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Real Complexity vs. Apparent Complexity in Modeling Social Processes

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Abstract. Complexity science, developed in the last few decades, starts from the unproved presupposition that the foundations of the processes which manifest themselves as complex are simple. Thus, it was easy to build quickly various models for complex processes. But, in the current stage of development we start, little by little, to become aware of the main limitations introduced by the deep simplicity hypothesis. Indeed, it is hard to explain the high *phenomenological* complexity by deep *structural simplicity*. Between phenomenon and structure we propose the intermediate concept of *architecture*, as a supporting environment for maximizing the complexity captured in our models.

Anti-motto:
The universe is built on a plan, the profound symmetry of which is somehow present in the inner structure of our intellect.

Paul Valéry

Really!?

1. Introduction

From the first half of the 20th century open minded people emphasized the need to develop the knowledge of the true complex aspects of existence. One of them, Alexis Carrel – Nobel Prize for medicine in 1912 – warned us in the middle of the 4th decade of the last century:

> *The renovation of modern society demands, besides a profound spiritual urge, the knowledge of man in his wholeness. But the wholeness of man has many different aspects. These aspects are the object of special sciences, such as physiology, psychology, sociology, eugenics, pedagogy, medicine, and many others. There are specialists for each of them. But none for man as a whole.* ([1], p. XV)

Certainly, the science about man and its social behavior must be a complex one. Traditional sciences, like geometry or mechanics, start in a reductionist way avoiding details which cannot be avoided when the human being and its collective behavior is studied. In the same book, the reluctant approach of complexity is attributed to the very nature of our mind:

> *Our ignorance may be attributed, at the same time, to the mode of existence of our ancestors, to the complexity of our nature, and to the structure of our mind.* ([1], p. 5)

Alexis Carrel emphasizes a predisposition of our mind for simple constructs:

> *Our mind is so constructed as to delight in contemplating simple facts. We feel a kind of repugnance in attacking such a complex problem as that of the constitution of living beings and of man. ... Geometry does not exist in the earthly world. It has originated in ourselves.* ([1], p. 8)

Indeed, the human being is an engineer born creature, ready to optimize any approach. This innate tendency allowed a fast development of the human society until now, when we cannot anymore avoid the direct confrontation with the whole complexity of our world and of our own nature.

The development of the experimental mathematics, triggered by the evolution of computing science, led to the occurrence of the first forms of complexity sciences. But, our trickster-like mind is unable to avoid its tendency toward simplicity. We are faced with the last attempt to avoid complexity by substituting the real complexity with an apparent one.

In this transient stage, we hope, the complexity science is based on the *unproved assumptions* that the complexity of the existence is grounded in a deep fundamental simplicity manifested by:

- simple rules in dynamic systems
  - chaos
  - cellular automata
  - fractals
- locality
  - spatial
  - temporal

  - functional

- computational modeling

In the first section of the paper the distinction between size and complexity is rigorously defined. The second section is a quick review of the domain of dynamic systems with emphasis on the simplicity of their formal description. The third section introduces the concept of apparent complexity. The last section provides a transitory solution: the architectural approach.

2. Size vs. complexity

How can we differentiate something which is *big* from something which is *complex*? In many books about complexity, *size* and *complexity* are confused. More precisely, the size is the only aspect considered, while the discussion about complexity is avoided.

We intend to expand, for our purpose, Chaitin's *algorithmic complexity*[1] of a stream of characters. Any real object or process which has a description can be evaluated in terms of complexity.***By the length of the minimal description used to describe a certain reality we can define the complexity of that reality.*** A short "story", even if it refers to something big, is possible only for the description of something simple, while a long "story", even if it refers to something small, is necessary for the description of something complex.

Definition 1. A *complex entity*, $E(n)$, has the size, $S_E(n)$, and complexity, $C_E(n)$, in the same range:

$$S_E(n) \sim C_E(n)$$

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Definition 2. A *simple entity*, $E(n)$, has its size much bigger than its complexity:

$$S_E(n) >> C_E(n)$$

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Example 1. Let be two streams of binary symbols:

1. 1001111000101010100100001000101111111001011010100111010100110 1, which represents a stream of 64 binary symbols

2. $(1101)^{250}$, which represents a stream of 1000 binary symbols

The first stream is a complex one because its 64 characters cannot be described in other way than listing them all, so its size is similar with its smallest description.

The second stream is a simple one, because it has 1000 characters and its shortest description is done using only 9 symbols.

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[1] An informal description of the concept can be found in [2].

In the previous example, the first stream is *pattern-less*, while the second has a *pattern*, 1101, repeated 250 times. What about the easiness of memorizing the two streams? Obviously the second stream is easy to memorize, while the first, the complex one, is too hard to be memorized by most of people.

Sometimes, there are difficulties to find the shortest description of an entity. Many times it is impossible. These are the reasons for which the actual complexity of an entity is hard to be defined.

3. Dynamic systems

Various models are proposed for dynamic systems used to study complex realities. The most important are described in the following subsections. We try to emphasize that the real complexity is reduced to deep simplicity in all the currently used models.

3.1. Chaos

One of the most spectacular ways to trick our understanding about complexity is the famous model of *deterministic chaos*. Let us use, in the following, an example provided by Melanie Mitchel in her book about complexity [5]

Example 2. The iterative expression $x_{t+1} = Rx_t(1 - x_t)$ generates a stream of values starting from the initial one x_0, let it be 0.2.

The allure of the stream of values depends strongly on the value of the constant R. In the next four figures are presented the behaviors of the previous simple expression for $R = 2$, $R = 3.1$, $R = 3.49$, $R = 4$. In Fig. 1, for $R = 2$, the variable x has a very simple evolution: after few steps it remains constant. If we increase the constant to $R = 3.1$, see Fig. 2, the behavior remains a simple oscillatory one with a constant amplitude. A more radical change occurs for $R = 3.49$, see Fig. 3, because the amplitude of the oscillation starts to be variable. The behavior degenerates in a completely chaotic one for $R = 4$, see Fig. 4.

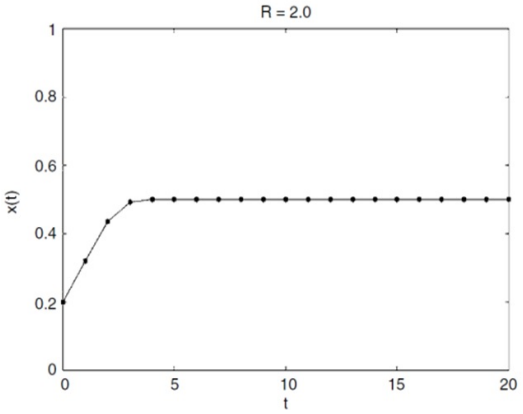

Fig. 1. The simplest behavior, for R=2: after few steps x(t) becomes constant.

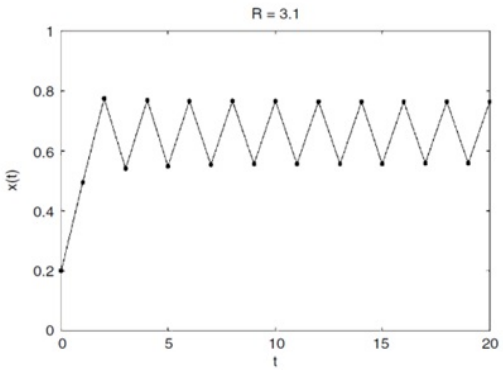

Fig. 2. For R=3.1: after few steps x(t) oscillates with constant amplitude.

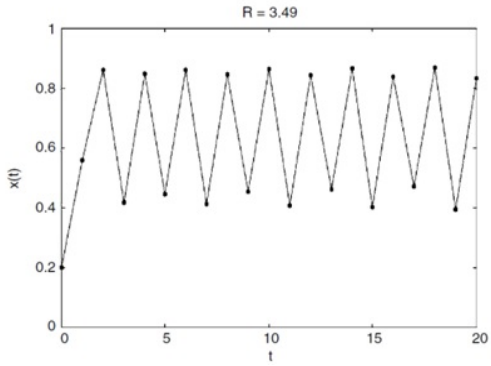

Fig. 3. For R=3.49: after few steps x(t) oscillates with variable amplitude.

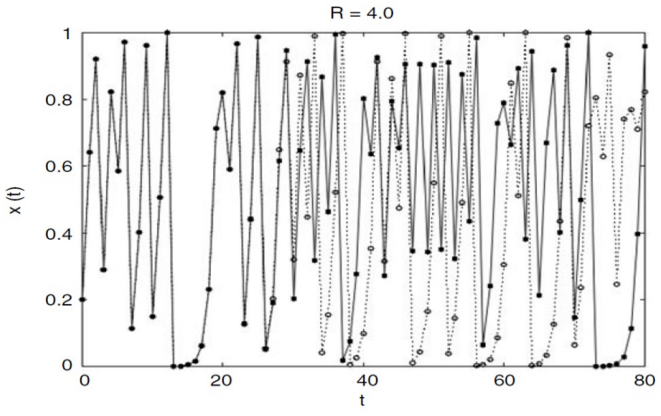

Fig. 4. The behavior for R=4 is chaotic. The continuous line is for $x_0 = 0.2$, while the dotted line is for $x_0 = 0.2000000001$.

For the first two cases, $R = 2$, $R = 3.1$, it is possible to easy provide the form of the equation if the behavior is given. But, for the next two cases it is impossible to find the equation if only the behavior in known. The evolution of the variable x ***looks*** very complex, even if in fact it is about a process described by a very simple equation which assumes a very small amount of computation. For the last case, $R = 4$, there is also another meaningful fact. If the initial value is changed only very little, from $x_0 = 0.2$ to $x_0 = 0.2000000001$, then the sequence generated changes dramatically after 25 cycles. The behavior is very sensitive to very small changes of the initial value x_0.

How can be adjusted the initial value of x_0 to obtain a certain behavior? It is certainly impossible to "tune" the behavior of a system governed by our so small & simple equation!

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3.2. Cellular automaton

Spectacular effects are provided by the use of another simple device: the cellular automaton. There are various forms of cellular automata. Some of them are represented in Fig. 5. The linear cellular automaton (see Fig. 5a) consists of a linear array of identical cells. In each cycle the state of each cell changes according to a unique rule which takes into account its own state, the state of the left cell and the state of the right cell. The two dimension cellular automaton consists of a two-dimension array of identical cells connected in the adjacent neighborhood in two versions: von Neumann's, in Fig. 5b, and Moore's, in Fig. 5c. The concept of cellular automaton was introduced by John von Neumann (obsessed by self-replicating systems) and Stanislaw Ulman (who studied the growth of crystals) at Los Alamos in 1940s.

Obviously, a n-cell cellular automaton is a simple entity, because its size is in $O(n)$, while its complexity is in $O(1)$. Indeed, the size increases proportionally with the number of cells, while de description of the function refers to the function of each identical cell which is connected in a constant sized neighborhood. Despite its simplicity, sometimes this big device shows a behavior hard to be explained as being provided based on a simple rule.

Example 3. Let's consider a linear cellular automaton with the smallest space of states in each cell: the cell has 2 states coded binary by one bit, S_i. The transition function is a 3-variable Boolean function. In our example the function is:

$$S_i^+ = S_{i-1} \oplus (S_i + S_{i+1})$$

The next value of the cell state S_i, S_i^+, is computed as a Boolean function which considers besides S_i, the state of the left cell, S_{i-1}, and the state of the right cell, S_{i+1}. The Verilog description of the cellular automaton is:

```
module linearCellularAutomaton #(parameter n = 95)
(output reg [n-1:0] out ,
 input  [n-1:0] in ,
 input init , clock);
```

```
always @(posedge clock)
 if (init) out <= in ;
  // rule 30: noise generator
  else out[n-2:1] <= (out[n-2:1] | out[n-3:0]) ^ out[n-1:2];
  // rule 90: Sierpinski triangle
  //else out[n-2:1] <= out[n-3:0] ^ out[n-1:2]   ;
endmodule
```

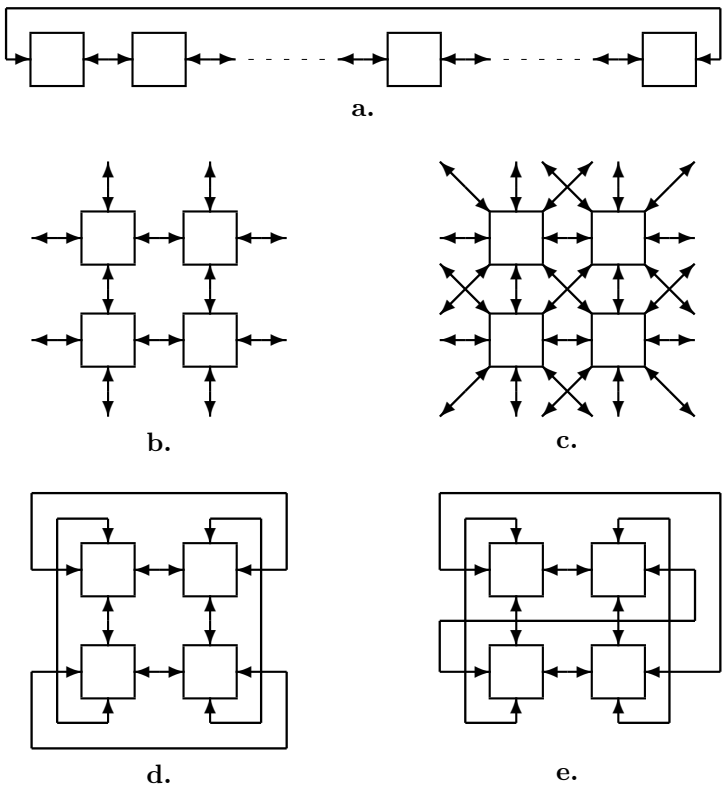

Fig. 5. Cellular automaton. a. One-dimension cellular automaton. **b.** Two-dimension cellular automaton with von Neumann neighborhood. **c.** Two-dimension cellular automaton with Moore neighborhood. **d.** Two-dimension cellular automaton with toroidal shape. **e.** Two-dimension cellular automaton with rotated toroidal shape.

For any n the description of the cellular automaton has the same size. Therefore, our system is a simple one. The result of the simulation shows the following behavior represented in Fig. 6, where the cellular automaton is initialized in the global state: 0001000 (a central 1 preceded and followed by 0s). The initial 1 generates a pattern-less binary sequence. Let us take from the middle of the binary array generated a

column of 8-bit numbers starting from the 7^{th} line (see the bolded binary characters in Fig. 6). The resulting sequence of numbers is:

01000010
11100111
00011100
10110010
00101111
01101000
11001100
00111011
11100010
10010111
11110100
10000110
01001101
11111001
00000111
10001100

The previous sequence is considered a good random sequence of numbers.

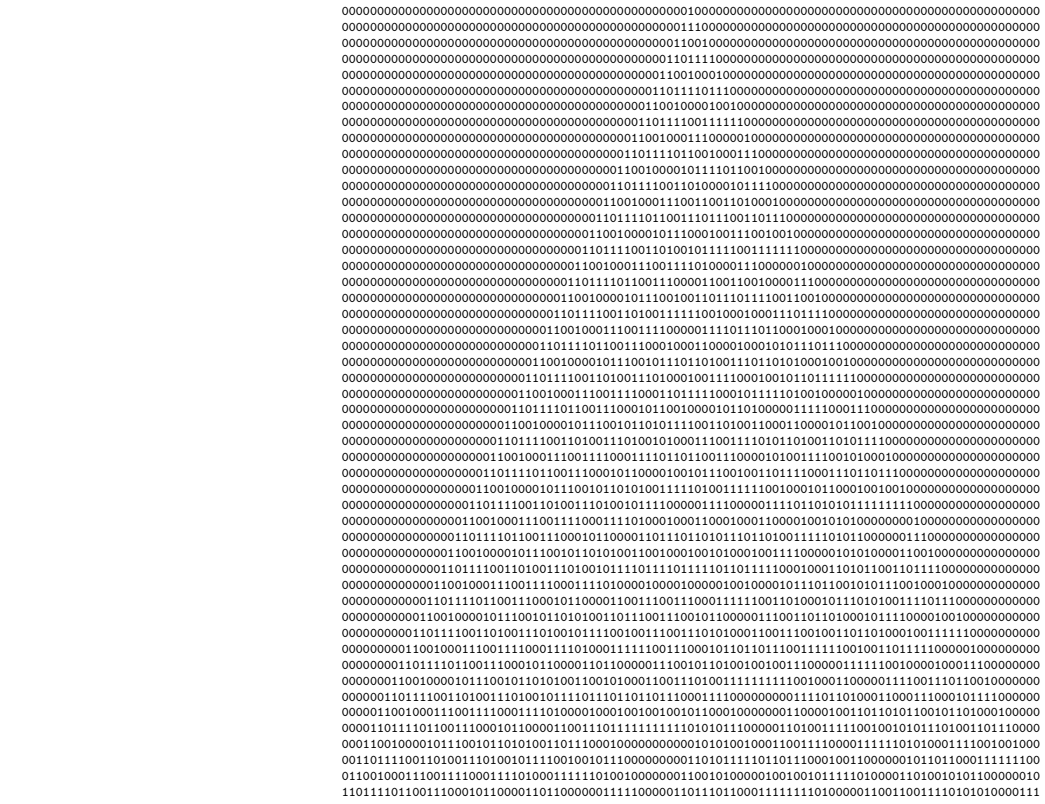

Fig. 6. "Noise" generated with a linear cellular automaton.

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3.3. Fractals

The concept of fractal, introduced by Benoit Mandelbrot [4] in 1975, refers to an infinitely, self-similar spatial or temporal mathematical construct.

Fig. 7. The Sierpinski triangle.

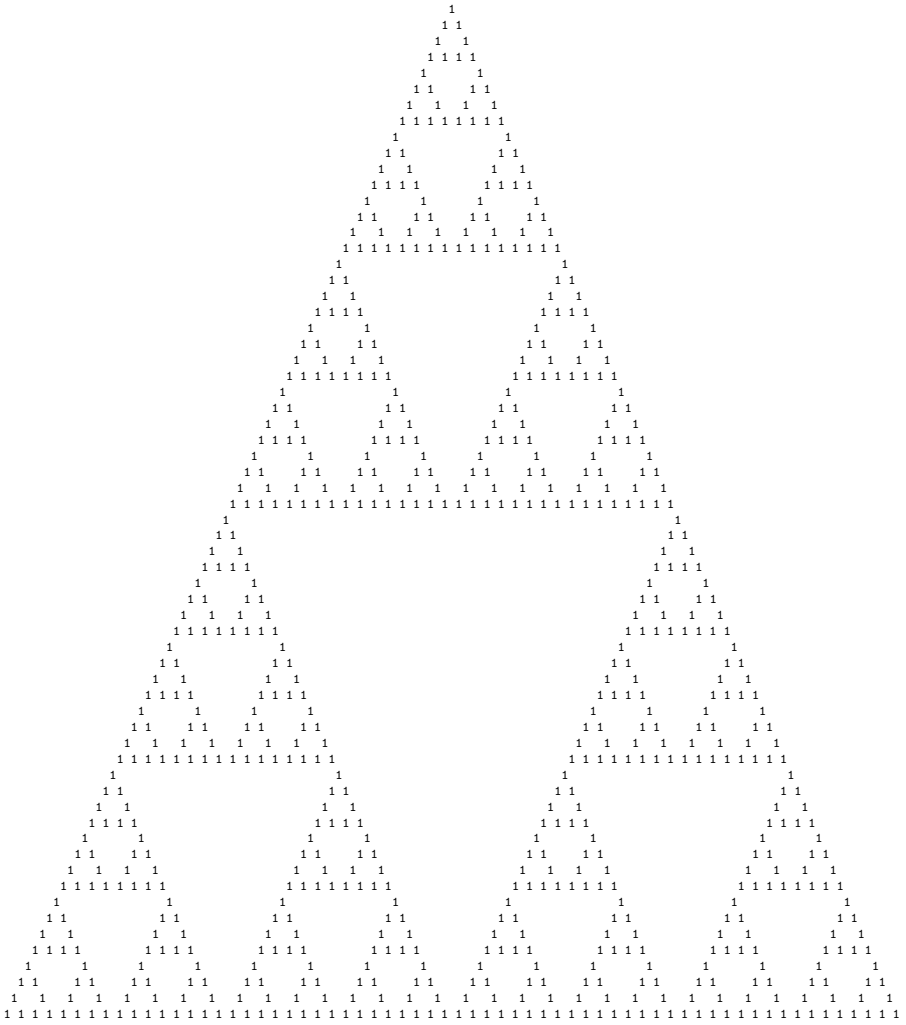

Fig. 8. The Sierpinski triangle generated by a linear cellular automaton.

Example 4. Sierpinski triangle is a good introductory example for the concept of fractal. In Fig. 7 is given the geometric representation of the rule for generating the Sierpinski triangle.

How complex is the Sierpinski triangle? In order to answer the question we must find "the shortest" description of the algorithm. Fortunately, there is a simple cellular automaton able to generate the shape of Sierpinski triangle. If in the previous Verilog description of `linearCellularAutomaton` the 7-th line is commented and the 8-th in uncommented, then results the description of another cellular automaton whose simulation provides the behavior represented in Fig. 8. Starting from the initial state 0001000, and applying the local rule:

$$S_i^+ = Si - 1 \oplus S_{i+1}$$

the iterative geometric shape of Sierpinski is generated. The parameter n and the running time determine the degree of details in drawing the Sierpinski triangle. Rhetoric question: who is able to deduce the previous simple Boolean expression starting only from the initial Sierpinski's geometrical representation? $\diamond$

Example 5. The Julia set (named after the French mathematician Gaston Julia) is generated by plotting the image generated by the function:

$$f_c(z) = z^2 + c$$

where c is a complex number ($c = a + ib$, where $i = \sqrt{-1}$). A spectacular, complex and chaotic behavior results for different complex values given to the constant c. Two examples are presented in Fig. 9 and Fig. 10 for two slightly different values of c. The full description of the first Julia set is done by the following stream of symbols:

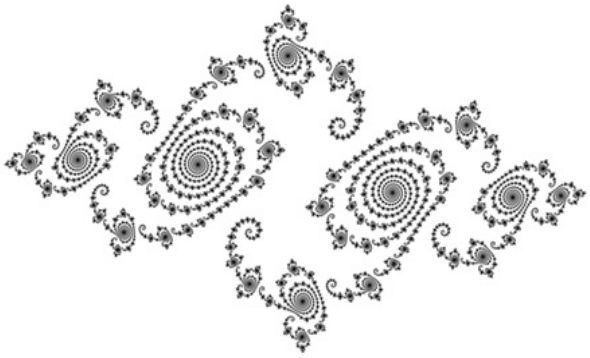

Fig. 9. The Julia set for $f_c(z) = z^2 - 0.75 + 0.11i$

$$f_c(z) = z^2 - 0.75 + 0.11i$$

while for the second set we have:

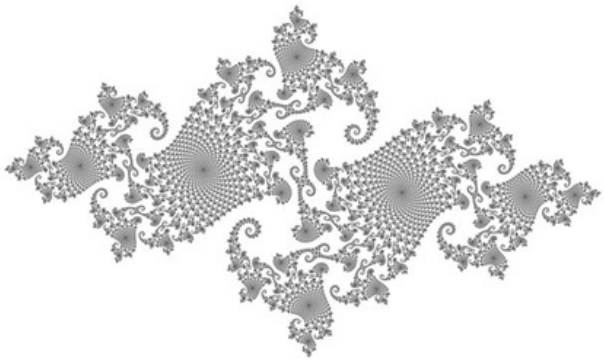

Fig. 10. The Julia set for $f_c(z) = z^2 - 0.74543 + 0.11301i$

$$f_c(z) = z^2 - 0.74543 + 0.11301i$$

Both descriptions are small sized compared to the resulting two-dimension representation, and, more, for a very small variation of the constants the geometric representations are very different.

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4. Apparent complexity

Besides simple and complex entities we must accept a third category, let us call it the category of ***apparent complex*** entities. The examples provided in the previous section have a special property: they could be considered simple or complex depending on how we approach them. If we know the mechanism used to generate them, then they must be considered simple, but, if we are faced directly with how they manifest, then we are forced to consider them complex, because the rule behind their appearance can't be discovered in most cases.

For example, the evolution presented in Fig. 4 is simple for those who know how it is generated, while it is complex for those who are asked to provide a description starting from the shape of the curve. The task is twice difficult. First, because is impossible to infer the form of the algebraic expression. Second, if by a miracle the expression is guessed, then it is much harder to tune the value of the initial value, x_0.

Maybe a skilled human mind is able to discover the rule behind the bolded binary sequence from Fig. 6, but is almost impossible to define a formal procedure to infer the mechanism and the rule used to generate it. Thus, the sequence is a simple one for the system designer, while the same sequence "looks" random, i.e., complex for the human or non-human user of the sequence.

The cellular automaton running *rule 90* was discovered to generate the Sierpinski triangle only investigating by turn all the 256 linear cellular automata with one-bit cells. There is no algorithmic way which starts form Siepinski's geometric definition leading toward *rule 90*.

The second example of fractal, the *Julia set*, is another way to generate a spectacular behavior starting from a simple rule. A very small change of the complex number c determines a very big difference in the generated shape. Somehow we are faced with a sort of chaotic behavior. For those who do not know the expression used to generate the *Julia set* is hard to accept that the expression is a simple one and it has a high sensitivity to the value of a constant number. Indeed, is hard to accept that the two forms presented in Fig. 9 and Fig. 10 are generated by the expressions which differ only by the small complex value: $-0.00475 - 0.00301i$.

Faced with this "contextual" complexity, where the same reality is simple or complex depending on the "position" of the evaluator, we are obliged to introduce a new kind of complexity. We call it ***apparent complexity***. A preliminary, informal definition for an apparent complex entity refers to an entity with a *complex phenomenal appearance backed by a structural simple generative rule*.

The development of computer science triggered the occurrence of ***experimental mathematics*** as the main research environment for apparent complex facts. The computational power of our machines is used to actualize the potential apparent complexity by running simple but intense programs.

Apparent complexity means:

- simple generative rules
- the iterative character of rules
- applying the rules requires intense computation.

The main question that arises is: ***are social processes really complex or only apparently complex?*** Do we have the chance to find simple rules behind the social phenomena? Or, a social phenomenon is by the rule a really complex one?

A more nuanced question is: how far can we go with the application of some reductionist mechanisms in order to be able to find simple rules behind social processes? In other words, does it make sense to reduce the actual complexity of a social process to the level of apparent complexity to be able to search for simple rules governing some aspects of social interactions? And, if it makes sense, then how could we establish a reasonable threshold for the reductionist process?

Too many questions!

5. The architectural approach: a necessary compromise

Fortunately, between phenomenon and structure we can insert a third concept: the concept of ***architecture***. The extended meaning of the concept refers to the ***set of functions defined at the interface*** of a reality with its own environment. Instead of associating a structure to a phenomenon there is a simpler solution to associate a set of functions to that phenomenon. There are the following advantages for the architectural approach:

- The functional description is simpler than the structural description allowing to capture more complexity in the same amount of information

- The function is partially irrespective of the structure
- The hierarchy function-structure is a "natural" one.

6. Concluding remarks

Maybe for investigating and modeling social processes we need a fundamentally new approach because of the inherent complexity we are faced. Instead of investigating the structure of the social relations, let's limit our investigations to the functional relations. There is no easy way or no way at all from phenomenon to structure. The complexity of the social space limits the investigation to an architectural approach able to disclose only functional relations.

The self-organizing mechanisms which dominate the systems analyzed in this paper are not, for sure, the only mechanisms to be considered. The next step in this approach is to investigate global control mechanisms working together with the self-organizing mechanisms to generate and to control the complexity of social processes.

Post-motto:
Life as manifested to us is a function of the asymmetry of the universe . . . I can even imagine that all living species are primordially, in their structure, in their external forms, functions of cosmic asymmetry.
Louis Pasteur

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