning task requires background knowledge, sufficient inputs and a learning goal to achieve success. In multistrategy learning, though, the pupil faces additional complexity: here, the pupil must derive several learning goals for sequential and possibly parallel application in the learning process. The pupil must use these goals then to choose relevant inputs and necessary strategies (among several) in a timely way in order to acquire the "right" target knowledge.

The aims of this research project are twofold: (1) to experiment with a formalism to specify goals for multistrategy learning and (2) to construct a processing mechanism to generate and apply learning goals appropriately. This project is based on the MTL methodology supporting the Inferential Theory of Learning. Such a formalism must be accurate and complete to enable the processing mechanism to create explicit learning goals to understand the context, direct the procedure, and evaluate the results of multistrategy learning tasks. The formalism must be domain-independent as well as task-adaptive.

Proper specification is essential for success. Learning goals must be specified to enable an examination of any newly acquired or more efficient knowledge. When the examination indicates that the results are implausible or incompatible with the target knowledge, the process must be capable of trying again. It should reselect inputs or learning strategies on the advice of the original learning goals or, where necessary, regenerate alternative learning goals to redirect the learning task.

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For more references, see Publication section.

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Data-driven Constructive Induction: AQ17-DCI

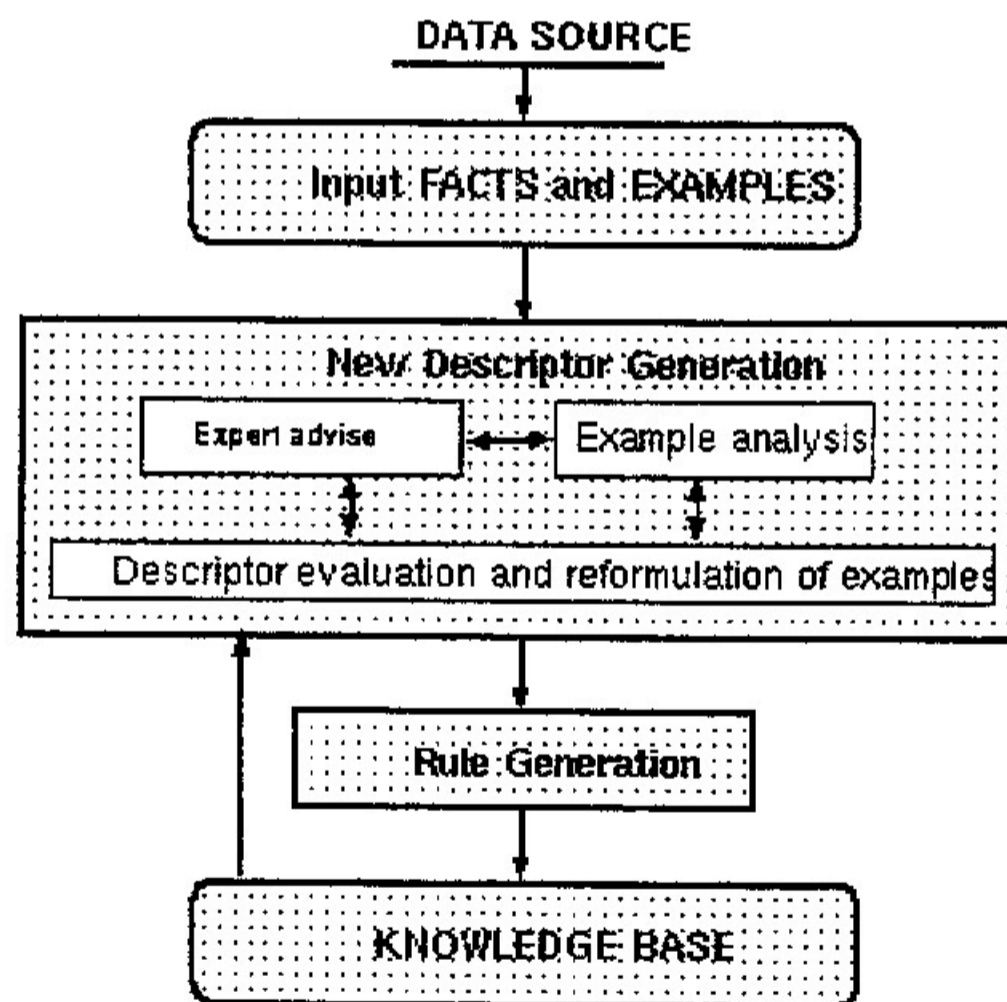
(Michalski, Bloedorn)

Most machine learning programs view the problem of learning an inductive hypothesis as a search for the "best" hypothesis in the given representation space. This works well if the problem is already well designed by some domain or machine learning expert using attributes which are relevant and simply related to the target concept.

However, finding a representation that is well suited to the problem is not a trival task. A number of different aspects have to be determined:

- 1) What attributes are relevant to the given task?
- 2) What values should those attributes take?
- 3) Are the concepts boundaries easily describable in the language and bias of the given learner?

In this project we have developed a method for automatically answering these questions. In our data-driven constructive induction approach we base decisions about the changes to make to the representation space on information and heuristics derived from the data. The data-driven approach can perform both expansions of the representation space through attribute construction, and reductions of the representation space through attribute removal, and abstraction.



A functional diagram of the DCI method. Changes to the Representation Space are based on Data and expert advise in the form of constraints provided by the user.

Data-driven constructive induction has been successfully applied to a number of different problems. These include artificial domains such as those in the 1st International Machine Learning Competition (Monk's Problems) to real-world domains involving predicting the voting pattern of members of the

House of Representatives to predicting the size of national Gross National Product (GNP) of countries around the world.

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For more references, see Publication section.

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Hypothesis-driven Constructive Induction: AQ17-HCI

(Michalski, Wnek)

Traditional concept learning methods express the learned hypothesis using descriptors that are present in describing the training examples. In other words, they learn in the same representation space in which training examples are presented. For many practical problems this is a serious limitation, because concepts to be learned require descriptors that go beyond those originally provided.

To attack such problems, a constructive induction approach splits the learning process into two intertwined searches: one-for the most appropriate representation space for the given learning problem, and second -for the best inductive hypothesis in the newly created space.

A hypothesis-driven constructive induction method changes the concept representation spaces in the process of the concept learning. The changes involve expansion and contraction of the representation space, and are based on the analysis of consecutively created inductive hypotheses.

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Buildings Using Constructive Inductive Learning", ASCE Journal of Computing in CE, Vol. 8, No. 3. July 1994. George Mason University, Fairfax, VA, 1994.

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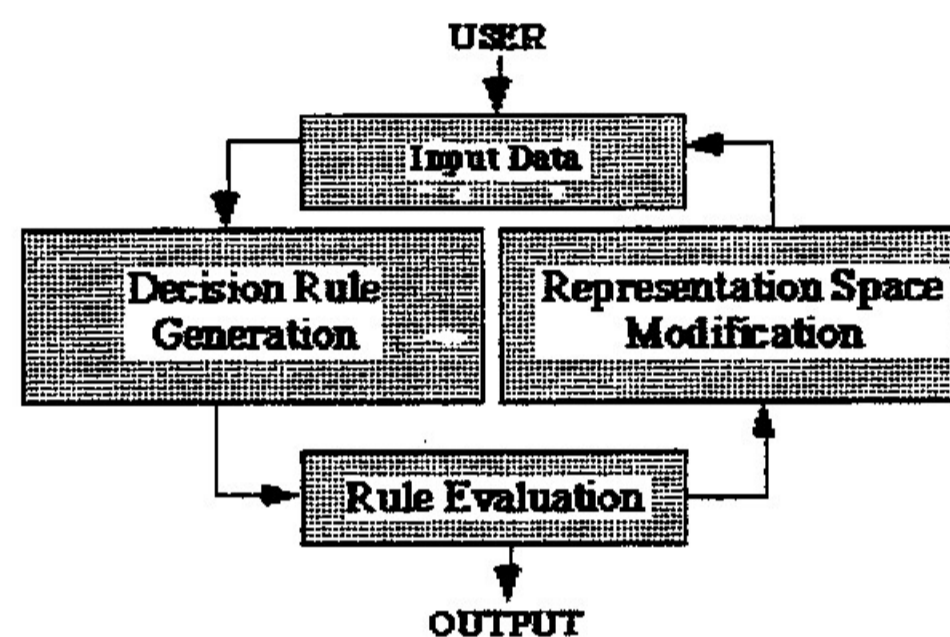
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Multistrategy Constructive Induction: AQ17-MCI

(Michalski, Bloedorn, Wnek)

Conventional concept learning techniques generate hypotheses in the same representation space in which original training examples are presented. In many learning problems, however, the original representation space is inadequate for formulating the correct hypothesis. This inadequacy can be evidenced by a high degree of irregularity in the distribution of instances of the same class in the original representation space.



A functional diagram of the AQ17-MCI program.

We have been developing a methodology and a system, AQ17-MCI, for interpreting a range of strategies for an automated improvement of the knowledge representation spaces.

The system includes three basic mechanisms: (1) for accepting expert advice about the rules and procedures for generating new attributes;

(2) for analyzing learning examples and generating new attributes as logical or mathematical functions of the original attributes (implemented in AQ17-DCI version, which stands for data-driven constructive induction)

(3) for detecting "strong patterns" in the rules generated in one iteration of the rule generation module, and then using these patterns for proposing candidate attributes for a new iteration (implemented in AQ17-HCI version, which stands for hypothesis-driven constructive induction).

The attributes generated by these mechanisms are evaluated for their relevance to the problem at hand. If they pass the relevance test, they are used to reformulate original learning examples, and the rule generation module (based on the AQ algorithm) generates new rules. The quality of the rules is determined, and those that pass the quality criterion are stored in the knowledge base.

AQ17-MCI significantly extends current machine learning capabilities, as it is capable for "multi-mechanism" improvement of the original description space. It is a powerful program that

represents a new generation of symbolic learning systems, and thus has a potential for important new applications. (See its performance on MONKS' problems, described in the project "A Comparative Study of Learning Methods.")

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Constructive Induction in Engineering Design

(*Arciszewski, Michalski, Wnek, Bloedorn*)

The ultimate objective of this project is to develop a class of constructive induction methods for the applications to engineering design and a practical methodology for their use. A feasibility study has been completed and its results presented in the research report (Arciszewski et al 1992) published at the Center for Artificial Intelligence at George Mason University and in the *ASCE Journal of Computing in Civil Engineering* (Arciszewski et al, P94-16). The study was conducted in the area of conceptual design of wind bracings in steel skeleton structures of tall buildings.

Design rules were learned from a collection of 336 examples of minimum weight (optimal) designs of wind bracings. Constructive induction was used to produce design rules which explain how design requirements can be optimally (in terms of minimum steel weight) satisfied through the proper selection of individual components of a wind bracing structural system. All examples were prepared under identical design assumptions for a three-bay skeleton of a tall building in cooperation with practicing structural designers. Actual minimum-weight designs were produced using SODA, a computer system for optimization, analysis, and design of steel structures. The design rules obtained were divided into four classes corresponding to the value of the decision attribute: recommendation, standard, avoidance and infeasibility rules.

Two types of constructive induction have been used in the study: data-driven and hypothesis-driven constructive induction. The performance of both learning systems was formally measured by two empirical error rates: 1. the overall empirical error rate, 2. the omission error rate in accordance to the method of evaluation of performance of learning systems developed at the Laboratory and published in Arciszewski et al (1994). These error rates were calculated for the entire collection of examples using the leave-one-out resampling method. The error rates for constructive induction were compared with rates for the "traditional" induction, based on the use of the AQ15 algorithm. The individual error rates are shown in the table below. There is a significant improvement in performance (more than 50%) between the system based on the "traditional" induction and systems based on constructive induction. The difference in performance between two constructive induction-based systems is insignificant (less than 5%), but this may change as the research progresses.

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Constructive Induction Approach to Growing Neural Networks

(Sazonov, Wnek)

With most symbolic machine learning methods, if the given knowledge representation space is inadequate then the learning process will fail. This is also true with neural networks learning based methods. To overcome this limitation, a method for automatically "growing" neural network is being developed.

The BP-HCI method is a hypothesis-driven constructive induction for neural networks trained by the backpropagation algorithm. The method determines topology of a neural network and the initial connection weights based on patterns in the behavior of the neural network. The behavior of the neural network is captured by concepts called ACCORD and ANXIETY of a neural network.

The method was successfully applied to ten problems including such problems as learning t"exclusive-or" function, MONK2, parity-6BIT and inverse parity-6BIT.

Selected References

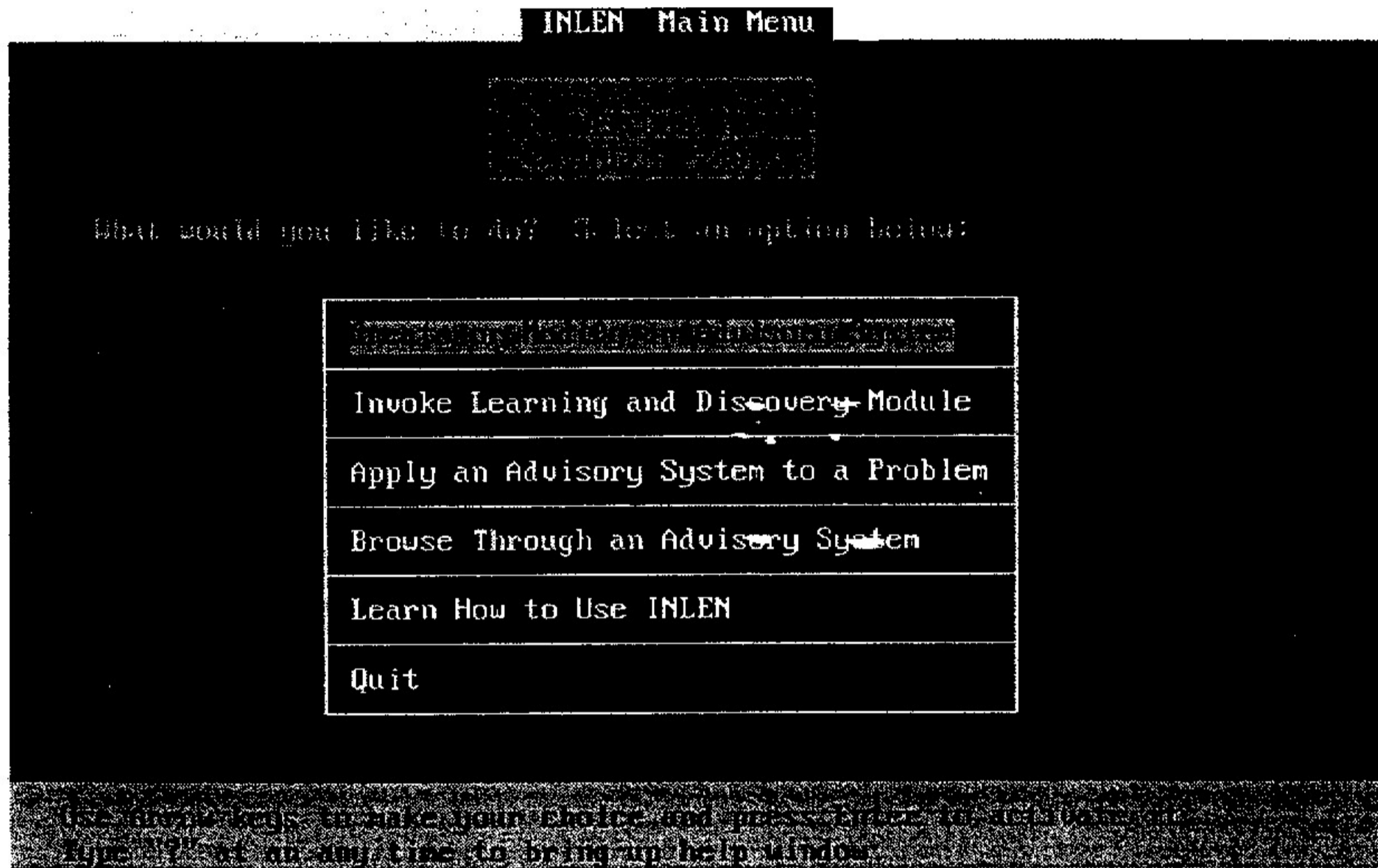
Sazonov, V.N. and Wnek, J., "Hypothesis-driven Constructive Induction Approach to Expanding Neural Networks," *Working Notes of the ML-COLT'94 Workshop on Constructive Induction and Change of Representation*, New Brunswick, NJ, July 1994.

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Knowledge Discovery in Databases: INLEN

(Michalski, Kaufman, Mitchell, Kerschberg, Bloedorn, Wnek, Imam, Ribeiro)



This project is concerned with the development of a large-scale multi-type reasoning system, called INLEN, for extracting knowledge from databases. The system assists a user in discovering general patterns or trends, meaningful relationships, conceptual or numerical regularities or anomalies in large databases. The volume of information in a database is often too vast for a data analyst to be able to detect such patterns or regularities. INLEN integrates symbolic learning and statistical techniques with database and knowledge base technologies. It provides a user with "knowledge generation operators" (KGOs) for discovering rules characterizing sets of data, generating meaningful conceptual classifications, detecting similarities and formulating explanations for the rules, generating rules and equations characterizing data, selecting and/or generating new relevant variables or representative examples, and testing the discovered rules on new data.

KEY	DECISION	EXAMPLES
VAR.	Region	17. Middle East, 18. South Africa
TYPE	normal	1000
#134	Saudi Arabia	Middle East
135	Senegal	West Africa
136	Seychelles	Indian Ocean
137	Sierra Leone	West Africa
138	Singapore	SE Asia
139	Solomon Islands	SE Pacific
140	Somalia	East Africa
141	South Africa	South Africa
142	Spain	South Europe
143	Sri Lanka	South Asia

PgUp	- Page up	F1	- Insert row	F6	- TYPE/CHR	F10	- Scan values
PgDn	- Page down	F2	- Insert column	F7	- Jump to decision	^F10	- Reverse Scan
Ctrl→	- Page right	F3	- Grab word	F8	- Jump to variable	F11	- Keys On/Off
Ctrl←	- Page left	F4	- Grab row	F9	- Edit domain		
		F5	- Grab column				

A screen in which the user may examine or modify the data set to be learned from. In this dataset each example describes a separate country. The Key field provides the country name (which is not learned from), and the values for the other attributes are presented in spreadsheet form

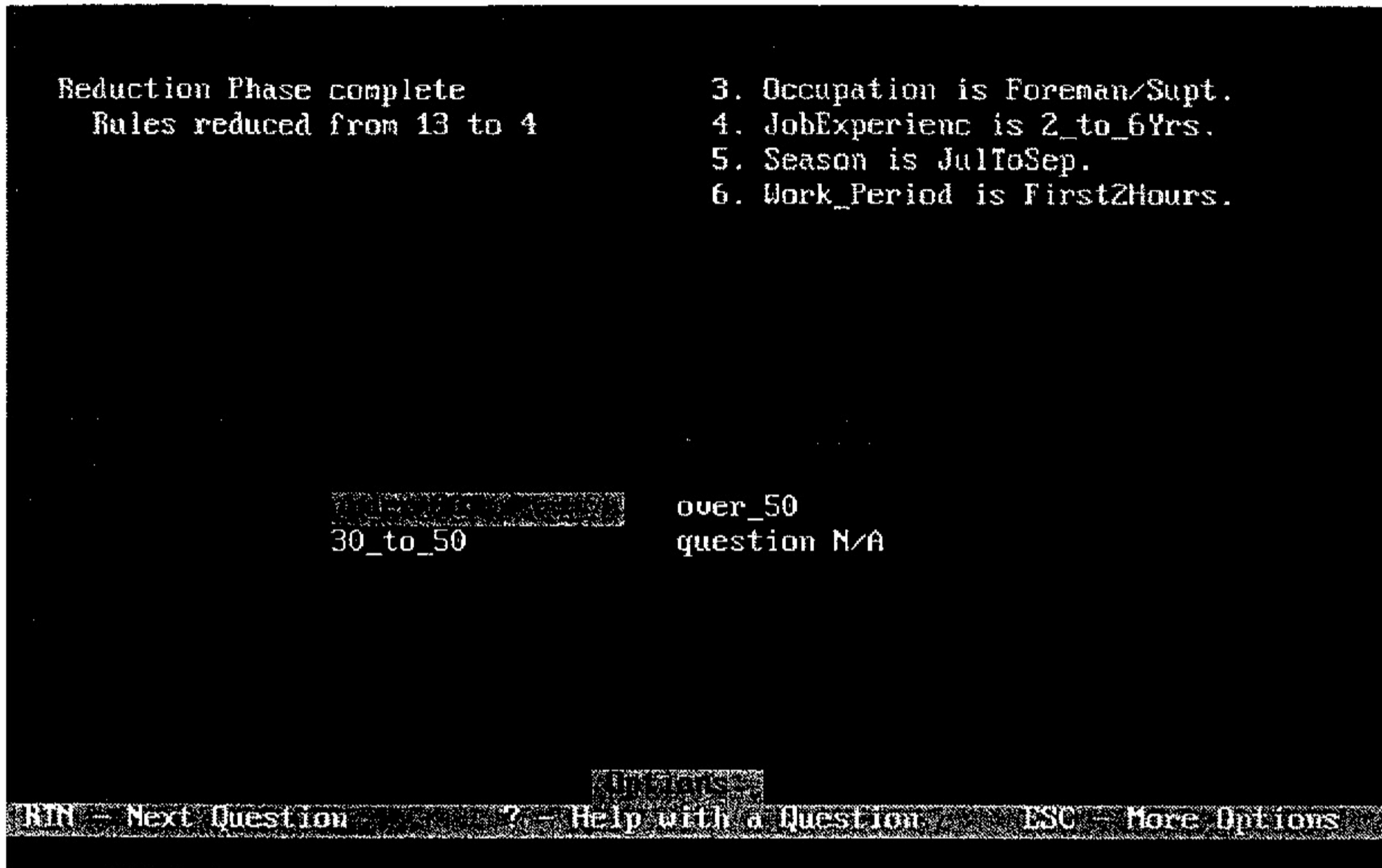
A.1. AccidentDesc is Heat/Cold or HitByFgmMtr or FallingObj or FallFromHt or AutoAccident or ElecShock,
2. Occupation is_not Foreman/Supt or Boiler/Pipe or Laborer,
3. Season is_not JulToSep,
or
B.1. AccidentDesc is Heat/Cold or Machine or HitByFgmMtr or FallingObj or FallFromHt or ElecShock,
2. Season is JanToMar or OctToDec,
3. JobExperienc <= 2_to_6Yrs,
or
C.1. Hour_of_Day is PM,
2. Season is AprToJun or OctToDec,
3. InjuryType is_not Infect/Infln,

PgUp - Previous Page PgDn - Next Page

? - Select a rule to view ESC - Other options
F1 - Example window on/off

GROUP	POSITIVE	NEGATIVE
14	1	73
15	7	29
16	8	44
17	14	85

A screen displaying rules learned from an example set. In this example the rules are displayed which describe the conditions under which eye injuries have occurred on a construction site. The numbers of examples supporting each part of the rules are measured in the columns on the right.



An example screen from the INLEN Advisory Module, in which a user may be assisted in making a decision or can speculate on unknown data. The current question for the user is displayed in the middle of the screen, and INLEN's current best hypotheses are displayed in the top right.

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Learning Problem-Oriented Decision Structures from Decision Rules

(*Michalski, Imam*)

This project is concerned with learning problem-optimized decision trees from rules. A standard approach to determining decision trees is to learn them from examples. A disadvantage of this approach is that once a decision tree is learned, it is difficult to modify it to suit different decision making situations. Such problems arise, for example, when an attribute assigned to some node cannot be measured, or there is a significant change in the costs of measuring attributes or in the frequency distribution of events from different decision classes. An attractive approach to resolving this problem is to learn and store knowledge in the form of decision rules, and to generate from them, whenever needed, a decision tree that is most suitable in a given situation.

An additional advantage of such an approach is that it facilitates building compact decision trees, which can be much simpler than the logically equivalent conventional decision trees (by compact trees are meant decision trees that may contain branches assigned a set of values, and nodes assigned derived attributes, i.e., attributes that are logical or mathematical functions of the original ones). The project describes an efficient method, AQDT-1, that takes decision rules generated by an AQ-type learning system (AQ15 or AQ17), and builds from them a decision tree optimizing a given optimality criterion.

The method can work in two modes: the standard mode, which produces conventional decision trees, and compact mode, which produces compact decision trees. The preliminary experiments with AQDT-1 have shown that the decision trees generated by it from decision rules (conventional and compact) have outperformed those generated from examples by the well-known C4.5 program both in terms of their simplicity and their predictive accuracy.

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For more references, see Publication section.

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Intelligent Agents with Learning Capabilities

(Michalski, Kaufman, Imam, Ribeiro, Wnek)

Standard expert systems do not have learning capabilities. Their knowledge bases are built entirely by hand-encoding of an expert's knowledge. Such a process is time-consuming and prone to error. This project is concerned with the development of a PC-based expert system shell with learning capabilities. The system incorporates a knowledge base for storing rules and a data base for storing facts and examples. It has a learning program for rule acquisition, and a powerful inference mechanism.

The project is based on our earlier experience with ADVISE and AURORA systems. ADVISE is a large-scale inference system with rule learning capabilities and multiple control schemes. The system served as a laboratory for experimenting with methods for knowledge acquisition, multiple knowledge representation and machine learning. Aurora is a PC-based inference system, and an expert system shell that incorporates a program for incremental rule learning and improvement.

A related project concerns a method for discovering qualitative and quantitative models from data characterizing the behavior of a system. This method builds upon our experience with the ABACUS system for quantitative discovery. The current system is capable of determining a set of equations that fit a given set of datapoints, and a set of symbolic descriptions characterizing preconditions for the application of these equations. ABACUS integrates methods for data-driven quantitative discovery, concept learning from examples and conceptual clustering. This research has applications in building advanced expert systems and discovering quantitative and qualitative regularities in data. This project is being done in collaboration with AGH.

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Machine Vision and Learning

(Michalski, Duric, Zhang, Maloof, Bloedorn)

The goal of this project is to develop methods and experimental vision systems that are capable of learning general visual concept descriptions from specific observed objects, and then use these descriptions to efficiently recognize new objects in a visual scene. It is assumed that the system should be able to recognize objects among other objects in a scene under a variety of conditions, such as changing viewpoints, changing illumination, object overlap, and in the presence of noise in the sensory data.

Our approach is based on a two-pronged architecture in which the first prong processes the surface information about objects, and the second prong processes the shape information. Learning unique surface characteristics ("surface signatures") involves problem-oriented transformations of the representation space, and an iterative application of an inductive learning program. The input to the system are classified samples of surfaces.

In the object recognition phase, the system applies the learned rules to identify the surface, and then uses this information to generate a set of candidate hypotheses about the object's identity.

These hypotheses are then employed to retrieve specific 3D structural models of the objects from a knowledge base. We use CAD/CAM descriptions of objects to discover their characteristic structural and symbolic features and feature relations, and to learn recognition strategies. These processes are also driven by vision tasks, such as localization, recognition and inspection. Learned models are then used to determine characteristics of objects sufficient to identify the object in the scene. These discriminatory characteristics are determined by a process called dynamic recognition.

The research on this project is conducted in collaboration with the Computer Vision Laboratory of the University of Maryland.

Our laboratory, in collaboration with the UMD Computer Vision Laboratory, organized the NSF/ARPA workshop on Machine Vision and Learning. The workshop was held in Harpers Ferry, WV, in October 15-17, 1992. It was the first workshop that brought together leading researchers in computer vision and machine learning. Below is a reference to the report that was partially based on this workshop and partially based on new material:

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Multi-Level Image Sampling and Interpretation: the MIST Methodology

(Michalski, Duric, Zhang, Maloof)

The goal of this project is to develop a general system (an environment) that allows a user to experiment with different methods and algorithms for learning descriptions of visual objects (images of objects, visual scenes, scene sequences, etc.), and to use these descriptions to recognize unknown objects or interpret new scenes. The underlying methodology for this purpose is called *multi-level image sampling and interpretation* (MIST).

The basic idea of MIST can be explained as follows. Given an image with labeled samples of different visual concepts (e.g., objects, textures, image areas), the learning system determines a sequence of operators that transform the image to an *annotated symbolic image* , briefly, ASI. In an ASI, picture elements are labels of indicating visual concepts. A sequence of operators that produces such a *target* ASI serves as an image description ("signature"). The central part of such an image description is a VL1 logical expression (a set of VL1 rules; where VL1 stands for the variable-valued logic attributional calculus one) that represents a symbolic characterization of the image samples of this visual concept.

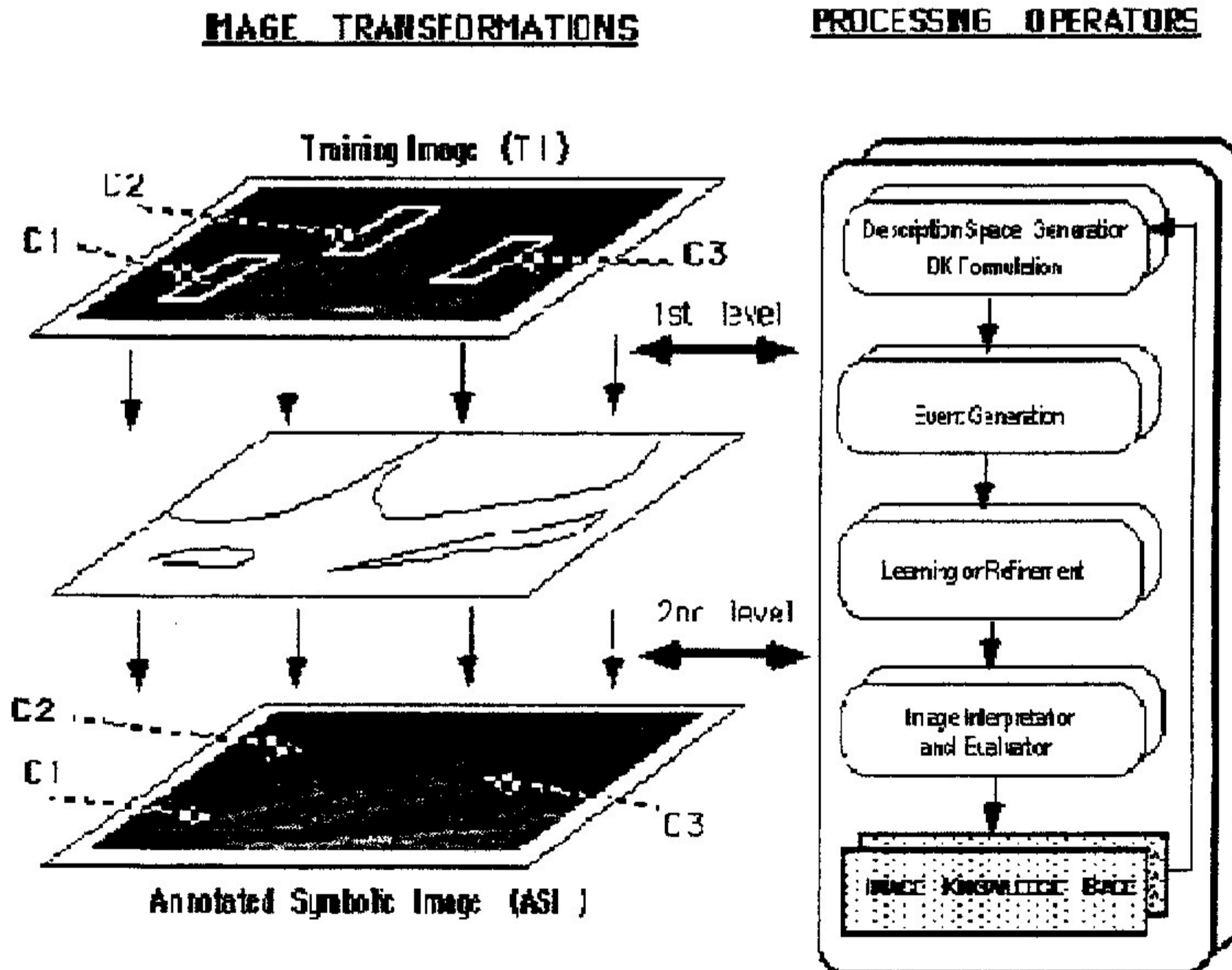


Figure 1. The MIST Training Mode

The VL1 rules can be applied sequentially or in parallel. They can be viewed as "logical templates" that are matched against "events" (attribute vectors) representing single "windows" in image samples. To interpret a new image sample, the system matches it with all candidate signatures, and determines the best match (e.g., the highest number of votes). Thus, even if some events in a sample are incorrectly recognized, the classification of the sample may be correct.

The MIST methodology is illustrated and formalized in Figures 1 and 2 and the following paragraphs.

The MIST methodology works in two basic modes: Training mode and Interpretation mode. In the Training mode, the system builds or updates the Image Knowledge Base (IKB) that contains visual concept descriptions, and the background knowledge relevant to image interpretation. A description (or model) of a visual concept is developed by inductive inference from concept examples specified by a trainer. Concept descriptions are arranged into procedures defining sequences of image transformation operators.

In Interpretation mode, a learned (or predefined) image transformation procedure is applied to a given image in order to produce an Annotated Symbolic image (ASI). In an ASI, areas that correspond to the location of concepts in the original image are marked by symbols (e.g., colors) denoting these concepts, and linked to concept annotations (text containing additional information about that concept, such as, degree of certainty of recognition, properties of the concept, relation to other concepts, etc.). The following paragraphs describe these two modes in a greater detail.

A. The Training Mode

This mode (Figure 1) is executed in four phases: LP1-Description Space Generation and Background Knowledge Formulation, LP2-Event Generation, LP3-Learning or Refinement, and LP4-Image Interpretation and Evaluation.

These four phases may be repeated iteratively creating images at different levels (Figure 1 shows just two levels).

LP1: Description Space Generation and Background Knowledge Formulation

A trainer assigns concept names to areas in the image(s) that contain objects (concepts) to be learned. These areas are divided into training and testing areas. Objects to be learned are presented in different poses and with different appearances (by changing perceptual conditions) so that the system can learn a description that is invariant to conceptpreserving transformations. The trainer also defines the initial description space, i.e., initial attributes and/or terms to be measured on image samples, specifies their value sets and their types (measurement scale). This phase also involves an optimization of the image volume, that is, a reduction of the image resolution and intensity levels (the hue and saturation in color images) accordingly to the needs of the given problem.

The trainer may also define constraints on the description space, initial concept recognition rules, and possibly forms for expressing the descriptions (e.g., conjunctive rules, DNF, the structure of the neural net, etc.). Procedures for the measurement of attributes/terms are selected from a predefined collection.

LP2: Event generation

Using chosen procedures, the system generates initial training examples (Rtraining eventsS) from each concept area. Concept areas are sampled exhaustively or selectively.

LP3: Learning or Refinement

The system applies a selected machine learning program to training examples to generate a concept description. Currently, we have the following programs available: AQ15c-for learning general symbolic rules from examples, NN-a neural net learning with backpropagation, and AQ-NN-a system that integrates AQ rule-learning with neural net learning[Zurada 1992].

LP4: Image Interpretation and Evaluation

The developed descriptions are applied to the testing areas to generate an Annotated Symbolic Image (ASI). In ASI, the areas corresponding to given concepts are marked by symbols representing these concepts (numbers, colors, etc.). These areas are also linked to texts that include additional information about concept descriptions. The quality of generated descriptions is determined by comparing the ASI with testing areas in the original image. Depending on the results, the system may stop, or may execute a new learning process (iteration), in which the ASI is the input (hence the term RmultilevelS in the name of the methodology). If the generated descriptions need no further improvement, the process is terminated. This occurs when the obtained symbolic image is Rsufficiently closeS to the target image labeling (indicating the RcorrectS labeling of the image). Complete object descriptions are sequences of image transformations (defined by descriptions obtained in each iteration) that produce the final ASI. Learning errors are computed by comparing the target labeling (made by the trainer) with learned labeling (produced by the system).

B. The Interpretation Mode

In this mode (Figure 2), the system applies descriptions from the Image Knowledge Base to semantically interpret a new image. To do so, the system executes a sequence of operators (defined by the description) that transform the given image into an ASI.

A given "pixel" in ASI is assigned a class on the basis of applying operators to a single event, or to a sample of events and applying a majority voting schema (typically within a 3x3 window). In ASI, different concepts are denoted by different colors and/or textures. The simplest form of annotation is to associate the degree of confidence with the ASI pixels denoting a given concept.

Advantages of the MIST methodology include the ease of applying and testing diverse learning methods and approaches in a uniform manner, the potential for implementing very advanced and complex learning processes, the possibility for parallel image interpretation, and the ease of testing the accuracy and the performance of the methods.

The current MIST methodology has been implemented with the following learning systems:

- Symbolic rule learning program AQ15c [Michalski et al., 1986].
- Multistrategy learning system, AQ-NN, that combines AQ rule learning with neural net learning [Michalski et. al., 1993; Michalski et. al., 1996].
- Multistrategy learning that combines rule learning with a genetic algorithm
- Class similarity-based learning for building descriptions of large numbers of classes (PRAX).

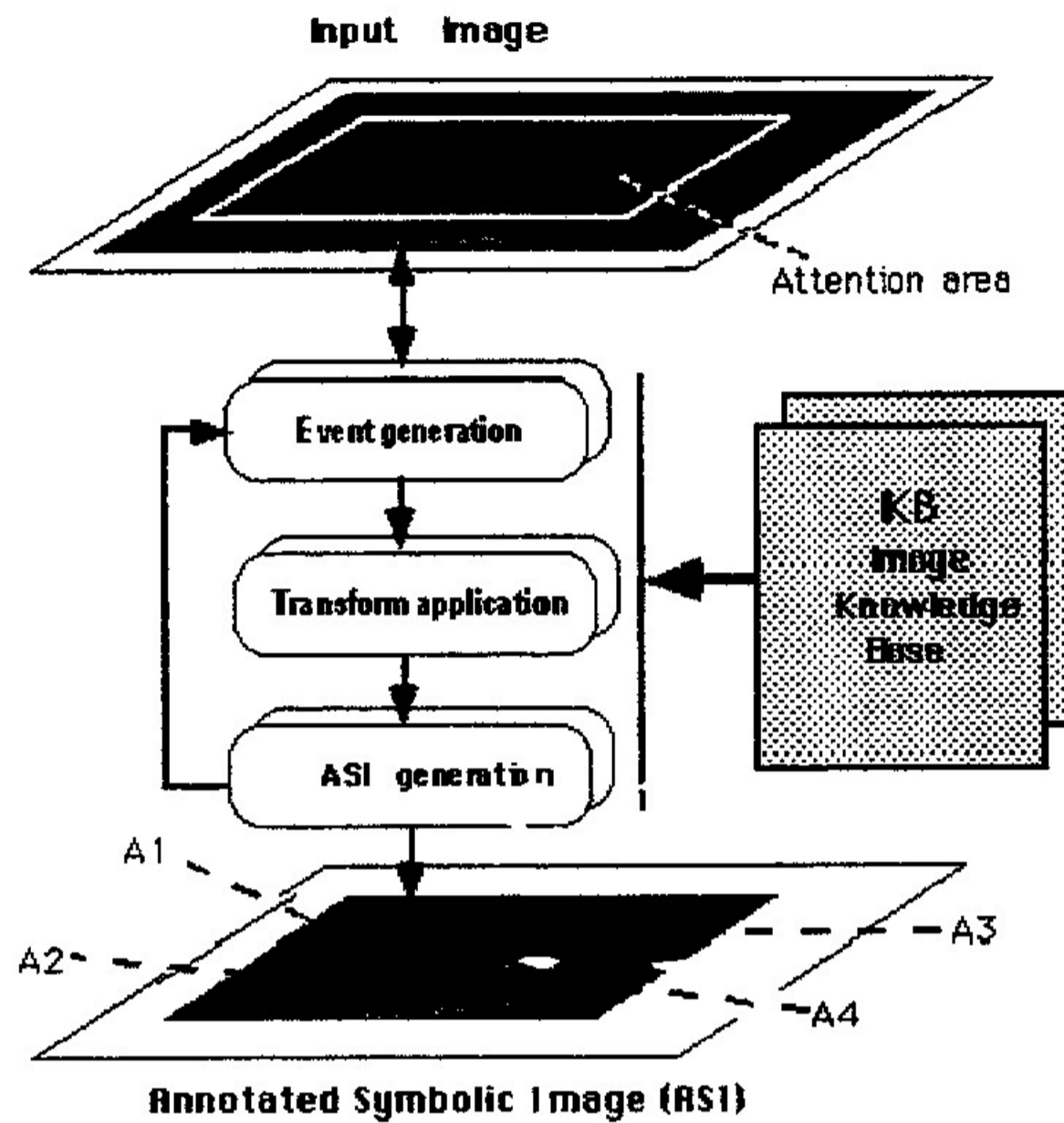


Figure 2. The MIST Interpretation Mode

A series of experiments have been conducted, in which various factors have been gradually changed, such as the image complexity, the amount of noise, and external conditions. The images used for experiments included: images of office environments, outdoor scenes, medical images, textures, human faces, blasting caps, etc.

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For more references, see Publication section.

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Multistrategy Learning in Vision: Integrating Symbolic and Neural Net Learning for Vision Tasks

(Michalski, Zhang)

The project concerns the development of a novel multistrategy learning methodology that is specifically oriented toward vision learning. The methodology combines symbolic rule learning and neural-based learning strategies in order to achieve high efficiency and accuracy in learning visual object descriptions, and in applying these descriptions to rapid object recognition.

The initially developed vision system has several advantages: it can be easily modified and applied to new problems (due to learning), its learning speed can be at least an order of magnitude faster than neural net learning (due to symbolic pre-structuring of the net), it has short recognition times (due to its parallel architecture), and its underlying recognition rules are easy to understand by a human operator (due to the symbolic knowledge representation of the basic decision rules). The developed system was experimentally applied to natural scene recognition.

The method works in two stages: 1) rule learning using the AQ algorithm. This phase generates rules that generally and approximately describe the training examples, 2) neural net learning to determine the final visual concept description. The network is structured according to the rules obtained in stage. Each node in the hidden-layer of the network corresponds to a single rule. The degree of match of an example to the rule represents node activation. This activation value is input to the sigmoid transfer function associated with each node. Weight values for the connections between nodes and outputs are obtained using backpropagation method.

Selected References

Michalski, R.S., Zhang, Q., Maloof, M.A. and Bloedorn, E., The MIST Methodology and its Application to Natural Scene Interpretation, *Proceedings of the Image Understanding Workshop*, Palm Springs, CA, February, 1996.

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Natural Scene Interpretation

(Michalski, Zhang)

The goal of this project is to apply the MIST methodology (see a description of the MIST project) for a semantic interpretation of outdoor scenes. For this purpose, we developed a set of image processing modules that extract attributes that are potentially useful for characterizing visual scenes. In one of the experiments, we used a collection of images representing selected mountain scenes around Aspen, CO (Figure 1).



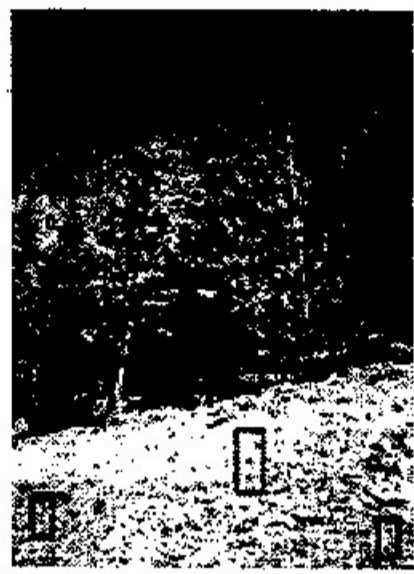
Figure 1. A typical image of a natural scene used in the experiments.

The input to the learning process was a training image in which selected examples of the visual concepts to be learned have been labeled by a trainer. Visual concepts included the tree area, the sky area, the road, the ground area and the grass area. We experimented with different sets of attributes defining the description space, with images obtained under different perceptual conditions, with different sizes and locations of training areas, and different sources of training and testing image samples (from different parts of the same image area, from different areas of the same image, from different images).

In the experiments described here, the description space was defined by such attributes as: hue, saturation, intensity, horizontal and vertical lines, high frequency spot, horizontal and vertical V-shape, and Laplacian operators. These attributes were computed for the 5x5 windowing operator (sample size) that scanned the training area. Vectors of attribute values constituted training events. Three learning methods were used: AQ15c, AQ-NN, and NN. Three different training areas were used: 10 x 10, 20 x 20, and 40 x 40 pixels. The validation methodology used here was a hold-out method in which a random selection of 60% of the samples from the training area were used for training, and the remaining 40% were used for testing. The learning process produces a sequence of operators that transform the original image into an *annotated symbolic image* (ASI) that closely matches the *target ASI*. In the image interpretation mode, the system applies the learned operator sequences to an unknown image, and produces an ASI, which represents a conceptual interpretation of the scene.

Figure 2 presents an example of the training image, and ASIs (annotated symbolic images) obtained from

applying the learned one-level descriptions to the whole image using two different evaluation schemes. As one can see in Figure 2c, most of the areas in the whole image were correctly interpreted, although the system learned concept descriptions from relatively small training areas (Figure 2a). In this experiment, the AQ-NN method (a combination of AQ and neural net) produced a slightly smaller neural net, and the interpretation of the image was about 50% faster than with the neural net (NN) method alone.



(a) An image with training areas for sky, tree, and ground.



(b) ASI based on the single-event evaluation scheme.



(c) ASI obtained using a majority voting scheme.

Figure 2. An example of the image interpretation process based on the operator sequences learned from a training image.

We also tested the application of the data-driven constructive induction method, AQ17-DCI to this problem. One of the interesting results for this experiments was a set of new, constructed, attributes for natural scenes description [Bloedorn et al., 1993].

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Michalski, R.S., Zhang, Q., Maloof, M.A. and Bloedorn. E., The MIST Methodology and its Application to Natural Scene Interpretation, *Proceedings of the Image Understanding Workshop*, Palm Springs, CA, February, 1996.

Bloedorn, E., Wnek, J., Michalski, R. S., and Kaufman, K., "AQ17--A multistrategy learning system: the method and user's guide," *Reports of the Machine Learning and Inference Laboratory*, MLI 93-12, George Mason University, Fairfax, VA. 1993.

Bala, J. and Michalski, R.S., "Learning Texture Concepts Through Multilevel Symbolic Transformations," *Proceedings of the Third International Conference on Tools for Artificial Intelligence*, San Jose, CA, November 9-14, 1991.

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Target Detection in SAR Images

(Michalski, Duric, Zhang)

This project concerns an application of the MIST methodology (see a description of the MIST project) to automatic target detection. In our experiments, SAR images were obtained from the MIT Lincoln Laboratory (they were collected in Stockbridge, New York). The method we developed was very successful in target detection. The architecture of our system is presented in Figure 1.

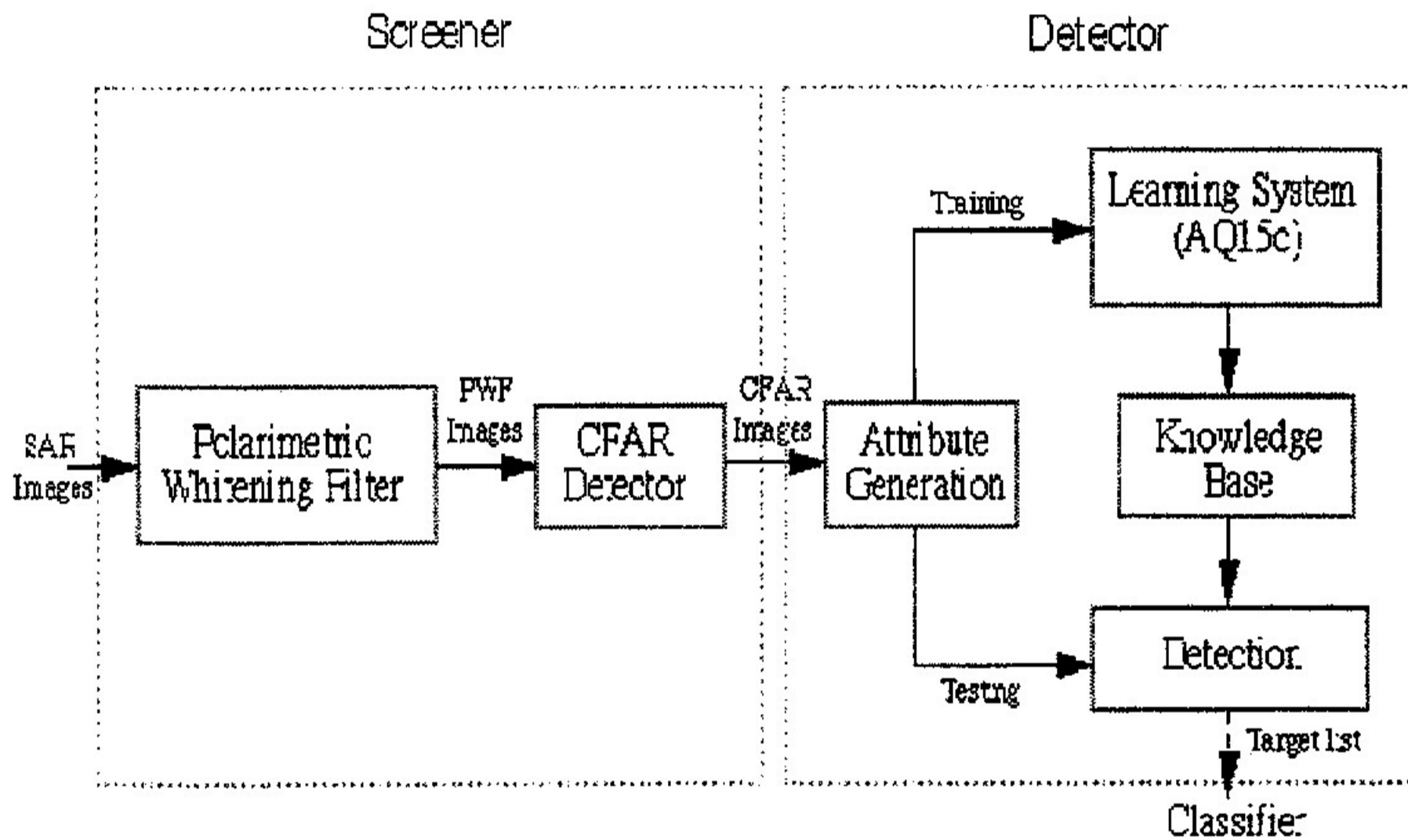


Figure 1. MIST/AQ system.

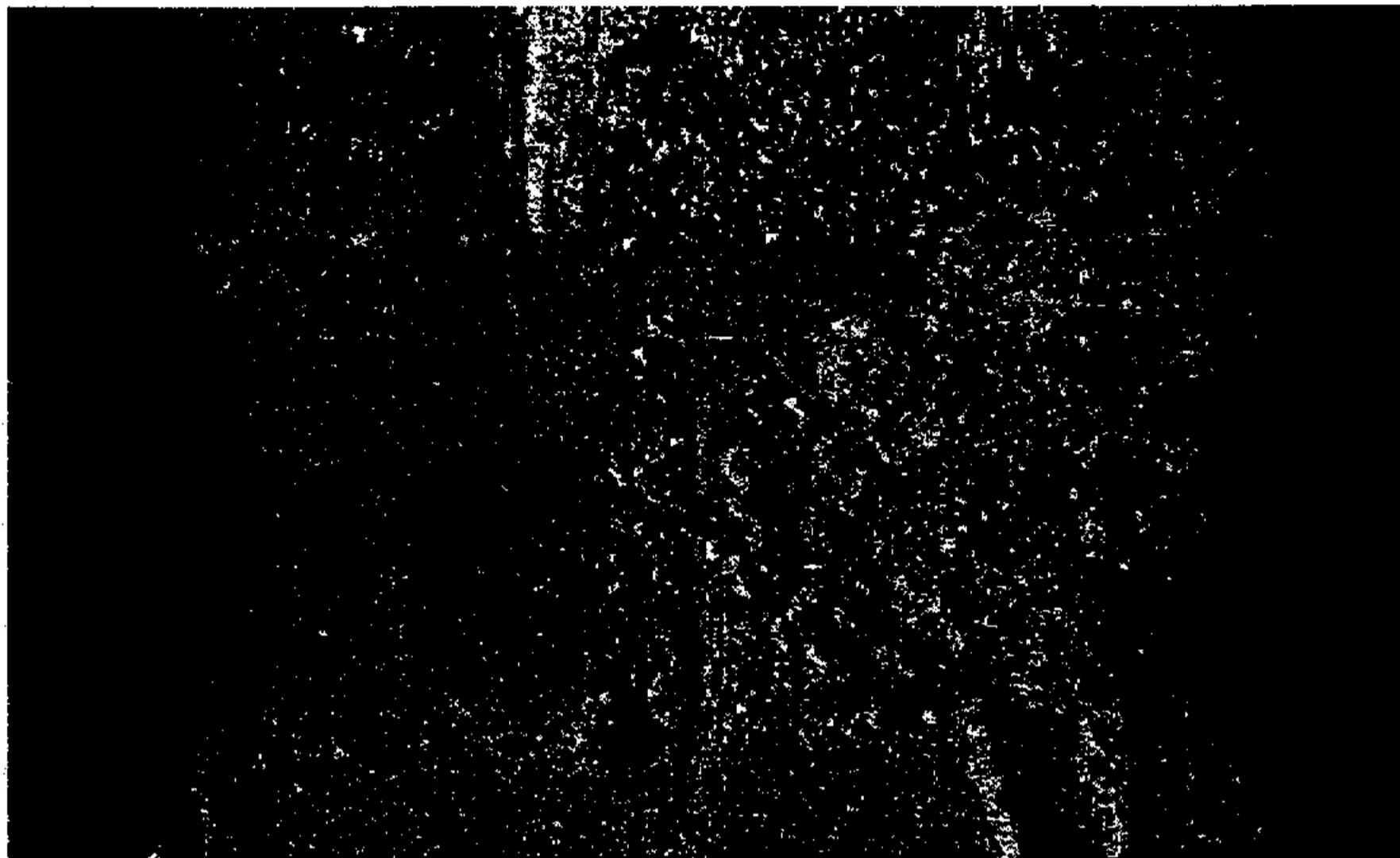
Due to the coherent nature of the SAR imaging process, there is a considerable amount of speckle (i.e., noise) in SAR images. The technique called the polarimetric whitening filter (PWF) (Novak et al., 1990), which combines the HH, HV, and VV channels from fully polarimetric SAR data, improves image quality in two aspects: minimization of the amount of speckle and sharpening the edges of objects in the images. We implemented this filter in our experiments with the image resolution preserved, which is crucial for target detection and recognition.

Various constant false rate alarm (CFAR) algorithms (e.g., Ravad & Levanon, 1992; Armstrong et al., 1991; Wang et al., 1994) have been used for screening purpose (though often called detectors), i.e., massively removing natural clutter (grass, trees etc.) and detecting potential targets in SAR images by examining intensities of radar returns. However, usually many false alarms (i.e. false targets) pass the screening by a CFAR detector. Consequently, a target detection phase is necessary to remove them before providing the target recognition phase with a list of potential targets/objects.


Each pixel that passed the CFAR detector is an example (or an event). For each example, attribute values are generated. Each attribute is defined on a small area either in a CFAR image or in its PWF

image, both of which can provide information about examples. Two circular areas were used in this work, one with diameter = 21 pixels and the other 31 pixels. For each example, these attributes were extracted from these two circles centered at this example: power, power deviation, fractal dimension, area size, weighted-rank fill ratio. The generated examples are input to AQ15c learning system to perform training and detecting.

Here are some examples.



(a)

Frame 1  Ground truth unknown

	Ground truth	2	4
Frame 2	M60-tank	:2,11	7
	M48-tank	:3,7,9	3
	M84-APC	:4,10	8
	M113-APC	:6	6
	M59-APC	:12	5
	M55-howitzer	:5,8	9

Frame 3

10 11 12

Testing

(b)

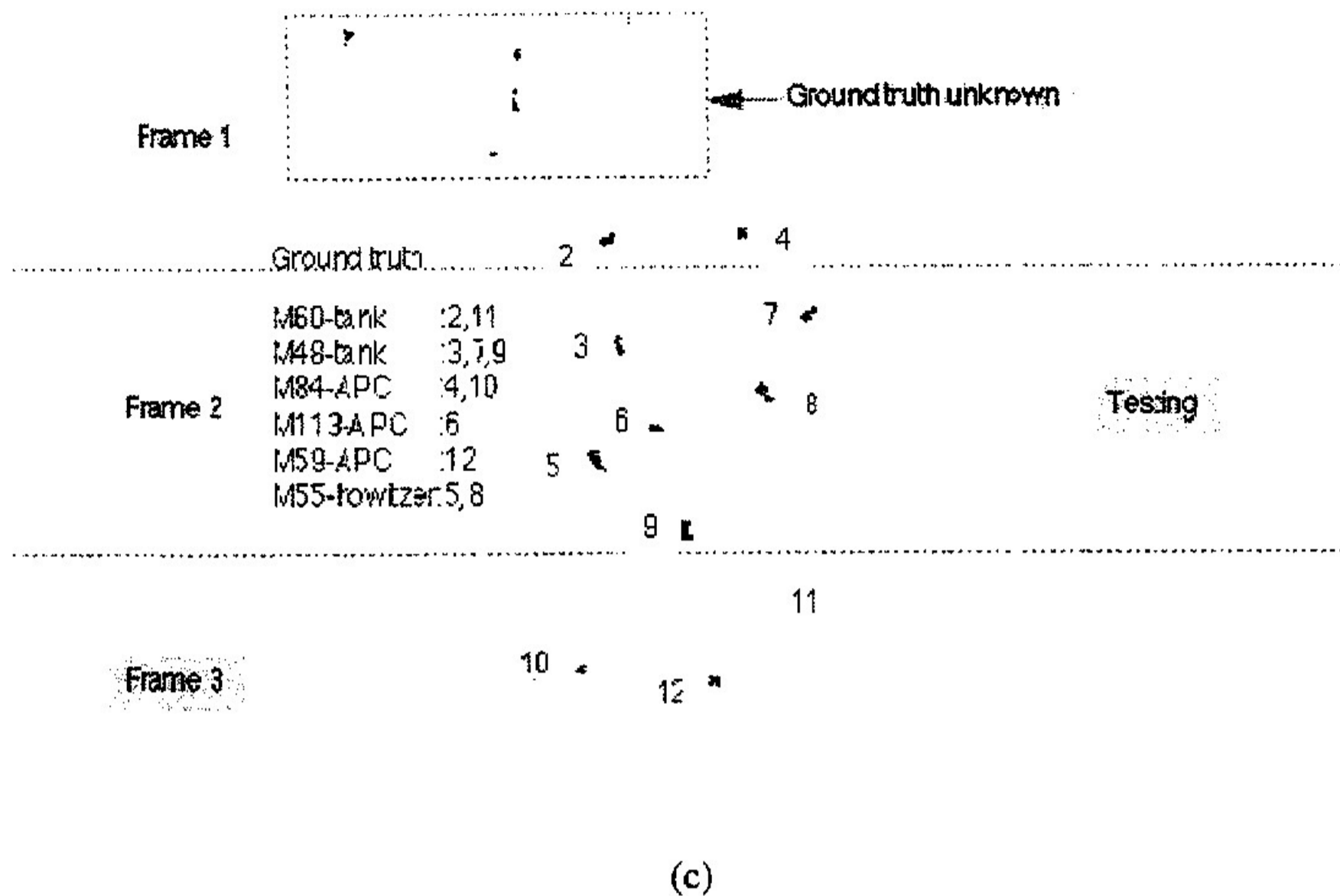


Figure 2. Pass 7: (a) the PWF image; (b) the CFAR image; (c) detection results by the MIST/AQ system.

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For more references, see **Publication section**.

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Learning to Recognize Shapes

(Michalski, Duric, Maloof)

The goal of this research is to apply inductive learning methods to problems of 2D shape recognition under highly variable perceptual conditions. The multilevel logical template (MLT) methodology is being used to detect blasting caps in x-ray images of luggage. An intelligent system capable of quickly and reliably performing this task could be used to assist airport security personnel in baggage screening.

We have acquired x-ray images of luggage containing blasting caps that appear at differing degrees of occlusion and at various orientations with respect to the x-ray source. Task-oriented image transformations are used to segment blasting caps and other objects, and to extract training events, which are vectors of attribute values. These training events serve as input to the learning process which induces descriptions of shape that are robust with respect to planar rotation and translation and partial occlusion. Induced shape descriptions can be used to recognize unknown objects.

Various symbolic, non-symbolic and statistical learning approaches are being investigated for acquiring descriptions of shape, including AQ15c, neural networks, and k-nn. These learning approaches are compared using predictive accuracy, and learning and recognition time. Experimental results have demonstrated strong advantages of AQ15c over neural networks and k-nn. AQ15c also has the advantage of producing comprehensible symbolic descriptions that can be optimized by either a human or by a machine process in post-learning phases.

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Dynamic Recognition

(Michalski, Bloedorn)

Any recognition process involves making a connection between a concept representation stored in the system's memory and a stream of observational data. Present recognition systems attempt to recognize objects by matching descriptions with the data stream. If the input data satisfies rules characterizing an object, the object is recognized. To implement such a system for practical tasks, a very large number of rules may be required.

This aspect severely limits present recognition systems, as it prevents them from being applied to the recognition of a large number of objects. In contrast to this approach, humans can recognize objects from a great variety of different cues, without "matching" rules. For example, they can recognize a known person from seeing a face, a silhouette, the characteristic way of walking, hearing the person's voice, or even from observing the person's gesticulation or seeing his/her shoes.

The dynamic recognition (DR) approach (initially proposed by Michalski in 1986) overcomes this problem by using inductive inference to dynamically determine discriminant object descriptions from characteristic object descriptions, and this allows the system to avoid matching rules. Only one characteristic description per concept is stored in memory. Potentially, the DR method can efficiently handle a great variety of different practical recognition problems. An initial implementation of the system has strongly supported the theoretical expectations.

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For more references, see **Publication section**.

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EMERALD:

An Integrated Large-Scale Learning and Discovery System for Education and Research in Machine Learning

(Michalski, Kaufman, Lee, Bloedorn, De Jong, Schultz, Wnek)



This project concerns the development and maintenance of an integrated system for machine learning and discovery, EMERALD, that serves as a tool for education and research in machine learning and cognitive modeling of learning processes. The system is regularly used in teaching the course INFT 811: "Principles of Machine Learning and Inference" and occasionally some other courses.

The EMERALD system (Experimental Machine Example-based Reasoning and Learning Discipline) consists of five modules ("robots"), each displaying a capability for some form of learning or discovery:

AQ learns general decision rules from examples of different classes of correct or incorrect decisions made by experts. An example of the program performance employs little robots like these:



INDUCE learns structural descriptions of groups of objects, and determines important distinctions between the groups. An example of INDUCE performance uses little trains like these:



CLUSTER creates meaningful categories and classifications of given entities, and formulates descriptions of these created categories. One of the examples illustrating CLUSTER performance involves the clustering of various geometric



objects into different classes as shown here.

SPARC predicts possible future objects or events by discovering rules characterizing the sequence of objects or events observed so far. One of the examples illustrating SPARC performance involves the prediction of a sequence of cards in the game ELEUSIS.



ABACUS conducts experiments, collects data, discovers mathematical and logical descriptions of data, and then uses these descriptions for predicting the behavior of some phenomenon. One of the experiments illustrating ABACUS involves the discovery of a law characterizing bodies falling through different media.



Each module is represented by a robot figure and employs a different voice (through a voice synthesizer) for communicating with the user.

An earlier and smaller version of the system, called ILLIAN, was a part of the exhibition "Robots and Beyond: The Age of Intelligent Machines," organized by a consortium of eight U.S. Museums of Science (Boston, Charlotte, Fort Worth, Los Angeles, Seattle, Chicago, Minneapolis and Columbus). Support for the development of the exhibit version was provided in part by the Boston Museum of Science, Digital Equipment Corporation, and the University of Illinois at Urbana-Champaign. The system was seen by few hundred thousand people.

EMERALD is the first system of its kind ever built, which integrates several learning capabilities with natural language processing, voice communication, and a highly user-oriented graphical interface. It enables users to experiment on-line with various learning and discovery programs under a unified control, and to use predefined objects to set different learning tasks for the system. EMERALD was developed under the direction of Professor R.S. Michalski in collaboration with his students and associates. The system has recently been adapted for SUN workstations, and used in teaching machine learning.

EMERALD has been distributed to a number of U.S. and European universities and organizations. **If you are interested in obtaining EMERALD, contact Dr. J. Wnek (jwnek@gmu.edu) or Ken Kaufman (kaufman@aic.gmu.edu).**

Although EMERALD modules are demonstrated in the context of certain predefined classes of problems, they are not specifically oriented toward these problems and objects. These modules are domain-independent programs that have already been used or have a potential to be used for concept learning and discovering regularities in such fields as medicine, agriculture, engineering, biology, chemistry, plant control, financial decisions, air traffic control, computer vision and intelligent robots.

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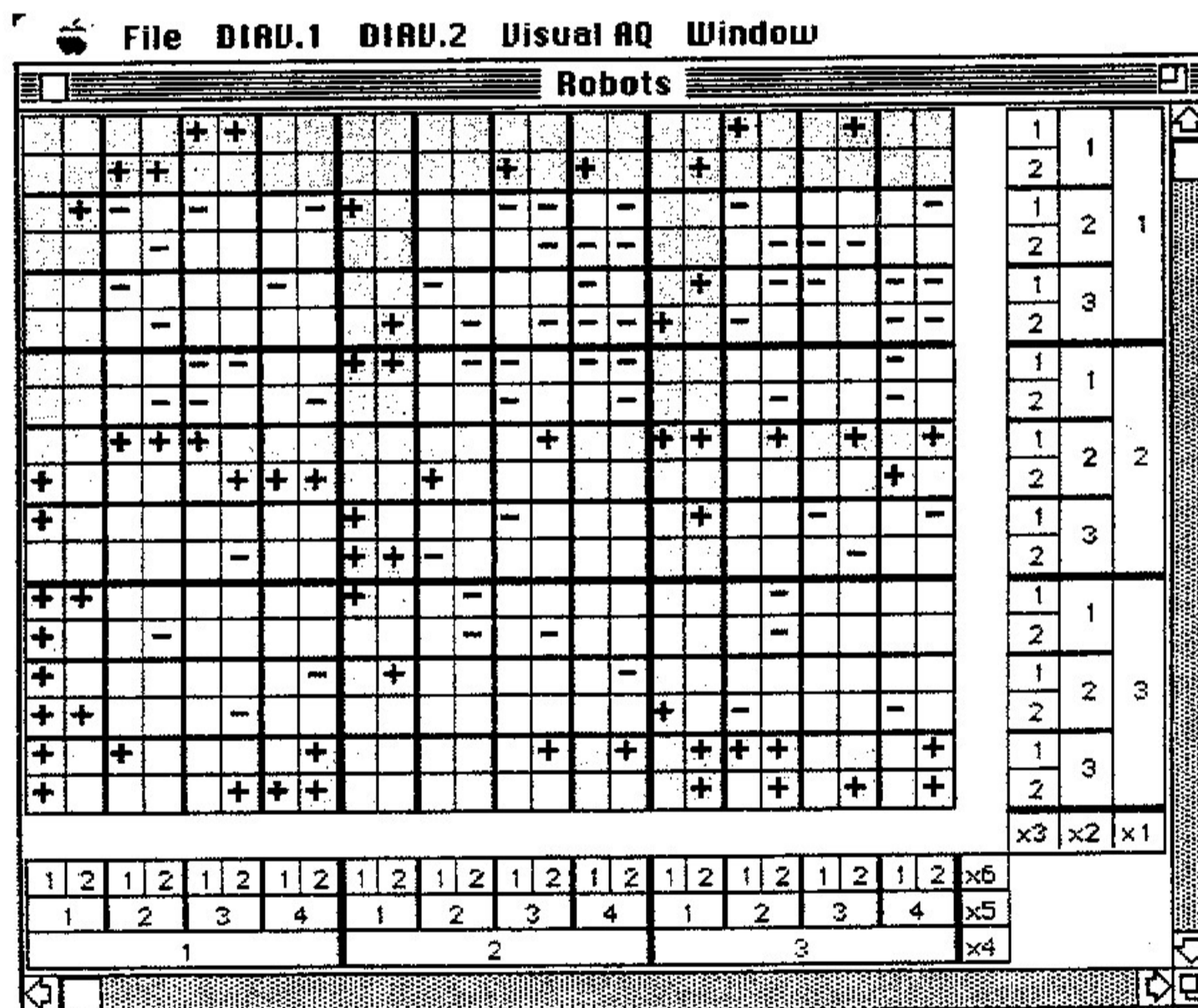
KNOWLEDGE VISUALIZER (KV)

A Diagrammatic Visualization of Data Mining and Machine Learning Processes

(Michalski, Zhang, Wnek)

The KV project concerns the development of a system for visualizing data mining, machine learning and knowledge discovery processes involving discrete multi-dimensional functions. It employs a planar model of a discrete multidimensional space, called *generalized logic diagram or GLD*, proposed by Michalski (1978). The diagram is spanned over a set of discrete attributes and consists of cells, each representing one unique combination of attribute values (a vector of attribute values). Thus, there are as many cells as there are possible vectors of attribute values. To determine the cell corresponding to a given vector, one seeks the intersection of the areas corresponding to the values of individual attributes.

For example, in the diagram below, the top-left cell represents the vector: $(x_1 = 1, x_2 = 1, x_3 = 1, x_4 = 1, x_5 = 1, x_6 = 1)$.



In the diagram above, Positive examples of a concept are visualized using "+", counter-examples of the concept are visualized using "-". A decision rule (a conjunction of conditions on attribute values) corresponds to regular arrangement of cells that can be easily recognized visually. A concept description is in the form of a collection of such decision rules (a ruleset). For example, the yellow area in the diagram represents a concept description described by the disjunction of two rules:

R1: [x5 = 1]
R2: [x1 = x2]

If the target and learned concepts are represented in the diagram, then their set-difference denotes errors in the learned concept ("error area").

The diagram can also illustrate results of any operation on the concept, such as generalization or specialization, or any change of the description space, such as adding or deleting attributes, or their values. Another interesting feature is that it can also visualize concepts acquired by non-symbolic systems, such as neural nets or genetic algorithms. Using the diagram one can directly express the learned concepts in the form of decision rules. Thus, the diagram allows one to evaluate both the quality and the complexity of the results of symbolic, as well as non-symbolic learning.

We have implemented two systems: DIAV-2 in Smalltalk, and KV in Java. These systems can display description spaces with up to one million events, i.e., spaces spanned over up to 20 binary variables (or a correspondingly smaller number of multiple-valued variables). The systems have proven to be very useful for analyzing behavior of learning algorithms. They are available to universities and industrial organizations.

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MLI Developed Software

Machine Learning, Inference and Discovery Systems developed in the Machine Learning and Inference Laboratory



The figure above is the opening screen of the EMERALD system developed in the Machine Learning and Inference Laboratory. The EMERALD system (Experimental Machine Example-based Reasoning and Learning Disciple) integrates five modules ("robots") each displaying a capability for some form of learning and discovery.

The Laboratory has developed a series of machine learning and Inference programs. Among these are: ABACUS, AQ15c, AQ16 (POSEIDON), AQ17-DCI, CLUSTER, EMERALD, INDUCE, and SPARC. These programs are described in more detail below.

● **ABACUS 2** is a program for assisting a user for determining integrated quantitative and qualitative descriptions of data (a system for integrated "quantitative and qualitative discovery"). Given numerical and possibly also qualitative data describing some system or process, it generates mathematical equations characterizing the system or the process, and conditions under which these equations apply. These equations can then be used for predicting the behavior of this system or process.

● **AQ Family**: All of the programs in the AQ family learn general decision rules from examples of decision classes. Here are standard features of the "base" version of the AQ program

The learned decision rules are optimized according to user-defined criteria or a default optimality criterion. The criteria refer to syntactic simplicity of the rules (measured by the number of rules, number of conditions in the rules, the simplicity of the conditions, or a combination of these

factors), and/or the evaluation cost of the rules (the cost of measuring the attributes involved in the rules). Programs allow the user to generate different types of descriptions ("rulesets"), such as *discriminant* (that discriminate among given decision classes), or *characteristic* (that specify common features of the objects in the individual classes). The programs can also generate rulesets that have different relations among the rules -- intersecting (rules of different classes may logically intersect over areas not covering training examples), disjoint (rules of different classes are logically disjoint) or ordered (rules for each class are totally ordered and must be executed in the given order when applied to a given object). Learned rules are evaluated either by a strict match or by a flexible match. Individual versions of AQ programs have some additional features above the "base" version of the program.

AQ15c: The latest, most popular plain version of the AQ learning program (implemented in the ANSI C). This version is available for SunOS 4.1, MacOS 7.5 and DOS 6.x

AQ16 (POSEIDON): Plain AQ with mechanisms for optimizing rules by applying rule modification mechanisms. There are two mechanisms: TRUNC--that truncates insignificant rules (which corresponds to performing a form of ruleset specialization) or TRUNC/SG that modifies rules conditions and truncates insignificant rules (which corresponds to performing of both specialization and generalization of rules). Rules are evaluated either by a strict match or by a flexible match. These version is oriented toward learning concepts from noisy data or learning "flexible" concepts, that lack precise definition. The program applies some simple forms of "two-tiered" concept representation. A two-tiered representation consist of a base concept representation (BCR) that captures typical concept properties, and inferential concept representation that captures non-typical, variable, or exceptional concept properties. (See MLI papers on two-tiered concept representation). This version is available for SunOS 4.1

AQ17-DCI: AQ program with Data-driven constructive induction capabilities. These capabilities allow the program to automatically modify the representation of the problem, e.g. adding or removing attributes or removing attribute-values. This version is available for SunOS 4.1.

AQ17-HCI: AQ program with Hypothesis-driven constructive induction capabilities. These capabilities allow the program to automatically modify the representation of the problem, e.g. adding or removing attributes.

● **CLUSTER** creates meaningful categories and classifications of given entities, and formulates descriptions of these created categories. Each class description is given in conjunctive form involving selected object attributes. CLUSTER has been applied to varied practical problems including classifying Spanish Folksongs, microcomputers, and reconstructing soybean disease categories.

● **DIAV**: Diagrammatic Visualization of learning algorithms and discrete knowledge transmutations.

● **EMERALD**: Integrated Learning Systems for Research and Education.

● **INDUCE** learns structural descriptions of groups of objects, and determines important

distinctions between the groups.

● **SPARC** predicts possible future objects or events by discovering rules characterizing the sequence of objects or events observed so far.

Sparc/G: General purpose Sparc

Sparc/E: Eleusis card playing version

To obtain a copy of any of these systems contact:

Qi Zhang, MLI Laboratory Software Manager. PHONE: USA 703 993 1716, FAX: USA 703 993 3729, Machine Learning and Inference Laboratory, George Mason University, 4400 University Dr. Fairfax, VA, 22030, USA

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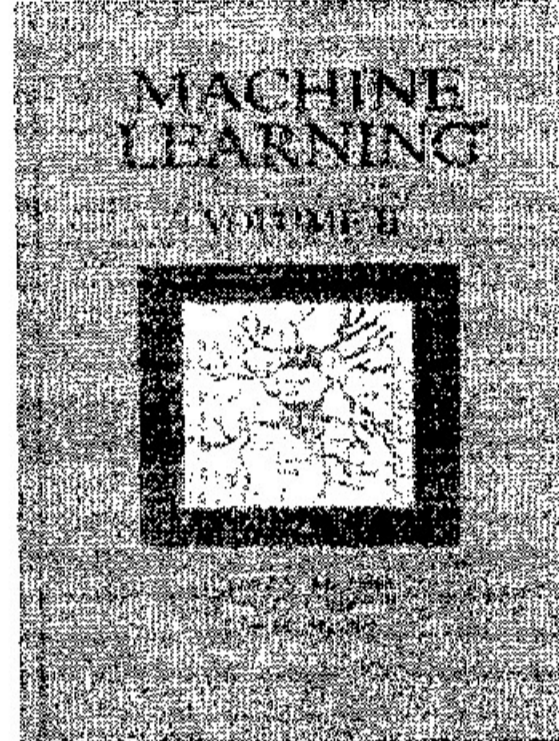
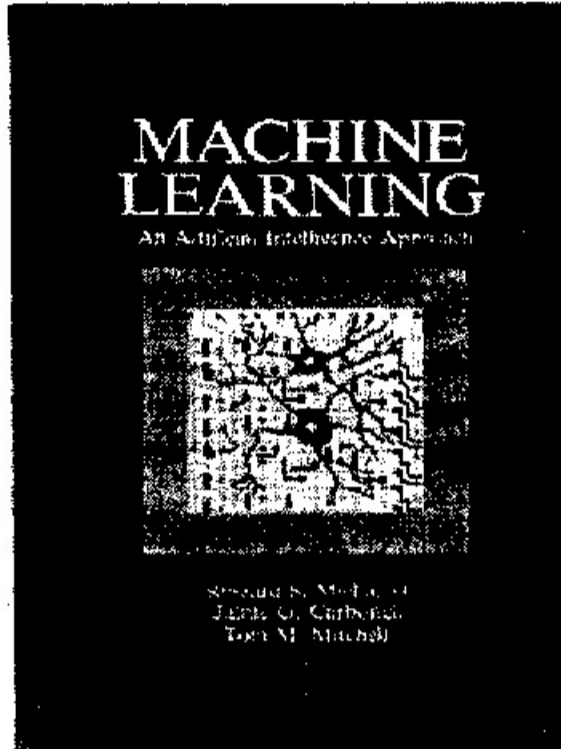
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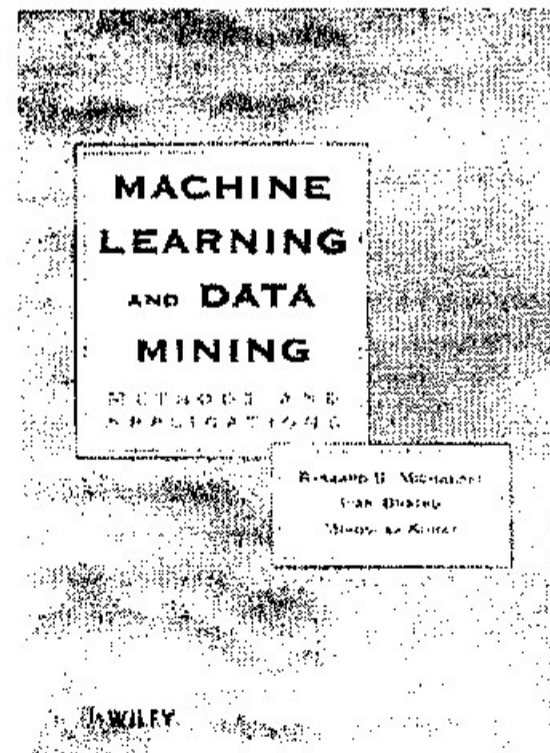
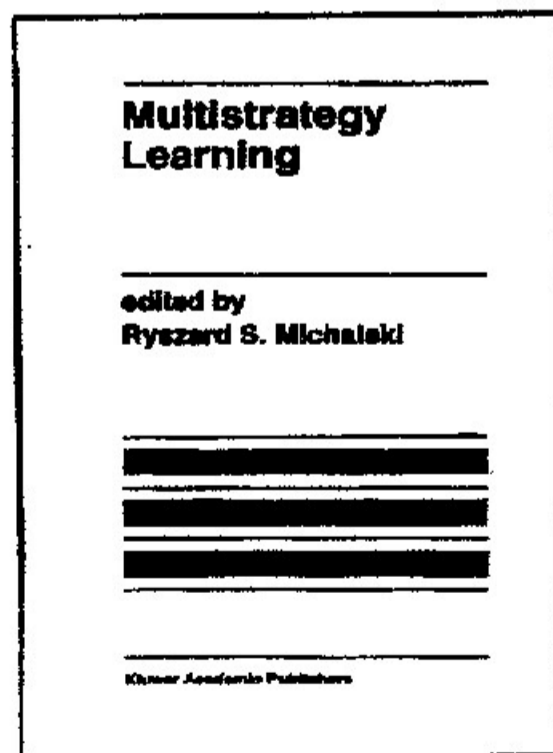
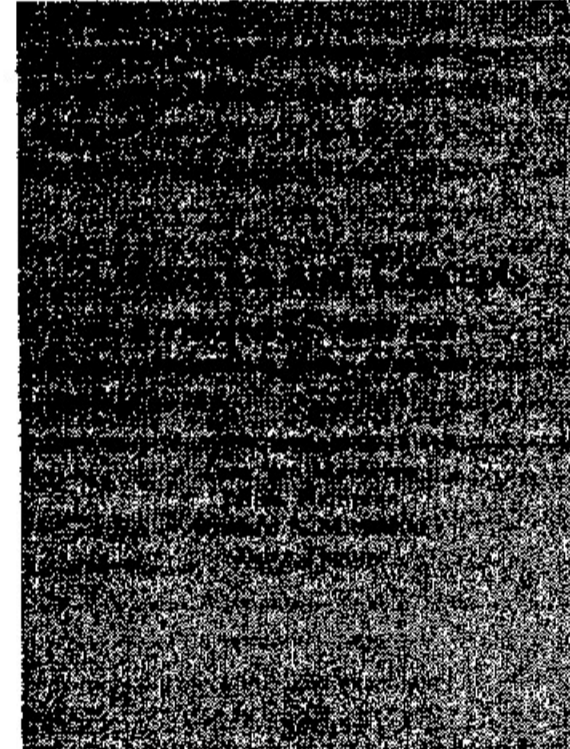
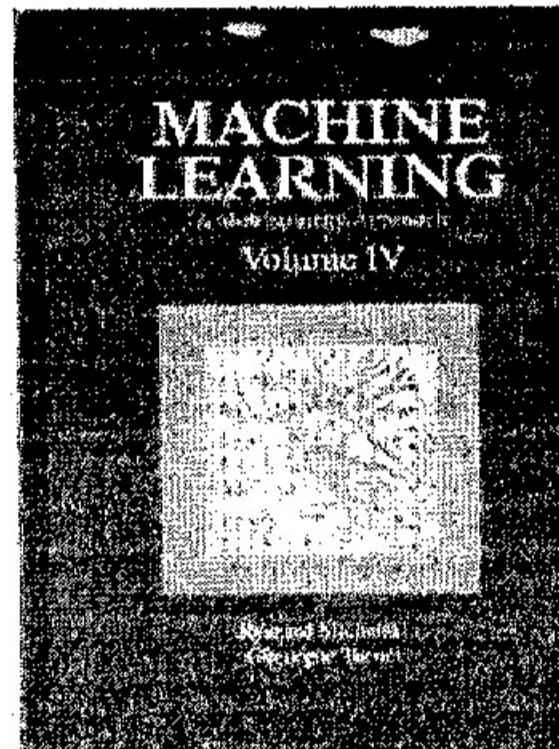
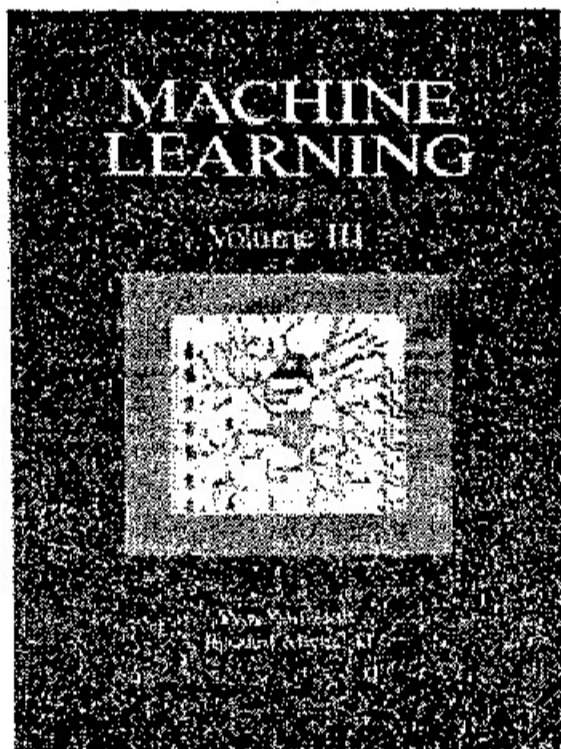


Machine Learning A Guide to Current Research

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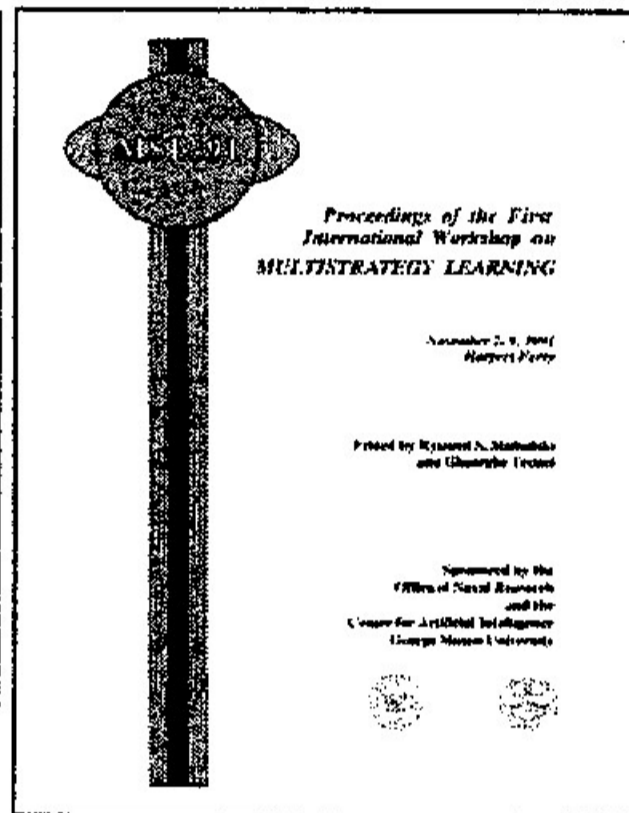




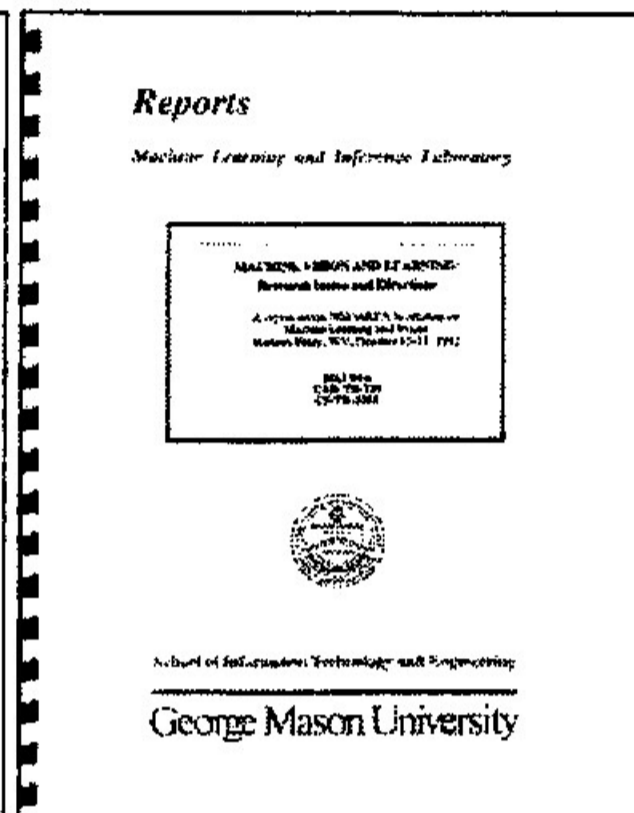
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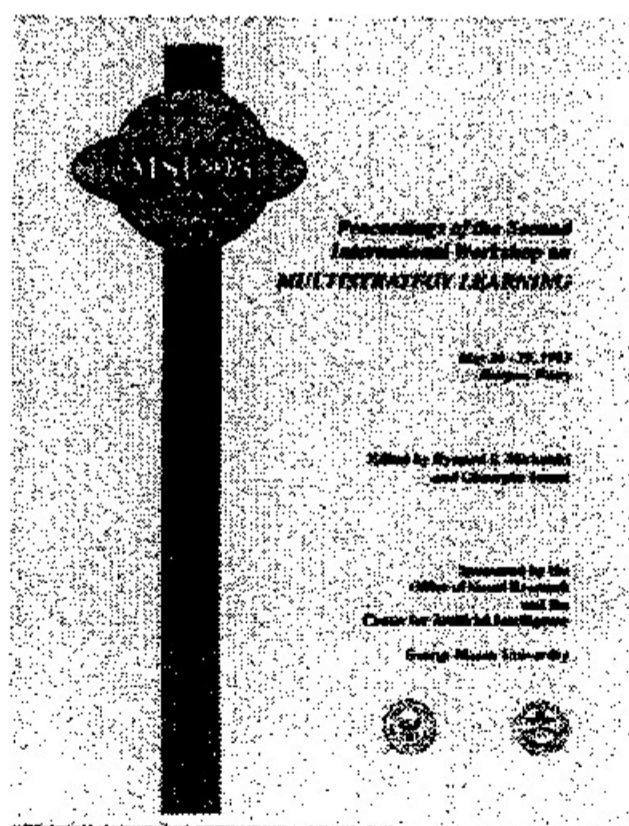
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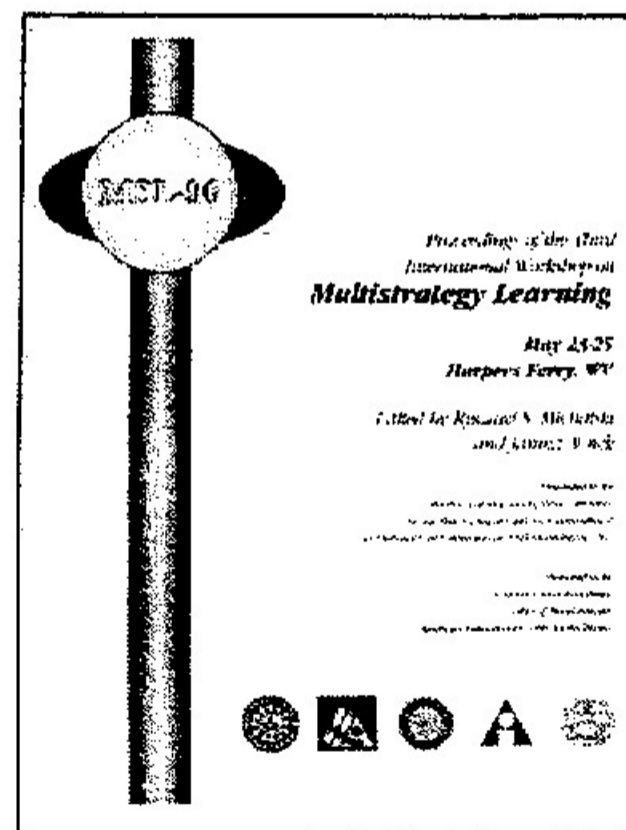
MSL'91



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