Title
Cognitive Attractors and the Cultural Evolution of Religion

Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 45(45)

Authors
Poulsen, Victor
DeDeo, Simon

Publication Date
2023

Peer reviewed

Cognitive Attractors and the Cultural Evolution of Religion

Victor Møller Poulsen (vpoulsen@andrew.cmu.edu)
Department of Social and Decision Sciences, Carnegie Mellon University, Pittsburgh, PA 15213 USA

Simon DeDeo (sdedeo@andrew.cmu.edu)
Department of Social and Decision Sciences, Carnegie Mellon University, Pittsburgh, PA 15213 USA
Santa Fe Institute, Santa Fe, NM 87501 USA

Abstract

We use data on a cultural fitness landscape, recently inferred from a large-scale cross-cultural survey of religious practices (6000+ years, 407 cultures), to provide new insights into the dynamics of cultural macroevolution. We report three main results. First, we observe an emergent distinction between the long-run fitness of a religious practice, and its short-term stability: in particular, some low-fitness practices are nonetheless highly stable. Second, despite the exponentially large size of the landscape, we find a small number of cultural attractors, and 70% of all observed configurations flow into just four, which we label "monastic", "evangelical", "indigenous", and "pre-Axial". Finally, we find large variation in the evolvability of different traits, with some (such as a belief in punishing gods) strongly fixed by context, and others (such as belief in reincarnation) much more fluid.

Keywords: religion; cognition; cultural evolution; cultural attractors; machine learning

Introduction

How can we make sense of both the diversity, and stability, of human culture? While the first versions of cultural evolution relied on simple analogies to biological evolution—some practices are more "fit" than others, *i.e.*, more able to pass on their traits to the next generation—a modern synthesis, which includes cultural attractor theory, highlights how cognitive and social constraints guide the development of culture over time (Acerbi, Charbonneau, Miton, & Scott-Phillips, 2021). The gradual transformations that accumulate as a practice is passed from person to person, and generation to generation, it is claimed, draw groups towards a small number of "attractors" (Scott-Phillips, Blancke, & Heintz, 2018). Work on these ideas has tended to focus on the microevolutionary properties of individuals, whose shared cognitive biases can favor some features of culture over others (for a review, see Miton (2022)). Progress has been made in understanding possible mechanisms through simulation (*e.g.*, Falandays and Smaldino (2022)) and through lab-based experiments which often use a transmission-chain paradigm to measure the effects of biased and directed transmission under controlled conditions (e.g., Ferdinand, Kirby, and Smith (2019); Miton, Claidière, and Mercier (2015)).

Much less is known, however, about how this process might play out on long timescales, or in non-WEIRD (Henrich, Heine, & Norenzayan, 2010) cultures, in the historical record. In these cases, data at the individual level is hard to come by, and even group-level data is incomplete. Such studies of the macroevolution of culture are made harder because they involve a complex combination of cognitive constraints (*e.g.*, what is easy or pleasant or compelling to think), social constraints (*e.g.*, what enables a group to solve free-rider problems), and material constraints (*e.g.*, what is possible given the resources a group has to hand). While various types of constraints have been investigated in the cultural attractor literature (a list of examples are provided in Falandays and Smaldino (2022)) they have typically been studied in isolation.

The paper shows how the combinations of inferred constraints can combine to favor some cultural configurations over others, and explores what this implies for the evolution of cultures over time. The estimation of cultural landscape models from data (Poulsen & DeDeo, 2023) provides a productive testing ground for ideas in cultural evolution, including the distinction between fitness and stability, the emergence of convergent evolution through attractor dynamics, and a spectrum of evolvability among traits. Our particular dataset is a curated sample of the *Database of Religious History* (DRH; Slingerland & Sullivan, 2017; Slingerland, Monroe, & Muthukrishna, 2022), which contains a diverse set of 407 religious groups drawn from around the globe and across more than 6000+ years of the cultural record.

The Cultural Landscape Paradigm

The landscape approach we adopt here begins with a set of features of interest; for the sake of simplicity, and to match the predominant format of the DRH, we take these properties to be answers to binary `YES/NO` questions. In our curated dataset, for example, one question is whether religions have a belief in "reincarnation in this world"; the full list of questions we use can be found at the end of the paper. A complete set of `YES/NO` answers to the question set is called a configuration, leading to a representation of a religion as an N dimensional cultural object.

A cultural landscape is built from this data: it is a parsimonious model of the underlying distribution that (in the long timescale limit) the historical record is "sampling" from. Because of the heterogeneity in the types of questions that are included in the present analysis, the distribution captures both cognitive, and social, constraints that make some configurations more or less likely than others, independent of any par-

In M. Goldwater, F. K. Anggoro, B. K. Hayes, & D. C. Ong (Eds.), *Proceedings of the 45th Annual Conference of the Cognitive Science Society*.

ticular genealogy. This inference step will, in principle, provide us with a slice of the theoretically "true" landscape—the idealized, complete account that would take into account all of the causally relevant features.

Inferring such a landscape is hard, because even a partial reconstruction, based on a small number of features, is radically undersampled by religions in the historical record. We use a "maximum entropy" model, an approach that has seen recent use in both the cognitive, social, and biological sciences (Lee, Broedersz, & Bialek, 2015; Louie, Kaczorowski, Barton, Chakraborty, & McKay, 2018; Stephens, Osborne, & Bialek, 2011), where the probability of a configuration is the emergent consequence of complex combinations of pairwise constraints; formally, for a configuration $\{\sigma_1,\ldots,\sigma_N\}$, where a `YES` (`NO`) to question i is represented by σ_i equal to $+1$ (-1, respectively). This "global" probability is given by

$$P(\{\sigma_1,\ldots,\sigma_N\}) = \frac{\exp\left(\sum_{i,j;i>j} J_{ij}\sigma_i\sigma_j + \sum_i h_i\sigma_i\right)}{Z}, \qquad (1)$$

where J_{ij} are the pairwise constraints, h_i, the "local fields", help fix the average values for each property, and Z is a normalization constant. Despite its simplicity, Eq. 1 can capture complex patterns and higher-order effects (Schneidman, Berry, Segev, & Bialek, 2006); it is sometimes known as a "Boltzmann machine" (Ackley, Hinton, & Sejnowski, 1985) or a "Hopfield network" (Hillar, Sohl-Dickstein, & Koepsell, 2012), and it has deep ties to models in psychometrics (e.g., MIRT) and logistic regression models (Epskamp, Maris, Waldorp, & Borsboom, 2018).

Fitness versus (Meta)stability

Before we introduce mechanisms for evolution on the cultural landscape we exploring the topology of the fitness landscape that the model implies. When Eq. 1 is learned on the particular sample of the DRH data curated in (Poulsen & DeDeo, 2023) it provides a probability distribution over a 20-dimensional space (because a religious culture is defined in this sample by answers to 20 questions). The sample consists of 407 religious cultures, and because some of these religious cultures are defined by the same value on all 20 features we will sometimes refer to 260 "unique observed configurations" (some of the 407 religious cultures in the sample have missing values in the DRH database, and in these cases we use the maximum likelihood estimate provided by the model to map each observed religious culture to its most probable configuration). If we think of the probability of each configuration as having a "height", we can draw on metaphors from geographical landscapes in physical space to approach an intuition about the landscape topography. For example, configurations that are improbable are said to be in low-lying "valleys", while more probable configurations might be though of as "hills" or "peaks".

These ideas are a central feature in evolutionary biology, which has a long tradition of talking in terms of fitness landscapes (Pitzer & Affenzeller, 2012; Fragata, Blanckaert, Louro, Liberles, & Bank, 2019). A key insight from this line of work is that while the global probability of a configuration (*i.e.*, Eq. 1) might measure overall fitness on very long timescales, it does not paint a complete picture of the landscape. To understand the evolution of a religious culture over time, we need to broaden this conception, because the presence of other probable "nearby" configurations—configurations that differ in only one or a few attributes—can make even a high-probability configuration less stable on shorter timescales, because the neighbours serve both as an attractive, and a cognitively and socially accessible, alternative. Conversely, a less probable point in the landscape that is surrounded by even less probable neighbours may achieve (meta)stability: it may not satisfy the cognitive and social constraints very well, but it will benefit from a lack of nearby alternatives that satisfy the constraints better.

An explicit model for transition dynamics, which has been explored in theoretical work on cultural attractors (Miton & DeDeo, 2022), is provided by Glauber dynamics (Glauber, 1963); given a particular base configuration i, if we restrict exploration to a set of neighbours, $\mathcal{N}(j)$, the probability that we move from i to one of those neighbours j is given by

$$P(i\to j) = \frac{1}{|\mathcal{N}|}\frac{P(j)}{P(i)+P(j)}. \qquad (2)$$

A natural choice for the neighbour set $\mathcal{N}(j)$ is the configurations that differ in only one question from the base configuration; this corresponds to the idea that religions change gradually, over time—either in response to social changes (*e.g.*, the loss of official political support) or more basic cognitive shifts (*e.g.*, the adoption of the idea that a god might practice surveillance).

We can then compare the global probability of a configuration, $P(i)$, to its local stability, $P(i\to i) = 1-\sum_j P(i\to j)$. This is shown, for the observed religions in the DRH sample in Figure 1. While there is a clear connection between high fitness (being globally preferred), and local stability, there is also a substantial spread around the trend line. Configurations that fall below the line are less stable than expected given their global probability, while configurations above the line are more stable than expected. For instance, the configuration that the Samaritans inhabit is more locally stable than the one associated with Donatism, despite the fact that it is more than an order of magnitude less globally probable.

Figure 1 naturally divides observed religious practices into four groups. A religion may be found at an "isolated peak": high probability, and surrounded by configurations that tend to be less probable. These are found in the top right corner, with the "Jehovah's Witnesses", and the "Aztec Imperial Core" being two examples. Other high-fitness religions are part of a "mountain range"; high probability, but surrounded by other probable configurations. These include "Donatism", "Iban traditional religion", and "Yolngu religion".

Among the less favored configurations, we observe both "valleys", and "hillocks". A configuration with low probabil-

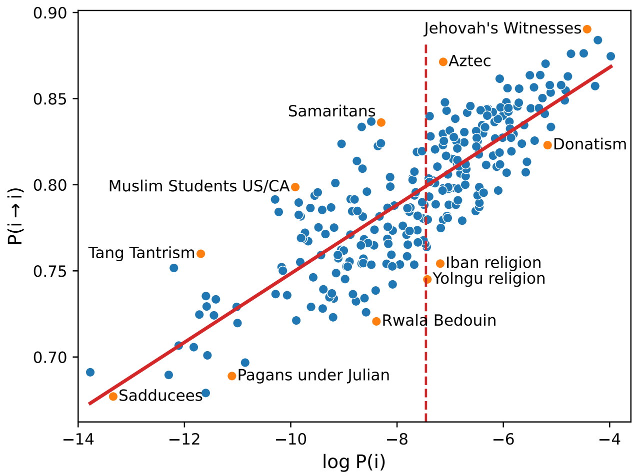

Figure 1: Fitness is not (necessarily) stability. Some religions (*e.g.*, Donatism) are relatively high in overall fitness, but have other attractive neighbours. Others (*e.g.*, the Samaritans) may have lower overall fitness, but are located in regions of the landscape where nearby alternatives are significantly less attractive. Vertical (dotted) red line is the median $\log P(i)$ for the 260 unique observed configurations. Solid red line shows the (best fit) trendline.

ity, which is additionally surrounded by relatively more probable configurations, is in a valley, and may tend to flow upwards in the landscape; examples of these cases (bottom left quadrant) include the "Sadducees", "Pagans under Julian", and the "Rwala Bedouin". Finally, there are hillocks—low-lying locally preferred configurations such as the "Samaritans", "Muslim Students in the US and Canada", and "Tang Tantrism". These configurations are sometimes referred to as metastable (Cortês, Kauffman, Liddle, & Smolin, 2022): on short timescales, they are expected to be resistant to changes, but—given their lower overall probability—may, eventually, evolve by longer, more unlikely, macroevolutionary leaps.

Cultural Attractors

A key claim of cultural attractor theory is that as practices are transmitted, within and between generations, they undergo a series of transformations that bias their future evolution and accentuate some features over others (Miton, 2022). In our case it is more natural to rephrase this to say that the probabilistic transitions of a mechanism such as Eq. 2 bias the future evolution of (in this case) religious groups to evolve towards a smaller set of cultural attractors, local maxima in the landscape, where further evolution is disfavored.

In the high-dimensional spaces that characterize cultural landscapes, forward evolution can lead to multiple attractors. Figure 2 shows one example, for the case of (contemporary) Irish Catholicism. For clarity, we show only the paths leading to higher-likelihood configurations, and do not visualize paths through configurations of lower probability which, under Eq. 2, are possible but disfavored. Flow is visualized as going "upwards" on the page, with the vertical position tracking relative log-probability. Beginning with a focal configuration, we show the most likely uphill transitions over the landscape. When a configuration corresponds to at least one observed religion, we choose one of those religions as its label; in the Irish Catholicism case, the forward evolution also involves passage through configurations that (despite being higher likelihood than Irish Catholicism) have no matches in our observed data; these are colored light blue.

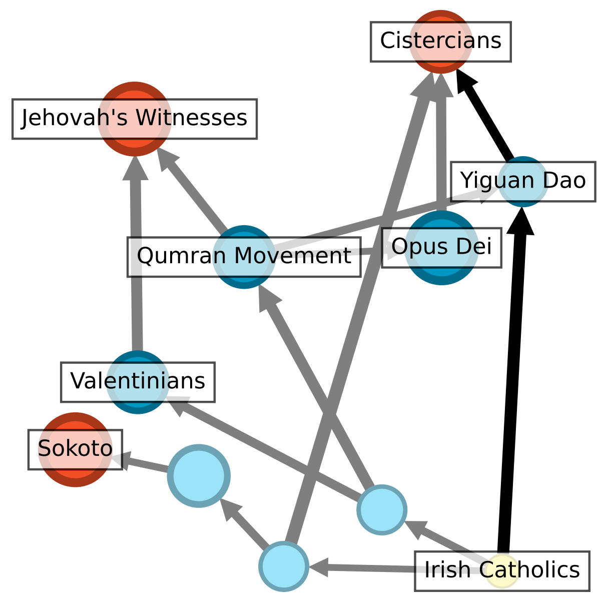

Figure 2: The evolutionary paths from "Irish Catholicism". Vertical position based on $log\ P_i$. Light blue nodes are configurations that do not correspond to an observed religion, dark blue nodes correspond to at least one observed religion, and red nodes are configurations that are more probable than any of their immediate neighbors. Node size is scaled by the Hamming distance (plus a constant) from the Irish Catholic configuration. Edge size is scaled by the relative probability of transition, and the black edges follow the "naive" highest probability path.

Allowing only for moves to more probable neighbors, the path from Irish Catholicism eventually terminates at one of three local maxima, colored in red. In descending order of probability, the terminal configurations are associated with (1) the Medieval Cistercian Order (and a number of other monastic orders, Christian and non-Christian); (2) the Jehovah's Witnesses (and a number of evangelical Protestant religions, such as the Anabaptists and Churches of Christ); and (3) the Sokoto Caliphate, a religious theocracy. The heavy black edges trace the maximum likelihood path: the most likely transition from the Irish Catholics is to the Yiguan Dao

N	$P(i)$	Characteristics	Example
83	0.018716	Monastic	12th c. Cistercians
42	0.007348	Indigenous	Iban religion
29	0.011989	Evangelical	Jehovah's Witnesses
26	0.014685	Pre-Axial	Ancient Egypt
17	0.001779	$\star$	Sokoto Caliphate
11	0.002316	$\star$	Pythagoreanism
10	0.005486	Evangelical	Free Methodist Church
9	0.005943	Pre-Axial	Ancient Thessalians
8	0.002682	$\star$	Messalians
7	0.001720	?	Unobserved
7	0.001617	$\star$	Hidatsa
6	0.000919	?	Unobserved
3	0.000466	?	Unobserved
2	0.000800	Pre-Axial	Aztec Imperial Core

Table 1: The fourteen cultural attractors that the 260 unique observed configurations flow into, following a prescription where only flow "upwards" in probability space is allowed. N refers to the number of configurations that terminate at this maximum-likelihood path attractor; $P(i)$ the global probability (Eq. 1). Many attractor configurations are associated with multiple religions in the data; "Characteristics" provides a rough description; where there is only one observed religion this is noted by $\star$. 16 paths terminate at 3 attractors that are not observed in the DRH sample.

configuration, and from there to the Cistercian configuration. This path involves two bit-flips: first, the group must acquire the "supernatural punishment" trait, then the "special corpse treatment" trait. In many cases we observe interesting path-dependent effects, where traits are acquired and subsequently lost (or vice-versa) while always improving the fitness of the cultural system. In the Irish Catholicism case, more than one of the indirect paths to the Cistercian configuration involves the loss of the "official political support" trait, and its later reacquisition.

Fig. 2 has three terminal attractor states. In Table 1, we list the 14 attractors found as terminal states for the 260 unique observed configurations in our sample. We recognize the Cistercian group, the Jehovah's Witnesses group, and the Sokoto, that we encountered as potential termination states for the Irish Catholics; there are others, including a number of configurations associated with pre-Axial traditions (Bellah, 2017). It is interesting that around 70% of the unique observed configurations flow into only 4 attractor states. It suggests that the landscape is at some intermediate point, where all cultures are not funneled towards one attractor, but where it is also not the case that there is a large number of disconnected solutions. The fact that the landscape has multiple local maxima (attractor states) is interesting because it suggest the possibility that (at least on shorter timescales) cultures might get "stuck" in sub-optimal solutions.

Flexible Practices

Most of the evolutionary transitions on the landscape involve only a subset of the 20 features that define a religious culture in our system. We formalize a notion of "rigidity" and visualize this in Fig. 3.

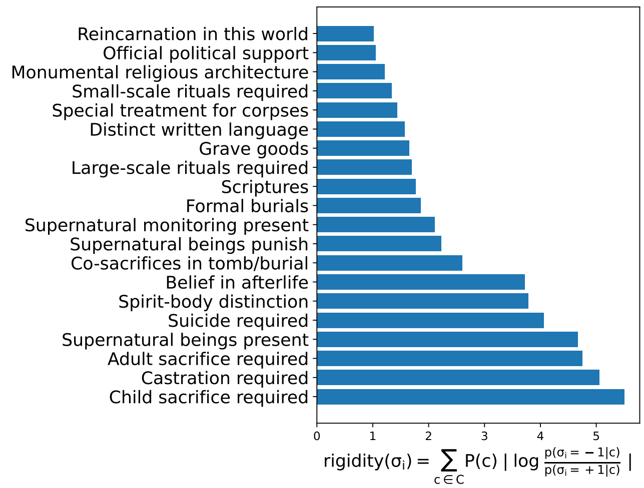

Figure 3: Rigidity index for all 20 binary features. For features that are high in rigidity the difference between the probability of a `YES` and a `NO` answer (given some set of values c for rest of the features) will tend to be large.

We calculate rigidity in the following way

$$\text{rigidity}(\sigma_i) = \sum_{c \in C} P(c) \left| \log \frac{p(\sigma_i = -1|c)}{p(\sigma_i = 1|c)} \right|, \tag{3}$$

where c ("context") indexes all combinations of the $N-1$ other features, and $P(c)$, equal to $p(\{-1,c\}) + p(\{+1,c\})$, weights each context by its marginal probability. Features that are high in rigidity are features where the difference in the probability of a `YES` and a `NO` answer will tend to be large given particular arrangements of values for the remaining 19 features.

With important caveats, discussed below, we might generically think of beliefs with low rigidity as ones that religious cultures will need to enforce more aggressively (*e.g.*, through explicit teaching (Miton & DeDeo, 2022) and scriptures). For some religious groups, of course, a trait may not be central to the identity of members: it seems intuitively correct that some traits (e.g., "official political support") will (on average) be considered less central than others (say, the participation of members in religious rituals). Danish Lutherans technically enjoy state support; but it seems implausible that they would consider themselves distinct in any important fashion from German Lutherans, who do not. In many cases, this flexibility can be found within the group itself; "Unitarian Universalists", for example, are coded in the DRH as diverging on questions of "reincarnation in this world", "belief in afterlife", and "spirit-body distinction", with the expert noting that none of these questions are matters of doctrine.

High rigidity is driven by two effects: the magnitude of the local fields (h_i), and the strength of the pairwise couplings (J_{ij}). In the first case, some features are simply disfavored overall (e.g. "child sacrifice") while some features are very favored (e.g. "supernatural beings present"). For the case of a disfavored trait, this will lead to a situation where, for most c, we will have $p(\sigma = -1|c) \gg p(\sigma = 1|c)$. The opposite will be the case for a strongly preferred trait where generally $p(\sigma = -1|c) \ll p(\sigma = 1|c)$. This means that evolution towards a disfavored trait, and away from a favored trait, will be rare, and we can attribute this primarily to the "main effect" of the strong (positive or negative) local fields (h_i). It is reasonable that features that are almost always high fitness, regardless of context, will tend to be preserved, while features that are almost always low fitness will tend to be lost.

Secondly, some features might not be strongly favored or disfavored intrinsically, but instead might couple strongly with other features in the system via the J_{ij} couplings. For instance, most religious cultures in the DRH either have both gods that monitor and punish (73.0%), or gods that do neither (14.5%), and the pairwise coupling between these features is among the strongest in the system. Although neither of these traits have strong local fields, the strong coupling can result in high rigidity: in almost all cases where "punishing gods" is `YES` our model will assign much greater probability to `YES` for "monitoring gods", and similarly, for cases where "punishing gods" is `NO` this will lead to high probability for `NO` for "monitoring gods". The combination of these two effects leads to a high rigidity for "monitoring gods". A similar effect can operate for clusters of traits that mutually constrain each other, but this will be more difficult to diagnose.

This leads to an important caveat to our rigidity results: rigidity is relative to the question set. This is because, in some cases, we may have a feature with small h_i, but large J_{ij} couplings to a second trait that is unobserved (i.e., not included in the question set). In this case, we will tend to underestimate the feature's rigidity, because we cannot model how it is fixed, in a contextual fashion, by other features in the system.

Consider, for example, the most fragile trait in the landscape: worldly reincarnation. Taken at face value, this is a claim with cognitive consequences—our model suggests that, across various religious sets of beliefs and practices, it is relatively easy to shift one's belief in worldly reincarnation, while maintaining the remaining features of a religious culture (e.g., other epistemic beliefs, social practices, etc.). Our model suggests that this epistemic shift is much easier compared to, say, shifting a belief in the idea that humans possess a spirit that is distinct from the material body ("spirit-body distinction"). Such a result is, however, relative to the question set: it may well be the case that there are other features, not tracked by the current question set, that stabilize the reincarnation belief in actual religious cultures.

Discussion

The use of landscapes to study cultural macroevolution has great promise, but a number of key challenges remain. One challenge is the construction of a good questions set, which we have briefly touched upon in the previous section. The specific questions that we use to define a religious cultural practice are (unfortunately, but naturally) intimately tied to the inferences that we can draw about the landscape of possibilities. Naturally, what constitutes a "good" question set will depend on the particular goal of the modeling effort, but in general this is a task which will require domain-specific theoretical knowledge. A distinct, but related, challenge is that the number of questions that we use to model a culture might alter the topology of the evolutionary landscape, and granularity might affect the fidelity of cultural transmission (Charbonneau & Bourrat, 2021).

A second issue is that we have only considered "small" steps— transitions to neighboring cultures that differ in by one bit. This choice directly affects our rigidity measure, because, if two traits are strongly coupled (e.g., monitoring and punishing gods), and we only allow one trait to flip at a time, then these traits will stabilize each other. Allowing for two mutations to happen simultaneously would, for example, lower the rigidity of both "big gods" features.

Research on cultural attractors has tended to focus on the favoring of a specific cultural feature (e.g., belief in the efficancy of bloodletting (Miton et al., 2015)) and to look for a more fundamental model to explain why that feature might be preferred across different cultures. Our work takes a complementary approach. We are still, naturally, interested in why a particular surface-level feature might or might not vary. We explain this variation, however, by reference to other surface-level features—what is captured by the J_{ij} constraints of Eq. 1.

Both approaches have benefits. A full account of cultural evolution, naturally, requires an understanding of fundamental processes that only lab-based experiments can provide. However, it also requires an understanding of how cultural context affects those fundamental processes, and this is what we believe the coarse-grained accounts provided by the cultural landscape perspective can provide. It has been argued that "culture is made of relatively discrete, relatively independent traditions" (Morin, 2016); this work takes a step towards quantifying this core claim.

Question List. Are supernatural beings present? Is supernatural monitoring present? Do supernatural beings mete out punishment? A spirit-body distinction? Belief in afterlife? Reincarnation in this world? Does the religion have official political support? Does the religious group have scriptures? Monumental religious architecture? Special treatments for adherents' corpses? Are co-sacrifices present in tomb/burial? Are grave goods present? Are formal burials present? Does membership in this religious group require castration? ..sacrifice of adults? ...sacrifice of children? ...self-sacrifice (suicide)?

Acknowledgements

This work was supported in part by the Survival and Flourishing Fund.

References

Acerbi, A., Charbonneau, M., Miton, H., & Scott-Phillips, T. (2021). Culture without copying or selection. *Evolutionary Human Sciences*, *3*, e50.

Ackley, D. H., Hinton, G. E., & Sejnowski, T. J. (1985). A learning algorithm for Boltzmann machines. *Cognitive Science*, *9*(1), 147–169.

Bellah, R. (2017). *Religion in human evolution: From the paleolithic to the axial age*. Harvard University Press.

Charbonneau, M., & Bourrat, P. (2021). Fidelity and the grain problem in cultural evolution. *Synthese*, *199*(3-4), 5815–5836.

Cortês, M., Kauffman, S. A., Liddle, A. R., & Smolin, L. (2022). *Biocosmology: Biology from a cosmological perspective.* Retrieved from `https://arxiv.org/abs/2204.09379` doi: 10.48550/ARXIV.2204.09379

Epskamp, S., Maris, G., Waldorp, L. J., & Borsboom, D. (2018). Network psychometrics. *The Wiley handbook of psychometric testing: A multidisciplinary reference on survey, scale and test development*, 953–986.

Falandays, J. B., & Smaldino, P. E. (2022). The emergence of cultural attractors: How dynamic populations of learners achieve collective cognitive alignment. *Cognitive Science*, *46*(8), e13183.

Ferdinand, V., Kirby, S., & Smith, K. (2019). The cognitive roots of regularization in language. *Cognition*, *184*, 53-68. doi: https://doi.org/10.1016/j.cognition.2018.12.002

Fragata, I., Blanckaert, A., Louro, M. A. D., Liberles, D. A., & Bank, C. (2019). Evolution in the light of fitness landscape theory. *Trends in ecology & evolution*, *34*(1), 69–82.

Glauber, R. J. (1963). Time-dependent statistics of the Ising model. *Journal of mathematical physics*, *4*(2), 294–307.

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). The weirdest people in the world? *Behavioral and brain sciences*, *33*(2-3), 61–83.

Hillar, C., Sohl-Dickstein, J., & Koepsell, K. (2012). *Efficient and optimal binary Hopfield associative memory storage using minimum probability flow.* (Neural Information Processing Systems (NurIPS) workshop on Discrete Optimization in Machine Learning (DISCML)) doi: 10.48550/ARXIV.1204.2916

Lee, E. D., Broedersz, C. P., & Bialek, W. (2015). Statistical mechanics of the US Supreme Court. *Journal of Statistical Physics*, *160*(2), 275–301.

Louie, R. H. Y., Kaczorowski, K. J., Barton, J. P., Chakraborty, A. K., & McKay, M. R. (2018). Fitness landscape of the human immunodeficiency virus envelope protein that is targeted by antibodies. *Proceedings of the National Academy of Sciences*, *115*(4), E564-E573. doi: 10.1073/pnas.1717765115

Miton, H. (2022). Cultural attraction. *PsyArXiv*. (To appear in *Oxford Handbook of Cultural Evolution*.)

Miton, H., Claidière, N., & Mercier, H. (2015). Universal cognitive mechanisms explain the cultural success of bloodletting. *Evolution and Human Behavior*, *36*(4), 303–312.

Miton, H., & DeDeo, S. (2022). The cultural transmission of tacit knowledge. *Journal of the Royal Society Interface*, *19*(195), 20220238.

Morin, O. (2016). *How traditions live and die*. Oxford University Press.

Pitzer, E., & Affenzeller, M. (2012). A comprehensive survey on fitness landscape analysis. *Recent advances in intelligent engineering systems*, 161–191.

Poulsen, V. M., & DeDeo, S. (2023). Inferring cultural landscapes with the inverse Ising model. *Entropy*, *25*(2). doi: 10.3390/e25020264

Schneidman, E., Berry, M. J., Segev, R., & Bialek, W. (2006). Weak pairwise correlations imply strongly correlated network states in a neural population. *Nature*, *440*(7087), 1007–1012.

Scott-Phillips, T., Blancke, S., & Heintz, C. (2018). Four misunderstandings about cultural attraction. *Evolutionary Anthropology: Issues, News, and Reviews*, *27*(4), 162–173.

Slingerland, E., Monroe, M. W., & Muthukrishna, M. (2022). The database of religious history (drh): Ontology, coding strategies and the future of cultural evolutionary analyses. *Religion, Brain and Behavior*. (Submitted)

Slingerland, E., & Sullivan, B. (2017). Durkheim with data: The database of religious history. *Journal of the American Academy of Religion*, *85*(2), 312–347.

Stephens, G. J., Osborne, L. C., & Bialek, W. (2011). Searching for simplicity in the analysis of neurons and behavior. *Proceedings of the National Academy of Sciences*, *108*(3), 15565–15571.