TEACHING ROBOTS SOCIAL AUTONOMY FROM IN-SITU HUMAN GUIDANCE

by

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Abstract

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Emmanuel Senft

Here is the abstract

my original contribution to knowledge is a new teaching paradigm for robotics: Supervided Progressive Autonomous Robot Competenties (SPARC) which has been validated in three studies: interaction with a model, interaction with a fixed environment and interaction with humans in the context of robotic tutors.

First demonstration of teaching a robot to interact with humans

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Author's declaration

At no time during the registration for the degree of Doctor of Philosophy has the author been registered for any other University award. Work submitted for this research degree at Plymouth University has not formed part of any other degree either at Plymouth University or at another establishment.

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Chapter 1

Introduction

Human-Robot Interaction (HRI) what it is and what it matters and why it is challenging

Robots will inhabit human spaces and need to interact with them in decent ways

1.1 Scope

1.1.1 Frame

1.1.2 Environment

Robot interacting in an environment shared with humans / directly with humans presence of a supervisor who can provide feedback/commands

1.1.3 Type of interaction

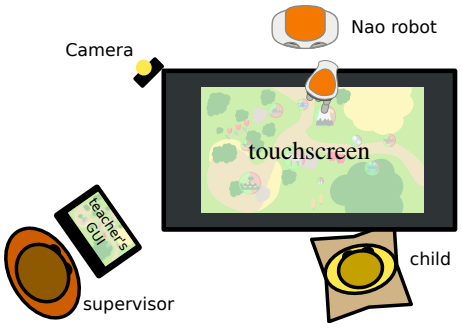


Figure 1.1: The setup used in the study: a child interacts with the robot tutor, with a large touchscreen sitting between them displaying the learning activity; a human teacher provides guidance to the robot through a tablet and monitors the robot's learning.

1.1.4 Algorithms

Three different algorithms have been used in the progress of this research. The first study presented in chapter 4 uses feed forward neural network with a single hidden layer. the second study in chapter 5 used Reinforcement Learning combining human and environmental rewards into a single reward source for the algorithm. And the last study presented in chapter 6 uses instance based algorithm adapted from Nearest Neighbours to enable quick and efficient learning. More details about each algorithms and their related work can be found in the associated chapters.

1.2 The Thesis

The main thesis that this document seeks to put forward is as below.

A robot can learn how to interact meaningfully with humans by receiving teaching content from a human supervisor which leads to an efficient, safe and low human-workload interaction policy.

Additional research questions have been explored during the progress of this work and are introduced here.

- **Does adding a learning component to a supervised robot can reduce the human-workload of the supervisor?**

  Wizard-of-Oz (WoZ) is an approach widely used in HRI (Riek, 2012), whereby a human teleoperates a robot to have it interact with other humans. However, this method applies a high workload on the operator and is not scalable. Using Machine Learning (ML) to learn from this operator online might decrease the operator's workload without decreasing the quality of the robot behaviour.

- **How control of a teacher over the robot's action impacts the robot's learning?**

  In the context of Interactive Machine Learning (IML), a human can provide inputs to an agent to speed up the learning. Other IML (Thomaz & Breazeal, 2008; Knox & Stone, 2009) focus on feedback from the human with limited or no control over the agent's actions. However increase the control should speed up the learning and reduce the number of errors made by the robot.

- **How could a human teach a robot how to interact with other humans?**

  SPARC has been designed to allow non-experts in ML to teach agents how to interact while interacting. Human-robot interactions provide a perfect test for this approach: using a human to teach a robot how to behave in this complex and non-deterministic environment.

1.3 Approach and Experimentation

1.4 Key Concepts

1.5 Challenges

1.6 Contributions

- Something

1.7 Structure

The structure of this thesis is outlined below to provide an overview of the content and context for each chapter. A summary of key experimental findings are included at the start of each relevant chapter for ease of reference.

- This chapter provided an introduction to the general field of this research (robot tutors for children), the research questions including the central *thesis*, scope, and contributions of the work presented in later chapters.
- Chapter 2
- Chapter 8 concludes the thesis with a summary of the main contributions.

Chapter 2

Background

This chapter describes the application of robot interacting with humans and related research in agent and robot control. The first section presents different fields of application of social HRI and then draws from them requirements for controlling a robot interacting with humans. The second section provides the current state of the art in robot control for HRI and analyses it through the constraints presented in Section 2.1.2. And the third and fourth sections present alternative methods to teach agents how to interact and how they could be applied to HRI.

2.1 Social Human-Robot Interaction

2.1.1 Fields of application

Human-Robot Interaction covers the full spectrum of interactions between humans and robots. However, as this thesis is focused on teaching robots to interact with humans, we used the following criteria on the interactions to select the subfields of HRI relevant to our research:

- presence of an interaction between a robot and a human: both the human and the robot are influencing each other's behaviour
- the social side of the interaction is key, the interaction involves a socially interactive robot as defined in Fong et al. (2003) (no physical human-robot interaction, such as an exoskeleton, physical rehabilitation or pure teleoperation as in robotic assisted surgery).

Socially Assistive Robotics

Socially Assistive Robotics (SAR) is a term coined in Feil-Seifer & Matarić (2005) and refers to a robot providing assistance to human user through social interaction and has been defined by Tapus et al. (2007) as one of the grand challenges of robotics.

One of the principal application of SAR is care for the elderlies. Ageing of population is a known challenge for today and the near future: the United Nations. Department of Economic and Social Affairs (2017) reports than *population aged 60 or over is growing faster than all younger age groups*. This will decrease the support ratio (number of worker per retiree) forcing society to find ways to provide care to an increasing number of persons using a decreasing workforce. Robots represent a unique opportunity to provide for this lacking workforce potentially allowing elderlies to stay at home rather than joining elderly care centres (Di Nuovo et al., 2014) or simply to support the nursing home staff (Wada et al., 2004).

However, the acceptance of these robots in elderly care facilities or at their homes, is still a complex task. Multiple studies report a good acceptance of robot and positive effects on stress in home cares both for the elderly and the nursing staff (Wada et al., 2004), but as mentioned in Broadbent et al. (2009), this acceptance could be increased by matching more closely the behaviour of the robots to the actual needs of the patients.

The second main application of SAR is Robot Assisted Therapy (RAT). In addition of providing social support, robots can also be used in the process of therapies, following a patient during their rehabilitation to improve their health, their acceptance in society or recover from an accident. In therapies, robots have first been used as physical platform to help patient to recover physically from strokes or cerebral palsy for example (Sivan et al., 2011). They were primally used as mechatronic tools helping humans to accomplish repetitive task. But in the late 90s, robots have started to be used for their social capabilities. For example the AuRoRA Project (Dautenhahn, 1999) started in 1998 to explore the use of robot as therapeutic tools for children with Autism Spetrum Disorder (ASD). Since AuRoRA, many projects have started all around the world to use robot to help patient with ASD, as shown by the review presented in (Diehl et al., 2012) or more recently the Development of Robot-Enhanced Therapy for Children with Autism Spectrum Disorders (European FP7 project) (DREAM) (Esteban et al., 2017). RAT is not limited to ASD only, the use of robots is also explored in hospitals, for example to support children with diabetes

(Belpaeme et al., 2012), to support elderly with dementia (Wada et al., 2005) or to provide encouragement and monitor cardiac rehabilitation (Lara et al., 2017).

Education

Social robots are also being used in education, supporting teachers to provide learning content to children. As presented in Mubin et al. (2013), the robot can take multiple roles such as peer, tutor or tool, however this *tool role* has been excluded for this overview due to its lack of social interaction.

Robotic teachers providing class lessons. One of the most obvious role robots could have in a classroom is replacing the teacher to provide the lesson content to children as presented in Verner et al. (2016). However this approach is seldom used in robots for education. The aim is not to replace teachers but to support them with new tools to improve the teaching process both for the teachers and the children, the review by Mubin et al. (2013) do not even mention robot teachers as a possible role for robots in educations.

Robotics tutors aim to provide tailored teaching content to the children they are interacting with. Studies reported that individualised feedbacks can increase the performance of students (Bloom, 1984), but due to the large number of students supervised by a single teacher in classes today, tutoring is complex to apply. Robotic tutors could provide this powerful one to one tailored interaction not available in current classroom without increasing the workload on teachers. Studies have also shown that adding robot in a classroom can improve the children learning outcomes (Kanda et al., 2004). Additionally, robots can be used at home to elicit advantages over web or paper based instructions (Han et al., 2005). However as pointed by Kennedy et al. (2015), social behaviours have to be carefully managed as a robot too social could decrease the learning for the children compared to a less social robot.

Peer robots learning alongside the children. A peer robot will not mentor the child to learn certain concepts, but will learn with or from the child. Unlike other roles of robots in education, peer robots can fit new roles still vacant in education today. For example, in Co-Writer (Hood et al., 2015), the child has to teach a robot how to write, and as the child demonstrates correct handwriting, they improves their own. Peer robots can leverage

the concept of learning by teaching Frager & Stern (1970) in a way hardly matchable by humans. The robot can take the role of a less knowledgeable agent with endless patience and encourage the student to perform repetitive tasks such as handwriting and improve.

Search and rescue, and military

Robots are already used during search and rescue missions. After a natural or artificial catastrophe, robots can be sent to analyse the damage area and report or rescue the surviving victims of the incident (Murphy et al., 2008). These robots have to interact socially with two kinds of human partners: the survivors and the rescue team. In both cases the social component of the interaction is key: the survivor can be in a shocked state and the robot could be the only link they received with the external world after the accident. In this case, a social response is expected from the robot and it has to be carefully controlled. On the other side, the rescue team monitoring the robots is under pressure to act quickly and can be stressed too. Even if the robot does not display social behaviour, rescuers interacting with it might develop some feeling toward the robots they are using during these tense moments and this has to be taken into account when designing the robot and its behaviour (Fincannon et al., 2004).

Similar human behaviours (emotional bonding with a robot) have also been observed in the army. Soldiers developed feelings toward the robot they use in a daily basis: taking pictures with it, introducing it to their friends and so on. This relation can go as far as soldier risking their life to in order to save the robot used by their squad (Singer, 2009). In that case, the social side of the robot have to be carefully managed to prevent it to have an opposite effect that the one desired: preventing the waste of human lives.

Hospitality and Entertainment

Robots are also interacting with humans in hotels around the world. The Relay robot (Savioke[1]) delivers commands for the guests of hotels from the reception to their room. Whilst the social interaction is still minimal today, these robots interact everyday with humans and provoke social reactions from them. On the research side, scientists have explored robots as receptionist in a hall at Carnegie Melon University (Gockley et al., 2005) and robots as museums and exhibitions guide since the late 90s (Thrun et al., 1999;

[1] `http://www.savioke.com/`

Burgard et al., 1999) and since, explore how to improve the social interaction for guide robots.

Similarly, robots guide and advices humans in shops and shopping mall. Long term studies explored how humans perceive and interact with robots in this environment (Kanda et al., 2009) and how robots should behave with clients (Kanda et al., 2008).

Robots have also entered homes and family circles. Twenty years ago, Sony created Aibo, a robotic dog to be used as pet in Japanese families. An analysis of online discussion of owners published 6 year after their introduction gives insights on the relationship that owners created with their robots (Friedman et al., 2003). For example 42% of the members assigned intentionality to the robot, like preferences, emotions or even feelings. Similar behaviours can also be observed when the robot is not presented as a pet, but just a tool. In Fink et al. (2013), authors reported that a participant was worried that their Roomba would feel lonely when they would be in holidays. More recently, the Pepper robot has been sold to family in Japan, however, as of March 2018 no english study has reported results of the interaction with family members or long term use.

Collaborative Robots in industry

Robots in industry used to be locked behind cages to prevent humans to interact with them and getting hurt. However recently, social robots such as Baxter (Guizzo & Ackerman, 2012) have been designed to collaborate with humans and share the same workspace interacting physically and socially with factory workers. These robots need to be usable and reprogrammable by non-robotic experts and need to convey and understand intentions from motions and eye gaze (Bauer et al., 2008). The topic of motion legibility: how to convey intention using only motion trajectory is being covered extensively by the literature: in Dragan et al. (2013) and successive work, authors present ways to improve clarity of intentions and so improve the collaboration between humans and robots.

In addition to legibility, an other important topic in human-robot collaboration is task assignment: if a goal has to be achieved by a human-robot team, the repartition of tasks should be carefully managed to optimise the end result in term of task performance, but also to ensure comfort for the human. Multiple sets of implicit rules have to be taken into account in a human-robot collaboration context, and so the task repartition system should be aware of them and follow them as proposed in Montreuil et al. (2007).

2.1.2 Constraints

The previous section demonstrated that robots are already interacting with sensitive populations: young children, elderlies, persons with handicap or in a stressful situations (victims of catastrophes, soldier or persons requiring healthcare for example). As pointed previously in the case of robots for the elderlies, this number of human-robot interactions is likely to rise for the other categories too. In this context, failure to meet expectations or lack of social norms or awareness might lead to physical injuries to surrounding humans or potentially to offence, anger, frustration or boredom. As such, the behaviour of robots interacting with humans need to be carefully managed to meet expectations and robots needs to behave socially.

These undesired behaviours can have many different origins: lack of sensory capabilities to identify necessary environmental features, lack of knowledge to interpret human behaviours appropriately, failure to convey intentions, impossibility to execute the required action or incorrect action policy. Due to the wide range of origins, this research focuses only on the last point, obtaining a correct action policy: assuming a set of inputs, how a robot should select the most correct action. The other issues are either orthogonal and would lead to failure even with an "optimal" action policy as external factors prevent the robot to solve a problem or can be handled by having a better action policy selecting suboptimal actions when the optimal ones cannot be used, or reacting correctly to human behaviours without having to interpret them on a higher level.

Appropriate actions are highly dependent on the interaction context: they could aim to match users' expectations of a robot behaviour, or complete a specific task. Nonetheless, the intention behind being *appropriate* here is that actions executed should be guaranteed not to present risk for the humans involved in the interaction; for example, preventing physical harm or mental distress while achieving the robot assigned objectives.

Additionally, interactions with humans "in the wild" (Belpaeme et al., 2012) do not happen in well defined environments or rigid laboratory setups: in the real world, robots have to interact in diverse environments, with a large number of different persons, during extended periods of time or with initial incomplete or incorrect knowledge: as such the action policy also needs to be adaptable to the context, to the users and over time. Robots need to be adaptive, both to react to changing environments, and to improve their action policy over time.

Lastly, in many cases today, interactive robots are not autonomous but partially controlled by a human operator. We argue that to have a real Human-Robot Interaction, the robot needs to be as autonomous as possible. As pointed out in Baxter et al. (2016), by relying too much on a human to control a robot, we are shifting from a human-robot to a human-human interaction using a robot as proxy. As a community, HRI should strive toward more autonomy for robots interacting with humans.

We define three axes to analyse a robot behaviour and evaluate how suited its behaviour is in the interaction:

- Appropriateness of actions
- Adaptivity
- Autonomy

And we will use these axes to analyse robots' controller types in Section 2.2.

HRI being a large field, other research axes are equally important such as the complexity or the depth of the interaction, the constraints put on the environment, the ability of the robot to set its own goals or the dependence on social rules, the range of application. However, these axes are more influenced by the goal and the context of the specific human-robot interaction taking place rather than the action policy itself, so this research focuses on the three axis mentioned previously.

To be able to sustain meaningful social interactions, robots should score highly in the three axes presented before, following these three principles:

1. Only execute appropriate actions.
2. Have a high level of adaptivity.
3. Have a high level of autonomy.

Appropriateness of Actions

As argued previously, much of social human-robot interaction takes place in stressful or at least sensitive environments where humans have particular expectations about the robot's behaviour or needs from the robot. Additionally, even in less critical situations,

human-human interactions are subject to a large set of social norms and conventions resulting from precise expectations of the interacting partners (Sherif, 1936). Some of these expectations are also transferred to interactions with robots (Bartneck & Forlizzi, 2004).

Failing to produce appropriate actions, for example by not matching the users' expectations, can have a negative impact on the interaction, potentially compromising future interactions if the human feel disrespected, confused or annoyed. Similarly failing to behave appropriately can harm the persons interacting with the robots: not reminding an elderly to take their medication, not taking into account the state of mind of survivors after a disaster or not behaving consistently with children with ASD can lead to dramatic consequences. We argue that robots require a way to ensure that all the actions they are executing do not present risks to the human involved in the interaction.

Surprise is an important element in social interaction, as it can revitalise the interaction and increase the engagement of users (Lemaignan et al., 2014). As such, a robot does not need to be consistently fully predictable, but in any contexts of interaction the robot should not present danger for humans it is interacting with. This requirement is simila to the first law of Asimov (Asimov, 1942), but not as a law that the robot should follow (as it would be impossible to implement it that way, and that the point of Asimov was that these laws are not sufficient), but as a design principle for the humans developing a robot behaviour or as defined by Murphy & Woods (2009): "A human may not deploy a robot without the human-robot work system meeting the highest legal and professional standards of safety and ethics."

Being able to behave appropriately is a tremendous challenge: real interactions involve a large sensory space, with the interactants often being unpredictable or at least highly stochastic. In addition, social interaction is grounded by a large number of often implicit norms, with expectations being highly dependent on the context of interaction. It seems unlikely that an action policy covering every possibility can be provided to the robot before the start of the interaction. For this reason, social robots need an action policy able to generate the appropriate reactions for the anticipated states, but they also have to manage uncertainty: being able to select a correct action even when facing a sensory state with no explicit predefined action to do.

For the review in the next section, the appropriateness of actions axis is a continuous spectrum characterising how much the system controlling the robot is in control of the

interaction and can act in a safe way for the users at any moment of the interaction. For example, a robot selecting its action randomly would have a low appropriateness as no mechanism prevent the execution of unexpected or undesired action. On the other hand, a robot continuously selecting the action that a human expert would select would have a high value as domain experts have the knowledge of which action is the correct one in this interaction domain.

Adaptivity

For reasons similar to the ones stated in Section 2.1.2 and as pointed by other research groups (Argall et al., 2009; Hoffman, 2016), an optimal behaviour of a robot is unlikely to be programmable by hand. End users can express behaviours not anticipated by the designers, the environment is probably not perfectly defined or the desired behaviour might need to be customisable by or for the end user. For these reasons, robots interacting with humans need to be able to update their action policy to improve their behaviour. We use the term *adaptivity* to represent this ability to change the action policy at runtime.

While many studies in HRI do not use adaptive robots, to interact meaningfully outside of lab settings or scientific studies, robots needs to possess this adaptivity to extend the range of application and improve its interactions with users.

We propose three components for this adaptivity: the adaptivity in space (being able to change an action policy according to the environment), the adaptivity in users (being able to change an action policy according to the user) and the adaptivity in time (being able to change an action policy over time).

The same robot might be expected to interact in different environments or the environment where the robot evolves might also change with time. For example a robot used as an assistant for elderly people will have to interact in the home of the owner, but can also have to follow the owner in the street or in a supermarket. In these different environments, different behaviour will be expected from the robot, as such to be able to behave accordingly, the robot has to be adaptive in space.

Additionally, in most of the application fields presented earlier, robots have to interact with a large number of users, and often, these interaction partners are not know in advance and can have different roles: in education the name and particularities of each child can hardly be specified in advance and the robot might have to interact with the students

or with the teacher. In entertainment or search and rescue, none of the user is known beforehand. Adaptivity can be a way to identify the different users and adopt an action policy that suit the current user more specifically.

Lastly, in these fields where the interaction is social, robots deployed in the wild might interact over extensive periods with the same user, e.g. companion robots for the elderly, military robots for a squad or robots used in RAT. With these long-term interactions, adaptivity in time allows the robot to tailor its behaviour to the current user and track the changes of preferences that could occur over long periods of interaction. Adaptivity in time can also allow the robot to learn from its errors and improve its action policy over time. This adaptation over time is critical, it is in essence *learning* and can provide for the other types of adaptivity and even allow a robot to satisfy the two other principles (appropriateness of actions and autonomy).

For this review, adaptivity is a continuous scale ranging from no adaptivity at all (the robot has a script that it follows in all the interactions), to high adaptivity (the robot dynamically change its action policy during an interaction and adapt it to the persons and context of the interaction). As this adaptivity is over three axes, some robots can have a high adaptivity in users (by adapting their behaviour to the actions of their interactants), but not in time (if the same inputs always trigger the same output), and not in space (if only one specific context of interaction is taken into account). In that case, the controller will receive a relatively low adaptivity rating.

Autonomy

To be deployable in the world and interact with humans, robots have to be autonomous. A limited supervision can support the robot and improve its behaviour, but the robot should not rely on humans for its action selection. Today, many experiments are conducted using a robot tele-operated by a human. Whilst having a human controlling the robot presents many advantages, e.g. the human can provide the knowledge and the adaptivity required and has sensing and reasoning capabilities not yet implemented on the robot, multiple reasons push us away from this type of interaction (Thill et al., 2012). It is not suited for deploying robots in the real world: it does not scale to interact for a long period of time or on larger scale, the human-robot interaction tends to become a human-human interaction (Baxter et al., 2016) and it might introduce multiple biases in the robot behaviour (Howley

et al., 2014). For these reasons among many, we argue that a robot used in social HRI should be as autonomous as possible.

The third axis of this literature review is the autonomy. As stated by Beer et al. (2014), autonomy is organised following a spectrum of different levels of autonomy from no autonomy at all: a human is totally controlling the robot (doing sensory perception, analysis and action selection) to a full autonomy: the robot senses and acts on its environment without relying on human inputs. Levels exist between these extremes where a human and a robot share perception, decision or action: for example the robot can request information from a supervisor or the supervisor can overide the action or goal being executed

2.2 Current robot behaviours in HRI

This section presents diverse approaches currently used in HRI to control a robot. As the number of individual techniques is too large for an exhaustive review, we organised the literature into broader categories. For each category, we will present the corresponding approach, indicate leading works done in this direction and qualitatively rate it on the three axes defined in the previous section.

2.2.1 Wizard of Oz

Wizard-of-Oz (WoZ) is a specific case of tele-operation where the robot is not autonomous but at least partially controlled by an external human operator to create the illusion of autonomy in an interaction with a user. It outsources the difficulty of action selection and/or sensory interpretation to a human operator. This technique has emerged from the Human-Computer Interaction (HCI) field in 1983 (Kelley, 1983) and is today common practice in HRI (Riek, 2012). WoZ can assume different levels corresponding to the involvement of the human in the action selection process. Baxter et al. (2016) differentiate two main levels: perceptual WoZ (the human only replace sensory system and feed information to the robot controller) and cognitive WoZ (the human makes decisions about what the robot should do next). This method can also be used to gather data to develop a robot controller from human demonstration (cf. Section 2.2.4).

Similarly to the different levels of autonomy presented earlier, systems can combine human control and predefined autonomous behaviour. Shiomi et al. (2008) proposes

a semi-autonomous communication robot. This robot is mainly autonomous, but has the ability to make explicit request to a human supervisor in predefined cases where the sensory input is not clear enough to make a decision. The human can also provide additional information on the state of the world to inform the robot of events or do natural language recognition, to inform an autonomous system about the sentences said by the users.

With WoZ, the adaptivity and the appropriateness are provided almost exclusively by the human, so these characteristics are dependent of the human expertise but are generally high. However, due to the reliance on human supervision to control the robot, the autonomy is low. For semi-autonomous robots, the picture is more complex: as explained by Beer et al. (2014), the initiative, the human's role and the quantity of information and control shared will influence the level of autonomy. For example, in Shiomi et al. (2008) the robot explicitly makes requests to the human, but the human cannot take the initiative to step in the interaction limiting the adaptivity (especially as the robot policy is fixed) and as no mechanism prevents the robot to make undesired decision, the appropriateness of actions is average compared to classical WoZ.

2.2.2 Fixed preprogrammed behaviour

One of the simplest ways to have a robot interacting with a human is to have an explicit fixed behaviour. The robot is fully autonomous and follows a script or a finite state machine for action selection. This approach is dependent on having a well defined and predictable environment to have the interaction running smoothly. If the interaction modalities (possible range of behaviour and goal) are limited enough, a desired robot behaviour can be predefined for all (sensible) human actions. This approach is followed in a large number of research in HRI. Many studies being human-centred, the focus is not in the complexity of the robot's behaviour but on how different humans would interact with and react to a robot displaying a fixed behaviour (for comparison purposes). Similarly to WoZ, while being useful to explore human's reactions to robots, this method can hardly be used to deploy robots to interact with humans on a daily basis due to the lack of well defined environments in real world applications.

By essence, this type of controller has a no adaptivity as the robot is following a pre-programmed script, but scores highly on autonomy as no external human is required

to control the robot and as the application domain is highly specified, the behaviour is mostly appropriate.

2.2.3 Adaptive preprogrammed behaviour

To go beyond a script, the robot can also react to the human behaviour. The robot could be programmed with different behaviours, and then select the one corresponding to the current interaction following rules given prior the experiment. For example, in Leyzberg et al. (2014) the robot can deliver some predefined content according to the current performance of the participant, presenting personalised behaviour as long as the participants is behaving within expectations.

Reactive controllers mapping directly input data to behaviour without trying to reach specific high level goals can also be used successfully in HRI. For example, homeostasis, the tendency to keep multiple elements at equilibrium, is constantly used by living systems to survive and have been used to control robot in social interaction. Breazeal (1998) uses a set of drives (social, stimulation, security and fatigue) which are represented by a variable each and have to be kept within a predefined range. If these values are outside the desired homeostatic range, the robot is either over or under-stimulated and this will affect its emotion status and it will display an emotion accordingly. Homeostasis approaches have also been extended to robotic pets (Arkin et al., 2003) or RAT (Cao et al., 2017).

Due to the implicit description of behaviours, homeostasis-based methods are more robust in unconstrained environments than a purely scripted controller, while remaining totally autonomous. However the action policy is not adaptive in time and as the behaviours are not totally defined and controlled, there is no guarantee against the robot acting in inconsistent way in some specific cases limiting the appropriateness of actions.

Efforts have been made to extend the homeostasis approaches beyond purely reactive systems with the use of hormone models (Lones et al., 2014). This method allows the previous experiences of the robot to impact the behaviour expressed providing limited adaptivity in time to the robot. However this approach was only applied to a robot interacting in a non-social environment and the robot behaviour was biased rather than fully adaptive.

Both predefined adaptation and homeostasis-based methods score highly in autonomy and can have a high level of appropriateness, but the adaptation is low as they can only

adapt within predefined and anticipated boundaries and the robot does not learn.

2.2.4 Learning from Demonstration

As stated by numerous researchers, explicitly defining a robot behaviour and manually implementing it on a robot can take a prohibitive amount of time or not be possible at all. This statement applies both to manipulation tasks and social interaction. However in both cases, humans have some knowledge or expertise that should be transferred to the robot. And in many case for social robots, experts of the field do not have the technical knowledge to implement this behaviour on a robot requiring numerous iteration of design between the users and engineers to reach a consensus.

The field of Learning from Demonstration (LfD) aims to tackle these two challenges: implementing behaviours too complex to be specified in term of code and empowering end-users with limited technical knowledge to transfer an action policy to a robot. Humans demonstrate a correct behaviour through different control means (Argall et al., 2009), and then offline batch learning is applied to obtain an action policy for the robot and if required, reinforcement learning can complement the demonstrations to reach a successful action policy (Billard et al., 2008).

In Learning from Demonstration (LfD) the interaction between the robot and the human teacher is key, however in most of the cases the object of the learning is not social interaction with humans, but manipulation or locomotion tasks. For example, Abbeel & Ng (2004) used telecontroled helicopters experts to demonstrate flying acrobatics, and extracted from these demonstrations a reward function used to train a controller to reproduce these acrobatics at a super-human level through Inverse Reinforcement Learning.

However, two approaches have explored using LfD to teach robots a social policy to interact with humans.

The first one is using human-human interactions to collect data about human behaviours and transfer them to a robot. Liu et al. (2014) present a data driven approach taking demonstration from human-human interactions to gather relevant features defining human social behaviour. Authors recorded motion and speech from about 180 interactions in a simulated shopping scenario, then behaviours have been clustered into *behaviour elements*. Finally, during the interaction, the robot uses a variable-length Markov model predictor to estimate the selection probability of each actions by the human demonstra-

tor, and then selects the one with the highest probability. According to the authors, the fianl performance of the robot was not perfect, but if this approach was scaled using a larger dataset gathered from normal human-human interactions in the real world, the performance should improve and become closer to natural human behaviours.

Alternatively, the data can be collected from a Wizard-of-Oz setup. (Knox et al., 2014) coined this approach *Learning from Wizard*: starting for a purely WoZ control to gather data, and then apply machine learning to derive an action policy. But this paper presents no description of which algorithm could be use or how, and gives no evaluation of the approach, but instead only offers a reflection on the application of this idea.

This Learning from Wizard have been implement by two groups of researchers. Sequeira et al. (2016) extended the idea to a full methodology to obtain a fully autonomous robot tutor. This method is composed of multiple steps starting with the observation of a human teacher performing the task. Then, the different features used by the teacher to select their actions as well as the actions themselves are encoded and implemented in a robot. The next step is setting up a WoZ experiment where the operator has access to the same features than the robot to make his decisions and controls the robot's action. Then, a combination manually derived rules and machine learning is applied on the data from the restricted-perception experiment and finally the robot is tested autonomously. Additional offline refinement steps are possible if the behaviour is not exactly the one desired.

Both Knox et al. (2014) and Sequeira et al. (2016) stress the importance of using similar features for the Wizard of Oz part than the ones available to the robot during the autonomous part: whilst decreasing the performance in the first interaction, it allows more accurate learning due to the similarity of inputs for the robot and the human controlling it.

Clark-Turner & Begum (2018) decided to bypass these limitations by using a deep Q network (Mnih et al., 2015) to learn an Applied Behaviour Analysis policy for RAT. They recorded videos, microphone inputs and actions selected in a WoZ interaction with participants. Then, the network learns from the raw inputs and the actions selected an action policy to control the robot and deliver the therapy. However in their study, the performance of the system was low (less than 70%) which means that the robot would provided inconsistent feedback at some point and they required limited human inputs to reach that level.

As these methods are based on real interactions either between humans, or between

humans and robots controlled by humans, with enough demonstrations the robot should be able to select the appropriate actions. However, as no intrinsic mechanism is present to prevent the execution of undesired actions which could happen if the robot ends up in an unseen state, the appropriateness of actions cannot be maximal. Additionally, the adaptivity in time is limited, as for most of the techniques the learning happens only once and then the behaviour is fixed. However, the framework proposed by restricted-perception Wizard of Oz should allow asynchronous adaptivity in time using the refinement phase. And finally, all these methods require the presence of humans in a first phase but the robots are fully autonomous later in the interaction, so the autonomy is high during the main part of the interaction.

2.2.5 Planning

An alternative way to interact in complex environments is to use planning. The robot has access to a set of actions with preconditions and postconditions and a defined goal. To achieve this goal state, it follows the three planning steps: sense, plan and act. The first step, sense, is to acquire information about the current state of the environment. Then, based on the set of actions available and the goal, a plan is created. This plan is a trajectory in the world, a succession of action and states which, according to the defined pre and postconditions, will lead to the goal. Finally, the last step is to execute the plan. The plan can be reevaluated at each state or only if a state differs from the expected one, in that case the robot update its plan to the new conditions and continue trying.

The efficiency of planning relies on having a precise and accurate set of pre and postconditions for each actions. And as humans are complex, if not impossible, to model precisely, planning have seen limited use for open social interactions with humans. However, due to the nature of planning, reaching a specific goal, it has been applied successfully to human-robot collaborative task achievement. Additionally, limiting the interaction to a joint task also simplifies the modelling of the human behaviour as the interaction is more constrained. One example of such an application is the Human Aware Task Planner (Alili et al., 2009). One property of this planner is the ability to take into account predefined social rules, such as reducing human idle time, when creating a plan specifying what the human and robot should do.

Planning performance depends heavily on the model of the environment the robot has

access to. A detailed model can ensure that the robot will select the appropriate action whilst being totally autonomous. Similarly, the adaptivity depends on the model the robot has access to and whether it can update it in real time. However, in many cases when interacting with humans, the model is static, only covering a subset of the different tasks that the robot can be required to achieve and the different contexts it is expected face.

Planning have also been extended with learning, which then allows for adaptive action policies. This has been done in motion planning, to obtain a better trajectory (Jain et al., 2013; Beetz et al., 2004) and action selection planning (Kirsch, 2009). But to our knowledge, no planner used in social HRI includes a module allowing it to change its model by increasing the number of actions, adding new rules or changing the pre and postcondition of actions at runtime, limiting the adaptivity of the planner.

2.2.6 Learning from the Interaction

A last type of controller seldom used for creating action policies to interact with humans is learning from the interaction. The robot can create an action policy by exploring and learning from interacting with the world. This method assumes that the agent can update its action policy online, or regularly, and refine its knowledge of the world or at least of how to interact within it.

However, due to the complexity to create such a system and to the challenges of social interactions with humans this approach is almost never used. One example where a robot learns a non social policy online by receiving spoken human commands and explaination is using the DIARC cognitive architecture (Scheutz et al., 2017). In this paper, authors describe how a robot can learn concepts and mapping actions to verbal commands by receiving human information.

This approach is the one with the most potential as the humans could provide only the required supervision or guidance and let the robot be autonomous most of the time. Learning online an action policy provides potentially open-ended adaptivity and finally, with enough data points and the presence of a human in the action selection loop if required, the appropriateness of actions could be guaranteed.

2.2.7 Summary

Table X presents a summary of the different approaches currently used in HRI with their rating on each of the categories and how widely their are applied. As shown in the paper, the most promising type of control is *Learning from the interaction*, but it is seldom used to learn how to interact with humans. However, other fields (Reinforcement Learning and HCI) have explored ways of controlling agents included in this larger approach and we will present them in the next sections.

2.3 Reinforcement Learning

2.3.1 Concept

Young infants and adults learn by interacting with their environment, by producing actions, analysing how the environment reacts and measuring progress toward a goal. Similarly, the field of Reinforcement Learning (RL) aims to empower agents by making them learn by interacting, using results from trials and errors and potentially delayed rewards to reach an optimal, or at least efficient, action policy (Sutton & Barto, 1998).

Reinforcement Learning (RL) considers the time to be discrete, the life to be a sequence of states and actions. The simplest version of RL is modelled as a finite Markov Decision Process (MDP), a 5-tuples $(S, A, P_a(s,s'), R_a(s,s'), \gamma)$, with:

- S: a finite set of states defining the agent and environment states
- A: a finite set of actions available to the agent
- $P_a(s,s')$: the probability of transition from state s to s' following action a
- $R_a(s,s')$: the immediate reward following transition s to s' due to action a
- γ: a discount factor applied to future rewards

The goal of the RL agent is to find the optimal policy π_* maximising the discounted sum of future rewards. The agent is not aware of all the parameters of the model, and only observes the transitions between states and the rewards provided by the environment and has to update its policy to maximising this cumulated reward. Different algorithms

exist to reach this policy, but the main features present in all of them is the concepts of exploration and exploitation.

Exploration reflects the idea of trying out new actions to learn more on the environment and potentially gain knowledge improving the policy whilst *exploitation* is the execution of the current best policy to maximise the current gain of rewards. All the algorithms have to balance these two features to reach an optimal action policy. One way to deal with this trade-off is to start with high probably of exploration to collect knowledge on the environment and then decrease this probably to converge toward a policy using this knowledge to make better choice of actions.

The more complex the environment is, the longer the agent has to explore before converging to a good action policy. It is not uncommon to reach numbers such as millions of iterations before reaching an appropriate action policy. And during this exploration phase, the agent's behaviour might seem erratic as the agent tries actions often randomly to observe how the environment is reacting.

2.3.2 Limitations

As explained in the previous section, traditional RL has two main issues: requirement of exploration to gather knowledge about the environment and large number of iteration before converging. Generally, RL copes with these issues by having the agent interacting in a simulated word. This allows the agent to explore safely in an environment where its actions have no impact on the real world and where the speed of the interaction can be highly increased to gather the required datapoints in a reasonable amount of time. However, no simulator of human beings exists today which would be accurate enough to learn an action policy applicable in the real world. Learning to interact with humans by interacting with them would have to take place in the physical world, with real humans, and this implies that these issues would have direct impacts.

To gather informations about the environment, the agent needs to explore, trying out random actions to learn how the humans respond to them and if the agent should repeat them later. When interacting with humans, executing random actions can have dramatic effect on the users, presenting risk of physical harm as robot are often stiff and strong or cause distress as explained before. This reliance on random exploration presents a clear violation of the first principle to interact with humans presented earlier (all actions need

to be appropriate).

Even if random behaviour were acceptable, humans are complex creatures, behaving stochastically, with personal preferences and desires. And as such, learning to interact with them from scratch would would require large number of datapoints and as interactions with humans are slow (not many actions can be tested per minute) the time required to reach an acceptable policy can prohibitive.

RL has been used in robotics despite these limitations (Kober et al., 2013), and, similarly to LfD, mostly to manipulation, locomotion or navigation tasks but not to learn social behaviours for HRI.

2.3.3 Opportunities

Despite the limitations presented in the previous section, changes can be made to RL to increase its application to HRI.

García & Fernández (2015), insist on *safe* RL, ways to ensure that even in the early stages of the interaction, when the agent is still learning about the world, its action policy still achieve a minimal acceptable performance. Authors present two ways to achieve this safety: either use a mechanism to prevent the execution of non-safe actions or provide the agent with enough initial knowledge to ensure that it is staying in a safe interaction zone. These two methods are not limited to RL but can also be used with other machine learning techniques.

The first method (preventing the agent to execute undesired actions) can be implemented by explicitly preventing the agent to execute specific actions in predefined states, however it seems unlikely that every case could be specified in advance. As such, the easiest way in to include a human in the action selection loop, as a way to be sure that undesired actions are pre-empted before being executed. Learning by interacting with humans is called Interactive Machine Learning and is described more in depth in Section 2.4.

The second method (providing enough initial knowledge) can be achieved by carefully engineering the features used by the algorithm or starting from a initial action policy to build upon. Abbeel & Ng (2004) propose to use humans demonstrations in a fashion similar to LfD but to learn a reward function and an initial working action policy. This method, Inverse Reinforcement Learning has been applied successfully to teach a flying

behaviour to a robotic helicopter. Once the initial policy and the reward function are estimated, RL is applied around the provided policy to explore and optimise the policy. That way, only small variation of the policy will happen around the demonstrated one. This small variations can ensure that policies leading to incorrect behaviours can be negatively reinforced and avoided before creating issues (such as crashing in the case of the robotic helicopter).

Whilst being promising and having been applied for agents in human environments (such as for personalised advertisement - Theocharous et al. 2015) these approaches have not been used social behaviour or to have robot interacting with humans.

2.4 Interactive Machine Learning

Machine learning is a promising method to provide a robot with an adequate action policy without having to implement in advance all the features used by the action selection mechanism. Offline learning is a technique allowing the robot to change its action policy over time by updating the action policy outside of the interaction. Between interactions, a learning algorithm is used to create a new action policy derived from the previous experiences.

However online learning (such as RL) have the advantage of benefiting from multiple updates, constantly refining the agent behaviour, rather than a single monolithic definition or update of a behaviour. As mentioned in the previous section for the case of RL, including humans in the action selection loop can provide tremendous advantages compared to fully autonomous learning.

Interactive Machine Learning (IML), as coined by Fails & Olsen Jr (2003), differs from Classical Machine Learning (CML) by integrating an expert end-user in the learning process. In classical supervised learning, such as deep learning (LeCun et al., 2015), the learning phase happens offline once to obtain a classifier for later use. On the other hand, IML is an iterative online process using a human to correct the errors made by the algorithm as they appear.

Amershi et al. (2014) presents an introduction to IML by reviewing the work done and presenting classical approaches and challenges faced when using humans to support machine learning.

2.4.1 Goal

The main goal behind IML is to leverage the human knowledge during the learning process to speed it up. To extend the use of classifiers from static algorithms trained only once, to evolving agents learning from humans and refining their policies over time. IML can be applied in a RL approach or Supervised Learning (SL) but tries to combine advantages from both worlds. As explained in Fails & Olsen Jr (2003), classifiers gain to be fast rather than highly inductive and RL can gain from using humans to provide rewards (Knox & Stone, 2009).

By allowing a human user to see the output of an algorithms and provide additional inputs, the learning can be faster and tailored to this human desires. Using human expert knowledge and intuition, the system can achieve a better performance faster.

Additionally, a key of IML is also to empower end-users. These users are often non-technical, but possess valuable knowledge about what the robot should do. IML provides an opportunity to allow these users to design the behaviour of their robot, to teach it to behave the way they desire.

2.4.2 Active learning

Active learning is a form of teaching used in education aiming to increase student achievement by giving them a more active role in the teaching process (Johnson et al., 1991). This approach has been transferred to machine learning, and especially classifiers by allowing the learner to ask questions, query labels from an oracle for specific datapoints with high uncertainty (Settles, 2009). The typical application case is when unlabelled data are plentiful, but labels can be limited in number or costly to obtained. As such a tradeoff arises between the performance of the classifier and the quantity of queries made by the algorithm. Often this oracle would be a human annotator with the ability to provide a correct label to any datapoint.

Using an oracle to provide the label of specific points aims to both improve accuracy and speed up the learning as obtaining label of point with high uncertainty increase the precision of the algorithm and should highlight missing features in the current classifier. However, this relation between the learner and the human teacher poses questions such as:

- Which points should be selected for the query?
- How often the human should be queried?
- Who controls the interaction? (i.e. who has the initiative to trigger a query?)

Researchers have explored optimal strategies for dealing with the relation between the learner and the oracle, and this research has been especially active in HRI with robots directly asking questions to human participants and how the robot's queries could inform the teacher about the knowledge of the learning (Chao et al., 2010). In a follow up study, Cakmak et al. (2010) showed that most users preferred the robot to be proactive and involved in the learning process but they also wanted to be in control of the interaction, deciding when the robot could ask questions even if it imposed a higher workload on the teacher. Authors proposed that when teaching a complex task requiring a high workload on the teacher, the robot would probably be expected or should be encouraged to take a more pro-active stance requesting samples to take over some workload from the teacher.

Active learning, being able to select a specific sample for labelling, can dramatically improve the performance of the learning algorithm. However, in interaction, the learner is not in control of which sample to submit to an oracle to obtain a label. Datapoints are provided by the interaction and are influenced by the learner actions and the environment reaction. To tackle this issue: not being able to decide which sample to evaluate but still profiting from an active stance of the learner, Chernova & Veloso (2009) presented the Confidence Based Algorithm. The robot is initially provided with demonstrations of a correct action policy and then has to interact in the world under supervision from an human user. Authors propose that the teacher should still be able to provide corrective demonstrations in case of incorrect behaviour, but the learner should also be able to request a demonstration if the confidence of which action to select is below a threshold. That way, the learner can mitigate autonomous behaviour and human support. However, the effectiveness of this approach is bounded by the capacity of the learner to estimate this confidence in the desired policy, to request demonstrations only to prevent incorrect behaviour without relying excessively on the human oracle. Timing issues can also arise when requesting a demonstration or a label.

2.4.3 Human as a source of feedback on actions

When the learner is agent learning an action policy (rather than a classifier) and the learner is expected to improve its behaviour by interacting with the environment, an intuitive way to steer the behaviour in the desired direction faster is to use human rewards. This approach is an adaptation of "shaping": tuning a animal's behaviour by providing rewards. In ML, using rewards from a human teacher is a *simple* way to bias the learning in the desired direction: the interface is easy, the teacher just need a way to provide a scalar or a binary evaluation of an action to steer the learning. However, this simplicity of interaction can be complex to interpret, ongoing research evaluates the best way to use this reward and combine it with environmental ones if existent (Knox & Stone, 2010) or how to understand the meaning of these rewards.

When used on their own, human rewards enable an agent to learn an action policy even in the absence of any environmental rewards, which is specially interesting to robots as it can be complex to define a clear reward function applicable to HRI or robotics in general. Early work in that field came from Isbell et al. (2006) who designed an agent to interact with a community in the LambdaMOO text based environment. Cobot, the agent had a statistical graph of users and their interactions and could execute some actions in the environment. Users of LambdaMOO could either reinforce positively or negatively Cobot's action by providing rewards. Isbell et al. presented the first agent to learn social interactions in a complex human online social environment.

While the goal of Cobot was to create an entity interacting with humans, Knox & Stone (2009) explored how a human can teach an agent an action policy with TAMER (Training an Agent Manually via Evaluative Reinforcement). The agent uses a supervised learner to model the human reward function and then takes the action that would receive the highest reward from the model. Other work explored how an agent can infer more knowledge from a reward than only its value. Advice (Griffith et al., 2013) models the confidence a learner can have in its teacher to make better use of rewards. Loftin et al. (2016) explore the strategy used by the teacher in the reward delivery: the meaning of not rewarding an action can vary between teachers, from a implicit acknowledgement of the correctness of an action to the active refusal to provide a positive reward (indicating the incorrectness of an action). MacGlashan et al. (2017) proposed COACH (Convergent Actor-Critic by Humans) to adapt the interpretation of feedback to the current policy, for example, a

suboptimal policy could receive positive feedback early on when it compares positively to the average behaviour, while receiving negative feedback later on the teaching when the average agent performance is better.

Other approaches combine traditional RL with critique from humans. A human is requested to evaluate specific behaviours (Judah et al., 2010) or compare to policies to select the most appropriate one (Christiano et al., 2017).

Thomaz & Breazeal (2008) aimed to explore how humans would use feedback to teach a robot how to solve a task, here baking a cake. They used Interactive Reinforcement Learning as a way to directly combine environment rewards and human ones. However, during early studies, Thomaz et al. discovered that participants tried to use rewards to convey intention, informing the robot which part of the environment it should interact with. The next study involved two communication channels, a reward one to provide feedback on the actions and a guidance one to provide information about which part of the environment the robot should interact with. This guidance has been actively decided to be ambiguous, participants could not explicitly control the robot, but just bias the exploration. Adding this second channel improved the performance of participants.

2.4.4 Importance of control

Results from both active learning and research using human to provide feedback have shown that human teacher desire control (Amershi et al., 2014). Humans are not oracle, enjoying providing labels and evaluating an agent's actions they desire to be in control of the learning and provide richer information to the agent. Kaochar et al. (2011) have shown than when given choice between different teaching methods, humans will never choose to limit themselves to use only feedback, but they want to teach using more modalities.

In addition to improve the teacher's experience in the teaching, providing the teacher with more control can improve the learning. By allowing the teacher to demonstrate online an action policy or pre-empt undesired actions the robot is about to execute, the learner can interact mostly in useful states of the environment, learn faster and improve its performance in early stages of the learning.

However providing the teacher with this control presents challenges for designing the interaction. Unlike a simple scalar for reward, being able to control the robot requires the teacher to be able to ask the robot to execute any actions, which can be complex when the

action space is bigger than few actions. Similarly, to give the opportunity to the teacher to pre-empt undesired actions, the learner needs to communicate its intentions to the teacher.

2.5 Summary

This chapter presented first an overview of fields where robots interact socially with humans. From these case of application, three principle have been defined that a robot controller should follow to interact efficiently with humans, the robot should:

1. Only execute appropriate actions.
2. Have a high level of adaptivity.
3. Have a high level of autonomy.

A review of current controller for robots in HRI reported that no approach applied today in the field validates these principles. The review was extended to more general methods in Machine Learning with potential to satisfy these principles. Interactive Machine Learning show promises for enabling a robot to learn how to interact with humans, however while humans have been used to teach robot behaviours or concepts, teaching them to interact with human in an interactive, online fashion has not been demonstrated in the field so far and could satisfy all these requirements.

Chapter 3

Supervised Progressive Autonomous Robot Competencies

Key points:

- Novel interaction framework to teach robots an action policy while interacting.
- A human teacher is in control of the robot actions whilst the robot learns from this supervision.
- The teacher provides feedback on intentions rather than actions.
- The robot behaviour (under supervision) can be assumed to be optimal.
- Workload on the teacher decreases over time as the robot learns.

Parts of the work presented in this chapter have been published in Senft et al. (2015) and Senft et al. (2017). The final publications are available from Springer and Elsevier via http://dx.doi.org/10.1007/978-3-319-25554-5_60 and https://doi.org/10.1016/j.patrec.2017.03.015.

As presented in Chapter 2, robots would profit from being able to learn from humans how to interact with other humans. Using IML to achieve this transfer of social and task knowledge from the human domain-expert to the robot would result in a faster learning than slow iterative update of behaviour by engineering an action policy or learning by trials and errors as with RL.

However, as stated in that chapter, IML is seldom applied to learning to interact with humans and no current system provides the teacher with enough control over the robot action to ensure that the first principle presented in Section 2.1.2 (“Only execute appropriate actions”) is validated. Techniques relying solely on feedback cannot prevent the robot to execute an incorrect action, but only reward negatively incorrect actions after their execution (Senft et al., 2017) and with techniques based on LfD the teacher relinquishes its control over actions executed by the robot.

In order to provide a robot with an appropriate action policy, adaptive to different context or behaviours and requiring a low workload on the teacher or supervisor, we introduced in Senft et al. (2015) the Supervided Progressive Autonomous Robot Competenties (SPARC) framework of interaction to allow end-users to safely teach a robot an action policy applicable to HRI.

3.1 Principles

SPARC defines an interaction between a learner and a teacher following these principles:

- The learner has access to a representation of the state and a set of actions.
- The teacher can select actions for the robot to execute.
- The learner can propose actions to the teacher.
- The teacher can enforce or cancel actions proposed by the learner and actions non evaluated are implicitly validated and executed after a small delay.
- The learner improves its action policy using the teacher’s commands and feedback on propositions.

q This way of keeping a human in the loop and in control of the robot’s actions is similar to the level 6 on the Sheridan scale of autonomy: "A computer selects action, informs human

in plenty of time to stop it" (Sheridan & Verplank, 1978) with the addition that the human can also select actions for the robot to execute. In addition, a learning algorithm improve the correctness of suggested actions decreasing the probability of requiring the teacher to correct actions or having to select new actions. Additionally, keeping the human in the loop also gives them opportunities to provide additional information to the algorithm to speed up the learning.

This approach can be compared to predictive texting as seen on phone nowadays. The user can select the words proposed by the algorithms (or implicitly accept then by pressing space) or write their own. The algorithm learns the user's preferences and habits and aims to suggest words more and more appropriate to the user. However, SPARC enables a more complex interaction between learner and teacher and is directed to interactive environments in continuous time where the context changes with time both dependently and independently to the agent actions.

3.2 Goal

The goal of SPARC is to allow non-experts in computer science to teach quickly an action policy to a robot by guiding its interaction within an environment, without requiring constant input from a human and whilst ensuring that the robot's behaviour is constantly appropriate.

Figure 3.1 presents an idealist comparison of the expected workload, performance and autonomy of three methods: autonomous learning (such as RL - Sutton & Barto 1998), feedback based teaching (such as TAMER - Knox & Stone 2009) and SPARC. Unlike other methods, by following the principles presented in the previous section, SPARC is expected to maintain a constant high performance even during early stages of learning, and to see a decrease of workload on the human teacher as the agent improve its action policy using machine learning and the suggestions become more accurate.

Once the behaviour is deemed appropriate enough by the teacher, the agent can be deployed to interact autonomously in the real world if this output is desired. Alternatively, in context where a human expert cannot be removed from the control loop, such as Robot Assisted Therapy, the teacher can stay in control of the robot actions in a supervised autonomous way (similar to the teaching phase) and only intervenes when the agent

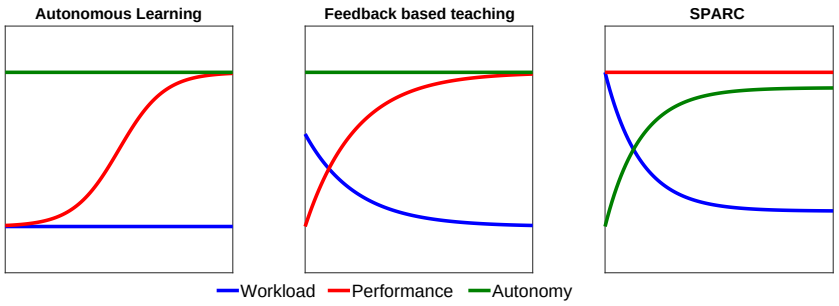


Figure 3.1: Idealistic comparison between autonomous learning, feedback base teaching and SPARC.

is about to do an error. This approach is similar to safety drivers behind autonomous vehicles but with information about the car's intentions rather than solely the car's actions.

3.3 Frame

Similarly to other applications of IML, SPARC requires the interaction with a teacher to learn an action policy to interact with the world. In this framework, the robot interacts with two entities: the target and the teacher, which results into two interlinked interactions: the application interaction (task the robot learns to achieve) and the control interaction (relation with the teacher), as demonstrated in Figure 3.2. In the generic case, the overall interaction is a triadic interaction (Teacher-Robot-Human target), such as a teacher teaching a robot tutor how to support child learning (as implemented in Chapter 6). But in specific cases, the overall interaction can be only dyadic (Teacher-Robot-Teacher or Teacher-Robot-Environment), such as robot at home learning from its user how to support them better.

However, unlike some other IML approaches, the requirement of a human in the action selection loop limits the timescale of interaction. As the human has to be provided with few seconds to react to the proposition, the rate of actions has to be 0.5 Hz or below. However, this can be mitigated by using higher level actions and this has the advantage to ensure that only correct actions will be executed without requiring the human to select them all.

SPARC presents many similarities with Learning from Demonstration (cf. Section 2.2.4) as it uses human demonstration of policies to learn. However, most of the applications of LfD (Argall et al., 2009; Billard et al., 2008) are focused on learning a manipulation skill in a mostly deterministic environment. LfD has seldom been used to teach an action policy to interact with humans (Liu et al., 2014; Sequeira et al., 2016) and never in an online fashion.

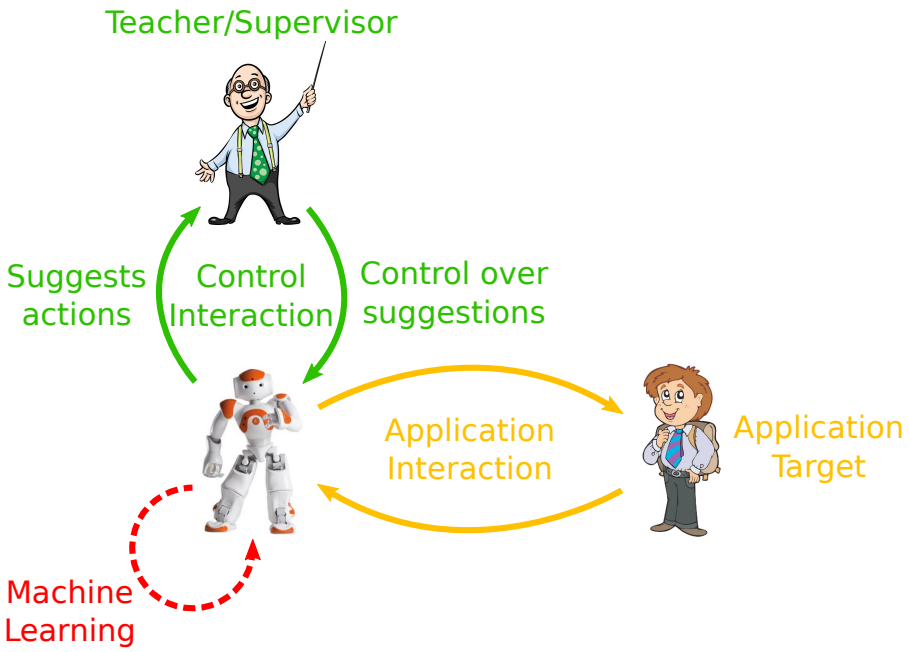


Figure 3.2: Frame of the interaction: a robot interact with a target and suggests actions and receive commands from a teacher.

Additionally, SPARC differs from Active Leaning (cf. Section 2.4.2) by the fact that the agent cannot decide which sample will be evaluated by the teacher. As the robot interacts with humans, the datapoints provided to the teacher for *labelling* will emerge from the interaction, and cannot be selected at will.

3.4 Implications

The principles described in section 3.1 have also implications on the interactions between the teacher and the agent and between the agent and the environment.

As the teacher can evaluate the actions proposed by the agent before their executions, it actually evaluates the intentions of the agent rather than its behaviour, and this difference is key as traditional IML approaches only evaluate the actions or their effects, but not the intentions. This implication is fundamental in HRI as we cannot accept to have a robot executing non appropriate actions when interacting with humans (cf. first principle in Section 2.1.2) and correctly evaluating intentions and not actions gives the opportunity to the teacher to pre-empt incorrect actions preventing the execution of undesired behaviours. The learner learns the expected impact of actions without having to handle the results of the execution of this action.

Most importantly, the control given to the teacher on the agent's actions ensures that every

action executed by the learner in the world has been either actively or passively validated by the teacher. This implies that each action executed can be assumed to be appropriate to the current state, potentially simplifying the learning algorithm.

3.5 Interaction with Machine Learning Algorithms

The principles of SPARC define it at the crossroads between Supervised Learning and Reinforcement Learning. The goal of the algorithm could be either to reproduce the teacher's policy, in a supervised way or using the teacher to bias the exploration and learn an action policy from the environment under the supervision of the teacher.

As such, SPARC only defines an interaction framework between a teacher and a learner, and is agnostic to the learning mechanism: it can be combined with any algorithms used in Supervised Learning or Reinforcement Learning. This research explored a combination with three types of algorithms: supervised learning using feed-forward neural networks in Chapter 4, reinforcement learning in Chapter 5 and supervised learning using instance based algorithm in Chapter 6. However SPARC could be combined with a wide range of other algorithms.

Similarly to Inverse Reinforcement Learning (Abbeel & Ng, 2004) or other techniques based RL and LfD (Billard et al., 2008), if combined with a reward function SPARC could go beyond the demonstrated action policy and achieve a performance higher than the demonstration. But this has not been evaluated in this work.

3.6 Summary

This chapter introduced Supervided Progressive Autonomous Robot Competenties (SPARC), a novel interaction framework to teach agent an action policy. This approach is suitable to teach a robot to interact with humans as it validates the principles defined in Section 2.1.2. SPARC starts in a similar fashion than WoZ: the teacher can select which action the robot should do, then using a learning algorithm, the learner proposes actions to the teacher who can let them be executed after a short time or cancel the action and select another one if appropriate. This suggestions/corrections mechanism provides the appropriateness of actions as a human could have cancel any inappropriate action in the learning phase and provides the adaptivity as the teacher can extend the behaviour beyond the current

action policy. The learning algorithm with the auto-executions ensure that once the robot has learnt, the human workload is low and the robot could even be deployed to interact autonomously if this is desired.

Chapter 4

Relation with Wizard of Oz

Key points:

- An experiment was designed to explore the influence of SPARC on the human workload and task performance compared to an approach based on WoZ.
- Application target replaced by a robot to ensure repeatability of target behaviour.
- Design of a robot model exhibiting probabilistic behaviour with a non-trivial optimal interaction policy.
- Results show that SPARC achieves a similar performance than WoZ while requiring a lower workload from the teacher.

Parts of the work presented in this chapter have been published in Senft et al. (2015) [1] . The final publication is available from Springer via `http://dx.doi.org/10.1007/978-3-319-25554-5_60`.

[1]Note about technical contribution in this chapter: the author used software from the DREAM project for the touchscreen and the robot functionalities. The author contributed to the material used within the robot control and the Graphical User Interface. Algorithm used from the OPENCV neural network library.

4.1 Motivation

SPARC as been designed to enable end-users non-experts in computer science to teach a robot an action policy while interacting in a sensitive environment. The argument behind this way of interacting is that SPARC allows a field expert to transfer their knowledge to an autonomous agent without wasting time to teach the agent and having to enforce each actions manually. As the agent is interacting in the target environment, displaying a appropriate action policy, the time spend to teach it is not lost as the desired interaction takes place also during the learning phase. For example, using the context of RAT, the therapist would teach the robot during a therapy session. As the therapist is in total control of the robot's action, the behaviour expressed by the robot fits the desired behaviour desired for the therapy.

In essence, SPARC, as a principle, allows to start a robotic application in a WoZ fashion, and then move away from it as the robot gains autonomy. The aim of SPARC is two fold: maintaining a high level of performance while reducing the workload of the teacher over time until reaching a point where the robot is autonomous or only necessitate minimal supervision to interact successfully. As explained in Chapter 3, SPARC involves two interactions the control interaction and the application ones. And when the goal is learning how to interact with humans, the robot is interacting simultaneously with two humans. These two dependent interactions complexify the evaluation of the approach, especially as both humans are impacting each other. The first step to evaluate SPARC was to focus on the relation between the robot and its teacher. To evaluate this aspect of the interaction, we decided to replace the target of the application by a robot running a model of a child and observe the impact of SPARC on the teacher. The setup ends up with two robots interacting together (the wizarded-robot and the child-robot) whilst the wizarded-robot is controlled by a participant. The child-robot has some inner variables (motivation and engagement) and has to keep them high to achieve a good performance.

4.2 Hypotheses

To evaluate the validity of SPARC and the influence of such an approach, four hypotheses were devised:

H1 A 'good' teacher (i.e. keeping the motivation and engagement of the child-robot high) will lead to a better child-robot performance.

H2 When interacting with a new system, humans will progressively build a personal strategy that they will use in subsequent interactions.

H3 Reducing the number of interventions required from a teacher will reduce their perceived workload.

H4 Using SPARC allows the teacher to achieve similar performance with fewer interventions than WoZ.

H1 represents a sanity check for the model, ensuring that the expressed performance represents the efficiency of the action policy demonstrated by the teacher. H2 tests that human teachers are not static entities, they adapt their learning target and their teaching strategy. H3 tests one of the motivations behind SPARC: does reducing the number of physical actions required for a robot to interact while requiring the teacher to monitor the robot suggestions lead to a lower workload. And finally, H4 is the main hypothesis, does SPARC enable a robot to learn a useful action policy: reducing the teacher's workload while maintaining a high performance.

4.3 Methodology

This study is based on a real scenario for RAT for children with ASD based on the Applied Behaviour Analysis therapy framework. The aim of the therapy is to help the child to develop/practice their social skills. The child has to complete an emotion recognition task involving a child playing a categorisation game with a robot on a mediating touchscreen device Baxter et al. (2012). And the robot can provide feedback and prompts to encourage the child and help them to classify emotions. Images of faces or drawings are shown to the child, and they have to categorise them by moving the image to one side or the other depending on whether the picture shown denotes happiness or sadness (e.g. fig. 1.1). In the therapy, the robot is remote controlled by an operator using the Wizard-of-Oz paradigm, and does not interact with the child directly.

This study explores if SPARC can be used to teach the robot a correct action policy to interact with the child. As timing in human-robot interactions is complex, for simplification

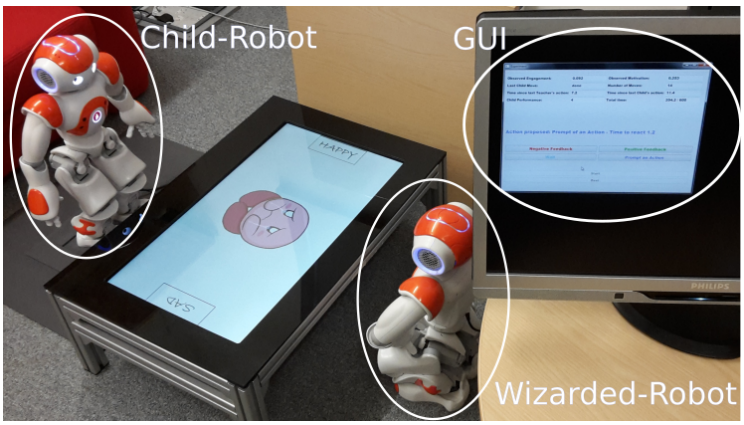


Figure 4.1: Setup used for the user study from the perspective of the human teacher. The *child-robot* (left) stands across the touchscreen (centre-left) from the *wizarded-robot* (centre-right). The teacher can oversee the actions of the *wizarded-robot* through the GUI and intervene if necessary (right).

reasons, the interaction has been discretised to have clear steps when the robot has to select an action. The basic interaction structure following SPARC is as follows:

1. the robot suggests an action to the teacher
2. the teacher can select an action for the robot to execute or let the proposed action be executed
3. the robot executes the selected action
4. both robot and teacher observe the outcome of the action until the next action selection step

Using SPARC, over time, the robot learns to replicate the teacher's policy by matching the inputs (child's state) to the outputs (action selected by the teacher).

Two conditions are compared: SPARC, where the robot learns from the human corrections and the WoZ condition, where the robot proposes a random actions instead of learnt actions to simulate a WoZ setup where the teacher would have to select every the actions.

The focus of the study being on the *control interaction* (the relation between the teacher and the robot), the second interaction (the application one) has been kept constant by replacing the child by a robot. A minimal model of child behaviour is therefore used to stand in for a real child. A second robot is employed in the interaction to embody this child model: we term this robot the *child-robot* while the robot being directly guided by the human teacher is the *wizarded-robot* (Figure 4.1).

4.3.1 Child model

The purpose of the child model is not to realistically model a child (with or without autism), but to provide a means of expressing some characteristics of the behaviours we observed in interactions with children in a repeatable manner. The child-robot possesses an internal model encompassing an *engagement* level and a *motivation* level, together forming the *state* of the child. The engagement represents how often the child-robot will make categorisation moves and the motivation gives the probability of success of the categorisation moves. Bound to the range $[-1, 1]$, these states are influenced by the behaviour of the wizarded-robot, and will asymptotically decay to zero without any actions from the wizarded-robot. These two states are not directly accessed by either the teacher or the wizarded-robot, but can be observed through behaviour expressed by the child-robot: low engagement will make the robot look away from the touchscreen, and the speed of the categorisation moves is related to the motivation (to which gaussian noise was added). There is thus incomplete/unreliable information available to both the wizarded-robot and the teacher, making the task non-trivial.

The influence of the wizarded-robot behaviour on the levels of engagement and motivation are described below (Section 4.3.2). In addition to this, if a state is already high and an action from the wizarded-robot should increase it further, then there is a chance that this level will sharply decrease, as an analogue of *frustration*. When this happens, the child-robot will indicate this frustration verbally (uttering one of eight predefined strings). This mechanism prevent the optimal strategy to be straightforward: always making actions aiming to increase motivation or engagement. The optimal strategy includes these actions but also waiting times to prevent the state values to overshoot. This non-trivial optimal strategy approximates better a real human-robot interaction scenario requiring a more complex strategy to be employed by the teacher.

4.3.2 Wizarded-robot control

The wizarded-robot is controlled through a GUI and has access to multiple variables characterising the state of the interaction as used by the learning algorithm:

- Observed engagement
- Observed motivation

- Type of last move made by the child-robot (good/bad/done)

Additionally, other metrics are displayed to the teacher but not used in the algorithm:

- Number of categorisations made by the child-robot
- Time since last teacher's action
- Time since last child's action
- Child's performance
- Total time elapsed

The wizarded-robot has a set of four actions, with one button each on the GUI:

- Prompt an Action: Encourage the child-robot to do an action.
- Positive Feedback: Congratulate the child-robot on making a good classification.
- Negative Feedback: Supportive feedback for an incorrect classification.
- Wait: Do nothing for this action opportunity, wait for the next one.

The impact of actions on the child-robot depends on the internal state and the type of the last child-robot move: good, bad, or done (meaning that feedback has already been given for the last move and supplementary feedback is not necessary). A *prompt* increases the engagement, a *wait* has no effect on the child-robot's state, and the impact of positive and negative feedback depends on the previous child-robot move. Congruous feedback (positive feedback for correct moves; negative feedback for incorrect moves) results in an increase in motivation, but incongruous feedback can decrease both the motivation and the engagement of the child-robot. The teacher therefore has to use congruous feedback and prompts.

However, as mentioned in Section 4.3.1, if engagement or motivation cross a threshold, their value can decrease abruptly to simulate the child-robot being frustrated. This implies that the optimal actions policy provides congruous feedback and prompts, but also requires wait actions to prevent the child-robot becoming frustrated and keep its state-values close to the threshold without crossing it. A 'good' strategy keeping the engagement and motivation high, leads to an increase in performance of the child-robot in the categorisation task.

To simplify the algorithm part, the interaction has been discretised: the teacher can not selects actions for the wizarded-robot at any time, actions can only be executed at specific times triggered by the wizarded-robot: two seconds after each child-robot action, or if nothing happens in the interaction for five seconds. When these selection windows are hit, the wizarded-robot proposes an action to the teacher by displaying the action's name and a countdown before execution. Only after this proposition has been done can the teacher select a different action for the wizarded-robot or let the proposed one be executed: if the teacher does nothing in the three seconds following the suggestion, the action proposed by the wizarded-robot is executed. This mechanism allows the teacher to passively accept a suggestion or actively make an *intervention* by selecting a different action and forcing the wizarded-robot to execute it.

4.3.3 Learning algorithm

In the SPARC condition, the robot learns to reproduce the action policy displayed by the teacher. For this study, the robot learns using a Multi-Layer Perceptron (MLP): with five input nodes: one for the observed motivation, one for the observed engagement and three binary (+1/-1) inputs for the type of the previous move: good, bad, or done. The hidden layer had six nodes and the output layer four: one for each action. The suggested action is selected applying a Winner-Take-All strategy on the value of the output node and then displayed on the GUI before execution. The network is trained with back propagation: after each new decision from the teacher a new training point is added with the selected action node having +1 while the others -1. The network is fully retrained with all the previous state-action pairs and the new one at each selection step.

This learning algorithm, MLP is not optimal for a real time interaction as the online learning should happens quickly between learning iteration. However as the length of interaction (and so the number of datapoints) is limited and the desired learning behaviour is purely supervised learning, this type of algorithm has been deemed suitable for this study.

4.3.4 Participants

In RAT scenarios using WoZ to control the robot, the wizard is typically a technically competent person with previous experience controlling robots or at least significant

training controlling this robot for the therapy. As such, to maintain consistency with the target user group, the participants of this study (assuming the role of the teacher) have been taken from a robotics research group. Ten participants were used (7M/3F, age M=29.3, 21 to 44, SD=4.8 years).

4.3.5 Interaction Protocol

The study compared two conditions: a learning robot adapting its propositions to its user (the SPARC condition) and a non-learning robot constantly proposing random actions (the WoZ condition). The child-robot controller was kept constant in both conditions, while the state is reset between interactions. The design was a within subjects comparison with balancing of order: each participant interacted with both conditions, with the order balanced between participants to control for any ordering effects. In *order LN* the participants first interact with the learning wizarded-robot in the SPARC condition, and then with the non-learning one in the WoZ condition; in *order NL* the order of interaction is inverted. Participants were randomly assigned to one of the two orders.

The interactions took place on a university campus in a dedicated experiment room. Both robots were Aldebaran Nao, one of which had a label indicating that it was the *Child-Robot*. The robots faced each other with a touchscreen between them, and participants assuming the role of the teacher sat at a desk to the side of the wizarded-robot, with a screen and a mouse to interact with the wizarded-robot (fig. 4.1). Participants were able to see the screen and the child-robot.

A document explaining the interaction scenario was provided to participants with a demographic questionnaire (cf Annexes.). After the information had been read, a 30s video presenting the GUI in use was shown to familiarise the participants with it, without biasing them towards any particular control strategy. Then participants clicked a button to start the first interaction which lasted for 10 minutes. The experimenter was sat in the room outside of the participants' field of view. After the end of the first interaction, a post-interaction questionnaire was administered. The same protocol was applied in the second part of the experiment with another post-interaction questionnaire following. Finally, a post-experiment questionnaire asking participants to explicitly compare the two conditions was administered.

4.3.6 Measures

Two types of measures have been recorded for this study: interaction data representing objective behaviours and performance of the participants and subjective data through questionnaires.

Interaction data The state of the child-robot and the interaction values were logged at each step of the interaction (at 5Hz). All of the human actions were recorded: acceptance of the wizarded-robot's suggestion, selection of another action (intervention), and the states of the child-robot (motivation, engagement and performance) at this step.

The first metric is the performance achieved in each interaction measured by the number of correct categorisations made by the child-robot minus the number of incorrect ones. This represents how correct was the action policy executed by the wizarded-robot when controlled by a participant.

The second important metric is the intervention ratio: the number of times a user chooses a different action than the one proposed by the wizarded-robot, divided by the total number of executed actions. This metric represents how often in average a user had to correct the robot and could be related to the workload the user had to face to control the robot.

Questionnaire data Participants answered to four questionnaires: a demographic one, before the interaction, two post-interaction ones where they were asked to evaluate the last interaction with the robots and a post-experiment where they had to compare the two conditions and select the one corresponding to a description. All the rating questionnaires used seven items Likert scale.

Post-Interaction

- The child-robot learned during the interaction
- The performance of the child-robot improved in response to the teacher-robot actions
- The teacher-robot is capable of making appropriate action decisions in future interactions without supervision
- The teacher-robot always suggested an incorrect or inappropriate actions

- By the end of the interaction, my workload was very light
- What did you pay most attention during the interaction? (child-robot, touchscreen, GUI, other)

Post-experiment

- There was a clear difference in behaviour between the two teacher-robots
- There was a clear difference in behaviour between the two child-robots
- Which teacher-robot was better able to perform the task? (first, second)
- Which teacher-robot did you prefer supervising? (first, second)

4.4 Results

4.4.1 Interaction data

Figure 4.2 presents the aggregated (results collapsed between orders) performance and intervention ratio for both conditions. While the number of participants are not sufficient to perform statistical comparison, overall interaction results seem to show that both conditions lead to similar performance (SPARC: 32.6 (95% CI [27.89,37.31]) - WoZ: 31.4 (95% CI [25.9,36.9])) while the SPARC condition required less intervention (SPARC: 0.38 (95% CI [0.29,0.47]) - WoZ: 0.59 (95% CI [0.52,0.67])).

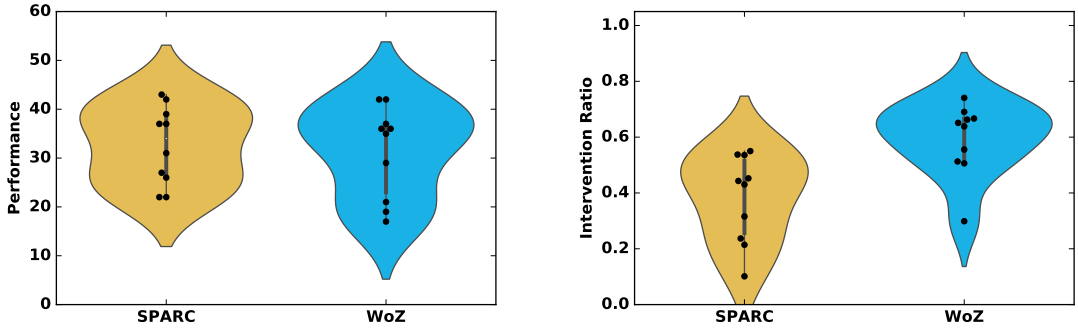


Figure 4.2: Aggregated comparison of performance and intervention ratio for both conditions

Figure 4.3 presents the evolution of intervention ratio for each condition and orders. During the first interaction, participants discover the interface and how to interact with

Table 4.1: Average performance and intervention ratio separated by condition and order.

	Order LN		Order NL	
	SPARC (int 1)	WoZ (int 2)	WoZ (int 1)	SPARC (int 2)
Performance M	29.6	38.2	24.6	35.6
95% CI	[23.61,35.59]	[35.46,40.94]	[18.1,31.1]	[29.34,41.86]
Intervention Ratio M	0.31	0.68	0.5	0.46
95% CI	[0.17,0.45]	[0.65,0.71]	[0.4,0.61]	[0.38,0.53]

it, which results in a high variation intervention ratio in the first 20 steps (each time the wizarded-robot proposes an action). However in the second phase of the interaction, when participants develop their teaching policy, there is a tendency of SPARC requiring a lower number of intervention than WoZ. This effect is higher in the second interaction, where as soon as 5 steps, the two conditions differentiate without overlap of the 95% CI of the mean, which would indicate that the two conditions differ in term of required interventions.

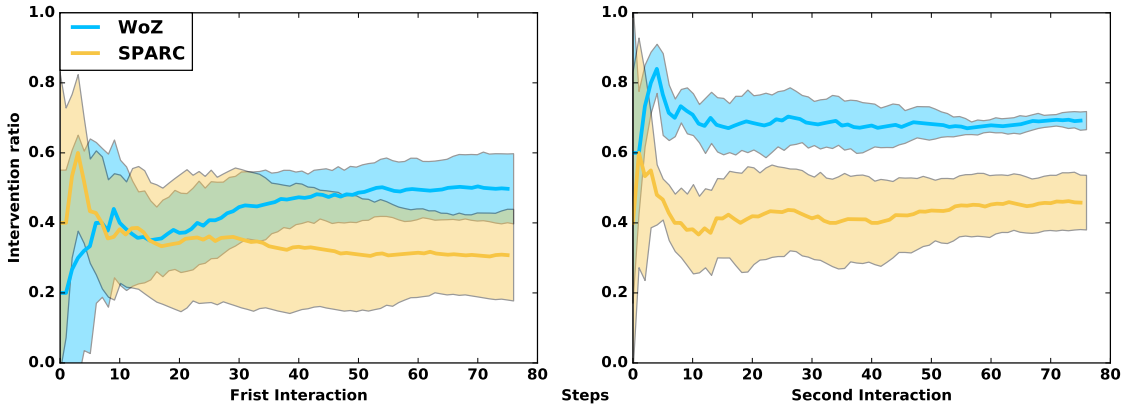


Figure 4.3: Evolution of intervention ratio over time for both conditions and both orders. Shaded area represents the 95% CI.

Both for the performance and the intervention ratio, a strong ordering effect have been observed. Figure 4.4 and Table 4.1 present the performance and intervention ratio separated by condition and order. In both orders, the second interaction had higher performance as the participants were used to the system and understood how to develop an efficient interaction policy. And the performance between condition is similar. However, regardless of the order, when only the interaction number is considered, the intervention ratio is lower when using SPARC compared to WoZ. This indicates that when the wizarded-robot learned using SPARC, a similar performance is attained as with WoZ, but the number of interventions required to achieve this performance is lower.

Additionally, a strong positive correlation (Pearson's r=0.79) was found between the average child-robot motivation and engagement and its performance which shows that

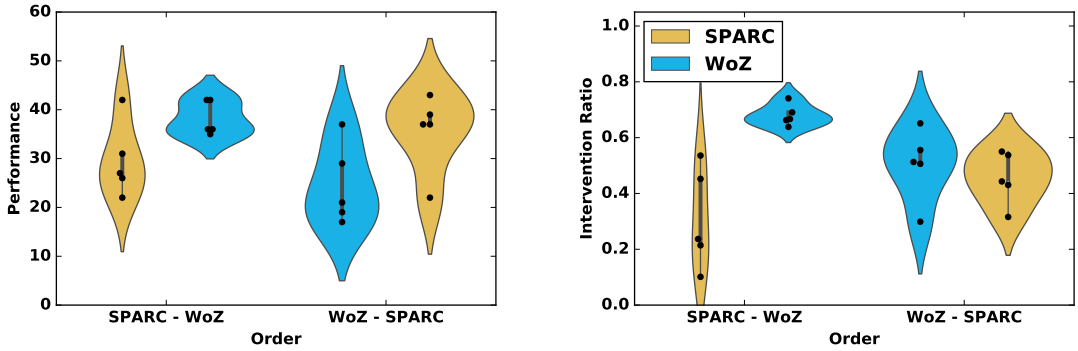


Figure 4.4: Performance achieved and intervention ratio separated by order and condition. For each order, the left part presents the performance in the first interaction (with one condition) and the right part the performance in the second interaction (with the other condition).

the performance achieved by the child-robot represents the capacity of the teacher to keep both engagement and motivation high.

4.4.2 Questionnaire data

The post-interaction questionnaires evaluated the participant's perception of the child-robot's learning and performance, the quality of suggestions made by the wizarded-robot, and the experienced workload. All responses used seven point Likert scales.

Table 4.2 presents separated results for the questions asked in the post-interaction questionnaires, with more details for the questions exhibiting differences in Figure 4.5.

Across the four possible interactions, the rating of the child-robot's learning was similar (M=5.25, 95% CI [4.8, 5.7]). As the child-robot was using the same interaction model in all four conditions, this result is expected. There is a slight tendency to rate the child's performance as being higher but the error margin is too high to conclude anything. This could indicate that the teachers were more aware of the child's behaviour as the workload was lighter to control the wizarded-robot.

Participants rated the wizarded-robot as more suited to operate unsupervised in the learning than in the non learning condition (confidence interval of the difference of the mean (CIDM) for LN ordering [-0.2, 2.6], CIDM for the NL ordering [1.6, 2.8]).

Similarly, a trend was found showing that learning wizarded-robot is perceived as making fewer errors than the non-learning robot (CIDM for LN ordering [1.3, 3.4], CIDM for the NL ordering [0.1, 1.1]).

Table 4.2: Average reporting on questionnaires separated by condition and order.

	Order LN		Order NL	
	SPARC (int 1)	WoZ (int 2)	WoZ (int 1)	SPARC (int 2)
Child learns M	5.2	5.2	5.2	5.4
95% CI	[3.69,6.71]	[3.8,6.6]	[4.18,6.22]	[4.7,6.1]
Child's performance M	4.6	5.0	5.0	4.4
95% CI	[3.41,5.79]	[3.25,6.75]	[4.04,5.96]	[3.7,5.1]
Wizarded-robot makes errors	1.6	4.0	2.6	2.0
M 95% CI	[0.9,2.3]	[2.76,5.24]	[1.9,3.3]	[2.0,2.0]
Wizarded-robot makes appropriate	4.8	3.6	3.0	5.2
decisions M 95% CI	[3.4,6.2]	[2.18,5.02]	[2.04,3.96]	[4.85,5.55]
Lightness of workload M	4.6	3.6	3.8	5.4
95% CI	[3.41,5.79]	[1.8,5.4]	[2.94,4.66]	[4.35,6.45]

The participants tended to rate the workload as lighter when interacting with the learning robot, and this effect is much more prominent when the participants interacted with the non-learning robot first (CIDM for LN ordering [-0.6, 2.6], CIDM for the NL ordering [0.7, 2.5]).

Most of the difference of mean interval exclude 0 or include it marginally, which would indicate tendency of difference (due to the low number of participants, no statistical tests are applicable).

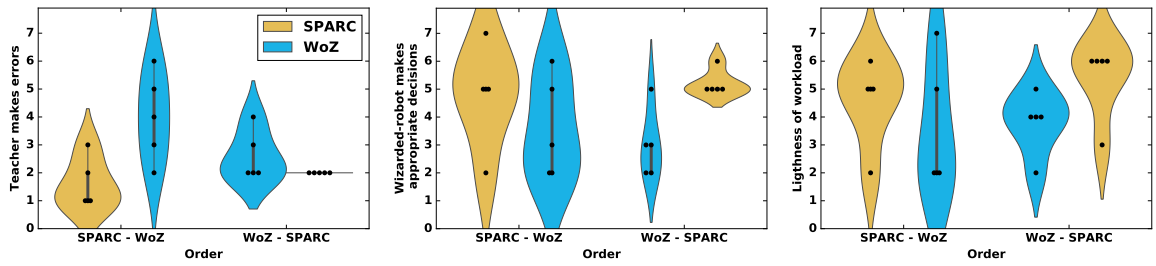


Figure 4.5: Questionnaires results on robot making errors, making appropriate decisions and on lightness of workload.

4.5 Discussion

Strong support for H1 (a good teacher leads to a better child performance) was found, a correlation between the average states (engagement and motivation) and the final performance for all of the 10 participants was observed (r=0.79). This sanity check confirms that the performance of the child robot reflects the performance of the teacher in this task: teaching the wizarded-robot an efficient action policy maximising the inner state of the child-robot. Additionally, the model of the child robot exhibited the desired behaviour:

allowing a wide range of performances without one obvious optimal action policy.

The results also provide support for H2 (teachers create personal strategies): all the participants performed better in the second interaction than in the first one. This suggests that participants developed a strategy when interacting with the system in the first interaction, and were able to use it to increase their performance in the second interaction. Looking in more detail at the interaction logs, different strategies for the wizarded-robot can be observed with a varying level of waiting actions compared to other types of actions.

H3 (reducing the number of interventions will reduce the perceived workload) is partially supported: the results show a trend for participants to rate the workload as lighter when interacting with the learning robot, and another trend between using a learning robot and the intervention ratio. However, when computing the correlation between the intervention ratio and the reported workload, a strong effect can only be observed in the second interaction ($\rho = -.622$). In the first interaction, the main effect of the workload is probably the discovery of the system and how to interact with it. Nevertheless, regardless of the order of the interactions, the learning robot consistently received higher ratings for lightness of workload which indicates that using SPARC could decrease workload on robot's supervisor compared to WoZ.

Finally, H4 (using learning keeps similar performance, but decreases interventions) is supported: interacting with a learning robot results in a similar performance than interacting with a non-learning robot, whilst requiring fewer active interventions from the supervisor. This has real world utility, it frees some time for the supervisor, to allow them to focus on other aspects of the intervention, e.g. analysing the child's behaviour rather than focusing on the robot control.

It should be noted that the actual learning algorithm used in this study is only of incidental importance, and that certain features of the supervisor's strategies may be better approximated with alternative methods – of importance for the present work is the presence of learning at all. Other algorithm and ways to handle time have been used in the following studies.

4.6 Summary

As expected, using SPARC to teach a robot to interact under supervision did allow the robot to partially learn an interaction policy which decrease the requirement on the teacher to physically enforce each robot's actions. Additionally, SPARC decreased also the workload imposed on the robot supervisors which has real world impact as today many subfields of HRI such as RAT still rely on WoZ for their robotic control.

Using a suggestion/intervention system, SPARC allowed online learning for interactive scenarios, thus increasing autonomy and reducing the demands on the supervisor. Results showed that interacting with a learning robot allowed participants to achieve a similar performance as interacting with a non-learning robot, but requiring fewer interventions to attain this result. This suggests that while there is always adaptation in the interaction (leading to similar child-robot performance given the two wizarded-robot controllers), the presence of learning shifts this burden of adaptivity onto the wizarded-robot rather than on the human. This indicates that a learning robot could allow the therapist to focus more on the child than on the robot, with improved therapeutic outcomes as potential result.

Chapter 5

Keeping the user in control

Key points:

- An experiment was designed to compared SPARC to another approach in IML: Interactive Reinforcement Learning (IRL) using feedback and partial guidance to teach a robot an action policy.
- Application domain is a replication of the world used in early studies on IRL.
- SPARC uses full control over the robot's action, implicit rewarding system and evaluation of intentions rather than actions.
- SPARC was combined with an algorithm from the Reinforcement Learning field.
- Results show that SPARC achieves a better performance, easier and faster than IRL.

Parts of the work presented in this chapter have been published verbatim in Senft et al. (2017) [1]. The final publication is available from Elsevier via `https://doi.org/10.1016/j.patrec.2017.03.015`.

[1] Note about technical contribution in this chapter: the author reimplemented every part of the system manually in Qt.

5.1 Motivation

Previous work in IML has been shown that humans want to teach robots not only with feedback but also by communicating what the robot should do (Thomaz & Breazeal, 2008). However, in most of the research teaching agents a policy using human guidance, the teacher is given few or no control at all on the agent's action and has to observe the agent executing an undesired actions even when knowing that this action is incorrect. This chapter explores how these IML approaches could be pushed further by applying the principles of SPARC defined in Chapter 3 and how it would influence the learning process, the agent performance and the user experience.

Additionally, the previous study explored how SPARC could be used with an algorithm from the SL domains, to replicate a teacher's action policy, but some of the most promising features of IML arise when combined with algorithm from the RL field. As such this study uses an reinforcement learning algorithm to teach the robot.

The goal of this study is twofold: exploring how to apply SPARC to algorithms from RL and comparing how this human control over the robot's actions impacts the learning. As such, it has been decided to compare an approach using SPARC to one offering less control but having been validated in previous studies: Interactive Reinforcement Learning (IRL) (Thomaz & Breazeal, 2008). The testing environment of Interactive Reinforcement Learning (IRL) have be reimplemented to stay as close as possible to the online version of the task.

5.2 Scope of the study

5.2.1 Interactive Reinforcement Learning

The IRL algorithms implements the principles presented in Thomaz & Breazeal (2008). In IRL the human teacher can provide positive or negative feedback on the last action executed by the robot. The robot combines this with environmental feedback into a reward which is used to update a Q-table: a table with a Q-values (the expected discounted reward) assigned to every state-action pair and used to select the next action. Three additions to the standard algorithm have been proposed and implemented by Thomaz and Breazeal and are used here as well: guidance, communication by the robot and an

undo option (Thomaz & Breazeal, 2008). Teachers have two way to transmit information to the robot: the reward channel (to give a numerical on the last action) and the guidance channel (to direct attention toward parts of the state).

The guidance emerged from the results of a pilot study where participants assigned rewards to objects to indicate that the robot should do something with these objects. With the guidance, teachers can direct the attention of the robot toward certain item in the environment to indicate the robot that it should interact with them. This guidance behaviour offer partial control over the robot's actions and restricts the next action the robot is executing, but it cannot be used to set explicitly the robot behaviour.

The robot also communicates its uncertainty by directing its gaze toward different items in the environment with equally high probability of being used next. The aim of this communication of uncertainty is to provide transparency about the robot's internal state, for example indicating when a guidance should be provided.

Finally, after a negative reward, the robot tries to cancel the effect of the previous action (if possible), resulting in a undo behaviour. As shown in the original paper, these three additions improve the performance on the task.

5.2.2 SPARC

SPARC uses a single type of input similar to the guidance present in IRL but without using the reward channel. However with SPARC, the guidance channel controls directly the actions of the robot. The robot communicates every of its intentions (i.e the action it plans to execute next) to its teacher by looking to a part of the environment and the teacher can either not intervene, letting the robot execute the suggested action or step in and force the robot to execute an alternative action. This combination of suggestions and corrections gives the teacher full control over the actions executed by the robot. This also makes the rewards redundant: rather than requiring the human to explicitly provide rewards, a positive reward is directly assigned to each action executed by the robot as it has been either forced or passively approved by the teacher.

5.2.3 Differences of approaches

Unlike IRL, SPARC offers full control over the actions executed by the robot. SPARC changes the learning paradigm from learning from the human evaluation of actions' effects to learning from the human's expectation of these actions' effects and preferences. An expert in the task domain evaluates the appropriateness of actions before their execution and can guide the robot to act as they see correct. This implies that the robot does not to rely on observing negative effect of an action to learn that this action should be avoided, but rather what the best action is for each state. Even in a non-deterministic environment such as HRI, some actions can be expected to have a negative consequence. The human teacher can stop the robot from ever executing these actions, preventing the robot from causing harm to itself or its social or physical environment.

Another noticeable difference is the way in which the robot communicates with the user: in IRL, the robot communicates its uncertainty about an action and with SPARC its intention to execute an action. It should also be noted that the quantity of information provided by the user to the robot is similar for both IRL and SPARC: in SPARC the user can offer the whole action space as commands to the robot, which removes the need for explicit rewards. While in IRL, the teacher can guide the robot toward a subset of the action space but has to manually provide feedbacks to evaluate the robot's decisions.

5.2.4 Hypotheses

Three hypotheses have been tested in the study:

H1 *Effectiveness and efficiency with non-experts.* Compared to IRL, SPARC leads to higher performance, whilst being faster, requiring fewer inputs and less mental effort from the teacher and minimising the number of errors during the teaching phase when used by non-experts.

H2 *Safety with experts.* SPARC can be used by experts to teach an action policy safely, quickly and efficiently, unlike other IML methods lacking control.

H3 *Control.* Teachers prefer a method in which they can have more control over the robot's actions.

5.3 Methodology

The task used in this study is the same as Thomaz & Breazeal (2008): Sophie's kitchen, a simulated environment on a computer where a virtual robot has to learn how to bake a cake in a kitchen. As the source code was not available, the task was reimplemented to stay as close as possible to the description in the paper and the online version of the task[2].

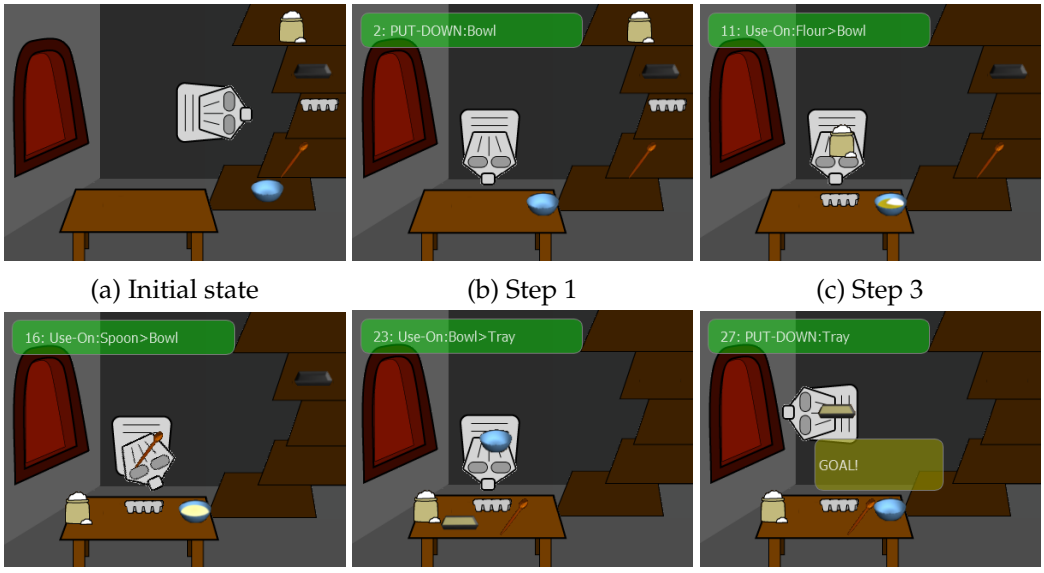
The scenario is the following: a robot, Sophie, is in a kitchen with three different locations (shelf, table and oven) and five objects (flour, tray, eggs, spoon and bowl) as shown in Figure 5.1a. Sophie has to learn how to bake a cake and the participant has to guide the robot through a sequence of steps while giving enough feedback so the robot learns a correct series of actions. As presented in Figure 5.1, there are six crucial steps to achieve a successful result:

1. Put the bowl on the table (Figure 5.1b).
2. Add one ingredient to the bowl (flour or eggs).
3. Add the second ingredient (Figure 5.1c).
4. Mix the ingredients with the spoon to obtain batter (Figure 5.1d).
5. Pour the batter in the tray (Figure 5.1e).
6. Put the tray in the oven (Figure 5.1f).

The environment is a deterministic Markov Decision Process, defined by a state, a set of actions (move left, move right, pick up, drop and use), a deterministic transition function and environmental reward function (+1 for success and -1 for failure and -0.04 for every other step to penalise long sequences). Different action policies can lead to success, but many actions end in a failure state, for example putting the spoon in the oven results in a failure. As argued by Thomaz and Breazeal, this environment provides a good setup to evaluate teaching methods to a robot due to the large number of possible states (more than 10,000), the presence of success and failure states and the sparse nature of the environmental reward function which increases the need for a teacher to aid the learning. More details on the environment are available in the original paper.

[2] `http://www.cc.gatech.edu/~athomaz/sophie/WebsiteDeployment/`

5.3.1 Task



(a) Initial state (b) Step 1 (c) Step 3

(d) Step 4 (e) Step 5 (f) Step 6

Figure 5.1: Presentation of different steps in the environment. 5.1a initial state, 5.1b step 1: the bowl on the table, 5.1c step 3: both ingredients in the bowl, 5.1d step 4: ingredients mixed to obtain batter, 5.1e step 5: batter poured in the tray and 5.1f step 6 (success): tray with batter put in the oven. (Step 2: one ingredient in the bowl has been omitted for clarity)

5.3.2 Conditions

Two conditions are compared for this study: IRL and SPARC. The underlying learning is strictly identical for both conditions, only the way to interact with it, how to provide it rewards changes: with IRL teachers have to explicitly provide rewards, while they are implicit with SPARC.

The learning algorithm (see Algorithms 1 and 2) is a variation on Q-learning, without reward propagating[3]. This guarantees that any learning by the robot is due to the teaching by the human, and as such provides a lower bound for the robot's performance. By using Q-learning, the performance of the robot would be higher.

[3]In Q learning the update function is $Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha(r_{t+1} + \gamma(\max_a Q(s_{t+1}, a)) - Q(s_t, a_t))$

Algorithm 1: Algorithm used for SPARC

while *learning* **do**
- a = action with the highest $Q[s, a]$
- look at object or location used with a
- **while** *waiting for correction (2 seconds)* **do**
  - **if** *received command* **then**
    - a = received command
    - reward, $r = 0.5$
  - **else**
    - reward, $r = 0.25$
- execute a, and transition to s'
- $r = r + r_{environment}$
- Learn:
- $Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha(r_{t+1} + \gamma(\max_a Q(s_t, a)) - Q(s_t, a_t))$

Algorithm 2: Algorithm used for IRL

while *learning* **do**
- a = action with the highest $Q[s, a]$
- indicate confusion if multiple a with similar high $Q[s, a]$
- **while** *waiting for guidance and reward on last action (2 seconds)* **do**
  - **if** *received command* **then**
    - Try: a = received command
  - **if** *received reward* r' **then**
    - $r = r + r'$
- Learn:
- $Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha(r_{t+1} + \gamma(\max_a Q(s_t, a)) - Q(s_t, a_t))$
- execute a, and transition to s'
- $r = r_{environment}$

Interactive Reinforcement Learning

We have implemented IRL following the principles presented in Thomaz & Breazeal (2008). The user can use the left click to display a slider providing rewards. The guidance is implemented by right-clicking on objects: it directs the robot's attention to the object if facing it (a click on objects in different locations has no effect). Following the guidance, the robot will execute the candidate action involving the object. The action space is not entirely covered by this guidance mechanism: for example, it does not cover moving from a location to another. This guidance if used correctly, limits the exploration for the current step to the part of the environment evaluated as more interesting by the user without preventing the robot to explore in further steps. The robot can communicate its uncertainty by looking at multiple objects having similarly high probability of being used.

Some modifications were required to the original study due to the lack of implementation details in the original paper, one of them being the use of a purely greedy action selection instead of using softmax, due to the absence of parameters descriptions. The reliance

on human rewards and guidance limits the importance of autonomous exploration, and thus, the greediness of the algorithm should assist the learning by preventing the robot to explore outside of the guided policy. Additionally, as the environment is deterministic and the algorithm is greedy, the concept of convergence is altered: once a trajectory has Q-Values high enough or a correct gradient of Q-Values on all state-action pairs, it will be reinforced automatically.

SPARC

SPARC uses the gaze of the robot toward objects or locations to indicate which action the robot is suggesting to the teacher. Similarly to the guidance in IRL, the teacher can use the right click of the mouse on objects to have the robot execute the action associated to this object in the current state and this has been extended to also cover locations. With SPARC, the command covers all the action space: at every time step, the teacher can specify, if desired, the next action executed by the robot. If an action is not corrected, a positive reward of 0.25 is automatically received (as it has the implicit approval from the teacher) and if the teacher selects another action, a reward of 0.5 is given to the correcting action (the corrected action is not rewarded). That way, actions actively selected are more reinforced and participants can still have give higher rewards when using IRL. This system allows for the use of reinforcement learning with implicit reward assignation, which simplifies the teaching interaction.

5.3.3 Interaction protocol

Participants are divided into two groups and interact first either with IRL or SPARC as shown in Figure 5.2. Before interacting, participants complete a demographic questionnaire and receive a information sheet explaining the task (describing the environment and how to bake the cake) and one explaining the system they are interacting with. Then they interact for three sessions with the assigned system. Each session is composed of a training phase and a testing phase. The training phase is composed of as many teaching episodes as the participant desires, a teaching episode ends when a success or failure state has been reached which returns the environment to the initial state. In the same way as in the initial experiment by Thomaz and Breazeal, participants can decide to terminate the training phase whenever they desire by clicking on a button labelled 'Sophie is ready', however

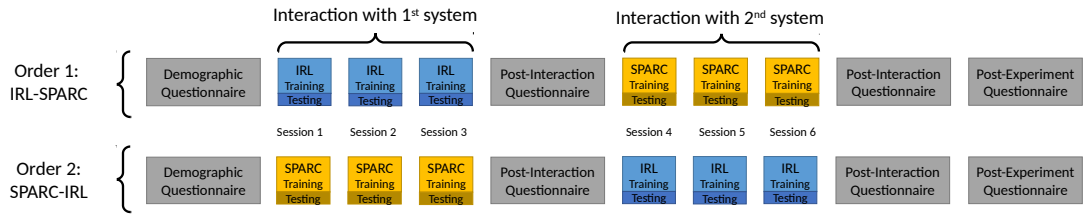


Figure 5.2: Participants are divided into two groups. They first complete a demographic questionnaire, then interact for three independent sessions (with a training and a testing phase each) with a system (IRL or SPARC). After a first post-interaction questionnaire, participants interact for another three sessions with the other system before completing the second post-interaction questionnaire and a final post-experiment questionnaire.

it is also terminated after 25 minutes to impose an upper time limit to the study. After the end of a training phase, the robot runs a testing phase where the participant's inputs are disabled and which stops as soon as an ending state is reached or the participants decide to stop it (for example if the robot is stuck in a loop). This testing phase is used to evaluate the performance of the participants for this session. The interaction with a system consists of three repeated independent sessions with their own independent training and testing phases to observe how the interactions evolve as participants are getting used to the system.

After participants completed their three sessions with the first system, they are asked to interact for three more sessions with the other system. This way, every participant interacts three times with each system (IRL and SPARC) and the order of interaction is balanced. Additionally, participants have to complete post-interaction questionnaires distributed after the interaction with the first system and the second one and a final post-experiment questionnaire at the end of the experiment. All information sheets and questionnaires can be found online [4].

This experimental design prevents the risk of having an ordering effect by having a symmetry between conditions. Both conditions having a identical experimental procedure only with the order of interaction varying.

5.3.4 Participants

A total of 40 participants have been recruited using a tool provided by the university to reach a mixed population of students and non-student members of the local community. All participants gave written informed consent, and were told of the option to withdraw

[4] `https://emmanuel-senft.github.io/experiment2.html`

at any point. All participants received remuneration at the standard U.K. living wage rate, pro rata. Participants were distributed randomly between the groups whilst balancing gender and age (age M=25.6, SD=10.09; 24F/16M). Participants were mostly not knowledgeable in machine learning and robotics (average familiarity with machine learning M=1.8, SD=1.14; familiarity with social robots M=1.45, SD=0.75 - Likert scale ranging from 1 to 5).

In addition to naive non-expert users, an expert user (the author) interacted five times with each system following a strictly optimal strategy in both cases. These results from the expert are used to evaluate H2 and show the optimal characteristics of each system (IRL and SPARC) when used by trained experts such as therapist in a context of assistive robotics.

5.3.5 Metrics

Interaction Metrics

We collected four metrics during the training phase: the number of times a participant reached a failure state while teaching, which can be related to the risks taken during the training and the teaching time (from 0 to 25 minutes), the training performance (how many steps participants reached in the training phase) and the number of inputs provided during the training, which can be seen as the efforts invested in the teaching. The testing phase is a single run of the taught action policy ending as soon as the robot reaches an ending state (failure or success) or if stopped by the participants. We only use the performance achieved during this single test as evaluation of the success of training. As not all participants reached a success during the testing phase, we used the six key steps defined in Section 5.3.1 as a way to evaluate the performance ranging from 0 (no step has been completed) to 6 (the task was successfully completed) during this testing run: for example a testing where the robot puts both ingredients in the bowl but reaches a failure state before mixing them would have a performance of 3.

Questionnaires

The post-interaction and post-experiment questionnaires provide additional subjective information to compare with the objective results from the interaction data. Two principal

metrics are gathered: the workload on participants and the perception of the robot.

Workload is an important factor when teaching robots. As roboticists, our task is to make the teaching of robots as undemanding as possible, meaning that the workload for user should be minimal. Multiple definitions for workload exist and various measures can be found in the literature. Due to its widespread use in human factors research and clear definition and evaluation criteria, we used the NASA-Task Load Index (TLX) (Hart & Staveland, 1988). We averaged the values from the 6 scales (mental, physical and temporal demand, performance, effort and frustration) to obtain a single workload value per participant for each interaction. So we have two measures for each participant, after interaction with the first system and after the interaction using the other system.

Finally, the perception of the robot has been evaluated in the post-interaction and post-experiment questionnaires using subjective questions (measured on a Likert scale), binary questions (which robot did you prefer interacting with) and open questions on preference and naturalness of the interaction.

5.4 Results

Most of the results are non-normally distributed. Both ceiling and floor effects can be observed depending on the conditions and the metrics. For the teaching time, some participants preferred to interact much longer than others, resulting in skewed data. Likewise for the performance: often participants either reached a successful end state or did not hit any of the sub-goals of the task in the testing phase ending often in two clusters of participants: one at a performance of 6 and one at 0. Similarly, some participants who interacted a long time with the system did not complete any step, while others could achieve good results in a limited time. Due to the data being not normally distributed, Bayesian statistics have been used from the JASP software (JASP Team, 2018). Each test: mixed Anova for omnibus comparison between condition for each interaction (first or second), independent t-test for post-hoc comparison between participants and dependent t-test for post-hoc comparison within participants have been performed using their Bayesian counterpart, which also remove the need of doing a correction on pairwise test such as Bonferroni. As such, no p-value is reported, but a B factor representing how much a parameter impact of a parameter on the metric (if $B < 1/3$ there is no impact, if $B > 3$ the impact is strong) (Dienes, 2011; Jeffreys, 1998).

Initial results of the first interaction of the participants have been reported in Senft et al. (2016).

Five objective metrics (performance, training performance, teaching time, number of inputs used and number of failures) and one subjective metric (workload) have been used to evaluate the efficiency of IRL and SPARC.

Performance

Figure 5.3 presents the performance of participants during the interaction. In the first three sessions participants interacted with either IRL or SPARC, and swapped for the remaining three sessions. The Bayes analysis shows important factor of condition on the performance on the three sessions both for the first interaction and the second one ($B_1 = 8.7x10^5$ and $B_2 = 888888$), which, according to the means and graph shows that participants using SPARC reach a higher performance than the ones using IRL.

There is a significant difference of performance between systems; a Friedman test shows a significant difference between systems during the first three sessions ($\chi^2 = 50.8$, $p < .001$) and during the next three sessions ($\chi^2 = 36$, $p < .001$). Similarly, a significant difference in performance is noted within participants (Order 1: $\chi^2 = 37.9$, $p < .001$ - Order 2: $\chi^2 = 55.3$, $p < .001$). So in all the cases, participants interacting with SPARC achieved a significantly higher performance than those interacting with IRL, regardless of the order in which they interacted ($p < .05$ for all pairwise comparison). No difference of performance has been observed when using Wilcoxon signed rank test on the three repetitions between participants when interacting with the same system, so interacting for a second or third session with the same system does not have a significant impact on participants' performance.

It must be noted that in our study, only a limited number of participants managed to teach the robot to complete the task using IRL, this observation will be discussed in more details in section 5.5.

5.5 Discussion

5.6 Summary

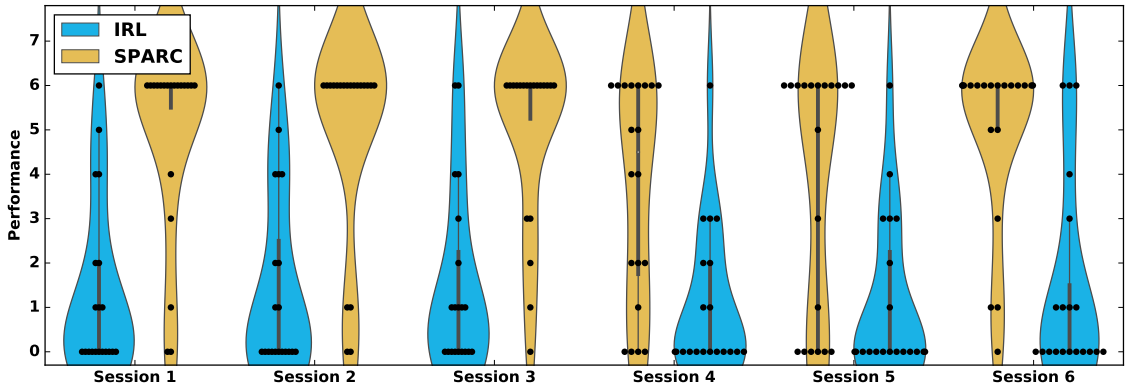


Figure 5.3: Comparison of the performance for the six sessions (three with each system, IRL and SPARC, with interaction order balanced between groups). A 6 in performance shows that the taught policy leads to a success. The circles represent all the data points (n=20 participants per group).

Chapter 6

Teaching a robot to support child learning

6.1 Motivation

6.2 Food chain task

6.3 Hypotheses

6.4 Methodology

6.5 Results

6.6 Discussion

6.7 Summary

Chapter 7

Discussion

7.1 Experimental Limitations

7.1.1 Ecological Validity and Generalisability

7.2 Ethical Questions

7.3 Summary

Chapter 8

Contribution and Conclusion

This chapter seeks to provide an overview of the findings and topics covered in this thesis. The contributions to the field of social HRI are outlined and summarised. Following this, a conclusion is provided to briefly encapsulate the primary outcome of this work.

8.1 Summary

8.2 Contributions

This section will revisit the contributions outlined in the introduction (Chapter 1), with further expansion and explanation. The main contributions of this thesis are as follows:

- Something

8.3 Conclusion

Acronyms

ASD Autism Spetrum Disorder. 6, 12, 41

CML Classical Machine Learning. 25

DREAM Development of Robot-Enhanced Therapy for Children with Autism Spectrum Disorders (European FP7 project). 6, 39

GUI Graphical User Interface. vii, 42–46, 48

HCI Human-Computer Interaction. 15, 22

HRI Human-Robot Interaction. 1, 2, 5, 11, 13, 15–17, 21, 22, 24, 27, 28, 30, 32, 35, 53, 58, 71

IML Interactive Machine Learning. 2, 24–26, 30, 32, 34, 35, 55, 56, 58

IRL Interactive Reinforcement Learning. 55–58, 60–64

LfD Learning from Demonstration. 18, 24, 32, 34, 36

MDP Markov Decision Process. 22

ML Machine Learning. 2, 3, 28, 30

RAT Robot Assisted Therapy. 6, 14, 17, 19, 33, 40, 41, 45, 53

RL Reinforcement Learning. 2, 22–26, 29, 32, 33, 36, 55, 56

SAR Socially Assistive Robotics. 6

SL Supervised Learning. 26, 36, 56

SPARC Supervided Progressive Autonomous Robot Competenties. i, vii, 3, 32–36, 39, 41, 42, 46, 48, 49, 52, 53, 55–58, 60, 62, 63

WoZ Wizard-of-Oz. 2, 15, 16, 19, 36, 39–42, 45, 46, 48, 49, 52, 53

Appendices

Appendix A

A1

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