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Instructive Social Learning on Jason

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Abstract This paper introduces three protocols that define Social Learning on Jason, the Java-based implementation of $AgentSpeak(L)$. The implementation of these protocols is based on the Instructive stage of a classification correlated with the developmental stages of a child. Agents defined in these protocols are able to share both the inputs and the output of a learning algorithm in order to improve the Multi-Agent System (MAS) performance. Compared with environments without social interaction, the performance of the MAS improves when any of these protocols is implemented. The results shown in this paper open the door to Social Protocols based on Collaborative Learning.

Keywords. Social Learning, Instructive Learning, Jason, AgentSpeak(L)

1. Introduction

According to Simon, [8] Artificial Intelligence is a science and not merely technology or engineering, and it is the science of possible forms of intelligence, both individual and collective. Intelligence is mainly a social phenomenon, and is because of the need of social life that there is the need to build both socially intelligent systems to understand it and social entities to have intelligent systems. If we want a computer to be not a simple tool but a collaborator, it is necessary to model social intelligence in the computer. In order to integrate intelligent functions in both the virtual and physical environment to support human action, these intelligent entities must be **social** in order to understand and help the users, and to coordinate, compete and collaborate with each other.

A way to provide intelligence to a system is enabling this with learning capacities. As a first approach, previous work on Intentional Learning based on First-Order Logical Decision Trees [5] had endowed BDI agents with the capability to learn about the failure of the executions of their plans. However, agents working in a Multi-Agent System are not able to learn together.

Dealing with this lack of social abilities, this paper presents some protocols for supporting Social Learning in Jason, based on the Instructive Stage of a classification correlated with the developmental stages of a child, proposed by Tomasello et al. [9] under the specialized term $Cultural\ Learning$.

2. Social Learning

Learning in human societies is an extensively studied topic in psychology, ethology and anthropology. Thereafter, there is a series of definitions of social learning in the literature [1,7]. A common definition which can be applied to both psychological and computational Social Learning is given by Conte et al. [4]:

> Social learning is the phenomenon by means of which a given agent (learner) updates its own knowledge base (adding to, or removing from it a given information, or modifying an existing representation) by perceiving the positive or negative effects of any given event undergone or actively produced by another agent on a state of the world which the learner agent has a goal.

Making use of the more specialized term *Cultural Learning*, Tomasello et al. [9] distinguish between three types of Social Learning, which are correlated with the developmental stages of a child: **Imitative**, **Instructive** and **Collaborative** learning. The *Imitative* Learning corresponds to the phenomenon of observation, where the learner agent observes and learns the behaviour of a model agent. In this case, the information flow is unidirectional and there is not a relationship between the model and the learner agents. The *Instructive* Learning can be seen as a student-teacher relationship. The information flow is bidirectional but asymmetric, being the instructor agent the main source of the information. In a bidirectional and symmetrical information flow, *Collaborative* Learning occurs after mutual cooperation between two (or more) agents.

In this paper we propose some protocols based on the Instructive stage of this classification and making use of the Top-Down Induction of Logical Decision Trees (TILDE) [2] as learning mechanism [1]. We refer as agent **S** (Source) to the one that executes the learning process and shares the information, whereas the agent **R** (Receiver) is that one receiving the information. The agents in these protocols can play both roles.

- *Sharing Examples When Fail (SEWF).* When S fails in the execution of a plan, a training example labelled as failed is added to his base of beliefs and shared with those R has a social relationship with it. When R receives a training example from S, the learning process is executed in order to learn why S failed.
- *Sharing Learned Hypothesis (SLH).* S shares the Learned Hypothesis after building a Logical Decision Tree. Once an Hypothesis is received, R compares this with the context of his plan. In case of being more specific, the plan is updated.
- *Sharing Learned Tree (SLT).* In this protocol S shares the full Learned Tree that was built in the learning process. The behaviour of R is similar regarding SLH protocol, with the difference that besides updating the plan, the training examples that formed the tree are added.

3. Experiments

A simple experiment has been designed to compare the behaviour of agents learning without social interaction and agents learning trough the *sewf*, *slh* and *slt* learning protocols. The aim of the experiment consists of painting a grid environment, for which, the

[1] The TILDE algorithm is basically a first-order version of the well known C4.5 algorithm. The algorithm is not described in this paper, due to space limitations, but it is advisable to consult the original report of TILDE [2] or the version of the algorithm reported in [6] for further details.

agents have plans to *move* around the grid and to *paint* a cell. However, these agents do not know the reasons for adopting a plan, leading them to adopt plans naively. The health of each agent is limited and this decreases every time the agent hits an obstacle or tries to get out of the grid. The amount of paint is also limited and is divided equally among the agents in the system. Besides, painting a painted cell means a waste of paint, so it is considered a failure.

The individual performance (P_{ag}) of every agent is calculated by dividing the final health h_f by the initial health h_i of the agent.

$$P_{ag} = \frac{h_f}{h_i} \tag{1}$$

The performance of the MAS system (P_{mas}) is calculated by multiplying the average of individual performance P_{ag} (Eq. 1) of the n agents in the MAS by a coefficient computed by dividing the painted cells pc by the total cells c, which penalizes the average of individual performance according to the cells that were left unpainted.

$$P_{mas} = \frac{\sum_{j=1}^{n} P_{ag}(j)}{n} \times \frac{pc}{c} \tag{2}$$

Figure 1 (left) summarizes the result of all the executed experiments (the average of 10 runs per protocol) for 2, 4, 8 and 12 agents. As expected, the performance of learning without social interaction is lower than learning through social learning protocols.

The protocol that maximizes the performance is **SEWF**. This is because in this protocol, agents store both their own experience and those coming from the rest of agents, and learn their own hypotheses. However, it has the disadvantage that the number of executions of TILDE increases so much as agents are in the system (see figure 1 (right)).

The **SLH** protocol has the lowest performance compared with the other social learning protocols. In this protocol, an agent can change the reasons for adopting a plan if the new hypothesis is less general than its current reasons to adopt the same plan. However, the agent may fail for other reasons. If this happens, the agent is unable to learn what he already knew (through others) because he has no the training examples that formed the known hypothesis. The **SLT** protocol deals with this problem, thereby improving the performance of **SLH** protocol. Agents learning in this protocol add the examples that formed the shared hypothesis, so in case of a new failure, agents are able to relearn what they already knew through others.

It can be seen that the performance does not vary significantly for simulations between four and twelve agents, which means that the performance of the Multi-Agent System does not necessarily improves by adding more than four agents to the system, but it does by adding more than one collaborator (i.e., at least three or four agents in the system).

4. Discussion and future work

The Instructive Learning Protocols shown in this paper have served to create agents capable of learning through the social interaction with other agents. These social protocols, open the door to the definition of Collaborative Learning, the last stage of what

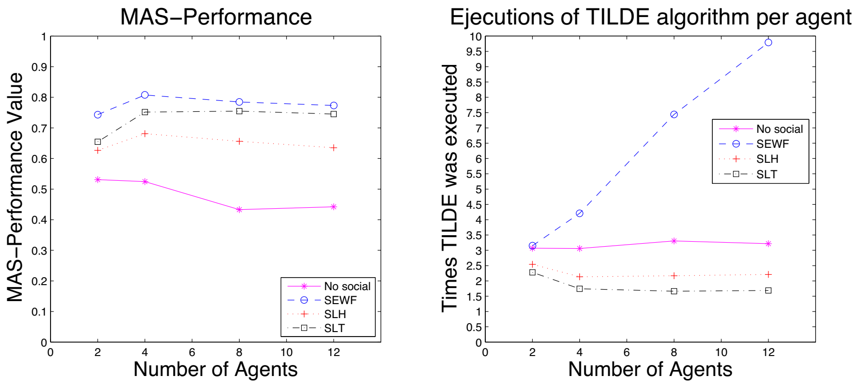

Figure 1. The experiment results. Left: MAS-Performance. Right: Times TILDE was executed

Tomasello et al. [9] classify as the developmental stages of a child. The definition of these Collaborative Learning Protocols constitutes the future short-term work.

Even when the experimental results are promising, there is enough work to do to formalize a complete theory of social learning. First, these protocols execute and idealized world where all of the agents always share all of their information. In a real society, this things does not happen, due to issues that have not be considered in these protocols (e.g. grouping, hierarchies, social commitment, delegation of tasks, coordination, rivalries, competitions). Castelfranchi [3] proposes five steps to reach a complete model of sociality. The Social Learning Protocols in this paper reach the second step (Learning from non-social action to weak social action), where agents communicate with each other their mental states, and the impact they have had in their actions. Reaching the next steps of sociality constitutes the future long-term work.

References

[1] A. Bandura and D. C. McClelland. Social learning theory. 1977.

[2] H. Blockeel, L. D. Raedt, N. Jacobs, and B. Demoen. Scaling up inductive logic programming by learning from interpretations. *Data Mining and Knowledge Discovery*, 3(1):59–93, 1999.

[3] C. Castelfranchi. Modelling social action for ai agents. *Artif. Intell.*, 103(1-2):157–182, Aug. 1998.

[4] R. Conte and M. Paolucci. Intelligent social learning. *Journal of Artificial Societies and Social Simulation*, 4(1), 2001.

[5] A. Guerra-Hernández, A. El-Fallah-Seghrouchni, and H. Soldano. Learning in BDI Multi-agent Systems. In J. Dix and J. Leite, editors, *Computational Logic in Multi-Agent Systems: 4th International Workshop, CLIMA IV, Fort Lauderdale, FL, USA, January 6–7, 2004, Revised and Selected Papers*, volume 3259 of *Lecture Notes in Computer Science*, pages 218–233, Berlin Heidelberg, 2004. Springer-Verlag.

[6] A. Guerra-Hernández, C. González-Alarcón, and A. El FallahSeghrouchni. Jason Induction of Logical Decision Trees (Jildt): A learning library and its application to commitment. EUMAS 2010, 2010.

[7] M. J. Matarić. Learning social behavior. *Robotics and Autonomous Systems*, 20(2):191–204, 1997.

[8] H. A. Simon. *The Sciences of the Artificial (3rd Ed.).* MIT Press, Cambridge, MA, USA, 1996.

[9] M. Tomasello, A. C. Kruger, and H. H. Ratner. Cultural learning. *Behavioral and Brain Sciences*, 16:495–511, 9 1993.