9

Analyzing time sequences

9.1 The tyranny of time

Events unfold in time. What distinguishes users of sequential analysis from many other researchers is that they attempt to move beyond this banal observation and try to capture aspects of this unfolding in quantifiable ways. For such purposes, it is often sufficient to know just the order of events, and to use the techniques for analyzing event sequences discussed in chapter 7.

Often, however, we want to know more than just the order of events. We want to know in addition how people (dyads, animals, etc.) spent their time. For that reason, it is common for investigators to record not just the *order* of events, but their *times* as well. In chapter 3 we described three ways such time information could be recorded (timing onsets and offsets, timing pattern changes, interval recording), and in chapter 5 we described three ways data could be represented preserving time (state sequences, timed-event sequences, interval sequences). Once recorded and represented, however, sometimes time information exerts a tyrannical hold on investigators who then seem reluctant to omit time from their analyses, even when this would be appropriate.

For many studies, especially when behavioral states are coded, we think time is worth recording primarily because "time-budget" information (amounts or percentages of time devoted to different kinds of events or behavioral states) has such descriptive value. For example, Bakeman and Adamson (1984), in their study of infants' attention to objects and people, recorded onset times for behavioral states, represented these data as state sequences, and computed and reported percentages of time devoted to the various behavioral states when with different partners (mothers or peers) at different ages.

However, when examining how behavioral states were sequenced, Bakeman and Adamson ignored time, in effect reducing their state-sequential data to event sequences. This approach has merit whenever investigators want to describe how a simple stream of events or states unfolded in time. For example, if state sequences are analyzed instead of event sequences,

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using a time unit instead of the event as the basic unit of analysis, values for transitional probabilities are affected by how long particular events lasted – which is undesirable if all the investigator wants to do is describe the typical sequencing of events.

As an example, recall the study of parallel play introduced earlier, which used an interval recording strategy (intervals were 15 seconds). Let U = unoccupied, S = solitary, and P = Person Play. Then:

Interval = 15; U, U, U, S, P, P . . .

Interval = 15; U, S, S, S, P, P . . .

Interval = 15; U, U, S, S, P, P . . .

represent three slightly different ways an observational session might have begun. All three interval sequences clearly represent one event sequence: Unoccupied to Solitary to Parallel. Yet values for transitional probabilities and their associated z scores would be quite different for these three interval sequences. For example, the $p(P_{t+1}|S_t)$ would vary from 1.00 to 0.33 to 0.50 for the three sequences given above. Worse, the z score associated with 0.33 would be negative, whereas the other two z scores would be positive. No one would actually compute values for sequences of just six intervals, of course, but if we had analyzed longer interval sequences like these with the techniques described in chapter 7, it is not clear that the USP pattern would have been revealed. Very likely, especially if each interval had represented 1 second instead of 5 seconds, we might have discovered only that transitions from one code to itself were likely, whereas all other transitions were unlikely. In short, we urge investigators to resist the tyranny of time. Even when time information has been recorded, it should be "squeezed out" of the data whenever describing the typical sequencing of events is the primary concern. In fact, the GSEQ program (Bakeman & Quera, 1995a) includes a command that removes time information, thereby transforming state, timed-event, or interval sequences into event sequences when such is desired.

9.2 Taking time into account

The simple example of a USP sequence presented in the previous section hints at the underlying unity of the four methods of representing data described in chapter 5. This unity, in turn, suggests a welcome economy. If we have already learned a number of techniques for analyzing event sequences (in chapter 7), and if state, timed-event, and interval sequences are logically the same as event sequences, then analyzing time sequences (sequential data that take time into account, i.e., state, timed-event, and

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interval sequences) does not require learning new techniques, only the application of old ones.

In fact, one underlying format suffices for event, state, timed-event, and interval sequences. These four forms are treated separately both here and in the Sequential Data Interchange Standard (SDIS; see Bakeman & Quera, 1992) because this connects most easily with what investigators actually do, and have done historically. Thus the four forms facilitate human use and learning. A general-purpose computer program like GSEQ, however, is better served by a common underlying format because this allows for greater generality and hence less specific-purpose computer code. Indeed, the SDIS program converts SDS files (files containing data that follow SDIS conventions) into a common format (called MDS or modified SDS files) that is easily read by GSEQ (Bakeman & Quera, 1995a).

The technical details need not concern users of these computer programs, but understanding the conceptual unity of the four forms can be useful. Common to all four is an underlying metric. For event sequences, the underlying metric is the discrete event itself. For state and timed-event sequences, the underlying metric is a unit of time, often a second. And for interval sequences, the underlying metric is a discrete interval, usually (but not necessarily) defined in terms of time.

The metric can be imagined as cross marks on a time line, where the space between cross marks is thought of as bins to which codes may be assigned, each representing the appropriate unit. For event sequences, one code and one code only is placed in each bin. Sometimes adjacent bins may be assigned the same code (consecutive codes may repeat), sometimes not (for logical reasons, consecutive codes cannot repeat). For state sequences, one (single stream) or more codes (multiple streams) may be placed in each bin. Depending on the time unit used and the typical duration of a state, often a stretch of successive bins will contain the same code. For timed-event sequences, one or more codes or no codes at all may be placed in each bin. And for interval sequences, again one or more codes or no codes at all may be placed in each bin. As you can see, the underlying structure of all forms is alike. Successive bins represent successive units and, depending on the form, may contain one or more or no codes at all.

Interval sequences, in particular, can be quite useful, even when data were not interval recorded in the first place. For example, imagine that a series of interactive episodes are observed for particular children and that attributes of each episode are recorded (e.g., the partner involved, the antecedent circumstance, the type of the interaction, the outcome). Here the *event* (or episode) is multidimensional, so the event sequential form is not adequate. But interval sequences, which permit several codes per bin, work well, and permit both concurrent (e.g., are certain antecedents

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often linked with particular types of interaction) and sequential (e.g., are consequences of successive episodes linked in any way) analyses. Used in this way, each episode defines an interval (instead of some period of elapsed time); in such cases, interval sequences might better be called multidimensional events. Further examples of the creative and flexible use of the four forms for representing sequential data are given in Bakeman and Quera (1995a, especially chapter 10).

Because the underlying form is the same for these four ways of representing sequential data, computational and analytic techniques are essentially the same (primarily those described in chapter 7). New techniques need not be introduced when time is taken into account. Only interpretation varies, depending on the unit, whether an event or a time unit. For event sequences, coders make a decision (i.e., decide which code to assign) for each event. For interval sequences, coders make decisions (i.e., decide which codes occurred) for each interval. For state and timed-event sequences, there is no simple one-to-one correspondence between decisions and units. Coders decide and record when events or states began and ended. They may note the onset of a particular event, the moment it occurs. But just as Charles Babbage questioned the literal accuracy of Alfred Lord Tennyson's couplet "Every minute dies a man, / Every minute one is born" (Morrison & Morrison, 1961), so too we should question the literal accuracy of a claim that observers record onsets discretely second by second and recognize the fairly arbitrary nature of time units. For example, we can double tallies by changing units from 1 to 1/2 second. The connection, or lack of connection, between coders' decisions and representational units is important to keep in mind and emphasize when interpreting sequential results.

9.3 Micro to macro

In this section we would like to share some wisdom based on our experience doing programmatic observational research with the same kinds of data for over a decade. Sequential analysis is interesting because so much theoretical clarity about interacting people is provided by the study of temporal patterns. Often when we have begun working in an area, we start with fairly small units and a large catalog of precise codes. A microanalytic description often is the product of these initial efforts (e.g., Brown, Bakeman, Snyder, Fredrickson, Morgan, & Hepler, 1975).

Sequential analysis of the micro codes then can be used to identify indexes of more complex social processes (e.g., Bakeman & Brown, 1977). For example, Gottman (1983) found that a child's clarification of a message after a request for clarification (Hand me the truck/ Which truck?/ The red

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truck) was an index of how connected and dialogic the children's conversations were. This sequence thus indexed a more macro social process. Gottman could have proceeded to analyze longer sequences in a statistical fashion, but with 40 codes the four-element chain matrix will contain 2,560,000 cells! Most of these cells would have been empty, of course, but the task of even looking at this matrix is overwhelming. Instead, Gottman designed a macro coding system whose task it was to *code* for sequences, to code larger social processes. The macro system used a larger interaction unit, and it gave fewer data for each conversation (i.e., fewer units of observation). However, the macro system used a larger interaction unit, and it gave fewer data for each conversation (i.e., fewer units of observation). However, the macro system was extremely useful. First, it was far more rapid to use than the micro system. Second, because a larger unit was now being used, new kinds of sequences were being discovered. This revealed an organization of the conversations that Gottman did not notice, even with the sequential analysis of the micro data (see Gottman & Parker, 1985 in press).

To summarize, one strategy we recommend for sequential analysis is *not* looking for everything that is patterned by employing statistical analysis of one data set. It is possible to return to the data, armed with a knowledge of patterns, and to reexamine the data for larger organizational units.

9.4 Time-series analysis

Time-series analysis offers a wide range of analytic options (see Gottman, 1981, for a comprehensive introduction), and, furthermore, it is possible to create time-series data from a categorial stream of codes, as we mentioned in section 5.7. In this section we shall review a few of the advantages provided by time-series analysis, and discuss further how to create time-series data from a stream of categorical data.

What are the advantages of creating time-series data from a stream of categorial data? First, one can obtain an overall visual picture of the interaction. This can be useful in two ways: One use is to create taxonomies of interactions. For example, Gottman (1979b) created a time series from data obtained from marital interaction (see Figure 9.1). The variable was the total positive minus the total negative interaction up to that point in time. In some couples, both the husband's and wife's graphs were quite negative. These couples tended to be high in reciprocating negative affect. In some couples, one partner's graph was negative and the other's was positive. These couples tended to have one partner who gave in most of the time in response to the partner's complaints. Couples whose graphs were flat at

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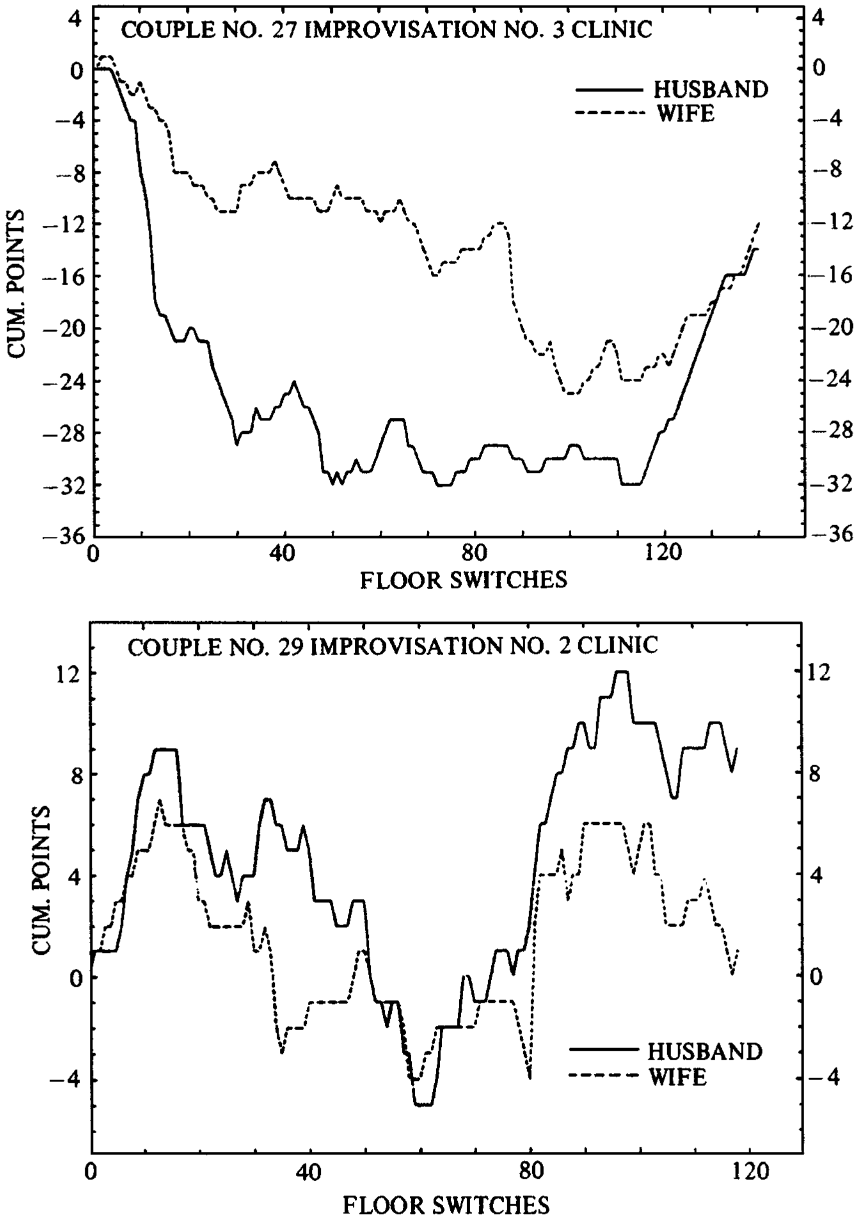

Figure 9.1. Time series for two clinic couples. From Gottman (1979b, p. 215).

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the start of an interaction tended to have social skill deficits in listening, whereas couples whose graphs were flat at the end of an interaction tended to have social skill deficits in negotiation.

A second use of a time-series graph is that it makes it possible to *discover the limitations of a coding system.* One can use the graphs to scan for shifts in slope or level. These may be rare critical events that the coding system itself does not know about. An example of this comes from a videotape that Ted Jacob had which was coded using the Marital Interaction Coding System (MICS). The interaction began in a very negative way but changed dramatically in the middle and became quite positive. The event that triggered the change seemed to be the husband's summarizing what he thought was the wife's complaint and then accepting responsibility for the problem. The MICS has no code for summarizing the other (which is a very rare event, but quite powerful); it does have a code for accepting responsibility, but this was miscoded on this tape. Despite the fact that the critical event was missed by the coding system, time-series analysis of the data detected the shift in the overall positivity of the interaction and pinpointed the time of the switch. Gottman refers to this use of time series as "Gödeling" because, like Kurt Gödel's work, it is concerned with using a system to view itself and discover its own limitations.

Creating time series from categorical data

In addition to these reasons for creating time-series data from categorical data, time-series analysis has some powerful analytic options, which we shall discuss briefly in a moment. First we would like to mention three options for creating time-series data from categorical data.

One option, used by psychophysiologists, is the *interevent interval.* This involves graphing the time between events of a certain type over time. Cardiovascular psychophysiologists, for example, plot the average time between heart beats within a time block of sufficient size. Interevent intervals can be computed with quite simple data. For example, imagine we had asked a smoker to keep a diary, noting each time he or she smoked a cigarette, and that a small portion of the data looks like that portrayed in Table 9.1. (For convenience, all times are given to the nearest 6 minutes or 0.1 hour.) Such interevent intervals are often averaged in some way. For example, if we used 2-hour time blocks, the averaged interevent intervals would be as given in Table 9.1. These scores are then available for graphing or subsequent time-series analysis.

A second option is the *moving probability-window.* Here we compute the proportion of times an event was observed within a particular block of

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Table 9.1. *Computing interevent interval time series*

Time	Interevent interval	Block	Block average
7:54 a.m.			
----------	2:12 (2.2)	----------	----------
10:06			
	0:42 (0.7)	10–12	1.45
10:48			
----------	1:30 (1.5)	----------	----------
12:18			
	0:24 (0.4)	12–2	0.95
12:42			
----------	1:48 (1.8)	----------	----------
2:30			
	1:18 (1.8)	2–4	1.55
3:48			

Note: Interevent intervals are given both in hours : minutes and in decimal hours.

observations, and then we slide the window forward in time. This option *smooths* the data as we use a larger and larger time unit, a useful procedure for graphical display, but not necessary for many time-series procedures (particularly those in the frequency domain).

A third option is the *univariate scaling* of codes. For two different approaches to this, see Brazelton, Koslowski, and Main (1974), and Gottman (1979b).

Each option produces a set of time series for each variable created, for each person in the interacting unit. Analysis proceeds within each interacting unit ("subject"), and statistics of sequential connection are then extracted for standard analysis of variance or regression. A detailed example of the analysis of this kind of data obtained from mother–infant interaction appears in Gottman, Rose, and Mettetal (1982). A review of time-series techniques is available in Gottman's (1981) book, together with 10 computer programs (Williams & Gottman, 1981).

Brief overview of time-series analysis

Brazelton, Koslowski, and Main (1974) wrote about the interactive cyclicity and rhythmicity that they believe characterizes the face-to-face play of mother and infant. They described a cycle of attention followed by the withdrawal of attention, with each partner waiting for a response from the

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other. They described the interactional energy building up, then ebbing and cycling in synchrony. Part of this analysis had to do with their confidence in the validity of their time-series variable. They wrote:

> In other words, the strength of the dyadic interaction dominates the meaning of each member's behavior. The behavior of any one member becomes a part of a cluster of behaviors which interact with a cluster of behaviors from the other member of the dyad. No single behavior can be separated from the cluster for analysis without losing its meaning in the sequence. The effect of clustering and of sequencing takes over in assessing the value of particular behaviors, and in the same way the dyadic nature of interaction supercedes the importance of an individual member's clusters and sequences. (p. 56)

Time-series analysis is ideally suited to quantitative assessments of such descriptions. It is a branch of mathematics that began to be developed in the mid-1700s, on the basis of a suggestion by Daniel Bernoulli, and later developed into a theorem by Jean Baptiste Joseph Fourier in 1822. The idea was that any continuous function could be best approximated in a least-squares sense by a set of sine and cosine functions. At first this idea seemed counterintuitive to mathematicians. However, it is true, and it is true even if the function itself is not periodic. Sines and cosines have an advantage over polynomials, because polynomials tend to wander off to plus or minus infinity after the approximation period, which is very poor for extrapolation if one believes that the data have any repetitive pattern. This is usually the case in our scientific work. For example, we tend to believe that if we observe the brightness fluctuations of a variable star, it really doesn't matter very much if we begin observing on a Monday or a Tuesday; we believe that the same process is responsible for generating the data, and that it has a continuity or stability (which, in time-series language is referred to as "stationarity").

Fourier proved his famous theorem incorrectly, and proving it correctly took the best mathematical minds over a century; furthermore, it has led to the development of much of a branch of modern mathematics called "analysis." Time-series analysis underwent a major conceptual revolution in the 20th century because of the thinking of an American, Wiener, and a Russian, Khintchine.

Without time-series analysis, attempts to describe cyclicity and synchronicity end in a hopeless muddle of poetic metaphor about interactive patterns. For example, Condon and Ogston (1967) tried to summarize 15 minutes of the dinner time interaction of one family. They wrote:

> We are dealing with ordered patterns of change during change, which exhibit rhythmic and varying patterns in the temporal sequencing of such changes. Metaphorically, there are waves within waves within waves, with complex yet

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> determinable relationships between the peaks and troughs of the levels of waves, which serve to express organized processes with continually changing relationships. (p. 224)

Time-series analysis offers us a well-elaborated set of procedures for passing beyond metaphor to a precise analysis of cyclicity, synchronicity, and the analysis of the relationship between two time series (called "cross correlation"), controlling for regularity within each time series (called "autocorrelation"), among other options.

The notion of cycles

A good way to begin thinking of cycles is to imagine a pendulum moving back and forth. The amplitude of the oscillation of the pendulum is related to the energy with which it is shoved. In fact, the variance of the pendulum's motion is proportional to this energy, and this is proportional to the square of the amplitude. The period of oscillation of the pendulum is the time it takes for the pendulum to return to the same spot; it is usually measured as the time from peak to peak of oscillations. Now imagine that we attach a second pendulum to the first and permit them to be able to oscillate independently. We can generate very complex oscillations just with the oscillations of two pendula. A new variable enters into the picture when we imagine two pendula, the relative phase of oscillation of the two. They can be moving in synchrony, or exactly opposite (180 degrees out of phase), or somewhere in between. So now we have three parameters: the energy of each pendulum (proportional to the amplitude squared), the frequency of oscillation of the pendulum (which is the reciprocal of the period of oscillation), and the relative phases of the pendula. These are the basic dimensions of what is called "frequency domain" time-series analysis.

Intuitive motions of the spectrum

What is the spectrum? Imagine Isaac Newton holding a prism through which white light passes on one side and the rainbow emerges from the other. The rainbow is called the spectrum; in general, it is the resolution of some incoming wave into its basic components. In the case of white light, all colors (or frequencies) are present in all brightnesses (energies, variances). For different kinds of oscillations, some of the colors would be missing entirely, some would be weaker, some would be stronger. Furthermore, the phase relationships of the different colors could vary. The

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Table 9.2. *Guessing that the period $t = 5$*

	1	2	3	4	5
	0.00	0.95	0.59	−0.59	−0.95
	0.00	0.95	0.59	−0.59	−0.95
	0.00	0.95	0.59	−0.59	−0.95
	0.00	0.95	0.59	−0.59	−0.95
	0.00	0.95	0.59	−0.59	−0.95
	0.00	0.95	0.59	−0.59	−0.95
Means	0.00	0.95	0.59	−0.59	−0.95

Table 9.3. *Guessing incorrectly that the period $t = 4$*

	1	2	3	4
	0.00	0.95	0.59	−0.59
	−0.95	0.00	0.95	0.59
	−0.59	−0.95	0.00	0.95
	0.59	−0.59	−0.95	0.00
	0.95	0.59	−0.59	−0.99
Means	0.00	0.00	0.00	0.00

spectrum, or the "spectral density function," tells us only which frequencies are present and to which degree; that is, we learn how much variance each frequency accounts for in the given time series.

We shall illustrate how this spectral density function is computed by using an old 19th-century method, called the periodogram (a technique no longer used). Suppose we generate a very simple time series, $x_t = \sin(1.257t)$, and let t go from 0 to 10. The values of the time series are 0.00, 0.95, 0.59, −0.59, −0.95, 0.00, 0.95, 0.59, −0.59, −0.95, 0.00. Suppose we did not know that these data repeated every five time intervals. Suppose we guess at the period and guess correctly that the period is 5, and we arrange the data as shown (Table 9.2). In this table, we can see that the variance of the series is equal to the variance of the means. The ratio of these two variances is always one when we have guessed the right period. Suppose we had guessed the wrong period, say $t = 4$. This situation is illustrated in Table 9.3.

In the case of Table 9.3, the variance of the means is zero, so that the ratio of the variance of the means to the variance of the series is zero. If we

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were to plot the value of this ratio for every frequency we guess (remember frequency equals $1/t$), this graph is an estimate of the spectral density function. Of course, this is the ideal case. In practice, there would be a lot of noise in the data, so that the zero values would be nonzero, and also the peak of the spectral density function would not be such a sharp spike. This latter modification in thinking, in which the amplitudes of the cycles are themselves random variables, is a major conceptual revolution in thinking about data over time; it is the contribution of the 20th century to this area. (For more discussion, see Gottman, 1981.)

Rare events

One of the uses of *univariate* time-series analysis is in evaluating the effects of rare events. It is nearly impossible to assess the effect of a rare but theoretically important event without pooling data across subjects in a study by the use of sequential analysis of categorical data. However, if we create a time-series variable that can serve as an *index* of the interaction, the problem can be solved by the use of the interrupted, time-series quasi-experiment.

What we mean by an "index" variable is one that is a meaningful theoretical index of how the interaction is going. Brazelton, Koslowski, and Main (1974) suggested an index time series that measured a dimension of engagement and involvement to disengagement. The dimension assessed the amount of interactive energy and involvement that a mother expressed toward her baby and that the baby expressed toward the mother. This is an example of such an index variable. Gottman (1979) created a time-series variable that was the cumulative positive-minus-negative affect in a marital interaction for husband and wife. The interactive unit was the two-turn unit, called a "floor switch." Figure 9.1 illustrates the Gottman index time series for two couples.

Now suppose that the data in Figure 9.2 represented precisely such a point graph of a wife's negative affect, and that a rare but interesting event occurred at time 30, when her husband referred to a previous relationship he had had. We want to know whether this event had any impact on the interaction. To answer this question, we can use an interrupted time-series analysis. There are many ways to do this analysis (see Gottman, 1981). We analyzed these data with the Gottman–Williams program ITSE (see Williams & Gottman, 1981) and found that there was no significant change in the slope of the series [$t(32) = -0.3$], but that there was a significant effect in the change in level of the series [$t(32) = 5.4$]. This is one important use of time-series analysis.

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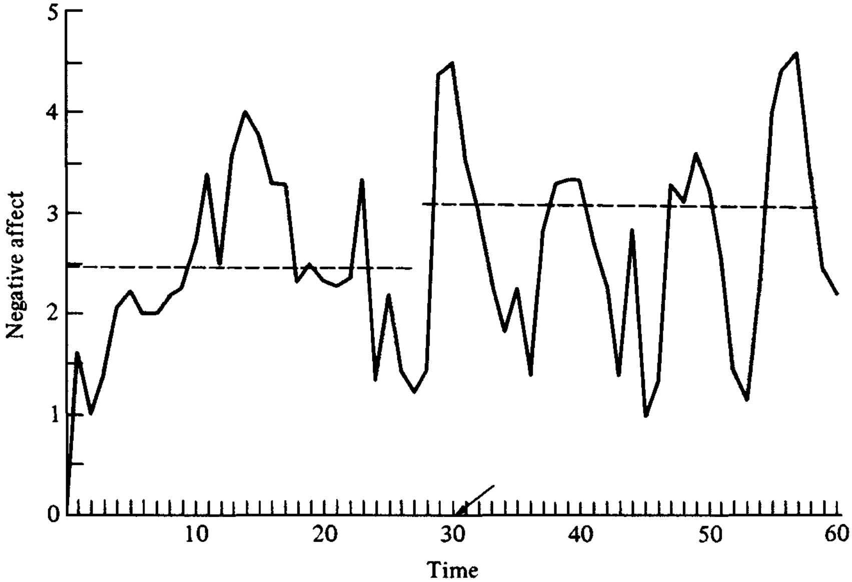

Figure 9.2. Interrupted time-series experiment.

Cyclicity

Univariate time-series analysis can also answer questions about the *cyclicity* of the data. Recall that to assess the cyclicity of the data, a function called the "spectral density function" is computed. This function will have a significant peak for cycles that account for major amounts of variance in the series, relative to what we might have expected if there were no significant cycles in the data (i.e., the data were noise). We used the data in Figure 9.2 for this analysis, and used the Gottman–Williams program SPEC. The output of SPEC is relatively easy to interpret. The solid line in Figure 9.3 is the program's estimate of the spectral density function, and the dotted line above and below the solid line is the 0.95 confidence interval. If the entire confidence interval is above the horizontal dashed line, the cycle is statistically significant. The x axis is a little unfamiliar to most readers, because it refers to "frequency," which in time-series analysis means cycles per time unit. It is the reciprocal of the period of oscillation. The peak cycle is at a frequency of 0.102, which corresponds to a period of 9.804 time periods. The data are cyclic indeed. It is important to realize that cyclicity in modern time-series analysis is a statistical concept. What we mean by this is that the period of oscillation is itself a random variable, with a distribution. Thus, the data in Figure 9.3 are *almost* periodic, not *precisely* periodic. Most phenomena in nature are actually of this sort.

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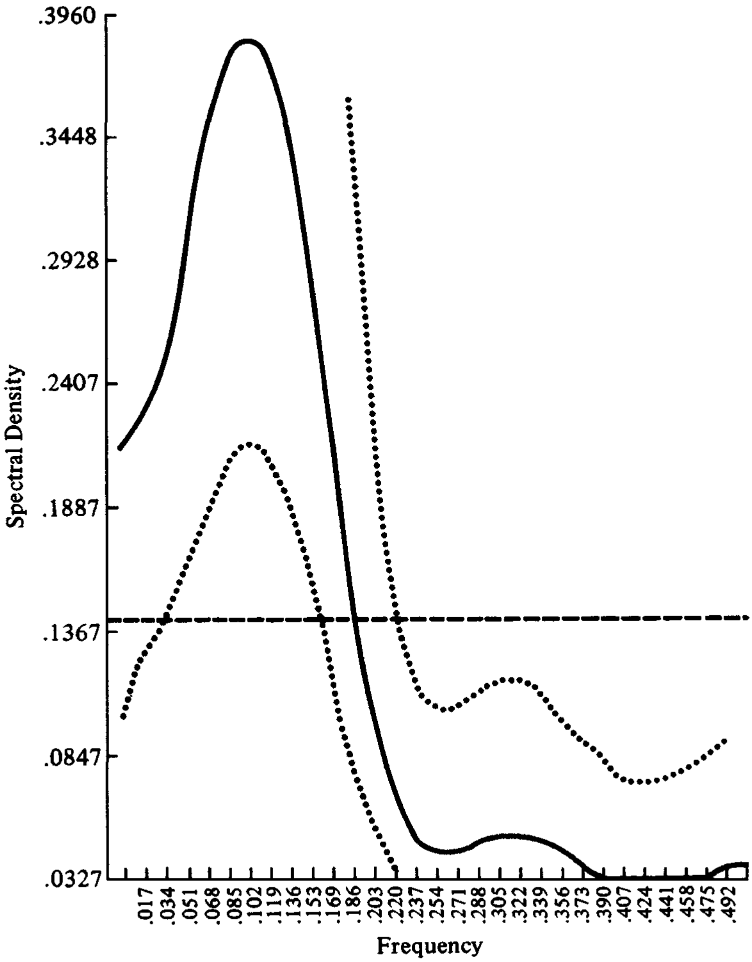

Figure 9.3. Plot of density estimates. The density is indicated by a solid line, and the 0.95 confidence interval by a dotted line. The white-noise spectrum is shown by a dashed line.

Multivariate time-series analysis

There are quite a few options for the multivariate analysis of time-series data. We shall discuss only one option here, a bivariate time-series analysis that controls for autocorrelation (predictability within each time series) in making inferences about cross correlation between two time series. This option is discussed in a paper by Gottman and Ringland (1981).

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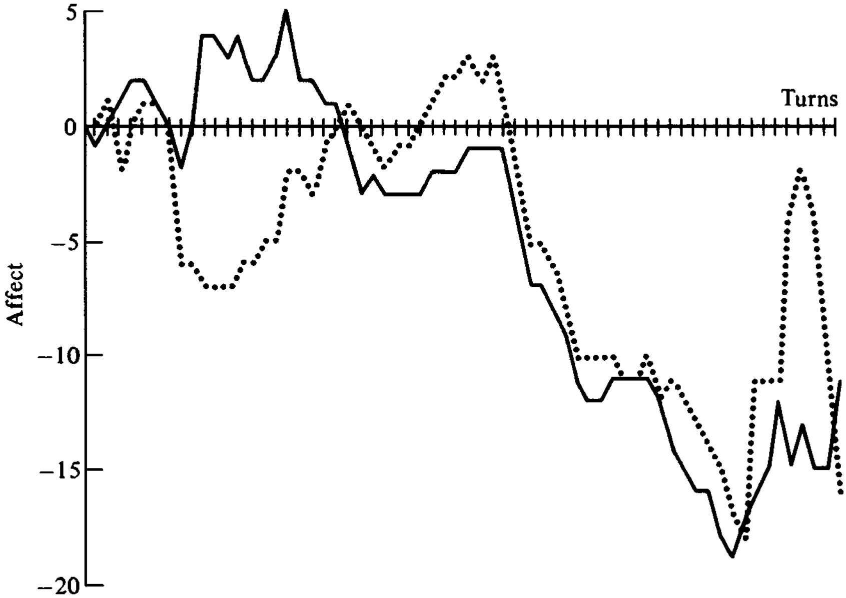

Figure 9.4. Couple mp48 conflict discussion. The solid line indicates the husband's affect; the broken line, the wife's affect.

The data in Figure 9.4 are a summary of the interactions of a happily married couple discussing a marital conflict. The y axis is a cumulative sum of positive minus negative affect in the discussion. This graph is fairly typical of happily married couples' discussions of an area of continued disagreement. The central third of the conversation shows a downward drift because most disagreements occur in the middle phase of the discussion; the final third shows the graph coming back up as the couple moves closer to resolving the issue. In making an inference of influence from one partner to another, what this procedure does is to attempt to predict as well as it can from the parts of each series and then see if any additional information is provided by the other series.

Table 9.4 summarizes the results of this analysis, which was accomplished with the program BIVAR from the Gottman–Williams package (see Williams & Gottman, 1981). Row 1 of the table shows that the initial starting values for the models is 8; this means that we shall go back 8 units into the past; this number is arbitrary, but should probably not exceed 10 (it is limited by the total number of observations). The second row shows results of the program's successive iterations to find the smallest model that loses no information; this is the model with one autoregressive term for the husband and four cross-regressive terms for the wife. The test of model 1

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Table 9.4. *Bivariate-time series analysis of couple mp48's data*

Model	Husband	Wife	SSE	T LN(SSE/T)[a]
1	8	8	133.581	44.499
2	1	4	150.232	52.957
3	1	0	162.940	58.803
1 vs 2:	$Q = 8.458$	$df = 11$	$z = -.542$	
2 vs 3:	$Q = 5.846$	$df = 4$	$z = .653$	
Model	**Husband**	**Wife**	**SSE**	**T LN(SSE/T)**
1	8	8	207.735	76.291
2	5	2	224.135	81.762
3	5	0	298.577	102.410
1 vs 2:	$Q = 5.471$	$df = 9$	$z = -.832$	
2 vs 3:	$Q = 20.648$	$df = 2$	$z = 9.324$	

[a] Weighted error variance; see Gottman and Ringland (1981), p. 411.

versus model 2 should be nonsignificant, which is the case. The third row of the table shows the model with all of the wife's cross-regressive terms dropped. If this model is not significantly different from model 2, then we cannot conclude that the wife influences the husband; we can see that the z score (0.653) is not significant. Similar analyses appear in the second half of the table for determining if the husband influences the wife; the comparison of models 2 and 3 shows a highly significant z score (this is the normal approximation to the chi-square, not to be confused with the z score for sequential connection that we have been discussing). Hence we can conclude that the husband influences the wife, and this would be classified as a husband-dominant interaction according to Gottman's (1979) definition. We note in passing that although these time series are not stationary, it is still sensible to employ BIVAR.

Interevent Interval

In the study of the heart, in analyzing the electrocardiogram (ECG), there is a concept called "interbeat interval," or the "IBI." It is the time between the large R-spike of the ECG that signals the contraction of the ventricles of the heart. It is usually measured in milliseconds in humans. So, for example, if we recorded the ECG of a husband and wife talking to each

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other about a major issue in their marriage, and we took the average of the IBIs for each second (this can be weighted or prorated by how much of the second each IBI took up), we would get a time series that was a set of consecutive IBIs (in milliseconds) that looked like this: 650, 750, 635, 700, 600, 625, 704, and so on.

We wish to generalize this idea of IBI and discuss a concept we call the "interevent interval." This is like an old concept in psychology, the intertrial interval. When we are recording time, which we get for free with almost all computer-assisted coding systems, we also can compute the time between salient events, and these times can become a time series. When we do this, we are interested in how these interevent times change with time within an interaction.

Other ways of transforming observational data to a time series

When the observational data consist of ratings, the data are already in the form of a time series. For example, if we coded the amount of positive affect in the voice, face, body, and speech of a mother during parent – child interaction, we can add the ratings on each channel and obtain an overall time series.

When the data are categorical codes

There are other ways to obtain a time series from a stream of categorical codes. One method is the idea of a "moving probability window," which would be a window of a particular sized time block (say 30 seconds) within which we compute the frequencies of our codes (estimating their probabilities); then the window moves forward one time unit, and we compute these probabilities again. Another approach we have used (Gottman, 1979b; Gottman & Levenson, 1992), as has Tronick, Als, and Brazelton (1977; 1980) is to weight the codes along some composite dimension. In the Tronick case the dimension was a combination of engagement/disengagement and positive/negative, so that positive scores meant engaged and/or with positive affect, and negative scores meant disengaged and/or with negative affect. In the Gottman cases, positive and negative codes were given positive or negative integer weights, and the number of total positive minus negative points was computed for each turn at speech (a turn lasts about 6 seconds on marital interaction). We have found it very fruitful for visual inspection of a whole interaction to cumulate these time series as the interaction proceeds. Figure 9.5 (a) and (b) shows these time series *cumulated*

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to illustrate two very different marital interactions. Losada, Sanchez and Noble (1990), in their research on six-person executive work groups, code power and affect on 3- point scales and then turn these into numerical scores within time blocks. They then compute directional cross-correlations between people, and use these numbers to create an animated graphic of a "moving sociometric" of affect and power over time. This moving sociometric is time-locked so that the researchers can provide instant replay video feedback to the group so that the group can see a video illustration of their moving sociometric.

Why transform the data to a time series?

Reducing the observational coding to these summary time-series graphs is very profitable. In marital interaction having these time series made it possible for us (see Cook et al., 1995) to construct a mathematical model of the data that led us to a new theoretical language for describing our divorce prediction data and led us to a new discovery about what predicts divorce.

9.5 Autocorrelation and time-series analysis

Autocorrelation function

We will begin by examining the nature of the dependent time-structure of time-series data. To accomplish this we start by examining what is called the "autocorrelational structure" of the time series. This gives us information about how predictable the present data are from its past. To explain the concept of "lag-1" autocorrelation, we draw a lag-1 scatterplot of the data, where the x-axis is the data at time t, and the y-axis is the data at time $t+1$. This means that we plot the data in pairs. The first point we plot is $(x1, x2)$; the second point is $(x2, x3)$; the third point is $(x3, x4)$; and so on. This gives a scatterplot similar to the ones we plot when we compute a regression line between two variables. The correlation in this case is called the "lag-1 autocorrelation coefficient," r_1. In a similar fashion we can pair points separated by two time points. The pairs of points would then be $(x1, x3)$, $(x2, x4)$, $(x3, x5)$, ...; the two axes are $x(t)$ and $x(t+2)$, and the autocorrelation coefficient would be the "lag-2 autocorrelation coefficient," r_2. We can continue in this fashion, plotting r_k, the lag-k autocorrelation coefficient against the lag, k. The autocorrelation function is useful in identifying the time-series model.

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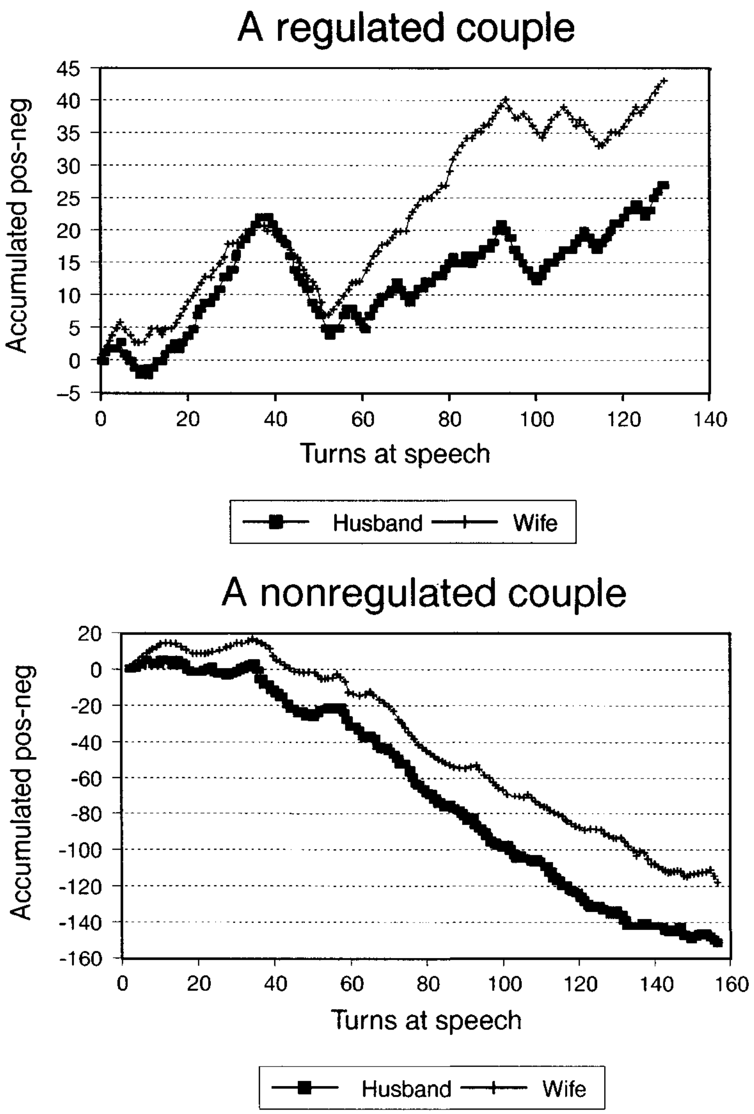

Figure 9.5. (a) Cumulative point graphs for a regulated couple, for which positive codes generally exceed negative codes. (b) Cumulative point graphs for a nonregulated couple, for which negative codes generally exceed positive codes.

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Model identification

Using the autocorrelation function, an autoregressive model for the time series can be identified exactly if the series is stationary (this means that the series has the same correlation structure throughout and no local or global trends) using a computer program (see the Williams & Gottman, 1981, computer programs). A wide variety of patterns can be fit using the autoregressive models, including time series with one or many cycles.

Spectral time-series analysis

In 1822 Jean Baptiste Fourier, a French mathematician, discovered a very important theorem (one that took mathematicians over a hundred years to prove correctly and led to the development of a branch of modern mathematics called mathematical analysis). He discovered that any piecewise continuous function could be fit best (in the least-squares sense of distance) by a series of specially selected sine and cosine functions. These functions are, of course, cyclic, but the representation is still the best one ever if the function being fit is not itself cyclic. This was quite an amazing theorem.

In time-series analysis we can actually use the data to compute the cycles present in the data, even if these cycles are obscured with noise. This analysis is called a Fourier analysis, or a "spectral time-series analysis." In a spectral time-series analysis, the end result is that we generate a plot, called the "spectral density function," of the amount of variance accounted for by each of a set of cycles, from slow to fast. We do not use all cycles, but only a particular set, called "the overtone series." If a particular time series were actually composed of two cycles, a slow one and a fast one, the spectral density function would have peaks at these two cycle frequencies. Usually, however, real data do not look as spikelike as this figure, but instead the spectral density function is statistically significant across a band of frequencies.

We can then actually use these frequencies to fit a function to the data and use it to model the time series. In most cases this type of modeling is not feasible, because the models we obtain this way tend to be poor fits of the data. For this reason we usually use models like the autoregressive model.

Interrupted time-series experiments

Once we have a time series, and we have established that the time series itself has some validity (e.g., Gottman and Levenson's time series predicted

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divorce versus marital stability), we can model the series, and then we can scan the time series for statistically significant changes in overall level or slope. This is called an "interrupted time-series experiment," or ITSE (see Figure 9.6). An ITSE consists of a series of data points before and after an event generally called the "experiment." The "experiment" can be some naturally occurring event, in which case it is actually a quasi-experiment. We then represent the data before the intervention as one function $b_1 + m_1 t +$ Autoregressive term, and the data after the intervention as $b_2 + m_2 t +$ Autoregressive term. We need only supply the data and the order of the autoregressive terms we select, and the computer program tests for statistically significant changes in intercept (the b's) and slope (the m's). The experiment can last 1 second, or just for one time unit, or it can last longer. One useful procedure is to use the occurrence of individual codes as the event for the interrupted time-series experiment. Thus, we may ask questions such as "Does the wife's validation of her husband's upset change how he rates her?" Then we can do an interrupted time-series experiment for every occurrence of Wife Validation. For the data in Figure 9.6, there were 48 points before and 45 points after the validation. The order of the autoregressive term selected was about one tenth of the preintervention data, or 5. The t for change in intercept was $t(79) = -2.58$, $p < .01$, and the t for change in level was $t(79) = -1.70$, $p < .05$.

For this example, we used the Williams and Gottman (1981) computer program ITSE to test the statistical significance of changes in intercept and slope before and after the experiment; an autoregressive model of any order can be fit to the data. Recently, Crosbie (1995) developed a powerful new method for analyzing short time-series experiments. In these analyses only the first-order autoregressive parameter is used, and the preexperiment data are fit with one straight line (intercept and slope) and the postexperiment data are fit with a different straight line (intercept and slope). An omnibus F test and t tests for changes in level and slope are then computed. This method can be used to determine which codes in the observational system have potentially powerful impact on the overall quality of the interaction.

Phase-space plots

Another useful way to display time-series data is by using a "phase-space" plot. In a phase-space plot, which has an x-axis and a y-axis, we plot the data as a set of pairs of points: $(x1, x2)$, $(x2, x3)$, $(x3, x4)$, ... The x-axis is $x(t)$, and the y-axis is $x(t + 1)$, where t is time, $t = 1, 2, 3, 4$, and so on. Alternatively, if we are studying marital interaction, we can plot the interevent intervals for both husband and wife separately, so we have both

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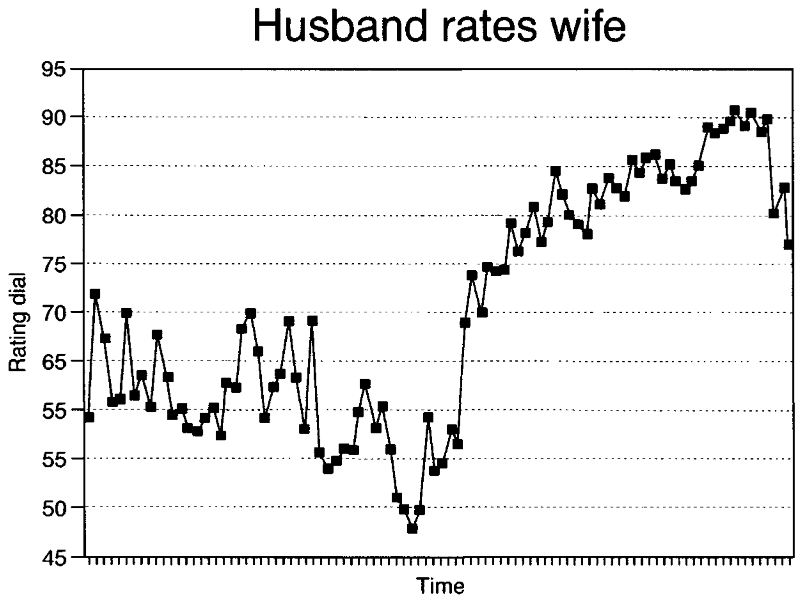

Figure 9.6. Plot of rating dial in which the husband rated his wife's affect during their conversation.

a husband and a wife time series. A real example may help clarify how we might use this idea (Gottman, 1990).

An example from an actual couple who subsequently divorced

For marital interaction many possible behavioral candidates exist for "the event" selected to be used for computing interevent intervals. As we have suggested, one promising event to select is negative affect, in part because it has a reasonably high base rate during conflict discussions, and because it tends to be high in dissatisfied marriages. Our interest here in computing the phase-space plot is not whether negative affect is high among an unhappily married couple, but whether this system is homeostatically regulated and stable, or whether it is chaotic. In this interaction of a married couple we computed the time between negative affect, independent of who it was (husband or wife) who displayed the negative affect. The times between negative affects were thus selected for analysis. These were interevent intervals for either partner in a marital interaction (Figure 9.7).

In phase-space plot the data look a lot like the scatterplot for the first-order autocorrelation coefficient, except for one thing. In the phase-space

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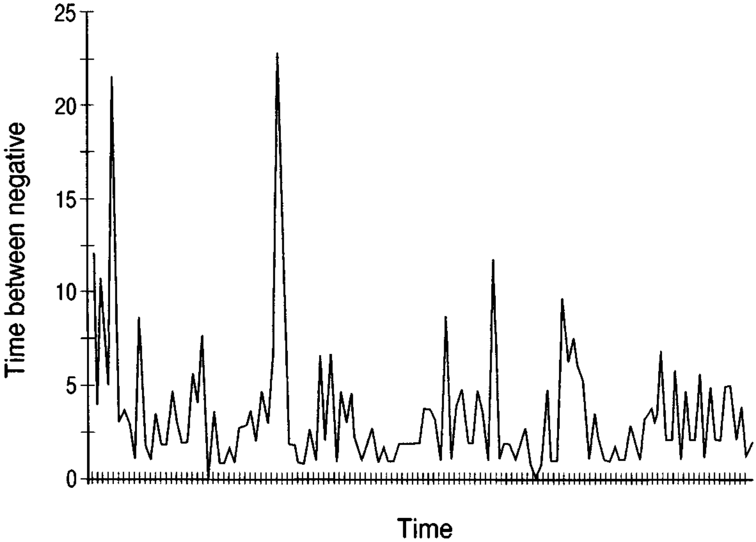

Figure 9.7. Interevent integrals for negative affect in a marital conversation.

plot we connect the successive dots with straight lines (see Figures 9.8 and 9.9). This gives us an idea of the "flow" of the data over time.

What does this figure mean in terms of the actual behavior of the marital system? It means that, insofar as we can ascertain from these data, we have a system whose energy balance is not stable, but dissipative; that is, it runs down. Like the pendulum winding down, this system tends toward what is called an attractor; in this case the attractor represents an interevent interval of zero. However, for the consequences of energy balance, this movement toward an attractor of zero interevent interval between negative affect may be disastrous. Specifically, this system tends, over time, toward shorter response times for negative affect. Think of what that means. As the couple talk, the times between negativity become shorter and shorter. This interaction is like a tennis match where that ball (negative affect) is getting hit back and returned faster and faster as the game proceeds. Eventually the system is tending toward uninterrupted negativity.

We can verify this description of this marital interaction using more standard analytic tools, in this case by performing the mathematical procedure we discussed called spectral time-series analysis of these IEIs (see Gottman, 1981). Recall that a spectral time-series analysis tells us whether there are specific cyclicities in the data, and, if there are, how much variance each cycle accounts for. See Figure 9.10.

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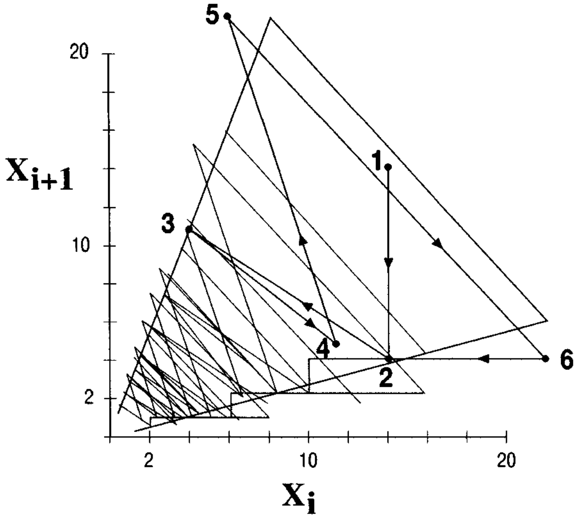

Time	Data Code		IEI
5:14	Husb	Anger	
5:27	Wife	Sad	13 Secs
5:40	Husb	Disgust	13 Secs
5:44	Husb	Anger	04 Secs

$(X_1, X_2) = (13,13)$
$(X_2, X_3) = (13,4)$

Figure 9.8. A scatterplot of interevent interval times with consecutive points connected.

Note that the overall spectral analysis of all the data reveals very little. There seem to be multiple peaks in the data, some representing slower and some faster cycles. However, if we divide the interaction into parts, we can see that there is actually a systematic shift in the cyclicities. The cycle length is 17.5 seconds at first, and then moves to 13.2 seconds, and then to 11.8 seconds. This means that the time for the system to cycle between negative affects is getting shorter as the interaction proceeds. This is exactly what we observed in the state space diagram in which all the points were connected. Hence, in two separate analyses of these data we have been led to the conclusion that this system is not regulated, but is moving toward more and more rapid response times between negative affects. From the data we have available, this interaction seems very negative, relentless, and unabated. Of course, there may be a more macro-level regulation that we

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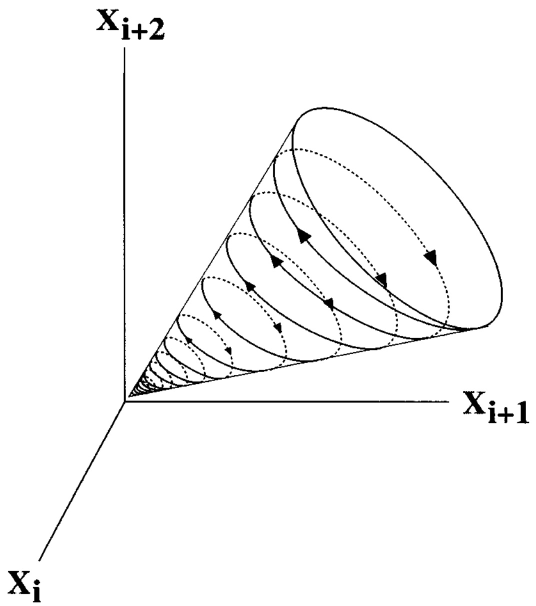

Figure 9.9. System is being drawn toward faster and faster response times in the IEI of negative affect.

do not see that will move the system out toward the base of the cone once it has moved in, and it may oscillate in this fashion. But we cannot know this. At the moment it seems fair to conclude that this unhappy marriage represents a runaway system.

There are lots of other possibilities for what phase-space flow diagrams might look like. One common example is that the data seem to hover quite close to one or two of what are called "steady states." This means that the data really are quite stable, except for minor and fairly random variations. Another common example is that the data seem to move in something like a circle or ellipse around a steady state. The circle pattern suggests one cyclical oscillation. More complex patterns are possible, including chaos (see Gottman, 1990, for a discussion of chaos theory applied to families); we should caution the reader that despite the strange romantic appeal that the chaos theory has enjoyed, chaotic patterns are actually almost never observed. Gottman (1990) suggested that the cyclical phase-space plot was like a steadily oscillating pendulum. If a pendulum is steadily oscillating, like the pendulum of a grandfather clock, energy is constantly being supplied to drive the pendulum, or it would run down (in phase space, it would spiral in toward a fixed point).

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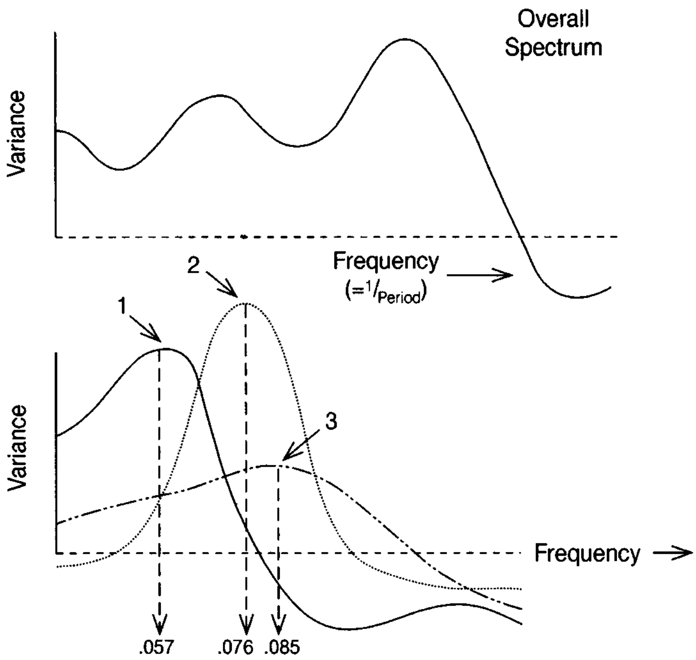

Figure 9.10. Spectrum for three segments showing higher frequencies and shorter periods.

9.6 Summary

When successive events have been coded (or when a record of successive events is extracted from more detailed data), event-sequential data result. When successive intervals have been coded, interval-sequential data result. And when event or state times have been recorded, the result is timed-event or state data. At one level, the representation of these data used by the GSEQ program, these four kinds of data are identical: All consist of successive bins, where bins are defined by the appropriate unit (event, time, or interval) and may contain one, more, or no codes.

In general, all the analytic techniques that apply to event sequences can be applied to state, timed-event, and interval sequences as well, but there are some cautions.

Primarily, the connection, or lack of connection, between coders' decisions and representational units is important to keep in mind and emphasize when interpreting sequential results because in some cases units represent decisions and in other cases arbitrary time units. It is also important to keep in mind how different forms of data representation suit different questions.

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When time is an issue – whether percent of time devoted to certain activities or average bout lengths for those activities – time must be recorded and represented, probably using either state or timed-event sequences. When the simple sequencing of events is an issue, event sequences may suffice, or an event-sequential version of state or timed-event sequences created (this can be done with the GSEQ program). Finally, when several dimensions of an event are important, data can be represented using the interval sequential form but, in this case, might better be termed multidimensional event sequential data.

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