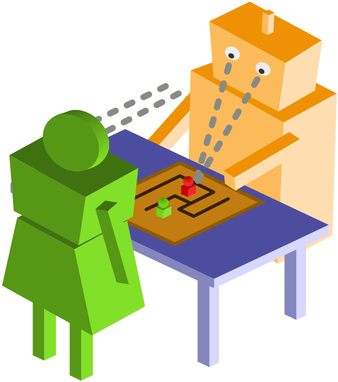
You can download the sources of this presentation here:
github.com/severin-lemaignan/presentation-research

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

SHORT BIO

- **2008–2012** Joint French (LAAS-CNRS) German (TU Munich) PhD
  - AI & Cognitive Robotics
- **2013–2015** Post-doc at EPFL
  - Child-robot interactions
- **2015-2018** Post-doc + lecturer at Plymouth University, UK
  - EU Marie Curie fellowship
  - Social Cognition in Robotics
- **2018–2021** Associate Prof. at Bristol Robotics Lab
- **2021–** ...??!

symbolic grounding

situation assessment

symbolic reasoning

SYMBOLIC SOCIAL COGNITION FOR ROBOTS

ontologies

perspective taking

cognitive architectures

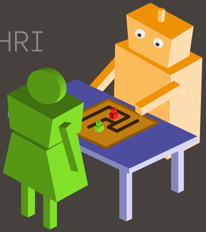
social situation assessment

joint action

ROS4HRI

natural language processing

REAL-WORLD SOCIAL AUTONOMY



DATA-DRIVEN HRI

learning of social policies

large datasets

theory of mind

group dynamics

human-in-the-loop ML

experimental robotics

robotics for learning

CHILD-ROBOT INTERACTION

trust

HUMAN FACTORS

engagement

responsible AI

anthropomorphism

social robotics

participatory design

persuasion

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**; **European priority**.

SOCIAL ROBOTICS

Major scientific challenges:

- Model open-ended, underspecified situations; rich semantics; complex social dynamics

SOCIAL ROBOTICS

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- Model open-ended, underspecified situations; rich semantics; complex social dynamics
- Close the interaction loop

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- Model open-ended, underspecified situations; rich semantics; complex social dynamics
- Close the interaction loop
- Understand and sustain long-term autonomous social interactions;

SOCIAL ROBOTICS

Major scientific challenges:

- Model open-ended, underspecified situations; rich semantics; complex social dynamics
- Close the interaction loop
- Understand and sustain long-term autonomous social interactions;
- Real-world algorithmic robustness;

SOCIAL ROBOTICS

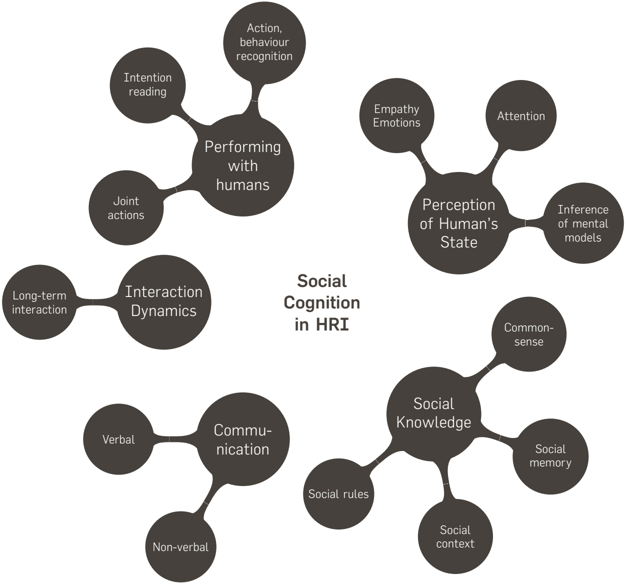
Major scientific challenges:

- Model open-ended, underspecified situations; rich semantics; complex social dynamics
- Close the interaction loop
- Understand and sustain long-term autonomous social interactions;
- Real-world algorithmic robustness;
- Complex ethical landscape;

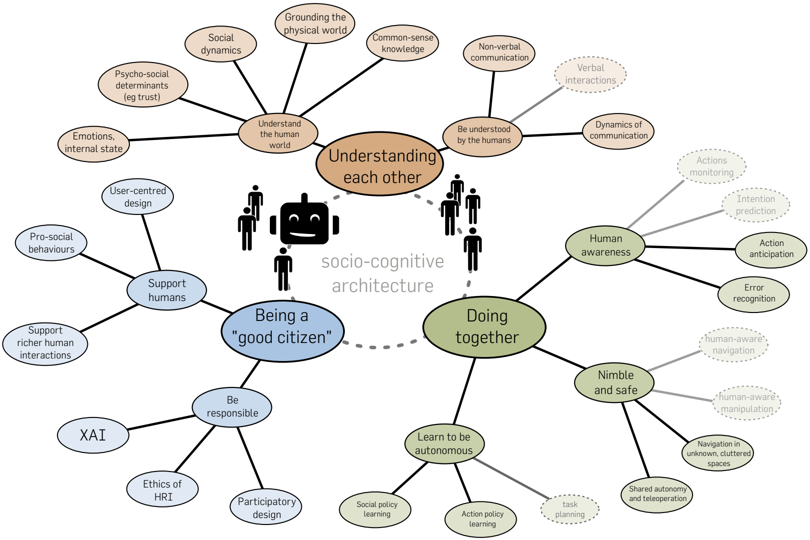
SOCIAL ROBOTICS

Major scientific challenges:

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



[Baxter, Lemaignan, Trafton **Workshop on Cognitive Architectures for Social HRI** – HRI 2016]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Social dynamics
Grounding the physical world
Common-sense knowledge
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
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Actions monitoring
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Action anticipation
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Nimble and safe
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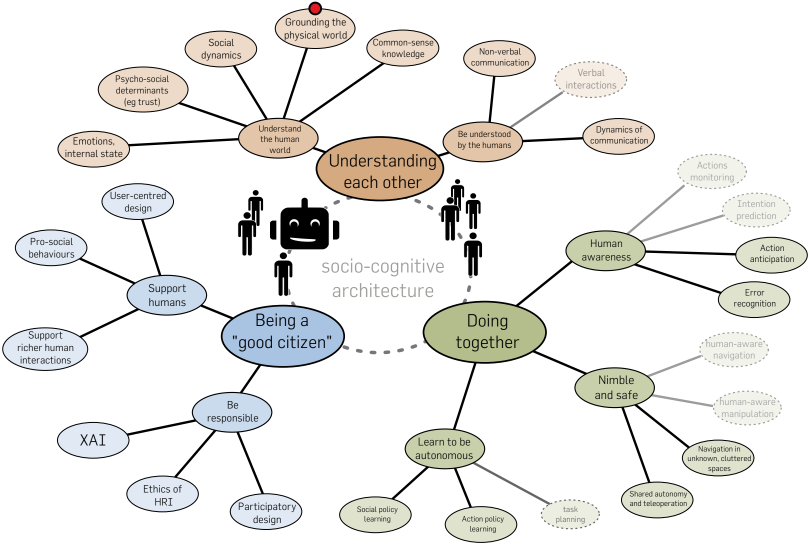
human-aware manipulation
Navigation in unknown, cluttered spaces
Shared autonomy and teleoperation
Learn to be autonomous
Social policy learning
Action policy learning
task planning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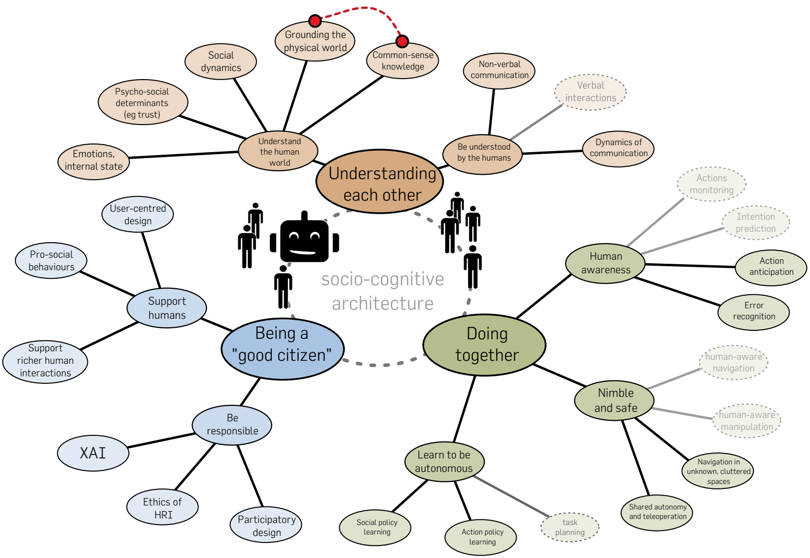
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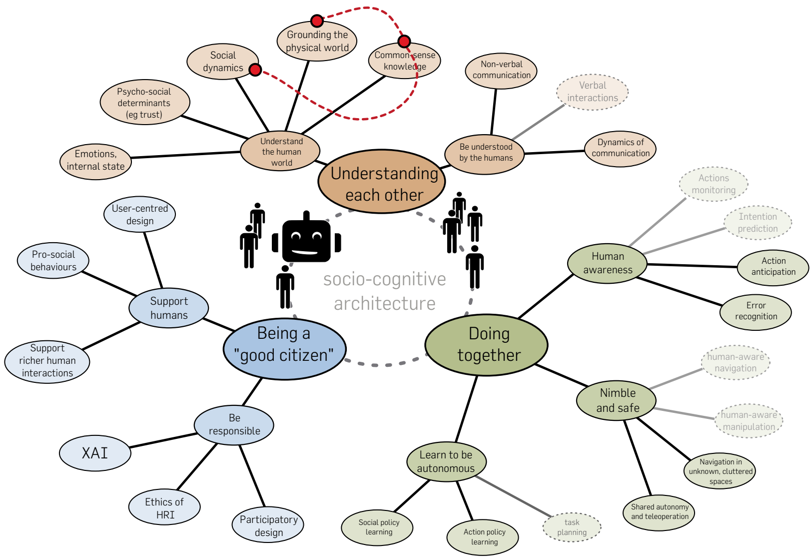
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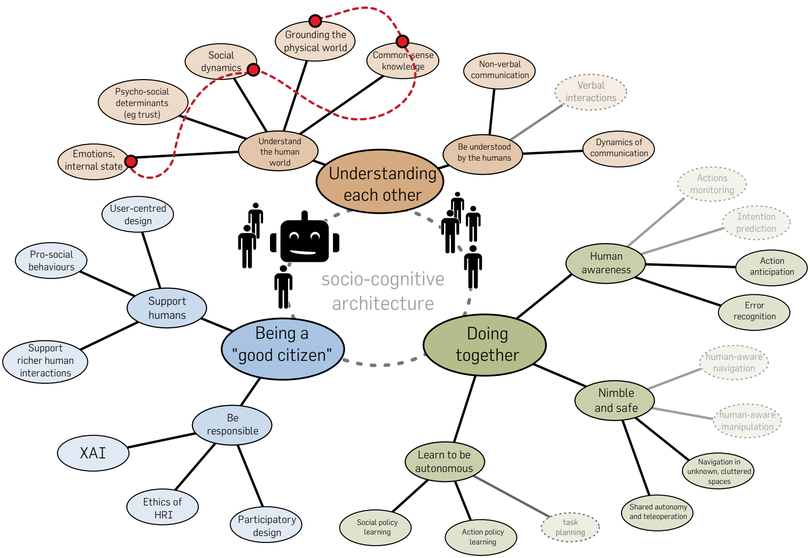

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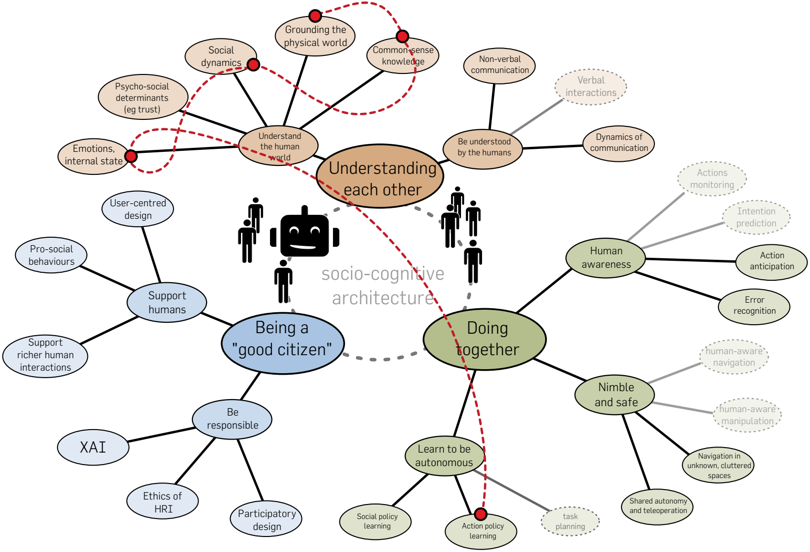

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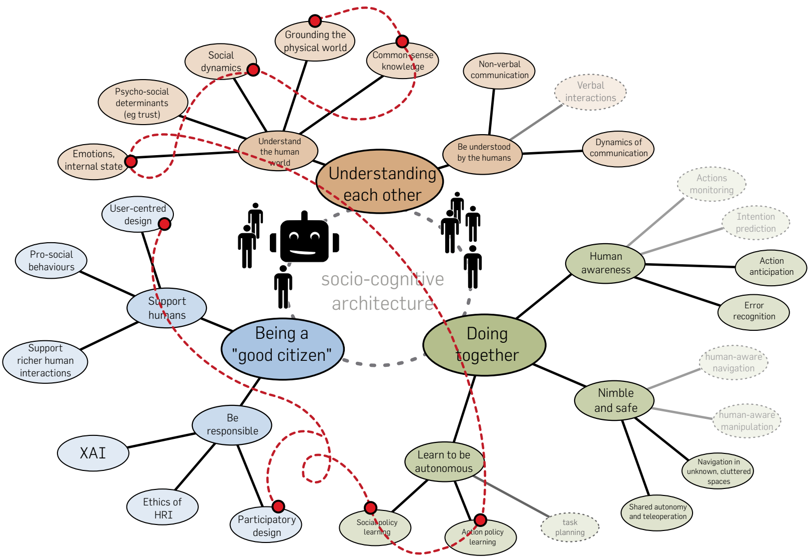

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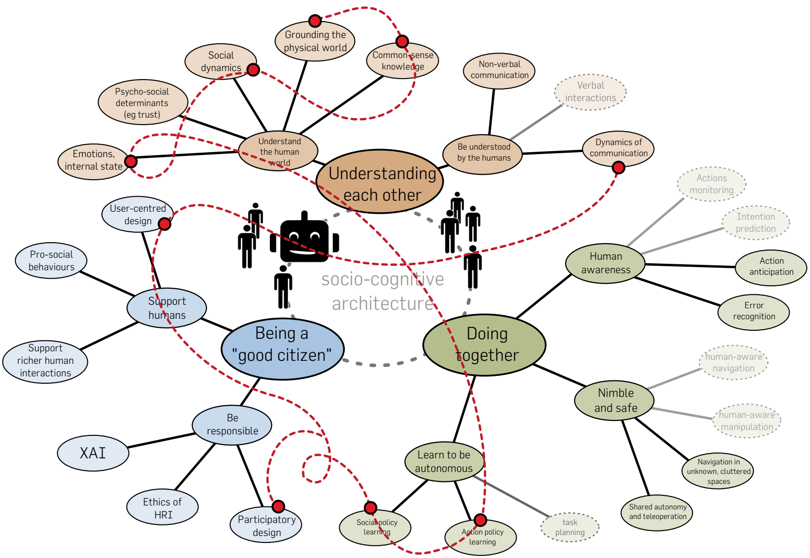

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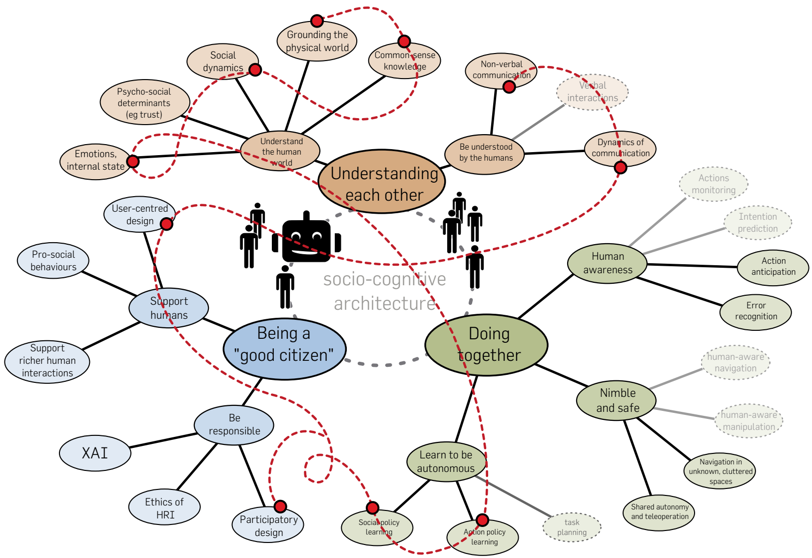
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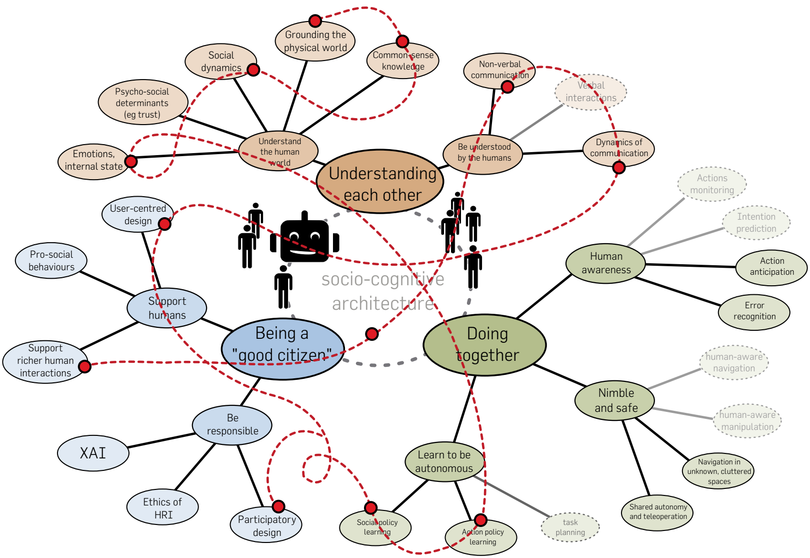
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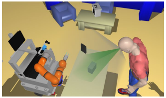
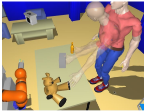
FROM SOCIAL SITUATION ASSESSMENT…

SITUATION ASSESSMENT

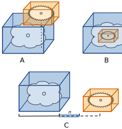
Yoan Sallami



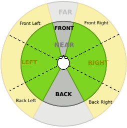
visibility



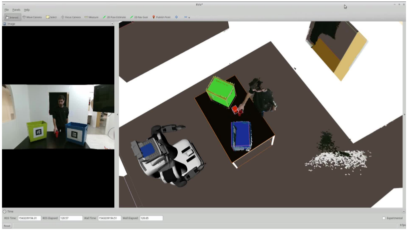
reachability



allocentric
spatial relations



egocentric
spatial relations

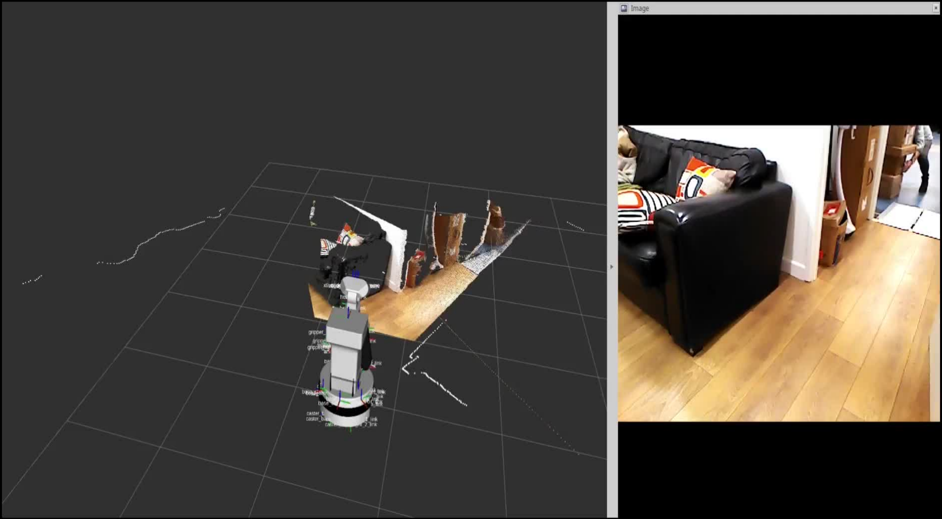


COMMON-SENSE: UNEXPECTED SITUATIONS

UDS: the Unexpected Daily Situations dataset

(idea borrowed from dev. psychologists Warneken and Tomasello)

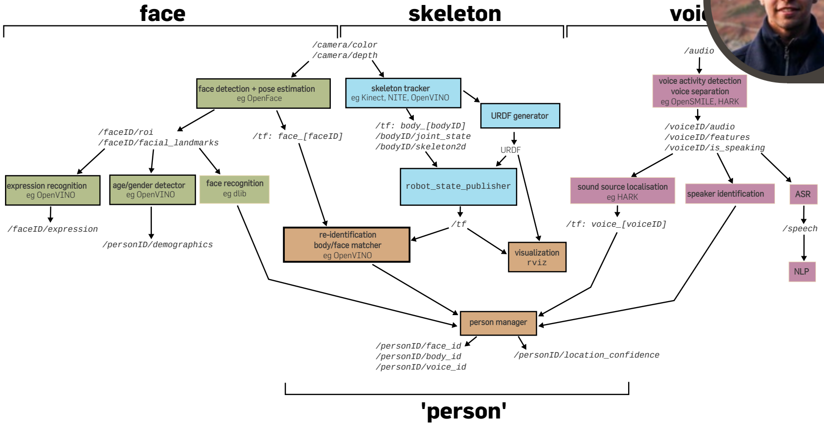
[Sallami et al. **The Unexpected Daily Situations Dataset: A New Benchmark for Socially-Aware Assistive Robots** HRI LBR 2020]



Image

ROS4HRI


Youssef Mohamed

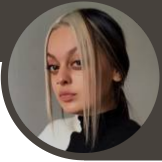


ROS4HRI: first integrated, multi-modal, ROS-based pipeline for social signal processing in robotics

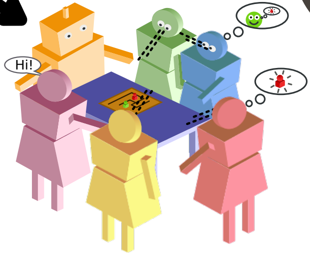
[Mohamed, Lemaignan **ROS for Human-Robot Interaction** Arxiv 2021 (under review IROS)]

…TO INTERNAL STATE…

SOCIAL MODELING

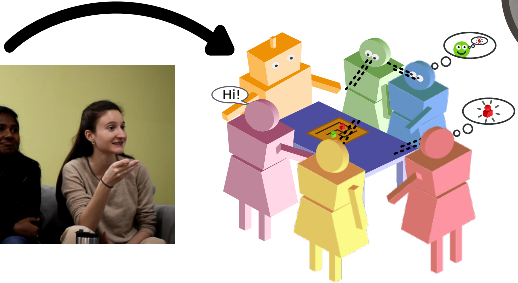


Nicola Webb



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

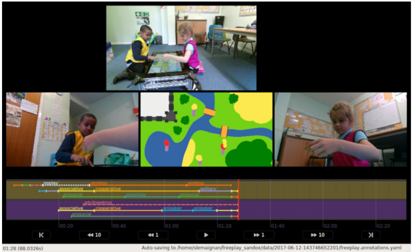
SOCIAL MODELING



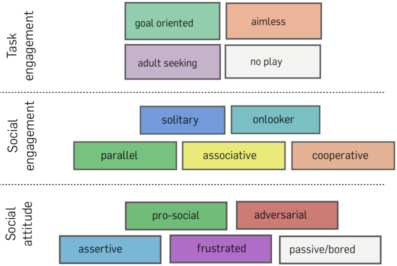
- multi-modal
- dynamic
- only partially observable
- complex pipeline; hard to make it robust

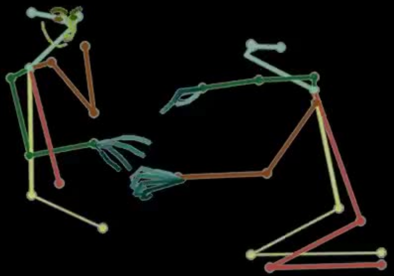
[Webb, Mohamed, Lemaignan **Framing the Challenge of Social Interaction Modelling** HRI LBR 2021]

DECIPHERING INTERNAL STATE

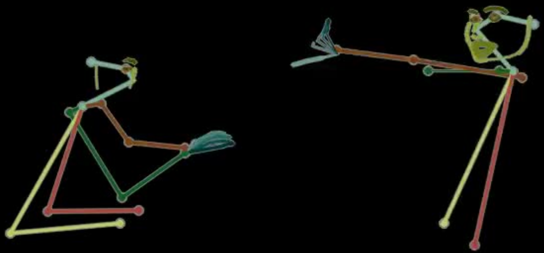


- PInSoRo dataset: 45h+ and 2M frames of annotated natural interactions. **freeplay-sandbox.github.io**
- first-in-kind dataset for data-driven study of social interactions in robotics
- new data analysis techniques to estimate internal state from body language






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	
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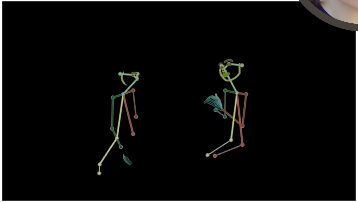
EFA: EXPLORATORY FACTOR ANALYSIS

	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]

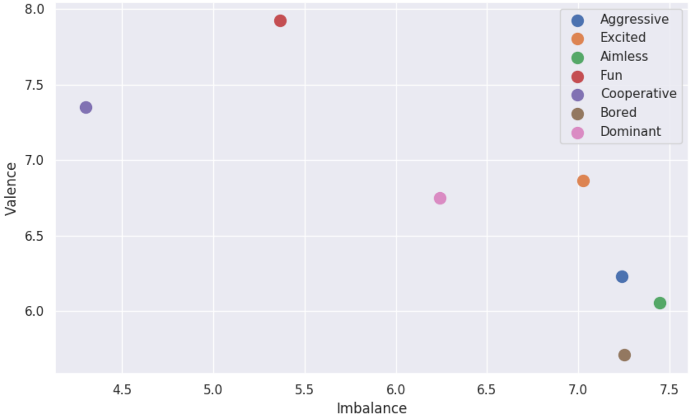
MEAN EFA PROJECTION OF CLIPS PER SOCIAL SITUATION

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



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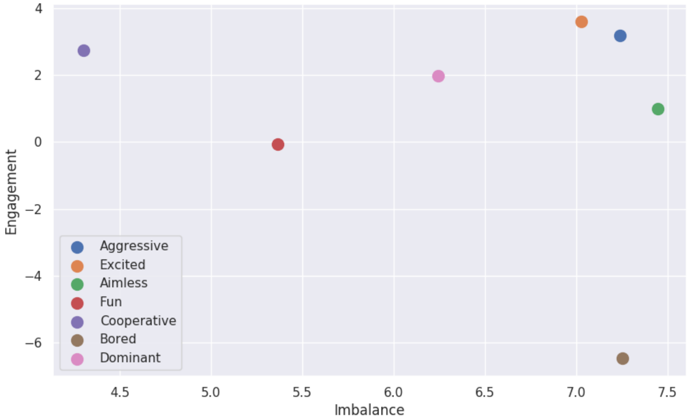
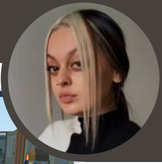
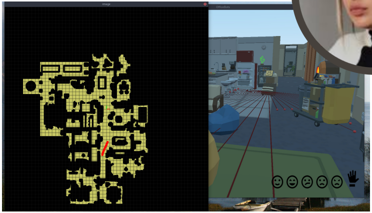


[Bartlett et al. **What Can You See? Identifying Cues on Internal States from the Kinematics [...]** FrontiersIn 2019]

ONLINE GAMES & SOCIAL DATASETS



Nicola Webb



…TO IN-SITU SOCIAL POLICY LEARNING

LET SET OURSELVES A CHALLENGE

Design & run a study with:

- a real robot

LET SET OURSELVES A CHALLENGE

Design & run a study with:

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

LET SET OURSELVES A CHALLENGE

Design & run a study with:

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

LET SET OURSELVES A CHALLENGE

Design & run a study with:

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

LET SET OURSELVES A CHALLENGE

Design & run a study with:

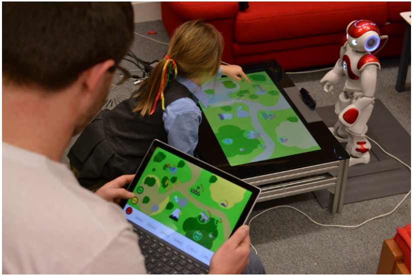
- a real robot
- a real interaction (...with a human!)
- a continuous interaction
- a realistic task (large state vector & action space)
- also including social behaviours & social dynamics

LET SET OURSELVES A CHALLENGE

Design & run a study 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
- ...and of course, the robot should be autonomous

IRL APPLIED TO SOCIAL ROBOTICS

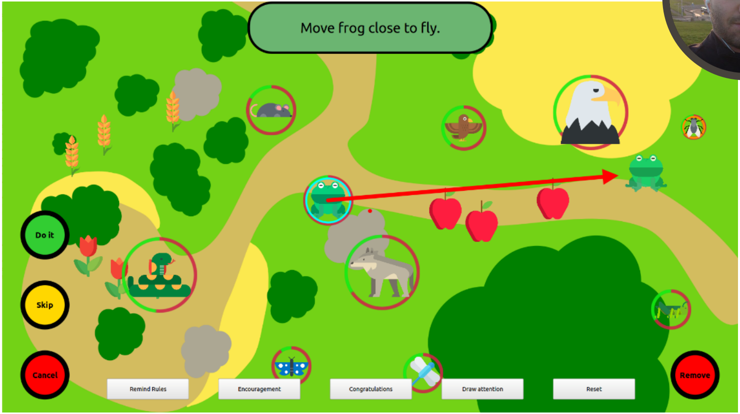


The children plays a game about food chains; the robot learns to guide them (*task-specific action policy*) and encourage them (*social action policy*)

Complex problem: $|state| = 210$ $|action\_space| = 655$

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

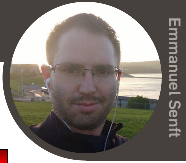
TEACHER'S INTERFACE



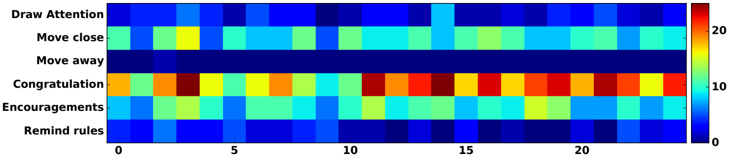
The robot's teacher (an end-user: might be the actual child's teacher) has a tablet interface that mirror's the child one, and add robot's teleoperation and rewards.

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

LEARNT ROBOT'S BEHAVIOUR



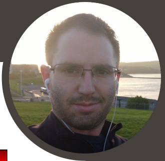
Distribution of actions for the 25 children participants:
Supervised



→ 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]

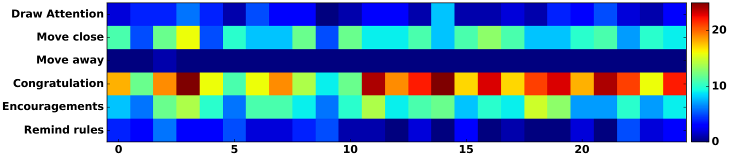
LEARNT ROBOT'S BEHAVIOUR



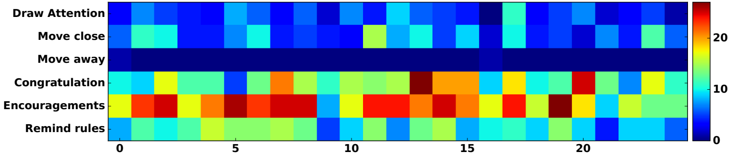
Emmanuel Senft

Distribution of actions for the 25 children participants:

Supervised



Autonomous



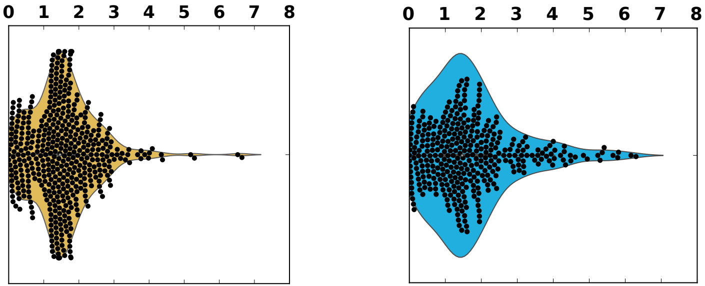
→ the robot personalises its action policies to the child's behaviour.

[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:

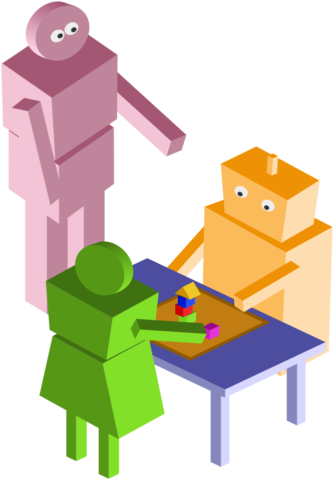
Time since eating event for each congratulation action (s)



supervised autonomous

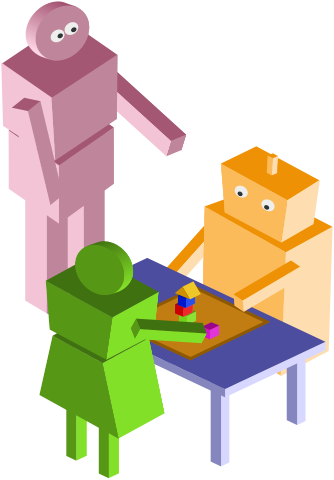
→ the robot has also learnt an appropriate social timing.

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**)

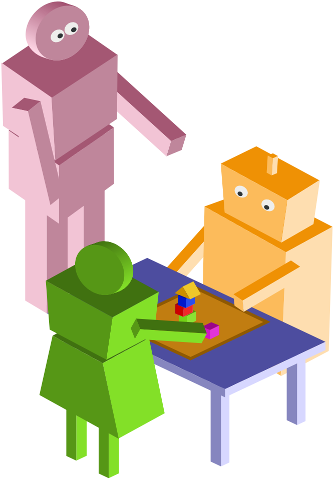
WHAT DOES THAT MEANS FOR THE EXPERT/TEACHER/END-USER?



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?
- Would that sustain long-term interactions?

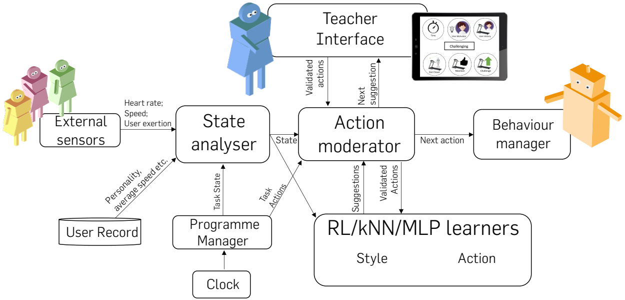
CO-DESIGN FOR REAL-WORLD, LONG-TERM INTERACT

Katie Winkle

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

EXPERT-IN-THE-LOOP MACHINE LEARNING

Katie Winkle

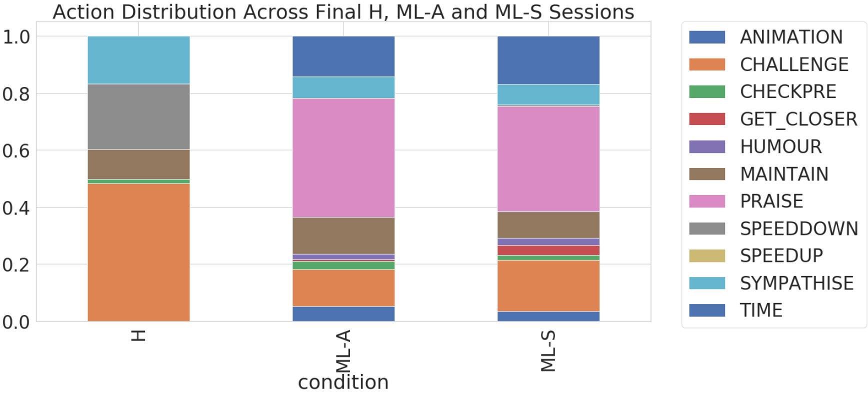


[Winkle et al. **In-Situ Learning from a Domain Expert for Real World Socially Assistive Robot Deployment** RSS 2020]

COUCH TO 5KM STUDY

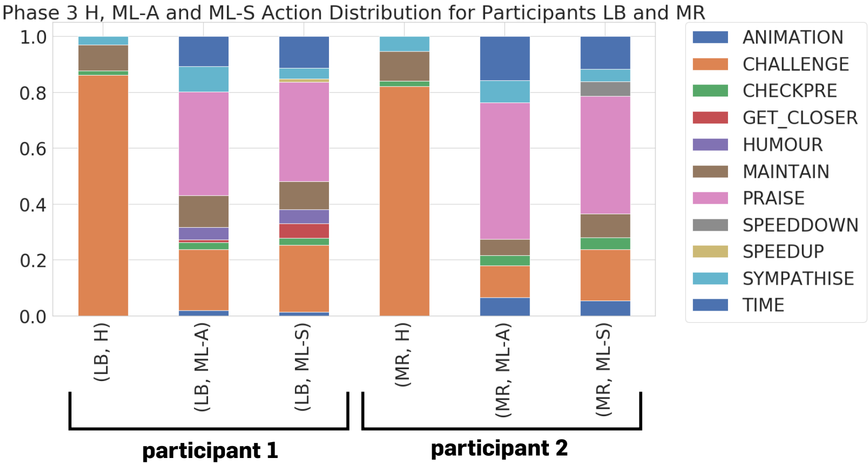
- 9 participants
- 3 months; 27 one-hour sessions per participants
- 20 input features; 11 actions (task-specific or social)
- human-in-loop design and machine learning
- robot evolving from full teleoperation to full task and social autonomy

LEARNT ACTION POLICY



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

LEARNT TO PERSONALISE

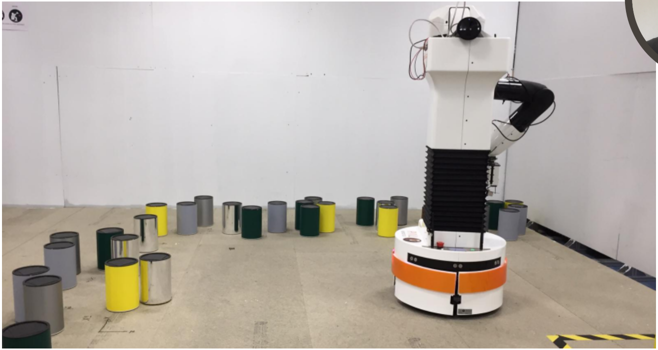


[Winkle et al. **In-Situ Learning from a Domain Expert for Real World Socially Assistive Robot Deployment** RSS 2020]

GENERATING SOCIALLY-CONGRUENT BEHAVIOURS

DYNAMIC VS NON-AMBIGUOUS LANGUAGE

Chris Wallbridge



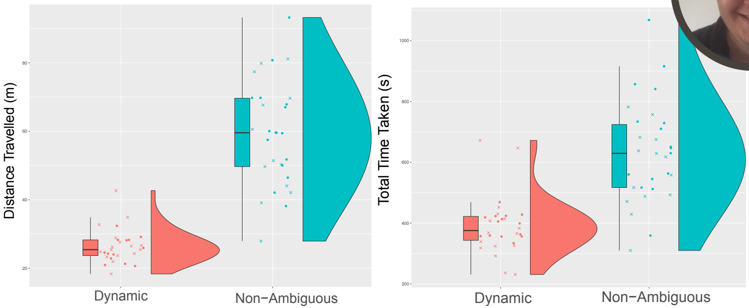
Condition Non-ambiguous: "A grey barrel is next to a grey barrel, next to a silver barrel and next to a green barrel."

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]

DYNAMIC VS NON-AMBIGUOUS LANGUAGE

Chris Wallbridge



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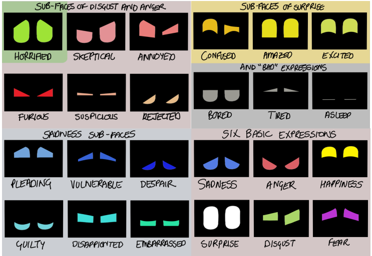
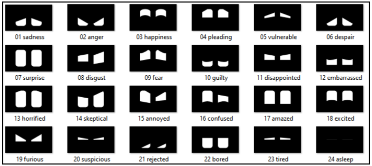
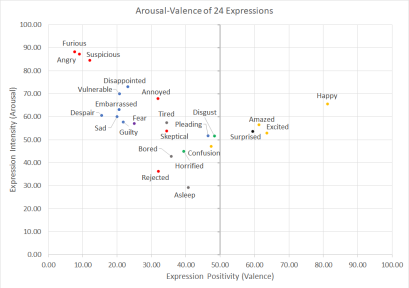
EXPRESSIVE EYES

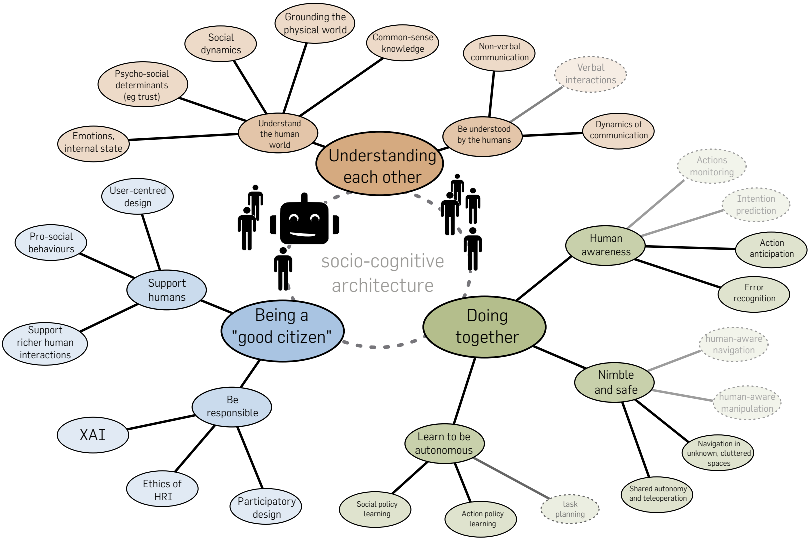




- inspired by Anki Cozmo/Vector
- expression interpretation validated online
- work by MSc student Catherine Chambers
- git.brl.ac.uk/s-lemaignan/expressive-eyes



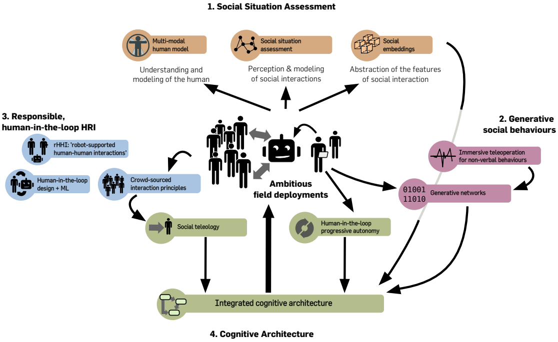
WHAT NEXT?



Understanding each other
Understand the human world
Emotions, internal state
Psycho-social determinants (eg trust)
Social dynamics
Grounding the physical world
Common-sense knowledge
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
Actions monitoring
Intention prediction
Action anticipation
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

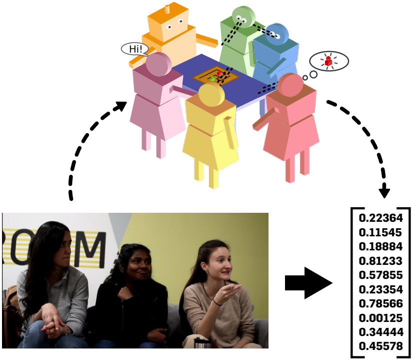
KEY SCIENTIFIC CHALLENGES

We want more real-world, long-term, autonomous interactions!



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**

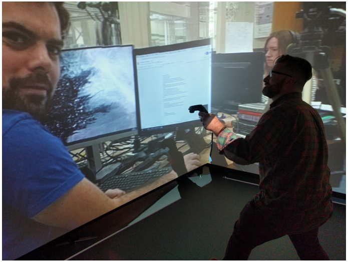
IDEA: SOCIAL EMBEDDINGS



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**

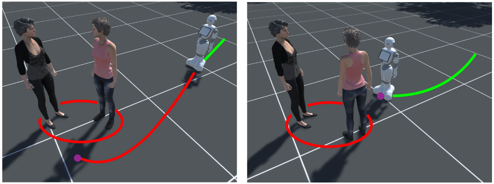
IDEA: GENERATIVE NON-REPETITIVE SOCIAL BEHAVIOURS

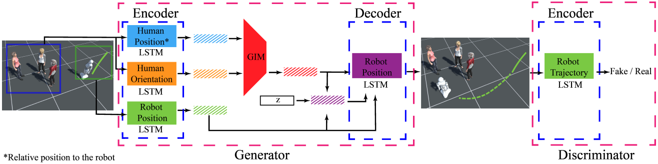


- Cracking the '**non-repetitive, socially congruent**' behaviour generation problem
- Extend **Generative Adversarial Networks** *à la* AppGAN to complex behaviours (re-use *social embeddings*)
- **Immersive technologies** to build datasets
- **Transdiscplinary approach**, incl. arts: choreographer,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

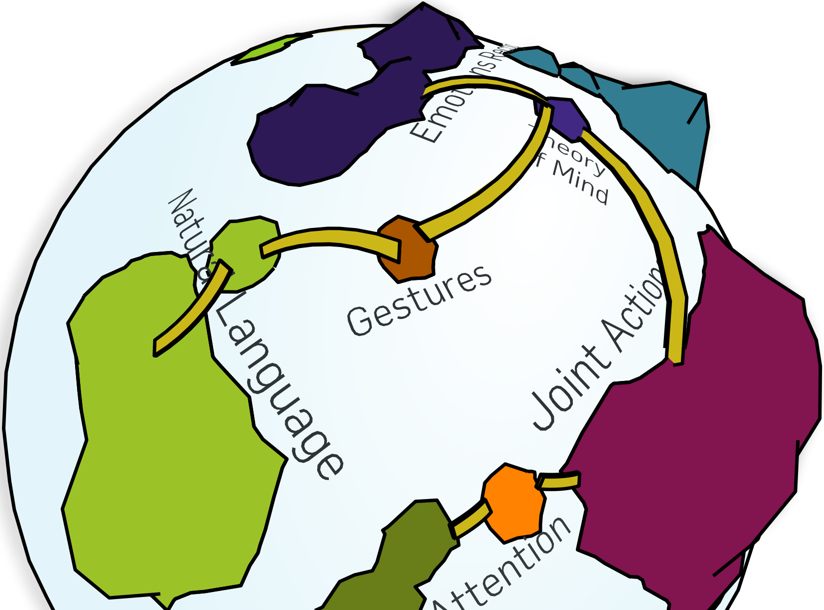


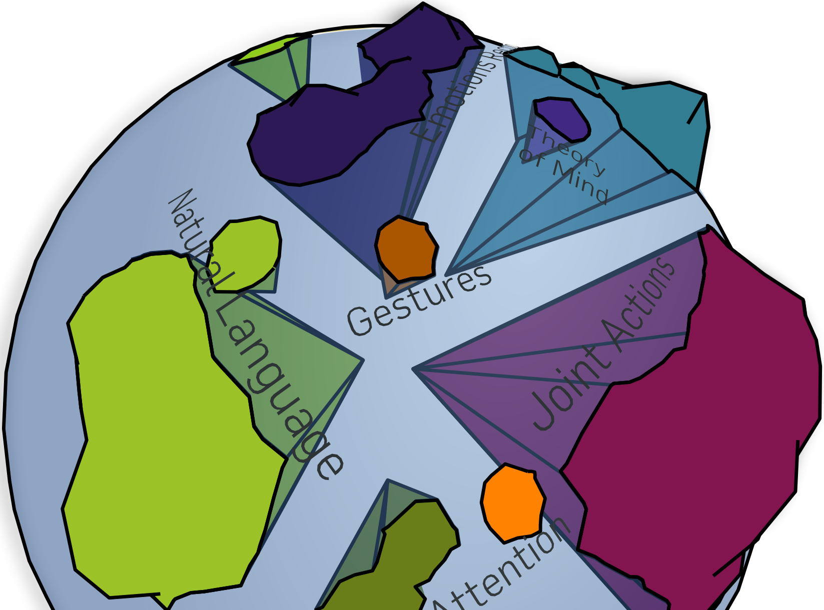


[Yang et al. **AppGAN: Generative Adversarial Networks for Generating Robot Approach Behaviours [...]** RoMan 2019]

Cognitive architecture?

Emotions
Theory
of Mind
Natural Language
Gestures
Joint Actions
Attention

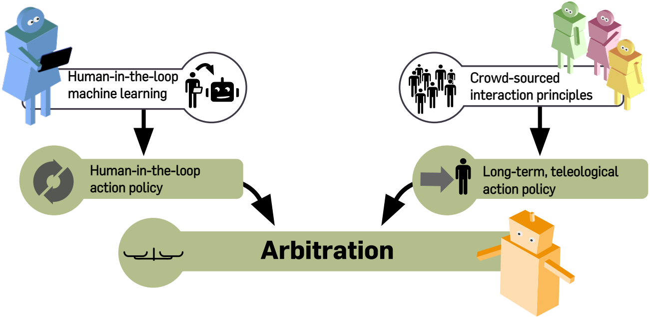

Gestures
Language
Mind
Attention



Emotions
Theory of Mind
Natural Language
Gestures
Joint Actions
Attention

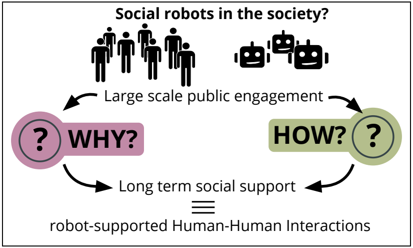
IDEA: SOCIO-TELEOLOGICAL ARCHITECTURE

Teleological → **goal-oriented** architecture



- **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**

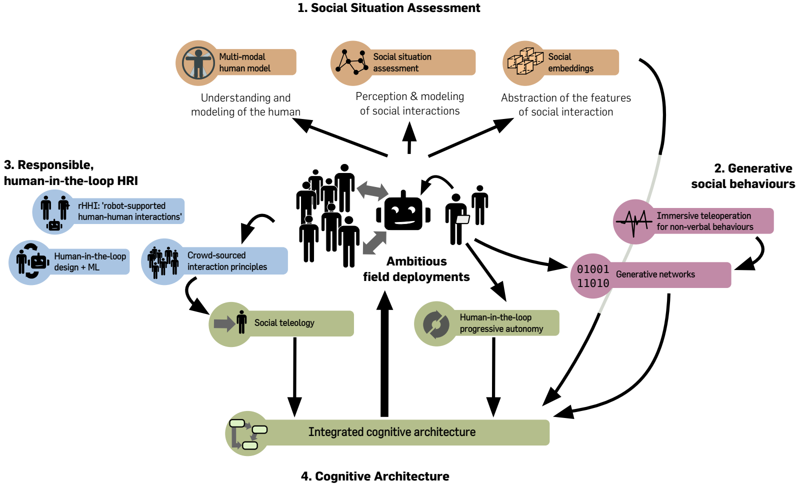
IDEA: ROBOT-SUPPORTED HUMAN-HUMAN INTERACTIONS

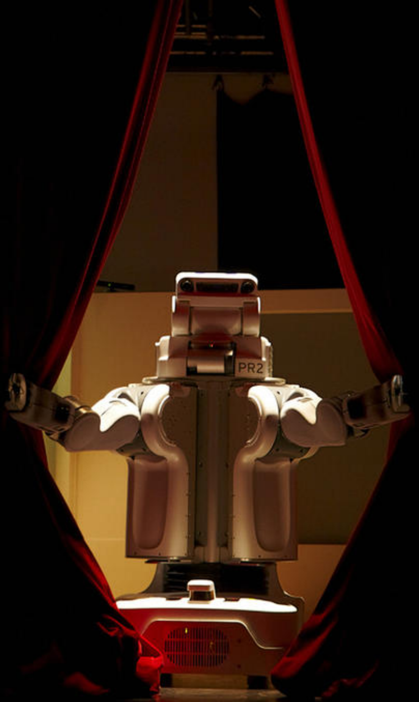


Social robotics might need a paradigm shift from *Human-Robot Interaction* to **robot-supported Human-Human Interaction**:

- 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)*