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Stimulated Variation and Cascades: Two Processes in the Evolution of Complex Technological Systems

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Abstract Michael Schiffer's theoretical and methodological contributions to archaeology are substantial. For the last two decades, Schiffer has become increasingly interested in the history of electrical technology, including portable radios, electric automobiles, eighteenth-century electrostatic technology, and, most recently, nineteenth-century electric light and power systems. Schiffer has long held a behavioral view, which focuses analytical attention on interactions between humans and material things, including complex technological systems (CTSs). For Schiffer, two key aspects of the evolution of CTSs are *stimulated variation*, defined as an increase in invention resulting from changing selective conditions, and *cascading*, defined as sequential spurts of invention that occur through the recognition of emergent performance problems in a CTS. To attain maximum usefulness, these concepts should be placed in a modern evolutionary framework that correctly identifies, and does not oversell, the role played by cultural selection. Research on individual and social learning provides the critical link between Schiffer's stimulated variation and cascade models and the diffusion of CTSs.

Keywords Cascade model · Individual learning · Innovation · Invention · Social learning · Tipping points

Introduction

Much of current American archaeology, both theoretically and methodologically, bears the influence of Michael Schiffer. His many years of commitment to the

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education of graduate and postdoctoral students are evidenced especially in his Laboratory of Traditional Technology at the University of Arizona (e.g., Schiffer and Skibo 1987, 1989; Skibo *et al*. 1989; Schiffer 1990). For Schiffer (2008b, p. ix), human life "consists of the ceaseless and varied interactions between people and material things," irrespective of place or time. This view led him in the 1980s toward a research focus on modern material culture, specifically the history of electrical technology—portable radios (Schiffer 1991, 1993), electric automobiles (Schiffer *et al*. 1994), eighteenth-century electrostatic technology (Schiffer *et al*. 2003), and, most recently, electric light and power systems in the pre-Edison nineteenth-century industrialized world (Schiffer 2005a,b, 2008a,b, 2010).

Across these phenomena, Schiffer has identified general principles that guide the creation of a complex technological system (CTS), which he defines as "any technology that consists of a set of interacting artifacts" (Schiffer 2005a, p. 486). Schiffer focuses on the various scales of CTS interactions—among people, artifacts, and environmental phenomena—that both create and sustain a system at these scales. Take, for example, a weapon-delivery system such as a bow and arrow. It represents a CTS at one scale, but moving one step down, the bow itself is a CTS, as is the arrow. Each comprises a number of components—the arrow has a shaft, a stone tip, fletching, and lashing—each of which affects the "fitness," or success, of the CTS.[1]

Our interest here is in Schiffer's work on *stimulated variation* and the *cascade model*, which he addressed most directly in two articles in *American Antiquity* (Schiffer 1996, 2005a). In these works, Schiffer defines stimulated variation as an increase in invention resulting from changing selective conditions. In the cascade model, sequential spurts of invention occur through the recognition of emergent performance problems in a CTS. Stimulated variation can create "tipping points" of technological change by triggering cascades through multiple scales, from massive networks of interconnected individuals (e.g., Watts 2002) all the way down to the singular mind (Gabora 2008).

Schiffer's work on stimulated variation and the cascade model represents a turning point in the long history of archaeological study of technological change,[2]

[1] As Wimsatt (1999, p. 283) noted, the seeming arbitrariness of cultural traits as cultural fragments provides "our ability to re-package and re-articulate cultural products into seemingly arbitrary larger or smaller constructions to be replicated and transmitted as units." In other words, "most cultural products are also compound products" (Wimsatt 1999, p. 285)—a characteristic not lost on early ethnologists. Driver and Kroeber (1932, p. 213), for example, had this to say: "Are our elements or factors, the culture traits, independent of one another? While we are not prepared to answer this question categorically, we believe that culture traits are in the main if not in absolutely all cases independent…. Essential parts of a trait cannot of course be counted as separate traits: the stern of a canoe, the string of a bow, etc. Even the bow and arrow is a single trait until there is question of an arrow-less bow. Then, we have two traits, the pellet bow and arrow bow." Similarly, Barnett (1953, p. 356) remarked, there are "persistent linkages between idea-sets as they diffuse across ethnic boundaries. Artifacts of this sort are called complexes because the analyst finds them to be made up of more than one component."

[2] Several archaeological studies have drawn inspiration in part from Schiffer's treatment of stimulated variation and the cascade model. For example, Lyman and O'Brien (2000) used a variety of data sets, including Schiffer's (1996) radio data, to show the usefulness of clade-diversity diagrams for exploring the origination of novel variants and explaining the history of artifact lineages. Similarly, Lyman *et al.* (2008, 2009) and VanPool *et al.* (n.d.) used clade-diversity diagrams to examine the evolution of prehistoric weapon-delivery systems in western North America, beginning with the atlatl and dart and ending with the bow and arrow.

which has mainly emphasized diffusion and trade (Lyman and O'Brien 2003). Schiffer (2005a, p. 499) believes we can do better, pointing out that "archaeologists have seldom exercised the generalizing research option when studying invention. This leaves the door open for devising new models and theories that can complement narratives by implicating widespread invention processes operative in specific behavioral contexts, such as CTSs." Indeed, the inventive process has been well studied in the social sciences generally (e.g., Basalla 1988; Petroski 1992; Rogers 1995; Ziman 2000; Ormerod 2006; Arthur 2009) but not particularly well in archaeology (Fitzhugh 2001).

There are, however, signs that the situation is changing, stimulated in large part by an ever-growing interest in the evolutionary relationship between biology and culture (e.g., Boyd and Richerson 1985; Durham 1991; Richerson and Boyd 2005; Lipo *et al.* 2006; Mace *et al.* 2006; Mesoudi, Whiten, and Laland 2006; Shennan 2009; O'Brien and Shennan 2010). Central to this interest is *cultural transmission*—how information makes its way across the social landscape (Cavalli-Sforza and Feldman 1981; Boyd and Richerson 1985; Henrich and Boyd 1998; Shennan 2002; Laland 2004; Mesoudi, Whiten, and Dunbar 2006; Franz and Nunn 2009; Mesoudi 2011a; Rendell, Fogarty, *et al.* 2011). Theoretical modeling of cultural transmission is based on the premise that genes and culture provide separate, though linked, systems of inheritance, variation, and evolutionary change (Cavalli-Sforza and Feldman 1981; Boyd and Richerson 1985; Durham 1991; Feldman and Laland 1996; Laland *et al.* 2010; Richerson *et al.* 2010). Cultural transmission produces similarity in behavior that cannot be accounted for by genetic transmission or continuity of environment (Mace and Pagel 1994; O'Brien and Lyman 2002; Bentley and Shennan 2003; Mace and Jordan 2011; Shennan 2011).

There is also a growing literature on simulating cultural transmission under laboratory conditions (Kameda and Nakanishi 2003; Baum *et al.* 2004; McElreath *et al.* 2005; Mesoudi 2007; Mesoudi and Whiten 2008). In a typical experiment, participants in small groups engage in a game designed to capture some simplified aspect of real-life cultural change. Over repeated experimental trials, representing generations, participants are allowed to learn from one another—that is, engage in cultural transmission. The experimenter can systematically control who learns what, and from whom and how, in order to examine the effects various cultural-transmission biases have on broader patterns of cultural change (Mesoudi 2010). These middle-range experiments (e.g., Mesoudi 2010, 2011b; Mesoudi and O'Brien 2008a,b) provide the necessary bridge between theoretical models and applications of the models to empirical data.

Here, we show how the key components of cultural transmission—*invention* and *innovation*—are also central to the development of a CTS. Although the terms are often used interchangeably in the social-learning literature (e.g., Laland and Reader 2010), we take a stricter stance, defining invention as a novelty and innovation as a novelty that has diffused through a population. If a novelty does not diffuse, then it does not qualify as an innovation. This distinction follows the work of Austrian economist Joseph Schumpeter (1942), and it allows us to keep separate two distinct processes: the production of variants and the subsequent diffusion of a subset of those variants.

Schiffer's Models

As a preface to our discussion, we summarize Schiffer's (1996, 2005a) take on stimulated variation and the cascade model. Establishing his position will then allow us in the next section to match what he has to say with results from studies of how people learn. We point out that we do not agree with Schiffer in several places, especially with respect to the role he assigns selection in the creation of technological variants. This is less a criticism of his work than it is an opportunity to demonstrate how our modern understanding of learning, which has grown exponentially over the past decade, can extend Schiffer's insights into how innovations are created and how they diffuse.

Stimulated Variation

Schiffer (1996) stated that variation in a population is a consequence of both prior selection, which reduces variation, and invention and borrowing, which generate variation. Because selection operates on variation, the state of variation at that point immediately constrains the outcome of selection. Schiffer (1996) identified two contexts for selection: immediate and extended. The *immediate selective context* consists of "all activities in the life history of an artifact type…procurement, manufacture, transport, distribution, storage, use, maintenance, reuse, disposal, etc. These activities exert selective pressures, and the result is the differential persistence of variants" (Schiffer 1996, p. 654). The *extended selective context* consists of "activities, agents, and mechanisms that…are…coupled, by flows of energy, artifacts, or people, to activities in the immediate selective context" (Schiffer 1996, p. 654).

To Schiffer, invention is not a random process. Rather, it is patterned, often highly patterned, by stimulated variation. For example, as radios became popular at the beginning of the twentieth century, inventions proliferated in terms of the parts and assemblies that went into transmitters and receivers—typical of the geometric growth that a successful new technology spawns. In evolutionary terms, some variants were functional—they affected the performance of a device—whereas others were not.

Schiffer used the vacuum-tube radio as an example of stimulated variation, tracing variation in radios as it occurred in the invention, commercialization, and adoption phases. He described how stimulated variation affected the commercialization process, as seen in Fig. 1a, which shows changes in the frequency of US companies manufacturing vacuum-tube radios for the home market from 1920 to 1955. Note the two dramatic increases in variation, one beginning in 1922 and the other in 1945, after World War II. Schiffer sees these as examples of stimulated variation—the first burst resulting from the advent of commercial entertainment broadcasting, in November 1920, and the second burst resulting from electronics companies seeking new product markets after wartime production ceased.

US portable radios were another example of stimulated variation, at a scale embedded within the radio category. In 1939 and 1940, there was a dramatic increase in the variety of portable models offered to consumers (Fig. 1b). This was caused not so much by consumer demand but by a changed selective context of radios and

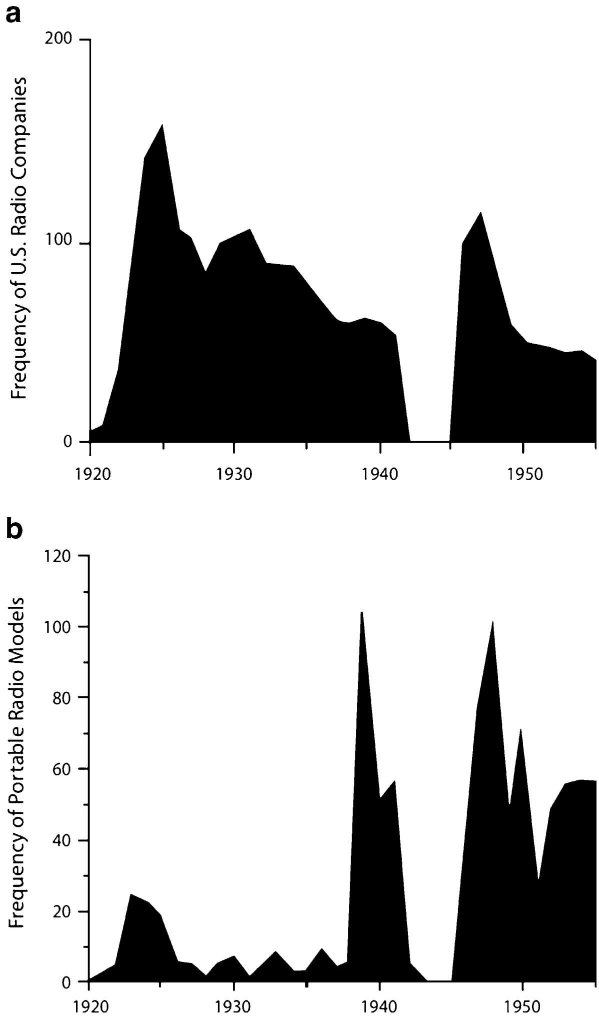

Fig. 1 Vacuum-tube-radio data used by Schiffer (1996) in his analysis of stimulated variation: **a** changes in the frequency of US companies manufacturing radios for the home market, 1920–1955; **b** changes in the frequency of portable-radio models manufactured and sold in the United States, 1920–1955

established radio-manufacturing companies, which saw an opportunity for Americans to hear war news anywhere.

Although the companies are the ones to introduce new variants, it is consumers who select them—consumers are the selective context—as sales grow and the technology is adopted. In 1953, nearly two million vacuum-tube portable radios were sold in the USA. Late in 1954, the first transistor portable radio was commercialized, and others were rapidly brought to market. Even though transistor radios were expensive at first, consumers quickly selected against the tube-based portables and, in less than 7 years, only transistor radios remained on the market (Schiffer 1991). Schiffer stated the adoption process is also an important source of variation, as consumers become inventors, trying out their new "toys" in new activities. The result is an expansion of activity variation, which can contribute to stimulated variation in processes of invention and commercialization.

The Cascade Model

Schiffer's (2005a) cascade model posits that during the development of a CTS, emergent performance problems are recognized, which stimulates sequential spurts of invention until the resulting object(s) contributes to an acceptable solution. Users then encounter new performance problems, which stimulate more inventive spurts, and so on. The result is a series of invention cascades, each stimulated by an immediate performance problem during the life history of a CTS. As variants of a particular technology, the inventions will necessarily differ in terms of performance, which affects their adoption. Inventions judged unsuitable are not replicated; some that look promising may be adopted only sporadically; and those regarded as successful are replicated and adopted widely. In some cases, no suitable variants are invented, which terminates or radically redirects the CTS.

Cascades occur at every scale of technological object, from part to subsystem. In complex CTSs, one often finds a hierarchy of invention cascades, such as portable radios within the cascade of radios. For another example, in the 1890s, with increased interest in automobile design, there was a cascade of prototype vehicles using steam, electricity, gasoline, compressed air, and even springs (Hiscox 1900). Manufacturers quickly selected in favor of gas, steam, and electric. Inventors in turn created myriad alternative designs for specific parts, assemblies, and so on for each vehicle type (e.g., ignition and cooling systems in gasoline automobiles, batteries and controllers in electric cars, and boilers and condensers in steam-driven cars). During the next two decades, the symbolic functions of gasoline and electric cars also stimulated invention cascades in body styles and interior furnishings (Schiffer *et al.* 1994; Mom 2004). As in the case of the automobile, inventors may initially adopt different approaches to achieving a CTS's core performance characteristic(s), leading to diverse technological objects at many scales. As we know, gasoline eventually won out with cars, but there was an element of historical contingency to this, and it could easily have gone in another direction (e.g., Beinhocker 2006).

The Transmission of Innovation

Schiffer's description of CTSs and cascades of invention is quite compatible with studies of cultural transmission. Part of this field is the study of cumulative cultural evolution (e.g., Tennie *et al.* 2009; Enquist *et al.* 2010), which asks, given that knowledge has been passed down (with occasional variation) from generation to generation throughout much of prehistory and history, what is it that has driven the explosion of technological complexity? Generally speaking, human knowledge has intensified exponentially in the millennia since the Neolithic, so that what exists today might be eight or nine orders of magnitude more than what existed even 10,000 years ago (Beinhocker 2006). Presumably this has occurred through the kind of positive feedback that Schiffer describes, in cascades of invention that are not only pruned by the immediate selective contexts but also filtered by the longer term process of knowledge accumulation. Over the generations, technological knowledge that becomes irrelevant (e.g., hunting implements for extinct prey) will not be retained. In addition, even technologies that are superbly adaptive can be lost if they become difficult to pass down, particularly when specialist knowledge becomes lost over the generations as a result of a decreasing population size—either in absolute terms, as in prehistoric Tasmania (Henrich 2004), or in effective terms, as when trade networks break down.

The point is that the core process of every prehistoric CTS development is the transmission of information between people, enabled by the extraordinary human ability for social learning, defined as learning by observing or interacting with others (Heyes 1994) as opposed to learning independently. Multiple animal species are able to learn (Laland and Reader 2010), but only groups of humans—more accurate and complex social imitators than any other animals—can substantially accumulate socially learned information over generations. Not all learning is social, however. As we will see, social learning spreads behaviors, but it depends on *individual learning* to generate them. This is why we find it necessary to distinguish between invention and innovation. We discuss each kind of learning below.

Social Learning

Humans use social learning for a variety of adaptive reasons (Richerson and Boyd 2000; Kameda and Nakanishi 2002; Reader and Laland 2002; Laland 2004; Rendell *et al.* 2010; Bentley and O'Brien 2011; Henrich and Broesch 2011). If we accept that large brains evolved through selection for complex social abilities (Dunbar and Shultz 2007a, 2007b), then it follows reasonably that behaviors usually become popular in human communities by means of social learning (Whiten *et al.* 1999; Laland 2004; Whiten 2005; Laland and Galef 2009; Laland and Reader 2010; Reader and Biro 2010; Laland *et al.* 2011). Humans learn their language, morals, technology, how to behave socially, what foods to eat, and most ideas from other people. This process is the basis for human culture, organizations, and technology (Whiten *et al.* 2011). Humans continue to "learn things from others, improve those things, transmit them to the next generation, where they are improved again, and so on," and this process continues to lead to the "rapid *cultural* evolution of superbly designed adaptations to particular environments" (Boyd and Richerson 2005, p. 4, emphasis in original). Human cultural transmission is thus characterized by the so-called ratchet effect, in which modifications and improvements stay in the population until further changes ratchet things up again (Tennie *et al.* 2009; Tomasello *et al.* 1993).

Much of the time, social learning is an effort to replicate another's behavior accurately without embellishment. Humans have a proclivity for imitation right from infancy (Gergely *et al.* 2002; Kovács *et al.* 2010). It is a powerful adaptive strategy that allows others to risk failure first (Henrich 2001; Laland 2004): Let others filter behaviors for you and pass along those that have the highest payoff (Rendell, Boyd, *et al.* 2011). As British economist John Maynard Keynes (1937, p. 214) put it, "Knowing that our own individual judgment is worthless, we endeavor to fall back on the judgment of the rest of the world which is perhaps better informed. That is, we endeavor to conform to the behavior of the majority or the average. The psychology of a society of individuals each of whom is endeavoring to copy the others leads to what we may strictly term a *conventional* judgment" (emphasis in original). The benefits of copying apply equally to inventors and commercial firms interested in maximizing profits (e.g., Shenkar 2010) and to prehistoric potters attempting to make functional vessels (e.g., Eerkens and Lipo 2005).

Copying others is itself a set of competing strategies in that one might preferentially copy based on identifying skill level as the main criterion (copy those who are better at something than you are, copy good social learners, copy those who are successful), whereas others might base their decisions on social criteria (copy the majority, copy kin or friends, copy older individuals). Figure 2 presents a simple taxonomy of social-learning strategies that involve copying. The various factors that can affect one's choice of whom or what to copy are often referred to as "biases," and hence, the term "biased learning" is commonly used as a synonym for certain social-learning strategies (Boyd and Richerson 1985).

Of more importance is the difference in the effects of copying based on selection for knowledge or a skill level as opposed to copying based on random social interaction. The best example of this difference comes from the computer-mediated tournament of learning algorithms held at St Andrews University in 2009 (Rendell *et al.* 2010; Rendell, Boyd, *et al.* 2011). Before the tournament, many expected the winning strategy to be some combination of majority individual learning (see below) supplemented by some social learning (Pennisi 2010). In fact, the most successful strategies relied almost exclusively on social learning, even when the environment was changing rapidly. The winning strategy, called "discountmachine," copied frequently and was biased toward copying the most recent successful behavior it observed. This, at last, is consistent with how we view the world—as a highly interconnected and distributed collection of minds, the power of which for social transmission is only now becoming apparent (Bentley *et al.* 2011). Our view mirrors that of Rendell, Boyd, *et al.* (2011): Copying confers an adaptive plasticity on populations, which allows them to draw on deep knowledge bases in order to respond to changing environments rapidly. High-fidelity copying leads to an exponential increase in the retention of cultural knowledge—the "ratcheting effect" mentioned above.

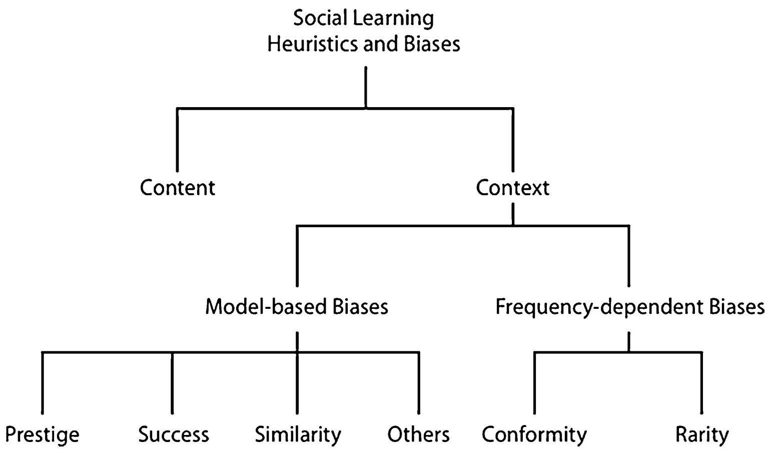

Fig. 2 Taxonomy of social-learning heuristics and biases (after Henrich and McElreath 2003). Content bias includes such things as pre-existing psychological beliefs that one tool is superior to another or that using one tool over another conforms to religious beliefs. Other forms of model-based biases are possible, including age, sex, and ethnicity

Individual Learning

As opposed to learning socially, one can learn individually or asocially. This is a slow process, wherein an individual modifies existing behaviors through trial and error to suit his or her own needs. Perhaps, a learner obtains the basic behavior from a parent or master and then begins to tinker with it with no influence from other people. He or she then passes the behavior on to others. Boyd and Richerson (1985) refer to this as "guided variation." The guided-variation model shows that, in the absence of selection for a particular trait, a population will move toward whichever trait is favored by people's individual-learning biases. This occurs even when the strength of guided variation is weak (Mesoudi 2011a).

Guided variation is featured, somewhat incorrectly, in Schiffer's (2005a) discussion of the cascade model, where he talks about the role of stimulated variation:

> Unlike "directed mutation" (Dawkins 1982, p. 112) and "guided variation" (Boyd and Richerson 1985, pp. 94–98), which more than flirt with Lamarckian mechanisms of change, the process of stimulated variation in no way obviates selection; after all, every variant produced during an instance of stimulated variation can be selected against. Selection thus retains its Darwinian role, but variety-generation becomes central to evolutionary inquiry, the study of its mechanisms and processes far from trivial.

Here, Schiffer greatly undersells his point with respect to guided variation and its attendant process, individual learning. Guided variation does not just *flirt* with Lamarckian mechanisms; it *is* Lamarckian, despite repeated claims to the contrary (e.g., Blackmore 2010). How could it be otherwise? Whenever a person is guided in developing a behavior—a skill, for example—and then passes it on, this is a case of Lamarckian inheritance. Where does a person learn a behavior such as a skill? It could be from a person at random—not very likely—or, more likely, as noted above, from a parent or master, which is how "traditions" are created (O'Brien *et al.* 2010). The adopter can then pass along the skill or tool unaltered, or he or she can experiment and make alterations before passing it on. Regardless, this is a Lamarckian process.

This form of learning is called "unbiased" (Boyd and Richerson 1985; Henrich 2001) because at the *population* level it approximately replicates the distribution of behaviors from the previous generation. After acquiring a behavior or tool, an individual can obtain environmental information about the relative payoffs of alternative skills or tools. If the difference in payoffs is clear, the individual adopts the behavior indicated by the environmental information. If not, the individual sticks with the behavior acquired through unbiased cultural transmission (Henrich 2001). Thus, Boyd and Richerson's (1985) "guided variation" has two equally important components: unbiased transmission and environmental (individual) learning. Henrich (2001) uses the term "environmental learning model" to include both the individual-level learning process, which may occur many times per generation, and its transgenerational counterpart, guided variation (unbiased transmission and individual learning).

Schiffer (1996), in describing how variation is generated, makes it sound as if innovation is the result of stimulated variation. This decidedly is not the case. There are only two ways in which variants can be created: random (copying) error and individual learning (experimentation). As Mesoudi (2011a) points out, individual learning does not need variation in the population to work, nor does its strength depend on the amount of variation present. A person might be "stimulated" by what is going on around him or her—lots of variants being created, for example—but this is an unnecessary condition for individual learning to occur.

Referring back to Schiffer's quote above, in which he states that "the process of stimulated variation in no way obviates selection," we emphasize that the production of variation has nothing to do with either selection or diffusion. The problem here is conflation of selection with diffusion. A trait can spread, and even become predominant in a population, as a result not of selection but of drift. The archaeological and ethnographic records are rife with examples (e.g., Neiman 1995; Eerkens 2000; Bentley *et al.* 2004; Eerkens and Lipo 2005; Buchanan and Hamilton 2009; Hamilton and Buchanan 2009). Stimulated variation affects the *amount* of variation that is produced, but not how variants diffuse. Let's see what Schiffer (1996, p. 655) had to say on the subject of stimulated variation and evolution:

> Variation in a population at one point in time is a consequence of both prior selection *and* variety-generating processes (e.g., invention and borrowing). Study of the latter is clearly crucial, for the creation of new variants in cultural populations occurs commonly and sometimes at high rates. Because selection operates on variation, the state of variation at one point in time immediately constrains the outcome of selection. . . . Thus one cannot explain evolutionary change in specific cases without documenting and accounting for large and rapid changes in the available variation. New variants can arise through an expansion of inventive activities in existing behavioral components, through the proliferation of behavioral components undertaking inventive activities, or both.

We agree with all but the fourth sentence; we do *not* have to document "large and rapid changes in the available variation" in order to explain evolutionary change in specific cases. "Large and rapid changes" may not even be present. There may be no change in available variation, and evolution can still occur, either through selection or drift. Likewise, there may be small and slow changes, and evolution can occur. Finally, there may be large and rapid changes, yet selection plays no hand in sorting it.

Selection, by definition, is a sorting process that reduces variation. Again, it is not, as Schiffer avows, a creator of variation. Selection is also a *population-level* process, not an *individual-level* process. At any point in time, the amount of variation affected by selection will be less than the potential variation that would be present in its absence. This is as true for parts of the extended human phenotype—here, tools—as it is for any genetically driven trait (O'Brien and Holland 1995). As many ways as there are to make tools that work, there are far more ways to make tools that do not work (VanPool *et al.* 2011)—especially "tools that are hard to learn to make, and easy to screw up" (Henrich 2006, p. 776). In other words, selection cannot *create* variants; it can only operate on a pool of existing variants by decreasing the relative frequency of those that do not work, often to the point of extinction.

Patterns of Diffusion

Individual learning and social learning create different patterns as they transmit innovations. One common pattern is the familiar S-shaped diffusion curve—labeled "social learning" in Fig. 3—which plots the cumulative frequency of adopters of a particular trait over some set period of time. The "S" can be flatter or steeper depending on the rate of adoption. A curve with a long tail on the left, for example, tracks a slow adoption of a trait. The slowness in uptake is, in the most parsimonious social-learning model, a result of the low initial frequency of a variant in the population and thus fewer opportunities for people to encounter it and adopt it. The sudden change in magnitude function of a curve—the point at which we see an adoption take off—occurs through the same social-learning[3] process; the cumulative rate depends only on the number of adopters choosing that particular variant at any one time.

Individual learning does not create S curves; instead, it creates *r*-shaped decelerating curves (Bass 1969; Henrich 2001). In contrast to the lead-in for S curves, *r* curves begin at their maximum growth rate (at $t=0$) and then approach their maximum frequency asymptotically (Fig. 3). Such curves may characterize the response to a major event, such that the population gets the information universally and more or less instantly rather than through social exchanges (Bentley and Ormerod 2010).

These curves can also describe a long-term intergenerational adoption of a behavior. As Henrich (2001) points out, *r* curves describe, for example, the cumulative adoption dynamics for the spread of milk bottle-opening behaviors among pigeons (Fisher and Hinde 1949; Lefebvre and Giraldeau 1994), the spread of potato washing among Japanese macaques (Kawai 1965), and the early phase of adoption of hybrid corn in the American Midwest (Ryan and Gross 1943). In these cases, the *r* curves reflect individuals in one generation discovering a beneficial new behavior (in their perception) and subsequently transmitting those behavioral outputs to their offspring, including intellectual offspring such as apprentices. With *r* curves, cultural transmission simply replicates the existing distribution of behaviors, beliefs, and so on. The actual driver of change is in the decision-making process, as people make cost–benefit evaluations based on low-cost experimentation as to whether to modify a behavior (Gladwin and Butler 1984; Henrich 2001). This is what leads to the steady uptake in the *r* curve as seen in Fig. 3. It is steady because it does not matter whether a behavior is common or not.

Learning Strategies Are Not Static

In the real world, r curves are relatively rare, given that they are sparked by a new discovery or rare event, whereas S curves are common. For Henrich (2001), this strongly suggests that biased cultural transmission—specifically, conformist-biased transmission (Fig. 2)—dominates the diffusion process. Conformity is unnecessary,

[3] There is some evidence that S-shaped curves can arise through a number of plausible asocial processes as well, even if the assumption of a well-mixed population with no spatial heterogeneity in resources is accepted (Hoppitt *et al.* 2010). This possibility does not affect discussion here.

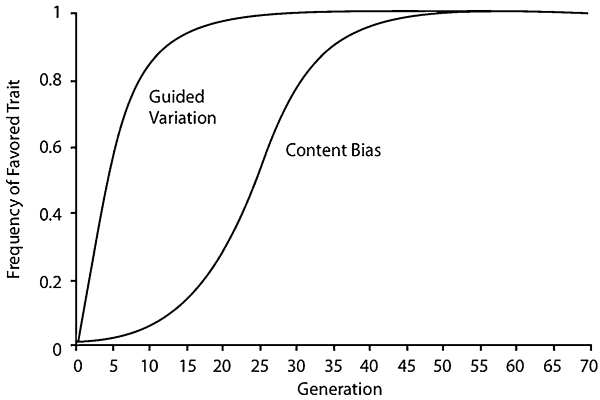

Fig. 3 Diffusion curves for individual learning and social learning

however, for S curves to occur. In marketing science—like archaeology, a study of change in behaviors through time—a classic model yielding S curves is the Bass (1969) diffusion model. In the Bass model, individuals may adopt a new behavior, such as buying the latest portable radio, when they encounter someone who has adopted it already. This is not conformity; it is just learning about the behavior socially. The reason that the Bass model yields an S curve rather than an *r* curve is that individuals do not learn about the new behavior until seeing someone else with it (Kandler and Steele 2010).

Models of conformist transmission often implicitly assume that individuals can sense how popular a behavior is overall in the population. This assumption is fine for small groups but unrealistic for large populations, where it can be better to assume individuals have only local, imperfect knowledge (Mesoudi and Lycett 2009). If we assume the latter, conformity at the individual scale can render the spread of new behaviors punctuated and unpredictable at the population scale, as conformity renders the social network poised for a cascade that still needs a trigger at the right time and place to start it (Kauffman 1995; Gladwell 2000; Watts 2002; Bentley *et al.* 2011).

Of course, for real-world data, the difference between S and *r* patterns of adoption is best seen along a continuous spectrum (Bentley *et al.* 2011). After all, there is no good reason for thinking that we do not employ a mix of strategies in everyday life, using individual learning for one behavior and social learning for another. At the population scale, the Bass model conveniently has parameters for both decision type so that real-world patterns can be characterized along this spectrum (e.g., Bentley and Ormerod 2010).

Characterizing the patterns along the S–*r* spectrum at the population scale can be used to complement more detailed investigations at the individual scale. Both scales are implicated when Henrich (2001, p. 1008) poses four questions: "How can environmental, cost-benefit learning account for the empirical phenomena of long tails and takeoff points? Why do diffusional processes sometimes begin so slowly and finish so rapidly? Why doesn't this occur at other times? Why do some behaviors have threshold adoption frequencies at which they begin spreading on their own?" There is a two-part answer to these questions. First, at the population level, is the size of the population involved in the learning matters. Second, at the individual scale, humans use a mix of learning strategies; sometimes, we learn individually—we produce information—and other times we learn socially—we scrounge information. The question is, when should we do one as opposed to the other, and how does the shift affect fitness?

Numerous studies have examined this question (e.g., Giraldeau *et al.* 2002; Kendal *et al.* 2009), many building on Rogers' (1988) earlier modeling. Rogers proposed that environmental change will lower the fitness of a group comprising individual and social learners because the latter cannot track new changes in the environment and thus will copy outdated information from each other (for reviews, see Enquist *et al.* 2007; Rendell, Fogarty, *et al.* 2011; Rieucau and Giraldeau 2011). If the environment does not change, group fitness increases because social learners are adopting optimal behaviors, and it costs less to scrounge than to produce, unless producers charge a price for copying. Mesoudi (2008, 2010), following on the work of Mesoudi and O'Brien (2008a,b), took a different tack, holding the learning environment constant but manipulating the landscape so that it did not remain unimodal. Mesoudi found that individual learning was significantly more adaptive on a unimodal adaptive landscape, where there is but a single optimal design or behavior, than on a multimodal adaptive landscape, where there are multiple locally optimal designs or behaviors of different fitness. On unimodal landscapes, simple reinforcement learning will always lead to the best possible design or behavior, irrespective of starting point. By contrast, on multimodal landscapes, such as the one in Fig. 4, individual learners can become trapped on locally optimal but globally suboptimal peaks, reducing the mean fitness of the population. The social-learning strategy of "copy successful individuals" allows individuals to jump from locally optimal peaks found by means of individual learning to the globally optimal peak located by a more successful member of the population (Rendell *et al.* 2010; Rendell, Boyd, *et al.* 2011). Mesoudi (2008) found that populations of flexible learners outperform both populations of pure individual learners and mixed populations of pure individual learners and pure social learners.

These findings are important to innovation research because actual cultural evolution, as opposed to what we model, takes place on multimodal adaptive landscapes (Boyd and Richerson 1992; Kauffman 1995; Mesoudi and O'Brien 2008a,c), where there are several (if not more) stable, locally optimal designs and behaviors of varying fitness. Almost any tool, especially a complex one, is a result of multiple trade-offs between and among competing demands for performance, as Schiffer (1996, p. 654) noted: "Selection pressures in the immediate selective context lead to artifacts that embody design compromises of many kinds, as in trade-offs between performance characteristics pertaining to manufacture, use, and maintenance processes…or even between activities within a given process (Schiffer and Skibo 1997). Compromises are necessitated because, ordinarily, no single design can maximize an artifact's entire set of activity-specific performance characteristics."

Echoing Dennett (1995) and Kauffman (1995), Mesoudi (2010) suggests that different locally optimal peaks in a technology's adaptive landscape can be seen as different potential *inventions*. Conversely, *innovations* would be peaks at which the majority of actual artifacts in a population can be found, which is not necessarily the highest, globally optimal peak. Individual learners explore this adaptive landscape by means of a random walk, leading to the discovery of one or more locally optimal

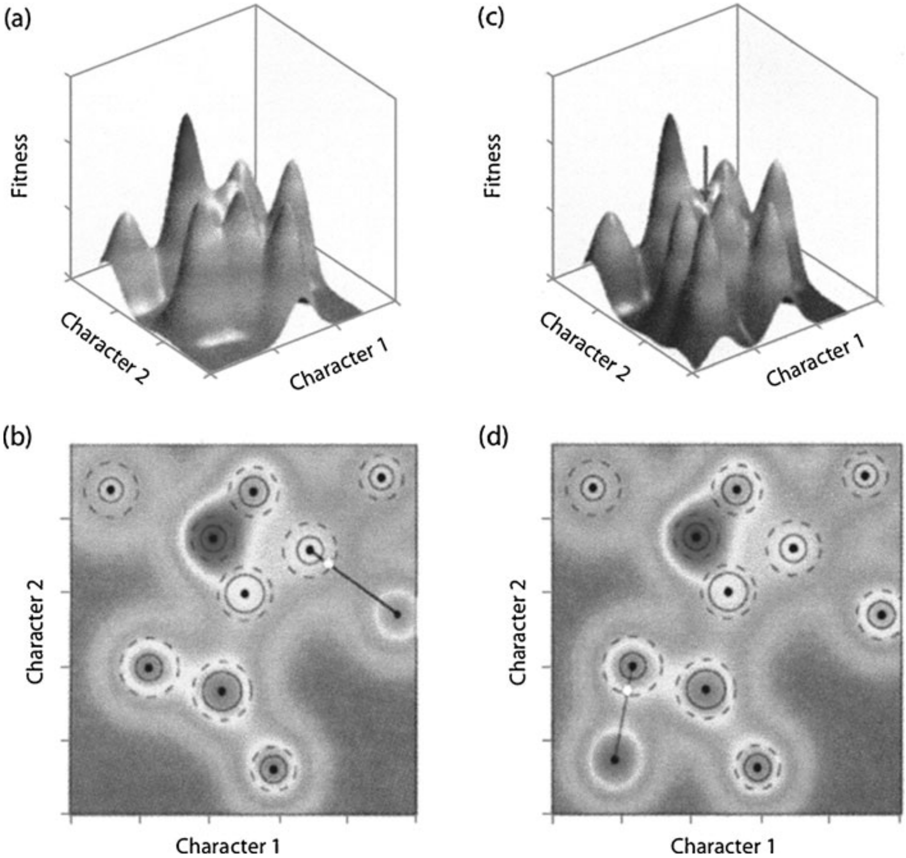

Fig. 4 Imaginary fitness landscape model created by intersections of individual states of two characters (adapted from Van de Peer *et al.* 2009): **a** and **b** the landscape at $t=0$; **c** and **d**, the landscape at a later time, say $t=5$. The *black dots* represent agents that occupy the peaks in the two-character technospace, representing niches in which that particular combination of character states is advantageous. At $t=0$, an agent (the *white dot*) is seen moving to an unoccupied peak. At $t=5$, a new adaptive peak has opened up, represented by the arrow in **c**. None of the existing agents has the evolutionary potential to make the jump and thus fill this niche, but over time one or more might be able to develop the necessary innovations

peaks or inventions. Social learning that is biased in some way (e.g., copy the successful) then allows people to jump across low-fitness valleys to a higher peak found by a more successful individual, making this peak/design the innovation (Kauffman 1995; Mesoudi 2010). The more peaks (alternative stable designs) on an adaptive landscape, the more difficult it might be to find the highest one.[4] Similarly, the greater the relief on the fitness landscape, reflecting fitness difference among alternative designs, the easier it is to identify the highest peak/best design by means of biased transmission, and the more adaptive that biased transmission should be relative to individual learning.

[4] If indeed there is one. The challenge of this approach is in defining the full landscape of possible inventions. Ancient Polynesians built ocean-going canoes, but they could not have invented jet skis. We might wonder, though, what else was on the Polynesian design landscape that they *might* have ventured upon?

Two other factors might be important. At the *individual* scale, when individual learning is costly, it pays to be a scrounger, and innovations should spread by social learning. Although social learning is advantageous for most, it relies on the remaining proportion of individual learners. Without *any* individual learners to constantly sample the environment—to produce information useful to the group—social learners cannot track environmental change (Henrich and McElreath 2003). They are simply "buying" whatever happens to be on the shelf. This could have deleterious effects on all individuals. Note that even in the most successful strategies that came out of the tournament of learning algorithms held at St Andrews University, where copying predominated, there had to be a source of new variation present, either through copying error or occasional innovation (Rendell, Boyd, *et al.* 2011). Without a source of variation, agents simply copy themselves into stasis—potentially a recipe for disaster in the face of a changing environment.

At the *population* scale, the larger the population, the more likely it is that someone will find the highest fitness peak through individual learning (Henrich 2010), resulting in higher fitness in the entire population *after* cultural learning takes over (Mesoudi and O'Brien 2008b; Mesoudi 2010). This is why population size is now being viewed as a heretofore-unappreciated driver of innovation, from the Upper Paleolithic Revolution (Powell *et al.* 2009) of 40,000 B.P. to the information cascade that confronts us today (Bentley and O'Brien 2011; Bentley *et al.* 2011). It also is recognized as a driver of cultural loss (Henrich 2004)—too few minds around to keep specialized knowledge alive. Of course, the minds must communicate in order to create this "collected mind" effect. Unconnected individuals are irrelevant to learning and the collective storage/retrieval of information (Bentley and O'Brien 2011).

Let us look at the switch from individual learning to content-biased learning using an example we mentioned earlier, the cumulative percentage of farmers in two Iowa communities who adopted hybrid seed corn between 1926 and 1941 (Ryan and Gross 1943). Notice in Fig. 5 the extremely long tail at the left, signifying slow adoption, followed by a significant upward shift in 1933–1934 and a peak in 1936–1937. It took 9 years for the relative frequency of hybrid planters to reach 20%, but only six more years for it to reach fixation at 99%. What might account for this curve, similar to those studied by Schiffer? Several factors undoubtedly kept the adoption rate low in the beginning, including the fact that expensive hybrid seed corn could not reproduce (Lowery and DeFleur 1995). Early on, a few farmers experimented with the hybrid corn, but this guided variation yielded almost no shifts in behavior until enough farmers began experimenting with it that it finally reached a point where social learning took over.

Henrich (2001, p. 1003) sees this transition as a result not only of social learning generally but of conformist transmission (Boyd and Richerson 1985) specifically, where "individuals use the frequency of a trait as an indirect indicator of its worth. Hence, a trait's frequency inhibits its diffusion when it is rare but encourages the diffusion once the trait becomes common." Given that S curves do not require conformity, however, the question is to what degree conformity was inherent in the uptake of hybrid corn, as opposed to merely the growing visibility of it among fellow farmers. The sudden start of the cascade suggests conformity, but perhaps this is more in the local-network sense of Watts's (2002) model.

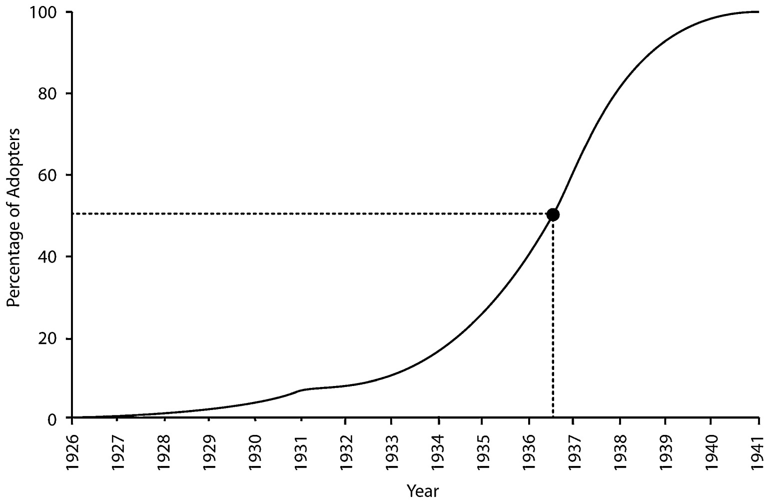

Fig. 5 Diffusion curve showing the cumulative use by year of hybrid corn in two Iowa farming communities, 1926–1941 (data from Ryan and Gross [1943]; curve after Henrich [2001]). This diffusion curve is a prototypical example of a "long-tailed" S-curve. The *dotted lines* mark the point on the curve with the highest rate of change

As hybrid-corn users became more prevalent in the Iowa communities (Fig. 5), the cost of the variant also decreased, but we would argue that the upswing in adoption that occurred in the 1933–1934 period was not so much a result of reduced price but rather of there being enough successful hybrid-corn users around that other farmers made the decision to switch. The adoption of hybrid corn changed from an individual-level to a population-level decision. All of the farmers, except the first, acquired the invention by imitating high-payoff farmers. This means that an entire population of social learners exploited the superior cost–benefit information of just one person (Henrich 2010).

Discussion

Research on individual and social learning provides the link between Schiffer's stimulated variation and cascade models and the larger spread of complex technological systems (CTSs). Many of us picture inventors as solitary individuals, working late into the night at the lab bench, tinkering with this, adjusting that, until the long-hoped for Eureka! moment arrives. It could be Samuel Morse experimenting with telegraph keys or an Iowa farmer trying to see how many more bushels of corn he will get using hybrid varieties. There is a rich literature on the conditions under which people will experiment, which usually concludes that inventiveness increases in times of economic crisis (e.g., Fitzhugh 2001). We wonder, though, about the accuracy of this widely held conclusion. The St Andrews tournament, for example, demonstrated that unlike previous theory that suggested that a reliance on social learning can sometimes hinder the adaptive tracking of changing environments (e.g., Rogers 1988; Feldman *et al.* 1996), heavy reliance on social learning did *not* compromise the ability of agents to adjust to shifting environments (Rendell, Boyd, *et al.* 2011). The *range* of behavior patterns increased, and there were more even distributions of behaviors—meaning that no single high-performance behavior was persistently optimal—but there was no increase in individual learning. Like Rendell and colleagues, we suspect that this reflects the fact that agents in the tournament were more biologically "real" than agents in other models. This means, simply, that humans can switch rapidly to an alternative high-performing behavior when an environmental change reduces the payoff of the current behavior.

Schiffer defines stimulated variation as a consequence of prior selection, invention, and borrowing. We would agree with the latter two variables, but as we noted previously, variation cannot be *created* by selection; it can only be *reduced* by selection. Variants start life as inventions, through individual learning. They can be the result of an inventive "spark," or they can result from copying error. Social learning, on the other hand, *is* selection; it does not create, it only sorts the relative frequency of variants across a population. As Mesoudi (2011a) argues, the more variation there is in the population, the stronger the learning bias (selection) should be, although this may be overwhelmed by information overload in the modern world, with millions of possible consumer choices (Bentley *et al.* 2011).

Schiffer (2005a) is interested in how much variation is "stimulated" before a cascade takes place. The individual-learning part of the tail of an S curve can be long or short, depending on the learning costs involved and the number of connected minds in a population.[5] In theory, the more minds there are, the greater the flux of new variants (Henrich 2010). Likewise, the higher the cost/risk of individual learning, the more copying there should be (Fitzhugh 2001). Figure 6 shows adoption curves for several CTSs. Some curves, such as those for cell phones and personal computers, have extremely short tails; others, such as those for televisions, radios, and VCRs, have moderately long tails; and still others, such as those for home electricity and cars, have long tails. Regardless, it is not difficult to recognize the onset of cascade events.

In Schiffer's view, variation is stimulated by other minds working on similar problems. We agree, but only provided that each mind knows what the others are doing, if even in a rough sense. For example, despite the secrecy that cloaks most inventive enterprises, especially highly commercialized ones, inventors have at least a broad feel for what the competition is doing. Depending on the stakes involved in a discovery, "stimulation" can be heightened simply by luring more minds into the contest. There could be, for example, dozens or even hundreds of inventors wandering across the technological landscape looking for optimal peaks, leaving a trail of variants behind them. Depending on how complex a CTS is, inventors will land on any number of peaks, many of which will be locally optimal but not globally optimal.

Take, for example, the case of locomotive spark arrestors, which were placed in the smokestacks of nineteenth-century wood-burning American locomotives to control the escape of live sparks. Despite the severity of the problem—trestles, homes, passengers' clothing, and sometimes entire countrysides were being set

[5] There is an extensive literature in the social sciences on computing the costs of learning. For an early example, using utility curves, see Friedman and Savage (1948). For a useful summary from the perspective of human behavioral ecology, see Fitzhugh (2001).

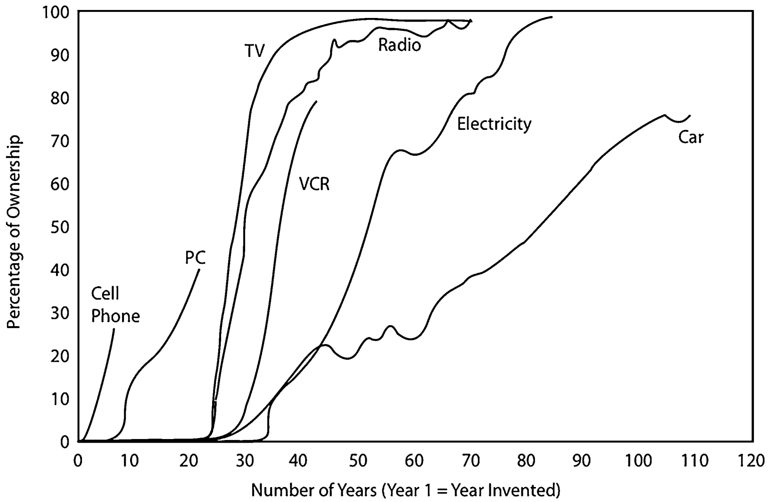

Fig. 6 Adoption curves for seven modern technologies, plotting percentage ownership by US households *versus* number of years since invention (adapted from *Forbes*, July 7, 1997)

ablaze (White 1997)—and the financial incentives that were in place, no truly effective arrestor was ever produced, despite the existence of over 1,000 patented devices (Fig. 7). This is an excellent case of Schiffer's cascade model: Emergent performance problems are recognized as shortcomings in a technology's constituent interactions, which stimulates sequential spurts of invention until one or more of the resulting objects contribute to an acceptable—here *barely* acceptable—solution. Put in terms of fitness landscapes, and with respect to spark arrestors, there was no optimal peak in the pure sense of the word, only a number of barely "adequate" peaks, none of which were readily apparent.

We can model this process as in Fig. 8, which shows an imaginary design space at four points in time, with each cell representing a potential solution to, say, the spark-arrestor problem. Figure 8a shows the number of potential solutions that individual learners found at time zero (t=0). Figure 8b shows the number of solutions at t=20. More solutions have been found, but some previous solutions have disappeared. In reality, they probably were not workable in the first place, although perhaps they were patented anyway. Figure 8c shows the number of solutions at t=25. Not only have many more solutions been found, they were discovered in a much shorter period of time than the number discovered between t=0 and t=20. In Fig. 8d, which shows the number of variants at t=40, the frequency has grown, but the rate of increase has slowed considerably, and social learning (selection) is poised to begin pruning the number of variants. The time period between t=20 and t=25 is of particular interest because it is there that we see the sharp increase in variation. What caused that cascade, or tipping point? The answer, of course, is case specific. In the case of radios, sociopolitical factors, including war, helped drive the variation that Schiffer (1996) reported. In other cases, it could also be the economic riskiness of the landscape, where guided variation—experimentation and invention—is the rule for companies trying to establish themselves, whereas dominant firms are more risk averse (Cosh *et al.* 1996; Fitzhugh 2001).

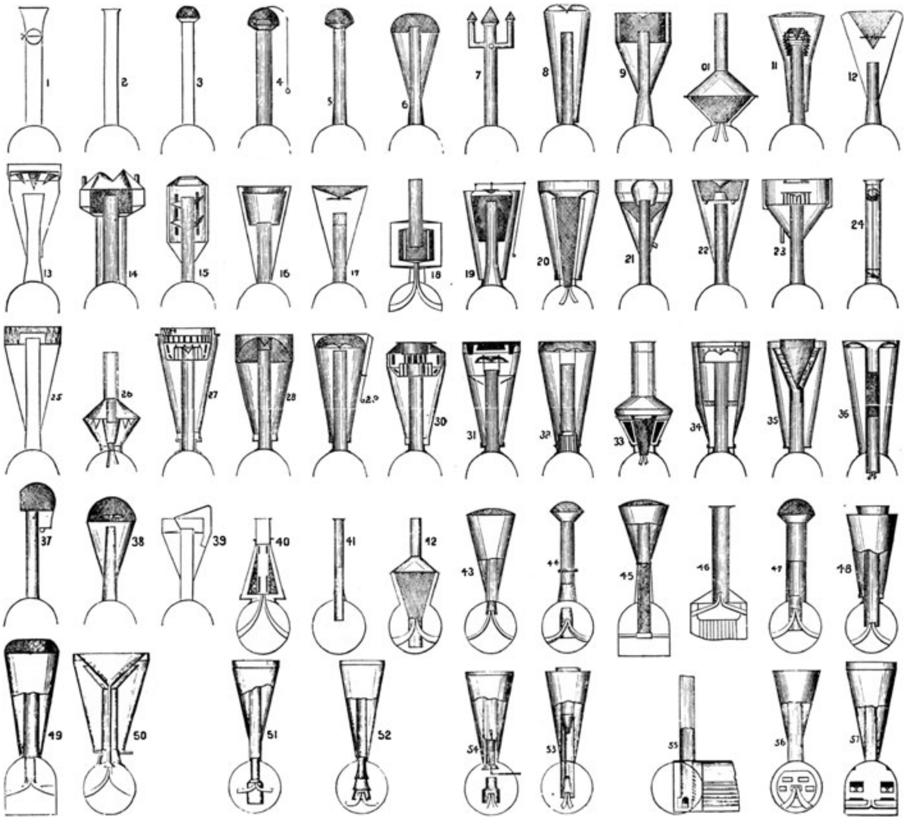

Fig. 7 Fifty-seven of the 1,000-plus locomotive spark arrestors patented in the United States prior to 1860 (drawing from the Baldwin Locomotive Works, Philadelphia; reproduced from White 1997). Sparks were a dangerous by-product of wood-burning American locomotives, but the problem was hard to fix. Smokestacks needed an unobstructed draft to work properly, and an effective spark arrestor obstructed the draft. Even the most popular arrestors were only partially successful in catching live sparks

Behavioral economists and complexity theorists use the same concepts, and they offer exciting insights. Rather than viewing technological invention traditionally as a probabilistic search within a fixed population of possibilities, newer models consider “dynamic fitness landscapes” (e.g., Kauffman 1995), in which *innovation* (adoptions by other agents) affects the landscape of *invention* (potential adaptiveness of current or new agent behavior). Kauffman *et al.* (2000), for example, extended the standard search model by introducing a *technology landscape* into the modeling framework. Their technology landscape consists of (1) a profit function that assigns a real-value number to each technology in the space of possible technological configurations and (2) a metric structure over the space of technological possibilities that measures how close or distant each is from the other. Locations in the landscape correspond to different configurations for a firm’s production recipe. Peaks and valleys represent local maxima and minima for the labor efficiency associated with each production recipe. The “ruggedness” of the landscape is in turn determined by the landscape’s correlation coefficient. This is exactly what we show in Fig. 4. Kauffman and colleagues label a firm’s search process an *adaptive walk*. Adoption of a new

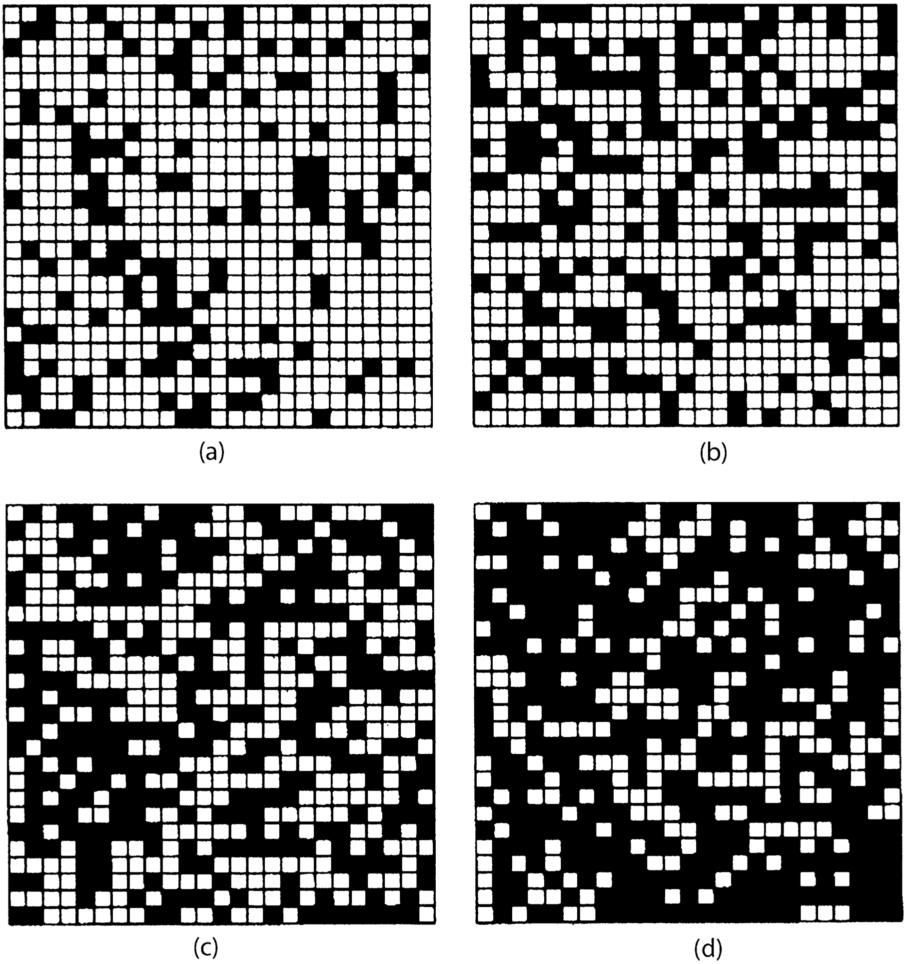

Fig. 8 An imaginary design space at four points in time, with each cell representing a potential solution to a technological problem (adapted from Gavrilets 1997): **a** the number of potential solutions that individual learners found at time zero (t=0); **b** the number at t=20; **c** the number at t=25; and **d** the number at t=40. Note the rapid increase in potential solutions between t=20 and t=25, followed by a slowdown. The period of maximum change would be somewhere between those two points in time. Note also that designs can disappear between points in time

technology is called an "uphill step" because the firm has changed its technological configuration and increased its profitability. In our terms, it has become more "fit."

Kauffman and colleagues (e.g., Kauffman 1995; Kauffman *et al*. 2000; see also Stuart and Podolny 1996; Lobo and Macready 1999) anticipated the conclusions of learning researchers (e.g., Mesoudi and O'Brien 2008a,b; Lake and Venti 2009; Mesoudi 2010): Searchers on a rugged technological landscape are likely to get stuck on a local optimum or even a technological dead-end, often depending quite sensitively on exactly where the search was started. A technological optimum may not even exist on the design landscape (Kane 1996), and even when there are ephemeral, optimal solutions, it is never possible to completely map out a dynamic, complex design space, and optimal peaks can become suboptimal with the behavior of other agents. A perfect example of this is the aforementioned locomotive spark arrestor.

Conclusions

By any measurement, Michael Schiffer has developed a rigorous approach to analyzing complex technological systems. Here, we have focused on two processes he identified as fundamentally important to the evolution of CTSs, stimulated variation and the cascade model. Interestingly, "stimulated variation" harks back to a letter to *Nature* in March 1895 by W. T. Thiselton-Dyer of Royal Gardens, Kew, UK, who worried that in his haste to get through a lecture he gave to the Royal Society, he had compressed some points, one of which regarded a statement by Charles Darwin (1868, p. 250) that "organic beings, when subjected during several generations to any change whatever in their conditions, tend to vary." Thiselton-Dyer (1895, p. 459) then offered that "a change in the external conditions, otherwise the *environment*, will provoke *some* variation in the organism, which I may call *stimulated variation*" (emphasis in original). Darwin and Thiselton-Dyer were referring to biological responses by nonhuman organisms, but the same can be said for the process that Boyd and Richerson (1985) and others have referred to as "guided variation" and its two components: unbiased transmission of behaviors and environmental scanning, the latter of which assists a learner in deciding whether or not to modify a behavior before it is passed on.

The related work of complexity theorists poses new questions for archaeological research and Schiffer's model: How is the invention process affected by others exploring the same technology landscape? If local searches are more cost efficient, how often did past technology get "trapped" on suboptimal technological peaks? In what archaeological cases did people use their knowledge of the physical environment to direct their conceptual search of the technological design space ("hill-climb"), and when did they just "muddle through" (Lindblom 1959)?

These questions depend on the complexity of the design space, which is affected not only by the complexity of current technologies (Arthur 2009) and the cost of production (e.g., Kandler and Steele 2010) but also by population size. Social learning, as a process of transmission of knowledge between minds, is inherently subject to population effects, and anthropologists studying technological evolution are increasingly considering population size explicitly (Henrich 2004; Powell *et al.* 2009; Kline and Boyd 2010; Rendell, Boyd, *et al.* 2011). As Schiffer (1996) considered, how many variants will be produced that go nowhere because the effective population is too small to find out about them and reproduce them? If critical population thresholds *are* crossed, then biased transmission—selection—can begin sorting the variants, as in the European Upper Paleolithic (Powell *et al.* 2009) or in prehistoric Polynesia (Kline and Boyd 2010). As Henrich (2010, p. 111) concluded:

> Invention and innovation are fundamentally evolutionary processes. Given that nearly all inventions build on existing ideas and often involve the recombination of existing concepts, methods, or materials, often fortified or

> integrated with a dose of lucky mistakes or happenstance, the overall inventiveness of a social group or population depends on the number of individual minds available to create recombinations, generate insights, and get lucky, as well as on their cultural interconnectedness….This implies that the more minds in one generation, the more novel recombinations, insights, and lucky mistakes will exist for the next generation to recombine, refine, and extend across domains. The more innovations in existence, the greater the opportunities for recombinations and the more inventions are possible. Because the elements of any recombinant are acquired by learning from others, the more individuals one can potentially learn from, the greater the opportunities for creating novel recombinant inventions.

This "distributed mind" concept is increasingly commonplace in our modern, wiki-media era of computers and information storage (Surowiecki 2004), and we are seeing more archaeological research into how humans have stored and retrieved information in other people, cave paintings, writing, built environments, and material culture (e.g., Renfrew and Scarre 1998; Powell *et al.* 2009). Arguably, however, as more and more information is stored, social learning becomes less selective (Bentley and O'Brien 2011), but at the same time, the searchable Internet allows like minds to find each other and to create cultural niches that branch off from one another, like technology itself does (Bentley *et al.* 2011). Interconnectedness, paradoxically, allows groups to differentiate by copying each other, which homogenizes the group but distinguishes it from all other groups. Perhaps, those interested in what Web 2.0 is doing to global society should seek answers from Schiffer and others in the human sciences who have a deep sense of history and technology.

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References

Arthur, W. B. (2009). *The nature of technology: What it is and how it evolves*. New York: Free Press.

Barnett, H. G. (1953). *Innovation: The basis of cultural change*. New York: McGraw-Hill.

Basalla, G. (1988). *The evolution of technology*. Cambridge: Cambridge University Press.

Bass, F. M. (1969). A new product growth model for consumer durables. *Management Science, 15*, 215–227.

Baum, W. M., Richerson, P. J., Efferson, C. M., & Paciotti, B. M. (2004). Cultural evolution in laboratory microsocieties including traditions of rule giving and rule following. *Evolution and Human Behavior, 25*, 305–326.

Beinhocker, E. (2006). *The origin of wealth: Evolution, complexity, and the radical remaking of economics*. Cambridge: Harvard Business School Press.

Bentley, R. A., Earls, M., & O'Brien, M. J. (2011). *I'll have what she's having: Mapping social behavior.* Cambridge, MA: MIT Press.

Bentley, R. A., Hahn, M. W., & Shennan, S. J. (2004). Random drift and culture change. *Proceedings of the Royal Society B, 271*, 1443–1450.

Bentley, R. A., & O'Brien, M. J. (2011). The selectivity of social learning and the tempo of cultural evolution. *Journal of Evolutionary Psychology*, (in press).

Bentley, R. A., & Ormerod, P. (2010). A rapid method for assessing social *versus* independent interest in health issues: A case study of 'bird flu' and 'swine flu. *Social Science & Medicine, 71*, 482–485.

Bentley, R. A., & Shennan, S. J. (2003). Cultural transmission and stochastic network growth. *American Antiquity, 68*, 459–485.
Blackmore, S. (2010). Memetics does provide a useful way of understanding cultural evolution. In F. Ayala & R. Arp (Eds.), *Contemporary debates in philosophy of biology* (pp. 255–272). Chichester: Wiley-Blackwell.
Boyd, R., & Richerson, P. J. (1985). *Culture and the evolutionary process*. Chicago: University of Chicago Press.
Boyd, R., & Richerson, P. J. (1992). How microevolutionary processes give rise to history. In M. H. Nitecki & D. V. Nitecki (Eds.), *History and evolution* (pp. 179–209). Albany: State University of New York Press.
Boyd, R., & Richerson, P. J. (2005). *The origin and evolution of culture*. Oxford: Oxford University Press.
Buchanan, B., & Hamilton, M. J. (2009). A formal test of the origin of variation in North American early Paleoindian projectile points. *American Antiquity, 74*, 279–298.
Cavalli-Sforza, L. L., & Feldman, M. W. (1981). *Cultural transmission and evolution*. Princeton, NJ: Princeton University Press.
Cosh, A., Hughes, A., & Wood, E. (1996). Innovation in UK SMEs: Causes and the consequences for firm failure and acquisition. Cambridge: University of Cambridge, ESRC Centre for Business Research, Working Paper no. 48.
C., Darwin. (1868). *The variation of animals and plants under domestication (vol. 2)*. London: Murray.
Dawkins, R. (1982). *The extended phenotype*. San Francisco: Freeman.
Dennett, D. (1995). *Darwin's dangerous idea*. New York: Simon and Schuster.
Driver, H. E., & Kroeber, A. L. (1932). Quantitative expression of cultural relationships. *University of California Publications in American Archaeology and Ethnology, 31*, 211–256.
Dunbar, R. I. M., & Shultz, S. (2007a). Understanding primate brain evolution. *Philosophical Transactions of the Royal Society B, 362*, 649–658.
Dunbar, R. I. M., & Shultz, S. (2007b). Evolution in the social brain. *Science, 317*, 1344–1347.
Durham, W. H. (1991). *Coevolution: Genes, culture, and human diversity.* Stanford, CA: Stanford University Press.
Eerkens, J. W. (2000). Practice makes within 5% of perfect: The role of visual perception, motor skills, and human memory in artifact variation and standardization. *Current Anthropology, 41*, 663–668.
Eerkens, J. W., & Lipo, C. P. (2005). Cultural transmission, copying errors, and the generation of variation in material culture and the archaeological record. *Journal of Anthropological Archaeology, 24*, 316–334.
Enquist, M., Eriksson, K., & Ghirlanda, S. (2007). Critical social learning: A solution to Rogers' paradox of non-adaptive culture. *American Anthropologist, 109*, 727–734.
Enquist, M., Strimling, P., Eriksson, K., Laland, K., & Sjostrand, J. (2010). One cultural parent makes no culture. *Animal Behaviour, 79*, 1353–1362.
Feldman, M. W., Aoki, K., & Kumm, J. (1996). Individual *versus* social learning: Evolutionary analysis in a fluctuating environment. *Anthropological Science, 104*, 209–231.
Feldman, M. W., & Laland, K. N. (1996). Gene-culture co-evolutionary theory. *Trends in Ecology & Evolution, 11*, 453–457.
Fisher, J., & Hinde, R. A. (1949). The opening of milk bottles by birds. *British Birds, 42*, 347–357.
Fitzhugh, B. (2001). Risk and invention in human technological evolution. *Journal of Anthropological Archaeology, 20*, 125–167.
Franz, M., & Nunn, C. L. (2009). Rapid evolution of social learning. *Journal of Evolutionary Biology, 22*, 1914–1922.
Friedman, M., & Savage, L. J. (1948). The utility analysis of choices involving risk. *Journal of Political Economy, 56*, 279–304.
Gabora, L. (2008). Mind. In R. A. Bentley, H. D. G. Maschner, & C. Chippendale (Eds.), *Handbook of archaeology theories* (pp. 283–296). London: AltaMira.
Gavrilets, S. (1997). Evolution and speciation on holey adaptive landscapes. *Trends in Ecology & Evolution, 12*, 307–312.
Gergely, G., Bekkering, H., & Király, I. (2002). Developmental psychology: Rational imitation in preverbal infants. *Nature, 415*, 755.
Giraldeau, L.-A., Valone, T. J., & Templeton, J. J. (2002). Potential disadvantages of using socially acquired information. *Philosophical Transactions of the Royal Society B, 357*, 1559–1566.
Gladwell, M. (2000). *The tipping point: how little things can make a big difference*. New York: Little, Brown.

Gladwin, C., & Butler, J. (1984). Is gardening an adaptive strategy for Florida family farmers? *Human Organization, 43*, 208–216.
Hamilton, M. J., & Buchanan, B. (2009). The accumulation of stochastic copying errors causes drift in culturally transmitted technologies: Quantifying Clovis evolutionary dynamics. *Journal of Anthropological Archaeology, 28*, 55–69.
Henrich, J. (2001). Cultural transmission and the diffusion of innovations: Adoption dynamics indicate that biased cultural transmission is the predominate force in behavioral change. *American Anthropologist, 103*, 992–1013.
Henrich, J. (2004). Demography and cultural evolution: Why adaptive cultural processes produced maladaptive losses in Tasmania. *American Antiquity, 69*, 197–214.
Henrich, J. (2006). Understanding cultural evolutionary models: A reply to Read's critique. *American Antiquity, 71*, 771–782.
Henrich, J. (2010). The evolution of innovation-enhancing institutions. In M. J. O'Brien & S. J. Shennan (Eds.), *Innovation in cultural systems: Contributions from evolutionary anthropology* (pp. 99–120). Cambridge, MA: MIT Press.
Henrich, J., & Boyd, R. (1998). The evolution of conformist transmission and the emergence of between-group differences. *Evolution and Human Behavior, 19*, 215–241.
Henrich, J., & Broesch, J. (2011). On the nature of cultural transmission networks: Evidence from Fijian villages for adaptive learning biases. *Philosophical Transactions of the Royal Society, 366*, 1139–1148.
Henrich, J., & McElreath, R. (2003). The evolution of cultural evolution. *Evolutionary Anthropology, 12*, 123–135.
Heyes, C. M. (1994). Social learning in animals: Categories and mechanisms. *Biological Reviews, 69*, 207–231.
Hiscox, G. (1900). *Horseless vehicles, automobiles, motorcycles operated by steam, hydro-carbon, electric, and pneumatic motors*. New York: Munn.
Hoppitt, W., Kandler, A., Kendal, J. R., & Laland, K. N. (2010). The effect of task structure on diffusion dynamics: Implications for diffusion curve and network-based analyses. *Learning & Behavior, 38*, 243–251.
Kameda, T., & Nakanishi, D. (2002). Cost-benefit analysis of social/cultural learning in a nonstationary uncertain environment: An evolutionary simulation and an experiment with human subjects. *Evolution and Human Behavior, 23*, 373–393.
Kameda, T., & Nakanishi, D. (2003). Does social/cultural learning increase human adaptability? Rogers' question revisited. *Evolution and Human Behavior, 24*, 242–260.
Kandler, A., & Steele, J. (2010). Social learning, economic inequality, and innovation diffusion. In M. J. O'Brien & S. J. Shennan (Eds.), *Innovation in cultural systems: Contributions from evolutionary anthropology* (pp. 193–214). Cambridge: MIT Press.
Kane, D. (1996). Local hillclimbing on an economic landscape. Santa Fe Institute Working Paper 96-08-065. Santa Fe, NM: Santa Fe Institute.
Kauffman, S. (1995). *At home in the universe: The search for laws of self-organization and complexity.* Oxford: Oxford University Press.
Kauffman, S., Lobo, J., & Macready, W. (2000). Optimal search on a technology landscape. *Journal of Economic Behavior and Organization, 43*, 141–166.
Kawai, M. (1965). Newly acquired pre-cultural behavior of the natural troop of Japanese macaques. *Primates, 6*, 1–30.
Kendal, J., Giraldeau, L.-A., & Laland, K. N. (2009). The evolution of social learning rules: Payoff-based and frequency-dependent biased transmission. *Journal of Theoretical Biology, 260*, 210–219.
Keynes, J. M. (1937). The general theory of employment. *Quarterly Review of Economics, 51*, 209–223.
Kline, M., & Boyd, R. (2010). Population size predicts tool complexity in Oceania. *Proceedings of the Royal Society B, 277*, 2559–2564.
Kovács, Á. M., Téglás, & Endress, A. D. (2010). The social sense: Susceptibility to others' beliefs in human infants and adults. *Science, 330*, 1830–1834.
Lake, M. W., & Venti, J. (2009). Quantitative analysis of macroevolutionary patterning in technological evolution: Bicycle design from 1800 to 2000. In S. J. Shennan (Ed.), *Pattern and process in cultural evolution* (pp. 147–162). Berkeley: University of California Press.
Laland, K. N. (2004). Social learning strategies. *Learning & Behavior, 32*, 4–14.
Laland, K. N., Atton, N., & Webster, M. M. (2011). From fish to fashion: Experimental and theoretical insights into the evolution of culture. *Philosophical Transactions of the Royal Society B, 366*, 958–968.

Laland, K. N., & Galef, B. G. (Eds.). (2009). *The question of animal culture*. Cambridge: Harvard University Press.

Laland, K. N., Odling-Smee, F. J., & Myles, S. (2010). How culture shaped the human genome: Bringing genetics and the human sciences together. *Nature Reviews Genetics, 11*, 137–148.

Laland, K. N., & Reader, S. M. (2010). Comparative perspectives on human innovation. In M. J. O'Brien & S. J. Shennan (Eds.), *Innovation in cultural systems: Contributions from evolutionary anthropology* (pp. 37–51). Cambridge, MA: MIT Press.

Lefebvre, L., & Giraldeau, L.-A. (1994). Cultural transmission in pigeons is affected by the number of tutors and bystanders present. *Animal Behaviour, 47*, 331–337.

Lindblom, C. (1959). The science of 'muddling through'. *Public Administration Review, 19*, 79–88.

Lipo, C. P., O'Brien, M. J., Collard, M., & Shennan, S. J. (Eds.). (2006). *Mapping our ancestors: Phylogenetic approaches in anthropology and prehistory*. New York: Aldine.

Lobo, J., & Macready, W. G. (1999). Landscapes: a natural extension of search theory. Santa Fe Institute Working Paper 99-05-037E. Santa Fe, NM: Santa Fe Institute.

Lowery, S. A., & DeFleur, M. L. (1995). *Milestones in mass communication research*. White Plains, NY: Longman.

Lyman, R. L., & O'Brien, M. J. (2000). Measuring and explaining change in artifact variation with clade-diversity diagrams. *Journal of Anthropological Archaeology, 19*, 39–74.

Lyman, R. L., & O'Brien, M. J. (2003). Cultural traits: Units of analysis in early twentieth-century anthropology. *Journal of Anthropological Research, 59*, 225–250.

Lyman, R. L., VanPool, T. L., & O'Brien, M. J. (2008). Variation in North American dart points and arrow points when one or both are present. *Journal of Archaeological Science, 35*, 2805–2812.

Lyman, R. L., VanPool, T. L., & O'Brien, M. J. (2009). The diversity of North American projectile-point types, before and after the bow and arrow. *Journal of Anthropological Archaeology, 28*, 1–13.

Mace, R., Holden, C., & Shennan, S. J. (Eds.). (2006). *The evolution of cultural diversity: A phylogenetic approach*. London: University College London Press.

Mace, R., & Jordan, F. M. (2011). Macro-evolutionary studies of cultural diversity: A review of empirical studies of cultural transmission and cultural adaptation. *Philosophical Transactions of the Royal Society B, 366*, 402–411.

Mace, R., & Pagel, M. (1994). The comparative method in anthropology. *Current Anthropology, 35*, 549–564.

McElreath, R., Lubell, M., Richerson, P. J., Waring, T. M., Baum, W., Edsten, E., *et al.* (2005). Applying evolutionary models to the laboratory study of social learning. *Evolution and Human Behavior, 26*, 483–508.

Mesoudi, A. (2007). Using the methods of social psychology to study cultural evolution. *Journal of Social, Evolutionary and Cultural Psychology, 1*, 35–58.

Mesoudi, A. (2008). An experimental simulation of the "copy-successful-individuals" cultural learning strategy: Adaptive landscapes, producer–scrounger dynamics, and informational access costs. *Evolution and Human Behavior, 29*, 350–363.

Mesoudi, A. (2010). The experimental study of cultural innovation. In M. J. O'Brien & S. J. Shennan (Eds.), *Innovation in cultural systems: Contributions from evolutionary anthropology* (pp. 175–191). Cambridge, MA: MIT Press.

Mesoudi, A. (2011a). *Cultural evolution: How Darwinian evolutionary theory can explain human culture and synthesize the social sciences*. Chicago: University of Chicago Press.

Mesoudi, A. (2011b). An experimental comparison of human social learning strategies: Payoff-biased social learning is adaptive but under-used. *Evolution and Human Behavior*, in press.

Mesoudi, A., & Lycett, S. J. (2009). Random copying, frequency-dependent copying and culture change. *Evolution and Human Behavior, 30*, 41–48.

Mesoudi, A., & O'Brien, M. J. (2008a). The cultural transmission of Great Basin projectile-point technology I: An experimental simulation. *American Antiquity, 73*, 3–28.

Mesoudi, A., & O'Brien, M. J. (2008b). The cultural transmission of Great Basin projectile-point technology II: An agent-based computer simulation. *American Antiquity, 73*, 627–724.

Mesoudi, A., & O'Brien, M. J. (2008c). The learning and transmission of hierarchical cultural recipes. *Biological Theory, 3*, 63–72.

Mesoudi, A., & Whiten, A. (2008). The multiple uses of cultural transmission experiments in understanding cultural evolution. *Philosophical Transactions of the Royal Society B, 363*, 3489–3501.

Mesoudi, A., Whiten, A., & Dunbar, R. I. M. (2006). A bias for social information in human cultural transmission. *British Journal of Psychology, 97*, 405–423.

Mesoudi, A., Whiten, A., & Laland, K. N. (2006). Towards a unified science of cultural evolution. *The Behavioral and Brain Sciences, 29*, 329–383.

Mom, G. (2004). *The electric vehicle: Technology and expectations in the automobile age*. Baltimore: Johns Hopkins University Press.

Neiman, F. D. (1995). Stylistic variation in evolutionary perspective: Inferences from decorative diversity and interassemblage distance in Illinois Woodland ceramic assemblages. *American Antiquity, 60*, 7–36.

O'Brien, M. J., & Holland, T. D. (1995). Behavioral archaeology and the extended phenotype. In J. M. Skibo, W. H. Walker, & A. E. Nielsen (Eds.), *Expanding archaeology* (pp. 143–161). Salt Lake City: University of Utah Press.

O'Brien, M. J., & Lyman, R. L. (2002). Evolutionary archaeology: Current status and future prospects. *Evolutionary Anthropology, 11*, 26–36.

O'Brien, M. J., Lyman, R. L., Mesoudi, A., & VanPool, T. L. (2010). Cultural traits as units of analysis. *Philosophical Transactions of the Royal Society B, 365*, 3797–3806.

O'Brien, M. J., & Shennan, S. J. (Eds.). (2010). *Innovation in cultural systems: Contributions from evolutionary anthropology*. Cambridge: MIT Press.

Ormerod, P. (2006). *Why most things fail: Evolution, extinction and economics*. New York: Pantheon.

Pennisi, E. (2010). Cultural evolution: Conquering by copying. *Science, 328*, 165–167.

Petroski, H. (1992). *The evolution of useful things: How everyday artifacts—from forks and pins to paper clips and zippers—came to be as they are*. New York: Vintage Books.

Powell, A., Shennan, S., & Thomas, M. G. (2009). Late Pleistocene demography and the appearance of modern human behavior. *Science, 324*, 1298–1301.

Reader, S. M., & Biro, D. (2010). Experimental identification of social learning in wild animals. *Learning & Behavior, 38*, 265–283.

Reader, S. M., & Laland, K. N. (2002). Social intelligence, innovation and enhanced brain size in primates. *Proceedings of the National Academy of Sciences, 99*, 4436–4441.

Rendell, L., Boyd, R., Cownden, D., Enquist, M., Eriksson, K., Feldman, M. W., *et al.* (2010). Why copy others? Insights from the Social Learning Strategies Tournament. *Science, 328*, 208–213.

Rendell, L., Boyd, R., Enquist, M., Feldman, M. W., Fogarty, L., & Laland, K. N. (2011). How copying affects the amount, evenness and persistence of cultural knowledge: Insights from the Social Learning Strategies Tournament. *Philosophical Transactions of the Royal Society B, 366*, 1118–1128.

Rendell, L., Fogarty, L., Hoppitt, W. J. E., Morgan, T. J. H., Webster, M. M., & Laland, K. N. (2011). Cognitive culture: Theoretical and empirical insights into social learning strategies. *Trends in Cognitive Sciences, 15*, 68–76.

Renfrew, C., & Scarre, C. (Eds.). (1998). *Cognition and material culture: The archaeology of symbolic storage*. Cambridge: McDonald Institute for Archaeological Research.

Richerson, P. J., & Boyd, R. (2000). Climate, culture, and the evolution of cognition. In C. Heyes & L. Huber (Eds.), *Evolution of congition* (pp. 329–346). Cambridge, MA: MIT Press.

Richerson, P. J., & Boyd, R. (2005). *Not by genes alone*. Chicago: University of Chicago Press.

Richerson, P. J., Boyd, R., & Henrich, J. (2010). Gene-culture coevolution in the age of genomics. *Proceedings of the National Academy of Sciences, 197*, 8985–8992.

Rieucau, G., & Giraldeau, L.-A. (2011). Exploring the costs and benefits of social information use: An appraisal of current experimental evidence. *Philosophical Transactions of the Royal Society B, 366*, 949–957.

Rogers, A. (1988). Does biology constrain culture? *American Anthropologist, 90*, 819–831.

Rogers, E. M. (1995). *Diffusion of innovations* (4th ed.). New York: Free Press.

Ryan, B., & Gross, N. C. (1943). The diffusion of hybrid seed corn in two Iowa communities. *Rural Sociology, 8*, 15–24.

Schiffer, M. B. (1990). The influence of surface treatment on heating effectiveness of ceramic vessels. *Journal of Archaeological Science, 17*, 373–381.

Schiffer, M. B. (1991). *The portable radio in American life*. Tucson: University of Arizona Press.

Schiffer, M. B. (1993). Cultural imperatives and product development: The case of the shirt-pocket radio. *Technology and Culture, 34*, 98–113.

Schiffer, M. B. (1996). Some relationships between behavioral and evolutionary archaeologies. *American Antiquity, 61*, 643–662.

Schiffer, M. B. (2005a). The devil is in the details: The cascade model of invention processes. *American Antiquity, 70*, 485–502.

Schiffer, M. B. (2005b). The electric lighthouse in the nineteenth century: Aid to navigation and political technology. *Technology and Culture, 46*, 275–305.

Schiffer, M. B. (2008a). A cognitive analysis of component-stimulated invention: Electromagnet, telegraph, and the Capitol dome's gas lighter. *Technology and Culture, 49*, 376–398.
Schiffer, M. B. (2008b). *Power struggles: Scientific authority and the creation of practical electricity before Edison*. Cambridge, MA: MIT Press.
Schiffer, M. B. (2010). Can archaeologists study processes of invention? In M. J. O'Brien & S. J. Shennan (Eds.), *Innovation in cultural systems: Contributions from evolutionary anthropology* (pp. 235–249). Cambridge, MA: MIT Press.
Schiffer, M. B., Butts, T. C., & Grimm, K. K. (1994). *Taking charge: The electric automobile in America*. Washington, DC: Smithsonian Institution Press.
Schiffer, M. B., Hollenback, K. L., & Bell, C. L. (2003). *Draw the lightning down: Benjamin Franklin and electrical technology in the Age of Enlightenment*. Berkeley: University of California Press.
Schiffer, M. B., & Skibo, J. M. (1987). Theory and experiment in the study of technological change. *Current Anthropology, 28*, 595–622.
Schiffer, M. B., & Skibo, J. M. (1989). A provisional theory of ceramic abrasion. *American Anthropologist, 91*, 101–115.
Schiffer, M. B., & Skibo, J. M. (1997). The explanation of artifact variability. *American Antiquity, 62*, 27–50.
Schumpeter, J. A. (1942). *Capitalism, socialism, and democracy*. New York: Harper.
Shenkar, O. (2010). *Copycats: How smart companies use imitation to gain a strategic edge*. Cambridge, MA: Harvard Business Press.
Shennan, S. J. (2002). *Genes, memes and human history*. London: Thames and Hudson.
Shennan, S. J. (Ed.). (2009). *Pattern and process in cultural evolution*. Berkeley: University of California Press.
Shennan, S. J. (2011). Descent with modification and the archaeological record. *Philosophical Transactions of the Royal Society B, 36*, 1070–1079.
Skibo, J. M., Schiffer, M. B., & Reid, K. C. (1989). Organic-tempered pottery: An experimental study. *American Antiquity, 54*, 122–146.
Stuart, T. E., & Podolny, J. M. (1996). Local search and the evolution of technological capabilities. *Strategic Management Journal, 17*, 21–23.
Surowiecki, J. (2004). *The wisdom of crowds: Why the many are smarter than the few*. New York: Random House.
Tennie, C., Call, J., & Tomasello, M. (2009). Ratcheting up the ratchet: On the evolution of cumulative culture. *Philosophical Transactions of the Royal Society B, 364*, 2405–2415.
Thiselton-Dyer, W. T. (1895). Variation and specific stability. *Nature, 51*, 459–461.
Tomasello, M., Kruger, A. C., & Ratner, H. H. (1993). Cultural learning. *The Behavioral and Brain Sciences, 16*, 495–511.
Van de Peer, Y., Maere, S., & Meyer, A. (2009). The evolutionary significance of ancient genome duplications. *Nature Reviews Genetics, 10*, 725–732.
VanPool, T. L., O'Brien, M. J., & Lyman, R. L. (2011). Innovation and natural selection in Paleoindian projectile points from the American Southwest. In N. Goodale & W. Andrefsky Jr. (Eds.), *Lithic technological systems: Stone, human behavior, evolution*. Cambridge: Cambridge University Press. in press.
Watts, D. J. (2002). A simple model of global cascades on random networks. *Proceedings of the National Academy of Sciences, 99*, 5766–5771.
White, J. H., Jr. (1997). *American locomotives: An engineering history, 1830–1880* (rev. ed.). Baltimore: Johns Hopkins University Press.
Whiten, A. (2005). The second inheritance system of chimpanzees and humans. *Nature, 437*, 52–55.
Whiten, A., Goodall, J., McGrew, W. C., Nishida, T., Reynolds, V., Sugiyama, Y., *et al.* (1999). Cultures in chimpanzees. *Nature, 399*, 682–685.
Whiten, A., Hinde, R. A., Laland, K. N., & Stringer, C. B. (2011). Culture evolves. *Philosophical Transactions of the Royal Society B, 366*, 938–948.
Wimsatt, W. C. (1999). Genes, memes and cultural identity. *Biology and Philosophy, 14*, 279–302.
Ziman, J. (Ed.). (2000). *Technological innovation as an evolutionary process*. Cambridge: Cambridge University Press.