process may not have been so smooth as initially thought, and numerical simulations performed by Tsiganis *et al*. (*4*) show that the passage of Jupiter and Saturn through a 2:1 resonance may have ignited a period of strong chaotic evolution of Uranus and Neptune. In this scenario, the two planets had frequent close encounters and may even have exchanged orbits before their eccentricities finally settled down, allowing a more quiet migration to the present orbits.

The presence of a thick disk of Trojans around Neptune is clearly relevant to understanding the dynamical evolution of the planet. The co-orbital Trojan paths are unstable when Neptune has repeated close approaches with Uranus, and the capture of the present population appears possible either at the time of the last radial jump related to an encounter with Uranus or during the final period of slow migration. In this last case, collisional emplacement—in synergy with the reduction of the libration amplitude attributable to the outward migration and by the mass growth of the planet—is the only viable mechanism for trapping Trojans in this phase, but it does not appear to be so efficient as to capture a large population. Moreover, the only frequent planetesimal collisions are those that are close to the median plane of the disk, and this fact is at odds with the presence of high-inclination Trojans such as the one found by Sheppard and Trujillo. A thick disk of Neptune Trojans seems also to rule out the possibility that Trojans formed in situ from debris of collisions that occurred nearby (*5*).

The chaotic capture invoked to explain the orbital distribution of Jupiter Trojans might have worked out in the same way for Neptune. The planet at present is close to a 2:1 mean-motion resonance with Uranus; however, the resonance crossing has not been reproduced so far in numerical simulations of the migration of the outer planets. Alternatively, some sweeping secular resonance might have provided the right amount of instability for the "freeze-in" trapping to occur. In the near future, after additional Neptune Trojans are detected, an important test would be to look for a possible asymmetry between the trailing and leading clouds. Theoretical studies have shown that the L5 Lagrangian point (the trailing one) is more stable in the presence of outward radial migration and that this asymmetry strongly depends on the migration rate. This finding would have direct implications for the capture mechanism and for the possibility that the outward migration of Neptune was indeed smooth, without fast jumps caused by gravitational encounters with Uranus.

Sheppard and Trujillo also sort out another aspect of the known Neptune Trojans: their optical color distribution. It appears to be homogeneous and similar to that of Jupiter Trojans, irregular satellites, and possibly comets, but is less consistent with the color distribution of KBOs as a group. This finding raises questions about the compositional gradient along the planetesimal disk in the early solar system, the degree of radial mixing caused by planetary stirring, and the origin of the Jupiter and Neptune Trojans. Did Trojans form in a region of the planetesimal disk thermally and compositionally separated from that of the KBOs? How far did the initial solar nebula extend to allow important differences among small-body populations? Additional data are needed to solve the puzzles of the dynamical and physical properties of Neptune Trojans, and the finding by Sheppard and Trujillo is only the first step.

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CLIMATE CHANGE

Can We Detect Trends in Extreme Tropical Cyclones?

Subjective measurements and variable procedures make existing tropical cyclone databases insufficiently reliable to detect trends in the frequency of extreme cyclones.

Christopher W. Landsea, Bruce A. Harper, Karl Hoarau, John A. Knaff

Recent studies have found a large, sudden increase in observed tropical cyclone intensities, linked to warming sea surface temperatures that may be associated with global warming (*1–3*). Yet modeling and theoretical studies suggest only small anthropogenic changes to tropical cyclone intensity several decades into the future [an increase on the order of ~5% near the end of the 21st century (*4*, *5*)]. Several comments and replies (*6–10*) have been published regarding the new results, but one key question remains: Are the global tropical cyclone databases sufficiently reliable to ascertain long-term trends in tropical cyclone intensity, particularly in the frequency of extreme tropical cyclones (categories 4 and 5 on the Saffir-Simpson Hurricane Scale)?

Tropical cyclone intensity is defined by the maximum sustained surface wind, which occurs in the eyewall of a tropical cyclone over an area of just a few dozen square kilometers. The main method globally for estimating tropical cyclone intensity derives from a satellite-based pattern recognition scheme known as the Dvorak Technique (*11–13*). The Atlantic basin has had routine aircraft reconnaissance since the 1940s, but even here, satellite images are heavily relied upon for intensity estimates, because aircraft can monitor only about half of the basin and are not available continuously. However, the Dvorak Technique does not directly measure maximum sustained surface wind. Even today, application of this technique is subjective, and it is common for different forecasters and agencies to estimate significantly different intensities on the basis of identical information.

The Dvorak Technique was invented in 1972 and was soon used by U.S. forecast offices, but the rest of the world did not use it routinely until the early 1980s (*11*, *13*). Until then, there was no systematic way to estimate the maximum sustained surface wind for most tropical cyclones. The Dvorak Technique was first developed for visible imagery (*11*), which precluded obtaining tropical cyclone intensity estimates at night and limited the sampling of maximum sustained surface wind. In 1984, a quantitative infrared method (*12*) was published, based on the observation that the temperature contrast between the warm eye of the cyclone and the cold cloud tops of the eyewall was a reasonable proxy for the maximum sustained surface wind.

In 1975, two geostationary satellites were available for global monitoring, both with 9-km resolution for infrared imagery. Today, eight

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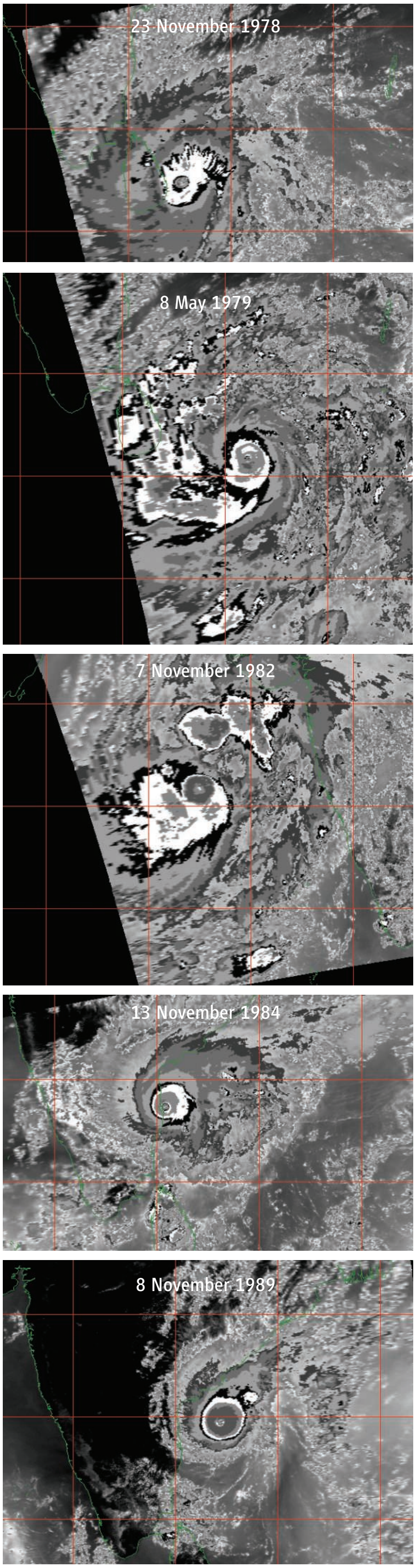
satellites are available with typically 4-km resolution in the infrared spectrum. The resulting higher resolution images and more direct overhead views of tropical cyclones result in greater and more accurate intensity estimates in recent years when using the infrared Dvorak Technique. For example (*13*), Atlantic Hurricane Hugo was estimated to have a maximum sustained surface wind of 59 m s^{-1} on 15 September 1989, based on use of the Dvorak Technique from an oblique observational angle. But in situ aircraft reconnaissance data obtained at the same time revealed that the hurricane was much stronger (72 m/s) than estimated by satellite. This type of underestimate was probably quite common in the 1970s and 1980s in all tropical cyclone basins because of application of the Dvorak Technique in an era of few satellites with low spatial resolution.

Operational changes at the various tropical cyclone warning centers probably also contributed to discontinuities in tropical cyclone intensity estimates and to more frequent identification of extreme tropical cyclones (along with a shift to stronger maximum sustained surface wind in general) by 1990. These operational changes include (*13*–*17*) the advent of advanced analysis and display systems for visualizing satellite images, changes in the pressure-wind relationships used for wind estimation from observed pressures, relocation of some tropical cyclone warning centers, termination of aircraft reconnaissance in the Northwest Pacific in August 1987, and the establishment of specialized tropical cyclone warning centers.

Therefore, tropical cyclone databases in regions primarily dependent on satellite imagery for monitoring are inhomogeneous and likely to have artificial upward trends in intensity. Data from the only two basins that have had regular aircraft reconnaissance—the Atlantic and Northwest Pacific—show that no significant trends exist in tropical cyclone activity when records back to at least 1960 are examined (*7*, *9*). However, differing results are obtained if large bias corrections are used on the best track databases (*1*), although such strong adjustments to the tropical cyclone intensities may not be warranted (*7*). In both basins, monitoring and operational changes complicate the identification of true climate trends. Tropical cyclone "best track" data sets are finalized annually by operational meteorologists, not by climate researchers, and none of the data sets have been quality controlled to account for changes in physical understanding, new or modified methods for analyzing intensity, and aircraft/satellite data changes (*18*–*21*).

To illustrate our point, the figure presents satellite images of five tropical cyclones listed in the North Indian basin database for the period 1977 to 1989 as category 3 or weaker. Today, these storms would likely be considered extreme tropical cyclones based on retrospective application of the infrared Dvorak Technique. Another major tropical cyclone, the 1970 Bangladesh cyclone—the world's worst tropical-cyclone disaster, with 300,000 to 500,000 people killed—does not even have an official intensity estimate, despite indications that it was extremely intense (*22*). Inclusion of these storms as extreme tropical cyclones would boost the frequency of such events in the 1970s and 1980s to numbers indistinguishable from the past 15 years, suggesting no systematic increase in extreme tropical cyclones for the North Indian basin.

Previously unrecognized category 4 and 5 tropical cyclones in the North Indian Ocean, 1978–1989



Underestimated storm intensity. The North Indian basin tropical cyclones shown here are listed in the best track data set as category 3 or weaker, but were probably category 4 or 5. Similar underestimates may have been common in all ocean basins in the 1970s and 1980s. Trend analyses for tropical cyclones intensities are therefore highly problematic.

These examples are not likely to be isolated exceptions. Ongoing Dvorak reanalyses of satellite images in the Eastern Hemisphere basins by the third author suggest that there are at least 70 additional, previously unrecognized category 4 and 5 cyclones during the period 1978–1990. The pre-1990 tropical cyclone data for all basins are replete with large uncertainties, gaps, and biases. Trend analyses for extreme tropical cyclones are unreliable because of operational changes that have artificially resulted in more intense tropical cyclones being recorded, casting severe doubts on any such trend linkages to global warming.

There may indeed be real trends in tropical cyclone intensity. Theoretical considerations based on sea surface temperature increases suggest an increase of ~4% in maximum sustained surface wind per degree Celsius (*4*, *5*). But such trends are very likely to be much smaller (or even negligible) than those found in the recent studies (*1*–*3*). Indeed, Klotzbach has shown (*23*) that extreme tropical cyclones and overall tropical cyclone activity have globally been flat from 1986 until 2005, despite a sea surface temperature warming of 0.25°C. The large, step-like increases in the 1970s and 1980s reported in (*1*–*3*) occurred while operational improvements were ongoing. An actual increase in global extreme tropical cyclones due to warming sea surface temperatures should have continued during the past two decades.

Efforts under way by climate researchers—including reanalyses of existing tropical cyclone databases (*20*, *21*)—may mitigate the problems in applying the present observational tropical cyclone databases to trend analyses to answer the important question of how humankind may (or may not) be changing the frequency of extreme tropical cyclones.

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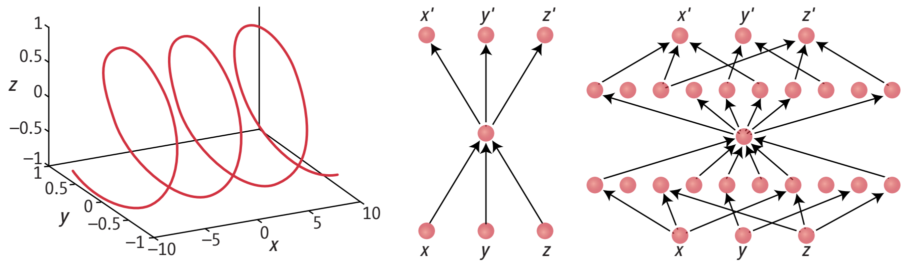
COMPUTER SCIENCE

New Life for Neural Networks

With the help of neural networks, data sets with many dimensions can be analyzed to find lower dimensional structures within them.

Garrison W. Cottrell

As many researchers have found, the data they have to deal with are often high-dimensional—that is, expressed by many variables—but may contain a great deal of latent structure. Discovering that structure, however, is nontrivial. To illustrate the point, consider a case in the relatively low dimension of three. Suppose you are handed a large number of three-dimensional points in random order (where each point is denoted by its coordinates along the x, y, and z axes): {(–7.4000, –0.8987, 0.4385), (3.6000, –0.4425, –0.8968), (–5.0000, 0.9589, 0.2837), …}. Is there a more compact, lower dimensional description of these data? In this case, the answer is yes, which one would quickly discover by plotting the points, as shown in the left panel of the figure. Thus, although the data exist in three dimensions, they really lie along a one-dimensional curve that is embedded in three-dimensional space. This curve can be represented by three functions of x, as $(x, y, z) = [x, \sin(x), \cos(x)]$. This immediately reveals the inherently one-dimensional nature of these data. An important feature of this description is that the natural distance between two points is not the Euclidean, straight line distance; rather, it is the distance along this curve. As Hinton and Salakhutdinov report on page 504 of this issue (*1*), the discovery of such low-dimensional encodings of very high-dimensional data (and the inverse transformation back to high dimensions) can now be efficiently carried out with standard neural network techniques. The trick is to use networks initialized to be near a solution, using unsupervised methods that were recently developed by Hinton's group.



Searching for structure. **(Left)** Three-dimensional data that are inherently one-dimensional. **(Middle)** A simple "autoencoder" network that is designed to compress three dimensions to one, through the narrow hidden layer of one unit. The inputs are labeled x, y, z, with outputs x', y', and z'. **(Right)** A more complex autoencoder network that can represent highly nonlinear mappings from three dimensions to one, and from one dimension back out to three dimensions.

This low-dimensional structure is not uncommon; in many domains, what initially appears to be high-dimensional data actually lies upon a much lower dimensional manifold (or surface). The issue to be addressed is how to find such lower dimensional descriptions when the form of the data is unknown in advance, and is of much higher dimension than three. For example, digitized images of faces taken with a 3-megapixel camera exist in a very high dimensional space. If each pixel is represented by a gray-scale value between 0 and 255 (leaving out color), the faces are points in a 3-million-dimensional hypercube that also contains all gray-scale pictures of that resolution. Not every point in that hypercube is a face, however, and indeed, most of the points are not faces. We would like to discover a lower dimensional manifold that corresponds to "face space," the space that contains all face images and only face images. The dimensions of face space will correspond to the important ways that faces differ from one another, and not to the ways that other images differ.

This problem is an example of unsupervised learning, where the goal is to find underlying regularities in the data, rather than the standard supervised learning task where the learner must classify data into categories supplied by a teacher. There are many approaches to this problem, some of which have been reported in this journal (*2*, *3*). Most previous systems learn the local structure among the points—that is, they can essentially give a neighborhood structure around a point, such that one can measure distances between points within the manifold. A major limitation of these approaches, however, is that one cannot take a new point and decide where it goes on the underlying manifold (*4*). That is, these approaches only learn the underlying low-dimensional structure of a given set of data, but they do not provide a mapping from new data points in the high-dimensional space into the structure that they have found (an encoder), or, for that matter, a mapping back out again into the original space (a decoder). This is an important feature because without it, the method can only be applied to the original data set, and cannot be used on novel data. Hinton and Salakhutdinov address the issue of finding an invertible mapping by making a known but previously impractical

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