

How can we think the complex?

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In this chapter we want to provide philosophical tools for understanding and reasoning about complex systems. Classical thinking, which is taught at most schools and universities, has several problems for coping with complexity. We review classical thinking and its drawbacks when dealing with complexity, for then presenting ways of thinking which allow the better understanding of complex systems. Examples illustrate the ideas presented. This chapter does not deal with specific tools and techniques for managing complex systems, but we try to bring forth ideas that facilitate the thinking and speaking about complex systems.

1. Complexity

Giving a sharp definition of complex system is hard, since the term is used in such a wide variety of contexts. Because of this, we will only give a notion, to have a better idea of what we are speaking about. A complex system is usually hard to describe (although simple systems can also be, therefore not to confuse complex with complicated), because it consists of several elements that *interact* with each other (see Bar-Yam (1997) for a detailed introduction). These interactions make the global behaviour of the system hard to track, in terms of its elements. If the interactions are *nonlinear*, then the description of the system cannot be reduced to the description of the elements. The properties present at the system level not present at the element level are called *emergent*.

Examples of complex systems are everywhere. We can mention a cell, a society, an economy, an ecosystem, the Internet, the weather, a brain, a city. They all consist of many elements, and the functions and properties of the system are a result of the elements' interactions. Nevertheless, tracking functions and properties of the systems to single elements or interactions is not an easy task.

There are several measures of complexity, useful in different contexts: information, social, economic, biological, etc. Also, we cannot draw a sharp boundary between simple and complex systems. What we can do is to compare according to an agreed frame of reference and say: this system is more complex than that one. Overall, we can say that *the complexity of a system scales by its number of elements, by the number of interactions among them, by the complexities of the elements and by the complexities of the interactions*. This is a recursive measure, but it can be general enough to be applied in different contexts. We just have to note that the more interactions, the more complex a system will be. And the more elements, the higher the complexity of the system. For example a firm will be more complex the more employees it has. However, for the same number of employees, a firm will be more complex than other if people need to interact more between them, since more coordination will be required. As we can see, complex systems

tend to be harder to manage than simple ones. The main reason for this is that we know how to think about simple systems, when we are only beginning to understand the complex.

2. Causality

Classical causality is very useful when A affects B, but B does not affect A too much. For example, the gravity of the sun affects the earth quite a lot, causing its rotation around it, whereas the effect of earth's gravity in the sun is neglectible. Then we can conclude that the sun causes the earth to orbit around it. We can say that classical causation is a relation where we ignore the effect of the "consequent" on the "cause". Classical logic is based on these premises, and it has served human kind tremendously: it enables us to make accurate *predictions* (Heylighen, 1989).

However, it seems that we run into problems when we cannot explain the behaviour of a system when its elements tend to affect each other simultaneously. It is a kind of chicken-and-egg problem. We have A affecting B, but simultaneously, B affecting A. Moreover, if there is some nontrivial time delay between these effects (Gershenson, 2002b; Gershenson *et al.*, 2003), it becomes very hard to make accurate predictions, because we do not know who will affect who first, and this can have drastic effects on the dynamics of the system. The more interactions and/or elements we have in a system, the higher the probability will be that two elements will affect each other. Therefore, classical causality runs into trouble when trying to understand or predict a complex system. We need to use a different way of thinking to understand them.

One example can be a stock exchange: people buy and sell stocks, but their price is determined by the buying and the selling. Since the buying and the selling also depend on the prices, we cannot *reduce* completely "cracks" of the stock exchange to its components, since their behaviour depends on the behaviour of others.

Now, when we have several elements (or quite a lot) interacting with each other, we cannot trace the "cause" of a state of the system to a single element. Notions like circular causality (for example, a cell producing another cell. The theory of autopoiesis (Maturana and Varela, 1987) has proposed very interesting ideas to understand circular causality) or multicausality are useful to get out of the problem that classical causality would get into. Such a system is just not possible to think with classical causality, because this simplifies the relations to be only unidirectional: from A to B, but not bidirectional, or multidirectional. Circular causality or multicausality can cope with this, simply accepting the possibility of mutual determination, along with its implications.

Classical causality has the property of predictability. Complex systems are not completely predictable¹. This is not because we may not know how they work, but because of chaos, which is common in complex systems: small differences can yield large effects. We will never have enough precession to predict the weather for the next month. Yet we can have enough to predict with *certain* reliability the weather for the next week. In a company, also small changes can have drastic effects (e.g. the new wife of the CEO). Nevertheless, we can also see the opposite: great changes can bring few or no effects (e.g. the new image of the company). The same happens in a stock exchange: we can understand its mechanisms very well, but we are just not able to predict accurately its behaviour for long periods, since small causes can lead to drastic effects, and vice versa.

¹It does not matter if the universe *is* deterministic or not. We cannot predict *in practice* the behaviour of many deterministic or non-deterministic models.

3. Nonlinearity

A common characteristic of models of complex systems, is that they are nonlinear. This means that the elements of a system interact in ways that are more complex than additions and subtractions. In a linear system, we just add the properties of the elements, and we can deduce and predict the behaviour of the system. Nevertheless, when there are many interactions, and these are nonlinear, small differences multiply over time, yielding often chaos and unpredictability.

In a nonlinear system, causes are not directly proportional to their effects. Big changes can have little or no effect, while small changes can have drastic consequences. This makes complex systems to be not completely predictable.

4. Tools

If complex systems are so unpredictable, how can we deal with them? Well, first we have to accept that we are not able to deal *completely* with them. It is natural that there will be problems and errors, as there have always been. We simply cannot predict everything that might happen! What we can do is to be prepared to *adapt* as good as possible to the unexpected changes, and to *expect* as much as we can.

As we can see, the *prediction* of classical thinking is turning into *expectation* in complex thinking. The main tool for this has been for a long time probability theory, with quite a success. Other tools for dealing with expectations are fuzzy logic and computer simulations. We cannot say for sure if a business will go into bankruptcy in the next year, but we can very well calculate its probability.

The other side of managing complex systems, *adaptation*, has been tackled with cybernetics (Heylighen and Joslyn, 2001), artificial intelligence, neural networks, multi-agent systems, chaos control (Chen and Yu, 2003), and many other disciplines. Research is going on still, trying to design and build systems that are even more adaptive. When a system is adaptive, unexpected events can be tackled, as the system is reconfigured or reconfigures itself without breaking.

We can say that a very useful concept in the adaptation of complex systems is the one of *self-organization* (Ashby, 1962; Beer, 1966; Heylighen, 2003; Heylighen and Gershenson, 2003). This is a tricky concept, because *any* dynamical system can be *described* as self-organizing (Ashby, 1962; Gershenson and Heylighen, 2003). Nevertheless, it is useful to do so when the desired behaviour of a system is too complex or too uncertain to design straightforward: we can design elements of a system, so that through their interactions they can search for configurations that solve the problem at the system level. The goal is for the elements to self-organize, without the intervention of an engineer or manager. Their advantage is not only that they can find unforeseen solutions for problems, but also that these systems are very adaptive: since they search by themselves for solutions, when unexpected changes come about, they can adapt seamlessly, by themselves.

An example of a self-organizing system can be the Internet. There is no central control, each node of the network has its own task, and the Internet protocol was designed so that a package of information can reach from origin to destination through many different possible paths. So if some servers go down, the traffic can be still maintained by other servers. The Internet also adapts constantly to the growing traffic of information.

Certainly self-organizing systems will not be able to adapt to all possible events, but they have proven to pose a good perspective to deal with complexity. A drawback is that we still do not have the appropriate language to speak and think clearly about self-organizing systems. In the next section we present a step towards this.

5 . Ontology

With classical philosophy, it is very easy to confuse what things are, and what we think they are. Actually it falls to the point where it seems that there is no difference between the thing itself, and the representations and models we can make of it. Because of this, people have engaged in controversies on “what things are”, when the difference lies in how people represent what things are.

It is hard to specify if we refer to the model or to the modelled each time we speak about something, because our language does not make such a distinction. Then falling into confusion is easy. Therefore, using different words for different concepts is useful. We have introduced an ontological distinction between “absolute being” and “relative being” (Gershenson 2002a). The *absolute being* (abs-being) is independent of the observer, and the same for all the universe. The *relative being* (rel-being) is dependent of the observer and its context. Since the observer is finite, rel-beings are limited, whereas abs-beings are unlimited. A rel-being can approach an abs-being “as much as we want to”, but it will never comprehend it completely. There can be an infinitude of different rel-beings for any abs-being. For example, if we have a sphere which is half black and half white, but we are looking at it from different perspectives, for some it will rel-be a white circle, for others it will rel-be a black circle, and for others it will rel-be a mixture. Suppose now that the abs-being is such a ball, only that with an infinite number of dimensions (since we can always find more properties for any object). Clearly, we can have different <rel-beings|representations|models|metaphors> about one abs-being. Noting that *things do not (abs)depend on the representations we have of them* is very important. Rel-beings depend on their observer, but abs-beings are independent of them.

With simple systems, different rel-beings are very similar for different observers, because the differences in them can be small and their contexts do not affect the rel-beings very much. However, with complex systems, there are so many properties and aspects, that observers can have different rel-beings of them, depending on which aspects and properties they take into account, and which do they simplify. In other words, the rel-beings depend on the *context* from which they are being observed.

Then we fall into the problem of deciding: If there are several rel-beings, which one is “the best”? This depends greatly on the *context* in which *this* is decided. There is no “best” rel-being, but different rel-beings are more appropriate for different contexts. It also depends on the *purpose* we set for the system (Beer, 1966; Gershenson and Heylighen, 2003). With a classical way of thinking, we can spend all our efforts in trying to decide what *is* the system, instead of concentrating on deciding which rel-being is more appropriate for our context. Moreover, with a complex thinking we can contemplate at different rel-beings at the same time (e.g. at different levels of abstraction), in order to have a less-incomplete understanding of the system. This cannot be done with classical thinking, where rel-being and abs-being are not distinguished.

This does not mean that we should throw away all the tools of classical thinking, since they are useful for simple problems, and they can be partially used to deal with the complex ones. Still, we have to expand our tools for thinking, and only then we will be able to have a deeper understanding of complex systems.

6. Emergence

The buzzword “emergence” has been overused without a doubt. Because of this, many people are skeptic about it. Nevertheless, we can draw a clear notion of emergence with the philosophical tools already discussed.

We often speak about emergent properties when properties at a system level are not present at the lower level. So, for example, we can measure temperature and pressure in a gas, but not in a molecule. The gas is composed by molecules *and* their interactions. The new properties, temperature and pressure emerge from them. Gold is yellow, shiny, and malleable, but we cannot deduce these properties by observing the atoms of gold (Anderson, 1972). We say that a cell is alive, but it is made of non living elements. Life emerges from them and their interactions.

Within a classical framework, it is indeed strange to speak about emergence, since Aristotelean philosophy presupposes that things can only be one thing at a time. How could a cell be at the same time a cell and a bunch of molecules? We cannot deal with this with Aristotelean thinking. We cannot speak about different levels of abstraction, since we assume only one “true” and “correct” representation for things. But now we can say that we can describe the same abs-thing at different abstraction levels, with different rel-beings. The thing itself does not change. What changes is our <model|representation> of it. Then the mystery disappears, and we can speak comfortably about emergence. We can understand it as a *change of model* (Rosen, 1985) in order to *understand* better and *predict* a system (Shalizi, 2001).

For example, making predictions when we speak about temperature is easier than making predictions about single kinetic energies of billions of molecules. It is easier to make predictions about markets in terms of macroeconomic factors than in terms of the profits and expenses of individual companies. There is no magic. We just change the <frame of reference|abstraction level>. We are just observing a different *aspect* (ten Haaf, et al., 2002) of the system. The molecules and the markets do not abs-change. Only our models change, what things rel-are for us. And changes in the rel-beings do not affect the abs-being.

7. Open and Closed Systems

One implication of classical causality is the tendency to model systems as closed. This means that we neglect the effects of elements outside our model. This is understandable, because we model only what we see, which is finite. Again, this brings problems when the system complexity is such that we cannot ignore unpredicted causes outside our model. With some experience we can see that all systems (abs)are open (e.g. affected by external gravitational or electromagnetic forces), although in practice we can model simple systems as closed. This is because we can neglect small perturbations, since they do not affect the behaviour of the simple system. But we cannot do this with complex systems. Unpredictable events very probably will come into existence when we have complexity. Moreover, small perturbations can propagate to produce drastic changes in the system. This is *natural*. A possible solution: imitate nature. Nature adapts to unpredicted changes and events. Many tools mentioned above take inspiration from nature to make artificial complex systems adaptive. Another example is ant colony optimization: its algorithms are inspired in the self-organization of the social insects.

Having this in mind, we should try to model all complex systems as *open* systems, in the sense that there will be unknown factors bringing things in and out of our system. The standard way of achieving this is introducing *noise*. In other words, we include in our model small random fluctuations. Noise allows us to observe and measure how robust a system is. Actually, many systems *require* noise to be robust and stable.

An example can be software development. Within a classic framework, there is a requirement, and the system should comply with it. However, if we are dealing with a complex software system, the requirements can change unexpectedly with a higher probability, for whatever reasons. If the software were developed from the beginning as an open system, changes and extensions are already expected, so the system can adapt much better. Object-oriented system

engineering has been a big step towards this, since it allows the easy reutilization of code. Therefore, in an ideal scenario, small modules can be adjusted without the need of reimplementing the rest of the system. Further research is being carried out for having modules that can adjust themselves to unexpected changes.

Another example can be a company. It can follow a strict business model. However, if the company is in an unpredictable environment, as all actual companies are, that business model should better expect the unpredictable, to be ready to adapt to unforeseen changes, such as new competition, new market opportunities, or new products in the market.

It is by realizing systems as open that we can be ready and face unforeseen changes. We cannot do this with classical thinking, because this one assumes that the world is predictable. Well, with complex systems we have seen that it is not, and we have to change our ways of thinking to cope with it better.

8. Conclusions

We still do not understand complexity very well. There is much to be done and explored in this direction. Our culture now is immersed and surrounded by complexity, and we have no other option than to face it. But facing complexity forces us to change our ways of thinking. We have presented some philosophical tools that allow us to better understand and speak about complexity.

One of the main things we have to be conscious about when we are dealing with complex systems is that they are not completely predictable, even if we know how they function. The fact that we understand a problem does not mean that we will be able to solve it. Yet what we can, and should do, is to be prepared to deal with the unexpected events that complexity most certainly will bring forth. We should not try to *determine* the behaviour of a complex system, but to *expect* certain possibilities. And we should try to be able to *adapt* when the unexpected comes. Because then we are ready to expect the unexpected.

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