

Phenomenology of Consciousness: from Apprehension to Judgment

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Abstract

We explore two different moments of human cognition, namely *apprehension* (A), whereby a coherent perception emerges by recruitment of large neuron groups and *judgment* (B), whereby memory retrieval of different (A) units coded in a suitable language and comparison of them leads to the formulation of a *judgment*.

The first one has a duration around 1 sec (from 0.5 to 3 sec), it appears as an a-temporal present and its neural correlate is a wide synchronization in the EEG gamma band. It may be described as an interpretation of sensorial stimuli in terms of some stored algorithm, via a Bayes procedure. The second one entails the comparison of two apprehensions acquired at different times, coded in a given language, and retrieved by memory. It lasts around 3 sec and requires *self-consciousness*, as the judging agent must be well aware that he/she is the same one who faces the two coded apprehensions under scrutiny in order to extract a mutual relation. At variance with (A) , (B) does not presuppose an algorithm, but it rather builds a new behavioural model by an inverse Bayes procedure. It will be shown how this build up of a novel model is related to creativity and free will.

Key Words:

neural synchronization, apprehension, judgment, Bayes inference, inverse Bayes

INTRODUCTION

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

The time frontier between (A) and (B) has been explored by E. Pöppel in several papers (Pöppel, 1997, 2004, 2009). The former one occurs over a time scale of a few hundred milliseconds up to 3 sec and it emerges from collective synchronization of the gamma band oscillations in wide brain areas; the end result is a coherent perception whereby the cognitive agent gains awareness of its environment (Rodriguez & al., 1999; Singer, 2007; Womelsdorf & Fries, 2007). The duration of (A) can be stretched up to 150 sec by meditation techniques (Lutz & al., 2004). The neural synchronization mechanism does not display relevant differences between humans and laboratory mammals (monkeys or cats); in fact, for (A) it makes sense to explore neural correlates of consciousness (NCC). Introduction of the term *consciousness* requires an adequate definition. Many papers and books have been recently written on this subject. Comprehensive reviews are provided by Van Gulick(2008) and Werner (2007) Broadly speaking, so far it has been common in this debate to identify consciousness with the awareness of a coherent perception, that is, the occurrence of a specific event that elicits a motor reaction; that's why a search for NCC has been pursued

The various (A) slots can be retrieved by memory processes and exploited for motor decisions; this occurs in the everyday life of the cognitive agent. Even a stretching of this time scale does not change the above picture; we speak always of (A) processes.

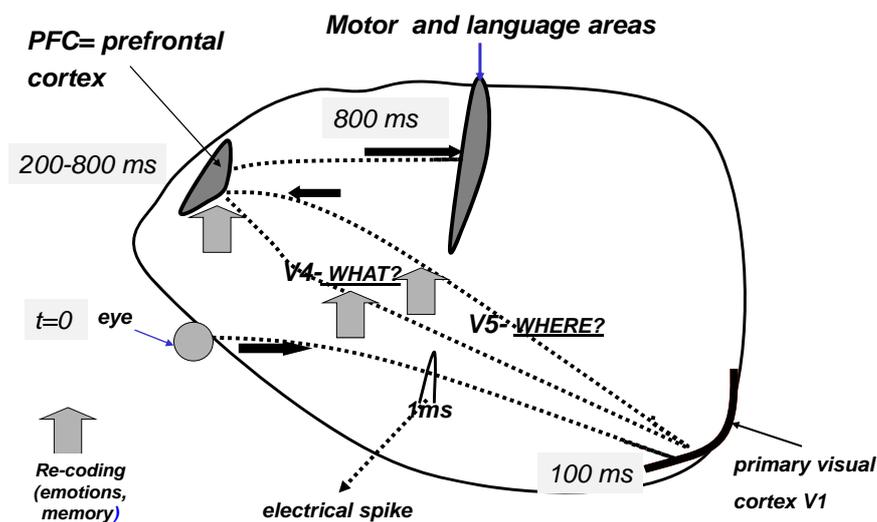
Ned Block (2005, 2009) has distinguished between phenomenal consciousness (P-C), the subjective "what is to be like" and access consciousness (A-C), that is, the content of P-C made available for further action as motor responses. This distinction refers to same time scale of (A) processes; in fact several authors question the same distinction between P-C and A-C (Kriegel, 2006).

In human beings (and, as far as we know, only in them) the (A) information can be encoded in a convenient language and stored not just as a motor decision but as a self-contained meaningful unit. The various linguistic slots can be mutually compared in order to extract a global trend in the sequence. This occurs over times above 3 sec; let us call (B) this operation that implies the previous coding of each (A) unit into some language. (B) is no longer a unique synchronization process, since the comparison implies the presence of differences between different units. In order for (B) to be effective, the cognitive subject ought to be conscious of his/her acting in a consistent way in exploring the different linguistic (A) units, thus, (B) is not mere *perceptual awareness* but *self-consciousness*. We will explain (B) in terms of what we call "inverse Bayes process". From now on, whenever we speak of consciousness we mean self-consciousness guiding the (B) process and not merely awareness of an apprehension (A).

As we shall see, the standard direct Bayes process (Bayes, 1763) has already been shown to play a crucial role in fast decisions (Wolpert & al.,1995; Kording & Wolpert,2006; Ma,Beck & Pouget,2008; Baratgin & Politzer,2006). It conveniently epitomizes the collective neuron synchronization that yields (A). The Appendix illustrates how a dynamical process as the feature binding can be seen as a Bayes inference. The inverse process, here outlined (Arecchi,2010), permits to formulate a *judgment*, whereas (A) with its neural synchronization basis is limited to *apprehension*. This is in line with the two successive cognitive actions which characterize human *insight* (Lonergan, 1957).

Fig.1 outlines the transient brain operations as a human subject performs a visual perception. We realize that we have had a coherent perception or *apprehension* as a sensorial stimulus elicits an adequate response (either a motor decision or a linguistic formulation). Referring to the visual perception, and exposing the subject to an image at time $t=0$, the visual stimulus is coded as a train of electric impulses (spikes) each one lasting for 1 millisecond and with a mutual separation (called ISI= interspike interval) which encodes the signal features. These spikes travel toward the primary visual cortex V1 at a speed of about 1m/sec, thus they arrive at V1 after 100 msec. From V1 they undergo a processing over two channels, namely, the *WHAT* (processing shapes and colours) and the *WHERE* (processing space and time relations). In the processing, the input stimuli (called bottom-up signals) are modified (re-coded) by top-down signals coming from the semantic memory (previous perceptions already categorized, emotions, attention, etc). The two separate streams converge toward the PFC (prefrontal cortex). After a further half a second, a decision is forecast to the motor and language areas and an official record of a coherent perception emerges through the agent's reactions.

I have outlined the times as reported in laboratory sessions (Rodriguez et al., 1999) , in normal situations; the long processing times in the PFC correspond to a tentative search with successive top-down presentations of multiple alternatives, selecting eventually the one that best matches the features of the input stimulus. The procedure has been modelled in many computational approaches; I find particularly suggestive the adaptive resonance theory (ART) by Steve Grossberg (Grossberg, 1987; Carpenter & Grossberg, 2003). If a rapid processing is requested (e.g. braking or steering the car in emergence, or responding to a fast tennis service), then 800 msec would be too long and we reduce the processing times avoiding a long search and recurring to learned procedures through a Bayesian strategy that will be illustrated later on.



1. Fig.1-Visual Perception: paths and times .The thin contour line is a schematic representation of the neo-cortex (thickness about 2 mm). Time sequence of brain events following a visual stimulus on the retina at time $t=0$. After 100 msec, the signal coded as a train of electrical pulses reaches the primary visual cortex V1. The signal from V1 is then elaborated in two distinct areas, V4 or WHAT area, and V5 or WHERE area. The

separate information is combined in the prefrontal cortex (PFC) together with top-down signals coming from the inner brain (emotions, memory). This mixing takes about half a second starting from 200 msec; at 800 msec after the sensitization of the retina, a decision emerges activating the motor and language areas,

THE CHAOTIC BRAIN

If we store in the memory just the end result, as the perception has been shaped, we must provide a suitable dynamical description for what goes on in the 800 msec (let us for simplicity round this perception time up to 1 sec; as a fact, there are wide timing fluctuations from one perception to another, and from an individual to another). Holding dynamical coherence over 1 sec is not compatible with the response of a single isolated neuron, due to the onset of deterministic chaos.

A single isolated neuron is a dynamical system affected by deterministic chaos (Arecchi, 2004). This is an outstanding challenge to the Newtonian –Laplacean tenet that the future of a physical system subject to known forces is uniquely determined, once we assign the initial conditions. As a fact, the initial conditions are a set of numbers, and in general we handle truncated versions of real numbers, whose geometric representation is a segment rather than a point. To explore the consequences of an ill-defined initial condition, apply a small transverse perturbation to a Newtonian trajectory. If the system is transversally stable, it will return to the ideal trajectory; if it is transversally unstable, the new trajectory after the perturbation will gradually diverge from the ideal one. Such behaviour is called *deterministic chaos*; as a result, some initial information is lost after a finite time that in the case of an isolated neuron is around 2 msec (Arecchi, 2004).

Deterministic chaos can be controlled by adding a suitable perturbation which modifies the transverse stability without affecting the longitudinal trajectory (Ott, Grebogi & Yorke, 1990). Thus, control amounts to a re-coding operation, say, from N degrees of freedom to $N+m$ (where the added m ones assure an increase of the transverse stability).

We arrive at a central result of neuroscience, namely, a perception is not just the imprint of an external object, as it occurs on the back of a photo-camera, but it is the result of an arrangement between bottom-up stimuli and top-down interpretations as shown in fig.2. Here global workspace (GWS) is the name given (Baars, 1989) to the processing unit from where a motor decision emerges. In the visual case (Fig.1) we identified the GWS with the pre-frontal cortex (PFC).

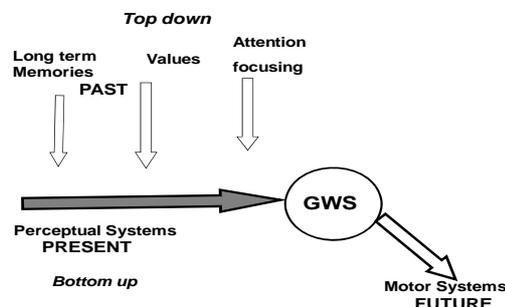


Fig. 2 Global workspace (GWS) dynamics . Combination of bottom-up stimuli and top-down perturbations to provide a coherent input (apprehension) that the GWS codes as a motor decision. The external stimulus (bottom up) is modified by interpretational hypotheses (top down) and becomes a coherent perception fed to the GWS from where a motor decision emerges

How does GWS choose among competing signal arriving to it? The *feature binding* hypothesis (Singer, 2007) says that all the neurons engaged in processing signals corresponding to the same feature emit trains of synchronized neuron spikes. Collective synchronization is a robust behaviour that can last long enough to elicit a GWS decision; it has to be considered as the outcome of individual sensory inputs plus mutual neuron couplings that all together implement the control of chaos, increasing the duration of some relevant information up to a time sufficient to alert the GWS. It is hypothesized (Baars, 1989, Dehaene & Naccache, 2001) that in presence of an external stimulus (bottom-up signal) different neuronal areas undergo collective synchronization, each one under different top-down perturbations corresponding to different interpretations of the input. The different synchronized areas compete among themselves. If GWS acts as a threshold system that reacts only above a given level, than, among the competing neuronal groups, the winner should be the one where the largest synchronized domain has occurred and its *interpretation*, that is, its way of looking at the input, will drive the GWS output, that is, the motor reaction.

Experimental evidence of synchronization is provided in laboratory animals by correlating the signals picked up by microelectrodes sensing the single axons (Singer, 2007). In human subjects, the microelectrodes would be too invasive; but the standard EEG does not provide enough resolution. However, filtering a quasi-sinusoid in the gamma band (range of frequencies between 40 and 70 Hertz, peculiar of the neural computation processes) one can uncover a phase locking between the filtered signals extracted from distant cortical areas ,e.g. V1 and PFC. This locking provides evidence of synchronization of the neurons belonging to the selected areas(Rodriguez et al., 1999)

APPREHENSION AS BAYES INFERENCE

So far, we have been treating synchronization as the collective behaviour of a large array of neurons, each one behaving as a chaotic dynamical system .As a fact, in a wet brain it is hard to exploit a Newtonian approach , whereby an equation establishes a functional relation F between data d and hypotheses h , that is,

$$d=F(h)$$

To be less model-dependent, we replace the dynamics with a statistical approach based on Bayes inference (Bayes, 1763). It consists of the following procedure.

- i) Starting from an initial situation, formulate a wide set of hypotheses h , each of which being assigned an a-priori probability $P(h)$;
- ii) Each h ,inserted into a *model of evolution*, generates data d with the conditional probability $P(d|h)$ that d results from h ;
- iii) Doing a measurement, we observe a particular data d , with an associated probability $P(d)$;
- iv) The combination of iii)+ii) selects a particular hypothesis h^* that has the highest *a posteriori* probability among i).

To summarize:

$$P(h^*) = P(h/d) = P(h) \cdot P(d/h) / P(d)$$

Whence h^* denotes the most plausible hypothesis, since it has the largest probability.

In a probability space, we can update the vantage point and repeat the procedure in a recursive way, sticking to the same algorithm corresponding to the chosen model $P(d/h)$. It is like climbing a probability mountain, whose top represents the maximum plausibility (Arecchi, 2007 a, b).

The model $P(d/h)$ is the *algorithm* that we provide to a computer, making it an *expert system* that formulates wide sets of hypotheses to be compared with the data.

We interpret an *apprehension* as a Bayes inference, as follows (Fig.3). Within the synchronization interval (around 1 sec) the following things occur. One has to select the most plausible hypothesis h^* among a large number of h . The memory is equipped with a procedural model $P(d/h)$ that generates a data d for each h ; on the other hand, the sensorial input consists of a precise d ; thus Bayes procedure selects the a posteriori h^* that best fits the actual data d . In conclusion, out of a wide set of hypotheses h , the actual data d constrains the selection of the most plausible hypothesis h^* , via the algorithm, or model, $P(d/h)$. (Fig3)

Swapping model is a re-coding operation that takes place during the half-second processing that occurs between the arrival of the bottom-up stimuli and the expression of a suitable reaction in terms of motor decisions. This top-down elaboration exploits a set of models $P(d/h)$ retrieved from the memory, selecting what the inner mechanisms (emotions, values, attention) suggest as the most appropriate. This model set is built in previous training stages in animals or inserted as instructions in robots, anyhow, the set is finite both for animals and robots.

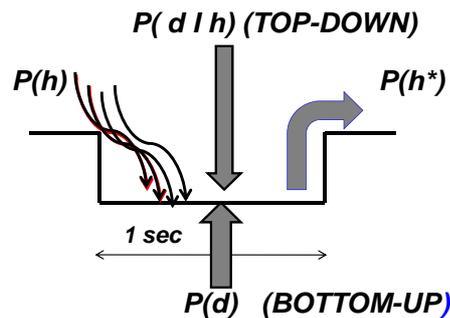


Fig.3- Apprehension as Bayes inference (h =a priori hypotheses; d = data). Selection of the a posteriori hypothesis h^* starting from a manifold of h , by joint action of a sensory stimulus (bottom-up) and an interpretation model (top-down).

THE PROBLEM OF COMPLEXITY - GÖDEL ARGUMENT

Successive applications of the Bayes inference using the same algorithm correspond to successive apprehensions whereby we increase the plausibility of the final guess h^* upon which the agent reacts (Fig.4). The procedure consists in climbing up the probability mountain through a steepest gradient line. Each point of the line carries information related to the local probability by Shannon formula. An investigator as Sherlock Holmes is strictly Bayesian. He has a model of the crime (algorithm) and he tests different hypotheses sets h , by comparing them at each step with collected data d and thus extracting the most plausible one h^* . The process is then re-iterated in a recursive way, sticking to the same model, but with updated datasets d . Such a procedure is nowadays implemented in *expert systems* that assist the medical diagnosis.

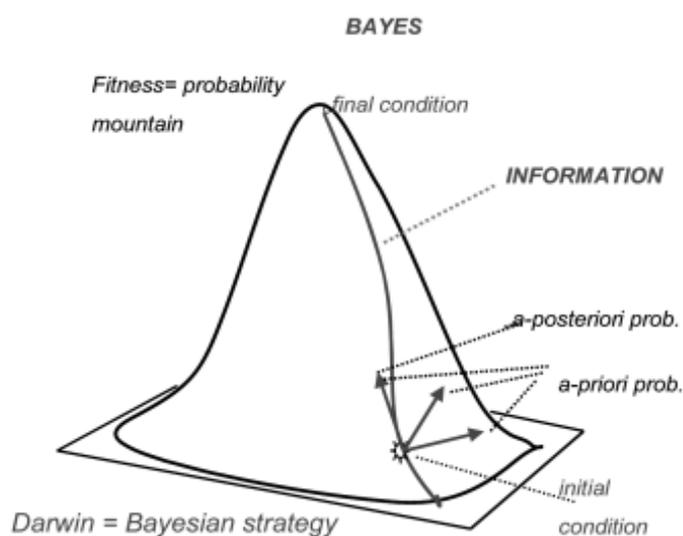


Fig.4- Successive applications of Bayes to the experiments.

However, living in a complex environment entails a change of algorithm in successive endeavours. Fig.4 can be seen as the implementation of an ecological process, whereby a cognitive agent, equipped with a world model $P(d/h)$, interacts in a recursive way with the environment, updating its starting point. This does not work in a complex situation. Based on two decades of intensive debate, we can define complexity as a situation that cannot be grasped by a single model. Swapping algorithm is a non-algorithmic procedure; a complex system is one with a many-mountain probability landscape (fig.5). Climbing up a single slope can be automatized by a steepest gradient program. It is a non-semiotic procedure, and the corresponding algorithm can be assigned a Chaitin algorithmic complexity (Chaitin, 1987). On the contrary, to jump to other slopes, and thus continue the Bayes strategy elsewhere, is a creativity act, implying a holistic comprehension of the surrounding world (*semiosis*). We call “*semantically complex*” the multi-mountain landscape and attribute a different meaning to each peak. It has been guessed that semiosis is the property that discriminates living beings from Turing machines (Sebeok, 1992). Here we show that a non-algorithmic procedure, that is, a jump from one Bayesian model to another is what we have called *creativity*. Semiosis is then equivalent to *creativity*, as outlined in Fig.5. The difference between a single Bayesian strategy and a creative jump is the same as the difference between normal science and paradigm shift (Kuhn, 1962)

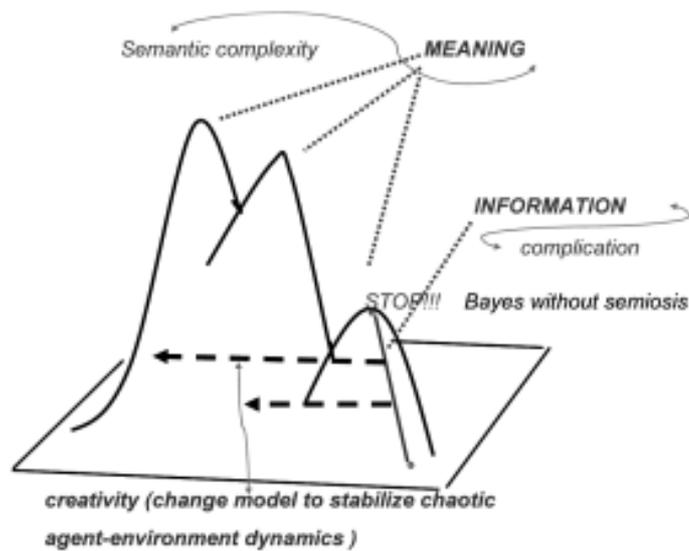


Fig.5- - Semantic complexity –

The Gödel’s first incompleteness theorem (1931) can be considered as a creative jump in a complex landscape, as illustrated in Fig.6. The theorem states that, for any consistent formal and computably enumerable theory that proves basic arithmetical truths, an arithmetical statement that is true, but not provable in the theory, can be constructed. “Provable in the theory” means “derivable from the axioms and primitive notions of the theory, using standard first-order logic”. The logical steps occurring in that statement are graphically represented in Fig.6. There is a computer equivalent of this theorem, that Turing (Turing, 1936) called the Halting *problem*, namely, a universal computer, for a generic input, cannot decide to stop.

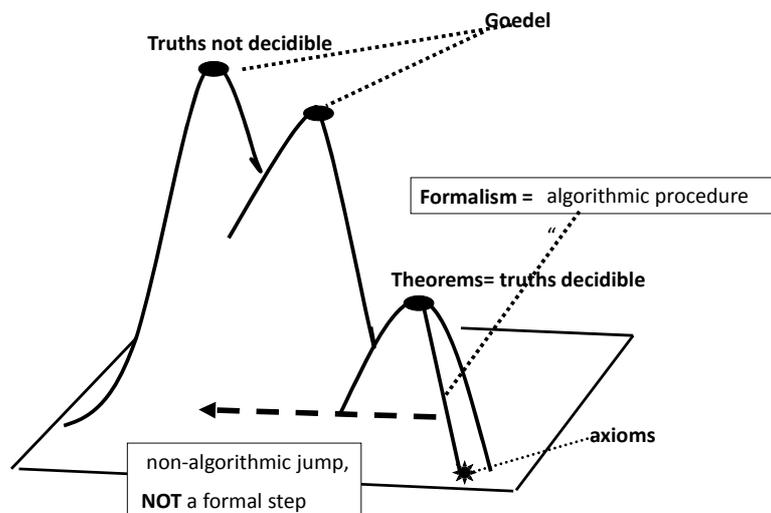


Fig. 6-From Bayes to Gödel

BIRTH OF LANGUAGES

The jump from a model to another, guided by *semiosis*, is a non-algorithmic operation, peculiar of a living being in interaction with the environment. The question arises: can we foresee an evolution of the computing machines, so that they can swap algorithm by an adaptive procedure? The answer is *yes* within a scenario with a finite repertoire. Furthermore, the swapping is based on a variational procedure whereby the next model is just a small variation of the previous one which by itself has to be structurally stable. Such is Holland's genetic algorithm (Holland, 1992).

However the application of a selected Bayes algorithm to a complex environment can lead to instabilities, in the sense that a small variation might introduce discontinuous jumps. This requires recurring to an altogether different algorithm, that is, violating the set of rules previously stipulated.. Such a *non algorithmic 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 Gödel theorem (fig.6). We do not see how a machine can violate the plan upon which it has been designed, going well beyond the variational changes allowed by a genetic algorithm strategy.

The birth of a language offers a solution to the above conundrum. In humans, an apprehension can be coded in a suitable language (literary, or musical or pictorial) .The encoded message is later retrieved by memory and compared to the linguistic formulations of other apprehensions, eventually modifying the model $P(d/h)$ in a way that corresponds to a hypotheses swapping. This amounts to revisiting the same situation, but from a different point of view. The next Section explores such a linguistic procedure. We just anticipate that it is not bound to a finite set, indeed human language has been denoted as "*Making an infinite use of a finite set of resources*" (credited to Wilhelm von Humboldt, 1836, see Nowak & Krakauer, 1999), thus, such a re-formulation of the same cognitive event from a different point of view must be considered as a non-algorithmic step.

This suggests a definition of *Consciousness* (C) as the exploration of various $P(d/h)$ strategies, selecting the one that best fits the stream of data as they arise in linguistic sessions. C. is distinct from *Perceptual Awareness*, for which suitable indicators (called neural correlates of consciousness (NCC)) have been explored (Koch, 2004). As a fact, C. does not seem to have a specific NCC, insofar as it builds up over several apprehension sessions, each one characterized by its own NCC (Arecchi, 2010).Such a question will be explored in better detail in the next Section.

JUDGMENT AS AN INVERSE BAYES PROCEDURE

Thus far, we have considered a single time scale around 1 sec, associated with *apprehension* (A). It results from synchronized clusters accessing GWS in a competitive way. It must be considered as an a-temporal present, since a coherent perception implies a readjustment of the time scales of different sensorial channels (auditory , visual, etc) which per se evolve with different speeds (Singer,2007). As we have seen above, (A) represents the implementation of a dynamical strategy, namely, control of chaos; it is however only partially deterministic, since in

a wet brain the deterministic evolution is better replaced by a Bayes inference. (A) is common to all higher animals and indeed it is mainly explored in laboratory cats or monkeys (Singer, 2007). The duration of this a-temporal synchronization event is extensible by suitable top-down feedback up to 150 sec, as reported for trained meditating subjects (Lutz &al., 2004).

A second crucial time scale is associated with the linguistic comparison between the present apprehension and a past one, both encoded in a suitable language. The two events are co-present in the central part of a 3 sec window. Roughly speaking, comparison requires three times the standard time necessary to acquire an apprehension (A); precisely, 1sec is required to be aware of the last presentation (say, d in Bayes jargon), another 1 sec to retrieve a previous presentation h^* , and an intermediate 1 sec to render d and h^* co-present, that is, to merge both in a common feature binding. We call this comparison lasting around 3 sec as *judgment* (B) Within B), one proceeds by inverse Bayes (Arecchi, 2010). Let us be more detailed.

In apprehension we operate via direct Bayes, that is, the unknown is the most plausible hypothesis h^* , and we recover it via the top-down algorithm $P(d|h)$ plus knowledge of the bottom-up data probability $P(d)$ as follows

$$P(h^*) = P(h/d) = P(h) \times P(d|h) / P(d)$$

On the contrary, as we compare a piece of a text d with a previous one h^* retrieved from memory (say, two successive verses of a poem or two successive measures of a melody), the unknown is now the most suitable algorithm that best matches d and h^* . It results as solution of the inverse Bayes relation, namely,

$$P(d|h) = P(d) \times P(h^*)/P(h)$$

This procedure, which occurs only in humans because it requires the encoding of apprehensions in a symbolic language, is represented in Fig.7.

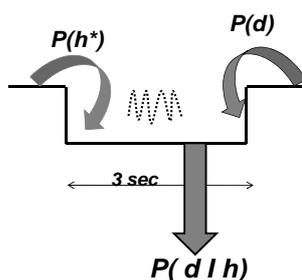


Fig 7-Judgment as inverse Bayes procedure. Comparison of d with h^* , whence the most adequate model $P(d|h)$ emerges a posteriori, instead of being presupposed a priori as in Fig.3.

This way, we have recovered a crucial point of cognitive philosophy. Pre-scientific cognitive formulations (Thomas Aquinas, 1269) were confident to grasp real *things*. On the contrary, Galileo’s formulation (Galilei, 1612) consisted of rejecting the notion of *thing* as meaningless and replacing it with the notion of *object*, as a collection of features measured by reliable apparatuses and hence valid for any observer. Since 1612, modern science has been built as a set of mathematical relations among the numbers encoding the measurements.

Nowadays the *object* as a collection of numbers has become a familiar notion as the bar code of an item in a market. However I do not know of anybody who takes pleasure in looking at the bar code of an apple rather than grasping a real apple. The exploration of complexity has shown the limitation of the notion of *object* and the inverse Bayes procedure recovers the *thing* whose features d are conditional upon the point of observation h , namely $P(d | h)$.

An object-based science is an investigation that can be automatized, in the sense that a computer program can retrieve the relations among different quantitative features. Such was the claim of Herbert Simon when he devised the program Bacon that inferred Kepler’s laws from the astronomical data available in early XVII century (Langley&al., 1987). In fact, the Keplerian problem has no complexity at all; on the contrary, if we explore complex problems we do not expect that a computer can replace the scientific creativity (Arecchi, 2007 b)

This re-adjustment of our mental codes to the thing is indeed the technical definition of truth as in Thomas Aquinas (1269): *Veritas est adaequatio intellectus et rei (Truth is the conformity of the intellect to the things)*. Furthermore, the re-adjustment of the point of observation in sequential inverse Bayes provides a solution to Plato’s paradoxical statement that our senses deceive us because we are like prisoners in a cave obliged to see only the shadows of reality projected on the wall of the cave. In fact, if we keep observing shadows under diverse vantage points, by comparing the data collected at different hours of the day, we succeed in building an adequate image of reality.

The two cognitive tasks, namely, *apprehension* and *judgment*, require further comparison. Fig.8 is a synopsis of what already sketched in Figs.3 and 7.

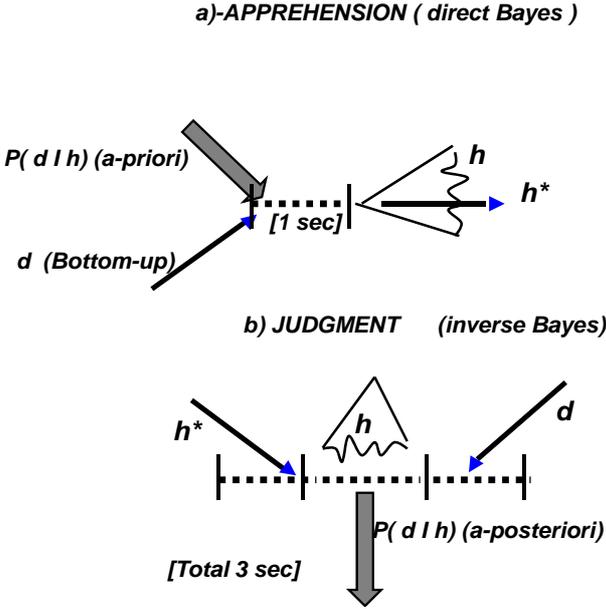


Fig. 8- a) *APPREHENSION*. It is a selection of h^* out of a fan of h , by the joint action of a bottom –up stimulus d and the interpretational model $P(d|h)$, given a priori. This task takes about 1 sec and it can be associated with some measurement (NCC). b) *JUDGMENT*. It is a comparison of two coded apprehensions d and h^* , whereby the most adequate link $P(d|h)$ emerges a posteriori.

Experimental research explores by different techniques the so-called neural correlates of consciousness (NCC) (Koch,2004). As a fact, NCC can visualize the recruitment of neuronal groups for tasks related to apprehension (1sec unit) .In the case of a judgment, it consists of three separate 1 sec units, namely, one corresponding to the apprehension and coding of d ,one corresponding to the retrieval of h^* and one for comparing the two encoded apprehensions so that a suitable interpretive model can be formulated (Fig.8). As discussed in Koch (2004), we should expect separate NCC's for the three 1 sec units, but no comprehensive NCC for the whole judgment.

Consciousness as discussed in NCC means awareness of a specific apprehension. When deciding some motor action, this awareness can be displayed with some delay with respect to the occurrence of the readiness potentials that trigger the action (Libet,2004). This has been taken as an experimental evidence of the lack of a free will, insofar as we become aware of a decision once that has already been taken without request of a consensus.

Instead of the above definition, we define consciousness or, better to say, *self-consciousness* as the awareness of an agent of being the same judge who scrutinizes the last data d and the retrieved data h^* in order to build a suitable a posteriori connection $P(d|h)$. This a posteriori $P(d|h)$ provides a guide rule upon which we uncover the deep relations of the parts of a linguistic piece (poem, music, painting, etc) or of a situation which requires some ethical decision on our side. This decision, being the result of a judgment, is free in the sense that it is based on the outcomes of a personal endeavor. Furthermore, it occurs over times much longer than Libet's times, thus it escapes the above reported order reversal.

BAYESIAN MODELS OF COGNITIVE BEHAVIOR - CREATIVITY

In the areas considered in this paper, there is a large amount of literature. To be more specific, in *psychophysics*. many aspects of human perceptual or motor behavior are modeled with Bayesian statistics (Kording and Wolpert, 2008); in *neural coding*, many theoretical studies ask how the nervous system could implement Bayesian algorithms (Doya, Ishii and Pouget, 2007); as for models of *cognition*, there is a vast amount of work, see e.g. Griffiths, Kemp and Tenenbaum (2008) and the homepages of these Authors.

From my point of view of a physicist active in dynamical systems and complex phenomena, two key points have been somewhat overlooked so far, namely, *i*) the logical connections between Bayes inference and nonlinear dynamics and *ii*) the time constraints of any judgment, that represent an ecological framework within which judgments are created in the scientific, aesthetic and ethical activity.

i) Bayesian inference versus nonlinear dynamics

Deterministic brain theories start from the dynamical equations ruling the single neuron (microscopic approach). What is common to all neuron models is that the dynamical landscape includes a saddle focus as the main singularity; the homoclinic return to such a singularity explains the trains of equal spikes with erratic interspike intervals (Arecchi,2004) in qualitative agreement with the observations done with microelectrodes probing a single axon

(Singer,2007). The transition to a macroscopic picture is done by connecting large networks of neurons with varying degrees of connectivity. A direct macroscopic approach has been built by adapting the quantum field theory of phase transitions in condensed matter, and looking for analogies with the EEG data (Freeman & Vitiello, 2006).

The Bayesian approach can be rooted to the above dynamical models as follows. The Appendix below shows how the central term of Bayes inference, namely, the conditional probability $P(d | h)$ of yielding data d from the hypothesis h , is in fact a smoothed version of the solution of a deterministic equation. This hints to a connection between the two approaches. Rather than postulating an appropriate $P(d | h)$ to implement a given goal, one can carry an ideal dynamical case, including the passage from the microscopic to the macroscopic level, and then spread the resulting deterministic solution to account for environmental noise. The resulting $P(d | h)$ is no longer an empirical artefact, but it has a sound logical foundation.

ii) *Time constraints in judgment formulation*

As discussed with reference to Figs.7 and 8b), judgment consists of the a posteriori extraction of the same inferential tool $P(d | h)$ that in *i)* was assigned a priori. Here, d and h^* are lumps of data gathered at different times, as e.g. two consecutive verses of a poem, or two consecutive measures of a melody, or two distinct areas of a painting focused by separate and consecutive eye fixations . The two lumps under comparison must be coded in the same language. Furthermore, they ought to be adjacent, whence the 3 sec requirement. If we extend the cognitive interval beyond 3 sec, we do not deepen the comparison, but rather include other lumps of data (Pöppel, 2004). If we have to increase the detail of $P(d | h)$, we must repeat the session with the same lumps d and h^* , over and over again.

As far as I know, such a type of investigation on time constraints has been faced so far only by Pöppel (1997 to 2009). In my research group we are exploring this issue with several experimental sessions (unpublished work).

Let us now elaborate on *creativity*. If we identify *creativity* with the discovery of a novel connection $P(d | h)$, then the time allotted for the comparison of the two lumps is a crucial parameter. In this approach, *creativity* has been considered as the most appropriate interpretation of the relation between two already existing lumps. This corresponds to a sensible reading of an already available text. The same creative steps are also the core of a new production, indeed, a new $P(d | h)$ is instrumental not only in building a bridge between the n -th and the $(n+1)$ -th verse of a given poem, but also in inspiring the $(n+1)$ -th verse once the deep meaning of the n -th verse has been grasped through its relation with the $(n-1)$ -th one.

The bridge toward a still not-existing lump can be extended to any artistic production (music, painting) and it is also the driving force of scientific creativity and ethical decisions. Thus, *creativity* as here considered might lead to new insights in scientific discovery and in social sciences.

iii) *Inverse Bayes versus Bayesian optimal experimental design*

A challenging novel area is that of Bayesian optimal experimental design (OED), reviewed by Nelson (2008). It deals however with situations described by a finite number of features; in such a case, it offers tools that can be implemented in a variety of information tasks (see Table 10 of Nelson (2008)). OED does not offer any helpful clue to linguistic endeavours, as discussed in our inverse Bayes approach.

APPENDIX - BAYES VERSUS DETERMINISTIC DYNAMICS

Recall Bayes formula

$$P(h | d) = \frac{P(h)P(d | h)}{P(d)} \quad (1)$$

In its original formulation, Bayes inference replaces dynamical determinism whenever the force law is not well assigned (noise or stochastic fluctuations)
In fact the so called *model*, that is, the conditional probability $P(d | h)$ of having a data d starting from a hypothesis h , replaces the solution

$$d = F(h, t) \quad (2)$$

of a dynamical equation, that establishes a precise relation between the hypotheses h assumed as initial conditions and the outcome d . We may rewrite the dynamical relation as a conditional probability by using Dirac delta function, namely

$$P(d | h) = \delta(d - F(h, t)).$$

However, due to a finite resolution Δd in measuring d , one in fact observes

$$P(d | h) = \int_{\Delta d} \delta(d - F(h, t)) dd = 1 \quad (3)$$

Thus, in the dynamical deterministic limit, data emerge with certainty from assigned initial conditions.

As for the denominator of Bayes, we can write it as

$$P(d) = \sum_h P(d | h)P(h) = P(d | h)P(h) + P(d | \neg h)P(\neg h) \quad (4)$$

where $\neg h$ denotes the hypotheses set complementary to h . In the deterministic case, the second conditional probability of reaching the narrow window Δd starting from $\neg h$ is zero, that is,

$$P(d | \neg h) = \int_{\Delta d} \delta(d - F(\neg h)) dd = 0 \quad (5)$$

Hence, in the dynamical case it results

$$P(d) = P(h) \quad (6)$$

Replacing (2) and (5) into (1), Bayes becomes the trivial identity

$$P(h | d) = 1,$$

That is, the dynamical retrieval of a hypothesis h from measured data d is 100% accurate.

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