Article

Dynamics of Consciousness

Complexity and Creativity

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Abstract. The cognitive problem is how a given sensorial input elicits a decision. Since the neuron dynamics are affected by deterministic chaos, information is lost over the course of time. Control of chaos reduces such a loss rate by adding extra degrees of freedom. This addition is a change of code; such a recoding occurs on two time scales, namely, (A) the cognitive one (lasting up to 3 s), within which the brain reaches a collective state associated with a perception, and (B) the linguistic one (beyond 3 s), whereby memory retrieves different (A) units and compares them. In (A) the neurons are mutually coupled in large networks; collective synchronization of neuron arrays elicit decisions. In (B), different (A) slots are compared after retrieval. This requires a subject to be conscious of him/herself as well as that the pieces of the stream be correlated. While in (A) the neuron synchronization is described in dynamic terms, in (B) the slot comparison is formalized by an inverse Bayes rule. Distinction of (A), where coherent perceptions are built, from (B), where we formulate attributions of truth, recovers the fundamental philosophical difference between apprehension and judgment.

Keywords: chaotic dynamics, neuron synchronization, apprehension, judgment, Bayes

Introduction

We explore two different types of cognitive process, namely, (A), whereby a coherent perception (apprehension) emerges by recruitment of large neuron groups and (B) whereby memory retrieval of different (A) units and comparison of them leads to the formulation of a judgment.

The time frontier between (A) and (B) has been stressed explicitly by E. Poeppel in several papers (Poeppel, 1997, 2004, 2009).

(A) occurs over a time scale up to 3 s; it results from collective synchronization of the gamma band oscillations in wide brain areas. The synchronization mechanism has been established in laboratory animals as well as in human subjects; for (A) it makes sense to investigate the NCC (neural correlates of consciousness). The various (A) slots can be retrieved by memory processes and exploited for motor decisions; this occurs in the everyday life of a cognitive agent.

Even a stretching of this time scale does not change the above picture; we speak always of (A) processes. Ned Block (2005, 2009) distinguished between P-C (phenomenal consciousness), the subjective "what is to be like" and A-C (access consciousness), which is the content of P-C made available for further action as motor responses. This distinction refers to the same short time scale of (A) processes; in fact several authors question the distinction between P-C and A-C (Kriegel, 2006); thus, Block's distinction has no relation with our separation into (A) and (B) processes.

In (B), different (A) slots are mutually compared in order to extract a global trend; this occurs over times above 3 s. (B) is no longer a unique synchronization process, since comparison implies the presence of differences among different (A) units. To accomplish (B), the cognitive subject must be conscious of his/her doing such a comparison; thus (B) does not entail mere awareness but *self-consciousness*.

We will explain (B) in terms of what we call an "inverse Bayes process." The standard Bayes process (Bayes, 1763) has already been shown to play a crucial role in fast decisions (Kording & Wolpert, 2008; Ma, Beck, & Pouget, 2008). The inverse process, here introduced for the first time, permits formulating a judgment, whereas (A) is just apprehension.Thus, we provide a scientific basis to the philosophical distinction of the two successive cognitive actions that characterize human insight (Lonergan, 1957).

Deterministic Chaos and Cognitive Abilities

Cognition means extracting from the environment some features on the basis of which to react. This occurs at any level, starting from unicellular organisms that build decisions by processing chemical and thermal gradients. In multicellular organisms, a processing speed up is obtained by electrical rather than chemical mutual communication. This is not limited to animals but is now observed in plants as well (Masi et al., 2009).

As animals get more complex, the distributed processing networks specialize into a dedicated organ, the brain. A

DOI: 10.1027/0269-8803/a000026

brain is made of huge networks of coupled units, the neurons. A single neuron displays chaotic behavior if studied in isolation; however small neuron networks are stabilized against chaos by a combination of inhibitory mutual feedbacks. They perform a specific function such as a stereotyped reaction to a stimulus as it occurs in the CPG (central pattern generator) or *encoding* mechanisms as explored in the olfactory system of insects (Rabinovich, Varona, Selverston, & Abarbanel, 2006).

Encoding is just the first step; then one must read the information and make good use of it. A possible paradigm is that of fixed-point attractors (Hopfield, 1982), that is, the neuron dynamics converge toward stable equilibrium points. Any input is classified according to its resemblance to a template previously stored in the system; this fact endows an attractor network with capacity scalable to its size. However, a stable attractor network has a strong limitation in its limited capacity. Resorting to the dynamic attractors associated with chaotic dynamics, one can build richer scenarios that are not restricted to a fixed repertoire.

Here the central cognitive issue emerges. In the presence of chaos, if the information loss rate is high, it precludes a convenient reaction. In fact, the only operational way to attribute cognitive ability to an agent is to look at its reactions. A smart cognitive agent can compensate for chaotic information loss by reverting to memory resources that add extra signals perturbing the original input and, hence, recoding the original dynamic space. This provides a reduction of the loss rate. This strategy is called *control of chaos* (Ott, Grebogi, & Yorke, 1990). In the case of many coupled chaotic units, a way of displaying a coherent behavior, that is, holding information for a time much longer than the chaotic decay rate of a single unit, is mutual *synchronization* (Pecora & Carroll, 1990).

Some open questions:

1. Consider a set of coupled neurons in an array acting as a feature-detector; it is hypothesized that the interplay between bottom-up stimuli arriving from sensory areas and top-down signals fed from memory stores (Carpenter & Grossberg, 2003) yields collective synchronization (Singer, 2007). How well do these attractive hypotheses match the observed types of behavior?
2. Calling cognition the loop perception-action, this can be fast (around 100 ms) and explained by Bayes procedures (Kording & Wolpert, 2008) or slower (around, say, 800 ms) and mediated – in the case of humans – by processing in the prefrontal cortex (Rodriguez et al., 1999). The cognitive problem is how a sensorial input elicits a decision. Once some early neuron groups encode the sensory signals into specific sequences of neuron spikes, is that code already driving an appropriate action or is further recoding necessary?
3. In this second case, the cognitive agent makes use of its own resources, in order to reduce the original information loss rate and be able to build an appropriate reaction to its environment. The amount of this reduction can change from one individual to another. We call *creativity* (Arecchi, 2007a, 2007b) the "best" recoding that lengthens the time over which information is lost (not too short, otherwise it would preclude an appropriate reaction, nor too long, otherwise it would make the agent blind to successive inputs). How can creativity be measured?

We will explore how a network of locally coupled chaotic oscillators can reach a state of collective synchronization. In the absence of synchronization, the time separations of spikes occurring at adjacent sites are spread over a wide distribution; technically, we say that the corresponding entropy is large. The indicator of the collective state is a reduction of this entropy, denoting the onset of an ordered state in that time separation. The onset of this state is either spontaneous, above a critical value of the mutual coupling, or is the response to an applied stimulus, for coupling below the critical one. The former case is *asemantic*, as it does not hint at an input; indeed, asemantic collective synchronization is an indicator of an epileptic seizure (Traub & Wong, 2009; Queiroz, Gorter, Lopes da Silva, & Wadman, 2009). In the latter stimulated case, the collective state lasts for a finite duration Δt, depending on the amplitude of the applied stimulus and the coupling strength. Thus, combinations of input stimuli and coupling strengths provide a specific response, and the network acts as a semantic network, which recognizes different inputs yielding different Δt. Adjustment of the coupling strength should provide *adaptability.*

Complexity and Code Change

A scientific problem formalized within a fixed code can be written as a computer program. We call *complexity (algorithmic)* the bit size of the shortest instruction that solves the problem (Chaitin, 1970). On the other hand, deterministic chaos entails loss of information over time. Control of chaos adds extra degrees of freedom: This is a *change of code* guided by criteria not included in the previous code and, thus, not reachable by the computer, that is, nonalgorithmic. We call *semantic complexity* the number of different codes that provide an adequate description of a *situation*, that is, a piece of world at a given moment. This corresponds to the attribution of *meaning* to that situation, which amounts to selecting a particular point of view from which to observe it. Notice that this is a *fuzzy* concept, since the situation can change because of the interaction with the cognitive agent (e.g., the variations in the stock market as an agent interacts with it).

The Two Time Scales of Cognitive Processes and Consciousness

Control of chaos explains collective synchronization of large neuron arrays, which elicit decisions. It is confined to time slots (A) called *presemantic islands* (Poeppel, 1997, 2004, 2009), within which separate sensorial channels with different onset times (acoustic, visual) adjust their occurrence in order to hint at the same object. (A) lasts at most 3 s, as established from bistable or binocular rivalry experiments. Within (A), the readiness potential can precede awareness (Libet, 2004), thus, the associated awareness is not really consciousness.

On longer times, different 3 s slots are not correlated in hardware. They rather represent a semantic stream (B) that requires interpretation, thus, a subject aware of him/herself as well as of the pieces of the stream to be correlated. In (B) the operation that provides a change of code is the exploration of diverse Bayes models until one attains the most plausible interpretation of the data stream, thus, concluding with an attribution of truth.

As we compare (A), that we have in common with other animals and that may be conveniently explained in terms of the NCC (Koch, 2004; Noe & Thompson, 2004), with (B) where we formulate attributions of truth, we recover a scientific basis for the difference between apprehension and judgment as discussed by philosophers (Lonergan, 1957).

Cognition (A) as Coherent Perception

In Newtonian dynamics, assigning a force law and starting from some initial conditions, a unique trajectory emerges, which means that at any later time we can predict the state of the system. This has been the basis of *determinism*, whereby the future can be evaluated in advance since it relies on the knowledge of the initial conditions. If the dynamic system is made of N variables, then we should assign N initial numbers. In general, these numbers are real, made of an infinite sequence of digits; but a measuring procedure or a storage device can handle only a finite number of digits, thus the initial point is, in fact, a fuzzy cloud.

In 1890, H. Poincaré (see Arecchi, 2007b) showed that for $N = 3$ or larger, the dynamics can have a sensitive dependence on the initial conditions, that is, points within the initial cloud can give rise to trajectories that diverge from the ideal trajectory over the course of time (*transverse instability*). This behavior, called *deterministic chaos,* is peculiar to *nonlinear dynamic systems,* that is, systems whose equation of evolution includes variables with powers larger than then 1. Such is the case for a neuron, the dynamics of which have been described by several models starting with Hodgkin and Huxley (1952).

In 1990, a method of chaos control was introduced by Ott et al. As some extra p variables are added to N, the new dynamic problem, recoded in $N + p$ dimensions, can still keep the same longitudinal trajectory; yet the transverse instability has been partially or totally removed. Take a chaotic system where the initial information is lost in 2 ms (this is the case for an isolated neuron). We consider two types of control: partial, whereby information lasts for about 500 ms, and total, whereby it lasts forever. Referring to brain operations, the first control is useful, since it gives time for a motor decision, the second one would be useless, because the neuron would be unable to respond to further stimuli.

The electric activity of chaotic neurons is represented by a sequence of equal short pulses of 1 ms duration (spikes), separated by erratic interspike intervals (ISI).

Such a dynamic behavior was first studied in a laser with feedback by my group and called *homoclinic chaos* (HC).The first observation was followed by an investigation of the spike synchronization, either by application of an external clock or by mutual coupling of many identical chaotic systems (see Arecchi & Meucci, 2008 for details of the investigation).

This synchronization effect suggested its application to the *feature-binding* phenomenon in the brain (Arecchi, 2004). In humans and most mammals, the retina is a mosaic of many photoreceptors separately channeling their information to the visual cortex (V1) through one million fibers. Each fiber is an elementary feature detector, thus V1 should receive plenty of uncorrelated information. Yet, if the cognitive agent is exposed to two relevant features all fibers whose receptive field is exposed to one feature synchronize their spikes even though they are individually receiving different inputs (Singer, 2007). This means that the original bottom-up signal from the retina has been modified by top-down corrections that imply an interpretation (Carpenter & Grossberg, 2003)

To observe such a behavior, it was crucial to resolve the spikes traveling on a single axon; this was obtained by placing several microelectrodes in the brains of laboratory animals (Singer, 2007).

Such an invasive method is forbidden on human subjects, however, a clever transient analysis has been reported (Rodriguez et al., 1999). A human subject, equipped with a 64-electrode EEG apparatus, was exposed at time $t = 0$ to either (1) a meaningful slide or (2) a meaningless one, where no sensible feature could be extracted. The frequency-time plots of the EEG in the gamma band (centered at 40 Hz) show that, in both cases, there is a signal at around 200 ms (mainly coming from the electrodes placed close to V1 and to the PFC (prefrontal cortex), then nothing for more than half a second and then again a signal at around 800 ms (mainly from the electrodes near PFC and the motor and language areas). The difference between (1) and (2) seems not qualitative but only quantitative.

If, however, the EEG signal is filtered out, then strong evidence of phase synchronization appears. At 200 ms, in the meaningful case V1 synchronizes with PFC; no synchronization occurs in the meaningless case. Thus, we see a transfer of relevant information from V1 to PFC, which in fact should appear as a mutual spike synchronization if we were able to resolve the single neuron signals as in the animal experiment. At 800 ms, in both cases there is a transfer from the PFC to the language areas; the subject reacts

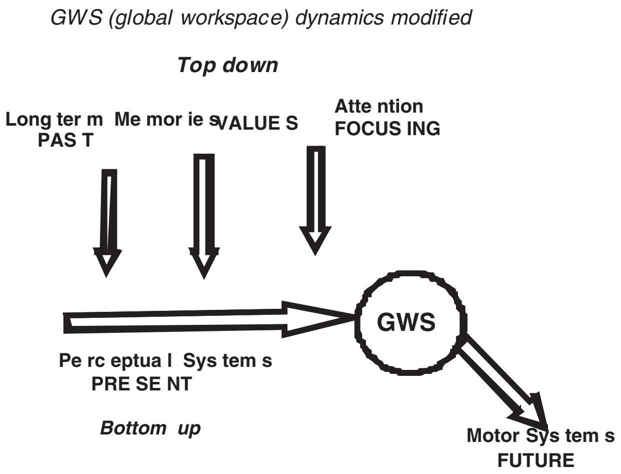

Figure 1. The GWS (global workspace) hypothesis: A network is fed by perceptual data consisting of bottom-up sensorial stimuli dressed up by top-down signals from memory, evaluation and attentional systems. As a result of the GWS elaboration, a signal emerges toward the motor systems.

by speaking about the stimulus and saying that he/she is seeing a meaningful or meaningless slide, respectively.

There has been a large amount of investigation of the temporal region up to around 1 s.

As discussed above, the PFC acts as an arrival station for different sensorial channels (visual, auditory, etc.) and as a departure station for the activation of motor and language areas.

Baars (1989) has formulated the GWS (global workspace) hypothesis, which has been extensively elaborated by Dehaene and Naccache (2001) and by Dehaene, Kerszberg, and Changeux (1998). The way GWS operates is explained by Figure 1. A sensorial stimulus, duly encoded, arrives at the perceptual systems (bottom-up signal) but its processing is affected by the agent's activity, which takes the forms of past memories, values, and attentional mechanisms (top-down recoding). The combination of bottom-up and top-down signals is "read" by the GWS and transformed into appropriate reactions that drive the motor and language areas.

A dynamic model (Leyva, Allaria, Boccaletti, & Arecchi, 2003) works as follows. Consider an array of HC systems, each one simulating a single neuron. The neurons have nearest-neighbor coupling, whose strength *e* models the amount of top-down perturbation. In the absence of a bottom-up input, each neuron yields HC spikes, depending on the initial condition and the amount of coupling. For $e = 0$ each neuron emits uncorrelated spikes. As *e* increases the spikes build strong mutual correlations, until the whole array is synchronized. Synchronization is not isochronism, that would be equal time of occurrence of spikes at different sites, but rather equal separation T_g of the spikes in adjacent sites.

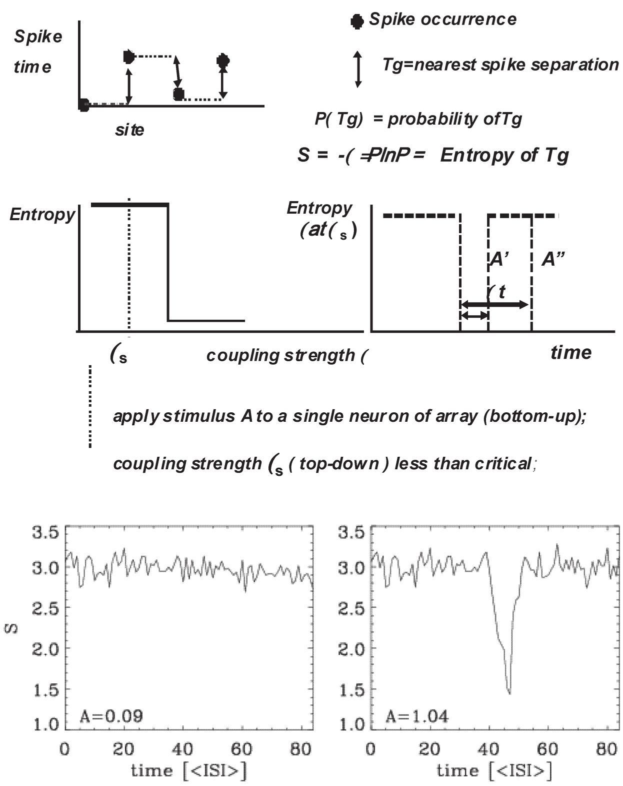

Figure 2. (Upper) Four successive sites with unequal spike separations T_g. The collection of all T_g is characterized by a probability distribution *P(T_g)*. We measured the disorder by the amount *S* of entropy of *P(T_g)*, using the Shannon formula. As we increase the coupling e, at a given threshold the entropy suddenly sinks; set T_g has become ordered, but in a semantic way, in the absence of an input. In order to transform the coupled array into a semantic network, we fix the coupling at e_s below the threshold value and apply input pulses of increasing amplitude A', A". Correspondingly, there are time windows of low entropy (collective synchronization) of variable durations Dt. The various Dt encode the different inputs.
(Lower) Numerical experiment (Ciszak et al., 2009): time evolution of entropy *S* for an array of 30 coupled systems with coupling below the threshold. At the first site an input pulse of duration dt = 1 *ISI* and amplitude either $A = 0.09$ (left) or $A = 0.104$ (right) are applied at time $t = 40$ *ISI*. In the first case, the input is insufficient to trigger a collective synchronization; in the second case, the stimulus induces an entropy reduction lasting for about 10 *ISI*.

So far, we have explored the role of the neuron couplings. The resulting collective synchronization is asemantic, as it occurs in the absence of an external (bottom-up) stimulus.

If, instead, we want to consider a semantic situation, we set the coupling low enough not to yield spontaneous synchronization, but sufficiently high to mimic an alert agent (Figure 2). Then the application of external inputs induces

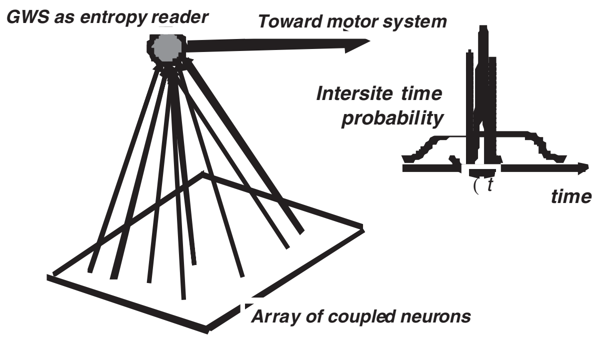

Figure 3. A dynamic model of GWS. GWS sums up all the spike amplitudes arriving from the array, which is equivalent to comparing the arrival times of the spikes from the array of coupled neurons where collective synchronization has occurred. Indeed, if the synchronized cluster is large enough, then many spikes from different sites sum up within a small time interval Dt, yielding a large signal, well above the low background corresponding to unsynchronized spike arrivals.

synchronized states lasting for a time depending on the stimulus (semantic encoding). As shown in Figure 2, the windows of ordered (low entropy) states depend on both the input and the coupling, thus, they represent a cognitive act as a combination of the stimulus and the agent's interpretation. The cognitive state appears as a time window of low entropy (Ciszak, Montina, & Arecchi, 2009).

Figure 3 shows how a GWS, seen as an entropy reader, can transform that cognition into an action. The amount of the top-down "dose" is crucial in shaping the cognition.

Do we claim that the final decision stemming from the GWS is an act of *free will*?

Not at all! Thus far we have utilized material stored in previous cognitive sessions, representing a finite repertoire. A cat, for example, seems free in its playing with prey; in fact, it is exploiting one option from a finite set it has learned during its training activity.

Even though we have called the large variety of possible elaborations *creativity*, it represents a finite set and, thus, it can, in principle, be interpreted in a deterministic fashion.

Altogether different will be the cognitive operation (B) that is peculiar to humans and where we will provide evidence of nondeterministic decisions, that is, the basis of free will.

Cognition (B) as Comparison of Different Presemantic Slots. The Inverse Bayes Inference

Bayes Inference

Thomas Bayes, looking for a reliable strategy to win games, elaborated the following probabilistic argument (Kriegel, 2006).

Let us formulate a manifold of hypotheses *h* about the initial situation of a system, attributing to each hypothesis a degree of confidence expressed by an a priori probability *P(h)*. Any hypothesis, introduced as input into a *model* of evolution, generates data. Let us assume that we know the model and, hence, can evaluate the probability of the *data conditioned* by a specific hypothesis *h*; we write it as *P(data|h)*. The model as an instruction to a computer represents an algorithm; it generates different data for different *h*. If now we perform a measurement and evaluate the probability *P(data)* of the data, we must conclude that there is an *h* more plausible than the other ones, precisely the one that maximizes the probability conditioned by the data *P(h|data)*, that we call the a posteriori probability of *h*.

This procedure is encapsulated in the formula, or theorem, of Bayes, that is

$$P(h|data) = P(h)\ [P(data|h)/P(data)]$$

To summarize, the a posteriori probability of *h*, conditioned by observed data, is given by the product of the a priori probability of *h*, times the probability *P(data|h)* of the data conditioned by a given *h*, that we call the *model,* and divided by the probability *P(data),* based on a previous class of trials.

Starting with a large number of presumed hypotheses *h*, the occurrence of the data selects the *h** that satisfies the above relation. Successive applications of the theorem yield an increasing plausibility of *h**; it is like climbing a mountain of probabilities along the maximum slope, up to the peak. After each measurement of the data and consequent evaluation of the a posteriori *h**, we reformulate a large number of new a priori *h* relative to the new situation, and so on. In this way, we climb a mountain, whose vertical

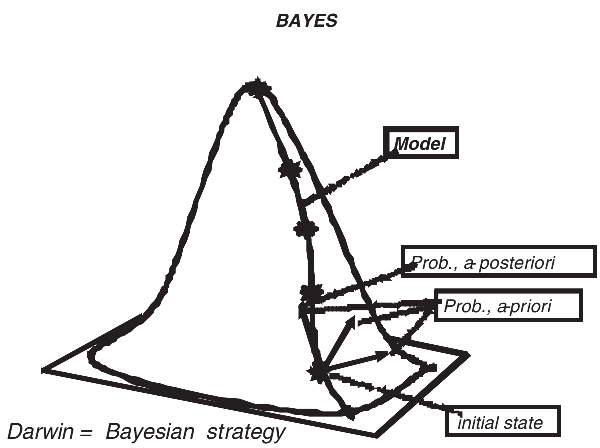

Figure 4. Successive applications of the Bayes theorem. The procedure is an ascent of the probability mountain through a steepest gradient line. Notice that Darwinian evolution by mutation and successive selection of the best fit mutant is a sequential implementation of Bayes theorem. Also the investigation style of Sherlock Holmes is Bayesian.

coordinate measures a probability while the horizontal plane represents the variables that rule the problem (Figure 4).

The evolutionary strategy put forward by Darwin, as sequences of mutations and selection, is an application of Bayes theorem, once we equate *fitness* with the probability mountain to be climbed. This procedure can be automatized on a computer, building an expert system that elaborates the experimental data formulating a diagnosis; it is useful in medicine, business, etc.

The procedure is *asemiotic*, that is, it handles symbols without raising questions on meaning. Some AI (artificial intelligence) experts have considered it as a paradigm of the way our mind operates.

However, this automatic procedure has a fundamental limitation. Once the peak has been reached, no further progress is possible; any further application would be a disastrous downhill trend. Having been limited by the uniqueness of the model or algorithm *P(data|h)*, the peak cannot be taken as the *truth;* at most, it represents the best we can do with the selected model.

Realizing that there are other possible models, and that the climbing can take place elsewhere, implies going beyond the empirical evidence provided by measurement and discovering a meaning in the observed aspects of the world under the guidance of the cultural background of the investigator.

We call *meaning* the existence of many peaks; it goes beyond information, which quantifies the increase of probability while climbing a single peak. We call *semantic complexity* the number of different peaks, that is, of different Bayes strategies we can undertake (Figure 5). Notice that it is a fuzzy concept, since the multiple peak landscape changes as our degrees of comprehension increases. Figure 5 is purely indicative; in general, the variables that rule our problem are more than two (for sake of presentation, we plot a horizontal plane as in Figure 4, even though the representative space should have as many dimensions as the variables) and the peaks more than three (as done for convenience in the figure). In fact, in models of complex systems, the number of different peaks increases exponentially with the number of variables. Furthermore, our interaction with the environment changes the number of peaks (think of a financial investor; the shape of the market changes as new investments are performed). For an insight on this matter, I refer to a book of mine (Arecchi, 2007a, 2007b).

The jump from one model to another is a nonalgorithmic operation.

The question arises: Can we foresee an evolution of the computing machines, so that they can swap algorithms by an adaptive procedure? The answer is *yes* within a finite repertoire. The swapping is based on a variational procedure whereby the next step is just a small variation of the previous one, which by itself has to be stable. Such is Holland's genetic algorithm (Holland, 1975).

In general, however, the selected Bayes model can be unstable and variations can introduce discontinuities. Furthermore, in the human case we can make *an infinite use of finite resources*, by building over the course of time *Chimeras*, that is, new models which combine parts of previous models in new ways.

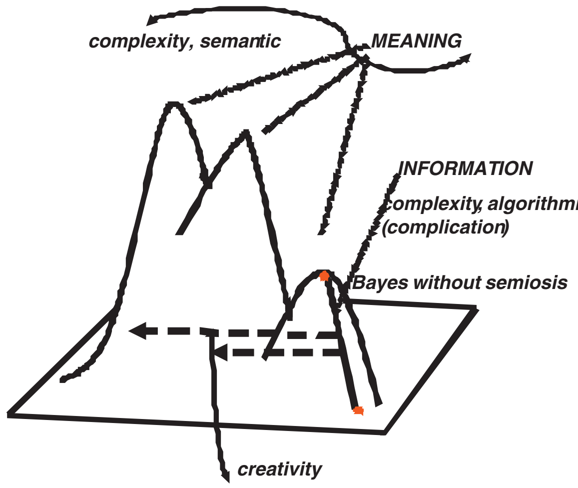

Figure 5. Semantic complexity. A complex system is one with a many-peaked probability landscape. The ascent to a single peak can be automated by a steepest gradient program based on a fixed algorithm as in the previous figure (Bayes without semiosis). On the contrary, to jump to other peaks, and thus to continue the Bayes strategy elsewhere, is a nonalgorithmic act of creativity, implying a holistic comprehension of the surrounding world. We call "meaning" the multipeak landscape and "semantic complexity" the number of peaks. We call "creativity" the nonalgorithmic jump from one model to another.

This implies violating the set of rules previously stipulated. We do not see how a machine can violate the plan upon which it has been designed. The nonalgorithmic jump enables a creative mathematician to grasp the truth of propositions compatible with a set of axioms but not accessible through the formalism one is using; this is the 1931 Goedel theorem (Arecchi, 2007b).

(B) Cognition as Inverse Bayes Inference

At a perceptual level, recoding in terms of past memories seems the most obvious type of consciousness. In fact, the top-down mechanism can be just an automatism. The 800 ms preceding a motor decision do not require explicit consciousness; free choice emerges on a much longer time scale as we repeat the same experiment with a memory of the best result.

We should account for two notions of consciousness.

(A), the *implicit* one, postulates a GWS, that is, an operation room for elaborate data acquired over different channels (auditory, visual). It operates on the global stimulus of large neuron arrays. The time associated with (A), called by Poeppel a *presemantic island* (Poeppel, 1997, 2004, 2009), can be up to 3 s, as the average switch time in the perception of ambiguous figures or in binocular rivalry. Within this island, the dynamic constitution of a collective state can precede awareness without having to raise philosophical problems of free will (Libet, 2004).

Explicit consciousness (B) is required to connect slots confined to different presemantic islands. The cognitive subject must be aware of him/herself combining pieces belonging to separate perceptions into a unique semantic whole. In doing this an articulated language is necessary.

A 3 s unit appears as the most convenient time window within which to compare each separate retrieved piece. Indeed, this is the best synchronization time in collective musical performances or in spoken narratives, as discussed extensively by Poeppel (Poeppel, 2004, 2009).

At this point I introduce the *inverse Bayes inference.*

If we have a sequence of acquired cognitions, we do not have to look for the most plausible hypothesis h^*, since it is already contained in the data stream. We simplify notation by writing the left hand side of Bayes formula as:

$$P(h^*) = P(h|data)$$

The unknown is no longer h^*, but rather the most adequate model that binds the subjective hypotheses h with data d and the already shown h^*. By inversion of the original Bayes formula we then have:

$$P(data|h) = P(data)\ P(h^*)/P(h)$$

In other words, (B) knowledge does not imply a model; on the contrary, (B) retrieves the most adequate model to connect the subjective hypotheses h with the reality stream, d and h^*.

Retrieving the best P(data|h) establishes an ontology, that is, truth can be defined according to Thomas Aquinas as *"adaequatio intellectus et rei."*

– *Question:* How does this strategy of inverse Bayes in semantic sequences compare to chaos control in dynamic sequences?
– *Answer:* In the same way as the chaotic dynamic is sensitive to the initial conditions (whence the information loss), here the model P(data|h) is sensitive to the accuracy of h.

In this case, the recoding consists of the "invention" of different models P1(data|h)), P2(data|h)) . . ., until one reaches the best one binding the chain of data.

One might object that Holland's algorithm (Holland, 1975) already explores different models; but it proceeds by gradual variations. Here instead we have a discontinuous jump, as it emerges from well-known instances of scientific creativity. Recall, for example, that Maxwell electromagnetism unified three distinct areas of investigation, namely, electricity, magnetism, and optics; however, the amount of knowledge available in those three areas was not sufficient to deduce the Maxwell equations.

Conclusion

We have explored two kinds of recoding, namely, (A) corresponding to a presemantic island, which relies on a limited repertoire; it is common to animals and a few of them are much better off than us (I would not like to meet a leopard in the wild . . .) and (B) that relies on self-consciousness and establishes an ontology.

The totality of the current literature on consciousness (J. Searle, A. Damasio, C. Koch, D. Dennett, J. Fodor, G. Edelman, G. Tononi, etc.) deals with the (A) time scales. Only Poeppel (Poeppel, 1997, 2004, 2009) has stressed the separation of the two time scales.

In a recent paper, Klonowski (2009) has emphasized the occurrence of two time scales widely separated for psychophysical processes, namely a short one for emotional states and a long one for thinking processes. From a dynamical point of view, both processes are treated by return maps, and the difference of time scales provides a simplified treatment. Consciousness is associated with the longer time scale.

In this regard, I have two remarks, namely, (1) no quantitative values are assigned to the two times, overlooking a plethora of experimental facts reviewed by Poeppel (Poeppel, 1997, 2004, 2009); (2) both processes are considered within the same dynamical formalism, whereas I discriminate between a dynamic process (A) where control of chaos plays a crucial role, and a linguistic endeavor (B), whereby a past event is retrieved from memory and compared with a new apprehension, thus reaching the most satisfactory comparison via an inverse Bayes process.

The dynamic process (A), (which seems to correspond to the whole "psychophysical" process in Klonowski, 2009), refers to apprehension and consists of stretching the duration of the GWS collective state in order to stimulate an appropriate motor reaction; in (A), consciousness does not seem to play a crucial role, even though the coherent GWS state may be accompanied by awareness.

On the contrary, in the (B) comparison of two different events, which triggers the inverse Bayes, self-consciousness is crucial insofar as the subject has to control the mutual correspondences of the two events in the effort to reach the best matching, which yields the judgment.

Acknowledgment

This work was done within the project "Dinamiche cerebrali" supported by Ente Cassa Risparmio Firenze.

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