Neural Networks
CC524

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Course contents

- 1- Biological Neural Nets and the Neuron model (Lecture 1)

  2- Neural network motivation, applications (Lecture 1)

  3- The perceptron as a neuron model. Linear and nonlinear decision boundaries (Lecture 2 + part of 3)

  4- the Multilayer perceptron and its graphical interpretation (MLP) (Lecture 4)

  5- The backpropagation learning paradigm (lecture 5)

- 6- The radial basis function neural networks (RBF) (Lecture 6)

  7- The Extreme learning machine (ELM) neural network (Lecture 7)

  8- Applications on classification using face recognition, phoneme data and MNIST data (comparisons between perceptron, MLP, RBF and ELM) (Lectures 8 & 9)

  9- Neural networks applications in regression and prediction (application in predicting synthetic data and real Forex currency exchange data) (Lecture 10)

- 10- Self organizing maps (SOM) and clustering
  (Lecture 11)
  application to phoneme data and/or MNIST digits data

  11- Learning vector quantization (LVQ) neural network
  (Lecture 12 & 13)
  (the idea of local learning and the probabilistic neural network)

  12- Hopfield associative memory neural network

Course Requirements

- Matlab is essential. I will show lots of examples and lots more in the tutorial. Matlab 2009 and above are preferred.
- 40 marks on final, 20 marks on take home projects, 10 marks on assignments and attendance and 20 marks on written exams.
- **The official book by Simon Haykin: Neural Networks, A comprehensive foundation**
- Three other books are available with me in pdf:

Duda and Hart: Pattern Classification

Chris Bishop: Neural Networks for pattern recognition.

Gurney: Introduction to Neural Networks.

Chapter 1: Biological and Artificial Neural Networks: An Introduction

- It has been the goal of science and engineering to develop intelligent machines for many decades. These machines were envisioned to replace humans in doing tedious and cumbersome tasks.
- The technologies that have emerged to meet this challenge include cybernetics, machine learning, automata, bionics, artificial intelligence AI, cognitive science, and artificial neural systems "ANS".
- Artificial neural systems "ANS" are mathematical models which borrow, and try to imitate theorized mind and brain activities.
- The "ANS" are also called artificial neural networks "ANNs", neural networks "NNs", connectionism systems, adaptive systems, neurocomputers, and parallel distributed processing systems.
- The primary intent of "ANS" is to explore and reproduce human information processing capabilities such as **speech, vision, olfaction, touch, knowledge processing and motor control**.
- In addition, ANS algorithms have been used for data compression, solving hard optimization problems, pattern recognition, system modeling and prediction.

- The attempt to make machines capable of human information processing tasks brings the comparison between the processing information capabilities of the human and the Von Neumann computers:

- The computer can multiply huge numbers or take their square root at blinding speed, while humans can't. On the other hand, humans can understand unconstrained, speaker-independent speech (speech recognition) and distinguish different faces (pattern recognition) in real-time, while computers are still far away from doing so.
- The difference between the human brain and Von Neumann conventional computers is because each one uses a different computing and processing method.
- Computers rely on a complex central processing unit "CPU", to run algorithm-based programs serially, as well as a centralized memory.
- Brain relies on a highly distributed simple processing units called "Neurons" which operate in parallel to produce the required activity. The memory or information storage is also distributed in the connections between the neurons. These connections are called the synapses.

- The following table illustrates some differences between the computers and the brain (biological neural network):

	Computers	**Brain**
Processing speed	Nanoseconds	milliseconds
Processing units	Single CPU	10^{14} neurons
Control unit	Central	distributed
Memory storage	Central	distributed
Fault tolerance	Fails by faults	Tolerant to faults

Difference # 1: Brains are analogue; computers are digital
Difference # 2: The brain uses content-addressable memory
Difference # 3: The brain is a massively parallel machine; computers are not
Difference # 4: Processing speed is not fixed in the brain; there is no system clock
Difference # 5 :Short-term memory is not like RAM
Difference # 6: Unlike computers, processing and memory are performed by the same components in the brain
And many more

- Thus, the computer is a high-speed serial machine, compared to the slow, highly parallel brain.
- The vision and speech recognition are highly parallel problems, requiring the processing of lots of different items of information and memory locations, which all interact to make the final output. The brain, with its parallel design, is able to represent and store this knowledge optimally.
- The approach of neural computing is to capture the guiding principles of the brain solutions to these problems and apply them to computer systems.
- We don't know yet how the brain represents high-level information, but we do know that it uses a massive number of simple, slow units that are highly interconnected (the neurons, where each neuron is connected to about 10^4 other neurons).
- Thus, artificial neural systems use parallel simple processing units (we call them neurons too) that are connected together.

- Also, one of the most important feature of the neural computing is that the brain is able to learn things. It can teach itself, either with an external teacher (teaching a child that he shouldn't touch a hot cup), or without an external teacher (humans can discriminate between different colors naturally).
- The learning means that the neural system is adaptive. It starts with ignorance and evolves gradually to knowledge of a problem.
- Finally, a neural system is able to generalize to situations it never seen before: humans can distinguish a cat from a dog even for types not seen before.
- Thus, an artificial neural system, or a neural network should have all the above features:

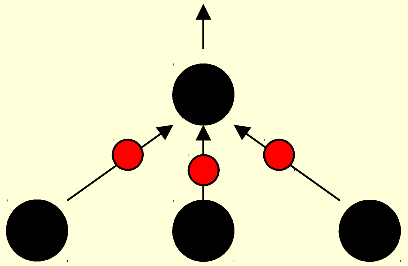
1. simple units (neurons) connected together and work in parallel.
2. The system is adaptive, and should be able to learn new problems, either with or without a teacher.
3. And, the neural network should be able to generalize to situations never seen during learning.

The goals of neural computation

- To understand how the brain actually works
  - Its very big and very complicated and made of mysterious elements that yet to be fully understood!
- To understand a new style of computation
  - Inspired by neurons and their adaptive connections
  - Very different style from sequential computation
  - should be good for things that brains are good at (e.g. vision)
  - Should be bad for things that brains are bad at (e.g. 23 x 71)
- To solve practical problems by developing novel learning algorithms
  - Learning algorithms can be very useful even if they have nothing to do with how the brain works

How the brain works

- Each neuron receives inputs from other neurons
  - Some neurons also connect to receptors
  - Cortical neurons use spikes to communicate
  - The timing of spikes is important
- The effect of each input line on the neuron is controlled by a synaptic weight
  - The weights can be positive or negative



- The synaptic weights adapt so that the whole network learns to perform useful computations
  - Recognizing objects, understanding language, making plans, controlling the body
- You have about 10^{14} neurons each with about 10^4 weights
  - A huge number of weights can affect the computation in a very short time. Much better bandwidth than a computer.

The structure of the brain (neurons and synapses)

- The human brain is one of the most complicated systems. Yet, it is still poorly understood. We still don't have satisfactory answers to the most fundamental questions such as "what is my mind?" and "how do I think?". However, we do have a basic understanding of its operation at the low level. It contains approximately 10^{14} basic units called neurons. Each is connected to about 10^{4} others.
- The neuron is the basic unit of the brain, and is a stand-alone analogue logical processing unit. The neuron accepts many inputs from other neurons through dendrites. See figure(1).

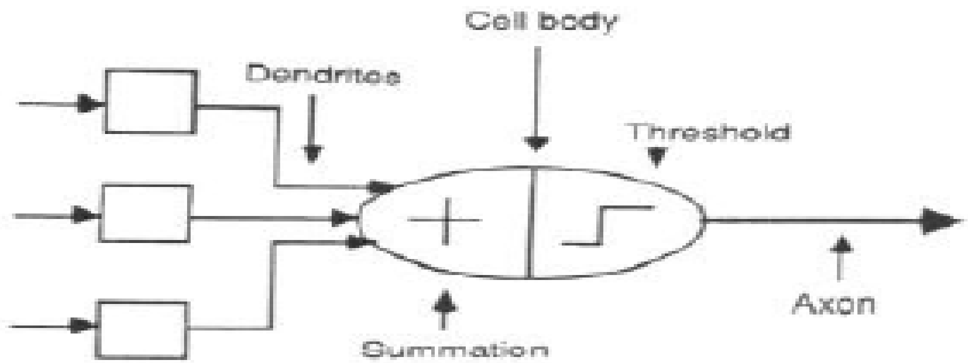


Fig.1: Basic neuron model.

- The dendrites act as the connections through which all the inputs to the neuron arrive. They perform a summation to the inputs they receive.

- The neuron's output cell is the axon, a nonlinear threshold device, producing a voltage pulse, called the **action potential**, that lasts about 1 msec.
- The axon terminates in a specialized contact called a synapse that couples the axon (output of one neuron) to the dendrite of another neuron.
- The synapse releases chemicals called neurotransmitters when its potential is raised sufficiently by the action potential.
- This chemical opens the gate of the dendrite and allow charged ions to flow, producing a voltage pulse on the dendrite, which is then conducted to the neuron with a certain weight depending on the amount of the opening of the dendrite gate.
- This whole process is approximated by the basic neuron model.

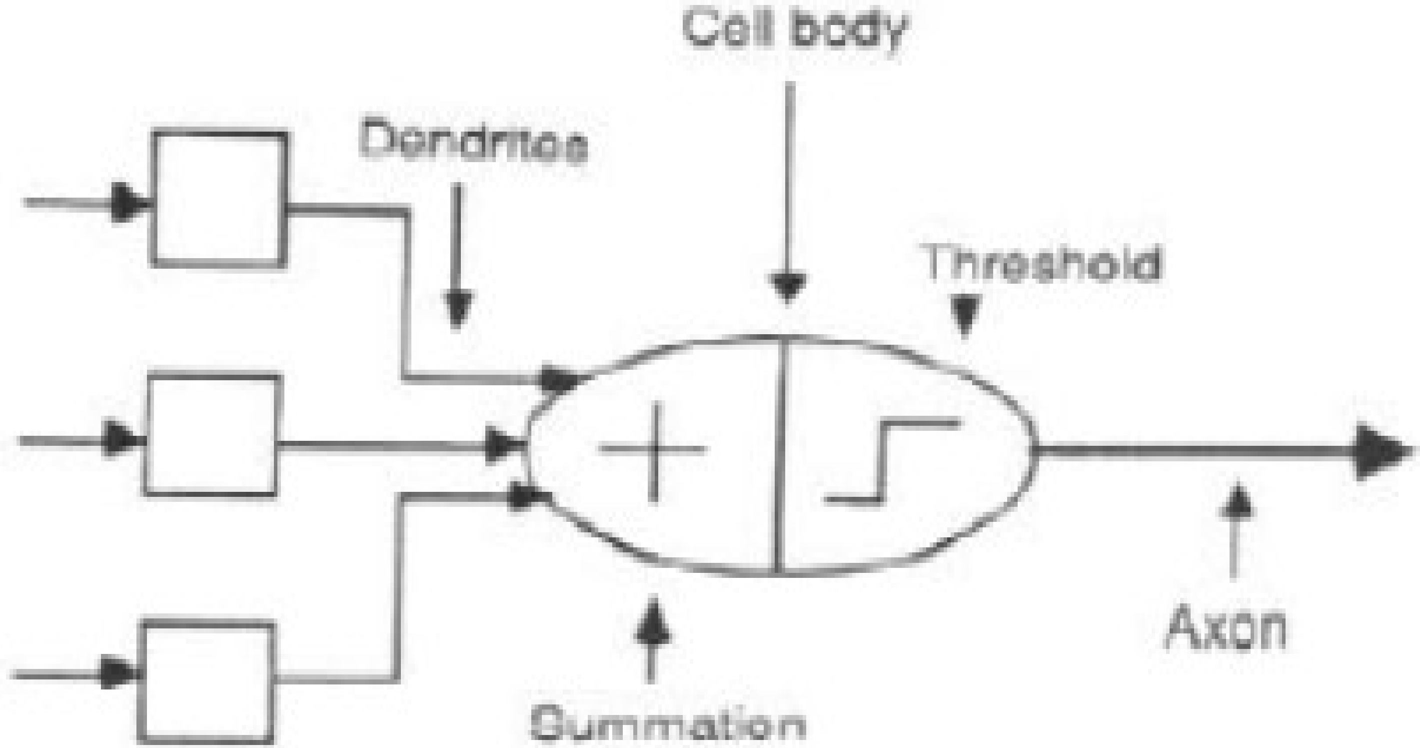


Fig.1: Basic neuron model.

History of Neural Networks

Era of Kernel Methods (SVM, Kernel-PCA, Kernel-Fisher Discriminants, etc.)
Neural Networks are however still and frequently used

1995 Support-Vector Networks (Cortes and Vapnik)

1992 A Training Algorithm for Optimal Margin Classifiers (Boser, Guyon and Vapnik), first paper on SVM

Era of Neural Networks

1986/1985 Backpropagation (Rumelhart, Hinton, Williams, Le Cun (actually first proposed by Werbos, 1974))

1982 Hopfield Network, (Hopfield), Recurrent Networks, Energy Function

Decline of neural network research

1969 Book: Perceptrons (Minsky and Papert)

1962/1960 Adaline (Widrow and Hoff), Perceptron (Rosenblatt)

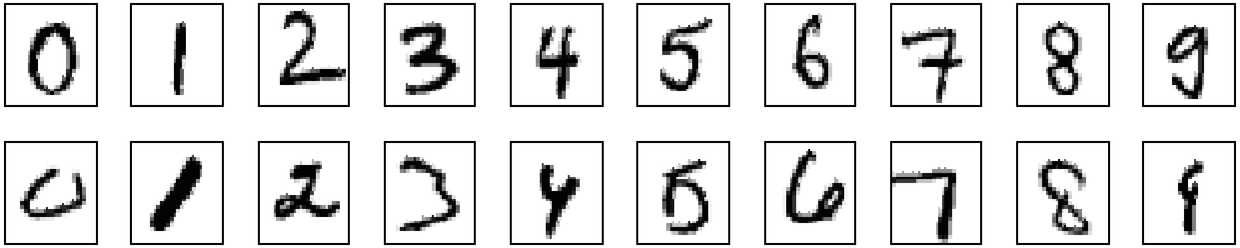
1943 Model of McCulloch and Pitts

Note, this historical overview is far from being complete (see books for detailed historical overview)

Since 2006, Deep Neural Networks and Deep Belief Networks have gained huge interest and importance again!

Motivation (Application of Neural Networks)

- Handwritten Digit Recognition



- Digits are size-normalized and centered in a 28×28 fixed-size image of gray color values $(0 - 255)$
- Given a vector $\mathbf{x} = [0, 0, 0, \ldots 67, 114, 72, \ldots 0, 0, 0] \in \{0, \ldots, 255\}^{784}$ which represents a new (unseen) digit, to which digit class belongs $\mathbf{x}$?

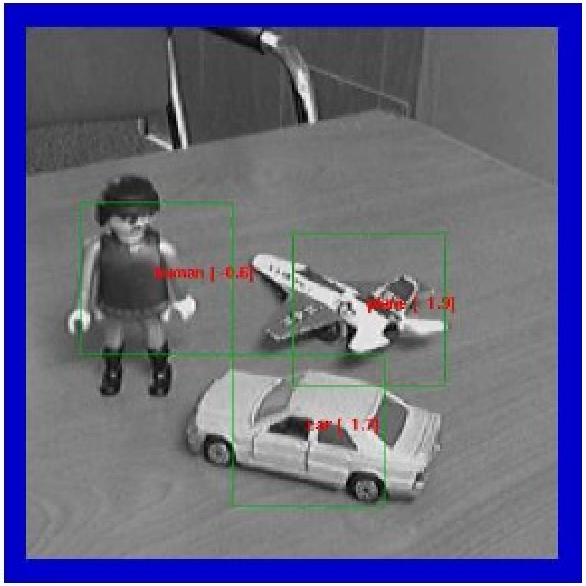
Motivation (Application of Neural Networks)

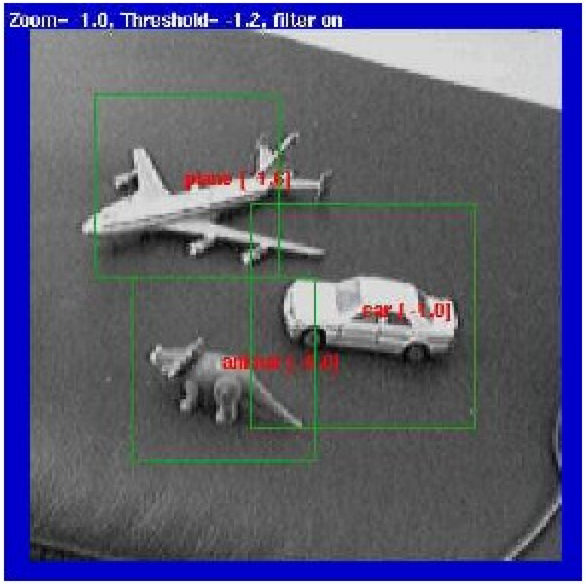
- Face Detection

see website of Yann LeCun
(http://www.cs.nyu.edu/~yann/research/cface/)

Motivation (Application of Neural Networks)

- Object Detection and Recognition

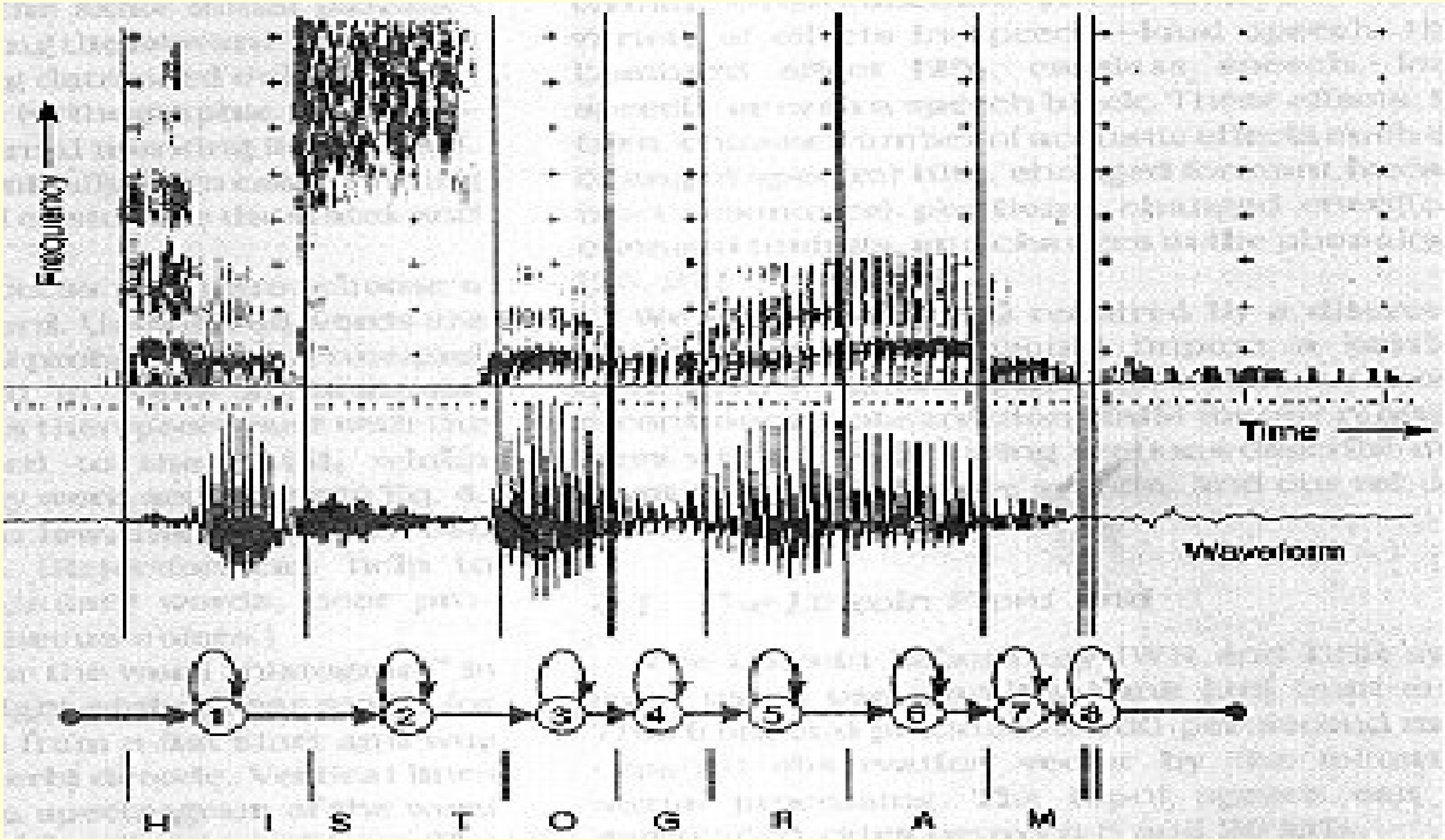




see website of Yann LeCun
(http://www.cs.nyu.edu/~yann/research/norb/)

Expression and Emotion Recognition

Speech and Speaker Recognition



More Applications of Neural Networks

Lie detector,
Handwritten digit/letter recognition
OCR of printed documents
Biometrics: voice, iris, finger print, face, and gait recognition
Speech recognition
Smell recognition (e-nose, sensor networks)
Time series prediction:
(Stock, Forex prediction, weather forecast, River flow prediction, etc.)

Fruit/vegetable recognition
Medical diagnosis
Network traffic modeling, intrusion detection
Topic identification
Biomedical signal classification (EEG) (BCI)
And More…