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Self-generated dynamic landscape: The message–receiver interaction case

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A B S T R A C T

In the present work we present a model, based on a particular differential stochastic equation, to study the interaction between an incoming message and its interpreter. The particular stochastic dynamic used to understand such process is written using a delayed Langevin equation with white noise. The results of this kind of interaction can be understood in a general framework that we name the *self generated dynamic landscape*.

1. Introduction

The transmission of some information and its effects on who receives it have been addressed under the assumption that information comes from an emitter which is responsible for encoding it and is trying to communicate something [1,2].

However, here we take a broader notion of information so that it can come from one transmitter or from some substrate liable to be taken as a source of information by the interpreter or receiver [3]. This information can come from a mark, symbol, text or sound generated by a speaker, or it may come directly from empirical aspects of a phenomenon that is being examined by an interpreter, either a living being or an artificial intelligence device.

The information in the communication process does not work deterministically: the delivered message is not always decoded or interpreted in the same way by different receivers, and also does not produce the same results when the same information is acquired by the same receiver at different times [4–6]. These characteristics cause us to consider the non-deterministic feature in the interaction between information and receiver, and its consequences for future interactions.

There are two processes in which communication between speakers involves indeterminism. The first happens when the emitter builds the message from its conceptual state. Messages are not in a one to one relation with conceptual states — there is a degree of indeterminacy between the conceptual state and the message. Notice that this is not the case when dealing with signs or information coming from natural phenomena independent of any intentional emitter. The other process of indeterminacy takes place when the message interacts with the conceptual state of the receiver (receptor). The model

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presented here addresses only the latter interaction and is consistent with a dynamic conception of the modification of sign meanings in short time periods, casting some light on individual learning, changes of communication in communities, and some pathologies in the language uses.

We consider a receptor which has a structured conceptual network [7,8], in such a way that only a portion of it is relevant for a given interaction with incoming information. In this network each node is represented by a valley (or attractor) with a central point: the paradigmatic or prototypical concept (in the sense of Rosch, [9]).

This network of conceptual attractors can have different levels, and is compatible with, although not necessarily committed to, the structure of a conceptual space as built up from geometrical structures based on a number of different dimensions (as suggested by Gärdenfors, [10]). Such a structure is highly related with the concepts discussed by Gell-Mann and others referring to the complexity of an entity [11,12]. Though largely outside the scope of this paper, these conceptual levels can illuminate the relationship between concepts and their composites. In particular, notice that the integration of many concepts can produce more complex or elaborated ones, leading to changes of levels (something that can be understood generally as emergent processes). In the same way relational concepts could correspond to attractors resulting from connections between lower level concepts.

In what follows, we use a stochastic dynamics framework to construct a model that takes into account the message–receiver interaction. The main idea behind the model is to capture the future possible outcomes of such interaction considering previous experiences. In the first section we will present and discuss briefly a static version of the model, where the processes take place in a landscape independent of time. Secondly, we show how changing the nature of the potential of the dynamics dramatically changes not only the possible path of this stochastic interaction but also the very nature of the model and its consequences for future events. Next we show numerical simulations of the latter differential stochastic equation for various sets of parameters. Finally we discuss our findings, the strengths of the model and conclusions.

2. Stochastic approach

The model assumes one conceptual dimension as the state of the receptor x (this can be straightforwardly extrapolated to many dimensions [13]). In this dimension there is a conceptual landscape, or potential, $V(x)$, which, as we will show below, gives the probability that a given concept x belongs to the attractor.

The proposed dynamics in this conceptual landscape are given by the following Langevin equation [14]

$$\frac{dx}{dt} = -\gamma \frac{dV(x)}{dx} + \varepsilon \xi(t). \tag{1}$$

The stochastic dynamics are represented by $\xi(t)$: a centered Gaussian white noise without temporal correlation, i.e.

$$\langle \xi(t) \rangle = 0,$$
$$\langle \xi(t)\xi(t') \rangle = \delta(t - t'),$$

ε is the strength of this stochastic term and γ is a relaxation parameter. This equation models a random exploration near x and allows association with a given probability weighted by the potential [15,16]

$$P(x) \propto e^{-V(x)}. \tag{2}$$

Then, if we consider a static potential $V(x)$, the receptor will interpret the incoming information or stimulus, $x(0)$, in terms of concepts related to the conceptual attractor, and will relate it to the stochastic path taken in a particular realization. Notice that depending on the initial condition the stochastic trajectory will relax to a local minimum of the potential (concept with greater relative probability in the potential $V(x)$).

In other words, the receptors interpretative process has two different active components (see Fig. 1). The incoming stimulus activates a given zone in the conceptual topography which follows a relaxation process to one of the local minima. Also, the relaxation does not always follow the same path (we will show below that each path could change the conceptual landscape, which is an important feature of our model). This path is not given *a priori* but *post factum*, and the model takes into account this fact through the stochastic term discussed above.

In short, the receptor carries out two active processes when receiving a particular packet of information: it activates a given zone in the conceptual landscape and this initial condition relaxes, *via* a stochastic path, to a more probable place in the landscape. These characteristics give the model the capacity to consider the receptor as an important active agent in the communication process.

So far we have analyzed the evolution within a static conceptual attractor. That is, the landscape cannot be changed through (for example) past experiences. It is natural to extend the characteristics of the model in order to change this rigid feature, which is far from a realistic human interaction. Then, we will propose a possible dynamics that takes into account changes in the conceptual landscape. We will propose the following stochastic differential equation

$$\frac{dx}{dt} = \gamma P'(x, t - \tau) + \varepsilon \xi(t). \tag{3}$$

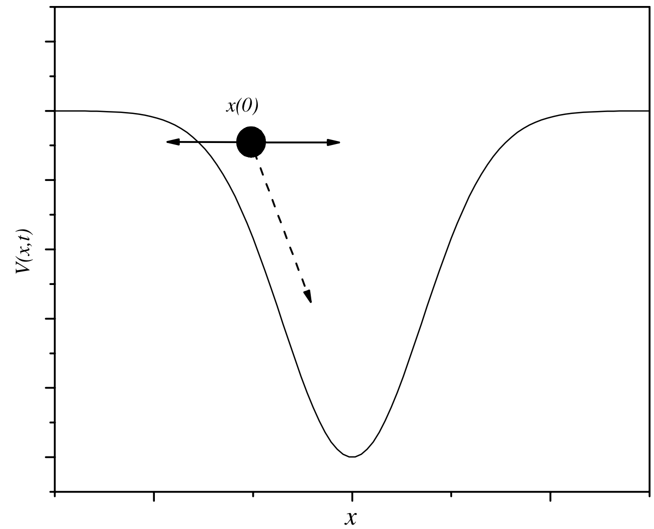

Fig. 1. Sketch of the model used. There is a potential, time dependent in the general case, where a stochastic relaxation process occurs. At any moment, exemplified here as the initial condition $x(0)$, there are two forces acting, the potential slope $V'(x,t)$ (dashed arrow), and the Gaussian noise (continuous arrow) with half of the probability of pushing to the right or to the left.

This equation, simple as it appears, has specific features that make it appropriate for the problem we address. It models the evolution of a given incoming stimulus, namely $x(0)$, into a space of a self-constructed potential, using the explicit information coming from the distribution $P(x,t)$. This potential is no other than the probability assigned to a concept x in the conceptual space so that this potential builds the conceptual probability landscape. The first term of this equation shows how the relaxation process depends on the previous probability distribution in the vicinity of x. Temporally speaking, it is a function of the delay parameter τ and the actual time t, so that the probability distribution acting on the relaxation process in every instant t is that which exists at a previous instant $t-\tau$. The second term is the usual stochastic process that allows for a random path in the neighborhood of $x(t)$, as previously mentioned in Eq. (1).

The dependence pointed out in the first term is similar to a restitutive force field. Note that its contribution to the path pulls in the direction of the gradient of probability. In other words, the stimulus will be forced to move towards the maximum probability of its surroundings so the environment makes the process evolve in that direction, if no other force is acting, namely without the stochastic field added in the second term.

Conversely, the second term, acting alone, will force the process to evolve in a randomly oriented path, because of the absence of a potential mapping the conceptual attractors in a landscape).

2.1. Simulations and the explicit dynamics of the model

Simulations of Eq. (3) were done considering a centered Gaussian distribution as an initial condition for the probability. The initial condition for incoming stimulus was set to $x(0)=1$, i.e. deviated from the minimum of the attractor. Each of the panels in Fig. 2 shows a different value for the ratio between the relaxation parameter and its sum with the strength of the noise, $\omega=\gamma/(\gamma+\varepsilon)$. The value of this ratio gives the proportion of the potential structure and the intensity of the stochastic process and how they impact the final interpretation by the receptor. Case (a) shows a very disperse path, small ω, while case (c) shows a more direct path to the final attractor. In this way ω can be interpreted as the degree of determinism in the interpretation, so we identify it as the determination coefficient.

This novel dynamics results fruitfully. The self-generation of the process is obvious: the greater the frequency of stimulus a concept receives, the higher the probability to be assigned to a given piece of incoming information.

This result comes from the fact that the relaxation process makes the stimulus stay for a while (one or more steps in the simulation run) in every interval of x, or bin, along its trajectory in the landscape. If the stimulus passes many times by a certain interval during the relaxation process, the probability will grow for that interval, shown by a higher bar than the initial for that interval in the histogram.

It is worth noticing that the search process is given by the derivative of the probability, as Eq. (3) shows, which is plausible, given that the search will be a process that navigates the conceptual landscape towards more probable concepts.

We should note that the distribution used in the simulation is a histogram obtained using a number of N counts equals $N=1000$. One can interpret N as an initial number of occurrences of concepts in a given area of the landscape which gives a concept probability distribution in that area. The role of N is not really important in isolation but in comparison with the number of steps of every simulation run to be added to the histogram, namely m (the relation between these two parameters will be analyzed in more detail below).

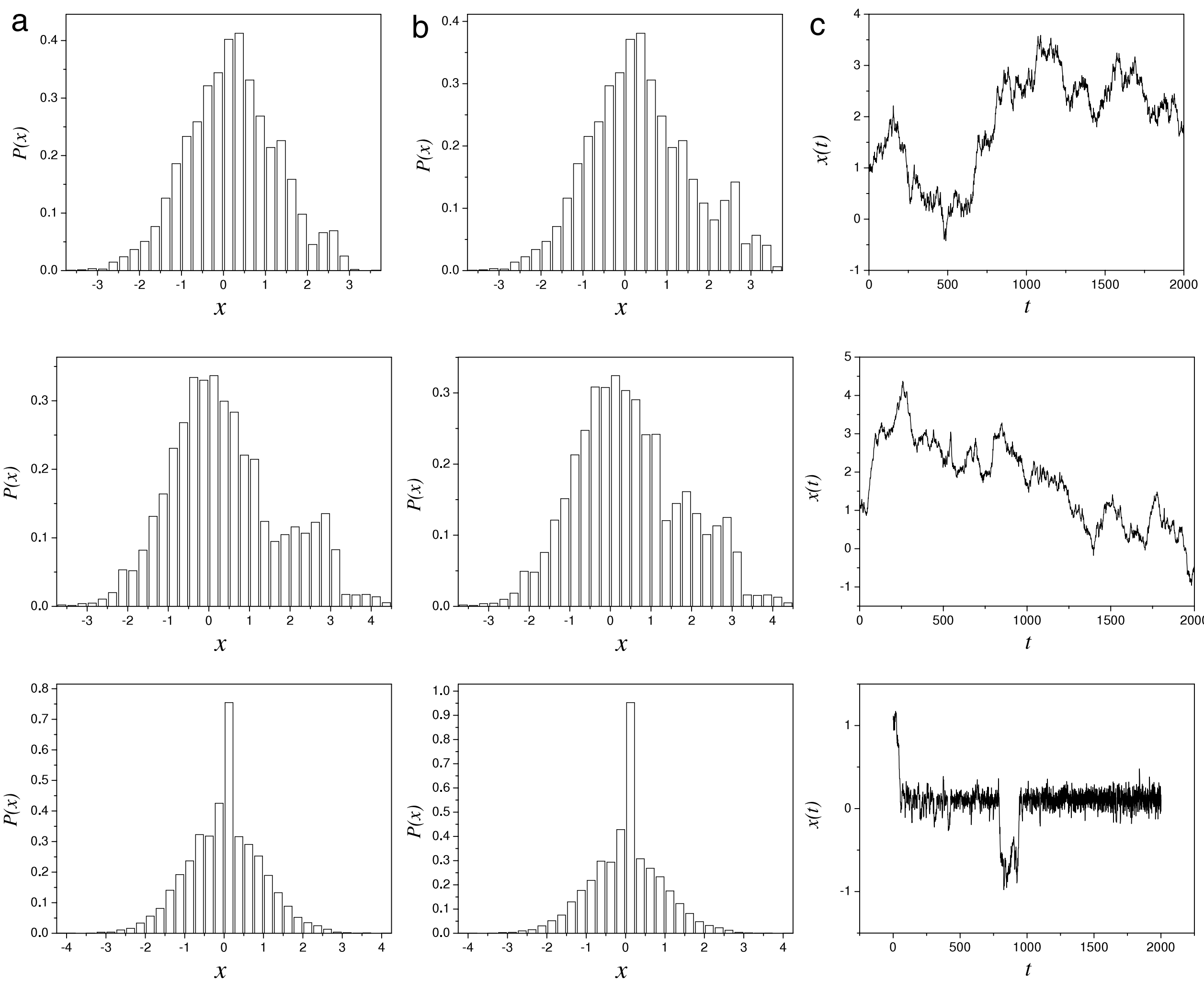

Fig. 2. Three examples of the evolution of a given initial condition and the resulting final shape of the conceptual landscape. In all cases the initial probability function was a centered Gaussian with a normalized variance, $x(0) = 1$. Columns (a) and (b) show the probability distributions for times 10^3 and 2×10^3 (the final state) respectively, and column (c) the stochastic path of the realization. Upper panel: $\gamma = 0.35$, $\varepsilon = 0.4$ ($\omega = 0.47$); middle panel: $\gamma = 2.5$, $\varepsilon = 0.4$ ($\omega = 0.86$); bottom panel: $\gamma = 5$, $\varepsilon = 0.4$ ($\omega = 0.92$).

When a stimulus is received, the path visits different parts of this histogram. The more stochastic the path (small ω) the greater the number of bins that are visited. In the same way, when $\varepsilon = 0$ the deterministic path will converge directly to the top of the distribution. Then, each relaxation process contributes to the initial histogram to obtain the final one. To avoid adding occurrences *ad infinitum* to the histogram, each realization (simulation run) introduces m counts, or steps in Eq. (3). If the stimulus reaches the final attractor with zero velocity, then no more occurrences (steps) are added. In the same way, the dynamics stop at m occurrences, even if the attractor is not reached.

When summed, and the histogram is normalized, the new configuration obtained depends on the particular path followed. In the general case with $\varepsilon \neq 0$ we can see how the same incoming stimulus $x(0)$ can produce a different final state, due to the stochastic nature of the search; importantly, the final conceptual landscape will be different in virtue of this stochastic contribution.

Given that the final state of the landscape is obtained by adding a maximum of m steps over N initial ones, we can understand the importance of the ratio between these two quantities $\phi = m/N$. We also see the importance of choosing the value of N, compared with that of m. The lower the value of N relative to m, the greater the change of the histogram shape. So, both, N and m, are parameters involved in the way the refreshing of the histogram takes place. The ratio $\mu = m/(m+N)$ gives a different degree of the histogram's refreshing after every process. We will call μ *mnemic modifiability* of the landscape. The zero value of μ would correspond to a situation where no modification to the original histogram is possible, and when μ increases, the final configuration of the landscape is more affected by a given path. The value of this parameter can change, giving rise to different stages of mnemic modifiability that can be associated with different learning stages, stages of implementation and adjustment.

In an extreme case the receiver would not have learning capacity ($\mu = 0$). This is the case of an entity with a fixed landscape configuration. In the other extreme case there will no interpretation using previous processes, and every final state of the system will be the result of the last followed path.

If a relaxation process occurs when $\mu > 0$, new attractors can appear in places where there were none, in the middle of two attractors, or even to make an attractor deeper. These processes can be understood as the existence of a fine-grain weft inside a conceptual attractor, allowing a generation of self-similar structures (for example in the neighborhood of $x = 2$ in the second example of Fig. 2).

When $\gamma = 0$ the process will erase the attractor structure of the landscape. This phenomenon results from the normalization of the histogram after each path, which is only stochastic in this case, producing the free diffusion process in the conceptual landscape.

With these two operations (generating and vanishing of different attractors) we can concisely simulate the hypothetical thought, which can generate spurious and temporal modifications to the conceptual landscape.

3. Model strengths and conclusions

With a few parameters, the model represents the basic processes of the emergence of attractors in the conceptual dimension x, the changing in the range of these, or even their disappearance. It also allows a facilitation in the liability of change of the conceptual space in various stages of processing stimuli. It takes from the very beginning the non-deterministic feature of the communication process, so it is able to show the possibility of misunderstanding and ambiguity in interpretation.

Moreover, we propose that there exists a topography acting as a potential in the receptor. The process of relaxation of a concept activated by an incoming stimulus allows us to understand why communication is effective most of the time.

If the process were indeterminate to such a degree that there did not even exist a tendency to organize stimuli according to some previous conceptual network, language itself should not be understandable, and the success of communication would remain unexplained, or worse, taken to be miraculous. The model explains why a receiver can understand or decode the same message differently at different times and, on the other hand, provides insight into the successful use of language because both senders and receivers are able to communicate with each other by means of the process of interaction between the input information and the receivers conceptual configuration, including how changes can endure in the structure. In this sense the model can give an account of learning as an acquisition of information through which the receiver is able to generate new concepts or eliminate the use of the initial concepts and changes in the relationships between concepts, the range of the concepts involved, the prototype associated with each attractor and even the composition or integration of concepts when they are conceived as the result of some operation between concepts of a lower level. This counts for dynamics in the category structure.

Finally, this model accounts for the pathological conceptual configurations, i.e. configurations that do not have the ability to change (represented by a zero or very low value of the parameter μ), or configurations that change almost completely with each stimulus (represented by a value close to the unity, of the last mentioned parameter) instead of providing a landscape for the incoming stimulus to be conducted by its slopes and noise to some final particular state. In other words, a conceptual attractor network that remains invariant with respect to the relaxation processes is a network inalterable by the use of concepts with different range by other speakers. That is, the receiver works as if it receives no information able to encourage it to change something about its conceptual structure. This difficulty would indicate an impossibility of learning.

At the other end of the spectrum are networks modeled entirely by each stimulus so that neither the basins nor its minimum operate as attractors, but the same stimulus creates permanent changes that themselves become the focal points of the resulting basins. This mode of operation of a network counts for a receptor as it has no chance to compare mismatched information against the conceptual network and is thus unable to reject the incoming information. The former can be characterized as stubborn, the latter as obsequious. Both extremes are pathological ways of dealing with the incoming information.

Another important phenomenon that this model can foresee and deal with is that of the phase changes, or rearrangements of the network by collective effects. These could be stimuli that, either by their long relaxation time (configurations with a very low coefficient of determination) or by the excessive separation from the active concept to the prototype concept of the attractor, will be more likely candidates to be rejected than to modify the attractor.

In terms of an example, if a speaker asks his interlocutor to admit that a causal signal cannot travel faster than the speed of light, and then to imagine two very distant points of the universe causally connected in a few seconds, it is highly probable that the receiver will try to reject the conjoined assumptions rather than accommodate his topography in a charitably way to give rise to an interpretation that validates both requirements. However, if we keep on trying with these kinds of stimuli, stressing the limits of the receiver structure through a series of thought experiments, and it is forced to process all these stimuli far from its prototypes, it may reach a point in which a wide collection of concepts can be rearranged dramatically and together, resulting in a phase change, an entirely new configuration of the topography. That result can be associated with a holistic change in classification.

We believe that this is a good representation of the change in worldview that can occur when several concepts change conjointly and give rise to a new network of conceptual connections between attractors, although to better account for these cases the model will have to be further developed, including attractor to attractor interactions in n dimensional space.

Finally, although the model has been presented concerning the information–receiver interaction, it is not limited to this field (priming phenomena is one of the fields where it can be applied). The model can give account appropriately of different dynamic landscapes; we can foresee, for instance, it being used to model the change of a natural landscape as ants pass through, or the way users increase the probability of some results of web-based search engines, or how share prices can change according to the offer or demand for them. Our primary aim in presenting the information–receiver field of application was to illustrate the model's features.

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