AN APPLICATION OF VARIABLE-VALUED LOGIC TO INDUCTIVE LEARNING OF PLANT DISEASE DIAGNOSTIC RULES

by

R. Chilausky
B. Jacobson
R. S. Michalski

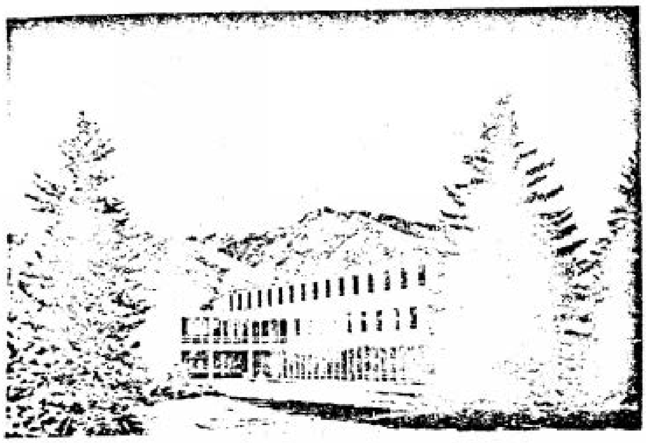
Proceedings of the Sixth International Symposium on Multiple-Valued Logic,
Utah State University, Logan, Utah, May 25-28, 1976.

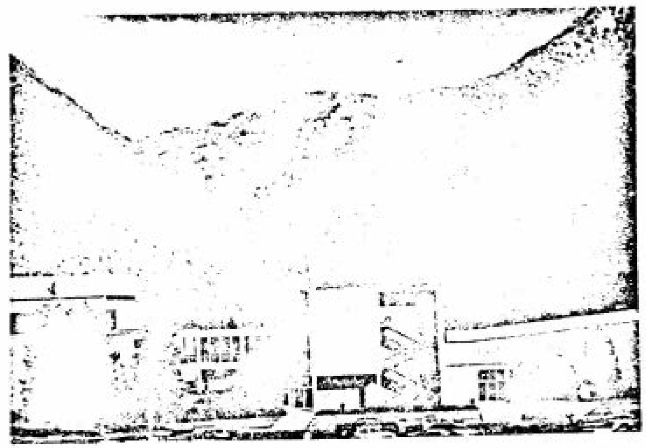
PROCEEDINGS OF

THE SIXTH INTERNATIONAL SYMPOSIUM ON MULTIPLE-VALUED LOGIC

May 25-28, 1976

University Center • Utah State University • Logan, Utah





SPONSORING ORGANIZATIONS:

acm

ASSOCIATION FOR COMPUTING MACHINERY

25 YEARS OF SERVICE

IEEE COMPUTER SOCIETY

ONR

MATHEMATICAL AND INFORMATION SCIENCE DIVISION OF THE OFFICE OF NAVAL RESEARCH

UTAH STATE UNIVERSITY

IEEE Catalog Number 76CH1111-4 C
ONR Contract Number N00014-76-G-0017
ONR Project Number NR 048-632

PROCEEDINGS ARE AVAILABLE FROM:

IEEE Computer Society
5855 Naples Plaza, Suite 301
Long Beach, California 90803
(213) 438-9951

Association for Computing Machinery
1133 Avenue of the Americas
New York, N.Y. 10036
(212) 265-6300

AN APPLICATION OF VARIABLE-VALUED LOGIC TO INDUCTIVE LEARNING OF PLANT DISEASE DIAGNOSTIC RULES*

R. Chilausky, B. Jacobsen, R. S. Michalski
Department of Computer Science
University of Illinois at Urbana-Champaign
Urbana, Illinois 61801

Knowledge acquisition and representation in machines is growing in importance to computer science research. Most of the work in this direction has used traditional binary logic as a theoretical framework. However, a more adequate treatment of these problems may be achieved by an advance into multiple-valued logic. In particular, the concepts of variable-valued logic (Michalski 72,73,74a) provide useful and flexible tools for representation and automated acquisition of knowledge. This paper describes an application of AQVAL/1, a set of programs implementing the variable-valued logic system VL_1, to determine diagnostic rules for soybean diseases through an inductive inference process. The methods of application and the results of an experiment are briefly described.

1. Introduction

There is a growing realization that one of the central issues for future research in computer science and related fields is the improvement of the acquisition and representation of knowledge in machines. This means, in part, the implementation of processes which will enable machines to acquire knowledge not through direct programming but rather through inferences from a demonstration of examples, results of experiments, ill-defined statements, and observations of cases of relationships for which a general expression is not known, etc. Such inferential processes can be considered a part of what Feigenbaum called 'Knowledge Engineering' in a talk at the NATO Advanced Study Institute on Machine Representation of Knowedge in Santa Cruz (Feigenbaum 75).

Moreover, it is becoming increasingly clear that new formal methodologies must be developed in order to treat the problem of machine learning more adequately. One promising theoretical base for the development of such new methodologies is the concept of multiple-valued logic. Specifically, this concept may lead to the development of a logic-based decision theory as opposed to statistic-based theory. This was the belief that prompted one of the authors (Michalski 72) to formulate the concept of a 'variable-valued logic system' which is a modification and an extension of a multiple-valued logic system and is specifically oriented toward applications such as automatic induction, machine learning and decision theory.

The belief that logic is an appropriate theoretical basis for such applications has been supported by a number of successful developments in the area of artificial intelligence and pattern recognition. The projects listed below exemplify efforts in which logical concepts (binary or multiple-valued) play a significant role:

- The development of a pattern recognition program ARITHMETIC in which logical concepts play the major role (Bongard 70, Maximov 74).
- A set of programs called Heuristic DENDRAL used to aid in the identification of chemical structures from mass spectrograms (Feigenbaum 68, Buchanan 69,73).
- A question answering information system called QA3, which uses theorem proving methods (Green 69).
- A system utilizing a logical rule base for modeling human belief structures (Colby 69).
- Development of various languages for artificial intelligence research which provide data and control structures based on logical rules (Hewitt 69,72, Bobrow 73).
- A system utilizing a logical rule base for playing poker (Waterman 70).
- Development of the concept of a variable-valued logic system and implementation of AQVAL/1 programs for automatic induction and pattern recognition (Michalski 72,73,74a, Larson 75).
- Development of the concept of Fuzzy-logic as a proposed means for handling imprecise information (Zadeh 74).
- Development of a consulting system MYCIN, which employs logical decision rules to advise physicians about the selection of antimicrobial therapy (Shortliffe 74).

Let us consider the form of the logical rules which were used successfully as decision rules to interpret mass spectrograms in the Heuristic DENDRAL programs. These rules were of the form

$$\underline{P} \rightarrow \underline{A} \qquad (1)$$

where $\underline{P}$ (premise) is a conditional statement in the form of a conjunction of predicates and $\underline{A}$ (action) is a specified action or decision made when the premise is satisfied. The more recent system, MYCIN (Shortliffe 74), extends the above form by adding a measure of the strength of the implication (called the certainty factor), so that its decision rules are of the form:

$$\underline{P} \overset{\alpha}{\rightarrow} \underline{A} \qquad (2)$$

where α, $-1 \le \alpha \le 1$, is the certainty factor. The rule (2) means that satisfaction of the premise ($\underline{P}$) implies action ($\underline{A}$) with the 'certainty factor' α.

The introduction of the certainty factor in MYCIN is an indication of the need for logical rules which are more general than binary logic rules, and thus can be interpreted as a move from binary logic to multiple-valued logic. The need for multiple-valued logic rules for decision making was clearly recognized in the development of the variable-valued logic systems VL_1 and VL_2 (Michalski 72,74a,74b).

A variable-valued logic system extends a multiple-valued logic system in two directions:

*Supported in part by the National Science Foundation under Grant No. DCR 74-03514.

1) It assumes that every formula and every variable in a formula is assigned its own domain from which it draws values (the domain may be a two-valued, a multiple-valued or an infinitely-valued set with its own structure).

2) It introduces new logical operators, beside the conventional binary and multiple-valued operators, (e.g. a selector) to increase the power for a concise expression of complex information.

The form of a VL_1 based decision rule is

$$V_p \rightarrow V_c \tag{3}$$

where V_p and V_c are, respectively, the input (premise) and the output (consequence) VL_1 formulas (Michalski 72). In order to make this paper self-contained, a description of a VL_1 formula is given in the appendix. The formula V_p may be two-valued (false-true), multiple-valued (e.g., false-unlikely-likely-true) or infinitely valued (e.g., takes values from the continuous 'degree of truth' interval [0,1]). The formula V_c can only be two-valued (false-true). The value of V_p is the minimum 'degree of confidence' that the formula V_c is true.* For example:

$$.9[x_1=2:5][x_3\neq 0] \vee .7[x_2=2,6] \vee 0.2 \rightarrow [\text{decision}=k] \tag{4}$$

is a decision rule which is interpreted: if x_1 is between 2 and 5 and x_3 is not equal to 0, the 'degree of confidence' for decision k is 0.9; if these conditions are not satisfied and x_2 is 2 or 6, the degree of confidence is 0.7. In every other case, it is 0.2. Degrees of confidence 0.9, 0.7, or 0.2 may be interpreted as, e.g., 'sure', 'possible', 'hardly possible', respectively (the latter reflects the chance for this decision even though the listed conditions fail).

Thus, if V_p is a conjunctive statement and V_c describes a specific decision, then the VL_1 rule (3) is equivalent to the Heuristic DENDRAL rule (1). To describe the decision rule (2) of MYCIN (i.e., $P \overset{\alpha}{\rightarrow} A$) in terms of the VL_1 system, one can use a VL_1 decision rule:

$$\alpha V_p \rightarrow [\text{decision}=A], \text{ if } \alpha > 0 \tag{5}$$

or

$$\alpha V_p \rightarrow [\text{decision}\neq A], \text{ if } \alpha < 0 \tag{6}$$

where V_p is a two-valued VL_1 formula whose satisfaction indicates decision A with the 'certainty factor' α.

In this paper we will briefly describe the initial results of the application of the VL_1 system to the development of decision rules for the diagnosis of disease in plans. Specifically, we describe results obtained by learning the diagnostic decision rules for soybean diseases from examples of sick plants.

*Thus, the implication is interpreted as the 'less than or equal to' relation between truth values of V_p and V_c.

2. Description of the Experiment

2.1 Introductory Remarks

The work on the implementation of automatic learning of diagnostic rules for plant pathology is part of a larger effort to develop an inferential computer consultant for plant pathology and pest management. The work described here is oriented toward the implementation of an 'automatic knowledge acquisition' module for the computer consultant, (hence forward, CC).

Any individual plant under consideration can be described in terms of various descriptors. A descriptor is a function which assigns to a given plant or its environment a specific value from a set called the domain of the descriptor. Examples of a descriptor are Canker Lesion Color (CLC), Time of Occurrence (TO), etc. Domains of these descriptors can be; e.g.:

D(CLC) = {Tan, Brown, Black, Does Not Apply}

D(TO) = {April, May, ..., October}

The descriptors can be functions with single or multiple arguments. (In this paper, we consider only one argument descriptors.) The values of descriptors can be interrelated. That is values of some variables may not be 'free' but may have to satisfy certain equations. For example, if the descriptor, Condition of Leaves (COL), takes the value 'normal' then the descriptors describing the abnormalities of the leaves of the plant (e.g., Leafspot Size) are not applicable, i.e., they take value 'does not apply'.

The experiment to be described here used descriptors listed in Table 1. The descriptors are hierarchically organized. The number in parentheses after each descriptor indicates the number of possible values that descriptor can take. A given plant is described by listing the values of its descriptors. Decision rules determine which diagnosis should be associated with a plant satisfying certain description and are of the form (3), i.e. $V_p \rightarrow V_c$. In the experiment, V_p and V_c are both disjunctive simple VL_1 formulas (DVL_1 formulas) with binary output domain (i.e., they can take only 2 different values, though the variables in the formula are multi-valued). For example,

$$[x_1=1:4][x_4\neq 2,3] \vee [x_3=1,3] \rightarrow [\text{decision}=k] \tag{7}$$

which means if x_1 is between 1 and 4 and x_4 is not equal to 2 or 3, or x_3 is 1 or 3, then decision takes value k, otherwise decision k is not taken.

The interrelations among descriptors are also represented as rules of form (3). An example of such a rule is

$$[x_1=2] \rightarrow [x_3=*][x_4+x_5+x_6=2:6] \tag{8}$$

It means: if x_1 is equal to 2 then x_3 takes the value * (i.e. 'does not apply') and the sum of x_4, x_5 and x_6 takes values between 2 and 6. Otherwise, there is no restriction on x_3, x_4, x_5, and x_6.

TABLE 1
Plant descriptors used in the experiment.

1. Environmental Descriptors				
1.1		Time of Occurrence	(7)	(x_1)
1.2		Plant Stand	(2)	(x_2)
1.3		Precipitation	(3)	(x_3)
1.4		Temperature	(3)	(x_4)
1.5		Occurrence of Hail	(2)	(x_5)
1.6		Cropping History	(4)	(x_6)
1.7		Damaged Area	(4)	(x_7)
2. Plant Global Descriptors				
2.1		Severity	(3)	(x_8)
2.2		Seed Treatment	(3)	(x_9)
2.3		Seed Germination	(3)	(x_{10})
2.4		Plant Growth	(2)	(x_{11})
3. Plant Local Descriptors				
3.1		Condition of Leaves	(2)	(x_{12})
	3.1.1	Leafspots - Halos	(3)	(x_{13})
	3.1.2	Leafspots - Margin	(3)	(x_{14})
	3.1.3	Leafspot Size	(3)	(x_{15})
	3.1.4	Leaf Shredding or Shot Holing	(2)	(x_{16})
	3.1.5	Leaf Malformation	(2)	(x_{17})
	3.1.6	Leaf Mildew Growth	(3)	(x_{18})
3.2		Condition of Stem	(2)	(x_{19})
	3.2.1	Presence of Lodging	(2)	(x_{20})
	3.2.2	Stem Cankers	(4)	(x_{21})
	3.2.3	Canker Lesion Color	(4)	(x_{22})
	3.2.4	Presence of Fruiting Bodies	(2)	(x_{23})
	3.2.5	External Decay	(3)	(x_{24})
	3.2.6	Presence of Mycelium	(2)	(x_{25})
	3.2.7	Internal Discoloration	(3)	(x_{26})
	3.2.8	Sclerotia - Internal or External	(2)	(x_{27})
3.3		Condition of Fruits - Pods	(4)	(x_{28})
	3.3.1	Fruit Spots	(5)	(x_{29})
3.4		Condition of Seed	(2)	(x_{30})
	3.4.1	Mold Growth	(2)	(x_{31})
	3.4.2	Seed Discoloration	(2)	(x_{32})
	3.4.3	Seed Size	(2)	(x_{33})
	3.4.4	Seed Shriveling	(2)	(x_{34})
3.5		Condition of Roots	(3)	(x_{35})

2.2 Description of the Input Data and the Results of the Experiment

Fifteen soybean diseases were selected as representative of the nature and scope of the problems which are faced in the diagnosis of plant diseases. The fifteen diseases and associated disease numbers were:

1) Diaporthe Stem Canker
2) Charcoal Rot
3) Rhizoctonia Root Rot
4) Phytophthora Rot
5) Brown Stem Rot
6) Powdery Mildew
7) Downy Mildew
8) Brown Spot
9) Bacterial Blight
10) Bacterial Pustule
11) Purple Seed Stain
12) Anthracnose
13) Phyllosticta Leaf Spot
14) Alternaria Leaf Spot
15) Frog Eye Leaf Spot

The purpose of the experiment was to determine the so-called discriminant rules for the fifteen diseases based on learning examples for each disease. VL_1 discriminant rules specify the minimum information necessary to discriminate a given disease from an assumed set of diseases. These rules are used to quickly and efficiently determine possible disease candidates after a few initial pieces of information. The final selection of a disease diagnosis from these candidates is based on descriptive rules which specify all basic characteristics of a disease, including those which may not be unique to this disease (as opposed to discriminant rules). The discriminant rules for each disease are inferred from a set of learning events by means of the inductive program AQVAL/1 (AQ7) (Michalski 73, Larson 75). The descriptive rules are derived through consultation with an expert in plant pathology. (It is also possible to use a computer program AQVAL/1-(AQ8) (Yuen 74) for determining such rules from examples. The adequacy of the rules so derived is, however, not yet well investigated.) Both types of rules are expressed as VL_1 decision rules. For example, the discriminant and descriptive rules for Diaporthe Stem Canker are

Discriminant Rule: $V_{dt} \rightarrow$ [dec=DSC] (9)

where V_{dt}: [precipitation=above normal] $\wedge$
[stem cankers=above second node] $\wedge$
[fruit pods=healthy]

Descriptive Rule: $V_{de} \rightarrow$ [dec=DSC] (10)

where V_{de}:

S([time=Aug,Sept] $\wedge$ (.9[precipitation=above normal] $\vee$ .7[precipitation=normal]) $\wedge$ [stem cankers=above second node] $\wedge$ [fruiting bodies=present] $\wedge$ [fruit pods=healthy])

L([temperature=normal or above normal] $\wedge$ (.9[cropping history=no rotation 4 or more years] $\vee$ .8[cropping history=no rotation 3 years] $\vee$ .7[cropping history= no rotation 2 years] $\vee$ .2) $\wedge$ [canker lesion color= brown])

Symbols S and L in front of a product of selectors (or VL_1 formulas) are used to denote the type of evaluation function which should be used in evaluating selectors in the product.

Selectors in the product with symbol S ('significant selectors') are evaluated to value 1 if they are satisfied and to value 0, otherwise. Selectors in the product with L ('Less significant selectors') are evaluated to value 1, if they are satisfied and to value 0.7, otherwise (the constants 1 and 0.7 in the above are values of adjustable parameters).

The program AQVAL/1 (AQ7) used in the experiment has been described in detail (Larson 75). The algorithms implemented in it were described during the Fifth Annual International Symposium on Multiple-Valued Logic (Michalski 75). Therefore, in the paper we will not discuss the problem of how inductive inference is executed but will restrict ourselves to the description of the format of the input data and then discuss the results obtained.

The examples used for the inference of discriminant rules by AQVAL/1 (AQ7) consisted of the sequence of values of the thirty-five descriptors from Table 1 for each plant with a known disease. In most cases, ten examples were used for each disease though twenty and forty examples were used for some diseases (see Table 3, Col. 6). The following is an example of such a vector description for a plant infected with Diaporthe Stem Canker:

32010210110220001030110000400000010 .

Individual numbers represent consecutive values for the descriptors in Table 1. These numerically correspond to certain descriptive values for each descriptor. For example, the 3 in the first place in the vector above corresponds to the descriptive value July for the descriptor Time of Occurrence. Each descriptor has a set of descriptive values with the number of values as listed in Table 1 (number in parentheses).

As was mentioned before, the decision rules derived by AQVAL/1 (AQ7) are discriminant rules, i.e. they include (ideally) only those descriptors and associated values which are necessary to distinguish a given disease from all other diseases as represented by learning sets of events. Those descriptors which are found unnecessary to distinguish the diseases are omitted. All discriminant decision rules found by AQVAL/1 (AQ7) are listed in Table 2. They are in the form $V_p \rightarrow V_c$, where V_p is a simple disjunctive VL_1 formula and V_c is a selector [dec=k] where each k represents disease k (listed at beginning of Sec. 2.2). For example, the discriminant diagnostic rule for Brown Stem Rot is

$$[x_{19}=1][x_{26}=1] \rightarrow [\text{dec}=5] \quad (11)$$

After translating the symbolic notation of the descriptors and their values to English the formula becomes:

[condition of stem=abnormal][internal discoloration= brown] $\rightarrow$ [dec=Brown Stem Rot] (12)

The symptomatic description of Brown Stem Rot as used by plant pathologists is:

> Dark, reddish-brown discoloration inside the lower stem. Certain fungus strains cause leaves to turn brown between the veins, wither and drop early. Seed size and number is reduced. Plants may lodge severely. The disease is favored by cool weather to mid-August.*

The underscored part of the symptomatic description corresponds to the discriminant VL_1 decision rule (12). It can easily be shown that the properties in this part of the description are unique for Brown Stem Rot among all fifteen diseases under consideration. The remaining properties in the symptomatic description although useful and descriptive for a confirmation of a diagnosis of the disease are not necessarily unique to Brown Stem Rot. The above illustrates well the distinction between a discriminant VL_1 rule and a descriptive VL_1 rule (which is a VL_1 formulation of a symptomatic description).

A discriminant rule does not have to be a product of selectors involving properties in the symptomatic description of a disease. The discriminant rule may involve a disjunction of terms while the symptomatic description is usually expressed as a conjunction of the properties given by the expert. The following is an example illustrating this case. The discriminant diagnostic rule for Bacterial Pustule is

$$[x_7=1][x_{12}=1][x_{13}=1][x_{15}=0][x_{18}=0][x_{19}=0] \vee [x_{12}=1][x_{14}=1][x_{19}=0] \rightarrow [\text{dec}=10] \quad (13)$$

or more concisely

$$[x_{12}=1][x_{19}=0]([x_7=1][x_{13}=1][x_{15}=0][x_{18}=0] \vee [x_{14}=1]) \rightarrow [\text{dec}=10] \quad (14)$$

which after translation is

[condition of leaves=abnormal][condition of stem= normal] $\wedge$ ([damaged area=low areas][leafspots-halos= with yellow halos] $\wedge$ [leafspot size=less than 1/8"] [leaf mildew growth=absent] $\vee$ [leafspots-margin= without water-soaked margin]) $\rightarrow$ [dec=10]

The symptomatic description for Bacterial Pustule is:

> Leaf spots are present which are small, angular, yellowish-green with dark, reddish-brown centers, without water-soaked margins. Centers slightly raised (pustule), especially on underleaf surface. Dead tissue may dry, rupture and tear away.

*Disease description taken from Report on Plant Disease No. 502, Department of Plant Pathology, University of Illinois.

TABLE 2
VL_1 discriminant rules for 15 soybean diseases found by AQVAL/1 (AQ7)

• $[x_3=1][x_{21}=3][x_{28}=0] \rightarrow [dec=1]$	1. Dia.Stem Canker
• $[x_{19}=1][x_{27}=1] \rightarrow [dec=2]$	2. Char.Rot
• $[x_{12}=0][x_{19}=1][x_{21}=1,2] \rightarrow [dec=3]$	3. Rhiz.Root Rot
• $[x_2=1][x_{19}=1][x_{22}=2][x_{29}=3,4] \rightarrow [dec=4]$	4. Phyto.Rot
• $[x_{19}=1][x_{26}=1] \rightarrow [dec=5]$	5. Br.Stem Rot
• $[x_{12}=1][x_{18}=1] \rightarrow [dec=6]$	6. Powdery Mild.
• $[x_{12}=1][x_{18}=2] \rightarrow [dec=7]$	7. Downy Mild.
• $[x_1=0,1,2][x_3=1,2][x_6=1,2,3][x_7=1,2,3][x_{12}=1][x_{13}=2][x_{15}=1,2][x_{17}=0][x_{18}=0,1] \vee$ $[x_1=0,1][x_{15}=1,2][x_{17}=0][x_{18}=0][x_{19}=0] \vee$ $[x_1=0,1,2,3,4,5][x_3=1,2][x_{12}=1][x_{13}=2][x_{15}=1,2][x_{18}=0,1][x_{19}=1][x_{23}=1] \vee$ $[x_3=2][x_{12}=1][x_{13}=2][x_{15}=1,2][x_{18}=0,1][x_{19}=1][x_{20}=0][x_{24}=0] \rightarrow [dec=8]$	8. Br.Sp.
• $[x_{14}=0][x_{15}=0][x_{19}=0][x_{30}=0] \rightarrow [dec=9]$	9. Bac.Bl.
• $[x_{12}=1][x_{14}=1][x_{19}=0] \vee$ $[x_7=1][x_{12}=1][x_{13}=1][x_{15}=0][x_{18}=0,1][x_{19}=0] \rightarrow [dec=10]$	10. Bac.Pustule
• $[x_1=2,3,4,5,6][x_3=2][x_8=0][x_{30}=1][x_{31}=0] \rightarrow [dec=11]$	11. Pur.Se.Stain
• $[x_3=2][x_{19}=1][x_{22}=2][x_{29}=2,3] \vee$ $[x_1=1,2,3,4,5][x_4=1,2][x_7=0,1,2][x_8=0,1][x_{14}=1,2][x_{19}=1][x_{22}=1,2] \vee$ $[x_1=0][x_7=2,3][x_{15}=1,2][x_{19}=1][x_{20}=0][x_{21}=2,3][x_{22}=2,3] \rightarrow [dec=12]$	12. Anthracnose
• $[x_1=2,3][x_3=0,1][x_{11}=0][x_{13}=2][x_{19}=0] \vee$ $[x_1=2,3,4,5][x_3=0,1][x_{13}=2][x_{16}=1][x_{19}=0] \rightarrow [dec=13]$	13. Phyl.Lf.Spot
• $[x_1=5,6][x_3=2][x_4=2][x_{12}=1][x_{15}=1,2][x_{18}=0][x_{19}=0] \vee$ $[x_1=3,4][x_3=2][x_7=1,2,3][x_{10}=1,2][x_{12}=1][x_{15}=1,2][x_{18}=0][x_{19}=0] \vee$ $[x_1=4,5,6][x_3=2][x_{15}=1,2][x_{18}=0][x_{19}=0][x_{30}=1] \vee$ $[x_1=5,6][x_{10}=0,1][x_{15}=1,2][x_{18}=0][x_{19}=0] \vee$ $[x_1=6][x_{15}=1][x_{18}=0,1][x_{19}=0] \rightarrow [dec=14]$	14. Alter.Lf.Spot
• $[x_1=4,5,6][x_3=2][x_{12}=1][x_{15}=1][x_{16}=0][x_{18}=0,1][x_{19}=1][x_{23}=0] \vee$ $[x_1=3,4][x_3=2][x_7=0][x_{12}=1][x_{15}=1][x_{16}=0][x_{19}=0][x_{23}=0][x_{30}=0] \vee$ $[x_1=3,4,5,6][x_3=1,2][x_{12}=1][x_{15}=1][x_{18}=0,1][x_{19}=1][x_{22}=2,3][x_{23}=0] \vee$ $[x_1=4][x_3=1][x_6=1,2,3][x_{15}=1,2][x_{16}=0][x_{18}=0][x_{19}=0] \vee$ $[x_{12}=1][x_{14}=0,1][x_{15}=1,2][x_{19}=1][x_{21}=1,2,3][x_{22}=2,3] \vee$ $[x_1=3,4][x_3=2][x_4=2][x_{15}=1][x_{16}=0][x_{19}=0][x_{30}=0] \vee$ $[x_1=3,4][x_3=2][x_7=3][x_{15}=1][x_{16}=0][x_{19}=0][x_{30}=0] \vee$ $[x_1=5][x_4=0,1][x_7=1,2,3][x_{15}=1][x_{16}=0][x_{18}=0,1][x_{19}=0] \vee$ $[x_1=4,5,6][x_3=2][x_4=0,1][x_6=0][x_7=1,2,3][x_{15}=1,2][x_{18}=0][x_{19}=0] \rightarrow [dec=15]$	15. Frg.Eye Lf.Spot

Disease favored by warm, wet windy weather from late June to August.**

In this case, none of the other diseases exhibits the symptoms 1) leafspots with yellow halos or 2) leafspots without water-soaked margin. Again AQVAL/1 (AQ7) derives a rule which utilizes features which are most discriminant.

To check the validity of the discriminant rules, they were tested using 'testing events', i.e., descriptions of plants with a known disease (events which were not used in the process of inferring the rules from examples). If more than one rule was best satisfied, i.e., the most highly satisfied rules were within three percent of each other, the plant disease was multiply classified. In this experiment, no more than three discriminant rules were equally satisfied by any description. The discriminant diagnostic rules classified (uniquely or multiply) the testing events 93% correctly.

The results of testing are summarized in Table 3. The labels for the Table are as follows:

CORRECT ASSIGN -	The correct decision for disease under consideration.
INDECISION RATIO -	The number of decision rules satisfied over the number of testing descriptions. This ratio captures the relationship between the unique classification of a given event and the multiple classification as mentioned above. The value 1 for the indecision ratio indicates the case when each testing event was assigned only one disease, i.e., only one rule was best satisfied by the event (the value of the rule satisfied was three (or more) percent greater than the value of any other rule).
TIES -	The number of descriptions which satisfied two or more rules.
MAX RULES PER TIE -	The maximum number of rules which were satisfied when ties occurred.
UNSP -	The number of events which were not classified by the present rules.
NR LEARNING EVENTS -	The number of learning descriptions used for the disease under consideration.
NR TEST EVENTS -	The number of testing descriptions used for the disease under consideration.
ASSIGNED DECISION -	The number of decisions made for each decision class where CORRECT ASSIGN is the correct decision. Also given as a percentage of the number of testing descriptions.

As can be seen from the table, despite a small number of events used for learning, the discriminant rules appear to perform quite well on the testing material. In order to improve discriminant rules which perform poorly, one can use a program AQVAL/1 (AQ11) which uses erroneously classified events as feedback information and modifies the rules in question. Such a process may be continued through a few iterations until a satisfactory decision rule is obtained.

**Disease description taken from Report on Plant Disease No. 504, Department of Plant Pathology, University of Illinois.

3. Conclusion

We have presented a brief description of the methods used for applying the variable-valued logic system, VL_1, to the development of diagnostic rules for soybean diseases. Experimental results indicate that variable-valued logic concepts were very successful for this application. The work described is directed toward implementing a knowledge acquisition module of an inferential computer consultant for plant disease diagnosis and pest management currently being developed at the University of Illinois.

Appendix

Description of VL_1 Formula

FORMULA is a DVL_1 expression in the form of disjunction of TERMS, i.e.

$$\bigvee_i \text{TERM}_i$$

TERM is a product of one or more SELECTORS

SELECTOR is either a CONSTANT (a CONSTANT or REDUCED SELECTOR) or a form

[LEFTP = RIGHTP]

LEFTP ('left part') is a DESCRIPTOR

RIGHTP ('right part') is a VLIST or VRANGE

VLIST is a list of values from the domain of DESCRIPTOR (VLIST is used when the domain is:

- UD - unordered discrete ('cartesian variable')
- OD - ordered discrete ('interval variable')
- HS - hierarchical structure ('hierarchical variable')

Examples: $\boxed{1,3,5,7}$

VRANGE is a pair:

A : B

where A and B are numbers in ascending order. Example:

$\boxed{2.55 : 6.20}$

(VRANGE is used when the domain of DESCRIPTOR is OC ('ordered continuous') i.e. an interval of real values)

The domain is UD if values of the descriptor are unrelated names (or numbers). The domain is OD if values of the descriptor are linearly ordered names (or numbers) and the cardinality of the domain is equal or is smaller than a threshold τ. The domain is OC if values of a descriptor are linearly ordered and the cardinality of the domain is greater than τ. The domain is HS if the values of the descriptor are nodes of an hierarchy (tree, or, more generally, the so-called 'generalization structure').

Examples:

UD descriptor:	blood type, domain = {0,A,B,AB,etc}
OD descriptor:	height, domain = {short,aver.,tall}
OC descriptor:	temperature, domain = [72:108]°F
HS descriptor:	position of a person in an institution, domain = administrative hierarchy

TABLE 3
Confusion matrix summarizing results of the experiment.

CORRECT ASSIGN	INDE-CISION RATIO	TIES	MAX RULES PER TIE	UNSP	NR LEARN-ING EVENTS	NR TEST EVENTS	ASSIGNED DECISION D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	D15
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
D1	12/10	2	2	0	10	10	10 100%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	2 20%	0 0%	0 0%	0 0%
D2	10/1:c	0	0	0	10	10	0 0%	10 100%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%
D3	11/10	1	2	0	10	10	0 0%	0 0%	9 90%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	1 10%	1 10%
D4	10/10	0	0	0	10	10	0 0%	0 0%	0 0%	10 100%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%
D5	24/24	0	0	0	20	24	0 0%	0 0%	0 0%	0 0%	24 100%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%
D6	10/10	0	0	0	10	10	0 0%	0 0%	0 0%	0 0%	0 0%	10 100%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%
D7	10/10	0	0	0	10	10	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	10 100%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%
D8	54/52	2	2	0	40	52	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	50 96%	0 0%	0 0%	0 0%	0 0%	2 4%	1 2%	1 2%
D9	11/10	1	2	0	10	10	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	10 100%	1 10%	0 0%	0 0%	0 0%	0 0%	0 0%
D10	13/10	3	2	0	10	10	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	2 20%	8 80%	0 0%	0 0%	3 30%	0 0%	0 0%
D11	12/10	2	2	0	10	10	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	10 100%	0 0%	0 0%	2 20%	0 0%
D12	26/24	2	2	0	20	24	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	2 8%	23 96%	0 0%	1 4%	0 0%
D13	16/10	4	3	0	10	10	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	4 40%	0 0%	0 0%	0 0%	0 0%	8 80%	3 30%	1 10%
D14	65/51	12	3	0	40	51	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	3 6%	0 0%	0 0%	2 4%	0 0%	0 0%	43 84%	17 33%
D15	55/51	4	2	0	40	51	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	0 0%	3 6%	0 0%	0 0%	0 0%	0 0%	0 0%	6 12%	46 90%

Note: Correctly assigned decisions are contained within the diagonal lines.

Examples of SELECTOR:

$$[x_{110}=2,3,7] \qquad (1)$$

$$[x_{21}=.8:13.5] \qquad (2)$$

SELECTOR is a function whose output domain (C-O domain) D is a set of truth-values (or degress of truth). The domain D is decided by the user. It can be, e.g.:

D = {false, possible, very possible, true}

or

D = [0,1] (0-1 interval)

or simply:

D = {false, true}

It is assumed that for a given application the set D is fixed for all selectors. Assume here that D = [0,1].

A SELECTOR takes value 1 if it is satisfied and 0, otherwise. E.g.,

SELECTOR (1) takes value 1, if variable x_{110} takes value 2, 3, or 7, otherwise value 0.

SELECTOR (2) takes value 1, if x_{21} has value between .8 and 13.5 inclusively, otherwise value 0.

Examples of TERM:

$$.9[x_{13}=2,5][x_{12}=3,7,8][x_{15}=0.8:0.9] \qquad (3)$$

$$[x_1=1][x_3=0:3] \qquad (4)$$

TERM (3) takes value 0.9 if all its selectors are satisfied. Product of selectors can be interpreted as minimum multiplication, average or other function of values of the selectors. Assume here that it is interpreted as minimum.

Examples of FORMULA:

$$.9[x_{10}=0,3][x_{97}=.9:10.7] \vee 0.7[x_{114}=5] \vee 0.3 \qquad (5)$$

FORMULA is a function which maps a set of values of DESCRIPTORS in it into the domain D. Symbol $\vee$ can be interpreted as maximum ('OR' when there are no CONSTANT SELECTORS and SELECTORS are either TRUE or FALSE), or addition (mod 1) or a list-creator (in this case the value of formula is a list of values of its selectors). Assume here that $\vee$ is maximum.

References

Bobrow, D. G. and Raphel, B., New programming languages for artificial intelligence research. Stanford Research Institute Technical Report 82, Menlo Park, California. August 1973.

Bongard, M., Pattern Recognition, translated by Theordore Chevon. Spartan Books, New York, N.Y., 1970.

Buchanan, B. G., Sutherland, G. L., and Feigenbaum, E. A., Heuristic DENDRAL: a program for generating explanatory hypotheses in organic chemistry. In Machine Intelligence 4 (B. Meltzer and D. Michie, eds.), Edinburgh University Press, 1969.

Buchanan, B. G. and Sridharan, N. S., Analysis of behavior of chemical molecules: rule formation on non-homogeneous classes of objects. AI Memo 215, Stanford Artificial Intelligence Laboratory, Stanford University, Stanford, CA. 1973.

Colby, K. M., Tesler, L., and Enea, H., Experiments with a search algorithm on the data base of a human belief structure. AI Memo 94, Stanford Artificial Intelligence Project, 'Stanford University, Stanford, CA. 1969.

Feigenbaum, E. A., Artificial intelligence: themes in the second decade. Proc. IFIP Congress, Vol. II, pp. 1000-1008, Spartan Books, Washington, D.C. 1968.

Feigenbaum, E. A., Knowledge Engineering: theme for the coming decade, Machine Representation of Knowledge, Proc. NATO Advanced Study Institute - June 30 - July 2, 1975, Santa Cruz.

Green, C. C., The Application of Theorm Proving to Question-Answering Systems. Ph.D. Thesis, Tech. Report CS 138, Computer Science Department, Stanford University, Stanford, CA. June 1969.

Hewitt, C., PLANNER: a language for proving theorems in robots. Proc. of the 1st International Joint Conf. on AI, Washington, D.C. 1969.

Hewitt, C., Description and Theoretical Analysis (Using Schemata) of PLANNER: A Language for Proving Theorems and Manipulating Models in a Robot. Ph.D. Thesis, Department of Mathematics, MIT, Cambridge, MA. 1972.

Larson, J. B., Michalski, R. S., AQVAL/1 (AQ7) User's Guide and Program Description, Report No. 731, Department of Computer Science, University of Illinois, Urbana, IL. June 1975.

Maximov, V., Computer-Oriented Learning Processes, NATO Advanced Study Institute on Computer Oriented Learning Processes, France, Aug. 26-Sept. 7, 1974.

Michalski, R. S., A Variable-Valued Logic System as Applied to Picture Description and Recognition, GRAPHIC LANGUAGES. Proceedings of the IFIP Working Conference on Graphic Languages, Vancouver, Canada, May 1972.

Michalski, R. S., AQVAL/1--Computer Implementation of a Variable-Valued Logic System and the Application to Pattern Recognition, Proceedings of the First International Joint Conference on Pattern Recognition, Washington, D.C., October 30-November 1, 1973.

Michalski, R. S., VARIABLE-VALUED LOGIC: System VL_1, 1974 International Symposium on Multiple-Valued Logic, West Virginia University, Morgantown, West Virginia, May 1974(a).

Michalski, R. S., A Variable-Decision Space Approach for Implementing a Classification System, 2nd International Joint Conference on Pattern Recognition, Lyngby-Copenhagen, Denmark, August 1974(b).

Michalski, R. S., Synthesis of Optimal and Quasi-Optimal Variable-Valued Logic Formulas, 1975 International Symposium on Multiple-Valued Logic, Indiana University, Bloomington, Indiana, May 1975.

Shortliffe, E. H., MYCIN: A Rule-Based Computer Program for Advising Physicians Regarding Antimicrobial Therapy Selection. Ph.D. Thesis Computer Science Department, Stanford University, October 1974.

Waterman, D. A., Generalization learning techniques for automating the learning of heuristics. Artificial Intelligence 1, Nos. 1 and 2, 1970.

Yuen, H. V., Uniclass Cover Synthesis. User's Guide (unpublished manuscript in Department of Computer Science), University of Illinois, Urbana, IL 1974.

Zadeh, L. A., Fuzzy Logic and Approximate Reasoning. ERL Memo M479, College of Engineering, University of California, Berkeley, CA. 1974.