

**AUTOMATED ACQUISITION OF DECISION RULES: THE PROBLEMS OF ATTRIBUTE
CONSTRUCTION AND SELECTION**

BY

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THESIS

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Dedication

To LJH now LHB for still thinking I was worth the wait...

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1 INTRODUCTION

Expert systems are computer programs which contain and are capable of applying expert knowledge of a particular problem domain to solving problems within the domain. Examples of such systems are Mycin [Shortliffe,1982], used for medical diagnosis, and Plant/ds [Michalaki,1982a], used for diagnosing soybean plant diseases. Each system identifies a given input example as belonging to a particular class within the system's domain of expertise. The Plant/ds system, for example, arrives at the most plausible diagnosis for an afflicted soybean plant based on the symptoms the plant exhibits. In this case, the domain of soybean diseases has been divided into a number of categories (classes) each representing a different disease. The task of the expert system is to identify which class (disease category) a given plant's symptomology represents.

Traditional expert system development techniques require an expert in the domain of interest to specify the important factors he uses to arrive at expert determinations. In the Mycin system, the experts were required to formulate a set of rules to apply to test cases to determine a plausible course of treatment for each case. The experts found that while they were capable of reaching determinations easily, they were less able to articulate the process they used to arrive at them. This approach requires the expert to analyze his own methodology from a perspective to which he is unaccustomed. The systems which result are often inefficient because they use unnecessary data in the process of analyzing a test case, and unreliable because contingencies not previously encountered may result in faulty or indeterminate results [Clancey,1981] [Hayes-Roth,1980]. To repair these shortcomings, the system designer resorts to iterative development methods in which the expert is presented with the faulty results and asked to augment the current system so that correct results are produced. When further testing uncovers new flaws, the development loop is repeated.

This paper describes a system which seeks to relieve the domain expert of the burden of analyzing his own methods. He uses his knowledge to reach expert determinations (classifications) for examples from his domain of expertise. Once the expert has classified each sample case, the system uses techniques patterned on a general model of the expertise development process to attempt to discover the relationships prevalent in each class used by the expert, and formulates general rules for classifying future examples. This approach, termed *learning from examples* minimizes the need for the expert to codify his technical knowledge. The system consists of three programs which are described in detail later in the paper. The first, CONVART, computes attributes of the time-varying characteristics of examples. The second, VARSEL, selects the "most relevant" attributes for formulating classification rules from those produced by CONVART and those initially available. The third program, GEM, uses the attributes identified by VARSEL to formulate classification rules for each of the classes represented by the set of examples. VARSEL was devised and written by the author, while CONVART and GEM were written by others [John Davis, and Robert Stepp, et. al., respectively].

1.1 Current Expert System Development Techniques

1.1.1 Knowledge Encoding

One traditional approach to the creation of expert systems is shown in Figure 1. A *knowledge engineer* works in concert with a domain expert to characterize the process used by the expert to reach decisions [Hayes-Roth,1980]. Unfortunately, domain experts are often unable to describe their own mental processes clearly enough to enable the production of efficient, complete and reliable systems. This problem makes many iterations through the development loop necessary. The knowledge engineer encodes the expert's knowledge, applies the resulting system to sample cases, uncovers insufficiencies or inconsistencies, and returns to the expert to overcome these difficulties. This iterative process strains the knowledge representation scheme and the process control structure until the system becomes unwieldy and difficult to use and maintain.

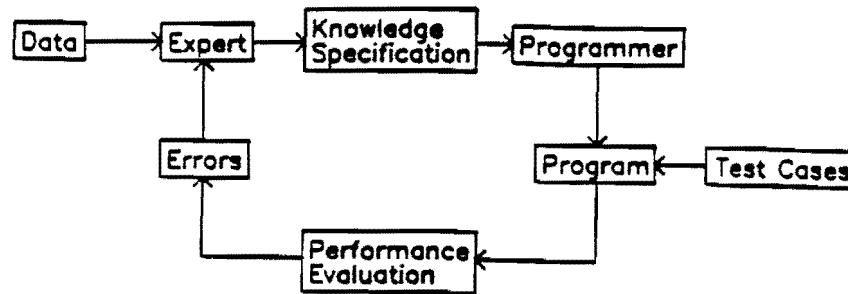


Figure 1. The traditional expert system development loop

A second failing of the knowledge encoding approach arises from the necessity of having a domain expert in the development process. This requirement precludes the possibility of expert-system development in domains in which no experts have developed because the area is too new or obscure. The development of domain expertise is a slow process because of the tremendous difficulties inherent in discovering relevant avenues of inquiry into the underlying processes and structures within the domain.

1.1.2 Automated Inductive Inference

A relatively new approach toward expert system development involves *inductive learning* systems which use empirical evidence, in the form of examples, to derive rules by which determinations may be made for data presented to the system. Such systems use *automated inductive inference*, a method whereby rules for classifying events are derived using computer programs which systematically process the data to discover patterns and interrelationships which may be useful for distinguishing each class from the others [Michalski, 1972, 1980, Angluin, 1982]. The failing of these systems arises from the limitations inherent in dealing with statistically valid populations of sample data. For some automated inductive inference methods, an exponential relationship exists

between data-set size and processing time required [Rabin,1974]. This causes a problem termed *combinatorial explosion* where the processing time for a large data set is often far too lengthy to be of practical value. Modern inductive learning systems, e.g., AQ11 or ID3 are able to avoid this problem by applying appropriate heuristic methods. However, the task of looking for patterns of interaction and interdependency within data is so complex, and since the amount of data should be large if the results are to be reliable, the modern systems must use some means of further *data-reduction* if the processing time for the learning programs is to be acceptable. Traditionally, system designers rely on domain experts to tell them which data are relevant and which should be ignored. Consequently, expert system development using automated methods is also prone to iterative development because the domain experts frequently misjudge which data are important or relevant. This produces systems with the same basic flaws encountered in knowledge engineered systems: inefficiency and unreliability.

1.2 Requirements for Better Expert System Development

The major shortcoming of current expert system development techniques is the continued dependency on domain experts to provide information they are normally unprepared to provide. System development techniques requiring the aid of domain experts for initial development are doomed to inadequate performance unless new insights can be gained into the ways in which domain expertise arises and is implemented. This paper describes a data-driven system which is largely domain independent and can operate without the explicitly stated *a priori* knowledge of the problem domain usually needed by system developers [Buchanan,1979]. Assuming that the necessary knowledge is contained in the pairing of sample events with expert determinations, sufficiently powerful methods for extracting the knowledge are needed [Tunstall,1974] [Shapiro,1981]. The ability to do this requires a method which can assess the relevance of attributes reliably while remaining so computationally efficient that extensive pre-selection of attributes by a domain expert is not required [Chen,1974]. Hence, the role played by the domain expert in ordinary automated system development paradigms is now also largely automated. The system can

deal with large amounts of data and indicate promising avenues of exploration for researchers in the problem domain and expert system implementors alike.

2 A MODEL OF THE EXPERTISE DEVELOPMENT PROCESS

The following definitions will be used throughout the discussion which follows:

- An *exemplar* or *example* is an object which exemplifies a given decision class.
- An *attribute* is a measurable characteristic of an exemplar within the problem domain.
Examples are color, height, and annual rainfall. Attributes fall into two categories: static attributes measure characteristics which have a constant value while dynamic attributes measure characteristics whose values vary relative to some other variable such as time, for a given exemplar.
- A *selector* is a relation between a given attribute and the value of that attribute.
Examples include $\text{color} \neq \text{red}$, $\text{height} = 1.75\text{m}$, and $\text{weight} \leq 95\text{kg}$.
- An *event* is a vector of attribute values characterizing a given exemplar. An event may be represented by a conjunction of selectors.
- A *decision class* or *class* represents the membership of one or more exemplars in a category characterized by some common denotation.
- An *event set* is a set of events which are members of known decision classes.

An example of an event set is given in Figure 2. The event set is comprised of two classes of two events each and one class of one event. Each event is in the form of a conjunction of four selectors. A Dodge-Dart, for example, weighs 6000lb, is twelve feet long, and can carry six passengers.

A model of the expertise development process, patterned after one in [Dietterich,1981], is presented in Figure 3. The sequential model of expertise development presented here has four major processing steps and feedback from any step to any previous step [Kanal,1978]. Each of the four processing steps— attribute construction, attribute selection, rule formation, and rule implementation— are described in detail below.

Class : Car
Examples : $[model=Dodge-Dart] \wedge [weight=6000lb] \wedge [length=12ft] \wedge [passengers=6]$
 $[model=Toyota-Corolla] \wedge [weight=5000lb] \wedge [length=11ft] \wedge [passengers=5]$

Class : Truck
Examples : $[model=Mack] \wedge [weight=36000lb] \wedge [length=35ft] \wedge [passengers=3]$
 $[model=Peterbilt] \wedge [weight=34000lb] \wedge [length=35ft] \wedge [passengers=3]$

Class : Bus
Example: $[model=Greyhound] \wedge [weight=21000lb] \wedge [length=32ft] \wedge [passengers=30]$

Figure 2. A sample event set.

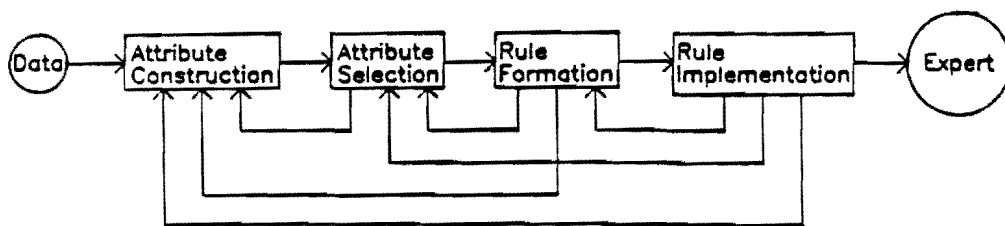


Figure 3. A model of the expertise development process

2.1 Attribute Construction

Once an initial set of attributes have been selected by the expert as potentially relevant, the first processing step involves the construction of derived attributes. Derived attributes are produced by applying a variety of logical, statistical, or mathematical operations to the initial attributes. For example, a derived attribute may be a mathematical product of some numerical attributes or a logical expression of propositional attributes (properties that are true or false).

Additional attributes may be derived by first noting that some attributes change over time. Rainfall would be one example of such an attribute. The rainfall on a given field could be given as a series of values representing "rainfall" on each day for a given time interval. New attributes can be constructed from this type of attribute using statistical operations such as averaging (e.g. "the average rainfall per week"). Arithmetic operators can be applied to numeric attributes. For example, if we have the attributes length, width, and height, we might apply the multiplication operator to construct the attribute "volume." Neither mathematical nor statistical operators can be applied to non-numeric (i.e., *symbolic*) attributes such as "blood type" or "eye color."

To perform attribute construction, operators are applied to the attribute values in the hope of discovering new attributes which have greater class-differentiating abilities than the original attributes. This process is termed *constructive induction* [Michalski,1982b] [Davis,1981].

2.2 Attribute Selection

After attribute construction is completed, the set of constructed attributes is joined to the set of initial attributes and each attribute is evaluated in terms of its potential *relevance* (i.e., its potential utility for differentiating classes based on its value for a given exemplar) [Kodratoff,1982]. This is the process of attribute selection in which unusable or less informative attributes are discarded and only those attributes which best distinguish the classes are retained.

2.3 Rule Formation

The third processing step is rule formation. Rule formation entails characterizing the classes by logic expressions involving selectors. The most interesting expressions are those which most compactly capture the knowledge necessary to classify a new event reliably. The two basic conditions that a set of such expressions (rules) must meet are *consistency* and *completeness*. Completeness requires that each exemplar must satisfy some rule from the rule set, and consistency requires that each exemplar satisfy *at most* one class from the set of classes.

A set of simple discriminant rules for the event set of Figure 2 is shown in Figure 4. The first rule reads: "If the length is less than 20 feet, the vehicle is a car." The second rule reads: "If the length is greater than 20 feet and the vehicle can carry less than four passengers, then it is a truck."

Rule 1:	$[\text{length} < 20\text{ft}] \Rightarrow \text{car}$
Rule 2:	$[\text{length} \geq 20\text{ft}] \wedge [\text{passengers} \leq 3] \Rightarrow \text{truck}$
Rule 3:	$[\text{length} \geq 20\text{ft}] \wedge [\text{passengers} > 3] \Rightarrow \text{bus}$

Figure 4. A set of discriminant rules derived from the event set in Figure 2.

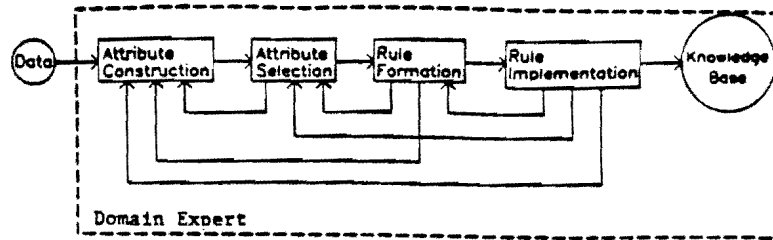
2.4 Rule Implementation

The final processing step is rule implementation. This is the encoding of the rules generated in the previous step in such a fashion that they may be applied to new events supplied by a user. Although implementing the rules is a simple process, designing the user interface is not. The most important characteristics of an expert system which will be used by people who are not intimately familiar with the software are: easy data entry, comprehensive presentation of results including

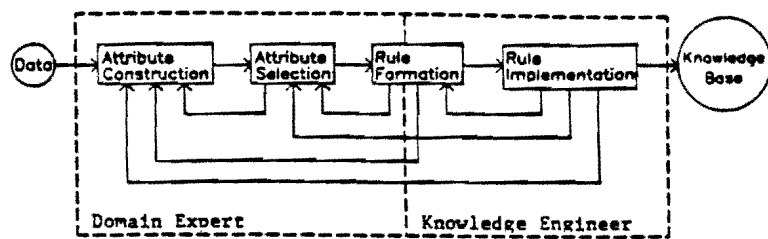
measures of how confident the system is in its analysis, and the ability to explain the reasoning processes which led to the result presented.

2.5 Conventional Methods in Terms of the Model

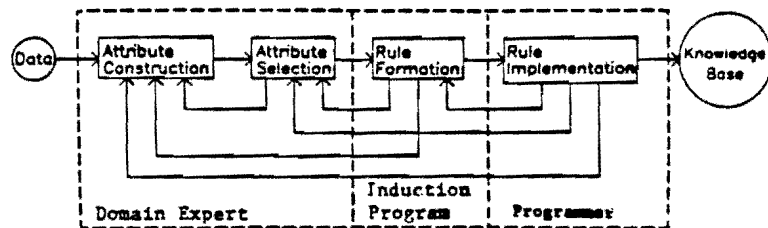
Figures 5a-c show the model of Figure 2 configured to correspond to its application to human expertise development, the knowledge engineering approach to expert system development, and the automated induction method respectively. In Figure 5a, human expertise development, we see that the human expert is responsible for all processing, implementation, and application of the resulting expertise. In Figure 5b, the knowledge engineering approach, the expert is still responsible for all attribute processing but now the knowledge engineer must share the task of rule generation and becomes responsible for implementing the rules on a computer. Figure 5c shows the automated inductive inference method in terms of the general model. The human expert is now responsible only for deciding which attributes are relevant. The data is then presented to an inference program in terms of the specified attributes, and the program develops rules which characterize the data. The software engineer must then implement the rule set on the computer. Figure 5d shows the software described below as it relates to the model.



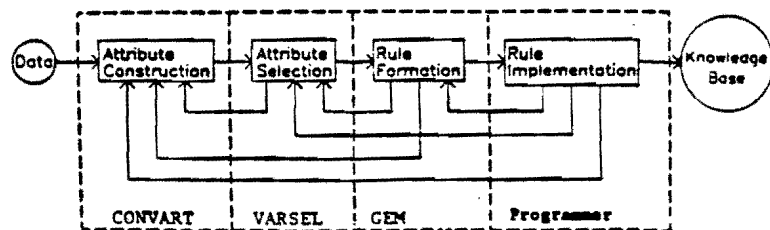
(a)



(b)



(c)



(d)

Figure 5. A progression toward increasing automation of the expert system development process:

- (a) Pre-expert-systems method
- (b) Classical expert systems development
- (c) Automated rule formulation
- (d) Automated attribute construction and selection and automated rule formulation using the software described in this paper

3 AN IMPLEMENTATION OF THE MODEL

3.1 Attribute Construction Using the Program CONVART

3.1.1 A Rationale for Attribute Construction

Time-dependent attributes are those that capture the value of some characteristic of an event as it changes with time. Such attributes are, therefore, useful for describing procedures or processes. If such attributes could be used by an inference engine, a broader range of problem domains would be approachable by expert systems. Current inference engines, however, are only capable of processing so-called static attributes which have only a single value for each event. If inductive inference techniques are to be applied to these problem domains, some method for representing dynamic (time-dependent) attributes by static attributes is needed. Two ways of describing dynamic attributes statically may be employed. The first involves characterizing the progression of values for the attribute over time as a polynomial or other functional entity. This is the method used in the series of Bacon programs [Langley,1982].

The second method is the computation of fundamental descriptive quantities for the set of measured values. Examples of such quantities for numeric attributes (i.e., attributes whose possible values have a natural partial-ordering) are maximum, minimum, average, etc. Examples of quantities for nominal attributes (i.e., attributes whose possible values have no inherent partial-ordering such as color or shape) are most-common-value and least-common-value. This is the method used by CONVART [Davis,1981]. CONVART is composed of a number of routines which compute such measures for dynamic attributes. It is implemented in Pascal on a Vax 11/780.

Another problem found in both dynamic and static attributes is the use of continuous variables which may take on any real value within some range of values. Interpreting the meaning of a given value for such an attribute is often difficult, and applying inductive inference techniques to them often produces unwieldy results. The solution CONVART applies to continuous attributes

is *discretization*. Discretization is the process of dividing the range of possible values for an attribute into a manageable set of discrete values based on the distribution of the observed values throughout the range of possible values. CONVART uses a nearest-neighbor algorithm to arrive at plausible discrete ranges.

3.1.2 Using CONVART in An Expertise Development System

Given that CONVART produces many derived attributes from each dynamic attribute and adds them to the original static attributes, the burden falls on the inference engine to weed out the bad attributes and use only the relevant ones. Although a rudimentary relevancy evaluator was incorporated in CONVART, the developer admits that it is far from sufficient for the task [Davis,1981]. Therefore, the rule constructor is still faced with the task of dealing with many attributes measured (or computed) for many events. Because of the complexity of the algorithms on which inductive inference programs are based, the processing required for event sets containing many attributes is unacceptable. Attribute selection is needed to make the process of expert system development practical for "real" event sets.

3.2 The Attribute Selection Program VARSEL

The program VARSEL performs the task of attribute selection based on a measure of attribute relevancy for class discrimination calculated using the method described below. It is implemented in Pascal on a Vax 11/780. The program evaluates each attribute individually and then compiles a subset of attributes which completely differentiates each class from the others. The user may select one of two ways in which the compilation is to proceed. The first method is an adaptation of a procedure proposed by [Lbov,1965] in which attributes are chosen randomly using a weighted selection scheme in which more relevant attributes are more likely to be chosen. The method described here uses this principle of *random adaptive search*, modified so that small subsets of attributes are evaluated and the individual relevancy measure of each constituent attribute is improved or degraded based on the performance of the selected subset as a whole

[Smith,1980] [Bethke,1981]. If the process converges, the most relevant attributes are then indicated by high relevancy measure.

The second method involves what has been termed a *greedy* search scheme in which attributes are added to a subset of attributes until a sufficiently discriminatory attribute set has been found. Both methods are described in detail below.

3.2.1 A Rationale for Attribute Selection

Attributes may be of three types. Numeric attributes have real or integer values which represent measured quantities directly. Examples of numeric attributes are "temperature" and "number of legs." Ordinal attributes have integer values which capture a true partial ordering present in the attribute values. An example of such an attribute is "quality" which may have the values "very bad", "bad", "acceptable", "good", and "excellent." The third type of attribute is a symbolic attribute. The values of symbolic attributes have no inherent partial ordering. One example of such an attribute is "shape." Another term often applied to symbolic and ordinal attributes is *nominal*.

The problem of selecting the most relevant set of attributes to describe objects for the purpose of inductive learning is traditionally approached using various methods of attribute selection such as factor analysis, multidimensional scaling, and linear transformation, developed in the fields of pattern recognition and statistical decision theory. These methods involve statistical or information-theoretic measures which identify the principal attributes in the event set [Andrews,1972] [Harmon,1960] [Lawley,1963]. These methods are most effective for numeric attributes when the size of the event set is statistically significant. When attributes are symbolic (categorical or propositional) and the event set is small, these methods are not adequate [Stearns,1976] [Zadeh,1981]. In fact, using the methods mentioned above, "it is almost impossible to formulate general guidelines regarding the selection of physical [attributes] and structural [attributes]" [Tou,1974]. To analyze such *nominal* attributes mathematically, numeric values must be

assigned to each possible value of the attribute (e.g., color might be encoded as: red=1, yellow=2, blue=3, etc.). When statistical methods are applied to such attributes, the results from the statistical methods may vary if the ordering of the values changes (e.g., red=2 and yellow=1). Thus, although the actual values of the attribute have not changed, the measures derived from them have. This is clearly erroneous. Therefore, there is a need for new methods applicable to multivalued or propositional symbolic attributes and for small numbers of events.

3.2.2 A Relevancy Measure

The difficulty of performing satisfactory attribute selection using statistically-based methods may be overcome by analyzing the observed values of the attributes using a method based on heuristic knowledge of the properties of attribute values typically found in event sets of interest. Such a system could deal effectively with symbolic and ordinal attributes since these attributes do not behave statistically in the same way that numeric attributes do.

The computation time necessary to process a set of events is large when the event set contains many attributes. A computationally inexpensive means of rapidly eliminating irrelevant attributes would reduce the computation time required. The method described below accomplishes all of these goals.

Classical information theory has been used to attack the problem of attribute relevancy measurement by modeling decision trees as information sources and attribute values as "messages." The information contained in a message "M" depends on the probability of the message and is expressed by:

$$I = \log_x \left(\frac{1}{P(M)} \right) \quad (1)$$

where: $P(M)$ is the probability of message "M."

In event sets of interest, a given value (message) may occur in events representing more than one

class. If we can assume that the message is *correct* for only one of the classes in which it occurs, then the information provided by the message depends not only on the probability of the message, but on the probability that the message is correct $P(c \cap M)$:

$$I = \log_x \left(\frac{1}{P(c \cap M)} \right) \quad (2)$$

Others have postulated that the information in such a "questionable" message is [Quinlan,1982]:

$$I = \log_x \left(\frac{1}{p^+} \right) + \log_x \left(\frac{1}{p^-} \right) \quad (3)$$

where: p^+ is the probability of the correct occurrence of the message.

p^- is the probability of the incorrect occurrence of the message.

The derivation of this expression relies on one fundamental assumption. The correct and incorrect messages are probabilistically independent. This, however, is incorrect. The two messages are, in fact, mutually exclusive by their very nature. This invalidates the expression. We might then hypothesize that, given the information measure in equation 2, that for "v" possible values (messages) for a given attribute:

$$I_{tot} = \log_x \left(\frac{1}{P(c \cap M_1)} \right) + \log_x \left(\frac{1}{P(c \cap M_2)} \right) + \dots + \log_x \left(\frac{1}{P(c \cap M_v)} \right) \quad (4)$$

holds if the messages are independent. Unfortunately, the most frequent case is that the different messages are not necessarily independent and such an assumption has an associated risk. In addition, these measures effectively assume that we are interested in viewing the messages as "correct" or "incorrect." While such a binary view is sometimes useful, the multi-class nature of event sets of interest calls for a more robust measure. Therefore, we require a measure which retains the multi-class view of the world and is immune to the vagaries of data collection and random occurrence of events which often produce widely disparate class sizes within an event set.

We approach this problem by first making a simple assumption: since we wish to measure a characteristic of the data (which, hopefully, reflects the nature of the domain of interest) we may take advantage of the fact that for a given attribute, for a given event, only one value may be observed in the data. This assumption allows us to further assume that the possible messages (values) for a given event are not independent, but mutually exclusive. Unlike the case of equation 3 above, we realize that dealing with such messages by combining their information contents can be misleading. Instead, we will manipulate their probabilities directly. The total probability of all possible messages given mutual exclusivity is:

$$P_{tot} = P(M_1) + P(M_2) + \dots + P(M_v) \quad (5)$$

If each of the terms is further divided into probability of correctness $P(c \cap M_i)$ and error $P(e \cap M_i)$, the total probability is:

$$\begin{aligned} P_{tot} = & P(c \cap M_1) + P(e \cap M_1) + P(c \cap M_2) + P(e \cap M_2) + \\ & \dots + P(c \cap M_v) + P(e \cap M_v) \end{aligned} \quad (6)$$

This equation may be separated into two:

$$P_c = P(c \cap M_1) + P(c \cap M_2) + \dots + P(c \cap M_v) \quad (7a)$$

$$P_e = P(e \cap M_1) + P(e \cap M_2) + \dots + P(e \cap M_v) \quad (7b)$$

capturing the probability of correctness or incorrectness for all messages (values). Each term in Equation 7b may be expanded into:

$$P(e \cap M) = \frac{n_{e_1} + n_{e_2} + \dots + n_{e_{(m-1)}}}{N_{tot}} \quad (8)$$

where: m is the number of classes in the event set.

n_{e_i} is the number of occurrences of the message in error class "i" of which there are $(m-1)$ since one of the classes is "correct," not in error.

N_{tot} is the total number of events in the event set.

We see that this value is sensitive only to the *relative sizes* of the class for which the value is correct and the remaining classes in the event set. Since this is not desirable as mentioned above, we introduce normalization factors into each term to remove this size bias. Since this will change our result into something other than a pure probability, we will designate our new result the *likelihood of error for a given message (value)* $l_{e,M}$:

$$l_{e,M} = \frac{1}{m-1} \left(\frac{n_{e_1}}{N_{e_1}} + \frac{n_{e_2}}{N_{e_2}} + \dots + \frac{n_{e_{(m-1)}}}{N_{e_{(m-1)}}} \right) \quad (9)$$

where: N_{e_i} is the total number of events in error class "i."

Given the likelihood that each possible value will be interpreted incorrectly, the total likelihood of error is:

$$L_{e,a} = \sum_{M=1}^v l_{e,M} \quad (10)$$

since the number of possible messages equals the number of possible values " v " of the attribute. The value of this measure is between 0 and 1 but the range is inverted in meaning (i.e., the best attribute has likelihood of error of 0). The final step is to invert the range to arrive at a measure we will call the *relevance* of an attribute denoted by p :

$$\rho = 1 - L_{e,a} \quad (11)$$

Which has value 0 for worst-case attributes and value 1 for perfectly discriminant attributes.

The final consideration is the determination of which class is the "correct" one for a value which appears in more than one class. We have assumed, for the purposes of this study, that the class for which the value is most likely is the correct class. In practice, this is the class for which the value of the term $n_{m_{\text{class}}} / N_{\text{class}}$ is greatest for a given attribute value "m."

An example will show the application of equation 11. In Figure 6a, a event set of three attributes measured for three classes is given. Figure 6b shows that, for attribute x_2 , the normalized probabilities of occurrence in each class of the value "1" is 1.0, 0.0, and 0.0 respectively. Since there are 3 out of 4 events with value 1 in class 1 (0.75), 0 out of 2 events with value 1 in class 2 (0.0), and 0 out of 1 events with value 1 in class 3 (0.0). The same analysis for the other messages (values) completes the table. Figure 6c shows the calculation of likelihood of error for each of the values. For example, assuming the "correct" class for value 2 is class 2 since the term in Figure 6b for value 2 is greatest for class 2, The calculation is the sum of the remaining 2 "error" classes times $1/(m-1)$ which is 1/2. Finally, Figure 6d gives the remaining calculation of relevance.

Three experiments were performed to examine the performance of equation 11 using the program PROMISE which calculates the value of ρ for attributes in a given event set. The inductive inference engine was the program AQ11 [Michalski,1978]. Both PROMISE and AQ11 were implemented in Pascal on a Cyber 175 computer.

	x_1	x_2	x_3
c_1	1	1	1
	1	1	1
	1	1	4
	1	2	2
c_2	2	2	2
	2	4	2
c_3	3	3	2

(a)

		Class		
		$\frac{n_{M_{class}}}{N_{class}}$		
Message		1	2	3
	1	0.75	0.00	0.00
	2	0.25	0.50	0.00
	3	0.00	0.00	1.00
	4	0.00	0.50	0.00

(b)

$$l_{e,1} = \frac{1}{2} \left(\frac{0}{2} + \frac{0}{1} \right) = 0.000$$

$$l_{e,2} = \frac{1}{2} \left(\frac{1}{4} + \frac{0}{1} \right) = 0.125$$

$$l_{e,3} = \frac{1}{2} \left(\frac{0}{4} + \frac{0}{2} \right) = 0.000$$

$$l_{e,4} = \frac{1}{2} \left(\frac{0}{4} + \frac{0}{1} \right) = 0.000$$

(c)

$$L_{e,x_2} = 0 + 0.125 + 0 + 0 = 0.125$$

$$\rho = 1 - 0.125 = 0.875$$

(d)

Figure 6. Calculating relevance:

- (a) A sample event set
- (b) A chart showing the number of events with a given value in each class divided by the total number of events in the class for each of the possible values of x_2
- (c) The calculations of likelihood of error for each the possible values of x_2
- (d) The final steps in the calculation of the relevance of x_2

3.2.2.1 Experiment I

The relevance ρ for more than one attribute at a time may be calculated by considering the values of several attributes in an event as a single *compound* attribute. To test the behavior of ρ for this type of processing, the "Animals" event set, described in [Michalski,1975], was processed by PROMISE. The Animals event set is shown in Figure 7. The data and a set of rules for Animals are given in Appendix D. The protozoan creatures in each of the fourteen classes may be described by thirteen attributes:

- x_1 is the number of black circles on the body.
- x_2 is the number of tails.
- x_3 is the number of crossmarks on tails.
- x_4 is the number of easily distinguished extremities.
- x_5 is the body texture.
- x_6 is the number of empty circles on the body.
- x_7 is the number of empty squares on the body.
- x_8 is the number of empty triangles on the body.
- x_9 is the type of tail.
- x_{10} is the shape of the body.
- x_{11} is the number of sharp or straight angles.
- x_{12} is the number of "eyes" (half-black circles).
- x_{13} is the number of black squares on the body.

First, the relevance of the individual attributes were evaluated by PROMISE, and the attributes were arranged in order of increasing value of relevance. Next, all projections on pairs of attributes were evaluated and the results were analyzed as follows: The combinations were ranked by increasing value of ρ and the range of observed values of ρ was divided into 10 equal-sized sub-ranges. The number of occurrences of a particular attribute in the set of pairs with relevance values in a sub-range is expressed as a percentage of the total number of occurrences of all

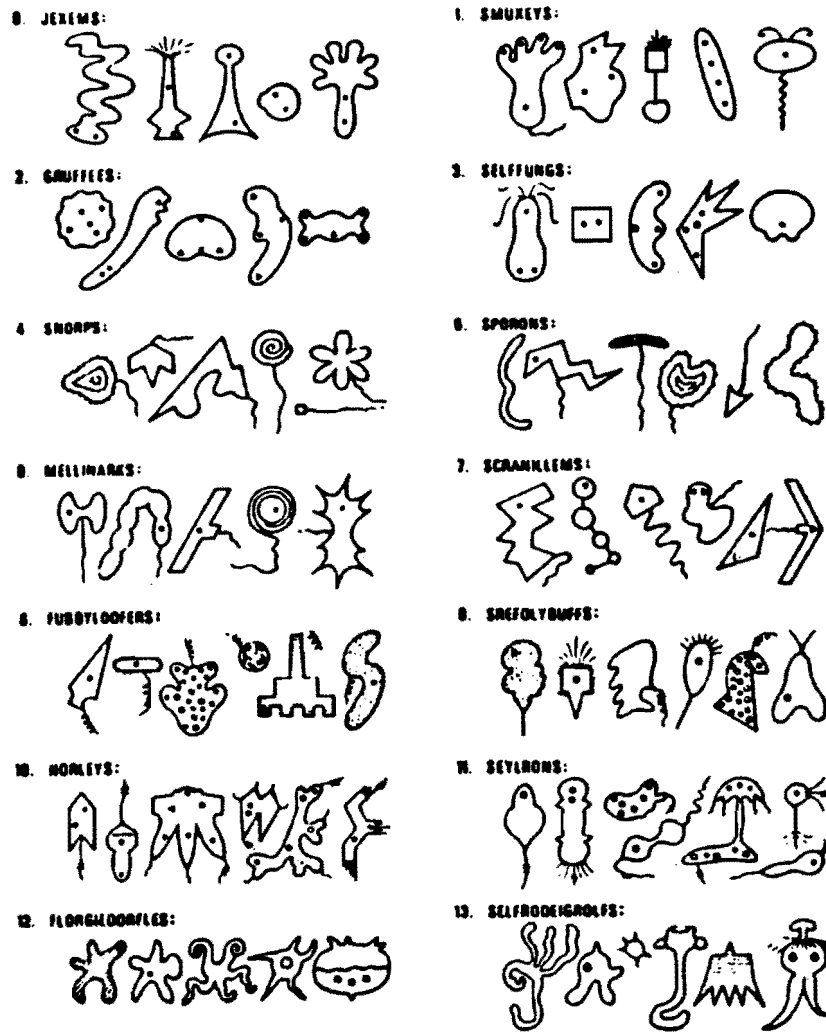


Figure 7. An event set showing fourteen species of "Animals."

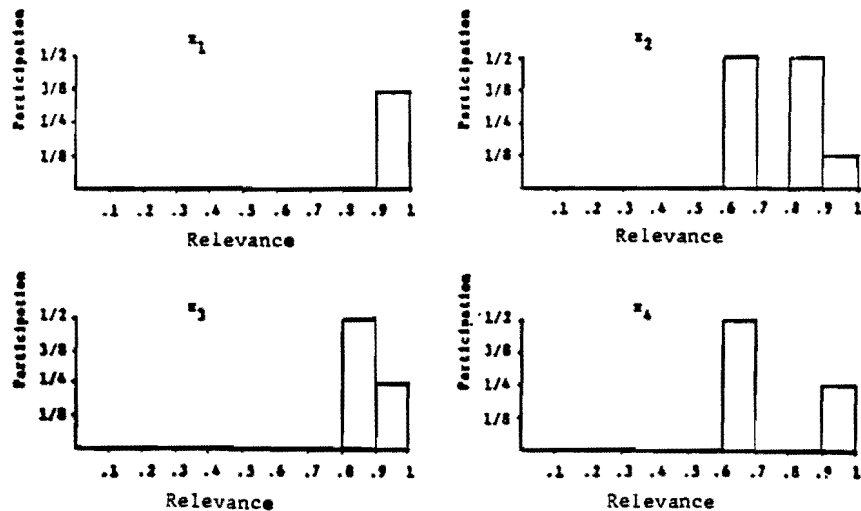
	x_1	x_2	x_3	x_4	Pair	ρ
c_1	1	1	1	1	x_1x_2	1.00
	1	1	1	1	x_1x_3	1.00
	1	1	1	1	x_1x_4	1.00
	1	2	3	1	x_3x_4	1.00
c_2	2	2	2	2	x_2x_3	0.87
	2	2	2	2	x_2x_4	0.67
	2	2	2	2		
c_3	3	2	3	2		
	3	2	3	2		
	3	3	3	3		

(a)

(b)

Attribute	Frequency of appearance of attributes from table above by relevance value.				
	0- .6	.6- .7	.7- .8	.8- .9	.9-1.0
x_1	0	0	0	0	3/8
x_2	0	1/2	0	1/2	1/8
x_3	0	0	0	1/2	2/8
x_4	0	1/2	0	0	2/8

(c)



(d)

Figure 8. Sample analysis of attribute groups for determining individual attribute relevance:

- Sample event set
- Value of ρ for all distinct pairs of attributes
- Table of counts of the number of times each attribute appears in each subrange of promise, divided by the total number of attributes appearing in the range
- Histogram plots of the values from the table in (c)

attributes in the subrange and plotted as a histogram. An example of such an analysis is presented in Figure 8. A relevant attribute should exhibit greater participation in the high-valued sub-ranges and irrelevant attributes should exhibit greater participation in low-valued sub-ranges. When linear regression analysis is applied to these plots, relevant attribute "profiles" should have more positive slopes and lesser y-intercepts and irrelevant attribute profiles should have more negative slopes and greater y-intercepts. Such an analysis was performed for all combinations of three and four attributes as well. The histogram plots for all of the analyses are given in Appendix D. The resulting attribute rankings are shown in Figure 9. Actual values from the analyses are not given since values computed for different size groupings of attributes are not directly comparable. The table shows that the relevance value measured for each attribute is independent of the interactions between attributes in this event set because the rankings are fundamentally the same independent of the size of the groupings used. Therefore, the values indicated by PROMISE for individual attributes are independent of the interactions between attributes in this experiment, and can be used to order the attributes.

Combinations	Best	Worst
Single Attributes	x_1	x_7
Pairs	x_1	x_7
Triples	x_1	x_7
Quadruples	x_1	x_7

Figure 9. Attributes ranked by their relevance when evaluated interdependently in pairs, triples, and quadruples. A sample of such an analysis is given in Figure 7 and all of the analyses are given in Appendix D

3.2.2.2 Experiment II

The event set used for experiment II is given in Figure 10. It includes attributes with widely varying degrees of relevance. The values of one attribute were arranged so that the classes could be distinguished by the value of that attribute alone. Another attribute had the same value in all events. Two more attributes were pseudo-random, and the rest differentiated the classes to varying degrees. The data comprised five classes (3 with 8 events, 2 with 5 events). The result of the analysis of the attributes individually is shown in Figure 11. The ordering of the attributes by p -value (Figure 11) matches the order of attribute relevancy designed into the event set. The results show that PROMISE evaluates attributes based on their ability to distinguish classes in the event set. This indicates that a set of attributes which uniquely characterizes each class in an event set and contains few extraneous variables can be obtained by examining attributes beginning with the most relevant attributes and adding more attributes in order of decreasing relevance until the projection of the event set on the attributes has $p=1$. For example, when the most relevant attribute is excluded, the next three attributes can distinguish the classes uniquely (two of them comprise the minimum number that do so in this event set when the best attribute is excluded).

3.2.2.3 Experiment III

Experiment three was undertaken to determine the magnitude of the computational advantage, if any, realized by removing as many extraneous attributes as possible using PROMISE before the data is processed by AQ11.

The data for the third experiment were the same data used in experiment II but with the most-relevant attribute removed and a number of pseudo-random attributes added (42 in this experiment) to simulate the common occurrence of event sets which include no perfect attributes and many irrelevant ones. The attributes were processed by PROMISE and ordered by increasing relevance value. Because the three most relevant attributes are not distinguished by different p -values, they were all accepted initially and the projection of the data onto those three attributes was

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}
c_1	0	0	0	0	0	1	0	1	2	3
	0	0	0	0	0	1	0	1	3	4
	0	0	0	0	0	1	0	1	3	0
	0	0	0	0	0	1	0	2	0	1
	0	0	0	0	0	1	0	3	4	1
	0	0	0	0	0	1	0	2	4	2
	0	0	0	0	0	1	0	1	1	2
	0	0	0	0	0	1	0	3	3	0
c_2	1	0	0	0	0	2	0	2	5	3
	1	0	0	0	0	2	0	4	5	3
	1	0	0	0	0	2	0	4	5	2
	1	0	0	0	0	2	0	3	5	1
	1	0	0	0	0	2	0	3	5	3
	1	0	0	0	0	2	0	1	5	2
	1	0	0	0	0	2	0	4	5	4
	1	0	0	0	0	2	0	3	5	3
c_3	2	1	0	0	0	3	0	2	0	2
	2	1	0	0	0	3	0	3	2	0
	2	1	0	0	0	3	0	3	0	0
	2	1	0	0	0	3	0	1	0	0
	2	1	0	0	0	3	0	1	1	3
	2	1	0	0	0	3	0	1	1	1
	2	1	0	0	0	3	0	0	0	4
	2	1	0	0	0	3	0	2	2	3
c_4	2	2	1	1	0	4	0	4	6	3
	2	2	1	1	0	4	0	0	6	3
	2	2	1	1	0	4	0	2	6	1
	2	2	1	1	0	4	0	1	6	0
	2	2	1	1	0	4	0	4	6	3
c_5	2	2	2	0	1	5	0	3	3	4
	2	2	2	0	1	5	0	2	1	0
	2	2	2	0	1	5	0	0	4	3
	2	2	2	0	1	5	0	2	1	1
	2	2	2	0	1	5	0	1	0	3

Figure 10. An event set containing attributes with a wide range of relevance used to test the performance of equation 11

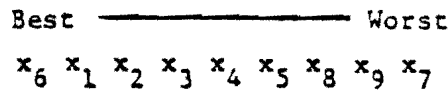


Figure 11. Attributes from the test event set ranked by individual relevance

evaluated by PROMISE and found to have $p=1$. Next, the projected event set was processed by the inductive-learning program AQ11 which derived rules to discriminate the classes. The rules derived from the projected event set were identical to those derived from the entire event set. Figure 12 shows a comparison of the time needed to derive the same set of rules using AQ11 on the entire event set versus running the program using only the three best attributes determined by PROMISE. In this instance, the computation time required to filter the data using PROMISE and derive rules using AQ11 was approximately one tenth the time required using AQ11 alone.

3.2.3 The Random Adaptive Search Algorithm

The relevance measure is intended for the analysis of single attributes independently of other attributes to find those that are most relevant. If such evaluation is not sufficient due to a high degree of interdependency between attributes, the Randomized Adaptive Search (RAS) algorithm may be used.

	Using PROMISE	Not Using PROMISE
PROMISE	0.319 CPU sec.	-
AQ11	0.227 CPU sec.	4.576 CPU sec.
Total	0.546 CPU sec.	4.576 CPU sec.

Figure 12. A comparison of CPU time required to formulate identical rule sets using and not using PROMISE to process the data before processing by inductive learning program AQ11

The algorithm iteratively evaluates groups of attributes and continuously updates an indicator of the relevancy of the individual attributes based on the performance of the groups. First, the relevance of each of the attributes is evaluated and stored as the initial *relevance index* (so-called because the values will no longer be based on p as the algorithm progresses) for that attribute. A user-specified number of attributes is then chosen by weighted random selection based on these values. Attributes with better relevancy values are more likely to be chosen. The relevance of the group of attributes is then computed as a whole. Based on a comparison between the value for this group and a reference value (0.5 initially), the relevance index for each of the constituent attributes in the group is increased by a small, fixed amount (0.05 for this study) if the group performed better than the reference, or decreased by the same amount if the the group score was worse than the reference. The individual values are kept within the 0 to 1 range of p . The reference value is then set to the new group's relevance. The attributes are re-ordered by the new values of their relevance indices and a new group is chosen by weighted random selection. The process iterates until the reference value converges to a constant value or until a specified number of iterations have transpired.

The object of RAS is to find interdependent groupings of attributes and promote their selection as a group, even if one or more of them has a low value of ρ when evaluated independently. As the algorithm progresses, groups of attributes which perform well are promoted and groups which perform poorly are suppressed. When the algorithm converges (if it does), a stable, high-relevance group of attributes has risen to the top of the list of indices and the poor attributes have fallen to the bottom.

3.2.4 The Greedy Attribute Selection Algorithm

A second method for applying the relevance measure to attributes is Greedy Attribute Selection (GAS). When attribute interdependency is not a problem, GAS may be an effective way to arrive at a quasi-minimal set of attributes in a less computationally intensive way than RAS.

The GAS algorithm begins with the independent evaluation of the relevance of each of the attributes. The list of attributes is rank-ordered by decreasing relevance. The first two (those two with the highest relevance) are chosen and evaluated as a group. If the relevance of the pair is greater than the relevance of the most relevant attribute alone, the second most-relevant attribute is deemed to have added useful information (as measured through the increased relevance) and is kept. If no improvement is noted, the second attribute is discarded since it added no information to that from the first attribute. The third most relevant attribute is then added and the group evaluated. The third attribute is also kept or discarded based on whether it contributes to an improvement in relevance score for the group. The scheme continues until a group of attributes is found which is perfectly discriminatory (i.e., $\rho=1$) or the list of attributes is exhausted.

The Greedy Attribute Selection scheme is based on the assumption that the relevance measure is a good indicator of the value an attribute has for discrimination and its ability to evaluate groups of attributes in a way that yields results which can be compared meaningfully.

3.3 The Rule Generation Program GEM

3.3.1 The A^Q Algorithm for Rule Generation

The A^Q algorithm is a method for generating generalized descriptions which *cover* all of the positive events (i.e., those within the class to be described) and none of the negative events (i.e., those within the other classes) [Michalski,1978]. The process of developing a cover involves partially computing the complement of the set of negative events and selecting logical conjunctions of selectors, called *complexes*, which cover positive events. The final cover may be a single complex or a disjunction of complexes. The algorithm proceeds depth-first using the method of *disjoint stars*. A positive event, c_1 , is chosen and an approximation of the set of all prime implicants which cover c_1 and are in the complement of the set of all negative events is developed. This set is called a *star*. The best complex in the star, l_q , is chosen using a lexicographic evaluation functional (see [Diettrich,1980]). The events covered by l_q are removed from further consideration. The process is then repeated but each new event, c_1 is chosen so that it has not been covered by any element of any previous star. This ensures that disjoint, well-separated stars are built. The process is repeated until all events have been covered by at least one star.

3.3.2 Using GEM in an Expertise Development System

The A^Q algorithm is implemented in a program called GEM written in Pascal on a Vax 11/780. The A^Q algorithm (and, consequently, GEM) is an attractive choice for an inductive inference engine because of its flexibility. GEM is domain dependent only within the confines of the data structures used. Any problem domain which can be described by events that can be characterized using acceptable data structures can be processed using GEM. The data structures used required for input to GEM are patterned after relational tables. This structure has proven to be very flexible.

4 EXPERIMENTATION

4.1 Experiment 1: Black-Cutworm Damage Prediction

4.1.1 Problem Domain

Black Cutworms are insect larvae which damage between two and ten percent of the corn acreage in the Midwest annually. The name derives from the effect of cutworm action on corn plants: the severing of the stalk just above the soil line. In mid-April, Black Cutworm (BCW) moths are carried into Illinois by southerly winds and they land in the fields they find most attractive and lay their eggs. The growth cycle of the cutworm is short enough to allow three generations of worms to mature each growing season. Because more mature plants are more resistant to the ravages of the larvae, only the first generation of worms typically causes damage to field corn. Two major factors have been identified by corn entomologists in explaining damage mechanisms. The first is the attractiveness of a given field for the moths. A more attractive field will be the target of more moths' egg-laying. One of the most commonly postulated factors in field attractiveness is weediness at the time of moth flight. The second factor has been termed *synchrony* or the correspondence in time between corn maturation and cutworm maturation. Both corn and cutworm larvae mature at rates proportional to temperature. When the corn is young and the larvae are large, damage will be severe. When the corn is mature before the larvae mature, damage is slight. Also, if the larvae mature into pupae before the corn emerges from the soil, the damage will be slight [Boulanger, 1983]. Many factors may effect the rate of cutworm development and the size of cutworm populations. The difficulty of identifying the most important factors lies in the lack of sufficient quantities of high quality data due to both the rarity of cutworm damage and the lack of sufficient manpower for data collection. The system described in this paper was applied to a selected subset of the data to attempt to uncover some of the important factors.

4.1.2 Data

The data for this experiment consists of seventeen static attributes and two dynamic attributes as well as time and cutworm damage percentage figures for each of 210 events (given in Appendix D) recorded for the 1978 growing season. A sample event is shown in Figure 13. The breakdown

Static Portion

```
[fieldowner=smith][year=1978][previous crop=clover]&
[bcw history=yes][adjacent water=no][surface slope=north]&
[surface character=level][fall tillage=plow][spring till=disc]&
[manure used=no][fertilizer regimen=none][insecticide=none]&
[planting date=june 1]&
```

Dynamic Portion

```
[date=mar 24] => [weed species=horsetweed][weed density=heavy]
[date=mar 24] => [weed species=smartweed][weed density=light]
[date=apr 15] => [weed species=smartweed][weed density=heavy]
[date=may 1 ] => [weed species=weedkill ][weed density=none ]
```

```
::> [damage= 75%]
```

Figure 13. A sample event for the black cutworm damage data showing static and dynamic attributes

of the data by damage percentage is shown in Figure 14. The zero number of fields damaged between 45 and 50% was thought to be a logical class division. CONVART used the original two dynamic attributes to construct 10 new attributes which characterize the behavior of the dynamic attributes over time. The attributes (both original and constructed) are given in Appendix A, with the range of possible values each may have. The original values for some of the attributes in some of the events were missing so values deemed plausible by an expert corn entomologist were inserted

where appropriate. If no plausible value was apparent, the value was left as "unknown". The final event set is missing approximately 20% of the data values and many of the events have limited time-dependent data. These factors combined to complicate the experiment considerably.

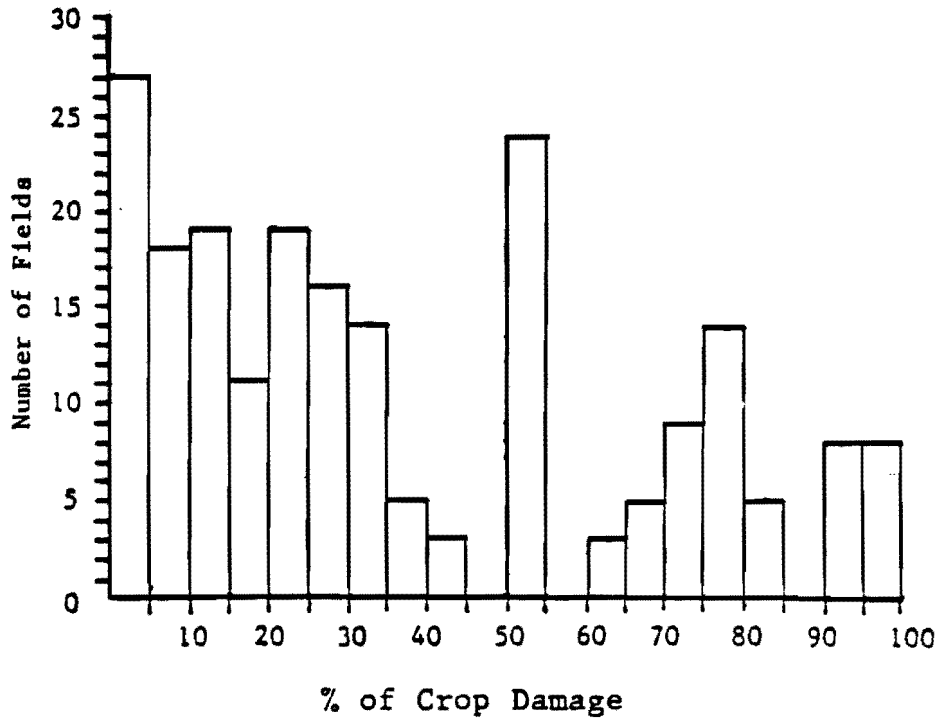


Figure 14. Histogram of the relative frequency of occurrence of different ranges of damage percentage in the 210 events used for this study

4.1.3 Results

Rules generated by applying GEM to this data are given in Appendix B. As the sparsity of the data could inject a significant amount of noise into the data, a corn entomologist was asked to

identify those complexes which might be extraneous or unnecessarily convoluted. A comparison of the performance of the random adaptive search method and the greedy method is given in Figure 15. The output of the test runs is given in Appendix D. The lists of attributes were comparable with only minor differences among the least relevant attributes.

Search Scheme	No. Attributes Per Sample	CPU Time	No. Iterations	No. Attributes Finally Chosen
Greedy	-	34 sec	1	11
Random	5	46	18	10
"	10	48	48	12
"	15	45	7	13

Figure 15. A comparison between different search schemes and varying search parameters for selecting a quasi-minimal set of attributes

4.1.4 Analysis

A comparison between the rules generated and the model outlined in 4.1.1 shows substantial agreement between the factors considered most important by corn entomologists and those identified by the processing. For example, factors such as planting date, several weediness measures, and tillage regimens reflect considerations of field attractiveness and synchrony presented earlier. Insecticide usage effects the survival of larvae during periods of low availability of food and during other periods of adverse conditions. The value of CONVART for this processing was considerable since it was required for the production of the attributes which capture the weed

population trends that indicate both synchrony and field attractiveness.

Comparison between the performance of random adaptive search and greedy search show that, for this event set, the differences in results in terms of attribute set size is small and the penalty for processing using the random adaptive search scheme is large. The results of the random search shows that no highly synergistic combinations of attributes are contained within the event set since RAS (designed to find such interaction) provided the same results as greedy search.

4.2 Experiment 2: Craniostenosis Syndrome Identification

4.2.1 Problem Domain

The study and classification of medical syndromes is a well established field of medicine and medical diagnosis. The task of diagnosing these syndromes is increasingly difficult due to the growing number of rare genetic disorders and poorly understood patterns of malformation and malfunction. In addition, the problem is compounded by disease symptoms and hereditary traits which resemble the indications of many of the disorders of interest. A genetics clinic must be capable of reliably diagnosing approximately 8000 disorders on a day to day basis.

One of the fundamental problems in this field has been the rarity of most of the syndromes. With only a few (sometimes only one or two) examples of a given disorder reported, it is difficult to differentiate true indications of the syndrome from individual peculiarities of the patients. This problem has been approached in the past by the merging of the findings of several geographically separate observers of the same findings to recognize patterns in the data.

The class of syndromes studied in Experiment 2 is named *Craniostenosis*. The cranium of an infant is composed of bony plates joined at their edges by flexible joints or sutures. When these joints ossify (become bony), the skull assumes its final shape and size. The now-hard joints are known as synostoses and occur normally during the course of growth and development. If a suture should harden before or after the others, the skull will develop abnormally, leading to asymmetry

of the skull and face or abnormalities such as unusually limited cranial size. Due to the large number of observable anomalies of the face and skull and the sparseness of the available data, the methods described in this paper were applied in an attempt to pinpoint the most definitive anomalies for differentiating the syndromes in this class of disorders.

4.2.2 Data

The data consists of 231 observed cranio-facial anomalies for 80 patients diagnosed as having craniostenosis (the data may be found in Appendix D). Craniostenosis may be divided into four major syndromes with many patients undiagnosable due to the large overlap between the indications of the syndromes. Despite this overlap, doctors have characterized each syndrome according to certain individual tendencies [Spackman,1983]:

- *Crouzon's Syndrome* patients exhibit premature craniosynostosis, shallow orbits and frontal bossing, and maxillary hypoplasia with or without a parrot-like nose. About a quarter of the reported cases appear to be fresh mutations.
- *Saethre-Chotzen Syndrome* is highly variable in almost all of its features. Among the more common abnormalities are: synostosis of the coronal sutures, low-set hairline, facial asymmetries, shallow orbits, ptosis (drooping eyelid), small ears, and partial webbing of two or more fingers or toes.
- *Apert's Syndrome* includes both craniosynostosis and severe syndactyly (fusion of two or more fingers).
- *Pfeiffer's Syndrome* also involves craniosynostosis and syndactyly, although it is milder in almost every similar feature.

Among the 81 patients, many were not diagnosed as to individual syndrome. When a single "normal" patient is added as a sixth control class, the data may be broken down as shown in Figure 16. A sample event is shown in Figure 17. A list of the 231 anomalies is given in Appendix C.

<u>Syndrome</u>	<u># Patients</u>
Apert	16
Crouzon	24
Saethre-Chotzen	8
Pfeiffer	1
Undiagnosed	31

Figure 16. Breakdown of data for craniostenosis patients by syndrome

4.2.3 Results

The attributes were all binary (i.e., syndrome present=1, not present=0), VARSEL identified a set of 20 attributes, among the original 231 in the event set, which successfully characterized each of the syndromes without characterizing any of the patients of indeterminate diagnosis or the normal patient. The chosen attributes are given in Figure 18. GEM then analyzed the new event set and used 16 of the twenty attributes to produce the rules shown in Figure 19. A physician who had been attempting to perform the same task manually, had invested approximately 4 man-months in the job. He also discovered twenty attributes but had only succeeded in characterizing about 75% of the patients successfully. These attributes are also given in Figure 18. The rules he derived using GEM and these attributes are given in Appendix D. The total real-time required for the computer processing was less than an hour.

If we compare the generated rules in Figure 19, with the clinical profiles presented earlier, we may note close correspondence between the rules for each class and the clinical findings. An important consideration is that the clinical profiles presented have a great deal of overlap so they are not a perfect "benchmark" for deciding rule validity. In addition, the data collected by different clinicians often varies as to quality and scope.

```
[patient number=000][date=1/1/81][flat forehead=present][syndactly=present]&
[craniosynostosis=absent] ... 228 other anomalies

::> [syndrome=Pfeiffer]
```

Figure 17. A sample event from the craniostenosis event set

Chosen by VARSEL

Craniosynostosis
 Craniosynostosis-Coronal
 Craniosynostosis-Saggital
 Facial Assymetry
 Flat Forehead
 Assymetric Forehead
 Ptois-Eye
 Shallow Orbit
 Exophthalmos/Proptosis-L Eye
 Exophthalmos/Proptosis-R Eye
 Byzantine Palate
 Midface Hypoplasia
 Cutaneous Syndactly-Hand
 Syndactly-Foot
 Partial Syndactly-Foot
 Hypertonia
 Plagiocephaly
 Pyloric Stenosis
 Position Anomolies-Digits
 Undescended Testes

Chosen by Expert

Craniosynostosis-General
 Ear Malformations
 Impaired Hearing
 Facial Assymetry
 Flat Forehead
 Beaked Nose
 Ptois
 Hypertelorism
 Proptosis
 Hallux Valgus
 Byzantine Palate
 Maxillary Hypoplasia
 Syndactly of Fingers
 Syndactly of Toes
 Webbing of Toes
 Webbing of Fingers
 Strabismus
 Cleft Palate
 Tear Duct Stenosis
 Proptosis

Figure 18. A comparative listing of the attributes chosen as most relevant by VARSEL and by a human expert for the discrimination of craniostenosis syndromes from the data used in this study

R1: [syndactyl_foot=absent][craniosynostosis=present]& [exophthalmos_eye=present][flat_forehead=absent]	(NEW, IND, COV) (18,16,18)
v	
[syndactyl_foot=absent][byzantine_palate=present][ptosis_eye=absent]	(1,1,3)
v	
[syndactyl_foot=absent][exophthalmos_eye=present][plagiocephaly=present]	(1,1,1)
v	
[craniosynostosis=absent][craniosynostosis_coronal=absent]& [midface_hypoplasia=present][cutaneous_syndactyl_hand=absent]	(2,2,2)
v	
[shallow_orbit=absent][craniosynostosis_coronal=absent]& [midface_hypoplasia=absent][flat_forehead=present][plagiocephaly=absent]	(1,1,1)
::> [syndrome=Crouzon]	
R2: [cutaneous_syndactyl_hand=present]	(5,3,5)
v	
[midface_hypoplasia=present][flat_forehead=present]& [byzantine_palate=absent]	(3,3,5)
::> [syndrome=Sathre-Chotzen]	
R3: [syndactyl_foot=present]	(16,16,16)
::> [syndrome=Apert]	
R4: [pyloric_stenosis=present]	(1,1,1)
::> [syndrome=Pfeiffer]	

Figure 19. A set of discriminant rules for the craniostenosis event set (the numbers in parentheses are the number of events first covered by this complex, the number of events only covered by this complex, and the total number of events covered by this complex)

Random adaptive search failed to converge for this event set, probably due to the low likelihood of synergistic interaction since the minimum number of binary attributes required to differentiate six classes would be three and 16 were actually required. The system has clearly operated cost-effectively on this event set, producing plausible rules within the limitations of the event set in a computationally attractive amount of time. The resulting data reduction from the use of VARSEL as a preprocessor was over 91% since only 20 of the original 231 attributes were needed.

5 CONCLUSIONS

A model has been presented which describes the process of domain expertise development in terms of the sequential application of four sub-processes with multiple feedback paths. The subprocesses include attribute construction (implemented in CONVART), attribute selection (implemented in SELECT), rule formation (implemented in GEM), and rule implementation (left for the system builder).

A system has been constructed which is capable of applying the model for the purpose of deriving expert decision rules from data using a minimum of explicitly stated domain knowledge and minimal iterative processing. The system contains modules for: the construction of attributes which describe time-dependent behavior of other attributes so that time-varying processes can be analyzed, the selection of most relevant attributes for class discrimination using a recently developed measure of attribute relevancy, and inductive rule inference based on established methods of automated inductive inference. The rule implementation process in which a set of rules is embedded in a program which can apply the rules to new events, remains as a task for the programmer.

5.1 System Performance

The constructive induction program CONVART was vitally important in the processing of Black-Cutworm damage data because cutworm damage is closely tied to time-dependent processes. It was not used for Craniofacial data since the attributes present were all static. The variable selection program VARSEL was useful in both cases but different search strategies were of different utility. Random adaptive search showed explicitly the lack of synergistic interaction between attributes in the BCW data since the attribute sets chosen by RAS were the same as those chosen by greedy search (these results are given in Appendix D). RAS failed to produce useful results of any sort for the craniofacial data because of the poor discriminatory value of binary attributes for multi-class event sets. Greedy search was effective in both cases since significant data

reduction was achieved in both cases and appropriate experts favorably evaluated the resulting attribute sets. The inductive inference engine GEM produced good rules from the pre-processed event sets which were thought to be reasonable and consistent with the input data when examined by experts from within the problem domains.

5.2 Indicated Future Directions of Inquiry

The potential for significant future inquiry exists throughout the processing chain used in this system. Specific avenues of study for the concepts embodied in CONVART and GEM are described in detail elsewhere [Michalski,1982b] [Davis,1981]. Future directions for applying and studying the measure of relevancy presented earlier include exploring its use as an indicator of potentially relevant groups of attributes for constructive induction purposes, and further refinement of the measure to enhance its resolution. In addition, new implementations of the greedy and random adaptive search schemes may overcome the limitations of the current implementations, and new search schemes may prove more effective than either.

APPENDICES

Appendix A: Attributes in BCW Damage Event-Set

The following is a list of the attributes, both original and constructed, used for the analysis of black cutworm damage in the state of Illinois.

* means this attribute was chosen by RAS.

** means this attribute was chosen by GAS.

*** means this attribute was chosen by both RAS and GAS.

Attribute		Possible Values (domain)
Static Attributes		
1.	Damage	<50%, >50%
2.	Field Owner	too numerous to list
3.	Growing Year	1978
***4.	Previous Crop	Corn, Beans, Weeds, Sorghum
5.	SCV History	Yes, No
***6.	Permanent Border Vegetation	Yes, No
***7.	Permanent Border Water	Yes, No
***8.	Surface Direction	North, South, East, West, None
9.	Surface Character	Level, Rolling, Bottomland
***10.	Fall Tillage	None, Plow, Chisel, Disc
***11.	Spring Tillage	None, Plow, Chisel, Disc
12.	Manure Usage	Yes, No
13.	Fertilizer Usage	Yes, No
***14.	Insecticide	None, Yes (nonspecific), Preventative, Rescue Treatment
*15.	Planting Date	Jan1-Apr10, Apr11-Apr20, Apr21-May15, May16-Jun9, After Jun9
16.	Planting Rate	<100%, 100%
Dynamic Attributes		
17.	Weed Species	None, Weeds (nonspecific), Very Few Weeds, Onion, Grass, Legume, Winter Annual, Other Broadleaf, Weedkill
18.	Weed Density	None, Light, Heavy, Heavy Patches
Static Attributes		
*19.	Most Common Weed Species	None, Weeds (nonspecific), Very Few Weeds, Onion, Grass, Legume, Winter Annual, Other Broadleaf, Weedkill
20.	Least Common Weed Species	None, Weeds (nonspecific), Very Few Weeds, Onion, Grass, Legume, Winter Annual, Other Broadleaf, Weedkill
21.	Number Of Observations Of Same Weed Species	1, 2
***22.	Number Of Different Weed Species	0, 1, 2, 3, >3
*23.	Average Density	None, Light, Heavy, Heavy Patches
*24.	Intercept of Density vs Time	
*25.	Slope Of Density vs Time	-.057, -.047, -.044, -.040, -.036, -.034, -.032, -.030, -.029, -.028, -.024, -.020, -.018, -.015, >0
***26.	Maximum Weed Density	None, Light, Heavy, Heavy Patches
27.	1st Time Of Max.	Before Mar24, Mar24-Apr13
*28.	Minimum Weed Density	None, Light, Heavy, Heavy Patches
***29.	1st Time of Min.	Apr5-Apr10, Apr10-22, Apr23-Apr27, Apr28-Apr30, May1-May2, May3-May7, May8-May12, May13-May19, May20-May21, May22-May26, May27-Jun3

Appendix B: BCW Damage Estimation Rules

The following two pages give rules for predicting black cutworm damage severity derived by GEM from 1978 BCW data after new attributes were constructed by CONVART and selection was performed by VARSEL. Each rule is quite complicated in that each has many complexes. The reason for this becomes clear when one examines the parameters on the right-hand side of the page:

- NEW - The first number is the number of events covered by this complex which were not covered by previous complexes in the list.
- IND - The second is the number of events covered by this complex alone of all complexes.
- COV - The third is the total number of events covered by this complex.

Examination of the numbers shows that the rules reveal a subtle and complex interaction between three factors: weediness, synchrony, and pesticide use. The interaction is suggested by the coverage numbers. Note that each complex covers several events but covers very few uniquely. Therefore, the complexes have significant overlap in coverage but each one accounts for a slight variation on one or more of these themes.

(NEW, IND, COV)

```

R1: [previous crop=corn,weeds,sorghum][permanent vegetation=no]&
[adjacent water=yes][terrain=level,rolling]&
[fall tillage=none,chisel,disc][planting date=after may15] (5,3,5)
      v
[previous crop=soybeans,weeds,sorghum][fall tillage=plow,disc]&
[spring tillage=none,plow,disc]&
[number of diff. weed species<3][maximum weeddensity=heavy..heavy patches] (7,2,7)
      v
[spring tillage=none,disc][planting date=after may15]&
[number of diff. weed species=3][maximum weeddensity not=heavy patches]&
[1st minimum weeddensity=after may2] (9,2,10)
      v
[permanent vegetation=yes][terrain=level][fall tillage=none,disc]&
[planting date=jan1..may15][maximum weeddensity=heavy patches] (2,1,2)
      v
[terrain=level,bottomland][fall tillage=plow][spring tillage=none,plow,disc]&
[planting date=after may15][number of diff. weed species=3] (5,3,9)
      v
[adjacent water=no][fall tillage=none,chisel][spring tillage=none,chisel]&
[number of diff. weed species=3..>3][maximum weeddensity=heavy] (3,1,3)
      v
[previous crop=corn,weeds,sorghum][permanent vegetation=yes]&
[fall tillage=chisel][planting date= after may15] (3,3,3)
      v
[permanent vegetation=no][1st minimum weeddensity=aft jun] (1,1,4)
      v
[adjacent water=yes][maximum weeddensity=heavy patches]&
[1st minimum weeddensity=may19..may21] (1,0,1)
      v
[previous crop=corn,weeds,sorghum][terrain=level][fall tillage=disc]&
[number of diff. weed species<3] (1,1,2)
      v
[permanent vegetation=yes][fall tillage=chisel,disc][insecticide=no]&
[number of diff. weed species>2][maximum weeddensity not= heavy patches] (2,1,6)
      v
[permanent vegetation=yes][terrain=level,bottomland]&
[fall tillage=chisel,disc][insecticide=no][maximum weeddensity=heavy] (2,2,4)
      v
[permanent vegetation=yes][adjacent water=no][fall tillage=chisel]&
[spring tillage=none,plow,disc][planting date=after apr30]&
[maximum weeddensity=no..lt][1st minimum weeddensity=before may2] (1,1,3)
      v
[permanent vegetation=yes][terrain=level][fall tillage=none,chisel,disc]&
[spring tillage=none,disc][insecticide=preventive][maximum weeddensity=heavy] (1,1,1)
      v
[permanent vegetation=no][terrain=level,bottomland]&
[fall tillage=none,plow,disc]&
[spring tillage=none,disc][planting date=after may15]&
[number of diff. weed species=3] (3,1,8)
      v
[previous crop=corn,weeds,sorghum][terrain=level,rolling]&
[fall tillage=none,chisel]&
[spring tillage=none,chisel,disc][planting date=after may15]&
[maximum weeddensity=no..lt][1st minimum weeddensity=before apr30] (2,2,3)
      v
[permanent vegetation=no][fall tillage=chisel]&
[spring tillage=none,plow,chisel][maximum weeddensity=heavy..heavy patches] (1,1,3)
      v
[permanent vegetation=yes][fall tillage=none,disc]&
[insecticide=no,rescue treatment][number of diff. weed species=3] (1,1,5)
      v
[permanent vegetation=no][adjacent water=no][terrain=level,bottomland]&
[spring tillage=none,disc][planting date=after may15]&
[number of diff. weed species=3] (1,1,7)

```

::> [damage >= 50%]

```

R2: [previous crop=soybeans,weeds,sorghum][fall tillage=none,plow]&
[spring tillage=none,chisel,disc][insecticide=preventive,rescue treatment]&
[number of diff. weed species<3] (12,2,12)
      v
[terrain=rolling][fall tillage=plow,chisel]&
[maximum weedensity not= heavy patches][1st minimum weedensity=before apr30] (10,5,11)
      v
[previous crop=soybeans,sorghum][adjacent water=yes]&
[terrain=level,rolling][insecticide=preventive,rescue treatment] (13,4,16)
      v
[permanent vegetation=yes][fall tillage=none,plow,disc]&
[spring tillage=none,disc]&
[number of diff. weed species>3][1st minimum weedensity=before may21] (4,1,6)
      v
[permanent vegetation=yes][fall tillage=plow,chisel,disc]&
[spring tillage=none,chisel][insecticide=preventive,rescue treatment] (6,2,7)
      v
[adjacent water=yes][terrain=level,bottomland][fall tillage=none,plow]&
[spring tillage=none,plow,disc][number of diff. weed species<3] (7,5,7)
      v
[terrain=level,bottomland][planting date=before apr30] (9,4,18)
      v
[previous crop=corn,soybeans,sorghum][permanent vegetation=yes]&
[insecticide=preventive,rescue treatment][maximum weedensity=heavy patches] (4,1,10)
      v
[permanent vegetation=yes][terrain=level,rolling][fall tillage=none,chisel]&
[insecticide=no,rescue treatment][number of diff. weed species<3]&
[maximum weedensity=no..lt] (4,1,4)
      v
[previous crop=soybeans,sorghum][fall tillage=plow,disc]&
[insecticide=preventive,rescue treatment][planting date=after may15] (4,3,8)
      v
[permanent vegetation=yes][fall tillage=none,chisel,disc]&
[insecticide=no,rescue treatment][number of diff. weed species<3]&
[maximum weedensity=heavy] (1,1,1)
      v
[previous crop=soybeans,sorghum][permanent vegetation=no]&
[terrain=level,rolling][fall tillage=chisel,disc]&
[insecticide=preventive,rescue treatment][number of diff. weed species>2]&
[1st minimum weedensity=before may26] (2,1,6)
      v
[permanent vegetation=yes][fall tillage=none,chisel]&
[insecticide=preventive,rescue treatment][number of diff. weed species<4]&
[maximum weedensity=heavy] (1,1,6)
      v
[permanent vegetation=no][terrain=level,bottomland]&
[spring tillage=none,plow,chisel][maximum weedensity=no..lt] (5,0,15)
      v
[permanent vegetation=yes][terrain=level,bottomland][fall tillage=none]&
[maximum weedensity=no..heavy] (2,2,12)
      v
[permanent vegetation=no][adjacent water=no][terrain=rolling] (2,1,11)
      v
[adjacent water=no][fall tillage=disc]&
[insecticide=preventive,rescue treatment][number of diff. weed species>2] (1,1,7)
      v
[permanent vegetation=no][adjacent water=yes][terrain=bottomland]&
[fall tillage=plow,chisel] (2,2,4)
      v
[permanent vegetation=yes][number of diff. weed species<3]&
[1st minimum weedensity=may2..may21] (2,2,4)
      v
[previous crop=soybeans,sorghum][permanent vegetation=yes]&
[terrain=level,bottomland][insecticide=preventive,rescue treatment]&
[number of diff. weed species>2] (1,1,5)
      v
[previous crop=soybeans,weeds,sorghum]&
[insecticide=preventive,rescue treatment]&
[number of diff. weed species>3][maximum weedensity=heavy patches][1,3] (1,1,3)
      v
[previous crop=corn,weeds,sorghum][planting date=apr30] (1,1,12)
      v
[terrain=level][spring tillage=none,chisel][maximum weedensity=no..lt] (1,1,16)
      v
[permanent vegetation=no][adjacent water=no][fall tillage=disc] (1,1,10)

```

::> [damage < 50%]

Appendix C: Attributes for Cranioostenosis Event Set

The following list gives the anomalies present in the original cranioostenosis data-set grouped by body system effected. See Figure 18 for lists of which attributes were chosen by VARSEL and which were chosen by a human expert.

Palate

- Incomplete Median Cleft
- Median Cleft
- Submucous Cleft (3 varieties)

Skull

- General
- Assymetric
- Macrocephaly
- Craniosynostosis
- Craniosynostosis-Coronal
- Craniosynostosis-Sagittal
- Faulty Sutures
- Shape Anomalies
- Brachycephaly
- Cloverleaf Skull
- Plagiocephaly
- Trigonocephaly
- Prominent Coronal Suture

Forehead

- General
- Assymetric
- Large
- Typical Aperts
- Bossing
- Prominent/Bulging
- Elongated
- Flat
- Midline Defect
- Typical Crouzons
- Supraorbital Ridge Anomalies

Midface

- General
- Facial Asymmetry
- Midface Hypoplasia
- Hypertelorism
- Hypotelorism
- Assymetric Orbital Placement (Right Higher)
- Hypoplasia (Left Side)

Jaw

- General
- Assymetric
- Micrognathia/Hypoplasia
- Antegonial Notching
- Prognathia
- Wide Gonial Angle

Left Eye

- General
- Anophthalmia
- Microphthalmia
- Exophthalmos/Proptosis
- Prominent/Protruding
- Setting Sun Sign
- Devil's Eye
- Shallow Orbit
- Small Orbit
- Malpositioned Orbit
- Blepharitis
- Ptosis
- Antimongoloid Slant
- Epicanthal Fold
- Synoché of the Lids
- Esotropia
- Strabismus
- Nystagmus

Right Eye

- General
- Anophthalmia
- Microphthalmia
- Exophthalmos/Proptosis
- Prominent/Protruding
- Orbit Anomalies
- Devil's Eye
- Shallow Orbit
- Small Orbit
- Blepharitis
- Ptosis
- Lids Fail To Close
- Antimongoloid Slant
- Epicanthal Fold
- Syneche of the Lids
- Esotropia
- Strabismus
- Nystagmus

Left Ear

- Small
- Preauricular Pit/Sinus
- EAC Atresia
- Low Set
- Posteriorly Set
- Ossicular Anomalies
- Cupped
- Lopped/Protruding

Right Ear

- Small
- Preauricular Tag
- Rotated
- Low Set
- Cupped
- Lopped/Protruding

Nose

- General
- Assymetric
- Bifid
- Narrow
- Broad/Bulbous
- Alae Anomalies
- Cleft Nostrils/Alae
- Pinched Nares
- Beaked
- Saddle Shaped/No Bridge/Flat Bridge
- Choanal Atresia/Stenosis
- Deviated Bridge/Nose
- Deviated Septum

Oral Cavity

- High Arched Palate
- Byzantine Palate
- Torus Palatinus
- Narrow Palate
- Maxillary Assymetry
- Commissural Lip Pits
- Macrostomia

Tongue

- Short Frenulum/Tongue Tie
- Dry

Dentition

- Open Bite
- Crossbite
- Dental Crowding
- Missing Teeth
- Typical Aperts

Mimetic Musculature

- Motor Problem
- Paresis

Muscles of Mastication
Motor Problem
Paresis

Neck
General
Torticollis
Short

Abdominal Wall
Hernia, Unspecified
Umbilical Hernia
Inguinal Hernia

Chest Wall
General
Asymmetry
Prominent
Pectus Excavatum

Back
General
Scoliosis
Kyphosis/Kyphoscoliosis

Respiratory System
Chronic URI or Other Respiratory Disease

Cardiovascular System
Cardiac Anomalies
Valve Anomalies
Rythm Anomalies
Aortic Arch Anomalies

GI System
Liver, Spleen
Pyloric Stenosis

Genital
General
Hypospadias
Undescended Testes
Scrotal Anomalies
Uterine Anomalies
Kidney Anomalies

Skin and Adnexia
Alopecia/Bald
Thin/Sparse Hair
Echzema

Left Arm
General

Upper Arm Anomalies
Joint -
Dislocation/Subluxation
Contractures

Right Arm
General
Upper Arm Anomalies
Joint
Contractures

Left Hand
General
Arachnodactly
Contractures
Syndactly
Complete Syndactly
Cutaneous Syndactly
Dermatoglyphics
Simian Crease
Phalangeal Anomalies
Position Anomalies/Digits

Right Hand
General
Arachnodactly
Contractures
Syndactly
Complete Syndactly
Cutaneous Syndactly
Simian Crease
Position Anomalies

Left Leg
Contractures
Joint
Knee

Right Leg
Contractures
Joint
Knee
Overlapping Toes

Left Foot
Overlapping Toes
Bifid Toe
Broad/Large Digits
Syndactly
Partial Syndactly

Cutaneous Syndactly
 Clubbing
 Abnormal Position
 Cleft/Seperation, Toes
 Abnormal Postion/Foot

Right Foot
 Broad/Large Toes
 Syndactly
 Partial Syndactly
 Cutaneous Syndactly
 Clubbing
 Abnormal Position
 Overlapping Toes
 Cleft/Seperation, Toes
 Abnormal Postition/Foot

Nervous System
 General
 Facial Nerves
 Retardation
 Developmental Retardation
 Epilepsy/Seizure Disorder
 EEG Abnormal
 Hyperactive
 Reflexes Hyperactive
 Cerebral Anomalies
 Corpus Collosum Anomalies
 Aplusia/Speech Problems

Skeletal (Primary Axial)
 General
 Cervical
 Cervical Fusions
 C-1 Anomalies
 Occipitalization, C-1
 Basilar Invagination
 Scoliosis
 Hip Anomalies
 Hip Dislocations
 Joint Anomalies, Generalized
 Spina Abifida

Muscular System
 General
 Hypotomia
 Hypertonia
 Contractures

Appendix D: Data and Miscellaneous Information of Interest

The following pages contain all of the data used in this work that has not been presented earlier, as well as certain other analyses and information that may be of interest.

1978 Black Cutworm Data for the State of Illinois

The following two pages list the attributes and their possible values for this data. The data follows with each new event preceeded by a "!. " Each event has one line consisting of the static attributes in order, followed by zero or more lines of dynamic data consisting of time in days followed by weed species followed by weed density.

bcwdom

lbcw_damag real 0.0 47.5 57.5

lfarm_code key

mussel skaer talbot helms wenzel solt fams herter schleu
 dannel briggs finfro albin lock carrol muelle muelle wetzel
 wetzel wiebur hisson zinder blacke dalton gregor lightl goodin
 duften gebhar poe wirth wirth ruff montgo rincke henton
 jeffco dasche thoren patter groezi ostrum nagel buchan ivers
 bunsel leigh beeler gustaf winkel fricke johnso hampto

schaef	crowly	ccline	blkbrn	blkbrn	vnrhdm	steder	steder	
slnskr	vnlnkn	rokers	rokers	stein	seifrd	short	sturm	willms
willms	borden	ascham	bauman	drisler	fahr	bgrstf	bryant	carter
curd	hammel	lamont	martin	sailer	white	stcklr	nelson	edward
holman	holman	ranwtr	staggs	vaugh	moobry	rowell	saader	schwrtg
sprngr	boldmn	lmig	kilby	kiley	acton	antaze	spain	wenard
hoffman	kelsey	kelsay	kelsey	gruenl	vander	notte	ferrer	woods
woods	brande	burt	cornwe	kitloy	leonar	newton	rogers	templi
weiler	baker	furry	halsey	whalen	clark	huddle	swinge	brown
fombel	evans	mckinz	reid	gaibel	klitzl	lidy	miller	mundt
schmid	uthell	cleer	toncra	hall	lingmi	fals	melby	frey
weaver	jorgen	bixler	elmore	poehle	wolf	cain	goss	simkin
pierse	hoxsey	logan	myer	stephe	warren	buchan	finely	henert
zapf	alvey	bertsc	flint	mcbroo	sancke	thorne	thorso	klenke
malau	malau	martin	gaines	vandev	walsh	young	young	buser
fiedle	laible	lasswe	stange	benedi	mackma	james	cole	drake
drake	rosent	ross	schruue	smith	travis	walqui	alliso	mcmill
myers	wolf	miller	dixon	langie	mercet	green	lafeve	evans
blair	mcfarl	graden	justis	lawler	manke	redeke	rovey	rupert
tucker	webb	wamsin	montco	montco	white	steven	steven	steven
alexan	gucker	olson	walsh	walsh	wilkin	davids	twordo	campbe
datard	eggeme	hersch	welge	karmic	klingsl	r_runy	ethert	frank
mccliel	osterm	stone	stout	bridge	buegh	gregg	hampto	montgo
ruff	schmit	addis	addis	elliott	gray	tracy	webste	wilson

schwen	reusch	shaffe	jenkin	ecthte	ecthte	fordha	fordha	stoner
gullet	rosebl	roseb2	roseb3	roseb4	roseb5	roseb6	roseb7	peal
eiten	schnei	ludwig	erlwin	arnull	ester	custin	lane	niemey
granch	tompio	thurma	johnso	larkin	rohrer	rohrer	robert	mccorm
schmid	bluffd	kins	guetin	thomps	everet	stineb	thomps	perkin
hofbau	nobis	landml	nasher	flint	shaw	larsen	graves	adams
zabel	harms	zigler	ruff	asper	sousy	kelly	freilan	pitts
boitno	jones	gibben	gibben	gulley	zindor	carrol	prohll	angelh
engelh	cress	cress	cress	vasque	kessle	schult	gress	adkins
syfert	cox	dustin	pedige	mcmill	fehien	jackso	shane	stalle
sager	gill	meng	skaer	yong	moll	boyce	devria	runte
drake	desutt	frahm	schmid	good	staher	rowell	weyhr1	weyhr2
green	bauman	herman	schert	kennel	wiegan	schert	bowald	

```

!year n/a 75 76 77 78 79 80
!prev_crop char corn beans bwhb whbe pasture bromegr weeds blugras
        wheat oats whcl whml whco clover hey sod pasture
        whsor
!bcw_hist n/a yes no
!perm_veg char yes no
!brdr_water char yes no
!surfacedir n/a n e s w
!surface char lev rol bld
!fall_till char none plow chisel disc cult fldclt harrow roter edisc ldisc
!sprngtill char none plow chisel disc cult fldclt harrow roter edisc ldisc
!manure n/a yes no
!fertilizer n/a fall complete anhydrous
!insecticid char yes no counter furadan thimet diazinon mocap
        ramrod lorsban dyfonate r_lorsban
        thimet aldrin isotox_dia heptachlor
        rescue_trt r_penncap r_sevin belt
!plantdate integer 0 100 110 120 135 160
!plantrate n/a 0 100
!risk_index integer 0 10 15 20 25
!dyn_count n/a 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14
$eos
!date integer 0 71 82 95 101 104 112 118 123 129 136 140
!weed_species struc
    none weeds very_few_wds onion
    @ weedkill d_weedkill f_weedkill h_weedkill p_weedkill
    @ grass grssod rye quackgrass h_grass foxtail volntercorn peppergrass
        watergrass orchardgrass giantfoxtail nutgrass hay johnsongrass
        ticklegrass sod barley wild_millet crab_grass bluegrass
        foxweed
    @ legume redclover peavine alfalfa h_alfalfa sweetclover clover
    @ winter_annl chickweed winterweed shephrdpurse blwinterweed mustard
        wmustard purslnespdwl spdwl yellowrocket vines
    @ otherbroad dandelion smartweed pigweed lambsquarter ragweed
        horseweed dock velvetweed wstrawberry milkweed ironweed
        cocklebur d_few velvetleaf chickweed giantragweed
        fall_panicum can_thistle jimson butterprint bull_thistle
        horseradish morningglory sourdock nutsedge button_weed
        sandbur henbit garlic fishscale hutsedge spineyside
        spurge
!weedensity lchar no lt hy hyps

```

cutworm data 1978. THIS DATA HAS BEEN HEAVILY EDITTED TO FILL IN MANY MISSING VALUES WITH PLAUSIBLE ONES. IT SHOULD NOT BE USED AS NATURAL DATA.

!	75	schaef	78	weeds	?	no	yes	?	lev	chisel	disc
	?		?	counter	148	?	1	1			
	83			pigweed	hy						
	83			smartweed	hy						
	83			velvetleaf	hy						
!	90	crowly	78	beans	?	yes	no	?	rol	disc	disc
	?		?	ramrod	128	?	1	1			
	83			peppergrass	hy						
!	27	ccline	78	beans	?	yes	no	?	rol	plow	disc
	?		?	counter	147	?	1	1			
	83			smartweed	lt						
!	75	blkbrn	78	beans	?	no	yes	?	bld	none	disc
	?		?	lorsban	157	?	1	1			
	83			smartweed	lt						
	156			d_weedkill	no						
!	80	blkbrn	78	beans	?	no	yes	?	bld	none	disc
	?		?	lorsban	161	?	1	1			
	83			smartweed	lt						
	156			d_weedkill	no						
!	35	vnrhdm	78	beans	?	no	no	?	lev	disc	fldclt
	?		?	no	147	?	1	1			
	83			smartweed	hyps						
	83			foxtail	hyps						
!	10	stader	78	corn	?	yes	no	?	rol	plow	disc
	?		?	counter	147	?	1	1			
	83			?	lt						
!	33	stader	78	corn	?	no	no	?	lev	none	plow
	?		?	counter	152	?	1	1			
	83			?	lt						
!	25	slnskr	78	beans	?	yes	yes	?	lev	none	plow
	?		?	lorsban	170	?	1	1			
	83			peppergrass	hyps						
	138			p_weedkill	no						
!	25	vnlnkn	78	beans	?	yes	yes	?	rol	chisel	fldclt
	?		?	no	142	?	1	1			
	83			smartweed	hy						

!	3	rokers	78	beans	?	yes	yes	?	lev	none	fldclt
	?			dyfonate	152	?		1	1		
	83			foxtail	hy						
!	95	stein	78	beans	?	no	no	?	lev	chisel	disc
	?			no	156	?		1	1		
	83			?	hy						
!	91	seifrd	78	corn	?	no	yes	?	lev	chisel	disc
	?			furadan	153	?		1	1		
	83			?	lt						
	135			d_weedkill	no						
!	75	short	78	beans	?	yes	no	?	lev	none	disc
	?			no	147	?		1	1		
	83			pigweed	lt						
	83			foxtail	hyps						
!	1	sturm	78	beans	?	yes	no	?	rol	none	plow
	?			diazinon	140	?		1	1		
	83			smartweed	hy						
	121			p_weedkill	no						
!	60	willms	78	beans	?	yes	no	?	bld	disc	disc
	?			no	146	?		1	1		
	83			smartweed	hy						
	140			d_weedkill	no						
!	100	willms	78	beans	?	yes	yes	?	bld	plow	disc
	?			no	146	?		1	1		
	83			horseweed	hyps						
	83			smartweed	hyps						
!	50	borden	78	pasture	?	yes	no	?	rol	none	plow
	?			counter	148	?		1	1		
	83			?	lt						
!	33	aschen	78	beans	?	yes	no	?	lev	none	disc
	?			no	151	?		1	1		
	83			foxtail	hy						
	83			vines	hy						
	83			cocklebur	hy						

!	3	bauman	78	beans	?	no	no	?	rol	none	disc
	?	?		no	150	?	1	1			
	83	foxtail		hy							
	83	smartweed		hy							
	148	d_weedkill		no							
!	50	drisler	78	corn	?	no	yes	?	lev	none	plow
	?	?		counter	138	?	1	1			
	83	foxtail		hyps							
	83	cocklebur		hyps							
	83	butterprint		hyps							
!	11	fehr	78	corn	?	yes	yes	?	rol	chisel	disc
	?	?		thimet	123	?	1	1			
	83	foxtail		lt							
!	90	bgrstf	78	beans	?	no	yes	?	rol	disc	chisel
	?	?		no	142	?	1	1			
	83	?		lt							
	135	f_weedkill		no							
!	4	bryant	78	corn	?	yes	no	?	lev	plow	chisel
	?	?		r_lorsban	155	?	1	1			
	83	smartweed		?							
	83	horseweed		?							
!	80	carter	78	beans	?	yes	no	?	bld	plow	disc
	?	?		no	149	?	1	1			
	83	chickweed		hyps							
!	75	curd	78	beans	?	yes	yes	?	bld	chisel	fldclt
	?	?		no	150	?	1	1			
	83	?		lt							
	150	f_weedkill		no							
!	2	hamel	78	corn	?	no	yes	?	bld	plow	disc
	?	?		yes	142	?	1	1			
	83	chickweed		lt							
!	70	lamont	78	corn	?	yes	no	?	lev	plow	disc
	?	?		furadan	146	?	1	1			
	83	chickweed		?							
	83	otherbroad		?							
!	50	martin	78	beans	?	no	no	?	bld	chisel	disc
	?	?		furadan	138	?	1	1			
	83	johnsongrass		lt							

83 giantragweed lt

! 50 sailer 78 corn ? yes no ? bld plow disc
? ? yes 147 ? 1 1

83 smartweed lt

135 d_weedkill no

! 90 stcklr 78 beans ? yes no ? rol none chisel
? ? furadan 147 ? 1 1

83 chickweed hy

83 smartweed hy

83 foxtail hy

83 giantragweed hy

! 37 nelson 78 corn ? yes no ? lev none plow
? ? furadan 143 ? 1 1

83 foxtail lt

121 p_weedkill no

! 100 edward 78 beans ? no no ? bld plow disc
? ? no 152 ? 1 1

83 smartweed lt

83 chickweed lt

! 50 holman 78 corn ? no no ? lev chisel disc
? ? yes 158 ? 1 1

83 ? lt

! 50 holman 78 beans ? no no ? lev chisel disc
? ? no 149 ? 1 1

83 ? lt

! 70 ranwtr 78 corn ? yes yes ? bld chisel disc
? ? yes 145 ? 1 1

83 ? lt

! 90 stagg 78 beans ? yes yes ? bld disc disc
? ? no 141 ? 1 1

83 foxtail lt

141 d_weedkill no

! 75 vaugh 78 beans ? no no ? bld chisel disc
? ? no 152 ? 1 1

83 cocklebur lt

! 50 moobry 78 corn ? yes no ? lev disc plow

?		?	counter	148	?	1	1		
83		?	lt						
121		p_weedkill	no						

!	10	rowell	78	beans	?	yes	no	?	lev	none	fldclt
	?		?	thimet	123	?	1	1			
	83		?	lt							

!	12	saader	78	beans	?	no	no	?	lev	none	fldclt
	?		?	dyfonate	117	?	1	1			
	83			foxtail	lt						

!	50	scwrtg	78	beans	?	no	yes	?	lev	none	disc
	?		?	no	148	?	1	1			
	83			smartweed	hy						
	83			horseweed	hy						

!	25	springr	78	beans	?	yes	no	?	rol	none	disc
	?		?	counter	121	?	1	1			
	83			smartweed	lt						
	118			d_weedkill	no						

!	3	boldan	78	corn	?	yes	no	?	lav	plow	disc
	?		?	counter	149	?	1	1			
	83			velvetleaf	hyps						
	83			pigweed	hyps						

!	30	imig	78	corn	?	yes	no	?	rol	plow	disc
	?		?	thimet	145	?	1	1			
	83			lambquarter	lt						

!	30	kilby	78	beans	?	yes	yes	?	rol	none	fldclt
	?		?	counter	149	?	1	1			
	83			smartweed	lt						
	149			f_weedkill	no						

!	35	kiley	78	oats	?	yes	no	?	lev	none	plow
	?		?	dyfonate	145	?	1	1			
	83			lambquarter	hy						
	145			p_weedkill	no						

!	75	acton	78	beans	?	no	no	?	lev	none	disc
	?		?	no	145	?	1	1			
	83		?	hyps							
	140			d_weedkill	no						

!	77	antaze	78	corn	?	no	no	?	lev	plow	disc
	?			thimet	150	?	1	1			
	83	velvetweed		lt							
	83	foxtail		lt							
!	50	spain	78	beans	?	no	no	?	rol	none	disc
	?			no	140	?	1	1			
	83			lt							
!	3	wenard	78	beans	?	yes	no	?	lev	none	fldclt
	?			no	140	?	1	1			
	83	grass		lt							
!	99	hoffm	78	corn	?	no	yes	?	bld	disc	disc
	?			yes	141	?	1	1			
	83	sourdock		lt							
!	20	kelsey	78	beans	?	no	yes	?	lev	chisel	disc
	?			furadan	150	?	1	1			
	83			lt							
!	20	kelsey	78	whbe	?	yes	no	?	rol	disc	disc
	?			furadan	147	?	1	1			
	83	ragweed		lt							
!	20	kelsey	78	corn	?	no	yes	?	lev	plow	disc
	?			furadan	140	?	1	1			
	83	morningglory		lt							
!	20	gruenl	78	whbe	?	yes	no	?	rol	chisel	disc
	?			furadan	152	?	1	1			
	83	smartweed		hy							
!	25	vander	78	whbe	?	no	no	?	lev	none	chisel
	?			no	151	?	1	1			
	83	smartweed		hyps							
!	10	notte	78	whcl	?	no	no	?	rol	none	plow
	?			counter	131	?	1	1			
	83			hy							
!	50	ferrer	78	beans	?	no	no	?	lev	chisel	fldclt
	?			furadan	147	?	1	1			
	83	smartweed		hy							

!	25	woods	78	beans	?	yes	no	?	lev	chisel	disc
	?		?	no	147	?	1	1			
	83	chickweed		hy							
!	20	woods	78	corn	?	yes	no	?	lev	chisel	disc
	?		?	counter	117	?	1	1			
	83			?	lt						
!	50	brande	78	beans	?	yes	no	?	lev	chisel	disc
	?		?	no	159	?	1	1			
	83	smartweed		hy							
!	50	burt	78	beans	?	yes	no	?	lev	none	disc
	?		?	no	151	?	1	1			
	83	ragweed		hy							
	83	nutgrass		hy							
!	75	cornwe	78	beans	?	no	no	?	lev	none	disc
	?		?	no	154	?	1	1			
	83	chickweed		hy							
	83	ticklegrass		hy							
	83	foxtail		hy							
!	20	kitloy	78	beans	?	yes	no	?	rol	none	disc
	?		?	furadan	152	?	1	1			
	83	chickweed		hy							
	83	winter_annl		hy							
	83	grass		hy							
	150	d_weedkill		no							
!	10	leonar	78	beans	?	yes	no	?	lev	chisel	disc
	?		?	no	152	?	1	1			
	83	foxtail		hyps							
!	20	newton	78	beans	?	yes	no	?	lev	disc	disc
	?		?	counter	152	?	1	1			
	83	chickweed		lt							
!	80	rogers	78	whbe	?	yes	no	?	lev	chisel	disc
	?		?	no	154	?	1	1			
	83	chickweed		lt							
	83	smartweed		lt							
!	40	templ	78	beans	?	no	no	?	lev	chisel	disc
	?		?	counter	152	?	1	1			
	83	foxtail		lt							
	83	ragweed		lt							

115	f_weedkill	no							
146	f_weedkill	no							
!	25	fombel	78	beans	?	no	no	?	lev chisel fldclt
	?	?		no	156	?	1	1	
	83	very_few_wds		lt					
	105	f_weedkill		no					
!	15	evans	78	beans	?	yes	no	?	lev plow disc
	?	?		no	148	?	1	1	
	83	chickweed		lt					
	83	ragweed		hyps					
	124	d_weedkill		no					
	147	d_weedkill		no					
!	70	mckinz	78	beans	?	yes	no	?	rol chisel disc
	?	?		furadan	148	?	1	1	
	83	smartweed		lt					
	125	d_weedkill		no					
!	67	reid	78	beans	?	no	yes	?	rol chisel disc
	?	?		no	141	?	1	1	
	83	morningglory		lt					
	125	d_weedkill		no					
!	30	gaibel	78	whbe	?	no	no	?	lev chisel disc
	?	?		dyfonate	154	?	1	1	
	83	foxtail		hy					
	83	smartweed		hy					
	83	ragweed		hy					
!	50	klitzl	78	corn	?	yes	no	?	lev plow disc
	?	?		isotox_dia	156	?	1	1	
	83	chickweed		hy					
	150	d_weedkill		no					
!	35	lidy	78	beans	?	no	yes	?	lev plow disc
	?	?		furadan	155	?	1	1	
	83	foxtail		hyps					
	83	ragweed		hyps					
	83	smartweed		hyps					
	151	d_weedkill		no					
	155	d_weedkill		no					
!	12	milller	78	beans	?	no	no	?	lev chisel disc
	?	?		no	152	?	1	1	
	83	ragweed		hy					
	83	foxtail		hy					

83 smartweed hy

! 70 mundt 78 whbe ? yes no ? lev plow disc
 ? ? no 157 ? 1 1
 83 foxtail hy
 83 smartweed hy
 153 d_weedkill no
 156 d_weedkill no

! 60 schmid 78 beans ? no no ? lev chisel disc
 ? ? aldrin 156 ? 1 1
 83 foxtail hy
 83 chickweed hy
 83 pigweed hy
 153 d_weedkill ?
 155 d_weedkill no

! 4 uthell 78 whcl ? no no ? lev plow disc
 ? ? no 156 ? 1 1
 83 foxtail hyps
 83 smartweed hyps
 83 ragweed hyps

! 3 cleer 78 beans ? no no ? lev plow fldclt
 ? ? no 147 ? 1 1
 83 foxtail hy
 83 milkweed hy

! 5 toncra 78 beans ? no yes ? lev none disc
 ? ? thimet 122 ? 1 1
 83 foxtail lt
 118 d_weedkill no
 121 f_weedkill no

! 9 hall 78 beans ? yes yes ? rol disc fldclt
 ? ? no 148 ? 1 1
 83 smartweed ?
 83 clover hyps
 147 f_weedkill no

! 28 lingm1 78 beans ? yes no ? rol none disc
 ? ? no 147 ? 1 1
 83 morningglory lt

! 100 fals 78 beans ? no no ? lev chisel fldclt
 ? ? no 145 ? 1 1
 83 smartweed hy
 135 f_weedkill no

!	10	malby	78	beans	?	yes	no	?	lev	none	disc
	?			no	140	?	1	1			
	83			hy							
!	50	frey	78	beans	?	yes	no	?	lev	chisel	disc
	?			no	146	?	1	1			
	83	smartweed		lt							
	83	ticklegrass		lt							
	140	d_weedkill		no							
!	75	weaver	78	beans	?	yes	yes	?	bld	plow	fldclt
	?			no	143	?	1	1			
	83	foxtail		lt							
!	7	jorgen	78	beans	?	no	no	?	rol	none	disc
	?			no	149	?	1	1			
	83	smartweed		lt							
!	20	bixler	78	corn	?	no	no	?	lev	chisel	disc
	?			furadan	157	?	1	1			
	83	chickweed		lt							
	83	foxtail		hy							
	83	smartweed		hy							
!	15	elmore	78	beans	?	no	no	?	lev	disc	disc
	?			furadan	149	?	1	1			
	83	chickweed		hy							
	83	smartweed		hy							
	83	ragweed		hy							
!	16	poehle	78	beans	?	yes	yes	?	lev	chisel	disc
	?			r_sevin	160	?	1	1			
	83			hy							
	153	d_weedkill		no							
	156	d_weedkill		no							
	159	d_weedkill		no							
!	99	wolf	78	whbe	?	no	yes	?	lev	chisel	disc
	?			no	155	?	1	1			
	83	chickweed		hyps							
	83	smartweed		hyps							
	145	d_weedkill		no							
!	66	cain	78	corn	?	yes	yes	?	bld	plow	disc
	?			thimet	149	?	1	1			
	83	chickweed		hy							

83	grass	hy							
!	5	goss	78	corn	?	yes	no	?	rol
	?		?	counter	120	?	1	1	disc fldclt
	83		?	lt					
	119	f_weedkill		no					
!	4	simkin	78	corn	?	yes	yes	?	lev
	?		?	dyfonate	142	?	1	1	none plow
	83	foxtail		lt					
	83	velvetleaf		lt					
	83	smartweed		lt					
	135	p_weedkill		no					
!	3	pierse	78	corn	?	no	no	?	lev
	?		?	counter	121	?	1	1	plow disc
	83	queckgrass		lt					
	106	d_weedkill		no					
	120	d_weedkill		no					
!	0	hoxsey	78	beans	?	yes	no	?	lev
	?		?	thimet	135	?	1	1	none disc
	83	velvetleaf		lt					
	83	grass		lt					
	115	d_weedkill		no					
	135	d_weedkill		no					
!	5	logan	78	beans	?	yes	no	?	rol
	?		?	no	146	?	1	1	plow disc
	83	velvetleaf		lt					
	118	d_weedkill		no					
	146	f_weedkill		no					
!	4	myer	78	beans	?	no	yes	?	lev
	?		?	furadan	140	?	1	1	none fldclt
	83		?	hy					
!	33	stephe	78	beans	?	no	yes	?	rol
	?		?	furadan	147	?	1	1	none disc
	83	grass		lt					
	121	d_weedkill		no					
!	7	warren	78	corn	?	yes	no	?	lev
	?		?	counter	142	?	1	1	disc disc
	83	velvetleaf		lt					
	83	smartweed		lt					

!	15	buchan	78	beans	?	no	yes	?	bld	chisel	disc
		?		no	151	?		1	1		
	83	foxtail	lt								
	83	smartweed	lt								
!	2	finely	78	corn	?	no	yes	?	bld	chisel	disc
		?		furadan	152	?		1	1		
	83		?	lt							
!	15	henert	78	sod	?	no	no	?	lev	none	disc
		?		no	121	?		1	1		
	83		sod	hy							
!	1	zapf	78	beans	?	yes	no	?	rol	none	disc
		?		heptachlor	124	?		1	1		
	83		foxtail	hyps							
!	30	alvey	78	beans	?	no	no	?	rol	none	disc
		?		r_lorsban	135	?		1	1		
	83		lambquarter	lt							
!	3	bertsc	78	beans	?	yes	no	?	lev	chisel	fldclt
		?		diazinon	147	?		1	1		
	83		giantfoxtail	?							
!	15	flint	78	beans	?	no	no	?	lev	disc	fldclt
		?		rescue_trt	142	?		1	1		
	83		clover	lt							
	83		smartweed	lt							
	142		f_weedkill	no							
!	12	mcbroo	78	beans	?	no	no	?	lev	disc	disc
		?		no	119	?		1	1		
	83		smartweed	lt							
	115		d_weedkill	no							
!	5	sancke	78	corn	?	yes	yes	?	bld	plow	fldclt
		?		furadan	146	?		1	1		
	83		smartweed	hyps							
	83		clover	hyps							
!	5	thorne	78	beans	?	yes	no	?	rol	none	fldclt
		?		no	145	?		1	1		
	83		smartweed	hyps							
	83		nutsedge	hyps							
	144		f_weedkill	no							

!	25	thorse	78	beans	?	yes	no	?	bld	chisel	disc
	?		?	thimet	143	?	1	1			
	83			?	lt						
	130	d_weedkill		no							
!	50	klenke	78	beans	?	no	no	?	lev	chisel	disc
	?		?	no	153	?	1	1			
	83			grass	lt						
!	70	malau	78	corn	?	yes	no	?	lev	disc	disc
	?		?	furedan	151	?	1	1			
	83			grass	lt						
!	30	malau	78	beans	?	yes	no	?	lev	none	disc
	?		?	furedan	153	?	1	1			
	83			grass	lt						
!	75	martin	78	whbe	?	yes	no	?	lev	chisel	chisel
	?		?	no	156	?	1	1			
	83			grass	lt						
	83			chickweed	lt						
!	20	gaines	78	beans	?	no	yes	?	lev	chisel	fldclt
	?		?	r_penncap	130	?	1	1			
	83			chickweed	lt						
	83			barley	lt						
!	90	vandev	78	beans	?	yes	no	?	lev	chisel	disc
	?		?	no	142	?	1	1			
	83			chickweed	hyps						
!	70	walsh	78	beans	?	yes	no	?	lev	chisel	disc
	?		?	no	156	?	1	1			
	83			?	hy						
!	65	young	78	bewh	?	no	yes	?	lev	disc	disc
	?		?	no	151	?	1	1			
	83			?	lt						
!	25	young	78	beans	?	no	yes	?	lev	none	disc
	?		?	no	152	?	1	1			
	83			foxtail	hy						
!	10	buser	78	beans	?	yes	no	?	lev	disc	disc
	?		?	thimet	144	?	1	1			

83		?	lt								
!	2	fiedle	78	corn	?	yes	yes	?	rol	none	disc
	?		?	counter	150	?	1	1			
	83	chickweed		hy							
	83	foxtail		hy							
	83	sourdock		hy							
	83	button_weed		hy							
!	25	laible	78	corn	?	yes	yes	?	rol	disc	disc
	?		?	counter	134	?	1	1			
	83	foxtail		hyps							
	116	d_weedkill		no							
	133	f_weedkill		no							
!	6	lasswe	78	corn	?	yes	no	?	rol	none	disc
	?		?	counter	144	?	1	1			
	83	foxtail		lt							
	83	smartweed		lt							
	124	d_weedkill		no							
	140	d_weedkill		no							
	144	f_weedkill		no							
!	50	stange	78	corn	?	no	yes	?	rol	none	disc
	?		?	furadan	142	?	1	1			
	83	smartweed		lt							
!	7	benedi	78	beans	?	no	no	?	rol	chisel	disc
	?		?		146	?	1	1			
	83	sweetclover		hy							
	83	foxtail		hy							
!	15	mackma	78	beans	?	no	no	?	lev	none	disc
	?			no	115	?	1	1			
	83	lambsquarter		lt							
!	12	james	78	beans	?	no	yes	?	bld	none	disc
	?			no	147	?	1	1			
	83	smartweed		lt							
!	50	cole	78	beans	?	no	no	?	lev	chisel	disc
	?			no	153	?	1	1			
	83	chickweed		hy							
	83	smartweed		hy							
	152	d_weedkill		no							
!	25	drake	78	whbe	?	yes	no	?	lev	chisel	disc

?		?	furadan	154	?	1	1		
83		smartweed	lt						
83		ragweed	lt						
!	70	drake	78 clover	?	yes	no	?	lev	chisel disc
	?		?	furadan	154	?	1	1	
	83		smartweed	hyps					
	83		ragweed	hyps					
!	50	rosent	78 beans	?	yes	no	?	lev	plow disc
	?		?	no	154	?	1	1	
	83		ragweed	hy					
!	80	ross	78 beans	?	yes	no	?	rol	chisel disc
	?		?	no	153	?	1	1	
	83		?	hyps					
!	25	schroe	78 beans	?	yes	no	?	lev	chisel fldclt
	?		?	mocap	154	?	1	1	
	83		watergrass	lt					
!	17	smith	78 corn	?	yes	no	?	bld	none disc
	?		?	furadan	135	?	1	1	
	83		?	lt					
!	20	travis	78 beans	?	yes	yes	?	bld	plow disc
	?		?	no	145	?	1	1	
	83		smartweed	lt					
!	20	walqui	78 beans	?	yes	no	?	rol	chisel disc
	?		?	furadan	140	?	1	1	
	83		nutgrass	hyps					
	83		cocklebur	hyps					
	83		grass	hyps					
!	35	alliso	78 beans	?	yes	no	?	rol	none fldclt
	?		?	furadan	147	?	1	1	
	83		smartweed	lt					
!	20	mcmill	78 beans	?	no	no	?	lev	none disc
	?		?	thimet	148	?	1	1	
	83		?	lt					
	144		d_weedkill	no					
!	20	myers	78 beans	?	no	no	?	lev	none disc
	?		?	furadan	151	?	1	1	

83 chickweed hyps
 83 smartweed hyps
 83 foxtail hyps

! 75 wolf 78 beans ? yes no ? lev chisel disc
 ? ? counter 145 ? 1 1
 83 ? lt

! 33 miller 78 beans ? yes no ? lev fldclt harrow
 ? ? thimet 138 ? 1 1
 83 ? lt
 137 h_weedkill no

! 4 dixon 78 corn ? no no ? lev plow plow
 ? ? counter 127 ? 1 1
 83 smartweed lt
 110 p_weedkill no

! 4 langle 78 corn ? yes no ? rol none disc
 ? ? counter 130 ? 1 1
 83 ? lt

! 5 mercer 78 corn ? yes no ? bld plow disc
 ? ? thimet 125 ? 1 1
 83 pigweed lt
 83 velvetleaf lt
 83 smartweed lt

! 75 green 78 beans ? yes yes ? lev plow disc
 ? ? no 140 ? 1 1
 83 sandbur lt
 83 grass lt

! 10 lafeve 78 corn ? yes no ? rol plow disc
 ? ? dyfonate 138 ? 1 1
 83 ? lt

! 90 evans 78 beans ? no no ? lev plow disc
 ? ? no 142 ? 1 1
 83 smartweed hyps

! 1 blair 78 beans ? no yes ? lev none disc
 ? ? no 155 ? 1 1
 83 chickweed hyps
 83 smartweed hyps
 153 d_weedkill no

!	5	mcfarl	78	beans	?	yes	no	?	lev	chisel	fldclt
		?		no	140	?	1	1			
	83	chickweed		lt							
	83	foxtail		lt							
!	6	graden	78	beans	?	yes	no	?	lev	chisel	fldclt
		?		no	154	?	1	1			
	83	foxtail		lt							
!	5	justis	78	corn	?	no	no	?	rol	disc	fldclt
		?		yes	140	?	1	1			
	83			lt							
!	65	lawler	78	beans	?	no	yes	?	lev	chisel	disc
		?		no	145	?	1	1			
	83	foxtail		lt							
	143	d_weedkill		no							
!	70	manke	78	beans	?	yes	yes	?	lev	chisel	disc
		?		no	156	?	1	1			
	83	chickweed		hy							
	83	pigweed		hy							
	83	smartweed		hy							
!	30	redeke	78	beans	?	no	yes	?	lev	chisel	fldclt
		?		dyfonate	156	?	1	1			
	83	smartweed		lt							
!	10	rovey	78	beans	?	no	yes	?	lev	chisel	disc
		?		mocap	146	?	1	1			
	83	smartweed		hyps							
	83	foxtail		hyps							
!	20	rupert	78	beans	?	yes	no	?	lev	chisel	fldclt
		?		no	151	?	1	1			
	83	lambquarter		hyps							
	83	smartweed		hyps							
	149	f_weedkill		no							
!	75	tucker	78	beans	?	yes	no	?	lev	chisel	disc
		?		heptachlor	154	?	1	1			
	83	smartweed		hy							
!	35	webb	78	beans	?	no	yes	?	lev	chisel	disc
		?		counter	148	?	1	1			
	83	smartweed		hy							

!	33	wamsin	78	beans	?	no	no	?	lev	disc	fldclt
	?			no	156	?		1	1		
	83	smartweed		hyps							
	83	pigweed		hyps							
!	50	montco	78	beans	?	yes	no	?	lev	disc	disc
	?			no	157	?		1	1		
	83	smartweed		lt							
!	5	montco	78	beans	?	no	no	?	lev	chisel	fldclt
	?			no	150	?		1	1		
	83	smartweed		lt							
	83	grass		lt							
!	60	white	78	beans	?	no	no	?	lev	none	disc
	?			counter	140	?		1	1		
	83	cocklebur		lt							
	83	Jimson		lt							
!	80	steven	78	corn	?	no	no	?	lev	none	disc
	?			thimet	152	?		1	1		
	83	pigweed		?							
	83	lambquarter		?							
!	50	steven	78	beans	?	no	no	?	lev	chisel	disc
	?			thimet	152	?		1	1		
	83	pigweed		?							
	83	lambquarter		?							
!	50	steven	78	wheat	?	no	no	?	lev	plow	disc
	?			thimet	152	?		1	1		
	83	pigweed		?							
	83	lambquarter		?							
!	20	alexan	78	corn	?	no	no	?	rol	disc	disc
	?			counter	118	?		1	1		
	83	lambquarter		lt							
	83	giantfoxtail		lt							
	83	smartweed		lt							
!	3	gucker	78	beans	?	yes	no	?	lev	none	disc
	?			no	145	?		1	1		
	83	foxtail		lt							
!	10	olson	78	corn	?	no	no	?	rol	disc	disc

?	?	counter	123	?	1	1			
83	wild_millet	lt							
122	d_weedkill	no							
!	10	walsh 78	pasture	?	no	no	?	lev	none plow
?		?	counter	146	?	1	1		
	83		?	lt					
!	10	walsh 78	beans	?	no	no	?	rol	none fldclt
?		?	no	140	?	1	1		
	83	smartweed	lt						
	122	f_weedkill	no						
	146	f_weedkill	no						
!	65	wilkin 78	corn	?	yes	yes	?	rol	disc disc
?		?	counter	116	?	1	1		
	83	milkweed	lt						
	83	smartweed	lt						
!	85	davids 78	corn	?	yes	no	?	rol	none disc
?		?	yes	148	?	1	1		
	83	ragweed	lt						
	83	crab_grass	lt						
!	17	twordo 78	corn	?	yes	no	?	rol	none disc
?		?	counter	123	?	1	1		
	83		?	lt					
	122	d_weedkill	no						
!	17	campbe 78	whbe	?	yes	no	?	rol	chisel disc
?		?	no	136	?	1	1		
	83	chickweed	hyps						
!	3	deterd 78	clover	?	no	yes	?	blt	plow fldclt
?		?	furadan	111	?	1	1		
	83	chickweed	lt						
	83	henbit	lt						
	110	h_weedkill	no						
!	20	eggeme 78	beans	?	no	no	?	lev	none disc
?		?	furadan	121	?	1	1		
	83	garlic	lt						
!	3	hersch 78	corn	?	yes	no	?	blt	none disc
?		?	yes	110	?	1	1		
	83	henbit	?						
	83	fishscale	?						

!	25	welge	78	corn	?	yes	yes	?	bld	none	disc
		?		yes	143	?		1	1		
	83	nutsedge		hyps							
!	0	kermic	78	wheat	?	yes	no	?	rol	none	plow
		?		furadan	151	?		1	1		
	83	hutsedge		?							
	83	clover		?							
!	17	klngl	78	beans	?	no	no	?	lev	disc	disc
		?		no	152	?		1	1		
	83	chickweed		lt							
!	42	r_runy	78	beans	?	yes	yes	?	rol	chisel	disc
		?		furadan	149	?		1	1		
	83			?	lt						
!	20	ethert	78	corn	?	no	no	?	rol	disc	fldclt
		?		counter	147	?		1	1		
	83	foxtail		hyps							
	83	velvetleaf		hyps							
!	33	frank	78	beans	?	yes	no	?	lev	chisel	disc
		?		counter	119	?		1	1		
	83	chickweed		hyps							
	83	foxtail		hyps							
!	50	mcclel	78	beans	?	yes	no	?	lev	chisel	fldclt
		?		no	147	?		1	1		
	83	peppergrass		hyps							
!	30	osterm	78	beans	?	yes	yes	?	lev	chisel	harrow
		?		counter	122	?		1	1		
	83			?	lt						
	122	h_weedkill		no							
!	10	stone	78	corn	?	yes	yes	?	lev	plow	disc
		?		counter	144	?		1	1		
	83	foxtail		hy							
!	3	stout	78	beans	?	no	no	?	lev	chisel	fldclt
		?		no	149	?		1	1		
	83	spurge		lt							
	83	smartweed		lt							
	83	grass		lt							

119	h_weedkill	no								
149	f_weedkill	no								
! 100	bridge	78	beans	?	no	no	?	lev	chisel	fldclt
?	?		no	155	?		1	1		
83	chickweed		lt							
83	smartweed		hy							
! 90	bughen	78	beans	?	yes	yes	?	lev	disc	disc
?	?		no	152	?		1	1		
83	grass		lt							
! 50	gregg	78	beans	?	no	no	?	lev	chisel	disc
?	?		no	149	?		1	1		
83	smartweed		lt							
! 25	hampto	78	beans	?	yes	no	?	lev	plow	fldclt
?	?		diazinon	150	?		1	1		
83	smartweed		hyps							
! 50	montgo	78	beans	?	yes	no	?	lev	none	fldclt
?	?		no	157	?		1	1		
83	smartweed		hyps							
! 8	ruff	78	beans	?	no	no	?	lev	chisel	fldclt
?	?		no	152	?		1	1		
83	chickweed		lt							
83	spineysida		lt							
150	f_weedkill		no							
! 75	schmit	78	whbe	?	yes	no	?	rol	disc	disc
?	?		no	151	?		1	1		
83	peppergrass		hyps							
150	d_weedkill		no							
! 22	elliot	78	corn	?	no	no	?	rol	none	plow
?	?		furadan	147	?		1	1		
83	velvetleaf		lt							
! 12	gray	78	pasture	?	no	yes	?	rol	none	disc
?	?		counter	123	?		1	1		
83	grass		hy							
! 5	webste	78	corn	?	yes	yes	?	rol	plow	disc
?	?		yes	147	?		1	1		
83	smartweed		lt							

!	13	wilson	78	beans	?	no	no	?	lev	none	disc
	?		?	thimet	130	?	1	1			
	83			?	lt						

Results from processing 1978 BCW data with CONVART and
VARSEL so as to compare RAS to GAS

The following pages give the input tables suitable for
use with GEM, produced by VARSEL after CONVART. Results
of greedy search and random adaptive search for sample sizes
of 5, 10, and 15 are given.

domaintypes

name	type	levels
prev_crop	nom	18
perm_veg	nom	2
brdr_water	nom	2
surface	nom	3
fall_till	nom	10
springtill	nom	10
insecticid	nom	19
plantdate	lin	6
nbrnotsame_of_weed_s	nom	4
maxvalue_of_weedensl	lin	4
lstmintim_of_weedens	lin	13

Results after VARSEL using
Greedy Attribute Search.

variables

#	name
1	var2.prev_crop
2	var4.perm_veg
3	var5.brdr_water
4	var7.surface
5	var8.fall_till
6	var9.springtill
7	var12.insecticid
8	var13.plantdate
9	var20.nbrnotsame_of_weed_s
10	var24.maxvalue_of_weedensl
11	var27.lstmintim_of_weedens

classl-events

#	var12	var9	var13	var8	var7	var27	var20	var2	var24	var5	var4
1	2	3	4	1	1	0	1	1	1	1	0
2	1	5	4	3	0	0	2	1	3	1	1
3	2	3	4	1	1	0	?	0	1	1	0
4	2	1	4	0	0	0	?	0	1	1	1
5	8	1	5	0	0	8	2	1	3	0	0
6	1	5	4	2	1	0	1	1	2	0	0
7	9	5	4	0	0	0	1	1	2	0	0
8	5	1	4	0	1	5	2	1	2	1	0
9	1	3	4	0	0	0	3	1	2	1	0
10	1	3	4	0	1	11	3	1	2	1	1
11	11	3	3	2	1	0	1	0	1	0	0
12	10	2	4	1	0	?	2	0	?	1	0
13	0	3	4	1	2	0	1	0	1	0	1
14	3	1	4	0	0	5	2	0	1	1	0
15	11	5	3	0	0	0	?	1	1	1	0
16	9	5	2	0	0	0	1	1	1	1	1
17	2	3	3	0	1	4	2	1	1	1	0
18	2	3	4	1	0	0	2	0	3	1	0
19	11	3	4	1	1	0	1	0	1	1	0
20	2	5	4	0	1	11	2	1	1	0	0
21	9	1	4	0	0	10	2	9	2	1	0
22	1	5	4	0	0	0	1	1	1	1	0
23	3	3	4	2	0	0	?	1	1	0	1
24	3	3	4	3	1	0	1	3	1	1	0
25	3	3	4	1	0	0	1	0	1	0	1
26	3	3	4	2	1	0	1	3	2	1	0

27	1	2	4	0	0	0	1	3	3	1	1
28	2	1	3	0	1	0	?	10	2	1	1
29	1	3	4	2	0	0	1	1	2	1	0
30	2	3	2	2	0	0	?	0	1	1	0
31	3	3	4	0	1	11	3	1	2	1	0
32	1	3	4	2	0	0	1	1	3	1	0
33	2	3	4	3	0	0	1	1	1	1	0
34	2	3	4	2	0	0	2	1	1	1	1
35	3	3	4	2	0	10	2	1	3	1	0
36	0	5	4	3	1	6	3	0	2	1	0
37	8	5	3	0	0	0	1	1	1	0	1
38	2	5	4	1	0	6	2	0	0	1	1
39	1	3	4	2	0	10	3	1	2	0	1
40	3	3	4	2	0	0	1	1	2	1	0
41	1	5	4	2	0	3	2	1	1	0	1
42	1	5	4	2	0	1	2	1	1	1	1
43	1	3	4	1	0	6	3	1	3	1	0
44	9	3	4	2	0	0	3	3	2	1	1
45	3	3	4	1	0	11	3	1	3	0	1
46	1	3	4	2	0	0	3	1	2	1	1
47	1	3	4	1	0	0	3	10	3	1	1
48	1	5	4	1	0	0	2	1	2	1	1
49	11	3	3	0	0	4	2	1	1	0	1
50	1	5	4	3	1	11	3	1	3	0	0
51	1	3	4	0	1	0	1	1	1	1	0
52	1	3	4	0	0	0	?	1	2	1	0
53	1	3	4	0	1	0	1	1	1	1	1
54	3	3	4	2	0	0	3	0	2	1	1
55	3	3	4	3	0	0	3	1	2	1	1
56	17	3	5	2	0	11	1	1	2	0	0
57	2	5	3	3	1	4	1	0	1	1	0
58	9	1	4	0	0	8	3	0	1	0	0
59	2	3	3	1	0	1	2	0	1	1	1
60	11	3	4	0	0	3	3	1	1	1	0
61	1	3	4	1	1	4	2	1	1	1	0
62	3	5	4	0	0	0	?	1	2	0	1
63	3	3	4	0	1	5	2	1	1	0	1
64	2	3	4	3	0	0	2	0	1	1	0
65	1	3	4	2	2	0	2	1	1	0	1
66	3	3	4	2	2	0	?	0	1	0	1
67	1	3	3	0	0	0	1	15	2	1	1
68	14	3	3	0	1	0	1	1	3	1	0
69	10	3	4	0	1	0	1	1	1	1	1
70	5	5	4	2	0	?	1	1	?	1	0
71	15	5	4	3	0	10	3	1	1	1	1
72	1	3	2	3	0	3	2	1	1	1	1
73	3	5	4	1	2	0	2	0	3	0	0
74	1	5	4	0	1	10	3	1	3	1	0
75	11	3	4	2	2	7	1	1	1	1	0
76	3	3	4	0	0	0	1	1	1	1	0
77	16	5	3	2	0	0	2	1	1	0	1
78	1	3	4	0	0	0	1	1	2	0	1
79	11	3	4	3	0	0	?	1	1	1	0
80	2	3	4	0	1	0	3	0	2	0	0
81	2	3	3	3	1	3	2	0	3	0	0
82	2	3	4	0	1	6	3	0	1	1	0

83	?	3	4	2	1	0	2	1	2	1	1
84	1	3	2	0	0	0	1	1	1	1	1
85	1	3	4	0	2	0	1	1	1	0	1
86	3	3	4	2	0	0	2	3	1	1	0
87	6	5	4	2	0	0	1	1	1	1	0
88	3	3	4	0	2	0	?	0	1	1	0
89	1	3	4	1	2	0	1	1	1	0	0
90	3	3	4	2	1	0	3	1	3	1	0
91	3	5	4	0	1	0	1	1	1	1	0
92	11	3	4	0	0	10	1	1	1	1	1
93	3	3	4	0	0	0	3	1	3	1	1
94	11	6	4	5	0	8	1	1	1	1	0
95	2	1	3	1	0	2	2	0	1	1	1
96	2	3	3	0	1	0	?	0	1	1	0
97	11	3	3	1	2	0	3	0	1	1	0
98	9	3	4	1	1	0	?	0	1	1	0
99	1	3	4	0	0	11	3	1	3	0	1
100	1	5	4	2	0	0	2	1	1	1	0
101	1	5	4	2	0	0	1	1	1	1	0
102	0	5	4	3	1	0	?	0	1	1	1
103	9	5	4	2	0	0	1	1	1	0	1
104	6	3	4	2	0	0	2	1	3	0	1
105	1	5	4	2	0	11	3	1	3	1	0
106	2	3	4	2	0	0	1	1	2	0	1
107	1	5	4	3	0	0	2	1	3	1	1
108	1	5	4	2	0	0	2	1	1	1	1
109	2	3	2	3	1	0	3	0	1	1	1
110	1	3	4	0	0	0	1	1	1	1	0
111	2	3	3	3	1	6	2	0	1	1	1
112	2	1	4	0	0	0	?	4	1	1	1
113	1	5	4	0	1	6	2	1	1	1	1
114	2	3	3	0	1	6	1	0	1	1	0
115	1	3	4	2	1	0	1	3	3	1	0
116	3	5	2	1	2	2	3	13	1	0	1
117	3	3	3	0	0	0	1	1	1	1	1
118	0	3	2	0	2	?	2	0	?	1	0
119	0	3	4	0	2	0	1	0	3	0	0
120	3	1	4	0	1	?	2	8	?	1	0
121	1	3	4	3	0	0	1	1	1	1	1
122	3	3	4	2	1	0	?	1	1	0	0
123	2	5	4	3	1	0	2	0	3	1	1
124	2	3	2	2	0	0	2	1	3	1	0
125	2	6	3	2	0	6	1	1	1	0	0
126	2	3	4	1	0	0	1	0	2	0	0
127	1	5	4	2	0	4	3	1	1	1	1
128	5	5	4	1	0	0	1	1	3	1	0
129	1	5	4	2	0	11	3	1	1	1	1
130	3	1	4	0	1	0	1	0	1	1	1
131	2	3	3	0	1	0	1	4	2	0	1
132	0	3	4	1	1	0	1	0	1	0	0
133	11	3	3	0	0	0	?	1	1	1	1

class2-events

#	var12	var9	var13	var8	var7	var27	var20	var2	var24	var5	var4
1	2	3	4	2	0	0	3	6	2	0	1
2	7	3	3	3	1	0	1	1	2	1	0

3	8	3	4	0	2	12	2	1	1	0	1
4	8	3	5	0	2	12	2	1	1	0	1
5	1	3	4	2	0	0	7	1	2	1	1
6	3	3	4	2	0	8	1	0	1	0	1
7	1	3	4	0	0	0	2	1	3	1	0
8	1	3	4	3	2	9	2	1	2	1	0
9	1	3	4	1	2	0	2	1	3	0	0
10	2	1	4	0	1	0	7	4	1	1	0
11	2	1	4	0	0	0	3	0	3	0	1
12	1	2	4	3	1	8	1	1	1	0	1
13	1	3	4	1	2	0	1	1	3	1	0
14	1	5	4	2	2	11	1	1	1	0	0
15	3	3	4	1	0	7	2	0	7	1	0
16	3	3	4	2	2	0	2	1	1	1	1
17	0	3	4	1	2	8	2	0	1	1	0
18	3	2	4	0	1	0	3	1	2	1	0
19	1	3	4	1	2	0	2	1	1	1	1
20	0	3	4	2	0	0	7	0	1	1	1
21	1	3	4	2	0	0	7	1	1	1	1
22	0	3	4	2	2	0	7	0	1	0	0
23	1	3	4	3	2	10	2	1	1	0	0
24	1	3	4	2	2	0	1	1	1	1	1
25	2	1	4	3	0	5	1	0	1	1	0
26	1	3	4	0	0	0	2	1	2	0	1
27	1	3	4	0	0	9	1	1	3	1	1
28	11	3	4	1	0	0	2	0	1	1	1
29	1	3	4	0	1	0	7	1	1	1	1
30	0	3	4	3	2	0	1	0	1	0	1
31	3	5	4	2	0	0	1	1	2	1	1
32	1	3	4	2	0	0	1	1	2	1	0
33	1	3	4	0	0	0	2	1	2	1	0
34	1	3	4	0	0	0	3	1	2	1	1
35	1	3	4	2	0	0	2	3	1	1	0
36	3	3	4	2	1	10	3	0	2	1	0
37	1	3	4	2	0	12	2	1	1	0	1
38	3	3	4	2	1	6	2	1	1	1	0
39	1	3	4	2	1	6	2	1	1	0	1
40	13	3	4	1	0	11	2	0	2	1	0
41	1	3	4	1	0	11	3	3	2	1	0
42	12	3	4	2	0	12	3	1	2	1	1
43	1	5	4	2	0	8	2	1	2	1	1
44	1	3	4	2	0	9	3	1	1	1	0
45	1	5	4	1	2	0	1	1	1	0	0
46	1	3	4	2	0	10	3	3	3	0	1
47	11	3	4	1	2	0	2	0	2	0	0
48	1	3	4	2	0	0	1	1	1	1	1
49	3	3	4	3	0	0	1	0	1	1	0
50	1	2	4	2	0	0	2	3	1	1	0
51	1	3	4	2	0	0	1	1	3	1	0
52	1	3	4	2	0	0	7	1	2	1	0
53	1	3	4	3	0	0	7	2	1	0	1
54	3	3	4	0	1	0	1	0	1	0	1
55	1	3	4	2	0	11	3	1	2	1	1
56	3	3	4	2	0	0	2	13	3	1	0
57	1	3	4	1	0	0	1	1	2	1	0
58	1	3	4	2	1	0	7	1	3	1	0

59	2	3	4	2	0	0	?	1	1	1	0
60	1	3	4	1	0	0	2	1	1	0	0
61	1	3	4	1	0	0	1	1	3	1	1
62	1	3	4	2	0	10	2	1	1	0	1
63	1	3	4	2	0	0	3	1	2	0	0
64	14	3	4	2	0	0	1	1	2	1	0
65	1	3	4	3	0	0	1	1	1	1	0
66	2	3	4	0	0	0	2	1	1	1	1
67	11	3	4	0	0	?	2	0	?	1	1
68	11	3	4	2	0	?	2	1	?	1	1
69	11	3	4	1	0	?	2	8	?	1	1
70	2	3	2	3	1	0	2	0	1	0	0
71	0	3	4	0	1	0	2	0	1	1	0
72	1	5	4	2	0	0	1	1	3	1	0
73	1	5	4	2	0	0	2	1	2	1	1
74	1	3	4	3	0	0	1	1	1	0	0
75	1	3	4	2	0	0	1	1	1	1	1
76	1	5	4	0	0	0	1	1	3	1	0
77	1	3	4	3	1	11	2	3	3	1	0

domaintypes

name	type	levels
prev_crop	nom	18
perm_veg	nom	2
brdr_water	nom	2
surface	nom	3
fall_till	nom	10
springtill	nom	10
insecticid	nom	19
plantdate	lin	6
mostcomval_of_weed_s	nom	9
nbrnotsame_of_weed_s	nom	4
averageval_of_weeden	lin	4
lstmintim_of_weedens	lin	13

Results after VARSEL using
Random Adaptive Search
Sample size = 5

variables

#	name
1	var2.prev_crop
2	var4.perm_veg
3	var5.brdr_water
4	var7.surface
5	var8.fall_till
6	var9.springtill
7	var12.insecticid
8	var13.plantdate
9	var17.mostcomval_of_weed_s
10	var20.nbrnotsame_of_weed_s
11	var21.averageval_of_weeden
12	var27.lstmintim_of_weedens

classl-events

#	var12	var8	var20	var9	var27	var13	var2	var4	var7	var5	var17	var21
1	2	1	1	3	0	4	1	0	1	1	9	1
2	1	3	2	5	0	4	1	1	0	1	9	3
3	2	1	?	3	0	4	0	0	1	1	?	1
4	2	0	?	1	0	4	0	1	0	1	?	1
5	8	0	2	1	8	5	1	0	0	0	9	2
6	1	2	1	5	0	4	1	0	1	0	9	2
7	9	0	1	5	0	4	1	0	0	0	9	2
8	5	0	2	1	5	4	1	0	1	1	9	1
9	1	0	3	3	0	4	1	0	0	1	9	2
10	1	0	3	3	11	4	1	1	1	1	9	1
11	11	2	1	3	0	3	0	0	1	0	9	1
12	10	1	2	2	?	4	0	0	0	1	9	?
13	0	1	1	3	0	4	0	1	2	0	9	1
14	3	0	2	1	5	4	0	0	0	1	9	1
15	11	0	?	5	0	3	1	0	0	1	?	1
16	9	0	1	5	0	2	1	1	0	1	9	1
17	2	0	2	3	4	3	1	0	1	1	9	1
18	2	1	2	3	0	4	0	0	0	1	9	3
19	11	1	1	3	0	4	0	0	1	1	9	1
20	2	0	2	5	11	4	1	0	1	0	9	1
21	9	0	2	1	10	4	9	0	0	1	9	1
22	1	0	1	5	0	4	1	0	0	1	5	1
23	3	2	?	3	0	4	1	1	0	0	?	1
24	3	3	1	3	0	4	3	0	1	1	9	1

25	3	1	1	3	0	4	0	1	0	0	9	1
26	3	2	1	3	0	4	3	0	1	1	9	2
27	1	0	1	2	0	4	3	1	0	1	9	3
28	2	0	7	1	0	3	10	1	1	1	7	2
29	1	2	1	3	0	4	1	0	0	1	9	2
30	2	2	7	3	0	2	0	0	0	1	7	1
31	3	0	3	3	11	4	1	0	1	1	9	2
32	1	2	1	3	0	4	1	0	0	1	9	3
33	2	3	1	3	0	4	1	0	0	1	9	1
34	2	2	2	3	0	4	1	1	0	1	9	1
35	3	2	2	3	10	4	1	0	0	1	9	2
36	0	3	3	5	6	4	0	0	1	1	9	2
37	8	0	1	5	0	3	1	1	0	0	9	1
38	2	1	2	5	6	4	0	1	0	1	9	0
39	1	2	3	3	10	4	1	1	0	0	9	2
40	3	2	1	3	0	4	1	0	0	1	5	2
41	1	2	2	5	3	4	1	1	0	0	9	0
42	1	2	2	5	1	4	1	1	0	1	2	1
43	1	1	3	3	6	4	1	0	0	1	9	1
44	9	2	3	3	0	4	3	1	0	1	9	2
45	3	1	3	3	11	4	1	1	0	0	9	2
46	1	2	3	3	0	4	1	1	0	1	9	2
47	1	1	3	3	0	4	10	1	0	1	9	3
48	1	1	2	5	0	4	1	1	0	1	9	2
49	11	0	2	3	4	3	1	1	0	0	9	0
50	1	3	3	5	11	4	1	0	1	0	9	2
51	1	0	1	3	0	4	1	0	1	1	9	1
52	1	0	7	3	0	4	1	0	0	1	7	2
53	1	0	1	3	0	4	1	1	1	1	9	1
54	3	2	3	3	0	4	0	1	0	1	9	2
55	3	3	3	3	0	4	1	1	0	1	9	2
56	17	2	1	3	11	5	1	0	0	0	9	1
57	2	3	1	5	4	3	0	0	1	1	9	1
58	9	0	3	1	8	4	0	0	0	0	9	1
59	2	1	2	3	1	3	0	1	0	1	9	0
60	11	0	3	3	3	4	1	0	0	1	9	1
61	1	1	2	3	4	4	1	0	1	1	9	0
62	3	0	7	5	0	4	1	1	0	0	7	2
63	3	0	2	3	5	4	1	1	1	0	5	1
64	2	3	2	3	0	4	0	0	0	1	9	1
65	1	2	2	3	0	4	1	1	2	0	9	1
66	3	2	7	3	0	4	0	1	2	0	7	1
67	1	0	1	3	0	3	15	1	0	1	9	2
68	14	0	1	3	0	3	1	0	1	1	9	3
69	10	0	1	3	0	4	1	1	1	1	9	1
70	5	2	1	5	7	4	1	0	0	1	9	7
71	15	3	3	5	10	4	1	1	0	1	9	1
72	1	3	2	3	3	2	1	1	0	1	9	1
73	3	1	2	5	0	4	0	0	2	0	9	3
74	1	0	3	5	10	4	1	0	1	1	9	2
75	11	2	1	3	7	4	1	0	2	1	9	1
76	3	0	1	3	0	4	1	0	0	1	5	1
77	16	2	2	5	0	3	1	1	0	0	9	1
78	1	0	1	3	0	4	1	1	0	0	9	2
79	11	3	7	3	0	4	1	0	0	1	7	1
80	2	0	3	3	0	4	0	0	1	0	9	2

81	2	3	2	3	3	3	0	0	1	0	9	1
82	2	0	3	3	6	4	0	0	1	1	9	0
83	7	2	2	3	0	4	1	1	1	1	9	2
84	1	0	1	3	0	2	1	1	0	1	9	1
85	1	0	1	3	0	4	1	1	2	0	9	1
86	3	2	2	3	0	4	3	0	0	1	9	1
87	6	2	1	5	0	4	1	0	0	1	9	1
88	3	0	7	3	0	4	0	0	2	1	7	1
89	1	1	1	3	0	4	1	0	2	0	9	1
90	3	2	3	3	0	4	1	0	1	1	9	3
91	3	0	1	5	0	4	1	0	1	1	9	1
92	11	0	1	3	10	4	1	1	0	1	9	1
93	3	0	3	3	0	4	1	1	0	1	9	3
94	11	5	1	6	8	4	1	0	0	1	9	1
95	2	1	2	1	2	3	0	1	0	1	9	1
96	2	0	7	3	0	3	0	0	1	1	7	1
97	11	1	3	3	0	3	0	0	2	1	9	1
98	9	1	7	3	0	4	0	0	1	1	7	1
99	1	0	3	3	11	4	1	1	0	0	9	2
100	1	2	2	5	0	4	1	0	0	1	9	1
101	1	2	1	5	0	4	1	0	0	1	9	1
102	0	3	7	5	0	4	0	1	1	1	7	1
103	9	2	1	5	0	4	1	1	0	0	9	1
104	6	2	2	3	0	4	1	1	0	0	9	3
105	1	2	3	5	11	4	1	0	0	1	9	2
106	2	2	1	3	0	4	1	1	0	0	9	2
107	1	3	2	5	0	4	1	1	0	1	9	3
108	1	2	2	5	0	4	1	1	0	1	9	1
109	2	3	3	3	0	2	0	1	1	1	9	1
110	1	0	1	3	0	4	1	0	0	1	9	1
111	2	3	2	3	6	3	0	1	1	1	9	1
112	2	0	7	1	0	4	4	1	0	1	7	1
113	1	0	2	5	6	4	1	1	1	1	9	0
114	2	0	1	3	6	3	0	0	1	1	9	1
115	1	2	1	3	0	4	3	0	1	1	9	3
116	3	1	3	5	2	2	13	1	2	0	9	1
117	3	0	1	3	0	3	1	1	0	1	9	1
118	0	0	2	3	7	2	0	0	2	1	9	7
119	0	0	1	3	0	4	0	0	2	0	9	3
120	3	0	2	1	7	4	8	0	1	1	9	7
121	1	3	1	3	0	4	1	1	0	1	9	1
122	3	2	7	3	0	4	1	0	1	0	7	1
123	2	3	2	5	0	4	0	1	1	1	9	3
124	2	2	2	3	0	2	1	0	0	1	9	3
125	2	2	1	6	6	3	1	0	0	0	9	1
126	2	1	1	3	0	4	0	0	0	0	9	2
127	1	2	3	5	4	4	1	1	0	1	9	1
128	5	1	1	5	0	4	1	0	0	1	9	3
129	1	2	3	5	11	4	1	1	0	1	9	1
130	3	0	1	1	0	4	0	1	1	1	9	1
131	2	0	1	3	0	3	4	1	1	0	5	2
132	0	1	1	3	0	4	0	0	1	0	9	1
133	11	0	7	3	0	3	1	1	0	1	7	1

class2-events

var12 var8 var20 var9 var27 var13 var2 var4 var7 var5 var17 var21

1	2	2	3	3	0	4	6	1	0	0	9	2
2	7	3	1	3	0	3	1	0	1	1	9	2
3	8	0	2	3	12	4	1	1	2	0	9	1
4	8	0	2	3	12	5	1	1	2	0	9	1
5	1	2	7	3	0	4	1	1	0	1	7	2
6	3	2	1	3	8	4	0	1	0	0	9	1
7	1	0	2	3	0	4	1	0	0	1	9	2
8	1	3	2	3	9	4	1	0	2	1	9	1
9	1	1	2	3	0	4	1	0	2	0	9	3
10	2	0	7	1	0	4	4	0	1	1	7	1
11	2	0	3	1	0	4	0	1	0	0	9	3
12	1	3	1	2	8	4	1	1	1	0	9	1
13	1	1	1	3	0	4	1	0	2	1	9	3
14	1	2	1	5	11	4	1	0	2	0	9	1
15	3	1	2	3	7	4	0	0	0	1	9	7
16	3	2	2	3	0	4	1	1	2	1	9	1
17	0	1	2	3	8	4	0	0	2	1	9	1
18	3	0	3	2	0	4	1	0	1	1	9	2
19	1	1	2	3	0	4	1	1	2	1	9	1
20	0	2	7	3	0	4	0	1	0	1	7	1
21	1	2	7	3	0	4	1	1	0	1	7	1
22	0	2	7	3	0	4	0	0	2	0	7	1
23	1	3	2	3	10	4	1	0	2	0	9	1
24	1	2	1	3	0	4	1	1	2	1	9	1
25	2	3	1	1	5	4	0	0	0	1	9	1
26	1	0	2	3	0	4	1	1	0	0	9	2
27	1	0	1	3	9	4	1	1	0	1	9	2
28	11	1	2	3	0	4	0	1	0	1	9	1
29	1	0	7	3	0	4	1	1	1	1	7	1
30	0	3	1	3	0	4	0	1	2	0	9	1
31	3	2	1	5	0	4	1	1	0	1	9	2
32	1	2	1	3	0	4	1	0	0	1	9	2
33	1	0	2	3	0	4	1	0	0	1	9	2
34	1	0	3	3	0	4	1	1	0	1	9	2
35	1	2	2	3	0	4	3	0	0	1	9	1
36	3	2	3	3	10	4	0	0	1	1	9	1
37	1	2	2	3	12	4	1	1	0	0	9	1
38	3	2	2	3	6	4	1	0	1	1	9	1
39	1	2	2	3	6	4	1	1	1	0	9	1
40	13	1	2	3	11	4	0	0	0	1	9	1
41	1	1	3	3	11	4	3	0	0	1	9	1
42	12	2	3	3	12	4	1	1	0	1	9	2
43	1	2	2	5	8	4	1	1	0	1	9	1
44	1	2	3	3	9	4	1	0	0	1	9	1
45	1	1	1	5	0	4	1	0	2	0	9	1
46	1	2	3	3	10	4	3	1	0	0	9	2
47	11	1	2	3	0	4	0	0	2	0	9	2
48	1	2	1	3	0	4	1	1	0	1	5	1
49	3	3	1	3	0	4	0	0	0	1	5	1
50	1	2	2	2	0	4	3	0	0	1	5	1
51	1	2	1	3	0	4	1	0	0	1	9	3
52	1	2	7	3	0	4	1	0	0	1	7	2
53	1	3	7	3	0	4	2	1	0	0	7	1
54	3	0	1	3	0	4	0	1	1	0	9	1
55	1	2	3	3	11	4	1	1	0	1	9	1
56	3	2	2	3	0	4	13	0	0	1	9	3

57	1	1	1	3	0	4	1	0	0	1	9	2
58	1	2	7	3	0	4	1	0	1	1	7	3
59	2	2	7	3	0	4	1	0	0	1	7	1
60	1	1	2	3	0	4	1	0	0	0	9	1
61	1	1	1	3	0	4	1	1	0	1	9	3
62	1	2	2	3	10	4	1	1	0	0	9	1
63	1	2	3	3	0	4	1	0	0	0	9	2
64	14	2	1	3	0	4	1	0	0	1	9	2
65	1	3	1	3	0	4	1	0	0	1	9	1
66	2	0	2	3	0	4	1	1	0	1	9	1
67	11	0	2	3	7	4	0	1	0	1	9	7
68	11	2	2	3	7	4	1	1	0	1	9	7
69	11	1	2	3	7	4	8	1	0	1	9	7
70	2	3	2	3	0	2	0	0	1	0	9	1
71	0	0	2	3	0	4	0	0	1	1	9	1
72	1	2	1	5	0	4	1	0	0	1	9	3
73	1	2	2	5	0	4	1	1	0	1	9	2
74	1	3	1	3	0	4	1	0	0	0	5	1
75	1	2	1	3	0	4	1	1	0	1	9	1
76	1	0	1	5	0	4	1	0	0	1	9	3
77	1	3	2	3	11	4	3	0	1	1	9	2

domaintypes

name	type	levels
prev_crop	nom	18
perm_veg	nom	2
brdr_water	nom	2
surface	nom	3
fall_till	nom	10
springtill	nom	10
insecticid	nom	19
plantdate	lin	6
nbrnotsame_of_weed_s	nom	4
yintercept_of_weeden	lin	15
maxvalue_of_weedens1	lin	4
minvalue_of_weedens1	lin	4
lstmintim_of_weedens	lin	13

Results after VARSEL using
Random Adaptive Search
Sample size = 10

variables

#	name
1	var2.prev_crop
2	var4.perm_veg
3	var5.brdr_water
4	var7.surface
5	var8.fall_till
6	var9.springtill
7	var12.insecticid
8	var13.plantdate
9	var20.nbrnotsame_of_weed_s
10	var23.yintercept_of_weeden
11	var24.maxvalue_of_weedens1
12	var26.minvalue_of_weedens1
13	var27.lstmintim_of_weedens

classl-events

#	var12	var8	var9	var20	var13	var26	var27	var23	var24	var7	var2	var5	var4
1	2	1	3	1	4	1	0	?	1	1	1	1	0
2	1	3	5	2	4	3	0	?	3	0	1	1	1
3	2	1	3	?	4	1	0	?	1	1	0	1	0
4	2	0	1	?	4	1	0	?	1	0	0	1	1
5	8	0	1	2	5	0	8	?	3	0	1	0	0
6	1	2	5	1	4	2	0	?	2	1	1	0	0
7	9	0	5	1	4	2	0	?	2	0	1	0	0
8	5	0	1	2	4	0	5	?	2	1	1	1	0
9	1	0	3	3	4	2	0	0	2	0	1	1	0
10	1	0	3	3	4	0	11	8	2	1	1	1	1
11	11	2	3	1	3	1	0	?	1	1	0	0	0
12	10	1	2	2	4	?	?	?	?	0	0	1	0
13	0	1	3	1	4	1	0	?	1	2	0	0	1
14	3	0	1	2	4	0	5	?	1	0	0	1	0
15	11	0	5	?	3	1	0	?	1	0	1	1	0
16	9	0	5	1	2	1	0	?	1	0	1	1	1
17	2	0	3	2	3	0	4	?	1	1	1	1	0
18	2	1	3	2	4	3	0	?	3	0	0	1	0
19	11	1	3	1	4	1	0	?	1	1	0	1	0
20	2	0	5	2	4	0	11	?	1	1	1	0	0
21	9	0	1	2	4	0	10	?	2	0	9	1	0
22	1	0	5	1	4	1	0	?	1	0	1	1	0

23	3	2	3	7	4	1	0	7	1	0	1	0	1
24	3	3	3	1	4	1	0	7	1	1	3	1	0
25	3	1	3	1	4	1	0	7	1	0	0	0	1
26	3	2	3	1	4	2	0	7	2	1	3	1	0
27	1	0	2	1	4	3	0	7	3	0	3	1	1
28	2	0	1	7	3	2	0	7	2	1	10	1	1
29	1	2	3	1	4	2	0	7	2	0	1	1	0
30	2	2	3	7	2	1	0	7	1	0	0	1	0
31	3	0	3	3	4	0	11	8	2	1	1	1	0
32	1	2	3	1	4	3	0	7	3	0	1	1	0
33	2	3	3	1	4	1	0	7	1	0	1	1	0
34	2	2	3	2	4	1	0	7	1	0	1	1	1
35	3	2	3	2	4	0	10	7	3	0	1	1	0
36	0	3	5	3	4	0	6	10	2	1	0	1	0
37	8	0	5	1	3	1	0	7	1	0	1	0	1
38	2	1	5	2	4	0	6	7	0	0	0	1	1
39	1	2	3	3	4	0	10	9	2	0	1	0	1
40	3	2	3	1	4	2	0	7	2	0	1	1	0
41	1	2	5	2	4	0	3	2	1	0	1	0	1
42	1	2	5	2	4	0	1	7	1	0	1	1	1
43	1	1	3	3	4	0	6	9	3	0	1	1	0
44	9	2	3	3	4	2	0	0	2	0	3	1	1
45	3	1	3	3	4	0	11	11	3	0	1	0	1
46	1	2	3	3	4	2	0	0	2	0	1	1	1
47	1	1	3	3	4	3	0	0	3	0	10	1	1
48	1	1	5	2	4	2	0	7	2	0	1	1	1
49	11	0	3	2	3	0	4	6	1	0	1	0	1
50	1	3	5	3	4	0	11	7	3	1	1	0	0
51	1	0	3	1	4	1	0	7	1	1	1	1	0
52	1	0	3	7	4	2	0	7	2	0	1	1	0
53	1	0	3	1	4	1	0	7	1	1	1	1	1
54	3	2	3	3	4	1	0	0	2	0	0	1	1
55	3	3	3	3	4	2	0	0	2	0	1	1	1
56	17	2	3	1	5	0	11	8	2	0	1	0	0
57	2	3	5	1	3	0	4	7	1	1	0	1	0
58	9	0	1	3	4	0	8	4	1	0	0	0	0
59	2	1	3	2	3	0	1	6	1	0	0	1	1
60	11	0	3	3	4	0	3	5	1	0	1	1	0
61	1	1	3	2	4	0	4	2	1	1	1	1	0
62	3	0	5	7	4	2	0	7	2	0	1	0	1
63	3	0	3	2	4	0	5	7	1	1	1	0	1
64	2	3	3	2	4	1	0	7	1	0	0	1	0
65	1	2	3	2	4	1	0	7	1	2	1	0	1
66	3	2	3	7	4	1	0	7	1	2	0	0	1
67	1	0	3	1	3	2	0	7	2	0	15	1	1
68	14	0	3	1	3	3	0	7	3	1	1	1	0
69	10	0	3	1	4	1	0	7	1	1	1	1	1
70	5	2	5	1	4	7	7	7	7	0	1	1	0
71	15	3	5	3	4	0	10	3	1	0	1	1	1
72	1	3	3	2	2	0	3	7	1	0	1	1	1
73	3	1	5	2	4	3	0	7	3	2	0	0	0
74	1	0	5	3	4	0	10	13	3	1	1	1	0
75	11	2	3	1	4	0	7	7	1	2	1	1	0
76	3	0	3	1	4	1	0	7	1	0	1	1	0
77	16	2	5	2	3	1	0	7	1	0	1	0	1
78	1	0	3	1	4	2	0	7	2	0	1	0	1

79	11	3	3	?	4	1	0	?	1	0	1	1	0
80	2	0	3	3	4	2	0	0	2	1	0	0	0
81	2	3	3	2	3	0	3	14	3	1	0	0	0
82	2	0	3	3	4	0	6	3	1	1	0	1	0
83	?	2	3	2	4	2	0	?	2	1	1	1	1
84	1	0	3	1	2	1	0	?	1	0	1	1	1
85	1	0	3	1	4	1	0	?	1	2	1	0	1
86	3	2	3	2	4	1	0	?	1	0	3	1	0
87	6	2	5	1	4	1	0	?	1	0	1	1	0
88	3	0	3	?	4	1	0	?	1	2	0	1	0
89	1	1	3	1	4	1	0	?	1	2	1	0	0
90	3	2	3	3	4	3	0	0	3	1	1	1	0
91	3	0	5	1	4	1	0	?	1	1	1	1	0
92	11	0	3	1	4	0	10	?	1	0	1	1	1
93	3	0	3	3	4	3	0	0	3	0	1	1	1
94	11	5	6	1	4	0	8	?	1	0	1	1	0
95	2	1	1	2	3	0	2	?	1	0	0	1	1
96	2	0	3	?	3	1	0	?	1	1	0	1	0
97	11	1	3	3	3	1	0	0	1	2	0	1	0
98	9	1	3	?	4	1	0	?	1	1	0	1	0
99	1	0	3	3	4	0	11	11	3	0	1	0	1
100	1	2	5	2	4	1	0	?	1	0	1	1	0
101	1	2	5	1	4	1	0	?	1	0	1	1	0
102	0	3	5	?	4	1	0	?	1	1	0	1	1
103	9	2	5	1	4	1	0	?	1	0	1	0	1
104	6	2	3	2	4	3	0	?	3	0	1	0	1
105	1	2	5	3	4	0	11	12	3	0	1	1	0
106	2	2	3	1	4	2	0	?	2	0	1	0	1
107	1	3	5	2	4	3	0	?	3	0	1	1	1
108	1	2	5	2	4	1	0	?	1	0	1	1	1
109	2	3	3	3	2	1	0	0	1	1	0	1	1
110	1	0	3	1	4	1	0	?	1	0	1	1	0
111	2	3	3	2	3	0	6	?	1	1	0	1	1
112	2	0	1	?	4	1	0	?	1	0	4	1	1
113	1	0	5	2	4	0	6	3	1	1	1	1	1
114	2	0	3	1	3	0	6	?	1	1	0	1	0
115	1	2	3	1	4	3	0	?	3	1	3	1	0
116	3	1	5	3	2	0	2	7	1	2	13	0	1
117	3	0	3	1	3	1	0	?	1	0	1	1	1
118	0	0	3	2	2	?	?	?	?	2	0	1	0
119	0	0	3	1	4	3	0	?	3	2	0	0	0
120	3	0	1	2	4	?	?	?	?	1	8	1	0
121	1	3	3	1	4	1	0	?	1	0	1	1	1
122	3	2	3	?	4	1	0	?	1	1	1	0	0
123	2	3	5	2	4	3	0	?	3	1	0	1	1
124	2	2	3	2	2	3	0	?	3	0	1	1	0
125	2	2	6	1	3	0	6	?	1	0	1	0	0
126	2	1	3	1	4	2	0	?	2	0	0	0	0
127	1	2	5	3	4	0	4	3	1	0	1	1	1
128	5	1	5	1	4	3	0	?	3	0	1	1	0
129	1	2	5	3	4	0	11	2	1	0	1	1	1
130	3	0	1	1	4	1	0	?	1	1	0	1	1
131	2	0	3	1	3	2	0	?	2	1	4	0	1
132	0	1	3	1	4	1	0	?	1	1	0	0	0
133	11	0	3	?	3	1	0	?	1	0	1	1	1

class2-events

#	var12	var8	var9	var20	var13	var26	var27	var23	var24	var7	var2	var5	var4
1	2	2	3	3	4	2	0	0	2	0	6	0	1
2	7	3	3	1	3	2	0	7	2	1	1	1	0
3	8	0	3	2	4	0	12	7	1	2	1	0	1
4	8	0	3	2	5	0	12	7	1	2	1	0	1
5	1	2	3	7	4	2	0	7	2	0	1	1	1
6	3	2	3	1	4	0	8	7	1	0	0	0	1
7	1	0	3	2	4	1	0	7	3	0	1	1	0
8	1	3	3	2	4	0	9	7	2	2	1	1	0
9	1	1	3	2	4	3	0	7	3	2	1	0	0
10	2	0	1	7	4	1	0	7	1	1	4	1	0
11	2	0	1	3	4	3	0	0	3	0	0	0	1
12	1	3	2	1	4	0	8	7	1	1	1	0	1
13	1	1	3	1	4	3	0	7	3	2	1	1	0
14	1	2	5	1	4	0	11	7	1	2	1	0	0
15	3	1	3	2	4	7	7	7	7	0	0	1	0
16	3	2	3	2	4	1	0	7	1	2	1	1	1
17	0	1	3	2	4	0	8	7	1	2	0	1	0
18	3	0	2	3	4	2	0	0	2	1	1	1	0
19	1	1	3	2	4	1	0	7	1	2	1	1	1
20	0	2	3	7	4	1	0	7	1	0	0	1	1
21	1	2	3	7	4	1	0	7	1	0	1	1	1
22	0	2	3	7	4	1	0	7	1	2	0	0	0
23	1	3	3	2	4	0	10	7	1	2	1	0	0
24	1	2	3	1	4	1	0	7	1	2	1	1	1
25	2	3	1	1	4	0	5	7	1	0	0	1	0
26	1	0	3	2	4	2	0	7	2	0	1	0	1
27	1	0	3	1	4	0	9	7	3	0	1	1	1
28	11	1	3	2	4	1	0	7	1	0	0	1	1
29	1	0	3	7	4	1	0	7	1	1	1	1	1
30	0	3	3	1	4	1	0	7	1	2	0	0	1
31	3	2	5	1	4	2	0	7	2	0	1	1	1
32	1	2	3	1	4	2	0	7	2	0	1	1	0
33	1	0	3	2	4	2	0	7	2	0	1	1	0
34	1	0	3	3	4	2	0	0	2	0	1	1	1
35	1	2	3	2	4	1	0	7	1	0	3	1	0
36	3	2	3	3	4	0	10	9	2	1	0	1	0
37	1	2	3	2	4	0	12	7	1	0	1	0	1
38	3	2	3	2	4	0	6	7	1	1	1	1	0
39	1	2	3	2	4	0	6	7	1	1	1	0	1
40	13	1	3	2	4	0	11	7	2	0	0	1	0
41	1	1	3	3	4	0	11	8	2	0	3	1	0
42	12	2	3	3	4	0	12	8	2	0	1	1	1
43	1	2	5	2	4	0	8	7	2	0	1	1	1
44	1	2	3	3	4	0	9	3	1	0	1	1	0
45	1	1	5	1	4	1	0	7	1	2	1	0	0
46	1	2	3	3	4	0	10	13	3	0	3	0	1
47	11	1	3	2	4	2	0	7	2	2	0	0	0
48	1	2	3	1	4	1	0	7	1	0	1	1	1
49	3	3	3	1	4	1	0	7	1	0	0	1	0
50	1	2	2	2	4	1	0	7	1	0	3	1	0
51	1	2	3	1	4	3	0	7	3	0	1	1	0
52	1	2	3	7	4	2	0	7	2	0	1	1	0
53	1	3	3	7	4	1	0	7	1	0	2	0	1
54	3	0	3	1	4	1	0	7	1	1	0	0	1

55	1	2	3	3	4	0	11	8	2	0	1	1	1
56	3	2	3	2	4	3	0	?	3	0	13	1	0
57	1	1	3	1	4	2	0	?	2	0	1	1	0
58	1	2	3	?	4	3	0	?	3	1	1	1	0
59	2	2	3	?	4	1	0	?	1	0	1	1	0
60	1	1	3	2	4	1	0	?	1	0	1	0	0
61	1	1	3	1	4	3	0	?	3	0	1	1	1
62	1	2	3	2	4	0	10	?	1	0	1	0	1
63	1	2	3	3	4	2	0	0	2	0	1	0	0
64	14	2	3	1	4	2	0	?	2	0	1	1	0
65	1	3	3	1	4	1	0	?	1	0	1	1	0
66	2	0	3	2	4	1	0	?	1	0	1	1	1
67	11	0	3	2	4	?	?	?	?	0	0	1	1
68	11	2	3	2	4	?	?	?	?	0	1	1	1
69	11	1	3	2	4	?	?	?	?	0	8	1	1
70	2	3	3	2	2	1	0	?	1	1	0	0	0
71	0	0	3	2	4	1	0	?	1	1	0	1	0
72	1	2	5	1	4	3	0	?	3	0	1	1	0
73	1	2	5	2	4	1	0	?	2	0	1	1	1
74	1	3	3	1	4	1	0	?	1	0	1	0	0
75	1	2	3	1	4	1	0	?	1	0	1	1	1
76	1	0	5	1	4	3	0	?	3	0	1	1	0
77	1	3	3	2	4	0	11	?	3	1	3	1	0

domaintypes

name	type	levels
prev_crop	nom	18
perm_veg	nom	2
surface	nom	3
fall_till	nom	10
springtill	nom	10
insecticid	nom	19
plantdate	lin	6
nbrnotsame_of_weed_s	nom	4
maxvalue_of_weedens1	lin	4
1stmintim_of_weedens	lin	13

Results after VARSEL using

Random Adaptive Search

Sample size = 15

variables

#	name
1	var2.prev_crop
2	var4.perm_veg
3	var7.surface
4	var8.fall_till
5	var9.springtill
6	var12.insecticid
7	var13.plantdate
8	var20.nbrnotsame_of_weed_s
9	var24.maxvalue_of_weedens1
10	var27.1stmintim_of_weedens

class1-events

#	var12	var9	var13	var8	var7	var27	var24	var2	var20	var4
1	2	3	4	1	1	0	1	1	0	
2	1	5	4	3	0	0	3	1	2	1
3	2	3	4	1	1	0	1	0	?	0
4	2	1	4	0	0	0	1	0	?	1
5	8	1	5	0	0	8	3	1	2	0
6	1	5	4	2	1	0	2	1	1	0
7	9	5	4	0	0	0	2	1	1	0
8	5	1	4	0	1	5	2	1	2	0
9	1	3	4	0	0	0	2	1	3	0
10	1	3	4	0	1	11	2	1	3	1
11	11	3	3	2	1	0	1	0	1	0
12	10	2	4	1	0	?	?	0	2	0
13	0	3	4	1	2	0	1	0	1	1
14	3	1	4	0	0	5	1	0	2	0
15	11	5	3	0	0	0	1	1	?	0
16	9	5	2	0	0	0	1	1	1	1
17	2	3	3	0	1	4	1	1	2	0
18	2	3	4	1	0	0	3	0	2	0
19	11	3	4	1	1	0	1	0	1	0
20	2	5	4	0	1	11	1	1	2	0
21	9	1	4	0	0	10	2	9	2	0
22	1	5	4	0	0	0	1	1	1	0
23	3	3	4	2	0	0	1	1	?	1
24	3	3	4	3	1	0	1	3	1	0
25	3	3	4	1	0	0	1	0	1	1
26	3	3	4	2	1	0	2	3	1	0
27	1	2	4	0	0	0	3	3	1	1
28	2	1	3	0	1	0	2	10	?	1

29	1	3	4	2	0	0	2	1	1	0
30	2	3	2	2	0	0	1	0	7	0
31	3	3	4	0	1	11	2	1	3	0
32	1	3	4	2	0	0	3	1	1	0
33	2	3	4	3	0	0	1	1	1	0
34	2	3	4	2	0	0	1	1	2	1
35	3	3	4	2	0	10	3	1	2	0
36	0	5	4	3	1	6	2	0	3	0
37	8	5	3	0	0	0	1	1	1	1
38	2	5	4	1	0	6	0	0	2	1
39	1	3	4	2	0	10	2	1	3	1
40	3	3	4	2	0	0	2	1	1	0
41	1	5	4	2	0	3	1	1	2	1
42	1	5	4	2	0	1	1	1	2	1
43	1	3	4	1	0	6	3	1	3	0
44	9	3	4	2	0	0	2	3	3	1
45	3	3	4	1	0	11	3	1	3	1
46	1	3	4	2	0	0	2	1	3	1
47	1	3	4	1	0	0	3	10	3	1
48	1	5	4	1	0	0	2	1	2	1
49	11	3	3	0	0	4	1	1	2	1
50	1	5	4	3	1	11	3	1	3	0
51	1	3	4	0	1	0	1	1	1	0
52	1	3	4	0	0	0	2	1	7	0
53	1	3	4	0	1	0	1	1	1	1
54	3	3	4	2	0	0	2	0	3	1
55	3	3	4	3	0	0	2	1	3	1
56	17	3	5	2	0	11	2	1	1	0
57	2	5	3	3	1	4	1	0	1	0
58	9	1	4	0	0	8	1	0	3	0
59	2	3	3	1	0	1	1	0	2	1
60	11	3	4	0	0	3	1	1	3	0
61	1	3	4	1	1	4	1	1	2	0
62	3	5	4	0	0	0	2	1	7	1
63	3	3	4	0	1	5	1	1	2	1
64	2	3	4	3	0	0	1	0	2	0
65	1	3	4	2	2	0	1	1	2	1
66	3	3	4	2	2	0	1	0	7	1
67	1	3	3	0	0	0	2	15	1	1
68	14	3	3	0	1	0	3	1	1	0
69	10	3	4	0	1	0	1	1	1	1
70	5	5	4	2	0	7	7	1	1	0
71	15	5	4	3	0	10	1	1	3	1
72	1	3	2	3	0	3	1	1	2	1
73	3	5	4	1	2	0	3	0	2	0
74	1	5	4	0	1	10	3	1	3	0
75	11	3	4	2	2	7	1	1	1	0
76	3	3	4	0	0	0	1	1	1	0
77	16	5	3	2	0	0	1	1	2	1
78	1	3	4	0	0	0	2	1	1	1
79	11	3	4	3	0	0	1	1	7	0
80	2	3	4	0	1	0	2	0	3	0
81	2	3	3	3	1	3	3	0	2	0
82	2	3	4	0	1	6	1	0	3	0
83	7	3	4	2	1	0	2	1	2	1
84	1	3	2	0	0	0	1	1	1	1

85	1	3	4	0	2	0	1	1	1	1
86	3	3	4	2	0	0	1	3	2	0
87	6	5	4	2	0	0	1	1	1	0
88	3	3	4	0	2	0	1	0	7	0
89	1	3	4	1	2	0	1	1	1	0
90	3	3	4	2	1	0	3	1	3	0
91	3	5	4	0	1	0	1	1	1	0
92	11	3	4	0	0	10	1	1	1	1
93	3	3	4	0	0	0	3	1	3	1
94	11	6	4	5	0	8	1	1	1	0
95	2	1	3	1	0	2	1	0	2	1
96	2	3	3	0	1	0	1	0	7	0
97	11	3	3	1	2	0	1	0	3	0
98	9	3	4	1	1	0	1	0	7	0
99	1	3	4	0	0	11	3	1	3	1
100	1	5	4	2	0	0	1	1	2	0
101	1	5	4	2	0	0	1	1	1	0
102	0	5	4	3	1	0	1	0	7	1
103	9	5	4	2	0	0	1	1	1	1
104	6	3	4	2	0	0	3	1	2	1
105	1	5	4	2	0	11	3	1	3	0
106	2	3	4	2	0	0	2	1	1	1
107	1	5	4	3	0	0	3	1	2	1
108	1	5	4	2	0	0	1	1	2	1
109	2	3	2	3	1	0	1	0	3	1
110	1	3	4	0	0	0	1	1	1	0
111	2	3	3	3	1	6	1	0	2	1
112	2	1	4	0	0	0	1	4	7	1
113	1	5	4	0	1	6	1	1	2	1
114	2	3	3	0	1	6	1	0	1	0
115	1	3	4	2	1	0	3	3	1	0
116	3	5	2	1	2	2	1	13	3	1
117	3	3	3	0	0	0	1	1	1	1
118	0	3	2	0	2	7	7	0	2	0
119	0	3	4	0	2	0	3	0	1	0
120	3	1	4	0	1	7	7	8	2	0
121	1	3	4	3	0	0	1	1	1	1
122	3	3	4	2	1	0	1	1	7	0
123	2	5	4	3	1	0	3	0	2	1
124	2	3	2	2	0	0	3	1	2	0
125	2	6	3	2	0	6	1	1	1	0
126	2	3	4	1	0	0	2	0	1	0
127	1	5	4	2	0	4	1	1	3	1
128	5	5	4	1	0	0	3	1	1	0
129	1	5	4	2	0	11	1	1	3	1
130	3	1	4	0	1	0	1	0	1	1
131	2	3	3	0	1	0	2	4	1	1
132	0	3	4	1	1	0	1	0	1	0
133	11	3	3	0	0	0	1	1	7	1

class2-events

#	var12	var9	var13	var8	var7	var27	var24	var2	var20	var4
1	2	3	4	2	0	0	2	6	3	1
2	7	3	3	3	1	0	2	1	1	0
3	8	3	4	0	2	12	1	1	2	1
4	8	3	5	0	2	12	1	1	2	1

5	1	3	4	2	0	0	2	1	7	1
6	3	3	4	2	0	8	1	0	1	1
7	1	3	4	0	0	0	3	1	2	0
8	1	3	4	3	2	9	2	1	2	0
9	1	3	4	1	2	0	3	1	2	0
10	2	1	4	0	1	0	1	4	7	0
11	2	1	4	0	0	0	3	0	3	1
12	1	2	4	3	1	8	1	1	1	1
13	1	3	4	1	2	0	3	1	1	0
14	1	5	4	2	2	11	1	1	1	0
15	3	3	4	1	0	7	7	0	2	0
16	3	3	4	2	2	0	1	1	2	1
17	0	3	4	1	2	8	1	0	2	0
18	3	2	4	0	1	0	2	1	3	0
19	1	3	4	1	2	0	1	1	2	1
20	0	3	4	2	0	0	1	0	7	1
21	1	3	4	2	0	0	1	1	7	1
22	0	3	4	2	2	0	1	0	7	0
23	1	3	4	3	2	10	1	1	2	0
24	1	3	4	2	2	0	1	1	1	1
25	2	1	4	3	0	5	1	0	1	0
26	1	3	4	0	0	0	2	1	2	1
27	1	3	4	0	0	9	3	1	1	1
28	11	3	4	1	0	0	1	0	2	1
29	1	3	4	0	1	0	1	1	7	1
30	0	3	4	3	2	0	1	0	1	1
31	3	5	4	2	0	0	2	1	1	1
32	1	3	4	2	0	0	2	1	1	0
33	1	3	4	0	0	0	2	1	2	0
34	1	3	4	0	0	0	2	1	3	1
35	1	3	4	2	0	0	1	3	2	0
36	3	3	4	2	1	10	2	0	3	0
37	1	3	4	2	0	12	1	1	2	1
38	3	3	4	2	1	6	1	1	2	0
39	1	3	4	2	1	6	1	1	2	1
40	13	3	4	1	0	11	2	0	2	0
41	1	3	4	1	0	11	2	3	3	0
42	12	3	4	2	0	12	2	1	3	1
43	1	5	4	2	0	8	2	1	2	1
44	1	3	4	2	0	9	1	1	3	0
45	1	5	4	1	2	0	1	1	1	0
46	1	3	4	2	0	10	3	3	3	1
47	11	3	4	1	2	0	2	0	2	0
48	1	3	4	2	0	0	1	1	1	1
49	3	3	4	3	0	0	1	0	1	0
50	1	2	4	2	0	0	1	3	2	0
51	1	3	4	2	0	0	3	1	1	0
52	1	3	4	2	0	0	2	1	7	0
53	1	3	4	3	0	0	1	2	7	1
54	3	3	4	0	1	0	1	0	1	1
55	1	3	4	2	0	11	2	1	3	1
56	3	3	4	2	0	0	3	13	2	0
57	1	3	4	1	0	0	2	1	1	0
58	1	3	4	2	1	0	3	1	7	0
59	2	3	4	2	0	0	1	1	7	0
60	1	3	4	1	0	0	1	1	2	0

61	1	3	4	1	0	0	3	1	1	1
62	1	3	4	2	0	10	1	1	2	1
63	1	3	4	2	0	0	2	1	3	0
64	14	3	4	2	0	0	2	1	1	0
65	1	3	4	3	0	0	1	1	1	0
66	2	3	4	0	0	0	1	1	2	1
67	11	3	4	0	0	?	?	0	2	1
68	11	3	4	2	0	?	?	1	2	1
69	11	3	4	1	0	?	?	8	2	1
70	2	3	2	3	1	0	1	0	2	0
71	0	3	4	0	1	0	1	0	2	0
72	1	5	4	2	0	0	3	1	1	0
73	1	5	4	2	0	0	2	1	2	1
74	1	3	4	3	0	0	1	1	1	0
75	1	3	4	2	0	0	1	1	1	1
76	1	5	4	0	0	0	3	1	1	0
77	1	3	4	3	1	11	3	3	2	0

Craniostenosis Data

The following pages give the original data for the Craniostenosis event set used in this study. The next page details the data format for each patient entry. For reference, the following are the syndrome codes for the patients in this event set:

Syndrome -----	Code ----
Apert's	15
Crouzon's	16
Pfeiffer's	152
Saethre-Chotzen	57
Other Descriptive Classes	
Brachycephaly	96
Plagiocephaly	80
Scaphacephaly	84
Other Craniostenoses	18

Card Layout - First for Each Patient

Columns	1/4	CCFA Number
	5/11	Blank
	12/20	Birthdate
	21	Race 1=white 2=black 3=oriental 4=other 5=unknown
	22	Blank
	23	Sex 1=male 2=female
	24/80	Blank
	81/83	Syndrome 0=no known syndrome
	84/86	Diagnostic Category

Card Layout - Others

Columns	1/4	CCFA Number
	5	Blank
	6/7	System Number 1=lip cleft description 2=palate cleft description
	8/10	Code Number
	11	Blank
	12/80	Description of Findings
	81/83	Syndrome 0=no known syndrome
	84/86	Diagnostic Category

1125		4/ 6/59 1 1	96 10
1125	7 21	CRANIOSYNOSTOSIS, CORONAL SUTURE	96 10
1125	9 4	MILD HYPOPLASIA	96 10
1125	11 0	SWELLING ALONG UPPER LATERAL PART OF ORBIT	96 10
1125	11 75	PTOSIS	96 10
1125	11 78	SLIGHT ANTIMONGOLOID SLANT	96 10
1125	12 75	PTOSIS	96 10
1125	12 78	SLIGHT ANTIMONGOLOID SLANT	96 10
1125	13 31	LOW SET	96 10
1125	14 31	LOW SET	96 10
1125	17 23	SHORT FRENULUM	96 10
1125	27 24	PECTUS EXCAVATUM	96 10
1125	36 41	SIMIAN CREASE	96 10
1125	37 41	SIMIAN CREASE	96 10
1125	42 31	SLOW RATE OF DEVELOPMENT	96 10
2223		10/28/64 1 2	96 10
2223	7 21	CRANIOSYNOSTOSIS, CORONAL SUTURE	96 10
3730		12/ 3/57 1 1	96 10
3730	7 21	CRANIOSYNOSTOSIS, CORONAL SUTURE	96 10
4124		11/26/60 2 1	84 10
4124	7 20	CRANIOSYNOSTOSIS, SAGITTAL & LAMBDROIDAL SUTURES	84 10
4124	32 23	UNDESCENDED TESTES	84 10
5738		5/28/57 1 2	84 10
5738	7 24	CRANIOSYNOSTOSIS, SAGITAL SUTURE	84 10
5738	42 41	FOCAL JACKSONIAN SEIZURES	84 10
5931		12/23/69 1 2	84 10
5931	7 24	STENOSIS OF SAGGITAL SUTURE	84 10
5931	8 21	FRONTAL BOSSING	84 10
5931	9 0	PROTRUDING	84 10
5931	10 4	SMALL	84 10
5931	11 20	PROPTOSIS	84 10
5931	12 20	PROPTOSIS	84 10
5931	13 31	LOW SET	84 10
5931	14 31	LOW SET	84 10
5931	15 4	SMALL	84 10
5931	16 21	HIGH ARCHED PALATE	84 10
5931	16 27	NARROW PALATE	84 10
5931	20 21	ANTERIOR OPEN BITE	84 10
5931	21 11	MOTOR PROBLEM?	84 10
5931	22 10	MOTOR PROBLEM?	84 10
5931	42 0	CNS PROBLEM?	84 10
7124		4/13/62 1 1	84 10
7124	7 24	CRANIOSYNOSTOSIS, SAGITTAL SUTURE	84 10
7124	8 21	BOSSING	84 10
9532		1/ 4/68 1 1	84 10
9532	7 24	CRANIOSYNOSTOSIS, SAGITTAL SUTURE	84 10
9532	32 22	MILD HYPOSPADIAS	84 10
9532	43 80	SPINA BIFIDA, L-5	84 10
143		11/11/59 1 1	15 3
143	2 66	SURGERY MEDIAN	15 3
143	7 45	PLAGIOCEPHALY	15 3
143	9 31	HYPOPLASTIC R/L	15 3
143	11 20	PROPTOSIS	15 3
143	12 20	PROPTOSIS	15 3
143	25 0	L TIGHTNESS	15 3
143	26 20	HERNIA	15 3
143	27 21	PROMINENCE L SIDE	15 3
143	30 41	SINUS ARRHYTHMIA	15 3
143	30 41	SLOW HEART RATE	15 3
143	36 30	SYNDACTYLY	15 3
143	37 30	SYNDACTYLY	15 3
143	40 30	SYNDACTYLY	15 3
143	41 30	SYNDACTYLY	15 3

227	9/23/44 1 2	57 10
227	7 40 HIGH VAULT	57 10
227	7 42 SHORT A-P DIAMETER	57 10
227	8 24 RECEDING FRONTAL BONES	57 10
227	9 4 HYPOPLASIA	57 10
227	16 27 NARROW HARD PALATE	57 10
227	36 34 WEBBING	57 10
227	37 34 WEBBING	57 10
227	40 63 GAP BETWEEN 1ST & 2ND TOES	57 10
227	41 63 GAP BETWEEN 1ST & 2ND TOES	57 10
241	1/27/74 2 1	80 10
241	7 2 ASYMMETRY	80 10
241	7 27 SAGITTAL SUTURE VERY WIDE	80 10
241	7 59 PROMINENT R CORONAL SUTURE	80 10
241	8 2 FLATTENED R SIDE	80 10
241	11 20 MILD PROPTOSIS	80 10
241	11 34 R EYE HIGHER THAN LEFT	80 10
241	12 20 MILD PROPTOSIS	80 10
241	12 91 EXOTROPIA	80 10
241	26 21 UMBILICAL HERNIA	80 10
241	36 41 SIMIAN CREASE	80 10
241	37 41 SIMIAN CREASE	80 10
243	5/ 3/74 4 1	152 10
243	7 20 CRANIOSYNOSTOSIS	152 10
243	9 4 HYPOPLASIA, MILD	152 10
243	11 32 SHALLOW ORBIT	152 10
243	12 32 SHALLOW ORBIT	152 10
243	31 22 PYLORIC STENOSIS	152 10
243	36400 INCURVED 4TH DIGIT	152 10
243	36500 INCURVED 5TH DIGIT	152 10
243	36560 OVERLAPPING 5TH DIGIT	152 10
243	37400 INCURVED 4TH DIGIT	152 10
243	37500 INCURVED 5TH DIGIT	152 10
243	37500 OVERLAPPING 5TH DIGIT	152 10
243	40 31 SYNDACTYLY, 2,3,4 TOES	152 10
243	40124 BROAD 1ST TOE	152 10
243	41 31 SYNDACTYLY, 2,3,4 TOES	152 10
243	41124 BROAD 1ST TOE	152 10
634	1/14/65 1 1	18 10
634	7 47 TRIGONCEPHALY	18 10
634	8 21 BOSSING	18 10
634	9 21 HYPOTELORISM	18 10
634	10 40 ANTEGONIAL NOTCHING	18 10
634	10 43 WIDE GONIAL ANGLE	18 10
634	13 31 LOW SET	18 10
634	13 62 LOP EARS	18 10
634	14 31 LOW SET	18 10
634	14 62 LOP EARS	18 10
634	33 23 ALOPECIA	18 10
634	36160 THUMBS HIGH SET	18 10
634	37160 THUMBS HIGH SET	18 10
634	39 62 TOES OVERLAP	18 10
634	40 62 TOES OVERLAP	18 10
637	8/20/65 2 2	16 10
637	7 20 CRANIOSYNOSTOSIS	16 10
637	8 29 TYPICAL CROUZONS	16 10
637	9 4 HYPOPLASIA	16 10
637	9 20 HYPERTELORISM	16 10
637	11 20 PROPTOSIS	16 10
637	11 33 SMALL ORBIT	16 10
637	11 86 SYNECHE OF LID	16 10
637	12 20 PROPTOSIS	16 10
637	12 33 SMALL ORBIT	16 10
637	12 86 SYNECHE OF LID	16 10
637	16 21 HIGH ARCHED	16 10
637	33 24 SPARSE HAIR	16 10
637	42 65 AGENESIS POSTERIOR PORTION OF CORPUS CALLOSUM	16 10

743		12/23/74 1 1	15 10
743	7 21	CRANIOSYNOSTOSIS-CORONAL SUTURE	15 10
743	8 2	FLAT L SIDE	15 10
743	9 2	ASYMMETRY, L/R	15 10
743	9 4	HYPOPLASIA?	15 10
743	11 34	LOW SET	15 10
743	16 22	BYZANTINE PALATE	15 10
743	36 32	SYNDACTYLY, COMPLETE	15 10
743	37 32	SYNDACTYLY, COMPLETE	15 10
743	40 30	SYNDACTYLY	15 10
743	41 30	SYNDACTYLY	15 10
749		10/16/75 1 1	16 10
749	7 20	CRANIOSYNOSTOSIS	16 10
749	7 43	CLOVERLEAF SKULL	16 10
749	8 0	BILATERAL INDENTATIONS	16 10
749	8 22	PROMINENT	16 10
749	9 4	HYPOPLASIA?	16 10
749	11 20	PROPTOSIS	16 10
749	11 75	PTOSIS	16 10
749	12 20	PROPTOSIS	16 10
749	12 75	PTOSIS	16 10
749	15 32	OBSTRUCTION R CHOANAE	16 10
749	25 35	SHORT	16 10
926		2/10/51 5 2	18 10
926	7 20	CRANIOSYNOSTOSIS?	18 10
926	8 23	HIGH	18 10
926	9 4	HYPOPLASIA	18 10
926	11 31	MILD DEVIL'S EYE	18 10
926	12 31	MILD DEVIL'S EYE	18 10
947		3/ 3/32 1 1	57 10
947	7 20	CRANIOSYNOSTOSIS	57 10
947	8 24	FLAT	57 10
947	9 4	HYPOPLASIA	57 10
947	10 41	PROGNATHISM	57 10
947	11 20	PROPTOSIS, MILD	57 10
947	11122	CONSTANT TEARING	57 10
947	12 30	POSTERIORLY SET	57 10
947	40 34	CUTANEOUS SYNDACTYLY	57 10
947	41 34	CUTANEOUS SYNDACTYLY	57 10
1120		10/ 4/56 1 1	80 10
1120	7 20	CRANIOSYNOSTOSIS	80 10
1120	8 21	BOSSING, L SIDE	80 10
1120	9 2	ASYMMETRY, L/R	80 10
1120	12 93	SLIGHT EXTERNAL STRABISMUS	80 10
1124		8/23/61 1 1	80 10
1124	7 21	CRANIOSYNOSTOSIS, L CORONAL SUTURE	80 10
1124	9 2	ASYMMETRY	80 10
1124	12 31	MILD DEVIL'S EYE ANOMALY	80 10
1124	16 32	ASYMMETRY MAXILLA, L/R	80 10
1434		3/16/60 1 1	18 10
1434	7 20	CRANIOSYNOSTOSIS	18 10
1434	9 4	HYPOPLASIA	18 10
1434	44 23	CONTRACTURES, CORRECTED BY PHYSICAL THERAPY	18 10
2244		12/ 2/42 1 1	16 10
2244	7 20	CRANIOSYNOSTOSIS	16 10
2244	9 4	HYPOPLASTIC	16 10
2244	11 20	EXOPHTHALMUS	16 10
2244	12 20	EXOPHTHALMUS	16 10
2244	15 25	BIFID RADIX NASII	16 10
2633		12/25/48 1 2	15 10
2633	7 20	CRANIOSYNOSTOSIS	15 10
2633	8 21	BOSSING	15 10
2633	9 4	HYPOPLASIA	15 10
2633	13 28	ATRETIC CANAL	15 10
2633	13 40	HYPOPLASTIC INCUS	15 10
2633	16 22	BYZANTINE PALATE	15 10

2633	36	30	SYNDACTYLY	15	10
2633	37	30	SYNDACTYLY	15	10
2633	40	30	SYNDACTYLY	15	10
2633	41	30	SYNDACTYLY	15	10
2637			3/ 4/64 1 1	16	10
2637	7	20	CRANIOSYNOSTOSIS	16	10
2637	8	22	BULGING	16	10
2637	8	23	HIGH	16	10
2637	9	4	HYPOPLASIA	16	10
2637	11	20	EXOPHTHALMOS	16	10
2637	12	20	EXOPHTHALMOS	16	10
2637	26	22	R INDIRECT INGUINAL HERNIA	16	10
2637	42	0	L CNS DAMAGE	16	10
2637	42	30	RETARDED	16	10
2637	43	23	UNILATERAL OCCIPITALIZATION C-1?	16	10
2734			7/ 4/64 1 1	15	10
2734	7	20	CRANIOSYNOSTOSIS	15	10
2734	9	4	HYPOPLASIA	15	10
2734	9	20	HYPERTELORISM	15	10
2734	11	93	INTERNAL STRABISMUS	15	10
2734	12	80	EPICANTHAL FOLD	15	10
2734	16	22	BYZANTINE PALATE	15	10
2734	20	61	TYPICAL APERTS	15	10
2734	36	30	SYNDACTYLY	15	10
2734	37	30	SYNDACTYLY	15	10
2734	40	30	SYNDACTYLY	15	10
2734	41	30	SYNDACTYLY	15	10
2936			5/10/64 1 2	18	10
2936	7	20	CRANIOSYNOSTOSIS	18	10
2936	9	20	HYPERTELORISM	18	10
2936	20	22	L MOLAR CROSSBITE	18	10
2936	21	13	R PARESIS?	18	10
2936	22	13	R PARESIS?	18	10
2945			3/10/58 1 1	16	10
2945	7	5	MACROCEPHALY	16	10
2945	7	20	CRANIOSYNOSTOSIS	16	10
2945	8	24	FLAT	16	10
2945	9	4	HYPOPLASIA	16	10
2945	9	20	HYPERTELORISM	16	10
2945	10	41	PROGNATHISM	16	10
2945	11	20	PROPTOSIS	16	10
2945	12	20	PROPTOSIS	16	10
2945	13	4	SMALL	16	10
2945	13	31	LOW SET	16	10
2945	14	4	SMALL	16	10
2945	14	31	LOW SET	16	10
2945	15	0	UPTURNED	16	10
2945	15	5	BROAD	16	10
2945	16	22	BYZANTINE PALATE	16	10
2945	25	35	SHORT	16	10
2945	27	0	PECTUS DEFORMITY	16	10
2945	28	0	GIBBONS DEFORMITY, THORACIC AREA	16	10
2945	28	21	KYPHOSCOLIOSIS, THORACIC AREA	16	10
2945	30	21	MITRAL VALVE PROLAPSE	16	10
2945	30	51	AORTIC ROOT DILATION	16	10
2945	34	72	CONTRACTURE, ELBOW JOINT	16	10
2945	35	72	CONTRACTURE, ELBOW JOINT	16	10
2945	36	22	LONG FINGERS	16	10
2945	36	26	CONTRACTURE OF HAND	16	10
2945	37	22	LONG FINGERS	16	10
2945	37	26	CONTRACTURE INTERPHALANGEAL JOINTS	16	10
2945	38	30	CONTRACTURE KNEE JOINT	16	10
2945	38	30	CONTRACTURE HIP JOINT	16	10
2945	38	40	ANKYLOSIS HIP JOINT	16	10
2945	38	42	ANKYLOSIS KNEE JOINT	16	10
2945	39	30	CONTRACTURE KNEE JOINT	16	10

2945	39	30	CONTRACTURE HIP JOINT	16	10
2945	39	40	ANKYLOSIS HIP JOINT	16	10
2945	39	42	ANKYLOSIS KNEE JOINT	16	10
2945	42	74	APHASIA	16	10
2945	44	20	HYPOTONIA	16	10
3022			8/29/58 1 2	15	3
3022	2	66	SURGERY MEDIAN	15	3
3022	7	20	CRANIOSYNOSTOSIS	15	3
3022	8	2	ASYMMETRY	15	3
3022	9	2	ASYMMETRY	15	3
3022	9	4	HYPOPLASIA	15	3
3022	11	0	CANTHAL DYSTROPIA	15	3
3022	11	20	PROPTOSIS	15	3
3022	12	0	CANTHAL DYSTROPIA	15	3
3022	12	20	PROPTOSIS	15	3
3022	27	2	ASYMMETRY, L PROMINENCE	15	3
3022	34	50	ANKYLOSED	15	3
3022	34	60	HUMERUS DISLOCATED ANTERIORLY?	15	3
3022	36	30	SYNDACTYLY	15	3
3022	37	30	SYNDACTYLY	15	3
3022	40	30	SYNDACTYLY	15	3
3022	41	30	SYNDACTYLY	15	3
3023			11/21/49 1 2	16	10
3023	7	20	CRANIOSYNOSTOSIS	16	10
3023	9	4	HYPOPLASIA	16	10
3023	11	20	PROPTOSIS	16	10
3023	12	20	PROPTOSIS	16	10
3023	16	26	TORUS PALATINI	16	10
3036			8/11/67 2 2	15	10
3036	7	20	CRANIOSYNOSTOSIS	15	10
3036	9	4	HYPOPLASTIC	15	10
3036	9	21	HYPOTELORISM	15	10
3036	11	20	PROPTOSIS	15	10
3036	12	20	PROPTOSIS	15	10
3036	16	22	BYZANTINE PALATE	15	10
3036	36	30	SYNDACTYLY	15	10
3036	37	30	SYNDACTYLY	15	10
3036	40	30	SYNDACTYLY	15	10
3036	41	30	SYNDACTYLY	15	10
3128			9/11/64 1 1	15	4
3128	2	86	SUBMUCOUS (U)	15	4
3128	7	20	CRANIOSYNOSTOSIS, CORONAL & ?LAMBDOID SUTURES	15	4
3128	8	20	TYPICAL APERTS	15	4
3128	9	4	HYPOPLASIA	15	4
3128	9	20	HYPERTELORISM	15	4
3128	13	31	LOW SET	15	4
3128	14	31	LOW SET	15	4
3128	15	31	SADDLE DEFORMITY	15	4
3128	15	32	UNILATERAL CHOANAL ATRESIA	15	4
3128	16	22	BYZANTINE PALATE	15	4
3128	20	21	OPEN BITE	15	4
3128	36	30	SYNDACTYLY	15	4
3128	37	30	SYNDACTYLY	15	4
3128	40	30	SYNDACTYLY	15	4
3128	40	41	CLUBBED	15	4
3128	41	30	SYNDACTYLY	15	4
3128	41	41	CLUBBED	15	4
3128	42	55	ABNORMAL EEG	15	4
3128	42	59	HYPOTONIC	15	4
3144			2/25/73 1 2	80	10
3144	7	21	PARTIAL CRANIOSYNOSTOSIS, CORONAL SUTURE, L	80	10
3144	8	2	L FLATTENING	80	10
3144	25	30	TORTICOLLIS	80	10
3144	38	40	DISLOCATED HIP	80	10
3144	39	40	DISLOCATED HIP	80	10

3236		2/22/70 1 1	16	10
3236	7	20 CRANIOSYNOSTOSIS	16	10
3236	9	4 HYPOPLASTIC	16	10
3236	11	20 PROPTOSIS	16	10
3236	12	20 PROPTOSIS	16	10
3245		3/24/74 1 2	80	10
3245	7	45 PLAGIOCEPHALY	80	10
3245	8	2 FLATTENED L	80	10
3245	9	2 ASYMMETRY, R/L	80	10
3245	11	34 LOW SET	80	10
3245	13	31 LOWSET	80	10
3245	42	27 FACIAL PALSY, L	80	10
3437		4/ 4/59 1 1	16	10
3437	7	20 CRANIOSYNOSTOSIS	16	10
3437	9	4 HYPOPLASIA	16	10
3437	11	20 PROPTOSIS	16	10
3437	12	20 PROPTOSIS	16	10
3437	15	30 PARROT BEAKED	16	10
3437	34	40 PROMINENT LATERAL EPICONDYLE, HUMERUS	16	10
3437	35	40 PROMINENT LATERAL EPICONDYLE, HUMERUS	16	10
3437	43	0 HYPOPLASTIC OCCIPITAL CONDYLES	16	10
3437	43	20 ANOMALOUS ODONTOID	16	10
3437	43	21 FUSIONS, C-2,3,4 & C-5,6	16	10
3437	43	22 ENLARGED LATERAL MASSES, C-1	16	10
3437	43	24 BASILAR INVAGINATION	16	10
3439		11/ 3/63 1 1	16	4
3439	2	86 SUBMUCOUS (U)	16	4
3439	7	20 CRANIOSYNOSTOSIS	16	4
3439	9	4 HYPOPLASIA	16	4
3439	11	20 EXOPHTHALMOS	16	4
3439	12	20 EXOPHTHALMOS	16	4
3439	13	31 LOW SET	16	4
3439	14	31 LOW SET	16	4
3439	20	45 MISSING TEETH	16	4
3439	32	26 BIFID SCROTUM	16	4
3439	40	31 INCOMPLETE SYNDACTYLY	16	4
3439	41	31 INCOMPLETE SYNDACTYLY	16	4
3439	42	55 ABNORMAL EEG	16	4
3446		3/27/74 1 1	18	10
3446	7	24 CRANIOSYNOSTOSIS, SAGITTAL SUTURE	18	10
3841	41124	LARGE BIG TOE	35	30
3935		10/26/71 1 2	80	10
3935	7	45 PLAGIOCEPHALY R	80	10
3935	8	2 FLATTENED, R	80	10
3935	8	21 BOSSING, L	80	10
3935	9	24 R EYE HIGHER THAN L	80	10
4021		2/20/47 1 2	18	10
4021	7	20 CRANIOSYNOSTOSIS, CORONAL & SAGITTAL SUTURES	18	10
4021	8	23 HIGH	18	10
4021	11	31 DEVIL'S EYE	18	10
4021	12	31 DEVIL'S EYE	18	10
4022		5/20/55 1 1	18	10
4022	7	20 CRANIOSYNOSTOSIS?	18	10
4022	8	5 LARGE	18	10
4022	8	21 HYPEROSTOSIS FRONTALIS	18	10
4022	8	23 HIGH	18	10
4022	11	93 INTERNAL ALTERNATING STRABISMUS	18	10
4022	12	93 INTERNAL ALTERNATING STRABISMUS	18	10
4125		4/ 9/63 1 1	15	10
4125	7	20 CRANIOSYNOSTOSIS	15	10
4125	8	22 BULGING	15	10
4125	8	23 HIGH	15	10
4125	9	4 HYPOPLASIA	15	10
4125	10	40 BILATERAL ANTEGONIAL NOTCHING	15	10
4125	11	32 SHALLOW ORBITS	15	10
4125	11	78 ANTIMONGOLOID SLANT	15	10
4125	12	32 SHALLOW ORBITS	15	10

4125	12	78	ANTIMONGOLOID SLANT	15	10
4125	13	61	CUPPED	15	10
4125	13	62	LOPPED	15	10
4125	14	61	CUPPED	15	10
4125	14	62	LOPPED	15	10
4125	16	22	BYZANTINE PALATE, MODERATE	15	10
4125	20	21	ANTERIOR OPEN BITE	15	10
4125	36	30	SYNDACTYLY	15	10
4125	37	30	SYNDACTYLY	15	10
4125	40	30	SYNDACTYLY	15	10
4125	41	30	SYNDACTYLY	15	10
4139		11/20/69	2 2	16	3
4139	2	63	INCOMPLETE MEDIAN	16	3
4139	7	20	CRANIOSYNOSTOSIS	16	3
4139	9	4	HYPOPLASTIC	16	3
4139	11	20	EXORBITISM	16	3
4139	12	20	EXORBITISM	16	3
4222		4/ 3/66	1 1	15	10
4222	7	20	CRANIOSYNOSTOSIS	15	10
4222	9	4	HYPOPLASIA	15	10
4222	16	22	BYZANTINE PALATE	15	10
4222	32	23	UNDESCENDED TESTES	15	10
4222	32	31	DOUBLE COLLECTING SYSTEM, L KIDNEY	15	10
4222	36	30	SYNDACTYLY	15	10
4222	37	30	SYNDACTYLY	15	10
4222	40	30	SYNDACTYLY	15	10
4222	41	30	SYNDACTYLY	15	10
4248		7/10/74	2 2	16	10
4248	7	20	CRANIOSYNOSTOSIS, R	16	10
4248	8	2	FLATTENED R	16	10
4248	11	20	PROPTOSIS	16	10
4248	12	20	PROPTOSIS	16	10
4248	13	25	MICROTIA I, PREAURICULAR SINUS	16	10
4248	14	24	MICROTIA I, EAR TAG	16	10
4248	44	21	SLIGHTLY HYPERTONIC	16	10
4323		8/19/49	2 1	18	10
4323	7	20	CRANIOSYNOSTOSIS	18	10
4323	11	21	PROTRUDING	18	10
4323	11	94	NYSTAGMUS, AT REST	18	10
4323	12	21	PROTRUDING	18	10
4323	12	94	NYSTAGMUS, AT REST	18	10
4323	15	41	SEPTUM DEVIATES TO L	18	10
4323	42	30	RETARDATION	18	10
4323	43	23	OCCIPITALIZATION, ATLAS	18	10
4348		8/ 4/56	1 1	16	10
4348	7	45	PLAGIOCEPHALY, L	16	10
4348	8	2	FLATTENED ON L	16	10
4348	11	20	PROPTOSIS, MILD	16	10
4348	12	20	PROPTOSIS, MILD	16	10
4348	13	4	SMALLER THAN R	16	10
4348	13	31	LOW SET	16	10
4348	13	32	POSTERIORLY SET	16	10
4348	15	34	DEVIATED TO L	16	10
4440		3/ 5/52	1 2	16	4
4440	2	86	SUBMUCOUS (U)	16	4
4440	9	4	HYPOPLASTIC	16	4
4440	11	20	PROPTOSIS	16	4
4440	12	20	PROPTOSIS	16	4
4440	18	20	SLIGHTLY DRY	16	4
4838		10/21/61	1 1	80	10
4838	7	45	PLAGIOCEPHALY	80	10
4838	8	2	R EYEBROW LOWER THAN L	80	10
4838	9	20	HYPERTELORISM	80	10
4838	11	31	DEVIL'S EYE	80	10
4838	11	80	EPICANTHAL FOLD	80	10
4838	12	80	EPICANTHAL FOLD	80	10
4838	15	2	ASYMMETRY	80	10

4839		4/15/71 1 1	15	4
4839	2	87 SUBMUCOUS (U)	15	4
4839	7	20 CRANIOSYNOSTOSIS	15	4
4839	9	4 HYPOPLASIA	15	4
4839	11	20 PROPTOSIS	15	4
4839	12	20 PROPTOSIS	15	4
4839	16	22 BYZANTINE PALATE	15	4
4839	36	30 SYNDACTYLY	15	4
4839	37	30 SYNDACTYLY	15	4
4839	40	30 SYNDACTYLY	15	4
4839	41	30 SYNDACTYLY	15	4
5024		9/14/54 1 2	80	10
5024	7	21 SYNOSTOSIS R CORONAL SUTURE	80	10
5024	8	2 ASYMMETRY	80	10
5024	10	2 ASYMMETRY	80	10
5024	11	31 DEVIL'S EYE	80	10
5430		5/ 5/42 1 1	57	10
5430	7	21 SYNOSTOSIS, CORONAL SUTURE	57	10
5430	8	23 HIGH	57	10
5430	8	24 FLAT	57	10
5430	11	75 PTOSIS	57	10
5430	12	75 PTOSIS	57	10
5430	15	41 DEVIATED SEPTUM	57	10
5430	16	22 BYZANTINE PALATE	57	10
5430	36	34 WEBBING BETWEEN 1ST & 2ND FINGERS	57	10
5430	37	34 WEBBING BETWEEN 1ST & 2ND FINGERS	57	10
5437		8/ 5/64 1 1	16	10
5437	7	20 CRANIOSYNOSTOSIS	16	10
5437	9	4 HYPOPLASIA	16	10
5437	11	20 EXOPHTHALMOS	16	10
5437	12	20 EXOPHTHALMOS	16	10
5437	16	22 BYZANTINE PALATE	16	10
5437	20	43 CROWDING	16	10
5531		10/26/69 1 1	80	10
5531	7	21 CRANIOSYNOSTOSIS, RT CORONAL SUTURE	80	10
5531	8	32 DEPRESSION OVER R BROW	80	10
5531	9	2 ASYMMETRY	80	10
5531	11	34 LOWER THAN R	80	10
5531	12	76 INABILITY TO CLOSE COMPLETELY	80	10
5639		5/31/72 1 1	15	4
5639	2	86 SUBMUCOUS (U)	15	4
5639	7	20 CRANIOSYNOSTOSIS	15	4
5639	9	4 HYPOPLASIA	15	4
5639	11	20 PROPTOSIS	15	4
5639	11	91 SOME EXOTROPIA	15	4
5639	12	20 PROPTOSIS	15	4
5639	12	91 SOME EXOTROPIA	15	4
5639	15	21 CONSTRICTED NARES	15	4
5639	16	22 BYZANTINE PALATE	15	4
5639	28	21 KYPHOSIS, LOWER BACK	15	4
5639	36	30 SYNDACTYLY	15	4
5639	37	30 SYNDACTYLY	15	4
5639	40	30 SYNDACTYLY	15	4
5639	41	30 SYNDACTYLY	15	4
5639	43	32 SCOLIOSIS?	15	4
6125		2/24/60 1 1	80	10
6125	7	21 CRANIOSYNOSTOSIS, R CORONAL SUTURE	80	10
6125	8	2 FLATTENED R SIDE	80	10
6125	10	2 ASYMMETRY	80	10
6125	11	31 DEVIL'S EYE	80	10
6125	32	23 UNDESCENDED TESTES	80	10
6127		2/12/52 1 2	16	10
6127	7	20 CRANIOSYNOSTOSIS	16	10
6127	8	2 ASYMMETRY	16	10
6127	9	4 HYPOPLASIA	16	10
6127	11	20 MILD PROPTOSIS	16	10
6127	12	20 MILD PROPTOSIS	16	10

6139		1/ 9/55 2 2	16 10
6139	7 20	CRANIOSYNOSTOSIS, POST OP	16 10
6139	9 20	HYPERTELORISM	16 10
6139	11 20	PROPTOSIS	16 10
6139	12 20	PROPTOSIS	16 10
6246		9/14/69 1 1	37 10
6246	7 20	SYNOSTOSIS	37 10
6246	11 80	EPICANTHAL FOLD	37 10
6246	12 80	EPICANTHAL FOLD	37 10
6246	13 31	LOW SET	37 10
6246	14 31	LOW SET	37 10
6246	32 23	UNDESCENDED L TESTICLE	37 10
6246	36 34	WEBBING BETWEEN 1ST & 2ND FINGERS	37 10
6246	37 34	WEBBING BETWEEN 1ST & 2ND FINGERS	37 10
6434		5/23/41 1 2	13 10
6434	7 20	CRANIOSYNOSTOSIS	13 10
6434	8 21	BOSSING	13 10
6434	11 78	ANTIMONGOLOID SLANT	13 10
6434	12 78	ANTIMONGOLOID SLANT	13 10
6434	15 2	ASYMMETRIC	13 10
6434	16 22	BYZANTINE PALATE	13 10
6434	20 43	CROWDING	13 10
6434	36 30	SYNDACTYLY	13 10
6434	37 30	SYNDACTYLY	13 10
6434	40 30	SYNDACTYLY	13 10
6434	41 30	SYNDACTYLY	13 10
6437		3/ 9/40 1 2	16 10
6437	7 0	BEATEN SILVER APPEARANCE	16 10
6437	7 20	CRANIOSYNOSTOSIS	16 10
6437	9 4	HYPOPLASIA, MILD	16 10
6437	11 20	EXOPHTHALMOS	16 10
6437	12 20	EXOPHTHALMOS	16 10
6634		1/ 9/72 1 2	18 10
6634	7 20	CRANIOSYNOSTOSIS	18 10
6730		5/10/72 1 2	80 10
6730	7 45	PLAGIOCEPHALY, CORONAL, LEFT	80 10
6730	11 0	DEEPER SET	80 10
6730	33 51	ECHZEMA	80 10
6741		11/ 9/74 1 1	18 10
6741	7 45	PLAGIOCEPHALY	18 10
6741	8 2	FLATTENED L	18 10
6741	11 1	ENOPHTHALMIA	18 10
6741	11 75	PTOSIS	18 10
6741	16 45	MACROSTOMIA	18 10
6741	42 27	L FACIAL PARESIS	18 10
7121		8/ 8/60 1 1	16 10
7121	7 42	SHORTENED A-P DIAMETER	16 10
7121	8 24	FLATTENED LOWER PART	16 10
7121	10 2	ASYMMETRY	16 10
7121	11 1	ANOPHTHALMIA	16 10
7121	11 75	PTOSIS	16 10
7121	12 1	ANOPHTHALMIA	16 10
7121	12 75	PTOSIS	16 10
7121	40 62	OVERLAP 1ST & 2ND TOES	16 10
7121	40 70	CALCANEVALGUS	16 10
7121	40160	HALLUX VALGUS	16 10
7121	41 62	OVERLAP 1ST & 2ND TOES	16 10
7121	41 70	CALCANEVALGUS	16 10
7121	41160	HALLUX VALGUS	16 10
7121	43 51	REDUCTION ROTATION & ADDUCTION R HIP	16 10
7121	43 52	CONGENITAL HIP DISLOCATION, L	16 10
7228		6/26/65 1 2	80 10
7228	7 20	CRANIOSYNOSTOSIS	80 10
7228	7 45	PLAGIOCEPHALY	80 10
7228	8 24	FLATTENED	80 10
7228	11 91	ESOTROPIA	80 10

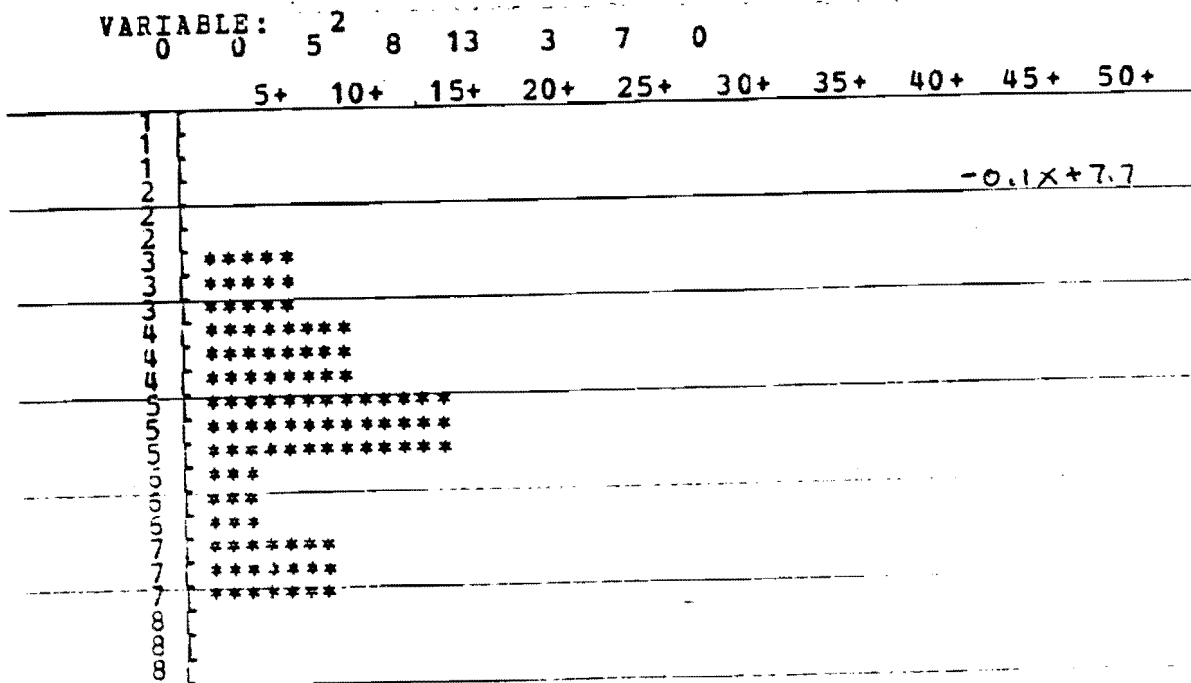
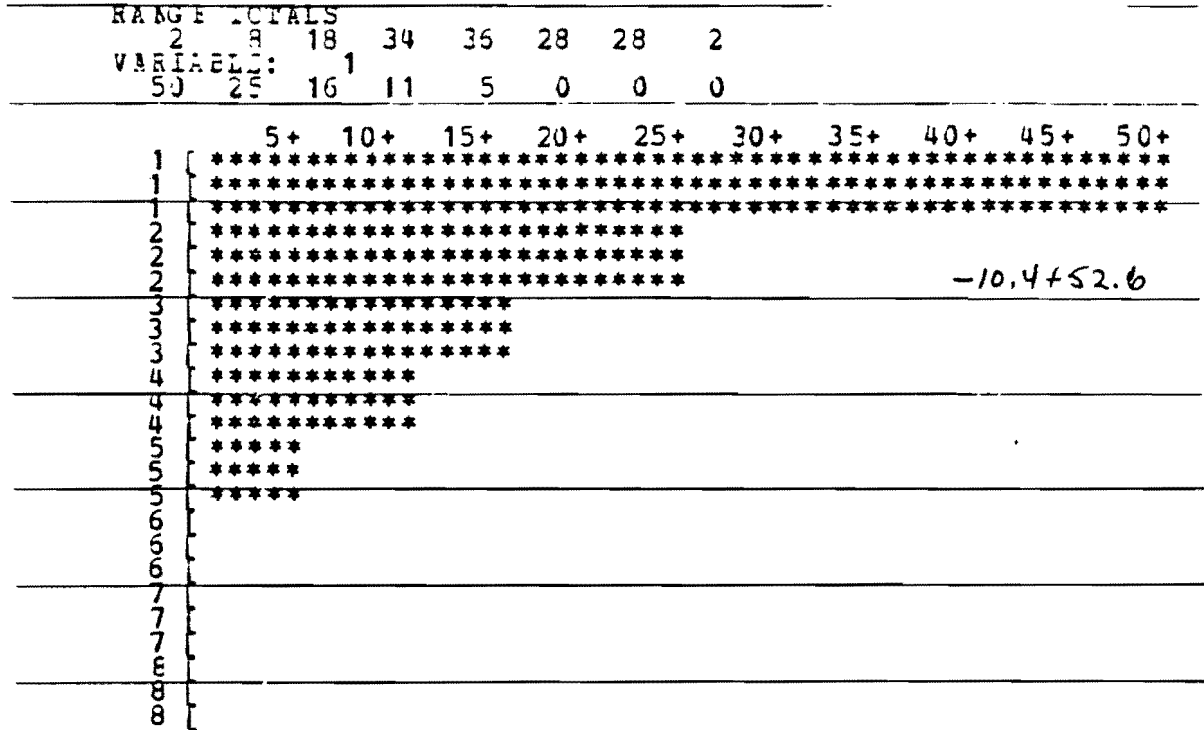
7321		6/ 4/53 1 2	18 10
7321	7 20	CRANIOSYNOSTOSIS	18 10
7321	8 23	HIGH	18 10
7321	8 24	DEPRESSIONS ABOVE EYEBROWS	18 10
7321	8 24	FLAT	18 10
7321	11 32	SHALLOW ORBIT	18 10
7321	12 32	SHALLOW ORBIT	18 10
7321	40 70	PES VALGUS	18 10
7321	41 70	PES VALGUS	18 10
7321	43 60	HYPERELASTICITY ALL JOINTS	18 10
7340		6/26/66 4 1	57 10
7340	7 20	CRANIOSYNOSTOSIS	57 10
7340	8 24	FLATTENED	57 10
7340	9 4	HYPOPLASTIC	57 10
7340	9 20	HYPERTELORIC	57 10
7340	36 34	WEBBING	57 10
7340	37 34	WEBBING	57 10
7340	43 20	WIDENING ATLANTO-AXIAL JOINT	57 10
7340	43 22	FIXATION ANTERIOR ARCH C1	57 10
7434		5/23/41 1 1	15 4
7434	2 86	SUBMUCOUS (U)	15 4
7434	7 20	CRANIOSYNOSTOSIS	15 4
7434	8 21	BOSSING	15 4
7434	9 2	ASYMMETRIC	15 4
7434	9 4	HYPOPLASIA	15 4
7434	10 2	ASYMMETIC	15 4
7434	11 20	PROPTOSIS	15 4
7434	11 75	PTOSIS	15 4
7434	12 20	PROPTOSIS	15 4
7434	12 75	PTOSIS	15 4
7434	13 62	LOPPED	15 4
7434	14 62	LOPPED	15 4
7434	16 22	BYZANTINE PALATE	15 4
7434	36 30	SYNDACTYLY	15 4
7434	37 30	SYNDACTYLY	15 4
7434	40 30	SYNDACTYLY	15 4
7434	41 30	SYNDACTYLY	15 4
7437		1/17/68 1 1	16 4
7437	2 86	SUBMUCOUS (U)	16 4
7437	7 20	CRANIOSYNOSTOSIS	16 4
7437	9 4	HYPOPLASIA	16 4
7437	10 0	BYZANTINE PALATE, MILD	16 4
7437	11 20	EXOPHTHALMOS	16 4
7437	12 20	EXOPHTHALMOS	16 4
7437	20 43	CROWDING	16 4
8226		5/25/45 1 1	16 10
8226	7 20	CRANIOSYNOSTOSIS	16 10
8226	9 4	HYPOPLASIA	16 10
8226	11 20	PROPTOSIS	16 10
8226	12 20	PROPTOSIS	16 10
8429		4/25/55 1 2	16 10
8429	7 20	CRANIOSYNOSTOSIS, CORONAL & SAGITTAL SUTURES	16 10
8429	8 23	BULGING	16 10
8429	8 24	HIGH	16 10
8429	11 31	DEVIL'S EYE	16 10
8429	12 31	DEVIL'S EYE	16 10
8429	13 31	LOW SET	16 10
8429	14 30	ROTATED	16 10
8429	14 31	LOW SET	16 10
8429	29 55	EMPHYSEMA	16 10
8429	31 21	2 ACCESSORY SPLEENS	16 10
8429	32 28	UTERUS DUPLEX BICORNIS	16 10
8434		1/ 8/54 1 1	15 10
8434	7 20	CRANIOSYNOSTOSIS	15 10
8434	8 22	BULGING	15 10
8434	8 23	HIGH	15 10

8434	11	78	ANTIMONGOLOID SLANT	15	10
8434	12	78	ANTIMONGOLOID SLANT	15	10
8434	20	43	CROWDING	15	10
8434	36	30	SYNDACTYLY	15	10
8434	37	30	SYNDACTYLY	15	10
8434	40	30	SYNDACTYLY	15	10
8434	41	30	SYNDACTYLY	15	10
8437			7/ 6/65 1 2	16	10
8437	7	20	CRANIOSYNOSTOSIS	16	10
8437	9	4	HYPOPLASIA	16	10
8437	11	20	EXOPHTHALMOS	16	10
8437	12	20	EXOPHTHALMOS	16	10
8946			10/15/72 4 2	57	4
8946	2	86	SUBMUCOUS (U)	57	4
8946	7	20	CRANIOSYNOSTIS	57	4
8946	8	24	FLAT	57	4
8946	9	4	HYPOPLASIA	57	4
8946	10	41	PROGNATHISM	57	4
8946	11	20	MILD PROPTOSIS	57	4
8946	11	73	CHRONIC BLEPHARITIS	57	4
8946	12	20	MILD PROPTOSIS	57	4
8946	12	73	CHRONIC BLEPHARITIS	57	4
8946	13	31	LOW SET	57	4
8946	14	31	LOW SET	57	4
8946	16	42	COMMISSURAL LIP PIT, LEFT	57	4
8946	40	34	CUTANEOUS SYNDACTYLY 2ND & 3RD TOES	57	4
8946	41	34	CUTANEOUS SYNDACTYLY 2ND & 3RD TOES	57	4
9126			6/15/63 1 2	15	4
9126	2	83	SUBMUCOUS (S-U)	15	4
9126	7	0	MIDLINE DEFECT	15	4
9126	8	25	MIDLINE DEFECT	15	4
9126	11	21	PROMINENT	15	4
9126	12	21	PROMINENT	15	4
9126	30	20	HYPERTROPHIC CARDIAC STENOSIS	15	4
9126	36	30	SYNDACTYLY	15	4
9126	37	30	SYNDACTYLY	15	4
9126	40	30	SYNDACTYLY	15	4
9126	41	30	SYNDACTYLY	15	4
9126	42	30	SEVERE RETARDATION	15	4
9126	42	64	HYPOPLASIA CEREBRAL WHITE MATTER	15	4
9129			7/ 2/64 1 2	16	10
9129	9	2	ASYMMETRY	16	10
9129	9	4	HYPOPLASIA	16	10
9129	9	20	HYPERTELORISM	16	10
9129	11	4	MICROPHTHALMIA	16	10
9129	11	31	DEVIL'S EYE	16	10
9129	11	33	ORBIT SMALL	16	10
9129	11	75	PTOSIS	16	10
9129	11	94	NYSTAGMUS	16	10
9129	12	4	MICROPHTHALMIA	16	10
9129	12	31	DEVIL'S EYE	16	10
9129	12	33	SMALL ORBIT	16	10
9129	12	75	PTOSIS	16	10
9129	12	94	NYSTAGMUS	16	10
9129	14	31	LOW SET	16	10
9129	15	3	BIFID	16	10
9129	28	20	SCOLIOSIS	16	10
9129	32	20	ANOMALOUS GENITALIA	16	10
9129	36	34	CUTANEOUS SYNDACTYLY 3RD & 4TH DIGITS	16	10
9129	36	53	DOUBLE PHALANGES, MID & DISTAL ZONE 4TH DIGIT	16	10
9129	40403		BIFID 4TH TOE	16	10
9129	41	31	2ND & 3RD DIGITS FUSED PROXIMALLY	16	10
9129	42	62	SUPERFICIAL ABDOMINAL REFLEXES ABSENT	16	10
9226			2/14/67 1 2	57	3
9226	2	63	INCOMPLETE MEDIAN	57	3
9226	7	20	CRANIOSTENOSIS	57	3

9226	9	20	HYPERTELORISM	57	3
9226	15	31	DEPRESSED NASAL BRIDGE	57	3
9226	36	34	WEBBING	57	3
9226	37	34	WEBBING	57	3
9534			6/ 8/67 1 2	15	10
9534	7	20	CRANIOSYNOSTOSIS	15	10
9534	8	24	FLATTENING	15	10
9534	9	4	HYPOPLASIA	15	10
9534	11	20	PROPTOSIS	15	10
9534	12	20	PROPTOSIS	15	10
9534	13	31	LOW SET	15	10
9534	14	31	LOW SET	15	10
9534	15	26	PINCHED	15	10
9534	16	22	BYZANTINE PALATE	15	10
9534	34	0	WIDE CARRYING ANGLE	15	10
9534	34	50	PROMINENT ACROMIO-CLAVICULAR JOINT	15	10
9534	35	0	WIDE CARRYING ANGLE	15	10
9534	35	50	PROMINENT ACROMIO-CLAVICULAR JOINT	15	10
9534	36	30	SYNDACTYLY	15	10
9534	37	30	SYNDACTYLY	15	10
9534	40	30	SYNDACTYLY	15	10
9534	41	30	SYNDACTYLY	15	10
9534	42	30	RETARDATION	15	10
9534	42	57	HYPERACTIVITY	15	10
9538			9/ 9/61 1 1	16	10
9538	7	20	CRANIOSYNOSTOSIS	16	10
9538	8	29	TYPICAL CROUZON	16	10
9538	9	4	HYPOPLASIA	16	10
9538	11	20	EXOPHTHALMOS	16	10
9538	12	20	EXOPHTHALMOS	16	10
9538	16	22	BYZANTINE PALATE	16	10
9925			0/ 0/ 0 5 2	18	10
9925	7	20	CRANIOSYNOSTOSIS?	18	10
9925	8	23	HIGH	18	10
9925	9	4	HYPOPLASIA	18	10
9946			5/15/74 4 2	57	4
9946	2	86	SUBMUCOUS (U)	57	4
9946	7	20	CRANIOSYNOSTOSIS	57	4
9946	8	24	FLAT	57	4
9946	9	4	HYPOPLASIA	57	4
9946	10	41	PROGNATHISM	57	4
9946	11	22	CHRONIC TEARING	57	4
9946	12	30	POSTERIORLY SET	57	4
9946	12	30	LOW SET	57	4
9946	13	31	LOW SET	57	4
9946	14	31	LOW SET	57	4
9946	16	42	COMMISSURAL LIP PITS	57	4
9946	40	34	CUTANEOUS SYNDACTYLY	57	4
9946	41	34	CUTANEOUS SYNDACTYLY	57	4

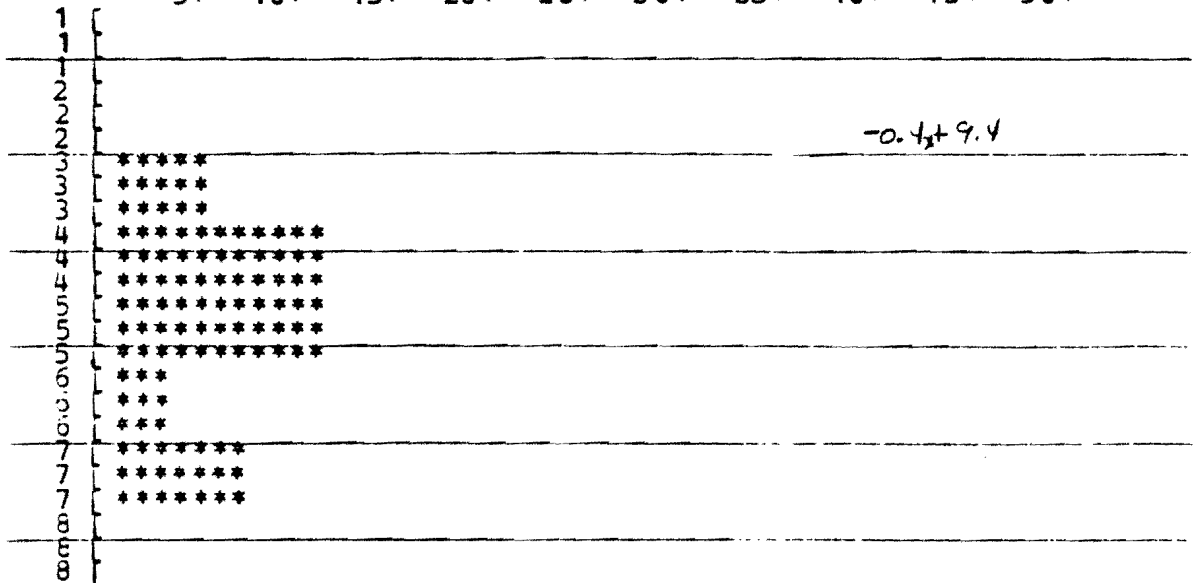
Histogram Analyses of Groups of
Attributes as described in the text

The following pages give the histograms for the attributes in the Animals event set when taken in pairs, triples, and quadruples. The hand-written numbers are the least squares fit line (in the form $mx+b$) calculated for each histogram.



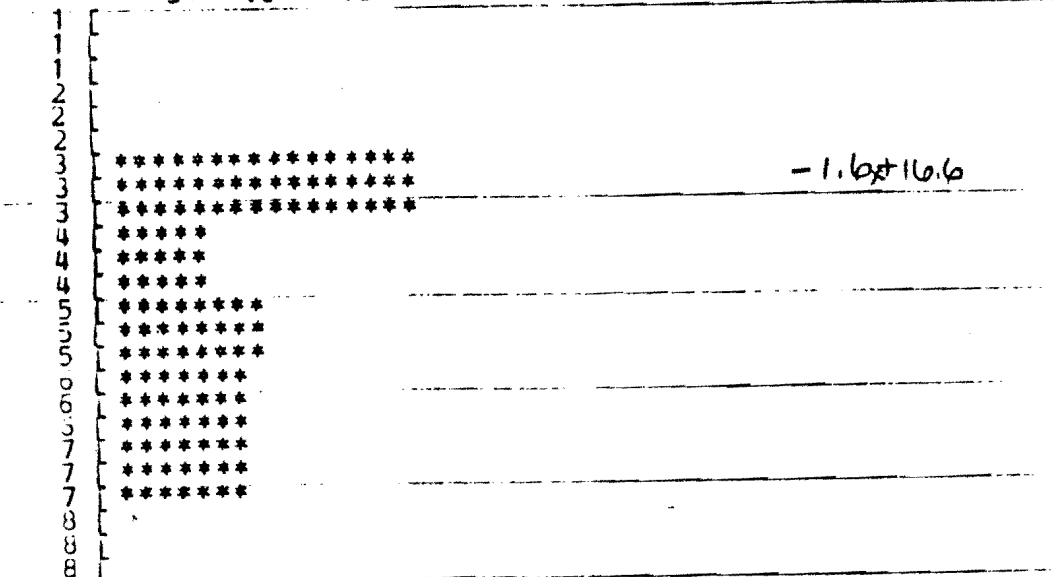
VARIABLE: 0 0 5 3 11 11 3 7 0

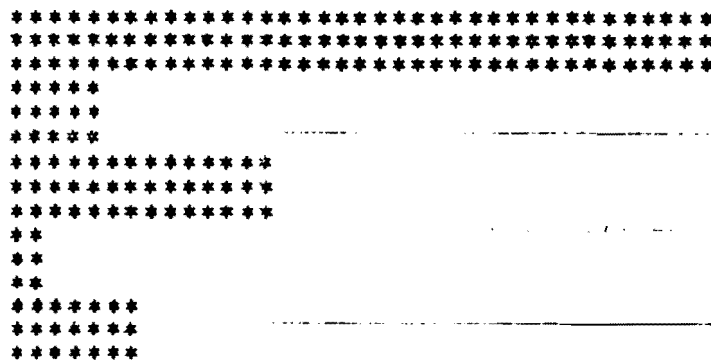
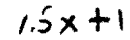
5+ 10+ 15+ 20+ 25+ 30+ 35+ 40+ 45+ 50+



VARIABLE: 0 0 16 5 8 7 7 0

5+ 10+ 15+ 20+ 25+ 30+ 35+ 40+ 45+ 50+





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$$0.4x + 6.4$$

VARIABLE: 9

[illegible]

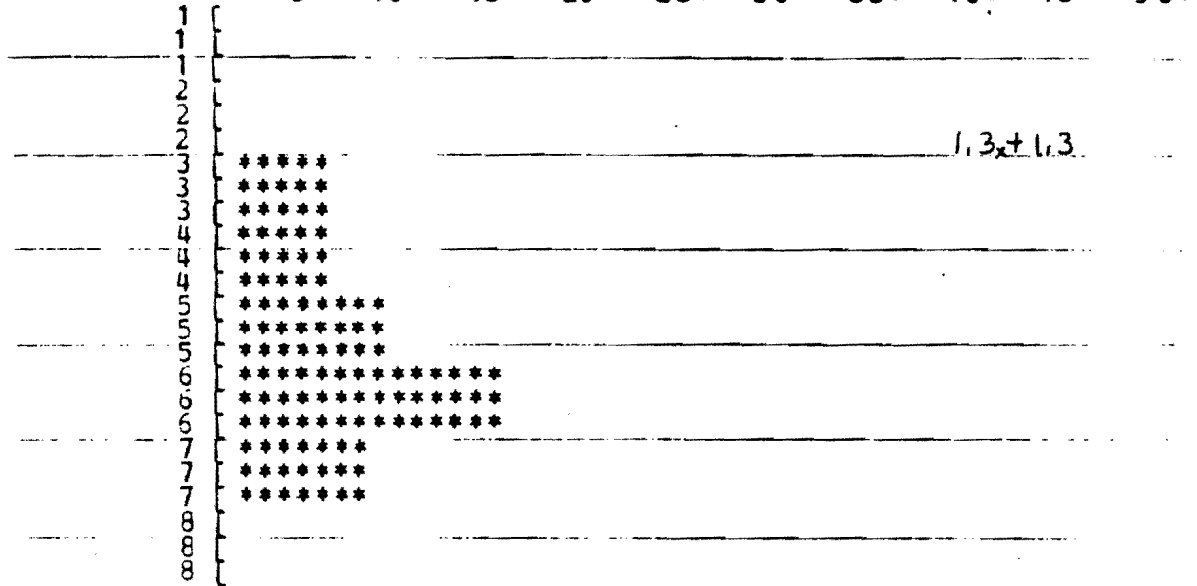
VARIABLE: 10

[illegible]

VARIABLE: 11

0 0 5 5 8 14 7 0

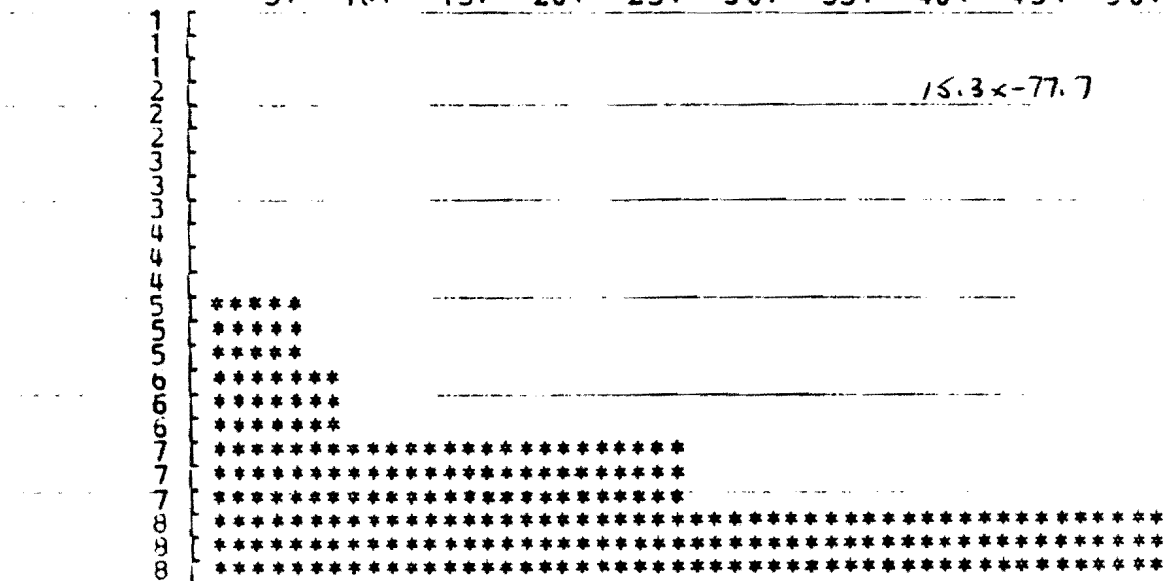
5+ 10+ 15+ 20+ 25+ 30+ 35+ 40+ 45+ 50+



VARIABLE: 12

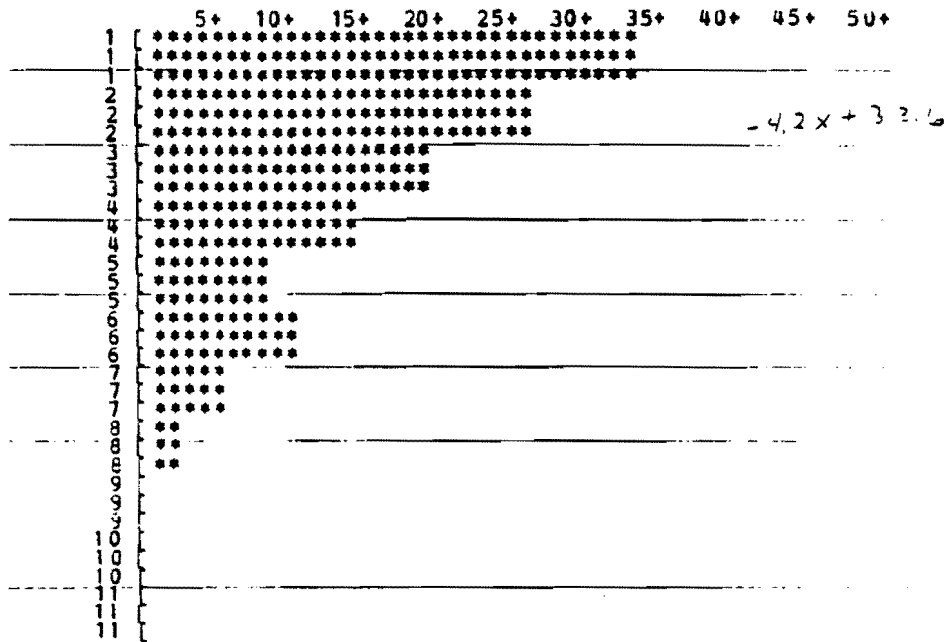
0 0 0 0 5 7 25 50

5+ 10+ 15+ 20+ 25+ 30+ 35+ 40+ 45+ 50+



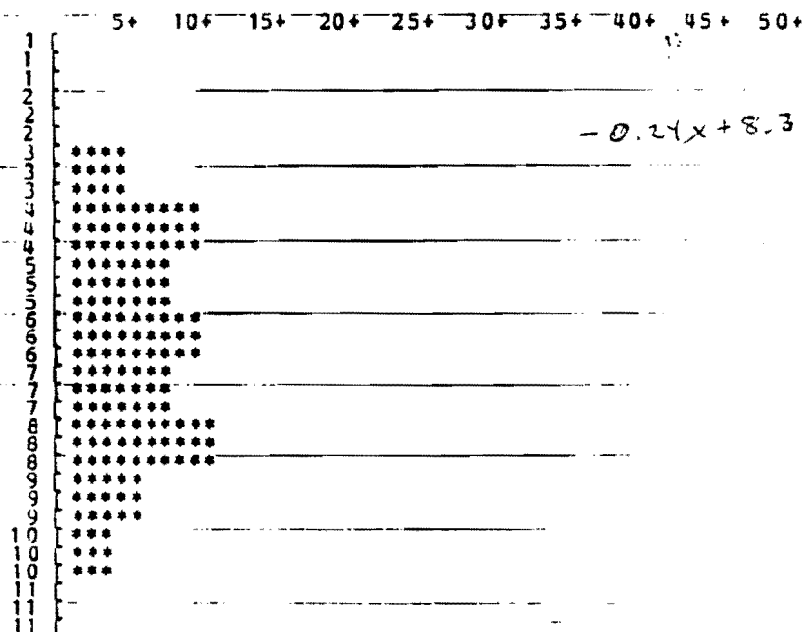
RANGE TOTALS

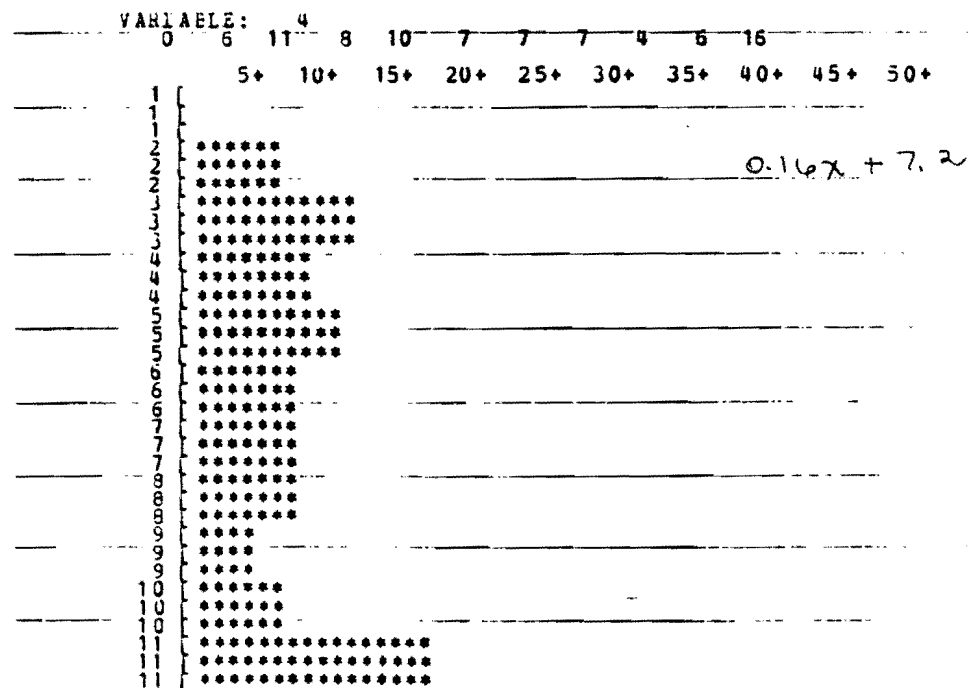
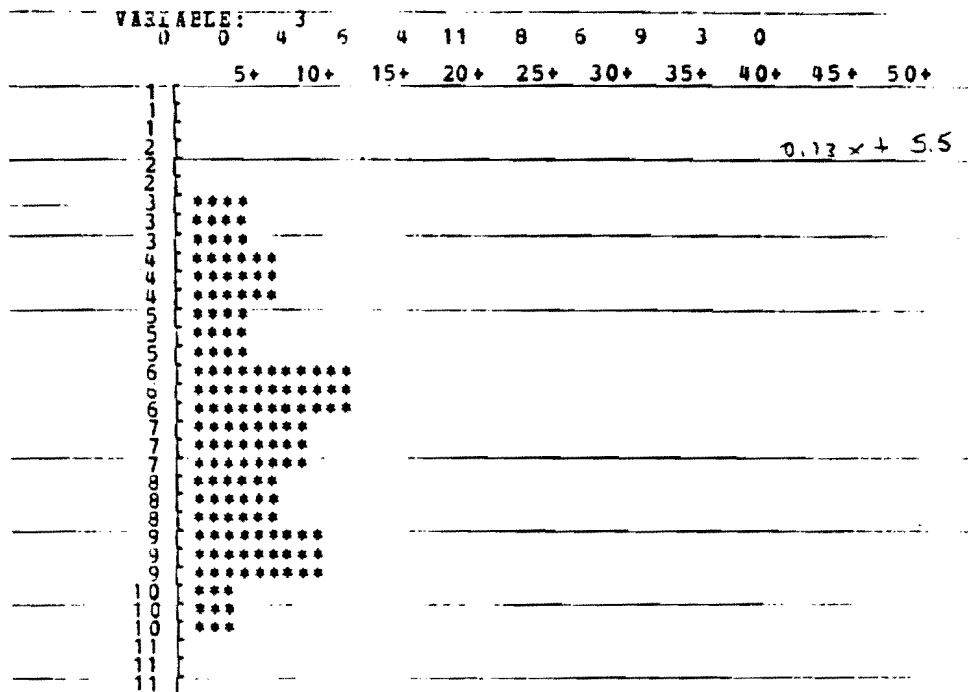
3	15	42	87	105	177	171	126	93	33	6
VARIABLES:										
33	26	19	14	8	10	5	2	0	0	0

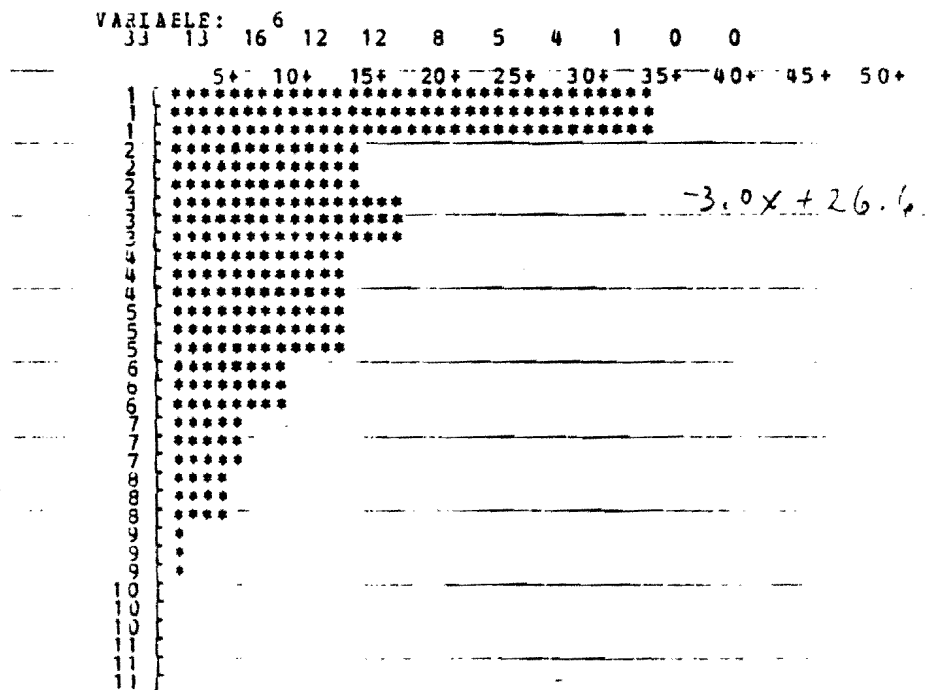
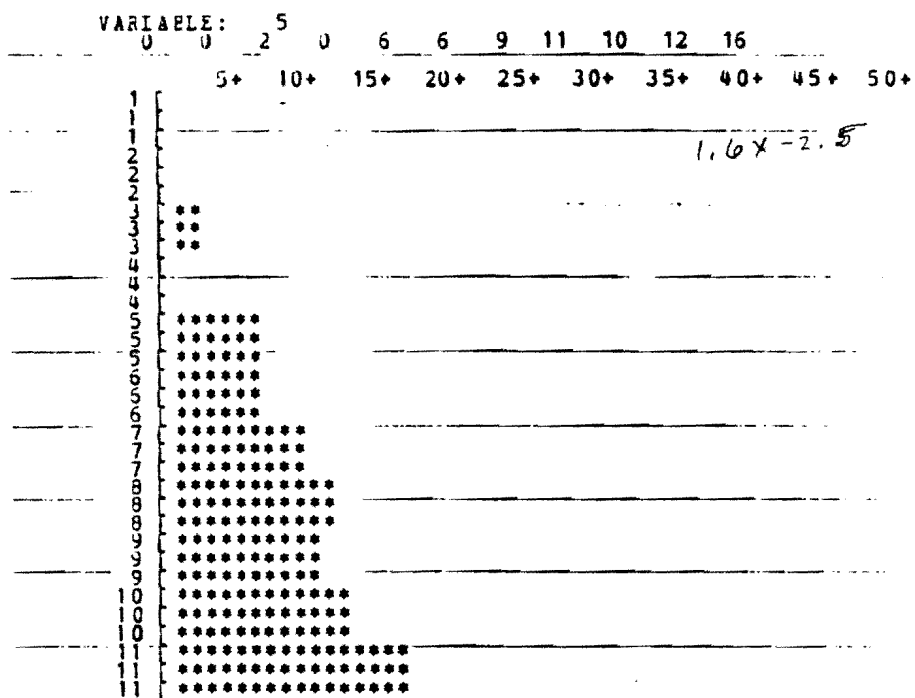


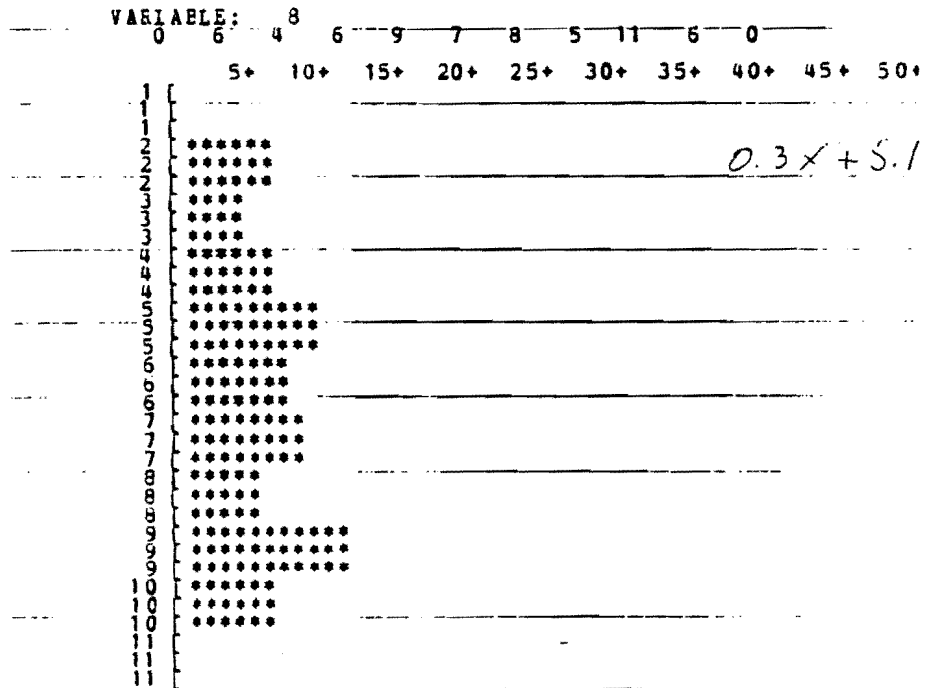
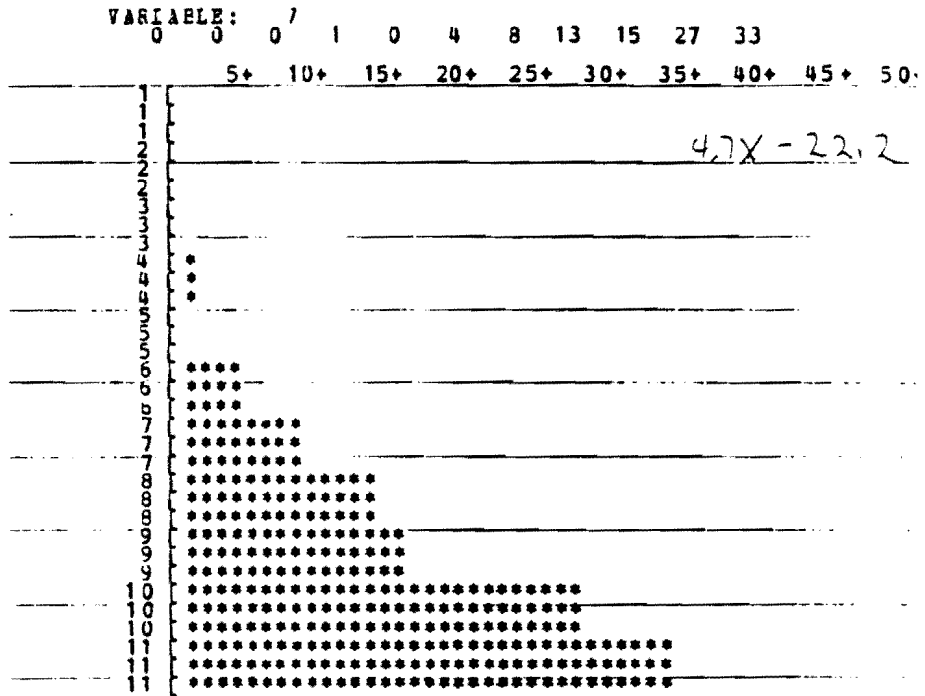
VARIABLE:

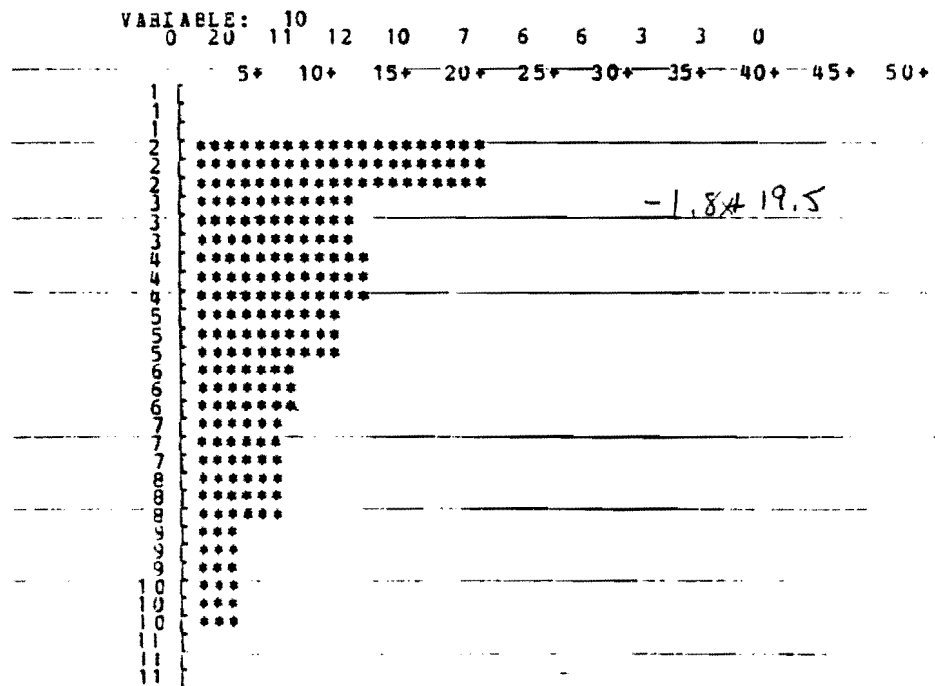
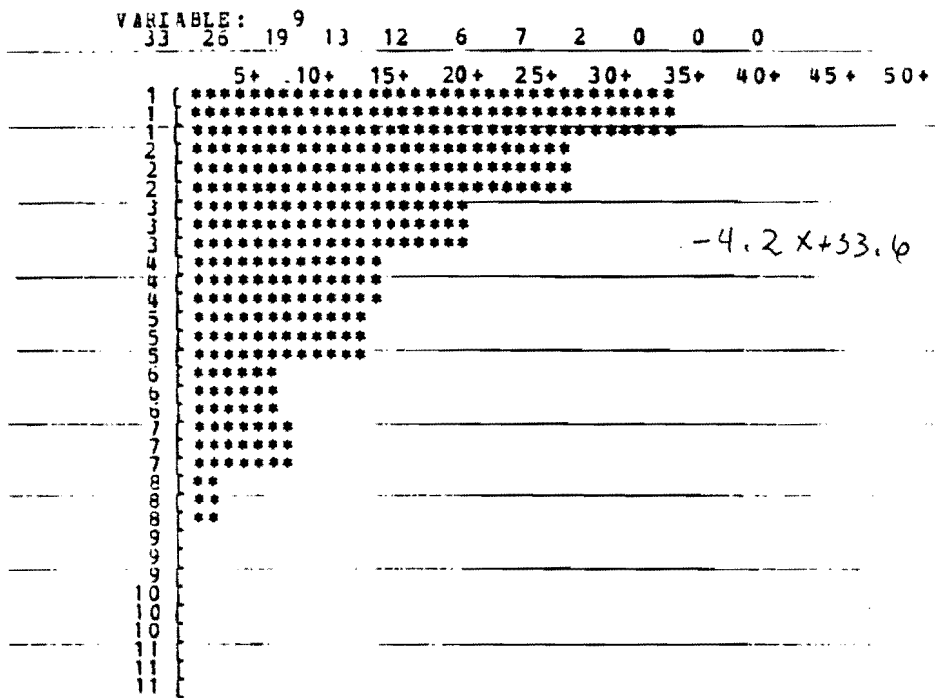
0	0	4	9	7	9	7	10	5	3	0
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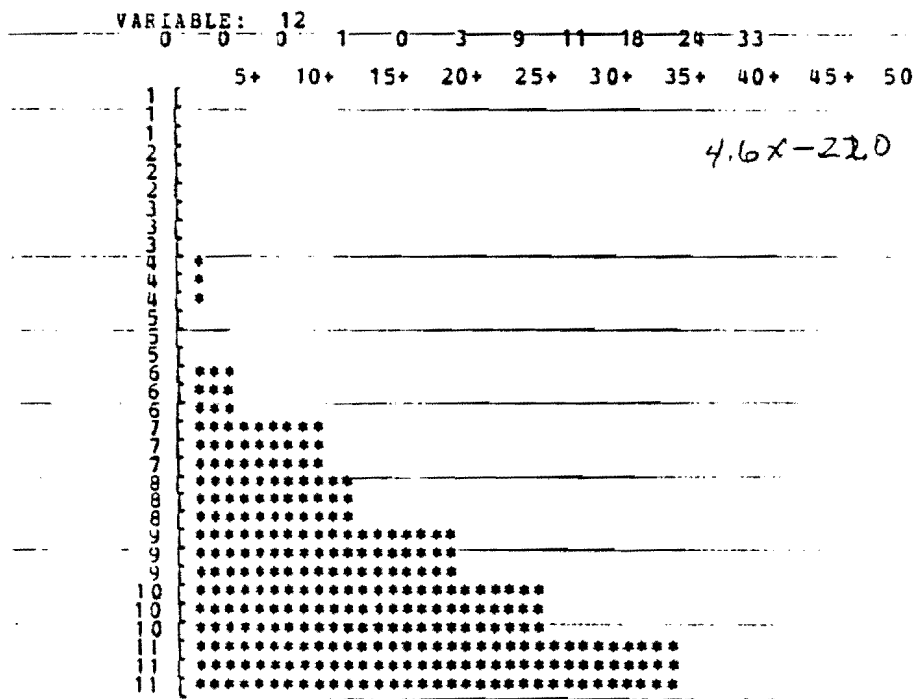
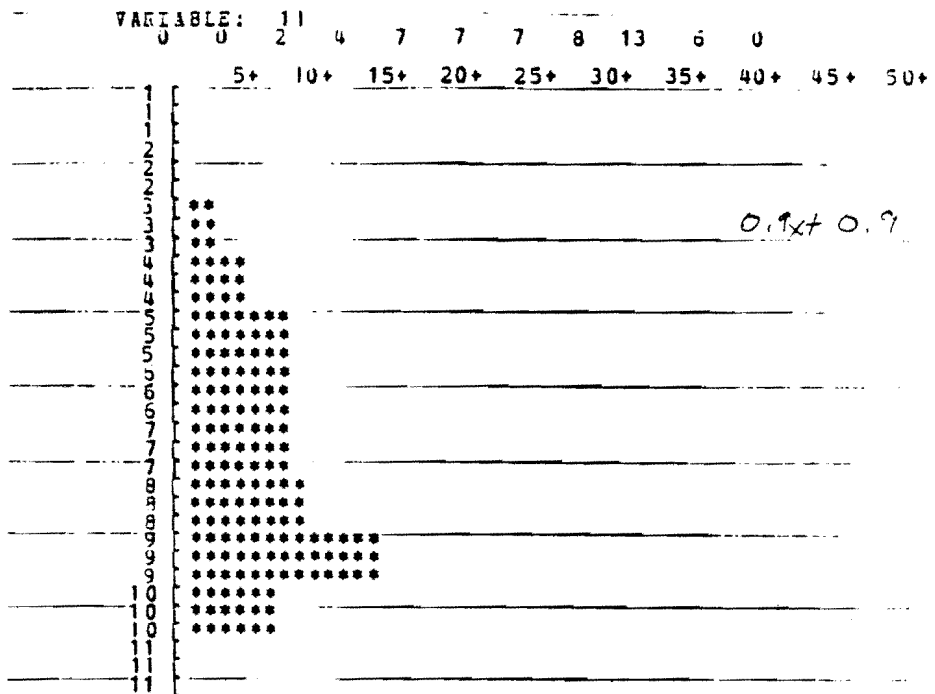


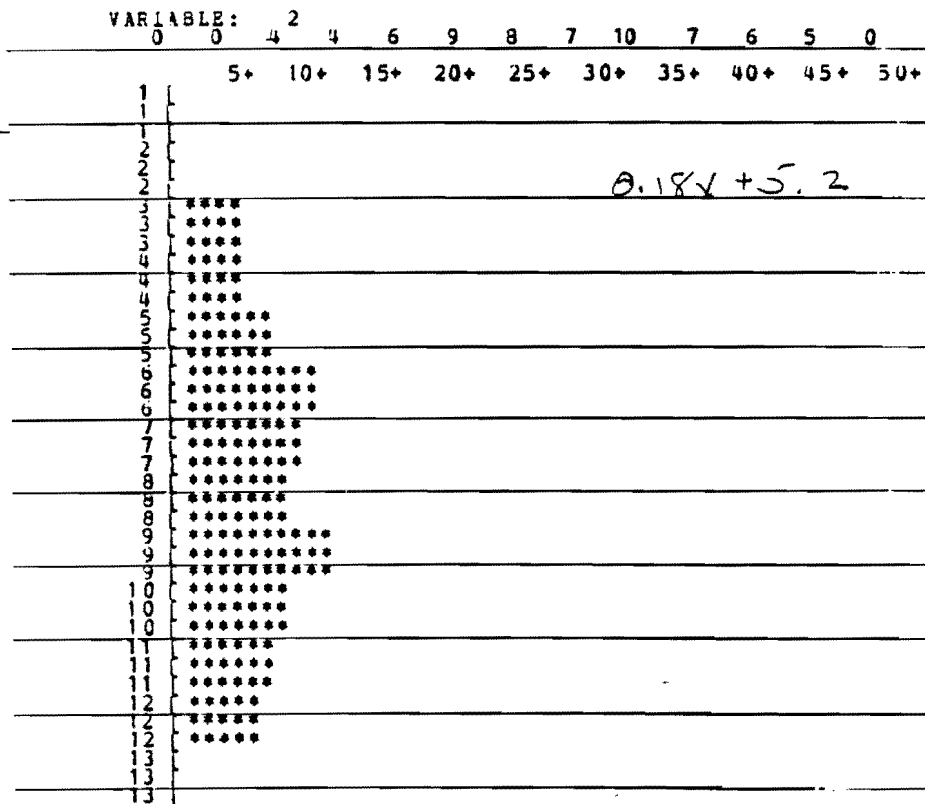
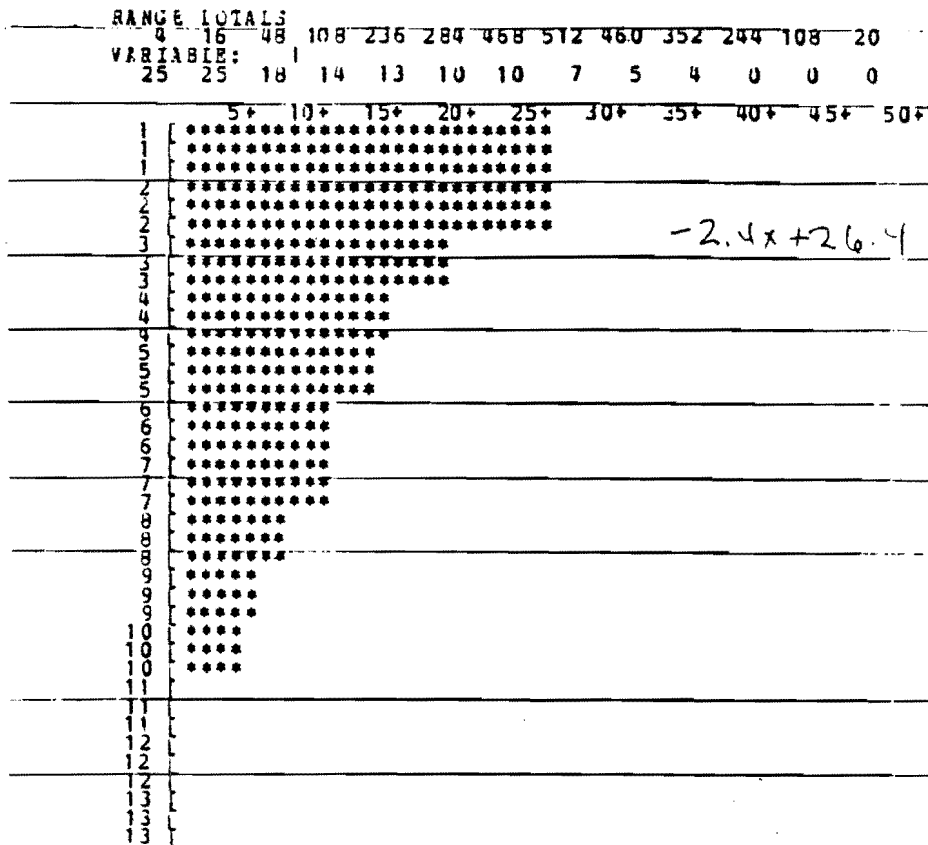


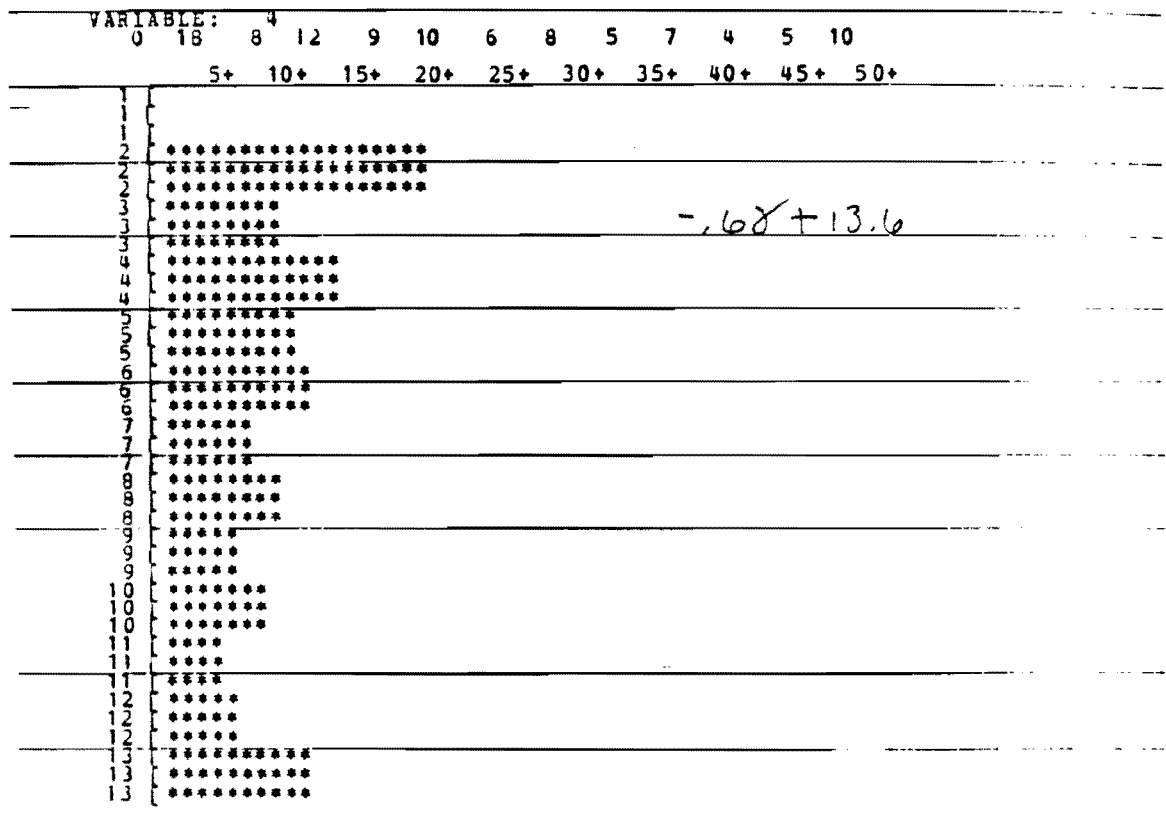
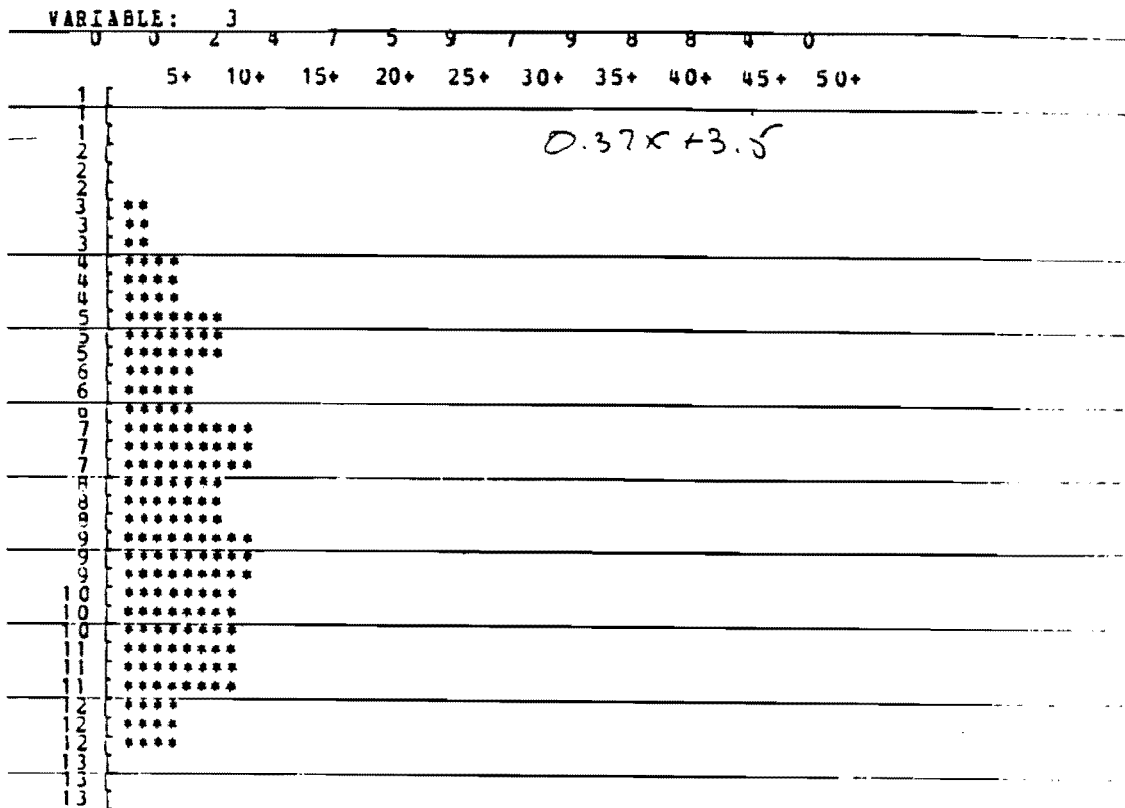


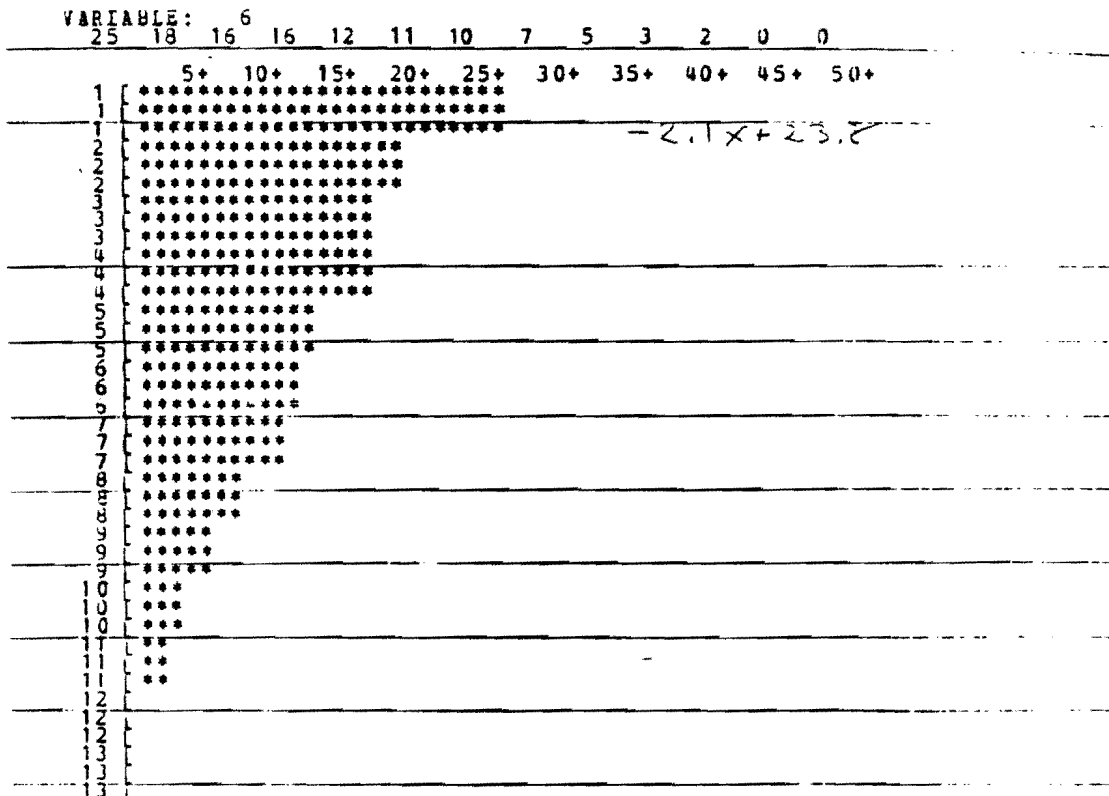
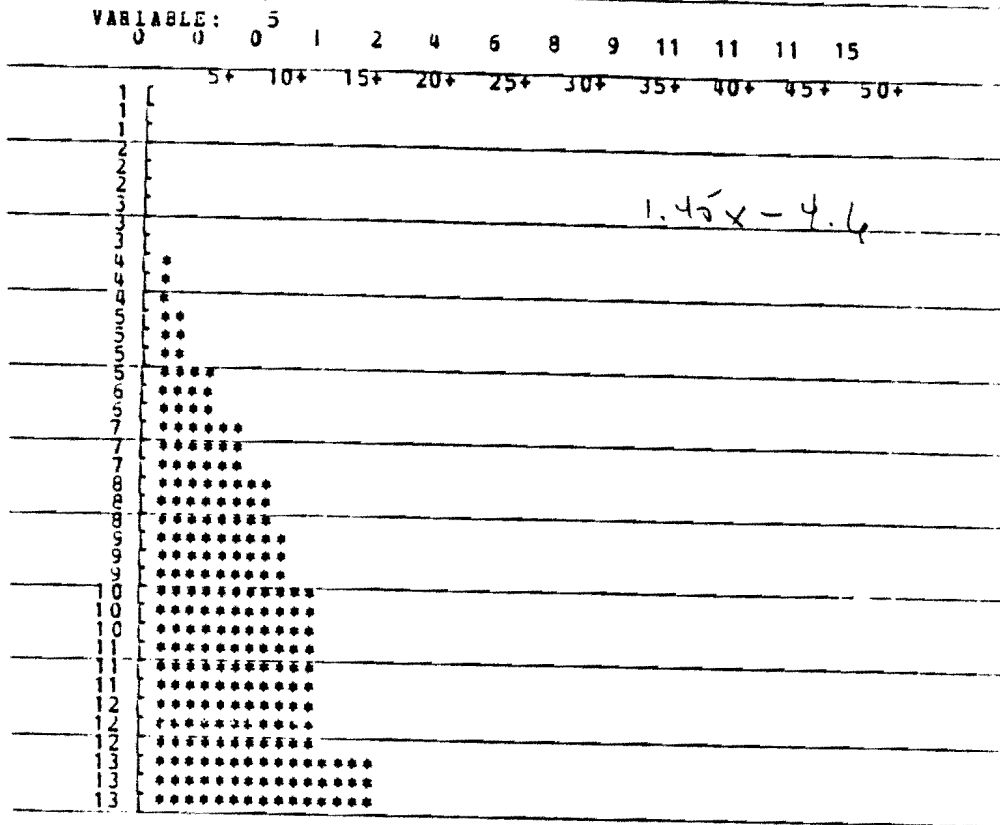


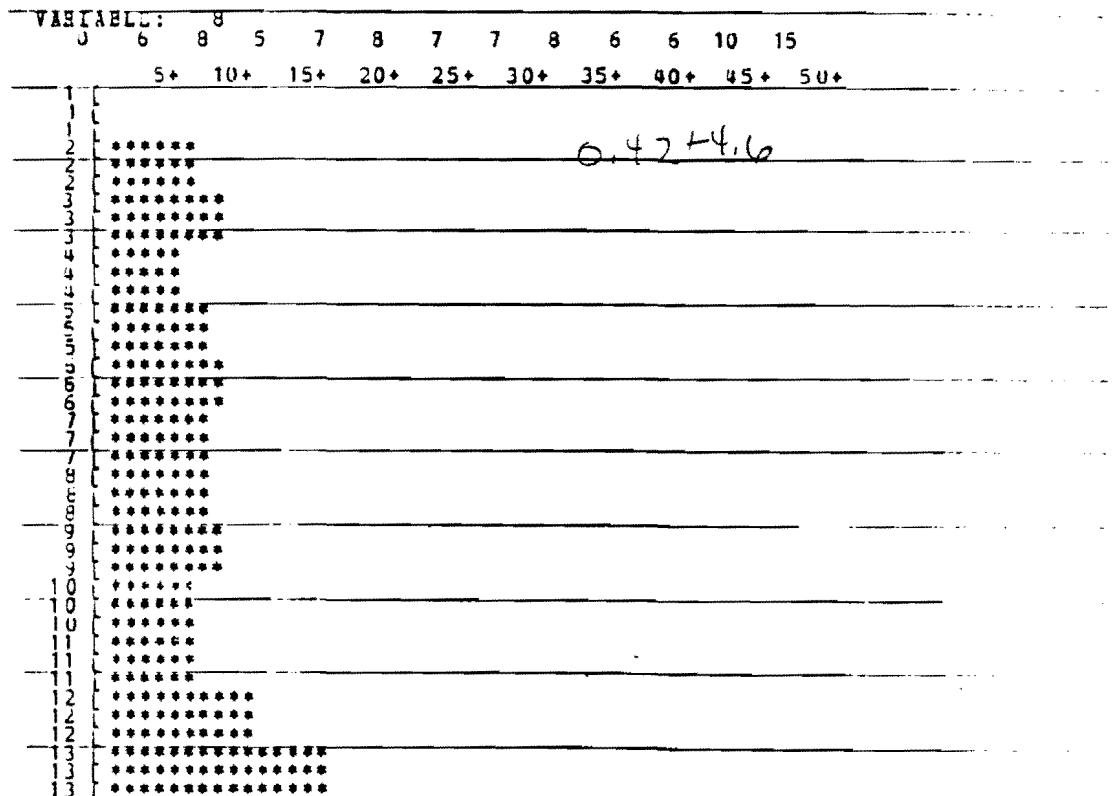
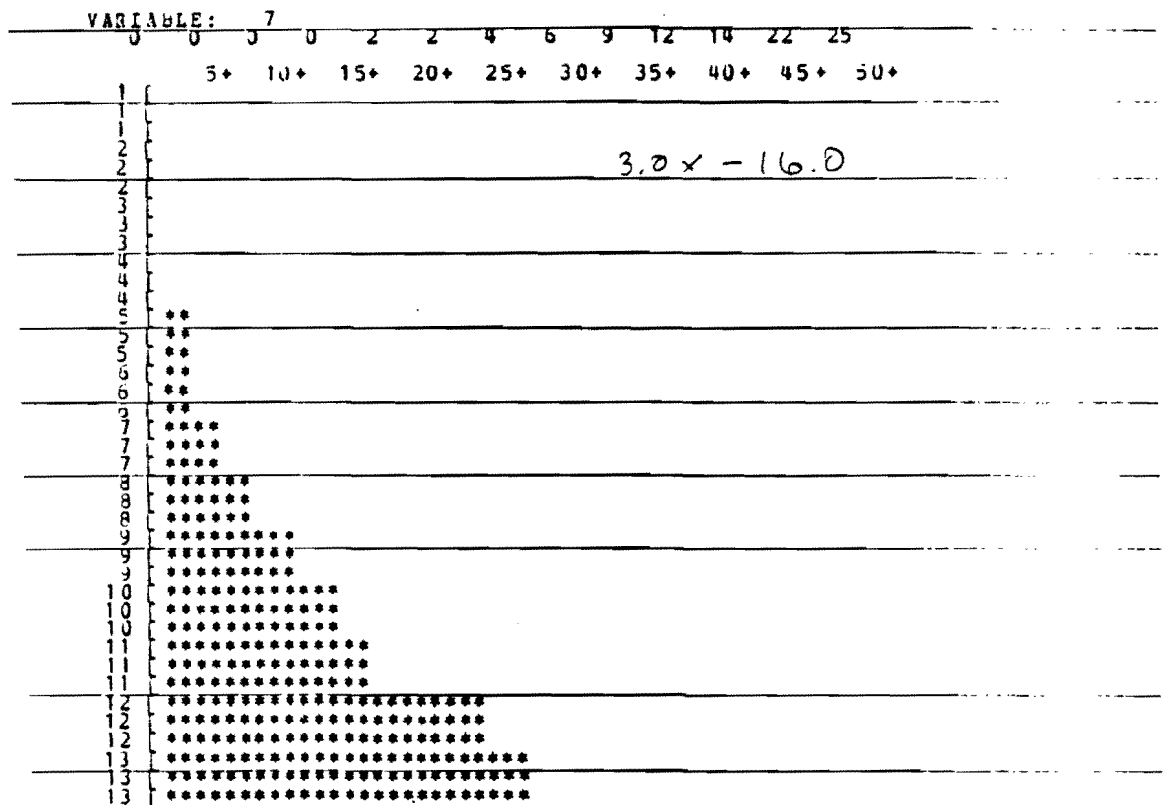






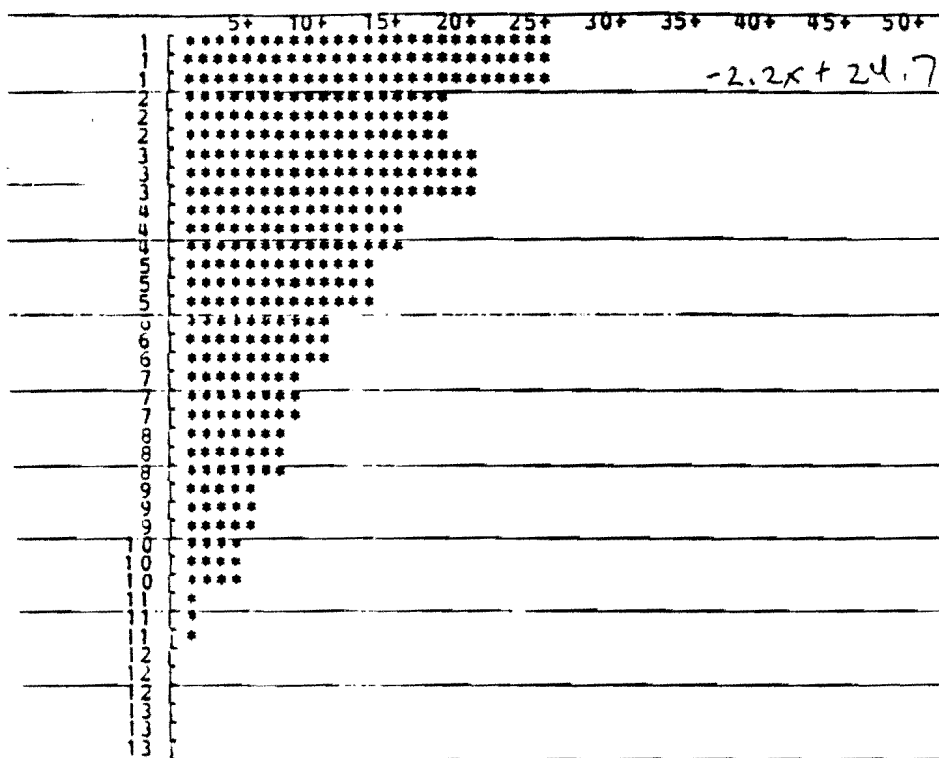






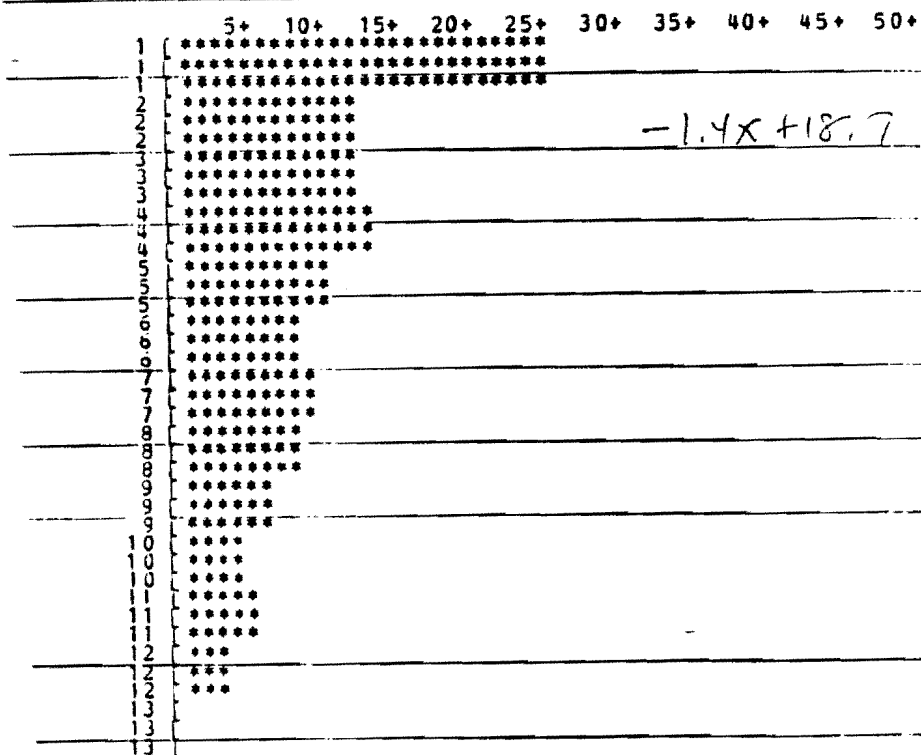
VARIABLE: 9

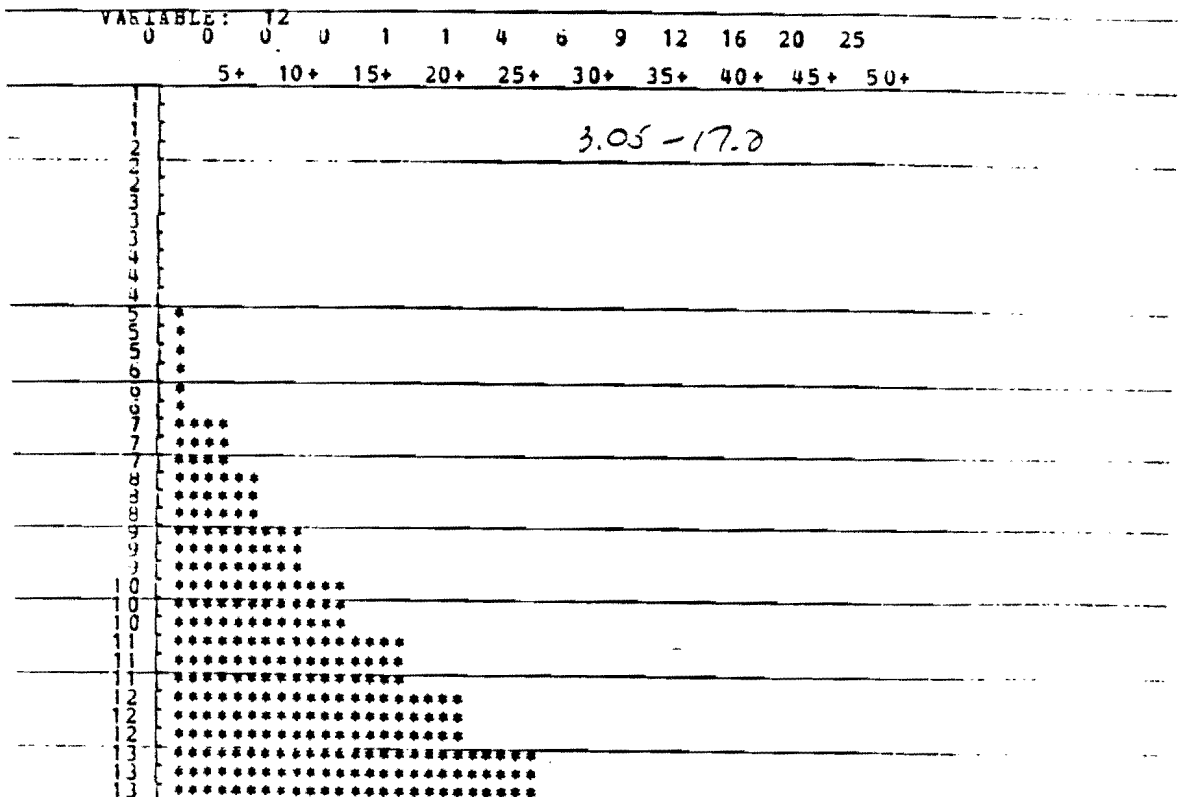
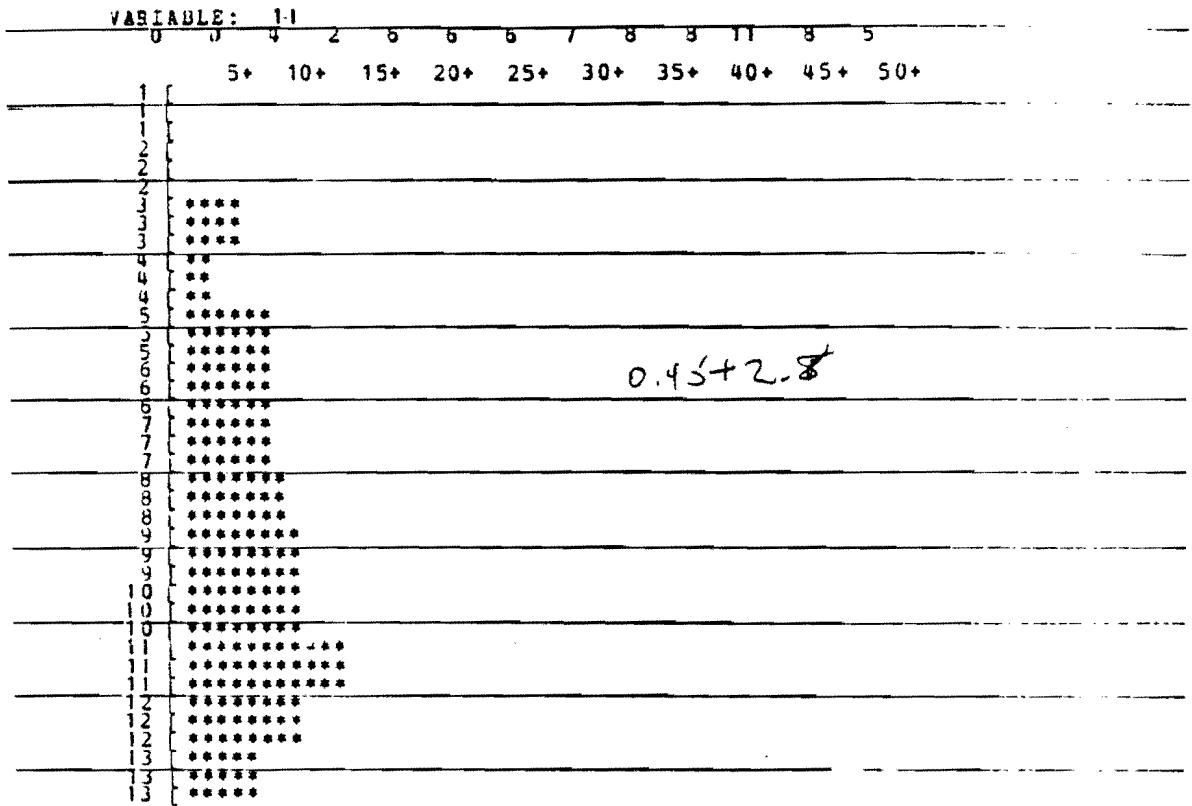
25 18 20 15 13 10 8 7 5 4 1 0 0



VARIABLE: 10

25 12 12 13 10 8 9 8 6 4 5 3 0





Rules for the Animals Event Set
Derived Using AQ11

***** HASP (J.1) SYCTEN LOG *****

18-19:21 JOB 112 FROM THE CYBER 76 BE PRINTED
18-19:21 JOB 112 CPFA017 ON PRINTER2 BIN=17

05/MVT (21.7) SYSTEM MESSAGE BLOCK

14111 PASCAL: MULTI-STEP AULE DETECTION AND REPINEMENT - VERSION 2.0.

DIFFUSION TIME: 0.60 CENTISECONDS

STILL STAYED IN
CLASS OF CLASS:
STAYED IN CLASS:
STAYED IN CLASS:

STYLISH & SUBVERSIVE VARIATIONS

WEDNESDAY, NOVEMBER 10, 1965

ALLOWABLE, EXCEPT

:STST 10 MAR EDN

25TH AUG 0407 0
CEHVIC 0407 0
HT 0407 0

ESTD 1905
4000
4000

RECYCLED FORMULAS?

PARABT2657
FAL

INSTRUMENTS

MCRT: 2

CRITICAL:

TOTALS: 0.00 0.00

TESTING: 1-25-71

ORD: ORDER COMP

PREVALENCE OF RHEUMATOID ARTHRITIS IN THE UNITED STATES

INDE: _____
 TRACK FORM: _____

ADDRESSES:

BASE PRICING:
SALES: 1000
INPUT: 1000
CONSUMPTION: 1000

OPR: PHIMT & CO

TEST: _____
CENT: _____
APPLY CRIST: _____
THIN CRIST: _____

TRANS: SNVBT
31075NHL

.....

CRYST SPECIFICATIONS

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5778
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1

TYPE: LIN 3
M14 OF LEVELS:

0 PERCENTAGE OF EVENTS T

Q. NO. OF INPUT EVENTS

TIME	TIME
0:00	0:00
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0:02	0:02
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PRIT

UNIT 2

UNIT 8

LIT
9:00

LIT
9:00

[illegible]

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