Statistical Mechanics and Information Theory

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Abstract

A workshop on *"Statistical Mechanics and Information Theory"* was held at Hewlett-Packard's Basic Research Institute in the Mathematical Sciences (BRIMS) in Bristol, England from 5-9 June 1995. This document contains a report on the workshop, the abstracts of the talks and the accompanying bibliography.

1 Report on the workshop

Statistical mechanics and information theory have been linked ever since the latter subject emerged out of the engineering demands of telecommunications. Claude Shannon's original paper on "A mathematical "theory of communication", [71], makes clear the analogy between information entropy and the "H" of Boltzmann's H-theorem. Earlier work of Szilard in attempting to exorcise Maxwell's demon gave a glimpse of the significance of information to physics, [7]. Since that time, the two fields have developed separately for the most part, although both have interacted fruitfully with the field of statistical inference and both have influenced the development of other fields such as neural networks and learning theory. In recent years, this apartheid has been breached by a number of tantalising observations: for instance, of connections between spin-glass models and error-correcting codes, [73].

To explore these developments, a workshop on "Statistical Mechancis and Information Theory" was held at Hewlett-Packard's Basic Research Institute in the Mathematical Sciences (BRIMS) in Bristol, England. The workshop was organised by Jeremy Gunawarden of BRIMS. The purpose was to bring together physicists, information theorists, statisticians and scientists in several application areas to try and demarcate the common ground and to identify the common problems of the two fields. The style of the workshop was deliberately kept informal, with time being set aside for discussions and facilities being provided to enable participants to work together.

Related conferences which have been held recently include the series on "Maximum Entropy and Bayesian Methods"—see, for instance, [41]—the NATO Advanced Study Institute "From Statistical Physics to Statistical Inference and Back", [34], and the IEEE Workshop on "Information Theory and Statistics".

The workshop revealed that the phrase "information" conveyed very different messages to different people. To some, it meant the rigorous study of communication sources and channels represented by the kind of articles that appear in the IEEE Transactions on Information Theory. To others, particularly the physicists influenced by Jaynes' work, [67], it meant a methodological approach to statistical mechanics based on the maximum entropy principle. To others, it was a less rigorous but, nevertheless, stimulating circle of ideas with broad applications to biology and social science. To others, particularly the mathematicians or mathematical physicists, it represented a source of powerful mathematical theorems linking rigorous results in statistical mechanics with probability theory and large deviations. To others still, it was the starting point for a "theory of information", with broad applications outside communication science. The abstracts of the talks, which are collected together in the next section, and the workshop bibliography, which appears after that, give some idea of the range of material that was discussed at the workshop.

Whether the workshop succeeded in "demarcating the common ground" is a moot point. The mathematical insights, particularly the lectures of John Lewis, Anders Martin-Löf and Sergio Verdu, certainly confirmed the existence of a common ground between information theory, probability theory and statistical mechanics, which in many respects is still not properly explored. But to single out this aspect reflects the peculiar prejudices of the organiser. Perhaps the best that can be said is that the workshop revealed to many of the participants the amazing fruitfulness of the information concept and brought home vividly the importance of developing an encompassing "theory of information", upon which biologists, physicists, communication scientists, statisticians and mathematicians can all draw. This still lies in the future.

The bibliography contains a number of references which are not directly cited in the abstracts but are relevant to the overall subject.

The workshop was entirely supported by BRIMS as part of its wider programme of scientific activity. Further information about BRIMS, including a copy of this report, is available on the world wide web at URL:http://www-uk.hpl.hp.com/brims/.

2 Abstracts of talks

A tale of two entropies

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For the purposes of this talk we divide the subject of abstract dynamical systems into two areas: ergodic theory and topological dynamics. In ergodic theory, a dynamical system is endowed with a probability measure so that one can study distribution of orbits in phase space; in topological dynamics, a metric so that one can study, stability, almost periodicity, density of orbits, etc. Ideas originating in Shannon's work in information theory have played a crucial role in isomorphism theories of dynamical systems. Shannon used notions of entropy and channel capacity to determine the amount of information which can be transmitted through channels. Kolmogorov and Sinai made his idea into a powerful invariant for ergodic theory; and then Ornstein proved that entropy completely classifies special systems called Bernouli shifts. Adler, Konheim, and McAndrew introduce into topological dyanamics an analogous invariant called topological entropy which turns out to be a generalization of channel capacity. Then Adler and Marcus developed an isomorphism theory in which this invariant completely classifies symbolic systems called shifts of finite type. The surprise is that this abstract theory has engineering applications: namely their methods of proof lead to construction of encoders and decoders for data transmission and storage. As a result the history of Shannon's ideas have come full circle. He used them to study transmission of information. Mathematicians took up his ideas to classify dynamical systems, first in ergodic theory and then in topological dynamics. Results in thesecond area then lead to methods for optimizing transmission and storage of data. For references, see [1, 2, 61].

(Editor's note: due to personal reasons which arose at the last minute, Roy Adler was unfortunately unable to attend the workshop.)

Non-commutative dynamical entropy

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The concept of dynamical entropy, called also Kolmogorov-Sinai invariant, proved to be very useful in the classical ergodic theory in particular for studying systems displaying chaos . Since twenty years several attempts to generalize this notion to non-commutative algebraic dynamical systems have been undertaken. In the present lecture a brief survey of the recent investigations based on the new definition of non-commutative dynamical entropy introduced by M.Fannes and the author is presented. Several examples of dynamical systems including classical systems, shift on quantum spin chain, quasi-free Fermion automorphisms, Powers-Price binary shifts, Stormer free shift and quantum Arnold cat map are discussed. The new dynamical entropy is compared with the alternative formalisms of Connes-Narnhofer-Thirring and Voiculescu. For references, see [3, 4, 22].

Non-equilibrium biology

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Abstract not available, but see [20, 21, 27, 28, 78].

Chaos and detection

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The low likelihood of linear models fit to chaotic signals and the ubiquity of strange attractors in nature suggests that nonlinear modeling techniques can improve performance for some detection problems. We review likelihood ratio detectors and limitations on the performance of linear models implied by the broad Fourier power spectra of chaotic signals. We observe that the KS entropy of a chaotic system establishes an upper limit on the expected log likelihood that any model can attain. We apply variants of the hidden Markov models used in speech research to a synthetic detection problem, and we obtain performance that surpasses the theoretical limits for linear models. KS entropy estimates suggest that still better performance is possible. For references, see [31, 32, 33].

Practical Entropy Computation in Complex Systems

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I will discuss the interplay between entropy production in complex systems and the estimation of entropy from observed signals. Entropy measurement in lag spaces provides a very general way to determine a system's degrees of freedom, geometrical complexity, predictability, and stochasticity, but it is notoriously difficult to do reliably. I will consider the role of regularized density estimation and sorting on adaptive trees in determining entropy from measurements, and then look at applications in nonlinear instrumentation and the optimization of information processing systems. For references, see [33, 79].

Origin and growth of order in the expanding universe

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I define order as potential statistical entropy: the amount by which the entropy of a statistical description falls short of its maximum value subject to appropriate constraints. I argue that, as a consequence of a strong version of the postulate of spatial uniformity and isotropy, the universe contains an irreducible quantity of specific statistical entropy; and I postulate that in the initial state the specific statistical entropy was equal to its maximum value: the universe expanded from an initial state of zero order. Chemical order, which shows itself most conspic-

uously as a preponderance of hydrogen in the present-day universe, arose from a competition between the cosmic expansion and nuclear and subnuclear reactions. The origin of structural order is more controversial. I will argue that it might have been produced by a bottom-up process of gravitational clustering. For references, see [44, 45, 46]. See also, [69].

On sequential compression with distortion

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Abstract not available.

Large Deviations, Statistical Mechanics and Information Theory

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In 1965, Ruelle showed how to give a precise meaning to Boltzmann's Formula. Exploring the consequences of Ruelle's definition leads to the theory of large deviations and information theory. For a reference, see [48].

(Editor's note: John Lewis also gave an additional tutorial lecture on large deviations. Among the texts he cited were [15, 29].)

Entropy in States of the Self-Excited System with External Forcing

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Self-excited systems with external driving force are characterized by a number of interesting features as synchronization of vibration, and transition to chaos. Using an one dimensional example of the self-excited system–Froude pendulum we examined the influence of parameters on the system itegrity. The motion is described by the following nonlinear equation with Raylaigh damping term

$$\ddot{\phi} - (\alpha - \beta\dot{\phi}^2)\dot{\phi} + \gamma \sin(\phi) = B \cos \omega t \quad .$$

There are two characteristic frequencies in the system: p – self–excited and ω – driving frequency. For the nodal driving force amplitude B the system oscillates with self–excited frequency. For $B \neq 0$, depending on the system parameters, two cases of regular solutions may occurred: mono–frequency solution and the quasi–periodic solution with the modulated amplitude. Except for regular solution the chaotic one appear. The chaotic vibrations correspond with the positive value of Kolmogorov Entropy K. Here the entropy is the measure of chaoticity of the system, indicating how fast the information about the dymamical system state is losing. The definition of Kolmogorov entropy is in analogy with Shannon's in information theory. In our paper the Kolmogorov entropy and other indicators of the dynamical system states

are examined. The regions of system parameters and initial conditions leading to chaotic, synchronized and quasi–periodic are obtained. The condition for the pendulum to escape from the potential well $V(\phi) = \gamma(1 - \cos(\phi))$ was also found. This is joint work with Wojciech Przystupa, Kazimierz Szabelski and Jerzy Warminski.

Sharpening Occam's razor

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Abstract not available.

Free Energy Minimization and Binary Decoding Tasks

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I study the task of inferring a binary vector $\vec{s}$ given a noisy measurement of the vector $\vec{t} = A\vec{s}\ mod\ 2$, where A is an $M \times N$ binary matrix. This combinatorial problem can be attacked by replacing the unknown binary vector by a real vector of probabilities which are optimized by variational free energy minimization. The resulting algorithm shows great promise as a decoder for a novel class of error correcting codes. For references, see [51, 36].

The Shannon-McMillan theorem from the point of view of statistical mechanics

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Abstract not available, but see [53]. Anders provided a set of handwritten notes for this lecture. Copies are available from Jeremy Gunawardena upon request.

Some Properties of the Generalized BFOS Tree Pruning Algorithm

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We first show that the generalized BFOS algorithm is not optimal when it is used to design fixed-rate pruned tree-structured vector quantizers (TSVQ). A simple modification is made in the algorithm that makes it optimal. However, this modification has little effect on the (experimental) rate-distortion performance. An asymptotic analysis is presented that justifies the experimental results. It also suggests that in designing fixed-rate, variable-depth TSVQ's, one can get as good a rate-distortion performance with a greedy TSVQ design algorithm as with an optimal pruning of a large tree.

Continuum entropies for fluids

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This paper reviews efforts to define useful entropies for fluids and magnetofluids at the level of their continuous macroscopic fields, such as the fluid velocity or magnetic field, rather than at the molecular or kinetic theory level. Several years ago, a mean-field approximation was used to calculate a "most probable state" for an assembly of a large number of parallel interacting ideal line vortices. The result was a nonlinear partial differential equation for the "most probable" stream function, the so-called sinh-Poisson equation, which was then explored in a variety of mathematical contexts. Somewhat unexpectedly, this sinh-Poisson relation turned out much more recently to have quanitative predictive power for the long-time evolution of continuous, two-dimensional, Navier-Stokes turbulence at high Reynolds numbers [54]. It has been our recent effort to define an entropy for non-ideal continuous fluids and magnetofluids that makes no reference to microscopic discrete structures or particles of any kind [55], and then to test its utility in numerical solutions of fluid and magnetofluid equations. This talk will review such efforts and suggest additional possible applications. The work is thought to be a direct but tardy extension of the ideas of Boltzmann and Gibbs from point-particle statistical mechanics. See also W.H. Matthaeus et al, Physica D51, 531 (1991) and references therein.

Statistical mechanics and information theoretic tools for the study of formal neural networks

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Abstract not available, but see [14, 34, 57, 58, 59].

Shannon Information and Algorithmic and Stochastic Complexities

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This is an introduction to the formal measures of information or, synonymously, description complexity, introduced during the past 70 or so last years, beginning with Hartley. Although all of them are intimately related to ideas of coding theory, I introduce the fundamental Shannon information without it. I also discuss the central role stochastic complexity plays in modeling problems and the problem of inductive inference in general. For references, see [65, 66].

Information and the Fly's Eye

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The design of compound eyes can be seen as a set of tradeoffs. The most basic of these was discussed by Feynman in his Lectures: smaller facets allow for finer sampling of the world but

reduces acuity due to diffraction. Good "ballpark" estimates of facet size can be made by equating the diffraction limit to resolution with the Nyquist frequency of the sampling lattice. But other factors are involved such as photon shot noise, which fundamentally limits all visual processing. In the 1970's, Snyder *et al*, [72], applied information theory to the compound eye, finding that maximizing information capacity gave reasonable estimates of design parameters. In this talk I extend the information-theoretic treatment by introducing the time domain. Basic questions such as "how fast should a photoreceptor respond as a function of light level and flight speed?" will be addressed, as will the use of moving natural images as a stimulus ensemble. Preliminary results suggest that information theory can provide a useful tool for understanding the tradeoffs and trends in compound eye design, both in the spatial and temporal domains. For references, see [64, 68]. This is joint work with S. B. Laughlin.

Entropy estimates: measuring the information output of a source

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Abstract not available.

On Tree Sources, Finite State Machines, and Time Reversal

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We investigate the effect of time reversal on tree models of finite-memory processes. This is motivated in part by the following simple question that arises in some data compression applications: when trying to compress a data string using a universal source modeler, can it make a difference whether we read the string from left to right or from right to left? We characterize the class of finite-memory *two-sided tree processes*, whose time-reversed versions also admit tree models. Given a tree model, we present a construction of the tree model corresponding to the reversed process, and we show that the number of states in the reversed tree might be, in the extreme case, quadratic in the number of states of the original tree. This answers the above motivating question in the affirmative. This is joint work with Marcelo Weinberger. For a reference, see [70].

Statistical physics and replica theory—neural networks; equilibrium and non-equilibrium

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Abstract not available, but see [16, 84].

Maximum Quantum Entropy

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We discuss a generalization of the maximum entropy (ME) principle in which relative Shannon classical entropy may be replaced by relative von Neumann quantum entropy. This yields a broader class of information divergences, or penalty functions, for statistics applications. Constraints on relative quantum entropy enforce prior correlations, such as smoothness, in addition to the convexity, positivity, and extensivity of traditional ME methods. Maximum quantum entropy yields statistical models with a finite number of degrees of freedom, while maximum classical entropy models have an infinite number of degrees of freedom. ME methods may be extended beyond their usual domain of ill-posed inverse problems to new applications such as non-parametric density estimation. The relation of maximum quantum entropy to kernel estimators and the Shannon sampling theorem are discussed. Efficient algorithms for quantum entropy calculations are described. For references, see [34, 35, 38, 60, 65, 87].

<u>Spin glasses and error-correcting codes</u>

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Abstract not available, but see [73, 74].

<u>Individual open quantum systems</u>

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The reduced density operator is the conventional tool used for describing open quantum systems, that is systems coupled to an environment such as a heat bath. However, this statistical approach is not the only one on the market. It is possible to describe instead the evolution of an individual system, one member of the ensemble. I motivate such an approach and illustrate it with some simple examples. One nice feature is the emergence of characteristic classical behaviour, such as chaos.

<u>Large deviations and conditional limit theorems</u>

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Abstract not available, but see [49].

<u>Topological Time Series Analysis of a String Experiment and Its Synchronized Model</u>

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We show how to construct empirical models directly from experimental low-dimensional time series. Specfically, we examine data from a string experiment and use MDL to contruct an "optimial" empirical model and show how this empirical model can be syncronized to the chaotic experimental data. Such empirical models can then used for process control, monitoring, and non-destructive testing. For a reference, see [75].

Asymptotic equipartition property in source coding

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Abstract not available.

Sequential Prediction and Ranking in Universal Context Modeling and Data Compression

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We investigate the use of prediction as a means of reducing the model cost in lossless data compression. We provide a formal justification to the combination of this widely accepted tool with a universal code based on context modeling, by showing that a combined scheme may result in faster convergence rate to the source entropy. In deriving the main result, we develop the concept of sequential ranking, which can be seen as a generalization of sequential prediction, and we study its combinatorial and probabilistic properties. For a reference, see [81].

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