Neural networks

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The attempts by the neuroscientists, computer scientists and physicists to capture the computational architecture and processes of the human brain and their implementation in silicon devices are now giving encouraging results. The studies of model neural networks and their properties are now at a very exciting stage. We start with a brief introduction of the developments made in neural network modelling. The current research activities in this field in India (to the best of author's knowledge) are then discussed and some suggestions regarding the future course of action indicated.

THE overwhelming superiority of human brain over digital computers in almost every task (e.g. faster recognition of objects, faces, processing visual information, etc.) motivates studies on the design and performance of artificial intelligence (AI) models of the brain, to capture the essential processes of neural computation. The prospect of implementing the basic architecture of the human brain (consisting of about 10^{11} neurons working in parallel and each operating in a typical millisecond time scale) in high-speed electronic computers (presently employing about 10^{10} constituent transistors operating typically in nanosecond time scale, with sequential operation program) is proving to be a new reality. What are the possible tasks an artificial neural network can do? Expectations from such simple networks are enormous:

i) Such networks should evolve in a flexible way – to be able to 'learn' and accommodate themselves to new environments and need not be programmed.
ii) Should be able to process informations which are fuzzy, probabilistic, noisy or even inconsistent.
iii) Should be fault-tolerant (robust) and compact (efficient).

Neural networks have emerged as an alternative paradigm for computation. Instead of the processing being sequential, as in the usual von Neumann architecture of computers, the instructions can be distributed amongst the different computing units of a neural network. Their potential applications lie mainly in computer science and engineering, in addition to their use as a paradigm for modelling in neuroscience and in sensory and cognitive psychology. They will also open an avenue to new investigations, by simulating processes that cannot be studied in live brain.

Brief review and state of the art

It is now more than a hundred years that the basic building blocks (or atoms), called neurons, of the neural network (in the human brain) were identified and discovered by Cajal in 1888 (see e.g. reference 1). Fifty years back (in 1943), McCulloch and Pitts[2], inspired by the knowledge gathered already in neurobiology, proposed a model for the (nonlinear) dynamics of the (state of) activity of a neuron interacting (via synaptic connections W_{ij}) with other neurons in the network. They introduced a simplistic binary-state (active and passive) threshold neuron model. If the state of the ith neuron is denoted as $n_i(t)$ at (discrete) time t (where $i = 1, 2, \ldots, N$, N being the total number of neurons in the network) then the dynamical law for the change of state for the model neuron is

$$n_i(t+1) = \Theta(h_i(t) - \phi_i), \quad i = 1, 2, \ldots, N, \tag{1}$$

where the net input on the ith neuron

$$h_i(t) = \Sigma_j W_{ij} n_j(t) \quad (j \neq i, j = 1, 2, \ldots, N).$$

The threshold function $\Theta(x) = 1$ for $x > 0$ and $\Theta(x) = 0$ for $x \leq 0$. ϕ_i denotes the threshold for the neuron i, such that it is in an active state ($n_i = 1$) if the net input (h_i) to it exceeds ϕ_i and remains inactive ($n_i = 0$) otherwise. McCulloch and Pitts[2] suggested that, with a suitable choice for the synaptic strengths W_{ij}, such networks can carry out any imaginable computation. With this started the investigations of artificial neural networks[3–18].

Around 1960, Rosenblatt and coworkers[3] studied a specific network architecture, called *perceptrons*, with a layered structure and feed-forward connections, W_{ij}, appropriate for a particular type of computational task (similar to processing of sensory information or perception). A severe criticism on the limitations of the (one-layer) perceptron model, by Minsky and Papert[4], left this model abandoned (virtually dead) for almost twenty years. In a very significant development in the last decade, the group led by Rumelhart *et al.*[5] rediscovered independently the merits of an (optimization) algorithm called *back propagation* (first found by Werbos[6] in 1974) to find the W_{ij}'s in a multilayer perceptron. Most of the successful implementations today of the neural network architecture for recognizing complicated patterns and quasichaotic time series *employ this back propagation algorithm* and its extensions. Some examples are:

(i) NETtalk (Sejnowski and Rosenberg[7]), having a three-layer feed-forward network (with 80 'hidden' units), could 'learn' (like a child) to pronounce written text. This, of course, is a compromise (solution) to the much harder (reverse) problem of speech recognition. The network was trained to associate a phonetic value with a certain group of letters provided by an example set of 1024 English words. After completion of the 'training' (typically 50 cycles or iterations), it could accurately pronounce 95% of the words from the training set and about 80% of the words from 'unseen' texts.

(ii) The primary structure of a protein consists of a linear sequence of amino acids, chosen from 20 possibilities, like a text with an alphabet of 20 letters. The secondary structure determines the local stereochemical form of the amino acid chain (e.g. α helix, β sheet, β turn or random coil). In an obvious parallel to NETtalk, Sejnowski and Rosenberg[7] and Bohr *et al.*[8] developed independently neural networks which learned from a set of samples and then predicted the secondary structure of the central sequence. The best reported accuracy is 62% for the training set and about 53% for 'unseen' sequences. One recognizes, therefore, the ability of such networks to extract the functional relations that have so far escaped human intelligence!

(iii) There are now multilayer networks (using essentially back propagation) for navigation of a car (so that the car could drive on a road through a wooded area), signal prediction and time series (e.g. sunspot activity series) prediction with impressive reported success (over non-network and even human attempts).

There has been another root of development of the McCulloch and Pitts[2] type of network[9-18]. In 1955, Cragg and Temperley[9] identified the McCulloch–Pitts (two-state) neurons as (Ising) spins or magnetic moments. Attempts were also made by Little[10] and others (in 1970s) to implement Hebb's[11] ideas about learning in the brain, to construct the synaptic connections W_{ij}; W_{ij}'s take positive (excitory) and negative (inhibitory) values determined by the patterns to be learned. However, the coupled dynamical equations were still not amenable to statistical physics. Hopfield in 1982 made a 'clever step backward' and assumed $W_{ij} = W_{ji}$ (which is not correct biologically) in a model network and introduced the 'energy function' or the 'hamiltonian' for the network. Memories were then identified as metastable minima (acting as local attractor fixed points in the dynamics) in the 'energy landscape'.

The energy function or the hamiltonian being very similar to that of spin glasses (in statistical physics), a remarkable understanding developed and most of the recently acquired ideas about the free-energy landscape of spin glasses were translated to those of such networks. These led to quite rigorous and formal theories[13, 14] regarding the network (loading) capabilities for associative memory. Extensions of such networks for learning, storing and recalling temporal sequences of patterns (replacing fixed points by limit cycles) have also been made. The ability of such Hopfield-type networks to associate local minima with the (desired or learned) patterns has been utilized by Hopfield and Tank[15] to suggest a neural-network approach for locating the (degenerate) solutions of TRAVELLING SALESMAN type of combinatorial optimization problems: the cost function, to be minimized, determines the synaptic connections. This brilliant idea (of utilizing the parallel functions of the neurons in the network to look for the associative solution of such NP-hard problems) has, so far, not led to any reasonable success (compared to that obtained using other non-network approaches).

Hardware implementations of the Hopfield model in the analog VLSI circuits have been achieved, and chips with (N =) 256 fully connected units or neurons, using about 130,000 ($\cong 2N^2$) resistors to simulate W_{ij}'s, have been made[16]. These connections (W_{ij}'s) are difficult to achieve in silicon technology (where units or the neurons are simpler to construct, using nonlinear amplifiers), which is reverse in optical technology. Mead and coworkers[17] have developed an electronic model of the retina of the visual system of the vertebrate animals: with 48 × 48 nearest-neighbour connected photosensors. The chip is reported to be able to perform the basic tasks of image processing for discontinuity and motion detection, in a manner quite similar to biological retina.

Criticism

There has been, however, some serious (mathematical and philosophical) criticism to the ultimate goal of such artificial intelligence research. Can such artificially intelligent systems (networks) be 'really intelligent'? Can such networks ever 'be aware of, or understand' what it is doing? Can it have its own mind (be self-conscious)? Penrose[19] argues that an extended Gödel's incompleteness theorem holds and that may preclude such possibilities.

Current work in India

Presently, there are many groups in various computer science, electrical engineering and physics departments of IITs, institutes and universities interested in neural network research. To my knowledge, there are groups in the computer science departments of TIFR (Bombay), IISc (Bangalore), ISI (Calcutta), IIT (Delhi and Kharagpur) where various neural network architectures for several kinds of pattern recognition problems are being investigated. A piece of such work investigated by one of these groups (see e.g. reference 20) uses fuzzy sets for replacing the binary-state neurons in a multi-layer perceptron network, for the classification of fuzzy (linguistic) patterns. A couple of physics groups, e.g., in IISc (Bangalore) and in SINP (Calcutta), are involved in the (statistical) physics of such networks[21, 22]. For example, an extended associative memory model for processing EEG oscillations was utilized to process the epilepsy-generating 'kindling' in the laboratory animals[21]. The predicting capacity of a perceptron (3-layer; using back propagation) was investigated[22] for quasichaotic (time series) sunspot data. Recent investigations of extending the Hopfield–Tank type of network for finding the optimal solutions of (randomly diluted) lattice version of the *TRAVELLING SALESMAN's* problem[22] have indicated encouraging possibilities. Physics groups in various universities (JNU, NEHU, etc.) are also showing keen interest in neural-network research. One of such groups (in JNU) is studying the time-dependent properties of neural networks with continuous spin variables. A few defence laboratories (e.g. DRDO, Hyderabad) are also doing research in pattern recognition aspects of neural networks.

This report on the Indian Work is certainly incomplete, as much of the work being done in various places has started recently (reports not yet published) and there is no regular interaction yet among the various groups in the community.

Future perspective

As discussed earlier, the interest in the functioning of the human brain exists not only for understanding man's superb ability to survive, but also this acquired knowledge will have profound implications in the development of (the next generation) computer. It will also have potential applications in neurobiology (in the sense of simulating live processes) and in medical treatments.

This multidisciplinary science of neural networks is presently at the threshold of development[23]. Its scope is thus enormous. The subject is truly multidisciplinary in nature: it involves neurobiology, computer science, (statistical) physics, mathematics, etc. This multidisciplinary nature is inherent to the subject. Here lies its strength and also perhaps the weakness (in the absence of regular dialogue across the disciplines)!

Suggestions

The DST may consider sponsoring the following:

(i) Multidisciplinary interaction meetings/workshops involving interested investigators, about once a year.
(ii) Funds for procuring books, journals for the investigator groups. (In most cases the university/institute libraries cannot procure them, as there are no precise groups of faculty engaged in such research.)
(iii) Funds for research fellows/associates, where necessary, and a minimal grant for procuring necessary capital instruments (e.g. dedicated workstations in physics groups).

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