Computational Intelligence and Decision Making: A Multidisciplinary Review

Review of
Integrative
Business &
Economics
Research

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ABSTRACT

The phenomenon of dynamic shift in our society called "*speed up*" has been part of the modern society since the middle of the eighteenth century. Its progressive development is already and will demand more speed in information processing. To cope with such fast pace demand of processing it is necessary to develop more sophisticated computational representation of the human brain. Computational Cognitive Neuroscience is the only realistic approach in reproducing the fundamental nature of human brain's neurology. We support the biological computational representation of the human brain, based on fMRI imaging analysis, as more effective in the process of decision making.

Keywords: Decision Making, fMRI, Computation Cognitive Neuroscience, Artificial Intelligence.

I INTRODUCTION

Information processing is the focus of twenty-first century society, and the way people will access information is by the Internet. The number of indexed webpages grew from 23,000 in 1995 to 55 million in 2005 (Schibrowsky *et al,* 2007). Nowadays, the numbers are in the order of 50 billion according to the indexed webpage: http://www.worldwidewebsize.com.

The Internet has been extremely useful in all areas of human knowledge; has helped overthrow international and inter-community barriers (Childs, 2005) helped with emergency management in the mitigation process of disaster aftermath (Gruntfest & Weber, 1998) and in continuing medical education (Wutoh *et al.* 2004).

The Internet has also changed the way we practice politics, and democracy itself has been vastly transformed The Internet is changing the way politicians are actually exercising the tenets of democracy, and democracy is gaining new interpretations in very dynamic ways, where institutions and concepts are being continually shifted (Bimber, 1998).

Between 1995 and 1999, the television, as a medium of electronic mass communication and entertainment lost one-third of its audience to the Internet (Morris, 2001). The Internet has the power of transferring to the people the way people will interact with information.

The phenomenon behind this dynamic shift in our society is called "speed up" and it has been part of human development for many years since before the French Revolution. Historians such as Reinhart Koselleck have pointed out that a general sense of a "speed-up" has been part of modern society since the middle of the eighteenth century Rosa (2003).

With the continuous establishment of the twenty-first century society an ever increasing capacity of information processing will be needed, which will transform the way we relate to each other and the way we do business. For example, in this new environment, managers will select coordination mechanisms from the Internet that better satisfy a variety of business needs, such as *business performance*, *revenue expansion*, *cost reduction* and *the ability to reach new markets*. In this context, the Internet will allow the online interactions necessary to improve: information sharing, auctions and high connectivity among members of the supply chain García-Dastugue *et al.,* (2003).

The important issue here is the speed all these processes require, and the real time decision making process it is creating. It is then, important to highlight the future of decision making based on a world where information and knowledge is seamlessly integrated into a single Internet environment. How will we best cope with this new scenario?

There is some movement towards the integration of social networks with financial networks exploring the evolution of financial transactions over time. Such integration takes into account the progress of *financial-decision-makers-interrelationship* Nagurney *et al.* (2006).

However it is well known that the human capacity to process information is ultimately biological – being almost solely determined by the vitality and complexity of the neuronal pathways within our brains. So it is only natural that we should be able to better cope with the new reality of a more dynamic society by improving our computational capabilities through a better understanding of the human brain functionality. The research field able to achieve high performance in computational information searching, decision making and neuroscience is *Hybrid Intelligence*.

In an attempt to improve our computational capacity, Moravec (1998) posed a simple question for researchers *"When will computer hardware match the human brain?"* and suggested that 100 million instructions per second (MIPS) is needed to simulate the human brain. Perhaps, it is still early to estimate the amount of MIPSs necessary to simulate the human brain, especially when much new information is still to come from researches, such as the one developed by Dr. Allan Jones, as further discussed in this article.

In order to simulate the human brain in computers, and avoid its biological restrictions, we need to understand the brain's structure and its function. According to Logothetis (2008) the way to achieve that is through functional Magnetic Resonance Imaging (fMRI) and future techniques in brain imaging.

However, there is some resistance about achieving such capacity Levine (2011). The development of areas like Neuroeconomics, (wherein the goal is a better understanding of our brain processes applied to economic decisions), encountered arguments such as the one published by Levine *"We have no reason to believe that better understanding the wiring of the brain would improve our models any more than understanding the microcode on an X86 chip lead to improvements in word processors"* (2011 page 303/304).
Camerer *et al.* (2004) however counter-argued that *"The tradition of ignoring the inside of the black box* (the human brain) *is so deeply ingrained that learning about the brain seems like a luxury we can live without… a field called neuroeconomics will arise whether we like it or not. So it makes sense to initiate a dialogue with the neuroscientist right away"* (2004 page 573).

Camerer *et al.* (2004) also argued that functional Magnetic Resonance Imaging (fMRI) will alter and bring new concepts to psychology, and because economic theories are increasingly sensitive to psychological evidences, economy will be impacted.

Decision making is of common interest to areas such as Neuroeconomics and Economic Behaviour. In fact, decision making has a multidisciplinary nature and appeal that make it possible to join different fields of knowledge and unify efforts from distinct research subjects. New questions arise from this, such as: How are the cognitive processes represented in the human brain? How is the process of Decision Making represented in our brain? How can fMRI help us to create new computational models through a better understanding of neuroanatomy and brain function?

II. COGNITIVE REPRESENTATION THROUGH FUNCTIONAL MAGNETIC RESONANCE IMAGING (fMRI)

The study of human intelligence gained a more specific direction with the development of cognitive psychology during the 1960's. It is still a recent research field and significant progress has been achieved in the explanation of the general nature of human intelligence, rather than focusing on individual differences, as it was prior to cognitive psychology Mackintosh (2011).

Researchers seek for cognitive information using paradigms and use functional Magnetic Resonance Imaging (fMRI) to map where these processes take place in our brain.

The investigation of brain activation was based on the principle of *pure insertion* described by Donders (1968), and later Sternberg that introduced a method named *additive-factor* in information processing Sternberg (1969). However, a later publication made by Friston *et al.* (1996) questioned the validity of *pure insertion* in relation to *cognitive subtraction* based on the fact that the processes in the brain follow a nonlinear path.

Friston *et al.* (1996) used modulation in the brain to assess the relationship between nonlinear neuronal interactions, and also used factorial design to address integration of components; proposing that the brain can be functionally specialized in representing physiological responses in the form of regional interactions and when we map the brain using, for example, fMRI, we in fact neglect the regional contextual interaction in the mapping process.

Logothetis conducted a review published by Nature in 2008 which shows of 19,000 papers related to fMRI, 43% related to functional localization and/or cognitive anatomy. fMRI, despite being an indirect way of measurement with its physical and biological restrictions, has become the most important non-invasive tool for brain mapping since the introduction of X-Ray in 1895.

For a good review about the principles of fMRI refer to Logothetis (2008) and Blaimer *et al.* (2004). Several techniques capable of functionally assessing the neural activations associated with Magnetic Resonance Imaging (MRI) resulted in the so called fMRI.

Among those techniques, Blood Oxygenation Level Dependent (BOLD) introduced in the early 1990s (Osawa, *et al.* 1992) is the most used, and often mentioned as synonymous with fMRI. It is an important approach, considering the non existence of anastomoses in the human brain capillary system, i.e. vessels do not fuse together after splitting into two branches. In other words, alterations in neural activity will proportionally imply in an oxygenation variation and demand blood perfusion for a specific active vascular density area Logothetis (2008) and Haller & Bartsch (2009).

To relate the neural activity in a cognitive process with the increase in the blood flow for a specific area of the brain, Jueptner and Weiller published an interesting paper where they addressed important assumptions in order to validate the BOLD technique as a true measure of synaptic activity and cognition Jueptner & Weiller (1995).

The consumption of energy in a specific part of the brain has to have a strong correlation to blood flow; also, the consumption of energy has to be correlated to synaptic activity. Jueptner and Weiller (1995) also posed two important questions: Does energy consumption reflect activity or inhibition or it is related to both processes? And what is the mathematical relation between energy consumption and cell activity?

The main conclusion from the Jueptner and Weiller review was that glucose was involved in both processes of inhibition and excitation. They also relate the consumption of glucose in the activity of glial cells as 15%, creating then a mathematical relation between glucose consumption and blood volume Jueptner & Weiller (1995).

The BOLD technique can be used by relating the content of glucose per blood volume to the demand for blood volume in a specific area of the brain and quantify the neural activity. fMRI can precisely determine areas of activity by measuring the blood flow in distinct areas of the brain.

However, Haller and Bartsch observed that BOLD responses can be influenced by the respiration of the subject, as CO_2 levels work as a potent vasodilator. Therefore, the same person can show different results depending on her or his anxiety state. They also point to the influence of drugs such as ethanol, nicotine and cannabis on a BOLD response Haller & Bartsch (2009).

Haller and Bartsch also pointed out the age of subjects and the state of brain health influences BOLD results. Research from authors such as Haller and Bartsch on the effects of CO_2 on BOLD technique and Haller *et al.* on the development of a new BOLD ceiling technique (that allows fMRI mapping of continuous neuronal activation as an alternative to situations where ON-OFF paradigms cannot be applied) contribute to a better definition and understanding of fMRI imaging technique, rather than a criticism to its use Haller et al. (2006) and Haller & Bartsch (2009).

Image construction in fMRI is a result of different relaxation processes among the biological tissues as due to their intrinsic nature. In a simple way, after the removal of an applied magnetic field the alignment of hydrogen in the water molecules present in the various biological tissues returns exponentially to its original state in a process called relaxation, termed T_1, T_2 and T_2^* Logothetis (2008).

T_1-weighted uses a gradient echo sequence with short echo and repetition times, resulting in a contrast between grey and white matter. T_2 uses a long echo time and repetition time, where water appears brighter and fat tissue appears darker. Therefore, the differences in relaxation rates are enough to reveal the anatomy of the brain, and because the dynamic nature of the brain tissue, these variations can be interpreted as time changes during the composition of the images, T_2^*, also called T_2^*- weighted imaging, became the base process in generating images in fMRI. The physical and chemical variations of neural activity can then be interpreted from the relaxation processes in a very reliable and consistent way Good (2011) and Logothetis (2008). To generate a brain image it is necessary to have Spatial and Temporal Resolutions; to have an anatomical and functional view of the brain Spatial Resolution is necessary and to access the neural activity Temporal Resolution is necessary.

Spatial Resolution is usually measured by means of a point-spread function (PSF) or systemic *impulse response*, which measures the degree of blurring of the object of focus as a measure of image quality. Temporal Resolution is obtained by single-shot echo planar imaging (EPI) and it is a function of how the sample offers resistance to the relaxation process, as cited above. This also has technical and physiological limitations, (Logothetis 2008) and Frank *et al.* (1999) Friston *et al.* (1995c) and on image smoothness Amit *et al.* (1991).

The interpretation of the brain image has been a subject of several publications with different approaches in order to relate the activated areas of the brain to a specific behaviour.

Friston, *et al.* used Statistical Parametric Maps (SPMs) to localize differences in regional cerebral activity Friston *et al.* (1991) This method consists in evaluating a large number of repeated measures of the brain with statistical models such as ANCOVA with multiple covariates, correlation coefficient and performing a t test to see if there were significant differences in activity for a specific area of the brain.

Because of the large number of comparisons among images, a threshold adjustment is made based on the smoothness, an empirical procedure that helps identifying significant foci. Also, in order to improve the analysis of imaging data, Friston, *et al.* (1991) in another publication, put together two distinct theories: general linear model and Gaussian fields Friston, *et al.* (1995a).

Through the use of fixed effects for factors, covariates and interaction of factors, Friston, *et al.* have created a simple, flexible and broad statistical approach in imaging interpretation Friston, *et al.* (1995a). However, the problem using a general linear model in interpreting the images of fMRI is that the images are not independent since the BOLD signal is corrected after continuous scans, Henson (2004) and Friston, *et al.* (1995b) and Kaas (2006).

When comparing images from fMRI, one of the concerns is the transformation needed to match the images. In a publication Friston, *et al.* developed an automatic and nonlinear method that minimizes the sum of squares between two images Friston, *et al.* (1995c).

This method can also be applied to Magnetic Resonance Imaging (MRI), structural MRI, in coregistration of Positron Emission Tomography (PET) and nonlinear spatial normalization of (PET). In another publication Friston, *et al.*(1995d) still focusing on linear models and assuming that physiological responses could have specific time adaptations to the proposed task, brought together an extension of a linear model, MANCOVA and canonical variates analysis in order to maximize the potential of fast fMRI techniques.

Together, both analyses allow the correlation between *erros* associated with physiological noise and a better characterization of the form of hemodynamic changes during a cognitive or sensorimotor process. Another important aspect on imaging processing in fMRI representing a functional anatomy was emphasized by Friston *et al.* (1999).

Using Conjunction Analyses, which is a joint refutation of multiple null hypotheses, Friston and co-authors in a more random-effect analyses approach, questioned the capacity of the analyses used in fMRI time series to infer, from the sample images, anatomical function related to the population these images came from; thereby minimizing the effects of using a fixed-effect analysis, that would be more sensitive and would compromise the significance of an estimated response, since the degrees of freedom would be more restricted and the variation among fMRI scans would also be less attributable to a population effect.

Lizier *et al.* developed a method based on asymmetric, multivariate, information-theoretical analysis that is able to capture non-linear, directional relationships and also collective interactions among the brain's regions; for example, when applied to fMRI data using multivariate measures, the method is able to establish the direct information structure existent between brain regions in a test conducted on a visuo-motor tracking task, and does so, by using small data sets, because of the use of specific information-theoretic estimator and the statistical significance Lizier *et al. (*2011).

A part of all the statistical treatment on fMRI images, the main idea behind the interpretation of fMRI images still remains, if a cognitive process can be inferred from regions or areas of the brain seen as compartments, where neural activity is captured by imaging technology.

The idea about cognitive processes occurring in areas or compartments has been questioned by many authors as pointed by Bressler & Menon, 2010. In this review Bressler and Menon support the idea that cognition is resultant of the dynamic interaction of distributed brain areas operating in large-scale networks rather than in isolated operations of a single brain area.

To visualize a brain network the way Bressler and Menon described, we need to imagine populations of interconnected neurons. The connections are made by synapses, dendrites and gap junctions.

Among all of these interconnections, there are areas with multiple unique neuronal configurations called nodes, with specific architectures, creating a larger scale structure. In this new view, the brain's area is defined as a subnetwork of a large scale network, which consists of excitatory and inhibitory neural populations or "nodes" with connecting pathways called "edges"; but as pointed out by Bressler & Menon (2010) still there is no consensus about how a functional node is defined.

Edges are composed of long range interconnections of axon-fibers or "white matter". These edges have directionality in the sense where the fibers leave the cell body to the synapses, but can be seeing as bidirectional between distinct brain areas Bressler & Menon (2010). However, edges do not necessarily reflect the actual axonal pathway and caution is recommended during the interpretation of results, it in fact opens new opportunities for questioning about understanding the human brain structure.

How are the functional interactions of the brain represented in such complex structural networks?

In order to study the brain in a process of reengineering, it would be plausible to consider a functional node or a functional network, as an area of the brain that presents elevated blood perfusion in functional Magnetic Resonance Imaging (fMRI). How are the functional interactions and networks organized in the human brain?

To answer this question, functional interactions can be seen as the result of a large-scale structural network and the best approach to understanding the complexity of such a structural network is through evolution, as suggested by Finlay *et al.* (2001). Kaas suggested a starting point in understanding such complexity, by focusing on the evolution of the neocortex from early mammals, because that is the part of the brain which has undergone great changes in the last 200 million years from the original dorsal cortex of reptiles Kaas (2006).

The diversity of evolution of the neocortex is represented in over 4600 species with great differences in brain complexity and sizes. The human brain, in particular, is composed of two layers of neocortex which represent the largest area in the brain, and several cladistic formal approaches have been described in order to characterize which structure was retained in the human brain from common ancestors Kaas (2006).

As the brain evolved and became bigger, the distance between neuronal bodies was solved with longer and thicker axons, but this presented to be biologically restrictive, and evolutively, the solution for long connectivity among neurons was the organization in modules, giving better advantages for local connectivity rather than long distant ones. The more specialized these areas became less need for thicker and longer axons was observed Kaas (2006).

Among mammals, larger brains contain proportionally larger neocortex, but the organization of the neocortex varies among mammals Finlay *et al.* (2001). Returning to the modular, or functionality of distinct areas of the brain (nodes) the representation of nodes of a large-scale network would be an area of the brain that, individually, or in association with other areas would activate or deactivate (requesting more blood supply areas in fMRI) as a response to a cognitive process in comparison to a base line signal Bressler & Menon (2010).

The study of the neocortex in different mammals could then elucidate the potential of each area and validate the mapping process of cognitive activities in the human brain. In this sense, Sugrue *et al.* defended the idea of taking cognitive processes such as, valuation and choice from the animal studies under the influence of intuitiveness and place these ideas in the field of quantitative measurements Sugrue *et al.* (2005).

The communication of distinct areas of the brain can be explained by the increasing metabolism resultant from a cognitive process and the increase in blood supply, as a response to the high neuronal metabolism. The interactions among distinct populations of neurons result in an oscillatory process with important functional consequences identified through fMRI and BOLD techniques, as for example the identification of cognitive functions such as, *attention*, *working memory*, *language*, *emotion*, *motor control and time perception* as published by Bressler & Menon (2010); *category learning* Seger *et al.* (2010); *interactive behaviour* Cisek & Kalaska (2010); *self regulation* Heatherton (2011) and *decision making* Wallis (2007) and Rilling & Sanfey (2011). In spite of, all those studies, the big gap in brain research is still the knowledge about its intricate connective anatomy among approximately 86 billion neurons.

The ultimate approach in terms of revealing the microscopic anatomy of neuronal connections is being conducted by the Allen Institute for Brain Science in Seattle, State of Washington USA led by Dr. Allan Jones, Chief Scientific Officer. Here the human brain has been submitted to MRI, diffuse tensor imaging (DTI) sliced in 20µm pieces, stained and the ribonucleic acid (RNA) measured in order to understand the deoxyribonucleic acid (DNA) expression in specific areas of the brain, Jones (2011). With these studies conducted by Allan Jones and his research team it will be possible, not just to relate the existent fMRI data with the neuronal anatomy, but also the gene expression in functional areas of the brain. It will be the ultimate approach to understanding the anatomy and functionality of the human brain.

The contribution to fields such as *brain pathology*, *cognitive psychology*, *neuroscience*, *economic behavior*, *decision making* and others will be immensurable. New concepts will replace old views and as cited above, researchers such as, Levine (2011) will have to adjust their ideas to a new reality. The impact on neuroeconomics will support researchers like Camerer *et al.* who knew we always have to address the biological nature of our brain in order to make assumptions about *thinking* Camerer et al. (2004). Still the question posed before has to be addressed here: How is the process of Decision Making represented in our brain?

III. DECISION MAKING

Decision Making is a very broad field of study which has been vigorously emphasized in the literature seeming to be a popular topic within many fields of human knowledge. It was pointed out by Fellows (2004) as being a fundamental human behaviour and has been studied from cognitive psychology to economics; Gold and Shadlen quoted the important areas of decision making neuroscience, psychology, economics, statistical, political science and computer science Gold & Shadlen (2007).

In the literature, decision making can be found in two vastly different points of view. Several authors describe procedures based on previous experiences where they report and suggest steps of actions to solve managerial problems, such as, Wang (2011) on *strategy*; Steinhouse (2010) on *brilliant decision* *making*; Shaw (2008) on *making difficult decisions*; Hardman & Macchi (2003) on *thinking*; Ellis & Newton (2010) on *mind and brain*.

The literature of decision making can be classified into two vastly different points of view. The first takes into account past experience as a basis for actions in the managerial problem solving process. This is supported by several authors such as Jossey-Bass (2010); Steinhouse (2010); Shaw (2008); Hardman & Macchi (2003) and Ellis & Newton (2010). The second approach to decision making, and the view we support in this chapter, is based on the biological nature of decision making focused on scientific investigation.

There is also a broad literature in support of the scientific approach, ranging from rational to heuristic decision making. Scientifically speaking, also a broad literature is available, ranging from rational to heuristic decision making Gigerenzer & Gaissmaier (2011); Lo *et al.* (2005) on *economic behaviour*; Camerer *et al.* (2005) on *neuroeconomics*; Coltheart *et al.* (2010) on *abductive inference*; Coltheart *et al.* (2011) on *delusional belief*; Heatherton (2011) on *self regulation*; Bohner & Dickel (2011) on *attitude change* and Baumeister *et al.* (2011) on *self affirmation, framing, overriding automatic responses, anticipation, simulation and planning* and Rilling & Sanfey (2011) on *social decision making*.

Decision making can also be seeing as an individual or social process. We will work with the individual perspective, but some interesting considerations should be made to a recent review Rilling & Sanfey (2011). In this review Rilling and Sanfey argue that even individual decisions are made in a social context, since decisions can affect others. They highlighted behaviours such as, *trust*, *altruism*, *reward*, *reinforcement*, *fairness*, *revenge*, *punishment*, *conformism*, *delaying gratification* and *emotional regulation* as influencing the process individual decision making.

The definition of the term *decision making*, when referring to individual decisions, has many interpretations in the literature, and also the number of tautological attempts of explaining it shows that it is not an easy task. An interesting explanation was given by Frank and Claus where they explained that inside our brain, decision making is based on two mental processes, action selection and reinforcement learning Frank & Claus (2006).

The first process is related to choosing amongst options, and the second is related to pondering, or selecting possibilities based on previous knowledge. In this chapter we have adopted the definition of Frank and Claus because of its cognitive and neuroanatomic character Frank & Claus (2006). The attempt to measure decision making can be traced back as much as 60 years ago, as in Cartwright and Festinger (1943); Edwards (1954; Charnes *et al.* (1978) and Mann *et al.* (1997) but an interesting review was published by Gold and Shadlen where they addressed the neuroscientific basis of decision making. They highlighted *deliberation* and *commitment* as a common element shared by different decision processes Gold & Shadlen (2007).

Gold and Shadlen in their publication of 2007 defined decision making "as *deliberative processes that result in the commitment to a categorical proposition*". This study focused on simple, brain measurable sensory motor tasks aiming at precision in controlling sensory inputs, quantifiable motor output and in measuring and analyzing the brain's areas. This was in order to understand if the *decision-making-system* was intuitive (based on previous experiences) or deliberative (related to achieving a specific goal in a changing environment) as described by Kahneman (2002).

As a result of this study conducted on monkeys, Gold and Shadlen presented insight into how elements of decision formation are organized in the brain. They also pointed out how central mechanisms that are common in different kinds of decision making are able to explain the balance between speed and accuracy on perceptual tasks Gold & Shadlen (2007).

As a result of Gold and Shadlen's study, the simplest sensory-motor decision was attributed to a deliberative decision-making system. Their study was mostly based on mathematical treatment of paradigms such as vibrotactile frequency (VTF) and random-dot motion (RDM), however, no association with fMRI was proposed. Often in studies of neurophysiology decision making is associated with a problem related to the selection of a physical movement, as in Glimcher (2003) on *Visual-Saccadic Decision Making* and Wallis (2007) on *OFC orbitofrontal cortex*. This strategy allows researchers to associate a specific movement to a cognitive process that was involved in the decision making Gold & Shadlen (2007).

However, a new question can be placed asked here. How do we investigate decision making processes that are not related to a physical body movement? An approach to this new question was published by Wallis *et al.* (2001) where the concept of abstract principles is attributed to the prefrontal cortex (PFC). Damages to the PFC result in lack of following rules and making decisions (see also Wallis, 2007).

The neurons that compose the PFC are responsible for encoding information related to the perception-action cycle They are also stimulated by all sensory modalities before and after actions and are related to past events memory. In other words, the PFC is responsible for the anticipation of an expected event and behavioural adjustment to the consequences.

Although, Willis and co-authors were focused in studying abstract rules, they also affirmed that it is still unknown how and if the PFC can encode abstract rules. As proposed by Frank and Claus, as referred above, decision making is basically explained based on two mental processes, *action selection* and *reinforcement learning* Frank & Claus (2006). The neural systems in our brain responsible for both processes are the basal ganglia (BG). These also called striatomedial pallidonigral and the neuromodulator dopamine (DA).

Several neurological conditions are related to a dysfunctional neuromodulator Dopamine (DA), such as Parkinson's disease, attention deficit/hyperactivity disorder (ADHD) and Schizophrenia. In mapping the dysfunctional areas of the brain, researchers can better understand the role these regions play in a healthy brain Cools *et al.* (2002); Frank (2005) and Frank & O'Reilly (2006). An interesting example of a methodological approach to computationally simulating the processes of decision making in the human brain was developed by O'Reilly and collaborators in 2000, and it is represented by artificial neural networks (ANN) as a model of the Basal Ganglia (BG). This has been subsequently improved and used in different cognitive situation studies, Frank *et al.* (2001); Norman & O'Reilly (2003); Frank *et al.* (2003); Atallah *et al.* (2004); Frank *et al.* (2005); Frank & Claus (2006) and Frank & O'Reilly (2006).

The model proposed by Frank includes a competing process of the indirect pathway, from the Striatum to the External Segment Globus Pallidus (GPe) to the Internal Segment Globus Pallidus/Substantia Nigra Pars Reticulata (GPi/SNpr); previous models did not take into account the No-Go step. Also, Frank's model includes a Substantia Nigra Pars Compact/Ventral Tegmental Area (SNpc/VTA) allowing the simulation of Dopamine (DA) role Frank *et al.* (2005).

The complexity of studying *Decision Making* not only relies on a better understanding of the biological structure and functions of the human brain, but also in overcoming the reluctance of researchers to break through their disciplinary boundaries and assume a holistic view. It is such a complex environment that it can only be embraced by the science of *Hybrid Intelligence*.

A more precise process of decision making will be possible through the development of computational representations of the human brain, including all its psychological and behavioural particularities, as it has been pointed out by several renowned researchers: Coltheart *et al.* (2010) on *abductive inference*; Coltheart *et al.* (2011) on *delusional belief*; Heatherton (2011) on *self regulation*; Bohner & Dickel (2011) on *attitude change* and Baumeister *et al.* (2011) on *self affirmation*, *framing*, *overriding automatic responses*, *anticipation*, *simulation and planning*.

IV. COMPUTATIONAL COGNITIVE NEUROSCIENCE

Computational Cognitive Neuroscience (CCN) is a recent field focused on the intersection of computational neuroscience, machine learning and network theory, also called connectionism Ashby & Helie (2011). The development of network theory started in 1943 with the studies of McCulloch and Pitts, but because of the tendency of modelling human behaviour, when not much was actually known about the neuronal biology of human behaviour, network theory took a distinct route from the nascent *Computational Neuroscience*.

Computational neuroscience came to the public mainly through the research published by Hodgkin and Huxley in 1952 where they modelled the generation action potential based on the giant squid axon. Axons and dendrites were modelled as compartments based on *compartment modelling approach* and partial differential equations were specified for each compartment, describing the propagation of action potentials. Hodgkin and Huxley were subsequently awarded the Nobel Prize for their ground-breaking research.

The modern Computational Cognitive Neuroscience started approaching the biological nature of the human brain through the work of researchers such as: Rumelhart and McClelland (1986) stated, "*It is some of the most exciting work in cognitive science, unifying neural and cognitive processes in a highly computational framework, with links to artificial intelligence*" (1986 page 318). Ashby and Helie pointed neural network models to have common features with the human brain, as in *distributed representation*, *continuous flow* and *changes in synaptic strengths in memory modelling* Ashby & Helie (2011).

Ashby & Helie (2011) highlighted the reality of neural network models as being the lack of compatibility with human brain, and in general there is no interest in associating units in neural network with specific brain regions. In their publication, Ashby and Helie also argued: "*Why using CCN approach rather than cognitive theory?*" Several arguments support the use of CCN strategy, such as the fact that CNN adds constraints and is more selective. The resulting model then is more consistent with the existent neuroscientific data, and also accessing neuroscientific data helps understanding the relationship among similar behaviours that are not related to each other.

A practical example is the potential capacity of prediction of CCN models. An example of prediction using CCN model is found on Ashby *et al.* (2007) where a model called SPEED (Subcortical Pathway Enable Expertise Development) is set to a single cell recording and behavioural data, and several pharmacological treatments are simulated. The simulations are possible based on the neurobiological nature of SPEED. When SPEED is adjusted relating neural activation and fMRI/BOLD signal, it is capable to predict BOLD signals in distinct brain areas and it is also capable of predicting how these BOLD signals vary with the subject learning practice as in the study published by Ashby and Valentin (2006).

The prediction capacity was also successfully tested on several neuropsychological patients suffering with Parkinson's and Huntington's disease. Other developments such as, the computer interfaces P300 has been of great use for people suffering from devastating neuromuscular disorders. The based-brain computer supports the idea that individuals disabled by amyotrophic lateral sclerosis (ALS) can use a P300-based brain-computer interface (BCI) for writing text in a stable way based on event-related potential (ERP) response and classification accuracy Nijboer *et al.* (2008).

As referred before by Jones (2011) as more details from the brain we have, better will be our capacity of understand the intricacy of the nodes. Also, reinforced by Ashby and Helie that stated the attempts of associating nodes from traditional connectionism and neural models with areas of the brain, with increasing biological considerations will culminate in more realistic biological models, or in other words, better computational representations of the human brain Ashby & Helie (2011). The days when *Cognitive Psychology* theories were accounted for just behavioural data from cognitive experiments and usually based on healthy adults seem to be part of a past.

Current cognitive theories are challenged by distinct data sources, such as in Ashby and Valentin (2006) on *fMRI, studies conducted in neuropsychological dysfunctional patients*, *recordings of event-related potentials* (ERPs), *transcranial magnetic stimulation studies*, *single unit recordings* and Logothetis (2008) on *parallel magnetic resonance imaging* (pMRI).

In this context of a more realistic biological model approach using CCN models, O'Reilly (1998) has published six principles which an ideal computational model of cortical cognition should consider. These principles establish the basics for a framework and are categorized as: *biological realism*, and in a more architectural approach: *distributed representation*, *inhibitory competition* and *bidirectional activation propagation* (*recurrence* or *interactivity*).

The importance of the *biological realism* is to keep a model in accordance with the nature of the cognitive processes in the human brain and it has an important implication in the error-driven learning, since any information that lacks the biological foundations should not be taken into account O'Reilly (1996) and O'Reilly (1998).

The architectural aspect of O'Reilly's principles take into account the biological nature of the cortex, where several neurons are involved in distinct representations rather than a specific neuron responsible for a unique representation, it is like numbers and letters in passwords, where several representations can be generated from few letters and numbers, and it is called *distributed representations* O'Reilly (1998).

Inhibitory competition participates in the process of selecting the most effective representation that is consequently reinforced and refined by learning. Also inhibitory competition can group representations in subcategories in order to generate a more general view of the environment, such as for example: grouping different investments in a subcategory called risk investments in a stock portfolio.

The *bidirectional activation propagation* is characterized by O'Reilly as critical to the flow of information in a network. In this case, input interpretations and processing, in both levels such as in perceptual and conceptual constraints could be supported at the same time. An easier way to understand this explanation is comparing the way the neocortex precepts the environment, in comparison with the hippocampus.

The neocortex would "learn" in a perceptual, more flexible, manner; where slowly, dispersed neural representations would construct a general vague idea of the environment, on the other hand, hippocampus, operating in a more structural conceptualized way, would represent the environment through isolated representations but structurally well defined. Also, to be stable and effective, a network would need to process information gradually in steps in order for the information to flow in both directions, bottom-up and top-down O'Reilly & Ruddy (2000).

A CCN model would also not contradict the neuroscientific knowledge. In this sense Ashby and Helie (2011) established four assumptions: *precisely address the anatomical nature of the human brain interconnections*; *discriminate if they are excitatory or inhibitory*; *the behaviour related to a brain region should be in accordance to with the single neuron study related to the same region,* and *the neuroplasticity should be taken into account in any assumption.*

In this sense, the evolution of new CCN models will run in parallel with the increasing acquisition of knowledge about our own brain structure and function; the result of this co-evolution will be beneficial for important research fields such as neuropathology, economical behaviour, neuroeconomics, decision making and others. Several publications are already considering the work from O'Reilly (1998) and Ashby & Helie (2011) as for example: Maddox & Filoteo (2011); Antzoulatos & Miller (2011); Lemay-Clermont *et al.* (2011); and Waldschmidt & Ashby (2011).

An interesting message from Kurzweil (1999) is that we are changing towards a hybrid intelligent society and the man-machine integration will slowly replace our taboos, values and beliefs. At the same time we create a new society, this new environment will change us.

V. CONCLUSION

Considering all the contribution that is still to come from the research conducted by Dr. Allan Jones, Chief Scientific Officer of Allen Institute for Brain Science in Seattle, State of Washington USA; and a part the necessary brain resolution, we will be working with in the near future, much of the potential use of fMRI will be explored as highlighted by Camerer *et al.* (2004) and Logothetis (2008); bringing us to a new dimension of insights in brain anatomy, psychology, neuroeconomics, Computational Cognitive Neuroscience and related fields.

However, it is important we, scientists from distinct fields such as biological and social science understand the need to empower researchers from the various distinct fields, with a more comprehensive explanation about our methodologies and terminologies.

The fact we have a limited biological human nature, and as we discover the more complex our biological outputs can be, still we are moving towards a more effective way to explain the nature of human behaviour in its various forms, as in O'Reilly and Frank's research works.

As reductionist as it sounds, in addressing the biological nature of our decision processes, we propose it will maximize the efficiency and precision of our actions, and with the replication of such complex "set of behaviour" in a computational environment, it will help us to respond to "real time" situations, in order to cope with a more fast and complex society as pointed by (Rosa 2003); (García-Dastugue *et al.,* 2003) and Nagurney *et al.* (2006).

ABBREVIATIONS

ADHD: Attention Deficit/Hyperactivity Disorder; **AI**: Artificial Intelligence; **ANN**: Artificial Neural Networks; **BG**: Basal Ganglia; **BOLD**: Blood Oxygenation Level Dependent; **CCN**: Computational Cognitive Neuroscience; **DA**: neuromodulator Dopamine; **DNA**: Deoxyribonucleic Acid; **DTI**: Diffuse Tensor Imaging; **EPI**: Echo Planar Imaging; **fMRI**: functional Magnetic Resonance Imaging; **GPe**: External Segment Globus Pallidus; **GPi**: Internal Segment Globus Pallidus; **MRI**: Magnetic Resonance Imaging; **MPI**: Million Instructions per Second; **OCR**: Optical Character Recognition; **OFC**: Orbitofrontal Cortex; **PD**: Parkinson's disease; **PET**: Positron Emission Tomography; **PFC**: Pre-Frontal Cortex; **PSF**: Point Spread Function; **RDM**: Random-dot Motion; **RNA**: Ribonucleic Acid; **SNpc**: Substantia Nigra Pars Compact; **SNpr**: Substantia Nigra Pars Reticulata; **SPMs**: Statistical Parametric Maps; **VTA**: Ventral Tegmental Area; **VTF**: Vibrotactile Frequency.

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