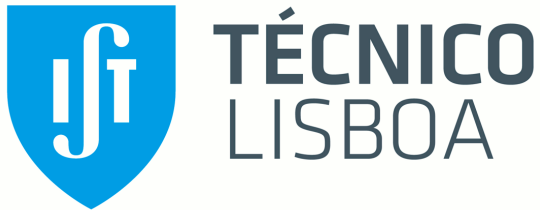


Information and Communication Theory: Overview and Applications

Mário A. T. Figueiredo



what is **information**?

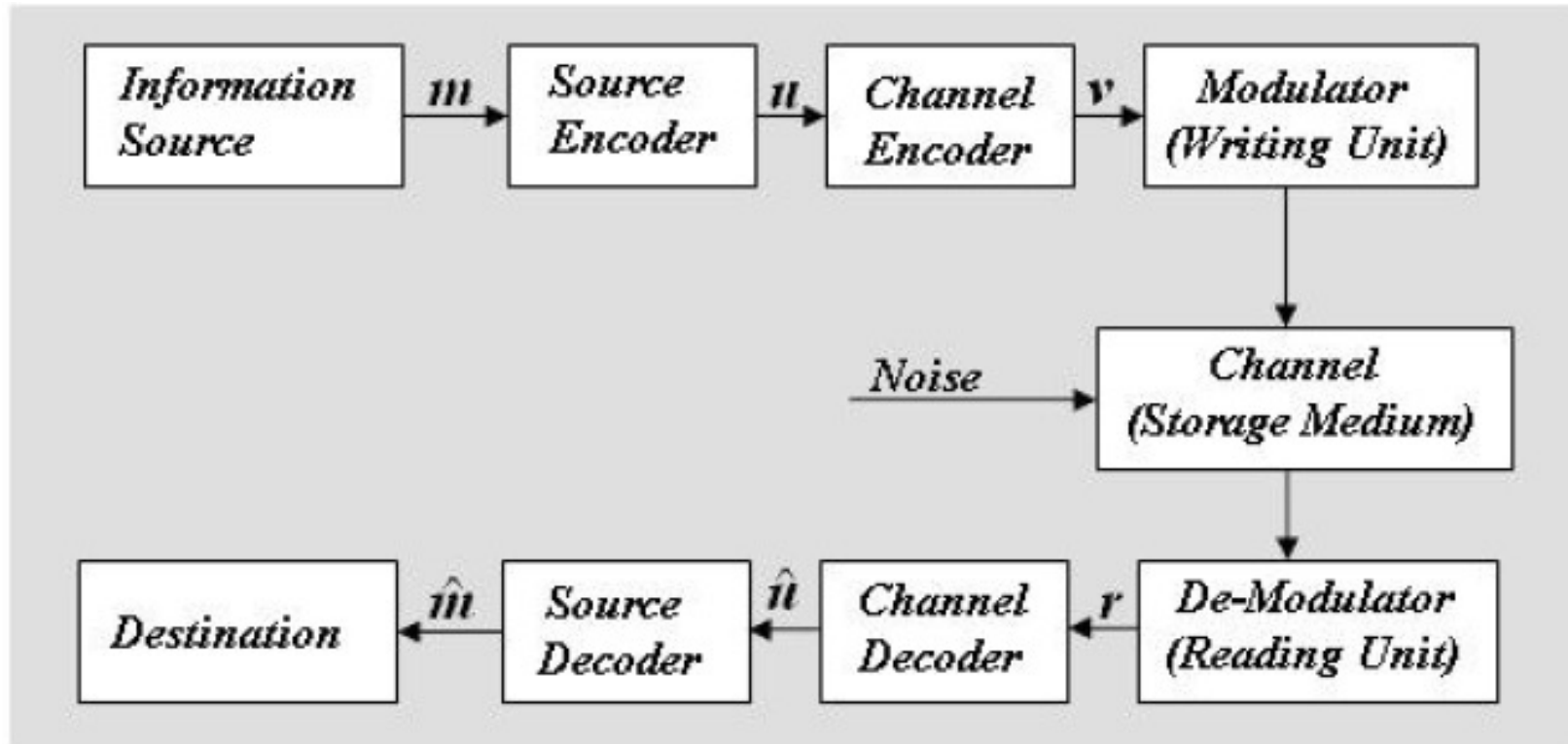
information \Leftrightarrow reduction of uncertainty



no uncertainty \Rightarrow no information

(Tele)Communications: The Big Picture

Shannon, 1948



We now consider the information source. How is an information source to be described mathematically, and how much information in bits per second is produced in a given source?



The Bell System Technical Journal

Vol. XXVII

July, 1948

No. 3

A Mathematical Theory of Communication

By C. E. SHANNON

A mathematical theory of communication

Authors Claude Elwood Shannon

Publication date 1948/7

Journal The Bell system technical journal

Volume 27

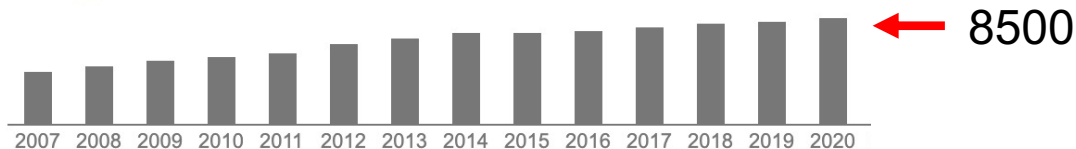
Issue 3

Pages 379-423

Publisher Nokia Bell Labs

Description The recent development of various methods of modulation such as PCM and PPM which exchange bandwidth for signal-to-noise ratio has intensified the interest in a general theory of communication. A basis for such a theory is contained in the important papers of Nyquist ¹ and Hartley ² on this subject. In the present paper we will extend the theory to include a number of new factors, in particular the effect of noise in the channel, and the savings possible due to the statistical structure of the original message and due to the nature of the final destination of the information.

Total citations Cited by 137371



Shannon's entropy

A measure of *uncertainty*, i.e., lack of *information*

Source
(discrete and memoryless)

$$X \in \{1, \dots, N\}$$

$$p_i = \mathbb{P}(X = i)$$

$$H(X) = H(p_1, \dots, p_N) = \sum_{i=1}^N p_i \log_2 \frac{1}{p_i} = \mathbb{E}[\log_2 \frac{1}{p(X)}]$$

Shannon's axioms (1948):

(bits/symbol)

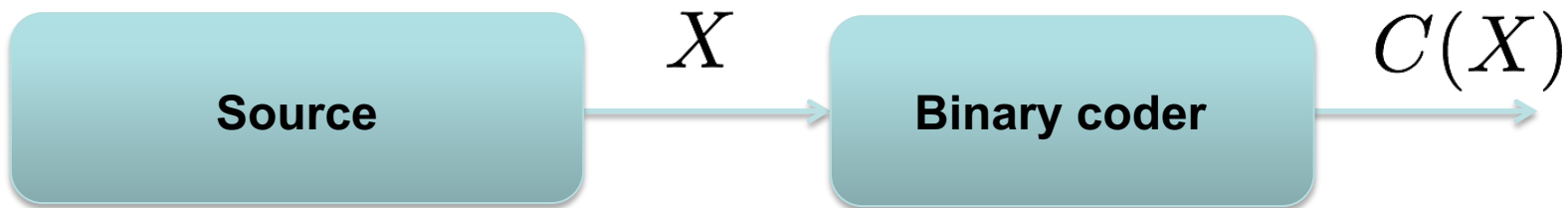
Continuity with respect to p_1, \dots, p_N

Uncertainty grows with N , if $p_i = 1/N$

Grouping doesn't change uncertainty: $H(\frac{1}{2}, \frac{1}{3}, \frac{1}{6}) = H(\frac{1}{2}, \frac{1}{2}) + \frac{1}{2}H(\frac{1}{3}, \frac{2}{3})$

This **entropy** is the unique function satisfying these axioms.

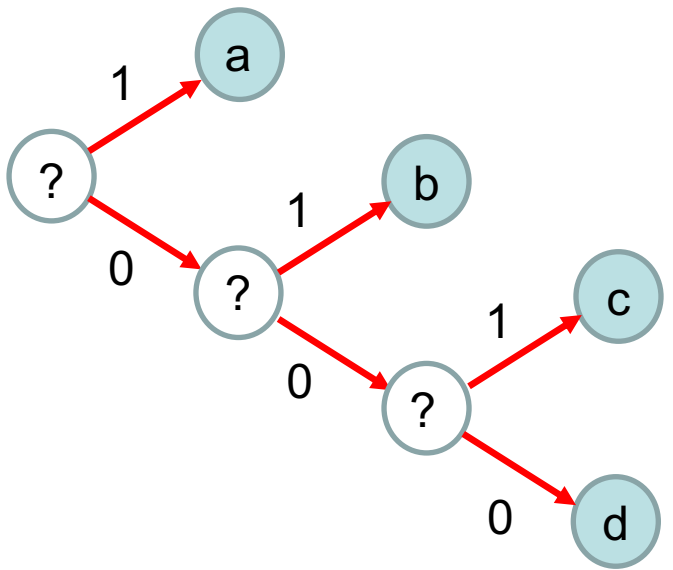
What did Shannon use entropy for?



$$\mathbb{E} [\text{length}(C(X))] \gtrsim H(X)$$

...if the code is “20-questions” type (called *instantaneous*)

i	p_i	$C(i)$
a	1/2	1
b	1/4	01
c	1/8	000
d	1/8	001



Optimal lengths:
 $\simeq \log \frac{1}{p_i}$

Optimal strategy/code:
Huffman (1952)

Easy to extend to
Markov sources

bits/questions: first, second, third.

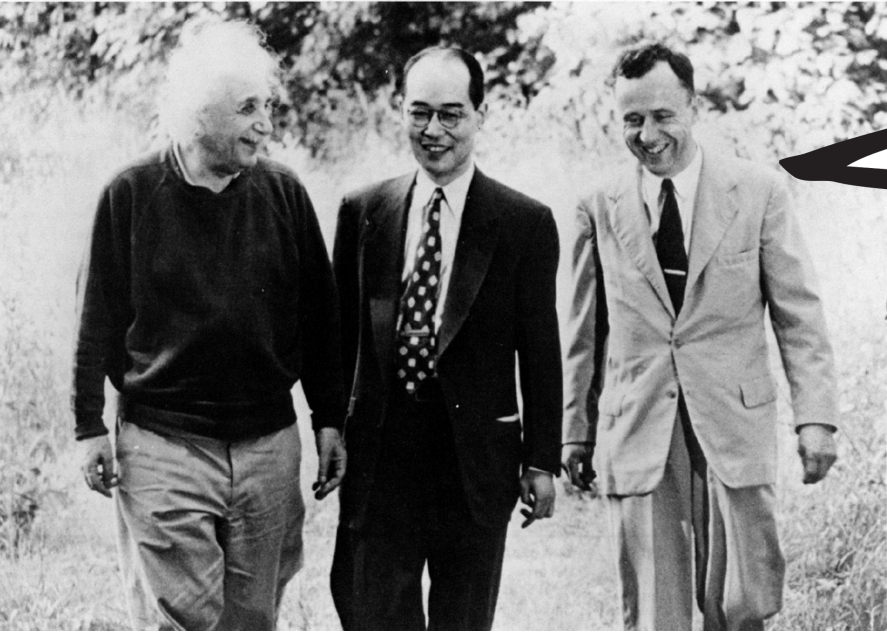
Information and entropy in physics and other sciences

Entropy provides a measure of **uncertainty/information**

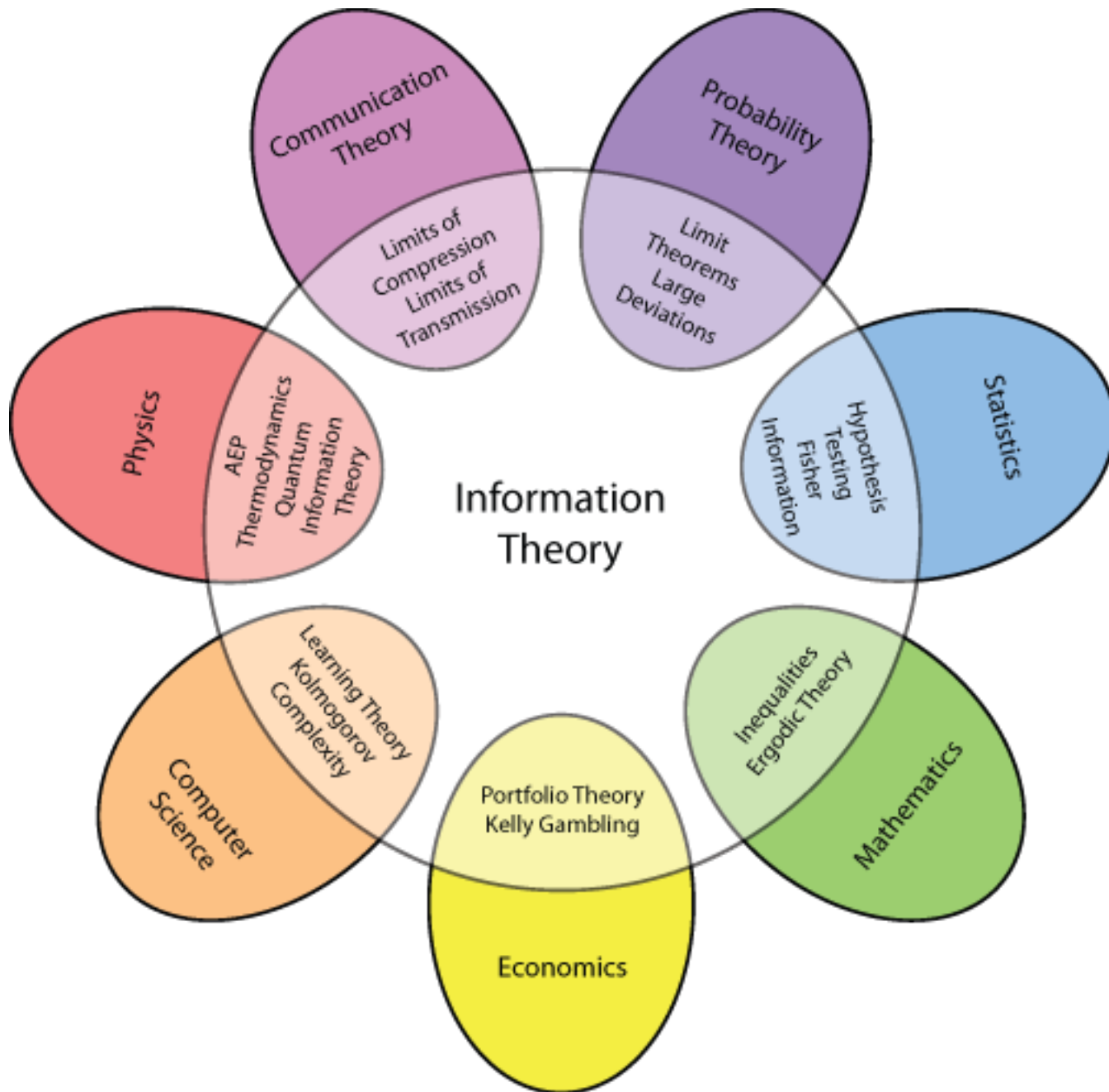
...**information** is a (**the?**) core concept in science!

At the very extreme, Wheeler (1989) claims:

*"**It from bit** symbolises the idea (...) that what we call **reality** arises in the last analysis from the posing of **yes-no questions** (...); in short, that **all things physical are information-theoretic in origin** and this is a participatory universe."*



"The universe is made of information; matter and energy are only incidental."



The impact of Shannon's IT work

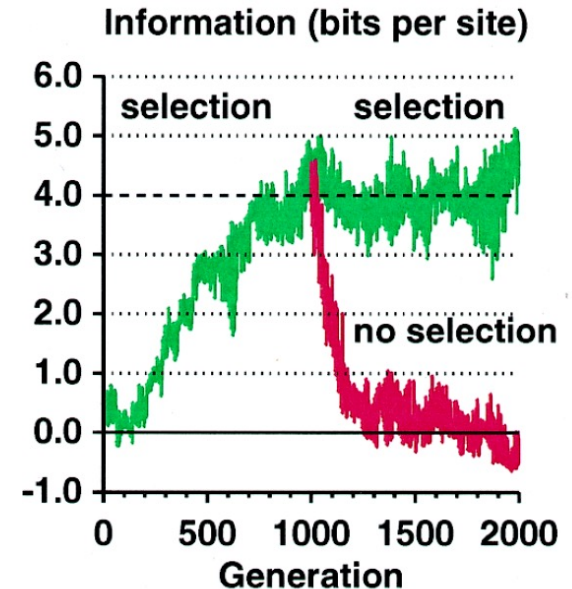
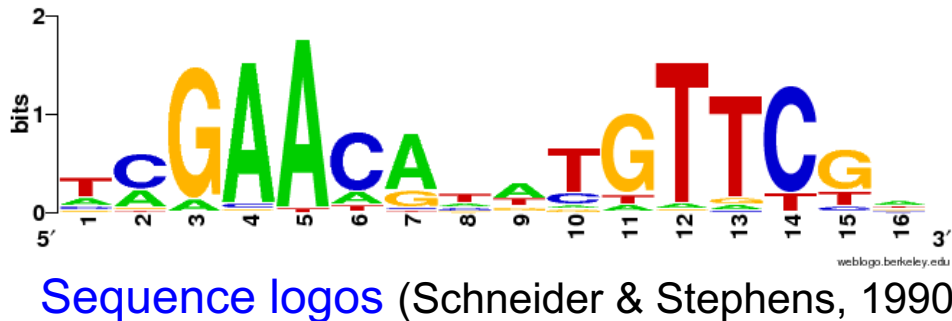
Soon after Shannon, biologists started using IT:

S. Dancoff and H. Quastler (1953). "The Information Content and Error Rate of Living Things". *Essays on the Use of Information Theory in Biology*.

“**How many bits** have to go in there? And what is the **informational** content of that which produces these **bits**?”

The impact of information theory in the biological sciences is **enormous!**

...impossible to even scratch the surface in 10 minutes!



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doi:1

Information theory applications for
biological sequence analysis

Information in evolution (Schneider 2000)

Research article



From **bit to it**: How a complex metabolic network transforms information into living matter

Andreas Wagner

Abstract

Background: Organisms live and die by the **amount of information** they acquire about their environment. The systems analysis of complex metabolic networks allows us to ask how such information translates into fitness. A metabolic network transforms nutrients into biomass. The better it uses information on available nutrient availability, the faster it will allow a cell to divide.

Results: I here use metabolic flux balance analysis to show that the accuracy I (**in bits**) with which a yeast cell can sense a limiting nutrient's availability relates logarithmically to fitness as indicated by biomass yield and cell division rate. For microbes like yeast, natural selection can resolve fitness differences of genetic variants smaller than 10^{-6} , meaning that cells would need to estimate nutrient concentrations to very high accuracy (greater than 22 bits) to ensure optimal growth. I argue that such accuracies are not achievable in practice. Natural selection may thus face fundamental limitations in maximizing the information processing capacity of cells.

Information-Theoretic Considerations Concerning the Origin of Life

Christoph Adami^{1,2,3}

“For cells, we now know that (...) [information](#) is stored in a cell’s inherited genetic material, and is precisely [the kind that Shannon described in his 1948 articles.](#)”

“[Information is the currency of life.](#) One definition of information is the ability to make predictions with a likelihood better than chance. That’s what any living organism needs to be able to do, because if you can do that, you’re surviving at a higher rate.”

Review

Entropy and Information Approaches to Genetic Diversity and its Expression: Genomic Geography

William B. Sherwin

Evolution and Ecology Research Centre, School of Biological Earth and Environmental Science,
University of New South Wales, Sydney, NSW 2052, Australia; E-Mail: W.Sherwin@unsw.edu.au;

“Shannon’s entropy-based diversity is the standard for ecological communities. The exponentials of Shannon’s and the related “mutual information” excel in their ability to express diversity intuitively, and provide a generalised method of considering microscopic behaviour to make macroscopic predictions, under given conditions.”

SCIENTIFIC REPORTS



OPEN

Human vision is determined based on information theory

Alfonso Delgado-Bonal^{1,2} & Javier Martín-Torres^{1,3}

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Published: 03 November 2016

It is commonly accepted that the evolution of the human eye has been driven by the maximum intensity of the radiation emitted by the Sun. However, the interpretation of the surrounding environment is constrained not only by the amount of energy received but also by the information content of the radiation. Information is related to entropy rather than energy. The human brain follows Bayesian statistical inference for the interpretation of visual space. The maximization of information occurs in the process of maximizing the entropy. Here, we show that the photopic and scotopic vision absorption peaks in humans are determined not only by the intensity but also by the entropy of radiation. We suggest that through the course of evolution, the human eye has not adapted only to the maximum intensity or to the maximum information but to the optimal wavelength for obtaining information. On Earth, the optimal wavelengths for photopic and scotopic vision are 555 nm and 508 nm, respectively, as inferred experimentally. These optimal wavelengths are determined by the temperature of the star (in this case, the Sun) and by the atmospheric composition.

Information transmission rates of the senses

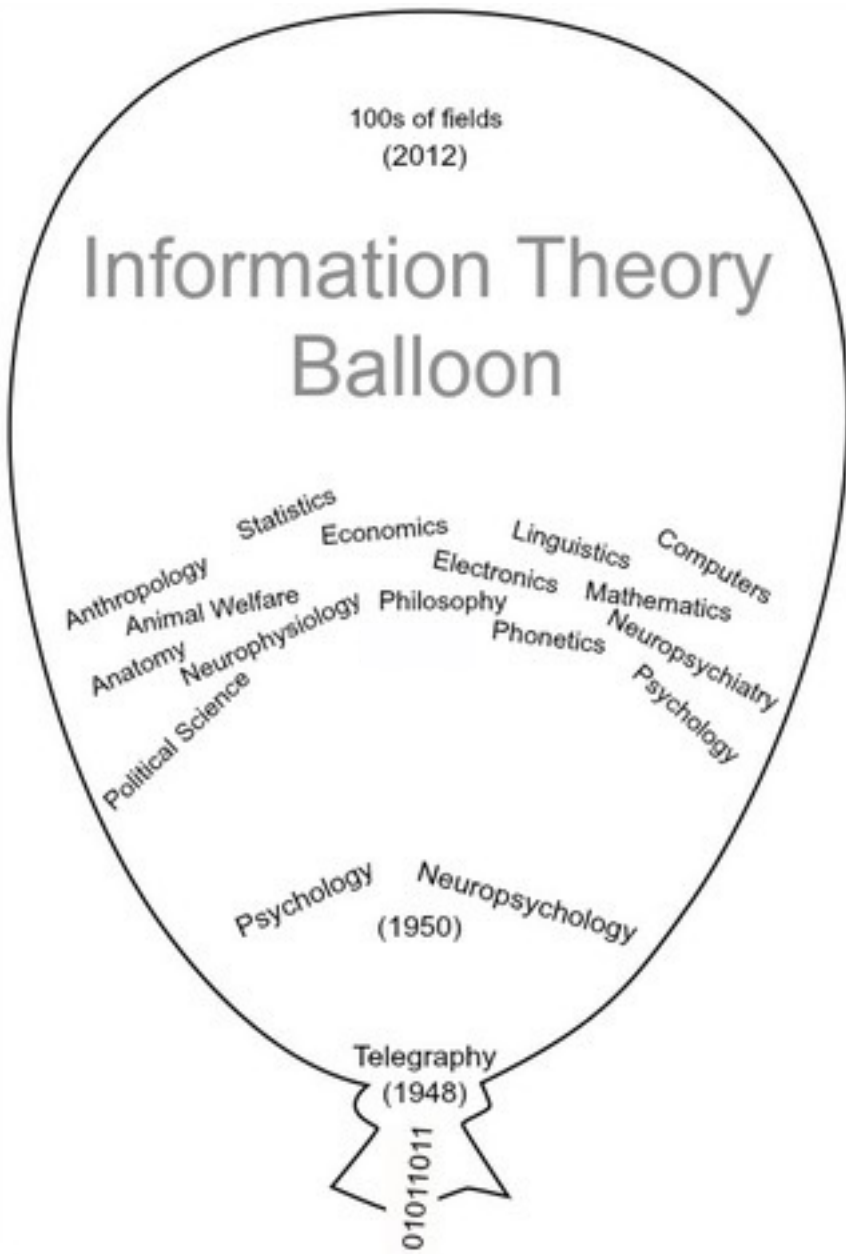
sensory system	bits per second
eyes	10,000,000
skin	1,000,000
ears	100,000
smell	100,000
taste	1,000

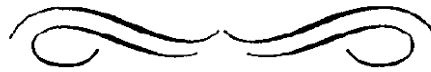
Concepts and Applications of Information Theory to Immuno-Oncology

Aleksandra Karolak   • Sergio Branciamore • Jeannine S. McCune • Peter P. Lee • Andrei S. Rodin • Russell C. Rockne

- **Information theory (IT)** may be used to define and guide new concepts in the study of immune signaling in health and in cancer.
- **IT** concepts are well suited for understanding biochemical signaling and cellular dialogues in the immune system in terms of **information flow, signal processing, and communication channels**.
- Cancer research can benefit from specific applications of IT to elucidate immune system defects in cancer, and, subsequently, cancer therapies can benefit from IT-informed modulation of the immune response.

Other uses of Shannon's entropy...





The Bandwagon

CLAUDE E. SHANNON

INFORMATION theory has, in the last few years, become something of a scientific bandwagon. Starting as a technical tool for the communication engineer, it has received an extraordinary amount of publicity in the popular as well as the scientific press. In part, this has been due to connections with such fashionable fields as computing machines, cybernetics, and automation; and in part, to the novelty of its subject matter. As a consequence, it has perhaps been ballooned to an importance beyond its actual accomplishments. Our fellow scientists in many different fields, attracted by the fanfare and by the new avenues opened to scientific analysis, are using these ideas in their own problems. Applications are being made to biology, psychology, linguistics, fundamental physics, economics, the theory of organization, and many others. In short, information theory is currently partaking of a somewhat heady draught of general popularity.

subject are aimed in a very specific direction, a direction that is not necessarily relevant to such fields as psychology, economics, and other social sciences. Indeed, the hard core of information theory is, essentially, a branch of mathematics, a strictly deductive system. A thorough understanding of the mathematical foundation and its communication application is surely a prerequisite to other applications. I personally believe that many of the concepts of information theory will prove useful in these other fields—and, indeed, some results are already quite promising—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. If, for example, the human being acts in some situations like an ideal decoder, this is an experimental and not a mathematical fact, and as such must be tested under a wide variety of experimental situations.

Review

(2014)

Applications of Entropy in Finance: A Review

Rongxi Zhou, Ru Cai and Guanqun Tong *

“The application of entropy in finance can be regarded as the extension of the **information entropy and the probability entropy**. It can be an important tool in portfolio selection and asset pricing.”

Pictish symbols revealed as a written language through application of Shannon entropy

BY ROB LEE^{1,*}, PHILIP JONATHAN² AND PAULINE ZIMAN³

¹*School of Biosciences, Geoffrey Pope Building, University of Exeter, Stocker Road, Exeter EX4 4QD, UK*

²*Department of Mathematics and Statistics, University of Lancaster, Lancaster LA1 4YF, UK*





Quantitative tools for comparing animal communication systems: information theory applied to bottlenose dolphin whistle repertoires

BRENDA McCOWAN*†, SEAN F. HANSER† & LAURANCE R. DOYLE‡

*California Regional Primate Research Center, University of California at Davis

†Marine World Foundation

‡SETI Institute, NASA Ames Research Center

“As an example of the utility of [information theory](#) to the analysis of animal communication systems, we applied a series of [information theory](#) statistics to a statistically categorized set of bottlenose dolphin whistle vocalizations.”

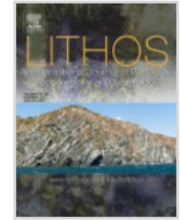
“[Information theory](#) measures (Shannon 1948; ...) provide (...) tools for examining and comparing communication systems across species.”

Yet another application of the Shannon entropy...



Lithos

Volumes 236–237, November 2015, Pages 299–310



Quantifying magma mixing with the Shannon entropy: Application to simulations and experiments

D. Perugini^a,  , C.P. De Campos^b, M. Petrelli^a, D. Morgavi^a, F.P. Vetere^a, D.B. Dingwell^b

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Received 8 July 2015, Accepted 8 September 2015, Available online 25 September 2015

“We introduce a new quantity to petrology, the [Shannon entropy](#), as a tool for quantifying mixing as well as the rate of production of hybrid compositions in the mixing system.”

Uncertainties have a meaning: Information entropy as a quality measure for 3-D geological models

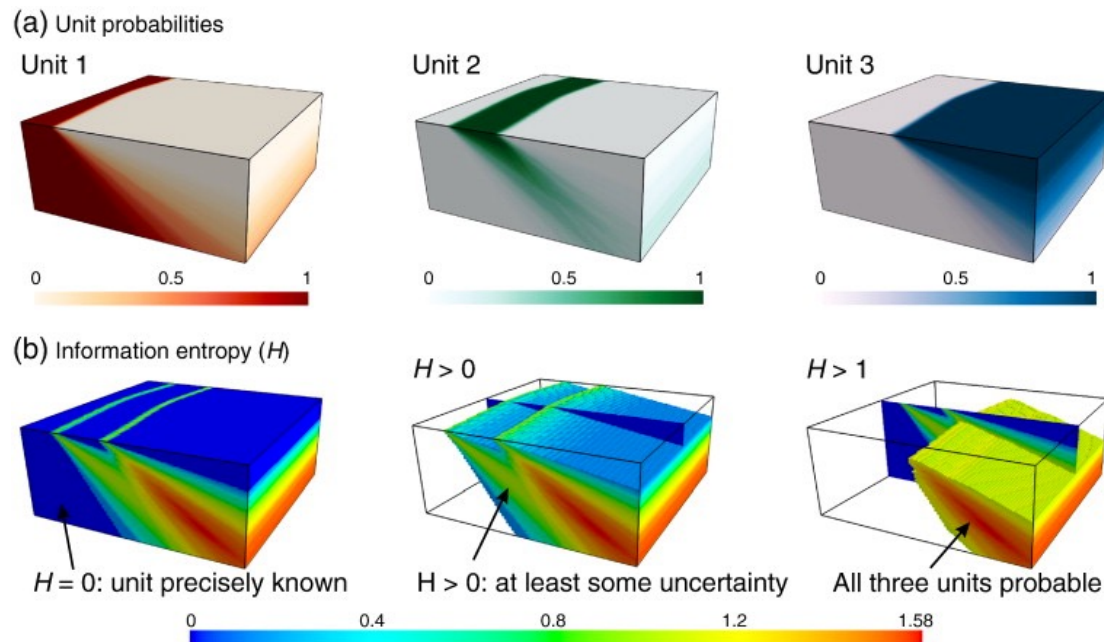
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Received 14 January 2011, Revised 8 April 2011, Accepted 2 May 2011, Available online 8 May 2011

 [Show less](#)



What about modern AI? Let's ask ChatGPT

MA

Are there any connections between Shannon's work and modern large language models?



Certainly!



Claude Shannon's work has foundational ties to modern large language models (LLMs):

1. **Entropy:** Shannon introduced entropy to measure unpredictability. LLMs aim to reduce entropy in their predictions by training on vast data.
2. **Probabilistic Models:** Both Shannon's information theory and LLMs use probabilistic models to estimate likelihoods, such as predicting the next word in a sequence.
3. **Compression:** While Shannon focused on data compression, LLMs "compress" knowledge by distilling vast textual data into parameters.
4. **Redundancy:** Shannon noted language redundancy aids in error detection. LLMs exploit this by learning common language patterns.
5. **Channel Capacity:** Shannon's theorem describes maximum information transmission rates. Similarly, an LLM's capacity determines its information storage and retrieval limits.
6. **Error Correction:** Shannon developed error correction for noisy channels. LLMs use mechanisms like attention layers for context-based corrections.

In essence, Shannon's principles in information theory have indirectly shaped the development of LLMs and AI.

Summary:

- The [Shannon entropy](#), as a measure of [information](#), has a **huge** impact, both inside and outside of its original field of application (telecommunications)



(from L. Thims, 2012)