INTRODUCTION TO EVOLUTIONARY INFORMATICS by Robert J. Marks II, William A. Dembski, and Winston Ewert. Hackensack, NJ: World Scientific Publishing, 2017. 350 pages. Paperback; $48.00. ISBN: 9789813142145.

Reviewed by Randy Isaac, ASA Executive Director Emeritus, Topsfield, MA 01983.

In this monograph, William Dembski joins his successors in the intelligent design movement to summarize three decades of publications. Their conclusion remains the same as in each of those publications: analysis of computer models of evolution show that evolution can succeed only with the input of "active information," which can come only from an external intelligent agent.

Robert J. Marks II is Distinguished Professor of Engineering in the Department of Engineering at Baylor University. He holds a PhD in electrical engineering from Texas Tech University. In 2007, Marks set up a research initiative to investigate the role of information in evolution. This work formed the basis of the Evolutionary Informatics Lab.

Dembski is well known to readers of this journal for his active role in promoting the concept of intelligent design. He holds a PhD in philosophy, a PhD in mathematics from the University of Chicago, and an MDiv from Princeton Theological Seminary. He is a Senior Research Scientist at the Evolutionary Informatics Lab.

Winston Ewert holds a PhD from Baylor University and is now a Senior Research Scientist at the Evolutionary Informatics Lab.

The authors have published numerous technical articles in the last few decades on mathematical and logical algorithms related to evolutionary searches. This book is not intended to provide any new ideas but rather to summarize and present their published work in a manner easier to understand by a larger audience than that of technical readers.

The eight-page preface provides a synopsis of each chapter and the conclusions of the book. For many, this will suffice, but others will look for the more detailed explanation in the text. In the authors' own words,

> This monograph serves two purposes. The first is explanation of evolutionary informatics at a level accessible to the well-informed reader. Secondly we believe *a la* Romans 1:20 and like verses that the implications of this work in the apologetics of perception of meaning are profound. (p. xiv)

Their conclusion is that "… all current models of evolution require information from an external designer in order to work" (p. xiii).

The first chapter is a six-page introduction with some general observations on the nature of science and the role of models and probability analyses.

The second chapter is an introduction to the concept of information. The authors make it clear that they are not limiting themselves to Shannon information which Claude Shannon developed to focus on communication. Rather, they are interested in the meaning of information, which Shannon explicitly pointed out was excluded from his engineering perspective. The authors claim to have made progress in measuring both meaning of information and design difficulty. They ignore Rolf Landauer's insight that "information is physical"; this foundation underlies the scientific field of information theory for which Shannon provided the basic tools of quantification of information entropy and communication channel capacity. Landauer's principle, pertaining to the lower theoretical limit of energy consumption of computation, has been theoretically and experimentally validated in the past 55 years. The authors favor Norbert Wiener's quote that "information is not matter; information is not energy." They interpret Wiener, the father of cybernetics, to mean that information is "… an independent component of nature" (p. xv). This chapter discusses two ways to measure and quantify information: Shannon for internal information, and Kolmogorov-Chaitin-Solomonov (KCS) for complexity, or lossless compression. Several examples are presented to show how these equations are applied. Neither approach satisfies the authors' desire to focus on meaningful information, leading them to suggest a new approach in chapter seven.

The third chapter discusses the role of search algorithms and design in evolution. Extensive discussion is offered of examples in which the goal is to design an optimal product, such as finding an optimal recipe for making pancakes and designing an optimized antenna. They introduce the concept of "active information" as the knowledge about the goal that must be provided during the search process in order to achieve the goal in a practical number of searches. They conclude the chapter by noting that "undirected Darwinian evolution has neither the time nor computational resources to design anything of even moderate complexity. External knowledge is needed" (p. 59).

Chapter four is titled "Determinism in Randomness" and provides a useful set of examples of how to think about randomness. The authors point out that the probability distribution functions obtained as solutions to Schrödinger's equation are deterministic. They also discuss the implications of a limit of complexity of algorithms in computer models, as articulated by mathematician William F. Basener.[1] Finally, the authors analyze Thomas Ray's model of evolution called Tierra, published in 1989, and claim to show that it, as well as all other models of evolution, is limited by Basener's ceiling of complexity.

The fifth chapter is devoted to the topic of conservation of information (COI) in computer searches and, together with Basener's ceiling, is the heart of the argument presented in the book. They trace the earliest origin of COI to Lady Lovelace (Augusta Ada King), who observed that computers cannot create anything but can do only that which intelligent agents ask them to do (p. 105). Wolpert and Macready are given credit for coining the related term "No Free Lunch" (NFL) which also deals with computer search originality (p. 106). With many examples and quotes, the authors explore and demonstrate COI and NFL. They show how active information is quantified and why it is essential. The law of COI is then applied to evolution. The authors assert that "the evolutionary process creates no information" (p. 181). There must be an external source of knowledge about the goal to be achieved.

Chapter six is devoted to an analysis of two popular computer models of evolution, EV and Avida. The authors show that the success of these models depends on the explicit or implicit addition of active information by the programmers. To the authors, this supports the concept that evolution cannot be successful without external knowledge. They also discuss Gregory Chaitin's algorithmic approach, dubbed "metabiology," and attempt to refute Chaitin's claim that evolution has been validated algorithmically.

The objective of quantifying meaningful information is addressed in chapter seven. Marks has introduced the concept of algorithmic specified complexity (ASC) as a measure of meaningful information. He defines it as the internal information minus the KCS complexity information. While this may be a theoretical upper bound to the amount of meaningful information that a system can contain, his formulation provides no methodology of how ASC can be calculated in a real world system. Marks acknowledges that the value of the KCS complexity, and therefore the amount of ASC, of an arbitrary set of information, cannot be algorithmically determined, leaving it quantifiable only for some cases. Examples are given of codebooks such as ASCII or Morse code or information in snowflakes. But no guidance is offered of how to determine whether an information state really is meaningful in a biological organism. He adds notation to indicate that meaning is dependent on the context, but he does not offer a means for quantifying contextual effects. The primary conclusion is not a quantification of meaningful information; rather, it is an observation that meaningful information is extremely rare, a very small fraction of possible information.

The concluding chapter eight contains a brief discussion of intelligent design and artificial intelligence. The limitations of computer creativity, as explained in this book, indicate that the reach of artificial intelligence falls far short of that which can be achieved by an intelligent agent and may always do so. The success of evolutionary processes can be explained only by a source of external intelligent knowledge, providing active information of the goal of evolution. They conclude the book by saying that "undirected Darwinism can't work. An intelligent designer is the most reasonable conclusion" (p. 288).

In the opinion of this reviewer, while the conclusions of the authors may or may not apply to the computer models they discuss, there is no relevance to the real world of biological and chemical evolution. Four distinct differences between their models and evolution will be discussed here: (1) the limited scope of their consideration of information, (2) the role of populations, (3) the effect of selection, and (4) the consequences of the presupposition of goals.

1. Limited Scope

The first difference lies in the type of information being considered. The authors readily acknowledge that they are not working in the realm of the scientific field of information theory. Rather, like everyone except physicists and engineers, they are interested only in the meaning of information. While many a theorist has pursued an attempt to develop an analytical approach to meaningful information, none has succeeded. The bold claim of these authors to have made progress in measuring meaningful information is therefore notable. However, in restricting their attention to meaningful information, the authors misjudge the role of information—with critical consequences.

By ignoring nonmeaningful information, the authors overlook a potent source of new meaningful information. Physical information states must exist before they can have meaning. Information without meaning can acquire meaning in various ways. A simple example from the English language illustrates this point.

Consider the case of five-letter English words. With an alphabet of 26 letters there are about 11.9 million possible permutations. Up to 0.1% of these are meaningful English words, truly a rare occurrence. How can new meaningful words be generated? One way is for meaningful words to be assigned new additional meanings, dependent on the context. A more fruitful way is for words without meaning to be given a meaning, usually by consensus usage of the people. Any approach that considers only meaningful words will not be able to account for all the sources of new meaningful words. In the same way, the authors have overlooked a key source of meaningful information.

It should be noted that the intelligent design community has long recognized that there are two different types of "meaning of information," as discussed by Stephen Meyer.[2] However, the implications of the distinction have not been acknowledged. The most common form is the abstract significance assigned to a physical state of information. For example, a particular permutation of letters is assigned a meaning that is not related to the physical characteristics of the particular letters being used. Such an abstract relationship is not rooted in nature and can be designated and understood only by an intelligent agent.

The second type of meaning is a useful function in some physical context. This is the form recognized by biologists as they pursue the meaning of various information states in an organism. The meaning is the biochemical activity performed by an assembly of biomolecules which is the information state. This meaning does not require an intelligent agent. New functions can arise from a reservoir of various physical information states as the contextual environment changes.

An argument often used by the intelligent design community is that all of our experience tells us that new information can be generated only by intelligent agents and therefore biological information can be generated only by intelligent agents. That claim, however, conflates the two types of meaning of information. The only experience we have in which meaning requires intelligence is in human-designed systems which predominantly have abstract information. There is no rationale for applying that experience to information that is functional in the physical sense, as in biological systems.

Another way in which their limited scope of information inhibits their conclusion is that it leads to the application of the wrong conservation principle to evolution. The law of conservation of information (COI) as expressed in this book applies only to computer models and information searches in the artificial sense. In a real biological organism, the information states must be considered from the fundamental Shannon/Landauer perspective. The number of bits of information is dependent on the number and type of component particles and on their configuration. The only conservation principle that applies is the first law of thermodynamics, namely, the law of conservation of energy. The amount of information can be changed by adding or decreasing energy or particles, while a particular information state can be changed by a new configuration or arrangement of particles.

A biological system is not a closed system; rather, it has an influx of energy as well as dissipation of waste energy. This energy flux enables the opportunity for changes in information and the creation of new physical information. New genomic and epigenomic information can be created every time there is a rearrangement of genetic material, a point mutation in DNA, or any of the many processes that can insert or remove segments of DNA. These changes introduce new biochemical activity which may be useful and therefore meaningful. Changes in the environment can also introduce new meaning when biochemical activity becomes useful in that context. Rarity of meaning is hardly relevant since the starting point of the genetic search is always a known successful system and the changes are usually small.[3] The authors fail to consider this primary source of new evolutionary information by restricting their focus to meaningful information.

2. Role of Populations

The second difference between the models used by the authors and real evolution is the effect of populations. The authors dismiss the effect of populations (p. 155). They reckon that a population of Q members is equivalent to a serial search of Q steps in terms of information added to the system. They consider this to be a more expensive query cost and set it aside.

However, the biotic world is composed of a large number of highly diverse species, each of which is composed of one or more populations, each of which is composed of many diverse members. In every reproductive cycle, each population produces a generation of offspring with a distribution of modifications ranging from minimal to radical. With a new arrangement of biological components in each individual and occasionally additional components, there is new information generated in each cycle. The authors average all of this into a single theoretical fitness parameter and ignore the accompanying increase in complexity and diversity. In other words, they set aside descent with modification, which is the primary driving force of complexity and new information.

3. The Effect of Selection

This leads to the third major difference between the authors' models and real evolution: the effect of selection. In a sequential serial search, such as those the authors consider, a life/death criterion cannot be used. If any step in the search meets with death, then the entire search is halted and must be restarted. Hence, any such events are washed away in an averaging parameter. However, in a real population, there is a massively parallel search with every member of the biotic world engaging in procreation from its unique information state. Each member of the offspring generation will either survive to reproduce in the subsequent generation or die in the sense that it will no longer procreate. The net effect is to have a new population, based on the parental population, with a new distribution of information states. These are the states modified from the parents which are successful, whereas the unsuccessful states are lost, never to be attempted again. In the terminology preferred by the authors, this is an injection of active information into the system.

No intelligent agent is needed to provide this active information. It is a direct result of life/death events, commonly known as "selection." Selection is not uniquely determined by fitness or complexity since numerous random contingent events can influence survival. In general, improved fitness in a changing environment will lead to a better probability of survival. The authors have therefore omitted consideration either of descent with modification or of selection, the two pillars of evolution.

4. Presuppositions of Goals

The fourth difference between the authors' models and real evolution is the assumption of a goal for evolution. Is the active information provided by selection sufficient? That depends on the goal being considered. If the goal is solely to reproduce a new successful offspring generation, then the active information from selection is sufficient. If, however, there is an ulterior motive or optimization goal for a future configuration, then it is not. It is argued here that it is the existence and nature of a teleological goal for evolution that leads the authors to the conclusion that an external source of knowledge is required. The authors point out that

> the fundamentals of evolutionary models offered by Darwinists and those used by engineers and computer scientists are the same. There is always a teleological goal imposed by an omnipotent programmer, a fitness associated with the goal, a source of active information … and stochastic updates. (p. 187)

However, such a goal is not derived from any study of nature. It is imposed externally, and it is this presupposition, and not nature itself, that leads directly to the conclusion that a source of external knowledge is required. A well-known example will illustrate this point.

Consider a dealer who shuffles and distributes a deck of 52 cards into four piles of thirteen cards each. As long as the cards are face down and equivalent, every hand looks identical. When the cards are turned over, each card has a distinctive marking. If all cards are equal in value and there is no difference in desirability of a particular arrangement, then no goal exists except to carry out the distribution which is successful in every case. However, as soon as someone values a particular arrangement, depending on the specific game being played, then it becomes possible to calculate probabilities. The more specific and rare the desired configuration is, the lower the probability that it will succeed. Very quickly, the probability drops below the plausibility level, and if a desired configuration is achieved, it could be argued that knowledge must have been transmitted to the dealer. If that knowledge affected the outcome in a positive way, the process is called "cheating." It is the goal itself that leads to the ability to calculate low probabilities, and not any inherent property of the cards or of the process of dealing the cards. It is also noteworthy that it is easy to fall into the well-known trap of a posteriori vs. a priori probabilities. Once a distribution is completed, that particular arrangement of cards can be noted. If it is applied as an a priori desire, it is easily shown that the probability is essentially zero. Yet, that arrangement was achieved.

In the real world of evolution, the change in populations of species is highly dependent on a vast complex set of environmental factors. The interaction between the biochemical activity in each cell and the environment is still beyond our complete understanding. It is easy to see that any goal with even the most modest level of specified complexity would lead to a mathematical calculation of essentially zero probability. However, nature knows nothing of such goals. The primary activity of a biological system is to reproduce in such a way as to generate viable offspring. As long as the change in the environment is relatively slow, the probability of success in each new generation is near 100% with no artificial bounds on what can or cannot happen; it is limited only by survivability. In other words, nature does not seek a specific goal: it seeks any state that survives. With the powerful role of descent with modification and selection operating in a reservoir of immense amounts of information, there are no limits to the complexity that can be achieved.

This brings us to the critical question of a teleological presupposition. The authors conclude that there is a need for an external source of knowledge. If that conclusion is due solely to the presupposition that there is a goal in the first place, which could only have come from an external source, then the conclusion is tautological and merely self-consistent rather than descriptive of the real world. On the other hand, if there is a presupposition that there is no goal, then no probability calculation is possible and the system continues to evolve without need of an external source of active information. It is noteworthy that virtually all arguments for an intelligent designer are based on probability calculations which in turn are possible only in the context of a preexisting goal. If it is assumed that there is no goal, then a self-consistent model will conclude that no external agent is needed.

The clash of major worldviews on the topic of evolution seems to center on whether evolution is purposeless and without guidance or whether it is guided with ultimate meaning and purpose. If a preexisting goal is assumed, then it is understandable that a mathematical model will conclude that information about that goal must be provided in order for the goal to be attained in a reasonable timeframe. If it is assumed that there is no goal, then it can be easily concluded that this world is meaningless and without purpose.

Which presupposition is correct? Nature cannot tell us. A preexisting goal is inherently outside the scope of this universe. On the one hand, no source or mechanism for such a goal has ever been postulated, let alone discovered. On the other hand, neither can nature tell us that such a goal or such an infusion of information does not exist. Each presupposition is self-consistent. Ockham's razor can be invoked on the side of those who argue there is no goal. On the other side, there is a sense of incredulity that the complexity of life could have come into existence without being planned. Furthermore, a common theological perspective is that God planned the current biotic world in advance. His goal can be interpreted generically with a reasonable probability of being met, either through convergent evolution or as a specific goal requiring divine guidance which may not be detectable. Evolutionary informatics will not settle the issue.

This book contains numerous examples of information, mathematics, and logic puzzles that are instructive and entertaining. However, anyone seeking insight into biological or chemical evolution is advised to look elsewhere. ✠

Notes

[1]William F. Basener, "Limits of Chaos and Progress in Evolutionary Dynamics," in *Biological Information: New Perspectives,* ed. Robert J. Marks II et al. (Hackensack, NJ: World Scientific Publishing, 2013), 87–104.

[2]Stephen C. Meyer, *Signature in the Cell: DNA and the Evidence for Intelligent Design* (New York: HarperCollins, 2010), 85–111.

[3]For a more detailed discussion of how physical information in DNA can be transformed into new meaningful information, see Loren Haarsma and Terry M. Gray, "Complexity, Self-Organization, and Design," in *Perspectives on an Evolving Creation*, ed. Keith B. Miller (Grand Rapids, MI: Eerdmans, 2003), 288–312.

Meeting Chaitin's Challenge

A Response to Randy Isaac's review of *Introduction to Evolutionary Informatics* (above)

by Robert J. Marks II, Distinguished Professor of Engineering, Department of Engineering at Baylor University, Waco, Texas.

Let my response to Randy Isaac's respectful review begin with thanks to James Peterson, the editor-in-chief of *Perspectives on Science and Christian Faith,* who, in concert with Isaac, solicited this response to Isaac's review. Such a practice is not common for book reviews. But we note that, in the venue of this journal, we are followers of Christ where we celebrate iron sharpening iron. One day, in front of our Creator, we will learn the degree to which of us is right. When this happens, I suspect the answer will matter little. Until then, let's continue to reason together.

Chaitin's Challenge

Gregory Chaitin, arguably the greatest and most creative mathematician of my generation, says: "The honor of mathematics requires us to come up with a mathematical theory of evolution and either prove that Darwin was wrong or right!" This question is answered in *Introduction to Evolutionary Informatics*: there exists no computer or mathematical model of Darwinian evolution not requiring the use of a guiding source of knowledge or oracle. Nor will there ever be an evolutionary algorithm that creates complex specified information without guidance supplied within the algorithm by one or more sources of knowledge such as oracles.

Regarding our book, Isaac concludes that those "seeking insight into biological or chemical evolution are advised to look elsewhere." We agree. But if you are looking for insights into the models and mathematics thus far proposed by supporters of Darwinian evolution that purport to describe the theory, our book is spot on.

Evolution Models: We Didn't Start the Fire

An honest attempt at computer modeling of evolution was Thomas Ray's fascinating program Tierra that, although displaying interesting properties, fell well short of Ray's goal of simulating something akin to the Cambrian explosion. Although Tierra had no explicit goal, Ray attempted to design an environment in which his digital organisms could evolve. He was not successful. After numerous failures and tweaks, Ray abandoned Tierra.[1]

More recent evolution simulations include the computer programs Avida and EV. Avida and EV pose evolution as a search algorithm with a specified goal. Engineering design has a long history of using evolutionary search with a design goal.[2] But Isaac protests that "such a goal [in evolution] is not derived from any study of nature." If true, Isaac has disqualified Avida, EV, and all other evolution models of which we are aware. For different reasons, we therefore find ourselves in agreement with Isaac: there yet exists no mathematical model that describes Darwinian evolution.

Avida is of particular importance because Robert Pennock, a co-author of the first paper describing Avida,[3] offered testimony at the Darwin-confirming *Kitzmiller et al. v. Dover Area School District* bench trial which ruled that work such as mine is religious. He testified, "In the [Avida computer program] system, we're not simulating evolution. Evolution is actually happening." If true, Avida and thus evolution is teleological, guided, and overflowing with active information supplied by the programmers.[4]

On the other hand, microbiologist James Shapiro says, "Most debates about evolution sound like the last fifty years of research in molecular biology had never occurred"[5] and maintains that organisms teleologcally generate novelties which other organisms later adopt. Palaeontologist Simon Conway Morris's book *Life's Solution: Inevitable Humans in a Lonely Universe* makes clear from the title that evolution has a goal as witnessed by observation of evolutionary convergence. So, maybe evolution does have a goal. If so, evolutionary models and the critique of them in our book apply. If not, there exists no mathematical model of Darwinian evolution.

From Whence Design?

Within evolutionary models, the evolutionary process is not the source of design. The design is, rather, due to the imbedded source of knowledge in the model or simulation. For Avida and EV, our group was able to use the same resident sources of knowledge and generate results much more efficiently using simple stochastic hill climbing. Gold miners can dig using a spoon or a shovel. Evolution can be an inefficient tool for mining results from an oracle. For those interested, we have interactive GUI's (graphical user interfaces) on our website that demonstrate this.[6]

Hitting a limit called Basener's ceiling, evolutionary models such as Tierra and Avida will evolve only to the resident oracle's level of expertise. An evolutionary program written to play chess will not evolve an ability to play GO unless programmed to do so. Doing so makes the problem even more complex, necessitating even more guidance from a source of knowledge.

Some Information about Information

Measuring the algorithmic specified complexity (ASC) of a design involves defining applicable information measures. ASC does not deal directly with evolution, but is useful in assessing the meaning of end design information.

An entire chapter in *Introduction to Evolutionary Informatics* is dedicated to various definitions of information. We like Claude Shannon's take on defining information:

> It seems to me that we all define "information" as we choose; and, depending upon what field we are working in, we will choose different definitions. My own model of information theory … was framed precisely to work with the problem of communication.[7]

Isaac's claim that "information is physical" is narrow. It is like saying "squirrels are mass and energy." In the strictest sense, Shannon's definition of information is based on probability—events in the future which have not yet happened and therefore have nothing directly to do with anything yet physical. Nevertheless, we today universally assign Shannon's binary digit as the measure of physical information storage.

And then there's the Kolmogorov-Chaitin-Solomonov (KCS) information model that differs from Shannon's. Although more difficult to measure, KCS information deals with existing structures and is as much a part of the universe as energy, mass, and time. KCS information can be used as the foundation for determining the ASC—or meaning—of an object.

Here's an illustration. Consider a computer program that instructs a 3D printer to construct a bust of Abraham Lincoln in sufficient detail to see the wrinkles on his forehead and the mole on his right cheek. Contrast this with a program for printing a new bowling ball. For both the bowling ball and Lincoln bust, there exists a shortest program to accomplish the print. These shortest programs are called "elegant." The length of the elegant program is an object's KCS information content. The elegant program for the bowling ball, in bit count, will be shorter than that of Lincoln's bust. Lincoln's bust, measured by the bit count of its elegant program, contains more KCS information than the bowling ball.

However, the elegant program for detailed construction of a bumpy rock might be similar in length to the program needed for Lincoln's bust. So, assuming the details of the rock are not as meaningful as those on Lincoln's face, KCS information is seen to not measure meaning. Lincoln's bust is more meaningful because it is specified via context. Consider short 3D-printer-assisting subprograms called MOLE, BEARD, and HUMAN HEAD to which the programmer has access. When computing the length of the Lincoln elegant program, the subprograms used by the master program are not included in the bit tally. The conditional elegant program will be shorter. The ASC measure of the meaning of an object is obtained by subtracting this context-conditional elegant program length from the information measure of the object based on chance construction by the best available theory, for example, the laws of physics. ASC appropriately bears a resemblance to Shannon's measure of mutual information.

Here are two examples from our book. A snowflake is very complex, but complex things like snowflakes happen all the time. Two arbitrary complex snowflakes have a low ASC whereas two identical snowflakes have a large ASC. In the context of poker, a two-of-a-kind poker hand has negligible ASC whereas a royal flush has an enormous ASC content.

"So You're Telling Me There's a Chance!"

… is *Dumb and Dumber*'s Lloyd Christmas's response to pretty Mary "Samsonite" Swanson who told Lloyd his odds with her were one in a million. The line is funny because Lloyd's response is clearly dumb. As I type, the odds of my right thumb quantum tunneling into my keyboard's space bar is finite but so small that saying "so you're telling me there's a chance" is also dumb.

How small must a probability be before we announce impossibility? The answer is fuzzy in the sense of Zadeh. So, to remove doubt, we must set chances beyond all argument.

Based on Landauer's contention that "information is physical," Seth Lloyd estimates the computing capacity of the universe throughout history to be 10^{120} operations on 10^{90} bits. Without guidance, 10^{120} bits is not able on average to generate unguided random creation of *any* sequence exceeding 165 Webster's dictionary words.[8] The low number of words is astonishing. For a specified phrase, the chances are smaller.[9]

Let's dwarf Lloyd's information bound. One Planck length stretched to an inch scales the diameter of a proton to several light years. A Planck time unit is the time it takes light to travel one Planck length. Consider a bit count equal to the number of Planck cubes in the universe integrated in Planck time units over 14 billion years. This number interpreted as bits is insufficient for generating any string of dictionary words as long as the Gettysburg Address. If you are astonished by this low figure, you are not alone. Even if multiplied by 10^{1000} universes in a multiverse, the resulting number, in bits, is insufficient for generating any sequence of words as long as the Declaration of Independence.

Isaac and others are critical of our use of probabilities. Even if "information is physical," these astronomical resources[10] eclipse the universe's current mass-energy parsed into single bit energies measured in von Neumann–Landauer lower energy bounds multiplied by the number of Planck time units in 14 billion years. Given the resulting staggeringly limited creativity of this bit count resource, creation requires enormous guidance to explain the ASC we see in nature, which certainly exceeds the length of the Gettysburg Address.

In a separate but related theory, the chance of generating a design decays at least exponentially as a function of the resulting ASC. The probability of a thousand bits of ASC occurring by chance is less than 2^{-1000}.

Are Meaningful and Meaningless Information Models Meaningful?

In his review, Isaac proposes his own information model to rebuke some of our research conclusions.[11] His theory consists of ideas such as meaningful information and meaningless information and the possibility of transforming the latter into the former. Isaac objects that we consider only meaninPPgful information while ignoring meaningless information. This is critical because, according to Isaac, it is possible to derive meaningful information from meaningless information.

If true, a DVD of bits generated by a quantum random number generator can be transformed into a DVD that has meaning—something like the movie *Braveheart*. Even if an enormous codebook translating random sequences into words were written, a source of knowledge in the form of human intelligence is required to establish the context required for meaning. We are simply agreeing on a new alphabet. In this sense, we concur that Isaac is correct in saying meaningless information can be defined as artificial context. In the same sense, hieroglyphics can be redefined into English without knowing hieroglyphics or caring about the meaning originally intended by some long-dead Egyptian writer.

Functional Information's Definition Is Abstract

Isaac points out that the information one might find in abstract symbols such as letters is different from functional information corresponding to a useful function in some physical context. He accepts that abstract information requires an intelligent agent, but argues that functional information does not. This begs a question: Does the instruction manual for my juicer contain functional information? No definition of functional information is given, and therefore the answer is not clear. "Functional information" needs to be defined in a mathematical sense. In molecular biology, functional information is "$-\log_2$ of the probability that a random sequence will encode a molecule with greater than any given degree of function."[12] I do not believe that this is what Isaac means. Curiously, functional information's definition according to Isaac looks to be abstract.

Isaac attempts to dismiss the applicability of our conservation of information results by arguing that one can increase meaningful information in a biological system by adding noise. But this is simply increasing the randomness of a system. Introducing randomness into a system is fully part of what is taken into account by the conservation of information. In a paper titled "Meaningful Information," Vitányi also disagrees with respect to KCS information.

> One can divide … [KCS] information into two parts: the information accounting for the useful regularity [meaningful information] present in the object and the information accounting for the remaining accidental [meaningless] information.[13]

Unlike our approach, the Kolmogorov sufficient statistic just described does not take into account context.[14] It is concerned only with the structure of an object. Nevertheless, the conclusion is the same: if you add random bits into a sequence, the pile of random meaningless information will simply be bigger. The meaningful information pile will remain the same size.

A fixed structure, such as Donald Trump's DNA, has fixed KCS information. But its ASC bound can increase as more context is found. Hieroglyphic texts were assigned more meaning when new context was provided by the discovery of the Rosetta stone. But, once successfully translated, a hieroglyphic text has no more meaning than that intended by the original writer. Likewise, the ENCODE project has given DNA more meaning than it had twenty years ago. The term "junk DNA" (Isaac's meaningless information?) is now rarely used because it has found function. DNA did not change but its meaning did. Was formerly meaningless junk DNA now meaningful? No. The meaning was always there but the context remained undiscovered. ASC, like KCS complexity, is expressed via a bound. KCS complexity is upper bounded by the shortest program thus far known. For a fixed theory of random object constrained construction, ASC is likewise lower bounded. Higher ASC can occur as more context is discovered.

Finis

If anyone generates a model demonstrating Darwinian evolution without guidance that ends in an object with significant specified complexity, let us know. No hand-waving or anecdotal proofs allowed.

We believe that Chaitin's challenge has been met in the negative and that no such model exists.

Space limitations prohibit further comment. Thanks for listening. ✠

Notes

[1]Citations for any material not explicitly referenced herein are in our book: Robert J. Marks II, William A. Dembski, and Winston Ewert, *Introduction to Evolutionary Informatics* (Hackensack, NJ: World Scientific, 2017).

[2]For example, check out the engineering journal, *IEEE Transactions on Evolutionary Computation*.

[3]Richard E. Lenski, Charles Ofria, Robert T. Pennock, and Christoph Adami, "The Evolutionary Origin of Complex Features," *Nature* 423, no. 6936 (2003): 139–44.

[4]One should not infer that knowledge sources were placed in Avida with any thought of deception on the part of the authors, who are all highly credentialed and respected researchers. Nevertheless, they are there.

[5]James Alan Shapiro, *Evolution: A View from the 21st Century* (Upper Saddle River, NJ: Pearson Education, 2011).

[6]http://evoinfo.org. See EV Ware, Minivida, and Weasel Ware.

[7]Quoted in P. Mirowski, *Machine Dreams: Economics Becomes a Cyborg Science* (New York: Cambridge University Press, 2002), 170.

[8]Eric Holloway and Robert J. Marks II, "Informational Cost of Generating Meaningful Text and Its Implications on Creativity" (in review).

[9]Marks, Dembski, and Ewert, *Introduction to Evolutionary Informatics*, 120–25.

[10]Pun intended.

[11]We could be wrong here, but Isaac provides no references concerning his model—nor are we aware of any.

[12]Jack W. Szostak, "Functional Information: Molecular Messages," *Nature* 423, no. 6941 (2003): 689.
[13]Paul Vitányi, "Meaningful Information," in *International Symposium on Algorithms and Computation: 13th International Symposium, ISAAC 2002 Vancouver, BC, Canada, November 21–23, 2002: Proceedings* (Berlin, Germany: Springer, 2002), 588–99.
[14]See Thomas M. Cover and Joy A. Thomas, *Elements of Information Theory*, 2nd ed. (Hoboken, NJ: Wiley-Interscience, 2006) or Ming Li and Paul Vitányi, *An Introduction to Kolmogorov Complexity and Its Applications* (New York: Springer Science + Business Media, 2008).

Rejoinder

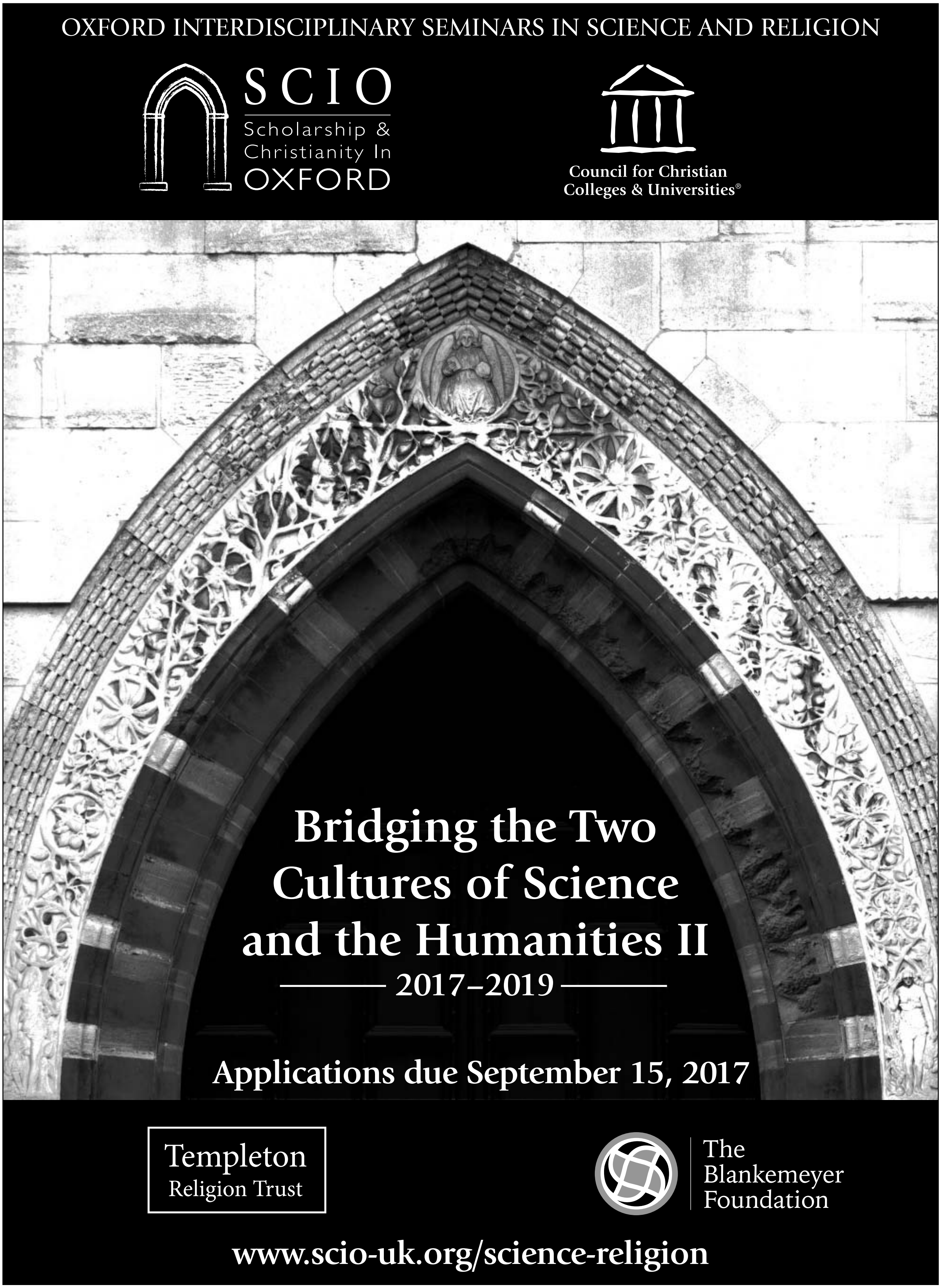
by Randy Isaac

I appreciate Robert Marks's kind remarks and his taking the time to clarify his perspectives. I would like to underscore several points.

1. Any input from an intelligent source required by a mathematical model or an algorithm such as Chaitin's is due to the fact that these models and algorithms are human simulations of a natural process. It cannot be inferred that the natural process itself requires an intelligent source of information. Whatever merit the law of conservation of information—which asserts that new information can be generated only by an intelligent agent—may have in computer models, it does not apply to information in general and is not relevant to DNA information.
2. A key assumption of the information argument for intelligent design is that functional meaning of information such as DNA is identical in every way to abstract meaning of information. Hence it is claimed that since abstract meaning can be generated only by an intelligent source, it is also true for functional meaning. However, the reason that abstract meaning requires an intelligent source is the abstract nature of the meaning and not the characteristic of information itself. Functional meaning does not necessarily have an abstract component.[1] Biochemical processes transform DNA information into functional biological activity without a single step of abstract relationships. Evolutionary processes associate useful biological activity with specific DNA information without the need for an a priori abstract blueprint.
3. The way in which Marks considers probabilities implies that complex biomolecules are assembled anew by starting from a random collection of components. No such process is proposed in biological evolutionary theory. Rather, each reproductive event starts with a proven successful set of DNA information. Descent with modification has a high probability of succeeding in generating a new living organism. Biological evolution works.
4. Biology abounds with examples of DNA altered through descent with modification which changes the DNA information set and generates new biochemical functions.[2] Such creation of new information is theoretically possible without an intelligent source, and it is experimentally observed.
5. The assumption of teleology is the primary reason why some mathematical models of evolution lead to impossibly low probabilities. The existence and nature of teleology in evolution is an open question of great interest.[3] I look forward to studying it further. ✠

Notes

[1]Randy Isaac, "Information, Intelligence, and the Origins of Life," *Perspectives on Science and Christian Faith* 63, no. 4 (2011): 219–30.
[2]Dennis Venema, *Letters to the Duchess: ID and Information* (blog series), http://biologos.org/blogs/dennis-venema-letters-to-the-duchess/series/id-and-information.
[3]Sy Garte, "Teleology and the Origin of Evolution," *Perspectives on Science and Christian Faith* 69, no. 1 (2017): 42–50.


OXFORD INTERDISCIPLINARY SEMINARS IN SCIENCE AND RELIGION
SCIO
Scholarship & Christianity In OXFORD
Council for Christian Colleges & Universities®
Bridging the Two Cultures of Science and the Humanities II
2017–2019
Applications due September 15, 2017
Templeton Religion Trust
The Blankemeyer Foundation
www.scio-uk.org/science-religion