End-to-End, Teen-in-the-Loop Design and Automation of a Social Robot for Improving Group Dynamics

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ABSTRACT

This article describes proposed work to undertake teen-in-the-loop design, automation and evaluation of a socially assistive robot over the course of a 2 week summer school. We will utilise participatory design and human-in-the-loop machine learning methods to facilitate participants' development of a social robot for improving group dynamics. We look to implement best practice recommendations published in previous works that have demonstrated the value of working with teenagers, and will take a mutual shaping approach that places great emphasis on mutual learning between the researchers and the participants, as well as recognising the multi-way interactions between participants, the robot and the research/development process.

KEYWORDS

social robots, groups, participatory design, mutual learning

1 INTRODUCTION

Young people naturally interact in groups in many aspects of their everyday life (e.g. school, sports in free time, families). Inherent to every group are the processes and factors that characterize that group and its dynamics, e.g. cohesion, which can have a substantive effect on those in that group. For example, developmental psychologists have found that teenagers who study in more cohesive classrooms demonstrate higher levels of generalized trust (i.e. more trust towards society in general) [21].

Recent advances in the field of human-robot interaction indicate that robots could influence groups and specifically group dynamics (e.g. [16, 19]). Therefore, the further study of how robots could improve group dynamics specifically among teenagers, at this key stage in their developmental psychology, appears promising.

Of special interest from a technical perspective is to understand how such a robot could/should act autonomously. Recent works have suggested that one can employ participatory design combined with expert-in-the-loop interactive machine learning (IML) to involve domain experts throughout robot design *and* automation, and hence to intuitively develop robot action policies that go beyond expert-created behaviour heuristics [24]. Therefore, we propose to apply the technique of participatory design and expert-in-the-loop ML with teenagers as experts to develop robot behaviours that aim to improve the social dynamics in their group interactions.

One critical aspect when working with young people, as highlighted by Björling and Rose [2] is the deceptive element inherent to many HRI studies: a Wizard of Oz (WOZ) controls the robot whilst the people interacting with the robot believe it is autonomous. We believe that asking teenagers to act as experts and secretly observe their peers in order to teach the robot might result in harmful power dynamics. Therefore, we decided to employ the participatory design guidelines proposed by Björling and Rose [2] whereby teenagers are involved end-to-end in the research, design and development process, and testing of the robot is done with high transparency. Specifically, the WOZ is always visible and interactions with them/reflections on their behaviour are actively encouraged. The proposed end-to-end design, teaching and evaluation process will be conducted in the context of a summer school to facilitate mutual learning between researchers, teenagers and robots.

2 ROBOTS IN GROUPS

Prior literature has investigated how robots could interact in groups. Specifically, prior works investigated behaviours which, when displayed on a robot, affected the group and its dynamics. Thereby, pioneering work by Mutlu et al. [10, 11] showed how robot gaze can be used to shape conversational roles. Further, robots' displays of vulnerability have been found to ripple to other team members [19] and robots could bring attention to interpersonal conflicts by calling on them [7]. Further, it has been shown that a robot's nonverbal behaviours can balance engagement [20] and participation [4]. Whereas the previously mentioned works concerned adults only, robots have been used for small group education facilitation in schools [12] and to improve inclusion between already present and newly arrived children [5]. Further, robots have been found effective in improving conflict resolution strategies among young children [16]. Strohkorb et al. [17] investigated if robots could use verbal statements to increase social or task cohesion among children. Their results indicate that utterances targeted at increasing social cohesion increased the perception of team performance.

These prior works give promising indications that robots can improve and benefit groups of children but also that the researcher designed behaviours do not always have the intended effects on groups. Therefore, we see potential in exploring how we could leverage the implicit knowledge that young people have about their social environment. Hence, we propose to use participatory design with young people as experts to develop effective and appropriate robot behaviours. In the first instance, as we explore the viability of this overall approach, we will specifically look to work with teenagers, rather than younger children, as we expect it will be easier to communicate the project goals and objectives to teenagers, and that teenagers will have greater ability to reflect on if/how social robots should/could influence their group dynamics.

To include teenagers in the process of developing robot behaviour beyond design, we will employ human-in-the-loop machine learning approaches which empower the young people to

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teach the robot until it has learned the desired behaviours. For the robot to learn from the human teacher(s), it will need access to the same (or at least to have enough overlap with) the input features on which the human bases their decisions. Therefore, it is important to understand how robots could perceive the group and its dynamics, and how this relates to those features observed and/or responded to, intentionally or otherwise, by human group members. Understanding e.g. cohesion is of interest for the social signal processing community [15] but the perception of group dynamics has also been studied in combination with robots. Prior works investigate how robots could predict childrens' dominance [18] and engagement [9] in group interactions. Whereas these works aim to explicitly capture group dynamics, we aim to implicitly capture the group situation, by way of identifying the correct robot (in)action to take, in a reinforcement learning fashion.

3 MACHINE LEARNING AS PARTICIPATORY DESIGN

Participatory design (PD) should empower non-roboticists to shape robotics research and development, and to actively collaborate in robot design [8]. To date in social robotics, PD has typically taken the form of researchers conducting focus groups and interviews with stakeholders to generate use case scenarios [6], design guidelines [22] and/or prototype robot behaviours [1]. Human-in-the-loop machine learning methods offer a way to augment these activities by allowing (potentially those same) non-roboticist stakeholders to be directly involved in the robot's *automation*. Online, interactive machine learning specifically [14, 24] particularly reduces the extent to which robot automation is something 'done' by roboticists, in the laboratory and away from the real-world use case environment.

We propose to combine PD with human-in-the-loop learning to undertake end-to-end, teen-in-the-loop design and automation of a socially assistive robot. We particularly look to implement design recommendations by Björling and Rose [2] and build specifically on their work with teens as robot operators in the wild [3]. In order to realise this ambition, we propose making this process the central activity of a 2 week summer school, hosted at our university, during which teenage participants will be invited to join us as co-researchers in achieving this task. Table 1 details the key steps of this end-to-end, *'design, automate, evaluate'* process, and related activities to be undertaken the summer school. These will be supplemented with additional 'activity stations' that groups can visit on rotation, to include an activity on algorithmic bias[1] and other robot outreach demonstrations. Whilst there is a clear educational component for participants, as they will learn more about robotics, programming, algorithmic bias etc.; we will specifically utilise methods that are designed to promote *mutual learning* such that it is clear to all involved that us researchers are similarly learning *from* the participants.

[1] see Melsión et al's upcoming paper 'Using Explainability to Help Children Understand Gender Bias in AI' at IDC 2021

1. Identification of Specific Application*
We will undertake a focus group session (following [23]) to identify group situations that teenagers find difficult/awkward explore if/how social robots could play a role in improving that. Example applications might be moving schools/classes, discussing complex societal issues or witnessing bullying or other inappropriate behaviour amongst peers.
2. Refinement of Application and Interaction Scenario(s)
Starting with the application(s) identified during step 1, we will refine and tailor the application scenarios, and the specific international goals of our robot to have (e.g. calling out inappropriate behaviour or prompting turn taking in a group discussion).
3. Co-Design of Action and Input Space
Based on the decisions made at step 2 and following [24], we will undertake co-design of the robot's action and input spaces; essentially representing *'what should the robot do?'* and *'what does the robot need to be aware of to decide what to do, when?'* respectively. This will involve iterative prototyping and testing via roleplays/mock interactions.
4. Robot Teaching Phase
Groups will undertake (co-)scripted roleplays during which one or more members of the group 'teaches' the robot what to do by teleoperating it (as per [2]) and/or other members might provide additional training data in evaluating those actions or actions 'suggested' by the robot learner. State and training data will be captured as per [24].
5. Robot Evaluation
Groups will swap (trained, autonomous) robots and repeat the roleplays to evaluate autonomous behaviour and overall effectiveness.

Table 1: Key activities/design stages for the socially assisitve robot production element of the summer school. **n.b. this will likely be undertaken ahead of the actual summer school, ideally with (at least some of) the same participants* to allow for maximum pre-preparation of the required technical elements (see Section 5).

4 MUTUAL LEARNING FOR EFFECTIVE, RESPONSIBLE ROBOT DESIGN

A key driver for utilising a summer school format for this work is to better facilitate mutual learning between the participants and researchers by allowing sustained dialogues 'back and forth' over the course of the school. In addition, we will utilise methodologies that are designed to ensure participants get to shape the proposed application and interaction(s) of the robot to be designed. For example, during early design sessions, we will follow focus group methodology that is designed to capture broad participant ideation un-biased by specific researcher goals that is then collectively refined based on researchers' sharing their insight into technical feasibility [23]. This approach, with its emphasis on allowing the teenagers (who represent experts in teen social behaviour as well as end users of the proposed system) represents a mutual shaping approach to the research project and robot design [13]. On this basis, we argue it also represents an responsible approach, as stakeholder engagement is an accepted tenet of responsible robotics practice[2]. In particular, we look forward to exploring the teenagers opinions on the acceptability of robots utilising (anthropomorphic) social design cues and persuasive/'nudging' behaviours to influence them. We suggest that there is a particular synergy in undertaking a summer school, focused on mutual learning, that also involves participants combining their inherent social intelligence with their (newly acquired) understanding of robotics to 'teach' their co-designed robot how to behave in the interaction scenario(s) they've co-designed. To this end, we suggest our approach demonstrates those research principles put forward by Björling and Rose [2].

5 TECHNICAL IMPLEMENTATION

Fundamentally, by the end of the summer school we will have produced a modular, ROS based architecture (as per [24]) that supports operation of the co-designed robot(s) based on the co-designed input space and trained machine learning system. The modular structure of our architecture allows us, ahead of the summer school, to pre-prepare a number of potential data input/autonomous perception systems that we might expect to be relevant based on previous literature. This might include e.g. reasoning about the interaction space (such as F-formations, head angles, eye gaze) through 2D and 3D cameras and measure of participation through directional microphones as in [4].

To determine the learning algorithm, we will take a top-down approach by starting from the reinforcing signal and the perception of group dynamics before moving on towards modeling and learning. By taking this approach, we will benefit from domain knowledge which we will expand throughout the process of mutual learning with the young people.

We are hoping that careful abstraction of the robot's action space might make it possible for different groups to use the same action space but utilise different action *instances* (i.e. different dialogues or animations in line with their robot's 'persona'). This may then allow all training data collected to be pooled for the purposes of preparing a single, trained machine learning system that could automate each group's robot. However, this very much depends on whether differences in robot design between groups can be captured by differences in those action instances rather than more substantial differences in e.g. which action is used and when. In either case, exploring the differences in each group's robot design and/or use of the action space will offer a number of opportunities for exploring if/how machine learning can be applied for personalised robot behaviour with relatively small amounts of expert-generated training data.

6 CONCLUSION

In this article, we have outlined proposed work to undertake teen-in-the-loop design, automation and evaluation of socially assistive robots for improving group dynamics. The proposed work represents an ambitious attempt at mutual shaping between robotics research and society, simultaneously exploring technical research questions regarding human-in-the-loop machine learning approaches whilst meaningfully engaging teens in a co-design and mutual learning process - the biggest challenge we face is ensuring both of these goal are met without either being compromised.

[2]https://responsiblerobotics.org/

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