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Article

Self-Organizing Systems: What, How, and Why?

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Abstract: I present a personal account of self-organizing systems. As such, it is necessarily biased and partial. Nevertheless, it should contain enough substance to motivate useful discussions. The relevant contribution is not my attempts at answering questions (maybe all my answers are wrong), but the steps towards framing relevant questions to better understand self-organization, information, complexity, and emergence. With this aim, I start with a notion and examples of self-organizing systems (what?), continue with their properties and related concepts (how?), and close with applications (why?) in physics, chemistry, biology, collective behavior, ecology, communication networks, robotics, artificial intelligence, linguistics, social science, urbanism, philosophy, and engineering.

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1. What Are Self-Organizing Systems?

"Being ill defined is a feature common to all important concepts."

—Benoît Mandelbrot

I will not attempt to define a "self-organizing system", as it involves the cybernetic problem of defining "system" (Ashby 1956; Heylighen and Joslyn 2001; von Bertalanffy 1968), the informational problem of defining "organization" (Ashby 1962; Rupe and Crutchfield 2024), and the ontological problem of defining "self" (Gershenson 2021). Still, there are plenty of examples of systems that we can usefully call self-organizing: flocks of birds, schools of fish, swarms of insects, herds of cattle, and some crowds of people (Camazine et al. 2003; Feltz et al. 2006). In these animal examples, the collective behavior is a product of the *interactions* of individuals, not determined by a leader or an external signal. There are also several examples from non-living systems, such as vortexes, crystallization, self-assembly, and pattern formation in general (Ball 1999; Cross and Greenside 2009). In these cases, elements of a system also interact to achieve a global pattern.

Self-organization or similar concepts have been present since antiquity (Gershenson 2023a; Juarrero-Roqué 1985; Kirk 1951; Stengers 1985) (see Section 3.12), so the idea itself is not new. Nevertheless, we still lack the proper conceptual framework to understand it properly. The term "self-organizing system" was coined by W. Ross Ashby (1947) in the early days of cybernetics (Ashby 1956; Heylighen and Joslyn 2001; Rosenblueth et al. 1943; Saratxaga Arregi 2024; von Foerster 1960; Wiener 1948). Ashby's purpose was to describe deterministic machines that could change their own organization. And ever since, the concept has been used in a broad range of disciplines (Skår and Coveney 2003), including statistical mechanics (Crutchfield 2011; Wolfram 1983), supramolecular chemistry (Lehn 2017), computer science (Kohonen 2000; Mamei et al. 2006), and artificial life (Gershenson et al. 2020).

There is an unavoidable subjectivity when speaking about self-organizing systems, as the same system can be described as self-organizing or not (Gershenson and Heylighen 2003) (see Section 2.1). Stafford Beer (1966) gave the following example: an ice cream at room temperature will thaw. This will increase its temperature and entropy, so it would be "self-disorganizing". However, if we focus on the function of an ice cream for being eaten, it would be "self-organizing", because it would approach

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a pleasant temperature and consistency for degustating it, improving its "function". Ashby (1962) also mentioned that one just needs to call the attractor of a dynamical system "organized", and then almost any system will be self-organizing.

So, the question should not be whether a system *is* self-organizing, but rather (being pragmatic) *when is it useful* to describe a system as self-organizing? The answer will slowly unfold along this paper, but in short it can be said that self-organization is a useful description when we are interested on describing systems at multiple scales, and understanding how these affect each other. For example, collective motion (Vicsek and Zafeiris 2012) and cyber-physical systems (Gershenson 2020) can benefit from such a description, compared to a single-scale narrative/model. This is common with complexity (De Domenico et al. 2019), as interactions can generate novel information that is not present in initial nor boundary conditions, limiting predictability (Gershenson 2013a).

So rather than a definition, we can do with a notion: *a system can be described as self-organizing when its elements interact to produce a global function or behavior* (Gershenson 2007). This is in contrast with *centralized* systems, where a single or few elements "control" the rest, or with simply *distributed* systems, where a global problem can be divided (reduced) and each element does its part, but there is no need to interact nor integrate elementary solutions. Thus, *self-organizing* systems are a useful description when we want to relate individual behaviors and interactions to global patterns or functions. If we can describe a system fully (for our particular purposes) at a single scale, then self-organization could be perhaps identified, but superfluos (not useful). And the "self" implies that the "control" comes from within the system, rather than from an external signal/controller that would explicitly indicate elements what to do.

For example, we can decide to call a society "self-organizing" if we are interested on how individual interactions lead to the formation of fashion, ideologies, opinions, norms, and laws; but at the same time, how the emerging global properties affect the behavior of the individuals. If we were interested in an aggregate property of a population, e.g., its average height, then calling the group of individuals "self-organizing" would not give any extra information, and thus would not be useful.

It should be stressed that self-organization is not a property of systems *per se*. It is a *way* of describing systems, i.e., a *narrative*.

2. How Can Self-Organizing Systems Be Measured?

> *"It is the function of science to discover the existence of a general reign of order in nature and to find the causes governing this order. And this refers in equal measure to the relations of man — social and political — and to the entire universe as a whole."*
>
> *—Dmitri Mendeleev*

Even when self-organization had been described intuitively since antiquity — the seeds of the narrative were present — the proper *tools* for studying it became available only recently: computers (Pagels 1989). Since self-organizing systems require the explicit description of elements and interactions, our brains, blackboards, and notebooks are too limited to consider the number of required variables to study the properties of self-organizing systems. It was only through the relatively recent development of information technology that we were able to study the richness of self-organization, just like we were unable to study the microcosmos before microscopes and the macrocosmos before telescopes.

2.1. Information

Computation can be generally described as the transformation of information, although Alan Turing (1936) formally defined computable numbers with the purpose of proving limits of formal systems (in particular, Hilbert's decision problem). In the same environment where the first digital computers were built in the mid XX$^{\text{th}}$ century, Claude Shannon (1948) defined information to quantify its transmission, showing that information could be reliably transmitted through unreliable communication channels. As it turned out, Shannon's information H is mathematically equivalent to Boltzmann-Gibbs entropy:

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$$H = -K \sum_{i=i}^{n} p_i \log p_i, \tag{1}$$

where K is a positive constant and p is the probability of receiving symbol i from a finite alphabet of size n. This dimensionless measure will be maximal for a homogeneous probability distribution, and minimal when only one symbol has a probability $p = 1$. In binary, we have only two symbols ($n = 2$), and information would be minimal with a string of only ones or only zeroes ('1111...' or '0000...'). This implies that having more bits will not tell us anything new, because we already know what the next bits will be (assuming the probability distribution will not change). With a random-like string, such as a sequence of coin flips ('11010001011011001010...'), information is maximal, because no matter how much previous information we have (full knowledge of the probability distribution), we will not be able to predict what the next bit might be better than chance.

In parallel, Norbert Wiener — one of the founders of cybernetics (Rosenblueth et al. 1943; Wiener 1948) — proposed an alternative measure of information, which was basically the same as Shannon's, but without the minus sign (Wiener 1950). Wiener's information measured what one knows *already*, so it is minimal when we have a random string (homogeneous probability distribution) because all the information we already have is "useless" (to predict the next symbol), and maximal when we have a single symbol repeating (maximally biased probability distribution), because the information we have allows us to predict exactly the next symbol. Nevertheless, Shannon's information is the one that everyone has used, and we will do the same.

Shannon's information is also known as Shannon's entropy, which can be also used as a measure of "disorder". We already saw that it is maximal for random strings, and thus minimal for particularly ordered strings. Then, we can use the negative of Shannon's information (which would be Wiener's information) as a measure of organization (Fernández et al. 2014; Gershenson and Heylighen 2003; Wiener 1950). If the organization is a result of internal dynamics, then we can also use this measure for self-organization.

Nevertheless, just like with many measures, the interpretation depends on how the observer performs the measurement. Figure 1 shows how the same system, divided into four microstates or two macrostates (with probabilities represented as shades of gray) can increase its entropy/information (become more homogeneous) or decrease it, depending on how it is observed.

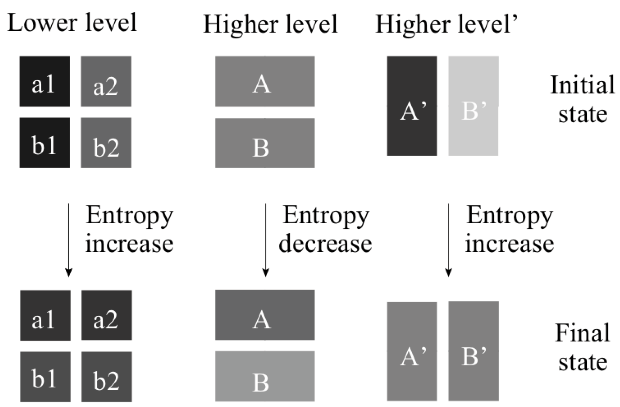

Figure 1. The same system, observed at different levels or with different coarse grainings can be said to be disorganizing (entropy increasing) or organizing (entropy decreasing) (Gershenson and Heylighen 2003), for arbitrary initial and final states. Probabilities of the system being in a state (a1, a2, b1, and b2 at the lower level, which can be aggregated in different ways at a higher level) are represented as shades of gray, so one can observe which configurations are more homogeneous (i.e., with higher entropy): if there is a high contrast in different states (such as between A′ and B′ in their initial state), then this implies more organization (less entropy), while similar shades (as between A′ and B′ in their final state) imply less organization (more entropy).

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Still, the fact that self-organization is partially subjective does not mean that it cannot be useful. We just have to be aware that a shared description and interpretation should be agreed upon.

2.2. Complexity

Self-organizing systems are intimately related to complex systems (Bar-Yam 1997; Mitchell 2009). Again, the question is not so much whether a system *is* self-organizing or complex, but when is it useful to describe it as such. This is because most systems can be described as complex or not, depending on our context and purposes.

Etymologically, complexity comes from the Latin *plexus*, which could be translated as entwined (De Domenico et al. 2019). We can say that complex systems are those where *interactions* make it difficult to separate the components and study them in isolation, because of their interdependence (Gershenson 2013a; Heylighen et al. 2007). These interactions can generate novel information that limit predictability in an inherent way, as it is not present in initial nor boundary conditions. In other words, there is no shortcut to the future, but we have to go through all intermediate steps, as interactions partially determine the future states of the system.

For example, markets tend to be unpredictable because different agents make decisions depending on what they think other agents will decide (Farmer 2024). But since it is not possible to know what everyone will decide in advance, the predictability of markets is rather limited.

Complex systems can be confused with *complicated* or *chaotic* systems. Perhaps they will be easier to distinguish considering their opposites: complicated are the opposite of *easy*, chaotic (sensitive to initial conditions) are the opposite of *robust*, while complex systems are the opposite of *separable*.

Given the above notion of self-organizing systems, then all of them would also be complex systems, but not necessarily vice versa. This is because *interactions* are an essential aspect of self-organizing systems, which would make them complex by definition. However, we could have a description of a complex system whose elements interact, but do not produce a global pattern or function we are interested in during the timeframe we are interested in. So, the narrative of complexity would be useful, but not the one of self-organization. Nevertheless, understanding complexity should be essential for the study of self-organization.

2.3. Emergence

One of the most relevant and controversial properties of complex systems is emergence (Anderson 1972; Bedau and Humphreys 2008; McLaughlin 1992; Prokopenko et al. 2009). It could be seen as problematic because last century some people described emergent properties as "surprising" (Carroll and Parola 2024; Casti 1995; Ronald et al. 1999). So then emergence would be a measure of our ignorance, and then it would be reduced once we understood the mechanisms behind emergent properties. Also, there are different flavors of emergence, some easier to study and accept than others. But in general, emergence can be described as information that is present at one scale and not at another scale (Gershenson 2023b).

For example, we can have full knowledge of the properties of carbon atoms. But if we focus only on the atoms, i.e. without interactions, we will not be able to know whether they are part of a molecule of graphite, diamond, graphene, buckyballs, etc. (all composed only of carbon atoms) which have drastically different macroscopic properties. Thus, we cannot derive the conductivity, transparency, or density of these materials by looking only at the atomic properties of carbon. The difference lies precisely in how the atoms are *organized*, i.e. how they interact.

If emergence can be described in terms of information, Shannon's measure can be used (understanding that we are measuring only the information that is absent from another scale). Thus, emergence would be the opposite of self-organization. This might seem contradictory, as usually emergence and self-organization are both present in complex systems (Feltz et al. 2006). But if we take each to its extreme, we can see that maximum emergence (information) occurs when there is (quasi)randomness, so no organization. And maximum (self-)organization occurs when entropy is

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minimal (no new information, and thus, no emergence). Because of this, complexity can be seen as a *balance* between emergence and self-organization (Fernández et al. 2014).

3. Why Should We Use Self-Organizing Systems?

"It is as though a puzzle could be put together simply by shaking its pieces."

—Christian De Duve

Self-organization can be used to build adaptive systems (Frei and Di Marzo Serugendo 2011). This is useful for *non-stationary problems*, i.e., those that change in time. Since interactions can generate novel information, complexity often leads to non-stationarity. Thus, when a problem changes, the elements of a self-organizing system can adapt through their interactions. Then, designers do not need to specify precisely the problem beforehand, or how it will change, but just to define/regulate interactions to achieve a desired goal (Babaoglu et al. 2005; Gershenson 2007; Schweitzer 1997).

For example, if we want to improve passenger flow in public transportations systems, we cannot really change the elements of the system (passengers). Still, we can change how they interact. In 2016, we successfully implemented such a change to regulate the boarding and alighting in Mexico City metro (Carreón et al. 2017). In a similar way, we cannot change teachers in an education system. But we can change their interactions to improve learning. We cannot change politicians, but we can regulate their interactions to reduce corruption and improve efficiency. We cannot change businesspeople, but we can control their interactions to promote sustainable economic growth.

There have been many other examples of *applications* of self-organization (Turcotte and Rundle 2002) in different field, and the following is only a partial enumeration.

3.1. Physics

The industrial revolution led to the formalization of thermodynamics in the XIX$^{\text{th}}$ century. The second law of thermodynamics states that an isolated system will tend to thermal equilibrium. In other words, it loses organization, as heterogeneities become homogeneous, and entropy is eventually maximized. Still, non-equilibrium thermodynamics has studied how open systems can self-organize (Nicolis and Prigogine 1977).

Lasers can be seen as self-organized light, which Hermann Haken (1981; 1988) used as an inspiration to propose the study of synergetics, which precisely studies self-organization in open systems far from thermodynamic equilibrium and is related to phase transitions (Stanley 1987), where criticality is found (Sánchez-Puig et al. 2023).

Self-organized criticality (SOC) (Bak et al. 1987) was proposed to explain why power laws and scale-free-like distributions (Caldarelli 2007; Clauset et al. 2009; Newman 2005) and fractals (Mandelbrot 1982) are so prevalent in nature. SOC was illustrated with the sandpile model, where grains accumulate and lead to avalanches with a scale-free (critical) distribution. Similarly, self-organization has been used to describe granular media (Jain et al. 2001; Török et al. 2000).

Generalizing principles of granular media, self-organization can be used to describe and design "optimal" configurations in biological, social, and economic systems (Helbing and Vicsek 1999).

3.2. Chemistry

Around 1950, Boris P. Belousov was interested in a simplified version of the Krebs cycle. He found that a solution of citric acid in water with acidified bromate and yellow ceric ions produced an oscillating reaction. His attempts to publish his findings were rejected, arguing that it violated the second law of thermodynamics (which only applies for systems at equilibrium, and this system is far from equilibrium). In the 1960s, Anatol M. Zhabotinsky began working on this reaction, and only in the late 1960s and 1970s the Belousov-Zhabotinsky reaction became known outside the Soviet Union (Winfree 1984). Since then, many chemical systems far from equilibrium have been studied (Knoll et al. 2024; Kondepudi and Prigogine 2014). Some have been characterized as self-organizing, because they are able to use free energy to increase their organization (Vanag and Epstein 2001).

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More generally, self-organization has been used to describe pattern formation (Cross and Hohenberg 1993), which includes self-assembly (Whitesides and Grzybowski 2002).

Molecules are basically atoms joined by covalent bonds. Supramolecular chemistry (Lehn 1990) studies chemical structures formed by weaker forces (Van Der Waals, hydrogen bonds, electrostatic charges), and can also be described in terms of self-organization.

3.3. Biology

The study of form in biology (morphogenesis) is far from new (Thompson 1917), but far from complete (Davies 2023).

Alan Turing (1952) was one of the first to describe morphogenesis with differential equations. Morphogenesis can be seen as pattern formation with local stimulation and long-range inhibition (skins, scales), or as fractals (capillaries, neurons). These processes are more or less well understood. Still, it becomes more sophisticated for embryogenesis (Levin 2005a) and regeneration (Levin 2007), where many open questions remain.

Humberto Maturana and Francisco Varela proposed autopoiesis (self-production) to describe the emergence of living systems from complex chemistry (Gershenson 2015; Maturana and Varela 1980; Varela et al. 1974). Autopoiesis can be seen as a special case of self-organization (to the disagreement of Maturana (1987)), because molecules self-organize to produce membranes and metabolism. Moreover, it can be argued that living systems also need information handling, self-replication, and evolvability (Muñuzuri and Pérez-Mercader 2022).

There are further examples of of self-organization in biology (Camazine et al. 2003), that include firefly synchronization (Strogatz 2003), ant foraging (Aron et al. 1990; Theraulaz and Bonabeau 1999), and collective behavior.

3.4. Collective Behavior

Groups of agents can produce global patterns or behavior through local interactions. Craig Reynolds presented a simple model of *boids* (Reynolds 1987), where agents followed three simple rules: separation (don't crash), alignment (head to average heading of neighbors), and cohesion (go towards average position of neighbors). Varying its parameters, this simple model produces dynamic patterns similar to those of flocks, schools, herds, and swarms. It was used to animate bats and penguins in the 1992 Batman Returns film and contributed to earning Reynolds an Oscar in 1998.

A flock of boids self-organize even only with the alignment rule and added noise (Vicsek et al. 1995). It has been shown that when the number of boids increases, novel properties emerge (Ikegami et al. 2017).

Slightly more sophisticated models have been used to describe more precisely animal collective behavior (Ballerini et al. 2008; Buhl et al. 2006; Couzin et al. 2003, 2004).

Furthermore, similar models and rules have been used to study the self-organization of active matter (Vicsek and Zafeiris 2012) and robots (see below).

3.5. Ecology

Species self-organize to produce ecological patterns (Levin 2005b). These include trophic networks (who eats who) (Goodnight et al. 2008; Pauly et al. 1998; Sahasrabudhe and Motter 2011), mutualistic networks (cooperating species) (Saavedra et al. 2011), and host-parasite networks (Runghen et al. 2021).

At the biosphere level, ecosystems also self-organize. This is central aspect of the Gaia hypothesis (Harvey 2015; Lenton and Williams 2009; Lovelock and Margulis 1974), which defends that our planet self-regulates its own conditions that allow life to thrive.

Self-organization can be useful to study how ecosystems can be robust, resilient, or antifragile (Equihua et al. 2020).

3.6. Communication Networks

Self-organization has been useful in telecommunication networks (Prehofer and Bettstetter 2005), as it is desirable to have the ability to self-reconfigure based on changing demands. Also, having local rules to define global function makes them robust to potential failures or attacks of central nodes: if there is a path that is not responsive, then an alternative is sought. These principles have been used in Internet protocols, peer-to-peer networks, cellular networks, and more.

3.7. Robotics

There have been a broad variety of self-organizing robots (Dorigo et al. 2004; Holland and Melhuish 1999; Ko et al. 2023; Pfeifer et al. 2007; Reina et al. 2015; Rubenstein et al. 2014; Schranz et al. 2020; Van Calck et al. 2023; Vásárhelyi et al. 2018; Werfel et al. 2014; Zykov et al. 2005), terrestrial, aerial, aquatic, and/or hybrid (for a review see Gershenson et al. (2020)).

A common aspect of self-organizing robots is that there is no leader, and the collective function or pattern is the result of local interactions. Some have been inspired in collective behavior of animals (Cully et al. 2015), and their potential applications are vast.

3.8. Artificial Intelligence

As mentioned in the first section of this paper, the study of self-organizing systems originated in cybernetics (Ashby 1960; Heylighen 2003), which had a strong influence and overlap in the early days of artificial intelligence. Claude Shannon (Lemov 2011), William Grey Walter (1950; 1951), Warren McCulloch and Walter Pitts (1959; 1943) contributed to both fields in their early days.

If brains can be described as self-organizing (Chialvo 2010; Haimovici et al. 2013; Rocha 1998), it is no surprise that certain flavors of artificial neural networks have also been described as self-organizing (Kohonen 2000). Independently on the terminology, adjustments to local weights between artificial neurons lead to an error reduction in the task of the network (Gershenson 2010).

Even when their interpretation is still controversial (Agüera y Arcas 2022; Mitchell 2023; Wei et al. 2022), large language models have been useful in multiple domains. Whether describing them as self-organizing would bring any benefit or not, still remains to be seen.

3.9. Linguistics

The statistical study of linguistics became popular after Zipf (1932). Different explanations have been put forward to try to explain statistical regularities found across languages (Baek et al. 2011; Corominas-Murtra et al. 2011; Ferrer i Cancho and Solé 2003), and in even more general contexts (Iñiguez et al. 2022).

Naturally, some of these explanations focus on the evolution of language. It has been shown that a shared vocabulary (Steels 1995, 1997) and grammar (Beuls and Steels 2013) can evolve using self-organization: individuals interact locally leading to a population converging to a shared language. This is useful not only for understanding language evolution, but also to build adaptive artificial systems. Similar mechanisms can be used in other social systems, e.g. to reach consensus (Axelrod 2005).

3.10. Social Science

Individuals in a society interact in different ways. These interactions can lead to social properties, such as norms, fashions, and expectations. In turn, these social properties can guide, constrain, and promote behaviors and states of individuals.

Computers have allowed the simulation of social systems, including systematic explorations of abstract models (Epstein and Axtell 1996). Combined with an increase of data availability, computational social science (Conte et al. 2012; Lazer et al. 2009) has been increasingly adopted by social scientists. The understanding and implications of self-organization are naturally relevant for this field.

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3.11. Urbanism

It is similar with the scientific study of cities (Batty 1971, 2005, 2013; Bettencourt and West 2010; Bettencourt 2013; Gershenson 2013b; Portugali 2000).

For example, city growth can be modeled as a self-organizing process (Murcio et al. 2015). And similar to the metro case study mentioned above (Carreón et al. 2017), self-organization has been shown to efficiently and adaptively coordinate traffic lights (Lämmer and Helbing 2008; Zapotecatl et al. 2017; Zubillaga et al. 2014), and is promising for regulating interactions among autonomous vehicles.

More generally, urban systems tend to be non-stationary, as conditions are changing constantly. Thus, self-organization offers a proven alternative to design urban systems that adapt as fast as their conditions change (Gershenson et al. 2021).

3.12. Philosophy

Concepts similar to self-organization can be traced to ancient Greece in Heraclitus (Kirk 1951) and Aristotle (Grassi 2020) and also to Buddhist philosophy (Gershenson 2023a).

There has been a long debate about the relationship between mechanistic principles and the *purpose* of systems. This question was at the origins of cybernetics (Rosenblueth et al. 1943). It has been argued (Juarrero-Roqué 1985) that self-organization can be used to explain teleology, in accordance with Kant's attempt from the late XVIIIth century, as purpose can also be described in terms of organization (Van de Vijver 2006).

Also, self-organization is related to downward causation (Bitbol 2012; Campbell 1974; Farnsworth et al. 2017; Flack 2017): when higher level properties cause changes in lower level elements. This is still debated, along with other philosophical questions related to self-organization (Gershenson 2013a; Heylighen et al. 2007).

3.13. Engineering

There have been several examples of self-organization applied to different areas of engineering apart from those already mentioned (De Wolf et al. 2005), such as power grids (Rohden et al. 2012), computing (Mamei et al. 2006), sensor networks (Dressler 2007), supply networks and production systems (Helbing et al. 2006), bureaucracies (Gershenson 2008), and more.

In general, self-organization has been a promising approach to build adaptive systems, as mentioned above. It might seem counterintuitive to speak about controlling self-organization, since we might think that self-organizing systems are difficult to regulate because of a certain autonomy of their components. Still, we can speak about a *balance* between control and independence, in what has been called “guided self-organization" (Prokopenko 2009, 2014).

4. Conclusions

“We can never be right, we can only be sure when we are wrong”

—Richard Feynman

There are many open questions related to the scientific study of self-organizing systems. Even when their potential has been promising, they are far from being commonly used to address non-stationary problems. Could it be because of a lack of literacy in concepts related to complex systems? Might there be any conceptual or technical obstacle? Do we need further theories? Independently of the answers, these questions are worth exploring.

For example, we have yet to explore the relationship between self-organization and antifragility (Taleb 2012): the property of systems that benefit from perturbaitons. Self-organization seems to be correlated with antifragility (Kim et al. 2019; López-Díaz et al. 2023; Pineda et al. 2019), but why or how still has to be investigated. In a similar vein, a systematic exploration of the “slower is faster” effect (Gershenson and Helbing 2015) might be useful to better understand self-organizing systems and vice versa.

Many problems and challenges we are facing — climate change, migration, urban growth, social polarization, etc. — are clearly non-stationary. It is not certain that with self-organization we will be able to improve the situation in all of them. But it is almost certain that with the current tools we have, we will not be able to make much more progress (otherwise we would have made it already). It would be imprudent not to make efforts to use the narrative of self-organization, even if for slightly improving situations related to only one of these challenges.

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