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Teaching Robots Social Autonomy From In Situ Human Supervision

by

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Abstract

TEACHING ROBOTS SOCIAL AUTONOMY FROM IN-SITU HUMAN SUPERVISION
Emmanuel Senft

To reach the potential promised to robots in interaction with humans, robots need to learn from them. Knowledge of expected robot behaviours does not lie in engineers' hand but in the end-users'. As a consequence, to reach new applications and enter daily lives, robot users need to be provided with a way to teach their robot to interact in the way they desire.

The thesis explored by this work is that a robot can learn to interact meaningfully with humans in an efficient and safe way by receiving supervision from a human teacher in control of the robot's behaviour. This work original contribution to knowledge is a new teaching framework applicable to robotics and addressing the thesis: the Supervised Progressively Autonomous Robot Competencies (SPARC) and its evaluation in three studies. SPARC aims at enabling non-technical users to teach a robot in high-stakes environments such as Human-Robot Interaction (HRI). By providing the teacher with control over the robot, SPARC ensures that every action executed by the robot has been actively or passively approved by the teacher. This approach demonstrated its applicability to HRI by successfully teaching a robot to tutor children in an educational game, resulting similar behaviours for the autonomous robot and the one controlled by a human.

Throughout evaluating SPARC, this work contributes to extend our knowledge on how humans teach autonomous agents and the impacts of the teacher-robot interface's features on the teaching process. It is found here that a supervised robot learning from a human could reduce the workload required to express a useful robot behaviour. Furthermore, providing the teacher with the opportunity to control the robot's behaviour improves substantially the teaching process and can lead to an autonomous robot interacting efficiently with humans.

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Chapter 1

Introduction

Human-Robot Interaction (HRI) explores the challenges of developing robots to interact in human environments and studies how human beings react to such robots. While not being present in every home yet, robots are quickly propagating through society and entering people's life. To interact in human environments and fill their role for society, robots require a way to interpret their sensory inputs and act on the social world; in other words, they need to be sociable (Breazeal, 2004). However, interacting socially with humans is a complex task: the social interaction happens on multiple levels and combines elements from various fields (Fong et al., 2003). Furthermore, by interacting with humans, robots are subjects to social norms and have to take them into account when behaving around people (Bartneck & Forlizzi, 2004). Providing robots with such a complex action policy is a challenge, and no static controller programmed manually would cover all the possible situations they could face. To interact meaningfully with humans, robots need to learn, constantly expanding and refining their action policy. As such, it stands to reason to use the experts in humans interactions, the humans themselves to teach robots to interact socially. By providing control over the robot's actions to a human teacher, a robot could learn efficient policies for social interactions from in-situ human supervision. Interactively learning from humans presents a change of paradigm compared to traditional machine learning, as the human possesses knowledge they can transfer to the robot, improving the learning process (Fails & Olsen Jr, 2003; Amershi et al., 2014). Finally, by initially framing this work in the context of HRI we added to the interaction a large set of constraints (high-stakes environment, complexity of state, low number of datapoint and real time interaction). Consequently, by exploring how to learn in such a complex environment this research work would have applications beyond HRI, e.g. to general robotic, Machine Learning (ML) and Artificial Intelligence (AI).

1.1 Scope

As shown in Goodrich & Schultz (2007) only a subset of HRI is designed to be inherently social. Using Goodrich and Schultz's definition of HRI, as the study of robots for use by or with humans, an important part of the field does not consider the social side of the interaction. Robots are often considered as asocial entities having a task to complete or simply tools to be used by humans. However, as demonstrated by Fincannon et al. (2004), even when used as teleoperated machines, robots still provoke social reactions and expectations from humans. Fong et al. (2003) make, among others, the distinction between "evocative robots" and "socially interactive robots". Evocative robots rely on human tendency to anthropomorphise to succeed in their task, while for "socially interactive robots" the social side of the interaction is key. However in HRI, the sociality of the interaction might not be intended or even desired but may simply emerge as a by-product of the interaction. As a consequence, in this work we will refer to 'social robots' as robots interacting in humans environments and considered as social agents by the humans interacting with them. The intentions of the robot designer or the actual robot's sociality are of minor importance if the humans interacting with the robot project social competencies or expectations on the robot. Regardless on the initial intentions, a robot interacting with humans needs to manage these expectations to ensure the safety and comfort of its human partners. In summary, as soon as a robot interacts with humans, the social side of the interaction needs to be taken into account, the robot needs a social policy.

However, enabling a robot to interact socially with humans is a complex task. The robot needs to make sense of a large input space, from low level sensory feedback (e.g. joint angles or camera pixels) to high level concepts (e.g. hand-coded events or learned features). And based on the interpretation of these inputs and rules defining a behaviour, the robot needs to select an action or a plan to achieve an assigned goal. As this task covers most of the areas of robotics (Fong et al., 2003), this section will precise the scope of the research conducted in this thesis.

1.1.1 Frame

The context of the research conducted here is finding a way for robots to interact efficiently with humans. It has been argued by many researchers (Dautenhahn, 2004; Billard et al., 2008) that robots need to adapt to their users and be able to learn from them. Social robots cannot simply apply a one-size-fits-all policy programmed in advance by engineers and suited to every possible interaction partners. Robots need the capability to learn an interactive behaviour, improving their skills as they inhabit the world and personalising their policy to their users. This thesis aims to tackle this challenge and enable robots to learn to interact with humans.

Throughout this thesis we make the assumption that a human knows how the robot should interact. A person, generally not the engineers initially developing the robot, possesses some expertise which should be transferred to a robot. This expertise is not related to theoretical knowledge in ML, robotics or other scientific fields but defines how the robot should behave. For instance, it could take the form of the steps of a therapy a robot should deliver to the child (known by a therapist) or more simply a senior's preferences and desires concerning a robot companion's behaviour. As a consequence, robot users should be able to teach their robot without requiring technical expertise.

Although the ultimate goal of this research is to explore how robots could learn to interact socially and efficiently with humans; by making the assumption that the interaction knowledge should be provided by a human, the resulting question of this thesis is: *'How humans could teach robots to interact?'*. As such, this research work aims to provide a convenient and efficient way for domain experts to inculcate robots with their interaction knowledge. To do so, this research explores the requirements on an interaction framework allowing humans to teach robots to interact socially in human environments and studies the impacts such a framework would have on the interaction.

1.1.2 Type of Interaction

In HRI a robot has to solve a task with or for a human, we coin this interaction the *application interaction*. However, by focusing the research on using humans to teach robots, we add a second human-robot interaction to this application interaction: the *teaching interaction* between the robot and the teacher. The end goal of this new teaching interaction is to achieve high standards in the application interaction. This results in two intertwined human-robot interactions: the application interaction, between the application target and the robot and the teaching interaction, between the teacher and the robot (cf. Figure 1.1), which is equivalent to a general triadic interaction between the human target, the robot and the human teacher.

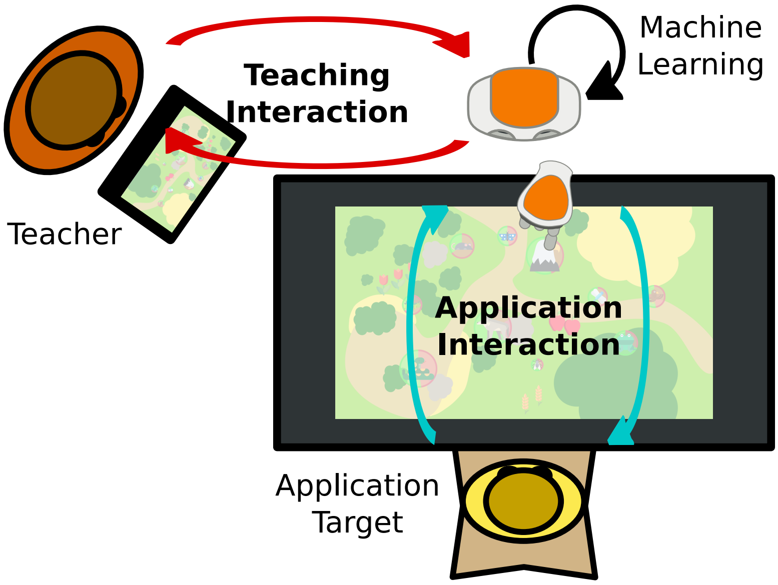


Figure 1.1: The typical interaction used in this research: a robot interacts with a target in an application interaction and learns from a domain expert through a teaching interaction.

While having been pursued by considering mostly HRI as the application interaction, the work presented in this thesis is applicable to teaching a robot, or more generally an agent, a behaviour not limited to human robot interaction. Indeed, interacting with a human is a high stake scenario, where misbehaving can be costly, where datapoints for learning can be tedious to acquire and with a high diversity between different partners. Other types of interaction could be less constrained, complex or with lower stakes. Consequently, by addressing a challenging task (teaching a robot to interact socially with humans), this approach would also suited to a wide range of other tasks (such as manipulation, classification or navigation). In the more general case, we consider scenarios where a user has a task they would like an artificial agent to complete and they have useful knowledge they want to transfer to this agent. Through the teaching interaction, the human can supervise the agent, demonstrating what it should do and teaching it an efficient action policy in the application interaction with the target.

1.2 The Thesis

The main thesis this document proposes is the following:

> **A robot can learn to interact meaningfully with humans in an efficient and safe way by receiving supervision from a human teacher in control of the robot's behaviour.**

Additional research questions are also introduced here. These research questions are used to support and direct the experimental research conducted in pursuit of demonstrating the primary thesis.

RQ1 *What are the requirements of a robot controller to ensure a behaviour suited to HRI?*

By interacting with humans, robots enter the social world and have to conform to human expectations while ensuring they can reach their goal. This research question studies the constraints put on the robot's controller by interacting in the human world.

RQ2 *What interaction framework would allow a human to teach a robot while validating the requirements from RQ1?*

This research question address what principles could lead to an efficient teaching interaction between a robot and a human whilst validating the requirements from RQ1 for the interaction between the robot and the target.

RQ3 *Could a robot decrease its supervisor's workload by learning from their supervision?*

Controlling a robot is a significant workload for the human supervisor. This question explores if including a learning component in the robot behaviour could alleviate the human workload by taking over some of the mental and physical requirements of the robot control. Additionally, this question explores if this learning impacts the performance in the task.

RQ4 *How providing the teacher with control over the learner's actions impacts the teaching process?*

Teaching robots has a unique property compared to teaching humans in the fact that the teacher can have total control over the learner's actions. This question explores if this control could lead to a faster and more efficient learning while lightening the process for the teacher.

RQ5 *How teaching a robot to interact socially impacts the two humans involved in the overall triadic interaction?*

Using humans to teach robots to interact with other humans results in two linked interactions. This questions studies the impact of the teaching process on these two interactions: are the requirements from RQ1 validated in the application interaction, and is the teaching interaction efficient and convenient for the teacher.

RQ6 *After receiving supervision from a human, could a robot behave autonomously in a social context?*

After having been taught, a robot could be deployed to interact autonomously in the real world. This questions analyses the robot's behaviour when interacting autonomously and explores the efficiency of a teaching in situ in providing the robot an autonomous behaviour validating principles from RQ1.

1.3 Approach and Experimentation

1.3.1 Review of the State of the Art in HRI

The first step toward answering the RQ1 and identifying the requirements interacting with humans puts on robot was to review the different fields of application of social HRI. In each type of interaction, the robot will interact with people with different specificities and needs, and by analysing these fields, we can draw the requirements such interactions put on the robot's controller. For this survey, we limited the applications to cases where humans consider the robot as a social agent, as this is the main feature we use to define social HRI.

1.3.2 New Teaching Framework

To address the requirements on a robot controller emerging by addressing RQ1, we propose the Supervised Progressively Autonomous Robot Competencies (SPARC), a novel teaching framework intended to provide a way for non-experts in robotics to safely teach a robot to interact with humans. SPARC is the cornerstone of this thesis and this research work describes and justifies this approach, and evaluates its impact though three studies of increasing complexity.

1.3.3 Study Design

To address the main thesis of this work and RQ3 to RQ6, we designed and ran three studies, which are described in details in the Chapters 4 to 6. These studies evaluated the impacts of SPARC on different parts of the teaching and application interactions. The first two studies focused on the teaching interaction, i.e. the impact of SPARC on the teachers and the relation between the teacher and the robot. As a consequence, they required repeatable environments to compare humans' efficiency and experiences when teaching a robot. The last study applied SPARC to a real HRI and was run in a school with a single human teaching a robot to interact with children over multiple sessions. Its main goal was to explore if SPARC can be used to teach a robot to interact with humans. All the studies used SPARC in the type of interaction presented in Figure 1.1, i.e. a teacher wants a robot to complete a task (included but not limited to human interaction) and can control the robot's actions through an interface. As each study focused on different features of SPARC, bespoke interaction environments and test benches have been developed for each study.

The first study (Chapter 4) explored if SPARC could be used to provide learning to a robot in a Wizard-of-Oz (WoZ) interaction and if this learning would impact the workload and performance of the teacher in the task. We took inspiration from Robot Assisted Therapy (RAT) and decided to replace the child interacting with the wizarded-robot by a second robot running a model of a child displaying typical features observed in children (such as non-deterministic behaviour, partial observability of state and absence of easily definable optimal action policy). This repeatable environment allowed us to evaluate in a controlled study the impact of SPARC on the teacher and compare SPARC to WoZ.

The second study (Chapter 5) compared SPARC to another Interactive Machine Learning (IML) method: Interactive Reinforcement Learning (IRL) in a replication of the virtual environment initially used to test IRL. The main difference between the two methods resides in the quantity of control provided to the teacher; unlike IRL, SPARC provides teachers with full control over the robot's actions. In this study, participants controlled a virtual robot on a computer and had to teach it how to solve a task in a deterministic virtual environment.

Finally, the last study (Chapter 6) deployed SPARC in a real interaction with humans, to teach children about food chains. This study used the paradigm described in Figure 1.1: a child is playing an educative game with a robot on a large touchscreen and the robot is remotely controlled and taught by an adult using a tablet. That way, using SPARC, the robot can learn to support the child in the educative activity and increase their engagement and performance in the task.

1.3.4 Learning Algorithms

To enable robots to learn from humans, they need to be equipped with Machine Learning (ML), i.e. an algorithm statistically learning a mapping between some inputs and outputs. Two main categories of ML are relevant for this research: Supervised Learning (SL) and Reinforcement Learning (RL).

SL aims to learn a mapping between inputs and outputs to automatically reproduce a desired known behaviour. It uses a dataset of labelled example and optimises an algorithm to minimise the prediction error of labels (Russell & Norvig, 2016). Typical examples of SL used in this study are Artificial Neural Networks (ANN) and nearest neighbours methods. ANN model loosely the way brains and neurons work by having a group of interconnected 'neurons' influencing each other. By changing the connections between the neurons, the network learns to reproduce the desired values on the output nodes according to the inputs. On the other hand, nearest neighbours methods are instance based methods, they compare the distance in a feature space between a point to classify and the different instances stored in a dataset and select the value of a majority of nearest neighbours in that space. With its goal, reproducing a desired behaviour, SL is especially connected with the work carried out in this research. By learning to reproduce the teacher's policy, the robot should reach an efficient behaviour in the target application.

Unlike SL which reproduces a known behaviour, RL aims at providing an agent with the capacity to discover and explore the world it inhabits and learn from this interaction with the world how to behave in this world (Sutton & Barto, 1998). The agent has access to a description of the state and actions it can do, and depending of the action selected, the state will change and the agent will receive a reward. The goal of the agent is to find an optimal policy maximising a notion of cumulated reward. RL is also linked to the work presented in this thesis: by allowing an agent (here a robot) to learn by interacting a world (here human environments), we would reach our goals of efficient human-robot interactions.

Due to the relevance of both fields to this research (enabling robots to learn to interact), algorithms from both categories have been used. The first study presented in Chapter 4 used a feed forward neural network learning to reproduce a teacher policy. The second study in Chapter 5 used RL to combine human guidance, and environmental and human rewards to learn an efficient action policy. The last study presented in Chapter 6 used an instance based algorithm adapted from Nearest Neighbours to enable online quick and efficient learning from human commands. More details about each algorithms and their related work can be found in the associated chapters.

1.3.5 Data Analysis

Graphs presented throughout this thesis have been generated using the seaborn package for Python and matplotlib (Waskom et al., 2017). Data have been usually represented using violin plots, a graphical representation featuring the probability density of the data. Statistical analysis in Chapters 5 and 6 have been made using the Jasp software (JASP Team, 2018). Jasp offers a Bayesian counterpart to classic statistical test, making them more robust and allowing to observe the presence or absence of effect. As such, instead of a *p-value*, the Bayes factor B is reported and represents how much of the variance on the metric is explained by a parameter (if $B < 1/3$ there is no impact, if $B > 3$ the impact is strong, and if $1/3 < B < 3$ the results are inconclusive; Jeffreys 1998; Dienes 2011).

1.3.6 Terminology

Throughout this thesis, the terms 'wizard', 'supervisor', 'user', 'expert' and 'teacher' have been used interchangeably to represent the people in control of a robot's action and teaching that robot an action policy. Similarly, we refers to the robot as 'robot', 'agent' or 'learner' depending of the situation.

1.4 Contributions

This research work contributed both scientifically (by creating and evaluating SPARC) and technically (by developing software for multiple projects) to the state of the art in HRI and especially in teaching robots to interact with humans. This section highlights the original contribution of this thesis and indicates the relevant chapters and published work.

1.4.1 Scientific Contributions

- Design of SPARC, a new interaction framework for teaching agents in a safe way (Chapter 3; Senft et al. 2015a,b).

- Evaluation of SPARC in three studies (Chapters 4, 5 and 6; Senft et al. 2015b, 2017a, 2018).
- Demonstration of the impact and importance of the teacher's control over the robot's action when teaching a robot (Chapter 5; Senft et al. 2016b, 2017a).
- Design of a lightweight algorithm to quickly learn from demonstrations in complex environments (Chapter 6; Senft et al. 2017b).
- Application of IML to safely teach robots social autonomy from in situ human supervision in a real human-robot interaction (Chapter 6; Senft et al. 2018). This contribution is the main one as allowing robot to learn to interact with human in situ presents many advantages compared to other types of learning but is seldom used in HRI due the challenges it presents.

1.4.2 Technical Contributions

- Partial development of a cognitive architecture and two tools for the DREAM project (European FP7 project: 611391) (Appendix A; Esteban et al. 2017).
- Development of an autonomous robot controller to support cardiac rehabilitation in the Human-Robot Interaction Strategies for Rehabilitation based on Socially Assistive Robotics project (Royal Academy of Engineering: IAPP\1516\137) (Lara et al., 2017; Casas et al., 2018).
- Development of a wizard interface for the Freeplay-Sandbox[1] (Lemaignan et al., 2017).

1.5 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 findings and relevant notions 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 (robots learning to interact with and from humans), the research questions including the central *thesis*, the scope and the contributions of the work presented in later chapters.

[1] `https://github.com/freeplay-sandbox`

- Chapter 2 provides a description of the different fields of social HRI and draws requirements for controllers of robots interacting with humans. In a second part, it analyses the current robot controllers used in HRI identifying that no current controller fits these requirements. Finally, it introduces IML and proposes to apply it to HRI as a way to validate the previously defined requirements.

- Chapter 3 proposes a new interaction framework, SPARC, as a way to apply IML to HRI while validating the three requirements proposed in Chapter 2. This chapter describes the principles behind SPARC and the expectations and limits this method could have.

- Chapter 4 presents a first study evaluating the impact of SPARC on the supervisor's workload and performance compared to WoZ. Results showed that SPARC allowed teachers to achieve a good performance, while reducing their workload.

- Chapter 5 presents a second study comparing SPARC to IRL, another interaction framework from IML. The main difference between the two approaches lied in the amount of control the teacher has: with SPARC, the teacher can correct any action executed by the robot. Results from a 40 participants study supported that this control improves the efficiency of the learning (improving the performance, reducing the time and the number of inputs required to teach as well as decreasing the risks taken during the teaching phase and imposing a lower workload on the teacher).

- Chapter 6 presents the first study where SPARC has been applied to a real world HRI, child tutoring, and to our knowledge one of the first time online learning has been used to teach robots to interact with humans. Results demonstrate that, while not impacting the learning gain of the session, a supervised robot elicited richer child behaviour compared to a passive robot. Furthermore, by learning using SPARC, an autonomous robot reached a policy similar to the teacher's one and achieved similar impacts on the children. These results support SPARC as a teaching method allowing to transfer in situ a social and technical action policy from a human to a robot in a safe way and leading to an efficient autonomous behaviour. The findings are key for this thesis as they demonstrate the applicability of SPARC to high-stakes, unpredictable, multidimensional, multimodal and complex environments.

- Chapter 7 presents a discussion of the main findings from the previous chapters in relation to the research questions introduced in this chapter, discusses the limitations and future directions of research for SPARC as well as its potential impact on HRI and other fields.
- Chapter 8 concludes the thesis and presents a summary of the main contributions.

Chapter 2

Background

This chapter describes social Human-Robot Interaction (HRI) and presents related research in agent and robot control. The first section introduces the different fields of application of social HRI and draws from them requirements for controlling a robot interacting with humans (the robot should: only execute appropriate actions and have a high level of adaptivity and autonomy). The second section provides the current state of the art in robot control for HRI and analyses it through the requirements presented in the previous section. And finally, building on the lack of controller satisfying the requirements from Section 1, the third section presents Interactive Machine Learning (IML), an alternative method holding promises to teach agents how to interact and how it could be applied to HRI.

2.1 Social Human-Robot Interaction

2.1.1 Fields of Application

Reviews of HRI and socially interactive robots have already been presented in Fong et al. (2003), Goodrich & Schultz (2007) and Sheridan (2016). However, these reviews are starting to be dated and/or did not have the same focus than this research. As mentioned in the introduction, this work is focused on social robots, robots perceived as social agents and interacting in a human-centred environment. Depending of the context of interaction, these social robots will have been designed to interact socially with humans, or sometimes, the perception of sociality and agency will simply emerge from the interaction (Fincannon et al., 2004). As such, the following criteria on the interactions were used to select the subfields of HRI relevant to this research:

- Presence of an interaction between a robot and a human: both the human and the robot are influencing each other's behaviour.

- The human partner considers the robot as a social agent, responding socially to the robot and potentially bonding with it.

We reorganised and edited Goodrich and Schultz's categories, to fit with the criteria presented above, which resulted in five subfields involving social interactions between robots and humans:

- Socially Assistive Robotics (SAR)
- Education
- Search and Rescue, and Military
- Hospitality, Home and Entertainment
- Collaborative Robots in Industry

We updated each category with recent research and highlighted the social component of the interaction and its impact on the controller used for the robot.

Socially Assistive Robotics

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

One of the main applications of SAR is care for the elderly. In the near future, the ageing of population will have large impacts on the world, and societies will have to find solutions to tackle this challenge. The United Nations' Department of Economic and Social Affairs (2017) reports that the "population aged 60 or over is growing faster than all younger age groups". This unbalance of growth will decrease the support ratio (number of workers per retiree) forcing societies to find ways to provide care to an increasing number of people using a decreasing staff. Robots represent a unique opportunity to compensate for this lacking workforce potentially allowing elderly to stay at home rather than joining elderly care centres (Di Nuovo et al., 2014) or simply to support the nursing staff (Wada et al., 2004).

The second main application of SAR is Robot Assisted Therapy (RAT). Robots might be used to provide therapies or to follow and support a patient during their rehabilitation to improve their health, their acceptance in society or recover better from an accident. In therapies, robots were first used as physical platforms to help patient in rehabilitation therapy during the 80s (Harwin et al., 1988). During this period, robots were primally used as mechatronic tools helping humans to accomplish repetitive task. But in the late 90s, robots started to be used for their social capabilities. For example the AuRoRA Project (Dautenhahn, 1999) started in 1998 to explore the use of robots as therapeutic tools for children with Autism Spetrum Disorder (ASD). Since AuRoRA, many other projects, such as the DREAM project[1], have started all around the world to use robots to help patient with ASD (Diehl et al., 2012; Esteban et al., 2017).

RAT is not limited to ASD only, this 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) and stroke recovering patients (Matarić et al., 2007) or to monitor and provide encouragement in cardiac rehabilitation therapies (Lara et al., 2017).

These examples demonstrate that already today, robots are interacting with vulnerable populations (children, the elderly or patients in therapy). This implies that robots' social behaviours need to be constantly correct to ensure that no harm will be caused to these populations. And due to the shortage of workforce, these robots also need to be as autonomous as possible.

Education

Social robots are being used in education, supporting teachers to provide learning content to children and transforming the teaching process from passive learning to active learning (Linder et al., 2001). In education, robots can take multiple roles such as peer, tutor or tool (Mubin et al., 2013). It should be noted that Mubin et al. stress that the intention of the robotic community is not to replace teachers by robots, but provide them with a new form of technological teaching aid. Nevertheless, Verner et al. (2016) presented positive results from an early stage study using a tall humanoid robot to deliver a science lesson to children. The remaining of the section will describe more in details the roles of tutor and peer robots (the 'tool' role has been excluded due its general lack of perceived gency and the lack social interaction between the robot and the students).

[1] `https://www.dream2020.eu`

Robotics tutors providing tailored teaching content in 1 to 1 interaction. Individualised feedback has been shown to increase the performance of students (Cohen et al., 1982; Bloom, 1984). However, tutoring requires a larger trained staff and as such is more costly than large classes supervised by a single teacher. For this reason, tutoring is seldom used in public education today. Tutoring is however often available through private teacher at additional cost for the parents, potentially increasing social inequalities (Bray, 2009). Robotic tutors could provide this powerful one to one tailored interaction to every student during school time, leading to higher learning gain for the children without dramatically increasing the workload on teachers or the price of education (Kanda et al., 2004; Leyzberg et al., 2012; Kennedy et al., 2016b; Gordon et al., 2016). In addition to classroom uses, robots could also support children at home as they have been shown to elicit advantages over web or paper based instructions (Han et al., 2005).

Peer robots learning alongside the children. Unlike other types of agents in education, peer robots have the opportunity to fit a special role seldom present in education today: the role of care-receiver rather than care-giver (Tanaka & Matsuzoe, 2012). Peer learning has demonstrated benefits both for the helpers and those helped in Human-Human Interaction (HHI) (Topping, 2005). In HRI, a peer robot does not mentor a child to teach them new concepts, but learns alongside or from them, supporting them during the process and encouraging these children to produce behaviours improving their own learning. For example, in the Co-Writer project (Hood et al., 2015), a child has to teach a robot how to write, and as the child demonstrates correct handwriting to the robot, they improve their own skills at drawing letters. Peer robots are able to leverage the concept of learning by teaching (Frager & Stern, 1970) and peer learning (Topping, 2005) in a way hardly matched 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. In a similar position, an adult would not be a believable agent requiring learning and a younger student might not have the compliance and the patience to learn from another child.

To provide efficient tutoring or peer support, robots need to be able to personalise their behaviour to the children they are interacting with in order to maximise the children's learning gain. Additionally, as pointed by Kennedy et al. (2015a), a robot too social could decrease the children's learning compared to a less social robot if its behaviour is not congruent, consequently the robot's social behaviours have to be carefully managed to ensure its effectiveness.

Search and Rescue, and Military

Robots are already deployed in the real world, outside of labs and used during search and rescue missions (Casper & Murphy, 2003; Murphy, 2004). For instance, after a natural or artificial catastrophe, robots have been sent to analyse the damaged area and report or rescue the surviving victims of the incident. During these missions, 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 is probably in a shocked state and the searching robot could be the first link they have with the external world after the accident (Murphy et al., 2008). 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 high pressure to act quickly and faces traumatic events too. Even if the robot does not display a social behaviour, rescuers interacting with it might develop some feeling toward the robots they are using during these tense moments (Fincannon et al., 2004).

Similar human behaviours (i.e. emotional bonding with a teleoperated robot) have also been observed in the army (Singer, 2009). Robots have been deployed as teleoperated drones and ground units alongside soldiers to complete scouting task or cleaning minefields. By interacting with a robot for extensive periods, some soldiers developed feelings toward this robot they used in a daily basis: taking pictures with it and introducing it to their friends. These relationships have gone as far as soldiers risking their own life to in order to save the robot used by their squad (Singer, 2009).

These examples in these two fields demonstrate that even in interactions where the robot is not supposed to interact socially with humans, its users might consider it as a social agent. Consequently, the sociability of the robot has to be taken into account when interacting in such stressful environments. Overlooking the importance of social relationships human will form can lead to dramatic consequences (e.g. soldiers taking risks for the robot). As such, during the interaction, the robot's behaviour needs to be constantly appropriate not to create misleading expectations and to ensure that the goal of the interaction will be met.

Hospitality, Home and Entertainment

Robots are also interacting with humans in hotels around the world; for example, the Relay robot (Savioke[2]) delivers amenities directly to the guests' rooms in more than 70 hotels in the US, Europe and Japan[3]. Whilst the social interaction is still minimal today, these robots interact everyday with humans and have been seen evoking social reactions from them[4].

Since the late 90s, scientists explored how robots could guide visitors in museums and exhibitions (Thrun et al., 1999; Burgard et al., 1999). These researches continue today to explore how to improve the social interaction between tourists and these guide robots (Bennewitz et al., 2005). In a similar context, researchers have designed and tested a robot as a receptionist in a hall at Carnegie Melon University (Gockley et al., 2005). Studies have also explored long term interactions and how humans perceive and interact with robots in shops and shopping malls (Kanda et al., 2009) and how robots should behave with clients (Kanda et al., 2008).

Finally, robots have already entered homes and family circles: from vacuum cleaners to companion passing by pet robots. A notable example is Aibo: twenty years ago, Sony created Aibo, a robotic dog to be used as pet in Japanese families and a new version was released in early 2018[5]. An analysis of online discussions of owners published 6 years after Aibo's first introduction gives insights on the relationship that owners created with their robots (Friedman et al., 2003). For example 42% of the community members assigned intentionality to the robot, such as preferences, emotions or even feelings. Similar behaviours have also been observed when the robot was used not as a pet, but even just as a tool. For instance, Fink et al. (2013) reported that one of their participants was worried that their Roomba (a robotic vacuum cleaner) would feel lonely when they would be away on holiday. More recently, the Pepper robot has been sold as a social robotic companion to families in Japan[6]. However, as of early 2018, no study in English has reported results of the interactions with families or long term use and acceptance.

[2] http://www.savioke.com/

[3] https://www.spectrum.ieee.org/view-from-the-valley/robotics/industrial-robots/ces-2018-delivery-robots-are-fulltime-employees-at-a-las-vegas-hotel

[4] https://www.fastcodesign.com/3057075/how-savioke-labs-built-a-robot-personality-in-5-days

[5] https://aibo.sony.jp/en/

[6] https://www.softbankrobotics.com/emea/en/robots/pepper

reread[ES] By entering our homes or hotel rooms, robots are penetrating some of our most intimate social spaces. These private spheres are ruled by a totally different set of social norms than public spheres such as streets or shopping mall (Weintraub, 1997) and social faux-pas in these private environment can lead to important loss of trust. As a consequence, these robots' behaviours and action policies needs to be especially appropriate and transparent when interacting in such private spaces. Additionally, robots in hospitality and entertainment will face a wide range of users' expectations, and will have to react to different unanticipated behaviours. Consequently, robots needs to be able to adapt their behaviours to these different users. Finally, robots in these fields will also interact with the same people over long periods (Leite et al., 2013). And, to sustain engagement over such time scales, these robots need to change their behaviour over time to overcome possible boredom due to the vanishing of the novelty effect in repeated interactions (Salter et al., 2004).

Collaborative Robots in Industry

In industry, robots 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; they share the same workspace and interact physically and socially with factory workers. However, to collaborate efficiently with humans, many challenges still need to be addressed. For example, the bidirectional communication between the robot and the humans needs to be as clear as possible. To interact efficiently and safely with humans, robots need to make their intentions clear to humans surrounding them (Dragan et al., 2013) and reciprocally, they also need to interpret humans' social cues to infer their goals and intentions (Scheutz et al., 2007).

Beyond legibility and interpretation, another key challenge in Human-Robot Collaboration (HRC) 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. Explicit and implicit rules and personal preferences describe the expected role and behaviours of each participant and have to be taken into account in HRC. As such, the task repartition system and other planners used in HRC should be aware of these social norms and follow them (Montreuil et al., 2007). For example, recent work done in the 3rd Hand project[7] explored how a robot should support a human in a collaborative assembly task by adapting its behaviour to this human's personal preferences and how this adaptation improves the team's efficiency (Munzer et al., 2017).

An last challenge related to the recent advances in Machine Learning (ML), and especially with the omnipresence of neural networks and deep learning, is Explainable Artificial Intelligence (XAI) (Wachter et al., 2017). As agents learning to interact will make mistakes and behave unexpectedly from time to time, they have to be able to provide explanations for these errors in a way understandable by humans. This challenge is especially visible in HRC where both humans and robots aim to collaborate to complete a task together. Hayes & Shah (2017) propose to achieve transparency through policy explanation, by allowing robots to answer questions and explain their behaviour by self observation and logic deduction. This transparency aims at increasing trust between the agents involved in the interaction and improve the team's efficiency.

As demonstrated in Munzer et al. (2017), intelligent systems involved in HRC should adapt their behaviour to their interaction partners, be aware of preferences and rules to follow to ensure that the robot's behaviour is always appropriate, efficient and safe for the humans involved in the interaction. Furthermore, their autonomy needs to encompass behaviour explanation, be able to explain the reasoning steps and justify each of their actions.

2.1.2 Requirements on Robots Interacting with Humans

maybe overlap with appropriate section[ES] The review in Section 2.1.1 demonstrated that robots are already interacting with vulnerable populations: young children, the elderly, people requiring healthcare or in a stressful situations (victims of catastrophes or soldiers for example). Additionally, people tend to a create emotional bonding with these robots even if they are not interacting socially with their users. As such, the behaviour of robots interacting with humans need to be carefully controlled to manage humans' expectations and ensure their safety. In other words, robots need to constantly behave in socially acceptable manners, avoiding any confusing, inappropriate or dangerous behaviour. Failure to do so might prevent the interaction to fit its goal, potentially elicit offence, anger, frustration, distress or boredom or even lead to physical injuries.

[7] http://3rdhandrobot.eu/

These undesired behaviours may come from 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 policies. Due to the wide range of origins of these potential social faux-pas, this research focuses only on the last point, obtaining an appropriate action policy: assuming a set of inputs, finding a way to have the robot select an appropriate action. The other issues are either orthogonal and would lead to failure even with an 'optimal' action policy as external factors prevent the robot from solving the problem or could be handled by having a better action policy (e.g. a policy generalising more efficiently or selecting suboptimal actions when the optimal ones are not available).

Appropriate actions are highly dependent on the interaction context: they could aim to match or reduce users' expectations of a robot's behaviour or complete a specific task. Additionally, actions correct in a certain context might be inappropriate in another one. Nonetheless, the intention behind being *appropriate* here is that actions executed should be guaranteed not to present risks for the humans involved in the interaction (for example, preventing physical harm or mental distress), while helping the robot to move toward its goal and achieving its 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 people, for extended periods of time or with initial incomplete or incorrect knowledge. As such, the action policy also needs to be adaptable to the context and users as well as evolve over time. In summary, robots also need to be adaptive, to react to changing environments, cover a larger field of application and improve their action policy over time.

Lastly, in many cases today, interactive robots are not autonomous but partially controlled by a human operator (Riek, 2012). We argue that to have a real and useful HRI, the robot needs to be as autonomous as possible. Robots are expected to be used in areas where the workforce is already in shortage (e.g. healthcare) and requiring humans to control these robots decreases widely their applicability. As a community, HRI should strive toward more autonomy for robots interacting with humans.

Based on these considerations, we define three properties to evaluate how suited robot controllers are to interact with humans. Each axis is associated to a principle the robot has to follow to sustain meaningful social interactions:

1. Appropriateness of actions - The robot should only execute appropriate actions.
2. Adaptivity - The robot should be adaptivity to its environment and in time.
3. Autonomy - The robot should be as autonomous as possible.

We will use these axes to analyse current robotic controller types in Section 2.2.

As HRI is 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, the dependence and knowledge of social rules or the range of application of a robot to cite only a few. However, we did not address these axes in the current work as they are more influenced by the goal and the context of the specific human-robot interaction taking place than the action policy itself. Additionally, an appropriate, adaptive, and autonomous robot should be able to safely and autonomously learn to interact in deeper and more complex interactions and learn to extend its abilities beyond the ones it initially started with, and increase its range of applications.

Appropriateness of Actions

As argued previously, much of social human-robot interaction takes place in stressful or sensitive environments, where humans have particular expectations about a robot's behaviour. 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). And some of these expectations are also transferred to interactions with robots (Bartneck & Forlizzi, 2004).

We define appropriate actions, as actions taking into account the social side of the interaction, and producing a correct robot behaviour at the right time. This behaviours needs to be safe for surrounding humans and help the robot to reach its goal. Failing to produce these appropriate actions, for example by not matching the users' expectations, may have a negative impact on the interaction, potentially compromising future interactions if the human feel disrespected, confused or annoyed. Furthermore, failing to behave appropriately can even harm the people interacting with the robot: not reminding an elderly to take their medication, not taking into account the state of mind of survivors after a disaster or behaving inconsistently with children with ASD might lead to dramatic consequences. Robots require a way to ensure that all the actions they execute do not present risks to the humans involved in the interaction while moving the robot closer to its goal.

For the review in Section 2.2, the appropriateness of actions axis is a continuous spectrum characterising how much the system controlling the robot ensures that the robot constantly acts in a safe and useful way for the users. For example, a robot selecting its actions randomly would have a low appropriateness as no mechanism prevents the execution of unexpected or undesired actions. On the other hand, a robot continuously selecting the same action as a human expert would have a high appropriateness as domain experts know which action is the correct one in this application domain.

Adaptivity

Humans are complex, indeterministic and unpredictable agents, as such an optimal robot behaviour is not likely to be known in advance or even programmable by hand (Dautenhahn, 2004; Argall et al., 2009). Specifically, end users will express behaviours not anticipated by the designers, the interaction environment is often not perfectly definable and the desired behaviour might also need to be customisable by or for the end user or evolve over time. While many studies in HRI use robots following a static script, to interact meaningfully outside of lab settings or scientific studies, robots need this flexibility to extend their range of application and improve their interactions with users. In other words, robots interacting with people need to be able to adapt their action policy to the environment and improve their behaviour over time. We use the term *adaptivity* to represent this ability to express a behaviour suited to different conditions and refine it over time.

We propose three components for this adaptivity. The basic one is the adaptivity to the environment, i.e. the generalisation of the behaviour (reacting accordingly to unseen inputs). The second one is personalisation and adaptation: being able to adapt a behaviour to the current user or context. Finally, the last component is the adaptivity in time which is, in essence, learning (the possibility to enrich and refine the action policy over time).

Generalisation: Robots are interacting in human centred environments which are complex and highly stochastic. These environments are often under specified and robot designers cannot explicitly anticipate every single possible human reactions or occurring events. Furthermore, the state representations often use large vectors with multiple possibilities for each values. As such, predefining a specific robot reaction for each state possibility or each possible human behaviour is not feasible. Consequently, robots should have an action policy able to generalise to unseen and unexpected situations and react appropriately to different environments.

Personalisation and adaptation: As robots are interacting with humans, they will encounter different type of environments, contexts of interactions and persons with different roles. For example a robot used as an assistant for elderly people will have to interact in the home of the owner, but also follow them in the street or in a supermarket. In these different interaction contexts, distinct behaviours will be expected from the robot. Similarly, different human beings might have distinct roles and the robot needs to adapt its action policy to the type of person it is interacting with. For instance, in education, an autonomous robot would have to interact both with the students and the teacher, and its behaviour needs to take into account the role of the people it is interacting with. Additionally, the robot needs to personalise its behaviour to the person it interacts with: in entertainment or search and rescue, none of the users are known beforehand but providing a personalised behaviour adapted to the context may significantly impact the outcomes of the interaction. In summary, robots need to be able to adapt their actions policy to the environment and context they interact in and personalise their behaviour to the different users and their status.

Learning: When deployed in the wild, robots will be expected to interact over extensive periods of time with the same user, e.g. companion robots for the elderly, military robots for a squad or robots used in RAT (Leite et al., 2013). With these long-term social interactions, a key aspect in the engagement and efficiency is the co-adaptation between the user and the robot. Learning would allow the robot to tailor its behaviour to the current user and track the changes of preferences and desires occurring over long-term interactions. Additionally, providing a robot with learning enables it to be used by non-experts in robotics, granting them a way to design their own human-robot interactions, and making use of their expertise and knowledge to have their robot interacting as they desire. This is crucial as many application of social robotics, such as RAT, happen in environment where non-technical people possess the domain expertise required to ensure that the robot is efficient. And, as stated by Amershi et al. (2014), learning reduces the requirements of expensive and time consuming rounds-trips between domain-experts and engineers and additionally decreases the risks of confusion between these different communities. Finally, this adaptivity in time allow the robot to learn from its errors and improve its action policy over time. Furthermore, this learning can enrich the robot's action policy to allow it to tackle new tasks beyond its initial role, increasing its application and use.

In summary, for this review, adaptivity is a continuous scale ranging from no adaptivity at all: the robot has a linear script that it follows in all the interactions, to high adaptivity: the robot can generalise to unforeseen situations, dynamically changes its action policy according to the context of interaction and its partners, learn new actions and tasks and improve its action policy over time.

Autonomy

Today, many experiments in HRI are conducted using a robot teleoperated by a human (Riek, 2012; Baxter et al., 2016), and whilst having a human controlling the robot presents many advantages (e.g. the human provides the knowledge and the adaptivity required to interact efficiently and has sensing and reasoning capabilities not yet available for robots), multiple reasons push us away from this type of interaction (Thill et al., 2012). First, relying solely on teleoperation is not suited for deploying robots in the real world. Human control does not scale to interact for long periods of time or in many places. Robots are also expected to interact in fields already lacking workforce (e.g. healcare), so if robots need to be continuously controlled, the advantage of automation is highly reduced. Second, for research, using humans to control robots reduces the transferability of knowledge gain to the real world. The human-robot interaction tends to become "a human-human interaction mediated by a 'mechanical puppet' " (Baxter et al., 2016), which decrease the relevance of the robot as an agent and as such reduces the applicability of results to future interactions with fully autonomous robots. And finally, human control of a robot's actions introduces multiple biases in the robot's behaviour (Howley et al., 2014), and these biases from human operators will affect the robots' behaviour, decreasing the replicability of behaviours. For these reasons, among many, we argue that a robot used in social HRI should be as autonomous as possible. A limited human supervision could support the robot and be used to improve its behaviour, but the robot should not rely on humans for its action selection during the main parts of the interaction.

To analyse the different robot controller's autonomy, we take inspiration from Beer et al. (2014). Beer et al. define three components of autonomy: sensory perception, analysis and action selection. As such, autonomy is organised following a spectrum of different levels 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 and/or action: for example the robot can request information from a supervisor or the supervisor can override the action or goal being executed (Sheridan & Verplank, 1978).

Interdependence of Factors

These three axes used for the review: appropriateness of action, adaptivity and autonomy are not independent. Especially, as a robot able to learn might be also able to improve its appropriateness of action and its autonomy as it refines its action policy. This impact of adaptivity on the two other axes is fundamental to increase the robot's fields of application, performance and usability. However, while a learning robot could eventually reach an optimal, perfect and autonomous action policy, the behaviour expressed by the robot in early stages of the learning, while the action policy is not appropriate yet, is critical. Even during this learning phase, the robot's behaviour needs to be safe and useful for humans interacting with it. As such, adaptivity is a key element for a robot controller to improve and reach a correct and autonomous policy, but a mechanism must ensure that at every step of the interaction the robot's behaviour is appropriate regardless of the learning progress.

2.2 Current Robot Controllers in HRI

The previous section presented three axes to evaluate a robot controller: the appropriateness of actions, the range of adaptivity and the level of autonomy. Based on these three axes, this section presents and analyses high level categories of robot control currently used in HRI to define a robot behaviour. For each category, we will present the corresponding approach, indicate representative works done and qualitatively rate it on the three axes.

2.2.1 Scripted Behaviour

One of the simplest ways to have a robot interacting with a human is probably to have an explicit and fixed behaviour. In this case, the robot is fully autonomous and follows a script for action selection. Success in using this approach is dependent on having a well defined and predictable environment to have the interaction running smoothly. However, if the interaction modalities (possible range of behaviours and goals) are limited enough, a constant action policy can be sufficient to handle all (sensible) human actions.

This approach is followed in a large number of research in HRI: as many studies are 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 behaviour with defined and controlled specificities. This also allows researchers to compare conditions with controlled differences and analyse the impact of small variations of behaviour. Whilst this has advantages when exploring people's reactions to robots, this method can hardly be used to deploy robots to interact with humans on a daily basis. Real world applications take place in undefined and open environments where potential human behaviours are almost infinite. Additionally, a fixed robot behaviour might also create boredom in users once the novelty effect vanishes (Salter et al., 2004).

By essence, this type of controller has a no adaptivity as the robot is following a preprogrammed script, but is fully autonomous as no external human is required to control the robot; and when the application domain is highly specified, the behaviour can be mostly appropriate.

2.2.2 Adaptive Preprogrammed Behaviour

To go beyond a simple script, robots can also be programmed to react in predefined ways to expected human actions. By adaptive preprogrammed behaviour, we denote a behaviour programmed before the interaction, but explicitly (or implicitly) including ways to adjust the action policy in reaction to anticipated human behaviours. This preprogrammed adaptation takes two forms: either having a fixed number of variables impacted by the actions of the partner and guiding the action policy (for instance using homeostasis), or explicitly planning for specific behaviours to be produced if predefined conditions are met (for example using a finite state machine).

Homeostasis, the tendency to keep multiple elements at equilibrium, is constantly used by living systems to survive and is also a good example of the first case of preprogrammed adaptation used in social HRI. For instance, Breazeal (1998) used 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 to represent a ‘healthy’ situation. If these variables reach values outside the desired homeostatic range, the robot is either over or under-stimulated, this will affect the robot’s emotional status and it will display an emotion accordingly. This behaviour have been shown to be enough to maintain human interacting with the robot for relatively long periods of time spanning more than ten minutes. Homeostasis approaches have also been extended to robotic pets (Arkin et al., 2003) or RAT (Cao et al., 2017).

On the other hand, a case of planned adaptation is clearly presented in Leyzberg et al. (2014). Participants have to play a cognitive game, and a robot delivers predefined advises on strategies depending on the performance and the current lack of knowledge of the participant. With these anticipated human behaviours, the robot can provide personalised support as long as the participants behave within expectations.

Similarly to other behaviour-based methods used in robotic control (such as the subsumption architecture; Brooks 1986), due to the indirect 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 similarly, the fixed set of rules limits the adaptability to unexpected event. Furthermore, with this indirect description of actions, there is no guarantee against the robot acting in inconsistent way in specific cases which limits the appropriateness of actions. Similarly, planned adaptation provides adaptivity to the environment but only in highly limited cases expected by the designers. This limits the adaptability of such an approach as the robot does not learn; and, as the robot may face situations not expected by the designers, the maximum appropriateness of actions is also limited.

In summary, both predefined adaptation and homeostasis-based methods score highly in autonomy and can have a moderate to high level of appropriateness, but the adaptivity is low as they can only adapt to the environment within predefined, anticipated and limited boundaries and the robot does not learn.

2.2.3 Wizard of Oz

Wizard-of-Oz (WoZ) is a specific case of teleoperation 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 (Kelley, 1983) and is today common practice in HRI (Riek, 2012). Similar to scripted behaviours, Wizard-of-Oz (WoZ) is mostly used in human-centred studies to explore how humans react to robot and not as a realistic way to control robots in the wild. A second use of WoZ is to safely gather data to develop a robot controller from human demonstrations (cf. Section 2.2.4).

Even in WoZ, part of the robot's behaviour is autonomous, and combining this robot autonomy and human control can be done in multiple ways. Baxter et al. (2016) define two levels of WoZ related to the levels of autonomy presented by Beer et al. (2014) and that correspond to the level of human involvement in the action selection process. Cognitive WoZ aims to provide a robot with human-like cognition or deliberative capabilities; while in perceptual WoZ, the human only replaces a sensory system and feeds information to the robot controller. Typically, perceptual WoZ replaces challenging features of the controller required for a study, but not relevant to the research question. One of such typical challenge is Natural Language Processing (NLP). Despite all the progress made in speech recognition, NLP is still a challenge in HRI, especially when interacting with children (Kennedy et al., 2017). And as some studies require a limited speech recognition element to test an hypothesis, using a human for that part of the interaction allows to run the study without having to solve complex technical challenges (for instance, see Cakmak et al. 2010).

This level of human control impacts the autonomy of a system: a robot relying on human only to do perception has a higher autonomy than a robot fully controlled by an operator. Controllers can also combine human control and predefined autonomous behaviour in mixed systems. For example, Shiomi et al. (2008) propose a semi-autonomous informative robot being mainly autonomous, but with 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.

With WoZ, the adaptivity and the appropriateness of actions 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 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, thus limiting the adaptivity (especially as the robot policy is fixed). And as the human only has limited control over the robot's behaviour, no mechanism prevents the robot to make undesired decision. Overall, this would lead to a higher autonomy, but a lower appropriateness of actions and adaptivity compared to classical WoZ.

2.2.4 Learning from Demonstration

As stated by numerous researchers, explicitly defining a complex behaviour and manually implementing it on a robot can take a prohibitive amount of time or even could not be possible for complex behaviours (Argall et al., 2009; Billard et al., 2008; Dautenhahn, 2004). This statement applies equally well to manipulation tasks and social interaction. In both cases, humans have some knowledge or expertise that should be transferred to the robot. However in social robotics, experts in the application domain often do not have the technical knowledge to implement efficient behaviours on a robot, which results in numerous design iterations 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. The learning process starts with a human demonstrations a correct behaviour (Argall et al., 2009), and then offline batch learning is applied to obtain an action policy for the robot. Later, if required, reinforcement learning can complement the demonstrations to reach a successful action policy (Billard et al., 2008). In LfD, the human-robot interaction is key, however in most of the cases this interaction is only in the learning interaction, the application interaction does not involve humans, but often manipulation or locomotion tasks such as grasping and moving an object, using a racket to hit a ball or throwing tasks (Billard et al., 2008).

However, two approaches have applied LfD to teach robots a social policy to interact with humans. The first one aims at learning directly from human-human interactions and replicate these human behaviour on a robot. For example, Liu et al. (2014) present a data driven approach taking demonstrations from human-human interactions to gather relevant features defining human social behaviours. Liu et al. recorded motion and speech from about 180 interactions in a simulated shopping scenario and then clustered these behaviours into high-level actions and implemented them on the robot. During the interaction, the robot uses a variable-length Markov model predictor to estimate the probability of a human executing each actions and finally winner-take-all is applied to select the most probable action. According to the authors, the final robot's behaviour was life like but not perfect. However, authors affirm that if this approach was scaled using a larger dataset gathered from more human-human interactions in the real world, the performance should improve and become closer to natural human behaviours.

In the second approach, the data is collected through a WoZ setup and aims to learn to replicate the wizard's action policy to reach an autonomous social behaviour. Knox et al. (2014) coined this approach "Learning from the Wizard (LfW)". The method starts with a purely WoZ control study to gather data, and then, an action policy is derived by applying machine learning on the collected data. However, this original paper did not present a description of which algorithm could be used or how, and did not evaluate of the approach, instead it only offered a reflection on the application of this idea. An implementation and evaluation is briefly discussed by the authors in Knox et al. (2016), but the lack of implementation details and results reduces the usability of the paper.

LfW is widely used in HCI (especially dialogue management; Rieser & Lemon 2008) and has also been implemented by other groups of researchers in robotics. For example, Sequeira et al. (2016) extended and tested this idea to a create a fully autonomous robot tutor. Their method is composed of a series of steps:

1. Collect observations of a human teacher performing the task.
2. Define the different actions used by the teacher and the features used for the action selection.

3. Implement these actions and features on a robotic system.
4. Set up a restricted-perception WoZ experiment where an operator uses only the identified features to select actions for the robot.
5. Combine machine learning applied on the data and hand-coded rules to create an autonomous robot controller.
6. Deploy the autonomous robot.

(7. If required, add offline refinement steps to fine tune the robot's behaviour.)

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

Clark-Turner & Begum (2018) aimed 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 neurotypical participants to train the network with the raw inputs and the actions selected to obtain a controller able to deliver the therapeutic intervention. However, in their study, the autonomous robot required additional limited human input to inform the algorithm of the state of the therapy and only reached a behavioural intervention with an accuracy inferior to 70%. This means that even with additional human input the robot would provide inconsistent feedback at some points in the interaction. However, this study only used a limited amount of data, and using more training examples should lead to better results.

LfD methods are based on real interactions either between humans, or between humans and robots controlled by humans; and, with enough demonstrations the robot should be able to replicate a human policy, thus select appropriate actions. However, efficiency is limited by the type of inputs recorded, the capabilities of the learning algorithm and the quality of the demonstrations which limit the appropriateness of the action policy (as seen in Clark-Turner & Begum 2018). Furthermore, after the learning phase, the robot's behaviour is mostly static, without any additional learning provided. As such, while possessing a good generalisation capability, LfD do not possess the adaptivity in time once the robot is deployed. Sequeira et al. (2016) propose to add offline learning steps, but online learning would allow for smoother transitions and improvements of the behaviours. 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 low in the first phase and then total during the main part of the interaction.

2.2.5 Planning

An alternative way to interact in complex environments is to use planning (Asada et al., 1986). The robot has access to a set of actions with preconditions and postconditions and a defined goal it needs to reach. To achieve this goal state, it follows the three planning steps: sense, plan and act. The first step, *sense*, consist on acquiring 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, should lead to the goal. Finally, the last step is to *act*, to execute the plan. The plan can be reevaluated at each time step or only if an encountered state differs from the expected one, in that case the robot updates its plan according to the new state of the environment and continues trying.

The efficiency of planning relies on having a precise and accurate set of pre and postconditions for each action. And as humans are complex and unpredictable, it is a serious challenge, if not impossible, to model them precisely. As such, planning have seen limited use for open social interactions with humans. However, due to the nature of planning, reaching a specific goal in a known environment, it has been applied successfully to HRC. Additionally, by limiting the interaction to a joint task, HRC also simplifies the modelling of the human: the interaction being more constrained and task-oriented, the human should limit its behaviour to a number of expected task-related actions. The Human Aware Task Planner (Alili et al., 2009) is an example of planning used to assign task between a robot and human in a HRC scenario. One specificity of this planner is the ability to take into account predefined social rules (such as reducing human idle time) when creating a plan to allocate tasks to the human-robot team. Including these social norms in the plan construction is expected to improve the user experience and maximise human compliance to the plan, which should lead to higher performance in the task.

A precise and correct model would ensure that the autonomously select the appropriate action whilst an incorrect one would lead to non appropriate behaviours. 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 the tasks the robot has to complete the different contexts and states it is expected to face and as such presents limited generalisation capabilities to unanticipated situations or non task-related human actions.

Planning has also been extended with learning, which then allows for more adaptive and personalised action policies. This type of learning planner has been mostly used in manipulation and navigation to obtain better trajectories (Jain et al., 2013; Beetz et al., 2004) but not exclusively. In HRI, Munzer et al. (2017) presented a planner adapting its decisions to human preferences in a HRC scenario. With this approach, the robot estimates the risk of each actions and depending of the risk value will execute them, propose them (and waits for approval before executing an action), or wait for a human decision. Between repetitions of the task, the robot will update its planner to fit more precisely to the human preferences and improve its action policy for the next iteration of the task. Munzer et al. adopted principles from LfD to planning to improve quickly and efficiently the performance of the robot. However, while planning is well suited for strictly defined and mostly deterministic tasks, many social human-robot interactions cannot be totally specified symbolically with clear actions and outcomes and as such the application of planning to social HRI has been limited. Nevertheless, it does provide robots with an autonomous, partially adaptive and appropriate action policy.

2.2.6 Summary

Table 2.1 presents a summary of the different approaches currently used in social HRI with their advantages and drawbacks for application in HRI and their evaluation on each of the three axes. The two most promising types of control are LfD and planning, however, both of them have their drawbacks: LfD is applied offline to create a monolithic controller with limited adaptivity after being deployed, and planning's reliance on a model of the world limits its application to open-ended social HRI in the wild.

reread[ES] Similarly to humans, an ideal robot controller would learn how to interact by interacting, by receiving feedback from the environment but also allowing humans to teach it an efficient action policy. The robot should use characteristics unique to artificial

Table 2.1: Comparison of robot controllers in HRI

Controller	Advantage	Drawbacks	Application in HRI	Appropriateness	Adaptivity	Autonomy
Fixed preprogrammed behaviour	Quick and easy to create Clear specified and repeatable behaviour	Limited to highly constrained interactions	Human-centred studies in highly constrained env.	Low	Null	Maximal
Adaptive preprogrammed behaviour	Relatively simple to program More robust and efficient than scripted behaviour	Only provide adaptability in limited anticipated context	Human-centred studies in constrained environments	Medium	Low	Maximal
Wizard of Oz	Use human expertise to select the best action	Require constant high workload from human Not scalable	Human-centred studies Highly critical HRI	Maximal	Maximal	Null/Low
Learning from Demonstration	Transfer knowledge from human to robot in the real application environment	Lack of learning once deployed	HRI case by case	High	Medium	High
Planning	Complex behaviours and adaptable to variations in the environment	Human too complex to be clearly modelled Limited application to social interaction	Complex defined environments HRC	Medium	High	Maximal

agents: endless patience, absence of tiredness and potential full control by another agent to learn faster from humans. However, while learning is important, an ideal robot behaviour should also ensure its actions are constantly appropriate. One way could be to use a human to control the robot in early stages of the learning, when the action policy is not correct yet. This would ensure an initial appropriate action policy in early stages. And in later stages, this robot could combine autonomous learning, and being taught by other agents. This supervised learning from interaction would be the approach with the most potential as this type of learning could validate the three requirements: appropriateness of actions, adaptivity and autonomy. By essence, this continuous online learning aims at providing open-ended adaptivity to the robot. Including a human with control over the robot's actions can also ensure that actions are appropriate. And finally, as the robot learns, accumulates datapoints and demonstrations from the teacher it improves its action policy, reducing the reliance and workload on the human to reach high levels of autonomy while conserving the constant appropriateness of actions and the adaptivity.

This type of interaction is similar to IML: learning from the interaction and using a human teacher to speed up the learning. As shown in the next section, researchers have explored how to teach agents interactively non-social action policy (Scheutz et al., 2017; Cakmak et al., 2010); but as of early 2018, no controller exists in HRI applying IML to the challenge of learning social interaction with humans in the real world.

2.3 Interactive Machine Learning

In Section 2.1.2, we stated that to be adaptive enough, a robot should be able to learn. Consequently, robot controllers used in HRI should make use of Machine Learning (ML). ML corresponds to a field of Artificial Intelligence (AI) aiming at providing artificial agents with learning capabilities to improve their behaviour and reach high level performances in a large range of tasks. ML has two main trends referring to the synchronisation between the learning and the use of algorithm: offline and online learning.

In robotics, offline learning is a technique allowing the robot to change its action policy over time by updating it outside of the interaction (such as Learning from the Wizard in Section 2.2.4). Between or before the interactions, a learning algorithm is used on a dataset previously accumulated to create a new action policy.

On the other hand, online learning (such as Reinforcement Learning (RL); Sutton & Barto 1998) learns during the interaction. Rather than single monolithic definitions or updates of the behaviour, this constant refinement of the agent's action policy benefits from a high number of updates, allowing the robot to learn even during the first interaction with the environment and never stop improving its behaviour.

Interactive Machine Learning (IML), as coined by Fails & Olsen Jr (2003), is a type of online learning with two specificities:

- Use of an end-user expert in the learning process.
- Learn by multitude of consecutive small updates of behaviour.

These two characteristics differ greatly from classical offline learning, such as deep learning (LeCun et al., 2015) which uses costly monolithic learning steps without human influence to define a static behaviour. On the other hand, IML is an iterative process where the behaviour is improved at each small step, and where the end-user can provide feedback on the learner's performance during all these iterations. IML aims to learn faster, by continuously using the human expert to correct the errors made by the algorithm as they appear, provide additional useful information to the learner and improve the knowledge gained at each learning step.

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.

2.3.1 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. As explained in Fails & Olsen Jr (2003), classifiers would gain from using human knowledge to iterate quickly to reach a good solution and agents learning from the interaction would gain from using additional feedback from humans (Thomaz & Breazeal, 2008; Knox & Stone, 2009). IML aims to combine the advantages from both Supervised Learning (SL) and online learning and applies this new type of learner to classification or interaction tasks.

Furthermore, by allowing a human user to see the output of an algorithms and provide additional inputs, the learning has the potential to be faster and tailored to this human's desires. By using human expert knowledge and intuition, the system can achieve a good performance faster (Thomaz & Breazeal, 2008). Additionally, a key advantage of IML is also being able to empower end-users of robotic or learning systems. 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.

These human inputs take three forms: labels for specific datapoints (cf. active learning; Section 2.3.2), feedback over actions (similarly to reward in RL; cf. Sections 2.3.3 and 2.3.4) or demonstrations to reproduce (cf. LfD - 2.3.5).

2.3.2 Active Learning

Active learning is a form of teaching used in education aiming to increase students' achievement by giving them a more active role in the learning process (Johnson et al., 1991). This approach has been transferred to machine learning, especially to classifiers, by allowing the learner to ask questions and 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 numbers or costly to obtain. As such, a trade-off arises between the performance of the classifier and the quantity of queries made by the algorithm. Often, the oracle would be a human annotator with the ability to provide a correct label to any datapoint, but their use should be minimised for reasons of cost, time or annoyance.

Using an oracle to provide the label of specific points with high uncertainty should highlight missing features in the current classifier resulting in improvements both in term of accuracy and learning speed. However, this specific relation between the learner and the human teacher raises new questions such as:

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

Researchers have explored optimal strategies for dealing with this relation between the learner and the oracle. This research has been especially active in HRI with robots directly asking questions to human participants and exploring how the robot's queries could inform the teacher about the knowledge of the learner (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. On the other hand, they also wanted to be in control of the interaction, deciding when the robot could ask questions even if it lead to a higher workload for them. However, 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 proactive 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 (Settles, 2009). However, when interacting in the world, the learner is not in control of which sample can be submitted to an oracle to obtain a label. Datapoints are provided by the interaction and are influenced by the learner's actions and the environment reactions. For agents learning during the interaction, the active learning approach working for classifiers is not applicable, so other methods have been applied such as RL, learning from human feedback or LfD.

2.3.3 Reinforcement Learning

The main framework to learn from interaction is Reinforcement Learning (RL). RL aims to solve the problem of finding the best action policy (i.e. a policy maximising a notion of cumulated reward) by observing the environment reaction to the agent's action.

Concept

Young infants and adults learn by interacting with their environment, by producing actions and receiving a direct sensory motor feedback from their environment. By learning the impact of their actions, humans can learn how to achieve their goals. Similarly, the field of 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 action policy (Sutton & Barto, 1998).

Most of the RL agents interact in a discretised version of the time, considering life as a sequence of states and actions. The simplest version of RL is interacting in a finite Markov Decision Process (MDP), a discrete environment defined by the tuple $< (S, A, P_a(s,s'), R_a(s,s'), \gamma) >$ (Howard, 1960), 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_* (assigning an action from A to each state in S) maximising the discounted sum of future rewards. The agent is not aware of all the parameters governing the environment, but only observes the transitions between states and the rewards provided by the environment and has to update its policy to maximise this cumulated reward. Different algorithms exist to reach this policy, but a challenge faced by most of them is to balance the exploration and the exploitation (Sutton & Barto, 1998).

Exploration consists on trying out new actions to learn more about the environment and potentially gain knowledge to improve the policy; whilst *exploitation* is the execution of the current best policy to maximise the current gain of rewards. RL algorithms have to balance these two objectives to reach an optimal action policy. One way to deal with this trade-off is to start with high probability of exploration, to rapidly collect knowledge on the environment and then decrease this probability to settle on an efficient behaviour.

The more complex the environment is, the longer the agent has to explore before converging to a good action policy. Thus, using RL, it is not uncommon to reach numbers such as millions of iterations before reaching an appropriate action policy (Sutton & Barto, 1998). And when the agent is exploring, its behaviour might seem erratic as the agent tries actions often randomly to observe how the environment is reacting.

Application to HRI

This approach presents many features relevant to HRI: it possesses the autonomy required for meaningful interactions with humans and provides the adaptivity desired for having a large impact. However, 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 iterations before reaching an efficient action policy. Generally, RL copes with these issues by having the agent interacting in a simulated world. This allows the agent to explore safely in an environment where its actions have limited impact on the real world (only time and energy) and where the speed of the interaction can be highly increased to gather the required datapoints in a reasonable amount of time. For example to solve heads-up limit poker (Bowling et al., 2015), an agent played two months while considering more than 24 trillions hands every second[8]. 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 of time and random behaviours would have direct impacts.

To gather informations about the environment, the agent needs to explore, trying out random actions to learn how the environment responds to them and if the agent should repeat them later. However, when interacting with humans, executing random actions can have dramatic effect on the users, presenting risk of physical harm as robots are often stiff and strong or cause distress. This reliance on random exploration presents a clear violation of the first principle to interact with humans presented earlier ('Only execute appropriate actions').

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

Despite similar real-world constraints, RL has been used in robotics (Kober et al., 2013), but mostly applied to manipulation, locomotion or navigation tasks. For the reasons stated above, as of early 2018, RL has never been used to fully autonomously learn rich social behaviours for HRI.

[8]4000 CPU considering 6 billions hands per second: `http://poker.srv.ualberta.ca/about`

Opportunities

Despite the limitations presented in the previous section, changes can be made to RL to increase its applicability to HRI. For example, combining RL and IML can ensure that the behaviour is appropriate to interactions with humans even in the learning phase.

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 achieves a minimal level of acceptability. The authors present two ways to achieve this safety: either by using a mechanism to prevent the execution of non-safe actions or by providing 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 are also applicable to other machine learning techniques to make them safer (for instance LfD; Billard et al. 2008).

The first method (preventing the agent to execute undesired actions) can be implemented by explicitly having 'forbidden' actions in predefined states or by having a list of safe actions (Alshiekh et al., 2017). Using this method, the anticipated cases of errors can be prevented. However it seems unlikely that every case could be specified in advance, so such a method might not be sufficient for applying RL to HRI.

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. For example, Abbeel & Ng (2004) proposed to use human 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 a reward function were learned from demonstrations, RL was applied around the provided policy to explore and optimise the policy. That way, only small variations of the policy happened and only around the demonstrated one. These small variations ensured that policies leading to incorrect behaviours were 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 interacting in human environments (such as for personalised advertisement; Theocharous et al. 2015) these approaches have not been used to learn social behaviours or to have robot interacting with humans.

2.3.4 Human as a Source of Feedback on Actions

When an agent is learning in a RL fashion and improves its behaviour by receiving rewards from the environment, an intuitive way to steer the agent's 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 (Bouton, 2007). In ML, using rewards from a human to bias and improve the learning presents multiple advantages which will be presented throughout this section. One notable advantage is the simplicity of the interface and its generalisability to any type of problem. As the teacher only needs a way to provide a scalar or a binary evaluation of an action to steer the learning, only a simple one-way interface is required. However, this simplicity of interaction is associated with a limited efficiency and a complexity of interpretation: the issues of how to interpret human rewards and how to combine them with environmental ones if existent are an active research field today (Knox & Stone, 2010).

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 robotics as a clear reward function applicable to HRI or robotics in general can be complex to define. 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 relations and executed actions in the environment. Users of LambdaMOO could either reinforce positively or negatively Cobot's action by providing rewards. While the interaction between the agent and the users was limited, Isbell et al. presented the first agent to learn social interactions with humans in a complex and social online environment.

While the goal of Cobot was to create an entity interacting with humans, Knox & Stone (2009) explored how humans could actively teach an agent an action policy in the absence of environmental rewards using TAMER (Training an Agent Manually via Evaluative Reinforcement). With this approach, 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.

However, unlike environmental rewards, human rewards are subjective evaluations of an agent's behaviour. As such by knowing humans tendencies and intentions when providing rewards, an agent is able to obtain more information from these human rewards than by treating them the same way as environmental ones. Many researchers explored how to obtain more information from human reward. For instance, Advice (Griffith et al., 2013) models how trustworthy the teacher is and as such how much importance the learner should give to their rewards. For example, rewards from inconsistent teachers will be reduced as the agent knows the source is not reliable. Alternatively, Loftin et al. (2016) explored how to infer the strategy used by the teacher in the reward delivery. Similar behaviours from different teachers might have different meaning: not rewarding an action might reflect an implicit acknowledgement of the correctness of an action or the active refusal to provide a positive reward (indicating the incorrectness of an action). By modelling this intention, the real meaning of rewards can be inferred and used to further improve the learning. Another relevant feature explored by this community is the dependence in time of the human reward policy. While reward functions are generally constant in time with RL, with humans they might vary according to the current performance of the agent. 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, when the average agent's performance is better. MacGlashan et al. (2017) proposed COACH (Convergent Actor-Critic by Humans) to model how humans adapt their rewarding scheme in function of the agent's performance and deal with this non-stationary reward function. Similarly to other factors biasing human rewarding strategies, this dependence of the reward function to the current agent's policy should be taken into account to maximise the knowledge gained from human rewards.

Even when environmental rewards are present, human rewards still have opportunities to improve the learning: they can enrich a sparse reward function, guide the robot faster to an optimal policy or correct incomplete or incorrect environmental rewards. Knox & Stone (2010) explore nine different ways to combine these two types of rewards and each methods' impacts on the learning. From this analysis, they explain how to select an approach according to the specificities of the environment and the reward function.

Teachers can also use rewards to communicate other information to the learner. For example, Thomaz & Breazeal (2008) aimed to explore how humans would use feedback to teach a robot how to solve a task in a virtual environment. They used Interactive Reinforcement Learning (IRL) as a way to directly combine environmental rewards and human ones. However, during early studies, Thomaz and Breazeal discovered that participants tried to use rewards to convey intentions, 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 channel to provide information about the action the robot should execute. This guidance has been actively decided to be ambiguous; participants could not explicitly control the robot, but just bias the exploration, and adding this second channel improved the performance of participants. This study presented a first attempt to combine environmental rewards, human ones and human guidance to teach an agent an action policy and demonstrated the importance of giving additional ways for the teacher to impact the robot's behaviour.

While not being applied to robotics but mostly to learning non-social interactions, these implementations of IML provide important research describing how robots could be taught to interact with humans. These human rewards are especially interesting when the environmental reward function is sparsely defined or non-existent, providing a way to teach robots in any environments. However, humans do not simply evaluate an agent's actions, they adopt teaching strategies influencing their way of rewarding and want to provide guidance, hints or commands to help the agent to learn better and faster. In summary, human teachers desire to go beyond simply evaluating what the agent is doing, they want to provide advices or commands about how it should behave.

2.3.5 Interactive Learning from Demonstration

As presented in Argall et al. (2009) and Billard et al. (2008), LfD is majoritarily used in an offline learning fashion to learn a defined task without extending the action policy once the task is considered mastered. However, tasks such as social interaction are complex even for humans and probably will never be fully mastered for robots. As such (and as argued before), robots would highly profit from learning throughout all their life, not only once before being deployed, but learning new tasks and improving their skills as often as required (Dautenhahn, 2004).

With Interactive Learning from Demonstration (ILfD), an agent receives demonstrations not only once, but as often as required after being deployed. ILfD is related to Mixed Initiative Control (Adams et al., 2004) where an agent and a human share control on the agent's actions. The robot acts mostly autonomously, but in some cases (at the initiative of the human or the robot), the human takes over the robot control and make a demonstration that will be used by the robot to refine its action policy for the future.

One approach giving teachers a total initiative on the interaction is Dogged Learning (DL) (Grollman & Jenkins, 2007). With DL, an agent is autonomously interacting and a teacher has the power to override the agent behaviour at any time by selecting desired actions or outputs. Facing a potential difference between the algorithm's outputs and the teacher's ones, the robot executes the commands with highest confidence (often the human's one) and the learning component aims at reproducing the executed output. If the teacher does not provide any commands, the ones from the algorithm are used. DL does not provide the robot with the opportunity to request a demonstration, but instead, the robot can communicate its uncertainty to the teacher, indirectly asking for demonstrations.

Alternatively, Chernova & Veloso (2009) propose a method with a more complex interaction between the learner and the teacher. The Confidence Based Algorithm (CBA) is composed of two components: the Confident Execution (CE) and the Corrective Demonstration (CD). The CE enables the agent to act autonomously when its confidence in its action policy is high and on the other hand to actively request a demonstration when the confidence is low. The CD allows the teacher to provide a corrective demonstration when the agent executes an incorrect action, which provide more information to the agent than a classic negative reward. These two components aim to leverage the complementary capabilities of the learner and the teacher. CBA has demonstrated efficient teaching in diverse scenario such as simple driving simulators or other classification tasks. But the effectiveness of this approach is bounded by the capacity of the learner to estimate this confidence to be able to request demonstrations and prevent incorrect behaviour to be executed. Another limit of such an approach is the impossibility for the teacher to correct undesired actions before they negatively impact world.

Both methods rely on the teacher being able to anticipate the robot's behaviour to provide demonstrations before an incorrect action is executed or before it impacts the agent and its environment. As such, the appropriateness of the robot controller is not at maximum as the teacher cannot ensure that no incorrect action will be executed during the learning, only that the robot would learn faster from its errors.

2.3.6 Importance of Control

Results from active learning, research using human to provide feedback and LfD have shown that human teachers take an active stance during the training of an agent and want multiple ways to influence the learner's behaviour (Amershi et al., 2014). Humans are not oracles, 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 that 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 improving the teacher's experience in the teaching process, providing the humans with more control improves the learning (Thomaz & Breazeal, 2008; Chernova & Veloso, 2009). By allowing the teacher to demonstrate an action policy online, bias the action selection and preempt or correct undesired actions, the learner interacts mostly in useful states of the environment and with a correct action policy. This lead to faster learning and would improving the robot's performance highly in early stages of the learning. Another fundamental feature added by this human control over the robot's actions is safety. If a domain expert can prevent a robot interacting with humans to make errors and can ensure that all its actions are efficient, it would increase greatly the quality of the interaction for the humans involved. This will further improve the applicability and use of the robot and would satisfy the two first principles: appropriateness of actions and adaptivity of the robot.

However providing the teacher with this control presents challenges for designing the interaction between the robot and its teacher. Unlike a simple scalar reward, being able to control the robot requires the teacher to be able to give commands or advice to the robot and to receive additional information about the learner beyond its observable behaviour. This enriched two-way communication might be complex to design, especially when the action space is bigger than a few actions or the learning mechanism not transparent. In addition to the communication interface, the time scales of the interaction are also key: to give the opportunity to the teacher to preempt undesired actions, the learner needs to communicate its intentions in a timely manner to the teacher which complexifies the relation between the learner and the teacher.

2.4 Summary

This chapter presented first an overview of the fields of HRI where robots interact socially with humans. From these cases of application, we defined three principles 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 and learn.
3. Have a high level of autonomy.

Secondly, a review of current controllers 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 ML with potential to satisfy these principles. IML shows promises for enabling a robot to learn online how to interact with humans, especially when the teacher is given control over the robot's behaviour and can demonstrate a correct action policy. However while humans have been used to teach robots behaviours or concepts, teaching them to interact with human in an interactive, online fashion has not been demonstrated in the field so far and no current method would satisfy all these requirements.

Chapter 3

Supervised Progressive Autonomous Robot Competencies

Key points:

- Proposition of a novel interaction framework to teach robots an action policy while interacting.
- A human teacher is in control of the robot's actions whilst the robot learns from this supervision.
- The teacher can select actions to be executed by the robot.
- The robot proposes actions about to be executed to the teacher.
- The teacher provides feedback on propositions (i.e. intentions) rather than executed actions; and can preempt actions.
- The robot's behaviour (under supervision) can be assumed to be optimal.
- The 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. (2015b) and Senft et al. (2017a). The final publications are available from Springer and Elsevier:

- `http://dx.doi.org/10.1007/978-3-319-25554-5_60`.
- `https://doi.org/10.1016/j.patrec.2017.03.015`.

3.1 Motivation

As presented in Chapter 2, robots would profit from being able to learn from human teachers how to interact with other humans. We propose to use Interactive Machine Learning (IML) to achieve this transfer of social and task knowledge from the human domain-expert to the robot. This would result in a faster and safer learning than slow iterative update of behaviours by engineering the action policy, learning from large quantities of data or learning by trials and errors as with Reinforcement Learning (RL).

However, as stated in this Section 2.3, IML has never been applied to teach robots to interact with humans. No current system provides the teacher with enough control over the robot's actions to validate the first principle presented in Section 2.1.2 ('Only execute appropriate actions'). Techniques relying solely on feedback from the teacher cannot prevent the robot to execute an incorrect action, but only reduce the chances of future errors by rewarding negatively incorrect actions after their execution (Senft et al., 2017a). And, with current techniques based on Learning from Demonstration (LfD) the teacher relinquishes its control over the robot when not demonstrating, only reacting in hindsight after the learner makes mistakes and its erroneous actions have impacted the real world (Chernova & Veloso, 2009).

The problem tackled in this research is to provide a robot with an appropriate action policy, adaptive to different contexts and partners' behaviours and requiring a low workload on the teacher. As such, in Senft et al. (2015b), we introduced the Supervised Progressively Autonomous Robot Competencies (SPARC) framework of interaction. SPARC aims to allow end-users to safely and easily teach a robot an action policy applicable to social Human-Robot Interaction (HRI).

3.2 Frame

Similarly to other applications of IML, SPARC requires inputs from a teacher to learn an action policy to interact with the world. As framed in the introduction, in this framework, the robot interacts with two entities: the target and the teacher (as shown in Figure 3.1). This results into two intertwined interactions: the application interaction (task the robot learns to achieve) and the teaching interaction (relation with the teacher). In the generic case, the overall interaction is a triadic interaction (Teacher - Robot - Human target or Teacher - Robot - Environment); for instance, a teacher could teach a tutor robot to support child learning in an education task (as implemented in Chapter 6). But in specific cases, the application target is not a human but only part of the environment, such as a robot at home learning from its user how to support them better.

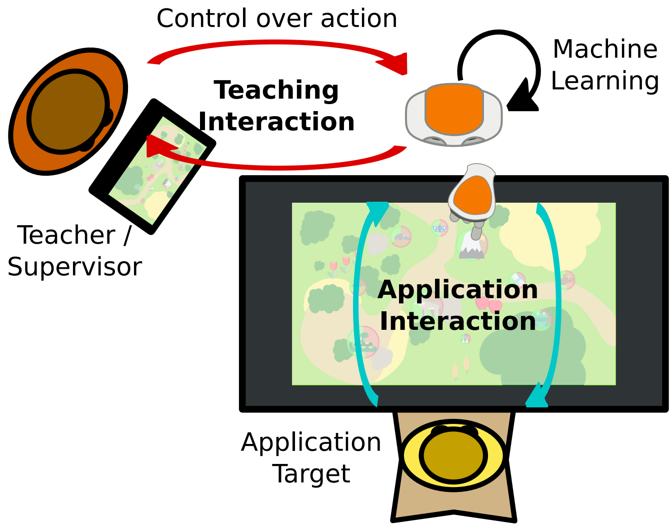


Figure 3.1: Frame of the interaction: a robot interacts with a target, suggests actions and receive commands and feedback from a teacher. Using machine learning, the robot improves its suggestions over time, to reach an appropriate action policy.

3.3 Principles

SPARC defines an interaction between a learner (virtual agent or robot) and a teacher following these principles:

- The learner has access to a representation of the state of the world and a set of actions.
- The teacher can select actions for the robot to execute.
- The learner can propose actions to the teacher before executing them (informing them about its intentions).
- The teacher can enforce or cancel actions proposed by the learner and actions non evaluated are implicitly validated and executed after a short delay.
- The learner uses Machine Learning (ML) to improve its action policy using the teacher's commands and feedback on propositions.

This type of interaction between the learner and the teacher is similar to the level 6 on the Sheridan scale of autonomy: "computer selects action, informs human in plenty of time to stop it" (Sheridan & Verplank, 1978); with the addition that the human has also the opportunity to select actions for the agent to execute. In this thesis, we will refer to this interaction as ‘Supervised Autonomy’: the robot interacts autonomously under the supervision of a human who can ensure that the robot’s behaviour is constantly appropriate.

This way of keeping a human in the learning loop, with the opportunity to override the agent actions, and the robot learning from these demonstrations is similar to Dogged Learning (Grollman & Jenkins, 2007). However, with SPARC, this ability to provide demonstrations is combined with the Supervised Autonomy. This results in a mixed control system where the teacher can select actions and have the robot execute them while the robot only proposes actions to the teacher. In response to this suggestion, the teacher has the choice between preempting the action or let it be executed. A learning algorithm on the robot’s side uses the feedback and commands from the teacher to improve the correctness of the suggested actions until reaching an efficient action policy. This learning mechanism coupled with auto-execution of actions aims to decrease the requirement of interventions from the teacher over time, thus reducing the workload on the teacher as the robot learns. Additionally, keeping the human in the loop also gives them the opportunity to provide additional information to the algorithm speeding up the learning and to create a mental model of the learner. The diagram in Figure 3.2 and the flowchart in Figure 3.3 represent in a graphical way this interaction between the learner and the teacher.

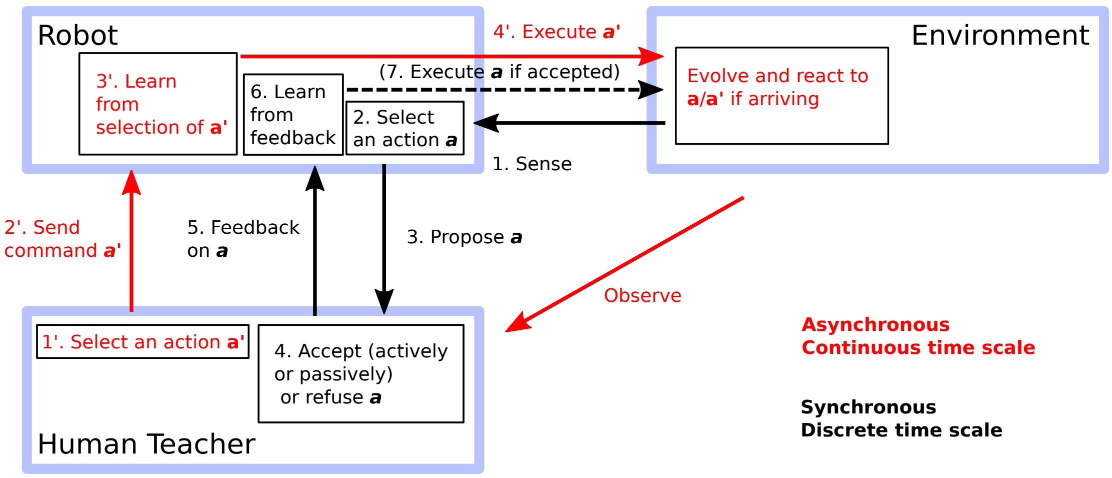


Figure 3.2: Diagram of interaction between the robot, the human teacher and the environment with SPARC: synchronously, the robot can propose actions to the teacher that evaluated (approved or cancelled). And asynchronously, the teacher can select actions to be executed.

Additionally, The main difference between SPARC and CBA (Chernova & Veloso, 2009) is that with SPARC, the robot communicates its intentions and the teacher has total control over the robot's action. With CBA and other classical IML, the teacher have to wait for an action to impact the world before correcting it or assigning it a negative feedback (Thomaz & Breazeal, 2008; Knox & Stone, 2009). However, using SPARC, the teacher is informed beforehand of the robot future actions and can preempt them before they impact the world. The agent learns to avoid actions with expected negative impacts without having to face the results of their execution. This implies that the behaviour executed by the robot can be assumed to be optimal (or at least as good as the teacher's), making the interaction safer and potentially simplifying the learning mechanism.

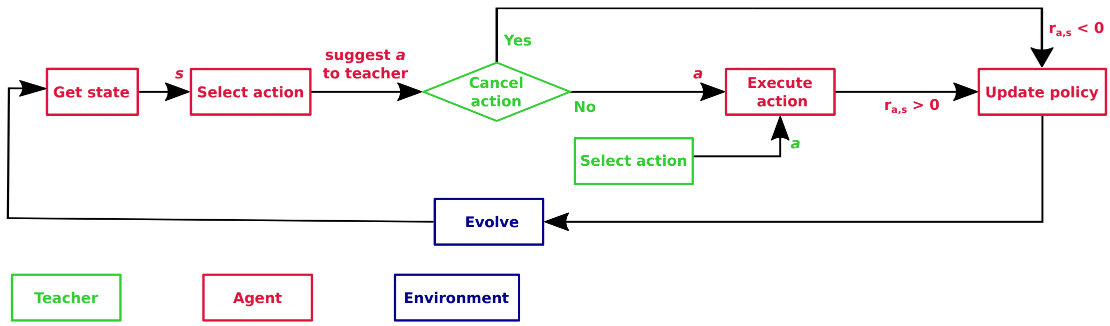


Figure 3.3: Flowchart of the action selection loop between the agent and the teacher.

This approach is comparable to predictive texting as seen on phone nowadays. The user can select the words proposed by the algorithms (or implicitly accept them by pressing the space bar) or write their own. The algorithm learns the user's preferences and habits and aims to suggest words more and more appropriate for the user. However, predictive texting aims mostly to correct users' errors and interact in a complex static environment. On the other hand, SPARC aims to replicate a teacher's action policy in continuous time, in a dynamic and interactive environment evolving both dependently and independently of the agent's actions.

Alternatively, SPARC can be seen as a way to provide proactivity to an agent. By observing interactions on longer time scales, such as an assistant robot at home, SPARC allows the robot to propose to help its user when the current state is similar to previous observation. This would compare to a passive case where each action executed by the robot has to be requested by the user or an autonomous robot interacting in the house without any transparency. By proposing actions to the teacher, the robot takes the initiative to support humans, possibly reminding its user something they forgot, while not imposing its presence. In human environments, executing actions (such as starting to play music, changing the lighting condition or cleaning the kitchen) without informing the surrounding humans could be perceived as rude or annoying if the timing is not right. On the other hand, this proactivity also needs to be kept in control as a robot proposing to help too often might be equally annoying.

3.4 Goal

SPARC aims to provide an interaction framework to teach robots an action policy possessing the following characteristics:

- Be usable by people without expertise in computer science.
- Allow fast policy learning from in-situ guidance.
- Require few or no human input for the robot to act in the world.
- Constantly ensure an appropriate robot behaviour.

Figure 3.4 presents an idealistic comparison of the expected workload, performance and autonomy of four methods: autonomous learning (e.g. RL; Sutton & Barto 1998), feedback based teaching (e.g. TAMER; Knox & Stone 2009), Wizard-of-Oz (WoZ) (Riek, 2012) and SPARC. Unlike other learning methods, by following the principles presented in Section 3.3, SPARC is expected to maintain a constant high performance even during early stages of learning. In later stages of the learning, the agent keeps improving its action policy, making its suggestions more accurate and allowing the auto-execution of actions to reduce the workload on the teacher.

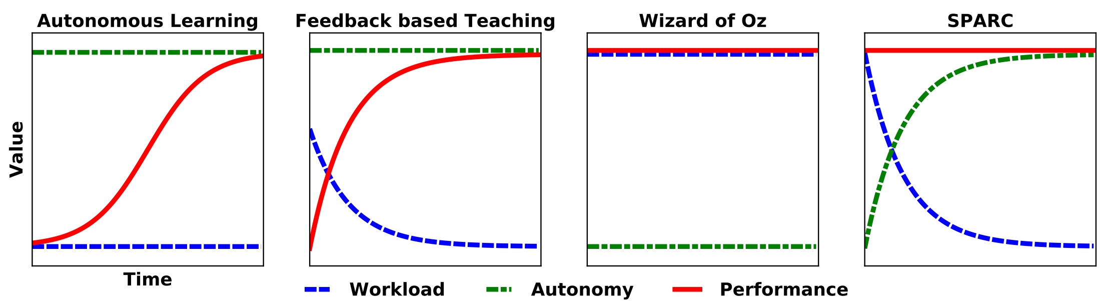


Figure 3.4: Idealistic evolution of workload, performance, and autonomy over time for autonomous learning, feedback-based teaching, WoZ and SPARC (arbitrary units).

tenses[ES] Once the behaviour is deemed appropriate enough by the teacher, the agent is ready to be deployed to interact autonomously in the real world, if this outcome is desired. Alternatively, in contexts where a human expert still cannot be removed from the control loop, such as Robot Assisted Therapy (RAT), a supervisor could stay in control of the robot's actions by using the Supervised Autonomy. Similarly to the teaching phase, with this Supervised Autonomy, the robot would inform the supervisor of its actions and the human would only have to intervene in case of incorrect propositions. While still requiring attention from the supervisor, this reduction of human actions to control the robots would reduce the workload on the supervisor. Furthermore, as the supervisor would accumulate a better knowledge of the agent's behaviour, they could be especially careful in cases where the agent would be prone to making errors. And as the control of the agent would require less effort from the supervisor, they could focus more closely on the application interaction rather than the teaching one.

3.5 Implications

3.5.1 Relation with Time

Similarly to other IML approaches, the requirement of a human in the action selection loop limits the time scale of interaction and this effect is an important consideration when applying SPARC to an interaction. With this type of IML, three time scales are coexisting: the robot's, the teacher's and the interaction's. The robot has an internal clock running probably multiple times per second, sensing the world and deciding if an action should be proposed. The human teacher has to be able to cancel proposed actions before their executions, so they need to be provided with a 'correction window' spanning more than one second to react to propositions. And finally, for some applications, actions are appropriate only during a short time, and if this amount of time (the validity window) is shorter than the correction window, action executed automatically would not be appropriate anymore, reducing the validity of SPARC.

Depending of the application, actions might have to be executed in a time critical environment (such as driving) or less critical ones (such as an assistant robot at home). While being easily applicable to slow interactions, SPARC could still be applied to these time critical ones. For instance, if applied to autonomous driving, SPARC could display to the driver the planned trajectory with augmented reality and let the driver correct this trajectory if not appropriate. However, more critical elements, such as emergency breaking, would probably have to be done with a much shorter correction window so the car can break in time.

Additionally, the presence of this correction window reduces the rate of actions selection to 0.5 Hz or below, which might reduce the applicability of SPARC compared to other IML methods. However, this limitation of application is the price to pay to ensure the appropriateness of actions, and this effect can be mitigated by using higher level actions or by focusing on applications less critical in term of time.

Finally, the rate of selection of high level actions will be much lower than the rate of the robot's action selection loop. At a human level, actions will be executed at a rate of few actions per minutes, while the robot's processing runs at multiple hertz. This indicates that unlike classical RL methods, in most of the steps, the robot should not select any action. When interacting with humans, the learning algorithm and the state representation needs to take into account these differences of time scales to ensure that the robot's behaviour is coherent and useful.

3.5.2 Difference with LfD

SPARC is an Interactive Learning from Demonstration (ILfD) method (cf Section 2.3.5) and as it uses human demonstrations of policies to learn, it presents many similarities with non-interactive LfD techniques (cf. Section 2.2.4). 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; Munzer et al., 2017) and never in an online fashion. Munzer et al. proposed an interactive planner that would learn offline the current user's preferences and desires, but two key differences exist between this approach and SPARC. The first one is the application domain. The learning planner is well suited to clearly defined environments (e.g. Human-Robot Collaboration (HRC)) where a similar task with clear steps has to be done multiple times. As such the learning can happen offline between the repetitions. SPARC is defined to be applicable to non-linear underspecified environments, with less constrained tasks, where the learning should happen online. Secondly, using a threshold, Munzer et al. define actions with low risk which are executed (and can be cancelled during the execution) and actions with higher risk which have to be validated first by the human. SPARC does not make this distinction, but proposes both types of actions to the teacher and will start executing them if no feedback is received. This removes the need for the human to explicitly approve correct proposed actions while ensuring that the human can cancel incorrect actions before their execution. This principle aims at reducing the number of required interventions from the human to teach and interact with the robot compared to methods such as the one presented by Munzer et al.

3.5.3 Interaction with Learning Algorithms

The principles of SPARC define it at the crossroads between Supervised Learning (SL) and RL. SPARC can be used in two ways: either to reproduce a teacher's policy in a supervised fashion or to help an agent discovering a useful action policy by using the teacher to bias the exploration, limiting the errors and only interacting in desired parts of the environment.

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 SL or RL. This research presented in this thesis explored combinations with three types of algorithms: supervised learning using a feed-forward neural network (Chapter 4), reinforcement learning (Chapter 5), and supervised learning using an instance based algorithm (Chapter 6). However SPARC could be combined with a wide range of other algorithms or techniques such as planning.

Similarly to Inverse Reinforcement Learning (Abbeel & Ng, 2004) or other techniques combining RL and LfD (Billard et al., 2008), if used with a reward function, SPARC could go beyond the demonstrated action policy and achieve a performance higher than the demonstration. However this aspect has not been evaluated in this work, but is discussed in Section 7.4.2.

3.6 Summary

This chapter introduced the Supervised Progressively Autonomous Robot Competencies (SPARC), a novel interaction framework to teach agents an action policy. This approach is suited to teach a robot to interact with humans as it validates the principles defined in Section 2.1.2 (appropriateness of action, adaptivity and autonomy). SPARC starts in a similar fashion than WoZ: the teacher selects actions at any time to be executed by the robot. Then, using a learning algorithm, the agent starts to propose actions back to the teacher who can let them be executed after a short time or cancel them if not appropriate. This mechanism combining selections, suggestions and evaluations of actions ensures the appropriateness of the policy as a human expert could have preempted any inappropriate action before their execution. This additionally provides the adaptivity as the teacher can extend the robot behaviour beyond the current action policy. Finally, the learning algorithm associated with the auto-executions of actions intends to decrease the human workload once the robot starts to learn; and, when an acceptable action policy is reached, the robot is ready to be deployed to interact autonomously if this outcome is desired.

Chapter 4

Study 1:
Comparison Between SPARC and WoZ

Key points:

- Design of an experiment to explore the influence of SPARC on the teacher's workload and task performance compared to an approach based on WoZ.
- Application target replaced by a robot to ensure repeatability of the target behaviour.
- Design of a robot model exhibiting probabilistic behaviour (simulating a child) with a non-trivial optimal interaction policy.
- Results from a within subject study involving 10 participants 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. (2015b). The final publication is available from Springer via:

- `http://dx.doi.org/10.1007/978-3-319-25554-5_60`.

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

The Supervised Progressively Autonomous Robot Competencies (SPARC) has been designed to enable end-users without expertise in computer science to teach a robot an action policy while interacting in a sensitive environment, such as Human-Robot Interaction (HRI). By using machine learning and Supervised Autonomy, SPARC intends to allow a field expert to progressively transfer their knowledge to an autonomous agent without having to enforce each action manually. Additionally, as the agent is interacting in the target environment, displaying an appropriate action policy, the time spent to teach it is not lost but used to deliver the desired interaction even during the learning phase. For example, in the context of Robot Assisted Therapy (RAT), a therapist would teach the robot during therapy sessions. And, as the therapist is in total control of the robot's action, the behaviour expressed by the robot always fits the desired goals for the therapy. This ensures that even the sessions used to teach the robot have a therapeutic value for the patient involved in the therapy.

SPARC, as a principle, allows to start a robotic application in a Wizard-of-Oz (WoZ) fashion and then move away from it as the robot gains autonomy. The aim of SPARC is twofold: maintaining a high level of performance in the target application while reducing the workload of the teacher over time. As the robot learns, the action policy is refined until reaching a point where the robot is autonomous or only necessitates minimal supervision to interact successfully.

As explained in Chapter 3, SPARC involves two interactions: the teaching interaction and the application one. As such, when the goal of the teaching is interacting with humans, the robot interacts simultaneously with at least two humans (the target(s) and the teacher). These two dependent interactions add complexity to the evaluation of the approach, especially as both humans are impacting each other.

The first step to evaluate SPARC was to focus on the teaching interaction, the relation between the robot and its teacher. To evaluate this aspect of the interaction, we decided use the context of RAT for children with Autism Spetrum Disorder (ASD). However, as the presence of two humans decrease the repeatability of the test bench, we replaced the child involved in the therapy by a robot running a model of a child. The setup ends up with two robots interacting together: the *child-robot* completing a therapeutical task and the *wizarded-robot*, controlled by a participant, supporting the child-robot in its task completion (cf. Figure 4.1). Actions from the wizarded-robot impact the child-robot's behaviour and to achieve a high performance in the task, the child-robot needs to receive an efficient supporting policy from the wizarded-robot. As such, the child-robot's performance is used as a proxy to evaluate the performance of the participant in the supervision. This environment with a single human-robot interaction allows us to observe and evaluate the impact of SPARC on the teaching interaction.

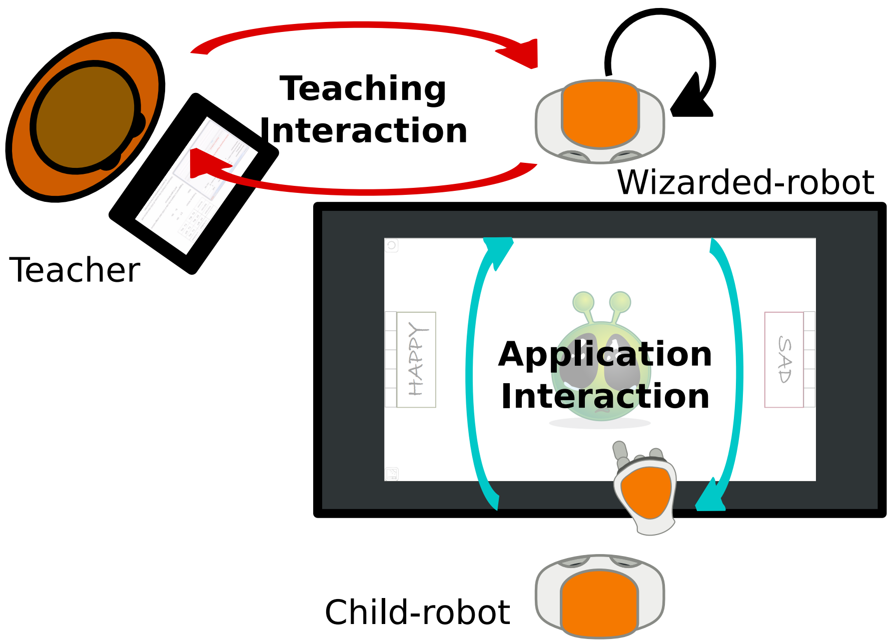


Figure 4.1: Setup of the interaction. The application target, a child has been replaced by a robot for repeatability.

4.2 Scope of the Study

mention the RQ?[ES] The study presented in this chapter intends to evaluate if the learning component of SPARC could allow participants to teach an efficient action policy for a robot interacting with humans. For repeatability concerns, the human-robot interaction target of the learning has been modelled by two robots interacting together. The control condition is a variation of WoZ, where participant still control a robot but without the learning component. By combining learning and Supervised Autonomy, SPARC aims to allow the teacher to maintain a high performance during the interaction while reducing the workload on the teacher over time.

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

H1 The child-robot's performance is a good proxy for the teacher's performance.

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

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

H4 Using SPARC allows the teacher to achieve similar performance than WoZ but with a lower workload.

H1 represents a validation of the model, ensuring that the child-robot performance represents the efficiency of the action policy applied by the teacher. H2 tests that human teachers are not static entities, they adapt their teaching target and their interaction strategy. H3 tests one of the motivations behind SPARC: does reducing the number of physical actions from a human to control a robot while requiring the teacher to monitor the robot suggestions lead to a lower workload. Finally, H4 is the main hypothesis, does SPARC enables a robot to learn a useful action policy: reducing the teacher's workload while maintaining a high performance.

4.3 Methodology

4.3.1 Participants

The study involved 10 participants (7M/3F, age *M*=29.3, 21 to 44, *SD*=4.8 years). While SPARC is expected to be usable by anyone, regardless of their knowledge of computer sciences, this first study involved members of a robotic research group assuming the role of the robot supervisor. This decision is supported by the fact that in RAT scenarios, the wizard is typically a technically competent person with significant training controlling this robot for this therapy. As such, as the participants come from a population expected to assume this type role, the results of the study maintain their applicability to HRI.

4.3.2 Task

This study is based on a real scenario for RAT for children with ASD based on the Applied Behaviour Analysis therapy framework (Cooper et al., 2007). The aim of the therapy is to help a child to develop/practice their social skills by completing tasks with a human or robotic partner. The child has to complete an emotion recognition task by playing a categorisation game with a robot on a mediating touchscreen device (Baxter et al., 2012). The robot can provide feedback and prompts to encourage the child and help them to classify emotions. In the task, images of faces or drawings are shown to the child on the touchscreen, and the child has to categorise them by moving them to one side of the screen or the other depending on whether the picture shown denotes happiness or sadness. In real therapies, the robot would be generally remote-controlled by an operator using WoZ (Riek, 2012).

This study explores if SPARC can be used to teach the robot a correct action policy to support the child in this therapy scenario. As timing in human-robot interactions is complex, for simplification reasons, the interaction has been made discrete to have clear steps when the robot has to execute an action. During these action steps, the selection of an action is decided by following the principles defining the Supervised Autonomy:

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 after a short delay.
3. The robot executes the selected action.
4. Both the robot and the teacher observe the outcome of the action until the next action selection step.

This study compares two conditions: SPARC, where the robot learns from the human selections and the WoZ condition where the robot is simply controlled by the participant. As mentioned before, in both conditions, actions can only be executed in predefined time windows dictated by the dynamics of the interaction. Additionally, a ‘wait’ action is present in the SPARC condition and presents an active choice for the participants. In a real WoZ scenario, participants would have to enforce every single action made by the robot, however, a ‘wait’ action in that context does not make sense. As such, in the WoZ condition, the robot proposes random actions, thus increasing the probability of having the teacher correcting the suggestion leading up to a setup similar to a real WoZ.

As mentioned earlier, the focus of the study being on the teaching interaction (the relation between the teacher and the robot), the second interaction (the application) 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 supervised by the human teacher is the *wizarded-robot* (cf. Figure 4.2).

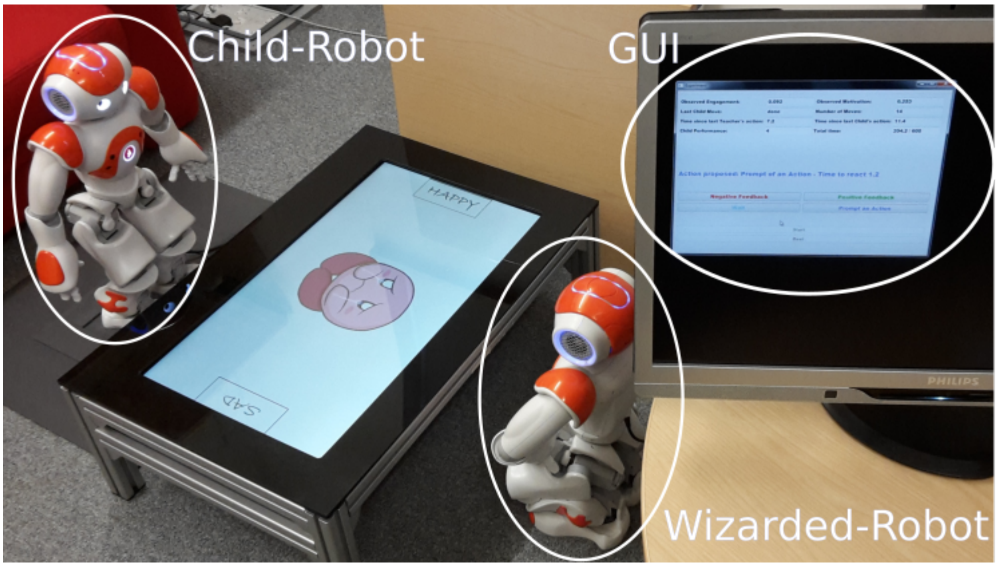


Figure 4.2: Setup used for the user study from the perspective of the human teacher. The child-robot (left) stands across the touchscreen (centre-left) from the wizarded-robot (centre-right). The teacher can oversee the actions of the wizarded-robot through the Graphical User Interface (GUI) and intervene if necessary (right).

4.3.3 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 these form the state of the child. The engagement represents the involvement of the child in the task, i.e. how often the child-robot will make categorisation moves. And the motivation relates to the seriousness of the child in solving task; in the model, the motivation gives the probability of success of each categorisation move.

These states are bound to the range [-1, 1] and influenced by the behaviour of the wizarded-robot. Values of 1 indicate that the child-robot's behaviour is positive, it is involved in the task. Values of -1 show that the child-robot is actively refusing to participate. And a 0 represents a neutral state where the child-robot is neither especially involved nor actively disengaged. To represent a tendency to return to a neutral state of mild engagement, both states asymptotically decay to zero with no 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.

As explained in Section 4.3.4, the wizarded-robot's action impact the child-robot state: congruent action will tend to increase engagement and motivation. However, if repeated, actions can lead to frustration for the child-robot. If a state is already high and an action from the wizarded-robot should increase it further, there is a chance that this level will sharply decrease. When this happens, the child-robot will indicate this frustration verbally by 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 combines feedback actions and waiting ones to maintain the state values high but prevent them from overshooting. This non-trivial optimal action policy approximates better a real human-robot interaction scenario requiring a more complex strategy to be expressed by the robot.

4.3.4 Wizarded-Robot Control

The wizarded-robot is controlled through a GUI (shown in Figure 4.3) and has access to the variables defining the state of the interaction used by the learning algorithm:

- Observed engagement.
- Observed motivation.
- Type of last categorisation made by the child-robot (good/bad/done).

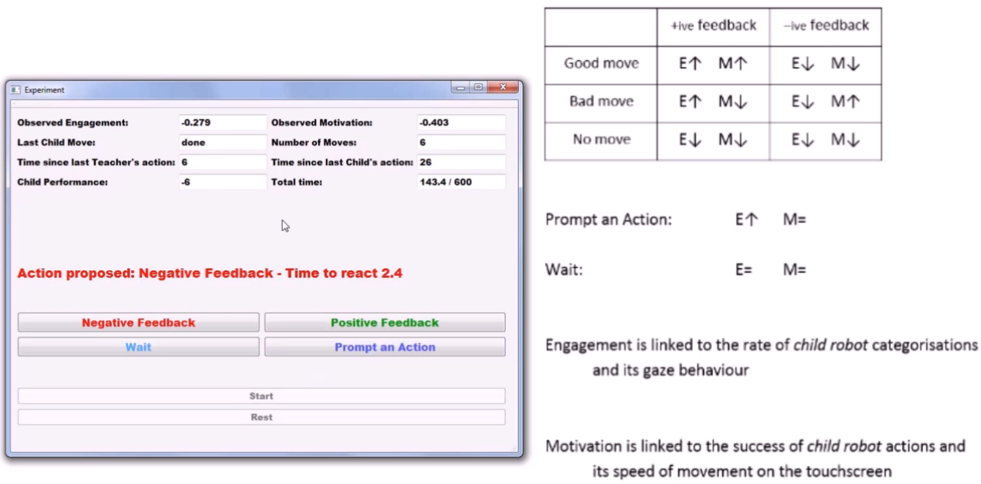


Figure 4.3: Screenshot of the interface used by the participants, the GUI on the left allows to control the robot and a summary of the actions' impact is displayed on the right.

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

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

The wizarded-robot has a set of four actions it can execute, each represented by a button 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 4.3.3, if the engagement or the motivation exceeds a threshold, their value can decrease abruptly to simulate the child-robot being frustrated. This implies that the optimal action policy consist on providing congruous feedback and prompts, but also requires wait actions to prevent the child-robot from becoming frustrated and maintain its state-values close to the threshold without exceeding it. A 'good' strategy keeping the engagement and motivation high leads to an increase in performance of the child-robot in the categorisation task.

As introduced previously, to simplify the algorithm part, the interaction has been discretised, the teacher cannot select 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 categorisation or if nothing happened for five seconds since the last wizarded-robot's action. 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. The teacher can only select an action in reaction to a proposition from the wizarded-robot; alternatively, 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 intervene by selecting a different action and forcing the wizarded-robot to execute it.

4.3.5 Learning Algorithm

In the SPARC condition, the robot learns to reproduce the action policy displayed by the teacher. For this study, the algorithm used for learning is 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 are set to -1. The network is fully retrained with all the previous state-action pairs and the new one between each selection step.

This learning algorithm, MLP, is not optimal for online learning for real time interactions as the learning should happen quickly between learning iterations. However, as the length of interaction (and so the number of datapoints) is limited, the network can be retrained between two consecutive uses. Finally, the desired learning behaviour being purely supervised learning, this type of algorithm has been deemed suitable for this study.

4.3.6 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 was reset between interactions. The study used a within subject design with balancing of order: each participant interacted with both conditions, and the order of interaction has been balanced between participants to control for any ordering effects. In the order S-W the participants first interact with the learning wizarded-robot in the SPARC condition, and then with the non-learning one in the WoZ condition; and in the order W-S, this interaction order is inverted (starting with WoZ then SPARC). 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. The participant, 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. 4.2). 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. After the information was read, a 30s video presenting the GUI in use was shown to participants to familiarise them with the interface, 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. Similarly, in the second part of the experiment, the participants interacted with the other condition and completed a second post-interaction questionnaire. Finally, a post-experiment questionnaire asked participants to explicitly compare the two conditions. All questionnaires and information sheet are available online[1].

4.3.7 Metrics

Two types of metrics 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). At each selection step, all of the human actions were recorded: acceptance of the wizarded-robot's suggestion, auto-execution and selection of an-

[1] `https://emmanuel-senft.github.io/experiment-woz.html`

other action (intervention) as well as the current state of the child-robot (motivation, engagement and performance).

The first metric is the performance achieved by participants in each interaction. As the policy applied by the participants cannot be evaluated directly, the performance of the child-robot in the task (number of correct categorisations minus number of incorrect categorisations) is used as a proxy for the participant performance. H1 evaluates if this approximation is valid by analysing the relation between the performance of the child-robot and the value of its inner states. If a correlation is found, it would demonstrate that a good supervision policy (managing to keep the engagement and the motivation of the child-robot high) leads to a high performance. As such, this child-robot performance represents how efficient the action policy executed by the wizarded-robot was 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 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 questionnaire where they had to compare the two conditions. All the rating questionnaires used seven item Likert scale. For clarity for participants, in the questionnaires the wizarded-robot is named ‘teacher-robot’ (as it was ‘teaching’ the child-robot).

Post-Interaction questions:

- The child-robot learned during the interaction.
- The performance of the child-robot improved in response to the teacher-robot’s 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 questions:

- 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 4.4 presents the aggregated results (collapsed between orders) for the performance and the final intervention ratio for both conditions. While the number of participants is not sufficient to perform statistical comparison, overall interaction results seemed 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])). As supported by the absence of overlap between the 95% CI, the SPARC condition tended to require less interventions (intervention ratio: SPARC: 0.38 (95% CI [0.29,0.47]) - WoZ: 0.59 (95% CI [0.52,0.67])).

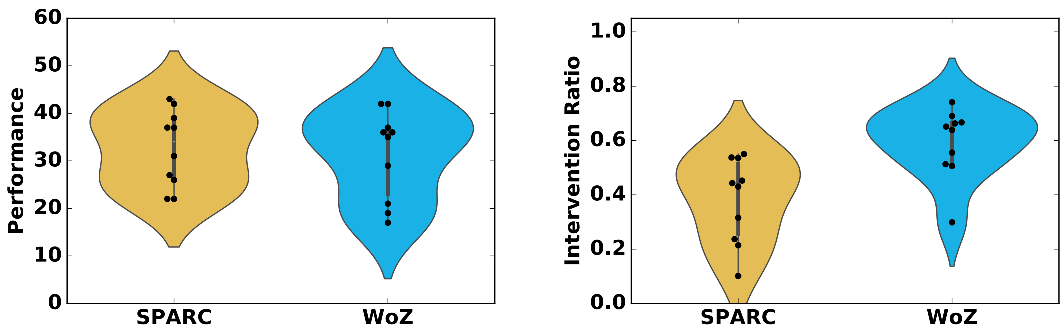


Figure 4.4: Aggregated comparison of performance and final intervention ratio for both conditions. Dots represent individual datapoint (N=10 per condition) and shaded area the probability distribution most likely to lead to these points.

Figure 4.5 presents the evolution of intervention ratio for each condition and orders. During the first interaction, participants discovered the interface and how to interact with it, which resulted in a high variation of the intervention ratio in the first 20 steps (with one step corresponding to one proposition of action from the wizarded-robot). However in the second phase of the interaction, when participants had developed their teaching policy, there was a tendency for SPARC to require a lower number of intervention than WoZ. This effect was higher in the second interaction, where as soon as 5 steps, the two conditions differentiated without overlap of the 95% CI of the mean. This would indicate that the two conditions differ in term of required interventions.

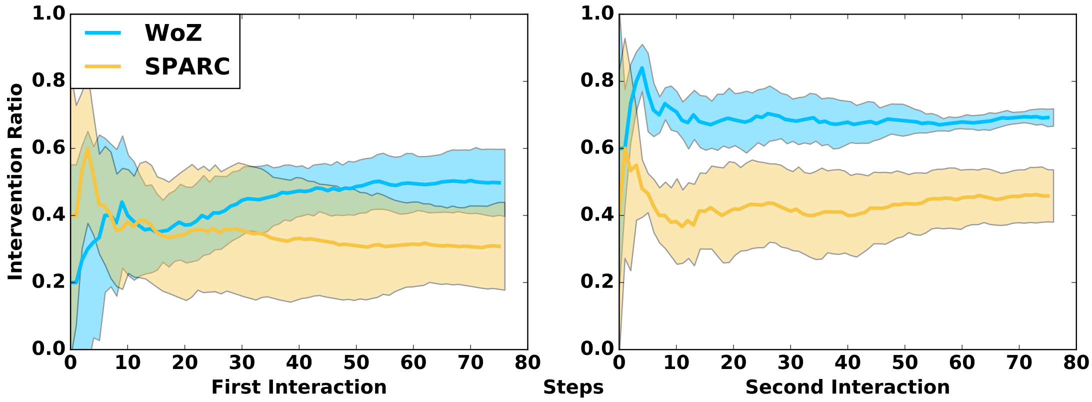


Figure 4.5: Evolution of intervention ratio over time for both conditions and both orders. Shaded area represents the 95% CI.

For both the performance and the intervention ratio, a strong ordering effect was observed. Figure 4.6 and Table 4.1 present the performance and final intervention ratio separated by condition and order. In both orders, the performance in the second interaction was higher than the one in the first interaction, as the participants were used to the system and developed an efficient interaction policy. On the other hand, the performance between condition for the same interaction number was similar (in both their first and second interactions, the condition of interaction did not impact the performance). However, for both orders, when comparing between condition for the same interaction number, the intervention ratio was lower when using SPARC compared to WoZ. This indicates that when the wizarded-robot learned using SPARC, a similar performance was attained as with WoZ, but the number of interventions required to achieve this performance was 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 the performance achieved by the child-robot represented the capacity of the teacher to keep both engagement and motivation high.

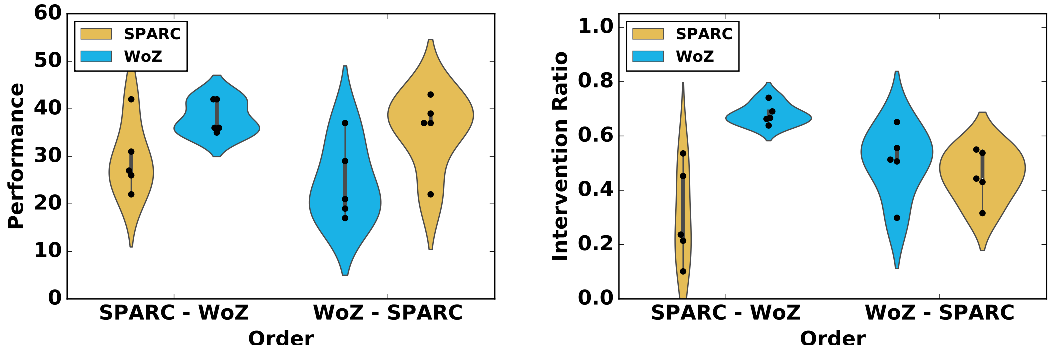


Figure 4.6: Performance achieved and final intervention ratio separated by order and condition. For each order, the left part presents the metric in the first interaction (with one condition) and the right part the performance in the second interaction (with the other condition).

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

	Order S-W		Order W-S	
	SPARC (int 1)	WoZ (int 2)	WoZ (int 1)	SPARC (int 2)
Performance M	29.6	38.2	24.6	35.6
95% CI	[23.6,35.6]	[35.5,40.9]	[18.1,31.1]	[29.3,41.9]
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]

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 4.7.

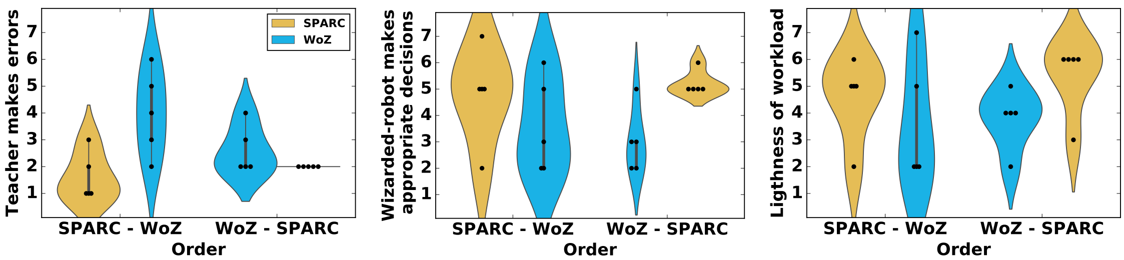


Figure 4.7: Questionnaires results on robot making errors, making appropriate decisions and on lightness of workload.

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

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

	Order S-W		Order W-S	
	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	[3.7,6.7]	[3.8,6.6]	[4.2,6.2]	4.7,6.1]
Child's performance M	4.6	5.0	5.0	4.4
95% CI	[3.4,5.8]	[3.3,6.8]	[4.0,6.0]	[3.7,5.1]
Wizarded-robot makes errors M	1.6	4.0	2.6	2.0
95% CI	[0.9,2.3]	[2.8,5.2]	[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]	[2.2,5.0]	[2.0,4.0]	[4.9,5.6]
Lightness of workload M	4.6	3.6	3.8	5.4
95% CI	[3.4,5.8]	[1.8,5.4]	[2.9,4.7]	[4.4,6.5]

all four conditions, this result is expected. There is a slight tendency to rate the child's performance as being higher in the WoZ condition but the error margin is too high to conclude anything.

Participants rated the wizarded-robot as more suited to operate unsupervised with SPARC than with WoZ (95% Confidence Interval of the Difference of the Mean (CIDM) for S-W ordering [-0.2, 2.6], CIDM for the W-S ordering [1.6, 2.8]).

Similarly, a trend was found showing that the wizarded-robot with SPARC is perceived as making fewer errors than with WoZ (CIDM for S-W ordering [1.3, 3.4], CIDM for the W-S ordering [0.1, 1.1]).

The also participants tended to rate the workload as lighter when interacting with SPARC, and this effect is much more prominent when the participants interacted with the WoZ first (CIDM for S-W ordering [-0.6, 2.6], CIDM for the W-S ordering [0.7, 2.5]).

Most of the difference of mean interval exclude 0 or include it marginally, which would indicate tendency of difference, but due to the low number of participants, no statistical tests are applicable and as such no significance can be demonstrated.

4.5 Discussion

Strong support for H1 (a good teacher leads to a better child performance) was found, a correlation between the average value of states (engagement and motivation) and the final performance for all of the 10 participants was observed (*r*=0.79). This validity check confirms that the performance of the child robot reflects the performance of the teacher in this task: supervising the wizarded-robot to execute 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 provided 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. For instance, the ratio of waiting action compared to other supportive actions varied between participants.

H3 (reducing the number of interventions reduces the perceived workload) is partially supported: the results show a trend for participants to rate the workload as lighter when interacting with the SPARC, and another trend between using SPARC 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 cause of the workload is probably the discovery of the system and how to interact with it rather than the requirement to manually select actions for the robot. Nevertheless, regardless of the order of the interactions, SPARC tended to receive higher ratings for lightness of workload and required fewer interventions to be controlled which indicates that using SPARC could decrease workload on robot's supervisor compared to WoZ.

Finally, H4 (using learning maintains similar performance, but decreases the workload) is supported: interacting with a learning robot in the SPARC condition resulted in a similar performance than interacting with a non-learning robot in the WoZ condition, whilst requiring fewer active interventions from the supervisor and a lower workload to control. Reducing the workload on the robot operator has real world utility, for example, in the context of RAT, it might free time for the supervisor to allow them to focus on other aspects of the intervention, such as analysing the child's behaviour rather than solely controlling the robot.

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 algorithms and ways to handle time have been used in the following studies presented in Chapters 5 and 6.

4.6 Summary

relation with RQ^{ES}

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 the learning component of SPARC 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 both conditions allowed the participants to reach a good performance, with SPARC, the presence of learning shifts part of the burden of selecting actions onto the wizarded-robot rather than on the human. Using SPARC, the robot partially learnt an interaction policy which decreased the requirement on the teacher to physically enforce each robot's actions. This indicates that a learning robot could reduce the workload on the operator freeing them to do more valuable tasks and that SPARC could be an efficient interaction framework to operate this learning. In addition to providing a robot with autonomy, this reduction of workload has real world implications, in the context of RAT, it could allow the therapist to focus more on the child than on the robot, with improved therapeutic outcomes as potential result.

Chapter 5

Study 2:

Importance of Control Over the Learner

Key points:

- Design of an experiment comparing SPARC and another IML method: IRL.
- The application domain is a replication of the world used in early studies evaluating IRL.
- IRL uses partial guidance to the robot and explicit rewarding of the robot's action to teach it a policy.
- SPARC uses full control over the robot's action, implicit rewards and evaluation of intentions rather than actions.
- Results from a mixed design study involving 40 naive participants show that SPARC achieves a better performance and an easier and faster teaching than IRL.

Parts of the work presented in this chapter have been published verbatim in Senft et al. (2017a). The final publication is available from Elsevier via

- `https://doi.org/10.1016/j.patrec.2017.03.015`.

Technical contribution in this chapter: the author reimplemented every part of the original system using Qt.

5.1 Motivation

Previous work in Interactive Machine Learning (IML) showed that humans want to teach robots not only with feedback on their actions but also by communicating the robots what they should do (Thomaz & Breazeal, 2008; Amershi et al., 2014). However, in most research where agents are taught policies using human guidance, the teacher is given little or no control over the agent's actions and has to observe the agent executing an action even when knowing that this action is incorrect (cf. Section 2.3.4). This chapter explores how these IML approaches could be improved by applying the principles of the Supervised Progressively Autonomous Robot Competencies (SPARC) defined in Chapter 3. This chapter also presents experimental results demonstrating how these principles influence the learning process, the agent performance and the user experience and how these results compare to other traditional IML approaches.

The study presented in Chapter 4 explored how SPARC could be used with Supervised Learning, to replicate a teacher's action policy. However, some of the most promising features of IML arise when combined with Reinforcement Learning (RL) as it might allow an agent to learn beyond the demonstrations (Abbeel & Ng, 2004). As such, this chapter proposes a way to apply the principles underlying SPARC to classical feedback based RL and evaluates how this human control over the robot's actions impacts the learning. This chapter presents results from a study involving 40 participants comparing the teaching efficiency and user experience of SPARC to Interactive Reinforcement Learning (IRL), another IML approach offering less control but having been validated in previous studies (Thomaz & Breazeal, 2008).

5.2 Scope of the Study

5.2.1 Interactive Reinforcement Learning

IRL implements the principles presented in Thomaz & Breazeal (2008)(hereafter the 'original study' or 'original paper'): a human supervises and teaches an agent to interact autonomously in an environment. This teaching is achieved by providing guidance and positive or negative feedback on the last action executed by a robot. In this study, the algorithm controlling the robot combines this human feedback with environmental ones to form a reward used to update a Q-table. This Q-table assign a Q-value (interest of taking an action) to every state-action pair and is used to select the next action. Three additions to the standard interaction mechanism have been proposed and implemented by Thomaz and Breazeal and are used in this study as well: guidance, communication by the robot and an undo mechanism (Thomaz & Breazeal, 2008).

The guidance channel emerged from the results of a pilot study where participants assigned rewards to objects to indicate that the robot should do something with them. With the guidance channel, teachers can direct the attention of the robot toward certain items in the environment, informing the robot that it should use them in its next action. This guidance behaviour offers partial control over the robot's actions restricting the executable options, but cannot be used to explicitly set the robot's behaviour.

Additionally, the robot communicates uncertainty by directing its gaze toward different parts of 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 the robot is unsure about its next action and that guidance should be provided.

Finally, the undo mechanism aims to provide a way for the teacher 'cancel' the robot's action, to bring it back to relevant part of the world after an error, in order to speed up the teaching. After receiving a negative reward, the robot tries to cancel the effect of the previous action on the environment (if possible), resulting in an undo behaviour. As shown in the original studies, these three additions improve the robot's performance on the task and the user experience.

In summary, Teachers have two ways to transmit information to the robot: a reward channel (providing a numerical evaluation of the last action) and a guidance channel (directing the robot's attention toward parts of the state to restrict the exploration).

5.2.2 SPARC

SPARC uses a single type of input from the human similar to the guidance in IRL and no reward channel. However with SPARC, the guidance channel directly controls the actions of the robot. On the other hand, the robot communicates all of its intentions (i.e the action it plans to execute next) to its teacher by looking at the corresponding part of the environment. Following the principles proposed in Section 3.3, 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 enforced or passively approved by the teacher.

5.2.3 Differences Between IRL and SPARC

Unlike IRL, SPARC offers the user full control over the actions executed by the robot. SPARC changes the learning paradigm from learning from the human's evaluation of actions' impacts to learning from the human's knowledge and the *expected* impact of actions. An expert in the task domain evaluates the appropriateness of actions before their execution and can guide the robot to act in a safe and useful manner. This implies that the robot does not rely on observing the negative effects of an action to learn to avoid it (as in IRL or more generally RL), but rather it learns what the best action is for each state. Even in a non-deterministic environment such as human-robot interactions, some actions can be expected to have a negative consequence. And the human teacher should be able to stop the robot from ever executing them, preventing the robot from causing harm to itself or its social or physical environment.

Another noticeable difference is the type of information the robot communicates with the user: in IRL, the robot communicates its uncertainty about an action and with SPARC its unambiguous intention to execute an action. Similarly, the communication from the user to the robot differs between the two approaches. 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 and has to manually provide feedback to evaluate the robot's decisions. A result is that the quantity of information provided by the user to the robot is similar for both IRL and SPARC.

5.2.4 Hypotheses

Three hypotheses have been tested in the study:

H1 *Effectiveness and efficiency with non-experts.* SPARC will lead to better learning than IRL when used by non-experts (higher performance, faster learning, lower number of inputs used, lower mental effort on the teacher and lower number of errors during the teaching phase).

H2 *Safety with experts.* SPARC can be used by expert users (knowledgeable in the interaction process) to teach an action policy safely, quickly and efficiently, achieving better results than 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

5.3.1 Participants

A total of 40 participants (age *M*=25.6, *SD*=10.09; 24F/16M) were recruited using a tool provided by the University of Plymouth to reach a mixed population of students and non-student members of the local community[1]. At the start of the experiment, all participants gave written informed consent, were told of the option to withdraw at any point and completed a demographic questionnaire. Participants were mostly not knowledgeable in machine learning and robotics (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: not at all familiar to 5: extremely familiar). The study lasted around one hour and followed a 2x2x3 mixed design where participants interacted with both conditions three times. To avoid ordering effects, the order of interaction was counterbalanced between two groups: group 1 interacting with IRL then SPARC and the interaction order is inverted for group 2 (see also Figure 5.2). Participants were distributed randomly between the two groups whilst balancing gender and age. All participants received remuneration at the standard U.K. living wage rate, pro rata.

In addition to naive non-expert users, an expert user (the author) interacted five times with each system following a strictly optimal strategy for both conditions. 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 in robot interaction, such as therapists in the context of assistive robotics.

5.3.2 Task

The task used in this study is the same as Thomaz & Breazeal (2008): "Sophie's kitchen", a simulated environment presented 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

[1] `https://uopsop.sona-systems.com/Default.aspx?ReturnUrl=%2f`

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) (see Figure 5.1a). The participant has to teach Sophie to bake a cake by guiding it through a sequence of steps while giving enough feedback so the robot learns a correct series of actions leading to the completion of the task. There are six crucial steps to achieve a successful result:

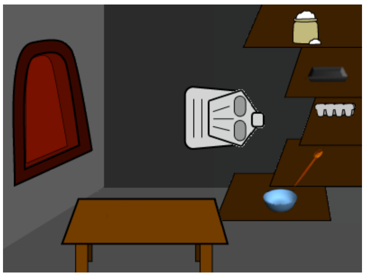
1. Put the bowl on the table (Figure 5.1b).
2. Add one ingredient to the bowl (flour or eggs).
3. Add the second ingredient (Figure 5.1c).
4. Mix the ingredients with the spoon to obtain batter (Figure 5.1d).
5. Pour the batter in the tray (Figure 5.1e).
6. Put the tray in the oven (Figure 5.1f).

The environment is a deterministic Markov Decision Process (MDP), defined by a state, a set of actions (move left, move right, pick up, drop and use), a deterministic transition function and an environmental reward function. The environment includes end states, corresponding to a success or a failure, which reset the simulation to the initial state and provide a reward (+1 for success and -1 for failure). All the other states corresponding to intermediate steps have a reward of -0.04 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. This environment includes a large number of possible states (more than 10,000), success and failure states and a sparse environmental reward function. These elements increase the value of having a teacher present to support the learning. As argued by Thomaz and Breazeal in the original paper, this environment provides a good setup to evaluate methods of teaching a robot.

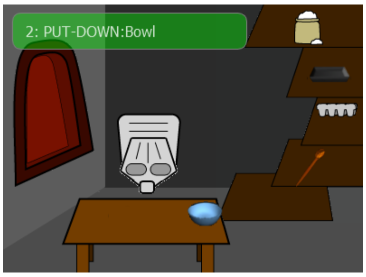
5.3.3 Implementation

Two conditions were constructed to compare the IRL and SPARC approaches to this task. The underlying learning mechanism is identical in both conditions. The only

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



(a) Initial state

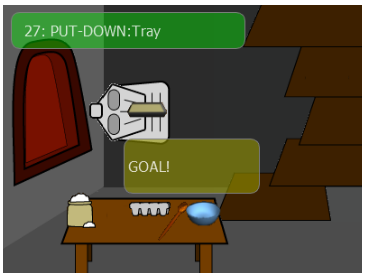


(b) Step 1

(c) Step 3

(d) Step 4

(e) Step 5



(f) Step 6

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

differences lie in the manner of interaction (inputs to and from the algorithm) and the amount of control over the robot's actions. With IRL teachers have to explicitly provide rewards and have a partial control over the action selection, while with SPARC rewards are implicit and the control over actions is total.

The learning algorithm (see Algorithm 1 and 2) is a variation on Q-learning, without reward propagation[3]. This guarantees that any learning by the robot is due to the human's teaching, and as such provides a lower bound for the robot's performance. Similarly to the original study, the algorithm uses a learning rate $\alpha = 0.3$ and a discount factor $\gamma = 0.75$.

As shown in Table 5.1, another difference between the conditions is that with SPARC, the algorithm learns immediately after executing an action (and only with positive rewards). On the other hand, IRL learns about an action just before executing the next one, based on a positive or negative evaluation received between the actions.

Interactive Reinforcement Learning

We have implemented IRL following the principles presented in Thomaz & Breazeal (2008). The user can use the left mouse-click to display a slider providing rewards.

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

Table 5.1: Simplified outline of algorithms used for both condition.

Algorithm 1: SPARC	**Algorithm 2:** IRL

while *learning* **do**
  $a_t = \underset{a}{argmax} Q[s_t, a]$
  look at object or location used in a_t
  while *waiting for command (2 seconds)* **do**
    if *received command* **then**
      a_t = received command
      $r_t = 0.5$
    else
      $r_t = 0.25$
  Act in the world:
    execute a_t, transition to s_{t+1}
  $r_t = r_t + r_{environment}$
  Learn:
    $Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha(r_t + \gamma(\underset{a}{max} Q(s_t, a)) - Q(s_t, a_t))$
	while *learning* **do**
	  $A_{t+1} = [a^1 ... a^n]$, n actions with high $Q[s_{t+1}, a^i]$
	  while *waiting for guidance and reward on a_t (2 seconds)* **do**
	    if $n > 1$ **then**
	      indicate confusion
	    if *received reward r'_t* **then**
	      $r_t = r_t + r'_t$
	    if *receiving guidance* **then**
	      if *guidance acceptable* **then**
	        a_{t+1} = guidance
	  Learn:
	    $Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha(r_t + \gamma(\underset{a}{max} Q(s_t, a)) - Q(s_t, a_t))$
	  Act in the world:
	    execute a_{t+1}, transition to s_{t+2}
	  $r_{t+1} = r_{environment}$

Guidance is implemented by right-clicking on objects to direct the robot's attention toward a specific object. Guidance can only be provided for objects the robot is facing, otherwise right-clicking has no effect. Following a guidance message, 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 one location to another. This guidance gives a partial opportunity to the user to limit the exploration for the current step, without preventing the robot to explore in further steps.

Some modifications to the original study were required due to the lack of implementation details in the original paper, one of them being the use of a purely greedy policy instead of using softmax. As, the presence of human rewards and guidance limits the importance of autonomous exploration, the greediness of the algorithm should assist the learning by preventing the robot from exploring outside of the guided policy.

It should be noted that the presence of the human in the learning process alters deeply the concept of convergence. By providing rewards, the teacher can manually force the robot's policy to converge or diverge.

SPARC

SPARC uses the gaze of the robot toward objects or locations to indicate to the teacher which action the robot is suggesting. Similarly to the guidance in IRL, the teacher can use the right click of the mouse on objects to send a 'command' to the robot and have it execute the action associated to this object in the current state. However, in this condition, this communication has been extended to also cover locations. With SPARC, the command covers the whole action space: at every time step, the teacher can specify, if desired, the next action to be executed by the robot. Similarly to the guidance, this command can be used on objects only if the robot is facing them. If a robot's suggested action is not corrected, a positive reward of 0.25 is automatically received (as it has the implicit approval from the teacher). If the teacher selects another action, a reward of 0.5 is given to the selected action (the corrected action is not rewarded). That way, actions actively selected are more reinforced than the ones accepted passively and participants still have access to a wider range of rewards with IRL. This system allows for the use of reinforcement learning with implicit reward assignation, aiming to simplify the teaching interaction.

5.3.4 Interaction Protocol

Participants were divided into two groups and interacted with both IRL and SPARC, with the order of presentation being counterbalanced between groups (see Figure 5.2). Participants in group 1 interacted with IRL first for three sessions and then with SPARC for the three remaining sessions; and the interaction order was inverted for participants in group 2.

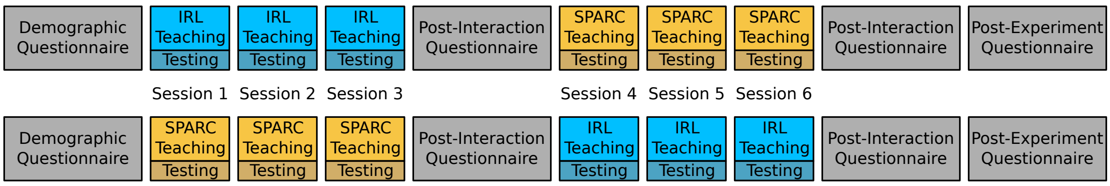


Figure 5.2: A representation of the timeline experienced by participants according to the order they were in. The top row corresponds to group 1 and bottom row to group 2.

After welcoming participants and before interacting with a system, participants completed a demographic questionnaire and received two information sheets. The first one explained the task (describing the environment and how to bake the cake) and the second one described the system they would interact with (IRL or SPARC).

After reading the sheets, participants interacted for three sessions with the system they were assigned to. Each session started with a teaching phase where the participants could interact with the robot to teach it to complete the task. This teaching phase was composed of a number of episodes, corresponding each to a trajectory from the initial state to an end state (success or failure) after which the environment was returned to the initial state. Similarly to the experiment by Thomaz and Breazeal, participants could decide to terminate the teaching phase whenever they desired by clicking on a button labelled ‘Sophie is ready’. But the teaching phase was automatically terminated after 25 minutes to impose an upper time-limit on the study.

After the teaching phase, the robot ran a testing phase where the participant’s inputs, other than a force stop, were disabled. The test stopped as soon as an ending state was reached or the participant forced a stop (e.g. if an infinite loop occurs). This testing phase aimed to evaluate the participants’ performance in the teaching task. The interaction with each system involved three repeated independent sessions with their own teaching and testing phases. This way, we can observe how the interactions evolved as participants got used to interact with a system.

After participants completed their three sessions with the first system, they were asked to complete a first post-interaction questionnaire. Then they received the information sheet for the second system, interacted with it for three sessions and completed a second post-interaction questionnaire.

At the end of the experiment, participants completed a last questionnaire, the post-experiment questionnaire, received the financial compensation and were explained the goal of the study. All information sheets and questionnaires can be found online [4] and the questionnaires are described in Section 5.3.5.

5.3.5 Metrics

Interaction Metrics

We collected four metrics during the teaching phase (teaching performance, teaching time, number of failures and number of inputs provided) and one during the testing phase (the testing performance). All interaction metrics were collected three times per conditions, once for each session. As not all participants reached a success during the testing phases, we used the six key steps defined in Section 5.3.2 as a way to

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

evaluate the performance ranging from 0 (no step has been completed) to 6 (the task was successfully completed) during the testing phase. For example a testing where the robot put both ingredients in the bowl but reached a failure state before mixing them would have a performance of 3.

The testing performance represents the success of participants in teaching the robot to complete the task. On the other hand, the teaching performance corresponds to the highest step reached by participants in the teaching phase and represents a teaching method's ease of guiding the robot. The teaching time is the duration of the teaching phase, ranging from 0 to 25 minutes. The number of failures is the number of times a participant reached a failure state during the teaching phase. It can be related to the risks involved by the teaching; a safe teaching process should lead to a low number of failures, while a risky one would have a high number of failure. The number of inputs corresponds to the number of commands, guidances or feedback inputs used in a teaching session. Similarly to the teaching time, the number of inputs can be seen as the quantity of efforts invested in the teaching process.

Questionnaires

The post-interaction and post-experiment questionnaires provided additional introspective information to compare with the quantitative data from the interaction. Two principal metrics were 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 minimise the workload for the robot's user and to make the interaction as smooth and efficient as possible. Multiple definitions for workload exist and various measures can be found in the literature (e.g. Wierwille & Connor 1983; Moray 2013). Due to its widespread use in human factors research (Hart, 2006) and clear definition and evaluation criteria, we used the NASA-Task Load Index (TLX) (Hart & Staveland, 1988). Following the methodology proposed to administer NASA-TLX, we averaged the values from all 6 scales (mental, physical and temporal demand, performance, effort and frustration) ranging from 0 (low workload) to 20 (high workload) to obtain a single workload value per participant for each interaction. This assessment was made during the post-interaction questionnaires. This resulted in two measures of workload per participant, one for each condition.

Finally, the participants' perception of the robot was also evaluated in the post-interaction and post-experiment questionnaires using rating questions (measured on a 5 item Likert scale), binary questions (where participants had to select one of the two system), and open questions on the preference of system and the naturalness of the interaction.

5.4 Results

Most of the results collected in the study were non-normally distributed. Both ceiling and floor effects could be observed depending on the conditions and the metrics. For instance, for the teaching time, some participants preferred to interact much longer than others, resulting in skewed data. Likewise for the testing 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 and the absence of possible transformation making them normal, Bayesian statistics were conducted using the JASP software (JASP Team, 2018). Three types of test have been used: mixed ANOVA for omnibus comparisons between conditions for the first and the second interaction (between participants), independent t-test for post-hoc comparisons between participants and paired samples t-test for post-hoc comparisons within participants. All tests have been performed using their Bayesian counterpart, which also removed the need for doing a correction on post-hoc tests such as Bonferroni. As such, no p-value is reported, but a B factor representing how much of the variance on the metric is explained by a parameter (if $B < 1/3$ there is no impact, if $B > 3$ the impact is strong, and if $1/3 < B < 3$ the results are inconclusive; Jeffreys 1998; Dienes 2011).

For each interaction metric, two mixed ANOVA between participants were calculated to explore the impact of the conditions on the metric. The first ANOVA was applied to the first interaction (session 1,2 and 3) and compared participants in group 1 interacting with IRL and participants in group 2 interacting with SPARC. The second ANOVA was applied on the second interaction (sessions 4, 5 and 6) and compared participants in group 1 interacting with SPARC and those in group 2 interacting with IRL. If required, additional post test were made within participants for the three sessions corresponding to each interaction to measure if successive interactions with a same system impacted the metric.

5.4.1 Interaction Data

Five objective metrics (teaching performance, testing performance, teaching time, number of inputs provided and number of failures) have been used to assess the efficiency of IRL and SPARC.

Teaching Performance

Figure 5.3 presents the maximum performance reached by participants during the teaching phase, i.e how far in the steps they brought the robot during the teaching phase. It relates to the ease of guiding the robot through the task using a method. If a method does not allow a teacher to direct the robot's behaviour, the robot will have issues reaching useful states which will lead to a poor teaching performance. On the other hand, methods allowing the teacher to steer the robot to the desired parts of the environment should achieve a high teaching performance. The teaching performance is also an upper bound for the testing performance as, due to the risk of failures or loop in the environment, the performance in the testing phase cannot (or has dramatically low probability to) achieve a higher performance than in the teaching phase.

In the first three sessions participants interacted with either IRL or SPARC and swapped for the remaining three sessions. The bayesian mixed ANOVA showed differences between conditions (and between participants) when interacting with the first system (participant in group 1 interacting with IRL and those in group 2 with IRL) and this effect was also present in the second interaction (first interaction:$B_1 = 2881$ - second interaction $B_2 = 76.2$). According to the medians shown in Table 5.2 and the graphs in Figure 5.3, for both interaction, participants using SPARC achieved a higher teaching performance than the ones using IRL. The session number (the repetition of additional sessions with the same system - within participants) had no impact on the teaching performance (first interaction: $B_1 = 0.089$ - second interaction $B_2 = 0.105$) which indicates that with additional interaction with a system participants did not reach a higher or lower teaching performance.

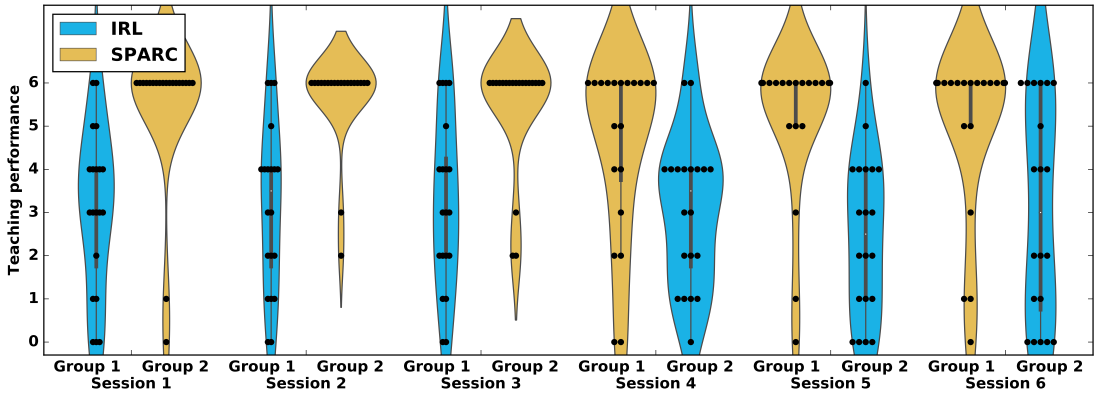


Figure 5.3: Comparison of the teaching performance for the six sessions (the left columns presents the data of participants in group 1 and the right ones those in group 2). The colours are swapped between session 3 and 4 to represent swapping of conditions. A 6 in teaching performance shows that the participant reached at least one success during the teaching phase. The vertical grey lines represent minimal barplots of the data and the shaded areas the probability distribution most likely to produce these results.

Table 5.2: Median performance in the teaching phase. Noted that between session 3 and 4 participants change system.

	$\widetilde{X}_1$	$\widetilde{X}_2$	$\widetilde{X}_3$		$\widetilde{X}_4$	$\widetilde{X}_5$	$\widetilde{X}_6$
IRL	3.0	3.5	3.0		3.5	2.5	3.0
SPARC	6.0	6.0	6.0		6.0	6.0	6.0

This higher teaching performance for SPARC provides partial support for H1 and its prediction: 'SPARC will be more effective and efficient than IRL when used by non-experts'.

Testing Performance

Figure 5.4 presents the performance of the system during the testing phase, and represents how successful was the participants' teaching. The bayesian mixed ANOVA showed an effect of condition on the performance for both interactions ($B_1 = 8.8\text{x}10^5$ and $B_2 = 7340$). The median performance scores in Table 5.3 show that a higher test performance was achieved when participants used SPARC compared to when they used IRL. The session number had no impact on the performance on the first interaction, but results were inconclusive for the impact of repetition on the second interaction ($B_1 = 0.084$ and $B_2 = 0.80$).

As shown in Table 5.3 and Figure 5.4, only a limited number of participants succeeded in teaching the robot to complete the task using IRL, this finding will be discussed in more details in section 5.6.

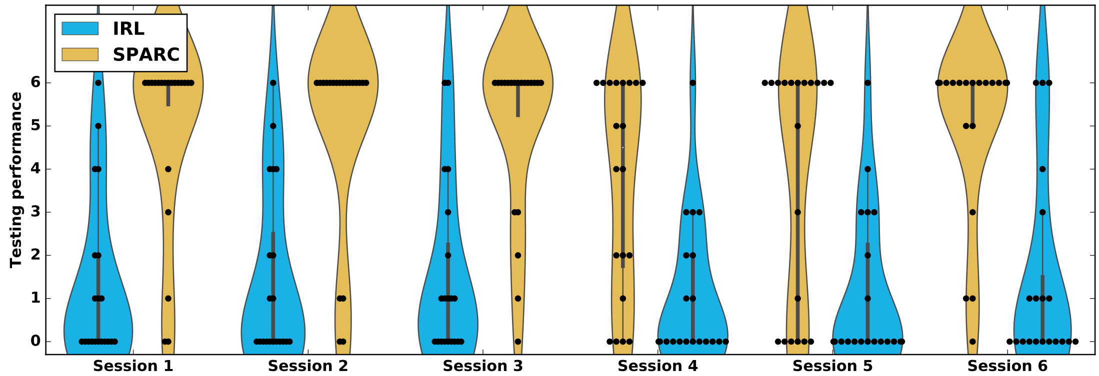


Figure 5.4: Comparison of the testing performance for the six sessions. A 6 in performance shows that the taught policy led to a success.

Table 5.3: Medians of the performance in the testing phase.

	$\widetilde{X}_1$	$\widetilde{X}_2$	$\widetilde{X}_3$		$\widetilde{X}_4$	$\widetilde{X}_5$	$\widetilde{X}_6$
IRL	0.0	0.0	1.0		0.0	0.0	0.0
SPARC	6.0	6.0	6.0		4.5	6.0	6.0

This higher testing performance for SPARC provides partial support for H1 and its prediction.

Teaching Time

Figure 5.5 presents the time participants spent teaching. They could stop whenever they decided or the session would stop automatically after 25 minutes. The bayesian mixed ANOVA showed the important role of condition ($B_1 = 31.4$ and $B_2 = 679$) and session number on the time spent teaching ($B_1 = 8.3\text{x}10^9$ and $B_2 = 3188$). Table 5.4 and additional post-hoc comparisons between the sessions in each interaction indicated that in the first interaction, the teaching time decreased between the first and the second session and then tended to stabilise between the second and the third sessions ($B_{12} = 4.4\text{x}10^5$, $B_{13} = 2.6\text{x}10^6$ and $B_{23} = 0.435$). A similar pattern occurred in the second interaction ($B_{45} = 850$, $B_{46} = 382$ and $B_{56} = 0.172$) with more support for a stabilisation of teaching time between session 5 and 6.

Table 5.4: Medians of the teaching time in each session (in minutes).

	$\widetilde{X}_1$	$\widetilde{X}_2$	$\widetilde{X}_3$		$\widetilde{X}_4$	$\widetilde{X}_5$	$\widetilde{X}_6$
IRL	16.34	7.43	6.16		9.36	5.18	3.0
SPARC	8.97	3.56	2.49		3.96	2.45	1.53

Combined with the consistent high performance of SPARC, this decrease of teaching time indicates that participants managed to learn an efficient way to use SPARC to

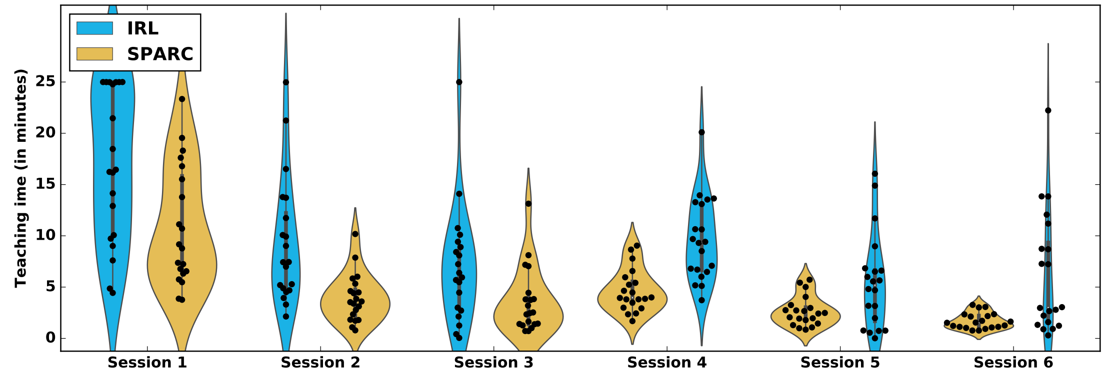


Figure 5.5: Comparison of the teaching time for the six sessions. At 25 minutes, the session stopped regardless of the participant stage in the teaching.

teach the robot a successful action policy. On the other hand, this similar decrease of teaching time and the lower performance with IRL could indicate that participants lost motivation to interact with IRL. As they did not find an efficient way to teach the robot with IRL, they dedicated less efforts to try in successive session. These interpretations provide partial support to H1 and its prediction.

Number of Inputs

Figure 5.6 presents the number of inputs the participants provided while teaching. The bayesian mixed ANOVA showed that in both interactions, the condition had an impact on the number of inputs provided ($B_1 = 27.4$ and $B_2 = 34.1$). On the other hand, the session number only had a clear impact for the first interaction, the results were inconclusive for the second interaction ($B_1 = 4.1\text{x}10^5$ and $B_2 = 1.5$). Table 5.5 and additional post-hoc comparisons between sessions indicated that in the first interaction, the number of inputs used decreased between the first and second sessions and then tended to stabilise between the second and the third sessions($B_{12} = 2707$, $B_{13} = 4.7\text{x}10^4$ and $B_{23} = 0.410$). Similarly, for the second interaction, a difference tended to be observed between session 4 and 5 and session 4 and 6 while the number of inputs was similar between session 5 and 6 ($B_{45} = 2.6$, $B_{46} = 2.7$ and $B_{56} = 0.17$).

Table 5.5: Medians of the number of inputs in the testing phase.

	$\widetilde{X}_1$	$\widetilde{X}_2$	$\widetilde{X}_3$		$\widetilde{X}_4$	$\widetilde{X}_5$	$\widetilde{X}_6$
IRL	248.0	107.5	109.5		142.5	79.0	80.0
SPARC	141.0	60.0	56.0		72.5	50.0	37.0

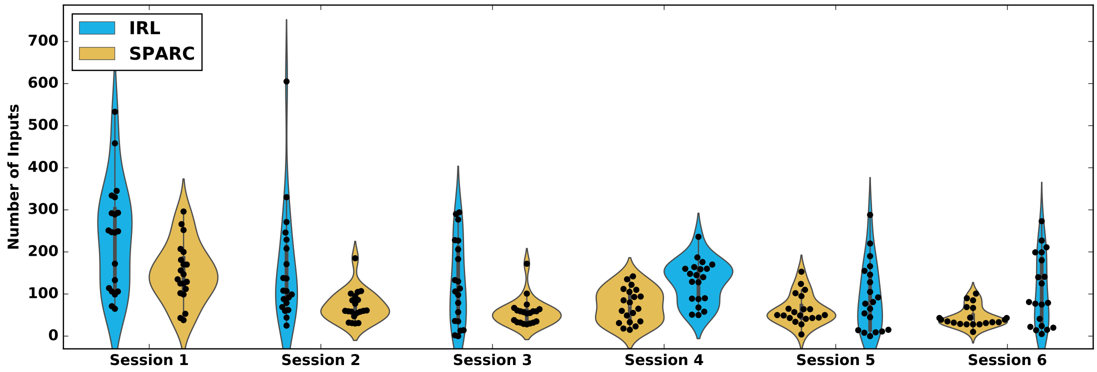


Figure 5.6: Comparison of the number of inputs provided by the participants for the six sessions.

Similarly to the teaching time, this reduction of inputs provided during the teaching, while maintaining a high performance for SPARC offers partial support for H1 and its prediction.

Number of Failures

Figure 5.7 presents the number of failure states participants encountered during the teaching phase. The bayesian mixed ANOVA showed that for both interactions, both the condition ($B_1 = 6.2\text{x}10^4$ and $B_2 = 2.6\text{x}10^4$) and session number ($B_1 = 1.5\text{x}10^4$ and $B_2 = 11$) played an important role on the number of failures. Table 5.6 and additional post-hoc comparisons between sessions indicated that in the first interaction, the number of failures decreased between the first and the second session and then stabilised between the second and the third one ($B_{12} = 619$, $B_{13} = 1.7\text{x}10^3$ and $B_{23} = 0.25$). Similar results have be observed in the second interaction ($B_{45} = 3.3$, $B_{46} = 7.5$ and $B_{56} = 0.2$).

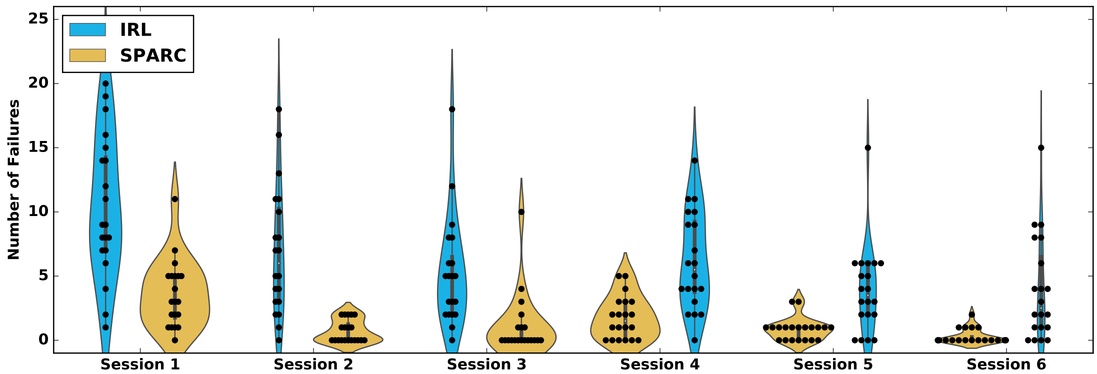


Figure 5.7: Comparison of the number of failures for the six sessions.

The fewer failures faced when using SPARC compared to IRL offers partial support to H1 and its prediction. Additionally, the low number of failures when using SPARC in the last sessions of both interaction (sessions 3 and 6) shows that participants became

Table 5.6: Medians of the number of failures in the testing phase.

	$\widetilde{X}_1$	$\widetilde{X}_2$	$\widetilde{X}_3$	$\widetilde{X}_4$	$\widetilde{X}_5$	$\widetilde{X}_6$
IRL	9.0	6.0	5.0	5.5	3.5	2.5
SPARC	3.0	0.0	0.0	1.5	1.0	0.0

more efficient with SPARC, reaching successes without facing failures, which partially support H2: 'SPARC can be used by expert users (knowledgeable in the interaction process) to teach an action policy safely, quickly and efficiently'.

5.4.2 Questionnaire Data

The main task of the post-interaction questionnaires was to assess the workload on participants when interacting with a condition using the NASA-TLX questionnaire. Figure 5.8 presents the workload for participants for each condition for both interactions (the average of the six ratings from 0 to 20 for each category). In the first interaction, participants using IRL reported an average workload of 12.9 ($SD = 2.33$), whereas the ones using SPARC reported 8.94 ($SD = 3.01$). In the second interaction, participants interacting with IRL reported an average workload of 13.87 ($SD = 2.84$) and the ones using SPARC reported 7.44 ($SD = 3.41$). Bayesian independent t-test show a strong effect of the condition for both interactions ($B_1 = 462$ and $B_2 = 8.1\text{x}10^4$) between participants. And bayesian paired t-test show a similar effect of the condition within participants for both orders (order 1: $B_{IRL-SPARC} = 1.7\text{x}10^6$ - order 2: $B_{SPARC-IRL} = 1.1\text{x}10^4$). Regardless of the comparison criteria (between or within subjects), participants reported a lower workload when interacting with SPARC than when interacting with IRL.

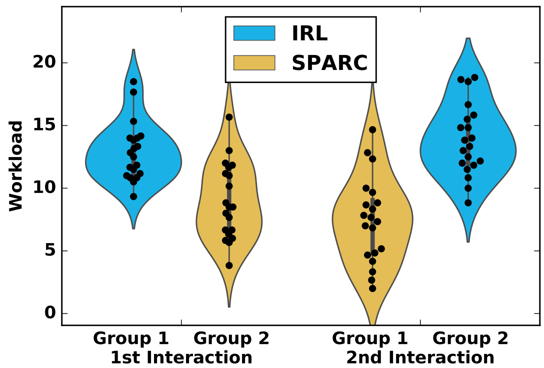


Figure 5.8: Average workload for each participants as measured by the NASA-TLX for each conditions in both interaction order.

This lower workload when using SPARC compared to IRL offers partial support for H1 and its predictions.

5.4.3 Expert

To evaluate the best case potential offered by SPARC and IRL, an expert in Human-Robot Interaction (HRI) knowing the detail of the algorithm and the interactions (the author) interacted five times with each system. For both systems, the expert followed a strictly optimal strategy. In the case of IRL the optimal strategy consisted on providing as much guidance as possible, rewarding positively correct actions and negatively incorrect ones. For SPARC the optimal strategy consisted on providing commands for every single action to demonstrate an optimal trajectory to the robot. This shows the expected behaviours in optimal conditions, the best metrics achievable. Results of the interactions are presented in Table 5.7. In both cases, the expert successfully taught the robot (as indicated by a performance of 6 during the teaching and the test), which indicates that both systems can be used to teach a robot an action policy. However as demonstrated by a bayesian independent t-test, the time required to teach the robot with IRL is higher than with SPARC ($B = 7102$). Due to the lack of variation of the number of inputs for SPARC, no Bayes factor can be computed for this metric. However, the results presented in the table clearly demonstrate that SPARC required less inputs from the expert to teach the robot a correct action policy than IRL.

Table 5.7: Results of an expert interacting 5 times with each system following an optimal strategy. When the variance is 0, Bayes Factor cannot be computed.

	IRL *M(SD)*	SPARC *M(SD)*	B factor
Performance	6 (0)	6 (0)	NA
Time (minutes)	4.5 (0.67)	0.60 (0.03)	7102
Inputs	115.6 (8.4)	28 (0)	NA
Number of Failures	3.2 (0.84)	0 (0)	NA

Additionally, when using IRL, even an expert cannot prevent the robot from reaching failure states during the teaching due to the lack of control over the robot's action. In contrast, when interacting with SPARC, due to the full control and clear communication, the teacher can ensure that only desired actions are executed. So, with sufficient knowledge of the interaction possibilities, an expert using SPARC can teach the robot to behave safely without having to explore or reach undesired states. This has real world applications in HRI, as random exploration is often impossible or undesirable when interacting with humans. SPARC offers a way for the teacher to stop the robot from executing actions with negative consequences whilst still guiding the robot toward useful parts of the environment.

Similar results to these were observed with our non-expert participants: in their last session with SPARC, both groups had a median of 0 failures and a performance of 6. This indicates that more than half of the participants successfully taught the robot the task without ever hitting a failure state after gaining understanding of SPARC in their first and second interactions with it.

The absence of failures, the lower number of inputs and the shorter time required to teach with SPARC compared to IRL when used by an expert user provide support for H2.

5.5 Validation of the Hypotheses

5.5.1 Effectiveness and Efficiency with Non-Experts

Results from the interaction data showed that despite spending a shorter time interacting with SPARC and using fewer inputs, participants reached a higher performance than with IRL and faced fewer failures during teaching. Additionally, when interacting with SPARC, the time participants took to teach the robot decreased to reach a plateau in the second and third sessions, without negatively affecting the performance. This indicates that after the first session, participants understood the interaction mechanism of SPARC and consistently managed to achieve a high performance whilst requiring less effort to teach the robot the task. On the other hand, when interacting with IRL, participants' performance remained low over the sessions, while their teaching time decreased between session 1 and 2 but not further between session 2 and 3. This decrease of effort invested in the teaching combined with the low performance might be due to a loss of motivation after session 1 where often participants did not succeed to teach the robot, reducing the desire to further interact in successive sessions. Overall, these results suggest that teaching the robot using SPARC allows the robot to achieve a higher performance than with IRL, in a shorter time, while requiring fewer inputs and making fewer errors when teaching. This conclusion is supported by subjective measures: the workload on the teacher was lower when using SPARC than when using IRL.

For these reasons, H1 and its prediction ('Compared to IRL, SPARC can lead 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 when used by non-experts.') is supported.

5.5.2 Safety with Experts

As presented in Section 5.4.3, when interacting with SPARC, an expert can reach a success easily and safely (requiring a low number of inputs and a short time and without facing a single failure). This effect is also observed after some training for the naive participants: most of them reached a success without encountering any failures in their last session with SPARC.

However, when interacting with IRL, even the expert applying a strictly optimal policy cannot prevent the robot reaching failures states. This effect is due to the lack of control of feedback-based IML methods. As teachers only rate the actions of the agent, they cannot prevent the learners from making errors. They can only negatively reward these errors to reduce their chance of being selected in the future. While the guidance in IRL allowed to partially mitigate this effect, the presence of actions not covered by this guidance limited the its efficiency during the teaching.

This difference shows support for H2 ('SPARC can be used by expert users to teach an action policy safely, quickly and efficiently, achieving better results other IML methods lacking control'). This also demonstrates how the principles presented in Chapter 3 provide the teacher with control over the robot's actions and by extend improve the teaching. Consequently, the principles underlying SPARC ensure that even in the early stages of teaching (when the robot's action policy is not mature to correctly select actions without supervision), the robot's action policy is already appropriate, which is not the case of most other IML methods (as demonstrated by the number of failures when teaching with IRL).

5.5.3 Control

One of the main differences between the two methods is the way in which the concept of teaching is approached. With IRL an exploratory individual learning approach is followed: the robot has the freedom to explore, whilst receiving feedback on its actions and limited guidance about what action to pursue next from a teacher. This social aspect of the teaching: with hints and guidance, partial control over the robot actions and bidirectional communication is inspired by the way humans teach. While not every member of the population is knowledgeable about Machine Learning (ML), people are experienced with social learning (Thomaz & Breazeal, 2008). This similarity between how humans teach robots and other humans has also been supported by behaviours displayed by participants in the original study. Participants gave motivational rewards to the robot, just as one would do to keep a child motivated during learning, despite the absence of effect or use in classical RL (Thomaz & Breazeal, 2008).

On the other hand, SPARC promotes a more direct teaching process: the supervisor explicitly tells the robot what to do and expects it to obey and learn. The robot is not totally considered as a social agent from the supervisor's point of view, but rather as a tool having to learn an action policy. This does not mean that the robot cannot be social: the supervisor can teach the robot in a non-social way how to interact socially. This approach is more task oriented, and we argue that it better fits many human-centred applications of HRI when the interaction with the teacher does not have to be social. For example, in Socially Assistive Robotics (SAR), the task (such as interaction with a child with Autism Spetrum Disorder (ASD)) is more important than the social relationship between the robot and its supervisor (a therapist for example) and as such the relevance of the social side of the interaction between the teacher and the robot is reduced.

The post-experiment questionnaire included the open question: 'which robot did you prefer interacting with and why?'. Almost all the participants (38 out of 40) replied that they preferred interacting with SPARC. Half of all the participants used vocabulary related to the control over the robot's actions ('control', 'instruction', 'command', 'what to do' or 'what I want') to justify their preferences without these words being used in the question. Furthermore, multiple participants reported being frustrated not to have total control over the robot's actions with IRL, they would have preferred being able to control each of the robot's actions.

To the question 'which interaction was more natural?', 10 participants rated IRL as being more natural, using justifications such as: 'The robot thinks for itself', 'Some confusion in the [IRL] robot was obvious making it more natural', 'More like real learning', 'Because it was hard to control the robot' or 'People learn from their mistakes faster'. But despite these participants acknowledging that IRL is more 'natural', closer to human teaching, they still preferred teaching using SPARC. This suggests that when humans teach robots, they are focused on the outcome of the teaching, on the learner's proficiency in the task. As mentioned previously, this might relate to the role of robots, they often interact in human-centred scenarios where they have to complete a task for their users. And, due to the absence of life-long learning for robots today, it is not worth investing time and energy to allow the robot to improve its learning process or explore on its own. These evaluations and comments from the participants show support for H3 ('Teachers prefer a method providing more control over the robot's actions.').

5.6 Discussion

Despite not being originally designed for use in combination with Reinforcement Learning, SPARC achieved good results in this study. This shows that the principles presented in Chapter 3 are agnostic to the learning algorithm and promote an efficient teaching interaction. Furthermore, SPARC achieved a higher performance, in a shorter time and facing less failures than IRL, whilst requiring a lower workload from the human teacher. And finally, when used by experts (designer or trained participants), SPARC demonstrated that teaching can be safe and quick. The full control over robot's action in the teacher's hands ensured that only desired actions will be executed. These results showed an important feature of teaching robots to interact in human environments. As robots interact in task oriented, human-centred environments, human teachers need approaches with direct control and more focused on commands rather than letting the robot explore on its own and only evaluate its actions.

5.6.1 Comparison with Original Interactive Reinforcement Learning Study

Unlike the original experiments evaluating IRL (Thomaz & Breazeal, 2008), in this study, most of the participants did not succeed in teaching the robot the full cake baking sequence using feedback and guidance (the IRL condition). In Thomaz and Breazeal's study, the participants were knowledgeable in machine learning: when asked to rate their expertise in ML software and system (1=none, 7=very experienced), they reported an above average score (M=3.7, SD=2.3), but the population in the presented study was drawn from a more general public having little to no knowledge of machine learning (M=1.8, SD=1.13 - on a 5-item Likert scale). This can explain why a much larger number of participants did not achieve success with IRL in this study whereas Thomaz and Breazeal only reported 1 participant out of 13 failing the task. In our study, only 12.5% of the participants and the expert did manage to teach the robot using IRL.

As demonstrated by the teaching performance, most of the participants did not manage to reach a single success even during the teaching phase in the IRL condition. We identify the lack of control over the robot's actions as a limiting factor for the teaching. As participants did not manage to steer the robot toward correct actions, they could not reward them and teach the robot an efficient action policy. Additionally, the requirement of explicit feedback made the learning task more complex. Participants often did not reward an action after a guidance, assuming that informing the robot about what it should do was enough, and would not require an additional explicit reward. In contrast, SPARC used implicit rewarding by automatically providing a positive reward to actions selected by the teacher and also every action not corrected by the teacher as it had been implicitly validated. This improvement of performance with SPARC and participants' preference for this system indicates that when teaching robots, humans should be provided with control over the robots and robots should take into account teacher's implicit teaching strategies. This is consistent with Kaochar et al. (2011) who note that feedback is not well suited for teaching an action policy from scratch, but better for fine tuning. For teaching the basis of an action policy, they recommend using demonstrations, a method much closer to SPARC.

5.6.2 Advantages and Limitations of SPARC

In the implementation of SPARC for this study, the algorithm mostly reproduced actions selected by the teacher. One could argue that no learning algorithm was required to produce that behaviour, instead the actions could just be blindly reproduced by the robot. However, using RL with SPARC does provide advantages. By using the Markov definition of states, a state visited multiple times in an episode would be considered as a single identical state for the learning algorithm. This means that by rewarding this state multiple times loops in the demonstrations can be removed for future executions of the action policy. Additionally, by update a Q-table, RL provides the algorithm with a way to deal with variations in teaching. Additionally, RL allows the robot to reach a success from the initial state but also to continue the action policy from any state in the trajectory. And finally, due to the suggestion/correction mechanism, the teacher can let the robot act on its own only intervening when the robot is about to execute an incorrect action.

Over the 79 successful trials using SPARC, the robot learned 47 different strategies to bake a cake. This shows how SPARC, as a single control mechanism, allows for different action policies to be learnt depending on the person teaching the robot and their preferences. With SPARC the robot can learn the specific way its user would like it to behave and take into account their personal preferences.

However SPARC also has limitations in the current implementation. The main limits are related to the quality and interpretation of the human supervision. If the teacher allows an action to be executed by mistake (through inattention or by not responding in time), this action will be reinforced and will have to be corrected later on. This might lead to loops when successive actions are returning to a previous state (such as move left, then right). In that case, the teacher has to step in and manually guide the robot to break this cycle. Furthermore, due to the automatic execution of actions, the teacher has to be attentive at all times and ready to step in when a wrong action is suggested by the robot. This is a limitation as a lack of supervision can lead to undesired reinforcement of incorrect behaviours.

5.6.3 Limitations of the Evaluation

In this study, SPARC has been applied to a scenario where a clear strategy with optimal actions was present. The interaction also took place in a virtual environment with a discrete time and a limited number of states. Real human-robot interactions are stochastic, happen in real time and often there is no clear strategy known in advance, and as such present limited similarity with this study. However, in these real HRI, human experts in the application domain know what type of actions should be executed when, and which features of the environment they used for their decision. And, as this knowledge might not be available to the robot's designers or could be complex to formalise in a set of rules a robot should follow, robots should be able to learn from a domain user in an interactive fashion. This study presented a simple environment allowing us learn more about how humans could teach a robot using SPARC.

Additionally, the participants were also biased. By using the tool provided by the university, a majority of the participants were students from the university, and might not be fully representative of the general population. However, as robots are by essence technological tools, they will probably be mostly used by people familiar with technology or people having been trained to use such tools.

Some limitations of this study (simulated deterministic world, limited number of state, discretisation of time and absence of interaction with humans in the target application) have been addressed in Chapter 6. In the study presented in that chapter, SPARC has been applied to a real-world social interaction with humans, possessing all the challenges typical to these interactions: complex non-deterministic world, with continuous time, real impact of actions and importance of the social factors in the interaction.

5.6.4 Lessons Learned on Designing Interactive Machine Learning for HRI

From observing participants interacting with both systems, we derived four recommendations for future designs of interactive learning robot that we also used to develop the study presented in Chapter 6.

Clarity of the Interface and Transparency

Algorithms used in machine learning often need precisely specified inputs and outputs and require an internal representation of the world and policies. These variables are often not accessible to a non expert: the weights of a neural network or the values in a Q-table are not easily interpretable, if at all. The inner workings of the machine learning algorithms are opaque, and people only have access to inputs and outputs of the black box that is machine learning. As such, care needs to go into making the input and output intuitive and readable. For example, in this study (following Thomaz and Breazeal's original study), the communication between the robot and the teacher occurred through the environment: using clicks on objects rather than a more classical Graphical User Interface (GUI) with buttons. This design decision had important consequences: as the interface was not explicit, participants first had to familiarise themselves with the interface, discover how to interpret the robot's behaviour, which actions were available for each state and learn the exact impact of the robot's actions. This lack of clarity led to a high number of failures and high teaching time during the first session in our study. So, we argue that to avoid this precarious discovery phase for the teachers, roboticists have to design interfaces taking into account results from the Human Factors community as advocated by Adams (2002), such as including the users in the design process or finding intuitive ways to train teachers to use these interfaces.

Limits of Human Adaptability

HRI today is facilitated by relying on people adapting to the interaction, often making use of anthropomorphisation (Fong et al., 2003; Złotowski et al., 2015). Roboticists use people's imagination and creativity to fill the gaps in the robot's behaviour. However, human adaptivity has its own limits: in our study, often participants adopted one particular way of interacting with the system and they held on to it for a large part of the interaction. For example, participants repeatedly clicked on an object requiring two actions to interact with, assuming that the robot had planning capabilities which it did not. Or when the robot was blocked in some cycles (due to constant negative reward in and undo behaviour IRL or a loop created and not stopped with SPARC), participants kept on trying the same action to break the loop, without really exploring alternatives. For these reasons, if robots are to be used by naive operators, they need mechanisms to detect these 'incorrect' uses, and either adapt to these suboptimal human inputs or at least inform the user that this type of input is not efficient and clarify what human behaviour is appropriate instead.

Importance of Keeping the Human in the Learning Loop

As argued in previous chapters, we think the presence of a human in the learning process is key. This human has the opportunity to provide important knowledge about the environment and allow the machine learning to deal with sensor errors or imperfect action policies. As in real world a robot's behaviour can hardly be perfect, keeping a human in the learning loop allows to continue improving the robot's behaviour even after an acceptable policy is reached. This is different to most of the Learning from Demonstration (LfD) approaches where the robot is left unsupervised to interact once an action policy is learned (Argall et al., 2009; Sequeira et al., 2016). This was one of the important points we considered when proposing SPARC: there is no distinction between a teaching and a testing phase, they are merged into a single phase, moving away smoothly from Wizard-of-Oz (WoZ) to Supervised Autonomy. The teacher can correct the robot when needed and let it act when it behaves correctly. In this study, participants used this feature of SPARC: many participants corrected SPARC only when required rather than forcing every action. For example, 37.5% of the participants even let the robot complete the task once without giving a single command before starting the test to be sure that the robot was ready. This demonstrates that keeping the human in the learning loop is important to ensure that the robot's behaviour stays appropriate; and this study demonstrated that SPARC allows human teachers to be actively involved in the teaching process without requiring important workload for them.

Keeping Teachers in Control

Most of the scenarios where a robot has to learn how to interact with humans are human-centred: the robot has to complete a task to help a human (such as SAR). In these scenarios, the goal of learning is to ensure that the robot can complete the task it has been assigned, not to provide the robot with tools to learn more efficiently in further interactions. Accordingly, participants in our study did not desire to have the robot exploring on its own and learn from its experience, they wanted to be able to direct the robot (see Section 5.5.3). In addition to reducing the effectiveness of the learning, a lack of control over the robot's actions can lead to frustration and loss of motivation for the teacher as shown with the results of IRL in this study. This human control is critical when teaching robots. This effect is even reinforced for robots designed to interact with humans because undesired actions can have dramatic impacts, such as causing physical or mental harm for the interaction partners or bystanders. For these reasons, we argue that when designing an interactively learning robot for HRI in human-centred scenarios, it is fundamental to keep the human teacher in control.

However, this control does not mean that the robot cannot learn and become autonomous. We take a stronger inspiration from LfD, using human input more efficiently to guide the learning, speeding it up and making it safer, especially in the early stages of the learning. With SPARC the human is in control during all the interaction, but has to be especially attentive when the robot is prone to making exploratory mistakes, so they can prevent these errors before they occur. However, once the action policy is appropriate enough, the teacher can leave the robot to interact mostly on its own, providing only limited supervision to refine the action policy.

5.7 Summary

As presented in Chapter 3, SPARC has been designed to allow naive humans to teach an action policy to a robot while maintaining an appropriate behaviour. This chapter presented a study where SPARC was combined with RL to teach a simulated robot to complete a baking task. SPARC used intentions communicated by the robot, teacher full control over the robot's behaviour and an implicit rewarding mechanism to allows participants teach the robot an action policy. A study involving 40 participants compared this approach with IRL, another IML approach using communication of uncertainty, partial control and explicit rewarding to teach the robot. When interacting with SPARC, participants took less time and fewer inputs to reach more successes, whilst facing fewer failures. Participants also reported a lighter workload when using SPARC than when interacting with IRL. Results from this study demonstrated that SPARC is usable by naive participants to successfully teach a robot an action policy quickly and safely.

Based on these results and our observations of the participants, we propose four guidelines to designing interactive learning robots: (1) the interface to control the robot should be intuitive, (2) the limits of human adaptability have to be taken into account (robots should detect deadlocks in human behaviours and adapt how they are controlled or inform the human about these incorrect behaviours), (3) the operator should be kept in the learning loop and (4) teachers should stay in control of the robot's behaviour when interacting in a sensitive environment (such as Robot Assisted Therapy (RAT)). The first two points can be seen to apply to all robot teaching methods, and should be addressed at the time of designing the interface. And, by definition, SPARC aims to address these last two points: maintaining the performance of an adaptive system by remaining under progressively decreasing supervision.

In summary, this chapter extended SPARC and compared it to other methods from the IML field. SPARC succeeded in its goal, allowing participants to teach easily and safely an action policy to a robot. Finally, insights from this study have been used to guide the design of study presented in Chapter 6, the final study of this research, which involved teaching a robot to interact with humans in real-world HRI.

Chapter 6

Study 3:

Application of SPARC to Tutoring

Key points:

- Design of an experiment to test SPARC in an educational application with children.
- Design and use of a new learning algorithm adapted from nearest neighbours to teach quickly and efficiently in an online fashion.
- Between participants study involving 75 children comparing 3 conditions: a passive robot, a supervised robot and an autonomous robot.
- Psychology PhD student teaching the supervised robot using SPARC.
- Similar children behaviours with the autonomous and supervised robot, and different to the passive robot.
- Demonstration of the applicability of SPARC to teach a robot online an action policy to interact with humans in a complex, indeterministic, high dimensional, multimodal and social environment.

Parts of the work presented in this chapter have been published verbatim in Senft et al. (2017b) and Senft et al. (2018) and an additional publication is under review. The final publications are available from AAAI, EPFL via:

- `https://aaai.org/ocs/index.php/FSS/FSS17/paper/view/16011`.
- `https://r4l.epfl.ch/files/content/sites/r4l/files/HRI2018/proceedings_2018/paper4.pdf`.

6.1 Motivation

Chapters 4 and 5 tested the Supervised Progressively Autonomous Robot Competencies (SPARC) in interactions between robots or in a virtual world but not for Human-Robot Interaction (HRI) as it was intended to be used. As such, this Chapter addresses the thesis of this research and evaluates if SPARC can efficiently be used to teach a robot an interactive behaviour for real human-robot interactions. HRI in the wild typically occurs in constrained but underspecified environments where social behaviours play an important role. Teaching a robot in such an environment is a challenge as the state and action spaces are high-dimensional, the environment is not deterministic and the interaction takes place in continuous time and is multimodal. And finally, the social side is fundamental as it impacts the flow and the success of the interaction and makes HRI a high-stakes environment Belpaeme et al. (2012). This would be one of the first times humans have been used to teach online a robot to interact with humans.

This study took place in the context of robot tutors for children in education. Tutoring is a framework widely used in HRI and which provides opportunities for a rich and complex interaction between a child and a robot (Leyzberg et al., 2012; Kennedy et al., 2015a). This scenario and the code are based on Lemaignan et al. (2017) but have been adapted to provide a new teaching task (teaching game and protocol), a knowledge test, a specific robot controller, a learning algorithm and an interface with the teacher supporting SPARC.

6.2 Scope of the Study

The main goal of this study was to explore the thesis proposed in this work: “A robot can learn to interact meaningfully with humans in an efficient and safe way by receiving supervision from a human teacher in control of the robot’s behaviour”. This thesis can be divided into two parts: “a robot can learn safely by receiving supervision from a human teacher” and “after learning, such a robot would have a meaningful interaction with humans”. To address these two statements, a study comparing three conditions was designed. The study consisted on an educational game children played with the robot and where they could gain knowledge about food chains. During this educational game, the robot could provide or not feedback, hints and supporting messages to the child participating depending of the condition. The objective of the study was to explore if the robot could learn how to provide an efficient tutoring support to the children during this game.

This study was focused on providing a robot with an efficient behaviour, not how a robot would compare to a touchscreen or to another agent (for instance a human). As such, to prevent confounds about novelty effect and potential excitements due to the presence of the robot, the control condition maintained the robot present through all the interaction. In this control condition, the 'passive' condition, the robot led the child through the study as in the other conditions, but was not interacting with the child during the educational game. This condition provided a benchmark against which the other conditions were compared to evaluate the 'meaningfulness' and efficiency of the robot's behaviours. In the second condition, the 'supervised' condition, the robot was supervised and taught by a human teacher using SPARC. This condition was the one in which the robot learned, and was used to evaluate the impacts of the principles underlying SPARC when teaching a robot to interact with humans. Lastly, in the 'autonomous' condition, the robot applied the learnt policy to interact without supervision with the children. This condition aimed at exploring the similarity between the autonomous policy and the supervised one, and evaluating if the teaching from the human was successful. And, as the robot needed to have completed its learning before interacting alone, this condition was run only after the supervised condition was completed.

These conditions allowed us to explore the statements presented above through three hypotheses:

- H1 In the supervised condition, SPARC allows the teacher to teach the robot while ensuring its behaviour is constantly appropriate.
- H2 The autonomous robot is able to interact socially and efficiently during the game sessions and maintain the child's engagement during the learning task.
- H3 An active robot (supervised or autonomous) supports child learning: learning gain in passive condition $<$ learning gain in autonomous condition $<$ learning gain in supervised condition.
- H4 Using SPARC, the workload on the supervisor decreases over time: the number of corrected actions and the number of actions selected by the teacher decrease

with the progress in the sessions, while the number of correct proposed actions increases.

6.3 Methodology

6.3.1 Participants

Children from five classrooms from two different schools in Plymouth were recruited to take part in the study. As both schools have an identical OFSTED evaluation (both school "require improvement"), all the children were combined into a single pool of participants. Full permission to take part in the study and be recorded on video was acquired for all the participants. In total, 119 children participated in the study, however not all of them have been included in the final analysis. Some participants took part in two pilot versions, with previous versions of the game or the protocol. For other participants, a breach in the protocol have prevented them to be included (such as freezing of the tablet due to an imperfect kernel version or children refusing to continue the interaction). Additionally, children with special needs were encouraged to participate but were not included in the results. In the end, 25 participants per condition were included (N=75 in total; age: *M*=9.4, *SD*=0.72; 37F/38M). The remaining children in the classrooms interacted by pairs (and were not included in the evaluation) to accelerate the ending of the study, and free the room used in the school while giving each child the opportunity to interact with the robot.

6.3.2 Setup of the study

Similarly to the study presented in Chapter 4, this study is based on the Sandtray paradigm (Baxter et al., 2012): a child interacts with a robot through a large touchscreen located between them and by interacting with the touchscreen and the robot, the child is expected to gain knowledge or improve some skills. Additionally, a teacher can use a tablet to control and teach the robot in the 'supervised' conditions (cf. Figure 6.1). This type of potentially triadic interaction is typical of the interactions we considered when framing this research (cf. Figure 1.1). We desire an efficient behaviour for the robot in the application interaction (i.e. child tutoring) and a human teacher has knowledge about how the robot should behave and can transfer it to the robot in situ by using SPARC.

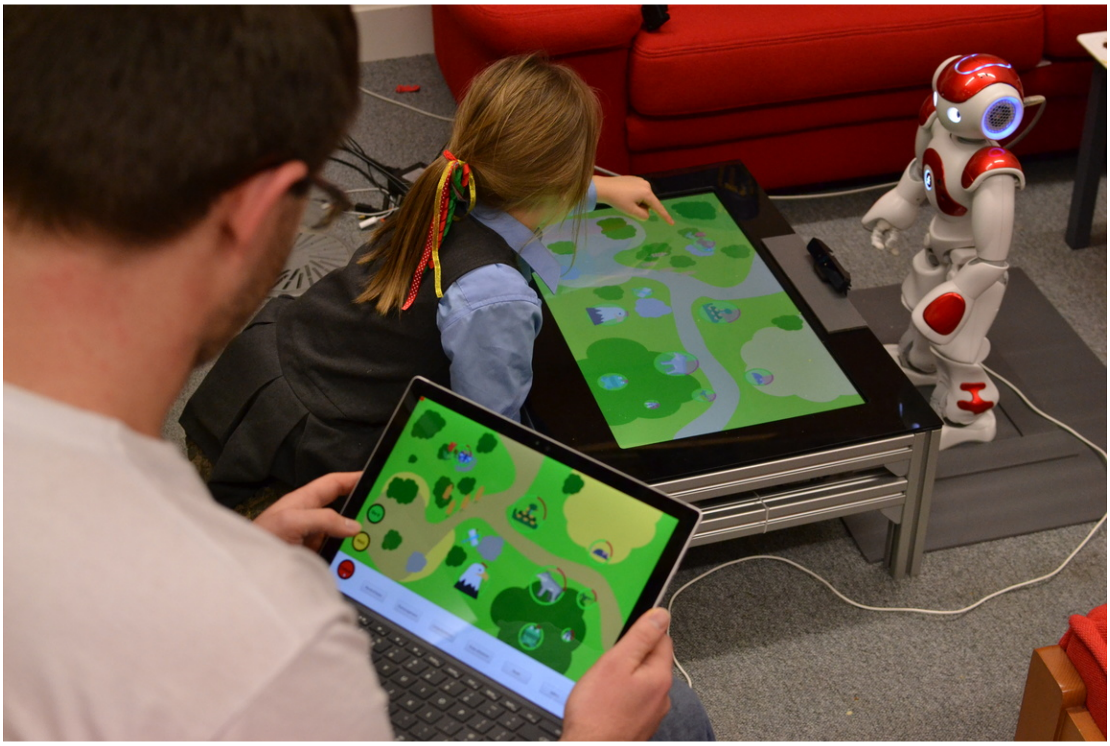


Figure 6.1: Setup used in the study: a child interacts with the robot tutor, with a large touchscreen sitting between them displaying the learning activity; a human teacher provides supervision to the robot through a tablet and monitors the robot learning.

For this study, the goal of the interaction is learning about food chains by exploring a specific food web (interconnections between multiple food chains) in an educational game. The child plays a game on the Sandtray where they can move animals to discover the interactions between them. Learning is evaluated by a test before, between and after the sessions; and the robot leads the child through the study and can, depending of the condition, support them during the game.

6.3.3 Food Chain Game

The main learning activity to teach the child the food web is a game composed of ten animals (a mouse, a grasshopper, an eagle, a frog, a snake, a fly, a wolf, a small bird, a butterfly and a dragonfly) and three types of plants (4 instances of wheat, 4 instances of apples and 3 instances of flowers, for a total of 11 plants). Animals have energy decreasing over time and they have to eat to stay healthy. Figure 6.2 presents an example of the game screen in the middle of a session. Animals are not moving unless the child or the robot moves them and can eat or be eaten when entering in contact with another animal or a plant. The child is instructed to keep the animals alive as long as possible, and consequently has to feed the animals by moving them to their food to give them more energy and by feeding the animals, children should learn the animals' diet.

Figure 6.2: Example of the game. Animals have energy in green and have to eat plants or other animals to survive. The child's task is to keep animals alive as long as possible.

6.3.4 Robot Behaviour

During the game, the robot can execute actions to provide hints and support to the child. The robot has access to five types of actions:

- Movements: moving any animal to, close to or away from any items (animal or plant) - the robot points to an animal and moves it on the game while describing its action (e.g. "The eagle needs help getting close to the mouse").
- Drawing attention: the robot points an item and says a reminder to the child (e.g. "Don't forget the frog").
- Reminding rules: the robot says one of 5 sentences describing the game's rules (e.g. "Move the animals to feed them" or "Feed animals with a low energy").
- Congratulation: the robot provides congratulations (e.g. "Well done").
- Encouragement: the robot provides encouragement (e.g. "You can do it").

Considering all the possible combinations of actions and items, the total number of actions adds up 655. Additionally, to prevent the robot's behaviour to be repetitive and annoying, each utterance joining an action has multiple versions, and a random one not used recently is said by the robot when an action is executed.

TOCHECK[ES] This set of actions has been selected to be generalisable to many type of scenario including a teaching activity on a screen. Furthermore, in this study, these actions represent different level of support, from general motivation and information on the game's goal to which animals the child should focus on or direct information about what an animal eats. It should be noted that as the goal of the interaction is having the child play the game, not the robot, when moving animals, the robot cannot feed them. Animals eat only when the child is moving them, that way, the robot can impact directly the game metrics only through the child, all the events and real changes on the game are created by the child. This selection of actions aims to cover a large range of possible tutoring behaviours humans could use and generalise easily to other task involving moving items on a screen.

6.3.5 Wizard of Oz Application

In this study, the communication between the teacher and the robot occurs through the Wizard-of-Oz (WoZ) application, a Graphical User Interface (GUI) running on a tablet and allowing the teacher and the robot to communicate. This GUI represents the state of the game as the child sees it, but with additional buttons and functionalities to communicate both ways with the robot (see Figure 6.3). The teacher can use a combination of buttons and moving animals on the tablet to have the robot execute any possible action. For example, to move animals close to another item, the teacher can drag and release the animal's image to a position to request the robot to execute this movement. The robot controller infers which action has been selected by the teacher by evaluating how the distances between animals change. Similarly, the teacher can select an animal and press the 'Draw attention' button to have the robot point at the select animal and remind the child to use it. For instance, by clicking on the frog and the 'Draw attention' button, the robot will execute the *drawing attention to the frog* action. Additionally, the teacher can use the GUI to highlight the features they used to select the action in order to speed up the teaching process and clarifying ambiguous actions. This features highlighting is done my selecting the items or plants relevant to action or by pressing on the image displaying the child gaze on the top right corner. This GUI has been designed to be as intuitive as possible, giving access to the teacher to more than

600 actions without requiring as many buttons and to interpret and react to the robot's propositions.

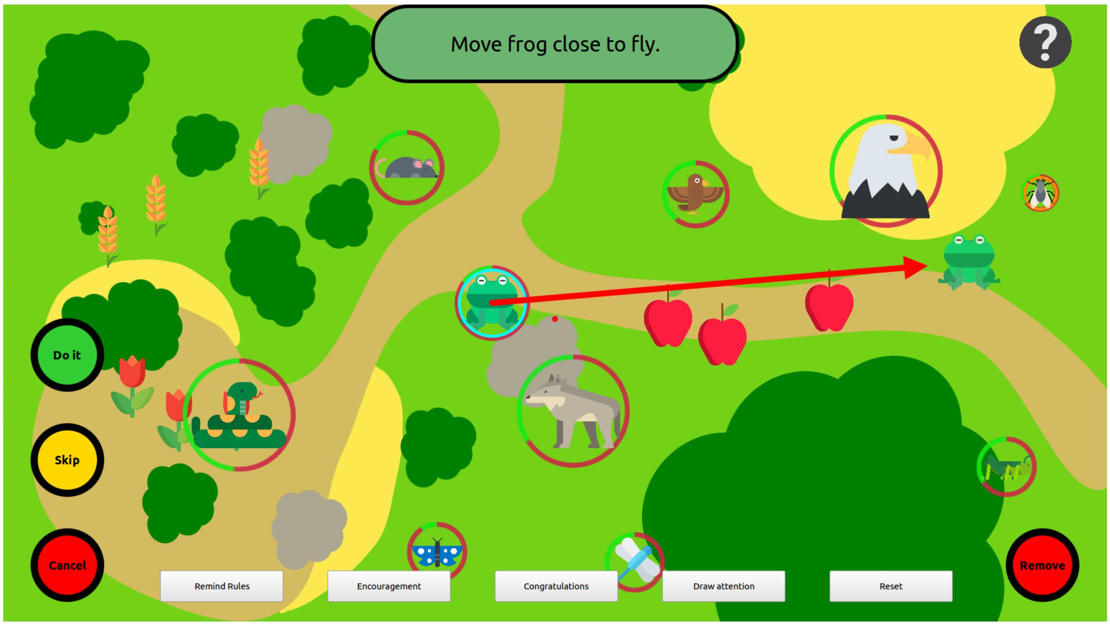


Figure 6.3: GUI used by the teacher to control the robot and respond to its suggestions. The game is in the same state as in Figure 6.2, and the robot proposes to move the frog close to the fly (text bubble, arrow, moving the *shadow* of the frog and highlight the frog and the fly).

Finally, the GUI is also used by the teacher to respond to the robot's propositions. Following the proposition of an action, a bubble describing the action appears on top of the GUI, the corresponding items are highlighted and if the action is a motion, an arrow shows the proposed motion. The teacher can react to the proposed action by pressing the 'Do it', 'Skip', 'Cancel' or 'Remove' buttons or let the action be automatically executed after 2 seconds, during which the bubble will become greener to represent the passive acceptance of the action. The 'Do it' button executes the action straight-away, the 'Skip' button sends the 'wait' action with a reward of 1 (indicating the robot should wait in this situation), the 'Cancel' sends the action with a -1 reward and does not execute it (indicating this action is not appropriate in this situation), and finally, the 'Remove' button looks for the closest previous instantiation of the action in memory and removes it, preventing this instance to be used in later action selection. Action executed by the robot (through 'Do it', automatic execution or selection) are assigned a reward of 1. In each cases, by using buttons or automatic execution, the features highlighted when the button is pressed (often the same as the one proposed by the algorithm) are sent with the action.

6.3.6 Control Architecture

The code used to create the game and control the robot is an adaptation of the Freeplay Sandbox (Lemaignan et al., 2017). Original sources are available online[1] as well as the code used for this study[2,3,4].

The control architecture is adapted from Lemaignan et al. (2017) and a simplified schematic is presented in Figure 6.4. All nodes are communicating through ROS and the communication with the robot is done through NAOQI. The tool rosbag is used to collect data throughout the interaction and the analysis of the child's focus of attention is performed using gazr (Lemaignan et al., 2016).

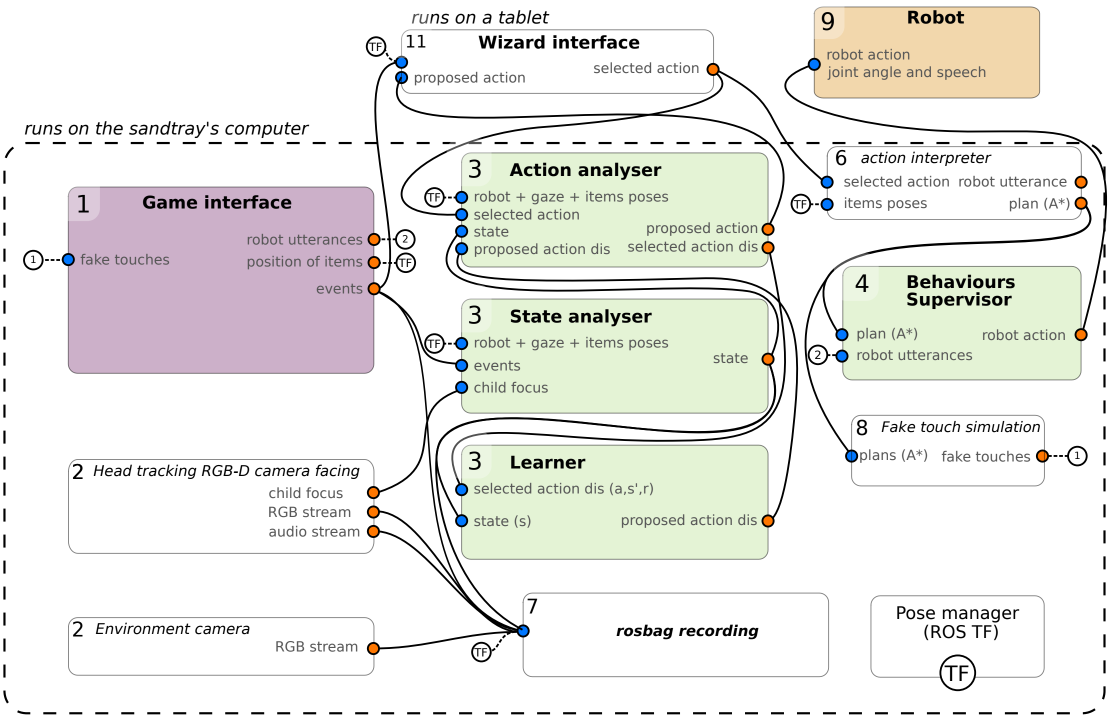


Figure 6.4: Simplified schematics of the architecture used to control the robot. In addition, all the topics related to the actions are recorded using rosbag. (Figure adapted from Lemaignan et al. (2017)).

It should be noted that to be able to learn actions, the algorithm use a discrete actions space: the 655 actions defined before. On the other hand, for the teacher, movement actions are selected by choosing an animal and moving to a destination while highlighting relevant features to clarify the action if needed or help the learning. The action analyser has the task of converting the actions from one world to another: interpreting movements

[1] https://github.com/freeplay-sandbox
[2] https://github.com/emmanuel-senft/freeplay-sandbox-qt/tree/food-chain
[3] https://github.com/emmanuel-senft/freeplay-sandbox-ros-sparc/tree/task
[4] https://github.com/emmanuel-senft/freeplay-sandbox-qt-supervisor

from the teacher as discrete actions for the algorithm and transforming the discrete actions from the algorithm to continuous action for the teacher and the game.

6.3.7 Learning and Action Selection

To learn and act autonomously, the robot has access to a representation of the state and a set of actions it can do; and the algorithm aims at finding the ideal action for each possible state based on the teacher's commands.

State

Table 6.1 presents the different dimensions composing the state the robot has access to.

Table 6.1: Definition of each category of the state space.

Name	Number	Description
Distance between items	155	Normalised distance between the animals and each other animal and the plants
Items' energy	21	Energy of the 21 items (10 animals and 11 plants)
Time since robot touches	10	Time since the robot touched each animal
Time since child touches	10	Time since the child touched each animal
Progress in the game	1	0.25 for 1st game to 1 for the last game
Generic events	3	Time since last feeding, failed interaction and death of an animal
Last robot's actions	5	Time since last type of robot action
Generic last action	2	Time since any child touch and robot action
Focus	3	Time of focus toward the robot, the screen and outside

All the state values are bounded by [0,1]. Distances between items are normalised with the maximum possible distance (the diagonal of the screen), and as there are 10 animals and 11 plants this results in a total of 155 possible distances between animals and other items. To include a representation of the temporal aspect of the interaction, some dimensions of the state represent the time since events and two methods have been used to transform the time since an event to a value bounded between 0 and 1:

- Accumulation: for the times since child touches and focus (effect being true or false).
- Decay: for robot actions and touches and generic events (discrete events).

The accumulation corresponds to effect that can be true or not, and aims at representing how long this effect as been true or false. When the effect is true for accumulation, the state value is set to 0.5 and increases each step (by $1 - e^{-\frac{1}{10}}$ of the missing value). And when the condition is false, the value is set to 0.5 and decreases (by being multiplied by $e^{-\frac{1}{10}}$) at each step. On the other hand the decay refers to discrete events, so only the time since the event is relevant. When the event happens the corresponding state value is set to 1 and then exponentially decreases by being multiplied by $e^{-\frac{1}{10}}$. That way event will have a 'half-life' of 7 steps, which corresponds to 3.5 seconds.

Parts of the states are hardcoded, such as the the generic events, generic last actions, focus and progress in the game. However, all the state dimensions related to the items (distance, energy and time since touches) are constructed on the fly. At start up, the state analyser node (cf. Figure 6.4), the node responsible for computing the state, receives a list of the moving items and one of the immobile items and it creates the appropriate state with the corresponding dimensions. During the game, the state values are updated using events related to specific item (through their name). Additionally, each instance of a plant is considered as a unique element. For example, there are four instances of wheat, however each one is considered uniquely as a non-moving image and its type is not taken into account in the state or actions space. It could have been possible to group the instances by categories, but it would require some add-hoc coding, limiting the generalisation of the approach.

The state dimensions have been selected to be generic to many teaching tasks involving movable items: each item has a value assigned to it (here energy, but this could be changed in other scenario), and some items can be moved (here animals) while other are immobile. With the rest of the state, these dimensions represent both elements that define the state of the game itself, but also events around which a social policy could be constructed. For example, the events: last feeding and last failed interaction could be interpreted as a successful and a failed action from a child and trigger each different social response from the robot. However, while having a semantic interpretation for humans, the state does not represent them as a positive or a negative event, but only as two dimensions of the state that could be used to select actions. And these dimensions, as well as all the other ones are considered in the same way, just as numbers that could be used to compute distances. Using these generic this state definition and way of treating them, this implementation could be easily repurposed to another teaching task. New events would have to be defined, but to adapt the state or action definition to another set of items, only the new names would have to be communicated, without any change in the code.

Actions

Table 6.2 present the list of actions used for this activity.

Table 6.2: Definition of each category of the action space.

Name	Number	Description
Move close	210	Action moving any animal close to any item
Move to	210	Action moving any animal to any item
Move away	210	Action moving any animal away from any item
Remind rules	1	Verbal utterance
Congratulation	1	Verbal utterance
Attention	21	Drawing attention to any item
Encouragement	1	Verbal utterance
Wait	1	Doing nothing

The total action space available is 655 actions. Each move action is composed of 210 possibilities as we have a total of 10 animals which can be moved in relation to each animal (10) and each plant (11), which resuts in 210 actions for moving close, 210 for moving to and 210 for moving away. It should be noted that technically 30 actions exist but cannot be selected by the teacher (moving animals to/close to/away from themselves), but this does not impact the learning as algorithm is an instance based algorithm only using already selected actions. Similarly to the states, each instances of a same category (such the different images of the wheat) is considered as a unique non-moving item unrelated to the other instances of the same type.

In the same way as the state definition, this action space has been selected to be general to many activities including movable and immobile images. The robot has access to a wide range of actions, the action space includes little semantic specific to this game. For example, many of actions are available even if they are not relevant in this specific game (such as moving close together two unrelated animals). This allows to repurpose this definition of actions (and by extend the learning mechanism) even if the rules of the game change. For this specific game, some actions are relevant and encompass the technical knowledge the tutor needs to have (such as which animal should be moved close to which one), while other are related to the social side, such as reminding the rules or providing encouraging feedback. Some other actions should simply be avoided as they could create confusion for the child. So, without having access to any semantic of the actions or rules of the game, the robot needs to learn which action are relevant to the task and when they should be executed.

Algorithm

The learning algorithm aims to reproduce the teacher's action policy by mapping an action (or no action) to each possible state. The state used in this study represents the situation of the game in a 210 dimensional vector, with continuous values from 0 to 1 and the action space is composed of 655 actions. In summary, the algorithm's task is to map an action from the 655 to each possible combination on the 210-dimension state, which without human feedback would be probably not possible to achieve in human environment.

The algorithm used for the learning is an adaptation of the one presented in Senft et al. (2017b). It is an instance based algorithm similar to the nearest-neighbours algorithm (Cover & Hart, 1967). However, two differences are notable compared to the initial algorithm.

Firstly, instead of being defined on the full state space, instances are only defined on a sliced version of the state. The intuition is that states needed to cover complex action policies require large numbers of dimensions, however for each single action, large parts of the state are irrelevant. For example, if a robot needs to pick-up a cup, the colour of the cup does not impact the optimal motion. In contrast, the colour matters if the robot has to answer the question: “which cup is on the left? The blue one or the red one?”. Consequently, the colour of the cup should be part of the state space, but should not be considered when selecting some of the actions. When selecting an action with SPARC, the teacher has the opportunity to specify features of the environment relevant to the selected action, then these features *activate* a limited number of the state dimensions related to the selection to this action in that state. Later, when selecting an action, the algorithm seeks for the instance in memory closest to the current state. In this evaluation, the similarity between the current state and the stored instances is only computed on the activated dimensions of the instances stored in memory. With this way of providing dimension reduction, the algorithm can have access to a large state, potentially covering different complex policies, but can still learn fast as if it were in a smaller state.

The second difference is that each instance saved has a reward assigned to it. To select an action, the algorithm looks through all the actions it has been using and for each action selects the closest instance to the current state (by computing the similarity on the activated dimensions of the stored instance) and computes the expected reward as a multiplication of the similarity by the reward. Then the algorithm selects the action with the highest expected reward and proposes it to the teacher if the value is higher than an adaptive threshold (cf. Algorithm 3).

Algorithm 3: Algorithm for selecting an action based on the previous instances tuples (partial state, action, reward) and the current state. Partial states (s') are defined on a subset of the state space with n' active dimensions.

inputs : s: current state, C: collection of (a, s', r)
output : selected action $\pi(s)$
foreach $a \in A$ **do**
  foreach $p = (s', r) \in C_a$ **do**
    compute similarity Δ between s and s': $\Delta(p) = 1 - \frac{\sum_i^{n'} (s'(i) - s(i))^2}{n'}$
  find closest pair $\hat{p}$:
  $\hat{p} = arg\,max_p \Delta(p)$
  compute expected reward $\hat{r}(a)$ for taking a in s:
  $\hat{r}(a) = \Delta(\hat{p}) \cdot r(\hat{p})$
  with $r(p)$ the reward r of the pair $p = (s', r)$
Select the action with the maximum expected reward: $\pi(s) = arg\,max_a \hat{r}(a)$
if $\hat{r}(\pi(s)) >$ *threshold* **then**
  Propose $\pi(s)$ to supervisor

For this implementation, when selecting actions, the teacher can touch a number of items in the screen and the image displaying the focus of the child to highlight the features of the environment which were relevant in her selection. Then, this *activates* the related dimensions of the state space which are used to store the instance in memory. Table 6.3 presents two example of the dimensions activated when some items are selected by the supervisor. When transferred to the algorithm for storing, the instance is composed of three objects: the action number (integer between 0 and 654), an array of the dimension of the state (210 float numbers) joined to a mask of the same dimension with a value of 1 for the activated dimensions and 0 for the others, and finally, the value of the reward. By default, all the generic events (death, feeding, failed interaction) and the generic times since the last child and robot actions as well as the time since that action was executed are *activated*. Later, when comparing the instance to the current state to select an action, only the dimensions with a mask value of 1 are be taken into account to compute the similarity.

Table 6.3: Example of dimension activation. By selecting features, the teacher can inform which dimensions of the state are relevant. By default, generic events and generic last actions, and time since selected action are activated.

Action	Features highlighted	Dimensions activated (number)	Total
Move eagle close to mouse	eagle and mouse	distance between eagle and mouse eagle's energy mouse's energy time since robot touched eagle time since robot touched mouse time since child touched eagle time since child touched mouse generic events (3) time since last move generic last action (2)	13
Draw attention to frog	frog	frog's energy time since robot touched frog time since child touched frog generic events (3) time since last drawing attention generic last actions (2)	9

In this type of HRI, the robot is expected to do an action every 3 to 15 seconds; however, some events might need a reaction around one second after happening. Consequently, to give enough flexibility in the timing of the suggested actions and enough time to compute the distance between the current state and each instance in memory, the algorithm ran at 2Hz (the rate of animals' life update due to hunger). So, unlike most of the discrete cases of action selection, in most of the steps no action should be executed. To handle this difference of timescale, a waiting action has been added (through the 'Skip' button) and an adaptive threshold limits the propositions to actions with a high expected reward. When receiving an action with a positive reward, if the threshold is higher than the previous maximum similarity between this action's instances and the current state, the threshold would be decreased of a tenth of the difference as the action should have been selected; and this effect is inverted for negative rewards (the threshold would be increased of a fifth of the difference as the action should not have been selected). These increase and decrease factors have been selected from simulations which led to good results. This aims to adapt the rate of action proposition to the desires of the teacher. A last mechanism filters propositions from the algorithm not to transfer them to the teacher when an action is already proposed, the teacher is selecting an action or the robot is currently acting. This filter also rewards negatively impossible actions (such as moving dead animals).

6.3.8 Protocol

The interaction protocol was as follows. Children were first introduced to the robot and the aim of the interaction and then had a first pre-test to evaluate their initial knowledge. After this test, and before starting the teaching game, children had to complete a tutorial where they were introduced to the mechanics of the game: animals have life and have to eat to survive and children can move animals to make them interact with other animals or plants and replenish their energy. After this short tutorial, they completed two sessions of the game where the robot could provide feedback and advices depending on the conditions they were in. Following these initial sessions of the game, children completed a mid-test before playing another two sessions of the game and completing a last post-test to conclude the study.

6.3.9 Conditions

The study evaluated three conditions: the passive condition, supervised condition and autonomous condition. In all the conditions, the robot's behaviour during the introduction, tests, tutorial and conclusion was identical. The only change of behaviour happened during the games sessions. The study design was between participants, so children were each assigned to a condition, and in all the game sessions, the robot would have always the same behaviour: passive, supervised or autonomous. When the robot was not acting, it simply oscillated slightly to simulate a breathing motion and followed the child's face.

Passive Condition

The *passive* condition served as a control condition. We decided to use a robot even in the control condition to prevent confounds related to the presence of a robot, such as novelty effect. The goal of the study is not to explore if a robot can be better than a human or than just the sandtray, but to study if by using SPARC, a human can teach the robot a behaviour having a positive influence on the children in the game. In this passive condition, the robot did not provide any advice nor feedback to the children during the game sessions.

Supervised Condition

The *supervised* condition was the one in which the robot learned, the one where SPARC was used by a human to teach the robot an efficient action policy. As such, it is not a static condition with an identical behaviour all the way, but a dynamic condition where the robot learns an action policy through the human supervision, while the teacher herself is evolving, getting used to controlling the robot. In theory, throughout the different interactions with the children, the behaviour expressed by the robot with the children should be similar and constantly appropriate. In contrast, during that time, the teaching interaction, between the teacher and the robot, should evolve due to the learning component on the robot side.

Autonomous Condition

The *autonomous* condition was used to evaluate if the learned behaviour was efficient and if the robot could display a useful social action policy without being supervised. During this condition, the robot used the action policy taught in the supervised condition, but without the teacher in the action selection loop. As such, this condition had to be ran after the supervised one, when the teaching was over.

In the autonomous condition, the robot used the suggestions from the algorithm and executed them with a probabilistic delay between 0 and 1.5 seconds based on the teacher's delay in answering the robot's propositions. This delay aimed to give a pace and synchronisation of actions similar to the ones exhibited by the teacher when reacting to the robot's suggestion.

6.3.10 Teacher

In the study, the teacher was a psychology PhD student from the university, with limited knowledge in computing and machine learning. She had been instructed how to control the robot using the GUI, the effect of each buttons and how to perform each action. She was knowledgeable of the methodology used to run the study (but not the underlying implementation) and experimented controlling the robot in two interactions with the author interacting with the robot and one with a child before starting to supervise the robot for the supervised condition. No information about the learning algorithm or the representation of the state and no feedback about optimal way of interacting or feedback on her action policy was provided before or during the supervision. As such, this robot teacher represented typical target populations for robotic applications: non-experts in machine learning or computing but with relevant domain knowledge such as teachers, psychologists or more broadly, people from the general population.

6.3.11 Metrics

To address the hypotheses presented in Section 6.2, we collected multiple metrics on both interactions (teaching and application). First, we recorded the actions executed by the robot in the supervised and autonomous conditions to characterise the two action policies. Additionally, two groups of metrics have been collected to evaluate the application interaction: the learning metrics (corresponding to the children's performance during the test) and the game metrics (corresponding to the children's behaviour during the game). And finally, in the supervised condition, we recorded the origin of the action executed by the robot (teacher vs algorithm) and the outcome of the proposed actions (executed vs refused).

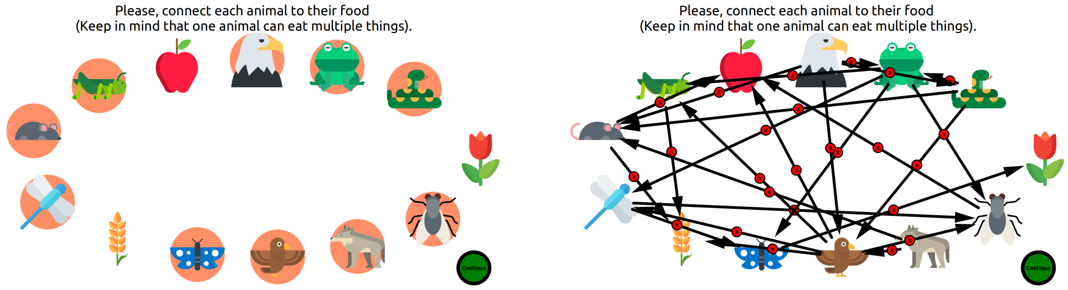
Policy Characterisation

During the game, the robot had access to 655 actions, which can be divided in seven categories: drawing attention, moving close, moving away, moving to, congatulation, encouragements and reminding rules. Due to this high number of actions, the largeness of the state space (210 dimension) and the complex interdependence between actions and states, totally defining a policy is impossible. Consequently, we decided to use the number of actions executed for each category per child to characterise the policy executed by the robot in the active conditions (supervised and autonomous). While not perfectly representing the action policy of each condition (e.g. the timing of actions is missing), this metric offers a proxy to compare these policies.

Learning Evaluation

The learning was evaluated through an open graph where children had to connect animals to their food. Figure 6.5 shows two examples of the test, with or without all the correct connections. Children were instructed to connect as many animals as possible. During the pre-test, the experimenter demonstrated how to connect animals by drawing an arrow from the frog to the fly, and then removing the arrow by pressing the *X* button.

When children thought they were done, they could press the ‘Continue’ button, showing a screen asking confirmation to quit the test or allowing children to keep connecting animals. Additionally, the robot informed the child if not all the animals were connected to a food or that animals could eat many types of food if no more than one animal was connected to two items.



(a) Empty screen that children face at each test. Red dots behind animals indicate that they are not connected to any food.

(b) Fully connected test with all the correct connections.

Figure 6.5: Test screen to evaluate children’s knowledge, empty starting screen (a) and fully connected and correct test (b).

tense?[ES] They are in total 25 different correct connections and 95 possible incorrect ones. As the child can connect as many arrows as desired, the performance is defined as the number of correct arrows above chance (for the number of connected arrows on the test) divided by the maximum achievable performance, to reach a score bounded to $[-1,1]$. For example, if a child connects 5 good arrows and 3 bad, their performance would be:

$$P = \frac{\#good - (\#good + \#bad)\cdot\frac{totalgood}{total}}{totalgood - totalgood\cdot\frac{totalgood}{total}} = \frac{5-(5+3)\cdot\frac{25}{25+95}}{25-25\cdot\frac{25}{25+95}} = 0.168 \qquad (6.1)$$

The three tests (pre, mid and post interaction) resulted in three performance measures. To account with initial differences of knowledge and the progressive difficulty to gain additional knowledge, we computed the learning gain as the difference between the final and initial knowledge divided by the ‘progression margin’: the difference between the maximum achievable performance and the initial performance. This learning gain indicates how much of the missing knowledge the child managed to gain from the game.

Game Metrics

Different metrics have been gathered during the game sessions to characterise the children’s behaviours:

- **Number of different eating interactions**: number of unique feeding action type [0,25].
- **Points**: cumulated sum of animals' energy over the game (typical range [550,1100]).
- **Interaction time**: Duration of game sessions, how long a game lasted until three animals ran out of energy (typical range [.5,3] minutes).

The number of different eating interactions informs on how many learning items the children have encountered in the games. A feeding interaction happens when an animal is moved to its food (or to a predator); and the number of different feeding interaction represents how many different unique correct connections the child been exposed to during the game (multiple feeding actions between the same animals would count only once). A game with a high number of different feeding represents a game where the child had the opportunity to learn many correct connections between animals. Consequently, by increasing this number, the children would be exposed to more learning items which should help them to perform better on the tests. Both the interaction time and the number of points reached in the game inform on the children's success in the task: keeping the animals alive as long as possible.

Robot Learning

In the supervised condition, the robot executed actions selected or validated by the teacher, and by using SPARC, the robot could propose actions to the teacher. Faced with a proposition, the teacher had multiple ways to react. They could accept the action (by waiting for it to be executed, pressing 'Do it' or selecting the same action manually) or refuse it (by pressing the 'Cancel', 'Skip' or 'Remove' buttons). As such, actions going through this pipeline can be divided in three categories: actions selected by the supervisor, robot's good propositions and robot's bad propositions. And the evolution of these categories represents how much the online component of the learning improved the quality of the robot's suggestions and reduced the workload on the teacher.

Some times the teacher cancelled actions and then selected them again, we called this effect the 'reselection'. To obtain the final numbers of accepted and refused actions, we removed these reselection from the bad propositions and we added them to the good propositions as it represents cases where the teacher refused an action by accident.

6.4 Results

Similarly to Chapter 5, we analysed the results using Bayesian statistics and the JASP software (JASP Team, 2018). We used a Bayesian mixed ANOVA as omnibus test to explore the impact of conditions or repetition on the metrics. Additional post-hoc tests use a Bayesian mixed ANOVA comparing the conditions one by one and fix the prior probability to 0.5 to correct for multiple testing.

6.4.1 Example of a Session

Table **??** presents an example of the first 50 seconds of a session. Propositions from the robot are in blue, and actions from the teacher in orange. For example, at t=14.6, the teacher accepted the proposition from the robot. Alternatively, in some cases, such as the suggestion at t=20.6, the teacher did not evaluate actions proposed by robot, but just selected another action. In that case, the action proposed is not evaluated and only the selected action is executed and used for learning. In other cases, such as at t=6.6, the algorithm suggested an action, the teacher decided to wait, before selecting it again after a short delay. This is an example of 'reselection' as mentioned before. Finally, at t=44.4 seconds, the teacher selected the action to move the mouse closer to the wheat, and after the robot moved the mouse, the child tried other animals and then fed the mouse with the wheat, demonstrating how the actions from the robot could help the children to discover new connections between animals.

6.4.2 Comparison of Policy

Figure 6.6 presents the number of actions of each types executed by the teacher (in the supervised condition) and the autonomous robot. Both action policies presented similarities: the action 'Move away' was almost never used, 'Move to' was never used, and the supportive feedback ('Congratulation' and 'Encouragement') were used more often than 'Remind rules' or 'Drawing attention'. However, some dissimilarities were also present, for instance, the autonomous robot used more encouragements than congratulations while the teacher did the opposite. The autonomous robot also reminded the rules more often and used the 'Move close' action less than the supervisor. These differences of actions are probably linked to the type of machine learning used; with instance based learning, some datapoints will be used in the action selection much more often than others, which might explain these biases. But these results show that the robot managed to learn a social and technical action policy presenting similarities with the one displayed by the teacher providing partial support for H1.

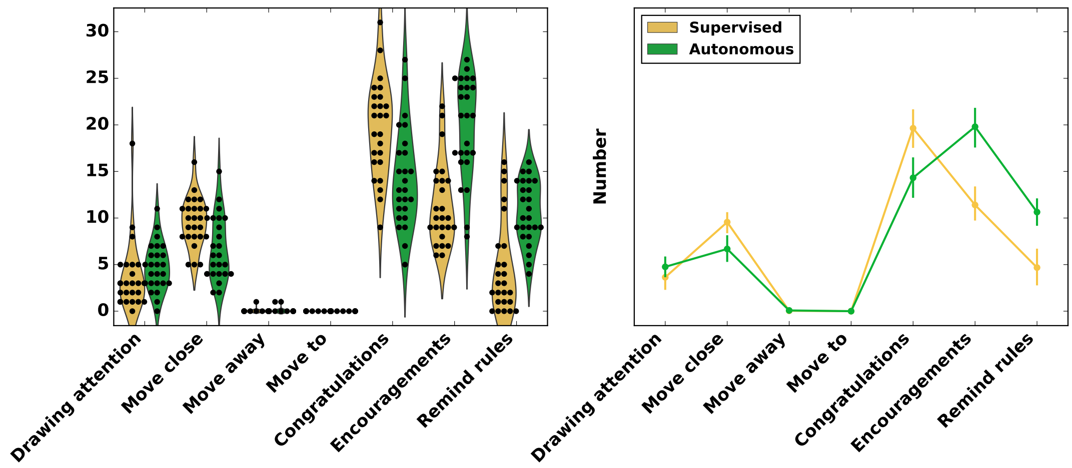


Figure 6.6: Comparison of actions executed by the robot in the autonomous and supervised conditions. The left graph is a violin plot of the data, while the right presents the means and the 95% Confidence Intervals

6.4.3 Test Performance

Figure 6.7 shows the evolution of children's performance across the three tests. A Bayesian mixed-ANOVA showed that in all conditions, children's performance increased across the tests ($B = 1.5\text{x}10^{12}$), however the impact of the condition on the learning was inconclusive with a tendency to show no impact ($B = 0.539$). This indicates that by being involved in the task, every children learned and improved their performances on the test (by gaining in average 13% of the missing knowledge), but the robot behaviour during the game did not have an important impact on the children's learning gain (see Figure 6.8), invalidating H2. should I discuss the inhomogeneity of the population, wide variation of P1[ES]

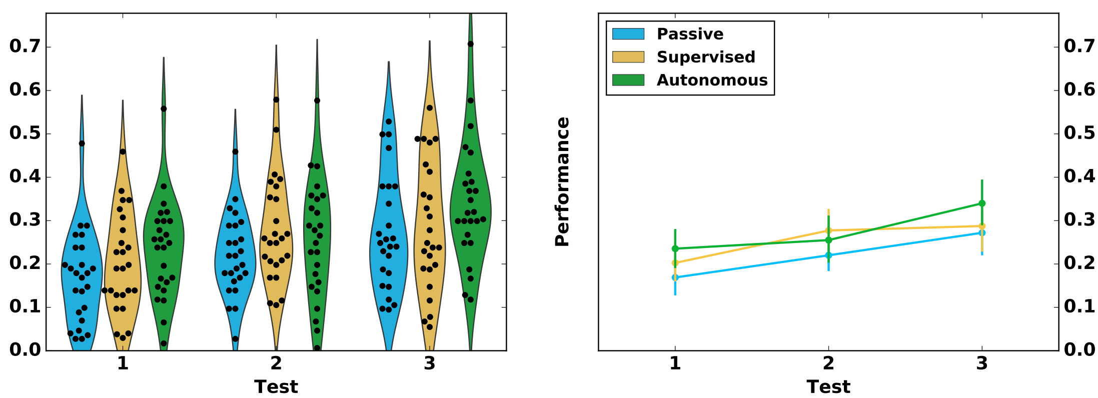


Figure 6.7: Children's performance for the three tests: pretest, midtest and posttest for the three conditions.

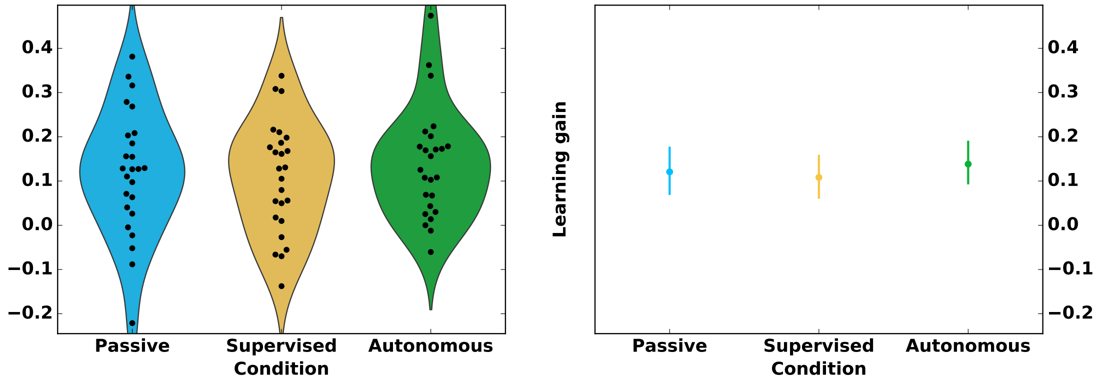


Figure 6.8: Children's normalised learning gain after interacting with the robot for the three conditions.

6.4.4 Game Metrics

Different eating behaviours Figure 6.9 shows the evolution of the number of different eating behaviours exhibited by the children across the four game sessions. A Bayesian mixed-ANOVA showed an impact of the condition on the number of different eating behaviours produced by the children in the game ($B = 6.1$). Post-hoc tests showed the absence of difference between the supervised and the autonomous conditions ($B = 0.154$), whilst differences were observed between the supervised and the passive condition ($B = 512$) and between the autonomous and the passive conditions ($B = 246$). This indicates that, compared to the passive robot, the supervised robot provided additional knowledge to the child during the game, allowing them to create more useful interactions between animals and their food, receiving more information from the game potentially helping them to learn. And the autonomous robot managed to recreate autonomously this effect without the presence of a human in the action selection loop.

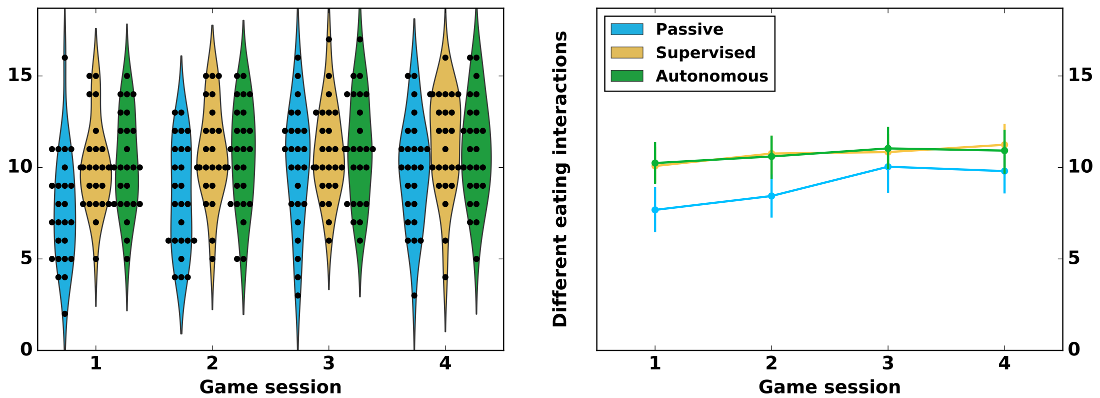


Figure 6.9: Number of different eating behaviour for the four games for the three conditions.

Points Figure 6.10 shows the evolution of the number of points achieved by the children across the four game sessions. A Bayesian mixed-ANOVA showed an impact of the condition on the number of points achieved by the children in the game ($B = 10.2$). Post-hoc tests showed a strong difference between the passive and the supervised conditions ($B = 5.1\text{x}10^4$) and differences between the supervised and the autonomous conditions ($B = 5.2$) and the autonomous and the passive condition ($B = 5.9$). This indicates that when the robot was supervised, it allowed children to achieve more points than a passive robot. And a similar effect was observed when the robot was autonomous, however the autonomous robot did not manage to reach the same efficiency as the supervised robot in helping the children to achieve a high score in the game.

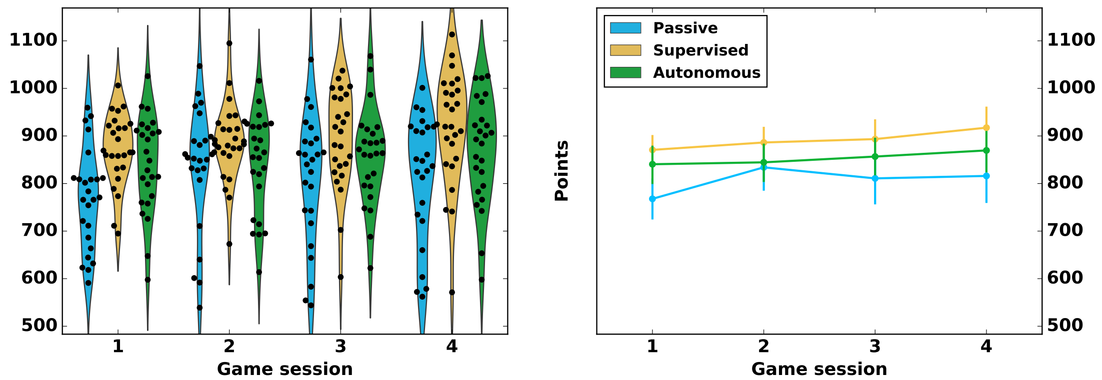


Figure 6.10: Points achieved by the children in each game session for the three conditions.

Time Figure 6.11 shows the evolution of interaction time across the four game sessions. A Bayesian mixed-ANOVA showed inconclusive results on the impact of the condition on the interaction time in the game ($B = 1.1$). However, post-hoc tests showed the absence of difference between the supervised and the autonomous conditions ($B = 0.287$), whilst differences are observed between the supervised and the passive condition ($B = 118$) and a tendency of difference between the autonomous and the passive conditions ($B = 2.9$). This indicates that the supervised robot allowed children to be better at the game, allowing them to maintain animal alive longer than a passive robot. And the autonomous robot learned and applied a policy tending to replicate this effect and without exhibiting differences with the supervised one.

Summary These game metrics showed that the action policy executed by the autonomous robot allowed children to achieve similar results in the game than when the robot was supervised, and better results than when interacting with a passive robot.

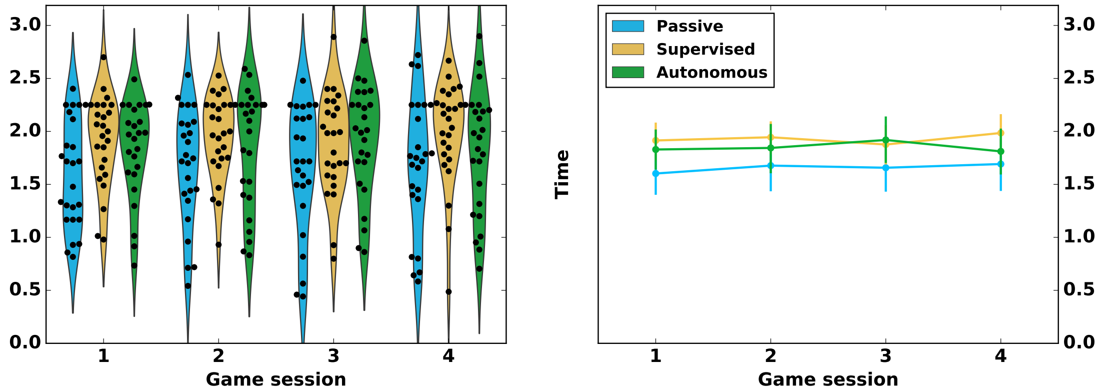


Figure 6.11: Interaction time for the four games for the three conditions.

This provides support for H1 ("The autonomous robot is able to interact socially and efficiently during the game sessions and maintain the child's engagement during the learning task").

6.4.5 Teaching the Robot

Figure 6.12 presents the reaction of the teacher to the robot's suggestions across all the supervised interactions. Unlike our expectations, the number of correct and bad suggestions as well as teacher selections stayed roughly constant through the interactions with the children. In average, the robot proposed 17.2 (SD=4.0) actions accepted by the teacher and 41.7 (SD=11.1) refused by the teacher per interaction. And the teacher selected manually 25.8 (SD=5.8) actions per interaction. These unexpected results are discussed in details in Section 6.5.2.

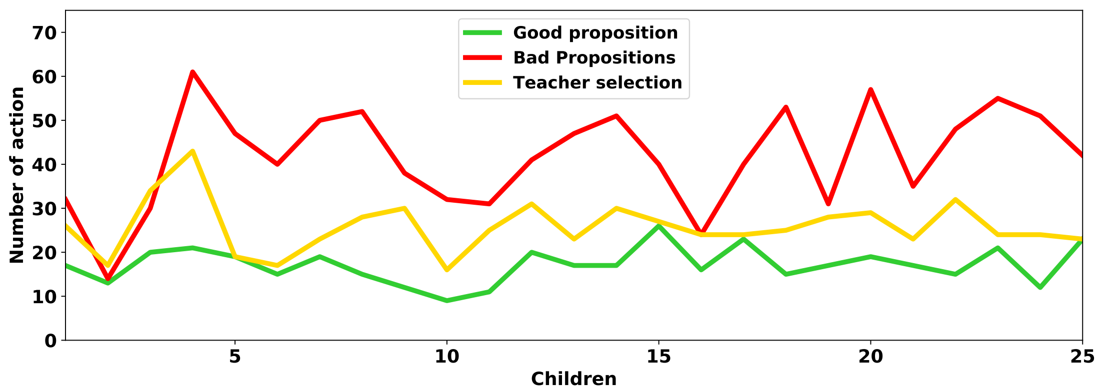


Figure 6.12: Summary of the action selection process in the supervised condition: the 'teacher selection' label represents each time the teacher manually selected an action not proposed by the robot.

Figure 6.13 presents the accumulated number of different actions in the policy the teacher used. We can observe a sharp increase in the first 5 interactions, when the teacher used the main actions for the first time. Then there is a mixture of small plateaus and small increases, indicating that the teacher alternated phases where she enriched her action policy and phases where she maintained her policy. And finally, the number of different actions in the policy seems to converge around 60 toward the last interactions.

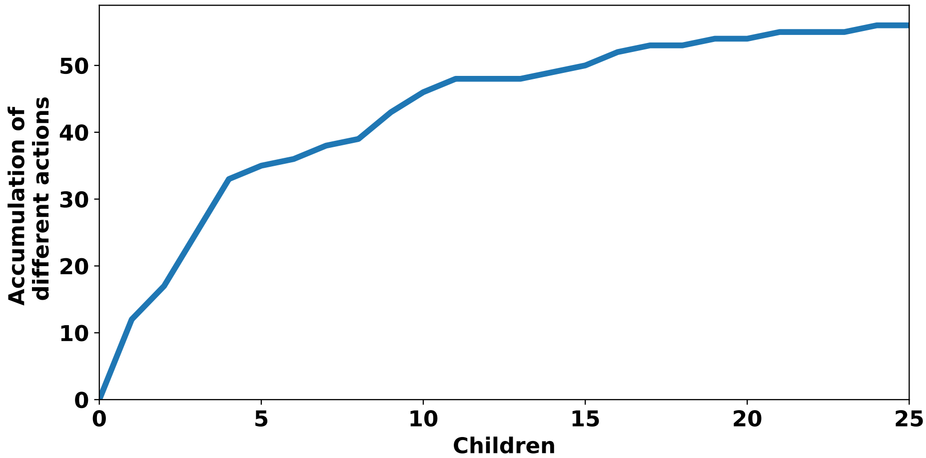


Figure 6.13: Number of different actions used by the teacher throughout the interactions with the children.

In post-hoc discussion, the teacher reported three phases in her teaching:

- First sessions: she was not paying much attention to the suggestions, mostly trying to have the robot executing a correct action policy.
- Session 6 to around 16: she was paying more attention to the suggestions without giving them much credit.
- Last sessions: she started to trust the robot more but without ever trusting it totally.

Appendix B presents a more detailed diary of the teacher throughout her supervision. Additionally, while the buttons cancel and skip has different impact of the learning, and were designed to be used in different cases, the teacher reported that she used them interchangeably.

The teacher did report a decrease of workload as she she progressed in the sessions number. This was supported by behaviours such as typing her observations on a laptop, while gazing at the interface in multiple interactions (especially at the start of a session). However, as shown by the evolution of curves in Figure 6.13, this decrease of workload seemed to be due mostly due to the teacher getting used to the interaction, and not to the online learning and the improvement of the suggested proposition, invalidating H3.

6.5 Discussion

6.5.1 Children Behaviours and Learning Gain

The active robots' behaviour encouraged children to produce more 'useful' behaviours during the interaction. When interacting with the active robots, children encountered more situations with learning potential (such as the different eating behaviours). However, this additional exposure to learning items did not transform into an increase in learning gain. In the three conditions, the children learned similarly; thereby not supporting H2. We identified two possible roots for this absence of transfer between positive game behaviours and performance in the test. The first one is that the game by itself, without the robot, encouraged the children to explore and interacting solely with it was sufficient to create learning. Consequently, the robot's behaviour might have distracted children from their exploration. In that case two effects might have cancelled each other: on one hand the behaviour of an active robot provided additional knowledge to the child, but on the other hand it might have perturbed their exploration of the game, potentially reducing their learning. This might explain the absence of effect of the robot's behaviour on the children's performance. The second possible origin would be in the test itself, it might not have been able to capture the exact knowledge of children. The test only asked children to connect as many animals as possible. However it might have been a too open-ended question, and might have not encouraged children to really draw all the connections they knew. In that case, the test would represent the real knowledge of children, but only be a lower bound. Having forced choices questions, for instance selecting randomly 20 connections and ask children if they are valid, might have provided a better evaluation of the children's knowledge.

6.5.2 Robot Learning

One of the motivation of SPARC is that it provides a way to smoothly move away from WoZ to Supervised Autonomy, potentially leading to pure autonomy. By learning online the action policy, the number of actions selected or corrected by the teacher would decrease and the number of accepted suggestions would increase, hence reducing the teacher's workload. However, this expectation (and by extend H3) was not validated by this study's observations. The number of actions accepted, refused and selected by the teacher stayed roughly the same throughout the interactions. We identified five potential reasons explaining this differences.

Suggestion rate too high. The first reason was that the robot proposed a large number of actions (58% more than the total number of executed action). This indicates that the adaptive threshold restricting actions to be proposed was constantly too low. This high number of proposed actions partially explains the high number of actions refused by the teacher. Additionally, as the robot tended to propose actions too often, the teacher reached a point in her supervision where she often preferred refusing the robot's propositions even in cases when they were correct rather than taking the time to evaluate them and the risk to have undesired actions executed.

Human adaptation. A second effect limiting the correctness of the propositions is the evolution of the teacher's policy. As the teacher progressed in the interactions, she increased the complexity of her action policy, adapting it to each child and using more different actions. As the algorithm only proposed actions previously used, this lead to a requirement on the teacher to select new actions enough times to inform the algorithm when they should be selected. Having such a moving target to learn limited the maximal performance achievable by the algorithm. Toward the last interactions, the number of different actions used by teacher tended to converge, this indicates that the algorithm might have achieved better results at predicting the teacher's actions in the following interactions.

Continuous time. This study also stood out from classic problems using Machine Learning (ML) on another point. In this study, the agent interacted in a continuous time, whereas generally agents in ML only exist in a discrete time. In classical Markov Decision Process (MDP) frameworks, an action has to be selected at each step, actions last one step, and optimal strategies might exist. However, when interacting in the real world, actions take many steps and in most of the steps no action should be selected. Additionally, due to the continuous side of the time, actions are not valid at a specific step, but around that step. This imply that to reduce the teacher's number of selected actions, the algorithm does not have to select the same action as the teacher at each step, but needs to anticipate the teacher's actions, so that the teacher does not select them first. Such a requirement for the algorithm limits the visibility of the results. The algorithm might select correct action around the time the teacher would select it, but if that proposition arrived a step after the teacher's selection, it would not be considered as a good proposition.

Algorithm. An other element potentially explaining the limited efficiency of the online learning is related to the algorithm itself. In its simplest form (and as used in this study), nearest-neighbours considers only one neighbour, making it highly sensitive to outliers. Consequently, some instances in memory could be used too often, leading to an imbalance of policy (as observed when comparing the autonomous and supervised policy). One of the way to tackle this issue could be to use the k nearest neighbours rather than only the closest one, this might have led to a more robust learning algorithm.

Difference of state representation between human and robot. Finally, in such complex tasks, humans are making use of a large number of 'states', such as temporal relations between events, to select actions, and if the state definition the robot uses does not contains or cannot deal with these features, the learning will be limited. As mentioned in Section 2.2.4, Knox et al. (2014) and Sequeira et al. (2016) stress the fact that the human teacher (or demonstrator) should have access to the same features as the algorithm to increase transferability. However, even when this recommendation is followed, the teacher can create temporal structures which would not be available to the algorithm (especially an instance-based one), reducing the potential for exactly learning the teacher's policy. In this study, for methodological reasons, we did not remove the teacher from the room where the child interacted. Consequently, this allowed the teacher to have access to features of the interaction absent from the state representation used by the algorithm. For example, the teacher used some times the results from the tests (initial and mid) to inform her action policy. However these features were not available to the robot, which might have limited the learning. Additionally, in this study, the teacher did not use 'complex' features selection. She mostly used the minimum number of features required for an action to be unambiguous even if she might have used other features for her decision. One example of a complex action would be to indicate to the child the food of the animal they are currently touching. To inform the algorithm that the fact the child is touching this specific animal matters, the teacher would need to select the animal touched by child while selecting the 'drawing attention' action on its food. Whilst being possible, this feature of the teaching was not used in this study, potentially preventing the algorithm to have access to the exact set of features used by the teacher when selecting an action.

Summary While the autonomous behaviour was different from the taught one, both policies still presented many similarities in the distribution of actions executed by the robot and the children's reaction to the behaviours. Additionally, the challenge of learning a suitable action policy for the robot should be highlighted: the state is large, continuous and with a large number of possible actions, the interaction is social and multimodal, and finally, the algorithm had no initial knowledge provided, all the semantic of the interaction was inferred from the demonstrations and feedback. With more training data and an improved algorithm, the robot learning could have been more efficient and might have lead to a decrease of workload for the teacher and an increased similarity between the the teacher's policy and the autonomous robot's one.

Stopping condition

During this study, for reasons of availability of children and time, each conditions involved 25 children. This means that the robot learning stopped at some point without possibility to refine its action policy, and this conditioned all the results observed in the autonomous condition. By involving more children in the supervised condition, the teacher's action policy might have converged. The learning algorithm might have increased its performance in suggesting more appropriate actions to the teacher, potentially reducing her workload. This relatively arbitrary cut-off the learning progress had important impacts on both the supervised and autonomous condition, and continuing with more children or stopping earlier might have lead to dramatically different results.

6.5.3 Importance of the Teacher

SPARC includes two distinct but simultaneous human-robot interactions. Thus, evaluating such interconnected interactions is a complex task as each human's behaviours impacts the other one's. To explore a in a repeatable and comparable manner an interaction, the other one needs to be as constant as possible. However, humans are not constant and consequently evaluating these two interaction simultaneously is a challenge. By deciding to keep the same teacher for all the interactions, we only have a sample of one participant as a robot teacher. Consequently, this study is in essence a case study of one participant teaching a robot to interact with children; and this could have created some biases in the supervision. As seen in previous chapters, different humans would teach the robot differently. It would have been interesting to explore this axis, try distinct teachers and observe how their different behaviours would impact the learning process and the final policy. We would expect that the resulting autonomous behaviours should match the multiple teachers' policy. However due to the variability of children, a large number of them are required to evaluate a robot and a teacher behaviour. As such, we did not evaluate more than one teacher in this study.

6.5.4 HRI is Human Centred

When a robot is supervised to interact with a human, and especially with a child, the main goal of the teacher is to ensure that the experience for the child is optimal. Consequently, the teacher will be more focused on the child's behaviour than the robot learning. For instance, if an action would help the child but hinder the learning for a reason (for example an unusual child behaviour), the teacher would most certainly 'damage' the robot learning to improve the child experience. Except specific cases (for instance when using actors or informed participants), teaching a robot to interact with humans will always be only a side activity or a by-product of the interaction.

Furthermore, in HRI the robot partners will be different persons; and, as of today humans have access to a much richer representation of the world and knowledge of social interaction teachers will tailor their policy to the specific person involved in the interaction in a way potentially unmatchable by a robot. This resulting human behaviour will not be one homogeneous policy applied to all the partners but potentially one per person. This is a challenge for ML as it further increases the complexity of the task. The algorithm either have to learn a much larger action policy (covering all the different types of human partners) or learn a multitude of policies and be able to switch between them. Alternatively, robot could start with an initial general policy and then use SPARC with a teacher to refine it and adapt it to the specific context of each interaction.

6.5.5 Opportunities

Despite the limitations of this implementation of SPARC, this study demonstrated the first application of SPARC to real HRI. A robot learned to interact efficiently in a complex and rich environment with humans from in-situ supervision. Would that be the first time?[ES] The autonomous robot produced an action policy similar to the one demonstrated by the teacher in the supervision, and the effects on the children were similar too (improvement of game metrics compared to a passive robot). This supports H1: the autonomous robot was able to interact socially with children and sustained engagement during the task (as demonstrated by the higher number of points and interaction time compared to the passive condition). This is an important contribution as the robot learned to interact in a complex, mutlimodal and social environment in the real world, including large state and action spaces and where errors could have an important cost on the interaction (for instance having a child refusing to continue the interaction, or having a negative image of robots).

Furthermore, this achievement also used a teacher without knowledge in robotics or ML. This support the applicability of SPARC by a large part of the population and by extend increases the potential for people to be able to teach robots complex behaviours. This might help to reduce the entry bar for creating interactions with robots. If people do not need to know robotics or how to code to teach a robot a social behaviour, it may help to democratise the use of robots.

Even if the online learning did not reduce the teacher workload much through the interactions, SPARC possesses two advantages compared to offline learning from WoZ or Human-Human Interaction (HHI) data using Learning from Demonstration (LfD) (Sequeira et al., 2016; Liu et al., 2014). Firstly, the learning algorithm has access to more datapoints: the teacher's selection but also their reaction to the algorithm propositions and in cases where the teacher evaluate each datapoint, this provides valuable additional knowledge. Secondly, by receiving feedback about the algorithm's knowledge, the teacher can create a mental model of the robot and have an idea of how accurate its action policy is. By interacting with the learning algorithm, the teacher can start building a trust grounded by their experience with the learner, potentially knowing its strengths and weaknesses. Finally, this teacher's knowledge of the learner's state can ease the decision of deploying the robot to interact autonomously as the teacher experienced the policy and knows what to expect from the algorithm.

reread[ES] Additionally, the state and action spaces were generic to tasks including movable images and events. There was a limited number of add-hoc features in the state definition: only two categories of images, the moving ones and the immobile ones, but without any semantic relations between them. Both the action space and the state were agnostic to the semantic of actions, just considering each dimension of the state as a number and each action in the same way. However, from this generic definition of the world, the robot learned an action policy tailored to this task, exhibiting actions making sense in this context and at appropriated time. This demonstrate that by using

SPARC, a precise action policy can emerge from a generic description of the world. For example it would require only a limited amount of work to repurpose this environment to another setup involving moving images (such as math or language in the context of education), and the robot could be taught a new action policy adapted to this new environment with the same algorithm. This has real world implication as it allow to learn actions policies specific to different contexts while having only generic description of the state. This is a important feature of the algorithm used in this study, by slicing the state space and using demonstration, the initial dimensions of the state and action spaces are irrelevant, adding additional dimensions in the space will not impact the learning if the teacher does not select them. The state could be as large as desired, as long as the teacher has a way to inform the algorithm of the relevant features, it can learn an action policy quickly.

6.6 Summary

To conclude, this study proposed a new task for robot tutoring: a learning game to teach children about food webs, and most children involved in the study learned and improved their knowledge through the interaction. Additionally, for the first time in this research SPARC has been applied to teach a robot to interact with humans in a complex and social environment. By using a novel algorithm adapted from the nearest-neighbours and designed to learning quickly in multidimensional states, the robot learned to produce a behaviour similar to the teacher's one. Furthermore, this teaching was performed by a user not expert in ML or robotics. While not leading to improvements in the children's learning gain, the behaviours from both the supervised robot and the autonomous one did improve the performance of the children in the game.

In summary, by this study we provided partial support for the main thesis of this research: "A robot can learn to interact meaningfully with humans in an efficient and safe way by receiving supervision from a human teacher in control of the robot's behaviour." And, while presenting limits in the current implementation (for instance by not reducing the teacher's workload over time), SPARC succeeded in its goal to allow a user non-expert in computer science to safely teach a robot to interact with humans in the real world.

Chapter 7

Discussion

Chapter 2 put the light on the absence of robot controllers today providing adaptivity to a robot with a low workload from humans and while ensuring that the robot's behaviour is constantly appropriate. Based on this observation, Chapter 3 presented the Supervised Progressively Autonomous Robot Competencies (SPARC), an interactive teaching framework designed to allow robots to learn a social interactive behaviour by being supervised by humans. Then Chapters 4, 5 and 6 evaluated this approach in three studies, the last of which evaluated SPARC in real Human-Robot Interaction (HRI) consisting of a learning activity involving 75 children. Combined together, these chapters sought support for the thesis of this research:

> A robot can learn to interact meaningfully with humans in an efficient and safe way by receiving supervision from a human teacher in control of the robot's behaviour.

This chapter combines the results from the different studies presented in this research to discuss the findings. It starts by presenting the limitations of the approach proposed in this work, SPARC. Then, Section 7.2 presents how the three studies executed in this research work answered the research questions raised in Chapter 1. Section 7.3 discusses the more general impact this research may have and the ethical questions raised by teaching robots to interact. Finally, the last section proposes axes where SPARC could be extended to increase our knowledge in how humans teach robots and improve SPARC's usability and application to HRI.

7.1 Limitations of SPARC

SPARC, as presented in Chapter 3, is a promising framework to teach robots to interact with humans or in high stake environments, but presents several limitations restricting the range of domains it could be applied to.

7.1.1 Requirement of a Human in the Loop

The first of these limitations is the requirement of a human to supervised the robot, even once it has learn an action policy. As stated earlier, SPARC aims to move away from Wizard-of-Oz (WoZ) or other teleoperation methods by learning an efficient action policy from the human commands. In its original framing, SPARC did not aim to create a fully autonomous agent behaving without supervision, but to smooth the teaching phase and the use phase into one single interaction using Supervised Autonomy. In this single phase, the workload on the supervisor would decrease as the robot learns while a high performance in the domain application would be maintained due to the control provided to the teacher. However, Supervised Autonomy still requires a human involved in the supervision and as such presents limited applicability to fields where robots are expected to fill gaps in human workforce or to reduce the requirements on humans.

Despite not being the original goal, SPARC can still be used to create a fully autonomous behaviour (as demonstrated in Chapter 6). In that case, the training process would be similar to Learning from Demonstration (LfD), with a training phase using SPARC and then the testing/deployment phase of the autonomous behaviour. However, by using SPARC two differences remain. First, during the training phase, instead of passively receiving commands from the teacher, the robot would proactively make suggestions to the teacher. As presented in Section 6.5.5 this aims to reduce the workload on the teacher during the training phase, provide more datapoints for the learning and inform the teacher about the state of robot's knowledge, potentially creating trust between the robot and its teacher. Second, even after being deployed to interact autonomously, the teacher could still step back in control using SPARC again to refine the action policy. Alternatively, if a different behaviour has to be applied (e.g. if the robots interact with a child with special needs rather than a typical one), the teacher can take over using Supervised Autonomy to ensure a personalised experience for this specific interaction.

7.1.2 Reliance on Human's Attention

A second limitation of SPARC lies in the constant need for the human's attention and the presupposition that human teachers will always ensure an appropriate robot behaviour if given the opportunity. Throughout this research, we assumed that even if the robot behaviour may be mostly correct, the supervisor would be attentive to the robot suggestions and ready to correct them at any time. This assumption is similar to autonomous cars using a safety driver or Tesla Autopilot requiring continuous human supervision. The agent is fully autonomous but may make mistakes and as such, a human needs to be ready to correct these errors before they impact the world. However, as demonstrated by the accidents in 2017 and early 2018 involving these supervised autonomous vehicles, this assumption is often violated, and a short moment of inattention may have dire consequence[1]. By observing a seemingly correct agent's behaviour for an extended period, the human supervisor might start to overtrust the agent, missing the occasion to react in time to anticipable errors potentially leading to frustration or death in the case of autonomous vehicles[1]. However, some ways exist to mitigate this limitation but have not been applied to autonomous driving or general Interactive Machine Learning (IML). For example, with Supervised Autonomy the agent informs in advance the supervisor about its actions, similarly a car could display the planned trajectory on a screen or in augmented reality. This would provide the supervisor with more time to analyse the situation potentially allowing them to react in time. Alternatively, the agent could communicate a lack of confidence in its actions or its interpretation of the environment, informing the supervisor that attention is specially required in that moment.

7.1.3 Time Pressure

check[ES] As pointed already in Section 3.5.1, with SPARC, the presence of the correction window and the auto-execution of actions may lead to issues. To be applicable and make use of the auto-execution of actions as a way to reduce workload, the validity window of an action needs to be wider than its correction window. That way, actions approved passively are still valid when executed. To increase the application of SPARC to a wider range of situations, the correction window has to be as narrow as possible. In contrast, the supervisor needs a correction window as wide as possible, to provide them with enough time to process the action and cancel it if required. Correction windows too narrow would put additional pressure on the supervisor to react in time or even prevent them to avert undesired actions. This results in two effects having opposite requirements on the correction window. However, while a longer correction window would only limits SPARC's applicability in some situations, one too short could have negative consequences. As such, this need of a correction window wide enough to

[1]Cf. the Tempe and Mountain view accident reported by the media in early 2018.

allow the teacher to react is probably on of the main limits of SPARC as it produces a significant delay in the robot's actions.

reread[ES] However, this requirement of a correction window wide enough for the teacher can be mitigated in multiple ways. For example, instead of communicating the action the robot is directly about to do, the robot could communicate a plan with multiple steps announced in advances. That way, the teacher would be informed beforehand of the next few steps and could anticipate their impact and react to any future actions instead of limiting their evaluation to the next one. Alternatively, the robot could adapt the length of the correction window to its confidence in the proposed action; for instance, an action with a low confidence would be given more time to be corrected. Likewise, each type of action could have a dedicated value for the correction window, for example actions needing to be executed quickly (such as emergency breaking for example) would have a much shorter correction window than other actions with less time constraints. Finally, a last possibility could be to allow the teacher to manually select the duration of this correction window, and so be in control of the pace of the interaction.

7.1.4 Overloading the Teacher

?[ES]

By giving an active roles to the robot in the teaching process (through proposing actions), SPARC requires from the teacher to monitor simultaneously two autonomous agents: the human target and the robot. This requirement might lead to another risk with SPARC: overloading the teacher with suggested actions. If the teacher has to correct more actions than they would have selected, their workload is not reduced but increased. While still providing useful information for the learning algorithm (and more than only the actions selected by the supervisor), this supplementary workload on the teacher is not desired. As explained before, this could lead to erroneous teacher's behaviours hindering the learning and potentially increasing the risks in the interaction. For example in the study presented in Chapter 6, the teacher some times just cancelled actions as soon as they arrived, even before she had time to evaluate the action. While reducing the workload on the teacher by not requiring them to evaluate the proposed action, this behaviour might limit the efficiency of the learning algorithm.

The learning algorithm needs to have the right balance between suggestions and waiting periods to allow the teacher to analyse and provide a correct evaluation of the proposed actions. In other words, the algorithm needs to adapt the rate of suggestion to the pace of the interaction not to overload the teacher.

7.1.5 Interface

check if makes sense[ES] The interface between the teacher and the robot is key when applying SPARC or other IML methods. Simple interfaces can be easy to create and used by the teachers, however they might only have limited efficiency in the learning process. For instance, approaches using only feedback require a single one-way communication channel between the teacher and the robot, and this channel only needs to send a scalar evaluation of the agent's actions. Consequently, both the design of the interface for the teacher and the communication are simple. On the other hand, to provide full control and accountability on the robot's actions, SPARC requires both ways communication. First, the teacher needs to receive inputs from the robot, such as its intentions, to decide if the action is valid or not. Second, the teacher needs to send information to the robot: feedback about the intentions, to preempt actions if required, but also demonstrations, to select actions for the robot to execute. As the robot may have access to hundreds of actions, assigning one button per action is not feasible, other ways of commanding the robot need to be found. Furthermore, as mentioned in Chapter 3, with SPARC the teacher can also provide additional information to the algorithm to speed up the learning. In summary, the interface between the robot and the teacher needs to provide the teacher with the robot's intention, allow the teacher to preempt actions, select any action and provide additional information to the learning algorithm. An interface providing all these features can easily be bloated and difficult to use by humans, increasing even more the required workload to control and teach the robot. As such, for applying SPARC to complex environments, efforts need to be invested in the interface to make it intuitive and clear.

For instance, in Chapter 6, the Graphical User Interface (GUI) used by the teacher represented the current state of the game, with some buttons for accessing a subpart of the action space, but the majority of actions was inferred by the way the teacher move items on the screen and the items selected. An alternative way could be to use natural language. Humans are expert in using natural language to communicate and the open-endedness of this tool makes it suited for applications of SPARC where the teacher can speak and where the time required to vocalise commands is not critical, such as a robot assistant at home.

7.1.6 Learning with Humans

?[ES]

SPARC has been designed to enable agents to learn safely in high-stakes environments where no simulator can be used to learn in a virtual world (e.g. HRI). By including a human in the action selection loop, SPARC aims to prevent erroneous actions to have negative impacts. However, this addition adds a time constraint: by including a human in the interaction, the interaction needs to go at a human pace. This implies that gathering datapoints through SPARC is a relatively slow process. As such, algorithms using SPARC need to be data efficient, be able to learn from a low number of datapoint and generalise quickly. However, by including the human in the loop and learning in the real world, we can have important additional features. First, the points accumulated are sure to be relevant to the learning process: they come from the desired interaction and as they have been validated by a human, their label must be correct. And secondly, the human can also provide additional information on the selection to quicken the learning (as implemented in Chapter 6).

7.2 Research Questions

This section will revisit the research questions identified in Section 1.2 and explain how the work presented in this thesis addressed them.

RQ1 **What are the requirements of a robot controller to ensure a behaviour suited to HRI?** Based on a review of the different fields of application of social HRI, we defined three requirements a robot controller should follow to ensure an efficient interaction. First and foremost, the robot's behaviour needs to be constantly appropriate: as robots often interact with vulnerable populations, their behaviour needs to be constantly safe for the humans they interact with. Secondly, the robot should be adaptive, be able to generalise to unexpected situations, but also personalise its behaviour to the different humans it interacts with and be able to learn, improving and extending its action policy. Finally, the robot needs to be as autonomous as possible, or at least require a low human workload to interact in the world.

RQ2 **What interaction framework would allow a human to teach a robot while validating the requirements from RQ1?** To validate the three principles expressed as answer to RQ1, we proposed SPARC, a new teaching framework for robots which provides control over the robot's actions to a teacher and use this control to learn in a safe way, validating the first and second requirements. Secondly, by allowing the teacher to passively accept the robot's propositions, we aim to decrease the workload on the teacher over time and progressively provide the robot with autonomy.

RQ3 **Could a robot decrease its supervisor's workload by learning from their supervision?** Study 1 showed that providing a supervised robot with learning can reduce the workload on its supervisor. Furthermore, study 2 demonstrated that, compared to other methods, SPARC is an efficient way to enable a safe teaching and requires a comparatively low workload.

RQ4 **How providing the teacher with control over the learner's actions impacts the teaching process?** Results from study 1 and 2 indicate that by informing the teacher in advance of its actions, the robot ensures that its final behaviour is correct. This implies that even in early phases of the learning, when the robot behaviour is not adequate yet, the teacher can prevent the robot's lack of knowledge to negatively impact the world. Furthermore, this control helps the teacher to steer the robot toward useful parts of the environment and a good policy, making the teaching faster, safer, more efficient and lighter (as requiring a lower workload) than other methods lacking control.

RQ5 **How teaching a robot to interact socially impacts the two humans involved in the overall triadic interaction?** When being used to teach a robot to interact with a human, SPARC does allow the robot to constantly have an efficient behaviour (as demonstrated by the improvement of children's behaviours in the supervised condition in Chapter 6). However, this performance in the application interaction might come with a cost for the teaching interaction. As the teacher needs to react to the robot's suggestions, they do have to monitor a second autonomous agent, which might lead to a heavier workload than other supervision methods.

RQ6 **After receiving supervision from a human, could a robot behave autonomously in a social context?** In Chapter 6, we used SPARC to teach the robot in the supervised condition, and then deployed the robot to interact autonomously. During this autonomous interaction, the robot applied a policy similar to the demonstrated one, and the impact on the children's behaviour was close to the one in the supervised condition. Consequently, in this study, the robot could behave socially in an autonomous fashion after having been supervised by a human in a learning phase.

7.3 Impact

Make better![ES]

7.3.1 Teaching Robot to Interact with Humans

With SPARC we proposed a new way to teach agents. By following the principles presented in Section 3.3 (combining Supervised Autonomy and Machine Learning (ML)), this method provides a robot with an adaptive policy while ensuring that its behaviour remains constantly appropriate. Furthermore, with the combination of proposition, correction and selection of actions, SPARC aims to reduce the workload on the teacher. Hence, this approach is fit to control and teach robots to interact with humans as it follows the requirements presented in Section 2.1.2. Furthermore, as demonstrated in Chapter 6, SPARC has been used to teach a robot to interact safely and efficiently in a real HRI.

By demonstrating its applicability to teach robots to interact with humans from in-situ supervision, SPARC opens up new opportunities to provide robots with action policies complex to define or not known in advance. This new method to teach robot safely to interact with humans might allow robots to be deployed in new contexts where they are absent today.

7.3.2 Empowering Non-Experts in Robotics

By allowing end-users non-expert in robotics to teach a robot how to interact, SPARC provides an opportunity for anyone to personalise their robot. As demonstrated in Chapter 4 and 5, from a single algorithm and state representation, SPARC can lead to different behaviours adapted to the teacher's strategy and preferences. Combined with efficient interfaces and learning algorithms, approaches such as SPARC have the potential to democratise the use of robotics by allowing anyone to teach a robot to interact efficiently in a wide range of domains. Robot developers and designers could use this learning ability to deploy robots as *blank slate*, with just a way to perceive the world, act on it and interact with a teacher, and let their behaviour be defined by their users. These users would start filling these blank slates, creating their own robot behaviour, teaching their robot how to fulfil their personal needs. As defended by Fails & Olsen Jr (2003) and Amershi et al. (2014), by allowing end-users to teach an agent to behave as they desire, IML methods have the potential to ease the deployments of technology and reach faster new application domains. This might allow users currently excluded from using robots (due to lack of interesting from developers and lack of technical skills from the users), to profit from this new technology.

7.3.3 Robots and Proactivity

Another way to interpret SPARC is as a way to provide proactivity to a robot. By using ML and proposing to execute actions, the robot is actually taking the initiative to do an action without executing it straight-away. For instance, a proactive robot assistant would anticipate its user's needs and desires and would propose help or services without having to be asked. This capability has two uses: first it allows robot users not to have to ask supportive behaviour for the robot every time they need it and second, it means that even if the user forgets to ask the robot, the robot might come up with the suggestion and remind its user by proposing to help.

By having the capability to learn new actions, or what action it should do, such a robot would move from a simple tool to use to an adaptive partner able to support its user in a large quantity of task. Finally by informing the surrounding humans of its actions, such a robot assistant would only execute action deemed useful by their users.

7.3.4 Ethical Questions

Having robots interacting in human environment and allowing any human to teach them, raise multiple ethical questions Lin et al. (2014).

The first one concerns people's jobs. Throughout robots and machines history, many jobs have been automated and more are expected to disappear in the next years (Frey & Osborne, 2017). As such, deploying robots in social environments, such as schools or care facilities, might lead teachers or social workers to fear for their jobs. However, in many of such social environments with no direct quantifiable return on investment, workforce is already lacking (e.g. nurses in the US; Nevidjon & Erickson 2001) and this shortage is expected to grow in the future. Consequently, robots provide an opportunity not to replace a workforce already in shortage of workers, but on the other end to support these people in their job, making these jobs safer and more pleasant for the workers or providing additional support for the clients or patients (Wada et al., 2005). However, the HRI community as a whole needs to be aware of these fears and ensure by their work that robots have a positive impact on society and communicate their vision of robots helping the human population.

By allowing robots to learn, we might increase the range of places where they are being used. However, having robots interacting with vulnerable populations such as elderly people or children in school raise multiple questions. Sharkey & Sharkey (2012) identify that using robots in elder care might “reduce the amount of human contact”, “increase the feelings of objectification”, create “a loss of privacy” and “personal liberty” and elicit “deception and infantilisation”. They also add the the conditions were an elderly should be in control of a robot are to be carefully identified. Similar, Sharkey (2016) expresses concerns about deploying robots in classrooms. As such, roboticists need to work with domain experts to ensure that robots do help their user and not harm them.

A major ethical questions concerning learning robots is privacy. As robots will interact with the general population, and especially will learn from and about it, issues concerning privacy arise. To have meaningful interactions with users, robots need to collect information about them. And the type of information collected, the storage, the use by third parties and the users’ perception about this collection have to be carefully considered before deploying a robot (Syrdal et al., 2007). This effect is further increased when robots learn from humans. These learning robots are not any more passively collecting data, but the interaction itself is designed to gather more information about the user, about their preferences, their desires and their needs. Finally, this effect is amplified when interacting with vulnerable populations. If robots take an important role in education and care, humans interacting with them will tend to be children or patient, and these people might not be able to ensure their privacy alone. The question of sharing these information and this knowledge between robots and beyond, to the manufacturer or to the governments, needs to be addressed before robots are deployed on large scales. Another ethical question linked with privacy is security. These data accumulated by robots need to be protected from malicious attacks. This issue is even more visible with the recent world wide hacks of the Internet of Things devices (such as Mirai[2]). Recently, Giaretta et al. (2018) present a report of numerous basic security flaws in the Pepper robot and express the idea that robot have moved too quickly from research to market product and that they often do not present the required security to ensure they users' privacy and security.

A last concern resides in the responsibility for the actions executed by the robot (Asaro, 2007). In a mixed-initiative interaction when both the autonomous agent and the human supervisor can impact the robot action policy, the responsibility of actions is complex to analyse. This effect is even increased when the robot can learn from its user. In that case, the role of the company or the entity distributing this robot and the role of the user have to be considered when looking for a legal entity accountable for the robot actions. To have a clearer accountability, Artificial Intelligence (AI) applied for robotics needs to be more transparent (Wachter et al., 2017).

7.4 Future Work

The work conducted in this thesis explored how robots could be taught to interact with humans and proposed a novel interaction framework, SPARC, to enable such a learning. However, SPARC could be extended in many ways and its principles applied to other applications.

7.4.1 Application Domains

Through this thesis, SPARC has only been applied to HRI in the context of tutor robots, to teach a robot to support child learning. However, the principles underlying SPARC could be applied to a much wider range of applications in robotics and other AI. For instance, SPARC would show promises in classical robotic applications and numerous fields in social HRI: from assistant robot at home to collaborative robotics including robots in hospitality, military or industry. For example a robot could learn the preferences of a user and act as an embodied personal assistant, connected to devices in the house, calendar on the internet and supporting its users in routine tasks. Such a robot could learn to anticipate its user's needs and propose to provide support proactively. In Human-Robot Collaboration (HRC), similarly to the work presented in Munzer et al. (2017), a robot could learn its partner preferences, informing them of its actions and

[2] https://en.wikipedia.org/wiki/Mirai_(malware)

helping them to complete the task faster and easier. As explained in Fails & Olsen Jr (2003), IML approaches, and by extend SPARC, could also be applied to classification tasks, maintaining the user informed about the state of the algorithm's knowledge and involving them in the learning process. For example, for semi-supervised image classification, the algorithm could automatically present a subset of classified images between learning steps to the user who could step in when a misclassification happen. In this case, where incorrect actions have limited impacts, the correction can happen in hindsight, as proposed in Chernova & Veloso (2009). Alternatively, the principles of SPARC could be also used to support agents using Reinforcement Learning (RL) in the real world. The supervisor could provide a safeguard preventing the agent to make errors, bringing it back to the correct parts of the environment or guiding the agent to relevant actions in complex environments.

mention how this could be applied in manipulation or navigation also[ES]

7.4.2 Learning Beyond Imitation

check[ES] Another potential feature of SPARC, and other methods based on demonstrations, not evaluated in this research is reaching capabilities beyond the demonstrations. As SPARC uses demonstrations and corrections from a human teacher to learn, by applying Supervised Learning (SL), the optimal outcome would be to match the teacher's performance. However, if the algorithm learn a value function or the teacher's goal, instead of reproducing the teacher policy, the agent could improve its action policy around the demonstrated policy and potentially become better than the teacher themselves. This achievement have been accomplished by Abbeel & Ng (2004), by using Inverse Reinforcement Learning. In their work, the agent learned a reward function and a basic action policy from the human demonstrations and then, by applying RL around the demonstrated policy, the agent improved it beyond the demonstrations reaching super-human capabilities.

Alternatively, instead of having the robot reaching capabilities beyond human ones on its own, a human-robot team could also together reach this kind of performance. For examples, Kasparov (2010) propose "Advance Chess", a new type of chess were players have access to a computer to help them during their decisions. This combination of human and machine, aims at profiting from the best of both worlds and would allow humans to make better use of their intuition and creativity while using computer's certainty to save human calculations. Similarly, a learning agent could interact with the human in a mixed initiative framework, such as SPARC, where the agent could suggest actions (such as moves in a Go or Chess game) and the human could accept them or refuse them. That way the human would be in control of the interaction, prevent errors from the artificial agent to have negative impact, while still being open to opportunities they did not anticipate. Hence, the team could reach together super-human capabilities, while ensuring with the presence of the human in control of the interaction that the behaviour would be at least of human performance. Additionally, this mixed initiative interaction might provide the human with the opportunity to learn from the robot, if the robot proposes better than anticipated actions.

However, to reach these super-human behaviours, the agent requires a way to learn in addition to the human. The agent needs to have access to a second level learning, such as a reward function directly from the environment or learned from the human demonstrations (such as with Inverse Reinforcement Learning). For example, the human could provide a mixture of demonstration, rewards and high levels goals which could be used to learn such a reward function or to update a planner with more correct models allowing them to reach the goals faster. Alternatively, the robot could learn simultaneously from the human and in simulation, while leaving the human in control when interacting in the real world and using their feedback during these real interactions to refine the simulation.

7.4.3 Sustained Learning

could be easily improved - but how?[ES]

This work, and general research in robotics, considered the problem of learning single tasks in isolation. However, once deployed, robots needs to address the challenges of lifelong learning (Thrun & Mitchell, 1995), being able to continuously learn in different domains and transfer knowledge from one situation to another. Methods such as SPARC could help framing this learning and potentially helping the robot to know which parts of the policy are transferable.

Another challenge is the dependency of time. For example, in Chapter 6, the temporal aspects of the interaction were taken into account only by including some notion of time since events in the state definition. The robot was not doing any temporal planning or explicitly taking time into account when behaving. However, to sustain continuous long term interaction, spanning multiple hours or days, the dependency in time of the action policy has to be taken into account through other means. The robot needs to learn spacio temporal features relevant to the human's behaviours and expectations (cf. STRANDS project; Hawes et al. 2017). For instance, a robot assistant at home should know its users are typically going to work every morning, except weekends and holidays. To sustain learning over long periods of time, robots needs algorithm that can scale well with large number of data and take into account the impact of time on the action policy.

7.4.4 Interface With the Teacher

Another axis to improve SPARC and which is critical for to reach other applications is the interface with the teacher. As mentioned in the Section 7.1.5, one of the main limitation of SPARC is also what provides it its strength: the inclusion of a human in the action selection process. Including this human and giving them the opportunity to preempt and select any actions comes with limits on the interaction. The robots needs to communicate its intentions and the human needs enough time to correct them before they impact negatively the environment or other humans interacting with the robot.

However, the interface used by the teacher to control the robot could mitigate these limitations, and further work could explore how to provide the best communication between the teacher and the robot. For example, in the case of a GUI on a tablet or a phone, the interface could combine buttons and a representation of the world where the robot could describe how it plans to act or its expected trajectories. Similarly, the teacher could use this representation of the world to select actions for the robot to execute (as used in Chapter 6 but including long-term information). Designing these GUI for SPARC could use the knowledge obtained from designing application for phone for example (Joorabchi et al., 2013).

However, GUI might not be the way to communicate with the robot, as they might scale difficulty with a high number of actions. Alternatively, future work could explore how natural language could be used to control a robot through SPARC. This would raise many challenges, such as natural language understanding, or creating a string to describe the robot's actions, intentions or explanation clearly yet concisely (Hayes & Shah, 2017). Despite these challenges, language possesses the qualities required to communicate between a teacher and a robot: familiarity for humans, open-endedness of description and precision for example. One other area of research which would improve

SPARC is Brain Computer Interfaces. For example, in case of error, the brain creates a specific pattern which can be detected using EEG (Gehring et al., 1993), that way instead of an explicit correction window, such an interface could automatically detect errors in robot suggestion without requiring the teacher to explicitly cancel the action. By having a much smaller delay between the proposition and its execution, SPARC could be applied to more applications.

7.4.5 Algorithms

read[ES] In the future, SPARC should be combined with richer learning algorithms. The three examples provided in this thesis represent only a small part of the algorithms SPARC can be combined with. More advanced ML would allow SPARC to learn faster and more efficiently; and, as mentioned previously, potentially reach super-human performance in the task. However, as mentioned in Chapters 2 and 3, many challenges remain when using learning for HRI. The first one, the main one tackled by SPARC, is the high stakes of the interaction, incorrect errors might lead to disastrous consequences. In addition, the data efficiency is fundamental: when interacting with humans, collecting information about human's reaction can be costly or take a large amount of time. As such, each datapoint should be used with high efficiency and the human included in the loop should provide additional knowledge to deal with this scarcity of data. Alternatively, the algorithm could combine data accumulated from different teachers to learn a more general policy. However, this would lead to a transfer problem, assumptions and policies correct with one user might not be valid anymore for another one. And doing this generalisation might decrease the potential for personalisation that ML provide. One way to address this personalisation vs generalisation issue is to group people by similarity and learn to detect the group of a person and an action policy adapted to this group to reach a better action policy (Brunskill & Li, 2014). Alternatively, the robot could learn or already possess a general action policy and then use SPARC to refine it and adapt it to its user.

SPARC and humans in general could also be used to teach hierarchical strategies (Botvinick, 2012). With hierarchical learning, agents learn subpolicies used to complete subgoals, and then combine these subpolicies to reach higher goals. By helping an agent to create subpolicies and informing it which ones are more appropriate in specific context, a human could allow an agent to learn to solve complex task much quicker. This teaching on multiple levels present a challenge for SPARC, as in the current implementation, the teacher only selection actions. This would require a way for the teacher to create higher level actions, organise them and switch between them. However, using a human provides a strong potential to quicken the learning of complex and rich policies.

Additionally, instead of providing demonstrations of a policy to follow, the teacher could also give symbolic rules defining a behaviour for the robot. This alternative way of teaching could generalise faster than simple demonstrations and might allow teachers to define a complex a complex behaviour quicker, and without having to encounter each situations to show the robot how to behave.

Another challenge that algorithms used with humans need to take into account is that humans are not static entities. As mentioned in Section 2.3.4, different humans will use different teaching strategies. Furthermore, as seen in Chapters 4, 5 and 6, in Thomaz & Breazeal (2008) and MacGlashan et al. (2017), human teachers adapt their teaching strategy overtime. Human policies and feedback are moving targets, and algorithms used to learn from humans need to take into account this variations and evolutions of behaviours.

7.5 Summary

This chapter started by presenting the main limitations identified for SPARC (requirement of a correction window and attention from the teacher, potential increase of workload on the teacher, complexity of the interface, low number of datapoint and slower interaction). Each limitation was described and we presented how they could be addressed when designing an interaction involving a human teacher. We then addressed the research questions identified in Section 1.2 and continued with discussing the potential impacts of SPARC on the wider field of HRI and potential for deploying robots in the real world, as well as the ethical questions raised by having humans teach robots. Finally, we proposed directions to extend the efficiency and applicability of SPARC that could be addressed in future work.

Chapter 8

Contribution and Conclusion

From James[ES] This chapter seeks to provide an overview of the findings and topics covered in this thesis. The contributions to the field of social Human-Robot Interaction (HRI) are outlined and summarised. Following this, a conclusion is provided to briefly encapsulate the primary outcome of this work.

8.1 Summary

The main thesis presented by this work is the following one:

> A robot can learn to interact meaningfully with humans in an efficient and safe way by receiving supervision from a human teacher in control of the robot's behaviour.

To explore this thesis and the research questions arising when addressing it, in Chapter 2 we first reviewed the field of application of social HRI. From this overview, we drew three requirements for a robot to interact efficiently in human-environments. The robot needs to constantly have an appropriate action policy, be adaptive and require a low workload from humans to act efficiently in the world. Then we analysed the current controllers for robots in HRI and identified the absence of a robot controller validating these requirements.

In Chapter 3 we aimed to address this lack a of method validating this requirements by proposing a new approach, the Supervised Progressively Autonomous Robot Competencies (SPARC), to teach robots to interact and which would be applicable to HRI. SPARC aims to provide control over the robot's actions to a human and use this supervision to learn online a correct action policy. To achieve this goal, SPARC is based on a set of principles allowing this teaching interaction to be efficient: the teacher can select actions for the robot, the robot can propose actions to the teacher, the teacher can preempt robot's propositions before their automatic execution and, finally, the robot learns from the teacher's selections and feedback to improve its action policy. These principles ensure that the robot's executed policy is constantly appropriate while reducing the human workload over time, leading to an autonomous behaviour if desired.

Once the method and the principles defining the interaction between the human teacher and the robot were set, we evaluated this approach in three studies with increasing ambition. Before testing SPARC in a real world interaction with humans (in Chapter 6), we needed to evaluate if the principles underlying SPARC could reduce the workload on the teacher and how the control over the robot's actions impacts the teaching process. A key effect to evaluate was if this control is sufficient to ensure a constant appropriate robot behaviour. The two first studies (Chapters 4 and 5) included humans only as teachers, but not as the target of the teaching. This allowed to gather initial information on SPARC in controlled and repeatable environments without having to tackle the challenges of interacting with humans in the real world.

The first study, presented in Chapter 4, evaluated the interaction between the supervisor and the robot in a controlled and repeatable environment inspired by Robot Assisted Therapy (RAT), where the child was replace by a second robot simulating a child. The study showed that SPARC could allow a robot to learn, subsequently reducing the teacher's workload by decreasing the number of actions required from the teacher to control the robot without negatively impacting the performance in the interaction.

Once SPARC demonstrated that it could allow a robot to learn and decrease the workload on the supervisor, we evaluated in Chapter 5 how the control provided to the teacher by SPARC could improve the learning process. To explore this aspect, we designed a second study comparing SPARC to Interactive Reinforcement Learning (IRL) an alternative approach used to teach robots, but providing the teacher with little control over the robot's action. Results showed that the control provided to the teacher helped them to guide the robot to relevant parts of the environment, thus improving the teaching process and making it safer and easier.

Since the two first studies demonstrated the efficiency of SPARC to teach a robot to interact in virtual environments and ensured that the control provided by SPARC could guarantee the appropriateness of the robot's actions, SPARC was ready to be evaluated in a real human-robot interaction. We decided to select the context of tutoring children in the wild as this a classic application of HRI encompasses many challenges faced by robots interacting with humans. This last study applied SPARC to teach a robot a social and a technical policy to support child learning. This study had three main goals. First, demonstrating the applicability of SPARC in teaching robots to interact socially with humans, consequently addressing the thesis of this research. Secondly, exploring the impact of SPARC during the teaching phase on the two humans involved in the triadic interaction. And finally, evaluating if, after having been taught by a human using SPARC, the robot could interact successfully with other humans in an autonomous manner. Results from this study demonstrated that during the teaching phase, the robot behaviour was efficient and appropriate to the interaction, but might have required a relatively high workload from the teacher. And finally, when deployed autonomously, the robot could interact efficiently with children, leading to a similar policy than with the teacher and having similar effects on the children's behaviours.

8.2 Contributions

From James[ES] This section will revisit the contributions outlined in the introduction (Chapter 1), with further expansion and explanation.

The main scientific contributions of this thesis are as follows:

- **Design of a new interaction framework for teaching agents in a safe way.** One of the main contribution of this research is SPARC: a new interaction framework enabling robots to learn to interact with humans from in situ human supervision. This method is the cornerstone of this thesis and aims to allow robots to be adaptive, while constantly ensuring an appropriate robot action policy and a low workload from humans.

- **Evaluation of SPARC in three studies.** Throughout this research, SPARC have been tested in three studies, which were specifically developed to explores different aspects of the human-robot interactions involved in SPARC and culminated with the teaching to a robot to interact with humans in the wild.

- **Demonstration of the importance of control over the robot's action when teaching a robot to interact.** As demonstrated by the last two studies, giving the teacher control over the robot's action has consequent impacts: it makes the teaching process safer, quicker and more efficient and it also give the opportunity to reduce the workload on the teacher.

- **Design of a lightweight algorithm to quickly learn from demonstration in complex environments.** Learning to interact in complex environments, where the states can be defined by a large number of dimensions is a challenging task, especially when the number of datapoints accessible to learn is low. By using a selective reduction of dimension decided by the teacher, this new algorithm inspired from nearest-neighbours allowed a robot to learn to interact in the complex environment that is child tutoring with a few datapoints.

- **Application of Interactive Machine Learning (IML) to safely teach robots social autonomy from in situ human supervision.** Finally, the second main contribution of this research is a demonstration of online learning of interactive policy for HRI supported by human supervision. By using SPARC a robot learned an action policy from scratch by interacting with humans and applied it successfully in further autonomous interactions with humans. This has real world implications as it shows that using SPARC, an agent can learn a precise policy from a generic perception of the world and a large set of actions.

  probably need to clean last bit and highlight why it matters[ES]

8.3 Conclusion

The thesis presented here is that a robot can learn to interact meaningfully with humans in an efficient and safe way by receiving supervision from a human teacher in control of the robot's behaviour. To support this thesis, this research work proposed the Supervised Progressively Autonomous Robot Competencies (SPARC), a new teaching framework for artificial agents seeking to give to the teacher full control over the agent's actions. The agents learns from this supervision in a safe and efficient way and progressively becomes autonomous. By proposing and evaluating SPARC in three studies, this work contributes to increase our knowledge on how robots could be taught to interact, especially in human environment. It has been shown that, while being a challenging task, providing a robot teacher with control over the robot's actions leads to significant advantages: the learning can be faster, more efficient and lightweight for the teacher. And most importantly, by preventing the robot's errors in early stage of the interaction, robots can be taught to interact in high-stakes situation, such as HRI, where methods lacking control could not be applied.

Finally, by exhibiting its application to child tutoring, SPARC confirms its applicability to complex and sensitive environments such as HRI. This demonstrates the potential for SPARC to provide humans non-expert in computing the ability to teach robots rich behaviours. This has the potential to foster the deployment of robots in more interactive domains and help their integration in society.

Glossary

Correction window The correction window is the time provided to a supervisor to correct an action before its execution. 129

Validity window The validity window is the duration of validity of an action, it represents how long an action is appropriate.. 129

Supervised Autonomy An agent acts autonomously in the world while being monitored by a human. The agent proposes actions which will be executed to the human who has the power to preempt them and to select actions to be executed by the agent at any time. 50, 53, 58–60, 100, 128, 129

Acronyms

AI Artificial Intelligence. 1, 7, 134, 135

ANN Artificial Neural Networks. 7

ASD Autism Spetrum Disorder. 13, 20, 58, 60, 96

CIDM 95% Confidence Interval of the Difference of the Mean. 70, 71

DREAM Development of Robot-Enhanced Therapy for Children with Autism Spectrum Disorders (European FP7 project). 9, 57

GUI Graphical User Interface. 61, 63, 65–67, 99, 109–111, 130, 137

HCI Human-Computer Interaction. 26, 29

HHI Human-Human Interaction. 14

HRC Human-Robot Collaboration. 17, 18, 31, 33, 54, 135

HRI Human-Robot Interaction. 1–3, 5, 9–11, 14, 19, 21, 23–27, 31–33, 36, 38–40, 45, 48, 58, 60, 92, 93, 96, 98, 101, 102, 105, 124, 127, 131, 132, 135, 137, 139, 140, 142

ILfD Interactive Learning from Demonstration. 43, 54

IML Interactive Machine Learning. 6, 9–11, 32, 34, 35, 39, 42, 45, 48, 51, 53, 54, 75, 76, 79, 95, 102, 130, 135, 142

IRL Interactive Reinforcement Learning. 6, 10, 42, 75–81, 83, 86–88, 90–97, 100–102, 140

LfD Learning from Demonstration. 28, 30, 32, 34–36, 39, 42, 44, 48, 54, 55, 100, 101, 125, 128

LfW Learning from the Wizard. 29

MDP Markov Decision Process. 37, 80

Appendices

Appendix A

Contribution to the DREAM project

As part of DREAM, I have been involved in various meetings, developed tools to automate tasks and contributed to a significant part of the software developed during the project.

A.1 Software development

WP6, composed of Plymouth and VUB, was responsible to develop the cognitive controller of the robot. I developed mostly alone the deliberative, expression and actuation and naoInterface subsystems. I also converted scripts provided by the therapist into steps the robot can follow and programmed a robot behaviour corresponding to each one of these steps.

A.2 Tools

In addition to the components developed to run the DREAM application, I created two tools to automate and simplify the use of the YARP middleware while conforming to the development standards imposed on the project.

A.2.1 yarpGenerator

The software development guidelines of DREAM imposed a specific structure for folders of new components developed with a number of constant part throughout the required 6 files. Additionally, adding or removing one port required changes in 5 files in more than 10 location. To ease this procedure, I proposed to add two new class: the yarpInterface and the yarpController. yarpInterface class exposes all the yarp output port required by the component to C++ function and integrates function asynchronously called when messages arrive on input ports. And the yarpController corresponds to a C++ only file where the code can be developed without reliance of YARP. This class (and others) can call functions from yarpInterface to send messages and be called by callbacks in yarpInterface to react to messages. The yarpGenerator is a tool generating automatically compilable code, complient with the development standards. Appendice B presents the techreport created to describe the tool.

A.2.2 scriptManager

The second tools aims at providing a graphical way to read and edit the xml files describing the scripts used in the therapies.

Appendix B

Teacher's Diary

This appendix section present the daily report of the teacher's impressions and feeling when teaching the robot in the study in Chapter6. It should be noted that among all the children supervised, many were special needs and as such have been removed from the result analysis. This also explains the difference of number between the children in the supervised condition (n=25) and in this diary (n=34).

Research Diary

N.B.: Record of my role in Emmanuel's Robot's for Learning Study

02 February 2018

My Role as Teacher

In order to test the usability of Emmanuel's system I will play the role of naive teacher to train the robot's behaviours. I am unfamiliar with how the system operates and have never used it before or anything similar. This Diary will denote my experiences as I learn to use the system to inform conclusions on how easy the system might be for real-world teachers.

Training with the System - no participants

Lots going on. It's difficult to pay attention to everything. Hardest aspect is probably moving animals around. We ran autonomous to see what the robot would do with training so far, it was mainly Encouragement and Congratulations. Very chatty. Need to make sure that my training encourages more silence and more suggestions for moving animals.

05 February 2018

Training and Passive Condition

Ran participants in the passive condition only so that I could continue to watch the activity on the tablet and get used to looking at everything that's happening.

Tablet froze in round 3 of game. Did not restart by its self. Not a WiFi issue as robot was still working.

Main focus when watching the passive condition is where I would move the animals to promote learning. This may be made slightly more difficult by having to track and change the robot's verbal feedback.

Problems with Tablet connecting to wifi - several restarts. Emmanuel says it's fairly normal.

Training on SPARC with Emmanuel as student (x2): Goals - try lots of actions and try to mediate the robot's timing using the skip and cancel buttons so it learns to leave silence gaps. Robot learns very quickly. Made a couple of mistakes - need to make sure I always select object and target before suggesting how to move an animal. Robot gets quite excited about its learned actions - will start making lots of suggestions rapidly. Need to pay attention to it a lot. The hardest part is keeping up with the participant/student.

06 February 2018

Training with non-participant and participant

Non-Participant with SPARC - Blank Robot. I skipped/cancelled a lot of the robot's suggestions, including ones which I wanted to approve. The robot's suggestion-execution speed takes getting used to. Spent a lot of time moving animals around. Tried to remember to use verbal feedback too. Tablet crashed during the final game session. Robot only learns exactly what I've shown it so I need to make sure I show it all the possible connections between animals. Teaching method: used demonstration during first game sessions, then started using "draw attention" more in the later sessions to see if the participant knew what to do with the animals. Also used "congratulations" and "encouragement" both when the participant followed robot's instructions correctly, and for a lot of their own correct actions which they performed without the robot's help.

Participant with SPARC - (Blank) Learning Robot.

Participant 1 - Slow to start, seemed like low confidence or not sure what to do. Followed instruction/demonstration well. Easy to work with. Lots of animal movement demonstrations as participant did not initiate many movements by themselves.

Participant 2 - aggressive play. I found it difficult to know how best to respond. Tried to reduce number of demonstrations and increase the use of "drawing attention" in later game sessions. Had to use "remind rules" a lot and found it difficult to suggest animal movements.

Participant 3 - gradually used a more aggressive play style. Responded fairly well to demonstration. Tried to reduce number of demonstrations and increase the use of "drawing attention" in later game sessions. Used "remind rules" a lot when play became more aggressive.

Teaching experience is fun but tiring. I find I'm dismissing robot suggestions more than I actually want to - some are valid but I am "playing safe" by skipping/cancelling all in order to avoid inappropriate suggestions. Need to trust the robot more. This does require more effort though as I need to pay attention to the robot suggestions better.

07 February 2018

Training with participant

Participant with SPARC - Learning Robot.

Participant 4 - Tablet crashed part way through game 2. Let participant make first move on each game. Tried to have a more balanced mix of demonstrations, drawing attention and verbal behaviours. Allowed the robot to perform more suggested actions, e.g. demonstrations. Robot suggests to start talking very early in each session (before participant's first move) so will try to teach it to wait. Remainder of game sessions were done in passive mode due to tablet crash.

Participant 5 - Achieving a better balance between my own actions and robot's suggestions. Sometimes the number of suggestions from the robot is a bit overwhelming. I try to use participants' performance on pre and mid tests to inform my teaching. Robot performed one action 3 times in succession which was very distracting and it threw me off a bit. Participant employed a waiting tactic in the last game session so had to ensure that the robot didn't perform any actions until the participant was ready.

08 February 2018

Training with participant

Participant with SPARC - Learning Robot.

Participant 6 - Started with an aggressive style of play so in sessions 1 and 2 I used "remind rules" a bit. Also started out using some demonstrations because they had made a few wrong connections in pre-test. Play style was also hectic, they would move animals around quickly and see what happened when they interacted with other animals. This was difficult to work with - often the animal I wanted to do a demonstration with or draw attention to was being used by the time the robot behaviour started. In sessions 3 and 4 I used a few demonstrations but mostly "encouragement" and "congratulations". I cancelled most of the robot suggestions due to how hectic the participant's behaviour was. Participant also employed a waiting tactic at the beginning of later sessions so robot behaviours were always cancelled until the participants' first move.

09 February 2018

Training with participant

Participant with SPARC - Learning Robot.

Participant 7 - aggressive play = keeps eating all "raw foods" at once. Makes game play difficult. Used "remind rules" a lot. Found it difficult to give demonstrations but managed some. Allowed some robot suggestions but not many as I wanted to slow game-play down.

Participant 8 - allowing more robot suggestions. Feel like I have a good balance between demonstrations and vocalisations. Didn't need to use "remind rules". Participant seemed to want to work more independently, occasionally finishing their own task before attending to the robot's suggestions. I used fewer demonstrations in the later sessions.

Participant 9 - slow deliberative play style. Participant is whispering to themselves about the animals and what they might eat - possible memory technique. I am not offering too many robot behaviours but am using a good balance of demonstrations and verbal feedback. Not using "remind rules". Participant employed waiting tactic in last round. Robot also waited before giving suggestions. Not sure if it waited for first move or if it just waited for a certain amount of time.

Participant 10 - stopped after first game session so was excluded. I used quite a few demonstrations. Participant was good at working things out for themselves though. When completing the game after the participant left the robot was autonomously giving encouragement followed by "remind rules" when Emmanuel was just eating animals to end the game. Robot was only giving 2 responses when Emmanuel was quick-finishing the game and I feel this is good spacing between responses - not too chatty. I will try to continue teaching the robot to space out the instructions/interactions.

19 February 2018

Training with participant

Participant with SPARC - Learning Robot.

Participant 11 - haphazard play style, sometimes hard to keep up. Ended up accidentally making a mistake in my demonstration. Need to make sure I don't hold the animals too long before moving them. Participant is very talkative so am trying to get the robot to behave as if it has heard him. Slowed down my responses in the second half. Was able to provide more useful behaviours. Had to use quite a few demonstrations and remind rules.

Participant 12 - the tablet crashed just before the end of game session 1. Participant was excluded. Up until then I had done a number of demonstrations. Cancelled most but not all robot behaviours (mainly "remind rules" as participant seemed comfortable with what was needed). Participant also got a lot of interactions right first time so used congratulations and encouragement a bit.

22 February 2018

Training with participant

Participant with SPARC - Learning Robot.

Participant 13 - Careful and slow play style. Tried not to make too many suggestions as participant as they were using an exploratory style to find out what animals ate. In sessions 3+4 participant adopted an aggressive style, using up all an animal's energy in one go. Difficult to work with, participant did not respond to "remind rules" and it was hard to give demonstrations.

Participant 14 - not responding to demonstrations in session 1, i.e. wouldn't feed the animal when I moved it to its food. Seemed to get better at this in session 2. I gave quite a few demos and only congratulated if they were followed through. Participant would often take food to the animal (so animal noises were "ouch"). Still congratulated this as they did it following demonstrations to feed target animals.

Participant 15 - Used a lot of demonstrations in session 1 but fewer in session 2. Participant adopted exploratory style but was also quite aggressive = using up all raw food resources quickly. One demo they weren't sure of so tried again in session 3 and 4, participant worked it out. Participant got really good at the game so mostly I just congratulated and encouraged. Let the robot carry out a lot of its suggested behaviours and only did demos so that the robot wasn't just talking but was also playing with the participant

Participant 16 - Very quick learner. Did a couple of demonstrations but not many. Will try to use more robot suggestions as robot was often suggested good things but I was auto-skipping them. Focused on the more difficult connections, e.g. dragonfly eats other bugs, frogs eat more than just flies. They seem to learn this in the game.

Participant 17 - Very talkative so easy to know what help to give. Learns quickly. Was frustrated with the fact that there's a point where you can't keep going because you run out of raw food. Was talking with the robot a lot and was excited about learning new things. Very fun and easy to teach with demonstrations.

16 April 2018

Training with participant

Participant with SPARC - Learning Robot.

Participant 18 - talks about what they're doing so easy to offer direction. Says things like "I don't know what xx eats" . Also does some exploration so often it was not necessary to give demonstrations. Picked up the game very quickly. Adopted the waiting tactic. Last game was mostly encouragement and congratulations.

Participant 19 - Seems to have a good grip on the game but plays at a relatively slow rate. Doesn't speak whilst playing. Mainly encouragement and congratulations with occasional demonstration. Also using draw attention more as they seem to know what they're doing but struggle to attend to all the animals. Adopted a destructive approach in the 3rd session. Started using remind rules more. Allowed quite a few robot suggestions. One went a bit weird but otherwise they were all good. It's now fairly easy to control the robot. The hardest thing is when participant is struggling to work out what an animal eats but you can't give a demonstration because they won't let the animal go.

Participant 20 - participant struggled so gave lots of demonstrations. Took them a while to understand the purpose of the demonstrations. Would eat all raw foods in one go. Chose not to use remind rules yet though as they were struggling to work out what each animal ate. Started using remind rules in sessions 3 and 4. They started picking up the rules in session 3 but reverted to destructive tactics in session 4.

Note on teaching experience: It's often frustrating that I can't pick exactly what the robot says, but at the same time, if I could there would definitely be too many buttons on the screen. The current layout is already difficult to get to grips with so there's not much that can be done about this.

17 April 2018

Training with participant

Participant with SPARC - Learning Robot.

Participant 21 - (excluded) very quiet but seemed to learn quickly. Made moves slowly and was nervous of making guesses or playing in an exploratory way so I did a lot of demonstrations and congratulations to build confidence. Controlling the robot is really easy now, although I still tend not to let it carry out its suggested actions even when they are valid.

Participant 22 - Allowed the robot to carry out more of its suggestions. Participant is very quiet and seems unsure of themselves/what to do so used a lot of demonstrations. Tried not to overwhelm them though as they seem to prefer moving at a slower pace. Seemed to get better at the game, but I'm not sure how much that has to do with my demonstrations. There is a risk of the teacher/robot taking over the task rather than just supporting the child's learning. This is especially true in cases where the participant does not like to explore/try out pairings.

Participant 23 - (excluded) was very unsure of what the animals would eat to start so encouraged exploration. They took on a destructive style of play so started using remind rules during session 3. Participant gave up.

18 April 2018

Training with participant

Participant with SPARC - Learning Robot.

Participant 24 - Was fairly exploratory to start. Used a fair few demonstrations and let the robot carry out a lot of suggestions. Robot was trying to remind rules following correct actions though. Not sure why but I will try to stop it from doing this. Participant seemed to get the hang of the game towards the end but would start every trial in an exploratory way - not remembering what animals ate what food? During test seemed to just connect animals fairly randomly but with some thought about what might make sense. Appeared to be making connections for the sake of making connections whilst still trying to be right, i.e. would start drawing an arrow then hold it in place until they decided on a food.

Participant 25 - Wasn't very confident to start (only 1 connection in first test). Gained confidence after a couple of demonstrations and some encouragement from the robot. Made a lot more connections in second test and was muttering (possible indicator of using memory of the game). Was much more confident in final test.

Participant 26 - Happy to explore. I gave (what I thought was) an even balance of demo, encourage and congratulate. Let the robot carry out a lot of it's suggestions. Have started using "cancel" button more, mainly for "remind rules". In session 3 and 4 I didn't need to do much, they have a good handle on the game and a good technique. Mainly encourage and congratulate, and more "draw attention" than I would otherwise.

19 April 2018

Training with participant

Participant with SPARC - Learning Robot.

Participant 27 - (excluded) I find it takes me the first session to work out what kind of behaviours the robot should perform so session 1 is often a bit slow. Participant seems confident with game rules but unsure of connections between animals and food so using demonstrations. Participant also uses aggressive play style so gradually incorporating more remind rules behaviours.

Participant 28 - Participant has a semi-aggressive style of play. Doesn't tend to eat all of a food source in one go but gets close occasionally. Sometimes when the robot congratulates correct moves participants seem to repeat the action immediately in response to this reward. The encouragement phrases sometimes have the same effect, especially ones like keep going. Play style got more aggressive in later sessions so used remind rules and intervening demonstrations more.

Participant 29 - Participant barely needed me. Almost every demonstration I tried they were already performing. Mostly just encourage and congratulate needed. However, seems to act a bit too slow for the game pace when left to own devices. Added a few more demonstrations in session 4 but it was difficult to synchronize with both the participant's pace and the game.

20 April 2018

Training with participant

Participant with SPARC - Learning Robot.

Participant 30 - (excluded) Seemed quite scared when the robot moved so kept demonstrations to a minimum. Participant got used to the robot in session 2 and even looked at the robot waiting for it to give a suggestion. Not sure if looking at the robot for help or because bored but used this as a cue to give directions/re-engage participant with game. This seemed effective.

Participant 31 - (excluded) talked through everything they did. Didn't need much help but did demos just to make the experience fun. Understood the game very well and played in a systematic way. Made a wrong action when trying to perform action on animal participant was holding. Not much can be done in these situations as sometimes we just grab the same animal at the same time.

Participant 32 - Quite chatty so fairly easy to give appropriate direction. I kept missing the skip button so a few erroneous behaviours slipped through. Participant's play style got very hectic towards the end so it was difficult to keep up. Ended up doing mostly vocal-only behaviours.

23 April 2018

Training with participant

Participant with SPARC - Learning Robot.

Participant 33 - Seemed nervous to start but picked up the game after a few demonstrations. Adopted a fairly aggressive style but did not do remind rules just yet. Robot did not suggest remind rules either. Not sure if this is good or bad. Used remind rules in sessions 3 and 4, participant seemed to apply these suggestions.

Participant 34 - Aggressive and haphazard play style to start, difficult to get them to slow down. Very chatty. Used remind rules quite a few times in the first 2 sessions. Found it easier to let the participant do most of the actions, whilst the robot just encouraged, mainly because the participants style was so hectic it was hard to keep up. Participant probably needed input to tell them to slow down both during the game and the test, they seemed to confuse themselves by trying to do everything quickly.

Participant with Autonomous.

Participant 1 - Participant seemed very capable and I felt that the robot was too active during session 1. Not sure why as I usually try not to do much during session 1 unless the participant seems unsure or nervous. 2nd session went better, the robot was less chaotic. 3rd session felt a bit more hectic with the robot performing behaviours which weren't necessary (e.g. draw attention to dragonfly immediately after demonstrating bird-dragonfly). Robot is using remind rules seemingly randomly - I wanted it to use it when the participant is aggressively eating when the animal does not need to.

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