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ABSTRACT

This paper introduces a new method for the detection of patterns or phases in small groups based on fuzzy pattern recognition procedures. It tells how the method provides an accurate description of all the patterns of group interaction, detects rather than assumes the number of patterns and their length, and is based on fuzzy set theory so that it takes into account transitions between patterns. An example of the use of the method is provided using interaction from three decision-making groups. (Author/TJ)

A NEW PROCEDURE FOR THE DETECTION OF PATTERNS IN SMALL GROUP INTERACTION

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Abstract

This paper introduces a new method for the detection of patterns or phases in small groups based on fuzzy pattern recognition procedures. The advantages of the method are: (1) it provides an accurate description of all the patterns of group interaction; (2) it detects rather than assumes the number of patterns and their length; (3) it is based on fuzzy set theory so that it takes into account transitions between patterns. An example of the use of the method is provided using interaction from three decision making groups.

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A NEW PROCEDURE FOR THE DETECTION OF PATTERNS IN SMALL GROUP INTERACTION

I. Introduction

A goal of scientific inquiry is to discover patterns or order in apparently random data. Tou and Gonzalez have characterized this process of pattern recognition as "...the categorization of input data into identifiable classes via the extraction of significant features or attributes of the data from a background of irrevelant detail (1974, p. 6)." Small group researchers have attempted to discover patterns of small group communication across many groups and settings: family communication, decision making, discussion, therapy interviewing and analysis, classroom discussions, etc. Essentially, the goal of this research has been to discover phases or nonstationary parameters of communications sequences. The phase hypothesis adopted by most researchers is formulated by Hewes in the following terms: "Essentially the phase hypothesis asserts that groups go through a series of discrete, qualitatively different states of development which are invariant in order, but not in rate of evolution (1977, p. 18)."

In recent years, the typical procedure for detecting stationarity or non stationarity of communication sequences has relied upon Markov analytical techniques. Once coded, a composit transition matrix is constructed for the entire group interaction. The interaction sequence is then arbitrarily divided into a preset number of segments. Transition matricies from each time segment are compared with the composite matrix to determine whether the segments differ in probabilities of movement from one state to another (Ellis & Fisher, 1975). This research procedure has led to confusing and mixed empirical results. While Ellis and Fisher (1975) and Stech (1975) found support for the existence of phases, Hawes and Foley (1973, 1976) and Scheidel and Crowell (1974) did not.

Theoretical and methodological problems may account for the inconsistent findings. Methodologically, two assumptions confound the discovery of phases. First, most researchers divide the interaction into an arbitrary number of time segments. As a result, the researcher assumes the existence of a given number of phases, usually three to five, before the data is even analyzed. As Stech (1977) indicated this also requires the assumption of stationarity within each time segment which may not be reflected in the data. Second, most researchers divide the interaction into time segments of equal length for ease of numerical analysis. Again, the assumption is made before the data is analyzed that if phases exist they must all be of equal length. Thus, the present method of phase analysis requires that the number and the length of phases is determined by the researcher rather than detected in the empirical data. Theoretically, the major problem with phase research is the explicit or implicit assumption that patterns occur in invariant order. While prescriptive writers have been criticized for this assumption (Fisher, 1974), most empirical researchers have succumbed to the same problem in their models and explanations of phases (Tuckman, 1975; Fisher, 1970; Hare, 1973).

The purpose of this paper is to present a new method for the discovery and characterization of patterns in small group decision making in which the existance, the number and the length of patterns are determined directly from the data. The term pattern is deliberately substituted for the term phase in order to clarify the assumptions underlying the theory and methodology of this approach. In short, a small group is assumed to exhibit structure in the form of recurrent patterns or sequences. These sequences may be long or short, few or many, and they may recur during interaction depending upon the nature of the group, task, and interaction coding categories. Thus, this paper seeks to test a more generalized form of the traditional phase hypotheses: groups exhibit patterns of interaction which may be characterized by prototypical transition matrices. This new method for discovering and characterizing patterns is based upon mathematical procedures known as fuzzy pattern recognition (Bezdek, 1974). Section II of this paper will briefly outline the fuzzy pattern recognition method. Section III will demonstrate the use of the fuzzy pattern recognition algorithm by applying it to the analysis of patterns in three decision making groups. Section IV will summarize the theoretical and methodological implications and discuss some areas for future research.

II. Fuzzy Pattern Recognition

While the search for patterns is an integral part of scientific inquiry, small group interaction is so complex that it is unlikely to be completely characterized by several easily-determined patterns. The task facing the researcher is to find a finite set of patterns which can represent small group interaction. Yet, even if such a pattern set is given, it is still highly unlikely that any chain of observed interaction would fall completely into one of the pattern categories. Rather, the sequence would most likely be characterized primarily by one pattern and yet contain elements of several other patterns from the pattern set. Hence, it is necessary to realize that any interaction will contain parts of several different patterns. While normal scientific requirements for mutually exclusive and exhaustive classification systems cannot easily handle this situation, a fuzzy pattern recognition scheme can overcome these descriptive and analytical problems.

Fuzzy patterns recognition uses fuzzy mathematics as developed by Zadeh (1965). Fuzzy mathematics is based on the premise that real world phenomenon contain characteristics which overlap any artifical category system or classification rules. Therefore, set membership is characterized by values of a function ranging between zero and one, each value indicating the degree of membership of an element in a given set (Spillman, Spillman, and Bezdek, 1977). A zero indicates that the element being described shares none of the characteristics of the given set and a one indicates that the element is a complete member of the set. Thus, a researcher who has discovered four patterns of decision-making might also discover that the interaction in a given time segment shared many characteristics of pattern one, receiving a .9 membership value for the pattern, and that it shared only a few characteristics of pattern three, receiving a .1 membership value for that pattern. For a more complete description of fuzzy set theory and its application to communication research, several articles are recommended: Bezdek, Spillman and Spillman, 1978; Spillman, Bezdek and Spillman, 1978; Spillman, Spillman and Bezdek, 1977, 1978.

Several techniques have been developed for machine recognition of patterns in data (Tou and Gonzalez, 1974). Recently a pattern recognition technique incorporating concepts from fuzzy mathematics was developed by

Bezdek (1974) called fuzzy ISODATA. The input data set for the fuzzy ISODATA algorithm is partitioned into c nonempty subsets or clusters. The value of c, the number of clusters, ranges between 2 and n, the number of data points in the input. The algorithm generates the optimum fuzzy partition for each value of c by minimizing the functional J_m which represents a fuzzy within group sum of squared errors criterion function. A complete description of the mathematical procedures is beyond the scope of this paper but may be found elsewhere (Bezdek, 1973, 1974).

The algorithm as applied to the analysis of small group interaction requires at set of transition matricies as input as well as the range for the value of c, the number of clusters sought. A separate output is produced for each value of c. Each output contains and entropy value, a prototype for each cluster or pattern, and the membership value of each input transition matrix across each of the clusters. The best set of patterns representing the data is the one which contains the lowest entropy value. Each prototype consists of a transition matrix which best represents the associated cluster.

Utilizing the fuzzy pattern recognition technique in small group research involves the following steps: (1) break up the interaction into as many interaction segments as is feasible for the generation of a valid transition matrix (at least 100 interacts for a 5-category system); (2) calculate a Markov transition matrix for each interaction segment (this serves as the input data set for fuzzy ISODATA); (3) run the fuzzy ISODATA program on the data generated in step two (this program is available upon request for the authors); (4) determine the best value for c by choosing the number of clusters associated with the lowest entropy value; (5) analyze the prototypical matricies to determine the characteristics and transition probabilities for each of the patterns. The membership values of each data matrix may be used to detect transitional phases between patterns.

III. Empirical Example

Method

Interaction from three discussion groups was recorded, transcribed and coded using the categories of the Ellis (1976) relational coding system. The Ellis system translates the coded acts into five relational categories, dominance, ↑+, structuring, ↑-, symmetry, → , deference, ↓-, and submission, ↓+. Groups one and two were drawn from communication fundamentals courses at a rural university and group three was drawn from a course in small group communication at a nearby urban university. Members of the three groups were informed that they were participating in a study, though no specifics were discussed with them. All three groups participated in the study while simultaneously fulfilling a class project in which they were to choose, analyze, and present a solution to a national or local problem. No leader was assigned. Discussion groups one and two met for seven and eight consecutive days. Group three met one day each week for half the quarter.

Analysis

Markov probability transition matrices were calculated for each interaction segment. Group one data were divided into seven segments with approximately 100 interacts in each. Data from group two were divided into eight interaction segments, again with approximately 100 interacts in each. Data from group three were divided into twenty segments under the same criterion.

These matrices were used as input to the fuzzy ISODATA algorithm. The output of this pattern recognition procedure was analyzed according to steps four and five in the previous section.

Results

Group one. Using the entropic criterion described earlier, data indicated that group one was best characterized by three interaction patterns (see Table I). The entropy value for this clustering was .0907, the lowest value obtained.

Table II shows the fuzzy membership values of each time period in each of the three patterns. Each time period had very strong membership in one of the patterns. For example, time period one was clearly a member of pattern one since its membership value in that cluster was .9987 while its membership value in the other two patterns was low (.0004, .0009). Figure I graphically displays the shift in patterns over time. The X in Figure I indicates that the time period had its strongest membership in the correspoding pattern.

The prototypical transition matricies for each of the three patterns for group one are shown in Table III. Since the fuzzy ISODATA formula calculates each cell individually, the rows in the matrices do not always sum to one. In this sense, then, the prototypes are not Markov matrices. Since the rest of the analysis and discussion will focus on a cell by cell comparison, the rows were not normalized so that they would sum to one. The numbers in each cell indicate the strength of the probability of moving from the state labeled in the row to that labeled by the column, just as one would read a traditional Markov matrix. For example, in pattern one, the probability of a transition from +- to +- is .166.

<u>Group Two</u>. Data from this group indicated that group two was best characterized by five interaction patterns. The entropy for this clustering was .74 (see Table IV).

In this group, as for group one, each time period demonstrated strong membership in one of the patterns (see Table V). In fact, three of the eight time segments exhibited membership in only one pattern with a membership value of 1.0. Time period two, for example, was completely contained in pattern two and exhibits no membership or characteristics of the other patterns.

Figure II graphically displays the shift in interaction patterns over time. As for group one, the shift was not an invariant progression over time from pattern one through pattern five.

Table VI indicates the prototypical transition matrices for each cluster.

<u>Group Three</u>. Group three, according to the entropy measure, was best characterized by two patterns (see Table VII). The entropy value for the two-cluster solution was .38. Unlike the other two groups the time periods showed strong memberships in more than one pattern. For example, time period eleven appeared to be a transition period between patterns one and two since its membership in pattern one was .6365 while its membership in pattern two was .3635 (see Table VIII). Because of the fuzzy membership values for some of the twenty time periods, Figure III not only indicates with an X the strongest membership of each time period in one of the patterns, but also indicates with a star those time periods which exhibited strong membership or characteristics of both patterns.

Characteristics of each interaction cluster are given by the two prototypical transition matrices in Table IX.

Discussion

Patterns. Because of the small number of groups in this study, generalizable conclusions about the exact empirical nature of patterns of decision making cannot be proposed. Data from this study strongly supports the revision of the phase hypothesis suggested in the first section of this paper. The results, although inconclusive, will be analyzed to demonstrate how researchers can use the kind of information provided by the fuzzy ISODATA algorithm.

In support of the pattern hypothesis, three conclusions seem justified. First, groups exhibit patterns during decision making discussions. The strongest evidence for this lies in the low entropy values ranging from .07 to .38 across the three groups. Second, patterns recur throughout a group's interaction (Figures I, II, and III). For group one, pattern one occurred at time periods one, three, and five of the interaction while pattern two occurred during time periods two and four. Group two also demonstrated the shift in patterns over time. Figure II demonstrated that pattern one occurred twice. Patterns two, three, four, and five, however, occurred only once during the discussion. Although it only occurred once, pattern five continued through three time periods. Group three shifted back and forth between pattern one and two, with pattern one occurring ten times and pattern two occurring ten. Third, patterns are maintained for variable time lengths and do not follow a progressive order from beginning to end, as implicitly suggested by phase researchers. Thus, the arbitrary division of group interaction into three or four equal time periods confounds the detection of underlying interaction patterns. To illustrate the importance of this conclusion, contrast the findings that would have been obtained by tranditional methods with the conclusions found by the fuzzy ISODATA program. If group one had been divided into four equal time segments, the phase for the first time period would have included patterns one and two. The second would have included patterns one and two while the third would have included patterns one and three. The final phase would have consisted of pattern three alone. The result is a loss of vital information about the underlying substructure and an inability to accurately label or describe the phases. Typical phase analysis would have incorrectly identified time periods one and two as demonstrating one phase when in actuality, both time periods exhibited a mixture of two identifiable patterns. Analysis of the structure of group three illustrates the difficulty with the traditional phase search more vividly. If group three had been divided into four equal segments, each with five time periods, the first phase would have included the following sequence of patterns: one, two, one two, one (Figure III). The transition matrix would have included probabilities from three occurrences of pattern one and two occurrences of pattern two. Phase two would have included the pattern sequence two, two, two, one, one. Phase three, while consisting of a different sequence of patterns (one, two, two, one, two), would have roughly the same transition matrix to that of phase two. It would have been incorrectly identified and its uniqueness lost in the overall analysis. Similarly, phase four would have been identified as a recurrence of phase one since its transition matrix would have included the same number of occurrences of patterns one and two as phase one.

These results, then, support the more generalized form of the phase phyothesis: groups exhibit patterns of interaction which can be characterized by prototypical transition matrices. The next section will analyze these prototypical transition matrices not to assert that all groups will exhibit the same kinds of patterns, but rather to demonstrate how such data might be analyzed in a study which would include a larger and more exhaustive data pool.

Prototype Analysis. Simply discovering the existence of patterns and regularities within phenomenon is not a sufficient goal for scientific inquiry. The further task of science is to identify and label the regularity of patterns and to discover the similarities and differences among patterns which lead to generalizable conclusions about the nature of the phenomenon under study. This goal can be accomplished in the context of pattern recognition in groups through the analysis of prototypical patterns of small group interaction. While the analysis to follow parallels the analysis of phases it should be remembered that the prototypes represent "pure" patterns. These prototypes provide the researcher with information concerning the most probable movements from an anticedent to a consequent act. Table III gives the prototypes for the three patterns exhibited by group one. Although a quantitive comparison cannot be made, conclusions concerning the likelihood of each state can be made by summing the probabilities in the columns and ranking them from the largest probability to the smallest. This is done because prototype data provides only probability matrices and not frequency matrices as output. Table X gives the column sums for the three patterns of group one. In all three patterns, the symmetrical state, + , was the most likely act. In pattern one, the second most likely state was the dominant, ↑+. In patterns two and three, however, deference, ↓-, was the second most likely. This seems to indicate that group members are more inclined to cooperative effort and are more inclined to agree with and defer to other group members rather than to work competitively and in a domineering fashion when the group is in patterns two or three. The likelihood of the remaining acts, ↓+, ↑-, was consistent across the three patterns.

Analysis of the interact matrices generate findings similar to the conclusions drawn from the act analysis (see Table III). While the differences between patterns one and two appeared small, there seemed to be a marked movement toward deference and equality and away from competition or dominance as the group moves from patterns one and two into pattern three. The only substnatial difference between patterns one and two was the transition from structuring, ↑-, to dominance, ↑+. This competitive relationship occurred more in pattern one than in pattern two, where structuring, ↑-, was more likely to be followed by equality, → .

A comparison of patterns one and two with pattern three revealed some striking differences. While a deferential comment was more likely to be followed by a symmetrical comment, ↓- →, in the first two patterns, the transition from deference to deference, ↓-↓-, was far more common in pattern three. In a similar fashion, the movement from equality to dominance, →↑+, decreased in pattern three while the movement from equality to deference, → ↑+, decreased in pattern three while the movement from equality to deference, → ↓- increased. Finally, the transition from structuring to further structuring and deference, → →, → ↓-, decreased. Since pattern three occurred at the conclusion of the groups' discussion and patterns one and two were exhibited in the first time periods, it appeared that most of the structuring and dominance attempts were made during the first 2/3 of the discussion, and more comments registering equality and deference were communicated at the end. Transitions from deference to deference as well as transitory relationships between deference and other states characterized the conclusion of the group's interaction. Relationships were apparently defined and stabilized toward the end of the group's interaction, and the probability of challenging or opposing these relational definitions was quite low.

Similar analysis can be made of act and interact probabilities for patterns in groups two and three. One should be careful, however, to note that the pattern recurrence in these groups is more complex than in group one. The order of the patterns, moreover, did not occur in numerical order as it did in the first group.

Five patterns were detected for group two. After summing the columns to determine single act frequencies, equality or symmetry, → , again predominated across all patterns. For patterns one and five, deference, ↓-, was the second most likely. For the other three patterns, however, dominance, ↑+, was the second most likely act. The rank ordering for the other three acts, ↓+, ↑-, → , was the same across all five patterns (see Table XI).

At the interact level, two of the most striking differences across the five patterns were the transitions out of dominance, ↑+, and out of symmetry, → (see Table VI). In pattern one, the state following ↑+ leads most often to the deference state, ↓- . The transition from dominance to deference, ↑+↓-, was more likely in pattern one than in any of the other patterns.

Pattern one also had a stronger likelihood to transist from dominance to structuring, ↑+↑-, then any of the other patterns. The transition from dominance to symmetry was less likely, however, in pattern one than in all other patterns. Patterns one and five showed approximately the same likelihood for the transition between symmetry and deference. This transition, moreover, was more likely in patterns one and five than in patterns two, three, and four. Pattern two demonstrated a lower likelihood than patterns three, four or five to transist from deference to deference, ↓-↓-. The transition from dominance to symmetry, ↑+→ , was also less likely in this pattern than in the latter three.

Pattern one was the only pattern which recurred in this interaction. It appeared to be slightly more competitive and to exhibit more dominance than the other patterns. Five appeared to be the final pattern-phase of the group, occurring three consecutive times at the end of the group's interaction. To pinpoint differences more precisely, more data would be necessary than was available at this point. It is apparent, however, that this method of analyzing group interaction reveals far more complexity and provides much more information that is usually available in traditional Markov analysis. The nature of this complexity is revealed one step further in a brief look at decision making in group three.

Adding the columns for group three revealed that the two patterns were strickingly similar in the relative order of the most probable states (see Table XII). They differed, however, in the relative strengths of probabilities within the ordering. While dominance was the most probable act in both phases, its likelihood was much stronger for pattern two (3.33) than for pattern one (2.58). Deference, the second most likely act for both patterns, was less probable for pattern two (.81) than for pattern one (1.16). The differences in the probabilities for the other three states were minimal.

At the interact level, three interacts accounted for the majority of the differences between the two patterns (see Table IX). Transitions from equality, → , to deference, ↓-, were more probable in pattern one than two. Transitions from equality to structuring, → ↑-, were also more likely to occur in pattern one than two. The transitory interact between equality and dominance, → ↑+, however, was more likely to occur in pattern two than one. Taking into account both act and interact differences, pattern two seemed to be a more competitive and challenging pattern than pattern one. Statements registering equality were more likely to be met with strongly dominant statements in the second pattern, and the sheer frequency of dominant statements was greater for this pattern. More attempts at cooperation were demonstrated by pattern one as reflected in the transitions from equality either to deference or to structuring.

Looking at the shifts in patterns across time and the strength of membership of each time segment in the two patterns provides another method for describing this group's behavior. The first time period reflected a strong membership in pattern one (.7983) and a relatively weak membership in pattern two (.2017). This means that while time segment one exhibited some characteristics of the less intensely competitive pattern, it also exhibited some characteristics of the second pattern. The second time segment was almost completely characterized by pattern two (.9902), increased competition and relationship challenge. The third time segment exhibited almost identical characteristics as time segment one as shown by its similar membership values (.8156, .1844). Time segment four was similar to the second time segment. Time segment five appeared to be a transistion time period in the back and forth shifting of patterns. It reflected more characteristics of pattern one (.6469) than two, though it maintained many of the attributes of both. This same analysis could be continued across all time periods to indicate the strength of the differences among time segments. In addition, a time series analysis could be performed on the membership values which would provide an equation to describe the pattern membership behavior over time and to predict pattern behavior which would have occurred if the group had continued interaction. It should also be noted that the group began and ended its interaction with pattern one. During the entire course of decision making, however, there were an equal number of time segments in each pattern. The group could almost be said to exhibit a fight and flight tendency, although the probability prototypes would have to be examined more thoroughly before such a conclusion could be stated as empirical fact. Fisher and Beach (1978) found a similar shift in their analysis of dynamic interaction. They explained the shift from mild conflict to equivalence as follows:

> Such movement may be an on-going characteristic of the maintenance function of on-going relationships. That is, a mature and stable social relationship need not be characterized by a constancy of the same interaction patterns (1978, p. 13).

As can be seen from this cursory examination of the data, the fuzzy ISODATA method for analyzing communicative interaction provides more information and more accurate picture of group interaction than those methods most often used to discover phases. Groups exhibit patterns and a complexity of interaction which has been untapped by most research techniques. In fact, the information is so massive and complex that more convenient methods for handling the data must be found. These will be presented in the final section of this paper. Suffice it to say here, however, that patterns do exist in communicative interaction, and that these can be illustrated through prototypical matrices and the changing membership values in patterns over time.

IV. Summary and Implications

The fuzzy ISODATA algorithm provides a useful mathematical technique for detecting patterns for interaction in small groups. It also provides an effective method for the description and analysis of such patterns by determining pattern prototypes and the membership of any interaction-time segment in the set of patterns. The information obtained form this algorithm may be analyzed by similar techniques now in use to analyze Markov probability transition matrices.

The empirical example illustrates some of the results of using this algorithm. One of the largest disadvantages of the method is in fact its greatest advantage: the sheer amount and complexity of the information it provides. Some methods for handling and analyzing this information are available. Anderson-Goodman statistics may be used to compare normalized prototype transition matrices to demonstrate the significant differences among the patterns. Stereotype statistics can also be calculated to compare the amount of structure in each of the pattern prototypes. Complexity may also be handled by noting the amount of time the group remains in each state across the different patterns. Time could be determined by both interact and clock time. State decay rates (Spillman and Spillman,

1976) may also be determined for each prototype matrix to calculate occupancy rates.

Though we have demonstrated this method through Ellis' relational coding system, it should be apparent that it is not dependent upon the type of coding scheme or even upon the type of group. All types of groups and coding systems which are analyzed by the traditional Markov method may be analyzed by the fuzzy ISODATA algorithm. The double interact level or even longer chains of interaction could also be analyzed by the program.

The major point to be made by this paper is that present methods of searching for phases have led to inconsistent results. We believe that the inconsistencies and confusions stem from theoretical and methodological problems. The fuzzy ISODATA method offers the following advantages over the traditional method: (1) it provides an accurate description of all the patterns of group interaction; (2) it detects rather than assumes the existence of phases and does not rely upon arbitrary time or interact divisions; (3) it determines the number of patterns displayed by the group and describes each pattern with a prototype transition matrix; and (4) because it is based upon fuzzy set theory, it takes into account transition time periods between patterns and thus more accurately describes a group's behavior and evolution.

c	Entropy
2	.181
3	.0907
4	.113
5	.131
6	.109

Table I: Group One Entropy

Time	Pattern 3	Pattern 2	Pattern 1
1	.0004	.0009	.9987
2	.0004	.9977	.002
3	.0022	.0058	.992
4	.0022	.977	.0207
5	.0063	.0056	.988
6	.9871	.002	.011
7	.9975	.0007	.0018

Table II: Fuzzy Membership of Group One

		↓+	↓−	→	↑−	↑+
	↓+	.0002	.0006	.0007	.0002	.0004
	↓−	0	.166	.4549	.0435	.3355
Pattern 1	→	0	.189	.5024	.0722	.2364
	↑−	0	.186	.388	.2164	.2092
	↑+	.0001	.2898	.3746	.0881	.2475
	↓+	.0447	.4719	.3478	.0447	,0895
	↓−	.0087	.2014	.4782	.0265	.2853
Pattern 2	→	.0131	.2365	.4975	.0584	.1945
	↑−	0	.2117	.4451	.2158	.1273
	↑+	.0192	.3096	.3827	.0423	.2461
	↓+	0	.0001	.0001	0	0
	↓−	0	.3587	.2509	.0077	.3827
Pattern 3	→	0	.4074	.4706	.0326	.0895
	↑−	0	.0003	.8752	.0001	.1244
	↑+	0	.3306	.3975	.0871	.1848

Table III: Prototypes for Group One

c	Entropy
2	.1
3	.081
4	.087
5	.074
6	.175
7	.19

Table IV: Group Two Entropy

Time	Pattern 1	2	3	4	5
1	.9966	.0015	.0002	.0001	.0015
2	0	1.0000	0	0	0
3	0	0	1.0000	0	0
4	.9873	.0048	.0004	.0003	.0072
5	0	0	0	1.0000	0
6	.0028	.0049	.0007	.0004	.9912
7	.0016	.0014	.0005	.0003	.9962
8	.0012	.0015	.0005	.0003	.9965

Table V: Fuzzy Membership of Group Two

		↓+	↓−	→	↑−	↑+
Pattern 1	↓+	.0064	.1878	.3618	.046	.3979
	↓−	.0238	.2247	.5002	.0619	.1895
	→	0	.3103	.5226	.0452	.1219
	↑−	.0127	.2994	.4122	.0502	.2254
	↑+	0	.8339	0	.1658	0
Pattern 2	↓+	0	.1002	.3	.0001	.5997
	↓−	0	.1253	.4792	.1041	.2951
	→	0	.1431	.5713	.1428	.1429
	↑−	.0322	.3226	.4514	.0323	.1614
	↑+	0	.3333	.6653	.0002	0
Pattern 3	↓+	.037	.0926	.5	.0556	.3148
	↓−	0	.3036	.4595	.0901	.1441
	→	0	.0952	.619	.1905	.0952
	↑−	0	.3421	.4737	.1053	.0789
	↑+	0	0	.9998	0	0
Pattern 4	↓+	0	.0976	.5122	.0244	.3659
	↓−	.065	.413	.2826	.087	.1522
	→	0	.1429	.2857	0	.5714
	↑−	0	.4828	.3793	.0345	.1034
	↑+	0	0	1.000	0	0
Pattern 5	↓+	0	.2245	.3203	.0338	.4214
	↓−	0	.3239	.4145	.057	.2046
	→	0	.3406	.4651	.1321	.0622
	↑−	.0025	.4211	.4421	.0122	.1222
	↑+	0	.0003	0	.0001	0

Table VI: Prototypes for Group Two

c	Entropy
2	.38
3	.43
4	.624
5	.527
6	.5
7	.404

Table VII: Group Three Entropy

	Pattern	
Time	1	2
1	.7983	.2017
2	.0098	.9902
3	.8156	.1844
4	.0514	.9486
5	.6469	.3531
6	.0179	.9821
7	.0626	.9374
8	.0062	.9938
9	.9229	.0771
10	.8672	.1328
11	.6365	.3635
12	.1492	.8508
13	.7922	.2078
14	.043	.957
15	.019	.981
16	.747	.253
17	.347	.653
18	.009	.991
19	.7851	.2149
20	.9186	.0814

Table VIII: Fuzzy Membership of Group Two

		↓+	↓−	→	↑−	↑+
Pattern 1	↓+	.0358	.2183	.0204	.0352	.4324
	↓−	.0351	.1689	.0233	.1105	.6592
	→	.142	.3365	.055	.2463	.2201
	↑−	.0401	.2231	.027	.0432	.6666
	↑+	.0428	.218	.0154	.1191	.6047
Pattern 2	↓+	.0991	.1465	.0229	.0919	.5873
	↓−	.0326	.1498	.0486	.1037	.6653
	→	.0294	.0656	.0087	.0993	.797
	↑−	.066	.2252	.0059	.0348	.6681
	↑+	.046	.2248	.0241	.0897	.6154

Table IX: Prototypes for Group Three

	Pattern		
	1	2	3
↓+	.0003	.09	0
↓−	.83	1.43	1.1
→	1.72	2.15	1.99
↑−	.42	.39	.13
↑+	1.03	.94	.78

Table X: Column Sums for Group One Prototypes

	Pattern 1	2	3	4	5
↓+	.03	.03	.04	.06	.01
↓−	1.85	1.02	.84	1.14	1.31
→	1.79	2.47	3.05	2.46	1.64
↑−	.37	.27	.44	.14	.23
↑+	.94	1.19	1.36	1.19	.81

Table XI: Column Sums for Group Two Prototypes

	Patterns 1	2
↓+	.29	.27
↓−	1.16	.81
→	.14	.11
↑−	.52	.42
↑+	2.58	3.33

Table XII: Column Sums for Group Three Prototypes

Pattern \ Time	1	2	3	4	5	6	7
1	X		X		X		
2		X		X			
3						X	X

Figure I: Pattern Membership over Time for Group One

Pattern \ Time	1	2	3	4	5	6	7	8
1	X			X				
2		X						
3			X					
4					X			
5						X	X	X

Figure II: Pattern Membership over Time for Group Two

Time

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	X*		X		X*				X	X	X*		X*			X*			X*	X
2		X		X		X	X	X				X		X	X		X*	X		

Figure III: Pattern Membership over Time for Group Three

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