

Organic Complex Systems

**A Comprehensive Theoretical Apparatus
for Modeling the Organization and Dynamics
of Living and Lifelike Systems**

Part I: Principles of Organization

**Part I is a work-in-progress and not ready
for distribution.**

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Preface

The phrase “organic system” conjures a rich and potentially exciting complex of ideas. Generally some kind of “lifelike-ness” and a generous amount of complexity is inferred. What make these systems special are the systemic properties that they exhibit.

Biological systems are the inspiration for this class of system, and are clearly the prime example. But if we can isolate, abstract and articulate a set of compelling systemic properties exhibited by bio-organisms then perhaps we can identify other systems that exhibit them as well – and that we would therefore be willing to call *organic*.

This research means to put mathematical rigor and specificity to these ideas. In Part I we shall identify some systemic properties that make us willing to say that a system is “organic”. We shall then use these properties as organizing principles and build a theory around them. Subsequently, in Part II of this treatise, we shall develop mathematical constructs for each of these organizing principles and integrate them into a framework for modeling organic systems. We shall name this theory *Organic Complex Systems* (OCS).

Thus, Organic Complex Systems is a theoretical framework for modeling systems that are “organic” - that exhibit certain lifelike properties. Such systems must, of course, include biological life on earth. But OCS seeks to go beyond – to represent possible “lifelike” domains that may exist outside of carbon chemistry; indeed, outside of chemistry. OCS seeks to develop a formal abstraction of the living.

As a discipline, OCS is at the nexus of complexity science, information theory, dynamical systems theory, cybernetics, and systems biology. It calls upon a number of other scientific disciplines and areas of mathematical research. In the process, it presents an argument for the prominence of a set of systemic properties that it identifies as *organizing principles*; and then it develops and presents a mathematical modeling framework that embodies these principles.

Such a framework could see a number of applications. Some of which provide models of existing systems, and others of which provide planning models for systems imagined but not yet realized.

Examples of such systems may be: non-carbon biochemical models for life on other planets; the engineering of artificial lifelike systems; complex adaptive systems in computer space and cyber space; information and memetics; and the modeling of various contending origins-of-life theories including “genetics first”, “metabolism first”, RNA worlds, the thioester world, the iron-sulfur world, clay life, heterotrophic versus autotrophic origins, and others.

OCS intends to present a platform for addressing such questions as: Can the stock market be considered in any sense to be lifelike? Can an economy? What about a tornado or a game of Go, an autocatalytic set, some viruses, a prion - or the planet Earth?

This text is intended for a general science audience, and no special knowledge of any specific discipline is assumed. OCS is essentially a mathematical theory of the lifelike. It chiefly deals with qualitative mathematical foundations while providing ample quantitative aspects. No mathematical knowledge beyond an elementary acquaintance with naive set theory and the concept of a probability distribution is expected in order to read Part I of this text.

It is often presumed that “life” is defined by membership in a particular lineage – carbon-based life on earth. But, OCS is based upon the premise that it can be fruitful to characterize notions such as “organic”, “aliveness” or “lifelike” by a set of *systemic properties* - rather than by membership in a single lineage.

In OCS theory, the essence of *living* is:

Self-perpetuation of organization within change through change.

In other words, to OCS, livingness is about the self-perpetuation of organization. But the continued existence of any organized entity is constantly threatened with various kinds of change, including growth and decay. In order to survive, a living entity continuously combats this deleterious change with change - by changing its organization in a manner that promotes the persistence of organization itself. While the identity of an organized entity itself may be lost through change, organization itself persists.

OCS develops these notions more formally by presenting a set of fundamental systemic properties that any system must exhibit in order to be considered life-like. These properties are carefully selected for the purpose of forming the basis of a more general theory of the living. They are then articulated into a set of seven organizing principles from which the OCS theoretical framework is derived. That is, these seven properties are abstracted from biological life, and then postulated to form a general theory of living systems.

OCS was described as “comprehensive” in the subtitle of this text. This is meant to suggest two things. The first is that OCS theory should provide a construct that can model the whole of a single organism instance. This means that the entirety of a single organism should be “model-able” – at least to some level of detail - by an OCS mathematical construct in such a way that the seven organizing principles of OCS are evident through this construct.

A second meaning that is suggested by the word *comprehensive* is that certain opposing theories concerning lifelike systems (e.g. metabolism-first versus genetics-first origins-of-life theories) can both be represented using OCS theory.

OCS is not a scientific theory - in the sense of making testable refutable predictions about nature. Rather, it is a mathematical system that is suitable for modeling ideas about the living and the lifelike. Admittedly, the selection of the seven organizing principles is an empirical act. But their abstraction to a general theory of the living is a purely arbitrary mathematical exercise – that, even so, hopes to see a number of modeling applications.

Of course, this is true of most mathematical theories. Differential Equations is a mathematical system that can be used to model many types of dynamical scientific theories about nature – regardless of the veracity of those scientific theories. The same can be said of Algebraic Topology, Nonlinear Dynamics and other mathematical disciplines. Although OCS is abstract, it does have an intended application domain: that of “lifelike systems”. The properties that define this theory, then, have been selected accordingly.

Obviously, OCS is not the first theory to toy with the idea of “life beyond biology”. Lifelike automata have been contemplated for some time. To be lifelike, automata would have to exhibit properties considerably beyond those of ordinary robots [Von Neumann 1966]. As described by Morowitz, “...the suggestion has been made that a future life form consisting of automata may be a possibility...Unless these automata contained stages to synthesize the components from molecules in the homogeneous phase in the environment, such systems would be far different from anything that we have previously recognized as being biological” [Morowitz 1992].

Of course, OCS is intending to go even beyond the biological. Nevertheless, Morowitz’ point is well taken. There are certain systemic properties of “the lifelike” that must be exhibited by anything that we are willing to call “living”. Morowitz infers such properties when he refers to the notion that “the lifelike” must synthesize its components from its environment. This implies a number of properties, which we shall be identifying in the course of this text.

OCS does *not* intend to be a final theory of the lifelike. The set of systemic properties that OCS identifies describes a particular style of lifelike entities. This class is hopefully very interesting, but it need not be unique. Certainly, an entirely different set of properties, and theory, may also represent a different view of what it means to be lifelike. This theory welcomes and encourages such alternative theories. Thus, it can be reasonably said that OCS represents a particular class of lifelike systems. It may be useful to refer to the members of this class as “OCS-lifelike”. Nevertheless, it is hoped that OCS-lifelike systems are found to be interesting.

In order to develop a consistent and coherent program, OCS offers its own operational definitions for a number of terms and concepts. Some of these terms include *system*, *organization*, *property*, *emergence*, *randomness* and *determinism*.

Likely, none of the elements of OCS is new. However, hopefully, the manner in which these elements are organized into an integrated system will provide some useful novelty.

In summary, the essence of OCS is to develop a general theory of the living by 1) Making some empirical observations of biological life on earth; 2) Carefully selecting a set of systemic properties that are exhibited by biological systems; 3) Articulating these systemic properties into a set of organizing principles; and 4) Developing these organizing principles into a theoretical framework that provides a general theory. This framework will then hopefully find a number of

modeling applications in science, engineering, the arts and education – some of which were enumerated above.

Toward a Formal Theory of Living and Lifelike Systems

Part I of this text develops a characterization of living systems as a set of *seven systemic properties*. These properties are then further elaborated into a set of principles that describe how biological systems are organized – or *principles of organization* of organic systems.

Since these seven properties, as well as their corresponding seven *organizing principles*, are *abstractions* from biological systems, then any system that exhibits them can be reasonably said to be *lifelike* – whether or not it is biological. In this way, then, OCS seeks to develop a general theory of the living and the lifelike.

The ultimate goal of OCS is to develop one or more mathematical frameworks whose structures embody these seven organizing principles. Such a mathematical framework, then, would provide a modeling system for living and lifelike systems. As such, it would be useful in modeling whole biological systems. As well, it would be useful in modeling existing non-biological systems that exhibit lifelike properties. Even beyond that, it could also be useful for designing artificial systems that exhibit lifelike properties.

Thus, OCS intends to provide both a theoretical foundation as well as an applicable modeling system from the same set of principles.

The question arises as to how these seven systemic properties of biological systems were identified. Lets now describe the process pursued by this researcher in arriving at these seven properties as foundational to the living.

A study of biological systems was undertaken. This study revealed a generous number of exhibited systemic properties that were observed and itemized. Finally after lengthy consideration of the published research in systems biology, biochemistry, genetics, origins of life research, information theory, systemics, cybernetics and a number of other disciplines, this list of the resulting seven properties emerged as the codification of this investigator's views and biases as to the basic nature of living systems.

Since I am only providing the result of this inquiry, then the question also arises as to the quality of the result. Are these seven systemic properties worthy of capturing the essence of livingness in biological systems?

The most I can claim is that they are interesting. In fact, it is the responsibility of OCS to develop these seven properties into an interesting theory of living systems. Whether the result is, in fact, interesting to some population of scientists or engineers is the criteria upon which it is to be judged.

Obviously, this set of seven properties is not unique; and, obviously these seven represent the biases of this investigator. There may be many other sets of systemic properties that are exhibited by biological systems that are equally valid – and equally interesting, and that represent the biases of other investigators. If so, then I would urge that they too be codified into alternate

theories of the living and put forth for consideration. Each of these theories would represent distinct “lifestyles”. To compare and contrast them would probably be of considerable value. And each may present its own “style of livingness”, and some population of scientists or engineers may find it useful.

In any event, as suggested above, the value of this theory should be calculated by its degree of interest – and in the applicability of any modeling frameworks that are fashioned from it.

OCS as a theory is fixated on *system organization*, and takes the position that it is how living systems are *organized*, and how they *change their organization*, that is responsible for the exhibition of these seven systemic properties. This is the essential bias of OCS and its principle working assumption – thus its name.

Therefore, the first step for OCS is to identify these (seven) systemic properties. And the second step is to elaborate them into *organizing principles*: statements regarding *system organization* that are sufficient for inferring a mathematical embodiment.

Grammatically, *systemic properties* are identified by adjectives, since they are describing organic systems. In formal logic, a *property* of a thing is a *true indicative statement about that thing*. Thus, each of the seven properties needs to be articulated as a true statement. The form of this statement should be: “Organic systems are <adjective>.” – where “<adjective>” is a unique label for each of the seven properties.

For example, the first of the seven properties is labeled “organized”. Thus, as a systemic property, it would be articulated as “Organic systems are *organized*.”

Subsequently, *organizing principles* are articulated for each of these seven systemic properties. By “organizing principle of a systemic property”, we mean a set of statements that elaborates the organizing principle with sufficient meaning to infer a mathematical model from it. A goal of OCS is the development of one or more mathematical frameworks that embody all seven of these organizing principles.

Thus, there is a need for the articulation of these systemic properties into organizing principles. Such articulation is put forth in this Part I. Subsequently; Part II will develop a mathematical framework that embodies these seven organizing principles.

So, we can summarize the purposes of Parts I and II of this treatise as:

The purpose of Part I, Principles of Organization:

- Identify these systemic properties as phrases,
- Elaborate them into organizing principles
- Further reveal the nature of these principles of organization through both explanation and citations of renowned scientists in order to develop both depth and support from the scientific literature.

The purpose of Part II, Organodynamics:

- Provide a mathematical implementation of these seven organizing principles in the form of a modeling framework for organic systems.

For now, though, let's begin by presenting the seven systemic properties of biological systems that have been selected by OCS as its building blocks.

Systemic Properties of Biological Systems

It is accepted practice in biology to define something as “living” when it is the offspring of something that is living – that is, to define biological life in terms of lineage [Hazen 2005]. But this is a circular definition, and does not lend itself to the foundation of a formal system based on organizing principles that can be embodied into a mathematical framework.

As already described above, OCS takes a different approach to characterizing the living: via the identification of a set of *systemic properties* of living systems, and by further articulating these properties into a corresponding set of *organizing principles* that are suitable for implementation into mathematical frameworks. The intention is to embody these frameworks into modeling and simulation development systems for applications in research and engineering.

In this section, we shall list the seven systemic properties of the living that OCS has selected as foundational to life. In preparation for that, we shall first address two preliminary issues.

The first of these argues that there is precedence in scientific literature for characterizing living systems via sets of systemic properties. We shall present two examples of this – each with its own bias, context and intended applications. We draw the conclusion that none is either “right” or “wrong” – but rather are variously appropriate to their intended goals and applications. We argue that the same is true of the seven selected OCS systemic properties.

The second issue is the posture taken by OCS regarding “the essence of livingness” that was presented in the Preface. It is the articulation of this essence that characterizes the biases of OCS and that is responsible for the selection of these particular seven systemic properties as its foundation. It is significant that this posture is not novel or unique on the part of OCS, but that it has precedence in scientific literature. To support this, a particularly poignant statement on the part of a renowned biologist is cited.

Corroboration for Characterizing Life by Systemic Properties

Certainly, these seven organizing principles represent the interests, predispositions and biases of this researcher. Other sets of organizing principles regarding the bases for a theory of living system are not only possible, but have previously been put forth by other investigators. For example, Nobel Laureate Christian De Duve [de Duve 1991] presents his “Seven pillars of Life”, a list of seven properties that, taken together, provide

necessary and sufficient conditions for to describe an entity that is living – at least biologically.

A second example is another renowned biochemist, Harold Morowitz [Morowitz 1992]. Morowitz lists 13 properties of living systems. Morowitz properties are generally in broad agreement with those of De Duve and of OCS. The differences can be explained as the results of intent, interest and application.

As far as emphasis is concerned, I think it fair to characterize Morowitz' properties as more biochemical and De Duve's as more systemic in nature. They both appear to limit their scope to biological systems. The OCS organizing principles make systemic observation about biological systems – but with the intent of generalizing them to apply to a broader category – deemed “the lifelike”.

Thus, there are similarities and differences among the three sets of systemic properties of living system that are proffered by three researchers. Rather than arguing about which is the “correct set”, it is likely more fruitful to view each as providing its unique characterization of what it means to be living, or, in the case of OCS, lifelike. One could say, then, that each characterizing a particular style of living.

Corroboration for The OCS Essence of Life Interpretation

Before presenting the seven system properties of systemic properties of life on earth that have been selected by OCS, it is important to provide some context that motivates their selection.

It was the good fortune of this author to recently encounter a single quotation that appears to include almost all of the OCS systemic properties – each to some degree. It is significant that the cited quotation is over a half-century old.

The biologist that is cited below may be somewhat obscure, and the citation somewhat dated, considering that it was published slightly prior to the publication of the structure of DNA by Watson and Crick.

But the insights of this biologist regarding the systemic properties of life have been echoed by the other scientists quoted below, in one form or another, even though they may never have read him – giving credence to a claim of some broad acceptability of this list of properties of living systems.

The biologist, who offered this insightful quotation, is Sergius Morgulis, who was the translator of the English edition of Oparin's historically significant *Origin of Life* [Oparin 1938]. Here are Morgulis' particularly poignant words from the introduction of his Oparin translation:

Thermodynamically directed chemical evolution could conceivably proceed indefinitely without changing from a non-living to a living state. Only when organic matter had achieved a high degree of organization, and had acquired diverse propensities through the concatenation of such substances (with chance as the only arbiter) did primordial life

emerge as a new dimension in nature: matter perpetuating its own organization. Natural selection, operating on chance variations, set the evolutionary direction along numerous pathways which living things have followed irresistibly. [Morgulis 1952]

The Seven OCS Systemic Properties of Living Systems

Hopefully, the Morgulis citation above sets some pregnant context for the seven OCS systemic properties of the living. These seven properties shall be elaborated into seven *organizing* principles that imbue them with the meaning intended by OCS and presented in the subsections below.

The seven systemic properties of living systems assumed by OCS theory are:

Organized
Emergent
Nested
Reorganizational
Autocogenerative
Uncertain
Persistent

The Seven Organizing Principles of Organic Complex Systems

In the previous section we motivated and listed seven systemic properties of living systems that OCS has selected as their foundational characterizations.

In this section, we shall imbue each of these seven properties with meaning by elaborating each into a description and explanation that is sufficient to be subjected to mathematical interpretation and embodiment into one or more mathematical constructions.

In Part II of this treatise, then, we shall develop a comprehensive mathematical framework by developing a set of interrelated mathematical constructs that constitute such a framework.

Since the posture of OCS is that *system organization* and *change of system organization over time* is adequate to explain the nature of living systems, then each of these seven systemic properties is further elaborated in this section by describing how it pertains to either the system organization or the change of system organization of living systems.

Consequently, these elaborations are referred to as *organizing principles*.

Introducing the Seven Organizing Principles of Organic Systems

In the following table, then, each of the seven systemic properties is associated with such an *organizing principle*.

Step 3
Principles of Organization of Organic Systems

Systemic Property	Organizing Principle
Organized	<i>Any organic entity is comprised of 1) a population of two or more components, as well as 2) a set of relationships among those components. This set of relationships specifies the organization of the entity. Thus, an organic entity constitutes a system; and shall be referred to as an organic system.</i>
Emergent	<i>Any organic system exhibits one or more properties that none of its components exhibits.</i>
Nested	<i>Any organic system has at least one component that is another system.</i>
Reorganizational	<i>Organic systems are dynamic – constantly undergoing change. This change involves some manner of reorganization of its components, or their components. The result is, generally, some form of buildup or breakdown – composition, decomposition, de-nesting, re-nesting, or any combination thereof.</i>
Autocogenerative	<i>The generative agent that initiates the reorganization of an organic system is the system itself. This reorganization is accomplished by virtue of the components of the system co-generating and co-organizing each other. Since the components co-generate and co-organize the other components, then the result is that they co-generate and co-organize the system. An organic system is co-generated by its components-in-relationship, and thus by itself. This phenomenology obviates the philosophical problem of a thing generating itself prior to its own existence. Consequently, the nature of this systemic reorganization, or dynamism, is that it is autonomous. All organic systems decay, or decompose, autonomously. But they also autonomously recombine in varieties of ways. These autonomous regenerations ramify into many flows that branch and loop. Some changes promote the propensity of the system to remain the same with respect to certain properties (regulation); while other changes cease such promotion (deregulation). Some changes promote the continued persistence of the system (adaptation), while some retard it (extinction).</i>
Uncertain	<i>All living processes depend upon both chance events as well as deterministic ones. Living processes operate along a spectrum between complete randomness and complete determinism, uncertainty and certainty. Where along that spectrum an organic system lies at any time is uncertain. Thus, the degree of predictability or uncertainty of an organic system is itself uncertain. (“Life is unpredictably unpredictable.”)</i>

Persistent	<i>The nature of the autocogeneration and uncertainty of an organic system is that it engenders the ongoing existence of these systems. Taken together, all of these static and dynamic elements have resulted in, at the least, a limited persistence of life itself. While no organic system persists, the existence of organic systems has.</i>

Examining the Seven OCS Organizing Principles

In the remaining sections of Part I, each of the seven systemic properties and its corresponding organizing principle are elaborated and examined.

The section header of each section is the articulation of its systemic property as a true indicative statement. Immediately following this section header is the articulation of its associated organizing principle.

Next, each section lists a number of citations from renowned scientists that OCS has interpreted as representing a corroboration of the principle. These citations are intended to set the context for the discussion that follows.

Following these citations, an in-depth discussion of the organizing principle is presented. This discussion defines the OCS theory on the organizing principle entertained.

Organic Systems are Highly Organized

[Any organic entity is comprised of 1) a population of two or more components, as well as 2) a set of relationships among those components. This set of relationships specifies the *organization* of the entity. Thus, an organic entity constitutes a *system*; and shall be referred to as an *organic system*.]

Citations from Scientists concerning Organization

This subsection presents a number of quotations from renowned scientists that support the notion that life, and its progenitors, is, in some deep and essential sense, highly *organized*.

The biological stage concerns itself with the appearance of biological organization, with the building of a coordinated population of large molecules with catalytic function out of a random assortment of building blocks. [Dyson 1999]

...[I]n biology, as in other complex systems, these origins are not to be found in the matter itself, but in its interactions. [Strohman 1997]

“Organization” signifies those relations that must be present in order for something to exist. [Maturana and Varela 1998]

Biological information is structural. [Morowitz 1992]

...definition of systems as ‘sets of elements standing in interrelation....’ [Von Bertalanffy 1968]

The current realization that the structure of DNA already allows us to understand practically all of its fundamental features at the molecular level is thus most significant. [Watson 1970]

There exists a universal network of intermediate reactions such that the metabolic chart of any extant species is a subset of the universal chart. [Morowitz 1992]

Is there a sharp distinction between living and nonliving systems? Or can there exist levels of organization that are between those of the present living and nonliving systems? [Kauffman 1994]

Objects and events are not primitive experiences. Objects and events are representations of relations. [von Foerster 2002]

The problem of the origin of life is for me the biological stage, the problem of the appearance of biological organization out of molecular chaos. [Dyson 1999]

[Regarding *order*] we may wish to account for apparent relationships between elements of a set... [von Foerster 2002]

The OCS Idea of Organization

Organization is the hallmark of living systems. All of life is an organized population of some kinds of entities. Freeman Dyson makes this point as well as anyone when he says: “The problem of the origin of life is for me the

biological stage, the problem of the appearance of biological organization out of molecular chaos.” [Dyson 1999]

The essence of organization is *relationships* – relationships between and among a set of components in such a way that the entire apparatus forms an integrated whole. And, the essence of *system* is organization – the organization of a population of elements that, in relationship, are worthy of being called *components*.

To be useful to the inquiry into, and the modeling of, any application domain, these principles should assist in “taking the system apart” and then “putting it back together” in a revealing manner. In commenting about the requirements for systemic inquiry, Arne Collen [Collen 2003] observes:

[W]e see two implicit emphases: analysis and synthesis. They are both central to understanding systemic thinking and method. The term “science” communicates the propensity of *splitting* the subject of inquiry. The term “systemic” emphasizes *integrating* the subject of inquiry. Hence, for those of any discipline of science, who would employ systemic methods for systemic change, the oxymoron “systems science” challenges them to surmount an intriguing and quixotic cognitive paradox.

OCS needs to meet the challenge of this paradox and provide a definition of *system* that enables and promotes both analysis and synthesis of application domains of which OCS models can be built. Somehow, the component parts as well as the interrelationships among them must be explicitly articulated by this definition.

{Collen 2003} points out a number of accepted definitions of the word *system* from research literature and other authoritative sources. All of them are legitimate in some context. But, of course, if taken together, there are inconsistencies among them.

As a systemic theory, though, OCS must provide its own consistent definitions – operational definitions. As such, we shall define our terminology in a manner that emphasizes the points of view we wish to take. After that, then, our responsibilities are 1) to provide definitions that do not stretch too far the bounds of common usage, and 2) to use them consistently throughout.

OCS defines *system* as:

System: A collection of entities, and a collection of relationships among those entities. The collection of *entities* is called the *population* of the system.

The entities are referred to as *components* of the population, or as *components* of the system. The collection of *relationships* among the entities is called an *organization of the system*, or as an organization of the population. It is also referred to as a *system organization*.

It is worth noting that any given population can have multiple *system organizations*.

Mathematical frameworks that implement OCS are free to use whatever mathematical structures desired to implement this notion of *system*. For example, the framework presented in Part II used a basic set-theoretic definition.

This approach to defining *system* is simple, intuitive, and consistent - and loses little of the generality of less well-defined notions of *system*. And, more elaborate concepts are easily erected on top of it. The idea to define the notion of *system* in this manner has been around for a long time. We have already cited von Bertalanffy in this regard, with his ...definition of systems as “sets of elements standing in interrelation....”. [Von Bertalanffy1968]

It will be useful later for us to have been precise in this definition. So, we want to present well-defined, set-theoretic description of a system that embodies von Bertalanffy's two ideas: 1) set of elements, and 2) interrelation among those elements.

Admittedly, the notion of *system* as we have defined in here is a *static entity*. But, OCS proclaims to be a dynamical system theory. So where is the dynamism in the system? As we shall see below in the section on *reorganization*, OCS prefers the term *process* to refer to a system-as-it-changes (a so-called “dynamical system”), and to restrict the usage of the word *system* to the static concept we have defined above.

As will be made clear, OCS is mostly about dynamical systems, and only defines them statically in order to subsequently define their dynamics. Perhaps an analogy to classical dynamics will make this clearer. In that discipline, a *system* is an entity whose state is defined by its position and momentum at a specific moment in time. The dynamical version of such a “system” is called its *trajectory*, and represents changes in position and momentum across several moments in time.

So, even in classical dynamics, the static version of an entity is called “system”, and the dynamical version is called something else (“trajectory”). We shall follow the same usage pattern in OC - even though we shall continue to use the colloquial expression “dynamical system” without apology.

Organic Systems are Emergent

[Any organic system exhibits one or more properties that none of its components exhibits.]

Citations from Scientists Concerning Emergence

This subsection presents a number of quotations from renowned scientists that support the notion that life, and its progenitors, is, in some sense, *emergent*.

The chemical combination of two substances produces, as is well known, a third substance with properties entirely different from those of either of the two substances separately, or of both of them taken together. Not a trace of the properties of hydrogen or of oxygen is observable in those of their compound, water....There, most of the uniformities to which the causes conformed when separate, cease altogether when they are conjoined; and we are not, at least in the present state of our knowledge, able to foresee what result will follow from any new combination, until we have tried the specific experiment. [Mill 1859]

The concepts of emergence trace back to the statistical mechanics of Ludwig Boltzmann, James Clerk Maxwell, and Josiah Gibbs....Thus while Perrin and others were pursuing the development of the reductionists view of atoms and molecules as the operative agents, the statistical mechanicians were showing that the microscopic particle view led to the macroscopic laws of thermodynamics in terms of emergent properties. [Morowitz 2002]

The laws of organic chemistry cannot account for those phenomena of a higher order which are encountered in the study of the living cell. The study of the protein molecule, its amino and carboxyl radicals, polypeptide or other linkages, etc., determine only the ability of this material to evolve and change into a higher grade of organization, which depends not only on the arrangements of atoms in the molecule but also on the mutual relationships of molecules toward one another. (p. 137) [Oparin 1938]

But the collective system does possess a stunning property not possessed by any of its parts. It is able to reproduce itself and evolve. The collective system is alive. Its parts are just chemicals. [Kauffman 1994]

In short, we will not understand life and living organisms until we understand emergence. [Holland 1998]

Evolution is an overall process, while emergence characterizes the punctuations. [Morowitz 2002]

Life emerged, I suggest, not simple, but complex and whole, and has remained complex and whole ever since...thanks to the simple profound transformation of dead molecules into an organization by which each molecule's formation is catalyzed by some other molecule in the organization. [Kauffman 1994]

Chemical systems create new properties through recombination of molecules via chemical bonds. New combinations between existing molecules and combinations of new molecules with other molecules, then define new functional properties in a system at large. [Rasmussen, Knudsen and Feldberg 1992]

[L]ife began as an integrated emergent property of complex systems of polymer catalysts. [Corning 2005]

It is unlikely that a topic as complicated as emergence shall submit meekly to a concise definition, and I have no such definition. [Holland 1998]

The OCS Idea of Emergence

Most contemporary complexity scientists would probably say that a hallmark of complex systems, especially living ones, is the fact that they are *emergent*.

But, when pressed to explain exactly what is meant by *emergent*, complexity scientists are likely to say that they don't know how to define it. For example, John H. Holland, arguably the contemporary father of emergence in complex systems, dared not tread into this dangerous territory. In [Holland 1998] he says (famously) "It is unlikely that a topic as complicated as emergence shall submit meekly to a concise definition, and I have no such definition."

Process Emergence

On the other hand, it is the observation of this author that there is some consistency that can be found in the general usage of the term *emergent* or *emergence*, by complex systems scientists. I believe that the usage of the term *emergent* by complexity theory scientists generally implies that at some certain point in the life cycle of a complex system, novel behavior begins to be exhibited that was not so exhibited earlier in its system dynamics. Indeed, such a concept is useful, even essential, in the study of complex system dynamics.

With apologies to those who, with good reason, refuse to define "emergence", I shall proffer the following working definition for this particular usage of this term, which I shall call *process emergence*, because it occurs in due time at a particular point, or stage, within a process:

Process emergence: the appearance of a systemic property at some stage of a dynamical system process, wherein such property is not exhibited before such stage in the same process. Such systemic property is referred to as a *process emergent property*.

Systemic Emergence

However, there is a second manner in which the notion of *emergence* within complex systems could also be defined - an approach to emergence that is essential to OCS.

This second notion of emergence pertains to a phenomenon that can occur in systems due to their multiple levels of organization – that is, their *part-whole* relationships. For that reason, we shall name it *systemic emergence*.

Occasionally, it happens that a *whole* system, the system itself, can exhibit a property that is not exhibited by any of its parts (which we are calling *components*). This phenomenon is what we shall call *systemic emergence*.

A simple example is a bicycle. As a system, a bicycle can be used as transport of a human from place to place. Such is not true of any of its components: handlebars, frame, pedals, chain, or even wheels.

A fruitful place to find examples of *systemic emergence* is physical chemistry. Macromolecules generally exhibit properties that none of their component molecules do. Many have put this idea forth. John Stuart Mill noted “The chemical combination of two substances produces, as is well known, a third substance with properties entirely different from those of either of the two substances separately, or of both of them taken together.” [Mill 1859].

This idea of *systemic emergence* can be seen in the work of Stuart Kauffman of the Santa Fe Institute in his description of autocatalytic sets, a notion that we shall see again in the development of OCS below. (The italics are mine.)

A set of molecules either does or does not have the property that it is able to catalyze its own formation from some simple food molecules. No vital force of extra substance is present in the *emergent*, self-reproducing whole. *But the collective system does possess a stunning property not possessed by any of its parts.* It is able to reproduce itself and evolve. The collective system is alive. Its parts are just chemicals. [Kauffman 1994]

The idea that we shall adapt from Kauffman is the “not possessed by any of its parts” portion of the above quote.

With this introduction, we shall define *systemic emergence*.

Systemic emergence: The exhibition of a property by a system, when at the same time none of its components exhibits that property. Such a property is called a *systemic emergent property*.

Such property is also said to be *emergent systemically*.

This notion of *systemic emergence* is not an invention of OCS. Rather, many researchers in the sciences frequently cite the idea – even though the phrase “systemic emergence” may be novel terminology introduced here. To corroborate this, I have reiterated here three quotations from those of renowned scientists from earlier in this article.

The laws of organic chemistry cannot account for those phenomena of a higher order which are encountered in the study of the living cell. The study of the protein molecule, its amino and carboxyl radicals, polypeptide or other linkages, etc., determine only the ability of this material to evolve and change into a higher grade of organization, which depends not only on the arrangements of atoms in the molecule but also on the mutual relationships of molecules toward one another. (p. 137) [Oparin 1938]

*Chemical systems create new properties through recombination of molecules via chemical bonds. New combinations between existing molecules and combinations of new molecules with other molecules, then define new

functional properties in a system at large. [Rasmussen, Knudsen and Feldberg 1992]

The concepts of emergence trace back to the statistical mechanics of Ludwig Boltzmann, James Clerk Maxwell, and Josiah Gibbs.... Thus while Perrin and others were pursuing the development of the reductionists view of atoms and molecules as the operative agents, the statistical mechanics were showing that the microscopic particle view led to the macroscopic laws of thermodynamics in terms of emergent properties. [Morowitz 2002]

An essential difference between a property that is *process emergent* and one that is *emergent systemically* is that *process emergence* requires at least two moments in time to ascertain. That is, at one moment in time, the process emergent property is not exhibited, while at the next moment in time it is. The use of the term by most complexity scientists is in the sense of *process emergence*.

On the other hand, *systemic emergence* can be detected by the inspection of a single time step. No dynamics are required. If within a single instant, a system exhibits a certain property but none of its components do, then that property is *emergent systemically*. As indicated earlier, OCS is primarily interested in systemic emergence.

It is important to note that very often an emergent property is simultaneously both *process emergent* and *emergent systemically*. In fact, this is probably most often the case.

But the distinction between these two forms of emergence is important to OCS, because it is systemic emergence that is responsible for the popular notion within systemics that “the whole is greater than the sum of its parts”.

Note: Since OCS shall emphasize systemic emergence over process emergence, we shall state the following convention for this article: whenever the term *emergence* is used, it shall mean *process emergence* unless otherwise stated.

The reason that, in systems, “the whole is greater than the sum of its parts” is because the whole system can have something that its parts do not – a systemically emergent property. Of course, this fact give the appearance that “something has come from nowhere” – which is the definition of “magic”. Of course, this appearance is false, because of the following explanation.

The “something” that appears to have “come from nowhere” is the *systemically emergent property*. It appears to “come from nowhere” because none of the system’s components exhibit it. However, it does actually come from somewhere – and that “somewhere” is the interrelationships among the systems components – the system’s *organization*.

Unfortunately, the casual observer is not aware that a system *has* an entity that is called its *organization* – that embodies the interrelationships of its components. Thus, there is the appearance that the systemically emergent property “came from nowhere”.

Therefore, it is the system's *organization* that appears to imbue it with "magic". But systems theorists peer beneath the "magic" and see what is really at work – the system's organization.

Another departure from traditional usage is that OCS is defining *properties* to be emergent (or not), rather than *systems*. OCS takes the position that, at the foundations, it is systemic properties that may, or may not, be emergent. Of course, a system can be called *emergent* if it exhibits at least one emergent property.

To further elucidate the notion of systemic emergence, let's present one more example, this time from biochemistry – specifically, genetics. Consider the enzyme RNA-polymerase. This molecule, taken as a system, exhibits the systemic property "x can synthesize messenger RNA". If one considers the components of the system RNA-polymerase to be its collection of amino acids, then none of its components, individually, can synthesize RNA. Thus, RNA-polymerase exhibits this property, but none of its components do. Thus, "x can synthesize messenger RNA" is a *systemically emergent property* of RNA-polymerase. Ergo, RNA-polymerase is an emergent system.

[Sidebar: To complicate the matter, one can easily prove, by the above definition, that *all systems* necessarily have at least one systemically emergent property, and thus that all systems are, then, emergent. This property is that "x cannot be a component of this system". For any system, this statement (property) is true of the system itself, but not of any of its components – and is therefore a systemically emergent property of the system by the above definition. That this property is an emergent property of any system is easily proved by invoking Russell's Paradox. Unfortunately, this argument does away with any distinction between "emergent systems" versus "non-emergent systems"; and proclaims that emergence is endemic to the very idea of *system*. On the other hand, if one is insistent on preserving this distinction between emergent and non-emergent systems, then one could define an *emergent system* to be any system that exhibits an emergent property beyond this trivial one.]

Systemic Emergence as an Ontological Phenomenon

Process emergence takes place in time. It is a dynamical phenomenon. The definition of *process emergence* makes this clear. This definition says that there must have been at least two stages, or times, in order to be able to talk about process emergence: some stage during which the property emerged and some stage prior to that when the property had not yet emerged.

But, systemic emergence is more primitive. It needs only a single moment in time – a single stage in the process – to be observed. Indeed, it needs no process at all – only a single moment in time. It is state – not process.

This is because, within a snapshot in time, one can observe the state of the system at that moment and determine whether it exhibits a property that none of its components exhibits. More than one snapshot is not needed.

Thus, *systemic emergence* is a state of *being* – not an aspect of *doing*. It is ontological. It concerns being. It is a static phenomenon. No dynamics are required.

Of course, it can also occur dynamically, because it can either be or not be across multiple states in time. So it can be both static and dynamic.

And, because – as shown in the sidebar above – every system exhibits systemic emergence, either trivially or significantly, it is at the heart of what it means to be a system. There is something about what it means to be a system that has to do with this kind of emergence – *systemic emergence*. All systems have something, at least some property, that none of their parts have. They are in some sense “greater than the sums of their parts”.

Organic Systems are Nested

[Any organic system has at least one component that is another system.]

Citations from Scientists Concerning Nested Systems

This subsection presents a number of quotations from renowned scientists that support the notion that life, and its progenitors, is, in some sense, of a *nested* organization.

The physiologists...associate the term hierarchy with organelles, cells, tissues, organs, etc., and so on, a scheme which implies a nested set of functional parts-wholes relationships. [Corning 2005]

Complex structures which carry out living processes I believe can be identified at seven hierarchical levels – cell, organ, organism, group, organization, society, and supranational system. My central thesis is that systems at all of these levels are open systems composed of subsystems which process inputs, throughputs, and outputs of various forms of matter, energy, and information. [Miller 1978, p. 1]

Each higher level of organization has its own rules, and there is no continuous gradual transition from one level or hierarchy to the other. [Strohman 1997]

At each level of observation the persistent combinations of the previous level constrain what emerges at the next level. This kind of interlocking hierarchy is one of the central features of the scientific endeavor. [Holland 1998]

The appearance of novelty occurs at many scales ranging from societies, to individuals, to cells, to genes, to molecules.... [Fontana 1992]

Something then happened that allowed prokaryotic cells to combine by a process of one cell being engulfed by and living within another, called endosymbiosis. This led to: cells with membrane-bounded organelles, the origin of complex chromosomes, the process of meiosis, and the accompanying massive exchange of genetic material. [Morowitz 2002]

All the biologists and molecular biologists today are 'mechanical materialists'. But the machines they study differ from the ones imagined by Descartes. As the philosopher and mathematician Gottfried Leibniz was the first to point out, natural (or 'divine') machines are infinitely divisible. If we analyze a living organism, we find that it is composed of micro-machines (metabolic cycles, enzymes). [Smith and Szathmary 1999]

The contemporary position of most neurobiologists is to try to go up the hierarchy from atoms to minds to understand the emergence of mind in terms of the underlying members of the hierarchy....This of course presents an epistemic circle. [Morowitz 2002]

The OCS Idea of Nested Systems

A component of a system may itself be a system. This organizing principle requires that an *organic system* must have at least one component that is another system.

Certainly all biological systems are nested systems. The smallest cell, a prokaryotic cell with no nucleus or other organelles, is constituted by a

population of carbon-based macromolecules. These are large molecules that are themselves constituted by an assemblage of smaller – yet still complex - molecules. Plant and animal cells are eukaryotes. Their components are organelles that, in turn, contain macromolecules as components, which is an added level of nesting as compared with prokaryotic cells. In OCS, we refer to these levels of nesting as “levels of organization”, or as “levels of abstraction”.

And, of course, complex plant and animal orders, classes and genera - composed as they are of eukaryotic cells - exhibit many levels of nesting, or levels of organization. Primate organisms consist of organs that consist of tissues that consist of cells that consist of organelles that consist of macro (polymer) molecules that consist of basic organic molecules that consist of atoms. The requirement above translates into the organizing principle that an organic system must exhibit at least two levels of organization.

Therefore, there are really two aspects, or dimensions, of system organization that must be considered. We have already discussed one aspect in the section above on the *organized* organizing principle, which considered the amount of organizational relationships of the population’s components with each other. We can call this the “horizontal” aspect of system organization.

But we must also factor in the *nestedness* aspect of system organization. This aspect must measure the degree to which there is nesting occurring within a particular system: how often it occurs within each population, and how deeply the nesting occurs whenever it does occur. We can call nesting the “vertical” aspect of system organization.

It may be of interest to OCS to measure the *degree of organization* exhibited by an organic system. If so, then OCS will need to develop a measuring function that associates any organic system with non-negative real number in a way that measures “how organized” a particular organic system is.

Such a function would have to take into account both the “horizontal” and the “vertical” aspects an organic system’s organization. Discussions of such a measuring function are beyond the scope tackled by this treatise presently. But it has been mentioned here in order to give some context to the notion of horizontal and vertical organization of an organic system.

The definition of such a measure is highly pertinent to OCS. However, an examination of such a measure will be presently postponed due to difficulty of the challenges involved. We shall leave such an investigation to further research.

An important side-effect of nestedness is that it provides increased opportunities for systemic emergence. For each level of organization nested within an organic system’s structure, emergent properties can arise. Thus, in deeply nested organizations, uncertain and sophisticated systemic properties often emerge.

This complexity can offer an explanation for some of the seemingly inexplicable properties of higher life forms, including various ill-defined notions as

intelligence, altruism, intention, purpose and other teleological concepts. John Holland asks “Can we explain consciousness as an emergent property of certain kinds of physical systems?” [Holland 1998].

Of course, investigators such as Peter Corning [Corning 2005] are convinced that some of these properties, such as purposefulness, are foundational to living entities. But OCS offers a model in which they are the result of emergence through many levels of organization within deeply nested systems – rather than being foundational.

Organic Systems are Reorganizational

[Organic systems are dynamic – constantly undergoing change. This change involves some manner of reorganization of its components, or their components. The result is, generally, some form of buildup or breakdown – composition, decomposition, de-nesting, re-nesting, or any combination thereof.]

Citations from Scientists Concerning Reorganization

This subsection presents a number of quotations from renowned scientists that support the notion that life, and its progenitors, is, in some sense, undergoing continuous *reorganization*.

Chemistry is mostly about reactions – processes in which groups of atoms are reorganized. [Zumdahl 2006]

...[I]n biology, as in other complex systems, these origins are not to be found in the matter itself, but in its interactions. [Strohman 1997]

To engage in the Darwinian saga, a living system must first be able to strike an *internal* compromise between malleability and stability. To survive in a variable environment, it must be stable, to be sure, but not so stable that it remains forever static. Nor can it be so unstable that the slightest internal fluctuation causes the whole teetering structure to collapse. [Kauffman 1994]

Most importantly, on all levels the interactions are constructive, in the sense that they enable, either directly or indirectly, the formation of new objects. [Fontana 1992]

A biological self-replicating entity is a molecular self-replicating entity that is capable of evolving. [Morowitz 1992]

The link between biosynthesis and biodegradation is the primordial link in the web of life. Most likely, it existed already in the first common ancestor of all life. [de Duve 1995]

...[C]omplexity alone is an insufficient measure for characterizing the transition from nonliving to living. This point has often been missed by theoreticians studying living systems. [Morowitz 1992]

The decisive events in a theory of the origin of metabolism are the rare statistical jumps when a molecular population in one quasi-stationary state happens to undergo a succession of chemical reactions that push it up, against a gradient of probability, over a barrier and down into another quasi-stationary state. If the initial state is disorganized and the final state is organized, the jump may be considered to be a model for the origin of metabolism. In a complete theory of the origin of life it is likely there would be several such jumps, each jump taking a population of molecules to a new quasi-stationary state. [Dyson 1999]

All growing cells have ribosomes which are the site of protein synthesis. [Morowitz 1992]

We are interested in reversible polymerization reactions, in which either two polymers *condense* to form a single long polymer, or a single polymer *cleaves* into two shorter polymers. Cleavage and condensation can be considered together as a single reversible reaction. [Bagley and Farmer 1992]

The OCS Idea of Reorganization

The first three organizing principles that we have discussed (*organized*, *emergent* and *nested*) define the *state* of an organic system. The remaining four systemic, beginning with the present one, describe its *dynamics*. And since OCS defines the *state* of organic system as its *organization*, then the dynamical aspects of OCS are defined in terms of how that organization *changes*.

In classical dynamics, as discussed above, changes to a system are tracked over time by tracing its path, or trajectory, through the six-dimensional space. This “phase space” is an ordinary Euclidean space, named R^6 , which provides three dimensions for the position of the system, and three more dimensions for its momentum. These six dimensions completely specify all that physicists want to know about the “state” of a system at any moment in time.

But these six dimensions of classical dynamics do not satisfy the interests of OCS regarding the “state” of an organic system. OCS is not terribly interested in where, within a larger space, an organic system currently is, or in its current momentum. (These would be “nice-to-know” characteristics, but not essential.)

OCS is interested in describing system change in a much richer and much more complex manner: as a change in system configuration that it calls *reorganization* – not merely a change in position and momentum.

Be aware that this change in attitude about what constitutes dynamics, or *systemic state change*, is profound. It turns the notion of “system dynamics” completely around. No more is a “trajectory” a simple path through a Hilbert Space. This new “phase space” contemplated by OCS consists of all possible “organizations” (structural arrangements) of a system’s components and their relationships, no matter how deeply nested.

Such a phase space is quite complex, and is difficult to characterize mathematically. Moreover, this space does not reduce to real or complex numbers, or vector space thereof, and therefore does not lend itself easily to quantification.

But the same is true of set theory, algebraic geometry and point set topology. Some spaces are simply too rich to be reduced to quantification. To do so would be to suffer too much loss of information. This is why OCS is fundamentally qualitative mathematics – as are the foundations of mathematics. We shall find there is ample opportunity to provide quantification and measurability in OCS, of course. But, at its foundations, OCS is highly qualitative mathematically.

So, OCS is very much interested in the *organizational state* of its systems. Therefore, OCS is willing to forego tracking the position and momentum information as an organic system changes; and will instead track how its organization changes. This is what is meant by the systemic property named *reorganizational*. This approach enables OCS to operate in spaces that are not necessarily Euclidean in nature – or that have no Euclidean space defined.

An example of this might be “Cyberspace”. OCS would like for a world of computer programs to be a candidate to host “lifelike” entities in the form of computer programming agents. It would be interesting to discuss the possibility of these entities exhibiting lifelike properties. However, since no Euclidean space has been defined for the hosting environment of these programs – and it may not even make sense to do so, then it would be most convenient if OCS does not require such an environment – or “phase space”.

Let’s return to the notion of “reorganizational” as a foundational systemic property of OCS. What is implied in the use of this terminology? Principally, the idea is that moving from one system organization to another represents change within organic systems. Some of these organizations are more highly organized and some are less. But the emphasis is always on describing the organization of the system before and after a change takes place.

In biological systems, this *reorganization* is represented by chemical reactions – most of which take place within cells. According to [Watson 1970], “...food molecules are extensively transformed after they enter the organism. In no case does a food source contain all the different molecules present in a cell. On the contrary, in some cases, practically all the organic molecules within an organism are synthesized inside it.” Watson goes on to explain that “Usually these chemical transformations do not occur in one step; instead intermediate compounds are produced.” [Watson 1970].

According to [Watson 1970], “The sum total of all the various chemical reactions occurring in a cell is frequently referred to as the *metabolism* of the cell.” Thus, for the specific case of biological systems, this *reorganization*, at the cellular level of organization, is primarily represented by metabolism.

Cellular metabolism in biological systems takes on a specific characteristic – has its “own style of reorganization”. In particular, as explained by [Watson 1970], food is used as a source of, not only the building blocks of molecules that the biological organism synthesizes (or, in the parlance of OCS, *reorganizes*), but also of the energy needed to perform these reorganizations (these breakdowns and syntheses).

This provision by food of both energy and building blocks is essential in biological systems because of the physics, in particular the thermodynamics, of the universe in which biological systems reside. This physics requires the use of energy in order for this work (reorganization) – in the form of buildup and breakdown – to transpire.

To accommodate this, biological metabolism provides some chemical reactions that release these building blocks and this energy and capture it for later use, as well as other chemical reactions that make use of these building blocks and this energy to synthesize the molecules of the organism, or to further decompose them. These are generally referred to as aerobic and anaerobic metabolism.

From a biochemical perspective, such decomposition consists of a reorganization of molecules to result in a molecular part and an energy part.

The energy part is either in the form of heat, which cannot be reused by the biological system, or it is in the form of the transfer of hydrogen atoms from the source molecule to a destination molecule. The “giving up of hydrogen” is called *oxidation*, while the acceptance of the hydrogen is called *reduction*. Together, this transfer of chemical energy in the form of hydrogen from source to destination molecules is called *oxidation-reduction*.

In order to get this chemical energy (in the form of hydrogen ions) to the places they are needed, they are often transferred several times from one molecule to another in a “chain” of transfers until they arrive at a destination where they are used. The molecules in this chain are often referred to as “electron carriers”, since the hydrogen ions are essentially a pair of electrons. These electron carriers are also often called *coenzymes*. According to [Watson 1970], “These are several different molecules whose roles is to receive hydrogen atoms. All are medium-sized organic molecules...that associate with specific proteins to form active enzymes. The protein components alone have no enzymatic activity. Only when the small partner is present will activity be present.” In other words, these chemical-energy-carrying coenzymes enable certain proteins to become active and to perform work (reorganization).

This explanation has omitted, for the sake of brevity, a number of essential dynamics of biological metabolism – including the very important roles of oxygen and certain phosphorus-based molecules (ADP and ATP). Nevertheless, the point has been made that life on earth has its own peculiar version of this *reorganization* that we are discussing.

In summary, this process of reorganization called biological metabolism breaks down source molecules (food), which it originally takes in from outside the organism, and then decomposes that food into other molecules plus chemical energy (oxidation-reduction). This reorganization of molecules and chemical energy is then reorganized in complex combinations (“metabolic pathways”) resulting the breakdown and synthesis of myriad molecular organizations that utilize this chemical energy, until it is eventually lost as heat.

So, biological life on earth presents its own style of this fourth organizing principle – *reorganizational* – in the form of cellular metabolism, including oxidation-reduction biochemistry. But OCS is interested in abstracting this systemic property and generalizing it to a class of entities and behaviors beyond that of the biological. So, at this time, let us return to that pursuit.

At a high level of abstraction, these reorganizational changes within *organic systems* over time can be categorized as *buildup*, *breakdown*, *nesting* and *de-nesting*. The mathematical framework of OCS, presented in Part II of this text, decomposes these broad categories of reorganizational change into a number of *primitive transforms*. Some of these transforms are models of chemical breakdown, others are models of chemical buildup, and others are models of both.

The most basic kind of breakdown is *decay*. In our physical universe, this is indicated for all systems via the second law of thermodynamics [Lawden 1987]. For example, one’s desk, in the absence of the discipline of personal hygiene,

tends to devolve into disorganization [Penrose, Oliver 2005]. These include several classes of conspicuously obvious processes in catabolic metabolism. As explained by Morowitz, “Living systems are far from thermodynamic equilibrium and are therefore at normal temperatures always being degraded toward the equilibrium state.” [Morowitz 1992].

Then there is so many types of *buildup* in biological systems - including aggregation, composition and integration - that there is scarcely need to cite examples here. Let it merely be mentioned that buildup, or synthesis, includes several classes of conspicuously obvious processes in anabolic metabolism, protein synthesis, and the synthesis of other biomolecules by proteins.

As for *breakdown* in biology, clearly each of these synthetic processes has its deconstructive counterparts. Anabolism has catabolism; and all other biomolecules eventually decompose – some with the help of protein catalysts.

This term *reorganizational* in OCS refers to any change that can occur anywhere within the structure of the hierarchy of systems at any level of organization within that hierarchy. This means that any system anywhere within the hierarchy can change. Recall that any system – as defined earlier - consists of two tuples: its *population* and its *organization*. Either of these can change. And change can occur in one or in many of the systems that are anywhere in the hierarchy that constitutes the state of an organic system.

The permutations and combinations of ways that this change, this buildup and breakdown, can occur is amenable to analysis and organization. In order to develop a mathematical theory of these dynamics, an identification and classification of the possible transformations is required. Any theory of living systems needs to address such classification.

It is obvious that the property “reorganizational” can apply to changes in both the *organization* and the *nested* static properties of an organic system. But it can also capture changes in the *emergent* properties as well. For example, suppose a protein is damaged in such a way that it can no longer fold properly. Then it loses its ability to perform its function – and this constitutes the loss of an emergent property. [Morowitz 1992] Thus, all three of the static organizing principles of OCS (organization, emergence and nesting) can change under the influence of this reorganizational organizing principle.

In OCS, this reorganization, this change in organization, is represented as a “transition” between one state of organization and another. And, a *re-organization*, or transition, can be represented in OCS as a *mathematical transform* that maps one *organic system state* to another from one moment in time to another. In OCS, these *system transforms* can be thought of as a generalization of metabolism of biological systems.

Taken together, an entire sequence of these “states” is represented by a mathematical *process*, consisting of a string of composite mathematical transformations. Thus, a mathematical foundation for representing this *re-organization* is beginning to surface from this discussion. More will be

discussed about this below in Part II of this article on the OCS theoretical framework.

Organic Systems are Autocogenerative

[The generative agent that initiates the reorganization of an organic system is the system itself. This reorganization is accomplished by virtue of the components of the system co-generating and co-organizing each other. Since the components co-generate and co-organize the other components, then the result is that they co-generate and co-organize the system. An organic system is co-generated by its components-in-relationship, and thus by itself. This phenomenology obviates the philosophical problem of a thing generating itself prior to its own existence. Consequently, the nature of this systemic reorganization, or dynamism, is that it is autonomous. All organic systems decay, or decompose, autonomously. But they also autonomously recombine in varieties of ways. These autonomous regenerations ramify into many flows that branch and loop. Some changes promote the propensity of the system to remain the same with respect to certain properties (regulation); while other changes cease such promotion (deregulation). Some changes promote the continued persistence of the system (adaptation), while some retard it (extinction).]

Citations from Scientists Concerning Autocogeneration

This subsection presents a number of quotations from renowned scientists that support the notion that life, and its progenitors, is, in some sense, and in some way, continuously *regenerating itself*.

The laws of nature are written by man. The laws of biology must write themselves. [von Foerster 2002]

...[T]he spontaneous emergence of self-sustaining webs is so natural and robust that it is even deeper than that specific chemistry that happens to exist on earth; it is rooted in mathematics itself. [Kauffman 1994]

A statistical chemistry approach would view the random emergence of diverse organic molecules, and their assemblies, as natural consequences of undirected prebiotic organosynthesis. It would then ask how life-like processes could emerge with such primordial random assortments, rather than study their specific molecular content. ...[T]he transition from random chemistry to self-replicating entities would occur because of intrinsic statistical factors, e.g. the probability for mutual catalysis among randomly selected counterparts within a mixture. [Segre' and Lancet 1999]

...[T]he potential diversification and plasticity in the family of organic molecules has made possible the formation of networks of molecular reactions that produce the same type of molecules that they embody, while at the same time they set the boundaries of the space in which they are formed. These molecular networks and interactions that produce themselves and specify their own limits are...living beings. [Maturana and Varela 1998]

It is as if the cell has interposed between its genome and its behavior a second informational system able to integrate environmental and genetic information into its dynamical process, and able to generate from this integration responses that are functional – adaptive. [Strohman 1997]

The emergence of autocatalytic sets is almost inevitable. [Kauffman 1994]

...[A]utonomy becomes synonymous with *regulation of regulation*. [von Foerster 2002]

The meaning of the signals of the sensorium are determined by the signals of the motorium; and the meaning of the signals of the motorium are determined by the signals of the sensorium. [von Foerster 2002]

What is distinctive about [living beings], however, is that their organization is such that their only product is themselves, with no separation between producer and product. [Maturana and Varela 1998]

...[S]elf-programmable matter is a dynamical system of interacting elements, with associated functional properties, which through their autonomous dynamics, develop new compositions of elements with new associated functional properties. Such systems are characterized by an *ability to construct novel elements within themselves*. [Rasmussen, Knudsen and Feldberg 1992]

This balance requires that the final flows of materials generated by the electronic transitions return to points in the network where they originated. Thus, the steady state is necessarily characterized by cyclic flows of material around loops in the reaction network. [Morowitz 1992]

...[A] fundamental challenge for autocatalytic, self-ordering theories of evolution is this: Can hierarchical, cybernetic controls evolve spontaneously...? [Corning 2005]

...[T]he very gratuitousness of these systems, giving molecular evolution a practically limitless field for exploration and experiment, enabled it to elaborate the huge network of cybernetic interconnections which make each organism an autonomous functional unit, whose performances appear to transcend the laws of chemistry if not to ignore them altogether. [Monod 1972]

No preformed and complete structure preexisted anywhere; but the architectural plan for it was present in its very constituents. It can therefore come into being spontaneously and autonomously, without outside help and without the injection of additional information. [Monod 1972]

Life is universally understood to require a source of free energy and mechanisms with which to harness it. Remarkably, the converse may also be true: the continuous generation of sources of free energy by abiotic processes may have forced life into existence as a means to alleviate the buildup of free energy stresses. [Morowitz and Smith 2006]

The essential characteristic of living cells is homeostasis, the ability to maintain a steady and more-or-less constant chemical balance in a changing environment.... Without homeostasis there can be no ordered metabolism and no quasi-stationary equilibrium deserving the name of life. [Dyson 1999]

In my version the history of life is counterpoint music, a two-part invention with two voices, the voice of replicators attempting to impose their selfish purpose upon the whole network and the voice of homeostasis tending to maximized diversity of structure and flexibility of function. The tyranny of the replicators was always mitigated by the more ancient cooperative structure of homeostasis that was inherent in every organism [Dyson 1999]

For a dynamical system...to be orderly, it must exhibit homeostasis: that is, it must be resistant to small perturbations. [Kauffman 1994]

Contemporary organisms achieve specificity through a codependent relationship between templates and enzymes. Proteins and nucleic acids synthesize each other through a

replication mechanism in which none of the components synthesizes itself. [Bagley and Farmer 1992]

Autonomy in living systems is a feature of self-production (autopoiesis), and...a living system is characterized only as a network of processes of production of components that is, continuously and recursively, generated and realized as a concrete entity (unity) in a physical space, by the interactions of the same components that it produces as such a network. [Maturana 1974]

A living system is in continuous change, and some of the changes lead to degradation....It follows that, if the system is to maintain itself, it must be able to overproduce its own material. That is why the metabolic system must be autocatalytic: autocatalysis is needed for self-maintenance, let alone for growth and reproduction. [Smith and Szathmary 1999]

Unquestionably, a factory could not originate through some natural phenomenon and independently of man, simply because every factory is constructed in accordance with some set, previously worked out plan. Everything in the factory, beginning with the erection of the building and machinery down to the arrangement of different sections, has been calculated by the engineer with a view to fulfill definite and foreseen aims. The natural elements could not accomplish such human objectives or fulfill a previously laid-down plan. (p.61) [Oparin 1938]

A harmonious coordination of velocities of the different reactions is prerequisite for the existence of this orderly succession, and this is possible only under the conditions of strict regulation of the activity of each enzyme catalyzing a particular reaction. (p. 176) [Oparin 1938]

Rather, it is by languaging that the act of knowing, in the behavioral coordination which is language, brings forth a world. We work out our lives in a mutual linguistic coupling, not because language permits us to reveal ourselves but because we are constituted in language in a continuous becoming that we bring forth with others. We find ourselves in this co-ontogenic coupling, not as a preexisting reference nor in reference to an origin, but as an ongoing transformation in the becoming of the linguistic world that we build with our other human beings. [Maturana and Varela 1998]

...[F]low-through of energy is required to counter the entropic decay. One anabolic process is growth. Without corresponding catabolic processes, limiting atomic components would be tied up in biotic material and further growth would cease. Catabolic processes keep up the cycling, both biological and chemical, of components. [Morowitz 1992]

The OCS Idea of Autocogeneration

What generates this dynamism, this change, and this “reorganization”? OCS proposes that an organic system mostly generates its own change. As observed by Monod: “...[A] living being’s structure results from a totally different process, in that it owes almost nothing to the action of outside forces, but everything from its overall shape down to its tiniest detail, to ‘morphogenetic’ interactions within the object itself.” [Monod 1972]

Paradox Resolved

But this raises a philosophical problem – the bootstrap problem. How does a thing generate – originate, grow, replicate, manage etc. – itself? How can a thing bring itself into existence if it does not already exist? It seems a paradox.

OCS gets around this paradox by leveraging the fact that organic systems, being systems, have components. Originally, the components coalesce and form relationships. And the system itself *is* those components and their relationships. Metaphorically, one could say: “From the perspective of a system, there is no such thing as that system. There are only the components and their relationships. That combination *is* the system.”

Interdependent Co-origination

At that point, the components can organize (form relationships with) each other and generate more of each other; and can perform all manner of co-generative operations on each other. Thus, the system does not have to suffer this paradox of generating itself from nothing.

But, since the organic system is constituted by its components and their relationships, then the organic system *is* generating itself as a result of its components generating each other through their relationships. This is autocogeneration.

In living systems, a consequence of all of these dynamics – this buildup and breakdown – is the maintenance of *organization*. Consider these words from a popular cell biology textbook:

One property above all makes living things seem almost miraculously different from nonliving matter: they create and maintain order, in a universe that is tending always toward greater disorder. To create this order, the cells in a living organism must carry out a never-ending stream of chemical reactions. In some of these reactions, small organic molecules – amino acids, sugars, nucleotides and lipids – are taken apart or modified to supply the many other small molecules that the cell requires. In other reactions, these small molecules are used to construct an enormously diverse range of proteins, nucleic acids, and other macromolecules that endow living systems with all of their most distinctive properties....[ECD 2004].

Autocogeneration can be seen as a generalization of the concept of cellular metabolism – depending on which biochemist’s definition of metabolism you choose. But buildup and breakdown are not enough machinery to describe all that transpires here. Both metabolism and genetics exhibit still more complex reorganizational feats.

These processes also produce complex network behaviors including branching of processes, cyclic behavior and regulatory management [Kauffman 1994]. For example, a widely discussed example from genetics is how proteins regulate gene expression, which controls the creation of RNA that determines the creation of proteins. As emphasized by Wilkinson, “Note that auto-regulation by its very nature implies a ‘loop’ in the reaction network.” [Wilkinson 2006].

Autocogeneration is not a new idea. We shall cite two specific theories as predecessors. First, we are obliged Humberto Maturana [Maturana 1974] with the theory of *Autopoiesis*. The essentials of the theory are that living systems

are both closed and open systems. At the risk of oversimplifying...they are open networks pertaining to their intake and outgo of food and energy. But they are closed with respect to their functions: they are networks of components whose function is to generate each other. [Maturana 1974]

Then there are the cross-catalytic theories of Santa Fe Institute biologist Stuart Kauffman [Kauffman 1993]. This is a somewhat abstract theory that demonstrates the possibility of complex molecule type A, consisting of components a1 and a2, behaving as a catalyst to construct complex molecule type B from components b1 and b2; while at the same time molecule type B behaves as a catalyst to construct complex molecule A from components a1 and a2.

This example immediately ramifies into the more complex idea of a directed network of a large number of such molecules that contrive to catalyze each other in a set of cross-catalytic relationships. This network is called an *autocatalytic set* [Kauffman 1993].

The OCS organizing principle named *autocogenerative*, then, embodies many of the implications of such theories as *autopoiesis* and *auto-catalysis*, as well as seminal ideas of autonomy that have been expressed by many others. The statement of the organizing principle reveals the manner in which autonomy operates within organic systems in order to encourage both continuation as well as adaptation in response to environmental conditions.

Homeostasis

A consequence of autocogeneration, however, is that it can enable the continuation of operations that are “working” while enabling a change (“correction”) in operations that that are no longer “working”. In short, autocogeneration can result in system *regulation*. One kind of system regulation is named *homeostasis*. Homeostasis, associated in Cybernetics by “negative feedback”, is a self-correcting mechanism [Wiener 1961].

The importance of homeostasis to the stability of organic systems cannot be overstated. Kauffman makes this case well. “For a dynamical system...to be orderly, it must exhibit homeostasis: that is, it must be resistant to small perturbations.” [Kauffman 1994]. And, again Dyson must have a word in this matter: “The essential characteristic of living cells is homeostasis, the ability to maintain a steady and more-or-less constant chemical balance in a changing environment.... Without homeostasis there can be no ordered metabolism and no quasi-stationary equilibrium deserving the name of life. [Dyson 1999]

Another kind of system regulation that is embodied by autocogeneration is the opposite mechanism to homeostasis, described in Cybernetics as “positive feedback”. Since it functions in the opposite manner as homeostasis, we shall name it *heterostasis*. (Whereas, homeostasis acts to keep the system organization “the same”; heterostasis acts to make the system organization in some state other than what it was.) Heterostasis functions as a mechanism for change, even “revolution”. It can be seen how this phenomenon of heterostasis

can enable adaptation. By itself, heterostasis can result in instability – such as a runaway train. (“The rich get richer and the poor get poorer.”)

However, in autocogeneration, both homeostasis and heterostasis cooperate and interoperate to result in a dynamic and adaptive regulation mechanism. The interplay between homeostasis and heterostasis is a relatively sophisticated expression of autocogeneration. Homeostasis serves to continue a process whenever it is “working”; while heterostasis serves to change a process when conditions change in such a way that it is no longer “working” (adaptation). Both of these, and their interplay and coordination, are expressions of autocogeneration.

This combined cooperation mechanism is identified by OCS and named *regularity selection*. Regularity selection is any mechanism that switches operation between homeostasis and heterostasis depending on which promotes persistence under current conditions. *Regularity selection* can be thought of as *the regulation of regulation* mentioned by von Foerster.

Within *regularity selection*, homeostasis serves system perpetuity whenever the environment is stable. But when the environment radically changes and heterostasis ceases to function optimally, then heterostasis can take over to move the system to a new set point at which it can function well again - to adapt. At such a set point, then homeostasis can take over once again.

An example of regularity selection is the development of a fever in humans. Heterostasis at 98.6 degrees F works fine for humans most of the time. It keeps the body temperature near the 98.6 degree F, moving it back toward the set point when “wanders” away from it. However, when invaded by a parasite, an appropriate response is for the body to elevate its temperature in order to fight the infection. This change in temperature is heterostasis. Once the proper new temperature is reached (new set point) then homeostasis takes over again to maintain the high temperature until the infection is defeated.

Another example of the co-operation between homeostasis and heterostasis is the interplay between chance mutations and natural selection in species evolution. DNA replication, including chance mutations, provides the opportunity for a species to “stay the same” if the replicates out-survive the mutants; and homeostasis wins the day. On the other hand, if the mutants out-survive the replicates, then the species evolves to a new “set point”; and heterostasis wins the day, and what has occurred is named “adaptation”. In either case, persistence is encouraged.

This genetics example is interesting for another reason – the “set point” is not a quantifiable variable such as temperature or heart rate. Rather it is much richer – a configuration of nucleotides; that is, a *system organization*. And yet, the notions of homeostasis, heterostasis and regularity selection are on display and fully operational.

Regularity and Regulation

But, OCS sees heterogeneity as a special case of “regularity”. We define the more general concept of regularity as the propensity of a system to maintain the same state or states. (This occurs in OCS whenever the system exhibits a propensity to return to the same organization or set of organizations.) We have seen that with homeostasis, the system is continuously brought back to the same “set point”. With the more general notion of *regularity*, the system may exhibit many diverse kinds of continued “regular” behavior – not only the “returning to the same set point” behavior of homeostasis.

For example, the system may enter a cycle of states (*organizations* in OCS). This occurs, for example, in metabolic cycles such as glycolysis or such as the citric acid (Krebs) cycle. A less predictable behavior, but still an example of regularity, would be a set of organizations, each of which are continuously revisited, but whose order of visitation is uncertain. This type of regularity is exhibited, for example, in autocatalysis [Kauffman 1993].

Instead of the term “regulation”, we shall adopt the form “regularity”. A problem with the choice of “regulation” is that it carries the connotation (even stigma) of “a set of rules” that is “enforced by an agent that is external to the system”. However, neither is generally the case in biological systems or in OCS. In fact, because the OCS version of regulation pertains to autocogeneration and is therefore autonomous, then regulation in OCS is generally an internal phenomenon.

In Cybernetics, “regulation” is performed by a system component, named a *regulator*, which is dedicated to the role of regulation. However, in OCS, there is no requirement for a regulator component to exist! It may exist, but it may not.

In OCS, regulation often occurs simply as a property of the system process itself. Regularity need not be implemented as a set of “rules”. Indeed, it can be a natural consequence of the architectural dynamics of an autocogenerative system.

An example of this endemic regularity is the well-known predator-prey model, discovered independently by the Italian mathematicians Lotka and Volterra in the early 20th century [Hazen 2002]. In this phenomenon, a predator species and a prey species co-exist as species through a mutual interdependence relationship. If the prey were to get too numerous, the species would suffer due to an inadequate supply of its own food source. If the predator species were to get too numerous, the same fate would befall it. If the predator consumes too many numbers of the prey species, then the predator species will also start to decline in numbers – at which point the prey species increases its numbers. Thus, the two species as a system exhibit a propensity to keep each other’s numbers in within two ranges – one range for the predator species and another for the prey.

In this dynamic, the population size of each species continuously rises and falls, one lagging slightly behind the other. Thus, we can see that “regular behavior”, or regulation, occurs. However, there is no particular component of the system that is “the regulator” and there is no apparent set of rules that are enforced by

any such regulator. Rather, the regulation is a result of the nature of the systems own organization and dynamics.

An alternate interpretation, also reasonable, is that the systems two components (the two species) regulate each other. In which case, all components of the system, together with their interrelationships (organization) result in the system being regulated (or exhibiting regularity). In either interpretation, the system is regulating itself.

Genetics

The reader may have noticed that the theme of Genetics is conspicuously absent from the list of seven OCS organizing principles. Certainly, many biologists would regard this as a serious oversight – if not blasphemy. However, this has been entirely intentional!

Why is this so? The reason is that OCS regards genetics as a special case of *regulation*, and therefore of autocogeneration.

This statement will certainly require a strong justification on the part of OCS – since many geneticists – even biologists – often define life in terms of genetics. OCS is not arguing that genetics does not play a key role in biological systems. Our proposal is that genetics is a special case of a more general phenomenon – the phenomenon of regularity.

While life in earth uses genetics as one of its peculiar mechanism for implementing regularity, genetics is not the only possible of such mechanisms available to the lifelike. In fact, even within the realm of the biological, we can generalize the notion of “genetics” to that of *information*. That is, genetics is a peculiar – even “stunning” – implementation of (special case of) information storage, reference and replication. Whereas, as we have already pointed out, this informational mechanism is, in turn, as specific implementation of regularity.

OCS does not regard genetics, then, as necessary for a system to exhibit lifelike behavior. Certainly, the kind of regularity that results from a genetics implementation is essential to the lifelike. But, genetics is only one possible implementation. It is the style of biological systems on earth. However, many other implementations are mathematically possible.

One needs only look to metabolism in biology to see other implementations of the type of regularity that genetics is “famous” for - replication. Any basic metabolic cycle operates in a manner that its principle result is replication. Both glycolysis and the citric acid cycle have these properties.

In short, OCS does not want to constrain *the lifelike* to the use of genetics as the only possible implementation of regularity – specifically of replication - in biological systems.

Organic Systems are Uncertain

[All living processes depend upon both chance events as well as deterministic ones. Living processes operate along a spectrum between complete randomness and complete determinism, uncertainty and predictability. Where along that spectrum an organic system lies at any time is uncertain. Thus, the degree of predictability or uncertainty of an organic system is itself uncertain. (“Life is unpredictably uncertain.”)]

Citations from Scientists Concerning Uncertainty

This subsection presents a number of quotations from renowned scientists that support the notion that life, and its progenitors, is, in some sense, *uncertain* – even *unpredictably uncertain*.

Physicists have abandoned determinism as a fundamental description of reality. The most precise physical laws we have are quantum mechanical, and the principle of quantum uncertainty limits our ability to predict, with arbitrary precision, the future state of even the simplest imaginable system. [Lemons 2002]

The important point is that this result is achieved without design or foresight. The mutations are caused by replication accidents, fortuitous events that bear no relationship to the production of better replicators. This is the essence of Darwin’s theory. Natural selection operates blindly on material offered by chance. [de Duve 1995]

One would think such a haphazard concoction of thousands of molecular species would most likely behave in a manner that was disorderly and unstable. In fact, the opposite is true: order arises spontaneously, order for free. [Kauffman 1994]

...[T]he wave nature of matter implies that matter itself must be described fundamentally in a probabilistic manner. [Greene 2003]

The temporal dynamics of a biomolecular reaction system is the evolution of the system state in time, which can be modeled as a Markov process that is generally described by the Chapman-Kolmogorov equation.... [Hlavacek and Yang 2010]

Consider a bi-molecular reaction....What this reaction really means is that a molecule of X is able to react with a molecule of Y if the pair happens to collide with one another (with sufficient energy), while moving around randomly, driven by Brownian motion. [Wilkinson 2006]

With the knowledge now in hand from statistical mechanics and quantum theory, no modern physicist could support such a view [that all of biology could be explained by the mechanics of Newton]. [Morowitz 1992]

In general, there is no set of observations conceivable which can give us enough information about the past of a system to give us complete information as to its future. [Wiener 1961]

The creation of energy channels by means of phase transitions provides a way to understand how the core biochemistry of life can have been stable throughout the age of the earth: a state of the geosphere which includes life becomes *more likely* than a purely abiotic process. The non-living earth would have become *metastable* under conditions of continuous geochemical free energy production. “Its collapse” to greater stability was the emergence of life. [Morowitz and Smith 2006]

Clearly, in any real situation even the nonrandom formation of products will be subject to noise. [Fontana 1992]

Once instability is included...the meaning of the laws of nature changes radically, for they now express possibilities or probabilities. Here we go against one of the basic traditions of western thought – the belief in certainty. [Prigogine 1996].

What is now emerging is an “intermediate” description that lies somewhere between the two alienating images of a deterministic world and an arbitrary world of pure chance. [Prigogine 1996].

The development of neuronal arborizations is a remarkable mixture of deterministic and stochastic events. [de Duve 1995]

A pattern emerges, dominated at the start by deterministic factors, increasingly affected by contingency as evolution progresses, though within constraints more stringent than is often assumed. [de Duve 1995]

Evolution involves both deterministic and random processes, both of which are known to contribute to directional evolutionary change. [Rice 2008]

This perpetual novelty renders it difficult to make predictions...[Holland 1998]

The thesis I shall present in this book is that the biosphere does not contain a predictable class of objects or of events but constitutes a particular occurrence, compatible indeed with first principles, but not deducible from those principles and therefore essentially unpredictable. [Monod 1972]

The whole process of metabolism still bears the marks of being somewhat chaotic, its different parts still lacking quantitative correlation. But gradually out of this chaotic metabolic activity strictly interrelated systems have evolved, which brought definite order and integration into the current chemical reactions. (p. 243) [Oparin 1938]

We call these [mutation] events accidental; we say that they are random occurrences. And since they constitute the *only* possible source of modifications in the genetic text, itself the *sole* repository of the organism's hereditary structure, it necessarily follows that chance *alone* is at the source of every innovation, of all creation in the biosphere. [Monod 1972]

Pure chance, absolutely free but blind, at the very root of the stupendous edifice of evolution: this central concept of modern biology is no longer one among other possible or even conceivable hypotheses. It is today the *sole* conceivable hypothesis, the only one that squares with the observed and tested fact. And nothing warrants the supposition – or the hope – that on this score our position is likely to ever to be revised. [Monod 1972]

With the globular protein we already have, at the molecular level, a veritable machine – a machine in its functional properties, but not, we now see, in its fundamental structure, where nothing but the play of blind combinations can be discerned. Randomness caught on the wing, preserved, reproduced by the machinery of invariance and thus converted into order, rule, necessity. A *totally* blind process can by definition lead to anything; it can even lead to vision itself.[Monod 1972]

...[H]ighly improbable “self-organized” assemblies may be shown to arise by a combination of random composition seeding and gradual mutation-like small compositional changes. [Segre' and Lancet 1999]

In physical systems, a similar lack of determinism becomes important whenever molecular fluctuations become important; an example is the uncertainty of the Brownian motion of small colloid particles suspended in a liquid and observed by microscope. [Penrose, Oliver 2005]

At any given time there are many possible spontaneous fluctuations. Each fluctuation that actually occurs generates a series of irreversible change, affecting both the probability that a given fluctuation will occur, and the probability it might initiate a modification. Externally catalyzed reactions are activated sequentially, in random order; the probability that a given reaction will be activated at a given time is altered by each preceding fluctuation. [Bagley, Farmer and Fontana 1992]

The OCS Idea of Uncertainty

If life on earth had not proven its own existence theorem by actually arising, then we would never have predicted it.

This is true not only because we would not exist to not predict it; but also because the emergence of life is absolutely uncertain. No reasonable scientist would ever have predicted it.

But this sixth organizing principle, the uncertainty of organic systems, goes beyond the epistemological and into the operational by characterizing how life inter-mingles determinism and randomness at every level.

OCS postulates that life persistently exhibits a spectrum of behavior that ranges along an entire continuum between *complete determinism (certainty)* and *complete randomness (uncertainty)* - with much of its time being spent between these two poles.

This postulation puts OCS squarely within the realm of *information theory* – whose mathematical foundation also postulates that *information* can be measured on a scale that ranges from complete certainty (total determinism) to complete uncertainty (total randomness). (OCS' dependence on *information theory* is explained in depth in *Appendix 1: Uncertainty and Information in OCS*.)

This organizing principle establishes two claims that may meet with resistance among some quarters. The first is that randomness is at work in organic systems. Some 400 years of Newtonian determinism have created a momentum in scientific endeavor against this idea of randomness; so some discussion is warranted in this regard.

Of course, there are some scientific constituencies that, today, have no quarrel with randomness being included in a formal theory regarding scientific phenomena. In fact, they require it. These include some quantum physicists, thermodynamicists, many researchers in chemical kinetics and others. For example, the late non-equilibrium thermodynamicist and Nobel laureate Ilya Prigogine has said "...we are now able to include probabilities in the formulation of the basic laws of physics. Once this is done, Newtonian determinism fails...." [Prigogine 1996].

And, again quoting biochemist Harold Morowitz: “With the knowledge now in hand from statistical mechanics and quantum theory, no modern physicist could support such a view [that all of biology could be explained by the mechanics of Newton] [Morowitz 1992].

Secondly, it is generally held that “situations” are either *deterministic* or they are *random* – that these are mutually exclusive concepts. Yet in OCS, rather than arguing about which of the two is “the nature of the universe”, we are postulating (as does information theory) that *determinism and randomness* are mere poles of a continuum. And the entire continuum characterizes living system, not merely one of its poles.

This idea maps very well to probability theory. The notion of a *probability distribution* spans both complete randomness and complete determinism, as well as anywhere in between.

That is, *complete determinism* is a special case that is captured by probability theory. This case occurs when the probability of one member of a sample space is equal to one (1) – in which case the probabilities of all the other members must be zero (0). Probability distributions for which this is true are called “constant distributions”. So, determinism is actually described by a specific family of probability distributions.

As explained by professor Lemons, “That all physical variables and processes are essentially random is the more general of the two viewpoints. After all, a sure variable can be considered a special kind of random variable – one whose range of random variation is zero. Thus we adopt the working hypothesis that all physical variables and processes are random ones.” [Lemons 2002].

Thus, probability theory spans all degrees of randomness or determinism, and is therefore a very good tool for OCS to use to support this *uncertainty* organizing principle.

Notice that the above implies that it is reasonable to talk about *degrees of randomness*. The implication is that some probability distributions (and the phenomena they model) embody more randomness and uncertainty than others.

In fact, most of the probability distributions used in science are of intermediate degrees of randomness between these two polarities. (We shall confine this conversation to the finite or discrete sample spaces.) For example, the Binomial, the Bernoulli, the Poisson, the Geometric, the Logarithmic, the discrete uniform, the Bose-Einstein, the Fermi-Dirac and many other theoretical distributions often encountered in science very often exhibit intermediate degrees of randomness.

But, this sixth OCS organizing principle goes beyond merely embracing both determinism and randomness. It suggests that “the lifelike” often spend more time hanging out between these two poles than *at* either of them. It asserts that there is a continuum between these polarities, and that most biological

processes spend most of their time within that continuum – rather than at either pole.

In other words, this sixth organizing principle says that most biological situations are “somewhat random”, “somewhat deterministic”, “nearly random”, or “nearly deterministic”, but not completely so. We shall show below how “numbers” can be put to these ideas. Yes, there is a broadly adopted measuring function for the *degrees of randomness* of a probability distribution. (In Part II, we shall develop a mathematical framework for OCS that makes much of the measuring function.)

A telling example is that of the process of DNA replication. When the enzyme DNA polymerase copies a DNA strand, the result is nearly always perfect - but not always. The random copy errors occur on the order of once in a billion copy attempts. The situation is “near-deterministic”, but not completely deterministic. Its *degree of determinism* is “on the continuum”, but very near the deterministic pole.

But, it is a very good thing that DNA replication is nearly deterministic, rather than perfectly so, because otherwise life would perish and cease to exist on earth! This is because these DNA copy errors provide an important mechanism (and it is a *chance* mechanism) for species adaptation, and therefore for Darwinian evolution. On the other hand, if, DNA replication were any more random than it is, then perhaps not enough of the “working parts” of parents would be preserved in their offspring.

So whenever a scientist claims that a certain bio-chemical process is “deterministic” [de Duve 1995; Hazen 2005], the claim is almost always exaggerated. The actual fact is that most often such phenomena are *near deterministic*. And also, very often it is quite fortuitous to life that such processes are not completely deterministic. And this fact can be described numerically.

A striking example of the introduction of increased randomness into the evolutionary process - resulting in an explosion of complexity, variety, adaptability, robustness and richness of life on earth – was the conspicuous emergence of sexual reproduction. This form of reproduction, through a process known as *meiosis*, functions by introducing a step which “shuffles the genetic deck” into the replication process [Watson 1970]. From a probability perspective, this step can be described as “interjecting a probability distribution whose degree of uncertainty is large into the dynamical process of gene selection.”

We shall demonstrate precedent for this idea of a *spectrum of degrees of randomness/determinism* in twentieth century scientific, engineering and mathematical thought. In physics there is a much-discussed *measuring function* that precisely describes the situational position on this exact determinism/randomness continuum.

To delve deeper into these thoughts, this section on the *uncertainty* organizing principle is divided into subsections. For each, we shall briefly proffer some context, followed by the OCS position.

There is a mathematical discipline that is dedicated to this *spectrum of uncertainty* referred to above. It is a *branch of probability theory* that was originated in the United States in the 1940s. It is called *Information Theory* – and, you may well know that it is at the heart of computer science.

As a matter of fact, OCS's position on this *uncertainty* organizing principle can be almost entirely reduced to statements from *information theory*. We shall have quite a bit to say about uncertainty and information theory at the end of this section. However, we shall first provide a more colloquial visitation of the idea of *uncertainty* and present a number of issues around uncertainty and the nature of living systems.

Non-intuitive Aspects of Chance

This article is going to talk a good deal about “chance”; or to be more specific, *probability* and *probability theory*. There are a number of non-intuitive aspects of “chance” and probability that must be addressed at this point, because they have a great bearing on how chance actually behaves in biology.

There are three specific ideas that are germane to OCS that need to be clarified. Two of them require the making of distinctions that are often overlooked in much contemporary scientific thought. The third is an epistemological issue regarding the reach and limitations of applied mathematics.

Understanding the Relationship between Chance and Determinism

It is often perceived that chance and determinism are binary conditions and that they are mutually exclusive. This absence of discernment was touched on above.

Among origins of life researchers, for example, the question is often raised as to whether life could have emerged by chance, or whether its emergence was deterministic [de Duve 1995]. This question pre-supposes that it had to be one or the other – and not some degree of uncertainty that resides somewhere between those two extremes.

But, as explained above, probability theory doesn't work that way. It does not force a mutually exclusive binary choice between complete certainty and complete uncertainty. In probability theory, determinism and randomness are simply two polarities on a spectrum that ranges between the two.

Most importantly, this notion *degree of uncertainty* is a *measurable phenomenon*. It has been “put to numbers”. Claude Shannon at Bell Telephone Laboratories, the inventor of *Information Theory*, which he called the Mathematical Theory of Communications, accomplished this in 1948 [Shannon 1963].

Essentially, Shannon showed that every probability distribution has a *degree of uncertainty* that can be measured by a formula that he developed. (Actually, he specialized a formula from statistical physics due to Josiah Gibbs, but showed it to have vastly broader application.)

Given a discrete probability distribution, Shannon's formula produces a value that measures its degree of uncertainty. The range of this value is from zero – representing maximum certainty (determinism) to some maximum positive value for that distribution (representing complete uncertainty).

Shannon's formula is called "information entropy", "Shannon's entropy, or just "entropy". Given a discrete probability distribution, Shannon's entropy of that distribution is a measure of the amount of uncertainty inherent in it. The value of Shannon's formula ranges between zero and $\log(N)$, where N is the number of sample points in the distribution.

The conclusion to be drawn here is that "evidence of determinism at work in the universe does not rule out the participation of randomness". OCS will show by example a number of instances of both – at work among living systems. In fact OCS insists that the interplay between the two extremes (and everywhere in between) is an essential systemic property of living systems.

Unfortunately, this conclusion is often misunderstood by some of the greatest men of science. Einstein's famous exhortation about "God not playing dice with the universe" is but another example of the tenacity of this misconception. Perhaps Einstein believed that the chance must not be allowed to operate anywhere for fear that it would leave no room for determinism.

Understanding Stochastic Dependence

When the knowledge of one event affects the calculation of the probability of a second event, then we say that the second event depends on the first.

This is called *stochastic dependence*. This happens, for example, when we know what cards have already been dealt from the deck.

On the other hand, sometimes the knowledge of the outcome of one event does not help us calculate the probability of another. For example, the rolling of a die in succession is like this. Knowing that the first outcome is a "2" does not alter our calculation of the second outcome. This is called *stochastic independence*.

Probability theory (and mathematics in general) does not contain notions of "cause and effect". This is unfortunate for scientists, because they are very concerned about cause and effect and would often like to use probability theory to model it. However, probability theory does provide the notion of *dependent events* as analogs.

Thus, the notion of dependent events in probability theory is used to model causation to some degree. However, such modeling must be done very carefully, because the dependent events are not the same as causation. The

most that can be said is that events in science that have a causal relationship can often be modeled as dependent events.

However, just because two events are stochastically dependent does not mean that they enjoy a causal relationship. Further, causation in science has a directional nature. But the stochastic dependence of two phenomena tells you nothing about such directionality.

Scientists often make the mistake that two or more events are stochastically independent when they are, in fact, statistically dependent. This misappropriation often causes problems because it can lead to wildly incorrect calculations of the probability that certain events occur jointly.

It is easy to understand why this mistake is made, because it is often vastly easier to calculate joint probabilities when the events involved are stochastically independent. In that case, the formula for the joint probabilities is very simple: multiply the probabilities of the individual events and you have the probability that they will occur jointly.

But, for dependent events, the formula varies by circumstance, and is sometimes complicated. All that can be said in general about the calculation of the joint occurrence of two dependent events is that it is *not* the product of the two events separately. (If it were, then the two events would by definition be stochastically independent.)

There is another difference between joint probabilities of independent versus dependent events. It is that stochastic independence is – in a particular sense – a “worse case” scenario. This is because the joint probabilities of independent events have more uncertainty than the joint probabilities of these same pair of events if they were dependent. This is measured by a special entropy formula called *relative entropy* [Kleeman 2009].

This can often result in the joint occurrence of independent events having a much lower probability than the joint occurrence of those same events if they were dependent. Therefore, if one assumes that a set of jointly occurring events are mutually independent, then your calculation of their joint occurrence can be much smaller than if you assumed that they were stochastically dependent.

This error is sometimes seen in the calculations of certain Origins of Life researchers.

In my estimation, this mistake has likely occurred in an often-quoted finding by Fred Hoyle and his collaborator Chandra Wickramasinghe [Hoyle and Wickramasinghe 2001]. They calculated the probability of a protein molecule coalescing “randomly” in the history of the universe as a value so small that it effectively ruled its occurrence out of admissibility.

However, their method of calculation exposed their unwitting assumption of stochastic independence. They assessed the individual probabilities of their amino acids being co-located, and then effectively multiplied them together!

However, it could well be that there are “reasons they are together”, such as the presence of some surface that they collected against. But the presence of such a surface is a *dependency*, and therefore these joint events would have been stochastically dependent. If so, then multiplying the separate probabilities in order to calculate the probability of joint occurrence could have vastly underestimated the results. Thus, stochastic dependency could drastically change the Hoyle and Wickramasinghe calculation – in the direction of making it larger.

My point is that the “chance” assembly of a protein molecule could be a reasonable proposition if their collection of components (the amino acids) were stochastically dependent.

This article will make the case that biology is, from a probability and information theory perspective, a case study in stochastically dependent events. Virtually any “causal” event in biochemistry can be modeled in the language of probability as stochastically dependent events. Here are some examples: mutually polar molecules, the relationship between catalysts and substrates, chemical synthesis (e.g. energy and condensation), protein synthesis by RNA, and gene regulation.

It's not that “chance” is nowhere involved. Rather, it is that stochastic independence is the wrong probability model for these so-called “causal” events. The right model is one that exhibits *stochastic dependence*.

Christian de Duve [de Duve 1995] happens upon this type of thought; although, not being a mathematician, he does not associate it with stochastic dependence. Rather, he calls the phenomenon “the constraints of chance”. Then he goes on to present a list of seven of these chance events “which are not truly random”.

In the parlance of OCS (and information theory), they exhibit an intermediate degree of uncertainty as measured by Shannon entropy. De Duve points out that this “constraint of chance” is due to any number of “sensitivities”, “influences” and “significance”. In other words, this “true randomness” is “constrained” by these “influences”. But this is precisely the meaning of *stochastic dependence*.

Part II of this text presents a mathematical framework of the seven organizing principles of living systems that are explored in this first part of this paper. In Part II, we shall leverage the theory of dependent stochastic processes to develop this framework for modeling living and lifelike systems. As a first approximation, we shall use the simplest type of dependent stochastic process: the Markov Chain.

Even in this first approximation, we shall see many of the kinds of behavior described that we expect to see in lifelike systems. For example, we shall see how improbable events can lead, with high probability, to highly probable ones. We will also see the degree of certainty (measured by Shannon's formula) oscillate dynamically among extreme values, and spend a considerable amount

of time in an intermediate value between complete predictability (determinism) and complete uncertainty (total randomness).

Understanding Chance and Causation

Mathematics does not explain causation. At its best, when applied to scientific domains, mathematics is a carefully articulated analogy. For example, differential equations do not show causation of phenomena from Newtonian mechanics. They can *model* those phenomena; but modeling is a kind of analogy – an analogical description. They do not unearth causation.

The same is true of probability theory and its branch information theory – mathematics disciplines that are well suited for modeling phenomena that embody varying degrees of chance and uncertainty. Discussion of either chance or of probability can never attribute cause to the astounding (that is, surprising to humans) phenomena of life on earth. However, probability theory can be used to attempt to *describe* it; to craft a carefully articulated analogy of it; but not to *explain* it – to attribute cause.

Nevertheless, it is often proposed – as do Hoyle and Wickramasinghe - that discussions of chance alone can either prove or disprove causative phenomena.

This unfortunate slip by scientists that “chance” could ever be a candidate to “explain” causation is captured in the following quote from the great Nobel Laureate biochemist and origins of life investigator Christian de Duve in his popular book “Vital Dust” when he warns that chance is the wrong answer:

Scientists, however, are condemned by their calling to look for natural explanations of even the most unnatural-looking events. They must even, in the present case, eschew the facile recourse to chance, as I hope I have made clear.

Chance, or probability, is not a candidate for explaining causation. The notions of stochastic dependence and independence can be used to describe, or model, causation – but not to explain it. OCS does not attempt to prove or disprove that life was or was not *caused* by chance. However, it does present a mathematical description, model, that involves probabilistic processes.

Chance Events at the Origin of Life

Origins of Life Research as a contemporary scientific endeavor can probably be traced to the Miller-Urey experiment of 1953, and before that to the writings of the Russian biochemist Alexander Oparin and the British Geneticists J.B.S Haldane in the 1920s [Hazen 2005; de Duve 1995].

Oparin postulated that life originated from a “primordial soup” of organic molecules enriching the earth’s early oceans. He imagined that life emerged from this soup as biomolecules randomly encountered each other, and then organized into more complex molecules that eventually became able, somehow, to replicate themselves [Oparin 1938].

Later, In the 1950s, graduate student Stanley Miller of the University of Chicago, decided to put this theory to the test by conducting an experiment, based upon certain theories about the composition of that soup by his teacher, Nobel laureate Harold Urey. Miller simulated Urey's theorized molecular constitution and environment of this primordial soup in a desktop apparatus, and then subjected it to a source of energy by simulating lightening via electrodes.

What Miller hoped to achieve by this experiment was the production of some of the basic biomolecules of living systems, including various amino acids. The results of his experiment were spectacular – producing at least a dozen of life's basic amino acids. Thus, an experiment had simulated the ability of life's basic building blocks to emerge spontaneously from natural processes [Hazen 2005].

If one looks at this experiment closely and also inspects Oparin's speculation about the origins of life, one can see that they are constituted by occurrences of chance events: the chance congregation of the right kinds of molecules, the chance occurrence of lightening at the right time, etc. The first step in the development of life on earth had to have been the creation of the basic chemical building blocks of life: the four kinds of simple biomolecules: sugars, amino acids, nucleotides and lipids.

In other words, questions about the foundations of biological life and its origins eventually get down to a question of chemical kinetics: questions about what happens when molecular structures randomly bounce around their micro environments under the sway of Brownian motion. "These do not appear to be simple cause-and-effect deterministic processes, but rather the random interplay of chance events informed the process." [Hlavacek and Yang 2010].

The writings of several noted researchers and theorists amplify these observations:

"We are now in a position to deduce the general law: it is that of chance." [Monod 1972]

"Most interesting biological processes exhibit stochastic variation, and understanding the nature and effect of the randomness can often be fundamental to understanding the process." [Wilkinson 2006]

"The central idea of information theory is to measure the uncertainty associated with random variables." [Kleeman 2009]

"There is no doubt that the formulations of probability theory and statistical mechanics as extensions of logic are here to stay; they will be the universally accepted basis of those fields for 100 years hence. Too many things are coming out right to allow any other outcome." [Jaynes 1997]

"And the ultimate source of the project that living beings represent, pursue and accomplish is revealed in this message.... [I]n its basic makeup it discloses nothing other than the pure randomness of its origin." [Monod 1972]

"The stochastic processes formalism provides a beautiful, elegant and coherent foundation for chemical kinetics...."[Wilkinson 2006]

“However, for any model where there can be only a handful...of molecules of any key reacting species, then stochastic fluctuations can dominate, and the models can (and often do) exhibit behavior that would be impossible to predict from the associated continuous deterministic analysis. ...Stochastic fluctuations are a normal part of life in the cell, which can have important consequences....” [Wilkinson 2006]

“It is indeed remarkable to find chance at the basis of one of the most exquisitely precise adaptation phenomena we know [the antibody system]. But it is clear (after the fact) that only such a source as chance could be rich enough to supply the organism with means to repel attack from any quarter.” [Monod 1972]

Thus, it is reasonable to postulate that chance occurrence played a major role at the origin of life on earth. Then OCS – being a framework for modeling lifelike phenomena - must be able to represent chance events.

It is also instructive to consider that if life did not emerge spontaneously, by chance, then there are few, if any, alternative explanations that are as acceptable in science. This is pointed out cogently by George Wald:

The reasonable view was to believe in spontaneous generation; the only alternative, to believe in a single, primary act of supernatural creation. There is no third position. For this reason many scientists a century ago chose to regard the belief in spontaneous generation as a "philosophical necessity." It is a symptom of the philosophical poverty of our time that this necessity is no longer appreciated. Most modern biologists, having reviewed with satisfaction the downfall of the spontaneous generation hypothesis, yet unwilling to accept the alternative belief in special creation, are left with nothing. [Wald 1954]

Uncertainty in Life's Networks

Biological organisms exhibit considerable network organization at many levels of complexity. Examples are: metabolic pathways, neural networks, epigenetic networks, endocrine networks and countless others. These networks function as delivery systems, communication systems and regulatory systems throughout the biosphere at the cellular, organ, organism and ecological levels.

The flow of these agents through these networks is open, closed and both open and closed – meaning that, generally, environmental resources flow into and out of these networks [Maturana 1974]. Thus resource availability affects the dynamics of these networks in an uncertain manner.

Every node of these networks must contend with this uncertainty at three levels: 1) the rate that needed resources (e.g. food) make themselves available to the node [Wilkinson 2006], 2) the time required for the resource to be processed by the node or to flow through the node, and 3) wherever a node branches to two or more pathways, which pathway(s) is (are) taken [Morowitz 1992].

One mathematical framework used in dynamic network modeling is called *stochastic networks* because it uses probability distributions to account for the three kinds of variability just described [Wilkinson 2006]. Stochastic networks have been used to model complex processes for several decades – even processes normally assumed to be deterministic. For example, in computer

system modeling, stochastic networks are a mainstay in the application of estimating the viability of particular hardware and software designs to perform against required loads [Kleinrock 1975].

Consequently, regardless of the amount of determinism or randomness that may be endemic to biological processes, there are nevertheless prevalent random elements that must be accounted for when modeling complex dynamical biological systems involving networks. Below, some notable scientists remark concerning the stochastic nature of biological networks.

...[M]eaningful information necessarily emerges only as an interplay between random events and deterministic selection. Each on its own are insufficient. [Vedral 2010].

The laws of chemical kinetics are well understood, and make it possible to model the behavior of the system at a fundamental level. These laws determine population levels and therefore determine fitness. As in biological systems, fluctuations are always present, generating random variation. Thus, for chemical networks we can define fitness at the fundamental level of dynamics. [Bagley and Farmer 1992]

“...[S]tochastic effects are particularly important and prevalent at the scale of genetic and biochemical networks.” [Wilkinson 2006]

“Every description of a system which has bifurcations will imply both deterministic and probabilistic elements....[T]he system obeys deterministic laws, such as the laws of chemical kinetics, between two bifurcation points, while in the neighborhood of the bifurcation points fluctuations play an essential role and determine the “branch” that the system will follow.” [Prigogine 1977]

Randomness, Nature and Science

Does nature itself actually behave probabilistically? Or does it behave deterministically as Newton and Maxwell insist? Is there any basis for the assumption that “all of biology [can] be explained by the mechanics of Isaac Newton”?

According to Morowitz, “That assumption was the basis of nineteenth century reductionism. With the knowledge now in hand from statistical mechanics and quantum theory, no modern physicist could support such a view.” [Morowitz 1992]. But, if biology is not intrinsically deterministic, then some element of randomness must be admitted.

According to developments in quantum mechanics in the 1920s, the laws of nature are actually non-deterministic and governed by probability laws. As explained by physicist Brian Greene in *The Elegant Universe*: “According to [the quantum mechanist Max] Born and more than a half century of subsequent experiments, the wave nature of matter implies that matter itself must be described fundamentally in a probabilistic manner.”

Regarding the random nature of matter, Greene goes on to explain: “In practice this means that if a particular experiment involving an electron is repeated over and over again in an absolutely identical manner, the same answer for, say, a measured position of the electron will *not* be found over and over again. Rather,

the subsequent repeats of the experiment will yield a variety of different results with the property that the number of times that the electron is found at any given location is governed by the shape of the electron's probability wave." [Greene 2003].

Whether or not the physical universe is random at its core, scientists must still contend with randomness in the practice of "doing science". Physics professor Don Lemons gets to the root of the matter: "For whatever reason – fundamental physical indeterminism, human finitude, or both – there is much we don't know. And what we do know is tinged with uncertainty...unpredictability...." [Lemons 2002].

Science is not nature; but rather is the empirical study of nature - through observation, analysis and synthesis. And these three occur in the human realm. Only the object of this study, nature itself, does (or may) not. If any one of these activities involves randomness, then the whole composite process does as well. As proffered by E. T. Jaynes, "I believe...that our present formalism contains two different things. It represents in part properties of the real world, in part our information about the world; but all scrambled up so that we do not see how to disentangle them." [Jaynes 1993].

Here are related comments of other theorists and researchers.

"...[B]ecause of our limited powers of observation, the observational state does not completely determine the dynamic state." [Penrose, Oliver 2005]

"Classical science emphasized order and stability; now in contrast we see fluctuations, instability, multiple choices, and limited predictability at all levels of observation." [Prigogine 1996].

"...[W]e go beyond the certitudes associated with the traditional laws of quantum theory, and emphasize the fundamental role of probabilities." [Prigogine 1996].

OCS Must Be Able to Model all Degrees of Randomness and Determinism

Determinism, or near determinism, enables the stability and robustness that are required by living systems in order for them to retain their successful adaptations whenever environmental conditions remain the same.

On the other hand, randomness plays a central role in adaptation itself. The hosting environments where living species live, can, and do, change disruptively. These disruptions often require species to change in order to adapt to these environmental changes in order to survive. At this point, continuity of a species' existing program no longer promotes their continued existence.

Thus, the "dance of life" can be described from a probability and information theory perspective as a dynamic movement at many levels of organization among multiple degrees of uncertainty and certainty.

OCS is not the first program to postulate the necessity of theoretically accommodating both randomness and determinism. Ilya Prigogine and his

associates have taken this approach with non-equilibrium thermodynamics over the past several decades.

Notes Prigogine, “Popper and many other philosophers have pointed out that we are faced with an unsolvable problem as long as nature is described solely by deterministic science.” [Prigogine 1996]. Because of this, Prigogine and his associates incorporated both randomness and determinism in their investigations. Prigogine explains about their research, “We can certainly understand Einstein’s refusing chance as the only answer to our questions. What we have tried to follow is indeed a narrow path between two conceptions that both lead to alienation: a world ruled by deterministic laws, which leaves no place for novelty, and a world ruled by a dice-playing God, where everything is absurd, acausal and incomprehensible.” [Prigogine 1996].

So this sixth postulate of OCS provides a mathematical mechanism that spans this spectrum between complete randomness, complete determinism, and every degree between these polarities.

Measuring the Degree of Uncertainty of a Probability Distribution

We have been making the case that every scientific scenario, or situation, no matter how deterministic or random, certain or uncertain, predictable or uncertain, can be effectively modeled by a probability distribution. Specifically, “certainty” can be included within this model because it is assigned a zero (0) degree of uncertainty by the measuring function used to assess the amount of uncertainty.

We have also suggested that a situation’s probability distribution embodies its inherent *degree of randomness*, or *degree of uncertainty*. And we have stated that such degree of uncertainty can be measured – and that there already exists in the mathematical literature a function, a formula, for measuring this uncertainty.

It is time now to detail this function, so that we can discuss, with no ambiguity, the degree of uncertainty of any biological situation. Claude Shannon of Bell Telephone Laboratories revealed this function as an instrument for measuring uncertainty in 1948. He gave it the name of *entropy* because of its similarity to formulas from statistical mechanics that also bear the same name.

Unfortunately, there is general confusion among professional and popular physicists as to precisely what the *entropy* of statistical mechanics actually measures. If one were to survey the usage of this term in physics texts, one would consistently find a variety of meanings ranging from “dissipation”, to “disorganization” to “disorder” to “uncertainty”.

Shannon was less ambiguous concerning his usage. In first place, he was “doing mathematics”, not physics. Actually, he was in the process of inventing modern Information Theory – which, at the time, he called Communications Theory. He introduced his notion of entropy in a now-famous 1948 paper entitled “The Mathematical Theory of Communications” [Shannon 1963].

Shannon described his formula as a measure of “uncertainty” and also of “information” and also of “choice”. However, it is conspicuous that he did not define it as “dissipation”, or of “disorganization”. Universally, Shannon’s entropy is held as a measure of uncertainty, and we shall apply it as such within OCS.

I did promise at the start of this paper that I would keep the mathematics in Part I of this article to a minimum. So I shall try to describe Shannon formula colloquially. This is fairly easy to do, as long as we restrict the theory to finite or discrete sample spaces. It is easy to do mainly because the formula is so simple. It also happens that, in biology, our sample spaces are finite – large, but finite.

However, since the formula is defined as a measurement of a probability distribution, we must briefly review how a probability distribution of a finite sample space is defined. The distribution begins as the collection of all of the possible outcomes that the “situation” allows. Then, it associates a probability value (number between 0 and 1) with each of these possible outcomes. In addition, the sum of all of these probabilities must equal to 1.

Now we have enough understanding to define this measure of uncertainty that Shannon has defined – at least on a finite or discrete distribution. Here is the essence of Shannon’s formula:

Take the probabilities each of the logical possibilities of the distribution, and multiply it by its base 2 logarithm. Now, sum all of those products. Finally, multiply this sum of products by minus one (-1). This result is the entropy of the distribution.

Now this choice of the term *entropy* by Shannon was in many ways unfortunate – because the field of Thermodynamics had already chosen it to mean something else – namely a measurement of the degree of “disorder” in a thermodynamic system. This has been a source of confusion even to this day.

It can be argued that the statistical mechanics definition of entropy by Josiah Gibbs is actually a measure of uncertainty and not a measure of disorganization – and thus means the same thing that Shannon means by his formula. (Show me within Gibbs’ formula any parameters that represent structure or organization – and not probabilities. I claim that probabilities are the only inputs to Gibbs’ formula.)

But most scientists today *do not* mean “uncertainty” when they use the word *entropy* – rather, they mean *disorder*. And by *disorder* they very often imply *disorganization*, *dissipation*, *unstructuredness* or *absence of discernable arrangement* – none of which mean *uncertainty*. Other scientists mean various other things by this term. So there is considerable ambiguity in the usage of this term by various contemporary scientists.

In any case, because of this confusion within the contemporary culture of statistical mechanics we are treading on dangerous lexicographic territory by using the term “entropy” in this paper to mean *a measure of uncertainty*.

But “uncertainty” is exactly what Shannon means by the term, and what we need to mean by it. Therefore, for the remainder of this article, we shall use the phrase “Shannon entropy”, or occasionally simply *entropy*. And we can only hope that the phrase is not misread to mean “measure of disorganization”.

So, to reiterate: We shall use either the term entropy or the phrase “Shannon entropy” to mean the specific measure described above of the degree of uncertainty embodied in a probability distribution.

Varying Degrees of Uncertainty in Biological Systems

This article makes the claim that life depends on varying degrees of uncertainty/certainty. The implication is that if only completely random or only completely deterministic behavior exist, then life could not exist. Furthermore, this organizing principle implies that many phenomena of life are of intermediate degrees of uncertainty.

It is time to present some examples if this, and describe how these measurements are calculated. From what has been said, clearly these calculations have something to do with probability distributions. So this fact must be brought into the conversation and related to real biology.

Three situations shall be presented: one representing near-complete determinism, another representing near-complete randomness, and a third representing an intermediate degree of uncertainty, but that is nearer to the determinism end of the spectrum (i.e. predictability) than to the complete randomness end.

The first example is one that has already been introduced: DNA replication. When the enzyme DNA replicase copies a DNA molecule to produce a replicate, a copy error occurs only once in the neighborhood of a billion times. This is *near-determinism* – not to mention extremely accurate copying. But it is *not* complete determinism. In fact, those “copy errors” are absolutely essential to biological evolution, and to the persistence of life on earth.

Every single act of evolutionary adaptation in the history of life on earth has been a result of randomness! Every innovation in the mechanisms of living systems has been an outcome of either random nucleotide copy error or of random nucleotide mutation. Without these random events, no adaptation would have occurred, no natural selection would have had an opportunity to act, and Darwin – even if he would have existed - would have had no theory to offer. So it very fortuitous indeed that this phenomenon is *not* completely deterministic!

And, this “inelegant” approach is a “shotgun” solution that every engineer worth the sum of his nucleotides would have eschewed. Yet, it dominates.

But, how can the entropy, the degree of uncertainty, of this scenario be measured? How can we apply Shannon’s entropy formula to produce a real number that provides that measurement?

We shall outline the process of calculation at this point – but avoid actually going through it to produce that real number because a good deal more information is required than we have at this point. In fact, it would require a research project to determine the precise probability distributions involved. But we shall outline the general approach by selecting simpler sub-cases and by making up realistic – if not empirically measured - probabilities.

Because we are only interested in errors-versus-accurate copies, we can define the sample space of these copy events as having two outcomes: 1) completely accurate copy events, and 2) copy events with at least one error. (This is one of the “simple sub-cases” I referred to.) Let’s call this approach number 1. If we wanted to be more descriptive, we could define the sample space as having the following logical possibilities: 1) zero nucleotide copy errors, 2) exactly one nucleotide copy error, 3) exactly two nucleotide copy errors, etc. For simplicity, we shall take approach number 1, at the expense of being less accurate.

For approach number one, we perform a large number of experiments in which we observe DNA replication. We count the relative frequencies of perfect copy events versus imperfect copy events and obtain a binomial sample distribution. We use statistical techniques to arrive at an estimated theoretical – but discrete - distribution for the experiment.

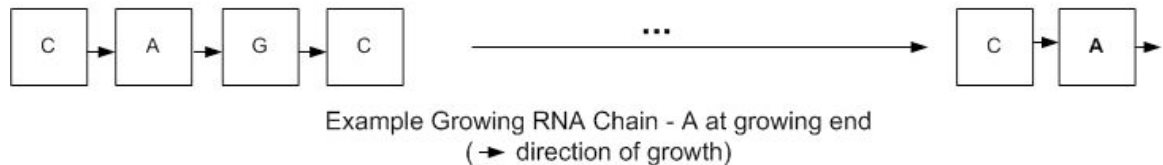
Now that we have a discrete probability distribution for this experiment, then we can apply Shannon’s entropy formula. This formula tells us to multiply the probability of a perfect copy times the base 2 logarithm of that probability, and then to multiply the probability of an imperfect copy times the base 2 logarithm of its probability. Next the formula has us add the two products together, and then multiply by -1, in order to produce the answer.

If a sample space describes two possible outcomes – such as either perfect copies or imperfect copies, as does our example experiment, then the range of DOUBT values that Shannon’s formula could result in is between 0 and 1. This value is a measure of the uncertainty of the situation; that is, the amount of uncertainty inherent in the probability distribution that describes DNA replication. The closer this number is to 0, the more predictable is the situation. The closer it is to 1, the more uncertain the situation. Believe me when I say that our answer for the case of DNA replication is very close to 0. But not equal to 0. It will be a very small positive number. This situation is near deterministic - but not completely so.

I need to point out that not all discrete probability distributions have an entropy measure (Shannon’s entropy formula) that ranges from 0 to 1. The DOUBT measure will always range from 0 to some positive value. But the value of the upper range depends on the number of logical possibilities there are in the (discrete) distribution. For discrete distributions, it turns out that the maximum values of Shannon’s formula (the maximum entropy) will be the logarithm (base 2) of the number of logical possibilities represented in the distribution. Thus, if there are 2 possibilities, then the maximum entropy is 1. For 4 possibilities, the maximum entropy is 2. For 8 possibilities, the maximum entropy is 3. And so on.

In the DNA replication example above, because there are two possibilities in our sample space, the upper bound is 1. However, the lower range is always zero, no matter how many possibilities there are in the sample space. The entropy, or Shannon entropy, then, of any probability distribution can be no smaller than 0 – which represents complete certainty. But it can be no larger than the logarithm (base 2) of the number of possibilities in its sample space.

Now, let's look at another example: RNA synthesis at the dawn of protolife! According to de Duve [de Duve 1995], "The first RNA molecules were probably random associations of nucleotides...." From the examples he provides, it is clear that he means that such a molecule grew in length by the spontaneous addition of nucleotide types to the end of the chain. And that he expects that which of the four types of nucleotides would be added next was equally likely. (Without necessarily realizing it, his assumption of "equally-likely" is what many scientists mean when they use the word "random".)



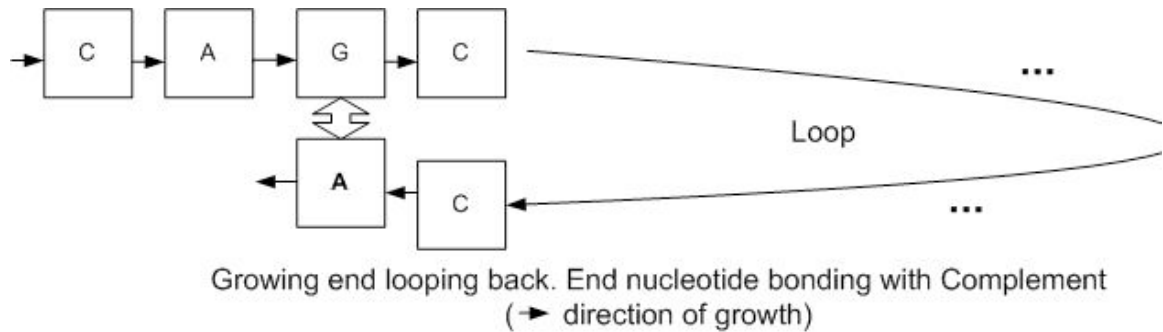
That is, the probability the next nucleotide would be each of the four types was equal to .25. Such a probability distribution is named the *uniform distribution*. Its graph is flat, with all logical possibilities having the same probability (.25). It is easy to apply Shannon's formula to this distribution. It is:

$$\begin{aligned}
 &= (-1) * (\log_2(.25)) * (.25) + (\log_2(.25)) * (.25) + (\log_2(.25)) * (.25) + (\log_2(.25)) * (.25) \\
 &= -\log_2(.25) * (.25 + .25 + .25 + .25) \\
 &= -\log_2(.25) * (1) = -\log_2(.25) \\
 &= -(-2) = 2
 \end{aligned}$$

But, for a finite distribution with four possible outcomes, the value 2 happens to be the maximum Shannon entropy possible. Therefore, this situation is of maximum uncertainty, maximum uncertainty, or is "completely random" – however you wish to describe it. This completes our second example – that of a completely random biological situation, as measured by Shannon's entropy formula.

Thus far, we have presented an example from biology with near-minimum uncertainty – DNA replication; and another example with maximum uncertainty – spontaneous RNA molecule growth at the dawn of protolife.

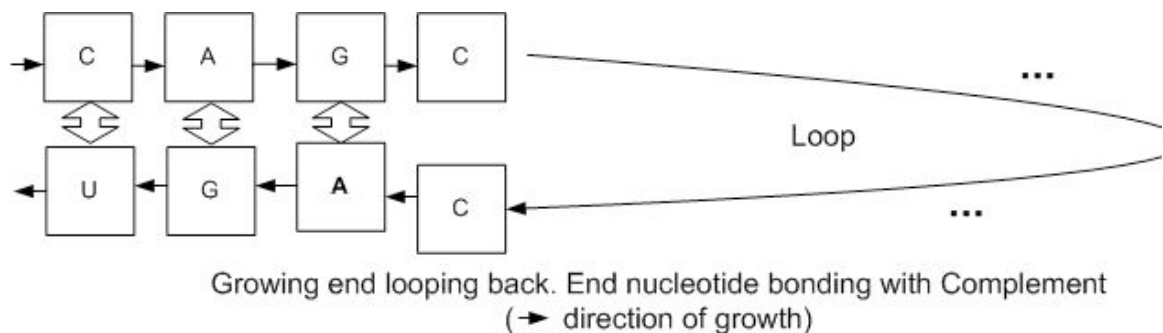
Let's now look at a pre-biological situation that is of an intermediate degree of predictability/uncertainty – again suggested by de Duve [de Duve 1995]. We shall work again with the previous situation – molecular growth at the dawn of protolife. However, this time we shall evolve from the subject of spontaneous RNA growth to the beginnings of RNA replication.



Let's begin by assuming that our RNA molecule from the above example has grown to a sufficient length that it could loop back upon itself. RNA molecules are chains of four types of nucleotide molecules that are abbreviated as A, G, C and U. Moreover, our example will *depend* on the fact that the A's and the U's easily bond, as do the G's and the C's. (The subject of *stochastic dependency*, or *conditional probability* has shown its face.)

Now, suppose that such a chain loops back upon itself in such a way that the molecule at the "growing end" of the chain is an A. Moreover, assume that it has come into contact with an earlier U molecule, is attracted to it and that they bond. And, assume that the U molecule just mentioned happens to have a C nucleotide adjacent to it in the direction that the end is growing.

Now, let's ask the question "What nucleotide is most likely to spontaneously attach itself to the growing end of the RNA molecule at the location where the A is situated? The answer is "G". This is because a G is more likely to be attracted by the C that is situated near it on the body of the molecule than would be any other of the three nucleotides (C, A or U). That is, under these conditions, the probability that a G will add itself to the end of the growing RNA is higher than the probabilities of the other three nucleotides.



For instance, it may be that the probability that a G will attach itself to the growing end is .7, and that the individual probabilities of the other three attaching themselves are .1 each. For such a distribution, the Shannon entropy is:

$$= -[(\log_2(.7))*.7) + 3*(\log_2(.1))*.1] = .692393$$

We saw above that the minimum possible value of Shannon's entropy for discrete distribution with 4 possible outcomes is zero (0), and that the maximum probability of such a distribution is 2. Thus, the entropy of this distribution (.692393) is intermediate between the two. Thus, this situation is of an intermediate degree of uncertainty. In fact, this Shannon entropy value of .692393 is a little closer to 0 than it is to 2. But it is closer to the midpoint of 1 than it is to either of the extremes of 0 and 2.

Thus, as promised, we have shown three examples from either the biotic or the pre-biotic having varying degrees of uncertainty as measured by Shannon's entropy.

Can Chaos give rise to Order?

In the previous section, an argument by Hoyle and Wickramasinghe was countered. Their argument is essentially that the formation of life as a single chance event is too unlikely to have occurred during the history of the earth.

The OCS argument is that an error was made by Hoyle and Wickramasinghe when they calculated this probability, and that this error resulted in their estimate being vastly too small. OCS claims that the root of their error was the unwarranted assumption of stochastic independence. This assumption often leads to unnecessarily miniscule probabilities, as is the case of their position that life is too improbable to have occurred by chance.

We showed that, when events depend on each other – when the probability of one is conditioned by the outcome of the other - then the probabilities of their joint occurrence can increase dramatically as compared with the case that they are stochastically independent.

Ultimately, the OCS argument is that the sequence of events that led to the chance formation of a protein polymer was stochastically dependent events – rather than stochastically independent events, as Hoyle and Wickramasinghe assumed (probably unwittingly).

The question we began to address with our example of spontaneous RNA elongation in the previous section is “How is evolution affected by stochastic dependence?” That is, whenever events are stochastically dependent, can we expect the degree of uncertainty of the situation to decrease over time? Should it be surprising, then, when jointly dependent events are involved, that a highly uncertain situation can evolve into a more predictable one over time? And, can probability theory model this situation?

The RNA elongation example shows that the answer is “yes”. We looked at the case wherein the growing RNA molecule looped back upon itself in such a way that the growing end bonded with its complement further back in the chain. When that occurred, the situation changed in a way that changed the probability distribution of the selection of growing nucleotides. And the new probability distribution had lower Shannon entropy than did the original one.

Prior to when the growing end bonded with its complement further back in the chain, the situation was described by the uniform distribution – which has the maximum degree of uncertainty of 2 according to Shannon's formula. But, once the loop-back and complement bonding occurred, the probability distribution changed to have lower Shannon entropy of an intermediate degree of uncertainty of .692393.

The reason for this change in probability distribution and concomitant change in degree of uncertainty is that the new situation introduced dependent events. That is, the probabilities of the next nucleotide type to be added to the growing polymer depended on another nucleotide that was already in the polymer. But this was not true before the complement bonding: the probabilities of the next nucleotide to be added to the growing chain were completely independent of any nucleotide that went before it in the polymer. The former situation was stochastically independent; while the latter is stochastically dependent.

Thus, the introduction of stochastic dependence altered the situation so as to *decrease* the degree of uncertainty (Shannon entropy) of the situation as this evolution progressed.

This is a very significant discovery, so we shall repeat the conclusion: the introduction of stochastic dependence into a process can decrease the degree of uncertainty of the events in the process as it proceeds forward in time. In other words, stochastic dependence can evolve a highly uncertain situation into a predictable one. So, introducing *dependence* can move chaos toward order!

It is remarkable that a number of important biological phenomena can be modeled as exerting precisely this influence on the biological processes in which they participate. That is, their contribution to the biological "situation" of which they are apart can be modeled in probability theory as *stochastic dependence*. We shall introduce a few of these here – and more as we go along.

Chief among these examples are these four: catalysis, energy, autocatalysis and the use information to synthesize biomolecules. We shall presently visit each, and indicate how it can be modeled as an event that conditions the outcome so that its probability distribution is altered in a way as to decrease its Shannon entropy. In other words, these biological phenomena can move randomness in the direction of determinism.

First, consider biological catalysis – which usually takes the form of enzymes, or sometimes, ribozymes. The term *catalyst* is defined in several ways in biological texts. The one we shall quote here is described according to [de Duve 1995] as follows. "...substances that help reacting molecules to get together and interact, but are not themselves consumed in the interaction, and, therefore can serve an indefinite number of times in succession."

This quote describes a situation wherein the catalyst generally interacts with a substrate to condition the outcome in a way that makes the outcome more predictable. That is, it moves a "random" situation to a more deterministic one.

Our next example, energy, generally operates as a “gating function” in biological phenomena. That is, without its presence in sufficient quantity, nothing happens. Often, once a critical quantity of it is present, then increased amounts of it can promote increase chemical reaction rates, at least to a certain threshold. In this sense, energy can behave like an *indicator function*.

Indicator functions can operate on probability distributions to produce resulting distributions. Often, the presence of absence of energy available to biological processes can condition the distribution to affect its before-and-after entropy in either direction. However, it often decreases it – therefore serving to remove uncertainty from the process in which it is participating.

Autocatalysis involves a set of catalysts “co-catalyzing” each other. Says [de Duve 1995], “Autocatalysis occurs when the product of a chemical reaction is catalytically helpful to the reaction.” He further explains: “This is a way of catching chance events and turning them into a growing concern.” That is, autocatalysis develops a process wherein a great deal of the uncertainty of the situation is removed as the process progresses. And, autocatalysis can proceed very rapidly to do this as compared with “single” catalysis.

Our next example is the use of “information” in biological processes. The most conspicuous example is the use of nucleotide polymers - i.e. RNA and DNA - as models of existing molecular structures for the purpose of synthesizing subsequent ones in specific configurations. Clearly, using this device, the Shannon entropy of the probability distribution of the population of synthesized molecules is decreased over the corresponding probability distribution of the synthesized population that would result without the introduction of this informational device. That is, the use of DNA to synthesize proteins leads to a more “repeatable”, or predictable, result than does protein synthesis without DNA. This, also, is a movement in the direction of determinism, and a concomitant reduction in Shannon entropy.

I can't help but present two final and highly significant examples of stochastic dependence in biological processes. The first is Natural Selection itself. Yes, natural selection can be modeled in terms of stochastic dependence – in fact a dependent stochastic process. The key to this marvel is the answer to the question “Upon what does Natural Selection depend?” Of course, the answer is the *selection factors* involved - such as strength, ferocity, virility, etc.

None of these selection factors, of course, guarantee selection. They merely alter the probability distribution so as to favor it. That is, they increase the probability of selection of the phenotypes that exhibit the selection factor. The model is that the conditional probability distribution that is conditioned on the selection factor substitutes for the unconditioned probability distribution. Whenever this change results in the dominance of the favored phenotype, then the Shannon entropy, the uncertainty, is reduced.

My final example of dependent stochastic processes in biology is homeostasis. You may recall that homeostasis is the hallmark of OCS organizing principle 5: Autogeneration. Here is how homeostasis is modeled as a Markov Chain. Whenever the state of the process is far from the set point, then the probability

distribution is such that the following state of the process will be closer to the set point of the process. Whenever the state is near the set point, then the probability distribution is such that the following state of the process can be any distribution. Thus, the probability distribution of the process depends on the outcome state. That is, it is a dependent stochastic process.

All of the above examples make use of stochastically dependent events that occur repeatedly in sequence over time. In probability theory, such a situation is named a “dependent stochastic process”. In Part II of this article – the presentation of the mathematical framework of OCS that is called “Organodynamics”, considerable use of dependent stochastic processes will be made. In fact, the simplest families of these processes will be extensively presented – Markov Chains.

Markov Chains can be a powerful tool to exemplify how highly random, or chaotic, events can give way to more predictable ones within a stochastic process.

Prigogine has indicated an example of this: “Using the Markov method they [his colleagues] then calculated the correlation between the occupation numbers of X in two different boxes. One would expect that chemical inelastic collisions together with diffusion would lead to a chaotic behavior. But that is not so....Again, the system acts as a *whole* in spite of the short range character of the chemical interactions. Chaos gives rise to order”. [Prigogine 1977]

As indicated, an overall decreasing trend in uncertainty is often detected in organic systems. Of course, *in real life*, dependent stochastic processes do not generally present a strictly monotonically decreasing sequence of Shannon entropies. Rather, the degree of uncertainty of living systems, itself, changes uncertain in time.

Summary of Chance and Determinism in Organic Systems

This section has made the case that biological systems exhibit a mixture of randomness and determinism along a spectrum that includes both as polarities. OCS insists that this spectrum is characteristic of life itself, and requires it as the sixth organizing principle.

As evidence of this organizing principle, a number of example biological processes were described, some of which tend to increase the uncertainty of their situation, and others that tend to decrease it, along this spectrum.

First, let's reiterate some examples of processes that tend to *increase* the uncertainty of their situation. That is, these specific examples have the effect of increasing randomness.

Specifically, this means that if you were to compare the Shannon entropies of the probability distributions that described the situation both before and after these phenomena occurred, you would find that the entropy of the earlier distribution would be higher than the entropy of the resulting distribution. We shall add some other biochemical processes to the ones already presented and

produce the following list of biological phenomena that have the effect of increasing the degree of uncertainty, or randomness, after they occur. These are:

- Nucleic acid mutations in RNA and DNA
- Copy errors during transcription of DNA to RNA
- Copy errors during replication of DNA
- Meiosis in sexual reproduction.

Notice that each of these has the very practical result in the evolution of life on earth of enabling species adaptation and thus promoting an increase in the persistence of life. That is, they allow life to change when it needs to.

Second, let's reiterate some examples of processes that tend to *decrease* the uncertainty of their situation. Specifically, this means that if you were to compare the Shannon entropies of the probability distributions that described the situation both before and after these phenomena occurred, you would find that the entropy of the former would be higher than the entropy of the latter. Their Shannon entropies would show a decrease. We shall add some other processes to the ones already presented and present the following list of biological phenomena that have the effect of increasing the degree of uncertainty, or randomness. These are:

- Natural selection
- Catalysis
- Autocatalysis
- Homeostasis (an application of negative feedback)
- Heterostasis (an application of positive feedback)
- Increased specificity (e.g. in enzymes)
- DNA and RNA templating (for use as bio-information)
- Modular assembly (the construction of high level units of combination – genes, chromosomes, cells, etc.)
- Complementarity (e.g. base pairing of nucleotides in DNA/RNA)
- Molecular affinity (the basis of selective chemical bonding)

Notice that each of these has the very practical result in the evolution of life on earth of encouraging species to persist their existing traits. That is, they allow life to stay the same when “things are working” and conditions permit.

These are a few among hundreds of potential examples of biological processes – most of which lend either a tendency toward increased Shannon entropy, or of decreased Shannon entropy. The result is a spectrum of degrees of uncertainty that range across the possibilities made available by Shannon's formula.

But, more interestingly, if a phenomena increases or decreases the degree of uncertainty of what comes later in its biochemical process; then that means that the statistical outcome has changed the probability distribution of some later step in that process. That is, the probability distribution of some later step is now *dependent on*, or *conditioned on*, the outcome(s) of some previous step(s).

Such a situation is called *conditional probability*. And such a process is called a *dependent stochastic process*, or a *conditional stochastic process*.

This opens the door for OCS to leverage the use of the theory of *dependent stochastic processes* in order to model these living (and lifelike) phenomena. In fact, application of this theory will be made in a concerted manner in Part II of this article – which presents a mathematical modeling framework for living and lifelike systems.

An Example from Genetics

Scientists in general, and geneticists in particular, are fond of saying things like “a gene is *information*”. But, is this really true? Let’s look at information theory to see.

Some Counterintuitive Aspects of Uncertainty and Information

We must contend with the fact that information theorists mean something quite different by the term “information” than does the casual reader.

To an information theorist, the only “information” is “new information”. Receiving data that you already know increases information by the amount of zero! A redundant message contains exactly the same “amount of information” as the same message with the redundancy removed – even though the redundant message contains much more data [Shannon 1963; Weaver 1963].

As explained by Quantum Information Theorist Vlatko Vedral [Vedral 2010]:

The reader probably comes to this book with a vague idea as to what information is. In everyday parlance information is often synonymous with knowledge. We believe we know something when we can talk about it with sufficient length and breadth without being contradicted by any of our listeners. However, although this is the common meaning of the word ‘knowledgeable’, it is not what a scientist would consider to be knowledge. To a scientist any knowledge always refers to knowledge of the future.

But, if *information* is not *knowledge* in this common sense, then – according to information theorists - what is it?

But, we have already answered that question above. The answer is that *information has to do with probabilities!*

For example, Vedral gives us the formula used by information theorists to measure the information inherent in an event. It is this:

$$\log(1/\text{Pr}(E))$$

We shall dwell on this formula in Part II. But or now, it should be clear that it cannot be applied to a gene. This is because:

A gene, by itself, has no probabilities – and thus, no information!

So, if a gene has no information, then where is it?

Where's the Information?

So, where does all of this put us with the idea that “A gene is *information*”?

In short, it renders the statement overly simplistic – and wrong!

What is conspicuous by its absence in this statement is any mention of *probability*.

Explains Vedral, “[W]e only need the presence of two conditions to be able to talk about information. One is the existence of events (something needs to be happening), and two is being able to calculate the probabilities of events happening.”

But, taking a gene by itself, *nothing is happening!* There are no events and there are no probabilities of “events happening”. Clearly, then, in order to have *information* we must have *process*. *State* by itself (such as a configuration of nucleic acids in a gene) is not process.

Clearly, a gene represents state - *data*, but not *information*. Where then is the *information* in genetics?

The answer is “in the protein synthesis apparatus”.

This apparatus is a *process* – not a *thing with state*. A gene is a “thing”; but the protein synthesis apparatus is a process.

This process, also called *gene expression*, takes a gene as its *input*, goes through a sequence of sub-processes (including some “translation” and some “transcription”), and, voilà, “out pops” a protein on the other side of the machinery. The textbooks treat this process as though it were deterministic. But – and a big “thank you” from Life on Earth – it is not. It is a probabilistic process.

Consider this gene synthesis apparatus for a moment. It contains some active and some passive elements. One could say that it starts with a gene, which is a passive element. But then an active element, an enzyme (another protein) “reads” this sequence of molecules and, as a result, constructs (“copies”) a corresponding RNA molecule that is a representation of the data inherent in the gene’s component molecules (nucleotides).

After a whole series of “recopying” operations (actually, more constructions), described as translation and transcription, the target protein is manufactured by a large molecule named a Ribosome.

In this complex series of compositional operations, there is ample room for “copy errors” along the way. Amazingly, the occurrence of these “errors” in

biological systems is extremely rare (one in millions or billions) due in part to the repair machinery that is endemic to the process.

The same kind of phenomena is evident in the process called “DNA replication”. The difference between gene expression and DNA replication can be simply described. In the first, a protein molecule is manufactured by using a gene. In the second, a copy is made of a DNA molecule. In both cases, what is of interest is that a process is at work. Also in both cases, “copy errors” are possible and do occur.

And, these errors do occur. And, particularly in the case of DNA replication, it is a good thing they do. Otherwise natural selection and evolution of species could not occur!

And, in both examples, the set of possible outcomes – the “correct” result plus all of the “erroneous” ones - form a sample space for the process. Moreover, since each of these outcomes (system organizations) has a probability then a probability distribution exists to describe the process. It is the probability distributions that enable the possibility of “information” being evident. Without the probabilities there is no information.

To be more precise, the probability distribution evidences the fact that *uncertainty* is present. But at the end of each process, a specific result is made manifest – a DNA molecule results from one and a protein from the other. This result may, or may not, be the “correct” result. Nevertheless, it is *the result of a process involving probabilities*. Therefore, that result is called *information*.

In other words, in the protein synthesis process, the *gene* is *data*; the *gene expression process* is the *uncertainty*, and the *resulting protein* is the *information*.

So the gene expression process is where the *probability* enters into the picture – and thus the possibility of *information*.

A Probability Model for Genes and Gene Expression

Specifically, here’s the picture. For any given gene, there is a probability distribution that describes the possible outcomes of a “copy operation” (an instance of the protein synthesis process “going to work” on the gene to build a single protein molecule.)

The *sample space* of this probability distribution is the set of all proteins that could possibly result from a protein synthesis (“copy”) operation on this gene.

We shall now describe what that sample space looks like – but first lets make a simplifying assumption that will make this analysis more understandable. It is this, we shall assume that for every “gene bit” in the gene (nucleotide triplet), exactly one “gene bit” (amino acid) will end up in the manufactured protein. Given, this assumption, then both the gene and the resulting protein molecule will have the same number of “gene bits”. Without loss of generality, lets call that number “K”.

Now, any “gene bit” in the manufactured protein has 20 possible configurations – because there 20 types of amino acid building blocks used to build proteins. Therefore, the number of possible proteins that can be produced by an execution of the protein synthesis apparatus against our gene is 20^K , exactly one of which is the “correct” one, and all the rest are “mistakes” (or mutants).

Notice that these configurations of gene bits are, in fact, *system organizations* of the gene. It is these 20^K possible *system organizations* that are the *sample space* of the probability distribution that represents an instance of the execution of the protein synthesis apparatus against our example gene.

Now, the question arises about the probabilities of this probability distribution. Because of the stability of this apparatus owing to its correction mechanisms and the general molecular repeatability of this gene expression process in the first place, this probability distribution has the property that one of its sample points (system organizations) is extremely high, while the probabilities of all the other are extremely low.

The *organization* whose probability is extremely high is the “correct one” – the one that is the target protein. The organizations whose probabilities are extremely low are all of the ones that we call “mutants”. They are protein polymers (organizations of amino acids) that are mutant versions of the protein that was “supposed” to be built.

Recall the quote from Khinchin above:

Thus, we can say that the information given us by carrying out some experiment consists in removing the uncertainty that existed before the experiment. The larger this uncertainty, the larger we consider to be the amount of information obtained by removing it.

In our “gene” example, the “experiment” is equated to the execution of the protein synthesis operation. And the “uncertainty that existed before the experiment” is actually the gene itself.

Thus, the *gene is uncertainty* – not information! And, of course, the “information obtained by removing it” is the protein that is manifest by the process. So, we must conclude that the gene represents *uncertainty* and the protein is the *information*.

Notice, that *information is process-oriented*. It is *dynamic* in nature. Thus, Information is a dynamical property of a dynamical system.

Lessons from this Example

This example presents an oft-repeated pattern in OCS.

We start with the *components* of the system we are interested in – in this case the “gene bits” (the four nucleotide types). Then we construct a collection of *system organizations* (gene configurations) from this set of components.

Each of these *organizations* (gene configurations) has a possibility of being realized at the next step in time. Moreover, each of these organizations has a *probability* of being realized at the next step in time. We therefore have a probability distribution for this set of possible gene configurations (organizations).

It is this probability distribution that becomes the way in which we describe how this system changes from one time step to the next. In other words, it is this probability distribution that we use to describe the dynamics of the system.

Organic Systems are Persistent

[The nature of the autocogeneration and uncertainty of an organic system is that it engenders the ongoing existence of these systems. Taken together, all of these static and dynamic elements have resulted in, at the least, a limited persistence of life itself. While no organic system persists, the existence of organic systems has.]

Citations from Scientists Concerning Persistence

This subsection presents a number of quotations from renowned scientists that support the notion that life, and its progenitors, is, in some sense, *persistent* or *ongoing*.

When is a piece of matter said to be alive? When it goes on 'doing something', exchanging material with its environment, and so forth, for a much longer period for a much longer period than we would expect an inanimate piece of matter to 'keep going' under similar circumstances [Schrödinger 1945].

Persistence of a pattern can occur by replication, as long as the pattern gives rise on average to more than one similar pattern, that pattern will exponentially increase. [Morowitz 1992]

The necessity of persistence in a nonequilibrium domain leads to a Darwinian-like struggle for survival long before there are organisms in a conventional sense. [Morowitz 1992]

...[T]he survival problem is ongoing, relentless and inescapable; it will never be permanently solved.... Life is, at bottom a survival enterprise. [Corning 2005]

The central feature in the organization of the organism lies in its manner of being a unity in an environment wherein it must operate with stable properties that permit it to conserve its adaptation, whatever the properties of its components may be. [Maturana and Varela 1998]

All functional adaptations in living beings, like all the artifacts they produce, fulfill particular projects which may be seen as so many aspects of fragments of a unique primary project, which is the preservation and multiplications of the species. [Monod 1972]

The stochastic chemistry approach is distinct from molecular dynamics in that no spatial details are obtained and only population time evolution of the different molecular species in the system are obtained. [Shenhav and Lancet 2004]

All or most such perturbations leave the system in the same basin of attraction. So the system will return to the same state cycle from which it was perturbed! That is the essence of homeostatic stability. [Kauffman 1994]

Here in this class of open thermodynamic systems, the spontaneous dynamics drive the system into an infinitesimal corner of its state space and hold it there, quivering for an eternity. Order for free....Nearby states converge in state space. In other words, two similar initial patterns will likely lie in the same basin of attraction, hence driving the system to the same attractor. Thus, such systems do not show sensitivity to initial conditions; they are not chaotic. The consequence is the homeostasis we seek. [Kauffman 1994]

The fact that their underlying deterministic dynamical equations appears to have a unique stable fixed point endows autocatalytic metabolism with a considerable degree of robustness to trauma. A perturbation in the concentration of one of its elements, for example, quickly

dies out. Thus, “self-repair” of autocatalytic metabolisms is built into their chemical kinetics. [Bagley and Farmer 1992]

The OCS Idea of Persistence

The end result of the combination of the other six organizing principles of OCS can lead to the organizing principle that organic systems are persistent – that is, that life, by its very nature, has the possibility of being self-sustaining.

Living systems specifically, and organic systems in general, are persistent because their dynamics conserve their “organicness”, or shall we say their *organicity*. From the OCS perspective, this means that all seven of the organizing principles of OCS have the possibility of being conserved.

The first organizing principle can be conserved. This means that organic systems remain *systems* under the dynamics of OCS. The second organizing principle can also be conserved: organic systems remain emergent – and also deeply nested, as required by the third organizing principle.

The fourth organizing principle states that organic systems are dynamic, can change; and furthermore identifies some classes of transformations by which they can change. These possibilities can also be conserved.

The fifth organizing principle describes the *mechanisms* behind the conservational nature of the dynamics of OCS. Essentially, this organizing principle says that *homeostasis*, involving negative feedback cybernetics, is the mechanism that promotes the conservation of organization through these dynamics; while the mechanism that we called *heterostasis*, involving positive feedback cybernetics, promotes the alteration of organization, or the *reorganization*, of organic systems. The homeostasis manifests as survival, while heterostasis as adaptation. Through these two mechanisms, organic systems stay the same as long as they can; but can change, adapt, in order to conserve their organicity.

The sixth organizing principle, *uncertainty*, says that although this conservation, this adaptation and all of the other aspects of organicity may, or may not occur – nevertheless there is some probability that it will. Moreover, it says that the degree of uncertainty throughout these organizational dynamics does itself change along a spectrum that ranges all the way from completely-deterministic to completely-random – as measured by Shannon’s entropy function. The persistence organizing principle means that this uncertainty, too, can be preserved.

Persistence is the third systemic property that we have introduced among these seven postulates that may be exhibited to varying degrees by organic systems. The other two were *organization* and *uncertainty*. In this sense, it should be sensible to speak of a “degree to which an organic system continues to persist”. Thus, persistence is also akin to “sustainability”.

In the case that OCS can be modeled with discrete stochastic processes, as we shall do in Part II of this article, *persistence* translates to the expected number of steps in a process before it terminates.

As we discussed above with *organization* and *uncertainty*, OCS should be able to provide a measure function for the concept of a *degree of persistence*. For example, in previous sections we have discussed the *degree of organization* and the *degree of uncertainty*. Similarly, we shall also present a *degree of persistence* measure.

Such a measuring function should associate a non-negative real number with each organic system that measures its degree of persistence – according to any properties required by measure theory [Doob 1953]. However, the identification and definition of such a measure is beyond the scope of this article, and is left to further research.

In summary, the principle of *persistence* means *the conservation of organicity through the dynamics of OCS*. Even though the *identities* of organic systems may be lost through their dynamics; nevertheless, their *organicity* can be conserved.

OCS Summary

Part I of this article has introduced Organic Complex Systems (OCS), a general theory of systems that exhibit lifelike properties. OCS embarks on the development of this general theory of the living and the lifelike by identifying and selecting a collection of seven systemic properties that are exhibited by biological life on earth.

After listing these seven systemic properties, OCS imbues them with meaning by articulating associated organizing principles. Having abstracted these seven principles from biological life on earth, OCS professes to have developed a general theory of the living by specifying that any system that complies with these organizing principles - whether biological or not - to be the subjects of its inquiry. It calls them *organic systems*.

In selecting these seven organizing principles, an attempt has been made to characterize the essence of what it means to be "alive". It is hoped that a critical population of readers will be inclined to agree that any system that exhibits all seven of them will be worthy of being called "lifelike". Of course, the selected properties also represent the interests and biases of OCS. Thus, it can be fairly said that OCS is a theory that describes a particular style of "livingness".

The intended application of OCS is the modeling of lifelike systems. This includes biological systems. But it also includes lifelike non-biological systems. Applications of OCS, for example, could be in such areas as non-carbon-based life on other planets, economies, autocatalytic sets and the planet earth.

OCS is a dynamical system. As such, it has a static aspect as well as a dynamical aspect. The static aspect of OCS is a system's *structure* – its organization, configuration or component arrangement. This aspect is referred to in OCS as the system's *organization*.

The dynamical aspect of a dynamical system describes how its state can change. For OCS, the dynamical aspect describes how the *organization* of an organic system changes. In OCS, the organization of an organic system changes by transforming into another *organization*. In other words, an organic system can change by *reorganizing* - *changing from one organization to another*. So, if the static aspect of OCS is defined as a system's *organization*, then the dynamical aspect of OCS is the *reorganization* of an organic system.

We shall now summarize the essential meaning of each of these seven organizing principles. The first three of these characterize the static aspects of an organic system; while the last four characterize the dynamical aspects.

1. Organized: The components of an organic system have relationships among themselves. These relationships are well defined as a collection of relationships of the components. This set of relationships is called the *organization* of the organic system.
2. Emergent: There is at least one property that is exhibited by an organic system that is not exhibited by any of its components. This fact is called

systemic emergence, and such a systemic property is called a *systemically emergent* property. OCS recognizes two types of emergence: *process emergence* and *systemic emergence*. Many emergent events are of both types simultaneously. OCS emphasizes *systemic emergence*.

3. Nested: An organic system has at least one component that is also a system – and may or may not be another organic system.
4. Reorganizational: An organic system is dynamic. That is, it changes in time. Moreover, the way that it changes is that its *organization* (as defined in organizing principle 1) transforms to another *organization*. In other words, the manner in which organic systems change is that they *reorganize*.
5. Autocogeneration: The components of an organic system create, organize, reorganize, regulate and terminate each other. In so doing, they create, organize, reorganize, regulate, manage and terminate the organic system of which they are components.
6. Uncertain: Organic systems reorganize unpredictably. Even this uncertainty is uncertain. This is because it may range all the way from completely certain (deterministic) to completely uncertain (totally random) or any degree of uncertainty between these two extremes.
7. Persistent: The above organizing principles coalesce to encourage the continued existence of organic systems.

Part II of this treatise will present a mathematical framework that embodies all seven of these organizing principles, and that will be useful for modeling the lifelike.

Appendix 1: Uncertainty and Information in OCS

This sixth postulate places the participation of OCS squarely within the discipline of *information theory*. As eloquently stated by Richard Kleeman of the Courant Institute of Mathematical Sciences at New York University,

The central idea of information theory is to measure the uncertainty associated with random variables. [Kleeman 2009].

The reason for this is that information theory equates – mathematically - the concepts of *uncertainty* with the concept of *information*. We shall investigate this conflation together with the significance of information theory in OCS in this subsection.

The meaning and degrees of *uncertainty*, its relationships to *information* and to *choice* portend much concerning its significance to OCS theory and to the formation of the Organodynamic modeling framework. In addition, these issues foreshadow the organization and practice method of Organodynamics modeling practice.

In this section, we shall investigate what pioneers and contemporaries in the field of information theory have to say concerning these relationships, and how these shape Organodynamic framework theory and practice.

Shannon's Conflation of Uncertainty and Information

In his famous 1948 paper [Shannon 1963], Shannon equates the concept of *information* with the concept of *uncertainty*. While he does not actually come out and say specifically that the two concepts are semantically equivalent, he treats them as though they are mathematically equivalent. This is evident by the fact that he describes his entropy function as a measure of both.

In fact, he adds a third idea as equivalent to the other two as well – that of *choice*. Within the span of three sentences in his famous 1948 paper, he uses the words "information", "uncertainty" and "choice" to describe what his concept of entropy measures. But he never goes into any semantic distinctions among the three - only that all three are measured by *entropy*.

In his book *The Information* [Gleick 2011], the science journalist James Gleick describes

Shannon wanted to define the measure of information (represented as H) as the measure of uncertainty: "of how much 'choice' is involved in the selection of the event are of how uncertain we are of the outcome."

Information theorist Vlatko Vedral, Professor of Quantum Information Science at Oxford University, sheds some light on this conflation. In his 2010 book [Decoding Reality: The Universe as Quantum Information](#); he traces the notion of information back to the ancient Greeks [Vedral 2010].

"The ancient Greeks laid the foundation for its [information's] development when they suggested that the information content of an event somehow depends only on how probable this event really is. Philosophers like Aristotle reasoned that the more surprised we are by an event the more information the event carries...."

Following this logic, we conclude that information has to be inversely proportional to probability, i. e. events with smaller probability carry more information...."

So *information* is inversely related to probability – just as we have already seen that *uncertainty* is. In other words both *uncertainty* and *information* are inversely related to probability. Aristotle's insight exposes the relationship between the *value* of information and the *degree of surprisingness* of the outcome of a random event that produced that information. Says Gleick, expounding on Shannon's view, "Information is surprise."

In other words, the *value* of an item of information is inversely proportional to its probability. In fact, Vedral goes on give the formula for the *degree of information* in an event. It is precisely the basis for Shannon's entropy formula.

Explains Gleick

Shannon reached an elegant solution to the problem of how to measure information in as a function of probabilities – an equation that summed the probabilities with a logarithmic weighting (base 2 was most convenient). It is the average logarithm of the improbability of the message; in effect, a measure of unexpectedness..."

We can conclude from what both Shannon and Vedral have to say that *information theory uses the same measuring function for both uncertainty and information* – and that measuring function is Shannon's entropy.

Khinchin's Distinction between Uncertainty and Information

So, information theory regards *uncertainty* and *information* as mathematically equivalent – and seems to ignore any discussion of whether they are semantically equivalent.

But we all intuit that the two concepts are ultimately semantically opposed - if for no other reason than *uncertainty* adds to confusion and *information* can help to clear it up. So what, really, is the semantic relationship between *uncertainty* and *information*?

We would hope that information theory would address this issue. We would hope that information theory would tell us how *uncertainty* and *information* are semantically opposite; yet at the same time deserve to be measured by the same mathematical function.

For such an explanation we must turn to the Russian probability theorist A. I. Khinchin. Seeing that the Shannon's paper lacked both mathematical rigor and satisfying semantic justifications, he set about to put the situation right with his slim but essential little volume entitled The Mathematical Foundations of Information Theory [Khinchin 1957]. He manages to make the pertinent distinction between 'information' and 'uncertainty' most cleanly in this single passage. (By "scheme" Khinchin means "probability distribution".)

"Thus we can say that the information given us by carrying out some experiment consists of removing the uncertainty which existed before the experiment. The larger this uncertainty, the larger we consider to be the amount of information obtained by removing it. Since we agreed to measure the uncertainty of a finite scheme A by its entropy, $H(A)$, it is natural to express the amount of information given by removing this uncertainty by an increasing function of the quantity $H(A)$

Thus, in all that follows, we can consider the amount of information given by the realization of a finite scheme [probability distribution] to be equal to the entropy of the scheme."

So, when an experiment is "realized" (the coin is flipped or the die is rolled), the *uncertainty* inherent in it "becomes" *information*.

Vedral's Assignment of the Significance of Information

Clearly, the interrelated notions of *uncertainty* and *information* are fundamental to system processes, and therefore to Organodynamics.

Professor Vedral makes a considerably bolder statement than this, however. In his book Decoding Reality: The Universe as Quantum Information [Vedral 2010], he states:

"This book will state that information (and not matter or energy or love) is the building block on which everything is constructed. Information is far more fundamental than matter or energy because it can be successfully applied to both macroscopic interactions, such as economic and social phenomena, and, as I will argue, information can also be used to explain the origin and behavior of microscopic interactions such as energy and matter."

OCS' Assignment of the Significance of Uncertainty

This present work on OCS and Organodynamics clearly has a good deal of sympathy with Professor Vedral's argument that *information* is foundational. But I would extend his argument to arrive at a related, but slightly different conclusion.

My argument is this: If information is as foundational as Vedral suggests, then the phenomenon from which it (information) derives is even more fundamental.

And, as made clear by Khinchin's insight above, *information* manifests from *uncertainty* when *choice* is *realized*.

Perhaps this is the reason that Shannon conflated information, uncertainty and choice. All three of these are completely correlated. And Shannon defined his entropy to be a measure of all three.

Implications for Modeling Practice and Methodology

But, to expand somewhat on Khinchin's insight, choice *is* uncertainty. And these two become manifest – *realized* – as *information*. So we have a time sequence established here. First, there is *choice* and concomitant *uncertainty*. Subsequently, at some point when “the die is cast or the coin is flipped”, this *uncertainty* becomes *realized as information*.

This time sequence is important to modeling practices, since modeling reveals the layers of a dynamical system according to this sequence. Pertaining to the dynamical processes that we are modeling, this time sequence, then, directs how we as modelers need our models to

- Firstly, identify the *choices* provided by a process,
- Secondly, represent our *uncertainties* regarding which of those choices will be realized, and
- Thirdly, represent the outcome (information) revealed once that realization has obtained.

Any modeling framework that implements the organization principles of OCS should provide a modeling program that provides these three sequential steps.

Appendix 2: Is Entropy a Measure of Disorder?

James Gleick, in his comprehensive and readable book *The Information* [Gleick 2011], sums up a widely held disposition about entropy in thermodynamics by most scientists and even by some thermodynamicists, by presenting a simple example. Says Gleick, referring to newsprint: “There is entropy in the arrangement of the ink spots”.

In this section, we mean to dispel the notion that “an arrangement can have entropy.”

What is Disorder?

To find out the lexical meaning of “disorder” lets turn to some dictionary definitions. As with many common terms, there are many meanings in popular usage. There are two lexical definitions in particular that I want to highlight, because both are at issue concerning the meaning of the terms “order” and “disorder” in popular usage of the meaning of *entropy*.

Of course, to define the term *disorder* is to define the term *order* at the same time. Because they are opposites, one is the negation of the other, and is therefore derivative of the other. This discussion is really about a spectrum with two polarities (order and disorder), rather than just one of the polarities.

Lexical definitions are not intended to be precise and unambiguous; but rather report the results of empirical observations concerning common usage. On the other hand, scientific definitions are operational. Investigators must decide what they are going to unambiguously mean within their own publication and be consistent with that usage internally. They use operational definitions of terms to do that.

The ambiguity of lexical meaning is not well tolerated in science where operational definitions are called for. However, I fear, concerning the use of the term “disorder” to describe the semantics of *entropy*, particularly in thermodynamics, that ambiguity has reigned. I hope to correct this issue in this section.

We shall therefore highlight two of the many lexical meanings found for the term “disorder”. It is the ambiguous and unspecified use of these two meanings of the term that I believe causes confusion and misunderstanding concerning the meaning of *entropy* – especially in thermodynamics.

Disorganization

The web site dictionary.com supplies the following definition of *disorder* as its first:

“lack of order or regular arrangement; confusion: Your room is in utter disorder.”

To OCS, the key word used in this definition is “arrangement”.

If disorder is the *lack of* arrangement, then *order* is the presence of it. Thus, we can speak either of the meaning of *disorder* or of *order*, because the meaning of the other is implied.

OCS emphasizes a specific concept that it calls *organization/disorganization*. What OCS means by *organization* is very close to the apparent meaning of the word *arrangement* in the above definition – and consequently to the term *disorder* as defined above.

Lets imbue this concept of *organization* as used by OCS with fuller meaning at this time and further relate it to the word *arrangement*. We'll begin by offering even more synonyms for *organization*: *arrangement*, *structure* and *configuration*.

The aspects of *organization* that OCS intends and that it wants to emphasize are these:

1. *Organization* concerns interrelationships among a system's components.
2. A system is *highly organized* if it has, in some sense, a lot of interrelationships among its components, and is *highly disorganized* if it has very few relationships among its components.
3. The presence of strong interrelationships contributes to its *degree of organization/disorganization*. The presence of weak interrelationships detracts from its *degree of organization/disorganization*.
4. *Organization/disorganization* is a static concept. It can be discerned and its degree measured instantaneously among multiple, simultaneously existing components of a system.

These comments about *organization/disorganization* are an embellishment of the lexical meaning of the term “disorder” above. They essentially present the same meaning, while being more specific.

In any event, there is one popular usage of the term “disorder” that is strongly similar to the OCS operational definition of *disorganization*. Both concern the *lack of interrelationships among members of a system at a specific moment in time*.

Uncertainty

On the other hand, other sources assign a distinctly different usage to the word *disorder* – that of *uncertainty, unpredictability*.

In fact, one [Wikipedia site on Disorder](#) displays

“Chaos, unpredictability”.

Uncertainty, or unpredictability, is also an important concept in OCS. OCS refers to this idea simply as *uncertainty*.

But, OCS views *uncertainty* as very different from the notion of *disorganization* – so much so that OCS avoids the use of the word *disorder* for fear that it will be misinterpreted to mean *disorganization* in cases where OCS actually means *uncertainty*.

To dispel any confusion regarding what OCS means by *uncertainty*, we shall now contrast its meaning to that of *disorganization* by listing the several of its aspects of *uncertainty*:

1. *Uncertainty* concerns a repeated process called an experiment. Even though the same experiment is repeated in exactly the same way many times, the outcomes may be different each time.
2. Each distinct outcome of an experiment is called an *event* and each repeat of the experiment is called a *trial*. The set of all possible outcomes is called the *sample space* of the experiment.
3. The outcomes, or events, of the sample space are *alternatives*, because exactly one is produced by each trial. Multiple outcomes of the sample space never result from a single trial. For this reason, the experiment is often called a *probability function*. This is contrasted with a *deterministic function*, which produces the same output for all trials. Whereas a *probability function* also produces exactly one outcome for each trial, but it can be any one of the events of the experiment's sample space.
4. Each event is also assigned a *probability weight* that relates to the *likelihood* that the event will manifest whenever a trial is repeated. This enables the various events of the sample space to be weighted differently from the others when warranted.
5. The probability weight is a non-negative real number. The sum of the probabilities of all events in the sample space is one (1).
6. *Uncertainty* is a property of an observer of the experiment who knows of the sample space and the probabilities of the events, but does not know the outcome of a trial prior to the conduct of the trial. Once the observer knows the outcome of the trial, then that knowledge is called *information* of the outcome of the trial.
7. Each individual event is also assigned a value that measures its *degree of uncertainty*, called its *surprisal*, which is inversely related to its likelihood, or probability. In other words, as an event's probability decreases, its degree of uncertainty increases.
8. Once the outcome of specific trial is known, then the trial is said to be *realized*. At this time, the probabilities of the event that is the realized outcome is reassigned a probability of 1, and the probabilities of all the other events are reassigned to be zero – for that specific trial.
9. As such, *uncertainty* pertains to the lack of knowledge of the outcome of a trial, on the part of an observer, at one moment, which can be revealed at a later moment in time. The fact that two distinct time instances are involved on the part of the observer gives *uncertainty* a *dynamical* aspect.

Thus, the notion of *uncertainty* and that of *disorganization* are quite different. *Disorganization* pertains to interrelationships among a set of simultaneously existing system components that can be observed during the moment in time.

On the other hand, *uncertainty* pertains to the unknown realization of exactly one alternative (from a set of alternatives). Moreover, the *uncertainty* concerning the realization occurs at one time step, while the realization occurs at a later time step.

Why this Distinction is Important to OCS

Not all audiences or disciplines make this distinction between *uncertainty* and *disorganization*. Certainly, popular news journalism does not.

For example, if a mob is reported to have behaved in a “highly disorganized manner”, it is reasonable to expect both that 1) its members were disorganized and lacking in structure or arrangement, and that 2) from one moment to the next, their behavior was unpredictable. In this case, there is no reason to distinguish unpredictability from disorganization. They are probably both true, anyway. And even if they are not, the news readership does not care which was displayed. Therefore, in this case the distinction is irrelevant. One might as well use the term *disorder* for both.

But, to OCS the distinction *is* important: for at least two reasons.

The first is that, in OCS, *uncertainty* and *disorganization* can vary independently. That is, each can rise as the other falls. Or each can move in synch with the other.

This is possible in OCS, because OCS represents living entities as compound events – compound because each consists of combination of components. For example, a living entity can consist of multiple molecules, cells, organs, etc.

However, each of these events, being compound, can have various degrees of organization or disorganization. For example, a cell can have a collection of molecules that have a lot of covalent bonds, or that can have only a few covalent bonds. That is, they can be highly organized, highly disorganized or somewhere in between.

On the other hand, given an instant in time, each of the possible ways that a cell can be internally organized has its own probability. But, having a probability, then, the cell has a *degree of uncertainty* (called its *surprisal*). This degree of uncertainty may be high, it may be low, or it may be somewhere in between.

But there are several possible ways that a cell can be organized. And each has its own probability (and its own surprisal). Thus, the set of all such ways of being organized forms a *sample space*. And any sample space has an *entropy* value – which we have seen is the average of the *surprisals* of its individual events (sample points).

Moreover, at any moment in time, each entity in this sample space has a *degree of uncertainty* of becoming manifest (realized) at the next moment in time. As well, each entity in the sample space has a *degree of organization/disorganization*. That is, each living entity is either highly organized, highly disorganized, or somewhere in between.

Thus, each entity in the sample space has both an organization and a probability – and thus both a degree of disorganization and a degree of uncertainty.

And, these two can vary independently. This means that each of the following four possibilities can be true of a living entity: organized and certain, organized and uncertain, disorganized and certain or disorganized and uncertain.

In order to capture all four of these possible states (and all gradations in between) by living entities, clearly a distinction has to be made between *disorganization* and *uncertainty* in OCS.

But there is a second reason for interest in this distinction. It is that *entropy* is defined in terms of *uncertainty* – but it *is not* defined in terms of disorganization. We shall investigate this factor further below.

What would a Measure of Organization/Disorganization Look Like?

We have said that OCS views the concept of organization/disorganization as pertaining to interrelationships among the components of a system.

Moreover, systems can exhibit varying degrees organization/disorganization. A system can be highly organized, highly disorganized, or anywhere in between. In fact, it should be possible to define a *measure* of this degree.

This treatise *shall not* define such a measure, because OCS has not yet solved the problem of how to do so, and is therefore leaving the issue to further research.

However, we shall make some remarks regarding some characteristics that such a measuring function must have – in order to, in fact, *be* a measure of the degree of interrelatedness.

Lets first note that any measuring function must have *variables* that represent possible values of the characteristic that is being measured. It may also have some constant values, and it will certainly describe relationships among the entities that are being measured.

Therefore, since the degree of relatedness of system components are being measured, then there must be variables in this measuring function that represent *relationships* among the system's components. For example, the measuring function might valuate groupings (pairs, triplets, etc.) of these component variables.

This is the least we would expect of a function that measures *degree of relationship* among multiple entities. If a measuring function does not compare multiple variables to each other, then it cannot be a function for measuring the degree of interrelationships.

Lets look at an example function that measures the degree of interrelatedness of the components of (or the *degree of organization*) of a system. Consider a closed system of atoms. Assume that some of these atoms may be connected to each other via covalent bonds, and that some of them may not. We would like to have a measure of the degree of organization of this system based upon this covalent bonding relationship.

One possible way to define such a function is as follows. Divide the number of covalent bonds currently in the system by the number of possible ways that the atoms in the system could form pairs. Such a measure would be a relative measure whose values could range from zero to one. This measure would have a value of zero if there were currently no covalent bonds in the system; and it would have a value of one if all pairs of atoms are currently covalently bonded to each other. While the latter is likely a chemical impossibility, it is nevertheless a theoretical one.

Notice that this measure fits our requirements. Chiefly, its principle consideration is the counting of the actual pairing of system components (atoms) against possible pairings of those components – at a specific point in time.

Actually, the measure we defined here is for the degree of *organization* (or arrangement, structure, configuration, etc.) A corresponding measure for the degree of *disorganization* can be defined as subtracting the degree of *organization* of a given system at a given time from one (1).

We are explaining this here, because we shall demonstrate below that *statistical entropy* cannot be a function that measures *degree of interrelatedness*.

What would the Uncertainty of an Event Look Like?

What would a measuring function of the uncertainty of a single event look like?

We mentioned above that if an event has a very low probability, then the event is uncertain. On the other hand, if an event has a very high probability, then we have a high degree of certainty it will occur. Obviously, then, *probability* and *uncertainty* are inversely related. As one goes up, the other goes down and vice versa.

Thus, it makes sense to define a formula that measures the uncertainty of an event so that the *degree of uncertainty* goes up as the *probability of the event goes down* – and conversely. An example of such a formula would be:

$$u = 1/p$$

where “u” is the degree of uncertainty of an event, and “p” is the probability of that same event.

Therefore, we would expect any formula that measures *degree of uncertainty* to 1) have *probability* mentioned, and 2) describe a relationship between uncertainty and probability whereby the degree of uncertainty goes up when the probability goes down, and conversely.

There are many possible formulas, however, for which this is also true – that is, as the probability of an event goes up, its degree of uncertainty goes down, and conversely. Lets identify another such function and select between it and the one above.

The following is a second example of this:

$$u = \log(1/p)$$

where u and p are defined as before, and “log” is the logarithm. (It doesn’t matter which logarithm base is used.) There are many other such formulas. But we emphasize this later one because it happens to be the basis of *information theory!*

One may wonder why information theory chose this formula instead of the first one. After all, the first one is simpler and more intuitive. If either function would work as a measure of uncertainty, why not pick the simpler? The reason that the second one is selected by information theory is because it has another desirable property that the first one does not: It is additive for two statistically independent events – and the first formula is not. It turns out that this additivity is more important to information theory than the relative simplicity of the first formula. The explanation of why the second formula is “additive” is beyond the scope of this appendix.

This second formula is so important to information theory that we are going to say more about it. Since this formula is a *measure of the uncertainty of an event*, then something about the event should be mentioned in the formula. Thus, we shall rewrite the formula so that this is taken care of, as follows:

$$u(E) = \log(1/p)$$

where E is an event, u is its uncertainty and p is its probability.

As we have seen from [Khinchin 1957], *before an event is realized, the event has uncertainty. Once the event is realized, the uncertainty becomes information.* So, if the formula “u” above, measures the uncertainty of an event before the event is realized, then it also measures the amount of information value after it is realized.

Another way to say this is that, if a particular outcome of a trial is highly improbable, and therefore highly uncertain, then to have that outcome be realized is highly *surprising*. For this reason, the formula for “u” above is also called the *surprisal* of event E, as well as its *uncertainty*.

From all of this, then, we can answer the question posed by the title of this subsection. This question asks “What would a measure of uncertainty look like?” We know several things that we want of it:

1. It must refer to the probability of the event(s) whose uncertainty we are interested in.
2. The value of uncertainty must increase whenever the probability decreases, and conversely.
3. It is preferred if the following expression figures into the formula somewhere, because it provides additivity for independent events: “ $\log(1/p)$ ”.

What would the Uncertainty of Probability Distribution Look Like?

What would a measuring function of the uncertainty of an entire probability distribution – containing many events - look like?

So far, we have discussed measuring the degree of uncertainty of a single event. But what we actually want is to measure the uncertainty in a probability distribution, because a probability distribution represents an entire phenomenon, and entire experiment with many possible outcomes, many possible events. And the probability distribution has many events – in fact, it has an entire sample space of them.

So, we want to somehow use the fact that we know how to measure the uncertainty single events in order to calculate the amount of uncertainty inherent in an entire probability distribution.

One approach we could take is to compute the *average* amount of uncertainty of all of the events in the probability distribution. In other words, we would take the formula we just developed for computing the uncertainty of a single event, $\log(1/p)$, and use it to find the *average amount of uncertainty* of all of the events in the distribution.

One way to take the average take each event, calculate $\log(1/p)$ for that event, add all of the results and divide by the number of events. But there is also a second way to calculate this average. It is this: Take each p that any of the events exhibits, calculate $\log(1/p)$ for it. Then multiply that value by p . Add up the results. This yields the same answer for the *average uncertainty (or average surprisal) of all of the events in the sample space of this probability distribution*.

Lets write this second method of calculating the average uncertainty as a formula:

$$\text{Average uncertainty of the events in a distribution} = \sum_{i=1, n} p_i \cdot \log(1/p_i)$$

What does Entropy Actually Measure?

The best way to answer this question is to inspect the formula for entropy, and try to interpret it.

The first question we must address is *which entropy and which formula?*

Unfortunately (or maybe fortunately) there are *four definitions of entropy* that have become historically significant, and we must decide which to use.

The first, historically, was that of Clausius, who in the middle of the nineteenth century was concerned with heat loss. His formula was articulated in terms of “heat energy” per unit of temperature. It contained no reference to probabilities. It therefore had no concern with the issue of uncertainty. In fact, it was a completely deterministic view of entropy. Thus, we shall not further discuss Clausius entropy – also called the classical entropy of thermodynamics.

The remaining three formulas, however, are defined in such a way that *probabilities are their only input parameters*. Thus all three are clearly concerned with *uncertainty*. Thus, we shall henceforth refer to them as *statistical entropy*. It is statistical entropy that we are concerned with in this appendix. Any further references to *entropy* should be taken to mean statistical entropy.

The equivalence or non-equivalence of these three forms of statistical entropy to classical thermodynamic entropy shall not be discussed here. However, the three forms of *statistical entropy* are essentially equivalent, which we shall now explain.

Of the three remaining formulas, two are from statistical mechanics and other is from information theory. One might expect that the two from statistical mechanics are “concrete”, while the one from information theory is “abstract”, since statistical mechanics is physics while information theory is mathematics. However, we shall see that in this case all three are equally abstract.

I have articulated these three formulas below using consistent variables, so that they are easy to compare.

One formula is from the statistical mechanist J. W. Gibbs [Gibbs 1902]. It defines entropy in statistical mechanics. His formula is:

$$\text{Entropy: } S = -K \sum_{i=1,n} p_i \log(p_i)$$

Here, the “K” is a constant, called Boltzmann’s constant. The only parameters are the p_i , which range from 0 to n. These are the probabilities and the range across a sample space.

Here is a simplistic explanation of this sample space. Think of a closed space containing the particles of an ideal gas. For a given temperature, each of these particles will have a position and a momentum – its “state”. You could make a list of all of the positions and momenta that were exhibited by any of these – and that list would constitute that sample space – each event of which is a (position, momentum) pair. In most cases, each (position, momentum) pair in the sample space would have a distinct number of particles that exhibited that state. Thus, the probability of that state would be the number of such particles divided by the number of total particles in the container.

Consequently, *there is a probability distribution* regarding this closed ideal gas system. *This probability distribution is characterized by Gibbs' formula for entropy.* Notice that the only input parameters to Gibbs' formula are the probabilities p_i .

The K is not a variable, but a constant. It does not matter to the semantics of the formula that it is "Boltzmann's constant". The name might be a reference to several complex ideas in statistical mechanics. But none of them are captured in the mathematics of this formula; so don't be misled by that.

There is also a second formula due to Boltzmann. But his formula is a special case of Gibbs', the case being when all of the probabilities are the same. Thus, we can reduce the number of formulas we need to consider by treating the Boltzmann formula as a special case of Gibbs'.

The third formula for entropy is from Claude Shannon [Shannon 1963], the inventor of information theory. The problem that he addresses is the *uncertainty involved in sending a communications message*. But, his theory is more general. It intentionally calculates the *uncertainty inherent in a probability distribution* – any discrete probability distribution.

Shannon's formula is:

$$\text{Entropy: } H = -\sum_{i=1,n} p_i \log(p_i)$$

Notice that Shannon and Gibbs' formulas are almost equivalent. The only difference is that the Gibbs' formula is multiplied by " K ". Now this " K " is a constant (Boltzmann's constant), and therefore only serves as a scaling factor. (Says Shannon about this "the constant K amounts to the choice of a unit of measure"[Shannon 1963].)

Otherwise, the two formulas are the same. In fact they behave the same. Having a different scaling factor is essentially the same kind of thing as using meters instead of yards. In fact, one could say that the two formulas are the same and that in Shannon's version K has been set equal to 1.

Thus, without loss of generality, we can say that the Gibbs and the Shannon formulas are equivalent. We shall use Shannon's formula for simplicity sake.

Notice this: It is admittedly the case that, in creating his formula, Gibbs was modeling gas particles that had the properties of positions and momenta. However, *his formula makes no mention of positions or of momenta*. It only makes mention of *probabilities*. It is true that the entities (gas particles) that have those probabilities do, in fact, also have positions and momenta. But Gibbs ignores them in his formula and abstracts out only the probabilities. As a result, his formula completely ignores any notions of positions or momenta.

And, notice something else about Shannon's formula: It is exactly the same formula that we derived in the previous subsection for measuring *uncertainty*!

Admittedly, the formula in the presented in the previous subsection looks slightly different. It is:

$$\sum_{i=1,n} p_i \cdot \log(1/p_i),$$

whereas, Shannon's formula is:

$$-\sum_{i=1,n} p_i \cdot \log(p_i)$$

But $\log(1/p_i) = \log(1) - \log(p_i) = 0 - \log(p_i) = -\log(p_i)$. Therefore, the two articulations are the same.

Therefore, we can say that

Shannon's formula for entropy calculates the degree of uncertainty inherent in all of the sample points of a discrete probability distribution.

And so does Gibbs! Gibbs' formula calculates *uncertainty*!

This was no surprise to Shannon. In fact he formulated his entropy as he did precisely because he was attempting to define a measure of *uncertainty*. Moreover, Shannon intentionally reused Gibbs' formula because he already knew that it is a measure of *uncertainty*.

What Entropy Does Not Measure

We just showed that *statistical entropy* is a function that measures the *degree of uncertainty* inherent in a system that is a probability space – a space that is represented by its probability distribution.

The question also arises as to whether *statistical entropy* can be a measure of the *interrelatedness* of the components of a space. In OCS, we use the term *organization* to mean interrelatedness. And, *disorganization* would be the lack of organization. So the above question is equivalent to “Can statistical entropy be a measure of *disorganization*?”

Earlier in this section, we showed that in order for a function to be able to measure degrees of interrelatedness of the components of a system, such function “must value groupings (pairs, triplets, etc.) of these variables”. This is of course not surprising. Any measure of interrelatedness must make comparisons between the components and apply numeric values to those comparisons.

But if we re-examine the above two formulas for *entropy* - either of them:

$$S = -K \cdot \sum_{i=1,n} p_i \cdot \log(p_i), \text{ or}$$

$$H = -\sum_{i=1,n} p_i \cdot \log(p_i)$$

It can be seen that there are no expressions in them that perform any such evaluations.

Consequently, entropy cannot be a measure of interrelationships between or among the components of a system for which entropy is a measure!

Specifically, we ask the question as to whether entropy can measure the *degree of organization, or structure or arrangement, or configuration* of a system; or the *degree of disorganization, or lack of structure, or disarray of a system*. Because all of these are measures of interrelationship, the answer to all of these is no.

Can an Arrangement Have Entropy?

Look again at the two formulas for entropy that we have been discussing:

$$S = -K \sum_{i=1,n} p_i \log(p_i), \text{ or}$$

$$H = -\sum_{i=1,n} p_i \log(p_i)$$

It is significant that these two formulas have only one type of parameter: *probability*. It is reasonable to say that a function that only has probability parameters is saying something about *uncertainty*.

Thus, whenever you wonder whether or not *anything* has *entropy*, the qualifying question should be “Does the thing have a probability”? A concomitant question that you can ask about the thing is “Is there any uncertainty surrounding the thing?”

If an “arrangement “ of components is already sitting there, and you are observing it, then most likely you do not have any uncertainty concerning it. And, if there is no uncertainty, then there are no probability assignments, and in fact no sample spaces and no probability distributions either.

And, if there are no probabilities, then you cannot use a statistical entropy formula – neither that of Boltzmann, Gibbs or Shannon, because they require probability assignments *as their only inputs*.

In short, one cannot have statistical entropy if one does not have a probability distribution.

This fact is not well understood.

In the beginning of this section, we quoted James Gleick [Gleick 2011], referring to newspaper, as saying: “There is entropy in the arrangement of the ink spots”.

If by this statement Gleick means that the arrangement of the ink spots, as they sit there already on the printed page, has entropy, then I must submit the he is incorrect. Where is the uncertainty and where is the probability distribution that models these ink spots as they sit there on the page? There is none, so there is no entropy.

On the other hand, if Gleick has inspected this very arrangement – as it sits there on the page – six times, and has come up with different descriptions and

understandings of what the pattern of that arrangement is, then of course uncertainty has entered the picture. Now there is a sample space of interpretations and they can be assigned probabilities. Now there is a probability distribution, and it has entropy.

Can Entropy be a Measure of Disorganization?

There is much confusion, even in scientific literature, about entropy and what it measures.

For example, Professor Penrose [Penrose, Oliver 2005] in his excellent book on Statistical Mechanics, provides an example that he posits as an instance of entropy at work in almost everyone's daily life – the tendency of one's desk to become messy if not occasionally reorganized. This is certainly a familiar example. It is frequently cited in explanations of entropy in textbooks and other publications.

In fact, we can easily agree with Professor Penrose that it is *almost certain* that, if left un-reorganized, one's desk will be messier (become more disorganized) at an arbitrary time in the future than initially.

So then this is an example of *certainty increasing – not decreasing*. As time progresses, Professor Penrose is *increasingly certain* that the messiness of the desk will increase.

But, this increasing *certainty* is a *decrease* in uncertainty, and thus a decrease in statistical entropy – not an increase in it.

What *is* increasing however is the messiness of the denizens of the desktop. But this is an increase in degree of *disorganization* – not an increase in degree of uncertainty.

So, it seems to me that Professor Penrose must be incorrect, because he has posited this as an example of increasing statistical entropy. It is certainly an increase in disorganization – but not of uncertainty, not of statistical entropy.

Is Entropy a Measure of Disorder?

So, let's now ask the question posed by the title of this section. Is entropy a measure of disorder?

If by "disorder" one means "disorganization", then the answer is no.

If by "disorder" one means "uncertainty", then the answer is yes.

Unfortunately, by "disorder" speakers often means "uncertainty", and the readers often interpret the meaning as "disorganization". This confusion can be avoided by dropping the usage of the word *disorder* from discussions of statistical entropy.