Introduction to Neural Networks and Computational Neuroscience

Neural networks:

Computer algorithms inspired by neurons and the brain

Computational neuroscience:

Computer simulations as a tool for understanding the brain

Neural Networks, Connectionist models, Neuromorphic systems :

Systems that are deliberately constructed to make use of some of the organizational principles that are felt to be used in the human brain.

- Parallel distributed elements
- Learning
- Structure
- Distributed representations
- Graceful decay

- Pattern recognition (Iamge, voice)
- Robots
- Automatic control
- Self-organizing maps
- Pattern classification
- ….

“Reverse engineer the brain”

Computational Neuroscience

One tool among many to study neural circuits

- Imaging techniques
- Neuron staining techniques
- Electrophysiological recordings of single and multiple neurons
- Voltage or calcium sensitive dyes
- Computer simulations

Various levels of analysis for computer simulations:

- Black box approaches that study input-output relationships (leaning theory at the level of whole organisms, reverse engineering techniques at the level of individual neurons or small circuits)
- Abstract models of cognitive phenomena (connectionist modeling)
- Models of small circuits and neural dynamics
- Non-linear dynamic models
- Models of neural circuits and what they compute
- Mechanistic models
- Detailed models of individual neurons

<u>Historical notes</u>

1890: William James

Detailed, mechanistical model on association that is almost identical in structure to later (1970) associative memory networks

"The amount of activity at any given point in the brain cortex is the sum of the tendencies of all other points to discharge into it, such tendencies being proportionate (1) to the number of times the excitement of each other point may have accompanied that of the point in question; (2) to the intensity of such excitements and (3) to the absence of any rival point functionally disconnected with the first point, into which the discharge might be diverted."

1943: Warren McCulloch and Walter Pitts

Networks of logical threshold units (all or nothing responses) can perform logic calculations. Any finite logical expression can be realized by these McCulloch-Pitts neurons.

Describes a true connectionist model, with simple computing elements, arranged largely in parallel, doing powerful computations with appropriately constructed connections.

1949: Donald O. Hebb

The organization of behavior was the first explicit statement of a physiological learning rule for synaptic modification (since become known as the Hebb rule).

"When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased."

1956: Rochester, Holland, Haibt and Duda

Probably the first attempt to use computer simulations to test a well formulated theory based on Hebb's postulate of learning.

Discovered the nearly universal finding for computer simulations designed to check brain models: the first attempt did not work. The results showed clearly that inhibition needed to be added to the theory.

1954: Gabor

Proposed the idea of a non-linear adaptive filter (which it took his research team SIX years to built using analog devices)

1950-1970: Many papers on associative memory models
(Taylor, Willshaw, Longuet-Higgins, Anderson, Kohonen, Nakano).

Correlation matrix memories

1956: F. Rosenblatt

The perceptron model and the perceptron convergence algorithm

Described a learning machine with simple computing elements that was potentially capable of complex adaptive behaviors.

1960: Widrow and Hoff

Introduced the least mean square error algorithm (gradient descent) which is the basis for most modern "error correction rules".

1969: Minsky and Papert

Used elegant mathematics to demonstrate that there are fundamental limits on what a one-layer perceptron can compute.

"In the popular history of neural networks, first came the classical period of the perceptron, when it seemed as if neural networks could do anything. A hundred algorithms bloomed, a hundred schools of learning machines contended. Then cam the onset of the dark ages, where, suddenly, research on neural networks was unlived, unwanted, and most important, unfunded. "

1973; 1976: Christoph van der Malsburg

Demonstrated self-organization in computer simulations motivated by topologically ordered maps in the brain.

1980s: Stephen Grossberg

Adaptive resonance theory

1982: John Hopfield

Used the idea of an energy function to formulate a new way of understanding the computation performed by recurrent networks with symmetric synaptic connections. He established the relation between such recurrent networks and an Ising Model used in statistical physics.

1982: Teuvo Kohonen

Self-organizing maps

1983: Kirkpatrick, Galatt and Vecchi

Simulated annealing for solving combinatorial optimization problems.

1983: Sutton, Barto and Anderson

Introduced reinforcement learning and showed that a reinforcement learning system could learn to balance a broomstick in the absence of a helpful teacher.

1986: Rumelhart, Hinton and Williams

Developed the backpropagation algorithm which solved the credit assuagement problem for multi-layer networks, which emerged as the most popular algorithm for the training of neural networks. It was discovered independently also by Parker and LeCun.