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ABSTRACT

The purpose of the three papers included here is to describe and illustrate three methods of sequential analysis as they were applied to an analysis of an actual counseling interview between Carl Rogers and "Gloria." In "Markov Models in Process Research," Edward J. Heck applies a Markov model to the analysis of the event-to-event transitions in the interview. The primary hypothesis was concerned with the central assumption of all Markov models, namely that the counseling process would be a process in which each speaker's acts at each point in time are, in part, contingent upon previous acts. In "The Use of Lag Sequential Analysis in Counseling Process Research," James W. Lichtenberg uses lag analysis to address the problem of identifying distant (as well as immediate) effects within behavior sequences. The responses used in this analysis did evidence a reliable sequential patterning. In "The Use of Information Theory in Counseling Process Research," Robert Reitz explicates the principles and assumptions underlying the use of information theory and demonstrates the use of Shannon and Weaver's measures of information. (BW)

METHODS OF SEQUENTIAL ANALYSIS FOR COUNSELING PROCESS RESEARCH

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PREFACE

As a preface to these papers we would like to review the purpose and intent of the papers and to provide a brief background of some of the important concepts and issues involved with sequential analysis. The papers and presentations are not exhaustive examinations of the topic by any means, but are intended as an introduction to stimulate interest in other colleagues and researchers.

The purpose of three paper presentations is to present a description and illustration of three methods of discrete sequential analysis as they were applied to an analysis of an actual counseling interview. The intent of these papers and presentations is to describe and compare the methodological techniques and not to evaluate the merits of this particular counseling session. The counseling session serves only as a means of illustration; and, in general, we will refrain from commenting on the dynamics or outcome of the interview.

The data (coded counselor-client verbal interactions) were derived from a well-known and exemplary interview between Dr. Carl Rogers and "Gloria" and were analyzed <u>non</u>-sequentially in a previously published study (Lichtenberg & Barke, 1981). Counselor/client responses were coded in accordance with a scheme developed by Mark (1971) and refined by Ericson and Rogers (1973) for analyzing dyadic relationship patterns. Following the procedure outlined by Ericson & Rogers, counselor and client responses were coded as to their "interpersonal control direction." Responses that suggested movement toward dominance (e.g., questions that demanded an answer, instructions, orders) were coded as "one-up." Responses that suggested movement toward being controlled by seeking or accepting the dominance of the other (e.g., questions that seek a supportive response) were coded as "one-down." And responses that were neither a move toward control nor being controlled, or which suggested movement toward neutralizing control (e.g., statements of continuance, filler phrases, noncommittal responses to questions) were coded as "one-across." As reported by Lichtenberg and Barke (1981), interrater reliability for the coding was K=.86 (maximum Kappa value = .98, p<.01). The above notwithstanding, for purposes for this collection of papers, we would note that in examining these interviews we were not particularly concerned with either the nature of the interview coding scheme or the interrater reliability utilizing that scheme. That is not to say, however, that these issues are not of importance; but we were primarily concerned with the "behavior" of the three sequential analysis techniques.

From a contemporary interactional perspective on counseling, it is generally agreed that many of the problems clients present can be construed as habitual patterns or sequences of interpersonal behavior which are perpetuated by the way clients behave and the responses to that behavior by others (Weakland, Fisch, Watzlawick, & Bodin, 1973). Further, it is assumed that within counseling these same general problematic interaction patterns and sequences will emerge as the client interacts with the counselor, and that it is the role of the counselor to alter these sequences (Cashdan, 1973). It follows from this perspective that assessment of outcome might focus on determining change(s) in the interactional patterns between counselor and client (i.e.,the counseling processes) as they emerge over time -- both within and across interviews. However, as Hertel (1972) and Raush (1969) have noted, traditional methods for investigating the counseling process as a sequence of interaction have suffered from their inability to capture the temporal or sequential ordering of events in the process. It is on the basis of this kind of conclusion that we began looking at the potential that these three techniques might offer.

As a brief background to these methodological strategies, we might briefly comment on certain characteristics of social interaction which form the conceptual basis of the techniques. There are at least three basic structural features of any social influence, interaction process: sequentiality, flexibility, and constraint (Raush, 1965).

1. Sequentiality - Interaction is not an event but a sequence of events (or acts) occurring over time. While the simplest case may consist of two contiguous acts (i.e., an "interact"), more often the interchange involves chains of concatenous interacts. Given a chain of concatenous interacts, Nth order contingencies may be involved; and given a sufficiently long chain, any level of sequential complexity may be achieved

(Ashby, 1968; Raush, 1965).

2. Flexibility - While the data of interaction may be construed as "determined", the data occur empirically as random phenomena obeying probabilistic rather than strictly deterministic rules (Hertel, 1972; Parzen, 1962). The position of "probabilistic determinism" suggests that while the effects of various stimuli upon behavior may be quite predictable, in the presence of certain stimuli certain behavior may be more or less likely to occur. This randomness or uncertainty permits behavioral flexibility which would not be possible under a strict deterministic system. Further, this response variability or flexibility not only is characteristic of the complexity involved in human behavior, but it allows for diverse forms of constraint within the ongoing interaction.

3. Constraint - Social interaction may be thought of as a process of constraint on the initial variability in the interaction system (Raush, 1965). That is, it is assumed that the statements participants make to each other constrain or control each other to some degree. Constraint may be either direct or indirect. It is direct when its influence is immediate, and indirect or remote when the effects are mediated by an intervening variable. For example, if a T1 antecedent response

increases the probability of the subsequent C1 over a a C2 response, the constraint is direct. If the T1 response increases the likelihood of the C1 response, which in turn increases the likelihood of a T2 response, the T1 response has a direct effect on P and an indirect effect on subsequent T responses.

In summary, these three characteristics of social interaction provide the framework for conceptualizing the counseling process and the three methods of analyzing sequential interaction which follow. Common to each of the three techniques is the search for sequential patterns or redundancies among behavioral events. While the specifics of each approach differ, each is conceptually derived from the conditional, sequential dependencies among events in the sequence. While our work is very preliminary in nature, we hope these methods may prove useful in providing a more "fine-grained" analysis of the counseling process (Fiske, 1977) -- a process we believe to be inherently sequential and patterned.

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MARKOV MODELS IN PROCESS RESEARCH

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Introduction

A fundamental premise underlying the view of counselor-client interaction presented in the Preface to these papers is that the interaction is a process in which the behaviors of each participant at each point in time are, at least in part, contingent upon past acts. By way of example, if during the course of counseling the counselor (T) were to ask a question, logic and common sense would suggest that the client (C) would likely feel some pressure to either answer or not answer the question. In turn, the client's response to the question is likely to be pursued by the counselor in terms of that response -- whatever it was. This pattern of responding suggests the interaction to be at least in the form of a first-order process; i.e., a process in which the occurrence of a particular response or response category (consequent) is contingent upon the previous category of response (antecedent).

	Antecedent	Consequent
	T_{t-1}	C_t
or	C_{t-1}	T_t

It is, of course possible (and some might suggest probable, e.g., Hill, Carter & O'Farrell, 1983; Howard, 1983) that the response sequences within counseling are of an order of dependency greater than one. For example, the client's response at time t may be dependent not only upon the counselor's immediately preceding response (at time t-1), but also upon the client's own previous response at time t-2. In this case, the process would reflect a two-step or second-order dependency, one in which the speaker's response (in this case the client's

Antecedent		Consequent
C_{t-2}	T_{t-1}	C_t

response) is contingent upon (or determined by) the two preceding events. That is, the client's response is in response to the counselor's response to the client's previous response.

Although the point could be debated (e.g., Truax, 1972), second-order dependency among events would seem, at least on a theoretical basis, to be a minimal pattern for capturing "accurate empathy." The notion of "accuracy" within the concept of "accurate empathy" necessarily would seem to imply that the counselor's "empathic response" be contingent upon (and appropriately related to) at least the preceding utterance by the client. At the same time, it has been argued that empathy is not really "empathy" unless it is received (i.e., responded to) by the client .... typically in terms of increased self-exploration and/or self-disclosure. Therefore, increased self-exploration (at time t) is contingent upon not simply the counselor's response at time t-1, but upon the counselor's response in relation to the client's previous response (at time t-2). In this sense, accurate empathy would be considered as a particular kind of interactional concept (rather than as simply a trait or characteristic of the counselor), the behavioral manifestation of which would reflect at least a second-order process.

Were a client's responses within the interaction sequence to be contingent upon the preceding three responses, the process would be said to evidence third-order (3-step) dependency. In such a case, the client's responses would be conditional upon

Antecedent	Consequent
$T_{t-3}\ C_{t-2}\ T_{t-1}$	C_t

(or in response to) a three-part antecedent event -- the counselor's response to the client's response to the counselor's previous responses.

It is also possible that the client's responses may be virtually uninfluenced by the counselor, but nevertheless show a coherence or pattern among themselves. This pattern may be first-order or greater. Although such self-contingent patterning could hardly be considered "communication" (at lest in the interpersonal sense referred to earlier in this paper), it would constitute a "pattern" in the counseling process, a pattern

	Antecedent	Consequent
	C_{t-1}	C_t
or	$C_{t-2}\ C_{t-1}$	C_t

exemplifying perhaps a client "with a story to tell" who continues undaunted in his/her personal narrative irrespective of counselor input (or, if the roles were reversed, a counselor in a clinical intake situation who responds more to a prescribed sequence of questions that he/she is required to ask than to the client who is providing information to which the counselor could respond -- but doesn't).

Finally, it should be noted that the absence of any patterning (or zero-order dependency) among events in the counseling process is possible -- although unlikely. In such a case, neither the counselor's nor the client's responses would be constrained by the other, nor by themselves. Not only would there be an absence of dialogue between counselor and client, but there would also be an absence of monologue on either person's part. Both would be responding at random.

One of the simplest models of such processes is the Markov model. Two assumptions are central to all Markov models: (a) that the current state of the process/interaction is contingent upon recent past states, and (b) that the contingency between previous states and the current state is stable (or stationary) across time (Chatfield, 1973).

The data necessary for the analysis of Markov models of counselor-client interaction consist primarily of contingency tables. Bishop, Feinberg and Holland (1975) have shown that log-linear models for analyzing such tables can be used to assess the fit of simple Markov models (such as those models of contingency relationships posed above) to the data. Log-linear models are analogous to factorial analysis of variance models, except that instead of accounting for the variance in some dependent variable, these models account for the differential frequencies in the multiway contingency tables that summarize the data. By assessing the "goodness of fit" of different contingency relationships (i.e., models) among the data using the log-linear maximum likelihood approach, it is possible to identify the model which best describes the data, i.e., the one which best describes the contingency relationships within the sequential interaction. Using this approach, then, it is possible to derive an empirical explication of the structure of influence within the counseling process which in turn may allow one to draw conclusions about the sequential patterning of mutual regulation within the interaction.

Before proceeding with a description and illustration of this approach one limitation of this approach should be noted; that is that as the order of sequential dependency investigated increases, the number of possible combinations of contingent events increases in a multiplicative fashion (specifically C^n, where C= number of categories and n= order of dependency +1). Unless the number of actual events in an interaction sequence is quite large, this inevitably increases the number of empty (or low frequency) cells in the multiway table, weakening the power of G^2, the maximum likelihood goodness of fit statistic (Chatfield & Lemon, 1970). Additionally, it may be noted that although providing interesting possibilities for the exploration of structural patterns in counselor-client interaction, this approach will not reveal the specific event-event patterns which constitute that structure.

Rationale and Assumptions

As presented in the Preface section to these papers, we are assuming that the "counseling process" shows the primary characteristics of sequentiality, flexibility, and constraint which are presumed inherent to all social interactive processes. Further, regardless of the number or type of response codes used to characterize counselor and client behavior, the "process" may be viewed as a series or sequence of transitions from event (response) to event (response). Thus an analysis of that process can be an analysis of those transitions.

For example, suppose there is a sequence of counselor-client exchanges using two response codes (A and B). If one observes the interaction sequence

ABAABABBABBAAABABBABAAABBAAABB

one can describe the interaction nonsequentially by noting that the frequency of A is 16, and the frequency of B is 14. The unconditional probability of A is thus p(A) = 16/30 = .53; and the unconditional probability of B is p(B) = 14/30 = .47. The conditional probability of B, given that A occurs just prior to B, is p(B/A) = 9/16 = .56. Hence one can reduce the uncertainty in our knowledge of B's occurrence by knowing that the immediately preceeding event in the interaction was A.

Using this example we can describe the sequence of events by specifying the likelihood of various event to event transitions; a transition being defined as a contingency between an antecedent and consequent event. Given a sequence of transitions, the empirical probability of a given event (antecedent) being followed by another event (consequent) may be determined. This probability is defined as the transition probability or contingency magnitude of that transition.

Transition probabilities are typically arranged in a matrix called a transition matrix in which the rows (i) represent the antecedent events and the columns (j) are the consequent events. It is important to acknowledge that this matrix is a summary of the occurrences of the transitions in terms of how they occurred in general throughout the sequence. That is, the matrix summarizes information only about the structural relationship or patterns among the events. The matrix ignores other properties of the sequence such as: (1) length of sequence and (2) who the speaker was who either began or ended the sequence. In short, this particular stochastic model is designed to portray the probabilistic rules and relationships among events in the process (Forrester, 1968).

To the extent that the transition probabilities within each row are not equal (i.e., are non-random), the antecedent events may be said to constrain the distribution of probabilities of the various consequents -- and the probability of occurrence of any given consequence is said to "depend on" the prior event. If the occurrence of an event is depended on (constrained by) only the immediately preceding event (Markov assumption) and if the probabilities are stable across the sequence (Markov assumption), the sequence is said to exhibit first-order (one-step) dependency and constitute a first-order Markov chain. It is quite possible that the interaction shows a higher-order dependency among events being constrained by a sequence of some <u>r</u> number of preceding events.

The procedure for testing the order of dependency among events under a Markov model is to test a series of models (of dependency) in which the number of events in the sequence on which the events are considered dependent is increased by one event in each subsequent "model-fitting" test. Thus, a first-order model is compared to a random (0-order) model with respect to its "goodness of fit" to the contingency data; a second-order model is compared with the first-order model; a third-order model with a second-order model, etc. To accomplish this requires the construction of successively larger multi-way contingency tables which consecutively present the contingencies between events from the first to the _r_th order.

Once the contingency or frequency tables are contructed, the table serves as a data base for the procedures used to estimate the order or constraint of the sequential data summarized in the table. The technique used to analyze the contingency data is the maximum lieklihood approach that employs the log-linear ratio statistic (G^2). Bishop, Feinberg, and Holland (1975) have demonstrated that log-linear models may be used to assess the fit of simple Markov models to the data.

It is important to note, at this point since this paper will not pursue the issue, that a number of different classes of Markov models can be used to model the interaction data. Indeed, once the particular Markov model is known, it is then possible to make a number of predictions from the known model about the eventual course of the process. We were not concerned with this as this leads into specifying and examining the "dynamics of the process" once the structural pattern (i.e., particular Markov model) is known. In our case we were simply interested in discovering the kind of Markov model or pattern structure that best fits the data. Thus our primary hypothesis was concerned with the central assumption of all Markov models, namely that we expect the counseling process to be at least a first-order process structure (i.e. a process in which each speaker's acts at each point in time are, in part, contingent upon previous acts).

Testing the Order of the Process

To assess the structural pattern or order of the process, we examined a four-dimensional contingency table in which the dimensions were: (1) actions of participant A at time t (i.e., consequent), (2) B at time t-1, (3) A at time t-2, (4) B at time t-3. We did not specify whether A or B was a counselor or client. The resulting matrix, presented in Table 1, is 3x3x3x3 because at each of the four times there may be only three mutually exclusive and exhaustive acts (up, across, down).

TABLE 1

OBSERVED FREQUENCY TABLE

D Time-3	C Time-2	B Time-1	A Consequence (time t) Up	Across	Down	Total
Up	Up	Up	3	7	1	11
		Across	7	0	3	10
		Down	2	0	0	2
	Across	Up	4	14	4	22
		Across	0	2	1	3
		Down	3	4	1	8
	Down	Up	3	3	0	6
		Across	0	2	0	2
		Down	0	2	0	2
Across	Up	Up	4	3	0	7
		Across	13	3	3	19
		Down	2	2	2	6
	Across	Up	2	3	2	7
		Across	3	0	0	3
		Down	0	1	1	2
	Down	Up	2	0	1	3
		Across	2	2	2	6
		Down	2	2	0	4
Down	Up	Up	4	1	1	6
		Across	2	0	2	4
		Down	1	0	0	1
	Across	Up	1	2	0	3
		Across	4	1	1	6
		Down	0	1	2	3
	Down	Up	1	1	0	2
		Across	1	2	1	4
		Down	0	0	0	0

Each cell in Table 1 (iA, iB, iC, iD) has an expected value, $M_{i_a i_b i_c i_d}$ and a series of log-linear models may be specified as follows:

1.	A+B+C+D	test of independent effects
2.	All 1 + AB,BC,CD,	first order other contingent effects
3.	All 1 + AB,BC,CD, AC, BD	second order, self-contingent effects (i.e., AC BD)
4.	All 1 + AB, BC, CD, AC, BD, AD	third order, other contingent effects (i.e., AD)
5.	All 1 + AB, BC, CD, AC, BD, AD, ABC, BCD	second order, other/self contingent effects (i.e., ABC, BCD)
6.	All 1 + AB, BC, CD, AC, BD, AD, ABC, BCD, ABD, ACD	third order, other/other + self/other effects (i.e., ABD, ACD)

These terms are similiar to the main and interaction effects in ANOVA except that these log-linear models account for the differential distribution of frequencies in the contingency table. The fit of model to the data is assessed by the likelihood ratio statistic, G^2 that is distributed as chi square.

Results

The results of testing each model in order to compare the relative fit of each to the data is presented in Table 2. The table includes, scanning from left to right, the following items:

1. The particular model tested
2. The G^2 value and degrees of freedom indicating the fit to the data (the larger the G^2 the poorer the fit)
3. The changes in G^2 and associated degrees of freedom
4. Distinguishing characteristics of the model

TABLE 2

Tests of Order and Contingency

Type of log-linear Model	df	G^2	Δdf	ΔG^2	P	Characteristics
1. A+B+C+D	72	124.68				
2. All 1+AB+BC+CD	60	87.98	12	36.7	p<.0005	1st order, other contingent
3. All 1+AB+BC+CD+AC+BD	52	68.00	8	19.98	p<.025	2nd order, self-contingent effects
4. All 1+AB+BC+CD+AC+BD+AD	48	63.77	4	4.23	NS	3rd order, other contingent effects
5. All 1+AB+BC+CD+BD+AD+ABC+BCD	29	37.40	19	26.37	NS	2nd order, other/self effects
6. All 1+AB+BC+CD+BD+AD+ABC+BCD+ACD	12	14.03	17	23.37	NS	3rd order, other/other + self/other effects

Before interpreting these results we might comment on the procedure used for interpreting the data in this table. The change in G^2 (ΔG^2) reflects changes associated with the different models which are a result of adding effects. Thus we can assess the relative contribution of different effects in accounting for the frequency distribution and our task is to identify the most parsimonious model which fits the data. For example, Model #2 (All 1+AB+BC+CD) represents the association between events or acts at t and t-1 (AB), acts at t-1 and t-2 (BC), and acts at t-2 and t-3 (CD). Taken together this particular model is a first order Markov model as it reflects the Markov assumption that current acts are solely dependent on the immediately preceding act. We further presume, based on the Markov stationary assumption, the this pattern will be stable over time although this assumption was not tested and is related to the "dynamics" of the process (e.g., type of Markov chain).

Examination of the results in Table 2 indicates that a first-order Markov model provides the best fit to the data (Model #2, AB, BC, CD). While there is some indication of statistically significant ($p<.025$) 2nd order effects, these effects have considerably smaller contributions than the first order effects. Therefore we conclude that the process in this particular counseling interview, using this coding scheme, is best described by a first-order Markov process. Thus, the Model is one of current acts being contingent primarily upon the immediately preceding act of the other actor and not on acts by self or other actor furhter down the chain in time.

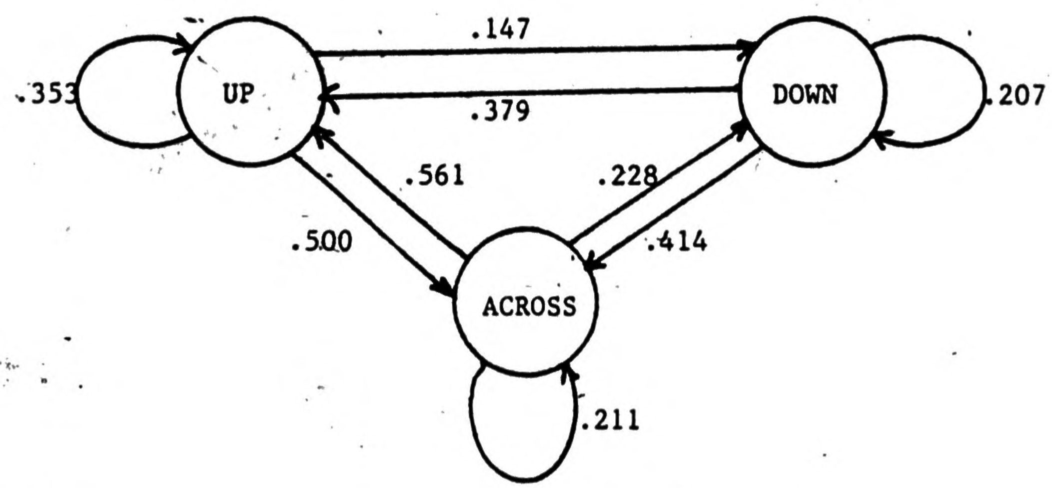
The transition matrix for the first-order Markov model is presented in Table 3. The cells contain the transition probabilities along with the frequency of occurrence for that particular transition. Frequencies of transitions are contained in parentheses.

TABLE 3

Transition Matrix for Three Category System at Time t and t-1

Time t-1 (immediate antecedent)	Time t (Consequent) Up	Across	Down
Up	.353(24)	.500(34)	.147(10)
Across	.561(32)	.211(12)	.228(13)
Down	.379(10)	.414(12)	.207(6)

Another method typically used for displaying a transition matrix for Markov models is to diagram them as directed graphs (diagraphs) (Issacson & Madsen, 1976). A diagraph of the first-order transition matrix is presented in the folloiwng figure. In this diagraph each possible state is represented by a circle with arrows connecting the states representing the transition probabilities from one state to another.



Discussion

In an attempt to understand the "process" represented by the diagraph it woould be helpful to recall two issues discussed in the Introduction sections of these three papers. First, this was an intitial interview, and second, the process dimension was that of "interpersonal or relational control" as reflected in the coding scheme. Further it should be noted that the order of frequency (most to least) of these three response categories was as follows: Up, Across, Down.

An examination of the diagraph would suggest that the primary process occurring was that of fluctuating back and forth between the Up and Across categories with an occasional movement into the Down state. However, once in the Down state it appears that the process moves back into the primary Up-Across cycle. It would appear that in this initial intervew the process looks like one of participants trying to work out their roles or positions as no clear "complementary or symmetrical" pattern (Haley, 1963) emerged. In short, Up responses were generally "neutralized" by Across responses. Perhaps this is a pattern that one might reasonably expect in many initial counseling interviews.

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The Use of Lag Sequential Analysis
in Counseling Process Research

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The issue of identifying pattern in counselor-client interaction rests fundamentally on an assumption of behavioral interdependency between participants in the counseling process. In a general sense, communication is said to occur between persons whenever they behave in a non-random manner with respect to each other. More specifically, it means that one person's actions are dependent (at least to some degree) on the preceding behaviors of the other. Indeed, were this not the case (i.e., were the counselor and client not to respond differentially or contingently to each other), it would be impossible to say that there was any exchange/communication process (much less counseling) going on between them (Barnlund, 1981). By this definition of communication, it should be understood that "communication" is not simply the response of one person to another, but rather a relationship between their responses (Cherry, 1957) -- a relationship of mutual and reciprocal constraint upon the behavioral variability of both the counselor and client. By virtue of this constraint, the interactive behaviors of the counselor and client, which are the "stuff" of the counseling process, become predictable, at least to some extent -- and it is this predictability that is referred to as "pattern" (Bateson, 1973).

In discussing their search for recurrent sequences (sic patterns) of counselor-client exchanges in their case study of time-limited counseling, Hill, Carter and O'Farrell (1983) comment that "counselor responses may not have an immediate impact; for example, an interpretation may not 'hit' until later" (p. 16). They go on to note that a limitation of many approaches to the analysis of behavioral (e.g., counselor-client exchange) sequences is their inability to go beyond the determination of immediate effects. As a consequence, such approaches may not be appropriate for analyzing counseling interaction.

Lag sequential analysis (Sackett, 1979) is presented specifically to address the problem of identifying distant (as well as immediate) effects within behavior sequences. In this regard, lag analysis provides a means for revealing and studying constraint and contingency patterns within the counseling process which may not be apparent when the scope of the analysis is limited to immediate effects.

A lag sequential analysis begins with the assumption of the counseling process (i.e., counselor-client interaction/sequence) as a discrete stochastic process -- one made up of a sequence of discrete events (counselor/client responses), coded in terms of a finite number of mutually exclusive and exhaustive categories. Analysis of the process becomes an analysis of the coded events as they occur temporally and sequentially.

Suppose, for example, one observes a sequence of counselor-client exchanges using two observational codes (A and B). If one observes the sequence

ABAABABBABBAAABABBABAAABBAAABB

one can describe the interaction nonsequentially by simply observing that the frequency of occurrence of A is 16, and the frequency of B is 14. The unconditional probability of A is thus p(A) = 16/30 = .53; and the unconditional probability of B is p(B) = 14/30 = .47. The conditional probability of B, given that A had occurred just prior to B, is the proportion of time that B occurs immediately after A: A occurs 16 times, and of those 16 times B occurs after A nine times. Thus, the conditional probability of B given A is 9/16 = p(B/A) = .56. Hence one can reduce the uncertainty in our knowledge of B's occurrence by knowing the immediately preceding event in the interaction was A. Lag analysis continues applying this procedure -- investigating the effect of increasingly distant "antecedent" events on the probability of occurrence of "consequent" events.

To proceed with the analysis, Sackett (1979) proposes that each of the possible event codes in the interaction sequence be viewed a starting point within the sequence. After initially computing the unconditional probability of occurrence of each of these codes, the conditional probability of each possible event code (including itself) is calculated as a function of the successive "lags" (steps) of each code from each possible criterion. This is accomplished by counting the number of times each event code follows the criterion as the next event code (lag-1), as the second event code following the criterion (lag-2), as the third event code (lag-3), and so on up to the largest lag size or sequential step of interest (MAXLAG). As in the above example, the lag probabilities are computed by dividing the frequency of occurrence of each event code following each criterion at lag-n (n=1 through MAXLAG) by the number of times the criterion code serves as a criterion for a lag of size n.

Using these lag probabilities, it is then possible to identify patterns/relationships among those events in the sequence. To do so involves a three-step procedure, referred to by Gottman (1979) as the "lag-one connection rule." Starting with one of the criterion codes (typically, the code with the largest unconditional probability of occurrence), the investigator selects for the next event in the pattern the event code with the highest lag-1 conditional probability. Next, the event code with the highest lag-2 probability from the criterion is selected, the highest lag-3 probability event code, etc. -- proceeding until the lag-n events become equivocal or until the generated sequence reaches some length of interest.

Next, Gottman (1979) notes that the sequence generated in the first step of the procedure is a likely or common pattern only if the lag-1 probability from event 2 to event 3 in the sequence is the highest conditional probability for that two-event sequence, having the second event now serving as the criterion. The second step in Gottman's prcedure consists of the of verification of the event-event connections along the sequence of events generated in the first part of the procedure--each time using the "next event" as the criterion from which to select subsequent lag events.

The last step in identifying a probable pattern of sequential events is to determine whether the conditional (lag) probability of occurrence of an event at any lag differs significantly from its simple unconditional probability (i.e., if there is no dependency between the sequential events). Even if an event code is the most likely code at some lag from the criterion, if its occurrence is not more probable than its simple unconditional likelihood of occurrence, that event is not to be entered into the identified common sequence or pattern. Sackett (1979) has proposed that "with a reasonably large N for the total number of criterion occurrences at a given lag (at least 30) and an expected probability that is not too close to zero (0.05 - 0.10 or larger)" (p. 625), the binomial test is the appropriate way of testing the statistical reliability of the difference between conditional (observed) and unconditional (expected) lag probabilities.

$$z = \frac{P_o - P_e}{SD_e}$$

where P_o = observ. prob.
P_e = expect. prob.
SD_e = stand. dev. of expect.

and $$SD_e = \frac{P_e \times (1 - P_e)}{N_{tot.crit.}}$$

If the standardized difference (z) between the conditional and unconditional probabilites equals or exceeds an absolute value of 1.96, the difference is considered statistically significant ($p < .05$). Statistically significant <u>positive</u> z values suggest that the event at lag-n is <u>more</u> likely than expected by chance. Sackett refers to this as an "excitation or positive dependency." A statistically significant z having a <u>negative</u> value suggests that the event at lag-n is <u>less</u> likely than expected by chance. That is, the event is inhibited from occurring at that lag (given the criterion), or there is a negative dependency between the event and the criterion at that lag.

Analysis of the interview

As noted in the introduction to this set of papers, three response categories were used for classifying counselor and client responses within the interview. Briefly, responses were coded in terms of their message control direction and were designated as "one-up," "one-across," or "one-down" -- coded A, B, and C respectively (Lichtenberg & Barke, 1982). To simplify presentation of the lag method, no distinction was made between the responses of the counselor and those of the client. Analysis of the interview consisted of analysis of the lag-dependencies among the one-up, one-across and one-down responses, irrespective of speaker. The search for response patterning within the interview was limited to a maximum lag of 20. As will become clear, however, within that sequence range, nonrandom conditional probabilities were found only up through lag-3.

Table 1 provides a summary of the event lag matching frequencies, probabilities and z-scores for the interview up through lag-5. The information is presented separately for each of the three response categories as criterion. Figures 1(a-c)

[Insert Table 1 about here]

through 3(a-c) profile the same information, although extending through lag-12. The unbroken horizontal line in each of the figures indicates the unconditional (expected) probabilities for the behavior being profiled. Significant deviations from expected values are noted by an asterisk (*).

[Insert Figures 1(a-c) through 3(a-c) about here]

From Table 1 it can be seen that overall (i.e., across the complete interview) "one-up" responses (=A) occurred 68 times, "one-across" responses (=B) occurred 58 times, and "one-down" responses (=C) occurred 29 times--yielding unconditional or expected probabilities of .439, .374, and .187 respectively.

With A as the designated "criterion code," it can be seen that within the interview A followed itself (autolag) at lag-1, 24 out of a possible 68 times (=.353), [z=-1.425]. Response A was followed by B at lag-1, 34 times (=.500) [z=2.144], and response A was followed by C at lag-1, 10 times (=.147) [z=-0.847]. The occurrence of A appeared to have an inhibiting effect on its own recurrence at lag-1 and an excitatory effect on B.

At lag-2, A followed itself 39 out of a now possible 68 times (=.582), [z=2.365]; and B followed A at lag-2, 16 times (=.239) [z=2.290]. Response C followed A at lag-2, 12 times (=.179) [z=-0.168]. These results suggest that A had excitatory effect on its own recurrence at lag-2 and an inhibitory on B.

At lag-3 the effect of A on its own recurrence and on B again reversed itself. Response code A followed itself at lag-3, 22 out of a possible 66 times (=.333) [z=-1.725]; and B followed A at lag-3, 34 times (=.515) [z=2.366].

Although a similar "switching pattern" between A and B continued for a number of lags [see Table 1 and Figure 1(a&b)], by lag-4 the effect of A on itself and B was no longer statistically reliable--i.e., the conditional lag probabilities no longer differ significantly from the unconditional probabilities.

Based on the information in Table 1, it is possible to identify a probable 5-lag response-response sequence. Starting with A as the criterion behavior, that sequence would be A-B-A-B-A-B. As already noted, however, the statistical reliability of the lag probabilities, limits the sequence to only 3 events beyond the criterion: A-B-A-B. [Note: The occurrence of A appeared to have no reliable effect on C--i.e., there appeared to be no sequential dependencies between A and C at lag-1 through lag-20.] According to Gottman's (1979) "lag-one rule," however, the above identified A-B-A-B sequential pattern can be considered a likely or common sequence only if the lag relationships from response event 2 in the sequence (as criterion) follow those specified in the sequence. That is, the identified sequence would be a likely sequence only if (beginning at reponse 2) the sequence were to be B-A-B. To test this , B was then designated as the "criterion code."

Referring again to Table 1, it can be seen that B was followed by A at lag-1, 32 out of a possible 57 times (=.561) [z=1.867], and by itself 12 times (=.2110 [z=-2.553]. Response C followed B at lag-1 a total of 13 times (=.228) [z=.793]. Response A was by far the most likely consequent to B (at lag-1), even though the excitatory effect of B on A dis not achieve statistical significance. On the other hand, B did have a reliable inhibitory effect on itself at lag-1, suppressing its own recurrence to a level similar to that of C. Thus, although the likelihood of A following B at lag-1 was not significanty greater than the unconditional probability of A, A was clearly the most likely event to follow B at lag-1. As such, confidence in the identified response pattern seems justified.

At lag-2, B was followed by A 17 out of a possible 57 times (=.298) [z=-2.137], and by itself 28 times (=.491) [z=1.826]. Response C followed B at lag-2, 12 times (=.211) [z=.454]. Interpretation here is analogous to that for the previous lag-1 probabilities: The occurrence of a B response appeared to have a reliable inhibitory effect on the occurrence of A at lag-2. At the same time, B seemed to have an excitatory effect on its own recurrence at lag-2 -- although this effect only approached statistical significance. As above, although the excitatory effect of B on itself at lag-2 did not achieve significance, the fact that B was the most likely event to follow B at lag-2, and the reliable inhibitory effect of B on A at that lag, seem to further justify confidence in the identified response pattern.

Beyond lag-2, none of the lag probabilities evidenced B having a reliable inhibitory or excitatory effect on any of the response codes. The B-A-B "switching pattern," however, continued to be apparent in the lag probabilities. As with A, the occurrence of B appeared to have no reliable effect on the occurrence of C.

Since C responses never enter the identified response sequence, it seems unnecessary to discuss in any detail its lag effects (sic) on the various response codes. Suffice it to say that were one to specify C as the criterion code for identifying a likely response sequence, the 5-lag sequence would be: C-B-B-A-(A/B)-A. None of the lag dependencies, however, evidenced statistical reliability; and thus the sequence can be dismissed as trivial.

Discussion

The intent of this section of the symposium was to present Sackett's method of lag sequential analysis and to show how it may be applied to counseling interaction in order to reveal response patterning within that interaction. Whether or not patterning is found in the interaction and whether that patterning, if found, has any psychological significance, is to a large extent a function of the response units and categories used in the analysis. The response units and categories used in this analysis did evidence a reliable sequential patterning: a series of exchanges characterized by one-up responses (controlling maneuvers) by one person being followed by responses by the other to neutralize that control. Lost in the analysis (for reasons of expediency and clarity) was speaker designation. Thus it becomes impossible to distinguish counselor one-up responses from client one-up responses, counselor one-across response from client one-across responses, etc. Regardless, the patterning evidenced , a pattern of interactants responding so as to neutralize the other's control,) appeared to coincide with the notion of relational struggles in the early stages of counseling (Cashdan, 1973; Haley, 1963; Tracey & Ray, 1984).

Conclusion

Although knowledge of the immediate effects of counselor responses on clients (and client responses on counselors) is important (Lichtenberg, 1984), it seems reasonable to expect that responses within counseling also may have distal effect. Lag sequential analysis offers a method for identifying both immediate and distant dependency relationships among events in behavioral sequences. By comparing the conditional probabilities of responses at various lags (distances) from specified criterion events with the expected (unconditional) probabilities of these responses, one it able to study the response inhibitory and excitatory effects of the various behaviors within the process. Taken together, these identified contingency relationships among counselor and client responses contitute recurrent sequential patterns of events within the counseling process--patterns which within the emerging interactional perspective on counseling (Anchin & Kiesler, 1982; Cashdan, 1973; Strong & Claiborn, 1982; Watzlawick & Weakland, 1977) become the foucs of and means for evaluating counseling interventions (Lichtenberg, 1982).

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Table 1 Event lag matching frequencies and probabilities for the counseling interview data. [The figures in parentheses are the z-scores for the corresponding conditional probabilities.]

	Number of Matched Occurrences				Probability		
Lag	One-up (A)	One-across (B)	One-down (C)	Total	One-up (A)	One-across (B)	One-dow (C)
Overall	68	58	29	155	.439	.374	.187
Criterion: One-up (A)							
1	24	34	10	68	.353 (-1.425)	.500 (2.144)	.147 (-0.847)
2	39	16	12	67	.582 (2.365)	.239 (-2.290)	.179 (-0.168)
3	22	34	10	66	.333 (-1.725)	.515 (2.366)	.152 (-0.741)
4	33	17	15	65	.508 (1.121)	.262 (-1.877)	.231 (0.903)
5	23	28	14	65	.354 (-1.379)	.431 (0.943)	.215 (0.585)
Criterion: One-across (B)							
1	32	12	13	57	.561 (1.867)	.211 (-2.553)	.228 (0.793)
2	17	28	12	57	.298 (-2.137)	.491 (1.826)	.211 (0.454)
3	30	16	11	57	.526 (1.333)	.281 (-1.459)	.193 (0.114)
4	19	28	10	57	.333 (-1.603)	.491 (1.826)	.175 (-0.226)
5	28	19	9	56	.500 (0.924)	.339 (-0.540)	.161 (-0.506)

Table 1 (cont.)

Criterion: One-down (C)

1	11	12	6	29	.379 (-0.645)	.414 (0.441)	.207 (0.273)
2	11	14	4	29	.379 (-0.645)	.483 (1.208)	.138 (-0.679)
3	14	8	7	29	.483 (0.478)	.276 (-1.094)	.241 (0.750)
4	13	13	3	29	.448 (0.104)	.448 (0.824)	.103 (-1.155)
5	13	11	5	29	.448 (0.104)	.379 (0.057)	.172 (-0.203)

Note: z-scores equalling or exceeding ±1.96, significant at p≤.05 .

Figure 1 Lag profiles for response codes using A (one-up) as criterion code

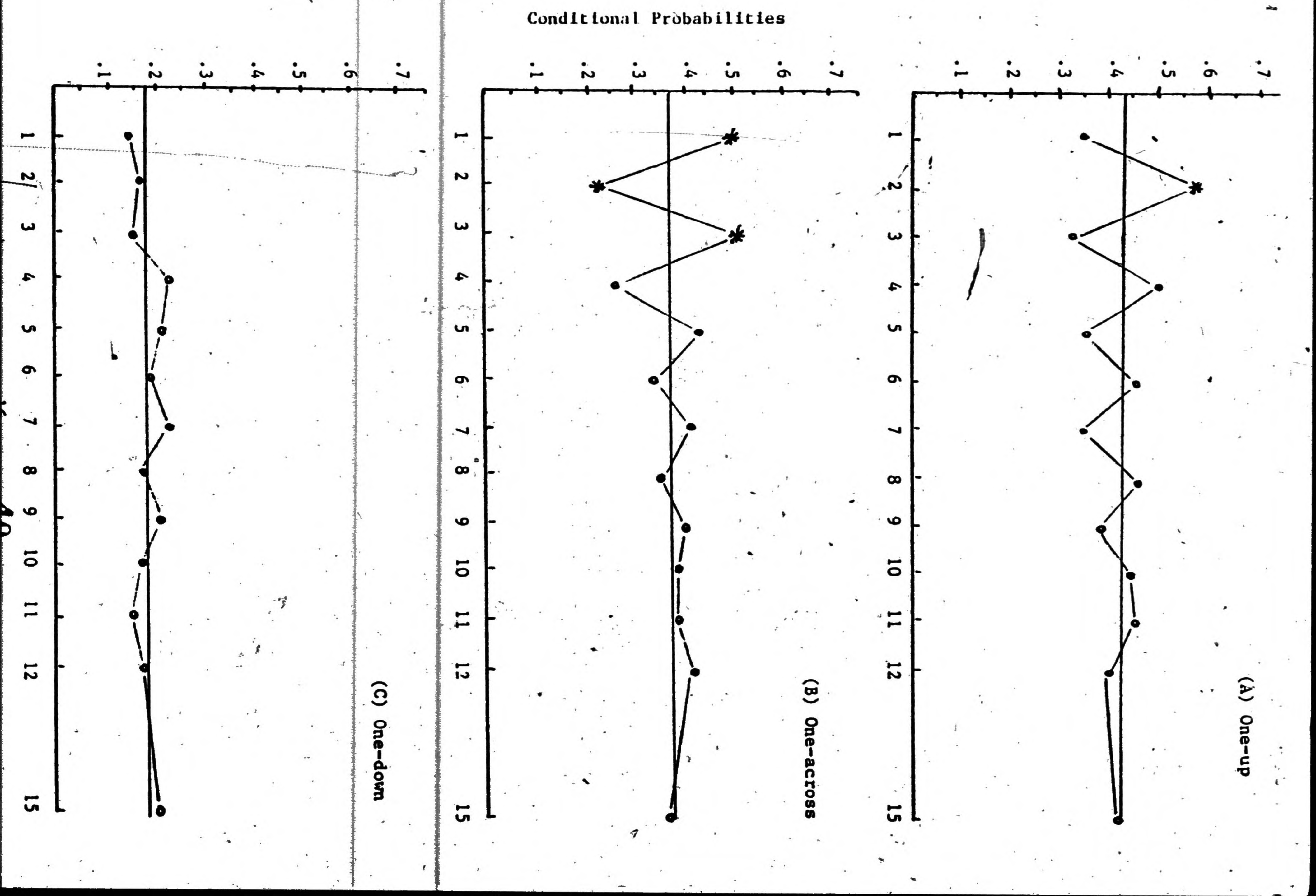


Figure 2 Lag profiles for response codes using B (one-across) as criterion code

Conditional Probabilities

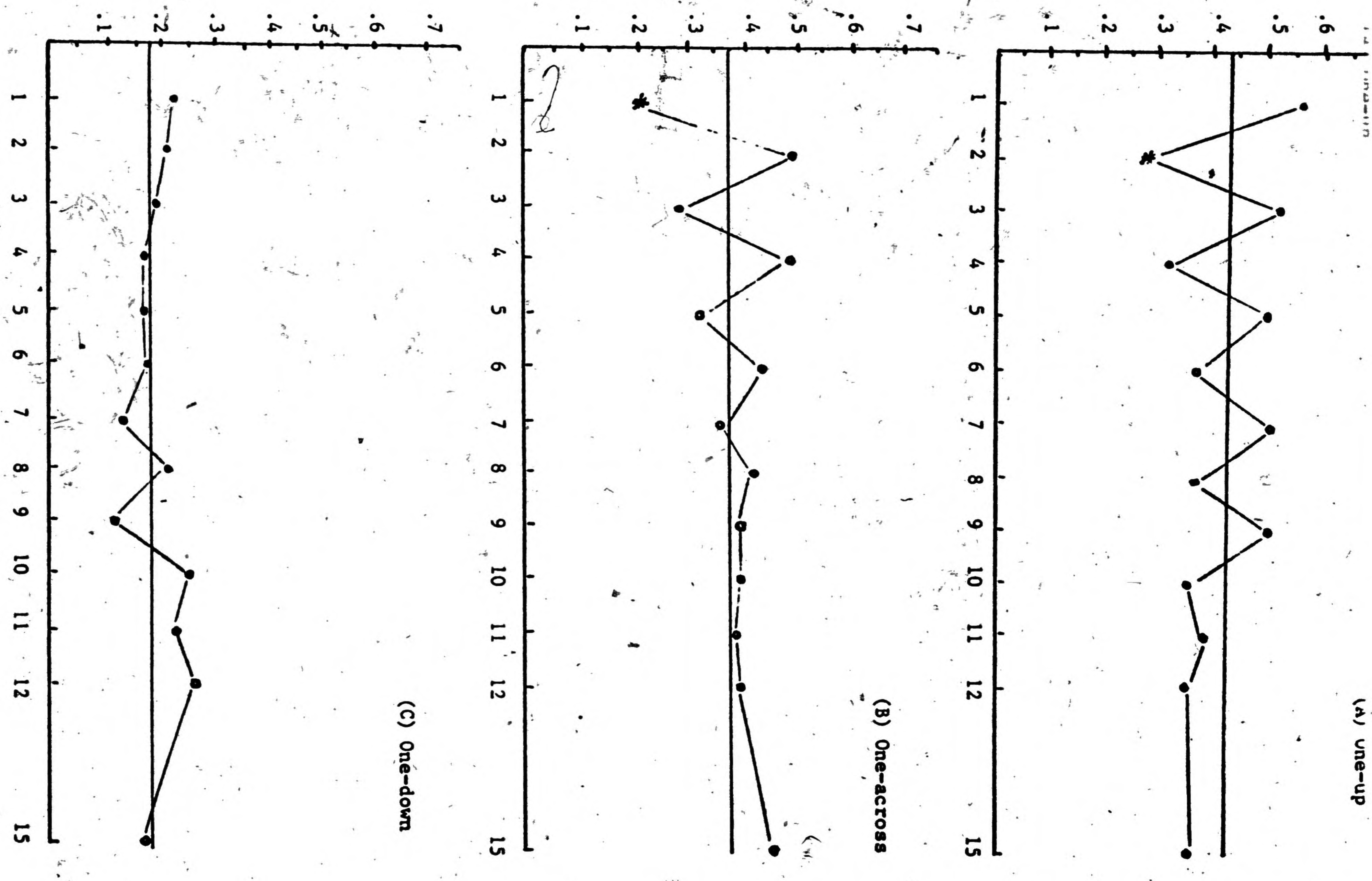
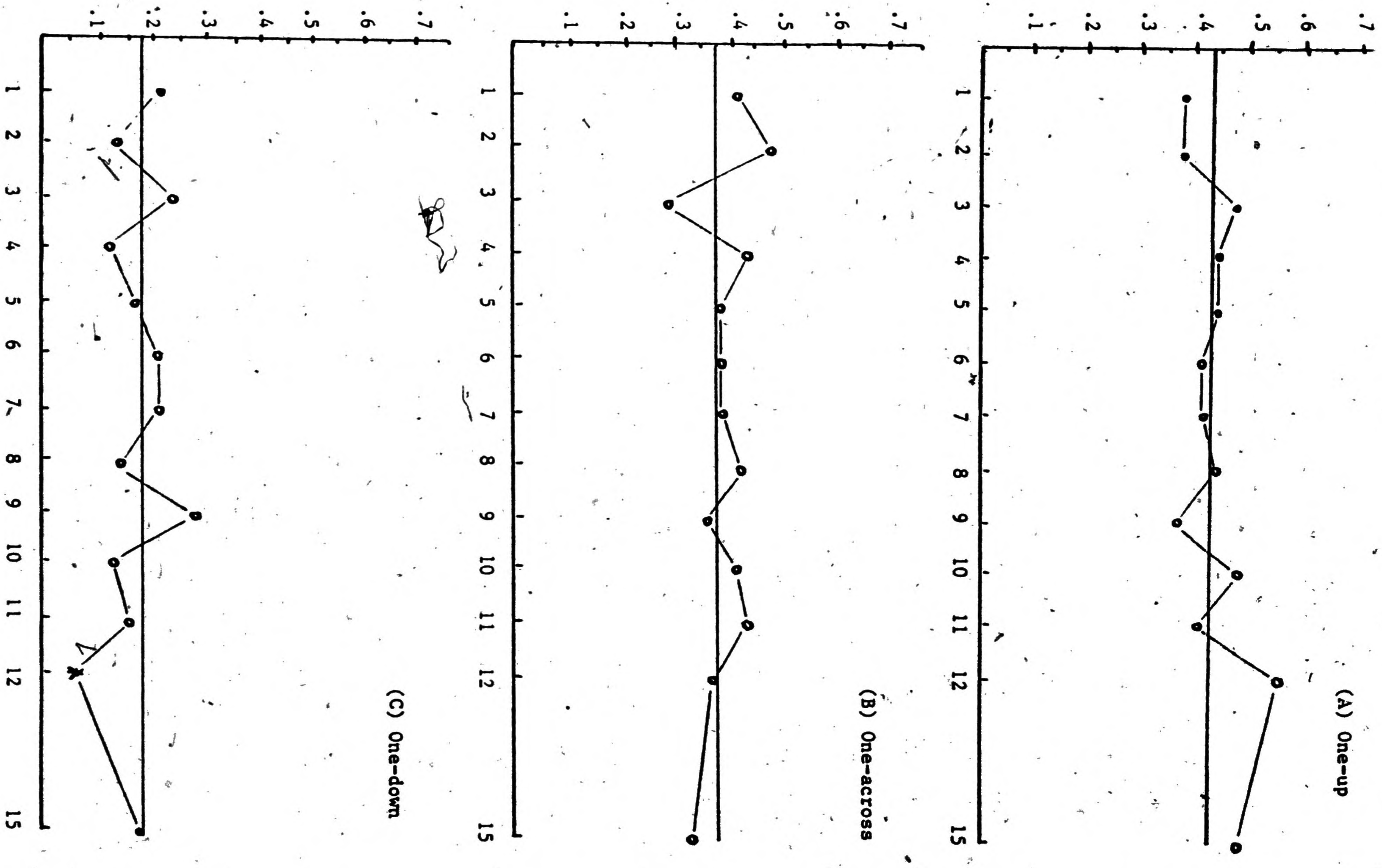


Figure 3 Lag profiles for response codes using C (one-down) as criterion code

Conditional Probabilities



The Use of Information Theory in Counseling Process Research

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Information theory, having its origins in communications engineering and later telecommunications, was designed as a method to quantify the amount of information inherent in communication and to describe the behavior of machines without knowledge of the mechanics of machines themselves (Losey, 1978). Attneave (1959) has stated that the applications of information theory in the field of psychology are varied and numerous. Penman (1980), for instance, has recently shown how information theory may be applied to the analysis of communication patterns of married couples. Attneave has suggested, however, that information theory has fallen short of its expectations as a powerful, analytic tool and a methological panacea. In this regard, Losey (1978) has written that information measures have declined in use (particularly their multivariate applications) due to the proliferation of more sophisticated and robust multivariate techniques. Interest in information theory remains, however, because of its ability to identify pattern in sequences of events and to analyze signal (i.e., stimulus) and response dimensions through the partialing of the sources of information associated with each dimension in a fashion analogous to the analysis of variance.

With regard to counseling process research, Lichtenberg and Heck (1984) have suggested recently that information theory may provide a means for determining the order of sequence and the amount of information that counselors and clients respond to in counseling interactions. Elaborating on an earlier study in which the relationship between cognitive complexity and counseling interactions was investigated (Lichtenberg & Heck, 1979), they propose the possibility that individuals with greater information processing abilities (e.g., cognitive complexity) may be better able to respond to antecedent stimuli of greater informational complexity--specifically, higher orders of event-event dependency than less cognitively complex individuals. In addition, information theory may be used in a manner analogous to Tracey and Ray's (1984) use of Markov chains to examine changes in interaction styles across stages of counseling for cases of successful and unsuccessful counseling.

In order to understand more fully how information theory might be used as a means of testing hypotheses regarding sequence or "pattern" in counseling interaction, this paper will attempt to explicate the principles and assumptions underlying the use of information theory and to demonstrate the use of Shannon and Weaver'(1949) measures of information through their application to the data set common to these presentations.

Uncertainty and Redundancy

Attneave (1959) has defined information as "that which removes or reduces uncertainty" (p. 1). Uncertainty exists when one is unable to specify the possible outcomes to events such as drawing a card, throwing a card, or possibly making an interpretation in a counseling interview. The greater the number of alternative outcomes that are likely to occur, the greater the amount of uncertainty associated with that outcome. Redundancy, on the other hand, refers to the degree of patterning in a sequence of events. When the interaction sequence generated by a counselor and client is viewed as a stochastic (random or probabilistic) process, redundancy refers to the degree of predicability for an event (e.g., a client's statement) when knowledge of the event preceding it (e.g., the counselor's statement) is taken into consideration. As a stochastic process, the counseling process can thus be characterized by some degree of redundancy between 0 and 100 percent. At the zero redundancy extreme, all events have an equal likelihood of occurrence and the history of the sequence of events prior to any given event has no effect on the predictability of the event. At the other extreme, that of 100 percent redundancy, the sequence of events is entirely predictable (i.e., redundant), and one can predict with complete certainty what each subsequent event will be.

At issue with respect to understanding patterning within counselor-client interactions is determining the redundancy in their interaction. Unless the interaction is completely redundant, the simplest form of redundancy is that which depends soley on the unconditional and unequal probabilities of the various possible counselor and client responses. Redundancy characterized by the simple unconditional and unequal probabilities of the individual responses is said to be first-order redundancy (zero-order dependency). Sequences in which the prediction of an event is possible given knowledge of the immediately prceding event are said to have second-order redundancy (first-order dependency). Any order of redundancy above the first necessarily implies that the events are more or less patterned and that sequential dependencies exist among them. A sequence has nth-order redundancy whenever the prediction of an event depends upon knowledge of the n-1 preceding events. In short, a sequence has nth-order redundancy when some of its patterns of successive events are more probable than others (Attneave, 1959).

The Measurement of Information

Shannon and Weaver (1949) have suggested that the amount of information or uncertainty associated with an event (represented as the letter H) can be expressed as the quantity log 1/P, where P refers to the probability of the event. This value is sometimes called the "surprisal" of an event because of the information provided by the occurrence of an infrequently occuring event (Attneave, 1959). When m alternatives are possible for an event, H is equal to the sum of the suprisal values for each alternative, weighted or multiplied by its own probability or:

$$\underline{H} = \sum P_i \log \frac{1}{P_i} .$$

This is said to be the average information provided by the occurrence of an event. H has a maximum value of log m when all alternatives are equally likely (random), and a minimum value of 0 when there is complete redundancy (predictability). Information values are expressed as logarithms to the base 2 to ensure the additivity of "information" and so that information can be expressed as binary digits or "bits" of information (Attneave, 1959).

Applying information theory to the analysis of sequential events requires the introduction of one additional concept, that of conditional uncertainty. In order to determine whether successive events are independent, *H* (the average amount of information provided by a response) is compared with the average information provided by *pairs* of responses. Following from Shannon and Weaver's measure of information for individual responses, *H*(pairs) is calculated as:

$$H(\text{pairs}) = \sum P_{ij} \log \frac{1}{P_{ij}}$$

The difference between *H*(pairs) and *H* is the average conditional uncertainty of a response given the preceding response. It is denoted by H_2.

$$H_2 = H(\text{pairs}) - H$$

In order to investigate higher order dependencies among events, a similar procedure is followed. For example, to investigate second-order dependency (third-order redundancy), one would compute:

$$H(\text{triplets}) = \sum P_{ijk} \log \frac{1}{P_{ijk}}$$

$$H_3 = H(\text{triplets}) - H(\text{pairs})$$

H_3 would be the conditional uncertainty of a response given the two preceding responses. As a general formula, the value of *H* for a sequence of *n* events is

$$H(n) = \sum P_n \log \frac{1}{P_n}$$

and the conditional uncertainty of that size would be

$$H_n = H(n)-H(n-1).$$

The difference between successive values of conditional uncertainty provides a measure of how much information is gained (i.e., how much uncertainty is reduced) by basing predictions for a given event on the sequence of _n_ previous events rather than _n_-1 events. This measure of shared information, _T_, can be tested for its statistical significance using an approximation of the X^2 goodness-of-fit statistic provided by the equation:

$$X^2 = 2(\log_e 2)\ T_n\ N_{n+1}$$

where $T_n = H_n - H_{n+1}$ and

N = number of observations of length n+1.

The degrees of freedom associated with X^2 is equal to $m^{n-1}(m-1)^2$. The order of redundancy contained in a sequence of events is said to be the longest sequence of events of length _n_ which is statistically significant (Chatfield & Lemon, 1970).

One can also plot the conditional uncertainty of a sequence against its length (order of redundancy) to display visually the reduction in uncertainty as one considers sequences of increasing length. The point at which conditional uncertainty begins to decrease relatively slowly after inital sudden decreases allows one to determine the order of the dependency among the events. That is, the point at which inclusion of an additional event no longer contributes information to the prediction is the key indicator of the order of redundancy.

One limitation of information theory as applied to the analysis of redundancy is that in and of itself it fails to reveal the specific patterning within the interaction sequence; i.e., although information theory will reveal the order of the patterning within an interaction sequence, it will not reveal the specific events which constitute that pattern. Inspection of the frequencies of particular types of event sequences at a particular level of redundancy, however, may shed some light on the nature of the interaction.

Before continuing with the examination of the counselor-client interview data which are common to this set of presentations, two problems associated with the use of information theory will be addressed. First, it should be noted that the value $\underline{H}_n$ tends to be an underestimate of the true value of $\underline{H}$ when small samples are used. Second, Losey (1978) in his monte carlo studies has found that X^2 tends to be a non-conservative test and may produce error rates greater than those provided by the alpha level provided in X^2 tables. Losey accordingly suggests that the inferences based upon a graphical analysis will often be more reliable than a series of significance tests based upon the X^2 approximation.

Analysis of the Interview

Figure 1 depicts conditional uncertainty as a function of sequence length. Unlike examples provided by textbooks in which

[Insert Figure 1 about here]

inferences about the order of redundancy (and consequently, dependency) are clearly illustrated by rather dramatic decreases in uncertainty preceding the point at which the order of redundancy may be established, the shape of the curve produced by the interview data when levels of uncertainty for each sequence of incerasing length are connected, provides little information regarding the order of dependency or redundancy.

Table 1 presents values of conditional uncertainty for sequences with up to eight events and their corresponding values

[Insert Table 1 about here]

of T (shared information) which indicate that amount of information with the sequence that follows it in length. The X^2 approximation and its level of significance for each sequence are also provided. As can be seen, only sequences with lengths of one and two events were found to be statistically significant, suggesting a second-order redundancy (first-order dependency) within the sequence of events generated in the present counseling interaction.

Finding pattern based upon only two events implies the the counselor and client respond to each other using information based soley upon the immediately prededing event and that their responses are little influenced to any reliable degree by other preceding responses. With regard to the hypothesis suggested by Lichtenberg and Heck (1984) regarding the relationship between information processing ability and order of redundancy in counseling interactions, the data would suggest an interpretation of information processing ability as being more simple than complex.

Finally, analysis of the patterning of sequence within the second-order redundancy evidenced in the interview data suggests that among the possible two-event combinations of states (one-up, one-across, one-down), the most likely occurrence would be either a one-up response followed by a one-across response or a one-across response followed by a one-up response. In other words, irrespective of whether the speaker were the counselor or client, a one-up response by the speaker is most likely to be followed by a one-across response by the other; and a one-across response, in turn, was most likley to be followed by a one-up response.

Multivariate Information Theory

Attneave (1959) discusses an extension of Shannon and Weaver's (1949) measure of information to a method which partials information in a manner analogous to analysis of variance. This method, referred to as multivariate informational analysis (Garner & McGill, 1956), has been used in signal detection experiments to quantify the amount of information shared (transmitted) between a subject's response and its signal, and conversely, the amount of information lost between the initial signal and the response of the subject. In the case of the study of counselor-client interaction, the "signal" is the antecedent response of one speaker and the "response" is the following response of the next speaker.

The method one may use to determine the amount of information transmitted between a signal and its response is similar to that provided earlier for determining the uncertainty of an event and the event preceding it. In the multivariate case, the amount of information associated with the response dimension, H(y), is provided by the formula:

$$H(y) = \log N - \frac{1}{N} \sum^{i} n_i \log n_i$$

N here refers to the sample size and n_i refers to the frequency with which the events associated with the y dimension have occured. As with earlier measures of information, the log of base 2 is used for convenience. The amount of information associated with the signal(stimulus) dimension, H(x), is computed in a similar manner.

The amount of information shared between the signal and response dimension, T(x;y), is provided by the formula:

$$T(x;y) = H(x) + H(y) - H(x;y) \ .$$

H(x;y) is said to be the amount of information contained between the signal and response dimension when considered jointly. The computation of H(x;y) utilizes the formula:

$$H(x;y) = \log N - \frac{1}{N} \sum^{i} \sum^{i} n_{ij} \log n_{ij} \ .$$

The analogy between analysis of variance and multivariate informational analysis is clear when one considers the manner in which each technique partials either variance or information. When several dimensions are taken into consideration, in the case of true multivariate informational analysis one can indeed determine the effect of the interaction of two or more signal dimensions upon the response. The means for determining the effect of interactions, shared information, and the like for the case involving more than two variables are provided by Losey

(1978) and Attneave (1959) and will not be described within the present text. For a complete treatment of the relationship between analysis of variance and information theory, the reader is referred to Garner and McGill (1956).

The implications of multivariate informational analyses for counseling process research are suggested mainly by the technique's unique ability to quantify the transmission of information between one or more signal dimensions and their response. Further, it is also the ability of multivariate information theory to handle categorical data used in the sequential analysis of stochastic processes that allows multivariate informational analysis to be considered an important technique in counseling process research.

Conclusion

This paper has attempted to explicate the principles underlying the use of information theory and the methods used to obtain the various information measures. Information theory was demonstrated as a method to identify pattern and sequence and to provide some understanding of information transmission in counseling interactions.

While information theory has generally been acknowledged as an analytic tool which enables investigators to identify pattern in sequences of events, it seeems to have been widely ignored in counseling process research. However, given the increasing interest in counseling as an interactional process (Strong & Claiborn, 1982), information theory may offer one means for assessing process in counseling interactions.

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TABLE 1

Sequence Length (n), Conditional Uncertainty (H_n). Shared Information (T_n), and Chi-Square (X^2) approximations.

n	H_n	T_n	X^2(df)	p
1	1.505	.054	11.46(4)	*
2	1.451	.113	24.05(12)	*
3	1.338	.200	46.16(36)	NS
4	1.137	.280	58.70(108)	NS
5	0.857	.348	72.30(324)	NS
6	0.509	.309	63.72(972)	NS

*$p<.05$
NS= Not Significant

Figure 1

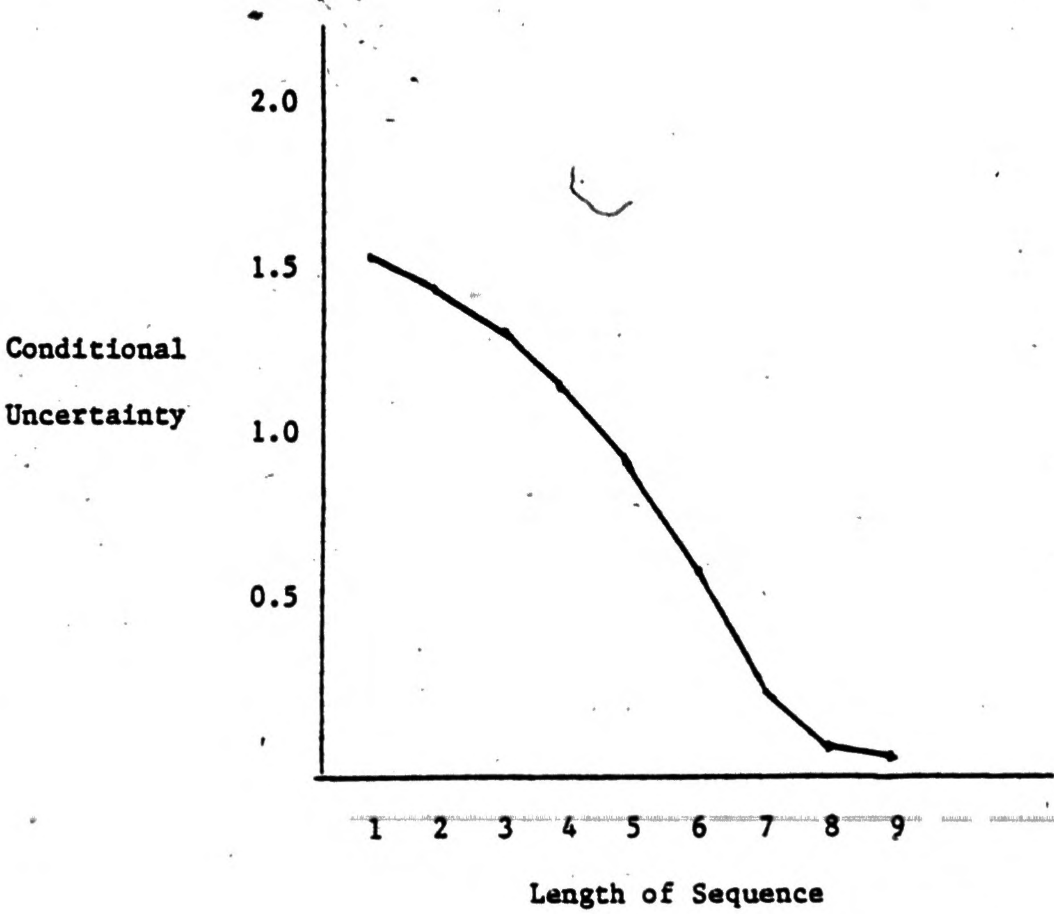

Figure 1. Conditional Uncertainty as a function of length of sequence.