Emergence, Intelligent Design, and Artificial Intelligence

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Abstract

We consider the implications of emergent complexity and computational simulations for the Intelligent Design movement. We discuss genetic variation and natural selection as an optimization process, and equate irreducible complexity as defined by William Dembski with the problem of local optima. We disregard the argument that methodological naturalism bars science from investigating design hypotheses in nature *a priori*, but conclude that systems with low Kolmogorov complexity but a high apparent complexity, such as the Mandelbrot set, require that such hypotheses be approached with an high degree of skepticism. Finally, we suggest that computer simulations of evolutionary processes may be considered a laboratory to test our detailed, mechanistic understandings of evolution.

Introduction

> *"Die allgemeine Form des Satzes ist: Es verhält sich so und so." – Das ist ein Satz von jener Art, die man sich unzählige Male wiederholt. Man glaubt, wieder and wieder der Natur nachzufahren, und fährt nur der Form entlang, durch die wir sie betrachten.*
>
> *"The general form of propositions is: This is how things are." – That is the kind of proposition one repeats to himself countless times. One thinks that one is tracing nature over and over again, and one is merely tracing round the frame through which we look at it.* – Ludwig Wittgenstein[1]

The origin of life's immense complexity and adaptability is tantalizing in at least two respects: 1) We want to understand where we and our world came from, and 2) We want to imitate nature in our engineering projects. Darwin is seen by most scientists as a bright beacon pointing to the answer. The Intelligent Design (ID) movement, popular among Christians in America though frowned upon by the scientific community, questions the sufficiency of natural processes to explain the profound complexity we see in nature, and furthermore declares that design by a higher intelligence can be inferred scientifically. Whether or not they denounce ID, scientists readily acknowledge that the precise mechanisms by which evolution has and does progress largely remain a mystery, and that Darwin, Watson, Crick, Gould etc. have provided only a vague outline of the story.

Those precise mechanisms, if they can be found, would be of extreme interest to technologists, and particularly in the software arena where programs can be written to match a well-defined model. Nature has solved some of the hardest problems we can imagine in the design of biological organisms. Artificial Intelligence (AI) can be briefly defined as the *science of solving hard problems automatically*, and thus it should be no surprise that recent advances in AI have come, not only from the hard-coded and meticulously designed algorithms we traditionally associate with computer applications, but from biology-inspired "soft computing" frameworks that exploit our new and growing understanding of how complexity can self-organize in an autonomous

[1]Trans. G.E.M. Anscombe, P.M.S. Hacker and Joachim Schulte, *Philosophical Investigations*, 4th ed. (UK: Blackwell Publishing Ltd, 2009), §114, p. 53.

way. Underlying this is an emphasis on *emergence* – systems whose behavior is more than the sum of their parts – which has been revolutionizing the world view of many sciences over the last few decades, as described by complexity theorists Ricard Solé and Brian Goodwin in their *Signs of Life: How Complexity Pervades Biology* (2000):

> *A remarkable burst of creativity in science is transforming traditional disciplines at an extraordinary rate, catalyzing movements whereby old boundaries are dissolving and newly integrated territories are being defined. The new vision comes from the world of complexity, chaos, and emergent order. This started in physics and mathematics but is now moving rapidly into the life sciences, where it is revealing new signatures of the creative process that underlie the evolution of organisms.*[2]

The same concepts that inspire soft computing, one of the most successful and promising branches of AI, fuel the optimist's hope that we are on the brink of discovering the secret behind life's success. By and large, ID has not confronted this paradigm. We thus consider the challenges that a discussion of emergent complexity poses to the inference of design in natural systems, while staying mindful of our ignorance. Finally, we draw attention to computer simulations of evolution under active research in Artificial Intelligence as a potential benchmark for our understanding of the details of evolutionary processes.

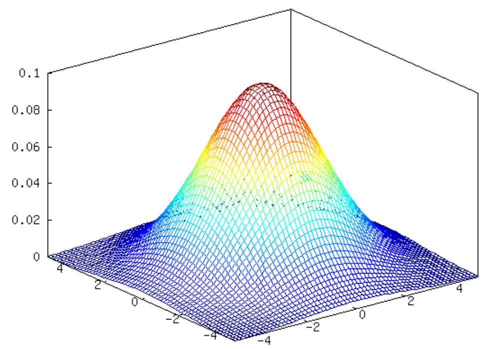
Evolution as Function Optimization

We begin by visualizing evolution as a search process, so we can quickly see how it is limited. Natural selection works by exploring a "fitness landscape" through mutations and sexual reproduction, looking for peaks which represent survival optimums in the current environment. The process works best when there is a smooth gradient leading upwards to a maximum, providing small steps that are achievable with probabilistically feasible mutations (see Figure 1). This corresponds to the gradualistic conception of evolutionary progress as a continuous, step-by-step march toward higher fitness and, under the right circumstances, greater complexity. Each correct mutation, i.e. one

[2] Ricard Solé and Brian Goodwin, *Signs of Life: How Complexity Pervades Biology* (US: Basic Books, 2000), ix.

which results in more offspring, takes part of the population a step up the hill, and eventually replaces lower fitness variants. All "nature's algorithm" (As Daniel Dennett calls it[3]) need do is stumble into the so-called "basin of attraction" of one of these peaks. In this sense the evolutionary process can be seen as a stochastic (random) optimization algorithm, although we acknowledge that the dynamics of biological evolution in real-world ecosystems are more subtle than this simple caricature would imply.

Figure 1: *A fitness peak with a wide basin of attraction conducive to discovery via natural selection.*

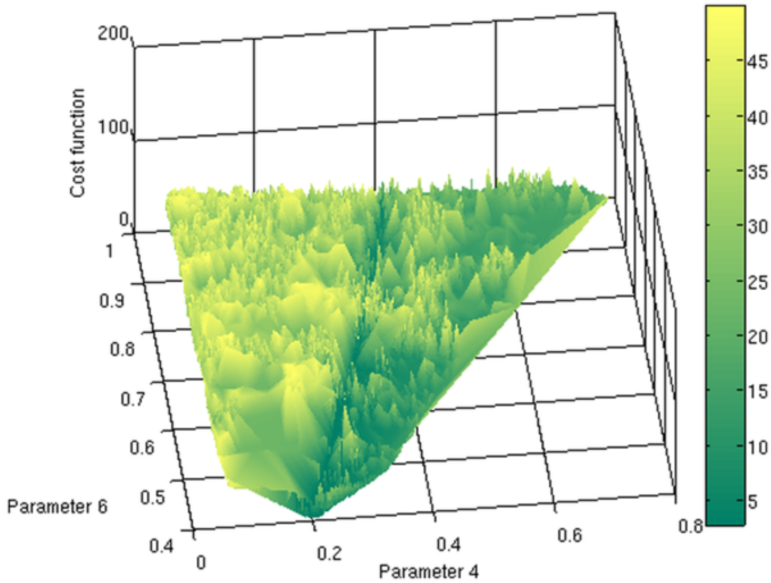


Constructing good solutions to real-world problems is more difficult than the smooth curve in Figure 1 makes it appear, which is why gradualistic models of evolutionary history have long been abandoned in favor of such ideas as punctuated equilibrium, in which progress occurs in occasional spurts. In practice all optimization algorithms suffer from the "local maximum" problem, as the fitness landscape is often tumultuous (See Figure 2).[4] The program happily climbs to the top of an easy-to-find, shallow peak, while altogether missing a much better solution with a narrow basin of attraction. There is no foreseen benefit to going towards the higher peak, since things don't get gradually better as we build that system (See Figure 3), and furthermore the valley between them may be too low for the organism to survive at all in an intermediate state.

[3]Daniel Dennett, *Darwin's Dangerous Idea* (New York: Touchstone, 1995), 48-60.

[4]Figure 2 is taken from Diego F. Slezak et al., "When Optimal is Not Best: Parameter Estimation in Complex Biological Models," *PLoS One*, 5(10), October 2010.

Figure 2: *A more realistic fitness landscape.*



Since a real fitness landscape has many more than two dimensions, going a long ways by chance and hitting the jackpot is extremely unlikely, and so a roadblock occurs in the evolutionary process. Intelligent Design focuses on instances where the local maximum problem appears to have been transcended in a manner inexplicable under the traditional neo-Darwinian synthesis of evolutionary theory.

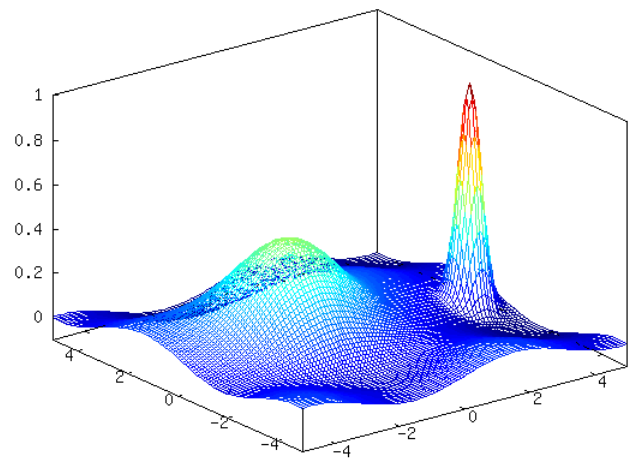
Design Inference

The premises that underlay ID are laid out by philosopher and mathematician William Dembski's three criteria for "Design Inference." The idea is that systems have been observed in nature which display the following properties, which taken together form Dembski's definition of Complex Specified Information (CSI):[5]

- **Contingency** requires that the system could have been built differently. It's like choosing Scrabble letters at random from a bag. If the bag contains only one type of letter, then our result is not contingent on

[5]William Dembski, *Intelligent Design: The Bridge Between Science and Theology* (IL: Intervarsity Press, 1999), 128.

Figure 3: *A simulated fitness function with two local maximums, the taller of which has a very small basin of attraction.*



anything, and we have no grounds to be surprised. However, if the bag contains a large variety of possibilities we may be able to infer design if a given selection can be shown to be unexplainable probabilistically.

- **Complexity** by Dembski's definition requires that the system have many interdependent parts, without any of which the system would be incomplete. [6]

- **Specification** requires that said system be well-suited for the problem we are attempting to solve. Out of the vast array of contingent possibilities, there are many "wrong" answers. In the Scrabble letters analogy, specification could be equivalent to drawing letters at random and trying to form a word in some particular language.

In applying these principles to biology, a system may provide survival value (specification), but with sufficient complexity it can be seen as impos-

[6]Note that this definition of "complexity" differs from the characteristics routinely considered by complexity theorists, which usually include *robustness* under change/damage as a key feature, while our discussion here is most salient when looking at particularly brittle systems.

sible to have been produced via natural selection. Dembski sets the threshold information content of such an "irreducibly complex" system (a term coined by Michael Behe) at 500 bits, a number well large enough that it cannot be attributed to chance mutation.

If evolutionary processes are insufficient, it is reasoned, materialist explanations have failed us, and we can infer the presence of design. And, indeed, if a system unexplainable by incremental evolutionary processes and requiring 500 bits of information to develop *simultaneously* and *by chance* can be shown to exist, it would form a compelling argument.[7]

To avoid misunderstanding, it should be noted that CSI is a term created by and for the ID movement. While it has philosophical overlap with Information Theory – the field founded by Claude Shannon's famous paper – CSI is quite distinct, and the term "complex specified information" does not appear in peer-reviewed mathematical journals. Furthermore, whether CSI is sufficiently well-defined to be the subject of experimental inquiry is a whole debate to itself. For a decade Dembski has confidently defended his proposed "Law of the Conservation of Information" (LCI), which is supposed to prove that novel CSI can never be created by a natural/algorithmic process. Scientists remain unimpressed by the "proofs" of LCI that Dembski has offered to date, and routinely point to simple computer simulations as seemingly obvious counter-examples, while ID proponents argue that the evolved information was indirectly provided by the programmer of the simulation.[8] Avoiding this debate and speculation over a strong law of the cosmos, we will limit the present discussion to the question of what sort of systems one can expect to manifest via chance mutation.

Philosophy of Science

Like many areas of science, the case for (or against) evolution is a gestalt pattern made up of diverse evidence. While some individual pieces of evidence

[7]The author is in disagreement with Eugene Scott and others who argue that Intelligent Design is fundamentally incapable of making an argument that is relevant to scientific discourse.

[8]For a pro-evolutionary perspective, see Dave Thomas, "War of the Weasels: An Evolutionary Algorithm Beats Intelligent Design," *Skeptical Inquirer*, Volume 34, Issue 3, May/June 2010 and Wesley Elsberry and Jeffrey Shallit, "Information theory, evolutionary computation, and Dembski's 'complex specified information,' *Synthese*, 178:237-270, 2011. For treatments by Dembski et al., see papers available for download from http://evoinfo.org

can be quite compelling, the immensity of the whole (which often cannot be reduced to its parts) leaves room for interlocutors and rhetoricians – honestly or otherwise – to weave a birds nest of antagonistic verbiage that leaves the constructive, step-by-step search for truth in the dust. It would be to our benefit, then, to pause for a moment and discuss the relationship of evidence to our confidence, especially if it helps us all get on the same page.

First, a word on the red herring of methodological naturalism. The present author does not feel the need to restrict the definition of science to exclude the divine *a priori* as impossible to approach through scientific inquiry. Many scientists feel that opening the door to the divine stifles inquiry by replacing the not-yet-understood with "God did it."[9] One need not sacrifice rigor to admit the possibility of an agent acting independent of the system in question, however. If solid evidence were at hand that extraterrestrials built the pyramids, scientists would have no qualms accepting it. Similarly, if we have solid evidence that a designer – divine or otherwise – was involved in life's mysteries, then scientists will not keep their paws off of it.[10] Dembski insists that the primary reason science steers clear of ID is because of a philosophical presupposition. The matter is deeper than that.

Considering the insufficiency of natural evolution to explain irreducible complexity as a valid scientific hypothesis, then, our strength of belief is updated by evidence. We begin with an initial belief, or *prior*, and update it as supporting evidence is accumulated, or as detracting evidence is uncovered. This process is somewhat subtle, since different people will still consider individual pieces of evidence to have different weights.

Some readers will recognize this approach – updating priors with evidence – as the *Bayesian* interpretation of probability theory, which has a large following in the philosophy of science. Along this vein, in the mid-1900's Thomas Kuhn famously drew our attention to the role that one's subjective paradigm plays in scientific belief, and the difficulties of communicating with those who have reached different conclusions.[11]

[9]For example, see Eugenie C. Scott, "American Antievolutionism: Retrospect and Prospect," in Michael Ruse and Joseph Travis, eds., *Evolution: The First Four Billion Years* (Cambridge, MA: Harvard University Press, 2009).

[10]That said, many scientists consider it infeasible to infer design in the natural world. Impressed by emergent complexity akin to what we will discuss, Stephen Wolfram has written that, "We cannot find an abstract way to give evidence of purpose or intelligence," extraterrestrial or otherwise. See Wolfram, *A New Kind of Science* (IL: Wolfram Media, 2002), 620, 838.

[11]Note that neither the Bayesian or Kuhnian systems are excessively relativistic. One's

Many religions – occidental and oriental – emphasize personal experience as the primary source of evidence for their faith. Such evidence can be a valid part of the *personal* induction process – vastly affecting a person's priors, and thus conclusions – but is not amenable to the *public* analysis of scientific discourse, especially since one person's epiphany is another's delusion. Similar private epiphanies and personal intuitions inform the research of scientists, and many of the scientific Greats in history were motivated by particular religious beliefs. Science as a discourse, however, is ideally (if not in practice) intended to be independent of such subjectivity, because it does not hold the anecdotal experience of individuals to be reliable. Design Inference holds our interest specifically because it promises a *public* way to infer the existence of a deity, bringing a scientific legitimacy to the monotheistic paradigm that is stronger than a postmodern respect for personal experience.

Evaluating ID

In an effort to navigate this murky terrain, we qualitatively use the Bayesian paradigm to consider the elements that lead toward materialist and ID interpretations of biology, respectively. Having a model of inference we can agree on can simplify communication. What we have are two (rather grandiose) competing hypotheses regarding how complex processes in life came to be which make the following broad statements and predictions, each of which are themselves hypotheses to be tested:

1. **Supernatural**:
    - A) Complexity exists that is difficult to explain with natural causes.
    - B) Complexity exists that has no natural explanation.
    - C) Some sort of supernatural entity designed this complexity.
2. **Natural**:
    - A) Simple *in vitro* and/or *in silica*[12] processes *can* produce a profound amount of superficial complexity.

prior biases are *always* based on previous evidence. Exactly how that evidence is converted to quantitative figures, or how it informs domains where we have little direct evidence to go on, is where the subjectivity lies. Without evidence, we should begin agnostic – but more often we begin with a strong bias based on our paradigm.

[12] *In silica* refers to an experiment conducted solely via computer simulation.

- B) Similar *in vivo* natural processes *do* produce some of the complexity we see in nature.
- C) Similar natural processes produce *all* the complexity we see in nature.

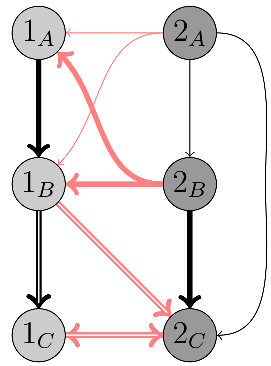


Figure 4: *Bayesian relationships between the hypotheses.*

Hypothesis 1(B), our focus, is a negative, and thus very difficult to prove. Its verification depends on an assurance as to the limits of *all* natural processes and *our ability to identify violations of those limits*, a prediction that can be supported by instances of evidence 1(A). 1(B) is not strictly falsifiable, but our confidence in it is reduced as we succeed in explaining more and more complex systems naturally, i.e. if 2(A) and (especially) 2(B) are verified in many cases. 1(C), which follows from the verification of 1(B), is only falsifiable by 2(C), which is equivalent to another negative (*no* complexity was created non-naturally) and thus all but impossible to prove conclusively. 2(C) is falsifiable, however, by a *single* counterexample via 1(B). Figure 3 summarizes these observations in a rough version of what is known as a Bayesian network. Single lines represent supporting (black) or detracting (red) evidence, thicker lines having more effect than thin ones. Double lines represent logical proof/disproof.

We have two general sources of evidence in this model: apparent irreducible complexity, and its potential explanation as computational and physical experiments threaten to unveil simple explanations for an arbitrary level of apparent complexity.

Apparent vs. Real Complexity

This is our central insight: *In seeking examples of irreducible complexity, our efforts are confounded by the difficulty of inferring the existence of "genuine" complexity to begin with.* Yaneer Bar-Yam, director of the New England Complex Systems Institute, underscores this awareness in his text on complexity:

> *"Complex phenomena require, by their nature, a complex model to generate them. This means we cannot expect simple models to*

generate truly complex behavior. Thus, a basic skepticism about the ability of theory to describe biological phenomena can be justified. What is missing, however, is an ability to know, a priori, what are truly complex phenomena and what properties of complex organisms can be attributed to simple universal behaviors."[13]

Here we find that simple physical and mathematical experiments can shed light on the matter. As one researcher observes,

> *"One possible approach [to the study of complex systems] is through realistic models, that include as much detail as possible. On the other extreme, simple models with a minimum number of parameters allow for the determination of the basic ingredients necessary for the emergence of complex structures."*[14]

While examining simulations of complexity in various fields may not tell us something for certain about natural systems, it does affect our picture of how apparent complexity may or may not arise from simple origins in a variety of situations, and thus the paradigm from within which we evaluate Dembski's work.

Kolmogorov Complexity

There are several meanings implicit in the word "complexity."[15] In colloquial usage, virtually anything that is hard for a human to understand all in one glance can be called "complex" – from abstract art to an introductory calculus course. Not all of these settings match with what scientists mean by "complex." Common definitions in the scientific realm often highlight the presence of many interdependent parts in a system, its robustness to change (as captured in the notion of a "complex adaptive system"), and (especially) it's resistance to reductionism – i.e. the inability to understand the system by reducing it to the sum result of its component parts. In this sense of "complexity," an "irreducible" system (not to be confused with "irreducibly

[13] Yaneer Bar-Yam, *Dynamics of Complex Systems* (CO: Westview Press, 1997), 690.

[14] Gomez Portillo IJ, Gleiser PM, "An Adaptive Complex Network Model for Brain Functional Networks", *PLoS ONE*, vol. 4 no. 9, 07 September, 2009.

[15] Several dozen definitions are listed in Seth Lloyd, "Measures of Complexity: a non-exhaustive list," *IEEE Control Syst. Mag.*, vol. 21, August 2001, 7-8.

complex") displays important properties that result or *emerge* from the interaction of the components. Biological organisms are the ultimate example of such a system. We will loosely refer to this sort of complexity as *intricacy*, and consider it to correspond to a an observer's nave intuition of "hard to evolve."

Another, somewhat distinct definition concerns what has been called *effective* complexity, and is formally related to the *information* required to describe a system.[16] This sort of complexity is relevant to Intelligent Design, because it deals directly with the question of how much information it takes to specify a system (i.e. via random mutation) that is "complex" in the above sense of having many interacting parts.

Dembski's definition of complexity implicitly deals with this question of the minimum information required to specify the system (genotype), as opposed the high-level intricacy we actually observe (phenotype). One well-known metric for this concept is Kolmogorov or "algorithmic" complexity, an extension Shannon's information theory which, like Complex Specified Information, rests on the notion of how probable a particular string of information is.[17] In this model certain systems can be compressed, described by an algorithm that can be expressed in a relatively small amount of data. For example, to transmit the string "ABABABABABABABAB" we needn't transmit each character individually, but can instead send "8*(AB)", meaning "AB" is repeated eight times. Or if we want to convey the base-1 message "1111111111111111111" it can be compressed to "10011" in base-2. Another example can be found in numbers: The integers 2^{100} and $(100!)!$ are easy to specify in just a few symbols given our number system, even though we can prove that most large numbers cannot be expressed so easily, i.e. they are more complex. Kolmogorov complexity is defined to be the shortest possible signal (or string of symbols) + algorithm pair that can be used to reconstruct the original signal within the given computational environment (be it chemical or digital).

Using this metric, the most complex string is a purely random one. Ran-

[16] An algorithm's description length depends on how it must be encoded for a specific computing environment. For a technical analysis of complexity as we mean it here, see Murray Gell-Mann and Seth Lloyd, "Effective Complexity", Santa Fe Institute Working Paper 03-12-068, Santa Fe, NM.

[17] For a thorough treatment of information theory and Kolmogorov complexity, see Thomas Cover and Joy Thomas, *Elements of Information Theory* (Wiley-Interscience, 1991).

domness cannot be compressed, since it displays no regularity. Ostensibly to distinguish CSI from randomness, Dembski has clearly stated that Complex Specified Information is correlated with *low* Kolmogorov Complexity.[18] This at first appears contradictory. We may take it to be a byproduct of the fact that specified information needs some degree of *order* to be useful. Intelligent Design's core argument still rests on the assumption that irreducibly complex systems exist which have *high* Kolmogorov Complexity, not to the point of being random, but to the point of being undiscoverable by simple mutations.

Emergent Complexity

One effective way of explaining biological complexity is to discuss the history of the system in question, and argue that similar systems existing in the species' ancestors for different roles could act as stepping stones to make the development of the present system easier. Feathers, for instance, are believed to have originated as thermal insulation for theropods. We do not wish to discount the importance of this line of explanation and research. However, we will focus here on a piece of the puzzle that appears less commonly in debate over Intelligent Design, namely instances where systems with low *effective* complexity can exhibit a great deal of intricacy.

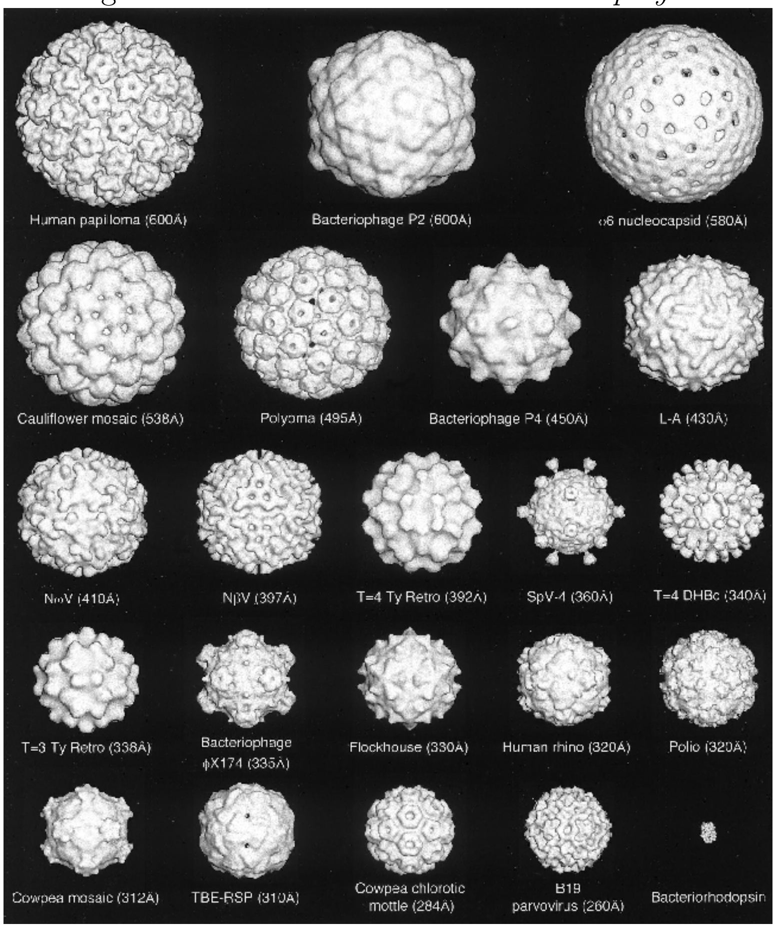
Among the most astounding results the study of complex systems brought us in the 20th century is the realization of the intricate patterns that can arise from simple specifications (i.e. low Kolmogorov complexity). A simplistic example is found in the icosahedral shells of viruses, which demonstrate how nature can exploit the laws of mathematics to create an intricate, ordered structure from a small amount of information (See Figure 4). Icosahedral structure self-assembles out of many copies of a single protein.[19]

These structures are visually appealing and apparently irreducible in the sense that removing a face of the icosahedron would destroy its functionality. But a small amount of genetic information is required to produce it. This is not terribly surprising – icosahedral structures can be rotated 60 different

[18] William Dembski, *No Free Lunch: Why specified complexity cannot be purchased without intelligence* (Ianham, MD: Rowman & Littlefield, 2004), 114.

[19] Roya Zandi et al., "Origin of icosahedral symmetry in viruses," *PNAS*, vol. 101, no. 2, November 2004, 15556-155560, T. S. Baker et al., "Adding the Third Dimension to Virus Life Cycles: Three-Dimensional Reconstruction of Icosahedral Viruses from Cryo-Electron Micrographs", *Microbiology and Molecular Biology Reviews*, December 1999, 862-922.

Figure 5: *Various virus shells which display icosahedral symmetry*

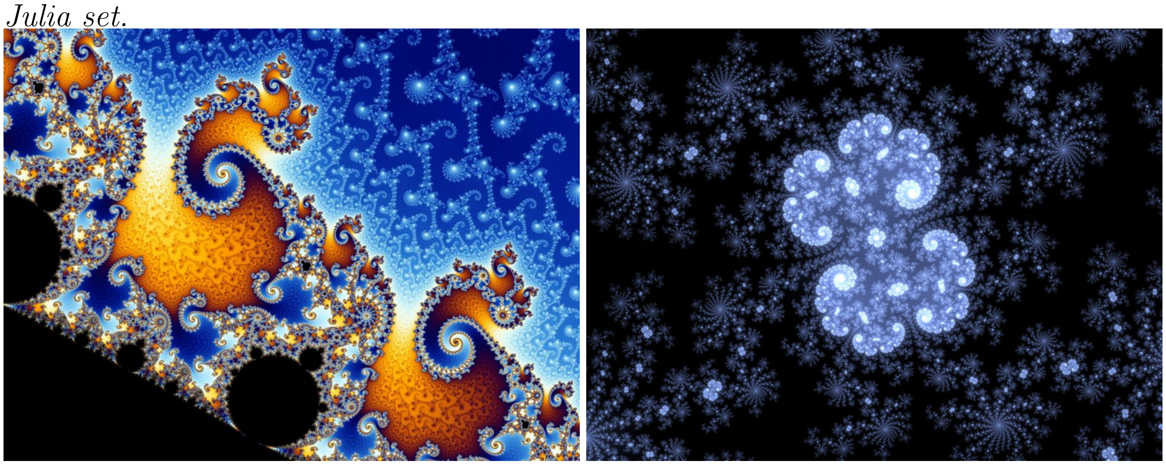


ways and still look exactly the same to the observer. It is clear that they have low Kolmogorov complexity.

More jarring to our intuition is the discovery that brief algorithms can be defined which, by repeating the same operation, self-organize or "emerge" into astounding structures which the viewer would assume have much more complex specifications. A classic example is the fractal pattern evident in the Mandelbrot set.

The idea of a "fractal" is somewhat ill-defined, but at its heart lies the concept of *self-similarity* – a property shared by many nonlinear and chaotic systems – in which a subsection of the system contains a scaled-down snapshot of the whole. Like the symmetry of the icosahedron, this betrays the

Figure 6: *Images from deep within the Mandelbrot set and the corresponding Julia set.*



underlying regularity of the system – and yet it is so intricate that it seems improper to say a fractal is not "complex." This is readily apparent in the famous Mandelbrot set, in which the scale models are accompanied by beautiful swirls that look like the brush strokes of a talented artist. And yet no human being specified this painting: the entire system is described by the straightforward complex (as in imaginary numbers) polynomial:

$$z_{n+1} = z_n^2 + c$$

which is arguably the simplest conceivable nonlinear map in the complex plane.[20]

At this point Dembski makes an important observation: it takes more than this simple equation to produce the famous picture.

> *"Any function that produces a graphic depiction of the Mandelbrot set will be a complicated algorithm employing a complicated set of input data... But by itself the function $h(z) = z^2 + c$ is too information-poor to produce this graphic depiction of the Mandelbrot set j. Once we examine the precise informational antecedents to j, the illusion that we have generated information for nothing disappears."*[21]

[20] The renderings of a 3D version of the Mandelbrot set in figure 7 were created by Daniel White. Learn more about the model at http://www.skytopia.com/project/fractal/mandelbulb.html

[21] Dembski, *Intelligent Design*, 165

Figure 7: *Scenes from a 3D rendition of the MandelBrot Set*

In our initial examples of Komolgorov complexity, we didn't discuss how much information is required to specify the algorithms that decompress "8*(AB)" or convert base-2 back into base-1. Like any computer graphics program, displaying the Mandelbrot set takes a good deal of code. Kolmogorov Complexity depends on the computing environment. Just like it is easier to write the code for a desktop application in a high-level computer language than in machine-level byte code (1's and 0's), systems like the Mandelbrot set require an underlying framework to operate in.

There is no reason that framework need be restricted to a single use, however. In biology, the genome specifies a highly interconnected array of regulatory connections between genes, providing an environment where feedback – the mechanism underlying the magic in equations like the Mandelbrot set – is paramount.

The structure of the Mandelbrot set is infinite and ever-changing, and its requisite algorithm is by no means large – Dembski describes the details in a single paragraph. [22] And no one designed the swirls and patterns in the image – they were discovered to manifest from an elementary application of the equation $z^2 + c$. If a computing environment exists in nature where similar *nonlinear* systems can be specified with a small amount of information, emergent complexity not unlike the Mandelbrot set could be quite common.

Once any system is reduced to its fundamentals, the "computing" environment in which our algorithm is interpreted consists of the laws of nature themselves. The semantics that define the results of biological complexity operate according to these predefined physical principles; only the initial (compressed) input string need be provided.[23]

A potent example of emergence in physics is found in the so-called "nanoflowers" that have been synthesized in laboratories under a variety of conditions. The structures apparent in Figure 8 were created by heating gallium nitride on a silicon substrate to 1100°C and then exposing the system to methane gas. "Interest in such structures," writes the Cambridge research team who developed the experiment, "centres around the combination of a simple growth process based on SiC nanowire formation, with a resultant structure having potentially complex mechanical and optical properties."[24]

The important idea in all of this is that *patterns which seem complex to our eye can actually emerge from a simple process* – that is, they have a low Kolmogorov complexity. This poses a hurdle to design inference, which claims to present a scientific method by which inexplicable complexity can be identified. Stephen Wolfram, whose developments in computer science have made significant contributions to our understanding of complexity, points out that

> *"We have seen a great many systems whose underlying rules are extremely simple, yet whose overall behavior is sufficiently*

[22]The algorithm for 3D versions of the Mandelbrot are more complicated. But the 2D rendition is considered the "true" Mandelbrot set.

[23]Readers who are interested in emergence demonstrated in computational environments analogous to physics and biochemistry are encouraged to further explore the role of *cellular automata* in both the study of complexity and the field of artificial life. The seminal works of Stephen Wolfram and Christopher Langton, respectively, are particularly relevant.

[24]Ghim Wei Ho et al., "Three-dimensional crystalline SiC nanowire flowers," *Nanotechnology*, 15 (2004), 996-999.

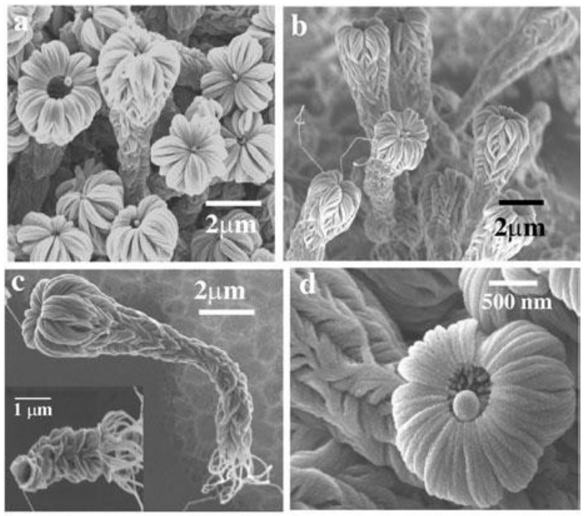


Figure 8: *These silicon carbide "nanoflowers" were inorganically synthesized via a simple chemical reaction.*

> *complex that even by thinking quite hard we cannot recognize its simple origins."*

These results (and many more like them) change our vision of what sort of phenomena are *en rapport* with the fundamental mathematics of the universe. Nonetheless, neither the Mandelbrot set nor nanoflowers, impressive though they are, meet Dembski's *specification* criterion, and thus are not sufficient for demonstrating the significance of emergence in biology.

To what extent emergent phenomena are exploited by biology to acquire "order for free," as theoretical biologist Stuart Kauffman calls it, is unclear, and we will not continue to discuss the evidence for and against its prevalence here. Many or most biological systems are composed of components which interact in nonlinear ways, i.e. they are more than the sum of their parts – genetic regulatory networks, for instance. Mathematically speaking, nonlinearity is a necessary, though not sufficient, condition for the sort of emergent behavior we see in the Mandelbrot set, and it is attractive to think that while most intricately complex systems are off limits to evolution, a few elaborate ones can be discovered relatively easily thanks to emergent properties. And Kauffman has shown that regulatory networks, amongst other things, are capable of a surprising amount of emergent behavior.[25] But we must stop short of saying that it has been demonstrated that emergence is *the* explanation for biological complexity.

Finally, then, we arrive at the following conclusion: While we cannot take all biomolecular systems and show that they are explained by low Kolmogorov Complexity genome alterations, emergent complexity gives us reason to be suspicious of any claims that a system we observe is *too* complex to have evolved.

Emergent Computing

A significant portion of modern Artificial Intelligence research seeks to imitate the emergent behavior of biological systems, from evolution to ant colonies to the human brain. We can think of these applications as a sort of *laboratory* to test our understanding of the natural mechanisms that might give rise to specified complexity. *If we genuinely understand how biological solutions arise, then we should be able to emulate those processes to solve our problems.* Indeed these attempts have allowed us to solve profoundly difficult problems and develop practical solutions that are otherwise intractable. The evolved solutions are furthermore often too complex to reverse engineer, and remain a black box to their creators. Melanie Mitchell summarizes the difficulty:

> *"The key [to artificial evolution], it turns out, is not [isolated] genes, but the way different genes interact, just as has been found in real genetics. And just as in real genetics, it's very difficult to figure out how these various interactions lead to the overall behavior or fitness."*[26]

Despite the success of these techniques in generating complex, irreducible solutions their creators never imagined, artificial neural networks are far, far off from the power of a biological brain, and artificial immune systems do not display the sort of powerful adaptability evident in their human counterpart. The evolutionary approach *in silica* is not a magic formula that can relieve the engineer from his responsibilities as designer, as Bar-Yam points out:

[25] Stuart Kauffman, *At Home in the Universe* (Oxford: Oxford University Press, 1995).

[26] Melanie Mitchell, *Complexity: A Guided Tour* (Oxford: Oxford University Press, 2009), 136

> *"While the GA/EA [genetic/evolutionary algorithms] approach can help in specific cases, it is well known that evolution from scratch is slow. Thus it is helpful to take advantage of the capability of human beings to contribute to the design of systems."*[27]

A major impediment to developing complexity *in silica*, as noted by Thomas Ray,[28] Luis Rocha[29] and others, is the difficulty in implementing the immensity of biological mechanisms and ecosystems: respectively the groundwork for emergence and the "unplanned openness of nature in which natural selection can turn to its advantage whatever chance offers"[30]. Even if we could deduce how to simulate such events, it's possible that a tremendous amount of computing power would be required to run a process capable of generating significantly complex artifacts. More research is required, and in recent years some scientists have been pushing for "a more sophisticated dialogue between computational and natural scientists about evolution."[31]

Real-world evolution operates in heterogeneous and changing environments that traditional applications of evolutionary computing seldom attempt to imitate. As mentioned above, arguably the most important explanation for irreducible complexity is *cooption*, in which existing biological material is reused for a new purpose (Darwin called this process *preadaptation*, an out-dated term that has been replaced by Stephen Jay Gould's *exaptation*[32]). In terms of search, one might imagine a phenotype (ex. feathers) evolving to suite purpose A (thermal insulation), and thereby finding itself in the basin of attraction of an optimum for purpose B (jumping/flying). A thus serves as a stepping stone for B. An endless variety of such stepping stones is posited to facilitate evolution of new traits, much like the myriad tools and technologies available to human engineers for a wide array of pur-

[27]Yaneer Bar-Yam, "When Systems Engineering Fails – Toward Complex Systems Engineering," *Conference on Systems, Man, and Cybernetics* 2003 Vol. 2 (IEEE Press, Piscataway, NJ, 2003) pp. 2021-2028.

[28]T. S. Ray, "Evolution, ecology and optimization of digital organisms", Santa Fe Institute working paper 92-08-042 (1992).

[29]Luis Mateus Rocha, "Evolution with Material Symbol Systems," *Biosystems* 60 (2001): 95-121.

[30]John Johnston, *The Allure of Machinic Life: Cybernetics, Artificial Life, and the New AI* (Cambridge, Mass: MIT Press, 2008), 217.

[31]Wolfgang Banzhaf et al., "From artificial evolution to computational evolution: a research agenda," *Nature Reviews Genetics*, vol. 7, Sep 2006, 729-735.

[32]Stephen Jay Gould, "Exaptation – a missing term in the science of form," *Paleobiology*, 8(1), 1982, pp. 4-15.

poses facilitates the invention of novel solutions.[33] This sort of event has played a vital role in evolutionary theory since Darwin, is evolution's first line of defense against the claims of Intelligent Design, and has been covered extensively elsewhere.[34]

Given the involved nature of real-world evolution, the models we have for how complexity emerges in nature have not provided us so far, whether for lack of insight or lack of computational power, with the detailed mechanistic understanding required to implement comparable artificial solutions. This signals us that we have more to learn, and that our models still require a lot of fleshing out before we can pretend that we fully understand the nature of high-level reality.

Conclusion

Design inference, we said, requires an assurance as to our ability to identify violations of the limits of natural selection, places where the local maximum problem has somehow been significantly transcended by a 500-bit leap in the dark. Dawkins laconically calls the identification of irreducibly complex systems the "argument from personal incredulity"[35]. In our exploration of *in silica* and *in vitro* complexity, we see that the limits of natural selection are indeed by no means easy to recognize. We simply have no method of confidently establishing the inherent complexity of a system. As such, whatever evidence there is for design is at present insubstantial, as our "incredulity" could well be unfounded.

It is the author's conclusion, then, that Intelligent Design does not stand on its own two feet as a public scientific theory. Nothing in this essay, however, has proved that a deity was never involved in the history of life. Simply because natural processes might be sufficient for producing life does not prove that they were the actual cause of all of it. Intelligent Design is plausible, then, only when an individual's prior experience leads them to be inclined

[33]For more on this perspective, see François Jacob, "Evolution and Tinkering," *Science*, vol. 196 no. 4295, 10 June, 1977, and John Gerhart and Marc Kirschner, "The Theory of Facilitated Variation," *PNAS*, vol. 104 suppl. 1, May 2007, 8582-8589. A rich area of related research – and compelling evidence – can be found in the homology of protein domains – see Christine Orengo and Janet Thornton, "Protein Families and Their Evolution: A Structural Perspective," *Annual Rev. Biochem.*, vol. 74, 2005, 867-900.

[34]See for instance R. H. Thornhill and D. Ussery, "A classification of possible routes of Darwinian evolution," *Journal of Theoretical Biology*, vol. 203, 111-116.

[35]Richard Dawkins, *The God Delusion* (2006), 128.

towards belief in a deity who is actively involved in the present and past development of life. That is, it can be a valid part of a religious world view already established via personal experience or some other evidence, but given our current scientific understanding, *ID cannot be used to prove the existence of a designer*, per se.

Finally, we highlighted computational research, and put forward the notion that such simulations can serve as a laboratory for testing hypotheses about the limits of natural evolution. We cannot say Computational Evolution has failed, because it is a young field, and its potential has not been fully realized. But much work needs to be done before one can take scientists' confidence that "evolution happened" and transmute it into the statement that we understand "how evolution achieved what it did."

Recommended Reading

There is a host of accessible literature written about complexity and its sister fields by scientists of great renown. Below are works that may be useful to those interested in learning more about the movement at an introductory or avocational level.

- Albert-László Barabási, *Linked: How Everything Is Connected to Everything Else and What It Means for Business, Science, and Everyday Life* (2003). Social and scientific complexity as modeled by small-world and scale-free networks.

- Nancy Forbes, *Imitation of Life: How Biology is Inspiring Computing* (2004). The story of soft computing.

- James Gleick, *Chaos: Making a New Science* (1987). The best-selling exposition of chaos theory's history and its relation to complexity.

- Douglas Hofstader, *Gödel, Escher, Bach: An Eternal Golden Braid* (1979). The Pulitzer-winning masterpiece on the emergent nature of intelligence that has inspired a generation of scientists and mathematicians.

- John Holland, *Hidden Order: How Adaptation Builds Complexity* (1996). Complexity as explained by the father of genetic algorithms. Considerably technical.

- Stuart Kauffman, *At Home in the Universe: The Search for the Laws of Self-Organization and Complexity* (1994). Inspiringly optimistic (if speculative) catalog of how complexity can solve our hard problems and show that life is not as improbable as one may suppose.

- John H. Miller and Scott E. Page, *Complex Adaptive Systems: An Introduction to Computational Models of Social Life* (2007). Agent-based computer models applied to social problems. Discusses the philosophy of modeling and how much faith we should invest in computer simulations.

- Melanie Mitchell, *Complexity: A Guided Tour* (2009). A captivating, accessible, and thorough summary of complexity theory and related fields. One of the best general introductions I've found for casual reading.

- Richard Solé and Brian Goodwin, *Signs of Life: How Complexity Pervades Biology* (2000). A beautiful exposition of the various aspects of complexity theory and how they relate to biology. Mathematics included, but optional and boxed off from the main prose.

- Steven Strogatz, *Sync: How Order Emerges from Chaos in the Universe, Nature, and Daily Life* (2003). Complexity as approached from the theory of coupled oscillators and nonlinear dynamics.

- Stephen Wolfram, *A New Kind of Science* (2002). Complexity as unveiled by cellular automata.