The importance of the observer in science

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Abstract

The concept of complexity (as a quantity) has been plagued by numerous contradictory and confusing definitions. By explicitly recognising a role for the observer of a system, an observer that attaches meaning to data about the system, these contradictions can be resolved, and the numerous complexity measures that have been proposed can be seen as cases where different observers are relevant, and/or being proxy measures that loosely scale with complexity, but are easy to compute from the available data. Much of the epistemic confusion in the subject can be squarely placed at science’s tradition of removing the observer from the description in order to guarantee objectivity.

Explicitly acknowledging the role of the observer helps untangle other confused subject areas. Emergence is a topic about which much ink has been spilt, but it can be understood easily as an irreducibility between description space and meaning space. Quantum Mechanics can also be understood as a theory of observation. The success in explaining quantum mechanics, leads one to conjecture that all of physics may be reducible to properties of the observer.

And indeed, what are the necessary (as opposed to contingent) properties of an observer? This requires a full theory of consciousness, from which we are a long way from obtaining. However where progress does appear to have been made, e.g. Daniel Dennett’s Consciousness Explained, a recurring theme of self-observation is a crucial ingredient.

1 Introduction

I have set myself the “humble” task of understanding how evolution leads to continuous generation of complexity and novelty. To circumscribe certain unproductive lines of argument, I take as given that biological evolution proceeds through a perfectly mechanistic process, that there is no supernatural intervention. What remains is the task of reverse engineering the evolutionary process.

Since the 1970s, various evolutionary algorithms 7 have been proposed and implemented on computers. None of these algorithms have clearly demonstrated
open-ended creativity, or growth of complexity[2]. In fact, the very notion of complexity is muddy[6], which is caused by the traditional scientific notion of objectivity as removing the observer from the description[14].

Complexity turns out to be intrinsically observer dependent. This is not the disaster many scientists might fear, however, as in all applicable cases there will be a natural choice of observer. Including the observer into the picture actually simplifies and unifies the disparate notions of complexity that have been proposed.

Complex systems theory is not the only area where including the observer makes theories comprehensible. There are three independent derivations of the fundamental postulates of quantum mechanics, based on assumed properties of the observer. Each of these has a slightly different starting point: Bruno Marchal assumes that an observer is equivalent to some unspecified computer program[10], Roy Frieden starts from Fisher information theory[8], a branch of statistics that predicts the observational error for an ideal observer, and my own derivation starts from an all universes ensemble with zero information, a psychological phenomenon of time (implicitly assumed in both Marchal and Frieden’s approaches) and projection as a model of measurement (observed outcomes are selected from the set of possible observation according to a probability distribution)[15].

2 Complexity as a quantity

We have an intuitive notion of complexity as a quantity; we often speak of something being more or less complex than something else. However, capturing what we mean by complexity in a formal way has proved far more difficult, than other more familiar quantities we use, such as length, area and mass.

In these more conventional cases, the quantities in question prove to be decomposable in a linear way, i.e. a 5cm length can be broken into 5 equal parts 1 cm long; and they can also be directly compared — a mass can be compared with a standard mass by comparing the weights of the two objects on a balance.

However, complexity is not like that. Cutting an object in half does not leave you with two objects having half the complexity overall. Nor can you easily compare the complexity of two objects, say an apple and an orange, in the same way you can compare their masses. However, the earliest attempts at deriving a measure took this approach.

The simplest such measure is the number of parts definition. A car is more complex than a bicycle, because it contains more parts. However, a pile of sand contains an enormous number of parts (each grain of sand), yet it is not so complex since each grain of sand is conceptually the same, and the order of the grains in the pile is not important. Another definition used is the number of distinct parts, which partially circumvents this problem. The problem with this idea is that a shopping list and a Shakespearian play will end up having the same complexity, since it is constructed from the same set of parts (the 26 letters of the alphabet — assuming the shopping list includes items like zucchini, wax
and quince, of course). An even bigger problem is to define precisely what one means by “part”. This is an example of the context dependence of complexity, which we’ll explore further later.

Bonner and McShea have used these (organism size, number of cell types) and other proxy complexity measures to analyse complexity trends in evolution. They argue that all these measures trend in the same way when figures are available for the same organism, hence are indicative of an underlying organism complexity value. This approach is of most value when analysing trends within a single phylogenetic line, such as the diversification of trilobates.

2.1 Information as Complexity

The single simplest unifying concept that covers all of the preceding considerations is information. The more information required to specify a system, the more complex it is. A sandpile is simple, because the only information required is that it is made of sand grains (each considered to be identical, even if they aren’t in reality), and the total number of grains in the pile. However, a typical motorcar requires a whole book of blueprints in its specification.

Information theory began in the work of Shannon in the 1940s, who was concerned with the practical problem of ensuring reliable transmission of messages. Every possible message has a certain probability of occurring. The less likely a message is, the more information it imparts to the listener of that message. The precise relationship is given by a logarithm:

\[ I = -\log_2 p \]  

where \( p \) is the probability of the message, and \( I \) is the information it contains for the listener. The base of the logarithm determines what units information is measured in — base 2 means the information is expressed in bits. Base 256 could be used to express the result in bytes, and is of course equivalent to dividing equation (1) by 8.

Writing the probability of a symbol \( x \) drawn from an alphabet \( A \) appears in message \( s \) as \( p(x) \), equation (1) can be approximated:

\[ I(s) \approx \sum_{i=1}^{n} \sum_{x_i \in A} p(x_i) \log_2 p(x_i). \]  

Shannon, of course, was not so interested in the semantic content of the message (ie its meaning), rather in the task of information transmission so the probability distributions \( p(x) \) were simply those of the symbols for the language in question, eg English, for which the letter ‘e’ is considerably more likely than the letter ‘q’. This equation can be refined by considering possible pairs of letters, then possible triplets, in the limit converging on the minimum amount of information required to be transmitted in order for the message to be reconstructed in its original form. That this value may be considerably less that just sending the original message in its entirety is the basis of compression algorithms, such as those employed by the well-known gzip or PKzip (aka WinZip) programs.
B is more complex (or has greater information) than A, because the set \( B \) is smaller than \( A \).

The issue of semantic content discouraged a lot of people of applying this formalism to complexity measures. The problem is that a message written in English will mean something to a native English speaker, but be total gibberish to someone brought up in the Amazon jungle with no contact with the English speaking world. The information content of the message depends on exactly who the listener is! Whilst this context dependence appears to make the whole enterprise hopeless, it is in fact a feature of all of the measures discussed so far. When counting the number of parts in a system, one must make a decision as to what exactly constitutes a part, which is invariably somewhat subjective, and needs to be decided by consensus or convention by the parties involved in the discussion. Think of the problems in trying decide whether a group of animals is one species of two, or which genus they belong to. The same issue arises with the characterisation of the system by a network. When is a relationship considered a graph edge, when often every component is connected to every other part in varying degrees.

However, in many situations, there appears to be an obvious way of partitioning the system, or categorising it. In such a case, where two observers agree on the same way of interpreting a system, then they can agree on the complexity that system has. If there is no agreement on how to perform this categorisation, then complexity is meaningless.

To formalise complexity then, assume as given a classifier system that can categorise descriptions into equivalence classes. Clearly, humans are very good at this — they’re able to recognise patterns even in almost completely random
data. Rorschach plots are random ink plots that are interpreted by viewers as a variety of meaningful images. However, a human classifier system is not the only possibility. Another is the classification of programs executed by a computer by what output they produce. Technically, in these discussions, researchers use a Universal Turing Machine (UTM), an abstract model of a computer.

Consider then the set of possible binary strings, which can fed into a UTM as a program. Some of these programs cause U to produce some output then halt. Others will continue executing forever. In principle, it is impossible to determine generally if a program will halt or continue on indefinitely. This is the so called halting problem. Now consider a program \( p \) that causes the UTM to output a specific string \( s \) and then halt. Since the UTM halts after a certain number of instructions executed (denoted \( \ell(p) \)) the same result is produced by feeding in any string starting with the same \( \ell(p) \) bits. If the strings have equal chance of being chosen (uniform measure), then the proportion of strings starting with the same initial \( \ell(p) \) bits is \( 2^{-\ell(p)} \). This leads to the universal prior distribution over descriptions \( s \), also known as the Solomonoff-Levin distribution:

\[
P(s) = \int_{U(p)=s} 2^{-\ell(p)} dp \quad (3)
\]

The complexity (or information content) of the description is given by equation (1), or simply the logarithm of (3). In the case of an arbitrary classifier system, the complexity is given by the negative logarithm of the equivalence class size

\[
C(x) = \lim_{s \to \infty} s \log_2 N - \log_2 \omega(s, x) \quad (4)
\]

where \( N \) is the size of the alphabet used to encode the description and \( \omega(s, x) \) is the number of equivalent descriptions to \( x \) of size \( s \) or less.

It turns out that the probability \( P(s) \) in equation (3) is dominated by the shortest program, namely

\[
K(s) \leq \log_2 P(s) \leq K(s) + C
\]

where \( C \) is a constant independent of the description \( s \). \( K(s) \) is the length of the shortest program \( p \) that causes \( U \) to output \( s \) and halt, and is called the Kolmogorov Complexity or Algorithmic Complexity.

An interesting difference between Kolmogorov Complexity, and the general complexity based on human observers can be seen by considering the case of random strings. Random, as used in algorithmic information theory, means that no shorter algorithm can be found to produce a string than simply saying “print . . . ”, where the . . . is a literal representation of the string. The Kolmogorov complexity of a random string is high, at least as high as the length of the string itself. However, a human observer simply sees a random string as a jumble of letters, much the same as any other random string. In this latter case, the equivalence class of random strings is very large, close to probability one, so the perceived complexity is small. Thus the human classifier defines an example of what Gell-Mann calls effective complexity[9], which measures the length of a
It is often thought that complex systems are a separate category of systems to simple systems. So what is it that distinguishes a complex system, such as a living organism, or an economy, from a simple system, such as a pair of pliers? This question is related to the notorious question of What is Life?, however may have a simpler answer, since not all complex systems are living, or even associated with living systems.

Consider the concept of emergence. We intuitively recognise emergence as patterns arising out of the interactions of the components in a system, but not implicit in the components themselves. Examples include the formation of hurricanes from pressure gradients in the atmosphere, crashes in stock markets, flocking behaviour of many types of animals and of course, life itself.

Let us consider a couple of simple illustrative examples, that are well known and understood. The first is the ideal gas, a model gas made up of large numbers of non-interacting point particles obeying Newton’s laws of motion. A thermodynamic description of the gas is obtained by averaging:

**temperature** \( (T) \) is the average kinetic energy of the particles;

**pressure** \( (P) \) is the average force applied to a unit area of the boundary by the particles colliding with it;

**density** \( (\rho) \) is the average mass of particles in a unit volume;

The ideal gas law is simply a reflection of the underlying laws of motion, averaged over all the particles:

\[
P \rho \propto T
\]

The thermodynamic state is characterised by the two parameters \( T \) and \( \rho \). The so-called first law of thermodynamics is simply a statement of conservation of energy and matter, in average form.

An entirely different quantity enters the picture in the form of entropy. Consider discretising the underlying phase-space into cubes of size \( h^N \), \( (N \) being the number of particles) and then counting the number of such cubes having temperature \( T \) and density \( \rho \), \( \omega(T, \rho, N) \). The entropy of the system is given by

\[
S(T, \rho, N) = k_B \ln \omega(T, \rho, N)
\]

where \( k_B \) is a conversion constant that expresses entropy in units of Joules per Kelvin. One can immediately see the connection between complexity (eq. 4) and entropy. Readers familiar with quantum mechanics will recognise \( h \) as being an analogue of Planck’s constant. However, the ideal gas is not a quantum system, and as \( h \to 0 \), entropy diverges! It turns out that in the thermodynamic limit \( (N \to \infty) \), the per-particle entropy \( S/N \) is independent of the size of \( h \).
The second law of thermodynamics is a recognition of the fact that the system is more likely to move to a state occupying a larger region of phase space, than a smaller region of phase space, namely that $\omega(T, \rho, N)$ must increase in time. Correspondingly, entropy must also increase (or remain constant) over time. This is a probabilistic statement that only becomes exact in the thermodynamic limit. At the syntactic, or specification level of description (i.e., Newton’s laws of motion), the system is perfectly reversible (we can recover the system’s initial state by merely reversing the velocities of all the particles), yet at the semantic (thermodynamic) level, the system is irreversible (entropy can only increase, never decrease).

The property of irreversibility is an emergent property of the ideal gas, as it is not entailed by the underlying specification. It comes about because of the additional identification of the thermodynamic state, namely the set of all micro-states possessing the same temperature and density. This is additional information to what is contained in the microscopic description, and that entails the second law.

The second example I’d like to raise (but not analyse in such great depth) is the well known Game of Life, introduced by John Conway, and popularised in Martin Gardner’s Mathematical Recreations column in 1970. This is a 2-dimensional cellular automaton (2D grid of cells), where each cell can be one of two states. Dynamics on the system is imposed by the rule that the state of a cell depends on the values of its immediate neighbours at the previous time step.

Upon running the Game of Life, one immediately recognises a huge menagerie of emergent objects, such as blocks, blinkers and gliders. Take gliders for example. This is a pattern that moves diagonally through the grid. The human observer recognises this pattern, and can use it to predict the behaviour of the system with less effort than simulating the full cellular automaton. It is a model of the system. However, the concept of a glider is not entailed by the CA specification, which contains only states and transition rules. It requires the additional identification of a pattern by the observer.

This leads to a general formulation of emergence. Consider a system specified in a language $\mathcal{L}_1$, which can be called the specification, or syntactic layer (see figure 1). If one accepts the principle of reduction, all systems can ultimately be specified the common language of the theoretical physics of elementary particles. However, an often believed corollary of reduction is that this specification encodes all there is to know about the system. The above two examples show this corollary to be manifestly false. Many systems exhibit one or more good models, in another language $\mathcal{L}_2$, which can be called the semantic layer. The system’s specification does not entail completely the behaviour of the semantic model, since the latter also depends on specific identifications made by the observer. In such a case, we say that properties of the semantic model are emergent with respect to the syntactic specification.

The concept of “good” model deserves further discussion. In our previous two examples, neither the thermodynamic model, nor the glider model can be said to perfectly capture the behaviour of the system. For example, the second
law of thermodynamics only holds in the thermodynamic limit — entropy may occasionally decrease in finite sized systems. A model based on gliders cannot predict what happens when two gliders collide. However, in both of these cases, the semantic model is cheap to evaluate, relative to simulating the full system specification. This makes the model “good” or “useful” to the observer. We don’t prescribe here exactly how to generate good models here, but simply note that in all cases of recognised emergence, the observer has defined at least one semantic and a syntactic model of the system, and that these models are fundamentally incommensurate. Systems exhibiting emergence in this precise sense can be called complex.

4 An Ontology of Bitstrings

Consider a program of explaining the world of appearances, of explaining Kantian phenomena. Kant distinguishes two categories of being — the phenomenon, or thing as it appears, and the noumenon, or thing as it is. If phenomena can be explained in a closed manner, ie without appeal to an underlying noumenon, then perhaps the noumenon can be dispatched in the manner of Laplace’s reply to Napoleon Bonaparte: Je n’ai besoin de cet hypothèse.

Phenomena (appearance) arises through the registering of data by the conscious observer, through the attachment of meaning to raw data. This is the situation captured in Fig. 1. Suppose, therefore that all possible bitstrings exist, in uniform measure. By virtue of equation (4), the information content of this complete set is precisely zero, independent of the observer. Such an assumption is a minimal ontology, on a par with assuming that nothing exists. One could also paraphrase it as saying no constraints exist. In deference to the influence of Plato, such an all encompassing object is often termed a Plenitude or sometimes Platonia. I use the indefinite article here, as alternatives do exist: eg all logically consistent systems, all mathematical systems, all possible computations.

Equation (1) implies that the phenomena observed should be more likely to be simple than complex, leading to an explanation of the value of Occam’s Razor: that things should not be multiplied unnecessarily.

Furthermore, by supposing that the observer is parameterised by an ordered set (called (psychological) time) such that only a finite number (but increasing as a function of time) of bits of the bitstring are meaningful, and also that observers’ interpretations are robust in the presence of noise (evolutionarily speaking, it is not a good idea to be fooled by lions in camouflage), we get a solution to the problem of induction. The world will, by and large, continue to follow the rules it has followed previously.

Some further elaboration of this concept of time is needed, as time is often considered to be an illusion. I find that “illusion” is an overly strong word here — it implies that we are tricked into observing something that is not, in fact, there. I would argue that the second law of thermodynamics is also a similar phenomenon — it comes about from our propensity to classify systems, for instance, according to thermodynamic variables. Yet there would be howls
of protest from my physicist colleagues if one were to assert that the second law of thermodynamics is an illusion. What we have in fact is two equally valid descriptions of the world — an “external” one, in which time appears as a coordinate, measured with clocks, and an “internal” one with present, future and past. Thus we should really speak of psychological time as emergent, just as real, but irreducible to the objective world of physics.

This is undoubtedly an *idealist* stance. Idealism contrasts with *realism* by giving primacy to the subjective world of appearances. In common with many idealist philosophies, there is a problem to solve with the appearance of consistency between different observer perceptions of reality. Unlike Bishop Berkeley, we need not appeal to beneficent deity, nor unlike Kant do we need to appeal to an unknowable *Noumenon* in order to explain this consistency. Rather we appeal to what is known as the *Anthropic Principle*, which effectively states that reality’s appearance must be consistent with our presence in that reality as an observer[1].

The Anthropic Principle is in fact a tautology, if one accepts a concrete reality (realism in other words). If the appearance of reality were not consistent with our existence, we would conclude that we have been imprisoned within a virtual reality of some kind, and that bodies occupy a greater reality than the one we see. In fact, the Anthropic Principle is not some quaint philosophical principle, but has real scientifically testable consequences. In all such cases, the Anthropic Principle has been confirmed, particularly in cosmology[1].

In an idealistic setting, however, the anthropic principle is somewhat of a mystery. Why shouldn’t we be spending our entire lives dreaming a reality that has nothing whatsoever to do with us as observers? If it weren’t for the consistency requirement of the anthropic principle, the Occam’s razor result would imply that we’d experience a universe that is too simple to support life. The complexity of our observed universe is in fact the minimum possible complexity that allows conscious life. We can only suppose that the still to be found theory of consciousness will require self-awareness as a necessary requirement for consciousness. This in turn implies that we, as observers are embedded in the reality we observe. This fundamental closure of observer and observed, closes the ontology of bitstrings, and cuts off the prospect of solipsism.

5 Quantum Mechanics

By reasoning about the appearance of reality, and of the nature of observation, we have lead to a number of properties of consciousness we expect a valid theory of consciousness to have. These include the property of classifying reality (attaching meaning), psychological time, meaning robustness and the anthropic principle. Combining classification with time, we have *projection*, namely the process of converting possible into actual. Periodically, we observe a few more bits of our reality bitstring, and our understanding is updated. By introducing the framework of probability theory, one can mathematically derive a predictive theory of what is actually observed. That predictive theory is the Hilbert space
structure of quantum mechanics, vectors in the Hilbert space evolve according to Schrödinger's equation and the probabilities are given by Born's rule\cite{14}. Quantum Mechanics is simply a theory of observation!

Roy Frieden uses a slightly different formulation of statistical inference\cite{8}. An observer trying to measure some physical quantity, will experience an error $e$, which at minimum is bounded by the inverse of something called *Fisher Information* $I$:

\[ e^2 I \geq 1 \quad (6) \]

The ideal observer will of course attempt to observe reality in such a way as to maximise $I$ — such an extremum principle he calls the *Principle of Extreme Physical Information*, and using it, along with assorted symmetry principles, he is able to derive all sorts of basic physics equations: the Klein-Gordon equation (which is the relativistic version of Schrödinger’s equation), Maxwell’s equations of electrodynamics and Einstein’s field equations of General Relativity.

As a third possible route to quantum mechanics from observerhood, Bruno Marchal considers the consequences of *computationalism*, that we as observers are equivalent to programs running on a Turing machine (an abstract model of a computer)\cite{10}. By adopting a theory of knowledge proposed by Plato in *Thaetetus*, and translating it into logical terms, he demonstrates that knowledge about observed reality must obey the axioms of quantum logic, a logic which also describes the behaviour of subspaces of a Hilbert space. Whilst the conclusions might be weaker than those derived by myself or Frieden, it has the advantage of being an independent derivation, and also of making use of fewer assumptions about the nature of conscious observation that Frieden and I make.

Thus we see a reversal in the usual ontology between the observer (“psychology”) and physics. Physics is actually emergent from psychology, and by the Anthropic Principle, must be emergent from physics.

6 Conclusion

The success in reversing the usual ontology between the observer (“psychology”) and physics in the case of quantum mechanics leads one to conjecture that the other pillar of 20th century physics, Einstein’s theory of relativity may also be related to properties of the observer.

If we take this approach seriously, by showing a possible reduction of physics to psychology, physics constrains the possible forms a theory of consciousness might take. We have seen that the Anthropic Principle is pivotal, and this implies self-awareness as necessary property of consciousness. We have also seen that psychological time, is also crucial. Even though brains are messy, asynchronous, parallel processors, somehow a sequential process emerges to give the appearance of psychological time. Finally, the mind attaches meaning to data in a robust fashion. This is a selection process, analogous to natural selection in Darwinian evolution.
If we take a look at Daniel Dennett’s *Consciousness Explained*[^1], we see all of these features appearing. Firstly much is made of self-awareness, which Dennett calls *autostimulation*, and is what he calls a *good evolutionary trick*. Secondly, he argues that a sequential *von Neumannesque* architecture must emerge from an underlying *Pandemonium*, something he calls the *Joycean machine*, in honour of James Joyce’s *stream of consciousness*. Finally, he argues that instead of a Cartesian theatre in which consciousness reside, a Pandemonium of independent parallel processes compete in an evolutionary process, that results in a series of rewritten “drafts” of understanding.

References

[^1]: For illustrative purposes, I'm not endorsing this particular theory as a complete, final theory of consciousness.
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