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ABSTRACT

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The Analysis of Sequential Behavior In Classrooms and Social Environments: Problems and Proposed Solutions

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Abstract

Problems in the analysis of sequential behavior are discussed in relation to observation-coding procedures. A set of heuristic constructs are presented toward the development of a solution strategy for the analysis of chains of interactive behaviors. A proposed analytic computer program is briefly outlined and discussed.

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The Analysis of Sequential Behavior

In Classrooms and Social Environments:

Problems and Proposed Solutions

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Considerable interest is currently being evidenced toward the measurement, description and understanding of complex interactive behaviors in classrooms and other social environments. A surfeit of observer-coding systems have been developed for the study of verbal interactions (Flanders, 1965), motor behaviors (Calloway, 1968) and cognitive behaviors (Gallagher, 1965), among others. Such schemes allow an investigator to categorize the events being observed in a systematic fashion. Early attempts to describe complex interactive behavior focused on the frequency with which various categories of behavioral events occurred, and the data-set was analyzed by computing the proportion of time spent in each category (see Medley & Metzel, 1963). Subsequently, interest focused on methods which retain the sequential elements of the events. Flanders (1965) recorded observations in a matrix with row and column indices identifying antecedent and consequent behavioral events. Hence, each cell entry is the frequency of occurrence of a particular two-stage Markov chain. The cell entries can be divided by the appropriate row total to obtain the probability of one event following another.

To our knowledge, relatively few workers have gone beyond the simple two-stage technique introduced by Flanders and his associates in applying Markovian constructs and analytic techniques to the study of interactions

in classrooms and other social environments. Jaffe (1968), Hertel (1968), and Rausch (1970) have recently presented interesting applications of the Markov chain model to the analysis of sequential interactive behavior. Kalter (1970) has presented an interesting application of the Markov model to the assessment of intercoder reliability in sequential analysis. Peña (1969) applied the Markov model directly to problems of Interaction Analysis data derived from the Flanders technique. Bobbitt, Gourevitch, Miller and Jensen (1969) have reported an interesting approach to the analysis of the order of events over time as well as the frequency of their occurrence.

Several methodological issues are generic to the analysis of sequential interactive behavior. The purpose of this paper is to discuss what we believe to be some of the more critical problems in this area and to recommend strategies toward their solution. Questions pertaining to the validity and reliability of specific observer-coding systems are considered beyond the scope of this paper, although some suggestions are made regarding the validation of categories within observation systems. Analytic problems associated with simultaneity, segmentation and the retention of sequence are discussed.

Issues in the Study of Sequential Behavior

Simultaneity

Most of the existing observation-coding systems assume that the interactors (i.e. the class and teacher) behave sequentially. This is an oversimplification since each student is obviously engaged in some type of behavior (e.g., listening) while the teacher is "behaving" (e.g., lecturing). It is, therefore, desirable that a general analytic strategy

have the capacity to deal with simultaneous coding of behavior from several sources (Fink, 1970). Fortunately, simultaneous codings can generally be transformed to a sequential code by creating a dummy category system which consists of all possible combinations from the sequential codes (e.g., pupil and teacher behavior diads). It is therefore assumed that any analytic method which deals satisfactorily with sequential coding will also be satisfactory for simultaneous coding systems.

The Problem of Segmentation

Both Kalter (1970) and Marsden (1970) have pointed out the lack of agreement among investigators regarding strategies for segmenting sequential behavior into units for analysis. Rules of segmentation include time-independent systems which record only transitions from category to category to time-dependent systems which code behavior according to fixed-interval schedules (see Medley & Mitzel, 1963). The inadequacies of time-independent analytic systems have been extensively discussed in the behavioral science literature (e.g., Zimmerman, 1963; Rausch, 1970), and need not be reiterated here. However, it has not been widely recognized that a time-dependent unit consists of two orthogonal components: transition into a behavioral category--the occurrence of the categorized behavior, and the duration of the recorded episode--the time spent in the category.

The problem is best illustrated with a hypothetical data matrix. Suppose that a twenty-minute session had been segmented using three-second time intervals, and each segment classified as one of five mutually exclusive categories of behavior. The hypothetical results are recorded in Matrix 1 of Table 1. Assuming that behavior is constant throughout each

three-second interval, the frequencies which would obtain using a one-second interval are tabulated in Matrix 2. Note that the off-diagonal cells remain constant while the diagonal elements are grossly inflated. We further note that the transitional cell probabilities will differ as a function of the interval size selected. Hence, transitional probabilities must always be reported in relation to the interval selected if misinterpretation is to be avoided.

Insert Table 1 about here

The matrices in Table 1 provide visual evidence that the diagonal and off-diagonal elements are conceptually independent. Mathematically, as interval size approaches zero, the diagonal entries approach time-in-category (that is, their respective row or column totals). Since the off-diagonal elements remain constant, there is zero correlation between diagonal and off-diagonal elements. Therefore, the diagonal cells (time-in-category) and off-diagonal cells (transitions from category to category) are orthogonal.

Primary Vector (PV). In order to facilitate discussion of a proposed solution strategy, we define any stream of behavior which has been segmented into discrete categories as a primary vector (PV). As demonstrated above, each segment of a PV has two orthogonal dimensions: nominal and temporal. We explicitly assume that behavior is continuous. Therefore, the nominal dimension, the advent of a specific behavior, is defined as the transition into a category. The temporal dimension is the duration of the categorized behavior. The analytic strategy suggested is a separate tabulation of transitions-into-category and category duration.

Separate tabulation does not preclude the use of equal time intervals as a sampling device. Assuming that the coded behavior applies to the entire interval, we record a transition each time the code changes, and a duration equal to the number of sequential intervals (observations) is assigned the same code. It should be pointed out that this procedure allows us to escape the problem of non-independence associated with fixed-time intervals. The frequency of appearance of a time-interval unit is a function of classroom tempo and interval size. Sequential segments are not truly independent since each unit tends to be followed by itself--a tendency which is increased by slowing the classroom tempo or reducing the interval size. Separate tabulation will permit both an assessment of classroom tempo and comparisons of behavior samples with tempo held constant by statistical means.

Sub-Vectors (SVs). We frequently have compelling *a priori* reasons to expect changes in patterns of behavior within a primary vector. For example, a typical lesson would probably exhibit different patterns during the introduction, presentation, and summation stages. In order to facilitate such within-group comparisons, we define a sub-vector as a sequence of behavior within a PV. Usually, PVs will be partitioned into SVs by elapsed time or proportion of time. However, any other method which assures mutually exclusive sequences is perfectly acceptable. For purposes of expositional brevity, only partition by proportion of time is considered in the subsequent sections of this paper.

Retention of Sequence

The fundamental purpose for analyzing sequential behavior is to discover patterns which provide a parsimonious description of PVs (i.e. samples

of behavior) and which are sufficiently stable to permit useful discriminations between samples and the prediction of future states of PVs. In order to discover patterns, our analytic procedures must retain the sequence of observed behaviors. Accordingly, there has been considerable discussion in recent years of the use of Markovian chains in analyzing sequential interactive behavior (Flanders, 1970; Jaffe, 1968; Hertel, 1968; Peña, 1969).

Rausch (1965) provides a coherent discussion of the advantages of a Markovian process model. He defines a process as "systematic changes over time as the result of intrinsic relations among a set of forces." A Markovian process then, is one which can be modeled by a finite Markov chain. Given a measure of the contingencies among events, it infers what will happen over time. Such a process is defined by a transition matrix in which the cell frequencies have been divided by the corresponding event totals to yield the probabilities of a given category being followed by any other category. The probabilities of longer chains can now be obtained by multiplying the contingency probabilities within the chain. It is important to note that the model specifically assumes that "all that is relevant for a particular state is given by the last preceding state," or in psychological terms, "the more distant past is contained and expressed in the last preceding event." Rausch suggests that the advantage of the Markovian model is that it permits the abstraction from the matrix of variables which are more stable than those available from direct observation.

The Markovian process described above is useful for predicting future states of the matrix, or predicting the frequency with which certain chains

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(patterns) will occur. It is less useful, however, if our interest is in discovering strategies (chains of categories) for eliciting a particular response (another category). In this case, the assumption that the event immediately preceding contains complete information is clearly inappropriate. The point can be illustrated using empirical data provided by Sprague (1970). In the following example, a sixteen-category coding system was used by the authors to code classroom verbal behavior into six cognitive categories based on the Massialas (1970) system. Our interest focused on determining strategies which would elicit hypotheses-testing behavior in students (category 16). Since odd number categories represent teacher behavior and even numbers represent student behavior, we were looking for the sequences of odd numbers most likely to elicit category 16. The matrix of transitional frequencies resulting from the analysis was tabulated, together with the corresponding transitional probabilities. We believe that the "best strategy" is unlikely to be predicted by Rausch's method outlined above. To illustrate this point, we have tabulated the strategies suggested by Markovian analysis with those suggested by recording the actual occurrences of particular chains of behavior. For convenience, we will illustrate using a five stage chain.

The best strategy according to Rausch's method can be estimated by the most probable Markov chains ending in category 16. Tracing back the highest and second highest probabilities yields the predicted chains on the left of Table 2. The data was subsequently reanalyzed to obtain the exact frequency of all chains. Using the exact observed frequencies to find those sequences most likely to elicit category 16 yield the chains on the right side of Table 2.

The results reported in Table 2 show that in this example the predicted chains failed to occur, yet longer chains ending in category 16 did occur. More important, however, was the fact that, on the whole, longer antecedents were more likely to be followed by category 16 than short antecedents. Empirical evidence is needed to determine the generality of this finding, the optimum length of such strategy chains, and the relationships between chain length and the characteristics of the category system used (e.g. number of categories). The hypothesis suggested here is that for any given consequent within a specified category system there exists a strategy (i.e. a chain of finite length) which regularly and reliably yields a maximal probability of eliciting the desired consequent. Hence, as Peña (1969) has also pointed out, the commonly used simple two stage chain is probably an inappropriate fit for data drawn from observation of human interactions in classrooms and other social environments.

Insert Table 2 about here

Problems with longer chains. The decision to analyze PVs for chains longer than those furnished by a two stage transition matrix introduces additional problems in data reduction. A PV consisting of N segments can contain as many as (N-1) two-category chains, (N-2) three-category chains ......, and (N-K+1) K-category chains. Yet obviously a complete set of higher order chains will contain within them all occurrences of lower order chains. How, then, do we decide which set to use? If all possible chains were collected the interpretive task would exceed that posed by the initial primary vector. Consequently, heuristic strategies are needed

for data reduction. The approaches recommended here are based on families of chains, and the redundancy and duration threshold.

Families of chains. A family of chains is defined as a set of chains with a common focal element. The focal element may be either a single category or a particular finite chain. In general, an investigator's interest will focus on either the strategies which produce a particular focal element or the patterns of behavior which follow the occurrence of a focal element. This suggests two types of chain families:

1. Precedent families of chains. These are chains having a common precedent; they begin with the same focal element (e.g. 5-11; 5-11-6; 5-11-7; 5-11-....). Precedent chains are collected and analyzed in order to study the sequential responses which follow a given stimulus (the focal element).

2. Consequent families of chains. These are chains with common consequences. They end in the same focal element (e.g. 11-5; 6-11-5;....-6-11-5). Consequent chains are analyzed to study the strategies (sequences of antecedent events) useful for eliciting a given response (the focal element).

Orthogonality of familial chains. The strategy of collecting families of chains raises the issue of orthogonality. Two chains containing identical sequences are orthogonal if, and only if, the identical elements come from different portions of the primary vector. To illustrate, suppose we obtain the family of precedent chains in Table 3. The frequency of orthogonal chains may be calculated from the observed frequencies in four steps. First the frequency of each chain is reduced by the number of times that the chain occurs in chain e. Thus, the frequencies of chains d and c are reduced by five and a and b by ten. The results are tabulated in

column f_{de}, with the subscripts de on the column title identifying the chains which are now orthogonal. Second, we subtract from the a, b, c frequencies the number of occurrences of that chain in chain d, and tabulate the results in column f_{de}. Similarly, occurrences accounted for by d and b are removed, with the resulting completely orthogonal frequencies appearing in the final column, f_{abcde}.

Insert Table 3 about here

Familial chain sets as variables. The implicit intent of the development of families of orthogonal chains is that the entire set provides useful means for discriminating among groups. Heuristically useful composite variables may be obtained by entering the frequencies of familial chains as variable values, and performing a discriminant function analysis to obtain the relative weightings which maximally discriminate among groups. Subsequently, empirically validated sets of weights for particular chain families can be used to assess experimental effects.

The heuristic procedure suggested by the concept of orthogonal familial chains is to search for only those chains which begin or end with pre-specified focal elements. In addition to the pre-specified familial chains, the system should tabulate any other chains which appear likely to provide experimentally useful discriminations or predictions. A heuristic procedure for facilitating serendipitous discoveries is suggested by the concept of a redundancy threshold.

Redundancy threshold (RT). The redundancy threshold (RT) is defined as the minimum frequency of occurrence necessary for useful experimental

inference. In general, the RT for a particular behavioral sequence should be high enough to permit some variance groupings of scores. Useful RTs may be determined empirically. However, our preliminary work suggests that a useful rule of thumb is to set RT at the number of "treatment" combinations in the experiment. Our preliminary efforts reveal that frequencies of one or two occur for literally thousands of chains, consequently RT should never be less than three. Once RT is established, it may be used to decide which chains to discard and which to retain. A suggested method by which this may be accomplished is discussed in a subsequent section.

Noise (NT). No matter how carefully planned a particular observation system may be, there exists the possibility that one or more behavioral categories within an observation-coding system may be non-functional. Non-functional categories are identified by the following characteristics:

1. They do not permit useful discriminations among groups when used unilaterally.
2. They have no effect on the sequence of events in which they are imbedded. For example, if category 10 were non-functional the sequences (3-9-3), (3-9-10-3), and (3-10-9-10-3) would be functionally identical.

We propose that all categories which do not meet the two criteria above be collapsed to a single category defined as noise in the system (NT). The noise category would be included in the usual summary statistics (frequency of appearance, percent of time accounted for, etc.), but would be ignored in the chain analysis. Operational definitions for application of the criteria for non-functionality are suggested in the proposed analytic procedure summarized below.

Duration threshold (DT). The relationship of the RT and the concept of noise in an observation-coding system is of special significance. Obviously, categories with low empirical frequencies will enter into sequences to produce low redundancy chains. However, it is possible that a category which has a low frequency of occurrence in a primary vector may have a high duration, thus accounting for a significant proportion of the time dimension. Low redundancy is a necessary but not a sufficient condition for classifying a set of behaviors as noise. It is therefore necessary to introduce the notion of a duration threshold (DT). DT is defined as the minimum proportion of time which a category must account for in order to be experimentally useful and psychologically meaningful.

We can now express through mathematical set notation that the primary vector may be partitioned according to formula (1) where PV is the primary

$$[PV] = \{S \mid (f_c \geq RT) \text{ or } (P_t \geq DT)\} \cup \{NT\} \quad (1)$$

vector, S is a behavioral segment in the vector, f_c is the frequency of occurrence for the category to which the segment belongs, RT is the redundancy threshold, P_t is the proportion of time accounted for by the category, DT is the duration threshold, and NT is noise. Thus, categories are retained if either the frequency or the proportion of time accounted for reach their respective threshold; only if the category fails both tests is it transferred to NT. The ratio of "noise" to "meaningful" behavioral categories may be an important criterion for determining the appropriateness of specific observation systems for characterizing specific interactive behaviors in different social contexts.

It should be noted that the use of RT and DT is consistent with the goal of parsimonious description of PV. We recognize that it is sometimes the case that an investigator is interested in the presence of rare events and/or events of limited duration. In such cases, RT and DT may equal zero in which case all categories within a system would maintain their identity and effects in the analysis of chains.

Just as some behavior categories within a system may be revealed to contribute little toward a parsimonious description of PVs, so it is possible that certain categories are too inclusive and lack precision in their descriptive power. Such categories account for too much of the PV data. It should be a rather simple matter to follow a strategy for determining over-inclusiveness of categories which parallels our suggested approach to overly exclusive (noise) categories. Hence, we believe that the general conceptual strategy presented here may have significant implications for both the construction of valid observation systems and the analysis of the sequential interaction data that such systems yield.

A Proposed Analytic Procedure

In order to assure that the strategies recommended here are feasible in terms of both cost and the prerequisite computer hardware, a computer program, consistent with the principles outlined in this paper, was developed and tested. In the interests of clarity and precision, the remainder of this section will consist of a brief description of the prototype. A technical description is available from the first author on request.

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Program CHAIN was constructed to analyze data from observation systems composed of up to ninety-nine different behavioral categories. Category names may be numeric, alphabetical or any alphanumeric combination provided no more than four characters are used for any one name (e.g. A34, B-3, 1.23, etc.). The computer assigns each of the category names a numeric code (1-99) which is used as an index for computing frequencies, time in category, and the like. The coded data is then stored on a scratch file for subsequent chain analysis.

The present program analysis consists of two phases: category validation and chain analysis. During the category validation phase, the frequency of occurrence of each category and the matrix of frequencies for category-to-category transitions (two-stage chains) are recorded. In addition, the sums and sums of squares of time-in-category are accumulated and subsequently used to compute means and standard deviations. At the users option any subset of these summary statistics may be printed for:

1. Primary vectors (PVs) such as a single complete class or lesson. Any number of PVs may be included in an analysis.
2. Sub-vectors (SVs) within PVs. An example of SVs might be the introduction, body, and summation within each lesson. The program accommodates up to five SVs per PV.
3. SVs summed over PVs.
4. Grand totals computed over the entire experiment.

Prior to the application of the RT and DT criteria, the program assessed each category's capacity to discriminate by computing the analysis

of variance F ratios to test the SV and PV effects for two dependent variables: (1) frequency-of-occurrence, and (2) time-in-category. The exact probability of each F ratio is then calculated and compared with a minimal alpha level which may be specified by the user. Since our primary concern is to retain any categories which provide useful discriminations, the level would normally be set relatively high ($\alpha \geq .10$) in order to minimize type two errors. Categories which fail to produce significant F ratios are subsequently tested against the user-prescribed RT and DT levels. If both these tests fail (i.e. if the observed frequency is less than RT and the proportion of time accounted for is less than DT) the category is listed as noise in the system. The program then prints out the obtained F values, the probability of each F, and the list of noise categories. At this point the categories listed as noise are normally collapsed into a single composite category and the summary statistics for noise computed and printed. However, the user has the option of overriding the computer decision and retaining any "noise" categories which he considers indispensible.

The second phase of the program is concerned with the tabulation of recurring sequences of behavior which have experimental interest to the user. For example, the familial chains to be collected may be defined by entering the appropriate sets of precedent categories (stimuli) and consequent categories (responses) to be traced. Since users will seldom be interested in a chain which occurs only once or twice in an entire experiment, the program also allows a redundancy threshold for familial chains (RTF) to be specified. The program will record a particular chain if and only if each component transition obtained a grand frequency $\geq$ RTF in the first phase of the analysis.

Identifying chains. Assume that an eight-category system has been used to segment a stream of behavior into the sequence illustrated in Table 4, and that the Phase I analysis has established the transitional frequencies listed below the vector. Thus, we see that the transition from E to G occurred twice in the initial analysis, the G to A transition occurred eight times, and so on. Suppose that this sequence is to be analyzed for "interesting" chains according to the following criteria: precedents = {A}, consequents = {B, C}, RTF = 3, and RTS = 7.

Insert Table 4 about here

Analysis proceeds by testing all possible chains, from left to right, against the criteria above. The testing procedure is defined by the flow chart in Figure 1. Using Table 4 data to illustrate, the first possible chain is (EG). However, the frequency of the (EG) transition is less than RTF. Therefore, no "interesting" chain could possibly be formed from EG, and the computer moves to the (GA) chain. Since the GA transition is greater than RTF, it is retained as a transitional element. But the GA chain per se will be recorded only if it qualifies as a precedent chain, a consequent chain, or a serendipitous chain. In this case, the first two tests fail, but the frequency of the GA transition exceeded RTS--the redundancy threshold for serendipitous chains. Therefore, GA was recorded as a serendipitous chain.

The succeeding transition in the PV is now examined. It will be added to the existing chain whenever its observed frequency is greater than RTF. In our example, the chain GAD is the result. This chain does not begin with a specified precedent nor end with a specified consequent, and the observed frequency of the AD transition was less than RTS.

Therefore GAD was not a recorded chain, but the sequence was retained as part of a possibly "interesting" longer chain. In the example the addition of the next transition formed GADC, which was recorded as a consequent chain. The program continues to form new chains by adding succeeding transitions until either the chain length reaches its maximum (maximums up to 8 may be specified), or a transitional frequency less than RTF is encountered. In the example, GADC is the longest "interesting" G chain formed because of the low CA frequency. At this point the chain is erased and analysis recycles with (A) as the first element in the chain. The results of the completed analysis for the exemplary data appear in Table 5.

Insert Figure 1 about here

Insert Table 5 about here

<u>Orthogonality</u>. At the option of the user, a subprogram calculates the orthogonal frequencies within each family of chains. For this purpose, serendipitous chains may be formed into either precedent or consequent families, or both. Note that the program does not remove any between-family overlap.

<u>Output</u>. The output of program CHAIN consists of alist of chains and their respective observed and orthogonal frequencies for each grouping specified by the user. As in Phase I, users may request groupings by:

1. Primary vectors
2. Sub-vectors within primary vectors

3. Sub-vectors summed over primary vectors
4. Grand totals

Storage Strategies. The inverval storage of chains may be envisaged as three lists similar to those in Table 3. Note that for each chain we must record two elements: (1) the name of the chain (i.e., the sequence of categories) and (2) the frequency with which that chain occurred. In order to permit more categories (up to 99) each category is represented internally by a two digit number (e.g. 01 = A, 02 = B etc.). Chains are named by a single sixteen-digit number formed by the concatenation of the component categories with double zeroes representing blanks. Thus GA becomes 0701000000000000, and AFGDEBEC becomes 0106070405020503. As each new chain is identified by the analysis, the computer must search through memory for a similar chain. If one is found, the frequency is increased by 1; if not, the chain name is recorded and its frequency set equal to 1.

Despite the data reduction achieved by recording only "interesting" chains, it is obvious that hundreds or even thousands of different chains may be encountered--especially in systems employing a large number of behavioral categories. A complete search of memory for each new chain would be prohibitively costly. Consequently, chains are stored in numerical order and a record is kept of the position of the first occurrence of each category as the initial element in a chain. Thus the computer search is limited to those chains having the same initial element as the chain to be stored. Preliminary results indicate that this strategy provides economical analysis for systems having as many as 99 behavioral categories.

Time In Chains. The proportion of time accounted for by any given chain within any given grouping can be estimated using the appropriate means and standard deviations obtained in Phase I of the analysis. Similarly, one can compare the times associated with particular families of chains across groupings.

Analysis of CHAIN Output. At the present time we have insufficient experience with the analysis of chains to offer any definitive emulative conclusions relative to the value of our technique. We have, therefore, chosen to conclude this presentation by raising two questions and possible strategies relative to the development of analytic procedures for future work in this area.

First, is it appropriate to ask if there is a point of diminishing returns with respect to the length of chains which are experimentally useful and psychologically meaningful? Intuitively, we would expect this point to be reached at about four or five elements--this corresponds to the number of moves ahead planned by a better-than-average chess player. Some useful information relative to this question might be gained by performing a multiple discriminate function analysis using an appropriate familial chain as the dependent variable. In the absence of a priori evidence for groupings of PVs (or SVs), one might first perform a cluster analysis in order to identify groups with common patterns of chain frequencies. The discriminant function analyses could then be based on the clusters obtained. In either case, the chain weightings obtained for various families of chains could be analyzed for a functional relationship with the number of elements in the chain.

Finally, it appears worthwhile to speculate how we might use chains to identify strategies or environments (Hunt, 1966) to elicit specific behaviors. A two-phase study design appears necessary to pursue this issue. First, we might identify promising strategy chains. A complete set of strategy chains, for a given experiment, may be obtained by deleting the last element from all consequent chains which end in the behaviors (category) of interest. The frequencies of these chains together with the remaining "interesting" chains may then be entered as predictors of the frequency of the desired category. The extent to which the various chains contribute to this prediction can be used to select the set of promising strategies for the second phase. Note that promising strategies are not restricted to the strategy chains identified above. Some of the serendipitous chains may prove to be important predictor and/or moderator variables. The second phase of the investigation might consist of an experimental assessment of the relative merits of the various strategies; existing research procedures appear entirely adequate for this purpose.

In conclusion, we have presented a tentative theoretical model for the analysis of sequential behavior in classrooms and other social environments. We have outlined a preliminary operational technique derived from several of the major constructs presented which we feel supports the heuristic merits of the model. Undoubtedly, future developmental and research efforts will produce data leading to appropriate modifications in our present theoretical position.

Table 1

Summary Matrices Obtained Using Two Different
Fixed Time Intervals

Matrix 1: Three Second Interval

Antecedent Behavior (s)	Consequent Behavior (R) 1	2	3	4	5	Sum
1	(50)	1	10	5	28	94
2	25	(65)	5	10	10	115
3	8	22	(35)	10	0	75
4	3	11	15	(60)	3	92
5	8	16	10	7	(40)	81
	94	115	75	92	81	457

Matrix 2: One-Second Intervals

Antecedent Behavior (s)	Consequent Behavior (R) 1	2	3	4	5	Sum
1	(238)	1	10	5	28	282
2	25	(295)	5	10	10	345
3	8	22	(185)	10	0	225
4	3	11	15	(244)	3	276
5	8	16	10	7	(202)	243
	282	345	225	276	243	1371

Table 2

Comparison of Observed Strategy Chains With Markovian Chains Predicted From The Transitional Probabilities

Markovian Prediction				Direct Observation			
Theoretical Rank	Chain	Obs f	Obs P(16)	Theoretical Rank	Chain	Obs f	Obs P(16)
Two-category chains							
First	5-16	18	.67	First	5-16	18	.670
Second	3-16	5	.18	Second	3-16	5	.180
Three-category chains							
First	11-5-16	1	.09	First	3-5-16	6	.5625
Second	1-5-16	0	.000	Second	5-3-16	5	.5555
Four-category chains							
First	3-11-5-16	0	.000	First	11-3-5-16	4	.800
Second	11-5-3-16	0	.000	Second	7-11-3-16	3	.600
Five-category chains							
First	5-3-11-5-16	0	.000	First	5-11-3-5-16	4	1.000
Second	3-11-5-3-16	0	.000	Second	5-7-11-3-16	2	.667

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Table 3

Obtaining Orthogonal Chain Frequencies

Chain	Observed f	Orthogonal Frequencies			
		f_{de}	f_{cde}	f_{bcde}	f_{abcde}
a. 1-2	23	13	11	10	7
b. 1-2-5	15	5	4	3	3
c. 1-2-5-1	7	2	1	1	1
d. 1-2-5-1-2	6	1	1	1	1
e. 1-2-5-1-2-5	5	5	5	5	5

Table 4

A Sample of Behavior Which Has Been Segmented By An Eight-Category System. Transitional Frequencies (Second Row) Were Obtained From Phase 1 of the Analysis

PV (Sequence of Events):	E-G-A-D-C-A-F-G-D-E-B-E-C-A-D-C . . . .
Frequency of Transitions:	2 8 6 3 2 6 9 8 7 6 4 5 2 6 3

Table 5

Results of Chain Analysis of Table 4 Data

Precedent Chains	f	Consequent Chains	f	Serendipitous Chains	f
AD	2	GADC	1	FG	1
ADC	2	ADC	2	FGD	1
AF	1	DC	2	FGDE	1
AFG	1	AFGDEBEC	1	GD	1
AFGD	1	FGDEBEC	1	GDE	1
AFGDEB	1	GDEBEC	1	DE	1
AFGDEBE	1	DEBEC	1		
AFGDEBEC	1	EBEC	1		
		BEC	1		
		EC	1		

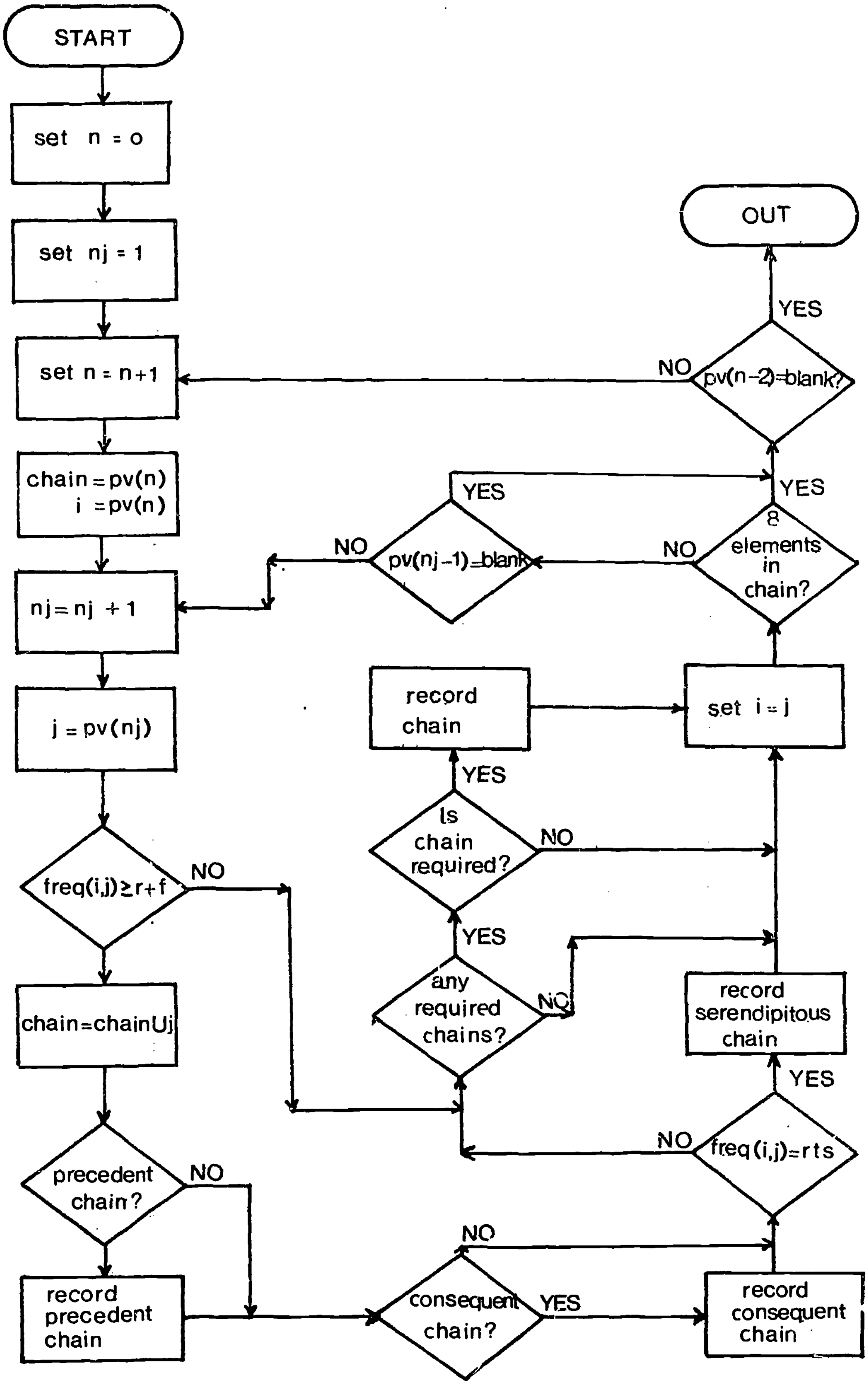
START
set n = o
set nj = 1
set n = n+1
chain = pv(n)
i = pv(n)
nj = nj + 1
j = pv(nj)
freq(i,j) ≥ r+f
NO
chain = chainUj
precedent chain?
NO
record precedent chain
consequent chain?
YES
NO
record consequent chain
freq(i,j) = rts
NO
YES
record serendipitous chain
any required chains?
NO
YES
Is chain required?
NO
YES
record chain
set i = j
8 elements in chain?
NO
YES
pv(nj-1) = blank
NO
YES
pv(n-2) = blank?
NO
YES
OUT

Fig. 1

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