

Claude Shannon: Biologist

The Founder of Information Theory Used Biology to Formulate the Channel Capacity

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Claude Shannon founded information theory in the 1940s. The theory has long been known to be closely related to thermodynamics and physics through the similarity of Shannon’s uncertainty measure to the entropy function. Recent work using information theory to understand molecular biology has unearthed a curious fact: Shannon’s channel capacity theorem only applies to living organisms and their products, such as communications channels and molecular machines that make choices amongst several possibilities. Information theory is therefore a theory about biology, and Shannon was a biologist.

The late Claude Shannon (30 April 1916 - 24 February 2001) is heralded for his major contributions to the fundamentals of computers and communications systems [1, 2, 3, 4]. His Massachusetts Institute of Technology (MIT) master’s thesis is famous because in it he showed that digital circuits can be expressed by Boolean logic. Thus one can transform a circuit diagram into an equation, rearrange the equation algebraically, and then draw a new circuit diagram that has the same function. By this means one can, for example, reduce the number of transistors needed to accomplish a particular function.

Shannon’s work at Bell Labs in the 1940s led to the publication of the famous paper “A Mathematical Theory of Communication” in 1948 [5] and to the lesser known but equally important “Communication in the Presence of Noise” in 1949 [6]. In these groundbreaking papers Shannon established information theory. It applies not only to human and animal communications, but also to the states and patterns of molecules in biological systems [7, 8, 9]. At the time, Bell Labs was the research and development part of the American Telephone and Telegraph Company (AT&T), which was in the business of selling the ability to communicate information. How can information be defined precisely? Shannon, a mathematician, set down several criteria for a useful, rigorous definition of information and then he showed that only one formula satisfied these criteria. The definition, which has withstood the test of more than 50 years, precisely answered the question

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“What is AT&T selling?” The answer was “information transmission, in bits per second”. Of course this immediately raised another question: “How much information can we send over existing equipment, our phone lines?” To answer this, Shannon developed a mathematical theory of the channel capacity. Before delving into how he arrived at this concept, which explains why Shannon was a biologist, it is necessary to understand the surprising (Shannon’s word) channel capacity theorem and how it was developed.

The channel capacity, C , in bits per second, depends on only three factors: the power, P , of the signal at the receiver, the noise, N , disturbing the signal at the receiver and the bandwidth, W , which is the span of frequencies used in the communication:

$$C = W \log_2 \left(\frac{P}{N} + 1 \right) \quad \text{bits per second.} \quad (1)$$

Suppose one wishes to transmit some information at a rate R , also in bits per second. First Shannon showed that when the rate exceeds the capacity ($R > C$), the communication will fail and at most C bits per second will get through. A rough analogy is putting water through a pipe. There is an upper limit for how fast water can flow; at some point the resistance in the pipe will prevent further increases or the pipe will burst.

The surprise comes when the rate is less than *or equal to* the capacity ($R \leq C$). Shannon discovered—and proved mathematically—that in this case one may transmit the information with as few errors as desired! Error is the number of wrong symbols received per second. The probability of errors can be made small, but cannot be eliminated. Shannon pointed out that the way to reduce errors is to encode the messages at the transmitter to protect them against noise, and then to decode them at the receiver to remove the noise. The clarity of modern telecommunications, CDs, MP3s, DVDs, wireless, cellular phones, *etc.* came about because engineers have learned how to make electrical circuits and computer programs that do this coding and decoding. Because they approach the Shannon limits, the recently developed Turbo codes promise to revolutionize communications again by providing more data transmission over the same channels [10, 11].

What made all this possible? It is a key idea buried in a beautiful geometrical derivation of the channel capacity in Shannon’s 1949 paper [6]. Suppose that you and I decide to set up a simple communications system (Fig. 1). On my end I have a 1 volt battery and a switch. We run two wires over to you, and install a volt meter on your end. When I close the switch, you see the meter jump from 0 to 1 volt. If I set the switch every second, you receive up to 1 bit of information per second. But on closer inspection, you notice that the meter doesn’t always read exactly 1 volt. Sometimes it reads 0.98, other times 1.05 and so on. The distribution of values is bell shaped (Gaussian), because the wire is *hot* (300K). From a thermodynamic viewpoint, the heat is atomic motions and they disturb the signal, making it noisy. You can hear this as the static hiss on a radio or see it as snow on a television screen.

Shannon realized that the noise added to one digital pulse would generally make the overall amplitude be different from that of another, otherwise identical, pulse. Further, the noise amplitudes for two pulses are independent. When two quantities are independent, one can represent this geometrically by graphing them at 90° to each other (orthogonal). Shannon recognized that for two pulses, the individual Gaussians combined to make a little *circular* smudge on a two dimensional graph of the voltage of the first pulse plotted against the voltage of the second pulse, as shown in Fig. 1. If three digital pulses are sent, the possible combinations can be plotted as corners of a cube in three dimensions. The receiver, however, does not see the pristine corners of the cube. Instead,

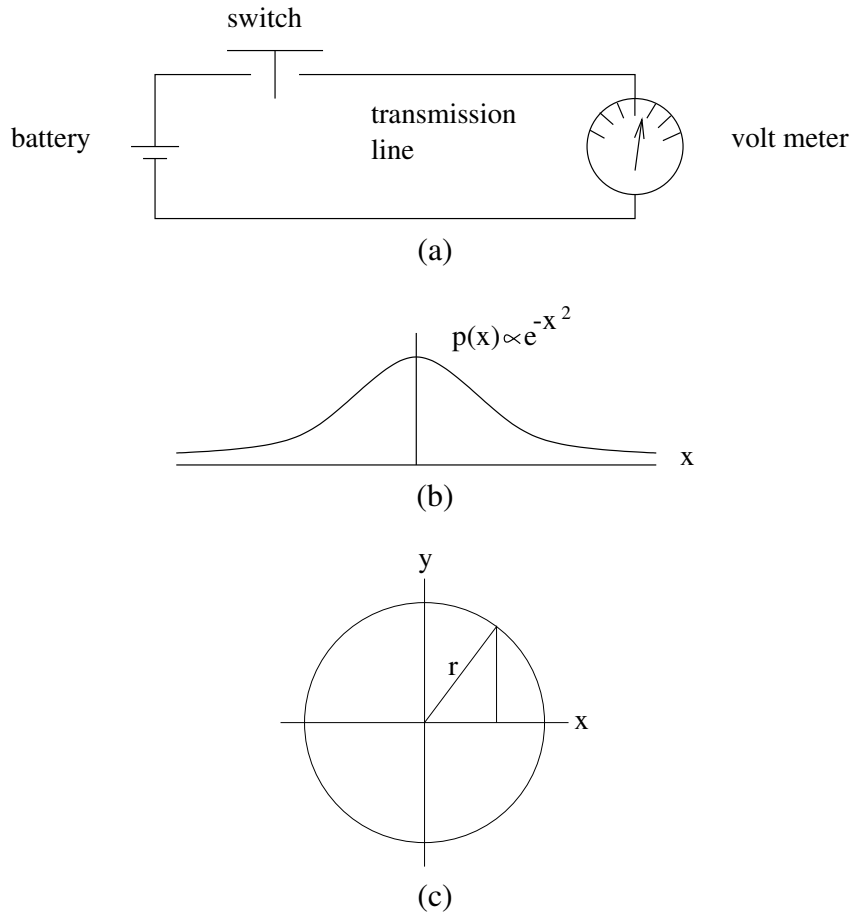


Figure 1: Representing a Message as a Hypersphere

(a) A simple electrical communications system consists of a battery, a switch and a volt meter connected by wires.

(b) The voltage of one pulse sent down the transmission line is disturbed, as in a drunken walk, by the motion of atoms in the hot wire, so the voltage received will vary according to a Gaussian distribution. For a first voltage pulse, x , the probability of the voltage variation is $p(x) \propto e^{-x^2}$.

A second voltage pulse, y , has a distribution $p(y) \propto e^{-y^2}$. Since noise is independent for the two pulses, the probabilities of the distributions are independent and the overall probability multiplies: $p(x,y) = p(x) \cdot p(y) \propto e^{-x^2} \cdot e^{-y^2} = e^{-(x^2+y^2)} = e^{-r^2}$.

(c) Plotting the voltage variation of x against the voltage variation of y , one finds that r is the hypotenuse of a triangle with x and y as the legs.

To see the shape of the distribution, set the probability $p(x,y)$ to be constant. This fixes r as the radius of a circle. So the distribution is circularly symmetric. With three pulses, $p(z) \propto e^{-z^2}$ and $p(x,y,z) \propto e^{-r^2}$ again, so the distribution is a sphere in higher dimensions.

surrounding each corner are fuzzy spheres that represent the probabilities of how much the signal can be distorted.

With four pulses the graph has to be made in 4 dimensional space, and the cube becomes a hypercube (tesseract), but the spheres are still there at each corner.

Shannon realized that when one looks at many pulses — a message — they correspond to a single point in a high dimensional space. “Essentially, we have replaced a complex entity (say, a television signal) in a simple environment (the signal requires only a plane for its representation as $f(t)$) by a simple entity (a point) in a complex environment ($2TW$ dimensional space)” [6]. (T is the message time and W is the bandwidth.) The transmitter picks the point and the receiver receives a point located in a fuzzy sphere around the transmitted point. This would not be remarkable except for an interesting property of high dimensional spheres. As the dimension goes up, almost all the received points of the sphere condense onto the surface at radius r , as shown by Brillouin and Callen [12, 13, 7]. At high dimension, the sphere density function becomes a sharply pointed distribution [7]. Shannon called these spheres ‘sharply defined billiard balls’ but I prefer ‘ping-pong balls’ as an analogy because they are hollow and have thin shells.

The sharp definition of the sphere surface at high dimension has a dramatic consequence. Suppose that I want to send you two messages. I represent these as two points in a high dimensional space. During transmission the signal encounters thermal noise and is degraded in all possible ways, so that you receive results somewhere in two spheres. If the spheres are far enough apart, you can easily determine the nearest sphere center because we agree beforehand where I will place my points. That is, you can *decode* the noisy signal and remove the noise! Of course this only works if the spheres do not overlap. If the spheres overlap, then sometimes you could not determine which message I sent.

The total power of the *received* signal allows me (at the transmitter) to pick only a limited number of messages, and they all must be within some distance from the origin of the high dimensional space. That is, there is a larger sphere around all the smaller thermal spheres that represent possible received messages. Shannon recognized this, and then he computed how many little message spheres could fit into the big sphere provided by the power and also the thermal noise, which extends the big sphere radius. By dividing the volume of the big sphere by the volume of a little one, he determined the maximum number of messages just as one can estimate the number of gumballs in a gumball machine (Fig. 2). Taking the logarithm (base 2) gave the result in bits. This gave him the channel capacity formula (1), and, using the geometry of the situation, he proved the channel capacity theorem [6].

We can see now that this theorem relies on two important facts. First, by using long messages one gets high dimensions and so the spheres have sharply defined surfaces. This allows for as few errors in communication as one desires. Second, if one packs the spheres together in a smart way, one can send more data, all the way up to the channel capacity. The sphere packing arrangement is called the *coding*, and for more than 50 years mathematicians have been figuring out good ways to pack spheres in high dimensions. This results in the low error rates of modern communications systems.

Even when they are far apart, the spheres always intersect by some amount because Gaussian distributions have infinite tails. That is why one can’t avoid error entirely. On the other hand, if the distance between two sphere centers is too small, then the two spheres intersect strongly. When random thermal noise places the received point into the intersection region, the two corresponding messages will be confused by the receiver. The consequences of this could be disastrous for the



Figure 2: A gumball machine represents a communications system, as seen by a receiver. Each gumball represents the volume of coding space a single transmitted message (a point in the space) could be moved to after thermal noise has distorted the message during communication. The entire space accessible to the receiver, represented by the outer glass shell, is determined by the power received, the thermal noise and the bandwidth. The number of gumballs determines the capacity of the machine and is estimated by dividing the volume enclosed by the outer glass shell by the volume of each gumball. A similar computation gives the channel capacity of a communications system [6]. The painting is by Wayne Thiebaud (b. 1920) *Three Machines* (1963) Oil on canvas, Fine Arts Museums of San Francisco. (c) Wayne Thiebaud/Licensed by VAGA, New York, NY., reproduced with permission. The image was obtained from <http://www.artnet.com/magazine/news/newthismonth/walrobinson2-1-16.asp>

sender or the recipient, who could even die from a misunderstanding.

Because a communications failure can have serious consequences for a living organism, Darwinian selection will prevent significant sphere overlap. It can also go to work to sharpen the spheres and to pack them together optimally. For example, a metallic key in a lock is a multi-dimensional device because the lock has many independent pins that allow a degree of security. When one duplicates the key it is often reproduced incorrectly and one will have to reject the bad one (select against it). If one's home is broken into because the lock was picked, one might replace the lock with a better one that is harder to pick (has higher dimension). Indeed, key dimension has increased over time. The Romans and middle-ages monks used to carry simple keys for wooden door locks with one or two pins, while the key to my lab seems to have about 12 dimensions.

All communications systems have the property that they are important to living organisms. That is, too much sphere overlap is detrimental. In contrast, although the continuously changing microstates of a physical system, such as a rock on the moon or a solar prominence, can be represented by one or more thermal noise spheres, these spheres may overlap, and there is no consequence because there is no reproduction and there are no future generations. A living organism with a nonfunctional communication system is unlikely to have progeny, so its genome may disappear.

Shannon's crucial concept was that the spheres must not intersect in a communications system, and from this he built the channel capacity formula and theorem. But, at its root, the concept that the spheres must be separated is a biological criterion that does not apply to physical systems in general. Although it is well known that Shannon's uncertainty measure is similar to the entropy function, the channel capacity and its theorem are rarely, if ever, mentioned in thermodynamics or physics perhaps because these aspects of information theory are about biology, so no direct application could be found in those fields. Since he used a property of biology to formulate his mathematics, I conclude that Claude Shannon was doing biology and was therefore, effectively, a biologist—although he was probably unaware of it.

It is not surprising that Shannon's mathematics can be fruitfully applied to understanding biological systems [14, 9, 7, 8]. Models built with information theory methods can be used to characterize the patterns in DNA or RNA to which proteins and other molecules bind [15, 16, 17, 18, 19] and even can be used to predict if a change to the DNA will cause a genetic disease in humans [20, 21]. Further information about molecular information theory is available at the web site <http://www.ccrnp.ncifcrf.gov/~toms/>.

What are the implications of the idea that Shannon was doing biology? First, it means that communications systems and molecular biology are headed on a collision course. As electrical circuits approach molecular sizes, the results of molecular biologists can be used to guide designs [22, 23]. We might envision a day when communications and biology are treated as a single field. Second, codes discovered for communications potentially teach us new biology if we find the same codes in a biological system. Finally, the reverse is also to be anticipated: discoveries in molecular biology about systems that have been refined by evolution for billions of years should tell us how to build new and more efficient communications systems.

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Thomas D. Schneider is a Research Biologist at the National Cancer Institute in Frederick, Maryland. He graduated from the Massachusetts Institute of Technology in biology (1978) and received his Ph.D. from the University of Colorado in molecular biology (1986). His primary work is analyzing the binding sites of proteins on DNA and RNA in bits of information. Since beginning this research, he thought that he was taking Shannon's ideas 'kicking and screaming' into molecular biology. But, after crawling out of many pitfalls, the connection between information theory and molecular biology became so clear and the results so plentiful that he dug deeper and eventually discovered that information theory was already about biology.

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