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REPRESENTING IN ORDER TO INTERACT: AN INTERACTIONIST APPROACH TO ONTOLOGY

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A dissertation submitted in satisfaction of the requirements for the degree of Doctor of Philosophy in the Post-Graduate Program in Philosophy
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Tutor: Prof. Dr. Décio Krause

Florianópolis
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REPRESENTING IN ORDER TO INTERACT:
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A dissertation submitted in satisfaction of the requirements for the degree of Doctor of Philosophy in the Post-Graduate Program in Philosophy

Florianópolis, de 2015.

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“Em ciência, não é necessário que um
homem trilhe seu caminho
pisando apenas em verdades, quando, às
vezes, é suficiente que ele inspire outros a
pensarem de forma diferente.”
Newton da Costa

RESUMO

A presente tese consiste em um ensaio de ontologia, o qual chamo de Interacionista. A Ontologia Interacionista afirma que a realidade consiste nessas restrições que limitam o campo de interações possíveis para aquele das interações com sucesso com o entorno. Contudo, como qualquer sentido de realidade que venhamos a ter advém de nossa experiência interna, meu primeiro esforço será o de relacionar nossa noção intuitiva e interna de realidade com essa de interação. Desse modo, no segundo capítulo, interpreto o Sistema Nervoso Central (SNC) como um sistema de controle que produz motricidade a fim preservar a vida do organismo. Nossas representações internas são entendidas como uma estratégia para melhorar o desempenho de controle. A eficiência do controle depende da capacidade de processamento de informação, que por sua vez reflete na qualidade de nossas representações. Nesse contexto, qualquer conteúdo representacional, quer sejam nossas representações biológicas ou qualquer representação formal, é interpretado como cumprindo um papel de produção de ação. No terceiro capítulo, questiono sobre se o processamento de informação do SNC teria alguma perda de informação – isto é, se nós seríamos capazes de "ver" toda a realidade. Defino uma medida do desempenho do SNC em termos de ações com sucesso: nenhuma perda implica nenhum acidente e alguma perda implica em algum acidente. No quarto capítulo, assumo que nossa percepção é um caso de processamento com perda de informação e investigo sobre como o SNC escolhe os bits adequados para a sobrevivência do organismo. Minha explicação reserva um lugar tanto para a contribuição evolucionária quanto para a cultural. A contribuição evolucionária a nossa percepção ocorre ao nível do sistema de processamento periférico a qual define um amplo conjunto de categorias – os aspectos mais gerais de nossa percepção. A contribuição cultural ocorre ao longo do desenvolvimento do organismo e define um conjunto mais específico de características da percepção. Defendo que fatores culturais, desde interações entre grupos sociais até o manuseio de linguagens formais, formam um espectro contínuo moldando nossa percepção. No quinto capítulo, questiono sobre como o SNC poderia aumentar seu processamento de informação. Interpreto o advento do surgimento das linguagens simbólicas como uma estratégia que reduz o custo de processamento de informação, desse modo, aumentando nosso controle sobre o entorno. No último capítulo, desenvolvo a tese ontológica interacionista em detalhes e comento outras consequências filosóficas.

Palavras-chaves: ontologia; modelo interno; sistema de processamento de informação; limites de processamento cerebral; teoria da codificação.

ABSTRACT

This thesis is an endeavor to construct an ontology which I call Interactionist. The Ontological Interactionist thesis claims that reality consists of those constraints which limit the range of all possible interactions to those that are successful with environment. As any sense of reality comes from one's internal experience, my first endeavor is to relate one's internal and intuitive notion of reality with that of interaction. Therefore, in the second chapter, I interpret the Central Nervous System (CNS) as a control system which produces motricity in order to keep the organism alive while one's internal representations are understood as a strategy to improve the control performance. The control efficiency depends on the information processing systems capacity, which reflects the quality of our representations. In this setup, any representational content, whether the biological internal representations or any formal representation, is interpreted as playing a role in the production of action. In the third chapter, I will question whether or not the CNS's processing has any loss of information – i.e. whether or not one is able to "see" everything in the outside world. I will define a measure of the CNS's performance in terms of successful actions; no losses imply no accidents and any loss implies some accident. As accidents are widespread in one's life, I conclude that we are treating a lossy case. In the forth chapter I will assume that one's perception is a lossy processing case and I will question how the CNS chooses the right bits in order to survive. My explanation reserves a place for the evolutionary as well as cultural contribution. The evolutionary contribution occurs at the peripheral processing system which defines a broad set of categories – the broad aspects of one's perception. The cultural contribution occurs along the organism's development and defines a more specific set of perception's features – like specific patterns. I will defend that cultural factors, from motor group interactions to the mastering of mathematical language, form a continuous spectrum shaping one's perception. In the fifth chapter I will question how the CNS can improve its information processing. I will interpret the devising of the symbolic language as a strategy that reduces the processing costs, thereby, increasing one's control over the environment. In the last chapter I will unfold the Ontological Interactionist thesis previously stated and will comment on some philosophical implications.

Keywords: Ontology; internal model; information processing system; brain processing limits; coding theory.

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1 INTRODUCTION

This dissertation intends to be a philosophical essay about ontology. I am looking for a very general "statement" or "idea," to say, on *the being qua being*, as opposed to *the being qua knowing*. The search for this very peculiar idea is represented by the question, "what (exists) is there?" The clause of generality means that I'm not interested in an idea that just describes a subcategory of entities – such as biological organisms, or inanimate objects, or numbers. Rather, I am interested in an answer that covers the whole domain of existence – in some sense of "existence" which has to be determined. Sometimes one has to offer more than just a simple answer since one's domain of existence is comprised of two or more ontological categories – e.g. material objects and souls. The being qua being, as opposed to the being qua knowing, is one of the most important distinctions qualifying an ontological project. How one decides to relate these notions will give rise to different ontologies. Some think the being qua knowing is everything that exists. Therefore, when they die, everything dies with them[1]. Others think there is something beyond someone's knowing's such that it transcends their own existence. One may suppose that those belonging to the first group would tend to be more selfish, while those belonging to the second group would tend to be more altruistic. Anyway, ontological questions are very important because they are lurking behind a very large domain of belief in our lives, ranging from our most common conceptions of daily life to our most complex ideas in the field of science.

In order to introduce the main idea of this philosophical dissertation, let me contrast it with a very broad picture of what I take to be the dominant philosophical approach to ontology. I think it wouldn't be a crime to say that the ideas of "representation" or "something representing something else" have been an obsession characterizing the dominant approach to ontology through the history of philosophy. From Plato's forms through Kant's representation, until the most abstract

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[1] In fact, there are many different conceptions of ontological idealism throughout the history of philosophy, such as subjective, objective, absolute idealism and even more obscure characterizations such as speculative idealism and transcendental idealism. However, it seems safe to say that within modern philosophy, idealism is understood as the conception in which something mental (the mind, spirit, reason, will) is the ultimate foundation of all reality (GUYER AND HORSTMANN, 2015).

logical structures in recent analytic philosophy, many philosophers seem to be looking for a representation that most generally "matches" with the outside world in some sense. Exceptions seem to be Heidegger, Maurice Merleau-Ponty, and few others. Their philosophies differ according to what one elects as the "correct" representation and the way it bridges the knowing subject and the world out there.

In recent analytical philosophy, the dominant philosophical approach has been either those projects grounded on the notion of univocal reference or those grounded on the notion of universal conceptual scheme. The univocal reference projects are the pragmatic versions which say that those devices which better individuate the outside entities constitute the representation which better match with the world – much of the ontologies blossomed by the linguistic philosophy are of this kind. The universal conceptual scheme projects are the epistemological versions which say that the conceptual scheme logically presupposed in our best descriptions of the world is the representation that better matches with the world outside – logicist and structuralist ontologies are of this kind. There still remains the possibility of rejecting the existence of the unique representation and accepting the possibility of infinite representations of the world – ontological pluralism. What all of these positions seem to have in common is the meta-ontology represented by the basic metaphor in which a painter is painting a view and the philosopher wants to inspect whether or not he has used the right colors, traits, and so on. The philosopher knows the painter can depict the same view by using different techniques, but he is looking for those that match ultimately and undoubtedly with the real world. Therefore, the philosopher has looked despairingly for criteria and arguments which hold up the correspondence between the paint and the view the painter sees. But what if this metaphor is not good enough?

Recent achievements in the new brain sciences have provided evidence that we seem to have been betrayed by the very impingent representational insight just as we have been betrayed by the Euclidian insight about the nature of space. First, recent results in cognitive science and neuropsychology have strongly suggested that any sense of reality we are able to become aware of is a brain's construct. This construct has much illusion and, mainly, doesn't have all the information about the outside world. But more importantly, if any sense of reality is inside the brain, how can we talk about *correspondence* with something out there? Second, the anthropocentric insight which says that our brain is a thinking machine is wrong. All the empirical evidence about the brain functions corroborate the interpretation that the brain is in fact an action machine. Of course, it is not to deny that we think – which we experience all the time – but it is to stress the fact that it is just a middle step in the production of action. If one refers to the brain as a thinking machine, he is using a very incomplete description; because it precludes the primary brain purpose: Motricity. From the philosophical point of view, the moral of the story is that in order to find any ontological substratum one better inquire into the concept of action rather than of representation. However, since any notion of "real" that one can make sense of comes from the representational and internal point of view, we cannot simply inquire into action directly. We have to first inspect the relation between the internal notion of reality constructed by our brain and the final product resulting from it: Motor Twitches. This is precisely the theme of my second chapter.

Assuming that our subjective experience is grounded on Central Nervous System (CNS) dynamics, I start the dissertation's second chapter by questioning why we have such a system. While static animals, like plants, haven't required a chordate system in order to survive, moving animals seem to have the necessity of it to perseverate. Moving through the environment seems to be much more dangerous than just staying static in the same spot. According to this view, the CNS is a system that garners information from the environment in order to predict future events and avoid eventual accidents. The CNS's performance depends on its information processing capacity. However, even in this conceptual framework it is not clear why it needs an internal representation of the environment. Robots do exactly the same but don't seem to have any such thing as an internal experience! The role played by the internal representation is understood in the difference between robotic and biological systems: Noise. While robotic systems are virtually noise-free systems, biological systems are fully noise systems. For example, much of the signals emitted by our ganglion cells, in the retina, don't arrive at the visual system on the occipital lobe. But, maybe, the most harmful kind of noise present in the biological system is time delay. The experience characterizing our subjective life cannot be *simply* caused by the environmental stimuli; if it were, we would be unable to do things as simple as catching fruit. Because our action plans cannot be chosen directly based on the environmental information affecting our sensory organs, the CNS seems to engulf the environment in order to avoid time delay noise. By doing so, the system chooses the better plan to survive now based on a time-noise-free signal: The internal model of the environment. However, how good is this "engulfing?"

The subjective experience understood as a middle step in the generation of actions assumes a very important place in the scene. As suggested by the Data Processing Inequality Theorem (DPI) in Information Theory, no encoding process can create new information; i.e. the complexity of our action plans cannot be greater than that exhibited by our internal representations. The worse the quality of the internal representation, the more dangerous our action plan is. This idea gives an objective criterion with which to measure the quality of our representations in terms of the efficiency of our action plans. In order to assert this idea, in the third chapter I interpret the Central Nervous System as a communication channel for which sensory stimuli are input and motor twitches (actions) are output. The channel input sequences are viewed as the different environmental situations, the motor output as the action plans, and our representations as a channel code conveying information through the channel. As the CNS's *raison d'être* is to maintain the integrity of the organism as it navigates through the environment, any accident can be interpreted as a processing error. In other words, the CNS wouldn't typically choose an action plan which ends up harming the organism unless it misperceives or doesn't perceive some environmental information. Accordingly, we just have to pay attention to the probability of one's accident (error) as one moves through the environment to find out whether or not he/she is "seeing" everything from the outside world. If the probability of an accident occurring is above zero, then we are not experiencing everything out there. Though the model is, *in principle,* testable, it is not necessary to test it to conclude that we cannot "see" everything out there. That's because accidents are abundant throughout our lives. Therefore, the "engulfing" is not as good as we used to think of it – or more precisely we're not processing every bit of information from the environment.

I think some readers may frown upon using these information theoretical notions to interpret the CNS, arguing that they are too simple to explain the dynamics of such complex systems. At this point it is important to emphasize the generality and adequacy of these metaphors. For example, I heard some time ago the following objection: "You've interpreted the CNS as a channel but, in fact, it is much more than a device that simply responds to an input. The CNS behaves more like a closed system having its own autonomy. Therefore, your model oversimplifies the CNS's dynamics." I think this kind of objection comes rather from the intuitive idea associated with the terms naming the mathematical notions than from the mathematical notions themselves. Concerning this specific case, the notion of a communication channel in information theory just requires that two points have some statistic dependence and nothing more. And it is undeniable that there is a statistical correlation between the stimuli affecting our sensory organs and our motor responses. Similarly, interpreting our subjective experience as channel code doesn't obligate one to find the functions the brain deploys to process sensory input and generate motor output. The theory is sufficiently abstract to describe the contours of relation between organism and environment without getting into fine-grained questions.

According to that argument, because we don't interact safely with environment all the time, our subjective experience seems to be a lossy representation of the environment – i.e. a representation that leaves something out. It seems to occur either because the CNS does not have sufficient capacity to lossless process all the environmental information or because the CNS is not using an optimum channel code. Either way, the argument seems to be satisfactory to convince one that we're not "seeing" everything out there. However, if we're not "seeing" everything from outside, how does the CNS choose the bits it processes? One may think that the CNS chooses randomly. Though it doesn't appear to be the case, since there seems to be a coarse-grained convergence in our experience through different cultures and a fine-grained convergence in the same cultural community. The coarse-grained convergence refers to the perception's inborn traits that we seem to share – such as color, form, texture characteristics. While the fine-grained convergence refers to the perspectival traits that the community's members share – such as the difference between melody and harmony as perceived by musicians, specific patterns in nature as perceived by scientists, or the cardinal points as perceived by the members of the Aboriginal community on the western edge of Cape York in northern Australia.

In the fourth chapter I will offer a model to explain how the CNS chooses the bits it processes. In the same way our subjective experience seems to present two levels of convergence, the CNS's information processing will also be divided into the model in two stages. The first one, which I call the innate perceptual stage, explains the coarse-grained convergence level through the cytoarchiteture of our sensory organs. The cytoarchiteture of our sensory organs is interpreted as encoding functions that encode the environmental information according to an evolutionary criterion – i.e. the information that has been important to the organisms survive. Hypothetically, a full range of encoding functions has been deployed since the beginning of life; those organisms whose cytoarchiteture had encoded mostly irrelevant information for life, has demised. The information encoded by the cytoarchiteture of the successful organisms defines a range of categories upon which the next perceptual level is constructed – the colors, size, velocities and smells we are able to perceive. A second processing stage is theoretically needed in order to explain the perspectival trait featuring our perception. If the higher order processing stages of brain deployed a lossless encoding, then we wouldn't have the opportunity to experience such a thing as a perspective of something – our perception would be rather like a photograph camera: every shot would contain all the possible perspectives in it, at a fixed time and localization. In the second processing stage, which I call learned perception, the brain extracts and encodes the most important information coming from the different sensory organs – eyes, ears, skin, and taste buds – into a multimodal representation. The perspectival trait means that the brain cannot construct a perfect representation, either because it does not have capacity enough to process the whole transmitted information through the sensory pathway or because it is not deploying an optimal channel code. The question is: What criterion is the brain employing to choose the bits at this second stage? According to my model, the brain chooses those bits of specific sensory modality that are mostly statistically dependent on the bits of another specific sensory modality – e.g. we tend to see that portion of environment that is most correlated with the sounds it emits. In my model, different patterns of signal have different statistical dependence on each other generating different representations with different degrees of informativeness. The different patterns of signal can be interpreted as everything that makes sense to our mind - such as language, graphs, symbols, pictures, movies – influencing our experience of the world – i.e. producing a different representation.

The interesting thing about choosing bits is that the CNS can improve its performance by processing only those bits that maximize the organism's survival chances, thereby, not wasting energy with irrelevant information. Therefore, musicians are good with sounds but not, in general, with colors; painters with colors but not, in general, with sounds; and scientists with patterns but not, in general, with details[2]. However, no matter how good the choice is, the amount of information reliably processed by the CNS cannot be greater than its cost-capacity. The explanation needs an amendment in order to match the abrupt

[2] I remember some scientists saying that music is mathematics and throwing most of its beauty away.

increasing of control that humanity has had since the rise of symbolic mathematics – mainly the invention of the differential calculus. If the choosing-bits hypothesis were responsible for this abrupt increasing of control, it would imply that we have succeeded as a species choosing mostly wrong bits – what doesn't make much sense. An alternative, in order to improve the information processing without changing the channel, is to use a different channel code. In real systems every transmission has a cost which limits the channel capacity – e.g. in biological organisms these costs range from energy to time delay. However, sometimes by using a different channel code one is able to transmit the same amount of information with lower costs than it was necessary to transmit by using the old channel code. Therefore, cheaper coding schemes may increase abruptly the transmission/processing.

In the fifth chapter I will interpret the symbolic language's role in increasing our control over the environment as a cheaper channel code. I will argue that our biological representation – the world as we used to conceive it – is a channel code that works reasonably well for a large range of cognitive tasks, but that is not so good to optimally perform specific tasks. The reason it is not so good is that it is too costly. Alternatively, the symbolic language is cheaper in various aspects; it is visually poor, doesn't occupy much of working memory, and has too little redundancy. Being visually poor means that it takes little visual system's capacity to be processed, and therefore, much more information can be processed through the visual system at the same time. The possibility of writing it down on a paper or a computer screen also frees the working memory to perform other cognitive tasks – i.e. one doesn't need to keep the information in the short-term memory to accomplish a cognitive task. And the actual status of symbolic language – mainly arithmetical language – displays very little redundancy. All of these aspects reduce abruptly the processing costs, providing ground for larger amounts of information being processed. But what about ontology? It is time to get back to our main theme.

Before stepping on the ontological ground, let me make it clear how the previous discussions seem to provide ground for my ontological thesis. What I've tried to do in the previous chapters is, first, to show how epistemology is grounded on interaction and, second, to highlight the contingent character of epistemology as opposite to the unique character of action. In the second chapter, the internal experience is understood as strategy to improve the organism's control over the environment. Therefore, internal representation is not a question of truth, but of being lead to better action plans. In the third chapter I tried to show that our performance in interacting with environment can tell us how good our representations are. And in the next two chapters I've tried to show two different strategies that the CNS may have used to improve its controlling performance: the first one, choosing bits; the second one, changing the channel code. Increasing control means getting close to that action plan that minimizes that risk of death. Though, while different processing (epistemological) strategies are available to the CNS in order to increase our control over the environment, only few (if not just one) possible action plans are available in order for the organism to stay alive. On one hand, the only aspect constraining our epistemological choice is the channel's nature (cost). On the other hand, what constrains my choice over the possible action plans? The answer is: Reality! When moving through the environment the organism gives the contours of the reality. When one commits a mistake, reality says one is not alone. One gets hurt! Then the accident gets its meaning.

Interactionism, as I refer to it, is a negative and realist ontology. The world reveals itself as long as we interact successfully with it. The clause "successfully" is important to contrast with the meaning of an "accident". In the same way a negation implies a whole range of possible predicates – e.g. saying "it is not red" entails the possibility of "it" to instantiate all the colors but red – choosing an action plan that results in an accident entails a whole range of possible interactions except that one already chosen. However, when interacting successfully I can have some faith that *to some extent* the world is like this. I call it negative because it is always virtually possible to choose a representation that produces a safer and more complex plan turning the contours of reality even more strictly. Whether or not we can know if we have arrived at the ultimate (true) contour of reality is a question I will leave open. If reality were continuous, then there wouldn't be an ultimate contour (interaction plan) of the reality. But if it were discrete, then there should be some[3]. However, there will be no ultimate representation ever, but only ultimate interaction.

As a last word, let me say something about the mathematical notation used in this dissertation. Mainly, I will use Information Theory and Dynamic (discrete) System Theory to better structure and present

[3] This conclusion about discrete versus continuous domains comes from Coding Theory. As in a continuous domain the sample space is countless, the probability of a specific result goes to zero. Therefore, infinite bits would be needed to perfectly represent the information source.

my points. The dynamic system's notion is taken from *Introduction to Mathematical System Theory (*HEIJ, et al. 2007), while the information theory's notion is taken from *Elements of Information Theory* (COVER, & THOMAS, 2006). As far as I can see, every model is formally defined through my dissertation.

REALITY AS AN INTERNAL MODEL TO MOTOR CONTROL

2 REALITY AS AN INTERNAL MODEL TO MOTOR CONTROL

In this chapter I present a perspective according to which our common conception of reality is found as an internal model to improve motor control. More specifically, the model is understood as a strategy to correct the corrupted signal used in motor coordination. First I will introduce the metaphor of a dynamic system to interpret the Central Nervous System (CNS). This metaphor gives structure to the ideas that (i) the only CNS's processing result is motricity and that (ii) our notion of reality must be thought of in the intelligent-motricity-production context. Second, I'll talk about the metaphor of an internal model in which (iii) our conception of reality is interpreted. Conforming to this interpretation, our subjective experience resides in an internal model of the environment created by the CNS in order to correct the transmitted signal corrupted by noise. Last, we will look at some consequences of these interpretations.

2.1 THE CENTRAL NERVOUS SYSTEM AS A DYNAMIC SYSTEM

From a materialist perspective, the brain, which is the CNS's processing center, is the typical object of reference when talking about thinking. However, as soon as one speaks about the brain without any reference to CNS, one runs the risk of thinking that one is able to

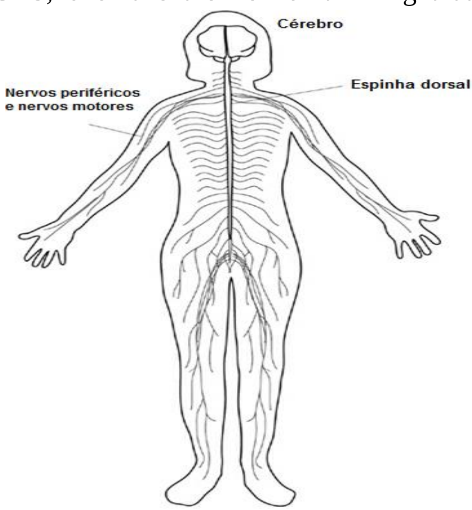


Figure 3 - Central Nervous System

understand brain processes dynamics without considering the CNS as a whole. The brain, or interneural space, consists of a set of CNS subsystems in which events that take place in its space must be understood related to the roles they play in the system as a whole (MAINZER, 2007). The term ‘interneural space’ comes from the fact that its neurons transmit information coming from the afferent neurons, sensorial organs, to the efferent neurons, motor neurons, resulting in muscle contractions (LLINÁS, 2001). The CNS comprises brain and spinal cord, which are bilaterally symmetric [Figure 1]. The spinal cord receives sensorial information from the skin through a set of long axions – the so-called peripheral nervous system and sends motor command to muscles (KANDEL, 2012).

2.2 THE CENTRAL NERVOUS SYSTEM AS MACHINE WITH INPUT

In understanding real entities, different kinds of metaphors can be used in order to better conceptualize them – e.g. entities can be viewed as little objects, possible worlds, or mathematical fields. A possibility is to view the CNS as a dynamic system, which can be intuitively understood as any group of elements exhibiting some kind of relation (LERNER, 1975; ASHBY, 1956). More strictly speaking, it can be expressed as any set of variables, where each variable is some entity’s feature. The values the system’s variables assume depend entirely on the purposes of the researcher. In the case of the CNS, one can describe it from a perspective of either its molecules, or action potential, or synapse, or neurons, or nucleus, or circuits, or webs, or maps, or systems--hence, central nervous system as a whole. However, for our purposes, it’s rather preferable to introduce an even more precise definition. Denoting the time axis by T and the outcome space for the system variables at each time instant by W, we define a (deterministic, $T = \mathbb{Z}$) dynamical system as follows:

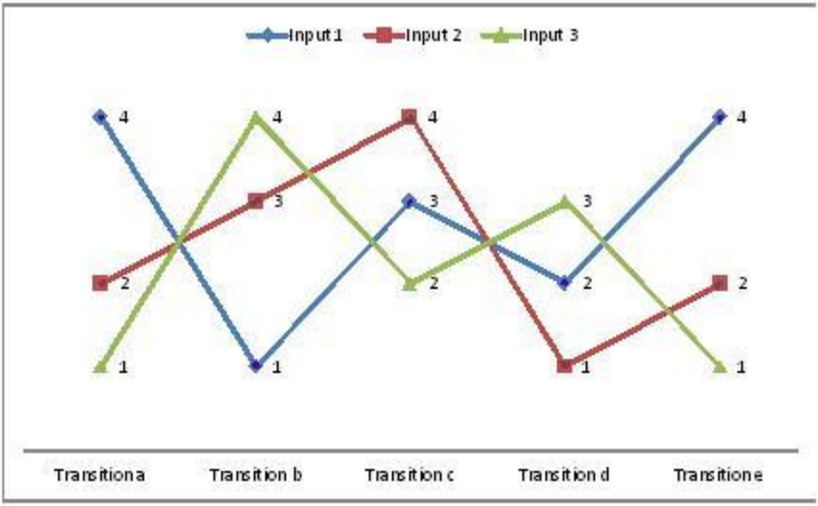
Definition 2.1 (dynamical system) *A dynamical system consists of a set of allowable trajectories of the system variables, i.e., it is characterized by its behavior* $\mathcal{B} \subset \{w \mid w: T \rightarrow W\}$.

Bearing that in mind, one should ask: what kind of system is the CNS? According to Prigogine (1961), the systems we find in our physical reality are divided into three categories, namely: *isolated systems*, the ones that are not able to exchange either energy or matter with environment; *closed systems*, the ones that exchange energy, but not matter with environment; and *open systems* which exchange energy or matter with environment,– clearly the CNS is understood as an open system (MAINZER, 2007, p. 98; PRIGOGINE & NICOLIS, 1977). From the formal point of view, it would be equivalent to say that the system's behavior depends on its relationship to the environment – or the external variety affecting the system. This kind of system is called machine with input (ASHBY, 1970, 1966). We define a *machine with input* in the following way:

Definition 2.2 (input-output dynamical system) *A system with input-output consists of a set of inputs (parameters)* $\{u | u: T \to U\}$ *and a set of outputs (trajectories)* $\{y | y: T \to Y\}$ *related by a function* F*. The system's behavior is given by* $\mathcal{B} = \{(u, y): T \to U \times Y; y = F(u)\}$.

By input one means any external event that is able to modify some variables' value, while output means any environment's change produced by the system's trajectory (ROSENBLUETH et al, 1943; ASHBY, 1970). This definition is determinist, since each input is mapped to only one output, but it is easy to extend the definition to the stochastic case (HEIJ et al., 2007).

Graphic 1 depicts the way each system's trajectory is related to a distinct input. Each colored line represents a distinct system's behavior related to each distinct input. The set of its possible behaviors is called, canonical representation. The main aim in enquiring about a specific system is to determine its canonical representation. That being said,



Graphic 1 - Canonical representation of system's behavior. Each line represents s different system's trajectory or behavior.

cases where one is able to completely figure out a system's canonical representation are rare, if in fact they exist. At the beginning, every system presents itself as a black box and mostly what one is able to find out is just an approximation of its 'real' canonical representation (ASHBY, 1970; MAINZER, 2007).

2.3 The cns as a black box: looking for the machine's structure

Black Box is a term used to describe a strategy for handling these veiled entities – which are a rule rather than an exception. The CNS is a typical example of a system for which one cannot directly access its transition of state. According to the Black Box theory, the right strategy consists in laying down the input and output sets and submitting the system to continuous disturbances. By repeating this procedure one looks for establishing the relation between each particular input and output in order to grasp a satisfying representation of the system's behavior, which doesn't need to be determined but, commonly, is a stochastic one. A 'disturbance' occurs when the system is affected by different inputs in a given span of time. Because one is mainly interested in the behavior's representation, this approach is also called behaviorist.

Let us assume that the CNS is an open system, therefore the following aspects seem to be the case. From a physiologic and anatomic point of view, the kind of output resulting from the CNS's dynamics is exclusively motricity–a part of the glandular and neuro-humoral by-products (KANDEL, 2012; FUSTER, 2006; LLINAS, 2001; ARBIB, 1981; SPERRY, 1952). In other words, motricity is the only way whereby the organism is able to affect the environment. According to Roger Sperry, "*the entire output of our thinking machine consists of nothing but patterns of motor coordination,* […] the only significant energy outlet and the only means of expression are over the motor pathways" (italics in original)(1952, pp. 296-298). From the psychological point of view, there seems to be a privilege of action over thought. Research about how the CNS reacts to sudden disturbs have shown that the sensorial system responds 100ms later than the motor system in some situations – such as bouncing a ball, braking the car in order to avoid a crash, and diverting an obstacle (EAGLEMANN, 2012; LLINÁS, 2001). From a phylogenetic point of view, moving down the evolutionary scale, one can notice that the purely mental activity becomes much less significant when compared with motor activity – the notion of 'mental' should be understood as 'neural activity without immediate motor correlate'. On the other hand, moving higher up in the evolutionary scale, one can find just a gradual sophistication of the brain mechanisms without any radical change in the fundamental brain principals (SPERRY, 1952).

Still, from the phylogenetic point of view, the existence of a creature, the primitive *Ascidiacea*, tunicates or "sea squirts," has been interpreted by neuroscientists and evolutionary biologists as a proof of the current conjecture about the CNS's function. The adult form of this creature is sessile, rooted by its pedicle to a stable object in the sea. The sea squirt carries out two basic functions in its life: it feeds by filtering seawater, and it reproduces by budding. The larval form is briefly free-swimming and is equipped with a brain-like ganglion containing approximately 300 cells. This primitive nervous system receives sensory information about the environment through a statocyst (organ of balance), a rudimentary, light-sensitive patch of skin, and a notochord (primitive spinal cord). These features allow this tadpole-like creature to handle the vicissitudes of the ever-changing world within which it swims. The surprising fact about this creature is that, as soon as it finds a suitable substrate, the larva proceeds to bury its head into the selected location and the larva absorbs—literally digests—most of its own brain, including its notochord, therefore, becoming a sessile creature once again. It also digests its tail and tail musculature, thereupon regressing to the rather primitive adult stage: sessile and lacking a true nervous system (LLINAS, 2001; CLONEY, 1982). According to the current position, the lesson here is that the evolutionary development of a nervous system is an exclusive property of actively moving creatures.

2.4 THE CNS AS A COMPLEX SYSTEM

In most cases a system can be decomposed in a set of subsystems connected among them. Whether or not this decomposing process has a limit is an open question which has to do with the ultimate character of reality. Therefore, a system, W, is able to be decomposed into two simpler systems, Z and Y, so that $Z = \{z_1, z_2, \dots, z_n\}$ and $Y = \{y_1, y_2, \dots, y_m\}$ are the variables defining each system respectively – for simplicity, both systems are assumed to be discrete [Figure 2]. Very importantly, as one can proceed almost indefinitely dividing a system into its subsystems and arranging them as system and environment it turns out that the way whereby one sets these notions is strictly arbitrary – in fact, there should be an ultimate way to set these notions if reality is

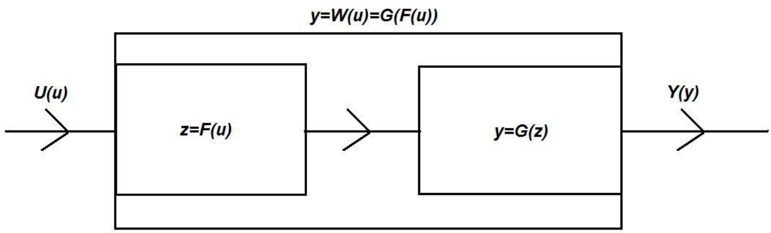


Figure 4 - W system composed of subsystems Z and Y.

discrete. Based on this view we can define the notion of *environment*.

Definition 2.3 (environment) *We call environment the subset* $Z^* = \{z^*{}_1, z_2{}^*, \dots, z^*{}_k\}$ *of Z's variables whose change modifies the Y' variable values at some extent.*

The systems we usually find in real life are complex systems composed of innumerable subsystems, such as rocks, tools, and biological organisms. Surprisingly, as soon as innumerable systems are coupled together these systems begin to display curious characteristics. For example, as long as any transmission in real life exhibits some quantity of quantum or thermodynamic noise, the system's dynamics acquires a stochastic feature. Therefore, determined descriptions get excluded, which decreases or sometimes precludes the possibility of prediction. Eventually, the increasing of complexity gives rise to parameter of order from the interaction of these simpler subsystems. However, the parameters of order themselves show to be irreducible to the simpler subsystems' properties and they interact causally with its simpler components. This irreducibility is termed *non-linearity,* and the causal interaction with subsystems is termed *downward causation.* Such systems composed of innumerable subsystems and with non-linear dynamics are called *complex system* (MAINZER, 2007; MITCHELL, 2009).

It is important to take into consideration the notion of 'complex system' in order to make it clear that the characteristics displayed by the complex systems don't preclude the use of dynamics system theory as a model for these systems – the theory also permits us to treat stochastic and non-linear systems. All the systems in real life are open systems constantly exchanging matter and energy with environment, which means that, strictly speaking, any system cannot be excluded from its interactional context. This idea seems to be lurking in Wiener's words: "[…] the structure of the machine or of the organism is an index of the performance that may be expected from it." (1989, p. 57). In other words, it's fair enough to see our internal representations as a CNS's middle-step processing stage in the production of motricity once the latter is its main purpose. If one is in agreement with this digression, then one can maintain that any research about how our subjective experience grasps the outside world cannot be thought out of the intelligent-motricity-production context. This perspective leads us to inquire as to the function of the Central Nervous System, and why moving organisms need such a system in order to survive?

2.5 The Living Organism

What role is played by the Central Nervous System in the biological organism as a whole? Not all biological organisms are gifted with a CNS. Plants, which have appeared late in the life-diversification process, seem to have chosen simply not to have a CNS and still they have been having great success as a specie (LLINÁS, 2001). In a special class of them, the CNS's role seems to be strictly related to the control of the organism's life.

According to definition 1.2, the organism, interpreted as a dynamic system, is characterized by certain behavior, which can be defined as a set of possible trajectories $\mathcal{B} = \{(u, y): T \to U \times Y; y = F(u)\}$ over a phase space, where $\mathcal{B}$ is the set of possible trajectories, U is a set of inputs, Y is the set of outputs, and F is a set of functions relating each input to some output. The input set U and the output set Y can be viewed as a random variable vector producing, at any time t, an input $u(t) = \left(u_1(t), \dots, u_m(t)\right)^T$ and an output $y(t) = \left(y_1(t), \dots, y_p(t)\right)^T$ so that the system's dynamics is given by the following equations

$$x(t+1) = Ax(t) + Bu(t) \qquad (1)$$
$$y(t) = Cx(t) + Du(t) \qquad (2)$$

Notice that the equation (1) can be plugged in the equation (2), therefore, representing the *function* F, A, B, C, and D are matrices of suitable dimension and the variable x is a *state variable*, which contains all past relevant information for a future transition. The set of U inputs can be understood as another G system's output set which is causally related with F system. Nonetheless, usually different inputs, $u_i(t)$ e $u_j(t)$ for $i \neq j$, when added to the same state x_0, tend to conduct the system through different trajectories $y_i(t)$ e $y_j(t)$ para $i \neq j$. Therefore, if $u_i(t)$ is for an automobile and $u_j(t)$ is for a soccer ball, both in collision course with someone's body, the outputs $y_i(t)$ and $y_j(t)$ will surely be different. Keeping that in mind, it seems reasonable to suppose that there will be, among the trajectories in $\mathcal{B}$, a subset of trajectories $\mathcal{A} \subset \mathcal{B}$ which represents the system's *desired trajectories* – the organism alive! In other words, the set of desired trajectories in the output set Y represent those vectors $y(t)$ whose component values correspond to some ideal values – e.g. the body's temperature around 36ºC, the pressure of blood between 100 and 140 mmHg, etc. The suggestion is that the biological organism wouldn't survive, if it were depending entirely on luck.

By way of the equation (2) one can notice that the system's trajectory $y(t)$ depends on the state x where the system is found. It means that if there were a mechanism that could choose the state x in (2), then there would be greater surviving chances. Such mechanisms are called control systems. The CNS is interpreted as a control system whose main purpose is to keep the whole organism alive. However, how is motricity related to the control system's purpose, and how can our subjective experience contribute to this enterprise?

2.6 The CNS as a Control System

A control system consists in a system coupled to another system whose function is to bring back to or to keep the controlled system's trajectory in the domain of desired trajectories $\mathcal{A}$. The control system emits a control input $i(t)$ changing the system's state value x so that its trajectory $y = Cx + Du$ remains in the domain $\mathcal{A}$. In general, a cost function $J(x_N, u) \to \mathbb{R}$ is defined over the summation of a state value string, at a span of time N, which measures how much the system's trajectory deviate from the desired trajectory set $\mathcal{A}$. Of course, the control system's aim is to decrease the cost function value.

The control input cannot be randomly emitted in order to reproduce the desired trajectory; therefore, the control system chooses the control input based upon some information source. There are at least two different kinds of information sources and, according to them, two different categories of control systems are distinguished, namely: *extrapolative* and *non-extrapolative.* Non-extrapolative control systems base their input choice on the information provided by the controlled system's state value $x(t+1)$ [Figure 5], while extrapolative control systems, on the another hand, base their input choice on the information provided by an observation $o(t)$ of the environmental input $u(t)$. Based on the observation, the extrapolative system estimates the environmental input $u(t+1)$ in order to choose the $x(t+1)$ so that $Cx(t+1) + Du(t+1) = y(t+1) \in \mathcal{A}$ (ASHBY, 1956; ROSENBLUETH et al., 1943; LERNER, 1975; ARBIB, 1981).

The non-extrapolative systems, which are also called feedback systems, choose the control input $i(t+1)$ based on the state variable value $x(t+1)$, for $t \in T$ – in other words, the control system acts *on* the future system's trajectory. For example, shivering, due to the feeling of cold, is an organism's response to decreasing body temperature. As soon as its temperature goes down to 36.5ºC, the CNS emits a shivering in order to bring the organism's body back to the desired temperature. The main drawback of the non-extrapolative systems is that the control input is a function of the future system state $x\,(t+1)$. Therefore, for great cost function values the non-extrapolative control systems might be inefficient to control the organism's life; if the organism dies, then $J(x_N, u) \to \infty$ and no control input can bring it back to $\mathcal{A}$.

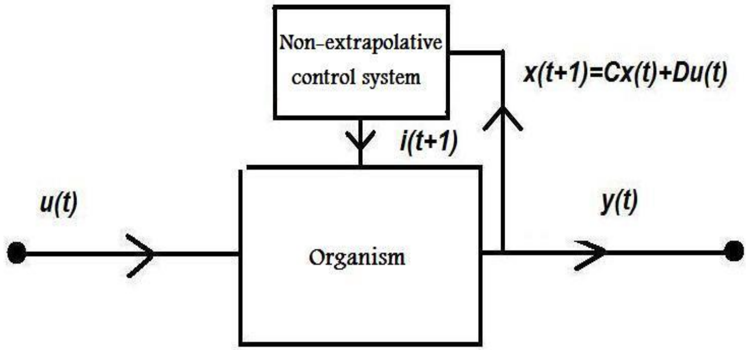


Figure 3 --Non-extrapolative control system (feedback)

The extrapolative control systems choose the control input $i(t)$ through an observation $o(t)$ of the present environmental input $u(t)$ in order to estimate the future environmental input $u(t+1)$ and the likely system's trajectory $y(t+1)$, given the state value $x(t)$ – i.e. the control input $i(t)$ ought be such that satisfies the following conditions: $x(t+1) = Ax(t) + Bi(t)$, $y(t+1) = Cx(t+1) + Du(t+1)$ and $y(t+1) \in \mathcal{A}$. Notice that much of the system's efficiency depends on the observation $o(t)$. If the observation has little information or the system is unable to efficiently process the observation's information, then it may misperceive the future environmental input and choose the wrong control input causing $y(t+1) \notin \mathcal{A}$. Extrapolative control systems are more efficient then non-extrapolative systems because their control input acts anticipatorily on the controlled system. Whereas the non-extrapolative control system tries to correct the controlled system's trajectory deviation, the extrapolative control system simple tries to avoid the trajectory deviation.

The observation $o(t)$ should contain the relevant information for the organism's surviving. The entities that typically threaten the organism's life are moving macroscopic objects. Differently, microscopic entities have no, or less, effect on the controlled system's trajectory. Because the relevant information for the organism's life contained in the environmental input consists mainly of the displacement of macroscopic objects, the control input information should have the same nature. That is why the CNS's output consists of motor twitches; motor information produces that desirable result in terms of spatiotemporal changes. But what is the connection between subjectivity and motor output?

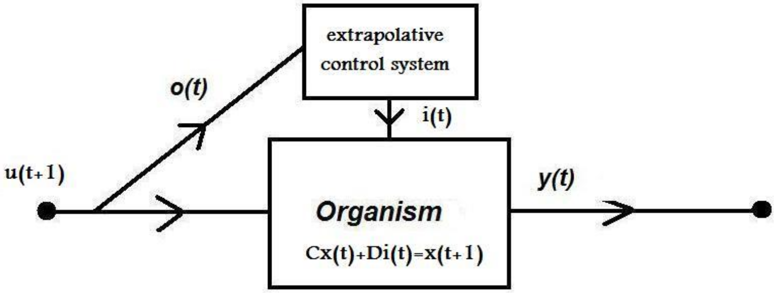


Figure 4 - Extrapolative control system

2.7 The Internal Model of the Environment as a Decoding Strategy

In the extrapolative control systems, the system's degree of control clearly depends on the system's information processing capacity to handle the observation $o(t)$[4]. In real life, every transmission/processing system is characterized by some amount of noise, which is additional information that corrupts the signal. In this last session, we will assume that the CNS is an extrapolative control system and interpret our common conception of reality as a strategy to correct the corrupted signal in the information processing.

2.7.1 Noise

Very often, external and internal factors contributing to a transmission may negatively interfere with the environmental information processing, thereby, impairing the control enterprise. It obligates the control system to implement strategies that correct this interference. This interference is understood as *noise*, which is an *unwanted* variety added to the transmission/processing signal[5]. This

[4] The idea of 'observation' can be modeled by using information theory or hidden Markovian models (PHAM, 2002; ATTNEAVE, 1954; ROGERS et al. 1999)

[5] The noise may also be seen from a positive perspective. Along with the organism's development the presence of noise obligates the organism to improve its information processing, therefore, conducting it to its optimal

additional variety is defined in contrast with the variety characterizing the transmitted message (ASHBY, 1956; SHANNON, 1964). Any additional variety that interferes somehow in the transmitted signal ought to be considered as noise – hereafter I will refer to the corrupted signal as noisy signal. Any noise is undesirable since the control system may interpret it as information about the environmental input and end up making a wrong decision.

2.7.2 Time delay

In robotic control systems, the information garnered by the transducer devices is transmitted to the control center through electronic circuits at a frequency of 500-1000 Hz, with negligible error rate. The information transmission in these systems is carried out at a rate of 1-2ms, making these systems very efficient in making their control decisions based *directly* on the information garnered by their "sensorial" transducers. Differently, in the biological systems the information is transmitted through electrophysiological processes at a transmission rate of 150-250ms (KAWATO, id.; FELDMAN, 2006). As the speed rate of our faster movements is 150ms and our intermediate movements is 500ms, there is a critical time delay that interferes with motor coordination. Therefore, it must be considered as noise by the control system (KAWATO, id.; NIJHAWAN, 2008). In this case, if the CNS were to make its control decision based directly on the in-time environmental information provided by the sensorial organs, then we wouldn't be able to bounce a ball in a tennis game. As the information takes a little longer to be transmitted we would always be late bouncing it. It can be concluded, most of what we "see" cannot be directly caused by environmental information.

2.7.3 Intrinsic and extrinsic signal's corruption factors

In a biological processing system, noise is everywhere; there is as much noise in intrinsic as in extrinsic aspects of information processing (DESTEXHE & RUDOLPH-LILITH, 2012; FAISAL et al., 2008; STEIN et al. 2005; WOLPERT et al. 2003). Nowadays, one of the most challenging problems in neuroscience is making a clear

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performance. From this positive perspective, a certain amount of noise is a desirable feature in the evolutionary process. The total absence of noise causes its underdevelopment; too much noise causes its demise; the right amount of noise causes its optimal performance.

distinction between noise and relevant information. As long as one doesn't know what the brain's code is yet, one can be treating noise as information and conversely. Until recently, temporal variety in the neural transmission has been treated as noise, but now there seems to be strong evidence supporting the idea that the temporal variety is rather relevant information for control (FAISAL et al., id).

There are extrinsic noise factors to the CNS in every sensorial modality. The photons impinging on the retina don't arrive at the photoreceptor cells exhibiting a perfect pattern – this process has been currently modeled as a Poisson Process (PIRENNE, 1959). The sound waves impinging on the hair cells in the auditory system are subject to Brownian Movement, which creates some randomness consistent with noise (HARRIS, 1968). Likewise, the chemical sensorial transducers are subject to thermodynamic randomness which is also consistent with noise (BERG & PURCELL, 1977; BIALEK & SETAYESHGAR, 2005). The neural cells' potential membrane is characterized by some degree of randomness which continually changes the action potential limit. Sometimes the action potential occurs even in the absence of pre-synaptic activity, or simply doesn't respond to the pre-synaptic input (DIBA et al. 2004). This randomness, owing partially to the ion channel noise, increases inversely proportional to the cell's size, since the membrane's input resistance increases quickly as its diameter decreases (RALL, 1969; FAISAL et al., 2005). The signal emitted through long axions has a high transmission failure rate, around 50-80% (DEBANNE, 2004). These examples give us an idea about how noise is present at different stages of the neural processing, and how these noises eventually end up affecting perception, cognition, and motor coordination.

2.8 The internal model as an error-correction strategy

In order to remove temporal and other forms of noise from a signal, some strategy is needed. The current hypothesis is that the CNS elaborates *an internal model,* an *emulator,* of the external events which makes an estimation of the future environmental inputs based on the statistical structure of the process (GRUSH, 2004; DESMURGET & GRAFTON, 2000; KAWATO, 1999; WOLPERT,1995). The estimation is made through the observations o of the input sequence u. The control system doesn't choose its control input based directly on environmental input information, but on the information provided by the internal model – notice that the information provided directly by the sensorial transducers would be information about a past event because of processing time delay. The suppositions here are that (i) the source has a stationary structure and that (ii) the source sample garnered through the observation has a sufficient statistic about the input process. Mistakes are possible because eventually the control system has no sufficient statistics to estimate the correct environmental input or because it just doesn't have the capacity to process the whole amount of information provided by the observation.

As the control system's guessing task depends on the statistical structure of the process, it depends on the experience. It is like trying to find out whether or not a dice is biased; there is no other way than throwing the dice continually until there is a representative sample of the process' statistical structure. In most of cases, all the possible events are not equally likely to occur – as a matter of fact, they are not in our world. Therefore, given that a specific event has occurred, it changes the probability of the next possible events. This statistical perspective on perception has had much success in explaining illusion and motor planning. As the interpretation implies, what we see is much based on our experience and is an estimation of the future – and therefore eventually ends up as a mistake induced by previous events. It is as if the perceptual data doesn't give the content, but just modulates the internal model's dynamics (LLINÁS, 1992, 2001, 2009; GRUSH, 2004; CHURCHLAND et al. 1994). In the same vein, probabilistic decision theory (Bayesian) has matched in a great deal with the way we really make decisions in our daily situation (WOLPERT & GHAHRAMANI, 2009; DOYA et al. 2007; SHADMEHR & MUSSA-IVALDI, 2012). The evidences supporting such interpretation are also found in neuroimaging experiments that suggest the existence of neural circuits grounding such emulators (JORDAN & RUMELHAR, 1992; MIALL et al. 1993; WOLPERT, 1995; FLANAGAN & WING, 1997; SNYDER, 1999; MERFELD et al. 1999; KAWATO, 1999; DESMURGET & GRAFTON, 2000; GRUSH, 2004).

2.9 The Internal Model as a Motor Parameter

The idea, according to which our subjective experience is viewed as a strategy to remove the noise from the signal, has still a more precise interpretation. In this more precise interpretation, the so-called strategy is a channel code; i.e. it is a structure that the signal assumes in order to better transmit the information and surmount the noise[6]. The perceptual categories –colors, forms, and so on – are viewed as particularities of the transmission code. However, the variety, or degrees of freedom, expressed in the transmission must convey the source properties. The code's particularities are contingent; they depend on the signal used and the kind of channel. However, the complexity is mandatory; it must respect the source complexity in order to achieve the control aim. A good code conveys the source information respecting the channel-cost capacity.

According to this more precise interpretation, a control input $i(t)$ results from the processing of information contained in the observation $o(t)$. As the control input consists of motor twitches and the code words of internal representations, our representations are better understood as a pre-motor parameter. As such, the complexity of our plans depends on the complexity of our representations[7]. The "pre" in pre-motor means that not every bit corresponds to an action – not every representation ends up in action. From this point of view, it doesn't make sense to ask whether a given code word corresponds to a given source bit – in other words, there is no sense in asking whether an object is blue or green. The optimum code just needs to express the source's degrees of freedom respecting the channel capacity – whether it is accomplished by means of binary electrical pulses or ternary mechanic hits is contingent. Two distinct channel codes can convey the same information and still use transmission signals completely distinct. Therefore, one can pass by the obsessive search for *the* representation of reality and search for the degrees of freedom of the reality.

2.10 Conclusion

In this chapter I presented an alternative according to which our common notion of reality is understood as an internal model elaborated by the CNS in order to improve the biological organism's surviving chances. More specifically, the internal model is viewed as a strategy to remove the noise from the transmission/processing signal. As the CNS's main purpose is to preserve the organism's life through motor coordination, the ultimate function of our notion of reality cannot be one of "represent' or "stand for something" out there. In order to be coherent with the organism's structure it has to be inquired in its connection with

[6] See chapter four for a complete discussion of this point.
[7] See chapter four for a complete discussion of this point.

motor output. As a result, on the one hand, the philosophical endeavor to fill the gap between reality and representation is simply a mistake, if one doesn't admit a missing piece between these two poles. On the other hand, the ultimate contact with reality cannot be through representation, whether subjective images or abstracts structures, but motor interactions.

THE CENTRAL NERVOUS SYSTEM AS INFORMATION PROCESSING SYSTEM: DO WE HAVE ACCESS TO THE ENTIRE OUTSIDE REALITY?

3 THE CENTRAL NERVOUS SYSTEM AS INFORMATION PROCESSING SYSTEM: DO WE HAVE ACCESS TO THE ENTIRE OUTSIDE REALITY?

In this chapter I will introduce a formal framework in order to give thorough treatment to the question: Do we have access to the entire outside reality? In this enterprise, the Central Nervous System (CNS) will be interpreted as an information processing system and the question will be translated in terms of the quantity of reliably processed information. A measure of the quantity of information reliably processed by the CNS will be defined in terms of the probability of error, or accident, in interacting with the environment. According to the defined measure, no accident will be viewed as optimal information processing performance and the presence of any error will be valued as suboptimal information processing performance. Since accidents are never completely preventable, the CNS seems not to be processing entire outside information. However, rather than seriously answering the above question, the main aim of this chapter is to provide a framework in which the philosophical question can be made stricter and its answer connected with the experimental data provided by empirical sciences.

3.1 A Brief Overview of Information Theory

From an intuitive point of view, the main idea underpinning information theory is that of measuring the degrees of freedom whereby a system $\mathcal{X}$ can affect another system $\mathcal{Y}$. The idea of degrees of freedom is grasped through the idea of 'surprise' so that the greater surprise concerning the $\mathcal{X}$ system's output, the higher the freedom with which it can affect the $\mathcal{Y}$ system. Because this picture matches exactly with the requirements necessary for communication it is called, Information Theory (SHANNON & WEAVER, 1964). From the mathematical point of view, the notion of 'surprise' can be conceptualized as a distribution of probability $p(.)$, and a measure function S is defined which gives the quantity of surprise. The S function has to respect intuitive conditions of the notion of surprise, such as: first, there is no surprise in hearing that an event sure to occur has indeed occurred; second, the more unlikely an event is to occur, the greater is the surprise evoked by its occurrence (monotonicity); third, one would intuitively expect a small change in $p(.)$ to correspond to a small change in $S(p)$ – i.e. $S(p)$ is a continuous function of $p(.)$*;* and finally, the surprise characterizing independent events is additive. It is easy to prove that the log function $C \log_2 p$ matches these conditions, where C is the base-change logarithm constant – if $C = 1$, then one refers to the quantity of surprise in terms of *bits* (ROSS, 1998; COVER & THOMAS, 2006). To measure the entire system's degrees of freedom one has to average over each surprise measure $C \log_2 p_i$, which is called, Entropy of a given source/system.

Definition 3.1. (Entropy) *Given a distribution of probability $p(m)$ over some finite sample space M, the entropy of M is defined by*

$$H(M) = H[p(m)] = -\sum_m p(m) \log p(m)$$

the log is to base 2 and the entropy is expressed in bits.

Very importantly, the function $H(M)$ depends exclusively on the probability distribution $p(m)$, irrespectively of what each $p(m_i)$ is for.

Returning to the situation in which the environment $\mathcal{X}$ affects the system $\mathcal{Y}$, I will define the random variables X and Y and the respective distributions of probability $p(x)$ and $p(y)$, and $p(x, y)$, which are the marginal probabilities of the random variables $X = x$ and $Y = y$, and the joint probabilities that $X = x$ occurs whenever $Y = y$ occurs, so that $x \in \mathcal{X}$ and $y \in \mathcal{Y}$. Thus, $\mathcal{X}$ is the set of all possible values (or assignments) to X. The notation $\sum_x$. means summation over all $x \in \mathcal{X}$, and $|\mathcal{X}|$ stands for the cardinality of X. As long as the entropy is defined for some value of probability $p(m)$, different notions of entropy are defined according to different distributions of probability, and along these lines different meanings as well. If $p(m) = p(x)$, then X is for the source information uncertainty and $H(X)$ refers to the quantity of information contained in the source. If $p(m) = p(x, y)$, then the joint entropy $H(X, Y)$ refers to the uncertainty characterizing the whole system's behavior. If $p(m) = p(x|y)$, so that $p(x|y) = \frac{p(x,y)}{p(y)}$, then the conditional entropy $H(X|Y_i)$ is the uncertainty in X's input since the Y's output is y_i. Notice that there will be $|Y|$ conditional entropies $H(X|Y_i)$, therefore one has to average over the $p(y)$ in order to produce a unique measure, $H(X|Y) = \sum_x p(y) \sum_1^{|Y|} H(X|Y_i)$. The meaning of these former notions can be better understood through the scheme shown in [Figure 5].

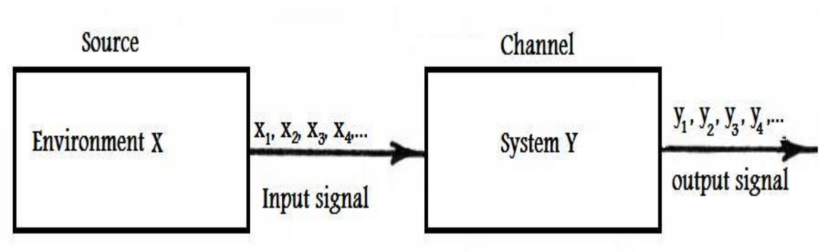

Figure 5 Simplified Communication System

In the typical communication system, the system Y stands for the communication channel, while the environment X stands for the source information. The source emits an input signal x_i according to a distribution $p(x)$ that is transmitted through the channel resulting in an output y_j. The channel is defined as a matrix of conditional distribution $p(x|y)$ and the uncertainty inherent to the transmission is grasped through the conditional entropy $H(X|Y)$. The subtraction of the source entropy $H(X)$ minus the uncertainty $H(X|Y)$ gives the quantity of information processed by the system – or the quantity of information reliably transmitted – which is defined as the *mutual information* $I(X;Y)$.

Definition 3.2. (Mutual Information) *Given a source distribution $P(x)$ and a joint distribution $p(x,y)$, the mutual information between two random variables X and Y is defined as*

$$I(X;Y) = \sum_{x,y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)}$$

The above definition measures the distance between the two variables X and Y. The more statistically dependent are the variables X and Y, the higher the mutual information values obtained. Notice that if the variables X and Y are statistically independent, then the mutual information equals zero. It is easy to prove that $I(X;Y) = H(X) - H(X|Y)$, it follows from the above definition (COVER & THOMAS, 2006).

In general, the source information cannot directly affect the channel, as they are different entities. Therefore, a more accurate description is to represent the source as a different random variable S and a distribution $p(s)$, and the channel exclusively as a matrix of conditional distribution $p(x|y)$. The source S generates a sequence $\boldsymbol{s}$ which is merged in the channel input $\boldsymbol{x}$. In the same way, the channel cannot directly affect the environment, thus the channel's output Y is decoded as a source representation $\hat{S}$ [Figure 6]. Commonly, there is also some noise disturbing the transmission through the channel, which is symbolized by the variable Z. In this new picture, one is able to notice the coding and decoding functions (F, G) which are called the source-channel code. The source-channel code can still be divided as different instances, namely, the source code and the channel code. The first would try to eliminate the source redundancy, while the second to add structured redundancy in order to combat the channel noise. However, focusing attention on just the source-channel code will suffice.

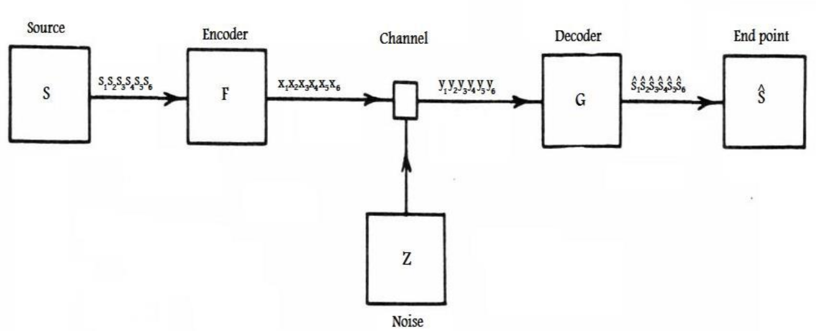

Figure 6 Information System

Many important results are provided by the above conceptual scheme. Among them Shannon has proved that: the lower bound for the lossless source code representation is the source entropy $H(S)$ (Source Coding Theorem); the information can be reliably transmitted through a noisy channel by using arbitrarily long length channel codes (Channel Coding Theorem); the source coding and the channel coding process can be accomplished in completely separate stages being still asymptotically optimal (Source-Channel Separation Theorem); the best rate R that a code can achieve for a fixed distortion value D is given by the Rate-Distortion Function $R(D)$. Shannon, and the latest research, show that there are numerous additional results (SHANNON, 1948, 1964; COVER, & THOMAS, 2006; EL GAMAL & KIM 2011). At this juncture, the main engineering endeavor concerns the devise of optimal codes and, sometimes, suitable channels. On the one hand, the main theoretical results establish the contours (or bounds) of the optimal communication systems. Very importantly, the theory doesn't explain how to transmit information optimally, but it gives the bounds of optimality. On the other hand, it doesn't describe how some information is being processed (which functions are carrying out the process), but only whether or not it is being processed optimally. It may sound pessimist because the formal method doesn't tell which functions accomplish the information processing, however, it is very interesting because it gives the system's contours without getting into those fine-grained problems.

3.2 Rate-Distortion Problem

Previously, Figure 6 showed the transmission process in which the source S is encoded in a channel input code X, transmitted/processed through the channel/processor $p(x|y)$, and decoded as a source representation $\hat{S}$. However, every transmission process in real life has some *cost* – like energy and time – and as the amount of a source's information increases, a perfect representation of the source becomes more demanding. The costs limit the *channel capacity* and they force one to limit the amount of information processed. Very often this limit ends up affecting the *quality* of the source representation, which will result in some *distortion*. When this happens, some bits of information will be lost while others will be reliably transmitted. The scene just described is the Rate-Distortion problem, which is informally captured by the following question: at fixed power budget, what is the highest quality at which the source can be represented at the end point?

3.2.1 Formal statement of the problem

To better understand the rate-distortion problem the previous italicized concepts, 'cost', 'channel capacity', 'quality', and 'distortion', will have to undergo a more formal treatment. Therefore, let us introduce some definitions. The notions of cost and distortion are expressed in the following functions:

Definition 3.3 (Distortion Function) *A Distortion Function, or distortion measure, is a mapping*

$$d: S \times \hat{S} \to \mathbb{R}^{+} \qquad 1.1.$$

from the set of source alphabet-reproduction alphabet pairs into the set of nonnegative real numbers.

Definition 3.4 (Cost Function) *A channel input cost function is a mapping*

$$\rho: \mathcal{X} \rightarrow \mathbb{R}^{+} \qquad 1.2$$

from the set of input alphabet into the set of nonnegative real numbers.

According to these definitions both cost and distortion are a measure of a certain kind. Since we will very often be interested in sequences of source symbols and channels signals, it's convenient to define cost and distortion for sequences, rather than only for single letters. Therefore:

Definition 3.5 (Distortion Between Sequences s and $\hat{s}$) *The distortion between sequences s and $\hat{s}$ is the expected value of the sequence*

$$D = d(s^n, \hat{s}^n) \stackrel{\text{def}}{=} Ed\left(S^n, \hat{S}^n\right) = \frac{1}{n}\sum_{i=1}^{n} d(s_i, \hat{s}_i) \qquad 1.3$$

Definition 3.6 (Input Sequence Cost) *The cost of an input sequence x^m is defined as*

$$\mathrm{P} = \rho(x^m) \stackrel{\text{def}}{=} E\rho(X^m) = \frac{1}{m}\sum_{i=i}^{m}(x^m) \qquad 1.4.$$

The representation's *quality* and the *channel capacity* are both defined in terms of how much information is reliably transmitted whether by the channel output Y or by the source representation $\hat{S}$ – i.e. in terms of mutual information between both $I(S;\hat{S})$ and $I(X;Y)$, above defined.

Definition 3.7 (Channel Capacity) *The "information" channel capacity of a discrete*
memoryless channel is defined as

$$C = \max_{p(x)} I(X;Y) \qquad 1.5$$

where the maximum is taken over all possible input distributions $p(x)$.

The representation's quality is defined solely as the mutual information between S and $\hat{S}$; i.e. $I(S;\hat{S})$, but notice that the two former definitions are not satisfactory as they stand! On the one hand, as the channel input distribution $p(x)$ depends on the source distribution $p(s)$ through the encoding function F, the transmission's costs can exceed the channel's physical limits, if no constraint is fixed. On other hand, when the channel limits the representation's quality so that one is forced to decrease $I\big(S;\hat{S}\big)$, the $I\big(S;\hat{S}\big)$ can be rendered zero, if no constraint is fixed as well – for example, encoding every source symbols s_i to the same channel input x_j. The new definitions that arise from these amendments are the Rate-Distortion Function and the Capacity-Cost Function.

Definition 3.8 (Capacity-Cost Function) *The capacity-cost function of the channel* $(p(y|x),\rho)$ *is defined as*

$$C(P) = \max_{p(x):E\rho(X)\leq P} I(X;Y) \qquad 1.6.$$

Definition 3.9 (Rate-Distortion Function) *The rate-distortion function of the source* $(p(s),d)$ *is defined as*

$$R(D) = \min_{p(s,\hat{s}):Ed(s,\hat{s})\leq D} I(S;\hat{S}) \qquad 1.7$$

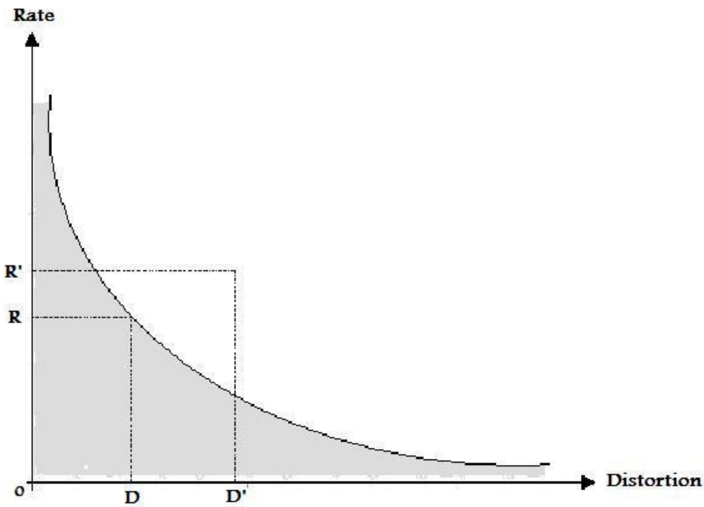

Figure 7 Rate-Distortion Function

According to the new definitions of channel capacity and representation's quality, the achievable channel capacity is restricted by the cost value P, and the reduction of the representation's quality is restricted by some distortion value D. The rate distortion function is a non-increasing convex function of the conditional distribution $p(s,\hat{s})$ [Figure 7]. The *rate-distortion curve* describes optimal channel codes so that the minimum rate is achievable for a fixed distortion value. The area above the curve are the pairs (R,D) trivially achievable, and the area under the curve are the pairs (R,D) unachievable irrespective of (F,G).

Since the channel input distribution $p(x)$ depends on the $p(s)$ through the encoding function F and the joint distribution $p(s,\hat{s})$ depends on the channel $p(y|x)$ through the encoding and decoding (F,G), it becomes clear that there is a trade-off between the cost P and the distortion D: The more cost one can use on the channel, the smaller distortion one can achieve. This trade-off is grasped by the following pair of values.

Definition 3.10 (Cost-Distortion Pair) *For a fixed source* $(p(s),d)$, *a fixed channel* $(p(y\,|x),\rho)$ *and a fixed code* (F,G), *the cost-distortion pair* (P,D) *is given by (1.3) and (1.4), respectively.*

For a given source $(p(s),d)$ and a given channel $(p(y|x),\rho)$, there is an entire set of pairs (P,D) achievable by means of different coding schemes (F,G) [Figure 8]. The cost-distortion curve as drawn in Figure 8 is the union of the pairs (P,D) satisfying

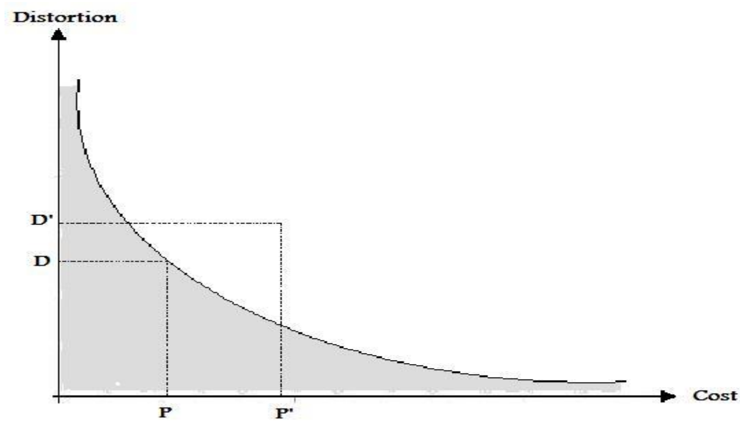

Figure 8 Distortion- Trade-Off Cost

$$D(P) = \lim_{n\to\infty} \min_{F_n, G_{n:E\rho(X)\leq P}} Ed(s, \hat{s}) \quad 1.8$$

With pairs (P, D) satisfying

$$P(D) = \lim_{n\to\infty} \min_{F_n, G_{n:Ed(s,\hat{s})\leq D}} E\rho(X) \quad 1.9$$

Notice that the minimization depends on the channel code (F, G). The points on the *cost-distortion curve* give, for every distortion D, the smallest possible cost P, and conversely, for every cost P, the smallest possible distortion D – what comprise the optimal coding schemes (F, G). The area above the curve gives all the trivially achievable pairs (P,D), while the area under the curve gives all unachievable pairs (P,D).

Shannon has proved the bounds for these notions in terms of the Source-Channel Separation Theorem (SHANNON, 1948; COVER & THOMAS, 2006; EL GAMAL & KIM, 2011). The theorem acclaims that the channel-cost capacity bounds that quantity of source information reliably transmitted – i.e. $R(D) \leq C(P)$. In other words, if the source entropy $H(S) \leq C(P)$, then there is a channel code (F, G) such that $D = 0$ for a fixed cost P – i.e. $R(0) \leq C(P)$ is achievable. Otherwise, if $H(S) > C(P)$, then the distortion D is bounded above zero irrespective of (F, G). The operational version of the theorem says that the maximum rate of source bits that can be safely compressed is upper bounded by the channel-cost capacity $C(P)$.

Still another way to look to the same problem is through the Distortion-Rate Function $D(R)$, which is the inverse function of the Rate-Distortion Function. The distortion-rate function is defined as follows:

Definition 3.11 (Distortion-Rate Function) *The distortion-rate function of the source $p(s)$ and a given rate R is defined as*

$$D(R) = \min_{p(s,\hat{s}):I(S;\hat{S})\leq R} Ed(s, \hat{s}) \quad 1.9$$

The distortion-rate function gives the smaller distortion D for a fixed rate $R = \frac{m}{k}$ where k is for bits per source symbol and m is for number of channel's use. At the same time, for a fixed rate R and channel code (F, G), the function gives a specific distortion value D.

Now, through these sets of formal definitions, the informal question at the beginning of the discussion is translated in the following way: Given a channel-cost capacity $C(P)$ and source $p(s)$, what is the smallest distortion achievable? Or even: given a channel-cost capacity $C(P)$, a source $p(s)$, and a coding scheme (F, G), what distortion value D is achievable? Is this coding scheme optimal? Is this coding scheme at least good enough to achieve a desirable distortion value D? This last question will become the most fertile.

3.3 Central Nervous System as a Communication Channel

I will use the same formal method of investigation to determine whether or not the

Central Nervous System (CNS) is able to process all the information coming from the environment. The aim is not to seriously defend one or another position, since empirical evidence shows that the CNS doesn't experience all information available from the outside world (FRITH, 2007; EAGLEMAN, 2011; GREGORY, 2009), but rather to setup a framework in which old problems will be treated in a different way – hopefully!

In order to assess the CNS's processing capacity it will be viewed as a communication channel. Very importantly, the only requirement to interpret something as a communication channel is that it can be viewed as two statistically dependent (or more) points. The CNS seems to meet this requirement since the sensorial pathway and the pyramidal motor trait can both be interpreted as the random variables X and Y with a set of distribution of probability $p(x|y)$ characterizing their statistical dependence. The environmental information, which includes our own body, is defined as the source information S and the set of all possible muscular twitches as the source's representation $\hat{S}$ – more precisely, both variables S and $\hat{S}$ will be a vector random variable. Our sensorial organs and the biological transducers, along with the early stages of perceptual processing, will be interpreted as the encoding function F whereas the decoding function G will be some process accomplished in the primary motor cortex (KANDEL, et al. 2000). Assuming that the different ways through which a cognitive task is accomplished, either the biological apparatus of cognition or cultural strategies as symbolic employment, are different coding schemes(F, G) (a detailed defense of this point will be done in the Fifth Chapter).

The CNS's information processing has different kinds of costs ranging from catabolic costs to time processing costs. The CNS consumes the average of 20% of energy generated in the catabolic process, which means that its information processing is a very expensive one to the organism (KANDEL, et al. 2000). On the other hand, since it is a control system and the environment is ever changing, information processing time is a very important matter – delay may cost the organism's life. Therefore, a cost function ρ restricts the CNS's information processing capacity in terms of energy and time delay. The crux is to find out whether or not the CNS's capacity $C(P)$ and their various coding schemes (F, G) are able to process all environmental information – i.e. whether $D = 0$. Clearly it is a case for a distortion-rate function (definition 1.9), in which, at a fixed rate $R = C(P)$ and a fixed channel code (F, G), it maps to a distortion value D[8]. To complete the setup a specific distortion function $d(S, \hat{S})$ is missing.

Suppose the source S is a system composed of a finite number of variables, a fair supposition as it is a logical consequence of the question at stake. Because interest is only in finding out whether all the source information is being reliably processed, a Hamming Distortion Function seems to be in order.

Definition 3.12 (Hamming Distortion Function) *A Hamming distortion function is given by*

$$d(s, \hat{s}) = \begin{cases} 0 \; if \; s = \hat{s} \\ 1 \; if \; s \neq \hat{s} \end{cases} \qquad 1.10$$

which results in a probability of error distortion, since $Ed\big(S, \hat{S}\big) = \Pr(S \neq \hat{S})$.

Interpreting the Hamming distortion function as an *Accident Function* so that 0 means a successful action and 1 means an accident, a sequence of sensorial input $\boldsymbol{s}$ is processed through the CNS resulting in sequences of actions $\hat{\boldsymbol{s}}$**.** The average distortion is calculated according the definition 1.3 resulting in a probability of error. If the CNS is processing all the environmental information, then the distortion value D goes to zero – i.e. the probability of error. Notice that measuring the information processing capacity in terms of successful action is in perfect harmony with standard cognitive tests. At almost any

[8] Notice that the distortion-rate function minimizes the distortion measure over the entire set of joint distributions $p(s, \hat{s})$. However, it is an easier task to calculate the function for a particular distribution $p(s, \hat{s})^*$ which is the joint distribution of the particular channel code $(F, G)^*$.

experimental setup the evaluation of the patient's performance is based on his motor feedback. If the source is continuous, then no representation can be perfect. The question at stake has no sense (COVER & THOMAS, 2006).

. To calculate the distortion-rate function, one must have the source distribution $p(s)$, CNS's processing capacity $C(P)$ which is the rate R. However, as we are not interested in the ideal situation of optimal coding schemes for a fixed source distribution and rate $R = C(P)$, we can just measure empirically the representation's distortion in order to evaluate the system's performance. The history of humanity is also the history of the measurement of the CNS's performance in finding a better action plan to handle environmental information. It is clear that in any moment of history, whether using scientific knowledge or not, we have never been able to avoid accident in our interactions, whether grasping a class, driving a car, or launching a spacecraft. Based on these considerations I conclude that the CNS is not processing the whole environmental information.

3.4 What Are the Future Problems in This Picture?

In the previous discussion I've modeled the CNS as a communication channel and have measured its processing capacity with a distortion function, namely, the so-called accident function. The accident function measures the CNS's processing capacity in terms of the right action plan for a given environmental situation. Therefore, the accident function emerges as a system's measure of control; by decreasing the distortion value D, one is increasing the system's control upon the environment. There are at least two reasons why the distortion value is above zero ($D > 0$), namely: The channel-cost capacity might be smaller than the source entropy – i.e. $H(S) > C(P)$; the coding schemes employed by the CNS might be suboptimal.

Beginning with the second reason, the coding schemes being suboptimal means that the distortion value D can be smaller than the one presented by the system for a fixed cost P (GASTPAR, 2002). In fact there is no reason to suppose that biological evolution has endowed an optimal coding scheme, but rather with a good-enough coding scheme – i.e. a coding scheme good enough to survive. As to the first reason, Shannon has already proved the quantity of source information reliably processed is upper bounded by the channel-cost capacity $C(P)$. Even though currently there seems to be no indisputable CNS's measure of capacity, there are a lot of empirical facts which support the belief that there is much more environmental information than our CNS is able to process. To give a simple example, we perceive only 0,0035% of the whole spectrum of light, and the encoding of this tiny portion is still a lossy one – i.e. the colors and hues we perceive are much less informative than the information contained in every color length wave range (GEGENFURTNER & SHARPE, 2001). Accordingly, it will be treated as a lossy compression case.

By treating a lossy compression case, in which all the source bits cannot be processed, the main problem is how to tell the right source bits from the irrelevant ones. In this case, our distortion measure cannot help anymore and new models must be devised – notice that the Hamming distortion doesn't discriminate any source bit. The main problem will be to devise models in which only the source bits that increase control are processed, while redundant bits are thrown away. In this enterprise, devices as scientific theories and technologies are viewed as artifacts that help in this task, where the main goal is to increase the organism's control upon the environment. This conceptual framework suggests a replacement of old and anthropomorphic concepts as truth and reference by concepts such as lossy encoding, redundancy, noise, complexity, and control.

3.5 Final Comments

It's important to remember that the formal model offered here doesn't intend to be a feasible one as it stands. A real model would include feedback, memory and much more complex distortion function. However, it doesn't limit the theoretical framework due to its generality. The main point of this discussion is to introduce a theoretical framework through which science and technology can be viewed in the context of control purposes – preservation of organism's life. A very important conclusion is that the gap between the processed information and the environment is not bridged by any mythical notion such as 'truth', or 'reference', but by successful interaction with environment. In this dissertation, ontology is a question of degrees of freedom in successful action, while epistemology is a question of optimal coding schemes.

CHOOSING BITS: HOW CULTURE SHAPES OUR THOUGHT

4 CHOOSING BITS: HOW CULTURE SHAPES OUR THOUGHT

Nowadays, our discourse includes many things our eyes have not been wired to see. Almost everyone is comfortable speaking about electrons, magnetic fields, galaxies, or black holes, even if almost no one has ever seen such things. To top it all off, we also seem to learn, through our biological development, how to see the world differently. Thereby musicians are able to categorize music according to melody, harmony, and counterpoint; painters are able to distinguish colors, hues and forms; and scientists are very attentive to specific patterns in nature; and so on. Whether determined by Mother Nature (innate) or shaped by culture (learned), our brain seems to be both processing and discarding parts of environmental information. The question is: How does the brain choose the relevant information that must be processed at any time?

In this chapter, I will offer a model which explains how our brain tells the difference between relevant and redundant information. I will divide this choosing process into two stages; innate and learned perceptions. The innate perception processing stage is determined by genetic factors and has little, or no, plasticity. Genetic factors, on their own, seem to have been set by the evolutionary process. On the other hand, the learned perception processing stage depends on multimodal processing interactions and is very plastic. In any specific situation, the brain generates a representation of one given modality of perception that is more informative about another modality. In this sense, the information coming from a given sensory modality becomes a relevant variable determining the information compressed in another sensorial modality. The cultural factors will be interpreted as relevant variables that interact with each other in order to generate more informative representations.

4.1 Sensory Processing Stages

The process generating the perception we experience, if we accept that it is grounded on the neural system's dynamics, can be divided into at least two stages; the peripheral nervous system and the higher-order processing centers in the neocortex (KANDEL, et al. 2000). The peripheral nervous system consists of two types of neurons; the sensory neurons, running from stimulus receptors that inform the

Central Nervous System, (CNS) of the stimuli; the motor neurons, called effectors, running from it to the muscles and glands, that take action. The higher-order processing centers in the neocortex are very complex neural structures responsible for the processing and integration of information sent by the peripheral nervous system – such as the visual area in the occipital lobe–and for elaboration and command of our motor plans. Very importantly, the preprocessed information that arrives at the higher-order centers is the only information to which our brain has access. In other words, the peripheral nervous system is our window to outside reality. What falls outside this window is simply not taken into consideration by the brain.

4.1.1 The innate perception processing stage.

The aforementioned window defines the spectrum of categories upon which our "world" is constructed, it is the first processing stage of perception. However, different from real windows by which light is the same signal carrying information from outside to inside the house, our metaphorical window requires this information being translated from the outside language to the organism's inside language – e.g. the kind of signal whereby outside objects' information arrives at eye's retina (bundle of photons) is not the same as the one that goes from the retina to the brain's visual area (strings of action potential)[9]. The translating task is accomplished by our sensory organs – eyes, ears, touch sensory receptors, taste buds, and olfactory receptors–which are stimulated by the external signals, thereby producing a string of internal signals. The structure exhibited by each string of internal signals defines the set of categories we are able to perceive, such as color, size, velocity, numerosity. The question is: How can we measure the quality of this translation?

To answer that question, the metaphor of translation shall be replaced by the notion of compression of information. In this new framework the environmental information is symbolized by a variable S and the signal emitted by a specific sensory organ by a variable X. An encode function F merges sequences of source bits $\boldsymbol{s}$ into string of internal signals $\boldsymbol{x}$. I will refer to the translation hereafter as encoding. A convenient modeling is to define the encode function as a set of conditional distributions $p(x|s)$ which relates each source bit to every

[9] Here seems to dwell grounds for the philosophical intuition that we don't have direct access to outside reality or reality as such.

string of internal signals according to some probability – the sensory organ is now an information channel. Notice that the closer the distribution $p(x|s)$ is to a determined distribution the more information is transmitted through the channel. In other words, if every source bit is one-to-one mapped to a different string of internal signals, then our spectrum of categories would be as informative as possible. On the other hand, as long as the number of source bits is mapped to one specific string of internal signals, the spectrum of category's quality decreases. This measure, which I will call the complexity of the encoding, can be grasped through the notion of conditional entropy $H(X|S)$ which is zero for perfect representations and increases along with the decreasing of their quality – see 2.3.2.1.for a detailed explanation of these concepts. The question is: On what does the coding complexity depend in biological organisms?

4.1.2 The cytoarchitecture and encoding's complexity

Each sensory organ is viewed as an encoding function which maps the outside information into strings of action potential relaying information to higher-order areas in the brain. The encoding function's complexity is revealed by the cytoarchitecture of the sensory cells. To exemplify the relation between complexity and cytoarchitecture let us look at how the eyes encode light information into strings of action potential.

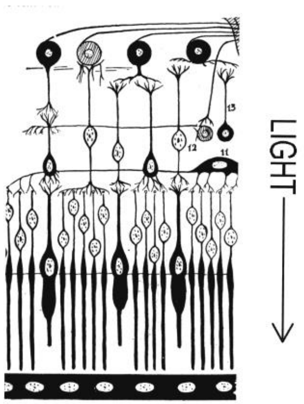

Figure 9 Layer of Photoreceptor Neurons

In all vertebrates' visual system, the light enters the lens and passes to the back of the eyes, where it traverses the retina, passing through layers of transparent cells to reach the *rods* and *cones*. The rods and cones are the light sensitive cells which, if sufficiently stimulated by light, produce an action potential stimulating the downward cells. This action potential will go through a set of *interneurons* until they reach the *ganglion cells* whose axons will form the sensory pathway [Figure 9]. All visual information processed by further brain stages is the information transmitted by the ganglion cells. Therefore, in order to estimate and compare the amount of visual information processed by the retina one has to inquire about the ganglion's response relative to a variety of stimuli.

Different cytoarchitecture may cause different ganglion response relative to the same bundle of stimuli, so as different functions may give rise to different images. Lettvin, Maturana, McCulloch, and Pitts (1959) found that the frog's ganglion seems to respond to just four categories of stimuli; boundaries, dark convex boundaries, moving or changing contrast events, and dimming events. The frog, however, has not shown any response to different stimuli if there is no change. For example, the frog doesn't snap at a flea if it is not moving; i.e., if a flea doesn't move, then it is identical to any other lifeless entity. Differently, Hubel and Wiesel (1962, 1965) found a much more abundant set of responses or categories in the cat's ganglion responses. The cat ganglion seems to react to characteristics such as hues, colors, and angles, resulting in a wider set of categories than that found in the frog's case. Similarly, a set of women seem to react to a more abundant light stimuli than a set of men, providing evidence that women see more colors on average than men (JAMESON, 2007).

The difference in the categories or representations' complexity among the species is grounded in the cytoarchiteture of the sensory cells. To illustrate this point, let us look at two examples. The first example is the neuron which signals temporal and movement pattern. In Figure 10, the neuron's dendrites receive an input from the photosensitive cells and generate an action potential only if the summation of all inputs A, B, C and D can pass the cell's threshold. The cell's threshold is the minimum potential difference between inside and outside cells such that once achieved it generates an electrical pulse that will actively propagate at full amplitude instead of fading passively. Notice that if the distances between the bottom input and the soma are gradually longer, so that the distance between D and the soma is longer than the distance between C and the soma and so on, then the inputs emitted by the photosensitive cells will take gradually longer to arrive at soma. Assuming that the threshold can only be achieved by the summation of all input, the neuron will fire only if a spot of light impinging the input bottoms is moving from right to left, and the velocity of that motion falls within certain limits.

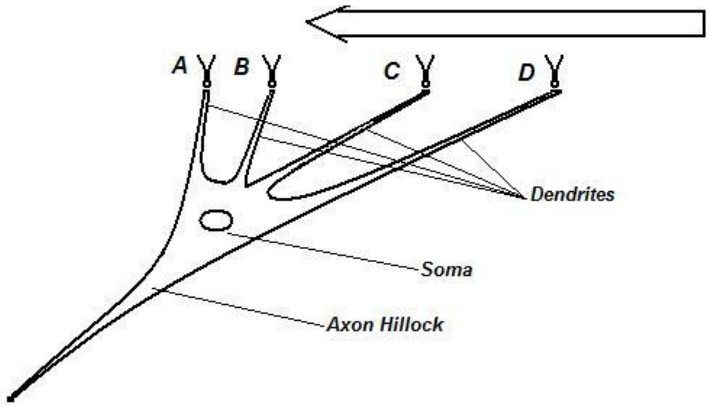

Figure 10 - Temporal and Movement Detector Cell

The second example concerns the case in which some animals are able to see a larger set of colors. This characteristic is called tetra chromatic color vision, and it happens when the organism's eyes have four retinal cone types plus the capacity to transmit four independent cone signals (two short, one medium, and one long-wavelength sensitive) (JAMESON, 2007). Some scientists conjecture that humans with four retinal photo pigment classes might experience a dimension of perceptual experience denied to trichromatic individuals (JORDAN & MOLLON, 1993); implying that cortically, humans might process four color channels, or otherwise learn how to use the additional information.

4.1.3 The innate perception stage is mostly genetically determined.

In all the above cases, the sensory cells are mapping outside information in strings of action potential – they are compressing the information. If every bit of information is one-to-one mapped into different strings of action potential, then the compression is called a lossless one; otherwise, it is called a lossy compression. How the information will be compressed in the peripheral processing stage is determined, if not absolutely, at least mostly, by genetic factors – room here is left for epigenetic factors. In the previous first example, the geometrical structure of the neuron signaling temporal and movement pattern was determined by genetic constraints. It has been shown that the cell differentiation process in the retina is controlled by multiple basic helix–loop–helix (bHLH) genes, which function as intrinsic regulators (HATAKEYAMA & RYOICHIRO KAGEYAMA, 2004; VETTER & BROWN, 2001; CEPKO, 1999). In the second example, the retinal expression of four distinct cone classes is determined by random X–inactivation during embryonic development, so that genes from both altered and normal pigment genes are alternatively expressed as photo pigments across the retina's cone cell mosaic (JAMESON, 2007). At this processing stage the individual has little or no chance to change it. The same applies to the other senses; i.e. eyes, ears, touch sensory receptors, taste buds, and olfactory receptors. The question is: Can the peripheral processing stage fully explain our cognitive experience?

4.2 Learned Perception Processing Stage

Is there any further processing stage beyond the genetically innate perceptual compression? It seems, intuitively, that there might be, since when viewing a particular scene it is possible to interpret it in many different ways. I will interpret this fact as another compression stage at which a portion of the information transmitted by the sensory pathway is processed and yet another portion is discarded.[10] In contrast to the innate processing stage, I will call this other compression stage, the learned processing stage since most of the categories defined at this stage seem to be learned through the organism's development[11]. The intention of my explanation is to both bring up perception's essential characteristics as well as provide a possibility for future research.

The two main ideas structuring my explanation are bottleneck encoding and statistical dependence. The bottleneck encoding refers to lossy compression cases in which the relevant information is chosen by

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[10] The idea that visual perception is compression, in some ways, is obvious simply by the scaling down of representation areas in the brain's visual system from the very large visual area V1 to the smaller V2 and still smaller V4 (RAO & BALLARD, 1999).

[11] If there were further processing stages, then every glance would contain every bit of information transmitted by the sensory pathway and the notion of "perspective" would lack any sense.

taking in consideration a target variable, thus called a relevant variable. The sensory system is viewed as a set of channels processing information so that the information resulting from a specific sensory organ Z (e.g. hearing or haptic) determines the relevant information encoded by another sensory organ X (e.g. vision); i.e. what one hears determines what one sees. However, it presupposes a statistical dependence between X and Z that has to be learned in some way by the brain. I will give a detailed empirical scenario, then will unfold the theoretical explanation.

4.2.1 Empirical scenario

The empirical scenario is characterized by three main ideas; the fragmented character of the perceptual visual onset, the preceding interaction routines, and the emergence of language. There seems to be a relation among these three ideas so that the interaction routines are a logical presupposition for the emergence of a unique intersubjective representation among the individuals of a same community, and the emergence of a unique intersubjective representation is a logical presupposition for the emergence of language.

4.2.1.1 Fragmented character of the perceptual visual onset

There is evidence supporting the interpretation that our perception is shaped by experience through the development of the organism. The internal representation generated at the onset of the ontogenetic process seems to be very fragmented – e.g. distinct objects may appear as one unique object and conversely. Within this evidence are the findings that infants can perceive a whole object as early as 2-months of age *only if* the object undergoes motion (JOHNSON & ASLIN, 1995). However, the ability to perceive the object as a whole, without motion, does not develop until the age of 6.5 months, and the ability to discern the form of the objects' hidden area does not appear until 8 months (OSTROVSKY, 2010; CRATON, 1996).

The fragmented character of perception not only features the perceptual onset of the newborn babe but it is also present in vision recovery cases. The same fragmented character is found in individuals who acquire sight late in life (VON SENDEN, 1932; GREGORY AND WALLACE, 1963; VALVO, 1971; FINE et al., 2003; OSTROBSKY, 2010). Although these individuals show a situation pretty much like the newborn baby, they need longer to acquire the visual skills, possibly due to decreases in plasticity (OSTROBSKY, 2010). This result corroborates the hypothesis of two levels of information processing, one determined mostly by genetic factors and the other determined mostly by environmental factors.

4.2.1.2 Interaction routines and joint attentional episodes

A fragmented representation of the environment is not useful because it conducts the organism to wrong action plans – i.e. taking a cup and a table as a unique object would conduct the agent to drop the cup on the floor in many cases. On the other hand, cooperation among the community's organisms requires a convergent representation in order to establish common action plans – how can we arrive at a consensus if we are unable to pay attention to the same environmental features? Psychologists seem to view *joint attentional episodes* as evidence for a convergent representation (TOMASELLO & FARRAR, 1986; TOMASELLO, 1988; CARPENTER, et al., 1995; TOMASELLO, 2003). According to Tomasello, "[j]oint attentional episodes [are] defined as relatively extended periods (at least 3 seconds) for which both parties are focused on the *same object* at the *same time* and the child acknowledges that jointness with, for example, a look to the mother's face" (TOMASELLO, 1988, p. 72; my emphasis). However, these episodes seem to be scaffolded by an even deeper stage in the organism development, namely, *interaction routines*. According to these authors, the first steps of communication are implemented by interaction routines in which the task structure of the routine and the maternal scaffolding play a central role (RATNER & BRUNER, 1978; NINIO & BRUNER, 1978; BRUNER, 1983; TOMASELLO, 1988; TOMASELLO, 2003). Then, it seems, that interaction routines are the path to a congruent representation, which has as a symptom, joint attention.

4.2.1.3 Language emergence

According to Tomasello, once joint attention focus has been achieved, around 6 months, the child begins to use actions – pointing and interactions with object – so as to direct the adult's attention. As we are going to see later, it means that they use proprioceptive information to determine the relevant visual/hearing/haptic information[12]. In other words, once the subjective experiences of two or more different individuals become similarly structured the language acquisition process starts. The first referential expressions usage appears – holophrastic speech - around 12 months. These referential expressions function as proper names conducting the adult's attention to specific portions of the scene. Around 18 months, for the first time, children share the focus of attention on some object or activity and proceed to make a linguistic comment about that topic (holophrastic predication). Later on, language starts to acquire its grammatical structure. It's very important to note that as soon as language has been acquired, it "[…] then becomes one of her [child] primary devices for establishing and maintaining joint attention with an adult […], making it a transitive process" (TOMASELLO, 1988, p. 1975). The term 'transitive' here means that the role played by action in determining joint attention is now transferred to language.

4.2.2 Theoretical framework

The explanation of how each modality of perception is compressed will be best expressed by the Rate Distortion theory or, more precisely, by an extension of the Rate Distortion Theory, i.e., Information Bottleneck Method (TISHBY et al. 1999; SLONIM, 2002). As we will see, this theoretical framework will give us interesting conceptual insights about philosophical questions.

Let X be a discrete random variable with a finite set of possible values, $\mathcal{X}$, distributed according to $p(x)$. Let Y denote some other discrete random variable which is a compressed representation (or quantized codebook) of X. This representation is defined through a (possibly stochastic) function associating the values of these two variables. Formally, this mapping can be characterized by a conditional distribution $p(y|x)$, inducing a soft partitioning of X values. Specifically, each value of X is associated with all the codebook elements (Y values), with some normalized probability. As the

[12] To say that a convergent representation has emerged is synonymous with saying that the philosophical notion of object has emerged. From this point of view, the notion of object is always an abstraction. A difference in between a less – particular – and a more abstract – general – entity is the difference between a compression with less distortion – particular - and with more distortion – abstract – measure.

cardinality $|\mathcal{X}|$ increases, a perfect representation of these random variables becomes more demanding. What determines the quality of this compressed representation?

It seems natural to determine the quality of the compressed representation by the quantity of information that Y conveys about X. In order to ensure the transmission of information occurs, sequences of different inputs from X have to produce disjoint sequences of outputs from Y – i.e., if two different bits x_i e x_j, for $i \neq j$, result in the same output y_i, then no information is conveyed. The uncertainty characterizing the association between each input and each output is given by the conditional entropy $H(X|Y)$, which is $H(X|Y) = 0$ when there is no uncertainty at all (when the system is determined) and is $H(X|Y) = H(X)$ when there is only uncertainty and no information is conveyed. Using the Asymptotic Equipartition Property (AEP) (COVER AND THOMAS, 2006), it is possible to see that for each typical *n*-sequence of Y symbols, there are $2^{nH(X|Y)}$ possible X "input" n-sequences, all of them equally likely. Again using AEP we see that the total number of typical X *n*-sequences is $2^{nH(X)}$. In order to ensure that no two X sequences will produce the same Y sequences, the set of possible X sequences has to be divided into subsets of size $2^{nH(X|Y)}$, where each subset corresponds to some different Y-sequence. The total number of such disjoint subsets is upper bounded by $2^{n(H(X)-H(X|Y))} = 2^{nI(X;Y)}$. Therefore, we can send at most $2^{nI(X;Y)}$ distinguishable sequences of length n from X to Y. The *mutual information* $I(X;Y)$ emerges as the natural measure for the representation's quality. Is it enough?

Very often one is looking for a more compact representation Y of the information source X. In the CNS case, for example, it is not interested all the time in the most detailed environmental representation, and there are a multitude of control tasks for the brain, so that it is always looking for the most parsimonious representation. Hence the objective becomes to minimize the amount of processed information – i.e., minimize the mutual information $I(X;Y)$, which is written as $I(X;Y) = \sum_x \sum_y p(x,y) \log \frac{p(x,y)}{p(x)p(y)}$. However, if one writes the joint distribution $p(x,y)$ as $p(x)p(y|x)$ and the probability $p(y)$ as $\sum_x p(x)p(y|x)$, then the mutual information can be written as $I(X;Y) = \sum_x \sum_y p(x)p(y|x) \log \frac{p(x)p(y|x)}{p(x)\sum_x p(x)p(y|x)}$. With the mutual information written in terms of the source distribution $p(x)$ and the conditional distribution $p(y|x)$, it becomes clear that minimize $I(X;Y)$ is the minimization problem over the entire set of all possible distributions $p(y|x)$ – which is easy to prove to be a strictly non-increasing convex set (COVER AND THOMAS, 2006). Notice that the minimum that the distribution $p(y|x)$ can assume is when, given a y_i in particular, all the n values of X are uniformly possible – i.e., when the two variables X and Y are statistically independent and no information is conveyed. Therefore a restriction over this minimization problem is necessary, otherwise all information is lost.

The restriction in the minimization problem is the main point of the Rate Distortion Theory (RDT), because it is what will determine the source's relevant information. In the Rate Distortion Theory's traditional approach, the restriction is given by the distortion measure (Definition 3.3), a function that measures the distance between the source variable X and the representation variable Y. A distortion value D is given by the expected value of the distortion function $D = Ed(x^n, y^n)$ over a sequence of n bits. The RDT gives us the Rate Distortion Function, $R(D) = \min_{p(y|x):\sum_{(x,y)} p(x)p(y|x)d(x,y) \le D} I(X;Y)$, which is the infimum of rates R such that (R, D) is in the rate distortion region of the source for a given distortion D. As already stated, the minimization is over all conditional distributions $p(y|x)$ for which the joint distribution $p(y,x) = p(x)p(y|x)$ satisfies the expected distortion constraint. This problem can be solved by introducing a Lagrange multiplier, β, and then minimizing the functional $\mathcal{F}[p(y|x)] = I(Y;X) + \beta \sum_t \sum_x p(x)p(y|x)d(x,y)$ under the normalization constraints $\sum_y p(y|x) = 1, \forall x \in \mathcal{X}$. The drawback with this approach is that the distortion function's design is a completely arbitrary subject matter and very often it is virtually impossible to imagine what such function could be[13].

Another approach to set a restriction in the minimization problem is called Information Bottleneck Method (TISHBY et al., 1999). In this approach, which can be viewed as an extension of the traditional approach (SLONIM, 2002), beyond the information source variable X and its compressed representation Y, we must also consider another variable, Z, the so-called *relevant variable*. In this case, instead of considering the source distribution $p(x)$ and an arbitrary distortion measure $d(x,y)$, we will consider just the joint distribution $p(x,z)$

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[13] The variational problem can be solved by using converging iterative Blahut-Arimoto Algorithm (COVER AND THOMAS, 2006).

between the variable X and Z, provided they are not statistically independent, and a Markovian property, characterizing the relation among the variables X, Z, and Y. Thus, we will look for a compressed representation Y of X that is more informative about Z – i.e., we want to minimize $I(X;Y)$ and maximize $I(Y;Z)$, so that $I(Y;Z) \geq \widehat{D}$, where $\widehat{D}$ is a minimum of relevant information. The distortion upper bound constraint is now replaced by a *lower* bound constraint over the *relevant information*, given by $I(Y;Z)$.

As in the traditional case, we are looking for the most compressed representation Y of X – i.e. we want to minimize $I(X;Y) = \sum_x \sum_y p(x)p(y|x) \log \frac{p(x)p(y|x)}{p(x)\sum_x p(x)p(y|x)}$, where the free parameter corresponds to the stochastic mapping $p(y|x)$. To correlate the representation's quality $I(Y;X)$ with the relevant information $I(Y;Z)$ we use the Markovian property. As the representation Y cannot convey more information to Z than the source variable X and there is no new information in Y about Z given X, the three random variables form a Markov Chain in the following order $Y \leftrightarrow X \leftrightarrow Z$. Therefore, we can use the Markovian property to compute the relevant information $I(Y;Z)$ in the following way:

$$\begin{cases} p(y) = \sum_{x,y} p(x,z,y) = \sum_x p(x)p(y|x) \\ p(z|y) = \dfrac{1}{p(y)} \sum_x p(x,z,y) = \dfrac{1}{p(y)} \sum_x p(x,z)p(y|x) \end{cases}$$

Where $p(x,z)$ is assumed to be given and $p(x) = \sum_z p(x,z)$. Notice that by minimizing the representation's quality $I(X;Y)$ we are automatically minimizing the relevant information $I(Y;Z)$. As in the traditional case, this variational problem is solved by using Lagrange Multipliers, $\mathcal{L}[p(y|x)] = I(X;Y) - \beta I(Y;Z)$[14]. The Lagrange Multiplier β controls the performance of the distribution $p(y|x)$ given a cardinal in $|Y|$. For $\beta \to 0$, every X values is assigned to just one Y value; and for $\beta \to \infty$, Y becomes the most informative representation given a fixed number of representatives – if $|X| = |Y|$ and $\beta \to \infty$, then Y just copies X in every aspect. In our case, as $|Y|$ can be viewed as

[14] As in the rate distortion case, the variational problem here can be solved by using a converging iterative Information Bottleneck Algorithm (TISHBY et al. 1999).

standing for the channel capacity, $|X| \gg |Y|$, thus even though $\beta \to \infty$, we still will have a lossy compression due to information processing limits. However, what is more interesting about this formalism is that it gives us optimum representations even for finite values of β and $|X| \gg |Y|$.

4.2.3 "What one hears determines what one sees."

Our experience of the world is multimodal – e.g. objects have color, sound, texture, and so on – even though we have a different sensory channel for each sensory modality. The *sensory stimuli* feeding the different sensory organs don't seem to be statistically independent since the association of their contents results in successful interactions in most cases. If so, then the *internal representation* we experience can be understood as the compressed representation which maximizes the statistical dependence among the different concomitant sensory stimuli. For example, our visual experience is a compressed representation of the stimuli emitted by the visual sensory pathway which holds the most statistical dependence with another *concomitant stimulus* – such as the proprioceptive feedback coming from our present movements. In the theoretical model, the *sensory stimuli* are for the X variable, the *internal representation* is for the Y variable, and the *concomitant stimulus* is for the Z variable [Figure 11]. Evidently, the variables X and Z can be for

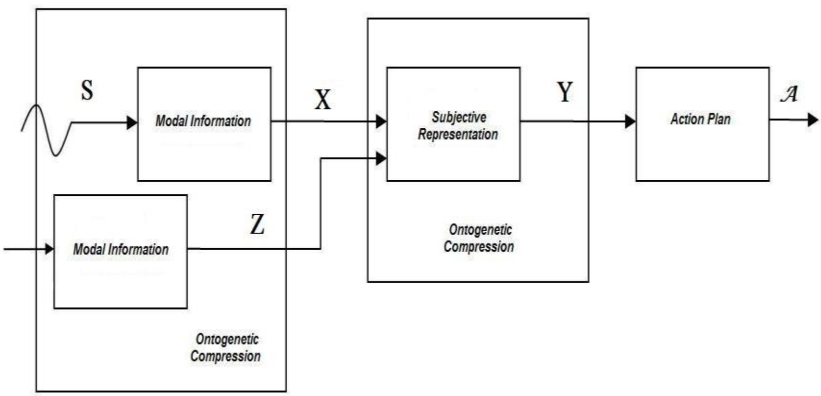


Figure 11 - The information X coming from the peripheral processing is compressed in a representation Y which maximizes the information about Z, another modal information. Y will serve as parameter for future action.

different sensory stimuli modalities – such as visual and hearing, hapic and visual, and so on.

The aforementioned statistical dependence has to be learned, *in most cases*, that cars (visuospatial pattern) honk "beep beep" or that the sound "chair" occurs in situations where one is interacting with the visuospatial pattern, chair. As soon as those statistical dependencies start getting wired into the brain – based on Herb's principal[15] – our internal representation starts to get unified. Based on a rough convergent representation, the learning process starts to bind multimodal features so that visuospatial patterns have taste, sounds precede events, form has texture, and so on. Language seems to be just one of those modal features – although one that we have more control over. Thereby the brain seems to grasp the recurrent event of a specific sound s given a representation y, which quickly becomes recorded as a memory m. If the recurrences are interpreted as a conditional distribution $p(m|s)$, interesting conclusions seem to follow.

To begin with, as the baby's world is pretty simple and recurrent, the conditional distribution tends to be almost determined – e.g. given the sound "chair", the baby's home chairs come to his/her mind. Determined conditional distributions can be interpreted as standing for proper names - i.e. the sound s brings to the baby's mind

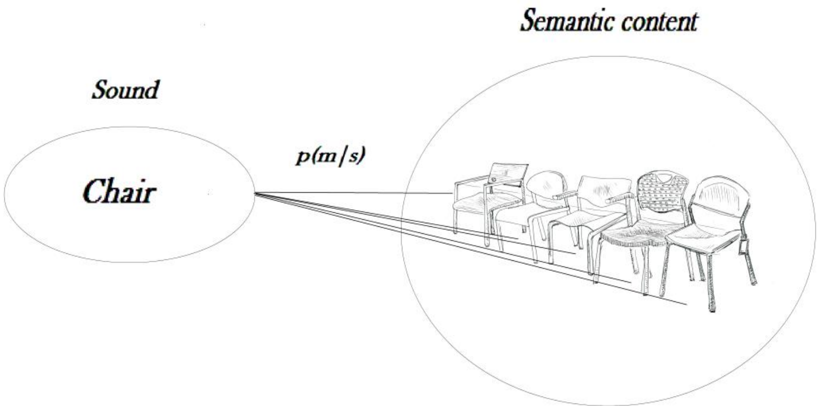


Figure 12 - The distribution of probability p(m|s) depicts the semantic relation between the sound S and the semantic content M.

[15] This learning process is pretty natural in the brain, provided that there is a neurological basis for that. Therefore, according to the Herb principal – neurons that fire together, wire together- frequent co-activation makes, gradually, more likely co-activation, again and again.

his/her home chair with probability approaching 1 and other chairs with probability approaching 0. As the learning processing goes on the M's domain gets larger, the conditional distribution gets more scattered and the meaning gets more abstract – predication gets in. Once the recurrent event gets wired into the brain, the stimuli S becomes the relevant variable Z. The occurrence of s_i gives a partition of the domain M according to the distribution $p(m|s_i)$. Now instead of considering just the joint probability $p(x, z)$ we will consider the distribution $p(x, m|s_i)$. Different stimuli s will induce different partitions of the M's domain, resulting in different representations Y of X. Therefore, what one hears determines what one sees [figure 12].

4.2.4 Does CNS have a model in the Information Bottleneck structure?

Despite of the brain's great complexity there seems to be some touch points between the theoretical model and the real system. Different processing stages are preceded before we are able to hear, or to see, or to feel, and act in the outside world (KANDEL et al., 2000; PANDYA & SALTZER, 1982). After the phylogenetic level of information processing, the sensory information is processed in a series of relays along several parallel pathways from peripheral receptors. This information arrives at the first information processing station, the *primary sensory cortex*, where it is processed in a fragmented way – e.g. the color information is processed separately from the form information, and so on. After the primary sensory cortex the information is relayed to the second processing station, the *unimodal association cortex*, where the fragmented modal information is integrated in a unique code – i.e. in a unique pattern of neural activation. Every modal station – i.e. visual, auditory, and somatosensory unimodal association cortex – projects itself to the next processing station, the *multimodal association cortex*, which integrated information from different modalities.

The sensory information is processed sequentially from the peripheral receptors through every processing station, and in parallel in the sense that every modality is processed at the same time converging to a multimodal representation. In fact, the multimodal association cortex has been seen as the neural substrate of consciences – patients with damage in the inferior parietal lobule cannot locate objects in their visual world or construct an internal representation of the world around them (amorpho-synthesis) (KANDEL et al., 2000). There are three main multimodal association cortex areas; *posterior multimodal sensory* *integration*, *limbic association area*, and *anterior multimodal motor integration*. The posterior parietal station is responsible for the sensory integration, which has been the philosophers' obsession. The limbic integration center is responsible for memory and emotional expression. The anterior multimodal motor integration station is responsible for converting all the information coming from these centers in motor plans – actually both centers project themselves to one another. In our model the posterior multimodal sensory integration station could be viewed as the representation Y and a unimodal station as the variables X. The variable Z in the model could be interpreted as any station coactivated with that specific unimodal station X.

The circular problem with this interpretation is that at the beginning of the ontogenetic development there must be a system in the CNS able to process modal information without any relevant variable – otherwise every compression would require a relevant variable Y and so on. Is there any kind of innate faculty in the brain?

4.2.4.1 Mirror neuron system, action understanding, and autism.

According to the empirical scenario above described, a convergent representation emerges from the routines of cooperation. According to our hypothesis, the brain encodes the information coming from one sense, maximizing the mutual information from another information source. The question is: What kind of information is available to the newborn infant which seems to be decisive in the compression of the perceptual information in the routines of cooperation scenes? A plausible explanation seems to be that the brain is taking proprioceptive information – routines of cooperation – as the information which is going to determine the relevant visual/hearing information to be compressed. In other words, the infant's brain seems to look for a visual – or hearing – compression which makes more sense to the adult's script of actions. If so, then action understanding must be an innate faculty and there should be severe impairments when this innate faculty is damaged. Is there anything such as an innate action understanding faculty? Is there any severe impairment related to the damage of this skill? Yes, there is! Mirror neurons have been identified as the action understanding system, and autism seems to be strictly related to damage in this system.

Mirror neurons are a particular class of visuomotor neurons, originally discovered in area F5 of the monkey premotor cortex, that discharge both when the individual does a particular action and when he/she observes another individual (monkey or human) doing a similar action (DI PELLEGRINO et al. 1992, GALLESE et al. 1996, RIZZOLATTI et al. 1996a; RIZZOLATTI & CRAIGHERO, 2004). Empirical evidence suggests that the mirror-neuron system is the basis for action understanding (BUCCINO et al., 2001; FADIGA et al., 1995; FLANAGAN and JOHANSSON, 2003; GALLESE et al., 2002; KEYSERS and PERRETT, 2004), imitative behavior (LACOBONI et al. 2001; LACOBONI et al. 1999; NISHITANI and HARI, 2000), face imitation (CARR et al. 2003; LESLIE et al. 2004), and joint attention (COLOMBI et al., 2009). The areas in which mirror-neurons are found – these areas comprise the opercularis of the inferior frontal gyrus lobule (BA44) and its adjacent ventral area 6 (inferior frontal cortex, IFC), the inferior parietal lobule (IPL), and the superior temporal sulcus (STS) – show activation during *mental representation* of one owns action, and mental representation and *observation* of another person’s action (BUCCINO et al. 2001; BUCCINO et al. 2004; DECETY and GREZES, 1999; DECETY et al. 1997; GRAFTON et al. 1996; GREZES et al. 2003; GREZES and DECETY, 2001; HARI et al., 1998; RIZZOLATTI et al., 1996). An important aspect to be noticed about the mirror-neuron system is that it is not sensory modality dependent; i.e., the mirror-neuron system is able to extract an action representation whether from visual or hearing information (KOHLER et al. 2002; RIZZOLATTI and FADIGa, 2005). Empirical evidence supports the thesis that the mirror-neuron system is an inborn faculty, because the skills that it seems to account for are present in neonates at only 36 hours old (FIELD et al., 1985; FIELD et al., 1982; MELTZOFF & MOORE, 1977, 1983; HADJIKHANI, 2007).

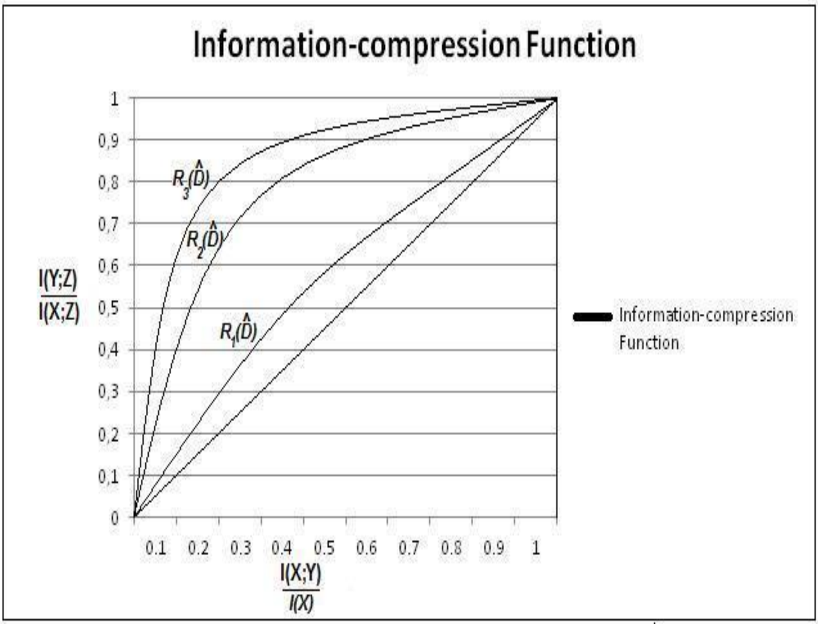
Autism is a disease which has been characterized as a mild to severe qualitative impairment in communicative abilities, reciprocal interactions, repetitive and stereotyped behavior, lack of attention to faces, and deficits in joined attention (OSTERLING & DAWNSON, 1994; MUNDY et al., 1993; HADJIKHANI, 2007). Much evidence has linked mirror-neuron system (MNS) impairment with autism. Scientists have found in anatomical studies that adults with HFA (high-functioning autism) display significantly reduced cortical thickness in areas of the MNS. In addition, the degree of cortical thickness decrease was correlated with the severity of communicative and social symptoms of the subjects (HADJIKHANI et al., 2006; HADJIKHANI, 2007). They also have found, in behavioral experiments using electroencephalographic studies that Asperger subjects, unlike normal controls, did not profit from mirror-image movement of others during an imitation task (AVIKAINEN et al., 2003; NISHITANI et al., 2004). By using functional MRI studies, scientists have found that areas of the MNS were hypo-activated in the HFA compared to controls. They found hypo-activation in right motor somatosensory cortex corresponding to the face representation; and they also found an inverse correlation between the activation in the IFC and the severity of the social symptoms (HADJIKHANI et al., 2004; HADJIKHANI et al., 2006; HADJIKHANI et al., 2007; DAPRETTO et al., 2006). Similar results have been found by using transcranial magnetic stimulation studies (THEORET et al., 2005), electroencephalographic studies (LAPAGE and THEORET, 2006; OBERMAN et al., 2005), and electromyographic studies (MCINTOSH et al., 2006).

4.3 Heuristic and Philosophical Conclusions: The Role of Culture

According to this interpretation, cultural factors are viewed as a concomitant stimulus which determines the relevant information in a given perceptual stimuli source. The concomitant stimulus activates the memory content, according to a statistical correlation learned in experience, which interferes in the perceptual processing. It explains why people with different backgrounds tend to have different perspectives of the world – they have learned different statistical correlations. Based on this theoretical model, important results follow as its consequence.

4.3.1 Cultural factors form a continuous spectrum.

According to the theoretical model, the quality of the internal representation depends on the degree of dependence between the concomitant stimulus and the sensory stimuli. This degree of dependence is quantitatively grasped through the formal notion of mutual information $I(X;Z)$. If so, notice the following facts: the $I(Y;Z)$ is always upper bounded by the original information, $I(X;Z)$ – i.e. the statistical dependence between the internal representation and the concomitant stimulus cannot be greater than that one held by the sensory stimulus and the concomitant stimulus. Additionally, $I(Y;X)$ is clearly upper bounded by the source information, $H(X;X) = H(X)$ (COVER & THOMAS, 2006) – i.e. a representation Y of a variable X cannot be more informative about X than the one X variable. Therefore, we must also consider the *normalized* relevance compression plane, where the vertical axis is determined by $\frac{I(Y;Z)}{I(X;Z)}$ while the horizontal axis corresponds to $\frac{I(X;Y)}{I(X;X)}$ [Graphic 2]. The normalized relevance-compression function is, thus, always bounded between one and zero, hence different joint distributions $p(x,z)$ can be characterized and compared by their corresponding curves in these normalized plane. Notice that as the set of all possible joint distributions $p(x,z)$ is also a non-increasing continuous convex set, the distance between less informative stimuli from more informative ones is continuous. Therefore, the putative different among religion, pseudo-science, and science is just contextual. All these sets of stimuli are informative in some extent, thereby, conducting to some internal representation; however, some of them are more informational than others. Graphic 1 demonstrates how different relevant variables give rise to different information-compression curves.



Graphic 2 – The different curves display different information processing performances relative to different relevant variables.

4.3.2 Theories, interpretation, and mathematics.

The mutual information $I(X;Z)$ can also be written $I(X;Z) = H(X) - H(X|Z)$, which means the difference between the entropy of X and the conditional entropy of X given Z. The entropy $H(X)$ is for the quantity of information transmitted by the perceptual source X, and the conditional entropy $H(X|Z)$ is the uncertainty about occurrence of the perceptual stimulus X given the concomitant stimulus Z has happened. The conditional entropy $H(Z|X) = \sum_{x \in X} p(x) \sum_{z \in Z} p(z|x) \log p(z|x)$ depends on the conditional distribution $p(z|x)$, so that the more scattered the distribution is over the X's domain given $z \in Z$, the greater uncertainty. For determined distributions there is not uncertainty at all. Notice that the degree of scatteredness of the conditional distribution $p(z|x)$ can be interpreted as the stimulus' ambiguity. For example, how many things will come to mind when the word "thing" is spoken? The conditional distribution for the occurrence of the stimulus "thing" is very scattered. On the other hand, how many things will come to mind when the word "snake" is spoken? According to this interpretation, stimuli that are amenable to varied interpretations are less informative, whereas stimuli that constrain our interpretative freedom are more informative. And that is why mathematics is the most suitable metaphor in most cases, because its concepts are often strictly well-defined, it constrains our interpretative freedom. This interpretation gives another perspective on the logical Popperian conclusion that "[a] theory which adds to all information which it asserts, can also negate this information, giving us no information at all" (POPPER, 1962, p. 319) – in our interpretation it means that Z is statistically independent of X.

4.3.3 Metaphysical implications.

We have seen that different variables Z will induce different representations Y of X. However, what does it mean to say that a variable Z_1 is different from another variable, to say, Z_2? All that counts here is the complexity involved in the relation between the variable X and Z which is expressed by the mutual information $I(X;Z)$. It means that if two concomitant stimuli Z_1 and Z_2 hold the same joint distribution $p(x,z)$, then they will give rise to the same representation Y of X. In summary, if two conceptual schemes present the same complexity, they are equivalent. In other words, if different scientific theories result in the same experimental plans, then they are equivalent.

The only relevant aspect of a source of stimuli is its statistical dependence with the occurrence of other stimuli. Equivalent theories induce the same representations, and better theories produce more informative representations.

4.4 Final Considerations

The theoretical model offered here introduces a new line of thought rather than an experimental model, as it stands. The brain's information processing involves more stages (more variables) even in its most general description. However, I believe that it doesn't make the model inappropriate since the general principal seems to be the same – i.e. to extract information from a variable while saving information from another one. It also should be noted that the motivating insight here – that some sort of information interacts with the perceptual information – is not a new one, and that psychologists already have noted this aspect of our cognition (BARSALOU, 1999; BERGEN, LINDSAY, MATLOCK, & NARAYANAN, 2007; ESTES, VERGES, & BARSALOU, 2008; GALLESE & LAKOFF, 2005; GLENBERG & KASCHAK, 2002; MATLOCK, RAMSCAR, & BORODITSKY, 2005; METEYARD, BAHRAMI, & VIGLIOCCO, 2007; RICHARDSON, SPIVEY, BARSALOU, & MCRAE, 2003; SPIVEY & GENG, 2001; STANFIELD & ZWAAN, 2001; ZWAAN, MADDEN, YAXLEY, & AVEYARD, 2004; ZWAAN, STANFIELD, & YAXLEY, 2002), even though the interaction mechanisms between abstract metaphors and perception still remain a moot question (DILS & BORODITSKY, 2010; RICHARDSON et al., 2003; BERGEN et al., 2007; BORODITSKY, 2000). Whether this theoretical model will provide a basis for experimentation is a future problem. Nonetheless, it seems a worthy enterprise, considering its possible conceptual gains.

THE SYMBOLISM AS A CHEAP CHANNEL CODE: THE SYMBOLIC LANGUAGE'S ROLE IN THE COGNITION

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In general, there seem to be different ways in which human beings cognitively handle sources of information. Tasks, such as number guessing, velocity, weight, and extension estimation, can be accomplished through different cognitive strategies – e.g. by counting, or comparing objects' characteristics, and so on. In most cases, these different ways imply different performances and costs to the subject. In this chapter, we offer an interpretation of these "different ways" in terms of different channel codes through which the environmental information is processed by the Central Nervous System (CNS). By considering the channel code's cost and performance, we will distinguish among three categories of codes; prompt processing, working memory, and symbolic coding scheme. The code metaphor affords alluring explanations to important questions, such as: Why do we have the internal representation that we have – in terms of colors, extension, and texture? Why are simple theories considered better than complex ones? Why do different representations of a given system, even if conflicting, result in the same action plans (experiments)? In most cases, examples will be given through the number guessing experiments, though the general principles seem to be applicable to cognitive tasks broadly.

5.1 Theoretical Framework

The information processing carried out by the Central Nervous System (CNS) is interpreted as the communication system whose performance is measured in terms of control. Therefore, environmental information is processed by the sensorial organs resulting in action plans whose objectives are to keep the organism alive. Whenever an accident occurs I will assume some bit of information had been wrongly decoded – the average over the suffered accidents gives the degree of control – or the lack of control. According to this interpretation, an information processing system is specified by six entities, grouped into three pairs: The source $(p(s), d)$, consisting of a probability distribution $p(s)$ and a distortion function d; the channel $(p(y|x), \rho)$, consisting of a conditional probability distribution $p(y|x)$ and a cost function ρ; and the code (F, G), consisting of the encoder F and the decoder G functions [Figure 13]. For the purpose of this paper, we are concerned with discrete and finite alphabets.

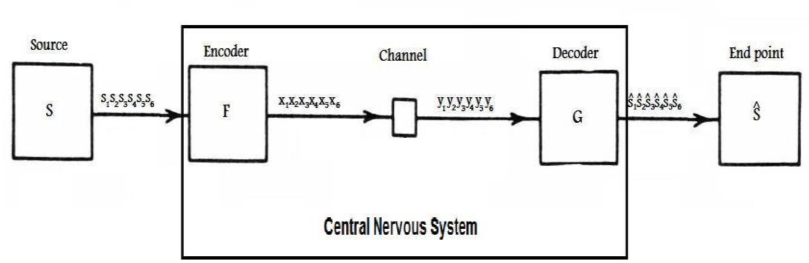


Figure 13 Information system

Definition 5.1 (Source) *A discrete-time memoryless source* $(p(s), d)$ *is specified by a probability distribution* $p(s)$ *on an alphabet* S *and a set of Hamming-like distortion functions. Let's take the power set* $\mathcal{P}(S)$*, so that* $\mathcal{P}(S) = \{\bar{\bar{S}}_1, \dots, \bar{\bar{S}}_i, \dots, \bar{\bar{S}}_{2^{|S|}}\}$*. Now let us define a set of Hamming-like distortion functions* $U = \{d_1(S,\hat{S}), \dots, d_i(S,\hat{S}), \dots, d_{2^{|S|}}(S,\hat{S})\}$ *so that*

$$d_i(S,\hat{S}) = \begin{cases} 0\ if\ s = \hat{s}\ e\ s \in \bar{\bar{S}}_i\ ou\ s \neq \hat{s}\ e\ s \notin \bar{\bar{S}}_i \\ \quad 1\ if\ s \neq \hat{s}\ e\ s \in \bar{\bar{S}}_i \end{cases}$$

is called the Accident Distortion Measure, which results in a probability of error, since $E d_i(S,\hat{S}) = \Pr_i(S \neq \hat{S})$*. This implicitly specifies an alphabet* $\hat{S}$ *in which the source is reconstructed. As the alphabets are discrete, we call this, a discrete memoryless source, and the probability distribution becomes a probability mass function (pmf).*

Definition 5.2 (Learning Function) *To choose among the* $2^{|S|}$ *distortion functions* $d_i(S,\hat{S})$*, a set of sequences* $A_\epsilon^n = \{\boldsymbol{s_1}, \boldsymbol{s_2}, \dots, \boldsymbol{s_n}\} \in S^n$ *is generated according to the distribution of probability* $p(s)$*, the so-called typical set of* S*. Then we define an index function* $\mathcal{L}$ *so that*

$$\mathcal{L}: A_\epsilon^n \to U$$

is called Learning Function. The learning process is a question of finding out the Learning Function $\mathcal{L}$*. The sequences in* A_ϵ^n *can be interpreted as the typical situations occurring in our world.*

Definition 5.3 (Channel) *A discrete-time memoryless channel* $(p(y|x), \rho)$ *is specified by a conditional probability distribution* $p(y|x)$, *defined on two discrete alphabets* X *and* Y *and a nonnegative function*

$\rho: X \rightarrow \mathbb{R}^{+}$ *1.3.*

called the channel input cost function. When the alphabets are discrete, we call this a discrete memoryless channel.

Definition 5.4 (Source-Channel Code) *A source-channel code of rate* R (F, G) *is specified by an encoding function*

$F: S \rightarrow X_n$, *1.4.*

yielding code words $x^n(1), x^n(2), \ldots, x^n(2^{nR})$, the set of code words is called the *codebook* or *coding scheme*.

And a decoding function

$G: Y_n \rightarrow \hat{S}$, *1.5.*

such that k/n = R, where m is for m uses of channel and k is for number of bits per source symbol.

For a fixed source $(p(s), d)$, a fixed channel $(p(y|x), \rho)$ and a fixed code (F, G), we can then easily determine the average incurred distortion,

$D_i \stackrel{\text{def}}{=} Ed_i(S^k, \hat{S}^k)$, *1.6.*

and the average required cost,

$\Gamma \stackrel{\text{def}}{=} E\rho(X^m)$ *1.7.*

The information source S is merged in a codebook $(n, 2^{nR})$ through the encode function F and transmitted through the channel $p(y|x)$ at a cost Γ. The channel output is decoded through the function G resulting in source estimation (or representation) $\hat{S}$, resulting in a distortion D. The maximum quantity of information transmitted through the channel, given the cost constraint Γ, is defined in terms of Mutual Information as following:

Definition 5.5 (Capacity-Cost Function) *The capacity-cost function of the channel* $(p(y|x), \rho)$ *is defined as*

$C(\Gamma) = \max_{p(x): E\rho(x) \leq \Gamma} I(X; Y)$ *1.8.*

The cost measure limits the quantity of information that the channel can transmit reliably. According to the Source-Channel Separation Theorem, if $H(S) \leq C(\Gamma)$, then there exist a source-channel code so that the probability of error goes asymptotically to zero. Otherwise, if $H(S) > C(\Gamma)$, then the probability of error is bounded above zero – which means that the $D > 0$ (COVER & THOMAS, 2006). In other words, if the source entropy is greater than the channel-cost capacity, then no compression can be carried out lossless. The function which gives the compression rate, for fixed distortion value D, is the Rate-distortion function.

Definition 5.6 (Rate-Distortion Function) *The rate-distortion function of the source* $(p(s), d)$ *is defined as*
$R(D) = \min_{p(\hat{s}|s):Ed_i(S,\hat{S})\leq D_i} I(S|\hat{S})$ *1.9.*

On the other hand, the function which gives the distortion value, for a fixed rate R, is the Distortion-rate function.

Definition 5.7 (Distortion-Rate Function) *The distortion-rate function of the source* $(p(s), d)$ *is defined as*
$D(R) = \min_{p(\hat{s}|s):I(S,\hat{S})\leq R} Ed_i(S, \hat{S})$ *1.10.*

We are most interested in the distortion-rate function, where the parameter $R = C(\Gamma)$; i.e. given the channel-cost capacity, we are interested in codes which can reduce the distortion value D as close as possible to its limit. The main objective of this chapter is to compare different coding schemes and their respective distortion values D_i in order to measure their efficiencies.

5.2 Prompt Processing Scheme: Subitizing

Prompt information processing is represented by the following setup: An information source S emits a sequence $s_1, .., s_i, \dots, s_m$, of m bits of information, which is compressed through a encoding function F onto a channel input sequence $x_1, \dots, x_i, \dots, x_n$ of n bits of information, for $i \in T$ and $m > n$. The m-bits sequence is the perceptual information consisting of size, color, texture, length, numerousness, and so on, and the n-bits channel input sequence consists of our internal representations about the outside world. The clause that $m > n$ means exactly that the coding function is lossy compressing the environmental information into the internal representation. The n-bits channel input sequence is processed through the channel $p(y|x)$ generating an output sequence $y_1, \dots, y_i, \dots, y_n$, which is the semantic meaning invoked by the internal representation. The output sequence generated by the channel is decoded through decoding function G in a motor plan $\hat{s}_1, \dots, \hat{s}_i, \dots, \hat{s}_k$, for $k \leq m$ [Figure 1]. The pair $(F, G)^p$ is precisely our ordinary representations which ground our intuitive notion of reality. The channel has a cost limit Γ so that sequences $x_1, \ldots, x_i, \ldots, x_n$ have their length constrained – supposing that we're just interested in cases of reliable transmission.

In order to measure the average of error of the code $(F, G)^p$, some psychological experimentation is needed. Some cognitive experiments assume the following general format: A perceptual sample is showed for a short period of time – often less than one second – and then it's asked for the subject to give the suitable motor answer for it – which is either voicing something or pushing a lever or executing more elaborate action plans. An example is the guessing experiments in which a given setup is quickly shown – e.g. a set of objects – and the individual has to guess the exact characteristics of the setup. Typically, the experiments' results present inconsiderable error average relative to sparse sources of stimuli – whether numerosity, extension, or velocity. But, as the source information rate is increased above a given quantity, the average of error starts to increase almost-linearly along with the source information rate. Sometimes this average of error is also expressed in terms of the Weber's Fraction, which is a constant describing of the slop of variance's growth recta related to the increasing of the quantity of information (KRUEGER, 1989)[16] – as the variance increases the error average does as well. The Weber's Fraction, for numerical processing is around 12% (TRICK, & PYLYSHYN, 1994), for size-constancy processing it is around 4% (MCKEE & SMALLMAN, 1998), and for the object's speed and trajectory processing it is between 5%-10% (MCKEE & WATAMANIUK, 1994; MCKEE & SMALLMAN, 1998; HARRIS & DEAN, 2003). Still other perception's modalities, such as color hues (BARLOW, 1956, 1977; LILLYWHITE, 1981; BIALEK, 1990; BANKS et al. 1987), show the same trade-off between the source information rate and error average.

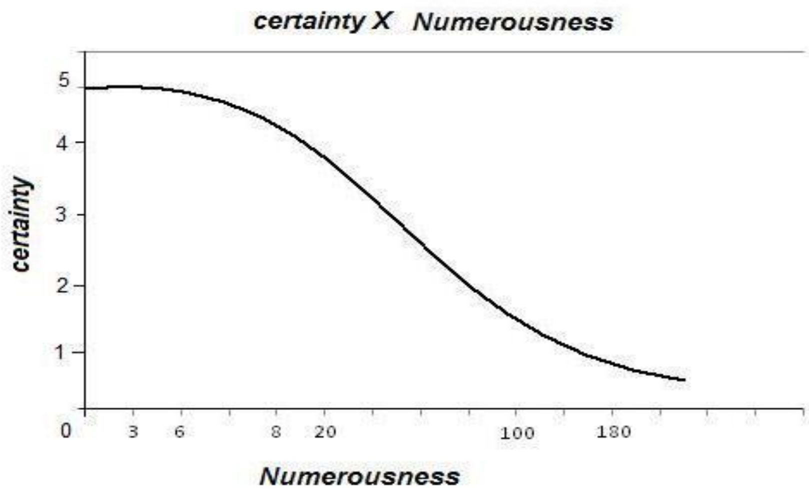
The trade-off between the source information rate and the average of error can be appreciated in the number processing case. In the number guessing experiment, a setup containing a given number of entities is shown for a short period of time – often less than one second – and the subject has to guess the setup's numerosity. The subject's test performance gives rise to two numerical processing phenomena; *subitize*

[16] The guessing performance's uncertainty can be conceptualized through different notions; for example, either in terms of variance, or entropy, or simply as a conditional distribution.

and *estimation.* In the former condition, one is able to subtly recognize the set's numerosity up to around 3 or 4 elements while, in the latter condition, only an estimation is possible KAUFMAN et al. 1949; TRICK, & PYLYSHYN,1994; DEHAENE, 1997). As the term "subitizing" suggests, it occurs when the individual subtly recognizes the set's numerosity as rapid as 40-100ms/item, effortless, and very accurate – practically error-free. On the other hand, for setup's numerosity greater than 4 only estimations with some degree of uncertainty are possible, which means that the average of error is bounded above zero.

Kaufman et al. (1949) represented the subjects' number guessing performance through the trade-off between uncertainty and the source information rate [Graphic 3]. The certainty axis is divided in 6 degrees, where 5 means complete certainty and 0 means complete uncertainty. Notice, that at 4 or 5 objects, there is almost complete certainty while it brusquely decreases after 6 objects. Graphic 3 shows clearly the almost linearly increasing of the average of error, after a given value, along with the source information rate increasing. Therefore, if few objects compose the setup, the visual representation achieves the right magnitude with high certainty; i.e. $D_i \approx 0$. Otherwise, for large setup's numerosity, the average of error is bounded above zero, $D_i > 0$. In summary, the code $(F, G)^p$ compresses the m-bits perceptual sequence in an n-bits channel input sequence, which consists of our internal representations about the outside world. As the channel-cost capacity limits the number of bits reliably transmitted, the perceptual sequence's bits are lossy compressed in the channel input code words. The compression carried out by the code $(F, G)^p$ is a kind of all-purpose one, for even in the situations in which only numerosity is interesting, color information, for example, cannot be stripped out from the representations. For this reason, the perceptual sequence's bits interact with each other so that a setup with exceeding color information disrupts the number processing, for example (KAUFMAN et al. 1949; ALVAREZ & CAVANAGH, 2004). The uninteresting information is called redundancy and the prompt processing scheme doesn't seem to be a good code to handle specific situations. But why has nature endowed us with such a code? The reason seems to be that the $(F, G)^p$ code is a good code, on average, over many different situations. When the average distortion D is calculated for whole set U of Hamming-like distortion functions $d_i(S, \hat{S})$, the expected value $E(U) = \frac{1}{2^{|S|}} \sum_1^{2^{|S|}} D_i$

results in a tolerable value – i.e. it keeps the organism alive in most cases.



Graphic 3 - Certainty Versus Numerousness

5.3 Working Memory Scheme: Biological Recoding

The main idea of the previous discussion was that the prompt coding scheme is a good one when handling a variety of situations, but it is not an optimal code when handling specific tasks – i.e. it is a good source-channel code averaging over all Hamming-like distortion measures $d_i(S,\hat{S})$, but it is a bad one for a subset of them. For specific situations, where just some specific bits are relevant, a different coding function would be better.

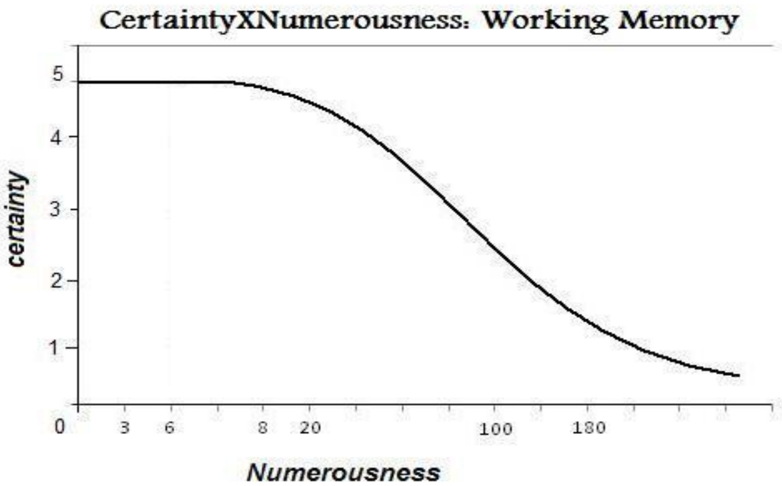
This time I will examine how the working memory's role in cognitive tasks fits into our previous theoretical model. The working memory is basically a memory system needed for executing complex motor tasks when the essential cues are not present in the environment at the time of the response (KANDEL et al., 2000). The system, in different ways, seems to help the performance of cognitive tasks. I will interpret the working memory as an encoder which employs different codes $(F,G)^w$ according to different distortion measures $d_i(S,\hat{S})$.

The term 'working memory' refers to a brain system that provides temporary storage and manipulation of the information necessary for such complex cognitive tasks as language compression, learning, problem solving, and action planning (REPOVS & BADDELEY, 2006). The working memory has two broad functional characteristics; maintenance and manipulation of information. According to the multicomponent model (BADDELEY, 2010, 2012), the information maintenance is putatively carried out by three distinct systems; the phonological loop, the visuospatial sketchpad, and the episodic buffer. The first two are modal subsystems, respectively, for auditory and visual information, while the last is a multimodal integration subsystem. Still each maintenance system has two functional distinctions; the passive storage and active rehearsal of information. The passive storage retains the information temporarily and it is subject to loss by decay or interference over time. The active rehearsal of information tries to simulate the retained information so as to keep it in mind – e.g. rehearsal would correspond to the common strategy of sub vocally repeating the sequence of digits to oneself. The other broad functional characteristic, manipulation of information, corresponds to the central executive, which is responsible for recoding the information in a new format – such as when one sub vocally repeats some sequence of digits according to a specific format. Neurological evidence suggests that the anterior regions of the cortex – such as inferior frontal cortex (BA 44; Broca's area) and premotor cortex (BA 6) – are responsible for rehearsal and manipulation, while posterior regions of the cortex are responsible for storage – such as inferior and superior parietal cortex (BA7/40) and right inferior parietal cortex (BA 40) (PAULESU et al., 1993; AWH et al., 1996; SMITH et al., 1997; HENSON, 2001).

Even if the temporary storage and manipulation roles can help in cognitive tasks separately, we will focus on the cases in which they seem to work together in order to recode the perceptual information (KANDEL et al., 2000; BADDELEY, 2010, 2012). The preprocessed information is retained in one of the storage systems and then it is recoded by the manipulation system. For example, for the case in which one is interested in the setup's numerosity, the subject can recode the setup's numerosity in terms of "chunks" so as to surmount the prompt processing limit (COWAN, 2001, 2006; FEIGENSON & HALBERDA, 2004; LUCK & VOGEL, 1997; IRWIN, 1992; 1996; MILLER, 1956). Therefore, if the processing of numerousness was limited to around 3 or 4 objects (subitizing), then by using working memory one is able to increase this number to around 7, with very low average of error [Graphic 4] – without counting! The encoder's role is viewed as an endeavor to deploy different source-channel codes $(F,G)^w$ in order to reduce distortion value D_i according to every specific i – remember that the index i is given by typical sequence (situation) occurring. The new mental representation (channel input) generated by the working memory is very poor concerning color, size or texture information, but it is much more informative about numerical information – it is a better code for handling redundancy.

If it is plausible to interpret the working memory as an encoder, then the information kept in it should be of a preprocessed kind. Neuropsychological evidence offers support for the independence between the working memory's information and the semantic content currently retrieved through it. Among this evidence is the fact that similarities in semantic content currently retrieved through a set of stimuli are irrelevant for the acuity with which these stimuli are kept in working memory. For example, if one were given a list of words, such as "map" "tap" "lap" "flat" and so on, it would be difficult to remember all those words because the stimuli displays similar pattern. On the other hand, if one were given a list of words, such as "house" "home" "abode" "apartment" someone would not have as much of a problem remembering even if the semantic content is about the same. This is because working memory functions at a preprocessed level not taking into consideration the semantic content. (COLLE & WELSH, 1976; SALAMÉ & BADDELEY, 1982). Still, the concurrent modal information tends to disrupt different modal information kept in working memory. There is a reduction in recalling lists of visually presented items brought about by the presence of irrelevant spoken material. The spoken material's semantic content is completely irrelevant, with unfamiliar languages or noisy sounds being just as disruptive as meaningful words in one's own language. These results are interpreted under the assumption that disruptive spoken material gains obligatory access to working memory (COLLE, 1980; SALAMÉ & BADDALEY, 1982).

Even if the working memory allows the brain to surmount its limits of prompt processing, it doesn't get far enough. This system appears to be strikingly limited in capacity, and can only store a small amount of information for short periods of time – it's around three items for not more than three seconds--in the number processing case (COWAN, 2001, 2006; LUCK & VOGEL, 1997; IRWIN, 1992; 1996; MILLER, 1956). On the other hand, working memory's representation is still structured with the same prompt processing code's properties – i.e. even if it privileges some kind of information, say numerosity, it cannot preclude the other kind of information, such as colors, forms, and so on. For example, if a dense colorful setup is presented, it causes the numerical capacity of visuospatial sketchpad, which is generally estimated to be about 4 items, to decrease (COWAN, 2001; MILLER, 1956). These results generalize the working memory's limits for the setup's complexity, rather than for just the number of objects (ALVAREZ & CAVANAGH, 2004).



Graphic 4 - Certainty Versus Numerousness by Using Working Memory

5.4 The Cultural Strategy: the Employment of Symbols

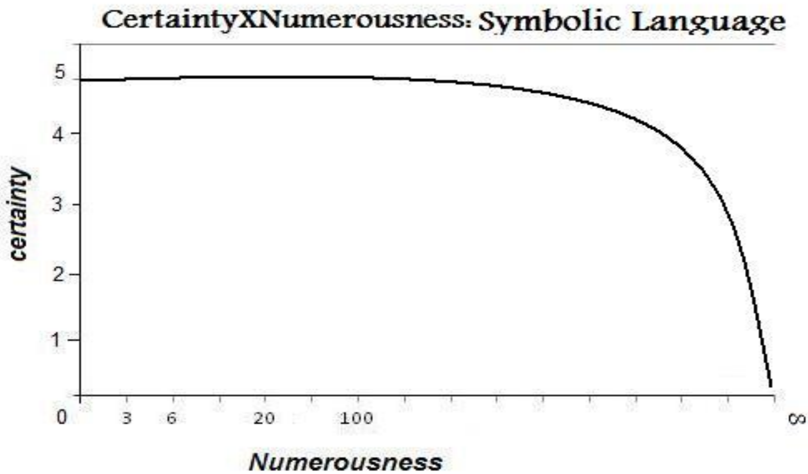
The working memory, as previously mentioned, is an encoding system which stores information and recodes it. The problem with this system is that it is severely limited in storage capacity. Additionally, the working memory code is too costly for optimally handling large amounts of information; its overload causes severe disruption to many cognitive tasks. A new and less costly format is the channel code $(F, G)^S$ [17], which represents symbolic language as another coding scheme. The symbolic language coding scheme has at least two advantages in comparison with the internal representation schemes. First, it is a cheaper and more efficient channel code than the internal representation schemes and, second, it liberates the working memory to

[17] A similar interpretation, in terms of two mental calculation systems, has been offered by Dehaene (1991).

help in learning, problem solving, and planning tasks. By using a more efficient code, much more information can be reliably transmitted, which ends up improving drastically the system's control upon the environment.

1.1. *Efficiency and cost*

The three-object prompt processing limit can be interpreted as the channel-cost capacity. An efficient channel code should achieve the smaller error rate by compressing the source information in code words that don't exceed the complexity expressed by that setup. To compare two codes' efficiency one should pay attention to its average of error on the cognitive tasks. By comparing the internal representation codes' performance with the symbolic performance in numerical tasks, one can see the huge difference in efficiency [Graphic 5].



Graphic 5 – Certainty Versus Numerousness by Using Symbolic Language

The graphic is, to some extent, speculative because mathematical skills based on symbolic language mastery vary according to cultural factors such as training, educational system efficiency, and so on. At least two groups of evidence support the interpretation of the symbolic language as a channel coding scheme; (*i*) the symbolic language deficit increases the error rate in retrieving the right numerical magnitude; and (*ii*) the symbolic systems' evolution proceeds seems to be constrained by brain processing cost-capacity.

(i) The symbolic language deficit increases the error rate in retrieving the right numerical magnitude. There is a correlation between the bloom of the mathematical skills and mathematical language competence. The burst of conceptual and interactive mathematical skills with which to handle quantities beyond the subitizing's and working memory's numerical capacity is concomitant with the numerical language acquisition. The ability to count and handle larger numerosities rises in children around $3\frac{1}{2}$ years old just when numerical linguistic devices start being mastered (GALLISTEL & GELMAN, 1992; WYNN, 1990). On the other hand, evidence from Amazonian Indigene groups have supported the thesis that language is a condition of possibility for exact representation of numerosities beyond subitizing quantities. The group's individuals, whose language misses linguistic devices for quantities larger than 3-or-4 objects, have shown only an ability to estimate over larger quantities (PICA et al., 2004; MCCRINK, et al., 2012). Neuropsychologists have found that disorders in number representation frequently are accompanied by disorders in language. Patients with brain damage in areas typically associated with language faculties have shown a severe impairment with exact numerical processing of larger quantities. These same patients, however, still keep their capacity to exactly represent quantities up to three objects and to estimate over larger quantities (SPELKE, & TSIVKIN, 2001; DEHAENE & COHEN, 1991; MCCLOSKEY, 1992; WARRINGTON, 1982).

(ii) The symbolic systems' evolution proceeds seem to be constrained by brain processing cost-capacity. As human interaction routines require the processing of larger quantities, it increases the demand for channel code bits. Different numerical notional systems have different costs, which eventually obligate us to change from one numerical notational system to another according to the increase of the demand. The complexity expressed by the around-three-objects representation can be interpreted as standing for the channel-cost capacity limit, which doesn't mean that this limit is the around-three-objects numerosity, as it contains figurative information as well.

Probably, the first numerical notational system used consisted of bundles of sticks paired one-to-one with the setup's objects [Figure 14]. It was the least efficient numerical notation, because its only advantage was that of keeping the informational content out of the ever changing environment, which saves short or long-term memory demand. However, as the number of sticks increases along with the set of objects' numerosity the bundle-of-sticks coding scheme meets the same subitizing's and working memory's limits. Therefore, the bundle-of-sticks numerical system is a costly channel code to process quantities larger than fifteen or twenty objects. Looking at the code's redundancy is another way to assess the code's efficiency. Notice that every stick can be permutated without changing the code's information, which means that the code uses much more bits than necessary to encode a given amount of information.

Figure 14 - Bunch-of-Sticks Number System

The second, the naming-summation numerical system is a channel code category under which, for example, are the Egyptian and Roman number systems, characterized by the employment of naming quantities and summation strategies. The notational marks are for numerical magnitudes and their repetition means their summation (VÁZQUEZ, 2001; HOLENDER & PEEREMAN, 1987). The marks retrieve numerical facts stored in long-term memory whose meaning is provided by inborn numerical skills or constructed by combining them (SIEGLER & SHRAGER, 1984; WYNN, 1995; SPELKE, & TSIVKIN, 2001). For example, the Egyptian inscription of the number 543 is HHHHHTTTTUUU, where the symbols H, T, and U denote the powers 100, 10, and 1, respectively. Through the use of the naming-summation numerical system the numerical information can be compressed in shorter code words than those provided by the bundle-of-sticks system (which is coextensive with the subitizing's and working memory's limits) – the Roman numerical system, which uses subtraction notations as well, produces even shorter compressions. However, as the permutation test indicates, the representation provided by the naming-summation numerical systems still contains too much redundancy; e.g. the code words HHHHHTTTTUUU and HHUHUHTTUHTT express the same numerical quantity. Even though the naming-summation numerical system permits us to process exact quantities in the hundred's magnitude, it becomes too costly to process numerosities around the thousand's magnitude, meeting the subitizing's and working memory's limits.

The third example is the multiplicative numerical system - e.g. Chinese number system (VÁZQUEZ, 2001; HOLENDER & PEEREMAN, 1987). The multiplicative numerical system is also based on underlying additive and naming principles, but a supplementary multiplicative principle allows for suppression of the cumbersome repetitions of the symbols belonging to the same rank. Different symbols for each unity $(u1, u2, \ldots, u3)$ are introduced. The Chinese 543 is therefore written in the form, $u5Hu4Tu3$. Although the multiplicative system uses five different symbols instead of three needed in hieroglyphic Egyptian, it makes it possible to compress the numerical information in shorter code words. However, as some permutation is still permitted – $u5Hu4Tu3$ means the same as $u4Tu5Hu3$ – the representation provided by this category of notation contains redundancy.

The last numerical system is the positional numerical system – the Arabic Number System (VÁZQUEZ, 2001; HOLENDER & PEEREMAN, 1987). This system was developed some time in the first half of the sixth century A.D. in India, from whence it spread more or less rapidly to the whole world through the Arabic people. The system uses only 10 symbols, the same former system's operations, and the rank of the units abstractly symbolized by the position occupied by these units in the code word. The Arabic numerical system encodes quantities in the usual way, as we know it, and produces very short compressions of huge quantities – e.g. 10^{80}, which is approximately the number of atoms in the entire observable universe. It also provides us with powerful algorithms by which different quantities and relations are compressed in shorter code words – equations. These algorithms can be viewed as a whole class of encoding functions producing the shortest code words possible. As easily noticed, permutation among the symbols are not permitted without changing the encoded information.

Although the above discussion has been restricted to the processing of quantities, the same interpretation can be applied to different dimensions of perceptual information processing. Therefore different areas of applied mathematics are connected with different cognitive processing limits; e.g. geometry and size-constancy processing, differential calculus and object's speed and trajectory processing, and so on. The interpretation also seems to give an explanation to the intuition "simple theories are the best theories" (POPPER, 1992; VAN FRASSEN, 1980), for the simple theories' costs are smaller, which decreases the probability of error. It's by no mere chance that much of the mathematician's work consists of, by exploring the isomorphism among different structures, finding simpler ways in which to solve a problem. However, it doesn't always mean that complex theories can be compacted into simple (low cost) representation. In fact, according to the source coding theorem, the lower bound compression is the $R(D)$, which is $R(0) = H(X)$. Therefore, as long as one looks for less lossy representations, the code words' cost inevitably is to increase.

5.5 Representations Stand for What?

The representational interpretation of the internal experience and the symbolic language's role has dominated the occidental thought at least since Plato. The general idea of this line of thought seems to be grasped through the Varela et al. words:

> "[…] that the world is *pre-given*, that its *features* can be specified prior to any cognitive activity. Then to explain the relation between this cognitive activity and a pre-given world, we hypothesize the existence of mental representations inside the cognitive system (whether these be images, symbols, or sub-symbolic patterns of activity distributed across a network does not matter for the moment)." (1993)(Italics mine).

In the representational interpretation, the particularities of a given representation – such as colors, extension, or commutativity – stand for real properties from the outside world and it is the relation of correspondence or adequacy, with its reference to the outside world that makes one representation better than another[18]. On the other hand, in the channel code interpretation of the representation's role, a code's intrinsic characteristics, for example, encoding light as colors or as wave lengths, has nothing to do with source information, all that matters is the source's and code's complexity. As we have seen, these particular coding aspects have rather a lot to do with channel and its cost, and not with the source itself. Speculatively, if the brain-cost capacity were greater (or infinity) than that suggested by cognitive experiments, the employment of symbolic language would be unnecessary.

What does it mean to say source and code complexity? The intuitive way to understand this complexity is in terms of the degrees of freedom of the system's behavior or the degrees of freedom through which a system can affect another one. Mathematically, any system can be conceptualized as a set of variables and its degrees of freedom as a distribution of probability (ASHBY, 1957). If so, the Shannon Entropy, which is a function of the distribution of probability, emerges as a suitable measure of complexity in terms of the minimum bits necessary to describe unequivocally the system behavior[19] (SHANNON, 1948; COVER & THOMAS, 2006). More importantly, the main purpose of a code is to convey the source's complexity as reliably as possible. However, very different codes can display the same complexity and their intrinsic characteristics will depend exclusively on the channel's nature. But how can we evaluate the code's performance? This is a very important question.

To evaluate the code's performance, one has to measure the distance between the source information and the processing information, which is properly the source representation $\acute{S}$. This distance is measured according to a distortion measure whose definition depends on the system's purpose. As we have said before, as the CNS is understood as a control system, the distortion measure has to be one that grasps this controlling dimension. In our model, the distortion measure is a Hamming-like distortion that we call Accident Function, $d_i(S,\hat{S}) = \begin{cases} 0\ if\ s = \hat{s}\ e\ s \in \bar{\bar{S}}_i\ ou\ s \neq \hat{s}\ e\ s \notin \bar{\bar{S}}_i \\ 1\ if\ s \neq \hat{s}\ e\ s \in \bar{\bar{S}}_i \end{cases}$. The accident function interprets,

[18] It is worth noting that in the representational interpretation, the belief that simple theories are better has, in principal, no clear explanation.

[19] Shannon Entropy is not the only measure of complexity. The Kolmogorov-Chaitin complexity is also a measure of complexity and both measures are mathematically related (KOLMOGOROV, 1963; CHAITIN, 1969; GALATOLO et al., 2010).

as an error, the decoding which results in accident. Therefore, the symbol “=” does not represent “equals” or “equivalent” but represents successful action – the symbol “≠” is for unsuccessful action. Therefore, if two coding schemes result in the same source representation (action plans), they will be equivalent for communication purposes. The perspective seems to be in agreement with one of the older philosophical insights; that we cannot compare the reality with subjective or symbolic representation. However, all the time, we compare and test the motor plans and empirical experiments resulting from these coding schemes. When a given code directs us to a successful motor plan, we say that “it represents the reality”. Putting these two ideas together we get to the following statement: Our epistemology (coding schemes) can be diverse, but our ontology (successful interaction) is unique.

5.6 Conclusion

I have been discussing, broadly, different paths taken by an organism to better perform cognitive tasks. In this interpretation, these “paths” are understood as different coding schemes through which information is processed by the Central Nervous System. Two main aspects concerning the coding schemes’ performance were pointed out. These are the coding scheme’s cost and its ability to handle with redundancy. We distinguished among three coding schemes to which the organism resorts: the prompt processing, working memory, and the symbolic coding scheme. The prompt processing scheme seems to be the better code on average; however, a bad one for specific tasks. The working memory coding scheme seems to be better than the former one, but still too costly to perform specific tasks optimally. The symbolic scheme seems to be the cheapest and the more dynamic one for handling redundant information. The coding scheme metaphor serves to explain the old philosophical insight that simple theories are better theories and to mark a division between the epistemological domains as diverse versus the ontological domain as unique.

AN INTERACTIONIST ONTOLOGY

6 AN INTERACTIONIST ONTOLOGY

In this chapter I will present my ontological thesis which is called, Interactionist Ontology. The interactionist approach is a realist ontology which establishes that what we are able to directly or indirectly interact with are the only things there are. The central tenet in this enterprise is grounded on the concept of action which is understood as our ultimate connection with the external world. Different from the common philosophical setup, the interactionist perspective doesn't assume a segregate picture in which there is a clear distinction between the knowing subject and the reality; rather it is built on a continuous picture in which the external world is a continuation of us and conversely. As I will defend, the Interactionist Ontology accounts for an independent and unique world with which we interact. The contours of this world – or 'the description' to use the wrong word – are given by the sequences of successful actions – i.e. the plans that keep the biological organism alive. Reality consists of those constraints which limit the range of all possible actions to those that are successful actions. As a conclusion, reality has, properly, no representation, but only restrictions of interaction.

6.1 What is Ontology?

Ontology may be described as consisting of a simple question: What is there, what exists? However, very often this question format is not considered very elucidatory; as Quine has pointed out, it promptly suggests the simple answer "everything" (QUINE, 1980). In order to give a more comprehensive question format, some cherished conceptual framework, some epistemology is required, in which the question will be reformulated. For example, Quine translates the traditional question format in terms of the first-order logic existential statement 'There is something which is such and such," (QUINE, idem) in order to avoid reference to undesired entities. The epistemological choice is very important since it doesn't only define the ontological question's new format, but also constrains the range of possible answers. Thus, as a first philosophical step, one must be concerned with the choice of the right epistemology – i.e. one that will conduct the philosopher to satisfactory conclusions.

Depending on what kind of ontology one is interested in defending, the previous question needs the additional clause "irrespective of whether or not we know it." The clause corresponds to one of our basics intuitions about the world: *Independence*. Independence tells us that whatever the reality is it is independent of us. Theoretically, it means the task of detaching the ontological domain from the epistemological domain. The problem of eschewing an epistemological infection of the ontological domain is called, epistemological predicament (BERGMANN, 1960). The failure in detaching these two domains is called, Idealism. What it says is, roughly, that knowing's are the only things there are (DICKER, 2011). Most philosophers try to keep the outside world's flame alive by offering some argument which, supposedly, saves independence – such as temporal endurance (STRAWSON, 1979) or data independence (BERGMANN, 1964). An ontology which saves, or intends to save, the reality's independence is called, Realism. As we will see, Interactionist Ontology is a Realistic Ontology.

Another important intuition is: *Unity*. Unity tells us that whatever the reality is, it is not multiple, but unique. In some sense, unity seems to be narrowly linked to the notion of independence. Its connection is anchored on the intuition that the same object can be described through diverse 'perspectives' and still be the same object. The contingent aspect of the description is commonly interpreted as inherent to epistemology, whereas the sense of sameness is interpreted as inherent to ontology. This opposition between contingency/perspective versus necessity/unity seems to presuppose independence since the detachment is required – even though the opposite is not true.

The way the epistemological choice permits one to articulate the concepts of independence and unity gives rise to distinct ontological positions. As previously pointed out, if one simply gives up independence, then he commonly ends up an idealist. If someone is willing to hold up the two-domain distinction, then one is talking about some form of realism. And realism, by itself, splits in different forms. For example, when some degree of *correspondence* between both domains is assumed, there comes semantic realism and its variants – constructive empiricism assumes just a partial correspondence (VAN FRAASSEN, 1980) while stronger forms of realism may assume total correspondence. If, on the other hand, correspondence in its strongest sense is denied, then a pragmatic relation is assumed; therefore ontological pluralism (CARNAP, 1950) and instrumentalism (SUPPES, 1967) are representatives. The biggest problem with semantic realism is that as soon as any attempt to describe the ontological domain is made, the philosopher steps back on the epistemological ground – very often he/she rejects the semantic position's defense and just assumes an ontological realism while remaining silent about it. A clear elucidation of the notion of instrument is still necessary (SUPPES, 1967).

This brief description of ontological enterprise sets the agenda for presenting the Interactionist Ontology. First introduced is the epistemological framework whereby I will reformulate the ontological question. Next, I will show how these conceptual tools permit me to articulate the concepts of independence and unity, and connect them to central ontological requirements. Even though the Interactionist Ontology is a realist one, I would like to say, in advance, that it is neither of a semantic kind nor of an instrumentalist kind. In fact, I will make severe criticisms of the semantic position while trying to explain its basic intuitions. And because the Interactionist position saves some basic intuitions from the semantic position, it cannot be considered as an instrumentalist one as well.

6.2 Interactionist Epistemology

As a methodological gambit, Interactionism is a naturalist position through which science and philosophy form a continuous rather than segregate spectrum – in the Quinean sense (QUINE, 1981). Therefore, the interactionist epistemology is free to use any scientific fact as long as it is helpful. The three basic facts grounding the interactionist epistemology are; that a biological organism is merged in a world; that it is in constant exchange of matter and energy with this world; that the only way the biological organism can interact with this world is by means of action (motor twitches). The first two facts come from thermodynamics of open systems, while the third one comes from the neuroscience. In this view, the *organism* is merged in the world continually exchanging matter and energy with the *surrounding*. However, not every *quantity of matter and energy* are desirable, since some quantities may cause the organism to die. Therefore, the organism needs a mechanism by which to choose the desirable quantities from the undesirable ones. This mechanism is the Central Nervous System (CNS) and it is called a control system. To accomplish its regulatory task, the control system has to know the quantities affecting the organism and to emit a *response* in order to keep it alive.

The notions of 'organism', 'surrounding', 'matter and energy', and 'response' can be made precise by the cybernetic concepts of ‘system’, ‘environment’, ‘input’, and ‘output’, respectively[20]. The notions of ‘system’ and ‘environment’ are interesting because they disclose the fact that the relation between organism and surrounding is continuous rather than discrete. When modeling a system, these two notions are always arbitrarily set – body can be environment to the CNS, surrounding can be environment to the body, and so on – in the sense that there is no definitive point at which these notions are fixed ultimately. The notions of ‘input’ and ‘output’ are very important because by understanding their relation one is able to represent the system’s dynamics and estimate its *degree of control* (as a function of the quantity of matter and energy). The input-output relation is established between sensorial stimuli and motor action, which shifts our attention from the *internal representations* to the *optimality of our motor reactions* – even though all of these events may occur in the middle steps.

To better understand the relation between ‘quantity of matter and energy’, ‘internal representations’, and ‘degree of control’, the previous framework is merged in information theory. The system/environment scheme is now understood in terms of a communication system in which the environment is viewed as an information source and the biological system as a communication channel [Figure 15]. In this scheme the quantity of matter and energy

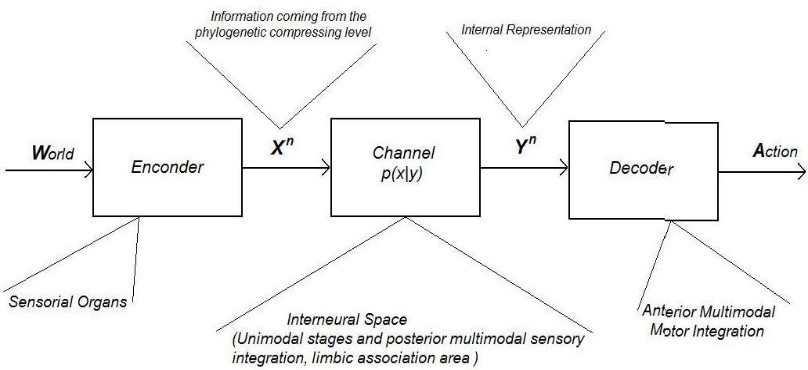


Figure 15 - Central Nervous System as a communication system

[20] Cf. chapter one for a detailed discussion of these concepts.

flowing through the biological system is viewed as the source complexity (the entropy), our internal representations are viewed as a channel code, and the degree of control as the system processing performance[21]. As we don't have complete control over the environment, it means that we're not processing the whole of environmental information – we don't "see" everything from the outside world.

As shown in the Figure 15, the internal representations are viewed as sequences of code words which, transmitted through the channel, are decoded as sequences of actions. This interpretation reveals the contingent character which is, in fact, inherent to the way we represent the surrounding – genetic factors may produce very different internal representations[22], mathematically different scientific theories can produce the same experimental results. Infinite coding schemes can be used to convey a given source complexity, varying in costs, complexity, and time processing. As long as the coding schemes result in the same action plans, they should be chosen according to the previous criteria[23], which vary with each specific channel. In summary, there is no privileged view of a specific scene, although the sequence of actions has to be the same in order for the organism to stay alive.

Now consider someone's life as a stochastic process resulting from the transmission process, as there will always be some accident (distortion) in the course of life – whether grasping a class, or driving a car, or sending a spacecraft into space – a quantity of source information is being lost[24]. Distortion is a symptom of two situations: Either the channel code is not optimal or the channel-cost capacity is smaller than the quantity of source information. Both situations are not exclusive and the CNS probability exemplifies both of them[25]. There are two defies in order to surmount these drawbacks: construct channel codes that, for a fixed cost P, achieve smaller distortion D[26] or find a criterion by which to choose those bits that decrease the distortion value from those that increase it[27]. This is the context in which science's role should be interpreted. As soon as better representations are devised – better

[21] Cf. chapter two for a detailed discussion about this point.
[22] Cf. chapter one for a detailed discussion about this point.
[23] Cf. chapter four for a detailed discussion about this point
[24] Cf. chapter one for a detailed discussion about this point.
[25] Cf. chapter one for a detailed discussion about this point.
[26] Cf. chapter four for a detailed discussion about this point.
[27] Cf. chapter three for a detailed discussion about this point.

scientific theories – more information is reliably transmitted – so the more control over the environment we have. We used to pay attention to more abstract aspects of scientific theory, but I'm pretty sure that if I were a long-life extraterrestrial studying the human development, science's evolution would be nothing more than the increase of control over the environment.

5.3 Interactionist Ontology

6.3.1 What is there (exists)?

Let me begin with the ontological question, 'What exists?" According to the Interactionist Epistemology, the question, "what exists?" can be translated as "what can be, in principal, directly or indirectly, the environment for our own system?" As so many clauses – 'in principal', 'directly or indirectly' – qualify this statement, let me unfold this formula. Imagine that we have two systems W and Y, so that $W = \{w_1, w_2, \dots, w_n\}$ and $Y = \{y_1, y_2, \dots, y_m\}$ are the variables defining each system, respectively – for simplicity, both systems are assumed to be discrete. A subset $W^* = \{w^*{}_1, w_2{}^*, \dots, w^*{}_k\}$ of W's variables are the variables in W whose change modifies the Y' variable values to some extent. Thereby, the subset W^* is, by definition 2.3, the environment of Y[28]. Eventually, the system W is bigger than that defined as environment – i.e. $k < n$ – so that the system contains hidden variables[29] – typically prediction failure is interpreted as the existence of hidden variables, but not necessarily. To unveil the W's hidden variables, a system Z is coupled between W and Y so that, now, $W^* = W$ – i.e. the hidden variables in W now modify the Y's variables through Z. In fact, we will have a new system $Y^* = Y + Z$. If $W = W^*$, then I will say that W is *directly* an environment for us. If $W > W^*$ so that another system Z is necessary in order to turn W into a complete an environment for us, then I will say that W is *indirectly* an environment for us. The term 'in principal' *allows for the possibility* of the existence of a system Z whose coupling ends up unveiling W. If there is no such system Z, then one should assume that $|W| = |W^*|$. In the above

[28] Cf. chapter one for a detailed discussion about this point.

[29] Complex non-linear systems are not easily predictable, even though this fact is independent of hidden variables' existence (MAINZER, 2007).

scenario, *Z* explains *part* of what we call technology[30]. This relation between system and environment gives sense to my use of the term 'interaction': two or more systems interact with each other if one of them can be environment to the other one.

6.3.2 The skepticism about the external reality

The skepticism about the external reality is broadly understood as the failure to ultimately justify the connection between our beliefs and their references. Its relevance to ontology is due to the fact that once the connection is in doubt, the notion of external reality is in doubt as well (NAGEL, 1987; STROUD, 2000). But let me break down this position in its details. According to this view, there is the subject who is responsible for the act of thinking, the content of thought, and the independent reality which serves as basis for thought content. The relation between these notions can be thought of in terms of two gaps; the gap between thought and its content, which is represented by the act of believing in something, and the gap between content of thought and independent reality, which is represented by the concept of truth. The two gaps are logically independent so that to believe in something doesn't imply that it is true and conversely. The first gap is bridged by the certainty of one's own intuition of believing in something. The second gap is the reason for endless philosophical quarrel. One may plausibly say that according to this view, the history of humanity is the history of trying to bridge the second gap – which one calls the achievement of knowledge. When one denies that this gap can be ultimately[31] bridged, he is called a skeptic.

The epistemological setup just described distances the knowing subject from the reality, thereby creating a gap which feeds the skeptical doubt. Because this gap is famous from Descartes' philosophy, I will call it, 'Cartesian Cut'. In this segregated view, the closest the knowing subject can get to the reality is through the concept of 'content of

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[30] Undoubtedly, part of what we call technology is a channel that we use to have access to portions of reality that we don't have in natural conditions. The thermometer is a typical case of *Z* system through which the complexity contained in given noisily processed bandwidth of the spectrum of light (temperature) is converted in another bandwidth which works as a more efficient code (colors, geometrical forms).

[31] The meaning of 'ultimately' here can vary. It may mean, for example, to bridge the gap in terms of necessary and sufficient conditions.

thought', which has been understood as 'representation', or 'proposition', or 'description', or 'theory'. Because 'representation' is a very comprehensive term in this context, I will call this view, Representationalist. The problem is that as soon as one tries to apply the Representationalist View to the present scientific scene – for example, to biology – one is quickly lead to the conclusion that our representations are the main channel of communication with environment – which is pretty false. Representations can be gorgeous; however, if they don't end up in successful actions, they are useless. Therefore, there is something missing in the Representationalist View.

It is in pretty contrast with the Representationalist View that I put the notions of system and environment to work. I said above that these notions disclose the fact that the relation between organism and surrounding is continuous rather than discrete. It means that what one considers a system and environment depends on their research interests, since there is no definitive point at which to make the cut – a conventional scale considers molecules, membranes, synapses, neurons, nuclei, circuits, networks, layers, maps, systems, the entire nervous system, the interplay among different organism's systems, the entire organism, a community, and the whole ecosystem. Every set of variables whose change shows some dependence can be considered a system. Because all these scale levels are arbitrarily set, the relation between system and environment is a continuous spectrum. But what is the relevance of this fact to ontology? What one has to perceive is that the Representationalist View only makes sense in a segregated scene – one in which system and environment are not arbitrarily set. But it just doesn't find place in the world as we know it – there seems to be no adiabatic system in this world. On the system/environment metaphor's ground the question cannot be raised without logically violating the epistemological presupposition. In summary, the gap created by the Cartesian Cut is only a conceptual one; rather the "external reality" is an extension of us. If this digression is correct, the skeptic's doubt is outflanked.

One possible objection here is the following: "In the same way one can fix the notions of input and output so that the input are sensory stimuli and the output are motor twitches, one can reinterpret it so that now our representations are the output. Therefore, we return to the Representational View once again – which saves the cherished reflexive method." Whereas the argument's premise is true, the conclusion doesn't follow. The reason is that considering the organism as a complex system, if one sets our subjective representations as the system output, then the environment will turn out to be not the usual surrounding, but the coordination of action in the frontal motor cortex[32]. And it brings up two important points. First that the interpretation of the notions of system and environment as biological organism and surrounding saves our mundane conception of "external world" and, second, that action was the missing piece in the Representationalist View. In the end, the Representationalist philosopher may still opt for the Cartesian Cut, since, from the reflexive method, the thought attitude of believe in something is the only thing one cannot mistake. However, the Cartesian Cut doesn't offer a complete scene; it is not in agreement with our actual knowledge about the structure of biological system. Therefore, there seems to be a choice to be made; either we reject science and embrace the Cartesian intuition, or we reject the Cartesian intuition and embrace science. I embrace science.

6.3.3 Ontology requires independence and unity

Where is the ontological piece in the previous epistemological scene? I've said before that the correct epistemological scene characterizing the human experience is one in which the path between what we usually call knowing subject and external world is continuous rather than discrete. For this reason, I've chosen the notions of system and environment, since they present this required dynamic feature. However, one should admit that there is no necessary element in choosing system theory instead of any other metaphor. This is what I mean by contingent, or plural, feature inherent to epistemology – epistemology goes well as long as it explains well. But according to our most intimate intuition, ontology requires *unity*, or necessity. Still another important aspect is about independence. Even if the epistemological path is continuous in some sense, the region that I intuitively consider as external world cannot be contained in the region that I consider as my own experience. The region I consider as my own experience is characterized by the fact that *I consider it as my experience* – the things to which I pay attention depend on me. If I die, then there is no more experience. On the other hand, the region that I consider as external world is characterized by the fact that it doesn't depend on me. Whatever it is, it is by itself. The ontological domain is *independent.*

[32] Cf. chapter three for a detailed discussion about the brain regions responsible for sensorial representation and motor output.

Let me begin with Ontological Independence. In speaking about biological chordate organisms, it's very reasonable to interpret the CNS as a control system controlling the organism's life and the environment as current surrounding. The control system must choose, based on the environmental information, the right output in order to keep the organism alive – otherwise it dies. But now, by merging this control system picture in information theory, we are able to evaluate the control system's performance; if there are hidden variables, eventually the organism will incur in accident – otherwise not[33]. The environment W becomes the source information W, the control system Y becomes a channel $p(x|y)$ – where the channel input x is environment w^* – , and the organism's performance becomes a error measure. In this scene hidden variables become lost information, and eventually ends up incurring in accident (error). When information is lost, decisions cannot be perfect. But now notice that the accident (error) is an authentic ontological criterion because it means that reality is claiming its own right of being. Whenever information is lost, the occurrence of accident doesn't depend on us anymore, but it depends on the reality in itself. What depends on me is epistemological, what doesn't is ontological[34]. This, therefore, defines the conceptual distinction between both domains.

Now, what about the ontological unity (or necessity)? In the communication system the information has to be encoded in a channel code in order to be transmitted through it. Likewise, the surrounding information is also encoded in a brain code in order to be processed, resulting in an action plan. How many different codes can convey the same complexity through a given channel? In fact, infinite codes can accomplish this task varying in costs and complexity. But now if we interpret our different conceptual schemes, through which we handle our environment as a given channel code, we have a good characterization of the plural, or contingent, aspect of the epistemology. This contingency is only restricted by physical constraints, like cost and time delay[35]. The same cannot be said about the source representation. Different source representations entail different distortion values and, for a discrete source, such that just one representation decreases the

[33] Cf. chapter two for a detailed discussion about this point.
[34] That is why I said that the Quinean criterion is not properly ontological. In his notion, 'To be is to be the value of a variable,' there is no principal of independence.
[35] Cf. chapter four for a detailed discussion about this point.

distortion value to zero[36]. It is in this precise sense that action represents, in a special sense, the ontological domain: Only one action plan can reduce the death risks to zero for a given perceptual sequence. As infinite channel code sequences can have the same complexity, every action plan sequence contains a different complexity – it is a different source representation.

6.3.4 Epistemological predicament: stepping outside the epistemological domain

I have said above that one of the main ontologist's task is to provide a detachment of the ontological domain from the epistemological domain. And I have said that, when the organism is handling with environment, the accident is the reality's reclamation of its own being. However, I think that a latent criticism to my position would go like this: "You have said that independence is characterized by accident, but you've defined 'accident' in terms of a distortion function – which is in fact a probability of error. After all, I would say that you've never left the epistemological ground and that, in fact, it would be a more comfortable position for you to assume an information metaphysics than to get stuck believing you are at somewhere else when, in fact, you're not." This criticism represents the gist of the epistemological predicament. When someone rejects the possibility of the outflanked, usually one just assumes dogmatically the independence of reality and remains exclusively on epistemological matters. My gambit to outflank the epistemological predicament consists in highlighting that the measure of error depends on the action, which is not a theoretical entity. Action is a part of us already in the world. As accident is something that concerns action and not a theoretical entity, we are already on ontological ground. Whether one doesn't like of the analysis in terms of distortion measure and information, in fact, doesn't matter, because all that matters is the way someone chooses to interact. In others words, one's own epistemology is just one among a plurality of possible ones, whereas the ultimate criterion is how they will improve our interactions with surrounding.

[36] Actually it is true just for a hamming distortion function as defined in chapter two.

6.4 What is really out there?

I have given a new format to the ontological question in terms of interaction and I also put action at the center of the scene. I have argued that action seems to fill the gap between knowing subject and reality by attending to the requirements of independence and unity. But, of course, there is much more than just action outside – in fact ‘action’ is still a vague concept. Therefore, there is still a “face” missing of the Interactionist Ontology. Let us begin elucidating the notion of action which is part of our ‘self’ that is already outside. The more abstract notion of action is given through the byproduct of the restriction of degrees of freedom. When walking through the house, my action plan is nothing but what results from the restriction imposed by the house’s setting in order to arrive someplace in the house. The trajectory of lifting my arm in order to grasp a class is what results from the restriction imposed by the surrounding’s setting in order to grasp the glass. It is in this sense that an action plan, understood as sequence of muscle twitches, is a decoding from the environmental setting.

But what is the portion of reality interacting with my action plans? Reality is exactly the restrictions over the degrees of freedom of successful actions plans. When acting successfully one is, to say, giving the contours of the world. Notice that it is a negative “description” of reality, since it tells us what is out there by telling us where there is no restriction. Therefore, there always remains the question about the possibility of a more strict description – i.e. a more complex plan. In trying to give a stricter contour of the real, accident will tell us the limit. If the reality is discrete, then this complexity has a limit, otherwise, there will always be a more complex plan to be executed. The connection between science and ontology is made by means of the notions of code and processed information. More efficient coding schemes result in more processed information, which means more complex action plans. As soon as our information processing becomes more efficient, it must reflect in our actions’ complexity, which is the second part of what we call technology. Technology in this new sense is the improvement of the output complexity. To be more illustrative, our body anatomy has the complexity propositional to our natural representation – in terms of colors, forms, and so on. As soon as this representation is replaced by a more efficient one – such as mathematical representation – our anatomy has to be enhanced with prostheses which increases the output complexity. These more complex action plans give a more refined contour of reality – they get us closest to the real.

6.5 Final considerations

The Interactionist Ontology dispenses any attempt to describe the real. In fact, it is on the epistemological ground and one will never get outside this way. The present ontology establishes, as a criterion for a good representation, the successfulness of the resulting actions plans (experimentation). As a conclusion it relaxes all the logical rigidity imposed by the traditional approaches to the philosophy of science, by focusing on how a given representation can guide us in interaction. Interactionism sets epistemology as an empirical science, where the central tenet is just how it improves action plans. I have treated epistemology as coding theory and I think it is a good metaphor for it. Even though, as any metaphor is a representation under which lies an ontology, one cannot intend any metaphor as the real metaphor – reality has no face; it is just the way our organism processes the information. In this scene, rationality is understood in terms of capacity of information processing, which results in degrees of rationality. These degrees of rationality form a continuous spectrum among the species ranking them according to the degree of control. Many points here mentioned deserve a stricter treatment, which is task for future work.

7. BIBLIOGRAPHY

ALVAREZ, G. A., & CAVANAGH, P. The capacity of visual short-term memory is set both by visual information load and by number of objects. *Psychological Science,* pp. 106-111, 15 Jan., 2004.

ARBIB, A. M. Perceptual Structures and Distributed Motor Control. *Comprehensive Physiology,* Supplement 2: Handbook of Physiology, The Nervous System, Motor Control, 1981.

ASHBY, W. R. *An Introduction to Cybernetics*. London: Chapman & Hall, 1956.
_____. *Design for a Brain.* New York: John Wiley & Sons. Inc, 1966.

ATTNEAVE, F. Some Informational Aspects Of Visual Perception. *Psychological Review,* vol. 61, No. 3, 1954.

AVIKAINEN, S., WOHLSCHLÄGER, A., LIUHANEN, S., HÄNNINEN, R., HARI, R. Impaired mirror-image imitation in Asperger and high-functioning autistic subjects. *Curr Biol*., pp. 339-41, 18 Feb., 2003.

AWH, E., JONIDES, J., SMITH, E. E., SCHUMACHER, E. H., KOEPPE, R. A., & KATZ, S. Dissociation of storage and rehearsal in verbal working memory. *Psychological Science*, pp. 25-31, Sep., 1996.

BADDELEY, A. Working memory, theories models and controversy. *The Annual Review of Psychology,* pp. 1–12, No. *63,* Dec., 2012.

____. Working memory. *Current Biology*, pp. 136-140, 2010.
BANKS, M., GEISLER, W., BENNETT, P. The physical limits of grating visibility. *Vision Res*., 27, pp. 1915–24, 1987.

BARLOW, H. B. Retinal noise and absolute threshold. *J. Opt. Soc. Am*. 46, pp. 634–396, 1956.

BARLOW, H. B. Retinal and central factors in human vision limited by noise. In: *Vertebrate Photoreception*, (ed.) H. B. Barlow, P. Fatt, pp. 337—51. New York: Academic, 1977.

BARSALOU, L. W. Perceptual symbol systems. *Behavioral & Brain Sciences*, 22, pp. 577-660, 1999.

BERG, H. C. & PURCELL, E. M. 'Physics of chemoreception'. *Journal of Biophysics*, Vol. 20, pp. 193–219, 1977.

BERGEN, B. K., LINDSAY, S., MATLOCK, T., & NARAYANAN, S. Spatial and linguistic aspects of visual imagery in sentence comprehension. *Cognitive Science*, 31, pp. 733-764, 2007.

BERGMANN, G. Strawson's Ontology. *The Journal of Philosophy*, Vol. 57, No. 19, pp. 601-622, 1960.

BERGMANN, G. *Logic and Reality*. Madison: University of Wisconsin Press, 1964.

BIALEK, W, & OWEN, W. G. Temporal filtering in retinal bipolar cells. Elements of an optimal computation? *Biophys. J.* 58, pp. 1227–33, 1990.

BIALEK, S. W. & SETAYESHGAR, S. Physical limits to biochemical signaling. *Proceeding of National Academy of Science of the United States of America*. pp. 10040–10045, May, 2005.

BORODITSKY, L. Metaphoric structuring: Understanding time through spatial metaphors. *Cognition*, 75, pp. 1-28, 2000.

BRUNER, J. The Acquisition of Pragmatic Commitments. In: *The Transition*
,from Pre-linguistic to Linguistic Communication, R. Golinkoff (ed.), Hillsdale, NJ: Erlbaum, 1983.

BUCCINO, G., BINKOFSKI, F., FINK, G. R., FADIGA, L., FOGASSI, L., GALESSE, V., ET AL. Action observation activates premotor and parietal areas in somatotopic manner: an fMRI study. *J. Cogn. Neurosci.*, pp. 400-404, Feb. 13, 2001.

BUCCINO G, LUI F, CANESSA N, PATTERI I, LAGRAVINESE G, BENUZZI F, PORRO CA, RIZZOLATTI G. Neural circuits involved in the recognition of actions performed by nonconspecifics: an FMRI study. J. Cogn Neurosci., pp. 114-26. Jan-Feb 16, 2004.

CARNAP, R. Empiricism, Semantics, Ontology. *Revue Internationale de Philosophie*, *4*, pp. 20–40, 1950.

CARPENTER, M., TOMASELLO, M., & SAVAGE-RUMBAUGH, S. Joint attention and imitative learning in children, chimpanzees, and enculturated chimpanzees. *Social Development*, pp. 18-37, Apr., 1995.

CARR, L., LACOBONI, M., DUBEAU, M. C., MAZZIOTTA, J. C., AND LENZI, G. L. Neural mechanism of empathy in human: a relay from neural system for imitation to limbic areas. *Proc. Natl. Acad. Sci*. USA, 100(9), pp. 5497-5502, 2003.

CEPKO, C. L. The roles of intrinsic and extrinsic cues and bHLH genes in the determination of retinal cell fates. Curr Opin Neurobiol, 9, pp. 37–46, 1999.

CHAITIN, G. J. On the simplicity and speed of programs for computing infinite sets of natural numbers. *Journal of the ACM* 16 (3), pp. 407–422, 1969.

CHURCHLAND, P. S., RAMACHANDRAN, V. S., & SEJNOWSKI, T. J. 'A Critics of Pure Vision'. Em: *Large-Scale Neuronal Theories of the Brain*. Cambridge, Massachusetts: The MIT Press, 1994.

CLONEY, R. 'Ascidean Larvae and the Events of Metamorphosis'. *American Zoologist,* Vol. 22, No. 4, pp. 817-826, 1982.

COLE, H.A., & WELSH, A. Acoustic masking in primary memory. *Journal of Verbal Learning and Verbal Behavior*, 15, pp. 17–32, 1976.

COLOMBI, C., LIEBAL, K., TOMASELLO, M., YOUNG, G., WARNEKEN, F., ROGERS, S. J. Examining correlates of cooperation in autism: Imitation, joint attention, and understanding intentions. *Autism*, 13, pp. 143–163, 2009.

COVER, T. M. & THOMAS, J. A. *Elements of Information Theory.* Hoboken, New Jersey: John Wiley & Sons, 2006.

COWAN, N. The magical number 4 in short-term memory: A reconsideration of mental storage capacity. *Behavioral and Brain Sciences, 24*, pp. 87–114, 2001.

COWAN, N. *Working memory capacity*. New York, NY: Psychology Press, 2006.

CRATON, L. G. The development of perceptual completion abilities: infants' perception of stationary, partially occluded objects. *Child Dev*., 67(3), pp. 890-904, 1996.

DANTZIG, T. *Number: the language of science.* New York: The Free Press, 1967.

DAPRETTO, M., DAVIES, M. S., PFEIFER, J. H., SCOTT, A. A., SIGMAN, M., BOOKHEIMER, S. Y., IACOBONI, M. Understanding emotions in others: mirror neuron dysfunction in children with autism spectrum disorders. Nat Neurosci. 9(1). pp. 28-30, Jan, 2006.

DECETY, J., GRÈZES J. Neural mechanisms subserving the perception of human actions. Trends Cogn Sci., 3(5), pp.172-178, May, 1999.

DECETY, J., GRÈZES, J., COSTES, N., PERANI, D., JEANNEROD, M., PROCYK, E., GRASSI, F., FAZIO, F. Brain activity during observation of actions. Influence of action content and subject's strategy. ,120 (Pt 10), pp.1763-77, Oct, 1997.

DEHAENE, S. *The Number Sense: how mind creates mathematics.* Oxford: Oxford University Press, 1997.

____. Variety of numerical abilities. *Cognition,* Vol. 44, pp. 1-42, 1992.

DEHAENE, S. & COHEN, L. Two mental calculation systems: a case study of severe acalculia with preserved approximation. Neuropsychologi*a*, 29(11), pp. 1045-54, 1991.

DESTEXHE, A. & RUDOLPH-LILITH, M., *Neuronal Noise.* New York: Springer, 2012.

DESMURGET, M. & GRAFTON, S. 'Forward modeling allows feedback control for fast reaching movements'. *Trends in Cognitive Science,* Vol. 11, pp. 423-31, 2000.

DI PELLEGRINO, G., FADIGA, L., FOGASSI, L., GALLESE, V., RIZZOLATTI, G. Understanding motor events: a neurophysiological study. *Exp. Brain Res*. 91, pp.176-80, 1992.

DICKER, G. *Berkeley's Idealism. A Critical Examination*, Cambridge: Cambridge University Press, 2011.

DISL, A. T. & BORODITSKY, L. Processing unrelated language can change what you see. *Psychonomic Bulletin & Review*, 17 (6), pp.882-888, 2010.

DOYA, K., ISHII, S., POUGET, A., RAO, R. P. N. *Bayesian Brain: probabilistic approach to neural coding.* Cambridge, Massachusetts: The MIT Press, 2007.

EAGLEMAN, D. *Incognito: the secret lives of the brain.* London: Canongate, 2011.

EL GAMAL, A. & KIM, Y. H. *Network information theory*. Cambridge University Press, 2011.

ESTES, Z., VERGES, M., & BARSALOU, L. W. Head up, foot down: Object words orient attention to the object's typical location. *Psychological Science*, 19, pp. 93-97, 2008.

FADIGA, L., FOGASSI, L., PAVESI, G., AND RIZZOLATTI, G. Motor facilitation during action observation: a magnetic observation study. *J. Neurophysiol.*, 73(6), pp. 2608-2611, 1995.

FAISAL, A. A., SELEN, L. P. J., WOLPERT, D., 'Noise in the nervous system'. *Nature Review Neuroscience*, Vol. 9, pp. 292-303, 2008.

FELDMAN, G. A. *From Molecule to Metaphor: a neural theory of language.* Cambridge, Massachusetts: MIT Press, 2006.
FIELD, T., GUY, L., AND UMBEL, V. Infants' responses to mothers' imitative behaviors. *Infant Mental Health Journal*, Vol 6, 1, pp. 40–44, 1985.

FIELD,T., WOODSON, R., COHEN, D., GREENBERG, R., GARCIA, R., AND KERRY, C. Discrimination and imitation of facial expressions by term and preterm neonates. *Infant Behavior and Development*, Vol 6, 4, pp. 485–489, 1983.

FINE, I., WADE, A. R., BREWER, A. A., MAY, M. G., GOODMAN, D. F., BOYNTON, G. M., WANDELL, B. A., MACLEOD, D. I. Long-term deprivation effects visual perception and cortex. *Nature Neuroscience*, 6(9), pp. 915-916, 2003.

FLANAGAN, J. R. & WING, A. M. 'The role of internal models in motion planning and control: evidence from grip force adjustments during movements of hand-held loads'**.** *Journal of Neuroscience*, Vol. **17**, pp. 1519-1528, 1997.

FLANAGAN, J. R., AND JOHANSSON, R. S. Action plans used in action observation. *Nature*, 424(6950), pp.769-771, 2003.

FRITH, C. D. *Making up the Mind: how the brain creates our mental world.* Malden: Blackwell Publishing, 2007.

FRITH, C. & WOLPERT, D., GHAHRAMANI, Z. & JORDAN, M. I. An internal modelo for sensoriomotor integration. *Science*, Vol. 269, pp. 1880-82, 1995.

FUSTER, J. The Cognit: A network model of cortical representation. *International Journal of Psychophysiology*, nº 60, pp. 125-132, 2006.

GALATOLO, S., HOYRUP, M., AND ROJAS, C. Effective symbolic dynamics, random points, statistical behavior, complexity and entropy. *Information and Computation*, 208: pp. 23–41, 2010.

GALLESE, V., FADIGA, L., FOGASSI, L., RIZZOLATTI, G. Action recognition in the premotor cortex. *Brain*, 119, pp.593-609, 1996.

GALLESE, V., FOGASSI, L., FADIGA, L., AND RIZZOLATTI, G. Action representation and the inferior parietal lobule. In W. Prinz and H. B. (Eds.), *Attention and performance XIX. Common mechanisms and perception and action* (pp. 334-355). Oxford: Oxford University Press, 2002.

GALLESE, V., & LAKOFF, G. The brain's concepts: The role of the sensory–motor system in conceptual knowledge. *Cognitive Neuropsychology*, 22, pp.455-479, 2005.

GASTPAR, M. *To code or not to code.* Doctoral Dissertation - École Polytechnique Fédérale De Lausanne, Lausanne, 2002.

GEGENFURTNER, K. R. & SHARPE, L. T.. *Color Vision: From Genes to Perception*. Cambridge Massachusetts: Cambridge University Press, 2001.

GLENBERG, A. M., & KASCHAK, M. P. Grounding language in action. *Psychonomic Bulletin & Review,* 9, pp.558-565, 2002.

GRAFTON, S. T., ARBIB, M. A., FADIGA, L., RIZZOLATTI, G. Localization of grasp representations in humans by positron emission tomography. 2. Observation compared with imagination. Exp Brain Res., 112(1), pp.103-11, Nov, 1996.

GREGORY, R. L. *Seeing Through Illusions.* London: Oxford, Oxford University Press, 2009.

GREGORY, R. L. & WALLACE, J. G.. Recovery from early blindness: a case study. *Quarterly Journal Psychology*. Monograph no. 2, 1963.

GRÈZES, J., DECETY, J. Functional anatomy of execution, mental simulation, observation, and verb generation of actions: a meta-analysis. Hum Brain Mapp., 12(1), pp.1-19, Jan., 2001.

GRÈZES, J., ARMONY, J. L., ROWE, J., PASSINGHAM, R. E. Activations related to "mirror" and "canonical" neurones in the human brain: an fMRI study. Neuroimage., 18(4), pp.928-37, Apr., 2003.

GRUSH, R. ‘The emulation theory of representation: Motor control, imagery, and perception’. *Behavioral and Brain Science,* pp. 377-442, 2004.

GUYER, P. AND HORSTMANN, R.-P., "Idealism", *The Stanford Encyclopedia of Philosophy* (Fall 2015 Edition), Edward N. Zalta (ed.), URL = <http://plato.stanford.edu/archives/fall2015/entries/idealism/>.

HADJIKHANI, N., JOSEPH, R. M., SNYDER, J., CHABRIS, C. F., CLARK, J., STEELE, S., MCGRATH, L., VANGEL, M., AHARON, I., FECZKO, E., HARRIS, G. J., TAGER-FLUSBERG, H. Activation of the fusiform gyrus when individuals with autism spectrum disorder view faces. Neuroimage., 22(3), pp.1141-50, Jul., 2004.

HADJIKHANI, N., JOSEPH, R. M., SNYDER, J., TAGER-FLUSBERG, H. Anatomical differences in the mirror neuron system and social cognition network in autism. Cereb Cortex., 16(9), pp.1276-82, Sep., 2006.

HADJIKHANI, N. Mirron Neuron system and autism. In Carlisle, P. C. (ed), *Progress in Autism Research*. New York: Nova Science Publishers, 2007.

HADJIKHANI, N., JOSEPH, R. M., SNYDER, J., TAGER-FLUSBERG, H. Abnormal activation of the social brain during face perception in autism. Hum Brain Mapp., 28(5), pp.441-9, May, 2007.

HAKEN, H. *Information and Self-Organization.* 2th ed.. Springer, 1999.
HARI, R., FORSS, N., AVIKAINEN, S., KIRVESKARI, E., SALENIUS, S., & RIZZOLATTI, G. Activation of human primary motor cortex during action observation: A neuromagnetic study. *Proc Natl Acad Sci* U S A. 95(25), pp.15061–15065, Dec. 8, 1998.

HARRIS, J. M. & DEAN, P. J. A. Accuracy and Precision of Binocular 3-D Motion Perception. *Journal of Experimental Psychology: Human Perception and Performance*, Vol. 29, No. 5, pp. 869–881, 2003.

HARRIS, G. G. ‘Brownian Motion in the Cochlear Partition’. *Journal of the Acoustical Society of America*. Volume 44, Issue 1, pp. 176-186, 1968.

HATAKEYAMA, J. & KAGEYAMA, R. Retinal cell fate determination and bHLH factors. *Seminars in Cell & Developmental Biology*. 15, pp. 83–89, 2004.
HEIJ, C., RAN, A. & VAN SCHAGEN, F., *Introduction to Mathematical System Theory: Linear systems, identification, and control.* Berlin: Birkhäuser Verlag, 2007.

HEILBRON, J. L. *Geometry Civilized: history, culture, and technique.* Oxford: Oxford University Press, 2000.

HENSON, R.N.A. Neural working memory: applications of the Working Memory model to neuropsychology and neuroimaging. In Andrade, J. (Ed.), *Working Memory: a work in progress* (pp. 151-173). London: Routledge, 2001.

HUBEL, D. H., WIESEL, T. N. Receptive fields, binocular interaction and functional architecture in the cat's visual cortex. J Physiol. 160, pp.106-54, Jan., 1962.

HUBEL, D. H., WIESEL, T. N. Receptive Fields And Functional Architecture In Two Nonstriate Visual Areas (18 And 19) Of The Cat. J Neurophysiol., 28, pp.229-89, Mar., 1965.

JAMESON, A. K. Tetrachromatic Color Vision. *The Oxford Companion to Consciousness*. Wilken, P., Bayne, T. & Cleeremans, A. (Ed.s).Oxford University Press: Oxford, 2007.

JOHNSON, S. P., & ASLIN R. N. Perception of object unityin 3-month old infants. *Developmental Psychology*. Vol. 31(5), 31(5), pp.739-745, 1995.

JORDAN, G. & MOLLON, J. D. A study of women hererozygous for colour deficiencies. *Vision Research*, 33, pp.1495–1508, 1993.

JORDAN, M. I. & RUMELHART, D. E. ‘Forward models: supervised learning with a distal teacher’**.** *Cogn Sci*, Vol. 16, pp. 307-354, 1992.

KANDEL, E. R., SCHWARTZ, J. H. & JESSELL, T. M. *Principles of Neural Science.* McGraw–Hill/Appleton & Lange, New York, 2000.

KANDEL, E. *The Agen of Insite: the quest to understand the unconscious in art, mind and brain, from Vienna 1900 to the present.* New York: Handle House, 2012.
KAUFMAN, E. L., LORD, M. W., REESE, T. W., & VOLKMANN, J. The discrimination of visual number. American Journal of Psychology, 62 (4), pp. 498–525, 1949.

KAWATO, M. Internal model for motor control and trajectory planning. *Current Opinion in Neurobiology*, nº 9, pp. 718-727, 1999.

KEYSERS, C. & PERRETT, D. I. Demystifying social cognition: a Herbbian perspective. *Trends Cogn. Sci.*, 8(11), pp.501-507, 2004.

KLINGBERG, T. Limitations in the information processing in the human brain. In: *Progress in Brain Research*, Vol 126. Elsevier Science BV. All rights reserved, 2000.

KOHLER E., KEYSERS C., UMILTA M.A., FOGASSI L., GALLESE V. AND RIZZOLATTI G. Hearing sounds, understanding actions: action representation in mirror neurons. *Science,* 297, pp.846-848, 2002.

KOLMOGOROV, A. On Tables of Random Numbers. Sankhyā *Ser. A.*25, pp. 369–375, 1963.

LACOBONI, M., KOSKI, L. M., BRASS, M., BEKKERING, H., WOODS R. P., DUBEAU, M. C., et al. Reafferent copies of imitated actions in the right superior temporal cortex. *Proc. Natl. Acad. Sci.* USA, 98(24), pp.13995-13999, 2001.

LACOBONI, M., WOODS R. P., BRASS, M., BEKKERING, H., MAZZIOTTA, J. C., AND RIZZOLATTI, G. Cortical mechanisms of human imitation. *Science*, 286(5449), pp.2526-2528, 1999.

LEPAGE, J. F., & THÉORET, H. EEG evidence for the presence of an action observation-execution matching system in children. *Eur J Neurosci*., 23(9), pp.2505-10, May, 2006.

LERNER, A. Ya. *Fundamentals of Cybernetics.* London: Plenum Press, 1975.

LETTVIN, J. Y., MATURANA, H., McCULLOCH, W. S., & PITTS W. H. What the frog's eye tells the frog's brain, *Proceedings of the IRE,* Vol. 47, No. 11, Nov., 1959.
LLINAS, R. *The I of the Vortex: from neuron to self.* Cambridge, Massachusetts: The
MIT Press, 2001.

LILLYWHITE, P. G. Multiplicative intrinsic noise and the limits to visual performance. *Vision Res*. 21: pp. 291–96, 1981.

LUCK, S.J. AND VOGEL, E.K. The capacity of visual working memory for features and conjunctions. *Nature*, 390, pp. 279–281, 1997.

MAINZER, K. *Thinking in Complexity*. 6th ed.. Berlin: Springer-Verlag, 2007.

MAROIS, R. & IVANOFF, J. Capacity limits of information processing in the brain. *Trends in Cognitive Science*. Vol. 9, No. 6, pp. 296-305, 2005.

MATLOCK, T., RAMSCAR, M., & BORODITSKY, L. On the experiential link between spatial and temporal language. *Cognitive Science*, 29, pp.655-664, 2005.

MCINTOSH, D. N., REICHMANN-DECKER, A., WINKIELMAN, P., WILBARGER, J. L. When the social mirror breaks: deficits in automatic, but not voluntary, mimicry of emotional facial expressions in autism. *Dev Sci.*, 9(3), pp.295-302, May, 2006.

MELTZOFF, A. N. & MOORE, M. K. Imitation of facial and manual gestures by human neonates. Science., 198(4312), pp.74-8, Oct. 7, 1977.

MELTZOFF, A. N. & MOORE, M. K. Newborn infants imitate adult facial gestures. Child Dev., 54(3), pp.702-9, Jun., 1983.

MENNINGER, K. *Number Words and Number Symbols*. Cambridge, MA: MIT Press. 1969.

MERFELD, D. M., ZUPAN, L., PETERKA, R. J. 'Humans use internal models to estimate gravity and linear acceleration'. *Nature*, Vol. 398, pp. 615-618, 1999.

MERKLE, R. Energy limits to the computational power of the human brain. *Foresight Update*, No. 6. Aug., 1989.
METEYARD, L., BAHRAMI, B., & VIGLIOCCO, G. Motion detection and motion verbs: Language affects low-level visual perception. *Psychological Science*, 18, pp.1007-1013, 2007.

MIALL, R. C., WEIR, D. J., WOLPERT, D. M., STEIN, J. F. 'Is the cerebellum a Smith Predictor?'**.** *Journal of Motor Behavior*, Vol. 25, pp. 203-216, 1993.

MILLER, G. A. The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review, 63,* pp. 81–97, 1956.

MUNDY, P., SIGMAN, M., AND KASARI, C. In S. Baron-Cohen, H. Tager-Flusberg and D. Cohgen (Eds.), *Understanding other mind: Perspective from autism* (pp. 181-203). Oxford: Oxford University Press, 1993.

NAGEL, T. *What Does It All Mean: a very short introduction to philosophy.* Oxford: Oxford University Press, 1987.
NINIO, A. & BRUNER, J. The Achievement and Antecedents of Labelling. *Journal of child language,* 5, pp. I – 16, 1978.

NIJHAWAN, R. Visual Prediction: psychophysics and neuropsychology of compensation for time delays. In: *Behavioral and Brain Sciences,* nº31, pp. 179-239, 2008.

NISHITANI, N. & HARI, R. Temporal dynamics of cortical representation for action. *Proc. Natl. Acad. Sci*. USA, 97(2), pp.913-918, 2000.

NISHITANI, N., AVIKAINEN, S., HARI, R. Abnormal imitation-related cortical activation sequences in Asperger's syndrome. *Ann Neurol.*, 55(4), pp.558-62, Apr., 2004.

OBERMAN, L. M., HUBBARD, E. M., MCCLEERY, J. P., ALTSCHULER, E. L., RAMACHANDRAN, V. S., PINEDA, J. A. EEG evidence for mirror neuron dysfunction in autism spectrum disorders. *Brain Res Cogn Brain Res*., 24(2), pp.190-8, Jul., 2005.

OSTROVSKY, Y. Learning to see: the early stages of perceptual organization. (Doctoral dissertation). 2010. Retrieved from http://dspace.mit.edu/bitstream/handle/1721.1/62087/707634656.pdf?sequence=1.

OSTERLING, J. & DAWSON, G. Early recognition children with autism: a study of first birthday home videotapes. *J. Autism Dev. Disord.*, 24(3), pp.247-257, 1994.

PANDYA, D. N., SALTZER, B. Association areas of the cerebral cortex. *Trends Neurosci*, 5, pp.386–390, 1982.

PAULESU, E., FRITH, C. D., & FRACKOWIAK, R. S. J. The neural correlates of the verbal component of working memory. *Nature*, 362, pp.342-344, 1993.

PHAM, T. D., Perception-based hidden Markov models: a theoretical framework
for data mining and knowledge discovery. *Soft Computing*, Nº 6, pp. 400-405, 2002.

PIRENNE. M. H. 'Some aspects of the sensibility of the eye'. *Annals of the New York Academy of Science.* Vol. 74, pp. 377-384, 1959.

POPPER, K. Conjectures and Refutations: the growth of scientific knowledge. New York: Basic Books, 1962.

PRIGOGINE, I. & NICOLIS, G. *Self-Organization in Non-Equilibrium Systems.* New York: John Wiley & Sons, 1977.

QUINE, W. V. On what there is. In: *From a Logical Point of View*. Harvard Univ. Press, pp. 1-20, 1980.

QUINE, W.V. *Theories and Things*, Cambridge, MA: Harvard University Press, 1981.

RALL, W. Time constants and electro tonic length of membrane cylinders and neurons. *Journal of Biophysics*. Vol. 9, pp. 1483–1508, 1969.

RATNER, N. & BRUNER, J. Games. Social Exchange, and the Acquisition of Language. *Journal of' Child Language* 5, 39, pp. 1402, 1978.
REPOVS, G., & BADDELEY, A.D. Multi-component model of working memory: explorations in experimental cognitive psychology. *Neuroscience Special Issue*, 139, pp. 5-21, 2006.

RICHARDSON, D. C., SPIVEY, M. J., BARSALOU, L. W., & MCRAE, K. Spatial representations activated during real-time comprehension of verbs. *Cognitive Science*, 27, pp.767-780, 2003.

RIZZOLATTI, G. & FADIGA, L. Higher-order motor disorders: from Neuroanatomy and Neurobiology to Clinical Neurology. Eds. Freund H.J., Jeannerod M., Hallett M. New York: Oxford University Press, 2005.

RIZZOLATTI, G., FADIGA, L., FOGASSI, L., GALLESE, V. Premotor cortex and the recognition of motor actions. *Cogn. Brain Res.* 3, pp.131–41, 1996a.

RIZZOLATTI, G., FADIGA, L., GALLESE, V., FOGASSI, L. Premotor cortex and the recognition of motor actions. Brain Res Cogn Brain Res., 3(2), pp.131-41, Mar, 1996b.

RIZZOLATTI G, & CRAIGHERO L. The mirror-neuron system. *Annu. Rev. Neurosci.* 27, pp.169-92, 2004.

ROGERS, P. R., MILLER, A., & JUDGE, W. Q, 'Research Notes and communications: using information-processing theory to understand planning/performance relationships in the context of strategy'. *Strategic Management Journal Strat. Mgmt. J.*, 20: 567–577, 1999.

ROSENBLUETH, A.; WIENER, N.; BIGELOW, J. 'Behavior, Purpose and Teleology'. *Phylosophy of Science*, Volume 10, Issue, p. 18-24, 1943.

ROSS, S. *A first course of probability 5th ed.* Prentice Hall, Upper Saddle River, New Jersey, 1998.

SAKITT, B. Counting every quantum. *J. Physiol*. 223, pp.131–50, 1972.

SHANNON, C. E. A mathematical theory of communication. *Bell Sys Tech J* 27, pp. 379-423 & 623-656, 1948.
SHANNON, C. & WEAVER, W. *Mathematical Theory of Communication.* University of Illinois Press, Urbana, 1964.

SLONIM, N. Information bottleneck: theory and applications. (Doctoral dissertation). 2002. Retrieved from http://www.cs.huji.ac.il/labs/learning/Theses/Slonim_PhD.pdf

SMITH, E. E., & JONIDES, J. Working memory: a view from neuroimaging. *Cognitive Psychology*, 33, pp. 5-42, 1997.

SNYDER, L. This way up: illusions and internal models in the vestibular system. *Nature Neuroscience*, Vol. 2, pp. 396-398, 1999.

SPIVEY, M., & GENG, J. Oculomotor mechanisms activated by imagery and memory: Eye movements to absent objects. *Psychological Research*, 65, pp.235-241, 2001.

STANFIELD, R., & ZWAAN, R. The effect of implied orientation derived from verbal context on picture recognition. *Psychological Science*, 12, pp.153-156, 2001.

STRAWSON, P. F. *Individuals: Essay of Descriptive Metaphysics*. London: Routledge, 1979.

STROUD, B. *The Quest for Reality: subjectivism and the metaphysics of colors.* Oxford: Oxford University Press, 2000.

SUPPES, P., What is a scientific Theory. In: Sidney Morgenbesser (Ed.), *Philosophy of Science Today*. New York: Basic Book; Inc., pp. 55-67, 1967.

THÉORET, H., HALLIGAN, E., KOBAYASHI, M., FREGNI, F., TAGER-FLUSBERG, H., PASCUAL-LEONE, A. Impaired motor facilitation during action observation in individuals with autism spectrum disorder. *Curr Biol*. 15(3), pp.84-5, Feb. 8, 2005.

TISHBY, N., PEREIRA, F. C. & BIALEK, W. The information bottleneck method. *Proc. 37th Allerton Conference on Communication and Computation*, 1999.

TRICK, L.M., & PYLYSHYN, Z.W. Why are small and large numbers enumerated differently? A limited-capacity preattentive stage in vision. *Psychological Review*, 101 (1), pp. 80–102, 1994.

TOMASELLO, M. Constructing a Language: A Usage-Based Theory of Language Acquisition. Harvard University Press, 2003.

TOMASELLO, M., & FARRAR, J. Joint attention and early language. *Child Development*, 57, pp.1454-1463, 1986.

TOMASELLO, M. The role of joint attentional process in early language development. *Language Sciences*, 10, pp.69-88, 1988.

VALVO, A. *Sight restoration after long-term blindness: the problems and behavior patterns of visual rehabilitation.* New York: American Foundation for the Blind, 1971.

VAN FRAASSEN, BAS. *The Scientific Image*. Oxford: Oxford University Press, 1980.

VÁZQUEZ, J.L. The importance of Mathematics in the development of Science and Technology, *Boletín Soc. Esp. Mat. Aplicada*, no 19, pp. 69-112, 2001.

VETTER, M. L. & BROWN, N. L. The role of basic helix–loop–helix genes invertebrate retinogenesis. *Semin Cell Dev Biol*, 12, pp.491–8, 2001.

VON SENDEN, M. *Space and Sight: the perception of space and shape in the congenitally blind before and after operation.* Reprint, Glencoe, Illinois: Free Press, 1960.

WOLPERT, D. (ed.). New York: Oxford University Press, 2003.

WOLPERT, D., DOYA, K., & KAWATO, M., A unifying computational framework for motor control and social interaction. *Philos Trans R Soc Lond B Biol Sci*. 358(1431), pp. 593–602, Mar. 29, 2003.

WOLPERT, D. & GHAHRAMANI, Z. Bayes rule in perception, action and cognition. http://learning.eng.cam.ac.uk/Public/Wolpert/Publications, 2009.

ZWAAN, R. A., MADDEN, C. J., YAXLEY, R. H., & AVEYARD, M. E. Moving words: Dynamic representations in language comprehension. *Cognitive Science*, 28, pp.611-619, 2004.

ZWAAN, R. A., STANFIELD, R. A., & YAXLEY, R. H. Language comprehenders mentally represent the shapes of objects. *Psychological Science*, 13, pp.168-171, 2002