



Regular Article

## Computation by Biological Systems

Robert L. Fry

Johns Hopkins University Applied Physics Laboratory, 11100 Johns Hopkins Road, Laurel, MD, USA

Correspondence Email: [Robert.fry@jhuapl.edu](mailto:Robert.fry@jhuapl.edu)

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### Abstract

What are biological systems and how do they work? Does there exist a physical explanation that captures both their complexity and their simplicity? Biological systems are, after all, just another type of physical system. It has the distinction that it is “alive” whatever this means. Otherwise, biological systems consume mass and energy like any other endothermic process requiring these to operate. This paper introduces a very fundamental theory of computation. So fundamental in fact that it is both simple and easy to overlook. It is based on the computational interpretation of two basic questions. The first is “What does it mean for a system to subjectively distinguish its environment?” This defines the “tokens” of computations. The second is “What does *causality* mean?” The answers and the implications of these questions lead a computational definition for what a “process” is at a very basic level. This applies to any process inclusive of biological ones. The theory is demonstrated through a brief description of how to reverse-engineer the cortical neuron. The simplicity and elegance of this model leads to the observation that the neuron provides perhaps the best possible biological exemplar of the computational theory. The synergistic and hierarchical nature of biological processes in living systems is what principally differentiates living from non-living systems. The extensive or additive nature of energy is posited as providing a possible coherent binding mechanism between and across such hierarchies. This is exemplified through the positing of a conjoint computational-morphological Hamiltonian that is explicative in how conjoint adaptation can occur across synergistically across multiple biological “domains”.

**Keywords:** Computation, probability, entropy

## 1. What are Biology Systems?

How do biological systems work? Indeed, what are they? One looks at the world and observes biological systems; animals, bacteria, viruses – all existing and interacting with their respective environments and each other. Each biological system exhibits its own unique behavior and often so in unimaginable and intriguing ways. One can speculate the existence of a physics-based explanation of biological systems. This paper does not suggest such a comprehensive theory, but rather suggests a useful course in this undertaking.

Physical, chemical, biological, and intelligent systems all consist of “processes.” Some of these processes generate energy like the burning of fossil fuels and transitions from states of low-entropy or order to higher entropic states and greater disorder. Conversely, other processes in nature require energy to operate and maintain or even decrease their entropies to achieve higher states of organization. Living systems are the hallmark of the latter as highlighted by the physicist Schrodinger in his famous book “What is Life?” [1]. They are capable of organizing mass and information into higher states of organization in bold defiance of the 2<sup>nd</sup> Law of Thermodynamics.

The above all suggests the fundamental importance of asking the question “What is a “process?” This must be then be followed by the question “What differentiates processes that increase entropy and those that reduce it?” Biological systems are of course examples of the latter. This paper looks at these two questions and suggests possible answers. Moreover, these answers are constructive and suggest the possibility of a quantitative framework for understanding what biological systems are and how they might work; at least in part.

A summary of this paper is as follows. Section II outlines a general theory of computation of processes. Unfortunately, the term “computation” comes pre-loaded with the *a priori* experiences and notions of the reader. Here, we strip the notion of computation down to two very fundamental axioms. The first defines the “tokens” of computation based on how a system subjectively distinguishes its environment. The second is that of causality which dictates the 2 kinds of computational dynamics possible. In this view, every process is a computation inclusive of physics and biological systems. This is even true of the synergistic interactions of subsystems within any given organism.

Unlike nonliving systems, biological systems require multiple synergistic and interacting biological subsystems to exist. These “subsystems” which for example include the endocrine, immunological, and neurological systems, require the existence of many lower-levels of processes down to the atomic scale. Section III briefly describes an energy formulation for how multiple process dimensions might synergistically interact. The end of the section that follows provides a simple example of conjoint computational-morphological adaption to form new dendritic and axonal connection by a cortical neuron. These are done in concert to maximize its information throughput capacity given in units of bits/second.

The cortical neuron provides the simplest possible example of optimal computation by a biological system. Section IV develops a simple model of how cortical neurons compute and adapt through a summary of previously published findings. It is described how to reverse-engineer the cortical neuron. This includes its biological architecture (soma, dendrites, etc), its Hebbian adaptation rules, spatiotemporal codes, and provides an explanation of the role and need of somatic noise induced by Quantum Synaptic Failure; the failure of a pre-synaptic potential to induce a post-synaptic response. Section IV ends with a summary of how a cortical neuron can synergistically optimize its computation and morphological connections to other neurons.

## 2. The Physical Nature of Computation

Before proceeding, consider a perspective of *autonomy* useful to this discourse. This view is not new to physics [2], ancient philosophies [3],[4], or even biology [5]. The idea is very simple. To truly understand a system, one must view the system from inside the system and how it subjectively distinguishes its environment. You must take the first-person view.

Any process has inputs, outputs, and methodology for converting inputs into outputs. Inputs can be information or mass. Outputs can be information or structure such as new neural connections. Regarding the latter, the biological system uses available energy to organize its biological structures to higher levels of complexity and correspondingly lower entropic states. Since both types of processes are required to obey the same basic computational rules and since information is easier to talk about, the focus of the present discussion is on information and not mass and structure. It should however be remembered that

discussion points made apply equally to mass or information and more typically, both at the same time.

Keeping the first-person view, how does a system distinguish its environment? There are 2 ways. First, it can try to observe its environment. Secondly, it can distinguish the varying ways it can change or control it. In science and engineering we are trained to assume the 3<sup>rd</sup> person view. After all, it is the *scientific method*. However, the external view is counterproductive in understanding how processes and in particular, biological ones, work. Instead, we challenge the reader to try to assume the first-person perspective so familiar to those in computer gaming.

We begin with two axioms. The first provides the tokens of computation while the second provides for possible computational dynamics. It is interesting that exactly two tokens and two possible dynamics will arise and that their interplay is sufficient to understand physical processes.

These proposed axioms are as follows:

1. *To distinguish is the most elementary operation that can be performed by a system.*
2. *Computational dynamics must abide by causality.*

The logical consequences of these two axioms are developed separately and then combined at the end of this section to make the following assertion. All physical, intelligent, and biological systems execute one of two possible computations and indeed are just computing.

The first axiom defines what it physically and mathematically means to *distinguish*. This idea is initially developed through a thought experiment. It is then formalized through the introduction of the concept and mathematical construct of the *logical question*. Formalizing what it means to ask a question is very important both philosophically and practically. Felix Cohen provides an excellent justification [6] for the void in logic for the lack of such. Consider the following thought experiment.

You are asked to look at a black computer screen and then asked “Do you see anything?” You study the screen for a few moments. You then answer “No.”

However, the displayed image contains the text “Do you see me?” Its font contrast with the black

background is so small, that it can barely be seen. Perhaps another person with better visual acuity might see the words displayed. In this instance, the observer has been asked a question and he in turn looks the screen and asks the same question. The answer will depend on both the visual acuity of the observer *and* the relative brightness of the text. The observer poses a question that is answered by what is subjectively seen. Information transfer actively occurs from the “environment” to the “observer” while this question is posed. If the observer looks away or simply gets up and leaves, then active information transfer is impossible.

So the notion of distinguishability requires an interaction between an observer and its environment. This is a dynamic characterization of the act of distinguishing. But this is only half of the story in so far as distinguishability is concerned. Systems don’t only act as “observers,” they also act as “controllers.” That is, they can also make decisions regarding how they would like to control their environments. Thus subjective decisions comprise its possible choices on how it wants to effect its environment. The suite of possible choices collectively form the question of what to do. However, unlike the information example where the question was posed, control requires that the system answer this question. Thus one can describe both the information acquisition and the control or output capabilities of a system in terms of the notions of asking and answering of questions. This provides a very simple and elegant way of thinking about what processes do, but not how they should do it.

Richard Cox last published paper [7] develops two important ideas. First, logic can capture the dynamic process of asking and answering questions. Secondly, Boolean Algebra is as we know it, incomplete. Including a joint and dual logic of questions captures a powerful complementarity that exists within Boolean Algebra. This rich structure is capable of capturing the physical flow of information and control within a physical system. Consider the following two examples to demonstrate basic concepts.

A question is defined by the set of all possible subjective answers. The observer viewing the computer screen asks  $S \equiv \{a, \neg a\} \equiv$  “Is there anything there or not?” The question  $S$  in this case is a *binary question*. Binary questions are the simplest possible question that admit the physical flow of information or control. Its possible subjective answers are denoted  $a$  and  $\neg a$ . The answer  $a$  corresponds to “yes” while  $\neg a$  is a “no.”

One or the other will be selected through the interaction of the environment with the system.

The selection of an answer through its interaction with its environment corresponds to the system being induced into one of two possible physical states defined within it. This same argument can be used to characterize what happens when a system makes a decision. There, the inverse happens; the system purposefully enters one of multiple possible output states. Each choice corresponds to one of a suite of actions to execute and in doing so, internally defined output states are specified.

As a constructive example, posit the following logical architecture of a cortical neuron. In the model to be developed, the neural input dendritic field poses the question  $X = X_1 \wedge X_2 \wedge \dots \wedge X_n$  where  $n$  is the number of distinct dendritic inputs. Formally, each question asks  $X_i =$  "Have I detected (seen) a post-synaptic "action potential or not?" Each  $X_i$  is a binary question having the form  $X_i \equiv \{x_i, \neg x_i\}$  with  $x_i$  an action potential being observed and  $\neg x_i$  not the case. This number is on the order of 10,000. Each  $X_i$  corresponds to a binary question asked the  $i^{\text{th}}$  dendrite of the neuron. Thus the tokens of cortical neural exchange are just action potentials. These action potentials correspond to the physical assertions [7] that are the answers generated by the collective cortical field. This is a very simple way of understanding the exchange of information between differing neurons.

The total cortical inquiry is  $X$  and as per above is described as the conjunction of each of these more elementary binary questions  $X_i$  in a logical sense. This just means that the composite question posed by the neuron is "What is the state of all my dendritic inputs?" The number of possible answers to  $X$  is unimaginable large and on the order of  $2^{10000}$ . The neuron simply wants to know what it "sees."

The collective information acquired through dendrites by posing  $X$  can then be causally used to guide how the neuron responds. The neural response arises through its answering the question  $Y \equiv$  "Should I generate an action potential or not?"

As will be seen, the best answers  $Y$  offered by the neuron should make efficient use of the *actionable* information it acquired through  $X$ . This is represented by the logical expression  $X \vee Y$  or the "disjunction" of the input information with its required decision  $Y$ . Recall that the conjunction " $\wedge$ " of two logical questions requests the

information obtainable by asking *both*. Conversely, the disjunction of two questions requests the information obtainable which is *common* to, i.e., provided by both questions.

As a trivial example, consider a card-guessing game. The interrogating player can ask the questions  $S \equiv$  "What is that is the suite of the card?" and  $C \equiv$  "What is the color of the card?" The "common" information is just  $S \vee C = C$ ; the color of the card. The information common to suite and color is just the color of the card. For the model neuron,  $X \vee Y$  simply describes the conversion of acquired actionable information into purposeful actions. This is a powerful and simple notion for quantifying the concept of *actionable information*. This is one reason why as it will be seen that computational efficiency translates to energy efficiency for the operation of the biological system. The presentation here is decidedly topical with the provided references providing the reader with a much more detailed development.

The first axiom has suggested that logic can be viewed as a language of computation and distinguishability. We will see that the second axiom will tell us the two possible ways a system can compute.

Recall that we see two possible kinds of processes in nature. Either a process can generate energy (exothermic) or require energy to operate (endothermic). This can be stated in an even more trite way; processes either work to provide energy or they require energy to work. Biological systems of course fall into the latter category. Both kinds of processes exist simultaneously in nature. In fact the existence of the latter is at the behest of the first in providing the free energy required for its operation.

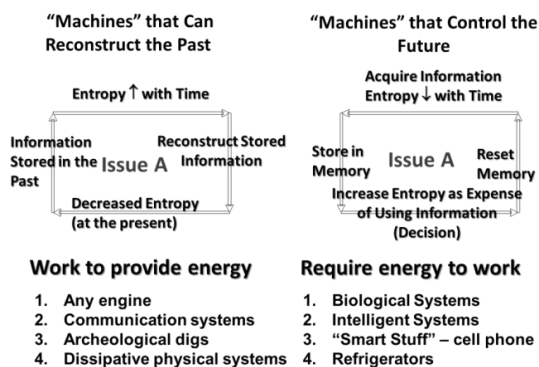
The second axiom deals the nature of causality and its implications. Just like in developing the term "distinguishability," we likewise seek a working definition of *causality*. This seems a difficult pursuit. Fortunately, a constructive and working definition already exists. It was provided by Claude Shannon in [8]. In this paper, Shannon develops the two fundamental problems of information theory; those of optimal source and channel coding. Towards the end of this paper he discusses the duality of these two problems and then goes on to make a very cryptic statement. Shannon claimed he would write and clarify it in the future, but he never did. This is what he said:

*“You can know the past, but not control it. You can control the future, but have no knowledge of it.”*

Consider the following possible computational interpretation. Natural processes can only operate in one of two possible ways. A system can work to reconstruct the past. Conversely, it can work to control future. The first dissipates energy and entropy. The second can decrease entropy but requires energy to operate. The first kind of system includes dissipative physical systems, communication systems, and even archeological digs. We will provide examples of these. The latter includes intelligent and biological systems.

Our focus is then on those kinds of systems that operate to control their future. Regardless, causality induces the need for the same 4 distinct phases in either process type. We will collectively recognize these phases as the familiar Carnot cycle of thermodynamics. The implication is that all physical processes execute Carnot cycles and that this cycle is a cycle of computation with its original realization within thermodynamics. Causality requires that processes that operate to control the future have the following sequential computational phases in their dynamics. As will be seen, each of these phases is epitomized by the cortical dynamics to be described.

Figure 1 below will be frequently referred to. It details the internal 4 phases both types of processes, i.e., ones that reconstruct the past and others that control the future. Both processes of course operate in the present. This is “where” computation is done.



**Figure 1.** Depiction of the two possible kinds of computation; those which are exothermic on the left and those which are endothermic on the right.

Both types of processes are depicted in Figure 1. We are principally interested in those systems of the type found on the right side of Figure 1. They must operate in the following way beginning with the phase labeled “Acquire Information” on top of the cycle. During this phase, the system acquires information from its environment as guided by the active question *X* it poses. This corresponds to a physical transfer of information into the system. For the neuron, this is the physical and successful transmission of a pre-synaptic potential across each synaptic cleft.

The system then stores acquired information in memory as depicted in Figure 1. Storage is necessary since information cannot be instantaneously converted into a decision since this requires a causal delay. By extracting “actionable information” from the collective measurements, memory storage requirements can be significantly reduced. The cortical neuron to be described stores its actionable information in its soma as a charge. This charge represents the knowledge the neuron has to make its decision to fire or not.

Once stored, information is no longer susceptible to noise and essentially becomes “frozen.” That is, information storage is analogous to a temperature decrease in a physical system giving rise to a “phase transition” within the system. Here, temperature takes on a more general interpretation corresponding to the computational operating temperature of the process. We shall see that temperature and operational noise-levels are computationally equivalent in general as demonstrated through the single-neuron computational model developed.

Then, as shown in Figure 1, stored information is then “expended” in its use to generate a decision. The term “expended” means that the next decision cycle will require new information. Consider the analogy of someone who likes to bet on horses in a race. Suppose this person knows someone else at the track with side information on which horse will win any given race. After gaining and memorizing the information of which horse will win the next race, the gambler goes to the window and places his bet. After winning the race; or not since no processes have 100% Carnot efficiencies, the gambler will likely return to his friend to obtain new information for the next race.

Finally, after the system converts its acquired information into decisions, it must *reset* its memory thereby allowing it to acquire new information. The term *reset* is preferred over the term *erasure* as used in other similar perspectives in the area of the

thermodynamics of computation. This is for instance the view in [9] where the physical limits of computation considered by Landauer. The view here is this “erasure phase” phase is really a “reset phase” required by the system to be able to acquire new information and begin the next cycle. However, this phase requires energy and sets the limits of achievable computational efficiency and this is in agreement with previous work [9].

No better example exists than the cortical neural model to be discussed. Its “reset phase” consists of the restoration of internal and external ion sodium and potassium concentrations across its cell membrane which were depleted through a firing event. This phase of its computational cycle is accomplished through the expenditure of energy via its  $\text{Na}^+/\text{K}^+$ -ATPase enzyme pumps. The success of this phase enables the neuron to observe new dendritic information.

Figure 1 provides a summary of what has been discussed so far. It contains the Carnot cycles for both types computation. One can go through an identical but reverse argument regarding the consequences of causality on exothermic processes. There, information is stored in the past and its reconstruction attempted at the present. However, information is lost over time making it impossible to perfectly reconstruct ostensibly anything.

Systems on the left side of Figure 1 generate energy and increase entropy. Conversely, systems on the right require energy and reduce entropy. Engines convert fossil fuel stored in the past into useful energy at the present. Past civilizations can be thought of as storing information in the past. Time and the 2<sup>nd</sup> Law contributes to the loss of this information as characteristic of the first process type. Archeologists try to reconstruct the past present despite information lost.

Communication systems work similarly. Consider use of fiber optics to transmit signals at light speeds under our oceans between continents in optical fibers. Initially, pulses have high-powers and are very short in duration as they are inserted into the fiber. The fiber channel causes signal attenuation (power loss) and pulse dispersion (temporal widening). Repeaters are required to periodically detect weakened and smeared pulses, and then amplify, and re-transmit them. They reconstruct information transmitted in the past at the present.

But what are intelligent and biological systems “trying to do”? This is described in Section IV in the context of the cortical neuron model that is developed there. As will be seen, the cortical

neuron is perhaps the simplest imaginable exemplar of a biological device that optimizes its computational and energy efficiencies. Before this though, there is a major distinction between living and nonliving systems that must be noted. It is critical to the development of a theory how complex biological systems work. The next section considers the requirement for a systems-level understanding of the following question. “How do biological systems operate harmoniously and synergistically across their multiplicity of sub-processes operating simultaneously at many hierarchical levels?” Until this question is answered, the search for any comprehensive theory of biological systems will be in vain.

### 3. The Functional Dimensions of Biological Systems

A more holistic view albeit computational should be taken of biological systems. They have multiple interacting processing dimensions vs. what might be called the boring singularity of the processing dimensions by nonliving systems.

In the next section, optimal computation by a single cortical neuron is summarized. This model serves to provide a succinct example of the optimization process carried out by biological systems. This optimization can be viewed from an information-theoretic perspective or from the standpoint of thermodynamics and energy efficiency. The hallmark of biological systems is their energy efficiency. This is certainly true of the brain [10], [11], and ostensibly all organs and processes including locomotion. Section IV briefly describes how the same computational model developed can easily be extended to include optimal morphological adaption by the cortical neuron. This means optimizing the formation of new dendritic pathways and axonal connections or creating entirely new ones as in neurogenesis [12].

### 4. Cortical Neurons

The simplicity and computational “purity” of the described cortical model are its compelling features. More amazing, as we have talked about the importance of the notion of distinguishability, this is essentially all that the cortical neuron does. It simply tries to distinguish.

The following is a synopsis of the findings described [13] - [19]. These have never been completely summarized in any one place. We begin with detailing each of the 4 phases of its “Carnot cycle” of the cortical neuron. This is followed by a description of the computational

objective of the neuron. That is, how should it adapt to better do what it is that it does.

A cortical neuron has on the order of 10,000 distinct input dendrites. They define the receptive field of the neuron through which neuron sees its “world.” Think of this as 10,000 computer screens with each dendrite asking “Is anything there?”

In this way, each synapse can be seen to correspond to a binary question  $X_i, i=1,2,\dots,n$  asked in concert in space. They are also asked in time but adding this dimension as simple as it is secondary only to note that neurons also adapt temporally in their advance or delay or dendritic signals to the soma. These temporal aspects represent but a minor and simple extension to the present discussion and which is also captured in the references [13] – [19].

Each dendrite is seen as logically corresponding to a binary question of the form  $X_i \equiv$  “Is there a detected post-synaptic assertion (answer) at this dendrite, or not?” The realization of a post-synaptic potential corresponds to the physical answer to this question. In total, the model cortical neuron asks the conjoint question  $X=X_1 \wedge X_2 \wedge \dots \wedge X_n$  thereby asking the same question of all  $n$  dendrites. Collectively, the model neuron just asks  $X$ ; what do I see right now? It is hard to consider a simpler question to ask.

Some pre-synaptic potentials will successfully conduct across their respective synaptic clefts to the subject neuron to induce a post-synaptic potential. Others will not. In information theory, this kind of communication channel is known as a “binary erasure channel.” Wikipedia provides a handy reference [20].

On the order of maybe 70% of presynaptic potentials will induce post-synaptic potentials. This fraction is interestingly enough roughly the Carnot efficiency of the neural system. Those that do transmit will induce a traveling potential along its respective dendritic pathway to the soma. This transmission requires time and the realization of a propagation delay and as has been suggested, it learned delay time.

The consideration of the temporal aspects of neural adaptation would lead to a single and simple conclusion. Every cortical neuron attempts to adapt so as to ensure the simultaneity of the arrival of the dendritic signal having the greatest relevance to the decision that the neuron must make. Assume that these both observed and relevant dendritic signals arrive within a defined time

window at the soma. The net effect will be the transmission of a proportional electrical charge to the soma from each dendrite as weighted by the so-called efficacy or gain of that dendrite.

Observe that the total integrated induced charge in the soma will have variations owing to the random transmission failure of pre-synaptic potentials. This effect represents an effective “noise” induced on each measurement  $X_i$  by the neuron and is important for the multiple reasons to be described. This noise source is formally known as *Quantum Synaptic Failure* or QSF.

Each “detected” post-synaptic potential races along its respective dendritic pathways to the soma of the neuron. Each “answer” arrives at the soma inducing an input current and its integration within the soma. Eventually, with prevailing dendritic gains and delays, the net effect is to exploit the capacitive response of the soma to perform a spatiotemporal integration of the totality of what it “sees” via its dendritic field of “eyes.” This represents the totality of actionable information available to the neuron to make its decision whether to fire or not.

The integrated somatic current leads to a proportional internal potential according to the integration of the differential equation given by  $\Sigma I_i = C_s dv/dt$ . The integrated potential; call it  $v_m$ , will contain the actionable information of the neural system inclusive of the random perturbations induced by QSF.

The induced potential is can be seen to be the inner product of the Boolean post-synaptic measurement  $n$ -vector  $\mathbf{x}$  and their respective synaptic efficacies denoted here by the  $n$ -vector  $\boldsymbol{\lambda}$ . Therefore,  $v = \boldsymbol{\lambda} \mathbf{x}^T$ . This is supposedly the entirety of the “evidence”  $v = \boldsymbol{\lambda} \mathbf{x}^T$  available to the neuron for it to make its decision. How can this be?

Now perhaps one of the most intriguing aspects of this model cortical neuron is how it operates in its real-time decision making. The neuron in the present model wants to answer  $Y = \{y, \neg y\}$ , i.e., fire or not. It can only observe and use  $\mathbf{x}$  in making this decision. Applying Bayes’ Theorem in logarithmic form we obtain

$$\log \frac{p(y | \mathbf{x})}{p(\neg y | \mathbf{x})} = \log \frac{p(\mathbf{x} | y)}{p(\mathbf{x} | \neg y)} + \log \frac{p(y)}{p(\neg y)} \quad (1)$$

This implies that one can practically implement Bayes’ Theorem using addition. Furthermore, it

follows that the probability of a firing decision is given by

$$p(y = 1 | \mathbf{x}) = \frac{1}{1 + \exp[-\beta\zeta]} \quad (2)$$

where  $\zeta = \log p(y|\mathbf{x})/p(\sim y|\mathbf{x})$ . Eq. (2) is of course the familiar sigmoidal response curve of cortical neurons in response to the level of input stimulus. Here,  $\beta = 1/T$  serves as an “inverse temperature” parameter dictating the degree of randomness with which decisions are made. Smaller temperatures guarantee less randomness and conversely so for higher  $T$ .

Let  $\mu$  correspond to the firing threshold of the neuron. As shown in [13], the total potential  $\zeta = \nu - \mu$  as a computation exactly corresponds to Bayes’ Theorem computed using its additive form. The log-prior odds is given by  $\mu = -\log p(y)/p(\sim y)$  or the logarithm of the probability it should fire or not while  $\nu$  corresponds to the log-likelihood  $\log p(\mathbf{x}|y)/p(\mathbf{x}|\sim y)$ . This means [13] that the probabilistic rule that the neuron must use in making its firing decision is guided by the logistic function as given by Eq. (2). The main conclusion is that the neuron uses Bayes’ Theorem to make its decisions and that this can be accomplished within a simple biological neuron. This in itself is amazing.

The total potential in Eq. (2) is perturbed by random temporal noise as induced through QSF. The consequence is simple and interesting. Random somatic noise as induced through QSF enables the neuron to probabilistically make decisions according to Eq. (2). This is accomplished by the fact that the probability of firing is derivable from the independence of  $\nu$  and additive noise  $\eta$  and is given by  $p(y=1 | \zeta + \eta) = \frac{1}{2} \text{erfc}[-\zeta / (2^{1/2} \sigma_\eta)]$ . Random QSF noise can be shown to be Gaussian being the sum of a large number of random terms. The consequence of this is that one can exploit the fact that one can relate the inverse temperature to noise level through the relation  $\beta \approx (2\pi)^{1/2} \ln 2 / \sigma_\eta$ . The significance of this is that QSF provides the ability for a biological neuron to realize and optimize required logistic response in Eq. (2) in its probabilistic decision making to control its future.

The implication is that the cortical neuron uses Bayes’ Theorem to make its decisions. This is an amazing finding if true. This suggests that the operation of biological processes may all in some fashion use Bayes’ Theorem to optimize their

respective processes and that it is our problem to explain in detail how each instance does so.

Let us now continue with the next cycle in neural information processing. In Figure 1, we have completed the phase of the model making a decision. If not, then neural  $\text{Na}^+$  and  $\text{K}^+$  ion concentrations are maintained across cell boundaries, e.g., a status quo. Conversely, the generation of an action potential and transmission of an axon potential has consequences. It means that the neuron must use energy resources to re-establish the pre-firing ion concentrations necessary to the acquisition and storage of new information in the future. The 4<sup>th</sup> and final phase is endothermic requiring the expenditure of metabolic energy for its completion readying the neuron to begin a new cycle. Sugar firing ATP cycles and sodium-ion pumps are required in this processing phase. This is the energy intensive phase of neural processing and is the cost of resetting itself for its next cycle of operation.

To summarize thus far, the cortical neuron operates cyclically. Moreover, their operation can be described as a generalized computation functional form of the “Carnot” cycle. For such systems, the  $x$ -axis coordinate frame in Figure 1 is system entropy change  $\Delta H$  and temperature change  $\Delta T$ . The second  $y$ -axis is system temperature, or as we have seen, measurement noise level.

The areas of the Carnot cycles as shown in Figure 1 are important as follows. The areas of the respective Carnot Cycles shown in each diagram correspond to the free energies either generated by the system (left) or required by the operation of a system (right) to operate. This means  $E = \Delta H \Delta T$  in either case. Furthermore, and in terms of endothermic systems, this means that the smaller we can make both  $\Delta H$  which is the information the system needs to operate and the differential “temperature”  $\Delta T$  over which the device must operate, then the greater the operational efficiency of the system.

Space limits the consolidation of [13] – [19], however a succinct description of the optimal operation and adaptation of a single cortical neuron can be captured as follows. To do so we again return to our test subject looking at computer screen asking “Is anything is there?” Consider a single neuron in the same way. It looks upon its pre-dendritic field and asks “Is anything there?” It does so with its own idea and local definition of what that any “thing” is. It makes a decision yes or



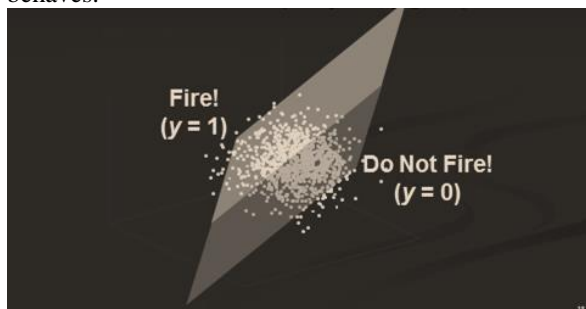
no. The question of how it learns to do so is therefore of critical importance.

What is the single doing and how does it adapt? What is it optimizing? Single-neuron optimization can be viewed from 2 complementary perspectives. The first is computational while the second is from the standpoint of energy efficiency and thermodynamics.

Computationally, the neuron is solving an important mini-max problem. It tries to maximize the rate it makes decisions while simultaneously minimizing the information it needs to do so. This problem exactly corresponds to the two most basic problems in information theory; the problems of source and channel coding [8]. Shannon considered these problems to be complementary. However, Gaspar [21] discovered that these problems can be solved jointly using what he calls *Double Matching*. Doing so leads to the complete optimization of the communication system.

Neurons also perform double matching [14], but do so in a way inverse to how it is thought about in information theory. They attempt to maximize their decision rate  $Y$  while balancing this with the amount of actionable information they need to acquire  $X \vee Y$  to make these decisions.

To maximize its information throughput, it must do so in a way that maximizes its output entropy  $H(Y)$ . In this case, the neuron only has two possible decisions  $Y$ , and so the objective becomes of maximizing  $H(Y)$  to 1 bit/decision. This can only occur if  $Pr(\text{Firing})=Pr(\text{Not Firing}) = 1/2$ . This has a very basic interpretation; the neuron is simply trying to distinguish. Consider the following figure that graphically depicts how a neuron learns and behaves.



**Figure 2.** Through learning, the neuron constructs a hyper plane that separates dendritic codes into two equally probably categories that either induce firings to do not.

Single-neuron adaptation can be graphically understood as follows. Define the hyper plane

given by  $\lambda^T x - \mu$  where again  $\lambda$  are  $\mu$  are the synaptic efficacies and decision threshold, resp., formed through adaptation. This hyper plane is oriented and located such that it bisects the space of  $2^n$  possible dendritic codes. Furthermore, it separates the cloud of dendritic codes it has observed in the past and does so in two ways. First, the hyper plane results from a principal component analysis such that the dispersion of points orthogonal to the hyper plane is maximized. Secondly, the two regions have approximately equal probabilities guaranteeing that the output entropy is maximized. An energy interpretation of the optimization is much simpler.

The endothermic process on the right side of Figure 1 corresponds to the complete computational cycle of the model cortical neuron. The product  $\Delta T \Delta H$  is the area of the cycle and the energy  $E$  required for it to complete a processing cycle. It is of course desirable that this energy be as small as possible. This means we can either reduce its decision rate to reduce energy requirements (undesirable), or it can reduce its operating temperature range  $\Delta T$ , or do both. The latter is accomplished by the cortical neuron by maximizing its number of inputs  $n$  subject to physiological constraints while regulating the somatic measurement noise level through quantum synaptic failure as described previously.

Ideally, the neuron will make probabilistic decisions to fire or not according to Eq. (2) recalling that  $\beta=1/T$ . The larger the temperature  $T$ , decisions become more random with measured information becoming disregarded. As  $T$  decreases, decisions become deterministic functions of measured data. As shown in [15], QSF provides a means for a cortical neuron to regulate its operation temperature. To see this all one needs to do is recognize the functional equivalences given by  $1/[1+\exp(-\beta\zeta)] \cong 1/2 \operatorname{erfc}[\zeta/(2^{1/2}\sigma_n)]$  if  $\beta \approx (2\pi)^{1/2} \ln 2/\sigma_n$ . The central limit guarantees that the somatic noise is Gaussian with the QSF failure rate regulating the effective noise  $\sigma_n$  or computational temperature  $T_n$ .

Moreover, the neuron can minimize its operating temperature range directly by simply maximizing its number of dendritic inputs, e.g., morphologically. As shown in [15], cortical “Carnot” performance gains asymptote around  $n=10,000$  suggesting a possible explanation for the observed numbers of cortical connections in biological neurons.

We conclude with a brief description of the idea of conjoint optimal computational-morphological

adaptation. The single cortical neuron possesses a computational Hamiltonian or energy function and it is given by  $E(x,y) = \lambda^T x y - \mu y$ . It is a function of the neural “microstates.”

In thermodynamics, energy is said to be an extensive property of a physical system. This means is that if bring two physically independent systems together then extensive properties “add.” Energy is extensive. Therefore, we can consider combining the computational and morphological systems together. One can posit a morphological Hamiltonian given by  $E(u,v,y)$  where  $u$  is a pre-synaptic axonal connection field of possible new inputs and  $v$  the post-axonal dendritic field. This means that the conjoint computational-morphological Hamiltonian is given by  $E_C$ .  
 $M(x,y,u,v) = E(x,y) + E(u,v,y)$ .

Hebbian feedback  $y$ , while guiding synaptic efficacies and decision threshold development, also can guide development of new pre- and post-neural connections having computational relevance. Of course, increasing the number of dendritic inputs  $n$  also means that the morphological system is synergistically aiding the computational domain by improving its efficiency by increasing its number of connections. At the same time it can be observed that the computational system guides the morphological one so it makes judicious use of its resources. It seems worthwhile to pursue this direction further and how multiple interacting biological functions might be computationally understood.

#### Conflict of Interests

The author declares no conflict of interests regarding the publication of this article.

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 [3] “The Tao Te Ching,” is collection of 81 poems attributed to Lao Tzo in the 4<sup>th</sup> Century BC. The well-known Tai-Chi symbol from the I-Ching exactly corresponds to a binary question as will be described.

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### **Author's Biosketch**

#### **R. L. Fry**

Robert Fry is Principal Professional Staff at the Johns Hopkins University Applied Physics Laboratory. There, divides his time between basic research and the development of advanced concepts for DoD. His research has focused on the development of systems can make robust decisions with uncertain information as performed with ease in natural intelligent systems. He has many patents including a laser photo-screener being licensed world-wide for the detection of amblyopia and strabismus in infants and pre-school children – at a time where these issues can be effectively addressed with medications vs. surgery. Current work is focusing on the development of intelligent imaging systems that may operate more like biological ones do.