Journal & Proceedings of the Royal Society of New South Wales, vol. 150, part 1, 2017, pp. 104–109. ISSN 0035-9173/17/010104-06

Modelling complex systems and guided self-organisation

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Abstract

We explore several opportunities created by a new approach to science, engineering and management: *complex systems*. By distinguishing between complex and complicated systems, we reflect on different design approaches, and discuss the advantages offered by guided self-organisation. Pointing out that several modern challenges are characterised by critical dynamics, cascading failures and non-trivial information flows, we attempt to highlight the importance of cross-disciplinary quantitative methods, as well as novel educational initiatives in Complex Systems.

Introduction

Complex systems is a new approach to science, engineering and management that studies how relationships between parts give rise to the collective behaviours of the entire system, and how the system interacts with its environment. Dynamics of a complex system cannot be predicted, or explained, as a linear aggregation of the individual dynamics of its components, and the interactions among the many constituent microscopic parts bring about macroscopic phenomena that cannot be understood by considering any single part alone ("the whole is more than the sum of the parts").

Complex systems are often confused with complicated systems which may also comprise a large number of components and interactions. This is not surprising: after all, both concepts express a notion opposite to being simple or straightforward. The two terms also 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 how significant is the difference between *weaving* and *folding* some parts together?

Naïvely, this subtle distinction reflects on different design approaches: one flexibly weaves and interconnects the elements, revealing elastic and resilient emergent forms; while the other rigidly folds the components and reduces their interaction potential, following a prescribed procedure towards a planned, if often brittle, structure with predictable behaviour.

This divergence becomes even more apparent when one compares natural organisms which have evolved their adaptive and self-organising responses, on the one hand, with artificial machines which conform to precise blueprints and operate under predefined protocols, on the other. As noted by a well-known biologist, Carl Woese: "Machines are stable and accurate because they are designed and built to be so. The stability of an organism lies in resilience, the homeostatic capacity to re-establish itself."

One striking example of biological complexity is a swarming behaviour exhibited by schools of fish, herds of wildebeest, and flocks of birds. In response to a predator, many schools of fish display complex collective patterns of spatial aggregation, so that small perturbations can quickly cascade through an entire swarm in a wave-like manner transferring the survival-critical information.

While complex self-organising systems adaptively process information in creating and exploiting emergent non-deterministic patterns, our engineering and management practice is driven by data, producing complicated designs and predictable deterministic regimes that prove brittle to unexpected malfunctions over and over again (cf. Table 1, Figures 1 and 2).

Table 1: Complex vs Complicated Systems.

Complex	**Complicated**
Evolved adaptive response	Designed for performance
Emergent non-deterministic patterns	Predictable deterministic regimes
Self-organisation: hard to predict	Blueprint: verification and testing
Resilient to perturbations	Brittle to malfunctions
Interdependent networks	Centralised management
Deals with information	Deals with data

As modern day infrastructure is growing more interconnected, the breakdown of a single transformer in a small substation can lead to massive cascading failures in a continent-wide electrical power grid, triggering further interruptions to traffic and communication systems; 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 (cf. Table 2).

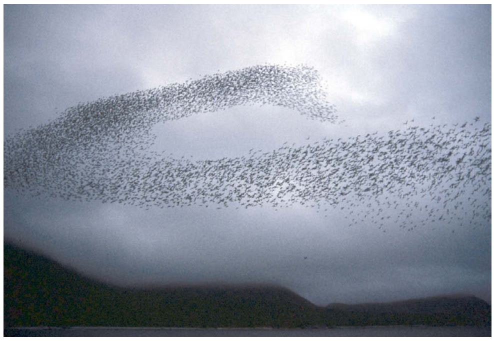

Figure 1: A complex system: a flock of auklets exhibiting swarm behaviour (source: Wikipedia).

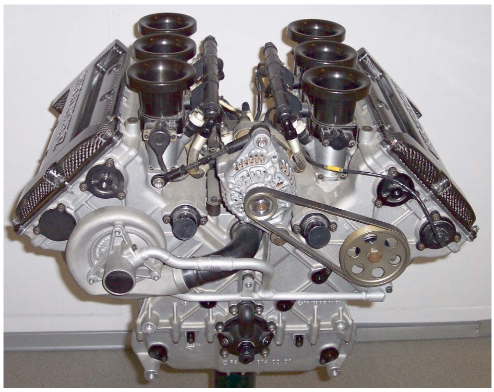

Figure 2: A complicated system: a V6 internal combustion engine from a Mercedes car (source: Wikipedia).

Table 2: Examples of interdependent challenges.

Demographic & social	**Technological**	**Environmental**
overpopulation and ageing population	infrastructure degradation	climate change
epidemics and pandemics	cascading power failures	natural disasters
surge in irregular migration	transport and supply chain disruptions	animal and plant diseases

Living at the edge of chaos

Humans are typically inclined to use reductionist logic and analyse a system through a series of short, discrete scenarios, expecting a "correct response" to each scenario. However, not all scenarios have clear endings or known, correct answers. Modern power grids, communication and transport networks, megaprojects, and diverse social systems exhibit critical phenomena, characterised by phase transitions and tipping points, when a small change triggers a strong or even catastrophic response in the overall dynamics (Scheffer et al., 2009; Lenton, 2011) (cf. Table 3).

Table 3: Self-organising critical dynamics.

Physics	Avalanches
Technology	Power grids
Socio-technical systems	Traffic jams
Socio-ecological systems	Epidemics
Biological organisms	Collective behaviour (flocks, swarms, etc.)

There are several common features of complex dynamics as the involved agents (particles, fish, cars) are independent but interacting (cf. Table 4). However, as we move from physics to biology to social dynamics,

- precise nature of the interactions is less defined;
- there are more hidden variables;
- it is harder to influence the desired outcome, to "guide" the system;
- there are fewer theories of the systemic behaviour/risk.

Many hidden variables may change quickly, but collective behaviours (encapsulated in the corresponding order parameters) can adapt to critical situations. By varying control parameters (e.g., the system composition and the strength of interactions within it) one may trigger the system-level phase transitions. Haken introduced order parameters in explaining structures that spontaneously self-organize in nature (Haken, 1983; 2006). When energy or matter flows into a system typically describable by many variables, it may move away from equilibrium, approach a threshold, and undergo a phase transition. At this stage, the behaviour of the overall system can be described by only a few order parameters that characterize newly formed patterns. In other words, the system becomes low-dimensional as some dominant variables "enslave" others, making the whole system to act in synchrony.

Table 4: Common features of complexity.

Microscopic interactions lead to macroscopic effects
Sensitivity to initial conditions
Critical thresholds (tolerance margins)
Cascades of failures (-ve) or information flows (+ve)
Dynamics self-organise to a critical regime
Guided self-organisation: • triggered avalanche (controlled release) • islanding of power micro-grids • re-routing of traffic • vaccination, quarantine during epidemics

Guided Self-Organisation

Some of the hope for harnessing and guiding resultant self-organisation (Kauffman, 1993) is offered by the emerging discipline of Guided Self-Organisation (Prokopenko, 2009). This field is aimed at formalising the art of "herding cats", i.e., guiding collective behaviours towards desired outcomes, by optimising the ways to define agent interaction rules, set relevant constraints and select network topology.

One exciting application prospect is "social thermodynamics", inspired by classical thermodynamics and its extensions such as "physics of information" or "information thermodynamics" (Bennett, 2003; Lloyd, 2006; Prokopenko et al., 2011; Parrondo et al., 2015; Prokopenko and Einav, 2015;

Spinney et al., 2016). The main insight is that emergence of patterns within social dynamics may be understood and traced analogously to macroscopic thermodynamic regularities emerging out of microscopic statistical mechanics. The most significant theoretical task is to carefully interpret thermodynamic notions, such as entropy and energy, dissipative structures and irreversible processes, bifurcations and self-organisation, in the context of social interactions. While this general goal may not be achievable in the near-term, some specific areas where social dynamics are restricted by physical constraints may be formalised successfully, e.g., urban flows within an industrial ecology (Hernando and Plastino, 2012; Bristow and Kennedy, 2015).

A universal "language" is typically needed in order to comprehensively analyse dynamics generated by diverse complex systems and recognise distinct patterns of information and computation flow. Such lingua franca is provided by Information Theory operating on probability distributions that require only minimal structure (a probability measure) on the space of interest, and make no assumptions about a spatiotemporal structure of the system's space, its symmetries, differentiability, etc. (Polani, 2009; Prokopenko et al., 2009).

A recently developed framework of information dynamics systematically studies information processing in complex systems (Lizier et al., 2008; 2010; 2012) relating it to critical phenomena, e.g., 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.

Changing the mindset

How can we predict the behaviour of systems that are too complex for our typical reductionist reasoning? The answers to this question are not intuitive or trivial, and in our opinion, would require a specific skill set which must be developed within educational programs explicitly dedicated to Complex Systems.

One of the biggest mysteries in the history of western cartography is a rather sinister image offered by Fool's Cap Map of the World, ca. 1580-1590 (cf. Figure 3). A possible interpretation of the map's message is that "the world is a sombre, irrational and dangerous place, and that life on it is nasty, brutish and short. The world is, quite literally, a foolish place." (Jacobs, 2014). And so, one may wonder if a "solution" to resolving numerous intricacies of our modern "post-truth" world, full of irrational and complex dependencies, should lie not within a novel mathematical framework, but rather in a new mindset.

Figure 3: Fool's Cap Map of the World (source: Wikimedia Commons).

Complexity, as a field of study, has shaped beyond the confines of physics, biology, mathematics, computer science and other disciplines which strongly contributed to its inception, and is on a verge of a rapid expansion within educational programs worldwide.

Professionals educated in science, engineering and management of Complex Systems will quantify the impact of unexpected events, design and analyse resilient socio-technological systems, and develop robust strategies for crisis forecasting and management. They will operate across discipline boundaries, in environments outside the experience of most professionals, providing key modelling and policy-informing inputs and insights to resolution of recurrent challenges across the globe.

The University of Sydney's postgraduate program in Complex Systems, including a Master of Complex Systems (MCXS) offered from 2017, is unique in the Southern Hemisphere. It leverages the research strengths of its newly created Centre for Complex Systems and is aimed at an exclusive cohort of high-achieving individuals.

MCXS provides strong comprehensive skills in computational analysis, modelling and simulation of collective and dynamic emergent phenomena, while engaging quantitative social and health sciences. The core units of study include large-scale networks, agent-based modelling, complex civil systems, self-organisation and criticality, statistics, stability analysis, and visualisation. The program also offers several internship opportunities, leading to specialisations in engineering, biosecurity, ecology, transport, and research methods, covering disaster management, computational epidemiology, nonlinear dynamics, smart grids, control theory, resilient supply chains and quantitative logistics.

It is expected that a number of MCXS graduates will continue on a pathway to a research career, advancing the field of Complex Systems in the 21st century, and harnessing the power of complexity in real-world applications.

More likely than not, the scope of Complex Systems research will keep expanding as we continue to explore our interconnected world: as pointed out by a physicist Heinz R. Pagels several decades ago, "Science has explored the microcosmos and the macrocosmos; we have a good sense of the lay of the land. The great unexplored frontier is complexity."

Acknowledgements

The author was supported through the Australian Research Council (ARC) grants DP160102742 "Large-scale computational modelling of epidemics in Australia: analysis, prediction and mitigation" and DP170102927 "Australian housing market risks: simulation, modelling and analysis", and The University of Sydney's postgraduate program in Complex Systems:
http://sydney.edu.au/courses/master-of-complex-systems

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