Digging for Peace: Using Machine Learning Methods for Assessing International Conflict Databases

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Abstract. In the last decade research in Machine Learning has developed a variety of powerful tools for inductive learning and data analysis. On the other hand, research in International Relations has developed a variety of different conflict databases that are mostly analyzed with classical statistical methods. As these databases are in general of a symbolic nature, they provide an interesting domain for application of Machine Learning algorithms. This paper gives a short overview of available conflict databases and subsequently concentrates on the application of machine learning methods for the analysis and interpretation of the CONFMAN mediation dataset.

1 INTRODUCTION

While enormous amounts of money have been and still are spent on the development of AI methods for military purposes, practically no effort is undertaken to use these methods to support the *prevention and termination* of conflicts and wars. The work presented in this paper is motivated by the deliberation that this area of research has not yet received the attention it deserves [29, 30].

An important primary step is to understand the genesis and development of international crises as well as the success or failure of conflict management actions. Artificial Intelligence has lately been recognized as having some potential for supporting social scientists in this area of research [15, 12, 31, 23]. Several approaches are possible:

- Understand the phenomenon 'conflict' itself and try to apply previously successful conflict resolution strategies to new or existing crises [27]
- Learn patterns in international events that lead to crises and use this information for early warning systems that can be used to timely alert peacekeeping organizations [17]
- Detect regularities and rules that are common to various conflicts and use this information to gain insight in the parameters that support the escalation/deescalation of crises [23, 16]
- Detect regularities and rules in conflict management actions and use this knowledge to increase the chance of success of subsequent mediation attempts [2, 3, 4, 5, 6]

The work presented in this paper concentrates on the last two of these approaches: the analysis of databases of international conflicts with machine learning algorithms. In section 2 we give an overview of some databases, and section 3 presents results of applying machine learning algorithms to the CONFMAN database of international mediation attempts.

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2 CONFLICT DATABASES

One can distinguish between two primary types of conflict databases:

- *Event Databases* describe the sequence of events that occur in crisis situations.
- *Case-oriented Databases* describe conflicts as a whole.

Both kinds of databases have their advantages and drawbacks: Event databases do not need a rigid definition of what defines a conflict and how to specify the dates of outbreak and settlement, respectively. Also, they allow a more natural representation of what actually makes up a crisis situation. On the other hand it is often not clear which events are relevant to which conflicts. Case-oriented databases provide a clear documentation of information such as issues, fatalities, military power, and others of past conflicts but need a strict and often arbitrary definition of what should be considered to be a conflict.

There exist quite a few databases of either type, nearly all of them created for statistical analysis. Some examples are: the Correlates of War Militarized Interstate Disputes dataset [11], the International Crisis Behavior (ICB) project [8, 34], the COPDAB dataset [1], the event data sets of the KEDS and PANDA projects [24, 33, 7], the Butterworth dataset [9], the KOSIMO database of conflicts [19], the CONFMAN database of mediation attempts [5], and the SHERFACS database [25].

We had access to three of the most comprehensive and well-known databases:

- KOSIMO [19]: This database has been developed under the supervision of Frank Pfetsch at the Institute of Political Science at the University of Heidelberg, Germany. One of the tables contained in this database describes 547 internal and international conflicts and wars between 1945 and 1990.
- SHERFACS [26]: A large and complex database describing 1600 cases of quarrels and conflicts from 1943 to 1984 with roughly 5000 conflict phase descriptions.
- CONFMAN [5]: A database of mediation attempts, developed under the supervision of Jacob Bercovitch from the Department of Political Science of the University of Canterbury, Christchurch, N.Z. The database contains descriptions of 921 mediation attempts from 241 disputes since 1945. Each dispute is described by 33 attributes, each mediation attempt by 12 additional attributes. The database also contains several attributes that have been derived from the basic attributes or are still experimental. Nearly all attributes contain nominal values. The database has been previously used for statistical analysis of influence factors for successful mediation [2, 3, 4, 5, 6].

3 A CASE STUDY IN PREDICTING MEDIATION OUTCOME

First we tried to learn decision trees for predicting the outcome of future conflict mediation attempts. The learning examples were taken from the CONFMAN database, but all entries where the outcome of the conflict management attempt is unknown were removed from the database. Furthermore we grouped the 5 different types of conflict management outcome into two classes: Mediation was *successful* when it resulted in a full or partial settlement of the conflict, or in a ceasefire. It was *unsuccessful* when a mediation attempt took place, but failed, or when mediation was only offered, but not accepted by the conflict parties. The resulting dataset consisted of 718 conflict management events, 408 (56.82%) of them resulting in failure and 310 (43.18%) being successful. Each event in this dataset was encoded with 52 attributes and one class variable that indicated whether the attempt has been successful or not.

As the basic induction algorithm we chose the standard decision-tree learning algorithm C4.5 [20], because of its availability and flexibility. In a first attempt we generated and analyzed an unpruned tree with C4.5 (section 3.1). However, most of the nodes contained only a few examples, so that it seemed natural to generate simpler trees by pruning (section 3.2) or by feature subset selection (section 3.3).

3.1 Analyzing an Unpruned Tree

The first experiment consisted of generating a decision tree that completely discriminates between all training examples of different classes. No simplification or pruning heuristics were employed. This unpruned tree consists of 547 nodes.[2] Its accuracy on the training set is 99.7%, while its predictive accuracy (estimated with a 10-fold cross-validation) is about 60.3% compared to the default accuracy of 56.8%. It contains more than 100 leaves which split the training data into disjoint sets of examples that share the same class. Most of them contain only one example and cannot be expected to be predictive of the outcome of conflict management attempts. On the other hand, some leaves contain a relatively high number of examples that all had the same result. The unpruned tree contains 12 rules that contain 10 or more conflict management attempts. Five rules describe successful attempts, the other seven cover failures.

Table 1 contains a summary of how many successful or unsuccessful conflict mediation events from how many different conflicts each of these rules describes. Together these 12 rules explain more than 25% (185 events) of the data set. Some of the rules are rather complicated, and it is unlikely that these regularities could have been detected by a human analyst. However, there are some simple rules testing only a few relevant conditions. For example rule **S1** says

> **If** *there have been less than 400 fatalities* **and**
> *party B's raw power index is not extremely high* **and**
> *the conflict management type was mediation* **and**
> *the conflict lasted between 1 and 3 months*
> **then** *the conflict management was always successful*
> *in 15 mediation attempts in 8 different conflicts.*

On the other hand, rule **F1** shows us that

> **If** *there have been between 400 and 700,000 fatalities* **and**
> *party B's raw power index is not extremely high* **and**
> *both conflict parties have comparably high civil liberties* **and**
> *the conflict management type was mediation*
> **then** *the conflict management was never successful*
> *in 12 mediation attempts in 2 different conflicts.*

[2] It has been generated by setting C4.5's `-m` parameter to 1. A short explanation of this parameter can be found at the beginning of section 3.2.

Rule	*# Conditions*	*Success*	*Failure*	*# Conflicts*
S1	5	15	0	8
S2	6	15	0	11
S3	10	14	0	5
S4	10	10	0	5
S5	12	12	0	7
F1	6	0	12	2
F2	9	0	19	4
F3	11	0	14	3
F4	12	0	16	5
F5	12	0	14	8
F6	8	0	13	3
F7	3	0	31	3
Total	–	66	119	–

Table 1. Rules that cover only successful (S1–S5) or only unsuccessful (F1–F7) conflict management attempts

Parameters	*Tree Size*	*Purity*	*Predictive Accuracy*
No Pruning (`C4.5 -m1`)	547	99.7%	60.3% (± 4.8)
`C4.5 -m2`	314	91.8%	60.1% (± 3.3)
`C4.5 -m5`	170	82.3%	60.4% (± 5.7)
`C4.5 -m10`	90	76.6%	60.0% (± 5.2)
`C4.5 -m15`	62	74.1%	61.6% (± 4.7)
`C4.5 -m20`	47	71.9%	62.7% (± 2.0)
`C4.5 -m25`	37	71.3%	63.0% (± 2.2)
`C4.5 -m30`	26	70.1%	65.1% (± 2.5)
`C4.5 -m35`	22	69.9%	65.0% (± 4.2)
`C4.5 -m40`	20	69.2%	64.8% (± 2.6)
`C4.5 -m50`	24	69.1%	64.5% (± 3.5)
`C4.5 -c75`	524	99.7%	61.0% (± 4.5)
`C4.5 -c50`	357	95.3%	60.2% (± 3.6)
`C4.5 -c25`	257	91.2%	62.3% (± 4.4)
`C4.5 -c15`	137	81.8%	64.8% (± 4.6)
`C4.5 -c10`	75	76.9%	65.9% (± 4.9)
`C4.5 -c5`	53	74.7%	63.8% (± 6.0)
`C4.5 -c1`	27	70.2%	63.4% (± 5.8)
`C4.5` Default	173	86.2%	62.5% (± 5.2)
`C4.5 -m30 -c10`	20	69.6%	66.7% (± 3.7)
Mode Prediction	1	56.8%	56.8%

Table 2. Decision tree learning results on the CONFMAN database.

A complete listing of the interesting rules can be found in [10]. However, in general an unpruned tree will contain too many leaves that cover only a very small number of examples. Therefore it seems natural to consider pruning heuristics for obtaining simpler trees and rules.

3.2 Analyzing Pruned Trees

Table 2 gives an overview of some results we have achieved with different settings of two parameters of the standard decision-tree learning algorithm C4.5 [20]. For each setting we report the number of nodes (including leaves) in the generated tree (*Size*), the percentage of the training examples that will be correctly classified by the tree (*Purity*), and the predictive accuracy estimated by a 10-fold cross-validation [28] and its standard deviation.

Varying the `-m` parameter allows the user to constrain the tree generation by allowing only tests that have at least two outcomes with more than the specified number of examples. In particular this means that nodes that contain less than the specified number of examples will automatically become leaves and no further tests are considered. This prevents unreliable tests that are chosen near the leaves of the tree to discriminate small sets of examples from each other. Removing them leads to an increase in accuracy. However, a too high increase will cause the performance to decrease again, because C4.5 is forced to discard some relevant tests along with the irrelevant ones.

Varying the `-c` parameter on the other hand allows to specify the degree of pruning of the generated trees. Contrary to the minimum number of examples criterion (`-m`, see above), pruning is a post-processing method that simplifies an existing tree[3] by replacing some of its internal nodes by leaves. The aim of pruning is the same as using `-m` (namely to discard unreliable nodes), but pruning is more flexible, because its parameter is independent from the actual number of training examples used. Small values of the `-c` parameter cause more heavy pruning than large values.

We have also tried C4.5's default parameter setting (`-m2` and `-c25`) as well as the combination of the best parameter settings (`-m30` and `-c10`). The tree resulting from the latter settings (figure 1) has an estimated predictive accuracy of 66.7% which is almost 10% above the accuracy of mode prediction.

The tree consists of 16 nodes,[4] producing 9 simple rules. Each rule covers both, successful and unsuccessful conflict management attempts. Rule **P1** for instance is a generalization of rule **F7** from table 1 and illustrates that conflicts with a very high number of fatalities can hardly be solved by mediation. Obviously, conflict management activities have to be tried before too many fatalities occur. Rule **F7** contained two additional conditions that separated two successes and two failures from the 35 examples so that a cluster of 31 failures remained. However, it can be assumed that the two conditions that separate only four examples are irrelevant. Only three of the nine rules (**P3**, **P7** and **P9**) cover a majority of successful conflict management attempts.

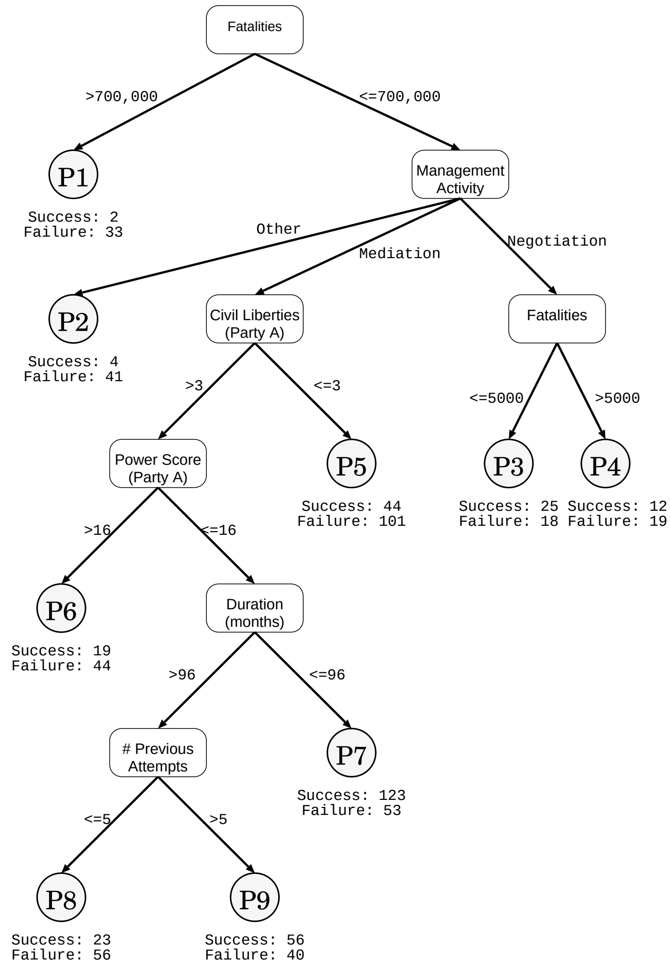

Figure 1. A decision tree generated with `C4.5 -m30 -c10` from the CONFMAN database.

3.3 Feature subset selection

Another method for obtaining simpler and more predictive trees is to limit the number of features that can be tested at the nodes of the tree. By admitting only a small number of highly relevant features are available, irrelevant tests near the leaves of a tree can be effectively avoided. Thus automatic *feature subset selection* can also be viewed as a form of pruning. We have used the wrapper approach of [13] to determine the set of attributes from which the best decision tree can be learned. The algorithm starts with an empty set of attributes and greedily adds the attribute that gives the highest increase in estimated predictive accuracy for the tree that C4.5 grows from the new set of attributes. Alternatively, the algorithm can also choose to delete an existing attribute from the current set of attributes. Predictive accuracy is estimated with consecutive 10-fold cross-validation experiments (with different random splits) until the standard deviation of the resulting estimate is below 1%. If no feature can be added or deleted without decreasing the estimated accuracy of the tree for two consecutive tries, the program stops with the current set of features. In order to avoid to be too short-sighted a one-time decrease is not sufficient for stopping the algorithm. In this case two features may be added at a time if this increases accuracy.

We have performed two experiments with different parameter settings for the basic induction module C4.5. The first series used the default parameter setting (`-m2` and `-c25`) and the second series used C4.5's `-s` option that allows the program to generate branches that not only consist of a single attribute value, but of a set of attribute values.

Table 3 lists the relevant aspects of a conflict management attempt that are encoded in the variables judged important by both experiments. In both cases the variable that describes the previous relationship of the mediator to the two conflict parties proved to be most important. Using a decision tree with only this one variable can raise the predictive accuracy from about 57% for always predicting the majority class to about 63%. Adding the next variable that in both cases reflects the power score of one of the conflict parties (although different sides have been suggested by the two experiments) further

[3] Unless specified otherwise the original trees in this series have been learned using `C4.5 -m1`.

[4] In figure 1 five branches of the node *Management activity* have been collapsed into one single branch labelled *Other*. Hence the tree consists of only 16 nodes instead of 20 as specified in table 2.

Previous Relation of Mediator
Power Score and Disparity
Number of Involved Parties
Mediation Environment
Issues

Table 3. Relevant aspects for predicting mediation outcome (using feature subset selection)

Fatalities
Mediation Environment
Mediation Strategy
Previous Relations of Mediator
Issues
Mediator Rank

Table 4. Relevant features for mediation outcome (using statistical analysis)

increases the predictive accuracy to above 65%. These decision trees that test only two variables are already competitive with the best trees of table 2.

It is interesting to compare the results of feature subset selection with the results produced with classical statistical methods [4] (see table 4). There is obviously a considerable overlap. Almost all of the variables of table 4 appear in one of the two experiments, most of them in both. The most notable exception is the absence of mediation strategy. The number of fatalities is also not among the most predictive features although if available it is very often chosen at the root of the trees. Obviously, C4.5's search heuristic based on information gain gives this attribute a high value, because one of its branches (fatalities $>= 700,000$) is almost pure. Nevertheless, using only fatalities for generating a decision tree would only yield 62.4% accuracy using the same grouping as in [4]. Thus the wrapper algorithm has attributed a higher significance to the previous relation of the mediator which yields 63.3% accuracy. However, the number of fatalities is partially reflected in the intensity of the conflict, which has been recognized as important, although only in one experiment. Further important variables are concerned with the power of the conflict parties and the number of parties involved on each side.

4 RELATED WORK

There have been several previous attempts to rule induction from international event databases (see [15, 21, 23] for overviews).

[22] has performed similar experiments in predicting interstate conflict outcomes using the Butterworth "Interstate Security Conflicts, 1945–1974" [9]. He used his own implementation of ID3, the predecessor of C4.5, to learn decision trees for predicting the effects of management efforts with respect to five different outcomes. In all his experiments the estimated predictive accuracy of the learned trees was below mode prediction accuracy, i.e. below the accuracy that one would achieve by always predicting the majority class. However, his implementation of ID3 was not capable of dealing with numeric data and, more importantly, did not have C4.5's extensive pruning facilities. The only method used for getting simpler trees was manual feature subset selection, which did not result in higher accuracies. In our study, on the other hand, simple decision trees usually were able to achieve a higher predictive accuracy than an unpruned decision tree. However, even the unpruned tree exhibited a significant gain in predictive accuracy compared to mode prediction. Predicting the outcome of conflict management attempts seems to be an easier task than to predict aspects of the outcome of the conflict itself. A reason for this might be that mediation events are more repetitive than the conflicts themselves.

[32] have developed I^2D, a variant of ID3 that was specifically developed to deal with the structured nature of the SHERFACS dataset [25]. [16] report a variety of rules that have been created by I^2D. Again, the only simplification criterion was manual feature subset selection. This research focussed on learning single rules. The issue of predictive accuracy has not been addressed.

Sim	Year	Conflict
		Bosnia-Herzegovina
0.62	1938	Germany-Czechoslovakia (Munich Treaty)
0.60	1948	Israel I (Palestine War)
0.57	1974	Cyprus IV (Turkish Invasion)
0.55	1965	India XVI (Kashmir IV)
0.54	1968	CSSR (Invasion)
		Germany-Czechoslovakia (Munich Treaty)
0.77	1968	CSSR (Invasion)
0.75	1953	GDR (17. June 1953)
0.72	1946	Greece (Civil War II)
0.67	1948	Berlin I (Blockade)
0.66	1961	Berlin III (Wall Erection)
		USA-Grenada
0.66	1959	Dominican Republic I (Intervention)
0.57	1962	Cuba IV ('Cuba-Crisis')
0.57	1954	Guatemala I (Intervention)
0.57	1973	Libya-USA
0.57	1945	Triest

Figure 2. The five best matches for three selected cases ordered by decreasing similarities (English translation of the original German KOSIMO database entries)

Situations of international conflict and war, like other complex human life situations, are often described and explained in terms of previous similar situations. Such comparisons often help to understand the various possibilities of actions the participants and international organizations can choose, and their possible consequences. Similarity-based case retrieval and analysis can therefore be a useful tool for analyzing a new conflict situation. An application of case-based learning and similarity-based case retrieval methods to the KOSIMO database of conflicts has been discussed in [18]. Figure 2 shows the retrieval of the five nearest neighbors of three selected cases in the database when using a similarity measure previously defined by a domain expert. The case "548 Bosnia-Herzegovina" has been coded and added to the database by one of the authors of the KOSIMO database for this experiment.

5 CONCLUSION AND FUTURE WORK

In this paper, we gave a short overview of databases of international conflict and conflict management actions and presented first steps of research on how inductive learning of rules with C4.5 can be used for the analysis of one of these databases, the CONFMAN dataset of mediation attempts.

Currently we are working on a much larger and more recent version of the CONFMAN database. Initial experiments with the C4.5 algorithm have promised a significant improvement of the results in terms of accuracy. We also plan to employ a wider range of machine learning and knowledge discovery techniques. An initial experiment in discovering *partial determinations* in this database is reported in [14]. Another goal is to further improve the results by including domain-specific background knowledge.

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REFERENCES

[1] Edward E. Azar, 'The conflict and peace data bank (COPDAB) project', *Journal of Conflict Resolution*, **24**(1), 143–152, (1980).

[2] Jacob Bercovitch, J. Theodore Anagnoson, and Donnette L. Wille, 'Some conceptual issues and empirical trends in the study of successful mediation in international relations', *Journal of Peace Research*, **28**(1), 7–17, (1991).

[3] Jacob Bercovitch and Allison Houston, 'Influence of mediation characteristics and behavior on the success of mediation in international relations', *Journal of Conflict Resolution*, **4**(4), 297–321, (October 1993).

[4] Jacob Bercovitch and James W. Lamare, 'The process of international mediation: An analysis of the determinants of successful and unsuccessful outcomes', *Australian Journal of Political Science*, **28**, 290–305, (1993).

[5] Jacob Bercovitch and Jeffrey Langley, 'The nature of dispute and the effectiveness of international mediation', *Journal of Conflict Resolution*, **37**(4), 670–691, (December 1993).

[6] Jacob Bercovitch and Richard Wells, 'Evaluating mediation strategies - a theoretical and empirical analysis', *Peace & Change*, **18**(1), 3–25, (January 1993).

[7] Doug Bond, Brad Bennett, and William B. Vogele. PANDA: Interaction events data development using automated human coding, 1994. Extended Version of a paper presented at the 1994 Annual Meeting of the International Studies Association in Washington, DC on April 1st, 1994.

[8] Michael Brecher, Jonathan Wilkenfeld, and Sheila Moser, *Crises in the Twentieth Century - Handbook of International Crises*, volume I, Pergamon Press, Oxford, 1988.

[9] Robert Lyle Butterworth, *Managing Interstate Conflict, 1945-74: Data with Synopses*, University of Pittsburgh Center for International Studies, Pittsburgh, 1976.

[10] Johannes Fürnkranz, Johann Petrak, Robert Trappl, and Jacob Bercovitch, 'Machine learning methods for international conflict databases: A case study in predicting mediation outcome', Technical Report TR-94-33, Austrian Research Institute for Artificial Intelligence, Vienna, (1994).

[11] Charles. S. Gochman and Z. Maoz, 'Militarized interstate disputes 1816–1976: Procedures, patterns, and insights', *Journal of Conflict Resolution*, **28**, 585–616, (1984).

[12] Valerie M. Hudson (ed.), *Artificial Intelligence and International Politics*, Westview Press, Boulder, CO, 1991.

[13] George H. John, Ron Kohavi, and Karl Pfleger, 'Irrelevant features and the subset selection problem', in *Machine Learning: Proceedings of the Eleventh International Conference*, pp. 121–129, Rutgers University, New Brunswick, NJ, (1994). Morgan Kaufmann Publishers, Inc.

[14] Stefan Kramer and Bernhard Pfahringer, 'Efficient Search for Strong Partial Determinations', submitted to *The 2nd International Conference on Knowledge Discovery in Databases (KDD-96)*. Also available as Technical Report TR-96-12, Austrian Research Institute for Artificial Intelligence, Vienna, (1996).

[15] John C. Mallery, *Thinking About Foreign Policy: Finding an Appropriate Role for Artificial Intelligence Computers*, Master's thesis, M.I.T. Political Science Department, Cambridge, MA, 1988.

[16] John C. Mallery and Frank L. Sherman. Learning historical rules of major power intervention in the post-war international system, 1993. Paper prepared for presentation at the 1993 Annual Meeting of the International Studies Association.

[17] Richard L. Merritt, Robert G. Muncaster, and Dina A. Zinnes (eds.), *International Event-Data Developments: DDIR Phase II*, University of Michigan Press, 1993.

[18] Johann Petrak, Robert Trappl, and Johannes Fürnkranz, 'The possible contribution of AI to the avoidance of crises and wars: Using CBR methods with the KOSIMO database of conflicts', Technical Report TR-94-32, Austrian Research Institute for Artificial Intelligence, Vienna, (1994).

[19] Frank R. Pfetsch and Peter Billing, *Datenhandbuch nationaler und internationaler Konflikte*, Nomos Verlagsgesellschaft, Baden-Baden, 1994.

[20] John Ross Quinlan, *C4.5: Programs for Machine Learning*, Morgan Kaufmann, San Mateo, CA, 1993.

[21] Philip A. Schrodt, 'Artificial intelligence and international relations: An overview', in [12].

[22] Philip A. Schrodt, 'Classification of interstate conflict outcomes using a bootstrapped ID3 algorithm', *Political Analysis*, (2), (1991).

[23] Philip A. Schrodt, *Patterns, Rules and Learning: Computational Models of International Behavior*, University of Michigan Press, forthcoming.

[24] Philip A. Schrodt and Shannon G. Davis. Techniques and troubles in the machine coding of international event data. Dept. of Political Science, University of Kansas, 1994. Paper presented at the 1994 meeting of the International Studies Association, Washington DC.

[25] Frank L. Sherman. SHERFACS: A new cross-paradigm, international conflict dataset, 1988. Paper written for presentation at the 1988 annual meeting of the International Studies Association.

[26] Frank L. Sherman, 'SHERFACS - research design, operational protocols, data representations and paradox 4.0 codebook', Project Report Number 3, Department of Political Science, Syracuse University, Syracuse, N.Y, (1992).

[27] Robert L. Simpson Jr., *A Computer Model of Case-Based Reasoning in Problem Solving: An Investigation in the Domain of Dispute Mediation*, Git-ics-85/18, School of Information and Computer Science, Georgia Institute of Technology, Atlanta, Georgia, June 1985.

[28] M. Stone, 'Cross-validatory choice and assessment of statistical predictions', *Journal of the Royal Statistical Society B*, **36**, 111–147, (1974).

[29] Robert Trappl, 'Reducing international tension through artificial intelligence: A proposal for 3 projects', in *Power, Autonomy, Utopia: New Approaches Toward Complex Systems*, ed., Robert Trappl, Plenum, New York, (1986).

[30] Robert Trappl, 'The role of artificial intelligence in the avoidance of war', in *Cybernetics and Systems '92*, ed., Robert Trappl, pp. 1667–1672, Singapore, (1992). World Scientific.

[31] Sigrid D. Unseld. A selective overview of recent projects in Artificial Intelligence / International Relations. Paper prepared for the Second Workshop on the Potential Contribution of AI to the Avoidance of Crises and Wars, Vienna, November 1994.

[32] Sigrid D. Unseld and John C. Mallery. Interaction detection in complex datamodels, 1993. MIT A.I. Memo No. 1298.

[33] William B. Vogele, Brad Bennett, C. Irvin and K. Rothkin. Global conflict profiles: Event data analysis using PANDA, 1994. Paper prepared for presentation at the annual meeting of the American Political Science Association, New York City, Sep. 1994.

[34] Jonathan Wilkenfeld, Michael Brecher, and Sheila Moser, *Crises in the Twentieth Century - Handbook of Foreign Policy Crises*, volume II, Pergamon Press, Oxford, 1988.