Learning from Each Other: An Agent Based Approach

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Abstract. This paper presents an agent based approach to knowledge representation and learning methods. Agent architecture is described and discussed, together with its advantages and limitations. Main purpose of the proposed approach is to gain further insight in current teaching methods with a foremost aspiration for their improvement. Two different experimental studies were conducted; the first one addressing knowledge representation and the second one regarding knowledge transfer between agents. Obtained results are presented and analysed.

Keywords: learning, artificial intelligence, machine learning, agent based systems.

1 Introduction

There are many different approaches in agent based learning like distributive [1], cooperative [2], [3], reinforced [4] and collaborative [5] learning, but most of these approaches make strict differentiation between teacher and learner agents. We intend to present an agent based approach in which, depending on different circumstances, agents possess the ability to act both as a teacher and as a learner. Although agents will not be differentiated by their role, each of them could possess individual characteristics (dimensions, mobility, number and type of sensors) making them unique or at least different from each other. As a result a system that is more flexible than those aforementioned should be designed. It should also enable much simpler and efficient transfer of knowledge among all agents acting within the system.

This paper aims to present a type of agent that can act both as a teacher and a learner, while using robots as physical representation of those agents. Primary reason for developing such kind of agents is to discover new or improve existing teaching methods. Accordingly, we are proposing a framework that could be used for those purposes. To successfully act as a teacher, it is desirable that agents are able to switch their role from the teacher to the student. Desired effect of such change of roles is an embracement of a same student mental model, thus allowing successful knowledge transfer between subjects and avoiding traps in form of potential misconceptions.

Every single individual has its own perspective of the surrounding world (egocentric view) that differs from the collective or global representation of that same world (allocentric view) [6], [7]. This should be taken into consideration when talking about teaching; anyone taking the role of the teacher should be aware that not everybody shares his/hers view of the world.

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When talking about knowledge transfer and teaching methods, regardless of a human or a robot actors, there are some different approaches considering the interaction between involved subjects [8], [9]:

- Individualistic – interactions between learners are not affecting the results of the learning. Each learner works on his own in order to complete her/his goal, without paying attention to other learners and their progress.
- Competitive – learners are competing between themselves in order to achieve their goals. They may not obstruct other learners on purpose, but they will certainly interact in a way to avoid helping others. Competition is unavoidable aspect of life and this type of learning is present in majority fields of education [10].
- Cooperative – learners are working together in order to achieve their goals. They can have one common goal or more individual goals, but all interactions among students are aimed to help each other to achieve those goals.
- Collaborative – similar to the cooperative learning, learners are also working together aiming to achieve their goal (to learn something), but with slightly different roles then in cooperative learning.

However, there are some differences between cooperative and collaborative learning [11]. In cooperative learning an instructor is the centre of authority in the class, with group tasks usually more closed-ended and often having specific answers. In contrast, with collaborative learning the instructor abdicates his or her authority and empowers the small groups who are often given more open-ended, complex tasks.

When discussing different types of learning methods and processes, emphasis is usually put on interaction between teacher and one or more students, while relations among students themselves are relatively often ignored. Nevertheless, interactions among students should also be considered as an important part of the whole learning process because they undoubtedly affect learning outcomes.

All the above mentioned approaches share one common characteristic – the roles of the subjects involved in an interaction are predetermined. Namely, it is clearly defined who the teacher is and who the learner is. In this paper we would like to expand current work in the field and introduce an approach to interaction between humans and robots which can be used as a two-way communication channel. By developing such type of interaction, we would not be using predetermined roles anymore. This implies that the knowledge could be exchanged in any direction between different subjects regardless of their initial role. Without strictly defined roles, such approach could reflect a universal interaction and could be applied to any human/robot combination and variation, regardless of their characteristics.

2 Proposed Approach

In this paper we consider the former teaching method (collaborative learning) in which the learning goals may be structured since the relevant literature provides recommendation for teachers to structure learning situations collaboratively majority of time, i.e. [8]. To further examine collaborative learning and interactions among students, we present an agent based approach to collaborative learning. In such approach agents are aiming to exchange knowledge between each other and therefore techniques from machine learning, agent based systems and distributed artificial intelligence should be employed.

2.1 Model of the World

In previous section, we have briefly discussed the difference between egocentric and allocentric view of the world. Now we will present a model of the world in which our agents are located. For the purposes of an experimental study, the model of the world is intentionally reasonably simple: (i) agents are located in a finite, discrete environment and (ii) there are two types of obstacles ("wall" and "hole") along with two types of paths ("empty field" and "goal") see Figure1.

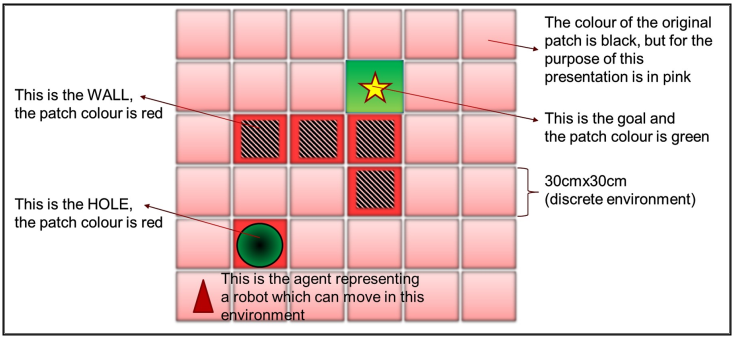

Fig. 1. Model of the World along with descriptions of concepts

2.2 Model of the Agent

There are many different ways to describe and define an intelligent agent [12]. Our agent is based on definition describing the agent as a computer system that is situated in some environment and that is capable of autonomous action in this environment to meet its design objectives [13]. In order to adhere to this definition, we are considering three main aspects of our agent model – abilities, knowledge representation and knowledge mapping. Each of these aspects is briefly described in following sections.

Abilities. Each agent possesses a different set of characteristics and abilities, depending on a construction of its physical representation. Common capabilities of all agents are their ability to navigate through their environment (i.e. they are all mobile) and their possession of a kind of perception (one or more sensors), allowing them to receive some kind of information from their surroundings. They also have perfect and unlimited memory, allowing them to store and use obtained knowledge.

Knowledge Representation. Agent's knowledge is represented through different concepts and relations between those concepts. Single concept can describe particular

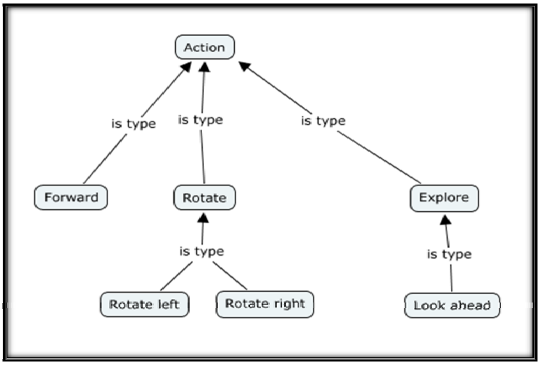

Fig. 2. Knowledge representation using concepts and relations

existing object (e.g. "wall", "house", "robot") but also some kind of abstract idea or action (e.g. "move" or "goal"). There is no strict distinction between those two types of concepts, since all are represented in the same way and have the same properties. Different concepts are connected with relations that define an interaction between two concepts. Relations between concepts are directed, making knowledge representation a type of directed graph, where concepts are represented with graph nodes and relations with directed edges between nodes. Figure 2 shows an example of knowledge representation using concepts and relations.

Quantity of knowledge that one agent possesses is equal to the number of different concepts that the agent is able to recognize in respect to total number of concepts existing in agent's world. Quality of that knowledge depends on how successful the agent is in recognizing each individual concept that has been learned and how well it can use that concept. Each agent should be capable to expand its knowledge, i.e. to be precise to learn new concepts. In order to acquire new concept, the agent must undergo the learning phase in which it makes connection between sensor input values and one particular concept. Consequently, each time when the agent receives that same input values, it should recognize the corresponding concept.

Our goal is to secure successful exchange of information between different systems (in this case different agents) without affecting the original ones. An achievable way to accomplish this goal is by mapping different types of knowledge.

Knowledge Mapping. Suppose we have two different types of knowledge K_1 and K_2. Knowledge mapping is an act of trying for every concept in K_1 to find a matching concept in K_2 that has same or similar meaning. This mapping can be injective (one-way) or bijective (two-way) [14]. There is a difference between partial and full mapping. Full mapping pairs every element from the source knowledge K_1 to the destination knowledge K_2, while partial mapping pairs only a sub-set of the knowledge K_1 to the destination knowledge K_2. In that way we are creating reference knowledge K_0, a common knowledge that contains concepts and relations that both sides wishing to exchange information agreed upon, see Figure 3.

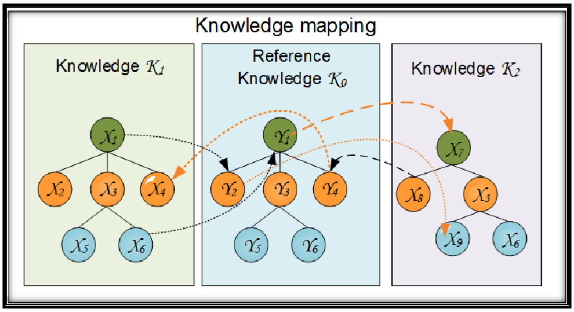

Fig. 3. Knowledge mapping

Therefore, to learn from each other agents must satisfy one main requirement for successful knowledge transfer. Namely, agents attempting to interact must have at least one common characteristic that will be used as foundation for knowledge exchange. It has been already mentioned that knowledge is represented through different concepts and that every single agent uses its sensors to recognize them. To successfully transfer knowledge regarding particular concept, the agent that is trying to learn a concept must possess the ability to receive same type of sensor input as the teacher agent. It is not crucial to have all common characteristics, just some of them (i.e. at least one sensor of the same type). Advantage of this approach is that one single agent can acquire knowledge from many different agents with different characteristics.

From a technical standpoint, process of teaching along with underlying interactions between teacher and student can be presented using a concept of interoperability. There are different definitions of interoperability [15-18], but generally speaking it represents an ability of two or more systems to successfully exchange some kind of information and also to effectively use it. There are also various standards for classifying different types and levels of interoperability. For the purposes of this research, we are considering European Interoperability Framework (EIF) [19], which recognizes three different levels of interoperability – technical, semantic and organizational. Our proposed approach corresponds to semantic level of interoperability, which defines local exchange of information using shared maps, key data and ontologies.

3 Experimental Study

For the purposes of this paper, we have conducted two different experimental studies aiming to address two questions: is there any difference in knowledge representation between two agents and is it possible to exchange that knowledge between agents.

3.1 Knowledge Representation Experiment

First experimental study was conducted in order to prove our claim that every agent has an egocentric view of the surrounding world and also a distinct representation of its knowledge.

Experimental Setup and Procedure. This experiment was conducted with a group of 10 students from the first year of Masters' degree, during their engagement in a "Knowledge management" course which lasted one semester (15 weeks). They were given the assignment in which they had to represent knowledge of a single agent located in simple environment described and depicted in previous section of this paper.

Knowledge had to be represented using different concepts and relations between those concepts, as described beforehand. Students were given some basic guidelines how to describe particular concept (e.g. "This is the WALL, the patch colour is red"). Some parts of instructions were intentionally emphasized while others were left vague. Students were not limited in a number of concepts and relations that they could use and there were no strict rules to be followed. Their task was to build a conceptual map of given environment using those descriptions. As the final result, ten individual conceptual maps were acquired, each one depicting the knowledge of a single agent in a simple, discreet space. The main goal of this experiment was to see if there will be any differences in obtained conceptual maps, considering simplicity of both the world and the agent. Figure 4 represents several conceptual maps used in the experiment.

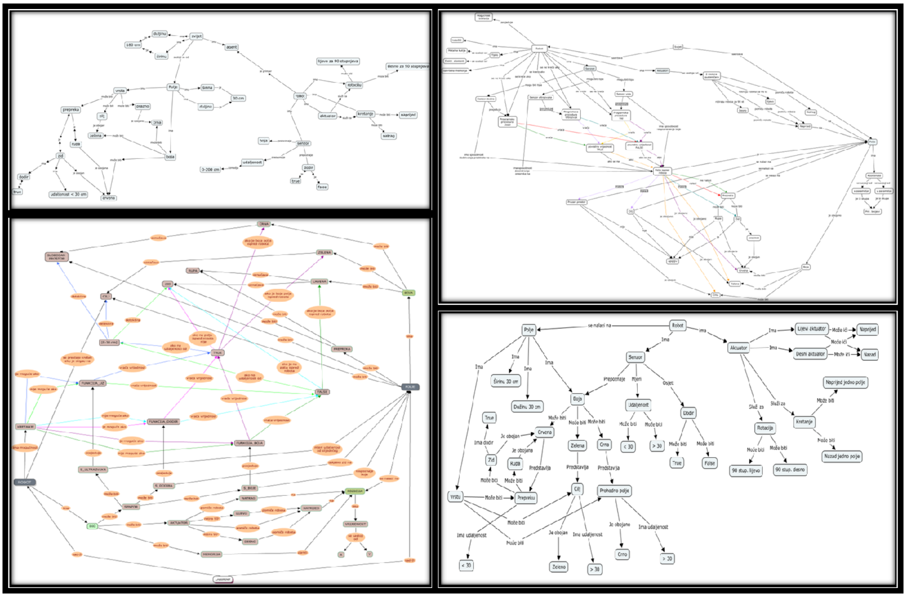

Fig. 4. Several conceptual maps obtained in the first experimental study

Results. At the end of the semester, we have analysed and compared all obtained conceptual maps. The maps were not associated with particular student, just numbered from 1 to 10. In order to compare obtained results, we first have conducted search for two basic concepts, "wall" and "red", in addition to any relation between them. These two concepts correspond to the first provided description of the world and should be part of every map attempting to represent the given environment. For every single map, information regarding the presence of the two concepts in the map along with the related relation (if applicable) is offered in Table 1.

Table 1. Analysis of concepts and their relations

Map	*Concept "red"*	*Relation (direction)*	*Concept "wall"*
1.	No	n/a	Yes
2.	Yes	Is coloured (←)	Yes
3.	Yes	Is (←)	Yes
4.	No	n/a	Yes
5.	Yes	n/a	Yes
6.	Yes	Is (←)	Yes
7.	Yes	Indicates (→)	Yes
8.	No	n/a	Yes
9.	Yes	Is coloured (←)	Yes
10.	Yes	n/a	Yes

Table 2. Concepts associated with the basic "wall" concept and their frequency

Concept	*Times used*
patches	3
ultrasound sensor	6
touch sensor	5
obstacle	7
red	4
memory	1
object	1
move	1

It was interesting to observe that three different maps didn't even include the concept "red", despite being the key concept for defining obstacles in the given environment. It can also be noted that some maps, although having both concepts, did not have a direct relation between them. Only half of them had defined both concepts and relation between those concepts, but those relations were differently named or directed. Only two pairs of conceptual maps could be considered to have the same representation of the two simple concepts, but only if they are analysed excluding the rest of the map. If we take into account other relations linked with those concepts, then even those two pairs of maps have different knowledge representations.

Additionally, we have also selected one basic concept that is present in all maps (concept "wall") and analysed how many different relations and concepts were associated with that one particular concept in the obtained maps. Throughout 10 maps, there were 8 unique concepts, some of which were used only once ("memory", "object") while others appeared in the majority of maps ("obstacle" and "red"). Another interesting remark is related to the fact that there was not a single concept that was used in all maps in relation to the "wall" concept. Table 2 shows those 8 concepts and frequency of their appearance in ten conceptual maps.

Table 3. Used relations and their frequency

Relation	*Times used*
Type of	1
Locates	2
Is	4
Has	2
Is coloured	2
Can be	7
Contains	2
Recognizes	2
Memorizes	1
Means	2

Regarding relations between concept “wall” and those other mentioned concepts, there were 10 different relations used. Yet again, some of them appeared only once, while others were used multiple times even in the same map. Table 3 shows used relations and frequency of their usage.

3.2 Knowledge Transfer Experiment

With the intention to test the proposed approach to knowledge exchange, another experiment was conducted in both physical and simulated environment. Two different software frameworks were used, Netlogo and Microsoft .NET.

The goal of the experiment was twofold: (i) to successfully train two different robots to effectively recognize different concepts in their environment and (ii) to try afterwards to exchange acquired knowledge between them. The physical representation of agents was achieved using Lego Mindstorms robots where different types of agents have been represented with differently constructed robots. Figure 5 shows few different robots that were used in the experimental study.

Experimental Setup and Procedure. A specific .NET application was developed for storing knowledge in a form of a database (MS SQL) containing a list of concepts and relations. That same application also handles the task of executing the learning phase, in which sensor values gained from the robot are used for training the agent to recognize a particular concept. Training was carried out by using artificial neural networks, also incorporated within the application. Single agent possesses a single artificial neural network for every concept that he/she can recognize.

In order to visually present those steps in the learning process, special simulated environment was developed. It was implemented using NetLogo, a multi-agent programmable modelling environment [20]. For the purpose of this experiment, several different simulations were developed, each representing a part of the agent architecture (learning phase, knowledge representation, knowledge exchange etc.).

One developed simulation used for training single artificial neural network (ANN) is presented in Figure 6.

Fig. 5. Lego Mindstorms robots used in the second experimental study

During the experiment, two differently constructed robots were used, one equipped with both ultrasound and colour sensor (agent A) and other with only colour sensor (agent B). Real sensor values were obtained from those robots and used within.NET and Netlogo applications. First, one robot (agent A) was trained to recognize three different concepts ("wall", "obstacle" and "hole") as they were described in model of the world. Detailed description of the learning phase can be found in our previous work [21]. Afterwards, agent A took the role of teacher and we have used his trained ANNs in order to teach other agent those same three concepts. For the both agents (robots), learned concepts were not organized hierarchically, as they were represented in mental maps. This would require more complex procedure and is behind the scope of this paper.

Results. At the end of experiment, we have analyzed how successful were both agents in recognizing given concepts. We also considered the outcome of knowledge exchange between the two agents. After finishing the learning phase, the agent A had

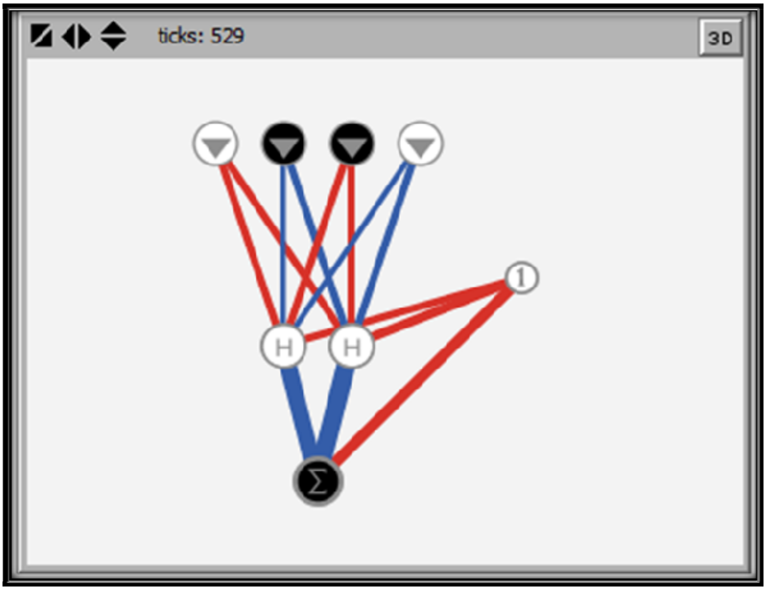

Fig. 6. Part of the Netlogo simulation used for visualization of a process of training a single ANN

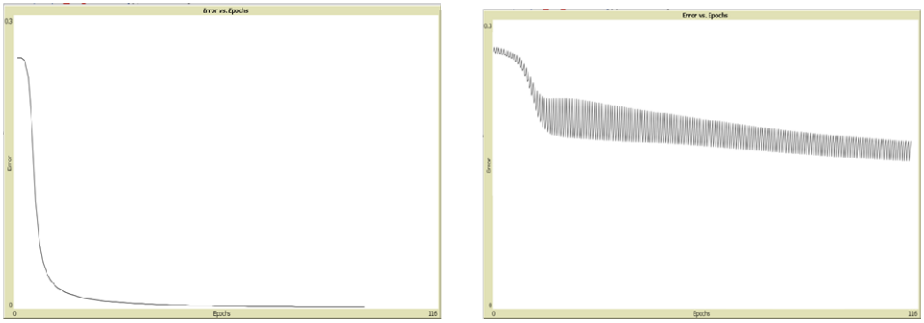

Fig. 7. Examples of successfully (left) and unsuccessfully (right) trained ANNs

nearly 100% success rate in recognizing all three different concepts and was used as a teacher for the agent B. The agent A was able to successfully train the agent B to recognize one concept ("obstacle") but was unable to teach him how to differentiate other two concepts ("wall" and "hole"). Process of training the ANN for one of those concepts could not be completed because error ratio could not be reduced to near zero value (indicator of a well-trained neural network), regardless of number of examples given to the particular ANN. Figure 7 shows difference between error ratios per epoch for successfully and unsuccessfully trained ANNs.

This was caused by the agent B's reduced abilities compared to the ones of the agent A, as it was not equipped with ultrasound sensor. There could possibly be some other ways for the agent B to differentiate those two concepts (e.g. adding a touch sensor), but the agent A would not be able to teach that. These results further support our statement regarding egocentric view of the world as well as different knowledge representations.

4 Conclusion

According to the acquired results, there were numerous differences in knowledge representation in conceptual maps obtained in the experimental study. Additionally, when taking into account simplicity of the world and relative similarities between test subjects (students with similar level of knowledge), these differences are even greater. This leads to a conclusion that given a more complex agent (with more sensors, abilities and the like) and a more complex world (different types of obstacles, other agents, movable objects etc.) differences between conceptual maps would be even bigger. Such conclusion coincides with our attitude in two aspects: (i) when discussing different teaching methods it is essential to consider particular characteristics of every individual and (ii) teaching must be regarded as something more than just a simple transfer of information from one subject to another.

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