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Generalitation of the function N in Computational Analysis

Rosanna Festa
Alumni Noi Sapienza
Università La Sapienza, Roma, Reggio Calabria, Italia

Abstract- The parallel research is contemporary to analyse processes and localisations in artificial intelligence (AI) associated with connexionism and learning algorithms.In machine learning, the perceptron (or McCulloch-Pitts neuron) is an algorithm for Boolean functions of binary classifiers. A binary classifier is a function which can decide whether or not an input, represented by a vector of numbers, belongs to some specific class. With a pattern N we use the calculator in synthesis applying polynomial advanced systems.

Keywords- Artificial Intelligence; Hyperplanes; Parallel Distribuited Processing Research Group; Radial parameter; INTEL 80170.

I. INTRODUCTION

The neuronal units in the realisation of the neural nets have alternating frequences according to a gaussian, above all in the no-convex domain, that unwind the function through hyperplanes, in the realization of artificial systems of first and second type. In classic exemples of artificial neurons with getting out in x we simulate the capacity test with two variables. The dependence of the synthetic connexions ought to be interpreted as the activation and then the frequence of a series of impulses, with absolute worth or a minimum potential; this model, inspired to biological neurons, represents the algorithmic basys of the teory of computational learning. The getting out in I represents the capacity of perceptron to emulate a cognitive behavior, and for this it is susceptible to have the misurability of a test in two or more functional variables. Independently from the choise of the operator, Minsky and Papert have demonstrated that some important topological predicates, as to establish the connexion of a form, can't be calculated. In the second half of 80' began to speak about the intelligence of a calculator, and for that neural network, above all for the studies of Parallel Distribuited Processing Research Group, have been studied neural architecture in acyclic graph, in which is defined a partial order on the vertexes, presupposing a central system of elaboration of the neural net. Actually, the research on parallel nets has occupied of the central system in artificial intelligence, as the neural nets, in fact, simulate the central cognitive processes and their relative functional localitation. The utilization of models of calculation based on artificial neural nets in basys of standards of softcomputing, has studied though the simulated operational capacity and the processual capacity of the computer, taking as refer also the connessionist model that support the neural activation is based on input systems at the level of neuronal unit, while, for that, the associated potential to the unit take part of the system of connected units. In particular, the activation of the unit I depends on the activation of the generic unit j by means of an associated parameter to the connexion between the two units, modeled on the elettrochemical principle of the synapsis. Beginning from the tests in two variables, or beginning some more from Boolean operators, it is possible to obtain frequencies and causal functions represented by the central worths, in similar way to an intelligent test. It is immediate to verificate that the sigmoidal neurons can't calculate all the

Boolean functions of two variables. In particular way, the functions x_1x_2 e x_1x_2 are not linearly separables, but in reality are so all the others remaining. In the case of neuron of Rosemblatt, in the singular cognitive tasks, as the recognition of forms, we will have a standarditation of processes. Though the operator of pre-processing φ(x) we provide significative features, this condition imposes that the domain of the operator shall to be limited, in way to establish local features presents in the image independently from translations and rotations. These sigmoidal neurons are potentially be able to simulate the architecture in series or a parallel architecture of the calculator, in fact, a perceptron has the role to establish if the elaborated figure is connected though the "periferic" centres of the neural network. Extending the concept of connexion, the feed-forward nets can realize every Boolean function. The architecture of the neural net is based on a connexion in three variables, a, b, and c based to principal function x, especially in the feed-forward net with structure in acyclic graph, as the multistrate net, which they exist different possible connections of the neural net, based on algorithmic frequencies or matrixes, or that on simulate at the least the behaviour. In the more complex structure, the connexion a stratum allows to reveal impulses to the perceptron though the generalitation and the propagation of getting out units, though the regulation able to measure off the impulses by means of the Boolean function XOR. In fact, the neurons in the decision process activate points for units of first and second type, and they excite for adjoining points in the centre, and they inhibit when there remove the electric currency, with a speed proportioned to the radial parameter σ_1. For convex domain the getting out can be determined as AND of specified neurons in the hidden stratum. For no-connected domains and/or convexes the getting out can be determined as the OR of specified hidden units (three stratum, except for the getting out). This model, more than based on a constructive process that also neurons in radial symmetry can execute, is based on a particular architecture, simulated in mathematic analysis, that represents the basys of the database architecture, and it is based, in fact, on a constructivist analysis of the synapsis function, either for the neural structure, or the force lines, build according to geometric models, the topology and the rational mechanics. A generical ricorsive net that widens this concept of a complex system, is an architecture based on mathematical laws by means of the periodicity of the synapsis function, and support their caractheristics in respect of the medium time and the frequencies of impulses with the aim to build artificial neural nets. A ricorsive neural net it is representable also though a straightedge variable in the position as that utilized by Einstein in the measurement of a relative time of the system K though the Lorenz's transformation. The Hopfield's net, utilized for general function of the neural net, is based on a elettromagnetic frequence and on the local connexion, the "elettronvolt"in this case is able to utilize alternated incitements based on a differential for the capacity to unfold the specific function. The postponement of the state happen in synchronic way, in despite of the alimentation of a new entrance in the sequence or of the informational structure. On be able also to memorize a number of pattern around 0, 15 N and over and it can be utilized as associative memory in elettromagnetism. Existing different levels of programmation, the capacity of calculation of an artificial neural net is synthetic, and they have to be resolved though the supervisioned learning, where the neural net develops a concept on the basys of interactions with a supervisor, that provide to learn the network. It exists, after, the problem for the neural network to effect simple calculations, without supervision, given the presence of problems computationally intractable, tied up to the generalitation of function N, nevertheless it is dimostrated that exists a polynomial solution for the determination of a standard configuration for the calculation of problems, above all in the Hopfield's net. In some cases, in computational analysis, the ricorsive problem can be presented though the problem of the commercial traveller, or the Hamiltonian course, setted to the phasys space of the neural net, at the born of analogical neural chip without need of modification, as for the INTEL 80170, that is one of the principal problems of softcomputing and of the codification system of advanced systems.

II. CONCLUSION

From the ultimate analysis of the function N with Introduction to the Mathematical Philosophy of Bertrand Russell the process of the Mathematical Induction begins with a possible generalisation. Every number m will have a relationship of succession with m+1. For the geometry not purely analytical, consider also the Principia Mathematic part VI, for the rational dynamics ibid., Part VII.

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