

# PART I

## COMPLEXITY SCIENCE RESEARCH PHILOSOPHY

*Professor Henrik Jeldtoft Jensen*

Complex systems science considers situations where multiple components evolve together in tangled webs of interdependencies. And complexity science acknowledges that what at one level is considered to be the components may themselves, as one so to speak zooms in, be studied in their own right as collections of subcomponents, for example, the components of sociology are individual humans (or classes of humans), each composed from myriads of individual cells and organs. Typical fields of science considered by complexity theory include evolutionary ecology, neuroscience, sociology, economics and finance.

Is complexity an altogether new kind of science? Not really. Any particular ‘thing’, say a glass of water, is always part of the larger surrounding world and what we see as a glass of water at our everyday level of experiencing our surroundings, may be seen as an intricate organisation of zillions of subatomic particles into water molecules, which in turn organise themselves into the liquid water with its ripples and bubbles. The traditional hard sciences are used to hierarchical organisation of reality, but physics, say, can very much be seen as a science for which meaningful results can be derived using ideas such as closed system, equilibrium or steady state dynamics where the components of the system don’t not undergo any fundamental change.

Physics has had great success in approximating the world by building blocks treated as things and derived laws applicable to each level: subatomic, atomic, molecule, liquids, solids and so on. However, this description is, after all, an approximation. The different levels of reality are connected and the world does not consist of ‘things’ with their own one and for all given properties. Bar-Yam discusses these aspects in Chapter 1.

The philosopher Alfred North Whitehead argued that not ‘things’ but processes are the basic ontological constituents of the world. Of course, we often pretend it is otherwise and sometimes, for instance like in physics, we even get away with simplistic approaches that ignore the basic interconnectedness and co-evolutionary nature of the world.

But as we move to aspects of the surrounding world involving processes typically classified as biology, sociology, economics and so on, it becomes very problematic to insist on, for example, equilibrium or a closed system. When analysing and modelling complex systems, it is important from the onset to apply a methodology that allows for co-evolution of hierarchical structures. Building blocks with a fixed set of attributes can then not form the basis for our analysis and model building. A much more appropriate starting point

consists of co-evolving processes. In Chapter 4 of this Handbook, Mitleton-Kelly discusses verbal models of co-evolution; such models can of course be developed further to go beyond the verbal descriptive level and allow for more quantitative approaches to co-evolution.<sup>1</sup>

The fact that the world really consists of co-evolving processes obviously complicates the research into the behaviour of complex systems significantly and perhaps also encourages the complexity scientist to be more humble and sober concerning what theory of complex systems can do. A complexity scientist is unlikely to think that it makes much sense to imagine that a ‘theory of everything’ exists, as some suggested by physicists. Such dreams seem unrealistic to a complexity scientist since complexity science is persistently confronted with the realisation that the hierarchical structure of our world leads to a staircase of emergent ontological levels. The collective cooperative processes at one level, say a tornado in the atmosphere are of course related to the individual air molecules, since the tornado is the flow pattern of air molecules. But a single air molecule doesn’t possess any microscopic ‘tornado property’. The tornado is entirely a collective process that only exists at the level of the cooperative motion of many air molecules. Hence, rather than looking for a model allowing for the prediction of the fluctuations of the stock market from the cells composing the traders’ brains, a complexity scientist will be more modest and acknowledge that phenomenological theories are what makes best sense. And, importantly, when trying to understand the stock market complexity science will investigate if collective emergent behaviour of the involved agents may perhaps typically be more important than the idiosyncratic personalities of the individual agents.

How about prediction? Does the co-evolution, the interconnectedness, the contingency, the hierarchies and so on force us to give up predicting the behaviour or the future of complex systems? These questions are discussed by Allen in Chapter 2. No, we can still develop models that help us to understand the behaviour and even to forecast future events. But our quantitative theories will predict with a precision that is meaningful for the given situation. Of course, we don’t expect predictions that deterministically determine when a given trader will submit a bid of a given value for a given stock. But we do think that it is possible to do much better than just storytelling. The experience from complexity sciences suggests that well-specified bounded quantitative predictions are possible. Think of the forecasting of the weather. The meteorologists are now able to attach likelihood estimates to the forecasting of the weather some days out in the future. These likelihoods are computed from an understanding of the lack of precision of the current state of the system and together with knowledge of the dynamics of the components involved. The consequences of the lack of precision of the initial state depend strongly on which dynamical regime the meteorological system is in at the moment of forecasting. Smooth dynamics will not suffer too much from inaccuracies in determining the initial configuration. This is because close by configurations will evolve more or less in the same manner and lead to more or less the same weather in a couple of days’ time. But if the forecaster determines that the configuration of the atmosphere is deep in a regime of turbulence, or chaos, the inaccurate initial configuration makes it impossible to predict with certainty which of a range of possible scenarios for the next few days is actually going to happen. In this case the specific forecast will be assigned a much lower likelihood.

Sociology, or economics, is of course even more complicated and involved than meteorology and we are unlikely ever to be able to have models that predict with certainty trajec-

tories of behaviour. But examples from, for example, finance, suggest that it is possible to determine which kind of dynamics that can be consistent with, say, the observation that crashes are recurrent phenomena.<sup>2</sup>

However, before we start thinking of forecasting we need to develop an understanding of how components are influencing each other. Network theory is well-suited as a way to describe sets of entities linked together in a web of interdependencies. To be able to capture the evolutionary aspects and the hierarchical emergent structures we'll typically need a flexible structure of dynamically evolving layered and/or nested networks. But the nodes and the edges, or links, of the relevant networks have to be identified before we can commence on a theoretical analysis of a specific network model of our given system. Pierson's correlation coefficient is often taken as a starting point for assigning a measure of interdependence between two entities. This approach can be applied whenever we have access to data relating one quantity to another. A famous example is how it was realised that smoking causes a specific type of lung cancer by studying the correlations between incidents of cancer and smoking habits. Correlations are symmetric and will therefore not give us any indication of causal direction. In the case of cancer, a causal direction is hardly needed, since clearly it seems unlikely that cancer makes people smoke, but quite plausible that smoke may stress the lung tissue and thereby induce cancer. But if we look at, for instance, financial time series it may not at all be clear which, say, stock price could be the driver and which could be the driven. In such cases, a directional interdependence measure is of great interest. At present, there is very active research effort in developing information theoretic causality measures (see Chapter 3 by Razak, Wan and Jensen) based on the ideas introduced a long time ago by Granger. Such approaches identify 'causal' directions by analysing the likelihood that we are able to better predict one time series if we have knowledge of another. These techniques are by now very powerful and can be used to establish directed network models of a given system. The nodes will be identified with the time series, so, for example, a node could be a given stock represented by the dataset of recorded prices for that stock. The directed edges are then obtained from the information theoretic analysis and allows one to assign a direction and a weight to an edge between two nodes, for example, two stocks.

Complexity science is complicated, but no more so than we have experienced during the last few decades a huge increase in the arsenal of tools and methodologies and approaches developed to quantify and model the co-evolutionary hierarchical dynamics of many types of complex systems. Some of these developments are discussed in this Handbook.

## NOTES

1. See, for example, H.J. Jensen and E. Arcaute, Complexity, Collective Effects and Modelling of Ecosystems: Formation, Function and Stability. *Annals of the New York Academy of Science*, **1195**, E19–E26 (2010).
2. E. Viegas, M. Takayasu, W. Miura, K. Tamura, T. Ohnishi, H. Takayasu and H.J. Jensen, Ecosystems Perspective on Financial Networks: Diagnostic Tools. *Complexity*, **18**, 34 (2013).

