Is any pattern nonreal?

McAllister, J.W.; Millhouse, T.; Petersen, S.; Ross, D.

This is a portion of the eBook at doi:10.7551/mitpress/15550.001.0001

7 Is Any Pattern Nonreal?

James W. McAllister

7.1 Introduction

The concept of pattern has been part of the toolbox of philosophy of cognition and science for over sixty-five years. Its value stems from its hybrid nature: A pattern is neither entirely of the world nor entirely of the knower. First, a pattern inheres in concrete experience, yet simultaneously represents an abstraction from it. Second, while it is an objective feature of a data string, a pattern acquires significance only once an observer individuates it. As a consequence, writers have turned to the concept of pattern as a resource to explain how cognition and science constructed stable, broad structures in the world from strings of observations.

One of the first was Norwood R. Hanson. In *Patterns of Discovery*, Hanson argued that observation in science was theory laden, meaning that what scientists observed was influenced by their theories and conceptual frameworks. As Hanson put it, “Physical theories provide patterns within which data appear intelligible. . . A theory is not pieced together from observed phenomena; it is rather what makes it possible to observe phenomena as being of a certain sort, and as related to other phenomena” (Hanson 1958, 90).

Building on this idea, James Bogen and James Woodward (1988) reexamined the relation between theory and observation. They argued that empirical data, due to their idiosyncratic nature, could neither effectively test scientific theories nor serve as their explananda. Instead, they introduced an intermediary based on the notion of pattern. Patterns in empirical data, they suggested, constituted evidence of what they termed “phenomena”—fundamental and stable modes in which reality was articulated. Phenomena, in turn, were the explananda of scientific theories.

Empirical data exhibit many patterns. The world, however, in Bogen and Woodward’s view, comprised a relatively small number of phenomena. This raised a crucial question: How we could tell whether a particular pattern was evidence of a phenomenon? I criticized Bogen and Woodward’s proposal for, as I saw it, failing to provide a coherent answer to this question (McAllister 1997).

Daniel C. Dennett (1991) independently proposed a similar role for patterns. His "real patterns" hypothesis suggested that cognition consisted largely in detecting patterns in experience. Among these patterns, some—the "real" ones—corresponded to structures in the world and constituted evidence of them. Other patterns were spurious and did not reflect anything in the world. Dennett recognized the need to distinguish real and spurious patterns, proposing projectability and economy of description as criteria.

James Ladyman and Don Ross (2007) adopted Dennett's real patterns hypothesis within a structural realist framework. Structural realism holds that what is real is not individual entities, but rather structures. These structures are also what scientific theories describe. Patterns in empirical data, Ladyman and Ross argued, were evidence of these fundamental structures. Like Dennett, they acknowledged the need to differentiate real patterns from spurious ones: They refined Dennett's criteria in order to close what they saw as loopholes.

In this contribution to the debate, I critically examine the real patterns hypothesis, focusing on the distinction that it draws between patterns in empirical data that correspond to structures in the world and patterns that do not. I argue that there is no means available to partition the infinite number of patterns that we can discern in empirical data into these two classes. In particular, the criteria that Dennett, Ladyman, and Ross have proposed are insufficient. I argue that, as a consequence, we are obliged to regard all patterns in data as having an equally strong claim to correspond to structures in the world. In short, if any pattern is real, then all patterns must be.

The chapter proceeds as follows. I review the epistemology and methodology of the approach that construes patterns in empirical data as evidence of structures in the world in sections 7.2 and 7.3. One conclusion is that there are infinitely many ways to decompose a dataset into pattern and noise. How should we respond to this multiplicity? In section 4, I explore the hypothesis that only some patterns in data constitute evidence of structures in the world, and I explain why it must offer criteria for distinguishing real and bogus patterns. In section 7.5, I reconstruct the criteria proposed by Dennett, Ladyman, and Ross, and critique them in section 7.6. In section 7.7, I turn to the alternative option: Accepting that all patterns in data constitute evidence of structures in the world. I present positive reasons for this view. In section 7.8, lastly, I summarize and discuss the implications for the real patterns hypothesis.

7.2 Epistemology of Patterns

Empiricism asserts that all our evidence about the world comes in the form of empirical data. The world as a whole generates each measurement outcome, every data point, and thus the entirety of any empirical dataset. In most cases, of course, scientists investigate not the world as a whole but individual structures within it. Since these structures are causal components of the world, we assume that each one gives rise to a component of the empirical datasets that the world generates. Evidence of individual structures in the world consists, therefore, of patterns exhibited in empirical datasets.

More precisely, we assume two reciprocal relations between structures in the world and patterns in empirical data. The first is causal-explanatory: Structures in the world cause, and therefore also explain, patterns in data. The second is evidential: Patterns in data are evidence of structures in the world. The causal-explanatory relation ensures the evidential significance of patterns: If patterns in data were not caused by structures, they would not convey information about them. Conversely, the evidential relation places a condition on the knowability of structures in the world: If a structure caused no pattern in data, we would have no epistemic access to it.

This means that our individuation of structures in the world depends on patterns in empirical data. The only way to ascertain the presence of a particular structure in the world is by finding a pattern in data that we label as its effect. Similarly, any distinction that we make among structures in the world must be reflected in patterns in data if it is not to be otiose. If we distinguish between two structures in the world, S_1 and S_2, then we must be able to indicate a respect in which a pattern in data that corresponds to S_1 differs from a pattern that corresponds to S_2. This requirement holds even when distinctions between structures are first made on theoretical grounds: Even theoretical posits must, sooner or later, demonstrate empirical significance.

Two examples from scientific practice illustrate the relation between structures in the world and patterns in data. In the first example, a distinction between structures reflects a difference between patterns; in the second, the inability to find a difference between certain patterns nullifies a proposed distinction between structures.

Chaos theorists distinguish two classes of phenomenon in the world: Ordered and chaotic. Each of these manifests itself in a recognizable class of pattern in data: Ordered phenomena are exhibited in periodic patterns, which appear as closed loops in state space, whereas chaotic phenomena are exhibited in nonperiodic patterns, which appear as unbounded phase space trajectories (Motter and Campbell 2013). This correspondence links properties of phenomena—ordered and chaotic behaviors—to which we have no direct epistemic access, to properties of patterns—periodicity and nonperiodicity—that are detectable in empirical data. We think that chaotic behavior in a phenomenon causes nonperiodicity in a pattern, and, reciprocally, that nonperiodicity in a pattern is evidence of the chaotic nature of a phenomenon; and the same for ordered behavior and periodicity. A difference among patterns in data empirically grounds a distinction between structures in the world.

Conversely, scientists regard an absence of difference in the former domain as invalidating distinctions drawn in the latter. For example, nineteenth-century physicists were led by theoretical considerations to hypothesize two distinct phenomena of electromagnetic induction, an effect in which an electric current arose in a conductor through interaction with a magnet. These differed depending on whether the conductor or the magnet was at rest or in motion with respect to the reference frame of the electromagnetic ether. The explanations of the rise of the current in the two cases invoked different physical mechanisms, one involving an electromotive force, the other an electric field.

As Albert Einstein noted in 1905, however, the difference between the two purported phenomena did not appear in the empirical evidence. The evidence took the form of patterns in empirical data consisting of galvanometer readings plotted against the velocities of the conductor and magnet. The patterns caused by a moving conductor were indistinguishable from those caused by a moving magnet. Einstein concluded that electromagnetic induction was a single phenomenon dependent solely on the relative motion of conductor and magnet, rendering the concept of ether irrelevant (Hon and Goldstein 2005, 479–491). The lack of a difference between patterns in data that corresponded to the two states of motion relative to the ether made the distinction between the two purported phenomena untenable, despite initial theoretical reasons for it.

These examples reinforce the principle that differences in the domain of patterns in empirical data are our only guide to differences in the domain of structures in the world.

7.3 Methodology of Patterns

Now for methodological aspects of this approach. A pattern exhibited in an empirical dataset is, according to this view, an additive component of it. If a dataset $E(x)$ is a string of digits of length L, then a pattern $A(x)$ within it is a string of length L such that the sum of $A(x)$ and of a second term, $R_A(x)$, also of length L, yields $E(x)$.

Empirical datasets in science typically have high algorithmic complexity, being the outcome of an indefinitely large number of causal factors. In contrast,

$A(x)$ generally has much lower algorithmic complexity—a pattern that we pick out from an empirical dataset typically shows much more regularity than the original data. This means that $A(x)$ can be generated by a formula much shorter than L. The remainder, $R_A(x)$, lastly, has algorithmic complexity approximately equal to that of $E(x)$: If a regular term is subtracted from an irregular term, what is left must be irregular.

The process by which scientists mine empirical data for evidence about structures in the world therefore consists of expressing an empirical dataset, $E(x)$, as the sum of two components: $A(x)$, a term that the scientists propose as evidence of a particular structure in the world, and $R_A(x)$, a remainder. This amounts to decomposing a dataset into pattern and noise. The noise term, $R_A(x)$, as defined here, is nothing other than the mathematical remainder left when $A(x)$ is subtracted from $E(x)$. Whereas some may think of $R_A(x)$ as an error term, there is nothing at this stage to suggest that it is the product of any observational or other error or corresponds to any misdescription of the world: It is simply a component of the empirical dataset not currently of interest.

Mathematically, any empirical dataset of length L can be decomposed into any one of all patterns of length L and the associated noise term. We may express $E(x)$ as $A(x) + R_A(x)$, as $B(x) + R_B(x)$, as $C(x) + R_C(x)$, and so on without end. The patterns thus picked out, $A(x)$, $B(x)$, $C(x)$, and so on, differ in mathematical form and algorithmic complexity; the noise terms with which they are exhibited in the dataset, $R_A(x)$, $R_B(x)$, $R_C(x)$, and so on, vary in magnitude.

Scientists routinely exploit the fact that a given empirical dataset can be decomposed into multiple pattern–noise pairs. They associate each of the patterns in this multiplicity with a different causal structure in the world, which they take to explain the pattern. This underlines two things. First, a typical empirical dataset contains information about many more causal structures in the world than just one. Second, patterns in data that scientists interpret as evidence of structures differ widely in mathematical form, in algorithmic complexity, and in the noise levels with which they are exhibited (Petersen 2023).

Two examples illustrate this multiplicity. The first pertains to spatial variations in sea surface topography. We measure sea surface heights relative to a reference frame based on the lithosphere. A global dataset of sea surface heights at a particular time has high algorithmic complexity. Oceanographers identify several different patterns in this dataset, which they take as evidence of distinct causal factors acting on sea water. One pattern consists of an ellipsoid: Mean sea level at the equator is around twenty kilometers higher than at the poles. Oceanographers attribute this pattern to the earth's rotation. A second pattern consists of "hills" and "valleys" on large geographical scales: For example, mean sea level around Iceland is some 150 meters higher than around Sri Lanka. Oceanographers attribute this pattern to variations in the earth's gravitational field due to inhomogeneous mass distributions in the crust and mantle. Further patterns consist of complex variations on regional and local scales: For example, mean sea level at the Pacific end of the Panama Canal is around 0.2 meters higher than at the Atlantic end. Oceanographers attribute these patterns to a variety of causal factors, including tides, currents, wind forcing, variations in atmospheric pressure, and variations in water density caused by temperature and salinity differences (Pugh and Woodworth 2014, 223–251).

These patterns correspond to alternative ways of accounting for the variance of the sea surface height dataset by decomposing it into a pattern and an associated noise term: They are superposed on one another in the dataset. They illustrate a trade-off, often seen in science, between a pattern's algorithmic complexity and the magnitude of the noise term with which it is exhibited in the data. For example, the pattern consisting of the ellipsoid has low algorithmic complexity and is exhibited in the global dataset with a high noise level: That is, there are relatively large discrepancies between the ellipsoid and actual sea surface heights around the globe. On the other hand, the patterns on the smaller spatial scales have higher algorithmic complexity than the ellipsoid and are exhibited in the dataset with lower noise levels: They track the measurement data more closely.

The second example concerns temporal variations in photosynthetic activity in evergreen conifers. Botanists have identified multiple patterns on different temporal scales in measurements of the photochemical reflectance index, an indicator of photosynthetic activity, attributing each of them to a distinct physiological process. One is a diurnal pattern: Botanists have explained this as the result of interconversion of xanthophyll pigments, which allows the tree to balance photosynthesis and photoprotection under varying light conditions. A second pattern has a period of a few days: Botanists have attributed this to changes in leaf albedo caused by fluctuating water retention in warm and cold weather spells. A third pattern is seasonal: Botanists have explained this as the effect of changing ratios of chlorophyll and carotenoid pigments in the leaves (Wong and Gamon 2015).

Again, these patterns represent different ways of analyzing an empirical dataset into pattern and noise. Each pattern is taken to correspond to a different causal process in the world, each has a different mathematical form and algorithmic complexity, and each is exhibited in the dataset with a different noise level. There are many similar examples in all branches of science (McAllister

2010, 807–808; 2011, 77–79): They illustrate the wide variety of patterns in empirical data that scientists have successfully taken as evidence of structures in the world.

7.4 Some Patterns or All?

As we have noted, there are infinitely many ways to decompose a dataset into pattern and noise. This creates a puzzle for anyone who believes that evidence of structures in the world comes in the form of patterns in empirical data. How many of these patterns are evidentially significant, and which patterns are they?

There are two possible answers: Either only some patterns in an empirical dataset correspond to structures in the world, or all do. Most writers have favored the first view. I shall therefore start by exploring this option, which I shall call "bipartition thesis"; I shall return to the second option in section 7.7.

The appeal of the bipartition thesis is clear. It accords with the view that the world is composed of a univocal, determinate, and perhaps relatively small set of structures that clearly shine through in empirical data. It says that some patterns that empirical data exhibit are caused by these structures in the world, and thereby constitute evidence of them. Other patterns have no evidential significance. It must be that the latter are not caused by anything in the world: If they were, then they would bear traces of their causes and thus constitute evidence of them. They must thus arise spontaneously or randomly in the data.

The bipartition thesis is a special case of a familiar class of claims in science: Claims that a specific set of structures in the world causes some patterns that we find in empirical data but not others. We encountered other cases in section 7.2. Chaos theorists maintain that particular structures in the world—chaotic phenomena—cause some patterns in empirical data but not others. Similarly, some nineteenth-century physicists believed that the phenomenon of electromagnetic induction in which the magnet was at rest relative to the ether caused some patterns in empirical data but not others. The bipartition thesis differs from these claims in scope: It ranges over the totality of causal structures in the world rather than just a particular kind. It does not differ from these more restricted claims in form, however.

As a consequence, the bipartition thesis faces the same challenge as these more restricted claims: It must explain how patterns in empirical data of the two sorts differ. Our earlier discussion of the epistemology of patterns concluded that differences among patterns in data were our only basis for positing distinctions between structures in the world, and any distinction in the latter domain had to be reflected in a difference in the former. If we maintain that chaotic phenomena cause some patterns in data but not others, for example, then we need to identify some difference between patterns caused by those structures and other patterns. Chaos theorists meet this challenge by saying that patterns in data caused by chaotic phenomena are nonperiodic, whereas other patterns are periodic. Conversely, Einstein observed that the absence of differences between patterns in data undermined the distinction between phenomena of electromagnetic induction in which the magnet and the conductor was at rest relative to the ether.

Proponents of the bipartition thesis must similarly demonstrate that the difference between patterns that are and are not evidence of structures in the world is empirically detectable. Failing to identify a difference between patterns of the two sorts would lead to skepticism about causal structures. If nothing distinguished patterns in empirical data that were caused by the world from patterns that were not, what need would there be to posit structures in the world at all? Empirical data would show patterns of the same sorts even if no structures existed to cause them. The bipartition thesis would then undermine itself: An account devised to explain how we could draw inferences about causal structures in the world from patterns in empirical data would end up casting doubt on the existence of structures themselves.

7.5 Candidate Criteria for Real Patternhood

How might we identify a difference between patterns that are evidence of structures in the world and patterns that are not? At the outset, we must acknowledge two restrictions. First, we may not rely on an assumption, expectation, belief, or purported knowledge that the world contains a particular structure. In this metaphysical project, we are investigating which patterns correspond to structures in the world before we know which the latter are; we cannot, therefore, presuppose particular structures in the world. We cannot respond to Einstein that the difference between patterns in electromagnetic induction data is that some patterns result from the motion of the conductor and others from the motion of the magnet relative to the ether: That would presuppose the very distinction that Einstein brought into question. In distinguishing between real and other patterns, similarly, we may not avail ourselves of any conclusion that assumes such a distinction.

Second, a criterion to distinguish between patterns that are and are not evidence of structures in the world must not depend on decisions, choices or stipulations made by us knowers, such as might follow from our cognitive interests or pragmatic preferences. The demarcation must depend solely on how the world is, not on our wishes or conventions. For example, we may not declare that only patterns exhibited in datasets with a noise level below 10% are evidence of structures in the world: A conventional threshold cannot serve as a guide to ontology. A preference that would be legitimate when choosing a pattern for some attractive or advantageous characteristic in order to work on it would not be admissible in the task of demarcating patterns into classes that had and lacked physical significance.

These two restrictions mean that any difference between patterns that have and patterns that lack evidential significance must consist of features that are both objective and detectable in empirical data. Still, these restrictions allow several possible accounts of the difference.

Dennett proposed two criteria for distinguishing "real" patterns in empirical data, which constituted evidence of structures in the world, from "bogus" patterns, which did not (Dennett 1991, 29). On Dennett's first criterion, a pattern in a given dataset was real if it provided a more economical encoding of the data than a bit map, or bit-by-bit transcription of the dataset: "A pattern exists in some data—is real—if there is a description of the data that is more efficient than the bit map, whether or not anyone can concoct it" (Dennett 1991, 34; Millhouse 2021). This wording implied that pattern reality coincided with existence, but the rest of the article made it clear that Dennett thought that bogus patterns existed too.

On Dennett's second criterion, a pattern in data was real if it was projectable, meaning that it could be used to make better-than-chance predictions about future occurrences. As Dennett pointed out, many distinct patterns exhibited in the same dataset with different noise levels could all lead to good predictions, implying that many patterns were real or that real patternhood was relative to an observer's tolerance for noise (Dennett 1991, 35–36).

Structural realists, too, have assumed that only some patterns in empirical data were real or corresponded to structures in the world. As Ladyman and Ross put it, "for a pattern to be real" is "for the object of a scientific theory or other description to be deemed an aspect of objective reality" (Ladyman and Ross 2007, 36).

Structural realists had good reason to take the view that the number of real patterns was limited. Structural realism arose as an alternative to traditional scientific realism. It lowered the bar for a scientific theory to achieve truth approximation: Instead of requiring a theory to describe correctly the entities that the world contained and their properties, structural realists demanded success only in capturing fundamental causal structures (Worrall 1989, 117–121). This meant that theories, to demonstrate truth approximation, no longer needed to account for all details of empirical data, as long as they accounted for significant patterns in them. The smaller the number of fundamental structures and significant patterns, the clearer the difference between structural realism and traditional scientific realism.

Ladyman and Ross agreed with Dennett that, for a pattern to be real, it should support predictions about unobserved occurrences. However, they wished to avoid the two outcomes that Dennett seemed to allow: An explosion in the number of real patterns and the relativity of real patternhood to an observer's noise tolerance (Ladyman and Ross 2007, 206). Ladyman and Ross thought that a conjunction of three criteria would be sufficient to block these outcomes. On their definition, a pattern is real just if:

> (i) it is projectible; and
>
> (ii) it has a model that carries information about at least one pattern P in an encoding that has logical depth less than the bit-map encoding of P, and where P is not projectible by a physically possible device computing information about another real pattern of lower logical depth than [the candidate pattern]. (Ladyman and Ross 2007, 233)

Condition (i) and the first part of condition (ii) incorporated Dennett's criteria of predictive power and economical encoding. The second part of condition (ii) prescribed that no other pattern should offer a more economical encoding, thereby linking real patternhood to predictive indispensability (Suñé and Martínez 2021).

In the next section, I shall examine the two key ideas underlying the approach of both Dennett and the structural realists—projectability and economy of description—as criteria for real patternhood. Before doing so, I will briefly outline two objections to the second part of Ladyman and Ross's condition (ii). I believe that it violates both the preliminary restrictions discussed earlier.

My first objection concerns the reference to a "physically possible device" in condition (ii). This reflects Ladyman and Ross's belief that projectability should be assessed from the perspective of our best current science: As they explained, "A pattern, to be real, must be projectible from a perspective that physics tells us could be physically occupied" (Ladyman and Ross 2007, 236). This reference breaches the first of my two preliminary restrictions, namely that we may not presuppose an assumption, expectation, belief, or purported knowledge that the world contains a particular structure in demarcating real patterns from bogus ones. If we are to demarcate patterns that are evidence of structures in the world from patterns that are not, we cannot help ourselves to conclusions of current science about which structures the world contains. Ladyman and Ross's appeal to current physics does just that.

Second, the effect of the second part of condition (ii) is that no more than one pattern in any given dataset counts as real. If two patterns, $A_1(x)$ and $A_2(x)$, encode the same dataset, but $A_2(x)$ is of lower logical depth or is more economical, then $A_1(x)$ is disqualified as real pattern. Ladyman and Ross offer no reason for thinking that only one pattern in a given empirical dataset is caused by or corresponds to a structure in the world, however. In the absence of such a reason, theirs is a purely pragmatic choice—it makes it easier to pick out a small set of patterns to designate as real. This violates the second of my two preliminary restrictions, namely that we may not allow a demarcation of real from bogus patterns to depend on decisions, choices, or stipulations made by us knowers.

7.6 Projectability and Economy of Description

We now turn to the two main ideas proposed by Dennett and structural realists to differentiate between real patterns from bogus ones: Projectability and economy of description.

The first proposal is that a pattern in empirical data is real, or is evidence of a structure in the world, just if it is projectable. A pattern is projectable if it is exhibited in a dataset broader than the one in which it is first identified, thereby allowing successful predictions. As Ladyman and Ross explained, "We want to associate the distinction between projectible and non-projectible patterns with the distinction between what's real and what isn't" (Ladyman and Ross 2007, 228).

This proposal is based on the intuition that a pattern that leads to a successful prediction has a stronger claim to reality than a pattern that does not. While scientists can easily fit multiple patterns to existing empirical data, we might reason, the stricter test comes when they check these patterns against future data. Patterns that persist in the new data seem more likely to correspond to structures in the world. In Ladyman's view, projectability "provides a criterion of ontological commitment: Real patterns are those that indispensibly figure in projectible generalizations that allow us to predict and explain the behavior of the world" (Ladyman 2017, 157).

But what does saying that a pattern is or is not projectable amount to? Consider a pattern observed in an initial dataset, *A*. This pattern is projectable if it is replicated in a subsequent dataset, *B*. Patterns, however, are exhibited in empirical datasets with certain noise levels, as we know: A more precise definition of projectability needs to reflect this fact. Suppose two patterns, $P(x)$ and $Q(x)$, are exhibited in *A* with a noise level of $n\%$. $P(x)$ is projectable if it is subsequently exhibited with a noise level no higher than $n\%$ also in *B*. This amounts to the confirmation of a prediction. Under what condition would $Q(x)$ be nonprojectable, by contrast? This condition cannot be that $Q(x)$ is not exhibited in *B* at all: After all, we can be sure that we can express *B* as the sum of $Q(x)$ and some noise level or other. Rather, $Q(x)$ is nonprojectable presumably if the noise level with which it is exhibited in B is higher than $n\%$. This amounts to the disconfirmation of a prediction.

These outcomes may represent interesting discoveries about datasets A and B. They do not, however, indicate that pattern $P(x)$ has any greater claim to correspond to a structure in the world than $Q(x)$. The fact that $P(x)$ is exhibited in both A and B with the same noise level, while $Q(x)$ is exhibited in B with a higher noise level than in A, has no bearing on the ontological question of which of them are evidence of structures in the world and which are not. It merely causes us to revise our estimate of the noise level with which $Q(x)$ is exhibited in B.

The concept of projectability is useful for keeping track of the scope of our claims: We often want to know whether a claim that we have established about a dataset A—namely, that a pattern $P(x)$ is exhibited in it with a noise level of $n\%$—holds also for a subsequent dataset B. As a criterion for distinguishing real from other patterns, however, it would serve only if we had reason to believe that patterns were evidence of structures in the world if and only if the noise level with which they were exhibited in B were no higher than that with which they were exhibited in A. This suggestion is implausible: It amounts to tying reality of patterns to an arbitrary noise threshold—in this example, $n\%$.

The projectability criterion, in short, offers no solution to the problem of distinguishing real patterns from other patterns. As Dennett noted, patterns exhibited in empirical datasets with different noise levels can all support successful predictions. Absent some reason for thinking that a certain noise level picks out patterns that have more claim to correspond to structures in the world, all patterns have equal such claim.

The irrelevance of the temporal sequence of making and verifying predictions to the ontological question is also evident in the following example. Consider an ultimate dataset, U, encompassing all observations made in science. Presumably, U provides the most reliable empirical base for establishing which structures the world contains. However, U exhibits all possible patterns, each with a certain noise level. The real patterns hypothesis assumes that some of the patterns displayed in U correspond to structures in the world, while others do not. But what distinguishes patterns belonging to these two categories? Clearly, the historical sequence in which we ascertained the noise levels associated with patterns in U is irrelevant for resolving this question.

Next, consider the criterion of economy of description, which associates real patternhood with a pattern's ability to encode data economically. Both Dennett and structural realists have suggested this as key to distinguishing real patterns from bogus ones. Yet, this criterion too falls short, or so I argue.

An economical description of a dataset typically consists of two items: A concise formula that generates a regular pattern and a bit-by-bit record of the discrepancies between the data and this pattern. Expressing the data in terms of these two items is typically more economical than a pure bit-by-bit transcription if the pattern accounts for a large part of the variance of the data, so the bit-by-bit element need contain less information.

The claim that a pattern's ability to compress a dataset reveals whether the pattern is physically significant is implausible, for the following reason. The effectiveness of a particular pattern in compressing a given dataset depends on two things: The form of the pattern and the bit-by-bit value of the dataset. The latter depends partly on the amount of noise that it contains, however. The amount of noise in a dataset is unrelated to the properties of the pattern. This suggests that the degree to which a pattern compresses a dataset tells us very little about the properties of the pattern.

Suppose we collect a certain empirical dataset, $E(x)$, in an experiment. This exhibits two patterns: $P_A(x)$, a real pattern that is caused by a structure in the world, A, and $Q(x)$, a bogus pattern that is not caused by anything. Suppose the most economical compression of $E(x)$ is in terms of $P_A(x)$—that is, as the sum of $P_A(x)$ and its associated noise term. In this case, economy of description would correctly designate $P_A(x)$ as a real pattern, and $Q(x)$ as nonreal.

But now consider the following. The noise term with which $P_A(x)$ is exhibited in the dataset is, of course, $E(x) - P_A(x)$. This noise term is the effect of various causal structures in the world distinct from A. Call this combination of structures B. We can rearrange the causal chains in the world in such a way that structure A interacts not with B but with a new set of causal factors, B', to generate a second empirical dataset, $E'(x)$, in a new experiment. Structure A in the world still causes its distinctive pattern, $P_A(x)$, which is displayed in the new dataset, $E'(x)$, with noise term $E'(x) - P_A(x)$.

By carefully choosing the new set of causal factors, B', we can determine the magnitude and distribution of the new noise term, $E'(x) - P_A(x)$, as we please. This means that we can ensure that $P_A(x)$ accounts for less of the variance of $E'(x)$ than $Q(x)$ does. As a consequence, we can ensure that the most economical compression of the new empirical dataset, $E'(x)$, is in terms of $Q(x)$, and no longer of $P_A(x)$. $Q(x)$ was, as we stipulated, a bogus pattern. This shows that economy of description is not a reliable criterion of evidential significance: It designates a pattern as having evidential significance, or as corresponding to a structure in the world, when exhibited in one dataset with one noise term, but as lacking evidential significance when exhibited in another.

In essence, which pattern economy of description picks out as real depends on the overall value of a dataset, and thus on the amount of noise that it contains. That is not a desirable characteristic for a criterion of real patternhood.

In passing, it is worth noting that this argument establishes more generally that a pattern's evidential significance cannot depend on the properties of the noise term with which it is exhibited in empirical data. No noise term, irrespective of its properties—in particular, its magnitude and whether it contains patterns of its own—can be grounds for ruling a pattern as lacking evidential significance. This is understandable: The properties of something that is only contingently associated with a pattern—the noise with which it is exhibited in a given dataset—cannot determine whether it corresponds to a structure in the world.

In conclusion, projectability and economy of description do not provide adequate criteria for distinguishing patterns that correspond to structures in the world from those that do not. The properties suggested as features distinguishing real patterns are, in fact, shared by all patterns found in empirical data (Beni 2017, 291–297).

Of course, projectability and economy of description are not the only conceivable ways for distinguishing real from bogus patterns. Other options include consilience, the idea that patterns in different datasets that constitute evidence of the same structures in the world are real, and grounding, the notion that we are justified in regarding a pattern in a given dataset as real in the light of discoveries about other patterns in previous datasets. I refer to other work for critical scrutiny of these further proposals (McAllister 2010, 808–809; 2011, 79–81).

7.7 All Patterns Are Real

Half-way through this chapter, we came to a pivotal choice. The fact that, mathematically, any empirical dataset could be expressed as the sum of any possible pattern of the appropriate length and an associated noise term gave us two options. The first was to say that only some patterns in data were evidence of structures in the world—what I called the bipartition thesis; the second was to say that all patterns were. We have thoroughly examined the first option. I argued that a distinction between patterns that did and that did not correspond to structures in the world would be otiose without a criterion for recognizing the two sets of patterns in empirical data. I contended that no such criterion existed, especially not in the forms envisaged by proponents of the real patterns hypothesis.

Now, let us consider the alternative view: That all patterns in data constitute evidence of structures in the world.

There are compelling grounds for supporting this conclusion. A pattern is simply an additive component of an empirical dataset. Since the world is the cause of the entirety of the variability of empirical data, it follows that any additive component of a dataset must be caused by some subset of causal factors in the world. In other words, regardless of how we pick out a pattern, there must be something in the world that generates it; if nothing did, then the magnitude of the dataset as a whole would also be undetermined. While the specific subset of causal factors in the world responsible for a given pattern may be unknown or unclear, it is undeniable that such factors exist, and that the given pattern is a trace of them in the data. Thus, any pattern exhibited in empirical data constitutes evidence of some structure in the world.

To illustrate, recall our dataset on sea surface heights. The totality of causal factors acting on the oceans ensures the overall measurement outcomes of sea surface heights that oceanographers obtain. Now take an arbitrary pattern, *S*, in those data: There exists a subset of causal factors affecting sea water that determines the magnitude of the additive component of the data that corresponds to *S*. Pattern *S* is, therefore, evidence of that subset. If that subset did not exist, the overall measurement outcomes would be undefined.

Some might object to this view by noting that science has yet to pinpoint causal factors behind the vast majority of patterns that we might pick out in empirical data. That is true, but unsurprising given the current, incomplete stage of scientific knowledge and the selective cognitive and practical interests of investigators. Another objection might be that there is no evidence of a physical factor responsible for an arbitrary pattern that is discernible in empirical data. This objection is misguided, however: The pattern itself is that evidence. Empirical evidence of structures in the world never consists of anything more than patterns in data. For instance, the patterns identified by oceanographers in sea surface height data are themselves the only empirical evidence of the physical processes responsible for them.

We may further test this view by scrutinizing one of its implications. If every component of an empirical dataset constitutes evidence of structures in the world, then even what is designated as the noise term for a particular research project must contain information about some structure in the world, albeit not one pertinent to that project's focus. In other words, noise in one context must be signal in another.

I believe this to be the case. What we call noise is also the result of causal influences in the world. We may label these as extraneous causes, perturbations, accidents, or confounding factors, and characterize them as random, irregular, incidental, or ephemeral. For all that, these factors are genuine components of the world's causal structure, and analyzing noise can unlock information about them. Indeed, scientists often make advances by reanalyzing components of empirical data previously dismissed as noise and extracting valuable information about further structures in the world. This suggests that the partition of a dataset into pattern and noise is contingent on the aims of a particular research project and corresponds to no objective difference among causal factors in the world, confirming that all discernible patterns in empirical data correspond to structures in the world.

There are numerous historical examples of the discovery of useful information in what was previously classed as noise. To give just one instance, astrophysicists using ground-based observation to study star spectra disregarded the absorption lines caused by atmospheric ozone in spectrographs as noise in their data: These lines were not relevant to the study of stellar spectra. However, R. Elizabeth Griffin (2005) reanalyzed those data to answer a question in a different branch of science: How ozone levels in the atmosphere varied during the twentieth century. What was noise for astrophysicists studying stellar spectra became evidence for climatologists studying atmospheric pollution.

While all patterns that datasets exhibit correspond to structures in the world, scientists are under no obligation to investigate them all. Most scientists will choose, from the infinitely many patterns available in a given empirical dataset, just one or two that they designate as the evidence in their research project, and attribute the rest of the variability to noise. They may choose these patterns on any criteria they please, of course. In most cases, they will pursue their cognitive and practical interests by choosing patterns on two criteria: A certain mathematical form, such as a polynomial function corresponding to a straight line or a harmonic function corresponding to a sinusoidal curve in a graphical plot, and a certain noise level, which picks out patterns that follow the variance of the data more or less closely. Patterns exhibited with lower noise often correspond to smaller-scale structures, while those exhibited with higher noise correspond to structures on larger scales. Variants of these criteria are also embedded in our sensory and cognitive apparatus, as well as in many observational instruments.

Of course, the pragmatic criteria on which scientists choose which patterns to study do not determine whether a particular pattern has or lacks evidential significance. Pragmatic criteria do not ground metaphysical claims, as we saw above. Indeed, investigators would not need to base choices of patterns on preferences for a certain mathematical form or noise level if it were clear that just some patterns in a given empirical dataset had evidential significance.

I leave open the further question how many distinct structures the world contains. The claim that all discernible patterns in empirical data are evidence of structures in the world does not, by itself, determine how many different structures these are. One possibility is that a single structure in the world gives rise to multiple patterns in data. If so, then the argument presented here would still be compatible with the claim that the world contained a finite and perhaps even relatively small number of distinct structures.

I doubt this view: I prefer to adhere to the principle that our sole way of individuating structures in the world is through patterns in empirical data. Distinct patterns are evidence of distinct structures. This leads me to hypothesize that there are as many distinct structures in the world as there are patterns in empirical data—a metaphysical perspective that I have termed “radically polymorphous” (McAllister 2011, 84–86). This further hunch, however, extends beyond the scope of the present chapter.

7.8 Conclusions

The real patterns hypothesis is a bold attempt to link the evidential content of empirical data, and by extension the ontology of science, to properties of patterns within those data. The hypothesis proposes a distinction between real and nonreal patterns to explain how scientists mine empirical data for evidence about structures in the world.

However, as I have argued, the hypothesis meets a critical problem: There is no criterion to distinguish real patterns from nonreal ones. Once we acknowledge that evidence of structures in the world manifests itself as patterns in empirical data, the very nature of patterns resists any attempt to limit evidential significance to just a subset. This opens up an unexpected ontological vista: All patterns have equal claim to reflect structures in the world. Every discernible pattern in empirical data holds insights into the structure of reality. In the terminology of the hypothesis, all patterns are real.

Some might see this conclusion as a refutation of the real patterns hypothesis. I, however, prefer to see it as complementing the hypothesis and bringing it to its logical fulfillment: The intuition that evidence about structures in the world comes in the form of patterns in data is now extended and placed on a stable footing. This expanded view invites further exploration of what the full spectrum of patterns entails for our understanding of the universe.

7.9 Acknowledgments

I discussed these ideas at the workshops: “Real Patterns,” Universitat de Barcelona, December 2018, “Real Patterns in Science and Cognition” (online), Santa Fe Institute, March 2022, and the 47th Annual Philosophy of Science Conference, Inter-University Centre Dubrovnik, April 2022. I am grateful to the organizers and participants for these opportunities. My thanks go also to the volume editors and three unnamed referees for critical remarks, which prompted me to reconsider several key issues.

References

Beni, M. D. 2017. "Structural Realism, Metaphysical Unification, and the Ontology and Epistemology of Patterns." *International Studies in the Philosophy of Science* 31 (3): 285–300.

Bogen, J., and J. Woodward. 1988. "Saving the Phenomena." *Philosophical Review* 97 (3): 303–352.

Dennett, D. C. 1991. "Real Patterns." *Journal of Philosophy* 88 (1): 27–51.

Griffin, R. E. 2005. "The Detection and Measurement of Telluric Ozone from Stellar Spectra." *Publications of the Astronomical Society of the Pacific* 117 (843): 885–894.

Hanson, N. R. 1958. *Patterns of Discovery: An Inquiry into the Conceptual Foundations of Science.* Cambridge University Press.

Hon, G., and B. R. Goldstein. 2005. "How Einstein Made Asymmetry Disappear: Symmetry and Relativity in 1905." *Archive for History of Exact Sciences* 59:437–544.

Ladyman, J. 2017. "An Apology for Naturalized Metaphysics." In *Metaphysics and the Philosophy of Science,* edited by M. Slater and Z. Yudell. Oxford University Press.

Ladyman, J., and D. Ross. 2007. *Every Thing Must Go.* Oxford University Press.

McAllister, J. W. 1997. "Phenomena and Patterns in Data Sets." *Erkenntnis* 47 (2): 217–228.

McAllister, J. W. 2010. "The Ontology of Patterns in Empirical Data." *Philosophy of Science* 77 (5): 804–814.

McAllister, J. W. 2011. "What Do Patterns in Empirical Data Tell Us About the Structure of the World?" *Synthese* 182 (1): 73–87.

Millhouse, T. 2021. "Compressibility and the Reality of Patterns." *Philosophy of Science* 88 (1): 22–43.

Motter, A., and D. Campbell. 2013. "Chaos at Fifty." *Physics Today* 66 (5): 27–33.

Petersen, S. 2023. "Multiple Patterns, Multiple Explanations." In *Conjunctive Explanations: The Nature, Epistemology, and Psychology of Explanatory Multiplicity,* edited by J. N. Schupbach and D. H. Glass, 38–48. Routledge.

Pugh, D., and P. Woodworth. 2014. *Sea-Level Science: Understanding Tides, Surges, Tsunamis and Mean Sea-Level Changes.* Cambridge University Press.

Suñé, A., and M. Martínez. 2021. "Real Patterns and Indispensability." *Synthese* 198 (5): 4315–4330.

Wong, C. Y. S., and J. A. Gamon. 2015. "Three Causes of Variation in the Photochemical Reflectance Index (PRI) in Evergreen Conifers." *New Phytologist* 206 (1): 187–195.

Worrall, J. 1989. "Structural Realism: The Best of Both Worlds?" *Dialectica* 43 (1-2): 99–124.

This is a section of doi:10.7551/mitpress/15550.001.0001

Dennett's Real Patterns in Science and Nature

Edited by: Tyler Millhouse, Stephen Petersen, Don Ross

Citation:

Dennett's Real Patterns in Science and Nature
Edited by: Tyler Millhouse, Stephen Petersen, Don Ross
DOI: 10.7551/mitpress/15550.001.0001
ISBN (electronic): 9780262052047
Publisher: The MIT Press
Published: 2026

The open access edition of this book was made possible by generous funding and support from MIT Press Direct to Open

The MIT Press

This book was set in Times New Roman by the authors.

Library of Congress Cataloging-in-Publication Data

Names: Millhouse, Tyler editor | Petersen, Stephen editor | Ross, Don, 1962-editor
Title: Dennett's Real patterns in science and nature / edited by Tyler Millhouse, Stephen D. Petersen, and Don Ross.
Description: Cambridge, Massachusetts: The MIT Press, [2026] | Includes bibliographical references and index.
Identifiers: LCCN 2025024102 (print) | LCCN 2025024103 (ebook) | ISBN 9780262052030 paperback | ISBN 9780262052047 pdf | ISBN 9780262052054 epub
Subjects: LCSH: Dennett, D. C. (Daniel Clement)–Influence | Philosophy of mind | Philosophy of science
Classification: LCC B945.D394 D475 2026 (print) | LCC B945.D394 (ebook)
LC record available at https://lccn.loc.gov/2025024102
LC ebook record available at https://lccn.loc.gov/2025024103

EU Authorised Representative: Easy Access System Europe, Mustamäe tee 50, 10621 Tallinn, Estonia | Email: gpsr.requests@easproject.com