Complex Systems

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Abstract

This entry describes key concepts and features of complex systems, including emergence, self-organization, feedbacks, nonlinearity, sensitivity to initial conditions, critical or edge-of-chaos dynamics, symmetry breaking, resilience, as well as adaptation and evolution. It briefly introduces a few contemporary cross-disciplinary methodologies in the overlap of physics, computational and life sciences, such as agent-based models, dynamical systems, analysis of order/disorder phase transitions, information dynamics and information thermodynamics, guided self-organization and complex networks. A number of biological and ecological examples are used to illustrate the concepts and modelling techniques across a wide range of systems, from gene regulatory networks to ant colonies to food webs. The examples cover collective behaviors, information cascades, optimal path formation, stigmergy, predator–prey interactions, and tipping points in climate and ecosystems. Three information-processing components (memory, communications and modifications) are placed in the context of system ecology, drawing parallels with ecological memory, ecological interactions and ecological modifications. The entry concludes with a comparison between complex and complicated systems, drawing a distinction in the ways that adaptive and engineered systems achieve stability in the face of external perturbations.

Introduction

A complex system typically contains a large number of individual components (often referred to as agents) that interact with each other and the surrounding environment. The number of agents is usually sufficiently large so that no specific feature controls or dominates the overall dynamics of the system, but not large enough to make individual features completely irrelevant. The agent interactions follow simple rules dependent on the agents' perceptions of their local conditions. For example, pheromone-depositing ants foraging for food indirectly interact with each other through their environment. The ants employ a form of autocatalytic behaviour called allelomimesis: the probability with which an ant chooses a trail, and therefore, deposits new pheromone there, increases with the number of ants that chose the same path in the past. As more ants, attracted by the pheromone, cross the same area and lay more pheromones, making the `chemical' path even more attractive. As pheromone slowly evaporates, shorter paths, which keep being reinforced by attracted ants, become more prominent than longer ones, and an optimal path emerges. The process is thus characterized by (i) positive feedback loops, making shorter paths stronger in terms of the deposited pheromone, and (ii) nonlinear dynamics of the pheromone concentration, which is increasing with the number of ants traversing the formed paths and decreasing due to the chemical's natural evaporation. Feedback loops and nonlinear dynamics are two other common features of complexity.

A variant of complex systems is complex adaptive systems (CAS), in which the agents adapt or learn during their interactions. Holland (2006) defined four distinguishing attributes of CAS: (i) parallelism: a large number of simultaneously interacting agents exchange signals concurrently (for example, the reaction cascades and cycles within biological cells are continually coordinated in order to ensure that a cell maintains its functions); (ii) conditional action: the agents' actions depend on the received signals or other local perceptions, constructing flexible behaviors that involve intricate positive and negative feedbacks; (iii) modularity: an agent's behaviour often includes different groups of rules, acting as `subroutines' or building blocks, that can be recombined to respond to novel situations; the usefulness of such modules may be confirmed or disconfirmed based on their success in dealing with the challenging circumstances (for example, the Krebs cycle — the citric acid cycle in biological cells, which incorporates 8 proteins that interact to form a loop — is a basic series of chemical reactions used to release stored energy by all aerobic organisms, ranging from bacteria to elephants); (iv) adaptation and evolution: the agents adapt in order to improve their performance over time (the adaptations, that can be structural, behavioural and physiological, help organisms survive in their ecological niche or habitat, for instance, the chameleon camouflage, birds migrations and the snakes ability to make venom).

Adaptive behavior can take many forms. One important example is homeostasis: a dynamic process of self-regulation and adaptation by which an overall system or individual agents adapt their behavior over time in order to stay close to a certain state (or a set of states). Homeostatic behavior is related to Ashby's Law of Requisite Variety which states that in order to maintain a dynamic stability under perturbation (or input), an active controller requires as much variety (the number of states) as that of the controlled system. In other words, the greater the variety within the system, the more resilient it is.

Turning our attention to the interaction aspect of complexity, we point out that the agents may interact not only with each other but also with the surrounding environment. This may play an important role in sustaining or maintaining its ecosystem, for example, bees pollinate flowers, facilitating the production of fruits or seeds. Such agent–environment interactions may have both positive and negative feedback loops, and typically create nonlinear dynamics.

There are also examples of interacting sub-systems such as predator–prey interactions which shape an integrated ecosystem. Predator–prey models, for example, the well-known Lotka–Volterra model, include a pair of coupled differential equations that describe the dynamics of two populations, one of which (the predator) grows at the expense of the other one (the prey). Under some simplifying assumptions, these models are able to demonstrate the coupled dynamics which are characterized by (i) oscillations in the population sizes of both predator and prey, and (ii) a time lag between the prey and predator abundances: the peak of the predator's oscillation follows the peak of the prey's oscillation. However, as predators consume the prey, the prey's abundance greatly diminishes causing the predator population to reduce. This eventually removes immediate threats to the prey, swinging its population up and resetting the coupled cycles. From the evolutionary perspective, predators and prey can influence one another's evolution, and such co-evolution need to be modelled on longer (slower) time scales than the dynamics of population sizes.

The `mass-action' models, such as the Lotka–Volterra model, have a broad range. They can describe chemical reactions, as well as the compartmental models of disease spread in mathematical epidemiology, in which the population is split into different compartments, such as susceptible to the infection; infected; recovered, and so on, interacting with each other over time. The `mass-action' models conceptually differ from agent-based models which are more applicable to studies of complex systems. The agent-based models attempt to explicitly represent behaviors of individual agents and their local interactions, including their short-term adaptations and the long-term evolutionary changes, and so the resultant global dynamics are not specified directly, for example, by some differential equations, but are expected to emerge.

Emergence

In general, the global dynamics of a complex system which result from the agents' interactions are emergent: they cannot be predicted, or explained, as an aggregation of the agents' individual dynamics. In other words, the interactions among the constituent microscopic parts (at the bottom level) bring about macroscopic phenomena (at the top level) that cannot be understood by considering any single part alone. These macroscopic features often display synergy (`the whole is more than the sum of the parts'). Continuing with the ant colony example, we note that an optimal path, or a network of paths, connecting the colony nest with food sources, emerges as a result of the pheromone-depositing ants navigating around various obstacles present in the environment. The result of this distributed process cannot be reduced to the local actions. In other words, the optimal path is an emergent property of the distributed behaviour of the ants, constrained by the locations and shapes of the obstacles.

Another example of emergent behavior is given by swarms of animals. Animal groups in nature often exhibit spatial aggregation, for example, schools of fish, swarms of locusts, herds of wildebeest, and flocks of birds (Parrish and Edelstein-Keshet, 1999). Such aggregations may provide individuals with protection, mate choices, foraging, habitat assessment, migratory routes, etc. (Camazine et al., 2001). Being a typical case of complex systems, an aggregated flocking behavior results from the local behaviours of individual birds which try to stay in close proximity, while avoiding collisions and flying in the same general direction. Again we point out that complex large-scale patterns and structures emerge within swarms and flocks through individual decisions, based on perception of the individuals' local conditions. Interestingly, these local perceptions propagate through the collective as waves or cascades. Formation of signalling waves is a widespread phenomenon observed in animal groups, rapidly transferring information over long ranges (Potts, 1984). Information cascades in collective systems often create a positive feedback loop, due to a rapid autocatalytic response to changing conditions. This heightened adaptive response allows the group to be sensitive even to weak or ambiguous external stimuli.

Emergent behaviour is related to tangled hierarchies exhibiting Strange Loops (Hofstadter, 1989):

> `an interaction between levels in which the top level reaches back down towards the bottom level and influences it, while at the same time being itself determined by the bottom level.'

Emergence is often confused with self-organization and the primary difference between these two concepts lies in their relation to the levels of system. While feedback loops are possible both within

and across the levels of the system, it is important to distinguish between (i) emergence, which assumes another level of description where the emergent properties can be used for better predictions by an external observer, and (ii) self-organization which occurs within a complex system, that is, within one level, affecting the functioning of the system itself (Prokopenko et al., 2009).

Self-organization

Self-organization is typically defined as the evolution of a system into an organized form in the absence of external pressures explicitly guiding the local behavior of the sub-systems. For example, an eco-system may develop spatial structures in order to deal with diminishing resources. The prefix `self' should not be taken literally: it only indicates the absence of centralized ordering or explicitly defined external template prescribing the internal dynamics. In general, we deal with open systems, exchanging energy, matter and/or information with the surrounding environment, and assume that the systems contain components and constraints which are defined prior to the organization itself (Prokopenko et al., 2009). Camazine et al. (2001) offered the following definition in the context of pattern formation in biological systems:

> `Self-organization is a process in which pattern at the global level of a system emerges solely from numerous interactions among the lower-level components of the system. Moreover, the rules specifying interactions among the system's components are executed using only local information, without reference to the global pattern.'

Another definition is offered by Haken (2006) from a more generic perspective:

> `A system is self-organizing if it acquires a spatial, temporal, or functional structure without specific interference from the outside. By `specific' we mean that the structure or functioning is not impressed on the system but that the system is acted upon from the outside in a non-specific fashion. For instance, the fluid which forms hexagons is heated from below in an entirely uniform fashion and it acquires its specific structure by self-organization.'

This physics-based view is related to the approach pioneered by Kauffman (2000) who suggested that the underlying principle of self-organization is the generation of constraints in the release of energy. According to this standpoint, the constrained release allows for such energy to be controlled and channelled to perform some useful work. This work in turn can be used to build better and more efficient constraints for the release of further energy and so on. The ability to constrain and control the release of energy may allow a system to produce behaviors which, although possible, would be extremely unlikely in its non-organized state (Kauffman, 2000; Prokopenko et al., 2009).

An interesting form of self-organization is stigmergy. Grassé (1959) introduced the term `stigmergy' (`previous work directs and triggers new building actions') to describe a decentralised pathway of information flow in social insects. Stigmergy is a mechanism of indirect coordination among agents acting in the environment, where local traces left in the environment by their decentralized actions stimulate the performance of subsequent actions, by the same or a different agent (which is exactly the case of pheromone-depositing ants). Thus, stigmergy allows the environment to structure itself through the activities: the state of the environment, and the current distribution of agents within it,

determine how the environment and the distribution of agents will change in the future (Bonabeau et al., 1998). Emphasizing the role of constraints in controlling the release of energy within a self-organizing system, we point out that an optimal path formation may happen by chance even with a random exploration of the landscape, but is much more likely when stigmergy is present.

One of the modern research themes in complex systems is Guided Self-Organisation (GSO). The main objective of GSO is to leverage the strengths of self-organization (such as simplicity of the local behaviors, parallelization, adaptability of the agents, robustness, resilience and scalability of the overall system), while still being able to direct the outcomes of the self-organizing process. In other words, GSO approaches differentiate between the concepts of `control' and `constraint': rather than trying to precisely control a transition towards the desirable outcomes, one puts in place specific constraints on the system dynamics in order to mediate agent behaviors, interactions and adaptations. Thermodynamically, a spontaneous increase in order within a self-organizing complex system must be offset by a production and export of entropy to the external environment. Thus, GSO attempts to harness the order-inducing potential of self-organization by guiding the system towards a desired regime or state, while `exporting' the entropy to the system's exterior.

Critical dynamics

Self-organization, and complexity in general, is strongly related to critical phenomena: the spatiotemporal behaviour of dynamical systems at an order/disorder phase transition: the critical regime separating the two phases is often referred to as the `edge of chaos'.

A system is said to exhibit the property of chaos if a slight change in the initial conditions results in large-scale but bounded differences in the result (in other words, the system is sensitive to initial conditions; such outcomes are often referred to as the butterfly effect). Importantly, there are transitions separating ordered and chaotic regimes, and by varying control parameters (for instance, the system composition and the strength of internal interactions) it is possible to trigger these phase transitions. Following Ginzburg-Landau theory of phase transitions developed in physics, Haken (2006) introduced order parameters in explaining structures that spontaneously self-organize in nature. In an ordered phase, the system becomes low-dimensional as some dominant variables `enslave' others, making the whole system act in synchrony (for example, a laser: a beam of coherent light created out of the chaotic movement of particles).

Phase transitions are often related to symmetry breaking. An example is a ferromagnetic system undergoing a second-order phase transition: (i) in the high-temperature phase the system has no net magnetization, is `disordered' and has a complete rotational symmetry (isotropy); (ii) at low temperature, the system becomes `ordered', and the net magnetization defines a preferred direction in space (anisotropy), breaking rotational symmetry. The low-temperature ordered phase is therefore less symmetrical and can be fully described by an order parameter — the magnetization vector. In this example, the temperature is a control parameter. But in a large complex ecological system, temperature can also be an order parameter, summarizing the effect of the sun, air pressure, and other atmospheric variables.

A well-studied model in the field of complex systems — random Boolean networks, used to simulate Gene Regulatory Networks — also exhibits a phase transition between ordered and chaotic dynamics, separated by a critical regime. The nodes of a random Boolean network may approximate interconnected genes with binary states, which switch on and off dependent on the input signals received along the network links from the connected neighbours. The `logic' of switching the nodes states on and off mimics the process of gene expression, and one of the main questions is whether the overall network, starting from a particular state or responding to a local perturbation, settles into a stable configuration, or keeps changing. A fundamental result is that, at relatively low connectivity (that is, a low average number of network links) or dynamic activity (that is, an extremely biased probability of state changes to either zero or one), a perturbed network remains in an ordered stable phase. This phase is characterised by high regularity of states and strong convergence of similar global states in state space, providing an analogue of high stability of the genotype. Alternatively, at relatively high connectivity and/or activity, the network never settles and ends up in a chaotic phase, characterised by low regularity of states and divergence of similar global states: an analogue of high adaptability of the genotype. In the critical regime (the edge of chaos), there is a balance between stability and adaptability.

A generic measure that has been found useful in studies of critical dynamics in complex systems is Fisher information. It quantifies the amount of information in an observable variable about a control parameter, and thus estimates sensitivity of the observed variable to changes in this parameter. Thermodynamically, Fisher information is proportional to the gradient of the corresponding order parameter, diverging when the system undergoes a phase transition at a critical point. Calculating this measure requires only appropriately defined probability densities and so the method can be applied to a wide range of systems, especially those in which computation of the order parameter is problematic.

Critical regimes are typical in proximity of various tipping points, occurring when a small change (or a number of previously accumulated changes) triggers a strong or even catastrophic response, amplified by positive feedbacks (Scheffer et al., 2009), for example, tipping points in climate and ecosystems such as the Amazon rainforest `die-back' and El Niño/Southern Oscillation effect. An example of a positive feedback intensifying the effects of the initial perturbation is a loop moving from deforestation reducing regional precipitation to increasing risk of fires to extending forest die-back to causing droughts.

Even robust and homeostatic systems may not withstand pressures accumulated in the lead up to a tipping point. A transition beyond a tipping point may be irreversible, but if the system which has undergone the transition is adaptive, then it may recover, and the speed of the recovery is dependent on the system's resilience. Resilience, thus, is the capacity of systems to survive and adapt despite acute shocks and chronic stresses they experience — it captures the ability to pull together and bounce back after a crisis. Resilience is directly related to self-organization, reflecting the degree to which a complex adaptive system is capable of self-organization while absorbing recurrent disturbances such as hurricanes or floods and retaining essential structures, processes, and feedbacks (Adger et al., 2005).

Entropy and Information in adaptation and evolution

Complex systems can also be viewed as distributed information-processing systems, with information being a crucial currency for animals and species from both a behavioural and evolutionary perspective. Behaviourally, many decisions benefit from a reduction in uncertainty: a school of fish reshapes to evade a predator, slime mould parallelizes its search for food, animals optimize their assortative mating choices, and so on.

Shannon entropy is a measure of potential knowledge, or if applied to a sequence, a measure of how much information a sequence could hold. For example, as argued by Adami (2002), Shannon entropy may quantify our uncertainty about the genetic identity of a randomly selected individual. Shannon information is a nonlinear form of correlation, with respect to the system that the information is about. Without such reference, it is only potential information (that is, entropy).

Following information-theoretic interpretation of Adami (2002), adaptation may then be seen to increase mutual (Shannon) information between a system and its environment. From this standpoint, the variation decreases the amount of information encoded in the system, whereas the selection acts to increase the information. The information loss due to variation must be less than the increase in mutual information due to selection. Assuming that the generations are coupled by inheritance with variation under selective pressure, the adaptive process reduces to evolution. In general, the evolution should increase the amount of information which a population (more precisely, its genome) contains about its niche, measured by `physical complexity' (Adami, 2002).

A similar idea about the relevant biological information is expressed by Haken (2006): the information `acquires its meaning only with respect to the surroundings and, in a way, with respect to its value for the survival of the whole species'. Haken (2006) concludes that

> `by the interplay of mutation and selection new types of molecules and their corresponding phenotypes are then generated and in this way we observe the creation of new information. But whether this information is useful or not can be checked upon only by the interaction of the particular species with its environment.'

In general, the increase in organization can be measured quantitatively as a decrease of Shannon entropy, exported by the self-organizing system into its surroundings (sometimes referred to as negentropy: the entropy that the system dissipates to keep its own entropy low.). The systems which continuously export entropy in order to maintain their organization are called dissipative structures.

A recently developed framework of information dynamics systematically quantifies information processing in complex systems (Lizier et al., 2014), relating it to critical phenomena and phase transitions. This methodology suggests that discovering and quantifying information flows in complex systems could be a key to guiding the system dynamics towards desirable outcomes. Importantly, rather than trying to quantify the level of system's complexity with a single general-purpose measure, the information dynamics framework includes several dimensions, capturing different aspects of distributed processing within the system: memory, communications

(interactions) and modifications. Memory refers to the storage of information by some agent(s) and can affect the future computation. Communication is understood as the transfer of information between one agent and another. Modification is the fusion of stored and/or transferred information into a new form. Within the space formed by these basic axes, the complexity of different systems may be measured and compared in terms of their specific components.

These three information-processing components originate in the field of distributed computation, but have been identified in many complex systems, ranging from natural to technological, where a system is seen as `computing' when it updates its states while moving along a global dynamic trajectory. For example, `ecological memory' can be seen in the biological legacies persisting after tipping points, various crises and disturbances, through mobile species and propagules that colonize and reorganize disturbed sites and refuges (Adger et al., 2005). The aspect of `ecological interactions' between species reflects diverse dependencies in ecological communities and food webs, exemplified by oppositional relationships such as predation and competition, as well as symbiotic relationships such as mutualism. Finally, `ecological modifications' are immediately evident in agricultural expansions and intensifications altering the quantity and quality of global water flows, deforestations or plant successions replacing forests with tundra, and ecological niche constructions, when organisms alter either their own environment or that of other species.

The concept of information modification is strongly related to the notion of synergy. Understanding and quantifying synergy, as well as modelling of critical phenomena, require a systematic consideration of system dynamics from a thermodynamic perspective which elucidates the analysis of phase transitions and synergistic interactions. Information thermodynamics is an emergent field of research attempting to treat dynamics of complex systems, while measuring and contrasting the entropic and energetic costs of manipulating information.

Complex networks

Sometimes, a complex system is modelled as a network where the nodes represent the components and the links their interactions. Network topology is the specific type of an arrangement of the nodes and edges, for example, a star topology, in which each node (vertex) is connected to a central hub with a node-to-node link (edge), or a random graph topology, which is generated by a probability distribution, so that a possible link occurs independently with a given probability. Network representations create the possibility of studying phenomena at multiple scales under the same formalism, relating topological and dynamics properties.

In models of complex networks it is possible to study various propagation, diffusion or contagion processes, when a single event or disruption triggers a cascade of failures. For example, the emergence of a new pathogen in a remote village can give rise to a devastating global epidemic; the introduction of an exotic new species can eventually contribute to a chain of food-web disruptions and wide ecosystem collapses.

In complex networks, the ability to function effectively arises not from individual network nodes, but rather from the way they interact. This means that a complex network, like any complex system, cannot be completely understood by examining each of its parts in isolation. Specifically, for

complex networks, the topology and function of such networks are tightly coupled (Newman, 2003): the function is constrained by the structure and the structure evolves due to function. Research into the structure, function, evolution, and design of complex networks has wide-ranging applications, from epidemiological modelling to understanding of food webs.

In a food-web network the nodes represent species in an ecosystem and a directed link indicates that one species preys on the other. This implicitly captures the flow of energy or carbon flow within the system, in the direction opposite to predation. As the structure of a food web typically affects the population dynamics, considering a network representation enhances the canonical predator–prey models. One complexity measure which has been found to be particularly useful in studies of food webs and their stability is `connectance': the fraction of all possible links that are realized in a network.

Complex networks is a vigorous field of research, comprising studies of network properties (such as the small-world effect, scale-free distributions, centrality); models of network growth (for instance, preferential attachment giving rise to scale-free topologies); mixing patterns such as assortativity (exemplified by the tendency where highly connected nodes are more likely to make links with other highly connected links representing assortative mating choices); community structure and modularity (for instance, communities in food webs might reflect subsystems within ecosystems); dynamic processes taking place on networks (for example, epidemiological processes, spread of cascading failures or food-web disruptions, percolation, reaction-diffusion), network motifs (such as a diamond food-web motif with a predator consuming two prey species which in turn compete for a shared resource), and so on.

In random and small-world Boolean networks, the ordered phase of dynamics is typically dominated by information storage (representing `memory'), while the chaotic phase is dominated by information transfer (which includes both the `interaction' and `modification' components of distributed computation). Interestingly, the small-world topology allows the information dynamics to attain a balance, with both memory and information transfer approaching their maxima near the small-world transition between ordered and random graphs.

A very-well studied topology is scale-free networks, in which a relatively small number of nodes are connected to a tremendous number of neighbors, while the vast majority of other nodes have only a very few connections (formally, the distribution of connections follows a power law). Importantly, this feature is preserved at many levels of magnification, as zooming into any part of the network does not change the profile of the observed distribution of connections. Scale-free networks are robust to random node failures but become fragmented after coordinated attacks targeting the nodes with the highest number of neighbors (the hubs).

Food webs are not generally classified as small-world or scale-free networks. Nevertheless, food-web topology is consistent with some patterns found within those networks classes, and such patterns can be used to explore and predict functional responses of ecosystems to structural changes (Dunne et al., 2002).

Conclusion: complex versus complicated

Complex systems should not be confused with complicated systems which may also contain a large number of components and conditional interactions. The two terms share a common Latin origin: complexus originates from complectī (`to entwine or encircle'), derived in turn from com- (`together') and plectere (`to weave'), while complicātus is a form of complicāre (`to fold together') which augments com- (`together') with plecāre (`to fold'). So the etymological difference reflects the distinction between (flexibly) weaving and (rigidly) folding some parts together.

This difference becomes even quite apparent when one compares (complex) natural organisms which have evolved their adaptive and self-organizing responses with (complicated) engineered machines which conform to precise blueprints and operate under predefined protocols. The machines, and engineered structures in general, are designed and assembled to repeatedly perform within some well-defined cycles, by exploiting their design and operational constraints which are not generated anew but only reset, by a precise channelling of the external energy. On the contrary, the stability and resilience of biological and ecological systems are explained by their capacity to self-organize and homeostatically re-establish itself, while re-using the external energy and information in composing new internal constraints. These two approaches deal with the question of robustness in significantly different ways: (i) traditionally engineered systems are well-tested and validated for a wide range of known conditions, but may crumble at an encounter with a new situation or when an individual component fails, (ii) complex adaptive systems are able to re-combine the distributed information-processing behaviors of their constituent agents in innovating new solutions, often even beyond tipping points. Nevertheless, when faced with accumulated and chronic adverse pressures, even an adaptive system may undergo a shift to a post-critical phase incompatible with its primary purpose, highlighting the need for more accurate and predictive analysis and modelling of complex systems. Understanding and managing complexity at multiple scales improves our ability to maintain and restore ecosystems with timely and precise interventions.

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Glossary

Allelomimesis: a range of activities in which the performance of a behavior increases the probability of that behavior being performed by other nearby animals.

Autocatalysis: a single chemical reaction is autocatalytic, if one of the reaction products is also a reactant and therefore a catalyst in the same or a coupled reaction.

Homeostasis: the property of a system to actively regulate a specific variable, keeping it practically constant.

Order parameter: a macroscopic variable used to describe and measure the degree of order across the boundaries in a phase transition system (normally ranges between zero in one phase and non-zero in the other).

Phase transition: a change in a feature of a physical system, often involving the absorption or emission of energy from the system and resulting in a transition of the system to another phase.

Propagule: any material that is used in propagating an organism to the next stage in their life cycle, for example, by dispersal of plant material (stem cuttings or seeds) for plant propagation in horticulture, or transmitting a disease by infectious components generated by pathogens.

Shannon entropy: the quantity is defined in the context of a probabilistic model and measures the uncertainty, or the average (expected) surprise of an entity, given an ensemble in which it is embedded. Shannon information is a measure of the reduction of uncertainty.

Small-world network: a graph in which the neighbors of any given vertex (node) are likely to be neighbors of each other (in other words, the average clustering is high), and most nodes can be reached from every other node by a small number of hops (formally, the average shortest path length is small). Small-world effect explains how strangers are linked by a short chain of acquaintances.

Stigmergy: a mechanism of indirect coordination, through the environment, between agents or actions.

Tipping point (environmental): a threshold beyond which some (typically accumulated) small changes may force an (eco-)system to rapidly and often irreversibly change to a new state, with significant effects on biodiversity at a regional or global scale.

Keywords: Adaptation; Collective behaviour; Complex systems; Complexity; Critical dynamics; Dissipative structure; Edge of chaos; Emergence; Entropy; Homeostasis; Information flow; Irreversible process; Phase transition; Resilience; Self-organization; Tipping point