This book is about understanding, designing, controlling, and governing adaptive collective systems. It is intended for readers from master's students to Ph.D. students, from engineers to decision makers, and anyone else who is interested in understanding how technologies are changing the way we think and live.

The authors are academics working in various areas of a new rising field: adaptive collective systems.

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Herding black sheep

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Preface

Herding black sheep

Have you experienced the anxiety (or relief) of not being connected for 24 hours? Have you witnessed the obsession of social networking? Have your ever felt that you have a lack of control over your life on the internet?

Common to these issues is that they involve people, ICT components (smartphones, apps, websites, routers, spam filters) and often a change of function by learning and reconfiguration based on experience. They are examples of adaptive collective systems.

We come to touch (and get dissolved in) these adaptive collective systems via the use of social ICT, via smart services and the like, but the class is much larger and in fact includes many natural and man-made systems from various biological systems, to societies, to artifacts.

These systems are out there, possibly out of control. They are black sheep. We need to breed them, to steer them, to herd them.

This book is a contribution to understanding, designing, controlling, and governing adaptive collective systems from the bottom up.

Case study: ants

Ant colonies provide a mesmerizing example of an adaptive collective system. While there are more than 14,000 different species, each with their own particularities, one can find regular patterns in the organization of each colony. A colony usually includes one or more queens, many sterile female ants and occasionally some non-sterile male and female ants. With the obvious exception of reproduction, the sterile female ants carry out nearly all the important tasks necessary for an ant colony to survive: nursing, nest building, exploration, combat, foraging, etc. The so-called queen does not actually rule anything, but is merely the part of the colony that is dedicated to reproduction.

Ants are capable of completing a vast number of tasks by relying on a very simple set of rules, without ever requiring a global scheme from any centralized component. They are able to follow very robust strategies for exploration and foraging, but also to change roles from nurturing to hunting during the course of their lives. They can also engage in tutoring activity and large coordinated actions. At the scale of the colony, the sum of these individual actions then looks like carefully designed mechanics, notwithstanding the fact that the colony is also remarkably able to cope with many kinds of unpredicted events in a completely decentralized fashion.

Case study: crowd management

We consider a crowd as an adaptive collective system consisting — aside from the people actually forming a crowd — of security guards, information screens, traffic lights, and so on. Most important for our purposes, we assume everyone is carrying a smartphone. Our example crowds are best thought to be situated in a city where a large event is taking place.

Typically, a smartphone is equipped with a myriad of sensors and actuators, as well as multiple networking interfaces, including ones that support direct peer-to-peer communication. These phones are used to capture the local state of a crowd: who the current neighbours are, what the local density is, what the current velocity or acceleration is, and so on. In this context, we speak of the texture of a crowd, which can be visually represented as a two-dimensional network in which a node represents a phone, and a link between two nodes that the respective phones are directly able to communicate across. Local measurements can be disseminated to neighboring phones, in addition to perhaps being transferred to central management.

There is a crowd-management system, partly centralized, partly decentralized, which not only collects data from a crowd, but also feeds information back. Such information is typically used to intervene with the intent of changing the current texture of the crowd. Actuation will take place by sending information to the phones, but can also take place by controlling traffic lights, temporarily closing sections of a street, or using large information screens, among other measures.

Case study: robot miners

In a plausible and not so distant future, groups of mining robots are utilized in deep-sea environments to collect ore. The group is composed of heterogeneous robots, with different morphologies (sensors and actuators), sizes, communication devices, and power systems. Naturally, their behaviours and the control software inducing these behaviours are different too, hence the group is highly heterogeneous. One of the major challenges of this application lies in the fact that deep sea environments are not well known and are likely to change from place to place and from time to time. Therefore, the robot designs cannot be optimized before starting the mission. Instead, the robots are enhanced with mechanisms that help them adapt to the environment.

In the simplest version of this adaptive collective system, adaptation concerns the control software only. Robots can individually learn useful tricks and skills based on their own experience and share these with each other through social interaction, e.g. imitation or direct knowledge transfer. In a more advanced version we have the technology to change the hardware part (robot morphology) as well. Then the robot population undergoes adaptation driven by environmental selection, much like the famous Galápagos finches described by Darwin. Over time they develop the right morphological features (e.g. grippers and wings) to operate effectively miles under the sea.

Chapter 1
The Thing

Nature

In a crowd, if we are dealing with only a handful of pedestrians, it will generally be impossible to observe any interesting patterns. This may change radically when considering huge crowds. Now suddenly all kinds of substructures can be witnessed: lanes, congested areas, clogging, repetitive patterns of movements, and so on. In other words, we will be able to witness the texture of a crowd. Note that there is nothing static about this texture. In fact, we define it here to express the spatio-temporal relationships resulting from the interdependencies in the social fabric of a group of people [Martella, 2014].

Throughout this text, we consider systems per se to have a 'size' beyond the tipping point after which collective dynamics can be observed. It is difficult if not impossible to provide any fixed number, but typically we will be looking at systems consisting of at least a few tens, if not hundreds, of elements, or perhaps many more up to astronomical numbers as is often the case in internet based human-ICT systems today.

In general, the behaviour of any entity is identified based on its actions. These actions can have an effect on the acting entity itself, on other system elements, and on the environment. In the adaptive collective systems we are concerned with we can distinguish behaviour of the elements individually and the behaviour of the system as a whole. Throughout this book we maintain the assumption that the behaviour of system elements is determined by their controllers. That is, we assume that each element has an instruction set — the

We consider systems beyond the point after which collective dynamics can be observed controller — in some functional form that prescribes and generates its actions under various circumstances. We could also say that the behaviour of such an individual element is the active and observable expression of its controller. The controller of a robot would be its control software, for a human being it would consist of all the biological, psychological and social rules that determine how a person would act in various situations in a given system. On a system level the picture is less crisp. The behaviour of the system as a whole can be simply identified as the behaviour of all of its elements. However, the controller governing this behaviour is not as easy to localize as for the system elements.

In most artificial systems we assume there is a separate controller consisting of a myriad of rules used to steer the system or its elements. Many of us often make a distinction between centralized and decentralized control. With centralized control, the rules are executed by a single entity which subsequently instructs the elements what to do. This model is akin to that of an orchestra in which the conductor guides the musicians through a piece of music. In decentralized control, the rules are located at and executed by the individual elements. This distinction makes sense only when dealing with spatial systems. In a nonspatial system, the underlying assumption is that interaction between any two randomly selected nodes is not influenced by their physical position in the network. As a consequence, disseminating information including control rules or decisions is independent of position, and can be done so quickly that any two elements are considered to have the same information to base decisions on. In other words, they all share the same global knowledge. Deploying epidemic protocols this is a suprisingly simple way to rapidly spread information in artificial nonspatial systems, as exemplified by Usenet news.

This situation changes radically in spatial systems, or, in general, when there is additional relevant information that is dependent on location. In a pure, artficial spatial system such as a large wireless network, the speed of information dissemination is readily influenced by distance, effectively preventing its elements from always having the same control base. Likewise, although it can be argued that the internet is a nonspatial system at the technical level, as soon as we consider its application as a communication channel for humans, local spatial contexts in which human participants operate can no longer be ignored. Decentralized control will then be very different from centralized control in such a system.

Adaptation

It is very difficult to discriminate between adaptive and nonadaptive systems. Firstly, a particular individual does not have to be adaptive to be able to handle many different contexts. Secondly, we may not be able to identify what, if any, environmental changes occurred that could explain an observed change in behaviour. From this perspective, we need to distinguish between identifying adaptation based on observation (external view), and identifying adaptation based on an analysis of the mechanisms at work within the system (internal view). Although having many observations to understand a particular system is likely to provide a good approximation of its internal organization, it is unlikely that we will get a complete exact description from these observations only.

You cannot observe adaptation

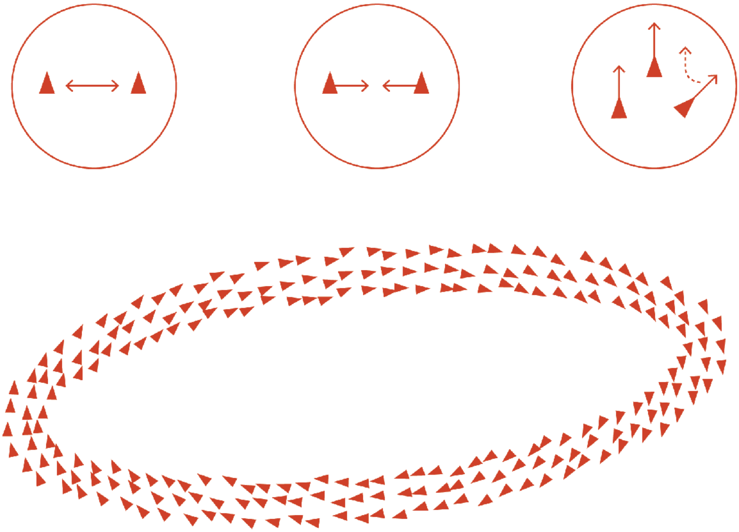
Let us come back to the example of crowd dynamics given earlier. Understanding crowd dynamics is critical when designing the layout of a department store, a train station, a stadium, a building, etc. In order to ensure that the flow of people can be channelled efficiently to the exits in the event of an emergency, it is essential that the reaction of the crowd is predictable. A well-known problem is that seemingly minor modifications in the environment may lead to completely different dynamics, rendering reliable predictions close to impossible. The catch is, that deducing the dynamics of a crowd of people from observations alone is intrinsically limited by the very conditions the observations were made in. As a consequence, there is no guarantee that the dynamics will remain the same under even slightly different conditions, as witnessed by the recurring casualties among crowds in seemingly well understood situations.

In the context of this book, we propose that an adaptive system is characterized by its ability to change its control rules through experience. What this means is that understanding observed differences in behaviour can be approached only by looking at the internal changes in the mechanics of a system. Note that according to our notion of adaptivity, many systems that modify their behaviour with regard to environmental changes may not be considered adaptive any more, namely when their modifications come from internal hard-coded control rules. Let's look at a few examples to illustrate this point.

Typically, a thermostat is an example of a nonadaptive system. Although from the outside it seems to adapt to its environment, the fact is that each of these changes has been hard-coded inside the system. We could also state that the reaction of the thermostat to its environment is completely deterministic.

This also can be illustrated by considering the Boids artificial system [Reynolds, 1987]. Bird-like individuals wander around in a free environment, each driven by three rules only: a repulsion rule (if the closest boid is too close, get away), an orientation rule (try to match the average direction of neighbouring boids) and an attraction rule (if the closest boid is far away, get close). While the behaviour of each individual in the flock is highly reactive to the context, and while the behaviour of the entire flock may display a singular pattern such as toroidal formation, this may not be considered as adaptive: if we are able to re-create the exact same situation, both in terms of environmental conditions and individuals' locations and orientations, that is, if every part of the setup is made the same, then we shall observe exactly the same individual and collective behaviour, because the internal rules have also remained the same.

What makes them fly in a circle?



Another example of a system that our characterization deems nonadaptive is the reaction of the internet to disasters. In September 2001, when the World Trade Centre's twin towers collapsed in New York City, not only were important message routers situated in the basements of one of the buildings destroyed, also a complete internet exchange point a few blocks away went down. Obviously, no manual repair could be done, yet the observed damage expressed in terms of how well messages could be routed to their final destinations showed a drop in performance that lasted no more that approximately 30 minutes. What happened, of course, was that routers were discovering that previously established routes were no longer operational. As a result, they started to establish alternative routes, rapidly leading to a stable situation again. For our discussion, it is important to realize that internet routing protocols have more or less hard-coded policies on deciding which routes are best. Thus they are not adaptive, yet do make sure that messages are always routed according to some fixed notion of a 'best' path. The system as a whole changes routing paths and seems to be adaptive, yet according to our approach is not, because control rules are fixed.

Drawing a clear line between adaptive and nonadaptive is sometimes tricky: for example, it has recently been shown that a particular species of ants, carpenter ants, are capable of changing roles as they age [Mersch et al., 2013]. Is it adaptation? On one hand internal mechanisms are indeed modified to accomplish this new role, however, it is now known that such modifications are determined purely by age and are not driven by the environment. Things are quite different when evolution is considered. Through reproduction, new ant colonies may sometimes acquire new characteristics. While most mutations are neutral or harmful, it may eventually occur that one particular ant colony benefits from a lucky mutation and becomes more fitted to the environment at hand; that is, more likely to generate successful offspring with similar characteristics.

Let us conclude by considering humans. As a collective system humans display many levels of adaptation. Similar to other species, humans can be studied from an evolutionary perspective, except that not only genotypic material may be considered, but also cultural and social organization. On a much shorter timescale, humans also display learning capabilities that make them able to solve new problems both as individuals and as a group. Among the many examples, the organization of whale hunters from the island of Lumbata, Indonesia is singular [Alvard et al., 2002]. Every year the rules for engaging in the Lumbatan whale hunt, as well as for sharing the benefits of the hunt among participants, are renegotiated. This negotiation involves multiple levels of interaction: maximizing benefits can be viewed from the perspective of individuals, families and boat crews, but also involves the importance of the role of each individual or boat.

Adaptation comes from the environment

For example, it matters whether you are the one throwing the spear or not, or whether your boat's team was the one which spotted the whale. As a result, the organization of the whaling is constantly refined year after year and is able to cope with any lack of fairness in sharing the benefits or changing environmental conditions. This illustrates adaptation at several levels: the ability to learn, both as an individual and as a group, and the ability to implement some kind of incremental evolutionary-like process that refines such a process of reciprocal cooperation through successive experiments.

Adaptation encompasses various aspects of learning on a variety of timescales; from learning new behaviours during the lifetime of (groups of) individuals, to the acquisition of new behaviours via an iterative process on a larger timescale, implying the replacement of individuals in a population (evolutionary timescale), or the renewal of concepts used in a population (timescale of the evolving organization of societies). The very nature of the learning process in an artificial system can also be challenged. The various machine-learning approaches, such as unsupervised, supervised, learning by reinforcement, and learning by optimization, are typically defined with having an a priori-defined objective to match. However, it is also possible to consider objective-free learning. In this case, the learning process is crafted by the very interactions among the individuals and the environment, and is ultimately driven by the need to adapt to an a priori unknown situation, possibly including interaction with other systems, such as human individuals or society. In the latter case, we may consider the environment and the systems involved as forming an artificial evolutionary ecology, where the adaptation process itself is conducted in an open-ended manner and where co-adaptation is possible.

Adaptation is important for evolution, but it may sometimes fail to bring us further. In that case, some additional help is needed to force the system into a new state from which we can make further progress. To illustrate, the societies of the 19th century in Europe and the USA were radically transformed by the First World War, while the Second World War triggered the development of computers, radar, advanced aircraft, nuclear weapons, social reform of health and welfare, and the emergence of the welfare state and social contract. Both wars were social-wise nothing less than shock treatments, yet in turn led to significant social changes that may otherwise never have taken place as they did.

Collectivity

A collective is a (large) collection of units that interact with each other. Interaction is essential here; units form a collective, rather than just a collection, because (or, if) there is some interaction between them. The definition of a collective requires the identification of its members, the units that belong to it, and the interactions among these members.

We should be warned: a collective is a nontrivial notion. Collectives get formed and dissolved by various processes in nature and among artificial systems. There is usually more to a collective than simultaneous existence and, possibly, interactions. Generally it is the other way around, interactions (and joint existence in a collective) are consequences themselves. There must be something common between the components to form a collective — in biology, for example, this is easier to fulfil because all organisms today share 4 billion years of common history. In ICT the same condition may be less trivial and may need to be introduced by hand: two devices that do not use the same communication protocol cannot exchange information. When humans are present the situation can become even more intricate, thus being part of the same melting pot. Again, consider crowds: Indian rail users tend to find Western behaviour in their very crowded stations extremely irritating because Westerners do not know how to behave. So the shared knowledge of the rules of engagement in stations makes Indian rail users a collective (of which many Westerners are not a member). In the collectives that involve humans, members often need to reflect on their situation and have some idea about the way behaviour happens (even if just from a personal perspective). And this is used as the basis for adaptive change.

Otherwise, there is an entire spectrum, from simple collectives, such as molecules that can enter reactions under some relevant conditions, through various stages of more and more complex involvement in collectives, to the delicate collectives of which humans can be members. For instance, species in biology have an emergent identity and that feeds back to the identification of membership – when a new species is formed, members of the forming species become more and more reproductively related to each other while at the same time reproductively isolated from members of other species, and at the end of this character displacement process the members may even be tagged by chemical signals or other means to express identity and difference from other collectives.

To have a well defined collective with clear criteria of membership there needs to be a focus for identification, and that is reflective knowledge or something similar, even in non-human systems. For example, for adaptive cars that get their engine control software changed overnight the reflection is the analysis of traffic conditions that forces change. We may ask ourselves whether a human being is a collective system. At first sight they are not, because a human is just one unit of its kind, and one unit is not a collective. However, the human body consists of cells. Considering these cells as units, a human being is a collective. This holds in the structural sense, since the body is constructed as a collection of its cells. This also holds in the functional sense, because the behaviour is the result of interactions amongst these cells. Here we encounter an example of two good answers to the question, depending on what we consider as the basic unit. This issue is strongly related to the concept of levels. On the individual level, where a basic unit is one individual, a human being is not a collective. On the cellular level, where a basic unit is one cell, a human being is a collective. Stepping up a level, a village or a city can be considered as a collective, where units are the humans.

In general, collectives can be designated as units for a higher level, thus introducing (or explicating) a hierarchy, as we will develop later.

So the units are relative, but then how real are they? Common sense says that if something is real then you can interact with it: the same common sense saying the opposite may just as well be true. If you can interact with something, then it must be real. (Or else how would you interact with it in the first place?) This point has been made precise in the famous notion of "instrumental realism" by Ian Hacking. The electron may be a disputed entity in fundamental physics: being a wave besides being a 'thing', as well as having other disturbing properties. However, assuming it is real is the very reason why we can do things with it, such as making a picture on a TV screen.

Different definitions of units give different opportunities for causal control. For instance, interacting with a human at a personal level would typically involve verbal or written communication, perhaps to teach them something. However, to cure an infection one should interact with the human body at the level of the cells and communicate via administering drugs to them.

Level concepts are fundamental to science and engineering. Loosely speaking, the level idea is to approach an object (such an entity or a system) from a given viewpoint. Such a viewpoint typically implies a level — such as a level of aggregation, a level of hierarchy, or similar. Level notions are intuitively suggestive but less completely understood in the scientific sense.

The best understood and maybe the historically oldest example for levels in a physical system regards the properties of gases. On one hand, we can describe an amount of oxygen at a microscopic (molecular) level, using kinetic theory referring to the number of molecules, their positions, speed, and motion. On the other hand, we can use the phenomenology of the macroscopic level that considers volume, temperature, and pressure in a state equation. Gases therefore illustrate multilevel systems, multiscale, multilevel and multifaceted modeling etc. Furthermore, we see here that the choice of a different level leads to the choice of a language — namely the kinds of questions and words we can use. We end up in 'volume temperature pressure' talk or 'speed mass velocity' talk, but we cannot have them both at the same time. What we can at least in principle mix or exchange is the information

Being real does not mean it can be directly sensed contained in the given level; in a perfect world, one can exchange (derive) information between the levels, e.g. temperature from velocity, but life is much larger even in this simple case.

In this example we can see how the 'level is in the eye of the beholder' — if we were as small as a molecule, we would probably never come to moving pistons and hence to introducing the volume concept, nor could we measure temperature. This also helps understand that levels are, at the same time, also context (parameter) dependent. Too high or too low a temperature changes a system too much to be treated by kinetic theory. Also it must be noted that levels are in nature not always as neatly stratified as we would like them here. Even when discussing molecular reactions, often we treat macroscopic variables together with microscopic ones, e.g. temperature and charge.

From the perspective of adaptive collective systems gases form the simplest collective system with no (or not much) heterogeneity and no adaptivity. Instead, we have the well-known assumption of indistinguishability, leading to the fundamental notion of entropy.

The introduction of collective as a collection of units introduces a notion of level in terms of parts and the whole. This view, however, is too simple. What if, within a collective, units can form groups, whereas those groups do not form the units of a collective? Consider the following example of a political party having factions within it.

A political party is a collective of its members united by shared political goals. In simple terms, we can say they are united by the same vision on the big 'what' issues. Thus they form a collective that is homogeneous regarding the 'what' aspect. However, party members may differ about operational details, for instance about whether or not to form coalitions with another party or on a particular choice of how to implement a policy. This means that the party is a homogeneous collective regarding one aspect (the 'what') and heterogeneous regarding another aspect (the 'how'). Members sharing the same view on the 'how' can form factions within the party, thus creating new collectives that are homogeneous in both aspects. It is natural to introduce a new intermediary level, that of the factions between the individuals (party members) and the party. Such intermediate levels are the locus for structures such as pressure groups that are in conflict and through that conflict they eventually bring about change in the overall mission of the party.

With this we face the question of how collectives are formed. Species share genetic information (often to extreme degrees, such as in plants that clone themselves) that is a very concrete notion of shared information. What about ants? If there are two ant colonies adjacent to one another belonging to the same species, do individual ants belong to one or the other colony? What is the basis of that belonging? Is it in the ant or is it in the environment? Can ants change colonies if they get lost? Usually ants and other animals that live in colonies use chemical identification and even members of the same colony are not always accepted. Yet mixing is sometimes possible and there are rare cases where different colonies live together, and also of parasitism or symbiosis, where different species constitute one system while retaining their identity at the same time, at least for a while (symbiosis can lead to dissolution). Some bee colonies bifurcate when a new queen appears so splitting is also possible, but as we see in these examples, merging is more seldom and more difficult. The case is quite similar in artificial systems where often the same cell phone won't work in a different network of even the same provider.

Can you devise general models for collective formation?

Chapter 2
Why Bother

They are here

A human observer may become instantly lost when it comes to considering an adaptive collective system. The behavioural pattern at the collective level as well as the single individual's behaviour may be difficult to identify, the link between the individual and collective levels may be almost impossible to establish in some cases. This is not only true when observing natural adaptive collective systems — from bird flocks to swarms of bees, from the complex division of labour in ant colonies to interactions in human societies — but also in many systems that surround us, most of which we have originally designed — from stock markets to the distribution of energy, from flows of people in cities to the mechanics of medical drugs. From this perspective, we can easily get lost in the collectives, facing collective systems we sometimes partly or completely fail to keep under control.

With collective and adaptive systems all around us, it is essential that we understand them in order to design and control them. Intellectually understanding these systems is highly challenging and requires interdisciplinary knowledge. As an illustration, early attempts at controlling the spread of mosquitoes using pesticides quickly led to the outcome of pesticide-resistant individuals. The answer was to develop new, more efficient pesticides, quickly followed by the advent of new, robust mutants. This seems (and actually is) a never-ending arms race. By carefully understanding the evolutionary mechanics at work, we know now why such an arms race occurs and how to define an efficient strategy, in particular by taking into consideration multiple factors, such as the seasonal variation of migration [Lenormand et al., 1999].

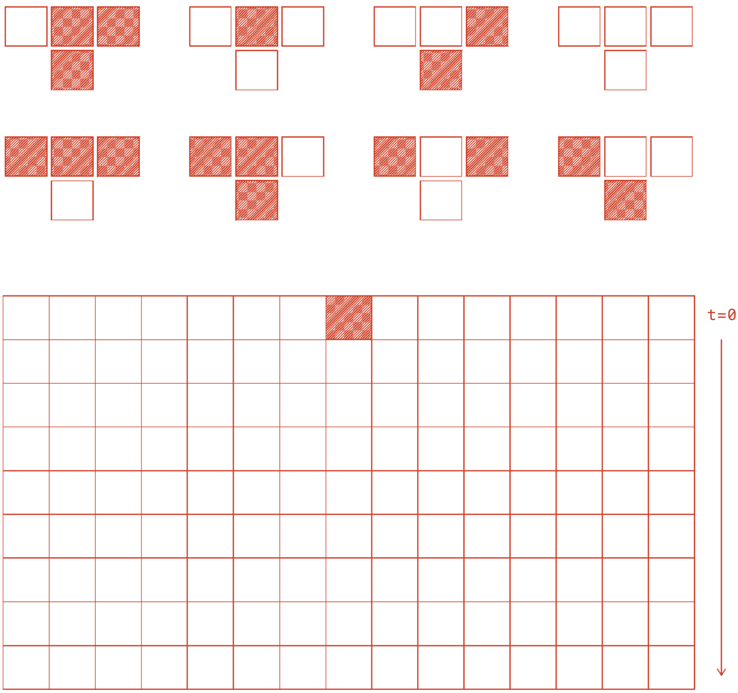
Designing an adaptive collective system does not imply controlling it

The challenge is exactly the same with artificial systems, and the fact that we actually design such systems does not change the game whether we follow a bottom-up or top-down approach. Designing the control rules for each individual does not give any guarantee that collective dynamics will be as expected. Cellular automata (a nonadaptive but collective system) provide an interesting illustration. Let's consider cellular automata in their simplest form: a limited number of cells, placed on a one-dimensional grid, where each cell may either be on, or off. At each step, the state of each cell is determined only by its previous state, the previous states of the two neighboring cells, and a set of local rules for which only one can be applied. Though this description is exhaustive, and the system quite simple, it is very unlikely that one could predict the outcome of the whole cellular automata after a few iterations, such as a general pattern that might emerge after a few repetitions (e.g. regularities, self-similarities, etc.).

Though cellular automata have not been intended to be used this way, we could also address the problem with a top-down approach: given a desired outcome, is it possible to define the local rules by identifying each possible situation? Possibly yes. However, the slightest change in the initial conditions will probably completely disrupt the dynamics of the cellular automata and lead to completely different patterns. From this perspective, the dynamics of a system may be predictable as long as we stay within the boundaries that have been assumed during the design process, something which is very challenging to guarantee in the real world. Indeed, we can hardly make a similar assumption for most of the collective systems out there. By nature, the real world is a changing, open world, where a seemingly insignificant element may suddenly wreck havoc upon an entire system.

We are in a difficult position indeed. The cellular automata example points out how even apparently very simple systems test the insight of individuals. It also poses challenging questions in terms of describing what it is we want them to do and in designing simple rules to achieve that outcome. The finance example below illustrates just how complex things can get in terms of the systems and how critical it is that the systems are under control. So, we are faced by tough problems with high stakes resting on whether we can solve them or not... and the problems are only getting harder with ever more at stake.

Can you predict the outcome without a pen?



A case study: the financial system

In 1973 economists invented option pricing. The theory demonstrated how to construct a so-called replicating portfolio where, assuming an efficient market, the prices are kept equal. An efficient market assumes perfect knowledge and the inclusion of all knowledge in the price of assets. A model-based approach to making profit in this market is called arbitrage. Arbitrage looks at assets whose price diverges from the price of its replicating portfolio; traders indulging in arbitrage buy the cheaper of the two assets and sell the more expensive. The theory involved a statistical risk model that looked at the overall holdings, taking account of diversity and how the pairs of assets moved relative to one another. The trading strategy was to ensure that the chances of making a loss in the long term were vanishingly small. This had been stress tested against very rare adverse events.

In the spring of 1998 an adverse event did happen when many financial companies went down, but the company of the founders of the theory, LTCM, narrowly survived. The game continued. Ten years on from the near failure, very little had changed. The markets were bigger and faster and the complexity of financial instruments had increased, but our understanding had not progressed much. The failure of Lehman in 2008 was little different from the near failure in 1998, involving all the formidable ingredients of complex models and their use as management tools.

Adaptive collective systems are at the heart of many global institutions and the financial system is one of the most critical. However, we just do not have a good intellectual grasp off the functioning of such markets, where complex mathematical models, their embodiment in trading systems, and a large population of traders, make for a highly complex system with the potential for catastrophic failure at its borders.

They are our melting pot

Adaptive collective systems can be seen as a new type of intelligent (computing) system. These systems have particular properties. Firstly, they consist of heterogeneous components that can have a large variety of architectures, sensors, computing and communicative capabilities, and can operate on different time scales. Secondly, it is essential that the components are adapting their behaviour over time. It is important that units undergo adaptation individually and collectively, even if each entity faces different circumstances, and focuses on different aspects of the world.

In the collective behaviour of the system we can recognize traditional aspects of artificial intelligence and collective computing, such as consensus and coalition formation, division of labour, planning, etc. The main challenge is thus about composition: the composition of information/knowledge, composition of functionality, and ultimately, composition of behaviour. In other words this means that the dynamic of the collective system is in fact a patchwork of dynamics, possibly interacting and even merging with one another through time. The emphasis is then put on the capability of the adaptive collective system to change the level at which the collective may be considered, for example by addressing problems from many perspectives, or reaching consensus from the sum of many diverse experiences.

This is quite different from the traditional distributed artificial intelligence setting, which is more concerned with decomposition, in the sense that an algorithm that could work on one single machine is converted into a distribution of itself without changing its function. Metaphorically, comparing good, old-fashioned, distributed artificial intelligence to adaptive collective systems is like considering music produced by an orchestra in comparison to the chorus of birdsong in a forest.

Adaptive collective systems are based on arbitrarily diverse components that are also inherently heterogeneous; as a conceptual category it refers to collectives of a priori unspecified components. Yet every such element can be useful, and together as a kind, can even be indispensable, for a given adaptive collective system. This is an entirely new situation where 'intelligence' or high level functionality arises not from the component properties but from the organization of the system. By studying the adaptive collective system framework, we study the systemic properties arising or emerging in this class of systems beyond the particular designs or implementations available.

With traditional (distributed) artificial intelligence now succeeded by a collective of intelligent machines, the question arises, what is next? It is important to realize that complexity does not come from distribution or size itself. Clearly the shift from single-machine intelligence to distributed-machine intelligence is an important one that comes from considering adaptive collective systems. Still, one has to realize that as long as we're dealing with a technological shift, some issues may be handled with methods and techniques developed in the field of distributed computing systems. New and challenging aspects include coping with the inherent dynamics and spatial aspects of such systems.

As we have argued before, our focus on problem solving should not be primarily drawn from central solutions and applied to distributed solutions. Assuming the dynamics of adaptive collective systems as we have done here, we are faced with handling the dynamics of the unknown. New elements will join a collective for which we know close to nothing. A new member may be semantically rich or poor, may be computationally strong or weak, may be mobile or static, yet as long as other members barely know how and what to communicate, they will need to go through a possibly long phase of discovery before the new member can be considered to have integrated. This requires adaptation, not only from existing members, but also from new members. Understanding how to effectively establish

There are no humans and machines any more integration of new members in a collective is perhaps one of the most prominent issues to address. Nevertheless, with humans being part of an adaptive collective system which also consists of machines, we are forced to think of the relationship between machine intelligence and human intelligence in a new form. This question is not original and has been explored in systems such as Amazon's Mechanical Turk and more recently IBM's approach toward cognitive computing.

Humans from the 21st century can no longer be considered as isolated individuals, but as members of adaptive collective systems, crucially dependent on services only available through such systems — whether engaged with city or traffic information, telecommunication or hotel reservation, regular human activities involve simultaneous participation in at least one and/or usually more adaptive collective system. Also, traditional boundaries get once and forever blurred — roles dissolve. In the old view of human-machine interaction, different players in the equation were treated in different ways according to their best abilities — a human-machine composition was supposed advantageous because of its complementary properties, for instance humans being creative, intuitive or good at making sense of things, with machines better at tasks of logical reasoning or the handling of large datasets and so on. But with adaptive collective systems the situation changes, in that systemic roles do not directly map to individual roles, and task allocation in an adaptive collective system may use different cost functions, where humans perform machine-like tasks and the other way around — the idea is thus reversed, and it is the organization of work that should produce the good results, not the use of the proper individual operation. Thus adaptive collective systems can naturally integrate smart and dumb, powerful and resource limited, fast and slow, reliable and unreliable elements and yet produce a 'good enough' functionality as a collective. In the future, we will all be talking to human and machines.

This immediately bears upon the famous Turing test which deals with the supposed difference in humans and machines (with 'machines' meaning mostly computer programs). But there are no separate humans and machines any more. Adaptive collective systems create chimeras. In the Turing test, the idea is to tell whether we are interacting with a human or a program, using some kind of instant messaging application (i.e. you interact only by reading and typing text on a computer). The entire test is based on the notion that this difference between a human and a computer exists, whereas adaptive collective systems thinking suggests exactly the opposite — that there is no longer any difference between talking to a human or a machine because they are linked in essential ways that cannot be undone. A human is already machine-augmented because in our everyday dealings we reach out for information available by way of machines only: even during a regular human to human interaction we can exchange links, check the weather on the Web, translate words or look up items using online engines and so on. But similarly, machine operations use human information for many tasks such as crowdsourcing or recommendation systems and these often include open elements: when a person is talking to a restaurant app, the latter can question the human restaurant-goer on the fly then use this information to update the answer in real time. Is this machine or is this human? Where is the dividing line?

Thus what we are facing is finding a new balance where humans augment machine intelligence, and machines augment human intelligence. In fact, the notion of collective intelligence needs to be rethought of in the context of hybrid systems in which humans and computing machinery collectively interact.

They are disruptive

The prototypical adaptive collective systems we have in mind in this book are social ICT systems. These are systems composed of three kinds of entities together: (a large collection of) ICT elements, such as computers and applications running on them, but also various networked devices from smart cars to smart cities; humans; as well as machines (artifacts operating in the real world).

The smart factory of the future is an adaptive collective system where each element of the factory workflow is wired and smart, that is, attached to sensors and wherever applicable, to actuators, and has the necessary software to operate as part of the collective. This provides groundwork for collective monitoring and action. Such a factory is ICT rich by way of the existence of components such as sensors, detectors, and applications processing the signals, making, executing and monitoring decisions collectively. Furthermore, a typical workflow also includes humans whose intelligence and actions are necessary for the given process. The collective consists of these together, probably subject to a centralized flow control. Emergence and adaptation are possible only to the degree that the goal of the workflow is not endangered.

Many different information and control flow patterns unforeseen at the moment of the workflow design can be realized dynamically. These together can help the identification of context in sub-workflows and hence decisions about workflow. For example, sensors on the arm of a human employee on an assembly line can provide real time motion information that can be combined with other sensor reports and process monitoring data. These can assist a local decision agent to infer which part of the workflow the human agent is carrying out and how. Based on such information (e.g. that an element was left out), the workflow can be redefined on the fly, leading to backtracking or — if compatible with the goal

— the reordering of steps. Such a system is clearly collective (each element would be lost without the others), and adaptive (changes the workflow), yet it also shows that in practical adaptive collective systems there is no complete democracy of components.

The capabilities of such a system can be further exploited for training purposes. Informed, instructed, and monitored by the collective — including the ICT and robotic components! — a new employee will achieve a high level of performance rapidly. Such systems will greatly increase efficiency and versatility of the human components. However, this will represent a radically different relationship between human and machine components of the system, not in the least in the degree of human autonomy.

Who is the boss here?

The existence and use of such systems will fundamentally disrupt our way of thinking about and interacting with technological systems. Earlier examples range from the introduction of cars (which disrupted, in fact destroyed, horse-drawn transportation), to desktop printers (that simultaneously disrupted the typewriter and offset printing industry), and so on. Adaptive collective systems are disruptive in the sense of inducing fundamental changes in the use and understanding of ICT and its impact on dealing with information.

A particular issue emerging from the development of ambient technology is that of human dependence. Even in today's forerunners of fully-fledged adaptive collective systems there is a symbiotic relationship between human and machine.

When was the last time you left home without your cell phone?

Further to the issue of overall control and dependency, in the adaptive collective system world we have to live with aiming at adequacy rather than optimality. An adaptive collective system is adaptive and may adequately fit a purpose but in the old-fashioned sense be at the same time suboptimal, and that (to add insult to injury) to an unknown degree. Whereas traditional computing and artificial intelligence were looking for an optimal algorithm with proven guarantees, they often only worked under assumptions about the organization of the human-machine system that no longer hold. These assumptions included: unlimited computational resources including time; central control and complete access to information; a guarantee of specified functionality and so on. Each of these are relaxed in an adaptive collective system that is constituted of many ad hoc, uncontrollably connected elements with limited resources and opportunistic communication, as well as heuristic changing methods that prefer quick answers to optimal ones.

As a result we should give up on the ideals of completeness and transparency of methods in problem solving and focus on some new family of methods that support viability: that is, aiming at satisfactory (rather than perfect) solutions in reasonable time, at an 'often enough' frequency (but maybe not always). This strategy makes computational simulation a major tool of inquiry about adaptive collective systems, where proof of function is no longer possible and exact boundaries of applicability are unknown but real-world experiments would be too slow and costly, an encompassing simulation-based analysis can reveal what can be expected.

Suboptimality is well known in biological evolution, which is the main example where we can witness adaptation at work. Biological organisms are not running against the clock, but against each other. As a result, just how good they are at beating the clock depends on a number of contingencies about the history of such competitions, and is generally unknown. In exchange for this, an evolving population has an advantage over any engineered solution in that it possesses versatility: it will compete with (and outcompete) any yet unknown opponent. The same mechanism of adaptation bringing

Biological organisms are not running against the clock, but against each other

forth the suboptimal solutions can be optimal (or at least, a best known method) for producing new suboptimal solutions to new and hitherto unknown problems.

Beyond their intellectual values, adaptive collective systems have real-world applicability in the design and analysis of future human-machine systems.

Life is never going to be the same

So, why bother about adaptive collective systems? We as individuals are playing an increasingly important role as units of adaptive collective systems. The more we enhance ourselves with devices that allow for easy monitoring of our state of being, the closer we come to a situation in which a collection of people and artificial actors will steer us and our environment. Automated self-quantification giving advice on how and when to exercise, rest, eat, sleep, take medicine, and so on, should be compelling enough to illustrate this point.

A step further is when tracking and predicting the behaviour of people will allow for the dynamic scheduling of public transportation: when, where, which, and how many buses are needed at a specific location is within reach. Likewise, intervening in crowds to circumvent problematic situations becomes feasible as soon as we can easily collect enough information about their whereabouts and can estimate their intentions.

As a collective, humans enhanced with monitoring and actuation devices jointly channel the intelligence for collective adjustments. The question of centralized versus decentralized control is one of implementation. Both are possible, and hybrid forms are most probable, but the essence is that control is materialized as a part of the collective and therefore, it can be changed by the same collective. Or perhaps by a different entity. Or perhaps exclusively by a different entity? Indeed, life is never going to be the same again.

For looking inside, we take as our starting position that each of us, is, or eventually will be, to a certain extent bionic: a mixture of the natural and the artificial. Prosthetics are a clear example that most of us are already used to. We are no longer surprised that specific defective parts of our body are replaced by newly fabricated replicas:

a knee, hips, and so on. Likewise, digital devices like pacemakers that provide assistance are also something that no longer surprise us. We may need to get used to the fact that less obvious parts will also soon be replaceable: eyes, ears, skin, glands, even parts of our brain. That these replacements may outperform their originals is obvious.

It doesn't require a lot imagination to take this one step further. With extreme miniaturization at the tip of our fingers, we are facing an era in which a total internal body scan will continually be performed by an adaptive colony of medical nano-robots, patrolling to perform measurements and intercept hostile bacteria and cancer cells. We will indeed have virus scanners in the most literal sense of the word that adapt to our own metabolism, our aging body, and perhaps to adjustable targets set by our own personal preferences.

As a bionic being, our body continues to operate as an adaptive collective system. Of course, as a pure biological system, it has always operated as such. With the integration of natural and artificial units into this collective, our awareness of this state of being will necessarily need to be enhanced. We trust Mother Nature, but do we trust our enhancements to her?

Who is watching the watchmen?

Further to the tremendous impact on our everyday lives, these developments will interfere with life on a planetary scale, i.e. life on Earth. The bionic human will change the natural concept of viability. Babies that would not be healthy enough to reach the age of maturity under natural circumstances could live and reproduce, thus propagating their genes. In evolutionary terms, this means a significant change to the process of natural selection. Ultimately, it means a distortion of the whole fitness landscape. This human interference with natural selection already began several millions of years ago with the very early beginnings of technology. What is new here

> Human and machine are co-evolving now

is the adaptiveness of the technology itself. Enhancing humans through adaptive collective systems as we envision here leads to a co-adaptive system where the natural (human) and the artificial (machine) components are both adapting to each other. Selection and fitness, therefore, will be defined in the context of this co-adaptive system as a whole. Putting this to the extreme, and forgetting the different time scales for the moment, this means that every new generation of technology will redefine viability for the new generation of humans and vice versa.

Would you be here today if not for technology?

Chapter 3
The Purpose of (not) Having a Goal

Purposefully goalless and happy

When engineering a system, be it social engineering, software engineering, electrical engineering, or any other flavour, we as engineers seem to have this perpetual habit of wanting our system to have a goal. In other words, our engineering efforts always seem to be steered to ensuring that the end product operates toward a point where we can say that it met its objectives. Those objectives have often been explicitly incorporated into the system in a way that it can, during its operation, measure to what extent it is meeting its objectives.

In addition, we have made sure to incorporate a myriad of mechanisms that will allow a system to keep on track. We may deliberately design a system to explore a variety of trajectories, and may thus temporarily observe deviations that seem to indicate the system is moving away from its objectives. However, as long as we eventually observe that goals are being targeted again, we agree that the system is behaving as intended.

Our engineered systems generally have a goal. But should our engineered systems always have a goal?

For many of us, even posing this question may come as a surprise. The simple idea of proposing a system that does not have a goal may be very difficult to explain as being valuable. The obvious question that would be raised is, 'but what does such a system do?' A system without a goal can explore simply to discover something that we did not yet know. That is, a general drive to explore can replace the specific goal to achieve. But is this valuable, does it have a purpose?

Being without goals has good purposes

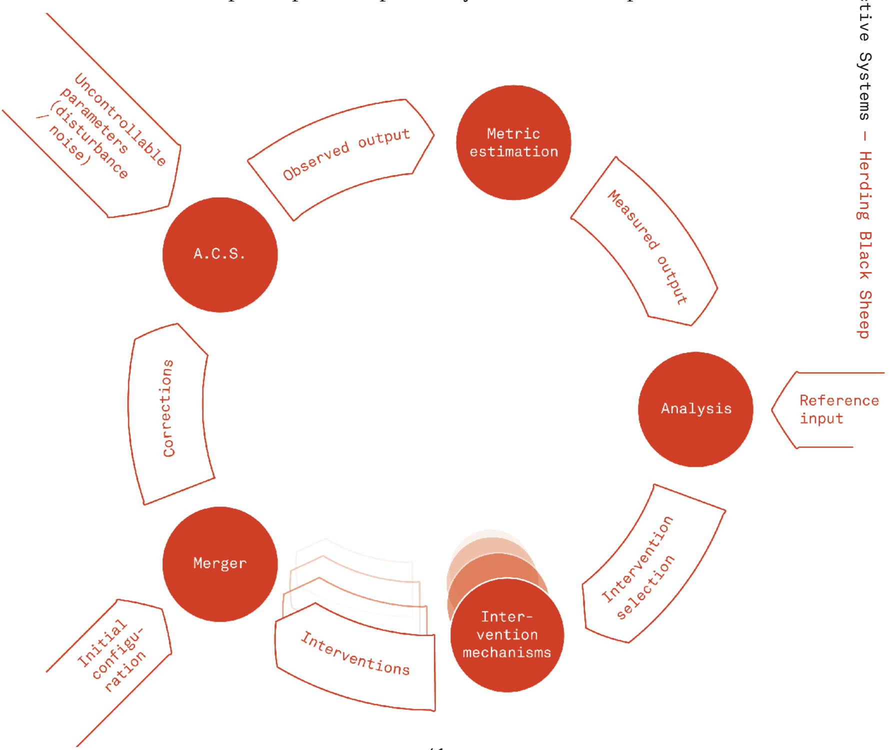
It is somewhat surprising to see how difficult we often find accepting that exploration is the only thing a system does, while, in reality, much of our own actions as humans cannot be attributed to being driven by a clear or useful goal. Yet most of us are curious and are used to spending much of our precious time on purely curiosity-driven actions and in most cases this is not considered useless or valueless.

If we accept that there can be good purpose in engineering systems for the sake of exploration and discovery alone, we need to address the question of how to actually engineer such systems. Before addressing that question, however, let us first consider the situation of when we have set goals, yet find these goals change while we are attempting to meet them.

Playing the changing game

Engineering an adaptive collective system seems to be much easier when its targets or objectives have been clearly set. If we assume that at any moment in time we can more or less accurately measure how well a system is meeting its objectives, we can also measure the effects of choosing specific actions to meet those targets. As a first step toward engineering goalless systems, let us consider a situation in which objectives may change while the system is operating.

When the system is designed explicitly as a feedback-control loop, this should, in principle, not pose any fundamental problems.



During the analysis phase, the choice for specific actions will most likely change in an attempt to meet the new objectives. In a well-designed system, we would need to change only the objectives, but none of the mechanisms. Even when the feedback-control loop is less explicit, targeting moving goals should not be an issue as long as we can evaluate how well the system is doing. In other words, as long as we have a feedback loop that provides self-evaluation about the working of the system to the system, we should be doing fine. In fact, such systems with self-evaluation are prominent in every day life, as for example, ABS braking systems in cars.

There are mainly only two conditions that need to be met to make this approach work. First, the rate at which objectives change should be lower than the rate at which we can see actions take effect. Second, the set of actions at hand should be appropriate to achieve the objectives. If a goal is to minimize monetary costs for resource usage, mechanisms should be in place to allow the system to switch between different resource providers. Evolutionary adaptation in natural as well as in artificial systems has been shown to be very successful in coping with changing environments and/or definitions of quality (fitness).

Radical changes in objectives may violate these constraints, requiring dynamic adjustments to the set of actions from which the system can choose. Humans may well be the cause of such radical changes, either intended or not. However, they may also be of great help if considered as part of the adaptation process. When following a specific path humans are often decidedly better at guessing it is leading to a dead end; they can be very good at instructing a component to momentarily ignore a specific evaluation criterion, thus bending evaluation toward exploring alternate and more promising paths. Finally, humans are also quite efficient at deciding when to reset an evaluation and start anew, assuming different initial conditions.

The good shepherd and the black sheep

Adaptation is not optimization. There are many ways to explain the difference between the two, but the essence is always related to the absence or presence of an explicit objective. Pure optimization is about maximizing (or minimizing) some quantity towards a given objective. For instance, we might want to find an optimal investment portfolio, i.e. a certain mix of shares, that maximises our profit over a year. In contrast, adaptation does not require a clear goal per se. A flock of birds populating a newly discovered island will adapt to the local circumstances, e.g. temperature, type of food, and predators, without being led by an optimization objective. Birds that can handle the new circumstances better will have more offspring and their genes will be more extensively spread from generation to generation. These genes determine the physical makeup of the birds as well as their behaviour. Over time the birds will acquire the right physical features for the island, e.g. thick feathers, long beak and good camouflage colours, and the corresponding behavioural patterns that make them successful. This population of birds is not maximizing any objective; it simply undergoes environmental selection. In this process, there is no crisply defined objective, like profit. Some changes can of course be quantifiable, such as the length of the beak, but having longer beaks is not a goal here. Rather, it is a means to an end — that of survival and reproduction.

In artificial populations adaptive mechanisms can be utilized for optimization purposes. Typically, the objective would be rooted in performing some task. Think, for instance, of a group of cleaning robots that has to minimize the number of soft drink cans left in a stadium after a concert. Depending on their control systems, these robots may find and collect fewer or more cans and we can make their task performance

Life on Earth does not have an objective

Adaptation should go off the beaten track

improve over time if we enhance them with adaptive mechanisms to adjust their controllers. In this process, new controllers will be generated and tested continually, keeping the good ones and discarding those with a poor performance. This process is driven by task-based selection. Over time, the population will improve and perhaps even achieve perfection at removing every single can after each concert.

The scenario presented at the beginning of this book about deep sea mining robots provides a different setting. It is clear that making a robot colony viable under the sea is a necessary condition for a successful mining operation. However, it is not sufficient, because in the end we want to maximize the amount of ore collected. To this end, we need to add a task-driven component to the adaptation mechanism. This leads to the principal point we want to make here: a good artificial adaptive collective system should benefit from the best of both worlds and feature objective-free, environment-driven adaptation as well as objective-based, task driven adaptation.

How can we mix environment-driven and task-driven adaptation in one system?

An inherent problem here is that user-defined objectives concentrate on the task, and not on the viability of the population. In turn, environmental selection is typically blind to the actual tasks the collective is supposed to perform. Thus, in general, these two drives (task-based and environmental) cannot be assumed to interact positively and help each other. Even worse, they may very well interact negatively and frustrate each other. A fundamental challenge for adaptive collective systems that are to utilize the full power of adaptation is the combination of the self-driven and goal-driven forces. Metaphorically speaking, they need a good shepherd who drives the herd up the hill (optimization), while allowing black sheep to wander off the beaten track (creative adaptation).

Adaptation can be [ab]used for optimization

Chasing serendipity

True innovations do not come from gradual changes. The automobile industry has done an impressive job of improving cars, yet we argue that these improvements are the result of a series of subsequent refinements. That process will not naturally lead to air planes. Something else is needed for that, illustrated by the “Eureka!” that Archimedes shouted when taking a bath. Taking some clues from a different source, he suddenly realized that the level of water was rising as he entered his bath and so solved a problem previously thought intractable: how to measure the volume of irregular objects, such as a crown for instance.

What we need is serendipity: mixing seemingly unrelated ideas to come up with an original, never-seen-before solution for a problem. A necessary condition for serendipity is to have many different perspectives from which to look at a problem, which, in turn, demands curiosity. But curiosity is often considered as an a priori useless investment for the simple reason that it is not driven by an event that already occurred.

So, what is needed to fulfil this curiosity requirement in terms of adaptive collective systems? The bottomline is to blend into the environment. Let’s zoom into this to make it more concrete. First, keep in mind that we are considering objective-free adaptations, or, more informally, goalless systems. Second, our systems always operate in some kind of ecological context. It’s easiest to think of this context in terms of a society with humans and their rules and regulations, yet one where changes will always take place. Blending into the environment means that a system is capable of finding efficient strategies that still meet its internal constraints, yet can be considered to

Being different is not enough to be innovative be an integral part of its environment. Meanwhile, it still operates toward increasing the global welfare of its collective.

The key observation is that a system can explore opportunities in its environment, and that it actually does so. This act of exploration is what blending is all about. Yet, because the environment does not belong to the collective and is thus largely unknown, exploring manifests itself typically through an extensive trial-and-error process. It forms the core of what we normally require for innovation to take place.

There are many reasons why adaptive collective systems are efficient through gradual adaptation, some of them due to their environment. Firstly, a large environment yields many opportunities, but also many paths to better, more efficient strategies as it may be easier to jump from one particular strategy to another if they are not too dissimilar. Secondly, exaptation can be expected in rich environments. Exaptation denotes re-use, by which features acquire functions for which they were not originally adapted or selected.

A canonical example of exaptation is the evolutionary transition from swimming to walking: the first fishes that came out of water used their fins to move on earth. While these fins later evolved to be more robust for their new function, their original use for crawling on earth originally resulted from a selection pressure in a different (watery) environment [Shubin, 2009].

But exaptation is not serendipity. There is more to it than that. The core idea of serendipity is that a true breakthrough requires two conditions to be met. Several key components must be put together, instead of just one, like for gradual adaptation. And then components which are seemingly useless must also be considered. The challenge is to acquire such components, and to retain them long enough so that they can be combined when the time and place are right. The

Innovation makes life easier, eventually important point with serendipity is that the combination of several components results in much more than the sum of the benefits taken from each of these components. This is the "Eureka!" moment we discussed earlier: Archimedes was considering how to measure irregular objects, happened to see that water level was affected by his body entering the bath, and knew his body qualified as an irregular object. If only one of these elements had been missing, he probably would have never come up with his famous law of physics.

Curiosity yields serendipity

What does this mean for adaptive collective systems? Let's consider computational evolutionary processes where we move from one candidate solution to another given a specific problem. The first condition states that serendipity is most likely to take place when we are simultaneously exploring at least two very different paths. More concretely we need to explore, simultaneously, two different problems. The second condition states that we need to be cautious about deciding when a solution is not good enough (e.g. when evaluated against a specific objective). Instead, we should consider retaining it. This leads to two independent threads of candidate solutions to two different problems. Where we would normally never think of bringing those threads together, chasing serendipity requires us to do exactly that: explore the combination of unrelated candidate solutions.

It is not difficult to imagine the space and time complexity of such chasing. The space complexity comes from retaining candidate solutions we would normally dispose of. The time complexity comes from exploring seemingly random combinations of candidate solutions from different threads. No one said it would be easy.

Chapter 4
Bring The Thing to Life

A new game

The adaptive collective system world is quite unlike that of conventional systems. The greatest challenge in such systems is that the required behaviour is specified at the level of the system as a whole, whereas it is primarily the components of the system and their local interactions we can engineer. The essence of the problem is that the engineerable parts have a complex, ill-understood relationship with the overall behaviour and performance of the system. Furthermore, as a consequence of the adaptive nature of the system, this relationship changes over time.

The engineering of adaptive collective systems nevertheless has a substantial conventional component that ensures we build the right thing in the right way.

First, we never engineer an adaptive collective system on a greenfield site. There is always some infrastructure; we have communication capabilities; there is a legal, governance and regulatory environment; and there are always people who are already in place. This shapes and constrains what we can do, but it also means that we have a group of people to engage with in order to get the engineering right.

Second, there is a small number of key perspectives to have in mind when engineering an adaptive collective system. There is the element of performance: what people and things actually do. Then, there is what is called 'ostention': what people and things tell each other to do. This is an important way of getting people to do the right thing but the relationship between performance and ostention is complex and full of potential for misunderstanding, negotiation, deception and confusion. Finally, we have the artifacts: those that codify/inform/document the performative/ostentive interplay. These are what we have more control over but this has an extremely complex relationship with the main performance/ostention interaction.

Regarding the artifacts we can identify three classes:

— *Actors, i.e. animate things that operate in the world: smartphones, robots, people, bacteria, actuators*
— *Computing resources: code, hardware, networks, sensors*
— *Regulation, such as laws, rules, advice, codes of practice or conduct*

Distinguishing these classes helps in focusing our engineering efforts and positioning them with respect to others.

Third, we argue that there are specific sorts of activities in the engineering of adaptive collective systems doing things in the world through the agency of people. We are not suggesting that these are the only activities, but we do think it will be important to consider them as part of the engineering methodology.

When it comes to operation, we should look at the needs that an adaptive collective system should meet. There are many pitfalls around this activity [Seddon, 2008]. The real point of this work is to identify need and work out how best to measure this outcome directly. This should avoid simplistic key performance indicator approaches because these often provide a rich environment for perverse incentives. Operational activities also include getting the legislation, incentives, and job descriptions to reward performance that meets the stated needs. This aspect of an adaptive collective system impinges most directly and comprehensibly on the people involved in performance. It sets out the values of the adaptive collective system and the working culture we want to engender. Finally, we need to recruit the relevant actors.

When designing, a key part of the information infrastructure is to make the work that is being done evident to those in the adaptive collective system. A consequence is that we need to develop a measurement and activity-capture subsystem, ensuring adaptive collective system performance meets the identified needs and perhaps identifies emergent or changing needs. Along these lines, we should be able to observe and facilitate interaction. Our engineering goal is to actuate the system so it supports performance needs. Design thus entails ensuring a way to form a rich picture of an adaptive collective system's use and then the means to show how best to support it. However, we should notice that we now also need to give people models and visualizations that help them understand how they meet needs. As far as possible, design of the information infrastructure should reinforce the central culture and values of the adaptive collective system, and should make evident that what and how people do things affects the outcome for the people the adaptive collective system serves.

Finally, in the context of development, we need to gather innovative suggestions for change from people on the ground. Here we should identify our key or lead users and look to them to help drive development. This will involve joining people up across sections so that they can identify conflicting demands and attempt to prioritize suggestions for change on the basis of how effective the change will be. Typically, we need to facilitate experimentation in a 'sandbox-like' environment with real people to see if innovations work in practice. At the same time, we need to ensure that we can respond as needs change. Often underestimated but equally important is to involve outsiders who will be able to offer a sceptical viewpoint on the performance of the adaptive collective system, and who can identify disruptive change because they are not signed up to the culture and values centred around the adaptive collective system.

Breeding

The first step in designing an adaptive collective system is to breed it from scratch up until deployment is possible. From this perspective, we distinguish between two different objectives. One, engineering an existing system is about building a model from observing an adaptive collective system from the real world, in order to better understand the world and possibly act on it. Two, we may also engineer new realities, that is designing an adaptive collective system that is meant to blend and act on the world in its own unique way, giving rise to fundamentally new dynamics.

Engineering an existing system

Engineering an existing adaptive collective system requires that we facilitate a virtually never-ending loop of monitoring, anticipating and intervening in behaviour. A crucial aspect in this process is ensuring that we have models that not only explain what we are monitoring, but have the capability of predicting what behavior we can expect. Having a register of monitored and predicted behavior allows us to reason about which interventions to apply in order to change what has been predicted, if that is what we want.

> Engineering an adaptive collective system implies building models of an adaptive collective system

There are three important elements in engineering adaptive collective systems from this perspective. First, we need to make sure that we can actually monitor a system, implying that there are sensors that can capture a myriad of behavioural aspects, along with the means for aggregating and fusing data into useful information.

Secondly, and symmetrically, we need the actuators to enable interventions, perhaps along with the means to dissect abstract notions of how to interact into signals that are meaningful for our set of actuators.

Thirdly, and most important, we need models that produce reliable predictions of the behaviour we can expect based on the input from sensors. From this perspective, engineering an adaptive collective system is all about developing models that capture the real-world operation of such systems and are able to tell us about how they will behave in the near future.

Engineering an adaptive collective system becomes a problem of building models of such systems. It places current reality in the service of model engineering.

How do we build models of adaptive collective systems? Models should be able to capture real-world operations, implying that we need real-world data to start with. Although collecting data has become easier compared to say, a decade ago, it remains a cumbersome effort requiring significant attention and patience, not in the least because for any collected data set it may not be obvious that, and if so how, meaningful information can be extracted for building a model. We have already noted that having to deal with a myriad of different (types of) information sources is a huge challenge for adaptive collective systems. Building models provides another reason for putting effort into solving the problems with such heterogeneity.

How do we meaningfully sense the (evolving) state of a real-world adaptive collective system?

Developing models is a creative process, and there is a lot of existing experience in producing models that make sense. Of course, the process of model development is far from being completely understood. Nevertheless, by stating that we need real-world data for building models, we have the obligation to validate our models by simply comparing their predicted behaviour to observed behaviour.

However obvious this may seem, it is remarkable how easily we seem to tend to ignore this step.

How can we build models including their validation?

In practice, many adaptive collective systems will take a more pragmatic approach. The participants in the adaptive collective system will have considerable expertise and will develop the system using commodity components in unusual configurations driven by a very local view of the needs the adaptive collective system is intended to meet. The adaptive collective system may grow by a process of accretion or bricolage (Do-It-Yourself) as people pick and choose what is appropriate to use.

Examples abound of this sort of engineering by tinkering. For example, in Finland there are groups focused around old-fashioned computer forums with a focus on innovating and exchanging advice on how to make the best job of heating your house (using boilers, heat pumps, solar, wind...). The system adapts because there is a continuous flow of new products that need learning to assimilate into the dialogue, plus a range of modifications and configurations that help get the best out of them. The system is also collective in the sense that there are many overlapping interest groups clustered around particular classes of product and particular kinds of modification. Many of these changes are not even according to the factory-issued guidelines and facts sheets, using (or re-using) the components in many unforeseen ways.

Understanding these self-organizing systems and how they survive in the long-term by developing, or being replaced by some other similar systems is fascinating: understanding birth and death processes for these systems helps us to understand more 'designed' or 'engineered' adaptive collective systems.

Engineering new realities

Suppose that we do not want to engineer an existing system, but instead want to create new ones. Doing so requires we have models that will explain to us how our intended system behaves. This brings us to the other side of our double-edged sword: reality engineering. This engineering places model development in service of creating reality.

Modelling and simulation methodology offers itself as an iterative, models-first approach. Starting from a dummy model (for instance, an agent-based model where the agents have – in an ideal approximation – no properties or as few as possible) we can gradually dress it up with more properties and monitor the behaviour space generated. To model a given complex environment, we can continue the process until a rich enough behaviour set is produced. (Note that this process is not algorithmic as it involves human ingenuity to invent and test supposedly useful properties specific for the given problem, which requires intuition about the system.) Using customary model and simulation testing methods, namely parameter sweeps, the behavioural possibilities of the system can be satisfactorily mapped to help the process. Once the growing behavioural space includes the desired elements (behaviours to be thought relevant or important for the real-world system considered), we can establish a catalogue of behaviours through the extensive model tests and the parameters or conditions leading to them. Equally important, we can at this point stop the iteration loop by having found a system with the desired properties.

Several remarks must be made. First and foremost, we do not build models of the real systems but models for them, as we are not directly using actual data for the production of the model. Secondly, this is a minimalist methodology which starts from scratch (as close as you can get) and then adds properties one at a time, thus maintaining minimalism throughout the steps. Still, strictly speaking, the final model is a sufficient one, as the process does not guarantee actual minimality (i.e. sufficient and necessary conditions). Despite this shortcoming, the intuitive understanding here is that we often nevertheless deal with a minimal of a 'smallest' system. Finally, in terms of emergent behaviours, we can include desired and exclude undesired outcomes by selecting one and not another part of the behaviour space and the parameters or conditions generating it.

One intriguing application is that the methodology can be used for social engineering. Given a rough specification of the kinds of behaviours to be realized in a real system, and the loose way that they are expected to be achieved (i.e. giving the available components and their properties spaces or possibilities), the methodology is suggestive of the actions to be taken out into reality to obtain the functionality desired. The model suggests the coordination and property set necessary (within the limitations discussed above) for achieving the goal.

Closing the loop: interventions

Regardless of whether we are developing models that capture reality or create it, engineering requires that we continuously refine our models. A standard approach is to simply pick up what a model generates and feed that back into the system under study. In essence, we are talking about interventions, either by acting on the real system that we are modelling or on the model that we are using to create a real system. Awareness of this aspect of engineering leads to thinking about which intervention mechanisms we need.

So the complete loop looks like this: data (of real systems), models, predictions generated by the models, optimization (of parameters and operations, using various utility functions — either explicit and formal or implicit and intuitive), generating real systems (or making modifications), thereby yielding new data (using carefully introduced observables defined over the system)... and so we are back at the beginning.

This loop tends to be realized in iterative cycles as discussed above so it should be noted that it makes little difference where exactly we start in the loop. It can be at the model stage or with the existing systems — the basic elements of the methodology and their essential connections are the same.

Steering

In the previous chapter we discussed how to breed an adaptive collective system, that is, how to build it from scratch prior to deploying it. Here we will concentrate on what happens after the system has been unleashed in the world. Although we expect the adaptive collective system to follow the directions sketched at breeding time, it may be required to intervene in, or steer the system, in order to refine its behaviour. There are indeed many reasons for steering an adaptive collective system: from helping it solve a particular problem for which you have hints, pushing it in some desirable direction, preventing it from developing in some undesirable direction (that is, keeping it within limits), or ultimately, if necessary, to shut it down.

On-the-fly control of an adaptive collective system

Previously, we considered the example of a group of mining robots sent to deep sea environments to collect some ore. What would happen if we wanted to move this group of robots to another environment, for example to a lunar setting, in order to conduct mining activity? Would it be possible to expect that past experience may be straightforwardly transferred and applied in the completely new setting? Probably not. Yet, we would not want to pay the cost of completely rebuilding the system for any new situations. Adaptation can play a key role in this process, though it may be idealistic to hope for adaptation to cope with changes of very large magnitudes. Then the question is: how to push the adaptive collective system towards a new regime.

Technically speaking, the essence of steering an adaptive collective system is to influence the forces that drive it. Therefore, it is important to identify the most important forces in adaptive collective systems. To this end we can distinguish two major categories: components and methods of adaptation.

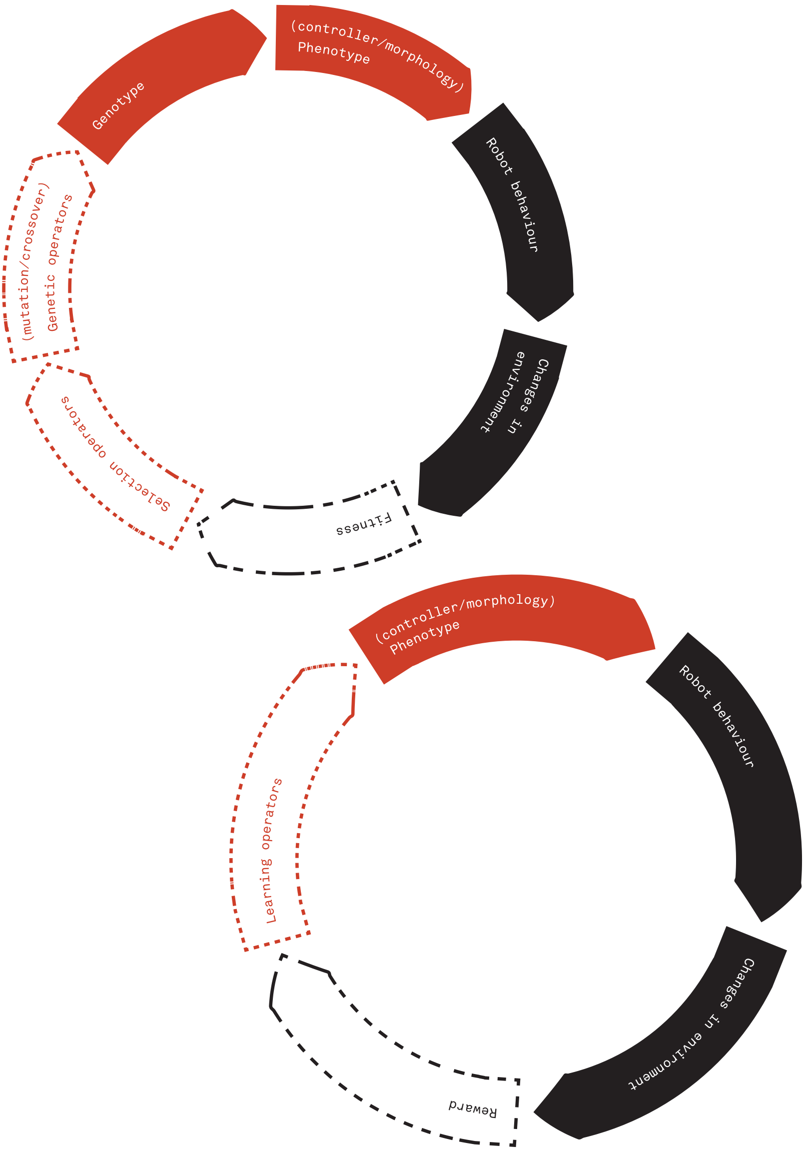
How many dogs does it take to herd?

When it comes to components, the individual elements are perhaps the most obvious points of entry here. Changing their behaviour can be naturally achieved by changing their controllers or physical makeup, e.g. their sensors. For instance, we can switch on traffic information receivers in a self-driving car. Then it will be still able to optimize its behaviour on a local, second to second level using its sensors, e.g. cameras and GPS, but also optimize on a larger scale taking its position and traffic information into account. Focusing on the collective, influencing coordination and regulation among the system elements is the obvious option. For instance, in case of a calamity, we may disseminate software code on cell phones in real time that would allow them to detect other phones in the vicinity and advise their owners to flock together at designated safe areas. Finally, while we may not have full control over the collective, we may be able to shape (at least part of) the environment in order to guide behaviour towards new collective dynamics. A well-known example here is the variable message signs on the highways that can change the maximum speed.

With respect to methods of adaptation, we should realize that it is here that different mechanisms separate evolution from learning [Haasdijk et al., 2013]. We perceive learning as a mechanism that does not influence inheritable material. In other words, learning may change the controller, and thus the behaviour, of a system element, but these changes will not be transferable to the offspring of this element by reproduction. Learned traits will thus die with the learner, unless explicitly communicated to others. For example, if a person learns a certain language or learns how to play a certain instrument her children will not be born with the ability to speak that language or play that instrument. However, the parent could pass these skills to the children by teaching them. We call this mechanism social learning. The mechanisms to implement the transfer of skills and knowledge can be very different, e.g. verbal teaching or imitation, but in all cases the knowledge to

Adaptive collective systems don't die

be transferred is not inheritable. Evolutionary learning on the other hand, only influences inheritable material, for instance skin colour or the metabolic rate of burning sugar.



Steering an adaptive system in real time requires changing the learning or evolutionary operators. For instance, in case of the deep sea mining robots, we may change parent selection by enforcing a preference for mating partners with good long range communication abilities, even though this property is not critical for executing the original mission of collecting ore. Remaining with the same example, let us assume that robots can learn from each other by imitating their peers. Then we could significantly influence the learning system by designating some robots as teachers and mandate that only teachers can be imitated.

Exerting control

What makes steering difficult is that one cannot assume that all elements of the system are within reach and that we cannot expect a centralized control scheme. We can assume only that complete absolute control over the system is not an option, and that we have to deal with the system's dynamics to achieve our objective. We are like a navigator steering a sailboat, fighting against and sailing with the winds and the sea to reach our destination. Matters are complicated in the sense that we now have multiple sailboats. A critical issue for steering an adaptive collective system is then to identify the relevant point of entry.

An example is organized crime networks. Shutting down the operation of an organization growing and selling cannabis can be done in many different ways, with different levels of efficiency. You may arrest the pushers who sell weed in the street, which is an easy task in practice, but has proven to be quite inefficient as new pushers quickly replace those gone. You may also try to arrest the head of the organization, but this is often much easier said than done. Or you may try to pinpoint the weakest point of the organization. The electricians are one of these weak points: they are essential to the production unit, which requires a robust electrical setup, and they are difficult to replace because of their particular skills. Catch the electrician, and you may kill the complete line of production and distribution.

Control demands understanding

Another example is that of mixed societies of insect or animals and humans, which have been studied in recent years [Halloy et al., 2007]. In a similar fashion to herding sheep, the goal is to steer a group of living individuals to comply with our goals. These living systems may be adaptive — cockroaches, fishes, bees — and may be challenging the steering. Firstly, the dynamics of the system must be understood before the relevant links on which to act may be identified. Then it is mandatory that the collective reacts positively to the steering. While a herd of sheep may accept the presence of a dog and shepherd, it is very unlikely that cockroaches would do the same. One main challenge is then how to blend into the system and steer it from the inside. Solutions that have been explored are quite straightforward in hindsight: the best way to be accepted in a society is to be part of it. Therefore, why not build a robot cockroach? However, this raises the question of how to modify the behaviour of one or several robot cockroaches so that they remain blended in the population, while being able to yield the required changes we were after in the first place.

The ultimate steering: shutting down an adaptive collective system

When it comes to steering an adaptive collective system after its deployment, the most radical question we may ask is, how to shut it down. This seemingly naive question which is relatively simple when considering a centralized system (where "turn off the switch" is an answer) suddenly becomes a major challenge in a possibly very large adaptive collective. Not only the decentralized nature of the system makes it difficult to shut it down all at once, but its adaptive component may well lead to strategies to disobey an order which is in complete opposition to what the adaptive collective system is about in the first place: to adapt and survive.

This challenge is very real, even for existing collective systems such as the internet and as well as some of the collective systems it encompasses. For example, botnets are programs designed to penetrate and take control of computers. Once a computer has been infected, it will be used as a new recruit to spread on the infection.

Botnets are very real as dozens of millions computers get infected every year. While botnets are mostly malicious software, and follow the command of the bot herder, i.e. a human accessing the internet through one, or several particular computers known by the many copies of the bots, the mesmerizing aspect of botnets is that they could well be completely autonomous, and possibly adapting over time. Now the important point is that, whether adaptation is at play or not, it is nearly impossible to shut down the existing botnets.

Shutting down or 'killing' a distributed adaptive system can be hard or impossible, as illustrated by biological examples. Extermination of a given species usually requires other organisms deployed in the same ecosystem, but the known examples are rather discouraging. Rabbits introduced to Australia have been attacked by a virus but that led to co-evolution rather than extinction. Now camels are the next target in Australia. In short, killing out a species by introducing another is a very controversial technique with adverse effects. Another well-known phenomenon is adaptive modification arising from the very nature of the system. The popular example is the spreading of antibiotic resistance in bacteria — they evolve new forms that fend off and even overkill drugs. Also HIV treatment faces the same problem with the arising of mutant forms of the virus with a different metabolism. Finally, and most importantly, there is 'function change', the habit of adaptive systems to survive in changed environments by abandoning their original functions and taking on new ones. One case of this was of the Bikini Atoll where radiation from H-bomb experiments did not kill the crabs but turned them into predators that kill young birds. In summary, an adaptive collective system is like a fluid, it tends to avoid being grabbed even while perhaps simply appearing to be like 'silly putty' — while looking soft and amorphous, the harder you hit it, the harder it hits back.

Reflecting

We argue that reflection is at the heart of collectivity and adaptivity in systems involving human collectives.

Reflection has its roots in foundational investigations of logical systems. It is the inclusion of some property of the system within the objects of the system. In logical systems this can be things like provability or equality. Famously, Gödel demonstrated that provided a system includes arithmetic, it is possible to encode the formulae and proofs of the system and to define a proposition that some coded proof p is a proof of a proposition P in the system. Using this mechanism he was able to construct true propositions that are unprovable in the system: this was his first incompleteness theorem. Reformulating this, Gödel proved that if a system had a voice, it could state "I contain a proposition that you cannot prove".

This property of reflecting some meta property of the system within the system is very widespread. For example, the notion of reflection in the Java programming language where programs have the capacity to observe and modify their structure is a very powerful. Many systems include some aspects of reflection. In designed systems this might be the inclusion of a model of the system that attempts to characterize the behaviour of the system given some initial environment.

The notion of model may also be very informal, based on past experience of a very loose match between past behaviour and the current situation. In systems involving humans this may be entirely based on their memory of system behaviour and on intuitive notions of the match between the current environment and some past experience.

If we accept that internal change in the control policy of a system is a distinguishing mark of an adaptive system then notions of

Notions of reflection take an important role in understanding adaptive collective systems in general

reflection take an important role in understanding adaptive collective systems in general. Reflection mechanisms allow us to explicitly capture or model aspects of the system that might otherwise be unobservable. Thus if we want to judge whether a system is adaptive or not we need some element of reflectivity because we must be able to make observations that go beyond the 'normal' behaviour of the system.

In socio-technical systems the notion of level is often closely related to particular types of reflection on the behaviour of the system. For example, in public-sector delivery organizations there are typically operational (mainly concerned with delivery and quality), strategic, policy and regulatory levels. Each level requires evidence from lower levels and some model of the system in order to adapt at the level and effect changes at the lower levels. In service-delivery systems also the culture and values of the different collectives play an important role. These features play an important role when it comes to combining adaptive collective systems in order to transform the systems to meet new missions.

As discussed before, the level at which we consider a system is an important issue when it comes to understanding whether systems are adaptive or not. Making such observations and deciding whether some system is adaptive depends on aspects of reflection as well, since we need to add extra observations and potentially fit a model to the new observations.

Reflection is at the heart of collectivity and adaptivity in systems involving humans

Chapter 5
The Future

Throughout this book we are assuming that we know our adaptive collective systems, both as what they are now and what they can be in the times to come — using the same components, the available or immediately reachable technologies and so on. What we have said this far about adaptive collective systems may sound far-fetched to some, but in reality it is all within the domain of research and technology co-development. That is, the existing or doable, undoubtedly with a high risk but that is only because we don't know how to do it or how to exploit it.

But adaptive collective systems as envisioned here can well be far more pervasive and supposedly persistent. If our assessment about adaptive collective systems is correct, entering the adaptive collective systems age is a one-way street. Once the systems become widespread, and this is happening as we speak, they become indispensable and we will increasingly depend on them. It is fair to expect that adaptive collective systems will be around 'forever' in some form (much as books and other fundamental information management technologies have always been used since they were invented).

Avoiding the fantasy world of the unseen adaptive collective systems of the future (the time where we live in glass bubbles and so on), yet to say something relevant about it, here is a question: will the inevitable addition of new, unknown kinds of ICT components to adaptive collective systems change the game?

Appendix

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