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Collective behaviour, uncertainty and environmental change

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A central aspect of cultural evolutionary theory concerns how human groups respond to environmental change. Although we are painting with a broad brush, it is fair to say that prior to the twenty-first century, adaptation often happened gradually over multiple human generations, through a combination of individual and social learning, cumulative cultural evolution and demographic shifts. The result was a generally resilient and sustainable population. In the twenty-first century, however, considerable change happens within small portions of a human generation, on a vastly larger range of geographical and population scales and involving a greater degree of horizontal learning. As a way of gauging the complexity of societal response to environmental change in a globalized future, we discuss several theoretical tools for understanding how human groups adapt to uncertainty. We use our analysis to estimate the limits of predictability of future societal change, in the belief that knowing when to hedge bets is better than relying on a false sense of predictability.

1. Introduction

Ecological sustainability—'meeting human needs without compromising the health of ecosystems' [1, p. 32]—is by any stretch of the imagination a complex challenge. New predictions and knowledge about Earth's safe ecological operating parameters have prompted calls for global social change within a generation [2–4]. It is more difficult to predict, however, how such knowledge feeds into human actions, whether in science, politics or public behaviour. As a result, there is new

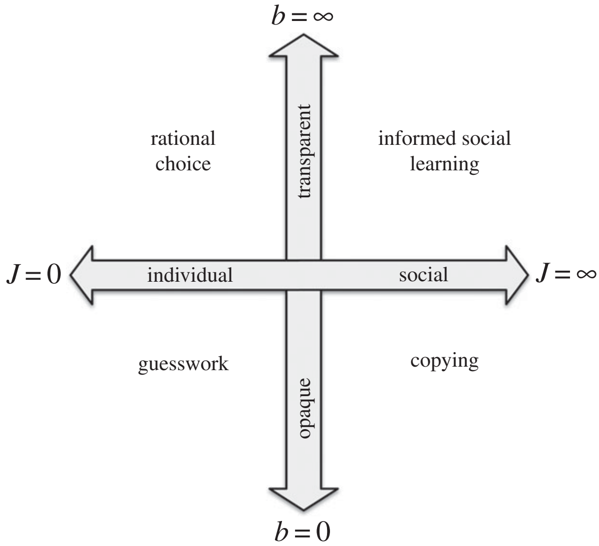

Figure 1. A diagram for understanding different domains of human decision-making, based on whether a decision is made individually or socially (horizontal axis) and the transparency of options and pay-offs that inform a decision (vertical axis) (adapted from [19,20]).

research interest in understanding how humans make decisions in the face of current challenges in global health, environmental change and population growth [5].

The discussion can benefit from the long view of cultural evolutionary theory, which is concerned with how human groups respond to environmental, and hence ecological, change through the dual inheritance system of biology and culture [6]. From an evolutionary perspective, the Anthropocene—the time in Earth's history when human activities began to significantly influence global environments [7,8]—poses a difficult challenge, namely, the ability to solve global problems in a short amount of time. We say 'difficult' because our highly social species is adapted to living in small cooperative social groups [9,10], where traditions, which evolved over many generations, solved many adaptive problems. As in modern small communities in the non-Western world, social learning was strategically directed towards familiar experts or best-informed members [11,12]. In an age deluged by information, options and social influences, however, the dynamics of collective decisions are becoming uncertain, especially if people crowdsource their decisions to artificial intelligences that rely heavily on copying recent popular decisions [13–15].

To understand how humans might adapt to twenty-first century challenges, we 'need to collect behavioural statistics on grand scales' [5, p. 366], but what will those statistics mean? As a new computational social science emerges to study rich new datasets on human behaviour—often referred to as 'big data' [16]—very different analytical approaches and scales of analysis are taken, from psychology and sociology to economics, computer science and physics [17]. These emerging studies show the importance of two dimensions: the magnitude of social influence—the effect people have on the beliefs and behaviours of others [18]—and the transparency, or intensity, of its effect. We view the dimensions as empirically discoverable from different time-stratified datasets on aggregated decision-making (figure 1). To resolve both dimensions together requires traditional and novel forms of time-series analysis and analysis of the form and temporal dynamics of popularity distributions, cross-referenced with studies from individuals to social networks to national scales.

Figure 1 introduces a two-dimensional diagram of decision-making that plots kinds of learning—individual versus social—against the clarity of risks and benefits involved in making a decision [19,20]. Brock *et al.* [21] described how to mathematically parametrize this space and show how the diagram can be applied to real-world data. Below, we discuss how a 'fitness landscape' constructed from this decision space illustrates the limits of predictability of future societal change. As background, we start by discussing what prehistory and even recent history might have to tell us about the evolution of human decision-making.

2. Why prehistory matters: traditions as long-term problem solvers

Our discussion will benefit from a basic knowledge of culture and cultural learning—concepts that are as important to understanding decision-making in complex industrial societies as they are to understanding decision-making among hunter–gatherers. First, a majority of what humans do—the languages they speak, the technology they use and so on—is learned, or otherwise inherited, from the cumulative knowledge of their society [22,23]. This is what is known as *social learning*—learning by observing or interacting with others [24]—as opposed to *individual learning*, whereby novel solutions to problems are the products of single individuals [25]. Regardless of learning mode, almost every novel solution is an incremental change to previous cultural habits and existing technologies as opposed to something that appears de novo.

Second, culture is cumulative [26], by which we mean that one generation does things in a certain way, and the next generation, instead of starting from scratch, does them in more or less the same way, perhaps with a few modifications. The succeeding generation then learns the modified version, which then persists across generations until further changes are made [23,27]. Cultural learning is thus characterized by the so-called 'ratchet effect', in which modifications and improvements stay in a population until further changes ratchet things up again [28,29]. The rate of innovation—slow as, say, among Australian Aborigines or fast as among the most technologically sophisticated nation—is irrelevant; the fact is, culture is cumulative.

Third, cultural behaviour is at times driven by the pay-off environment [30]. In other words, humans have evolved a utility function that enables them to respond adaptively to different ecological conditions by estimating, not necessarily consciously, the cost/benefit ratio of different potential behaviours [20,31]. The view of behaviour as a learned, deeply historical phenomenon can appear to be at odds with the view of behaviour as a pay-off-maximizing response to present conditions, but in reality they are simply ends of a continuum that defines human behaviour [32–34]. Any particular case will fall somewhere in between.

Until recently, humans did not typically need to overcome problems such as climate change in a single generation. Climates changed, but culture, working over longer periods of time and on small groups of people, solved most problems through simple adjustments made to existing lifeways. Even the so-called 'agricultural revolution', which was brought on by population growth and environmental change at the end of the Pleistocene some 11 700 years ago, was more of a refinement and acceleration of then-current food-procurement practices than it was a true revolution [35]. Living in small groups renders social pay-offs more transparent, which counteracts any tendency to discount the interests of others and instead cultivates group advantages through intergenerational cultural inheritance. Prehistorically, cultural 'recipes' were polished through generations and generations of vertical transmission—a process that selects for information that is not only useful but also learnable [36]. As a result, notable cultural change was not the norm for most lifetimes of the past.

From the beginning of the Neolithic era, *ca* 7500 BC, human biology and social norms co-evolved with the domestication of crops and animals, the waxing and waning of diseases and, in Europe, the advent of dairying (e.g. [37]). The archaeological record reveals transmission of cultural recipes that were surprisingly faithful, accurate and resilient. Some of the cultural memory was literally built-in. For example, walls in the Early Neolithic village of Çatalhöyük in southern Anatolia were re-plastered 700 times in 70 years and the houses built over and over, literally on top of each other, with ancestors buried under the floor and living spaces arranged virtually the same from one generation to the next [38]. It was during the Neolithic that humans became active shapers of Earth's systems [39]. For example, anthropogenic increases in atmospheric carbon dioxide around *ca* 6000 BC and methane *ca* 3000 BC were caused by forest clearance, agriculture and livestock pastoralism (e.g. [40,41]). Nutrition, disease resistance, climatic adaptations and group alliances were factors that affected survival rates during population bottlenecks [42].

Ownership of food production fundamentally changed in the Neolithic—a change that has contemporary relevance as the world debates who 'owns' new genetically modified crops [43]. In Europe, with the evolution of land ownership and socio-economic inequality [44,45], owners of large dairy herds probably had a selective advantage, not just in terms of dairy nutrition but also in terms of livestock wealth, which predicts better reproductive success [46]. This selective advantage would have favoured wealthy, lactose-tolerant cattle-owning lineages for generations. As certain groups, potentially family lineages, began to acquire preferential access to local resources, patriliny—tracing descent through the paternal line—would have been conducive to the growth of hereditary wealth [47]. This basic development—hereditary ownership of land and livestock—is still relevant to contemporary debates concerning climate change.

Traditions perpetuated in small communities can thus solve complex adaptive problems over long, multigenerational time scales—problems of which possibly no one individual is fully cognisant [48]. Subsistence systems reliant on community cooperation, such as irrigated rice farming, can affect more cooperative social norms over many generations [49]. In complex adaptive systems, this long-term feedback is exemplified nicely by Lansing's [50] study of Balinese water temples, a social–religious tradition of cooperation maintained over many centuries that optimized the distribution of irrigation water, yields and fallow periods for pest control among rice paddies in steep mountain terrain.

Our treatment above is a broad-brush approach to prehistory—one that of necessity overlooks considerable variation in such important factors as population size and socio-political organization. In simple terms, not all prehistoric groups were hunter–gatherers, nor did they all live in small groups. Many groups remained small throughout prehistory, but others evolved into complex chiefdoms and states [51] that comprised thousands of individuals. Further, there is substantial evidence of boom and bust at all levels of prehistoric socio-political organization, from the Early Neolithic village culture of Neolithic Germany [42] to the Maya states of southern Mesoamerica [52], that were environmentally based.

Three points are important here. First, irrespective of societal complexity, cultural learning in the past was still managed in large part by the continuance of vertical learning—mother to daughter, for example—mixed with social-learning strategies such as copying those with prestige [53,54]. Second, population size played a significant role in the pool of available knowledge. A general premise has been that more people mean more ideas: larger populations can create, share and, over time, accumulate a greater complexity of specialized information stored in those pre-bottleneck populations, and technological capability [11,55,56]. Third, irrespective of the level of socio-political organization, kinship was an important component in that it allowed one to keep track of descent, affinity, generation, siblingship and the like [57,58]. In the modern world, we are witnessing a weakening of the importance of kinship, which severely disrupts vertical transmission of information.

3. Reframing the challenge

Meeting today's global ecological challenges transcends 'tradition' and requires aggregated actions of billions of people, channelled through hierarchies and coalitions of the leading nations of the world. The coordination problem is considerable. Even installing wind turbines offshore is a complex problem, as it may face legal challenges from environmental groups; economic competition with other energy sources such as natural gas; structural-engineering challenges; and political opposition, often from local groups [59]. In short, sustainability in the twenty-first century presents a massive data-management problem [5] to be addressed much faster than human traditions are capable of handling.

Nevertheless, adapting to global environmental change is something individuals, groups and communities must do. If we consider the conservative intergenerational learning discussed

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above, the obvious challenge is that targets are often within a single generation. In the past, collective wisdom was accumulated as social norms and traditions over many generations. One could say the collective memory in traditional societies was very long and the input data not particularly noisy. The question is how well matched the response of traditional ways of getting things done are to environmental change. Responses will be limited, of course, by constraints such as poverty and politics, but even within those considerable constraints there will exist some range of potential adaptive strategies.

One strategy might include crowdsourcing and 'nowcasting', which are significantly different from the intergenerational learning from experts in traditional societies. A decade ago, economics journalist James Surowiecki's [60] engaging best-seller, *The Wisdom of Crowds*, sparked a new generation of research on crowd behaviour [61]. The thesis was that the 'wisdom' extracted from aggregating decisions or judgements across a population requires that decision-makers be reasonably well informed and independent. As Surowiecki discussed, the aggregated information is lost when agents copy each other indiscriminately [11,62,63].

We might see this simplification via horizontal transmission happening already, in the dynamics of misinformation spread in contemporary discourse on climate change [64]. Rumours are, by virtue of their evolution through transmission, easy to replicate and therefore to understand [36]. In such cases, it may be that transparency in decisions is important only among a minority [65,66]. For example, an experiment conducted by Dyer *et al.* [67] showed that a small, informed minority of agents—5%—could effectively guide a large uninformed group to a destination without speaking or gesturing. A related study suggests that it is not just the size of this minority of informed individuals but the intensity of their direction (transparency of decision) that determines the collective direction of the school [68]. Whereas simple problems—guessing the number of jellybeans in a jar—might be addressed by crowdsourcing, complex problems such as sustainability might require the identification of the most knowledgeable experts [11,65], who in turn are informed by generations before them (but see below).

This kind of research exemplifies how collective wisdom depends not just on how many judgements are averaged and how independently they were made but also on how decisions cluster in social networks and what social-learning biases operate in how those decisions are made. In controlled experiments where individual expertise may be transparent, small groups—as small as two individuals—can often score better than even the most skilled/knowledgeable single individual on complex tasks [69–71]. Controlled experiments show that where there is social-network clustering, useful information can be better retained by groups than by individuals on their own [72–74].

Still, as Wasserman [75] notes, the 'quantification of social contagion is one of the big, unanswered problems of this new century' because of the inherent difficulty in distinguishing between genuine social influence (contagion) and homophily using observational data [76]. As defined by McPherson *et al*. [77, p. 416], homophily 'is the principle that a contact between similar people occurs at a higher rate than among dissimilar people' and can be conflated with social influence because 'distance in terms of social characteristics translates into [social] network distance [between] two individuals'. The debate is not whether social influence exists but whether one can prove causation, such as the social spread of behaviours, with observational data, as any attempt to do so requires strong assumptions about the social process or about the covariates involved.

In any case, assortative mixing, and possibly social influence, is greatly facilitated online. This can have advantages. For example, networks of friends on Twitter actually do a better job than large-scale aggregation of data (e.g. Google Flu) in detecting disease outbreaks [78]. Similarly, with a sample of over 60 million Facebook users, Bond *et al.* [79] found that the social sharing of messages between close friends had a greater effect on voting preferences than the direct effect of the messages themselves. In villages of rural India, another natural experiment [80] involving the introduction of microfinance found that passive members of the social network—those who did not adopt the behaviour but still shared the message—were collectively on a par with the community leaders in terms of influencing collective decisions of the village.

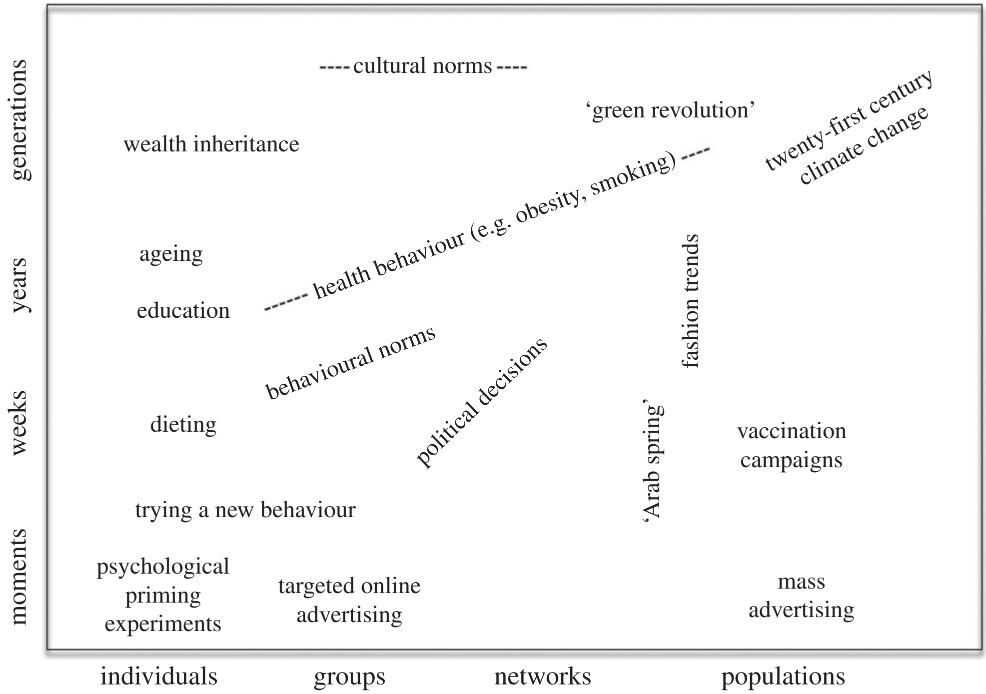

Figure 2. A heuristic view of the vast range of time scales and population scales in human behaviour and cultural evolution.

Studying change over time explicitly will move this research forward. Using transmission-chain experiments [81] to better understand the process of 'iterated learning' as a mode of transmission [82], one might test how subtle themes of environmental change or sustainability are retained or transformed as a story is passed along. If replicated in different populations—in, say, China, India, Ethiopia and Micronesia—the evolution along the chain could reveal different biases than in the West. This in turn might reveal a spectrum of direct experience of climate change, ranging from those who acutely experience change to those for whom climate change is a relatively distant political topic.

'Since people generally only have significant contact with others like themselves, any quality tends to become localized in sociodemographic space' [77, p. 415]. Ultimately, distinguishing between social influence and homophily requires an explicit time dimension in order to clarify causality. Studies of online behaviour often have explicit time details that enable homophily to be distinguished from genuine influence [83]. There are also opportunities in the field. Hobaiter *et al.* [84] recorded the order in which chimpanzees observed another chimpanzee using a novel moss sponge for obtaining water. As a result, they obtained a structured time-stratified network representation of how the behaviour spread from one individual to another, such that each individual could be observed to witness the behaviour first and then subsequently adopt it. Similarly, a temporal dimension is needed to sort out influence in online contexts. The larger issue is that time scales are often conflated, as in using a short psychological experiment to explain evolved psychology in humans, or vice versa. In terms of time and population scale (figure 2), a particular barrier to sustainable behaviour will be long-standing habits and cultural norms. These norms exist on scales from individuals and small groups to the climate politics of nations.

Figure 2 draws attention to the scales of behavioural/social change and the evidence used to explain or predict it. For example, a worldwide Gallup poll from 2007 to 2008 reveals that education ranks highest as overall predictor of climate change awareness, both worldwide and in numerous individual countries [85]. In many individual countries, however, the top-ranked predictor of climate change awareness [85, electronic supplementary material, fig. S4a] ranges from personal characteristics to national governance and economics, to the regional ecology. The top factor in each country [85] also varies temporally from intragenerational (civic engagement, extreme weather events, access to communication technologies and government policy) to intergenerational (wealth, education and rate of degradation) to multigenerational (religion and regional ecology). A useful activity therefore is to plot the spatial versus temporal scale of change in these factors on a log scale. The tendency for incidental public violence to increase with ambient temperature, for example, plots at the momentary or hourly scale, whereas the stability of ancient civilizations may correlate with changes in rainfall patterns over centuries [86].

4. Landscapes of decision-making

As we have seen, sustainability is not only highly complex, but its urgency motivates cultural change in just a few generations or less [4]. Considering the Neolithic ancestry of modern agriculture, for example—intensive fertilizer-driven farming, on fixed plots of land, of cereals, meat and milk—we might say that human subsistence traditions have climbed a 'fitness peak' of land use for thousands of years. The use of fossil fuels, by contrast, represents a peak climbed relatively more recently. In any case, the sustainability challenge is to shift billions of people to different peaks from the ones they now occupy. This is a stark challenge in fitness-landscape terms, because crossing a fitness valley to a different complex, high-fitness peak may take considerable time (e.g. [87]). The necessary change is thus unprecedented in both tempo and even mode, in that there is not the time for intergenerational traditions to climb their local peaks, irrespective of whether those are locally or globally optimum peaks.

Navigating the landscape efficiently requires a particular balance of invention and innovation. Following Schumpeter [88], if we define *invention* as the creation of a new idea—as opposed to *innovation*, which is the diffusion of an invention [89,90]—a fitness landscape is 'searched' through the random 'movement' of new inventions. If an agent searches from atop a local peak, most inventions will be neutral or disadvantageous, and it may take multiple successive inventions to cross the 'valley' to a new peak. Inventions, as random moves on the fitness landscape, are generated through what cultural evolutionary theory terms *individual* learning. Innovation—exploiting advantageous moves through diffusion of inventions—is effected through *social* learning. In order for it to be the case that larger populations produce more technological breakthroughs (e.g. [55,91]) optimizing the network that facilitates innovation is an advantage. For example, hierarchical network structures tend to amplify selection of fitter variants, whereas more diffuse network structures tend to suppress it, i.e. to favour more random drift [92]. In hierarchical networks that make specialized expertise transparent to other agents, social interactions among specialized agents can accelerate the ascent of a fitness peak of a complex solution, which is distributed among the agents [87].

Recombination of ideas or technologies is also important [93,94]. We can consider an 'ecology' of ideas. In island-biodiversity terms, the number of coexisting species is expected to increase with area size of an island but to decrease with the isolation of the island. This isolation need not be geographical; it may be economic in terms of trade networks [95]. Because international trade can facilitate the recombination of technologies or infrastructures, economic isolation can effectively curtail this potential for 'speciation', i.e. technological invention and innovation [94]. When we combine this with our detailed knowledge of human travel and trade networks, which are based on transport infrastructure rather than on geography (e.g. [96]), we have a framework for estimating the adaptive potential in the future, if not an ability to predict that future specifically.

In terms of ability to amplify versus to suppress advantageous inventions, not only does the structure of an interaction network matter, so does its temporal depth. From a selfish individual point of view, the highest pay-offs may go to copying recent information, or 'scrounging'. Economic game theory refers to this as 'recency bias', or a discounting of older information [97], as proved successful in a social-learning tournament held at St Andrews University in 2009 [98], whereas Bayesian approaches to cognition [99] may simply consider a moving window of memory, which updates the cognitive model of reality, stretching back from the recent to some specified time in the past.

On the one hand, if sustainability requires rapid change, a lack of historical memory could be an advantage rather than a burden. On the other hand, by flattening the learning landscape into the recent past, short-term individual gains may come at the cost of lost traditional knowledge. This echo-chamber effect is undesirable in the long term, and contributors to it include 'nowcasting' from recent social-media data, the tendency for online peer-reviewed articles to have more recent bibliographies, automated bots that copy and re-use online text, and academic reuse of text in peer-reviewed articles [100–103].

In essence, sustainability by definition seems contrary to a fitness landscape populated by agents biased towards recent social information. In traditional societies, a population bottleneck resulting from war or famine, for example, could lead to a substantial loss of specialized information. In literate or digital societies, however, the information may be securely stored in written or digital media, but transparency may decrease through the sheer volume of it. For example, as online scientific publishing has become the norm in the last decade (in concert with a geometric increase in the volume of pages published), the average age of bibliographic citations has become progressively more recent [103]. A reasonable suggestion is that older science becomes forgotten as the wheel is reinvented by increasingly fragmented groups of collaborators. In other words, cumulative knowledge requires transparency in accessing the 'best' or most useful information stored by the collective and an assurance that that information can always be accessed.

5. Dimensions of decision-making

In modelling the challenge of ecological sustainability as cultural evolution on a fitness landscape, we emphasize three important factors: the balance of individual to social learning in a population, the transparency of both kinds of learning and temporal dynamics of the popularity of decisions within a population. We believe that with caveats [104] big data can be used to assess these important measures, in contrast to the current focus on prediction of individual behaviour by using personal data [100]. Figure 1 draws on the field of discrete-choice theory to create a multiscale comparative diagram that, like a principal-components representation, captures the essence of decision-making along two axes [20]: (i) the horizontal axis represents the degree to which an agent makes a decision independently versus one that is socially influenced and (ii) a vertical axis that represents the degree to which there is transparency in the pay-offs and risks associated with the decisions agents make (figure 1).

To both explore the dynamics and make the diagram applicable to real-world data, Brock *et al.* [21] defined the diagram analytically in continuous space as functions of observable covariates and estimated parameters. The vertical axis, which we parametrize as b (or b_t if b changes through time), runs from absolutely transparent at the top ($b_t = \infty$) to opaque at the bottom ($b_t = 0$). This integrates with the horizontal axis, measured by parameter J_t, which represents the extent to which a decision is made individually at the far left edge ($J_t = 0$) to pure social decision-making, or copying, at the far right edge ($J_t = \infty$). The following equation expresses this parametrization in terms of how probability, P_k, of choice k (versus null-choice probability, P_0) depends on transparency of choice (b: vertical axis) and social influence (J: horizontal axis):

$$\ln \frac{\mathrm{Pr}_{igt}(k)}{\mathrm{Pr}_{igt}(0)} = \underbrace{b(\theta, z_{igt})}_{\text{transparency}} \; [\underbrace{\varphi_1(x_{ikgt} - x_{i0gt})}_{\text{individual}} + \underbrace{J(\varphi_2, y_{igt})(P_{tkg} - P_{t0g})}_{\text{social}}],$$

where x represents the pay-off of the individual choice, y represents the presence of social influence and z represents the variability of choices through time. Parameter vector φ_1 represents an individual's sensitivity to differences in choice, acting on the pay-off difference between options, and parameter vector φ_2 represents the transparency of social influence, which acts on the popularity of the option.

To simplify, think of the diagram in terms of how an agent might behave. An agent in the upper half of the diagram is more attuned to costs and benefits of a decision than is an agent in the lower half. Our agent in the upper half might make a decision individually, as shown in the upper left of figure 1, or there might be socially identified authoritative experts, as shown in the upper right of figure 1. As we move down the vertical axis, the relation between an action and its impact on performance becomes less clear. At the extreme lower edge of the diagram are cases that correspond to total indifference, where choice is based either on randomly guessing among all possible choices (lower left) or copying from a randomly chosen individual (lower right). This area of the cost/benefit spectrum represents cases in which agents perhaps are overwhelmed by decision fatigue—for example, when the number of choices becomes prohibitively large to be processed effectively.

To articulate this diagram with the fitness-landscape model, we face a novel problem in that the optimal decision depends not only on intrinsic utility of the decision or behaviour but also on transparency and social learning as well as on the relative popularity of each possible choice in a population. We are finding that social influence and loss of transparency can quickly lead to unpredictability. A recursive relationship between popularity and social influence gives rise to multiple equilibria in terms of decisions that optimize the sum of the individual and social pay-off function [105]. This fundamental unpredictability is broadly consistent with other models of cultural niche construction that combine selection and social sorting mechanisms (e.g. [106]). The implication is that the current focus on nowcasting and prediction of decisions using big data [5,100] should be complemented by an assessment of social influence and transparency on the same data in order to assess how predictable the decision patterns are in the longer term.

6. Conclusion

> The ecosystem no longer produces as much entrepreneurship mutations that fuel evolution. Data-driven [political] candidates sacrifice their own souls. Instead of being inner-directed leaders driven by their own beliefs, they become outer directed pleasers driven by incomplete numbers.
>
> David Brooks (*New York Times*, 4 November 2014)

As members of a social species, humans are unique in their capacity for accumulating knowledge over generations [29,107,108]. As we have pointed out, this is how cultural traditions solved ecological problems for human communities, collectively and intergenerationally, through long time scales that allowed small alterations to prove themselves adaptively through cultural selection (e.g. [55,109]). Populations can adapt when 'generation times are short relative to the time scale of environmental variations' [110, p. 7], but in the twenty-first century, substantial environmental change is occurring within generation times and over unprecedented spatial and social scales [4].

The heuristic in figure 1 was designed to assess how these changes affect cultural evolution. Aside from data-driven attempts to measure or change *what* people do and believe around the world [85,111], we suggest they can usefully reveal more about *how* decisions are made within the dimensions of figure 1—the transparency of pay-offs and nature of social learning. If, for example, the accuracy of social learning decreases as an innovation diffuses [112], this could be represented by movement downward in figure 1. The farther down one moves—the lower individual and/or social transparency—the less predictable the dynamics are of collective decision-making. In the lower half, an increase in social learning—moving to the right—increases the unpredictability in what emerges as the choice of the majority [62,105]. As information producers become distanced from the environment, different majority outcomes become freer to be perceived as cultural differences, even if their pay-offs are not transparent. Among social animals, a lack of transparency allows increases in the propensity for group members to follow a small but determined minority [68,113]. For extremely politicized issues such as global warming—among the most contested topics online [114]—the social pay-offs become high enough that people (on both sides) will fit the scientific evidence into their existing worldview and group identity [115,116].

When the pay-offs of environment are no longer transparent, then social learning, the fundamental mechanism of human cultural adaption, can actually lead us astray. In terms of figure 1, we might hope to move things towards the upper left corner, which increases both the level and transparency of individual learning. This most readily occurs with direct experience of environmental change in the areas most affected, such as high latitudes or low coastal elevations. Less directly, messages about environmental and health benefits can promote conservation more effectively than monetary incentives [117].

Much evidence of global change, however, such as the slow increase of invisible carbon dioxide in the atmosphere, is not directly notable by individuals. In this case, enabling people to use science rather than merely receive it can engage the cultural-evolution mechanism of individual learning in a social context. US farmers, for example, are adapting to annual extremes of climate (such as floods or drought) through high-precision farming, data-driven insurance policies and genetically modified crops increasingly oriented towards climate extremes [118]. City dwellers are now collecting and sharing data on air quality through personal sensors [119] and are using online apps to interpret local effects of sea-level rise or mean temperature change. People around the world are adapting to climate change in ingenious ways, from engineering artificial glaciers in the Himalayas, to painting Peruvian mountains white, to re-discovering ancient irrigation techniques to using satellite technology to find potable water [120].

With more well-informed individual learners and inventors, the next goal is to scale up the best inventions into widespread innovations, which requires a transparency of social learning. A collective commitment to looking after future resources, for example, increases when decided by transparent, democratic vote [121]. Markets, too, could provide transparency, such as a property market already speculating on the best cities to live in under global warming. Such markets, however, may well be prone to bubbles and echo-chamber effects, as social learning is increasingly mediated by non-human technologies designed to increase popularity, rather than validity, of vested ideas [14]. A response is to encourage social transparency by pooling knowledge among experts [122] and among genuine social relations in the wider population [78,79].

As we illustrate in figure 2, change occurs on different time and population scales, and translating between them is essential for understanding the future of adaptation. Culture evolution involves potentially differing selection at the levels of individual producers of information, consumers of that information, and social networks or markets among those consumers [112]. As diverse groups produce inventions, and local organizations scale them up as innovations, local innovations may, in turn, function as inventions at the global scale of markets. If public communication of environmental science catalyses individual learning at a small scale, then adaptive innovations will diffuse through social learning at the population scale. Whereas the optimal balance between these types of learning depends on the specific context, the history of human adaptation suggests it is best that both types be as transparent as possible.

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