Cultural stability without copying

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Abstract

What causes cultural stability? Culture can be studied as an evolving system, and the comparison between biological and cultural evolution has inspired a productive research agenda in which cultural stability is commonly attributed to the existence of mechanisms of high-fidelity cultural transmission. Other researchers have argued that no such copying processes are necessary to explain cultural stability, and that stability can also emerge as a by-product of convergent transformation (in which an item causes the production of another item whose form tends to deviate from that of the original item in a non random way). To investigate this issue, we present a series of stochastic simulation models of cultural evolution that make no prior assumptions about the type of processes by which cultural units propagate through a population. Results show that cultural stability can emerge and be maintained by convergent transformation alone, even in the absence of any form of copying or selection process. We also show that high-fidelity copying and convergent transformation are, contrary to some previous arguments, not opposing forces, and can in fact jointly contribute to cultural stability. Finally, we analyse how convergent transformation and high-fidelity copying can have different evolutionary signatures at the level of the population, and hence how their differing effects can be distinguished in the empirical record. Our models can be read as formalisations of Cultural Attraction Theory.

Introduction

Anthropologists have long documented the richness and diversity of human cultures (Benedict 1934, Murdock 1981, Brown 1991, Ember et al. 1998), and biologists have observed and described cultural traditions in several non-human species (e.g. Whiten et al. 1999, Rendell & Whitehead 2001, Laland & Galef 2009, Danchin et al. 2018, Aplin 2019). Researchers from many disciplines have emphasised the critical role that culture plays in the ecological success of humans (Richerson & Boyd 2005, Henrich 2016). However, in explaining culture, a critical question remains unresolved: what are the possible causes of cultural stability? This is important because without some degree of stability nothing would ever be recognised as cultural in the first place. Do humans, or other species, possess psychological mechanisms of inheritance able to copy cultural items—recipes, technology, belief systems, word meaning, and so on—with a degree of fidelity high enough to produce stable traditions? Are such mechanisms necessary to explain long-term cultural persistence or can cultural stability emerge as a byproduct of communication, mindreading, and other forms of ordinary social interaction?

Here we present a series of stochastic simulation models to investigate the different ways in which stability can emerge in an evolutionary system, such as culture. We focus in particular on the role of convergent transformation: the possibility that one item causes the production of another item whose form tends to deviate from that of the original item in a non random way. Some formal models examine how convergent transformation and selection can interact with one another (Claidière & Sperber 2007, Claidière 2009, Claidière et al. 2018). Other models show how convergent transformation can support the evolution of social learning (Boyd & Richerson 1995, 1996) or have examined how convergent transformation influences the subsequent co-evolution of culture and cognition (Griffiths et al. 2008, Kirby et al. 2007, Thompson et al. 2016). Complementary to these research agendas we investigate the contribution that convergent transformation can make to the emergence of stable cultural traditions. We contrast convergent transformation with other hypothesised causes of cultural stability, in particular those inspired by the comparison with biological evolution, such as faithful transmission (copying), random error, and model selection.

We show that: (1) Cultural stability can emerge and be maintained by virtue of convergent transformation alone, in the absence of any form of high-fidelity copying or selection process. This effect is robust, not idiosyncratic, and occurs under a wide range of conditions; (2) As processes, copying and convergent transformation can be complementary (rather than opposite) in bringing about cultural stability, and convergent transformation, even if weak, drives the stabilization; (3) While both selective high-fidelity copying and convergent transformation can produce stable cultural traditions (either separately or jointly), the underlying processes can be empirically distinguished through different evolutionary signatures at the level of the population. Collectively these findings suggest that cultural stability can emerge even in the absence of any biological adaptation for culture. They also provide an important tool for empirical research, because they identify a way to distinguish between the effects of different sources of stability in specific cases. These models are highly general, allowing us to investigate the causes of cultural stability with very few prior commitments about either (i) the granularity of cultural units, or (ii) the processes by which cultural units propagate through a population.

In the next section we describe the general framework that applies to all our models. We then describe each of our specific models in detail, and their results. Code for all models is available in an Open Science Framework repository at https://osf.io/yncws/

General methods

We consider a population of N items. (In Study 1 and Study 2, $N = 100$. In Study 3, $N = 10; 100; 1000$.) At the beginning of each simulation, items are randomly placed in a continuous bidimensional (square) space with coordinates in the range $(-1, 1)$. This is effectively a variation space (inspired by Sperber 1996), with each axis representing an arbitrary dimension of a cultural item (e.g., size and width of an arrow-head). At each time step, the original population of items is replaced by a population of new items of equal size N. We study the evolution of the location of these items over time.

The location of each item at time $t+1$ is determined by applying a stochastic transformation function that takes the location of an item at time t as input. The process proceeds through three stages:

1. *Sample population.* The population at time t is sampled in one of two different ways, either randomly or with bias. The sampled item's location is then used as input for

the transformation function.

2. *Apply transformation function.* A transformation function is applied which modifies the input location in either a convergent or a random way.

3. *Iterate & measure.* The transformations described above determine the output of the simulation at time t. This output is then used as the input for the same process at time $t+1$. Measures of stability and similarity are taken at this stage.

Sample population

For each item at $t+1$, the population at t is sampled in one of two ways, either random or biased.

- *Random sampling.* One item from the population at time t is sampled at random and used as input for the transformation function.

- *Biased sampling.* Two items from the population at time t are sampled at random, and whichever is closest to the origin $(0,0)$ (the centre of the space) is used as input for the transformation function. This effectively represents a selection process in which variants closer to the origin are fittest. The overall space can be understood, in this case, as a continuous, smooth fitness landscape with a single peak at the origin.

Apply transformation function

New items undergo one of two transformation functions: random or convergent. For each new item, both its distance from, and angle relative to, its input are determined by probability distributions, as described below (see also Figure 1).

- *Random transformation.* The position of the item at $t+1$ is equal to the position of its input modified by a distance δ_r and an angle β_r:

  - δ_r is drawn from a lognormal distribution in the range $(0,k)$, where k is a parameter of the simulation. k can be thought of, intuitively, as the magnitude of 'copying error' of a mechanism of transmission.

  - β_r is drawn from a uniform distribution in the range $(-\pi,\pi)$ with 0 oriented towards the origin. Because this distribution is uniform, the angle between an item at time $t+1$ and its input at time t is random.

- *Convergent transformation.* The position of the item at time $t+1$ is equal to the position of its input at time t modified by a distance δ_b and an angle β_b:

  - δ_b is drawn from a uniform distribution in the range $(0,2d)$, with d being the distance of the input to the origin. This means that the distance between an item and its input is a function of the distance between the input and the origin. The closer an input is to the origin, the smaller the distance between it and the item at $t+1$ will be.

  - β_b is drawn from a normal distribution in the range $(-\pi,\pi)$ with $\sigma=1$ and $\mu=0$, and with 0 oriented towards the origin. Because this distribution is normal, the direction between an item at time $t+1$ and its input at time t is not random. Instead, items are most likely to be located closer to the origin rather than away from it.

In case the final position of an item results out of the boundaries of the variation space, the transformation function is repeated until the item falls within it (different ways to handle these occurrences do not change our results, also because they are relatively rare).

These various functions reflect empirical aspects of the different processes by which stability might be achieved. For random transformations, δ_r is defined as a lognormal distribution to reflect the idea that while most copying errors are small, exact replication is a marginal case; and β_r is defined as a uniform distribution to reflect the idea that copying errors are undirected. These two ideas are both common in the cultural evolution literature. For convergent transformation, δ_b is defined in terms of d to reflect the idea that similarity between items and their inputs is not a fixed quantity, as it usually is with copying-errors, but traits tend to transform more or less over time in virtue of their properties (Sperber 2000, Mesoudi & Whiten 2004, Claidière, Scott-Phillips & Sperber 2014), in our case represented by their position in the variation space.

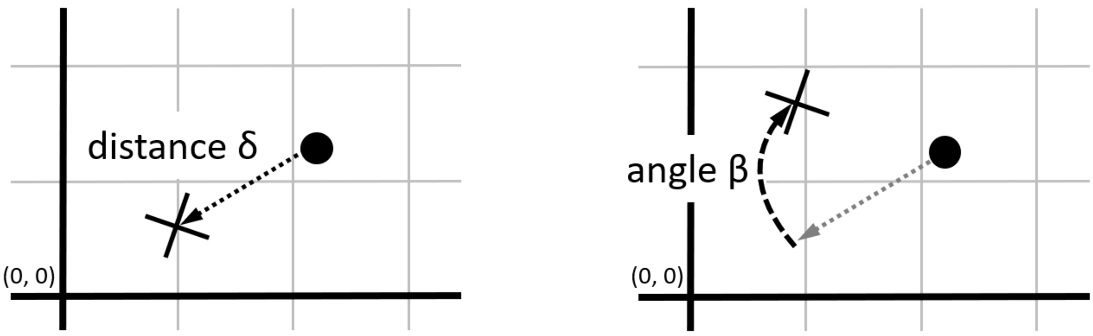

Figure 1: **Transformation function.** The input is depicted with a filled circle and the output with a cross. The transformation function determines a distance and an angle (see main text). The distance, δ, is measured absolutely (left panel), whereas the angle, β, is measured relative to a straight line between input and origin (right panel).

Iterate & measure

Items of time step t are removed, and the items from time step $t + 1$ serve as the inputs for the next time step. Once the location of each item at $t + 1$ is set, we measure two aspects of the evolution of the system: stability and similarity.

- *Stability.* We take two types of measures relevant to stability: change in mean trait value and spread of the population .
  - The mean trait value of the population (first moment) is, in evolutionary biology, the most common measure used to represent whether a population is evolving or not (Hartl & Clark 1997). We take two types of measures of stability based on mean trait value. First, we measure the change in mean trait value over time by calculating the barycentre of the population and then calculating the Euclidean distance between the barycentres at two different time

steps. These two time steps are either 1 time step apart, to measure short-term stability, or 100 time steps apart to measure longer-term stability. Second, we measure longer-term stability by measuring whether the population remains in the same location or instead drifts. To do this, we measure the distance between the barycentre as it is measured at time step 100 and the barycentre every 1000 time steps (1000, 2000, etc). We choose time step 100 as a reference because by this time the populations have generally converged upon a stable state (see Study 1).

  - The spread of the population is a measure of the clustering of the items at a given time step. This is defined as the average distance of all items from the barycentre of the population. This measures the statistical distribution of variant in a population (second moment). This is relevant to cultural stability because it determines how scattered are items in the variation space.

  Both types of measure (spread and change in mean trait value) are important as they can vary independently. For example, in cases of, say, disruptive selection, or stabilizing selection, the mean trait value could remain the same while the spread would change. In other words, stability is best understood in light of both spread and change in mean trait value.

- *Similarity.* The degree of similarity between an item and its input is measured as the Euclidean distance between them. Similarity at the level of the population is then the mean of these distances for all items in the population. This measure is used in Study 3 only, where we investigate whether different possible causes of stability have different evolutionary signatures at the level of the population.

This approach is highly general in two key ways. First, although for simplicity we referred to items and their inputs, the items could be seen as (i) individuals with cultural traits (with parent individuals as inputs), (ii) populations of cultural traits (with one trait being the 'cultural model' for another), or (iii) token expressions of cultural items (with tokens at one time step influencing the production of tokens at a later time step). Second, because both the sampling and transformation functions are defined strictly in terms of their effects, the model is agnostic about how these functions are realised materially, i.e., about what sorts of processes are involved. Two examples are: (i) biased sampling can be thought of as a selection process acting on cultural trait with differential fitness, or as representing how individuals differentially acquire information from others based on factors such as prestige or success (i.e., model-based social learning strategies Hoppitt & Laland 2013, Kendal et al. 2018) (ii) convergent transformation can be thought of as a prior or cognitive bias in the reconstruction of cultural traits (Miton et al. 2015, Morin 2016, Claidière et al. 2018) or as an ecological bias (Schillinger et al. 2014).

Study 1: Stability without copying or selection?

We first investigate the different conditions under which cultural stability obtains, or not.

Methods

We compare five conditions ($N = 100$ in all cases):

a) *Baseline.* Here the position of all items at each time step is determined wholly at random i.e. there is no sampling or transformation, and hence no relationship between the population at time t and time $t-1$.

b) *Replication.* Random sampling with no transformation (i.e. $k = 0$).

c) *Unbiased.* Random sampling with random transformation, under three distinct values of k ($k = 0.01; 0.1; 0.5$).

d) *Biased Sampling.* Biased sampling with random transformations, under three distinct values of k ($k = 0.01; 0.1; 0.5$).

e) *Convergent Transformation.* Random sampling with convergent transformation.

In this way we are able directly compare the effects of different sampling and transformation functions on the behaviour and, in particular, the stabilisation, of the evolving system. We omit the final possibility—biased sampling with convergent transformation—only because this will simply magnify the results observed in 'Biased Sampling' and 'Convergent Transformation'.

Results

Figure 2 summarises the behaviour of the model under the different conditions that we study. All results presented are an average of 10 runs of simulations. Videos of representative runs of simulations (b) to (e) are provided in the Supplementary Information[1].

'Baseline' (row (a)) behaves in a genuinely random way, as expected. There is no evolution towards stability. Items remain uniformly spread in the space, the mean trait value oscillates at random around the origin, and there is no effect of the scale of time steps at which the mean trait value is measured. This is because there are no causal relations between the items at any two time steps.

We do observe an emergence of stability in 'Replication' (row (b)). Spread decreases to 0, as does mean trait value. This is due to the random sampling of inputs which, by chance, eventually leads some items at time t not to serve as an input for the next time step. Since an item at $t + 1$ is always located at the same position as its input at time t (because no new variation is introduced), the population eventually drifts to one of the locations occupied by an individual item at the beginning of the simulation. In short, stability is achieved here through the gradual elimination of variation in the population.

In 'Unbiased' (row (c)) we allowed new variation to be introduced randomly, and we find that this also leads to the emergence of stability over time. Spread decreases towards

[1] Supplementary Information will be available with the final version of the draft.

0, as does change in mean trait value (both across 1 and 100 time steps)—but never quite reaches it. This is because novel variation is introduced at every time step. The asymptote is determined by the value of k: the lower the value of k, the more stability in the system.

In 'Biased Sampling' (row (d)), we observe a faster evolution towards stability than in 'Unbiased', for all three values of k. The most stable populations remain those with low values of k, as the selection can only winnow the novel variation once it has already been introduced by random transformations in the previous generation[2].

Finally, in 'Convergent Transformation' (row (e)), we observe a quick evolution towards stability, with both spread and change in mean trait value decreasing asymptotically towards 0. As in 'Biased Sampling', the population is very stable in the long term (it remains located around the origin). Convergent transformation is sufficient, on its own, to cause long term stability.

Collectively, these results highlight two particularly relevant aspects of cultural stability.

First, a population under random transformation achieves stability only when coupled with a biased sampling process. This is clear when 'Unbiased' and 'Biased Sampling' are compared (see Figure 3). In 'Unbiased', in which sampling is random, there is short- but not longer-term stability, even when k is extremely low. Indeed, mean trait value drifts through time: although there is very little change in mean trait value between two successive time steps, over the long term the population drifts away randomly. High-fidelity transmission produces long term stability only when coupled with selection. In contrast, in 'Biased Sampling', the population clusters around the origin and stabilizes there.

Second, neither high-fidelity transmission nor selection are necessary for stability, either short- or longer-term. This is clearly shown in 'Convergent Transformation', in which both short- and longer-term stability occur despite the ubiquity of transformations and the absence of any biased sampling. 'Convergent transformation' produces dynamics more akin to 'Biased Sampling' than to 'Unbiased': in both cases the population converges towards the origin and stabilizes there, both in the short and long term.

Study 2: Mixing random and convergent transformation

In Study 1, convergent transformation produced on its own both short and long-term stability. In reality, we might expect only some items in a population to undergo convergent transformation. Indeed, the relative importance of copying and small, convergent transformation is often debated (Claidière & Sperber 2007, Claidière, Smith, Kirby & Fagot 2014, Acerbi & Mesoudi 2015, Claidière et al. 2018). To calrify these issues we develop a model mixing both types, and examine their interactions.

[2] The "attractor" model in (Miśta 2018) in fact reduces to our Biased Sampling condition, as there is no convergent transformation in the model.

Methods

To mix convergent and random transformations we constructed a model with random sampling and a function that determines which type of transformation—random or convergent—will occur. Specifically, the probability that the transformation will be convergent is equal to $1 - d^{\alpha}$, where d is the Euclidean distance between the input and the origin (scaled to a unit of $\sqrt{2}$, the maximum possible distance), and α is a parameter of the model ranging between 0 and ∞. Otherwise, the transformation is random. Thus, the closer an input is to the origin, the more likely that transformation is convergent. The parameter α controls the strength of this effect; or, more informally, the 'reach' of convergent transformation (see Figure 4). A high α increases the overall probability that an item is transformed directionally instead of randomly. As α decreases, so does the overall probability that an item is transformed in a convergent rather than random way. $\alpha = 0$ reduces to model (c) in Study 1, and $\alpha = \infty$ reduces to model (e). As in study 1, $N = 100$.

Results

For all the results described below $\alpha = 0.1$ (Other values of α ($0 < \alpha < \infty$) produce qualitatively similar results.) k is set to either to 0.1 or 0.5 (parameter k regulates what can be thought as the magnitude of copying error). When k is lower ($k = 0.1$) the population is more stable over both short- and longer-term, as expected (Figure 5). We see a clear increase in stability from the 'Unbiased' model with an equal value for k (compare to Figure 2(c)). Moreover, convergent transformation ensures that the population does not drift from the origin, even over the long term, but instead remains stable around it. In this way, convergent transformation has a similar effect as biased sampling.

Furthermore, this effect occurs even when most transformations are random. Indeed, the proportion of items that undergo convergent transformation is higher when k is lower than when it is higher (Figure 6). This occurs because once an input is brought within the vicinity of the origin by convergent transformation, future items are more likely to remain within that vicinity when k is low than when it is high. This means that in situations where there is both convergent transformation and high-fidelity transmission, these two factors can reinforce one another to secure stability.

Collectively these results open up questions of high relevance to the empirical study of culture. Stability can be achieved in more than one way, so how might we differentiate between these different possible causes? Is there a way to identify, in empirical records, whether one or the other of the different processes we have modelled is in fact at play in a given case? Study 3 investigates these questions.

Study 3: Evolutionary signatures of different causes of stability

Study 1 showed that the patterns of stabilisation observed in 'Biased Sampling' and 'Convergent Transformation' are similar, such that on the basis of observed stability alone we cannot infer which processes are responsible. Here we investigate whether these different possible causes of stability have different evolutionary signatures at the level of the population. We do this in two ways. First, we examine how a population already clustered around a particular point evolves over time. We are particularly interested in whether there is a qualitative difference in population behaviour, and whether the two different types of transformation, random and convergent, affect differently the observed similarity from one generation to the next. Second, we investigate whether such effects are affected by population size.

Methods

In this study, we investigate how populations with a limited spread evolve over time. (A simulation starting with a large spread, as in the previous studies, is included in the Supplementary Information, showing equivalent results). To cluster the population, we started the simulation by first locating the items in one of the four corners randomly, with a 0.8 distance from the origin for both x and y coordinates, and then randomly distributing the items within 0.05 distance from that point. We ran simulations 'Biased Sampling' (with $k = 0.1; 0.5$) and 'Convergent Transformation' with this new starting condition.

To examine how the populations evolve towards the origin, we track similarity between items and their inputs (see General Methods). As in previous models, $N = 100$. To investigate the impact of population size, we repeat the above process but now for three different population sizes ($N = 10; 100; 1000$). We then measure how many time steps it takes for the populations to reach a stable state, which we operationalise as a change in mean trait value at each time step ≤ 0.01.

Results

Qualitative description. Videos (available as Supplementary Information) show that biased sampling and convergent transformation have qualitatively different evolutionary behaviours over time. In the case of 'Biased Sampling', the clustered population move together, in small steps, until it reaches the origin. We observe gradual evolution similar to a hill-climbing behaviour. In contrast, in the case of 'Convergent Transformation', the population rapidly re-converges on the origin. This can be described as the population 'jumping' to the origin, with little effect of cultural inertia. This effect mirrors patterns observed in a number of real-world cases, such as rapid changes followed by quick stabilization in technological systems (e.g. Schiffer 2005).

Fidelity. In 'Biased Sampling' the mean distance between items and inputs is relatively low (depending on k) and remains so throughout the simulation (see Figure 7). This is due to constant rate of random transformations. This represents well the assumption that transmission processes possess a specific degree of fidelity, both as it is characterized in the theoretical literature (e.g. Mesoudi 2011), and how it is implemented in other formal models [e.g.][](Henrich & Boyd 2002, Enquist et al. 2010). In contrast, in 'Convergent Transformation' we observe at first high distance between items and their inputs (i.e. a low degree of similarity) and then a rapid decrease of distance (see Figure 7). This is due to the fact that the expected degree of similarity is not fixed, but instead depends on the specific location of the input. The further from the origin an item's input is, the less similar we can expect the item to be from the input. This reflects the idea that the degree of fidelity by which a cultural trait is transmitted can depend on the specific variants of cultural items (e.g. Sperber 2000). In this latter case, the similarity of the items and the overall degree of fidelity is not guaranteed by an intrinsic property of some underlying transmission process, but instead are emergent phenomena at the level of the population.

Population size. By varying population size we observe that the two different simulations show very different sensitivity to population size (Figure 8) There is no evidence of sensitivity to population size in 'Convergent Transformation', but there is in 'Biased Sampling', with larger populations taking less time to reach the same degree of stability as smaller ones. In fact, this is true both for populations that are at first randomly scattered, and for those that are at first already clustered (see Supplementary Information). This dependency on population size occurs because biased sampling is, fundamentally, a sorting process dependent on sample size: it is more likely to sample one item closer to the origin in a large population than in a small population.

In conclusion, two evolutionary signatures can distinguish between different causes of cultural stability: (1) qualitative and quantitative differences in the behaviour of the population as it converges on a stable form; (2) differences in sensitivity to population size.

Discussion

A key question for any scientific study of culture is, what are the causes of cultural stability? Many distinct research traditions, across evolution, psychology, and anthropology, have either argued or assumed that cultural stability, whether over shorter or longer timespans, necessarily requires psychological mechanisms (e.g. imitation) capable of copying cultural items with some high degree of fidelity (Tomasello 2008, Tennie et al. 2009, Mesoudi 2011, Henrich 2016, Laland 2017). Accepting this assumption, some researchers have further argued that there has been biological natural selection for mechanisms of high-fidelity copying in humans, because such mechanisms are necessary to facilitate the emergence and persistence of culture, thus helping to explain how humans have adapted to an extraordinarily broad range of ecological conditions(Boyd & Richerson 1996, 2005, Tomasello 1999, Henrich 2016, Laland 2017).

We show that these conclusions cannot be reached so quickly. Stability can emerge in an evolutionary system without any mechanism of high-fidelity transmission (in Study 1). This stability can hold for both short and long periods of time, if the mechanisms of transmission exhibit some some degree of convergent transformation. These points have previously been argued for mostly in a verbal way (Sperber 2000, Claidière & Sperber 2010, Charbonneau 2019; but see, for formal treatments Claidière & Sperber 2007, Claidière 2009, Claidière et al. 2018). Here we have subjected them to further formal probing and made them comparable with concurrent models, and found the arguments robust. High-fidelity copying is only one of several factors that can ensure intergenerational stability in an evolutionary system (see also Henrich 2004, Griffiths et al. 2008, Acerbi et al. 2012, Dean et al. 2014).

Another important issue is the combined effect of high-fidelity copying and convergent transformation when they act together in an evolutionary system. Previous models have shown that, when copying is biased, and the biases act in the same direction of convergent transformation, the effects will reinforce each other (Henrich & Boyd 2002, Claidière et al. 2018). When instead the effects of copying biases and convergent transformation are in opposition, the end-state depends on the relative force of the two (Claidière & Sperber

2007, Claidière et al. 2018). We analysed, in Study 2, the case of high-fidelity copying with unbiased sampling and convergent transformation, showing that the more faithful the copying the stronger the effect of convergent transformation. This result may appear surprising, because intuitively faithful copying will 'lock' items in a configuration different from where they would end if convergent transformation operates alone. However, given that copying is unbiased, it reinforces the only directional mechanism present, convergent transformation, making items close to the origin more stable than what they would be with a less faithful copying. This suggests that convergent transformation, even when of low magnitude, can counteract—or might in some cases even dominate—the effects of other factors with shifting directionality such as, for instance, model-based social learning strategies (Hoppitt & Laland 2013, Kendal et al. 2018).

Our results also identify evolutionary signatures of different possible sources of stability in an evolutionary system. The first signature concerns different levels of similarity while a population is undergoing change. A specific and clear example comes from the experimental literature on language evolution, which consistently shows the pattern observed for 'Convergent transformation' in our Study 3. Levels of intergenerational similarity are at first low, when the languages are unstructured and relatively inefficient, and later high, once the languages have evolved structure and greater levels of communicative efficiency. (Compare, for instance, our Figure 7 with Figures 2a and 4a from Kirby et al. 2008). Similar points apply to several other experimental datasets too, across a range of different cultural domains (e.g. Mesoudi et al. 2006, Lewandowsky et al. 2009, Miton et al. 2015, Ravignani et al. 2017, Claidière et al. 2018)

Our second evolutionary signature is differential sensitivity to population size. Many recent studies investigate the relationship between population size and the cumulative complexity of cultural items, in particular technology (Henrich 2004, Powell et al. 2009, 2010, Querbes et al. 2014). The hypothesis here is that larger populations increase rates of technological progress, because larger population ensure lower risks that cultural traits become rare and are lost. Our study adds to this empirical literature an important additional finding about the relative rates of convergence upon new cultural items. More generally, where the stabilization of a cultural item in a population is influenced by the size of that population, this may be interpreted as (partial) evidence that biased selection plays a role; and conversely where there is no such relationship, convergent transformation is likely to be more important (Acerbi et al. 2017).

Our simulations can also be read as formal models of cultural attraction. Cultural Attraction Theory (Sperber 1996, Claidière & Sperber 2007, Claidière, Smith, Kirby & Fagot 2014, Morin 2016, Heintz 2017, Scott-Phillips et al. 2018) argues that convergent transformation is common in human social life, and that cultural stability is best seen as a condition where convergent transformations gravitate closely around an attractor. This claim is often presented and discussed in contrast with other evolutionary approaches to culture (Acerbi & Mesoudi 2015, Morin 2016, Sterelny 2017, Scott-Phillips et al. 2018). However resolution of these debates has been somewhat hindered by the relative absence of formal models of cultural attraction (but see Henrich & Boyd 2002, Claidière & Sperber 2007, Claidière 2009). We have here removed that barrier, advancing debate onto key empirical questions about the exact psychological mechanisms that facilitate the emergence, spread, and stability of culture.

By virtue of their generality, our models can be extended in many ways to study cultural dynamics of many different types. Here we highlight three possibilities. (1) In our models, the convergent transformation function is oriented towards one single point in the space (the origin), but the model can be easily adjusted to include multiple points of convergence (e.g. Claidière & Sperber 2007). (2) The functions for convergent transformation and biased sampling are presently both oriented towards the origin, but this can be easily altered by re-defining one or the other to be oriented to some other point in the space. (3) At present, the convergent transformation function is defined in such a way that the closer an item is to the origin, the more convergent are its effects. This can be modified by changing the convergent transformation function, or by changing the way in which convergent and random transformation interact (see Study 2).

More broadly, our findings suggest that cultural stability requires no cognitive adaptations (Sperber 2000, Sperber & Hirschfeld 2004, Morin 2016, Charbonneau 2019, Heyes 2018). Cultural traditions can instead emerge and remain stable (over various time spans) also as a consequence of processes whose proper function is not high-fidelity transmission, such as communication, mindreading and other forms of social interaction, as long as those processes lead to convergent transformation.

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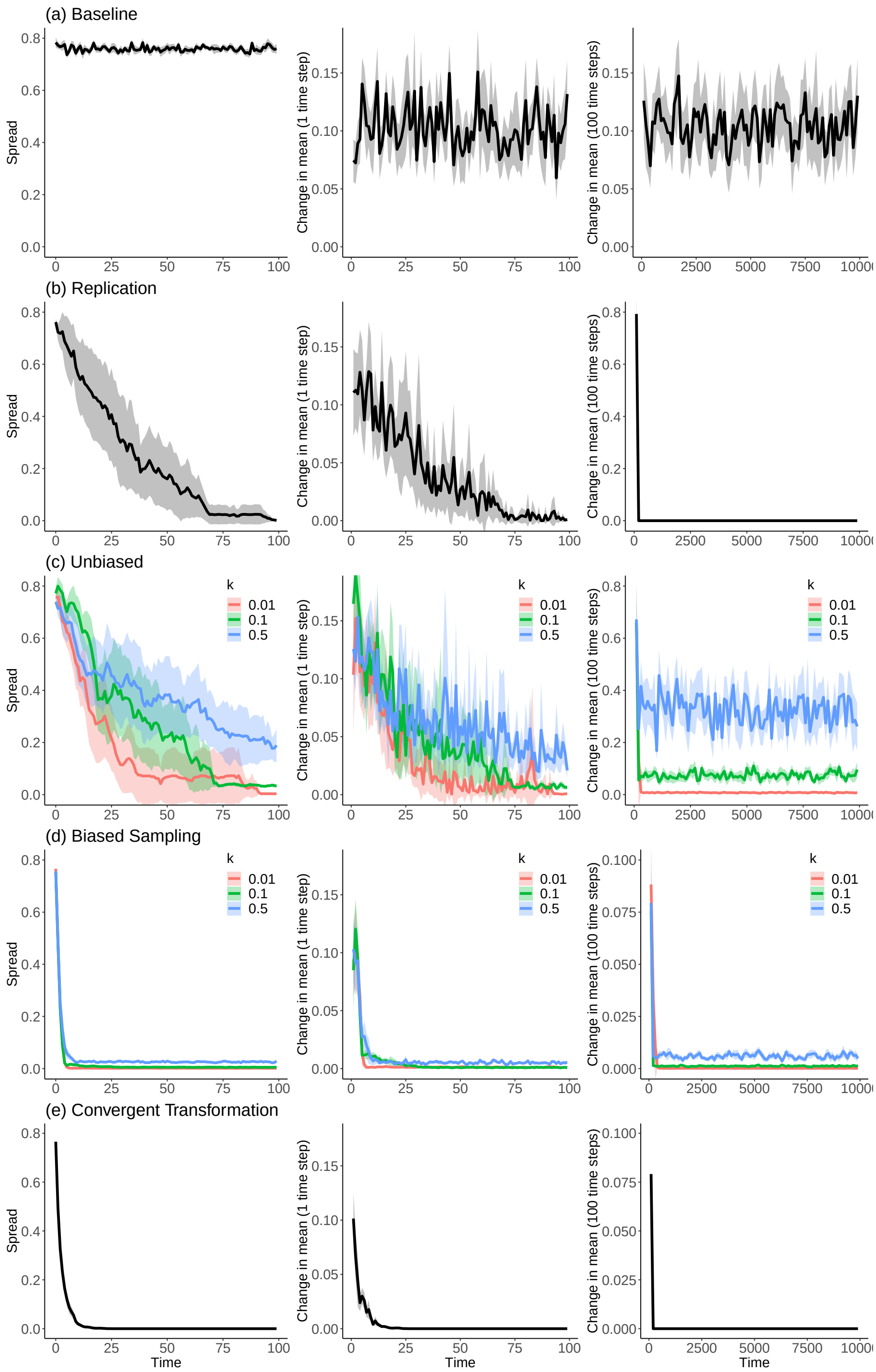

Figure 2: **Under what conditions does stability occur?** These 15 graphs report the behaviour of the model under the various conditions considered in Study 1. Each row represents a different simulation, or set of simulations, and each column measures a different aspect of stability. Simulations from top to bottom: (a) Baseline; (b) Replication; (c) Unbiased; (d) Biased Sampling; (e) Convergent Transformation. Measures of stability, from left to right: (i) Spread; (ii) Mean trait value across 1 time step (simulation ran for 100 time steps); (iii) Mean trait value across 100 times steps (simulation ran for 10,000 time steps). All results are averaged over 10 runs of simulations. The shaded area shows standard deviations. In all conditions $N = 100$.

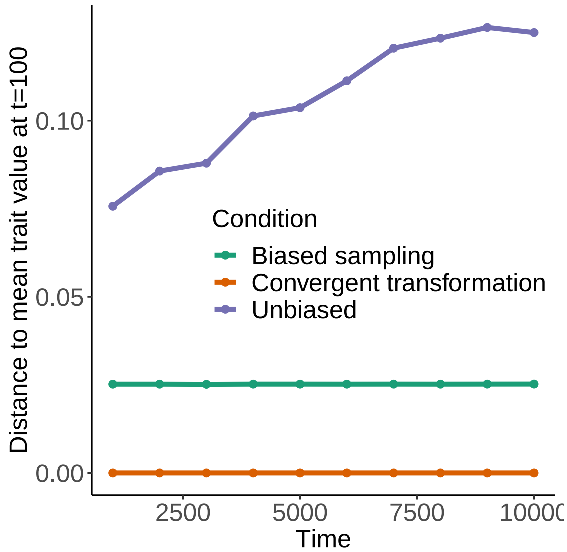

Figure 3: **Long term stability: comparisons.** Here we compare the distance between the mean trait value of the population at time step 100 with the mean trait value of the population at subsequent timesteps (1000, 2000, etc., up to 10000), across simulations 'Unbiased', 'Biased Sampling', and 'Convergent Transformation'. This distance increases monotonically in 'Unbiased' simulation, but it does not change in either 'Biased Sampling' or 'Convergent Transformation'. In other words, there is evolutionary drift in 'Unbiased', whereas 'Biased Sampling' and 'Convergent Transformation' produce long-term stability. The difference in distance between 'Biased Sampling' and 'Convergent Transformation' is due to the fact that 'Biased Sampling' was slightly slower to converge. Figure displays average of 10 runs. In all cases $N = 100$ and $k = 0.01$ (except in 'Convergent Transformation' where there is no k).

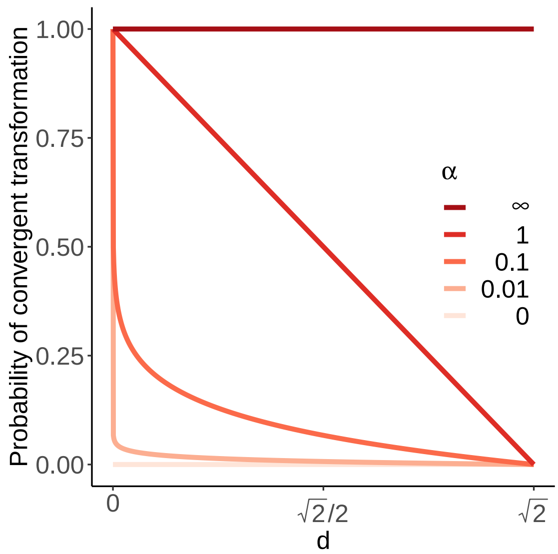

Figure 4: **Varying α in the mixed model.** Probability landscape that a given item undergoes convergent transformation instead of random transformation, under different values of α. With $\alpha = \infty$, all transformations are convergent, and with $\alpha = 0$ all transformations are random. With $0 < \alpha < \infty$ the further items are from the origin, the less likely they are (with decreasing probability) to undergo convergent transformation. Note that, for all $\alpha > 0$, there is always a non-null probability to undergo convergent transformation.

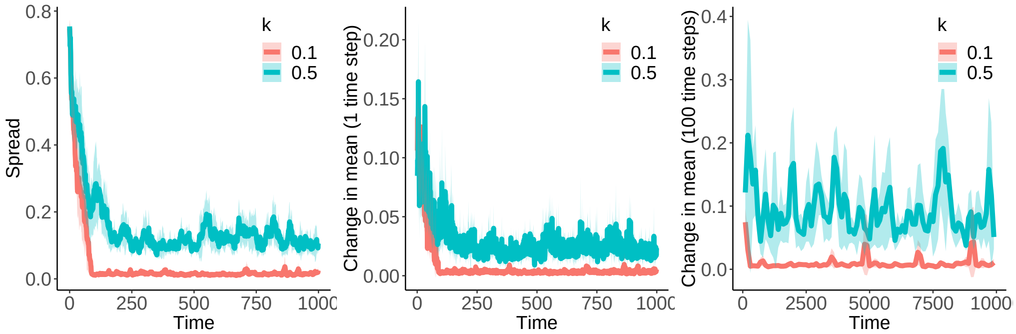

Figure 5: **Mixed model of random copying and convergent transformation.** Mixed model, with $\alpha = 0.1$ and different copying fidelity ($k = 0.1; 0.5$). Left: Spread; Centre: Mean trait value across 1 time step (simulation ran for 100 time steps); Right: trait value across 100 times steps (simulation ran for 10,000 time steps). All results are averaged over 10 runs of simulations, all with $N = 100$. The shaded area shows standard deviations.

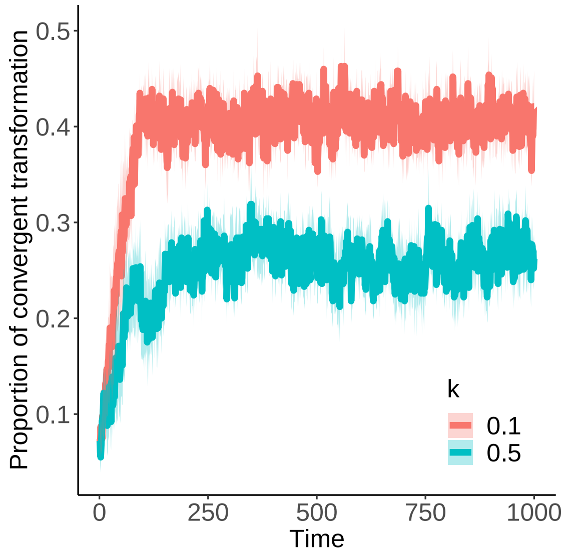

Figure 6: **Proportion of convergent transformation in mixed model.** Mixed model, with $\alpha = 0.1$ and different copying fidelity ($k = 0.1; 0.5$). Proportion of items that, at each time step, are subject to convergent transformation. The lower the value of k, the more it leads to convergent transformation, showing that a smaller value of k increases the mean probability of convergent transformation. Results are averaged over 10 runs of simulations, all with $N = 100$. The shaded area shows standard deviations.

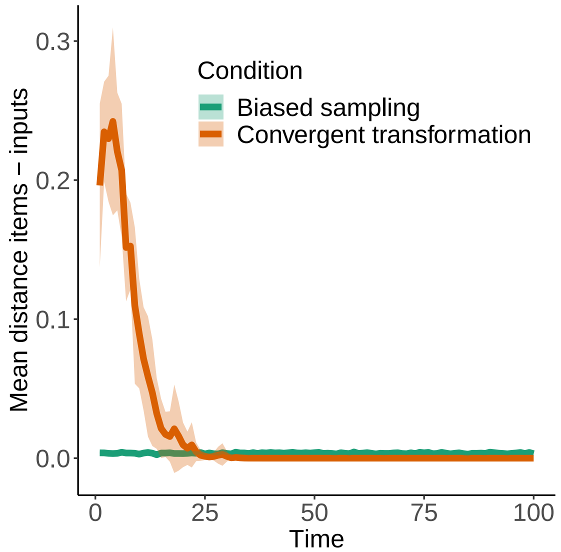

Figure 7: **Population-level similarity.** 'Biased sampling' with $k = 0.1$. 'Convergent transformation' as in Study 1. The population is clustered in one of the corners of the space (see text), and then evolves towards the origin. Similarity between items and their inputs remains low throughout the 'Biased sampling' simulation, whereas it varies in 'Convergent transformation', depending on the mean distance of the population to the origin. Results are averaged on 10 runs of the model. The shaded area shows standard deviations. In both conditions $N = 100$.

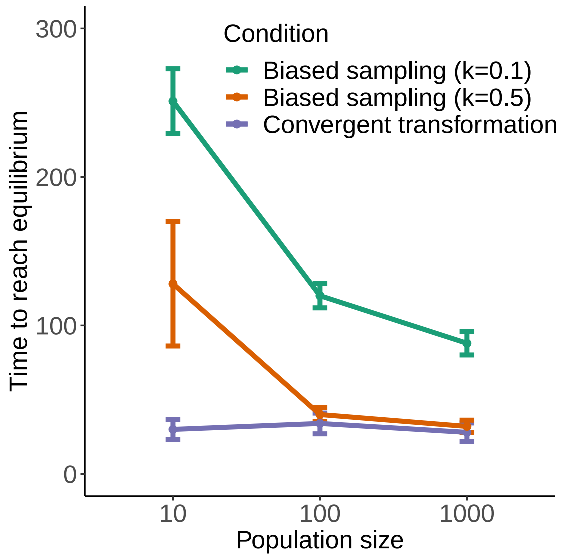

Figure 8: **Effects of population size.** Starting with a clustered population in one of the corners of the space (see text), we measure the number of time steps it takes for the change in mean trait value of the population to be ≤ 0.01 (we call this 'equilibrium' for short). This is measured for 'Biased sampling' at two different levels of k ($k = 0.1; 0.5$) and for 'Convergent transformation'. Results are averaged on 10 runs of the model. Bars show standard deviations.