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Perspective

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Four faces of information in natural systems

Fernando E. Rosas[1,2,3,4] ✉, **Pedro A. M. Mediano**[5,6], **Andrea I. Luppi**[3,7,8,9,10], **Alexander B. Boyd**[11,12], **Mario Berta**[5,13], **Henrik J. Jensen**[4,14], **Michael Gastpar**[15] & **Sean M. Carroll**[16,17]

Abstract

The idea of 'information' has been instrumental to advances in multiple fields of physics and natural science more broadly. However, despite – or perhaps because of – its pervasiveness, this key notion is used in such a wide range of settings that it is unclear whether there is coherence underpinning all these applications. Instead of advocating for a monolithic perspective, we posit that information has come to bear a number of different technical interpretations, which are usually not sufficiently disambiguated. Following this idea, in this Perspective, we put forward a pluralistic approach towards information, wherein multiple technical interpretations coexist – each bringing its own affordances and restrictions. We outline four different technical senses in which information is currently used in scientific research, which we describe as the engineering, statistical, thermodynamic and ontological 'faces' of information. Disambiguating the domain and scope of these faces may help to avoid misinterpretations. We also highlight the complementarity of distinct, yet equally valid applications of an information lens for natural systems.

Sections

[1]Sussex AI and Sussex Centre for Consciousness Science, Department of Informatics, University of Sussex, Brighton, UK. [2]Department of Brain Science, Imperial College London, London, UK. [3]Centre for Eudaimonia and Human Flourishing, University of Oxford, Oxford, UK. [4]Centre for Complexity Science, Imperial College London, London, UK. [5]Department of Computing, Imperial College London, London, UK. [6]Division of Psychology and Language Sciences, University College London, London, UK. [7]Department of Psychiatry, University of Oxford, Oxford, UK. [8]St John's College, University of Cambridge, Cambridge, UK. [9]Division of Information Engineering, University of Cambridge, Cambridge, UK. [10]Montreal Neurological Institute, McGill University, Montreal, Canada. [11]The Beyond Institute for Theoretical Science, San Francisco, CA, USA. [12]School of Physics, Trinity College Dublin, Dublin, Ireland. [13]Institute for Quantum Information, RWTH Aachen University, Aachen, Germany. [14]Department of Mathematics, Imperial College London, London, UK. [15]School of Computer and Communication Sciences, EPFL, Lausanne, Switzerland. [16]Departments of Physics and Philosophy, Johns Hopkins University, Baltimore, MD, USA. [17]Santa Fe Institute, Santa Fe, NM, USA. ✉e-mail: f.rosas@sussex.ac.uk

Introduction

Although originally formalized in the context of engineered devices[1], the idea of 'information' plays a foundational role today in physics (thermodynamics, quantum computation and biophysics, to name a few), biology (for example, genetics and neuroscience) and human sciences (such as in cognitive science and economics)[2,3]. The fertility of this idea, when applied to natural processes, has been demonstrated by its fundamental role in shaping present-day understanding of the genetic code[4,5], quantum entanglement[6,7] and the patterns of activity of neurons in the brain[8,9]. This success has even led to proposals such as 'it from bit'[10] and more recently 'it from qubit'[11,12]. Perhaps, after all, the idea of information is larger than something solely pertaining to communication systems.

This excitement is, however, overshadowed by the fact that the application of the notion of information to natural, non-engineered systems is highly non-trivial, and the challenges of this translation are not always thoroughly considered. Already at the dawn of information theory, pioneering researchers warned[13,14] about potentially harmful 'bandwagon' effects stemming from the premature appropriation of information-theoretic terms from other scientific disciplines — concerns that remain just as valid today. For better or worse, these warnings have often been ignored, resulting in a rich landscape of applications that are not always well-founded.

As a result, the notion of information is currently used in diverse contexts denoting different things, making it challenging to evaluate if its various usages still refer to the same underlying idea and to establish the validity of dissimilar applications. A possible way to address this colourful but unruly state of affairs would be to adopt a rigid stance in which there is only one legitimate way to characterize information (often one based on engineering principles with clear operational interpretations) and declare all interpretations that do not fit into this framework as invalid. We believe that such an approach would be unnecessarily restrictive, with the risk of limiting the potential that this powerful idea has to offer. The root of the problem is that the term 'information' has come to bear a number of different technical meanings[15]. In addition to distinguishing between an informal and a technical meaning (analogous to 'work' in thermodynamics or 'stress' in mechanics versus their colloquial uses), we posit that even in the scientific domain 'information' has also come to bear different but equally valid interpretations that are rarely disambiguated — often leading to confusion, misinterpretations and disagreements.

As a way forward, in this Perspective, we propose a pluralistic approach wherein rigorous alternative views of information coexist. Following this view, we outline what we consider to be the main approaches to conceptualize information that are used in science today, which we describe as the engineering, statistical, thermodynamic and ontological 'faces' of information (Fig. 1). These faces of information are not circumscribed to specific disciplines (such as engineering or statistics) or quantities (such as Shannon's entropy or mutual information); rather, they correspond to ways in which scientists use this notion in their work. Crucially, we do not regard any of these faces of information as more legitimate than others, as each of them has its own distinctive features and domain of applicability. Accordingly, we characterize each of these faces in terms of what they require for their proper application and also in what they enable. In doing so, our goal here is not to derail the information bandwagon[13] but rather to guide it — that is, to clarify what exactly information can and cannot do.

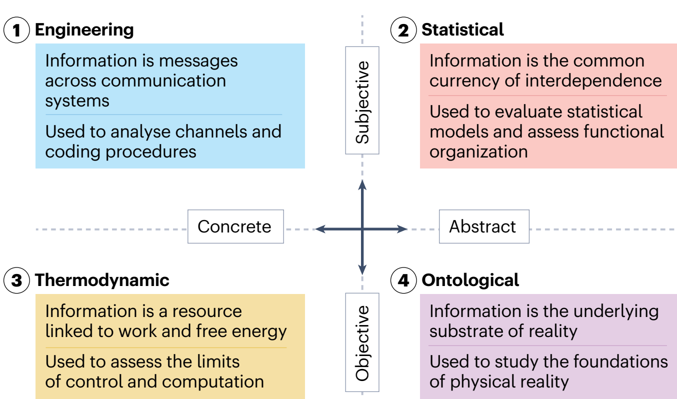

Fig. 1 | The four faces of information reviewed in this Perspective. The numbering goes from more familiar to less familiar to a general audience, corresponding to the order we present the topics in this Perspective. These faces of information can also be arranged according to the degree to which they assume information is 'real' versus useful and to the degree in which they relate to concrete phenomena or abstract constructs.

The engineering face

We start by presenting the view that treats information as referring to messages carried or stored across communication systems.

Messages and channels

Communication systems are physical devices built to convey messages, be they a love letter, a passcode or a digital image[16]. Such systems leverage properties of their structure (such as the propagation of voltage differences across a copper wire) that induce correlations between different physical variables. These interdependencies can be used as channels to allow information transfer (between two points in space) or information storage (between different points in time)[17].

From this engineering perspective, information corresponds to messages that can be sent through or stored via communication systems. In this context, a message corresponds to the specification of an outcome among a number of alternatives[18], which in practice is often described in terms of sequences of symbols (Box 1). By focusing on symbolic sequences, this view of information puts an emphasis on the syntactic aspects of messages while placing their semantics (that is, what they refer to) in a second place (see Supplementary Information section 1).

Formally, communication systems consist of five elements: an information source, a transmitter (or encoder), a channel, a receiver (or decoder) and a destination[1]. The information source produces messages, the channel is the physical medium used to transmit the message from transmitter to receiver, and the destination is the entity for which the message is intended. Important questions are: for a given information source, channel and destination, what is the best communication quality one can obtain? How should encoder and decoder be designed to get there? A fundamental result that makes these questions tractable is Shannon's separation theorem (theorem 11 in ref. 1), which establishes that under mild conditions (chapter 7.13 in ref. 19), an optimal solution can be achieved by breaking the problem into two separate parts: compression of the information source and reliable communication across the channel.

Optimal compression

To understand how compression works, consider an information source represented by a random variable X specifying messages among a

Box 1 | Choices, probability and subjectivity at the foundations of information

In the early twentieth century the notion of 'message' was often conflated with the meaning of the words or their physical substrate (chapter 6 in ref. 3). A first step towards our modern understanding was taken by Harry Nyquist[128], who in 1924 identified the limits of information transfer over telegraph wires — without having a clear definition of what information was. Building on these findings, Ralph Hartley[18] proposed to strip the notion of message of its semantic meaning and its physical realization (Supplementary Information section 1), focusing purely on the act of selection. Hartley defined a message to be a sequence of symbols selected from a finite alphabet, associating it with the freedom of choice available to the sender. This framed information in terms of set theory and combinatorics. In addition, following intuitive desiderata, Hartley derived that the 'amount of information' in n symbols selected over an alphabet of size M should be $H = n\log M$.

Twenty years later, Claude Shannon redefined how messages are understood by proposing a probabilistic perspective[1]. Building on insights from cryptography[129], Shannon defined information sources not just as senders making selections but as random variables. In this view, a message is a realization of a stochastic process. Interestingly, the evolution from Hartley to Shannon has a strong resemblance with earlier developments in thermodynamics and statistical mechanics — specifically, with the original difficulties to define the 'state' of a physical system[130] and the subsequent developments from Ludwig Boltzmann's to Josiah Willard Gibbs' definitions of entropy (The thermodynamic face).

Thus, Shannon's approach introduces an intimate connection between information and probability. This brings useful tools to reason about the information of independent, joint and conditional events (Supplementary Information section 3). However, the idea of probability itself has a colourful history, which has led to standard rules of how it works (the Kolmogorov axioms) together with long-lasting disagreements about what it means[131,132]. The debate is marked by two major camps: the frequentist interpretation, which argues for an objective view that associates probabilities with the limit of relative frequencies in repeated experiments, and the Bayesian interpretation, which argues for a subjective view in which probabilities are a measure of the 'degree of belief' assigned by an observer with incomplete knowledge. These positions, in turn, bring distinct interpretations about information: either as an encapsulation of structural properties of nature or as a tool for reasoning about the world while not being a part of it.

We posit that all the faces of information reviewed here can be interpreted with objectivist or subjectivist overtones — even though some interpretations may seem more natural than others. That said, some of the most interesting works explore ways for bridging these seemingly opposite perspectives. For example, the work of Edwin Jaynes[63] aims to explain thermodynamics in terms of macroscopic observers that handle their uncertainty about microscopic states via optimal, objective procedures (The thermodynamic face). The ability to bridge subjective and objective domains is arguably one of the most powerful features of information.

discrete set of alternatives $\mathcal{X}$ with probability $p(x)$ (Box 1). Compression is about how to assign unique binary strings to each possible message x in $\mathcal{X}$ so that the average string length is as small as possible – in which the average is taken overall messages according to $p(x)$ (ref. 20). Intuitively, savings can be attained by assigning shorter strings to messages that happen more often (in other words, those with higher probability).

Following this intuition, the celebrated source coding theorem shows that the shortest achievable average code length is given by the Shannon entropy (section 6 in ref. 1)

$$H(X) = \sum_{x\in\mathcal{X}} p(x)\log\frac{1}{p(x)}. \tag{1}$$

It is therefore optimal to encode x using roughly $s(x) = -\log p(x)$ symbols (see Supplementary Information section 2 for details). However, optimality can usually only be achieved by considering increasingly long sequences of independent and identically distributed realizations; hence, it is best to think of the entropy as a tight lower bound.

Thus, the Shannon entropy $H(X)$ determines the shortest average length that an encoding of the events associated with the variable X can achieve. In this way, Shannon's entropy captures the 'size' of messages when they are maximally compressed (chapter 5 in ref. 19), corresponding to the smallest average number of questions that one needs to ask to determine an outcome (chapter 3 in ref. 21). Interestingly, equation (1) implies that a variable X is less compressible, and hence more informative, when many possible realizations x are likely – that is, when $p(x)$ is relatively flat.

Notably, Shannon's work not only clarified the limits of lossless compression but also provided a general framework to study lossy compression under various fidelity conditions via rate-distortion theory (chapter 10 in ref. 19). Rate distortion theory has been useful for a range of engineering applications[22,23] and also for investigating resource-constrained encoding in biological settings[24,25].

Reliable transmission

Consider now the question of how to encode a sequence of k symbols to transmit them by using a noisy channel n times, in such a way that the decoder can retrieve the sequence with high reliability. A simple approach would be to use repetition coding: by sending multiple copies of each symbol, one can achieve a vanishingly small probability of decoding error, at the cost of reducing the throughput so that k/n tends to zero as n grows (chapter 3.2 in ref. 26). This leads to a natural question: is it possible to achieve vanishingly few errors while keeping a non-zero rate of symbols successfully communicated per channel use? If so, how large can one make the transmission rate k/n while keeping the error probability arbitrarily small?

The answer to this question is a sharp phase transition between transmission rates that can be achieved with arbitrarily low error and others that cannot, and the boundary between these is determined by Shannon's mutual information (section 12 in ref. 1; see also ref. 27). If a channel's input and output correspond to variables X and Y, then the mutual information between them is given by

$$I(X;Y) = H(X) + H(Y) - H(X,Y). \tag{2}$$

Box 2 | Implications of the engineering face of information

Affordances: Adopting an engineering stance to information allows scientists to study communication processes within systems of interest. They can, for example, track how often messages are being exchanged between parts of the system or between the system and its environment or how efficient different communication resources are used. Moreover, an engineering stance to information allows scientists to devise and study codes — that is, ways of representing a message by means of symbols tailored for different purposes. By disambiguating stages involving encoding, transmission and decoding, the engineering face of information allows one to identify distinct coding procedures: source coding[20], involving the compression of a message by removing redundancies and making its transmission as efficient as possible, and channel coding[27], which adds redundancy to protect the message from errors through the transmission via error-correction mechanisms (The engineering face).

Restrictions: There are three key requirements for a communication-theoretic view of information to be applicable: coding, causality and normativity. Communication processes involve the existence of a transmitter and a receiver: the transmitter uses an encoder to translate messages into an alphabet that is compatible with the physical substrate that is used as the channel, and the receiver uses a decoder to undo this operation and retrieve the original message. Therefore, for this view to be applicable there have to exist an encoder and a decoder (or, at least, the potential existence of them has to be reasonable). In addition, when considering information transmission, the observed interdependence between the channel's inputs and outputs must be of causal nature. Technically, this implies that conditional probabilities need to reflect the result of interventions[133]. Finally, note that a communication process is said to be successful if a message gets across from transmitter to receiver without error or approximately with respect to a given fidelity criterion. This definition requires the possibility of error in the transmission: therefore, this face of information only properly applies when there is an unambiguous way of assessing whether the message has been conveyed faithfully.

These conditions limit the type of conclusions that can be drawn from information quantities in scenarios that do not satisfy some of these requirements. For example, when analysing physical systems at critical points one often observes long-range two-point correlations, but such correlations may not serve as communication channels — unless causality between the corresponding points can be guaranteed.

Another important caveat for applications of this face of information is that most of the classic results from Shannon are related to messages encoded in long sequences of symbols, which require the channel to be used repeatedly (sometimes even infinitely) before the reception of information. Thus, the reviewed information-theoretic quantities admit a simple operational interpretation only when the delay of these operations is not of interest[134]. Techniques for accounting for the effect of imposing finite delays have been developed[135]. Thus, if delay is of importance, then these adjustments should be considered. Otherwise, information quantities can be interpreted as upper or lower bounds of what is achievable in finite time, delineating feasibility regions.

Overall, interpreting information-theoretic quantities using the engineering face requires careful consideration, as their simplicity tends to hide important underlying assumptions. For example, although equation (2) is often explained in terms of Venn diagrams that interpret information as areas, this interpretation can lead to counterintuitive implications (such as negative intersections) when considering three or more variables (Supplementary Information section 3).

In this precise sense, mutual information universally quantifies communication quality – the amount of information that can be reliably transferred per channel use. This simple relationship between channel capacity and mutual information holds when the channel is memoryless and communications use no feedback – the capacity of a channel in more complex scenarios follows more elaborate formulas (for example, ref. 19, chapter 15, and ref. 28). There have been substantial extensions of these ideas to more general communication scenarios, including quantum settings, some of which are discussed in Supplementary Information section 4.

The main affordances and restrictions of the engineering face of information are discussed in Box 2.

The statistical face

Whereas the previous section described a view of information focused on the architecture of transmission (that is, encoders and decoders), a separate line of work treats information as the common currency of interdependence, serving as a tool to reason about statistical models.

Bits without channels

Statistical models are mathematical objects that describe relationships between variables and our degree of uncertainty about them. The first step in linking information and statistical models is to provide an interpretation of the meaning of the 'bits' measured by the entropy of random variables not in terms of messages but as raw uncertainty. For this, one can establish a fair coin flip as a reference value of uncertainty – being, by definition, equal to 1 bit. The Shannon entropy of other discrete variables can then be shown to determine how many fair coin flips one needs to reproduce the uncertainty associated to the original variable. In continuous variables, the entropy is related to the volume of the occupied phase space. These derivations are discussed in Supplementary Information section 5.

Just as the engineering stance is supported by the source and channel coding theorems, the statistical view of information is backed by the asymptotic equipartition principle, which is based on the Shannon–McMillan–Breiman theorem[29,30]. In essence, this fundamental result states that long sequences of independent realizations of a given random variable can be accurately described as belonging to one of two classes: a group of equally likely sequences (the 'typical set') or a group of extremely unlikely sequences (Supplementary Information section 5). Using this, the Shannon entropy of a random variable can be derived as the rate of growth of the typical set, reflecting the portion of the phase space that the variable effectively occupies. Using this result, one can identify the number of fair coins that would span an effective phase space of the same size – that is, that would generate the same amount of uncertainty.

Overall, these arguments place entropy as a universally applicable measure of generalized variance and bits as a fundamental unit of uncertainty. Unlike variance, entropy remains meaningful when applied in a variety of settings, including categorical, ordinal, multimodal or skewed distributions[19]. Furthermore, this interpretation of entropy still holds in quantum systems by replacing bits with qubits and Shannon entropy with von Neumann entropy (Supplementary Information section 4). These ideas also apply to temporal processes using extensions of these results to ergodic processes[31], revealing the entropy rate as a general metric of dynamical uncertainty[32–34].

Mutual information as a general metric of interdependence

Entropies can be seen as derived from more fundamental information metrics known as divergences, which are distance-like mappings that quantify the dissimilarity between two probability distributions[35]. The most well-known divergence is due to Kullback and Leibler (KL)[36], which is given by

$$D(p||q) = \sum_{x \in \mathcal{X}} p(x) \log \frac{p(x)}{q(x)}, \tag{3}$$

in which p and q are two probability distributions over $\mathcal{X}$. Note that if X distributes following p and u is the uniform distribution over $\mathcal{X}$, then $D(p||u) = \log|\mathcal{X}| - H(X)$, recovering the Shannon entropy. Other divergences exist[35,37], which enable more nuanced comparisons between models – by focusing more on the peaks or the tails of probability distributions[38], for example. However, the KL divergence has an important interpretation in terms of statistical inference: it corresponds to the likelihood (that is, the probability of the data as a function of the model's parameters) of observing a given dataset under a particular statistical model. A derivation of this is provided in Supplementary Information section 6. Thus, inferences based on the maximum likelihood criterion (in which parameter values of a model are chosen such that they maximize the probability of observing a given data) are often equivalent to minimizing the KL divergence.

Likelihoods are also important in that they allow us to compare alternative models – what is known as 'model selection'[39]. In this process, the likelihood of two competing models is compared, and the model with the highest likelihood is chosen. Crucially, the log-likelihood ratio between two models often converges to their KL divergence as the size of the dataset grows[40]. Hence, the KL divergence is a general tool for rejecting null hypotheses pertaining to statistical models. For quantum models, the analogue of KL divergence is Umegaki's quantum relative entropy[41], which has a similar interpretation in terms of statistical inference and has an equally important role in statistics of quantum systems[42].

The model selection view of the KL divergence can be harnessed by recasting Shannon's mutual information as a tool for statistical inference. Using the fact that

$$I(X\,;Y) = D(p(x,y)||p(x)p(y)), \tag{4}$$

in which $p(x)$ and $p(y)$ are the marginals of $p(x,y)$, following the above discussion one can conclude that mutual information is the KL divergence between a statistical model in which the two parts are coupled and another model in which they are not[43–45]. Therefore, in this context, the mutual information can be interpreted not as measuring messages flowing over a communication channel but as the strength of the evidence supporting the existence of interdependence[43]. Similarly, derived measures such as transfer entropy[44] and other information metrics[46] can be interpreted as hypothesis tests on specific types of statistical regularities that characterize systems[47,48]. Furthermore, building upon the interpretation of the Shannon entropy as the number of fair coins one needs to reproduce a given degree of variability, one can understand the mutual information as accounting for how many more coins one would need to describe the system if the variables were decoupled. Remarkably, although the mutual information between continuous variables in principle is a comparison between mere lengths, it can still be interpreted as measured in bits – even if the underlying entropies are not (Supplementary Information section 5).

In summary, these approaches establish information as a common language for comparing functional properties across systems. Specifically, the mutual information measures the number of bits associated to specific degrees of freedom in a given scenario, and as such, it can be used for model selection (namely, to perform inference on the significance of a particular interdependence) and also to characterize the relevance of such interdependence (assessing its 'effect size'). Both assessments are intrinsic to the system (Supplementary Information section 5) and commensurable to a unique unit (the fair coin or bit), being suitable to assess and compare interdependencies across systems. This statistical notion of information thus provides a 'common currency' of interdependence, which allows the assessment and comparison of diverse systems in a principled and substrate-independent manner.

These ideas have been extended in multiple directions. For example, variations of the KL divergence have been investigated, including the Rényi divergence[49] and other information measures[50–53] (see ref. 54 for a survey). The study of information divergences has also led to the study of information geometry, which explores the geometric properties (such as curvature and geodesics) of manifolds of models[35,55]. In addition, various aspects of the time domain have been investigated[33,56], including how mutual information can be calculated between the entire past and future of a single process[57] or between stochastic trajectories of different processes[58–60].

The main affordances and restrictions of the statistical face of information are discussed in Box 3.

The thermodynamic face

The next face of information consists in relating what is known about a system to what can be predicted about its behaviour and how this can be used to extract work. Thus, this view sees information as a distinct type of thermodynamic resource.

Information as a fundamental component of statistical thermodynamics

Early studies of thermodynamics in the nineteenth century[61] had the ambition of explaining heat dynamics via a 'caloric' fluid. However, it soon became apparent that a more effective approach was provided by kinetic theory, in which materials are made of particles – atoms and molecules – that display predictable aggregated behaviours[62]. In this setting, information becomes a natural component of the characterization of systems that are impossible to fully observe[63].

These ideas took a more precise form through the notion of thermodynamic entropy. Its original formulation, known as Clausius' entropy[64], defined a change of a system's entropy as the heat absorbed by it, divided by the temperature. The study of thermodynamic entropy led to the second law of thermodynamics, which states

Box 3 | Implications of the statistical face of information

Affordances**:** An understanding of entropy as a generalized variance leads to useful inference techniques such as the maximum entropy principle (MEP)[74,136]. The MEP is a heuristic for model selection (which can be formally derived either from large deviation theory[137] or information geometry[138,139]), which suggests picking statistical models that maximize entropy and hence offer an unbiased representation of the available knowledge. The MEP has great versatility[140], which has led to a wide range of applications including the study of protein families and amino acid contact prediction[141,142], the coordinated firing patterns of neural populations[143–145] and the abundance and distribution of species in ecological niches[146,147].

Furthermore, just as mutual information contrasts models with or without an interaction, multivariate extensions of it can be used to study interactions involving three or more variables[148–150]. For quantum systems, entropy-based correlation measures (such as quantum mutual information; Supplementary Information section 4) play a fundamental role in quantifying the strength of quantum correlations — often termed entanglement[7]. In condensed matter physics, the scaling of quantum correlation measures based on quantum entropy is a fundamental tool to reveal the structure of quantum many-body systems[151]. A key advantage of the mutual information for studying many-body systems is its decomposability: the mutual information between groups of variables can be decomposed into smaller terms via the 'chain rule' of information (ref. 19 (chapter 2.5), and ref. 152). The resulting terms of the chain rule can be further decomposed into minimal 'information atoms' via an approach known as partial information decomposition[153–155], which can be used to investigate not only how much but also what type of information is present (Supplementary Information section 7). One such insight refers to synergistic organization: patterns that can be seen in the whole but not in the parts[156,157], which has been shown to be relevant in a range of systems including artificial neural networks[158–160] and the human brain[161–164].

Restrictions: Compared with the engineering face, the statistical interpretation of information is much more widely applicable. Indeed, these tools can be used regardless of whether the observed interdependence is due to correlation, causation, hidden variables or other reasons. That being said, the extent of the corresponding interpretations needs to be aligned with the assumptions.

For example, scientific investigations often seek not just regularities but rather causal relationships underpinning phenomena of interest[133]. However, information quantities (such as transfer entropy) used within the statistical face do not by themselves yield causal conclusions, unless additional assumptions are made (see refs. 165,166 for related discussions). Thus, numerous works, for example within biology and neuroscience, use information in a statistical manner but with additional causal assumptions (Supplementary Information section 8).

Similarly, the relationships revealed by information decomposition refer to observed patterns of interdependences, which may have highly non-trivial relationships with the underlying mechanisms that generate them — for example, synergistic high-order patterns can be generated by low-order mechanisms[167]. The development of a principled understanding of the relationship between mechanisms and the resulting patterns is an important topic of ongoing investigation[168–171]. It is worth noting that quantifying the fundamental constituents of information decomposition (such as pure synergy terms) requires non-trivial choices between alternative frameworks, which can involve challenges in certain applications (see Supplementary Information section 7 for details).

that the entropy of a closed system cannot decrease[62]. Subsequent investigations revealed that the Second Law implies the impossibility of fully transforming disordered heat energy into coherent work without the expense of some additional resource[65,66]. In this way, the second law became a 'no-free-lunch theorem' that sets precise bounds to what is possible in terms of work extraction − precluding the existence of perpetual motion machines.

Later, the idea of thermodynamic entropy was further developed in statistical mechanics by relating it with the number of microstates consistent with each macrostate[67]. These ideas were later extended by considering densities in phase space, leading to the Gibbs entropy[68]

$$S_G = -k_B \sum_{i \in \mathcal{I}} p_i \ln p_i, \tag{5}$$

in which i sums overall the available microstates $\mathcal{I}$, and k_B is the Boltzmann's constant (see Box 1 for a discussion about the interpretation of probability). This interpretation made entropy applicable to a broad class of systems. Later, this functional form was shown to be unique under natural assumptions[69,70].

When the Shannon entropy was introduced in the twentieth century, many physicists viewed the similarity between it (equation (1)) and equation (5) as a mere structural isometry. However, others[71,72] advocated for identifying thermodynamic entropy with information, understanding the latter as in an engineering or statistical sense. This idea was later developed by identifying the acquisition of information about a physical system with an equivalent loss of thermodynamic entropy[73] and by positing that thermodynamic entropy is a measure of the amount of information lacking to a macroscopic observer that only has access to coarse-grained physical variables[74,75]. These approaches imply that an observer has more information when the system's entropy is low, because in that case the macroscopic features provide tight constraints on the possible microscopic states.

The plausibility of a strict identification of thermodynamic entropy with information has been the subject of intense debate, including concerns about epistemic relevance and potential categorical errors (Supplementary Information section 9). Moreover, it has been found that the Gibbs and Shannon formulations of entropy can diverge from Clausius' in specific settings[76–80]. This divergence does not invalidate a link between information and entropy but suggests that their link requires a more general and flexible formulation. For example, it has been shown that the Rényi entropy (a generalization of the Shannon entropy[49]) is often more appropriate than Shannon's to describe the thermodynamics of single quantum systems[81] or macroscopic conditions associated to nonlinear averages[82]. These ideas have led scientists to consider more general functional forms of entropy with distinct domains of applicability, leading to various theoretical and empirical advances (Supplementary Information section 10).

Information, free energy and dissipation

Building on these findings, additional advances — particularly in stochastic thermodynamics[83] and resource theory approaches[84,85] (Supplementary Information section 11) — indicate a distinctly physical face of information. Indeed, these advances suggest a view of information not as related to telecommunications or statistical inference (Supplementary Information section 9) but rather to conceive it as a specific kind of thermodynamic resource that can be used to extract energy or perform work.

The catalyst for these developments was Maxwell's Demon: a thought experiment that conceived a 'very observant and nimble-fingered being' that could spontaneously organize a box of gas into a hot and a cold compartment by selectively opening and closing a small frictionless door separating the two compartments[86]. This thought experiment seems to suggest that it is possible to generate a temperature gradient without spending any work, which would violate the second law. This apparent paradox made physicists realize that the demon's information processing capacity — specifically, its ability to perform computations to decide whether or not to open the door — ought to be considered as an integral element of the thermodynamic equations.

These ideas led to the proposal that the second law should still hold once one includes the thermodynamic costs of the demon's intelligent feedback[87–89]. For instance, in Szilard's engine[90] a single bit of information is used to extract $k_BT \ln 2$ J from the thermal reservoir with temperature T as work, and thus, the second law requires the demon to dissipate at least $k_BT \ln 2$ J of heat into the environment during erasure episodes. It has been argued that the logical irreversibility of erasure requires heat to balance out the decrease in the memory's information[87]. However, the memory device can be structured to shift the energy cost away from erasure and towards logically reversible measurement operations[91]. Thus, it has been proposed that the net operation of the demon — combining both measurement and erasure — is what balances the thermodynamic benefit of the information obtained through feedback[92,93]. These theoretical predictions have been experimentally validated with colloidal Brownian particles[94,95] and superconducting flux qubits[96,97].

Modern developments in stochastic thermodynamics and resource theory have further deepened the liaison between thermodynamics and information, revealing fundamental links between informational quantities and thermodynamic notions such as work, free energy and irreversibility in both equilibrium and far-from-equilibrium scenarios[93,98–101]. For example, a positive mutual information between systems is indicative of the existence of a thermodynamic resource — for example, the knowledge of how two systems are correlated via an energetic coupling allows observers to decorrelate them and extract work[102,103]. For a discussion about stochastic thermodynamics, resource theory and related findings, see Supplementary Information section 11.

The main affordances and restrictions of the thermodynamic face of information are discussed in Box 4.

The ontological face

In contrast to treating information as something that can be explained in terms of other primitives (as in the previous interpretations), in this section we look at information as a fundamental and irreducible building block from which other entities and phenomena can be explained. In all its attractiveness, this face of information is still more of a research programme than a fully spelled-out proposal. In what follows, we present the most promising findings supporting this view and outline some open challenges.

Conservation of information

Despite not having a formal understanding of it, the relevance of information was already appreciated by physicists before Shannon. For example, in the 1800s it was noted that a 'vast intellect' (later called Laplace's Demon) could in principle encompass all information about the present physical state and use the laws of physics to calculate everything about the past and future[104]. In modern language, this observation about the use of information (which dates back at least to Roger Boscovich in 1758[105]) can be interpreted as a statement about the conservation of information in classical mechanics; the information in question being the data needed to specify the classical state at any one moment in time.

Quantum mechanics complicates this story. The standard presentation of quantum mechanics[106] features two different types of evolution: 'process 1', when a system is measured, and 'process 2', when a system evolves undisturbed. Process 2 is deterministic, reversible and conserves information in Laplace's sense, but process 1 is indeterministic, invoking stochastic 'collapse' of the state. This indeterminism seems to suggest that information is not conserved in quantum theory due to the measurement process, but whether it is fundamental or merely apparent is unclear. In Everettian or pilot-wave theories, the fundamental dynamics is deterministic, and apparent indeterminism arises from self-locating uncertainty or the presence of hidden variables; in objective-collapse models the indeterminism is a fundamental feature of reality[107].

Physicists have mostly become used to the idea that quantum evolution conserves information except for measurement[108], but this uneasy consensus is challenged by various physical phenomena, such as black-hole evaporation[109]. There, a naive combination of quantum field theory and general relativity suggests that information may be lost, even if both theories independently conserve information. Furthermore, the relevant entropy to use for their thermodynamics is also still an open research question[110]. It is widely believed[111,112] that a complete theory of quantum gravity will show how information is conserved after all, but how that might happen is not yet clear[113].

Computational universality

In parallel with the development of the foundations of the engineering face of information (Box 1), it was found that a simple device obeying certain rules (now called a Turing machine) can carry out any feasible algorithmic computation[114]. Building on this, the Church–Turing thesis is the idea that any computable function can be implemented by a Turing machine[115]. This insight came with a powerful implication: computational universality, the idea that what matters in the performance of a computation is the algorithm that is being carried out, not the physical substrate responsible for the computation. Computational universality forefronts the notions of multiple realizability and substrate independence — for instance, one expects the result of multiplying two numbers to be the same whether carried out on an abacus, a laptop or a powerful supercomputer.

The Church–Turing thesis was later extended to connect it to physics, via the proposal that "Every finitely realizable physical system can be perfectly simulated by a universal model computing machine operating by finite means"[116]. Versions of this idea are sometimes called the physical Church–Turing thesis, which is not a version of the original thesis or a statement about computation itself, but rather a separate conjecture about the nature of physical reality.

Taken together, computational universality and the physical Church–Turing thesis can inspire an ontological view of information.

Box 4 | Implications of the thermodynamic face of information

Affordances: This face of information opens the door to thermodynamic analyses via generalized entropies over a broad class of systems, including non-extensive[172] and super-exponential[173] settings. These analyses have led to numerous technical and empirical advances, some of which are discussed in Supplementary Information section10.

This face is also useful for guiding investigations on the frontiers of the thermodynamics of computation, in which energy costs on the order of $k_B T$ materially affect hardware efficiency[93,174–176]. For example, generalized second-law inequalities explicitly include informational terms, showing that correlations and feedback modify thermodynamic bounds on work extraction[177]. Modular computations — in which computational elements are energetically decoupled — can be shown to waste that work, generating irreversible entropy production that is proportional to the reduction in mutual information between modular components[79,174,178]. Stochastic thermodynamics therefore reveals design principles for effective information processing: minimizing irreversible entropy production dictates the logical architecture of thermodynamically efficient computing[178].

Another important consequence of this face of information is the conceptual and quantitative understanding of the Heisenberg uncertainty principle[179]: namely, even when full information about a quantum mechanical particle is available (that is, when its quantum mechanical entropy is zero), it is in general not possible to sharply predict all properties of the quantum system. For example, it can be shown that, when either observing the position or the momentum of the particle, the sum of the two respective post-measurement classical entropies is lower by the reduced Planck constant[180]. These entropic uncertainty relations were originally proposed to deal with conceptual shortcomings in the original formulations of Heisenberg and others, but, recently, these ideas have been further generalized to incorporate quantum correlations between the observed objects and their environments[181]. This generalization, in turn, reveals a fundamental trade-off between the present uncertainty and the amount of entanglement between the observed object and the observer. Such extended entropic uncertainty relations are then at the heart of modern security proofs in quantum cryptography[182].

Restrictions: Although this thermodynamic face of information is of wide applicability within physical systems, it can become problematic when one tries to apply it beyond physics. In particular, thermodynamic analyses based on work and energy require a well-defined notion of (physical) energy, which determines the degrees of freedom that are accessible to a macroscopic observer, which in turn brings in the notions of dissipation, free energy and related quantities.

For example, there is a long history of successful application of methods from stochastic thermodynamics and statistical mechanics to the analysis of artificial neural networks, such as work to understand processes of memory consolidation and retrieval[183]. Other related methods include variational principles for parameter estimation in latent statistical models using notions of free energy[184]. It is important to keep in mind that these successful approaches to develop new insights and computational methods are based on formal analogies, and, hence, their relation to physical thermodynamics is symbolic in nature. Therefore, despite the language used, these approaches are closer to the statistical rather than the physical face of information.

Finally, potential puzzles arise when comparing two observations: the phenomenological fact that Boltzmannian entropy, based on coarse-graining, increases with time; and the informational observation that Gibbs entropy, based on knowledge of the system, tends to decrease when one makes measurements[185]. In response, it is possible to derive a 'Bayesian' version of the second law, demonstrating that an appropriately defined cross-entropy does increase over time[186].

This view suggests that what matters is not the physical stuff evolving according to certain rules, but the more abstract algorithmic pattern it is obeying[117] – in other words, the information needed to describe the relevant aspects of a given physical entity and the rules by which that information is processed.

It from bit

The 'it from bit'[10] perspective corresponds to a strong instantiation of an ontological perspective on information, which suggests that it is possible 'to understand and express all of physics in the language of information'[10]. The original intention of this perspective, however, has become somewhat obscured over time: it is not a way of understanding the basic constituents of the universe but rather emphasizes the role of (discrete) measurement outcomes. Building upon the Copenhagen interpretation of quantum mechanics, this suggests a shift in emphasis from what 'really exists' to instead focus on the outcomes of measurements[118]: "every it – every particle, every field of force, even the spacetime continuum itself – derives its function, its meaning, its very existence entirely – even if in some contexts indirectly – from the apparatus elicited answers to yes or no questions, binary choices, bits"[10]. In this view, it is the 'elicited answers' (that is, measurement outcomes) that are the bits, not an underlying pre-measurement reality, making 'it from bit' an epistemological proposal aligned with the Copenhagen interpretation.

Following these ideas, it has been argued that information-theoretic considerations may be sufficient to define what quantum theory is. Specifically, modern attempts to construct more well-defined theories along these lines are known as 'epistemic' versions of quantum mechanics[119–122]. Here, what matters is not primarily any underlying 'actual' ontology but the information contained in measurement outcomes. Quantum states (wave functions), in particular, are generally not thought to represent reality but simply to be a way to make experimental predictions. This view has been characterized as 'participatory realism', because it does not deny that there is an objectively existing reality but emphasizes that 'reality is more than any third-person perspective can capture'[122]. There is also an alternative strand of thought in the philosophy of quantum mechanics that insists on the reality of the quantum state, which regards the complex wavefunction as capturing all, or some, aspects of reality (for details, see Supplementary Information section 12).

At this point, it is useful to recapitulate how we came to recognize energy as a fundamental element of our universe. Despite how intuitive and tangible the notion of energy is for us today (being encapsulated in batteries and other everyday objects), it refers to a non-trivial formal concept. In the context of classical mechanics energy cannot be directly measured, representing an abstraction within other abstractions: what one can actually see and measure is movement, which is then explained in terms of forces, which are then in turn explained in terms of energy. However, the development of modern physics has promoted energy from an algebraic trick into something regarded as 'more real' than the observable reality. The reason for this development is essentially related to the fact that energy is conserved by virtue of a fundamental symmetry – namely, time translational invariance. The conservation of energy is so fundamental that it has allowed the discovery of new particles (the neutrino) while enabling comprehensive physical analyses by simply keeping careful bookkeeping of the energy. Similarly, our theory of electromagnetism leads us to see fields as more fundamental than charges, and the field theory takes a step forward using fields as the fundamental building blocks. The success of these theories is what confirms that this conceptual 'leap of faith', from observable movement to energy and fields, pays off. Should we take a similar leap of faith with information? It is hard to say – the case is still open, and only time will tell.

The main affordances and restrictions of the ontological face of information are discussed in Box 5.

Outlook

We have reviewed four different ways of thinking about what information is and how it can be used scientifically. These faces of information all have distinct characters, having their own affordances in terms of what they allow us to do, and specific conditions that restrict their applicability. We see no reason to regard any of these perspectives as being more legitimate than the others; rather, we see them as complementary. Hence, following previous philosophical work[15,123,124], we advocate for a pluralistic approach to information, in which different technical frameworks coexist and are adopted according to what is most useful for the task at hand. Some of the milestones in the evolution of these faces of information are summarized in Fig. 2.

Acknowledging the existence of these divergent but equally valid ways of conceptualizing information can reduce misunderstandings

Box 5 | Implications of the ontological face of information

Affordances: Thinking about information as fundamental offers an interesting angle on the nature of spacetime and the matter fields within it. Within conventional quantum theory, it suggests focusing directly on quantum states and entanglement between subsystems, rather than in terms of some particular classical ontology that is then 'quantized'. Information then provides a path by which the observed semiclassical world can emerge from an austere underlying quantum state, in agreement with the correspondence principle[187] and Feynman's path integral[188] formulation of quantum mechanics.

The most popular version of this idea has been in the context of the holographic principle and the bulk–boundary correspondence[11,12,189–192]. The idea here is that there is a d-dimensional 'boundary' quantum theory without gravity that is equivalent, via a holographic dictionary, to a $(d+1)$-dimensional 'bulk' theory with gravity[193]. It has been argued that the spacetime geometry of the bulk theory is encoded in the entanglement properties of the state of the boundary theory, suggesting that what is 'real' in the bulk depends on information encoded in the boundary. There have also been attempts to understand how spacetime can emerge through entanglement directly in the bulk, at least in the weak-field limit of gravity[194,195].

There are also more speculative scenarios, which are provocative but as yet less firmly connected to established physics. Computational hypergraphs, based on classical work on cellular automata[196], could potentially serve as models for quantum processes and emergent spacetime — and indeed all of physics[117,197]. In a different vein, in constructor theory, dynamical differential equations are replaced by rules governing what physical transformations are possible or impossible[198]. In both of these cases, the focus is diverted from 'stuff' (matter, energy, particles and fields) onto the informational relations between abstract formal structures.

The view of information being fundamental has also played an important role in biology in general, being particularly influential in theoretical neuroscience (Supplementary Information section 13).

Restrictions: Despite these promising aspects, this face of information should be handled with care as the extent of its viability is still being investigated. Although information clearly plays a central role in how higher-level structures emerge from lower-level dynamics, it is not known what the final lowest level is — or even whether there is such a thing. The history of physics provides examples of theories that aspire to be fundamental, only to be replaced by something even more fundamental. These paradigm shifts tend not only to replace dynamical rules but to alter the very ontological structures that are supposed to represent what really exists.

Instead of focusing on what is fundamental and what gets replaced, one may note that, although the fundamental physical entities might change dramatically in the transition between theories (for example, Newtonian to relativistic spacetime or classical phase space to quantum Hilbert space), there are structural elements that remain intact through such transitions[199,200]. This is consistent with the fact that physical theories do not really replace each other, but rather new theories extend the realm of applicability. That is, when considering very different theories, it remains possible to identify relations between entities within them that represent known features of reality. For instance, spacetime is a different kind of thing in relativity as opposed to Newtonian mechanics, but it is still possible to compare predictions for the motion of a planet around the Sun in each theory. This perspective brings information once again to the fore: even if it is not possible to be confident that the entities posited by the best theories are truly fundamental, one can aspire to understand informational relationships between them that capture something lasting and true about reality.

At this stage, it is impossible to discount a future in which, through further progress in physics, it becomes possible to identify the most fundamental level of reality and recognize it as being constructed from perfectly definite 'things' acting in well-defined ways, rather than via more abstract informational constructions. The ultimate future of physics is hard to predict; in the meantime, we suggest recognizing the usefulness of information for capturing important aspects of reality, whether or not there is something more to it than that.

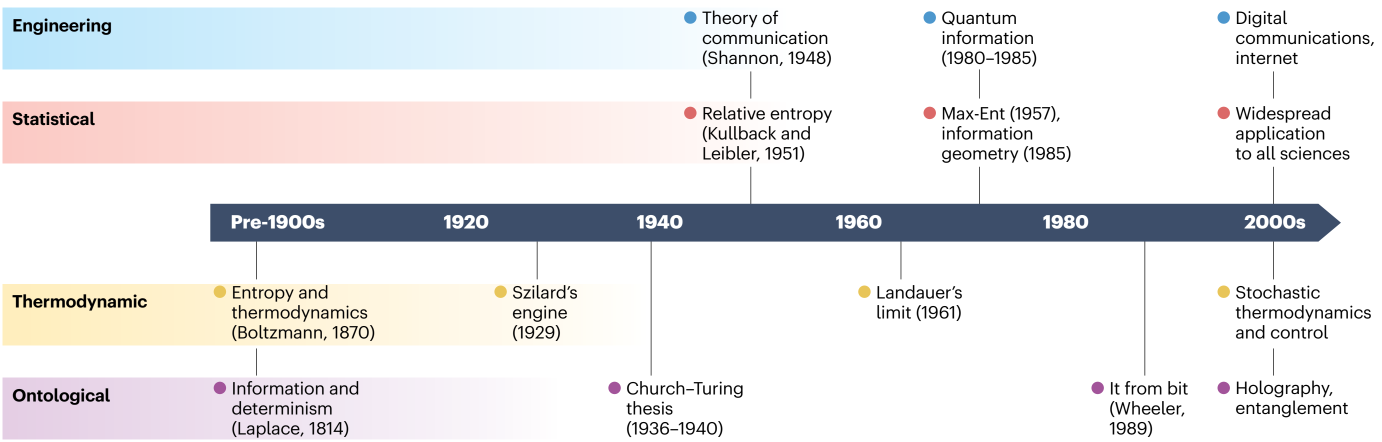

Fig. 2 | Some key milestones in the evolution of the four faces of information. Although foundational ideas for the thermodynamic and ontological faces were established before the twentieth century, the advent of the engineering and statistical faces was instrumental in revealing information's full potential. Max-Ent, maximum entropy principle.

and unproductive disagreements between scientists operating under different frameworks. Clarifying which faces of information one is using allows others to better understand the presented position and supplies tools for the verification of whether the necessary conditions for use are truly met. For example, embracing a statistical view on information allows one to measure the mutual information between parts of a physical system without requiring that they are 'sending bits' to each other over some channel (which requires an encoder and decoder), but this may come at the price of restricting the kind of interpretations and conclusions that one can draw from the analysis. In addition, distinguishing the various faces of information can clarify the interpretation of specific quantities (see Supplementary Information section 2 for an illustration regarding the interpretations of information-theoretic 'surprisal').

Although we have highlighted four faces of information, it is hard to say at this point whether this list is exhaustive or if more faces ought to be added in the future. Also, although our presentation highlights Shannon's quantities, there exists a rich array of other informational functionals on probability distributions – including Rényi's[49], Tsallis'[125] and others – which extend Shannon's measure and have their own domain of applicability (Supplementary Information section 10). Furthermore, there exist many quantities with information in their names (such as Fisher information[126] or Chernoff information[127]), but most of them can be grouped into one of the presented perspectives (see Supplementary Information section 14 for a discussion about algorithmic information). The main contribution of this work is the framing of a pluralistic approach embracing distinct but equally valid technical interpretations of information, but the specific taxonomy of interpretations itself may need to be revisited as our scientific understanding evolves. It is our hope that this framing may contribute to a robust development of information-based frameworks in physics and beyond, following Shannon's prescient advice: "many of the concepts of information theory will prove useful in these other fields [...] but the establishing of such applications is not a trivial matter of translating words to a new domain, but rather the slow tedious process of hypothesis and experimental verification"[13].

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