The Complexity Sciences: An Introduction

By Greg Fisher, 9 May 2023 (v 1.0)

> I think the next century will be the century of complexity.
>
> – Stephen Hawking (January 2000)

This paper provides a general introduction to the complexity sciences, which are "an effort to discern and theorize common patterns in complex system from multiple scientific perspectives." (Krakauer, 2019, p. 229).

The first section below sets out a number of 'defining features' of complex systems. These describe the general characteristics of such systems, including agents, interdependence, and time.

Following this, the second section outlines some of the 'conceptual features' of the complexity sciences. These differ from defining features because they are concepts and principles that have either arisen out of the study of complex systems or they preceded the subject but are emphasised by it, e.g., 'emergence'.

This second section focuses on concepts that are the most relevant to the social sciences and are described in a manner that dovetails with the material discussed in other, related papers. The section is not exhaustive: a sub-set of the concepts emphasised in the complexity sciences are included.

1 The Complexity Sciences: Defining Features

When describing or defining the complexity sciences we are faced with three problems: (i) it is a relatively new subject; (ii) it is studied by researchers in different disciplines; and (iii) it has evolved since it emerged in *circa* the 1970s. These issues make the field somewhat difficult to define.

Moreover, Arthur (2013) describes the complexity sciences not as a distinct field or academic discipline but as a *movement* in academia. This seems apt because it is used by - and applied to - a wide variety of disciplines, e.g., quantum mechanics, chemistry, biology, evolution studies, and the social sciences.

Despite the difficulties of defining the complexity sciences, what follows is a summary of what are typically viewed as the main features of complex systems at the time of writing.

These *defining features* are organised in to three themes, which are discussed in more detail in the first three sub-sections below. The fourth sub-section discusses the idea of 'patterns' in complex systems.

The sub-sections that make up the rest of this section are as follows:

1. Multiple (heterogeneous) agents;
2. Interdependence;
3. Time; and
4. Patterns.

1.1 Multiple Heterogeneous Agents

Complex systems typically contain 'agents' as the primary focus of analysis, e.g., sub-atomic particles in quantum mechanics, planets within solar systems, stars in their constitutive galaxies, ants in ant colonies, and people in social systems. Furthermore, complex systems typically contain multiple agents that are often viewed as heterogeneous, i.e., where each contains unique features[1].

Importantly, these agents can themselves be viewed as:

(i) complex systems of nested complex systems;

(ii) having semi-permeable boundaries;

(iii) using internal / mental models to make sense of their reality; and

(iv) existing in broadly decentralised systems.

Let us now look at these in turn.

1.1.1 Nested Complex Systems

It is easy to interpret the above description as implying agents in complex systems are 'atomized' (in the philosophical sense). In Greek Philosophy *atomism* was the idea that atoms are the most basic and indivisible particles that make up the whole universe.

Equivalently, in sociology, atomism refers to "the tendency for society to be made up of a collection of self-interested and largely self-sufficient individuals, operating as separate atoms." (Heywood, 2011, Glossary).

Either of these descriptions of atomism would lead us to believe that agents: (i) were simple, single points of reference; and (ii) have impermeable boundaries. However, agents can themselves be complex systems with semi-permeable boundaries (Holland, 2012) that render them open to flows of matter, energy, and information.

The idea that agents are themselves complex systems is not difficult to imagine if we consider organisms like ants and people. The word 'organism' implies a system of organs and these can be viewed as complex because they fit the features described in this sub-section. Furthermore, organs themselves

[1] It is possible to imagine complex systems of homogenous agents but, in general, agents in complex systems are viewed as heterogeneous.

can be viewed as complex systems, and this can continue 'downwards' until we consider atoms as complex systems of subatomic particles. All of this presents a picture of complex systems of *nested* complex systems (this is related to the idea of a *stratified ontology* which is discussed in a separate paper on Complexity Economics.

When modelling (cognitively or formally) these systems, abstraction often requires simplification so agents might be presented in an abbreviated way. With complex systems of nested complex systems, this must be done carefully.

1.1.2 Semi-Permeable Boundaries

The atomistic view is also criticised here because of its association with impermeable boundaries: agents are viewed as isolated entities. Holland (2012) explores the issue of boundaries in complex systems, referring to the idea of 'semi-permeable' boundaries. For agents, this means their boundaries would be impermeable enough for an agent to be identifiable; but permeable (open) enough for flows to occur between the agent and its environment (including other agents).

Consistent with Holland (2012), we take the view that agents are semi-permeable in nature, notably with regard to flows of information. This is especially important in the context of agents' mental models co-adapting when they interact.

1.1.3 Mental Models

Related to information flows, a number of researchers in the complexity sciences (e.g., Holland et al., 1986; and Arthur, 1994) have emphasised the idea that agents use *mental models* to make sense of their environments and to make decisions by processing information in a structured way.

For the purposes of clarity, here we use the phrase 'internal models' to refer to all forms of agents, including non-biological types like atoms; whereas the phrase 'mental models' is used for biological organisms, including humans.

This idea that agents use mental models is of course not unique to the complexity sciences, e.g., in orthodox economics, firms seek to maximize profit and people seek to maximize utility. Maximization algorithms like this (referred to as substantive rationality) are equivalent to mental models where the 'agents' are firms or people[2].

Internal models can be highly simplistic in nature, e.g., cellular automata that switch between 0 and 1 depending on the state of their neighbours; or they can be highly complex, e.g., containing large neural networks. Indeed, we can think of neural networks as complex systems themselves - this brings us back to the idea of nested complex systems.

It is helpful to distinguish between simpler mental models that are generally *reactive* to information and events (information is collated and then some decision made); and sophisticated mental models that include *anticipation* of potential events, i.e., the imagination of future scenarios. The cognitive 'depth' of human agents leads to particular challenges in human social systems, e.g., mutual

[2] Firms can be thought of as 'agents' in a very crude sense. It is perhaps better to think of them as assemblages, or patterns, of relationships between people and various types of assets.

contingency in which people try to anticipate the actions of others who are, in turn, anticipating them.

1.1.4 Decentralised Control / Bottom-Up Focus

Arthur (2013) referred to an economy as a "parallel system of concurrent behavior" (p. 2). This description can be applied to complex systems in general: the idea that there is no master controller and that agents make decisions synchronously. Control of the system - if there is such a thing - is devolved to the agents.

This does not imply, however, that agents are equal with respect to the influence they have vis-à-vis other agents or the system as a whole. This relates to the concept of power, which is defined here as the ability to influence future events.

Furthermore, this emphasis on local behaviour does not mean that patterns and structures do not emerge within the system. In fact, one of the central concepts of the complexity sciences is *emergence*, which is discussed below.

Given this focus on devolved behaviour, researchers in the complexity sciences tend to focus their attention at the local level when trying to understand complex systems. The 'bottom-up' approach to making sense of complex systems is often emphasised in the complexity sciences, e.g., Epstein (2012) refers to "growing" phenomena of interest, both conceptually and via computational modelling.

1.2 Interdependence

If the agents in complex systems are equivalent to (semi-permeable) nodes in a network, here we focus on the links in that network, i.e., the connections between the agents.

In complex systems, agents typically have relationships with other agents, e.g., parents and children, planets in the same solar system, and electrons in the same atom. If we imagine each agent as having a set of bilateral relationships, we can appreciate that multiple agents will exist in a larger network of ties.

Clearly, this picture of a network with nodes and links is highly abstract - agents and how they relate to each other will vary considerably between types of complex system. For example, the relationship between planets in the same solar system will be mostly gravitational in nature; the relationship between a predator and its prey will be one of hunting and avoidance; and the relationship between parents and children is often emotional, with children being initially dependent on their parents.

Regarding the relations between agents, the nature of mental models is important here also. When agents have simple (non-anticipatory) mental models, the ties between the agents might simply reflect one agent affecting another on a systematic basis. The effected agent might then respond in some way that then affects the agents it is linked to. Here, interdependence will be *reactive* in nature. For an example of this type of phenomena and how change can propagate across entire networks, see Watts (2002).

By contrast, sophisticated mental models might include perceptions of other agents, e.g., expectations of other agents' behaviour in particular circumstances. This awareness will help agents to anticipate the actions of others. Therefore, we can see that with human agents, agent interdependence can be anticipatory in nature and not only reactive.

1.3 Time

The third defining feature of complex systems is that they are dynamic. There are a number of related concepts worth mentioning here: adaptation; evolution and co-evolution; and path-dependence.

In complex systems, adaptation is the characteristic that an agent will adjust to its environment, e.g., by reacting to others' actions. An example would be some prey avoiding a predator.

The concepts of evolution and co-evolution are discussed in more detail in a seperate paper on Complexity Economics. Evolution is viewed as including the processes of variation, inheritance, and selection; and co-evolution is interpreted as reciprocal changes between two or more groups of agents.

In terms of history, an important concept in the complexity sciences is *path-dependence*. This is the idea that the current *state* of a system reflects its past, and that its current state will influence its future. Hence, the past, present and future of the system are inherently connected. See David (2007) for a detailed discussion of this concept and its use (and misuse) in economics.

The mapping of the past in to the present can occur in two broad ways, via: (i) agents' mental models (either because of memories or because knowledge / learning from previous experiences is carried forward in some way); and/or (ii) the relationships between the agents. Both of these can be understood as historical patterns brought forward from the past in to the present.

We can infer from this that some complex systems will not exhibit path dependence. This will be true if agents have no memories and/or they do not learn; and/or if any form of relationship between the agents is not carried forward over time.

1.4 Patterns

Complexity scientists often refer to 'patterns'. This is a useful term but it is somewhat vague so let us consider it more closely.

There are two broad types of pattern: (i) structural; and (ii) dynamic.

Structural patterns are when some 'entities' have relationships with each other: this was discussed above as interdependence.

Dynamic patterns are those involving time. The simplest form would be an algorithm, or rule, which states "when A happens, do B." Perhaps the most ubiquitous dynamic pattern in social systems are conventions and social norms (Hodgson, 2006) but they also include laws, regulations[3], and the vast array of corporate processes.

Structural and dynamic patterns can be related to each other. For example, we can think of most technology as (deliberately designed) structural patterns that give rise to helpful dynamic patterns.

[3] Laws and regulations can be ignored, of course.

For example, a processor inside a computer is a set of physical components that are patterned in a way that means information is processed in specified ways over time.

In fact, some seemingly structural patterns can be interpreted as a set of expected dynamic patterns, e.g., the parent-child relationship can be understood as roles that include specific behaviour rules (dynamic patterns). For example, a parent is expected to care for and enable a child who is, in turn, expected to behave in particular ways.

2 The Complexity Sciences: Conceptual Features

The previous section focused on the three main defining features of complex systems: agents, interdependence, and time. In this section we focus on analytical features. As mentioned previously, these are features that are emphasised by the complexity sciences but either pre-date the movement or have arisen from the study of such systems. A more extensive list of concepts can be found online at The Santa Fe Institute (2023).

2.1 Feedback

Feedback is defined in The Oxford English Dictionary (OED) as "The modification, adjustment, or control of a process or system (as a social situation or a biological mechanism) by a result or effect of the process." (OED, 2021, Definition 2).

In the complexity sciences, there are generally two types of feedback: positive and negative.

Positive feedback is viewed as amplifying change, e.g., if a variable related to an agent (say, temperature) is increased then positive feedback will further increase that variable. By contrast, negative feedback is seen as moderating change, e.g., if the same variable increases then negative feedback will reduce it, and vice versa. A thermostat is a classic example of a mechanism that gives rise to negative feedback.

2.2 Non-Linearity

Non-linear is defined in the OED as "involving or possessing the property that the magnitude of an effect or output is not linearly or proportionally related to that of the cause or input." (OED, 2021, Definition 1a).

With linear systems, the impact (Δy) of any perturbation (Δx) will be proportional to the magnitude of the perturbation, i.e., $\Delta y = \beta \Delta x$ where β is a constant[4]. By contrast, non-linear systems will see perturbation having a disproportional (large or small) effect, e.g., $\Delta y = (\Delta x)^\beta$ when $\beta \neq 1$.

[4] and $\beta \neq 0$.

2.3 Space of Possibilities

In the complexity sciences (and elsewhere) it is common to consider the 'state space' of a system, which is the complete set of *potential* states the system could be in. For our purposes this will include every possible location and trajectory of every agent in the system and all of the possible configurations of their mental models.

If we consider that a specific agent will have limited knowledge of the system in which it finds itself, the 'space of possibilities' for this agent will be the sub-set of the state-space *it can imagine*[5]. Moreover, an agent can improve its limited knowledge of the wider system by exploring it, e.g., by moving around a geographic region and/or interacting with other agents. This exploration would also increase the agent's range of states it can imagine, hence the phrase used by some complexity scientists, of agents "exploring the space of possibilities."

The idea of exploring the space of possibilities is discussed in Mitleton-Kelly (2003). The following quote gives us a sense of the challenging localised dynamics faced by agents in complex systems:

> Complexity suggests that to survive and thrive an entity needs to explore its space of possibilities and to generate variety. Complexity also suggests that the search for a single 'optimum' strategy may neither be possible nor desirable. Any strategy can only be optimum under certain conditions, and when those conditions change, the strategy may no longer be optimal. Mitleton-Kelly, 2003, p. 35

This quote also helps us understand that complex systems might never reach an optimum, nor an equilibrium: agents might have to continuously explore the system they occupy, allowing their mental models to adapt, and adjusting strategies as other agents adjust to theirs.

2.4 Far-From-Equilibrium

This is the idea that complex systems could be forced away from equilibrium conditions, or might never experience these conditions at all. Chan (2001) describes how this phenomenon was explored in Nicolis and Prigogine (1989):

> In 1989, Nicolis and Prigogine showed that ... [t]he "far from equilibrium" phenomenon illustrates how systems that are forced to explore their space of possibilities will create different structures and new patterns of relationships. Chan, 2001, p 6

We explore the ideas of non-equilibrium and dis-equilibrium further in a separate paper covering Complexity Economics.

2.5 Emergence

Emergence is defined by the The Santa Fe Institute (2023) as a "process by which a system of interacting subunits acquires qualitatively new properties that cannot be understood as the simple

[5]It is possible the agent will not be aware of many parts of the system so it will only be able to imagine a localised part of the sub-set of the whole state-space.

addition of their individual contributions."

This feature of complex systems is essential for differentiating the complexity sciences from 'reductionist strategies' for making sense of such systems (which break down systems into component parts). Classic examples of emergence are the properties of water from its constituent atoms (like 'wetness'): these properties are not reducible to hydrogen or oxygen. Language is also a good example as are social norms.

Hodgson (2000) includes a helpful discussion of the history of the term 'emergence', noting that it was first suggested by the philosopher George Lewes in 1875. We can appreciate, therefore, that this term precedes the complexity sciences by about a century so while it is associated with that field, it is not attributable to it.

In discussing non-reducibility, Hodgson (2000) quotes Morgan (1932) who explains:

> the hypothesis is that when certain items of "stuff," say o p q, enter into some relational organization R in unity of "substance," the whole R(o p q) has some "properties" which could not be deduced from prior knowledge of the properties of o, p, and q taken severally. (Morgan, 1932 as quoted in Hodgson, 2000, p. 65)

Furthermore, in terms of emergence, Hodgson (2000) quotes Morgan (1925):

> the emphasis is not on the unfolding of something already in being but on the outspringing of something that has hitherto not been in being. It is in this sense only that the noun may carry the adjective "emergent." (Morgan, 1925 as quoted in Hodgson, 2000, p. 66)

Hodgson (2000) also notes that interest in emergence "re-emerged" after the late 1960s, which coincided (approximately) with the formation of the complexity sciences.

Consistent with this, Axtell (2007) notes "[t]here is a large and growing literature on the idea of emergence in physical, biological, and social systems (cf. Haken (1987), Baas (1994), Morowitz (1999), Howitt and Clower (2000), Johnson (2002), Sawyer (2001a), Morowitz (2004), Sawyer (2001b))." (p. 111).

Cognitive Emergence and Immergence

It is common among researchers to discuss emergence as if it were external to the agents, e.g., Arthur (1994) refers to traffic jams as forms of emergence among driver agents. The ensuing traffic problem is a result of agents reacting to each other's actions but the emergent pattern can be thought of as essentially external to each agent.

However, it is also possible for emergence to involve the adjustment of mental models, i.e., for the emergent pattern to be internal to the agents. Conte and Castelfranchi (1995) refer to 'cognitive emergence', which is related to 'immergence' in the social simulation literature. *Cognitive emergence* occurs "when agents become aware, through a given 'conceptualisation', of a certain 'objective' pre-cognitive (unknown and non-deliberative) phenomenon that is influencing their results and outcomes, and then, indirectly, their action." (Castelfranchi, 1998, p. 27, emphasis removed).

The related concept of *immergence* is defined here as "the process through which the macro-level emerging structure or global result [feeds backs] into the micro-level, re-shaping the 'elementary' behaviours." (Castelfranchi, 1998, p. 26).

Once again, if we think of an agent (including its mental model) as a complex system, we can imagine a pattern of behaviour having immerged from the agent's interaction with other agents. This idea of immergence being endogenous 'within' agents' mental models is a powerful one. Our minds are made up of a variety of 'immergent' properties.

2.6 Self-Organisation

This concept is a type of emergence: self-organisation is the process in which patterns emerge spontaneously in a way that is helpful to the agents, e.g., by enhancing their likelihood of survival. An example would be the practice of wolves hunting in packs. This skill is not reducible to individual wolves because it requires coordination between them but, also, it is not achieved through some kind of centralised command and control process. It arises from agent-to-agent interaction. Furthermore, it enhances the ability of the pack to survive because hunting is more effective this way.

Sheehan and Wahrman (2019) date the origins of this concept to the Mississippi and South Sea financial bubble of 1719-1720 so it clearly precedes the complexity sciences. Furthermore, the related (but not identical) idea of 'spontaneous order' pre-dates that of self-organisation by millennia[6] (even if the phrase was coined in the 20th Century by Michael Polanyi).

The complexity scientist most known for promoting 'self-organisation' is Stuart Kauffman. Kauffman (1993) argues that evolution by natural selection is not the only 'force' that determines the likelihood of a species surviving. Kauffman writes "[i]t is this single force view which I believe to be inadequate, for it fails to notice, fails to stress, fails to incorporate the possibility that simple and complex systems exhibit order spontaneously." (p. xiii).

Another way of describing self-organisation is that it is the endogenous creation of new order in some system. Indeed, a useful way of understanding self-organisation is to contrast it with order imposed from outside of that system.

Other examples include swarming behaviour of animals such as birds, insects, and fish; and communication within human systems: language can only have emerged endogenously, it could not have been imposed from outside. Luhmann (1995) emphasises this point, noting also that a social system can only reproduce itself if there is communication between people.

2.7 Lock-In

This idea is related to the concept of path dependence, which was mentioned in Section 1.3 above. It refers to some pattern of behaviour that is maintained in some system through endogenous factors.

The classic (though contested) example of lock-in is the QWERTY keyboard. The story goes that this design was originally intended to slow typists down - engineers thought that mixing keyboard

[6]The earliest known reference is from the fourth century BC Chinese Philosopher Zhuang Zhou (Hamowy, 1987, p. 6).

letters in a relatively random way would achieve this task. However, typists became familiar (and efficient) with the new layout so manufacturers sold keyboards with this design. In turn, new users of this layout learned to type with the same design. Over time, the QWERTY keyboard became 'locked in'.

David (2007) provides additional examples of what he believes are "sub-optimal equilibria" that have been " 'selected' by a dynamic process" (p. 130). He refers to "640K lower memory in the IBM PC, AC vs. DC electrical current, light-water reactors, and VCR formats" (ibid, p. 136).

More broadly, Foxon (2002) discusses how in economics increasing returns to scale can ensure certain technologies can be locked in place, citing four 'forces' as developed in Arthur (1994): scale economies, learning effects, adaptive expectations, and network economies. Foxon also mentions North's references to institutional lock-in: the same four forces can sustain an institution within a population.

To understand the points of contention here, let us first differentiate between the lock-in of behavioural patterns in general and a sub-group of such patterns that lead to sub-optimal outcomes. Liebowitz and Margolis (1990), for example, do not dispute the idea that QWERTY has become locked in; rather they dispute the inefficiency aspect, as argued by David. They state that "the continued use of Qwerty is efficient given current understanding of keyboard design" (p. 2); and that the "trap constituted by [this] obsolete standard may be quite fragile" (p. 21), i.e., the lock-in effect is relatively weak.

Clearly, the issue here is not so much about keyboard designs. Rather, there are important questions about whether inferior outcomes can become locked in and, if so, how prevalent they are in economic systems. This is particularly important in free market economics because locked-in sub-optimal equilibria are examples of market failures that are durable by nature.

This is not the place to answer the above question of the prevalence of sub-optimal 'traps'. Instead, we can simply state that, from a complexity sciences point of view, we should keep an open mind to such phenomena. Moreover, David's (2007) framing of the issues at play here is particularly helpful so let us briefly look at this.

David refers to positive feedback effects that move agents into a "trapping region - the basin of attraction that surrounds a locally (or globally) stable equilibrium." (David, 2007, p. 131). The problems of "escaping from lock-in of the system to a globally inferior (but locally stable) attractor are rooted in 'pure' coordination costs." (ibid, p. 132). The sides of the attractor basin (steepness and length) correspond to the stability of the locked-in phenomenon and how difficult (or expensive) it is to escape. This gives rise to context-specific practical problems and questions about the net present value of the costs and benefits of changing to a globally preferred outcome, if this is even feasible.

However, it is important to consider that such "trapping regions" do not necessarily persist. Economies can re-pattern themselves over time, which means that following " 'exogenous [to the attractor basin] innovations' (in the state of relevant knowledge, or in the regulatory institutional regime), the previous attractor(s) may be destroyed, freeing the system to endogenously begin to evolve some new configurations." (ibid, p. 132). David (2007) gives the example of deregulation in the US's telecommunications networks in the 1950s, which "formed new 'attractive paths' ... for the evolution of digital telecommunications technologies." (p. 133).

In addition, David argues that by being aware of positive feedback effects that result in sub-optimal trapping regions, we can take pre-emptive, ameliorative actions if we were to observe them playing out.

The final point to note here is that David (2007) uses his framing of lock-in to describe the state of orthodox economics itself. "For many economists, their own sunk cost in mastering that discipline have produced a facility for reasoning that suppresses natural, human intuitions about historical causation." (p. 138). He refers to this as "intellectual sunk cost hysteresis" (ibid), which is analogous to an attractor basin.

2.8 State of Paradox

This is the idea that complex systems can exist in states that exhibit seemingly contradictory phenomena. Chan (2001) writes "[t]his reinforces the idea of bounded instability or the edge of chaos that is characterised by a state of paradox: stability and instability, competition and cooperation, order and disorder." (p. 6).

A simple example of the co-existence of order and disorder is a professional football league. The rules of the league are typically codified and known to all the teams, and games tend to be agreed months in advance. Furthermore, the 'rules of the game' are also generally known by the players. All of this amounts to 'order' within the league.

However, individual football games tend to exhibit a considerable amount of disorder (even if the rules are followed perfectly): notably, a team's tactics, as well as those of individual players, will generally seek to confound the expectations of their opponents. Furthermore, the tactics of both teams often co-evolve during a game. Hence, in professional football leagues we tend to observe a co-existence of order and disorder.

Looking at economics, Hayek viewed 'the market order' as the coexistence of order and disorder. Certain phenomena, notably entrepreneurial behaviour and 'liberal legislation', would support a broadly ordered system. However, within this 'order', phenomena like new technologies and changing consumer preferences would create a degree of disorder.

2.9 Sensitivity to Initial Conditions / Predictability

The idea that the future path of a complex system is sensitive to its initial conditions was famously observed by Edward Lorenz when he developed a set of differential equations in the 1960s to approximate the state of - and changes in - the weather.

This concept is related to non-linearity: Lorenz noticed that infinitesimally small changes in initial conditions meant that, over time, a system exhibits significantly different outcomes. Lorenz first conducted his experiment in 1960 where the initial conditions of his state variables were measured to 6 decimal places. When he repeated the experiment in 1961, these initial conditions were measured to 3 decimal places (see New York Times, 2008). Lorenz had expected the results of the two experiments to be identical; however, they were not. Over a sufficiently long enough time horizon, the results were significant different.

Lorenz's experiments were conducted using (deterministic) differential equations; however, the same effect can also be observed in any complex system that exhibits non-linearity (e.g., due to positive feedback effects).

This idea that outcomes are sensitive to initial conditions when non-linearity exists is one factor that warns us about the ability to predict outcomes. If we are unsure about initial conditions and / or the patterns that describe some system, how confident should we be that we can predict the outcome?

The final point to note here is the butterfly effect, which is a lesson in sensitivity to initial conditions. However, a popular misconception is to refer to this effect as a lesson in non-linear causation: the butterfly is thought to 'cause' a hurricane a few months later elsewhere on the planet. This is an inaccurate framing: consider what gives rise to hurricanes and the role a butterfly plays within that.

2.10 Symmetry Breaking

As the name suggests, symmetry breaking occurs when a type of equilibrium, balance, or symmetry in some system is changed or broken.

The following description, which appears in Castellani (2003), is helpful. Symmetry breaking is:

> ...the process by means of which the considered symmetry is broken and is therefore usually ascribed a "dynamic" character in the literature (in contrast with the "static" character attributed to a situation of symmetry). Castellani, 2003, p. 321-322

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