

Complexity and its observer

Does complexity increase in the course of evolution?

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Abstract

The paper endeavors to gain a better understanding of the role of the *observer* in attempts to answer questions like “what is complexity?”, “can it be measured?” and “does it increase?”. Following Heinz von Foerster and others in considering complexity observer-dependent, conceptions of Spencer-Brown, of Luhmann and of Varela and Maturana are taken to draft a formal conception of observation and to discuss on its base suggestions like informational (Shannon), algorithmic (Solomonov, Kolmogorov, Chaitin), statistical (Crutchfield) and physical (Adami) complexity. Finally, in order to illuminate the concept of the observer further, the presumably indispensable aspect of complexity reduction is illustrated with the help of a Genetic Algorithm.

Does complexity increase in the course of evolution? Or does it decrease? According to the Second Law of Thermodynamics the latter should be the case. But looking just superficially at the richness of nature, one comes to believe in an ongoing and open-ended emergence of increasingly complex structures that stabilize further and further from thermodynamic equilibrium - with humans and their creations possibly being the latest manifestations of this. But is this apparent rise in complexity an objective feature of the world? Or is it just the impression of an observer who's capacity to cope with complexity is categorically limited? And if it is so, can we learn something about complexity by observing the observer?

Among the numerous considerations on complexity, there are several suggestions on how to measure and therewith “objectively” prove it. Some biologists for example suggest to count the number of structural components and functional properties of organisms, such as number of limbs or number of possible behaviors, and deduct from rising numbers an evolutionary increase in complexity (McShea 1995, 2000).¹ Information theorists and physicists propose to measure the predictability of an event happening in a certain possibility space or a symbol being chosen from a sequence of symbols in a given alphabet (Shannon 1948). Computer scientists suggest to capture complexity in terms of the size of the shortest algorithm needed to reproduce complex phenomena (Solomonov 1964, Kolmogorov 1965, Chaitin 1966) and further refine this suggestion in regard to the runtime of the shortest algorithm when applied to an Universal Turing Machine (Bennett 1988) or in regard to the “thermodynamic depth” which would inform about how hard to build such algorithms are. (Lloyd/Pagel 1988, Crutchfield/Shalizi 1999, for further suggestions see: Lloyd 2001, Biggiero 2001, Mitchell 2009, and below)

As interesting and inspiring these suggestions are, they all seem to run up on a fundamental epistemological (and thus philosophical) problem. As Foerster (1982), Casti (1994), Gell-Mann (1995, 1996) and others emphasized, methods to measure complexity depend on the knowledge and the understanding of the one who perceives a phenomenon as complex and

¹ Complexity theorists, however, object that the multitude of structural or functional parts might indicate *complicatedness* rather than *complexity*. In terms of informational complexity measures - Shannon-entropy or algorithmic-complexity for instance (see below) - small and weakly coupled systems can exhibit more complexity than large and strongly coupled ones. Even an increase in fitness cannot unambiguously be taken as increase of complexity, as bacteria for instance might be quite fit in their niches compared to more complex multi-cellular organisms.

wants to measure it. In short, they depend on the one who observes complexity as such. They are *observer-dependent*.

A simple example, suggested by Heinz von Foerster (1993), might introductorily illustrate this problem. In the realm of mathematics the sequence {8, 5, 4, 9, 1, 7, 6, 3, 2, 0, ...} seems pretty unpredictable, meaning that no formula is conceivable which reproduces the sequence while being shorter than the sequence itself. In terms of Shannon-entropy (to which I come back below), the complexity of the sequence would be considered quite high. In the realm of the English language, however, the sequence, when transformed to its verbal expressions {eight, five, four, nine, ...}, turns out to be alphabetically ordered and hence of low entropy. Knowing about this order, one will not perceive much complexity in it, whereas not knowing could entail far-reaching speculations. On this background, complexity reveals as a *relative* phenomenon depending on the one who observes it.

This necessitates, so to speak, a “more complex” approach to the quest for understanding complexity and “proving” its growth. It necessitates to observe the observer and its relation to the complexity he observes. When doing so - and this is the point I want to put forward in this paper - , it becomes obvious that the observer observes by *reducing complexity* which implies the apparently paradox assumption that complexity - since being observer-dependent - emerges and *increases* only if it can be reduced. Or in other words, complexity occurs and increases only when it can be *observed*, with observation being conditioned on a viable reduction of complexity. Hence, only a decrease in complexity can provide a stable footing for a (next-order, and may be evolutionary) increase in complexity. In short, complexity might increase in the course of evolution, but if it does so, it increases via decreasing.² While neither increase nor decrease can be measured directly, their relation might be embodied by an observer who reduces complexity in order to cope with it and therewith sustains its existence. In specifically reduced (sic) contexts, the emergence of this observer might be simulated with the help of Genetic Algorithms.³

I. The observer

What I call observer in this context does not have to be taken for a *human* observer. In this context, the observer is an abstract conception, probably most basically defined in the calculus of George Spencer-Brown commonly referred to as the formal rule “distinct and indicate” (Spencer-Brown 1969). This observer observes its “world” by differentiating it and indicating one of the distinct sides as the one relevant for further operations, i.e. observations. An air-con for instance observes its world by differentiating warm and cold temperatures and indicates one of them as reason for sending an on-signal to a heater. A computer differentiates binaries and indicates one of them as the state from which to start the next computation. An organism distinguishes, say, usable resources from unusable and indicates usable as the ones relevant for sustaining its existence.

On a hardly less abstract level than Spencer-Brown, Niklas Luhmann (1984/1995) uses this formula to explain the emergence of a system by being distinguished by an observer from its environment and indicated as the relevant observable entity. The clue however in this conception is the fact that *complex systems* can become *self-observing* and therewith might

² Elsewhere, I have speculated on this paradox as “synchronously asynchronously” increasing and decreasing. cf Füllsack 2010b, 2011.

³ There is a second aspect to this picture, apt to render it even more paradox. This aspect will be pursued in a sequel to this paper. It consists of the possibility of “paying” for a gain of order (that is, a decrease in entropy) with a loss of order on a $n - 1$ -order level (i.e. with an increase in entropy), as it is suggested by research on pheromone-based ant-foraging for instance (Parunak/Brueckner 2001). The observer, as seen as conditioned on some kind of complexity reduction in this paper, would thus depend on a complexity increase on another order-level as well.

maintain the distinction from their environment *themselves*. Luhmann symbolizes this self-maintenance with the following formula

$$\text{system} = \overline{\text{system}} \Big| \text{environment}$$

which, when expressed in words (and hence admittedly a bit paradoxically), says that a system becomes a system if (and only if) it manages to (at least temporarily) distinguish itself from its environment and to indicate itself as the relevant part of the distinction. In other words, a system becomes a system if it manages to construct and sustain a border, a delimitation, between itself and its environment. The system produces itself by generating and sustaining its distinction and indication. Or even more paradoxically: the system generates itself by *observing* itself. Maturana and Varela (1987) famously suggested the term *autopoiesis* for this kind of self-maintenance.

II. Autopoiesis

In order to productively affiliate the interesting, but may be for some researchers still rather “fuzzy” and ambiguous conception of autopoiesis to the debates about the increase of complexity, it seems necessary to entangle the various assumptions that go into it. As a first step, it might help to shortly review a model which Varela and Maturana themselves suggested to illustrate the notion of autopoietic self-maintenance. This is the SCL-model of autopoietic cell construction, as suggested by Varela et al. in 1974. (see also McMullin/Varela 1997, McMullin/Groß 2001) SCL stands for “Substrate-”, “Catalyst-“ and “Link-”particles and indicates a model world which eventually consists of nothing more than constellations of these three particles. Initially, two of these particles – substrates (S) and catalysts (C) – are freely moving on a two-dimensional lattice world (a checkerboard). Whenever two S-particles meet in the Moore-neighborhood of a C particle (i.e. in the eight surrounding fields on the checkerboard) they disappear and a Link- (L) particle is generated in place of one of them. L-particles which neighbor each other are bonded together with a certain probability if they are at least one field away from C particles and from other L particles which are bonded already. In general, bonding is restricted to a maximum of two bonds per L-particle with a minimum of 90 degrees to each other.

While S-particles can freely diffuse through bonded links, C particles cannot. At times, therewith, loops can emerge which enclose C-particles and thus can be interpreted as semi-permeable membranes of cells containing one catalyst as a nuke. With a certain probability however, L particles – whether bonded or not – may decay and form two S particles. The loop around a C-particle may break, the membrane opens up and the cell is destroyed. If the environment is sufficiently fecund however, meaning that there are enough S-particles constantly diffusing through the membrane and therewith “feeding” the “cell” with material with which to repair the broken loop, chances are good that the “cell” can (self-)maintain its existence as a delimited system. The “cell” therewith autopoietically generates itself by maintaining a border to its environment (see figure 1).

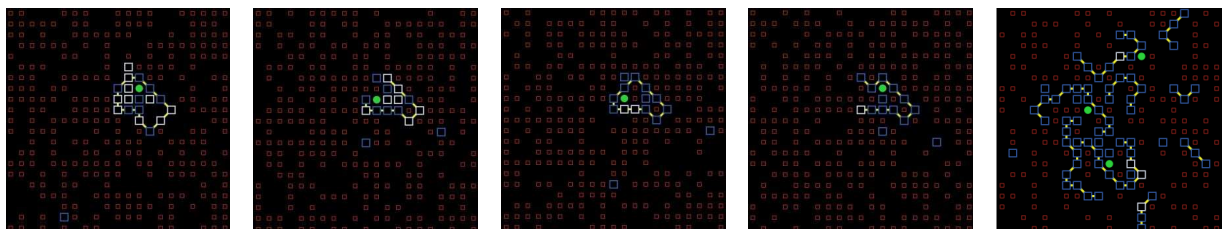


Figure 1. SCL-model according to McMullin/Varela 1997 (re-implemented by the author with Netlogo). S-particles red, C-particle green, L-particles blue, respectively white when a S-particle diffuses through them.

Bonds between L-particles yellow. At step 197 a closed loop around a C-particle has developed (left picture). At step 204 the loop breaks open (second left picture), but is repaired at step 210 (middle picture). At step 273 (second right picture) the loop breaks open again and the “cell” diffuses. The right picture shows a seemingly chaotic world with three C-particles of which none manages to form a loop at the time being (see to this below).

III. Teleology

Note that the border-generating and -maintaining mechanism that the SCL-model exhibits depends essentially on a rich residuum of S-particles. Without them, the reconstruction of borders could not be sustained. S-particles thus are an indispensable mean of subsistence for this self-delimiting process. They are what the process needs as “resources” to sustain its continuation.

However, as Varela (1992: 7) claims, resources become resources only in the presence of the entity which depends on them. Sucrose for instance, on which bacteria feed, has no whatsoever significance as resource without the bacteria feeding on it. So the resource stands in relation to the entity feeding on it. The resource, in being a resource, is dependent on the entity which *observes* it as a resource in order to maintain its existence.

In the case of the SCL-cell, maintaining existence of course means just to be (or emerge as) some kind of “regularity” in an otherwise seemingly irregular world. The regularity in this case simply consists of a rather fragile circular containment of a C-particle by bonded L-particles which stands out from a seemingly chaotic (that is: irregular) background of other bonding L-particles, errant C-particles and floating S-particles which do not manage to form and maintain a cell (as illustrated in the last picture in figure 1). Perceiving the SCL-cell as a regularity hence, means to *distinct and indicate* it as some kind of relevant order, and therewith potentially to treat it as a “resource” in its own right. One might easily imagine a bacterium which feeds on sucrose becoming a resource in its own right for some other organism that feeds on bacteria. If one is ready to conceive this “mutual feeding” again in terms of the abstract Spencer-Brownian observation, a “world”, or more to the point, a *network* of mutually observing entities emerges which maintain themselves by “observing” other entities as resources - or more abstractly expressed, which maintain themselves by *capitalizing on certain regularities they perceive in their environment*. These regularities in their turn emerge through entities which manage to sustain their existence on the grounds of again other regularities which can be observed and used as resources.

IV. Complexities

However, the term “regularities” could be misleading in this context. It seems more correct to speak of complexities. To see the difference and to further understand how a reduction of complexity is involved in this process, it might help to have a short look at the concept of Shannon-entropy as it is deployed in information theory.⁴

Mathematically defined as $H(X) = -\sum p(x_i) \log_n p(x_i)$ ⁵, Shannon entropy (aka uncertainty) measures the expectation of an event happening in a given possibility space. Or expressed in terms of information, it measures the expectation that a symbol is chosen from a given set of possible symbols, for instance from an alphabet. In a possibility space of binaries for example, that is, in a world with only two possibilities, the Shannon-entropy of a series of fair coin tosses would be 1 since it is expected that none of the tosses can be predicted and the

⁴ I am aware of the redundancy of discussing information theory at some length in a paper on complexity. However, as these considerations are presented on a congress of philosophers, who might be not so familiar with information theory, I try to be as comprehensible as possible.

⁵ with X denoting a sequence of events $\{x_1, x_2, \dots, x_n\}$ and p indicating the probability of a single event x_i . When measured in Bits \log_2 is taken.

probability of a coin falling on head or tail is equally 0.5. In other words, uncertainty in this case is 100%. The Shannon-entropy of sequences like {111111 ...} or {10101010...} on the other hand, is 0, since the next symbol in the sequence seems completely predictable from the symbols that are already part of the sequence. Thus, with uniform or periodic processes having very low values and random processes having high values, Shannon-entropy measures the certainty or uncertainty with which a sequence, a process or a development can be predicted.

Simple periodical processes would seem regular, while random, unpredictable ones can be called irregular. None of these classifications, however, is what the above mentioned entities might prefer as “resources”. In terms of Spencer-Brownian observation, it seems obvious that there is not much to distinct and indicate in uniform or simple periodical sequences. What would you distinguish in an all-1-sequence? And there is also not much to distinct and indicate in a completely random process, since each new event might change the picture completely. In terms of information theory both extremes are not very surprising. Regular as well as completely irregular sequences do not seem to be attractive as “resources” – at least not for entities that we, the scientific observers, can observe. The attractive level of order seems to lie somewhere *in-between*. Usable “resources” seem to consist of a sort of “amalgam” (Crutchfield 1994b: 17) of order and chaos which neither are completely regular nor completely irregular, but *complex*.

But note that this complexity depends on the capacity of an entity to *use* a “resource” as such. It depends on the capacity of the entity to capitalize on an “amalgam” of order and chaos in order to maintain its own existence.

V. Computational power

As mentioned above, a sequence can be considered to be ordered if a rule or a formula can be derived with the help of which this sequence can be reliably reproduced. Kolmogorov- or, as it is should probably be more correctly called, algorithmic-complexity extends this definition to computational power, measuring the complexity of a sequence in Bits needed to store a computer algorithm which reliably generates the sequence. This extension, which is unified in regard to the computational power of a Universal Turing Machine, gives a first hint about what is meant by the possibility of increasing complexity through reducing complexity. If any kind of computation is able to reliably reproduce a structure while being “smaller” than this structure itself, it can be seen as a *compression* of it and therewith a *reduction* of its complexity. And if this computation can be used to maintain a certain structure in time and in space, that is for instance to enable an entity to capitalize on it by observing “resources” with which to maintain itself – therewith becoming observable as an *identity* –, the “world” in which this identity emerges seems to get *more* complex than it has been before.

However, as Shannon-entropy before, algorithmic-complexity does not allow to capture the interesting “edge of chaos” at which observing entities might emerge. Either sequences are uniform or periodic in some way and can be reproduced by more or less small algorithms, indicating low complexity, or they are random and cannot be reproduced other than by generating the sequence itself, indicating high complexity. The “in-between”, that is, the complexity at the “onset of chaos” at which interesting “resources” might be found, cannot be grasped in terms of algorithmic complexity.

To answer this deficit, James Crutchfield and Karl Young (1989) suggested a measure which they called “statistical complexity”.

VI. Statistical Complexity

At first sight this suggestion stands out from the earlier conceptions of complexity by its apparent awareness of the observer-dependency of complexity, which James Crutchfield has detailed in some later papers (cf. Crutchfield 1994a, 1994b). Especially in *The Calculi of Emergence* (1994b: 3f) he endeavors to base the concept of statistical complexity on an elaborate holistic understanding of the role of observation in defining complexity. For this he sort of “internalizes” the observer into the observed via a kind of system-immanent operation which he calls “intrinsic emergence” or “intrinsic computation”. In this conception the observational process is seen as the operation of the system itself. The system, so to speak, observes patterns or structures generated by itself.⁶ The “outside observer” is drawn into the system. No external referent for patterns, for structure or for order seems necessary.

The role of this internalized “outside observer” is taken by so called “ ε -machines”, which by operating on their own onboard means, as Crutchfield constructivistically emphasizes (- with a “codebook at hand” rendering everything not decodable to noise -), are looking for “statistical complexity”. These ε -machines are computing devices which try to (statistically correctly) predict the occurrence of an event from a sequence of other events that have been stored in its memory. “Statistical complexity” thus simply regards the computational power needed to (statistically) predict certain events from experiences. In the experimental setting, it is the computational power that is needed to predict the right half of a given sequence of symbols from the left half of this sequence. Following Noam Chomsky, Crutchfield and Young conceive this so called “intrinsic computation” in terms of computational classes, that is, in terms of size and kind of computer memories, for instance finite memories, infinite one-way stack memories, first-in first-out queue memories, infinite random access memories, and others (Crutchfield/Young 1989, Crutchfield 1994a). The minimal class needed to (statistically correctly) predict a sequence thus can be seen as the minimal representation of this sequence and therewith reflecting its complexity.

Experimentally, the minimal class thereby is found “evolutionary”, that is, by exposing the computational devices to selection in Genetic Algorithms, with the smallest and most correct one obtaining highest fitness, that is, highest reproductive probability. Therewith, and differently to algorithmic-complexity, “statistical complexity” peaks at the “onset of chaos” since ε -machines select rising computational classes as long as they manage to find predictable regularities in a run from order to chaos, but they give in to select anything when no regularities (no “resources”) are to be found.

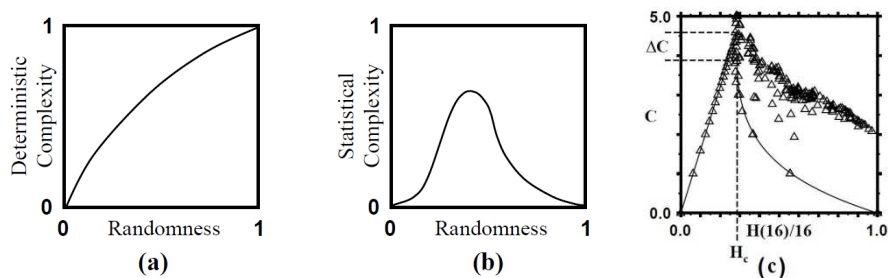


Figure 2. Complexity distributions. (a): according to Shannon-entropy and algorithmic-complexity. (b): according to “statistical complexity”. (c): Results of an evolutionary run towards chaos via the period-doubling route of the logistic map. Triangles denote the distribution of ε -machines. Their position on the y-axis indicates their complexity, that is their computational class. The peak relates to the “onset of chaos” found in the logistic equation at $r \approx 3.57$. (Taken from Crutchfield

⁶ Crutchfield (1994a: 3) gives the example of “competitive agents in a capital market” who control their individual production-investment and stock-ownership strategies based on the optimal pricing that has emerged from their own collective behavior.

In this regard, a selected ϵ -machine “represents” a given environment. With its adaptation it seems to become a *model* which relates to the complexity of this environment, but in itself is *less* complex than what is modeled. We might say that by emerging and persisting it finds a way to *reduce complexity*, but at the same time, by doing so, that is by existing, it also provides a possibility for a next-order *increase* of complexity, which would occur *if* another (that is, a new) entity emerges by finding a way to observe it as a “resource”.

Although implied in Crutchfield’s conception, this circumstance, however, is not really in the focus of his investigations. His prime concern is a consistent *measure* for complexity and not an *explanation* about whether and how complexity is increasing. In regard to this concern, the way he “internalizes” the observer of complexity into the system seems legitimate. For my understanding however, this internalization stands somehow apart from the actual concern of the research work. Dividing a sequence of binaries into two halves and trying to predict the right one from the left one, doesn’t seem to leave classical objectivism far behind. What is more, it does not help to further specify the *role* the observer plays in the process of increasing complexity. It does not capture the *contribution* of the observer to the rise of complexity. As I see it, Crutchfield considers the observer, but, by regarding the system holistically (that is, as observing itself, or in his words, as intrinsically computing), moves it so far from center stage that it is in danger to become invisible again. Taking a step backwards, it still seems somehow unclear who or what is trying to predict an event from a sequence of experiences and who or what is benefitting from this prediction.

VII. Physical Complexity

In order to put the observer back into focus, it might help to consider the conception of “physical complexity” as suggested by Christof Adami (2000, 2002). Despite the labeling “physical”, Adami seems more interested in biological and evolutionary aspects of complexity than in informational or physical ones. Nevertheless, his conception as well seeks to quantify complexity along the informational path.

Adami starts out by accentuating that information (– although mathematical formalization tends to decouple it from its meaning –) never is information by itself, but only if it is information *about* something (2002: 1087). What mathematically, algorithmically or statistically is measured therefore is only “sequence complexity” which by itself might be interesting to a scientific researcher, but doesn’t have to have relevance to an observer in a general sense. In biology, a typical example of sequence complexity might be seen in the way the genome encodes information. But obviously this information is meaningless outside of the context it is used. A genome of a bird does not make sense under water. Therefore, sequence complexity (or information) has to be viewed in the specific context in which the sequence – e.g. the genome – is applied to sustain the entity using it. Sequence complexity is nothing without the environment in which it is selected. As the actually relevant complexity measure therefore, Adami suggests “physical complexity” as a form of algorithmic-complexity which is *shared* between the sequence and a description of the environment in which the sequence is to be interpreted. (Adami/Cerf 2000) Although physical complexity (as other deterministic complexity measures) cannot be measured directly, it can be approximated by the “mutual information” a sequence (the genome) and its environment (the niche an organism lives in) provide to each other. Physical complexity thus measures the *relation* between a sequence and its specific context. And as the optimum of this relation is found in nature through natural selection, that is through adaptation, it can be found experimentally in artificial selection with the help of Genetic Algorithms. Adami (2002) demonstrates this in experiments with the digital ecology *Avida*. Physical complexity increases in his experiments as long as the

environment is kept static. Carothers et al. (2004) confirm these results in regard to biomolecules, and Bleda et al. (2003) extend Adami’s experiments to changing environments. On the background of this physical complexity, the observer of complexity eventually seems to gain profile. The observer in this regard is an entity (a structure, a mechanism, an organism ...) which capitalizes on the complexity, that is, on the “amalgam“ of order and chaos, that it (evolutionary) can make out in its environment by evolving a way to *reduce* this complexity to a viable level. This reduction might have the form of a sequence, a genome for instance, which contains the information needed to emerge in and to cope with this environment (to “live” and to “survive” in it). This sequence then “represents”⁷ the specific (i.e. the observer-dependent) complexity that prevails in this context. But the reduction is not necessarily conditioned on a separated sequence, such as a genome, or (as I experiment with in Füllsack 2011b), as a memory allowing artificial agents to anticipate future environmental conditions. Sequence complexity might as well manifest, so to speak, *embodied* in the form of the entity itself, such as in the form of a plant for example “representing” regularities in the supply of sunlight. The aspect to be put forward in this context is the (albeit temporal) reduction of complexity that comes with it, and that can in its turn increase complexity again, if - and only if - an observer emerges who can maintain its existence by finding a way to capitalize on the regularities provided by this reduction.

VIII. A simple model

In order to finally illustrate the seemingly paradox relation of increasing complexity by reducing it with the help of a model, I put up a simple simulation of a population of computer-generated agents which face an environment with seasonally changing resources supply. The agents are endowed with individual metabolisms with (random-normally distributed) higher and lower degrees of consumption. Some of them have high consumption in summer and low in winter, there are others with high consumption in spring and low in fall and again others with high consumption in fall and low in spring, and so on. Having high consumption in winter however, when supply is zero, and low consumption in fall, when supply is highest, is unfavorable for them. It impairs fitness and therewith diminishes their reproductive success. The outcome of this little Genetic Algorithm is straight forward. Allowing for a small mutation rate, the simulation, within a couple of steps, generates a population of well adapted agents whose metabolism is high when supply of resources is high, and whose metabolism is low when supply of resources is low.

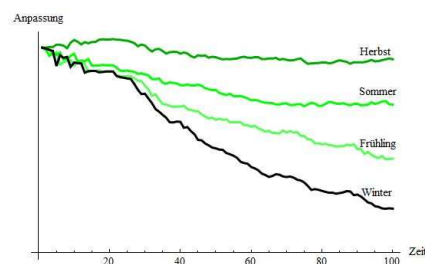


Figure 3: Evolution of agent’s mean metabolisms over 100 steps, in respect to a supply of resources in spring of 30, in summer of 60, in fall of 200 and in winter of 0, modeled with Netlogo.

⁷ “Representation”, however, (or “modeling” or “mapping”, as I said in another paper) is a complex conception on its own, which would need extra explanation for not misleading the notion of “mutual information”. See to this Füllsack 2010a.

At the end of the run, agents, so to speak, “observe” their environment by having found regularities in it to which to adapt and therewith to maintain themselves in this specific environment. A “blind teleology” (Depew, Dawkins) seems to have taken effect. The agents have evolutionary synchronized their consumption with their environmental conditions and therewith “represent” or “embody” these conditions. They relate to these conditions. Their complexity is “informed” by the complexity of their environment. When compared to the initial multitude it has become clearly less complex.⁸

With the existence of these agents however, the environment has become more complex than before. And this circumstance can entail new observations, which - in this experiment - I imposed on the agents themselves. For this, I assumed that agents by adapting and therewith surviving in this environment start to alter it again. Or in other words, agents by simply surviving, start to generate a “self-made” (or “artificial”) environment. One might think of greenhouse-gases emitting agents for instance that by becoming numerous start to change the climate of their world and subsequently the seasonal supply of resources. In order to make the process graphically more distinct, I chose a rather abrupt influence starting after 70 steps and turning the seasonal order upside down in the simulation from which the following picture is taken.

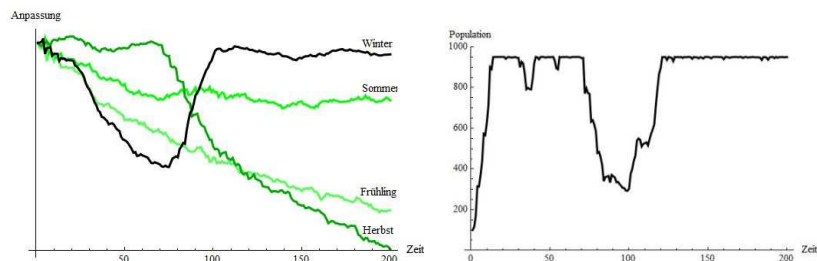


Figure 4: Meta-adaptation. Agents adapt to seasons, and after 70 steps to their own influence on their environment.

Hardly surprising, the population adapts again. Despite rather high individual costs (see the downward hump in the population plot), it again manages to find the relevant regularities on which to capitalize and therewith to sustain its existence. One might interpret such meta- or second-order adaptation as a sort of self-provision of regularities that triggers new observational processes. The system, so to say, in exploiting discovered regularities, generates new regularities to which it - or another system - might adapt on a next level. And this new adaptation again generates regularities to which again new observation is triggered, and so on. Similar to a Russian Matrioshka, one could imagine a potentially endless sequence of dissipative structures building one on the other by exploiting the regularities generated by the regularity exploiting process of the $n - 1$ -level. Observing, in other words, gets complex by observing and therewith seems to generate a remarkable heterogeneous and versatile world. This increase of complexity, however, is conditioned to the *observation* of complexity. And this observation has to be seen as a reduction of complexity, which only in its turn might trigger a next-order-increase *if*, on the base of the existence of a complexity reducing entity, another entity emerges by finding a chance to observe the first entity as a “resource”. Therefore, it might be justified to say that complexity increases, if it increases, via reduction of complexity, with the “if” conditioning the increase on the emergence of an entity that

⁸ However, one might stress here that this complexity reduction (an *increase* of entropy) was “bought” at the price of a complexity increase (a *decrease* in entropy) in the form of those agents who did not survive this adaptation process. Emphasizing this aspect, seems to come up with the otherwise apparently contradicted Second law of Thermodynamics. As mentioned above, I intend to elaborate on this aspect in a sequel to this paper.

manages to *observe* the increase as such by finding a way to *decrease* complexity in order to capitalize on it.

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