Active Learning between a Robot Learner and a Human Teacher

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Abstract

A relative new trend in machine learning is interactive learning. Rather than passively absorbing knowledge, a learning agent can shape its learning experience through interaction with its teacher. As such, the learning becomes a bidirectional exchange. In a series of experiments, both in simulation and using a robotic platform, we examine how a learner that actively tries to influence the learning session can become more effective. Results show how interactive learning leads to more effective and faster learning, as social cues provided by the robot are picked up by human teachers. In addition, we observed gender differences, with female interactants being significantly more receptive to social cues displayed by the robot.

Introduction

Background

Within developmental robotics the aspect of learning is crucial. Through effective learning mechanisms a robotic system may gain those skills that are relevant for its task. As autonomous robots are envisioned to work in the same environment alongside humans, it would be most natural if people could teach the robot what to do. And rather than having humans, who may not be familiar and/or trained to instruct robots, adapt to the robot, it would be better if the robot could adapt to its human teacher. As such, robots might be instructed in a manner similar to how adults teach young children. To allow for this kind of teaching, a robot should be able to tap into the communication channels that come natural to people, such as speech and non-verbal behaviours like facial expressions, gestures and gaze.

Recently, interactive learning has gained attention; different studies have demonstrated that robots can benefit from employing interactive strategies in which the robot learner is not passively absorbing new knowledge, but rather actively engages in the learning experience through social interaction with a human teacher (Brooks et al. 2004; Thomaz and Breazeal 2008). In (Cakmak, Chao, and Thomaz 2010) different robot behaviours were investigated, indicating that robots may benefit from active querying as opposed to standard supervised learning. People appear to appreciate an active learner, but like to stay in control. Thus, balanced behaviour may be most optimal, and this can vary for different users. Moreover, optimal robot behaviour might require fine-grained understanding of the social situation in order to be effective (Knox et al. 2012); as such, more exploration of appropriate robot behaviour remains to be done.

In the study reported here we focus on the acquisition of words and concepts by an agent. Language and conceptual knowledge lie at the root of human intelligence, and the acquisition of both relies heavily on social interaction and tutelage (Bloom 2000). Many social interactions between carers and infants are actively aimed at providing opportunities for acquiring words and their meanings, with carers overtly describing objects, actions, sensations and agents and young learners steering linguistic interactions, for example through deictic points and naming salient features in the environment. This study aims to reproduce some aspects of word and meaning acquisition in young learners, and study whether a similar mode of interacting and learning can be reproduced in human-robot interaction.

Category representation and learning

To represent categories we use the Conceptual Spaces (CS) framework (Gärdenfors 2000). A CS consists of a geometrical representation in vector space along various quality dimensions such as colour, shape, size etc. Within a conceptual space we can model the learning of categories by exposing the model to examples with associated labels. After training the model is able to classify new examples as belonging to some known category, and specify the typicality of the example; i.e. to what extend the example represents the category. This allows for the representation of categories with a prototype-like structure (Rosch 1973).

To govern category learning process we use the *Language Games* model (Steels 1999). This allows agents to learn word labels for objects through interaction with other agents. Language games were proposed as a model for studying the dynamics of linguistic interactions between agents. The model has been extensively explored in a number of domains, for example in the domain of colour (Steels and Belpaeme 2005).

The simplest form of the language game takes two agents.

Both agents perceive a common scene (called the *context*) and one of the agents initiates a game by describing an element of the scene, which is called the *topic*. The second agent then attempts to interpret the description by pointing to its interpretation of the word. If the second agent points to the element that the first agent has intended, then the interaction succeeds. If it fails to point out the intended element (or it does not know the word), the interaction fails. The failure or success of an interaction is an opportunity to adapt the words, categories and scores of the agents.

When games are played repeatedly, the effect is that both agents gradually acquire and adapt a repertoire of words, categories and scores, with which they can describe their environment. One agent can be initialised with certain categories and words and can act as a teacher to agents with a blank memory that have no pre-existing knowledge. Further details can be found in (Belpaeme and Bleys 2005).

The choice of the topic from the elements in the context is the basis of active learning. In a non-active learning setting this choice is made by the teacher, typically at random. In an active-learning setting, the learner tries to influence this choice.

Robotic platform: LightHead robot

As a robotic platform we used the LightHead robot, which has the appearance of a young child (see figure 1). This robot sports a novel robotic face that exhibits a *retro-projected face technology* (Delaunay, de Greeff, and Belpaeme 2009; 2010). As such, the robot offers advantages over the more classic mechatronic faces, most notably the ease of projecting computer animations which allow for rich social interaction. Retro-projected faces rely on the rear projection of an animation onto a semi-transparent surface shaped as a face, which is generated in real-time by an off-board computer.

To support the interaction, the robot head is mounted on a robot arm, with the arm acting as a thorax and neck. This allows the robot's head to move, giving the impression of scanning the environment, and to crane over a table, for example to inspect objects in front of it. For more details about the design, materials, software architecture and implementation see (Delaunay, de Greeff, and Belpaeme under review).

Experiment

In order to test the effects of an active learner, we set up a series of experiments in which the learner tries to influence the interaction with the teacher as to achieve the most optimal learning experience. This is was done in simulation first and later tested in a setup in which the LightHead robot embodied a learning agent and human subjects acted as teachers.

To teach the robot categories, we use the Zoo Data Set from the UCI Machine Learning Repository (Frank and Asuncion 2010) which is a simple database containing 101 exemplar animals with 16 different properties. All properties are binary, except for the 'number of legs', which is normalized to allow for proper representation using a Conceptual Space. The exemplars are divided into 7 different categories: MAMMAL, FISH, BIRD, INVERTEBRATE, AMPHIBIAN, INSECT and REPTILE. We removed 'girl' as an exemplar of MAMMAL to avoid confusion.

Figure 1: the LightHead robot face, mounted on a robot arm (Jennie Hills, Science Museum, London).

We compared the performance of learning agents that utilizes active learning (AL) to learning agents that do (non-AL).

Simulated experiment

Active learning Active learning in simulation very much followed the setup that is described in more detail in (de Greeff, Delaunay, and Belpaeme 2009). In short, during a guessing game it is not the teacher but the learner that decides on the topic of the guessing game. The learner does this through examination of the context and choosing the item that is least familiar as the topic of the guessing game, thus exhibiting a novelty preference. As such, it allows for a quicker exploration of the conceptual space and thus yields better learning results in terms of speed and final guessing game success. In the simulation, the teaching agent will always follow the topic of choice of the learning agent.

Experimental setup The agents played 50 guessing game interactions. The context consisted of 3 animal exemplars, randomly drawn from the data set. The experiment was replicated 50 times to obtain an average measure.

Results We measure the ability of agents to successfully play guessing games over the course of development. The guessing success is the percentage of language game interactions in which the learner correctly identified the topic from the context based on the teacher's word. As can be seen in figure 2, on average the AL condition performs better than the non-AL condition, both in terms of speed (AL reaches higher guessing game success quicker), and on the long run (difference between final guessing game success). The difference in performance for the two conditions is significant with $p < 0.001$.

Robotic experiment

Materials Participants were recruited around the University of Plymouth campus. This resulted in a pool of 41 participants who were randomly assigned to one of the two

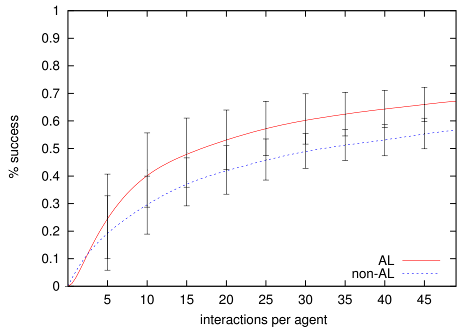

Figure 2: guessing success in simulation for the AL and non-AL groups.

conditions. Due to technical reasons (the robot facial projection malfunctioned) two participants were removed from the pool, thus bringing the total to 39. There were 20 female and 19 male participants, with an average age of 24.82. Participants were paid £7.50 for their participation.

Participants interacted with the robot by means of a touchscreen. For every round of the guessing game the touchscreen displayed 3 pictures of animals along with 7 buttons to indicate animal categories (figure 3, top). The LightHead robot was placed behind the touchscreen facing the participant and equipped with speakers to allow for speech. The robot's actions were cued by interaction events picked up by the touchscreen and the camera mounted in the robot head served to run face tracking.

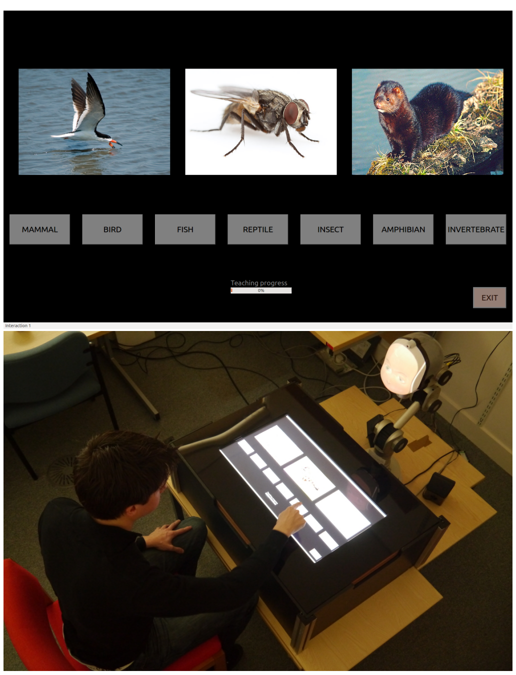

Figure 3: top: the GUI that participants used to play guessing games with the robot. Bottom: experimental setup showing the participant, the touchscreen and the robot.

Procedure Participants were asked to sit in front of the touchscreen facing the robot, (figure 3, bottom). After a brief explanation they were invited to sit through a tutorial in which the robot explained how the guessing game was to be played, and they played a practice round which involved teaching the robot colour categories. After this the real experiment was run with the animal categories. When participants expressed doubt or uncertainties about what to do (e.g. because they were unsure about a category) the experimenter would tell them to "just try to teach as best as you can".

The guessing game was played in a fashion similar to the one in simulation, with a human participant acting as teacher and the LightHead robot embodying the learner. During each round both the teacher and learner examined the context (3 random animal pictures displayed on the touchscreen), and depending on the condition (AL or non-AL) the robot expressed a learning preference through looking back and forth from a particular exemplar to the participant while making a verbal statement along the lines of "what about this one?" or "I would like to learn this". The teacher mentally decided on a topic and then provided the corresponding category label by pressing the relevant button. Upon perception of the category the robot tried to guess which exemplar the teacher had in mind. The teacher then indicated which exemplar was the topic of the guessing game, thus providing feedback to the learner. Teacher and learner played 50 guessing games.

Results

Guessing game success All participants succeeded in teaching the robot animal categories. For the final guessing success, on average the AL group was bit more successful than the non-AL group. Final average success for AL was 0.626 ($SD = 0.077$) and for non-AL 0.566 ($SD = 0.087$). This difference was significant with $p = 0.028$. As can be observed in figure 4, the learning trend of both conditions is very similar to the one obtained in simulation (figure 2). What can also be observed from the figure is that AL speeds up learning: the slope of the AL curve is steeper and at 10 interactions the difference between AL and non-AL is also significant with $p < 0.001$.

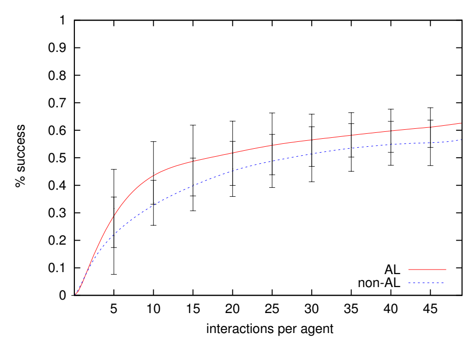

Figure 4: guessing success from the AL and non-AL groups.

Response to active learning We measured the proportion in which the robot's preferred topic was similar to the one the participant indicated they had chosen as the topic. For non-AL this is 0.32, as the robot does not provide a social cues and hence the topic choice is random. For AL however, this proportion turned out to be 0.56, indicating that the level at which participants followed the robots choice was more than chance ($p < 0.001$). Thus, on average, participants did respond to the robot's social cues. There are quite some individual differences amongst the AL group; some participants completely ignored the robot's social cues, while others strongly responded to this. Figure 5 (left) plots the responsiveness to AL against the final success rate of the teaching. Because of this high variance only a weak correlation between the participants responsiveness to AL and the guessing game success rate was found (AL condition, Pearson's $r = 0.09$).

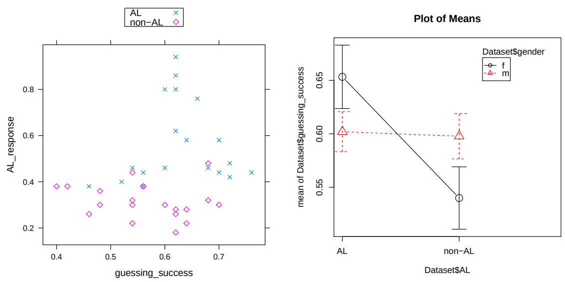

Figure 5: left: responsiveness to social cues against performance for AL and non-AL groups. Right: guessing success split into AL/non-AL and gender.

Gender differences We found an interaction between active learning condition and gender. It appears that in the case of female teachers the robot was more successful in guessing games in the AL condition (0.653) than with male teachers (0.602), while in the non-AL condition this is reversed with (0.540) and (0.597) for female and male groups respectively (figure 5, right). This interaction is significant with $p = 0.040$. Thus, it appears that an active learning robot might be more effective with a female teacher.

Conclusion

The ability of a robot to learn from a human teacher is important for achieving an effective robotic system that can coexist with humans in an unstructured environment. Furthermore, to utilize learning experiences to the fullest potential, an active learner may be able to shape the learning interaction in such a way as to experience a more optimal teaching.

We have presented experiments in simulation and with a real robot in which an active learner is able to positively influence the learning experience offered by a teacher through utilization of social clues. This allows the learner to learn quicker and more effectively. We showed that human participants are responsive to these kind of clues, suggesting that a robot learner might well utilize active learning mechanisms. Moreover, we found gender differences, indicating that the most effective learning experience might be achieved by a learner that personalizes its use of social clues with respect to different teachers.

Acknowledgements

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