

**Contextual Geometric Structures: modeling the fundamental components
of cultural behavior**

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Abstract

The structural complexity of culture cannot be characterized by simply modeling cultural beliefs or inherited ideas. Formal computational and algorithmic models of culture have focused on the inheritance of discrete cultural units, which can be hard to define and map to practical contexts. In cultural anthropology, research involving structuralist and post-structuralist perspectives have helped us better understand culturally-dependent classification systems and oppositional phenomena (e.g. light-dark, hot-cold, good-evil). Contemporary research in cognitive neuroscience suggests that complementary sets may be represented dynamically in the brain, but no model for the evolution of these sets has of yet been proposed. To fill this void, a method for simulating cultural or other highly symbolic behaviors called contextual geometric structures will be introduced. The contextual geometric structures approach is based on a hybrid model that approximates both individual/group cultural practice and a fluctuating environment. The hybrid model consists of two components. The first is a set of discrete automata with a soft classificatory structure. These automata are then embedded in a Lagrangian-inspired particle simulation that defines phase space relations and environmental inputs. The concept of conditional features and equations related to diversity, learning, and forgetting are used to approximate the goal-directed and open-ended features of cultural-related emergent behavior. This allows cultural patterns to be approximated in the context of both stochastic and deterministic evolutionary dynamics. This model can yield important information about multiple structures and social relationships, in addition to phenomena related to sensory function and higher-order cognition observed in neural systems.

Introduction

Why is cultural change so complicated? Intuitively speaking, it seems as though cultural change should be easy to predict. Given the adaptable nature of culture, changes in the environment should be quickly matched by corresponding changes in cultural representations. However, the need for cultural change often does not result in an adaptive response. In some cases, culture often seems to be maladaptive in the face of adaptive pressures. These anecdotal observations demonstrate that cultural change is highly complex. How can we represent this complexity using a computational framework? The patterns that define cultural behaviors across generations and contexts are most likely created via emergent and evolutionary processes. Unlike goal-directed behaviors such as reaching for a cup of water or following a scent, there is often no clear outcome to pursue. Cultural representations should “make sense” of procedural knowledge in a way that is not only flexible but also constrained by conceptual interlinkage.

Cultural systems have been understood using a number of theoretical perspectives. Structural [1] and post-structural [2] perspectives are based on the notion that cultural life is based on a set of structures orthogonal to human cognition. These structures ostensibly emerge from common patterns of behavior over multiple generations, and represent the outcomes of cultural evolution. One signature of these ephemeral structures is the cognitive representation of oppositional sets, which are bounded by extreme concepts for each category. For example, there may be a phenomenological and objective category shared across cultures bounded by maximal

luminance (light) and absolute lack of luminance (dark). The extremes of this category are bounded by human perceptual abilities, so that experience of each culture can be contained within.

A "structure" can be defined as sets of relationships between objects in the environment, or experiences that can vary from person to person but are grounded in the same underlying concepts. These structures, which are a critical and implicit component of human cultural practice, have an underappreciated computational potential. This is particularly useful since many of these features are essential to understanding the evolution of culture across multiple generations [3]. Even more importantly, these structures might be an essential feature of how cultural practices are represented in a neural architecture. In recent years, brain scientists have applied this idea to a system of oppositional sets called complementary pairs [4]. In this approach, oppositional sets are contingent upon coupling, oscillatory, and heterogeneity in the dynamics of neural circuits. While these approaches hold much promise for the study of culture and symbolic systems, there remains a need to more fully integrate dynamical and structural approaches. I propose that by combining the structural features of cultural practice with a quasi-evolutionary perspective will result in a model of cultural evolution that maps to both social phenomenology and physiological function.

In addition, cultural and symbolic behavioral systems share many features with physical systems that exhibit chaotic behavior. It is this combination of quasi-evolutionary and chaotic dynamics that makes my approach unique. The approach presented here, called **Contextual Geometric Structures (CGS)**, is a Lagrangian-inspired approach that focuses on the structural complexity of cultural and other symbolic behavioral phenomena. In this paper, I will introduce a **hybrid soft classification/hydrodynamics model** in the context of cultural phenomena. Initially, basic features of the contextual geometric structure model will be introduced. It will then be demonstrate how this model fits into the milieu of cultural diversity and evolution. This includes features that approximate complex and diverse phenomena. Finally, we will consider this model in the context of neuronal processes.

Contextual Geometric Structures

Prior approaches to modeling culture have included forays into population genetics and game theory [5-7], memetic representations [8, 9], specialized genetic algorithms [10, 11], and conceptual blending models [12, 13]. In this paper, a computational approach focusing on the structural complexity of culture will be introduced. While the CGS approach incorporates some elements of these prior approaches, this is a fundamentally new approach to the problem.

Contextual geometric structures provide advantages that previous models do not. Models inspired by population genetics and game theory are explicitly discrete and focus on inheritance, and so do not produce many of the nonlinear behaviors that culture embodies. While memetic and conceptual blending models may provide insights into the combinatorial potential of cultural change, neither are explicitly dynamical. While computationally efficient, specialized genetic algorithms do not express the fluid output of cultural behaviors not explicitly associated with beliefs. Perhaps greatest advantage of this approach is the mapping of both these properties to a set of formal, computable structures.

Model Components

The CGS approach consists of a hybrid model: a “soft” computational structure representing the individual automata and a dynamical system representing the environment. Each automaton represents an individual with a brain that houses multiple conceptual spaces we call kernels. The automata then interact in a flow field. The dynamics of this flow field reinforce evolutionary behaviors and complex structural patterns.

Single automata

The cultural repertoire of each automaton (or particle) uses a soft classification scheme to represent the elements of culture. **Soft classification** [10], a fuzzy logic-inspired methodology, provides several advantages. One of these advantages involves the capacity to represent different cultural contexts in the same model. Another advantage involves the capacity to represent degrees of specific cultural and symbolic behaviors rather than merely its presence or absence.

All natural phenomena classified by any single cultural group has a membership function on a membership kernel (Figure 1), bounded by the capacity of a sensory system. The resulting cultural representation of a phenomena will sit somewhere on this scale. Unlike probabilistic or likelihood models, soft classification does not require related objects and categories to be transitive, distributive, or symmetrical. This allows for the generation of context, which is central to many existing theories of culture.

n-dimensional “Soft” Kernels

Figure 1 shows one- and two-dimensional examples of cultural representations of "hot" to "cold". Figure 2 demonstrates the membership kernel for three different cultures. The logical structure consists of various **membership kernels** which serve to classify the experience of each automaton into a common, objective scale. This graded scale acts to link together related concepts as shown in Figure 1. In this sense, they can be high-dimensional structures. One- and two-dimensional structures tend to represent concepts related to practice, while higher-dimensional structures represent a mapping from neurobiology to the cultural domain (see equations 1-5).

In Figure 2, the objective scale for hot and cold stimuli has been mapped to a 2-tuple surface for three cultures (A-C) and their overlap. There will be **variability between individuals and cultures**, which can be evaluated using a common scale. To map physiological function to cultural and symbolic representations, **contextual anchors** will be used (see 3-tuple surface, Figures 1 and 2). In context, contextual anchors provide a means to mediate the membership between hot and cold with procedural knowledge.

When different cultural categories overlap, it may be indicative of **previous contact**. However, separation between categories may also be indicative of cultural diversity in the form of **distinction**. Cultural distinction is a common feature of cultural evolution which can sometimes be imposed by its practitioners. In our context, we will assume that cultural distinction is an emergent feature, and is specified by the segregation factor (see Equation 6). Segregation or distinction is characterized by the non-overlapping region between B and C in Figure 2.

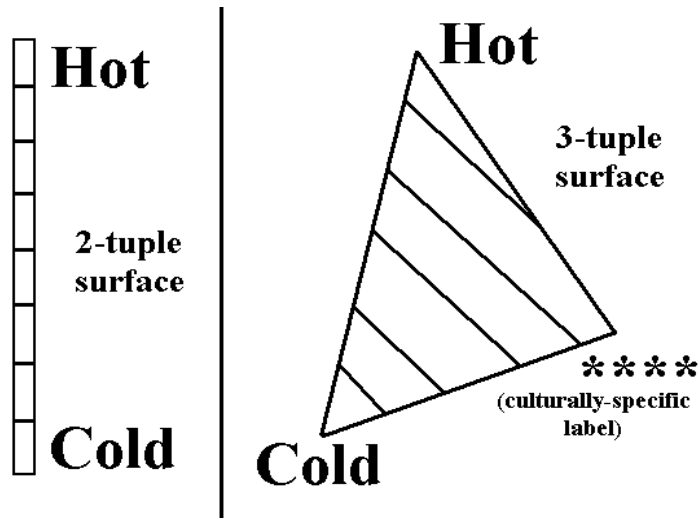


Figure 1. One- and Two-dimensional kernels embedded with n -tuple encodings.

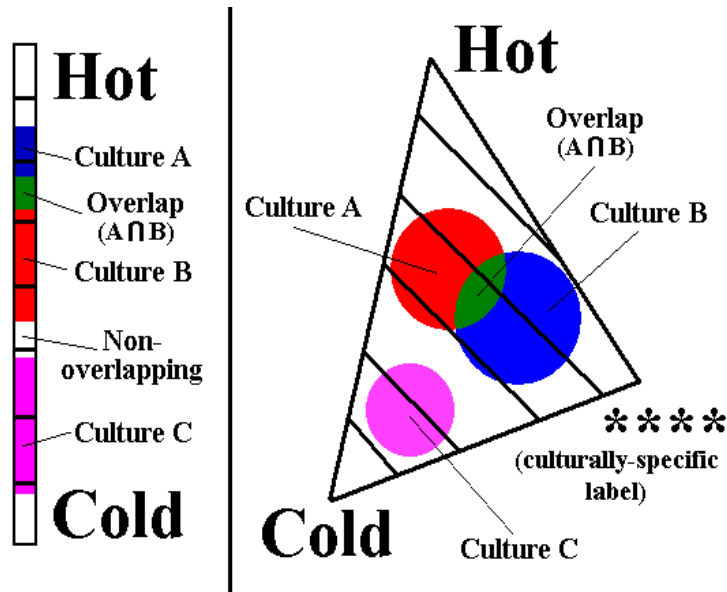


Figure 2. A soft classification kernel populated with the space for three different cultures. In this case, the same automaton is a carrier for three sets of cultural knowledge simultaneously.

Environment

The environmental component of contextual geometric structures involves a second-order Lagrangian system with dynamics that produce solutions analogous to **Lagrangian Coherent Structures** (LCS) [14]. LCS structures are defined as “ridges” of particles that aggregate in different portions of the flow field. Quantitatively, comparisons between particle positions can be made using either the **Finite Time Lyapunov Exponent** (FTLE - solved with regard to temporal divergence) or the **Finite Space Lyapunov Exponent** (FSLE - solved with regard to spatial divergence) [15-16]. Characterization of these features can be encapsulated in a measure called the **iterated temporal divergence** (see Equation 7). This methodology has previously been applied as a generalized analogy for evolvability in biological evolution [17]. This work is an extension of this application, the schematic of which is shown in Figure 3.

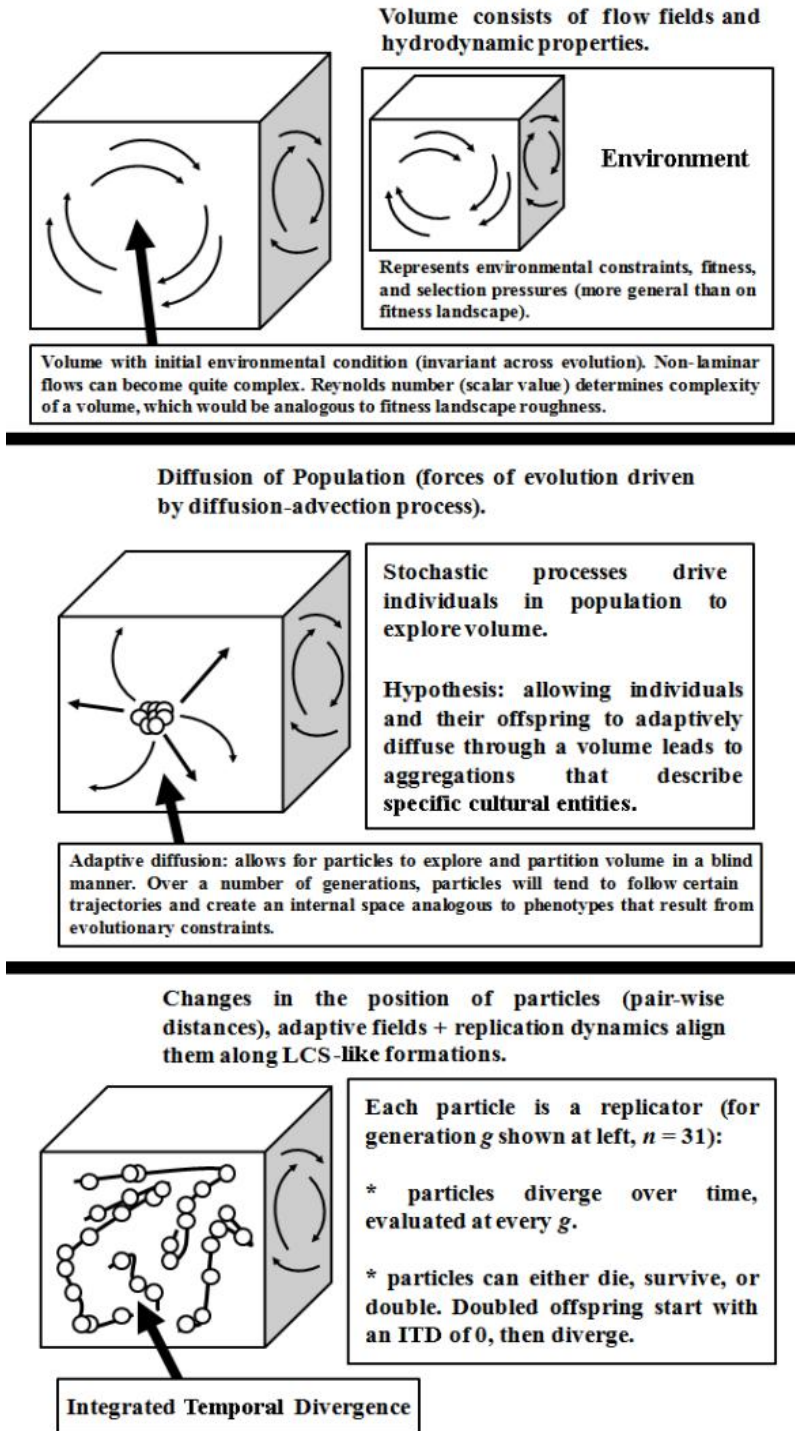


Figure 3. Cartoon depicting a typical contextual geometric structure simulation over the course of cultural evolution. TOP: initial condition, MIDDLE: active diffusion of the automata population, BOTTOM: final volume features contextual geometric structures.

As can be seen in Figure 3, the automata are initialized in the same location and then get diffused by the force field environment. The automata also have properties of **replicator vehicles** that reproduce according to specified parameters. While the selective component of the model

has yet to be specified completely, LCS-like models should produce outcomes dominated by evolutionary neutrality [18]. In addition, our goal is to observe cultural diversity, which involves far-from-equilibrium and sub-optimal behaviors obscured by strong selective pressures.

When applied to cultural systems, the LCS approach [19] typically involves **observing the diffusion of particles** in a **hydrodynamic force field** and **tracking the structures** that result (Figure 3). These structures are observed to collide, pull apart, and intermingle over time. Yet external forces introduced by the flow field can influence diffusion, and so the particles will still aggregate into recognizable and orderly structures. Contextual geometric structures show form as a consequence of evolutionary constraints and interactions between agents over time.

Structures, Diversity, and Evolution

In order to better understand the role of evolution in the emergence of contextual geometric structures, it is important to take a closer look at the outcome of interactions between three distinct automata populations. Figure 4 shows an example run using automata from three distinct cultures (red, blue, and black). This 2-D LCS volume features 165 automata present at the following frequencies: black (0.35), blue (0.35), and red = (0.30). This allows us to observe a number of purely physical outcomes after the evolution of an initial population. The first of these are loosely-organized vortices, which can either be homogeneous (all automata of the same color) or heterogeneous (automata of multiple colors). The second physical feature is a cluster often found along edges of the volume. These aggregates can be either homogeneous or heterogeneous, and can be considered products of pure diffusion. The third physical feature is a ridge, which can be either homogeneous or heterogeneous and often leads to the formation of vortices. The fourth physical feature is a vortex, which is a tightly packed aggregation of automata which is usually homogeneous.

Yet how exactly do these formations map to the evolution of culture? Using a mixed initial population can lead to competition, selection, and other quasi-evolutionary dynamics. The soft classifications inherent to each automaton must be coordinated using a series of features based on principles of attraction and repulsion to allow the diffusion of automata within a flow field to exhibit behaviors relevant to cultural structures and practice. Three features are expected to produce a broad range of highly-complex and realistic cultural scenarios.

Initial condition of model

The choice of a hybrid soft classificatory/hydrodynamics model may allow us to observe evolution enforced by self-organization. The tracking of particle populations allows for complex dynamics to emerge out of interactions between automata and the environment. In the model presented here, a forcing mechanism more complex than uniform diffusion may be required to produce quasi-evolutionary dynamics (see [Supplemental Information](#)). I propose the use of virtual flow jets (embodied in rulesets), which can mimic the uniform diffusive properties of neutral evolution [20]. Likewise, we can approximate natural selection by adding $1/f$ noise to the flow field. This and other forms of asymmetric perturbation can mimic the directional properties of selection [21].

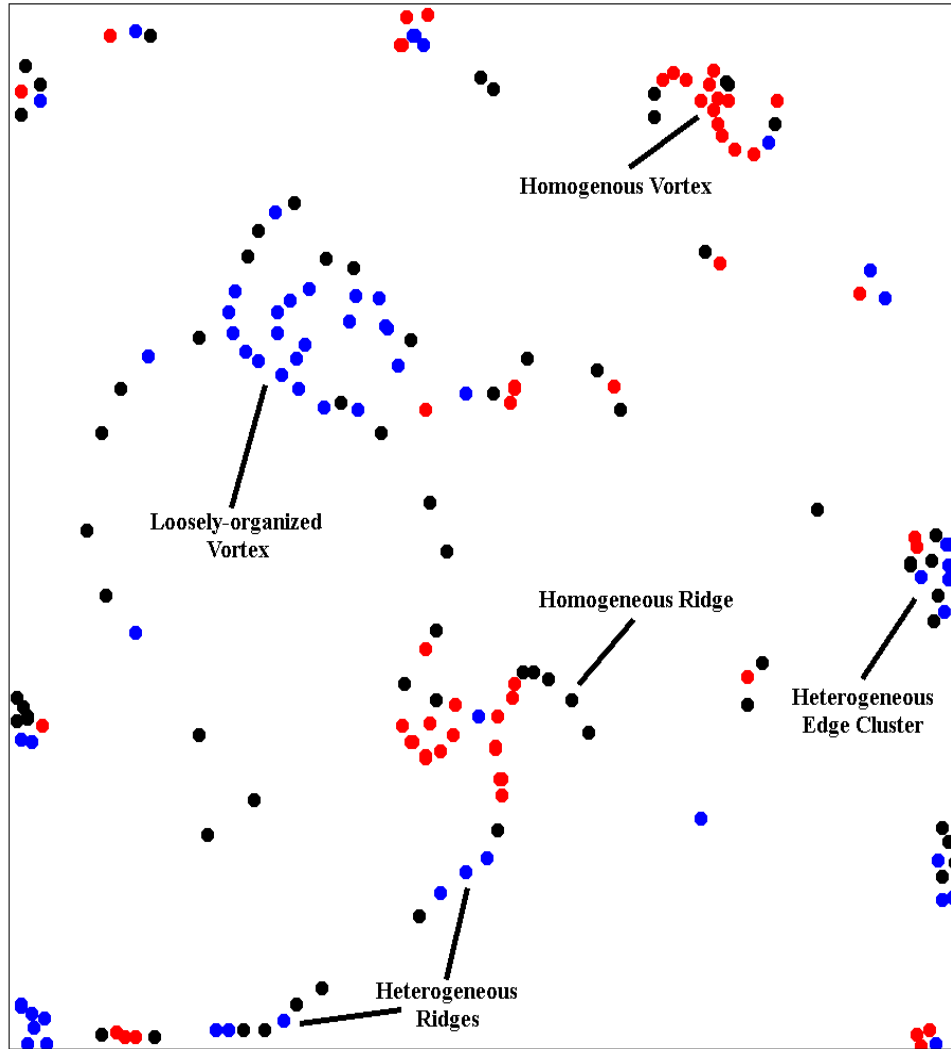


Figure 4. A 2-dimensional space representing an evolved population of automata representing three distinct cultures (Black, 58 automata; Blue, 58 automata; Red, 49 automata). Each subpopulation has a multifaceted set of relationships with regard to the other two.

Depending on force parameters that constrain the simulation environment, the simulation can yield vastly different behaviors. Yet the relational structure between concepts can remain quite similar across contexts. One feature of evolutionary systems is that they are often constrained to a particular evolutionary trajectory by past trajectories and current features [22]. These constraints combined with environmental fluctuations simulated by the addition of systematic noise produce quasi-evolutionary dynamics.

Features that shape evolution

As previously mentioned, systematic noise can be used to perturb the flow field. This perturbation can approximate different evolutionary dynamics. In a like manner, **conditional features** are top-down, deterministic perturbations of the flow field that act like selective mechanisms. Three conditional features are proposed: purity, associativity, and syncretism. These features are predicted to produce a wide range of contextual geometric structures that may be identified as complex cultural dynamics (see Figure 5). Each conditional feature operates on the

n -dimensional kernels of each automaton. While a lack of selection can produce evolutionary dynamics, higher-level organizational features can also increase the adaptive capacity of an evolutionary system [23, 24]. In this model, this is realized via simple interaction rules which lead to complex and highly-ordered outcomes.

Purity is successfully enforced when two or more distinct structures are formed. These structures are distinct in that all automata flow inward towards discrete vortices (Figure 5, Scenario #1). Over time, automata of different subpopulations exhibit total separation from one another. Associativity is successfully enforced when automata flow outward from established vortices along several trajectories towards one another (Figure 5, Scenario #2). Associativity often results in heterogeneous structures, and may lead to interactions between subpopulations.

The effectiveness of the purity and associativity sorting mechanisms can be detected using the **conditional diversity measure**, shown in Equation 8. This measure provides a profile of all automata within a certain level of Lagrangian divergence in the flow field by using a single parameter D . When the value converges upon 0.5, the collection of automata that compose a loosely-associated structure or ridge is highly homogeneous. When the value approaches 0.0, the collection of automata is highly heterogeneous.

Syncretism involves the dispersion of automata towards automata of a competing population. This generally involves automata that are aggregated around two or more vortices. Based on this conditional feature, automata spiral outward from these aggregation centers towards each other in overlapping patterns (Figure 5, Scenario #3). The particles (automata) are freely interchanged in the resulting vortex and trailing flow (Figure 5, Scenario #3).

The predicted features shown in Figure 4 are approximations of what could be referred to as cultural practice space. In this sense, structures represent the aggregation of different cultures, which are distinct from individual automata holding representations for multiple cultures. This may allow us to make complex cross-cultural comparisons.

Intermittent and transient dynamics

One of our main assumptions is that variation in a flow field of variable turbulence might contribute to local changes in the rate of evolution. Indeed, actively manipulating the flow parameters is another way to observe the “churn” of cultural evolution. Yet the relationship between the two model components might also allow us to observe selective conservation across cultural structures and practices.

What is the evolutionary relationship between the kernel values housed by individual automata and the Lagrangian unfolding in environmental space? To address this, we constructed a rate measure for learning and forgetting (see Equation 9). This measure bridges the gap between model components by tying kernel value segregation between populations to their distance in the Lagrangian flow field. These distances between concepts of practice and the evolutionary trajectory of individual automata (respectively) can be thought of as gaps that are translated between the two models. Learning occurs in cases where the gap between kernel values for different populations of automata is transferred to the evolutionary space (e.g. where

the ITD value becomes larger over time). Forgetting occurs when the gap between kernel values for different populations of automata is transferred to the evolutionary space (e.g. where the ITD value becomes smaller over time).

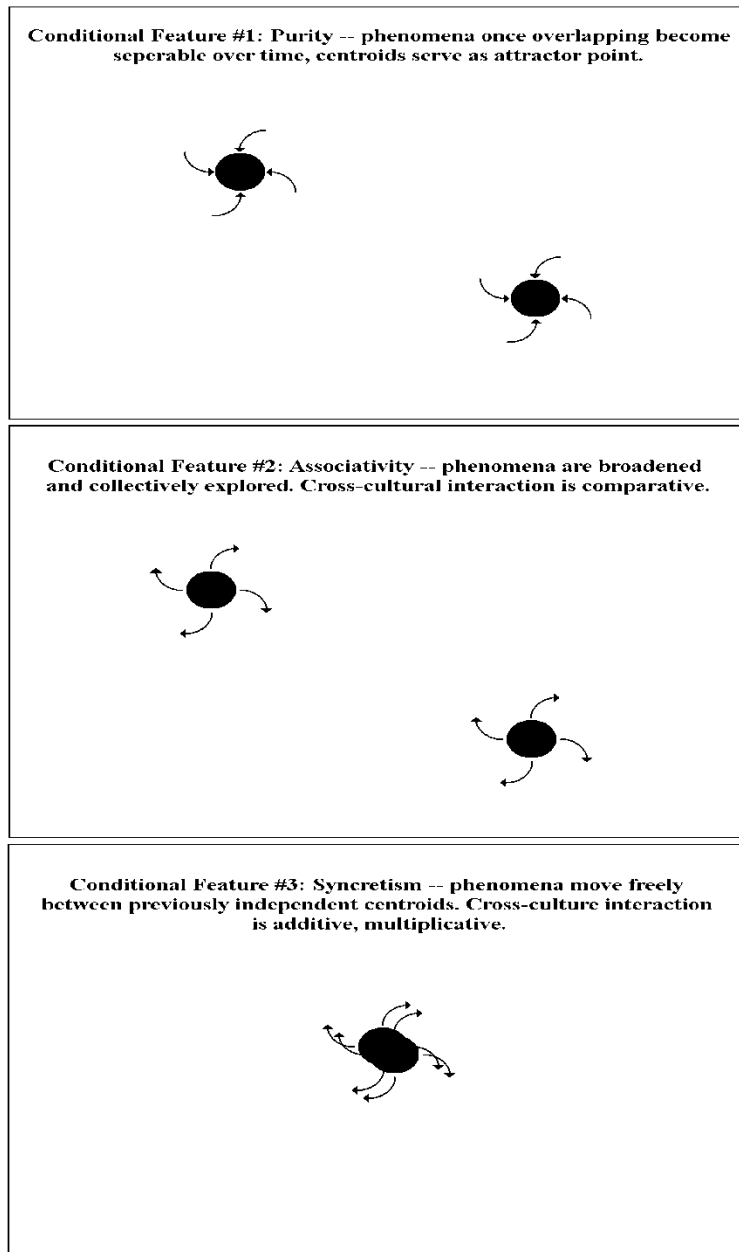


Figure 5. Three types of enforcing selection (conditional features) for the evolution of contextual geometric structures. Cartoon illustrates the general shape and mode of action characterized by each flow field modification.

Applying this measure when comparing subpopulations refines the model’s ability to simulate the navigation of culturally-specific structures, which result in more coherent structures and life-like behavior. When very large r_{LF} values occur, learning predominates. When very small r_{LF} values occur, forgetting predominates. As in real culture, we expect representations of

practice to fluctuate between extremes when the environment is unpredictable. In our model, this could be accomplished when the flow parameters produce a turbulent regime.

Conclusions

In this paper, I have proposed both an architecture and set of testable predictions for a model of cultural evolution focused on approximating the structures of practice. There are also several conclusions regarding the applicability of this model to real-world settings. The ultimate goal is to model the diversity and evolutionary dynamics of context. The common features and shortcomings of this model can tell us something about the cultural structures related to practice.

Why choose this particular model? The soft classificatory structures were chosen as a way to map cultural practices to **both** a quantitative scheme **and** perceptual mechanisms in the brain. The fuzziness of this model is particularly useful in capturing the nuance that cultural representations tend to exhibit. Coupling this to a LCS-inspired model is done to extend the static nature of the classification scheme to an evolutionary context. It is my contention [see 17] that LCS-inspired models capture evolutionary phenomena that fitness landscapes cannot. In the model presented here, flow fields can help us better understand the dynamics of intermingling during cultural contact and intentional segregation based on cultural content. This can lead us to better theories about cultural universals and perhaps even the neural bases of culture.

The take-home message from this work is twofold. One part of the message is that the inability of culture to adapt to rapidly-changing environments is not simply inertia. The other part of this message is to suggest that the ability of culture to adapt rapidly to environmental challenges is not free of constraints. Given these conclusions, this method is not meant to be a general-purpose model for understanding every cultural phenomenon. Rather, the focus is on cultural practices and the structures that underlie descriptive structures.

To better understand the adaptive capacity of cultural systems, our ultimate goal is to characterize the labyrinthine features of a practice or ritual. This might explain why some practices are resistant to change (such as religious rites), while others can be highly improvisational (such as a jazz score). Notably, this model does not account for hierarchical and ecological relationships between cultural and social groups. Our focus is more on the origins of cultural complexity and the spontaneous nature of cross-cultural interplay.

Idiosyncrasies observed in the adaptive capacity of culture can be seen in behaviors unique to our approach. The [supplemental information](#) section provides a link to an Animation that demonstrates how automata and even entire structures can exhibit recursive behaviors such as local cycling and clustering by automata type. These are essential ingredients for determining cultural context, but need further development.

One key advantage of this model over previous approaches to modeling culture is its relevance to neurobiological processes. Objective categories that incorporate information about cultural context can be placed explicitly in the context of integrative mechanisms in the brain. Similar to a typical model of brain function, the fine-grained biological details are implicit in our

soft classification model. Yet unlike a typical model of brain function, the evolution of collective behavior and shared cultural information over time are simulated using a physics-based model.

One example of dynamic, nonlinear neuronal processing related to symbolic behavior is multisensory integration. Multisensory integration involves the integration of visual, auditory, and somatosensory information at selective sites in the brain [25]. In mammals, the superior colliculus integrates visual and auditory sensory information for further processing relevant to the orienting function of attention [26]. This combination of senses is not linear, and the coincidence of stimuli in space and time results in a superadditive electrophysiological response [27].

However, neural integration may not be limited solely to combining information from sensory systems [28]. In this model, the soft classification schemes form the basis of cultural practice structures as they might be represented in the brain. For example, a group membership ritual or political campaign can involve many procedures, classifications, and judgements about the natural world that make no sense in isolation or outside the context of a specific ritual. As a neural mechanism, integration may also play a critical role in switching between the logic of cultural structures and active cognition, and may be particularly important when approximating diverse responses to common stimuli that due to context.

Future work should also focus on several common phenomena in cultural systems. One example of this is when selected dimensions of a kernel (such as the light-dark or good-bad oppositions) are treated as the entire practice. This often occurs in fundamentalist religions. Another target for future research involves understanding seemingly illogical behaviors, such as reinforced ritualized behaviors, despite the need for cultural change. Placing the evolution and information processing of these phenomena within a logical framework may lead to further advances in understanding behavior and ultimately human nature.

Supplementary Information

Please visit <http://syntheticdaisies.blogspot.com/p/fluid-models-of-evolutionary-dynamics.html> for supplemental materials (graphs, animations, and practical examples).

Methods and Equations

Particle structures. The number of potential structures that can interface with cognitive and neural processes can be quite large. We constructed five distinct particle structures, which can be defined as combination of dimensions representing both the fundamental limits of a neural subsystem (e.g. vision, touch, auditory, gustatory) and the centroid of a contextual variable (e.g. fluctuation, umami, modulation). The contextual variable has cultural meaning, and site in relation to these perceptual limits.

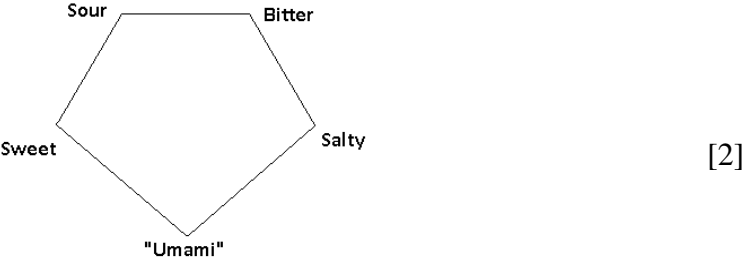
Soft classification allows for an n -tuple representational scheme which is not mutually exclusive. Phenomena can belong to two or more categories simultaneously, differing only in terms of degree. For example, changes in “light” do not result in corresponding changes to the “dark” classification. The use of contextual anchors (which also employ soft classification

schemes) concurrent with the neural mechanism dimensions allows for non-additive cultural representations that approximate the sub- and super-additivity common in neural mechanisms of sensory integration.

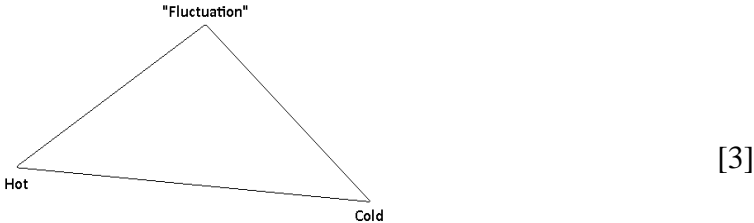
2-tuple without a contextual anchor. The first (and simplest) kernel design is the 2-tuple without a contextual anchor based on light sensing and visual perception. The example in [5] shows a binary opposition representing the transition between light and dark, an exemplar of which can be stated as [0.6, 0.2].



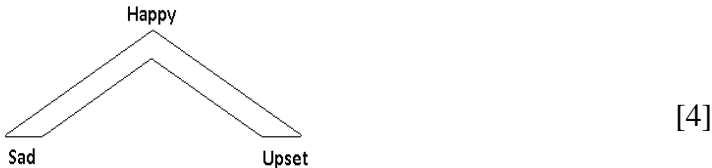
5-tuple with a contextual anchor. The second kernel design is a 5-tuple with a contextual anchor, and maps to the human gustatory system. The example in [6] shows a discrete set of tastes, an exemplar of which can be stated as [0.2, 0.2, 0.4, 0.8, 0.2].



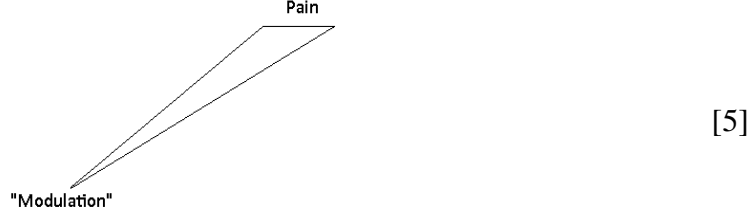
3-tuple with contextual anchor. The third kernel design is a 3-tuple with a contextual anchor, and maps to the function of thermoreceptors in the haptic system. The example in [7] shows a discrete set of tastes, an exemplar of which can be stated as [0.6, 0.2, 0.9].



3-tuple without contextual anchor. The fourth kernel design is a 3-tuple without a contextual anchor, and maps to the functions of arousal and emotion. The example in [8] shows a discrete set of emotional states, an exemplar of which can be stated as [0.1, 0.5, 0.3].



2-tuple with contextual anchor. The fifth kernel design is a 2-tuple with a contextual anchor, and maps to the function of nociceptors in human tissues. The example in [9] shows the degrees between the pain state and modulation of pain (a highly parallel process but represented here as a point), an exemplar of which can be stated as [0.6, 0.8].



Iterated Temporal Divergence (ITD). Iterated Temporal Divergence is defined using the following equation

$$L_t(X_0) = \int_t^{t+1} (\nabla - v) | F_t^s(X_0) ds \quad [6]$$

where the divergence between two particles subject to the same flow field is integrated over a finite time period, $t: \rightarrow t + 1$.

Segregation Factor. The segregation factor is used to understand changes in the distribution of values for a particular soft classification kernel. Sets that define the structure of a certain cultural feature can become segregated over time, resulting from interactions with other particles in the flow field. This can be defined as

$$S = |\sum I_{ij}|, |\sum I_{ij}| > 0 \quad [7]$$

where a value of $S \rightarrow 1.0$ results in a maximization of movement towards discrete positions on the particle.

Conditional Diversity. To measure the distribution of automata within a given ridge or vortex, we can use a measure of conditional diversity. This measure provides us with a distribution of automata in the flow field for all automata within a certain value of the ITD measure (see equ. [6]). This measure can be stated as

$$D = \sigma(p_1, p_2, \dots, p_n)$$

$$p_i = \frac{A_i}{A_{tot}} \quad [8]$$

$$A_i = \underset{X_0}{argmax} L_t X_0 \leq L_t X_0 \geq 0$$

where σ equals the variance of set p_n , A_i equals all automata for a specific subpopulation below the threshold value for the ITD measure, p_i is the number of automata in a specific subpopulation, A_{tot} is the total number of automata, and p_n is the number of subpopulations in the simulation.

Rate of learning and forgetting. To measure the relationship between the kernel representing the structure of practice and the Lagrangian model representing evolution, a rate can be used to characterize a cultural distance between populations based on distinctions in practice. The can be expressed as

$$r_{LF} = \frac{L_t(X_0)}{S_{p_i} - S_{p_j}} \quad [9]$$

where $L_t(X_0)$ is the iterated temporal divergence, and S_{p_i} and S_{p_j} are segregation factors for different automata populations housing a particular kernel.

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