

Patterns, Models, Complexity

Notes on Mapping Patterns in Analysis of Complexity

Abstract- Design Patterns, which were pioneered for building architecture by the British/Austrian architect Christopher Alexander, have proven to be very powerful in designing complex systems. Especially in software architecture they have become the most common way of describing and building complex software applications. This inevitably has resulted in efforts to use patterns to study complex systems, in other words to use them as a methodological construct to analyse certain phenomena. Most notably, patterns promise to bring certain consistency to complex phenomena across various scientific domains which currently are hardly mutually interacting, such as engineering and the humanities. Through their simple, graphical style, they may provide a vocabulary that can be used by researchers from many disciplines and also to educate students from an interdisciplinary perspective on matters relating to complexity. However, this begs the question on the methodological justification of this 'reverse trajectory'. This paper explores some of the issues that are raised by this approach.

Keywords: Complexity, Complex Systems, Patterns, System Theory

INTRODUCTION

A *pattern* is often used in science to identify a recurrent and vaguely familiar phenomenon, although in general it is used in a colloquial manner. In building architecture, patterns were pioneered as a *methodological* construct by the Austrian/British architect Christopher Alexander, who considers ‘design patterns’ to be answers to design problems (Alexander, 1977). When designing towns or buildings, certain architectural and infrastructural approaches and solutions for certain problems can be traced back to the same underlying patterns. To Alexander, these patterns contribute to the harmony he sees in medieval cities.

Alexander’s idea was taken over for software engineering by the ‘Gang of Four’ (GoF) in 1994 (Gamma et al., 1994), and currently it has become the predominant means of designing software architecture. Here design patterns usually take the form of ‘miniature systems’ with specific interfaces and supportive descriptions, which map to certain blocks of software. As an example, the following figure shows one of the most widely used patterns in modern software applications, and which any frequent Web surfer will use daily, called the Model-View-Controller (MVC) pattern.

MVC shows –at an abstract level- how information from for instance a database (a model) is transformed to a view that makes sense for a user, for instance a web page.

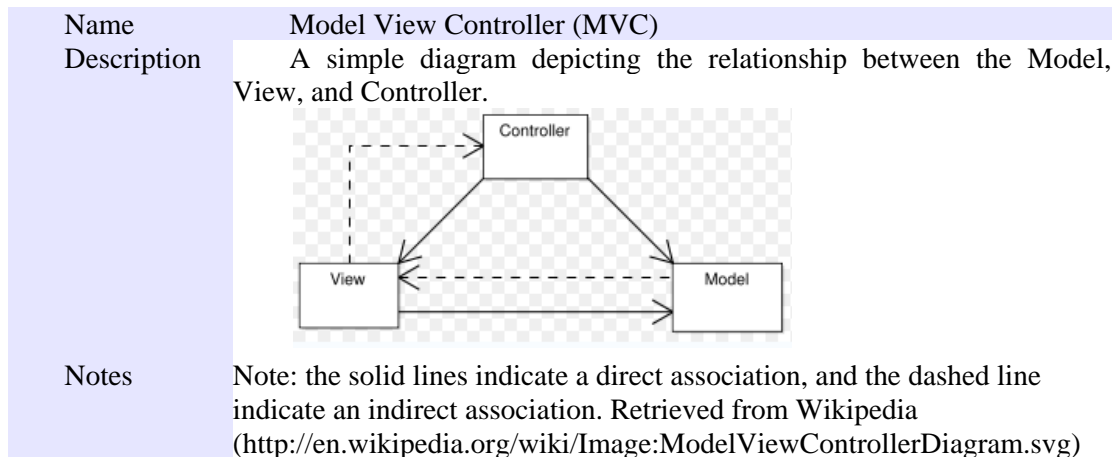


Figure 1: MVC Pattern

The controller supervises the interaction between user and the model by monitoring user events –clicking a button or a selecting a link- and taking the appropriate actions.

For the purposes of this article, one of the interesting aspects of a design pattern is the fact that it shows the internal structure of the miniature system, and that it usually also describes the interfaces with which it interacts with its environment or connects to other design patterns. Certain recurrent problems are coupled to design patterns and as software engineers consistently use them in various applications, it becomes easier to understand these systems. Not only do they describe the software application at a higher level of abstraction, but because programmers are stimulated to use the same patterns as much as possible, it becomes easier for them to quickly grasp each other’s designs. This consistency is enforced through the use of *pattern libraries*, collections of proven and often used design patterns. This approach is very similar to practices in electronics and other technical branches, although the notion of pattern has never taken off there, probably simply for historical reasons. Electrical, mechanical and other technical schematics have been around much longer than Alexander’s design patterns.

Practically, design patterns have also shown to improve communications with other stakeholders of the eventual application, such as end users, managers and so on. Their ability to bridge the gap between various stakeholders of a technical application is interesting, because it resonates in the notion of *pidgin languages* that some sociologists see becoming vital for the development of science towards socially contextualised knowledge production systems (Nowotny et al., 2001:146). Coarsely stated, they see that science is moving away from theoretical specialisations, and is actively taking position –and being positioned- in a larger, societal context. This means that communicating knowledge to society becomes more important, but also that society is affecting the knowledge that is being produced, for instance through governmental policies or research for the market place. As an effect, communications in this ‘Mode-2 knowledge production system’ between various domain experts need to be adjusted so that the various, and often incompatible, expertises can find a common vocabulary which reflects the most essential or crucial aspects of their interactions, and in which they can convey their knowledge more or less accurately. Research has shown that *truly* inter-disciplinary efforts, that is, research that requires a collaboration of different scientific disciplines –I will call this cross-disciplinary-, often develop a shared language that consists of a number of key concepts which captures the essential topics, which allows the different knowledge domains to effectively ‘connect’ with each other. These key concepts, from the perspectives of the specialists of *all* the knowledge domains, are somewhat ‘naive’, but sufficiently adequate to allow cross-domain communications. The resulting language therefore tends to be comparable to the ‘pidgin languages’ that often evolve when people who do not share the same human language have to interact intensively. There is some research that seem to address this particular use of patterns as means for cross-disciplinary communications between computer scientists and biologists in bio-informatics research (Wiles et al., 2005 281-288), but these are usually to specific and fragmentary to address complexity. Besides this, these efforts usually focus on research disciplines which are fairly ‘compatible’ in the first place.

The focus of design patterns as means of a *construction method*, has often obscured Alexander’s original double entendre, where design patterns were also used to *analyse* towns and buildings. One can walk through a city and observe the patterns, for instance ‘A Place to Wait’, on a plaza or in a town hall. These patterns, to some extent, therefore can correspond with *multiple*, often seemingly unrelated instances, which are thus mutually associated *through the pattern*. This aspect of a pattern is more radically enforced in software engineering, where the underlying principle of correspondence is one of *isomorphy*, which they share with the system theories (Bertalanffy, 1976, 33-34). Isomorphy is the –often implicit- link between *any* scientific model and that what is modelled; it drives the correspondence between a neural network modelled *in silico* on a computer and the aspects of biological neural networks that are modelled. Technological patterns and biological ones are currently therefore used more and more often, especially in interdisciplinary research areas such as artificial life, bio-informatics, or the neuro-sciences. The social sciences and the humanities however, are hardly aware of such patterns that are well-researched in the technical and natural sciences, even though they may be manifest in a social system. One possible reason for this is that many patterns in the ‘hard sciences’ are described mathematically, which means that they are hard to grasp for the more linguistically oriented humanities. Complexity itself also constrains this isomorphy through limits of *scale-invariance* (Schroeder, 1992). A pattern such as feedback, or exponential growth, may return in technological, biological and social systems, but they do need to be verified at these different levels. A concept such as *emergence* also seems to constrain the scale-invariance of patterns. As a result, some patterns may not be able to ‘percolate’ into the social, for instance because they hit an interface or boundary such as ‘consciousness’ (Pieters, 2009: 126-134).

In complex systems, the manifestation of pattern in various guises is not uncommon, and intuitively the notion of patterns could be an interesting way to better understand complexity (Pieters, 2008: 268-275). However, as a methodological construct to analyse complex systems, it

deserves closer attention to look into the consequences of such an approach, especially since the notion of ‘pattern’ has received little methodological attention.

One of the problems of complexity is, that it is currently still approached from within the confines of scientific disciplines, which tend to be somewhat closed through the specific cultures and the rules and constraints of the ‘game of science’ that is played within those domains (Atlan, 1993: 32). This is very important, but as the theme of complexity is being taken up from very mathematical domains as well as the social sciences and the humanities, complexity itself advocates certain openness towards the various contributions. As a very practical consequence, this particular contribution, to some, may be a bit on the philosophical side, but personally I would strongly oppose against this view, as there is a simple *methodological* reason why complexity to some extent dissolves these distinctions. As research on complexity is *itself* a complex activity, any methodological contribution to complexity should to some extent account for its own metaphysics (Pieters, 2007: 80-81)(Pieters, 2009: 269-274), . Research constrains the researched, and the researched constrains research. This is not just a ‘philosophical’ game of self-referentiality, but the very practical consequence of patterns of feedback manifesting themselves both in subject matter as well as research enterprises.

Even though one may move towards more specialised variants of complexity that reflect the requirements and cultures of individual scientific domains from this point of departure, the opposite approach of constraining the theme of complexity from individual disciplines should be taken with some caution. Complexity does not care too much about human distinctions between, say, philosophy and science. Acknowledging this may even help to achieve a ‘helicopter view’ on complexity, which may serve as a departure point for cross-scientific research or assist in attaining certain consistency in education on the various specialisations of complexity research.

Model and Target

Any systems theory aims at modelling something. The ‘something’ can be subject matter, an object (or subject) or a phenomenon ‘in reality’. As most of these terms are often philosophically volatile, the more neutral term ‘target’ will be used here, which is borrowed from research on metaphors (Piquer Píriz, 2002: 363-374), (Gentner et al., 2001, 199-253). In other words, a systems theory aims to model a certain target, in which the model usually is the ‘system’ that corresponds with the target. Some ‘systems dialects’ advocate a different approach, where ‘system’ corresponds with the target (Luhmann, 1996: 2), but even more often ‘system’ is not exactly defined, but rather rests on an implicit choice. This becomes problematic particularly when analysing a complex target, because complexity typically has two faces. One tends to obfuscate and is sometimes called ‘uncertainty’ or ‘disorder’ (Gershenson et al., 2007: 5-29), (Morin, 2008: 40-43)(Atlan, 1993:107-108), (Darbellay et al., 2008: 43-50). The other face reveals itself to an external observer, and is often called ‘order’ (Kauffman, 1993). A complex target could therefore be considered the combination of order and uncertainty¹. Of course, any target could be split up this way, but for many systems the uncertainty is not a big issue. In a technical system, for instance, or most other activities where the target is *constructed* from the model, the uncertainty may be manageable. This is why models generally work well for construction purposes; the eventual target (the construction) usually only has a slight level of uncertainty (or error) with respect to the model. A software model (source code) will have to work in hardware and this brings in some uncertainty, but in practice this difference can often be

¹ I have some reservations of using the more intuitive dichotomy of order-disorder, or organization/disorganization, as I think that a fundamental problem of observation in complex systems rests on the *not knowing* certain aspects of a complex target; we *do not know* if those aspects behave disorderly or are disorganised. Uncertainty better captures this observer-centric position

ignored as it doesn't affect the predictability of the eventual application that much. However, having said that, there are many construction activities in engineering that have to work in severely contingent environments.

In complexity, uncertainty contributes to the 'radical contingent nature' (Cilliers, 2001: 135–147) of a complex system and can thus not be ignored as 'details' or as a 'trivial' aspect of that target. In a way, these terms become normative *per se* in a complex system, for either such claims need to be proven or experimentally verified. Even then, if this is at all possible, it at best remains an informed assessment on the side of the observer. It will be clear that a model tends to focus on the order and aims to minimise the uncertainty. To some extent, uncertainty is the difference between model and target.

Although some attempts have been made to use patterns as means of analysing complexity, the problem of uncertainty is often not explicitly investigated. Grimm *et al.* come closer to addressing uncertainty in their approach of “*pattern oriented modelling*” (POM) (Grimm et al., 2005: 987-991). POM seems to focus on making a specific model of a target through multiple approaches, which usually are determined by instrumentation. These approaches provide the patterns to optimise the model. The example that Grimm and his co-workers provide makes this clear:

“For example, Chargaff’s rule of DNA base pairing was not sufficient to decode the structure of DNA—until combined with patterns from x-ray diffraction of DNA and from the tautomeric properties of the purine and pyrimidine bases. Thus, in POM, multiple patterns observed in real systems at different hierarchical levels and scales are used systematically to optimize model complexity and to reduce uncertainty.”²

Here I will generalise this and consider these approaches to provide certain *perspectives* on the target (through instrumentation) that are used to improve the model. These multiple perspectives also introduce the problem of *optimisation* to the modelling activities. Although it seems intuitive that more perspectives yield a better model, there is an optimum where the additional work no longer gives much novel insights. The resulting relationship between the ‘complexity’ of the model and the payoff is optimal in the so-called *Medawar Zone*.

With this, one can now see that the correspondence between model and target can be problematic. First, the question arises exactly what one aims to model, and secondly the quality of the model needs to be monitored. Therefore a model in itself is never sufficient; it needs additional criteria to substantiate claims of correspondence.

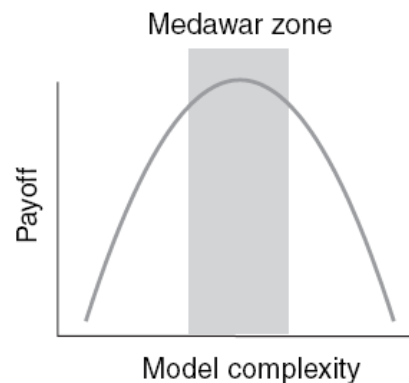


Figure 2: Medawar Zone

In system theories, the correspondence between model and target is usually one of isomorphy. In fact, isomorphy contributes heavily to the ‘general’ in Bertalanffy’s general systems theory (GST) (Bertalanffy, 1976: 33):

² ‘Real systems’ should be translated with ‘target’ for the purposes of this paper

“A consequence of general systems properties is the appearance of structural similarities or isomorphisms in different fields. They are correspondences in the principles that govern the behaviour of entities that are, intrinsically, widely different.”

This quote immediately reveals a difference between GST and POM, because a ‘system’ (model) in GST aims to capture the similarities of multiple targets. Every target provides patterns for an underlying corresponding model.

The importance of isomorphy also distinguishes system theories from other branches of science and the humanities, which may predominantly rely on, for instance, metaphors and analogies. These may sometimes provide clues for the existence of isomorphy but only as base intuitions for experiments that aim to prove this (Bertalanffy, 1976:35-36), (Gershenson, 2008: 103-104). In a way, metaphors and analogies provide a weak correspondence as model for a target. Isomorphy, (mathematical) equivalence, but also *power laws* (Schroeder, 1992)(Barabasi, 2003), aim to provide stronger correspondence between target and model, which can sometimes also be bi-directional.

Despite their aims, GST has never really offered a strong methodological framework to analyse cross-target correspondences that would allow different targets –to some extent- to become models of each other. GST usually relies on mathematical correspondences to make this mapping, for instance between exponential growth curves in biological systems and, say, monetary interest rates. However, such correspondences often tend to fail in the interpretations at some point. This criticism has also been posed against the Santa Fe school of complexity; even though the (often mathematical) models they make correspond in many ways to patterns observed in various scientific fields, the correspondence between their models and their acclaimed targets are much harder to prove (Horgan, 1995), (Lewin, 2000). I will return to this issue at a later stage.

In complex systems, mathematical correspondence may not always be feasible. Mathematical descriptions require a too detailed level of granularity and thus may result in models at the far side of the Medawar curve. Here the visual ‘mini-systems’ of design patterns may provide a more optimal solution.

It is clear that such target-to-target correspondence ‘moves through’ the specific models of those targets. The specific models reveal the order of the targets, while some general aspects of these specific models result in ‘toned-down’ mini-models that capture the isomorphy. These generic models that capture characteristics of multiple targets are very similar to design patterns, and have the following characteristics:

- A pattern is an *organisational* construct, i.e. it itself is a model.
- There is a 1..n relationship; a pattern can correspond with multiple targets.
- Patterns describe isomorphy between targets
- A pattern is a subset of the characteristics of the targets and/or their specific models
- There is a bi-directional correspondence between model and target

Data, Pattern, Information

The POM approach captures another way that patterns are used, in the sense that patterns reveal certain observed correspondences through instrumentation (perception) without as yet being clear to what that correspondence is. Data analysts will probably recognise this aspect of patterns when they look at a sheet of data (say a list of numbers from a measurement, or a quantitative or qualitative questionnaire) in which certain regularities seem to emerge, but where it is not as yet sure what it will lead to. In this sense, ‘pattern’ seems to hold a middle ground between ‘data’ (which is unstructured by definition) and ‘information’.

The problem with ‘information’ however is it has been implicitly ‘kidnapped’ by an ‘atomic’ perspective, which considers information as being packed onto a carrier and which can be relocated elsewhere (Hayles, 1999). This view of information can be traced back to the founders of information theory such as Claude Shannon and Warren Weaver, but here ‘information’ was used pragmatically as Shannon focused on the capacity of message transfer and not on the ‘essence’ of information itself (Shannon Weaver, 1998).

A full understanding of message transfer between agents, requires a theory that includes how information is formed (pre-processing) and how this is interpreted at the receiver (post-processing). A Dutch speaking person will never be able to convey information to someone who does not understand the Dutch language. It is clear that information gets lost ‘in transmission’. Apparently something is missing at the receiver to effectively process the transmitted message³.

‘Information’ can thus also be seen as a *relationship* between the *availability* of certain data in a message and its *acceptability* at the receiver, which allows the receiver to interpret the data. Many researchers therefore prefer a more ‘embodied’ view of information, in which a *context* is required in order to make information (Klimesova, 2009: 255-263). One could say that information is the combination of ‘concept’ and ‘context’, where concept signifies a selection of data that has focus of a process that transforms data into information. Such a process needs a context to achieve this task (Pieters, 2008: 268-275), (Cilliers, 1998: 72). The resulting perspective on information is closer to the original meaning of the word, which means ‘having taken up form’.

Information can now be seen as the result of the processing of data, and ‘pattern’ is an intermediate stage where data begins to ‘take up form’. Pattern here seems to reveal the process of mapping certain correspondences in observations of an unknown target with existing schemas, which eventually will result in a match (Damasio, 2000), (Choe, 2002:713-719). A pattern in this sense is the observation of certain regularity in an unknown target, which the data processor aims to map with schemas in its context. Putting this even stronger, the sense of regularity itself is the result of such mapping.

This notion of pattern being ‘pre-form’ pushes the notion of ‘pattern’ before that of ‘form’ and (thus) information. Basically the major concepts of information theory can be organised along a hierarchy; randomness-potentiality-data-pattern-form-information; which also aligns with similar notions expressed by others,

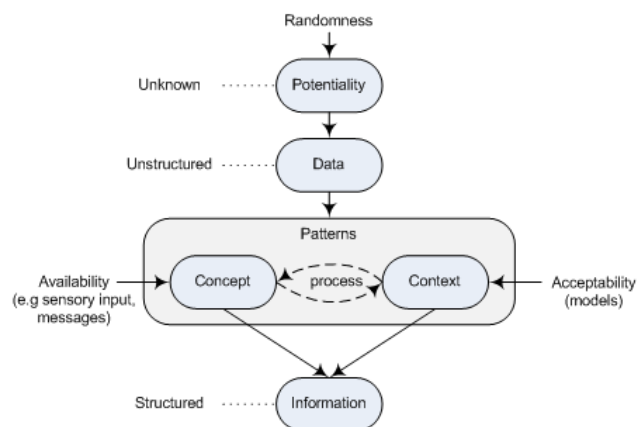


Figure 3: An ‘Embodied’ View of Information

such as between ‘uncertainty-information’ (Kauffman, 2002:112-113) or ‘pattern-randomness’ (Hayles, 1999:25).

With this, the two meanings of ‘pattern’ can be pinpointed as the two sides of availability-acceptability or concept-context. As observations are matched with existing schemas, both observation (availability/concept/perspectives) as the models or schemas (acceptability/context/models) take shape until the ‘aha-Erlebnis’ of knowing takes place. At this point both patterns have become ‘information’. One can thus distinguish *conceptual and*

³ The fact that Dutch speaking persons understand the message proves that the problem is located at the receiver.

contextual patterns that have to co-evolve in order to create information. Alexander’s design patterns can now clearly be seen as the latter form, while POM focuses on conceptual patterns.

It will be clear that message transfer amongst highly contextualised human beings often can afford a perspective that omits the pre- and post-processing phase. In these conditions, the ‘atomic’ view of information may be an optimal model of message transfer, in terms of the Medawar zone.

Note that this information does not need to be ‘correct’ at this stage. Usually the ‘correctness’ of the model is governed by implicit or explicit goals that drive the modelling activities. Information that is sent, is likely to ‘contextualise’ differently at the receiver, and so more elaborate forms of communication are usually needed to minimise the resulting error.

The notion of ‘context’ in the way it is used here should not be dramatised. Take for instance von Bertalanffy’s example of a photo-electric cell (Bertalanffy, 1976: 42), such as those used to open doors in shopping malls when the light beam they receive is interrupted. According to von Bertalanffy, *information* is conveyed to the photo-electric cell. The contextualised view on information would however rather speak of the transmission of pattern, which is contextualised *by design* in the photo-electric cell. In other words, the cell is able to detect the pattern ‘beam/no-beam’, which is transformed to information (on/off or open/close) systems-internally. Note here that ‘system’ contextualises this pattern at two levels. There is ‘on/off’ at the level of the photo-electric cell, and ‘open/close’ at the level of the aggregate system that includes both the cell, the door and the devices that connect these two entities. Thus the pattern of light/darkness, flow/non-flow, or 0/1, or true/false percolates through an increasing larger context and is expressed as information at various intervals (on/off or open/close). But the pattern does not restrict itself to the technical system alone, for it flows into a social context through halting/walking and similar manifestations. Here pattern expresses itself through conscious beings, who *know* that the door opens or closes and can take appropriate actions. Pattern emerges here as events of communication that synthesizes contexts, but it will also eventually dissolve in interaction with other patterns. Patterns may no longer allow themselves to be traced; they may vanish, disappear, but they may also move on invisibly; a person has to wait for an opening door, thereby hindering another who misses his train and an appointment.... Here patterns become like probability waves, and thus uncertainty follows pattern, as it remains difficult to see how pattern expresses itself as information on its journey through the various contexts. Or, in terms of Latour, which traces it leaves behind (Latour, 2007:1-17).

Complexity and Complex systems

We can now capture modelling activities in a pattern, that is called *convergence-inducing process* (Pieters, 2008: 268-275), (Hassoun, 1995: 424).

Name	Convergence Inducing Process
Description	An actor samples a target by an iterative cycle of testing and evaluation until a certain goal criterion has been met.
a.k.a	Problem Solver, Global Search
	<pre> graph TD Goals[goals] --> Model[Model] Model -- testing --> Target[Target] Target -- evaluation --> Model </pre>
Notes	The model is matched against a target, typically in an iterative fashion, which results in a convergent process

Figure 4: Convergence Inducing Process

It will be clear that, for instance, the experimental method of contemporary science adheres to this pattern (White, 1999), but also many implementations of computational intelligence, such as genetic algorithms and the learning phase of neural networks (Hassoun, 1995), (Michalewicz, 1998). This multi-target isomorphy justifies ‘convergence inducing process’ to be a pattern.

In previous work, the hierarchy of information-theoretical concepts that were described in the previous section were used to re-evaluate the paradigms of the ‘system theories’ (Pieters, 2008: 268-275). The base concepts, such as ‘system’, ‘environment’, ‘entity’ and ‘relationship’ were supplemented with the framework of complex systems that was proposed by John Holland (Holland, 1996). (Design) patterns conform to his ‘building blocks’ idea of complexity, in the sense that new, more complex patterns can be constructed from existing ones. With this, and with acknowledgement of the fact that an ‘entity’ or ‘relationship’ itself can be a (sub-)system, the system theories were ‘upgraded’ to analyse complex systems. This notion of ‘systems of systems’ (Morin, 2008)(Luhmann, 1996)⁴ intuitively connect to design patterns as in software design, patterns tend to return *at various levels of complexity*.

This may require some explanation. First, of course, ‘complexity’ is a quite diffuse term and as yet has many meanings (Gershenson, 2008). The working definition proposed here follows the more mathematical definitions by stating that:

“The complexity of the system corresponds with the amount of non-redundant information it contains”

As ‘system’ is equivalent to the *model* of a target, the observer is implicitly taken up as a factor. This is done because, for instance a ‘solar system’ is much more complex for an astronomer than for a layman. Likewise, scientists calculating the ideal route for a satellite to Mars or Jupiter will have a different perspective on ‘solar system’ than someone who is studying plasma storms.

The second aspect of the definition -the amount of information-, is related to this. As the most ‘explosive’ data of a system is in the *relationships* between entities or subsystems, this aspect tends to govern the complexity of the system. From this angle, the above definition corresponds with the complexity in the way it is used to study data structures (Goodrich Tamassia, 2005). The ‘non-redundancy’ is added to ‘clean up’ information on the far side of the Medawar curve. The importance of this will become more clear at a later stage.

Perspectives on Complex Systems

Chris Langton, one of the pioneers of the Santa Fe school of complex systems, sees two fundamental perspectives at work in classical science (Lewin, 2000: 235-237). The ‘mechanistic’ view builds on knowledge from a material world-view and usually concerns itself with the way a system structured or organised. This results in predictions of its behaviour in its environment. I will call this the structural perspective, and is closely related to what in technical research is called ‘white box approach’.

The ‘vitalistic’ view tends to look at the system ‘from the outside’⁵, and focuses on how the system behaves in or interfaces with its environment. This *phenomenological* or *ecological* perspective is related to ‘black box approaches’ in technical areas, but is broader than the traditional vitalistic perspective, as this tends to a more limited ‘outside-in’ view. In a phenomenological perspective the response of the system itself is taken into account and thus

⁴ Luhmann actually iterates –more correctly- through system-environment pairs

⁵ The original vitalists saw the movement of objects to be governed from ‘outside’, such as through divine intervention

inherently acknowledges feedback through the system. In biology and other scientific disciplines one can also see an *evolutionary* or *historical* perspective, that concerns itself with the question how a target has been constructed over time; what needs to be in place in order for it to have become what it is. Last, in complex systems one can also identify a perspective in-between the structural and evolutionary. This ‘complexity perspective’ follows a structure from its smallest entities upwards along the various aggregate forms that can be observed. This perspective can, for instance, move up from quantum particles to atoms to cells to organisms and so on. Basically, this perspective follows the ‘growth’ of aggregates and identifies different structural perspectives at various levels of aggregation. Although this perspective is very similar to the evolutionary one –subsystems need to be in place to make the aggregate- they are not quite the same, as the complexity perspective shows an ‘as-is’ situation and not one of temporal causality. As the observer ‘knows’ the growth of systems through aggregation along this perspective, it is the most ‘information-rich’ perspective, and thus complexity rapidly accumulates here through the expansion of relationships. This is why this perspective is called the ‘complexity perspective’. Ideally, any model of a target should account for all these perspectives⁶, or rather, as complexity goes, these perspectives *at least* should be accounted for. POM, for one, also defines certain perspectives through instrumentation! It can be seen here how these perspectives can contribute to a more complete model of a complex target. Every perspective produces conceptual patterns that guide modelling activities. In other words, these perspectives assist in making the model ‘Medawar zone compliant’. However, the three-and-a-half perspectives that were introduced earlier have the enormous advantage that they do not accidentally assign different perspectives to the same underlying conceptual patterns, which is a risk with patterns obtained by measurement. For example, one may perform different measurements (or refer to different research) that all seem to point at certain exponential growth, for instance between the sales of mobile telephones, Internet use, subscriptions for new media, and the production of electronic devices and components. At first blush, these may seem to be unrelated, but it is possible that all these can be traced back to one underlying pattern, for instance the introduction of a new technology in a society. Even though the various results yield important data, it does not mean that different perspectives have been provided to complete the model. As a result, it may appear that the introduction of the technology has been very successful, but when population growth is taken into account (another perspective), the result may be less optimistic because the assumed growth becomes statistically irrelevant with respect to this perspective. It is therefore of importance to aim for perspectives that provide data that cannot be traced to the same underlying patterns, and the perspectives introduced earlier achieve this; they ‘meet each other’ in the model and not earlier, which improves the coherence of the model that is made or tested.

Of course, in some disciplines some perspectives may be trivial; in engineering sciences, the evolutionary perspective can usually be ignored, as engineering typically works with what is available. It normally does not matter how nuts, bolts, beams, transistors or integrated circuits are made in order to use them, let alone give an account of the historical developments that led to such components or materials.

The various perspectives offers an explanation of how patterns can return at different levels of complexity. As subsystems coagulate into aggregates along the complexity perspective, these aggregates may become more or less self-contained, thereby forming –from a structural or phenomenological point of view- loose relationships with other (meta-) aggregates. Thus while an observer may follow the perspective of increasing complexity, certain *simpler* configurations can form along a structural or phenomenological perspective.

⁶ Note that ‘accounting’ can also mean that a certain perspective may be trivial. A technical system for instance often does not need an evolutionary or complexity perspective in order to describe its structure or function.

Thus isomorphy can be seen at different levels of complexity, or in different sub- systems, and thus become patterns. This aspect is for instance also acknowledged in complexity through so-called *power laws* (Schroeder, 1992).

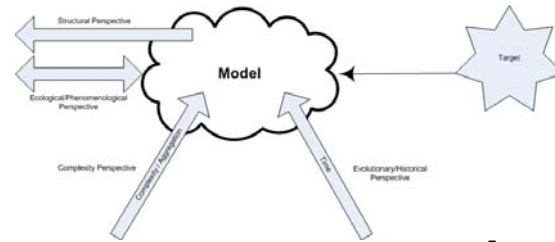


Figure 5: Perspectives on Complexity⁷

Note that the occurrence of patterns reduces the amount of information in the system and thus its complexity, as some aspects of the system are generalised through the pattern. This way redundancy is countered.

Contextual patterns usually provide both a structural and a phenomenological perspective on the systems they model. Besides this, the pattern library guides the other two perspectives.

Perspectives thus, like POM, provide conceptual patterns which guide the construction of the model using contextual patterns. With additional criteria, such as predictability, explanatory power, mathematical correctness, etc., these models may be ‘upgraded’ to ‘theory’ or ‘law’. But all of these efforts, in the end, aim to minimise the uncertainty, or error, between target and model. The four perspectives of a complex systems are needed to increase the quality of the model to ‘Medawar zone level’. This is of importance not only because the models themselves may be more refined, but *also* because it may help to prevent the biggest shortcomings of patterns to go unnoticed. For patterns are not without risk, as the following section may make clear.

The Risks of Patterns

Suppose we have a fairly straightforward mathematical pattern, such as an exponential curve. As may be known, these curves are quite common, and can be seen in the growth of capital on a bank account and in population growth in some countries⁸. A researcher now adds a few recurrent non-linear equations to such an exponential curve, so that the resulting curve starts out growing exponentially until suddenly it collapses. Then he looks at the DOW Jones index, sees a similar form and exclaims “Hey, I’ve just modelled the credit crisis!” (Gershenson, 2008: 31)

Intuitively this example makes clear that the assumption is rather premature. However, this mistake is often made and has been coined ‘reminiscence syndrome’ by former Santa Fe researcher Jack Cowan (Horgan, 1995):

"They say, 'Look, isn't this reminiscent of a biological or physical phenomenon!' They jump in right away as if it's a decent model for the phenomenon, and usually of course it's just got some accidental features that make it look like something.' The major discovery to emerge from the institute thus far, Cowan suggests, is that 'it's very hard to do science on complex systems.'"

This shows that a pattern should never be used as proof in itself, but needs additional contextual embedding to complete a claim to correspondence. This it shares with modelling activities in general (Oreskes et al., 1994: 641-646). The manner of contextual embedding may vary per scientific discipline, for the simple reason that ‘theory’ or ‘proof’ may have different meanings. However, these risks are often also latent in the analogies, metaphors and theories that are used to advance scientific thought. These are often used implicitly, allowing bias and prejudices to contaminate the modelling activities. At least patterns are used explicitly, thus opening them up for criticism by peers and falsification (Popper, 1965).

⁷ The arrows align with the flow of information for the modeller

⁸ Note that an exponential curve models multiple targets, and thus can be considered a pattern.

The ‘multiple perspectives’ approach enforces various consistency checks for the model that is being made; the *phenomenological* perspective of the mathematical curve alone is not sufficient, for it needs to be completed with a structural analysis (‘what do the combined equations imply or mean?’) and possibly an evolutionary perspective (‘can the used formulas be matched to known historical developments that led to the credit crunch?’). In this light, the Medawar zone seems to warn against claims to correspondence of models or theories based on a limited set of perspectives. The multiple perspective approach of POM, and the pattern approach advocated here seems to be a step towards a remedy to the ailment that Cowan sees in research of complex systems.

However, patterns in the way that is analysed here, offer some other means of constraining overly enthusiastic claims of correspondence. For one, the use of pattern libraries of established and mature patterns restrict the ‘selection space’ of possible methodological constructs. Even though researchers are free to introduce novel patterns in their endeavours, it requires some argumentation to substantiate such alternatives.

At this point, one can of course raise the question why ‘mature’ patterns should have prevalence over more or less obscure ones. A target, such as an observed phenomenon may be granted utmost individuality or and thus may not be subject to a ‘rule of the democratic majority’, which patterns seem to advocate. Although on a personal note, I can fully appreciate such a stance, I think there are two arguments that would substantiate the use of patterns of mature pattern libraries for scientific modelling of complex targets. One of these, the simplest to answer, is that science itself has historically always had a preference for unification. Provided the pattern libraries of complex systems do not become a constraining straight jacket for research, a plausible model based on generally accepted patterns will, on this account, be preferable over one that is constructed with obscure ones.

The second reason is based on issues of a somewhat more philosophical nature. If we accept the model-target distinction as being somewhat analogous to the human perception of our life-world, then we must be open to the consideration that our understanding is founded in recognition of patterns that were formed by previous experiences. These patterns may *not have any relevance* to the target under investigation, but as they are *the only means we have* to organise novel experiences, our understanding of that target can only be guided by the patterns that have been formed from previous experiences. It stands to reason that patterns that are recalled the most, are those who are the first deployed when information is formed. This, in much more detail, has also been analysed by the French biophysicist and ethicist Henri Atlan. His analysis of *interpretands* and *explanatory schemes* are fairly similar to the concept-context distinction of patterns argued here (Atlan, 1993: 161-162).

From this angle, pattern libraries organise novelty in a fashion that aligns best with our own means of learning. Besides this, as we had seen earlier, patterns can also be communicated across specific knowledge domains and, through pattern libraries, they also enforce democratic interaction. Everyone is free to create their own patterns, but it is the community that accepts them and maintains them through such libraries. In this sense they are much more powerful than metaphor and analogy as these tend to be –if not implicitly- used in a rather liberal fashion (Reydon Hemerik, 2005: 9-33).

Discussion

This article has aimed to draw attention to patterns as a methodological construct to research complex systems, and especially as a cross-scientific modelling tool. Even though at first blush they seem to be derivative of the system theories, the use of pattern libraries offer more consistency than is now currently is often achieved in the various systems dialects. On the other hand, pattern libraries are not prescriptive and seem to offer a better means to engage in interdisciplinary or cross-disciplinary research. In a concise analysis of the nature of patterns,

they are seen as taking up an intermediary position between (unstructured) data and (structured) information, of which the latter is seen as the merger of two types of patterns, contextual ones and conceptual ones.

As patterns traverse different levels of complexity through the characteristic of isomorphy, they offer a means of 'aligning' theories in different research disciplines, but complexity itself does constrain this isomorphy through concepts of limits of scale and emergence.

Complexity may challenge the parsimony that once was attributed to our universe (Aerts et al., 2005: 38-58) and likewise (post-)modern philosophy may have paved the way for a world-view that is based on interpretation, subjectivism and relativism. In the world of fragmented knowledge that is thus formed, there may be only one fundamental means of understanding, informing, sharing and exploring, and this is through patterns.

References

- Christopher Alexander (1977). *A Pattern Language*, ISBN 0195019199
- Erich Gamma, Richard Helm, Ralph Johnson, and John M. Vlissides (1994). *Design Patterns*, ISBN 0201633612
- Helga Nowotny, Peter Scott, and Michael Gibbons (2001). *Re-Thinking Science*, ISBN 0745626084
- J. Wiles, N L Geard, J. Watson, K. Willadsen, et al. (2005). *There's more to a model than code, Proceedings of the 2005 workshops on Genetic and evolutionary computation*, ISBN:1-59593-010-8
- Ludwig Von Bertalanffy (1976). *General System Theory*, ISBN 0807604534
- Manfred Schroeder (1992). *Fractals, Chaos, Power Laws*, ISBN 0716723573
- Cornelis P. Pieters (2009). *Patterns, Complexity and the Lingua Democratica*, ISBN 1-934272-37-X
- Cornelis P. Pieters (2008). *Complex Systems and Patterns*, ISBN 978-960-474-064-2
- Henri Atlan (1993). *Enlightenment to Enlightenment*, ISBN 0791414515
- Cornelis P. Pieters (2007). *Rethinking the Obvious*, ISBN 978-90-5638-183-7
- Ana María Piquer Píriz (2002). *Notes on metaphorical schemata and the search for equivalence in translating English and Spanish*, ISSN 0210-8178
- Dedre Gentner, Keith J. Holyoak, and Boicho N. Kokinov (2001). *The Analogical Mind*, ISBN 0262571390
- Niklas Luhmann (1996). *Social Systems*, ISBN 0804726256
- Carlos Gershenson, Diederik Aerts, and Bruce Edmonds (2007). *Worldviews, Science and Us*, ISBN 9812705481
- Edgar Morin (2008). *On Complexity*, ISBN 1572738014
- Frederic Darbellay, Moira Cockell, Jerome Billotte, and Francis Waldvogel (2008). *A Vision of Transdisciplinarity*, ISBN 1420092286
- Stuart A. Kauffman (1993). *The Origins of Order*, ISBN 0195079515
- Paul Cilliers (2001). *Knowledge, Limits and Boundaries*, ISSN 1447-9338
- Volker Grimm, Eloy Revilla, Uta Berger, Florian Jeltsch, et al. (2005). *Pattern-Oriented Modeling of Agent-Based Complex Systems*, ISSN 1095-9203
- Carlos Gershenson (2008). *Complexity*, ISBN 8792130135
- Albert-Laszlo Barabasi (2003). *Linked*, ISBN 0452284392
- John Horgan (1995). *From Complexity to Perplexity; Can science achieve a unified theory of complex systems?*
- Roger Lewin (2000). *Complexity*, ISBN 0226476553
- N. Katherine Hayles (1999). *How We Became Posthuman*, ISBN 0226321460
- Claude E Shannon and Warren Weaver (1998). *The Mathematical Theory of Communication*, ISBN 0252725468
- Dana Klimesova (2009). *Data, Information and Knowledge Transformation*, ISBN 978-960-474-064-2
- Paul Cilliers (1998). *Complexity and Postmodernism*, ISBN 0415152879

Antonio R. Damasio (2000). *The Feeling of What Happens*, ISBN 0099288761

Yoonsuck Choe (2002). *TAMU CS Techreport #2002-2-2 Analogical Cascade*, ISSN: 0925-2312

Stuart A. Kauffman (2002). *Investigations*, ISBN 0195121058

Bruno Latour (2007). *Reassembling the Social*, ISBN 0199256055

Mohamad H. Hassoun (1995). *Fundamentals of Artificial Neural Networks*, ISBN 026208239X

Michael White (1999). *Isaac Newton*, ISBN 073820143X

Zbigniew Michalewicz (1998). *Genetic Algorithms + Data Structures = Evolution Programs*, ISBN 3540606769

John Holland (1996). *Hidden Order*, ISBN 0201442302

Michael T. Goodrich and Tamassia (2005). *Data Structures And Algorithms in Java*, ISBN 0471738840

Naomi Oreskes, Kristin Shrader-Frechette, Kenneth Belitz (1994). *Verification, Validation, and Confirmation of Numerical Models in the Earth Sciences*, ISSN: 0036-8075

Karl R. Popper (1965). *The Logic Of Scientific Discovery*, ISBN 06-130576-6

Thomas A.C. Reydon and Lia Hemerik (2005). *Current Themes in Theoretical Biology*, ISBN 1402029012

Diederik Aerts, Bart D'Hooghe, and Nicole Note (2005). *Worldviews, Science and Us*, ISBN 9812561900