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Removing Discordance from Quantitative Analysis

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Since the mid-1960s, American archaeology has witnessed an exponential increase in the use of quantification, basic statistics, and multivariate methods in research (Clark 1982:225). These advances have crosscut many topics, including subsistence analysis (Reidhead 1981; Keene 1981; Winterhalder and Smith 1981), settlement analysis (Winters 1969; Limp 1981; Parker 1985; Kvamme 1985), intrasite spatial analysis (Peebles 1971; Whallon 1973, 1974, 1984; Carr 1984, 1985b), mortuary analysis (Brown 1971; Braun 1979), demographic analysis (Zubrow 1975), exchange (Greber 1976), artifact typology (Spaulding 1953; Whallon 1972; Christensen and Read 1977; Hoffman 1985), seriation (Hole and Shaw 1967; Johnson 1968; Marquardt 1978; Braun 1985), and sampling (Muller 1974; Lafferty et al. 1981). The developments have helped archaeologists both to express complex ideas succinctly in the language of mathematical structures and to model and simulate complex archaeological and behavioral variation.

Simple experimentation with and mastery of *technique* has been a predominant concern in these efforts (Thomas 1971, 1978; Cowgill

1977; Speth and Johnson 1976; Hole 1980; Vierra and Carlson 1981; Scheps 1982). More recently, however, a systematic interest in the logic of analysis has developed. In particular, attention is being given to formally developing and maintaining, during analysis, logically consistent relationships between the nature of archaeological and behavioral phenomena, the structure of data expressing them, technical assumptions, and theory (e.g., Carr 1984, 1985a, 1986; Martin 1983; Moore and Keene 1983; Whallon 1984; Whallon and Brown 1982; this volume). Such efforts facilitate an analysis becoming relevant, accurate, meaningful, and efficient, whereas mastery of technique, alone, does not.

This chapter summarizes the problems involved in developing and maintaining logical consistency during analysis. First, it clarifies the ways in which theory, quantitative technique, and data can be discordant with each other and a phenomenon of interest during analysis. Second, it enumerates various sources of discordance from statistical, philosophical, and psychological perspectives. Next, several methodological strategies for removing discordance from analysis are described. Finally, I mention how explicit statement of the procedures used in bringing concordance to analysis is critical to theory development. Abstract concepts and frameworks are illustrated with examples pertinent primarily to intrasite spatial analysis. This is the subject for which I have thought about these issues most thoroughly (e.g., Carr 1984, 1985b, 1986).

Philosophical Assumptions and Context

Only certain aspects of the logical, philosophical basis of meaningful scientific investigation are considered in this paper. It is desirable, therefore, to place its content in a larger, philosophical perspective.

First, it is necessary to comment on the nature of meaningful scientific investigation that is assumed. Informally and intuitively, a scientific study and its results can be taken to be meaningful if they allow or lead to the assignment of appropriate meaning to phenomena or to explanation of them. More formally, a meaningful scientific investigation will: (1) give accurate insight into a problem and lead to the development of theory, (2) allow the accurate and logical testing of models or hypotheses that represent extant theory, or (3) allow a

particular case to be accurately and logically subsumed under extant theory, constituting a valid explanation. The accuracy of insight, test, or logical subsumption and the appropriateness of an assignment of meaning, of course, are not absolute qualities. They can be assessed only within the limits of the researcher's guiding paradigm.

By implication, the theories, models, or hypotheses that are developed or evoked in a meaningful scientific investigation and that allow or lead to the assignment of appropriate meaning must, themselves, be meaningful. A meaningful proposition or construct is taken here to be not only *testable and confirmable* in the minimal, least demanding usage of the term in philosophy of science (Carnap 1936: 420-427) but also *nontrivial.* It is taken to have "worthwhile" content from the perspective of the goals of the researcher's paradigm (Read and LeBlanc 1978: 307-308, 332; Salmon and Salmon 1979: 72) and to organize information efficiently and parsimoniously (Hemple 1966: 40-45; van der Leeuw 1978: 328).

For a scientific investigation to produce results that are meaningful within the limits of a researcher's paradigm, three conditions are minimally required:

Condition 1. At least some aspects of the data brought forward for study must be relevant to the researcher's problem domain and accurately represent the phenomenon of interest (i.e., a population or process) and its nature.

Condition 2. Those aspects of the data's structure that reflect the phenomenon of interest and its nature must be identified, and then accurately represented when summarized as patterning.

Condition 3. These patterns must be interpreted in a manner consistent with the nature of the phenomenon of interest.

These minimal requirements, in turn, necessitate that the theories, models, hypotheses, test implications, mathematical techniques, data collection methods, and/or the data that are involved in an investigation be relevant to and logically consistent with each other, and ultimately to the empirical phenomenon of interest.

How to develop and maintain relevance and logical consistency between these entities at different levels of abstraction is a subject matter of philosophy of science that involves a great diversity of topics. Some examples include the correct forms of a logical deduction and induction; the role of auxiliary hypotheses and assumptions in operationalizing higher-level abstractions in terms of observables; the use of bridging arguments in making logical

deductions and inductions; and the setting of boundary conditions to generalizations, hypotheses, models, and theories.

This chapter focuses on only a small subset of these issues but also some that philosophers of science typically have not explored in depth. In particular, I will discuss the *choice and logic of application of quantitative methods* of analysis to archaeological data and *choice of data*, each within the context of theory and the empirical world.

Terminology

To be precise about concordant relations in the discussions to ensue, it is necessary to define several terms. These refer to different categories of information or portions of reality: (1) a portion of the real world, (2) a phenomenon of interest, (3) data brought forward for study of a problem domain that includes the phenomenon of interest, (4) aspects of the data that are truly relevant to only the phenomenon of interest, and (5) aspects of the data that are expected to be relevant to the phenomenon of interest. These categories hold a nested, hierarchical relationship to each other. Higher numbered (lower level) categories embody decreasing amounts of information on the real world as a result of the partially controllable processes of selective observation and analysis.

A portion of the real world. Of the several categories of information, this is the broadest. It is the subset of entities or objects in the real world that the researcher selects for study in relation to his paradigmatic orientation and his more particular problem domain. Similar concepts are the research universe or study area.

A portion of the real world may be selected for study with a purpose in mind and in regard to certain of its characteristics. However, it is taken to have, simultaneously, a very large number of characteristics (properties, structures, organizations, natures) that are determined by a very large number of processes. This gives any portion of the world many *facets* or *phenomena*, such that it can be explored from many different perspectives and paradigms.

An example of a portion of the real world is an earthen archaeological site. This land parcel would have a large number of characteristics—e.g., artifactual, topographic, pedological, hydrological, archaeomagnetic, and others. Only some of these might serve as a basis for selecting it for study. The site could be studied from many different perspectives and paradigms.

Phenomenon of interest. This is the one facet within a portion of the real world—among its many facets—that is the object of study. Like the portion of the real world that is selected for study, the phenomenon of interest is chosen in relation to the researcher's paradigmatic orientation and problem domain.

A phenomenon of interest can be either a homogeneous population or a single process. If the phenomenon is a population, its organizational nature is determined by the process(es) that structure it—one or several of the many processes that structure the portion of the world of which it is a part. If the phenomenon is a process, its form is determined by the constraints that define it—a subset of the many constraints within the portion of the world of which it is a part.

An example of the phenomenon of interest is a population of several toolkits of some one kind within the behavioral domain, e.g., a collection of hide-working sets of knives, scrapers, and borers. This population is the set of outcomes of a single process—an activity, hide-working. The organizational nature of the population of tool kits—for example, whether their constituent tool types covary or only co-occur among the multiple toolkits and whether the tool types are symmetrically or asymmetrically distributed among the toolkits (Carr 1985)—is determined partially by the nature of the hide-working process.

A phenomenon of interest can also be a set of *multiple, parallel,* and *coterminous* processes or the population they generate. By these concepts is meant several processes that operate over and affect the same range of observations, so as to still define only one organizationally homogeneous population rather than multiple, organizationally differentiated populations (Carr 1986). In other words, the multiple processes are concatenated, with the output of one serving as the input of the next so as to effectively define a single process and a homogeneous population of final outcomes that can be treated as such analytically. This occurs despite whatever conceptual distinctions among the processes may be made.

Continuing the toolkit example, above, two parallel processes can be envisioned. One would be the activity of hide-working, involving the repeated use of knives, scrapers, and borers and defining a population of several toolkits of these in the behavioral domain. The second process would be one or more depositional formation processes and postdepositional disturbance processes that operate over the same toolkits and result in their being transferred into the

archaeological domain as a population of deposits. The first process might involve the use and organization of knives, scrapers, and borers in constant proportions among the toolkits. The second group of processes might systematically alter the tool types' organization to simple co-occurrence relationships. However, because the two processes are parallel, coterminous, and concatenated, they effectively define a single process and a homogeneous population of outcomes (deposits of "toolkits" in the archaeological domain), which can be treated as such analytically.

Data brought forward for study. This category usually involves more and less information than that pertinent to the single phenomenon of interest. Data brought forward for study often include variables and cases that pertain to multiple phenomena (populations or processes), rather than a single phenomenon. They also may exclude critical variables or certain observations that reflect the phenomenon of interest. These circumstances have analytic, physical, and practical causes, all to be discussed later.

An example of data brought forward for study, to elaborate our toolkit illustration, would be the spatial locations of knives, scrapers, and borers that were used for multiple purposes—hide-working, woodworking, and bone-working. These data would reflect multiple phenomena of potential interest—multiple populations of toolkits that organizationally reflect multiple kinds of activities (processes). The data also might lack locational information on some items as a result of their not being recovered during excavation or other postdepositional processes.

Relevant data structure. In contrast to a data set brought forward for study are those aspects of it that are relevant to some one phenomenon of interest. These may be simply a subset of pertinent variables, observations, and relationships within the data. The relevant aspects may also be more complex dimensions or components of the data matrix that can be extracted only analytically (e.g., with factor or Fourier analysis). Note that those aspects of the data that are relevant to the phenomenon of interest often express only a portion of the information that is potentially available and pertinent to it. This is a product of the constrained manner in which data that are brought forward for study are collected and selected.

Examples of relevant data structures within a data set brought forward for study can be found in the case of the artifact palimpsest of multipurpose knives, scrapers, and borers just described. One

relevant data structure would be spatial locations of only those artifacts that were used and deposited together as hide-working toolkits (the population of interest) during hide-working (the defining process). A second relevant data structure would be the locations of only those artifacts that were used and deposited together during woodworking, and a third would pertain to the locations of only bone-working artifacts that were deposited together. Use-wear or Fourier procedures (Carr 1986) might be used to analytically segregate these several relevant subset structures within the data brought forward for study.

It is important to realize that a single population of observations (a phenomenon of interest) can have any of several organizations and can be represented by any of several relevant data structures. This is possible when the observations are the outcomes of parallel, coterminous processes and when some of those processes are optional. An example would be a population of toolkits (deposits) in the archaeological domain. These might exhibit and be definable by ratio, ordinal, nominal, or polythetic scale relationships among the artifact types comprising them. The scale of the defining relationships would depend on the kinds and number of formation and disturbance processes responsible for them. The nature of generation of the archaeological toolkits would determine their organization and the kind of relevant data structure that would represent them accurately. The potential for phenomena of interest to have multiple organizations and representations stands as the basis of the "entry model" strategy of analysis, which is discussed later.

Expected relevant data structure. It is necessary to distinguish those aspects of a data set's structure that are expected to be relevant to a phenomenon of interest and its nature from those that are actually relevant. Aspects that are expected to be relevant are derived from some theoretical-interpretive framework and are expressed in the form of a model of relevant structure (Read 1985, schema D; Carr 1985b). They may bear little similarity to aspects of the data that actually reflect the phenomenon of interest, depending on the adequacy of both the primary premises and the auxiliary assumptions within the theoretical framework. For example, in our toolkit illustration, the population of hide-working toolkits (phenomenon of interest) might be manifested empirically as nominal scale spatial relationships between knives, scrapers, and borers as a result of the particular nature of the hide-working activity and other depositional

processes. In contrast, the researcher might expect, on the basis of theoretical postulates (Carr 1984), that the population of toolkits would be defined by ratio scale spatial relationships.

The Need for Concordance in Analysis and Causes of Discordance from a Statistical Perspective

Meaningful scientific investigation requires the researcher to choose data and an analytic technique such that logical consistency is developed and maintained during analysis in three kinds of relationships. There must be concordance between: (1) the structure of the *data* to be investigated vs. the empirical phenomenon of interest; (2) the assumptions about the phenomenon of interest that underlie a chosen *technique* vs. the aspects of the data that are relevant to the phenomenon and the nature of the phenomenon itself; and (3) assumptions about the phenomenon of interest that are made by the *theoretical framework* that guides or emerges from analysis vs. technical assumption, relevant data structure, and the nature of the phenomenon. The need for logical consistency in each of these relationships is equivalent to the three conditions for successful scientific investigation that were discussed more informally, above.

Concordance in the first relationship ensures simply the *relevance* of analysis. Concordance in the first and second ensures the relevance and *accuracy* of analysis. Concordance in all three allows analysis to be *meaningful* as well as relevant and accurate—the most difficult state to achieve. I will elaborate on these three points after discussing each relationship in greater detail.

The Relation of Data Structure to the Phenomenon of Interest

If a quantitative analysis is to be relevant, which is a minimal requirement for its success, at least some aspects of the data brought forward for study must accurately reflect the empirical nature of the phenomenon of interest. Relevant variables must be designed, and relevant observations must be selected for use.

Data that are brought forward for analysis in early stages of a scientific project, however, usually have a great potential for

reflecting both more and less information than that pertinent to some single phenomenon. This results from several conditions.

First, the variables and observations that are initially chosen for analysis are usually selected for their potential pertinence to a *broad problem domain* that involves *multiple, potential phenomena of interest*, rather than a single phenomenon. As Cowgill (1982: 39) notes:

> In theory we may base our selection of variables and their possible values entirely on considerations of their relevance for specific purposes, but in practice . . . the tendency seems to be begin with a sizable number of *possibly relevant* variables and to decide that the truly relevant ones are those variables that in fact do, in terms of their patterning within the assemblage, show some sort of structure. (stress by Cowgill)

Second, data that are initially chosen for analysis often are selected deductively on the basis of the *expected* nature of the potential phenomena of interest rather than their *actual* nature, which remains to be investigated and understood. If the theoretical framework employed to make such deductions is weak, any single phenomenon of interest may manifest itself in unsuspected sets of variables and observations that may be left out of analysis, and extraneous data may be thought relevant and analyzed. Similarly, if a strong theoretical framework is improperly used beyond its boundary conditions, the variables and observations that are predicted to be relevant to a phenomenon may differ from those that are actually relevant.

Third, variability that is irrelevant to a phenomenon of interest may reside in the data initially presented for study because of the researcher's inability to physically isolate the phenomenon from others in the real world. Sometimes, the isolation of a phenomenon is possible only analytically. For example, consider three spatial distributions of simple backed blade knives within a site: one comprised of knives used for woodworking, another of knives for butchering, and a third of knives for cutting hides. Although a researcher might be interested in only the population of woodworking knives (the phenomenon of interest) and their spatial distribution, these might be impossible to isolate physically without information on use-wear. The researcher would have to begin analysis with distributional data on backed blade knives of all kinds (multiple phenomena). The single knife population of interest might

be definable only analytically, perhaps with factor analysis (Schiffer 1975) or Fourier and filtering methods (Carr 1986).

Fourth, data brought forward for study may include information on undesirable processes such as observation and data-recording biases and errors. These may or may not cause a phenomenon of interest to not be physically isolatable.

Finally, practical limitations—economic, legal, or otherwise—may prevent a researcher from developing a data set that is fully pertinent to the phenomenon of interest. "Stand-in" or "proximate" populations or variables may have to be used for those actually pertinent (e.g., Winterhalder 1981: 20; Smith 1981: 38). Also, "summary variables," which describe aggregate behavior and one hopes are "sufficient" (Levins 1966: 427-430), may have to be used in place of detailed measures that are directly relevant to the phenomenon of interest (e.g., Winterhalder 1981: 19; Smith 1981: 52).

When data presented for analysis do not fully pertain to the empirical phenomenon of interest, two undesirable circumstances may arise. Both involve a loss of relevance. First, and obviously, the analysis may measure or characterize some phenomenon other than the one of interest or may reflect the one of interest only obliquely. If the latter is the case, the researcher may be able to compensate for quantitative irrelevance at the level of qualitative interpretation of results, providing that he is aware of the problem, can estimate the amount of irrelevant variability in the analytic results, and the problem is not too great.

The second problem that can arise when data do not fully pertain to the empirical phenomenon of interest is less direct and harder to compensate for. It is the logical discordance that is caused between the data's actual structure and the structure of the data that is assumed by the analytic technique. Being chosen in relation to a broad problem domain, the variables and observations that are brought forward for analysis typically reflect *multiple processes* that define *multiple populations*, i.e., multiple phenomena. In contrast, many statistical techniques assume a statistical model that specifies some *single process* as responsible for the variability within the data and a *homogeneous population* defined with respect to that process, i.e., a single phenomenon (Read 1985). For example, tests of model sufficiency in linear regression assume that the analyzed observations and variables refer to a single, multivariate normal population. Equivalently, many statistical techniques can be viewed as assuming

a statistical model that allows multiple processes to be responsible for the variability within the data; however, these processes must be *parallel* and *coterminous* in the range of observations that they affect, so as to still define only one homogeneous population rather than multiple populations (Carr 1986).

To the extent that the model that underlies a statistical technique assumes a single process and population, or parallel processes and a single population, whereas the deducted set of possibly relevant variables and observations pertain to multiple processes and populations, technique and data will be logically discordant with each other. This discordance will be additional to that which occurs between the data's structure and the empirical phenomenon of interest. It will lessen not only the relevance of analytic results, but also their accuracy in representing any one phenomenon. Results will reflect an uncontrolled mix of several kinds of relationships among observations: relationships among observations within populations, which may differ from one population to another, and the relationship of populations to each other (Christensen and Read 1977: 170).

A good illustration of the effects of discordance between data structure and technique that can arise when data are not fully relevant to a single empirical phenomena of interest is purposefully provided by Whallon (1984). Using correlation analysis, he measured the similarity of the spatial distributions of several artifact classes within the Mask site, a Nunamiut Eskimo hunting stand. A global analysis and several local analyses were performed, each using local proportional artifact type densities (similar to proportions of artifact types within grid cells) as the observations. In the global analysis, a set of intertype correlations were calculated for density observations distributed over the whole site, as if the densities constituted a single population; however, they actually came from several different kinds of "activity zones." In contrast, the local analyses each involved the calculation of a separate set of intertype correlations using density observations from only one of the several kinds of activity zones. The global correlation coefficients differed from the local ones and were presumably less relevant to and a less accurate representation of past activities than the local coefficients. The global analysis involved a discordance between (1) the technique of correlation, which assumed a homogeneous population of observations (here, density observations) generated by a single process or parallel processes (an activity and/or other depositional processes) and (2) the data's actual

structure, which encompassed multiple populations (density observations from multiple kinds of activity zones with different type-proportions), each generated by different processes (activities and/or other depositional processes). The local analyses minimized this discordance, and hence, gave different results.

Thus *relevant quantitative analysis requires a logical concordance between data structure and the empirical phenomenon of interest.* The data must reflect, as much as possible, no more nor less than the process or population of interest. This concordance is seldom found in the initial stages of analysis. Its development is the subject of later sections of this chapter.

The Relation of Technique to Data Structure and the Phenomenon of Interest

For a quantitative analysis to be both relevant and accurate—a more demanding requirement for analytic success than simple relevance—there must be concordance between more than data structure and the phenomenon of interest. These must be consistent with analytic technique. More exactly, the technique that is chosen for analysis must make assumptions about the organization of the phenomenon of interest that are concordant with those aspects of the data's structure that reflect the phenomenon's actual organization. This can be seen in the following way.

(1) A data matrix can explicitly and implicitly contain many different kinds of relationships between variables and observations. These include nominal, ordinal, and ratio scale relationships among variables, monothetic and polythetic relationships among observations, and overlapping and nonoverlapping relationships among observations. These various kinds of relationships can represent different phenomena or some single phenomena with varying degrees of accuracy. Any one phenomenon of interest will be accurately represented by only certain aspects of the data matrix's structure. Which aspects of the data's structure are relevant to the phenomenon will depend on the phenomenon's nature of organization.

For example, consider two artifact types that covaried in their frequencies when used in the behavioral domain. This covariation would reflect the nature of their functions and organization for use

and the nature of organizations of the toolkit (phenomenon of interest) in that domain. However, as a result of parallel, coterminous depositional formation processes and postdepositional disturbance processes, the two types might only co-occur in the archaeological domain, and the toolkit (the same phenomenon of interest) would have a different organization: a *nominal* scale of organization rather than a *ratio* scale organization. Now consider a data matrix composed of the densities of each of the two artifact types within grid cells over the site. The membership of the two types in the same toolkit and the existence of the toolkit would not be expressed accurately by the ratio scale relationship among the densities of the two types over the grid cells. Instead, they would be indicated by the nominal scale relationship among the presence-absence states of the types over grid cells that is *implicit* in the density data. The phenomenon of interest would be expressed in only certain aspects of the total information that is contained within the data matrix.

(2) A quantitative method, by the nature of its procedures and design, can be sensitive to and accurately represent only certain aspects of the total structure of the data to which it is applied. In this regard, the application of a technique to data implies assumptions that only certain, specific aspects of the data are important for representation and interpretation whereas others are not. It implies that certain aspects of the data accurately reflect the phenomenon of interest and its nature whereas others do not. For example, an R-mode technique, operating on relationships among variables, might be sensitive to ratio scale patterns of covariation among variables, but not to nominal scale patterns of association among them. Application of such a technique to a data set would imply an assumption that only ratio scale patterning in the data is of interest, is concordant with the nature of the phenomenon of interest, and accurately reflects it. Likewise, a Q-mode method, operating on relationships among observations, might be sensitive to monothetic relationships of similarity among items as opposed to polythetic ones. Application of such a method to a data set would imply an assumption that only the monothetic relationships in the data are of interest, are concordant with the nature of the phenomenon of interest, and accurately reflect it. In either case, if those data patterns that actually reflect the phenomenon of interest are not those to which the applied technique is sensitive, the results of analysis will not

be accurate. Results will not reflect the relevant patterns in the data accurately, nor will they allow accurate insight into the phenomenon of interest. Consequently, choice of technique is critical.

For example, continuing the toolkit case, above, suppose that a researcher expects that artifact types in the same toolkit will covary in their frequencies over a site as a result of their use and discard in constant proportions while achieving a task. Suppose that he also expects the randomizing effects of postdepositional disturbance processes on artifact organization to be minimal. He then might logically use the above-described matrix of artifact type densities within grid cells as given, along with correlation analysis, to search for covarying artifact types and toolkits over the site. The use of correlation analysis, however, would be discordant with the actual nominal scale organization of the archaeological toolkits containing the types and with those aspects of the total information implicit in the density matrix which reflect that organization. Not being consistently sensitive to nominal scale patterning among variables, correlation methods would not necessarily lead to the discovery of the toolkit.

During early stages of analysis, there is a high potential for discordance between relevant aspects of a data set that reflect the phenomenon of interest and technique. Often at this stage, the researcher knows little about the nature of organization of the phenomenon and how it is expressed in the data. He must choose an analytic technique deductively, on the basis of the *postulated* organization and expression of the phenomenon rather than its *actual* organization and expression. Any discordance between the postulated and actual nature and expression of the phenomenon will, in turn, result in the choice of a technique that is discordant with the relevant aspects of the data's structure and that cannot accurately represent them. Such was the case in our toolkit example just cited.

In sum, when applied to data, a technique makes assumptions about which aspects of the data reflect the phenomenon of interest and its organizational nature. These assumptions should concord with those aspects of the data's structure that actually do reflect the phenomenon and its nature empirically. Only under this condition will analytic results characterize the phenomenon of interst accurately. *Accurate quantitative analysis requires logical concordance between technical assumption, relevant data structure, and the phenomenon of interest.*

The Relation of Theory to Technique, Data Structure, and Phenomenon of Interest

For a quantitative analysis to be meaningful as well as relevant and accurate, the theoretical framework that guides or emerges from it must be logically concordant with the empirical phenomenon of interest, aspects of the data that reflect it, and the assumptions that the technique makes about it. Only if the theoretical framework concords with these entities can the data pattern that emerges from analysis be assigned an appropriate meaning. If the patterns within a data set that are relevant to the phenomenon of interest are accurately revealed using an appropriate technique with one set of assumptions, but the patterns are interpreted within a theoretical framework that makes a different set of assumptions, then the meaning assigned to the patterns will probably be incorrect. For example, two tool types within the same toolkit might only associate rather than correlate in their spatial distributions over a site as a result of certain postdepositional disturbance processes having operated over that same area. Appropriately, they might also be found to associate using spatial techniques that are sensitive to nominal scale relations among types and not to correlate using techniques that are sensitive to ratio scale relations. It is unlikely, however, that these results would be assigned appropriate meanings—the existence of the toolkit and the operation of the postdepositional processes—if it were expected theoretically that tool types within toolkits always covary over space and that the effects of disturbance processes on this relationship are minimal (Carr 1977, 1984). Thus it is possible to identify, with appropriate techniques, data patterns that accurately reflect the phenomenon of interest but to then impart inappropriate meaning to the patterns if one's guiding theoretical framework is not consistent with the phenomenon of interest, aspects of the data's structure that are relevant to it, and assumptions that the applied technique makes about the phenomenon. *Meaningful quantitative analysis requires logical concordance among theory, technique, relevant data structure, and the phenomenon of interest.*

The logically consistent relationship between technical assumption and theoretical framework that is necessary to meaningful scientific investigation can be envisioned in a manner that is different from the above and more in line with discussions of philosophy of science. The assumptions that are implied by the application of a

technique to data and that pertain to which aspects of the data reflect the phenomenon of interest and its nature can be treated as *auxiliary assumptions* within the employed theoretical framework (Hempel 1966: 22-23; Salmon 1982: 36). This is true whether one is building hypotheses and theory, testing them, or using them to explain a particular case. Thus meaningful investigation can be said to require logical consistency between these auxiliary assumptions and other aspects of the theoretical framework, i.e., *internal* theoretical consistency.

This viewpoint is strictly correct. However, it focuses undue attention on the need for concordance between technical assumption and theoretical constructs; it does not imply the equally important need for concordance among technique, data, and the phenomenon of interest. It also makes it difficult to visualize and discuss the need for and the nature of concordance among technique, data, and phenomenon separate from consideration of other aspects of the theoretical framework. Consequently, in this chapter technique and technical assumptions about the nature of the phenomenon of interest that a technique is expected to monitor during its application are considered to constitute an ideological construct in their own right—separate from theory, model, hypothesis, and test implication and serving to interface test implication with data.

Summary

Quantitative analysis within the context of scientific investigation is a complex thought process involving many entities at different levels of abstraction. These include the empirical phenomenon of interest, aspects of a data set's structure that are relevant or irrelevant to it, technical assumptions about it, and theoretical assumptions about the phenomenon of interest as expressed in test implications, hypotheses, models, or theory. An analysis will vary in the degree to which it is successful, depending on how many and which of these entities are related to each other in a logically consistent manner during the thought process. An analysis may be simply relevant; relevant and accurate; or relevant, accurate, and meaningful in the most successful circumstances (Figure 10.1).

Many discordances among the phenomenon of interest, data structure, and technique result from the processes of selecting data and technique. These problems can be summarized by defining more

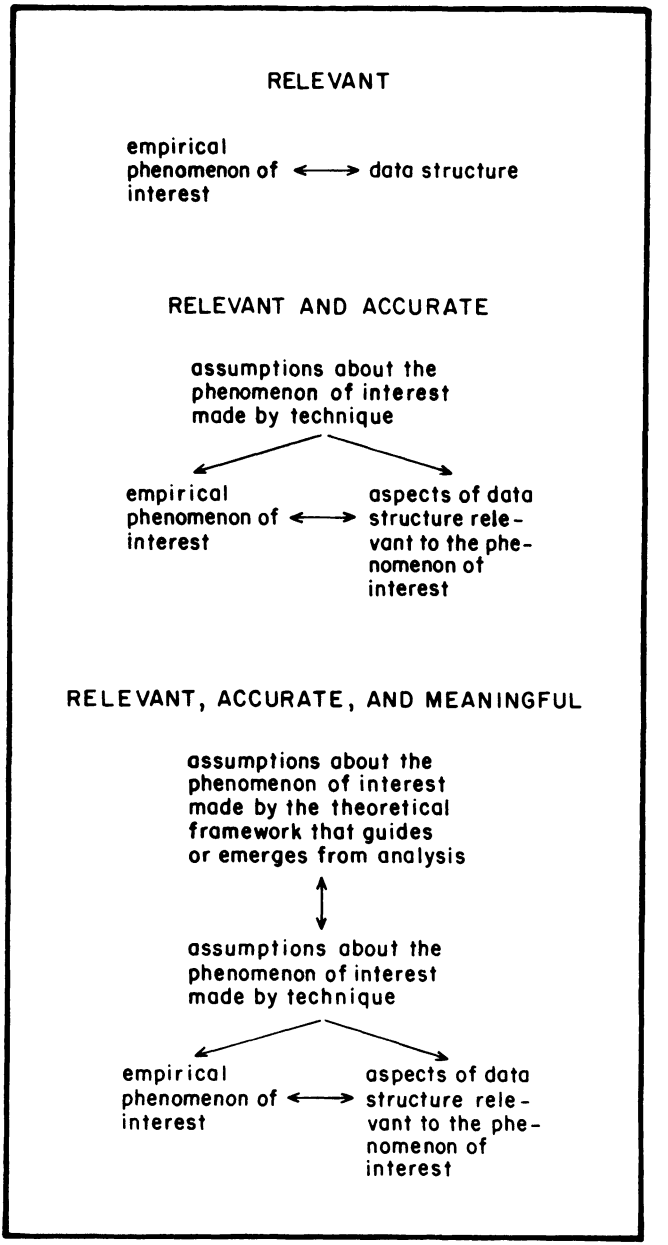

Figure 10.1 Relationships of concordance required for an analysis to be relevant, accurate, and meaningful.

completely and differentiating some of the terms presented at the beginning of this paper, using a matrix perspective. Two pairs of contrasting terms are offered. They are: all data brought forward for analysis, or simply *data structure* vs. *relevant data structure*, and (2) *relevant subset structure* vs. *relevant relational structure*.

Data structure. This term is used to refer to all the variables, observations, and the relationships among them that occur within a data set brought forward for study, regardless of whether or not they reflect the population or process of interest. A data structure may include "extra" variables or observations and relationships among them that are not pertinent to a single process (or parallel processes) and a single population of interest, as well as those that are. It may also include, simultaneously, multiple kinds of relationships among the *same* variables or observations (e.g., nominal scale and ratio scale relationships, monothetic and polythetic relationships)—only some relationships of which reflect the organization of the phenomenon of interest. For example, ratio scale data simultaneously express interval, ordinal, and nominal scale relationships among variables, not all of which need be relevant. Finally, a data structure may lack crucial information on the phenomenon of interest as a result of theoretical or practical limitations on data collection.

Relevant data structure. In contrast to the term "total data structure," this term is reserved, as defined before, for those aspects of a data set that reflect the single phenomenon of interest and its nature of organization. A data set's relevant structure includes only those variables and observations that pertain to a single process or parallel, coterminous processes that define a homogeneous population. It also includes only those kinds of relationships among variables and observations that reflect the form of organization of the phenomenon of interest.

A data set's relevant structure, particularly for archaeological data, usually will not have a physical correlate in a specific set of data items. This results partly from the fact that a single variable may reflect multiple processes (underlying dimensions of variability) and stochastic variation. It also relates to the fact that data at a measurement level higher than the nominal scale simultaneously reflect relationships at that higher level scale and relationships at all lower-level scales. Finally, it can reflect a more fundamental circumstance: the organization of the phenomenon of interest in the physical world, as opposed to data about it. A phenomenon may not exist

separate from other phenomena; it may be possible to isolate it only analytically, not physically.

Relevant subset structure vs. relevant relational structure. The relevant structure of a data set has two distinguishable, usually cross-cutting components. These are its relevant subset structure and its relevant relational structure. Consider a matrix of variables and observations that have been selected in regard to a broad problem domain rather than as a reflection of some single phenomenon of interest. The relevant subset structure of that matrix can be defined as the *subset of data items* that pertains to variables and observations reflecting the phenomenon of interest, although not necessarily only that phenomenon (see above). A data matrix that is defined in regard to a problem domain will usually have multiple relevant subset structures, each pertinent to different phenomena.

In contrast, the relevant relational structure of a data matrix is comprised of those particular *relationships* among variables and observations that are of a kind that reflect the organizational nature of the single phenomenon of interest. A data matrix may simultaneously contain several relational structures pertinent to several phenomena, even if the matrix has but one relevant subset structure. The value of each data item may reflect multiple underlying dimensions of variability pertinent to different phenomena; multiple, implicit levels of variability and relationships at different scales of measurement which are pertinent to different parallel, coterminous processes; and stochastic variation. For example, a matrix of cell densities of two artifact types contains a nominal-scale relevant relational structure, which might be pertinent to their organization as a toolkit in the archaeological domain, and a ratio-scale relevant relational structure, which might be pertinent to the disorganization of the types by postdepositional disturbance processes.

Two general kinds of discordance between data and technique can be summarized using the above distinctions. One pertains to the way in which *data* are selected, the *number of phenomena* that a data set reflects, and the number of relevant *subset structures* that comprise it. During early stages of research, variables and observations are usually chosen in regard to some general problem domain, reflect multiple phenomena (processes and populations), and are composed of multiple potentially relevant subset structures. This multiphenomenal nature of the data is logically discordant with the theoretical bases of many statistical techniques, which assume a model of the

data positing a single population produced by a single process.

The second kind of discordance pertains to the way that *technique* is chosen, the assumptions that the technique makes about *the nature of organization* of the phenomenon of interest, and the particular relevant *relational structure* of the data to which the technique is sensitive. During early stages of research, technique is often chosen deductively, with its assumptions reflecting the expected nature of organization of the phenomenon of interest and its expected expression as a relevant relational structure within the data. These expectations often will not concord with the actual nature or organization of the phenomenon and its expression as a relational structure in the data.

Both kinds of discordance typify early stages of research, when a single phenomenon of interest has not been envisioned and little is known about the number or nature of the phenomena that are responsible for the data or their manner of expression in the data. However, the discordances can also occur in later stages of analysis, depending on the success that the researcher has had in formulating specific questions, focusing on a single phenomenon, and coming to understand the kinds and causes of variability in the data.

A General Cause of Discordance from a Philosophical and Psychological Perspective

In this section, a cause of discordance among data structure, technical assumption, and theoretical framework is described in philosophical and psychological terms. The cause is made clear by comparing the logical processes that are involved in analyzing *complex* data sets, which requires mathematical pattern recognition procedures, to those involved in analyzing simple data sets, which requires only mental pattern recognition abilities.

The complexity of a data set is defined here to be a function of its size (number of variables and observations), the number and complexity of patterns within it, and the strength of patterning. A complex data set can be either of two kinds. The first is a *multivariate* data set in which the number of variables, observations, and patterns among them are too large for the patterns and meaning of variation among data items to be assessed mentally. A data set having a structure resolvable only by principal components analysis would be

an example. The second kind of complex data set is a univariate response to multiple factors, which form a *time or space series* that is too complicated for mental dissection. To investigate a data set having this structure, Fourier analysis, spatial filtering techniques, or time series analaysis would be required (Carr 1982b, 1986; Braun 1985). In contrast to these complex data sets, a *simple* data set is taken to be one having a very limited, mentally manageable number of variables and observations that exhibit uncomplicated patterning.

It is important to emphasize that the dichotomy drawn here between complex and simple data sets pertains to only those of their characteristics that determine whether mathematical procedures are necessary to *recognize patterns* within them. The distinction is not used to refer to other data characteristics, which determine the *ease with which appropriate meaning is assignable* to the patterns found within them. These additional characteristics include, for example, the number and complexity of assumptions involved in collecting, subsampling, and/or screening the data. In regard to these kinds of characteristics, all data sets are more or less complex (Schiffer, personal communication 1983).

With these qualifications in mind, let us now consider a general cause of analytic inconsistencies. Archaeology seeks to reconstruct and understand *nonobservables* (past behavior and ideas) through the discovery and investigation of patterning among *observables* (archaeological phenomena). This places archaeological method within the realm of scientific method, which involves the generating and testing of hypotheses or models (complexes of hypotheses). Hypotheses or models that are concerned with nonobservable activities and ideas are formulated through the discovery of patterns (generalizations) and are tested through the seeking of specific patterns (test implications) in archaeological observables.

The logic that is involved in formulating or testing hypotheses can vary in its consistency and potential for leading the researcher to relevant, accurate, and meaningful conclusions. The degree to which these desirable circumstances are realized depends on the three conditions for successful analysis discussed at the beginning of this chapter.

The arguments to follow pertain to Conditions 2 and 3. They regard the proper identification, accurate summarization, and appropriate interpretation of relevant data structure within a total data set. However, focus will be on the identification and summarization of

relevant data structure, and particularly whether pattern-seeking *mathematical techniques* (e.g., factor analysis) are required for this and the logical effect of this requirement. Also, it will be used to assign meaning to recognized data patterns, and the data and empirical phenomenon of interest pertains to the framework's *primary propositions* (hypotheses, laws, or models) rather than its auxiliary assumptions (e.g., sample representativeness). The difficulties posed by erroneous auxiliary assumptions are considered at the end of this discussion.

During hypothesis development and testing, two kinds of situations can arise, varying in the logic that they involve. In the first, a researcher studies relatively simple phenomena of interest. Observables and data on them pattern themselves clearly such that the researcher can observe the patterns without the aid of mathematical pattern-searching algorithms. In this case, the logic involved in the formulation or testing of hypotheses can be carried out with consistency among data structure, generalization/test implication, and hypothesis and can lead to accurate and meaningful conclusions. This can be done in the manner envisioned by philosophers of science (Hempel 1966; Hanson 1972). In the second situation, the phenomena that are studied are relatively complex. Observables and data observations pattern themselves in ways that require the researcher to use pattern-finding mathematical techniques rather than his own senses and mental capabilities, alone, to search for pattern. In this case, logical inconsistencies among the phenomenon of interest, data structure, technique, test implication, and hypothesis can creep into the analysis. Inaccurate quantitative results and distorted understanding may result.

Let us see how the study of complex phenomena and patterning among observables with mathematical techniques presents a problem in logic, whereas the study of simpler phenomena and patterning among observables with one's own mental capabilities does not, by comparing the two.

In the analysis of either simply or complexly structured data, the researcher's task is twofold: to *find* patterns inherent in the data and *interpret* them with regard to the phenomena that produced them. Finding a pattern can involve choosing subsets of variables and observations as well as defining relationships among them. Interpreting an empirical pattern can be achieved in two ways. The first involves comparing the empirical pattern to those patterns implied by

extant predictive laws or models and then matching it to one of the expected patterns (Toussaint 1978: 191-192). This allows the logical subsumption of the specific case under the accepted general law or model (i.e., explanation). Alternatively, interpretation of a pattern can be achieved through the formulation of a new hypothesis/model that implies an expectable pattern which matches the one found (theory/hypothesis building), followed by logical subsumption of the specific case under the new general principle. This amounts to explanation only if the new principle can be confirmed with other, independent data. The problem with the logic of analysis of complex data sets is most apparent in those analyses that require the second means of interpretation—hypothesis generation—but also is an aspect of analyses that involves the application of extant laws/models for interpretation. Analysis involving hypothesis generation will be considered first.

For simply structured data sets with simple patterning among observations, the tasks of finding patterns and interpreting them through the generation of adequate explanatory hypotheses can be done with a *single* mental operation called *abduction* (Hanson 1972). Abduction is the simultaneous discovery of a *pattern* and its *significance* in suggesting a hypothetical cause of the pattern, as one searches data. Abductive reasoning is the simultaneous dawning that a pattern exists in one's data, and that "the pattern could be explained if hypothesis X were true."

Abduction is more than induction, the process by which generalizations (patterns) are formulated (Hempel 1966). Abduction involves the realization of the higher-level *meaning* of a generalization (i.e., the development of a hypothesis) as well as the formulation of the generalization, itself. Abduction is also more than retroduction, the process of understanding that a pattern could be explained if a given, new hypothesis were true. Abduction involved the *perception* of a new pattern—previously unperceived—as well as the retroduction of a new explanatory hypothesis. Abduction, then, is the seeming "conceptual gestalt" by which, simultaneously, new hypotheses are born and patterning in data suddenly becomes clear and explicable. (Here I have departed from Hanson's [1972] use of the term retroduction.)

For more complexly organized observables, the processes of discovering patterns among data items and inferring the phenomenon that produced those patterns in a more intricate, *multistep,*

serialized task. In the most common approach to analysis, first sophisticated, pattern-finding mathematical techniques are used to search the data for multidimensional patterns and to summarize those patterns in two- or three-dimensional representations that humans can visualize, or with a few statistics. (An exception is the "entry model" approach to data analysis, described below.) This step, which involves the generalization of patterns among observables, is equivalent to logical *induction*. Second, the patterns that are found and summarized are then interpreted in terms of the phenomena that produced them. This step, which involves the logic that a pattern would be explicable if a given, new hypothesis were true, is equivalent to logical *retroduction*.

The difference between the multistep, serialized logic of analysis of complex data structures and the single-step logic of analysis of simple data structures is critical. It involves a separation of the process of *finding patterns* from the process of interpreting patterns by the mathematical technique used to search the data. *This separation and serialization has the fundamental consequence of leaving room for the development of logical inconsistencies among the phenomenon of interest, data structure, pattern-finding technique, and interpretive framework during the course of analysis. These inconsistencies, in turn, may result in the definition of patterns that do not accurately reflect the phenomenon of interest and the drawing of false conclusions.*

To elaborate on this point, in the simple abductive process, data are searched for patterns by the human mind. The mind both *knows* what kinds of data and patterns are possibly meaningful and expectable from an interpretive standpoint, and *selects and searches* the data for precisely those patterns in some appropriate way. At the same time as the data are selected and searched, the interpretive framework, the set of possibly meaningful patterns, the data's subset and relations structures that are considered relevant, and the mode of search all are questioned and reformulated continuously in light of the patterns found in the data. Feedback is instantaneous and continuous among phenomena of interest, data structure, mode of pattern searching, and interpretive framework. This helps to bring and keep all four into logically consistent relationships with each other. Such feedback and logical consistency are possible only because the mental activities of finding patterns and interpreting

pattern occur simultaneously, in parallel, as part of the process of abduction.

In the case where mathematical techniques are used to search for patterns in complexly structured data items that pertain to complex phenomena, such feedback does not occur on a continuous basis. Data are not searched for patterns by a human mind with a *variable* search strategy, a variable theoretical framework, and a variable list of potentially relevant data structures—all of which may change as knowledge is gained about the data's structure during the search. Rather, data are examined using a mathematical technique with a *fixed* search strategy that is consistent with a fixed interpretive framework. A fixed list of variables, observations, and relationships in the data is considered potentially relevant. None of these change as the technique is applied to the data. Critically, in a single pass over the data, results that accurately represent the data's relevant structure and the phenomenon of interest may or may not be derived, depending on the degree of logical consistency among the subset of data that is assumed relevant for analysis, the relational aspects of the data that are assumed relevant by the technique and revealed by it, and those aspects of the data that are truly relevant. Interpretation only *follows* the search for patterning *after* logical inconsistencies between the phenomenon of interest, relevant data structure, technique, and implied theoretical framework, as well as misrepresentation of the data, have had a chance to be incorporated in the analysis. Interpretations and conclusions of questionable relevance, accuracy, and meaning may be derived. Thus logical inconsistencies in analysis and erroneous conclusions can result from the *separation and serialization* of the processes of searching for pattern and interpreting pattern. This removes the opportunity in a single search-pass over data for feedback between currently known aspects of its structure and the nature of the search technique and the interpretive framework.

The separation of the processes of searching for pattern and interpreting pattern by technique, and the undesirable effects of this on the logic of analysis, characterize not only analyses that involve the formulation of new hypotheses for interpretation. They also characterize analyses that involve the application of extant laws/models for interpretation. First, test implications are deduced from alternative models/laws that might have interpretive value for the specific

case under investigation. Then a data subset that is thought to be relevant according to the theoretical framework is chosen and searched by a mathematical technique that has assumptions also thought to be relevant. This is done in order to find patterns that match one or more of the test implication(s) and that allow the logical subsumption of the specific case under one or more of the explanatory models/laws. The patterns that are found may or may not accurately represent the phenomenon of interest and the data's relevant structure, depending on whether there is consistency among the data's subset structure that is assumed relevant and used, the data's relational structure that is assumed relevant by the applied technique, and those aspects of the data that are actually relevant to the phenomenon of interest. The matches obtained between found patterns and deduced test implications, and the interpretations made, will correspondingly vary in their accuracy and meaning. Once again, in a single search-pass over the data, there is no opportunity for feedback between currently known aspects of the data's structure and the search technique and interpretive framework. Logical inconsistencies are allowed to develop, and erroneous conclusions are allowed to be drawn.

In a real analysis, an interpretive framework involves uncertain auxiliary assumptions in addition to potentially erroneous hypotheses, laws, or models. The problem of how to analyze complex data with logical consistency and how to define relevant data patterns that have potential for being assigned appropriate meaning becomes all the more apparent and troublesome. In a real analysis, choice of data and technique and the patterning of the data that is revealed may be influenced by the auxiliary premises as well as the primary premise assumed true. A delay in the feedback between known aspects of data structure and the interpretive framework (including the auxiliary assumptions) may result in poorer choices of data and search techniques, a greater potential for inconsistency in analysis, and the definition of less relevant and accurate patterning. This circumstance will increase the possibility of assigning inappropriate meaning to analytic results, additional to the effects of any inaccuracies in the auxiliary assumptions themselves.

In sum, maintaining logical consistency during the analysis of a complex data set often cannot be achieved for any single pass over the data. This problem does not result from the use of a pattern finding technique per se. Both mental scanning of simple data sets and

mechanical scanning of complex ones require the use of some search technique, yet the effectiveness of the latter may not match that of the former. Rather, the problem with the analysis of complex data, as typically approached, results from separating and serializing the processes of finding pattern and interpreting pattern. This does not allow continuous feedback among the phenomenon of interest, data structure, search technique, and theoretical framework. For circumstances involving hypothesis formulation as opposed to hypothesis testing, the problem posed by complex data sets, compared to simple ones, can be summarized in logical terms. *Analysis of complex data requires inductive and retroductive logic, whereas analysis of simple data can be achieved through abduction.*

The "Methodological Double Bind"

The serial process of finding pattern and interpreting pattern that is commonly involved in the analysis of complex data sets can result in the two potential kinds of discordances that were described earlier in this chapter. In brief, an analytic technique and the interpretive framework with respect to which it is chosen may assume the data of interest to pertain to a single process and population (relevant subset structure) and have a certain organization (relevant relational structure). In contrast, the data may actually reflect multiple processes and populations and have a different relevant relational structure.

These discordances can occur at any stage in the analysis of complex data sets. They are particularly problematic, however, at the beginning of the analytic process. At this point, little may be known about the data's relevant structure. As a consequence, the researcher is put in a double bind. He cannot choose an appropriate technique of analysis and an appropriate subset of the data for analysis without some knowledge about the data set's structure; at the same time, he cannot obtain this knowledge without applying some pattern-searching technique to summarize the data's structure in a simpler form that is comprehendable by the human mind.

A very simple example of this bind during the initial stages of analysis of complex data is given by Christenson and Read (1977: 171). Concerned with the typology of a set of projectile points, they note that they could not do an R-mode factor analysis of the data to

determine relevant dimensions of morphological variability without first identifying and eliminating extreme cases and defining a homogeneous population. (To not do so would introduce distortions in the magnitudes of the correlation coefficients serving as a basis for the factor analysis.) At the same time, proper multivariate (as opposed to univariate) identification of the outliers required that the dimensions of variability present in the data be known.

The methodological double bind has the unfortunate effect of encouraging the researcher to proceed directly with fine-grained analysis using unscreened data and standard techniques that have not been chosen in relation to the case-specific nature of the phenomenon of interest and its particular expression in the data. If the data and technique are not concordant with each other and the phenomenon of interest, the patterns that are found may be irrelevant or inaccurate. At worst, the results are accepted at face value and as final, with little attempt to evaluate the degree of discordance in analysis and possible distortions in the representation of the data and phenomenon. At best, fine-grained analysis is undertaken in order to obtain information about the data and phenomenon, which then is used to choose relevant data and techniques for subsequent reanalysis. However, if the initial analysis produces distorted results, these may serve as a poor basis for modifying the choice of data and techniques. Convergence on relevant and accurate results through repeated analysis alone is not guaranteed.

Thus complex data pose the researcher with the problem of how to "open" them and learn about their structure without violating their relevant aspects.

Overcoming the Methodological Double Bind and Developing Analytic Concordance

On "General Knowledge"

In order to begin overcoming the methodological double bind and developing concordance in analysis, it is necessary for the researcher to secure what I term (Carr 1986) "general knowledge" about the data's relevant structure. By general knowledge is meant an understanding of the general *classes* of observations, variables, and relationships among them that most likely do and do not reflect the

phenomenon of interest accurately. General knowledge about a data's structure contrasts with the detailed understanding of particular observations, variables, and relationships that result from a concordant, fine-grained analysis. For example, in intrasite spatial analysis, general knowledge about a spatial distribution of artifacts would include insights into the approximate range of scales of artifact clusters, whether clusters typically overlap, and whether or not they tend to contrast greatly in artifact density with the background artifact scatter. It would also include information on whether coarranged artifact classes (depositional sets) are organized on a ratio, ordinal, nominal, or polythetic scale of measurement and whether they tend to overlap. This general knowledge would contrast with documentation of the precise limits, positions, and density contrasts of specific clusters and the precise relationships among artifact types as members of specific depositional sets, which would be revealed in a fine-grained, concordant analysis. General knowledge is not restricted to deductively derived postulates about the phenomenon of interest and the data, although it may include information having this origin (see below).

The methodological double bind seems insurmountable if it is assumed that the particulars of a relevant data structure must be known prior to analysis to choose an appropriate data set and technique (see above). However, this is not so. It is possible to overcome the problem by: (1) somehow developing a general knowledge of the data's relevant structure, (2) choosing data and technique in relation to this knowledge, which guides analysis initially in the right direction, (3) using robust tactics and techniques rather than assuming, fine-grained ones to initially explore the data and gain knowledge about the more detailed aspects of its relevant structure and the phenomenon of interest, and (4) examining the data multiple times, with feedback of new insights about details from early steps to later steps. These means for overcoming the methodological double bind and developing analytic concordance can be achieved with four complementary tactics of analysis:

(1) deductive specification of potentially relevant variables and observations, and an appropriate technique;
(2) "constrained" exploratory data analysis;
(3) the "entry model" approach; and
(4) stepwise, cyclical analytic designs.

Each of these strategies allows the researcher to develop general knowledge about the data brought forward for analysis and the phenomenon of interest. They aid him in selecting a relevant subset of variables and observations and an analytic technique that is sensitive to the data's relevant structure.

Deductive Specification of Potentially Relevant Variables and Observations and an Appropriate Technique

One direct strategy for developing general knowledge about a data set and a phenomenon of interest is the evoke extant theory about the nature of the kind of phenomenon in general. On the basis of such theory, the subset of the data and the technique that are most *likely* to be relevant to the phenomenon of interest can be deduced. To the extent that the expected nature of the phenomenon of interest does not concord with its actual nature, irrelevant variables and items may be included in analysis, and some relevant ones may be deleted. In addition, the technique that is chosen for analysis may assume that certain kinds of relationships among variables or observations are relevant when in fact other kinds reflect the phenomenon of interest more accurately.

This strategy is usually employed at the very beginning of a multistep analysis, when little is known about the structure of the data presented for analysis or the causes of their variability. It can be followed and checked by inductive exploration using data and techniques that are justified on the basis of the insight that is gained initially and deductively.

In archaeological studies, middle-range theory (e.g., Binford 1977a; Schiffer 1976; Raab and Goodyear 1984) is frequently used to deduce the subset of data and/or the technique that is likely to be appropriate for analysis. Middle-range theory is useful for this because it specifies the archaeological observables that are expected to manifest particular phenomena of interest, and/or their expected nature of organization. Let us consider some examples of this application of middle-range theory.

Middle-Range Theory Used to Specify Relevant Subsets of Variables and Observations

One area of currently active research in which middle-range theory has been used to deduce potentially relevant variables and observa-

tions for analysis is artifact style analysis for the purpose of testing or formulating propositions about prehistoric social organization. Wobst's (1977) information exchange theory of style specifies the kinds of items that are likely to indicate group affiliation through their design, thereby suggesting the *observations* in any particular case that are probably relevant to the study of prehistoric social organization. Items having this potential are those that: (1) probably were used in contexts ensuring their visibility to all members of the group and members of other nearby groups, as opposed to items used in the domestic sphere; (2) are long-lived, making their expression of group affiliation efficient over time; and (3) probably were not exchanged between groups.

Voss (1980a: 4), following Wobst, goes on to specify for such items the different kinds of stylistic *variables* that are often useful for determining group affiliation vs. group interaction. Discrete characteristics that are highly visible and that thus can function effectively as symbols, such as discrete design elements and configurations (Fredrick 1970; Stanislawski and Stanislawski 1978), are more likely to be accurate measures of group affiliation. In contrast, continuous variables that encompass the "nuances" of style, such as the dimensions of design zones and counts of design element repetitions, are more likely to be accurate measures of group interaction. In addition, Braun and Plog have suggested that the stylistic characteristics of an artifact define a hierarchy. Attributes at different levels of the hierarchy represent different stages of the decision process that is involved in the manufacture of the artifact (Plog 1978: 161) but are also sensitive to different social factors and groups (Braun and Plog 1982: 511), perhaps at different geographic scales (Braun 1980: 12-13).

A framework for more systematically isolating the different style variables within an artifact that can reflect different kinds of processes has been offered by Carr (1984b, 1985c). Carr defines four correlated hierarchies of observable and measurable characteristics of style variables: a hierarchy of manufacturing decisions involving the variables, a hierarchy of manufacturing execution steps involving the variables, a hierarchy of the visibility of variables' states, and a hierarchy of the geographic extent of alternative states taken by variables under the assumption of no artifact exchange. The visibility of a variable's states is measurable in relation to their absolute size, their color, textural, and size contrasts from each other and their background, the number of alternative states the variable can take,

the social context of use, and other considerations. The place of an attribute in each of these hierarchies constrains its potential for operating in and reflecting any of a hierarchy of processes. These include processes that are pertinent to solely technological or raw material constraints, active symbolization of boundaries between groups of various expanse, active symbolization or passive reflection of cooperation within social groups of various expanse, expression of individual identity and personality, and individual motor habits. The systematic dependency of the hierarchy of processes upon the hierarchy of characteristics of style variables allows the researcher to predict the one or few processual meanings that a style variable can have on the basis of its observable characteristics. Those attributes of an artifact that are most likely to be relevant to a technological, social or individual-level process of interest can be isolated.

In total, the middle-range principles of these several researchers define a very powerful framework. From them, the kinds of observations and variables in an artifact style data set that are likely to be relevant to prehistoric social organization can be deduced with a great degree of specificity. When applied within the bounds of their limitations (Wiessner 1983), these principles suggest the data's relevant subset structure, which in turn would tend to be concordant with statistical techniques assuming some single process. Thus, here is a case where deductive specifications of variables and observations can improve the likelihood of concordance between data structure and technique.

Some studies of prehistoric social organization that have used these principles in this manner include those of Braun (1977, 1980), Plog (1976, 1978, 1980), Voss (1980a, 1980b), and Hinkle (1984). We may also note that Spaulding's emphasis on using nominal scale measures (or higher-scale measures reduced to a nominal scale) as a basis for artifact typologies derives from conclusions of his that are concordant with the information exchange theory. Spaulding (1982: 5-6, 10) argues that it is nominal scale (discrete) variables that indicate culturally imposed patterns of artifact manufacture and that may be used to define types having cultural significance (i.e., types indicating the group affiliation of the artifact's makers).

Another field of study in which middle-range theoretical arguments have been used to deduce variables and observations that are probably relevant to some phenomenon of interest is mortuary analysis. Braun (1979: 69) has argued that the archaeological

variables that are relevant to the identification of ascriptive, hierarchical social distinctions include grave good classes that do not occur in village middens, that occur rarely overall within burials, that involve a relatively substantial labor input to produce, and that do not associate with age or sex. He also argues (p. 67) that it is qualitative rather than quantitative burial ritual attributes that symbolize formal authority and hereditary ranking. These arguments were then used by Braun to select a potentially relevant subset of variables from a burial set for analysis.

Middle-Range Theory Used to Specify the Nature of the Phenomenon of Interest, Relevant Relational Data Structure, and Appropriate Technique

Middle-range theory does not deal only with the archaeological indicators of past phenomena, that is, with the variables and observations that comprise relevant subset structures. It also addresses the nature of organizations of such indicators—relevant relational structures—and by implication, appropriate techniques of analysis.

An example of a field in which linkages have been specified among the organization of archaeological observables, relevant relational data structure, and technique is intrasite spatial analysis. I (Carr 1984) have constructed a model of intrasite artifact organization that commonly typifies archaeological sites. The model posits the internal and external set organization of archaeological "toolkits," or "depositional sets," as polythetic and overlapping. It also specifies that archaeological "activity areas" or "depositional areas" may vary in their size, shape, orientation, spacing, artifact density and composition, border crispness, and in whether they overlap and are hierarchically arranged in space. Most spatial quantitative methods that have been used in intrasite studies then were reviewed for their concordance with this model, providing an assessment of their appropriateness for application to most sites. In a later publication (Carr 1985b), I expand the set organizational model to a continuum of 12 models, which specify depositional set structures ranging from monothetic, ratio scale form to highly polythetic forms, and from completely nonoverlapping to overlapping. Then, some behavioral and natural contexts in which depositional set organization can be

expected to be similar to those stipulated by the models are enumerated; also, some quantitative techniques (new and old) that are appropriate for use when depositional sets are organized in these ways are specified. In this way, with a limited understanding of the behavioral and natural context of a site, it is possible to deduce the probably relevant organization of artifacts within it and the techniques most likely concordant with that organization. Similarly, Whallon (1984) has enumerated many kinds of variability encompassed by depositional areas. He then evaluated the use of factor analysis and other global methods for their concordance in analyzing artifact distributions. Finally, Whallon's and my efforts have involved the development of new spatial analytic techniques, which are designed specifically to be concordant with archaeological organizations and relevant data structures of a kind likely to be encountered (Whallon 1979, 1984; Carr 1977, 1981, 1982b, 1984, 1985, 1986).

The progress that has been made in these studies is based on nearly a decade of previous research that has focused on evaluating the response of various techniques to different spatial organization of artifacts (see Carr 1984 for references). These earlier studies, however, did not involve the construction of models of artifact organization and relevant relational structures, making their results difficult to apply in other analyses. In contrast, the development of middle-range theory and models about artifact spatial organization, and the enumeration of techniques concordant with them, allows particular sites to be subsumed under the models and appropriate techniques to be identified more easily.

Another example of middle-range theory providing a model of organization and being used to deduce concordant analytic techniques pertains to mortuary analysis. Braun (1977, 1979: 67) has argued or implied that ascribed and achieved status and leadership positions differ in two ways. First, ascribed status positions require greater predictability and temporal continuity (institutionalization) of the behaviors of those who occupy them than do achieved status positions. This constancy in behavior is postulated to be symbolized at death by a more coherent, stable set of mortuary rituals and burial treatments, some of which are manifested archaeologically. Second, ascribed positions of status and leadership involve more social roles, which are symbolized at death by more numerous, redundant, and associated ritual practices and burial treatments. On the basis of these two different multivariate, *dimensional* characteristics of ascribed

and achieved status positions and their mortuary remains, Braun deduced that factor analysis is an appropriate technique for investigating mortuary data sets. It can be used to define within them a status dimension of social organization and for assessing whether status was ascribed or achieved.

In sum, during initial stages of analysis, the nature of the phenomenon of interest and the relevant subset and relational structures of the data in hand often are not well known. In this circumstance, middle-range theory can be used to deductively specify the most likely nature of the phenomenon, the subset of data that has the greatest potential for reflecting it, and a technique that concords with it and the data's relevant relational structure. As middle-range theory develops, we can expect this means for overcoming the methodological double bind to become more reliable.

"Constrained" Exploratory Data Analysis

Extant theory and deductive arguments can help the researcher to develop general knowledge about a data set's relevant structure and a phenomenon of interest. However, they are seldom sufficient. Individual data sets need not—usually will not—conform to expectation in every way. If the theory to make deductions does not have strong predictive capabilities, the phenomenon of interest may manifest itself in unsuspected sets of variables and observations and forms of relationship among them. The same problem can arise if the predictive theory is incorrectly applied beyond the limits of its boundary conditions or if the auxiliary assumptions that are made when relating the theory to the data at hand are wrong. For example, consider the auxiliary assumptions that are made about sources of variation that are supposedly controlled during data collection. When unsuspected extraneous factors as well as those of interest affect the measurements brought forward for study, the data set's relevant structure may take an unexpected form. An expected linear relationship between two natural environmental variables, for example, might instead take the form of a cyclical function with a linear trend, as a result of the compounding of diurnal variation with the variation of interest. Thus totally deductive specification of the variables and observations to be analyzed and the techniques to be used need not ensure their complete relevance to the phenomenon of interest nor the concordance of the technique to the data's relevant structure.

To compensate for these problems, it is necessary to supplement the deductive strategy with an inductive one that examines the data on its own terms. "Constrained exploratory data analysis" (CEDA), having at least two variants that differ in the kinds of techniques they employ, is useful for this purpose.

CEDA vs. Exploratory Data Analysis

As defined here, CEDA includes all the analytic methods that comprise exploratory data analysis (Tukey 1977; Hartwig and Dearing 1979; Clark 1982) but only a portion of the philosophy of exploratory data analysis that motivates their use. Like exploratory data analysis, CEDA is an inductive approach to recognizing patterns in a data set. Both have the goal of finding "any unanticipated structures or relationships that occur within a data set, regardless of expectation" (Tukey and Wilk 1970: 371). Both involve searching for any patterning in the data in order to reach a better understanding of the nature and causes of its total structure. Unlike exploratory data analysis, however, CEDA aims at developing this understanding of the data's structure in order to *isolate* the relevant aspects of it—*those that reflect some one explicitly specified phenomenon of interest as defined deductively* within the larger theoretical framework or paradigm of the researcher. In contrast, exploratory data analysis aims at developing an understanding of the data explicitly in order to generate new ideas, problem areas, and hypotheses (Tukey 1979: 122, 1980: 23-24) within a primarily inductive framework. Discovery of *many* relevant data structures pertinent to many phenomena, rather than the *single* structure pertinent to the single phenomenon of interest, is the goal of exploratory data analysis. Because CEDA is undertaken within a larger deductive framework and is more focused in its aim, whereas exploratory data analysis occurs within an inductive, less focused context, the designation *constrained* exploratory data analysis is used.

Whereas exploratory data analysis was developed by Tukey in reaction to the strongly deductive, "confirmatory" mode that has dominated theoretical statistics (Tukey 1979), CEDA is meant to articulate with it. Analysis is begun in a deductive manner with the specification of variables and observations that are probably relevant to the phenomenon of interest. Data items that are thought to be

irrelevant are dropped from analysis. The search for relevant and irrelevant data items is continued in an inductive manner with CEDA procedures. The subset of the data that results from *both* the deductive and CEDA steps can then be used in either hypothesis testing or hypothesis formulation. In either case, both "data-screening" steps are motivated by the researcher's larger theoretical framework, which specifies the phenomenon of interest. *CEDA, then, is an inductive middle-step within a stepwise analytic design that has an overall deductive orientation and that is begun with deduction.* In contrast, exploratory data analysis is an inductive approach for initiating analytic process. (See Carr 1985a, for a discussion of the strengths and weaknesses of exploratory data analysis in this capacity.)

To examine the total structure of a data set and determine those aspects of it that are probably relevant to the phenomenon of interest, CEDA uses the same methods as exploratory data analysis, plus some additional ones. First, to view the multiple structures within a data set, CEDA involves the reexpression of the data on various scales of measurement (e.g., nominal, ratio, logarithmic, square root) and the examination of the reexpressed data with different techniques that are concordant with those scales of measurement (Tukey 1979: 24; Hartwig and Dearing 1979: 10). Also, techniques assuming multiple mathematical models are used to investigate the data from multiple perspectives. An effort is made to find any patterns in the data, regardless of whether they reflect the phenomenon of interest, and to consider how potentially relevant structure in the data then might be isolated from irrelevant patterning (e.g., removal of outliers, selection of variables, expression of the data on a particular scale, use of a technique that is sensitive to the scale most likely appropriate to the relevant structure). Second, CEDA, like exploratory data analysis, stresses the importance of graphic representations of the data (e.g., histograms, crossplots, the box and whisker, and maps) as aids in searching for patterns (Tukey 1979: 373; Hartwig and Dearing 1979: 9).

CEDA vs. Data Screening

CEDA and exploratory data analysis involve many of the same techniques and operations traditionally used to screen and restructure data in preparation for applying higher-level statistical tech-

niques. These include: histograms; crossplots; simple univariate descriptive statistics; bivariate techniques of association, rank correlation, and correlation analysis; elimination of outlying observations; segregation of modalities for separate analysis should the data be composed of observations within several suspected populations; and transformation of the form of the frequency distributions of individual variables or the functional relationships between variable pairs. All of these techniques and operations can be used in CEDA to obtain a basic understanding of the data to be analyzed.

However, CEDA departs from traditional data screening in that these methods are not applied primarily to transform the structure of the data into one that concords with some analytic technique that has been chosen a priori. Data are not screened to *fit a technique.* Rather, the data set is examined to find and isolate the potentially relevant aspects of its structure *in regard to which an appropriate technique of analysis is chosen or developed.*

Two Forms of Constrained Exploratory Data Analysis

CEDA encompasses two variants that differ to some extent in the nature of the techniques they encompass. One emphasizes the use of techniques that make *minimal assumptions* about the data's structure when displaying them for patterning-searching. The second variant emphasizes the use of techniques that are capable of handling and dissecting a *heavy load of irrelevant variables or observations, or variation in general within the data.* This is a common characteristic of data sets initially presented for analysis or modified only by deductive selection.

A good example of a technique that makes minimal assumptions and that might be used within a CEDA framework, but which to date has been used in only an exploratory data analysis framework, is Whallon's (1984) *unconstrained clustering* method of intrasite spatial analysis. As Whallon (p. 35) notes, unconstrained clustering "is hardly more than an elaborate approach to a descriptive summary or display of the data or a series of such summaries and displays." (For a more detailed discussion of the method in relation to exploratory data analysis, see Carr 1985.) Other examples include other graphic displays such as the stem-and-leaf display, the box-and-whisker, and scatter plots, and certain "resistant" descriptive statistics such as the

trimmed mean, the Winsorized mean, and the median absolute deviation (Tukey 1977; Hartwig and Dearing 1979: 16-26). These techniques can be used to determine the variables, observations, or the relationships among them that are probably relevant to the phenomenon of interest.

One example of a technique that is capable of handling a heavy load of irrelevant variables but that does not make minimal assumptions, is *R-mode factor analysis*. Although it can be used for multiple purposes, R-mode factor analysis is ideally suited for defining clusters of variables, making it "easier to decide upon their relevance to a problem" (Christenson and Read 1977: 174) within a CEDA framework.

Christenson and Read (1977: 167, 170-174) have used factor analysis along with a multivariate identification-of-outliers program explicitly to prepare for developing a projectile point typology with cluster analysis. A factor analysis of projectile point data was used to identify two dimensions of morphological variability (groups of variables) that seemed relevant to the researchers' typological goals and other dimensions that seemed irrelevant. The two relevant dimensions were then selected as the "variables" to be used in creating the point typology. Read (1985) illustrates how factor analysis and scatter plots of factor scores can be used in an alternating, interactive manner to refine the selection of variables (factors) and set of observations that are chosen to represent the one or more phenomena of interest potentially reflected in a data set's structure.

A second example of a technique that is capable of handling a heavy load of irrelevant variation and that does not make minimal assumptions is *spectral analysis*. This technique allows the researcher to identify multiple forms of variability of different scales that are compounded within the track of a *single* response variable over time or space. The results of a spectral analysis can be used by a researcher to design "filters" that allow the extraction and isolation of these individual forms of variation from the compound response variable, which in turn are defined as new variables. Those of the new variables that are considered to reflect the phenomenon of interest can then be subjected to further analysis, free of the confusing effects of the other, irrelevant sources of variation. I (Carr 1982a) have used spectral analysis in this manner to identify and analyze several sources of variability within an intrasite resistivity survey data set. I have also suggested its application to composite artifact distributions (palimp-

sests) that have been formed by the partial spatial overlap of multiple depositional processes (e.g., different kinds of activities of different scales), in order to identify artifact density variables attributable to the different processes. Density variations that are thought pertinent to each of the processes of interest (relevant data structures) can then be extracted from the palimpsest using filtering techniques so that they can be studied individually (Carr 1982b, 1984, 1986.)

In conclusion, analysis of complex data sets often requires inductive as well as deductive specification of the variables, observations, and relationships among them that are potentially relevant to the phenomenon of interest and a potentially concordant analytic technique. In this regard, for complex data those phases of scientific investigation that are concerned with hypothesis testing and that are supposedly "deductive" are seldom *completely* deductive. Theory may be used to deduce a model or hypothesis. However, the formulation of a test implication—which states an expectable relationship among observables in *terms of the variables, cases, and technique that are selected for analysis*—is a process that often requires both deductive and inductive logic. The expectable relationship follows from the theoretical framework, but its expression depends on the data and technique to be used, which often must be selected in part by induction.

Entry Models

A third strategy for familiarizing oneself with an unknown data set while maximizing consistency between its relevant structure and technical assumption involves what may be termed *entry models* and *parallel data sets*. This strategy uses both inductive and deductive logic and requires the development and use of middle-range theory. It gives the researcher insight into the organizational nature of the phenomenon of interest and the relevant relational structure of the data that represent it. This allows the researcher to choose an analytic technique which is more concordant with that form of organization. It does not necessarily involve the selection of relevant observations and variables (relevant subset structure), though it may. The strategy is summarized in Figure 10.2.

The entry model approach centers around the development of several alternative entry models. Each implies a concordant pairing of a relevant data structure that potentially represents the phenom-

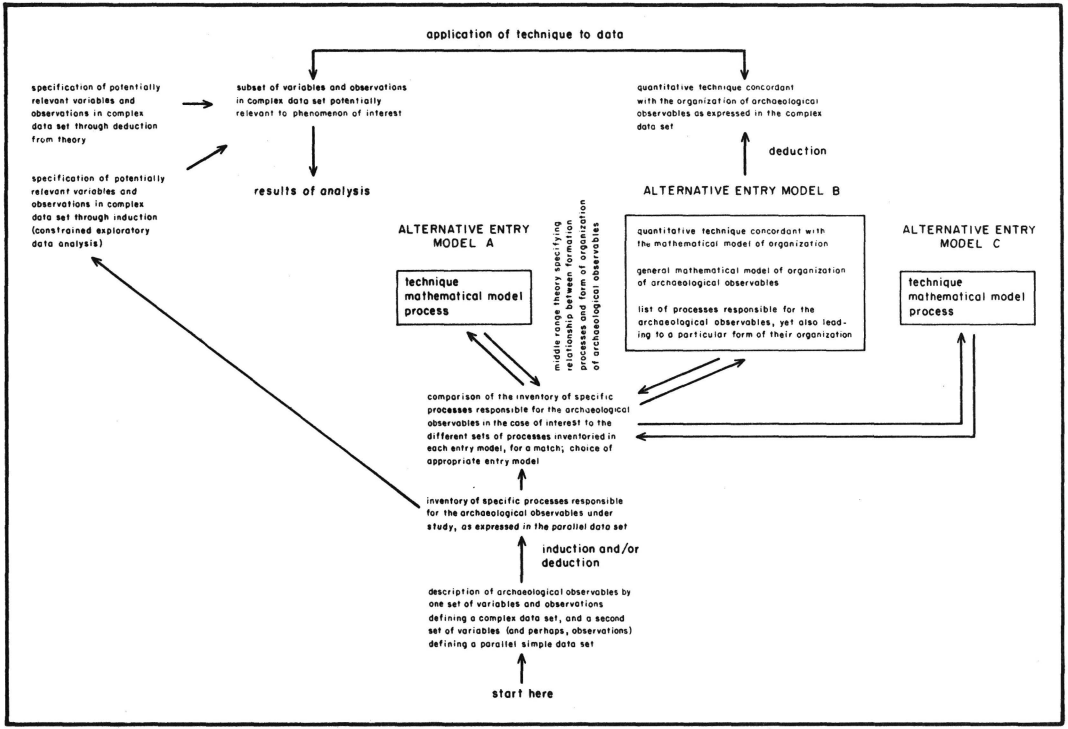

Figure 10.2 The use of entry models and parallel data sets to become familiar with a complex data set.

enon of interest, one or a few techniques, and the formation processes responsible for the data's relevant structure.

Each entry model has three essential components. (1) The most critical is a *general mathematical model* or description of the *form of organization* that might be taken by the archaeological observables representing the phenomenon of interest. If the archaeological observables in a particular study area do empirically have this form of organization, then the model of their organization will imply the relevant relational structure of the data describing them. In intrasite spatial analysis, samples of alternative mathematical models would be ones specifying the various forms of spatial organization that coarranged artifact types (observables) representing "toolkits" or "depositional sets" (the phenomena of interest) within archaeological sites might have. These would include models of ratio scale, ordinal scale, nominal scale, or various polythetic scale forms of organization (Carr 1985b). If, at a particular site, a series of artifact types were actually coarranged in accordance with one of these models, then the data describing the artifacts' locations would have a relevant relational structure of the form implied by the model.

(2) The second component of an entry model, concordant with the first, is an *enumeration of the kinds of processes* that can lead to the archaeological observables being organized in the way that the mathematical model specifies. These would be processes postulated to be responsible for the organizational nature of the phenomenon of interest and its archaeological satisfaction. If the archaeological observables in a particular study area are empirically organized in the way the model specifies, these will also be the processes responsible for the relevant relational structure of the data describing the observables. The processes will always include cultural and natural formation processes of the kind documented by middle-range archaeological theory (e.g., curation, lithic reduction and maintenance processes, means by which rank is symbolized in mortuary remains). However, they may also include "formation processes" to which general anthropological theory pertains (e.g., the pattern and tempo of fission-fusion of hunter-gatherer bands). Continuing our intrasite spatial example, one of several alternative entry models might describe a polythetic form of spatial organization of artifact types within "toolkits" in the archaeological domain and include a list of formation processes that could lead to that organization. These might include differential artifact preservation, artifact curation,

artifact recycling, misclassification of artifacts, or the occurrence of alternative tool types within a toolkit.

Although specification of such linkages among forms of archaeological organization and processes may be difficult, it is currently the subject of active research on middle-range archaeological theory. Use of the entry model approach, by its very nature, encourages the development of middle-range theory.

(3) The last component of an entry model is an inventory of the *quantitative techniques* that are concordant with the mathematical model of organization of the archaeological observables. If, in a particular study area, the archaeological observables are empirically organized in the way the model specifies, these will also be the techniques that are concordant with the relevant relational structure of the data describing the observables. For example, continuing from above, the one entry model describing a polythetic form of spatial organization of depositional sets might list a "polythetic association" method of spatial analysis (Carr 1985b). Polythetic association is concordant with that form of organization.

An entry model usually is one of a series of such models. Each entry model specifies a different mathematical model of the organizational form that the archaeological observables might take and implies a different relevant relational structure that the data describing them might have. The differences among the entry models in the organization of observables and the relevant data structures that they postulate or imply reflect the effects of the different formation processes or higher-level processes that the entry models enumerate as responsible for the observables and data. The differences also can reflect the fact that a single phenomenon of interest can have multiple organizations and representations when it is the product of parallel, coterminous, and optional processes. This was discussed at the beginning of this chapter. Similarly, several alternative entry models will specify different quantitative techniques that are concordant with the different mathematical models of organization.

An example of a set of alternative entry models and their application is given in Carr (1985b). This study involves twelve entry models, six to be discussed here. These postulate six different mathematical models of the internal set organization of spatially coarranged artifact types (observables) that comprise a depositional set or "toolkit" in the archaeological domain. Figure 10.3 and Table 10.1 illustrate and define the characteristics of these different

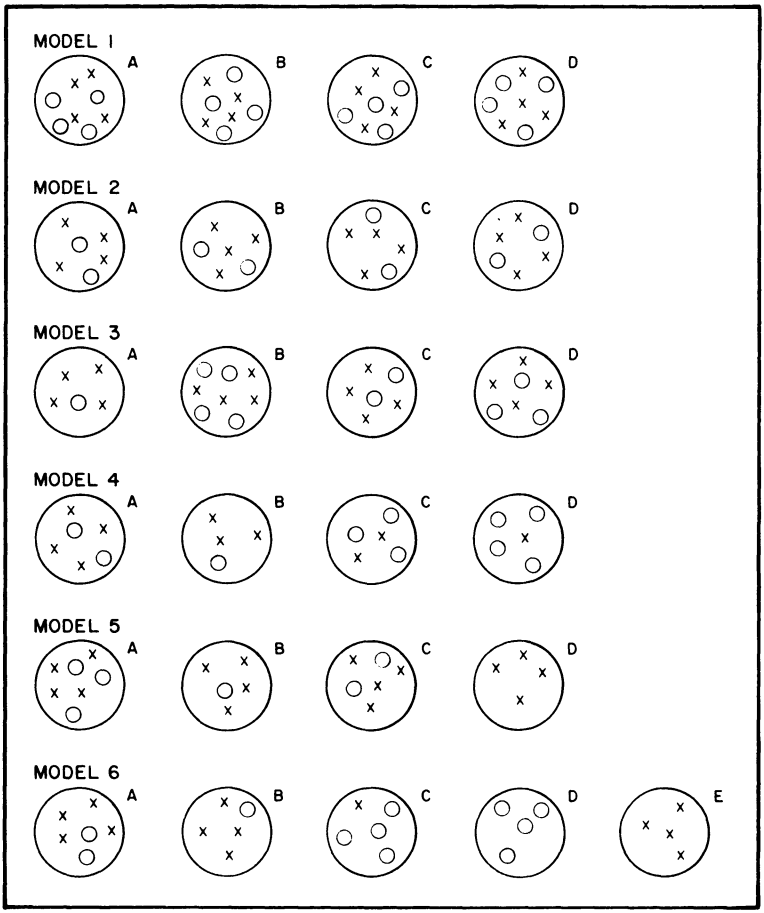

Figure 10.3 Six models of the internal set organization of artifact types among archaeological deposits fall along a monothetic-polythetic continuum. Only one pair of types within the same set of deposits is shown; other types are assumed to have analogous forms of organization. The organizational characteristics of each model are described in Table 10.1

organizational forms. The several structures are alternative possible manifestations of the one phenomenon of interest—depositional sets as representations of artifact types that were manufactured, used, stored, or deposited together in the behavioral past. Their different

TABLE 10.1
Mathematical Characteristics of the Six Models of Organization of Artifact Types in Figure 10.3

Characteristic:	Asymmetry within groups of artifacts allowed for one or more pairs or types	Differences among groups in the magnitudes of their asymmetries allowed for one or more pairs of types	Differences among groups in the directions of their asymmetries allowed for one or more pairs of types	Asymmetry within groups taken to the extreme, where one type, of one or more pairs of types, does not occur in some groups	Global monothetic or polythetic organization using A, B, C, D, E as groups of interest	Local monothetic or polythetic organization using pairs of items as groups of interest
Models:						
1.	–	–	–	–	Monothetic	Monothetic
2.	+	–	–	–	Monothetic	Polythetic
3.	+	+	–	–	Monothetic	Polythetic
4.	+	+	+	–	Monothetic	Polythetic
5.	+	+	–	+	Polythetic	Polythetic
6.	+	+	+	+	Polythetic	Polythetic

organizations reflect their generation by different kinds of formation processes, which also are enumerated by the entry models but not shown here. Finally, the six entry models specify different sets of quantitative techniques that are concordant with the different forms of depositional set organization and that might be used to search archaeological data for patterns that indicate depositional sets (Table 10.2). These techniques vary in the scale of measurement of spatial coarrangement to which they are sensitive—from ratio scale coarrangement to the loosest forms of polythetic coarrangement.

A second example of a set of alternative entry models is given in Carr (1986). Here, six entry models are defined. Each postulates a different mathematical model of the spatial and content characteristics of clusters of artifacts (observables) comprising depositional areas or "activity areas" and their background artifact scatters in the archaeological domain. For example, depositional areas are modeled as to whether they overlap spatially, the degree to which their artifact densities contrast with those of their background, and their degree of boundary crispness. The different structures are alternative forms that the single phenomenon of interest—depositional areas—can take. Each structure is then associated with some archaeological formation processes that might generate it and spatial analytic techniques that are concordant with it, completing the entry models. The techniques include various Fourier and spatial filtering methods for enhancing the "visibility" of depositional areas and segregating different kinds of areas.

Entry models are useful when two circumstances occur. (1) The data set that is slated for analysis, and that describes the archaeological observables representing the phenomenon of interest, is very complex. As a result, the researcher is unable initially to specify—by simple inspection of the data—the aspects of its structure that are likely to be relevant, the probable organization of the archaeological observables that represent the phenomenon of interest, and an analytic technique that probably is appropriate. (2) There exists a simpler, parallel data set that gives the researcher insight into the processes that are responsible for the archaeological observables, their consequent organization, and the relevant and irrelevant structural aspects of the complex data set.

In these two circumstances, it is possible for the researcher to learn something about the complex data set's relevant relational structure

TABLE 10.2
Similarity Coefficients Appropriate for Analyzing Spatial Arrangements of Artifact Types Having Various Forms of Organization Along the Monothetic-Polythetic Continuum

*Form of Organization**	*Appropriate Coefficient for Item Point Location Data***	*Appropriate Coefficient for Grid Cell Data***
Model 1	AVDISTM	–
Model 2	–	Pearson's r
–	–	Kendall's tau and tau-b, Goodman and Kruskal's gamma, Spearman's rho
Model 3	–	–
Model 4	AVDISTLP1	Jaccard similarity coefficient, Cole's C-7, Hurlebert's C-8
Model 5	AVDISTGP	–
Model 6	AVDISTLP2	–

*Models shown in Figure 10.3 and described in Table 10.1.
**References to the coefficients are given in Carr (1985b).

and to specify a potentially concordant analytic technique by examining the *parallel data set* and using the entry model. This is done in lieu of *directly*, but possibly discordantly, examining the *complex* data with a higher-level pattern-searching technique (p. 208). In this way, the researcher is removed from the bind of not being able to choose an appropriate analytic technique without knowledge of the complex data set's structure, yet not being able to obtain this knowledge without applying some pattern-searching techniques to it.

The logical and analytic process involved in using a parallel data set and entry models is shown in Figure 10.1. It can be described as follows.

(1) Two data sets are established. The first is a complex one that is the ultimate target of analysis and that describes the observables representing the phenomenon of interest. The second is a simple, parallel data set that is sensitive to the processes of formation of the archaeological observables described in the complex one.

An example of a complex data set would be a matrix of point locations of artifacts of many classes within a hunter-gatherer site.

An example of a simple data set that parallels this complex one and gives insight into its organizational nature would be one that documents various indicators (Schiffer 1983) of archaeological formation processes that affect artifact deposition and disturbance and, thus, the matrix of point locations. The parallel data set might contain information on intrasite spatial variation in soil acidity, which would reflect the potential for differential preservation of bone artifacts over space; and/or the orientation and dip of artifacts, which would indicate the possibility of disturbance in the artifacts' spatial distribution by fluvial activity; and/or the grain of the surrounding environment, which would suggest the likelihood of tethered mobility patterns, repeated reuse of the site, and the palimpsest nature of the artifact distribution.

(2) The processes that are responsible for the archaeological observables described in the complex data are reconstructed on the basis of information in the parallel data set. This reconstruction can be accomplished by logical deduction, in which case the specific patterns within the parallel data set are subsumed under general, accepted models of the observable consequences of formation processes. For example, in deductive mode, the disturbance of an intrasite artifact distribution by fluvial processes might be determined by noting patterns in the orientation, dip, and size sorting of artifacts and then subsuming such patterns under established models of fluvial displacement of artifacts (Behrensmeyer and Hill 1980; Shackley 1978). Reconstruction can also be achieved by abduction from patterns within the parallel data set, followed by testing of one's conclusions with other, independent data that also comprise the parallel data set. This step conforms to Schiffer's (1983) call for "up front" identification of the processes that are responsible for archaeological observables prior to behavioral interpretation.

(3) The specific processes that are found to be responsible for the organization of the archaeological observables of interest and that determine the relevant structure of the complex data set are then matched with processes that are enumerated in a more general way in one or more of the entry models.

(4) Several conclusions are reached based on: (a) the association of the archaeological observables of interest and the complex data set with a particular entry model via common processes, (b) the entry model's specification of the effects of such processes on the organization of archaeological observables of the kind described by the

complex data set, and (c) the entry model's specification of the analytic techniques that are concordant with that organization. First is the probable general nature of organization of the archaeological observables described in the complex data, which is specified in mathematical terms. By implication, general knowledge of the complex data's relevant relational structure can also be inferred. Finally, the techniques of analysis that are most apt to be appropriate for investigating the archaeological observables in the complex data set can be concluded. Note that information in the *parallel* data set is used to determine the appropriate entry model, whereas information on the relevant structure of the *complex* data set is derived from the entry level. Also note that the process of associating the archaeological observables in the complex data set with a given entry model is equivalent to logically subsuming them under the entry model.

An example of the steps that have been outlined is given in Carr (1985b). Here, the target complex data set is composed of the spatial locations of many artifact types (observables) within a French Magdalenian reindeer hunting camp, Pincevent habitation no. 1. The phenomenon of interest (to be discovered) is sets of artifact types that were manufactured, used, stored, or deposited together in the behavioral past and that are similarly arranged in the archaeological domain according to some relevant scale of organization. Initially, the organization of whatever depositional sets might exist at the site, and the relevant structure of the complex distributional data manifesting them was unknown. Nor were these conditions obvious from the data upon their visual inspection. It consequently was unclear what spatial technique would be appropriate for analyzing the data.

Various kinds of information constituting a parallel data set were used to identify formation processes at Pincevent that would have affected the nature of organization of any depositional sets and the relevant relational structure of the complex data. Some examples of the kinds of parallel data evoked include: tool morphology, which indicated patterns of tool recycling and reuse; spatial patterns of conjoined pieces of broken artifacts, which indicated patterns of refuse disposal and cleaning; anomalously low counts of some reindeer bone elements relative to those expected on the basis of estimated minimum number of individuals, which indicated differential preservation patterns; site seasonality as an indicator of expectable general patterns of refuse generation and disposal; etc.

The formation processes reconstructed from the parallel data then were compared to those enumerated in six alternative entry models, each of which also postulated a mathematical model of relevant depositional set organization (Figure 10.3, Table 10.1). On the basis of matches between the formation processes reconstructed for Pincevent and those specified in the entry models, and the linkage among process, data structure, and technique in the entry models, it was concluded that most depositional sets at the site were probably organized like mathematical models 4 or 6 (Figure 10.3, Table 10.1). It was also concluded that the two techniques most apt to be concordant with depositional set organization at Pincevent and that should be used to analyze the complex data set of artifact spatial distributions were AVDISTLP1 and AVDISTLP2 (Table 10.2). These measure the degree of spatial coarrangement of artifact types using certain polythetic scales of measurement.

(5) The one or few quantitative techniques that are determined to be most probably concordant with the relevant relational structure of the complex data set are applied to that data or some subset of its variables and observations that is thought to be relevant to the phenomenon of interest. The potentially relevant subset can have been specified by deduction from theory or by inductive examination of the parallel data set (Figure 10.3). In the Pincevent case, for example, artifacts (observations) of the type flint pebbles were considered for deletion from the complex data set of artifact locations and from the search for depositional sets. This was done inductively on the basis of a piece of information in the parallel data set: the fact that many of the smaller pebbles were probably of natural, fluvial origin, and thus irrelevant to behavioral reconstruction. Finally, having established the most probably relevant subset structure of the complex locational data and concordant techniques, one of the methods was applied to the data. Twenty-one depositional sets were defined.

In sum, the entry model strategy can be a powerful approach for a researcher to familiarize herself or himself with a complex data set without violating relevant aspects of its structure with some quantitative technique. The strategy allows the researcher to determine the probable general nature of the data set's relevant structure (general knowledge), and thus the technique(s) that are most likely appropriate for its analysis, *without directly analyzing it with some possibly discordant method.* This is accomplished through the examination of

a simple, parallel data set for the processes of formation of the archaeological observables described in the complex data set, rather than through a direct, inductive examination of the many facets of the complex data set's structure using multiple techniques. In essence, the strategy allows one to gain insight into complex data obliquely, by reconstructing the history of their development rather than by affronting them with a technique.

Although the entry model strategy can be more powerful and bring greater concordance between data and technique than the deductive or CEDA strategies, it has a limitation. It requires a good foundation of middle-range theory on the processes that are responsible for the archaeological and behavioral variability of interest, and also processes that are not of interest. As this foundation broadens—in part through the development of entry models themselves—the strategy will become more practicable (see Schiffer 1983).

Stepwise, Cyclical Analytic Designs

A final means for improving consistency among data structure, technique, and theoretical framework during analysis is the well-known stepwise, cyclical process of scientific investigation (Figure 10.4). This process requires repeated analysis of a data set. Each analysis involves modifications of the data, the analytic technique(s), and/or the interpretive framework that guides analysis such that all three approach greater concordance with each other. Modifications of these three entities with each cycle are made in light of: (1) discrepancies between expectable results and those obtained (external inconsistencies), (2) discrepancies between the interpretive implications of different subsets of the results that are obtained (internal inconsistencies), (3) whether the discrepancies increase or decrease from trial run to trial run, and (4) the general knowledge, and ultimately, the detailed knowledge that is gained about the phenomenon of interest and the data's relevant structure. The deductive approach, CEDA strategy, and entry model approach all may be involved in various cycles of analysts.

In short, the stepwise approach to data analysis is a logical process that *simulates*, in serial format, the continuous, simultaneous feedback between data, technique, and theoretical framework that characterizes the mental process of abduction.

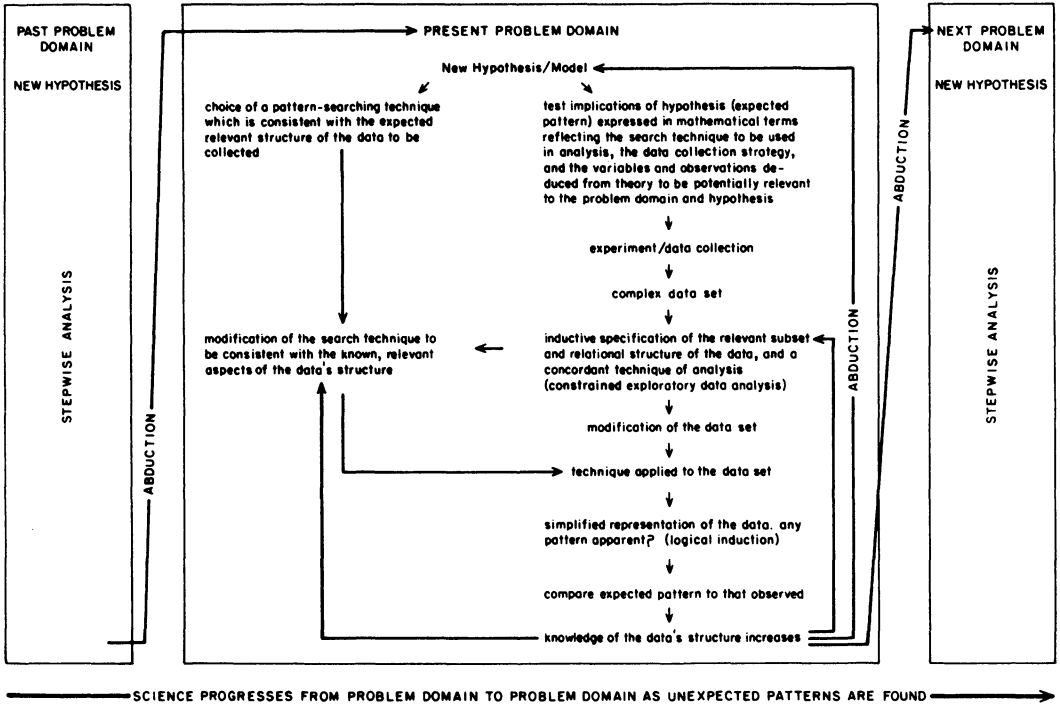

Figure 10.4 The sequential, stepwise, cyclical process of scientific investigation.

Conclusion

Analysis is a complex thought process that requires the researcher to choose appropriate data and techniques if it is to be relevant and accurate. These must be chosen such that the population or process of interest, the data expressing them, technical assumptions about them, and theoretical assumptions about them all concord with each other as much as possible.

In early stages of analysis, this condition is difficult to secure. The researcher may not have narrowed the scope of study to a single phenomenon or may know little about the number or nature of the phenomena that are reflected in the data. Also, any investigation of the data to overcome these deficiencies must be done sequentially, without feedback between the processes of finding pattern and interpreting pattern during any one analytic step. This allows discordance between data structure and technique to occur. The researcher thus has a problem of how to initiate analysis without violating its relevant structure.

Two kinds of relevant discordance can arise between data structure and technique during the analysis of complex data. First, the data may pertain to multiple processes that define multiple populations, whereas the statistical technique of analysis may be based on a model specifying some single process as responsible for the data and some one homogeneous population defined in respect to that process. The data may have multiple relevant subset structures, whereas the technique may assume it to have only one. Second, the employed analytic technique may imply that the phenomenon of interest has an organization that is different from its actual organization and the expression of this in the data. The technique may assume the data to have a relevant relational structure different from the one it has.

Deductive specification of potentially relevant data or techniques using middle-range theory, constrained exploratory data analysis, entry models, and stepwise cyclical analysis can be used to minimize these two kinds of discordance during initial stages of analysis or to reduce them from analytic step to step. These tactics encourage the researcher to explicitly state the single phenomenon that is of interest and its nature or organization, and to justify the data and analytic technique to be used in relation to it, to each other, and/or to theory.

The tactics involve the formalization of *bridging arguments* (Hemple 1966: 72-75) that link phenomenon, data, technique, and theory to each other.

Explicit statement of bridging arguments between these entities and justification of analytic choices is an extremely important scientific activity. Not only does it aid in making specific analyses relevant, accurate, and meaningful, but it goes hand in hand with the refinement of theory and scientific advance generally (e.g., Read 1974). Bridging arguments pertain, in part, to the relevant structure of a data set and the nature of a phenomenon of interest. Their formalization provides a means by which logical inconsistencies and false premises in current theory about a phenomenon are uncovered and new theories can be developed.

In a well-established scientific discipline, bridging arguments that link regularly investigated phenomena, data, techniques, and theories to each other are well known and part of accepted theory and methodology. Though they may be evoked in designing an analysis, it is superfluous to report them in detail. However, in a quickly growing and groping discipline like archaeology, where such bridges are not yet formalized and accepted, it is critical that they be thought about, stated explicitly, and reported openly and systematically for criticism. Only within such a milieu can archaeological knowledge advance in an orderly manner.

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PROGRESS and PROSPECTS

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