

Classification of Interstate Conflict Outcomes using a Bootstrapped CLS Algorithm

**Philip A. Schrodt
Dept of Political Science
Northwestern University
Evanston, IL 60201**

Bitnet: SCHRODT@NUACC

April, 1987

**Paper prepared for the meetings of the International Studies Association,
Washington, DC**

ABSTRACT

The CLS algorithm is an inductive technique developed in artificial intelligence for generating classification trees from a set of data. These trees are similar to those used in expert systems; the advantage of the CLS algorithm is that the trees are generated automatically rather than via human experts. This paper applies a bootstrapped version of CLS to the Butterworth Interstate Conflict data set. By generating a number of classification trees from randomly selected subsets of the complete data set, the variables which are most effective in correctly classifying the cases can be identified, and the degree of unpredictability in the data can be ascertained by computing the accuracy of the tree in classifying those cases not in the training set. In general, the technique works very well: the original set of 38 independent variables can be reduced to five or fewer with almost no loss of classification accuracy. Classification trees generated with these variables have 95%-100% accuracy when fitted to the entire set, and an average 50%-60% accuracy when tested against validation samples in split-sample tests. Unlike existing statistical techniques, the knowledge representation structures inductively constructed by bootstrapped CLS are plausible models of human inductive theorizing since they fit within the known cognitive constraints of the brain.

1. Introduction

In the past five years a number of researchers have begun to apply techniques developed in the field of artificial intelligence to the modeling of international behavior. These "computational models" differ from existing statistical models in at least two major ways: the use of non-algebraic (i.e. algorithmic) methods of computation and knowledge representation, and the predominant use of categorical data over interval data. The role of artificial intelligence models in the context of international relations is reviewed extensively in Schrodt (1984a, 1984b, 1985b, 1986b); surveys of contemporary work in this field are found in Sylvan and Chan (1984) and Cimbala (1987).

In the field of AI generally, the most successful empirical technique has been the ruled-based expert system and there is a general consensus that expert systems have brought AI out of the laboratories and into the marketplace. MYCIN, which dealt with the diagnosis of blood diseases, was the first well-publicized expert system to achieve human-expert accuracy; in the ten years following the success of MYCIN expert systems have been applied to problems ranging from robot repair to credit card authorization.

The most common application of expert systems is to solve classification problems, that is, to categorize a particular case into one of a number of discrete categories based on a set of variables (or questions) concerning that case. In the language of conventional statistical analysis, an expert classification system predicts a nominal dependent variable from a set of nominal independent variables. The difference between an expert system and a conventional nominal/nominal statistical technique such as contingency table analysis or log-linear analysis is in the amount of information which is used and the number of rules which can be applied. Most expert systems employ around 10^2 to 10^4 rules, and frequently employ a large number of variables.

While expert systems employ a variety of techniques, most of the power of the system resides in the knowledge contained in the system rather than in any complex manipulation of that knowledge. The simplest representation of "expert" knowledge -- and one which is sufficient to solve many problems -- is a tree. Each of the nodes of the tree contains a question, and the branches of the tree correspond to answers to those questions. Figure 1 shows the simplest form of a tree -- the binary tree -- in a classification problem which identifies animals. In principle, a tree with N levels of questions and K branches per question can classify K^N categories; e.g. a binary tree (with two branches per question) with ten levels of questions can classify $2^{10}=1024$ categories. While the complete tree involves $K^{(N-1)}$ questions, only N questions are required to categorize a case, so a tree is computationally a very efficient means of storing classification information.

Classification trees are not wholly unfamiliar as a means of everyday knowledge representation. Anyone who has tried to identify birds, wildflowers, mushrooms or the like is familiar with "keying out" an identification of a species using a field guide. For example, to identify a dandelion, a typical field guide would probably go through a series of questions something like:

Color: yellow
Blooms in: spring, summer
Flower type: compound
Leaf shape: [series of shapes]
 etc.

Eventually one reaches a point where the identification is reduced to a small number of candidates and the final classification can be done by comparing the flower to one of a small number of pictures. A good key starts with the most obvious information (i.e. the information with the least acquisition "cost") and then goes to uses the more detailed information which provides the most discrimination. In this respect a key in a field guide differs substantially from a biological classification. For example, a yellow dandelion has more in common biologically with a white daisy or blue chicory than it does with a yellow jewelweed. Nonetheless, because "color" is information which is acquired at virtually no cost whereas the biological concept "compound flower" is more difficult to learn, "color" is the characteristic used first in the key

The earliest use of an AI-based classification tree in international relations was the Alker-Christensen-Greenburg model (1972,1976) of UN dispute resolution. Classification trees have been used in a number of recent papers in political science:

<u>Paper</u>	<u>Dependent variable</u>
Tanaka (1984)	Chinese foreign policy
Kaw (1986)	Soviet intervention
Grunbaum (1986)	Supreme Court decisions on discrimination
Hudson (1987)	Foreign policy behavior
Garson (1987)	Satisfaction with legislative process

In addition, there are several LISP or PROLOG-based systems which make heavy use of rules and tree-like structures and probably could be reduced to classification trees: Job and Johnson (1986) [US foreign policy towards the Dominican Republic] and Bobrow, Sylvan and Ripley (1986) [Japanese energy supply policy] are two examples of these. With the exception of Garson, all of these papers use "hand-coded" rules.

While expert systems have been phenomenally successful commercially, the approach employed in MYCIN contained a clear bottleneck: knowledge was obtained from human experts. With the bells and whistles removed, essentially all the expert system did was codify what the human expert already knew. Getting this knowledge out of the expert was a phenomenally time-consuming operation, and more importantly, the system was constrained by the degree of understanding of the experts from whom the information was obtained.

An ideally "intelligent" system, in contrast, would inductively generate the classification system. Induction of general rules from specific cases is, after all, how human expert knowledge is derived (though not necessarily how it is transmitted from expert to student) in the first place. An inductive rule-generating system would have two advantages over human-derived expert knowledge. First, the knowledge acquisition bottleneck would be removed. Second, a machine-generated set of rules might contain information which would be superior to those derived from a human based on the machine's potentially superior information processing capabilities. The development of such systems has been a major focus in the artificial intelligence field of "machine learning": Forsyth and Rada (1986) and Michalski, Carbonell and Mitchell (1983) provide two reasonably up-to-date references on this field.

This paper employs a bootstrapped version of one of the most common inductive learning algorithms, ID3/CLS, which is employed in most commercially-available inductive expert systems. Thompson and Thompson (1986) provides a very readable description of the technique; Garson (1987) describes it in the context of a political science modeling problem. The data analyzed are the Butterworth data on interstate security conflicts.

2. The Bootstrapped CLS Algorithm (B/CLS)

The core of the algorithm used in this paper is the tree-building CLS ("Concept Learning System") technique developed by Earl Hunt (1966). Hunt's CLS created a classification tree by successively determining which variable out of a given set to use to make the next node of the tree. Quinlan (1979, 1983) made a key modification to CLS by employing the information-theoretic concept of entropy to determine that variable order; his overall system was called ID3. Quinlan was working on the problem of chess-end games and the full ID3 algorithm involved a scheme for iteratively generating rule sets out of very large sets of data by looking at subsets of data and then seeing what exceptions existed in the full set (see Cohen and Feigenbaum, 1982:406). In the problem I'm working with, and the problems discussed in Thompson and Thompson (1986), the data sets are relatively small and entropy-based CLS is computationally efficient so only the CLS part of the algorithm is used. So technically the algorithm being used is Quinlan's modification for ID3 of Hunt's CLS, but I will refer to it as simply CLS (inconveniently, both Thompson and Thompson and Garson call the method ID3, which I suspect will be the term to catch on...). ID3/CLS can be modified to work with interval as well as nominal data (see Garson, 1987) but in this paper the data are nominal.

The basic mechanism of CLS is simple. The data are a set of cases, each containing a set of categorical (nominal) independent variables and a single categorical dependent variable which is to be predicted. CLS starts building the classification tree by choosing the independent variable which minimizes the total entropy of the dependent variable after the cases have been split on that variable. Entropy is defined using the standard information theory definition:

$$H = \sum_i p_i \log_2(p_i) \quad \text{where } p_i = \text{proportion of dependent variable values in category } i$$

CLS operates by successively partitioning the data set based on the values of variables in the tree. For any subset of the data C , the entropy given a specific value of a dependent variable a_j is given by

$$H(C|a_j) = -\sum_i p(c_i|a_j) \log_2(p(c_i|a_j))$$

where $p(c_i|a_j)$ = proportion of the cases in the subset C where the dependent variable has the value i and the independent variable A has the value a_j

The total entropy of the subsets generated by an independent variable A is just the sum of the entropies of each category in that variable times their probabilities:

$$H(C|A) = \sum_j p(a_j) H(C|a_j)$$

Because CLS works by successive partition, the classification tree can be constructed recursively. In pseudocode, the basic algorithm is:

Procedure Split(C,V)

(* Find the optimal partition of the data set C based on the independent variables in V *)

begin

Find A in V which minimizes H(C|A)

for each value a_j in A do

if $H(C|a_j) > 0$

then

Define the subset $C^* = (C|A = a_j)$

Define $V^* = V - A$

(* remove A from V *)

Split(C^*, V^*)

(* partition the subset *)

else

Finished (* all cases in C have the same value *)

end

In plain English, CLS starts by choosing the variable which will maximize the probability of classifying the cases. It then splits the cases into M subgroups based on their value on that variable. For each of those subgroups, the procedure is repeated to find which of the remaining variables provides the best classification on that subgroup. Note that this choice can be -- and usually is -- different depending on the branches taken before. This variable is used to generate sub-sub-groups, and the procedure is repeated on those groups. The procedure is repeated until all of the cases in a subgroup have the same value for the dependent variable, or one runs out of variables.

Because CLS uses different variables depending on the subset being classified (equivalently, depending on where it is in the tree) a classification tree is quite different from a contingency table. In a contingency table, the nesting of variables is identical for all cases, whereas in a classification tree a variable necessary to classify one set of cases may be irrelevant for others. To use a non-political example, if one were building a classification tree which identified both birds and mammals, the branches involving "birds" were presumably ask questions about feathers that would not be asked about the mammals.

On the surface this asymmetry of the tree leads to a more complex knowledge representation structure than those traditionally used in social science research. In terms of the information demands, however, it is probably more robust against extraneous data. If a variable contributes nothing to classification of a subset, it can simply be ignored and have no effect on the classification within that subset. In fact, a rather quirky feature of CLS is that a missing value is treated the same as any other value, and hence can, under some circumstances, carry information. From a statistical standpoint, this is quite weird, but from a common-sense standpoint this is quite a nice feature, since "missing" may in fact carry information. For example, as any user of survey research information knows, people who are never home, who terminate interviews early or who refuse to answer certain questions are not randomly distributed: the fact of the data being missing may tell one something about the case. Similarly, if two variables carry redundant information, one is simply ignored without causing the problems that colinearity causes in a similar situation in the general linear model.

In a data set with a large number of independent variables, CLS will usually classify 100% of the variables correctly. The only situation where this would fail would be a case where two cases were identical on all independent variables and had different values of the dependent variable; this did not occur in the Butterworth set with all variables, though it did occur when the variable set was restricted.

While 100% accuracy sounds impressive, the pragmatic value of this is dubious because many roots of the tree terminate in single cases. In order to ascertain the predictive value of the variables, one must do some form of split-sample test, building the tree on part of the data (training case) and then testing it on the remaining part (validation cases). This method is commonly employed in expert systems work, since 100% prediction on the training cases is the rule rather than the exception in inductive rule based systems such as ID3 and AQ15 (see Michalski, Carbonell and Mitchell, 1983).

Following the contemporary statistical practice of "bootstrapping" (see Diaconis and Efron, 1983) to empirically ascertain the random structure of a non-repeatable set of data, I have extended the simple split-sample test characteristic of machine-learning work to a full-scale statistical bootstrap by doing a large number (variously 50 to 200 in these studies) of random split samples. The basic bootstrap involves

```

for i:=1 to Number_of_Experiments
  begin
    Randomly select half of the cases as a training set
    Compute a tree describing that sample using CLS
    Classify the remaining cases -- the validation set -- using that tree
    Compute statistics on the accuracy of that classification
  end;
Compute summary statistics
Construct trees using only the most frequently used variables

```

This method in effect does a series of "what-if" experiments on the data, asking how accurately CLS could predict the unknown cases if only half of the cases were known. This method I am calling "Bootstrapped CLS", or B/CLS.

The final step is to look at the variables which most commonly used in building the trees and use this subset only to construct trees. This potentially provides two advantages:

- **Parsimony with respect to the information required to classify a case:** It is quite likely that most of the classification can be done with only a small subset of the independent variables. The identification of that subset is consistent with the usual statistical enterprise.

- **Increased accuracy through general rather than specific rules:** A trade-off exists between accuracy and generality. Because CLS tends to classify cases with 100% accuracy, it has no generality — i.e. it classifies every case down to the last specific characteristic required to classify the case. Such a tree may work fine for the training set but then fail on the validation set because of the specificity. By forcing CLS to use a smaller number of independent variables, rules can be kept more general, and possibly work more accurately on the validation set. This is a hope, however, not a rule, and depends on the amount of regularity in the data itself.

The B/CLS method has been implemented in a fairly straightforward Turbo Pascal program running on an Apple Macintosh. A summary of that program is found in Appendix B. A copy of the program is available from the author: it uses no Macintosh features and should port to an IBM without the slightest difficulty. The program runs fairly quickly, producing a classification tree in about 45 seconds for 38 independent variables and 100 cases. Running the bootstrap samples takes forever (more exactly, about 14 hours for 200-experiment samples running all 5 dependent variables) but can be done easily and inexpensively by letting the data lab Macintoshes run overnight.

3. Data

Data in this study are from the Butterworth "Interstate Security Conflicts, 1945-1974" data set (Butterworth, 1976; ICPSR 7586). This set covers 310 cases of interstate conflict and codes 47 variables dealing with conflict characteristics, actions to manage the conflict and the outcome of that management. The variables in the data set are listed in Appendix A.

Variables dealing with characteristics and management actions were treated as independent variables. Variable 23 ("Specific agent") was not included in the analysis: this contains 45 categories and in many cases there is only one conflict per category due to the specificity of the agent (e.g. "Pope Paul VI", "US/Argentina/Brazil/Chile"). Obviously under CLS this variable would have a large amount of discriminatory power since it predicts many single cases; equally obvious is that it would have no generalizability. The general character of the management agent (i.e. states, type of international organization, individuals) is coded in variable 22, "Management Agent". For obvious reasons, the case number was not used as a variable; and since I wanted to deal only with nominal variables, I also did not include variable 2, "Number of Agents".

The variables on the management outcome (variables 43-47) were treated as dependent variables. All dependent variables have the same codes: in the absence of activity by the agent, the outcome of the conflict with respect to the dependent variable would be

0	No different
1	Somewhat different
2	Very different
9	Variable is inapplicable to this situation

Cases were selected on the following criteria:

1. Only those cases identified by Butterworth as "Core Cases" (variable 3) were used. This means that each conflict was considered only once; the full data set has multiple entries on some conflicts because multiple agents attempted to manage it.
2. If a dependent variable was coded '9' ("Inapplicable"), the case was not included.

Application of these two criteria left between about 100 and 200 cases depending on the variable. The five dependent variables, the number of valid cases and the distribution of their values is given in the Table 1:

Variable	N	Values		
		< 0 >	< 1 >	< 2 >
Stopping Hostilities	98	65%	26%	9%
Abating the Conflict	192	57%	31%	12%
Isolating the Conflict	106	74%	18%	8%
Restraining the Conflict	191	54%	32%	13%
Settling the Conflict	192	73%	16%	10%

Table 1
Distribution of Dependent Variables

4. Measures of Success

Two measures of success were computed. The first was simple "accuracy", i.e.

$$\text{Accuracy} = (\text{correct predictions}) / (\text{total cases})$$

The problem with the accuracy measure -- in this and most other international relations data -- is that these data are heavily modal. International affairs are boring: the same thing happens most of the time. Because the modal category accounts for about 55% - 75% of the cases, the simple rule "predict the mode" will have an accuracy of 55% - 75%, and is thus a tough horse to beat. This problem was also encountered in earlier work using a Holland classifier (Schrodt, 1986a) and is a problem in Kaw (1986) where a complex classification model does worse than the modal prediction.

At the same time, the mode is an extremely unsatisfactory null model in the sense that it has little practical utility. Clearly the objective of any predictive model is to predict non-modal cases as well as modal cases. Human analysts can be excused for inaccurately predicting escalation in a number of cases where a crisis does not in fact escalate if they manage to correctly predict the ones that do. In other words, there is more value to predicting rare events than common events.

One could assign any number of different weights to this but given that we are working in an entropy framework, the obvious weight is the entropy measure $\ln(p_i)$. The measure I've used is "entropy explained", defined as follows:

$$\begin{aligned} \text{ME} &= \sum_i (\text{correct predictions}_i / \text{cases}) \ln(p_i) && \text{(Model entropy)} \\ \text{DE} &= \sum_i p_i \ln(p_i) && \text{(Dependent var entropy)} \end{aligned}$$

$$\text{Entropy Ratio} = \text{ER} = \text{ME}/\text{DE}$$

The index i is over the values of the dependent variable; p_i in both equations is the proportion of each value in the observed cases of the dependent variable. ER will vary between 0.0 (no correct predictions) and 1.0 (perfect prediction). ER can be computed for the modal prediction as well as the ID3 predictions and the two compared. Note that since the natural logarithm of a number is equal to a constant times the logarithm base 2, there is no loss of generality in using $\ln(p)$ rather than $\log_2(p)$.

5. Results

5.1. Computational Design

The results reported here are reported on two series of computer runs with the following stages:

1. Run two sets of 200 Monte-Carlo split-sample tests and accumulate aggregate statistics on how frequently each independent variable was used in the classification tree and on the fit of the trees on the validation set. This is the process I am calling B/CLS.
2. Based on the results in [1], run a series of 50 split-samples using the N most highly ranked variables where $N=3, \dots, 10$. This provides an indication of the accuracy of trees using a small number of variables.

This design was done with two different sets of independent variables. The first included all 38 of the independent variables discussed above. The second set deleted the four "Technique of Management" variables, leaving 34 variables. The second set was used because the "Technique of Management" had the largest number of categories of any of the variables and naturally were chosen very frequently; the specificity of these variables also made them somewhat suspect since the specific technique is presumably closely related to the expected outcome.

5.2. Classification Trees

Complete classification trees were initially run using the complete set of variables. Unsurprisingly given the large number of variables, these trees correctly classified 100% of the cases. The trees were fairly parsimonious, rarely going deeper than five levels; though this was substantially aided by the availability of the "Technique of Management" variable to initially partition the set.

A more interesting (and much more parsimonious, as these things go...) set of classification trees are presented in Figure 2-5. These trees use only the top five variables identified from the B/CLS on the 34-variable set. To interpret the trees: the variables are in bold face, the values are in plain text followed by a '|' character. Each level of indentation represents another level of the tree; at the root of the tree the set of numbers identifies the case numbers (see Butterworth, 1976) which were classified at that root, and the number in '<_>' is the value of the dependent variable for those cases.

Because a limited number of variables were used, some cases were not accurately categorized — these are indicated by a set of case numbers followed by '(_)': the number in '[>_<]' following this set is the value at that root which is used to minimize the unexplained entropy at that root. These nodes have been edited for parsimony: the unedited tree would keep adding levels until it ran out of variables to try to reduce the entropy. These were pruned for clarity: this has no effect on the classification power of the tree.

At a number of points in the tree, only some of the values of the variable are used as branches: this occurs when those other values did not occur in the subsets examined at that node. If the system encounters a value which is not present at a node it predict the modal value of the variables in the subset at that point. This doesn't happen in the trees displayed here because the entire set of cases was used for

training but it occurs fairly frequently (10%-20% of the cases) in the B/CLS process. In effect this "unrecognized" branch is an additional part of the B/CLS trees not present in these trees built from the entire set of cases.

Examining the trees (a magnifying glass helps...), several things are apparent. First, despite the fact that only five of the original 40 variables in the Butterworth set are used, the classification accuracy is very high: between 95% and 100% as measured by either simple accuracy (Acc) or entropy-explained (ER). The Acc and ER measures have roughly the same values. Also in this instance we do manage to beat the mode.

Second, the trees are still fairly complex, though they are not so complex as to always terminate in single cases. The "Abating Conflict" tree has about 140 roots to classify 192 cases and in general the number of roots is proportional to the number of cases. However, these roots are so numerous in part because the tree is purely conjunction (i.e. consists solely of "and" branches. By allowing even simple rules of logic to simplify branches the trees could be simplified considerably. For example, at the end of the **Action[Weak Resolution] / Likelihood Disappear[5-10 yrs]** branching in the "Abating Conflict" tree are four branches off Leadership which classify 12 cases. These could be reduced to two by using a rule of the form

1 Superpower Leadership [yes/no]

or eliminating the final rule altogether at the cost of one incorrect classification. As far as parsimony is concerned, these trees have achieved a lot in terms of the required information but could still be reduced a lot in terms of structure.

Third, note that quite a few cases are classified without going very deeply into the tree -- usually cases begin to be classified at the third level of the tree (i.e. knowing the values of only three variables would allow classification). Thus while the global structure of the tree is relatively complex, the local structure required to classify a particular case is not, and the specific rules are certainly well within the information processing capabilities of humans.

5.3. B/CLS Rank-Order Results

The tables on pages I-9 to I-18 give the aggregate results of the B/CLS runs for all dependent variables and both the 38- and 34-variable independent variable sets. Several statistics are presented:

- **Modal prediction Acc and ER:**

The values of these statistics which would be obtained following the rule "predict the mode". Note that due to some inconsistency in the tables these aren't always in the same order...

- **"Accuracy" and "Average ER"**

The average values for each statistic across 200 random split-sample tests

- **Level where used:**

This shows the frequency with which each variable was selected for use in the trees. Level 0 is the top of the tree -- i.e. the first variable used to partition the cases. Levels below 4 are not recorded: use of variables at the lower levels are reflected in a difference between the total of the levels and the Total frequency.

• **Total:**

The total number of times a variable was used in the tree. If a variable is used more than once in the same tree, it is counted multiple times. Variables are listed sorted on this value.

The rank-order tables reveal several general characteristics of the trees generated in the bootstrap samples. First, the trees rarely go very deep -- level 4 is close to the limit -- despite the availability of about 35 variables. 5 or fewer variables seems to almost always suffice for classification. This may be due in part to sample size: the split-samples have only about 50-100 cases.

Second, there are unquestionably patterns in the variables which are used. The frequencies seem to follow pretty much a rank-size-law-style curve (i.e. a hyperbola) and there is a great deal of consistency across the dependent variables. Variables are clearly not being chosen at random, though all of the variables are used at least once. The rank-orders produced by the two independent runs on each of the data sets were also quite similar, particularly for the most frequent variables.

Third, unsurprisingly the "Technique of Management" variables are used frequently when they are available. More interesting is the fact that inclusion of these variables has little effect on the relative rank of the remaining variables except for the "Action" variable, which carries much the same information as the "Technique" variables.

5.4. Distribution of Accuracy and ER

Both the Acc and EE measures are roughly normally distributed; figures 7 and 8 show the distributions of ER. In none of the cases examined did either Acc or ER exhibit any noticeable departure from a bell-shaped curve. While the standard deviation was not computed, it appears to be about 0.07 for Acc and 0.1 for ER. Due to this rather boring normality of the distributions, all discussions of these summary statistics will be done with respect to their means. These are reported in Table 2.

Table 2
Fit of the Model

Variable	38 Model*		34 Model*		Mode	
	Acc	EE	Acc	ER	Acc	ER
Stopping Hostilities	.583	.407	.581	.430	.653	.329
Abating the Conflict	.503	.401	.495	.407	.568	.342
Isolating the Conflict	.668	.397	.663	.414	.745	.303
Restraining the Conflict	.484	.407	.484	.416	.545	.344
Settling the Conflict	.619	.370	.603	.372	.734	.300

*Statistics for CLS are mean values over 200 bootstrap experiments

As fully expected, the mean accuracy was well below that of the modal prediction. If accuracy is the only criterion, just predict the mode... On the ER measure, in contrast, the models consistently did better than the mode, usually around 20% - 30% better. There is a slight advantage of the 34-variable models over the 38-variable modes on the ER measure: while numerically this is quite tiny it is probably still statistically significant given the size of the samples.

While the accuracy and EE statistics are not overly impressive, a point which should be kept in mind is that these are computed on split-sample tests -- the training set contained none of the cases that were in the validation sets. Since the classification trees are generally 100% accurate, the accuracy and EE on the total sample would be around 0.7 - 0.8 ($50 + 0.5 * EE$ or Accuracy) for the total set when only the training set was used to construct the tree. These statistics are the ones that would be comparable to an R^2 and are fairly impressive; they would also be greater than the model prediction on the complete sample. As noted above, Acc and ER both approach 1.0 when the entire set is used to construct the tree.

5.5. Restricting the Number of Variables

Figures 9 and 10 report the results of restricting the number of variables which could be used. The objective of these experiments was to increase the number of variables allowed in the classification tree to see how much information was gained or lost using smaller trees. Variables were added according to their rank order in the initial experiments. 50 experiments were done at each level; earlier experiments indicated that the mean values of Acc and ER stabilize by this number. The smallest number tested was [supposedly] 3, stepping up by one to ten. Due to a minor, late-detected bug in the program, the program only allowed N-1 levels to the tree, so we are testing something slightly different from that originally [the bug was not corrected prior to ISA due to the fact that this program requires 20 hours to run...]

As is clear from the figure, the number of variables can be reduced to about 4 or 5 without much loss in either ER or Acc, and in fact in some cases the reduced set of variables does slightly better than the full set. Beyond this, the curves are essentially flat and at no place is there a clear increase in the statistics. Some of this stability is due to modal predictions, though in just eyeballing the runs, I would guess that usually fewer than 20% of the cases are classified through modes.

There are two key implications to this. First, there is tremendous redundancy and noise in the information contained in the independent variables -- a relatively tiny subset holds about the same amount of classification information as the full set. However, it is not the case that any subset will work -- I tried an additional experiment of progressively deleting the top-ranked variables and, as expected, the average values of Acc and ER dropped as the best variables were eliminated. Second, the B/CLS algorithm obviously has some utility as a data reduction technique, at least if the Butterworth data set is representative. Just as step-wise regression can take a large set of variable (assuming absence of collinearity) and reduce it to a much smaller number, so can B/CLS ascertain the small set of variables which has almost the same classification power as a larger set.

Now, for a dog that didn't bark in the night: I did this experiment in the hopes that the ER/variables curve would be arch-shaped, not flat. This would be expected if it were the case that the additional variables only confuse things and lead one to overly complex models which are erroneous when validated with additional data. This didn't happen in any major way, though in these figures we again see a slight advantage to the models which do not use the technique of management variables.

6. Conclusion

The first conclusion is simply that the B/CLS algorithm works. Used on a set of data with between 100 and 200 cases and 38 independent variables, B/CLS is able to reduce the independent variables to a small set of five or so which can achieve between 95% and 100% accuracy when used to construct a classification tree using

the entire data set, and which can do better than the mode in an entropy-based measure even in split-sample tests. The technique appears to be quite robust and did not exhibit any unusual behaviors in any of the various tests. While it is certainly not the fastest technique ever devised, most of the computational burden comes in doing the bootstrapped tests, and these in turn are inherently parallel: the core CLS algorithm is reasonably efficient. The computer time involved in these experiments was in large part due to the fact I was working with five dependent variables and doing 200 Monte-Carlo samples. To analyze one dependent variable using 50 samples -- a design which would probably produce results quite similar to the 200 sample protocol -- the computational time would have been less than one Macintosh-hour.

Given the effectiveness of even a simple machine-induction method like CLS there it seems to me little point in constructing expert systems classification trees by hand. Human expertise is still necessary to identify the relevant variables, but if a classification tree is to be the knowledge representation structure, then CLS is probably going to achieve a far better global structure than a human expert because it is more systematic. As noted above, CLS still leaves a lot to be desired in terms of the aesthetics and parsimony of the tree, and of course trees are not the only possible non-statistical knowledge structure, but if one is going to construct a tree by induction, I suspect machine induction will be superior to human induction just as statistical regression is superior to "eyeballing" a line if least-square is a criterion. More sophisticated algorithms for doing logical operations on a CLS-produced tree could also improve the aesthetics without a lot of human intervention.

From the standpoint of human cognition about international affairs, this experiment has a couple of implications. First, it indicates how in modeling an issue such as international conflict the relatively limited information processing of humans can still be relatively successful. To the extent that the Butterworth data is a good characterization of the problem, the task of successful classification (i.e. prediction) simply isn't that difficult from an information standpoint and a fairly simple model works as well, or better, than a complex one. The Butterworth set focuses on the sorts of categorical variables which human theorists are likely to use in trying to predict conflict outcomes (unlike interval variable models, which tend to use measures quite different than those used by human analysts) and the experiments indicate that focusing on a small number of variables can still lead to highly accurate classifications, provided that the knowledge structure is sufficiently complex. Since the limitations in human information processing are primarily in the serial processing of information (that is, the maintenance in short-term memory of sufficient information to classify a case) rather than the storage and recall of rules (i.e. the complete tree or something similar to it), this is a knowledge representation model which is one could easily conceive of being implemented in a human, unlike regression analysis. Classification involves only the application of a tree structure to five or fewer variables and hence has limited short-term memory requirements; the storage of 200 or more rules in associative memory is an equally trivial task for the human brain.

Second, the experiments open the possibility that very different models of international conflict may have almost exactly the same empirical accuracy. The amount of regularity in this data, as measured through split-sample tests, isn't all that great, so any split-sample model is going to contain a lot of error. Models attempting to predict future behavior on the basis of past observed behavior are, of course, a form of split-sample test. While human analysts do not look at all historical data in a systematic split-sample fashion, a sophisticated analyst might go through a mental procedure somewhat like a bootstrap through examining an increasing number of cases and tweaking his or her mental model sequentially to adjust for those.

Eventually the analyst arrives at a mental model which uses those variables which seemed to be the most useful most of the time, which is exactly what happens with B/CLS. These models may not be formally stored as a tree given the differences between human and machine memory, but the success of classification trees in implementing expert systems in a broad range of human expertise shows that such expertise can be thoroughly captured by using trees as if they were the actual knowledge structure.

More importantly, the collective development of models international behavior in an organization or within a theoretical paradigm clearly works through sequential bootstrapping, using only some set of cases in recent memory and a biased sample of "classical" cases. As that set shifts through time (assuming it isn't highly autocorrelated, and for an analyst looking at the entire world probably is the case -- Nicaragua doesn't have a whole heck of a lot in common with Lebanon and neither of those with Cambodia) and nobody bothers to go back and systematically validate the model against cases in the distant past. As these experiments indicate, because of the redundancy in the data, two analysts or organizations constructing very different perfectly-fitting models from selected cases may find that those models fit just about as well on future cases.

In short, somewhere in the data set we encounter a fundamental limit in the predictability of international events. The approach of B/CLS has, in effect, decided to drop parsimony as one of the sources of noise -- the model is allowed to reach 100% predictive accuracy on the training set, which a linear model, in general, would not do. As it happens, this doesn't lead to a whole lot of loss of parsimony -- the trees do not nest very deeply, and a small number of variables will categorize most training sets. But 100% accuracy on a training set does not lead to 100% accuracy on the validation set: instead 50% accuracy is more the rule. In other words, on average about 50% of the cases in a validation set are not described by information from the training set when the two are chosen randomly.

This, in turn, gives us a good idea of just how much noise is in the real world data, at least with respect to the variables of the Butterworth data set. Consider two extreme cases. At one extreme, suppose the data set consisted of the characteristics of 1,000 separate species of birds are subjected to B/CLS (i.e. the dependent variable has 1,000 different values). Here, the accuracy of split-sample tests is zero -- none of the cases in the validation set overlap with the training set and therefore none can be predicted inductively. At the other extreme, suppose the data set consisted of the characteristics of 1,000 birds of only 10 very distinct species. In this instance, the accuracy would be close to 100%, because the only way a bird could be misclassified is if it had no representatives in the training set, which would occur with a probability of [roughly] 0.99^{500} , a small number.

The Butterworth data are somewhere in between these two extremes. There is sufficient replication that about half of the cases are classified correctly (albeit some of this may be blind luck), but the other half have not been correctly characterized. In contrast to statistical treatments, I would argue, this is not a case of a limitation of the method or the model: we can, after all, correctly classify 100% of the existing cases if we wish by using the full set of variables. That 100% accuracy tells us little, however, about the chances of classifying the next, unknown, case correctly, whereas the B/CLS distributions of the fit statistics probably tell us a lot. Furthermore, B/CLS probably exhausts the information which can be obtained from this set of variables, by machines or by humans, though obviously a variety of more elegant or parsimonious structures may be available for representing that information.

A final didactic and prophylactic note on the position of this research in the political science "artificial intelligence" literature. Is B/CLS AI? On the one hand, it is purely and simply an inductive technique, differing little from a standard statistical method such as discriminant analysis (DA). Just as DA takes a set of examples, computes a set of discriminant functions, then makes predictions (with a certain computable accuracy) based on those functions, so B/CLS takes a set of examples, produces a tree, and makes predictions based on that tree. In terms of outputs, the two are almost identical except for the fact that DA uses interval independent variables and B/CLS uses nominal.

In terms of the underlying model, however, B/CLS and discriminant analysis are very far apart. The mathematical basis of DA is the general linear model and the normal family of distributions. The mathematical basis of B/CLS is the decision-tree and information theory. DA rests in least-squares minimization and the calculus of the real line; B/CLS rests on recursion.

I would contend, of course, that B/CLS is artificial intelligence. The technique was developed in the AI community; it uses a knowledge representation structure which comes out of computer science, not statistics, and that representation structure can certainly be argued to parallel human cognitive abilities, at least to the extent that systems utilizing such structures can perform at human expert levels of accuracy. In fact only thing about this system which is not typical of AI is that it shows performance rather than promise: B/CLS works on a real problem in finite time, and the mechanism by which it works is quite straightforward. I worry, of course, that because inductive machine learning techniques are "only" inductive, one will miss the fact that they successfully accomplish things which were a few years ago thought to be all but impossible.

A method such as B/CLS provides knowledge representation which one can imagine a human analyst employing. In this respect, I would suggest, it is quite different from either statistical or dynamic models. We know, on the basis of experiments in cognitive psychology, that the information processing requirements of either a general linear model or a complicated differential equation are beyond the capabilities of the brain. I have also argued, more controversially, that the information requirements of rational choice/expected utility models also eliminate most of those models from consideration as plausible modes of human cognition about international events. B/CLS and related models (e.g. syntactic or template-based pattern recognition) have neither restriction: their information requirements, processing requirements and storage requirements are arguably within the bounds of human cognitive faculties, to the extent that those are known. This is not to say that precisely the same techniques are used by humans and machines -- given the different architectures of the physical hardware involved, one cannot expect total convergence -- but the AI methods come considerably closer than existing alternative models. To that degree an inductive method such as B/CLS is clearly artificial intelligence -- it is an artificial approximation of a technique which could be plausibly implemented in human intelligence.

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APPENDIX A
VARIABLES IN THE BUTTERWORTH DATA SET

Variable 1 Case ID
Variable 2 N of Agents
Variable 3 Core Case

>>> Independent Variables <<<

Variable 4 Fatalities
Variable 5 Duration
Variable 6 Likelihood of Abatement
Variable 7 Likelihood of Disappearance (in terms of time until likely disappearance)
Variable 8 Likely Degree of Spread
Variable 9 Likelihood of Superpower War
Variable 10 Type of Warfare
Variable 11 Strategic Category
Variable 12 Strongest Antagonist
Variable 13 Power Disparity
Variable 14 Degree of Spread
Variable 15 Type of Issue
Variable 16 Alignment of Parties
Variable 17 Ethnic Conflict
Variable 18 Ideological Conflict
Variable 19 Past Relationship
Variable 20 Great Power Interests
Variable 21 System Period
Variable 22 Management Agent
Variable 23 Specific Agent
Variable 24 Other Managers
Variable 25 Initiative for Intervention
Variable 26 Previous Involvement
Variable 27 Agent's Bias
Variable 28 Agent's Autonomy
Variable 29 Phase of Agent's Intervention
Variable 30 Phase of Agent's First Action
Variable 31 Phase of Agent's Strongest Action
Variable 32 Technique of Management Action(1st)
Variable 33 Technique of Management Action(2nd)
Variable 34 Technique of Management Action(3rd)
Variable 35 Technique of Management Action(4th)
Variable 36 Agent's Previous Role
Variable 37 Leadership (type of agent taking leadership in resolving conflict)
Variable 38 Joint Leadership
Variable 39 Level of Agreement
Variable 40 Action
Variable 41 Agent's Relative Power
Variable 42 Agent's Primary Role

>>> Dependent Variables <<<

Variable 43 Stopping Hostilities
Variable 44 Abating the Conflict
Variable 45 Isolating the Conflict
Variable 46 Restraining the Conflict
Variable 47 Settling the Conflict

APPENDIX B SUMMARY OF PROGRAM CODE

This appendix gives a summary of the code in the B/CLS program. In order to save space, this is very abbreviated but does include the full code on the core CLS algorithm.

I would not advise trying to reconstruct the entire program from the code: if you want to try that, just send me a disk and I'll make a copy for you. The source is considerably more commented than this summary.

The program is standard Turbo Pascal without any funny tricks or Macintosh-specific procedures, and should port virtually without change to an IBM-PC. The chief disadvantage is that the input is real specific to the Butterworth set, and since I store the entire data set in memory the program is coming close to the 32K variable limit. Output is simple text to a "dumb terminal" rather than Macintosh output.

PROGRAM B_CLS;

(* This is a bootstrapped implementation of the Quinlan/Hunt CLS classification algorithm for use with the Butterworth Interstate Security Conflict Data set (ICPSR 7536).

Version 1.0 07.4.2 Philip A. Schrodt *)

Const

```
N_Var = 47; (* Total variables in data set *)
N_Indp = 42; (* N of independent vars *)
N_Case = 310; (* N of cases (what else...) *)
Max_Value = 14; (* Maximum number of categories in a variable *)
Debug = 1; (* Control level of output *)
Max_Level = 6; (* Max recursion level Var_Record array will keep track of *)
N_Ex = 200; (* N of Monte Carlo experiments *)
```

(* ***** INITIALIZATION ROUTINES ***** *)

Procedure Init_Var;

(* Initializes assorted variables *)

Procedure Init_Labels;

(* Labels from the Butterworth data set *)

Procedure Init_State;

(* Zero the various statistical counters and print out some information on the dependent variable *)

(* ***** INPUT/OUTPUT ROUTINES ***** *)

Procedure Read_Case(var ok:boolean);

(* Reads a case from the Interstate Security Conflicts data set, throws out if missing (value=9) or non-core. *)

Procedure Read_Input;

(* Read in the data and put it in the Data array *)

Procedure Init_Disk;

(* Initialize Diskout and cycle the random number generator *)

Procedure Print_Record;

(* Print the various aggregate statistics in the disk file Diskout. *)

(* ***** CLS ROUTINES ***** *)

Function Predict(i:integer):integer;

(* Uses the tree to make a prediction on case i. Basically just follows out the tree until it finds a prediction. If the case can't be followed out to the bottom of the tree, the mode (at that point in the tree) is predicted, having conveniently stored this information earlier *)

Procedure Expand_Node(Sub:VSubSet;LUsed:UArray;lev:integer;var link:integer);

(* Expands the node given Sub, LUsed. This is a recursive procedure which constructs the whole tree. *)

Function Entropy(i:integer):real;

(* Computes entropy of y given var i *)

```
var ka,kb: integer;
    e,p,pc: real;
    kount: array[0..max_value,0..max_value] of integer;
    tot: array[0..max_value] of integer;
    gtot: integer;
```

begin

(* Initialize the various tallies *)

```
gtot:=0;
for ka:=0 to max_value do begin
for kb:= 0 to max_value do kount[ka,kb]:=0;
tot[ka]:=0;
end;
```

(* Go through the data and kount frequencies given the current subset *)

```
for ka:=1 to N_Size do
if sub[ka] then
begin
gtot:=gtot+1;
tot[Data[ka,i]] := tot[Data[ka,i]] + 1;
kount[y[ka],Data[ka,i]]:=kount[y[ka],Data[ka,i]]+1;
end;
```

(* Now compute entropy *)

e:=0.0;

```
for ka:=0 to max_value do
```

```
if tot[ka]>0 then (* Ignore codes which don't show up in the data... *)
```

```

begin
  pc:=tot[ka]/gtot;
  for kb:=0 to max_value do
    if kount[kb,ka]>0 then begin
      p:=kount[kb,ka]/tot[ka];
      e:=e + pc*p*ln(p); (* log2(x) equals a constant*ln(x) so this is okay... *)
    end;
  end;
  entropy:= -e;
end; (* Entropy *)

Function Dep_Entropy(var mode:integer):real;
(* Computes entropy of the dependent variables. Mode returns the modal value of the dependent
variable in the current subset. This returning a value (Mode) in a function call is VERY BAD
FORM but it saves a second pass through the data... *)

Procedure Val_Freq(i:integer;var kount:Value_Array);
(* kount returns counts of entries in var i *)

Procedure Compute_E(var ind:integer;var low:real);
(* Find the variable with the lowest classification entropy. This actually
does the classification at any given level *)

var ka: integer;
    Et: real;

begin
  ind:=1;
  low:=9999.0; (* This conceivably could cause a problem someday... *)
  for ka:= 1 to N_Indp do
    begin (* Go through all vars and select one with the lowest entropy *)
      if not L_Used[ka]
      then begin
        Et:=entropy(ka);
        if Et<low then begin
          low:=Et;
          ind:=ka;
        end;
      end;
    end;
  end;

  if keypressed then begin (* An escape hatch to interrupt program... *)
    Print_Record;
    Close(diskout);
    halt;
  end;
end; (* Compute_E *)

```

```

(* *** Main procedure *** *)
begin
  (* This terminates either when we reach an entropy of zero or when there are no
more variables left to use in the tree. *)

  If Dep_Entropy(mode) = 0.0 then begin (* Terminate on zero entropy *)
    for ka:= 1 to N_Size do
      If Sub[ka] then begin
        Write(outfl,Case_ID[ka]-4);
        kb:=Y[ka];
        link:=-kb;
      end;
      WriteIn(outfl, '<,kb:2,');
      Exit;
    end;
    (* Set to the value maximizing ER if
we've run out of variables *)

    If Lev = N_Used-1 (* N_Used is the number of variables available *)
    then begin (* This was a bug -- it should have been N_Used, not N_Used-1 *)
      for kb:= 0 to max_value do ValAr[kb]:=0;
      for ka:= 1 to N_Size do
        if Sub[ka] then begin
          ValAr[Y[ka]]:=ValAr[Y[ka]]+1;
        end;
      e:=ValAr[0]*Dep_Inp[0];
      lowi:=0;
      for ka:= 1 to Max_Value (* find the prediction which will minimize ER *)
        if e>ValAr[ka]*Dep_Inp[ka] (* Note that Dep_Inp is negative... *)
        then begin
          lowi:=ka;
          e:=ValAr[ka]*Dep_Inp[ka];
        end;
      link:=-lowi;
      Exit;
    end;

    Compute_E(lowi,e);

    (* Build the tree -- this is done in arrays rather than dynamically
to aid debugging and gain a little speed *)

    TrInd:=TrInd + 1;
    link :=TrInd;
    with Tree[TrInd] do begin
      VarN:=lowi;
      BrLoc:=BrInd;
      for kc:=0 to Max_Value do
        if ValAr[kc]>0 then begin
          Branch[BrInd].BVal := kc;
          BrInd:=BrInd + 1;
        end;
      end;
    end;
  end;
end;

```

```

end;
Brlen := Brind - BrLoc;
Branch[Brind].BVal := 99;
Branch[Brind].Blink := -mode;      (* Record the model value *)
Brind := Brind + 1;
end; (* with *)

(* Do the various categories by calling Expand_Node recursively... *)
LUsed[lev] := true;
LBrind := Tree[Trind].BrLoc;
for kb := 0 to Max_Value do
  if ValAr[kb] > 0 then begin
    for ka := 1 to N_Size do
      if sub[ka] then Lsub[ka] := (Data[ka,lev] = kb)
      else Lsub[ka] := false;
      Expand_Node(LSub,LUsed,lev+1,Branch[LBrind].Blink);
      LBrind := LBrind + 1;
    end;
  end; (* Expand_Node *)
end;

Procedure Computa_Stats;
(* Code for checking the predict function *)

(* ***** MAIN PROGRAM ***** *)

begin
  Init_Disk;      (* Initialize things *)
  Init_Labels;
  Init_Var;
  Dep_Var := 43;  (* Designate dependent variable *)
  Repeat         (* Repeat for all variables *)
  Read_Input;
  Init_Stats;

  for Ex := 1 to N_Ex do      (* Repeat Monte-Carlo experiments *)
  begin
    Init_Var;
    for ka := 1 to N_Size do  (* Select a sub-sample *)
      if GSub[ka] then MCSub[ka] := Odd(Random)
      else MCSub[ka] := false;
      Expand_Node(MCSub,Used,0,kb); (* Construct the tree *)
      Computa_Stats;          (* See how well it works on remaining cases *)
    end; (* for *)

    (* Code for constructing the bootstrapped trees goes here *)

    Print_Record;          (* Save information on Diskout *)
    Dep_Var := Dep_Var + 1;
  until Dep_Var > N_Var;
  Close(diskout);
end.

```

Dependent Variable: Stopping Hostilities

N = 98
 Acc = 0.990
 ER = 0.995

Leadership

1 superpower	Type of Issue						
	Interstate, cold	67	83	09	95	<0>	
	Internal, cold	Fatalities					
		26-100			263	<0>	
		101-1K			274	<0>	
		10K-100K			21	<1>	
	Internal, gen	158	250	291		<0>	
	Colonial	Fatalities					
		26-100			60	<0>	
		101-1K			16	<2>	
		2K-10K				Action	
						Discussion only 63 <0>	
						Coercive ops 167 <2>	
	Interstate, gen	Fatalities					
		1-25	Strongest Antagonist				
			Smallest Power 99 <2>				
			Small Power 25 <0>				
		26-100			125	<2>	
		101-1K			53	<1>	
		1K-2K			52	<1>	
		2K-10K			47	<1>	
2 superpowers		10	15	304		<1>	
Large powers	Strongest Antagonist						
	Middle Power	254 <1>					
	Large Power	100 122 228 <0>					
	Superpower	162 <0>					
Middle powers		92	178	260	273	<0>	
Small powers	Fatalities						
		1-25			108	<0>	
		26-100			229	<0>	
		101-1K			4	62 95 216 <0>	
		1K-2K			282	<2>	
		>100K			97	<0>	
Smallest powers	Fatalities						
	None	192 <0>					
	1-25	221 258 <0>					
	26-100	Strongest Antagonist					
		Smallest Power 259 <1>					
		Middle Power 161 <0>					
		Superpower 110 <1>					
	101-1K	Strongest Antagonist					
		Smallest Power 202 223 257 269 <0>					
		Middle Power 143 213 253 <0>					
		Large Power Type of Issue					
						Colonial Action	
						Strong resoluti 103 <0>	
						Noncoercive ops	
						86(0) 114(1) >1<1	
						Interstate, gen 227 <0>	
						Superpower 265 <0>	
	1K-2K	Strongest Antagonist					
		Smallest Power Type of Issue					
						Internal, gen 239 <0>	
						Colonial 217 <0>	
						Interstate, gen 198 <1>	
						Small Power 128 <1>	
						Middle Power 65 <0>	
						Large Power 68 <0>	
	2K-10K	43 310 <0>					
	10K-100K	154 <0>					
	>100K	179 <0>					
Sec-general	Fatalities						
		1-25	159 <0>				
		26-100	277 302 <0>				
	101-1K	Strongest Antagonist					
		Smallest Power 280 <1>					
		Small Power 308 <0>					
	>100K	194 <0>					
Inapplicable	Fatalities						
		1-25	57 <0>				
		26-100	292 <0>				
	101-1K	Action					
						Ancillary ops 132 190 <1>	
						Noncoercive ops 281 <1>	
						Coercive ops 175 231 <2>	
						Inapplicable Type of Issue	
						Internal, gen 244 <1>	
						Colonial Strongest Antagonist	
						Small Power 30 <1>	
						Large Power 75 <2>	
						Interstate, gen 243 <2>	
	1K-2K	119 130 <1>					
	2K-10K	Strongest Antagonist					
		Middle Power 29 <1>					
		Superpower 139 <0>					
	10K-100K	Strongest Antagonist					
		Smallest Power 265 301 <0>					
		Large Power 245 <1>					
		Superpower 118 211 <0>					
	>100K	Strongest Antagonist					
		Smallest Power 298 <1>					
		Middle Power 207 <0>					
		Large Power 11 <1>					
		Superpower 218 <0>					

Dependent Variable: Isolating the Conflict

N = 106 valid cases

Acc = 1.000

ER = 1.000

Leadership

1 superpower | Agent's Bias

Yes in this case

Strongest Antagonist

Small Power | 52 <0>

Middle Power | Action

Discussion only | 63 <0>

Coercive ops | 167 <2>

Large Power | 21 291 <0>

Superpower | 33 67 83 89 112 233 250 263 274 <0>

No | Action

Discussion only | 14 <1>

Strong resoluti | 53 <2>

Noncoercive ops | 37 61 99 152 <1>

Coercive ops | 47 157 <1>

2 superpowers | Fatalities

None | 60 <1>

1K-2K | 15 <0>

10K-100K | 10 <2>

Large powers | Strongest Antagonist

Middle Power | 264 <1>

Large Power | 19 71 100 122 182 228 <0>

Superpower | 162 <0>

Middle powers | Strongest Antagonist

Smallest Power | 260 <0>

Middle Power | 70 272 <0>

Large Power | 105 <1>

Superpower | 165 178 234 <0>

Small powers | Fatalities

None | 35 39 64 <0>

1-25 | 108 <0>

26-100 | 229 <0>

101-1K | 96 216 <0>

1K-2K | 282 <1>

>100K | 97 <0>

Smallest powers | Fatalities

None | 22 80 144 192 237 <0>

1-25 | 151 224 289 <0>

26-100 | 161 259 <0>

101-1K | Agent's Bias

Yes in this case | 222 241 253 257 265 269 <0>

No | Strongest Antagonist

Smallest Power | 202 <1>

Large Power | 86 227 <0>

1K-2K | 65 128 196 217 239 <0>

2K-10K | 43 310 <0>

10K-100K | 154 <0>

>100K | 179 <0>

Sec-general | Fatalities

1-25 | 159 <0>

26-100 | 302 <0>

101-1K | Strongest Antagonist

Smallest Power | 280 <1>

Small Power | 308 <0>

1K-2K | 230 <0>

>100K | 194 <0>

Inapplicable | Fatalities

None | 54 102 184 261 <0>

1-25 | Strongest Antagonist

Smallest Power | 37 <1>

Superpower | 206 <0>

101-1K | Action

Ancillary ops | 190 <1>

Noncoercive ops | 281 <2>

Coercive ops | 231 <1>

Inapplicable | 75 243 <2>

1K-2K | Strongest Antagonist

Large Power | 119 <2>

Superpower | 130 <1>

2K-10K | Strongest Antagonist

Middle Power | 29 <1>

Superpower | 139 <0>

10K-100K | Strongest Antagonist

Smallest Power | 265 301 <0>

Large Power | 245 <1>

Superpower | 118 211 <0>

>100K | Strongest Antagonist

Middle Power | 207 <0>

Large Power | 11 <2>

Superpower | 218 <0>

Dependent Variable: Abating the Conflict

N = 192 cases
 Acc = 0.943
 ER = 0.956

Action

Discussion only		Likelihood Abatement		
Very likely		Leadership		
1 superpower	94	138	173 <0>	
Middle powers	273	<0>		
Small powers	Fatalities			
	None	Likelihood Disappear.		
		<1 year 109(1) 135(0) 11(1)		
Smallest powers	79	80	<0>	
Possibly		Leadership		
1 superpower	14	233	<1>	
Large powers	Likelihood Disappear.			
	<1 year	127 <0>		
	1-5 yrs	182 <1>		
Small powers	20	35	108 <0>	
Smallest powers	Fatalities			
	None	Likelihood Disappear.		
	1-5 yrs	226(1) 236(0) 1(1)		
50/50		Leadership		
1 superpower	33	89	271 <0>	
2 superpowers	78	<1>		
Large powers	24	<0>		
Middle powers	148	<0>		
Small powers	197	<1>		
Smallest powers	221	<0>		
Unlikely	71	206	213 274 <0>	
Very unlikely	43	63	68 <0>	
Weak resolution		Likelihood Disappear.		
	<1 year	98 163 <0>		
	1-5 yrs	Fatalities		
	None	Likelihood Abatement		
		Very likely 237 <0>		
		Possibly 74(2) 144(0) 288(1) 1(2) <1		
	1-25	25 83 <0>		
	26-100	17 <0>		
	101-1K	92 178 <0>		
	10K-100K	291 <0>		
5-10 yrs		Leadership		
	1 superpower	13 <1>		
	Middle powers	6 70 165 234 <0>		
	Small powers	4 39 62 171 <0>		
	Smallest powers	40 65 279 <0>		
10-20 yrs	1	95 <0>		
>20 yrs	254	<1>		
Strong resolution		Fatalities		
	None	Leadership		
		1 superpower Likelihood Disappear.		
		<1 year 164 <1>		
		1-5 yrs 50 112 <0>		
	Large powers	Likelihood Disappear.		
		<1 year 58(2) 76(0) 1(2) <1		
		1-5 yrs Likelihood Abatement		
		Very likely 124 <2>		
		Unlikely 295 <0>		
	5-10 yrs	122 <2>		
	Small powers	64 <0>		
	Smallest powers	Likelihood Disappear.		
		<1 year 180 <2>		
		5-10 yrs 38 <0>		
		>20 yrs 238 <0>		
	1-25	224 258 <0>		
	26-100	Likelihood Abatement		
		Very likely 169 <1>		
		50/50 242 263 <0>		
	101-1K	Likelihood Abatement		
		50/50 53 <2>		
		Unlikely 223 241 257 <0>		
		Very unlikely 103 260 <0>		
	2K-10K	199 <1>		
	10K-100K	154 <0>		
	>100K	97 <0>		
Ancillary ops		Fatalities		
	None	Leadership		
		Sec-general 35 284 <1>		
		Inapplicable 102 261 <0>		
	1-25	Leadership		
		Smallest powers 151 200 <1>		
		Sec-general 159 220 <0>		
		Inapplicable 191 <1>		
	26-100	Likelihood Disappear.		
		1-5 yrs 277 302 <0>		
		5-10 yrs 212 <1>		
	101-1K	132 190 280 <1>		
	1K-2K	230 <1>		
	10K-100K	162 <0>		
	>100K	194 <0>		
Noncoercive ops		Likelihood Abatement		
	Very likely	Likelihood Disappear.		
		<1 year Fatalities		
		None 152 <2>		
		26-100 158 <0>		
		1-5 yrs 89 <0>		
		5-10 yrs 110 <1>		
	Possibly	Leadership		
		1 superpower Fatalities		
		1-25 97 <1>		
		101-1K 16 <2>		

Abating the Conflict, cont.

Large powers		100	<1>
Middle powers		240	<2>
Smallest powers		Likelihood Disappear.	
		<1 year	255 <2>
		1-5 yrs	46 <1>
Inapplicable		130	146 <1>
50/50 Leadership		1 superpower	Fatalities
		none	Likelihood Disappear.
			1-5 yrs 61 <1>
			20 yrs 8 <0>
		1-25	99 <2>
2 superpowers		60	<1>
Middle powers		Likelihood Disappear.	
		1-5 yrs	272 <0>
		5-10 yrs	28<2> 105<1> >2<1>
Small powers		218	<0>
Smallest powers		Fatalities	
		1-25	247 <0>
		26-100	259 <1>
		101-1K	Likelihood Disappear.
			1-5 yrs 86<0> 114<1> >1<1>
		5-10 yrs	202 <1>
		1K-2K	239 <0>
		2K-10K	310 <0>
Sec-general		66	<1>
Inapplicable		11	281 <2>
Unlikely Fatalities			
		1-25	289 <0>
		101-1K	96 233 265 <0>
		1K-2K	196<1> 217<0> >1<1>
		2K-10K	Likelihood Disappear.
			1-5 yrs 250 <0>
		10-20 yrs	29<1> 139<0> >1<1>
		>100K	179 <0>
Very unlikely Fatalities			
		none	19 22 32 <0>
		26-100	161 <0>
		101-1K	143<1> 227<0> >1<1>
		10K-100K	Leadership
			1 superpower 21 <1>
			Inapplicable 118 <0>
Coercive ops Fatalities			
		None	192 <0>
26-100 Likelihood Abatement			
		50/50	125 <2>
		Unlikely	229 <0>
		Very unlikely	228 <0>
101-1K Leadership			
		1 superpower	157 <1>
		2 superpowers	304 <1>
		Smallest powers	260 <0>
		Sec-general	308 <0>
		Inapplicable	Likelihood Abatement
			50/50 175 <2>
			Unlikely 231 <1>
1K-2K Leadership			
		1 superpower	52 <0>
		2 superpowers	15 <1>
		Small powers	282 <1>
		Smallest powers	128 <1>
		Inapplicable	119 <1>
2K-10K		47<1> 157<2>	>2<1>
10K-100K		10 245 264	<1>
>100K Likelihood Abatement			
		Unlikely	207 <0>
		Very unlikely	67 <1>
Inapplicable Fatalities			
		None	Likelihood Disappear.
			<1 year 300 <2>
			1-5 yrs 189 <1>
			5-10 yrs 184 <0>
			10-20 yrs 54 <0>
1-25 Likelihood Abatement			
		Very likely	205 <2>
		50/50	87 <2>
		Unlikely	57 134 <1>
20-100 Likelihood Abatement			
		Possibly	129 <2>
		50/50	292 <1>
101-1K Likelihood Disappear.			
		1-5 yrs	75 243 <2>
		5-10 yrs	244 <1>
		>20 yrs	30 <1>
10K-100K		211 285 301	<0>
>100K		218 296	<1>

Dependent Variable: Restraining the Conflict

N = 191 cases
 Acc = 0.963
 ER = 0.971

Action

Discussion only | Strongest Antagonist

Power Level	Likelihood	Abatement	Other
Smallest Power	Very likely	80 <0>	
	Possibly	226 <1>	
	50/50	148 <0>	
Small Power		135 236 <0>	
Middle Power		43 63 213 <0>	
Large Power	Likelihood		
	Very likely	109 <1>	
	Possibly		Leadership
			1 superpower 14 <1>
			Large powers 182 <1>
			Small powers 20 <0>
	50/50	78 197 <1>	
	Unlikely	71 <0>	
	Very unlikely	68 <0>	
Superpower	Likelihood		
	Very likely	79 94 138 173 273 <0>	
	Possibly		Leadership
			1 superpower 233 <1>
			Large powers 127 <0>
			Small powers 35 108 <0>
	50/50	24 33 89 221 271 <0>	
	Unlikely	206 274 <0>	
Weak resolution	Likelihood		
	Very likely	98 163 237 <0>	
	Possibly		Strongest Antagonist
			Smallest Power 40<0> 74<2> 1>2<1>
			Small Power 25 <1>
			Large Power Fatalities
			None Leadership
			Small powers 254 <1>
			Smallest powers 144 <0>
			101-1K 4 <0>
			Superpower 279 298 <1>
50/50	Fatalities		
			None 1 39 171 <0>
			1-25 95 <0>
			26-100 13 234 <1>
			101-1K 62 92 <0>
			1K-2K 65 <0>
	Unlikely	6 17 70 53 165 178 <0>	
	Very unlikely	291 <0>	
Strong resolution	Fatalities		
			None Strongest Antagonist
			Small Power 64 <0>
			Middle Power 124 164 190 <2>
			Large Power 53<2> 76<0> 1>2<1>
			Superpower 38 50 112 <0>
	1-25	224 250 <0>	
26-100	Likelihood		
	Very likely	169 <1>	
	50/50	242 263 <0>	
101-1K	Likelihood		
	50/50	53 <2>	
	Unlikely	223 241 257 <0>	
	Very unlikely	103 260 <0>	
	10K-100K	154 <0>	
	>100K	97 <0>	
Ancillary ops	Strongest Antagonist		
	Smallest Power		Fatalities
			None 261 <0>
			1-25 Likelihood
			Possibly 220 <0>
			50/50 200 <1>
			26-100 302 <0>
			101-1K 280 <1>
			1K-2K 230 <1>
Small Power		102 151 <0>	
Middle Power	Likelihood		
	Very likely	277 <0>	
	Possibly	191 <1>	
	50/50		Fatalities
			1-25 159 <0>
			26-100 212 <1>
Large Power		36 132 190 284 <1>	
Superpower		162 194 <0>	
Noncoercive ops	Likelihood		
	Very likely		Strongest Antagonist
			Smallest Power 158 <0>
			Small Power 152 <1>
			Superpower Leadership
			1 superpower 69 <0>
			Smallest powers 110 <1>
	Possibly		Strongest Antagonist
			Smallest Power 37 46 <1>
			Small Power 146 <1>
			Middle Power 240 <2>
			Large Power Leadership
			1 superpower 16 <2>
			Large powers 100 <1>
			Superpower Fatalities
			None 255 <2>
			1K-2K 130 <1>

Restraining the Conflict, cont.

50/50	Leadership				
	1 superpower	Strongest Antagonist			
		Smallest Power	99	<2>	
		Small Power	61	<1>	
		Superpower	8	<0>	
	2 superpowers		50	<1>	
	Middle powers	Strongest Antagonist			
		Middle Power	272	<0>	
		Large Power	28(2)	105(1)	1(2)
	Small powers		216	<0>	
	Smallest powers	Fatalities			
		1-25	247	<0>	
		26-100	239	<1>	
		101-1K			
		Strongest Antagonist			
		Smallest Power	202	<1>	
		Large Power	85(0)	114(1)	1(1)
		1K-2K	239	<0>	
		2K-10K	310	<0>	
	Sec-general		65	<1>	
	Inapplicable		11	201	<2>
Unlikely	Strongest Antagonist				
	Smallest Power	Fatalities			
		1K-2K	196(1)	217(0)	1(1)
		>100K	179	<0>	
	Middle Power		29	253	<1>
	Large Power		96	289	<0>
	Superpower	Leadership			
		1 superpower	250	<0>	
		Smallest powers	265	<0>	
		Inapplicable	139	<1>	
Very unlikely	Fatalities				
	None		19	22	32
	26-100		161	<0>	
	101-1K	Strongest Antagonist			
		Middle Power	143	<1>	
		Large Power	227	<0>	
	10K-100K	Strongest Antagonist			
		Large Power	21	<1>	
		Superpower	118	<0>	
Coercive ops	Fatalities				
	None		192	<0>	
26-100	Likelihood Abatement				
	50/50		125	<2>	
	Unlikely		229	<0>	
	Very unlikely		226	<0>	
101-1K	Leadership				
	1 superpower		157	<1>	
	2 superpowers		304	<1>	
	Smallest powers		269	<0>	
	Sec-general		300	<0>	
	Inapplicable	Likelihood Abatement			
		50/50	175	<2>	
		Unlikely	231	<1>	
1K-2K	Leadership				
	1 superpower		52	<0>	
	2 superpowers		15	<0>	
	Small powers		282	<1>	
	Smallest powers		126	<1>	
	Inapplicable		119	<1>	
2K-10K	Strongest Antagonist				
	Middle Power		167	<2>	
	Large Power		47	<1>	
10K-100K	Leadership				
	2 superpowers		10	<2>	
	Large powers		264	<1>	
	Inapplicable		245	<1>	
>100K	Likelihood Abatement				
	Unlikely		207	<0>	
	Very unlikely		67	<1>	
Inapplicable	Likelihood Abatement				
	Very likely		205	300	<2>
Possibly	Strongest Antagonist				
	Smallest Power		164	<0>	
	Middle Power		129	<2>	
	Large Power		189	<1>	
50/50	Fatalities				
	1-25		87	<2>	
	26-100		292	<1>	
	101-1K		243	<2>	
	10K-100K		285	<1>	
Unlikely	Fatalities				
	None		54	<2>	
	1-25		57	134	<1>
	101-1K	Strongest Antagonist			
		Small Power	30	<1>	
		Large Power	75(2)	244(1)	1(2)
	>100K		218	<1>	
Very unlikely	Fatalities				
	10K-100K		211	301	<0>
	>100K		298	<1>	

Dependent Variable: Settling the Conflict

N = 192 cases
 Acc = 0.948
 EPE = 0.968

Action	Discussion only	Leadership	1 superpower	Likelihood	Abstain			
2 superpowers	Likelihood	Very likely	94	136	173 <0>			
		Possibly	14 <1>	233 <0>	1 >1 <1>			
		50/50	33	89	271 <0>			
		Unlikely	274 <0>					
Large powers	Likelihood	Very unlikely	63 <0>					
		78 <0>						
		24	71	127	182 <0>			
		148	273 <0>					
Middle powers	Likelihood	Very likely	109 <1>	135 <0>	1 >1 <1>			
		Possibly	20	35	108 <0>			
		50/50	197 <1>					
		70	80 <0>					
Smallest powers	Likelihood	Very likely	226 <1>	236 <0>	1 >1 <1>			
		Possibly	221 <0>					
		50/50	213 <0>					
		Unlikely	213 <0>					
Weak resolution	Fatalities	Very unlikely	43	68 <0>				
		206 <0>						
		None	Likelihood	Disappear				
		<1 year	58	163 <0>				
1-5 yrs	Likelihood	74 <2>	144 <0>	288 <0>	1 >2 <1>			
		6	39	40	70	165	171	276 <0>
		1 <0>						
		254 <0>						
10-20 yrs	Likelihood	>20 yrs	254 <0>					
		25	83	95 <0>				
		Leadership	1	superpower	13 <1>			
		Large powers	17 <0>					
101-1K	Likelihood	Middle powers	234 <0>					
		4	82	92	178 <0>			
		83 <0>						
		10K-100K	201 <0>					
Strong resolution	Likelihood	Very likely	Leadership	Likelihood	Disappear			
		1	superpower					
		<1 year	104 <1>					
		1-5 yrs	50 <0>					
Possibly	Fatalities	58	76	124 <2>				
		64 <0>						
		Leadership	Likelihood	Disappear				
		<1 year	160 <2>					
5-10 yrs	Likelihood	169 <1>						
		38 <0>						
		None	238 <0>					
		224 <0>						
26-100	Likelihood	242	263 <0>					
		53 <1>						
		97	122	154	223	241	257	265 <0>
		103	260 <0>					
Unlikely	Likelihood	<1 year	151	261 <0>				
		1-5 yrs	Likelihood	Abstain				
		Very likely	Fatalities	None	Leadership	Sec-general	Inapplicable	284 <1>
		26-100	277 <0>					
Precillary ops	Likelihood	Possibly	Leadership	220 <0>				
		Inapplicable	191 <1>					
		50/50	159	190	200	302 <0>		
		212	280 <1>					
5-10 yrs	Leadership	Sec-general	132 <0>					
		36 <1>						
		230 <0>						
		194 <0>						
10-20 yrs	Fatalities	>100K	194 <0>					
		None	Likelihood	Abstain				
		69	139 <0>					
		16 <2>						
>20 yrs	Leadership	Very unlikely	32 <0>					
		Likelihood	Abstain					
		Possibly	37 <0>					
		50/50	99 <1>					
Noncoercive ops	Superpower	1	Likelihood	Abstain				
		Very likely	152 <2>					
		50/50	8	61 <0>				
		Very unlikely	32 <0>					
2 superpowers	Large powers	Likelihood	Abstain					
		26-100	69	139 <0>				
		101-1K	16 <2>					
		2K-10K	230 <0>					
10K-100K	Fatalities	10K-100K	21 <0>					
		60 <1>						
		None	19 <0>					
		101-1K	100 <1>					

Settling the Conflict, cont.

Middle powers	Likelihood Disappear.					
	1-5 yrs	Likelihood Abatement				
		Possibly	240	<2>		
		50/50	272	<0>		
	5-10 yrs	28(2)	105(1)	(12)		
Small powers	96	218	<0>			
Smallest powers	Likelihood Disappear.					
	<1 year	235	<2>			
	1-5 yrs	Fatalities				
		None	46	<0>		
		1-25	86(0)	114(1) (11)		
		1K-2K	239	<0>		
		2K-10K	310	<0>		
	5-10 yrs	110	202	259 <0>		
	10-20 yrs	Likelihood Abatement				
		Unlikely	196	217	253	265 <0>
		Very unlikely	143(1)	227(0)	(11)	
	>20 yrs	22	161	179 <0>		
Sec-general	66	<0>				
Inapplicable	Fatalities					
	None	146	<1>			
	101-1K	291	<1>			
	1K-2K	130	<1>			
	2K-10K	29(1)	139(0)	(11)		
	10K-100K	118	<0>			
	>100K	11	<2>			
Coercive ops	Leadership					
	1 superpower	Fatalities				
		25-100	125	<1>		
		101-1K	157	<1>		
		1K-2K	32	<0>		
		2K-10K	47(0)	167(2) (12)		
		>100K	67	<0>		
	2 superpowers	Fatalities				
		101-1K	304	<0>		
		1K-2K	15	<0>		
		10K-100K	10	<2>		
Large powers	228	264	<0>			
Small powers	229	282	<0>			
Smallest powers	128	192	269 <0>			
Sec-general	308	<0>				
Inapplicable	Fatalities					
	101-1K	Likelihood Abatement				
		50/50	175	<2>		
		Unlikely	231	<0>		
	1K-2K	119	<2>			
	10K-100K	245	<1>			
	>100K	207	<0>			
Inapplicable	Likelihood Abatement					
	Very likely	205	300 <2>			
	Possibly	Likelihood Disappear.				
		1-5 yrs	129	189 <1>		
		5-10 yrs	184	<0>		
	50/50	Fatalities				
		1-25	87	<2>		
		25-100	292	<0>		
		101-1K	243	<2>		
		10K-100K	285	<0>		
	Unlikely	Likelihood Disappear.				
		1-5 yrs	Fatalities			
			1-25	57 <0>		
			101-1K	75 <2>		
	5-10 yrs	Fatalities				
			101-1K	244 <1>		
			>100K	218 <0>		
	10-20 yrs	Fatalities				
			None	34 <0>		
			1-25	134 <1>		
	>20 yrs	30	<0>			
Very unlikely	Fatalities					
		10K-100K	211	301 <0>		
		>100K	298	<1>		

Stopping Hostilities

All Management Action variables included

Modal prediction ER = 0.329
 Modal prediction Acc = 0.653

Accuracy: 0.583
 Average ER = 0.407

Level where Used					Total	Variable
0	1	2	3	4		
66	97	16	1	0	180	Tech of Management Action(1st)
21	92	40	1	0	154	Leadership
69	60	22	0	0	151	Tech of Management Action(2nd)
0	90	46	12	0	148	Fatalities
0	67	26	1	0	94	Strongest Antagonist
0	47	39	4	0	90	Likelihood Disappear.
0	45	31	5	1	82	Likelihood Abatement
0	38	39	3	0	80	Duration
26	23	3	0	0	64	Tech of Management Action(3rd)
0	41	13	1	0	55	Type of Warfare
0	31	20	0	0	51	Type of Issue
0	32	16	3	0	51	System Period
6	26	12	2	0	46	Action
0	23	14	4	0	41	Level of Agreement
0	23	14	2	0	39	Alignment of Parties
0	23	16	0	0	39	Other Managers
0	22	13	2	0	37	Agent's Autonomy
0	20	15	1	0	36	Strategic Category
0	20	9	3	0	32	Likely Degree of Spread
0	7	19	3	0	29	Initiative for Intervention
0	5	20	4	0	29	Agents Relative Power
0	8	15	5	0	28	Agents Previous Role
0	11	14	0	0	25	Agent's Bias
0	11	10	1	0	22	Degree of Spread
0	15	5	1	0	21	Previous Involvement
0	15	4	1	0	20	Phase of Agent's Intervtn
0	9	9	2	0	20	Management Agent
0	9	9	2	0	20	Past Relationship
0	9	8	1	0	18	Ethnic Conflict
0	12	3	0	0	15	Phase of Agent's First Action
0	11	2	1	0	14	Likhd Superpower War
0	6	5	1	0	12	Joint Leadship
0	7	3	2	0	12	Great Power Interests
0	1	8	2	0	11	Phase of Agent's Strongest Act
0	6	3	1	0	10	Ideological Conflict
0	2	5	1	0	8	Agents Primary Role
0	6	1	0	0	7	Tech of Management Action(4th)
0	5	1	0	0	6	Power Disparity

Stopping Hostilities

All Management Action variables deleted

Modal prediction ER = 0.329
 Modal prediction Acc = 0.653

Accuracy: 0.581
 Average ER = 0.430

Level where Used					Total	Variable
0	1	2	3	4		
19	209	67	0	1	296	Fatalities
115	44	43	5	0	207	Leadership
54	51	33	3	0	141	Action
6	79	25	0	0	110	Strongest Antagonist
1	78	24	1	0	104	Type of Issue
1	48	34	5	0	88	Likelihood Disappear.
0	52	33	2	1	88	Alignment of Parties
0	44	35	2	0	81	Likely Degree of Spread
0	34	43	2	0	79	Duration
0	24	47	5	0	76	Likelihood Abatement
0	24	48	3	0	75	Level of Agreement
0	13	33	1	0	47	Degree of Spread
0	15	30	0	0	45	Agent's Bias
0	17	22	4	0	43	Other Managers
0	14	27	1	0	42	Strategic Category
0	6	34	1	0	41	Previous Involvement
0	14	21	2	0	37	System Period
2	7	22	1	0	32	Type of Warfare
0	6	21	2	0	31	Agent's Autonomy
0	12	12	2	0	26	Ethnic Conflict
0	6	16	0	0	22	Power Disparity
0	2	19	1	0	22	Agents Relative Power
0	9	10	1	0	20	Past Relationship
1	7	12	0	0	20	Management Agent
0	6	12	0	0	18	Agents Previous Role
0	7	9	0	0	16	Initiative for Intervention
0	10	4	0	0	14	Phase of Agent's First Action
1	1	12	0	0	14	Phase of Agent's Intervtn
0	3	9	1	0	13	Ideological Conflict
0	3	7	1	0	11	Phase of Agent's Strongest Act
0	4	6	0	0	10	Joint Leadship
0	5	5	0	0	10	Great Power Interests
0	4	5	0	0	9	Agents Primary Role
0	4	1	0	0	5	Likhd Superpower War

Abating the Conflict
All Management Action variables included

Modal prediction ER = 0.342
Modal prediction Acc= 0.568

Accuracy: 0.503
Average ER= 0.401

Level where Used	Used				Total	Variable
	0	1	2	3		
0	173	145	34	2	354	Fatalities
12	177	90	27	1	315	Leadership
0	186	55	12	0	251	Tech of Management Action(2nd)
0	108	128	13	0	249	Likelihood Abatement
0	69	106	49	5	230	Likelihood Disappear.
135	50	34	4	0	223	Tech of Management Action(1st)
1	88	89	15	0	193	Strongest Antagonist
0	69	94	16	1	180	Duration
0	63	75	15	0	153	System Period
42	50	45	12	0	149	Action
0	48	91	7	0	146	Phase of Agent's Intervtn
0	69	43	19	0	131	Level of Agreement
0	72	49	8	0	129	Strategic Category
0	80	35	9	0	124	Degree of Spread
0	23	78	11	1	113	Likely Degree of Spread
0	51	46	2	0	99	Alignment of Parties
0	18	66	9	0	93	Type of Warfare
2	37	30	7	0	85	Type of Issue
0	33	38	9	1	81	Past Relationship
0	16	51	10	0	77	Agent's Bias
0	10	44	9	0	63	Ethnic Conflict
0	32	15	10	0	57	Agents Previous Role
0	11	34	10	0	55	Great Power Interests
0	17	31	7	0	55	Other Managers
0	7	38	5	0	50	Previous Involvement
0	6	40	2	0	48	Tech of Management Action(3rd)
0	13	20	11	1	45	Power Disparity
0	10	30	4	0	44	Initiative for Intervention
0	12	22	3	0	37	Phase of Agent's First Action
0	10	19	6	0	35	Phase of Agent's Strongest Act
0	7	18	8	0	33	Ideological Conflict
0	10	21	2	0	33	Agent's Autonomy
0	11	14	7	0	32	Management Agent
0	2	16	5	0	23	Agents Relative Power
0	8	8	2	0	18	Likhd Superpower War
0	4	12	0	0	16	Joint Leadship
0	3	3	0	0	6	Agents Primary Role
0	1	1	0	0	2	Tech of Management Action(4th)

Abating the Conflict
All Management Action variables deleted

Modal prediction ER = 0.342
Modal prediction Acc= 0.568

Accuracy: 0.495
Average ER= 0.407

Level where Used	Used				Total	Variable
	0	1	2	3		
0	215	231	52	2	500	Fatalities
21	115	211	38	3	368	Leadership
0	95	147	49	10	301	Likelihood Disappear.
0	119	136	30	1	286	Likelihood Abatement
146	38	44	12	0	240	Action
3	102	97	24	1	227	Strongest Antagonist
1	48	103	37	2	191	Likely Degree of Spread
0	21	128	28	2	179	Duration
1	63	96	18	0	178	System Period
0	56	100	14	2	172	Strategic Category
1	44	77	20	0	142	Alignment of Parties
2	45	61	31	2	141	Level of Agreement
25	51	47	9	0	132	Type of Issue
0	55	58	13	1	127	Past Relationship
0	31	64	20	3	118	Phase of Agent's Intervtn
0	14	73	12	2	103	Type of Warfare
0	24	52	21	0	97	Agent's Bias
0	34	43	9	1	87	Degree of Spread
0	24	45	6	0	75	Other Managers
0	6	44	23	2	75	Power Disparity
0	3	49	4	0	56	Ethnic Conflict
0	7	34	10	0	51	Great Power Interests
0	20	22	8	0	50	Phase of Agent's Strongest Act
0	3	31	11	2	48	Previous Involvement
0	11	22	12	2	47	Phase of Agent's First Action
0	8	34	4	0	46	Agents Previous Role
0	1	35	10	0	46	Initiative for Intervention
0	2	41	2	0	45	Agents Relative Power
0	3	30	5	1	39	Agent's Autonomy
0	9	23	6	0	37	Ideological Conflict
0	16	16	0	0	32	Management Agent
0	0	28	2	0	30	Joint Leadship
0	2	6	0	0	8	Likhd Superpower War
0	0	4	1	0	5	Agents Primary Role

Isolating the Conflict

All Management Action variables included

Model prediction ER = 0.303
 Model prediction Acc = 0.745

Accuracy: 0.668
 Average ER = 0.397

Level where Used					Total	Variable
0	1	2	3	4		
50	104	7	0	0	170	Tech of Management Action(1st)
0	107	53	2	0	162	Fatalities
91	58	13	0	0	162	Tech of Management Action(2nd)
25	87	26	0	0	138	Leadership
1	42	34	2	0	79	System Period
13	48	6	1	0	70	Tech of Management Action(3rd)
1	33	28	3	0	65	Level of Agreement
3	37	22	2	0	64	Type of Issue
0	48	12	3	0	63	Likelihood Disappear.
0	30	21	1	0	52	Strongest Antagonist
2	30	18	2	0	52	Action
0	22	18	7	0	47	Agent's Bias
0	23	17	3	0	43	Likelihood Abatement
0	16	25	1	0	42	Joint Leadship
2	25	13	0	0	40	Alignment of Parties
0	11	22	0	0	33	Type of Warfare
1	19	13	0	0	33	Strategic Category
0	18	14	0	0	32	Phase of Agent's Interact
0	13	18	0	0	31	Phase of Agent's First Action
0	14	13	2	0	29	Ethnic Conflict
0	12	14	0	0	27	Likely Degree of Spread
0	14	11	0	0	25	Power Disparity
0	12	11	1	0	24	Phase of Agent's Strongest Act
0	10	14	0	0	24	Other Managers
0	12	11	0	0	23	Initiative for Intervention
0	4	16	0	0	20	Agent's Autonomy
0	9	8	2	0	19	Ideological Conflict
0	8	8	1	0	17	Duration
0	9	7	0	0	16	Degree of Spread
0	5	11	0	0	16	Agents Previous Role
0	10	4	0	0	14	Management Agent
0	2	12	0	0	14	Agents Relative Power
0	5	8	0	0	13	Previous Involvement
0	5	4	0	0	9	Past Relationship
0	6	3	0	0	9	Likhd Superpower War
0	3	3	0	0	6	Great Power Interests
0	3	2	0	0	5	Agents Primary Role
0	3	1	0	0	4	Tech of Management Action(4th)

Isolating the Conflict

All Management Action variables deleted

Model prediction Acc = 0.745
 Model prediction ER = 0.303

Accuracy: 0.663
 Average ER = 0.414

Level where Used					Total	Variable
0	1	2	3	4		
10	158	54	2	0	224	Fatalities
116	54	33	1	0	204	Leadership
34	42	30	0	0	106	Action
1	53	32	2	0	88	Strongest Antagonist
4	70	14	0	0	88	Agent's Bias
0	47	23	2	0	82	Likelihood Disappear.
6	47	23	0	0	76	Alignment of Parties
5	24	36	0	0	65	Likelihood Abatement
6	37	15	3	0	61	Strategic Category
0	33	24	0	0	57	Level of Agreement
1	28	28	0	0	57	Duration
8	20	14	0	0	51	Type of Issue
1	30	17	0	0	48	System Period
1	20	12	1	0	43	Phase of Agent's First Action
0	16	25	0	0	41	Other Managers
0	27	11	1	0	39	Type of Warfare
2	9	26	2	0	39	Joint Leadship
0	28	10	0	0	38	Ideological Conflict
3	6	25	1	0	35	Likely Degree of Spread
2	20	12	0	0	34	Degree of Spread
0	10	12	0	0	22	Initiative for Intervention
0	10	11	0	0	21	Phase of Agent's Interact
0	14	7	0	0	21	Power Disparity
0	8	10	1	0	19	Past Relationship
0	9	9	0	0	18	Ethnic Conflict
0	0	18	0	0	18	Agents Previous Role
0	8	7	0	0	15	Great Power Interests
0	4	10	0	0	14	Phase of Agent's Strongest Act
0	0	13	1	0	14	Agent's Autonomy
0	1	10	0	0	11	Previous Involvement
0	7	2	0	0	9	Management Agent
0	4	4	0	0	8	Agents Primary Role
0	1	3	0	0	4	Likhd Superpower War
0	0	1	0	0	1	Agents Relative Power

Restraining the Conflict

All Management Action variables included

Modal prediction ER = 0.344

Modal prediction Acc= 0.545

Accuracy: 0.484

Average ER= 0.407

Level where Used					Total	Variable
0	1	2	3	4		
0	180	184	31	0	395	Fatalities
11	158	94	12	0	275	Leadership
6	199	61	6	1	273	Tech of Management Action(2nd)
0	95	122	24	0	241	Likelihood Abatement
127	44	37	9	0	217	Tech of Management Action(1st)
0	79	94	19	0	192	Strongest Antagonist
0	78	77	20	0	175	Likelihood Disappear.
52	64	35	10	0	161	Action
0	74	72	10	0	156	Duration
0	76	61	10	1	148	Strategic Category
4	73	42	10	0	129	Type of Issue
0	64	49	12	2	127	Level of Agreement
0	68	57	2	0	127	Alignment of Parties
0	51	64	9	1	125	System Period
0	34	79	11	0	124	Likely Degree of Spread
0	46	62	14	0	122	Phase of Agent's Intervtn
0	33	59	13	1	105	Type of Warfare
0	28	62	15	0	105	Agent's Bias
0	65	30	7	0	102	Degree of Spread
0	31	49	18	1	99	Past Relationship
0	9	59	14	2	94	Ethnic Conflict
0	19	45	7	0	71	Other Managers
0	23	30	8	1	62	Agents Previous Role
0	10	42	7	0	59	Great Power Interests
0	18	38	3	0	59	Tech of Management Action(3rd)
0	14	33	12	0	59	Power Disparity
0	21	30	4	0	55	Agent's Autonomy
0	19	25	6	0	50	Phase of Agent's Strongest Act
0	11	31	6	0	49	Previous Involvement
0	8	34	4	0	46	Initiative for Intervention
0	9	17	4	0	30	Phase of Agent's First Action
0	3	21	5	0	29	Ideological Conflict
0	9	11	5	0	25	Management Agent
0	7	12	1	0	20	Agents Relative Power
0	1	13	2	0	16	Joint Leadership
0	4	5	0	0	9	Likhd Superpower War
0	1	5	1	0	7	Agents Primary Role
0	0	4	0	0	4	Tech of Management Action(4th)

Restraining the Conflict

All Management Action variables deleted

Modal prediction Acc= 0.545

Modal prediction ER = 0.344

Accuracy: 0.484

Average ER= 0.416

Level where Used					Total	Variable
0	1	2	3	4		
0	166	196	48	1	411	Fatalities
24	115	194	32	1	366	Leadership
1	147	122	21	1	293	Strongest Antagonist
1	124	130	32	0	287	Likelihood Abatement
153	31	25	6	0	215	Action
0	72	114	24	0	210	System Period
0	47	140	20	0	207	Likely Degree of Spread
0	66	104	23	0	193	Likelihood Disappear.
0	71	91	19	0	181	Strategic Category
0	16	137	24	2	179	Duration
0	93	65	15	1	174	Alignment of Parties
2	29	84	24	1	140	Level of Agreement
16	50	55	11	0	132	Type of Issue
0	24	83	8	2	117	Type of Warfare
0	49	44	14	0	107	Degree of Spread
0	54	40	9	2	105	Past Relationship
0	30	48	22	1	101	Phase of Agent's Intervtn
0	13	59	16	0	88	Other Managers
0	4	65	11	0	80	Ethnic Conflict
1	17	44	16	0	78	Agent's Bias
0	27	37	2	0	66	Phase of Agent's Strongest Act
0	4	44	15	0	63	Previous Involvement
0	4	32	20	2	58	Power Disparity
0	19	22	14	0	55	Agent's Autonomy
2	5	36	6	0	49	Ideological Conflict
0	3	37	7	0	47	Initiative for Intervention
0	10	30	6	0	46	Great Power Interests
0	14	23	4	1	42	Phase of Agent's First Action
0	5	28	5	0	38	Agents Previous Role
0	3	31	3	0	37	Agents Relative Power
0	13	10	2	0	25	Management Agent
0	2	11	5	0	18	Joint Leadership
0	0	5	1	0	6	Likhd Superpower War
0	0	3	0	0	3	Agents Primary Role

Settling the Conflict

All Management Action variables included

Model prediction ER = 0.300

Model prediction Acc= 0.734

Accuracy: 0.819

Average ER= 0.370

Level where Used	Total					Variable
	0	1	2	3	4	
1	159	119	20	0	0	309 Fatalities
18	147	92	18	2	2	277 Leadership
149	48	17	5	0	0	219 Tech of Management Action(1st)
14	132	49	4	0	0	199 Tech of Management Action(2nd)
1	66	91	20	2	2	180 Likelihood Abatement
0	92	56	12	0	0	160 Likelihood Disappear.
0	68	66	13	1	1	150 Duration
6	68	47	14	2	2	137 Action
0	66	44	5	1	1	126 Level of Agreement
1	45	68	12	0	0	126 Strongest Antagonist
0	42	62	9	0	0	113 System Period
0	54	41	4	0	0	99 Phase of Agent's Intervtn
0	41	39	9	0	0	89 Strategic Category
0	12	50	11	1	1	63 Agent's Bias
0	41	35	3	0	0	79 Alignment of Parties
0	25	40	10	0	0	75 Type of Warfare
0	21	46	6	0	0	73 Likely Degree of Spread
0	37	31	3	0	0	71 Degree of Spread
1	29	33	7	0	0	70 Tech of Management Action(3rd)
0	17	38	6	0	0	61 Previous Involvement
0	32	17	10	1	1	60 Power Disparity
0	15	33	7	0	0	55 Other Managers
0	10	30	7	0	0	47 Ethnic Conflict
9	23	12	2	0	0	46 Management Agent
0	12	24	7	2	2	45 Type of Issue
0	22	17	3	0	0	42 Agents Previous Role
0	16	21	4	0	0	41 Joint Leadership
0	12	23	5	0	0	40 Post Relationship
0	20	16	4	0	0	40 Phase of Agent's Strongest Act
0	13	21	4	0	0	38 Agent's Autonomy
0	15	21	1	0	0	37 Initiative for Intervention
0	11	22	3	0	0	36 Great Power Interests
0	15	16	5	0	0	36 Agents Relative Power
0	16	12	3	0	0	31 Phase of Agent's First Action
0	2	16	1	0	0	20 Ideological Conflict
0	4	2	0	0	0	6 Agents Primary Role
0	1	3	1	0	0	5 Likhd Superpower War
0	0	0	0	0	0	0 Tech of Management Action(4th)

Settling the Conflict

All Management Action variables deleted

Model prediction ER = 0.300

Model prediction Acc= 0.734

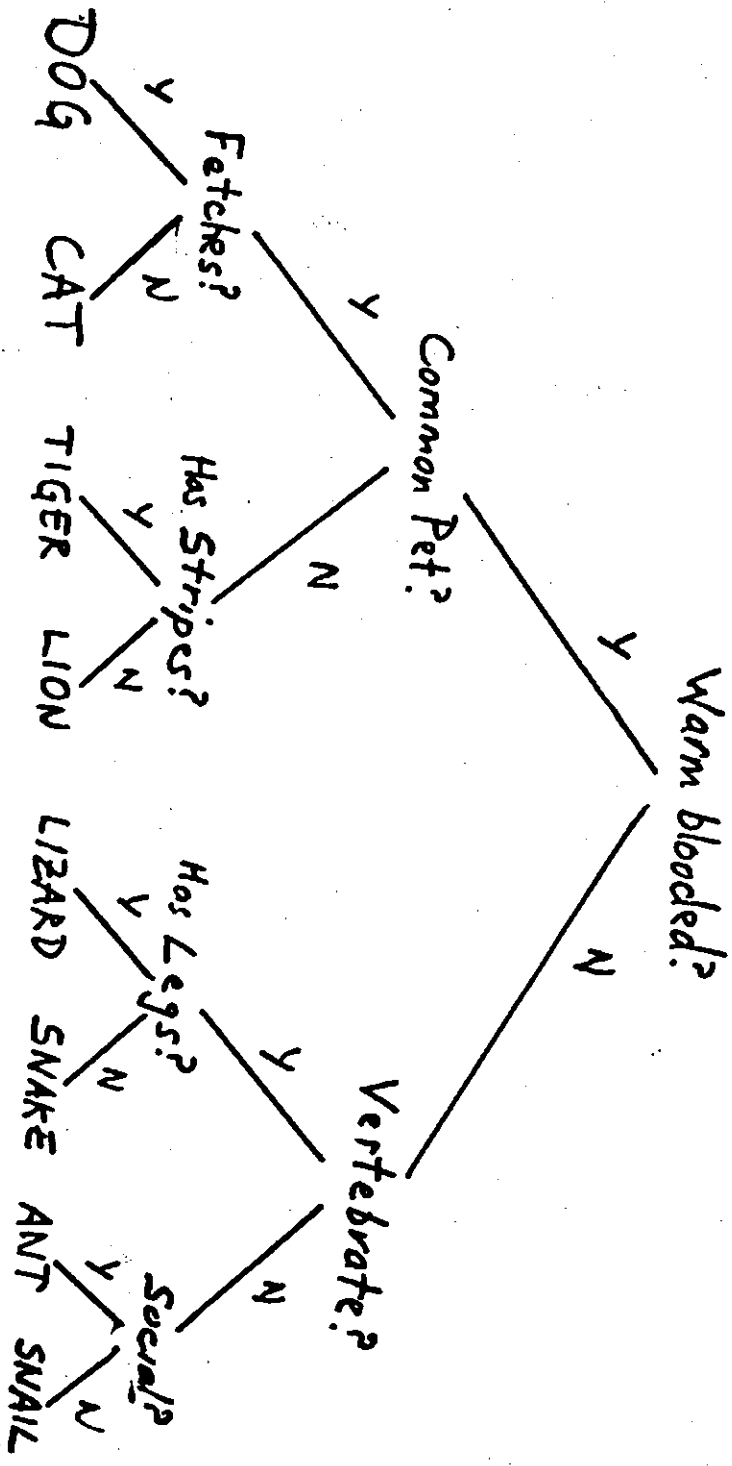
Accuracy = 0.603

Average ER= 0.372

Level where Used	Total					Variable
	0	1	2	3	4	
67	109	109	26	3	3	315 Leadership
7	123	134	39	5	5	308 Fatalities
54	86	89	18	5	5	253 Action
4	102	103	35	3	3	247 Likelihood Abatement
4	75	89	27	4	4	199 Likelihood Disappear.
9	64	104	16	2	2	105 Strongest Antagonist
0	59	93	32	3	3	187 Level of Agreement
0	32	68	30	3	3	133 Duration
2	27	76	20	1	1	126 Likely Degree of Spread
0	32	71	15	2	2	120 System Period
0	48	54	16	0	0	118 Alignment of Parties
1	29	65	18	1	1	115 Type of Warfare
26	36	33	9	1	1	105 Type of Issue
2	53	32	8	1	1	96 Degree of Spread
2	34	44	13	1	1	94 Strategic Category
0	15	51	19	2	2	87 Phase of Agent's Intervtn
20	27	16	9	0	0	72 Management Agent
2	14	48	6	0	0	70 Phase of Agent's Strongest Act
0	8	29	25	8	8	70 Previous Involvement
0	10	46	11	2	2	69 Agent's Bias
0	21	37	8	0	0	66 Other Managers
0	11	31	16	0	0	58 Power Disparity
0	10	27	19	1	1	57 Ethnic Conflict
0	5	36	12	0	0	53 Agent's Autonomy
0	13	30	7	1	1	53 Initiative for Intervention
0	6	38	8	0	0	52 Agents Relative Power
0	12	24	6	1	1	43 Great Power Interests
0	5	29	6	1	1	41 Joint Leadership
0	18	16	7	0	0	41 Phase of Agent's First Action
0	13	16	9	2	2	40 Ideological Conflict
0	3	23	8	1	1	35 Agents Previous Role
0	16	15	4	0	0	35 Post Relationship
0	2	6	2	0	0	11 Agents Primary Role
0	1	3	0	0	0	4 Likhd Superpower War

FIGURE 1

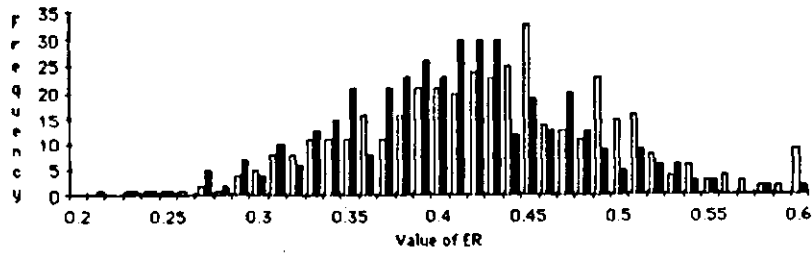
A Simple Classification Tree



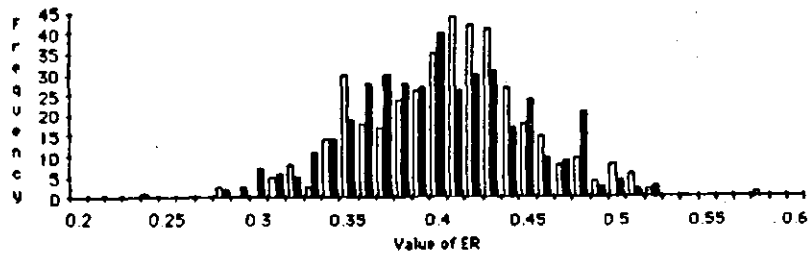
1	Warm blooded	2	3
2	Common pet	4	5
3	vertebrate	6	7
4	Fetches	8	9
5	Has stripes	10	11
6	Has legs	12	13
7	Social	14	15
8	Dog	0	0
9	Cat	0	0
10	Tiger	0	0
11	Lion	0	0
12	Lizard	0	0
13	Snake	0	0
14	Ant	0	0
15	Snail	0	0
16			
17			
18			

Distribution of ER over 400 Experiments

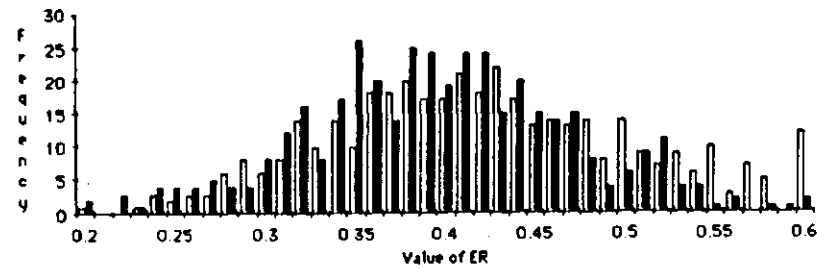
Stopping Hostilities



Abating the Conflict



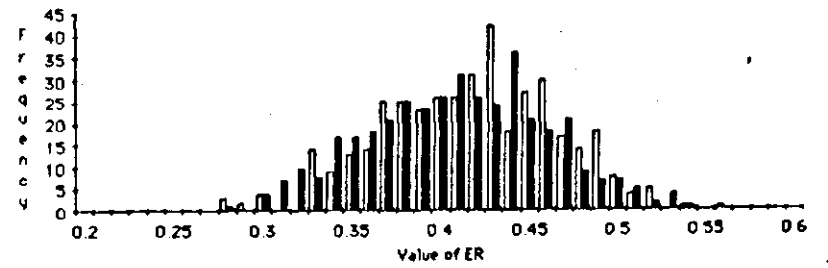
Isolating the Conflict



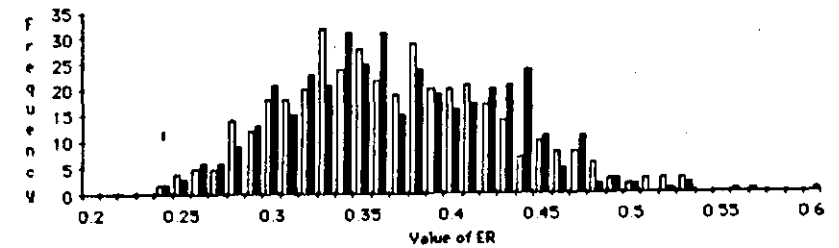
All variables included
 Technique of management variables excluded

Distribution of ER over 400 Experiments

Restraining the Conflict



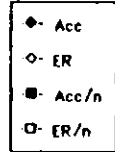
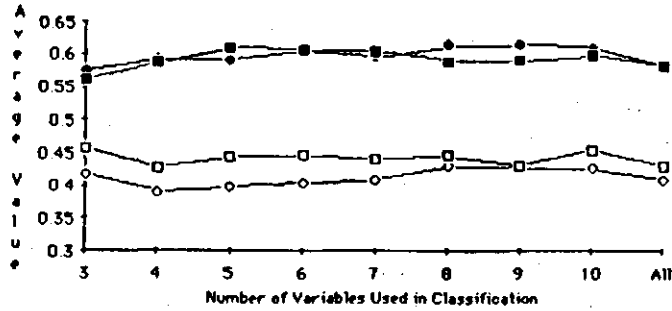
Settling the Conflict



All variables included
 Technique of management variables excluded

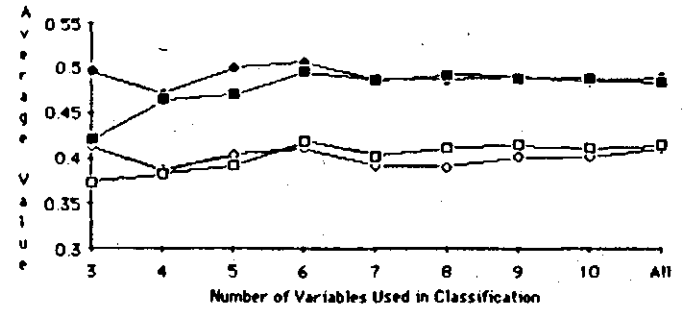
Fit as a Function of Number of Variables

STOPPING HOSTILITIES

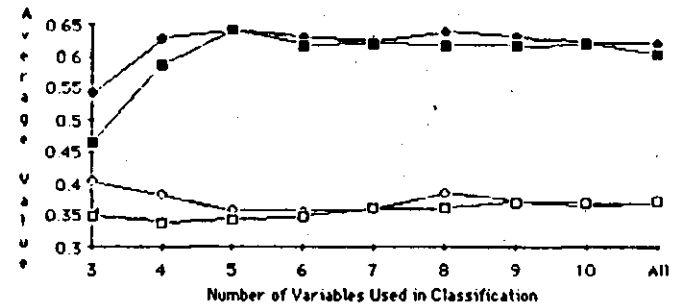


Fit as a Function of Number of Variables

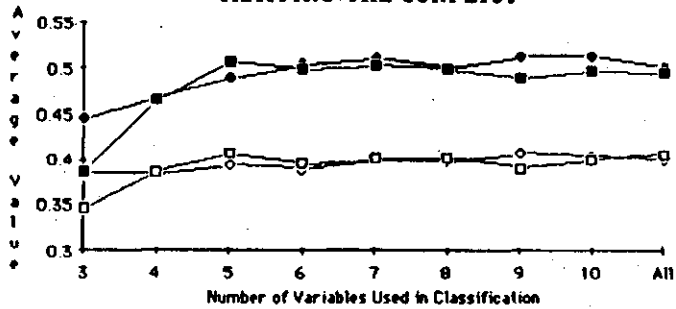
RESTRAINING THE CONFLICT



SETTLING THE CONFLICT



ABATING THE CONFLICT



ISOLATING THE CONFLICT

