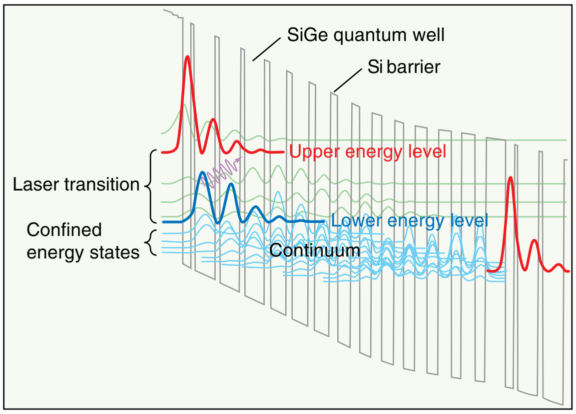

One period of a silicon/germanium quantum cascade laser. Traveling from left to right, the carriers enter the upper energy level, emit a photon upon falling to the lower level, and then move rapidly through the continuum to be reinjected into the upper level of the next period. A terahertz quantum cascade laser can have more than 100 such periods. Population inversion is achieved by designing the upper level to have a longer lifetime than the lower one, which is rapidly depopulated by the continuum.

optical phonon scattering. In III-V terahertz quantum cascade lasers, the upper state lifetime is substantially reduced above 40 K, but in silicon/germanium structures, time-resolved experiments have shown constant lifetimes up to ~150 K (*13*). Silicon also has a higher thermal conductivity than III-V materials. A silicon-based quantum cascade laser therefore promises to be a good candidate for a room-temperature terahertz source.

Because of material considerations, all silicon/germanium quantum cascade structures investigated to date have been based on transitions in the valence band. Unfortunately, the valence band is made up of many interacting subbands, and the carriers are holes (as opposed to electrons in the conduction band) with a very high effective mass. These and other factors make the design of successful silicon/germanium quantum cascade structures more challenging than is the case for III-V materials.

Lynch *et al.* demonstrated electroluminescence at 2.9 THz from transitions between energy levels in the same well (*14*). Bates *et al.* obtained similar results at 1.2 THz from transitions between energy levels in neighboring wells; such interwell transitions promise an increased upper state lifetime (*15*). Recently, Paul *et al.* have grown a cascade structure with a buried tungsten silicide layer (*16*). Such silicides may provide the means to grow cladding layers with good electrical conductivity but low optical absorption, vital for successful laser operation.

Optically pumped silicon impurity lasers in the terahertz range have been around for some years (*5*–*8*), but a compact, electrically pumped terahertz laser operating at room temperature remains elusive.

The quantum cascade approach is arguably the most promising; here, silicon/germanium structures may offer key advantages over III-V materials for high-temperature operation. However, serious obstacles must be overcome before a working silicon quantum cascade laser can be produced.

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10.1126/science.1109831

SOCIOLOGY

Network Theory—the Emergence of the Creative Enterprise

Albert-László Barabási

In the *Foundation Trilogy*, Isaac Asimov placed psychohistorian Harry Seldon so far into the future that Earth, the birthplace of the Galactic civilization, has been forgotten (*1*). Indeed, Star Trek's teleporting characters appear far more grounded in reality than Seldon's mathematical equations that accurately predict the multigalactic society's fate thousands of years into the future. Today, when reports about quantum teleportation fill the pages of the best physics journals, we wonder how long it will be until a real Harry Seldon produces an accurate mathematical theory of human behavior.

It may be hard to believe, but conditions for such a quantitative approach are increasingly in place. Indeed, records of human actions are already stored in numerous databases. E-mail and phone records document our social and professional interactions; travel records and GPS navigation systems capture our travel patterns and physical locations; credit-card companies maintain records of our shopping and entertainment habits. Although in the wrong hands, these data sets represent Orwellian tools of power, for scientists they offer incredible insights into human behavior. Combine this capability with the sophisticated tool of network theory (*2*–*7*), which analyzes relations between millions of individuals, and you get a glimpse of an unprecedented opportunity to quantify human dynamics. Although a mathematical theory of social complexity remains a pipe dream, it is not as farfetched as it may have appeared in 1942, when *Foundation* was first published. Proof of this can be found in the study by Guimerà *et al.* on page 697 of this issue (*8*). By taking advantage of publicly available data sets from both artistic and scientific fields, the authors offer powerful insights into the mechanisms governing collective human behavior.

Traditionally, the achievements of individuals such as Darwin and Einstein have dominated the public's image of science, yet today some of the most groundbreaking work is collaborative in nature (see the figure). But how do such creative teams come about? Are there discernible differences between collaborations that are sparklingly creative and those that are less inventive? Guimerà *et al.* use network theory to answer these questions. Their starting point is a collection of fascinating data sets: a century-long record of Broadway musicals and the publication records of several fields of science. These data sets allowed them to reconstruct the collaborative history of the individuals who contributed to a particular show or research publication. The investigators document a changing creative enterprise in which advances require an increasing number of contributors. The history of Broadway is particularly illuminating: The team size responsible for producing a show increased until the 1930s, after which it leveled off, fluctuating at around seven contributors for the past 70 years. In contrast, science continues to search for its optimal collaborative setup: The number of

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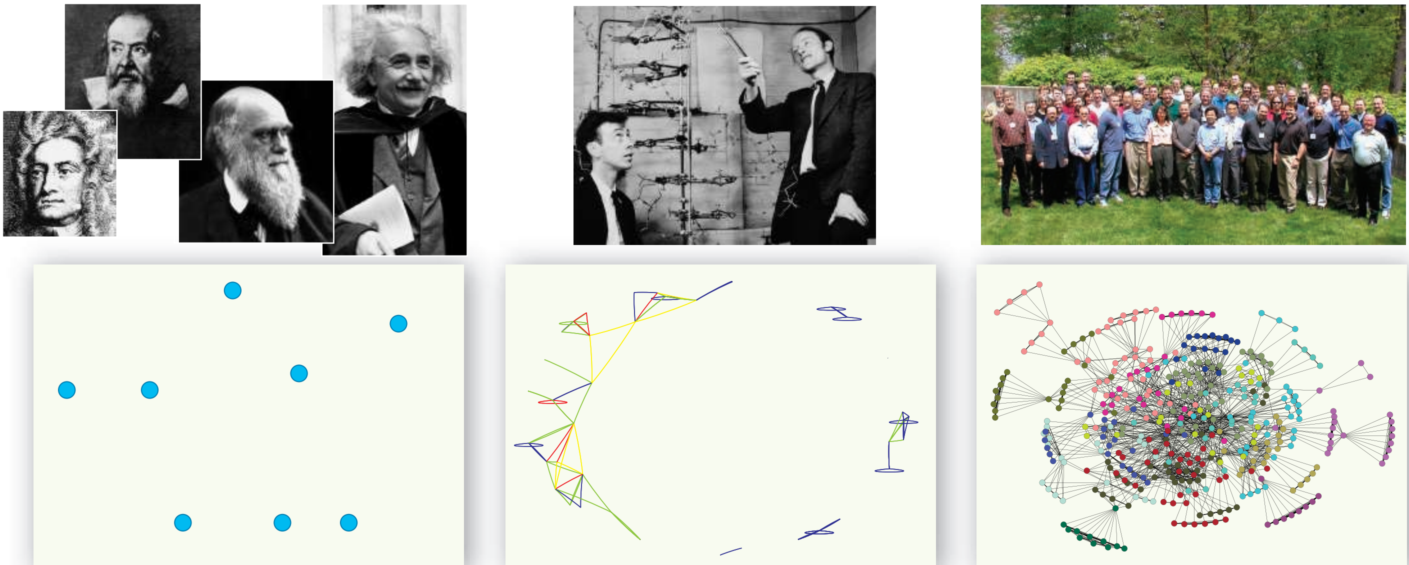

Evolution of the scientific enterprise. (**Left**) For centuries, creative individuals were embedded in an invisible college, that is, a community of scholars whose exchange of ideas represented the basis for scientific advances. Although intellectuals built on each other's work and communicated with each other, they published alone. Most great ideas were attributed to a few influential thinkers: Galileo, Newton, Darwin, and Einstein. Thus, the traditional scientific enterprise is best described by many isolated nodes (blue circles). (**Middle**) In the 20th century, science became an increasingly collaborative enterprise, resulting in such iconic pairs as the physicist Crick and the biologist Watson (left), who were responsible for unraveling DNA's structure. The joint publications documenting these collaborations shed light on the invisible college, replacing the hidden links with published coauthorships. (**Right**) Although it is unlikely that large collaborations—such as the D0 team in particle physics or the International Human Genome Sequencing Consortium pictured here—will come to dominate science, most fields need such collaborations. Indeed, the size of collaborative teams is increasing, turning the scientific enterprise into a densely interconnected network whose evolution is driven by simple universal laws.

coauthors in each scientific field has increased monotonically during the past decade. It is anyone's guess when and where it will reach a maximum.

Until the late 1990s, the bulk of network research focused on static properties, which do not change with time (*9*). Yet a proper understanding of most networks requires that we characterize the assembly process that generated them. Indeed, a map of such networks is not sufficient to understand the structure of the World Wide Web—we must describe how documents and links are added and removed (*3*). Uncovering all interactions between proteins is only the first step toward understanding cellular networks—we must also explore the importance of gene duplications and mutations that shape the interactions between proteins and genes (*10*). Similarly, to comprehend the structure of the collaboration map, we must understand how people form friendships and alliances. Given that in the professional world friendships are just as crucial as hard-nosed professional interests, modeling the evolution of creative teams may appear to be impossible. Guimerà's results indicate otherwise: They show that a simple model successfully captures many qualitative features of the network underlying the creative enterprise. In their study, they distinguish between veterans, who have participated in collaborations before, and rookies, who are about to see their names appear in print for the first time. Two parameters are key: the fraction of veteran members in a new team, and the degree to which veterans involve their former collaborators. If choosing experienced veterans is not a priority, the authors find that the network will be broken up into many small teams with little overlap between them. As the likelihood of relying on veterans increases, thanks to the extra links to earlier collaborators, the teams coalesce through a phase transition such that all players become part of a single cluster.

Many professional networks—from the web of actors in Hollywood to scientific collaborations (*11*, *12*)—are scale-free (*13*), that is, although most individuals have only a few collaborators, a few have hundreds and operate as hubs. The legendary Paul Erdös, the father of random network theory, with more than 500 collaborators, was probably the best known hub within mathematics. The model that Guimerà and co-workers propose does indeed account for hubs, the emergence of which is rooted in the rookies' desire to involve their friends in new teams. Indeed, the more collaborators an individual has, the higher the chances are that he or she will be invited to participate again. This process—called preferential attachment in network theory—is responsible for the emergence of hubs through a rich-gets-richer process (*13*) in which well-connected individuals continue to be in high demand.

How does this assembly process affect the team's performance? The results of the Guimerà *et al*. study indicate that expertise does matter: Teams publishing in high-impact journals have a high fraction of incumbents. But diversity matters too: Teams with many former collaborative links offer inferior performance. Thus, the recipe for success seems relatively simple: When forming a "dream team" make an effort to include the most experienced people, whether or not you have worked with them before. The temptation to work mainly with friends will eventually hurt performance.

In Asimov's classic story, Harry Seldon's theory could not handle innovation. To stay on the predictive side, the Foundation went to great lengths to freeze all technological development. Indeed, the most disruptive social changes humanity has experienced are intimately tied to new technologies, from the steam engine to the Internet. It is tempting to conclude, therefore, that given the unpredictability of potential technologies, a theory of human dynamics will have no chance of success until scientific innovation ceases. A more constructive approach, and one taken by Guimerà *at al*., takes us in the opposite direction, bringing innovation into a scientific and mathematical perspective.

Finally, will there ever be a Harry Seldon and a mathematical theory of human behavior? It is easy to maintain that human actions are too complex to be predictable. But skeptics are proven wrong each time a waiter brings them ketchup with their fries, without having been asked to. A master of consumer behavior, the waiter concludes that very likely they will ask for it. In the same way, a data-driven understanding of human actions could help us to translate into a predictive mathematical language the fundamental principles that drive a society's collective behavior. In a world in which all events are recorded by computers, the conditions for this research are increasingly in place. The quantitative accumulation of such data could easily spark a qualitative change, helping many disparate facts to fall into a coherent predictive theory. By demonstrating that the Web, the cell, or society is driven by similar organizing principles, network theory offers a successful conceptual framework to approach the structure of many complex systems. Perhaps a predictive framework that captures the dynamics and the behavior of networks is not too far behind either. In the light of Guimerà *et al.*'s results, we can be sure of one thing: While pursuing a theory of human behavior, we could overlook a Harry Seldon. A mathematical theory of human dynamics may not be the solitary achievement of a genius scientist (*14*), but will likely emerge from the combined efforts of an expert team with just the right combination of expertise, collaborative experience, and fresh ideas.

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10.1126/science.1112554

OCEAN SCIENCE

Ocean Mixing in 10 Steps

Bill Merryfield

Ocean waters are warm in some places, cold in others, and also vary widely in their salt content, or salinity. As masses of water transit the globe in ocean currents, these properties are modified by air-sea exchanges (including warming by sunshine and freshening by rain) and by subsurface hydrodynamic processes referred to as ocean mixing (*1*). On page 685 of this issue, Schmitt *et al.* (*2*) report direct measurements of one such mixing process.

Enhanced online at www.sciencemag.org/cgi/content/full/308/5722/641

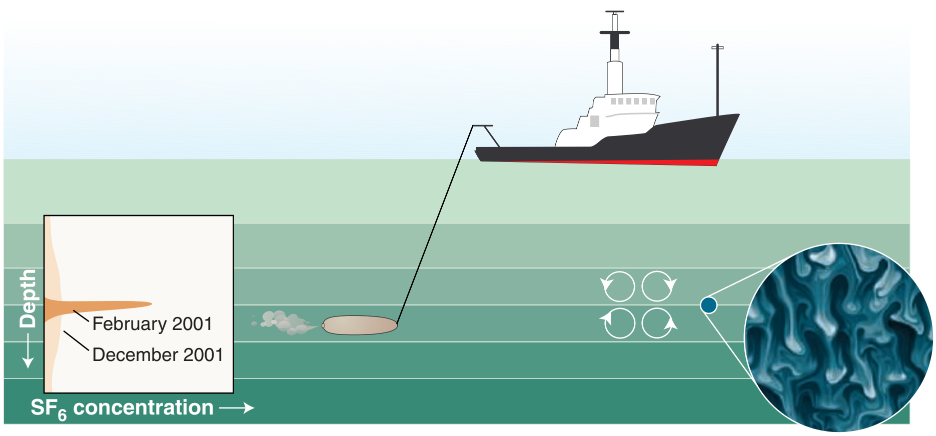
Measurements of this kind are important because the temperature and salinity of a water mass govern its buoyancy, and hence determine how it rises or sinks across ocean surfaces of constant density. For example, the Atlantic overturning circulation, which transports heat from tropical to subpolar regions, is supplied with sinking water through buoyancy loss (mainly from surface cooling) in the far North Atlantic. For the water mass to complete the circuit, the lost buoyancy must be regained further south through some combination of air-sea exchange and ocean mixing.

Knowledge of ocean mixing is thus a prerequisite for understanding ocean circulation. Such understanding is greatly aided by ocean circulation models. Although these models have become more sophisticated in recent years (*3*), much room for progress remains in how they treat mixing, which occurs on spatial scales much smaller than the models can represent explicitly. To this end, measurements like those of Schmitt *et al.* (*2*) provide vital guidance.

In the absence of extensive data, early models imposed relatively strong mixing that was either uniform or a prescribed function of depth. The prescribed values were consistent with theoretical estimates of mixing that likewise assumed horizontal uniformity (*4*). Meanwhile, indirect evidence was accumulating that mixing throughout much (and perhaps most) of the ocean might actually be much weaker. However, these measurements relied on theoretical constructs to link small-scale temperature and velocity fluctuations to mixing (*5*, *6*), and were thus not immune from skepticism.

A more definitive answer was provided by revolutionary direct measurements that involved injection of a nearly inert compound, sulfur hexafluoride (SF_6), into the ocean. SF_6 can be detected in minute concentrations months or even years after injection. Three large-scale experiments of this kind have been performed to date. The first of these, the North Atlantic Tracer Release Experiment of 1992 to 1994, followed the vertical spread of SF_6 about the 300-m injection depth and showed that conclusions drawn from earlier indirect measurements were substantially correct (*7*).

Though uniquely definitive, tracer-release experiments require large commitments of funding and ship time and therefore must be carefully targeted. The second study, from 1996 to 1998, involved the



Staircase mixing in the ocean. In early 2001, 175 kg of inert SF_6 were released into a "thermohaline staircase" in the western tropical Atlantic. Subsequent vertical dispersion of this tracer (**inset, bottom left**), measured 10 months later, revealed the extent of mixing by salt fingers in the thin interfaces (**inset, bottom right**) and by convection within the thicker layers. The mixing rate, which applies to salinity, was approximately double that of heat.

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