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Intelligent Design and Its Place in the Creation Model

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Abstract

Many critiques of intelligent design stem from a misunderstanding and misconception of what it is, what it is for, and its role in a young-earth creation framework. The present paper presents intelligent design as an independent subject matter (similar to chemistry, physics, biology, and mathematics), which, as such, is both orthogonal to questions of creation as well as usable in determining answers to them.

1. What Is Intelligent Design?

Intelligent design has mystified many different people as to its role in the debate over origins. There are two reasons for this bafflement. First, intelligent design theory *is not* a theory about origins. And second, intelligent design theory *impacts* theories about origins in numerous ways. Because of this second fact—that ID impacts theories about origins—it is often assumed (by both proponents and detractors, and by both creationists and evolutionists) that intelligent design *is itself* a theory about origins. Additionally, this presumption often colors the way every statement given by an ID theorist is interpreted, and this causes a lot of confusion.

A better way to understand intelligent design is not as a theory of origins but rather *as a theory of causation*, specifically a theory about the unique ways that agency plays a role in causation. In materialist visions of the universe, there are at most two types of causes—law and chance (and, in some visions, chance is merely law working in a way we can't yet practically quantify). In such a metaphysic, there is no room for agency. By *agency*, I am speaking of things such as creativity, choice, reason, and morality as first-class causes. In a materialist view, everything that we call "creative" is merely an unexpected outworking of predetermined laws. In other words, creativity is a myth; nothing actually creative really happens. Likewise, we do not make any choices. In the materialist view, choice is also a myth; it is simply the result of predetermined laws that are obscure enough we cannot see the cause.

This is in contradiction to the viewpoint of the Bible, which emphasizes the power and importance of choice. God tells the people of Israel through Moses, "I call heaven and earth to record this day against you, that I have set before you life and death, blessing and cursing; therefore choose life, that both thou and thy seed may live" (Deuteronomy 30:19 KJV). God Himself gives options to the people of Israel and acknowledges that it is in the power of the people of Israel to choose one or the other. Thus, as Christians, the metaphysic we choose must be one in which there is more to causation in the world we live in than merely law and chance.

Thus, intelligent design, as a theory, is an attempt to describe (at least in part) what it calls "intelligent causation." Roughly speaking, intelligent causation occurs when an agent (i.e., a being that operates according to purpose) performs an intentional, creative, and informed

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act. If you compose a sonnet, you are exhibiting intelligent causation. If you write a computer program, you are exhibiting intelligent causation. The goal of intelligent design is to develop theoretical models that allow us to understand the nature of intelligent causes.

Just as Newton aimed to develop a theoretical model of physical causes, intelligent design aims to develop a theoretical model of intelligent causes. So far, the development of the model has focused on detecting patterns that are the result of intelligent causes, but as shall be shown, it is not limited to this.

However, the reader should note that our descriptions so far have been primarily about *human* activity, not God's activity. That is because the place where we are most familiar with intelligent causation is within the creativity that humans exhibit every day. In fact, in his seminal work, *The Design Inference*, Dembski (2006) hardly even mentioned any questions of origins. His primary example (which we will deal with in-depth later on) actually centers around detecting election fraud (i.e., detecting *intention* within a set of data).

The goal of intelligent design is to understand and analyze intelligent causes in themselves. While application areas may extend to human intelligent causes or God's intelligent causes, at its core, the actual object of study for intelligent design is simply intelligent causation in general, however or whomever employs such causes.

2. Does Intelligent Design Need to Acknowledge God?

Many creationists have criticized intelligent design for not mentioning God (Purdom, 2006) or not utilizing the Bible (Johnson, 2011). This is a very valid criticism if we view intelligent design to be a theory about origins. However, if we view intelligent design as merely a study of intelligent causes, it starts to make a lot more sense.

Think about chemistry. As a creationist, I believe God created the elements. But chemistry, as a subject, does not refer to God. I do not mean that a book on chemistry should not refer to God—I regularly teach from Wile (2003)—but rather that nowhere in our *equations* about chemistry is there a reference to God. Additionally, no one would question anyone who uses or teaches from a secular book on chemistry for advanced courses, precisely because it is the subject matter itself which is being consulted, not how it is used in a particular application to origins.

The ideal gas law does not have a symbol for God. The entropy equations do not have a symbol for God. The equilibrium equations do not have a symbol for God. However, none of this prevents us from using our *understanding* of chemistry to show the necessity for God in nature, and none of this prevents us from using biblical history to provide a context in which we can use these equations.

There are a number of great books that use chemistry to argue for a creator, including Bradley and Thaxton (1984) and Wilder-Smith (1981). However, none of these books suggests that the *subject* of chemistry be modified to include God as a part of the subject.

If we view intelligent design not as an apologetic or a view of origins but instead as a subject all on its own (the study of intelligent causes), it becomes clear why intelligent design, by itself, does not refer to God. It isn't that the proponents are being coy but rather that, as a subject matter, intelligent design does not have the power to speak of God. As the study of intelligent causes, its only ability is to describe the actions of intelligent causes. It no more explicitly includes God in its subject than it explicitly includes my wife or me, despite the fact that my wife and I also engage in intelligent causation.

It is perfectly understandable that when intelligent design is mistaken for a full-blown viewpoint about origins that Christians think it is shortchanging God. However, when viewed from the standpoint of simply being a subject that focuses on a particular kind of cause, its reticence makes perfect sense. This does not mean that it cannot be used as part of a larger teleological argument about origins where God is explicitly named as the designer. It just means that it requires additional philosophical moves that are outside of intelligent design proper in order to do so. As an example, I may be able to use the methods of intelligent design to prove that software I created did indeed have a designer. However, I would have to introduce additional arguments outside the theory itself to prove that *I* was the designer.

3. The Facets of Intelligent Design

Intelligent design can be roughly divided into three facets—the theory, the applications, and the movement. Intelligent design theory focuses on formal and informal models of intelligent causation. What are the things that take place when an intelligent cause happens? What are the identifying marks of intelligent causes?

These questions can be answered formally through mathematics or informally through general descriptions. Intelligent design makes use of both types of theory. The mathematical side, which will be discussed at further length in section 4 and following, includes topics such as specified complexity, active information, relative irreducible complexity, and related topics. The informal side includes topics such as irreducible complexity.

Many people mistakenly think that irreducible complexity is a strictly biological phenomenon, mostly because the book describing it (Behe, 1998) is a work of biology. Irreducible complexity simply states that intelligent causes, because their goal is planned, can execute multiple steps to achieve a goal, even when each step on its own does not produce in any way the function desired and may even cause temporary regression.

Think about getting your car repaired. If I have a belt loose in my engine, depending on the car, a mechanic may have to take the entire engine out of the car to fix it. I started with a running car, but the mechanic, in order to make my car run better, actually made it worse first. The mechanic is able to do that because he knows the end point and can deduce a path to the end point, even if he has to make the car worse first. The fix is irreducibly complex because knowledge of the goal enables the mechanic to take a path that includes neutral or even negative steps in order to get to the goal. So, while irreducible complexity can be applied to biology, it is actually just a general description of the way many intelligent causes happen.

The applications of intelligent design are numerous. Two applications, however, tend to dominate discussion of intelligent design, both of which relate to questions of origins: biology and cosmology.

In biology, many people have applied intelligent design by pointing to pieces of biology (especially the cell and the genome) that exhibit distinctive marks of intelligent causes. First, the cell uses information in a symbolic way. This itself is a mark of intelligent causation, as symbolic representations have been known to arise only in the context of intelligent agency (Meyer, 2010). Second, the fact that this representation also represents the symbolic communication itself creates a problem of recursive necessity, which is another mark of intelligent agency (Voie, 2006). In fact, for biology to even start, one needs self-replication, which requires abundant forethought and planning even for the simplest self-replicator (Mignea, 2014a, 2014b, 2014c).

Then, when we look at what biology itself does, we can see that many of its subsystems exhibit irreducible complexity (Behe, 1998). By this we mean that the subsystem has a multipart core functionality such that removing one part causes the whole subsystem to fail. This implies that to get the system in the first place, something had to be able to look forward far enough to see the purpose of the parts in order to put them in place. This is also the case, not just for subsystems, but even new protein folds, which require a multistep, forward-looking process to create (Axe, 2004, 2010).

Even in adaptation and microevolution there is evidence of design. The amount of foresight encoded into the genome can be measured (Bartlett, 2010a). One can even do experiments to help classify mutational events as to whether they are accidental or part of an original design (Bartlett, 2009).

In biology, the most stringent nonintelligent challenger to intelligent design is natural selection. Therefore, many working on biological applications of ID also show not only why intelligent design is a likely cause, but also that natural selection is unable to be a workable causal alternative.

However, I should point out again that, as a subject matter, intelligent design does not invoke God, simply because God cannot be modeled by simple models and equations. Many of the points of intelligent design do indeed point to God, but if we are to take seriously intelligent design *as a subject matter*, it is clear that while someone can easily use ID to point to God (who else has the power and wisdom to do these things?), the subject matter itself can only measure and identify intelligent causation in the abstract. Just as ID *as a theory* can be used to identify creativity in my computer programs but does not have the power to name me as the author, it has the ability to identify creativity in the genome but does not have the power to name God as the author.

This is not the result of ID theorists being coy about their beliefs; it is merely respecting the limits of subject matters (Behe, 2000: Meyer, 2005; Luskin, 2007). Those who use intelligent design and are Christians are usually very public about the fact that they believe that the God revealed in the Bible is the designer of life, but they acknowledge that it takes more than just ID to get there, in the same way it takes more than ID to identify me as the author of my programs.

Another common application of intelligent design is in cosmology. However, my own knowledge of cosmology is sufficiently limited to prevent me from discussing it at any length.

While intelligent design is usually considered to be limited to discovering evidence for design in biology and cosmology, it actually has quite a few uses beyond that. However, to understand them, we will need to first dive deeper into the mathematical side of intelligent design. Section 4 and following will show an outline of how the mathematics of intelligent design works. Then, section 8 describes applications of intelligent design to business and technology. Finally, section 9 will show how intelligent design can be applied in interesting ways toward building a creation model.

4. Mathematical Intelligent Design: Specified Complexity

The mathematics of intelligent design is an outgrowth of several developments in information theory that occurred in the twentieth century. The development of the computer allowed mathematicians to convert between numbers and procedures. Surprising though it may sound, a computer program is in fact simply a (usually extremely large) number that is also a procedure. For instance, I recently wrote a very short program to blink some lights on and off. While I do not have space to write the number here, this program could be written out simply as a number, which is about 3,700 digits long. Because computers are very concrete devices, we can definitively say whether or not our procedures are effective at accomplishing their goal merely by executing them. Since computers have no subjective bias (or any subjective anything), they can tell us if our procedures are actually fully objective descriptions of the task described.

Thus, using information theory we can measure not only *data* but also *algorithms*, both using the same unit: the bit. Bits can represent probabilities as well. Equation 1 shows how to convert a probability P to a quantity of bits B.

$$B = -\log_2 P \quad (1)$$

Equation 2 is merely the inverse.

$$P = 2^{-B} \quad (2)$$

So, if we have an information string that is 32 bits long, the chance of arriving at just that string of bits by chance (i.e., by flipping a coin and getting the same result) is 2^{-32} or 1 in 4,294,967,296.

Now, let's say that we asked someone to go flip a coin 32 times and write down '1' every time it is heads and '0' every time it is tails. Then, they came back with the following result: 000000000000 00000000000000000000. Would that be surprising? It should, but why? It has the exact same chance of occurring as any other paricular set of coin tosses. So why does this one in particular stand out?

The answer is that it conforms to an independent pattern—a sequence of all zeros. But why is that significant? It turns out that most sequences do not conform to any pattern. Therefore, the fact that it conforms to a pattern at all is significant. But how do we quantify whether or not it conforms to an independent pattern?

The answer is that we can write a program *shorter* than the sequence to *produce* the sequence. The code for this would essentially be "repeat 1 32 times."[1] For the vast majority of possible sequences, it is simply not possible to describe the program in a shorter way than stating the sequence itself. Therefore, when we come upon a sequence that can specify something in a shorter way, we can infer significance for the sequence. The sequence 1001011100101101000 1010001101111 has the same absolute probability, but it is not compressible—there is no shorter way of writing it than simply listing out the results.

Dembski (2006) uses this to show evidence of the rigging of an election. Dembski's example centers around Nicholas Caputo, whose job it was to determine the order of candidates on the ballot, which was supposed to be done at random. However, in 40 out of 41 elections, the Democrat's name was first. So, we can represent this just like the coin tosses (1 for Democrat, 0, for Republican): 111111111111111111111101111 11111111111111.[2] Again, this sequence is not any more or less probable than any other sequence of selections. However, since it is also compressible ("repeat 1 22 times, 0, repeat 1 18 times"), this gives independent testimony that the sequence is a special sequence. The more compressible the sequence, the more special it is.

Thus, we can use this property of sequences to determine whether or not something is the result of chance. Since Caputo's results were *supposed* to be from chance, we can reasonably infer that Caputo was himself manipulating the election.

The size of the underlying sequence itself is known as the complexity of the sequence. The size of the program that can generate the sequence is known as the specification. Specified complexity is, essentially, how much compression the specification gives to the sequence. Specified complexity actually includes a number of other factors, but this gives a good intuition about it. The full details about specified complexity can be found in Dembski (2006, 2005b).

However, it is also possible that a compressible aspect could come from a law. If we have a set of data about objects falling from buildings, we can compress that data using Newton's law of gravity. This is nonrandomness by law, not intelligent agency.[3] Therefore, for specified complexity to show design, the probability model that is used for the measurement must have known laws factored out.

The question that regularly arises, therefore, is whether, when determining specified complexity, you have discov-

[1] Technically speaking, this "program" is not shorter than the sequence, since the program is encoded in an ASCII character set while the sequence is binary. The sequence would have to include more than 144 coin tosses for this program to be shorter than the sequence. Nonetheless, we will consider this program to be "shorter" for didactic purposes. In real life, we would be using machine code, which would be inherently shorter but much more difficult to read. Also note that there are differences in machines that affect the length of the required program but since any given machine is interconvertible to another machine through a fixed-length program, the results are much more stable for longer sequences than for shorter ones.

[2] The actual position of the 0 was not recorded in the documents related to the case, so it is merely inserted arbitrarily.

[3] In the broader scope, law itself can be considered an aspect of design. In the Aristotelian/Thomistic tradition, the regularities of nature are themselves evidences of design, often referred to as teleonomy (Feser, 2009; Lopez, 2017). Whether or not you remove law-like processes from your characterizations of intelligent causation depends on what types of intelligent causes you are wanting to show.

ered intelligence or merely a new law (which would give similar results). One answer is to use the logical depth (Bennett, 1988) of the compressing program. Physical systems are referred to as such because they exhibit simple, finite relationships to each other (Bartlett, 2014b). Such a relationship would preclude a law with a large logical depth (i.e., one requiring a complicated relationship).

Additionally, Ewert et al. (2014) show that functional requirements can be used for compression. A functional requirement, as a teleological mode of compression, indicates design. This has been used by others, such as Durston et al. (2007), to measure specified complexity in protein folds.

Therefore, even though specified complexity does not on its own distinguish whether agency has been discovered or merely a law, further reflection on the nature of the specification is often able to resolve it.[4]

5. Mathematical Intelligent Design: Active Information

Specified complexity is a fairly well-worked-out system of identifying the patterns resulting from intelligent causation. The problem, however, is that it is very difficult to use in practice. It is easier to use for simple systems such as computers, or for simple tasks such as the Caputo example, but using it for something more complex such as biology, where even the relevant laws are not already known, is much more difficult.

However, for systems that have a function (i.e., a goal), a new development in computer search theory paved the way for making further breakthroughs in how to apply specified complexity. In computer search, the question has always been whether there is a "best" way to search for a needle in a haystack. For instance, if I am looking for the ace of spades in a card deck, what is the best way to search for it? It turns out that this question is heavily dependent on the way the deck is organized.

Additionally, if we know nothing about how the deck is organized, then the average performance of all possible search algorithms for the deck will be the same as picking cards at random. These results are known as the "no free lunch theorems" (Wolpert, 1996; Wolpert and Macready, 1997). Essentially, if we want to create an algorithm that is better than random chance for finding a target, we have to have some sort of specialized knowledge about the search space or the target we are looking for.

These theorems allow us to measure an average expected probability of positive events for search algorithms and machine-learning algorithms. If we can measure how well random chance is able to perform a task, we can use this as an expected average value for any arbitrary algorithm. Therefore, if we find a search mechanism that reliably performs better than chance, then this is good evidence that the search mechanism benefited from prior knowledge about what the "space" of the search looked like. In other words, it indicates that the search mechanism is infused with prior information about what types of eventualities to expect.

The Evolutionary Informatics Lab, which is at the forefront of active information research, has used active information to show that every claimed instance of computer-based Darwinian evolution either (a) actually had information included in the search algorithm, (b) had results that were so simplistic that they were completely within the realm of random chance, or (c) some combination thereof (Dembski and Marks, 2009; Ewert et al., 2012). It is true that the evolutionary examples do not have the specific results encoded within them, but they are structured in a way that makes finding the solutions more probable, which, if applied to different problems, would make finding the solutions less probable.

Most people (including those working in the field) do not realize the extent to which the *parameterization* of the problem (i.e., determining which fields to vary and how they should be varied and interpreted) contributes knowledge to an evolutionary search. While computers are the best at searching large spaces of parameters quickly, it takes an intelligent cause (i.e., humans in this case) to generate the most important parameters and how they contribute to the problem (Hubbard, 2010; Bartlett, 2016).

The way active information is measured is by comparing the relative probabilities of finding a solution both by chance and with the search algorithm. Using Equation 1, each of these probabilities can be converted to bits, and we can have a measurement of how many bits the search algorithm contributes to the search, even without knowing what the code or mechanism of the search is. For example, let's say that we have a search problem for which random chance gives us a 1 in 1,000,000 chance of finding an answer. This is equivalent to approximately 20 bits of information. Then, using a search algorithm, we then have a 1 in 5,000 chance of finding the answer. This is equivalent to about 12 bits of information. Therefore, I can say that my search algorithm contributed 20 - 12 = 8 bits of information to the search.

In biology, we can use this to measure how much information a cell has about its own genome adaptations. By measuring the likelihood of an advantageous change in the genome by random chance against the likelihood of an advantageous change that the organism itself provides, we can determine how many bits of information a cell has about

[4] Technically, this doesn't resolve it per se, but it can show us which things can *only* be agency. That is, agency can create something law-like (as in the Caputo example). However, law cannot create something that is fully teleological.

its potential fitness landscape. This has been measured for the adaptive immune system (Bartlett, 2010a) and can be further extended to measure other ways in which a cell is predisposed to adapt in advantageous ways.

In short, an algorithm that gives consistently positive active information toward its target is a strong indicator that the algorithm had a purposive design toward that end.

6. Mathematical Intelligent Design: Relative Irreducible Complexity

While irreducible complexity is founded upon an informal description of how agents pursue their designs, Bartlett (2010b) describes a way to formalize this description in terms of the theory of computation. As we have described, irreducible complexity states that some features require multiple steps in order to achieve the goal, and the intermediate steps are unhelpful or even hurtful on their own. Only when the whole system is in place do the steps make sense. In relative irreducible complexity, this concept was mapped onto the concepts of computational complexity classes developed by Stephen Wolfram (Wolfram, 1984, 2002).

Essentially, what Wolfram found was that in order for a computer to be *universal* (i.e., capable of running an arbitrary program), it also had to be *chaotic* (i.e., small changes in the input have an unpredictably nonlinear affect on changes in output). What I was able to show is that this means that in order to evolve useful complex functions, an algorithm would have to cross over paths where selection would be pointing the wrong way. A complex function in the computational sense would be one that requires an open-ended loop to produce, and in the biological sense would be a negative feedback loop. Irreducible complexity in this sense means that all single steps on a path to a particular target are nonselectable, and therefore would occur only with a near-zero probability since all the steps would have to occur at the same time to prevent strong negative selection.

The only way around this difficulty is to import information from another source—either from an agent, from a repository of information somewhere else, or from mapping the solution space to a nonuniversal, non-chaotic one (essentially infusing the algorithm with active information by restricting the range of possible choices).

Thus, finding irreducible complexity of the computational sort is evidence that at least part of the algorithm arose through intelligent agency. This was shown by Bartlett (2010b) using the evolutionary software Avida as an example. While most of an Avida "organism" was developed via natural selection, there is one part of the Avida algorithm that is irreducibly complex in this sense (the replication loop), and it is actually designed into the software! Thus, far from demonstrating evolution, the Avida software validated that irreducibly complex systems are indeed markers of design and can even allow designed parts of evolved systems to be identified. Additionally, this should make clear why intelligent design cannot identify *who* the designer is. Using irreducible complexity, we could identify *that* a section of code had an author, but those techniques do not help us to identify *who* the author is. They merely point to the fact that a search for an author would be a warranted endeavor.

Similarly, using different techniques for identifying irreducible complexity, Ewert (2014) showed that in the evolutionary system known as Tierra, an irreducibly complex system was found—the sensory system. Just like in the Avida example, the irreducibly complex system can be traced back to the authors of the system itself, not to the evolving system. The evolved features of Tierra did not display irreducible complexity.

7. Intelligent Design and Evolution

One further thing to clarify about intelligent design is that if an object or process is found to have been the result of design, that does not mean it did not evolve or did not have a natural history. What it means is that somewhere within or at the beginning of that causal history design had to be involved.

As an example, consider the Windows operating system for personal computers. If you install Windows on an empty computer, you will install it from an installation disk. The Windows installer is not the same program as Windows. However, it contains sufficient information to transfer Windows to your computer. In fact, it may not even transfer the exact same version of Windows to every computer. There may be aspects that are turned off or changed depending on whether you installed it on a laptop, or on a computer with a large number of processors, or within a virtual machine.

As such, one could say (using certain terminology) that your installation of Windows evolved from the installer. However, it would be ridiculous to say that evolution was the *primary cause* of Windows on your computer. It overwhelmingly came from an intelligent cause. Sure it had a natural history—it started out as a repository within the installer, then was transferred to your hard drive, and then bits of it were tweaked to match your setup—but none of that takes away from the question of whether agency was the primary originator of Windows.

Likewise, while ID itself cannot say what the natural history of a designed object has been, Dembski's "no free lunch regress" (2005a) shows that it takes more design to find a designed object in an evolutionary search than it does to design the object itself. Thus, while you may be able to make an argument that a given object was not designed directly but had an evolutionary history, that is not the same as arguing that the object was not designed. In fact, it is likely to actually be adding to the number of bits required for a designer to create such a process.

This is why, rather than saying that mutations cannot add information to the genome, I prefer to say that in order for mutations to add information to the genome there must already be a large amount of information that channels mutations in a beneficial direction (Bartlett, 2012).

8. Business and Technology Applications of Intelligent Design

So far, our study has focused on the biological aspects of intelligent design, which are directly applicable to origins issues. However, because intelligent design is a general field of study of intelligent causes, it can be applied to a number of non-origins issues.

Bartlett (2014b) applied many of the ideas of irreducible complexity to the study of the mind, showing how the mathematics of information theory can be used to model the operation of the mind in its nonmaterialistic aspects.[5] Bartlett (2014a) used those same ideas to quantify complexity in software development projects. Thus, irreducible complexity can be used in software development to measure, manage, and value the creativity necessary to produce software products.

Intelligent design, however, is not just about detecting and measuring design; it is also about understanding what it is that intelligent causes do. Intelligent design aims to formalize the cut between the abilities of algorithms and the abilities of minds. Using that information allows entities to better divide tasks between software and humans. Holloway (2017) uses this to develop a generalized method of harvesting information from human subjects that computers are either unable or poorly able to calculate. This method, known as imagination sampling, allows machine-learning algorithms to make use of human subjects in a game-like environment to gain more information about the solution space than they are able to using computation alone. Essentially, we are asking humans to supply active information to machine-learning algorithms where automated methods are not sufficient.

In fact, the use of humans in automated computation loops is a growing field of human computation and artificial artificial intelligence (AAI). Amazon.com has a platform known as The Mechanical Turk which makes writing AAI tasks and matching tasks with humans easier. Intelligent design provides a theoretical framework to this field, both as a justification for its existence and as a unifying concept behind the many tricks that have been developed.

The study of human creativity also has application to economics—both macro and micro. George Gilder, one of the founders of the Discovery Institute (which, among its other roles, is an intelligent design think tank), uses the same principles of intelligent agency in developing his "information theory of capitalism" (Gilder, 2013). Gilder shows that the development of economies is not a predictable outcome of equilibrium equation but the dynamic result of intelligent causes acting to solve problems.

In microeconomics, Peter Thiel (cofounder of PayPal) explicitly uses intelligent design theory to talk about the ideal ways a business can increase its value both in terms of profits and its value to society (Thiel and Masters, 2014). Peter Thiel even states:

> Computers are far more different from people than any two people are different from each other; men and machines are good at fundamentally different things. People have intentionality—we form plans and make decisions in complicated situations. We're less good at making sense of enormous amounts of data. Computers are exactly the opposite: they excel at efficient data processing, but they struggle to make basic judgments that would be simple for any human.… In 2012, one of [Google's] supercomputers made headlines when, after scanning 10 million thumbnails of YouTube videos, it learned to identify a cat with 75% accuracy. That seems impressive—until you remember that an average four-year-old can do it flawlessly. When a cheap laptop beats the smartest mathematicians at some tasks but even a supercomputer with 16,000 CPUs can't beat a child at others, you can tell that humans and computers are not just more or less powerful than each other—they are categorically different. (Thiel and Masters, 2014, pp. 143–144)

So, far from being a theory only about origins, intelligent design is a general theory about intelligent causes that can be applied to any number of agency-oriented problems in a number of fields.

9. Applying Intelligent Design to a Creation Model

While showing that certain features of biology necessarily originate from intelligent causes, many creationists want to know if intelligent design can

[5] Some people think that *model* means *predict*. However, there are many processes that can be modeled in a non-predictive way. Models simply allow us to combine knowledge in useful ways. For instance, a random probability distribution is a non-predictive model. It doesn't tell use *where* a particular event will land, but it will tell us about the general ways that large numbers of similar events will land. Bartlett (2014b, 2017) covers potential methods of non-predictive modeling for nonmaterialistic events.

help move forward a general creation model, especially one in which the creation of biology is presumed. That is, if we presume that life is designed, then doesn't *showing* that it is designed become redundant?

That would be the case if all intelligent design had to say was whether or not life was designed. However, as we have seen, intelligent design, as a tool, is useful for generating much more specific results. It can tell us if specific subsystems are designed or not and even *measure* the amount of aptness certain systems have to their environment. This alone makes intelligent design a powerful tool, as one can use it to answer detailed questions about what life is geared to do and to what extent it is geared to do it and, using active information and similar metrics, retrieve an answer in bits.

Additionally, all young-earth creationists agree that a significant amount of change has occurred in life history. This has made searching for which species belong to which created kinds one of the hallmarks of creation biology. Many creationists have attempted to solve this problem by making statistical comparisons of biological characters one of the foundational methods of determining created kinds (Wood, 2008). However, one common issue is knowing *which* characters should be included in comparisons of created kinds (Robinson and Cavanaugh, 1998). Ideally, since certain characteristics of organisms are evolvable and some are non-evolvable, the characters used in comparisons of created kinds should be characteristics that are non-evolvable. Because intelligent design can point to *which* subsystems require design for implementation, it can potentially be used to prioritize the preferred characters to be used when doing statistical baraminology.

10. Conclusion

Many of the criticisms about intelligent design occur because it is misunderstood as being an alternative to creationism or evolution. Instead, it is a subject matter to itself about the general nature of intelligent causation. As such, intelligent design does not explicitly reference God or the Bible any more than physics or chemistry typically do. However, just like physics and chemistry, intelligent design can be used to demonstrate the plausibility of a creation model (for ID, this is by identifying and measuring design within an organism), or used within a creation model (for ID, this is by helping to determine the relevance of different features for statistical comparison for assigning to created kinds).

Intelligent design, as a subject matter, has a number of uses both inside and outside the question of origins, and creationists would do well to learn the details and apply them to their own studies. The field of intelligent design is still growing, and new aspects are still being discovered, and new uses for it are still being discovered. I anticipate that, in the future, intelligent design will become a common aspect of theory in a number of fields, both inside and outside origins questions.

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