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Cultural Transmission and the Analysis of Stylistic and Functional Variation

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The analysis of formal variation among artifacts has a long history in archaeological research. For example, in the earlier part of the twentieth century the study of stylistic variation in artifacts over time and space was central in culture-historical reconstructions (e.g., Cressman et al. 1940; Heizer and Fenenga 1939; Jennings 1957; Kidder 1931; Kroeber 1919; Nelson 1916), and the artifact sequences that were created continue to form the backbone of much of our research (Lyman et al. 1997). Similarly, considerable effort was expended in interpreting variation as it relates to form and function, that is, what variation in form can tell us about variation in behavior (e.g., Bennett 1943, 1944; Steward and Setzler 1938). The study of variation continues today, with many evolutionary (e.g., Bettinger and Eerkens 1997, 1999; Bettinger et al. 1997; Lipo et al. 1997; Lyman and O'Brien 2000; Neiman 1995; Shennan and Wilkinson 2001) and behavioral (e.g., Schiffer and Skibo 1997; Skibo and Schiffer 2001; Stark 1998) approaches centering on variation.

Most of these studies focus attention on central tendency, that is, on the propensity of artifacts to vary in their average shape and size, particularly over time and space. Such research has provided powerful insights into prehistoric behavior and the evolution of human material culture. In this chapter we redirect attention to an equally important but much-less-studied topic, namely, dispersion, or variation around central tendencies. We believe such a focus is particularly valuable because formal cultural transmission theory (e.g., Boyd and Richerson 1985; Cavalli-Sforza and Feldman 1981) can be used to derive quantitatively rigorous predictions about change in dispersion over time. Thus, instead of using variation to help determine time or artifact function (as in culture history or functionalism), cultural transmission models can be used to generate hypotheses about variation.

Here we apply ideas from cultural transmission theory to help tackle a problem that has long concerned archaeologists, the difference between "style" and "function." Over the last 30 years these two concepts have generated considerable debate (e.g., Binford 1989; Bleed 1986; Braun 1995; Bronitsky 1986; Dunnell 1978a; Franklin 1986, 1989; Neiman 1995; Neitzel 1995; O'Brien et al. 1994; Sackett 1977; Schiffer et al. 1994; Sinopoli 1991; Voss and Young 1995; Wiessner 1983, 1984, 1990; Wobst 1977; see also chapters in Hurt and Rakita 2001), much of it centering on the definition of style and function and how they are patterned in the archaeological record. The lack of agreement on what these concepts are and are not, especially "style," and how they operate may account for some of the recent arguments in our field (e.g., Hurt et al. 2001; Ortman 2000, 2001). In many ways, the authors of these debates seem to be talking past one another, each employing a different conception of style and the processes that influence artifact variation. As O'Brien and Leonard (2001) point out, some of the confusion may relate to the conflation of function with purpose.

Additionally, many investigators make assumptions about what classes of data (e.g., artifacts, attributes on artifacts) ought to be stylistic or functional before they begin their analysis—for example, assuming decorations on pots are selectively neutral. Moreover, such a viewpoint necessarily assumes that objects are exclusively the product of one process or the other, an assumption we believe does not accurately reflect the nature of material culture (see also Franklin 1989). There has been little work (but see Allen 1996; Neiman 1995; Rick 1996; VanPool 2001) in which explicit criteria are set forth objectively to identify that fraction of variability in material culture that results from what we commonly call style and to segregate it from the complementary fraction contributed by what we commonly call function—or to distinguish either of these from variation that is simply random. These issues have prompted some archaeologists to suggest that we drop the terms *style* and *function* from our analyses and descriptions (Schiffer and Skibo 1997; Skibo and Schiffer 2001).

In the sections below we attempt to show how we can devise quantitative models to bypass some of these issues by focusing on measurable variation in artifact assemblages instead of using vague concepts of style and function. Ultimately, some of the patterns we observe can be related back to the specific conceptions of style and function that have been put forward by previous researchers. However, the real focus is on linking artifact variation to different ways in which cultural information is transmitted through space and time. In this line, we follow the work of Neiman (1995; see also Bentley and Shennan 2003; Shennan and Wilkinson 2001), where predictions are offered about empirical patterning in artifacts to diagnose the operation of different transmission processes. Our main concern is differentiating between variation that is affected mainly by physical (engineering) constraints, which we call "function," and variation that is affected mainly by social constraints (signaling or information bearing), which we refer to as "markers," though some would call this "style." We recognize that both physical constraints and markers may or may not be subject to some type of "selection" but certainly are subject to the influences of different cultural transmission processes (Bettinger et al. 1997).

THE MODEL

Our model can be applied to any artifact attribute measured on a continuous scale and involves the analysis of variation, more explicitly, attribute central tendency and dispersion. However, we note that large samples of artifacts described by discrete attributes can be transformed into a suitably amenable form. Our model does not rely on conventional wisdom regarding attribute nature—for example, that large and visible attributes express emblemic information, whereas small-scale, less visible ones express individual preference, and still others are related only to design or mechanical constraints. Rather, it infers these differences from patterning over time and space in the attributes themselves. As such, the model can be used to test such notions rather than assuming them to be true.

We argue that different processes guiding the transmission of cultural traits, whether selectively neutral or conferring adaptive fitness, will leave behind distinctive signatures in measures of artifact variation. Thus, artifacts or attributes used to mark group identity ("emblemic markers" following Wiessner [1983, 1984] and Greaves [1982]) should pattern differently than those used as markers to establish individual identity within a group ("assertive markers"; see below). Similarly, attributes constrained by engineering principles, often referred to as "fitness conferring," will have different signatures depending on whether they are context dependent. For example, the requirement that skinning tools in general be sharp is more or less context free in a way that skinning knife length is not, varying in accord with such things as raw material availability and the size of the animal being skinned.

Definitions

Consider a region with three site-specific assemblages containing a particular projectile point form in equal quantity. Assume further that each assemblage represents a different social group of constant, equal size and that the assemblages are equivalent in time and preservation. Given these heuristic assumptions, imagine that we measure a major attribute, say length, and obtain a mean and standard deviation for each assemblage, giving us three assemblage means and three assemblage standard deviations. From these we can obtain three useful measures of attribute variability within and between our three assemblages. Together, these three measures capture different aspects of the strength of the forces that produced variation in projectile point length.

The standard deviation of the three assemblage means provides a measure of between-assemblage differences in the location of the mean (the differences in mean length from assemblage to assemblage), which we call "variation of the mean" (VOM). The average of the three assemblage standard deviations provides a measure of overall variability in length within individual assemblages (the average amount of variation around the mean disregarding its location), which we call "average variation" (AV). The standard deviation of the three assemblage standard deviations measures assemblage-to-assemblage differences in variation around the mean (between-assemblage differences in attribute variability), which we call "variation of variation" (VOV).

VOM indicates whether length is under global or local (assemblage-specific) control. Global control will most likely be the result of inherent physical constraints related to functionally critical elements of artifact design within the sampling universe, such as flight characteristics. Local control may be the result of social forces or context-driven functional constraints within the sampling universe, such as variation resulting from raw material availability. Where there is strong global control, VOM should be low—local context does not matter. If design constraints on length are severe, average length will be roughly the same from assemblage to assemblage. Conversely, where variability in local context matters, VOM should be higher. If social or raw material constraints on length are severe, average length will vary from assemblage to assemblage.[1] AV indicates the strength of this control. High AV indicates that control (global or local) is weak—variation around the mean is generally large. Conversely, low AV indicates strong control—variation around the mean is generally small. Finally, VOV indicates the degree to which an attribute is homogeneous with respect to strength of control and, by implication, kind of control. High VOV indicates global heterogeneity (substantial local variability) in strength and kind of control—amount of variation around the mean varies from assemblage to assemblage. Conversely, low VOV indicates global homogeneity in strength and kind of control—variation around the mean is roughly the same from assemblage to assemblage. We propose that the functional (selective) and social (selectively neutral) dimensions of artifact variation can be monitored by these three measures.

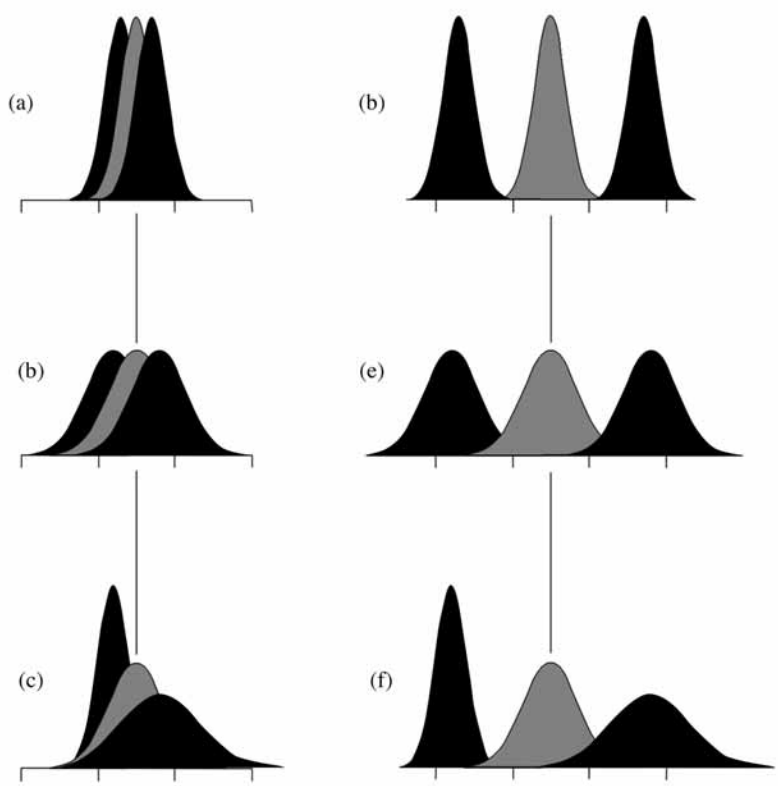


Figure 3.1. Six curves showing variation of mean and variation of variation (see text for discussion).

Signatures

Figure 3.1 graphically presents six situations that might describe length in our three hypothetical projectile point assemblages. Pooled mean length is the same in all six cases, but VOM, AV, and VOV of length are quite different. The cases in the first column (Figure 3.1a–c) strongly tend toward one common (global) length (VOM is low). This is the signature of cases in which global forces are playing a dominant role. In fitness-conferring attributes, global design constraints can heavily influence the final product in just this way. Artifacts increasingly outside the range of functionality are suboptimal and avoided. Attributes constrained by such design requirements will have relatively low between-assemblage variability in mean (low VOM), but the strength and consistency of this force may vary, as in Figure 3.1a–c. In contrast, the second column (Figure 3.1d–f) displays situations in which mean point length differs more from assemblage to assemblage (VOM is high). Local control is dominant here, related either to the influence of social factors or to variation in functional context. Again, the strength and consistency of such forces may vary by situation. At the most general level, then, our model distinguishes between global functional control, which is characterized by relatively low VOM, and local control, characterized by relatively high VOM. It is possible to distinguish additional meaningful variation within these two basic situations.

Figure 3.1a represents a case in which point lengths are similar in mean (low VOM) and consistently invariable within assemblages (low AV and low VOV). All points in all assemblages strongly conform to one specific central or ideal length. This is the signature of strong global control imposed by unvarying physical or social constraints. In contrast, Figure 3.1b displays the signature for attributes subject to weaker global control. Relative to Figure 3.1a, length is more variable within assemblages (intermediate AV), and uniformly so (low VOV), and means vary more from locality to locality (intermediate VOM). Finally, Figure 3.1c represents a situation in which low VOM again indicates global functional control, but VOV is high. As we have said, high VOV indicates local variability in strength and kind of control, in this case global functional control indicated by low VOM. Perhaps physical environment or adaptive strategy is regionally heterogeneous with respect to selection of point length such that the attribute is much more crucial to success in some areas than in others. More likely, however, high VOV signals the local intrusion of selectively neutral social factors discussed below. In any event, attributes characterized by high VOV are behaving strangely and should be flagged and evaluated thoughtfully.

In contrast to attributes shaped by global functional constraints, some attributes are characterized by greater variability in VOM or AV. Attributes shaped by strong local functional control will display consistently low average variation (low AV, low VOV) but will differ locally with respect to mean, and thus VOM will be higher than for variables under global functional control (intermediate to high VOM). Where functional constraints of any kind are either negligible or compensated by social rewards for signaling, individuals are free to load attributes with social information, leading to differences in the items produced by individuals and groups of individuals. The scale at which this variation is expressed defines the difference between emblemic and assertive markers. As defined by Wiessner (1983), emblemic markers convey information that distinguishes groups of people, such as linguistic groups, from other similarly conceived groups. Assertive markers carry information that distinguishes one individual from others within a group. Emblemic attributes, then, should be highly similar within a group, whereas assertive attributes should be highly variable.

If all groups use the same attribute as a locus of an emblemic marker, that attribute will display low within-assemblage variability (low AV) and will be uniformly invariable in this respect from assemblage to assemblage (low VOV), but its mean will differ locally (high VOM), as in Figure 3.1d. By contrast, if all local groups use the same attribute as a locus for individual expression (assertive), that attribute will tend to be maximally variable within assemblages (high AV) and uniform from assemblage to assemblage (low VOV), and its mean will tend to differ locally to the extent that assertive variation causes local populations to “drift” away from each other (intermediate to high VOM).

Signature Confusion

In practice, it may be difficult to distinguish between an attribute that is used by all groups as a locus of group-level emblems and one that is subject to strong local functional selection. As the functional importance of local context increases, variation around local means will be consistently low (low AV, low VOV), but the mean will increasingly vary from place to place, causing VOM to be high, which is the same for emblemic markers. The two should still be distinguishable, however, because the processes that shape emblemic markers tend to exaggerate local differences, producing much sharper contrasts than those responding to local functional differences, as shown by Boyd and Richerson (1987). Thus, VOM should be higher for universal emblemic attributes than attributes responding to strong local function. Pattern overlap may also cause individual (assertive) markers to be confused with functionally neutral variation. The neutral attribute will vary simply because it can (high VOM, high AV, low VOV), without carrying any social information. The assertive attribute will show the same pattern because individuals gain enough in social recognition to offset the cost of using suboptimal artifact forms.

Both kinds of confusion, however, will disappear if the model expectations are cast in terms of continuous variables in reasonably large regions. The expectations for markers detailed above assume that all groups use the same attribute as a locus of expression. This is possible where the groups are closely spaced and closely interacting as in a tightly knit interaction sphere, such as Karok and Yurok basket weavers in northern California (O'Neale 1932). Even here, a continuous attribute in theory permits use as an emblemic marker by just two groups—one of which will display unusually large, and the other unusually small, values for that attribute. For attributes such as projectile point length, it is highly unlikely that a larger number of groups will be emblemically identified by discrete metrical intervals. In short, as the number of groups and the amount of social and geographical space included in the analysis increase, it becomes extremely unlikely that all groups will use the same attribute as either an emblemic or an assertive marker. For this reason, it is unlikely that emblemic markers will be characterized by high VOM, low AV, and low VOV in the way described above except on the boundary between two local groups (e.g., Boyd and Richerson 1987). In large regions with many groups, we expect that attributes will emerge serendipitously as local emblemic markers (Leach 1965), distinguishing adjacent pairs of groups. Therefore, a distinguishing feature of attributes used as emblemic markers should be high VOV; groups using the attribute emblemically will show much smaller AV than the rest.

The same logic applies to assertive markers but in a more limited way because there is no theoretical limit to the number of groups that may simultaneously use the same assertive marker (assertive distinctions are relevant only within a group). Accordingly, one can never be sure whether an attribute characterized by high VOM, high AV, and low VOV is neutral or an assertive attribute that happens to be used by all groups. It is possible, however, to identify assertive attributes that are not used universally, which is much more likely. If only some groups choose to use a specific attribute assertively, they will display much larger than average AV, and the result will be high VOV.

In sum, the signature of emblemic and assertive markers in archaeological samples from even moderately large regions should be high VOV. At this point deciding whether high VOV is a result of unusually low AV (emblemic) or unusually high AV (assertive) requires visual inspection of the individual values contributing to VOV (the variation expressed in individual assemblages) to determine the nature and source of the anomalies. Our distinctions boil down to a matter of scale at three levels: the artifact, the assemblage, and the region. These criteria are summarized in Table 3.1.

Dimensions of Variability and Data Structure

Our model requires independent measurements for VOM, AV, and VOV because any structural dependency between measures would cripple the model. Strictly speaking, we cannot fully attain this goal. Because both the mean and standard deviation are drawn from the same set of observations, they cannot be independent unless the population size is infinite, which of course it never

Table 3.1. Expectations for Attributes under Global Functional Control and Local Functional Control, and Those Serving as Emblemic Markers and Assertive Markers.

Force	VOM	AV	VOV
Strong global function	Low	Low	Low
Moderate global function	Intermediate	Intermediate	Low
Neutral (afunctional)	High	High	Low
Variable strength global function	Undefined	Undefined	High
Strong local function	Intermediate–high	Low	Low
Moderate local function	High	Intermediate	Low
Emblemic style, universal attribute	High	Low	Low
Emblemic style, local attributes	Undefined	Undefined	High
Assertive style, universal attribute	Intermediate–high	High	Low
Assertive style, local attributes	Undefined	Undefined	High

will be. However, this problem is not unduly serious because, except for the impossibility of obtaining large standard deviations in the presence of small means, it is possible to derive values for standard deviation that are largely independent of the value for the mean. We have demonstrated elsewhere (Bettinger and Eerkens 1997; Eerkens and Bettinger 2001) that there are significant correlations between means and standard deviations in projectile point data and specifically that standard deviation increases linearly with increasing mean. As a result, use of the coefficient of variation (CV), which scales the standard deviation as a percentage of the mean, is preferable as a measure of variation. In effect, CV measures how far a particular sample is above or below this linear relationship. Larger CV values indicate relatively high sample variation, and lower values indicate low sample variation.

Our approach is comparative and in this sense relativistic. The signatures outlined above make it possible only to determine which artifact attributes are behaving more or less in accord with the predictions for different processes (e.g., local versus global functional constraints or loading of social information). The best one can do is discuss and analyze relative differences between artifact types and attributes and assign degrees of confidence to the interpretation that various processes are contributing to the patterns observed. As the sampled universe increases and one observes more attributes and variation in different contexts, one can better understand how these processes express themselves metrically at a general level. Because our approach is relativistic it is also circular: To some degree we will find what we are looking for. Thus, even if emblemic markers are poorly expressed, some subset of attributes will simply look more "emblemic" than the rest. However, with a reasonable number of attributes and samples it should be possible to gain a solid understanding of these signatures and the relative importance of different dimensions of artifact variability.

Finally, we acknowledge that many factors contribute to artifact variability. For example, variation in chipped-stone projectile points is affected by raw material fracture properties (Andrefsky 1994; Odell 1989); curation, resharpening, and length and intensity of use (Bamforth 1986, 1991; Basgall 1989; Parry and Kelly 1987; Shott 1986); discard behavior (e.g., Close 1996; Kelly 1988); and number of flint knappers (e.g., Eerkens 1998). That this list is not complete, and the factors are not mutually exclusive, points up the complexity of the situation. Our model is designed to simplify these complexities in the sense that many can be regarded as local functional constraints. How important these are relative to other forces is an empirical question that can be resolved only by doing the kind of analysis we propose.

IMPLEMENTING THE MODEL

To operationalize our model we used measurements obtained by David Hurst Thomas from more than 5,500 projectile points belonging to nine major types represented in 38 different Great Basin site and survey collections (Figure 3.2; for details, see Bettinger and Eerkens 1997; Thomas 1981, 1983). Below, we use the term *site specific* to refer to these 38 collections, even though some actually are collections from surveys. These collections represent a broad range of locations throughout the Great Basin, spanning several thousand years of prehistory.

The points were measured by a small number of individuals, thus minimizing interindividual measurement error, and classified using the quantitative Monitor Valley typology (Thomas 1981). Measuring the nine different projectile point types (Desert Side-notched, Cottonwood Triangular, Rosegate, Elko Eared, Elko Corner-notched, Gatecliff Split Stem, Gatecliff Contracting Stem, Large Side-notched, and Humboldt Concave Base) for six attributes (maximum length, axial length, maximum width, basal width, neck width, and thickness) yields 52 type–attribute combinations (for a discussion of chronology for these points, see Bettinger and Taylor 1974; Thomas 1981). There are only 52, rather than 54, because neck width is inapplicable to two neckless point types (Cottonwood Triangular and Humboldt Concave Base). Each of the 52 type–attributes has an associated variation of mean, average variation, and variation of variation across the 38 site-specific point collections. Because some points were broken and could not be measured for every attribute and not all 38 collections contained every point type in sufficient quantity to be considered in the study (see below), the number of collections representing individual type–attributes varies from 13 to 34, with a mean of 20.7. For example, only 13 of the 38 collections had

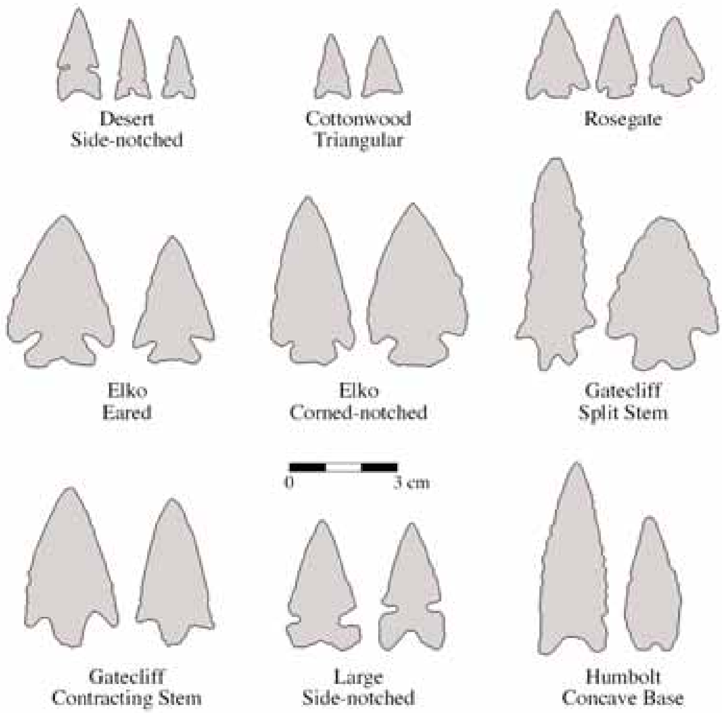


Figure 3.2. Projectile point types from the Great Basin, western United States.

enough maximum-length measurements on Cottonwood Triangular points to be included, whereas 34 had enough maximum-length measurements for Elko Corner-notched points.

To review the structure of our data, each projectile point type (n = 9) was measured for several attributes, for a total of 52 unique type–attributes. These data sets represent over 5,000 unique projectile points and 30,000 individual type–attribute measurements. For each site or survey collection (n = 38), a sample mean and standard deviation were calculated for each type–attribute, yielding a potential of 1,976 (38 $\times$ 52) unique sets of means and standard deviations. In actuality, only 1,076 were used because not all sites had every projectile point type in large enough numbers to be statistically relevant (see below). Measures for VOM, AV, and VOV were then calculated for each point attribute based on analyses among the site-specific collections (varying in size between 13 and 34 collections).

Unfortunately, there are no standard statistics available to compute VOM, AV, and VOV. Although some analogues exist, such as using ANOVA to calculate VOM, pooled standard deviation to calculate AV, and homogeneity of variance to calculate VOV, certain structures in the data prevented us from using these techniques. A discussion of the pitfalls and problems that beset application of the model, presented below, will be instructive in understanding how it works, the types of data needed, and how we set about calculating VOM, AV, and VOV.

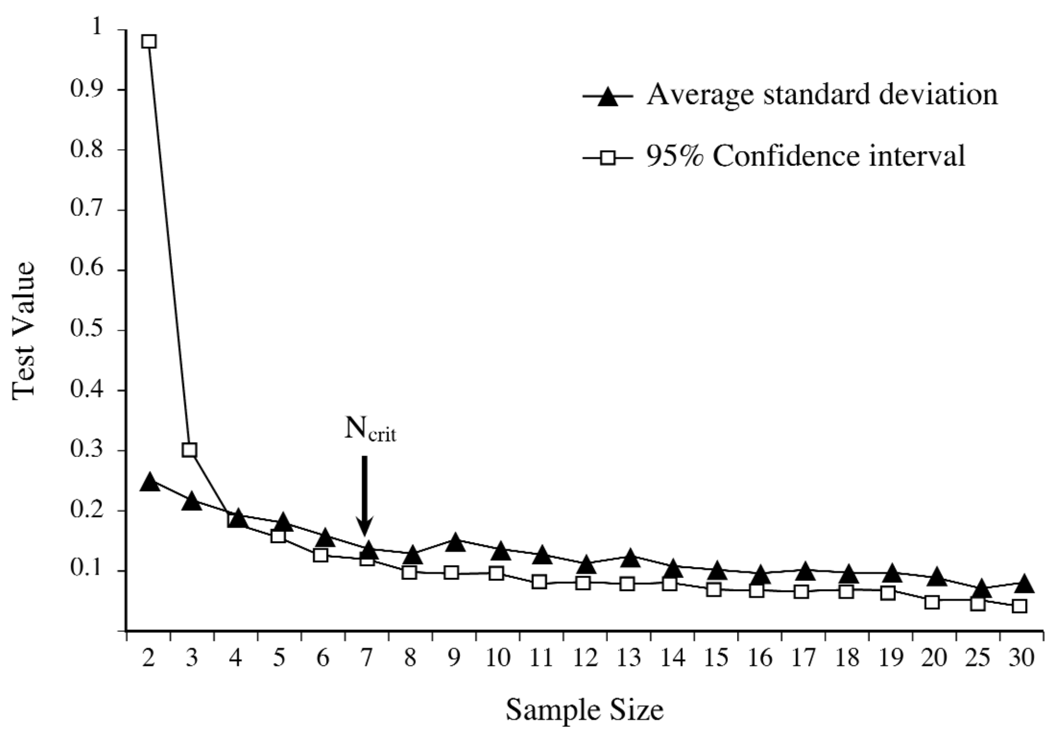
Finally, it is worth considering the degree of correlation between the different metric attributes. For example, it is worthwhile considering whether maximum length and maximum width are free to vary independent of one another on a single projectile point. If they are unable to do so, our analysis of the type–attributes essentially boils down to a comparison of the point types only, given that all the attributes within a type will behave in the same manner. As we have shown elsewhere (Bettinger and Eerkens 1999), the degree of correlation between attributes varies greatly, from a near-perfect correlation between axial length and maximum length to almost no correlation between thickness and basal width. Most attributes show only minor positive correlations. However, because we did not have access to the original data, it was impossible to remove these effects, for example, by regression and extraction of residuals. Because there is little that can be done, we simply acknowledge that some attributes are more correlated than others and continue with the analysis, trying to minimize the effects such relations might have on our ultimate interpretations. Thus, we do not give added weight to our interpretations if maximal and axial lengths show similar patterns in variation, given that we know these attributes measure similar phenomena.

Statistical Implementation: Sample Size

The first statistical problem is sample size. How many projectile points are needed to provide a meaningful estimate of mean and standard deviation for a site-specific assemblage? Obviously two or three is too few, and 100 is more than enough. There is a tension here between minimizing sampling error at the assemblage level (having enough points within a site-specific collection such that the mean and standard deviation are well characterized) and minimizing sampling error at the regional level (including enough collections to make statements about regional patterns). To minimize sampling errors at the assemblage level one would include only samples with large numbers of projectile points. To minimize sampling error at the regional level one would include as many samples as possible regardless of size: The more locations included, the more confident one can be in interpretation. A crucial decision for the model, then, is the selection of a critical sample size, N_{crit}, that constitutes the threshold at which site-specific samples will be included for study.

There are several standard methods for computing N_{crit} (e.g., Mendenhall et al. 1974; Neter et al. 1990). Using observed standard deviation, mean, and sample size, such statistical tests indicate how many observations are needed to be confident, at some probability value or level, that the mean and standard deviation are within a given range. With such tests one decides to include samples when the confidence interval is within this range, say, ±.05 mm or ±1 percent of the sample mean, and to exclude those with confidence intervals outside these limits. Unfortunately, a major feature of these tests is that as sample standard deviation increases, confidence about the true mean and true variation decreases. This is unacceptable because we wish to consider means and standard deviations independently. Using such tests would bias our investigation by systematically including collections with lower variation measurements (at a given sample size) and excluding the more variable collections. This would exclude the very information about artifact variation that our method is designed to investigate. Another approach clearly is needed. Ultimately, we inspected the data visually using two separate criteria described below and settled on a critical sample size of $N_{crit} = 7$. This value represents a tradeoff between minimizing errors in estimating individual sample means and standard deviations and maximizing the number of samples in our analysis. Using a fixed sample size rather than a measure dependent on the standard deviation allows all samples above the critical size to be included irrespective of observed variation.

The first inspection exploited our previous finding (Bettinger and Eerkens 1997) that the mean and standard deviation are highly correlated for all variables and projectile point types in the Great Basin (r = .90). That is, one can predict a



given variable's standard deviation based on its mean, irrespective of point type, measurement, or provenience. Using this relation, it is possible to determine at what point diminishing sample size causes sample standard deviation to deviate significantly from its expected value, given a mean. Critical sample size is the point at which increasing sample size causes observed standard deviation to "settle down" and approximate its expected value. The triangular symbols in Figure 3.3 plot the average standard deviations of samples relative to their means with increasing sample size. As shown, the analysis suggests that samples of six or more projectile points do not vary significantly from the predicted mean–standard deviation relation. They are apparently no more or less variable than samples with larger numbers of points.

The second inspection uses a common statistical method for creating a 95 percent confidence interval around a mean (e.g., Dunn and Clark 1987). We sought to determine at what point the size of this confidence interval, expressed as a percentage of the mean, became unresponsive to changes in sample size. As shown in Figure 3.3, the 95 percent confidence interval for samples with eight or more projectile points is 9 percent (on either side) of the observed sample mean. Because a confidence interval will continue to drop as sample size increases, the optimal point is not the minimum value but again the point at which the values settle down. Figure 3.3 shows that samples of eight or more have reasonably small confidence intervals.

Splitting the difference between these two results, we concluded that samples consisting of seven or more measurements furnish reasonable values for means and standard deviations. Samples approaching the minimum of seven certainly suffer some from sampling error, but we feel we have significantly reduced this while gaining the strength that results from a large number of samples, lending greater credibility to the results achieved in the application of our model.

Statistical Implementation: Sample Size Dependence

The second problem is that many statistical tests that might have been used to estimate VOM (e.g., standard ANOVA [Dunn and Clark 1987; Neter et al. 1990]) and VOV (e.g., homogeneity of variance [Conover et al. 1981]) are sample size dependent. In other words, the significance of the test is heavily influenced by the number of observations. This makes it impossible to compare results between independent tests unless the sample sizes in them are approximately equal. For example, ANOVA, which is commonly used to compare means among more than one population, could have been used to evaluate VOM. Thus, we could have performed two separate ANOVA tests to evaluate VOM in Elko Corner-notched and VOM in Desert Side-notched maximum lengths. We then could have compared the results of these tests (*p* values) against one another to determine if means are more similar among lengths in the former or latter point type. However, ANOVA is very sensitive to sample size. All other things being equal, results from such a comparison would suggest that the point type with the smaller sample size has lower VOM than the sample with more points. Bootstrapping is one way to circumvent this problem, but because we had access only to Thomas's summary statistics (mean, variance, and sample size), we could not perform this procedure. Moreover, standard ANOVA requires that samples have similar variances, a situation that we cannot demonstrate and explicitly do not want (although for alternative methods that do not require equal variance, see Dijkstra 1988). We want to analyze variance, not control it. Likewise, using pooled standard deviation to estimate AV would give an estimate only of total variation among all projectile points in the 38 site-specific samples for a particular attribute, and this value is not quite the statistic we are trying to evaluate. We seek a measure of the average amount of variation within individual collections of points, not the total variation when all points are pooled. As a result we had to apply some simple but nonstandard techniques to estimate VOM, AV, and VOV. Several measures exploiting various structures in the data were used to derive these values and are discussed below.

Raw values of VOM were obtained by calculating the CV of sample means—the standard deviation of sample means divided by their average, which is simple and straightforward (we express this as a decimal value rather than as a percentage). To measure AV we took an average of the CV values for all the relevant site-specific assemblages for that particular point attribute.

Figure 3.3. Graph of sample size analysis.

Similarly, VOV was calculated by taking the CV of the site-specific CV values. These methods differ slightly from those we have used in earlier research, namely, using residual values derived from the linear standard deviation–mean relationship discussed earlier (see Bettinger and Eerkens 1997), but are slightly easier to compute and give similar results. The final values of VOM, AV, and VOV were obtained by standardizing the raw values to remove scalar effects (rescaling to produce distributions with a mean of .0 and a standard deviation of 1.0).

We note that our methods are exploratory in nature, allowing us to look for patterns in artifact variation rather than to statistically test for differences between samples. For example, we do not attempt to calculate the probability that VOM is statistically different between two point attributes, only whether certain projectile points or attributes are consistently higher or lower than others and how patterns in VOM relate to AV and VOV. Of course, it is possible to estimate VOM, AV, and VOV by alternative means and obtain slightly different results. However, given the fact that the two methods we tried produced similar results, coupled with our overall experience with the numbers, we believe that patterns in the data will be similar regardless of the specific technique used to derive these values. At this point, it will be helpful to review the steps that were followed to obtain the values used for this analysis: (1) measure the type–attributes (e.g., Desert Side-notched basal width) in site-specific samples (data provided by Thomas); (2) compute sample means and CVs for type–attributes represented by seven or more observations; (3) obtain raw VOM for each type–attribute; (4) obtain raw AV for each type–attribute; (5) obtain raw VOV for each type–attribute; and (6) standardize raw VOM, raw AV, and raw VOV to obtain equally scaled (normalized) values for each type–attribute.

RESULTS

Table 3.2 presents the standardized values of VOM, AV, and VOV for the 52 type–attribute combinations. Before interpreting them, it is important to ascertain whether the measures are independent in the way our model assumes. As mentioned earlier, there is no obvious reason to suspect this would be the case; mean and standard deviation measurements from samples are relatively free to vary from sample to sample. As it turns out, the interactions between VOM and VOV (r^2 = .12) and between AV and VOV (r^2 = .12) are minor, indicating that these variables are nearly independent. Specifically, as the mean of an attribute varies more from sample to sample (as VOM increases), there is only a small tendency for variability around the mean to vary more from sample to sample (increasing or decreasing VOV). Similarly, as variation around sample means increases (as AV increases), there is no accompanying tendency for variability around the mean to vary more (or less) from sample to sample (increasing or decreasing VOV).

There is, however, a slightly higher positive correlation between AV and VOM (r^2 = .29), which is inherent to the data and not an artifact of the statistics used. As projectile point attributes become increasingly variable locally (as AV increases), they become more variable regionally (VOM increases). It is possible to eliminate this correlation through regression and extraction of residuals, but this would remove what is clearly a major and interesting source of variability in the sample. Indeed, a strong positive correlation between AV and VOM is precisely what one would expect if variation in the strength of global functional control were important in determining Great Basin projectile point attributes. This seems to be the case. Attributes that tend to be narrowly distributed around local means (low AV) tend to have the same mean from locality to locality across the Great Basin (low VOM). Attributes that tend to be loosely distributed around local means (high AV) tend to vary widely in mean from locality to locality (high VOM). Thus, variation from strong to weak or negligible global functional control is a (perhaps *the*) major source of metric variation in Great Basin projectile points. This conclusion is in keeping with our intuitive understanding that projectile points are mainly functional objects. The result clarifies this intuition by telling us that this function was determined more by universal design constraints than by such context-dependent constraints as raw material availability. To determine the extent to which individual type–attributes are affected by these and other sources of control requires closer inspection of the data.

The first step is to identify cutoff points for high, medium, and low values of VOM, AV, and VOV in accord with our model. We did this by ordering the values of VOM, AV, and VOV sepa-

Table 3.2. VOM, AV, and VOV Scores for Type-Attributes.

Point Type	Attrib.	Number Sites	Number Points	VOM	Score	AV	Score	VOV	Score
Cottonwood Triangular	ML	13	176		0.19	low	-0.78	low	0.16
Cottonwood Triangular	AL	13	161		0.52		-0.05	low	0.32
Cottonwood Triangular	MW	14	178		-0.63	low	-0.74	low	0.02
Cottonwood Triangular	BW	14	166		-0.65	low	-0.69	low	0.25
Cottonwood Triangular	Th	14	178		0.55	low	-1.24	low	0.28
Desert Side-notched	ML	19	308		-0.17	low	-0.75	low	-0.07
Desert Side-notched	AL	20	295		-0.41		0.35	high	1.00
Desert Side-notched	MW	20	308		-0.53	low	-1.51	low	-0.80
Desert Side-notched	BW	20	303		-0.24	low	-1.03	low	-0.64
Desert Side-notched	NW	19	293		-0.11		-0.14	low	0.43
Desert Side-notched	Th	20	305		0.11		0.45	high	1.38
Rosegate	ML	26	849		-0.38		-0.04	low	-0.72
Rosegate	AL	27	800		-0.38		-0.18	low	-0.67
Rosegate	MW	27	863		-0.61		-0.38	low	-0.34
Rosegate	BW	27	831		-0.01		0.21	low	0.42
Rosegate	NW	27	828		0.04		-0.41	low	-0.28
Rosegate	Th	27	872		-0.97	low	-0.99	low	-0.46
Elko Corner-notched	ML	34	1416		-0.47		0.50	low	-0.53
Elko Corner-notched	AL	34	1383		-0.58		0.42	low	-0.47
Elko Corner-notched	MW	34	1425		-0.44	low	-0.88	low	-0.13
Elko Corner-notched	BW	34	1442		-0.62		0.58	low	-0.34
Elko Corner-notched	NW	33	1338		0.11		0.37	high	0.77
Elko Corner-notched	Th	34	1458		0.08	high	1.19	high	1.23
Elko Eared	ML	21	529		-0.27		-0.30	low	-1.31
Elko Eared	AL	21	514		-0.14		-0.07	low	-1.27
Elko Eared	MW	21	519	low	-1.30	low	-1.14	low	-0.13
Elko Eared	BW	21	527		-0.69		-0.13	low	-0.98
Elko Eared	NW	20	490		0.86	low	-0.69	low	-0.96
Elko Eared	Th	21	549	high	1.66		-0.26	high	3.06
Gatecliff Contracting Stem	ML	13	307		-0.03		0.85	low	-1.82
Gatecliff Contracting Stem	AL	13	303		-0.13		0.85	low	-1.75
Gatecliff Contracting Stem	MW	13	358		-0.05		-0.08	low	0.36
Gatecliff Contracting Stem	BW	15	327	high	2.34	high	3.04	high	1.12
Gatecliff Contracting Stem	NW	13	305		-0.04	high	2.67	high	2.45
Gatecliff Contracting Stem	Th	15	365		-0.33	high	1.18	high	1.70
Gatecliff Split Stem	ML	17	332		-0.61		0.47	low	0.03
Gatecliff Split Stem	AL	17	330		-0.43		0.74	low	0.03
Gatecliff Split Stem	MW	17	327		-0.87	low	-1.28	low	-0.73
Gatecliff Split Stem	BW	17	328		0.84		0.06	high	1.49
Gatecliff Split Stem	NW	16	308		0.74		0.66	high	0.72
Gatecliff Split Stem	Th	17	335	high	1.28		-0.15	high	1.71
Large Side-notched	ML	14	315	low	-1.28	low	-1.18	low	-1.22
Large Side-notched	AL	15	315	low	-1.25	low	-0.84	low	-0.96
Large Side-notched	MW	14	306	low	-1.33	low	-1.86	low	-0.82
Large Side-notched	BW	13	322	low	-1.36	low	-1.47	low	-0.02
Large Side-notched	NW	15	314		-0.96		0.63	low	0.12
Large Side-notched	Th	15	323	low	-1.22	low	-0.81	low	-0.71
Humboldt Concave Base	ML	26	537	high	2.05	high	1.25	low	-0.90
Humboldt Concave Base	AL	25	536	high	1.89	high	1.54	low	-0.58
Humboldt Concave Base	MW	26	569	high	1.94		0.10	low	0.22
Humboldt Concave Base	BW	27	525	high	2.74	high	1.26	low	0.24
Humboldt Concave Base	Th	27	581	high	1.55		0.81	low	0.12

Notes: Attrib. = Attribute; ML = Maximum Length; AL = Axial Length; MW = Maximum Width; BW = Basal Width; NW = Neck Width; Th = Thickness; Number Sites = Number of site-specific samples of projectile points for this type-attribute; Number points = Total number of projectile points in analysis with complete measurement for this type-attribute (distributed among site-specific samples).

rately and visually inspecting their distribution and associated probabilities for discontinuities that suggest natural divisions. Figure 3.4 shows these cutoffs. The ordered distribution of VOM showed relatively clear breaks separating sets of outlying high values (>1.28, *n* = 8) and low values (<–1.22, n = 6) from intermediate ones (>–1.22 to <1.28, *n* = 38), thus making it possible to characterize type–attributes in accord with our model (high, medium, or low VOM). The ordered distribution of AV also showed outlying high (>1.18, *n* = 7) values and a slight break for lower values (<–.69, *n* = 17), permitting similar characterization. VOV showed a clear break only at the higher end (>.72, *n* = 11), below which values decreased gradually without obvious discontinuity. This suggests a simple dichotomy between the 11 outliers characterized by high VOV relative to the remaining 41 values, which are characterized by low VOV (<.43). These assignments and the actual values of VOM, AV, and VOV are shown for all 52 type–attributes in Table 3.2, where

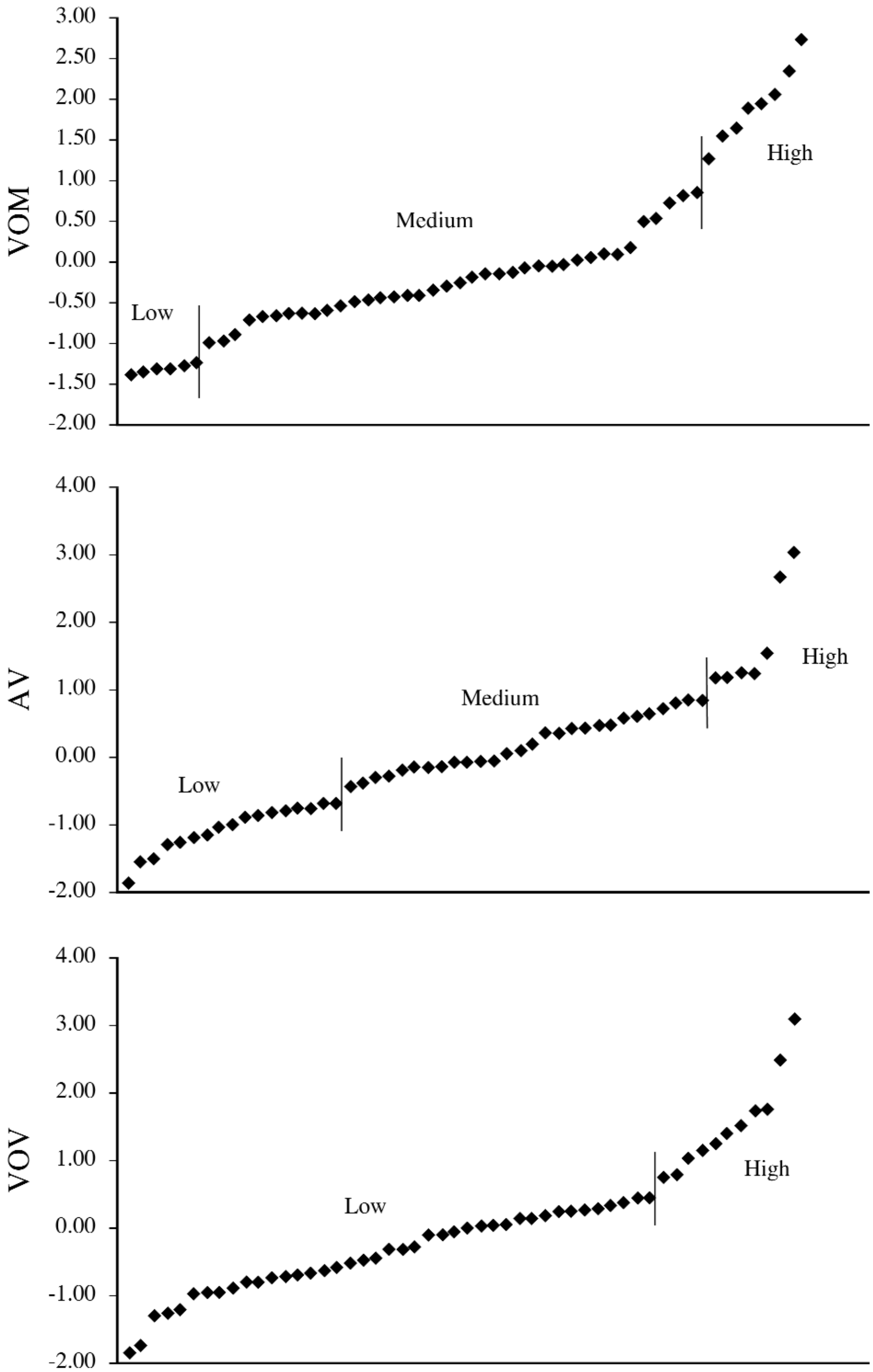


Figure 3.4. Residual values for variation of mean, average variation, and variation of variation for all 52 projectile point attribute measurements.

blank assignments indicate the more numerous medium values.

Table 3.3 shows the observed combinations of VOM and AV for all 52 type–attributes. It demonstrates the strong association (correlation) between these measures, hence the dominant effect of global functional constraints on Great Basin projectile point morphology. Most values fall on the diagonal running from the lower-left cell (low VOM, low AV) to the upper-right cell (high VOM, high AV), describing a trajectory of declining global control. AV is never high when VOM is low (the upper-left cell is empty), and AV is never low when VOM is high (the lower-right cell is empty). It may be recalled from our earlier discussion that the latter combination—high VOM, low AV (lower-right cell)—is the signature of an attribute used universally as a locus of emblemic markers. The absence of such type–attributes in our Great Basin sample is in keeping with our expectation that universal emblemic attributes are improbable across large regions. There is strong evidence in our sample, however, that some type–attributes served as local emblemic markers. The signature for this is high VOV, suggesting heterogeneity in strength and kind of control. It will be useful, however, to begin our analysis with type–attributes characterized by low VOV, indicating homogeneity with respect to strength and kind of control.

Homogeneous Type–attributes (Low VOV)

Table 3.4 tabulates VOM against AV for the 41 type–attributes exhibiting low VOV, indicating homogeneity in strength and kind of control. As does Table 3.3, it reveals the strong association between these measures, hence the importance of global functional constraints acting on Great Basin projectile point morphology. The cases on the diagonal running from the lower-left cell to the upper-right cell are readily interpreted as reflecting the force of these global constraints from high (lower left) to low or neutral (upper right). Thus, six cases indicate strong global control, 19 cases indicate "average" global control, and three cases indicate little or no global control (neutral). As noted in our earlier discussion, it is possible that these three neutral cases—high VOM, high AV (upper-right cell)—are type–attributes that were used universally as assertive markers. The point involved in all three cases is the Humboldt type (axial and maximum length and basal width), a type that is noteworthy by the fact that it is less temporally sensitive than the other types (e.g., Bettinger and Taylor 1974). Basal width would have been hidden by hafting and seems an unlikely locus for an assertive marker unless such signaling was meant to be expressed prior to hafting, that is, during manufacture or exchange. More likely, these three point attributes are cases of truly neutral traits or traits as close to neutral as occurs with Great Basin projectile points.

The six cases of strong global selection (low VOM, low AV) are noteworthy in that only two types are involved, Large Side-notched (basal width, maximum width, maximum length, and axial length) and Elko Eared (maximum width). We have elsewhere observed that maximum width is the least variable of all Great Basin point attributes (Bettinger and Eerkens 1997), so it is not surprising that it should be critical in the two point types that display the strongest global control. It is less clear why, relative to all other types, the Large Side-notched type should be so strongly subject to global control across multiple attributes. The type dates to a middle Holocene interval (7000–4500 B.P.), when big-game hunting was substantially more important relative to plant pro-

Table 3.3. Combinations of VOM and AV for All Type-Attributes.

	Low	VOM	High	Total
High	0	3	4	7
AV	0	24	4	28
Low	6	11	0	17
Total	6	38	8	52

Table 3.4. Combinations of VOM and AV for Homogenous Type-Attributes (Low VOV).

	Low	VOM	High	Total
High	0	0	3	3
AV	0	19	2	21
Low	6	11	0	17
Total	6	30	5	41

curement than later in time, which may explain the findings.

However, it is not the case that all points used for big-game hunting are subject to strong global selection. That is, big-game hunting alone does not require special and regionwide control over projectile shape. Perhaps this point was used to hunt specific animals or was used within a highly specialized projectile technology requiring exact point shape and size. We must also point out, at risk of undoing our whole analysis, that the Large Side-notched type has a distinctively northern distribution, centering in the plateau. It occurs only rarely, if at all, in the southern half of the Great Basin. There is the possibility that its presence in the Great Basin represents the occasional intrusion of northern groups for whom it served as an emblemic marker. An examination of the type in its area of major concentration might resolve the issue. For the moment we prefer to interpret the Large Side-notched type as an unusually effective but highly unforgiving point form that was under strong global functional control.

Strong local selection is indicated for 11 cases below the diagonal, where AV is low and VOM is intermediate (lower-middle cell). Relative to those on the diagonal, these are cases in which VOM is larger than it should be given AV, indicating that attribute values cluster tightly around local means that tend to vary from locality to locality. Cottonwood and Desert Side-notched points account for seven of the 11 cases, and Rosegate, Elko Eared, Elko Corner-notched, and Gatecliff Split Stem make up the remaining four. Seven of the 11 cases measure some kind of width (four maximum width, two basal width, and one neck width), two measure maximum length, and two measure thickness. Thus, the functional importance of maximum width is again attested, in this case responding to local adaptive context. It is notable that late-prehistoric-period projectile points (Cottonwood and Desert Side-notched) seem to have been responding especially strongly to local context. It is only in these two types, for example, that variation in length is constrained in this manner. That basal and maximal widths are similarly constrained in these same types suggests that late in time the force of this local control was directed to overall size or shape as a package rather than to width and length independently.

The remaining cases below the diagonal (middle-right cell, $n = 2$) illustrate the trajectory of weakening local control. As one moves from the lower-middle cell to the middle-right cell, AV increases but remains lower than expected relative to VOM; local constraints (AV) remain more important than global constraints (VOM). Raw material availability is a potential explanation. In contrast, values above the diagonal (middle-left cell and middle-upper cell) represent instances in which AV is higher than expected relative to VOM, suggesting weakening global control (increasing VOM) that is different from the normal trajectory of declining global control illustrated by cases on the diagonal. Such above-diagonal cases would represent situations where global constraints are important but difficult to manage; AV is higher than expected given VOM. In such instances, the penalties for varying from a specific attribute value would seem to be significant but somehow unavoidable. Raw material availability again comes to mind, but other things might be involved. Craftspersons might be unable to achieve a desired result consistently, for example. As shown in Table 3.4, this situation clearly is rare, as no cases were observed.

Heterogeneous Type–attributes (High VOV)

Table 3.5 tabulates VOM against AV for the 11 type–attributes with high VOV indicating heterogeneity in strength and kind of control, which is the suggested signature of types used locally for emblemic or assertive markers. Although the values for VOM and AV are all intermediate or high, suggesting moderate to negligible functional control, this is partly a result of outlying values in site-specific assemblages where social information may be expressed (the ones causing high VOV). Determining which kind of information is represented, and at which specific localities, requires sample-by-sample examination of the CV values contributing to high VOV (recall that VOV is calculated as the CV of site-specific CV values).

Five point types (Desert Side-notched, $n = 2$; Elko Corner-notched, $n = 2$; Elko Eared, $n = 1$; Gatecliff Split Stem, $n = 3$; and Gatecliff Contracting Stem, $n = 3$) and four attributes (thickness, $n = 5$; neck width, $n = 3$; basal width, $n = 2$; and maximum length, $n = 1$) display high VOV. Two different patterns are evident within these 11 cases, one where a single anomalous CV value is causing high VOV and one where both large and small values are increasing the spread of CV values beyond the norm witnessed among

Table 3.5. Combinations of VOM and AV for Heterogeneous Type-Attributes (High VOV).

	Low	VOM	High	Total
High	0	3	1	4
AV	0	5	2	7
Low	0	0	0	0
Total	0	8	3	11

other point attributes. Elko Eared thickness measurements, shown in Figure 3.5, typify the former, whereas Elko Corner-notched neck width measurements, shown in Figure 3.6, typify the latter. For example, it is clear from Figure 3.5 that VOV is high for Elko Eared thickness owing to a single outlying value representing a location where standard deviation around the mean is high enough to suggest use of the attribute as a locus of an assertive marker (O'Malley Shelter in southeast Nevada). Similarly, Figure 3.6 suggests the presence of two localities where Elko Corner-notched neck width is variable enough to suggest use as an assertive marker (Rose Spring site in eastern California and Freightor's Defeat in northern Nevada). Figure 3.6, however, also reveals two additional localities where Elko Corner-notched neck width varies much less than it should, suggesting emblemic markers (Conoway Cave in southeastern Nevada and Newark Cave in central Nevada). In general, thickness measurements on Great Basin points seem to conform to the former pattern, where one anomalously high CV value brings the whole VOV statistic above the norm. By contrast, basal and neck width measurements typify the latter pattern, where both anomalously high and anomalously low values are present.

It is possible to conjure rationalizations for these cases, but one would have been hard-pressed to predict them beforehand. It makes sense, for example, that neck and basal widths might serve as a locus to convey social information because they are more closely related to the method of hafting than projectile function (although they do affect breakage rates). It is not clear, however, why they seem to have been employed in such a capacity only by certain points—Elko and Gatecliff, for example. Conversely, we might have predicted the same for length measurements, which are much more outwardly visible and might therefore carry social information. Yet we did not discover such a pattern. Similarly, it is unclear why thickness measurements vary as though they were selectively neutral or serving as loci of social information. We conclude from all this that predicting where and how social information will be expressed, at least in projectile point attributes, is likely to remain elusive.

Overall, there is a pattern in the data, indicat-

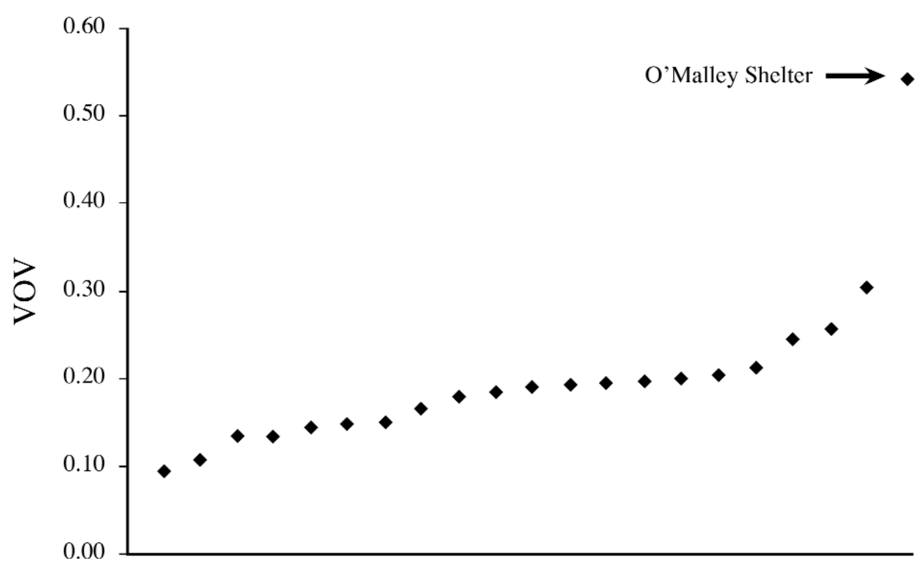


Figure 3.5. Coefficient of variation values for Elko Eared thickness measurements.

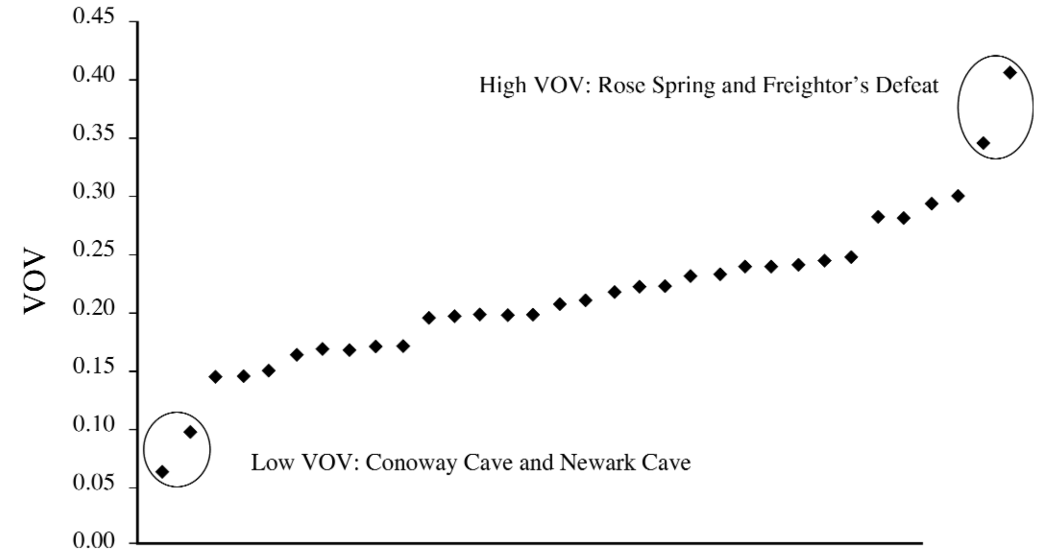
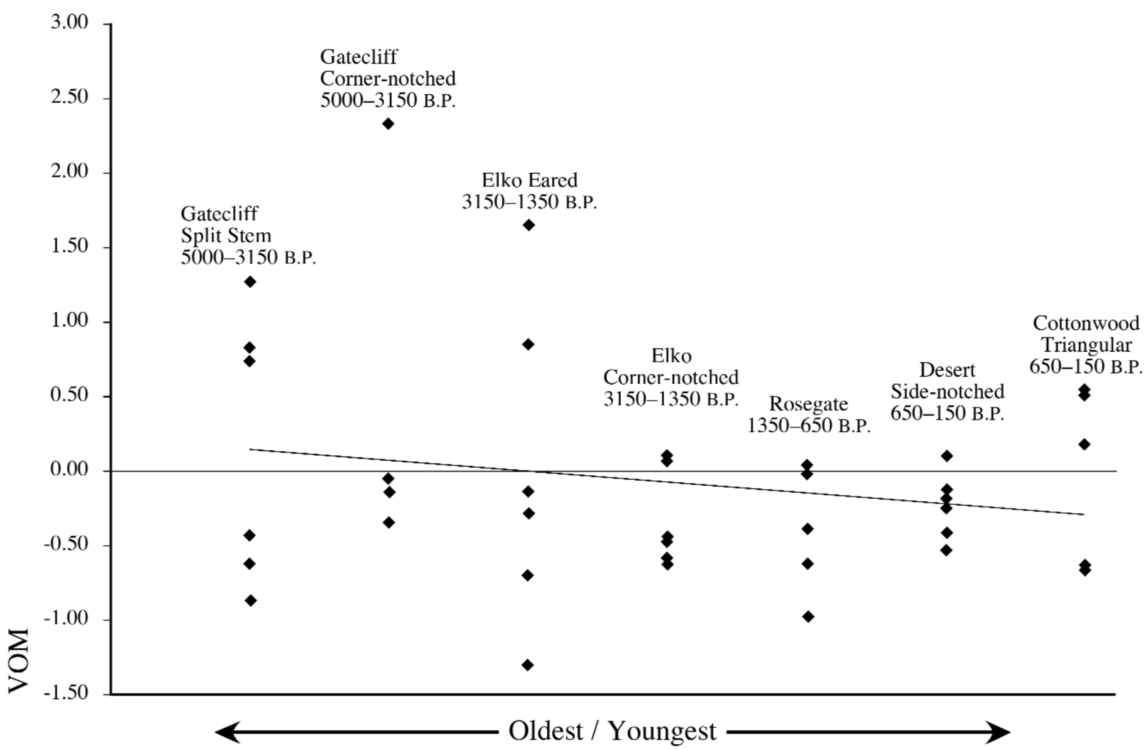


Figure 3.6. Coefficient of variation values for Elko Corner-notched neck width measurements.

ing a gradual trend toward increasing local control in Great Basin projectile points through time. Attributes of the earliest points (Gatecliff series and Large Side-notched) tend to be constrained by global control or to serve as social markers. Middle-period points (Elko series and Rosegate) are more often characterized by only moderate global control and are less apt to carry social information. The latest points (Desert Side-notched and Cottonwood Triangular) are most often characterized by local functional control and rarely carry social information. In other



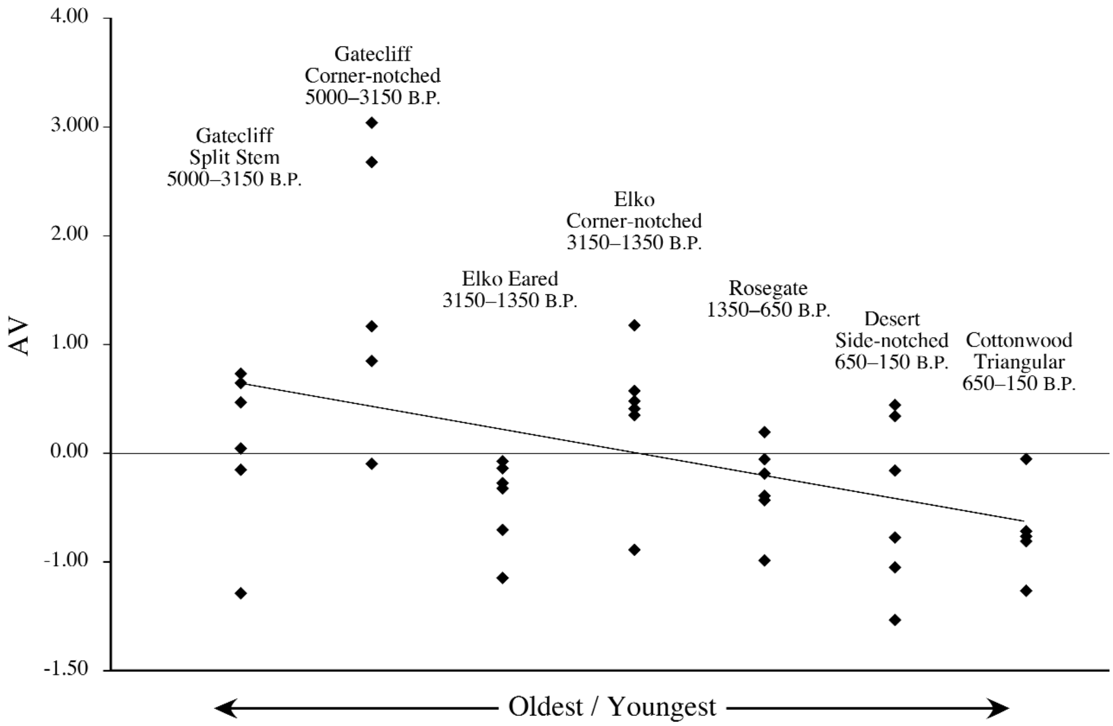


Figure 3.8. average variation measures plotted against time for projectile point types.

words, there is a trend toward decreasing VOM and AV through time, which is shown in Figures 3.7 and 3.8.

During the evolution of projectile technologies in the Great Basin, that technology seems to have become increasingly specialized and adapted to local conditions. Perhaps as groups became more restricted in their yearly movements over time, they came to know local sources of stone and the local environment better. As well, contact with peoples living at great distances may have been reduced, diminishing the flow of information over large areas. As a result, people may have modified their hunting gear to better suit the more immediate physical and social environment. Together, this information suggests that in the course of the transmission of hunting technologies, variability was increasingly restricted. Note also that this phenomenon is not simply the result of a decrease in projectile point size, which also occurred in the Great Basin. Scaled variation measurements (CVs) have been used to account for this phenomenon (see Bettinger and Eerkens 1997).

Figure 3.7. variation of mean measures plotted against time for projectile point types.

SUMMARY

We suggest that different kinds of functional constraints (local and global) and loci of social information (assertive and emblemic markers) can be recognized in the archaeological record by distinctive patterns in attribute variation. Our model distinguishes among these patterns with reference to three different measures of variation: variation of sample means, average sample variation, and variation of sample variation. Our model draws on an analysis of large data sets and uses common statistics of attribute central tendency and dispersion (mean and coefficient of variation). It does not predict beforehand which attributes should display which properties (functional constraints or those bearing social information) but, rather, can be used to test these notions. As such, it is applicable to a wide range of archaeological data sets, provided they include a relatively large number and wide range of observations.

Certain specific trends are apparent from the application of the model to Great Basin flaked-stone projectile points. Clear from the beginning is the dominance of global functional control, from strong to weak, over the 52 type–attributes considered. This was not surprising given the traditional interpretation of projectile points as functional objects used primarily in hunting. Several attributes of Large Side-notched points, and maximum width more generally, appear to be dominated by strong global selection. These attributes conform tightly to mean values that vary little from site to site, reflecting strong constraints operating on a pan–Great Basin scale. The transmission of information concerning the proper proportions of such attributes was obviously quite conservative in these cases. Little error accompanied the transmission of this information, leading to consistently low rates of variation over large geographic areas. Conversely, certain point types (notably Desert Side-notched and Cottonwood) and certain attributes (notably length and thickness) reflect more localized functional control, varying in mean value from site to site while displaying consistently low variation around those means.

Only 11 type–attributes exhibit variation, suggesting a significant nonfunctional, or selectively neutral, component. Thickness measurements of five different point types and basal and neck widths of three and two point types, respectively, display such variation. Attributes of Gatecliff and Elko points most commonly display high VOV values as a result of regional outliers, suggesting use as local emblemic or assertive markers. Significantly, none of these or any other type–attribute we examined displays a pattern suggesting use as a universal emblemic marker (high VOM, low AV, high VOV). This was not surprising. It is highly improbable that the same attribute would be chosen as an emblemic marker from one end of the Great Basin to the other, partly because individual attributes are incapable of conveying the emblemic information needed to differentiate among so many different ethnic groups at once. Emblemic information is likely better expressed through attribute combinations (e.g., specific combinations of length and width), which would substantially increase the space for emblemic expression. Whereas it is possible that the point types themselves are emblems of ethnic affiliation, no major spatial differences among point types have been discovered to date.

In conclusion, variation in artifact attributes has much to tell us about human behavior. Perhaps the most important lesson learned from this particular exercise is that it is important to construct models that produce objective, explicit predictions about how variability should behave under different natural and cultural forces at various spatial and temporal scales. We hope to have started this process by examining these processes within Great Basin projectile points at different local and global scales. These processes are of considerable relevance to evolutionary theory, especially where cultural transmission is concerned. Because selection operates on extant variation, characterizing the nature of that variation in archaeological data is critical to understanding how transmission processes operated to shape the record. As we have shown, variation can be evaluated at different levels and on different dimensions. These levels should be of varying relevance to different kinds of selection (e.g., individual- versus group-level selection). Attributes under strong design constraints are subject to different kinds of selective forces than attributes under neutral or other selective forces. As a result, they will pattern differently in the archaeological record than those serving as loci of social information. Teasing apart these patterns from the archaeological record requires characterization of variation at different spatial scales in artifact assemblages.

ACKNOWLEDGMENTS

We thank Hector Neff, Fraser Neiman, and James Skibo for providing valuable comments on an earlier draft of this essay. Their insightful comments forced us to rethink some of our earlier notions regarding artifact variation and have made the chapter much better. Finally, we thank David Hurst Thomas for measuring the thousands of projectile points used in this analysis and making his data available to us.

NOTE

1. Local control will mimic global control in regions that are homogeneous, i.e., in cases where an attribute is shaped mainly by a local context (e.g., raw material availability) that is the same in every locality. However, this plainly amounts to global control within the universe in question, i.e., the study area. This highlights the importance of thinking carefully about scale when doing this kind of analysis.