Artificial Neural Nets with

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Extended Abstract

The aim is to obtain computationally more powerful, neurophysiologically founded, artificial neurons and neural nets.

Artificial Neural Nets (ANN) of the Perceptron type evolved from the original proposal by McCulloch an Pitts classical paper [1]. Essentially, they keep the computing structure of a linear machine followed by a non linear operation. The McCulloch-Pitts formal neuron (which was never considered by the authors to be models of real neurons) consists of the simplest case of a linear computation of the inputs followed by a threshold. Networks of one layer cannot compute any logical function of the inputs, but only those which are linearly separable. Thus, the simple exclusive OR (contrast detector) function of two inputs requires two layers of formal neurons.

Those logical limitations where overcome by McCulloch and Blum [2] by a formalization of the, by then recently encountered, presynaptic inhibition in *Rana Pipiens*. In essence, fibres reaching a neuron bifurcate in a way that they may drastically inhibit other input fibers to the neuron. Posterior and more recent findings emphasize the importance and role of presynaptic inhibition and facilitation in the complexity of neuronal computation [3], [4], [5].

The systematic formulation of presynaptic inhibition, for logical functions, consists in substituting the simple linear weighted addition prior to the non-linear operation given by the threshold function. Thus, the typical weighted summing computation (for $x_1, \ldots, x_n$ lines) $\sum \alpha_i x_i$ is, in general, substituted by the more complete (redundant) operation

$$\sum_i \alpha_i x_i + \sum_{ij} \alpha_{ij} x_i \bar{x}_j + \sum_{ijk} \alpha_{ijk} x_i \bar{x}_j \bar{x}_k + \cdots \qquad (1)$$

where $\bar{x}_i$ denotes logical negation; $x_i \bar{x}_j$ denotes presynaptic inhibition of fiber x_i by fiber x_j; $x_i \bar{x}_j \bar{x}_k \ldots$ denotes the presynaptic inhibition of x_i by x_j, x_k, and so on. Figure 1 illustrates equation 1 where small 'loops' indicate inhibition presynaptic to the neuron. In formal neural nets, the inhibition is total, that is, the 'loop' completely inhibits the input signal x_i.

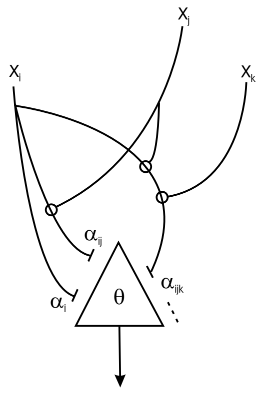


Fig. 1. Illustration of general lateral inhibition interaction of afferents for McCulloch-Pitts neurons.

For a single unit with a fixed threshold, the number of degrees of freedom for M inputs lines, is

$$M + M(M-1) + M\binom{M-1}{2} + \cdots + \binom{M-1}{M-2} + M = M \cdot 2^{M-1}$$

which is larger than the number of possible functions for M inputs, 2^M, and which clearly points to the redundances effects provoked by the presynaptic inhibition.

It can be argued that this redundancy can be used to increase reliability for a net computing any arbitrary logical function. In fact, there is a trade off between reliability and versatility provoked by the presynaptic inhibition.

We propose a natural generalization of the logical formulations of presynaptic inputs inhibitory interaction, which allows for a richer model of formal (artificial) neuron, whose potentialities as computing units are to be investigated. The formulation reduces to classical interaction of afferents for logical inputs.

First, normalize input signals so that $0 \leq x_i \leq 1$. The presynaptic inhibition of signal x_i by signal in fiber j, x_j is given by a multiplicative effect $x_i(1 - x_j)$. Similarly, for the rest of the fibers.

Thus, the argument of the activation function of the corresponding artificial neuron, is

$$A = \sum_i \alpha_i x_i + \sum_{ij} \alpha_{ij} x_i (1 - x_j) + \sum_{ijk} \alpha_{ijk} x_i (1 - x_j)(1 - x_k) \qquad (2)$$

If F is the activation function, the output, y, of the AN is

$$y(k+1) = F[A(k)] \quad \text{discrete time}$$

$$\frac{dy}{dt} = \dot{y} = F[A(t)] \quad \text{continuous time}$$

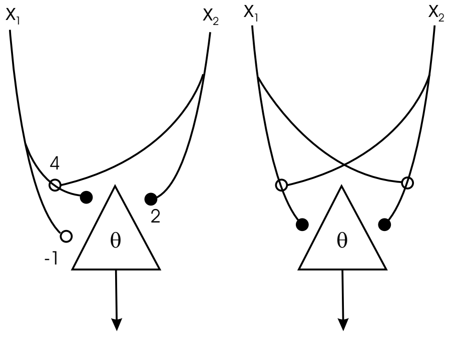


Fig. 2. Examples of two realizations for an AN computing the 'exclusive OR'. a) Neuron in this figure is more versatile in the sense that relatively small changes in the activation function (e.g. a thresholding) provokes significant changes in the discriminating behaviour. b) Neuron in this figure is more insensitive to threshold changes.

In general, for an ANN with arbitrary feedback, the expressions are similar than those of formal neural nets [7], [8]. In the present case, the networks are given by

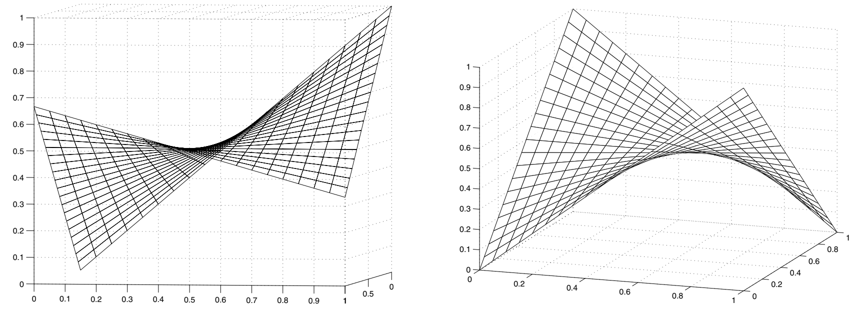
$$y_i(k+1) = F[A(x_1(k)\dots x_M(k); y_1(k)\dots y_N(k))] \quad i = 1, 2, \dots, N$$

or

$$\dot{y}(t) = F[A(x_1(t)\dots x_M(t); y_1(t)\dots y_N(t))]$$

The activation function F is assumed to be the same for all neurons of the net. Essentially, the new formulation substitutes the linear activation argument of typical ANN (Hopfield type) formulations for a neurophysiological plausible non-linear argument, result of presynaptic interaction.

As preliminary results, various examples are presented of non linear activation arguments and their input pattern discriminatory power, their reliability and their functional versatility (range of functions that can be computed by each AN). This is illustrated for the case of an AN of two inputs, in Figure 2. Figures 2(a) and 2(b) are two realizations for the 'exclusive OR' (contrast detection). Neuron in figure 2(a) is more 'versatile' in the sense that relatively small changes in the activation function (e.g. a thresholding), provokes significant changes in the discriminating behaviour. Neuron in figure 2(b) is more insensitive to threshold changes. The corresponding activation arguments are shown in Figure 3(a) and 3(b).



(a) (b)

Fig. 3. Activation arguments of AN in Figure 2(a) and 2(b). Notice that the patterns [(only x_1)] and [(only x_2)] are better discriminated by activation argument in figure 3(b)

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