RESEARCH ARTICLE

Causal Capabilities of Teleology and Teleonomy in Life and Evolution

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Abstract: Teleological causes have been generally disfavored in biological explanations because they have been thought to lack rigor or act as stand-ins for non-teleological processes which are simply not yet understood sufficiently. Teleological explanations in biology have been limited to only teleonomic causes, which are teleological causes that are due to codes or similarly reified mechanisms. However, advances in the conceptualization of teleological and teleonomic causation have allowed for more quantitative analyses of both. Additionally, although teleonomy has been historically excluded from potential causes of evolution, new research has shown that teleonomy actually plays a significant role in evolution. Combining these advances with advances in computability theory and information theory have allowed for a more rigorous and quantitative analysis of the capabilities and limitations of teleonomy in evolution.

Keywords: Teleology; teleonomy; evolution; information theory; active information; causation.

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1. Introduction: teleonomy and teleology

Teleology is the direction of causal outcomes of an entity (usually an organism) towards a purpose. Teleological concepts in biology (and especially in evolution) have had a troubling history for the simple reason that teleology tends to allow a lot of handwaving regarding causation (Hanke 2004; Turner 2017). Teleology has often been viewed by biologists (especially in the 19th and early 20th centuries) as being a temporary stand-in for more rigorous (i.e., reductive) ways of analyzing nature (Morgan 1905; Hanke 2004; LeMaster 2017; Crawford 2020). Biology in the twentieth century was therefore largely restricted to reductive forms of causation. This limitation allowed for tremendous growth in understanding certain *parts* of the organism, but it tended to leave out the organism itself (Woese 2004). Ultimately, while the twentieth century yielded large advancements in understanding the *mechanisms* of organisms, the results failed to include many defining traits of organisms, such as purpose and desire (Turner 2017).

Historically, biology has included teleology in one of two ways—externalist teleology (where teleology *outside* the organism plays a defining role) or internalist teleology (where the focus is on the purposes of the organism itself). Interestingly, while modern biology generally excludes external teleology in its causal toolkit, it can now be found as an undercurrent within physics in the question of cosmological fine-tuning (Barrow and Tipler 1998). While less favored in biology, discussions about biological fine-tuning have started to appear (Carr and Rees 2003; Bialek and Setayeshgar 2005; Thorvaldsen and Hössjer 2020), sometimes even connecting an externalist teleological framework of physics to the emergence of life as we know it (Morris 2004; Barrow et al. 2007). More recently, others have suggested external "teleological fields" operating at several levels that combine to produce teleological results (Babcock and McShea 2021).

Biologists, however, tend to favor an internalist teleology, where the focus is on the organism itself, focusing on aspects of causation such as intention and choice (Kull 2022). This is sometimes even connected to evolution (Fodor and Piatelli-Palmarini 2010; Kull 2022). In this understanding, biological language such as "selection for" are not merely artifacts of

language that are used accidentally, but represent some form of purpose within biological evolution.

Additionally, the present manuscript makes a distinction between "primary teleology," where teleology is a first-class (irreducible) cause in the system, and "general teleology" which includes both primary teleology and also teleonomy, which is purposeful behavior which is due to a code or mechanism.[1] Usually, biologists will favor appeals to teleonomy over primary teleology, as teleonomic explanations do not require anything beyond physico-chemical explanation (Mayr 1992). Teleonomy was originally thought to allow for goal-directed processes but without requiring any connection to primary teleology—either internalist or externalist.

To illustrate these types of teleology, a non-exhaustive list of examples is shown in Table 1. The goal of this list is to not say which of these types of causes are real (the present author does not subscribe to all of them) but to give a clear picture on how various types of causes would be categorized under this taxonomy of teleology.

This paper has three primary goals. The first is to further develop Mayr's teleonomy as a useful concept for biology to account for mechanistic aspects of purposeful biological causation without necessarily reducing the entire organism to a mechanism. The second is to show how recent advancements in information theory can be used to build an operationalized view of teleology that can be practically measured within organisms. The third goal is to combine these concepts to show new ways that the internal teleology of organisms can be helpfully embedded within a larger evolutionary framework.

2. The usefulness and distinctiveness of teleonomy

Recently, some have argued for changing the definition of teleonomy to cover all of internal teleology, without distinguishing primary teleology and teleology that has been reified into a mechanism (Corning 2019). The idea

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[1]   When the word "teleology" is used without a modifier in the present manuscript it will be considered as a shorthand for "general teleology." Additionally, unless otherwise specified, "teleonomy" will refer to teleonomy in internal teleology.

is that Mayr's view of biology is too tied to a gene-centered, reductionist view of biology, where the organism is an inert entity that evolution happens to, rather than a participant in the process. However, there is nothing in Mayr's definition of "teleonomy" that ties one to this approach. In fact, having a *distinction* between teleonomy and primary internal teleology actually allows one to talk intelligibly about the differences between causes that are the result of true intentionality (primary internal teleology) and causes that are the result of intentionality reified in mechanism or code (teleonomy). If one conflates the two definitions, then this important distinction is lost. One can easily reject Mayr's conclusions *about* teleonomy while embracing the distinction and definition itself.

Others, such as Nagel (1977), have argued that there is not a clear distinction between Mayr's concepts of teleonomic processes (processes that exhibit ends due to a code) and teleomatic processes (processes which exhibit ends due to physics). An example of a teleomatic process would be a baseball being thrown. The end is the target that the ball is being thrown at, but the moving force here is physics. The reason that some view these as identical is that, in both cases (teleonomic and teleomatic processes), physics is essentially the only process under consideration, and therefore could be considered the "cause" of the outcomes in both cases. However, further analysis shows that teleomatic and teleonomic processes really do have distinct causal patterns.

Let us start by considering a process which is neither teleonomic nor teleomatic—processes for which no distinct end exists. In such a process, no end may exist either because the process is open (there are too many degrees of freedom so that it is indeterminate from initial conditions) or because the process is chaotic (while the outcome may be deterministic, it is not determinable through computable means). A teleonomic process is similar, except that a code or other control mechanism exists which controls the outcome based on logical principles, either reducing the inherent degrees of freedom of the physical process or making an unpredictable process predictable or understandable from logic, even if it is not tractable using equations. To illustrate this distinction, consider the difference between a traditional bomb dropped from an airplane and a smart bomb. A traditional bomb uses entirely teleomatic processes in-flight. The physics of the system is what

guides the outcome. A smart bomb, however, can use a control system to make adjustments in-flight according to the logic of what it is trying to do, such as follow a heat source. While the initial conditions *determine* the outcome, the outcome is likely not tractably predictable from mere mechanical considerations. However, someone understanding the logic of the control system would be able to largely predict the outcome to a high degree of accuracy.

To understand why this is the case, it is important to understand the nature of code and software systems. Software is usually written using Turing-complete programming languages. In such languages, in most cases it is impossible to mechanically predict any non-trivial property of the system in the general case (Rice 1953). Additionally, this unpredictability is not specifically the result of sophistication in the programming system, but is available even in extremely trivial cellular automata (Cook 2004). However, a program provides a control mechanism which makes the outcome predictable by the logic of what the program's outcome is intending. In the example of the smart bomb, if we know what the code on the bomb is tracking, we can predict where it will hit, even if it is not tractably determinable by mechanical modeling. So, with both teleomatic and teleonomic processes, initial conditions largely determine the outcome. However, with teleonomic processes, the prediction of that outcome requires understanding the logical structure of the control process, which would not be possible (or at least tractable) by direct analysis of the physical quantities.[2]

In any case, a teleological process is one whose causes are organized around purposes, and a teleonomic process is a teleological process that has been reified into a code or a mechanism. Keeping teleonomy as a distinctive category will allow us to analyze the limitations of teleonomy, which are not coextensive with the limitations of general teleology, as teleonomy is also limited by the fact that it must be reified into mechanism or code, and thus will inherit additional limitations from that reification.

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[2]   As a note, there are processes which are teleonomic but which are also tractable, such as if someone created a very simple code or mechanism to accomplish a goal. In such a case, someone would be able to understand the system in both teleonomic and teleomatic ways, as you could understand what was happening either from understanding the logic of the code or from modeling the states of the physical system.

3. Mathematically modeling non-mechanistic causation

The biggest hurdle in analyzing primary teleology has been a lack of mathematical frameworks for doing so. While mathematics may not be able to incorporate all that is included within the concept of primary teleology, there is no reason to think that there are no aspects of it which allow for mathematicization. This is especially true if we do not arbitrarily restrict our mathematical concepts to those that are computable.

While the definition of what counts as "mechanical," "materialistic," or "physical" has varied considerably over the centuries (Bartlett 2017c), many people today draw a rough equivalency between computability and material causation (Wolfram 2002; van Rooij 2008; Bartlett 2014; Copeland and Shagrir 2020).[3] This equivalency goes by many names, including "the principal of computational equivalence," "computationalism," "the physical Church-Turing thesis," and the "tractable cognition thesis." Computationalism is naturally considered by many to be associated with mechanical causation because computation includes all results achievable by finitary processes. Thus, to go beyond what is achievable computationally would require non-finitary action in the world, which many view as being beyond what is meant by the idea of mechanism.

Even if one does not fully adhere to this equivalency, it at least provides a less ambiguous starting point for helping to understand and model primary teleological processes as distinct from mechanical processes, with primary teleological processes being those which are not directly computable. Computation, however, is only one aspect of mathematics, even if it is the most well-known. Mathematics has grown beyond solely being about computation and computable problems, especially since the 1930s with Kurt Gödel and Alan Turing. Gödel's "incompleteness theorems" (Gödel 1931) demonstrated that one could prove mathematically the existence of

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[3]   Here, "material causation" refers to what is also generally known as "naturalism," not to the Aristotelian notion of material causes. However, using the term "naturalism" to refer to a specific understanding of metaphysics seems to be prejudicial, as it implies that any cause stated within that metaphysical paradigm is "natural," and therefore any other cause would be "unnatural," prejudicially implying that one would not expect to encounter such causes on an ordinary basis.

mathematical statements that were non-provable within their own axiomatic framework. While initially Gödel's result did not turn many heads, the application of it by Alan Turing's seminal paper (Turing 1937) started to show that Gödel's theorem had merit.

Turing, while inventing the concept of a computer program, was able to prove that we cannot write a computer program which will tell whether or not another arbitrary computer program will ever halt. For context, though the word often has negative connotations, "halting" is generally considered good in computer science—halting means that the computational task actually completes and has a result, as opposed to getting, say, an endlessly spinning cursor waiting for a computation to finish that never does. The fact that we cannot write a computer program which will tell us if another arbitrary program will halt is known in computer science as the "halting problem." This result has been further generalized to Rice's theorem, which says that any non-trivial property of a computer program cannot be proven using computation in the general case (Rice 1953). Given the Church-Turing thesis that Turing machines effectively exhaust what can be deduced through computation (Kripke 2013), this presents quite a limit on the abilities of computation (and therefore material causation) alone.

However, humans do not appear to be so limited. Humans can do a variety of tasks which have appeared to many mathematicians and computer scientists to be beyond the boundary of computation, such as determining whether or not computer programs will halt, determining new mathematical axioms, formalizing propositions, and deriving non-trivial properties of computer programs (Robertson 1999; Bringsjord 1997; Bringsjord and Zenzen 2003; Bringsjord and Arkoudas 2004; Bringsjord et al. 2006; Bartlett 2014).

Even though there are tasks which are beyond the reach of computation, there is no problem reasoning about such tasks mathematically, nor problems reasoning about entities which are capable of those tasks. Shortly after describing the limits of computation, Turing (1939) demonstrated the ability to mathematically reason about non-computable tasks using a concept now called "Turing oracles," which are essentially non-computable functions. The lack of being able to directly compute the *value* of such functions does not prevent the ability to *reason* about them (Copeland 1998; Bartlett 2014).

As noted in prior work (Bartlett 2017a), using such functions in models does bring some additional (but not insurmountable) problems to testability. Testability always plays an important role in science because it allows reality to push back against our ideas. Since values cannot be precomputed for such functions, other means of testing have to be applied. For instance, we might be able to predict the frequency of occurrence, or some parameter of the distribution of effects, or even a qualitative aspect of the distribution of effects.

While this doesn't test every aspect we might wish (after all, we wish we could know the value of the function ahead-of-time), complete empirical testability has never been absolute for any model in science. Empirical testing is by its nature more limited than the theories that it tests, as there are actually an infinite number of models which match *any* given set of data (Kukla 1996). In fact, the very existence of p-values tells us that there is *some* probability that the empirical testing was insufficient. Testing does not prove the validity of theories, it is merely a means to give voice to external reality about the content of theories.

The testing of and for randomness already shows that this sort of testing is practiced in science. Whether a finite set came from a random process cannot be determined by any finite set of data. However, for the purposes of testing, oftentimes randomness is determined by checking to see if the anticipated statistical parameters of the dataset match the expected distribution. For instance, in Luria-Delbrück experiments, the data are presumed to be following a Poisson distribution if the mean is equal to the variance (Luria and Delbrück 1943), despite the fact that there are an infinite number of ways that the mean can equal the variance without following a Poisson distribution.

The main criteria for an empirical test are that it is able to compare the consistency of *some* empirical parameter to one that is expected from the theory. This parameter does not have to be the specific value obtained, but can also be meta-information about the values, the preconditions of achieving them, the means of achieving them, their distribution, etc.

In short, primary teleological causes can be thought of as non-algorithmic functions, and can also be thought about and reasoned about as such.

4. Measuring teleological causation

One of the key limitations of current teleological thinking is the lack of measurements for the amount of general teleology in a process (Lee and McShea 2020). So how might teleology be measured?

In many recent expositions (Koons 1998; Hitchcock 1996; Hawthorne and Nolan 2006), teleology is identified with shifting probabilities towards some occurrence ϕ when (a) ϕ brings about result ψ and (b) ψ is good. This is illustrated conceptually in Figure 1. This shifting of probabilities based on outcomes is, essentially, a reduction or alteration of possibility space towards beneficial outcomes. Within the constraints of physics, an organism has many potential options. Teleology reduces those options to one particular value (or a smaller subset of values), or shifts probabilities in their favor, in service to a goal or holistic form (Asma 1996). If one needs a more objective way of determining a goal in biological systems, one can use the criteria established by Mossio and Bich (2017), where the goal is at least an aspect of the maintenance of the state of closure of the teleological system (though there are likely other ways to determine goals in an objective manner as well).

These reductions are typically "surprising" within the context of the physical system. That is, while statistical entropy encourages us to rely on systems achieving their most probable end-state, organisms tend to make choices and create configurations that are highly improbable statistically. This is sometimes referred to as the "cybernetic cut" that exists between outcomes whose causes are dominated by non-teleological causes and teleological causes (Abel 2008; Trevors and Abel 2004). This reduction in possibility space to an improbable but goal-conforming outcome is a key marker for teleological activity.[4]

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[4]   Note that many of the attempts to reconcile or reduce all teleological causation into non-teleological processes such as natural selection have so far failed to accomplish their goals. As pointed out by Fodor and Piatelli-Palmarini (2010), this reconciliation, as it has been performed so far, only works if selection itself is teleological instead of strictly material. Block and Kitcher (2010) criticize this view, but merely by assertion. They state that "causation is extensional," but their only support is that they can provide an *example* of a cause which is extensional. The fact that a

What makes teleology special is that the solution space tends to be extremely small within the possibility space. Therefore, we can measure the "power" of the teleological action by measuring this reduction in space. This is not always easy or exact because what has to be measured is the size of the destination space which matches the desired goals. We cannot presume that there is only one possible outcome that fits the goal, even though in biology (as well as in computation) the solution space is usually quite miniscule compared to the possibility space (Abel and Trevors 2005; Langdon 2006; Montañez 2017).

Because these solution spaces represent a tiny fraction of a possibility space, the probability of them occurring by chance are usually measured in bits for convenience, which is the negative log (base 2) of the probability (Marks II, Dembski, and Ewert 2016). This also allows for more convenient manipulation of values, as well as more intuitively-connected ways of manipulating information measurements (i.e., information is sub-additive, and therefore "adding information" is truly analogous to addition in this scheme). Thus, using the concept of bits from information theory provides a convenient methodology for representing reductions from possibility space to solution space in teleology.

Therefore, the amount of information that is added to a system to direct its outcome can be quantified by examining the change in probabilities that occurs. One way this can be measured is using the concept of active information (Dembski and Marks II 2009). Active information measures the difference in probability of finding a solution in a general space I_Ω (such as

particular cause is extensional does nothing to say whether or not there exists causes which are intensional, yet this is precisely what these critics do. Then they use this to simply rule that "selection for" must be an extensional cause, saying, "But if causation is extensional, then so is selection-for, since selection-for is a causal idea." Mossio and Bich (2017) do a better job by describing the requirements for a physical process to be understood as being teleological. While I am in agreement with their assessment (such processes would fall under the category of teleonomy in the taxonomy of teleology presented here), their assessment does not include a reason to think that *all* teleological processes can be implemented entirely by physical processes, nor that such teleological processes are reasonably likely to *originate* in the prior total absence of a primary teleological process.

among physical possibilities) and finding a solution in a space I_S that is informed by an an information source. The difference, I_+, represents active information.

$$I_+ = I_\Omega - I_S \tag{1}$$

In terms of direct probabilities, this can be reformulated in an equivalent manner using p_Ω as the probability of success in the general space and p_S as the probability that is informed by an information source.

$$I_+ = -\log_2\left(\frac{p_\Omega}{p_S}\right) \tag{2}$$

The concept of active information does not specify a source for the information, or even how the information is stored, it only measures its effects.[5] Active information is typically used to measure the amount of information present in various algorithms, such as in Ewert, Dembski, and Marks II (2009) and Montañez et al. (2010), but it has also been used in measuring the degree of fine tuning in cosmology (Díaz-Pachón, Hössjer, and Marks II 2021) and judging the effectiveness of machine learning models (Bartlett and Holloway 2019). The fact that it is being designated as "information" does not mean that it is stored in an explicit digital format (it would be difficult to even conceptualize a "digital format" for cosmological fine-tuning, for instance), but merely that it can be reasoned about using information theory.[6]

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[5]   For understanding the information content itself from an "inside the information" perspective, the reader is referred to the subject of teleosemantics.

[6] While there are many who object to the overuse of information theory in biology, I believe such criticisms do not hold here. Using information theory for analyzing genetics itself is relatively uncontroversial, whether it is the maintenance of genetic information through time (Kuruoglu and Arndt 2017), the calculation of the entropy of the genetic code (Yockey 2000), or the measurements of the genetic "address space" provided by binding sequence lengths (Schneider et al. 1986). Any wider usage of information theory tends to be criticized as taking the information concept too far, and assuming that the entirety of causal factors for organisms reduce to computational ones (Griffiths 2001). These are not completely unfounded criticisms, as many improper or overly-encompassing analogies to computer systems have been

4.1. Comparison with the persistence measurement

Recently, Lee and McShea (2020) developed an empirical measurement of goal-directedness that they labeled as *persistence* which has similar goals as the previous concept of active information. This section will show that while the persistence metric heads in the right direction to some extent, active information appears to be a mathematically superior way of measuring goal directedness using equivalent inputs.

In their formulation of persistence,

$$P = \frac{\frac{G}{N} - R}{1 - R},\qquad(3)$$

where P is the persistence measurement, $\frac{G}{N}$ is the ratio of good moves to total moves, and R is the expected ratio given the probability structure of the space. For any ratio $\frac{G}{N} \geq R$, since $G \leq N$ and $0 \leq R < 1$, the result will be in the range $0 \leq P \leq 1$.

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made throughout the years. However, information theory, in its more abstract incarnations, applies much more widely than most assume, and does not even necessarily rely on computational metaphors. Demirel (2014) and Griffiths et al. (2015) both provide good examples of applying information theory without relying on computational metaphors.

The present discussion focuses on information theory in two ways. First, as a measurement tool, using active information. As mentioned already, active information does not rely on any computational metaphor to be usable for measurement, and has already shown its usefulness both inside and outside of computational systems. Second, as a source of providing limiting behavior or conservation rules for teleonomic systems. Here, the analogy to computation is more direct, but its application is more limited. That is, we are not applying information theory to the whole of the biological organism, but only to parts which can be determined to follow computable rules as delineated in the physical Church-Turing thesis. Information theory provides both the necessary requirements for inclusion in this analysis as well as the analysis tools themselves. For aspects of biological organisms which do not fit these requirements, the application of these limitations simply does not apply. This is what makes the taxonomy of teleology described in Section 1 helpful—it provides a way of at least naming the type of causality being proposed and therefore the tools relevant to its investigation.

To adequately compare persistence to active information, we need to establish some sort of equivalency between the terms in each formulation. For a first-order comparison of the measurements, we can use the equivalencies $I_\Omega = -\log_2(R)$ and $I_S = -\log_2\left(\frac{G}{N}\right)$ to bridge the two measurements.

While the measurements have some similarities, there are several advantages to active information over persistence. The first advantage is that, as an information measure, active information is sub-additive, while persistence is not. This means that active information measurements can be combined in meaningful ways. Being *sub*-additive means that adding information measures leads to an upper bound, not to a single value. Nonetheless, in the case of persistence, no means of combining values are provided at all. In Lee and McShea (2020), they suggest separating out different subspaces by probability structure. Separating such spaces in persistence measurements means that the results of the spaces are not combinable, while they would at least be sub-additive using active information.

The second advantage of active information is that the structure of the space generated by persistence does not make as much sense as that of active information. Both active information and persistence attempt to discount the teleological process when the probability structure dictates high success rates, and they both yield negative values when those processes point away from the goals. However, in both cases active information makes more mathematical sense than persistence, and it also provides additional structural benefits as well.

For instance, the negative side (where the "teleology" is actually pointing the wrong way) of persistence seems degenerate—the positive case yields values from 0 to 1, but the negative side can diverge to any negative value. If $\frac{G}{N} = 0.99$ and $R = 0.9$, the result is 0.9, but, if they are reversed, the result is -9. Active information is symmetric on both the positive and negative sides. For the same probabilities, the active information is ≈ 0.095 bits, but, if $\frac{G}{N}$ and R were reversed, the active information is ≈ -0.095 bits. Lee and McShea (2020) actually considers all negative values to be zero, as all such values indicate that the organism is not oriented towards the goal. While this may be true, the lack of symmetry indicates that the measurement is not well-grounded mathematically.

As for discounting for the environmental assistance, while persistence does do some discounting, the discounting for persistence is neither sufficiently high nor does it track well. For instance, if the process performs 100% good moves, that isn't especially surprising if the environment dictates a probability space that is 99.99% favorable. Persistence, however, measures this as a 1 (the highest score). Active information, on the other hand, would only count that as ≈ 0.000144 bits. Where the environment entirely dictates the outcome, persistence is indeterminate while active information is zero, indicating that there is nothing being enhanced to the environment's distribution (persistence is simply undefined in this case). As noted in Griffiths et al. (2015), causal specificity is an important aspect of causation, and here active information is much better able to measure this specificity than persistence.[7]

Additionally, when considering degenerate cases where where success is literally impossible but success occurs anyway (i.e., R is 0 but $\frac{G}{N}$ is positive), active information correctly yields infinite values, while persistence simply yields $\frac{G}{N}$. It is difficult to imagine how we should not be impressed by the teleological accomplishment of the impossible, but here persistence is giving it an equal or lower score than for the easy accomplishment of 100% accuracy when the environment yields 99.99% assistance. Likewise, this continues to be problematic in non-degenerate cases where R is merely miniscule or infinitesimal where the limit is likewise $\frac{G}{N}$. Essentially, while persistence

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[7]   In reference to Griffiths et al. (2015), I should make a note about the relationship of their measurement of causal specificity using mutual information and our measure of teleology using active information, as the two measurements are closely related. Mutual information essentially averages active information across all available possibilities, while active information focuses on the specific possibilities of interest (here, teleological goals). In other words, mutual information as used by Griffiths et al. (2015) measures total causal influence between cause and effect, while active information focuses on causes related to specific classes of effects (i.e., meeting a goal). Mutual information is always non-negative, so it would measure a cause pointing away from the goal as having positive mutual information, even though the information is in the wrong direction. Active information (which is a form of *pointwise* mutual information) allows for indicating both causal specificity *and* directionality.

can provide a limited ability to factor *out* the help the environment provides, it seems to fail completely to factor *in* the difficulty the environment provides.

4.2. How might primary teleology interact with physics?

One potential problem with any approach to teleology which includes primary teleology and distinguishes physical and teleological probability spaces (whether active information, persistence, or some other measurement) is that models and methodologies have not been established for the intereractions of the physical and the teleological, leaving open the question of how I_S can come to be different from I_Ω or how $\frac{G}{N}$ can come to be different from R.[8] Babcock and McShea (2021) have suggested that teleology operates as a field much like other fields that have been discovered. They note that fields "are multiply realizable and diverse in their composition," and, thus, there is no fundamental issue at play. Whether one takes an internalist or externalist view to primary teleology, the same question arises—how does one think about the interaction of the teleological and the non-teleological? While it is an open question (and not directly addressed by the present methods), it is certainly not *problematic* for the present methodologies.

An example means of addressing such a question would be to take the physical possible outcomes and the teleological possible outcomes and, with the intersection of their possibilities, combine their probabilities in some fashion and then remap the probabilities so that they add up to 1. For instance, let Ω be an array of possible future states of the universe, and let α be an array of the probabilities of each of those states where the index of α matches the index of Ω that it is standing in for. Now let β be a similar array but for the probabilities based solely on primary teleology. We can

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[8]   This question is not as directly relevant when dealing with teleonomic causes, because the information or control system manages the change in probability space, as noted in Section 2. However, even then, a more ultimate question remains about how those control systems came to be, and, as will be discussed in Section 7, the degree of difficulty gets larger, not smaller, as it gets pushed back in time, thus indicating that, at some point, primary teleology will likely be required.

combine these distributions into a new array, γ, by performing the operation

$$\gamma_i = \frac{\alpha_i \, \beta_i}{\sum_j \alpha_j \, \beta_j}$$

with potentially some additional failsafes to prevent an undefined distribution.[9] The point here is not that this particular suggestion is the correct model (or even an approximation of a correct model), but merely to demonstrate that there is not a conceptual problem with having models that distinguish primary teleological and physical probability spaces.

5. What requires teleological causation?

To begin a quantitative investigation into teleological processes (whether primarily teleological or teleonomical), we first need to be able to identify them qualitatively. What we need to know are what sort of outcomes require teleological processes to occur.

There are many processes which might occur either through teleological means or through non-teleological means. A rock could tumble down a mountain either because the wind blew it down or because someone pushed it. There is usually nothing in the nature of the tumbling rock which would give a clue as to which type of cause occurred. However, because teleological solutions *can* narrow the solution space by many orders of magnitude, we can in fact detect certain types of solutions which require (within a miniscule margin of error) teleological processes.

It is insufficient, though, to simply measure differences in probabilities of outcomes given certain starting points. In order for something to qualify as being teleological, it has to be identifiable as having a goal. For the purposes of biology, one can postulate that a goal is something that an organism can do or cause to happen which benefits the organism itself in some way. This is categorized as an "intrinsic purpose" by Koons (1998). In biology, a more objective way of identifying a goal is given by Mossio

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9   For instance, if there is no overlap between physical and teleological possibility space, all terms become $\frac{0}{0}$ under this formalism.

and Bich (2017), where the goal should be something involved with the maintenance of the closure of the organism. However, benefit itself is insufficient to establish something as teleological, as there may be processes which are beneficial but also simply expected from the environment. Instead, one needs to demonstrate in some way that an operation is sufficiently more likely to occur when beneficial than when not. That is, if the end-goal modifies the probability space to a sufficient degree to lean towards the goal, then we have justification to call the organism's actions teleological.

The degree of probability-space modification required for justifying attributing a process to teleological causes is determined by convention just like p-value or α-level thresholds are determined by convention for justifying material causes. This is a new area of inquiry, so official conventions have not been established. Since active information is a specified complexity model (Bartlett 2020a) and α-levels in such models can be converted to bits $(-\log_2(\alpha))$ for comparison (Montañez 2018), we can use α-level conventions for significance tests. This would yield 4.33 bits for an α-level of 0.05, or 6.65 bits for an α-level of 0.01. These represent the low end of what might qualify for recognizing an event as teleological.

On the other end of the spectrum is what is often referred to as the "universal probability" bound. This is a probability limit which, when used in specified complexity models, render the specified outcome not just unlikely, but that it would go beyond exhausting the probability resources of the whole history of the universe to achieve the result (Dembski 2006; Abel 2009). Depending on the source, this has been variously calculated as being between 360 and 500 bits.

Unfortunately, 4.33–500 bits is a huge range for which conventions have not been established. However, keeping in mind that the upper end of this range is only there to provide near-certainty across all time and space, I would offer 10 bits as generally being good evidence for teleological behavior, as it is an order of magnitude beyond the conventional requirements for inferring material causation.

6. Limitations of teleonomy compared to primary teleology

Teleonomy is essentially teleology that is due to a code or program (Mayr 1961). In the present theoretical framework, teleonomy represents prior, existing information that can be leveraged by an organism in order to accomplish a goal. In other words, this code provides information to the organism about likely ways that possibility space can be reduced to solution space. The information need not be total—partial reductions in possibility space are helpful as long as they reduce it to within an amount that allows for an organism to reasonably find a solution.

Therefore, teleonomy can function similarly to primary teleology within this framework. However, teleonomy can only function this way within a bounded (though possibly large) scope. Once outside this scope, teleonomy no longer supplies information to the process, and in fact can potentially detract from the process if the boundaries of the usefulness of the code do not match the organism's present circumstances.

Teleonomy does not have to be a code per se, but any sort of mechanism (as defined in Section 3) suffices for teleonomic considerations. However, teleonomy occurring through a code is both easier to analyze (as the possibility space is easier to examine qualitatively and quantitatively) and it is present (and required) for evolvable systems, as certain types of reproduction require code-based reproduction (Mignea 2014).[10] Therefore, although teleonomy does not require codes per se, our analyses will tend to be code-focused for simplicity, straightforwardness, and applicability to reproducing evolvable systems. However, information theory can be applied to any biophysical system through entropy analysis, as shown in Demirel (2014). Processes involving codes merely make the process much more tractable in common cases.

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[10] A simple explanation of why reproduction requires a code is to imagine a copier of physical structures compared to a code-based copier. For many physical structures, the actual process to achieve the end-result is not inferable from the structure itself. Therefore, the "thing" that is copied has to be some form of information, not the thing itself.

Interestingly, because we are analyzing code-based teleonomy, many of its properties can be investigated using computability theory.[11] We can use computability theory to determine the limits of what the teleonomic codes *themselves* are capable of. This does not necessarily limit the capabilities of the *organism*, as it may have other sources of teleology (primary internal teleology or general external teleology). But we can find limits of what internal teleonomy alone may be able to accomplish within an organism.

One interesting insight is that many tasks that require primary teleology for a general solution can be supplied a specific or semi-specific solution using code. For an abstract example, take the halting problem discussed previously. While the halting problem is not solvable for programs *generally*, code can be added to solve for specific instances or classes of the halting problem. That is, in code, we could write detection code to determine if, say, a loop counter did not go in the proper direction in order to reach a termination condition. Likewise, we could write detection code that detected when the same state was acheived more than once (which necessarily indicates an infinite loop in deterministic systems).

However, what is generally not possible is teleonomy (code) that produces new code that performs outside the classes of solution that it already considers.[12] This is often known as Levin's law, and it is colloquially stated as "torturing an uninformed witness cannot give information about the crime" (Levin 1984). This result is stable in deterministic, non-

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[11]   Against the objection that biological codes are unlike computer codes, here we are only considering computability theory in general, which finds general truths applicable to all coded systems, regardless of the specifics of the way that the codes are mapped onto function. Additionally, for those considering material causes to be coextensive with computation as described in Section 3, this would apply to all material causes whether or not we conceptualized the underlying system as a "code."

[12]   It is possible for someone to separately *identify* additional classes of solutions. The problem, however, is that an organism (or program) does not encounter new classes of challenges based on their appropriateness to in-built solutions, but rather as the environment presents them. Therefore, while there will likely be additional classes of problems that the code can solve, the provisio "generally not possible" refers to the fact that organisms are encountering challenges that are from outside, and therefore independent of what the organism might have programming to solve.

deterministic, and mixed contexts, and is sometimes termed as "conservation of information" (Holloway 2020).

Note that, unlike other conservation laws, conservation of information is not absolute. Information content (measured in bits) *can* grow; it just grows extremely slowly. Since informational bits are the negative log (base 2) of probability, information content can only grow with the *logarithm* of the number of probabilistic attempts at a solution (see Figure 2). In this case, while geological time can provide some amount of information, the universal probability metric (which takes into account the estimated age and size of the universe) limits the amount of information gained to 500 bits as previously noted. Indeed, as noted in Hössjer, Bechly, and Gauger (2021), without imposing external sources of information, waiting times increase exponentially with the size of the needed mutation.

So, while teleonomy can be used to contain a relatively static amount of information towards organismal teleology, it does have limits based on the initial information content. These limits cannot be stated *a priori* because, for any finite set of mechanistic (i.e., computable) challenges, there could be code that assisted the organism in solving or mitigating the challenge. Some such mechanisms in biology have been reviewed in Payne and Wagner (2019). However, because the amount of code or number of mechanisms itself is finite, there will be potential challenges whose solutions are unattainable strictly through teleonomy.

7. Teleonomy and evolution

Evolutionary theory has often excluded teleological causes historically. However, the recent advent of evolutionary teleonomy (Corning 2014; Bartlett 2017b) has started to reincorporate teleonomic causes into the process of evolution. Additionally, recent advances have shown that the evidences that were previously used to exclude teleonomic understandings of evolutionary processes were misinterpreted (Bartlett 2023).

Within evolution, the role of teleonomy and teleology generally to produce evolutionary novelty effectively occupy the same basic roles as for producing goal-oriented solutions during an organism's life, with the important difference that, here, the target is the genetic code itself. Effectively,

evolution is acting (at least mathematically) as a search for a solution within code to solve a problem. Therefore, since it is operating mathematically as a search, that means that the mathematics of search apply to the production of evolution, whether or not evolution is ontologically a search (which is a matter of debate). When dealing with teleonomy, this leads to a conservation of information problem that mirrors the one in the previous section. That is, we cannot add significant amounts of information by simply processing what is already there.

However, what can be done is for an organism to have information about what sorts of external environments require what sort of internal changes. Essentially, organisms maintain not only the explicit genome, but what Caporale calls an "implicit genome," which consists of not only the present state of the genome but also of the states which it is programmed to achieve (Caporale 2006). Teleonomy can maintain a partial mapping of external environments and potentially successful DNA configurations, or even just a mapping of likely biologically valid operations on existing DNA. This has been observed repeatedly by many investigators at least as far back as the 1990s (Hall 1999), many of them reviewed in Caporale (2006), Zhang et al. (2013), Bartlett (2017c), and Bartlett (2020b).

Stochasticity does play a role here. However, because the number of possible configurations grows exponentially with the size of a search space, teleonomy is required in order to bring the number of attempted states down to a reasonable level that selection can sort through on timescales required by the population (see Figure 3). Such teleonomy in evolution can be measured using the techniques described in Section 4. Bartlett (2020b) provides several equations that can be used in this measurement along with examples of it being applied.

One example of its application is in measuring the amount of teleology *E. coli* demonstrates when adapting to starvation in the presence of citrus, as explored in Hofwegen et al. (2016). They found that, when under selection, *E. coli* produced *Cit+* mutations faster than when not under selection. When under selection, getting a *Cit+* mutation is needed for maintaining self-closure, so it qualifies as a teleological goal. To quantify the teleology using active information, we would compare the probability that the mutation occurred when not under selection to the probability that the mutation

occurred when under selection, showing that *E. coli* contributes ≈ 12.4 bits of information towards the search for *Cit+* mutations when under selection.

This was measured by using the probability of a mutation to yield a *Cit+* phenotype when occurring in absence of selection, which is $\frac{1}{10^{10}}$, compared to the probability of a mutation to yield a *Cit+* phenotype when occurring in the presence of selection (i.e., when needed), which is $\frac{1}{1.8\times10^6}$. Therefore, the active information metric is calculated from (2) as $I_+ = -\log_2\left(\frac{1.8\times10^6}{10^{10}}\right) \approx 12.4$ bits. This is greater than the threshold proposed in Section 5, and indicates that this process is indeed teleological. We can go further with some additional simplifying assumptions (which may or may not turn out to be true). If we assume that the teleology is teleonomic, and that the teleonomy is codified within DNA, then we can expect that there is a mechanism encoded within the DNA which is causing these mutations to be more likely when under selection. However, active information is not equivalent to data length, so the amount of DNA required to accomplish this cannot be inferred from active information alone. Thus, as a practical benefit, active information can be used to help know when the search for a mutational mechanism is justified, as such experiments can have significant associated costs.

Many, such as Caporale (2006), suppose that, with time, evolution will be able to add to its ability to find solutions using material mechanisms alone (e.g., the mechanisms provided by the modern synthesis, or some other material mechanism). Since selection favors the ability to find solutions, it is supposed that organisms will evolve an increased ability to find solutions over time. However, the mathematics of search says that this is not likely. In the mathematics of searching, evolving a more evolvable system would be equivalent to a search for a search. However, a search for a search actually requires *more* initial teleonomy than the search itself, not less. This result has been formalized in search as the "displacement theorem" (Dembski and Marks II 2010). Essentially, this means that teleonomy only provides for bounded or parameterized amounts of novelty, which is in accord with what is known from information theory (Holloway and Marks II 2018). This is backed up by empirical studies of the general capabilities of evolutionary algorithms (Woodward and Bai 2009; Yampolskiy 2018).

One common objection to the above idea is that the information could be in the environment rather than the organism. This is technically true, but doesn't actually solve the problem. The reduction of possibility space to solution space is a massive reduction, and performing the reduction requires specific information which matches the structure of the *organism*. In order for the organism to take advantage of this, one of two things must be true. Either the organism already knows the range of variation in the environment, and is already coded to search and match it (in which case we are back to the information actually residing in the organism), or the environment has specific information on how to modify the organism to match the environment. In the latter case, this merely reduces to an externalized teleonomy.

This is much like a factory which contains information about how the objects it produces should turn out. It is true that the information is external to the objects being produced, but it does not get around the need for teleonomy in the process as a whole, it just locates it externally.

Note that these limits are not the limits of evolution per se, only the limits of teleonomically-directed evolution (and, by extension, evolution without general teleology). There is nothing here which excludes primary teleology, whether internal or external, for which limitations are not known. Even though the limits of teleonomy are not equivalent with the limits of evolution, making such a distinction is important because recognizing the fundamental limiting principles of mechanical types of causes help us to locate, discover, and analyzes those types of causes. It does not imply a limitation on the total range of causes available, just a way to analyze those that are encompassed by the prerequisites of teleonomy.

8. Conclusion

As we have seen, we can generate a more mathematical conception of teleology by looking at it from the perspective of probability spaces and information theory. The mathematical form of teleology is the ability of an organism to reduce the possibilities from the ones provided by physics to ones that are more likely to be in accord with the organism's own goals. This reduction, or at least aspects of it, is measurable.

Teleonomy is essentially encoded teleology. As such, information theory and computability theory provide abstract tools that enable further investigation of teleonomy's capabilities and limitations. Teleonomy, while historically not applied to evolution, has been shown in recent years to have a much more important role in the evolutionary process. However, the limitations imposed by information and computability theory give a limitation to how much teleonomy can contribute to evolution without relying on additional teleological causes.

Figures and Tables

Table 1: Examples of Types of Teleology

	Internal Teleology	External Teleology
Primary Teleology	hylomorphic form, soul, free will	other organisms with primary teleology, cosmic teleology (such as teleology inherent in nature or the universe, deity, etc.)
Teleonomy	biophysical control systems, developmental processes, DNA, histone code, sugar code	cultural rules and expectations, physical laws of form (see Denton and Marshall (2001))

*Figure 1: Teleological Causes Shift Distributions: Conceptual Illustration*
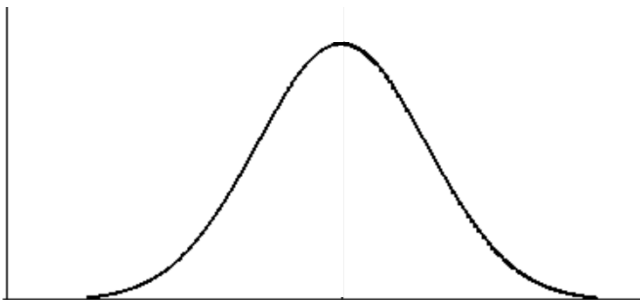
The graphic above represents a distribution of possible outcomes as might be expected from physics.
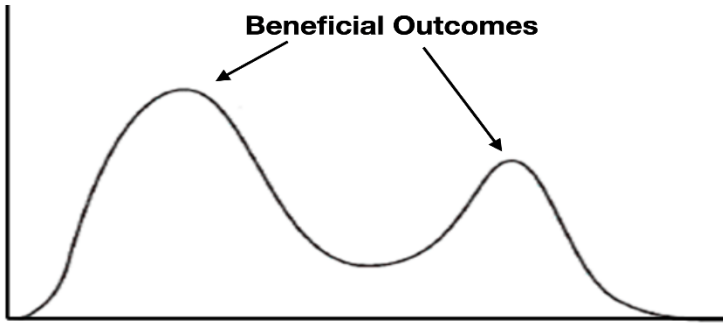
The graphic above represents a shifting of probabilities of outcomes due to teleology, where beneficial outcomes are now favored. The possibility space can remain the same even as the probabilities of outcomes change. The teleology of these shifts can be quantified using active information.

Figure 2: Information Generation Under Conservation of Information
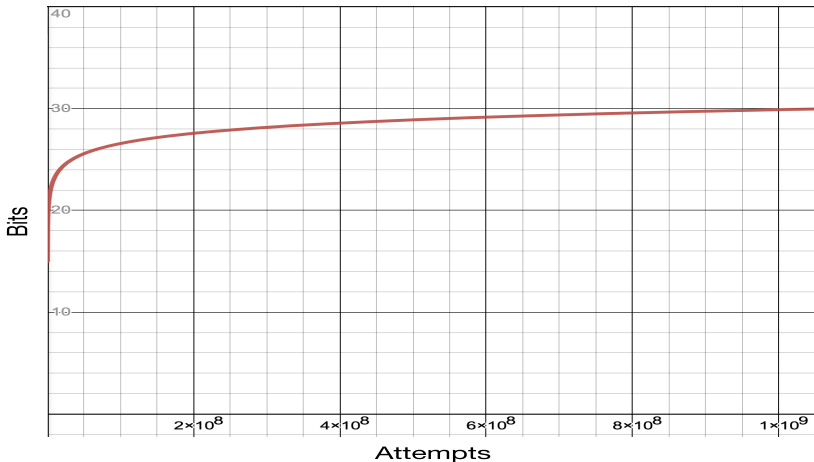
The maximum number of bits of information content that can be generated from teleonomic sources according to conservation of information is the log (base 2) of the number of attempts. As pictured, even with 10^9 attempts, not even 30 bits of information content can be generated. Note that information content here is not necessarily equivalent to code or data size.

Figure 3: A Depiction of Evolutionary Teleonomy
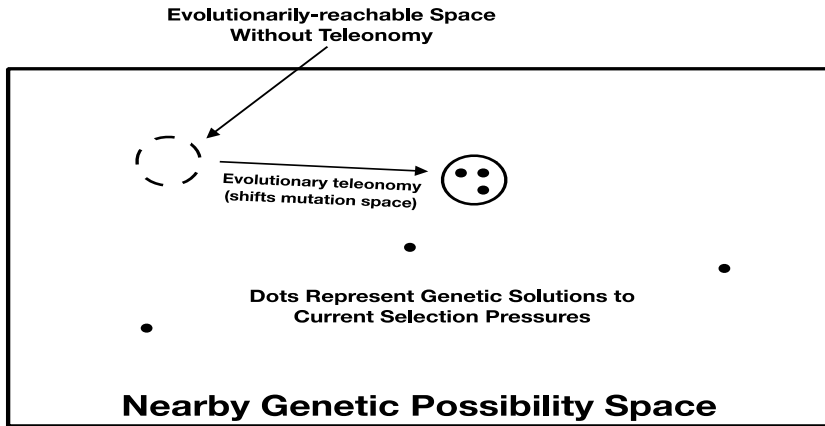
Although the possible genetic space that a population can search is large, it is miniscule compared to even the nearby possibility space (orders of magnitude more miniscule than depicted here). The dashed circle represents the size and location of genetic search space of a population by unassisted mutations (in the modern synthesis, selection does not change local mutation space). Evolutionary teleonomy represents the shifting of the mutation space for the population so that individuals are more likely to hit targets. As shown, not all possible targets need to be included in this new possibility space, only more targets than were included in the prior probability space.

References

Abel, David L. 2008. "The 'Cybernetic Cut': Progressing from Description to Prescription in Systems Theory." *The Open Cybernetics & Systemics Journal* 2 (1): 252–62. https://doi.org/10.2174/1874110X00802010252.

Abel, David L. 2009. "The Universal Probability Metric (UPM) & Principle." *Theoretical Biology and Medical Modelling* 6 (27). https://doi.org/10.1186/1742-4682-6-27.

Abel, David L, and Jack T Trevors. 2005. "Three Subsets of Sequence Complexity and Their Relevance to Biopolymeric Information." *Theoretical Biology and Medical Modeling* 2 (1): 1–16. https://doi.org/10.1186/1742-4682-2-29.

Asma, Stephen T. 1996. "A Neglected Teleology." In *Following Form and Function: A Philosophical Archaeology of Life Science*, 128–46. Northwestern University Press.

Babcock, Gunnar, and Daniel W McShea. 2021. "An Externalist Teleology." *Synthese* 199: 8755–80. https://doi.org/10.1007/s11229-021-03181-w.

Barrow, John D, Simon C Morris, Stephen J Freeland, and Charles L Harper Jr, eds. 2007. *Fitness of the Cosmos for Life.* Cambridge University Press. https://doi.org/10.1017/CBO9780511536557.

Barrow, John D, and Frank J Tipler. 1998. *The Anthropic Cosmological Principle.* Oxford University Press.

Bartlett, Jonathan L. 2014. "Using Turing Oracles in Cognitive Models of Problem-Solving." In *Engineering and the Ultimate: An Interdisciplinary Investigation of Order and Design in Nature and Craft*, edited by Jonathan L Bartlett, D Halsmer, and M R Hall, 99–122. Blyth Institute Press. https://doi.org/10.33014/isbn.0975283863.5.

Bartlett, Jonathan L. 2017a. "Describable but Not Predictable: Mathematical Modeling and Non-Naturalistic Causation." In *Naturalism and Its Alternatives in Scientific Methodologies*, edited by Jonathan L Bartlett and Eric M Holloway, 113–27. Blyth Institute Press. https://doi.org/10.33014/isbn.1944918078.7.

Bartlett, Jonathan L. 2017b. "Evolutionary Teleonomy as a Unifying Principle for the Extended Evolutionary Synthesis." *BIO-Complexity* 2017 (2): 1–7. https://doi.org/10.5048/BIO-C.2017.2.

Bartlett, Jonathan L. 2017c. "Philosophical Shortcomings of Methodological Naturalism and the Path Forward." In *Naturalism and Its Alternatives in Scientific Methodologies*, edited by Jonathan L Bartlett and Eric M Holloway, 13–38. Blyth Institute Press. https://doi.org/10.33014/isbn.1944918078.2.

Bartlett, Jonathan L. 2020a. "Active Information Is a Specified Complexity Model." *Communications of the Blyth Institute* 2 (2): 40–41. https://doi.org/10.33014/issn.2640-5652.2.2.bartlett.1.

Bartlett, Jonathan L. 2020b. "Measuring Active Information in Biological Systems." *BIO-Complexity* 2020 (2): 1–11. https://doi.org/10.5048/BIO-C.2020.2.

Bartlett, Jonathan L. 2023. "Random with Respect to Fitness or External Selection? An Important but Often Overlooked Distinction." *Acta Biotheoretica* 71 (2). https://doi.org/10.1007/s10441-023-09464-8.

Bartlett, Jonathan L, and Eric M Holloway. 2019. "Generalized Information: A Straightforward Method for Judging Machine Learning Models." *Communications of the Blyth Institute* 1 (2): 13–21. https://doi.org/10.33014/issn.2640-5652.1.2.bartlett.1.

Bialek, William, and Sima Setayeshgar. 2005. "Physical Limits to Biological Signaling." *Proceedings of the National Academy of Sciences* 102 (29): 10040–45. https://doi.org/10.1073/pnas.0504321102.

Block, Ned, and Philip Kitcher. 2010. "Misunderstanding Darwin." *Boston Review.*

Bringsjord, Selmer. 1997. "An Argument for the Uncomputability of Infinitary Mathematical Expertise." In *Expertise in Context*, edited by P Feltovich, K Ford, and P Hayes. AAAI Press.

Bringsjord, Selmer, and Konstantine Arkoudas. 2004. "The Modal Argument for Hypercomputing Minds." *Theoretical Computer Science* 317: 167–90. https://doi.org/10.1016/j.tcs.2003.12.010.

Bringsjord, Selmer, Owen Kellett, Andrew Shilliday, Joshua Taylor, Bram van Heuveln, Yingrui Yan, Jeffrey Baumes, and Kyle Ross. 2006. "A New Gödelian Argument for Hypercomputing Minds Based on the Busy Beaver Problem." *Applied Mathematics and Computation* 176 (2): 516–30. https://doi.org/10.1016/j.amc.2005.09.071.

Bringsjord, Selmer, and M Zenzen. 2003. *Superminds: People Harness Hypercomputation, and More.* Kluwer Academic Publishers.

Caporale, Lynn H, ed. 2006. *The Implicit Genome.* Oxford University Press.

Carr, B J, and M J Rees. 2003. "Fine-Tuning in Living Systems." *International Journal of Astrobiology* 2 (2): 79–86. https://doi.org/10.1017/S1473550403001472.

Cook, Matthew. 2004. "Universality in Elementary Cellular Automata." *Complex Systems* 15 (1): 1–40.

Copeland, B J. 1998. "Turing's O-Machines, Searle, Penrose, and the Brain." *Analysis* 58 (2). https://doi.org/10.1111/1467-8284.00113.

Copeland, B J, and Oron Shagrir. 2020. "Physical Computability Theses." In *Quantum, Probability, Logic*, 217–31. Springer. https://doi.org/10.1007/978-3-030-34316-3_9.

Corning, Peter A. 2014. "Evolution 'on Purpose': How Behaviour Has Shaped the Evolutionary Process." *Biological Journal of the Linnaean Society* 112 (2): 242–60. https://doi.org/10.1111/bij.12061.

Corning, Peter A. 2019. "Teleonomy and the Proximate–Ultimate Distinction Revisited." *Biological Journal of the Linnaean Society* 127 (4): 912–16. https://doi.org/10.1093/biolinnean/blz087.

Crawford, Annie L. 2020. "Metaphor and Meaning in the Teleological Language of Biology." *Communications of the Blyth Institute* 2 (2): 5–24. https://doi.org/10.33014/issn.2640-5652.2.2.crawford.1.

Dembski, William A. 2006. *The Design Inference: Eliminating Chance Through Small Probabilities.* Cambridge University Press. https://doi.org/10.1017/CBO9780511570643.

Dembski, William A, and Robert J Marks II. 2009. "Conservation of Information in Search: Measuring the Cost of Success." *IEEE Transactions on Systems, Man and Cybernetics A, Systems & Humans* 5 (5): 1051–61. https://doi.org/10.1109/TSMCA.2009.2025027.

Dembski, William A, and Robert J Marks II. 2010. "The Search for a Search: Measuring the Information Cost of Higher Level Search." *Journal of Advanced Computational Intelligence and Intelligent Informatics* 14 (5): 475–86. https://doi.org/10.20965/jaciii.2010.p0475.

Demirel, Yaşar. 2014. "Information in Biological Systems and the Fluctuation Theorem." *Entropy* 16: 1931–48. https://doi.org/10.3390/e16041931.

Denton, Michael, and Craig Marshall. 2001. "Laws of Form Revisited." *Nature* 410: 417. https://doi.org/10.1038/35068645.

Díaz-Pachón, Daniel A, Ola Hössjer, and Robert J Marks II. 2021. "Is Cosmological Tuning Fine or Coarse?" *Journal of Cosmology and Astroparticle Physics* 2021 (20). https://doi.org/10.1088/1475-7516/2021/07/020.

Ewert, Winston, William A Dembski, and Robert J Marks II. 2009. "Evolutionary Synthesis of Nand Logic: Dissecting a Digital Organism." In *Proceedings of the 2009 IEEE International Conference on Systems, Man, and Cybernetics*, 3047–53. IEEE. https://doi.org/10.1109/ICSMC.2009.5345941.

Fodor, Jerry, and Massimo Piatelli-Palmarini. 2010. *What Darwin Got Wrong*. Farrar, Straus; Giroux.

Gödel, Kurt. 1931. "On Formally Undecidable Propositions of Principia Mathematica and Related Systems I." *Monatshefte Für Mathematik Und Physik* 38: 173–98. https://doi.org/10.1007/BF01700692.

Griffiths, Paul E. 2001. "Genetic Information: A Metaphor in Search of a Theory." *Philosophy of Science* 68 (3): 394–412. https://doi.org/10.1086/392891.

Griffiths, Paul E, Arnaud Pocheville, Brett Calcott, Karola Stotz, Hyunju Kim, and Rob Knight. 2015. "Measuring Causal Specificity." *Philosophy of Science* 82 (4): 529–55. https://doi.org/10.1086/682914.

Hall, Barry G. 1999. "Transposable Elements as Activators of Cryptic Genes in E. Coli." *Genetica* 107: 181–87. https://doi.org/10.1023/A:1003936706129.

Hanke, David. 2004. "Teleology: The Explanation That Bedevils Biology." In *Explanations: Styles of Explanation in Science*, edited by John Cornwell, 143–55. Oxford University Press.

Hawthorne, John, and Daniel Nolan. 2006. "What Would Teleological Causation Be?" In *Metaphysical Essays*, edited by John Hawthorne. Clarendon Press. https://doi.org/10.1093/acprof:oso/9780199291236.003.0015.

Hitchcock, Christopher. 1996. "A Probabilistic Theory of Second Order Causation." *Erkenntnis* 44 (3): 369–77. https://doi.org/10.1007/BF00167664.

Hofwegen, Dustin J Van, Carolyn J Hovde, Scott A Minnich, and T J Silhavy. 2016. "Rapid Evolution of Citrate Utilization by Escherichia Coli by Direct Selection Requires *citT* and *dctA*." *Journal of Bacteriology* 198 (7): 1022–34. https://doi.org/10.1128/JB.00831-15.

Holloway, Eric M. 2020. "Independence Conservation and Evolutionary Algorithms." *Communications of the Blyth Institute* 2 (1): 32–35. https://doi.org/10.33014/issn.2640-5652.2.1.holloway.2.

Holloway, Eric M, and Robert J Marks II. 2018. "Observation of Unbounded Novelty in Evolutionary Algorithms Is Unknowable." In *ICAISC 2018: Artificial Intelligence and Soft Computing*, edited by L Rutkowski, R Scherer, M Korytkowski, W Pedrycz, R Tadeusiewicz, and J M Zurada, 395–404. Springer. https://doi.org/10.1007/978-3-319-91253-0_37.

Hössjer, Ola, Gunther Bechly, and Ann K Gauger. 2021. "On the Waiting Time Until Coordinated Mutations Get Fixed in Regulatory Sequences." *Journal of Theoretical Biology* 524 (110657). https://doi.org/10.1016/j.jtbi.2021.110657.

Koons, Robert C. 1998. "Teleology as Higher-Order Causation." *Minds and Machines* 8: 559–85.

Kripke, Saul A. 2013. "The Church-Turing 'Thesis' as a Special Corollary of Gödel's Incompleteness Theorem." In *Computability: Turing, Gödel, Church, and Beyond*. MIT Press.

Kukla, Andre. 1996. "Does Every Theory Have Empirically-Equivalent Rivals?" *Erkenntnis* 44: 137–66. https://doi.org/10.1007/BF00166499.

Kull, Kalevi. 2022. "Choices by Organisms: On the Role of Freedom in Behaviour and Evolution." *Biological Journal of the Linnean Society*. https://doi.org/10.1093/biolinnean/blac077.

Kuruoglu, Ercan E, and Peter F Arndt. 2017. "The Information Capacity of the Genetic Code: Is the Natural Code Optimal?" *Journal of Theoretical Biology* 419: 227–37. https://doi.org/10.1016/j.jtbi.2017.01.046.

Langdon, William B. 2006. "The Halting Probability in Von Neumann Architectures." *Lecture Notes in Computer Science* 3905: 225–37. https://doi.org/10.1007/11729976_20.

Lee, Jong Gwan, and Daniel W McShea. 2020. "Operationalizing Goal Directedness: An Empirical Route to Advancing a Philosophical Discussion." *Philosophy, Theory, and Practice in Biology* 12 (5): 1–31. https://doi.org/10.3998/ptpbio.16039257.0012.005.

LeMaster, James C. 2017. "The Relationship of Bacon, Teleology, and Analogy to the Doctrine of Methodological Naturalism." In *Naturalism and Its Alternatives in Scientific Methodologies*, 67–89. Blyth Institute Press.

Levin, Leonid A. 1984. "Randomness Conservation Inequalities; Information and Independence in Mathematical Theories." *Information and Control* 61: 15–37. https://doi.org/10.1016/S0019-9958(84)80060-1.

Luria, S E, and M Delbrück. 1943. "Mutations of Bacteria from Virus Sensitivity to Virus Resistance." *Genetics* 28 (6): 491–511. https://doi.org/10.1093/genetics/28.6.491.

Marks II, Robert J, William A Dembski, and Winston Ewert. 2016. "Conservation of Information in Computer Search." In *Introduction to Evolutionary Informatics*, 105–86. World Scientific.

Mayr, Ernst. 1961. "Cause and Effect in Biology." *Science* 134: 1501–6. https://doi.org/10.1126/science.134.3489.1501.

Mayr, Ernst. 1992. "The Idea of Teleology." *Journal of the History of Ideas* 53: 117–35. https://doi.org/10.2307/2709913.

Mignea, Arminius. 2014. "Developing Insights into the Design of the Simplest Self-Replicator and Its Complexity: Part 2—Evaluating the Complexity of a Concrete Implementation of an Artificial SSR." In *Engineering and the Ultimate: An Interdisciplinary Investigation of Order and Design in Nature and Craft*, edited by Jonathan L Bartlett, Dominic Halsmer, and Mark R Hall, 187–212. Blyth Institute Press. https://doi.org/10.33014/isbn.0975283863.10.

Montañez, George D. 2017. "The Famine of Forte: Few Search Problems Greatly Favor Your Algorithm." In *IEEE International Conference on Systems, Man and Cybernetics (SMC)*, 477–82. IEEE. https://doi.org/10.1109/SMC.2017.8122651.

Montañez, George D. 2018. "A Unified Model of Complex Specified Information." *BIO-Complexity* 2018 (4): 1–26. https://doi.org/10.5048/BIO-C.2018.4.

Montañez, George D, Winston Ewert, William A Dembski, and Robert J Marks II. 2010. "A Vivisection of the Ev Computer Organism: Identifying Sources of Active Information." *BIO-Complexity* 2010 (3): 1–7. https://doi.org/10.5048/BIO-C.2010.3.

Morgan, Conway Lloyd. 1905. *The Interpretation of Nature.* Macmillan.

Morris, Simon C. 2004. *Life's Solution: Inevitable Humans in a Lonely Universe.* Cambridge University Press. https://doi.org/10.1017/CBO9780511535499.

Mossio, Matteo, and Leonardo Bich. 2017. "What Makes Biological Organisms Teleological?" *Synthese* 194: 1089–1114. https://doi.org/10.1007/s11229-014-0594-z.

Nagel, Ernst. 1977. "Goal-Directed Processes in Biology." *The Journal of Philosophy* 74 (5): 261–79. https://doi.org/10.2307/2025745.

Payne, Joshua L, and Andreas Wagner. 2019. "The Causes of Evolvability and Their Evolution." *Nature Reviews Genetics* 20: 24–38. https://doi.org/10.1038/s41576-018-0069-z.

Rice, H G. 1953. "Classes of Recursively Enumerable Sets and Their Decision Problems." *Transactions of the American Mathematical Society* 74 (2): 358–66. https://doi.org/10.2307/1990888.

Robertson, D S. 1999. "Algorithmic Information Theory, Free Will, and the Turing Test." *Complexity* 4 (3): 25–34. https://doi.org/10.1002/(SICI)1099-0526(199901/02)4:3<25::AID-CPLX5>3.0.CO;2-E.

Schneider, Thomas D, Gary D Stormo, Larry Gold, and Andrzej Ehrenfeucht. 1986. "Information Content of Binding Sites on Nucleotide Sequences." *Journal of Molecular Biology* 188 (3): 415–31. https://doi.org/10.1016/0022-2836(86)90165-8.

Thorvaldsen, Steinar, and Ola Hössjer. 2020. "Using Statistical Methods to Model the Fine-Tuning of Molecular Machines and Systems." *Journal of Theoretical Biology* 501. https://doi.org/10.1016/j.jtbi.2020.110352.

Trevors, Jack T, and David L Abel. 2004. "Chance and Necessity Do Not Explain the Origin of Life." *Cell Biology International* 28 (11): 729–39. https://doi.org/10.1016/j.cellbi.2004.06.006.

Turing, Alan M. 1937. "On Computable Numbers, with an Application to the Entscheidungsproblem." *Proceedings of the London Mathematical Society* s2-42 (1): 230–65. https://doi.org/10.1112/plms/s2-42.1.230.

Turing, Alan M. 1939. "Systems of Logic Based on Ordinals." *Proceedings of the London Mathematical Society* s2-45: 161–228. https://doi.org/10.1112/plms/s2-45.1.161.

Turner, J S. 2017. *Purpose and Desire.* HarperOne.

van Rooij, Iris. 2008. "The Tractable Cognition Thesis." *Cognitive Science: A Multidisciplinary Journal* 32 (6). https://doi.org/10.1080/03640210801897856.

Woese, Carl R. 2004. "A New Biology for a New Century." *Microbiology and Molecular Biology Reviews* 68 (2): 173–86. https://doi.org/10.1128/MMBR.68.2.173-186.2004.

Wolfram, Stephen. 2002. *A New Kind of Science.* Wolfram Media.

Woodward, John R, and Ruibin Bai. 2009. "Why Evolution Is Not a Good Paradigm for Program Induction: A Critique of Genetic Programming." In *Proceedings of the First ACM/SIGEVO Summit on Genetic and Evolutionary Computation*, 593–600. Association for Computing Machinery. https://doi.org/10.1145/1543834.1543915.

Yampolskiy, Roman V. 2018. "Why Do We Not Evolve Software? Analysis of Evolutionary Algorithms." *Evolutionary Bioinformatics* 14: 1–11. https://doi.org/10.1177/1176934318815906.

Yockey, Hubert. 2000. "Origin of Life on Earth and Shannon's Thoery of Communication." *Computers and Chemistry* 24: 105–23. https://doi.org/10.1016/s0097-8485(99)00050-9.

Zhang, Zongghe, Jing Wang, Maksim A Shlykov, and Milton H Saier Jr. 2013.
    "Transposon Mutagenesis in Disease, Drug Discovery, and Bacterial Evolu-
    tion." In *Stress-Induced Mutagenesis*, edited by D Mittelman, 59–77. Springer.
    https://doi.org/10.1007/978-1-4614-6280-4_4.