"The changes for learning must be at synapses where circuits are recruited into functional assemblies." Wolf Singer.

This individual retains the ability to learn new skills or habits, but is unable to acquire new cognitive memory. Based largely on this example, researchers segregate procedural learning, or habit formation, from cognitive learning. But they debate about how neuronal assemblies fit into the picture.

For instance, Mark Konishi of the California Institute of Technology in Pasadena thinks there are qualitative differences between learning and memory in lower organisms and in man. He sees a neuronal assembly as a population of neurons that performs a function, such as song production in birds, or coordination of walking or swimming. Konishi thinks simple organisms, like *Aplysia* and *Hermissenda*, have neuronal assemblies, although their form of learning is mostly procedural. But at the same time, he says, "the term assembly is unfortunate because it is theoretical and hypothetical."

In contrast, Mortimer Mishkin of the National Institute of Mental Health associates a cell assembly more with cognitive processes. He thinks that the brains of higher organisms, including man, store copies or representations of activity present when some object in the environment is processed by the brain. He calls the storage of this form of learning representational memory and equates it with cognitive memory. Mishkin views the brain's stored copy of a representation as a neuronal assembly.

Despite their unending struggle to define terms and processes, Dahlem participants agreed that neuronal assemblies are coactivated sets of neurons, capable of changing depending upon the kind of activity they experience. They theorized that a Darwinian-like selection process may operate during the generation of neuronal assemblies. Certain patterns of cooperative activity might reinforce and stabilize connections within the assembly. Thus, one assembly could survive another because it experiences more cooperative activity, from within itself and from external sources.

Understanding the bases for learning from gene regulation to functional neuronal assemblies is an ambitious objective. But the recent Dahlem conference left behind some basic principles and observations.

Coactivation of neurons is fundamental to the learning process. Researchers have evidence from models of gene regulation, long-term potentiation in hippocampus, synapse maturation during development, and neuronal assembly formation that activity of presynaptic and postsynaptic cells is important for long-term modifications. But why?

Neurons are more likely to achieve a threshold level of activity, triggering calcium entry, when they fire together. Calcium itself functions as a second messenger and enhances other second messenger systems, stimulated by neurotransmitters like norepinephrine, serotonin, and acetylcholine.

"How one synapse learns tells you nothing about what can be learned." Pasko Rakic.

Such relatively transient changes may set the stage for longer lasting ones in gene expression, increased neurotransmitter synthesis, and membrane structures. Some changes may be highly localized and restricted to specific synapses. Others may be neuron-wide and affect all the synapses on a cell, which in turn, could induce changes in more neurons. ■ DEBORAH M. BARNES

What Does It Mean to Be Random?

A new theory of randomness multipliers may explain what randomness is and why most phenomena that are thought to be random are not so random after all

PERSI Diaconis has spent much of the past several years thinking about randomness—a subject that is proving to be as slippery as it is important. Diaconis, a statistician from Stanford University who is spending this year at Harvard, says his work is leading him to conclude that, "the more you think about randomness, the less random things become. But sometimes you can take advantage of a lack of randomness."

In particular, Diaconis and his colleagues Bradley Efron and Eduardo Engle are developing a tool that they call randomness multipliers that, Diaconis explains, "take a small amount of uncertainty and deterministically produce highly random outcomes." As a direct consequence of this work, these researchers have, for the first time, a quantitative definition of chaos.

This is not the first time that researchers have tried to analyze randomness, of course. "There have been heroic efforts to understand randomness," Efron remarks. But the concept remains elusive. "Randomness is not an easy concept to define," says Efron. In fact, books on probability do not even attempt to define it. "It's like the concept of a point in geometry books," Efron says. "What we're trying to do is like taking points apart and seeing what's inside."

Randomness is of interest not only to statisticians, Diaconis stresses. It touches all aspects of life and can have political and sociological importance. For example, in 1970, a draft lottery was carried out and, in order to make the drawing appear as fair as possible, the planners decided to have individuals pick birthdays out of an urn. The 365 days were put in capsules and placed in the urn, the urn was shaken for several hours, and then the capsules were chosen, one by one, from the urn. But, says Diaconis, "when you looked at the data, it was very striking that the dates were not random." Birthdays in December tended to be drawn first, those in November next, then those in October, and so on.

The reason the draft lottery drawing was not random is that the capsules were put in the urn according to a definite pattern. The January birthdays were put in the urn first and fell to the bottom, the February capsules were put in next and sank down, then the March capsules were put in. Last of all, the December capsules were put in. Even though the urn was turned for several hours, "it turns out that it takes much longer than people think to mix things up," Diaconis remarks.

Another example of the uses and abuses of randomness is the generation of random numbers by computer. These computer-generated random numbers "are the mainstay of modern computations," says Diaconis. "Scientists from every area of science use millions and millions of these random numbers every day." They are used, for example, in Monte Carlo methods and for integrating higher dimensional functions. But they are not really random. Computers generate these numbers according to fixed recipes. And although they pass certain tests for randomness—a high number is followed by a lower one as often as a lower number is followed by a higher one, for example—their intrinsic lack of randomness is troublesome to many investigators.

Several years ago, George Marsaglia of Washington State University in Pullman found examples of simple randomness tests for which numbers generated by all the standard random number generating programs failed. Now there are several new ways of generating random numbers so that they pass Marsaglia's tests, but in all likelihood other simple randomness tests will be devised that show up the new random number generators as well. What this means, says Diaconis, is that "scientists should be worried." If they are naïve about the randomness of these computer-generated numbers they could end up with misleading results.

A final example of the pervasiveness of randomness is in the use of probability models. "I'm worried about the way people use probability models," says Diaconis. "It seems to me there is a lot of automated, nonthinking use of probability. People write down probabilistic models and often assume the standard postulates of randomness. But frequently their assumptions are just crazy and their conclusions are meaningless."

This sort of use of probability models occurs in large-scale models of the economy, according to David Friedman of the University of California at Berkeley. These models are used to make all sorts of predictions—from the rate of inflation to the rate of depletion of the nation's energy resources—and have become an industry in themselves. But, Friedman and others argue, they are fundamentally unsound, in part because of their misuse of probability models. "It concerns me," says Diaconis. "It is a use of probability that I think is way out of control."

It actually was Efron who started Diaconis thinking about what it really means to be random. Efron gave Diaconis an example. Suppose a wall is painted with 10-foot-wide black and white stripes. If you throw a dart at the wall, you can decide ahead of time whether it will land on a black or a white stripe. There is nothing random about it. Now suppose you start shrinking the stripes until they are only 1/10 inch wide. You would say that it is uncertain—random—whether the dart will land on a black stripe or a white one. "Brad gave me that example and then asked, 'Can you make a theory of that?' " Diaconis recalls. "It was a key image and a crucial question."

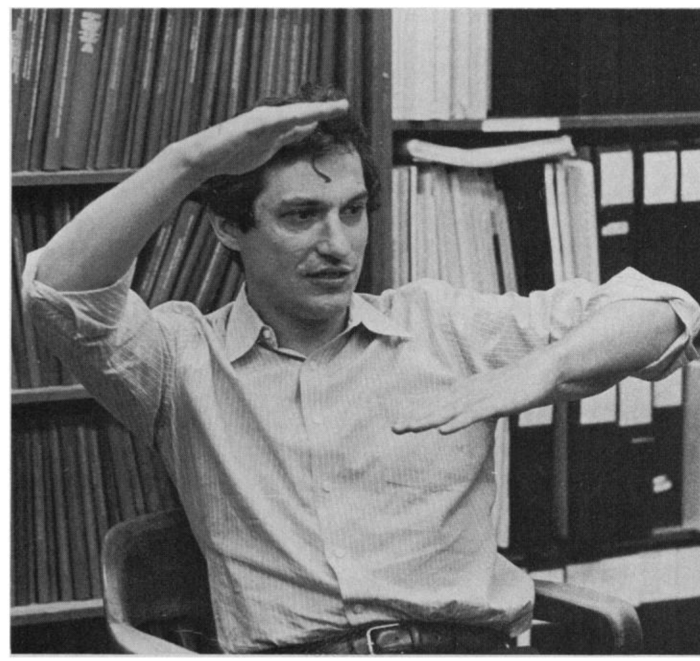
Diaconis began by going back to the clearest, simplest examples of randomness and asking what it means to be random. "The simplest, or one of the simplest, examples is coin tossing," Diaconis says. "It is an image we all have of a fundamentally random thing. But the first thing to say about it is, it's not random—it's physics. The upward velocity of the coin, the rate of spin, and Newton's laws all determine where the coin will land." Recently, three groups of investigators, including Diaconis and Joseph Keller of Stanford, independently analyzed the physics of coin tossing. (The other two groups are Vladimir Vulovic and Richard Prange of the University of Maryland and Yue Zeng-Yuan and Zhang Bin of Beijing University.)

Diaconis and Keller began by drawing a graph. On the x-axis they plotted velocity and on the y-axis they plotted spin. A point on the graph is the initial conditions for a coin toss. Their graph showed which initial conditions result in a final outcome of heads or tails. This divides the graph into regions. The regions get closer and closer together as the initial conditions get farther and farther from the origin, meaning that tiny changes in initial conditions make the difference between heads and tails. They showed experimentally that most coin tosses fall in this region where tiny changes in initial conditions make all the difference. Thus coin tossing turns out to be almost random—you would have to flip a coin millions of times to see any bias. The two investigators were able to prove that the regions must get closer together as you move out from the origin—it is not just a matter of inferring this from a graph.

In a similar manner, Diaconis and Keller analyzed roulette, the rolling of dice, and card shuffling. "Each is its own long story and for each the results are roughly similar," Diaconis says. "If you look hard, things aren't as random as everyone assumes."

Persi Diaconis

"The more you think about randomness, the less random things become."



Stanford University

In some cases Diaconis and Keller saw cutoffs after which a phenomenon that is not random at all suddenly becomes nearly so. For example, if cards are shuffled five or fewer times, they simply are not randomly mixed. After seven or eight shuffles, they are suddenly mixed well.

Diaconis is building a theory that allows him to come to terms with these examples. To do so, he had to take into account the two competing views of randomness in the scientific community. The first view is the so-called frequentist view. If you ask a frequentist what it means to say that coin tossing is random, he will respond that if you flip a coin often enough, it will come up heads half the time and tails half the time. But this definition of randomness is not entirely satisfactory, Diaconis points out. "We often think of randomness in situations where there is no chance of repeating a process over and over. We talk about the chance of a Mideast war in the next year, for example, although we can't even repeat things once in that case."

The other standard notion of randomness is the subjectivist view. The idea here, says Diaconis, is that "coins don't have probabilities, people have probabilities. A probability is a measure of someone's degree of belief in an outcome—'For me, it's random.' "

A number of statisticians have developed theorems to explain why the frequentists and subjectivists will come to similar conclusions about simple repetitive phenomena. The idea is that as more and more data accumulate—a coin is tossed over and over, for example—two people with different starting assumptions must come to the same conclusions. Or, as statisticians say, the data swamp prior beliefs. Diaconis's theory of randomness multipliers explains why subjectivists and frequentists agree, even when phenomena are not repeated, and captures, he proposes, the essential nature of objective chance devices like spinning wheels, spinning urns, and flipping coins.

It is a theory, Diaconis points out, that is based on the nearly forgotten work of a statistician, Eberhard Hopf, who began such studies in the 1930's. Hopf's work never got much attention, however, and Diaconis believes it was underappreciated in part because Hopf himself and other statisticians soon became focused on the completely unrelated subject of quantum mechanics. "Much of what I'm doing is reinterpreting Hopf's work and bringing it up to date," Diaconis says.

Diaconis's theory has three ingredients. First, there is the space of initial conditions—the velocities and spins of a coin, for example. Then there is a space of outcomes—heads or tails, in the coin-tossing case. Finally, there is the family of probability distributions—all possible opinions on a coin's particular initial velocity and spin.

To get at the notion of a randomness multiplier, Diaconis explains what it means for a family of probability distributions to have a depth. "You and I can have very different ideas of how fast a coin is flipping. I may be sure it is flipping 15 times, and you may guess that it's more like 5 to 20 times," he remarks. The depth of a probability distribution asks, with a family of distributions, what's the most different the guesses can be.

Diaconis's randomness multipliers map the probability distributions that represent guesses about the initial conditions into the space of heads or tails. "The system is a randomness multiplier if it decreases depth," he explains. In the coin-tossing example, two people could differ widely in their opinions on the initial conditions, but would be forced to agree that there is a 50–50 chance that the coin will come up heads. "Very different opinions merge," Diaconis says.

Using this theory of randomness, Diaconis continues, he can identify, quantitatively, just how random the standard examples of chance phenomena are. And he also can quantify chaos.

Randomness is "like the concept of a point in geometry books," Efron says. "What we're trying to do is like taking points apart and seeing what's inside."

In chaos, a little bit of uncertainty in initial conditions is quickly and enormously magnified. The system is unpredictable because the initial conditions can never be specifed so precisely that you can tell where the system will end up. "It is a perfect example of a randomness multiplier," Diaconis observes. Investigators who study chaos have analyzed hundreds of systems. Diaconis says the questions he asks are, How much uncertainty is there in the initial conditions? How many times does the mathematical procedure creating chaos operate? And, finally, after this many iterations, How close is the system to random?

This then provides an objective definition of chaos: To say a system is chaotic to a particular degree means it is a specific distance from random after a specific number of iterations.

Diaconis's theory of randomness is not a simple one, unfortunately. But perhaps that is inevitable. If randomness were simple, it would not have remained undefined for so long in standard probability texts. It may well be that this multistep definition of randomness is the best that can be done. In any event, the new theory will soon be put to use as Diaconis teaches a semester-long course on it at Harvard this semester and instructs other statisticians and mathematicians on how to use it to analyze random events. ■ GINA KOLATA

Briefing:

Stanford Synchrotron X-Ray Beamline Dedicated

After days of drenching rains that caused widespread flooding in California, on the morning of 20 February the sun broke through and a rainbow appeared over the Stanford Synchrotron Radiation Laboratory (SSRL). Laboratory officials hoped it was a sign of good times to come, as that afternoon they dedicated what Stanford's George Brown calls "the brightest source of hard x-rays in the world."

The source is a beamline attached to the PEP electron-positron storage ring, a high-energy physics facility of the Stanford Linear Accelerator Center (SLAC). With the PEP beamline, where the first two experiments are now under way, researchers can tap the intense, highly collimated x-rays emitted by the circulating electrons in PEP when they pass through a special magnet called an undulator. When PEP runs at its normal high-energy physics energy of 14.5 gigaelectron volts, the undulator generates radiation in the wavelength region from about 0.5 to 1 angstrom.

Because of the high brightness or spectral brilliance of their light, undulators are the coming thing in synchrotron radiation, most of which now comes from electrons as they follow a circular trajectory through the bending magnets of a storage ring. The disadvantage of undulators is that the most intense radiation comes at longer wavelengths than it does from bending magnets. Hence, undulators in SPEAR, a smaller storage ring that SSRL shares with SLAC, can make lots of longer wavelength soft x-rays at the normal SPEAR operating energy of 3 gigaelectron volts but not so many hard x-rays. PEP's much higher energy pushes the undulator spectrum to shorter wavelengths.

According to Brown, who oversaw construction of the approximately \$3.6-million project (including building, undulator, beamline optics, and an experimental station), the high brightness of the PEP beamline will be immediately useful in the first two experiments. The first is a so-called glancing-angle x-ray diffraction study of the structure of thin films and surfaces. The second is a high-resolution inelastic x-ray scattering study of the momentum dependence of processes in solids with characteristic energies in the range from 0.03 to 2 electron volts. The high brightness both compensates for comparatively weak signals and permits the use of small samples. ■

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