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A Learning Language for Intelligent Agents

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O. Soueina Sidi H. Hashimoto S. Saniepour H. Hajji B. H. Far
シデイ O. スエナ 宏美 橋本 S. サニエプール H. ハジ B.H. ファー
Department of Information & Computer Sciences, Saitama University
埼玉大学情報システム工学科

Abstract: A Multi-Agent Learning Language (MALL) is defined as being necessary for agents in environments where they encounter crucial situations in which they have to learn about the environment, other parties moves and strategies, and then construct an optimal plan. The language helps to implement a variety of algorithms that uses an extensive *explanation* based inferences. Tow major factors are taken in consideration. Those are level of *certainty* (decision making under uncertainty) in which the decision maker has to select among alternatives (explanations) depending on the level of information he has about the state of the world and the degree of optimism, and, *fully monitoring* (surveying) the agents and the environment, while devising the plan. In this introductory paper we present the layout of the language and how it works. The language is being implemented in *Electronic Commerce* competitive dealer agents, and, generally can be implemented in any game theoretical environment.

1 Introduction

Uncertain and Ambiguous domains are found to be a very exciting environments for Intelligent actions. In order to make decisions, compete, negotiate etc, in a multi-agent environment, agents have to reason about the environment, predict its changes, predict agents future moves, and estimate the actual beliefs of other agents. However, any lack of information and/or noise, affect the quality of the decision to be taken or the move to be performed. This happens in many cases in real life, where human beings and/or any entity that models them (e.g. agents) are present. Therefore they should have *the ability of learning*, based on the primary information about rivals through *signals*. A variety of methods and techniques have been suggested to deal with multi agent environments, eg. cooperation [1], coordination [2], etc. The concept of Agent Oriented Programming (AOP) defines an agent as to be an entity that recognizes and deals with the outside world as having mental qualities such as beliefs, commitments and desires [3]. Nevertheless, this multi-agent environment creates challenging opportunities for learning, that can take various perspectives and forms for example In this work we approach *Learning in Multi Agent Systems* (LMAS) and the from a new point of view. We introduce a new language, aimed at making agents learn from their environments about the strategies of their rival and, making their own plans depending on the other players moves. The language is an implementation of some multi-agent, Uncertainty, and Game Theoretical approaches. The language represent the missing tool for competitive and uncertain environment where incompleteness and noise in information required to making useful decisions is a major hindrance.

連絡先: Sidi O. Soueina 〒 338-8570 埼玉県浦和市下大久保 255, 埼玉大学工学部情報工学科, Tel. 048-858-3489, Fax. 048-858-3716, E-mail. sidi@cit.ics.saitama-u.a.c.jp

1.1 Decision Making Under Uncertainty

The lack of knowledge about any property is very crucial, if we want to use that property in a beneficial interaction. In LMAS, agents are to encounter uncertainty, engendered by this lack of knowledge when selecting optimal explanations to observable actions of other parties. MALL gives the facility to apply certain criteria in which certainty is divided into three levels according to the amount of information about the environment and about other parties, given the signal function observed before choosing among several choices [4]. These are: In case where the agent is certain (*Decision Making under Certainty*); agent knows exactly what state of nature to choose, and therefore will selects the alternatives that give the highest payoffs. In case the agent is not quiet sure (*Decision Making under Risk*); the case in which the agent knows with the probability $0 < P < 1$ that S is/was/will be the state of nature. Thus, after calculating the expected payoffs of each alternative (A) $C_A = \sum C_A * P$ (where C_A is the payoff of alternative A) it selects the alternative with the largest payoffs $C^* = MaxC_A$. The third situation is when agent does not know anything about the state of nature except that it is in some set $S = S_1, S_2, ..., S_n$, (*Decision Making under Uncertainty*). Nevertheless, in order to deal with this defined uncertainty, [8] suggested a four decision strategies as shown below:

1. *Pessimistic:* is selecting the worst possible outcome.

2. *Optimistic:* is selecting the best possible outcome.

3. *Hurwicz:* selecting the value $\alpha = [0, 1]$ for each alternative a weighted average of the best payoffs C^* and the worst C_* is taken $MaxH = \alpha C^*_A + (1 - \alpha)C_{*A}$.

2 The Multi-Agent Learning Language

In this work, we used FOL to represent the knowledge and to perform inference as shown in the coming sections. The language of game theory and various learning concepts are defined using FOL [5]. The following table depicts some of the basic names, predicate symbols and functions symbols. In a previous related work [9] the Baccus Naur Form (BNF) of the language and other inference was introduced.

Names	predicate symbols	Functions Symbols
agent	action	action(agent)
signal	decept	signal(action(agent))
action	spy	profile(action,action,action)
certLev	pun	strategy(agent)
postBel	profile	degrcrt(action)
stack	strategy	decept(strategy(agent))
.	abduct	getsig(agent)
.	push	spy(setsig(agent))
.	pessi	pun(action(agent)
	bluf	push(action,stack)
	plan	pop(action,stack)
	getsig	opti(action,stack)
	selec	pessi(select(degrcrt(action)))
	pop	bluf(action(agent))
	opti	plan(profile(agent))
	.	type(agent(profile))
	.	select(profile(action(agent), action(agent),action(agent)))
		sigfunc(posbel(profile (action,action,action)))

2.1 Learning Components (Categories)

Using the Inference-based Theory of Learning, agents are able to perform transformation of knowledge, i.e. to *infer* and, to have a *memory* which supplies the agent with the Background Knowledge (BK) necessary to infer, and store information for future performances [6]. The agent uses his *inference* capabilities such as abduction, deduction, etc. When the BK is not sufficient to make such comparison, another further step is crucial to reach an *Explanatory Hypothesis (EH)*. The explanation is triggered by the *Signals* in most cases, depending on the level of certainty (`degrcrt()`) about the relations between those signals and their explanations; whether it is a *Certain, Risk, or Uncertain*, the inference takes place.

3 Implementation

An agents model of *Electronic Commerce* (EC) was proposed by [7] in which, EC is viewed as a society of agents, manufacturer, customer, catalog, dealer, etc, all interacting (e.g., negotiating and competing) with each other. In such atmosphere the dealer agents will be applying individual strategies attempting to increase *utilities*; e.g., a dealer applying a strategy with lower cost and better services to the customers will be more likely to increase his income. For the purpose of this example, let us say that given the basic knowledge of the environment (the market), plus, the signals of agent A, agent B is trying to learn A's strategy. Obviously, agent A is omniscient about his own strategy and given that his utility (benefit) is higher than B, we can say that the game is zero-sum (since the benefit of A is the loss of B) and B by analyzing the signals that A gives will be getting some hints. Agent A can be said to *play partially revealing* to make his opponent get the least indicating signals. On the other side, B in this situation would construct his own plan through a process of explanation and analysis of the information revealed by A.

4 Cloclusion and Future Work

A new tool aiming at making possible agents autonomously learning other agents strategies and construct their own plans, was introduced. A first step towards a Multi-Agent Learning Language, we belief is to be the base of a new era of making agents, learn (reason) and act , etc, independently. This version of the language is based on a game theoretical concepts. The very first layout of the language was stated. In a coming work we intend to define more detailed components we believe are necessary for standardizing the multi-agent learning, such as Belief Estimation, cost estimation and optimal move calculation. MALL is to be used in EC's Competitive Dealer Agent at a first stage.

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