AN ARCHITECTURE-ALTERING AND TRAINING METHODOLOGY FOR NEURAL LOGIC NETWORKS
Application in the banking sector

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Abstract: Artificial neural networks have been universally acknowledged for their ability on constructing forecasting and classifying systems. Among their desirable features, it has always been the interpretation of their structure, aiming to provide further knowledge for the domain experts. A number of methodologies have been developed for this reason. One such paradigm is the neural logic networks concept. Neural logic networks have been especially designed in order to enable the interpretation of their structure into a number of simple logical rules and they can be seen as a network representation of a logical rule base. Although powerful by their definition in this context, neural logic networks have performed poorly when used in approaches that required training from data. Standard training methods, such as the back-propagation, require the network's synapse weight altering, which destroys the network's interpretability. The methodology in this paper overcomes these problems and proposes an architecture-altering technique, which enables the production of highly antagonistic solutions while preserving any weight-related information. The implementation involves genetic programming using a grammar-guided training approach, in order to provide arbitrarily large and connected neural logic networks. The methodology is tested in a problem from the banking sector with encouraging results.

1 INTRODUCTION

Being a methodology that aims to the integration between artificial neural networks and AI's rule-based systems (Quah et al. 1996), the neural logic networks paradigm (Teh 1995) has been developed and applied nowadays, in a number of domains (Quah et al.1995). Neural logic networks have been proved successful when used in the AI framework, by providing network representations for nearly every logical rule base. The potential of using neural logic networks within the computational intelligence framework has been proposed since their first presentation (Teh 1995). Various training methods have been developed since then. In (Teh 1995), a training methodology related to back-propagation was proposed. Later, the Supervised Clustering and Matching (SCM) algorithm (Tan and Teow 1997) was introduced. However, when used within the CI framework, the extracted networks almost always resulted into non-interpretable forms, eliminating this way their potential advantage over common neural network models. These early training methodologies used refinements of the edge weights, which resulted in non-interpretable solutions. This drawback led the research to alternative solving methodologies such as the genetic programming (Chia and Tan 2001). However, their system provided a model that was capable of producing only a limited set of neural logic network representations (Chia and Tan 2001), which were actually neural logic binary trees. The latter problem is solved in the methodology of this paper, by providing indirect representation of neural logic network architectures within the genetic programming framework. The indirect representation is based on the cellular encoding (Gruau 1994), and is applied into the genetic

$$P_{(a,b)} = \begin{cases} (1,0) & if \sum_{j=1}^{k} a_j x_j - \sum_{j=1}^{k} b_j y_j \geq 1 \\ (0,1) & if \sum_{j=1}^{k} a_j x_j - \sum_{j=1}^{k} b_j y_j \leq -1 \\ (0,0) & otherwise \end{cases}$$
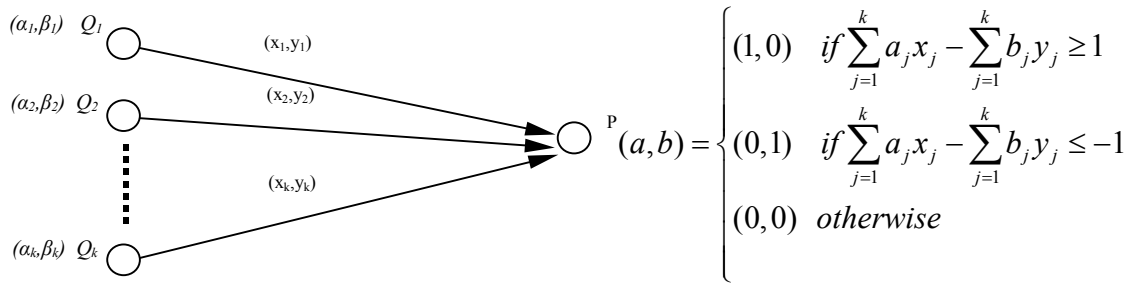
Figure 1: Neural logic network and its output.

programming (Koza 1992) using a context-free grammar system. The problem where the system is applied comes from the banking sector and involves the loan management for enterprises.

The paper is organized as follows. In section 2 we introduce the theoretical background of the neural logic networks and the genetic programming framework. The paragraph covers also a review in grammar-guided methodologies for genetic programming and the cellular encoding advances for connectionist systems representation within genetic programming individuals. Section 3 contains the design and the implementation description of the proposed system. In section 4 we include the description of the problem domain, our system configuration and the obtained results together with a discussion. Finally, section 5 contains our conclusion regarding this work and proposes future directions for this domain.

2 BACKGROUND

2.1 Neural Logic Networks

A neural logic network is defined as a finite directed graph. It consists of a set of input nodes and an output node. In its 3-valued form, the possible value for a node can be one of three ordered pair activation values (1,0) for true, (0,1) for false and (0,0) for don't know. Every synapse (edge) is also assigned a an ordered pair weight (x,y) where x and y are real numbers. An neural logic network and its output value (a,b) of node P is shown in *Figure 1*. It is possible to map any rule of conventional knowledge into a neural logic network by using different sets of weights, which enable the representation of different logical operations. In *Figure 2*, some examples of these logical operators and their implementation into neural logic networks are presented. The neural logic networks have not applied in many domains

within the CI framework, although they are powerful by their definition. The main reason can be located in the fact that for the known training methodologies (Teh 1995), (Tan and Teow 1997), the adjustment of the synapse weights eliminates the ability to interpret the extracted solution into a number of logical rules, thus depriving these networks from their valuable feature. In *Figure 3(a)* it is shown an easily interpretable neural logic network, while in *Figure 3(b)*, a network with adjusted synapse weights fails to be interpreted. Some steps for the preservation of the interpretability have been performed by (Chia and Tan 2001), which however proposed a system that lacks the ability to express arbitrarily large and connected neural logic networks. In *Figure 4(a),* a network that is produced by the methodology of by (Chia and Tan 2001) is shown. In *Figure 4(b),* it is shown a neural logic network, which performs the fundamental logical operation of XOR, and it cannot be represented using the direct encoding of (Chia and Tan 2001). In order to make the networks able to handle any real value (i.e. not only 3-valued pairs), the fuzzy extension for neural logic networks has been proposed (Teh 1995), a design that is also adapted here for the needs of the problem examined in this paper.

2.2 Genetic Programming

Genetic programming (Koza 1992) is an evolutionary computation approach, which in its canonical form enables the automatic generation of mathematical expressions or programs. Genetic programming retains a significant position among successful evolutionary computation approaches due to its valuable characteristics, such as the flexible variable-length solution representation and the absence of population convergence tendency. In most implementations, a population of candidate solutions is maintained, and after a generation is accomplished, the population increases its fitness for
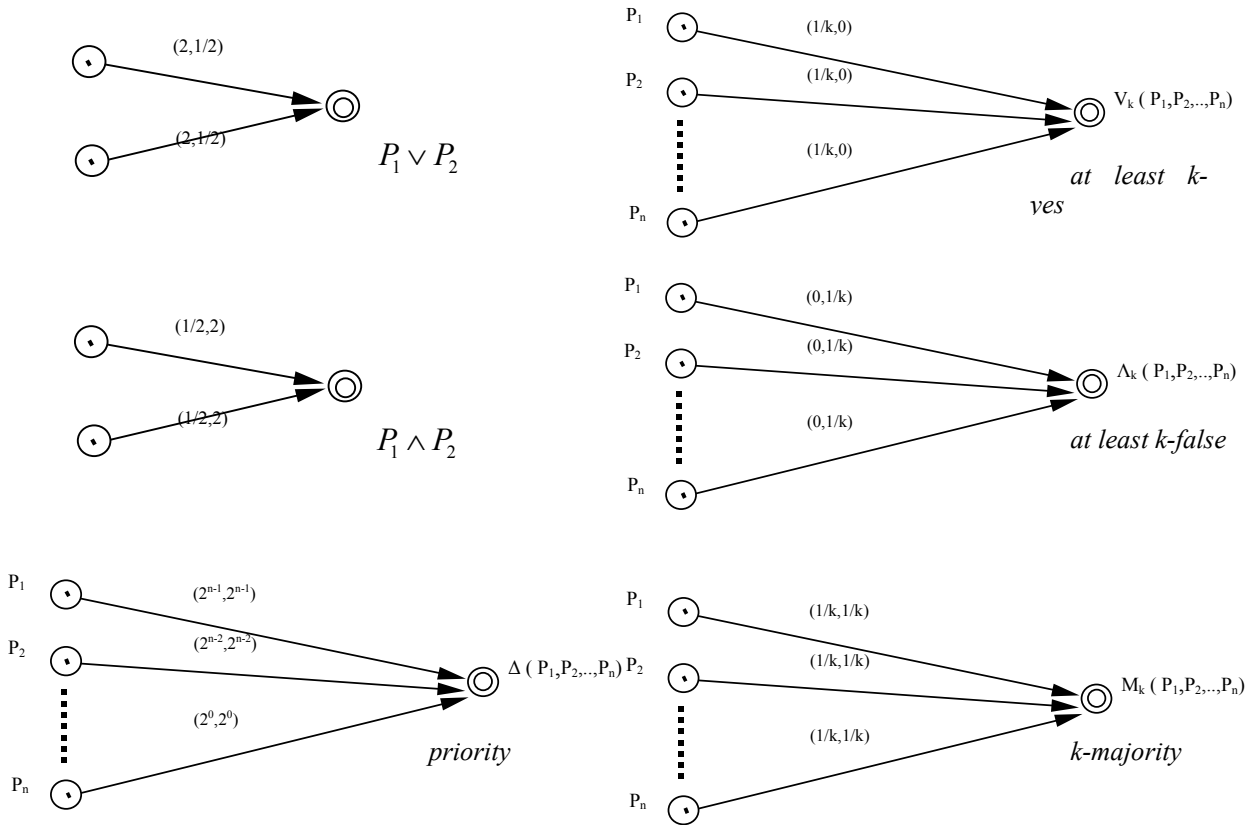
Figure 2: Example logical operations in neural logic networks

a given problem. The genetic operators that are mostly used in these algorithms are reproduction, recombination (crossover) and mutation. The first operation copies an individual without affecting it, the recombination exchanges genetic material between two individuals and mutation alters a part of a randomly selected genetic material. A genetic programming training cycle usually includes the following steps:

1. Initialise a population of individuals at random.
2. Evaluate randomly an individual and compare its fitness to other (this fitness determines how closely is an individual to the desired goal).
3. Modify an individual with a relatively high fitness using a genetic operator.
4. Repeat steps 2-3 until a termination criterion is met.
Common termination criterions are the

$Q1 \Leftarrow$ At least 2-yes(V_4, V_8)
$Q2 \Leftarrow$ Conjunction(V_4, V_8)
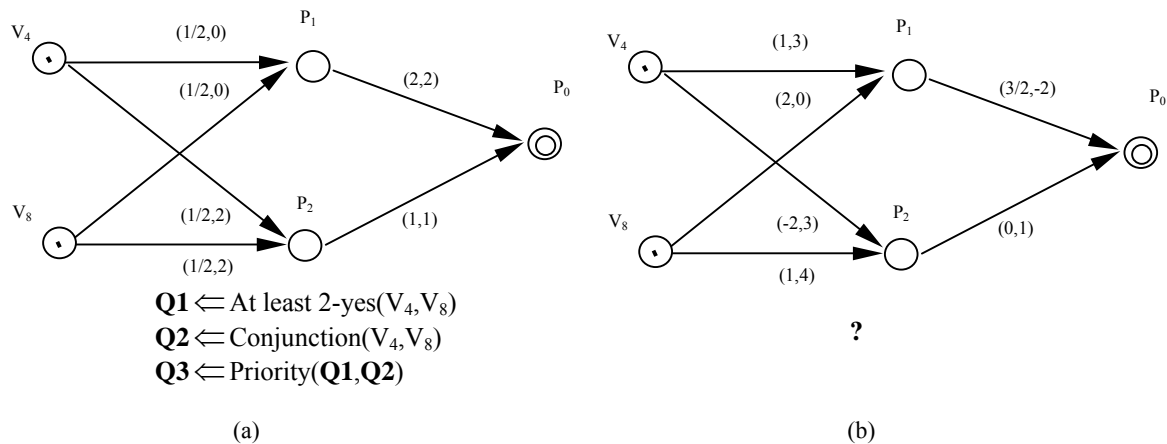$Q3 \Leftarrow$ Priority(**Q1**,**Q2**)

(a)

?

(b)

Figure 3: (a) Interpretation of a neural logic network into logical rules. (b) a network with refined edge weights that cannot be interpreted.
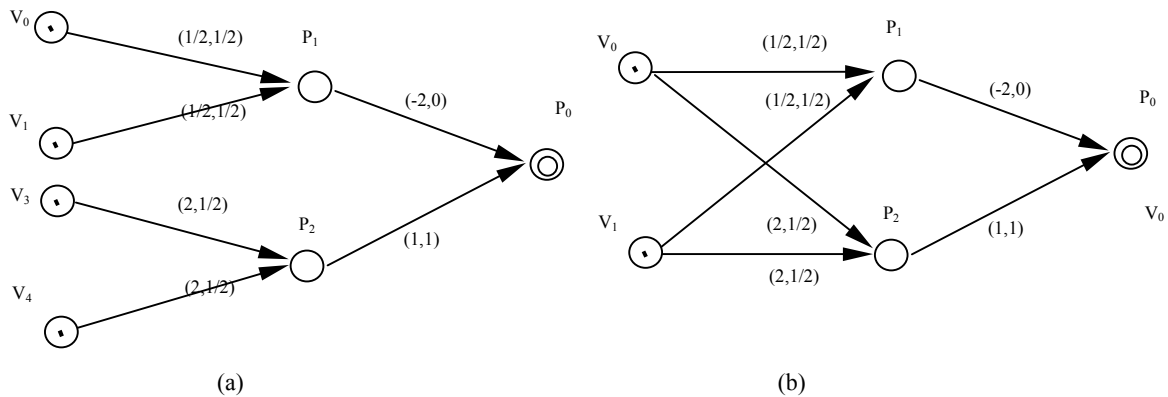
Figure 4: (a) Tree-like neural logic networks as generated in (Chia and Tan 2001). (b) a neural logic network that performs the XOR operation needs the general structure of a finite graph and cannot be described directly by the approach of (Chia and Tan 2001).

accomplishment of a number of generations, the achievement of a desired classification error, etc.

As previously stated, the genetic programming has been proved an advance over traditional genetic algorithms due to its ability to construct functional trees of variable length. This property enables the search for very complex solutions that are usually in the form of a mathematical formula - an approach that is commonly known as symbolic regression. Although later paradigms extended this concept to calculate any boolean or programming expression, the task of implementing complex intelligent structures into genetic programming functional sets in not rather straightforward. The function set that composes an intelligent system retains a specific hierarchy that must be traced in the genetic programming tree permissible structures. This writing offers two advantages. First, the search process avoids candidate solutions that are meaningless or, at least, obscure. Second, the search space is reduced significantly among only valid solutions. Therefore, when the syntax form of the desired solution is well defined, it is useful to restrain the genetic programming from searching solutions with different syntax forms (Gruau et al. 1996), (Montana 1995). One of the advantageous methods to implement such restrictions is to apply syntax constraints to genetic programming trees, usually with the help of a context-free grammar (Gruau 1994), (Janikow 1996), (Ryan et al. 1998). The execution of massively parallel processing intelligent systems such as the neural logic networks within the genetic programming framework is not considered a straightforward task. In order to explore variable sized solutions, it is required the application of an indirect encoding system. The most common one is the *cellular encoding* (Gruau 1994), in which a *genotype* - a point in the search space- can be realised as a descriptive *phenotype* - a point

in the solution space. More specifically, within such a function set, there are elementary functions that modify the system architecture together with functions that calculate tuning variables. Related implementations include encoding for feedforward and Kohonen neural networks (Gruau 1994), (Hussain and Browse 1998), (Tsakonas and Dounias 2002) and fuzzy Petri-nets (Wong 2001). A similar technology, called *edge encoding*, developed by (Koza et al. 2003) is also today used with human competitive results in a wide area of applications.

3 DESIGN AND IMPLEMENTATION

As mentioned in the previous paragraph, the characteristic feature of neural logic networks should be the ability to interpret any network architecture into a set of logical rules. For this reason, the *cellular encoding* is used in our model to represent the candidate solutions into genetic programming trees. One cellular encoding scheme includes (I) functions for architecture altering and (II) functions for parameter tuning. The functions for parameter tuning have common properties with the usual genetic programming functions, which operate as procedures or program elements. The functions that are used for architecture altering however are not used in standard genetic programming systems. They comprise a function set that alters an embryonic neural logic network, by entering nodes sequentially or in parallel onto an initial (elementary) neural logic network, in order to form the final / desirable architecture. Hence, among the architecture altering functions we may discriminate between (I-a) functions that enter a node serially, and (I-b) functions that enter a node in parallel. The problem that has arisen during the prime
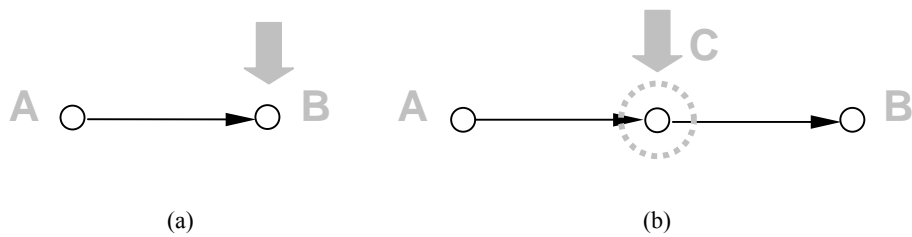
(a)   (b)

Figure 5: Application of the function S1 on the B node.

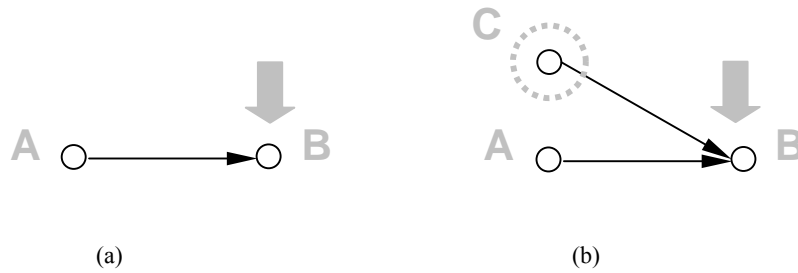(a)   (b)

Figure 6: Application of the function P1 on the B node.

implementations of cellular encoding concerns the grammar description, which enabled the existence of networks without inputs (Gruau 1994), a situation that can easily lead into premature population convergence.

Thus, in order to be able for a system to include at least one input, we incorporated different functions for the architecture altering on the system inputs, than those used for the architecture altering on internal nodes. Hence, we may further divide the architecture altering functions into two additional sub-classes, (I-1) functions that are applied on the system inputs and (I-2) functions that are applied on internal nodes. To conclude with, we use a function that enters a node in serial to an input node (S1), a function that enters a node in parallel to an input node (P1), a function that enters a node in serial to an internal node (S2) and, finally, a function that enters a node in parallel to an internal node (P2). In *Figure 5*, we demonstrate the operation regarding function S1. The application of this function on the B node in *Figure 5(a)*, results in the construction of the network shown in *Figure 5(b)*. The grey-coloured arrow shows the running cursor, which marks the point from which any further network expansion will occur. *Figure 6* illustrates the operation of P1 function. Application of this function on the B node in *Figure 6(a)*, results to the network shown in *Figure 6(b)*. *Table 1* depicts in short the functions that we used in order to describe the evolutionary neural logic networks. The system grammar is presented in *Table 2*. Initial symbol (root) of a tree can be a node of a type `<PROG>`. The logical functions that construct in this work

the operator set for the neural logic networks expressed in our system are shown in *Table 3*.

Table 1: GP- function set for neural logic networks.

Class	Function	Operation
Archi-tecture altering	P1	Enters a node in parallel to an input node
	S1	Enters a node in serial to an input node
	P2	Enters a node in parallel to an internal node
	S2	Enters a node in serial to an internal node
	PROG	Initial function. Creates the embryonic network
Para-meter tuning	CNR	Applies logical operator based on the CNRSEL and K values
	LNK	Cuts links based on the NUM and CUT values
	IN	Enters an input parameter value into the network
	NUM	Supplementary to the LNK function, selects the link to cut
	CUT	Supplementary to the LNK function, determines whether the link will be cut or not
	CNRSEL	Supplementary to the CNR function, its value determines the operator that will be applied to a node

| | K | Supplementary to the CNR, function, its value determines the logical operator's parameter (determined by CNRSEL). |

Table 2: Context-free grammar for neural logic networks.

<PROG>	: =	**PROG** <PLACE1><SYNAPSE>
<PLACE1>	: =	**S1** <PLACE1><SYNAPSE><PLACE2>
		| **P1** <PLACE1><PLACE1>
		| **IN**
IN	: =	Data attribute (system input)
<PLACE2>	: =	**S2** <PLACE2><SYNAPSE><PLACE2>
		|**P2** <PLACE2><SYNAPSE><PLACE2>
		| **E**
E	: =	$\varnothing$
<SYNAPSE>	: =	**LNK** <NUM><CUT><SYNAPSE>
		| **CNR** <CNRSEL><K>
<NUM>	: =	**NUM**
<CUT>	: =	**CUT**
<CNRSEL>	: =	**CNRSEL**
<K>	: =	**K**
NUM	: =	Integer in [1,256]
CUT	: =	Integer in [0,1]
CNRSEL	: =	Integer in [0,10]
K	: =	Integer in [0,9]

3 RESULTS AND DISCUSSION

The proposed system was applied in a banking sector aiming to both provide high classification rates and the ability to interpret the extracted solution. This data is acquired by an Australian bank (Quinlan, 1992). The features in this data are given as simple elements and their interpretation is not known, since this data set has been considered as classified information. However, the application of our methodology to this problem may provide useful conclusions regarding the system's effectiveness, since enough successful applications of other approaches exist (Quinlan, 1987), (Statlog, 2005), in related literature. The data is consisted of 688 records from which 344 were randomly used as training set, 172 as validation set and another 172 as test set (unknown data). There are 67 missing values in total, which were substituted with zeroes. *Table 4* presents the related attributes and the encoding that was used. This data is primarily composed by discrete attributes,

which are encoded into independent binary features for further processing by our system. The percentage of cases for which the application was finally accepted, reaches 44.5 % of the total (307 records). A total of 37 records have one or more missing values (5% of total data). After the training process was accomplished (200 genetic programming generations), our algorithm generated the neural logic network shown in *Figure 7*.

Table 3: Implemented logical functions.

Conjunction (AND)
Disjunction (OR)
Priority
At least k-true
At least k-false
Majority influence
Majority influence of k
2/3 majority
Unanimity
IF-Then (Kleene's model)
(logical) Difference
Exclusive OR (XOR)
Negative exclusive OR (XNOR), or equivalence (EQV)
Negative conjunction (NAND)
Negative disjunction (NOR)
Exactly k-true

Table 4: Feature description for the Australian bank credit-scoring problem

Variable	Values	Encoded features
T1-T3	discrete (b, a, ?), 12 missing values	1 (discrete) → 3 binaries, 1 of 3 (b="1 0 0", a="0 1 0", ?="0 0 1")
T4-T5	continuous (13.75...80.25)	1 (continuous) → 2 (1 continuous 0..1, 1 binary, 1: absent 0: non-absent)
T6	continuous (0...28)	1 (continuous) → 0..1
T7-T11	discrete (u, y, l, t, ?), 6 missing values	1 (discrete) → 5 binaries, 1 of 5
T12-T15	discrete (g, p, gg, ?), 6 missing values	1 (discrete) → 4 binaries, 1 of 4
T16-T30	discrete (c, d, cc, i, j, k, m, r, q, w, x, e, aa, ff, ?), 9 missing values	1 (discrete) → 15 binaries, 1 of 15
T31-T40	discrete (v, h, bb, j, n, z, dd, ff, o, ?), 9 missing values	1 (discrete) → 10 binaries, 1 of 10

T41	continuous (0…28.5)	1 (continuous) → 0..1
T42	binary	1 (binary) → 0..1
T43	binary	1 (binary) → 0..1
T44	continuous (0…67)	1 (continuous) → 0..1
T45	binary	1 (binary) → 0..1
T46-T48	discrete (g, p, s)	1 (discrete) → 3 binaries, 1 of 3
T49-T50	continuous (0…2000),13 missing values	1 (continuous) → 2 (1 continuous 0..1, 1 binary, 1: absent 0: non-absent)
T51	continuous (0…10000), 13 missing values	1 (continuous) → 0..1

The main conclusions regarding this extracted decision-rule follow:

· Only one simple attribute conjunction (AND operation) is contained in the resulting network, a result showing that no complex rules should necessarily be expected for building up an effective decision – making strategy from the bank's viewpoint, regarding credit applicants' evaluation.

· Getting into greater detail, attribute (feature) T15 seems to be of significant importance for the overall decision-making process. This feature is binary. The initial data feature from which T15 was derived, receives values from the set {g, p, gg, ?}, with
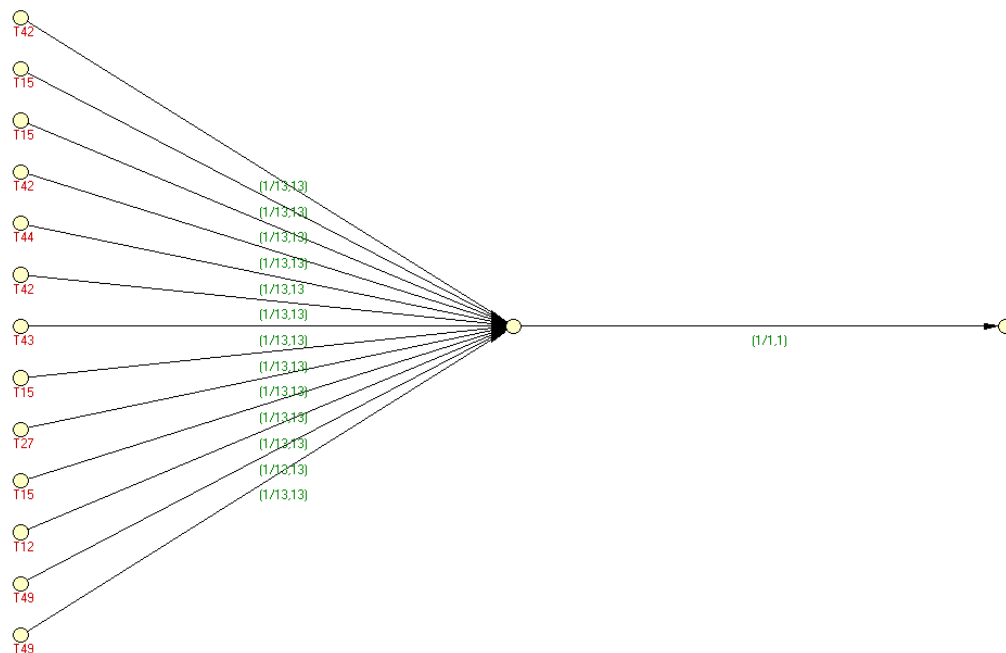
(CNLN (P1 (P1 (In T42) (P1 (In T15) (P1 (In T15) (P1 (P1 (In T42) (P1 (In T44) (P1 (P1 (P1 (In T42) (P1 (In T43) (P1 (In T15) (In T27)))) (In T15)) (In T12)))) (In T49))))) (In T49)) (Rule 0 0))))

Figure 7. Neural logic network (description and representation) generated for the Australian credit-scoring problem

The classification rate of this solution in the test set (unknown data) reaches 89.53% (154/172) which is higher than those reported in literature (Quinlan, 1992). The corresponding classification rates in the training and the validation set were 85.47% (294/344) and 87.21% (150/172) respectively. The generated neural logic network can be described by the following extremely simple decision rule:

Q ← *Conjunction* (AND) (T12, T15, T15, T15, T15, T27, T42, T42, T42, T43, T44, T49, T49)

T15 corresponding to the last value.

· Feature T42 is also of significant importance for the decision-making process.

Methodology	Classification rate in unknown data (%)
Cal5	86.9
Itrule	86.3
LogDisc	85.9
Discrim	85.9

Dipol92	85.9
Radial	85.5
Cart	85.5
Castle	85.2
Bayes	84.9
IndCart	84.8
BackProp	84.6
C4.5	84.5
Smart	84.2
BayTree	82.9
KNN	81.9
Ac2	81.9
NewId	81.9
LVQ	80.3
Alloc80	79.9
Cn2	79.6
QuaDisc	79.3
Default	56.0
This work (NLN)	89.5

· Another significant feature is the T49, which in the initial data set receives values within the range [0,2000].

The Australian bank data problem is particularly interesting, since it enables the comparison of our model with a number of competitive statistical and intelligent approaches. *Table 5* presents our results as compared with 22 other competitive approaches presented in (Statlog, 2005). Among the provided methodologies of *Table 5*, the proposed approach succeeded in obtaining the highest classification score using the specific neural logic network.

4 CONCLUSIONS AND FURTHER RESEARCH

Neural logic networks are a family of artificial neural networks designed with the aim to provide network interpretation into simple logical rules. Although successful in representing any set of logical rules into a network structure, the opposite has been proved unsuccessful. This result derived from the training procedures used so far which, based on edge tuning, destroyed the network's interpretation. Aiming to successfully use the neural logic networks family in the CI framework, this paper presented an architecture-altering and training methodology. This methodology overcomes the problems encountered in previous approaches and succeeds in producing highly accurate and interpretable neural logic networks. The methodology is tested in a problem from the banking domain with very encouraging results. It is acknowledged that further experiments are needed in similar or different domains in order to obtain a wider valuation of the examined methodology.

Further research includes the application of the system into more domains, especially from the financial sector where the neural networks have been proved an effective classifying and forecasting methodology and at the same time, the interpretation of a network has always been a desirable target. Moreover, the research will be driven to implement higher order recursive neural logic network, in an attempt to develop neural logic networks for financial problems dealing with time-series data.

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