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Causal Mathematical Logic as a guiding framework for the prediction of "Intelligence Signals" in brain simulations

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Abstract

A recent theory of physical information based on the fundamental principles of causality and thermodynamics has proposed that a large number of observable life and intelligence signals can be described in terms of the Causal Mathematical Logic (CML), which is proposed to encode the natural principles of intelligence across any physical domain and substrate. We attempt to expound the current definition of CML, the "Action functional" as a theory in terms of its ability to possess a superior explanatory power for the current neuroscientific data we use to measure the mammalian brains "intelligence" processes at its most general biophysical level. Brain simulation projects define their success partly in terms of the emergence of "non-explicitly programmed" complex biophysical signals such as self-oscillation and spreading cortical waves. Here we propose to extend the causal theory to predict and guide the understanding of these more complex emergent "intelligence Signals". To achieve this we review whether causal logic is consistent with, can explain and predict the function of complete perceptual processes associated with intelligence. Primarily those are defined as the range of Event Related Potentials (ERP) which include their primary subcomponents; Event Related Desynchronization (ERD) and Event Related Synchronization (ERS). This approach is aiming for a universal and predictive logic for neurosimulation and AGi. The result of this investigation has produced a general "Information Engine" model from translation of the ERD and ERS. The CML algorithm run in terms of action cost predicts ERP signal contents and is consistent with the fundamental laws of thermodynamics. A working substrate independent natural information logic would be a major asset. An information theory consistent with fundamental physics can be an AGi. It can also operate within genetic information space and provides a roadmap to understand the live biophysical operation of the phenotype.

Keywords: Causal Mathematical logic, Whole brain emulation, Brain simulation, Artificial General Intelligence, biological replication.

1. Introduction

The current state of progression in the neurosciences is approaching the software engineering equivalent of a critical mass. We are faced with the task of integrating a large body of fragmented data, conflicting and incomplete models, where incomplete understanding can impact across entire attempts to integrate this information. Large scale brain simulation projects and their various types (emulation, replications etc) aim to approach this problem in the full diversity of sub-disciplines by centralizing a sorting process, with some independent projects already processing the data for neuron types (neuromorph) and their electrophysical properties (Neuroelectro). Other projects cover connectomes, summary by Seung (2012). Neuro-transcriptomics (Hawrylycz et al., 2012), developmental transciptomes (Johnson et al., 2009) and many new fine scanning techniques may even bring us atomic fMRI (Staudacher et al., 2013). The exponential data increase from these technologies will require both the generation of new technology and conceptual models to deal with this information.

To reduce the problem difficulty high level principles, integrative or top down models can play a role by providing simplifications or guiding frameworks for this type of scenario. Examples are the work of Fuster which gave us a hierarchy of categories for the cortical feature extraction processes (Fuster, 2002) and for the limbic system we have derived principles of recurrence (Papez loop), or integrations of these two extremes such as the thalamocortical loop, the hippocampus, cortico- striatal and cingulated cortex (Bear, Connors and Paradiso, 2006). These latter sub-systems are now included in the recent version of the global workspace theory (GWT) model (Baars, Franklin and Zo, 2013), which is a general framework for neuroscience. Other recent projects outline general computational approaches to explain the structural mathematical qualities required for particular brain modules (and the entire brain) to generate conscious function (Tononi, 2008; Balduzzi and Tononi, 2008).

Our contribution to this process is an attempt to frame the data from high neuroscience level (i.e. entire general input/outputs) in terms of a pure natural mathematical approach steeped in the fundamental physical laws yet remain very specific to the neuroscience. Questions arise such as what does the integration of our highest level biophysical and neuro-structural models tell us if we put them together, in a rough and general manner. This was already attempted by (Lanzalaco and zia 2009a, 2009b) from which top down developmental structure overview appeared to indicate novel high level principles with structure predictions later verified (Striegel and Hurdal, 2009; Fleury, 2011; Sandersius et al., 2011). One result of this was that the entire cortico-limbic structure appeared like it might possess some type of basic "information engine" attribute. However the model was incomplete, similar to many projects when faced with the problem of integrating disparate disciplines across genetics, developmental principles and the current body of neuroscience. To resolve this problem it seemed there would need to be a logic that works across these levels and substrates yet is still deep enough to be derived from basic natural principles.

The work of Pissanetzky (2011c) called casual logic, based on the body of work on causality and complexity was primarily targeted towards AGi yet appeared broad enough to cover all the primary neuroscience domains. It is a logic that describes how information works as a principle of physics, but still works independently at the higher level of the information, when we are not considering physics. All such schemes based on physics cannot right now be completely verified, so for this reason we are open minded that it may even turn out not to be a physical theory at all and proceed with our own skepticism also. Now called Causal Mathematical logic (CML) (Pissanetzky, 2010, 2011), this logic attempts a tie together of extremes in physics such as *least action* and *entropy* into a cohesive framework based on the most basic level of thermodynamics. It then works its way up into the more specific physics derived, make predictions and experimental concepts for processes of intelligence based on these fundamental principles. Some which have been successful so far (Pissanetzky, 2010, 2013a, 2013b). Use of the CML approach appeared for the primary author as method which might clarify the brains "information engine".

If the approach works, there is a simple test. Its success can then be defined by whether we generate useful concepts that lead to the right type of questions and predictions. Primarily this would be the testing of input/output processes in integrative approaches to neuroscience such as brain simulations.

1.1 Introduction of least action and entropy in physics and information sciences

In the Physical sciences the least action principle has been used to re-derive the works of Newton, Einstein, Maxwell and Dirac (Gray 2009; Brown 2005; Dalrymple, 2012) and the entropy principle more latterly being proposed as force in itself to define the electroweak and strong force (Freund, 2010), dark matter / energy (Chang and Li 2010) and electrostatics (Wang, 2010; Di Caprio, Badiali and Holovko, 2008; Sheykhi and Hendi, 2010). Both least action and the law of maximum entropy are examples of physical extrema (Feynman in Brown 2005). Extrema are system states, invariant or distributed into equilibrium respectively. More specifically Wang (2007, 2008a, 2008b) helps relate these extremes into one physical framework by defining the least action principle as a case of the maximum entropy principle, so that least action can be stated to be a result of the mechanical equilibrium condition extended to the case of stochastic dynamics.

Least action was proposed by Jaynes (1963, 1968, 2003) as applicable to information and has been recruited in the physical information sciences (Lerner, 2012; Berut et al., 2012; Still et al., 2012; Hartonen and Annila 2012; Wissner-Gross and Freer 2013). The least action principle is a primary component of CML, (Pissanetzky, 2013a). CML is built by codifying the principles pf causality, symmetry, least-action, and the laws of Thermodynamics. The work of Pissanetzky expounds the application of least action and its counterpart entropy in terms of all complex information systems (Pissanetzky, 2010, 2011) into a current format called the "action functional" which proposes that much information is in a state of partial order between entropy and the information which is most suitable to be minimized to a least action state (Pissanetzky, 2013a). This conclusion arose from experiments to understand how intelligence can translate information across disparate domains, such as code refactoring (Pissanetzky, 2009) or deriving of mathematical conclusions (Pissanetzky, 2013b).

The other primary component in CML, the information attribute of entropy as an information states (or set of such states) deregulated from invariance and partial order has long been used in the information sciences defined as maximum entropy (Gzyl, 1995; Jaynes 1963, 1968, 2003; Dewar, 2009). Recent work proposes entropy has a computational function which if increased produces a statistical distribution of options (Wissner-Gross and Freer 2013). Self replication itself has been proposed to be an entropic process providing a new physics based clarity to Darwinism (England, 2013). CML seeks to define the entire range of both least action and entropic process features in terms of one theoretical information system, where increased options give rise to a more integrated partial order for invariants to emerge. It should be mentioned at the start that problems in the causal theory are not solved in the traditional spacetime used in Physics. They are solved in causal space, which is simply the collection of all total orders for a causal set. The total orders represent the symmetry of the causal set, so the causal space is also the space of symmetries of the causal set. This will be explained more specifically in section 2.3.

1.2 Strategy for this paper.

This paper attempts to integrate separate disciplines of biophysical neuroscience and a basic mathematical approach to AGi. Such previous attempts have resulted in a product removed from basic neuroscience (Tononi, 2008), so the idea here is retain clear specifics for either discipline to not compromise the original details. To ease the cross discipline approach, some of the neuroscience will be referred to in italics with explanations in a glossary at the end of the paper. For the AGi aspect, any math included will be kept either minimal or if there is more depth, explained as easily as possible for general readability. The more in depth mathematics underlying this approach can be found in the references within those parts of the paper.

The neuroscience parts are a summary of existing work which do not require a controversial neuroscientific paradigm, but clarification of mainstream data. Also the thermodynamic casual approach to the neuroscience we highlight has existing ground, in the work of (Papo, 2013) and (Friston, Daunizeau and Kilner, 2010; Friston, Harrison, and Penny, 2003). There have also been recent questions raised on why fMRI of the brains prediction mechanisms in the limbic system appears to be driving us towards high entropy information (Davis, Love and Preston, 2012) with some degree of coding of entropic information occurring in the process (Schiffer, 2012). More recently (Carhart-harris et al, 2014) use causality based fMRI/MEG tools to argue that entropy is a primary (lower) component of consciousness. That entropy is to be found prominently conserved as a critical realm for the entire brain system to scale its functionality between order and disorder.

Our contribution to this puzzle is the primary original proposal for this paper will be in section 4. This is the thermodynamic “information engine”. An integrated view for the bulk of the brains primary processes, that is considered to be revealed which viewing the brains input and output signals in terms of the casual view where least action is the most fundamental description of a systems order. To get to that stage in section 4 we need to use two Sections (section 2 and 3) to justify the casual approach for both the extremes of least action and entropy in general terms of information. For each of these extremes to determine what is consistent with general principles of neuroscience, derived from the brains primary input and output signals. These primary signals are well known in neuroscience found in the EEG as the range of *event related potentials (ERP).*

Casual approach is not so general we can assign any casual construct to any brain signal and propose it fits with neuroscience. The work of Pissanetzky is very specifically focussed on the relationship between action and entropy. On this basis of the above we require two very specific classes of neural operation. One set associated with action, and another associated with entropy. If the approach here is complete there should not be any other types of primary signal but these two. There may however be “partial order” type ERP sub-signals which mark the transition stages between these primary signals and of course sub-signal components for the primary signal types. We already know the primary components in the ERP signal, but first for a summary that the ERP can even be said to be the key signal that is a measure of perception, refer to section 2.2.

ERP signals are comprised primarily of two signals, *Event Related Desynchronization (ERD*) and *Even Related Synchronizations (ERS).* Figure 5 shows this more clearly. ERD is primarily the total action set (say of a cortex) with varying sets (specific to required information context) of cortical columns, inhibiting one another in a non linear dynamic manner where the systems stationary energy becomes minimized as a result. ERS is primarily the set of oscillations which bind together the brains operation into an integrated whole for the set of operations which require that. This activity is primarily more linear and continuous in nature. We will go into the specific of these signals in more detail.

- *Section 2* deals with ERD and summarizes the cortex as the primary source for ERD. The ERD processes are described in terms of the action function of neurons, concluding with how CML produces invariants with a similar action process.

- *Section 3* deals with ERS and summarizes the limbic system as primary source for ERS. The ERS processes are then described in terms of entropic oscillation, ideas for the computational contribution by such entropy and then reviews the causal modelling which currently exists for this.

- *Section 4* then integrates ERD and ERS back together into the brains primary ERP to describe the proposed model for this paper. That the *cortico-limbic* brain structure is a casually predicted “information engine” cycle that operates between the extremes of ERD (action) and ERD (entropy). ERP is then proposed to be generally understood as represented by the process of partial order described by CML, as this partial order is also the area which lies between action and entropy.

This overall view then involves justifying a view of the mammalian brain in terms of two integrated structures (cortex and limbic system) as being derived from the extremes of the physical principles, least action and entropy (respectively for each structure). The work of (Lemm et al., 2009) used in figure 5 has also provided us with such a complete view of the primary ERD and ERS in ERP it assists in justifying a complete thermodynamic information engine which integrates the brains detail as a derived view of operations representing the basic “natural” operations of CML described above. In summary the strategy here is we are attempting taking apart and putting together the brain system in terms of its thermodynamic extremes to propose that the partial order concept of CML has captured the full range of processes required for a general “information engine” based on a *cortico-limbic* summary of the brain.

2. Causal Mathematical Logic Consistency with Neuroscience

This section summarizes *cortical* processes in several levels. Section 2.1 in terms of least action function giving rise to invariance’s in cortical columns. Section 2.2 looks more in depth at the ERD signals and their function in intelligence. Section 2.3 lays out how CML produces similar result to the existing cortical models for invariants, while showing it is based purely on first physical principles.

The block hierarchies that we will derive from CML are an application of the least action principle (Pissanetzky, 2013a, 2013b). These will be proposed to correspond to the invariant representations that are generated in the cortex as defined by (Hawkins, 2004, 2006; Hinton, 2009). Biophysically the activity we review as the neural correlates for invariant generation are very specific for this process. These are the *lateral inhibitions* which give rise to the sharp dynamics in *nonlinear spreading waves*. These are a known primary signal in feature extraction called Event Related Desynchronization (ERD). Section 2.2 justifies looking at ERD in terms of least action, but first section 2.1 has to provide depth that the cortical neurons involved in ERD can support this least action proposal. Primarily because ERD is a macroscopic signal reduction across the cortex which is the product of the neurons involved in signal suppression.

2.1 Summary of invariants, detail and hierarchy in neural systems

A primary aim of computational neuroscience is to understand how the cortex is able to produce detailed feature extractions, with the current understanding focusing on specific architectures and functions of the cortical columns. The blue brain column modeling has simulated the result that neurons connect by a growth pattern where they are pushing into each other (Hill et al., 2012). This is consistent with the results from the brain on a dish experiments (DeMarse et al., 2004; Potter et al., 2004), and the *"greedy growth" principle* for neurons (Cuntz et al., 2010, 2012), where dendrites branch into space with optimally short wiring refining the concept of a precise computational law for neurons. The area of dendritic computation has focused on the two primary groups of cortical ionotropic neurons. *GABAA/GABAC* and *Glutamate AMPA/KAINATE* as having division / multiplication scaling power laws for inhibition (Wilson et al., 2012) and excitation (London and Häusser 2005; Cuntz at al., 2012) respectively. The proposal is that dendritic self computation drives self re-enforcement in the neurons for mathematical power functions with a logic basis in the dendrites (London and Häusser, 2005). An optimal least action type wiring principle can then in principle provide the basis for the development of an efficient cortical hierarchical structure.

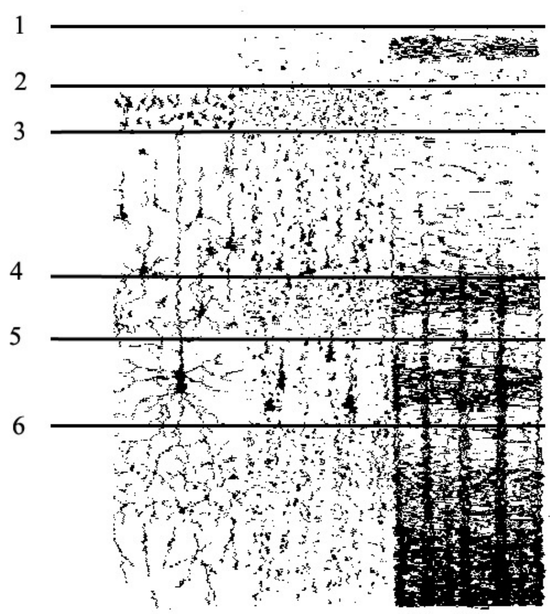

Figure 1. The bottom layers of the cortical column are where the highest density of connections to the limbic system are located, while the upper to top layers are where the invariance's are proposed to emerge by means of an intracortical hierarchy. Notice the layer 1 density where the proposed top down action from the glial cells are more densely located, and the sparseness of the underlying connectivity in layer 2 and 3.

Current models propose the most stable invariants are sparsely coded at the top layer of the cortical column, and the lower cortical layers have the highest connection density to other brain areas (Hawkins, 2004, 2006; Hinton, 2009). *Astrocytes* are most densely proliferated at these uppermost cortical layers and have long been proposed to have some top down enforcement function on the columns (Ingber 1983, 2011, 2012; Ingber and Nunez 2012; Banaclocha, 2002, 2004, 2007; Pereira, 2011; Pereira and Furlan, 2010). Recent experiments implanted the more complex human astrocytes in rodents resulting in increases to their memory (Han et al., 2013).

Pre-existing data had already proposed a correlation between astrocyte to neuron ratio, *cortical surface gyration* (Eriksen and Pakkenberg, 2007) and intelligence (Sherwood et al., 2006; Karlsen and Pakkenberg 2011; Marino et al., 2007).

One idea taken from this is the astrocytes act as gain capacitors (Banaclocha, 2002, 2004, 2007) where the invariants are located in the uppermost columns, so re-enforcing the top layer invariants power to suppress neurons in the lower layers. From this we can propose the least action principle is at its most prominent at the brain surface, operating as a topographical sheet covering the brain, comprised of strong local actions which can impose the top down efficiency of sparse coding in the lower cortical layers. As a result over evolutionary time scales this invariant sheet has become the most separated from the rest of the internal system. This point is illustrated in figure 2. In essence, action has emerged at the top of the system in topographical terms.

2.2 What are the cortical "life signals" we look for in brain simulation?

Non linear cortical activity operates on stochastic feed forward amplification (Rodriguez et al., 2004; Ward et al., 2006; Moss et al., 2004; Tiesinga and José, 2000; Ringach and Malone, 2007) that shifts dynamically from one local region to another by *lateral inhibition* in response to perturbation of its states. A cortical perturbation can be a novel input, conflicting inputs (oddball processes) or an unexpected requirement on attention. The differences between cortical and limbic system EEG are primarily non linear and linear respectively (Nunez and Srinivasan, 1981; Anokhin et al., 1999; Crick and Koch, 2003). The non linear cortical activity manifest itself biophysically as sporadic *spreading waves* (Freeman and Kozma, 2010), such that the appearance of these waves via *non explicit programming*, are used by the blue brain project to demonstrate the success of their simulations.

The spreading waves are mass action attractors, scale free phenomena built from the optimal power law principle of neurons. We know that such physical dynamics can be described by the least action principle (Gray 2009; Dalyrmple 2012; Brown 2005). The combination of optimal wiring, with lateral inhibition by sharp dynamic competition works across local and cross hemisphere regions. The cortical system is so highly ordered in the power wielding invariant upper layers that a dynamic system of local functions evolve which can suppress other cortical areas and the limbic system. So cortical activity paradoxically results in reduced energy output when dealing with problems, which we will describe next.

The biophysical reading for such cortical suppression processes (in response to stimulus) are one of two of the most prominent signals, found in the brains ERP. The cortical contribution to ERP is the previously mentioned Event related Desynchronization (ERD). An important point here is that ERD reduces the resting coherent self oscillating energy from the limbic system (Polich, 2007; Lemm et al., 2010), where such oscillations are ongoing and continuous *stationary dynamics* (see figure 5) that will be defined as primarily entropic in section 3. So input in the form of information with a stimulus value, lowers the systems energy (Lemm et al., 2009) by means of the existing maximally efficient cortical hierarchy which is built on least action neuronal components.

The cortical operations are primarily fitting the probable set of local invariants most suited to process a response to the incoming information by means of lateral inhibition and *dynamic attention allocation* (Hawkins 2004, 2006; Hinton 2009). This activity lowers the systems energy, desynchronizing the resting and continuous limbic systems baseline *alpha, theta, delta, mu* and *beta* oscillation (Polich, 2007; Lemm et al., 2010) and so removes the baseline entropy from the system. From this perspective, the cortex is "stimulation greedy" in that it builds its order by increased information gain to local parts of the system which compete with each other. Refer to table 1 for a summary of oscillations and the known sources in the brain.

To justify the ERP as “intelligence signals”, the ERP primarily in the cortical ERD range are correlated to a wide variety of high level perceptual processes. E.g. Stimulus identification (Pfefferbaum et al., 1985), response inhibition, response conflict, error monitoring, novelty detection, intentional deviation (Patel and Azzam 2005), inhibition of motor responses, overcoming stereotypical responses, conflict monitoring, maintenance of context information (Azizian et al., 2006), response selection timing (Gajewski et al., 2008), detection of novelty or mismatch (Folstein and Van Petten, 2008) and object recognition (Vianin et al., 2002). We will look at the later onset ERP that occur when ERD is relaxed but to summarize the above in comparison to the later onset ERP’s these appear to reflect the processes of a system trying to increasing efficiency of the information it processes by means of decision making.

So if the cortex is primarily a least action, high order greedy growth system that produces clear decisions and builds functional extraction hierarchies where does this leave the *limbic system* which has a low neuron to white matter ratio of 6:10, interestingly the inverse of the cortex at 10:5 (Collins et al., 1998; Evans et al., 1996). Will the limbic system have reduced least action power as a result of such an inverse ratio? Also we have referred to the limbic system as being entropic without justification. That will be covered in section 3. First of all we will expound how CML produces similar results to the work of Hinton and Hawkins on the cortical columns, without any reference to neuroscience by minimizing of the action of casual sets. Following that we can move on from the cortex to highlight evidence that the limbic system can be viewed as a phase coupled self oscillation system which serves to increase entropy. We would ask why, and the answer is similar to the introduction about current work on entropy in AGi. That entropy has a domain of powerful processing functionality which generates a wide variety of novel probabilities by increasing the global network re-connections required for long range system integration.

2.3 Introduction to Causal Mathematical Logic applied to least action problems

The operations of CML when codifying least action as a mathematical construct have produced a similar type of invariant hierarchy and deep learning process we associate with the work of Hinton’s cortical column inspired deep belief networks. A simplified version of this process will be presented here, for more detail refer to (Pissanetzky, 2013a). This is to emphasize certain features of the theory that distinguish it from other theories of Physics or AGI and apply it to neuroscience. The theory emerges directly from the principle of causality that effects follow their causes. The principle says that all systems in nature, including biological systems and the brain are causal. It does not say that we need to actually discover all the causes before attempting an analysis of the system. Causal systems are described by a collection of ordered (cause, effect) pairs, known as a partial order, say ω, on a certain set of elements, say S. The set with the partial order is known as a causal set, hence:

$$\Sigma = (S, \omega) \qquad (1)$$

Where Σ is the causal set. We conceive of the brain as a giant causal set with say 90 billion elements, the neurons, and trillions of (cause, effect) pairs, the dendrites. If a dendrite connects from neuron a to neuron b, then the causal pair is (a,b). But this approach is also flexible so that casual pairs can be assigned to further findings such as logical functions in dendrites themselves.

An example of a causal set in mathematical notation:

$$S = \{a,b,c,d,e,f,g,h,i\} \tag{2}$$
$$\omega = \{a \prec b,\ a \prec c,\ b \prec d,\ c \prec e,\ c \prec g,\ d \prec f,\ e \prec h,\ g \prec i\} \tag{3}$$
$$\textstyle\sum = (s, \omega) \tag{4}$$

Where the symbol $\prec$ means “precedes”. For example $a \prec b$ means that a is one of the causes of b, where a and b are some observed phenomena, say the firing of neuron a is one of the causes of the firing of neuron b. The causal set is the mathematical model used in the causal theory. Because the principle of causality is universal, then the causal set is also universal. Every system in nature can be mathematically described in full detail by a causal set. Irrespective of the scale, irrespective of the substrate. If it is a system, then it is a causal set. Procedures for constructing causal set models of different systems are available. A set, say $\{a,b,c\}$, has no order. We can write $\{b,c,a\}$, or $\{c,b,a\}$, and it is still the same set. This is called symmetry. It is symmetry because the same set can be represented in more than one way. The symmetry is the collection of all different total orders that a given causal set can be represented.

Causal sets always posses some symmetry, a key point, as it means that causality and symmetry go together, where there is causality there is also symmetry. Hence, symmetry is present in all systems. But this is not the same as geometric symmetry used in neuroscience. Let us call it causal symmetry. The principle of symmetry is the second fundamental principle of nature. It says that any system that has symmetry also has an invariant quantity. An invariant quantity is something that is certain and is conserved, something that we can observe and understand and measure. The principle of symmetry and the fact that causality is found everywhere tells us that invariants also exist everywhere, and in very large numbers. This theory predicts the existence of millions of recognizable signals and structures in the brain. Much of the effort that follows is directed towards the analysis of these invariants and their quantitative calculation directly from the causal set. No other known theory of Physics can achieve this, which is why the causal theory is proposed as necessary for complex systems like the brain that work across many substrates.

The principle of least-action is the third fundamental principle of nature. It says that the dynamics of a conservative dynamical system converges towards an invariant behavior, sometimes called an attractor. This principle tells us exactly how our invariants are to be calculated: we need to minimize the action first. A system becomes conservative when the action in the system is minimized. In causal logic this says that the causal symmetry of a causal set – the collection of different total orders that represent the causal set S will converge to an invariant behavior when the causal action is minimized. For the definition of action let t be one of the total orders in the collection. Number the elements of S starting from 1 and in the order they appear in t. So now every element of S has a number, say $v(a)$ for element a. Next, consider the ordered (cause, effect) pairs in the partial order ω, say pair a $\prec$ b, and define the action of that pair as $v(b)$- $nu(a)$. This is a positive integer number. Finally, define the action in the causal set as the sum of the actions of all pairs, multiplied by 2:

$$F = 2\sum(v(b_i) - v(a_i)), \tag{5}$$

Where the sum extends to all pairs $(a_i \prec b_i)$. The quantity F is known as the *action functional,* and defines the action in the causal set under the given causal order t (recall that the numbering v is determined by t). Now we have a collection of legal total orders of set S, and for each total order t in the collection we can apply Eq. (5) and calculate the action for that order. So at this point we have the collection of total orders and each has a number, its action, and those numbers may or may not be the same. In a natural system such as the brain a legal ordering would be the structures with the highest strength in their connections. In today's neuroscience network strength and precedence of relations can occur by a variety of mechanisms and models which are beyond the scope of this paper. To find the least action, select from the collection of the total orders that have the least value of the action. The principle of least action simply says that this selected subset of least-action total orders has an invariant.

The final step is to calculate the invariants. The general procedure involves the use of group theory. For more details refer to (Pissanetzky, 2013a). Once the subset of least-action total orders has been obtained, the structures are easily calculated. Fig 2 shows an example of the structures that are obtained when these calculations are completed for the set of Eq. (1). Of course, not much can be said about their meaning for an example this small, but several examples published elsewhere do result in structures that are meaningful for us (Pissanetzky, 2010, 2013a, 2013b).

(note: For disambiguation in cross discipline use in this paper, mathematical symmetry and asymmetry are different from biological e.g. radial symmetry or bilateral asymmetry. See symmetry in glossary)

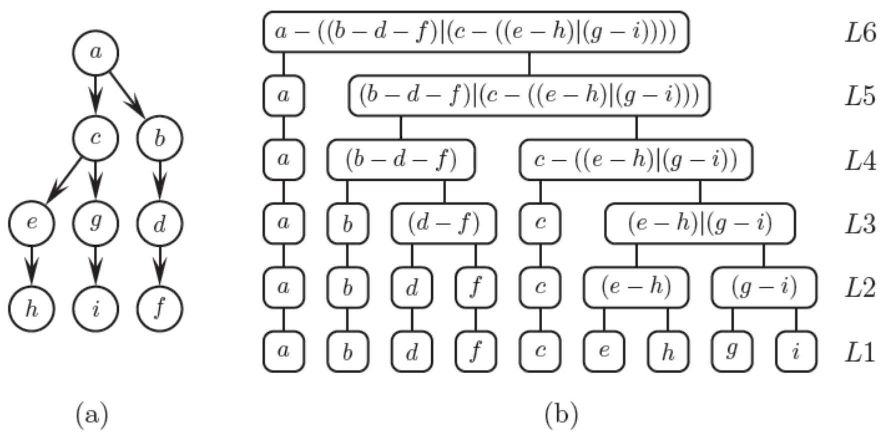

Figure 2: (a) The original partially ordered causet with the arrows showing legal orders *(in a brain represented by network strength).* (b) Shows the operation of the functional (natural processes) on each ordering cycle. i.e. From L6 to L1. Each cycle partitions the partial order *(while retaining the legal orders)* into a set of relations which have minimized all the possible combinations of the original causet into a hierarchy of relations. This appears similar to the simplified structure of the cortical column operations proposed by Hawkins, with the advantage that the operations itself are derived from codifying natural forces.

The definition of the symmetry is then a partition (or splitting) of the causet, named a "block system" that remains invariant under transformations or associations attempted by the ordering cycle. This ordering operating on the causet creates *(with the restrictions imposed by the invariants),* induces associations amongst the previous blocks of the causet into a new causet that then minimizes the action of the previous causet. To give an example of one cyclic operation of the functional operating on $\dot{\alpha}$, it induces the relations of $\dot{\alpha}$ into the next block system $\dot{\alpha}2$, where *f2* and *g2* are found not to be legal, and so can be discarded, and in doing so the $\dot{\alpha}2$ is a minimized set of $\dot{\alpha}$. This partial order is conserved and $\dot{\alpha}2$ contributes to the discovery of L2 in figure 2(b). For more depth on this operation refer to (Pissanetzky, 2013a).

$$\dot{\alpha} \quad (a \prec b)(a \prec c)(b \prec d)(c \prec e)(c \prec g)(d \prec f)(e \prec h)(g \prec i) \tag{6}$$
$$\dot{\alpha}2 \quad (a2 \prec b2)(a2 \prec e2)(b2 \prec c2)(c2 \prec f2)(e2 \prec g2)(c2 \prec d2)\ f2 \quad g2 \tag{7}$$

That is, these minimized actions, are an inferred set of conservations (attractors) derived from the ordering symmetry operation on the causet. The logic has then associated elements of the causet so they are bound together to form the levels of a nested hierarchy of invariant partitions. When the cycles reach L6 the system is minimized to *"exhaustion"* (Pissanetzky, 2013a) in regard to the domain of information it was operating on. In a real world example, conditions for the domain are often changing so the operations are ongoing and increasing in complexity. As this scheme is derived from causality, symmetry, least-action, and the laws of Thermodynamics it is based on a strong theoretical foundation that the organization of information is a result of the functional which is aiming for a representation of natural process.

Obviously we do no apply this process to everything in the natural world, but only those systems which have attributes that allowed a convergence of the natural principles more than other systems. For more detail on how the induced associations are derived refer to (Pissanetzky, 2013a). It is important to note, the operation of this system would generate too many possibilities to be simply represented here. The primary point is that the operations itself are a result of the information working on itself to minimize the number of possibilities, according to natural physical laws, and that the proposal is that the brain represents the development of these laws in its entire complex structure.

The generation of invariants here is similar to the work of Hawkins or Hinton (Hawkins, 2004, 2006; Hinton 2009). As we are deriving this from first principles we can direct the CML perspective to any aspect of the system, whether it be the genetic substrate or other aspects of its operation. Emphasis above on the functional here is in defining the causets as possessing blocks relations which are attractors. It is based on the most difficult requirement which is to build an informatics theory of detail extraction as a consequence of the natural laws mentioned. If codified this can then cover the entire thermodynamic range of least action and entropy. So this approach to causal sets, and causal set-based dynamics is by definition acyclic. So there are also methods for an implementation of causality to generate neural cycles such as oscillations which will be expounded upon in the following section.

3. Defining the limbic systems oscillations as primarily entropic

This section looks at the other operation mentioned, which is that entropic processes correspond to the set of coupled self oscillations which we know occur primarily within the limbic system of the brain as Event Related Synchronizations (ERS). The ERS in the brain will be proposed to increases entropy which helps globally "loosen" the system within the constraints (or rules) set by the invariants top down order. Why would we want entropy to play a prominent role in information processing? Disorder has negative connotations. The work of Gross-freer proposes that increasing disorder tunes a system to give rise to increased information options as combinatory possibility increases. A system which is completely invariant will enforce its previous states and lose flexibility by losing such combinatory options. An optimal system may exist in the space between order and disorder, but first we need to look at the extreme of entropy from the view of Causal logic and neuroscience to justify that neural oscillation is itself the biophysical information form of entropy.

A complex system tuned only to removing entropy by least action will by its own definition produce asymmetries of function, whether it be the block system of causets described or the action of neurons operating against each other by greedy growth principles and lateral inhibitions. The asymmetry arises as sets of least action attractors are involved in building structure during the process of replacing or suppressing other sets. It follows that entropy in such a system would reduce the asymmetry by distributing the systems energy more evenly. For example by heating a solid into a liquid, all movements have a more constant volume. To justify the oscillations in the brain as entropy, we already know that systems in a state of entropy resolve into self-oscillation in both quantum (Nachtergaele et al., 2012; Puttarprom et al., 2013 ; Campisi, 2008) and classical domains (Shapovalov, 2008; Jenkins, 2011). The self oscillation is natural consequence of internally directed geometrical symmetry resonating with no external rate acting on the system (Jenkins, 2011). The AGi proposal of gross-freer visualizes entropic forces into several animated scenarios, where the result of the entropy acting upon an object forces other objects within a closed space into a state of statistical equilibrium. The forced objects appear to have been moved toward the centre of the system space or moved equally around the space by an oscillation typical movement. However oscillation is not stated in their work and their examples have rough motion. An example below illustrates how entropic forcing can tend towards the smooth functions we find in oscillations.

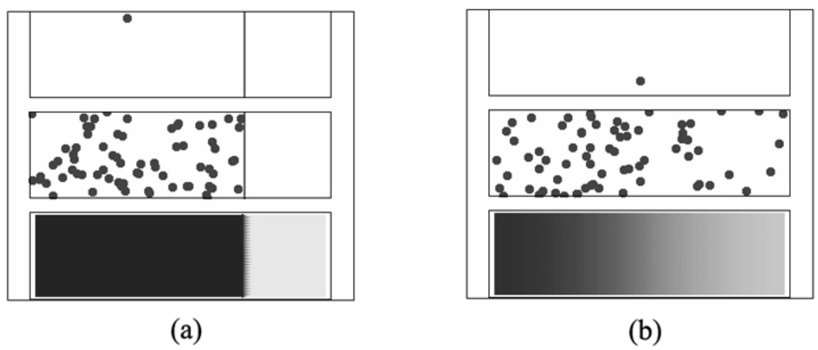

Figure 3. (a) Solution of gaseous molecules on the left side of a barrier, to the barrier opened (b). From top to bottom in the three panels the number of molecules are increased. The single molecule much like the Gross freer examples will move around but tend to settle around the middle of a geometrically symmetrical space (see original animation Sbyrnes321, 2013). As molecules are increased this movement tends towards smoothness.

For a more complex visualization example oscillators in space are coupled (figure 4). A mathematical generator has been applied to generate coupled phase oscillation on data to describe spatial-temporal coding in computational neuroscience (Orosz et al., 2007). As long as the inputs are quantized to the graphs cyclic format, the result of a change to the systems inputs is spatially unpredictable but in general there is a global coherence in terms of the tendency towards an even symmetry in space being retained in the manner of entropic forcing. The relevance of these points on symmetrical oscillations tending towards the centre of the system will be expanded further, as it applies to the brain. First we review what we understand about the self oscillatory nature of the brain

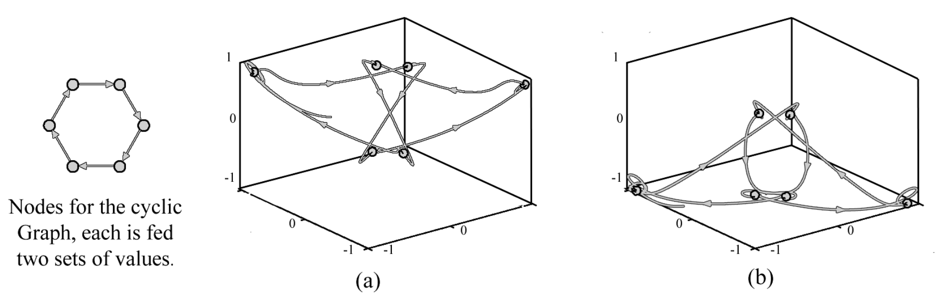

Figure 4. Image adapted from Orosz et al., 2007. An example of coupled oscillations maintaining coherence under altering conditions by cyclically permuting their phases. The cyclic graph shows the flow of information into the oscillator with two sets of values. The cyclic permutation gives rise to phase coupling for two oscillators each representing one of the two set of values.

How would symmetrical spaces evolve in the brain ? Such a question is beyond the scope of this paper but has been initially tackled (Lanzalaco and Zia 2009a). For now we concentrate on symmetrical signals like oscillation as these have been more clearly defined. The first life signals in the prenatal state are known to be oscillations (Isler et al., 2005; Uhlhaas et al., 2010). In neuroscience high level perceptual functions such as, consolidation, integration, consciousness and binding are tied to oscillation, and coupled oscillation (Buzsaki, 2006; Polich 2007; Engel et al., 1991; Crick and Koch, 2003). Brain simulation projects now commonly use *non-explicitly programmed* self oscillation as a proof that their system can produce some of the causality associated with brain function. To specify a single oscillatory phase in the brain at the biophysical level the thermodynamic *Hopf bifurcation* is commonly recruited in models (Hoppensteadt and Izhikevich, 1996). This is used because Hopf bifurcation is found as a natural chemical bistability in the entropy production between a steady state and an oscillatory state (Dutt, 1999).

$$z_i' = b_i z_i + d_i z_i |z_i|^2 + \sum_{j=1}^{n} c_{ij} z_j \, , \tag{8}$$

The canonical model for a Hopf bifurcation derived system of weak coupled oscillators. *z, b, d, c* are complex numbers, $i = 1,\ldots,n$ and the domain is the dynamical system of neural oscillators in weakly connected neural networks near equilibrium. The Andronov-Hopf bifurcation is one of many possible bifurcations for the dynamics of each neural oscillator. It is produced here for several reasons. It provides us a bridge from the physics of entropy to oscillation. Also Izhikevich oscillators are a basis commonly used in brain simulations and these will be expanded upon further in terms of dynamic casual modeling (DCM) for neural oscillation.

Referring to table 1. There is enough current data for all the known oscillations that a pattern emerges where the cortex is demarcated from the limbic system, and the limbic system can be proposed as a primarily continuous oscillation driven system. The lower frequencies from 0-30hz are primarily associated from the *thalamus, hippocampus, and basal ganglia*. Above 30hz the *Gamma* location is to the lower cortical areas. We also find “mirrors” of *Beta* and *alpha* in the cortical motor areas (*mu* wave). Both the Cortical Gamma and the Mu wave are sporadic, asymmetrical (across the hemispheres) and prone to decoherence. Cortical self oscillation is a sporadic sub-process of the suppressed lower cortical areas, rather than the pervading symmetric principle that never stops in the limbic system. Phase coupling for the cortical Gamma cycles is primarily driven by the limbic system and when we find cycles in the cortex they are prone to decoherence and asymmetry.

So in summary we can propose that oscillation is primarily a limbic system product but the cortex possesses it also. Any exception to this view is that the hippocampus can give rise to higher energy oscillations frequencies, the most well know is high gamma in epilepsy. The hippocampus (particularly the temporal end) is a neuron dense focal integration and feedback point for the cortex to the limbic system. The highest density of neurons are located there, and it is the area where most adult neurogenesis occurs. The Casual system here does provide a method to understand these cortico-limbic subsystems. Most are beyond the scope of a single paper, but we do tackle hippocampal complexity in sections 4.6 and 4.7.

3.1 Defining the oscillations in terms of emerging from the brains midline.

As we are stating that neural oscillation is a symmetrical collapse of energy into the centre of a system, this requires some justification in terms of neuroscience correlates. A large body of work exists for *Dynamic Causal Modeling* (DCM) applied successfully to brain imaging which is a novel basis for establishing the brains "intelligence signals" and their primary subcomponents (Friston, Harrison and Penny, 2003; Stephan et al., 2007; Moran et al., 2009; Pinotsis, Moran, and Friston, 2012). For review see (Daunizeau, David, and Stephan, 2011). In particular this has been applied to the brains *phase coupling* and *phase reset* mechanisms with some establishment of the location of the signals as deriving from the *central pacemaker* of the brain in the *septal areas.* (Penny et al., 2009) which are close to the *third ventricle* located in between the *thalamus*. This information allows us to now explore with more detail further studies that have mapped out the location for the oscillations to the limbic areas, and our current ideas on their role in brain function. This process is necessary if we are to understand the general relationship of entropic structure to function concepts which are described here.

The self oscillations in the mammalian brain primarily derive from the central limbic system areas such as alpha to the *third ventricle* area (Brazier, 1980; Karson et al., 1988). The *septum*, between the *lateral ventricles* is the pacemaker for *hippocampal theta* (Ujfalussy et al., 2007; Sotty et al., 2003; Lawrence et al., 2006; Brazier, 1980; Wang, 2002; Kocsis and Li, 2006). *Thalamic reticular nucleus,* also at the brains centre give rise to ≤1 Hz *delta* rhythms (Beierlein et al., 2000). Delta can be proposed as the baseline rhythm of the brain from which we know that these signals form the basis for binding integration via *coupled oscillation* (Polich 2007; Fiebelkorn 2013; Sauseng et al, 2008).

We have not included the higher frequency *Gamma rhythm* here, as we will expound this as being at the end off the ERS range when the neural oscillations tend towards geometrical (hemispherical) asymmetry and decoherence in the cortex (where Gamma is generated). We do know that Striatal Beta and Cortical Gamma couple in ERP (Sauseng et al, 2008; Fiebelkorn, 2013) and such Cortical to limbic coupling will be addressed in section 4.6 and 4.7. The main point is that Cortical cycles are less symmetric, less continuous and less global to the system. i.e. They are local to particular cortical areas. So these higher frequency oscillations are what would be expected if we look at EEG on the range of possessing less coherent properties as the frequency rises and their source is furthest from the centre of the brain (see table 1). The point being the manner in which the brains most continuous and symmetrical self oscillation signals emerge from the brains centre can be proposed to reflect the previously mentioned conditions in which natural self oscillation tends to occur as an internal bifurcation in the centre of a geometrical symmetrical closed system.

With the limbic system having a *neuron to white matter ratio* of 6:10 (Collins et al., 1998; Evans et al., 1996), the oscillations have more facility to travel globally across the axons to at least the lower cortical areas where connectivity with the limbic system is most dense. So in essence structurally the brain system can now be seen as comprised of the extremes of the Cortex which has the highest density of neurons giving rise to least action invariants on a surface sheet, and the white matter dominated limbic system with low density of neurons giving rise to phase coupled sources from the very centre of the brain (see figure 6). To propose this general structure model for the brain we have to consider the role of the limbic system as an equivocal but inverted convolution of the cortex which occurs somehow in developmental evolution. i.e. Evolution gives rise to a system which generates inverted structures that can cycle between action and entropy. It should be mentioned now there is a common misconception the human brain is a cortex evolved over an assortment of older limbic system parts with lower functions.

First of all the limbic system to cortex still has a volume ratio of about 1.6:1 (Collins et al., 1998; Evans et al., 1996). Most importantly the limbic system and cortex, have always evolved together, yet have conserved independent developmental trajectories that obey a mathematical scaling and time law across mammalian species (Clancy at al., 2001). The oscillation quality of the limbic system is also no minor player in the neural processing as it comprises a primary bulk of the systems energy (Lemm et al., 2009).

Table 1: EEG with their known anatomical origins, their participation in phase coupling and susceptibility to decoherence (ERD)

Frequency (Hz)	Origin	Phase locking	ERD
Delta 0-4	Thalamic reticular nucleus *(Beierlein et al., 2000)*	*(polich 2007; Fiebelkorn 2013; Sauseng et al, 2008).*	No data
Theta 4-8	Septal pacemaker *(Ujfalussy et al., 2007; Sotty et al., 2003; Lawrence et al., 2006; Brazier, 1980; Wang, 2002; Kocsis and Li, 2006)*	*(polich 2007; Fiebelkorn 2013)*	No data
Alpha 8–13	Third ventricle *(Brazier, 1980; Karson et al., 1988)*	*(Sauseng et al, 2008;Klimesch et al., 2004).*	No data
Beta 12-30	Subthalamic nucleus, globus pallidus *(Bevan et al.,2002; McCarthy 2011)*	*(Sauseng et al, 2008; Fiebelkorn, 2013).*	No data
Mu 8-30	Unkown maybe a cortical model of, alpha-beta i.e. mu-alpha and mu-beta *(Jones et al., 2009)*	No data	*(Haufe, 2010)*
Gamma 30-100 +	Lower cortical layers *(Bartos, Vida and Jonas, 2007)* Modulated*(Buzsáki and Wang, 2012)*	*(Sauseng et al, 2008; Fiebelkorn, 2013; Fründ, 2007)*	*(Polich, 2007, Edwards, 2007)*

3.2 What contribution do the oscillations play in intelligence?

To emphasis the limbic systems power, a bulk of our processing on any given stimulus will be found to have important correlates in the *thalamus, basal ganglia* and *hippocampus*, with well known computations for each giving rise to a powerful aggregate of processes. *Re-enforcement learning, autobiographical processing, episodic encoding and recall, sensory routing, system consolidation and pattern conflict resolution* are easily justified as being as important as the cortex. The binding qualities we derive from the limbic systems oscillations in perceptual processing are primarily the ERS which along with ERD compromise the other major part of the brains perceptual ERP intelligence signals. So ERP is composed of ERS and ERD (see figure 5). In ERP we find that limbic system modules phase lock together. i.e. *phase-locked delta* (thalamocortical) and theta (hippocampus) in the *P300* (Polich 2007; Fiebelkorn 2013). Alpha (thalamus) and theta in the *N1-P1 ERP signal* (Klimesch et al., 2004).

Latterly delta and beta (*striatum*) cross-frequency coupling occur (Sauseng et al, 2008) and are verified to have perceptual functions also (Fiebelkorn, 2013). Baars well known Global Workspace Theory (GWT) based on *thalamocortical* phase interaction has also been updated to accommodate these newly discovered phase locks (Baars, Franklin and Zo, 2013). Phase locked cortical gamma does occur (Fründ, 2007) but this is within the cortical ERD Desynchronization peaks. Oscillations as mentioned previously do occur in the cortex primarily as Gamma cycles, but these are asymmetrical and as sporadical as the spreading waves they appear in. They also become desynchronized quickly (Polich, 2007; Edwards, 2007) and are modulated by the slower rhythms like alpha (Buzsáki and Wang, 2012). This is in line with the previously mentioned concept that the cortical structure is primarily for action and not to generate the combinatory options and global binding integration which can occur from oscillatory computations. Some specific pattern features of Gamma will be expounded upon in section 4.6, 4.7 and conclusions on combinatrics in section 4.5.

3.3 Casual modeling approaches to entropic oscillation

To summarize the above, for ease of understanding we can propose that the oscillations have an analogy to music, where the lower frequencies from the more central areas of the brain provide the fundamentals to which higher frequencies that are increasingly prone to decoherence lock to, so phase locking would be driven from the lower frequencies with their source in the centre of the brain. The two primary brain structures of cortex and limbic system are not completely different. They do still possess aspects of each other, i.e. they both spike and oscillate, but in different ratios, which might reflect the almost inverted *grey to white matter ratios* previously mentioned for each structure. As mentioned this principle overall may derive from structural inversions which have origins in biophysical principles of development, but this is beyond the scope of this paper. In terms of the framework of (Pissanetkzky, 2013a), at the centre and surface of the brain respectively the extremes of self-oscillative entropic coupling and least action invariance appear most prominent.

With self-oscillation as a principle of entropy, then the limbic system of the brain would have to be defined as inducing physically symmetrical global entropy into the system (as ERS) and that its own structure has emerged from the basic principles of thermodynamics. Conceptually this is not difficult, as information enters the system in its raw form it has high entropy and as it makes it way through to the final cortical layers it is pruned into its highest order form. Coupled self-oscillations are proposed as a product of the entropic principle re-distributing information resources equally across as much of the entire system. This is in contrast to the cortical activity where the invariants are sparsely coded at the topmost layers furthest away from the reach of wide reaching global oscillations which might influence a reduction of the local ordering.

The current focus of CML has been on the hardest problem of how to find least action paths in amongst seemingly random data with equivalence to current deep learning systems based on the cortical system for generating invariants. A casual modeling system for the phase coupling is usually a sub-application in neuroscience. It is often as overlooked in computational modeling as the concept of entropy is to AGi. This is because these entropic facets of the system appear apposed to the generation of the clear type of functions that have previously been of higher scientific priority, such as understanding feature extraction in neuroscience and producing modeling functions in Ai.

To approach how we can model the limbic systems oscillatory nature, causal sets are finite and they have a finite number of states. A dynamical system evolves by changing states, but at some point it will run out of new states and return to one of the states it has already been in, causing a cycle where the same dynamics repeats indefinitely (if undisturbed) with a certain period. In general this oscillation is not harmonic, and there can be many different superposed periods, giving rise to complex waves and oscillations that can be observed in EEG. Specifically when it comes to the periodic aspect in a proposed entropy oscillation or sets of such oscillations in coupled forms, the causal set is both data and algorithm.

If we define the sets as a harmonic oscillator, causal sets can be periodic and represent any locking of periodic phases if necessary. Taking the initial/final states say I, F of a dynamical system, and any rules that represent trajectories from I to F, then when I = F, the causal set is said to be periodic and it lends itself to the emergence of harmonics. Because of Fourier theorem, there exists a unique one-one bijective correspondence between causal sets and their Fourier spectra. If the conditions emerge for a causal set to be a perfect harmonic, or a perfect second harmonic, and so on, the corresponding spectra will emerge and this will be generated as rules within the sets. The critical point is that Fourier spectra satisfy superposition, so any periodicity in causal sets will have to as well. However a harmonic oscillator theorem is yet to be proved in CML or neuroscience. It is only mentioned so we can describe the most extreme case of locked oscillations. For a less extreme example of a causal framework locking phases more suited to neuroscience, we look here at Dynamic Casual Modelling (DCM) where the sets for the oscillators are finite and its phase can be reset. Eq. (9) below (Penny et al., 2009) has already been derived from the phases we looked at in ERP by recruiting weakly coupled Izhikevich oscillators (8) .

$$\phi_{ki} = f_i + \sum_{j=1}^{Nr} \tau_{ij}(\phi_{ki} - \phi_{kj} + u_m c_{im} \cos \phi_i) \qquad (9)$$

ki and kj are phases in the ith and jth regions on the kth trial. f_i is intrinsic frequency of the $_i$th oscillator. This provides the rate of change of phase, equivalent to the instantaneous frequency. The term $u_m c_{im} \cos \phi_I$ has been added here as a means to model the phase locking in coupled ERD oscillations. When c_{im} is sufficiently large the coupled cycle is limited and resets as the dynamics are forced around limit cycles.

So we propose in light of the justification for such oscillators as entropic forces that casual modeling is also capable of specifying the entire range of processes from least action in CML Eq. (5) to entropic coupling causal modeling correlates in neuroscience Eq. (9). Further work can attempt to integrate the least action functional with the output of an entropic phase cycle for the purpose of attempting an integrated neuroscience inspired approach to the entire range of thermodynamic extremes of information. Primarily because CML has not been previously applied to phase locks and it would be required to be consistent with these.

It would be predicted that when this is attempted phase locking the stream of data entering and exiting the action functional in this manner can provide some of the self directed integration features sought after in computational neuroscience, and the trade-off will be we keep re-introducing entropy and reduce the systems action efficiency. Within the conceptual limits of the work done so far we now proceed with the primary proposal for this paper. An integration model derived from the application of the casual approach to the current neuroscience information. This has involved generating data from the action functional to make predictions about ERD in neural signals as well as predictions on the role of entropy with its correlates as phase cycles (ERS).

4. Putting order and disorder together. The CML framework predicts the brains primary structures are a complete thermodynamic "information engine"

To summarize where we are, the mammalian brains primary computations emerge from two systems, cortex and limbic system which it has been useful to analyze as separate systems. However such separation is purely for the purpose of studying the system, but in reality cannot be this clear as the limbic system attempts to reach into every part of the system and the cortex then tries to exert top down control over this process. This view is assisted by evidence that both

Cortex and limbic system have their own developmental timelines trajectory known to be separately defined by a systematic variation which works across mammalian species (Clancy et al., 2001). The point being that even in neurodevelopment one of these systems has some definable separation from the other.

Based on the justifications in the previous sections it is proposed that each structure (primarily) possess the extreme properties of least action (cortex) and entropy (limbic system) respectively increasing towards their most separate locations. i.e Least action at the uppermost cortical sheet layers, and highest entropy principles from the self oscillating midline limbic structures. The final conclusions in this section will put together the proposed "information engine" derived from this perspective more clearly, and propose this is a general principle for mammalian intelligence with a clear thermodynamic basis (figure 6). First we must justify some more of the existing general work carried out in understanding the entire input-output of the cortico-limbic brain system. Note we have missed out the cerebellum and brainstem in this approach for the reasons pointed out by Tononi (2008), in that the system is most emergent, developed and functional in the cortico-limbic domains.

On that note there already exists previous proposal for a dual process model for a core brain or AGi system to operate based on demarcating the system into the two extremes of functional specialization and integration (Tononi and Sporns, 2003; Tononi, 2008; Balduzzi and Tononi, 2008). The authors do frame some of their calculations on the concept of maximum entropy, but did not extend it as we are doing here. Here we apply such a dual process more completely to thermodynamics and the ERP signals of the brain. More specifically the functional specialization will be the equivalent of least action (ERD) and the integration to entropic coupling (ERS). The formulization for the system viewed in this approach (equation, 10) also relies upon the dual process definitions of Tononi and colleagues.

4.1 ERP as markers of intelligence processes

As reviewed previously, ERP are the primary signal we can detect that is associated with both information and the complex processing of information. Lie detection technology looks to ERP, because the ERP can tell us if precise information or sets of information are recognized and processed by the brain (Farwell and Smith, 2001). The timeline for the ERP signals begin primarily in the cortical ERD range of up to 300ms. These have a wide variety of perceptual intelligence processes (See section 2.2). In lower times below 300ms the signals represent single sensory modalities associated with cortical processes. Above 300ms it is less clear if the limbic system dominates. We know these later ERP's do seem to indicate less specialization and increased multi-modal global synchrony assisted integration. Known post P300 processes are general context updating, perception stabilization, maintenance in working memory, syntax processing and generation of expectancies that are associated with conscious awareness (Melloni et al., 2007). We can see from figure 5, that the primarily cortical ERD action is reducing after 300ms, so less cortical activity then is also consistent. That we have a problem in defining clear decision functions to later ERP might reflect the increased entropy in the signals.

4.2 Event related potentials; the brains "intelligence signals", as the integration of action (ERD) and entropy (ERS)

ERP are then proposed as the primary biophysical emergent "live intelligence signals" when we look at the brain in terms of its input and output operating over the systems internal resting or *stationary state* over time (see figure 5). The work of Papo (2013) proposes we should focus our models of cognition on what happens to the brain in terms of these signals and the physical principles they represent over time in thermodynamic principles. Authors in the DCM field also attempt a causal definition to specific brain locations in terms of suppression of energy in the cortical areas (Garrido, 2008) and free energy principles (Friston et al., 2010). We extend this further by integrating together the general conceptual framework of causality and principles of physical brain structure outlined so we can derive a general thermodynamic model that represents the complete generalities of physics and the full complexity of the system. Not so general that anything can become anything else.

We are very specifically looking at the two extremes of the primary biophysical signals, previously described in terms of least action (ERD) and entropy (ERS). Note when we discuss the term "energy" in the following text the "energy" is the form of sets of complex information or processes acting upon them. i.e. For the reasons mentioned previously the ERD and ERS are both complex computational processes, yet still emerge clearly enough to demarcate overall systems energy at the same time (see figure 5).

ERP are composed primarily of the two signals discussed previously that have their origins in the cortex and limbic system (ERD, and ERS respectively). For the definition in a thermodynamic timeframe, we now look at how ERD and ERS have been found to operate on a continuum whereby both are activated following input stimulus to the systems resting state (lemm et al., 2009). After stimulus to the resting state, ERD and ERS occur in the following sequence with a midline integration of both ERD and ERS occurring at 300ms (figure 5).

1. ERD (Event Related Desynchronization) comprised primarily of evoked cortical activity. Non linear - cortical spreading waves initially increases up to about 300ms, then falls off suppressed by ERS to restart at about 750ms.

2. ERS (Event Related Synchronization) comprised primarily of several phase coupled linear limbic system oscillations, starts at around 300ms, then falls of suppressed by ERS at about 750ms.

3. The range of the brains perceptual ERP's (P100-P600) which are comprised of both stationary activity and varying combination of the evoked ERD and ERS signals, see timeline in figure 5.

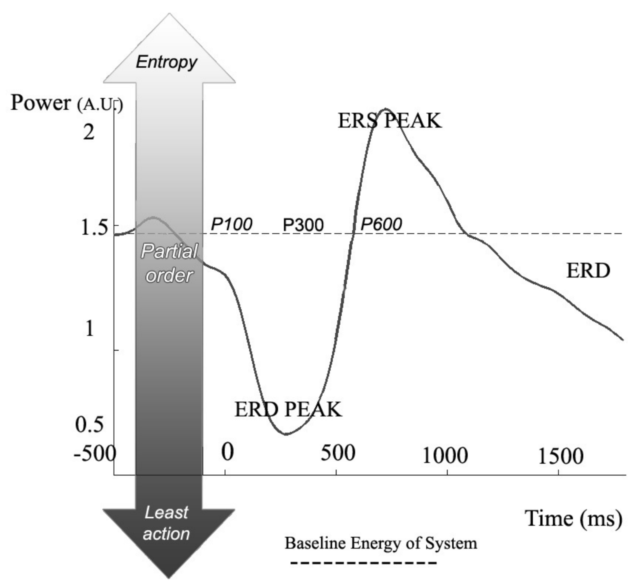

Figure 5. Diagram above modified from (lemm et al., 2009) where known ERP (P number represents milliseconds) signals are added as well as our interpretation of the data in terms of the entire systems energy as least action and entropy. The energy of the system at the midline represents the brains resting state before a stimulus. Which is initially desynchronized (ERD) by cortical activity to a more efficient and lower energy state by the lateral inhibition of local cortical invariants. The suppression of baseline synchrony gives rise to a rebound in global synchrony from the limbic system (ERS), increasing the entire systems entropy before falling back to the resting balance between order and entropy (partial order).

This fresh integration of ERD/ERS into an elegantly cohesive timeline after stimulus to the systems baseline oscillations could be a full thermodynamic operation of the brains input and output, where the energy is now minimized after stimulus. The systems initial stationary state is in a partial transition between lowered energy processes (least action) and the higher energy of entropic self-oscillations. After stimulus, if processing is required the range of ERP's associated with higher perception (P100-P600) occur.

There is a natural connection between action and entropy. We know that entropy is connected with uncertainty. Action, in turn, is connected with the flow of energy responsible for the dynamics of the system. The two quantities are intimately related. When the energy is high we say that the system is "hot". There is a great deal of energy moving around and shaking the system and causing it to react in many unpredictable and uncertain ways. This situation happens when "hot" and hence highly entropic information obtained by our senses first arrives in the brain. It consists of bits and pieces, whatever the eyes and ears and touch can capture, all scrambled without much organization or meaning. The collection of total orders includes all kinds of behaviors. But then, when we select the least-action total orders, we are in fact causing the excess energy and entropy in the brain to flow back to the environment. The system "quiets down" by losing its energy and entropy, and hence its uncertainty. It reaches the quietest of its states, known as a conservative or resting state, with action at minima.

4.3 When is the critical phase transition between least action (ERD) and entropic oscillation (ERS) ?

Expounding the DCM work on P300 and system energy (Garrido, 2008) it is proposed here the P300 represents the critical phase transition point between cortex (least action) and limbic system (entropic). The limbic / cortical integration cycle, here is proposed as sensory input leads to cortical propagation, or wave expansion (Xu et al., 2007), followed by desynchronization or decoherence of the baseline partially ordered state. The baseline of partial order is proposed as the most prominent aspect of the brains energy to which it returns to, as the highest density of connections exist in integration areas between the previously mentioned extremes of the cortex (surface) and limbic system (centre). i.e In the lower cortical layers, the *cingulate*, *basal ganglia*, and *hippocampus.*

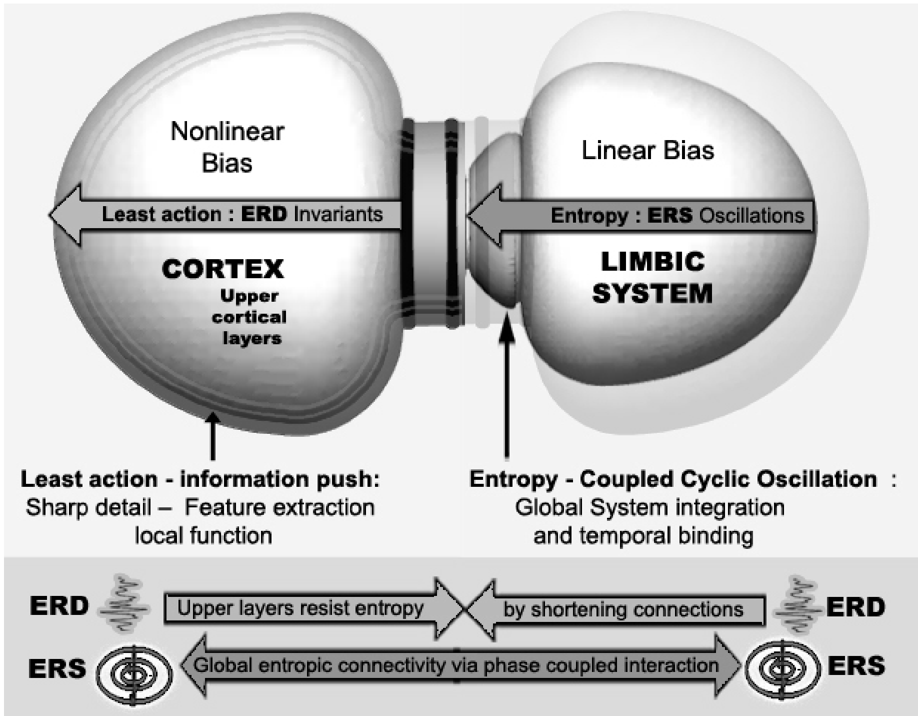

Figure 6. A structural cortico-limbic "information engine" model in terms of the thermodynamic principles derived from CML, using the ERD/ERS cycle translated from figure 5 with the previous justification to specific brain structures. The concept is that of a cycle ready to push or pull on baseline system states. The cortex surface which reacts to inputs minimizes the systems energy by desynchronization as it enforces invariants by the least action principle which are the systems rules. The limbic system generates global coherence into the information by entropic oscillations which integrate the system into linear time as coupled phases operating in the partial ordered system. Entropy structure are symmetrical from the brain centre (thalamus, septal areas), Ordered structures are asymmetrical surface sheets split across corpus callosum (functional asymmetry). *Please note that each of the primary structures "tends towards" the extremes, the bulk of the brain in between the central midline and cortical surface sheet are transition (or partial ordered) states between least action and entropy.*

To recap the importance of ERP signals, the P300 generation is entirely cortical, covering much of its area and involved in a wide range of perceptual selection processes such as object recognition and onset of conscious access (Polich, 2007). Maximal efficiency for the entire set of relevant cortical categories has to be acquired by 300ms, before the suppressed oscillations from the limbic system restart cross-frequency oscillation coupling. The coupling proposed to give rise to the previously mentioned multi-modal integration functions, that de-localize spreading cortical activity. Interestingly as the systems energy becomes maximally entropic in terms of self oscillation after 600ms (Figure 5) we are unable to pick out any clearly defined processes in response to a stimulus. In the absence of processing activity it can only be guessed that the increase in global synchrony is giving rise to a globally cyclic "system reset" of fresh combinatric options with a resting phase which is maximal at 750ms, before dropping the system back to a baseline state between order and disorder. Brandt (1997) proposed from experimental data that ERS system reset could be required in a non linear system (like the cortex) in response to a perturbation such as viewing a flashing light. In systems terms these twin peaks of ERD – ERS do appear conceptually similar to the chaos/regularity transitions which occur when harmonically oscillating linear systems are exposed to non linear amplifications (Bolotin, 1995).

From this perspective of using CML principles as a guide to the brain, ERP then represents the integration of these two extremes of ERD and ERS in the key emergent biophysical signals of mammalian intelligence. To summarize the lower ERP's below P300 represent more cortical process, but after 600ms there is too much phase coupled entropy to clearly define any process in the system. The first thoughts from viewing the system in this manner are that revealing the biophysical correlates of such entropic vs action principles integrated together in high level brain function bridges the evolutionary gap between simple physics to complex physical information sets. That is that the physical principles have remained consistently conserved to become ever clearer throughout evolution and complexity in brain structure and function. If this view is correct it raises several issues. Is this the optimal "blueprint" of a natural information engine ? If it is it generates an AGi problem. Because the engines operation requires a particular physical structure to operate an AGi may have to be built with such structures. All the math for example that we have used here, and referred to elsewhere, is still not a physical construct. It is a product which runs in our own information engine. We can use mathematics to understand and describe the plan for such a system, but at some stage the system will have to be one that is producing such physically thermodynamic information operations.

Simple analogies have their problems, but they do however make things easier to understand as long as we understand their limits, so on the basis of caution we proceed with comparing the approach here to a more familiar engine concept. Or more specifically a variable piston, compression variant. If we entertain the topological distribution for entropy phase cycles and cortical columns as hierarchical pistons with the most action at the surface, it is not hard to see the analogy to a variable piston engine. Except that there are millions of pistons (mini-columns) in a sparse coding hierarchy dominated by macro-columns and their known functional specifications in wider areas. So within each piston a lot of information can be pushed around. An engine also requires a balancing shaft at the centre which distributes the energy load by synchronizing all these pistons and so this is then locking phase cycles as in ERS.

However the problem is far more complex. For example if the axis for the engine runs along the temporal poles to the hippocampus, and the split hemispheres say, represents how a flat or V engine gains power by spreading its piston load across poles, we then do not have a clear analogy for the complexity of hippocampus layout to any known regular engine. Perhaps the hippocampus has both gearing and engine integrated, which we can tackle later as a specific implementation of CML. However taking into account the topological complexity of other known brain topologies mentioned in table 2 (in section 4.6) the analogy clearly here has its limits as information requires coding which is not a problem for such simple energy systems.

Currently there are both studies and real world systems which bolster the view for ideal physical topologies which reflect aspects of the proposal here. For example stacked linear matrix systems for parallel computing (Sardar, Tewari and Babu, 2011) have some analogy to the regularity in axon bundles (Weeden et al., 2012). Toroidal topologies (Jin et al., 2010) with 3d similarity to the cingulate bundles have a scale free optimal aspect for both information integration and isolation. More recent computational analysis of the ideal geometrical topology for understanding neural synchronization proposes that an ideal system (in simple form) will self organize a greater degree of connectivity in the centre of the system and more importantly this structural identity is retained under transformation when the system complexity is increased to resemble finer aspects of a more conventional neural network (Mi et al., 2013). Overall though we are still far from designing or identifying a particular set of universal topological principles which produces the complex structure of the brain and can apply to other generally optimal information systems. There may be many such configurations yet undiscovered, and so this is stated as a limitation of this proposed general model.

4.4 Definition of the system as an integrated summation of functions.

We now finalize by formalizing the above in general form then check if the predictions so far are verified or not by the data from the output of the CML functional. In figure 6, the limbic systems ERS spread out symmetric oscillations in reaction to the cortex pull on information, which had moved the system into the set of asymmetrical attractor states we equate with cortical functional asymmetry across the temporal lobes (see figure 6). *(note these are the neuroscience definitions of symmetry/asymmetry).* When information does not require to be acted on the system returns to a baseline state, which now possesses a refreshed partial order and minimized action in the system. The effect of the minimization is maximal compression as sparse coding of invariants in the upper layers. The engines cycle at its least action extreme is then an information compressor that operates via lateral inhibition which can operate across the hemispheres. This coding system is still as unknown as the current understanding of functional asymmetry, although we shall touch on some current ideas for coding aspects in section 4.6 and 4.7. The ERS part of the cycle operates to allow a global refresh for integration of information across as much of the system as it can reach. Details for viewing the brain in terms of integration and functional specialization have already been started to be defined by Tononi and colleagues. Here we will describe the system more generally in thermodynamic information terms pertaining to the ERP components.

$$\mathrm{dU}\,\gamma = \left(P\left(\prod_j ERDj \right) \right) + \left(p\left\langle \sum_i^o ERSi \right\rangle \right) - Rs \tag{10}$$

A change $\mathrm{dU}\,\gamma$ in the total information energy product of the system is the sum of changes in terms of the global entropic increase in energy and the decrease in energy by minimization of action. In information terms energy is defined as the probability distribution P of the information in regard to its domain. As the sets for the domain are too complex to define with current knowledge, here we resort to using the definitions of Tononi (2008) where there is a probability distribution derived from the product of independent information (here defined by ERD) and the probability distribution of the averaged sum of integrated information (here defined by ERS).

Integrated information is the set of extensive information distributed across the system. Parameters, $\{a_i\}$ are the set consisting of the number of intensive ERD processes, defined by their independence, and reflect that the least action principles of the grey matter are independent of system size (Zhang and Sejnowski, 2000). Set, $\{A_J\}$, are the set consisting of the number of extensive ERD processes and reflect that the entropic principles of the white matter are dependent of system size and scale to fill the volume of the system (Zhang and Sejnowski, 2000). Because the set of all global cycles is limited as in Eq. (9) o is simple representation of the limit value for the phase locking of the oscillations. i.e. this was proposed as $u_m c_{im} \cos\phi_I$ by the DCM model in Eq. (9). $Rs = (\alpha, \beta, \Delta, \mu, \partial)$ is the initial resting state, the combination set of any given continuous synchronous resting states *alpha, beta, delta, mu, theta* (the systems previous state returned to equilibrium, see figure 5). The range of continuous oscillations is included because a typical system is not in the ideal alpha resting state in the ERP experiments of (Lemm at al., 2009), and there may be many types of resting states consisting of various summations of these oscillations yet to be clarified.

To summarize, a solution has been proposed by a physical information theory which explains how entropy and least action unify spreading waves and oscillation in terms of partially ordered sets, and to propose that event related potentials occur as partially ordered states, which under the action of the "information engine" proposed give rise to another set of partially ordered states after ERD has minimized the systems action. In terms of CML, Limbic ERS is the equivalent of the DCM limit cycles operating on a causet. The cycles are present and (see section 3.3) have enough global entropic reach in the system to generate new global associations to be induced amongst the previous blocks of the causet. The outcome of the process is still a partial order where ERS is the system refresh that generates a new causet with more predictive detail. A domain specific probability distribution is then ready to perform the equivalent of cortical ERD on current information if required. The function of the ERD is to minimize the action of the previous causet and increase the detailed relevance of its feature extraction functions.

4.5 Application of CML to predicting ERD/ERS cycles

After the systemization occurred to build the integrated model above, a data set was derived from the functional operating on the combinations of a set with 12 elements and ordered pairs. The plot shows it reaches maximum entropy (the combinatorial peak) in what appears like a Gaussian distribution with a right skew towards least action. The combinatorial peak occurs when there are the least rules to favour configuration of one order over another. The neuroscience prediction was that as the system increases its complexity least action takes place as the equivalent of the ERD cortical processes, outlined in section 2. These high level invariants requires sub processes that partition the data. We know already that the action functional partitions the data into such sub-process. i.e. each differential equation when working on the Euler problem (Pissanetzky, 2013b). The other prediction is that the ERS entropy as outlined in section 3 would be equivalent to the entropic product of CML. However, the data in figure 7, did then not fit as predicted, in fact figure 5, which proposed itself as a general model for ERD/ERS seemed to show that the entropy ERS is occurring after the least action processes, which was not consistent with this hypothesis.

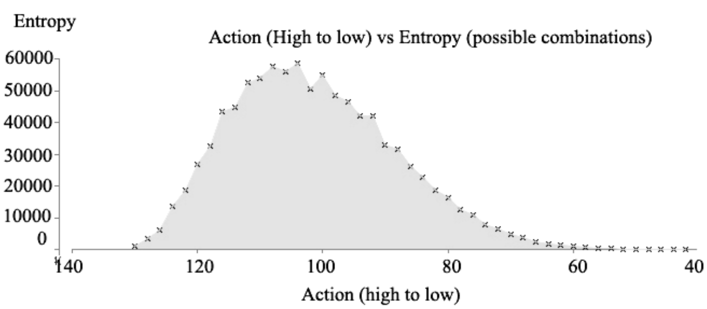

Figure 7. The data was derived using minimization of action by the action functional. Action vs entropy is correlated to a normalized power law with the entropy distribution pushed out of the least action range towards most action as a right skew.

Not even inverting the process of the action functional could explain the disparity. On reviewing (lemm at al., 2009) however, it seems their general framework did not include the oscillations primarily associated with high level perception in the generation of the P300. Specifically hippocampal theta and delta (polich, 2007). Reviewing older data we did find the theta and delta (ERS) appear to be present before the time of the ERD dip contradicting the general model proposed by Lemm and colleagues, (Başar-Eroglu et al., 1992; Yordanova and Kolev, 1997). This is because in the Lemm model, it is alpha which is primarily suppressed (Aftanas et al., 2001). This is not surprising as Alpha ERS has sensory input peaks which occur earlier briefly in the pre-processing to shorter ERP such as *N1-P1* (Polich, 2007). The work of (Kawamata et al.,

2007) now illustrates more clearly the theta ERP and ERD peaks in regard to the P300, and so the ERS precedes action. These are now as CML has predicted (see figure 8).

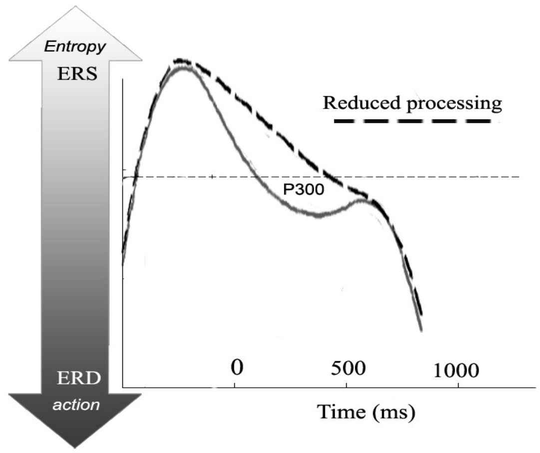

Figure 8 –In the diagram above (Kawamata et al., 2007) the hippocampal theta oscillation is re-drawn. The the readings taking during decision making under the condition of the video game tetris from the central cortical areas. The dashed lines indicate reduced oddball processing (less decisions over conflicting information). ERS justified previously to be defined as entropy, peaks before the onset of the decisions, and ERD (justified previously as action) drops more sharply (so less action) when increased decisions are required. i.e. The global coherence of the system becomes quiet.

Further data in (Kawamata et al., 2007) suggest that the theta ERS/ERD restarts in a cycle (like figure 5) when there is less pressure for decisions. Its seems to suggest both that entropy is continuously being re-introduced into the system, which may be to increase the number of combinatric options as described by gross-freer, and so cycles of entropy are a neural principle. The function of the entropy could be to globally re-introduce the system to refreshed options, or the various integration aspects mentioned previously that occur when ERS onset occurs. As we can see from figure 7 entropy is always pushed out the reach of the least action, because the invariants have only a single direction and so the combinatric direction for phase coupling cannot exist there. This is also proposed to be similar to the more complex sets of operation in the brain. i.e. why ERS (entropy oscillation) is suppressed with latency before decisions from ERD (action) in figure 8. From this view the brain is both a cost minimizing system and an entropically binding system. It increases cost to enable global integration and re-generate variation as combinatory options.

As the brain system is highly cyclic, a future prediction for CML when adapted more rigorously for neuroscience is that the bias for the action functional to minimize action cost as the priority is de-regulated by inverting the operations of the action functional by the addition of a limit cycle phase oscillator which binds together coupled phases. Perhaps a simplified version of that used in the DCM Eq.9. Although it was mentioned in section 3 CML could self-discover principles of phase cycling, the theoretical question has not been solved as to whether those cycles would take over control of the action functional, invert its function then release it within such a limit cycle without then submitting the entire action functional to mathematical decoherence. For now we have set out the starting principles and such problems can be tackled in later projects.

4.6 Dealing with more complex implementations in brain structures

To summarize, the approach given here is a general model which seeks to establish its case by consistency with the largest sets of signals and provide a general approach to a structural information engine by location of the generalized sources for entropy (ERS) and action (ERD) at extremes in the centre and surface of the brain.

Because the mammalian brain system is complex just this simplification alone takes a paper. The model still has to be consistent with more specific complex implementations where both cortical and subcortical areas integrate cohesively at various scales or it is not a model. The First problem here is that neuroscience is still working towards finalizing understanding (understanding as in general theory) of the brains complex high level sub-systems (sub-system as in sub-ordinate to an entire set of system principles). Some basic descriptions for the medium scale have emerged to work with (see table 2).

Table 2. Outlining some prominent brain modules and their functions.

System definition	Primary function
Hippocampus - Cortical	Encoding, recall
Striatum – Cortical	Action selection
Cingulate	Information resolution
Thalamocortical loop	Input filtering
Cortical columns	Feature extraction and attention

Each of the parts is themselves complex to describe, such that a simplification with a biophysical based principle extraction scheme could not be brief, at least not in the initial approach to justify what would be hoped to be a simplified description. Justification is required for prioritizing. Why are cingulate processes more important to describe than why mu waves appears to be a “mirror” of the beta and alpha wave (Jones et al., 2009). Or why are hippocampal ripples or precession more important to describe than the alpha coherence which arises from the thalamus ? A partial justification for prioritizing the hippocampus is that is has complexity at multiple scales. Highest neuron density at the temporal lobes (Thompson et al., 2003), highest frequency and most complex oscillations, (Buzsáki and Silva 2012; Chance, 2012), highest neurogenesis (Bear et al., 2006), increased wiring complexity, morphology and cellular signal complexity (Bear et al., 2006). And of course the more dramatic deficit to memory, consciousness and encoding when disrupted (Bear et al., 2006). This is still not a deep theory reason to prioritize it, but for now there is so much going on in the hippocampus as a key hub of the brain that aspects of its signal complexity should at least be covered as a special case and from there determine if its complexity tells us more about the proposed engines operation.

We have previously considered the level of ERP as marker of intelligence processes. i.e. for example oddball resolution of conflicts at P300. Here information coming into the system has to be processed against information within the system at the same time. Decisions have to be made whether to allocate attention (resources) to incoming data for storage in (Short Term Memory) STM and then any required buffering to Long term memory (LTM). At the same time pattern recall is required. So the system has to associate these two primary information streams. It appears like the hippocampus is the region to juggle both the set of encoding and retrieval processes without a conflict of overlaying patterns (Koene, 2001).

Further to this recent work by Buskazi and Peyrache (2013) proposes the hippocampus as the key hub for many outstanding signal mysteries, such as sharp wave ripples (SPW-Rs). These are proposed in terms of a coupling to decoupling model from septal to temporal ends of the hippocampus. Previous septal – temporal models also propose to resolve how long term time and information chunking operates along this axis (Lytton and Lipton, 1999). We will conceive of this decoupling in terms of a "gearing mechanism" for the information engine proposed here. First of all we need to address that the hippocampus can integrate both pattern completion and separation processes (Edmund, 2013). So we have defined the pattern processes for CML based on these extremes.

1. Complete sync - entropy oscillations (ERS). The system has regular phase locked sequential loops for iteration and completes its pattern. This process is most marked with Alpha-Beta phase locked oscillation for the striatum (Sauseng et al, 2008; Fiebelkorn, 2013).

2. Complete decoupling of sync – least action (ERD). The cortex has sparse compression which gives rise to feature extraction. Decoherence of cortical gamma is the most prominent feature of ERD (Polich, 2007; Edwards, 2007).

3. Integration of 1 and 2 in the hippocampus. Both locking and decoupling of theta and gamma respectively (Polich 2007; Fiebelkorn 2013; Buzsáki and Peyrache 2013; Jensen and Lisman, 1996b). i.e. The hippocampus can both complete and separate patterns simultaneously.

4.7 A "gearing" model for the information engine ?

Referring to figure 5, we can see that the proposed entropy function of oscillations demands a clear energy input, and we know that the lower frequency oscillations (delta to alpha) have well known long range network reach which allows them to remain coherent through much of the system. As the cortical system only suppresses energy in reaction to relevant stimulus (ERD) the systems energy can be distributed in a more internally equalized manner (ERS) when ERD is not present. As the frequencies in ERS rises coherence drops (table 1) and ERS decouples in a transition to the lower energy states of ERD. Buzsaki proposes that the neocortex and hippocampus is a hub where ERS cross frequency coupling can break down and the decoupling indication signal is the extremely high frequency SPW-Rs (Buzsáki and Peyrache, 2013). So as highlighted in table 1, as we move towards more cortical (temporal) processes the phase locking is disrupted as we are moving to the brains surface. Note that there would also be predicted to be gear decoupling in the action selection cycle of the striatal-cortical loop but for the reasons stated we are focusing on the hippocampus.

We know the role of the hippocampus is key in high level perception (Polich, 2007). The proposal here is that the hippocampus has a gearing mechanism, except the number of gears is as high as the number of phase timings which can integrate and decouple. Such a number has been defined for STM as correlated to the theta - gamma interaction intitally as 7 +/- 2 (Jensen and Lisman, 1996a) and more latterly as 2 items per hemisphere (Buschman et al., 2011). To bolster the gearing concept as present in critical transition areas between the cortex and limbic system, hippocampal place cells are also proposed as speed-controlled oscillators (Geisler et al., 2007). That is their rate increases with coding requirements. As we outlined previously higher oscillations give rise to ERD and decoherence (decoupling of phase lock). So how does ERD and ERS translate to encoding and recall ? Both encoding and recall within the hippocampus queue up numerous buffers and molecularly intricate sub systems (Koene, 2001). Specifically multiplexing between gamma and theta (Jensen et al., 1996) has been used to to resolve overlay conflicts for short term memory.

The hippocampus ability to deal with contradictory processes is proposed to outline the implementation of a transition state between entropy and action with cortical gamma phase (ERD) for action. i.e. Action primarily encodes information. The Gamma phase appears to be more involved in truncating, compressing and encoding information into varying discrete chunks (Koene, 2001). By contrast the origins for theta oscillation (ERS) are at the septal end of the hippocampus (see table 1) where Lytton and Lipton (1999) propose that recall processing is more prominent. Jensen and Lisman, (1996b) also favor place recall as a theta dominated process and place encoding as a Gamma orientated process. To complicate matters slightly encoding – retrieval bias is also proposed as having asymmetry across the entire hemispheres (Habib et al., 2003). This model called "Hemispheric asymmetries of memory" (HERA) does have numerous inconsistencies (Owen, 2003) and also conflicts with lytton and Lipton (1999). However we will proceed on the presumption these problems might be resolved in future because to also include such larger general encode-retrieval models might prove useful for a CML approach, and it seems the problem is these models did not address the complexities for specific time locations in the memory buffer que (i.e. Long term memory, early Long term potentiation, etc).

The well known Inter-theta precession found in place firing (Chance, 2012), but also with sub correlates in the ventral striatum (Malhotra et al., 2012), can conceptually provide a scheme to resolve the conflict that can arise between simultaneous encoding/decoding. Multiple sites in the hippocampus produce inverted cycles of the same phase, with one cycle dealing with the encoding and one with the inputs from the recall (Koene, 2011). From the model proposed here such precession is still an inter-frequency phase lock, because the place length remains linear (Jensen and lisman, 1996b). To be self consistent with CML all such phase locks have to be indicated as entropic in nature as outlined in this paper. Also figure 7 in results shows how CML was found to predict that combinatory options increase with entropy and that this graph has some consistency with increases in oscillation locking (see figure 8). To be more function specific for the hippocampus phase lock facilitates the interleaving of multiple processes such as encode-decode which would conflict otherwise (Koene, 2001).

At some point we may have hardware options to select the most optimal substrate independent platform for differing biophysical aspects of neural simulation/emulation for these neuro-computational aspects to be scaled with similar brain like efficiencies. So it is worth mentioning interleaving is a term derived from digital computing where as convolution is an analogue option. Current tools are arriving for us to analyze brain networks to unravel which (or both) of these aspects are more prominent in particular circuits (Mochizuk and Shinomoto, 2013). In general we equate interleaving here with combinatorial options, but mention that both interleaving (Burnett and Coffman, Jr., 1973) and the process of convolution have combinatory basis in previous computer science (Askey, 1975).

In summary we have attempted to determine consistency with some prominent aspects of the hippocampus but cannot tackle all neuroscience specific implementations of CML in this paper. Some recent works have attempted to integrate the striatum with hippocampus (Yin and Troger, 2011). CML would predict some type of signal decoupling for action selection which allows the cortex to select which striatal loop option to pick and also some coherence for action selection mechanism to couple with the proposed hippocampal gearing is a predicted possibility based on recent findings (Yin and Troger, 2011). In general the primary principle is we propose that the gearing operates when we find oscillation decoupling, and the mechanism for this decoupling is a dynamically stepped increase in oscillation rate, with higher rates eventually leading to loss of coherent synchronization (table 1).

Conclusions and Outlook

CML appears promising in that it helps to make sense of the brains morphology in a manner that may clarify its highest level functions as a highly evolved and conserved for "push/pull thermodynamic information engine". Our previous position led us to conclude the brains morphology revealed no principles except ad hoc growth. With this model it is proposed these structures are a physical expression of the fundamentals laws of causality and thermodynamics in terms of least action, entropy and partial order.

The model itself is not as controversial at it seems, because it does not require rethinking the function of morphology to work. The data for the ERD/ERS cycle in the generation of the ERP was already present, as was the data for the locations and mechanisms in the two primary brain structures which produce the ERD and ERS extremes in the information cycle. This all stands on its own, without a controversial model of morphology, but the morphology can help with the neurodevelopment, internal structure and evolutionary side of the system. Without a general physical theory of intelligence and information there had been no previous method to bring all this high level information and the associated systems together into one cohesive framework. The system here appears to work also for more specific integrative parts of the internal system (hippocampus, thalamocortical loop, cingulate, basal ganglia). The models for these are intricate and partly incomplete so would take another paper and like the body of neuroscience so far, would be yet more parts that are hard to understand without a complete general description.

In terms of applications one of the key questions in brain simulation, replication and whole brain emulation (WBE) in particular are what is required in the brain to retain a functional copy and what can be discarded or farmed out to a different type of substrate. The framework presented here is used to approach some general simulation/emulation issues regarding the big picture. For WBE the biggest picture concern is will a WBE system produce a "live intelligence" capable of accessing previous information and processing it as the brain previously did. CML tries to tackle the system generally and informs us that when we make decisions on what to retain for the WBE signals understanding we may need to consider general principles of the system to simplify ground up details. This route into the system treads a different path to the regular detailed route. i.e. The dendrites and synapses had a partial role when put in context with glial cells, developmental principles, matter ratios and their principles, evolutionary frameworks, macroscopic brain structure and highly integrated aspects of brain signals. Of course this does not mean we need to acquire all this information for a final emulation/simulation just that its important to be active in as many aspects of neuroscience as possible till we understand what is most relevant about the entire systems operation.

A general model has to explain every part of the system or it is not general model. It has been outlined how cortical invariants seem consistent with least action and the limbic systems self oscillation for entropy and that partial order is the transition state between these extremes. These extremes appear to be tied to locations in the brain which accords with deeper physical principles and the signal predictions so far have been verified in a general manner by the CML algorithm. Currently brain simulation struggles to understand the physical principles which give rise to the basic components in signals of intelligence, never mind the entire picture of the integration of such signals. With high level intelligence processes represented in the ERP as biophysically live input - output processes, the test of brain simulations will naturally move *(without a CML model)* from trying to elicit the current basic signals so the range of ERP's emerge without being explicitly programmed. We propose here that general theories which provide an explanatory model for ERP well in advance of simulation type projects are helping us move towards a more complete general view for the brain's understanding.

Limitations

CML is a new concept and its AGi verification is still underway. The question remains whether it has been so general that any perspective of the natural world could have been shoe-horned into causality and so is the basis circular ? In any case even if so, the casual schemes are still helping researchers to format complex data into a manageable means. This aids putting together known first principles schemes like least action and entropy into manageable sets and physical theories. We bear in mind that there have been many frameworks which attempt to define the general process of the brain in an over-confident manner, so we restrict this to a tentative thermodynamic principle for the cortico-limbic process in terms of "information energy", which will hopefully undergo falsifications as we uncover complete principles for ERP.

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Glossary of terms: Words in italics refer to other glossary terms

Alpha: The 8-13 hz EEG oscillations primarily associated with the thalamus activity

Alpha-beta. The range of oscillations in the alpha to beta range, 8-30 hz. Used to assist with the classification of *Mu* (8-30hz) in terms of mu-alpha (8-13hz) and mu-beta (12-30hz).

AMPA/KAINATE: One of the two primary classes of cortical neurons, these are the excitatory neurons.

Astrocytes: Cortical *Glial cells* (support cells that outnumber neurons) that are primarily the most dense at the uppermost cortical layers. Previously considered just support cells, newer research suggest a role in computation function. Maybe gain capacitors for cortical columns.

Autobiographical processing: The brain processes which string together *episodes* into a sequence, that may for example tell a story.

Basal ganglia: A subcortical structure of various linked parts associated with a variety of functions, including voluntary motor control, procedural learning relating to routine behaviors or re-enforcement "habits" cognitive, emotional functions and action selection.

Beta: The 12-30hz EEG oscillations found in the *striatum* to cortex activity.

Central pacemaker: Areas in the centre of the brain which are thought to be the source clock for a wider range of neural oscillations.

Cingulate: Is the part of the cortex which wrap around the limbic system and is so highly integrated with it, and separate from the corpus callosum some propose it is part of the limbic system. Its function seems to be to integrate and resolve conflictions between cortex and limbic system.

Cortical surface gyration: The folds of the cortex. As neuron to glia ratio increases the gyrations increase. Increased gyration is thought to be linked to intelligence.

Corticolimbic: A reference to the cortex and limbic system in terms of its integrated function.

Delta: The 0-4hz EEG oscillation. Primarily subcortical, but also found in the cortex to thalamus cycle.

Dynamic attention allocation : Frontal cortex, executive control can suppress various signals in other areas of the brain to allow focus on other stimulus, which could originate as *Spreading waves* arising from *lateral inhibition.*

Dynamic Causal Modeling: The aim of dynamic causal modeling (DCM) is to infer the causal architecture of coupled or distributed dynamical neural systems. It is a Bayesian model comparison procedure that rests on comparing models of how data were generated

Episodic encoding and recall: Episodes are memories which are a set of associations that cover many sensory modalities. e.g. The experience of being in a particular location with somebody.

Event Related Potential, ERP : is the brains EKG equivalent for the heart. It is where we look when we measure the brains perceptual operation at its highest and most integrated level.

Event related Desynchronization (ERD): This is the lowering of the brains ongoing *stationary resting state* energy. Mostly found as cortical *lateral inhibition.*

GABAA/GABAC : One of the two primary classes of cortical neurons, these are the inhibitory neurons.

Gamma rhythm: The 30hz upwards oscillations generated in the cortex. Tend towards decoherence.

Glutamate: The primary excitatory neurotransmitter in the cortex.

Globus pallidus: The globus pallidus is a major component of the *basal ganglia* core along with the *striatum*

"Greedy growth" principle: A mathematical term now used for neurons to describe each neurons dendrite growth in terms of a mathematical power law

Grey to white matter ratios: (or the inverse). The ratio of grey to white matter either in individual brain areas, modules or the entire system.

Hippocampus: Primary roles is the consolidation of information from short-term memory to long-term memory, recall and spatial navigation.

Hippocampal theta: The 4-8hz EEG oscillations primarily associated with hippocampal activity.

Hopf bifurcation: A local bifurcation in which a fixed point of a dynamical system loses stability as a pair of complex conjugate eigenvalues of the linearization around the fixed point cross the imaginary axis of the complex plane.

Invariants: Both mathematical and computational neuroscience invariants have roughly the same general equivalence.

Lateral inhibition : an excited neuron or set of neurons such as cortical columns can reduce the activity of its neighbours. This can even extend to transcallosal inhibition across the two cortical hemispheres.

Limbic system. The set of subcortical structures which are separate from the brainstem and cerebellum.

Mu wave: EEG oscillation in the range 8-30 hz. It mirrors the *alpha* to *beta* range but has no known subcortical source, so maybe a cortical model of the alpha-beta range.

N1-P1 signal: An ERP composite signal associated with visual recognition in the time range of 100ms. There are also other types of N signal.. N just means the signal has a negative energy deviation to baseline, while P is positive. 1 is just an abbreviation so it could be called N100 on its own, just as P3 would also be *P300*

Non linear cortical activity: A reference to the manner in which most cortical activity is considered to be primarily non linear dynamical in nature.

Non explicit programming: For example programming all the neuronal components into a brain simulation wiring them together and seeing if ERS arises without programming that. But there are various levels of this. i.e. CML is first principle based, so if ERS/ERD arose from its program this would be considered a more pure example.

P100-P300 or P600 etc: These are the various positive event related potentials with their onset time (see *N1-P1 signal* for more clarification)

P300: Most well known *ERP* component occurring at 300ms as it is clearest in decision making and onset of conscious access. All ERP numbers describe the milliseconds of their onset after stimulus

Phase coupling - *coupled oscillation***:** Neural oscillations of various frequencies in the brain are found to lock together for a wide variety of neural sub processes, coding, recall and high level perceptual functions.

Phase-locked delta: the timing of spikes in the delta wave becomes *phase coupled* to the activity of other oscillations, such as alpha.

Phase reset: Neural oscillations may reset another set of neural activities, such as one set of oscillations, restarting the phase of another when coupled.

Re-enforcement learning: The brain processes associated with learning and repeating routines and habits.

Sensory routing: Allocation of inputs to outputs, mostly associated with *thalamus* function.

Septal areas: the region of the cerebral hemisphere, forming the medial wall of the *lateral ventricle's* frontal horn

Spreading waves: There are many terms for this in neurodynamics, but basically it is mass attractor activity that is non linear dynamic in nature. Sporadic bursts across cortical areas that spread across columns, or even larger macroscopic areas.

Stationary dynamics - ***stationary resting state***. The brain has continuous oscillations such as alpha, delta, beta and mu even when it is not processing information. i.e. just sitting doing nothing.

Striatum: The major input station of the *basal ganglia* system.

Subthalamic nucleus: The subthalamic nucleus is a small lens-shaped nucleus in the brain where it is, from a functional point of view, part of *the basal ganglia* system

Symmetry: For disambiguation in cross discipline use in this paper, mathematical symmetry and asymmetry are different from biological e.g. radial symmetry or bilateral asymmetry. This is clarified as here we attempt to use CML to predict brain signals and structures that are using the biological definitions. So if we mention such terms in a neuroscience context it will not be mathematical. An example is we may say an alpha wave emerges with symmetrical spread over a symmetrical structure like the thalamus, but if we were to describe the computations the use of the term symmetry would not automatically infer a mathematical invariance.

System consolidation: The ability of the brain to filter out irrelevant information over longer term time periods.

Thalamic reticular nucleus: A sheet of inhibitory neurons which surround the thalamus.

Thalamus: The brain module where nearly all incoming information passes through.

Thalamocortical: Refers to the interaction between thalamus and cortex which is usually an ongoing loop driven by locked *Delta, Gamma* and *Alpha* oscillations.

Third ventricle: The brain ventricle most central to the brain, in between the thalamus.