Cultural transmission, copying errors, and the generation of variation in material culture and the archaeological record

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Abstract

Archaeologists are adept at analyzing variation in artifacts. The discipline has well established and tested methods to track change through time and to evaluate the function of artifacts that depend upon measures of variation in the archaeological record. Although a critical concept, the means by which variation in material culture is generated is not well understood. This paper explores one source of variation, copying errors, and systematically examines how cultural transmission processes act to amplify, reduce, or maintain such variation. Using simple models, we generate expected distributions for the amount of variation that occurs through time under varying circumstances. This variation is caused by small errors that are transmitted from one person to another in the propagation and replication of cultural traits. These baseline values provide useful null models for explaining variation in prehistoric assemblages of artifacts. We use measurements of projectile points from Owens Valley and Woodland ceramics from Illinois to demonstrate the value of this approach.

Keywords: Cultural transmission; Evolutionary archaeology; Copying errors; Owens Valley; Projectile points; Woodland ceramics

Over the last 25 years there has been a renewed interest among social scientists to explain human culture change within an evolutionary framework, especially using cultural transmission theory. Building on the foundation of culture historians (e.g., Kroeber, 1916) and the works of evolutionary scientists such as Boyd and Richerson (1985) and Cavalli-Sforza and Feldman (1981), the number of articles following this approach has steadily increased. Recent and lively debate over the pathways, patterns and constraints of cultural transmission demonstrate a continued interest in the evolutionary study of cultural change (e.g., Atran, 2001; Auinger, 2000, 2002; Bentley and Shennan, 2003; Boyd and Richerson, 1995a,b; Boyer, 1999; Henrich, 2001, 2004; Henrich and Boyd, 2002; Mesoudi et al., 2004; O’Brien and Lyman, 2000; Plotkin, 2002; Shennan, 2000, 2002; Sperber, 1996; Wheeler et al., 2002).

To date, the main emphasis in evolutionary research on the archaeological record has been on identifying the processes that guide and regulate the transmission of the cultural traits. We have, for example, increased our understanding of what we should expect to see in cases of transmission that are strongly structured by conformist biasing and other kinds of sorting (e.g., Bettinger and Eerkens, 1999; Boyd and Richerson, 1985; Henrich and...
Lipo, in press) that examines the generation of variation. In the absence of variation, the others being the generation of variation and differential success between variants (Lewontin, 1974). Among the three, the generation of variation has received much less attention from anthropologists. Variation is the raw material upon which selection operates to cause changes in the frequency of cultural traits through time. Though transmission can operate in the absence of variation, evolution (i.e., change) cannot take place. This paper builds on our previous research (Eerkens and Lipo, in press) that examines the generation of variation as a result of small errors when cultural traits are replicated. Specifically, we consider the effects of cultural transmission processes and how they act on sources of variation. We focus our attention on the reproduction of material culture, though our arguments could be extended to other aspects of human culture.

Variation in archaeological studies

Archaeologists have used variation in material culture to study prehistory since the inception of the discipline (e.g., Evans, 1850, 1875; Holmes, 1890, 1891, 1894; Rau, 1896; Wilson, 1891). Beginning with the emergence of culture history as an explanatory paradigm, interest in variation has been primarily focused on its use in temporal and spatial frameworks for tracking change through time and interaction across space (e.g., Ford, 1935; Kidder, 1917; Kroeber, 1916, 1919; Spier, 1917). Alfred Kroeber (1916, p. 15), for example, noticed that the relative abundance of corrugated pottery in the area around Zuni Pueblo in the American Southwest seemed to be correlated with the age of a site; the greater the abundance of this kind of pottery the more recent the site was interpreted to be. Variation in the abundance of certain pottery types, he recognized, seemed to be a function of change over time. This observation about variation allowed Kroeber to construct a method for ordering ceramic assemblages through time (Lyman et al., 1997), a step critical to the formation of culture history as an explanatory framework in archaeology. In this sense, studies of artifact variation form a vital part of the methodology of our discipline. Work in this area has continued since the early part of the twentieth century (Dunnell, 1986). On the basis of these efforts, we now have excellent tools for studying change through time based on variation in material culture including ceramic decoration and composition, projectile point morphology, and architecture (e.g., Cochrane, 2002; Cordell, 1993; Ford, 1938; Graves and Cachola-Abad, 1996; Lipo, 2001; Lipo et al., 1997; Neiman, 1995; O'Brien and Lyman, 2003; O'Brien et al., 2001; O'Brien and Holland, 1990).

Variation in artifacts, however, is not restricted to dimensions that change through time. Even prior to the advent of culture history as a cohesive paradigm, archaeologists were interested in the study of technological variability in artifacts (e.g., Holmes, 1891, 1894). Much later, the new archaeologists of the 1960s and 1970s began to change the focus of research from temporal sequences to the means by which behavior is reconstructed. New emphasis was placed on the study of artifacts as representations of functional activities (e.g., Binford, 1962, 1973; Hill, 1977a; Plog, 1976; Wobst, 1977). In the study of ceramics, for example, researchers began to investigate the role ceramics played in the organization of household, craft, subsistence and social activities (e.g., Blitz, 1993; Costin and Hagstrum, 1995; Ericson et al., 1972; Evans, 1978; Hill, 1977b; Kramer, 1985, 1979; Mills, 1989; Schiffer, 1990; Schiffer et al., 1994; Skibo, 1992; Skibo et al., 1989; Smith, 1985; Turner and Lofgren, 1966). Overall, in the last 30 years we have seen an increasing body of literature on the means for relating artifacts and structures to past functional activities (e.g., Ahler, 1979; Beck, 1995; Binford and Binford, 1966; Dunnell, 1978a; Levin, 1976; Meltzer, 1981; Scheinsohn and Ferretti, 1995; Skibo, 1992; Symens, 1986; Weissner, 1983).

Despite our reliance on and adeptness in using variation to study the past, we know little about the processes related to its source. We have limited knowledge about the conditions which encourage the generation of variation and the conditions under which variants disappear. In addition, we have not developed firm theoretical grounds to determine whether variation is generated as part of a single process or is differentially produced along indepen-
dent dimensions that vary based on the content and environment of transmission.

Several recent studies have attempted to fill this gap. Drawing on the models of Boyd and Richerson (1985), researchers such as Shennan and Wilkinson (2001), Bentley and Shennan (2003), and Kohler et al. (2004) have explored how social processes, such as conforming to norms or copying prestigious individuals, can sometimes reduce the amount of variation within sets of artifacts. Models proposing how variation is increased within an evolutionary framework, however, are less common despite the fact that one of the most striking aspects of the archaeological record is the tremendous increase in the range of artifacts used from 2.5 million years ago until the present. Neiman’s classic study (1995) of stylistic variation of Woodland ceramics, Shennan and Wilkinson’s (2001) analysis of Linearbandkeramik pottery, and Kohler et al.’s (2004) study of Southwestern pottery are notable exception in this regard. Using measures of ceramic sherd thickness, Neiman examined how random drift processes operate on selectively neutral variation and how such processes affect the number of types (i.e., diversity) and their longevity within an assemblage. Similarly, Shennan and Wilkinson (2001) and Kohler et al. (2004) examine patterns of pottery styles and infer the social processes that shaped their generation and transmission through time, finding either greater than expected or less than expected diversity in ceramic assemblages. Both studies compare archaeological data against that generated from “null models” using computer simulation, which assume purely random copying and transmission. Such null models are useful because they provide a way to contextualize archaeological data, that is, a way to understand apparent patterns (e.g., Brantingham, 2003). Our study takes a similar tack, but explores metrical variation within types, instead of the types themselves.

**Sources of cultural variation**

How is variation in material culture generated and retained? Answering this question requires us to consider how culture is transmitted. Unlike genetic transmission, which is based on the duplication of relatively well-studied molecules of DNA and RNA, there are no agreed-upon empirical units of cultural transmission. Cultural units are sometimes referred to as memes (after Dawkins, 1976) or culturgens (after Lumsden and Wilson, 1981) in the literature, but despite the fact that they are named, the unit of culture and how it is transmitted is still not well understood. However, this is not a deficiency per se. The lack of a readily identifiable physical unit for cultural transmission is a consequence of the fact that the physical forms of cultural information come in a variety of sizes and scales and are constantly changing. There are no boundaries on the types of physical entities that can carry information; particulate inheritance, the form common in genetic transmission, is not required. For evolution to happen, and for us to be able to study it, all that matters is that information is passed from one individual to another and that there are one or more sources of variation for this information.

Although biologists routinely refer to the “gene” as a concrete empirical entity, the lack of boundaries is true for both cultural and genetic forms of transmission. Biologists still struggle to define and understand a “gene.” When studying all processes of transmission, we must keep the physical package separate from the information being transmitted. Genes in this view are conceptual measurement units, constructed only for purposes of analysis—not “things” that are found discretely in nature. This is true for any entity we might conceive of for cultural transmission. When we study cultural transmission it is not the physical package or suite of characters that matter but rather the cultural information that the transmission units convey.

The definition of the gene proposed by Williams (1966) provides a good starting point for discussing the unit of cultural transmission. Williams defined the gene as the unit that segregates and recombines with appreciable frequency. Extending Williams’ definition, Pocklington and Best (1997, p. 81) state that cultural transmission units are “the largest units of socially transmitted information that reliably and repeatedly withstand transmission.” In this sense, cultural units represent any measurable units that we can delineate within the suite of cultural variation that displays heritable continuity, measured as a greater than random degree of coherence of information traced through time and across space. Importantly, the units of transmission are ideational and not directly observable. They consist of information and are conceptually analogous to “recipes” for behavior, artifacts, and ideas (Lyman and O’Brien, 2003). Studies of cultural transmission must focus on identifying patterns of repeated co-occurring attributes while also measuring the effect of transmission on the production of variation.
Elsewhere (Eerkens and Lipo, in press) we have attempted to conceptually categorize the sources of cultural variation and define classes for the processes in which new variants are introduced into the pool of variation. This framework is summarized in Table 1. In the table, the vertical axis represents the location of the variation within the transmission process. Variation can be defined to occur in three different conceptual locations during transmission and materialization: (1) in the transmission of an instruction set itself (i.e., how to do something), (2) during the execution of that instruction set (i.e., actually doing it), or (3) as a result of heterogeneity in the raw material out of which a variant is generated. The second two categories are related to the effects of the medium in which transmission occurs rather than being related to a mistake on the part of the producer of culture. Thus, in reproducing a piece of music, variation in the final product can come from an inaccurate transmission of the song itself (e.g., a person hears or remembers the song in a way that is distinct from the way actually played), from a slightly different playing of the song (e.g., a pianist hits the wrong key during a rendition of the song despite having an accurate copy of the song in his/her head), or from the use of a different instrument or performance hall, for example with different acoustic properties, to recreate the music.

The horizontal axis in Table 1 classifies the mechanisms by which variation is produced. First, variation can be produced simply as the result of an error in copying. These errors are a consequence of inaccuracies in observation and not perceived or intended. In this case, the observer simply copies instructions but inadvertently introduces errors that he/she is unaware of. Alternatively, variation can be produced by cognitive mechanisms that sort and recombine information in order to create new forms that may be evident and perceptible to the replicator. The latter process of variation generation is often considered to be “biased” and/or “intentional” variation, or the result of “invention,” “discovery,” or “innovation.” For our purposes “intent” is not pertinent to the discussion. Variation is either derived from simple copying error not perceived by individuals, or it is modified by internal cognitive processes, regardless of the intention of the inheritor of culture. The latter may or may not be conscious decisions by the inheritor. That is, they may copy a prestigious individual but purposefully modify the behavior according to their own worldview (e.g., Gabora, 2004), for example, adopting a particular clothing style but changing the color scheme, or they may subconsciously adopt the modal behavior within a population.

We argue that these two processes on the left and right side of Table 1 generate distinctly different kinds of variance. The former generates primarily random variation and is analogous to mutation in genetic transmission. There is no predefined or predictable direction to the variants produced by these processes. Over time random error accumulates, increasing the tails of the distribution of variants. If people make errors in copying the instruction set (first entry in the first column of Table 1), we might think of this as inaccuracy in learning or approximation, most likely due to errors in perception. For example, this inaccuracy would occur if something is perceived as larger or as smaller than it really is. On the other hand, the error could occur during execution of the instruction set (second entry in first column) and would be due to imprecision in manual dexterity. Alternatively, if the variation is produced as a result of the heterogeneity in raw materials or the medium used (third entry in first column) we might refer to this as compositional or structural variation. This category would include when there are flaws in the raw materials that cause unintended variation, despite having exact copies and correct execution of the instruction set.

<table>
<thead>
<tr>
<th>Location of variation</th>
<th>Process of variation generation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transmission of instruction set</td>
<td>Copying error below perception threshold</td>
</tr>
<tr>
<td>Execution of instruction set</td>
<td>Error in learning</td>
</tr>
<tr>
<td>Medium of execution</td>
<td>Error in implementation/manual dexterity</td>
</tr>
</tbody>
</table>

Note: “Invention” is effectively recombination—rearrangement of existing information/instructions/memes (Gabora, 2000). Also, variation in this table is historical—and thus homologous.
It is expected that the scale of variation due to copying error, especially the first and second entries in column 1, should be relatively small (Eerkens, 2000; Eerkens and Bettinger, 2001). Below, we present a model for predicting how small. These figures are especially relevant in prehistoric settings before the advent of weighing scales, meter sticks, written instructions, and other standards that provide means and checks for reducing variation in copying errors. Variation due to differences in raw material (third entry in first column) may have more widely varying magnitude, depending on the structure of the material and inherited rules for material selection.

The second mechanism (second column of Table 1), on the other hand, produces variation that is of much greater magnitude and can be directional due to the cognitive mechanisms that act to sort variation. As Gabora (2000) describes, our evolved brains do not solve problems through random or exhaustive experimentation with all possible solutions. Thus, an individual may create a new tool to solve a particular problem, but would be unlikely to randomly create objects of different sizes and shapes until a workable form was discovered. Rather than being random, cultural variation from the second column of Table 1 starts with inherited variability and modifications are generated “strategically, using an internal model of the relationships amongst the various elements of the problem domain, and contextually, responding to the specifics of how the present situation differs from previously encountered ones” (Gabora, 2000). This inherited “internal model” relates to the “worldview” that Gabora defines in a later work (2004). We predict that the scale of variation generated by this process will be much higher relative to copying error.

This second mechanism for the generation of variation, the process of invention, discovery, and/or innovation, has received significant attention from scholars of technology (Basalla, 1988; Rogers, 2003), including archaeologists (e.g., chapters in van der Leeuw and Torrence, 1989). Although invention, discovery, and innovation invoke notions of entirely new technologies or processes to solve problems, most diachronic studies demonstrate the continuous and historical nature of material technologies (Basalla, 1988). Even in today’s technology industry in the United States, innovation almost always results from the merging of ideas from different fields and/or a reconfiguration of an existing technology (Hargadon, 2003). Thus, most change in material culture comes about through relatively small changes that build up over time, and not through radical departures from existing technologies (Shennan, 1989, 1991). This process has been well studied by scholars of western industrialized technology and is variously referred to as “re-invention” (Rogers, 2003), “recombinant technology” (Hargadon, 2003), or “self-conscious design” (Alexander, 1970).

Although there may be other ways to classify the generation of variation, this model provides a starting point for parsing out different kinds of variation and their consequences in the archaeological record. Here, we would like to focus on the first column in Table 1, particularly the first two rows. One of the reasons why we think this area of investigation is of particular interest is because we can generate quantifiable expectations about the degree of variation that should be involved. Determining the degree to which random variation is introduced into the transmission and execution of instructions gives a means for studying how change occurs in the absence of other factors—a null model against which we can evaluate change. Thus, if there is change through time in the variation within artifact types, we can evaluate change. Thus, if there is change through time in the variation within artifact types, how much of this change can we attribute to the simple effect of copying errors? Similarly, when there is less variation than expected due to these copying errors, we can then begin to attribute this lack of change to other factors.

Human perception and error

The human senses (e.g., sight, hearing, taste, etc.) operate by measuring various physical phenomena in our physical environment (e.g., wavelengths of reflected light, vibrations in the air, levels of different chemical compounds in food, etc.). These measurements help us to perceive and adapt to our surroundings, and allow us to manipulate objects. Clearly, the ability to compare and evaluate these measurements and to differentiate, for example, between large animals and small ones, shallow holes and deep pits, poisonous plants and edible ones, and so on, is crucial to our survival.

Research in the psychological sciences has helped to identify the empirical limits of the acuity of human sensory systems, especially our ability to perceive differences (Coren et al., 1994; Norwich, 1983; Palmer, 1988). Due to physiological constraints humans have great difficulty observing differences below certain threshold values. These
limits vary depending on what sensory system is being used to measure (i.e., perceive) the phenomenon of interest, and differ slightly from person to person, but are surprisingly constant. As a result of these limits, variation below these thresholds is virtually imperceptible and everything is interpreted as the same. Limits in perception are produced by the logical structure of individual cognition as well as physiological constraints (van Doorn et al., 1984). For example, the eye is predominantly composed of water and its composition limits optical quality and the available spectral window. These hardwired limits produce constraints that have implications for the production of variation in artifacts, and hence, change through time in the amount of variation we can expect in sets of artifacts (see below).

For humans, errors in perception are always relative to the size or intensity of the phenomenon being measured, unlike machines such as mechanical weighing scales which have absolute error terms (e.g., plus or minus 1 gram). For example, in order to tell if two lines are different in length, one must be about 3% longer than the other (Coren et al., 1994; see also Eerkens and Bettinger, 2001). If the lines are within 3% of one another they will appear equal in length to the naked eye, though this does not apply when an external standard, such as a ruler, is used as the method of measurement or when the lines are placed directly next to each other (in which case one serves as a ruler to measure the other). This 3% value is referred to as the Weber Fraction for estimation of length. Each sensory system has a unique Weber Fraction indicating the acuity of the human body to distinguish difference for that particular sensory input.

Since the manufacture of discrete objects is heavily dependent upon memory and manual dexterity, inaccuracy in human perception, especially of size, is likely to be relevant to archaeological studies of artifact change. If there are physiological limits to the human ability to perceive differences, then it is reasonable to assume that small amounts of error below the limits of detection will be introduced during transmission. This small amount of error is introduced in any copying event in which information is communicated about what an artifact should look like and how it should be made. We refer to this source of variation as “copying error.” Although the error is imperceptible at each transmission event, it is cumulative and can become perceptible over time. As we show in our simulations, in the absence of a fixed reference template, these errors can accumulate quite dramatically and be subject to change by different evolutionary forces, resulting in visible change over time (Simons et al., 2000). Below we model the generation and propagation of copying error to determine how much variation we may expect over time from such processes.

**Modeling the generation of variation**

Given simple rules about cultural transmission we can build expectations for the amount of variation present in artifact assemblages due to copying errors. As a starting point, we take 3% as the smallest difference that might be detectable for two measurements, the Weber Fraction for visual measurement of line length. This value represents the magnitude of values that are thought to be inherent in human cognition (Coren et al., 1994; see also Eerkens and Bettinger, 2001). What this means is that if individuals cannot tell the difference between the length of two bifaces that are within 3% of each other, and transmission processes consist of simple copying or imitation, it stands to reason that people may be off by up to 3% during the transmission of information about what size to make an artifact. As a result, we can expect a certain amount of drift during the process of transmission, whether horizontal, vertical, or oblique. How much drift can we expect? Modeling this process using simple simulations of the transmission of information provides one way to answer this question.

**Unbiased transmission**

In our simplest simulations we focused only on vertical transmission of information. The simulation consisted of several lineages with direct replacement in each generation. Each “parent” passes information to a single “offspring” about an attribute. This configuration is akin to asexual reproduction with one-to-one replacement of a parent by an offspring in each generation. The attributes are arbitrary but could be imagined as “the length of an arrowhead.” In each subsequent generation, error is added to the attribute value and transmitted to the next generation, in a Markov chain fashion. In this way, the values for arrowhead length could change over time. We can describe this situation with a simple time series equation

\[ Y(t + 1) = Y(t) + Y(t) \cdot c \cdot N(0, 1), \]  

(1)
where $Y(t)$ represents the attribute at any time $t$, and $Y(t + 1)$ represents the attribute at the next point in time (i.e., $t + 1$ or the next generation). In the equation above, $c$ represents the error rate divided by two and $N(0, 1)$ is a normal random variable with mean of zero and variance of one. Thus, the length of the arrowhead at time $t + 1$ is the length at the previous time plus a small amount of error. This error is normally distributed around the value 0 and is scaled by both the error rate (3%) and previous attribute value. The amount of error, therefore, can be positive or negative. Over time, the cumulative results of this error will behave in a stochastic fashion. This particular stochastic process has been well studied by mathematicians and is known more generally as a multiplicative linear white noise process (Gardiner, 1985, pp. 103–104).

We modeled this process across 400 generations with 10 individuals in each generation (i.e., 10 lineages), where there is no interaction between contemporary individuals (i.e., vertical transmission only). Ten such Markov chains are shown in Fig. 1. As seen, each population drifts around the mean, increasing or decreasing slightly with each generation. While, individual lineages can drift quite far from the mean, the overall average stays about the same. This is a result well known from biological studies on genetic drift (e.g., Wright, 1970). What clearly changes over time, however, is the amount of variation between the ten lineages. The coefficient of variation (CV) is one way of tracking the amount of variation within a population of measures. The CV is a dimensionless measure of variation across populations and represents the sample standard deviation divided by the sample mean multiplied by 100. If we calculate the CV in our simulation we can see that it increases monotonically through time. In fact, we can express the CV as a function of the number of generations that have passed (i.e., time) and the error rate. The general formula describing the relationship between CV, error rate, and time is:

$$CV = \sqrt{e^{2c t}} - 1,$$

where $e$ equals 2.7183 (sometimes called Euler’s constant), $c$ is the error rate divided by two, and $t$ is time measured in the number of generations. This equation implies that the CV strictly increases but that the rate of increase slows over time, much like a parabola turned on its side. The dashed line depicting CV in Fig. 1 shows the relation between these parameters.

These basic simulations show that, in the absence of interaction and selection but with copying error, variation will be transmitted and amplified over time. This is due simply to imprecision in how humans are able to visually measure, remember, and replicate artifacts. The rate of CV increase, however, slows down over time, roughly as the square root of the number of generations.
Biased transmission

Of course, the transmission of culture rarely operates in such a fashion. People often transmit information obliquely and/or horizontally using a range of techniques (i.e., transmission rules) such as conformist transmission, prestige-biased transmission, guided variation, and/or indirectly biased transmission (e.g., Boyd and Richerson, 1985; Cavalli-Sforza and Feldman, 1981; see review by Henrich and McElreath, 2003). Each of these kinds of sorting mechanisms can potentially influence the range of variation that occurs within a population.

Table 2 presents one way in which cultural transmission sorting mechanisms can be classified. Rules for sorting may depend on the direction of inheritance. In most transmission models (e.g., Boyd and Richerson, 1985; Cavalli-Sforza and Feldman, 1981) rules for inheritance are determined by whether a trait is being adopted from a peer (i.e., horizontal transmission), from someone of a previous generation (i.e., oblique transmission), or from a parent (i.e., vertical transmission). In addition, traits can be adopted from a single individual (e.g., a prestigious individual or a parent), some subgroup of the population (e.g., a clique) or from the entire population (e.g., an average population value). These factors create a set of eight potential transmission scenarios. In the case of cultural transmission, however, the status of “parents” is indeterminate: anyone can serve as a “parent” for traits and biological parents only have the potential to be one of the “prestigious individuals.” In our next set of simulations, we focus on the effects of conformist and prestige-biased transmission on variance during trait inheritance.

### Conformist transmission

To model conformist transmission we set up a similar simulation to the one above. In conformist transmission, individuals conform to the average value (with attending error) from the entire previous generation, that of their parent. Using the average value is only one way of framing a conformist model; modal or median values produce similar results. In our simulations, the probability of conforming to the average was held constant for all individuals within a particular simulation run. Different runs allowed us to vary the probability of conformance for each transmission event from 0 to 100%. For example, in one simulation individuals might have a 5% chance of conforming to the average of the previous generation while in another they might conform 50% of the time. We refer to this value as the strength of conformance.

In theory, a conformist transmission process should have the effect of reducing the amount of variation within the population compared to unbiased transmission. This is because lineages that run off to one extreme or the other, as in Fig. 1, will have a chance of returning back to the average value at each generation. The probability of this occurrence depends on the strength of conformance. If the strength of conformity is 0%, transmission will be unbiased and variation will increase as discussed above. If the strength of conformity is 100%, variation will remain constant, equal only to the error rate.

Fig. 2 shows the effects of six different levels of strength of conformance on the CV. Data points represent average CV values calculated for 10 different simulations. As shown, the CV increases over the generations in each simulation until a threshold is reached. After this threshold, CV stays constant in equilibrium. The greater the strength of conformance the faster it converges on the equilibrium value. A simple mathematical formula (i.e.,

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Table 2

<table>
<thead>
<tr>
<th>Direction of inheritance</th>
<th>Traits copied from:</th>
<th>Subset of individuals (1 &lt; n &lt; N)</th>
<th>Population (n = N)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vertical</td>
<td>Direct transmission (i.e., parent)</td>
<td>Direct transmission (i.e., both parents)</td>
<td>N/A</td>
</tr>
<tr>
<td>Oblique</td>
<td>Direct transmission (e.g., teacher)</td>
<td>Conformist transmission (i.e., group)</td>
<td>Conformist transmission (e.g., parental generation)</td>
</tr>
<tr>
<td>Horizontal</td>
<td>Prestige-biased transmission (e.g., individual)</td>
<td>Prestige-biased transmission (e.g., peer clique)</td>
<td>Conformist transmission (e.g., peers)</td>
</tr>
</tbody>
</table>

Notes. N refers to all individuals from which copies can be made. This number varies depending on direction of inheritance.

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1 In an infinitely large population this threshold value would represent an asymptote. Given a finite population and a stochastic process, however, this value is actually reached within the simulations.
analytical solution) describing either the number of generations required to reach this value or the equilibrium value itself is not evident to us. However, when the simulation data are plotted a clear relationship between the final CV and the strength of conformity is evident. Fig. 3 shows this relationship. A regression through these points suggests that the CV is roughly equal to the inverse of the cube root of the strength of conformity, multiplied by a constant.

Overall, the CV values from the conformist transmission simulations show that this method of acquiring cultural information reduces the amount of variation within populations, as expected. The amount of variation removed depends on the strength of conformist transmission. Surprisingly, only a small amount (5%) of conformity is required to reduce the final CV by over half its original value when there is only unbiased transmission. This result suggests, as other recent studies have also shown (e.g., Henrich, 2004; Henrich and Boyd, 2002; Henrich and McElreath, 2003; McElreath et al., 2003; Shennan, 2000), that even small changes in how some people obtain information can have significant effects on the structure and composition of culture over time. Moreover, the use of conform-
ist transmission greatly reduces the effect of drift and keeps attributes near the initial starting values over time.

**Prestige-biased transmission**

In prestige-biased transmission, traits are not equally likely to be adopted from all individuals within a population. Instead, certain individuals—those who are “prestigious”—have a disproportionate probability of having traits copied. Our simple simulation assumes that all individuals are equally likely to be prestigious. In each generation a single prestigious individual is chosen at random. In the following generation instead of adopting the trait of their parent, each individual has a chance to adopt the trait of this prestigious person. The probability with which individuals do this is set for each simulation, but can be varied from simulation to simulation (i.e., the strength of prestige-biased transmission). If we keep prestige within certain lineages rather than picking prestigious individuals randomly each generation, individuals will be biased to copy this attribute values within the prestigious lineage instead of the average. However, the overall effect in our simulations will be the same as in conformist transmission.

Results from the prestige simulations show that the effects on CV are very similar to those of conformist transmission (Fig. 4). This result was expected because both models work in a similar way; when individuals do not inherit a trait directly from their parent they copy an alternative. In conformist transmission this alternative is the mode or an approximation of the average within the population, in prestige-biased transmission it is a randomly selected prestigious individual.

Again, even small amounts of such prestige-biased transmission act to greatly reduce the amount of variation in each generation, but not as much as conformist transmission. This result occurs because in conformist transmission individuals must copy the average value of the previous generation which does not vary much from generation to generation. In contrast, individuals engaged in prestige-biased transmission could copy traits from an individual with highly unusual values. As a result, prestige-biased transmission allows for much greater drift in attributes over time, unlike conformist transmission. Increasing the number of prestigious social models individuals can copy from (i.e., instead of only one as we have simulated) will serve to increase variation even further from that shown in Fig. 4. Thus, as the number of “prestigious” models approaches the population size the results will look more and more like unbiased transmission with respect to the generation of variation.

In sum, many different biasing transmission processes will act to reduce variation over time. In our simulations above we have started with a homogenous population and allowed variation to build up over time. If, on the other hand, variation is high to begin with, the introduction of conformist and prestige-biased transmission can act to quickly

![Fig. 4. Effects of different levels of prestige-biased transmission on CV.](image-url)
reduce variation, even with copying error. How quickly this happens will depend, of course, on the relative strength of these modes of acquiring cultural information.

Case studies

Simulations provide the basis for generating null models. Their usefulness relies on application in the empirical world. We now use the simulated data to help explain the range of variation in two archaeological case studies. The case studies are not presented as exhaustive analyses of artifacts in a particular cultural setting (such analyses will form the basis of future work). They are merely used to show how we can apply the ideas discussed above to examples using real archaeological data. Each study examines changes in variance in assemblages of material artifacts over time and evaluates whether copying error is sufficient to explain the data, or if other variance amplifying or reducing cultural transmission processes must be considered.

Owens Valley projectile points

The first study focuses on projectile point variation in California and the Great Basin. Rose Spring or Rosegate points (Bettinger and Taylor, 1974; Thomas, 1981) were introduced into Owens Valley around 1500 years ago and were used until roughly 650 BP. These points have been well studied because many have been recovered and they represent the transition from atlatl to bow and arrow hunting (e.g., Bettinger and Eerkens, 1997, 1999; Delacorte, 1999; Fenenga, 1953; Lanning, 1963, p. 249; Thomas, 1981; Yohe, 1992). Moreover, most are made out of obsidian, a material which allows for an independent measurement of age of manufacture using hydration techniques (Ericson, 1989; Hall and Jackson, 1989; Hull, 2001; Jones et al., 1997; Meighan, 1983).

Over 100 individual Rose Springs points from Owens Valley with hydration measurements were arranged from youngest to oldest based on their age estimates. We calculated a running CV across the age-stratified sample (16 projectile points representing each data point). In other words, the data are organized much like paleoclimatic graphs where a running average through data points, such as tree ring width, represents trends through time in past climate, not actual climate. Since successive data points along the x-axis are correlated, sharing 15 out of 16 projectile points in the calculation of the CV, such running data make change appear gradual, when in fact it may be abrupt. Thus, the gradual increase and decrease of variation shown in Fig. 5 is partly a product of the way the CV data are generated.

Fig. 5 shows running CV for basal width and thickness of Rose Springs points. These two attributes were selected for analysis because they represent different kinds of patterns in CV over time. We also examined other attributes, but do not report them here because they mimic patterns in these other attributes.

In the upper part of Fig. 5, variation in basal width decreases through time, especially after 1250 BP. This pattern suggests that basal width was not subject to copying error alone, in which case we would expect rising CV. Instead selection or winnowing of forms seems to have taken place over time. For example, the use of either conformist or prestige-biased transmission (or both) around 1250 BP could also account for such winnowing. In fact, if we assume an error rate of 5% during copying and production of points, a rate determined experimentally by Eerkens (2000), 25 years per generation, and a large population (over 20 point makers), we can estimate the strength of conformity it would take to reduce the CV from 0.27 at 1250 BP to 0.17 at 750 BP, roughly 20 generations. Using Eq. (2) and the results from the conformist transmission model above, it would take a conformity rate of about 10% at each transmission event. In other words, only 10% of the population would need to copy the average of the previous generation while the remaining 90% could inherit this trait directly from their parents, with attending copying error in both cases. Thus, despite the addition of copying error, the CV would decrease through time by this amount with a small amount of conformity.

Thicknes in Rose Springs projectile points behaves quite differently, getting increasingly more variable through time. Such an increase is akin to our simulations for copying error above. In fact we can determine how much copying error is required by using Eq. (2) and solving for \( c \), the error rate. Doing so, we find that to increase the CV from 0.15 at 1250 BP to 0.20 at 750 BP, representing roughly 20 generations, would require 5.8% of copying error in each generation, close to experimentally determined rates (Eerkens, 2000). This suggests that the increase in variation we see in thickness may be due primarily, if not completely, to errors in copy-
ing. In other words, from the initial value at the time of invention or introduction of the point type in Owens Valley, thickness values seem to be drifting in a random-like process due to copying error, therefore, increasing slowly in variation through time. Other variation-increasing explanations such as experimentation or innovation are unlikely and not necessary to account for these changes.

These findings are in line with what we know about projectile technologies and previous archaeological findings in the region. It is not surprising that variation in an attribute like basal width decreases due to selection while thickness changes more in a drift-like fashion. In previous analyses we found that the introduction of the bow and arrow in Owens Valley appeared to correspond with patterns of variation consistent with heavy experimentation (Bettinger and Eerkens, 1999). Since basal width controls the hafting of a point to a foreshaft and strongly affects the function of an arrow, it stands to reason that inefficient shapes would be quickly winnowed from the pool of variants. Such winnowing would be accelerated if it occurred in tandem with the type of sorting caused by prestige and conformist transmission. Perhaps certain individuals experimented with different forms and arrived at improved forms in this newly introduced technology. Aspiring hunters may have opted to copy the technology of these successful variants or copy their approximation of the average or mode within the population, rather than have to expend effort experimenting (i.e., innovating) themselves. This kind of pattern is expected. Patterns of exploration and sorting are commonplace in many instances of evolution when new kinds of forms are introduced—whether those forms are technological (e.g., Basalla, 1988; Hargadon, 2003) or biological (e.g., Gould, 1990).

On the other hand, within certain tolerances, thickness has less influence on the function of a projectile point and thus is more likely to vary as expected for a stylistic attribute (sensu Dunnell, 1978b; Weissner, 1983). With less contribution to the overall function, greater magnitudes and rates of copying errors in thickness could have been tolerated. As a result, variation would have been free to increase in this dimension.
Illinois Woodland Pot Sherds

The second case study uses data published by Braun (1977, 1985) and subsequently analyzed by Neiman (1995) for Woodland-period ceramics (ca. 2500–900 BP) from Illinois. Each pottery assemblage is associated with a unique radiocarbon-dated feature. While Neiman (1995) used the data to examine drift and innovation of ceramic types (i.e., classificatory or non-continuous attributes), we focus on two attributes that Braun measured on a continuous scale akin to the simulations presented above, thickness and pot diameter. We used these two attributes precisely because they are the only two measured on a continuous scale, and for that reason are comparable to our model and simulations.

We calculated a CV for each assemblage for these two attributes and sorted the assemblages by radiocarbon date. Fig. 6 plots the data. Thus, unlike the projectile point data, successive data points in Fig. 6 are not correlated and are composed entirely of independent observations. As a result, the CV is much more variable around the trend line. This is not a product of sample size of pot sherds, as small samples (8–12) have the same range of CV values as large samples (over 50). Instead, this variability about the trend line is inherent in the data.

Braun (1985, 1987, 1991) focused mainly on sherd thickness in his work. In particular, he examined rates of change in the average thickness of sherds. Using the first-order derivative of a time series curve through the average sherd thickness, he extracted five ceramic “trends” indicating different selective regimes for thickness (Braun, 1987). The most significant of these include a period of selection for thicker pots between 2200 and 1900 BP (from 7.5 to about 8.5 mm), a strong and prolonged period of thinning pots between about 1900 and 1600 BP (from 8.5 to 6.0 mm), and a shorter and weaker period of selection for thinner pots between 1500 and 1300 BP (from 6.0 to 5.5 mm). Braun referred to these as Trend 1, Trend 2, and Trend 4, respectively.

Fig. 6. Variation in Woodland ceramics from Illinois.
We expected to see that changes in variation somehow followed these selective regimes. Periods of high selection should be followed by periods displaying a reduction in variation. Unfortunately, as seen in Fig. 3, there seem to be only minor changes in variation for thickness, despite the fact that average thickness changed substantially over this time (Braun, 1977, 1987, 1991). Our binomial regression indicates a slight increase in variation during the early part of the sequence between 2400 and 1900 BP, similar to the results obtained by Neiman (1995, :20). Significantly, the magnitude of this increase is less than we would expect from copying errors, suggesting that some variation-reducing processes were in effect during this period. The increase in variation corresponds temporally to Braun’s ceramic trend 1, which represents an increase in average thickness (Braun, 1987). Thus, the increase in thickness is accompanied by a slight increase in variation as well, though less of an increase than we would expect by copying errors alone. This pattern is consistent with the expectation that a sorting process such as conformist or prestige-biased transmission favored thicker pots, dampening the effects of the transmission of copying errors. In any event, the changes are not clearly explicable as the result of random stochastic processes alone.

The increase in variation in Fig. 3 is followed by a leveling off after 1900 BP, corresponding to Braun’s trend 2, and a slight decrease in the later part of the sequence, after 1400 BP, corresponding to Braun’s trend 4. Both the leveling off and decrease in variation imply that greater selective or winnowing processes were at work to offset the effects of copying errors. These effects may be what Braun identified as “selective regimes” that acted to change the average thickness of sherds.

Overall, the patterns in CV suggest that thickness of Woodland pots was not transmitted in a drift-like process, but instead were subject to fairly stable rates of selection. This is consistent with our understanding of functional traits such as thickness. It is expected that vessel thickness is directly related to performance of the vessel (e.g., Juhl, 1995), and is only practical within a range of values for a particular pot type. If a relatively stable number of pot shapes were made, variation in thickness may have remained quite stable over time despite changes in modal values. Thus, individual selection and removal of pots with inferior thickness for whatever purpose they were put to may have played a role here, keeping variation nearly constant over time. Conformist and/or prestige-biased transmission may also have been factors in these prehistoric developments. Additional research would be necessary to tease these processes apart.

Changes in the CV of diameter measurements over time are more pronounced. Variation appears to be rather high in the earliest assemblages and drops perceptibly from 2500 BP until around 1800 BP, is steady between 1800 BP and 1400 BP, and rises noticeably after this date. Overall, this pattern suggests pots were initially fairly variable but that over time became increasingly standardized in diameter, likely as certain sizes and shapes were removed from the pool of variants. Again, these patterns may be explicable by invoking processes such as conformist or prestige-biased transmission that resulted in the decrease in variation. Note that such processes can operate in a complementary fashion to others, such as production standardization and intensity of production as recently outlined by Roux (2003). Thus, production specialists can invoke certain transmission processes to achieve standardization or increase production intensity.

After 1400 BP, however, variation increased again from a CV of ca. 0.3 at 1400 BP to a CV of 0.45 at 1000 BP. If we again assume 25 radiocarbon years per generation these 400 years represent about 16 generations. As with the projectile points above, we can compare this increase to our simulated curves and use Eq. (2) to solve for the error rate necessary to achieve such an increase. If we assume the increase in CV was due solely to copying errors, we would need an error rate of approximately 15.7% to see such an increase. Even given noise in our data set this is much larger than experimentally determined rates (Eerkens, 2000). Thus, the increased variation in pot diameters witnessed from 1800 to 1400 BP was likely due to processes that were above our hypothetical perception threshold. The introduction of variation—also known as discovery, invention, or innovation—is one process by which this increase could have come about, though other variation-increasing forces may also have been at work such as those listed on the right side of Table 1. Such innovation may have come about for a number of reasons, including changes in the function or social role of pots, or an increase in the number of potters and how they learned, copied, and interacted with one another. Again, future research could seek to specify such factors.
Conclusions

The simulation results provide a means for generating potential explanations about our observations of temporal changes in variance in projectile points in Owens Valley, California and Woodland ceramics in Illinois. Without null-hypotheses to generate expectations it is unclear whether the changes we see in these cases are culturally or behaviorally significant or whether they are simply due to drift-like processes. Null hypotheses give us a means of asking questions of our data (e.g., Brantingham, 2003). Unless there are good reasons, Occam’s Razor should generally apply. That is, one should not provide complex arguments or invoke multiple and complex entities when trying to explain something when a simple answer will suffice. The use of null hypotheses can help us in this regard.

In the case of Rose Spring projectile points, simple errors in copying can fully account for the variation witnessed in thickness measurements. It is not necessary to invoke other explanations, though of course we cannot rule out that other factors may have been at play. This was not the case for basal width measurements, where variation was much less than expected due to drift-like processes. There, variance-reducing mechanisms must have been in effect. In the case of vessel diameter in Late Woodland pots, small copying errors are also not enough to explain an increase in variation over the last 400 years of the sequence. Thus, other variation-increasing factors must have been at play, such as experimentation or “invention,” leading to an increase in the range of diameter measurements for ceramic vessels.

Our point in this paper was not to generate full explanations for the specifics of Great Basin points or Woodland pots. We do not suggest that hunters or potters always produced their tools entirely from memory, without comparison to external standards, or that their ideas about what the ideal size and shape for stone tools and pots was constant throughout their lives. Nor do we argue that changes in settlement patterns, social organization, and the like are irrelevant to the structure of variation in artifacts (though we believe copying error to be a human universal that can transcend such changes). Instead, our goal was to introduce a framework for investigating copying errors and their effects when transmitted through time. As we have seen, imperceptibly small differences passed on during transmission can lead to significant increases in variation over time. Moreover, we aimed to examine how cognitive sorting processes amplify, reduce, or keep constant variation introduced due to copying error. Modeling these processes enables us to establish baseline measurements against which we can compare artifacts from the archaeological record to provide more powerful explanations for the data we generate.

Archaeological explanations require theoretically robust descriptions. The approach taken here gives us tools for making measurements of artifacts in a way that can then be explained. Our theoretical structure provides a falsifiable hypothesis for changes in artifact variation through time. This is a key component of the formal structure of archaeological explanations: we have no means for directly observing artifact variation as the result of copying errors related to particular artisans. Instead, we must describe the world in theoretically explicable ways and build hypotheses that we can use to explain these descriptions (sensu Lewontin, 1974). For this reason, modeling the behavior of aggregate measurements like the CV or the average is desirable because we can rarely examine change in the archaeological record at the scale of the individual. We need methods and measurements that model change at the level of aggregates, even though such changes are the composite result of innumerable decisions by individuals.

Furthermore, it is important that we collect data at the proper scale to employ such baseline measurements. For example, when archaeologists collect categorical data about artifacts, as is most commonly done (e.g., “types” or “presence/absence” of some trait) it is difficult to track the kinds of small-scale processes we talk about here. Types are ideational structures built by us for measuring variation in the archaeological record (Dunnell, 1971). Our “types” are merely measurement tools without any necessary relation to the units used by past populations. One of the issues with using decorative elements or presence/absence attributes (e.g., serration on projectile points) is that it is more likely that these will be subject to modification by cognitive processes such as “invention,” rather than simple copying error. This does not mean that change in these kinds of attributes cannot be modeled by errors accumulated during the copying process. As shown by Neiman (1995) relative abundances of such types clearly drift due to copying errors when objects are made in large enough numbers. However, establishing baseline measurements for
the actual innovation rate for “types” is poorly known and requires further research, simulation, and consideration.

To date, the most amenable attributes for tracking changes in variation due to copying errors are those that are measured on continuous scales such as length, width, thickness, angle, weight, and so on. It is usually possible to collect such information from discrete object-type artifacts. For example, we can easily measure line thickness on decoration motifs instead of categorical statements about presence or absence of some design. Most cultural historical types, however, reduce metric variation to attribute classes. This makes it difficult to model expected changes through time given copying error, because we have no basis upon which to calculate an expected rate of variation generation (i.e., “innovation” in this case).

Finally, not all archaeological problems require an understanding, or the application, of cultural transmission theory. However, we believe that the application of such models can in many cases provide great insight into the explanation of the archaeological record, particularly when we are tracking changes through time. The processes by which people obtain and transmit cultural information fundamentally structures many elements of material culture. In particular, it has strong effects on variation in artifacts, something archaeologists have long been interested in. Thus, cultural transmission has important implications for many aggregate assemblage measures such as the number of types, average size, median diameter, CV, and standard deviation, among others, measures that are commonly reported in the archaeological literature. To this end, we believe that frameworks that can be used to tease apart different cultural transmission processes will enable us to explain the archaeological record in a more scientifically structured manner.

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