Synthetic Cognition

Implementing a Testable Hypothesis

Abstract

This research proposal intends to design, build, and test a novel approach to synthetic cognition. Although aspects of its implementation will employ digital strategies, this project will employ additional strategies directly inspired by physical open systems, such as embodied animal neural assemblies, which have been investigated in depth by neuroscience. The central claim is that increasing amounts of order can be accrued by self-adaptive systems to increasingly useful ends by internally superimposing many diverse patterns into one integrated pattern, which is simultaneously composed of both parts and their inter-related whole. The sparse order inherent in this interference pattern is harvested by the system so as to increase the saliency, diversity, *and* higher-order patterns of adaptive work that can be done by the adaptive system through time; thereby, increasing both the breadth of patterns and depth of their inter-dependency that can be usefully assimilated by the self-adaptive agent. This proposal will provides a both the buildable synthetic system and the theoretical concepts to empirically test for evidence of cognition.

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Introduction

We know that cognition exists, because all mammals exhibit its tell-tail signs of learning and adaptation to the nascent organisms inherited world. Furthermore, the great body of knowledge about the embodied brains that implement this adaptive behavior has been accrued by neuroscience for more than a century. It's conclusion is that this implementation is very similar among all animals that exhibit; specifically, they all involve neurobiological assemblies of cells like neurons and their frequent neighbors, glia. This fantastic shared evolutionary inheritance, illuminated by earnest and diligent scientific efforts, is our only proof of concept for cognition.

Ironically, most interested in Artificial Intelligence, or AI, are only mildly interested in this proof of concept, at best, and openly dismissive, at worst. But the name itself gives it away, because “intelligence” is a subset of evolved cognition. In true reductionist fashion, half a century of researches have sought the grail of how mind works by isolating its most salient and idiosyncratic human properties. These properties are often the subjective observations of such ill-defined concepts of “consciousness” and “intelligence” itself. Unfortunately, the project of AI has and will continue to fail because such observations are taken out of context. They are plucked from billions of years of physical processes, isolated, and plugged into artificial labyrinths of intrinsically ill-adaptive logic. The irony is that we have isolated the most uniquely human aspects of cognition, which is not much of cognition as a whole, and restrained it by one of the most inflexible aspects of human behavior.

This project is in no way against reductionist approaches or logic per se, not at all. It will use them for all their worth. However, this project, as a design project, understands that, like all tools, they have their place and practical limits in a wider context. Furthermore, as a design project, this process concedes the human tendency for preconceptions. It is understandable that many very intelligent people will have wanted “intelligence” to be a closed system like our very successful tools, e.g. the digital computer. The bad news is that cognition, like all evolved systems, is not a closed sequentially causal system, like all Turing equivalent machines. The neuroscience is unambiguous on this point. Cognition is an open system. The designer's approach is especially suited to such open and complex systems where there is no *a priori* “right” answer. Creativity, just one example of cognition not even touched by 50 years of AI research, is quite antithetical to such preconceptions and rigid rules. Never the less, animals at many different levels of complexity exhibit exquisite creativity in navigating their intrinsically dynamic and often unpredictable world.

This project does not presuppose *human* intelligence, exactly because it is such a recent entrant to the evolutionary race. There is no guarantee that our very salient and symbolic forms of language and abstraction are adaptive in the long run. It *has* been shown by natural selection, however, that basic animal skills in creatively learning and navigating a complex world are quite adaptive over billions of years, from bacteria to humans, exactly because such strategies are so conserved across species. This is where this project begins.

How is it that any system, “living” or not, can absorb patterns from its environment and integrate them in such a way that increases that agent's chances for survival? Nature has evolved a way for self-adaptive agents, such as most animals, to integrate less ordered, and relatively less useful, patterns into higher-order, and more useful, patterns. This trait to varying degrees is inherent within the entire biosphere, a trait Erwin Schrodinger called Negative Entropy in his book *What Is Life?* The physical realization of this illusive capacity is the overarching design guideline of this project. A theory and practical technology are the tests of its veracity.

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According to the Computer Industry Almanac, between 1996 and 2000, 444 million IBM PCs were sold grossing just over a trillion dollars in sales.[1] As a whole, the digital industry today is worth orders magnitude more, let alone the creative and scientific advances afforded by this technology. This is impressive, but is it the only form of computation? Are discrete symbols the only form of information? To both, the answer is no.

Digital computation using discrete, *independent*, and closed information systems was created by human minds, minds that evolved over billions of years in distributed, *dependent*, and open information systems. We haven't even begun to understand the implications of this fact, let alone the practical applications for our species. This project will change this.

This project in synthetic cognition will not only augment human cognition, it will augment the existing digital infrastructure. Based on these two factors alone, this project will give birth to a trillion dollar industry within 15 years. Of course, the AI community has been promising this for over 50 years. What is different about *this* project? A great deal, but mostly the fact that this

[1] http://www.c-i-a.com/pr0806.htm

project is inspired by our *only* proof of concept, animal cognition; a self-adaptive information system that has evolved to accrue order from within the distributed, *dependent*, and open system it is embedded. By building and industrializing this novel form of computation, this project will infuse the inherent strengths of animal cognition into existing human tools, such as digital computation.

In spite of the unimaginable benefits, however, a very real obstacle stands in the way of this innovation. This obstacle is not the lack of some fundamental knowledge or some exotic quantum technology. It is our own inherited preconception of what information fundamentally is, a preconception that has been leveraged to great utility in our digital forms of computation. However, to move forward we must understand the practical limits of this preconception.

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As one might imagine for a millennial old question, an answer will not be trivial, but neither is it inaccessible to the curious individual of average imagination. Just as a few simple sentences won't communicate evolutionary or relativity theory, so too will this theory resist simplistic summary. Never the less, it is actually a relatively simple concept.

The main reason it has remained so illusive for so long, I posit, is that its very nature is counter-intuitive to our long held cultural preconceptions. Our species has evolved to consciously perceive distinct events one at a time, often at the expense of their inter-relations – a conception leveraged to great effect in our digital technologies. Contrary to this conscious perception, however, the actual behavior of any object at any scale can only *truly* be understood in the context of other surrounding objects at the same exact moment. In other words, the evolution of information, and nature itself, is about *both* distinct events *and* their inter-relations, *simultaneously*.

For example, the trajectory of a celestial body, say a planet, is the result of many surrounding bodies simultaneously. The gravity of each local body superimposes to create a physically real terrain that governs the trajectory of each other body. This is the counter-intuitive crux: *the behavior of the local whole system both causes and is caused by the distinct parts within it*. The real kicker is that this whole is fundamentally *simultaneous*. Sure, a change in gravity between two isolated parts will propagate at the speed of light. But any given mass will be influenced by many local bodies *simultaneously*, just as a musician in the middle of an ensemble will hear all other musicians, again, *simultaneously*. In essence, an open system at any instant is an evolving and indivisible whole, as much as it is a collection of distinct parts.

Towards a more accurate understanding of mind, the neuroscientific evidence is unambiguous. Neurons, like all cells, behave within an open system like the celestial body example. Instead of gravity, however, electromagnetism is the primary mediating force. Similarly, the behavior of any one neuron is simultaneously the result of its own nature and that of the superimposed collective whole. *O.k.*, what does this mean?

Consider a water molecule. It has distinct parts: two hydrogen and one oxygen atom. But how do these parts come together to make a whole? Each atom certainly isn't discrete and independent from one another. They can come together as one, because their behavior is *dependent* upon each other. The water molecule is both the distinct parts, the atoms, *and* the whole, water, *simultaneously*. But how?

All atoms have an extensive property described in physics as an electromagnetic field, whose strength falls off as the inverse of the distance squared. If a donor atom, such as hydrogen, comes in proximity to an acceptor, like oxygen, their extensive fields will superimpose to create a novel physical terrain. As such, a reaction will tend to occur as their respective electrons head their new shared electromagnetic terrain. Specifically, two hydrogen partially donate one electron each to an acceptor oxygen. The Bohr model, taught in undergraduate courses, is fine for stoichiometric book-keeping between donors and acceptors, but this abstract model is quite misleading in understanding the truly distributed nature of electron orbitals. To understand how these shared distributions, say in a water molecule, create a union greater than the sum of its parts, it is helpful to imagine a shared physical terrain, which both molds and is molded by the behavior of each atom, simultaneously.

The complex and causal topographies of these superimposed forces cannot be directly perceived like the terrain out your window can. Never the less, exiting out your second story window will provide a quick proof of concept for gravity. And all of perceivable matter, in all its complex and dynamic form, is possible because of the very real, continuous, and shared terrains of the physical electromagnetic force. It is of *critical* importance to understand that these forces are not *other than* observed objects. Each exists of the other so that they are both the whole and the parts, *simultaneously*. Gravitational and electromagnetic terrains are more accurately conceived as the extensive *attributes* of material objects, not a mere by-product. So, how does this relate to mind?

Minds are built of cells, for example neural and glial cells. These cells are composed of molecules, which are composed of atoms, as in the water example. These atoms and molecules, within cells, have co-evolved to be electrically active based upon their intrinsic electromagnetic nature; their extensive attributes superimpose with one another to create a physical reality greater than each distinct atom alone. Scaling up, the resultant electrical activity from cells similarly pervades each other and their shared space. As these fields superimpose to create more complex fields, more complex and novel behaviors from neurons becomes possible. Together they create something more than discrete and independent events, such as bits, can *ever* create. They have created a patterned and complex whole that is both each part and their physical inter-relations, simultaneously, just as the physical world is both distinct parts and their inter-relations, *simultaneously*.

A rigorous understanding of how distinct entities, like atoms or cells, come together into vital self-adaptive wholes is the crux. But, again, it is no more complex than basic physics and evolutionary theory. The main obstacle is our inherited predilection for seeing the world as populated by discrete objects. We describe their complex behaviors in a one-to-one manner with abstract rules and functions. These descriptions certainly have utility, but these rules are not the *reason* bodies behave the way they do. They are descriptions, and like all abstractions of reality, are limited. This project digs deeper into the reasons, which are at least in part the *distributed* attributes of matter that superimpose with each other to create a shared and unified terrain, as described previously. This project seeks not only to describe these vital behaviors, but to physically build them to great human utility and improved understanding of the world around us.

Understandably, the conception of both parts *and* their whole existing simultaneously confounds our evolved sense of seemingly discrete events one at a time. But our senses have led us astray before, and they will certainly do it again. However, the empirically established physics is uncontroversial. So much opportunity in better understanding this physical world is available if we are willing to explore these unfamiliar, if temporarily disorienting, facts. The rewards are innumerable. The fruits of these labors are nothing less than a trillion dollar industry at least as ubiquitous as the digital revolution, within 15 years, but only if we start in earnest *now*. The theory and the testable implementation that follow are seeds that will manifest unimaginable fruits if set in the amenable soil.

Chapter 1

Refinement of Sparse Order from Local Interference

What directs cognition? What organizing force wires neurons in the brain to increase the adaptive chances of the living agent? How do diverse individual living systems at any scale increase their collective ability to adapt and survive? At the heart of any self-adaptive system, like cognition, is one main question: what physical phenomenon enables an agent to tend towards an increased capacity to perform increasing amounts of useful work within the environment it is born into. There is some selective adaptation at the genetic level, which evolved cognition of all kinds throughout the animal kingdom via eons of generations. Some have described cognition itself as a kind of micro-evolution within one agent's lifetime.[1] [2] But like the evolution of life, cognition begs the same questions above. The intent of this publication is to very briefly outline a research project in synthetic cognition, which is fully described in the complete research proposal under a separate cover. The project being summarized has every intent to not only rigorously describe how such self-adapting systems are physically possible in theory, but how to design, build, test, develop, and implement them in useful practice.

Two central concepts will be highlighted in this Chapter as fundamental to cognition in general, and the project of synthetic cognition in particular. Future research and publications will extend these ubiquitous principles to adaptive systems at all scales. The two concepts highlighted here are easily observable physical phenomena common in nature, namely: *work* and *superposition*. The first can most simply be stated in its most familiar form:

Work = Force x distance **equation 1.1**

The second concept can and will be described mathematically in the full proposal, but for now its most familiar manifestation is described via the observable phenomenon of music. As each musician plays their instrument, sound waves are transmitted through the medium of air as illustrated in **Figure 1.1**. Each sound, though from a diverse source, superimpose with each other in air to become just one pattern that the human ear perceives. Electric circuits can behave similarly whereby each circuit has both its internal relationship between current and voltage and may also be sensitive to electromagnetic (EM) fields in the space around it. For example, a cell phone's internal circuits have their own internal circuit characteristics. But the principle function of this device is to communicate via microwave EM radiation with local towers.

These EM signals permeate the interstitial space among all cell phones; each phone is designed to physically resonate with only a limited bandwidth from within the vast number of signals that actually permeate local space. In the medium of air, acoustic signals similarly superimpose to manifest music. Unlike cellular signals for phone service, however, music is about the higher-order relationships among diverse constituent signals from different instruments. This does not mean, however, that the EM signals, currently limited to a one-to-one relationship for cellular phone technology, cannot be employed like sound waves from instruments in a musical application to similarly accrue higher-order patterns in the superimposed interference.[3] But, how exactly this proposed potential order is harvested, retained, and used by a cognitive agent is the crux of the project. And the capacity to discern sparse order within the superimposed interference is predicated on the capacity of the system to turn potential order within the superimposed interference pattern into useful physical work for the agent.

Superposition is a phenomenon of *simultaneity*. The ear does not receive each instrument's sound separately and sequentially. It receives the energy from each instrument simultaneously. Therefore, this superimposed pattern can contain more information than each instruments' signal alone, because the relationship between each diverse signal within this one pattern is *in addition to* the information inherent in each signal alone.

Of course, within this mix of signals, whether as music through air or signals through electrical circuits, noise always competes with useful information. In general, mixing of signals in traditional electrical circuits is best kept to a minimum. Here in lies the success of digital technologies, which are specifically designed to filter out noise. Noise, however, depends on the observer. Whether a signal is “noise” or not depends on whether it does useful work. This in turn depends on whether some signal resonates in some way with the organization of the circuit, whether a microchip or a neural assembly. This is the fundamental principle of AM, PM, and FM radio. Tuning in a station changes the circuit so that it selects from different available EM signals in space. As one changes the dial all the other signals don't disappear; they still exist in space. It's just that the radio device has tuned to resonate with one signal over the others. The circuit is structured to be selective. But selectivity doesn't have to preconceive the signal it resonates with; a system may be evolved or designed so that it literally *learns* to select for, not only predominant signals in the environment, but higher-order relationships between these salient signals, i.e. patterns of patterns. And this is where the relationships between signals can be leveraged to evolve the system's relationship to its complex surroundings.

Imagine a device that rebuilt itself to select for any salient signals in the so-called "noise" of the agent's environment. Again, "noise" is in the "eye", or circuit structure, of the perceiver. Perfectly pure noise is truly without information about its context. But open adaptive systems like embodied brains are always being informed by their context; therefore, what was once noise can become useful information. Living systems have been specifically selected for because of their sensitivities to many diverse signals. Although, this certainly makes biological systems "noisy" with all the interference, it is *not* pure noise. It is what this project will call *structured noise* in that the origin of noise is not merely thermodynamic random activity. It is a terrain literally formed by many specific ranges of internal and external signals, which the organism has evolved to absorb and embody. Structured noise – i.e. the superposition of many diverse, yet relevant, signals – will tend to have persistent distinctions just waiting to be discovered and exploited for the sparse, yet useful, information they contain about an agent's relationship to its complex world; it is as if an FM radio "learned" to tune into distinct stations from what was once just "noise" prior to learning. This structured noise, for example, can be the interference pattern among many active nodes – whether cell towers, radio stations, neurons, or diverse electrical circuits – and it contains very useful information about the surroundings of some group of nodes immersed in these dynamic terrains of energy. Their collective response to this patterned energy, like the symphony analogy, is itself a superimposed higher-order pattern. For example, imagine a novice band learning not only how to play each of their respective instruments, but how to make music together. Noise is the initial product, but within this relatively unrewarding interference is sparse order. It is the capacity for living systems to leverage this sparse, though real, order among the noise and remember it. The band becomes better as they cohere upon the sparse order that exists within the superimposed terrain of acoustical energy that each musician simultaneously molds and is molded by.

Even competent musicians must learn to work together over time; they must synchronize while preserving some individuality. And, this paradoxical balance must forever be evolved between the distinctness of the individual agent and the integration among many unique individuals into more complex, relevant, and effective assemblies. The rewards for striking this balance among musicians is rewarding music for the musicians and the audience, which are engaged by how each musicians' unique contribution is integrated into higher-order communal patterns. Similarly, early humans gathered in groups to take advantage of both their diverse and common approach to a shared problem, namely, survival. This paradoxical balance is a prime premise for the project of synthetic cognition in particular and open systems in general:

Nature is both distinct events and their inter-relations, *simultaneously.*

Like early social humans and the musicians they became, living systems within their open environments must strike this balance by adapting to the diverse patterns within their local environment that are relevant to their survival. Individuals within any species have been selected for by evolution if their individual sensitivities to and aptitudes within that environment prove advantages. But evolution has selected for more than just a reflexive one-to-one mapping between sensory stimulus and an animal's behavior. Nature also selected for a capacity to make relationships between many sensory inputs within each living agent. The same principle works at the cellular level where diverse cells aggregate to manifest multicellular organisms that can "know" more breadth *and* depth of their environment than the single-cell alone; and, at the social scale, the community is collectively more diverse *and* integrated than any one individual. There is no real limit to the level of relevant complexity that the evolutionary process can imbue into commensurately complex agents; these paradoxical tendencies of open adaptive systems are scale invariant. Practical questions of implementation, however, are still begged: how is the sparse order among co-active agents found and how is it remembered to advantages ends for the cognitive agent?

One simple way to visualize this phenomenon is ripples on water, as shown if **Figure 1.2**. Here is a physical example of superimposition whereby each drop on water is a distinct event, but their interfering ripples create an integrated interference pattern. Even if many drops co-occur, there is still relevant structure within the interference that instantiates in water the spatial and temporal relationship between each event within the shared pattern at each instant.

And it is the sparse order within these relatively complex patterns that can be selected for if the agent has evolved to feel it and then literally re-*form* to further instantiate it. **Figure 1.3** abstractly marks "paths" between the drop events, which are physically distinct regions within the interference pattern that do in fact indicate relationships between drop events. This is potential order. This sparse order amongst co-active nodes, or "drops", exists and can be leveraged to harvest higher-order patterns that are potentially relevant to the agent that embodies these nodes, whether organic neurons or human fabrications

This potential higher-order information that is over and above the energy in each signal, e.g. drop events, alone will prove critical to cognition when work is defined in a different context from

equation 1, namely, currents and voltages in physical circuits.

Work = $\int$ I x V dT **equation 1.2**

Equation 1.2 is intuitively related to **equation 1.1** above in that some force changes the system. In the more familiar case of **equation 1.1**, a box, for example, can be pushed along the ground as illustrated in **Figure 1.4**. This is work in that a force is applied to the box to move it through a distance, i.e. Work equals Force through a distance. Work as defined in **equation 1.2** is moving electrons, i.e. current (**I**), through space via a force that is applied by a potential, i.e. voltage (**V**).

Like all work, it depends on the relationships between forces & masses or potential & charges. Work as defined in **equation 1.1** above is the former scenario, while work as defined in **equation 1.2** is the latter scenario. This second work definition intrinsically embodies superposition, because it matters how distinct charges, with their own extensive EM properties, engage the fields they both influence and are influenced by, simultaneously. Even though current and voltage can be measured separately, they intrinsically work as one system in an active circuit, not unlike the music example above. Each molds the behavior of the other in real time.

This project of synthetic cognition will employ both superimposed systems and work. It will help, however, to start by describing superimposition in simple adaptive organic systems. Work will then be employed to describe and implement nature's lessons into self-adaptive systems.

One way to understand how order can accrue out of superimposed systems, is to start with a single cell organism in its environment. And here in lies the origins of sentience, awareness, and any embodied capacity to “know”. The term sentience is from Latin *sentire*, to feel. The adaptive behaviors that result from these sensitivities are as simple and ubiquitous as avoiding toxins and predators while often simultaneously moving towards nutrients and prey. The single-cell will have evolved to sense toxins and nutrients that are relevant to itself. Many will also have evolved motility to move away from and toward these gradients, respectively. In fact, they can do both at the same time, a primitive form of decision making where the cost of the toxin is weighed against the benefit of the nutrient. How exactly this weighing is performed is extensively discussed in the full proposal. The main point for now is that these superimposed environmental gradients exist and are navigated by the organic agent away from danger and/or towards satiation. If there is no distinct gradient, the agent will engage in an indeterminate dance with no discernible direction.[4] This will proceed until a discernible gradient is perceived. The ability for the organism to feel this environmental order directly affects its capacity to survive; this would therefore be selected for by evolution. The chemical mechanisms that are the single-cell's ability to perform this task is informative, but beyond the scope of this Chapter. In any case, this capacity exists not just for the single-cell organism but for all cells in multicellular organisms, especially neurons. Specifically, not only do cells travel as in the developing brain, but they send out projections to make useful connections with other cells, as with axonal and dendritic projections and connections.[5] And, again, the question can be begged: how are these projections "led" to useful connections that produce better than chance outcomes for the organism that embody them?

The answer advocated by this project is that the system itself creates its own "luck", so to speak. In other words, there are many different cells with slightly different sensitivities, like many single-cell organisms in close proximity that, instead of just moving away from or towards toxins and nutrients, emit chemicals and EM potential fields in response to sensing specific phenomena that it has evolved to sense. Again, each of these cells have a different "perspective" in that they are sensitive to different compounds or different electromagnetic frequencies from the interstitial, or endogenous, space between cells.[6] [7] [8] When these diverse chemicals or frequencies co-occur in this community of cells, they will emit their own "call" or electro-chemical emission. The sparse number of cells that are co-stimulated by specific environmental stimulations will create a complex interstitial superimposed topography of diverse electro-potential and chemical gradients that will persist for a moment. This superimposed chemical terrain is simultaneously a distinct, diverse, and integrated pattern. And it is along the distinct features of this persistent physical terrain that projections can grow among the stimulated cells. Subsequently, this growth is *not* random. It is ordered along the gradients among the co-active cells not unlike the ripple analogy above. So, not only is there the information of each distinct individual response to diverse coincident stimuli, but there is also the integration of these diverse and distinct events into an integrated organization that *did not exist* before. This re-organization is a relevant and physical, e.g. electro-chemical, assimilation of higher-order. The more this pattern persists, the more robust the connections are made among the relevant, yet sparse, cells within the agent. Furthermore, these physically instantiated higher-order patterns can now be associated with other distinct higher-order patterns over time to create ever more complex assemblies of higher-order patterns within the agent's similarly complex environment.

As a result, the adaptive agent can recognize and potentially respond to these higher-order complex patterns with greater alacrity, saliency, and ultimately knowledge. The system learns by physical assimilation of, not only particular things, but relations between these things. And, in the case of cognitive animals, the central nervous system is embodied within not only the agent's environment but, more locally, within the inner environment of the agent's own body. As a result, coincident patterns that a brain receives are not just from external sensory modalities, but internal sensitivities as well. These internal patterns then integrate via superimposition, as described above, with external patterns to create a unified simultaneous pattern that is composed of both distinct internal and external events, and their integration into a single pattern. The phenomenon of significance and meaning follows from this physically relevant co-stimulation of external and internal stimulations. External stimulations have meaning for the organism in that they co-occur with corporal internal responses and instantiate complex patterns like diverse drops on water creating an integrated interference ripple. *To manifest knowledge, it is not enough to have a one-to-one mapping between sensory stimulation and behavior. The cognitive agent must be able make physical higher-order patterns that embody both distinct events and their spatial and temporal relationships, simultaneously.*

Commonly available technology is not to the level of implementing organic cell growth as exemplified by dendritic connectivity between neurons. Never the less, current technology is able to implement the basic attributes necessary to realize cognitive capacity synthetically. The physical interstitial terrain described above can be implemented by currently available circuit and network technologies. Novel and adaptive circuits can literally grow as a result of the collective open system activity. And to more rigorously understand this phenomenon, work is a concept that captures the necessary attributes of self-adaptive systems. For example, imagine again the box being pushed by diverse forces. Since force is a vector, it matters which direction the forces are being applied relative to each other as illustrated in **Figure 1.4**.

In the first case, forces 1 through 4 are mostly against each other. Because the force vectors largely oppose each other, it is quite possible that the box is not moved along the plane. If no distance is traveled, no work is done. In the scenario on the right, however, the force vectors add more constructively thereby ensuring that some distance is traveled and therefore some work is done. **Figure 1.4** illustrates that a great deal of force may be applied, using energy to produce that force, but that no useful work is actually done. This is because work requires some level of order between forces, the matter they are engaging, and the environment. These relationships are illustrated in **Figure 1.4**, and it also matters how each force relates to the matter they are engaging. For example, a force that is both normal to the object's surface and the direction of greatest free motion, e.g. direction **d** in **Figure 1.4**, will produce the greatest potential for work. The relationship between matter and energy is relevant. This is also the case in cognition, whereby work is employed to best understand and implement the dynamic, open, and diverse system that will be synthetic cognition.

A superimposable system, which employs work as defined in **equation 1.2**, is able to cohere towards, not just one pattern or "goal", but towards many diverse patterns *and* their inter-relations. And these inter-relations become higher-order patterns in their own right. It is argued in the full proposal that systems that can superimpose many patterns on each other are required for higher-order adaptive cognition. Work, as introduced in **equation 1.2**, is the physical description of its implementation. The common denominator for synthetic cognition are the physical oscillations of currents in circuits and electric potential both within circuits *and* around them.

One way to understand how these concepts lead to implementation is to extend the music example towards the application of synthetic cognition. Specifically, imagine a large population of diversely tuned oscillators, which can simply be thought of as tuning forks. **Figure 1.5** shows a small portion of a larger population that is being stimulated by its environment. As specific nodes are stimulated by specific signals from the environment, their specifically tuned circuits resonate so that work can be done by them. **Equation 1.3** below extends **equation 1.2** from the analysis of just one circuit's capacity to do work, to the summation of many diverse circuits' capacity.

$$\text{Work}\Big|_b^a = \sum_i^n \int_b^a \mathrm{I}_i \, \mathrm{x} \, \mathrm{V}_i \, \mathrm{d}\tau$$ **Equation 1.3**

In general, adaptive systems must re-create environmental energy patterns, or "terrains", in their own internal common medium. These assimilated terrains can then be leveraged to do useful work. For example, physical reality is full of acoustic, EM, and chemically superimposed patterns in diverse mediums such as air, space-time, and volume. Music is an example of such a pattern in the medium of air. This patterned and distinct energy is transduced[9] into the system's medium, which for this project will be populations of connectable oscillators that both mold their collective local electromagnetic terrain and are molded by that same terrain. For illustration purposes, however, the system will be visualized in **Figure 1.5** as if it were ripples in water as in **Figures 1.2** and **1.3**. Importantly, if the system has not evolved to resonate with certain environmental phenomena, then the system will not perceive such phenomena. Humans, for example, do not perceive the vast majority of physical reality. Vision only perceives a very small portion of the electromagnetic spectrum and human hearing is only sensitive from about 10Hz to 20,000Hz. But the sparse population of diversely tuned oscillators, or nodes, that have evolved to respond to distinct signals, thereby co-occurring with diverse physically coincident phenomena, will create a unique pattern that is composed of both the distinct events of individual oscillators being stimulated, and their inter-relations via the superimposed EM pattern among them. The response of each node is then able to do work back on its local environment as described in **equation 1.3**.

But to accrue these inter-related layers of order, these patterns must be recognized and adaptively acted upon at a relevant moment in the future. This literal re-membering is a re-knowing in that the complex inter-related patterns among distinct sub-agents, e.g. oscillator nodes, must be re-created based on subsequent environmental stimulation. To achieve this behavior among oscillators, connections are created and strengthened as patterns among these coincident nodes persist to sustain the sparse order among them. The full proposal goes into great detail on how this is technically achieved. The important point for this Chapter is that connections which have accrued among former exposure to sparse order biases the system so that the system “learns” to expect some patterns over others. **Figure 1.6** illustrates how this strategy can be scaled to increasing levels of complexity, thereby facilitating the system's ability to recognize and adaptively respond to future environments that exhibit previously learned patterns.

Within the system the auditory sub-system superimposes distinct notes, while the visual sub-system superimposes distinct colors and forms into unique internal patterns. These distinct patterns from different sensory inputs can now be superimposed into even higher levels of the system that are responsible for integrating diverse sensory modalities, e.g. audition and vision. Note how the system can scale to integrate diverse external patterns from diverse external mediums into a unified, unique, and distinct internal pattern that also preserves some of the original constituent signals, e.g. notes, colors, and forms. Other internal sub-systems can be further integrated with those illustrated in **Figure 1.6**, such as motor systems (not shown).

These connections, biasing the internal structure of the system, increase the capacity of the system to do useful work within its particular environment. **Figure 1.7** uses the chord example where four nodes respond to component frequencies within the Cmajor chord. Without learning, the nodes are only stimulated by environmental stimulation. After learning and the creation of physically relevant connectivity between those nodes, however, the four nodes act as an assembly not unlike the Work = Force x distance example above. Unconnected nodes tend to act independently, only being stimulated by external patterns. Once connected, however, they are not only stimulated by the relevant Cmajor external chord, *but by each other internally*. As a result the four inter-connected nodes do more work than the four nodes alone. This is because each inter-connected node is not only stimulated by a dynamic and varied environment, but also stimulated by an ordered internal structure in-formed by persistent relevant patterns over time.

Not only is more work available to increase the saliency of the system's response to the learned pattern, but complex spatial and timing relationships are adeptly assimilated by this strategy. Timing, for example, among elements can be physically instantiated in the nodal assemblies illustrated in **Figures 1.6** and **1.7**. Each note of Cmajor may be played simultaneously or sequentially at different timing intervals. In any case, these physically relevant relationships are literally learned and re-creatable by the system itself via its common internal medium. Furthermore, other nodal systems, as described in **Figure 1.6**, can then literally feel the interference pattern of Cmajor along with any other chord or any other spatially or temporally proximal environmental patterns from diverse mediums. Distinct patterns, which the agent has evolved to be sensitive to, can now be integrated in a way similar to individual nodes dedicated to individual notes but at a higher-order of complexity. And, in turn, even more complex and useful work can be done at these higher levels of pattern complexity.

The inequality in **Figure 1.7** leverages **equation 1.3** to compare the potential work output between an unconnected system versus a system that was inter-connected by relevant physical activity from its environment via superimposed interference patterns. Time interval a-b is before learning, whereas interval x-y is after learning. The system in the latter time interval is more ordered. It has literally been molded and biased by coincident physical phenomena from its environment. This complex bias increases synchrony not only among internal nodes, *but between the system itself and its surroundings*. This inclusive open system increase in order provides greater capacity for the system to do more useful and increasingly complex work over time. This is self-adaptation, an attribute fundamental to cognitive systems at the animal scale and to a vital biosphere at the planetary scale. To realize this capacity synthetically, to integrate it with digital systems, and to apply it to a wide array of human applications is the intent of this project.

Chapter 2

Implementing Synthetic Cognition; SOARSE^{tm}

SOARSE^{tm} is an acronym for Self-organizing Adaptive Resonant Systems Engine. This overall project in synthetic cognition is a research and development process. SOARSE^{tm} is the applicable technology that will be created by this process. It will be the object of testing and development so as to either nullify or validate the proposed theory and hypothesis of synthetic cognition described within these chapters.

Any living agent must do work to survive and thrive. This work is both internal within the agent and done on the environment by the agent's activities. Work, as illustrated in the last Chapter, is ordered energy. And, as one might imagine, not just any activity by an agent in a given environment will be useful to that agent. This is why learning is essential to the survival of the agent. Living agents, at all levels of complexity, have evolved to be informed by their surroundings. In other words, they have evolved to be sensitive to certain patterns of energy in their environment and then to respond to those patterns in a way that increases their chances of survival and procreation. Put another way, agents have evolved to do useful work on their environment by being molded by work done on them by the environment. There is no magic or uncaused emergence involved. Life is describable with a classical understanding of physical reality. And, as introduced in the last Chapter, work as the integral of real power is one path to this understanding.

This Chapter proposes an actual synthetic agent, which will be used along with the concept of work to explain how a synthetic system can adapt to its physical environment. This adaptation will be shown to be an assimilation of relevant information, or “learning”. It will then be demonstrated via work that the increasingly informed agent can do more useful work on its environment, thereby increasing its capacity to navigate and manipulate that world. This Chapter will start where the last left off as illustrated in **Figure 1.7**.

Figure 1.7 illustrates graphically and mathematically how learning will enable the adaptive system to do more work with the same amount of resources. This Chapter will more completely explain this claim and how it can be implemented with current arts and means.

Fundamental to any adaptive system, whether single-cells or societies, is a diverse population of individuals that are able to interact with their environment and other individuals. What constitutes "interaction", however, is a significant stumbling block for understanding complex adaptive systems. This is because our inherited analogies for interaction are limited to discrete objects that interact per rules determined before hand, like billiard balls bouncing into each other per classical physical understanding of matter to matter interactions with no consideration for the environment around this very focused system. To understand cognition is to have a more complete understanding of 20th century physics by realizing that "objects" in reality are not discrete, only distinct. In other words, contrary to popular belief, the behavior of objects are subject to the physical nature of their pervasive context.

A rock falls, not because it has been programmed to do so by some rules, but because it finds itself raised to some height within a gravitational field with nothing to support it. The rock itself has gravity and does actually exert a force on the earth, but the gravity of the much more massive earth dominates the behavior of the rock. In any case, humans have not evolved to perceive the actual gravitational field. They can perceive the rock's behavior, but not the fact that space-time itself is bent by the presence of the earth and the rock. Never the less, modern physics empirically demonstrates that there is in fact a predictable field that is both created by mass and simultaneously molds the behavior of those same exact masses. Subsequently, objects in reality are physically extensive in nature. And the extensivity of one distinct object will superimpose with the extensive attributes of other objects to jointly mold each of their now shared fates. The same is true for neurons in cognition, but instead of gravity being the dominant force molding the inter-dependent fate of each neuron, the electromagnetic (EM) force is the dominant agent of shared interaction and engagement.

The pressing question for self-adaptation and cognition is how a system may re-configure itself to do more useful work over time; i.e. how does a system learn patterns from its surroundings and employ what is learned to increase its ability to adapt in that environment? Put another way: who or what will cause an agent to tend towards adaptive order better than chance? The answer is the capacity for the sentient agent to feel the superimposed interactions among diverse sub-agents, e.g. neurons in brains or people in societies. And who or what does this "feeling"? The answer to this question is the sub-agents themselves. In other words, like the rock and the earth that both modify space-time and behave according to the shared gravitational field that results, neurons in animal brains both create complex EM interference patterns and behave according to this shared EM field.

So, what might this look like synthetically and how will such a system be informed by its environment to increasingly do more adaptive work within it over time? **Figure 2.2** illustrates just such a schematic system designed to implement such self-caused adaptive behavior.

The analog portion in **Figure 2.2** is the same as the two-dimensional matrix of nodes illustrated in **Figure 1.7**, which is recreated in **Figure 2.2** as a three dimensional surface. In each are red Primary nodes and smaller, yet more numerous, blue Secondary nodes. The Primary nodes are designed to resonate with distinct signals from their local environment. Each Primary node is unique in that they respond to a distinct distribution of signals. They respond most strongly at their resonant frequency. For example, a tuning fork tuned to 440Hz will respond strongly when a 440Hz signal permeates it's form. The example from the first Chapter of chords is useful in that Primary nodes will be tuned to resonate with particular frequencies within a given octave in the audible range, e.g. 440.0Hz to 880.0Hz. It is not important that each node resonate with an exact note's frequency. What is important is that, for a given range (e.g. 440Hz to 880Hz), there is a diverse population of Primary nodes that resonate with a diverse distribution of frequencies within that range.

When specific frequencies from the environment – like a Cmajor chord played by a piano, for example – specific Primary nodes will resonate with the particular frequencies within that chord. These specific Primary nodes are the nodes in **Figure 1.7** that send out their own ripples in response to resonating with the physical phenomenon of sound through the air from the piano. If this chord persists the interference pattern among the nodes will also persist thereby creating distinct ripple pattern as illustrated in both **Figures 1.7** and **2.2**. These distinct patterns are the causal result of particular nodes responding to physical events in their environment. As discussed in the previous Chapter, not only are these distinct events instantiated in this interference pattern among nodes, but also the spacial and temporal relation between these events. The interference pattern embodies these events and their relations, simultaneously. As a persistent pattern in its environment, it could potentially benefit the system to remember this pattern. To do this, the Secondary nodes have been designed to be sensitive to distinct regions within the interstitial interference pattern as illustrated in **Figure 2.3**.

These Secondary nodes (S1 through S5 in **Figure 2.3**) can convert their analog sensory response to a persistent pattern into a digital representation. These digital representations of what the Secondary nodes sense are then compared via simple Boolean logic so as to discern distinct regions within the larger local pattern as in **Figure 1.7** and **2.2**. Once discerned, virtual vectors will be established between co-active Primary nodes. These virtual connections can now be uploaded back to the Primary nodes. These connections are analogous to neural connections in the embodied animal brain and artificial neural networks.

These connections bias the behavior of the updated Primary nodes so that they will respond differently the next time similar groups of nodes are stimulated by physical signals in their environment. Specifically, once a connection is made between two Primary nodes based on past coincident activity, each Primary node will stimulate the other via the accrued connections if either node is stimulated at some future time. As a result, when a formerly learned pattern, e.g. Cmajor, re-occurs the system will respond much more vigorously so that, from the system's "1st person" perspective, the Cmajor chord is the most salient event in its external environment, because that is the most salient internal pattern. In other words, the Cmajor chord has more significance to the system than other as yet unlearned or imperceptible patterns. **Figure 2.4** schematically illustrates the circuitry of a typical Primary node.

Prior to any connections between nodes, a signal emitted from some Primary node is only a result of the local field. For example, a Primary node that has no inter-connections with other nodes will only be stimulated by the field via a receiver @ **g** in **Figure 2.4**, if the oscillator/filter group @ **d** is tuned near a signal present in the environment; e.g. an oscillator tuned to 100Hz will respond to a local field signal near 440 Hz. If it is stimulated to excitation, the Primary node will emit a signal into the interstitial space among nodes via the transmitter @ **h**. As Primary nodes fire simultaneously, they will create distinct regions of sparse order within their shared local field. Connections will then form between these coincident nodes as described above. Once connections are made between nodes, the tendency for a Primary node within a connected assembly to fire will change. This Primary node can now receive stimulation from not only local EM signals in the ambient local space, but also from formerly connected nodes via accrued inter-connections via inputs x_i @ **b** in **Figure 2.4**.

The critical event for any Primary node is whether it is stimulated enough by these influences to reach a threshold and "fire", which is analogous to an action potential in neurons. Whether a node fires depends on the voltage at the Threshold Trigger @ **f** reaching the threshold for a given Primary node.[10] If left only to input from the oscillator/filter group @ **d** in **Figure 2.4**, a Primary node will have less of a chance of firing than if the Primary node is stimulated by both the oscillator/filter group and inputs from formerly accrued inter-connections, x_i @ **b** in **Figure**

2.4. This is because the inputs from inter-connections will increase the voltage in the RC Network portion of the circuit @ **c**. This increase in voltage will increase the voltage at the mixer @ **e** thereby bringing the circuit closer to threshold and therefore firing. The rate of inputs @ **a** and the number of connections, x_i, matters because the resistors within the RC Network will drain the current at a certain rate depending on the RC time constant, and therefore reduce the contribution of voltage at the Threshold Trigger @ **f**. As such, inputs via x_i must be fast enough and numerous enough to overcome this current drain.[11] This is a direct way in which inter-connections contribute to the ability for a Primary node to do Work on its environment, because without this boost in voltage from the RC Network, the chances are reduced that the node will fire.

More stimulation from both resonant signals via a Primary node's reciever and inputs from accrued inter-connections with other Primary nodes will increase the chances that a node will fire. This means that even if a partial Cmajor chord can excite the entire trained assembly for that pattern, because the system is not only stimulated by its environment, but stimulated by itself based on its formerly learned biases. It will also cohere the firing *timing* of formerly connected nodes even if a future Cmajor chord event contains notes that are played slightly out of time with each other. Whether presented with a partial pattern or a slightly incoherent pattern, the assembly of inter-connected Primary nodes will tend to respond more strongly than if there were no inter-connections. This is an implementation of learning based on physically relevant patterns in the agent's environment.

The saliency of response by an in-*formed* nodal assembly is proportional to the strength of inter-connections within that assembly. This distinct and salient response is an ordered use of energy, and, therefore, results in the capacity to do more work such as recognition and the expression of formerly learned behaviors. This is because the energy consumed by each node coheres relevant individual responses to their shared environment with the response of other nodes. Like the work example with the box in the last Chapter, this coordinated use of energy increases order and therefore increases the amount of work possible by the group compared to each node acting independently.

In a very real and physical way inter-connections among nodes are based on real world patterns that re-*form*, or in-*form*, the system. Therefore the system becomes biased in favor of responding more vigorously to that learned pattern, e.g. sound of Cmajor, when it occurs in the future. This “vigor” can be more rigorously defined as power, which enables the distinct internal assimilation of Cmajor (the ripple pattern illustrated in **Figures 1.7** and **2.3**) to more effectively rise above the noise floor around it. And the power by which any Primary node transmits a signal to both the interstitial space via the transmitter and formerly connected nodes via inter-connections, is a function of the circuit configuration, the selective oscillator, and inter-connections via x_i and y_i. The mathematical analysis of the behavior of each individual circuit involves Real Power.

Real Power = I x V; where **I** and **V** are phasors **equation 2.1**

Real Power, and the concept of phasors, is illustrated in **Figure 2.5**. The red and blue sinusoids in **Figure 2.5** are current (**I**) and voltage (**V**) phasors, respectively. They are called phasors because their relative phase matters. In other words, in phase current and voltage behavior with the same phase and frequency will elicit the most Real Power, and Real Power is the only power that can contribute to Work in **equation 2.2**, whereby Work is generally defined as the integral of Real power.

Work = $\int$ I x V dT **equation 2.2**

Graphically, available Work is illustrated in **Figure 2.5** by the shaded area under the 'available power' curve. The shaded area in the first diagram of **Figure 2.5** is more than the area in the second, because current and voltage are slightly out of phase in the second. If some environmental signal is close to resonant frequency for a tuned Primary node circuit then current and voltage are brought closer to being in phase with each other, and, therefore, more real power is available for that node to do work both internally and on its local environment. This is technical nature of resonance in an electric circuit. So, relative phase and frequency of input signals from both the EM field and inter-connections affect Real Power and the ability to do Work for each Primary node. A third parameter is the amplitude of each signal. **Equation 2.3** is the general equation for a standing wave.

$A_i \sin(\omega_i t + \varphi_i)$[12] **equation 2.3**

$\mathbf{A}_i$ is the i^{th} amplitude

$\boldsymbol{\omega}_i$ is the i^{th} frequency

$\boldsymbol{\varphi}_i$ is the i^{th} phase shift

All three of these parameters affect how each Primary node behaves. And the main factors that shape these waves are the circuit design of each Primary node, their accrued inter-connections, and EM stimulation from their surroundings. So, as patterns from the environment, like chords, stimulate the system, a sparse number of Primary nodes will respond to the component signals within this patterned energy. The more closely the tuning of select individual nodes resonate with these signals, the more powerful the response by those Primary nodes. This results in a greater amplitude of response because current and voltage within a resonant node will be more phasically in sync and therefore have a more powerful response. In addition, as many different nodes are co-stimulated by many diverse signals at the same time, connections will be made among these nodes. As will be described shortly, these connections will increase both the amplitude of current activity and phasic synchrony among nodes. Per **equation 2.1** and **2.2**, this will increase Real Power and Work. This increase for a given assembly in turn will increase the response of each Primary node within that assembly thereby increasing the ordered interference pattern among them. Secondary nodes will then strengthen the connections among nodal assemblies with the more powerful response relative to their neighbors. This in turn will increase the power of that assembly's response, and so on in a positive feedback loop. This positive feedback loop will continue until a different external response out-competes the current feedback loop or some internal inhibition is employed to keep the system from over-cohering on any one pattern. Such competition and internal inhibition will be discussed at length in subsequent summaries and articles. For now, the important point is that this phenomenon of coherence can happen at all, because it is the basis of learning for the adaptive system.

And adaptive systems must learn many such patterns in order to remain relevant to their physical environment. The potentially useful Work that a system may do is directly proportional to the number of distinct patterns it has assimilated. And this assimilation is implemented by distinct groups of inter-connected Primary nodes. For example, a human can respond to many different chords it has learned over time. Many items, from plants to animals, friends to family members, and dangers to opportunities are actual physical patterns in an human's environment that can be learned. This project proposes that learned patterns are assimilated patterns, and that assimilation occurs when nodal assemblies inter-connect based on physical stimulation from distinct patterns in the environment. **Equation 2.4** sums the responses of each individual node within diverse nodal assemblies over a specific time interval. The more saliently assemblies respond to patterns in an agent's environment, the more completely that agent has learned those patterns by making relevant connections among nodes in response to actual physical signals within their environment, e.g. notes in a chord, forms and colors of objects, or the frequencies within a friend's voice. The degree of saliency for each distinct assembly, and therefore the amount of Work they can do, is assessed by **equation 4**.

$$\text{Work}\Big|_{b}^{a} = \sum_{i}^{n} \int_{b}^{a} I_i \times V_i \, d\tau \qquad \textbf{equation 2.4}$$

More specifically, each i^{th} Primary node with its own circuit characteristics and inter-connections will produce its own unique real power curve through the time interval [**a, b**], based on the amplitude, frequency, and relative phase of current and voltage both inside and around the circuits. The Work for each individual node is expressed by **equation 2.2**, whereas **equation 2.4** sums the work from each Primary node over the same time interval. And as the adaptive system accrues connections among nodes, Work summed over the whole system over a subsequent time interval will tend to be greater than a previous and less learned interval. The potential to do Work, therefore, must increase for a system to be truly adaptive. This is expressed by the inequality at the end of the first Chapter, and reiterated in **equation 2.5**.

$$\text{Work}\Big|_{b}^{a} = \sum_{i}^{n} \int_{b}^{a} I_i \times V_i \, d\tau \;<\; \text{Work}\Big|_{d}^{c} = \sum_{i}^{n} \int_{d}^{c} I_i \times V_i \, d\tau \qquad \textbf{equation 2.5}$$

~ … … … ~

The devil, of course, is in the details. How exactly the system builds upon the concepts and schematics introduced above to accomplish this increase in overall Work potential[13] is non-trivial; however, the solution is not prohibitively complex or exotic. The solution has been illusive through recent human history not so much because technicians and scientist don't know enough about cognition, but because certain cultural preconceptions obfuscate the most parsimonious solution. For example, the tendency of the well trained technician is to minimize entropy or maximize Work defined in **equation 2.4**. But this causes the system to over-cohere on one or a few patterns at the expense of many diverse patterns, which are required to navigate a complex world. Such strategies also compete against the critical capacity for such patterns to superimpose into higher levels of order, and even greater potential for Work. These claims will rigorously be argued in the next Chapter. The task at hand, however, is to illustrate one possible implementation for a self-adaptive system capable of higher-order assimilation of potentially limitless environmental patterns given fixed resources. **Figure 2.6** situates the schematic circuit from **Figure 2.4** within a wider system diagram similar to **Figure 2.2** in order to illustrate how analog Primary and Secondary nodes work with digital strategies to implement learning and the capacity for an agent to internally create their own unique higher-order patterns out of lower-order patterns.

The organizing principle in **Figure 2.6** is that connections among Primary nodes are the result of each node's unique behavior and their collective behavior, simultaneously. Any adaptive system at any scale must mediate between the part and the whole. If not, higher-order adaptation is not feasible.[14] To implement this, the behavior of Primary nodes is simultaneously influenced by their own distinct physical configuration, i.e. their circuit design, and activity from the local whole via the superimposed EM output from local nodes. Each Primary node receives potential stimulation from the shared local field @ **a** in **Figure 2.6** and other nodes via hard connection **d** in **Figure 2.6**. As introduce in **Figure 2.2**, Secondary nodes illustrated in the top portion of **Figure 2.6**, will sense the sparse order among active Primary nodes, P1 and P2. This order will be assessed by a digital device and the resulting connections will be uploaded to the relevant Primary nodes, as illustrated by connection **c**. In this way, when a Primary node "fires" in the future, it will not only send its signal into the interstitial field, but it will also directly ping the nodes it has been formerly connected to. In this way, the analog portion of the system is able to run in real-time unimpeded by the time required for analog to system-wide sampling by Secondary nodes, analog to digital conversion, calculations to asses inter-connections among coincident Primary nodes, and uploading of virtual connections back to Primary nodes.

It is difficult to visualize these processes, because a number of distinct processes are superimposing upon one another at once. And, in the mix, the Primary nodes are responding in a very non-linear fashion to different types of stimulation, namely, the collective interstitial field and accrued inter-connections with other nodes, simultaneously. It helps to always remember that each Primary node is like any living agent. It has its own internal inertia in the way it behaves, but the environment also influences its behavior. It is the relationship between the two, the inherited form of the agent and the nature of the world it finds itself, that inter-mix within the agent to produce ordered, yet not totally predictable, behaviors. This balance between the individual and its evolved capacity to be sensitive to, or in-*formed* by, its surroundings is crucial to adaptability. One can reasonably argue that this balance is selected for exactly because it mediates between the distinctness of the individual and that individuals capacity to self-organize itself, other individuals, and its environment into a more vital arrangement.

Let's look at the system again from this perspective of balance and the ability to remain vital in one's environment. Observing the possible behavior of just one Primary node, **Figure 2.7** illustrates the inputs and the output in simplified wave form. The high frequency component occurs within the node when the filter/oscillator group resonates with a signal from its local field. The low frequency modulation of the high frequency signal is the influence from the RC Network, the result of input from formerly connected nodes. As illustrated, these two distinct inputs – i.e. resonant signals from the local field and stimulation from inter-connected nodes – modulate each other to make one wave. When this superimposed signal combines in a constructive way such that the Trigger Threshold is met, the node fires. This “firing” is represented by the bottom-most signal in **Figure 2.7**. It is the circuit output, which is broadcast both into the interstitial field and sent as inputs to stimulate other formerly connected Primary nodes down stream.

This output mimics the behavior of an important cell type in the animal brain, called a bursting neuron. It has two very important attributes: 1) each burst contains a sample of the frequency a distinct node will have selected for, and 2) the period of each group of bursts reflect the firing coherence of active local neurons.[15] In this way, the output reflects both the nature of the individual and that of the local group, simultaneously. This is closely analogous to musicians playing individual notes on the same beat. Each note makes its own contribution to the collective pattern, but the shared beat organizes many notes into a higher-order structure that has the potential to be more salient than notes acting alone with no shared order. Similarly, human groups optimize around this principle; whereby, the group that best leverages both unique individual contributions and the ability to synchronize these contributions in a way relevant to their shared surroundings will tend to out-compete less organized and relevant assemblies by doing more Work with the same access to limited resources.

This balance between individual responses and the group response to an environmental pattern is mediated by connectivity. As described earlier, many individual nodes respond to different aspects of the same environmental pattern. In response, each node transmits their own signal into the interstitial field. At first, this interference pattern may be considered mere “noise”. But the system is designed to harvest the intrinsic order within the *structured noise*. As connections accrue among relevant nodes, assemblies of increasingly coherent activity will emerge with consistent exposure to a pattern. This is because the only way to rise above the noise floor for an assembly of nodes is to muster enough power to out-compete the local noise. The only way to do this is to form connections to pull more current and to then cohere firing times – as illustrated by the lower frequency modulation in **Figure 2.7** – which will synchronize each individual nodes' output thereby, again, increasing the expressed Real Power. This capacity to rise above the noise floor can then be sensed by the Secondary nodes, which will in turn increase connectivity; and, the positive feedback loop self-reinforces as introduced above. As mentioned before, this self-reinforcement will be kept in check by a number of mechanisms, which will be discussed in subsequent summaries; not the least of which, to name one, is the emergence of other assemblies that are selected for by the changing environment.

Figure 2.8 illustrates this learning process over time in order to introduce another mathematical tool, which will help describe system dynamics more accurately. Wave forms have so far been discussed as if they are standing waves or waves of constant amplitude. In reality, oscillations in nature come and go, grow and die. **Equation 2.3** above generally describes the more simple fixed wave. **Equation 2.6** increases the accuracy of **equation 2.3** by adding an exponential growth/decay term. It simply accounts for the fact that waves wax and wane in reality; i.e. “whatever goes up must come down.” And this is good for the adaptive system, because only a sparse amount of system activity is relevant to a given time and place. As an agent's environment changes so must that agent's internal activity change to recognize and behave adaptively within its dynamic surroundings.

$$\mathbf{A_i \sin(\omega_i t + \varphi_i)\, e^{xt}} \qquad \textbf{equation 2.6}$$

There are a great many EM and circuit signals that will both surround and pulse within each Primary node. These diverse signals interact within each individual Primary node to affect the current and voltage behavior of that node. As has been discussed, and will be discussed again, these behaviors result in the amount of Real Power available over time, and thus the potential Work each node can contribute back to the scenario it finds itself. For simplicity, however, **Figure 8** focuses only on the growth of a nodal assembly's activity over other potential assemblies.

At $\mathbf{t_0}$, many diverse nodes will tend to respond at least slightly to a rich and novel environmental pattern. Some Primary nodes, however, will respond more strongly than others, because they will be tuned more relevantly to some sub-signal within this environmental pattern. This population of strong responders will output their signals more strongly into the interstitial field. As a result, at $\mathbf{t_1}$, the strong responders will tend to form connections with the other active nodes, because Secondary nodes sense the sparse order caused by the selective Primary nodal activity. Due to these preliminary connections nascent nodal assemblies will self-stimulate each other. Therefore, their collective activity will decay slower than nodes acting alone, as at $\mathbf{t_0}$. This process of selectivity also occurs at higher levels of order whereby some assemblies will out-compete other fledgling assemblies, because the more active assemblies will have formed connections among Primary nodes whose tunings have proven more physically relevant to the environmental pattern. As such, the illustration at $\mathbf{t_3}$ represents an assembly whose decay term is less than at previous times. This persistence will encourage even more focused inter-connections and therefore contribute to the positive feedback loop discussed earlier. Other, less relevant, assemblies will have dissipated because the selected assembly will have consumed all the local available system current. This and other restraints will prove very important to a viable adaptive system capable of homeostatic behavior, and will be discussed at length in future summaries.

Figure 2.9 graphs the general growth and decay of nodal activity introduced above relative to the ambient noise floor. This is important because Secondary nodes are unable to discern sparse order of just one Primary node or an assembly of nodes if their output power level does not emerge out of the ambient noise, like a volcano emerging above sea level to create an island. Again, this noise is structured in that it contains many potentially relevant signals, but until a sparse number of signals are amplified above the average ambient activity, no salient activity can be discerned and learning cannot commence.

Another interesting aspect of **Figure 2.9** is that it is scale invariant in its application to the adaptive system. In other words, the graphs above are just as applicable to a single node's activity as they are to groups of nodes at any level of complexity. At any scale, the discernment of sparse order must rise above the surrounding noise floor. It's conceivable that the noise floor will drop locally as an assembly within this locality pulls the available current away from less relevant nodal responses. Therefore, saliency of a pattern within the system increases as the contrast increases between the rise of the selected assembly and the subsidence of the deselected noise.

The shape of the growth and decay behavior between the two scenarios in **Figure 2.9** is also important as it relates directly to the Work capacity of a Primary node or assembly of nodes; and, therefore, it is proportional to the survivability of the agent in its environment. The curve in diagram **a** ramps up slowly and it descends quickly. This curve represents a node or assembly of nodes that have not cohered enough connections to quickly accrue available current to then exhibit enough power to emerge above the surrounding noise floor. This latter scenario is represented in diagram **b**, which is a general representation of the the inter-connected assembly illustrated in **Figure 2.8 @ t_2**. Graph **b** in **Figure 2.9** will also tend to sustain itself above the noise floor, which will encourage even more inter-connectivity and increase the amount of Work it can do. This is because more power expressed by more nodes over more time equals more Work per **equation 4**. **Figure 2.9** nicely illustrates the inequality in **equation 2.5**, since graph **a** in **Figure 9** can represent time interval [a, b] and graph **b** can represent the more learned time interval [x, y]. This relationship is summarized in **Figure 2.10**.

This capacity to increase the potential to do Work is Negative Entropy, as introduced by Erwin Schrodinger in his short book *What is Life?*, and a relatively rigorous description of how living systems can adapt to their dynamic and complex environments.

Up to now one might claim that the schematic circuits above can reasonably be simulated by digital means. And, it is not hard to imagine diverse sensors being connected virtually in a digital neural network based on their coincident excitation. Analog to digital conversion with a digital coincidence function could relatively easily implement a simple version of the above system. However, what has been discussed above is only the beginning in terms of complexity. The decades old project of AI has proven fruitful in simulating very narrow aspects of animal cognition, but nothing approximating the complexity of even the simplest animal behaviors; e.g. the capacity of a mosquito to evade a human all night long employing just 100,000 neurons and near zero power compared to the most powerful supercomputers that can't match this level of navigation and complexity of behavior. And here in lies the fundamental crux of animal level intelligence – more inclusively called cognition – namely, the problem of energy efficient and useful behavior at arbitrary scales of complexity. This is the fundamental reason why the decades old project of AI has failed, namely, the capacity to reasonably scale in complexity.

A fundamental premise of I*for*AM's proposed project is that perfect accuracy of information, as implemented in digital machines, comes at the cost of the inter-relation of many types of relevant information into higher-order patterns that become their own whole composed of distinct parts. An appreciation of this attribute of nature, i.e. the distributed integration of many distinct patterns into more complex patterns, is at the core of this particular effort. It embraces complexity, not for the sake of itself so as to merely simulate complexity in nature, but to leverage the inherent capacity within this complexity to do increasingly more useful Work over time. In other words, an adaptive system must assimilate not just one pattern very coherently, but many patterns coherently enough to do increasingly complex and relevant Work. Not over-cohering on any one pattern too much allows for the system to switch from one recognized or behavioral pattern to the next relevant pattern with considerable ease; this is a ubiquitous brain behavior called metastability in neuroscience.[16] This permits the adaptive system to not only change their internal activity to resonate relevantly with the current state of their body and environment, but also to integrate many patterns into higher-order assemblies able to discern increasingly complex patterns and their inter-relations in the world. This useful complexity and how it builds upon the concept of useful Work to implement learning and adaptation is the subject of the next Chapter.

Chapter 3

Entropy and Adaptive Complexity

The previous summaries introduced superposition and work as fundamental to adaptive systems such as cognition. A necessary ingredient of creative adaptation is interference among distinct events. This interference, in evolved adaptive systems such as life, is the result of superimposition of multiple distinct patterns into one pattern, like the music example in the last Chapter. These more complex patterns will tend to contain more sparse order that living systems have evolved to harvest. The adaptive system physically re-*forms* itself to instantiate this sparse order. This is the assimilation of in-*formation*, the process of being in-*formed*. Then, as the term 'harvest' implies, ordered patterns are superimposed into even higher and more complex patterns. This project hypothesizes that these physically internalized higher-orders can be leveraged to do increasingly complex, useful, and adaptive work over time.

This Chapter rigorously defines a measurable attribute of self-adaptive systems able to exhibit the behavior described above. This attribute is *Complexity*. Its main inspiration is entropy from information theory. The fundamental attribute of Complexity for any adaptive system, such as living animals, is that they assimilate not just one or a handful of patterns so as to do more useful work over time, but that innumerable patterns may be learned *and then* associated with each other and other internal patterns so as to increase the adaptive capacity of the agent. In a colloquial usage, this increase in “complexity” is ill-defined. This Chapter, and the full research proposal, formalize this phenomenon based on the concepts of entropy, work, and the capacity to accrue many patterns into higher-order patterns of patterns. Once defined, Complexity can be employed to assess the success by which a synthetic system re-organizes itself to increasingly adaptive ends.

Adaptive complexity, i.e. Complexity, is not one solution for one problem at a time. It is the system's capacity to physically assimilate many adaptive patterns in response to a very rich, diverse, and inter-connected world so that more Complex, and therefore potentially useful, work can be done by that system in that world. It will be argued more rigorously in a future paper that digital strategies in general are specifically designed to edit out the intrinsic relationships between events in nature, which then must be added back later at great entropic cost in order to model the world to any degree of accuracy. Adaptive systems, on the other hand, have evolved to assimilate both distinct events and their inter-relations, simultaneously. Here again is the central premise of this project:

Nature is both distinct events and their inter-relations, *simultaneously.*

In order for a system to more usefully adapt to its local surroundings, it must physically assimilate both the innumerable distinct events, i.e. distinct patterns, in that world *and* the many relevant relations between them. The discrete and noiseless accuracy of digital strategies is very useful in many problem domains, but not all. Many problem domains are ill-defined and complex with inter-dependent and continuous patterns. The fixed functional nature of Turing equivalent computation, i.e. “digital”, does not apply itself to the wider ill-defined world. Sentient designers work a great deal to render their rule based systems relevant to an environment whose rules are not obvious. The discreteness of digital systems are clearly useful tools for their makers; however, the makers that made them are less constrained than the tools they make.

Life is a balance between constraint and freedom. For example, imagine the work example in **Figure 3.1** is an adaptive system. If the force vectors in System 1 are too divergent, or “under-coherent”, little or no work can be done. If, on the other hand, the force vectors converge perfectly on the desired free direction, **d**, maximum work is possible, since none of the vectors compete with each other. However, this convergence, or “over-coherence”, comes at a cost to adaptivity. Namely, such similar and focused forces lack diversity that may be relevant to different patterns in the adaptive agent's world. This cost is not realized as the system over-coheres on that one task in a single moment. Never the less, this cost is realized later when the agent's world has changed and that direction, **d**, is no longer relevant. Without a diversity of available forces, the agent has little or no diversity within it to respond usefully to diverse future environments. The over-coherent system is able to be very efficient when employed to do very limited tasks; as such, it is extremely constrained. At the other end of the spectrum, the under-coherent system is not able to do effective work in any case as its internal form is not distinct or constrained in any useful way. The discussion on entropy below lays the foundation for this important balance between over and under-coherence in self-adaptive systems, such as cognition.

entropy

Fundamental to the development of synthetic cognition is a means to test built iterations for "success". Such benchmarks, however, put the researcher in the precarious position of presupposing what successful cognitive behavior is at its core. This begs a functional benchmark or threshold for progress. But, as this project will repeatedly argue, cognition is an open system within a wider open system. To completely presuppose proper network behavior and its efficacious relevance to that open system is to model the open system. This modeling effort alone would preclude the researcher from building the cognitive system, let alone the opportunity to test it. In other words, the adaptive system, including any robust form of cognition, necessarily evolves within its dynamic, indeterminate, and model-resistant environment. To suppose what a distinct cognitive system – from its unique perspective – must assimilate from that environment would be a prohibitive effort. Never the less, if this caution is headed, some statistical tools can be used to *infer* progress. One of these tools is entropy.

Entropy for a system will always increase unless free energy can be imported from its surroundings and excess entropy can be exported. The capacity for life on earth to do just this – import free energy and export excess entropy – is what Erwin Schrödinger called Negative Entropy in his short book *What is Life?.* Life on earth does dodge an inexorable slide to disorder as observed by the second law of thermodynamics. In doing so, without contradicting this second law, life does in fact export entropy as heat and waste while importing free energy as solar energy and nutrients. But this is just one observable attribute of life. The reduced rate of local entropic increase is a necessary aspect of life, but not sufficient in of itself. It is not enough to maximize the order and predictability of a system's behavior. Such predictability is the main attribute that entropy measures. Cognition, as an extension of life, is highly ordered relative to its surroundings, but order per se is not enough to implement a process such as cognition. Never the less, understanding what order is provides a foundation for understanding the mystery of mind, and one of many tests that will be employed to infer project progress. The definition of entropy is useful in this task.

If rolling a fair die, it will have an equal probability of landing on each side, specifically 1/6 probability per side per role. The distribution looks like **Figure 3.2a**. If, however, the die is unfair, the die will have an increased chance of landing on one particular side. In this way, this particular die is structured and its behavior is distinct. After many roles, its outcome distribution might look like **Figure 3.2b**. It takes more information to describe the unfair die because of its distinctness. To just say that each side will occur $1/6^{th}$ of the time is more simple than listing the probability separately for different sides as is the case for **Figure 3.2b**. The relevant corollary to information systems is that the unfair die embodies more information. It is distinct in its physical formation.

In terms of entropy, the deformed die is more structured and therefore more ordered. This means that the outcome is biased so that the number six side can be expected more often. Therefore, if one were to put money on this die, after a number of roles, they would tend to bet on the six outcome. A fair die offers no such information because the system is not biased. It has no intrinsic order across many roll events. Formally, the information entropy for the dice example can be written as follows:

$H(x) \equiv \ln(N!/x_1!x_2!x_3!x_4!x_5!x_6!)$ equation 3.1

Entropy is essentially the measure of how surprising an outcome is. The greater the entropy the greater the surprisal. The more distinct and biased a system is in its behavior, the more an observer is able to predict the outcome. This correlates to the system's order, therefore many describe entropy as inversely proportional to the order of the system, which is a useful analogy generally speaking. In this case, the denominator of **equation 3.1** is representative of the distinctness of the system's behavior. For example, x_1 through x_6 are the possible outcomes of landing on any one side. As the die is rolled x_1 through x_6 are populated accordingly. If the fair die is rolled 18 times, then it is probable that x_1 through x_6 will be populated evenly such that each factorial will tend towards 3!, which equals 6. The denominator is then 6^6, which equals 46,656. If, however, the unfair die is rolled, side six will come up disproportionately. As such, x_6 will tend to be more populated than the other possible outcomes. Assuming, again, 18 rolls and that the actual outcome reflects the probability distribution in **Figure 3.2b**, then $x_6 = 9$ and $9! = 362,880$. Now, this number, which doesn't even include the other factorials, is much larger than 6^6, which is the entire denominator for the fair die. As a result, the Shannon entropy for the unfair die is smaller than that for the fair die because of its structural bias.

Entropy above relates to the box pushing example in **Figure 3.1** in that aligned forces are less probable and, therefore, more ordered. If, for example, the fair die above is used to decide how forces are to be distributed around the box, then less work will be done than if an unfair die is used. This is because one outcome will be biased for the unfair die so that forces will tend to cohere together as with the second diagram in **Figure 3.1**.

Cognition, of course, is neither dice nor a box being pushed by different forces. Never the less, an aspect of cognition can be understood in terms of order, expectation, and distinct behavior as with an unfair die. The consistent and sparse response that is observed in fMRI studies in response to a particular image or percept, is usefully analogous to the distinct distribution of a deformed unfair die. The principle difference is that neural assemblies in the mind have many “dice” or “box systems”, each with a unique “deformation” or “diverse forces acting upon them”; furthermore, these forces change over time and are dependent on each other. A mind learns to recognize many percepts, and when a taught percept, such as a musical chord or an apple, is repeatedly presented to the agent, chances are good that a similar population of neurons will be stimulated with each exposure. The animal brain has evolved to literally deform itself in response to distinct and persistent forces, i.e. physically perceived patterns, from its environment. This is how the brain learns; this is how it is in-*formed*.

In the animal brain, which is sensitive to many different patterns in the environment through different senses, sparse networks are active at any one time. Local neurons relevant to persistent environmental forces, i.e. the percept, will fire coincidentally with some and not with others. This coincident activity between nodes and assemblies of nodes will create sparse order among co-active nodes as described in the previous Chapter. The system has evolved to solidify this sparse order, thereby increasing structural system order. But, again, the animal brain does not minimize entropy, maximize order in a functional sense; i.e. it is not programed to decrease entropy in any formal sense. This would be over-coherence upon a limited array of salient patterns, not a recipe for adaptation. Homeostasis within living systems is predicated upon a balance between the assimilation of many different ordered forms and the sometimes messy integration among these diverse patterns. This is the fundamental pre-condition for being an adaptive system and it tends to increase complexity.

basic complexity

If no neurons fire, no assimilation of information about the featured and integrated world is possible. Likewise, if neurons fire in a completely random fashion like the fair die, then no information is remembered by that system until it becomes biased. But, contrary to intuition, perfect order, which is the case where a system works in complete synchrony, as in **Figure 3.2c**, is not a perfect living system. Perfect order, in the entropic sense, necessitates perfect predictability at every level of the system. This presents all manner of problems for the agent that must adapt to its highly dynamic and indeterminate environment in order to survive. Essentially, order is constraint. Some constraint is necessary to persist as a distinct agent at all at any scale. But too much order over-constrains the agent to a fate that may prove incompatible with the changing world it is born into. Such forms are deselected for. The result of this selective pressure is evolution, namely, a balance between order and disorder. A brain with no activity can convey no information, and a brain whose every single cell is active at the same time similarly conveys zero information. A balance between the two is necessary, and a parabola can be used to illustrate this point as in **Figure 3.3**.

Appropriately, parabola means *balance* in Greek. Points **a** and **c** in **Figure 3.3** represent under and over-coherence, respectively. The x-axis is a spectrum of order. Zero order is on the left and maximum order is to the right; this is analogous to **Figure 3.2** and the different dice distributions. Under-coherence at point **a** represents no coincident behavior or complete noise. Over-coherence at point **c** represents total coincident behavior where every aspect of the system works in unison. The y-axis will be called Complexity.

In general, Complexity, as employed by this project, is intended to capture Gregory Bateson's notion of "patterns of patterns."[17] Within embodied cognition, distinct neural activity and the interstitial energy and chemical activity among them, constitute a pattern. Patterns are defined as the sparse order that persists above the *noise* floor, which is composed of the indeterminate surrounding activity for some arbitrary length of time, discussed at the end of Chapter 3. For example, the order that emerges amongst the coincident nodal activity, as in the chord examples, is in contrast to the ambient relative disorder in the local surroundings.[18] As such, useful patterns will reside in between complete randomness and total order, because the extreme states have no capacity to impart more information than a single bit. Patterns, in general, require some contrast between a figure and the surrounding ground. Patterns, as defined for this project, employ both order and disorder to provide this distinction as illustrated conceptually in **Figure 3.4**.

Both **Figures 3.4a** and **d** are under and over-saturated, respectively. In an information sense they each have the capacity to encode one bit of information with respect to their environments. **Figures 3.4b** and **c** are different. They each have the capacity to encode much more information. Another way to think of this is how much information it requires to encode each state.[19] One bit can encode the state of **a** and **d**, namely OFF and ON. Significantly more information is required to encode **b** and **c**. Intuitively, one can imagine an urban landscape. States **a** and **d** clearly have no capacity to represent the rich figure grounds of a city landscape. States **b** and **c**, however, can offer something. With greater resolution, states **b** and **c** can communicate more. The same increase in resolution is wasted in states **a** and **d**.

In cognitive systems, the “noise” that composes the noise floor, is not equivalent to random activity as discussed earlier, because the network and interstitial nodal activity is caused by the nodes themselves. In other words, the interstitial interference pattern may be composed of mostly indeterminate patterns. Never the less, minus truly thermal noise, it is largely compsed of potentially relevant information, because it is composed of the nodes themselves. Furthermore, this rich noise floor can serve as a “fertile soil” whereby relatively more ordered behavior is set against it in contrast, as in **Figure 3.4**. As such, there is always the potential for nodal activity to cohere out of this rich “soil” whereby a particular pattern raises above the noise floor depending on the state of that local assembly's environment.

Extending the soil analogy, the ambient noise floor is like the soil where potential plants grow by organizing the nutrients, water, and surrounding air into more ordered forms. The soil is not random per se as it is composed of atoms and molecules that are themselves highly structured. And these structures have intrinsic potential to be organized into more complex patterns. To the human observer, however, soil is relatively disordered. Similarly, to the neuroscientist, the observable patterns within the animal brain remain inexplicable and “random” when in fact they are merely indeterminate. It is tempting to model them as statistical distributions which, like dice, are based on independent random variables. Unlike dice, however, neural interactions are not independent nor random. They are based on the structured patterns within their environment, which is a product of local nodal activity. As a sparse number of nodes fire in a way that increases the amount of work they can do, they have an increased capacity to raise their collective signal above those of surrounding nodes, which are relatively less coherent. As time progresses, different nodal assemblies will rise and fall from this potential “soil” based on the patterned behavior within their environment. What physically causes some assemblies to cohere over others is the degree to which Primary nodes within the system are sensitive to actual physical signals within their environment, as discussed in Summaries 01 and 2. The point right now is that patterns cohere out of the collective noise floor. They then compete and collaborate with other patterns to persist as long as they remain relevant to their local environment. As Primary nodes cease to resonate with local environmental signals, they decohere back into the noise floor from whence they came. More relevant nodal assemblies then compete to rise above the noise floor and into the agents realm of awareness.

Complexity is born and dies with the capacity of patterns to not only rise above the surrounding noise, but to relate with other patterns creating increasingly involved *patterns of patterns*. Complexity is more than a just a two dimensional pattern as illustrated in **Figure 3.4**.

Complexity is the capacity for groups of distinct patterns to integrate with each other becoming higher-order patterns as illustrated in **Figure 3.5**.

The notion of "higher-orders" describes how at least two patterns, which persist in their own right, integrate into a pattern of patterns. For example, musical notes are their own patterns regardless of patterns such as chords and songs. These notes, while maintaining their individual nature, can relate with other coincident notes to form chords. Each of these notes, when coincident with other notes, will create specific chords. Chords are patterns of patterns. Similarly, songs are composed of chords that are arranged in a non-random fashion to reproduce a particular song. Assuming that notes are 1^{st} order patterns, chords would be 2^{nd} order, and songs would be 3^{rd} order patterns relative to the notes that compose them all. This should not be interpreted as a strict hierarchy since notes alone can still constitute a song, and notes in reality are not single tones, but composed of many diverse sub-harmonics, which can themselves create atonal "songs". In any case, the essence of Complexity, as defined herein, is the existence of higher-order patterns built by superimposing other patterns. The sub-patterns preserve some of their individual nature, like each note, as they simultaneously contribute to a higher-order, distinct, and discernible whole, like chords and songs.

Discerning these hierarchies of integrated distinctions is not a trivial task because the actual implementation of a pattern is distinct, but not discrete. Therefore, categorization – a time honored philosophical endeavor – is not as obvious as some would prefer. For example, the pattern that assimilates a blue hue in a particular part of the visual field can be associated with an incredibly vast number of higher-order patterns. This would not be a problem if the "blue @ visual field location x,y" neural assembly had a perfectly consistent and discrete behavior from moment to moment. By their very nature, however, adaptive systems have evolved to be physically molded, or in-*formed*, by their environments. And this capacity works at every scale of the system, so that an internal representation of some attribute, like nodal assemblies assimilate the color blue, will be molded by other coincident local nodal activity, which have assimilated the color green, to create a higher-order assimilation that internally represents yellow. And at even higher-orders of Complexity, blue, green, and yellow can all be integrated with objects such that a human might look at red and tend to think of fire or danger or hotness depending on the context. As such, internal representations are not a one-to-one mapping of attribute to object. This makes numerically assessing Complexity difficult.

Never the less, reasonable approximations will be made if access to the activity of each node is available. And SOARSE provides a very accessible data structure that is constantly updated, and which can be monitored and analyzed by a secondary system devoted to such a task. The history, and therefore its trends over time, can be examined as will be discussed further below. It is important to remember at this point that Complexity or any other numerically analyzable attribute of the system is *not* the system itself. These concepts, however, do help to understand the system by empirically exploring their behavior. The feedback will aid subsequent system designs.

complexity defined

If there was just one pattern in an agent's environment that is relevant to its survival, then that agent would merely need to internally assimilate that one pattern with increasing fidelity. For example, imagine a bacterium that only needs glucose to survive, and that there is only glucose in the environment. If such an organism evolved in such a world, then the bacterium would only need to recognize one pattern. Assuming, however, that the glucose is not evenly distributed, the bacterium would need motility and this motility itself is a pattern that would be best associated with the organism's ability to perceive glucose. As it consumed local glucose, the more evolved bacterium would tend to do work that moves it along the gradient of greatest glucose concentration. In reality, where many environmental influences exist, the simplest of bacteria can not only sense nutrients but toxic substances as well. In the presence of competing patterns, e.g. nutrients in the same direction as a toxin, the bacterium must "decide" whether the pursuit of nutrients is worth the presence of toxins. The tendency to execute specific behaviors in the presence of mixed and varied patterns in the environment is complex and can be modeled probabilistically even if physical reality isn't itself a probability distribution.[20]

Complexity starts with the correlation between environmental patterns and the agent's capacity to assimilate them internally. In addition to the assimilation of external patterns, internal patterns are also relevant, such as behaviors and states of existence like hunger or fatigue. For example, behavior inducing patterns can be associated with assimilations of environmental patterns, such as glucose abundance or paucity. Complexity involves both distinct environmental patterns that have been assimilated by an agent *and* the capacity to integrate relevant assimilated patterns, into higher-order patterns.

The saliency of a single internal percept can be discerned statistically over time. In other words, the exposure of the system to an environmental pattern, called an *event*, will elicit an internal response from nodes within the system. As described at the end of Chapter 2, it is expected that, prior to learning, exposure to a specific pattern will elicit a relatively weak and inconsistent response. This can be statistically illustrated by the flat distribution with a standard deviation of 5, at best, in **Figure 3.6**, or a perfectly random response at worst. Such "random" behavior is analogous to the rolling of a fair die whose distribution is more closely related to the straight white line in **Figure 3.6**. Both of these relatively indistinct distributions are indicative of a system that has not accrued structured internal assemblies relevant to patterns in its environment, and therefore not representative of a system capable of recognition of a said environmental patterns. With training, however, the response to a particular event is expected to become more coherent, again, discussed technically in Chapter 2. The correlation between the environmental pattern and local organized stimulation of a nodal assembly is expected to become more biased like the biased unfair die, therefore establishing a correlation between this external event and a corresponding internal percept. This increase in correlation between an environmental pattern event and the consistent response of internal nodal activity above the local noise floor indicates an increase in system order and a decrease in local entropy.

The adaptive system will assimilate many inter-connections among Primary nodes, which assimilate many relevant environmental and internal patterns. This increasing acquisition of physically relevant internal structures will increase the tendency of the system to respond coherently to patterns in its environment. Statistically, this can be represented by more salient and distinct probability distributions like the biased unfair die example. As internal inter-connectivity accrues in response to environmental stimulation that is discernible by a self-adaptive agent, many statistically distinct distributions are populated by measured correlations between external events and consistent internal activity. As these statistical distributions accrue, Complexity increases.

For any correlation between between an external event and consistent internal nodal activity, a standard deviation of less than one is indicative of internal order (as illustrated by the purple and gold distributions in **Figure 3.6**). Based on these observed correlations, an inference can be made that there is a causal link between external and accrued internal structures.

These statistical tools, as with the majority of scientific studies, will aid in discerning whether progress is being made towards cognition. It is important to understand, however, that statistical analysis does not indicate causality per se. It creates an empirical basis to infer it. Never the less, SOARSE will be designed so that relations between external stimulations and internal percepts – and between percepts within the system – are physically causal and not random. Statistical analysis assumes initially that nodes are independent and essentially random in their response to their environment. However, as the system's behavior incrementally deviates from random behavior through learning, structure can be inferred through statistical analysis. Just as an unfair die will have a skewed distribution, so too is it expected that learning an environmental pattern will skew the behavior of SOARSE as, for example, the internal system response to a specific external pattern moves from $\mu=0$, $\sigma^2=5$ to $\mu=-2$, $\sigma^2=0.5$ through learning.

As the system more accurately “learns” or internally assimilates an external pattern, the more tightly and consistently physical internal activity will cohere upon a particular network behavior. Although SOARSE will be designed to tend towards this structure in response to sparse order in its environment, it is not efficient to preconceive how the system actually coheres upon this sparse response to a particular environmental event. This is analogous to teaching a child. They can be tested to demonstrate that they have learned the intended material, but how each neuron continuously grows to instantiate the relatively ephemeral local sparse order does not need to be understood in detail once the system is set in motion. Similarly, it is very useful to establish that, with training, the artificial system has in fact done so. Other tools, such as the assessment of work discussed in the previous Summaries, will be employed to further understand the system's response over time. Intuitively, this dynamic behavior in response to the environment can be illustrated by a die that is incrementally deformed with each roll in such a what that it becomes more and more unfair towards one consistent outcome.

Complexity, as defined for this project however, is not only the number of distinct and relatively coherent patterns that correspond to similarly coherent patterns in the agent's environment. It is also the degree to which these diverse percepts are inter-connected within the system into higher-order patterns as illustrated in **Figure 3.5**. For example, as the internal pattern for hunger associates increasingly with more varied food patterns and the behaviors required to acquire and consume those foods, the internal structural terrain becomes more complex. As the physical nodes accrue relevant connections and respond to varied learned environmental patterns, probability distributions are populated for distinct patterns *and* their inter-correlations.

Quantitatively, Complexity will be numerically assessed by summing the inverse of the variance (i.e. σ^2) for each network response that is significantly above the noise floor (i.e. $p < .01$). Therefore, as an internal assimilation becomes more salient its variance will decrease, as described for the unfair die. The more biased and structured the die, the more predictable its behavior. The inverse of the variance is taken in order that a decrease in variance contributes to greater Complexity as defined. Another advantage of the inverse relation is that any sparse population response will have a variance less than one in order to contribute more than a Gaussian distribution would contribute to Complexity. But, again, it is not enough for a cognitive system to embody just one salient response to one environmental stimulation. The system will be exposed to, and expected to learn, many diverse patterns of stimulation. The more patterns the system responds coherently to, the more variances of each distribution is summed, thereby contributing again to Complexity. Furthermore, internal patterns that demonstrate significant correlative behavior with other internal patterns will themselves create their own distinct statistical distribution of expected activity with learning and continued testing. These distributions of associated behavior between populations will also contribute to Complexity, **Č**, as defined here:

$$\check{C} \equiv \Sigma_i (1/\sigma_i^2) + \Sigma_{ij} (1/\sigma_{ij}^2) + \Sigma_{ijk} (1/\sigma_{ijk}^2) + \ldots \qquad \textbf{equation 3.2}$$

Each $\mathbf{i^{th}}$ assembly summed in the first term are distributions whose random variables are populated by nodal activity with enough saliency so that their statistical variance is below 1 as described above. As the variance of each local population decreases, thereby becoming more coherent and salient, first order Complexity, i.e. $\mathbf{\Sigma_i (1/\sigma_i^2)}$, increases. But first order Complexity is not complexity enough for adaptive systems that hope to adapt to their complex environments. Nodal activity that populates the first order term can correlate with other distinct assembly activity, which is then represented by its own salient statistical distribution. Subsequent correlations between first order distinct assemblies, each with their own discernible distribution, become a second order statistical distribution. These second order correlations are represented by the $\mathbf{ij^{th}}$ assemblies. All second order system activity within a system contributes to Complexity in the second order sum, i.e. $\mathbf{\Sigma_{ij} (1/\sigma_{ij}^2)}$. These distinct second order assemblies, composed of distinct first order activity, can now exhibit correlative activity with both first and other second order assemblies to create third order distributions, i.e. $\mathbf{\Sigma_{ijk} (1/\sigma_{ijk}^2)}$, and so on to ever increased levels of Complexity and higher-order assembly activity.

There are three main paths to increased Complexity: 1) increase the quantity of distinct environmental patterns that are assimilated, 2) increase the saliency of each individual pattern (i.e. the accuracy), and 3) increase the levels of inter-related order between assimilated patterns (i.e. patterns of patterns). As defined, the first path to Complexity listed happens when the number of significantly[21] assimilated patterns is increased. In other words, the first term in

equation 3.2 represents one nodal assembly, which have no distinct sub-assemblies within them, but whose joint activity is salient enough to measure against the noise floor. The greater the quantity of measurably distinct assemblies, the greater the number of terms in **equation 3.2**, the greater the tendency for Complexity to increase, and the greater amount of work that tends to be done by the system as a whole. The second path occurs when an environmental pattern is assimilated, or "learned", more faithfully over time. As connections accrue among diverse nodes in response to a distinct environmental pattern, the system's speed and saliency of real power response to future occurrences of that pattern will increase. In other words, the system's response to a learned pattern will become more coherent like a child that responds more quickly and definitively to an adult's repeated questions about their shared world. This is physically described at the end of the last Chapter and statistically represented by a smaller standard deviation for each assembly's activity. The third path occurs when distinct assemblies, which have their own statistically significant activity, can be correlated with other distinct assemblies into ever higher-order assemblies of assemblies.

The assessment of Complexity is a relatively straight forward statistical task. The virtual data structure within the digital portion of SOARSE will provide the necessary data based on routine measurements of the free-running activity within the analog portion of SOARSE. As the system learns and discernible assembly activity rises from and falls back into the noise floor, the digital virtual data structure, which empirically tracks analog activity, updates without slowing the analog system down. Simple calculations can them assess Complexity as needed by the developer or the system itself. It is important to keep in mind, however, that the purpose of this assessment is only to discern progress towards the goal of synthetic cognition. Complexity, in of itself is not cognition. As defined, it is but one observable attribute of the proposed digital/analog hybrid, which will inform both the operation and design process of SOARSE.

From a more theoretical perspective, this empirically observable attribute captures the balance between over and under-coherence necessary for living systems introduced above. The coherence of each discernible pattern is necessary for any percept to rise above the background of cognition. However, a broad population of diverse recognizable patterns is also necessary in order for a self-adaptive agent to assimilate and potentially navigate its diverse environment. This simultaneous "depth" and "breadth", respectively, of pattern assimilation provides an endless opportunity for evolution of the self-adaptive agent. In other words, there is always more to learn about both individual events in the world and their relationships to their context. Although **Equation 3.2** does not represent specific physical patterns, it is a numerical indicator of progress along a limitless process towards Refinement, a concept that will be rigorously defined in the next Chapter and integrates concepts of Work and Complexity into one useful and falsifiable concept with many human applications.

Chapter 4

Relevance and Refinement; a Vital Balance

The last Chapter described the numerically assessable attribute of Complexity, an attribute that is necessary for a self-adaptive system to exhibit. This quantity along with both the amount of Work each Primary node actually does versus the amount of energy consumed by the system as a whole will further distinguish a system as a cognitive agent. Bringing Work together in relation to Complexity grounds an adaptive agent in its surroundings. In other words, Complexity alone is insufficient to indicate a truly self-adaptive cognitive agent, because some measure of Complexity can be presupposed and programmed into a system without concern for the environment that system is meant to adapt to. The inclusion of Work in the assessment of a system insures that the system is actually performing complex behaviors that are relevant to its physical environment. Subsequently, this Chapter will define a quantity called *Relevance*, which will be shown to oscillate, in a homeostatic fashion over time, as the adaptive agent learns.

Like most homeostatic behaviors in living systems, the oscillatory behavior will follow an average trajectory that is more dynamic that the fixed trajectory shown in **Figure 4.1**. For example, the metabolism, internal blood pressure, and even temperature will oscillate around a relatively fixed value over short periods of time, say 24 hours. The internal temperature of a human hovers around 98.6 degrees Fahrenheit when measured orally. Assessed over longer time periods, however, the maturation of the living agent will cause this averaged trajectory to change. For example, the average metabolism and blood pressure of a human is different as a teenager and different again as an adult. Throughout a 24 hour period, all of these attributes of living organisms will oscillate around a relatively stable average. Over years, however, that average value will change.

This homeostatic “drift” is a result of both change in the organism and the organism's environment. Change in the organism is the result of growth. Change in the organism's environment is typically the result of the organism engaging more of its environment, which is in turn dependent upon that growth. Each change, internal and external to the agent, converge to compel the organism to adapt. If it does not adapt it will die. Humans, and most complex animals, have a childhood where their world is relatively limited compared to the ability and necessity of the adult to navigate a wider range of their world, both in terms of physical area and in terms of diverse experience. Learning, even in insects such as bees[22], is an evolved adaptive trait found in the vast majority of the animal kingdom. Learning is dependent upon the organism's circadian cycles, especially the sleep-wake cycle[23], which is also homeostatic in its oscillatory behavior. Subsequently, it is argued that learning itself is an evolved behavior that is physically dependent upon homeostatic cycles. Therefore, an important clue about self-adaptive cognition can be inferred by this evolved, and perhaps counter-intuitive[*], behavior.

As discussed in the last Chapter, the assimilating of useful information, i.e. learning, in the self-adaptive agent is a balance between over and under-coherence, or more generally order and disorder. The paradoxical nature of self-adaptive learning is that disorder must be allowed to accrue momentarily for increasing amounts of Complexity, and therefore order, to be physically assimilated. Intuitively, this is the trajectory of an organism learning more about its ever expanding world throughout its life. Put another way, as the organism expands its awareness of its world, it encounters many diverse patterns of sensory input that may conflict, or compete, with each other at first. Technically, an increase of sensory input increases the tendency for noise to out-compete the capacity for the system to maintain an ordered internal state. To refine its higher-order understanding of the world, the organism must somehow organize these myriad of interfering patterns into a more Complex pattern, whereby both distinct events and their inter-relations are simultaneously embodied internally. This is the Prime Premise. This Chapter will formalize this useful oscillation between over and under-coherence, order and disorder, as *Refinement*, which will informally be defined as follows:

> **Refinement: A process whereby an arbitrary system expands its awareness of its surroundings while simultaneously increasing its own internal capacity to resolve the increase in disorder, which is the result of this expanded awareness, into a higher order internal structure.**

This Chapter will articulate what Refinement is and how it serves as a testable design guideline for SOARSE technology based on Work and Complexity. Starting with Complexity as defined in the last Chapter:

$$\check{C} \equiv \Sigma_i (1/\sigma_i^2) + \Sigma_{ij} (1/\sigma_{ij}^2) + \Sigma_{ijk} (1/\sigma_{ijk}^2) + \ldots \qquad \textbf{equation 4.1}$$

As discussed over previous summaries, the self-adaptive system must learn many patterns from

[*] Learning is often framed as an incremental process where progress moves inexorably towards increased coherence upon the intended behavior. It will be argued that the observed oscillatory behavior of learning in animals actually involves regular intervals of disorder, and that these intervals of disorder are actually required to achieve ever higher-orders of adaptive Complexity.

its environment to survive in that environment. It must also be evolved/designed to be sensitive to the diverse signals within that environment that constitute these patterns. To learn the internal structure of the self-adaptive system must not only have diverse nodes sensitive to diverse signals from its environment, it must also be able to re-configure the relation between these nodes to build more complex resonant assemblies, which will respond to ever more complex signals within its environment. The self-adaptive system does not presuppose these inter-connections between basic component signals. It literally feels the sparse order among the electromagnetic field that results from the interference patterns created by active Primary nodes. This sparse order is then leveraged to formulate physically relevant connections. Higher-order assemblies result.

To review the story so far, **Figure 1.5** from Chapter 1, which illustrates schematically how a 2-dimensional array of Primary and Secondary nodes can resonate with actual signals from the environment. The interference pattern between them embodies the sparse order that can be literally felt by Secondary nodes. These feelings will then be instantiated as inter-connections between Primary nodes, as described technically in the second Chapter. These connections will then make the self-adaptive system more sensitive to more complex patterns that formerly persisted in the environment to create the assimilated pattern in the first place.

From here, both the abstract attribute of Complexity, as defined in the third Chapter, is physically realized, *and* the capacity to do more Work over time is possible. These two attributes together contribute to a system's Relevance to its environment.

For this project, Relevance will be defined as follows:

Relevance ≡ Complexity / Cost **equation 4.2**

Where **Cost** is defined as follows:

Cost ≡ $\mathbf{U_{input}} / \mathbf{W_{nodes}}$ **equation 4.3**

$\mathbf{U_{input}}$ is the total amount of energy put into the system. $\mathbf{W_{nodes}}$ is the work done by each Primary node to both emit a signal and "ping" other nodes it has previously been connected to. For the self-adaptive agent to do anything useful in its world it must pay a Cost. The degree to which the internal structure of the system is suited to the diverse and complex patterns of its environment is proportional to the amount of useful Work that system can do in that environment. There is a very intimate relationship between the Complexity of the internal structure of a living agent and the environment it has evolved to do work within. A simple paramecium, for example, will need to internally assimilate different patterns to survive than a bird in its. In either case, of all the species that have existed on this planet less than 0.1% have maintained the careful balance necessary to survive today. This balance is between the evolved capacity to assimilate Complex patterns from its environment and the Cost that organism expends to do so.

As $\mathbf{W}_{\mathbf{nodes}}$ increases while $\mathbf{U}_{\mathbf{input}}$ is held constant **Cost** goes down. Human built machines are designed to maximize efficiency, which is inversely proportional to Cost. But, if the machine is designed to maximize the efficiency of a singular task designed by its creators, then all work is over-committed to that one task to the detriment of other potentially useful tasks. Furthermore, the work done in discovering such *potential* tasks is often perceived as a "waste" of energy. But animals "waste" energy all the time; one example being play. Play is intrinsically a process of discovery in one's world. As such, Cost as defined above is not called efficiency exactly in order to differentiate it from efforts to maximize it. Again, it is an evolved balance between Cost *and* Complexity. Animals have evolved to incur Cost in order to acquire what was before an unrealized means for survival, usually through learning and unstructured play. If an arbitrary system is constrained to maximizing the efficiency of one or a handful of preconceived functions, however, such exploratory engagements of one's world and the means to reap their benefits are lost. Human exploration incurs significant Costs in the short term because the useful work produced is low compared to the energy input. But this Cost of exploration and re-organization is necessary for living systems to increasingly engage their world and increase the chances that life in general will collectively survive in the long term. This increased ability to remain Relevant by engaging one's afore unexplored world is a balance between Cost and Complexity.

This balance can be figuratively visualized in **Figure 4.3** as a double overlapping parabola. The bottom parabola is the numerically definable parabola of Complexity introduced in the last Chapter, where the x-axis is order and the y-axis is Complexity at different degrees of order. The top parabola is a mirror of the bottom parabola. It represents the patterns in a system's environment that can possibly be perceived by that system. In other words, any organism will have a certain amount of internal Complexity capable of resonating with diverse patterns within its environment. If, however, it does not have an evolved sense to perceive a vast gamut of natural signals or does not have cognitive capacities to make relationships between these phenomena, it can not possible perceive them. A paramecium does not contemplate super nova, even if it might be hit by photons from such an event. It cannot discern these photons from a vast array of other similar photon events. Humans can, because we evolved the senses and internal Complexity to do so.

The upper parabola is less rigorous than that for internal Complexity, And, since the world is an open system, it is numerically intractable. Furthermore,

The lower parabola in **Figure 4.3** is rigorously based on **equation 4.1**. The upper parabola is not rigorous. It represents the patterns that are potentially perceivable within the world by an organism given the current level of Complexity within a self-adaptive agent. As a system evolves more Complexity or learns more Complex patterns based on this evolved capacity, the upper parabola will grow to reflect the phenomena in physical reality now potentially conceivable by that agent. It is not intended to be rigorous since to represent the open environment in a numerical manner is not the intent of this project. The upper parabola is a “mirror” to the lower one to indicate the inextricable relation between internal form in the agent and patterns from its environment that helped shape them. As the system learns and is empirically demonstrated to become more Complex, the more Complexity can potentially be assimilated by the system. Subsequently, as the area within the lower parabola increases, the upper parabola is proportionally increased. This illustration is meant to convey the general observation that adaptive agents are situated in a context and that the agent can only perceive as much of that environment as it has evolved, and then learned, to perceive. This may seem obvious to some, but it is often forgotten as many misinterpret Turing's ideas regarding “universal computation” to mean that computation, in any sense, can compute anything in the universe. This was in no way Turing's intent.[24] Any system capable of calculations, whether biological or Turing equivalent, is only sensitive to that which it has evolved or is designed to be sensitive to, respectively. Again, as a system becomes more Complex its capacity to assimilate or represent information, for biological or digital systems, is commensurately increased.

The vertical dimension **y**, which bounds both parabolae, reflects the amount by which the agent is physically dependent upon, or “engaged” with, its current environment. If, for example, each parabola does not overlap at all, there is no opportunity for the agent's internal system to be relevant to its environment at all. In this case, the ability for the agent to do useful work in that environment is removed. The agent has little to no chance of survival in this scenario. The other extreme is if the parabolae are allow to overlap maximally. In this latter scenario, the agent has little or no distinction because the majority of its deepest internal structures are directly affected by the real-time environment. This negates any opportunity for the agent to maintain some kind of autonomy or individual behavioral distinctness. The agent *is* essentially its environment, and the capacity for that agent to contribute to the overall order of its environment is ironically removed if some measure of autonomy is not available. The optimal relation to enhance the persistence and accrued order of both the agent and its local environment is a careful balance between engagement and autonomy. In this way, the paradox of the prime premise is made manifest physically, namely, the agent must be internally distinct while it also retains the capacity to engage its world. But, again, this dynamic balance can only be maintained if this balance is struck at every scale both inside the system (e.g. multi-cellular) and outside (e.g. speciation). And like all processes in nature this balance is a dance between these tendencies, each being relatively dominant for a moment only to give way to the other in a rhythm that is selected for over time based on its capacity to persist.

At any given moment a system may be operating predominantly at points **a**, **b**, **c**, or **d** in the overlap, as illustrated in **Figure 4.3**. Although not rigorous, it provides a conceptual understanding of adaptive behavior by providing operational constraints, which will serve as design guidelines for synthetic cognition. In other words, the system must have a requisite amount of internal autonomous Complexity that can also be in-formed by relevant patterns from the environment. If the agent operates outside of the constrained region it is at significant risk of either over or under-coherence, thereby significantly mitigating its fitness. The balance, or homeostasis, sought by the agent is not existence on a "knife's edge". It is the operational space evolved by a complex organization that is neither over nor under-coherent. Within this space the agent oscillates back and forth in order to iteratively cohere what it has learned, to then learn more. Different parts of the operational space indicate different operational states. Points **a** and **b** signify the operational gamut between under and over-coherence, respectively. Along the line defined by these points, the system maintains a medium level of Complexity, but the nature of that Complexity changes whereby point **a** typifies lower orders of Complexity, e.g. $\mathbf{\Sigma_i\ (1/\sigma_i^2)}$, and point **b** typifies higher-orders, e.g. $\mathbf{\Sigma_{ijk}\ (1/\sigma_{ijk}^2)}$. Points **c** and **d** signify the operational gamut between the system's potential relevance and irrelevance, respectively, to its external environment. Along the line defined by these points the system operates between minimum and maximum Complexity. The more Complex the internal organization of the system the more environmental events and relations can potentially be assimilated. Conversely, less internal complexity means less complex environmental patterns can be assimilated. Potential assimilation anywhere along the vertical dimension is contingent on how the actual system is designed. Specifically, it depends on how both the types of sensory modes – e.g. vision and hearing – and the amount of information is absorbed per each of these modes. Quantity of sensory information is contingent upon both the design of each respective sensory pathway and the operational state of the system, e.g. “awake” or “asleep”, which will be described in greater detail shortly.

In addition to these general concepts of Complexity, the double parabolae in **Figure 4.3**, illustrates the relationship between Complexity and Cost, which we have defined as Relevance in **equation 4.2**. The Cost of Complexity is a direct result of the second law of thermodynamics. Metabolism, or $\mathbf{U_{input}}$, is required to create a scenario where an internal interference pattern may be created among co-active nodes; and once interconnections are made based on these interference patterns, the capacity to communicate via these accrued connections also requires energy. The result of this expended energy will be an increase in the capacity for an agent to do useful work in its environment. However, as the second law of thermodynamics stipulates, some of this input energy will be lost to the environment as useless heat. Never the less, the self-adaptive agent will increase its capacity to do useful work per lost energy as heat. In other words, the amount of entropy exported as entropy may remain the same for an organism, but it will able to do relatively more useful work via learning and development within its environment. This is what Erwin Schrodinger called Negative Entropy in his short book *What is Life?*

Paradoxically and unintuitively, however, this remarkable attribute of life to increase its work output per entropy exported through development, requires that intermittent periods of *disorder* occur in the system. This is necessary, because newly perceived information must have some capacity to re-order existing, and potentially less adaptive, internal formations. This is the true nature of becoming increasingly in-*formed* over time. The internal system structure must be re-formed as new information becomes available. However, this re-ordering constitutes momentary periods of relative disorder in the self-adaptive system. This relative level of disorder is in direct relation to the important balance between over and under-coherence discussed throughout these summaries. This, at first, is counter-intuitive and seemingly contradictory since disorder is associated with an increase in entropy, not a decrease. But, again, entropy may remain the same, or in fact increase a little with maturation of an organism. What increases is the proportional amount of useful work that that organism can do in its environment. There is always a cost for increased adaptability. Never the less, nature has evolved to increase what it receives in the long run in exchange for a consistent near term cost. Subsequently, this project has defined Cost as the ratio of the Work done by the system to the energy consumed, U_{input}, to do that Work. U_{input} is expended to do Work in order to increase internal Complexity, which in turn is capable of doing even more useful Work. As such, Complexity at some Cost is defined as adaptive Relevance, as in **equation 4.2**. And an average increase in adaptive Relevance over time will be called *Refinement*.

The balance between Cost and Complexity in living systems has evolved since life began and is genetically inherent within the species that have survived to date. This evolved balance can be studied for its capacity to leverage both order and disorder in a careful oscillation that underlies everything from evolution, to Negative entropy, to cognition. The proposed hypothesis for this project is that this balance and, by extension cognition, can be synthesized. Its Relevance will be an oscillation of Complexity at some Cost, which will also fluctuate in direct relation to Complexity. It will further be demonstrated that this oscillation is a drifting homeostasis, or "homeodynamic"[2], whose average trajectory for the successful system shall be shown to increase over time. This homeodynamic trajectory of Relevance is the empirical expression of Refinement.

refinement

Like evolution, cognition is an incremental process where some patterns persist in their environment because they prove Relevant over time whereas others do not. Refinement is a reflection of this process based on the empirically determined attribute of Relevance. **Figure 4.5** illustrates the general expected behavior of a system that successfully exhibits Refinement. Like an athlete in training, physical behaviors are practiced which refine the muscles relevance to the task at hand while simultaneously increasing their strength in those tasks. Muscles, in essence are molded by the tasks they are willed to perform in their surroundings. Muscles are formed by both the existent will of the athlete agent that embodies them and the environment they navigate within. The animal brain is similarly molded. But this molding requires that their former forms, which are less specialized and less strong, be literally broken down. Some patterns must parish so that new more Relevant patterns can emerge based on the external patterns they are exposed to.

This "two steps forward one step back" strategy clearly separates this project from the vast majority of all other AI projects in existence, which focus on an incremental one-way progress towards perfecting singular goal functions. Functions are strung together like independent

[2] Instead of a process hovering around a static level as in homeo-stasis, the behavior of a learning systems will oscillate around a dynamic level, thus homeo-dynamic. Homeo, or "same", indicates that the behavior of the system will still hover about a linear function; but, instead of that function being single valued (i.e. static), Refinement will have its own trajectory as shown in Figure 4.12.

beads on a string, each function not easily integrated into higher-order functions by virtue of their discrete substrates as discussed earlier. This project is fundamentally different in that the "beads" are not preconceived as independent goal functions. They are physically embodied patterns that, while maintaining their own distinctness, are truly integrable into higher-order patterns. Like the athlete's muscles, this intimacy among parts requires that former patterns be re-configured, re-formed, and re-organized. These behaviors in cognitive systems will ideally move towards greater Complexity over time, which will exact a Cost. But in order to re-organize the internal system towards greater Complexity, some less Relevant integrated parts must be disintegrated intermittently so that, when more environmental information is assimilated by the agent, the more Relevant parts of the system can be re-formed into higher-order forms. This results in an oscillation that allows Complexity to be temporally reduced so that it can be increased in the longer term.

Refinement is not a mathematical model. It is simultaneously a design guideline and hypothesized expectation. The hypotheses definitively stated:

H_0 – The Null Hypothesis

The null hypothesis will be achieved if the designed system does *not* accrue increasing amounts of order in the form of internal connectivity when exposed to environmental patterns. Furthermore, the system will not manifest consistent nodal activity in response to consistent stimulations. Complexity, as defined, will not increase over the systems life-cycle, thereby negating Refinement.

H_1 – The Alternative Hypothesis

The proposed hypothesis will be achieved if the designed system does in fact exhibit the behaviors above. Furthermore, statistically significant nodal assemblies or patterns will organize into patterns of patterns over time, thereby accruing higher-order learning by "harvesting" increasing amounts of sparse order among nodes and their statistically significant assemblies. In general, increased Complexity over time and Refinement will be achieved over time.

To achieve the Alternative Hypothesis, initial design efforts will be inspired by the oscillatory, developmental, and homeostatic behaviors of existent living systems. These guidelines must reach all the way down to the design of each nodal circuit and how they interact with each other. The next chapter focuses on the "nuts and bolts" of implementation, but to get there a more detailed look at a single cycle of Refinement is useful. This detail view starts with the double parabolae in **Figure 4.4**, but with the reality of time incorporated. Oscillations, like homeostasis introduced in **Figure 4.1**, are often organized by a temporal competition between two opposing forces. For example, a class C amplifier is an oscillation between capacitance and inductance, called the "fly wheel effect". Pendulums are the interplay between gravitational and lateral forces upon a hung mass. The main players in this project of synthetic cognition are the internal structure of the agent and the external patterns they have evolved to be sensitive to. The resulting cycle will be informally referred to as the "Sleep-wake cycle".

Zooming in on one single cycle of Refinement from **Figure 4.5**, **Figure 4.6** illustrates a schematic of how it is hypothesized that an agent increases its Relevance to its environment over time. Starting at the left, the "awake" agent is exposed to environmental stimulation. Incoming sensory stimulation excites nodes that resonate with relevant signals within that stimulation pattern. The interstitial activity among nodes creates a topography of sparse order among relative disorder. The system instantiates this order as discussed previously. The increased order decreases the cost for recognizing learned patterns from the environment and repeating higher-order learned behaviors. But, as the system tries to assimilate more and increasingly diverse patterns, the system struggles to discern more order. More energy is expended, $\mathbf{U}_{\mathbf{input}}$, and less useful work, $\mathbf{W}_{\mathbf{nodes}}$, is done in response as the system begins to under-cohere with over-stimulation. This means that Relevance decreases significantly and so the system can be considered "fatigued".

The system will sense this loss in Relevance and will respond by shutting down external stimulation. This is analogous to sensory deprivation through the thalamus and the onset of "sleep" in the animal brain. Initially, $\mathbf{U}_{\mathbf{input}}$ and $\mathbf{W}_{\mathbf{nodes}}$ will go down as the environmental stimulation is thwarted. From here the system goes through a number of internal sub-cycles that re-stimulate the networks that were active during the previous "wake" sub-cycle. In essence, "sleep" insulates the system from external perturbation while the order that was accrued during wakefulness is able to interact among themselves and with internal, formerly assimilated, memories. These "sleep" sub-cycles ramp $\mathbf{U}_{\mathbf{input}}$ and $\mathbf{W}_{\mathbf{nodes}}$ back up, but this time internal coherence is allowed to accrue more quickly without the input of external perturbation. This occurs a handful of times, analogous to animal cycles of R.E.M. sleep. But once the system begins to over-cohere upon its own internal structures, "wakefulness" is initiated so as to mitigate this self-focus by absorbing external stimulation once again. Now, the coherence based on the previous "wake" sub-cycle that was accrued while "asleep", can be leveraged to assimilate higher-orders of environmental patterns. The practical timing of these cycles requires feedback mechanism, a number of which will be discussed in the next Chapter.

These higher-orders contribute to increased Complexity. And the acquisition of more patterns found in an agent's environment increases the likelihood that the agent will be able to do more Work with less energy for more tasks; therefore, Cost will tend to decrease. As such, over time, Relevance will oscillate and tend to increase with each full cycle, it's average trajectory being Refinement.

The next section will describe how Complexity and Work will be measured empirically to discern whether or not Refinement is achieved. With these two quantities the trajectory of Refinement will be discerned so as to justify, or not, the Alternative Hypothesis (H_1) stated above. Of course, this is a design project, so the intent is that if the result is the Null Hypothesis (H_0) for any given attempt, it by no means indicates a failure. It is merely an opportunity to learn and revise the physical implementation so that it *will* exhibit Refinement, the Alternative Hypothesis.

Chapter 5

Implementing and Testing for Refinement

There are, of course, many conceivable ways that cognition can be realized. For example, as discussed in the introduction to these summaries, evolved cognition will remain distinct in its implementation from synthetic cognition. Never the less, the essence of self-adaptation is the same, namely, the instantiation of sparse order from the apparent disorder among interactive individuals. And this remains true at any scale of any living system: a vital balance between the autonomy of diverse individual agents that simultaneously have the capacity to inter-relate so as to create a shared terrain of information greater than the sum of individuals behaving independently. This is the Prime Premise restated, and Refinement is the process by which this vital balance is acquired.

In order to better understand both the theoretical concepts and how they will be implemented in a practical application, the behavior of a preliminary schematic of SOARSE™ will be described in this Chapter. To start, it helps to visualize a three dimensional representation of an actual technology. A three dimensional matrix of Primary and Secondary nodes is proposed schematically in **Figure 5.1**. As with any design process, one must be careful not to become to attached to this schematic. Never the less, it will serve as a useful initial step in developing an testable and applicable technology.

There are three main parts to any cognitive system: 1) Sensory, 2) Transmission, and 3) Processing. They are not necessarily mutually exclusive. However, they are distinct in their functionality. The Sensory portion is a transducer that changes the energy of external patterns of stimulation into a common internal energy medium. For example, electromagnetic energy in the visual spectrum is converted from very high frequency patterns to internal low frequency electrochemical and electromagnetic patterns in organic animal brains. Some important pre-processing is done at the Sensory level as with the retina in the human eye. The Transmission portion, e.g. the optical nerve, does relatively little processing and is tasked with transmitting patterns of inter-dependent information as quickly as possible to the Processing portion of the system. The Processing portion of the system has many different sub-types, but its primary role is to both create memories of incoming patterns and inter-connect them into higher-order patterns with more significance and capacity to do useful work than independent patterns alone.

A very schematic representation of this higher-order system might look like **Figure 5.2**, where two different sensory modes, e.g. sight and sound, come together deeper in the system to create patterns of patterns, so to speak. In other words, different sensory transducer will change their respective patterns of energy from the external world into a common medium of energy. For SORASEtm, this common medium is a shared EM field and inter-connections that accrue between Primary nodes as a result of the sparse order withing the interference pattern among nodes. Distinct patterns from diverse sensory inputs, having been transduced into a common energy pattern, can now interfere with each other to create higher-order patterns of patterns. For example in **Figure 5.2**, two sensory arrays at each end each have their own processing matrix that can store inter-connections relevant to their respective patterns. These patterns are also patterns of patterns in that auditory patterns, for example, will be composed of inter-connections between distinct sub-sounds, as described in the chord example a number of times in past summaries. Similarly, visual patterns are composed of superimposed sub-patterns. But now, in the center matrix in **Figure 5.2**, these two sensory patterns can come together to form even higher-order patterns of patterns.

A detailed examination of how Work and Complexity are realized by the schematic system above will more clearly describe how Refinement and synthetic cognition are implemented via SOARSEtm technology.

It helps to think of information, as described throughout these summaries, as a mix of both distinct events and their physical integration. As notes are superimposed to make chords, chords are superimposed to make songs. This is a physical phenomenon. It is not an abstraction. Distinct sound waves traveling through the medium of air constitute each note, chords, and whole songs, simultaneously. This terrain of patterned energy will then resonate with sensory systems in the agent that has evolved to perceive such forms of energy. If not, these physical patterns of energy do not exist to the agent just as distant galaxies did not exist to pre-telescope humans.

A critical adaptation is that the self-adaptive agent will have evolved both the capacity to sense many different forms of patterned energy – e.g. sounds, sights, temperatures, pressures, etc. - and to “translate” or transduce these diverse forms of energy into a common internal medium. In the evolved animal brain, this common medium is inter-dependent electrochemical and electromagnetic activity among diverse cell types. In SOARSEtm, the common medium is electromagnetic fields and digital inter-connections among diverse synthetic nodes. In **Figure**

5.2, light and auditory energy patterns through space and air, respectively, are converted to this internal common medium.

Distinct external patterns are converted to distinct internal patterns of Primary node excitation and an interstitial EMF terrain. Just as external patterns are composed of inter-related sub-patterns, e.g. notes, and their higher-order patterns, e.g. chords and then songs, so too are internal patterns composed of distinct sub-patterns and their higher-order inter-related patterns. Importantly, however, internal patterns will be composed of oscillatory signals between 0 and 200 Hz, similar to evolved organic brain activity. This range of signals will be employed internally among Primary nodes to assimilate not only external auditory signals, which range from about 10 to 20,000 Hz, but to assimilate external visual patterns that range from about 400 to 790 THz. Obviously, the 0 to 200 Hz range is insufficient to have anything close to a one-to-one correspondence between the external and internal physical worlds. Never the less, natural selection over billions of years has evolved the amazing capacity to represent these broad spectrums of reality in a much more compact and common range. And it is exactly this common range that allows for diverse sensory phenomena to be inter-related into higher-order assimilations such as feelings and memories composed of many inter-related sensory experiences. Even within a single modality certain mental precepts are higher-order representations that don't actually exist in nature per se. For example, pink and magenta aren't actually in the electromagnetic spectrum. They are integrations of different frequencies that are never the less perceived as a single “color”.[25] Furthermore, our familiar music analogy is a clear example of how the evolved human mind perceives many diverse frequencies as a single, yet rich, chord.

Yet, just as these percepts are perceived as apparently singular patterns, they are each specifically relatable to other patterns that contain shared sub-patterns. For example, pink is related to red because of their shared wavelength around 650 THz. And the Cmaj chord is related to the Gmaj chord because of the possible shared frequencies that are sub-patterns within each chord, e.g. 49Hz, 98Hz, 196Hz, and any other octave of the 'g' note. This project refers to this physical phenomenon of superimposing distinct sub-patterns into higher-order patterns as *overlapping distributions*.

overlapping distributions

A prime example of this phenomenon is the visual spectrum as illustrated in **Figure 5.3**. In general, there are three different types of color sensitive cells, called cones, within the human retina that tend to respond to the electromagnetic spectrum as shown in **Figure 5.3**. Each general cell type population has many diverse individual cells that will respond as a distribution, just has human populations will exhibit a distribution of heights. Importantly, the response of these three cell types overlap. This is how only three retinal cone types can assimilate upwards of 10 million distinct colors and their respective intensities. Of critical importance is the capacity to assimilate not just distinct frequency events, but the co-occurrence of different frequencies into a higher-order assimilation, such as pink or magenta.

Different sensory cells, such as cilia cells in the auditory system, are sensitive to very different physical phenomenon, but they are never the less able to transduce the patterned information into a common range of physical activity. Synthetically, this will be implemented with diverse populations of sensory nodes that respond in a similarly distributed manner. For example, each Primary node will have a distinct resonant frequency, but each will also respond more weakly to signals around their respective resonant frequency like a bandpass filter.

Many individuals nodes at the sensory portion of the system, as in **Figure 5.1**, will be stimulated by distinct signals, such as notes, within the environment. The activity of these sensory nodes will then stimulate specific Primary nodes that are proximal to the active sensory nodes. These select excited Primary nodes will then emit their distinct signal to local Primary nodes both adjacent to themselves and deeper within the system. Importantly, these EM emissions will be in the frequency range of, say, 0 to 200 Hz. Similarly, visual sensory nodes will respond to the visual spectrum, but will then excite local Primary nodes that will emit signals in the common internal range of 0 to 200 Hz. This may seem at first like a great deal of information will be lost, but it is exactly the capacity of Primary nodes sensitive to frequencies between 0 to 200 Hz to be co-stimulated creating a shared and distinct interference pattern among themselves. We can re-use the chord example as in **Figure 5.5a**, where this two dimensional ripple pattern is a section through the three dimensional system in **Figure 5.1** and **5.2**. But, instead of chords, the Primary nodes shown can be any nodes deep within the system. For example, they may be responding to patterns from both visual and auditory patterns as schematically illustrated by the center matrix in **Figure 5.2**. Try to imagine ripples through the system in Figure 8 from either side that were initiated by very different natural phenomena. These phenomena, e.g. visual or auditory patterns, will be specific and distinct signals that relate with each other in time and space in a very specific way. It is both the distinct signals and their inter-relations that must be captured to some degree by each respective sensory mode. And then, like three dimensional ripples these distinct events and their inter-relations are preserved as they progress deeper into the system until they meet ripples from other sensory modalities or even memories of the same sensory mode.

Figure 5.5a is representative of the actual physical phenomenon within the system at a single instant in time. **Figure 5.5b** and **5.5c** are more abstract representations of the tuned sensitivity of individual nodes, which are necessary to understand how Work and Complexity can both be explained and tested within an actual system. **Figure 5.5b** shows a series of overlapping distributions that reflect the resonant frequencies of the active nodes in **Figure 5.5a**. Frequencies $f1 - f4$ in **Figure 5.5c** show how actual signals in these node's physical surroundings might only partially stimulate each node. Their resonant frequencies remain the same, but the purple arrows indicate actual frequencies from the nodes' surroundings. In other words, it is highly *un*likely that ambient signals will coincide with the exact resonant frequencies of local nodes. Having a distinct distribution, however, allows that at least some nodes will be stimulated to some degree some of the time. Furthermore, their respective response distributions will overlap thereby tending to create distinct higher-order interference patterns as in **Figure 5.5a**, because – like the vision example in **Figure 5.3** – overlapping distributions within populations at any scale of living systems will facilitate both distinct and inter-related patterns.[26] This is the Prime Premise and an paradoxical nature of living systems, which must balance their capacity to discern both distinct events in their environment and inter-relations between these events.

Looking at just a few nodes at a time in **Figure 5.6**, the relevance of overlapping response distributions is grounded in an actual implementation. As discussed in detail in Chapter 2, each Primary node's behavior is affected both by EM signals in the ambient surroundings and stimulation from other formerly connected Primary nodes. The two distributions for Primary nodes 1 and 2 are shown on either side of P1 and P2. These distributions overlap, but not so much that they are not distinguishable individually. This is because their resonant frequencies are sufficiently close so that it is more probable than not for a signal to stimulate both nodes simultaneously, but not so close that they are stimulated in the same way by ambient signals. For example, a signal near 20 Hz will stimulate P2 more strongly than P1. Conversely, a signal near 50 Hz will stimulate P1 more than P2. If both are sufficiently stimulated to transmit their own signal, the interference pattern would be distinctly different for the 20 Hz vs. 50 Hz scenarios. In addition, surrounding nodes, shown below P1 and P2, may contribute to the stimulation of P1 and P2 if they too are stimulated to fire based on their own tunings and accrued connections. For example, P1 and P2 may be two nodes stimulated in **Figure 5.5a**.

They are tuned for an ambient signal somewhere close to 40 and 30 Hz, respectively. And they are being stimulated by other nodes that similarly find themselves being stimulated by distinct ambient signals. As described at the end of Chapter 2, a sparse formerly inter-connected assembly will self-stimulate each other if a formerly taught pattern continues to stimulate the system. This self-reinforcing behavior will then draw available current and convert it into power, some of which will do work. This "ramping up" of assembly activity all happens because distinct individual nodes are relevant to the ambient pattern in their shared EM topography.[27] And, again, both nodal assembly activity and the local field are molded, or in-*formed*, by each other as one cohesive system.

measuring work and complexity

The amount of work any Primary node can do is a direct function of both stimulation from the ambient EM field and from inter-connections with other nodes. This means that the Primary node most able to do useful work will have connected to other nodes over time based on their co-activity, and it will have a resonant distribution that is responsive to a signal that occurs regularly in its local ambient environment. The amount of work a any assembly of inter-connected nodes can do is a direct function of the relevance their inter-connections and their overlapping distributions of sensitivity. At any scale, the relevance of a single node or assembly of nodes is in direct proportion to their specific response to specific signals in the physical environment. Complexity, Cost, Relevance, and Refinement are all defined quantities that will track a synthetic system's capacity to accrue potential to do work over time.

Maximum possible work occurs if a signal present in the EM field is exactly at a given node's resonant frequency and if the timing of incoming stimulation from other nodes is synchronous with each other incoming signal, which are also coincident with resonant stimulation via the ambient field. It is unlikely that all these dynamic behaviors will align perfectly, but as discussed before, perfect order is not conducive to the self-adaptive system. This is because a perfect one-to-one mapping between input and output, though maximizing order, significantly mitigates the capacity to create higher-order assemblies able to assimilate and do more complex work through adaptation. Overlapping distributions are attributes of self-adaptive systems necessary for this higher-order assimilation. And, their very necessity ensures that maximum work will not be realized by any one node, because adaptation is not about a one-to-one synchronization of a signal to a node at the lowest order of Complexity. A self-adaptive system may Refine its capacity to do increasing amounts of higher-order Complex Work over time exactly because "imperfect" inter-dependencies are intrinsic to the system.

It is exactly this capacity to create relationships between distinct physical events from the environment that distinguishes this project from the vast majority of efforts to date. Revisiting **Figure 5.7** from Chapter 3 illustrates how any one-to-one functional system, like digital computation, exists at the lowest order of Complexity. It is deceiving because our digital machines seem quite complicated. But in reality they are only lists of discrete states mapping to other discrete states in a one-to-one manner. As such, they can certainly become very long lists. However, they are not Complicated in the same useful way that cognitive systems are because discrete lists will always just be that, *symbolic lists*. It is the map vs. territory argument, which argues that the map is an abstract representation of physical reality, not reality itself. Cognition, it can be argued, is also a representation of its wider surroundings. However, it is a very special representation that is very distinct from any Turing equivalent implementation, exactly because the Turing equivalency is first and foremost a list of discrete states and the fixed rules to change those states based on other discrete states, i.e. lists of lists. Cognition, however, is a territory in the same sense that the world outside is a territory. In other words, the capacity to physically integrate distinct physical phenomena into higher-order phenomena, like the chord example, is a very distinct form distinct state strategies. To define this rigorously, Turing equivalent machines will always be at the lowest order of Complexity, essentially along the x-axis in **Figure 5.7**. They may be fantastically ordered, but this coherent order comes at the cost of higher-orders of Complexity, which are available to Cognitive systems.

To assess this adaptation numerically Complexity and Work exhibited by the Cognitive system must be measured as it assimilates distinct patterns from its environment. Work and Complexity, although inter-dependent in practice, will be assessed empirically as separate quantities. The measurement of Work is relatively straight forward. Both current and voltage will be measured directly at the diode at point **e)** in **Figure 5.8** for each Primary node.

These values multiplied together equal real power as discussed in Chapter 2. This power over time is the work that is done by the individual Primary node being measured. The work from each individual node within a nodal assembly in response to a distinct environmental stimulus is summed to provide Work. As a system increasingly learns some patterned stimulus the response of some nodes within the system is expected to become more distinct and coherent. This was described mathematically in Chapter 2, whereby the Work done by the system in response to some external stimulus will be expected to change from time span [a,b] to [c,d].

$$\text{Work}\Big|_b^a = \sum_i^n \int_b^a \mathrm{I}_i \, x \, \mathrm{V}_i \, d\tau \quad < \quad \text{Work}\Big|_d^c = \sum_i^n \int_d^c \mathrm{I}_i \, x \, \mathrm{V}_i \, d\tau \qquad \textbf{equation 5.1}$$

Complexity at separate time intervals will also be assessed with the aid of the digital portion of SOARSE[tm]. The abstract data structure within SOARSE[tm] will record connections that accrue among Primary nodes in response to environmental patterns. **Figure 5.9** uses the chord example once again to illustrate how distinct patterns will accrue to contribute to Complexity, but also how patterns of patterns will accrue to further increase Complexity in the vertical y-axis dimension in **Figure 5.7**. Importantly, the actual physical implementation of synthetic cognition contains Primary nodes that are physically sensitive to a distinct distribution of physical phenomena, such as a small range of frequencies. The abstract data structure, however, can not assimilate such relationships because its internal states are discrete and insensitive to the environment by design. This is not a problem if seen for what it is, and can be used to keep track of inter-connections between Primary nodes that have accrued as described in past Summaries. With this discrete information from the data structure, Complexity can be numerically assessed over time.

For example, **Figure 5.9a** shows the co-activity of distinct nodes that are probably responding to notes in the chord Cmajor. With continued exposure the co-activity of the distinct nodes that resonate with actual frequencies within Cmajor will cause SOARSE[tm] to accrue the interstitial sparse order within the interference pattern between them by creating inter-connections. These inter-connections are stored in the abstract data structure within SOARSE[tm]. As the response of these particular nodes occurs significantly greater than chance (e.g. $p < 0.5$) in response to Cmajor, Complexity is increased and learning is exhibited. **Figure 5.9b** shows the same for learned inter-connections for Eminor. Cmajor and Eminor are two distinct assimilations of two distinct environmental stimulations at an i^{th}-order level of Complexity. **Figure 5.9c** illustrates inter-connections between Primary nodes that will have responded to the co-occurrence of i^{th}-order patterns Cmajor and Eminor. This is the higher-order chord of Cmajor 7^{th}, say at the higher i,j^{th}-order of Complexity. Again, the assessment of this higher-order pattern of response to Cmajor 7^{th} as a contribution to Complexity is based on standard statistical thresholds for significance (e.g. $p < 0.5$). As the statistical improbability, or coherence, of any one nodal assembly in response to a given stimulus increases, its contribution to Complexity also increases. This is visually represented in **Figure 5.9c** as heavier inter-connection lines among specific nodes.

It is critical to remember that not only do many distinct patterns at one level of Complexity (e.g. Cmajor and Eminor) contribute to overall Complexity, but patterns at higher-orders of Complexity (e.g. Cmajor 7th) also contribute significantly to overall Complexity. These higher-orders of Complexity are critical to the capacity for an agent to assimilate more Complex patterns from its environment. And, this requires inter-connections among lower-order patterns, which in turn will mitigate the saliency of these lower-order patterns. As such, ever higher accuracy of any one assimilation is not possible, but nor is it the most important goal of the self-adaptive agent. Accuracy of the single pattern certainly matters, but not to the complete inability of the agent to physically embody higher-order patterns as wholes in of themselves. Here, again, resides the practical expression of the paradoxical Prime Premise.

This paradoxical between the parts and the integrated whole can be numerically understood via Complexity whereby the assimilated pattern of Cmajor 7th in **Figure 5.9c** is physically embodied in the analog portion of SOARSE™ via inter-connected nodes. Cmajor 7th is not only more Complex than Cmajor or Eminor alone because more nodes are involved, but because Cmajor 7th also incorporates the two patterns of Cmajor and Eminor within itself. In other words, not only will the system respond significantly, in the statistical sense, to Cmajor 7th, but it will also respond distinctly to Cmajor or Eminor alone when exposed to the relevant environmental stimulations.

	1st Order	**2nd Order**	**3rd Order**	**4th Order**	**5th Order**	**6th Order**
Cmajor	$\Sigma\ (1/\sigma_i^2)$ +	$\Sigma\ (1/\sigma_{ij}^2)$ +	… +	$\Sigma\ (1/\sigma_{ijkl}^2)$ +		
Eminor	$\Sigma\ (1/\sigma_i^2)$ +	$\Sigma\ (1/\sigma_{ij}^2)$ +	… +	$\Sigma\ (1/\sigma_{ijkl}^2)$ +		
Cmajor 7th	$\Sigma\ (1/\sigma_i^2)$ +	$\Sigma\ (1/\sigma_{ij}^2)$ +	… +	$\Sigma\ (1/\sigma_{ijkl}^2)$ +	… +	$\Sigma\ (1/\sigma_{ijklmn}^2)$

Table 5.1 – Contributions to Complexity
This table lists the contributions to Complexity for each pattern in **Figure 5.9**. 1st order terms contribute to Complexity when single nodes respond significantly to a consistent stimulation. 2nd order terms contribute when two distinct nodes coincidentally respond significantly to another more complex stimulation, and so on. Note that higher-order terms, which respond significantly to a stimulation cannot be decomposed into contributing sub-terms unless those sub-terms exhibit their own significant response to a distinct stimulus. As such, it is possible to have a 100th order term, i.e. a 100 node assembly, that responds significantly to a stimulus, but that there are no sub-assemblies that respond significantly to their own distinct stimuli.

Table 5.1 tabulates the statistically significant responses of distinct nodal assemblies in the presence of an environmental stimulation as diagrammed in **Figure 5.9**. **Table 5.1**, along with

Figure 5.9, show how there is not a strict one-to-one mapping between environmental pattern and internal pattern. This makes sense for the self-adaptive system, which must embody patterns from the world in a way relevant to its inherited, or designed, internal structure. For example, a single note from the environment may only stimulate a single internal node. This would be a 1st, or "i th", order contribution to Complexity if the internal node responded with significantly greater than chance consistency to a given stimulation. However, it is very likely that a single external note will stimulate just one internal node at a time. **Figure 5.6** illustrates this possibility well, since a 35 Hz signal would stimulate P1 and P2 equally. In this way, a single sound will be represented by overlapping distributions, just as any higher pattern would. This actually makes a great deal of practical sense and provides humans with the capacity to discern a single c-note played on a piano from the same general frequency played on a violin. This is because each unique instrument, although the root frequency is that of the c-note, imparts numerous harmonics that are indicative of a unique instrument. As such, a single note can be assimilated by an arbitrarily large nodal population at a 1st, 2nd, 3rd, or higher order internal pattern, even if it is a pure tone. The chord example above assumes that a single note will significantly stimulate at most two internal nodes. As such, the chords Cmajor and Eminor, each composed of just three notes each in **Figure 5.9**, are imagined to significantly stimulate at most a 4th order assembly. In practice, however, the assembly that embodies these chords could be much more populated; again, this argues that the coincident activity of internal nodes is not, and should not be, a one-to-one mapping to external events, which are only distinct in so far as they are perceived as such by some agent sensitive to such physical events.

Figure 5.10 is also a simplification, but it is better at illustrating the distributions of activity that will occur in practice. Given a single stimulus, e.g. Stimulus I in **Figure 5.10**, the system will be designed to respond in a more biased way to that stimulus given exposure to it. This is directly related to the unfair dice example used in Chapter 3 to describe entropy. But in the case of synthetic cognition, in general, and SOARSEtm, specifically, the bias of the system changes over time in response to particular patterns within the agent's environment. For example, Test 1 in **Figure 10** shows the response of a few nodes to Stimulus I in an hypothetical system. In this hypothetical experiment the system is exposed to a stimulus for a given time t_i, say 100 seconds. The number of excitations for each Primary node is graphed. The distribution of activity among nodes *i,j,k,...,n* is relatively flat and wide. The distribution of higher-order co-activity for *i,j;j,k;etc.* is even flatter. Akin to a fair die, the internal structure during Test 1 is relatively indistinct. As such, it embodies less information; it is literally less *formed*. After some learning, Test 2 reveals more distinct behavior in response to the same stimulus. As such, the distributions at each level of order are more peaked and narrow, as the available resources are biased towards nodes that prove more relevant to the learned stimulus.

Note that in Test 1 Primary node k responds more than it does in Test 2 after learning. The claim is that a self-adaptive system, such as SOARSE™, will reconfigure itself internally so that more relevant nodes, e.g. Primary nodes i and j, will respond more than less relevant nodes. And relevance is the degree to which some component signal within an environmental stimulus resonates with the tuning of a Primary node. In the case of **Figure 5.10**, it may be imagined that the k^{th} node has a resonant frequency that is centered on 15Hz, whereas nodes i and j are tuned to a bandwidth whose resonant frequencies are 30 and 40Hz, respectively as in **Figure 5.6**. If the stimulus contains a signal at 35Hz, then the k^{th} node may still be somewhat stimulated but the i^{th} and j^{th} nodes are significantly more stimulated. As these two nodes form a connection between them, they will self reinforce each other thereby biasing the system to draw more of the available current towards themselves and away from the k^{th} node, which can not compete with the i^{th} and j^{th} nodes working together with some semblance of synchrony. The chord example is a little misleading because it is a simple snapshot of the expected nodal activity. In reality, many nodes will be stimulated even if they are not necessarily part of the so called “assembly”. Here, again, is our species' predilection for a one-to-one naming of some event. In reality, however, there is a distribution of activity where many surrounding nodes will be activated by some stimulus.

The important point is that this distribution of activity coheres with learning so that it tends to be focused upon fewer and more relevant nodes over time. In this way, energy input into the system is increasingly focused on the Primary nodes that, by their physical sensitivities, actually have more capacity to do work in the presence of a specific environmental stimulus. Another important point is that, due to learning, an increase in higher-order activity does not necessarily mean a proportional increase in lower-order activity. This is illustrated in **Figure 5.10** when the distributions between Test 1 and Test 2 are compared. This is a fundamental point: *it is the increasingly synchronous activity among lower-orders that creates higher-order activity, not a mere increase in quantity of lower-order activity*. The quality, or form, of inter-nodal behavior becomes more ordered via environmental stimulation, thereby increasing the capacity for Work that is relevant to the agent's surroundings.

Given this evolved and/or designed capacity for self-bias, the simple chord example used throughout illustrates how available energy is leveraged to create patterns of patterns to accrue Complexity, a concept that reflects a system's capacity to internalize complex patterns from the world in order to do useful Work. Again, patterns in reality, which are essentially in-*formation*, are innumerable configurations of physically integrated distinctions. For example, Cmajor 7th is a physical phenomenon composed of the distinct patterns Cmajor and Eminor. The system that can respond significantly to single notes, then chords, and then combinations of chords is more Complex than the system that only responds significantly to single notes or even simple chords. **Table 5.1**, for example, shows that Cmajor 7th will not only have contributions to Complexity from single notes and simple chords, but also from the co-activity of simple chords, which constitute a more complex chord at the 6th level of order. As a result, the system can not only respond usefully to single notes, simple chords, and more complex chords as distinct wholes, but to the physically relevant spatial and temporal relations between each of these distinct patterns, i.e. patterns of patterns.

Figure 5.10 illustrates the hypothesized empirical outcome whereby higher-order activity, which is essentially the coordination among the more relevant nodes in a population, will in turn bias the consumption of available energy so that less relevant nodes are subdued and more relevant are excited. The system grows more distinct and responsive to the specific nature of the environment it is born into.

It is this ability to internally assimilate both distinct patterns and their inter-relations into an internal physical terrain that creates the foundation of self-adaptive cognitive systems. These internal assimilations at ever higher levels of Complexity correlate with the capacity for the system to do useful Work. This Work, as described above, will be numerically assessed separately. Together, Work and Complexity constitute Relevance. And, the average trajectory of Relevance over time constitutes Refinement.

relevance and refinement

Given a particular stimulus over time, SOARSE™, as a self-adaptive system, will be expected to learn the pattern of that stimulus to the degree it is capable given the number and diversity of its internal Primary nodes. The progress of such learning will be assessed via Relevance, which is the Complexity divided by Cost; Cost being energy input into the system divided by Work done by the nodes.

Like **Figure 5.10**, **Figure 5.11** is a description of hypothesized behavior for the successful self-adaptive system. It is not actual data. It illustrates how a synthetic self-adaptive system can be measured to discern whether the null, H_0, or the alternative hypothesis, H_1, by comparing the Relevance of the system before and after learning some specific stimulus. In the case of **Figure 5.11**, Stimulus I is shown to stimulate internal assemblies of varying degrees of order. And the events of active assemblies at each of these levels of order will populate their own random variables, thereby populating their own statistical distributions. Each of these distributions will have their own variance. And it is hypothesized that this variance will change with learning as suggested in **Figure 5.11**.

It is important to reiterate that the so-called assemblies – such as "*i,j,m,n*" in **Figures 5.10** and **5.11** or the chord examples – are expected assemblies like the mean of a population is the expected value of an experiment. In other words, a given assembly is named based on the nodes that are most active. This, however, does not mean that there aren't other co-active nodes, such as node k in **Figure 5.10**. If there was a perfectly fixed mapping from stimulus to internal assembly, not only would the notion of statistical distribution of activity be meaningless, but self-adaptation is not possible because this distributed behavior is the foundation for overlapping distributions and the physical implementation necessary for acquisition of higher-order assemblies. Once this concept is appreciated, the idea of a distribution and its variance makes more sense.

It is the Secondary nodes, having assessed the interstitial field, that are able to empirically measure co-activity from within the distribution of many diverse active nodes. And it is the degree of distinctness of nodes and their higher-order assemblies that constitutes the variance (σ^2) listed in **Figure 5.11**. This is the basis for Complexity, as defined. Primary nodes can be directly measured, as discussed earlier, for both the energy they consume and their work output. Within a Test regime, e.g. t_i = 100seconds, the summation of energy input is divided by the summation of work output to calculate Cost. And, Complexity divided by the Cost equals Relevance.

Relevance ≡ Complexity / Cost **equation 5.2**

Where **Cost** is defined as follows:

$\mathbf{Cost \equiv U_{input} / W_{nodes}}$

Figure 5.11 diagrams the assessment of energy input, Work output, and accrued Complexity over time. These values are stored in data structures whose matrices can then be manipulated per **equation 5.2** in order to assess Relevance in near real-time.

Relevance after learning is expected to significantly increase. This is a design specification of the successful self-adaptive system, such as SOARSE™. Never the less, it is also expected, as discussed in the last Chapter, that this increase in Relevance is not and can not be a steady increase as shown in **Figure 5.12**. It is not the nature of self-adaption or cognition in general. The self-acquisition of higher-order internal patterns is predicated on a system's capacity to be open to re-configuration. Lower-orders can only cohere into higher-orders if those lower-orders can be re-ordered, or physically in-*formed,* based on continuous input from the physical world. This necessitates distinct periods of disorder for the self-adaptive system. Life it seems is intrinsically a “two steps forward, and one step backward” type of process. In essence, this is the reason for death in all its forms: death of the organism, death of the idea, death of the sub-optimal pattern so that it can continually be reborn as an increasingly Relevant and Refined pattern. Matter and energy are not destroyed in any absolute sense. In the evolving Universe, they are merely reconfigured into more vital forms. And the degree to which any one pattern remains vital is directly related to two factors: 1) its own distinctness, and 2) the degree to which that distinctness is physically engaged with its surroundings. These are often competing tendencies, and it is in the evolved balance between them that ever more vital and complex forms emerge.

Fundamental to self-adaptive systems is a diverse population of physically sensitive individuals, or nodes. These sensitivities must respond to information in the system's environment and aid the system, i.e. agent, in navigating and surviving that environment. Also, fundamental is the ability to create a physical interference pattern among these nodes that is itself a relevant internal terrain in-*formed* by many external energy terrains. Overlapping distributions of sensitivity help insure that the diverse population is not so diverse that individual nodes cannot co-respond to their shared world, thereby creating a joint and unified pattern that is truly greater than the sum of their independent selves. This joint pattern is implemented as an electromagnetic interference pattern that is a physically unified whole. Its distinct pattern is composed of not just individual events, as in the drops on water analogy, but their spatial and temporal inter-relations, simultaneously. Furthermore, this distinct pattern is created by the sparse number of nodes that are physically resonant, i.e. 'sensitive', to the distinct nature of information from the agent's environment. And, again, information is the material and energy relationship among parts. To the best of human knowledge, it is a physical attribute of physical reality. They are distinct enough to contribute something unique to a higher-order internal assimilation of the external world, yet they are close enough in their response to their shared world of information

An important leap in understanding cognitive systems is that the idea of 'outside' vs. 'inside' the system is arbitrary. To the animal, perhaps skin marks the boundary. But, to some neural assembly inside that animal's brain, 'outside' is the activity of cells surrounding it. In this way, each sensory nodes are certainly sensitive to signals from the system's terrain of energy stimuli – e.g. light, sound, etc. – but Primary nodes within the system are not evolved to be sensitive to such stimulation. They respond to the system's own internal terrain of dynamic EM energy. Complexity, as defined, reflects the system's tendency to restructure its internal material structure to more effectively resonate with higher-order patterns of complex patterns in both nature *and* within the system itself. Future occurrences of some formerly learned higher-order pattern in the environment will cause a more powerful and coherent response from the incrementally more Complex agent. This more focused response means more energy is spent on doing more focused Work. Together, Complexity – an attribute of the system's internal structure – and Work – the degree to which the system responds to environmental patterns that in-formed the system's structural Complexity in the first place – are two side of the same coin, namely the Relevance of the system to its wider world. If the system is so evolved and/or designed to autonomously increase its Relevance over time, it exhibits Refinement.

Un-intuitively, however, the acquisition of Relevance is not a linear path. It oscillates in a homeostatic fashion. It must in order to realize Refinement, because future higher-order assimilations of reality will inevitably render past lower-order assimilations inefficient, obsolete, or just plain incorrect. As new information becomes available to the more Complex system, formerly learned and once useful patterns may be exposed as inaccurate given a wider awareness of one's vast world. This is the history of human knowledge and the path of Refinement.

> **Refinement: A process whereby an arbitrary system expands its awareness of its surroundings while simultaneously increasing its own internal capacity to resolve the increase in disorder, which is the result of this expanded awareness, into a higher order internal structure.**

It is in the disorder of interacting diverse agents that previously non-existent patterns of sparse order are incrementally accrued. This is the seat of human creativity and, arguably, the means by which higher-order forms emerge from less vital forms via evolution. The inter-connected nature of reality makes ever more Complex configurations of matter and energy possible, but it is exactly this overlapping self-interfering nature of reality – as shown in the ripple analogy – that creates disorder. Perfect order is perfectly static, perfectly still and stagnant. Perfect disorder is perfectly dynamic with no distinctness to build more complex forms upon. Perfection is an human abstraction, not an evolutionary principle.

1 Gerald Edelman's theory of "Neural Darwinism".
2 Gregory Bateson *Mind And Nature* (E.P. Dutton, New York, 1979).
3 Steve Perlman's nascent DIDO technology proposes just such an implementation, whereby interference among many transceivers is employed for commercial applications in the near term. See review article here, and white paper here.
4 Taxis of all kinds, including chemotaxis, is summarized well here.
5 Joseph LeDoux Synaptic Self; How Our Brains Become Who We Are (Penguin Books, New York, 202).
6 Thomas Radman, Yuzhuo Su, Je Hi An, Lucas C. Parra, Marom Bikson *Spike timing amplifies the effect of electric fields on neurons: implications for endogenous field-effects* The Journal of Neuroscience **27(11)**, 330-336 (2007)
7 E. J. Peterson, O. Izad, D. J. Tyler *Predicting myelinated axon activation using spatial characteristics of the extracellular field* Journal of Neural Engineering **8**, 4630(12pp) (211)
8 Costas A Anastassiou1, Rodrigo Perin, Henry Markram, Christof Koch *Ephaptic coupling of cortical neurons* Nature Neuroscience **14(2)**, 217-223 (211)
9 Conversion of energy from one medium to another as in the conversion of acoustical signals from musical instruments to electromechanical and then electromagnetic forms in recording devices.
10 Where this threshold is set for a population of Primary nodes will be a matter of empirical research. The optimal system will need to be discovered since analog circuitry, let alone complex open system feedback loops, cannot reasonably be modeled in advance. It is easier to adjust and optimize the threshold in situ. Future iterations of the system may have variable thresholds, which will be self-assessed by the system itself. More will be said about this and other feedback loops in future publications.
11 Ref studies describing how rate of charge acquisition at the hillock interacts with LFP to predict whether a neuron fires or not.
12 Note that phasors with the same frequency can be added by transforming the phasors into their complex forms and then simply added. Phasors, however, with different frequencies essentially modulate each other. Converting them to their complex form and then trying to add such phasors essentially results in the multiplication of two different signals. The signal with the lower frequency tends to be the base frequency that is modulated by the higher frequency as in Amplitude Modulation (AM). Here are some web resources for review:
http://class.ee.iastate.edu/ee224/Notes/review2.pdf
http://web.science.mq.edu.au/~cassidy/comp449/html/ch3s3.html
http://s3.amazonaws.com/cramster-resource/3131_n_14391.pdf
http://people.clarkson.edu/~jsvoboda/eta/SlideShows/addingSinusoids/addingSinusoids.html
http://en.wikipedia.org/wiki/Phasor
http://www.ece.unh.edu/courses/ece41/Referernce/Adding%20Sinusoids.pdf
13 For those familiar with *What is Life* by Erwin Schrodinger, this benchmark for success is directly related to Negative Entropy. Entropy will be discussed at length in the next Chapter.
14 This claim will be discussed and justified extensively in Chapter_3.
15 That reference with signal within signal.
16 Finklekurtz brothers ref.
17 Gregory Bateson
18 This can be imagined via the box example where many boxes are moved by many diverse forces. Most boxes will be moved indeterminately by randomly distributed forces. Set against this majority behavior, however, will be a sparse number of boxes that are pushed in a distinct direction by a small group of relatively ordered forces. This relatively ordered trajectory is set against the back drop of indeterminate box behavior. As such, these sparse number of directed boxes will stand out against their relatively disordered surroundings.
19 Kolmogorov Complexity and how the lowest entropy means little complexity, not a recipe for cognition.
20 It will be argued in a subsequent article why the probabilistic model, or "map", is only a limited simulation, and is therefore not actually, physical reality, or the "terrain". First stated in a paper by Alfred Korzybski in 1931 and later used by Gregory Bateson in his essay "Form, Substance and Difference", the concept "the map is not the territory" illustrates the limitations of representations of reality. See FAQ for more on this subject.
21 'Significance' in this context indicates a physical response of the cognitive system that emerges observably above the system's noise floor. The exact threshold for 'observability', in the proposed synthetic implementation under a separate cover, will be a function of the measuring devices being employed and the algorithm developed to discern connectivity among Primary nodes.
22 Article about bees being taught to distinguish colors...
23 Studies out there linking sleep with learning capacity...

24 Describe what his intent was...

25 http://en.wikipedia.org/wiki/Visible_spectrum

26 Discussion in https://sites.google.com/site/iforamrandd/experiments/exp-1-6-visualizing-emf-with-processing

27 It is useful to *not* conceive of "external" and "internal" as fixed, discrete, and absolute boundaries. They too overlap, because according to some arbitrary group of nodes deep within the system, "outside" is that which is just beyond that group which is still perceivable, and no farther. The environment perceived by the larger agent may have some distant causal impact on the deep nodal group's perception, but it is a mistake to equate them.