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Entropy as diversity and order in living systems

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Abstract: This empirical study of the statistical entropy of physiological time series, and of numerical series generated with simple mathematical equations, shows that entropy increases with diversity and with order, rather than with uniformity and disorder. The statistical entropy of data points is a function of their diversity, and the entropy of patterns of data is a function of their order. Physiological data, more complex that mathematical models, had high diversity and intermediate levels of order; thus complexity was not related with either entropy or order. As entropy was measured with the equation that defines it in statistical mechanics and in communication theory, these observations indicate that the current interpretation of entropy as disorder and uniformity is a philosophical overlay that does not stem from the mathematical formulation. We offer an alternative formulation of entropy as a symmetry or equilibrium of opposites. In natural processes, complexity of organization is associated with greater internal production of thermodynamic entropy, suggesting that entropy production may serve as a driving force for evolution, biological function and health, not only for decay, illness and death. This is in contrast to Schrödinger-Prigogine's view of evolution as resulting from a reduction in the internal entropy of living systems.

Key words: asymmetry; chaos; complexity; diversity; electrocardiography; entropy; evolution; information; process theory; statistical mechanics; symmetry; thermodynamics.

A bird's eye view

The concept of entropy is of general interest, transcending physics to enter biology [1, 6, 23], medicine [26], economics [15, 25], sociology [4], and art [2]. There is a profound contradiction between evolutionary science, that postulates a net increase in organization with time, and classic thermodynamics, that interprets the increase in entropy as decay towards random disorder (figure 1). We think that evolution and decay are twin results of the increase in entropy. A force naturally moves things in one direction until it finds an opposition capable of arresting it; similarly free energy naturally, spontaneously, produces change towards a state of equilibrium, when opposite forces are equal (figure 2). The equilibrium of two or more forces may resolve itself in heat and disorder (the traditional concept of entropy) but it can also create complex structures, such as a building or an organism. As heat flows from the hot sun to our warm planet and to cold space (figure 3), organization is created on earth. This increase in organization is accompanied by an enormous increase in the production of entropy (figure 3). We thus propose that entropy is not disorder, but the equilibrium of opposite forces, and that the production of entropy drives both evolution and decay.

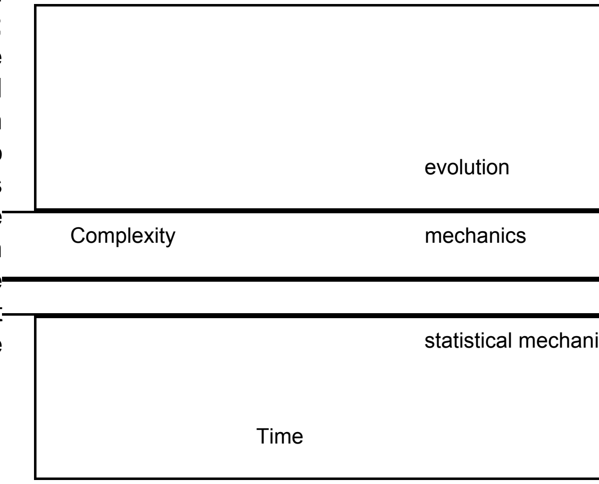

Figure 1 Three views regarding net changes in the complex
organization in natural history

Figure 2 A fourth view: the co-existence of evolution and decay as result of the flow from asymmetric free energy states to more symmetric and stable symmetries of opposite forces.

To test this view, we measured the entropy of random numbers, highly ordered periodic series, and much more complex series, namely the intervals between heart beats (figure 4). Using the basic equation that defines entropy, we measured the entropy of the series of numbers, and also the entropy of their combination in sequences (likewise to understand a message one attends to the individual letters and to their combination in words). We found that these measures of entropy increased with diversity and with order, not with disorder and uniformity. These results support the concept of entropy as an equilibrium of opposites; entropy-production may thus drive and steer evolution, rather than being solely a tendency towards disorder that must be overcome.

Figure 3 Complexity emerges from heat flow, associated with high entropy production. Free en
flow density from [9].

There are four basic concepts of entropy. Thermodynamic entropy $S = dQ/T$, where dQ means flow of heat, and T is the absolute temperature. Statistical mechanics associates thermodynamic entropy with the distributions of particles, for which Boltzmann adopted an equation developed by DeMoivre (1756) [6, 38]. Shannon [34] extended this statistical view of entropy to probability distributions of any kind. Finally, there is a philosophical conceptualization of entropy as disorder, that we shall contrast here with empirical data.

Empirical study

Statistical measures of entropy are used to study the dynamical parameters of time series, i.e. data that presents the temporal evolution of a process. The statistical entropy of physiological processes can be readily quantified. For instance, an electrocardiogram in which there are as many short as long beat to beat intervals has high entropy, while if most intervals fall within a narrow range of values, the entropy of the electrocardiogram is low. Such electrocardiographic measurement of entropy have been shown to be clinically meaningful [28,31]. This is not surprising, as variability is known to be clinically significant. Using the same statistical methods, one can measure the entropy of mathematical curves taken as models for time series of empirical data. Here we study the entropy of cardiac rhythm (as an example of a psychophysiological data) and of computer-generated numerical series. As the information of a system is not reducible to that of its component parts, we use two measures of entropy, one that measures the entropy of the individual data points, and another that measures the entropy of sequences of data points. In the case of electrocardiographic recordings, individual data are durations of beat-to-beat intervals, and the sequences is temporal order, so the corresponding entropies portray the distribution of durations (regardless of order) and the distribution of temporal sequences (regardless of duration).

Figure 4 Entropy of cardiological data. N = Normal subjects
Coronary patients; P = Psychotic patients (not taking antipsychotics). Recurrence entropy at 50 embeddings.

Method

Entropy (H) was measured as defined by Shannon's equation $H = - \Sigma P_i \log_e (P_i)$, in units of information. The information content of a distribution increases with the number of possible values, and with the uniformity in their relative frequency. The entropy of numerical series was measured with a program developed by Patel which measures the regularity of the distribution of data points, such as beat-to-beat intervals in the electrocardiogram, in a histogram. The value of entropy measured for a given time series increases with the number of bins (class intervals) used in the calculation up to a maximum, when the number of bins is identical to the number of different numbers in the series. Numbers reported in this article are calculated with 100 bins, in samples of 3500 points. We shall denote this measurement as **information entropy** H_I as in communication theory the informational value of a message depends on the number of possible messages and in their relative probability.

A second measure, which we shall call **recurrence entropy** (to be denoted H_R), was obtained using the method and the computer program developed by Webber and Zbilut [37] based on the recurrence method developed by Eckmann el al [12] to reveal hidden patterns in natural processes. H_R is also measured with Shannon's equation, but the data considered are recurring sequences of data in the series, rather than individual data points. Recurrences are calculated from a numerical series by creating Euclidean vectors of N successive members, comparing each of them with each of the others, and noting similarities of vectors (within 10 % in our study) as recurrences. N is the number of embeddings. As the origin of the vector is advanced 1 data point, one identifies sequences of two or more successive recurrences are found in patterned data, but not in random series; these sequences are represented as diagonal line segments in recurrence plots [37]. Recurrence entropy is measured by counting the number of such line segments, and distributing them over integer bins of a histogram according to their length (which is inversely proportional to the largest positive Liapunov exponent [12]). To measure H_R with Shannon's equation, we take P_i as individual bin probabilities of all non-zero bins greater than or equal to the shortest line segment. If sequences of different number of recurrences occur with the same frequency, the recurrence entropy is high, while if sequences of a given duration predominate, the entropy is low. For the comparisons of recurrence entropy we used 5 embeddings (table 1) and 50 embeddings (figure 4). The actual value calculated for H_R depends on the number of embeddings used in the calculation: it increases monotonically for random distributions (rectangular and Gaussian) and for physiological data (albeit some periodicity was observed in some cases); and it varies periodically in periodic and for chaotic distributions (for instance, an irregular pattern of period 19 had H_R 8.9 when embeddings were multiples of 19, and 2.2 one embedding above or below). To avoid this problem, we also compared the entropy measured at the median embedding dimension [31] (the embedding, different for each sample, at which 50% of the recurrences belong to a sequence of consecutive recurrences, rather than being isolated.

Recurrence entropy was also measured after shuffling the data 20 times; destroying sequential order, shuffling creates a random series of numbers with the same statistical distribution as the original time-ordered series. The recurrence entropy measured after shuffling is denoted H_S. As entropy is an extensive, additive property, entropy measures can be subtracted from each other. We define **ordering entropy** $H_O = H_R - H_S$.

With these methods we studied computer-generated numerical series (described in figure 4), chosen as models for fundamental natural processes: uniformly distributed (rectangular) random numbers (range 70 to 130), normally distributed (Gaussian) random numbers (10 ± 3), random alternations of two values, harmonic distributions such as sine waves and the Fibonacci series (a pattern found in botany, anatomy and esthetics), and the logistic equation $x_{n+1} = R X_n (1 - X_n)$ (used to model population development on a limited environment [24]) taking X = 0.1 varying R to generate harmonic and chaotic distributions (3.2 for period 2; 3.5 for period 2 doubling; R = 3.6 for chaotic pattern; 3.84 for period 3; 3.85 for period 3 doubling; and R= 3.9 for chaotic pattern).

Physiological data consisted in cardiac beat to beat intervals, estimated by measuring the interval between R waves (the most prominent deflection of the electrocardiogram) in 24 hour recordings obtained during the course of daily activities from cardiologically normal adult volunteers (N=5), and from patients with either coronary artery disease (N= 5) or with affective psychosis (N=5), as representative of dysfunctions at higher and lower levels of anatomical organization. After scanning the electrocardiogram for artifacts, it was sampled at the rate of 128 observations per second to determine the R-R intervals. Three samples of 7000 R-R intervals each, recorded during wakefulness, were processed per subject.

The range and the standard deviation (S.D.) of R-R intervals were recorded as measures of statistical variability, and as estimates of energy consumption by the heart and by the organism (within limits, cardiac and total body energy consumption increase with heart rate, provided that force of contraction and ventricular filling time be maintained).

Results

Examination of computer generated curves indicates that neither informational H_I nor recurrence H_R entropy were correlated with disorder: H_I was equally high in random as in sine wave distributions, and equally low in random or ordered series of two numbers. H_R actually increased with pattern in the data, and was markedly reduced by shuffling periodic, chaotic, or physiological series (table 1 and figure 4). Shuffling did not change the recurrence entropy of randomly ordered data (rectangular or Gaussian), so their H_O was zero. H_O does readily differentiated chaotic from random data.

Both measures of entropy depend on the uniformity of distribution of the data analyzed in each case. For instance, in recurrence calculations, high entropy curves such as periodic and chaotic curves have a flat histogram, while low entropy curves such as random data (including all data after shuffling) show a decline in the relative frequency of longer sequences of recurrences.

Entropy values also depend on the diversity of the data. H_I increases with the diversity of numbers in the series (compare for instance in table 1 the H_I for binary and N-ary random or sine wave distributions). H_I, however, is not a measure of variability, as increasing the diversity of values beyond the number discriminated by the number of bins used for its calculation does not increase its value.

Figure 4 presents the data in a coordinate plane defined by H_I and H_R axes. A random sequence of any two numbers (binary random) is low in both informational H_I and recurrence H_R entropy. Random series of many different values show high informational entropy and low recurrence entropy. Conversely, binary alternations showed high H_R and low H_I. Sine waves and other periodic data that combine both temporal order and diversity, are high on both entropies. At 5 and at 50 embeddings, Gaussian distributions, chaotic attractors, and helices (monotonic increase + periodicity) occupied intermediate places between these four extremes. Thus, informational H_I and recurrence H_R entropy are not correlated either directly or inversely, but represent two different measurements: H_I is a function of the diversity and uniformity of distribution of the data in the series, while H_R is a function of the order of the data.

Recurrence entropy H_R depends on both temporal and statistical organization. Shuffling the data destroys the sequential order while leaving intact the statistical distribution. In random distributions, recurrence entropy was increased when their range was decreased, whereas shuffling did not change it. Shuffling markedly decreased the measure of recurrence entropy for all other data. Subtracting the value for recurrence entropy obtained after shuffling H_S from H_R provides an estimate of the entropic contribution H_O of the temporal organization of the data. H_O is 0 for random and Gaussian distributions, and it is comparable for chaotic distributions and for cardiac data.

Physiological data: Series of beat-to-beat intervals were high in H_I (3.809 ± 0.219 for controls; 3.404 ± 0.350 for cardiac patients and 3.350 ± 0.171 for psychotics) and moderate in H_R (1.561 ± 0.203 for controls; 2.138 ± 0.435 for cardiac subjects; 2.178 ± 0.339 for psychotic patients) at 50 embeddings. Also at the median embedding dimension (57.7 ± 3.0 embeddings for healthy awake subjects), the recurrence entropy of cardiac data occupied an intermediate place (1.91 ± 0.08) between the low entropy of rectangular random numbers (1.23, at 215 embeddings) and of normally distributed random numbers (1.24, at 24 embedddings), and the high entropy of sine wave distributions (5.86 at 10 embeddings). Among clinical populations, H_I was lower in psychotics, and even lower in coronary patients than in normal controls, while H_R was higher in coronary and in psychotic patients than in control subjects. The differences between clinical populations were demonstrable statistically, but were not clinically valuable, as there was overlap between patients and controls (figure 4).

In comparison to controls, heart rate was reduced in coronary subjects, and accelerated in psychotic subjects (both groups were medicated). During sleep, heart rate and informational entropy decreased, while recurrence entropy increased.

Discussion

Entropy is not disorder: The statistical interpretation of entropy asserts a tendency to a uniform distribution, or equal probability, of different states. However, using the mathematical equation that defines entropy in both statistical mechanics and communication theory,, neither informational nor ecuerrence entropy were found to measure "disorder" as we would intuitively describe it. Informational entropy was equally low for randomly distributed and for regularly alternating pairs of numbers, and it was high for distributions with many values, regardless of whether they were randomly distributed or organized in a sine wave pattern. Recurrence entropy was lowest for random distributions, and highest for ordered oscillations between opposites, whether the series had two or many values. Further, after shuffling, which increases disorder, recurrence entropy decreased, indicating it is a measure of sequential pattern. These results contradict the mechanical interpretation of entropy as disorder. The mechanical interpretation of the maximization of entropy as a tendency towards more symmetric distribution of particles and velocities, implies disorder when applied to a gas expanding in a close container. It does not apply to an open system, as Brooks and Wiley [6] have shown for biological systems, and Layzer [21] has shown for the universe, cases in which the expansion of the system more than compensates for the disordering tendency of entropy maximization. In open, complex systems, a tendency to uniform distribution of its component parts, does not necessarily result in disorder and simplicity. Even mechanical systems, such as coupled non-linear oscillators, fail to satisfy the equipartition hypothesis required by statistical mechanics [11].

Entropy maximization generates diversity and order: In the study of time series, H_I and H_R

represent two aspects of time, duration and order, and were found to be related to the diversity and to the patterning of the data --opposite to the classical interpretation according to which greater entropy implies uniformity and disorder. These results suggest to us that also in nature, the maximization of entropy leads to an increase in variety of processes and states, and to an increase in their range of complexity, including both local greater disorder and local greater complexity. Entropy is a diverse order.

The results obtained do not contradict Boltzmann's mathematical formulation of entropy. Entropy increases with the diversity of microstates in statistical mechanics. There is nothing in the model, however, that predicates that these microstates must be absolutely identical, devoid of differences capable of affecting physical processes, and of being discernable by human observers. As natural processes have a multiplicity of properties, not only position and velocity, it is conceivable that whenever there is a force sufficiently strong as to impose uniformity of distribution in one respect, variety and complexity can increase in other respects. For instance, a selective force that determines that the number of balls be the same in all available bins may lead to a non-uniform mass distribution, or a heterogenous color distribution, if the balls are of different mass or color. In support of the view that tendencies to equilibrium with respect to one selective force may cause differences regarding others, we observed that informational entropy and recurrence entropy varied independently from each other when different numerical series were compared; and that they varied inversely to each other when the same physiological parameter was measured in health and disease, suggesting that equilibrium in one respect may imply disequilibrium in another.

The range of patterns of organization may likewise be expected to increase with entropy, as the latter implies an equal probability for all possible configurations, including simple and complex ones. Any statistical interpretation has to allow for the spontaneous creation of order as well as of disorder, and the empirical evidence calls for an equal or greater occurrence of evolution than of decay.

Physiological entropy: distinguishing order from organization: The association of higher entropy with greater diversity and order is biologically significant, because variability, orderliness, and complexity are major characteristics of living organisms. In comparison with simpler mathematical curves, physiological data had moderate values of entropy, i.e. relatively high informational entropy (yet lower than either random or sinusoidal distributions), and relatively low ordering entropy (yet much higher than random data). Physiological data differed from Gaussian distributions of similar informational and recurrence entropy by the existence of a temporal patterning (as revealed by shuffling). Cardiac variations hence do not reflect random beat-to-beat variability.

Pathology increased recurrence entropy and decreased informational entropy, suggesting that these two measures of entropy vary inversely in at least some natural processes. In the logistic equation, informational entropy and recurrence entropy were also inversely related for most patterns. If health appears to be associated with organized variation, illness appears to represent lesser diversity and greater order, at variance with the view of pathology as a "disorder." As illness certainly implies decay, such an increase in order clashes with the interpretation of an increase in entropy as synonymous with decay.

As biological data is obviously more complex than mathematical series, the intermediate levels of entropy calculated for cardiac data, and the relatively greater entropy observed in pathological cases, indicate that entropy is not a measure of complexity of organization. The entropy equation measures order, not organization. The association of entropy with disorder and of organization with order may only reflect semantic looseness [38]. Our results support the view that complexity of organization requires an intermediate level of order [16], and further suggest that it is associated with intermediate degrees of statistical entropy for individual components (informational entropy) and for their composites (recurrence entropy). Organization is a form of order, and diversity is a component of complexity [16, p 29]; as diversity and order are in some ways opposites, it is not surprising that complexity of organization is associated with a balance between diversity (informational entropy) and order (ordering entropy).

Statistical entropy and energy consumption: Heart rate provides an estimate of energy consumption, and hence of entropy production in the heart and in the organism. Heart rate was faster in psychotic than in non-psychotic individuals, probably reflecting emotional turmoil, and slower in medicated cardiac patients, as one of the aims of treatment is to reduce the heart's oxygen consumption. Thus neither informational nor recurrence entropy reflected what we presume was the actual rate of thermodynamic entropy. Undoubtedly the entropy of beat-to-beat intervals can hardly be expected to reflect the entropy of molecules in the heart, because we are dealing with differences processes. In fact, entropy is always defined in relation to the processes being measured, as the total number of degrees of freedom can never be simultaneously considered [18]. The formal similarity between thermodynamic, statistical and informational entropy raises an interesting question: Do these observations regarding statistical entropy H reveal anything about thermodynamic entropy S ?

Process theory of entropy as symmetry of opposites

The contradiction between evolution and thermodynamics: Three mutually contradictory views regarding natural history have been held: progress, decay, and conservation (figure 1). The idea of progress was embodied by theories of natural evolution and human revolution. Classic thermodynamics interpreted the maximization of entropy as decay towards rest, thermal uniformity (Clausius), and disorder (Boltzmann). Classical mechanics kept the middle ground, postulating the reversibility (Newton) and space-likeness (Einstein) of time, and hence the conservation of information, attempting to account for thermodynamic irreversibility as a macroscopic statistical phenomenon (Boltzmann) that does not apply to the microscopic world of quantum mechanics. We have proposed a fourth view, in which evolution and decay are opposite and complementary aspects of the same process of equalization of opposites [29-32].

Figure 5 Contrasting closed system model (A) and Prigogine's model (B) with Process Model (C) which postulates a net increase in internal entropy as a result of increased free energy flow density.

The apparent contradiction between evolutionary theory and thermodynamics has been accounted for by postulating that the expansion of the universe compensates for the tendency to mixing [21], or by postulating that living organisms [33] and other systems far from equilibrium [27] are capable of importing free energy from, and exporting entropy to their environment (figure 5 B). We have proposed instead that the natural tendency of processes from unstable to more stable configurations creates all forms of symmetry, including not only the static attractor of uniformity and disorder, but also more complex forms of stability, such as the cyclic and chaotic attractors described by non-linear dynamics, as well as atoms, molecules, and living organisms (figure 2). At slightly higher temperature than their surroundings, and processing free energy faster, living organisms and other complex systems would increase their internal entropy faster than the environment (figure 5 C), in contrast to Prigogine's model, in which the internal entropy decreases (figure 5 B). These alternative hypotheses cannot be readily compared by measuring physically the internal entropy of living organisms. However, it is possible to compare them empirically via the statistical concept of entropy.

Statistical and thermodynamic entropy: The second law of thermodynamics portrays an asymmetry: work becomes heat more than heat becomes work (Carnot). Statistical mechanics generalizes this thermodynamic definition of entropy in its hypothesis that entropy represents a uniform distribution of the relative frequencies with which different states of particles and velocities occur. This view has come to dominate scientific language, so the term entropy has been made synonymous with disorder. Shannon's equation has been viewed as a further generalization applicable to probability distributions that frees it from thermodynamic phenomenology. These views are not universally accepted, as the statistical mechanical interpretation of entropy allows for reversibility, while thermodynamic entropy increases irreversibly [14,15]. Wicken [38] differentiates Boltzmann's entropy that implies the impossibility of distinguishing microstates, from Shannon's, as in communication theory uncertainty disappears with the arrival of the message. We would argue for an objective interpretation of entropy in terms of flux between various states, not a subjective interpretation in terms of the uncertainty of the observer. Uncertainty needs not be implied by the mathematical formalism, if one applies DeMoivre's equation to a determined distribution, and interpretes P_i as a relative frequency. The tendency from asymmetric states towards more symmetric, uniform and stable distributions, can be determined by the generation of opposites --such as action generates collisions, movement produces friction, and living leads to illness and death. The formal identity between thermodynamic, statistical and informational entropy may reflect a universal form of nature, namely that every action generates opposites.

Entropy as symmetry of opposites: Carnot's formulation of the second law postulated the need for a temperature asymmetry to produce work, and the tendency of processes to create a thermal symmetry. We generalize this view as a universal tendency from asymmetry to symmetry [29]. The gradient of recurrence entropy from maximal disorder (randomness) to simple orders (such as the normal distribution), to physiological data, and to symmetric distributions in which opposites alternate, is compatible with the definition of entropy as symmetry, and at variance with equating entropy-production with either evolution or decay. It is in the way from asymmetry to symmetry that complexity emerges, and that also disorder is created.

The independent, and at times inverse, variation in two measures of entropy illustrates how the coexistence of multiple equilibrium attractors may create diversity, order, and complexity, not only in biological organisms but also in physical structures. As an attractor, the maximization of entropy can create multidimensional complexity (instead of simple and uniform disorder). Diversity and temporal pattern represent two manifestations of asymmetries in the entropic attractor created by the multifarious balance of multiple pairs of opposite forces. Exemplifying this concept, symmetry is conserved for simultaneous inversions of time, charge and parity, but not for each separately. In fact, although mechanics does not include this fact among its postulates, real time cannot be inverted.

Dynamic nonequilibrium and structure formation can result from a balanced combination of opposing and complementary forces, as one predominates over the other in some respects but not in others. Such oppositions are universal, as from the perspective of faster processes, slower ones appear to be moving in the opposing direction [6]. The sum of all forces that are not moving in a given direction results in an oppositely directed vector [Sabelli, this volume]. We propose that a major consequence of these universal oppositions is a tendency to symmetry. Entropy represents the partial but ever increasing uniformity that results from determined processes of balance between opposites. This asymmetric flow towards attractors and structures of greater symmetry is expressed thermodynamically as a maximization of entropy. Work becomes structure more than structure becomes work.

Cosmic asymmetry and symmetry: Although numerous examples support the concept of cosmic symmetry as a fundamental principle, from which predictions can be made regarding the existence of as yet unidentified particles, asymmetric features have been demonstrated at all levels of organization. Pasteur developed a concept of cosmic asymmetry [17] from this observation of the asymmetry of biomolecules. As asymmetry could not arise from symmetric structures and processes, Pasteur reasoned that the most fundamental physical entities must be asymmetric. This hypothesis has been confirmed by a number of discoveries, beginning with the non-conservation of parity in beta decay [36]. The unified theory of electromagnetism and weak interactions indicates that asymmetry is not limited to nuclear processes; asymmetry exists also in atoms and molecules. The optical rotation of atoms has been demonstrated empirically [5,13], and may explain biomolecular asymmetry [Garay, see 3; 19]. String theory [35] postulates that elementary particles and forces are asymmetric, one-dimensional curves rather than point-like. Other naturally occurring asymmetries include the asymmetric preponderance of matter over anti-matter; the time-asymmetric collapse of the wave function in quantum mechanics; the role of highly asymmetric, non-equilibrium states in the thermodynamics of open processes [27]; the violation of gauge symmetry by superfluids; the lack of time symmetry in magnets [1]; cellular asymmetries, such as the ionic asymmetry across plasma membranes; left and right brain asymmetries, and psychological asymmetries [10]; and social asymmetries of class, sex, race, nationality [29]. Energy is asymmetric in its features of unidirectional temporality, unidirectional causality and unidirectional entropy increase. Information is an asymmetry between alternatives; without difference, there can be no information. Even the Maxwell-Boltzmann's distribution is asymmetric. Statistical mechanics explains time-asymmetry and thermodynamic irreversibility postulating that the universe started as a low entropy (Penrose), more ordered (Feynman) state [22], hence asymmetric; other current theories postulate a total symmetry for the early universe that was spontaneously and progressively broken [20], as the symmetrical state or pattern is unstable, and asymmetrical patterns are more stable [1]. The statistical definition of entropy as a uniformity of distribution, and the unidirectional maximization of entropy with time suggest instead a universal and asymmetric process of flow from asymmetric to more symmetric states. Symmetry and asymmetry are coexisting opposites in natural processes.

Entropy as evolution and decay: Biological evolution consists in the increase in diversity and complexity (Dollo's law) [7]. The increase in diversity and order associated with greater entropy thus support the view of that the production of entropy not only fuels but also steers evolution [6, 23] --in contrasts to the more accepted view that evolution consists in a local decrease in entropy [27,33]. This is consistent with the view of biological organisms as physical processes, and of a continuity of inorganic and organic evolution.

The directionality of the second law may be expressed in evolution, and tie the mechanical world of quantum phenomena and mechanical cause to the biological world in which purpose is evident. As complex configurations in principle have the same statistical probability as the simple original configurations, it seems likely that a tendency to equalize the frequency of various possible states does not preclude, and in fact favors, local increases in complexity. We do not mean to imply that evolution simply results from a tendency to fill in more complex niches which were initially empty, only that both inorganic and organic evolution (each a complex process, with a multiplicity of specific mechanisms) include similar processes of diversification and ordering implicit in the maximization of entropy.

Entropy production may be expected to promote inorganic evolution because the forces of nature are largely attractive, bonding separate entities to form more complex systems; for instance, subatomic particles tend to have higher entropy when separated than when bound [38, p 63]. In this sense one could say that the direction imposed by the second law to maximize entropy may "drive" evolution, as the consumption of free energy creates atomic and molecular organization. The fact that mechanics makes good use of ideal models in which processes are reversible, does not imply their existence.

Entropy production may also be expected to promote organic evolution. Contrary to the postulated association between biological complexity and decreased thermodynamic entropy, which is untested [38], the production of entropy appears to be directly related to complexity. Thus, free energy flow density (in ergs s^{-1} gm^{-1}) is greater for brain (150,000) than for the rest of the body (17,000), and much greater than for the biosphere as a totality (500) or for the sun (2) or the galaxy (1) [9]. There is likewise a temperature gradient from the sun to the planet to galactic space, and since thermodynamic entropy $S = dQ/T$, biological processes in the planetary surface have the highest density of entropy production (figure 3). Local concentrations of free energy, of entropy production, and of informational complexity, are thus associated with each other, suggesting that the creation of pattern by the flow of energy may be the cause of evolution. Biological complexity emerges at the moderate temperature of our planet because heat produces work only as it flows from a hot to a cold body (Carnot's formulation of the second law).

Entropy-production of course also spawns disorder, waste, decay. Opposite in sign, evolution and decay may result from the same fundamental process of entropy maximization. In fact we know not of a process that increases organization separately in time or place from the production of disorder and waste. It thus seems likely that the maximization of entropy increases both order and disorder, as postulated from the earliest process theorist, Heraclitus, in his concept of enantiodromia (Greek: enantio = opposite; dromos = race).

Concluding remarks: In summary, entropy, as a measure of the regularity or symmetry of a distribution, is associated with diversity and order. These ideas challenge widely held views, yet traditional concepts regarding entropy are being actively re-examined from many perspectives. There is a multiplicity of different, and often mutually exclusive, definitions of entropy [8,18,22]. Information is widely viewed as negentropy, but Shannon [34] defined entropy as equivalent to information, and "negative entropy" has no thermodynamic meaning [38]. Boltzmann's microstate/macrostate distinction requires to assert paradoxical ideas, such as that Newtonian mechanics is only microscopic, and that the second law of thermodynamics is the only macroscopic law of physics [6]. The macrostate-microstate distinction is currently being challenged by Prigogine's group, and we would argue that the very definition of a microstate depends on an abstract (and hence unreal) definition of a "slice of time", and that physical processes must be equally symmetric or asymmetric at all levels of organization.

Knowing the history of so many scientific ideas, we understand that the proposed interpretation of entropy as symmetry will eventually turn out to be wrong. Yet, we must propose hypotheses, because science advances with their formulation and refutation.

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Table 1. Entropy of computer-generated numerical series calculated with Shannon's equation $H = - \Sigma P_i \log_2 (P_i)$ applied to raw data (informational entropy H_I), to sequences of recurrences (recurrence entropy H_R), recurrence entropy after shuffling (H_S), and ordering entropy ($H_O = H_R - H_S$). 3500 point samples.

Numerical series	Informat. entropy H_O 100 bins	Recurrence entropy H_R 5 embeddings	Shuffled Recurrence entropy H_S	Ordering entropy H_O (integer > 0)
Binary random	0.996	1.616	1,612	0
Alternate	0.996	10.772	1.595	9
N-ary random	6.599	0.246	0.222	0
Sine wave	5.290	6.443	0.206	6
Gaussian	4.478	0.188	0.188	0
Logistic period 2	1.109	10.772	1.579	9
Logistic period 2 doubling	2.053	4.835	0.632	4
Logistic chaos R=3.6	5.692	1.581	0.060	1
Logistic period 3	1.667	6.804	0.870	6
Logistic period 3 doubling	3.111	1.747	0.345	1
Logistic chaotic R=3.9	6.271	2.257	0.123	2