Rudiments of Neural Cryptography

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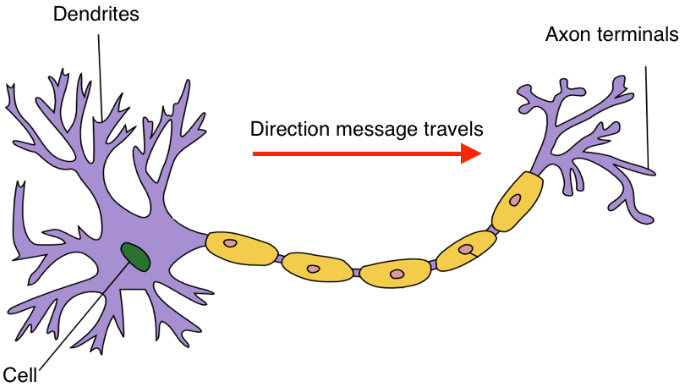
Overview

Neural Networks

Artificial Neural Networks (ANNs) are models of computation based loosely on the way in which the brain is believed to work. A biological neural network consists of interconnected nerve cells, whose bodies are where neural processing takes place.



Artificial Neural Networks

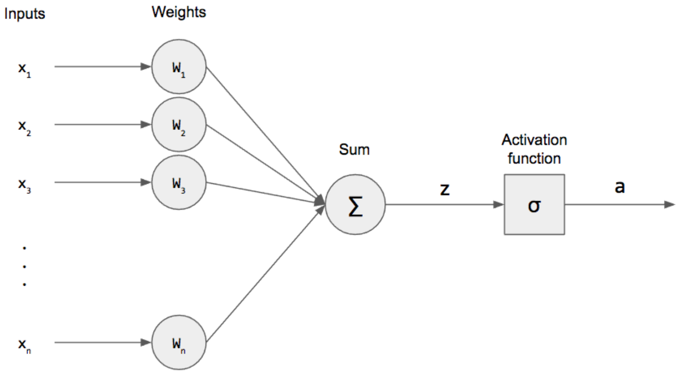
Interconnections between cells are not all equally weighted: this is the key feature modeled by ANNs. Their theoretical principles were firstly formulated in the forties. Among them, a fundamental, widely applied learning principle is the following.

Hebbian Learning Law

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

Perceptron: 1

The first complete neural model is called Perceptron and appeared in the late fifties. It serves as a building block to most later models.



Perceptron: 2

The input/output relations of the Perceptron are defined to be

$$z = \sum_i w_i x_i \quad \text{(summation output)}$$
$$y = f_N(z) \quad \text{(cell output)},$$

where w_i is the (adjustable) weight at input x_i. Function f_N is nonlinear and is called activation. Typical activation functions used in ANNs include

- sigmoid function;
- hyperbolic tangent;
- Heaviside step function.

Training

The training of an ANN is the procedure of adjusting its weight. This task can be performed with several techniques. For the simplest architectures, we recall

- **Least Mean Square Training**
- **Gradient Descent Training**

Perceptron: 2

Heading

1. Statement
2. Explanation
3. Example

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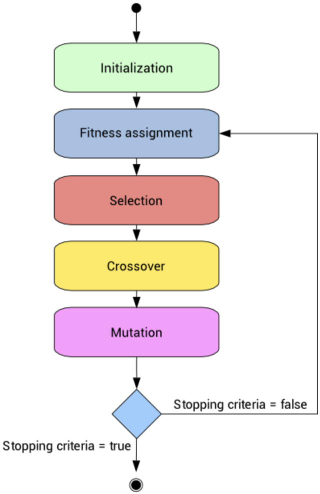
Genetic Algorithms: 1

Genetic Algorithms (GAs) were invented by John Holland in the 1960s and can be considered a key building block of artificial intelligence. These are stochastic search algorithms that can generate "sufficiently good" solutions to an optimization problem. Nowdays GAs are widely employed in applied science and, in neural cryptography, they can be used to

- optimize network architectures involved in communication;
- perform effective cryptanalitic attacks.

Genetic Algorithms: 2



- The GA is a method for evolving from a population of "chromosomes" (elements of a solution space) to a new population by using an imitation of natural selection together with the genetic-inspired operators of crossover and mutation.
- The main theoretical result on the behavior of GAs is known as Holland Theorem. It implies that the best "building blocks" of the solutions propagate exponentially over time in the population.

Neural Cryptography

- From the nineties on, researchers have made attempts at combining the features of neural networks with cryptography: this field is commonly known as neurocryptography.
- One of the first attempts can be found in [Volná(2000)]. In this work, the author builds a symmetric cryptosystem by making use of neural networks, whose parameters constitute the key of the cipher.
- GAs are used for the optimization of the designed NN topology. Adaptation of the best found network architecture is then finished with BP.

The NNs of Volná

The GA of Volná evolves the architecture of feedforward NNs whose weights are initialized as follows. For every existing connection, three digits are generated and weights are computed as

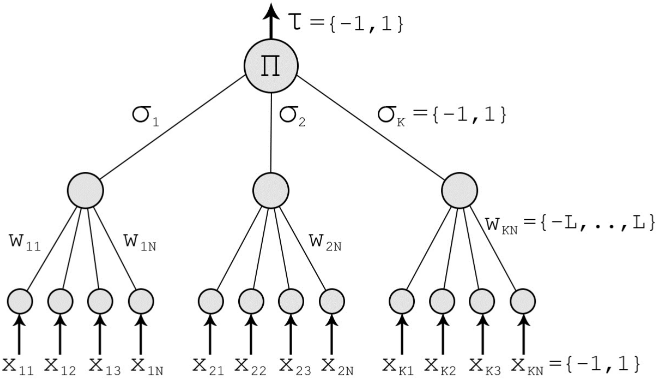
$$w_{ij,kl} = \eta[e_2(e_1 2^1 + e_0 2^0)]; \quad \begin{aligned} i, k &\in \{1, \ldots, L\}, \\ j &\in \{1, \ldots, n_i\}, \\ l &\in \{1, \ldots, n_k\}, \end{aligned}$$

where $w_{ij,kl} = w(x_{ij}, x_{kl})$ is the weight value between the j-th unit in the i-th layer and the l-th unit in the k-th layer and

$$\begin{aligned} \eta &= \text{learning parameter}; \quad \eta \in (0, 1) \\ e_0, e_1 &= \text{random digits} \\ e_2 &= \text{sign bit.} \end{aligned}$$

KKK Key Exchange Protocol

The first complete cryptosystem based on neural network is known in literature as KKK, from the surnames of its inventors [Kanter, Kinzel and Kanter(2001)].
This protocol is based on the synchronization of the weights of two tree parity machines, that represent the participants.



- The two NNs participating in the communication start from private key vectors $E_k(0)$ and $D_k(0)$. Mutual learning from the exchange of public information leads the two nets to develop a common, time dependent key: $E_k(t) = -D_k(t)$. This is then used for both encryption and decryption.
- At each step of the training process (and of encryption/decryption), a common public input vector is needed.
- Sender and recipient send their outputs to each other and in case they do not agree on them, weight are updated according to a Hebbian learning rule.
- As soon as the two NNs are synchronized, so they stay forever.

KKK: Shamir's Insights

In the paper cited before, no mathematical proof of its core principle, synchronization, is given. This result was instead attained in [Klimov, Mityagin and Shamir(2002)]. Such work also contains a section dedicated to the cryptanalysis of KKK. Besides it is robust against attacks based on intercepting the key using the same neural network structure, this protocol can be broken using

- Genetic Attacks;
- Geometric Attacks;
- Probabilistic Attacks.

These results marked the beginning of a long period without any substantial contribution to neural cryptography.

Neural Cryptanalysis

The End

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