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Michael Chibnik

University of Iowa

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THE USE OF STATISTICS IN
SOCIOCULTURAL ANTHROPOLOGY

Michael Chibnik

Department of Anthropology, University of Iowa, Iowa City, Iowa 52242

INTRODUCTION

Sociocultural anthropologists have never used statistics as much as their colleagues in other social sciences. When sociologists (92), political scientists (33), and economists (98) were urging the increased use of statistics in their disciplines in the 1920s, Boas (7, p. 120) was asserting that the success of attempts to apply statistics to ethnographic phenomena was “more than doubtful.” Kluckhohn (73, p. 350) wrote a decade later that the professional folklore included an a priori resistance to any use of statistics; and even as recently as the 1950s, Driver (28, p. 54) stated that anthropologists avoided mathematics and statistics “like the mother-in-law.” Early statistical analyses, moreover, were largely restricted to cross-cultural comparisons (e.g. 29, 58, 90). Although quantitative data were sometimes collected in field work, analyses of such data rarely went beyond tabular presentations and calculations of means and medians.

In the 1950s and 1960s the use of mathematics in sociocultural anthropology increased dramatically (66; 123, pp. 2–5) and statistical analyses of field data became common. While new theoretical and methodological orientations in anthropology (see 62, 91, 96, 97) obviously influenced this increased emphasis on quantification, the changing nature of field work was also important. Whereas most ethnographers in the earlier part of the century tried to provide holistic descriptions of many aspects of culture, by the 1950s research tended to be problem-oriented, emphasizing intensive examinations of particular topics. Since problem-oriented studies often involved the systematic collection of quantitative data, the need for statistical methods of description and inference became apparent. The statistics used in the 1950s and 1960s, however, tended to be rather simple bivariate tests of significance and measures of association rather than the multivariate methods increasingly employed by psychologists.
and sociologists. Reviews of "mathematical anthropology" written at the end of this period (12, 59, 66, 132) emphasized model building and abstract algebra more than statistics. Kay (66, p. xvi) predicted that anthropologists in the future would use abstract algebra more than statistics and speculated that there would be a slight deemphasis on correlational methods and a great deemphasis on tests of significance.

Kay's predictions have not been fulfilled. While algebraic modeling is still occasionally attempted (e.g. 3, 126, 127), the most striking development in mathematical and quantitative anthropology in the past decade has been the increased use of multivariate statistical methods. Computer packages have allowed researchers with limited statistical expertise to use complex analytic methods such as multiple regression, path analysis, and multidimensional scaling. Furthermore, simpler bivariate statistics involving correlation measures and tests of significance are now routinely included in articles in North American journals and are not uncommon in publications elsewhere.

The types of data collected by sociocultural anthropologists conducting field work frequently pose problems for statistical analyses. Samples are usually small, and causal connections between numerous possibly important variables are often complex. The extent of quantification that is possible for many important variables is limited. An excellent book on research methods (97) and a sensible although unfortunately error-riddled text (123) discuss the use of bivariate statistics despite these problems. However, no comprehensive discussion of the use of multivariate statistics by anthropologists has yet been published.

This review of the recent use of statistics by sociocultural anthropologists emphasizes multivariate methods. I begin by discussing (a) how well the assumptions behind statistical tests and measures—especially those concerning sampling, level of measurement, and distribution—apply to data commonly analyzed by anthropologists, and (b) the extent to which such tests and measures can be used when these assumptions are violated. I then discuss problems associated with bivariate analyses. The next and longest section of the essay is a description of some of the multivariate methods most frequently used in sociocultural anthropology. I attempt to characterize these methods in simple, nontechnical language and provide examples of the use of each method. I conclude with remarks about the likely future role of statistics in sociocultural anthropology.

Space considerations preclude an exhaustive coverage of all the ways that sociocultural anthropologists have used statistics. For this reason I restrict my review for the most part to analyses of data collected within single field settings and do not examine problems associated with cross-cultural analyses. I also do not discuss the use of statistics in demography, nor do I treat other techniques either only occasionally used by sociocultural anthropologists (e.g. analysis of
This essay is not aimed at the few statistically sophisticated sociocultural anthropologists. Although such readers may find some of the citations useful, they will be familiar with much of the material and may regard the presentation as insufficiently critical of past statistical sins [for discussions of abuses of statistics in sociocultural anthropology and archaeology see (60, 75, 124)]. Instead, the essay is aimed at the majority of sociocultural anthropologists, who know something about statistics but would like to know more about how they have been and should be used in analyzing data collected in field work.

ASSUMPTIONS OF INFERENTIAL STATISTICS

Inferential statistics are methods and procedures used to make generalizations about a population (universe) from a subset (sample) of the population. The tests and measures that comprise inferential statistics make assumptions about the nature of the sample, the measurement of variables, and the distribution of the data. Introductory texts on statistics and research methods in the social sciences (e.g. 5, 62, 97, 123) characteristically contain statements about the perils of using tests and measures when these assumptions do not hold. Field work conditions and the nature of the variables being examined, however, often prevent sociocultural anthropologists from using data that completely meet such assumptions. Although anthropologists have sometimes been ingenious in devising techniques to overcome some of these difficulties, they have not sufficiently recognized the extent to which many assumptions underlying statistical tests can be relaxed.

Sampling

Inferential statistics require probability samples, where each member of the population has a known probability of being included in the sample. The best known probabilistic sampling method is random sampling, where each member has an equal probability of being selected; other frequently used methods are systematic, stratified, and cluster sampling. Several books (e.g. 62, pp. 54–59; 97, pp. 127–40; 123, pp. 439–40) discuss the special problems sociocultural anthropologists have in obtaining probability samples and the advantages and disadvantages of various sampling methods. Of the techniques devised to overcome sampling problems, Johnson’s (61) method of random visits to examine productive activities is worthy of special note. While this method obviously could not be applied everywhere and can be difficult to use, researchers making random visits have generated useful information about the work activities of commercial Swiss farmers (85), Bolivian “peasants” (130), and remote Peruvian tribal groups (87).
Sociocultural anthropologists usually are inexplicit about what constitutes the population (universe) from which their sample is drawn. In many cases this population is hypothetical. For example, researchers often use inferential statistics to examine interrelationships of variables in villages where every household has been censused. The implicit universe in such cases is sometimes a limited geographical area that includes the village. More often, however, it is a hypothetical universe of all villages and interrelationships that could have existed under similar conditions (19, pp. 366-67; 123, pp. 441-44).

**Level of Measurement**

Observed phenomena can be classified according to their level of measurement (119). Nominal scales simply place observations into categories, ordinal scales rank observations, and interval scales specify the numerical differences between ranked observations. In a famous article, Stevens (119) argued that only nonparametric statistics (those that make no assumptions about distributions of the data) could be used on nominal and ordinal data. Parametric tests and measures such as the t-test, the Pearson correlation coefficient, and multiple regression could be applied only to interval data. The relationship between measurement scale and statistics proposed by Stevens has been accepted by many social scientists and statisticians (e.g., 5, 62, 115).

Sociocultural anthropologists applying statistics seem generally unaware that Stevens’s ideas have not been universally accepted. Stevens has been challenged on the rather abstract grounds that measurement theory and statistics are unrelated since “the numbers do not know where they come from.” (See 40 for a review of this literature.) More importantly, various empirical studies have been interpreted as showing that using parametric statistics on ordinal data does not always cause statistical problems (77, pp. 19-24); and in recent years statisticians have sometimes been willing to use parametric techniques on mixed nominal, ordinal, and interval data (see 18, pp. 171-211).

**Distributions**

Parametric statistical tests usually assume that the variables in the sample and the population are distributed normally. However, variables of interest to anthropologists are often nonnormally distributed. Marriage distances are sometimes leptokurtic (22, 65, 83, 103, 122), most wealth measures are lognormal (116), and the number of wives men have in African societies usually has a negative binomial distribution (118). Moreover, sociocultural anthropologists frequently have little information concerning the shape of the distribution of a particular variable. Since distributions are often either nonnormal or unknown, anthropologists make great use of nonparametric tests and measures such as chi-squares and Spearman correlations.

Parametric tests can often be used even when assumptions about distributions are not met. Assumptions underlying statistical tests can be classified
according to their robustness. The more robust an assumption is, the less the interpretation of the results of the test must be altered when an assumption is not completely met. The assumptions of normality underlying many commonly used parametric tests are quite robust (139, pp. 263–66).

When either parametric or nonparametric tests can be used, parametric tests are usually preferable because they are less wasteful of data. Nonparametric tests, however, have the advantage of being easier to understand and present (97, pp. 161–62). Sociocultural anthropologists occasionally use complex parametric tests when they could make their point more easily with nonparametric tests. An excellent example of this is an acrimonious debate concerning (among other things) whether or not societies with warfare are more likely to have a higher percentage of male children (presumably because of female infanticide) than those without warfare (25, 26, 56, 57). Part of the argument hinges on whether or not data on sex ratios met the assumptions about distributions of the (parametric) t-test. Much of the vituperous and arcane debate that took place in several issues of the *American Anthropologist* could have been avoided if someone had recoded the sex ratio data into categories (e.g. high and low) and then used nonparametric tests and measures such as chi-square, Spearman, and gamma.

**BIVARIATE METHODS**

Most statistical analysis in sociocultural anthropology consists of descriptions of relationships between two variables. Such *bivariate analyses* often have two goals; testing independence and measuring association. Two variables are *independent* if a knowledge of the numerical value (or category in the case of nominal data) of one does not aid in the prediction of the value (or category) of the other. Tests of independence indicate the probability, given sample data, that in the *population* the two variables are independent. If two variables are not independent, they are said to be *related*. Measures of association describe the amount of relationship in the *sample* between the two variables.

The selection of an appropriate test of independence and measure of association is partially determined by the level of measurement of the data. Although many of the issues I examine pertain to interval and ordinal statistics, I restrict my discussion here to independence tests and measures of association for nominal level data. Sociocultural anthropologists very often use such data but are frequently unaware of certain fundamental analytic problems.

**Tests of Independence**

Cross-tabulations (contingency tables) of two variables are a staple feature of social science publications. Each variable is divided into two or more categories, and frequencies (counts) are presented of the numbers in the sample under examination that fall into each possible cross-classification of categories.
Either the chi-square or (less often) the Fisher exact test is ordinarily used to test independence.

If two variables are independent, fairly simple calculations (see any introductory statistics text) provide the expected frequencies in each cell of a contingency table. Observed frequencies ordinarily will not exactly match the expected frequencies because of chance fluctuations. If, however, observed frequencies differ enough from expected ones, the two variables are likely to be related. The familiar chi-square test indicates the probability that differences between observed and expected frequencies in a sample could be the result of chance fluctuations. Books on research methods (e.g. 97, pp. 162–63) usually recommend that a significance level be set prior to calculating the chi-square. If the probability of chance occurrence of differences between observed and expected frequencies in the sample is less than or equal to the significance level, the researcher concludes that the variables are related in the population. In practice, researchers often set no significance level in advance and report the probability (e.g. “significant at the .01 level”) that a result could have occurred by chance.

There exists a vast literature on the use and abuse of significance tests (e.g. 19, 89), and common mistakes are routinely pointed out in introductory texts (e.g. 97, pp. 162–64; 123, pp. 459–68). Nevertheless, two errors are so prevalent in the anthropological literature that they bear yet another mention here.

The single most common error made by social scientists making statistical analyses of nominal data is the combined overemphasis on independence tests and underemphasis on measures of association. Independence (significance) tests provide information about whether differences from chance exist, but say little about the magnitude of such differences. The reason for this is that any fixed significance level means something quite different for a large sample than for a small one. Fairly minor proportional differences between observed and expected frequencies will be significant for large samples and fairly large proportional differences will not be significant for small samples. Nevertheless, of 19 articles in the American Ethnologist from 1974 to 1983 in which researchers used chi-square or Fisher tests on nominal data collected in the field, only 2 provided measures of association indicating the magnitude of differences between observed and expected frequencies.

Another pervasive mistake found in statistical analyses by anthropologists (and other social scientists) is an overemphasis on avoiding “Type I” error and an underemphasis on avoiding “Type II” error. Researchers making statistical tests examine data in attempts to reject a null hypothesis and accept an alternative hypothesis. A Type I error is incorrectly rejecting the null hypothesis, while a Type II error is incorrectly rejecting the alternative hypothesis (see 19 and 123, pp. 212–17 for lucid detailed discussions). Social scientists typically use chi-square and other statistical tests to calculate the level of
significance, the probability that a Type I error has been made. By insisting that results attain a certain level of significance (usually \(0.05\)), journal editors and article reviewers insure that not many Type I errors are made. Unfortunately, researchers, editors, and reviewers almost never comment on Type II error, the probability of being too conservative in interpreting results. For the small samples of 20–60 cases characteristic of much field research, a mandatory or recommended significance level of \(0.05\) insures that the probability of Type II error will be high. (The size of this probability depends on the “power” of the statistical test being used.) As Siegel notes (115, p. 10), researchers setting significance levels should reach some compromise that optimizes the balance between the probabilities of making Type I and Type II errors. Sociocultural anthropologists seem to make little effort to seek such a compromise.

** Measures of Association

Since anthropologists frequently calculate Pearson and Spearman correlations for interval or ordinal data, their reluctance to calculate measures of association for nominal data cannot be entirely attributed to their overemphasis on tests of significance. Another reason for their reluctance may be the plethora of association measures of nominal data [“literally dozens” (105, p. 14)] and various theoretical and methodological problems associated with their use (for details see 43–46, 105).

Association measures can be either symmetric or asymmetric. If theory or common sense suggests that one variable causes the other, asymmetric measures should be used; otherwise, symmetric measures are preferable. Lambda (38, pp. 71–78), and tau (105, pp. 41–45) are examples of asymmetric measures; phi-squared (123, pp. 419–23), the odds ratio (105, pp. 20–27), and the contingency coefficient (115, pp. 196–202) are examples of symmetric measures. Association measures can also be classified according to their statistical basis. Some are based on the odds ratio, others on chi-square, and still others on how well cross-classifications can be predicted (105, pp. 29–45).

The principal difficulty of most measures of association for contingency tables is that marginal distributions (row and column totals) affect their numerical values. Two tables with different marginal distributions will not produce the same numerical value of association even when they record the same underlying relationship. Two common solutions to this problem are standardizing tables via an iterative procedure (4, pp. 83–102) and calculating the ratio of the numerical value to the maximum possible value, given the marginal distribution (105, pp. 18–19).

**MULTIVARIATE METHODS**

The holistic orientation characteristic of sociocultural anthropology often leads researchers to collect data systematically on many interrelated variables. Two
related difficulties hamper efforts to analyze such data. First, there are problems in describing the relationships between pairs of variables because of the confounding effects of other lurking variables. Second, simplification of data frequently is useful since numerous variables on which information has been collected seem to measure the same thing.

The recent availability of "canned" computer packages has enabled an increasing number of anthropologists and other social scientists to employ a variety of complex multivariate techniques to control for confounding or lurking variables and to reduce or simplify data. Multiple regression and path analysis are the methods sociocultural anthropologists have most often used in their efforts to untangle interrelated variables, while cluster analysis (numerical taxonomy), factor analysis, and multidimensional scaling are the most commonly used data-reduction techniques.

Biological anthropologists and archaeologists have used multivariate techniques more extensively and for a longer time than sociocultural anthropologists. In both of these anthropological subfields articles appeared some years ago (74, 124) decrying the uncritical use of these methods. Problems were noted that arose from both the complexity of multivariate methods and the relative lack of statistical expertise among most biological anthropologists and archaeologists. Multivariate methods have been inappropriately or unnecessarily used, and the results of even well-done published analyses can often be understood by only a small fraction of the readers. As a result inept, pretentious, incomprehensible, and overly complicated analyses have frequently passed the not-so-critical scrutiny of journal and book referees and have been published. (See 60, 112, 124 for discussions of this issue.) Since sociocultural anthropologists as a group are less knowledgeable about statistics than their colleagues in biological anthropology and archaeology, the possibility of similar problems is obvious.

Although it would be easy to compile a catalog of abuses of multivariate statistics by sociocultural anthropologists, I have chosen not to do so here. I do agree with Thomas (124, p. 241), however, that multivariate techniques should be used only after simpler analytic methods have been fully investigated. The danger of using multivariate statistics to obfuscate rather than to clarify is ever present.

Controlling for Confounding Variables

Statisticians have devised three basic methods—randomization, elaboration, and residualization—to "control for" confounding variables when examining bivariate relationships (139, pp. 150–78). The use of randomization is ordinarily restricted to experimental research in which subjects can be assigned randomly to different experimental treatments. Although randomization is common in medicine and psychology, the nonexperimental nature of almost all sociocultural anthropological research generally rules out the use of this
method. Elaboration, however, is frequently used in sociocultural anthropology (e.g. 15) and is the simplest and most straightforward way to control for the effects of specific confounding variables. Elaboration involves examining the association between two variables within separate categories of a third (and possibly confounding) variable. Suppose, for example, that a researcher wishes to examine the relationship between number of household consumers and annual cash income in a multiethnic community. Using elaboration, the researcher can control for any confounding effects of ethnicity by examining the bivariate relationship separately for each ethnic group.

Although elaboration makes possible perfect control of specific third variables, application of the technique to several third variables is difficult (139, p. 153). The number of tables required multiplies rapidly as the number of variables controlled for increases, and there may not be enough observations in every table to allow reliable conclusions to be drawn. This problem is especially important in sociocultural anthropology, where sample sizes are typically small.

In situations where there are too many confounding variables and/or too few cases for elaboration to be used, researchers can control statistically for the effects of several third variables by using "residualization" (139, pp. 154–78). Two techniques employing residualization frequently used by sociocultural anthropologists are multiple regression and path analysis. A third technique, which has not often been used by anthropologists despite certain advantages, involves the use of log-linear models.

MULTIPLE REGRESSION Anthropologists commonly wish to analyze the relationship between a dependent variable and several independent (or predictor) variables. For example, a researcher might wish to compare the relative importance of number of consumers, land holdings, and ethnicity in predicting the annual cash income of a "peasant" household. The researcher might also want to determine how well a household’s annual cash income can be predicted from a knowledge of these variables.

Multiple regression is a statistical technique that provides the linear equation of independent variables that best predicts the dependent variable. The multiple correlation coefficient is a measure of the predictive accuracy of this equation. The multiple regression equation is frequently calculated after all variables have been transformed so that each has a standard deviation of one. For such standardized multiple regression equations of the form \( Y = A + b_1X_1 + b_2X_2 + \ldots + b_nX_n \) (where \( Y \) is the dependent variable, \( A \) a constant, and the \( X_i \)s independent variables), the \( b_i \)s are called standardized regression coefficients. The magnitude of any particular \( b_i \) is a measure of the relative importance of \( X_i \) in predicting \( Y \).

Hirschfeld’s (55) analysis of aesthetics among the San Blas Cuna of Panama
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illustrates well how multiple regression can be applied to anthropological questions. The Cuna produce molas, rectangular panels of reverse appliqué worn by women on the front and back of indigenously made blouses. One question Hirschfeld was interested in was the criteria Cuna used to rank the aesthetic quality of mola designs. He asked 20 women to view 34 color reproductions of molas and pick the three they liked best. The dependent variable in Hirschfeld’s analysis was the number of times a particular mola was chosen. Most of the independent variables were various design features. Hirschfeld was able to generate a regression equation with a high multiple correlation coefficient. He also presented standardized regression coefficients showing that “density” (a measure of complexity) and asymmetry predicted mola preference better than most color features analyzed.

Sociocultural anthropologists have used multiple regression most often (35, 41, 82, 99, 100, 135) to examine the determinants of various measures of economic productivity or wealth. Somewhat controversial economic analyses employing multiple regression have also been made of the determinants of bride price in Nigeria (48) and the number of wives of Palestine men in the nineteenth and early twentieth centuries (95). Other sociocultural applications have been diverse, including examination of the determinants of leadership among Mayas in Chiapas (125), male bias in remembering kin among Belgrade factory workers (50), propensity to adopt innovations among Maine fishermen (1), “deferred gratification orientation” among the Buganda (102), and traditional beliefs about disease causation among “Rhodesian” students and teachers in training (86).

Although multiple regression has conventionally been restricted to intervally measured variables, in recent years statisticians have come to accept the use of the technique on ordinal and even nominal independent variables. This has been done through the use of dummy variables, in which one or more dichotomous variables (values at 0 or 1) are established for each nominal scale (see 18, pp. 171–211). The expansion of multiple regression to include variables measured nominally and ordinarily has greatly increased the technique’s applicability in sociocultural anthropology, where many variables of interest (e.g. ethnicity, place of residence, sex) cannot be measured intervally. Multiple regression, however, should not be used if the dependent variable is measured nominally. In such circumstances, discriminant analysis, an analytic method rarely employed by sociocultural anthropologists, is appropriate.

Multiple regression assumes that the underlying relationships among variables are linear and additive. Anthropologists (35, 41, 99) have sometimes borrowed techniques from economists to make logarithmic transformation of variables that convert nonlinear relationships into linear ones (see also 18, pp. 242–61). Although methods exist (18, pp. 291–337) to apply multiple regression in certain situations where relationships among variables are nonadditive,
Sociocultural anthropologists have generally assumed additivity even in situations where it might not be reasonable.

Several technical problems can arise when nonstatisticians attempt multiple regression analyses. Anthropologists and other social scientists often use the "shotgun approach," investigating a large number of independent variables in order to ensure that substantive issues are well covered and no important factors are overlooked. However, Cohen & Cohen (18, p. 160) note that "having more variables when fewer are possible increases the risks of both finding things that are not so and failing to find things that are." Another problem arises from multicollinearity, when some or all of the independent variables are highly intercorrelated. A paradoxical situation occurs. The more strongly related the independent variables are, the greater the need to control for confounding effects. However, the greater the intercorrelation of independent variables is, the less reliability can be placed on the relative importance indicated by the standardized regression coefficients (69, pp. 340–41). Finally, there are several methods of multiple regression analysis, each of which can give different results. The uncritical use of "stepwise regression," the method most often used by sociocultural anthropologists, has been cogently criticized (18, pp. 102–4).

**Path Analysis**

Social scientists examining the effects of several independent variables on a dependent variable are often willing to make fairly specific assumptions about causality. In such circumstances path analysis is more informative about relationships among variables than multiple regression. Path analysis was developed over 60 years ago by the geneticist Sewall Wright (137) and was introduced to sociologists by Boudon (8) and Duncan (30) and to anthropologists by Haddon & DeWalt (49). Within sociology the technique, described as being of "almost revolutionary importance" (10), has been applied extensively, if somewhat indiscriminately (84). Substantive applications in sociocultural anthropology (23, 24, 31, 51, 52, 63, 67, 94, 120, 125), while hardly routine, are not uncommon.

Path analysis requires that the researcher create a model of explicit causal relations among the variables being considered. This usually involves a series of weak causal orderings in which variable $X_1$ may or may not affect variable $X_2$, but $X_2$ cannot affect $X_1$. However, path analysis has also commonly been carried out when there is noncausal (within the confines of the model) correlation between certain variables (see some of the examples in 49) and occasionally (although not in sociocultural anthropology) where there is mutual causality among some variables (see 2, pp. 50–61). Path analysis assumes "causal closure" (see 69, p. 385), certain constraints on the direction of hypothesized causal effects or paths (see 2, p. 33; 138), and the same assumptions about linearity and additivity as multiple regression.

Path analysis has two major advantages when compared to multiple regres-
sion (49, p. 106). First, the technique forces a researcher to be more explicit about theoretical assumptions concerning causality. Second, path analysis allows systematic examination of the effects of intervening variables in a causal model. A bivariate correlation between variables \(X\) and \(Y\) (where \(X\) is causally prior to \(Y\)), for example, can be “decomposed” into three components (49, p. 112). There are direct effects of \(X\) on \(Y\), indirect effects of \(X\) on \(Y\) via one or more intervening variables, and the joint effects arising either from unanalyzed correlation or when a single causally prior variable \(Z\) exerts direct or indirect effects on \(X\) and \(Y\) and thereby causes them to vary concomitantly.

Thomas’s (125) study of the sociocultural determinants of political leadership in a Tojolabal community in Chiapas, Mexico, illustrates the advantages of path analysis. Using “action theory,” Thomas assumed that wealth, family size, and number of friends were causally prior to leadership. Employing stepwise multiple regression, Thomas found that wealth was the most important of the independent variables in predicting leadership, followed by family size and number of friends. Thomas thought, however, that the multiple regression provided an incomplete picture of relationships among the variables because of the effects of family size and wealth on the number of friends a man had and the effects of family size on wealth. Using path analysis, Thomas not only was able to compare the direct effects of family size, number of friends, and wealth on leadership (as with multiple regression) but also could assess the indirect effects of family size on leadership via the intervening variables of wealth and number of friends. He concluded that family size, because of its substantial indirect causal effects via the intervening variables, was a more important determinant of leadership than was indicated by multiple regression.

Not long after path analysis was introduced to sociologists, enthusiasm in the field became so great that one editor announced his journal would not accept “mindless” applications of the technique (114, p. 13) and critics suggested many articles were more exercises in data manipulation than examinations of substantive, theoretically grounded models (84, p. 200). Similar problems have not arisen in sociocultural anthropology, where path analysis seems to be underused rather than overused.

LOG-LINEAR MODELS  Social scientists often confront great difficulties in analyzing contingency tables involving more than two variables. Consider, for example, a situation in which a researcher wishes to examine the interrelationships among three nominal variables, \(A\), \(B\), and \(C\). A few of the several possible relationships that might exist are: 1. All three variables are independent of one another; 2. \(A\) and \(B\) are related (not independent), but both are independent of \(C\); 3. \(A\) and \(B\) are related for some categories of \(C\), but are independent for other categories of \(C\) (this is called an “interaction” effect); and 4. \(A\), \(B\), and \(C\) are all related to one another, but there are no interaction effects.
Although techniques such as analysis of variance and multiple regression have enabled statisticians to unravel possible confounding relationships for interval-level data, until recently the prevailing methods (involving elaboration) for analyzing categorical data have not been satisfactory in situations where there are more than a few variables, especially when sample sizes are small (105, pp. 53–56).

In the past two decades statisticians have made great progress in analyzing discrete multivariate data (see 4, 34, 42, 105). One technique that has been developed, log-linear models, is said to "put the investigation of nominal data on a par with the study of interval-level variables" (105, p. 57). The goal of this analytic method is to develop a linear equation, with logarithmic terms, that accounts for the observed frequencies of cross-classifications. The results of a log-linear analysis allow a researcher to determine whether or not particular variables are independent of one another and whether or not interaction effects exist (for details see 4; 34; 105, pp. 57–81). They can also be used (with some difficulty) to evaluate the comparative strength of various relationships (105, p. 59).

Log-linear approaches are beginning to be used in sociocultural anthropology (36, 88, 121) to evaluate competing models of interrelationships among nominal variables. For example, Fleuret & Fleuret (36) were interested in the relationships among hereditary caste, father's occupation, and son's occupation for overseas Sikhs in Tanzania. They used log-linear methods to show that there are relationships between father's occupation and caste and between father's occupation and son's occupation, but not (controlling for the aforementioned effects) between son's occupation and caste.

Although log-linear analysis has clear advantages and should be considered by sociocultural anthropologists analyzing numerous categorical variables, the technique is not easy for nonstatisticians to use, present, and understand. Contingency tables used in elaboration, in contrast, can be understood by many anthropologists with little statistical background. When only three variables are being analyzed, simpler methods such as elaboration may be preferable to log-linear approaches.

**Data Reduction**

The goal of descriptive statistics is to summarize data by substituting a few measures for many numbers. Such reduction or simplification inevitably involves the loss of information but has the great advantage of enabling researchers to more readily see what is in the data (5, p. 4). Means, medians, and standard deviations are familiar descriptive statistics that reduce data to manageable proportions.

Multivariate descriptive statistics are most often used to reduce a data matrix, a rectangular array of cells. The rows of the matrix are cases (entities),
while the columns are variables (attributes, characteristics) on which data have been collected for each case. The cell values consist of nominal, ordinal, or interval measurements for specific combinations of cases and variables. For a census, cases might be households, with four variables being the number of males, females, people over 18, and people under 18. One cell entry would be the number of females in a particular household censused.

Researchers using multivariate data-reduction techniques generally begin by constructing measures of similarity between pairs of rows or columns. Pearson correlation coefficients are commonly used when data are intervally measured, but there are many other measures of similarity (proximity). These measures are then used to divide cases or variables into fairly homogenous groups. Members of each group are similar to one another and dissimilar to members of other groups. Descriptive statistics are then used to measure the extent of intergroup and intragroup similarities and differences. Multidimensional visual representations ("maps") are sometimes also used to show the distances (amounts of dissimilarity) between all pairs of cases or variables.

Cluster analysis is the technique most commonly used in sociocultural anthropology to delineate groups of similar cases, while factor analysis is the method most often used to lump variables into groups. Multidimensional scaling, a method creating visual representations of distances, has frequently been used on both cases and variables.

Cluster analysis The goal of cluster analysis (numerical taxonomy) is to subdivide a number of cases (or occasionally variables) into homogenous subgroups. These subgroups are frequently arranged hierarchically. The construction of nonintuitive typologies simplifies observations with a minimal loss of information and may contribute significantly to an understanding of the problem studied (79, pp. 3–4). Cluster-analytic techniques can be used on nominal, ordinal, and interval data and in situations where some attributes (variables) are measured nominally while others are measured on ordinal and interval levels.

When a cluster analysis is carried out, a similarity index is chosen that summarizes multiple measures of differences between cases. Using the matrix of similarity indexes of each pair of cases, a clustering technique is used to create groups of similar cases. There is no consensus about which similarity indexes and clustering techniques are most appropriate in particular situations, primarily because of different ideas about what forms an "acceptable" classification (6, p. 281).

Although cluster analysis was first used in sociocultural anthropology over 50 years ago (29), the technique was not widely employed in any social science until the 1960s (6, p. 28). Biological anthropologists (e.g. 9, 54, 93) rapidly began using the method after the publication of Sokal & Sneath’s influential
book (117) on the application of cluster analysis to biological taxonomy. Archaeologists (e.g. 17, 27, 104), no doubt because of their great interest in morphological typology, also were quick to adopt the technique. Although some archaeologists do not like cluster analysis (16, 124), numerical taxonomy is so common in the field that it has been (unenthusiastically) referred to as a "highly visible bandwagon" (124, p. 236).

In contrast to researchers in other subfields, sociocultural anthropologists have only occasionally applied cluster analysis to their field data. The method has been used to isolate Navajo household economic types (136) and to classify games in the Yucatan (129) and military pilot errors in the United States (108). Most applications (e.g. 37, 80, 128, 134), however, have been psychologically and linguistically oriented, often using a clustering technique developed by a psychological anthropologist (20). White's study (134) of psychological characteristics of status types on Santa Isabel in the Solomon Islands is a good example of this kind of application. White asked 29 middle-aged men about the personality traits associated with 10 types of "Big Men." From a corpus of 37 terms and phrases commonly used to describe personal traits, each informant selected 8 "appropriate" and 8 "inappropriate" attributes for each status type. White used the data to create a similarity index of status types. He then isolated two clusters that seemed to correspond to an overall contrast of mission- and government-related statuses and also isolated various subclusters (e.g. priest and bishop, catechist and teacher) within the larger clusters.

The results of a cluster analysis can be difficult to interpret. There is often no obvious label to put on the clusters of cases lumped together. These interpretive difficulties and the arbitrariness associated with choices of similarity indexes and clustering methods are the major nontechnical problems associated with the use of numerical taxonomy.

**FACTOR ANALYSIS** Anthropologists and other social scientists frequently collect information about many interrelated variables for a number of cases. Researchers often suspect that some variables are redundant since they are measures of more or less the same thing or dimension. For example, a household economic survey in a peasant community might ask three separate questions about ownership of bicycles, radios, and kerosene stoves. The ownership of any one of these items might correlate highly with ownership of the other two and reflect overall wealth.

Factor analysis is the technique social scientists most often use to reduce data redundancy. Factor analysis was developed by the psychologist Spearman in an attempt to see how many dimensions underlie variables measured on so-called "intelligence tests." There exists a well-developed, mathematically sophisticated literature on the assumptions, methodology, and interpretation of factor analysis (e.g. 53, 70, 71, 111).
The fundamental assumption of factor analysis is that one or more underlying "factors" are responsible for covariation among variables (71, p. 12). Given an array of correlation coefficients for a set of variables (or occasionally cases), factor-analytic techniques reduce data to a smaller set of factors, which may be taken as source variables accounting for observed interrelationships (68, p. 469). The results of analysis include a list of factors, the "loadings" (correlations) between each individual variable and each factor, and the percentage of total variance accounted for or resolved by each factor.

Factor analysis has primarily been used in sociocultural anthropology to explore data (e.g. 23, 32, 52, 81, 86, 101, 102, 106, 107). The technique enables researchers to get some idea how much redundancy is in their data and to simplify statistical operations such as multiple regression by using factors instead of a myriad of confounding variables. After examining the particular variables loading highly on the different factors, researchers often attempt to improve their understanding of the data by labeling (giving names to) factors.

DeWalt's examination (23) of agricultural innovation in a peasant community in Mexico illustrates the exploratory use of factor analysis. "Development agents" had been working to increase productivity of corn and to change the region to a dairy economy. DeWalt therefore expected that innovations related to corn production (the use of fertilizers and tractors) would be adopted as a unit and that other innovations related to livestock production (e.g. sowing forage crops and vaccination of animals) would also be adopted as a set. A factor analysis of innovations, however, resulted in the identification of four factors (explaining 69% of the variance) rather than two. Furthermore, innovations associated with corn production were found in several factors, as were innovations associated with livestock. DeWalt was thus able to show via factor analysis that adoption strategies in the community were not what he had initially hypothesized.

Several serious problems limit the usefulness of factor analysis. There is no consensus about which of the many factor-analytic methods is most appropriate, and the results of the various methods differ. For instance, psychologists using different analytic techniques disagree sharply about the extent to which one factor (labeled "general intelligence") can explain the results of mental testing (47, pp. 234–320). The results of factor analysis, moreover, are often difficult to interpret. The labeling of factors is something of an art, and the literature is full of statements such as "this factor . . . link(s) such strange bedfellows as travel and brutality" (32, p. 239) and "the third factor is difficult to define . . . it seems to represent an alternate line to the classical gods of the Hindu pantheon" (107, p. 138). That factor analysis is not based in theory may be one cause of its hard-to-interpret results. As Gould (47, p. 316) notes, "the choice of factor analysis as method records the primitive state of knowledge in a field. Factor analysis is a brutally empirical technique, used when a discipline
has no firmly established principles, but only a mass of crude data, and a hope that patterns of correlation might provide suggestions for further and more fruitful lines of inquiry."

MULTIDIMENSIONAL SCALING  The data used in multidimensional scaling consist of a number of items (either cases or variables) and measurements of the distances between all pairs of items. The goal of multidimensional scaling is to produce a map in which each item is represented by a point near the points of other similar items. When maps have three or fewer dimensions, visual representations are often made to aid researchers in their data interpretations.

Perfect correspondeces between map distances at low dimensions and measurements of distances (proximities) are rare because of errors and noise in the data. Suppose, for example, that items are cities and proximities are averages of several informants' statements about the distances between pairs of cities. Informant disagreement and error will likely result in a two-dimensional map that does not quite match either mean perceived or real distances.

One measurement of how well a particular configuration of points fits the data is the stress associated with the configuration. The map of best fit in one dimension will have more stress than the map of best fit in two dimensions, which will have more stress than the map of best fit in three dimensions, and so forth. There are no fixed rules for selecting the number of dimensions, but two relevant considerations are that the amount of stress should not be "too high" and that dimensions should not be added if they do not reduce stress much (76, pp. 23–27).

Once a map is created, the researcher must choose the axis for each dimension. This choice can be handled objectively via multiple regression, but the interpretation of each dimension remains problematic. Although factor analysis and multidimensional scaling make different mathematical assumptions and yield different results (111, pp. 190–191, 507–513) the substantive meaning of and interpretive problems associated with factors and dimensions are similar.

Multidimensional methods have been developed for both metric (intervally measured) and nonmetric distances. One of the greatest attractions of multidimensional scaling for sociocultural anthropologists is the possibility of using the technique where distances can be compared in magnitude but not given numerical value. Multidimensional scaling, sometimes in conjunction with hierarchical cluster analysis (e.g. 20, 80, 108, 134), is the multivariate data-reduction method most often used in sociocultural anthropology.

Although multidimensional scaling can be applied to a variety of distance measures (see 76, 109), sociocultural anthropologists have almost always used the technique to analyze informants' perceptions of similarities and differences. Topics examined include disease terms (21, 39, 131), occupations, roles and statuses (11, 14, 134), kin terms (78, 110), personality traits (13, 72, 133,
134), pottery types (63), ethnic groups (113), and pilot errors (108). Attempts are sometimes made to compare the mental maps of various subgroups in the sample (e.g. 13, 21, 32, 72).

Lutz’s analysis (80) of emotion words on Ifaluk in Micronesia is a clearly presented recent use of multidimensional scaling. She asked 13 informants to sort 31 emotion words (identified as “about our insides”) into piles of similar words. Pairs of words were given a similarity score according to how many times they were put into the same pile. A multidimensional scaling of these scores gave a two-dimensional result with low stress. Lutz provides a visual representation of her results (80, p. 121), with circles around groups identified with a cluster analysis. She concludes from the position of terms on axes that one dimension represents a pleasant/unpleasant continuum while the other indicates ego’s power or strength compared to other actors in an emotion-eliciting situation.

The major advantage multidimensional scaling has over other methods of multivariate data reduction is the possibility of visual representation when there are three or fewer dimensions. When analysis results in four or more important dimensions (e.g. 32, p. 226), this advantage disappears and factor analysis, with better-known mathematical properties, may be preferable.

FUTURE DIRECTIONS

The growing interest in intracultural variation (96) and systematic research design (62, 97), an increased demand for rigor by funding agencies and scholarly journals, and the availability of easily used computer packages all make it likely that sociocultural anthropologists will use statistics in the future more than they do now. The use of bivariate statistical methods to analyze data collected in the field is already routine in North America, if not elsewhere, and the application of multivariate methods is increasing rapidly. The lack of statistical expertise of most sociocultural anthropologists and the experiences of other anthropological subfields (74, 112, 124) suggest that multivariate applications will sometimes be incompetent and that researchers will occasionally overemphasize methodology and underemphasize substantive importance.

The eclectic methodology employed by sociocultural anthropologists makes it unlikely that they will ever use statistical methods as much as their colleagues in psychology and sociology. The heavy reliance by psychologists on laboratory experiments and by many sociologists on mass surveys has necessitated extensive and sophisticated use of statistical methods in those fields. Sociocultural anthropologists, however, rarely experiment, and they use surveys as only one of many research tools in their efforts to gain in-depth holistic understandings of particular cultural processes. The use of qualitative methods
of data analysis such as the presentation of detailed case studies and life histories is one way in which sociocultural anthropology is distinct from other social sciences. Almost all sociocultural anthropologists, including those most committed to the use of statistical methods (e.g. 62, pp. 9–12; 97, pp. 67–77), regard qualitative data-analytic procedures as essential.

The diverse subject matter and theoretical breadth of sociocultural anthropology also insure that statistical methods will continue to comprise only part of the set of many useful research tools. Topics such as religion, law, and economic and political dependency are ordinarily not examined by statistical analyses of quantitative data. Moreover, theoretical approaches such as symbolism, structuralism, and Marxism make quite limited use of statistical analysis.

Nevertheless statistical methods are becoming increasingly important to sociocultural anthropologists. Many anthropology departments already require graduate students to take an introductory statistics course, and more are likely to do so in the future. Such requirements are reasonable since even sociocultural anthropologists who do not use statistics in their own work need to know something about them to understand much important current research.

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