P88-38

P ~~89~~ 88

Machine Learning as a Tool for Analysis in Social Sciences

by

Subutai Ahmad

Department of Computer Science,
University of Illinois at Urbana-Champaign

Machine Learning

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Abstract

This paper shows how Machine Learning techniques can be used for analysis in the Social Sciences. The general paradigm and the relevance of Machine Learning is described and then a specific problem is addressed. A program is used to produce rules to solve that problem and the performance of the rules are tested. Various different types of rules are considered. It is shown that these techniques can indeed be very useful in this sort of a study, and that the reliability of the results can be very high.

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[2] Department of Computer Science, University of Illinois at Urbana-Champaign, Urbana, IL 61801, USA.

1 Introduction

The objective of this paper is to show that techniques developed in AI and Machine Learning (ML) research (the study of machines which learn) can be useful tools in the quantitative study of social systems. In particular, we will use a program developed at the University of Illinois AI Laboratory to study those countries which reported a high incidence of riots and armed attacks during the year1977. Each country will be described by a set of measurements and variables and classified according to the number of incidences per million people. The idea is to try to generalize these individual event descriptions into meaningful class descriptions.

2 Machine Learning and Induce

A large part of Machine Learning research has been concerned with the problem of learning rules to classify events into a number of different classes, rendering it relevant to this sort of study. The program that we will use is called **Astra**. It is based on the Induce algorithm and was developed at the AI Laboratory at the University of Illinois at Urbana-Champaign under the direction of Prof. R.S. Michalski (Hoff, Michalski and Stepp, 1983).

The general paradigm is as follows. A set of mutually exclusive classes is identified together with a set of variables presumed to be sufficient for distinguishing between the different classes. The algorithm takes a set of events described by these variables, together with the class that each event belongs to, and produces general rules in terms of these variables for classifying new events. It is hoped that the rules, or hypotheses, produced by the algorithm are good classifiers of future events.

In general there are numerous hypotheses which are consistent with a given set of examples, although there is probably only one that is going to be correct for all future examples. Since, a priori, the entire set of examples and their associated classes is unknown, there is no reason for choosing one consistent rule over another, hence the identification of the correct rule becomes a probabilistic event dependent on the the number of consistent hypotheses. This, together with the fact that the number of consistent hypotheses grows exponentially with the number of variables, has the unfortunate consequence that the probability of getting the right hypothesis approaches zero very quickly.

There is one way to overcome this problem. The above argument rests on the fact that there is no inherent structure to the events, and that the hypotheses can be arbritrarily complex. Usually this is not the case. The user normally has some information about the events and the possible hypotheses which can be used as criteria for choosing or rejecting certain hypotheses, i.e., the information can be used as a bias in the algorithm. For example, one bias which seems to work well in most domains is to identify regularities in the example set and choose hypotheses which are consistent with these regularities. Another common bias is to choose hypotheses which tend to classify events which are "similar" to each other into the same class. Here similarity between two events is defined as the extent to which the values of their variables are similar. In addition to the above, there are several other ways that one can affect the rules which are chosen by Astra. One can specify certain lexical criteria (such as choosing the simplest or shortest rule) which are used to order the hypotheses. One can enter domain knowledge directly in the form of logical rules. One can also associate a cost with each variable and the rules which have minimum cost are selected.

The Input to Astra

Events are entered into Astra as a series of descriptors, with each descriptor denoting one event. A descriptor has a left hand side containing a sequence of selectors, which denote the values of the different variables, and a right hand side which contains a selector describing the class that the event belongs to. A selector is of the form [term = value(s)] and corresponds roughly to a predicate in predicate calculus. The term can be either a variable or a function of several variables (denoting a relationship between the variables. For example, the following are legal selectors:

[literacy(c1)=19,20]	- c1 has a literacy value of 19 or 20
[next_to(c1,c2)=true]	- c1 and c2 are characterized by the relationship next_to.

A complete event descriptor is of the following form:

[literacy(c1)=19,20][sanctions(c1)=0] => [strife = low].

This represents the fact that a country with a literacy value of 19 or 20, and whose government has imposed no sanctions is classified as having low strife. Note that all the selector are assumed to be true, i.e., the selectors represent a conjunction of predicates.

The Induce algorithm, which is used to generalize rules of the above form, and its various properties are described in detail in (Hoff, Michalski, and Stepp, 1983).

Discriminant and Characteristic Rules

There are two types of rules that can be generated by Astra: discriminant rules and characteristic rules. Discriminant rules are rules which classify the input events in such a way that no input event of one class is classified by a rule for another class. Characteristic rules are rules generated by generalizing the input events of a particular class without considering whether they also classify events of other classes. Both types of rules can be very useful when studying a domain. Discriminant rules are well suited for classification tasks and for predicting which class a new event would fall into. Characteristic rules are useful for identifying which variables are important and may be used to help develop a model of the domain and to gain insight into the particular problem being studied.

Previous work with Induce

Induce has previously been used to classify soy bean diseases (Michalski and Chilausky 1980). A number of examples were supplied and rules for diagnosis were generated from them. The performance of these rules were then tested against a set of rules provided by a human expert. It is worthwhile to note that the rules generated by Induce outperformed the rules provided by the expert. Thus the Induce algorithm has already shown itself to be an effective classification tool in at least one domain.

The Relevance of Astra to Analysis in Political Science

Astra is particularly well suited for this study for several reasons:

- It is complete, i.e., every input event is classified under one of the rules.

- It is consistent, i.e., the rules that are generated are consistent with the example events. The rules classify the original events into their originial classes.

- Induce automatically determines which variables are relevant to the particular set of examples given.

- The program can handle a large number of variables at one time (limited only by the resources abailable). This is a strong advantage in domains, such as the one being considered here, where there are a large number of potentially important variables and it is not known a priori which ones are the relevant ones.

- The rules that are generated are easy to read, easy to test on more data, and meaningful to humans. This is not true of many other ML programs and is an important point. If the rules are to be used for tasks which have important consequences, it is essential to be able to check these rules by hand. Moreover, in this particular case, the readability of the rules allows one to develop new theories and not just test hypotheses.

- Lastly, the algorithm is not just a formula that you plug your data into. One can affect the rules that are generated by putting in knowledge about the domain and how the variables relate to one another.[1]

3 Coding of the data

The source of data for this work is from (Taylor and Jodice, 1983), a two-volume set which contains the data for numerous important political indicators. All of the variables that were used are either directly from the book or derived from some of the indicators in the book. An attempt was made to choose a wide variety of different variables representing different types of indicators. In particular, there were variables representing the extent of governmental restraints (polright and civright), the population density (popul), presence of social mobilization (highered and literacy), the economic structure (mml, mgdp, kind), state coercive behaviour (sanctions, relaxsanc), social discontent (polstrikes), and

[1] Although it is possible to do this in Induce to a limited extent, the current state of research in ML is such that one is still restricted in the types of knowledge that can be conveniently entered. Expanding this capability is an important area of research in this field.

geographical location (continent). Also included were variables which measured changes in some of the above values (prshift, crshift, enshift, and litshift). Each variable is fully described below.

Altogether there were 51 countries in the data set. 28 of the countries were classified as low strife countries and 23 were classified as high strife.

The variables.

The following variables were used to describe the countries:

strife - This was the main variable, used to classify the countries into two sets - low and hi, and was determined by the number of riots and armed attacks that were reported by the countries. A riot is defined as a violent demon-stration and an armed attack is defined as an act of violent political conflict carried out by an organized group. The number of riots and armed attacks was summed up and divided by the population of the country in millions. If this value was less that 0.3, then the country was said to have low strife. If it was greater than or equal to 0.3, then it was said to have high strife.

literacy - This variable indicated the percentage of adults in a country considered to be literate. The value of the variable was the percentage divided by 5 plus 1, and ranged from 1 to 20.

popul - This variable measured the concentration of the population. It was defined as 10 times the log of the population concentration. The logarithm of the concentration was taken since the graph of this variable (with the countries ordered by concentration on the x-axis) tends to be exponential. The possible values for this variable ranged from 1 to 30.

highered - Measures the number of students enrolled in higher education, per million population. The value of the variable was :

0 if the number was less than 1500

1 if the number was between 1500 and 4099

2 if the number was between 4100 and 8999

4 if the number was greater than 9000

polright - Measured the extent of political rights in the specified country. The value of the variable is the mean value of the Political Rights Index as compiled by Raymond Gastil, (Gastil 1973-1979) during the years 1973 to 1979, rounded to the nearest integer. It varied from 1 (indicating the most rights) to 7 (indicating the least rights).

civright - Measures the extent of civil liberties in a country. The value of this variable is the mean score of the Civil Rights Index of the specified country during the years 1973-1979, also compiled by

Raymond Gastil, rounded to the nearest integer. As above, the value ranged from 1 to 7.

sanctions - Measured the number of sanctions that were imposed by the government of the specified country during 1977. A sanction is defined an action taken by the authorities to control a perceived threat to the political system. The values of the variable were:

0 - number of sanctions were between 0 and 5.

1 - number of sanctions were between 6 and 15.

2 - number of sanctions were between 16 and 69.

3 - number of sanctions were greater than 69.

relaxsanc - Measured the number of sanctions that were relaxed by the authorities. The values of the variable were the same as above.

prshift - Measured the maximum shift in the Political Rights Index during the years 1973 to 1979. The value of the variable was the shift + 6. The possible values ranged from 0 to 11.[2]

crshift - Measured the maximum shift in the Civil Rights Index during the years 1973 to 1979. The value of

[2]Since negative shifts were present, and Astra is limited to positive values for the variables, the encoding for the variables indicating shift were adjusted to a positive scale. There was a further limitation in that the version of Astra that was used could only hand a maximum of 30 different values per variable.

this variable was the shift + 4. The possible values ranged from 0 to 8.

enshift - Measured the shift in school enrollment for a particular country. The value of this variable is the shift plus 4. The possible values ranged from 0 to 23.

litshift - Measured the shift in the literacy rate of a country. The value of this variable is the shift plus 18 divided by 3. The possible values ranged from 0 to 22.

continent - the value of this variable was one of the following: europe, namerica, samerica, africa, and asia. It represented the continent that a particular country was in.

polstrikes - Measured the number of political strikes that took place in the year 1977. A political strike is defined as a strike or work stoppage by a group of workers or students in protest of the government. The value of this variable was the actual number of strikes.

kind - This variable represented three economic sectors: services, industry, and agriculture. The value was either services, indus or agr.

mgdp - This variable was a predicate of two arguments (representing economic sectors) and was true if a larger share of the Gross Domestic Product of a particular country was due to the first sector.

mml - This variable was also a predicate of two arguments representing economic sectors and was true if a larger share of the manual labor in a country worked for in the first sector.

4 Results

Discriminant rules were generated by randomly selecting half of the low strife countries (14) and half of the high strife countries (12) and generating rules differentiating the two classes. The generated rules were then tested on the remaining events to see how well they performed on new events. The set of countries which were used to generate the rules will be called the sample, and the rest of the countries will be said to comprise the test set. Since the countries were picked randomly, the rules were tested with several sample sets. This tends to negate the effects of any specific sample being particularly good or bad. The results are as follows:

For both the low and high strife countries the rules performed very well on the test set. The percentage of the low strife countries that were correctly classified ranged from 79% to 93% with a mean of 86%. The percentage of the hight strife countries that were correctly classified was slightly lower and ranged from 64% to 91% with a mean of 80%. We believe that the rules performed better on the low strife countries because there were probably more regularities in their descriptions than in the descriptions of the high strife countries.

The rules that were produced support this argument (see below). In general however, the rules tended to be very good predictors for events that had not been seen while generating the rules.

In all cases, due to the consistency and completeness criteria, the rules were 100% correct on the sample set. Thus the average performance of the rules on the entire set of events was 93% for countries with low strife and 91% for countries with high strife.

The following is an example of a rule that was generated for countries with low strife. It correctly classified 26 out of the 28 low strife countries. Both of the countries that were misclassified were very close to at least one of the descriptors below.

[popul(c1) = 17,19..28][sanctions(c1) # 2][3] (10)
OR [literacy(c1)#2,7..9,15][popul(c1)=1..10] (7)
OR [polright(c1)=3,5..7][popul(c1) >= 13] (14)
OR [literacy(c1)=6,10..16,19,20][sanctions(c1)=0] (9)

The rule is specified as a set of disjuncts, any one of which may be satisfied. Each of the disjuncts focuses in on one of the regularities in the sample set. The numbers in parentheses on the right show how many countries in the entire set satisfied that particular disjunct. When developing a theory, these numbers would become very useful as they would indicate the realative effectiveness of each of the rules. Thus the third disjunct seems to be the most important rule here. Basically it says that a country which has a Political Rights Index of 3, 5, 6, or 7 (a suppressive country) and whose population

[3]Here 19..28 specifies a range of numbers and is equivalent to: 19,20,...,28. The symbol # represents "not equal to".

density figure is greater than or equal to 13 (average to very densely populated) is to be classified as having low strife.[4] It is worthwhile to note that the final rule is much shorter than the descriptor for even one country.

The following is an example of a rule that was generated for countries with high strife. It correctly classifed 21 out of the 23 countries with high strife.

[literacy(c1)#2..4,8,14,16,20][litshift(c1)#12..17] (13)
OR [sanctions(c1)=2] (4)
OR [popul(c1)#1..4,9,10,16..21,28] (14)
OR [polstrikes(c1)#0..4] (6)

The first and third selectors seem to be the most important although it is not clear that anything meaningful can be interpreted from them. The performance of the rule on the test set is somewhat surprising in this context.

There is a way to get more meaningful results. Rather than picking the sample set randomly, the user might want to pick descriptions of a specific set of countries, such as the countries in Europe and N. America. It is a relatively simple matter to extract countries according to one of the variables and generate rules based on those. The following rule classifies European and N. American countries with high strife:

[4] Since strife here is defined as the number of riots and armed attacks per million people, it seems reasonable to conjecture that the more suppressive a government, the less likely a country is to have any incidents.

[polstrikes(c1)#0] (5)
OR [civright(c1)=2..5,7] (7)

Note that this rule is much simpler than the previous rule of high strife countries and thus might provide insights into the nature of strife in Western countries.

The second type of rule that Astra generates, characteristic rules, can also provide insights. The following is a characteristic rule for countries in Europe and N. America with high strife:

[civright(c1)#5,6][enshift(c1)=5..7][highered=2..3]
[literacy(c1)=12..20][litshift(c1)=6..11][polright(c1)=1..4]
[popul(c1)=12..20][relaxsanc(c1)=*][sanctions(c1)=*]

The * indicates that the value of a particular variable is irrelevant. Due to the nature of these rules, every European and N. American country with high strife in the database will match the above rule. Although low strife countries may also be covered by the rule, it does indicate what characteristics are *not* present. For example, none of the Western countries with high strife are countries where the political rights are heavily suppressed (polright values of 6 or 7). Several low strife countries do have that characteristic.

5. Discussion

The above results point out some of the strengths and weaknesses of this methodology as compared to some of the more traditional analysis methods, such as correlation studies, regression analysis, and factor analysis. One of the features of Astra is that it attempts to correctly classify *all* of the countries in the data base. Although this is a useful property to have, it can lead to less meaningful rules if there are some irregularities. The system attempts to give the user some indication of which rules might be meaningful by printing out how many events are covered by each rule, however, as was indicated above, this is not always sufficient. It would be interesting and useful if some other measure of the "goodness" of a rule could be calculated. A flexible, user defined measure might be necessary in order to be able to handle a wide variety of situations. One could then incorporate this measure into the part of the algorithm that influences the possible hypotheses.

One of the main deficits of the traditional methods is that although some of these methods can handle multiple variables, they are not able represent the complex relationships that can sometimes exist among them. They assume some sort of a simple constraint on the possible relationships, such as a linear relationship. Furthermore, since the representation is strictly numerical, only numerical factors can be considered. Because Astra's representation language is an extension of predicate calculus, Astra can represent *any* relationship that can be expressed in predicate logic. The variables used don't have to be numerical. They can also represent values which have no particular relationship between them (such as the values of

continent) or they can represent values which have a hierarchical structure to them. [5]

A further consequence of such a representation language is that the rules which are produced are readable and meaningful to humans. Thus it can be a powerful aid in the formulation of theories as well as in their verification. A disadvantage of using such a language is that a simple mathematical relationship (e.g. linear) would not be well represented.

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6. Conclusion

The results show that techniques developed in Machine Learning can be effectively used as an aid in the analysis of social systems. There are several advantages to using this system. The language used for expressing hypotheses is more powerful. The types of variables that can be used are not limited to numerical types. The relationships that can be expressed between the variables are more complex and the hypotheses produced are usually meaningful to humans and reliable. In the case studied, the algorithm produced rules that were excellent predictors, achieving average success rates greater than 80% while pointing out some factors that merit further research.

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There are some disadvantages in the system such as an inability to express simple mathematical relationships between the variables.

[5] This feature was not used in this study.

The algorithm attempts to correctly classify every sample event and this can lead to rules which are not easily interpreted by humans. Finally the means of entering domain knowledge into the system needs to be extended to achieve more flexibility and better results.

Perhaps the most important point of the methodology presented in this paper is the philosophy behind it. The procedure is not viewed as one where you simply plug in some variables into a formula, but instead attempts to automate the *search* for a correct theory. In order to this well it is important to have a flexible means of entering domain knowledge to influence the search. The system used in Astra for ordering the possible hypotheses is a start in that direction, however much more needs to be done. Ultimately, one envisions a large, flexible system which can be used by scientists as an intelligent tool for the formulation of theories.

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          Data for countries for the year 1977.


Explanations of predicates:
literacy (Percentage of adults considered literate):
         int(pct/5)+1

popul (Concentration of population):
         10*log(conc.)

sanctions = impositions of sanctions:
            > 69      -> 3 (very high)
         16 - 69      -> 2 (high)
          6 - 15      -> 1 (medium)
          0 - 5       -> 0 (low)

highered (Students enrolled in higher education, per million):
               > 9000   -> 3 (very high)
         4100  - 8999   -> 2 (high)
         1500  - 4099   -> 1 (med)
            0  - 1499   -> 0 (low)

strife = (riots + armed attacks)/pop.(millions):
         0.000 - 0.299  -> low
         0.300 - 0.599  -> med
               > 0.600  -> hi

polright = Politicial Rights Index:
         1    -> Most rights
         7    -> Least rights

civright = Civil Rights Index:
         1    -> Most rights
         7    -> Least rights

polstrikes = Number of political strikes.
relaxsanc  = Relaxations of sanctions:
      same scale as imposition of sanctions.
continent = continent that a country is in
             {namerica,samerica,europe,asia,africa,australia}
prshift - shift in the political rights index. (shift + 6)
crshift - shift in the civil rights index.     (shift + 4)
enshift - shift in school enrollment.          (pct + 4)
litshift - shift in literacy enrollment.       ((pct + 18)/3)
poprate - rate of population growth (pct)      (pct)
wpshift - shift in working age population      (pct + 12)

%
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%----------------------------Logical Rules--------------------------
        mml(e1,e2)  -> More Male Labour in e1 than e2
        mgdp(e1,e2) -> A larger share of the GDP was due to e1 than e2
%

1
[mml(e1,e2)][mml(e2,e3)] => [mml(e1,e3)].
1
[mgdp(e1,e2)][mgdp(e2,e3)] => [mgdp(e1,e3)].



% ------------- Descriptors for Countries with Low Strife -------------%
% Canada %
e
[literacy(c1)=20][sanctions(c1)=1][popul(c1)=3][highered(c1)=3]
[mml(e1,e2)][mml(e2,e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=1][civright(c1)=1][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=6][crshift(c1)=4][enshift(c1)=5][litshift(c1)=6]
[continent(c1)=namerica][polstrikes(c1)=0][relaxsanc(c1)=0]
                  => [strife=low].
% Brazil %
e
[literacy(c1)=14][sanctions(c1)=1][popul(c1)=9][highered(c1)=3]
[mml(e3,e1)][mml(e1,e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=4][civright(c1)=5][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=7][crshift(c1)=5][enshift(c1)=7][litshift(c1)=8]
[continent(c1)=samerica][polstrikes(c1)=2][relaxsanc(c1)=0]
                  => [strife=low].
% Thailand %
e
[literacy(c1)= 16][sanctions(c1)= 1 ][popul(c1)= 16][highered(c1)= 1 ]
[mml(e3,e1)][mml(e1,e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)= 5 ][civright(c1)= 4 ][mgdp(e1,e3)][mgdp(e3,e2)]
[prshift(c1)=11][crshift(c1)=1][enshift(c1)=5][litshift(c1)=9]
[continent(c1)=asia][polstrikes(c1)= 0 ][relaxsanc(c1)= 0 ]
                  => [strife= low ].
% Belgium %
e
[literacy(c1)=20][sanctions(c1)=0][popul(c1)=21][highered(c1)=3]
[mml(e1,e2)][mml(e2,e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=1][civright(c1)=1][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=6][crshift(c1)=4][enshift(c1)=4][litshift(c1)=6]
[continent(c1)=europe][polstrikes(c1)=0][relaxsanc(c1)=0]
                  => [strife=low].
% Uganda %
e
[literacy(c1)=7][sanctions(c1)=1][popul(c1)=14][highered(c1)=0]
[mml(e3,e1)][mml(e1,e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=7][civright(c1)=7][mgdp(e3,e1)][mgdp(e1,e2)]
[prshift(c1)=6][crshift(c1)=4][enshift(c1)=6][litshift(c1)=9]
[continent(c1)=africa][polstrikes(c1)=0][relaxsanc(c1)=0]
                  => [strife=low].
```

```
% India %
e
[literacy(c1)=8][sanctions(c1)=1][popul(c1)=19][highered(c1)=2]
[mml(e3,e2)][mml(e2.e1)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=2][civright(c1)=3][mgdp(e1.e3)][mgdp(e3,e2)]
[prshift(c1)=5][crshift(c1)=7][enshift(c1)=8][litshift(c1)=9]
[continent(c1)=asia][polstrikes(c1)=1][relaxsanc(c1)=2]
                   => [strife=low].
% Nepal %
e
[literacy(c1)=4][sanctions(c1)=0][popul(c1)=16][highered(c1)=1]
[mml(e3,e1)][mml(e1,e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=6][civright(c1)=5][mgdp(e3,e1)][mgdp(e1,e2)]
[prshift(c1)=6][crshift(c1)=4][enshift(c1)=10][litshift(c1)=10]
[continent(c1)=asia][polstrikes(c1)=0][relaxsanc(c1)=0]
                   => [strife=low].
% Soviet Union %
e
[literacy(c1)=20][sanctions(c1)=2][popul(c1)=9][highered(c1)=3]
[mml(e2,e1)][mml(e1,e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=7][civright(c1)=6][mgdp(e2,e1)][mgdp(e1,e3)]
[prshift(c1)=5][crshift(c1)=4][enshift(c1)=5][litshift(c1)=6]
[continent(c1)=europe,asia][polstrikes(c1)=0][relaxsanc(c1)=1]
                   => [strife=low].
% Singapore %
e
[literacy(c1)=14][sanctions(c1)=0][popul(c1)=28][highered(c1)=3]
[mml(e1,e2)][mml(e2,e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=5][civright(c1)=5][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=6][crshift(c1)=4][enshift(c1)=6][litshift(c1)=9]
[continent(c1)=asia][polstrikes(c1)=0][relaxsanc(c1)=0]
                   => [strife=low].

% US %
e
[literacy(c1)=20][sanctions(c1)=2][popul(c1)=11][highered(c1)=3]
[mml(e1,e2)][mml(e2,e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=1][civright(c1)=1][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=6][crshift(c1)=4][enshift(c1)=4][litshift(c1)=6]
[continent(c1)=namerica][polstrikes(c1)=0][relaxsanc(c1)=1]
                   => [strife=low].

% Venezuela %
e
[literacy(c1)= 17][sanctions(c1)=0  ][popul(c1)=  9][highered(c1)= 3 ]
[mml(e1,e2)][mml(e2,e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=  2][civright(c1)= 2 ][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=7][crshift(c1)=4][enshift(c1)=6][litshift(c1)=17]
[continent(c1)=samerica][polstrikes(c1)= 0 ][relaxsanc(c1)= 0 ]
                   => [strife= low].
```

```
% North Korea %
e
[sanctions(c1)= 0 ][popul(c1)= 18]
[mml(e3,e2)][mml(e2,e1)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)= 7 ][civright(c1)= 7 ]
[prshift(c1)=6][crshift(c1)=4]
[continent(c1)=asia][polstrikes(c1)= 0 ][relaxsanc(c1)= 0 ]
                 => [strife= low].

% Sweden %
e
[literacy(c1)= 20][sanctions(c1)= 0 ][popul(c1)= 10][highered(c1)= 3 ]
[mml(e1,e2)][mml(e2,e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=  1][civright(c1)=1  ][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=5][crshift(c1)=4][enshift(c1)=4][litshift(c1)=6]
[continent(c1)=europe][polstrikes(c1)= 0 ][relaxsanc(c1)= 0 ]
                 => [strife= low].

% Japan %
e
[literacy(c1)=20][sanctions(c1)=0][popul(c1)=20][highered(c1)=3]
[mml(e1,e2)][mml(e2,e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=2][civright(c1)=1][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=6][crshift(c1)=4][enshift(c1)=4][litshift(c1)=6]
[continent(c1)=asia][polstrikes(c1)=0][relaxsanc(c1)=0]
                 => [strife=low].

% Hungary %
e
[literacy(c1)=20][sanctions(c1)=0][popul(c1)=17][highered(c1)=3]
[mml(e2,e1)][mml(e1,e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=6][civright(c1)=6][mgdp(e2,e1)][mgdp(e1,e3)]
[prshift(c1)=6][crshift(c1)=5][enshift(c1)=5][litshift(c1)=6]
[continent(c1)=europe][polstrikes(c1)=0][relaxsanc(c1)=0]
                 => [strife=low].
% Austria %
e
[literacy(c1)=20][sanctions(c1)=0][popul(c1)=16][highered(c1)=3]
[mml(e1,e2)][mml(e2,e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=1][civright(c1)=1][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=6][crshift(c1)=4][enshift(c1)=5][litshift(c1)=6]
[continent(c1)=europe][polstrikes(c1)=0][relaxsanc(c1)=0]
                 => [strife=low].
% S. Korea %
e
[literacy(c1)=18][sanctions(c1)=0][popul(c1)=21][highered(c1)=2]
[mml(e3,e2)][mml(e2,e1)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=5][civright(c1)=6][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=7][crshift(c1)=5][enshift(c1)=6][litshift(c1)=12]
[continent(c1)=asia][polstrikes(c1)=0][relaxsanc(c1)=0]
                 => [strife=low].
```

```
% Chad %
e
[literacy(c1)= 3 ][sanctions(c1)= 0 ][popul(c1)= 4 ][highered(c1)= 0 ]
[mml(e3,e1)][mml(e1.e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)= 6 ][civright(c1)= 6 ][mgdp(e1,e3)][mgdp(e3,e2)]
[prshift(c1)=5][crshift(c1)=5][enshift(c1)=15][litshift(c1)=9]
[continent(c1)=africa][polstrikes(c1)= 4 ][relaxsanc(c1)= 0 ]
                    => [strife= low ].
% Nigeria %
e
[literacy(c1)=4][sanctions(c1)=0][popul(c1)=15][highered(c1)=0]
[mml(e3,e1)][mml(e1,e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=6][civright(c1)=4][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=7][crshift(c1)=6][enshift(c1)=7][litshift(c1)=0]
[continent(c1)=africa][polstrikes(c1)=0][relaxsanc(c1)=0]
                    => [strife=low].
% West Germany %
e
[literacy(c1)=20][sanctions(c1)=1][popul(c1)=20][highered(c1)=3]
[mml(e1.e2)][mml(e2,e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=1][civright(c1)=1][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=6][crshift(c1)=3][enshift(c1)=4][litshift(c1)=6]
[continent(c1)=europe][polstrikes(c1)=0][relaxsanc(c1)=0]
                    => [strife=low].
% China %
e
[continent(c1)=asia][literacy(c1)=17][sanctions(c1)=0][popul(c1)= 16]
[mml(e3,e2)][mml(e2,e1)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=7][civright(c1)=7]
[prshift(c1)=7][crshift(c1)=5][enshift(c1)=12][litshift(c1)=17]
[polstrikes(c1)=0][relaxsanc(c1)=0]
                    => [strife=low].

% Poland %
e
[literacy(c1)=20][sanctions(c1)=1][popul(c1)=17][highered(c1)=3]
[mml(e2.e3)][mml(e3,e1)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=6][civright(c1)=6][mgdp(e2,e1)][mgdp(e1,e3)]
[prshift(c1)=6][crshift(c1)=5][enshift(c1)=5][litshift(c1)=6]
[continent(c1)=europe][polstrikes(c1)=0][relaxsanc(c1)=0]
                    => [strife=low].
% Switzerland %
e
[literacy(c1)=20][sanctions(c1)=0][popul(c1)=18][highered(c1)=3]
[mml(e2.e1)][mml(e1,e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=1][civright(c1)=1]
[prshift(c1)=6][crshift(c1)=4][enshift(c1)=4][litshift(c1)=6]
[continent(c1)=europe][polstrikes(c1)=0][relaxsanc(c1)=0]
                    => [strife=low].
```

```
% Morocco %
e
[literacy(c1)=5][sanctions(c1)=0][popul(c1)=13][highered(c1)=1]
[mml(e3,e1)][mml(e1,e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=5][civright(c1)=4][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=8][crshift(c1)=6][enshift(c1)=8][litshift(c1)=9]
[continent(c1)=africa][polstrikes(c1)=0][relaxsanc(c1)=0]
                 => [strife=low].
% Haiti %
e
[literacy(c1)= 5 ][sanctions(c1)= 0 ][popul(c1)= 18][highered(c1)= 0 ]
[mml(e3,e1)][mml(e1,e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)= 6 ][civright(c1)= 6 ][mgdp(e1,e3)][mgdp(e3,e2)]
[prshift(c1)=7][crshift(c1)=4][enshift(c1)=6][litshift(c1)=10]
[continent(c1)= namerica,samerica][polstrikes(c1)= 0 ][relaxsanc(c1)= 0 ]
                 => [strife= low].
% Kenya %
e
[literacy(c1)=8][sanctions(c1)=0][popul(c1)=11][highered(c1)=0]
[mml(e3,e2)][mml(e2,e1)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=5][civright(c1)=5][mgdp(e1,e3)][mgdp(e3,e2)]
[prshift(c1)=6][crshift(c1)=3][enshift(c1)=9][litshift(c1)=12]
[continent(c1)=africa][polstrikes(c1)=0][relaxsanc(c1)=0]
                 => [strife=low].
% Malaysia %
e
[literacy(c1)=12][sanctions(c1)=0][popul(c1)=13][highered(c1)=1]
[mml(e3,e1)][mml(e1,e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=3][civright(c1)=3][mgdp(e1,e3)][mgdp(e3,e2)]
[prshift(c1)=5][crshift(c1)=3][enshift(c1)=6][litshift(c1)=11]
[continent(c1)=asia][polstrikes(c1)=0][relaxsanc(c1)=0]
                 => [strife=low].
% Indonesia %
e
[literacy(c1)=13][sanctions(c1)=0][popul(c1)=15][highered(c1)=1]
[mml(e3,e1)][mml(e1,e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=5][civright(c1)=5][mgdp(e1,e3)][mgdp(e3,e2)]
[prshift(c1)=6][crshift(c1)=4][enshift(c1)=7][litshift(c1)=12]
[continent(c1)=asia][polstrikes(c1)=0][relaxsanc(c1)=0]
                 => [strife=low].



% ------------ Descriptors for Countries with High Strife --------------%

%  Zimbabwe %
e
[literacy(c1)= 8 ][sanctions(c1)= 0 ][popul(c1)= 10]
[mml(e3,e1)][mml(e1,e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)= 6 ][civright(c1)= 5 ][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=7][crshift(c1)=4][enshift(c1)=5][litshift(c1)=12]
[continent(c1)=africa][polstrikes(c1)= 0 ][relaxsanc(c1)= 0 ]
                 => [strife= hi].
```

```
% Pakistan %
e
[literacy(c1)=5][sanctions(c1)=2][popul(c1)=16][highered(c1)=1]
[mml(e3,e1)][mml(e1.e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=4][civright(c1)=5][mgdp(e1,e3)][mgdp(e3,e2)]
[prshift(c1)=3][crshift(c1)=5]
[continent(c1)=asia][polstrikes(c1)=5][relaxsanc(c1)=2]
                   => [strife=hi].
% Greece %
e
[literacy(c1)=17][sanctions(c1)=1][popul(c1)=15][highered(c1)=3]
[mml(e3,e1)][mml(e1,e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=3][civright(c1)=3][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=11][crshift(c1)=8][enshift(c1)=5][litshift(c1)=7]
[continent(c1)=europe][polstrikes(c1)=1][relaxsanc(c1)=0]
                   => [strife=hi].

% Angola %
e
[sanctions(c1)= 0 ][popul(c1)= 6 ]
[mml(e3,e1)][mml(e1,e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[enshift(c1)=21]
[continent(c1)=africa][polstrikes(c1)= 0 ][relaxsanc(c1)= 0 ]
                   => [strife= hi].
% Portugal %
e
[literacy(c1)=15][sanctions(c1)=0][popul(c1)=16][highered(c1)=3]
[mml(e1,e2)][mml(e2,e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=4][civright(c1)=3][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=9][crshift(c1)=8][enshift(c1)=7][litshift(c1)=9]
[continent(c1)=europe][polstrikes(c1)=0][relaxsanc(c1)=0]
                   => [strife=hi].
% Zambia %
e
[literacy(c1)=8][sanctions(c1)=0][popul(c1)=7][highered(c1)=1]
[mml(e3,e1)][mml(e1,e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=5][civright(c1)=5][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=6][crshift(c1)=5][enshift(c1)=8][litshift(c1)=5]
[continent(c1)=africa][polstrikes(c1)=0][relaxsanc(c1)=0]
                   => [strife=hi].

% Mexico %
e
[literacy(c1)=15][sanctions(c1)=1][popul(c1)=12][highered(c1)=2]
[mml(e1,e3)][mml(e3,e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=4][civright(c1)=3][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=7][crshift(c1)=3][enshift(c1)=7][litshift(c1)=9]
[continent(c1)=namerica][polstrikes(c1)=3][relaxsanc(c1)=0]
                   => [strife=hi].
```

```
% United Kingdom %
e
[literacy(c1)=20][sanctions(c1)=2][popul(c1)=20][highered(c1)=3]
[mml(e1, e2)][mml(e2, e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=1][civright(c1)=1][mgdp(e1, e2)][mgdp(e2, e3)]
[prshift(c1)=6][crshift(c1)=4][enshift(c1)=5][litshift(c1)=6]
[continent(c1)=europe][polstrikes(c1)=10][relaxsanc(c1)=0]
                  => [strife=hi].
% Argentina  %
e
[literacy(c1)=19][sanctions(c1)=1][popul(c1)=8][highered(c1)=3]
[mml(e1, e2)][mml(e2, e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=4][civright(c1)=4][mgdp(e1, e2)][mgdp(e2, e3)]
[continent(c1)=europe][polstrikes(c1)=0][relaxsanc(c1)=4]
[prshift(c1)=10][crshift(c1)=0][enshift(c1)=5][litshift(c1)=17]
                  => [strife=hi].
% France %
e
[literacy(c1)=20][sanctions(c1)=1][popul(c1)=16][highered(c1)=3]
[mml(e1, e2)][mml(e2, e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=1][civright(c1)=2][mgdp(e1, e2)][mgdp(e2, e3)]
[prshift(c1)=6][crshift(c1)=5][enshift(c1)=5][litshift(c1)=6]
[continent(c1)=europe][polstrikes(c1)=6][relaxsanc(c1)=0]
                  => [strife=hi].
% Libya %
e
[literacy(c1)=9][sanctions(c1)=0][popul(c1)=1][highered(c1)=2]
[mml(e1, e2)][mml(e2. e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=7][civright(c1)=6][mgdp(e2, e1)][mgdp(e1, e3)]
[prshift(c1)=7][crshift(c1)=3][enshift(c1)=13][litshift(c1)=11]
[continent(c1)=africa][polstrikes(c1)=0][relaxsanc(c1)=0]
                  => [strife=hi].


% Lebanon %
e
[sanctions(c1)= 1 ][popul(c1)= 20]
[mml(e1, e2)][mml(e2, e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)= 3 ][civright(c1)= 3 ][mgdp(e1, e2)][mgdp(e2, e3)]
[prshift(c1)=4][crshift(c1)=2][enshift(c1)=5]
[continent(c1)=asia][polstrikes(c1)= 6 ][relaxsanc(c1)= 0 ]
                  => [strife= hi].
% Ethiopia %
e
[literacy(c1)= 2 ][sanctions(c1)= 1 ][popul(c1)= 11][highered(c1)= 0 ]
[mml(e3, e1)][mml(e1, e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)= 6 ][civright(c1)= 6 ][mgdp(e1, e3)][mgdp(e3, e2)]
[prshift(c1)=4][crshift(c1)=2][enshift(c1)=14][litshift(c1)=8]
[continent(c1)=africa][polstrikes(c1)= 0 ][relaxsanc(c1)= 0 ]
                  => [strife= hi].
```

```
% Turkey %
e
[literacy(c1)= 12][sanctions(c1)= 1 ][popul(c1)= 14][highered(c1)= 2]
[mml(e3,e1)][mml(e1,e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)= 2 ][civright(c1)= 3 ][mgdp(e1,e3)][mgdp(e3,e2)]
[prshift(c1)=7][crshift(c1)=5][enshift(c1)=7][litshift(c1)=11]
[continent(c1)=asia,europe][polstrikes(c1)= 0 ][relaxsanc(c1)= 0 ]
                  => [strife= hi].
% Spain %
e
[literacy(c1)=18][sanctions(c1)=3][popul(c1)=15][highered(c1)=3]
[mml(e2,e1)][mml(e1,e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=4][civright(c1)=4][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=9][crshift(c1)=8][enshift(c1)=6][litshift(c1)=7]
[continent(c1)=europe][polstrikes(c1)=10][relaxsanc(c1)=3]
                  => [strife=hi].
% South Africa %
e
[literacy(c1)=12][sanctions(c1)=2][popul(c1)= 11][highered(c1)=1]
[mml(e1,e2)][mml(e2.e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=4][civright(c1)=5][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=5][crshift(c1)=3][enshift(c1)=6][litshift(c1)=13]
[continent(c1)=africa][polstrikes(c1)=3][relaxsanc(c1)=0]
                  => [strife=hi].
% Peru %
e
[literacy(c1)= 15  ][sanctions(c1)= 1  ][popul(c1)= 9 ][highered(c1)= 3 ]
[mml(e1.e3)][mml(e1,e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)= 6 ][civright(c1)= 5 ][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=8][crshift(c1)=6][enshift(c1)=7][litshift(c1)=10]
[continent(c1)=samerica][polstrikes(c1)=  7][relaxsanc(c1)=  0]
                  => [strife= hi].
% Iraq %
e
[literacy(c1)= 5 ][sanctions(c1)= 0 ][popul(c1)= 12][highered(c1)= 2 ]
[mml(e3,e1)][mml(e1,e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)= 7 ][civright(c1)= 7 ][mgdp(e2,e1)][mgdp(e1,e3)]
[prshift(c1)=6][crshift(c1)=5][enshift(c1)=9][litshift(c1)=7]
[continent(c1)=asia][polstrikes(c1)= 0 ][relaxsanc(c1)= 0 ]
                  => [strife= hi].

% Colombia %
e
[literacy(c1)=17][sanctions(c1)=0][popul(c1)=11][highered(c1)=2]
[mml(e1,e3)][mml(e3,e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=2][civright(c1)=3][mgdp(e1,e3)][mgdp(e3,e2)]
[prshift(c1)=6][crshift(c1)=3][enshift(c1)=7][litshift(c1)=11]
[continent(c1)=samerica][polstrikes(c1)=1][relaxsanc(c1)=0]
                  => [strife=hi].
```

```
% Zaire %
e
[literacy(c1)= 7 ][sanctions(c1)= 0 ][popul(c1)= 8 ][highered(c1)= 0 ]
[mml(e3,e2)][mml(e2,e1)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)= 7 ][civright(c1)= 6 ][mgdp(e1,e3)][mgdp(e3,e2)]
[prshift(c1)=6][crshift(c1)=2][enshift(c1)=7][litshift(c1)=5]
[continent(c1)=africa][polstrikes(c1)= 0 ][relaxsanc(c1)= 0 ]
                  => [strife= hi].

% Burma %
e
[literacy(c1)=14][sanctions(c1)=4][popul(c1)=14][highered(c1)=1]
[mml(e3,e1)][mml(e1,e2)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=7][civright(c1)=6][mgdp(e3,e1)][mgdp(e1,e2)]
[prshift(c1)=7][crshift(c1)=3][enshift(c1)=10][litshift(c1)=8]
[continent(c1)=asia][polstrikes(c1)=0][relaxsanc(c1)=0]
                  => [strife=hi].

% Italy %
e
[literacy(c1)=20][sanctions(c1)=2][popul(c1)=19][highered(c1)=3]
[mml(e2,e1)][mml(e1,e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)=1][civright(c1)=2][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=5][crshift(c1)=4][enshift(c1)=6][litshift(c1)=8]
[continent(c1)=europe][polstrikes(c1)=0][relaxsanc(c1)=5]
                  => [strife=hi].

% Israel %
e
[literacy(c1)= 18][sanctions(c1)= 0 ][popul(c1)= 18][highered(c1)= 3 ]
[mml(e1,e2)][mml(e2,e3)][kind(e1)=services][kind(e2)=indus][kind(e3)=agr]
[polright(c1)= 2 ][civright(c1)= 3 ][mgdp(e1,e2)][mgdp(e2,e3)]
[prshift(c1)=6][crshift(c1)=5][enshift(c1)=4][litshift(c1)=5]
[continent(c1)=asia][polstrikes(c1)= 4 ][relaxsanc(c1)= 0 ]
                  => [strife= hi].
```