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Socially-driven Autonomous Robots for Real-World Human-Robot Interactions

KTH seminar | 06 Apr 2021

Séverin Lemaignan

Bristol Robotics Lab
University of the West of England

situation assessment

symbolic grounding

symbolic reasoning

SYMBOLIC SOCIAL COGNITION FOR ROBOTS

ontologies

perspective taking

cognitive architectures

social situation assessment

joint action

ROS4HRI

natural language processing

REAL-WORLD SOCIAL AUTONOMY

DATA-DRIVEN HRI

learning of social policies

large datasets

theory of mind

group dynamics

social robotics

human-in-the-loop ML

responsible AI

trust

experimental robotics

HUMAN FACTORS

robotics for learning

child-robot interaction

engagement

anthropomorphism

persuasion

participatory design

SOCIAL ROBOTICS

Creating interactive robots that are **embedded and understand their (human) social context**; **generate and adopt appropriate social behaviours**; have a **positive impact on human society**.

⇒ designing and implementing the **assistant and companion robots** for tomorrow.

⇒ direct impact on ageing society, education, customer service; **major socio-economic challenge**; **UK & European priority**.

SOCIAL ROBOTICS

Major scientific challenges:

- Model open-ended, underspecified situations; rich semantics; complex social dynamics
- Understand and sustain long-term autonomous social interactions;
- Real-world algorithmic robustness;
- Complex ethical landscape;
- $\Rightarrow$ cross-disciplinary & holistic approach required

[Baxter, Lemaignan, Trafton **Workshop on Cognitive Architectures for Social HRI** – HRI 2016]

Understanding each other
Understand the human world
Grounding the physical world
Social dynamics
Acquiring common-sense
Psycho-social determinants (eg trust)
Emotions, internal state
Be understood by the humans
Non-verbal communication
Verbal interactions
Dynamics of communication
socio-cognitive architecture
Being a "good citizen"
Support humans
User-centred design
Pro-social behaviours
Support richer human interactions
Be responsible
XAI
Ethics of HRI
Participatory design
Doing together
Human awareness
Action anticipation
Intention prediction
Error recognition
Nimble and safe
human-aware navigation
human-aware manipulation
Navigation in unknown, cluttered spaces
Shared autonomy and teleoperation
Learn to be autonomous
Social policy learning
Action policy learning
task planning

SOCIAL SITUATION ASSESSMENT

THE UNEXPECTED DAILY SITUATION DATASET

[Sallami et al. **The Unexpected Daily Situations Dataset: A New Benchmark for Socially-Aware Assistive Robots** HRI LBR 2020]

Image

RViz*
File
Panels
Help
Interact
Move Camera
Select
Focus Camera
Measure
2D Pose Estimate
2D Nav Goal
Publish Point
Image
Time
ROS Time: 1543239194.31
ROS Elapsed: 120.57
Wall Time: 1543239194.51
Wall Elapsed: 120.65
Experimental
Reset
8 fp

SOCIAL MODELING

[Webb, Mohamed, Lemaignan **Framing the Challenge of Social Interaction Modelling** HRI LBR 2021]

SOCIAL MODELING

- multi-modal
- dynamic
- only partially observable
- complex pipeline; hard to make it robust

[Webb, Mohamed, Lemaignan **Framing the Challenge of Social Interaction Modelling** HRI LBR 2021]

ROS4HRI

ROS4HRI: first integrated, multi-modal, ROS-based pipeline for social signal processing in robotics

[Mohamed, Lemaignan **ROS for Human-Robot Interaction** Arxiv 2021 (under review IROS)]

DECIPHERING INTERNAL STATE

- PInSoRo dataset: 45h+ and 2M frames of annotated natural interactions. **freeplay-sandbox.github.io**
- first-in-kind dataset for data-driven study of social interactions in robotics
- new data analysis techniques to estimate internal state from body language

[Lemaignan et al. **The PInSoRo dataset: Supporting the data-driven study of child-child and child-robot [...]** PLOS One 2018]

Focused!
ILLUMINATED POLITICAL
& PHYSICAL GLOBE

open me

Page 1 of 4.

How much do you agree with the following statements?

The children were competing with one another.

Strongly Disagree	Disagree	Not Sure	Agree	Strongly Agree

200 participants, 4 clips each, on MTurk

The child on the left was sad.

Strongly Disagree	Disagree	Not Sure	Agree	Strongly Agree

EFA: EXPLORATORY FACTOR ANALYSIS

	Factor 1 *full-scene*	Factor 2 *full-scene*	Factor 3 *full-scene*
△ Sad	0.41		
Σ Sad		0.72	
△ Happy	0.49		
Σ Happy			-0.55
△ Angry	0.40		
Σ Angry		0.81	
△ Excited	0.53		
Σ Excited			-0.71
△ Calm	0.45		
Σ Calm			
△ Friendly	0.69		
Σ Friendly			-0.43
△ Aggressive	0.78		
Σ Aggressive		0.80	-0.36
△ Engaged			0.65
Σ Engaged			-0.64
△ Distracted			0.65
Σ Distracted		0.63	
△ Bored			0.61
Σ Bored		0.58	0.48
△ Frustrated	0.53		
Σ Frustrated		0.70	
△ Dominant	0.75		
Σ Dominant		0.53	
△ Submissive	0.68		
Σ Submissive		0.54	

[Bartlett et al. **What Can You See? Identifying Cues on Internal States from the Kinematics [...]** FrontiersIn 2019]

EFA: EXPLORATORY FACTOR ANALYSIS

	Factor 1: imbalance *full-scene*	**Factor 2: (negative) valence** *full-scene*	**Factor 3: engagement** *full-scene*
△ Sad	0.41		
Σ Sad		0.72	
△ Happy	0.49		
Σ Happy			-0.55
△ Angry	0.40		
Σ Angry		0.81	
△ Excited	0.53		
Σ Excited			-0.71
△ Calm	0.45		
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EFA: EXPLORATORY FACTOR ANALYSIS

	Factor 1: imbalance		Factor 2: (negative) valence		Factor 3: engagement	
	full-scene	*mov.-alone*	*full-scene*	*mov.-alone*	*full-scene*	*mov.-alone*
△ Sad	0.41	0.52				
Σ Sad			0.72	0.53		0.49
△ Happy	0.49	0.53				
Σ Happy				-0.51	-0.55	
△ Angry	0.40	0.62				
Σ Angry			0.81	0.85		
△ Excited	0.53	0.63				
Σ Excited					-0.71	
△ Calm	0.45	0.63				
Σ Calm				-0.45		
△ Friendly	0.69	0.56				
Σ Friendly				-0.60	-0.43	
△ Aggressive	0.78	0.79				
Σ Aggressive			0.80	0.72	-0.36	
△ Engaged		0.39			0.65	0.52
Σ Engaged					-0.64	-0.64
△ Distracted					0.65	0.63
Σ Distracted			0.63			0.82
△ Bored		0.44			0.61	0.54
Σ Bored			0.58		0.48	0.83
△ Frustrated	0.53	0.61				
Σ Frustrated			0.70	0.69		
△ Dominant	0.75	0.81				
Σ Dominant			0.53	0.52		
△ Submissive	0.68	0.72				
Σ Submissive			0.54			

[Bartlett et al. **What Can You See? Identifying Cues on Internal States from the Kinematics [...]** FrontiersIn 2019]

THREE CONSTRUCTS TO RULE THEM ALL

Maddy Bartlett

Interaction imbalance

Interaction valence

Engagement

[Bartlett et al. **What Can You See? Identifying Cues on Internal States from the Kinematics [...]** FrontiersIn 2019]

MEAN EFA PROJECTION OF CLIPS PER SOCIAL SITUATION

The 20 clips were labelled after their salient social features (*aggressive*, *excited*, *aimless*, *fun*, *cooperative*, *bored*, *dominant*).

What happen if we project the ratings for 'aggressive' clips, 'excited' clips, etc. onto the 3 EFA factors?

[Bartlett et al. **What Can You See? Identifying Cues on Internal States from the Kinematics [...]** FrontiersIn 2019]

MEAN EFA PROJECTION OF CLIPS PER SOCIAL SITUATION

[Bartlett et al. **What Can You See? Identifying Cues on Internal States from the Kinematics [...]** FrontiersIn 2019]

MEAN EFA PROJECTION OF CLIPS PER SOCIAL SITUATION

[Bartlett et al. **What Can You See? Identifying Cues on Internal States from the Kinematics [...]** FrontiersIn 2019]

DATA-DRIVEN HRI

ONLINE GAMES & SOCIAL DATASETS

Nicola Webb

Beyond the question of the practical integration of robots into the classroom, how to address **teachers' acceptance**, and specifically, the **tension between robot autonomy and teacher control**?

AUTONOMOUS ROBOT, YET TEACHER IN THE LOOP?

One experiment with:

- a real robot

AUTONOMOUS ROBOT, YET TEACHER IN THE LOOP?

One experiment with:

- a real robot
- a real interaction (...with a human!)

AUTONOMOUS ROBOT, YET TEACHER IN THE LOOP?

One experiment with:

- a real robot
- a real interaction (...with a human!)
- a continuous interaction

AUTONOMOUS ROBOT, YET TEACHER IN THE LOOP?

One experiment with:

- a real robot
- a real interaction (...with a human!)
- a continuous interaction
- a realistic task (large state vector & action space)

AUTONOMOUS ROBOT, YET TEACHER IN THE LOOP?

One experiment with:

- a real robot
- a real interaction (...with a human!)
- a continuous interaction
- a realistic task (large state vector & action space)
- also including social behaviours & social dynamics

REINFORCEMENT LEARNING APPLIED TO SOCIAL ROB

The children plays a game about food chains; the robot learns to guide them (*task-specific action policy*) and encourage them (*social action policy*)

Complex problem: $|state| = 210$ $|action_space| = 655$

[Senft et al. **Teaching robots social autonomy from in situ human guidance** Science Robotics 2019]

TEACHER'S INTERFACE

The robot's teacher (an end-user: might be the actual child's teacher) has a tablet interface that mirror's the child one, and add robot's teleoperation and rewards.

[Senft et al. **Teaching robots social autonomy from in situ human guidance** Science Robotics 2019]

cycling
theme

LEARNT ROBOT'S BEHAVIOUR

Distribution of actions for the 25 children participants:
Supervised

$\rightarrow$

the robot personalises its action policies to the child's behaviour.

[Senft et al. **Teaching robots social autonomy from in situ human guidance** Science Robotics 2019]

LEARNT ROBOT'S BEHAVIOUR

Distribution of actions for the 25 children participants:

Supervised

Autonomous

→

the robot personalises its action policies to the child's behaviour.

[Senft et al. **Teaching robots social autonomy from in situ human guidance** Science Robotics 2019]

LEARNT ROBOT'S BEHAVIOUR

Time between a child's successful action and a praise:

Time since eating event for each congratulation action (s

supervised

autonomous

→ the robot has also learnt an appropriate 'social timing'.

[Senft et al. **Teaching robots social autonomy from in situ human guidance** Science Robotics 2019]

WHAT DOES THAT MEANS FOR THE EXPERT/TEACHER/END-USER?

- **Progressively transferring autonomy** demonstrably works in non-trivial tutoring scenarios
- (it also learns some elements of **social behaviours** and **social timing**)

WHAT DOES THAT MEANS FOR THE EXPERT/TEACHER/END-USER?

Key properties:

- **progressive autonomy** yet **transparency** of the behaviour;
- **observability** and possibility to **take over**;
- because the training takes place in-situ, the robot behaviours are **co-constructed** by the teacher and the child

WHAT DOES THAT MEANS FOR THE EXPERT/TEACHER/END-USER?

Yet:

- Design of the input state tricky and largely task dependent;
- What about more complex social behaviours?
- Nothing yet on group dynamics

EXPERT-IN-THE-LOOP MACHINE LEARNING

[Winkle et al. **In-Situ Learning from a Domain Expert for Real World Socially Assistive Robot Deployment** RSS 2020]

COUCH TO 5KM STUDY

- 9 participants
- 3 months; 27 one-hour sessions per participants
- 20 input features; 11 actions (task-specific or social)
- human-in-loop design and machine learning
- robot evolving from full teleoperation to full task and social autonomy

[Winkle et al. **In-Situ Learning from a Domain Expert for Real World Socially Assistive Robot Deployment** RSS 2020]

[Winkle et al. **In-Situ Learning from a Domain Expert for Real World Socially Assistive Robot Deployment** RSS 2020]

GENERATING SOCIALLY-CONGRUENT BEHAVIOURS

DYNAMIC VS NON-AMBIGUOUS LANGUAGE

Condition Non-ambiguous: "A grey barrel is next to a grey barrel, next to a silver barrel and next to a green barrel."

Condition Dynamic: "Turn left about 90 degrees."... "Keep going"... "Go forward"... "The silver barrel next to the chrome barrel."

[Wallbridge et al. **The Effectiveness of Dynamically Processed Incremental Descriptions in Human Robot Interaction** Transaction on HRI 2021, to appear]

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EXPRESSIVE EYES

- inspired by Anki Cozmo/Vector
- expression interpretation validated online
- work by MSc student Catherine Chambers
- git.brl.ac.uk/s-lemaignan/expressive-eyes

Social Cognition in HRI
Performing with humans
Action, behaviour recognition
Intention reading
Joint actions
Perception of Human's State
Empathy Emotions
Attention
Inference of mental models
Interaction Dynamics
Long-term interaction
Commu-nication
Verbal
Non-verbal
Social Knowledge
Common-sense
Social memory
Social rules
Social context

WHAT NEXT?

SOCIAL ROBOTICS

Major scientific challenges:

- Model open-ended, underspecified situations; rich semantics; complex social dynamics
- Understand and sustain long-term autonomous social interactions;
- Real-world algorithmic robustness;
- Complex ethical landscape;
- $\Rightarrow$ cross-disciplinary & holistic approach required

SOCIAL ROBOTICS

Major scientific challenges:

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Socially-Driven Autonomous Robots for Real-world Human-Robot Interactions

Sensors
SENSE
PLAN
ACT
Actions

Sensors
HUMANS
SENSE
Social signal processing
Group dynamics
Human internal state modeling
PLAN
Joint goals;
Human-aware task planning
Human-the-loop ML
ACT
Social actions
Joint actions
Actions

The robot has its own (pro-social) goals, driving long-term behaviours.

Goal-directed (eg teleological) architecture; the robot exhibits intentionality.

KEY SCIENTIFIC CHALLENGES

1. beyond state-of-art **robust real-world social modelling**; **social embeddings**
2. **public-in-the-loop** approach to design of **intrinsic social motivation**
3. **generative social behaviours** for robots
4. **cognitive architecture** for **long-term interaction**

IDEA: SOCIAL EMBEDDINGS

social embeddings: learning a compact, sub-symbolic representation of social interactions

- real-world social interactions are highly dynamic, noisy, multi-modal
- hard for the robot to model and reason about
- → **learn an embedding**: Attention nets, Deep graph nets
- can be used by the robot to **recognise social situation** and **generate congruent social behaviours**

IDEA: GENERATIVE NON-REPETITIVE SOCIAL BEHAVIOURS

- Cracking the '**non-repetitive, socially congruent**' behaviour generation problem
- Extend **Generative Adversarial Networks** *à la* AppGAN to complex behaviours (re-use *social embeddings*)
- **Immersive technologies** to build datasets
- **Transdiscplinary approach**, incl. arts: choreographer, sound expert

GENERATIVE ADVERSARIAL NETS FOR BEHAVIOUR GENERATION

Some of the most exciting recent work in using ML for robot behaviour generation involve **Generative Adversarial Networks** (GANs):

[Yang et al. **AppGAN: Generative Adversarial Networks for Generating Robot Approach Behaviours [...]** RoMan 2019]

IDEA: A SOCIAL-TELEOLOGICAL ARCHITECTURE

IDEA: LONG-TERM/SHORT-TERM POLICY ARBITRATION

- **end-users and public to play a key role**:
- **crowd-sourced pro-social goals** (eg 'show attention', 'appear alive') drives long-term behaviours
- **short-term/domain-specific policies learned** via interactive reinforcement learning (IRL)
- **cognitive arbitration** between the two, based on **experience transfer**

IDEA: ROBOT-SUPPORTED HUMAN-HUMAN INTERACTIONS

Social robotics might need a paradigm shift from *Human-Robot Interaction* to **robot-supported Human-Human Interaction**:

- not so much: how to robot can interact with human
- instead: why robots? what positive impact can robots uniquely deliver? (and *then*: what technology is required)

A HOLISTIC APPROCH TO SOCIAL ROBOTICS

Thank you!

(roboscopie *2012)*