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GENERALIZED NET MODEL OF THE INTUITIONISTIC FUZZY FEED FORWARD NEURAL NETWORK

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Abstract
In previous paper we introduced feed forward neural network changed into the definition of the Intuitionistic Fuzzy Logic (IFL). All its parameters used IFL characteristics. In this paper a generalized net model us constructed that introduces work in the IFFFNN.

Index Terms — Intuitionistic fuzzy set, Feed forward neural network, Generalized nets

Introduction

In a series of papers the process of functioning and the results of the work of different types of neural networks are described by Generalized Nets [10, 12, 14, 15, 16,17]. The possibility for combination of ideas of Neural Networks (NNs) and Intuitionistic Fuzzy Logic (IFL) are discussed in [6, 7, 12]. In [13] we show that the concepts of Feed Forward Neural Networks (FFNNs) and IFL can also be combined.

In this paper we design a Generalized Net model (GN) [2,3] that presents work of the Intuitionistic Fuzzy Feet Forward Neural Network (IFFFNN).

All definitions related to the concept of "IFFFNN" are taken from [13].

Let us have a neuron with R inputs. Let them have intuitionistic fuzzy values

$$\langle \mu_{p_1}, \nu_{p_1} \rangle, \langle \mu_{p_2}, \nu_{p_2} \rangle, \ldots, \langle \mu_{p_R}, \nu_{p_R} \rangle .$$

Let each input p have respective elements $p = \langle \langle \mu_{p_1}, \nu_{p_1} \rangle, \langle \mu_{p_2}, \nu_{p_2} \rangle, \ldots, \langle \mu_{p_R}, \nu_{p_n} \rangle \rangle$ with weight coefficient from the IFW-matrix $w = \langle \langle \mu_{w_{1,1}}, \nu_{w_{1,1}} \rangle, \langle \mu_{w_{1,2}}, \nu_{w_{1,2}} \rangle, \ldots, \langle \mu_{w_{1,R}}, \nu_{w_{1,R}} \rangle \rangle$.

Thus, the indices in say that weight $\langle \mu_{w_{1,2}}, \nu_{w_{1,2}} \rangle$ represents the connection to the first neuron from the second source.

The transfer functions in neural network are:

- linear transfer function. Output $a = n = \langle \mu_n, \nu_n \rangle$;

- logical sigmoid transfer function with expression:

$$a = \frac{1}{1+e^{-n}} \tag{1}$$

According to the IFL

$$F_{sigm} = \left\langle \frac{\varepsilon}{1+\frac{1}{e^{\mu}}}, \frac{\varepsilon}{1+\frac{1}{e^{\nu}}} \right\rangle \tag{2}$$

where $$\varepsilon = \frac{2}{e+1}. \tag{3}$$

A GN-model

All definitions related to the concept "GN" are taken from [2, 3]. The GN, describing the process of the work of the Intuitionistic Fuzzy Feed Forward Neural Network, is shown on Fig.1.

Initially the following tokens enter in the GN:

- in place P - α^1-token with initial characteristic

$$x_0^{\alpha^1} = p^1 = \langle \mu_{w_{1,1}}, \nu_{w_{1,1}} \rangle, \langle \mu_{w_{1,2}}, \nu_{w_{1,2}} \rangle, \ldots, \langle \mu_{w_{1,R}}, \nu_{w_{1,R}} \rangle;$$

- in place W^1 – β^1-token with initial characteristic

$$x_0^{\beta^1} = w^1 = \left| \langle \mu_{w_{1,1}}, \nu_{w_{1,1}} \rangle \quad \langle \mu_{w_{1,2}}, \nu_{w_{1,2}} \rangle \quad \ldots \quad \langle \mu_{w_{1,R}}, \nu_{w_{1,R}} \rangle \right|$$

- in place b^1 - γ^1-token with initial characteristic

$$x_0^{\gamma^1} = \langle \mu_b, \nu_b \rangle;$$

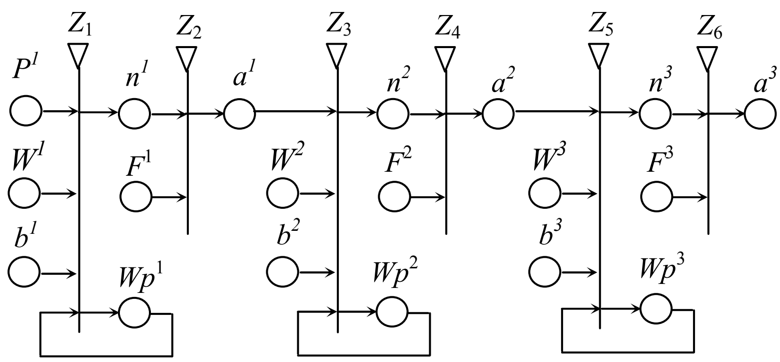

Figure 1. GN of the Intuitionistic Fuzzy Feed Forward Neural Network

- in place F^1 - one δ^1-token with initial characteristic

$$x_0^{\delta^1} = a = n = \langle \mu_n, \nu_n \rangle \text{ according to [12];}$$

- in place W^2 – β^2-token with initial characteristic

$$x_0^{\beta^2} = w^2 = \begin{vmatrix} \langle \mu_{w_{1,1}}, \nu_{w_{1,1}} \rangle & \langle \mu_{w_{1,2}}, \nu_{w_{1,2}} \rangle & \dots & \langle \mu_{w_{1,R}}, \nu_{w_{1,R}} \rangle \\ \langle \mu_{w_{2,1}}, \nu_{w_{2,1}} \rangle & \langle \mu_{w_{2,2}}, \nu_{w_{2,2}} \rangle & & \langle \mu_{w_{2,R}}, \nu_{w_{2,R}} \rangle \\ \dots & \dots & \dots & \dots \\ \langle \mu_{w_{S,1}}, \nu_{w_{S,1}} \rangle & \langle \mu_{w_{S,2}}, \nu_{w_{S1,2}} \rangle & & \langle \mu_{w_{S,R}}, \nu_{w_{S,R}} \rangle \end{vmatrix}$$

- in place b^2 - γ^2-token with initial characteristic

$$x_0^{\gamma^2} = \langle \langle \mu_{b_1}, \nu_{b_1} \rangle, \langle \mu_{b_2}, \nu_{b_2} \rangle, \dots, \langle \mu_{b_S}, \nu_{b_S} \rangle \rangle;$$

- in place F^2 - one δ^2-token with initial characteristic using (1), (2) and (3).

- in place W^3 – β^3-token with initial characteristic

$$x_0^{\beta^3} = w^3 = \langle \langle \mu_{w_{1,1}}, \nu_{w_{1,1}} \rangle, \langle \mu_{w_{1,2}}, \nu_{w_{1,2}} \rangle, \dots, \langle \mu_{w_{1,R}}, \nu_{w_{1,R}} \rangle \rangle;$$

- in place b^3 - γ^3-token with initial characteristic

$$x_0^{\gamma^3} = \langle \langle \mu_{b_1}, \nu_{b_1} \rangle, \langle \mu_{b_2}, \nu_{b_2} \rangle, \dots, \langle \mu_{b_S}, \nu_{b_S} \rangle \rangle;$$

- in place F^1 - one δ^1-token with initial characteristic

$$x_0^{\delta^3} = a = n = \langle \mu_n, \nu_n \rangle;$$

The GN is presented by a set of transitions:

$$A = \{ Z_1, Z_2, Z_3, Z_4, Z_5, Z_6 \},$$

where transitions describe the following processes:
Z_1 – Calculating influence of the first layer of the IFFNN (n^1);
Z_2 – Calculating the output of the first layer of the IFFNN (a^1);
Z_3 – Calculating influence of the second layer of the IFFNN (n^2);
Z^4 – Calculating the output of the second layer of the IFFNN (a^2);
Z^5 – Calculating influence of the third layer of the IFFNN (n^3);
Z^6 – Calculating the output of the third layer of the IFFNN (a^3).

Transitions of the GN-model have the following forms.

$$Z_1 = \langle \{ S_{P^1}, S_{W^1}, S_{b^1}, S_{Wp^1} \}, \{ S_{n^1}, S_{Wp^1} \}, R_1, \wedge(\vee(S_{P^1}, S_{W^1}), \vee(S_{b^1}, S_{Wp^1})) \rangle,$$

where:

$$R_1 = \begin{array}{c|cc} & S_{n^1} & S_{Wp^1} \\ \hline S_{p^1} & False & True \\ S_{W^1} & False & True \\ S_{b^1} & True & False \\ S_{Wp^1} & True & False \end{array},$$

Tokens α^1, β^1 and γ^1 union, into the χ^1-token according to [13].

$$Z_2=<\{S_{n^1}, S_{F^1}\}, \{S_{a^1}\}, R_2, \wedge(S_{n^1}, S_{F^1})>,$$

where:

$$R_2=\begin{array}{c|c} & S_{a^1} \\ \hline S_{n^1} & True \\ S_{F^1} & True \end{array},$$

Tokens δ^1 and χ^1 union into the σ^1-token according to [13].

$$Z_3=<\{S_{a^1}, S_{W^2}, S_{b^2}, S_{Wp^2}\}, \{S_{n^2}, S_{Wp^2}\}, R_3, \wedge(\vee(S_{a^1}, S_{W^2}), \vee(S_{b^2}, S_{Wp^2})>,$$

where:

$$R_3=\begin{array}{c|cc} & S_{n^2} & S_{Wp^2} \\ \hline S_{a^1} & False & True \\ S_{W^2} & False & True \\ S_{b^2} & True & False \\ S_{Wp^2} & True & False \end{array},$$

Tokens σ^1, β^2 and γ^2 union, into the χ^2-token according to [13].

$$Z_4=<\{S_{n^2}, S_{F^2}\}, \{S_{a^2}\}, R_4, \wedge(S_{n^2}, S_{F^2})>,$$

where:

$$R_4=\begin{array}{c|c} & S_{a^2} \\ \hline S_{n^2} & True \\ S_{F^2} & True \end{array},$$

Tokens δ^2 and χ^2 union into the σ^2-token, using [13].

$$Z_5=<\{S_{a^2}, S_{W^3}, S_{b^3}, S_{Wp^3}\}, \{S_{n^3}, S_{Wp^3}\}, R_5 \wedge(\vee(S_{a^2}, S_{W^3}), \vee(S_{Wp^3}, S_{b^3}))>,$$

where:

$$R_5=\begin{array}{c|cc} & S_{n^3} & S_{Wp^3} \\ \hline S_{a^2} & False & True \\ S_{W^3} & False & True \\ S_{b^3} & True & False \\ S_{Wp^3} & True & False \end{array},$$

Tokens σ^2, $\beta^3$and γ^3 union, into the χ^3-token according to [13].

$$Z_6=<\{S_{n^3}, S_{F^3}\}, \{S_{a^3}\}, R_6, \wedge(S_{n^3}, S_{F^3})>,$$

where:

$$R_6 = \begin{array}{c|c} & S_{a^3} \\ \hline S_{n^3} & True \\ S_{F^3} & True \end{array},$$

Tokens δ^3 and χ^3 union into the σ^3-token, using [13].

III. Conclusion

The proposed feed forward neural network is changed into the definition of the Intuitionistic Fuzzy Logic (IFL) and Intuitionistic Fuzzy Set (IFS) [1]. All its parameters used IFL characteristics. This paper is generalized net model that introduces work in the IFFFNN.

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