

Knowledge Acquisition including Tags in a Classifier System

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Abstract- One of the major problems related to Classifier Systems is the loss of rules. This loss is caused by the Genetic Algorithm being applied on the entire population of rules jointly. Obviously, the genetic operators discriminate rules by the strength value, such that evolution favours the generation of the stronger rules. When the learning system works in an environment in which it is possible to generate a complete training set, the strength of the rules of the CS will reflect the relative relationship between rules satisfactorily and, therefore, the application of the Genetic Algorithm will produce the desired effects. However, when the learning process presents individual cases and allows the system to learn gradually from these cases, each learning interval with a set of individual cases can lead the strength to be distributed in favour of a given type of rules that would in turn be favoured by the Genetic Algorithm. Basically, the idea is to divide rules into groups such that they are forced to remain in the system. This contribution is a method of learning that allows similar knowledge to be grouped. A field in which knowledge-based systems researchers have done a lot of work is concept classification and the relationships that are established between these concepts in the stage of knowledge conceptualization for later formalization. This job of classifying and searching relationships is performed in the proposed Classifier Systems by means of a mechanism, Tags, that allows the classification and the relationships to be discovered without the need for expert knowledge.

1 Introduction

Classifier Systems (Holland 1975, 1980, 1985, 1986, 1986a, 1995, Golberg 1989, Mitchel 1996), the subject of this paper, are studied from the viewpoint of behaviour, an approach referred to as behaviourist, which considers exclusively the change in system behaviour and is defended, among others, by Narendra, Thathachar and Simon, (Thathachar 1989).

Classifier Systems (CS) combine the advantages of rule-based systems with the possibility of applying a domain-

independent learning system, such as Genetic Algorithms. The relative value of the different rules is one of the key information items to be learnt in a CS. In order to promote this learning, CS's oblige the rules to coexist in what is called an information-based economy service. Rules are made to compete, where the right to respond to the activation stems from the highest bidders, which will pay the value of their bids to the rules that are responsible for their activation. A chain of intermediaries is formed along this path, ranging from manufacturers (detectors) to consumers (actions to the environment). The competitiveness of the economy assures that the good (beneficial) rules survive and the bad ones disappear. There is a high level of relation and communication between the different levels of a CS (Golberg 1989).

The conditions and messages of a CS form a system of rules, making them a special class of production system. One of the main problems raised by production systems is the complexity of rule syntax. CS's find a way around this problem by restricting each rule to a fixed-length representation. This constraint has two benefits: first, all the rules, within a permitted alphabet, are syntactically meaningful and, second, a representation using fixed-length strings allows the application of genetic-type string operators. This opens the door to search of the space of permitted rules using Genetic Algorithms (Holland 1975).

As discussed above, traditional Classifier Systems combine rule-based knowledge representation with genetic learning. There is an obvious difference between systems that use Genetic Algorithms for learning and Classifier Systems. In the former, the solution to the problem is fully encoded in the binary representation used by the Genetic Algorithm, that is, the evaluation of one individual is tantamount to the evaluation of the whole solution (Mitchell 1996). In Classifier Systems, however, the evaluation of an output is equivalent to the evaluation of a rule that partly contributes to solving the problem. This evaluation is distributed across all those rules that contribute to the activation of the end rule, using the credit reassignment algorithm. In no case, however, is it an evaluation of the system composed of all the rules. This is the approach proposed by the University of Michigan (Holland 1986a).

New rules or sets of rules are generated from these evaluations. So, any rules that have been activated and provide a satisfactory solution to part of the problem will be the source of new rules.

The manner in which Classifier Systems operate has some drawbacks, of which the following deserve a special mention:

- With regard to the system's ability to learn chains of rules which, moreover, do not break from one learning instant to another; the loss of a rule from the chain can lead to a loss of all the knowledge due to the interrelations between rules. The rules make sense not individually but only as groups which are unknown *a priori*.
- With regard to the need to apply the discovery algorithm to generate increasingly better classifiers and, finally,
- With regard to the sequencing of the cases put to the system in order to guide learning towards an improvement in overall system behaviour.

The problem addressed in this paper is in particular how to combat the problem of the loss of rules and the need to "maintain acquired knowledge". Both problems are due to CS discovery level action, which leads the mechanisms of the CS to fail when forming and maintaining associations between rules. The discovery level acts on the set of classifiers that have just been executed in such a manner that the new rules are generated from the best rules prior to discovery level action. This operation can lead to the loss of rules that are necessary for solving certain points of the problem and which appeared at the start of the learning period but failed to do so later on. This means that rules which were very good at the start of the execution can be considered by the GA as less valuable, because other rules are stronger.

"Internal Tags" (IT), proposed by Holland (Holland 1995) and others for application to Genetic Algorithms, were introduced for this purpose, giving rise to a new class of CS, Classifier Systems with Tags (TCS). Apart from preventing the loss of rules, different rules must be made to coexist at all times, thus stopping the rules becoming uniform, leading to a loss of variety in the rule population. The remainder of this article will provide examples of the formats of all the major components of your paper. Please follow these directions as closely as possible to ensure that our proceedings looks like the quality publication the content will make it.

2 Related Works

2.1 Ad-hoc internal CS hierarchies

The problems of rule loss have been addressed from various viewpoints in the literature with a view, in all cases, to improving CS's. Shu et al. (Shu 1991) consider introducing

hierarchies into CS's, that is, groups of rules that have to be maintained throughout the learning process. The rule groups are formed *a priori* and are given by the expert problem-solver. This is an attempt to solve the problem which DeJong (Booker 1989) solved by means of *crowding* in the field of Genetic Algorithms. So, on the one hand, they establish rule groups (families) and, on the other, they propose genetic operators that act intrafamily and interfamily. The payment system is also modified, and when a rule from one group wins, all the other rules in its group also partake of that prize.

Basically, the problem with discovery level action is that all the rules are considered to be equal. This idea, which is logical in other Evolutionary Computing techniques, where each individual is a solution to the problem, and they, therefore, all have to compete with each other, is not directly extendible to CS. This is because no one rule is capable of solving the problem on its own in many cases, which means that not all the rules are equal. A rule that is fired in a particular situation and whose action solves the problem is not the same as a set of rules that must be fired in order so as to address a different situation. Here, the strength of the first rule is likely to grow much more than the strength of all the rules chained in the second case. In order to solve this problem, Shu proposes dividing the CS rule set into subsets, each of which has rules specialized in a particular point of the problem, in such a manner as to make the members of the same family of rules compete.

2.2 Hierarchically Organized Independent CS

In 1995, Dorigo (Dorigo 1995) presented the results of solutions designed to make Classifier Systems learn faster. The tools he used are: parallelism, a distributed architecture and training. With respect to parallelism and the parallel architecture, he proposes a parallel version of ICS (Dorigo 1993), and designed a parallel Classifier System, called *Alecsys*, applied to what is termed the "animal problem" (Wilson 1985). This problem is addressed from the viewpoint of dividing the problem into smaller parts, based on a hierarchical architecture in which a series of ICS's learn to cooperate in solving the learning problem. The different ICS levels are executed in parallel on different machines, and, moreover, different ICS's, responsible for different tasks, are also executed in parallel. The author (Dorigo 1995) takes up Brooks's idea of "reactivity" (Brooks 1991), that is, the existence of a set of behaviours, each of which is implemented by means of an ICS and which are independent of each other and produce an output for each input. The whole system is composed of three systems: an ICS to overcome obstacles, another to attain a goal and, finally, a system that decides which of the two possible outputs is the output of the combined system.

The author proposes that internal conditions be included to achieve rule chaining (which is equivalent to behaviour

chaining in this case). This allows messages from the environment to be distinguished from messages from earlier cycles. Dorigo's study centres on the usefulness of the internal conditions without clearly explaining how they are used internally by the CS. The results of this part of the paper show that the size of these internal conditions, as applied in this case, is not very relevant for learning.

3 Knowledge Classification In TCS

Automatic category generation within a CS has not been addressed in any paper to date. The idea can perhaps be borrowed from nature: some species use "tags" to limit a "call or warning" to a set of individuals, discriminating a subset among the total set. In the same manner, parts can be included in rules that allow some to be discriminated from others. What we will call *Internal Tags* (IT) can be defined in an *ad hoc* manner by creating a given string of calls (Shu 1991) or can be defined in such a manner that the ITs themselves evolve, determining what groups are necessary. In short, each rule can be provided with a field which will evolve genetically and which identifies that the rule in question is a member of a group, similarly to the tags proposed by Holland (Holland 1995).

The proposed solution must, therefore, combine the ability to learn without *a priori* knowledge and the capability of generating some kind of internal subdivision within the CS to allow categories of rules to exist. A CS, called TCS, has been designed that allows groups to evolve automatically. For this solution to be implemented, the encoding of the classifiers will have to be modified to include a field that represents the type or group to which each classifier belongs. So, for example, given a CS, A 1-bit field can be reserved to establish the classes making up the CS. This field can be used to subdivide the CS into several groups of classifiers, each of which contains the classifiers that have the same value in the new field. This field can be said to establish the classifier type or group. According to the definition of the value of the field that establishes the classes, there are 2 classes: one defined by classifiers whose value is 1 and the other by those whose value is 0. Note that the definition of a class is determined by the value of the above field in the condition part of the rule, that is, rules that must have the same value in the field for activation are members of the same group.

This field, which appears in the encoding, evolves in the same manner as the other fields, which means that the number and size of each class in the CS hierarchy is variable and must be learnt. Wide ranging groups can be established, and all the classifiers could actually have the same value, in which case the system would operate like a classical CS.

Apart from establishing the classifier type according to the value of the condition part, as it is included in the

message part which evolves similarly, not only are the rule groups evolving, so is the form of intergroup activation.

Finally, it is important to take into account that the inclusion of a field in the classifiers means that a value must also be entered in the input message in the above position. This value is not determined by the environment; it is defined *a priori* by means of a value encoding the fact that the message in question is the environmental message. In this manner, the CS will have to learn which rule group having the same group definition field value is to be activated in response to the environmental message.

The appearance of hierarchies in the CS is subject to the information about the category to which the rule belongs being maintained in each rule. This information must evolve genetically; obviously, if the information about the category in each rule is capable of representing "n" different categories, the solution to the problem could be composed of m ($m < n$) categories and the remaining categories would be irrelevant. If this information is represented in each rule and it is allowed to evolve, the number of rules associated with a particular category is also variable; in this respect, the genetic evolution of the categories will not only allow the categories required to evolve but also for each one to have the size required to solve the problem.

4 TCS Evaluation In The Game Of Draughts

In this paper, we seek to get a measure of the contribution of Internal Tags (IT) to the learning process in a Classifier System. A clear evaluation of the contribution of ITs in the encoding calls for a problem that is solved in a perfectly defined environment. The environment chosen in this case was the learning of draughts end games, that is, draughts matches where only a few pieces remain on the board at an advanced stage of the game.

The objective of applying the TCS to learning the game of draughts is not to obtain a CS that plays draughts; it is to apply Classifier Systems in a clear and defined environment that allows traditional Classifier Systems to be compared with the modification proposed in this paper, including IT. Obviously, there are a lot of systems that play draughts, some very successfully (Schaeffer 1997). However, for the purposes of this study and comparison, a player following a random strategy will be used, and measurements will be taken of the games each type of CS (classical/with IT) wins against the random player using different configurations.

4.1 Game Rules

There are a lot of variations on the game of draughts. In this paper, a 64-square board is used with black and white squares. The game is played by two players one with white pieces and the other with black pieces, which are either pieces or kings. Initially, the white pieces are placed at the bottom of the board and the black pieces at the top, and

there no kings. In this paper, the opening boards are not used, as we work only with end games, where the maximum number of pieces is 5. These can be pieces of any kind and be situated in any valid position on the board.

4.2 Information encoding

This involves analysing how and what information about the board, the pieces, players, turns, moves, etc., can be supplied to the CS as an input message. The encoding chosen for the game of draughts is such that an output from the CS is always interpreted as a move. This means that the CS decisions are interpreted depending on the system status. Obviously, the system must be able to play with both black and white pieces, so an encoding was chosen that does not take into account "the colour" of the piece. Additionally, the directions of the moves have been taken to be absolute.

4.3 Payment function

The objective of the payment function that analyses the quality of the classifiers is to guide CS learning. The CS will learn depending on the payment function, and this, precisely, is the central objective of the CS developer when the CS's are applied to a particular problem. For the purposes of this paper, the CS should be able to beat a random player, that is, a player who has no strategy and whose moves are not determined by the situation. This objective means that the payment function does not need to be able to evaluate different situations and detect the finest distinction in the moves decided by the CS; on the contrary, the payment function should be simple and objectively evaluate the decisions made by the CS, assessing each move on the basis of "quantitative" results. In this manner, the CS will be able to beat a random, though not an experienced, player, and it will be possible to compare the classic CS and the TCS objectively.

The payment function takes into account the following factors: whether or not a piece has been captured, whether or not a king has been crowned, and the number of pieces taken. The payment will be made once the opponent has made a move. So, the payment function employed is based on the results achieved by the opponent and the results obtained by the CS move. In this case, payment can be represented by means of Table 1, where n_{cs} is the number of pieces taken by the CS and n_{op} the pieces captured by the opponent.

Table 1: Payment function for CS's and TCS's applied to the game of draughts.

		CLASSIFIER SYSTEM			
		TAKES n_{cs} KING	Does not TAKE KING	TAKES n_{cs} No KING	Does not TAKE No KING
OPONENT	TAKES n_{op} KING	$n_{op} \geq n_{cs} : -100 * n_{op}$ $n_{op} < n_{cs} : 100 * n_{op}$	$-200 * n_{op}$	$n_{op} \geq n_{cs} : -100 * n_{op} - 10$ $n_{op} < n_{cs} : 100 * n_{op} - 10$	$-200 * n_{op} - 10$
	Does not TAKE KING	$200 * n_{cs}$	20	$200 * n_{cs} - 10$	-20
	TAKES n_{op} No KING	$n_{op} \geq n_{cs} : -100 * n_{op} + 10$ $n_{op} < n_{cs} : 100 * n_{op} + 10$	$-200 * n_{op} + 10$	$n_{op} \geq n_{cs} : -100 * n_{op}$ $n_{op} < n_{cs} : 100 * n_{op}$	$-200 * n_{op}$
	Does not TAKE No KING	$200 * n_{cs} + 10$	70	$200 * n_{cs}$	0

At the end of the game, the opponent player makes no move on the basis of which to evaluate the preceding move by the CS, so the result of the game is evaluated directly:

IF (the game ends in a draw) THEN (the payment is 400)
 IF (the game does not end in a draw and the CS wins)
 THEN (the payment is 700)
 IF (the game does not end in a draw and the opponent player wins)
 THEN (the payment is -700)

The payment developed is totally objective and depends on whether or not a piece is taken and on whether or not a king is crowned. This means that no payment is made if the move did not have a quantifiable result. Indeed, if there is no measurable quantity, the payment is 0. This payment 0 defines situations that will not be evaluated and, therefore, limits Classifier System learning ability. This limitation rules out any subjectivity coming into the payment that assesses CS operation, thus distorting the comparison between the classical CS and the TCS.

5 Comparison between CS and TCS

The objective of this section is to compare the traditional CS with the TSC. For this purpose, the above systems will be played against a player who makes random moves, having a variable degree of randomness and starting from different situations. The two systems commence without any previous knowledge, that is, their entire population is randomly generated, which means that their rules and messages are not adapted to any particular case and their moves will, in principle, also be random.

The three types of experiments conducted under this point were performed by gradually increasing their difficulty level in order to examine the behaviour of the two systems in face of the above changes.

Three groups of experiments with a different starting situation were performed for the comparison. The experiments were defined in increasing order of complexity, depending on the opening board with which each game that was to be played commenced: first, the opening board will be fixed for all the games, then the positions of the pieces that appear on the board in each game will be altered and, finally, the opening board will be generated at random for each game. In the first experiment, differing degrees of randomness will be applied to the opponent player, starting with 0% randomness and increasing this percentage up to 100% randomness. In the last two experiments, the opponent will 100% random throughout, and the opening boards will be modified incrementally, either by changing the position of the pieces or by generating a new board.

The result will show the evolution of the games won and lost by the two types of Classifier Systems. These results correspond to the average of five groups of games. In order to analyse the results obtained in more detail, the

percentages of games won at the end of learning for each CS and for each experiment, and the percentage improvement of the TCS as compared with the CS are set out in Table 2, Table 3 and Table 4. Analysing the results, we find that the contribution of ITs to the CS is not relevant in all situations. In problems where the CS has to learn a very simple sequence of operations, because the problem to be solved is less complex, the ITs can turn out to be more of a handicap, as their inclusion means that the system is forced to "learn" how to chain rules, when such chaining may be unnecessary. As the problem becomes more complex, the need for rule chaining increases, and the contribution of the ITs becomes evident, since their existence encourages rule chaining. So, we find that the results of the TCS in the first experiments (Table 4) only improve on the CS in the last case. On the other hand, an improvement is seen in the results obtained with the TSC as compared with the CS in the subsequent experiments performed (Table 5 and Table 6).

Table 2: Summary of the results of CS and TCS: Same Opening Board.

	0%	20%	30%	40%	50%	60%	70%	80%	90%	100%
CS	0.95	0.95	0.95	0.95	0.95	0.9	0.95	0.96	0.85	0.75
TCS	0.9	0.68	0.78	0.77	0.79	0.9	0.77	0.68	0.7	0.8
% Im	-5	-27	-17	-18	-16	0	-18	-28	-15	5

Table 3: Summary of CS and TCS results: Modified Opening Board.

	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
CS	0.77	0.62	0.65	0.7	0.78	0.78	0.78	0.76	0.76	0.55
TCS	0.9	0.7	0.8	0.82	0.85	0.85	0.84	0.86	0.84	0.58
% Im	13	8	15	12	7	7	6	10	8	3

Table 4: Summary of CS and TCS results: Randomly Generated Opening Board.

	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
CS	0.76	0.76	0.7	0.7	0.7	0.7	0.68	0.64	0.6	0.45
TCS	0.89	0.9	0.9	0.88	0.86	0.82	0.8	0.8	0.75	0.5
% Im	13	14	20	18	16	12	12	16	15	5

Table 2 shows the results of the experiments in which the opening board was unchanged. In this case, the problem appears not to require rule chaining to develop strategies that can be used in unexpected situations, since the opening board is fixed and there are, therefore, only limited possibilities of different moves. So, the CS is faced with a player who, for all intents and purposes, makes a well-defined series of moves whose variability is very restricted. This is why the TCS results are 14% worse on average than those obtained by the CS. Considering that this is the simplest possible case, it appears that is counterproductive to force the CS to employ ITs, as it makes the TCS play worse than the CS. In the last case, where the systems face

maximum variability, the results are very similar, and those obtained by the TCS are slightly better, mainly because the need for chained strategies starts to become evident.

Table 3 shows the results obtained when the opening board is modified using an incremental degree of randomness. In this case, the TCS performs 10% better on average than the CS; this is because the system has to start to generate more complex actions to be able to respond to more diverse situations. It is noteworthy in this case that the two systems obtain poor results at the maximum level of randomness, compared to the results that they obtained at lower levels of variability. This is perhaps due to the fact that these are very indeterminate situations where it is difficult for the system to be able to extract knowledge.

In Table 4, the results obtained show that as the degree of uncertainty in opponent player performance is increased, a higher percentage of the results of the TCS are better than those of the CS, in this case 15% on average. Again neither of the two CS are able to obtain results of over 60% of games won with the effect of maximum randomness.

In short, we can infer from the results obtained that Classifier Systems are able to learn in games environments and that when the game is complicated, it requires a complex solution which is not satisfactorily provided by classical CS's and thus requires the inclusion of tags.

The results presented show how the proposed Classifier Systems are capable of improving on the classical approach of Classifier Systems in cases in which rule chaining is relevant. The importance of this contribution is the discovery of a learning method that allows similar or related knowledge to be grouped. This property of ITs, the automatic grouping of rules that share the same objective, is of special interest, and a study has, therefore, been conducted to analyse what effect they have and what results are obtained in each of the proposed Classifier Systems.

6 Analysis Of Groups Of Rules Learnt

The encoding used to represent the rules in the Classifier System used to play draughts employs a lot of symbols. Not only is the number of symbols extensive, the encoding is very complex so as to ensure that all the outputs given by the Classifier System are valid. The need to generate valid responses at all times means that the meaning of the rule depends on the position of the pieces on the board. The meaning of the rules belonging to one group is, in this case, a problem for which there is no accurate analysis. Although the study of the meaning of the groups appears to be the best means of understanding what the Classifier System has learnt, this is ruled out by the extent and complexity of the chosen encoding. Therefore, we will study the different situations in which the inclusion of the IT improves Classifier System learning. How the groups have evolved and the number of rules belonging to each group in the

learning process is also of special importance. In order to perform the experiments with the TCS, 4 bits were reserved in the condition part and message of each classifier. 81 groups could be generated with 4 bits as shown in Table 5, each described by the value of its tags.

Table 5: Tags for the possible groups that can be generated with 4 bits.

0000	1000	000#	00#0	0#00	#000	00##	0#0#	#00#	0###	####
0001	1001	001#	00#1	0#01	#001	01##	0#1#	#01#	1###	
0010	1010	010#	01#0	0#10	#010	10##	1#0#	#10#	#0##	
0011	1011	011#	01#1	0#11	#011	11##	1#1#	#11#	#1##	
0100	1100	100#	10#0	1#00	#100	0##0	#0#0	##00	##0#	
0101	1101	101#	10#1	1#01	#101	0##1	#0#1	##01	##1#	
0110	1110	110#	11#0	1#10	#110	1##0	#0#0	##10	###0	
0111	1111	111#	11#1	1#11	#111	1##1	#1#1	##11	###1	

After analysing the TCS obtained in the different experiments, we find that 10 groups are formed, whose tag values are as shown in Table 6. All the groups are formed using the alphabet {1,#}, which allows all the rules included in the TCS to be matched with messages that have the values "1111" in their IT area. This is because all the environmental messages have been identified with IT values "1111", and the TCS learns rules that can respond to these situations. However, not all the rules have the value "1111", which would mean that they only match with the environmental message, because the TCS learns the need to generate different groups and chain rules in internal cycles, where the environmental message is no longer involved.

Table 6: Tag values of the groups formed in the experiments with the TCS.

1111	111#	11#1	1#11	#111	11##	1##1	1###	##11	####
------	------	------	------	------	------	------	------	------	------

The chosen encoding means that it is out of the question to interpret the classifiers obtained. Therefore, we will analyse how the number of rules in each of the groups formed changes as the experiment advances. The most complicated case of those shown was chosen, based on an opening board generated with 10% to 100% randomness. It is in this experiment that the inclusion of ITs in the CS improves most on the results obtained without ITs. The evolution of the number of rules of the different groups are shown from Figure 1 to Figure 10. The figures show that the number of rules belonging to each group levels out as of the experiment with 70% randomness (Exp 70) in opening board generation. "1##1" and "##11" are the groups whose number of rules increase most. The groups with the most pronounced fall in the number of groups are: "111#", "1#11", "#111" and "####". Although they do undergo changes throughout the experiments, the number of rules in

the other groups remain within a relatively narrow margin of values.

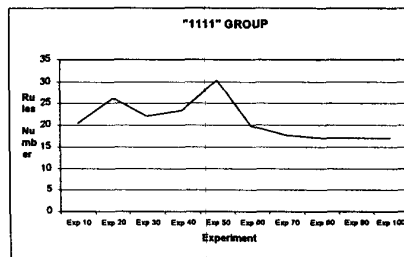


Figure 1: Evolution in the number of rules of group "111" with increased board generation randomness.

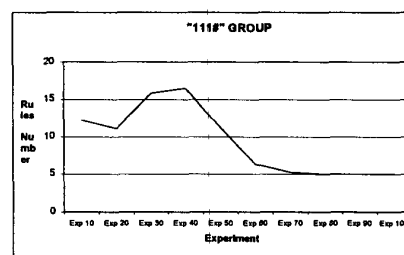


Figure 2: Evolution in the number of rules of group "11#" with increased board generation randomness.

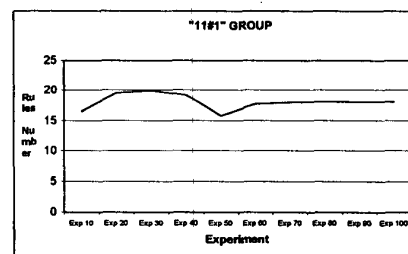


Figure 3: Evolution in the number of rules of group "1#1#" with increased board generation randomness.

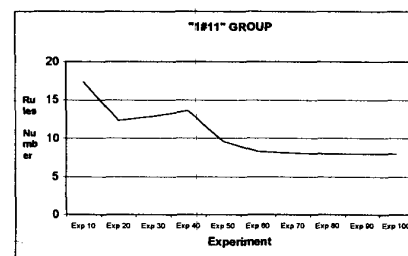


Figure 4: Evolution in the number of rules of group "1#11" with increased board generation randomness.

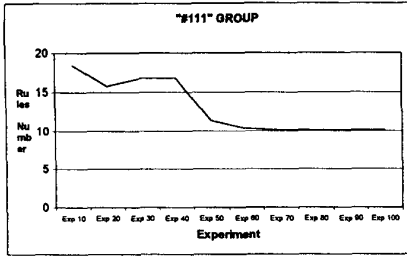


Figure 5: Evolution in the number of rules of group "#111" with increased board generation randomness.

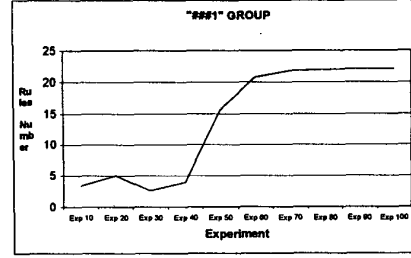


Figure 9: Evolution in the number of rules of group "###1" with increased board generation randomness.

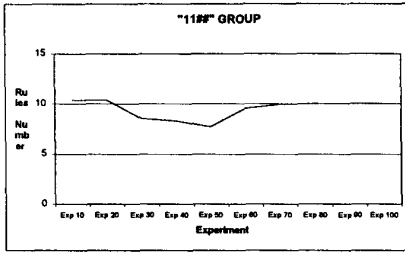


Figure 6: Evolution in the number of rules of group "11##" with increased board generation randomness

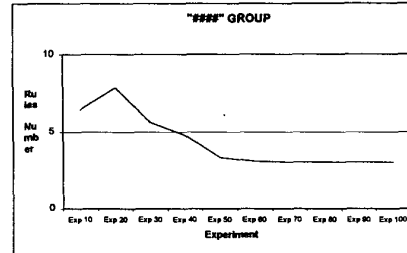


Figure 10: Evolution in the number of rules of group "####" with increased board generation randomness.

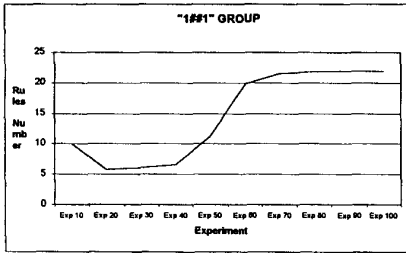


Figure 7: Evolution in the number of rules of group "1##1" with increased board generation randomness.

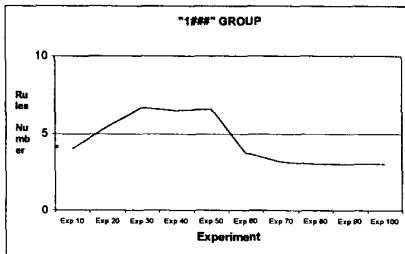


Figure 8: Evolution in the number of rules of group "1###" with increased board generation randomness.

The evolution of the number of rules of the groups that increase and decrease most is related to the specificity of the IT values. The groups that decrease are more specific (except the one defined by "####" which will be dealt with separately) than those that increase; however, the three specific groups are included in the more general ones. In this manner, rules that belonged to the three groups and represented similar situations, even if they were in different groups, have been able to migrate to another group that represents that common situation. As the target group is less specific, the rules include the response to the IT values of the groups to which they belonged before they migrated.

With respect to group "####", which is the most general group and includes all the others, it is found that, first, in no experiment does it have a very significant number of rules (the maximum value is 7). Apart from not containing many rules, this group decreases precisely because the generation of possible strategies does not require rules that are totally general and fail to discriminate the rules by which they are activated. The final leveling value of this group is 3.

As we have seen, the only groups formed are those required to solve the problem, as opposed to all the possible groups. In this case, this finding appears to be influenced by the IT values learnt, as, although no more groups are necessary, these groups did have to act according to a particular hierarchy. In these experiments, we find that not only is the TCS able to learn groups of rules, it is also

capable of establishing hierarchies between groups, using the '#' symbol.

7 Conclusions

The objective of this paper was to obtain an encoding structure that would allow the genetic evolution of CS groups in such a manner that their number and relationship would also be learnt in the evolution process. For this purpose, an area that allows the definition of rule groups has been entered into the condition and message part of the encoded rules. This area will be named Internal Tags. This term was coined as the system has some similarities with natural processes that take place in certain animal species, where the existence of tags allows them to communicate and recognize each other.

As an encoding that uses symbolic knowledge of the problem is used in Classifier Systems, combined with genetic techniques for learning, this classification of concepts can evolve as part of the solution to the problem. In response to the question of how the system is able to learn what concepts are related, the Genetic Algorithm establishes relationships between concepts not by analysing their meaning, but depending on the results obtained, that is, the Classifier System evolves the groups of rules so that the solution to the problem improves all the time. A rule's membership of a group does not depend on its symbolic meaning, but on how good it is for the whole system to solve the problem, evaluated by means of the payment function.

These ideas allow the generation of complex strategies which solve problems that require an elevated chaining depth and where each rule in this chain is essential for attaining the final solution. For example, for a CS that plays draughts, the need to output complex solutions and for different rule types to coexist (such as rules for taking and rules for moving, for example) gains in importance, and these rules could disappear as a result of Genetic Algorithm action, if some of the rule types are not employed during a certain number of cycles. The CS with tags (TCS) was proposed to solve this problem, in which positions are reserved in the rules to encode information with regard to the group to which they belong.

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