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Reducing Error Signal in Multilayer Perceptron Neural Networks using MLP for Label Ranking

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Abstract: - This paper describes a simple tactile probe for identifying error signal in Multilayer. In multilayer having the number of hidden layers error signal can be process as irrespective manner so difficult to find out the error signal. The multilayer perceptron having the number of hidden layers with one output layer. This networks are fully connected i.e. a neuron in any layer of this network is connected to all the nodes/neurons in the previous layer signal flow through the network progress in a forward direction from left to right and on a layer by layer. In this networks we can identify the two kinds of networks. First one is Function Signal-A function signal is an input signal that comes in at the Input end of the network. Second one is Error Signal- an error signal originates at an output neuron of the network and propagates backward i.e. layer by layer through the network. In this paper, we adapt a multilayer perceptron algorithm for label ranking. We focus on the adaptation of the Back-Propagation (BP) mechanism.

Keywords: Label Ranking, back-propagation, multilayer perceptron.

1. INTRODUCTION

This class of networks consists of multiple layers of computational units, usually interconnected in a feed-forward way. Each neuron in one layer has directed connections to the neurons of the subsequent layer [11][18]. In many applications the units of these networks apply a sigmoid function as an activation function.

Multilayer Perceptron. The term "multilayer perceptron" often causes confusion. It is argued the model is not a single perceptron that has multiple layers. Rather, it contains many perceptrons that are organized into layers, leading some to believe that a more fitting term might therefore be "multilayer perceptron network". Moreover, these "perceptrons" are not really perceptrons in the strictest possible sense, as true perceptrons are a special case of artificial neurons that use a threshold activation function such as the Heaviside step function, whereas the artificial neurons in a multilayer perceptron are free to take on any arbitrary activation

function[16][18]. Consequently, whereas a true perceptron performs binary classification, a neuron in a multilayer perceptron is free to either perform classification or regression, depending upon its activation function. The two arguments raised above can be reconciled with the name "multilayer perceptron" if "perceptron" is simply interpreted to mean a binary classifier, independent of the specific mechanistic implementation of a classical perceptron. In this case, the entire network can indeed be considered to be a binary classifier with multiple layers[11][12]. Furthermore, the term "multilayer perceptron" now does not specify the nature of the layers; the layers are free to be composed of general artificial neurons, and not perceptrons specifically. This interpretation of the term "multilayer perceptron" avoids the loosening of the definition of "perceptron" to mean an artificial neuron in general.

1.1. ARCHITECTURE

The network topology used in this study is based on fully connected feed-forward ANNs. The number of nodes in the input layer is equal to the number of features presented by the data, while the number of nodes in the output layer (L) is equal to the number of classes that this data map to. At least one hidden layer must be added to the architecture in order to treat the non-linear separation among classes. Several networks with one and two hidden layers, with different number of nodes in each hidden layer, have been used[11][12][15]. The architecture for a multilayer perceptron with two hidden layers.

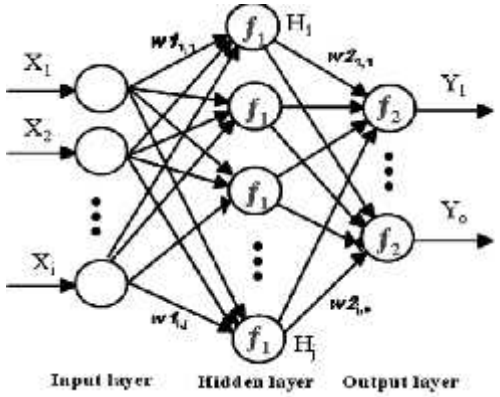
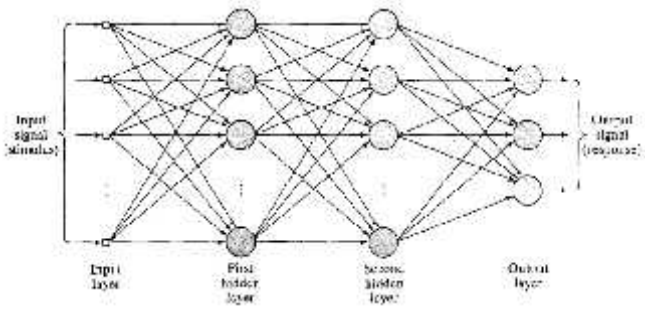
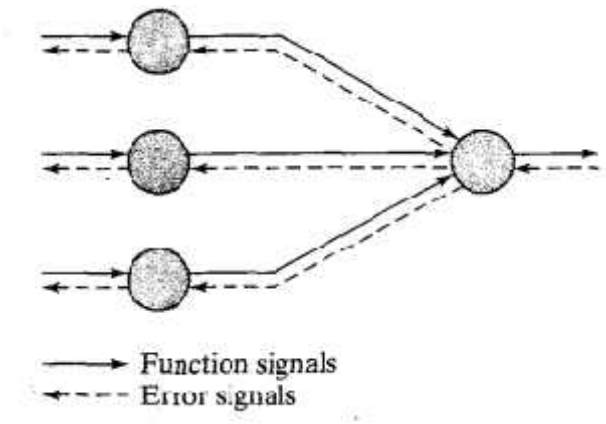


Fig 1. Artificial neural network, Three layers MLP





The fig.2. Depicts a portion of the multilayer perceptron. Two kinds of signals are identifies in this network.

i). Function signal

A function signal is an input signal tbat comes in at the input end of the network, propagates forward through the network, and emerges at the out put end if the network as ab output signal[11]. We refer to such a signal as a function signal for two reasons. First, it is presumed to perform a useful function at the output of the network. Second, at each neuron of the network through which a function signal passes, the signal is calculated as a function of the input and associated weights applied to that neuron. The function signal is also referred to as the input signal.

ii). Error signal.

An error signal originates at an output neuron of the network, and propagates backward(layer by layer) through the network. We refer to it as an error signal because its computation by every neuron of the network involves an error-dependent function in one form or another[11]. The output neurons constitute the output layers of the network. The remaining neurons constitute hidden layer of the network. Thus the hidden units are not part of the output or input of the network hence their designation as "hidden"[15] The first hidden layer is fed from the input layer made up of sensory units, the resulting outputs of the first hidden layer are in turn applied to the next hidden layer and so on for the rest of the network[11][12][15]. Each hidden or output neuron of a multilayer perceprton is designed to perform two computations:

1. The computation of the function signal appearing at the output of a neuron, which is expressed as a continuous nonlinear function of the input signal and synaptic weights associated with that neuron.
2. The computation of an estimate of the gradient vector. Gradient of error surface with respect to the weights connected to the inputs of a neuron. Which is needed for the backward pass through the network.

In many real-world applications, assigning a single label to an example is not enough. For instance, when trading in the stock market based on recommendations from financial analysts, predicting who is the best analyst does not suffice because 1) he/she may not make a recommendation in the near future and 2) we may prefer to take into account recommendations of multiple analysts, to be on the safe side[1][2][3][5]. Hence, to support this approach, a model should predict a ranking of analysts rather than suggesting a single one. Such a situation can be modeled as a Label Ranking (LR) problem: a form of preference learning, aiming to predict a mapping from examples to rankings of a finite set of labels. Recently, quite some solutions have been proposed for the label ranking problem. including one based on the Multilayer Perceptron algorithm (MLP). MLP is a type of neural network architecture, which has been applied in a supervised learning context using the error back-propagation (BP) learning algorithm. In this paper, we try a different approach to the simple adaptation proposed earlier[1][8][9]. We adapt the BP learning mechanism to LR. More specifically, we investigate how the error signal explored by BP can use information from the LR loss function. We introduce six approaches and evaluate their (relative) performance. We also show some preliminary experimental results that indicate whether our new method could compete with state-of-the-art LR methods.

2. PRELIMINARIES

Throughout this paper, we assume a training set T ={x_n, π_n} consisting oft examples x_n and their associated label rankings π_n. Such a ranking is a permutation of a finite set of labels $L=\{\lambda_1,...,\lambda_k\}$, given k, taken from the permutation space Ω_L.Each example x_n consists of *m* attributes $x_n = \{a_1,...,a_m\}$and is taken from the example space X. The position of λ_a in a rankingπnis denoted by $\pi_n(a)$ and assumes a value in the set{1,...,k}

2.1 Back-Propagation Algorithm.

The Back Propagation network to be the quintessential Neural Net. Actually, Back Propagation is the training or learning algorithm rather than the network itself. The network used isgenerally of the simple type shown in figure 4 [11][16][17][18].

A Back Propagation network learns by example. You give the algorithm examples of what you want the network to do and it changes the network's weights so that, when training is finished, it will give you the required output for a particular input. Back Propagation networks are ideal for simple Pattern Recognition and Mapping Tasks 4[12][15]. As just mentioned, to train the network you need to give it examples of what you want – the output you want (called the Target) for a particular input as shown in Figure 5.

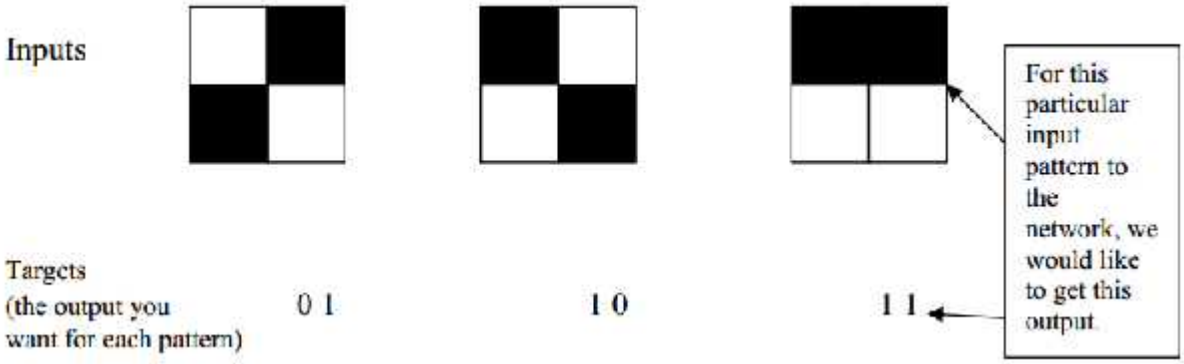


Fig. 5. Back Propagation training set.

So, if we put in the first pattern to the network, we would like the output to be 0 1 as shown in figure 6. (a black pixel is represented by 1 and a white by 0 as in the previous examples). The input and its corresponding target are called a Training Pair.

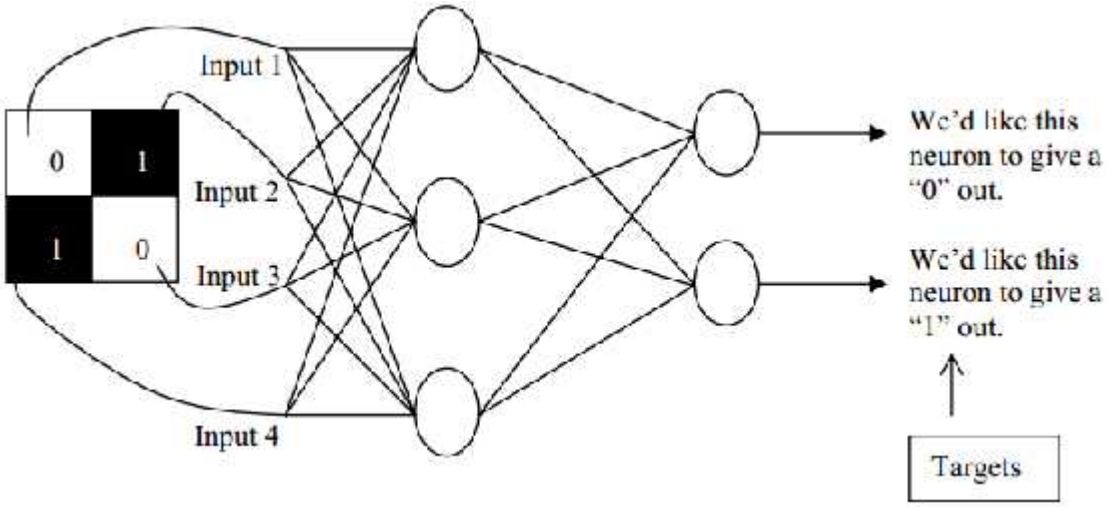


Fig. 6. applying a training pair to a network

The network is first initialised by setting up all its weights to be small random numbers – say between –1 and +1. Next, the input pattern is applied and the output calculated (this is called the forward pass). The calculation gives an output which is completely different to what you want (the Target), since all the weights are random. We then calculate the Error of each neuron, which is essentially: Target - Actual Output (i.e. What you want – What you actually get). This error is then used mathematically to change the weights in such a way that the error will get smaller. In other words, the Output of each neuron will get closer to its Target(this part is called the reverse pass). The process is repeated again and again until the error is minimal Let's do an example with an actual network to see how the process works[11][15]. We'll just look at one connection initially, between a neuron in the output layer and one in the hidden layer in fig. 7.

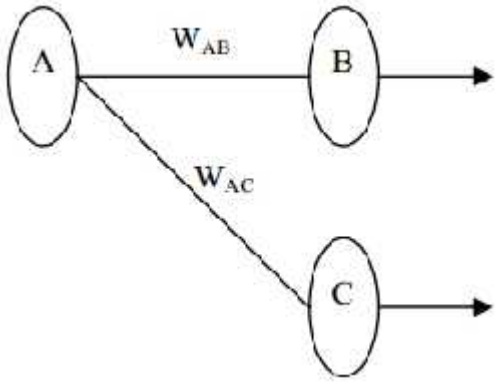


Fig. 7. single connection learning in a Back Propagation network.

The connection we're interested in is between neuron A (a hidden layer neuron) and neuron B (an output neuron)and has the weight WAB. The diagram also shows another connection, between neuron A and C, but we'll return to that later[10][14].

2.2. The algorithm works :

Step 1. First apply the inputs to the network and work out the output – remember this initial output could be anything, as the initial weights were random numbers.

Step 2. Next work out the error for neuron B. The error is What you want – What you actually get, in other words:

$$Error_B = Output_B(1-Output_B)(Target_B – Output_B)$$

The "Output(1-Output)" term is necessary in the equation because of the Sigmoid Function – if we were only using a threshold neuron it would just be (Target –Output).

Step 3. Change the weight. Let W^+_{AB} be the new (trained) weight and W_{AB} be the initial weight. $W^+_{AB} = W_{AB} + (Error_B x\ Output_A)$.Notice that it is the output of the connecting neuron (neuron A) we use (not B). We update all the weights in the output layer in this way.

Step 4. Calculate the Errors for the hidden layer neurons. Unlike the output layer we can't calculate these directly(because we don't have a Target), so we Back Propagate them from the output layer (hence the name of the algorithm). This is done by taking the Errors from the output neurons and running them back through the weights to get the hidden layer errors. For example if neuron A is connected as shown to B and C then we take the errors from B and C to generate an error for A.

$$Error_A = Output_A(1 - Output_A)(Error_B W_{AB} + Error_C W_{AC})$$

Again, the factor "Output (1 - Output)" is present because of the sigmoid squashing function.

Step 5. Having obtained the Error for the hidden layer neurons now proceed as in Step 3 to change the hidden layer weights. By repeating this method we can train a network of any number of layers.

2.3. Calculation of Reverse pass of Back Propagation.

let's clear that up by explicitly showing all the calculations for a full sized network with 2 inputs, 3 hidden layer neurons and 2 output neurons as shown in figure. 8. W^+ represents the new, recalculated, weight, whereas W represents the old weight[16][17][18].

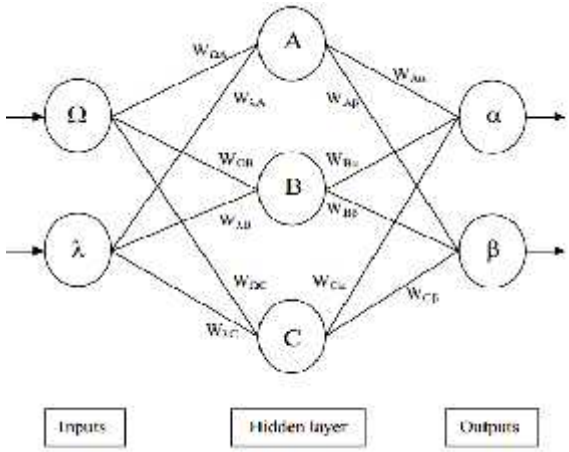


Fig. 8 Three layers full sized network

All the calculations for a reverse pass of Back Propagation.

1. Calculate errors of output neurons

$\delta_\alpha = out_\alpha(1 - out_\alpha)\ (Target_\alpha - out_\alpha)$

$\delta_\beta = out_\beta(1 - out_\beta)\ (Target_\beta - out_\beta)$

2. Change output layer weights

$W^+_{A\alpha} = W_{A\alpha} + \eta\delta_\alpha\ out_A$ $W^+_{A\beta} = W_{A\beta} + \eta\delta_\beta\ out_A$

$W^+_{B\alpha} = W_{B\alpha} + \eta\delta_\alpha\ out_B$ $W^+_{B\beta} = W_{B\beta} + \eta\delta_\beta\ out_B$

$W^+_{C\alpha} = W_{C\alpha} + \eta\delta_\alpha\ out_C$ $W^+_{C\beta} = W_{C\beta} + \eta\delta_\beta\ out_C$

3. Calculate (back-propagate) hidden layer errors

$\delta_A = out_A(1 – out_A)\ (\delta_\alpha W_{A\alpha} + \delta_\beta W_{A\beta})$

$\delta_B = out_B(1 – out_B)\ (\delta_\alpha W_{B\alpha} + \delta_\beta W_{B\beta})$

$\delta_C = out_C(1 – out_C)\ (\delta_\alpha W_{C\alpha} + \delta_\beta W_{C\beta})$

4. Change hidden layer weights

$W^+_{\lambda A} = W_{\lambda A} + \eta\delta_A\ in_\lambda$ $W^+_{\Omega A} = W^+_{\Omega A} + \eta\delta_A\ in_\Omega$

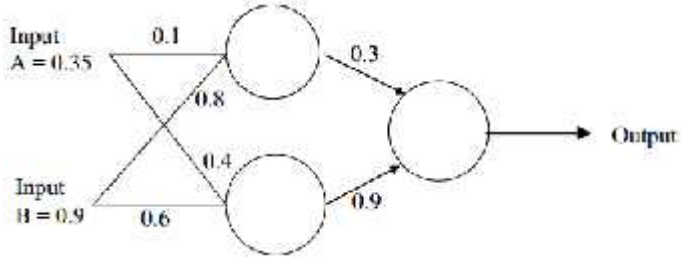
$W^+_{\lambda B} = W_{\lambda B} + \eta\delta_B\ in_\lambda$ $W^+_{\Omega B} = W^+_{\Omega B} + \eta\delta_B\ in_\Omega$

$W^{+}_{\lambda C} = W_{\lambda C} + \eta\delta_C\, in_\lambda \quad W^{+}_{\Omega C} = W^{+}_{\Omega C} + \eta\delta_C\, in_\Omega$

The constant η (called the learning rate, and nominally equal to one) is put in to speed up or slow down the learning if required.

2.4. Example:

Consider the simple network below:



Assume that the neurons have a Sigmoid activation function and

(i) Perform a forward pass on the network.

(ii) Perform a reverse pass (training) once (target = 0.5).

(iii) Perform a further forward pass and comment on the result.

Answer:

(i) Input to top neuron

= (0.35x0.1)+(0.9x0.8) = 0.755. Out = 0.68.

Input to bottom neuron

= (0.9x0.6)+(0.35x0.4) = 0.68. Out = 0.6637.

Input to final neuron

=(0.3x0.68)+(0.9x0.6637) = 0.80133.Out =0.69.

(ii) Output error

δ=(t-o)(1-o)o = (0.5-0.69)(1-0.69)0.69 = -0.0406.

New weights for output layer

$w1^{+}$ *= w1+(δx input) = 0.3 + (-0.0406x0.68)*

= 0.272392.

$w2^{+}$ *= w2+(δx input) = 0.9 + (-0.0406x0.6637)*

= 0.87305.

Errors for hidden layers:

δ1 = δx w1 = -0.0406 x 0.272392 x (1-o)o

$= -2.406 \times 10^{-3}$

δ2= δx w2 = -0.0406 x 0.87305 x (1-o)o

$= -7.916 \times 10^{-3}$

New hidden layer weights:

$w3^{+} = 0.1 + (-2.406 \times 10^{-3} \times 0.35) = 0.09916.$

$w4^{+} = 0.8 + (-2.406 \times 10^{-3} \times 0.9) = 0.7978.$

$w5^{+} = 0.4 + (-7.916 \times 10^{-3} \times 0.35) = 0.3972.$

$w6^{+} = 0.6 + (-7.916 \times 10^{-3} \times 0.9) = 0.5928.$

(iii) Old error was -0.19. New error is -0.18205. Therefore error has reduced.

2.5. Total Error in Network:

Error falls to some pre-determined low target value and then it stops.

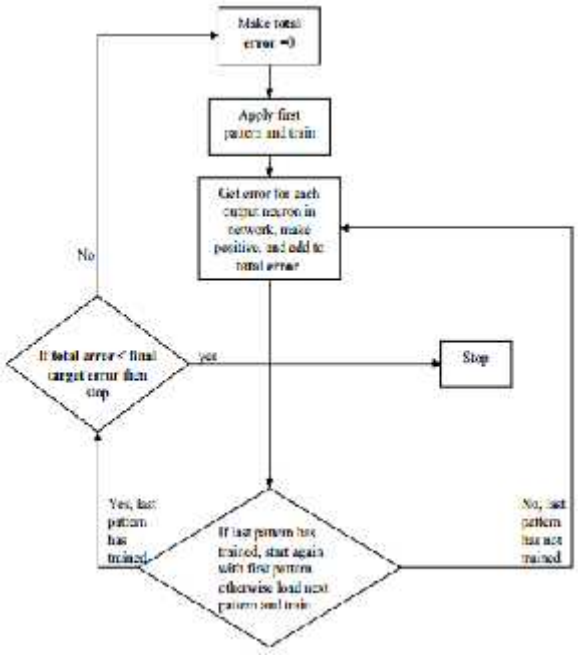


Fig. 9. The network keeps training all the patterns repeatedly until the total

Note that when calculating the final error used to stop the network (which is the sum of all the individual neuron errors for each pattern) you need to make all errors positive so that they add up and do not subtract[11][16][17][18].

Once the network has been trained, it should be able to recognise not just the perfect patterns, but also corrupted In fact if we deliberately add some noisy versions of the patterns into the training set as we train the network (say one in five), we can improve the network's performance in this respect. The training may also benefit from applying the patterns in a random order to the network. There is a better way of working out when to stop network training - which is to use a Validation Set[11][13][16]. This stops the network overtraining. It does this by having a second set of patterns which are noisy versions of the training set. Each time after the network has trained; this set (called the Validation Set) is used to calculate an error. When the error becomes low the network stops.

The following shows the use of validation set.

When the network has fully trained, the Validation Set error reaches a minimum. When the network is overtraining (becoming too accurate) the validation set error starts rising [7]. If the network overtrains, it won't be able to handle noisy data so well.

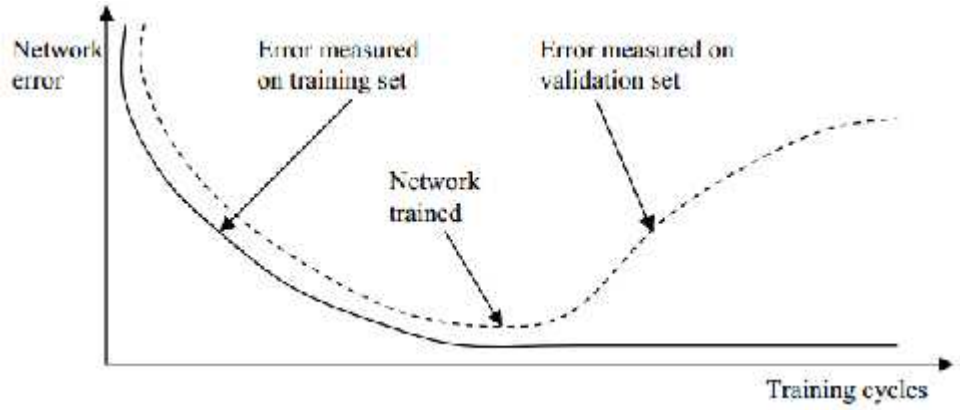


Fig.10 Use of validation sets

3. MULTILAYER PERCEPTRON FOR LABEL RANKING

Our adaptation of MLP for LR essentially consists of 1) the method to generate a ranking from the output layer and 2) the error functions guiding the BP learning process. The output layer contains k neurons (one for each label). The output y_j of a neuron j at the output layer does not represent a target value or class but rather the score associated with a label λ_j. By ordering all the scores, the predicted ranks $\pi'_n(j)$ of the label λ_j and, thus, the predicted ranking[1][2].

The tricky point of adapting an MLP for LR is the weight corrections in the BP process: minimizing the individual errors does not necessarily lead to minimizing the LR loss. We propose six approaches to define the error signal c_j at the output layer[5][6]. The weight connection $w_{ji}(n)$ is updated based on the estimated $c_j(n)$ using the delta rule $\Delta w_{ji}(n)=\eta c_j(n)y_i(n)$.

Local Approach (LA). The error signal is the individual error of each output neuron,

$c_j(n)=e_j(n)=\pi_n(j)-\pi'_n(j)$, as in the original MLP. The LR error, e_τ, is only used to evaluate the activation of the BP.

*Global Approach (GA).*The error signal is defined in terms of the LR error. In this case, it is simply given by $c_j(n)=e_\tau(n)$

Combined Approach (CA). CA is a combination between GA and LA, $c_j(n)= e_j(n)e_\tau(n)$. We note that a neuron which returns the correct position $\pi_n(j)=\pi'_n(j)$ (i.e.,$e_j(n) = 0$) is not penalized even if $e_\tau > 0$.

*Weight-Based Signed Global Approach (WSGA).*The error signal is defined in terms of the LR error and the incoming weight connections of the output layer. We assume that a high LR error means that some weights of neurons are too high and other are too low. The output neurons are ranked according to their average weights $\tilde{\omega}_j = \frac{1}{q}\sum_{i=0}^{q} = \omega_{ij}$ resulting in a position $p_\omega(j)\in[1,...,k]$. The error of the neurons with a position above the mean is negative and it is positive otherwise:

$$Cj = \begin{cases} -e_\tau(n) & \text{if } p_w(j) > (\frac{k}{2} + 0.5) \\ e_\tau(n) & \text{if } p_w(j) < (\frac{k}{2} + 0.5) \\ 0 & \text{if } p_w(j) = (\frac{k}{2} + 0.5) \end{cases} \quad (1)$$

*Score-Based Signed Global Approach (SSGA).*The motivation for SSGA is the same as for WSGA. The difference is that we rank the output neuron scores y_j instead of the input weights. The positions of the weights, $p_w(j)$ is replaced in eq. 1 with the positions of the scores, $p_s(j)$

Individual Weight-Based Signed Global Approach (IWSGA). This assumes that all the weight connections at the output layer are important to define the error signal and are considered independently of the neurons they connect to. The error signal denoted $c_{ji}(n)$ is associated with the weight of the connection between output neuron i and hidden neuron j. This is similar to WSGA but we rank all weight connections individually, rather than the average weights for each output neuron. The weight corrections are given by $\Delta w_{ji}(n)=\eta c_{ji}(n)y_i(n)$, where:

$$c_{ji}(n) = \begin{cases} -e_\tau(n), & \text{if } p_{gw}(ji) > \frac{gk}{2} \\ e_\tau(n), & \text{if } p_{gw}(ji) \le \frac{gk}{2} \end{cases}$$

4. EXPERIMENTAL RESULTS

The goal is to compare the performance of the proposed approaches on different datasets. The datasets used for the evaluation. These datasets, which are commonly used for LR, are presented in Table 1. Our approach starts

Our approach starts by normalizing all attributes, and separating the dataset into a training and a test set. On each dataset we tested the six approaches with $h= 3$ hidden neurons, $\eta=0.2$, using 5 epochs with 5 random restarts. The error estimation methodology is 10-fold cross-validation. The results are presented in terms of the similarity between the rankings π_i and π'_i with the Kendall τ coefficient.

In Table 2, we show the resulting τ-values for each approach, and associated rank (lower is better) per dataset. The bottom row shows the average rank for each approach, which allows us to compare the relative performance of the approaches using the Friedman test with post-hoc Nemenyi test [13].

Table 1. Datasets for LR

Dataset	Type	k	m	Instances	Dataset	Type	k	m	Instances
Authorship	A	4	**70**	841	Iris	A	3	4	150
Bodyfat	B	7	7	252	Pendigits	A	10	**16**	10992
Calhousing	B	4	4	20640	Segment	A	7	**18**	2310
Cpu-small	B	5	6	8192	Stock	B	5	5	950
Elevators	B	9	9	16599	Vehicle	A	4	**18**	846
Fried	B	5	9	40768	Vowel	A	11	10	528
Glass	A	6	9	214	Wine	A	3	**13**	178
Housing	B	6	6	506	Wisconsin	B	16	**16**	194

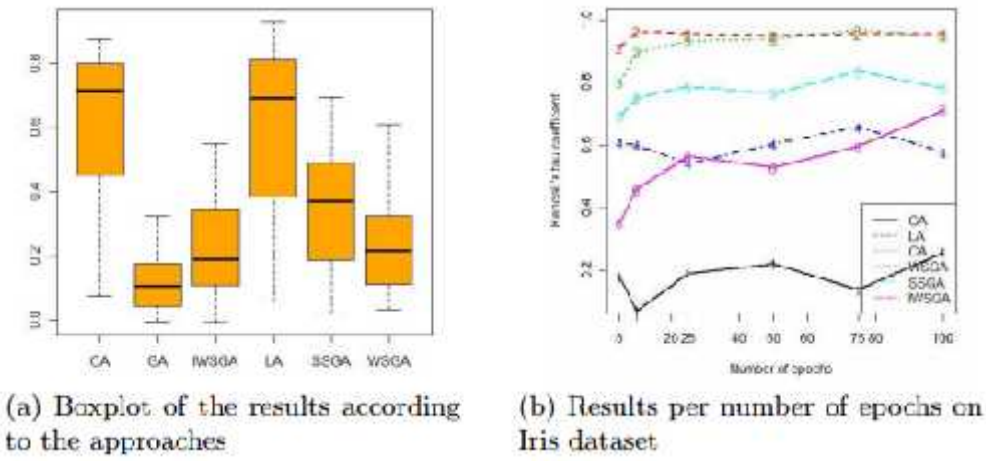
Table 2.Experimental results of MLP-LR and their ranks

Dataset	GA		LA		CA		WSGA		SSGA		IWSGA	
	τ	r_i^j	τ	r_i^j	τ	r_i^j	τ	r_i^j	τ	r_i^j	τ	r_i^j
Authorship	0.291	6	0.889	1	0.829	2	0.307	5	0.528	4	0.548	3
Bodyfat	-0.004	5	0.056	2	0.075	1	0.033	3	0.022	4	-0.006	6
Calhousing	0.054	6	0.083	3	0.106	2	0.078	4	0.130	1	0.076	5
Cpu-small	0.109	6	0.295	2	0.357	1	0.176	5	0.293	3	0.181	4
Elevators	0.110	6	0.687	1	0.684	2	0.135	5	0.419	3	0.168	4
Fried	-0.002	6	0.532	2	0.660	1	0.157	4	0.446	3	0.133	5
Glass	0.317	5	0.818	1	0.757	2	0.258	6	0.475	4	0.493	3
Housing	0.077	6	0.531	2	0.574	1	0.290	3	0.241	4	0.094	5
Iris	0.178	6	0.911	1	0.800	2	0.609	4	0.693	3	0.351	5
Pendigits	0.161	5	0.694	2	0.752	1	0.122	6	0.314	3	0.257	4
Segment	0.177	6	0.799	2	0.842	1	0.341	4	0.338	5	0.346	3
Stock	0.032	6	0.732	2	0.745	1	0.303	4	0.403	3	0.197	5
Vehicle	0.106	6	0.801	1	0.800	2	0.482	4	0.504	3	0.339	5
Vowel	0.065	6	0.474	2	0.545	1	0.098	5	0.130	3	0.125	4
Wine	0.324	6	0.931	1	0.874	2	0.503	4	0.598	3	0.341	5
Wisconsin	0.007	6	0.221	2	0.235	1	0.066	3	0.060	4	0.028	5
R_j	5.8125		1.6875		1.4375		4.3125		3.3125		4.4375	

The Friedman test proves that the average ranks are significantly unequal (with $\alpha=1\%$).Then the Nemenyi test gives us a critical difference of $CD=2.225$ (with $\alpha=1\%$). The test implies that for each pair of approaches A_i and A_j, if $R_i < R_j - CD$, then A_i is significantly better than A_j. Hence we can see from the table that approaches *LA* and *CA* significantly outperform all other approaches except for SSGA. However, at

α= 10% the critical difference becomes *CD=1.712*, so at this significance level *CA* significantly outperforms *SSGA* too.

These experiments are performed with a rather arbitrary set of parameters. Varying parameters such as the number of hidden neurons in the MLP, the number of epochs used when learning the neural network, and the number of random restarts, could benefit performance. To illustrate this, Figure 1b displays the variation of τ-values for the different approaches on the Iris dataset, when varying the number of epochs. As we can see, we can substantially improve the results when tweaking the number of epochs. For some approaches using more epochs is better, but for others this monotonicity does not hold. We see similar behavior when varying the number of stages and hidden neurons. When the dataset at hand has relatively many attributes, our approaches have relatively many input signals in the MLP.



(a) Boxplot of the results according to the approaches

(b) Results per number of epochs on Iris dataset

Fig. 9 Results of Kendall's τ correlation coefficient.

Hence there are many more connections with the hidden layer, and much more interactions between the neurons in the network.

5. CONCLUSIONS

In this paper, the most commonly used networks consist of an input layer, a single hidden layer and an output layer. The input layer size is set by the type of pattern or input you want the network to process. And reducing the error signal in multilayer perceptron neural network shown in example Empirical results indicate that the two methods that directly incorporate the individual errors perform significantly better than the methods that focus on the LR error. However, the best results are obtained by combining both errors (CA). A comparison with results published for other methods additionally indicates that our method has the potential to compete with other methods. This holds even though no parameter tuning was carried out, which is known to be essential for learning accurate networks. Our method becomes more competitive when the data contains more attributes; this increases the amount of input neurons, and the MLP-LR

predictions benefit from the more complex network. As future work, apart from parameter tuning we will investigate other ways of combining the local and global errors and we will investigate how to give more importance to higher ranks.

6. REFERENCES

[1]. Geraldina Ribeiro, Wouter Duivesteijn, Carlos Soares, and Arno Knobbe Multilayer Perceptron for Label Ranking. (2011)

[2]. Aiguzhinov, A., Soares, C., Serra, A.P.: A Similarity-Based Adaptation of Naïve Bayes for Label Ranking: Application to the Metalearning Problem of Algorithm Recommendation. In: Discovery Science (2010).

[3]. Vembu, S., G¨ artner, T.: Label Ranking Algorithms: A Survey. In: F¨ urnkranz, J., H¨ullermeier, E. (eds.) Preference Learning. Springer (2010)

[4]. H¨ ullermeier, E., F¨urnkranz, J.: On loss functions in label ranking and risk minimization by pairwise learning. JCSS 76(1), 49–62 (2010)

[5]. Brinker, K., H¨ ullermeier, E.: Label Ranking in Case-Based Reasoning. In: Weber, R.O., Richter, M.M. (eds.) ICCBR 2007. LNCS (LNAI), vol. 4626, pp. 77–91. Springer, Heidelberg (2007).

[6]. Dekel, O., Manning, C.D., Singer, Y.: Log-linear models for label ranking. In: Advances in Neural Information Processing Systems (2003)

[7]. H¨ ulermeier, E., F¨urnkranz, J., Cheng, W., Brinker, K.: Label ranking by learning pairwise preferences. Artif. Intell., 1897–1916 (2008)

[8]. Cheng, W., Dembczynski, K., H¨ ullermeier, E.: Label Ranking Methods based on the Plackett-Luce Model. In: ICML (2010)

[9]. Cheng, W., Huhn, J.C., H¨ ullermeier, E.: Decision tree and instance-based learning for label ranking. In: ICML (2009)

[10]. de S´ a, C.R., Soares, C., Jorge, A.M., Azevedo, P., Costa, J.: Mining Association Rules for Label Ranking. In: Huang, J.Z., Cao, L., Srivastava, J. (eds.) PAKDD 2011, Part II. LNCS, vol. 6635, pp. 432–443. Springer, Heidelberg (2011)

[11]. Haykin, S.: Neural Networks: a comprehensive foundation, 2nd edn (1998).

[12]. F. J. Maldonado Williams-Pyro, M. T. Manry University of Texas at Arlington Electrical Engineering Dept Optimal Pruning of Feedforward Neural Networks Based upon the Schmidt Procedure.

[13] K. Liu, S. Subbarayan, R.R.Shoults, M.T. Manry, C.Kwan, F.L. Lewis, J.Naccarino, "Comparison of Very Short-Term Load Forecasting Techniques,"IEEE Transactions on Power Systems, vol.11, no.2, May 1996, pp. 877-882.

[14] V. Maniezzo, ìGenetic evolution of the topology and weight distribution of Neural Networksî, IEEE Transaction on Neural Networks, 1994, vol. 5, No. 1, pp. 39-53.

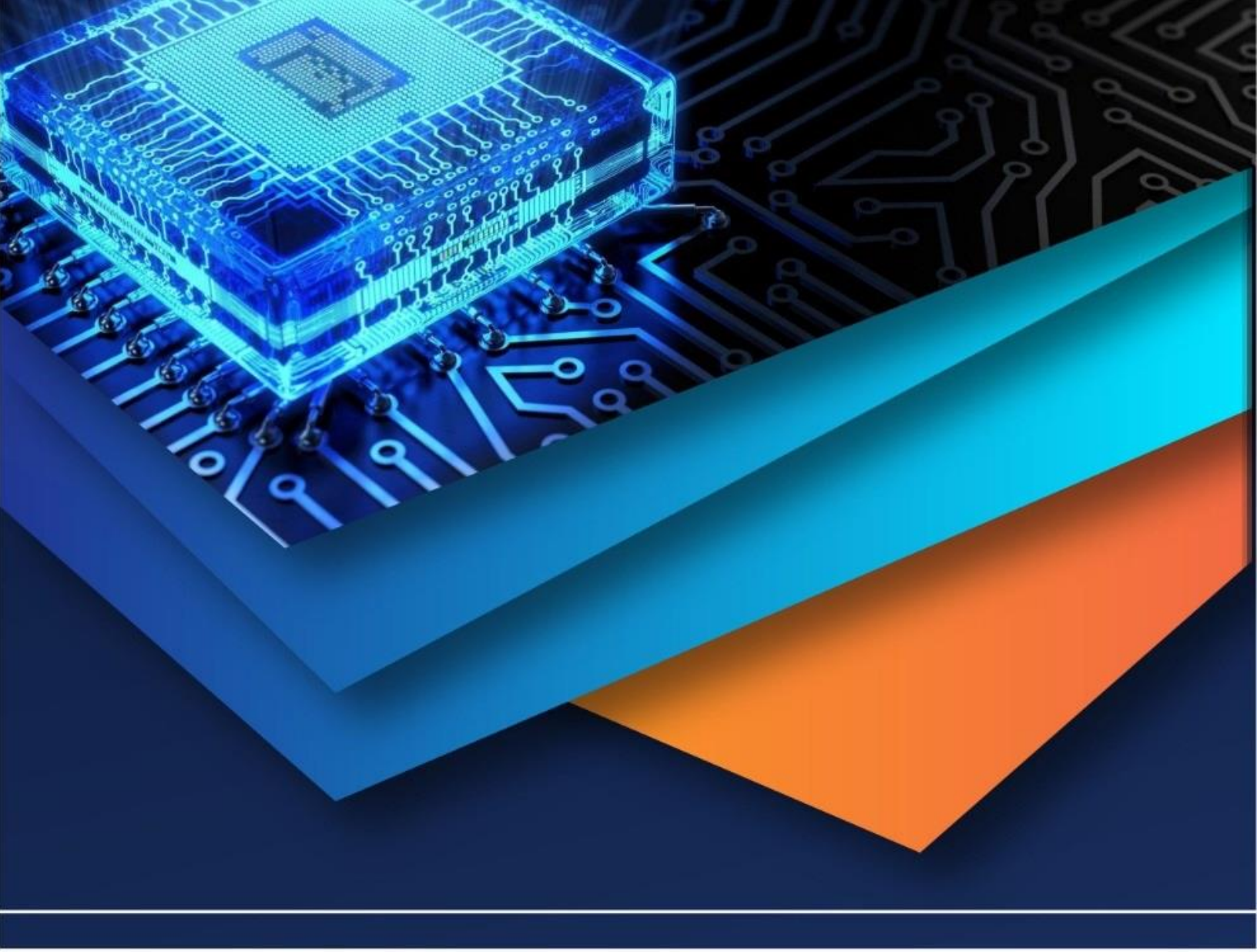
[15] Ponnapalli, ìA formal selection and pruning algorithm for feedforward artificial network optimizationî, IEEE Transaction on Neural Networks, 1999, vol. 10, No. 4, pp. 964-968.

[16]. Alsmadi, M. K. S., Omar, K., & Noah, S. A. (2009). Back Propagation Algorithm: The Best Algorithm Among the Multi-layer Perceptron Algorithm. International Journal of Computer Science and Network Security, 9 (4), pp. 378-383.

[17]. Bi, W., Wang, X., Tang, Z., & Tamura, H. (2005). Avoiding the Local Minima Problem in Backpropagation

Algorithm with Modified Error Function. IEICE Trans. Fundam. Electron. Commun. Comput. Sci., E88-A (12), pp. 3645-3653.

[18]. Nazri Mohd Nawia, R.S. Ransingb, Mohd Najib Mohd Sallehc, Rozaida Ghazalid, Norhamreeza Abdul Hamid The Effect Of Gain Variation In Improving Learning Speed Of Back Propagation Neural Network Algorithm On Classification Problems p 120-124.



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