

An ability to respond begins with inner alignment: How phase synchronisation effects transitions to higher levels of agency

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Abstract

How do multiple active components at one level of organisation create agential wholes at higher levels of organisation? For example, in organismic development, how does the multi-scale autonomy of the organism arise from the interactions of the molecules, cells and tissues that an organism contains? And, in the major evolutionary transitions, how does a multicellular organism, for example, arise as an evolutionary unit from the selective interests of its unicellular ancestors? We utilise computational models as a way to think about this general question. We take a deliberately minimalistic notion of an agent: a competency to take one of two possible actions to minimise stress. Helping ourselves to this behaviour at the microscale, we focus on conditions where this minimal type of agency appears spontaneously at a higher level of organisation. We find that a simple process of positive feedback on the timing of individual responses, loosely analogous to the natural phase synchronisation of weakly coupled oscillators, causes such a transition in behaviour. The emergent collectives that arise become, quite suddenly, able to respond to their external stresses in the same (minimal) sense as the original microscale units. This effects a dramatic rescaling the dynamical behaviour of the system, and a quantifiable increase in problem-solving competency, serving as a model of how higher-level agency emerges from a pool of lower-level agents or active matter. We discuss how this dynamical ‘waking-up’ of higher-level collectives, through the alignment of their internal dynamics, might relate to reproductive/cell-cycle synchronisation in evolutionary transitions and development.

keywords: connectionism, associative learning, evolutionary transitions in individuality, adaptive networks

Introduction

How do many become one (Levin 2019, Levin 2021)? At many different levels of organisation from molecular biology to human society, multiple individuals can sometimes change from acting separately, with individual goals and competencies, to working together in a way that produces a new entity, behaving as a single agent at a higher level of organisation, with new goals and new competencies (Bar-Yam 2002, Levin 2019, Manicka and Levin 2019, Hoel and Levin 2020, Levin 2021). Each of us, for example, is a collection of cells (each retaining a repertoire of semi-autonomous behaviours and functions), that work together to create and maintain a coherent whole capable of collective action and goal-directed behaviour one (Levin 2019). This higher level of agency is not present at the outset of development but emerges over developmental time; from the quiescent matter of the oocyte, to tissue and organ-level behaviours such as coordinated alignment, migration and pulsing that maintain morphogenetic order, to the complex metacognitive level of human agents. In the developmental emergence of an individual from the active matter of which it is composed, the salient level of agency repeatedly transitions from one level of organisation to another, pivoting through different dynamic and behavioural spaces, including gene-expression, metabolic activity, cellular spatial coordination, electrical excitation (of neural and aneural cells), to large-scale behavioural alignment and coordinated action at the organismic level (Levin 2021).

At a quite different timescale, and in relation to a different kind of competency, the process of evolution by natural selection has also scaled-up through multiple levels of organisation. In the

evolutionary transitions in individuality, “entities that reproduced independently before the transition can reproduce only as part of a larger whole after the transition” (Maynard Smith and Szathmary 1997). These include transitions from multiple self-replicating molecules to the first chromosomes, the first protocells with multiple chromosomes, eukaryote cells with multiple previously free-living organelles, to multicellular organisms, to eusocial colonies (Michod 2000, Godfrey-Smith 2009, Buss 2014, West, Fisher et al. 2015). In these transitions, the ability to exhibit heritable variation in reproductive success has been repeatedly rescaled from parts to wholes recursively, moving from one level of organisation to another (Okasha 2006, Watson, Levin et al. 2022)

These transitions in organismal and evolutionary agency are intimately related. A change in the level of evolutionary unit partly explains why components work together so well in organismic development and behaviour. On the other hand, the causal relationship may well be the other way around; i.e. it is the change in the level of organismal agency, when directed at the competency of survival and reproduction, which originates the new level of evolutionary unit (Watson, Levin et al. 2022). Understanding how new levels of agency arise (including new levels organismic competency in developmental time and transitions in the evolutionary unit over evolutionary time) is an open problem (Okasha 2006, Walsh 2015, Levin 2021, Mozcek&Sultan 2022).

Agency shares some conceptual problems with non-reductionist accounts more generally. Although any behaviour of an agent can be traced to the behaviours of its component parts, it is also quite obvious that in one organisation the parts may behave differently than they do in another. Whilst the apparent generality and completeness of lower-level explanations can be attractive, ignoring the circumstances by which higher-level organisations constrain the ‘options’ or offer new ‘affordances’ to the component parts tends to make-invisible the biology that is interesting (Walsh 2015). Moreover, in biological systems in particular, the relevant scale of causal processes is not only frequently ambiguous but can also change over time; an account that fixes exclusively on one scale of explanation, whatever scale that is, fails to engage with such transitions (Okasha 2006, Hoel, Albantakis et al. 2016, Hoel and Levin 2020, Levin 2021).

We wish to understand, in a simple mechanistic way, how multiple individuals can co-create the necessary relationships among themselves to cause them to work together in this way; in particular, when doing so appears to oppose the self-interest of component members. This transitional way of thinking about agency turns focus away from trying to define a categorical notion of agency sufficient to distinguish between agential and non-agential systems (Walsh 2015). Instead, it focusses on how a given competency at one level of organisation transitions into a (perhaps similar) competency at another higher level of organisation (Okasha 2006, Watson, Levin et al. 2022). This can still be an interesting question even when the notion of competency employed is relatively simple. In particular, we consider the competency to take an action (from a finite set) that optimises some quantity, e.g. maximises utility (or reward or fitness), or minimises stress (or frustration or energy), in response to a small signal in this quantity. This notion of agency is not difficult to satisfy even with a very simple physical model such as a ball rolling downhill over a landscape (with a suitably shaped surface as we will detail). But the interesting question is whether a collection of units with this competency can organise themselves to create a higher-level agent with this same kind of competency. In particular, can a collective take an action that reduces its collective stress (in the long term) when this requires the components to take actions that increase their individual stress (in the short term)? More generally, if we assume that an agent acts “on its own behalf” (Mozcek&Sultan 2022), how do multiple self-interested agents at one level of organisation, work together to create agency at a higher level of organisation? In particular, can this higher-level agency cause its component members to act in a manner that serves long-term collective interest, over-ruling the short-term self-interest of the parts?

We thus seek a microscale mechanistic model, complete in determining the behaviour of the system. But we seek to understand a phenomenon that is interesting precisely because a macroscale mechanistic process emerges that changes the outcomes of the system. What does it mean to be a macroscale process if the microscale process completely defines the dynamics of the model? Can it really be the case that the macroscale process is absent before the transition and present only afterwards? Is it always there implicitly, or conversely, is it never really there at all – just an explanatorily-redundant epiphenomenon of the microscale process? These questions are at the heart of agency debates (Walsh 2015). They arise in organismal development and what it means to be a ‘self’ (Levin 2019), and in evolutionary transitions and what it means to be an evolutionary unit (Okasha 2006, Godfrey-Smith 2009, Bourrat 2021, Watson, Levin et al. 2022). In this paper, we build a very simple and abstract model to investigate these questions. Whilst the example model we present omits many features desirable in a general model of agency, it enables us to address some of these conceptual questions clearly.

Our methodology is to use computational models, not as accounts of, or substitutes for, empirical study, but as tools to think with – to explore the logical consequences of different abstract scenarios and general assumptions (Di Paolo, Noble et al. 2000). What follows therefore is not a specific model of development, nor of evolutionary transitions. Rather it is a model that illustrates some general underlying principles involved in multi-scale competencies and transitions, to help us think about what that might mean, and how to make sense of some conceptual difficulties.

In the following section we clarify the ‘transitions problem’ and introduce our approach. In the remainder of the paper we describe the model, demonstrate its ability to produce a transition in agency, and the change in problem-solving competency that this confers. We then discuss some implications of our findings for organismic development and its interactions with evolutionary transitions in individuality. Finally, we use this model to discuss some of the conceptual problems of micro- and macro-scale mechanistic processes, and their interpretation for transitions in agency.

Background and Approach

The transitions problem: Conflict between levels of agency

To concretise the issues involved, it is useful to have a simple and familiar example. Consider a world with many countries and many drivers. Each driver needs to decide whether to drive on the left of the road or the right. Their utility is a sum of many pairwise interactions with other drivers. Collisions confer a cost (stress), so to avoid this cost drivers need to reach consensus, i.e. agree which side to drive on. For each driver in the same country the interaction weight is strong (i.e. they meet them often) and for each driver in a different country the interaction weight is weak (i.e. they meet them less often). It is easy for the drivers within each country to arrive at a consensus by driving on the side that agrees with the majority of others in that country. But, as is familiar in the real world, it may be the case that different countries arrive at a different consensus (Fig. 1). This is a locally optimal state. Each driver suffers no collisions with others in their own country, but suffers occasional collisions with foreigners.

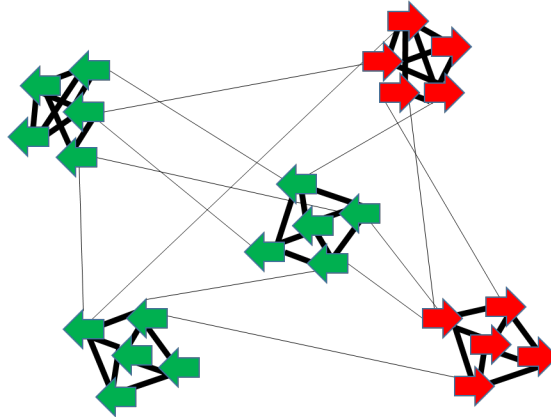


Figure 1. The driving conventions problem has multiple sub-optimal attractor states. Drivers in the same cluster (country) meet one another much more often (thick lines), than drivers in different countries (thin lines) (not all interactions shown). Each driver drives on the side that minimises the collisions/stress they experience. This is sufficient for each driver to arrive at a local consensus (either all left/green or all right/red depending on the local majority). However, this is only a locally optimal state since all drivers experience some (less frequent) collisions with drivers in other countries. No one driver can change their decision unilaterally to reduce these collisions. Even a driver in the global minority (red drivers in this example) cannot change because, if acting alone, the cost of increasing their collisions with locals is greater than the benefit of decreasing collisions with foreigners. Two global optima exist, where all collisions are avoided. To escape a local optimum and arrive at (or move toward) a global consensus requires individuals to move against their short-term self-interest (increasing stress). If only all the drivers within a country were capable of acting together such that they all changed simultaneously in the right direction (toward the global majority) this would satisfy more external conflicts without creating any internal conflicts. But although an individual driver can respond to the influence of other drivers in their country, a country is not an agent that has this competency. That is, a country is not a level of organisation that is able to respond to the influence of its environment (including other countries). It is locked in place, trapped at the local equilibrium, by the pull of its internal stresses.

Countries are (in the sense of an average over their components) incentivised to agree with the majority of other countries to reduce collective stress, just like individuals are within a country. If only it were possible for a country to change their decision, to flip to the other side to agree with the majority of other countries, it would be possible to arrive at a state where no-one suffers any collisions internally and less-so externally. But countries are not a level of organisation that has this basic competency – countries are not a thing that is able to take decisions or actions. In fact, each driver is unable to change their decision (even though they each suffer the collisions with foreigners) because the cost of increased collisions with locals is larger. A country therefore does not have the same agential competency that an individual driver has (minimal though that is).

This scenario affords an objective test for our sense of a transition in agency that does not depend on conceptual or rhetorical subtleties. Put simply, if a transition in agency occurs then we will know this because we will see a rescaling in competency or problem-solving ability such that the system will escape local equilibria and arrive instead at one of the equilibria that globally minimise stress. This requires that collectives emerge with the right members and the ability to take collective actions that minimise collective stress, rather than individual stress.

This kind of problem, a modularly weighted coordination game (Mills and Watson 2007, Davies, Watson et al. 2011, Watson, Buckley et al. 2011, Watson, Mills et al. 2011) can be used as a fulcrum to think about multi-scale agency and multi-scale optimisation in other domains (Watson, Palmius et al. 2011, Watson, Buckley et al. 2011, Watson, Mills et al. 2011). For example, in developmental systems, a similar scenario may obtain for a tissue where each cell has a phenotype, such as planar polarity, that needs to be coordinated with neighbouring cells, but only local

communication is available. This may result in local patches that are internally consistent but disagree with neighbouring patches (like the domains of a two-dimensional Ising model). Cells on the boundary suffer from mismatched polarity with neighbours on one side but are unable to change since this would cause mismatched polarity with the other local neighbours of their patch. If only it were possible for a whole patch to change state simultaneously, then it would be possible to resolve all these external constraints without creating any conflicts within the patch. These scenarios describe a coordination game on a weighted graph with localised connections (modular connections in the driving example and a spatial lattice in the cell polarity example). More generally, any set of pairwise constraints has the potential to exhibit multiple locally optimal configurations, some with higher total utility than others.

In a genetic evolutionary context, an example is provided by the evolution of alleles at multiple freely-recombining loci with epistatic fitness interactions (Hofbauer and Sigmund 1998) (more specifically with reciprocal sign epistasis (Weinreich, Watson et al. 2005)). The fitness of each allele with respect to the alternative allele at the same locus will depend on the genetic contexts provided by the population. This may result in the population arriving at a local fitness peak where no single allelic substitution is beneficial. Nonetheless, other adaptive peaks with higher fitness may exist. No single locus is able to change the allele under natural selection, even if it brings the genotype closer to the higher fitness peak (by definition of a local optimum), yet if all the genetic differences between the lower peak and the higher peak were somehow substituted simultaneously, this would jump across the fitness valley and confer a fitness increase without visiting the lower fitness intermediate points. Accordingly, there is a deep homology between the transitions in agency problem (maximising long-term collective fitness given short-sighted self-interested agents), and the evolutionary problem of crossing valleys in a fitness landscape (with a natural selection process that can only respond to local fitness gradients) (Watson 2005).

The possibility of long-term collective gains suggests that if only some suitably structured relationships could be put in place, to alter the short-term incentives or responses of the parts in the right way, these would be to everyone's benefit in the long-term. For example, mandated driving regulations (that over-rule individual choices), a widely diffusing morphogen that incentivises long-range cellular coordination (over-ruling local cell interactions), or a gene-regulation network that coordinates gene-expression (taking the control of gene products away from mutations at individual genetic loci). However, such relationships need to coordinate action among many parts simultaneously because changing only some of the parts is worse than staying as you are (e.g. a country with a fraction of the drivers using the foreign convention, or a genotype with only a fraction of the substitutions necessary to cross the fitness valley). A partially constructed relationship structure can therefore be worse than none. So even if such relationships or incentive modifiers (see also 'individuating traits' in an evolutionary process (Clarke 2016, Watson, Levin et al. 2022)) were evolvable or learnable in principle, and beneficial when fully established, this does not on its own explain how self-interested individuals could create such organised relationships bottom-up through individual incentives (Watson, Levin et al. 2022). Even if we assumed the existence of a higher-level selection process or utility-maximisation process that rewarded collectives not individuals, incremental improvements would not be sufficient to explain how a relationship structure arises that facilitates working together when a partial relationship structure is worse than none. Moreover, a microscale mechanistic model for transitions in agency must operate without presupposing the higher-level agency it intends to explain (Watson, Levin et al. 2022).

So, what would it take for a collective to self-organise such that it transitions from not having this basic competency (even though its component parts do) to a new level of agency that does have this competency? Who belongs in the collective? What kind of relationships would cause them to act together, maximising long-term collective utility, instead of short-term individual utility? And how do the members create or organise their relationships with one another in a manner that

produces this outcome given that relationships producing partial collective action are worse than none?

Timing

Higher-level agency thus carries an apparent contradiction created by the notion of a microscale behaviour (that fully describes the system) and a macroscale behaviour that over-rules the microscale behaviour. One way or another, when a system does something that seems paradoxical this means we have not fully described the system. Here we explore how the apparent paradox of agency is alleviated by thinking about timing. Intuitively, changes in timing have the subtlety that they don't tell you what to do – only when to do it. At first glance, this suggests that changing the timing of behaviours does not obviously alter which behavioural outcomes obtain, only whether they occur now or later. But this is not generally true whenever the effect of one component depends on the state of another. By altering the timing of behaviours, such influence is not just earlier or later, but can be different. Accordingly, with one kind of timing, the same individuals with the same competencies may exhibit quite different behavioural outcomes than they do with another kind of timing (Frean 1994, Saif and Gade 2009). Thus, there is a sense in which (specifically, the sense in which we ignore their timing) there is no need for anything to over-rule the microscale dynamics, or to change what individuals 'want' to do - the microscale dynamics can be described by the same forces, influences and competencies throughout. Yet, the system dynamics can be effectively altered to produce different outcomes (i.e. by changing the organisation of their timing). Of course, in a full account, the timing, and changes to timing, are also part of the microscale dynamics, and there is no real contradiction when these are fully described. Nonetheless, we will show how this conceptual separation between behaviours and the timing of behaviours can be developed in a way that helps explain transitions in agency.

Specifically, our model modifies the timing of behaviours via a simple process of positive feedback loosely analogous to the natural phase synchronisation of weakly coupled oscillators. The entrainment of weakly-coupled oscillators, causing synchronisation or phase locking (Kopell and Ermentrout 1986, Izhikevich and Kuramoto 2006), is a ubiquitous physical phenomenon that spontaneously organises the timing of repetitive behaviours (e.g. from pendulum clocks, to fireflies, to pedestrians) (Ercsey-Ravasz, Sárközi et al. 2008, Belykh, Jeter et al. 2017). Unlike many previous models of multi-agent synchronisation, it is not the synchronisation *per se* that constitutes the macroscale behaviour we are interested in. Rather we are interested in how synchronisation enables a higher-level composite, a collection of primitive units, to exhibit a new competency – a different behavioural outcome that was not possible before they were organised in this way.

In order for synchronisation to effect a transition in agency, we will show that it needs to have the right structure – neither all individuals acting at once, nor all asynchronous, nor an arbitrary subset – but the right individuals need to be coordinated. However, if we were to impose the right structure of synchronisation exogenously, this would not be a model of a spontaneous transition. So, the change in the structure of the timing between individuals must also be explained endogenously, as a consequence of the behaviour of the individuals (Okasha 2006). The conditions we investigate involve changes to timing that are altered by relationships between agents. These relationships do not directly affect *which* actions individuals prefer (e.g. being caused to take action *A*, say, over action *B*), they simply modify the synchronisation of *when* actions are taken (e.g. being caused to decide between *A* and *B* at time *t*₁, say, over making this decision at time *t*₂). These relationships are organised by a principle of positive feedback on correlations; the more two things have been correlated in the past, the more the relationship between them changes in the direction that makes their behaviour more correlated in future (Watson, Mills et al. 2016, Buckley and Watson 2022). Positive feedback on correlations is also the basis of unsupervised associative learning familiar in connectionist models of distributed cognition, e.g. 'neurons that fire together wire together' (Hebb 1949). It does not depend, however, on any sophisticated learning machinery or an external teacher, reward signal or selection process (Watson, Buckley et al. 2011, Watson, Wagner et al. 2014, Power,

Watson et al. 2015, Watson, Mills et al. 2016, Watson and Szathmary 2016). It is analogous to *unsupervised* learning (Watson and Szathmary 2016), and it occurs spontaneously in dynamical systems described by networks of viscoelastic connections, i.e. connections that give-way or deform slightly under stress (Buckley and Watson 2022).

An essential characteristic of the model is that all the features of this process (the individual behaviours, their mutual synchronisation, and the organisation of relationships that coordinate who synchronises with whom) can all be described by microscale equations of motion, i.e. without reference to collectives or collective behaviours. Nonetheless, the emergent collectives that arise become, in a quite sudden transition, able to take actions in response to their external stresses in the same (minimal) sense as the original microscale units. This drastically changes the level of behaviour that occurs in the system. Thus we are not merely talking about the emergence of a macroscale pattern, but a new structure that does causal work, i.e. alters outcomes, by becoming a new locus of sensitivity and control that was not previously present at that scale (Batterman 2001, Noble 2012, Hoel, Albantakis et al. 2016, Hoel and Levin 2020).

Model

Our model describes a system of many active units with interactions (or constraints) between them, the entrainment of their timing, and the formation of relationships that structure this entrainment.

A primitive ‘decider’ or a unit with a minimal lifecycle

Each unit is a primitive ‘decider’ that repeatedly takes one of two possible actions (Fig. 2). A Newtonian mechanics model, like that depicted by Waddington (Waddington 1957, Wang, Zhang et al. 2011) to represent developmental differentiation, is sufficient. Specifically, a ball rolling downhill and passing a saddle point causes it to branch left or right, as used in many models of development including cell-cell communication (Ferrell Jr 2012, Fooladi, Moradi et al. 2019, Matsushita and Kaneko 2020, Thompson 2021).

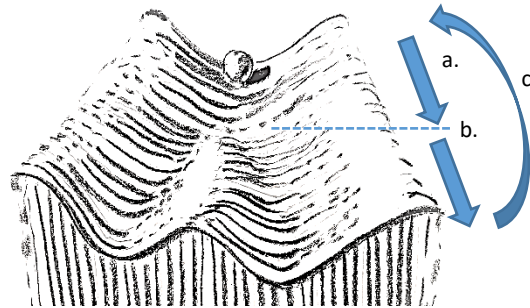


Figure 2. A single unit or primitive ‘decider’ modelled as a Newtonian system, in the style of Waddington’s epigenetic landscape. In the ‘lifecycle’ of the decider, there is a growth or amplification period which conceptually divides into two parts, an undecided or labile period (a), before the saddle point, when the unit is sensitive to small inputs but its outputs are weak; and a decided period (b), when the unit is not sensitive to small inputs but its outputs are strong. After these two parts of the growth period, a new lifecycle is begun by degrowth (turning off amplification and allowing the state to decay), i.e. resetting the unit to the high-energy saddle point (c) to begin again.

For a single unit, the approximate dynamics are described by:

$$s_{(t+1)} = s_{(t)}(1 - \tau_1) + \tau_2 s_{(t)} + \tau_3 R_{(t)} \quad (\text{Eq. 1})$$

where $s_{(t+1)}$ is the state of the unit at time t , $\tau_1 = 0.1$ is a constant controlling the decay rate, τ_2 is a variable controlling the growth rate (below), and $\tau_3=0.01$ adds a small amount of noise determined by the random variable, $R=[-1,1]$, drawn uniformly in the range. τ_2 , the coefficient of the growth term, is either 0.1 or 0 depending on whether the unit is in the growth period (i.e. rolling

down the hill) or being reset to the undecided state from where it can ‘decide again’. This lifecycle is controlled by the phase variable, $\theta_{(t+1)}$, which increments by 0.01 in each time step. Specifically, $\tau_2 = 0.1H(\sin(\theta_{(t+1)}) + \rho)$, where $H()$ is a Heaviside step function (i.e. returning 1 if the argument is greater than 0, and 0 otherwise) and $\rho = 0.8$ is a constant controlling the length of the growth period. In other words, the unit grows or differentiates (or decides) for some time period, then during degrowth its value decays, returning to the undifferentiated (undecided) state, until it decides again, in the next ‘lifecycle’.

Each unit thereby repeatedly takes one of two possible actions according to small differences in conditions at the decision point. This is essentially just an amplifier – a dynamical system that has sensitive dependence on initial conditions, and a ‘decision cycle’ that repeatedly puts it back to this sensitive state. This kind of unit can represent many different types of basic components including a strategic utility-maximising agent that repeatedly decides what action to take, or a cell-cycle where an undifferentiated cell differentiates into one phenotype or another according to a threshold function of the morphogens/environmental cues it receives, or a selective process that retains one copy or another based on fitness differences. Computationally, it is equivalent to a neuron that repeatedly fires (or not) according to a threshold function of its inputs.

We will refer to it as a unit repeatedly making decisions about how to act. But we make no claims whatsoever about an individual unit as an interesting model of agency. This Newtonian model is adopted rather than an explicit selection-based or utility-maximisation model to make the point that nothing ‘clever’ is required on the part of an individual agent – its behaviours can be described by only a simple microscale equation of motion – and because we need a model where decisions are not instantaneous. What is interesting about the model is not the individual units but rather the behaviour of many units in interaction with each other, and how the organisation of the connections between them facilitates a transition in agency.

Timing is important in our model. It is necessary that making a decision, or rolling down the hill, is not an instantaneous or atomic event (an *argmax* model of utility maximisation, or a natural selection model without a developmental process, is insufficient). In the initial part of the lifecycle the unit is undecided. In this period, it is not acting strongly (its output is not amplified) but it is sensitive to the influences of its inputs as it approaches the decision point. We can think of the inputs as tilting the decision surface slightly in favour of left or right. In the latter part of the lifecycle, after the bifurcation, the unit is decided. In this period, it is no longer sensitive to its inputs (i.e. a slight tilt is not sufficient to move it from one basin to the other) but it is acting strongly (its outputs are amplified strongly enough to produce detectable ‘tilting’ influences on others). The behavioural timescale of a unit thus has a basic division between a period where it is sensitive to the world (but not acting) and a period where it is acting on the world (but not sensitive) (see a and b Fig. 2). For a cell, for example, maturing from an undifferentiated state to a particular cell phenotype, it may have an initial stage where it is sensitive to the phenotypes of neighbouring cells (but not producing any influence itself since it is not yet expressing either phenotype), and later, after it is differentiated, neighbours are less likely to change its phenotypic state (and its own phenotype contributes to influencing the differentiation of others) (Fig. 3).

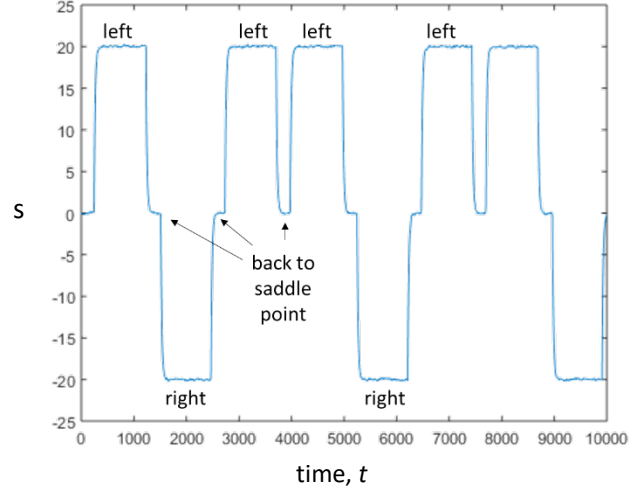


Figure 3: numerical simulation of a single unit (Eq. 1). A single unit has a ‘lifecycle’ which repeatedly pulls it back to the undecided saddle-point and then ‘grows’ or amplifies, falling to either the left or right path (see Fig. 2). In this simulation, the left/right decision is arbitrary, determined only by the noise term. After the unit is decided, a small influence (or noise) is insufficient to change the decision. In the experiments that follow the decision is a response to the sum of inputs from other units (Eq. 2).

Interactions between units

For multiple interacting units, where c_{ij} is the interaction strength (or constraint) of unit s_j on unit s_i , the dynamics are described by a similar equation but with the growth term replaced by a non-linear weighted sum of inputs from other units, as follows:

$$s_{i(t+1)} = s_{i(t)}(1 - \tau_1) + \tau_2 \sigma \left(\sum_j^N c_{ij(t)} s_{j(t)} \right) + \tau_3 R_{i(t)} \quad (\text{Eq. 2})$$

where $\sigma(x) = \tanh(x)$ is a sigmoid function that limits s from growing too quickly (other variables as per Eq. 1, using a different randomly initialised θ_i for each unit).

For the modular driving conventions problem described in Fig. 1, the constraints can be defined by Equation 3.

$$c_{ij} = \begin{cases} 1, & \text{if } \left\lfloor \frac{i-1}{k} \right\rfloor = \left\lfloor \frac{j-1}{k} \right\rfloor, \\ 0.001, & \text{otherwise.} \end{cases} \quad (\text{Eq. 3})$$

where i and $j \in \{1, \dots, N\}$ are the indexes of the pairwise constraints over N variables, $\lfloor x \rfloor$ is the floor of the value x , and k is the number of variables in each module (‘country’). In the following experiments, $N=300$ and $k=10$, creating 30 countries of 10 drivers each. Following Hopfield (Hopfield 1982, Hopfield 1984), it is useful for such problems to define an energy function, Equation 4, describing the extent to which all the constraints in the system are satisfied by the different combinations of discretised unit states.

$$E_{(t)} = - \sum_{ij}^N c_{ij} s_{i(t)} s_{j(t)} \quad (\text{Eq. 4})$$

When the interaction terms are symmetric ($c_{ij} = c_{ji}$), as they are in Eq. 3, the behaviour of a system with discrete states is described by state changes that effect the local minimisation of this energy function, and is guaranteed to arrive at a fixed point (Hopfield 1982). Such points correspond to a Nash equilibrium where no unit can increase their utility or reduce stress by changing state

unilaterally¹. For the drivers' scenario, this means that all drivers agree with the other drivers within their own country (but not necessarily with those in other countries). In this system with these parameters, there are 2^{30} different local optima (i.e. each of 30 countries can adopt either of 2 conventions). Only two of these fixed points is globally optimal, however (i.e. when all drivers in all countries adopt the same convention) (Fig. 4).

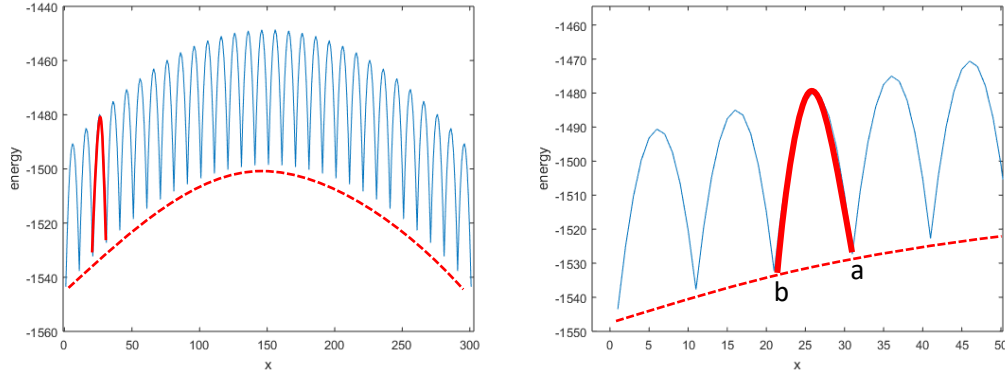


Figure 4. The energy (or stress) landscape of the driving convention problem. Left) A cross-section (blue) through the energy surface (Eq. 4) from one global minimum (all left) to the other (all right) (through the state configurations described by the regular expression $L^{(N-x)}R^x$) shows some of the 2^{30} locally optimal configurations. The red dotted curve indicates the energy contribution from only the (weaker) between-country interactions. The solid red curve is an example of the energy contribution from only the within-country interactions. The complete energy surface is a sum of these two local and global components. Right) A close-up of part of the energy surface. Notice that between point **a** (one of the local optima) and point **b** (the closest local optimum to **a** that is in the direction of the global optimum) there are 10 units that need to change state. To change one unit at a time would mean climbing up the energy barrier caused by the strong within-country interactions (solid red), i.e. this moves against short-term self-interest (increasing stress) even though it would serve their long-term collective interest to be at **b**. Notice that if somehow this energy barrier were temporarily removed there would remain a downward gradient between **a** and **b** caused by the between-country interactions.

With this kind of two-scale energy function in mind, one way to understand our aim is to describe a dynamical system that changes how it behaves: before the transition it follows individual gradients (and is unable to follow the global gradient), whereas after the transition it follows the global gradient (ignoring individual gradients). A system that transitions in this way must exhibit specific coordinated collective action to overcome the pull of the individual-level stress gradient, and in so doing will be able to move through the energy landscape to the global optimum unhindered².

Entraining lifecycles

Each unit, at a particular time t , has a phase, $\theta_{i(t)}$, that controls the timing of their decisions, i.e. the beginning of their lifecycle (Eq.1). Initial values are drawn randomly, uniformly in the range $\theta_{i(t=0)}$

¹ The utility of a unit is just the weighted sum of constraints acting on it (Watson, Mill, Buckley 2011a, 2011b) i.e. $U_{i(t)} = \sum_j^N c_{ij} s_{i(t)} s_{j(t)}$. It is Eq. 2 that determines the behaviour of units in our simulations but this is consistent with an individual utility-maximisation (or energy-minimisation) policy for discrete states. Likewise, the energy function, Eq. 4, is synonymous with the (negation of) total utility or the sum of individual utilities.

² Biological organisms often exhibit many levels of agency, but here we focus on a simple case of just one level of emergent agency to understand and clarify sufficient dynamics.

$=[0:2\pi]$. Each unit, i , has a learned connection, w_{ij} , with each other unit, j , which controls the change in θ_i (Equation 5). Each θ_i advances with each time step and also moves asymptotically toward each θ_j if the learned connection w_{ij} is sufficiently strong.

$$\theta_{i(t+1)} = \theta_{i(t)} + \varepsilon + \alpha \sum_j^N f(d) H(|w_{ij}| - p) \quad (\text{Eq. 5})$$

where $\varepsilon = 0.01$ is a constant time increment, $\alpha = 0.04$ is a constant controlling the rate of change, d is the angular difference between θ_i and θ_j , $f()$ is a function that controls the direction of the movement and how quickly synchronisation occurs (here we use $f(d) = \frac{d}{1+d^2}$), $H()$ is a Heaviside step function (as before), and p is a threshold value used to identify the stronger elements of the interaction matrix³.

The coupling values, initially zero, are updated according to Equation 6. This is a positive feedback on correlations, as discussed above. Over time, this has the effect that the connection between units i and j is increased in strength (magnitude) when the states are correlated (either often the same sign or often opposite signs).

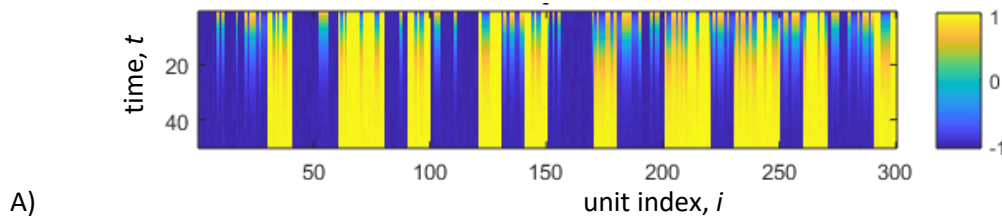
$$w_{ij(t+1)} = w_{ij(t)} + r s_i s_j \quad (\text{Eq. 6})$$

where $r = 2.5 \cdot 10^{-6}$ is a learning rate. If units have no, or unreliable, state correlation their connection will stay low in value and they will therefore not synchronise their timing, whereas units whose correlation or anti-correlation is reliable will develop strong coupling⁴ and thus increase the synchronisation of their lifecycles as per Equation 5. This does not attempt to model the synchronisation of weakly coupled oscillators in any detail, but it causes units with more strongly correlated states to become more in phase with each other over time.

Experiments and results

Basic dynamics of multiple coupled units (without entrainment)

Figure 5 illustrates the dynamics of interacting units according to Eq. 2 with the modular constraints defined by Eq. 3.



³ Specifically, $p = \min(|W|) + 0.7(\max(|W|) - \min(|W|))$, identifies elements in the top 30% of the magnitudes. The thresholded interaction matrix (i.e. after the application of the Heaviside function) is also normalised to sum to 1 (we speculate that this thresholding and normalising might be unnecessary if W is learned more slowly by reducing r).

⁴ Eq. 5 uses the highest magnitude values in W to adjust synchronisation. Eq. 5 can therefore only *increase* synchronisation. Increasing synchronisation is not the same as causing them be positively correlated, however. If the states were reliably anti-correlated because it was an anti-coordination game, then making them (positively) synchronise still has the effect of increasing sensitivity to their environment (and does not use foreknowledge of whether it is correlation or anti-correlation that maximises utility).

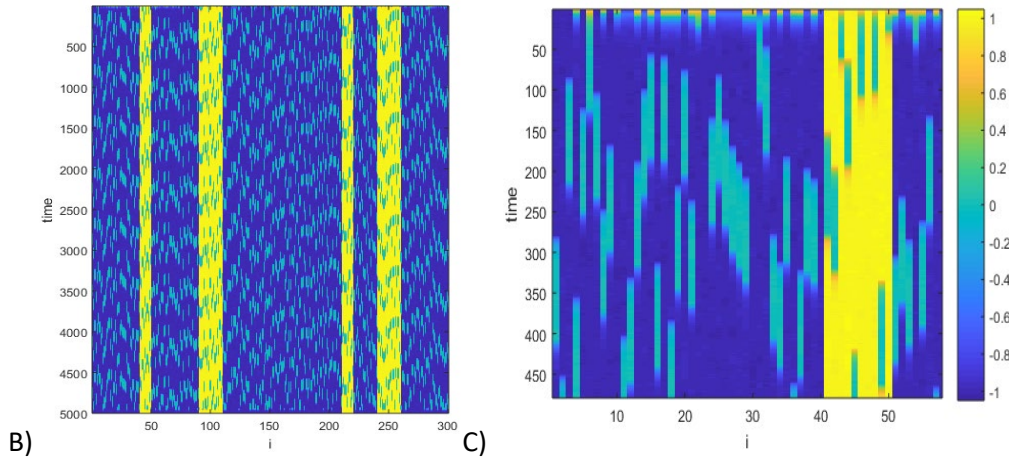


Figure 5. Simulation of 300 units with modular interaction constraints (no entrainment, no disturbances). A) 300 units simulated for 50 time steps from random initial conditions. Here only, for clarity, no degrowth periods are shown (i.e. τ_2 in Eq. 2 is permanently set to 0.1). Blue/yellow indicates the left/right decision of each unit, s_i . Blocks of 10 units in the same module quickly adopt the same convention, either 10-left or 10-right. (Note that there is no spatial proximity of units; we have drawn units in the same module with neighbouring indexes (Eq. 3) so that we can see the stripes of 10 units easily in these figures, but their positions could be shuffled without altering the dynamics of the system). B) 5000 time steps (including degrowth as per Eq. 2). C) An enlarged section of the top left corner, i.e. the first 60 units for the first 500 time steps. At this resolution we can see more clearly the light blue degrowth periods where the states of the units are decayed close to zero (Fig.3, Eq. 1), returning to their sensitive (undecided) states. Notice that (without synchronisation) although they decide many times they always re-make the same decision since the influence of their neighbours has not changed.

In Fig. 5 we see that the system falls to one of the 2^{30} possible attractor states, which are minima of Eq. 4. That is, each stripe of 10 units indicates that a subset of units has arrived at a configuration where they all agree with other units in the same module. But, in general, the likelihood that their decision agrees with some other module is approximately 0.5. Since there are 30 such modules, and 2^{30} minima, the probability of reaching the globally optimal attractor is very small (Watson, Buckley et al. 2011, Watson, Mills et al. 2011). In any one run of the system, the particular agreements between different pairs of countries will be arbitrary, depending on the random initial conditions. If, like the units, we did not know in advance which units were in the same country, we would not know from one run whether agreement between any two units was due to being in the same country or just a coincidental agreement between drivers in different countries. Indeed, we do not even know in advance that equal states are favoured over unequal states. Accordingly, one such trajectory tells us nothing about which units ‘go together’ (despite the visual stripes apparent in this rendering). However, if the system is repeatedly perturbed or shocked, e.g. such that the states of the system are effectively reinitialised after some interval, this will cause the system to visit a distribution of such local optima (Watson, Buckley et al. 2011). In Fig. 6.A, the states of the system (continuing from Fig. 5) are randomised every 5000 time steps (i.e. $s = \{-1, 1\}$ with equal probability, independently for each unit). The global optimum is not found in any of 50 episodes (i.e. a disturbance and following relaxation), but the distribution of attractors found reveals who depends on whom. It is this simple modular structure that is learned by the reinforcement of correlations, Eq. 6 (i.e., over multiple episodes, the entries in w will record strong correlations between units in the same module and weak correlations between units in different modules).

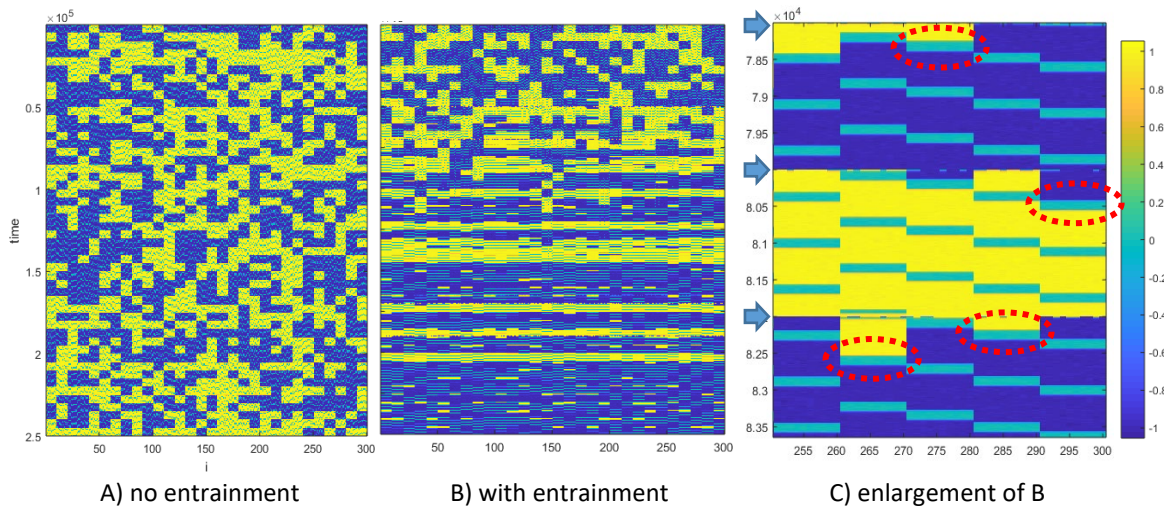


Figure 6. Multiple episodes with repeated disturbances, without and with entrainment. 300 units simulated for 50×5000 time steps with random disturbances every 5000 time steps. A) No entrainment. After each of the disturbances, the decisions of the units within each module may arrive at a different convention than that before each disturbance. However, since this is true for all the modules, the system is no more likely to find global resolution of constraints in any particular episode than in any other. B) With entrainment. Notice that at the start of the simulation the units are unable to coordinate between modules (as per A). However, after about 30 episodes, the system is fully coordinating all units in every episode (i.e. stripes are 300 units wide). C) A zoomed-in section late in the run of B, showing 50 of the units over three episodes. Arrows indicate disturbances/the beginning of a relaxation. Notice that the system still falls into stripes of 10 units very quickly, but a block is able to change its decision (some examples are circled in red), acting like a single macro-scale unit in responding to agree with the majority of other blocks.

Dynamics of coupled units with entrainment

In Fig. 6. B and C we show a simulation of the system utilising the synchronising effect (Eq. 5) organised by the learned connections (Eq. 6). This shows how the system organises itself bottom-up (i.e. without assuming any mechanisms of selection or reward above the level of individuals) in such a way that a specific collection of units becomes sensitive to and able to respond to its environment in a way that was not previously able (Fig.6.C, compared with Fig.5.C). Its behaviour is not just different, but more specifically a larger scale version of the original dynamics, i.e. before the transition, units responded and acted as individuals, after the transition, units respond as part of a single higher-level unit. That is, the collective makes a decision left/right in response to the pull of other collectives, just like an individual unit (before the transition) made a decision left/right in response to the pull of other individual units.

This collective action causes the units to move through configurations that would be opposed by uncoordinated individual changes in state. That is, when the members of the collective were changed one by one (or any less than half of them) they simply moved back to the local optimum (as shown in Fig.5.C). Nonetheless, the collective action facilitated by synchronising their lifecycles causes them to move to a state where all of them are less stressed – not just a different equilibrium, but a better one where more of the constraints between units are satisfied. In other words, they exhibit collective action that facilitates long-term collective benefit that was previously opposed by short-term self-interest. Fig. 7 shows the energy of the end-of-episode states visited in Fig. 6. This shows clearly how entrainment causes the system to find globally optimal states (Fig.6.C), not just locally optimal states (Fig.6.B).

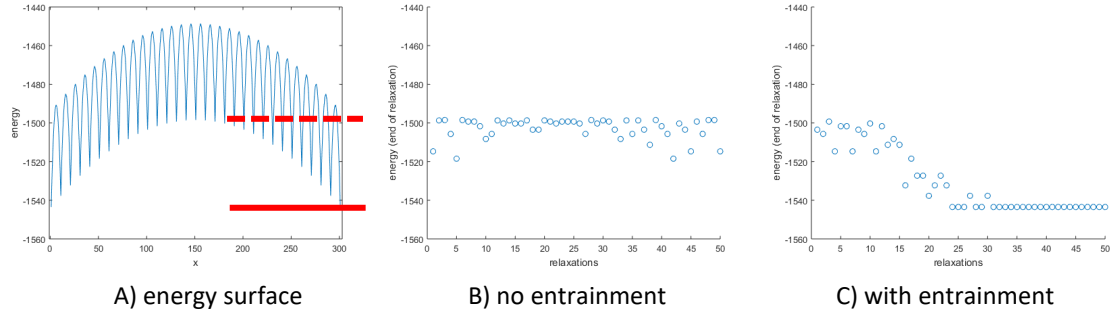


Figure 7: Energy surface of the system and energies of the attractors found without and with entrainment. A) A cross-section through the energy landscape (as per Fig. 4). The energy level of the most common local minima (where 50% of countries take one convention and 50% take the other) is indicated with a dotted red line. The energy level of the global minima is indicated with a solid red line. B) The energies that the system finds at the end of each episode (just before a disturbance) without entrainment (as per Fig. 6. A). C) The energies that the system finds with entrainment (as per Fig. 6. B and C). Notice that without self-organised synchronisation the system commonly finds the worst local optima (corresponding to the level of the dotted red line), and with self-organised synchronisation, after only about 30 episodes, the system finds only the globally best local optima in every episode.

We then test whether the energy minimisation behaviour is a result of organised and specific synchronisation or merely a result of increased synchronisation. Fig. 8.A shows the behaviour of the system when the synchronisation is system-wide, global across all the units in all the countries. This does not exhibit transitions or the increased energy minimisation behaviour.

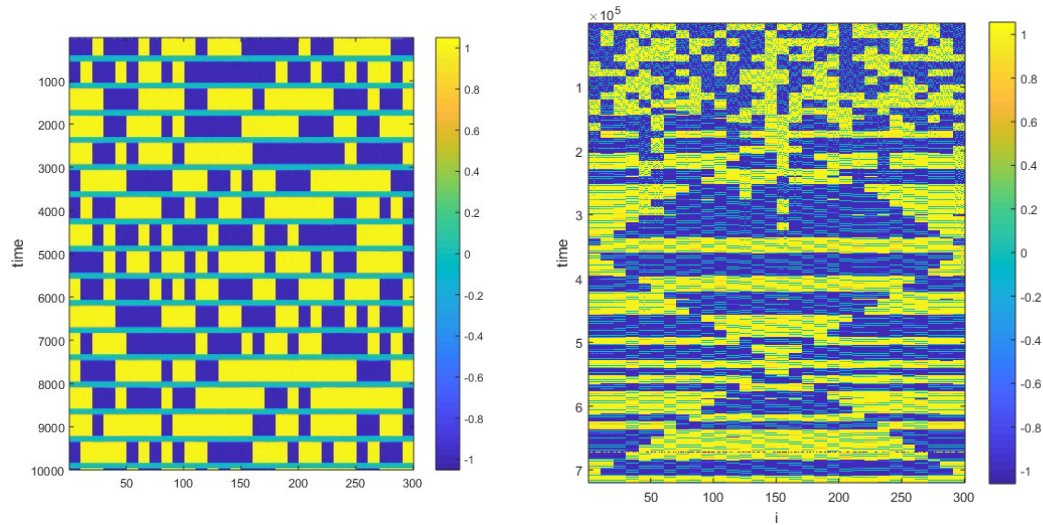


Figure 8: Global synchronisation does not facilitate global energy minimisation, specific synchronisation enables global energy minimisation in a sequence of different problems.

A) Behaviour of the system when the synchronisation is global, i.e. across all the units in all the countries (no self-organising entrainment). Note that this does not resolve conflicts between countries. Specifically-organised synchronisation is required to enable one country to respond to another. B) In contrast, the specifically structured synchronisation emerging from the positive feedback dynamics, results in agency that can not only find configurations of globally minimal energy, but can do so even in a 'moving target' problem. Specifically, the dynamics of the units with entrainment is exposed to a sequence of different environments (alternative constraint problems). Specifically, rather than a simple game of global coordination, the game used here rewards a middle section of countries for disagreeing with the remainder, and the size of the middle section increases and decreases over time. This shows that the modules can be identified from a non-stationary problem, so long as the within-module interactions are consistent, and

more importantly, they not only enable effective stress-reducing responses for the problem in which they originated, but for any problem based on these modules (i.e. that can be solved by following an energy gradient at the macro-scale). Notice that the 'waking-up' of modules as units that are able to respond is quite sudden (just before $t=2.10^5$).

In contrast, with entrainment, we note that the ability of the system to find the global optimum does not derive from having learned the specific location of the global optimum, or from learning that all units and all modules should be positively correlated. It has not learned the solution to one particular problem; rather, it has learned to solve *any* problem composed of the same modules. When higher-level agents have emerged, they can solve any problem that involves solutions made from combinations of these modular constraints (more exactly, by hill-climbing in modules). Accordingly, if the environment rewards a different combination of modules, or the problem changes over time, agents are able to respond appropriately, tracking a non-stationary problem (Fig. 8.B).

Discussion

The results show that a system of linked units, with a simple positive feedback mechanism affecting the timing of their activity, exhibits emergent collectives that show a transition in agency in the following sense:

- A new sensitivity/ability to respond: After the transition the collection of units has a new competency, an ability to respond to its environment, including others external to the collective, which was not previously available at that level of organisation.
- Goal-directed behaviour: This new sensitivity/response is not arbitrary; it moves systematically and specifically in the direction that increases long-term collective utility.
- A new level of behaviour over-ruling individual behaviours: Individuals are caused to change behaviour in a manner that opposes their (short-term) individual interest, with a specific collective action, that causes them to arrive at a state that better-satisfies (long-term) collective interest.

Consequently, the change in system behaviour passes our test for a transition: it has the quantitative consequence of changing from merely finding the nearest local optimum of the problem space to being able to find the global optimum (Fig.6.B; and the global optimum of any problem solvable by searching in different combinations of the same modules, Fig. 8.B).

Timing and the apparent paradox of agency

First, we discuss how this transition occurs with reference to the microscale dynamics only. Then we look at the apparently paradoxical conflict between micro- and macro-scale interpretations, and then offer some new ways of understanding.

Being sensitive to small influences (from the outside world) is the opposite of exerting strong forces (on the outside world). These are mutually exclusive; you cannot be both pushing hard and easily pushed, strong and labile, at the same time. When units are in the undecided sensitive state their influence on others is necessarily weak. When the units within a collective are disorganised, each (and every) unit is repeatedly pulled back from its sensitive state to agree with the strong influences acting on it from the other units that are not in their sensitive state. In contrast, when all the units within a collective are in their sensitive state at the same time, none of them is exerting strong forces on the others. In this moment, they each can be influenced by the weak forces external to the collective (of other units or collectives).

The units of a collective then lock-in this decision through mutual amplification of their states (just like the amplification of initially small influences in a single unit). This then makes the collective state strong enough to influence the decisions of other collectives. Note that one collective is responsive to another only if it is in the sensitive state when the other is not in the

sensitive state. This is why global synchronisation (i.e. all sensitive at the same time) does not produce the same result (Fig. 8.C) and the specific structure of the synchronisation delineates the identity of the higher-level agent.

At the macroscale, the collective moves from one local optimum to another following the macroscale energy gradient, even though all intermediate configurations have higher energy. The direction of change in these movements is goal-directed, i.e. arriving at configurations with lower collective stress. But if the behaviour of the collective can be traced entirely to the behaviour of its parts, how can the collective cause its components to do things that 'they don't want to do', i.e. increase stress in the short term, even if it is to reduce stress in the long term? True energy-minimisation processes do not go uphill but, at an intuitive level, this is exactly what is required for goal-directed behaviour, and this is what appears to happen. How do we make sense of this?

There are different ways to understand this. In a state dynamics way of thinking, synchronisation enables 'effectively simultaneous' action. It 'folds-away' the fine-resolution timescale where immediate individual influences are restrictive to individual actions, and effects a new dynamical timescale where mass influences cause discrete mass actions. Note that this is not the same as a continuous aggregate statistic over the fine scale; the average change in stress over the collective increases if it moves smoothly from one local optimum to another (this is what is plotted in Fig.4). Rather the effect of synchronisation is to cause movements that 'tunnel', or discretely 'jump', from one local optimum to another without spending any time at the higher energy points in between, changing many states within the short period when the agents are, so to speak, 'not looking'.

In terms of stress, a sensitivity to *external* stresses (and an ability to respond to them) is not possible when the stresses *inside* the collective are overwhelming due to their disorganisation. In contrast, when *internal* behaviours are synchronised, there is a moment when their effects on one another are momentarily suspended, all at the same time, and in this moment the system is exquisitely poised to be sensitive to and respond to the external stresses acting on it. In short, timing does not merely alter when you are sensitive and when you are not, but through coordination, it alters who you are sensitive to and who you are insensitive to. This synchronisation of behaviours within the collective, i.e. *inner alignment*, thus creates an ability to respond to external influences at a new level of organisation.

More formally, we can recognise that, as previously implied, the energy function described by Eq.4 (also Fig. 4) is not the full story. Specifically, it ignores the high-energy state occurring when a unit is reset to the saddle point. Ignoring this is reasonable when the behaviours of units are uncoordinated; local minimisation of Eq.4 *does* describe the behaviour of the units well when they are disorganised because the high-energy states are effectively lost in noise (Fig. 5). However, as their behaviour becomes synchronised, these high-energy states enable the units to escape from the apparent local optimum they are trapped in. Thus, properly understood, the behaviour of the system does not take it to states that are higher in energy, of course. By using units that have a lifecycle that repeatedly draws them back to a high-energy (undecided) saddle point, the problem becomes one that is less about overcoming energy gradients and more about *getting organised*. That is, when the timing of these high-energy states is uncoordinated and disorganised, it is essentially an entropic pressure that keeps the collective at the local minimum. The information needed for this organised action comes from the history of the system, i.e. from natural learning.

Learning: decentralised positive feedback on correlated behaviour

This model belongs to a family of models that build networks of relationships between components using simple positive feedback principles. In all cases, the organisation of the relationships is conditioned on the history of the system (Watson, Buckley et al. 2011) in a manner equivalent to unsupervised correlation learning (familiar in the context of learning neural networks) (Watson, Mills et al. 2016). The learning principles are the same in each case, and natural for adaptive networks of

various kinds, including gene-regulation networks, ecological networks, social networks and even networks of particles connected by springs (Watson, Buckley et al. 2010, Davies, Watson et al. 2011, Watson, Mills et al. 2011, Watson, Wagner et al. 2014, Power, Watson et al. 2015, Buckley and Watson 2022). In some cases these models are explicitly Hebbian (Hebb 1949), like Eq.6, in other cases, the same kind of change is produced by natural selection at the component level, or the natural differential easing of physical frustrations in viscoelastic materials, but in all cases, the effect is a positive feedback on correlations (Buckley and Watson 2022).

The models in this family differ primarily in the meaning or function of these relationships. In the “*rHN-s*” model (Watson, Buckley et al. 2011, Watson, Mills et al. 2011), relationships alter the *selection* of behaviours, or the energy landscape describing their dynamical paths. In “*rHN-g*” (Watson, Mills et al. 2011), relationships alter the behaviours that are *generated*, or the movements and macro-movements that are possible in the landscape. The unique feature of the current work (“*rHN-t*”), is that relationships alter the *timing* of behaviours. Whilst each of these models demonstrates system-level behaviours that arise spontaneously from changes to the organisation of relationships, *rHN-t* demonstrates a rescaling in its problem-solving ability using only microscale equations of motion, i.e. without presupposing a higher-level equation of motion. In particular, there is no selection among alternative macrostates, such as a higher-level selection or utility-maximisation process that compares or competes one collective with another.

The way that one module is caused to agree with another in the current work has the opposite intuition to some previous work. Specifically, it might seem unavoidable that, in order to cause the members of one module to agree with the members of another, it is necessary to increase learn which modules go together and increase the strength of learned interactions between modules until this overpowers the interactions within modules. This can be done but it is not easy to do, and as it turns out, not necessary. The interactions between modules are weak compared to the interactions within modules (by definition). This means that, although it is possible to observe some slightly positive correlation between units in different modules on average, in a problem with these parameters it takes many thousands of samples (episodes) to identify the sign of all interactions correctly (Watson, Buckley et al. 2011, Watson, Mills et al. 2011). It is thus very difficult to learn which modules go together - learning must proceed in small increments, so that many observations can be averaged, and for a long time, until eventually the initially strong interactions within blocks are overpowered. However, *rHN-g* showed that it is not necessary to learn which modules go together in this way (Watson, Mills et al. 2011). The blocks can put themselves together correctly by following the pull of the weak interactions between blocks, *so long as the pull of the interactions within blocks does not prevent this* (Watson, Mills et al. 2011). Put differently, although it is necessary to increase the ratio of inter-module to intra-module interaction magnitudes, this can be done by *decreasing* intra-module frustrations (even if momentarily) rather than by *increasing* inter-module interactions. Furthermore, it is much easier to modify the strength of interactions *within* modules because the signal from correlated behaviours within modules is much stronger and easier to learn than the signal from correlated behaviours between modules. Hence *rHN-t* has not learned which modules go together – it has not learned the specific location of the global optimum. But, it has learned *the competency to find* the global optimum after only 30 episodes. *rHN-g* learned within-module correlations and then used this to apply explicit macrostate changes, comparing the energy of one macro-state change to another. *rHN-t* is the first model to achieve the same result using only a microscale equation of motion. This is significant for understanding evolutionary transitions in individuality because a bottom-up process cannot presuppose a higher-level selection mechanism.

Significance for evolutionary transitions in individuality

The main problem with understanding evolutionary transitions in individuality is the conceptual switch from comparing the fitness of individuals to comparing the fitness of collectives (a.k.a. fitness-1 vs fitness-2 (Okasha 2006)). How does the collective become a thing that has a fitness? How does it become a salient variable? Our model demonstrates how, using only a microscale equation of motion, it is possible for a macroscale unit to emerge.

The emphasis on intra-module correlations (rather than inter-module) is also biologically meaningful. Managing internal conflict, e.g. equalising internal fitnesses, is characteristic of evolutionary transitions (Okasha 2006, Godfrey-Smith 2009, Clarke 2016, Watson, Levin et al. 2022). By similar reasoning as above, it might be easier and more likely, at least initially, that selection acts mainly to reduce the stress between internal components than to find ways to capitalise on external fitness interactions that are weaker and less predictable (see also robustness vs innovation in evolvability (Watson 2021)).

The emphasis on timing alleviates another problem. Namely, why would individuals evolve relationships that enable them to work together if doing so caused them to do things they didn't want to do? Whilst it might be tempting to appeal to the long-term collective benefit of collective action to explain such organised relationships, remember that the collective is not a thing that has a fitness until *after* the transition, and relationships that cause only partial changes in behaviour are worse than none (to the individual and to the collective). A focus on timing alleviates this because, before the transition, changing the timing of behaviours does not actually change the behavioural states at all, and therefore carries no fitness cost. Yet, when the units are in synch with each other, they can all change behaviour at the same time, providing a fitness benefit to all. Thus changes to timing provide evolutionary intermediates toward a transition in individuality that are at least *non-decreasing* in fitness. These changes can then be favoured by selection for a different more subtle reason but immediate reason, e.g. because they decrease internal stresses, rather than because they will enable collective action in the future.

So how is such timing biologically relevant (both to stress in the short term and to individuality in the long term)? Behavioural synchronisation is common across many biological systems including synchronisation in development (e.g. of cell-cycles in early embryogenesis, multicellular lifecycles characterised by periodic growth from a propagule or single-celled population bottleneck, and coordinated cell differentiation from an undifferentiated embryonic cell mass) (Godfrey-Smith 2009). Pulses of activity and inactivity are also found in many complex systems exhibiting interesting collective behaviours, from brains, to slime moulds, to hearts, to ant colonies (Bonabeau, Dorigo et al. 1999, Bar-Yam 2002, Noble 2002). Intuitively, having a developmental process that repeatedly transforms a mass of undifferentiated embryonic cells into a differentiated adult phenotype is an intrinsic part of what distinguishes an organism from an ecology of individual cells (Watson, Levin et al. 2022). And the consequence of the complex functional interactions that play-out in this process is likewise intrinsic to what distinguishes an evolutionary unit from a population (Godfrey-Smith 2009, Watson, Levin et al. 2022). Reproductive synchronisation in particular (e.g. synchronised flowering, spawning, mating, etc.) is common in many organisms and fundamental to the equalisation of within-collective fitness characteristic of evolutionary transitions (Satake and Iwasa 2000).

The reasons for synchronisation to be favoured could be various, e.g. reduced predation or increased mating rates. But we speculate that it may be related to a more general principle of self-organisation such as a principle of 'least rattling' (Chvykov, Berrueta et al. 2021). That is, changes to organisation that increase the influence of high-energy states on further reorganisation tend to change (again), whereas changes to organisation that decrease the influence of high-energy states

on further reorganisation tend to be retained. From the point of view of individual cell fitness, if we imagine that anything interfering with the timing of the cell cycle causes stress, then a trait that makes reproductive timing aligned with that of others allows a cell to coordinate its sensitive period with a moment when others influence it less, reducing the stress it experiences.

These observations suggest some interesting implications for the significance of developmental processes to evolutionary transitions in individuality. It is common that in multicellular lifecycles, cells of the initial developing embryo are all in the undifferentiated pluripotent state at the same time (otherwise we might identify such growth as budding or regeneration rather than organismal development). In this state, the organism is exquisitely poised at a saddle point in its developmental dynamics – able to differentiate in different ways responsive to local context (e.g. deciding the handedness of a limb bud). This is evolutionarily significant because it also changes the kind of effect that genetic mutations can have, e.g. affecting which phenotypic attractor is attained. Accordingly, a synchronised developmental process moves the phenotypic response to genetic changes, and hence selective response, to a higher level of organisation, i.e. it rescales the evolutionary unit. This type of developmental synchronisation could therefore be necessary (though perhaps not sufficient (Watson, Levin et al. 2022)) for an evolutionary transition in individuality.

Lastly, if a specific synchronisation structure that is favoured by selection in the short term, e.g. for reasons of internal stress reduction, happens to be the same as the specific synchronisation structure that is needed for a transition in individuality in the long term, e.g. facilitating a benefit from collective action, is this merely fortuitous happenstance? This apparent disconnect between short-term and long-term selective advantages also arises elsewhere in evolutionary thinking; notably, in the evolution of evolvability (Watson 2021). We suggest that a resolution is available through the conceptual expansion of adaptive processes to include inductive (learning) processes as well as selective processes (Watson, Mills et al. 2016, Watson and Szathmary 2016, Buckley and Watson 2022). Learning systems do not change their model of the world (e.g. the connections in an artificial neural network) because doing so will, at some point in the future, enable them to correctly generalise to some as-yet-unencountered problem or input. Nonetheless, it is not a coincidence that changes to a model that improve the fit to past experience also enable learning systems to generalise correctly to previously unseen future experiences (Kounios, Clune et al. 2016, Kouvaris, Clune et al. 2017, Watson 2021). The underlying ‘common cause’ is that the correlations in behaviours (observable over multiple episodes) and the connections needed to facilitate a transition in agency both depend on the same underlying constraint structure intrinsic to the problem (Watson 2021). It is therefore not a coincidence that the interactions with the most stress are the same interactions that, when alleviated, enable higher-level responsiveness.

Doing without choice

Agential behaviour is often associated with a notion of choice (Barlas and Obhi 2013) – as though a system *could have done otherwise*. This introduces notions of ‘deliberating’ among future possibilities, such as explicitly enumerating alternatives and selecting among them (Campbell 1983). A classical *argmax* model of a utility-maximising agent, for example, is an explicit enumeration of possible actions and their consequences. Likewise, in a natural selection process, an entity is duplicated with variation, developed and the phenotypic outcomes naturally subject to differential survival and reproduction. We specifically wanted to exclude a mechanism of explicit deliberation in this study. We refer to the units we model (Fig. 2) as deciding on an action, but clearly there is no sense in which a ball rolling downhill could have done otherwise. This exclusion seems necessary; a mechanistic model of agency is one that utilises only a microscale equation of motion and explicitly does without an explicit process that compares the fitness or utility of one macrostate to another. Nowhere in our model is there any enumeration of future possible states or comparison between them.

Whilst a process that enumerates possibilities and selects among them can be physicalized in principle (e.g. evolution by natural selection is not unphysical), making the *assumption* that such a process applies would preclude any possibility of explaining how such a process originated. In other words, we wanted to show how something that appears to be ‘deliberate’ (i.e. a movement toward a specific long-term outcome) can arise without presupposing a deliberative process. Accordingly, it was critical that no such process was presupposed at either the individual or collective level (and this is why we started with the Newtonian model of a primitive decider). Nonetheless, although we helped ourselves to a dynamical unit that appears deliberate, the point is that, before the transition, this is something that a collective cannot do. But after the transition, a particular subset of units becomes an analogue of a primitive unit at a higher-level of organisation. It also does not deliberate – it does not consider the local optima on either side and choose between them. It simply rolls downhill – in the macroscale energy landscape (broken red curve, Fig. 4) instead of the microscale energy landscape (solid red curve, Fig. 4). This has outcomes equivalent to equilibrium selection, but without assuming a higher-level selection process.

Toward more sophisticated agents

A limitation of the model is that there is no sense of an agent that maintains its boundaries or physical integrity in space, an internal metabolism or any complex behavioural repertoire. The new level of agency also has no internal computation or information integration – each unit continues to respond independently to units outside the collective and receives no inputs from other members. Although this is limited as a model of agency, this is a point of interest in this model. That is, they work together, not because they receive useful inputs from one another, but because they stop receiving interfering inputs from one another. Nonetheless, the coherence of their response is dependent on the fact that they all see the same external environment. If, in some other scenario, their experiences of the external context were localised or otherwise different, coherent collective action would at least require internal communication, and/or internal information integration (Watson, Levin et al. 2022). Perhaps, though, these sorts of refinements first require a change in the level of agency or selection provided by the sort of collective benefit demonstrated here.

Lastly, some cross-disciplinary connections with more sophisticated and familiar agents, ourselves, are intriguing, if one is that way inclined. Specifically, the idea that, in order to be responsive to one’s environment, including the needs of others, it is first necessary to find a stillness that *quiets the inner chatter* is broadly familiar in the teachings of the ancient Eastern wisdom traditions such as yogic philosophy (Stone 2018, Lent 2021). Non-attachment to ego, or to one’s own internal history, is necessary if you want to be responsive to the outside world. In other words, being able to make a decision or take a choice that is appropriately sensitive to one’s environment, requires being poised in a suitably sensitive state. If our internal milieu is disorganised, this is more difficult to attain, and we are less able to respond to the world around us, including others. Practices of meditation, posture and breath are understood to support this. Perhaps, at a suitable level of abstraction, these concepts of personal realisation and the mechanistic principles of agency modelled here share some common ground.

Conclusions

We presented a simple abstract model of a transition in agency. The inner workings of the model can be described at the microscale in a reductionist way that finds only parts in interaction with other parts. Because of this, the model helps us to think about the general problem of such transitions in new ways. First, we avoid the notion of any special scale or minimal level of sophistication where agency originates from non-agential components. Instead we focus on the conditions where a very simple agential competency, deciding among actions to maximise individual utility or minimise stress, arises at the collective level. Second, we can quantifiably detect the consequences of such a transition by an increased ability to minimise total stress or a problem-solving competency at a new

scale. We demonstrate that this involves a collective action that moves against individual utility in the short term in order to arrive at improved collective utility in the long term; i.e. apparently goal-directed behaviour. Third, we provide a specific mechanism of spontaneous lifecycle synchronisation that produces this transition.

More importantly, the model helps us think about the apparent contradictions involved in such transitions and suggests that changes to timing might be a key mechanism to mediate between micro- and macro-scale processes. In particular, the higher-level agent is not a variable in any of our equations of motion, and in this sense is causally redundant. On the other hand, the behaviour of the microscale components in one organisation (before the transition) is non-mysteriously different from their behaviour in another organisation (after the transition). More specifically, the behaviour after the transition is not just arbitrarily different but affords this apparently goal-directed behaviour. This is possible because the organisation of the relationships between the components after the transition has learned something about the structure of their constraints, i.e. which units have had reliably coordinated state changes in the history of the system (Watson, Buckley et al. 2011). It is this learned information, acquired bottom-up through natural distributed processes (without an external teacher or higher-level selection process), which enables a collective to overcome the apparent energy barrier created by disorganised internal behaviour. By differentially synchronising the timing of primitive units, they create effectively instantaneous collective action that ‘tunnels’ through the high-energy barriers. We suggest that this principle of spontaneous synchronisation has some alignment with properties common to developmental processes and their effects on evolutionary individuality.

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