Social Computing Article*

Tabajara, Lucas

Institute of Informatics
Federal University of Rio Grande do Sul
Brazil

Imtabajara@inf.ufrgs.br and Prates, Marcelo
Institute of Informatics
Federal University of Rio Grande do Sul

Abstract

Brazil

System Overview
morprates@inf.ufrgs.br

Abstract

1 Introduction

For years multi-agent systems have been used to research cooperation as a tool for problem-solving. Recently, however, there has been an increasing interest in the use of human beings as problem-solving agents. Several studies have been conducted in which subjects are connected in a network with the goal of searching for the solution of a specific problem, and those have helped shed some light on the way humans interact in order to solve problems.

The experiments conducted by [Farenzena et al., 2011] had human beings trying to solve constraint satisfaction problems, namely Boolean Satisfiability (SAT) and the popular Sudoku game, with individuals connected through the network being able to exchange partial solutions of the problem in question. The behaviour observed in that study has provided evidence that human beings in a cooperative problem-solving environment might not evaluate solutions proposed by their peers, instead choosing the most readily available one.

Another result of those observations is that there is a higher probability of individuals copying peers' solutions when those are shared by several neighbours, referred to as an evidence of *conformist behaviour*. A similar behaviour was observed in [Mason and Watts, 2011] for a different problem.

We have built a multi-agent system that simulates the experiments of [Farenzena *et al.*, 2011] with the aim of verifying whether the strategies employed by humans are competitive with other heuristics. After identifying the points in which those are lacking, we will then propose methods to increase the efficiency of human problem-solving networks.

2 Background

Background

3 Contribution

Contribution

We developed a system in which the environment of the sudoku problem-solving social network presented in [Farenzena *et al.*, 2011] could be modelled through autonomous agent networks and analysed through a series of experiments. The optimization technique of *Memetic Networks* [Lamb and Araujo, 2008] was employed on the modelling, providing a basis for the dynamics of the agent network.

5 Sudoku Solving Memetic Network

A Memetic Network Algorithm is composed of an ordered set of N agents, each encoding a complete solution to the optimization problem, and a binary $N \times N$ matrix representing possible connections between agents. Additionally, a Memetic Network Algorithm is composed of a set of rules specifying how connections between agents are formed and erased and how interactions between these agents take place. These rules are grouped under the categories of Connection Rules, specifying how agents will connect and disconnect from each other; Aggregation Rules, specifying the dynamics of the information flow through connections; and Appropriation Rules, specifying how agents are supposed to add local changes to the information received through their connections [Lamb and Araujo, 2008].

Our solution adapts the *Memetic Newtork* technique - originally intended for use in optimization problems - to the context of constraint satisfaction problems. In this specific case (sudoku solving), we treat problems with one unique solution. To deal with this scenario, we propose a *Memetic Network* variation in which each agent encodes not a complete, but a partial solution to the problem.

Our solution employs a fixed topology for the agent network and models cooperation through a set of aggregation rules and reasoning through a set of appropriation rules. Our aggregation rules specify how sudoku partial solutions are copied from agent to agent, while our appropriation rules specify how agents increment these solutions with sudoku solving techniques such as naked singles, swordfish, etc.

5.1 Aggregation Rules

The experiments conducted by [Farenzena *et al.*, 2011] point out a series of observations about the dynamics of cooperation in problem solving with human beings. For instance, the

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authors analysis has shown that users tend to copy not the most complete solutions, but, instead, the first solutions on the graphic interface. Additionally, we know from this same paper that users rarely copy solutions from more than 6 neighbours. In order to analyse and compare this behaviours, we developed a collection of aggregation rules, each modelling a copying strategy.

Pick Most Filled

This rule employs the intuitive strategy of copying from the neighbour with the most filled sudoku, namely the most complete solution.

Pick Among First

We know that users tend to copy the first (from left to right) solutions on the graphic interface [Farenzena *et al.*, 2011]. The authors have provided us with a mathematical model of this behaviour, stated as $X(k) = (1 - p)^{k-1}p$, where the parameter p is fixed as p = 0.5479 and X(k) denotes the probability of an agent copying the k_{th} neighbour solution.

We inserted this behaviour into our model by firstly generating a random ordering of neighbours for each agent in order to compose a simulated graphic interface. As a result, each agent visualizes some neighbours before or after others. Secondly, we translated the above mathematical model into an aggregation rule in which the solution copied by an agent is the k_{th} with probability X(k).

5.2 Appropriation Rules

In sudoku strategy literature, as in chess, we find multiple techniques with iconic names. Some popular examples are *naked singles*, *naked twins*, *swordfish*. These strategies intend to, given a sudoku puzzle in a partial state of completion, generate movements to mark blank cells of the puzzle, as "*mark cell 1 of column 3 with value 5*". We reproduced a variety of these strategies, modelling each one of them as a function that maps a sudoku partial solution to a set of movements.

Only Choice

This technique marks a sudoku cell with a value only if this cell is the last blank cell on its row, column or 3×3 block. For instance, the *only choice* rule would mark cell (1,2) with value 4 in the below sudoku puzzle:

$$\begin{pmatrix}
& 7 & & 5 & 8 \\
5 & 6 & 2 & 1 & 8 & 7 & 9 & 3 \\
& & & & 1 & & \\
& & & 8 & 1 & \\
& & 3 & 7 & 6 & & \\
9 & 6 & & & & \\
& & 4 & 2 & 1 & 8 & 3 \\
8 & 7 & & & 3 & &
\end{pmatrix}$$

Single Possibility

This rule marks a sudoku cell with value v only if v is the single possible value to mark that cell. The other values must have been eliminated through a process of verifying that they are all present in the span encompassing the cell's row, column and 3×3 block. For instance, the *single possibility* rule would mark cell (4,1) with value 7 in the below sudoku puzzle, since the values 1, 2, 3, 4, 5 and 8 were already present in the cell's column (leaving the possibilities 6, 7 and 9). Additionally, the values 6 and 9 were already present in the cells' row, thus leaving the single possibility 7.

$$\begin{pmatrix} 8 & 2 & 5 & 6 & 3 & 1 & 9 & 7 & 4 \\ & 6 & 7 & & 2 & 4 & & & 8 \\ 4 & & & & 7 & 6 & & 2 \\ & 5 & 9 & & 4 & 8 & 2 & 6 & 1 \\ 1 & & 8 & 2 & 6 & 9 & 7 & 4 & 5 \\ & 4 & & 1 & 7 & 5 & & 8 & \\ 3 & & 1 & 4 & & & & \\ 5 & & & & 3 & 4 & & \\ 2 & 9 & 4 & & & 6 & 5 & & \end{pmatrix}$$

Two out of Three

This rule applies to groups of three contiguous 3×3 blocks. It aims to find a value v such that v is present in two of the three 3×3 blocks encompassed by the group, but missing on the third. It proceeds by enumerating all the candidate cells - namely the empty cells - on this block, and then, by eliminating from this set all the cells that are encompassed by the rows or columns in which v is placed on the other two blocks. If the resulting set has cardinality 1, the rule has successfully found one cell to mark. For instance, the *two out of three* rule would mark cell (2,9) with value 1 on the below sudoku.

$$\begin{pmatrix} & 9 & 5 & 1 & & 6 & 2 \\ 6 & 3 & 4 & & & 5 & 9 \\ 1 & 2 & 5 & 6 & 3 & 9 & 7 & & 4 \\ 2 & 5 & & 8 & 4 & 7 & 6 & 3 \\ 4 & 6 & & 5 & & 1 & 7 \\ & 8 & 7 & 3 & 6 & 1 & & 2 & 5 \\ 5 & & 6 & 1 & 7 & 3 & 2 & 4 & 8 \\ & 1 & 2 & & & 9 & 7 & 6 \\ 7 & 4 & & & 9 & 6 & 1 & & \end{pmatrix}$$

$$\begin{pmatrix}
6 & 3 & 4 & & & 5 & 9 & 1 \\
1 & 2 & 5 & 6 & 3 & 9 & 7 & & 4 \\
2 & 5 & 8 & 4 & 7 & 6 & 3 \\
4 & 6 & & 5 & & 1 & 7 \\
8 & 7 & 3 & 6 & 1 & & 2 & 5 \\
5 & 6 & 1 & 7 & 3 & 2 & 4 & 8 \\
1 & 2 & & & 9 & 7 & 6 \\
7 & 4 & & 9 & 6 & 1
\end{pmatrix}$$

Naked Twins

6 Results

Results

7 Conclusions

Conclusions

References

[Farenzena et al., 2011] Daniel Farenzena, Ricardo Araujo, and Luis Lamb. Collaboration emergence in social networks with informational natural selection. In 2011 IEEE International Conference on Privacy, Security, Risk, and Trust, and IEEE International Conference on Social Computing, 2011.

[Lamb and Araujo, 2008] Luis Lamb and Ricardo Araujo. Memetic networks: analyzing the effects of network properties in multi-agent performance. In *AAAI'08*, pages 3–8, 2008

[Mason and Watts, 2011] Winter Mason and Duncan J. Watts. Collaborative learning in networks. 2011.