Learning of the Artificial Neural Networks with Multilayer Models and Industrial Tasks

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Abstract – **Two approaches of graphical multilayer modeling are introduced - by graphs and by tables. Examples with the architecture and the learning paradigm of the artificial neural networks interpreted with multilayer models are presented. Special attention is dedicated to the formulations of problems about modeling industrial tasks.**

Keywords – **multilayer models, neural networks, architecture, learning**

I. Introduction

The scope of the paper is modelling the learning process of artificial neural networks (ANN) by multilayer models and its implementation for industrial tasks. Also the authors present two approaches of visualizing the multilayer models - by graphs and by tables. Both ways have their advantages and limitations.

The graphical visualization may be applied in every possible case. It is an appropriate base for application of the graph theory, of Petri nets, etc. The visualization scheme may consist of one main multilayer model. Separate points in its layers may be magnified to corresponding multilayer models next to the main model. In this way the main multilayer model is surrounded by a ring of multilayer models *of lower weight* ([2], see also Fig. 1). Instead this paper is a demonstration of the table approach with multilayer models for main features of the ANN. The visualization approach by tables is applicable for *separate* multilayer models in which besides the *layer number* and the *layer name*, the *feature of the layer* defines the layer-characterizing mark (see chapter III for more about the table visualization of multilayer models).

The paper consists of the following chapters. Chapter II formulates the problem about the ANN learning with multilayer models. Chapter III introduces examples of multilayer models of ANN features based on the degree of their sophistication. Chapter IV marks the design of industrial tasks with ANN and multilayer models. Finally the paper resumes the contents with conclusions.

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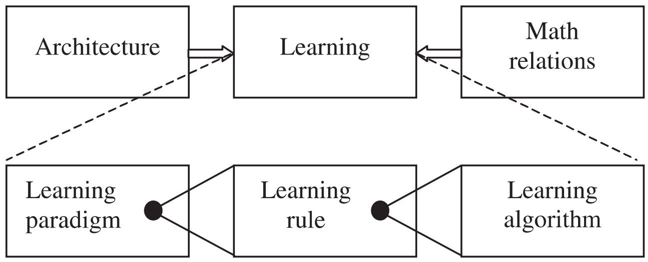

Fig. 1. The ANN learning process with multilayer models

II. The Formulation of the Problem about the Artificial Neural Network Learning with Multilayer Models

ANN learning is the most time-consuming step (if any).

Two determining factors: the goal ANN architecture [1] and the corresponding mathematical description [2] feed the learning process. The architecture is the most directly connected with the physical 'nature' of the ANN while the mathematical formalism present in the discrete time domain the relations between the information streams. The mathematical model is decisive for the ANN learning because it is *defined by the learning rule* but it itself *defines the learning algorithm*.

The ANN learning process consists of the learning paradigm, the learning rule and the learning algorithm. It is influenced by the chosen architecture and the corresponding mathematical formalism.

The learning paradigm presets the possible learning rules which in turn preset the possible learning algorithms. The learning paradigm is the most abstract feature and the learning algorithm is the most concrete one. Starting from left in a direction to the right the learning characteristics become

Table 1. Mathematical formalism for unsupervised learning

UNSUPERVISED LEARNING	**Differential**	**Nondifferential (Signal)**
Hebbian	Differential Hebbian Learning	Signal Hebbian Learning
Competitive	Differential Competitive Learning	ART-Competitive Learning

more concrete and this corresponds to a 'descent' from the peak of a pyramidal structure towards its base; the peak is analogous to the learning paradigm and the base - to the concrete application task. The very 'descent' during the ANN learning corresponds to a draw up to the final ANN design.

The scheme in Fig. 1 presents the links between these aspects in the learning process for ANN with multilayer models.

The mathematical description is of a principal importance for the self-organizing maps when the mathematical formalism may be presented according to Table 1. This example of data representation by tables is similar to the example in [3] when the application of multilayer models is not recommended (the same reference contains more information about details).

Table 2. Most abstract multilayer models of two ANN features

ANN ARCHITECTURE MULTILAYER MODEL		
Layer Name	Layer No.	Feature of the layer
FFNN	1	Linear separability
RNN	2	Sophisticated architectures
HNN	3	FFNN – preprocessors and RNN – the main ANN
FeedForward Neural Networks Recurrent Neural Networks Hybrid Neural Networks		

ANN LEARNING PARADIGM MULTILAYER MODEL		
Layer Name	Layer No.	Feature of the layer
SL	1	Learning modes
UL	2	Input-output transform
HL	3	Combined learning rules (error correction, competitive)
Supervised Learning Unsupervised Learning Hybrid Learning		

III. Examples of Multilayer Models of ANN Features Based on the Degree of Their Sophistication

The following sections present ANN multilayer models in which the layers are numbered from the periphery (layer number 1) to the center (the core) according to the feature sophistication degree.

ANN Learning Paradigm Models by Tables

Additional information about the ANN learning process the reader can find in [3].

Multilayer Models of ANN Architectures and Learning Paradigms by Tables

Detailed description of these models is given in the following sections; see also [3]. The difference between the present paper and [3] is the presence of the *feature of the layer* (see chapter II).

ANN Architecture Multilayer Models by Tables

Table 3 gives a detailed description of the architecture which is analyzed by the authors in [4].

Table 3. ANN types of architectures

RECURRENT NEURAL NETWORKS MULTILAYER MODEL		
Layer Name	**Layer No.**	**Feature of the layer**
SLP	1	Simple architectures
MLP	2	Approximate optimum (Stochastic approximation)
RBF	3	Multivariable interpolation (Statistical approximation)
Single-Layer Perceptron Multilayer Perceptron Radial Basis Functions		

RECURRENT NEURAL NETWORKS MULTILAYER MODEL		
Layer Name	**Layer No.**	**Feature of the layer**
HNN	1	Speed not critical
ARTN	2	Pattern stability
WfdMM	3	Equal dimensions of the input and the output
KSOM	4	Data compression
Hebbian Neural Network Adaptive Resonance Theory Network Willshaw - von der Malsburg Map Kohonen's Self-Organizing Map		

ANN Learning Paradigm Models by Tables

Additional information about the ANN learning process the reader can find in [3].

IV. Industrial Tasks with ANN and Multilayer Models HNN

This chapter illustrates the both approaches of visualizing the multilayer models in the serial production – with graphs and with tables.

The Industrial Task Model Creation – An Environment for Industrial Multilayer Models

This section resumes the sequence of creating multilayer models for application tasks in the industry based on [4,5]: 1) the user gives the designer his task for the production device; 2) the designer analyses the physical nature of the task; 3) a solution is proposed based on the modern scientific paradigms in the area supported by developed mathematical models and oriented towards the existing technologies; 4) the task solution is adapted to concrete industrial producer(s) and a zero series is produced; 5) the designer takes under consideration opinions and remarks from the exploitation of the zero-series device(s) and the technological cycle is corrected in a corresponding way; 6) finally the negotiated industrial

Table 4. ANN supervised and unsupervised learning paradigms

UNSUPERVISED LEARNING MULTILAYER MODEL		
Layer Name	**Layer No.**	**Feature of the layer**
EC	1	Perceptron
HL	2	Linear discriminant analysis
BL	3	Statistical physics (optimization task)
CL	4	ART map, learning vector quantization
Error correction Hebbian learning Boltzmann learning Competitive learning		
UNSUPERVISED LEARNING MULTILAYER MODEL		
Layer Name	**Layer No.**	**Feature of the layer**
EC	1	Multilayer feedforward Sammon's projection
HL	2	Principal-component analysis & associative-memory learning
CL	3	ARTx, SOM, vector quantization
Error correction Hebbian learning Competitive learning		

production series are started. The last two steps may be iteratively repeated creating a sequence of production models which explains the role of the evolutionary and genetic approaches to the design of industrial tasks.

It is clear that the design of such models is complex and sophisticated implying strong penalties for the different production features. The authors chose the multilayer interpretation of industrial tasks due to the distinct hierarchial stratification of the goal task. There are cases which are not recommended for interpretations by multilayer models [3]. Such cases outline the natural bounds of the applicability for multilayer models. Table 5 is complemented by possible applications in other fields, e. g. production control.

Industrial Tasks, ANN and Multilayer Models

[5] investigates an application of multilayer models for modelling serial production of ANN. Fig. 2 and Table 5 introduce multilayer models of applications for production control by ANN. The graphical visualization may be applied in every possible case while the visualization by tables is applicable for *separate* multilayer models.

The serial production multilayer model may be presented not only by tables, but also by graphs [3]. Table 5 is chosen as an approach for this model of serial production for the sake of unity of the presentation style. Briefly said, the serial production model consists of a series of production models – the *generations* which demonstrate concrete tendencies in the *evolution* of the current production model. The mathematical description is given in [5]. It describes the penalty

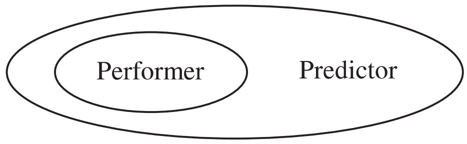

Fig. 2. Multilayer model for prediction and control

functions modeling the search space embedded in the unity global space. The core of the serial production model is the *ANN design model* (ANNDM) which determines the practical application of the ordered by the user concrete production model.

Table 5. Multilayer production models

SERIAL PRODUCTION MULTILAYER MODEL		
Layer Name	Layer **No.**	**Feature of the layer**
Production	1	Production
GEANNDM	2	Generalized Evolutionary ANN Design Model
ANNDM	3	ANN Design Model
MULTILAYER CONTROL MODEL		
Layer Name	**Layer No.**	**Feature of the layer**
P	1	Proportional control
PD, PI	2	Proportional-Differential or Proportional-Integral control
PID	3	Proportional-Integral-Differential control

V. Conclusions

Modelling goal tasks with multilayer models by two different types of presentations is introduced. Special attention is dedicated to the formulation of the ANN-learning problem with such models. Multilayer models of different levels of the ANN architecture and their learning paradigm are presented based on essential features for the levels which in turn may be modeled by multilayer models of lower levels.

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