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On the Positive Role of Noise and Error in Complex Systems

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Abstract: Noise and error are usually considered to be disturbances negatively affecting the behavior of a system. Nevertheless, from a systemic perspective, taking into account openness and incompleteness of complex systems, noise and error may assume a creative, constructive, and positive role in that they are a source of novelty that can trigger the reorganization of the system, the growth of complexity, and the emergence of new meaning. Examples of this phenomenon can be found in evolutionary phenomena driven by affordances, the formation of new attractors in dynamic systems responding to external perturbations, and improvisation in music. We argue that it is possible to identify general properties that enable the positive effect of noise and errors in complex systems, namely, multilevel organization, redundancy, incompleteness, and criticality. These properties play a major role in living systems and can guide the design of robust and adaptive artificial systems.

Keywords: noise; error; redundancy; incompleteness; multilevel; criticality; affordance; evolution

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1. Introduction

Noise and error are usually associated with phenomena that harm or produce detrimental effects to a system. Classical reductionist scientific and engineering approaches try to protect a system from perturbations, reduce internal noise, and provide strict rules and control procedures to constrain the behavior of the system to precise dynamics. Noise is an undesirable perturbation or fluctuation; it is typically treated as a quantity to be minimized, as it might introduce variability and imprecision into the behavior of a system. On the other hand, error is commonly associated with the discrepancy between a desired target behavior and the actual one. Therefore, error typically depends upon an observer [1] in that it is a deviation from what the observer considers the correct, expected behavior of a system. Error functions are indeed used to control a system and keep it within predefined functional ranges or as an objective function in training.

However, noise and error can also have positive and constructive effects. A prominent example is stochastic resonance [2], which exploits random noise to improve signal-to-noise ratio in nonlinear systems. The impact of stochastic resonance on the improvement of the performance of a (nonlinear) system has also been found in biological systems, e.g., in the brain [3]. Also errors can bring benefits; for example, a deviation from the "correct" DNA replication process may introduce beneficial mutations.

While the positive role of noise and error in complex systems (both natural and artificial) has been discussed in detail in specific cases, general theories of these phenomena are still missing. The aim of this work is to contribute to the definition of an abstract and general systemic perspective on this subject. In this paper, we identify general conditions that can make the impact of noise and error positive on the behavior, adaptation, or evolution of a system, including the possibility of generating novel behaviors, meanings, and increases in internal complexity. We will first illustrate three representative examples that provide the basis for the introduction and discussion of general mechanisms and properties. In the following, we will use the two terms *noise* and *error* as all-encompassing words expressing perturbations, fluctuations, variability, and deviation from a target behavior.

2. Three Examples from Different Realms

We illustrate three examples from different domains that we think provide a characterization of the relevant aspects concerning the positive contribution of noise and error in the dynamics of complex systems. The first case illustrates the advantage of unexpected events in adaptation and evolution in natural systems; conversely, the second one deals with robots that have to learn a given task and adapt their perceptual mechanisms while operating with noisy sensors. Finally, the last example comes from social interaction in the arts and concerns improvisation in music. Starting from the properties identified in these examples, in the subsequent sections, we depict a general view of our argument.

2.1. Adaptation and Evolution through Affordances

The notion of *affordance* was introduced in psychology by Gibson [4]. This concept has been subsequently adopted in other areas, such as biosemiotics [5] and robotics [6]. Affordances refer to what the environment offers to an organism, for good or ill. In this light, an affordance is "a possible use of *A* by an organism to accomplish *B*". For example, a hole in a rock affords a wasp a safe place to build a nest, or a suitable shell affords a shelter for the hermit crab *Pagurus bernhardus*. Notably, affordances can be manifested either as opportunities or as obstacles on the organism's path to achieving a goal. It is important to remark that affordances are not independent features of the environment [7], as a change can be neutral or not depending on the conditions of the organism, its goals, and its repertoire of actions [8–10].

This psychological ("agential" [7,11]) notion of affordance is at the basis of numerous adaptive processes in living organisms. For example, unexpected changes in the environment (i.e., errors with respect to a prediction) can be a source of affordances. Changes in the environment consist of alterations of the portion of the environment that an organism perceives and with which it can interact, including other organisms. In biosemiotic terms, this niche is the *Umwelt* of the organism [12,13]. A change in the environment triggers in the organism a process to detect affordances: the ones useful for the organism are selected. An example from human behavior is jury-rigging: a problem to be solved (e.g., a window accidentally broken by hail) is an opportunity to find a quick and effective solution by using what is currently available (e.g., the cover of a cardboard box and adhesive labels).

Besides the psychological notion just discussed, affordances also play a major role in evolution. Most adaptive steps happen in evolution by means of affordances, which are seized by heritable variations and natural selection (heritable variations include gene mutation and also epigenetic phenomena [14]). In the history of evolution, one can find abundant examples of adaptations that emerged by using the same organ for a new use. These evolutionary phenomena are called Darwinian *pre-adaptations* or exaptations [15]. In these cases, the organ affords a new use for the organism. For example, feathers evolved for thermal insulation but were later co-opted for the new function of flight stabilization [16,17]. Another case in point is that of lens crystallins, which first originated as enzymes [18].

Abstracting, we can view affordances as open possibilities in evolution; heritable variation and selection then seize some of them. Crucially, a possibility can be driven by random events and accidents, such as genetic mutations. For example, noise and errors in protein synthesis produce an increase in variety and diversity of cell behaviors. Again, a change in the environment of organisms triggers an implicit process of affordance detection; the ones useful for the survival of the organisms are seized by selection [19].

Natural systems composed of more than one species are a prominent case of higher-order dynamics, in which the niche of each species is composed of the environment and other species. For example, the waste produced by a species can be exploited by another one, i.e., the waste produced by an entity can be seen as an affordance by another entity. Systems composed of interacting species have an evolutionary advantage if they can mutually offer each other complementary capabilities [20]. This symbiotic cooperation also produces rich semiotic networks [21], which confer both robustness and plasticity by enabling multiple alternative signaling pathways and diverse mechanisms to act in the environment. This property, also called degeneracy [22], is crucial for complex natural systems.

In summary, both adaption and evolution can take advantage of noise and errors as they trigger a process of affordance detection, i.e., they create the need or the opportunity for a change in either organism behavior or heritable material. This change often introduces novelty, as it expands the actual possibilities of the organisms.

2.2. Adaptation of Robots Controlled by Noisy Sensors

The example we illustrate here comes from the domain of artificial systems, namely robots, and it makes it possible to identify another context in which noise and error can be beneficial. The results we describe show that a robot subject to a simple adaptation mechanism can attain a high performance even in light of sensor damages; furthermore, the robot's performance seems to be improved by a small amount of noise. We first illustrate the experimental setting, then we focus on the effect of noise and error in sensing.

Adaptation in noisy contexts is a typical scenario in nature. We recently explored an analogous case in simulation, where we let robots adapt to performing a simple task under the condition that some of their sensors needed for accomplishing the task were noisy or broken [23]. The experiment involved a robot controlled by a Boolean network [24–26] that has to learn to go towards the light (phototaxis behavior). The behavior of the robot is produced by the dynamics of the Boolean network, which updates the values of its nodes synchronously. Some nodes of the network, called "input nodes", are connected to the light sensors, and some others (the "output nodes") are connected to the motors controlling the wheels of the robot. If a light sensor is connected to a node of the network, the value of this node is set to 1 if the sensor reading is higher than a given threshold. The other nodes assume the values according to their Boolean update function. The value of the output nodes is used to move or halt the wheels (in our experiments, robots have two wheels).

The robot is subject to a simple adaptation process based on the possibility of changing the connections from its light sensors to the network during its life. Note that the structure and the update functions of the network remain unchanged during adaptation. An adaptation step is illustrated in Figure 1. The robot starts with an initial configuration of sensor-to-node connections and undergoes an evaluation phase in which the distance covered towards the light is taken as the evaluation function (to be maximized). After this phase, a random perturbation of the current sensor-to-node connection is exerted, and the robot is evaluated again. If the incumbent configuration provides a better evaluation than the previous one or it does not decrease it, this configuration becomes the current one, and the process proceeds by perturbing the new configuration; otherwise, a new random perturbation of the previous configuration is sampled. This adaptive process is a kind of stochastic adaptive walk in the space of sensor-to-node connections.

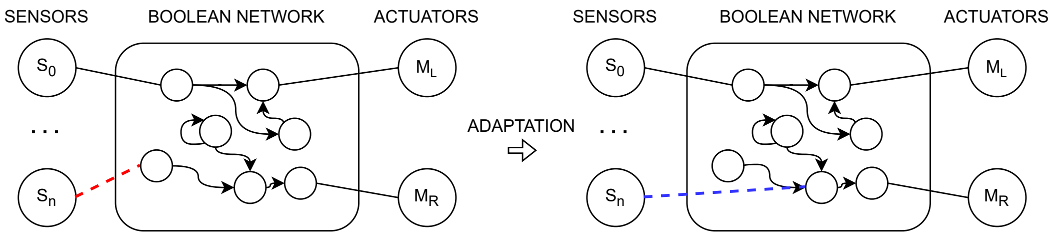

Figure 1. Example of an adaptation step (taken from [23]). A light sensor is connected to a different network node. The adaptation affects only the node to which a sensor connects, leaving the topology of the network unchanged.

The focus of this experiment is on sensors, which can be broken and, therefore, carry incorrect pieces of information to the network. Sensors can simply be detached from input nodes (hence, they do not carry information), can be set to a random constant value, or can produce random signals. The robot is equipped with 24 light sensors evenly distributed along the perimeter of its cylindrical chassis. We consider the case of a varying number of contiguous faulty sensors, from 0 to 24. For each sensor damage amount and for each possible kind of damage, statistics are collected on the performance of the robots, measured as the final distance to the light (details can be found in [23]).

Surprisingly, the overall performance does not monotonically degrade with the number of faulty sensors. Instead, we found that a limited amount of faulty sensors (between 3 and 6) enables the robot to perform better than in the case with all the sensors correctly working. In other words, the addition of errors in sensor readings turns out to be beneficial to the behavior of the robot.

The kind of noise considered in this example apparently differs from the one previously discussed. Nevertheless, in the case of robots, the perturbation exerted by noise and errors in the sensors forces the robot adaptation process to find a configuration that can distinguish between relevant and irrelevant information. To some extent, even in this case, errors generate the need to search a novel model of the environment (namely, a new sensor-to-node configuration) able to deal with a discrepancy between what is expected and what is actually perceived.

2.3. Improvisation in Music

Music is acknowledged to be a universal trait of humans [27], and it traverses and involves all the aspects that characterize our species. Here, we briefly discuss improvisation in music from a systemic perspective, emphasizing its main general mechanisms.

Improvisation is "the creation of a musical work, or the final form of a musical work, as it is being performed. It may involve the work's immediate composition by its performers, or the elaboration or adjustment of an existing framework, or anything in between. To some extent every performance involves elements of improvisation, although its degree varies according to period and place, and to some extent every improvisation rests on a series of conventions or implicit rules. [. . .] One of the typical components of improvisation is that of risk: that is, the need to make musical decisions on the spur of the moment" [28].

While varying across time and culture, independent of the degree of improvisation in a performance, musical improvisation stands as a prototypical case of impromptu creation that requires a fast answer to external stimuli that are not planned and internal decisions that might also be affected by mistakes, which in turn trigger further reactions (by the other musicians or the same performer). In general, improvised musical performances rely on stylistic constraints (e.g., basic chord sequences) as well as musical structures that are dynamically created during the performance (e.g., temporary key changes). When more musicians are involved in the performance, an action a musician takes might not match with the expectations that another musician has. In other words, there may be an error or a discrepancy in the expected behavior observed by the latter musician. A prominent example is jazz: an extemporaneous variation in a chord perturbs the *adjacent possible* [29,30] of future musical decisions, perhaps limiting some options, but also disclosing opportunities that could not be reached without the variation. Errors of this kind, as well as mistakes and accidental events, can trigger novelty. For example, a distraction can cause a mistake in the execution of a note on a trumpet, which might suggest a new melodic direction to the other musicians.

In this third example, the role of noise and error is similar to that illustrated in Section 2.1, as they can be seen as a perturbation that triggers the exploration of a new space of possibilities. Nevertheless, improvisation in music emphasizes a typical (cognitive) mechanism to explore the adjacent possible: breaking some of the rules originating from shared conventions and performance practice (e.g., a response to an error can be the temporary change of the meter) or from the current structure of the music performed (e.g., a chord change to respond to an error).

2.4. A General Mechanism

The three examples illustrated above share a common, general mechanism: noise or error generates a tension between the expected state and the actual one, and this tension triggers a local exploration process aimed at finding a solution to this tension. This solution consists of a structural change in the system.

Formally, let suppose that the behavior B of a system in general depends on the model of the environment, M_e, the model of itself, M_s, the repertoire of actions, $\mathcal{A}$, and the goals, $\mathcal{G}$. The repertoire of actions $\mathcal{A}$ includes actions that produce the behavior and other "meta-actions" that manipulate the models, the goals, and the actions themselves (these meta-actions are required for executing the adaptation process). In summary, $B = f(M_e, M_s, \mathcal{A}, \mathcal{G}) = f(\mathcal{U})$, where $\mathcal{U} = \langle\, M_e, M_s, \mathcal{A}, \mathcal{G}\,\rangle$. For the sake of readability, we omit the dependence on time. Whenever noise or error intervenes, $\mathcal{U}$ is likely to require a change to enable the agent to reach its goals (which also includes maintaining a specific behavior). A schematic representation of this process is as follows:

i. The system's behavior is determined by $\mathcal{U}$. The space of possible variations and extensions of $\mathcal{U}$ is, in principle, "unprestatable" [31].
ii. A perturbation in the form of noise or error takes place.
iii. A process for revising or extending $\mathcal{U}$ is triggered. The *adjacent possible* of the system depends on the perturbation received, the goals, and the repertoire of actions.
iv. A new configuration $\mathcal{U}'$ is seized.

The processes for changing $\mathcal{U}$ are multiple and depend on the kind of system and adaptive process involved. We can identify necessary properties a system needs so as to exploit noise and error in a positive, constructive way. This is discussed in the next section.

3. Positive Effects of Noise and Error as Well as Conditions Enabling Them

One of the main effects of noise and error is that they can be sources of novelty. Obviously, the generation of novel behaviors or structures is not simply produced by random and accidental events. Genetic mutations do not correspond to novel useful phenotypic traits per se; the accidental appearance of a new species in an ecosystem is not guaranteed to produce changes in the environment; a fault in a robot sensor is very often detrimental rather than producing novel opportunities; and a mistake in playing a chord on a guitar might simply introduce an unpleasant and distracting dissonance. Therefore, the question arises as to what the conditions are that enable noise and errors to generate novelty and have a positive impact on the system.

3.1. Multilevel Organization

The starting point of our discussion is the work by Atlan [32], who points out that one main effect of noise on biological systems is that it enables them to create meaning. The first step of his argument is that, in the usual Shannon approach, noise acts as a disturbance on a communication channel between a source X and a destination Y. Noise introduces ambiguity in the destination message; it leads to an augmentation of $H(Y/X)$. However, still according to the Shannon theory, the entropy (now intended as the complexity) of the compound system that contains both X and Y is $H(X,Y) = H(X) + H(Y/X)$. Noise increases $H(Y/X)$: the higher the amount of noise, the higher the conditional entropy between Y and X, because higher is the chance that the destination receives a different symbol than the one sent by the source. While, from the communication channel perspective, this is detrimental for accurate signal transmission, the diversity or complexity of the system as a whole clearly increases. In other words, a richer diversification of the intra-system causal pathways occurs because of more complex relationships between X and Y. As Atlan remarks, it is always possible to consider this increase in the entropy of the compound system as an increase in its complexity (i.e., reduction of its redundancy; see below) because the Shannon entropy functions cannot distinguish meaningful complexity from mere disorder (i.e., meaningful from meaningless messages).

This entropic complexity growth is the very source of change under the condition that the compound system (source plus destination) is just one level of the system, i.e., if the transmission of information from X to Y is a lower-level mechanism in a multilevel system. This is the case for biological systems; for example, variance in the synthesis of proteins makes it possible to explore novel protein variants and so create affordances and, hence, new possibilities for adaptation. Here, a crucial step takes place: among the new affordances that are available, the ones that carry a specific advantage for the system are seized. This newly established advantage is the origin of the creation of meaning. For example, take a new protein that works as a receptor for a molecule providing elements that boost cell metabolism. Once this new receptor stably enters the system dynamics, the detected molecule assumes a meaning because it "matters" to the system. Before the appearance of the new receptor, the molecule was in fact invisible and nonexistent in the system. Analogous considerations hold for evolution by selection and heritable variations. Meaningless noise produced by random mutations generates affordances that are then seized by higher-level interpretation (i.e., selection) as useful new phenotypic traits [8]. One can easily identify the same mechanism in improvisation. Not all variations produced by a musician trigger a specific reaction from the others, just the ones that are recognized by another musician as opportunities and assume meaning (this is, of course, subjective).

Tomasello [33] points out that the higher the amount of unpredictability in the environmental niche of an agent, the more complex its behavior mechanisms have to be. A simple negative feedback loop is sufficient for a constant and predictable environment, but it is largely ineffective in dynamic and varying environments.

A minimal example is provided by a simple threshold response behavior mechanism equipped with the possibility of adjusting the threshold. This mechanism can work if noise is limited and its intensity is not subject to quick changes. In the frame of the formalization introduced in Section 2.4, the behavior of the agent can be expressed as an action $a \in \mathcal{A}$ taken if the sensor percept $s \in M_e$ is greater than a threshold $t \in M_s$. An action $\hat{a}$ can be triggered to adjust the threshold t so as to dampen the effect of a constant noise; however, such a mechanism is ineffective if the intensity of noise is wide and quickly changes over time.

Complex behavior mechanisms imply multiple and complex internal structures. As a consequence, we identify a first necessary condition for enabling noise to produce positive effects: the **multilevel organization** of a system.

We observe that a multilevel organization in artificial systems, such as robots, permits the reconfiguration of sensors, the emergence of new sensors [34], and even the use of *metasensors* [35] that make it possible to reconfigure and rearrange the system so as to reduce the discrepancy between the environment and the *Umwelt* of the robot.

3.2. Redundancy

A second necessary property is **redundancy**, which can also manifest as *degeneracy* [22]. An interpretation of redundancy in terms of syntactic information (*à la* Shannon) sheds light on the connections with the previous argument.

Rephrasing Atlan [32], redundancy is the reduction of entropy due to limits, constraints, and stable structures in the system. In terms of information theory, for a system composed of two variables X and Y, the redundancy R is defined as: $1 - \frac{H(X,Y)}{H(X)+H(Y)} = \frac{H(Y)-H(Y/X)}{H(X)+H(Y)}$. In general, $R = 1 - \frac{H}{H_{\max}}$, where $H_{\max}$ is the maximum entropy of the system, attained when its parts are totally independent.

As previously noted, noise augments the ambiguity function $H(Y/X)$; hence, the lower the amount of noise, the higher the redundancy. A non-negligible degree of redundancy is therefore initially needed for being converted into meaningful complexity by a noise-induced increase of $H(Y/X)$. This process is equivalent to the reduction of (parts of the) redundant or constrained causal relations between the elements of the systems that concur with the overall X,Y correlation. Indeed, a system working at maximal entropy (no internal constraints, i.e., X and Y are free to vary independently) has no resources to rearrange to make sense of new stimuli. It is then able to reshape redundant structures and processes so that a complex system is able to create new meanings (as Atlan dubbed it, following von Foerster [36], to generate "complexity from noise").

As in Section 2.4, redundancy makes it possible to change $\mathcal{U}$ by reusing, rearranging, and recombining the objects already contained in $\mathcal{U}$. For example, let us consider a robot controlled by an artificial neural network. An unexpected external condition requires a weight update (which in general corresponds to a change in M_e and M_s). If the entropy of the network is not maximal, i.e., if its maximal classification capacity has not been reached, there is a possibility of weight adjustments such that the new situation can be considered in the responses of the network, hence the behavior of the robot. No redundancy would mean no possibility of keeping the current abilities and adding new ones.

3.3. Incompleteness

The modifications of $\mathcal{U}$ can also introduce new degrees of freedom, i.e., new relevant variables, because redundancy and degeneracy open the possibility of evolutionary adaptations and exaptations happening because "each molecule and structure in evolving cells and organisms in the biosphere stands ever-available to be co-opted and selected, alone or with other things, for indefinite adaptive new uses such that myriad new adaptations [...]" [37].

In general, creation of meaning and complexity growth in a system take place through the act of seizing affordances or, in general, of choosing one among several options that have "appeared". We remark that options appear because the system is triggered to look at its adjacent possible because of a change or a stimulus. As this process depends on the current structure of the system, its goals, and its repertoire of actions, the path that the system can take for a self-rearrangement to make sense of a new stimulus is in general open and "unprestatable" [31]. For example, in evolution, new interactions may arise over time, either by the emergence of new organs or by new ways for using the current ones. Analogously, a new melody produced by mistake by a musician can be subsequently used as a pattern by other musicians (as is often said among musicians: "It's not the note you play that's the wrong note: it's the note you play afterwards that makes it right or wrong" [38]). *En passant*, we observe that this interpretation of "enabling error" has strong similarities with MacKay's notion of information as "the distinction that makes the difference" [39].

This *incompleteness* plays a fundamental role in the evolution and adaptation of complex systems because it makes it possible to provide new interpretations of external and internal stimuli. Incompleteness is of course also a consequence of the fact that the processes in the system are not univocally specified and can be executed by following alternative, non-equivalent paths. Such a property is called *logical openness* [40–42], which characterizes living organisms as well as biological and social organizations. Artificial systems lack logical openness because they can be articulated in precise functional parts, each designed for a precise function, while the structure and behavior of evolved complex systems emerge through a dialectic interaction with the environment [38,43–46]. Finally, we observe that the steps involving the modification of $\mathcal{U}$ as a consequence of noise and error are in general path-dependent [47].

3.4. Criticality

The ability of a system to change itself to make sense of a stimulus possibly originating from noise or errors also requires the ability to balance robustness and flexibility because only the stimuli that can assume meaning in the system should trigger an adaptation process. A case in point is the ability of living organisms to properly balance robustness against mutations and phenotypic innovation. In general, the property of achieving a good balance between a coherent response to external stimuli and the ability to classify inputs into a sufficient number of classes is achieved by systems characterized by dynamic

criticality, i.e., systems poised at the edge between order and disorder [25,48,49]. There is evidence that many natural and artificial systems are critical: from cells [50–52] and brains [53] to robots [54]. Remarkably, the property of dynamical criticality nicely fits into the framework of multilevel, open, and redundant systems that can undergo processes of self-configuration, adaptation, and creation of meaning to cope with and exploit noise and errors.

Lastly, we discuss a final aspect of noise and errors, shown in the example of adaptive robots with faulty sensors discussed above, which requires further elaboration. In abstract terms, this case is characterized by the fact that the inputs of the system are noisy and can carry incorrect information (i.e., not coherent with the state of the environment). According to Shannon's theory of information, this is the typical situation with a noisy communication channel, which is exactly the same setting we discussed at the beginning of this section. In the scenario of robots with faulty sensors, the effect of noise and errors is to help the system focus on relevant parts of the external stimuli and optimize its internal resources to properly and reliably respond to external inputs. This kind of noise lessens the redundancy of sensors, enabling the internal control mechanism of the system to achieve a higher efficiency in interpreting the inputs coming from the sensors and computing the actions to take. Notably, works in criticality and parallelism in optimization by means of stochastic local search [55] provide evidence that the relaxation of some constraints of a problem or a reduction in information make it possible to obtain better results than the ones that could be achieved with the complete and correct description of the problem [56–58].

4. Conclusions

We have discussed some general properties and conditions that enable complex systems to profit from noise and error to improve their performance, increase their complexity (in terms of structure or behavior), and create meaning. These properties are: multilevel organization, redundancy, incompleteness, and dynamical criticality. Further steps are aimed at the formalization of these properties and conditions in the various scenarios in which they play a role, both natural and artificial. Regarding artificial systems, it is important to remark that the dynamics and the adaptive abilities of artificial systems strongly depend on their substrate. While robots controlled by typical programs are subject to the limitations of computation based on Turing machines, therefore not considered to be truly logically open [40,59,60], different substrates make it possible to overcome these limits. A case in point is that of molecular robots built on the basis of chemical networks. Indeed, molecules and reactions are not just computing nodes and connections belonging to a computational domain. Rather, molecules have access to a potentially unbounded space of interactions, whose dimensions are not restricted and can unpredictably evolve as a result of previous interactions [61].

The connection between these processes of creation of meaning and complexity growth with Shannon information theory may provide a basis for establishing a formal link between information theory based on syntax (i.e., without semantics) and semantic information [62–64] and the way organisms and complex systems in general can make sense of their experiences.

Finally, we observe that the process of self-adaptation triggered by errors and unexpected percepts can be suitably described inside the theory of active inference [65], which can also provide a grounded probabilistic framework for the topics discussed in this paper.

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