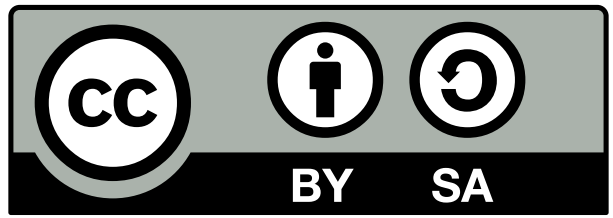
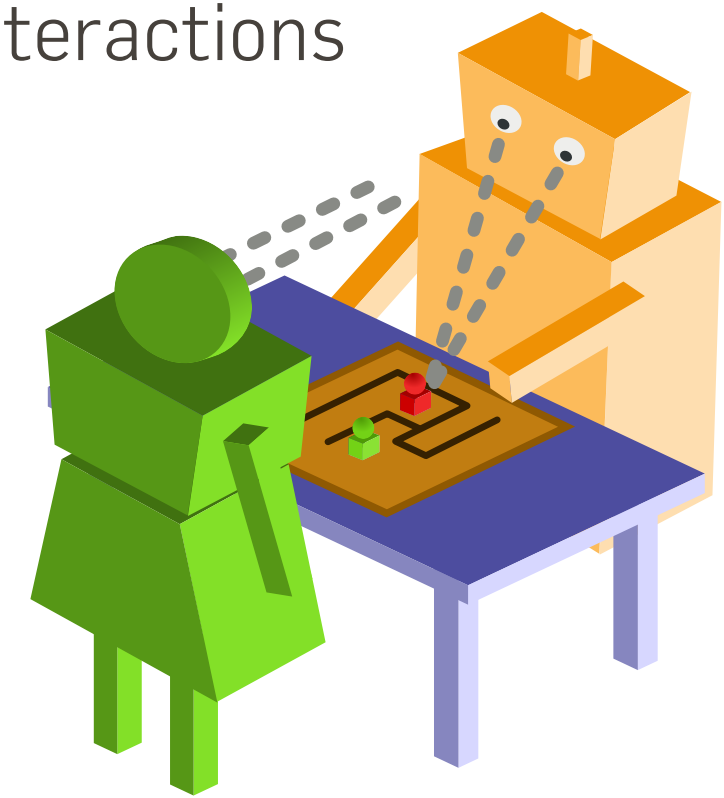


You can download the sources of this presentation here:

github.com/severin-lemaignan/presentation-research

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

10 Mar 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

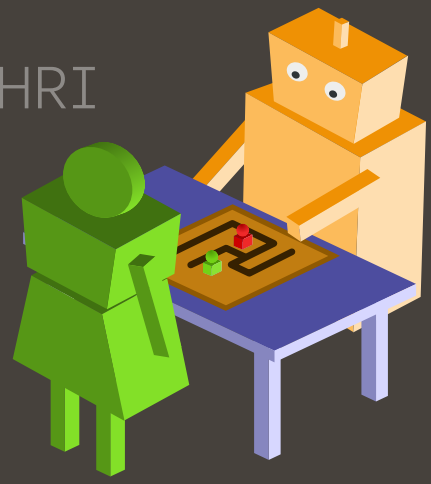
cognitive architectures

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

human-in-the-loop ML

social robotics

responsible AI

trust

experimental robotics

HUMAN FACTORS

child-robot interaction

robotics for learning

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**.

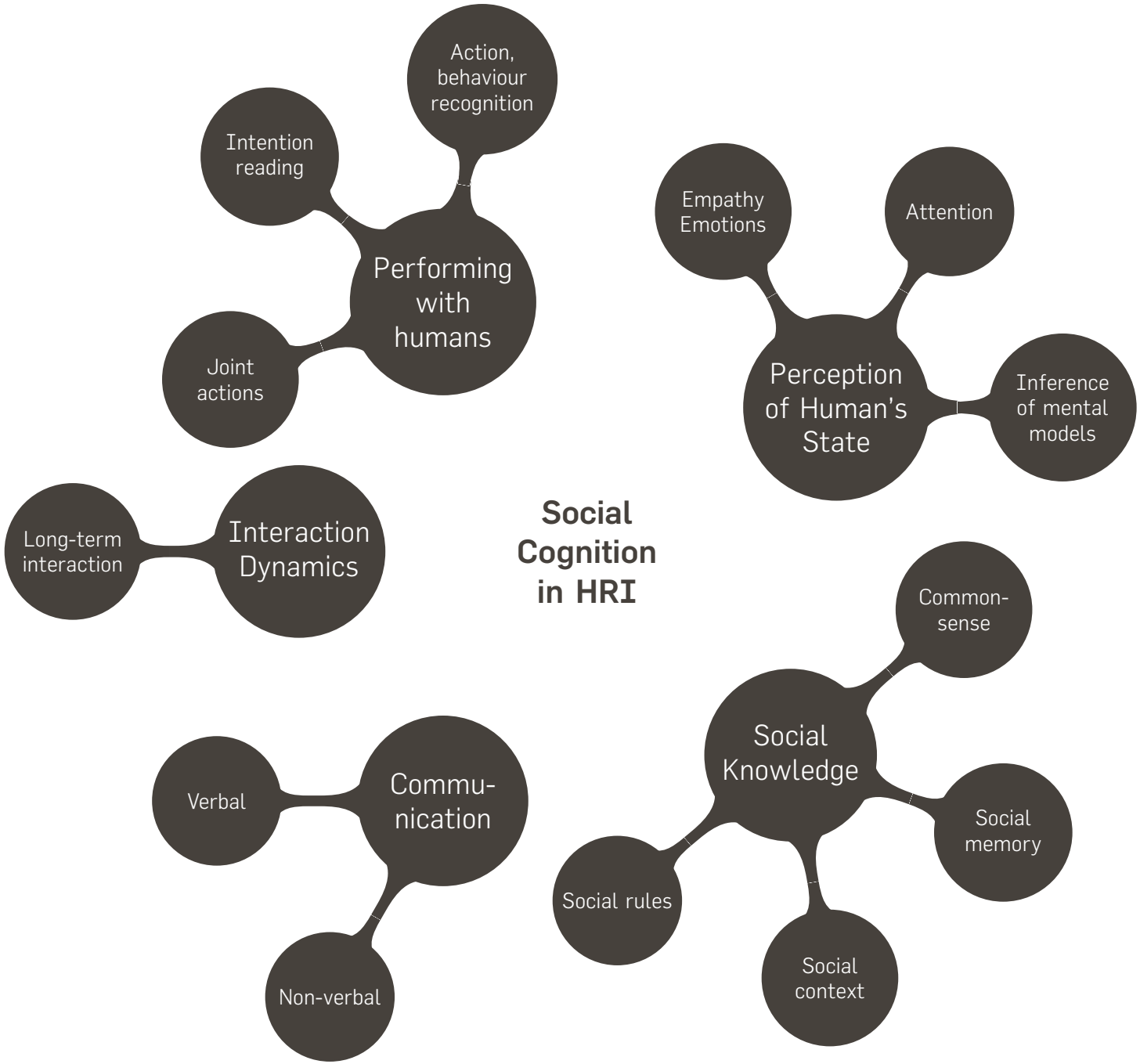
⇒ designing and implementing the **assistant and companion robots** for tomorrow.

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

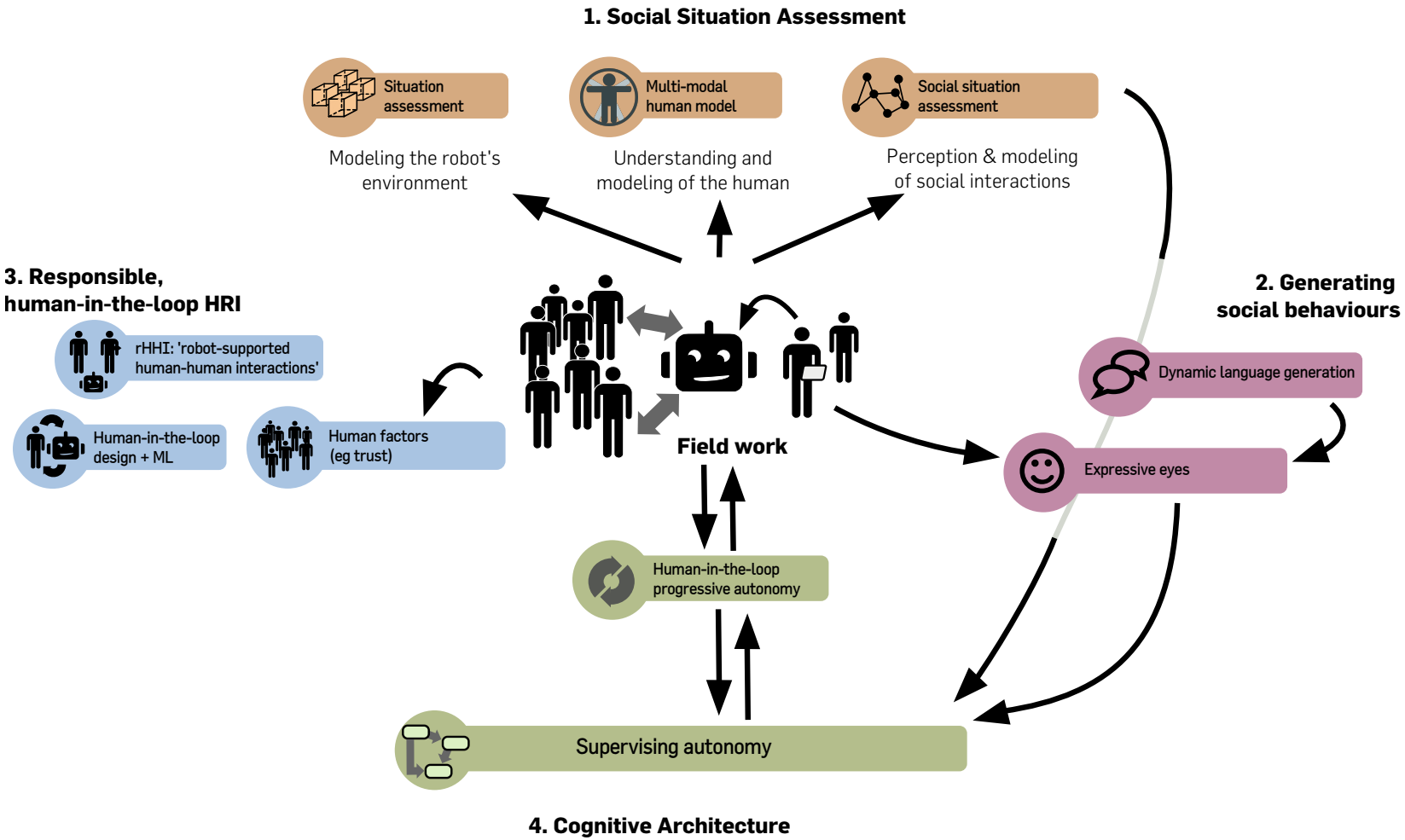
SOCIAL ROBOTICS

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


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
Social Knowledge
Common-sense
Social memory
Social rules
Social context
Commu-nication
Verbal
Non-verbal

WHAT HAVE WE BEEN UP TO OVER THE LAST 3 YEARS?

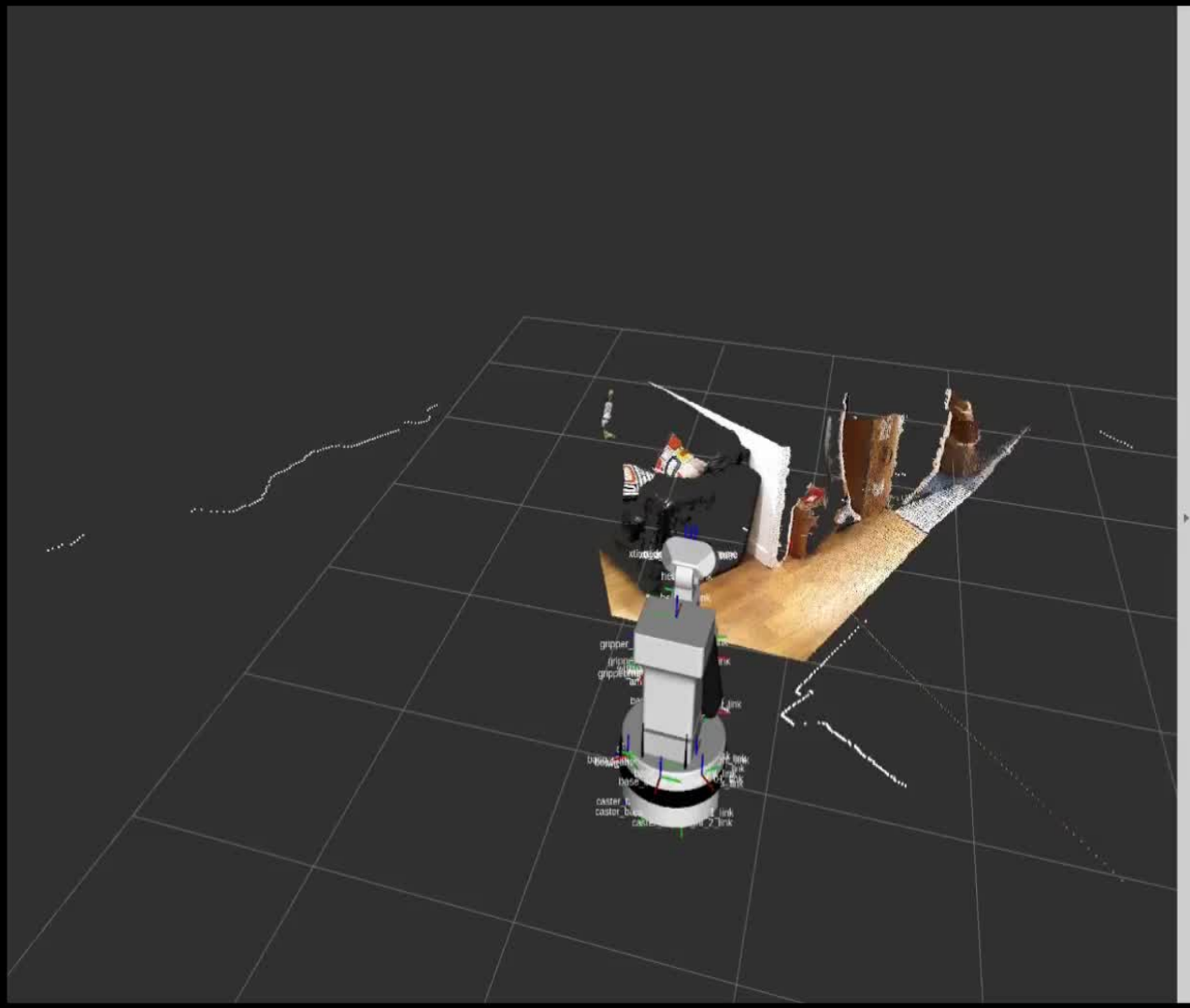


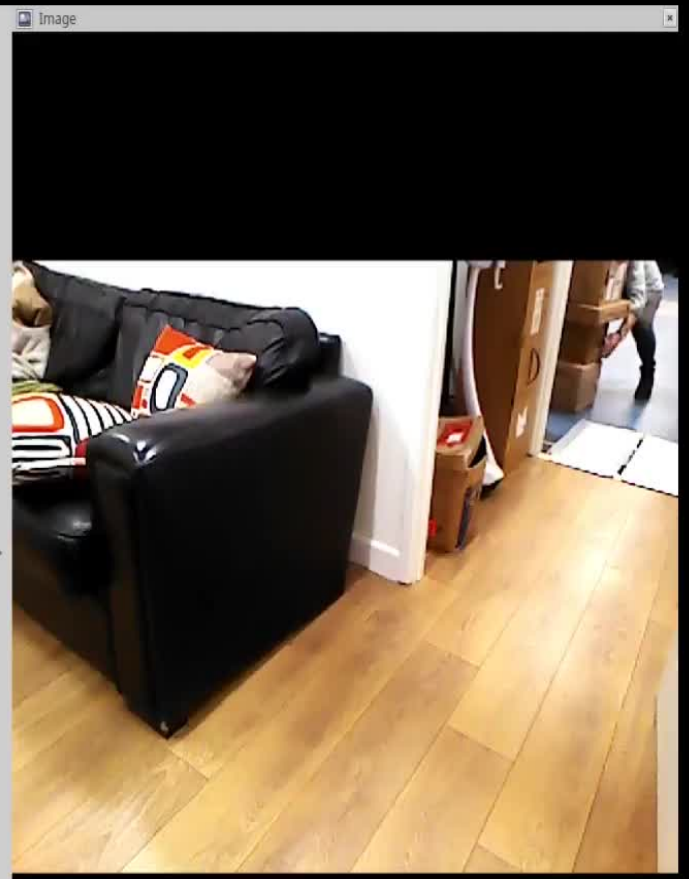
SOCIAL SITUATION ASSESSMENT

THE UNEXPECTED DAILY SITUATION DATASET

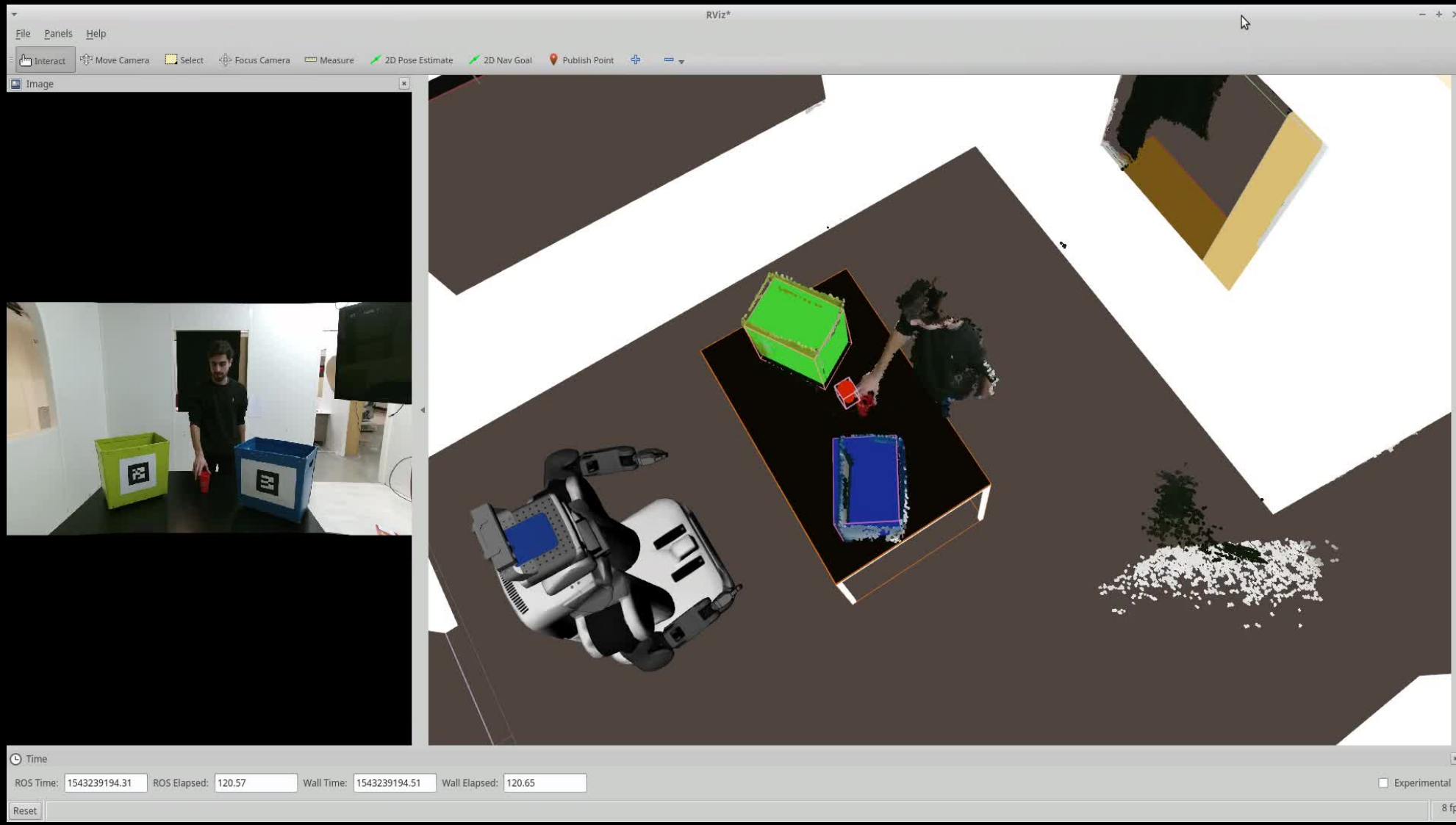
Yoan Sal

[Sallami et al. **The Unexpected Daily Situations Dataset: A New Benchmark for Socially-Aware Assistive Robots** HRI LBR 2020] 8

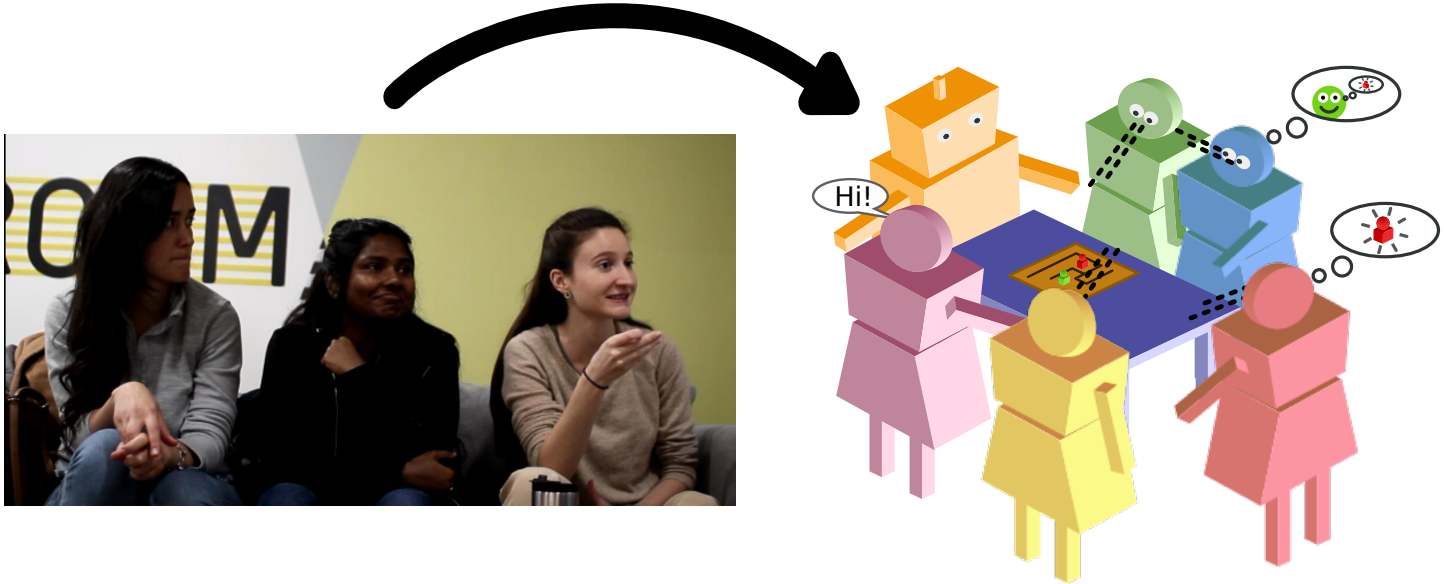




Image


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

SOCIAL MODELING

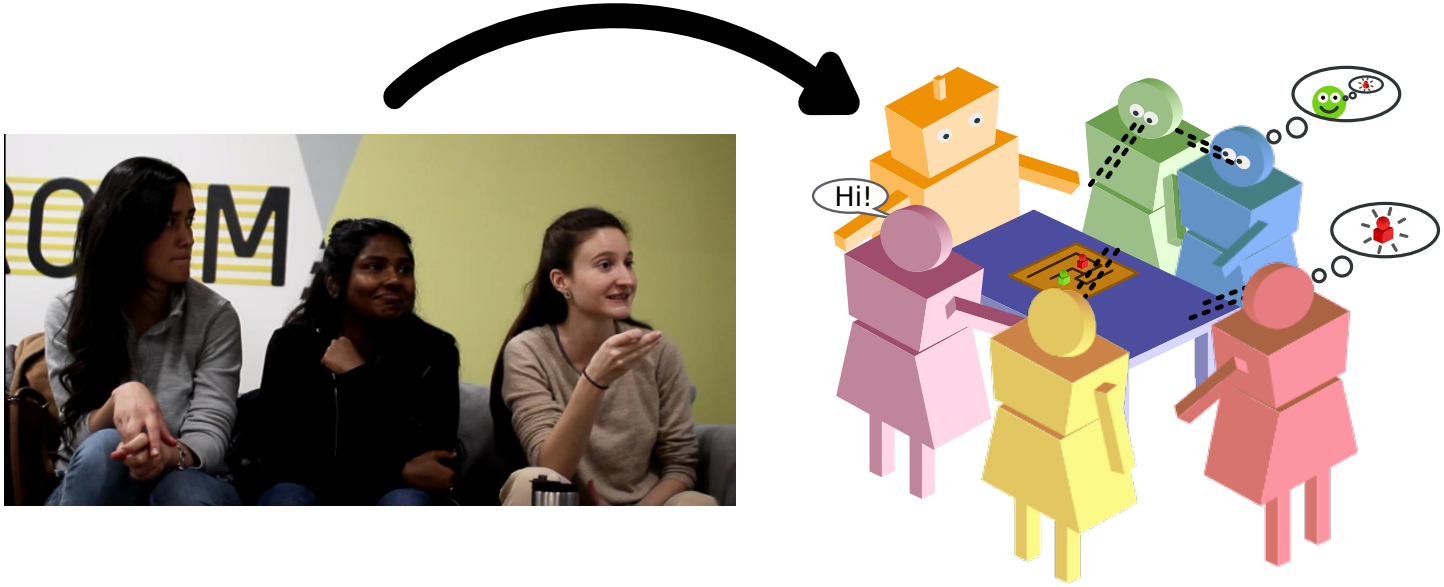


Nicola W

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

Nicola W

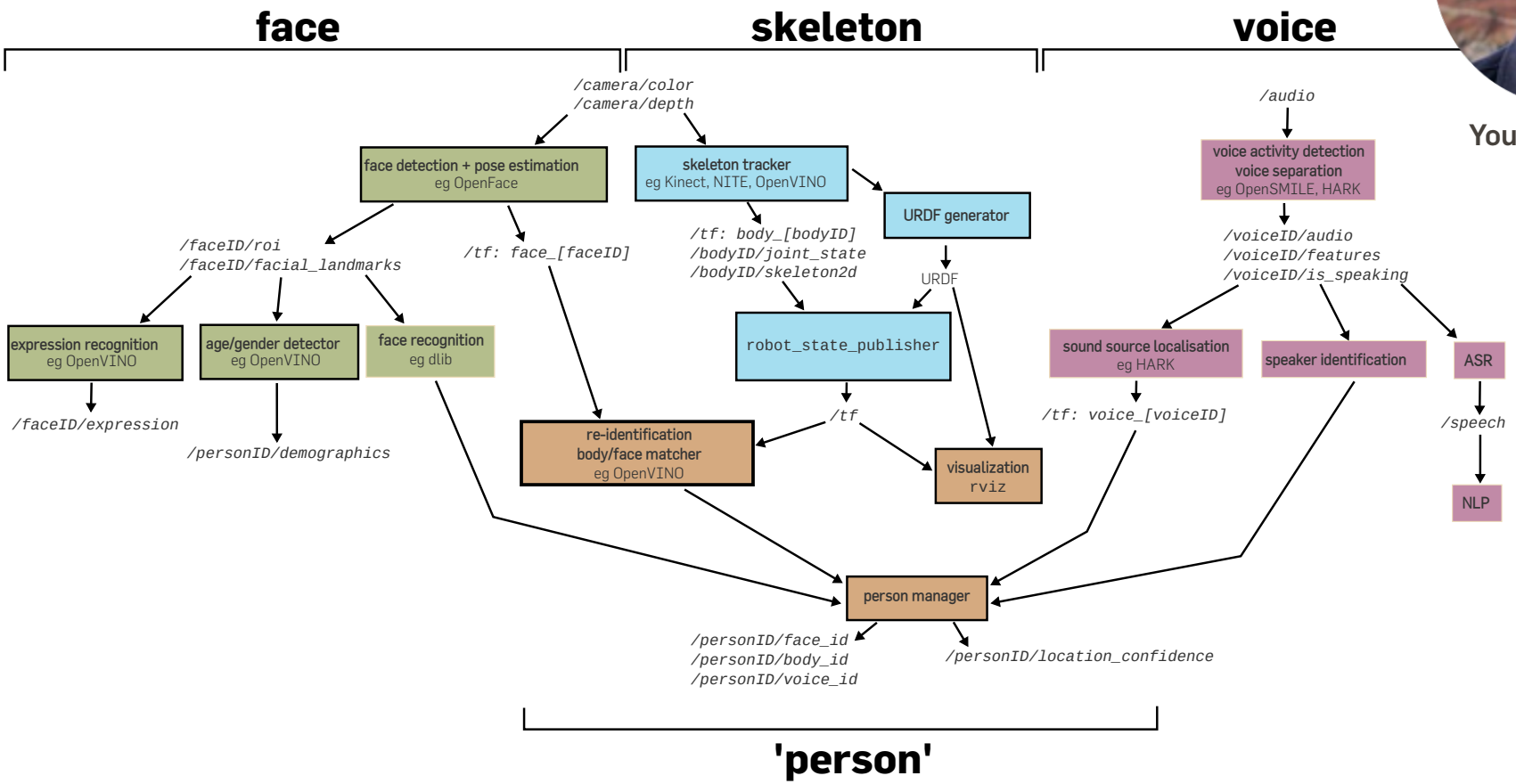
SOCIAL MODELING



- 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]

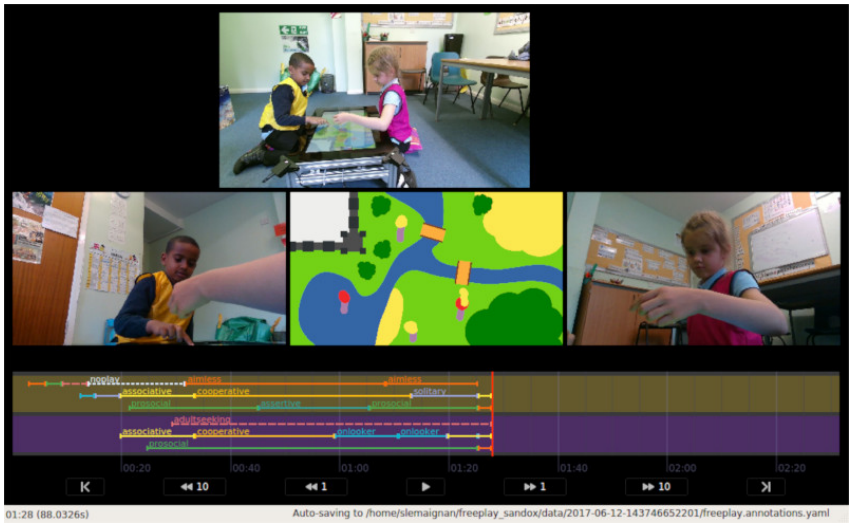
ROS4HRI

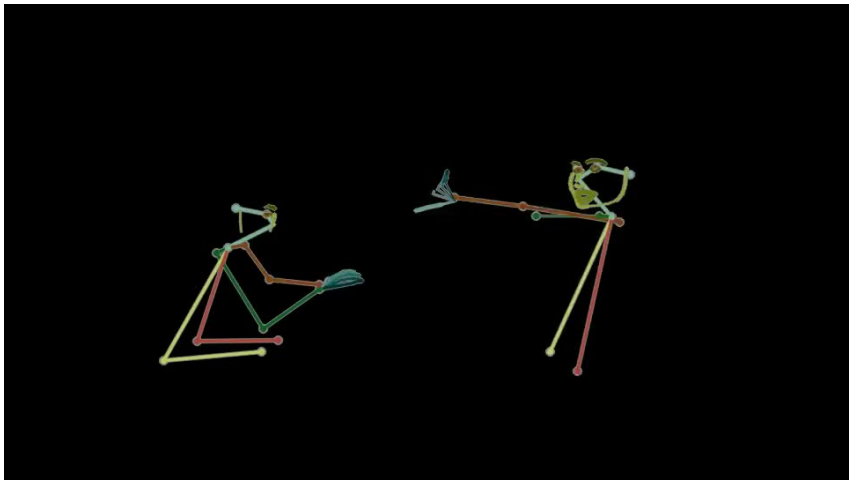


ROS4HRI: first integrated, multi-modal, ROS-based pipeline for social signal processing in robotics

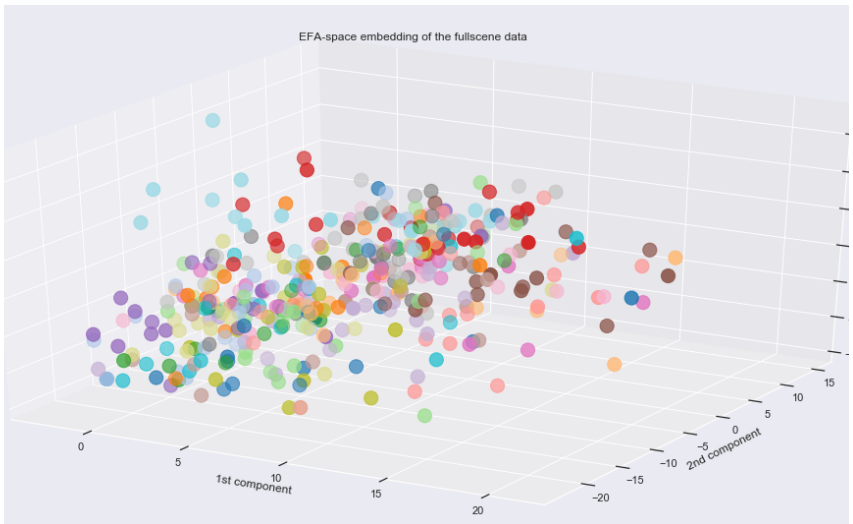
[Mohamed, Lemaignan **ROS for Human-Robot Interaction** Arxiv 2021 (under review IROS)]

DECIPHERING INTERNAL STATE

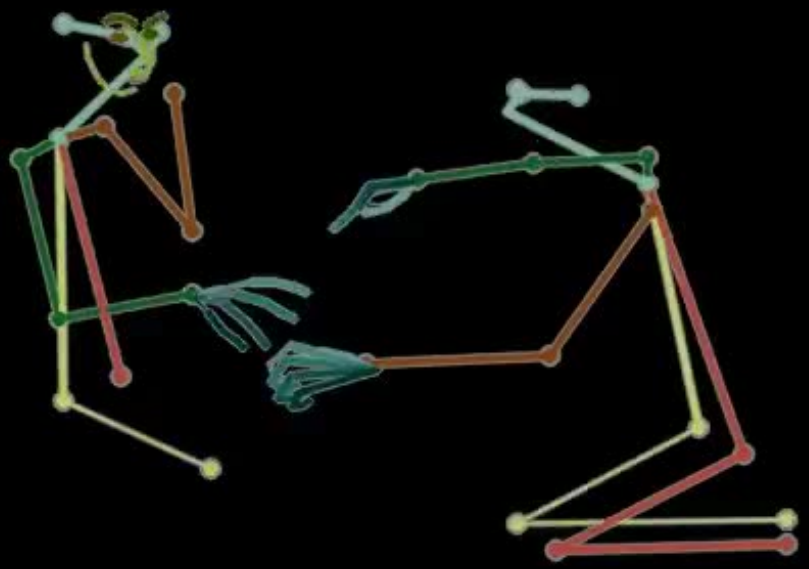




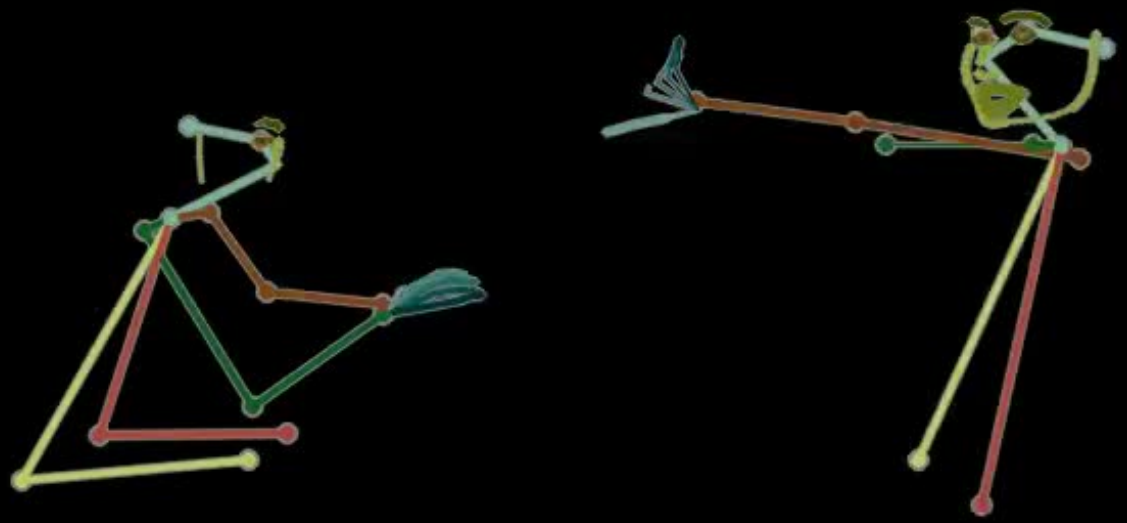
- PInSoRo dataset: 45h+ and 2M frames of annotated natural interactions
- new data analysis techniques to estimate internal state from body language
- first-in-kind dataset for data-driven study of social interactions in robotics



[Lemaignan et al. **The PInSoRo dataset: Supporting the data-driven study of child-child and child-robot [...]** PLOS One 2018]
[Bartlett et al. **What Can You See? Identifying Cues on Internal States from the Kinematics [...]** FrontiersIn 2019]




Focused!
ILLUMINATED POLITICAL
& PHYSICAL




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

The child on the left was sad.

Strongly Disagree	Disagree	Not Sure	Agree	Strongly Agree

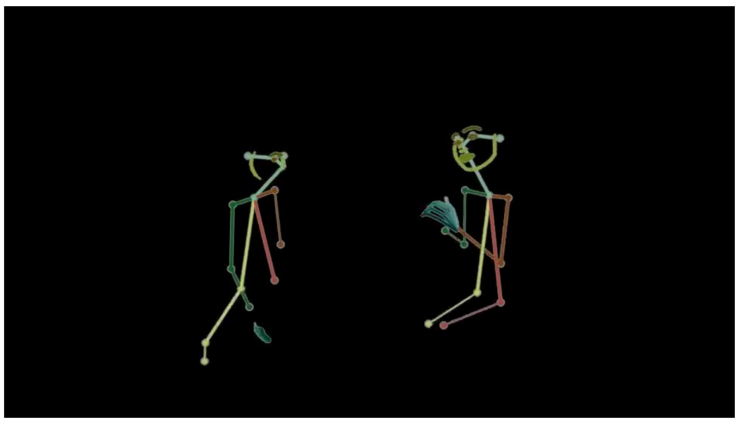
200 participants, 4 clips each, on MTurk

EFA: EXPLORATORY FACTOR ANALYSIS

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



Interaction imbalance

Interaction valence

Engagement

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

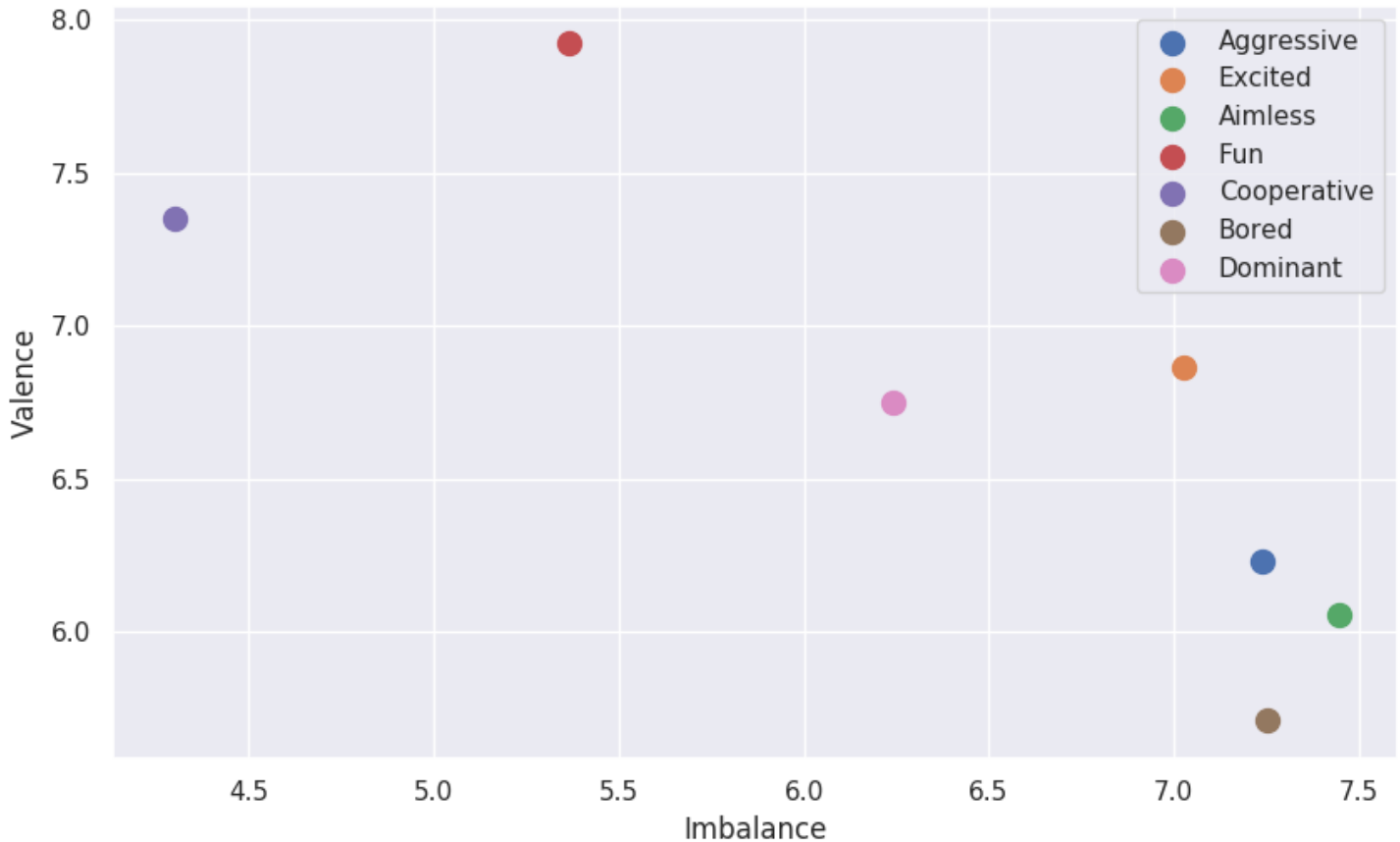
MEAN EFA PROJECTION OF CLIPS PER SOCIAL SITUATION

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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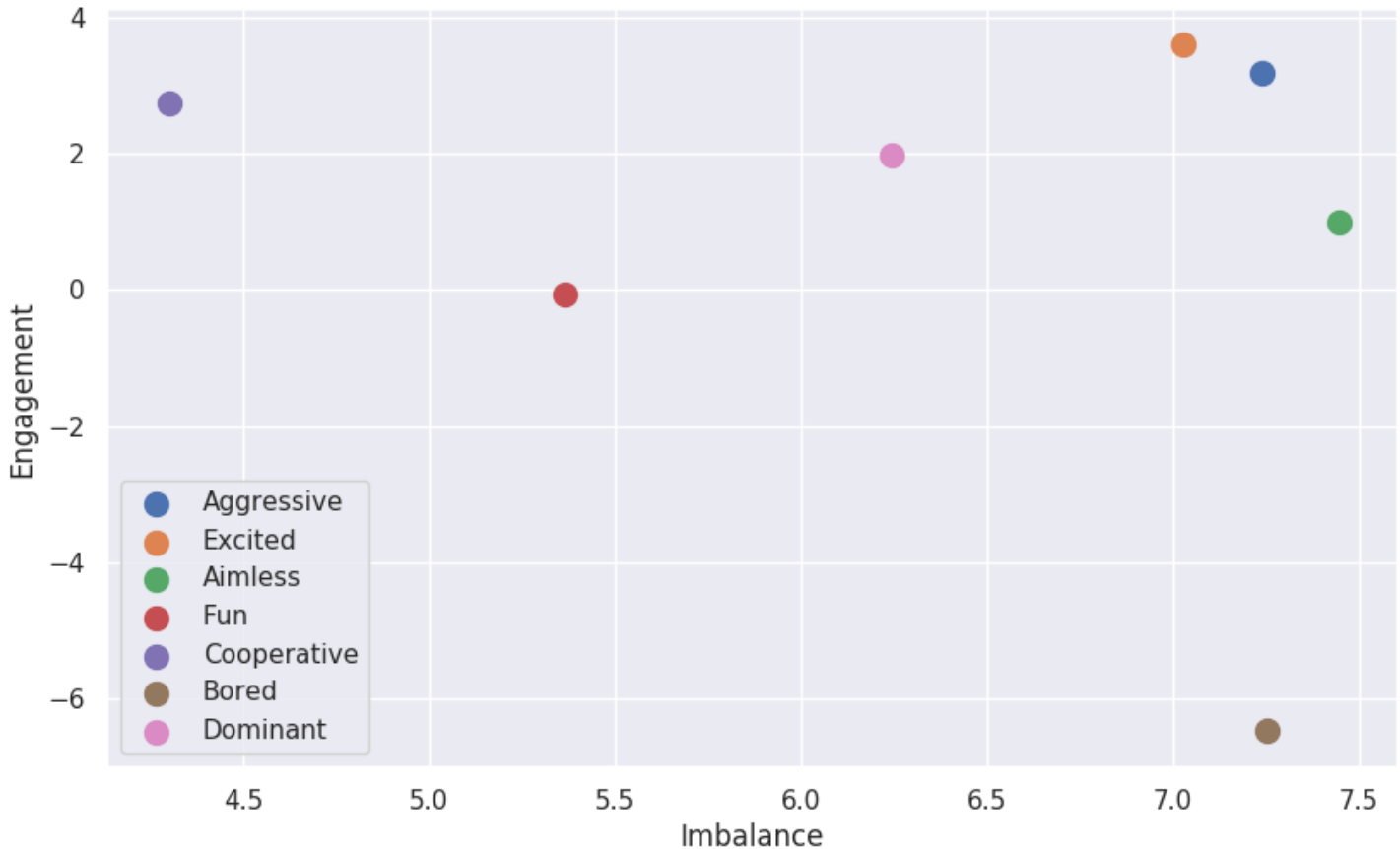
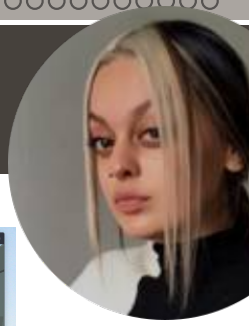


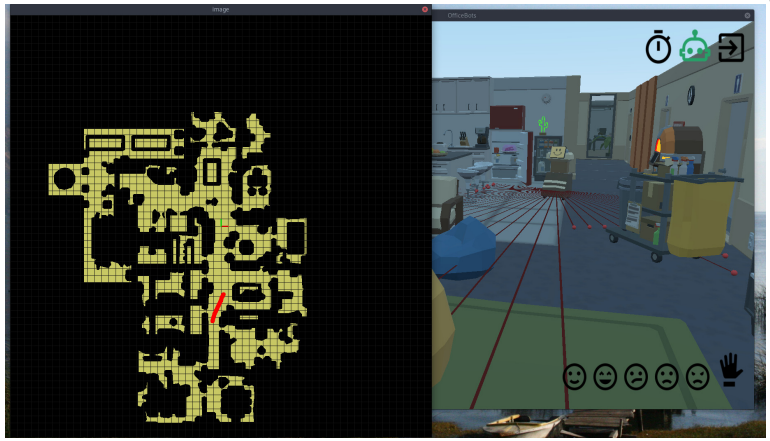
[Bartlett et al. **What Can You See? Identifying Cues on Internal States from the Kinematics [...]** FrontiersIn 2019]

DATA-DRIVEN HRI

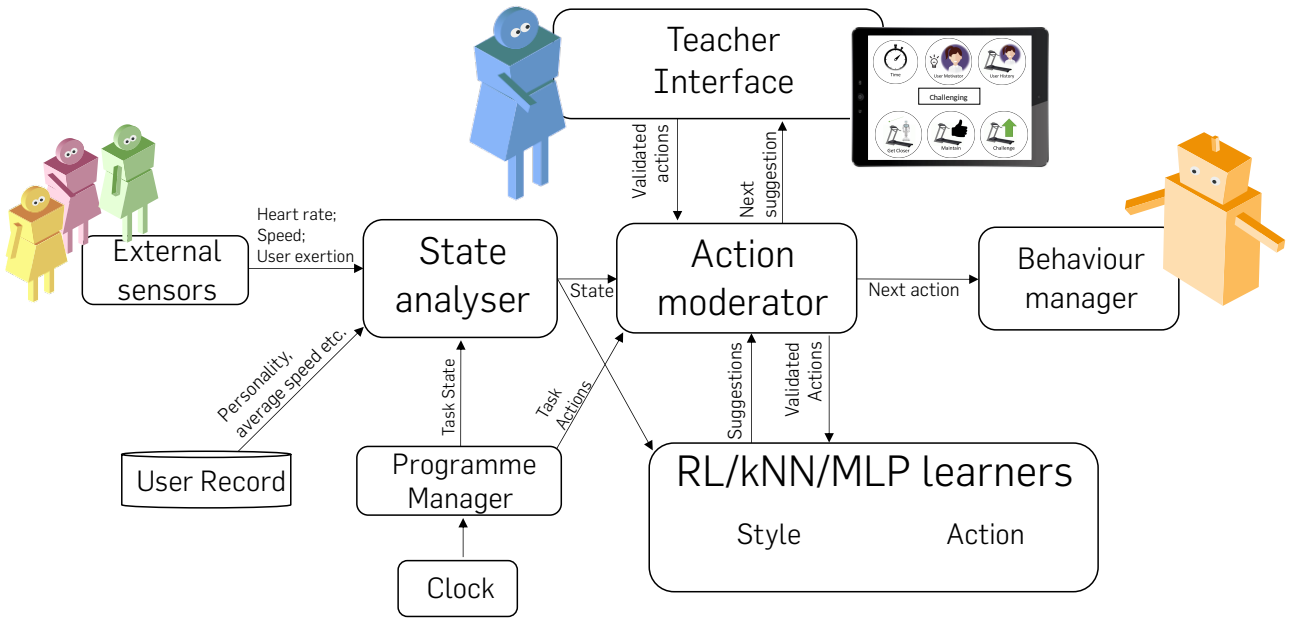
ONLINE GAMES & SOCIAL DATASETS



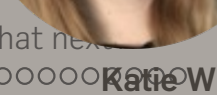
Nicola W



EXPERT-IN-THE-LOOP MACHINE LEARNING



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

Chris Wallbr

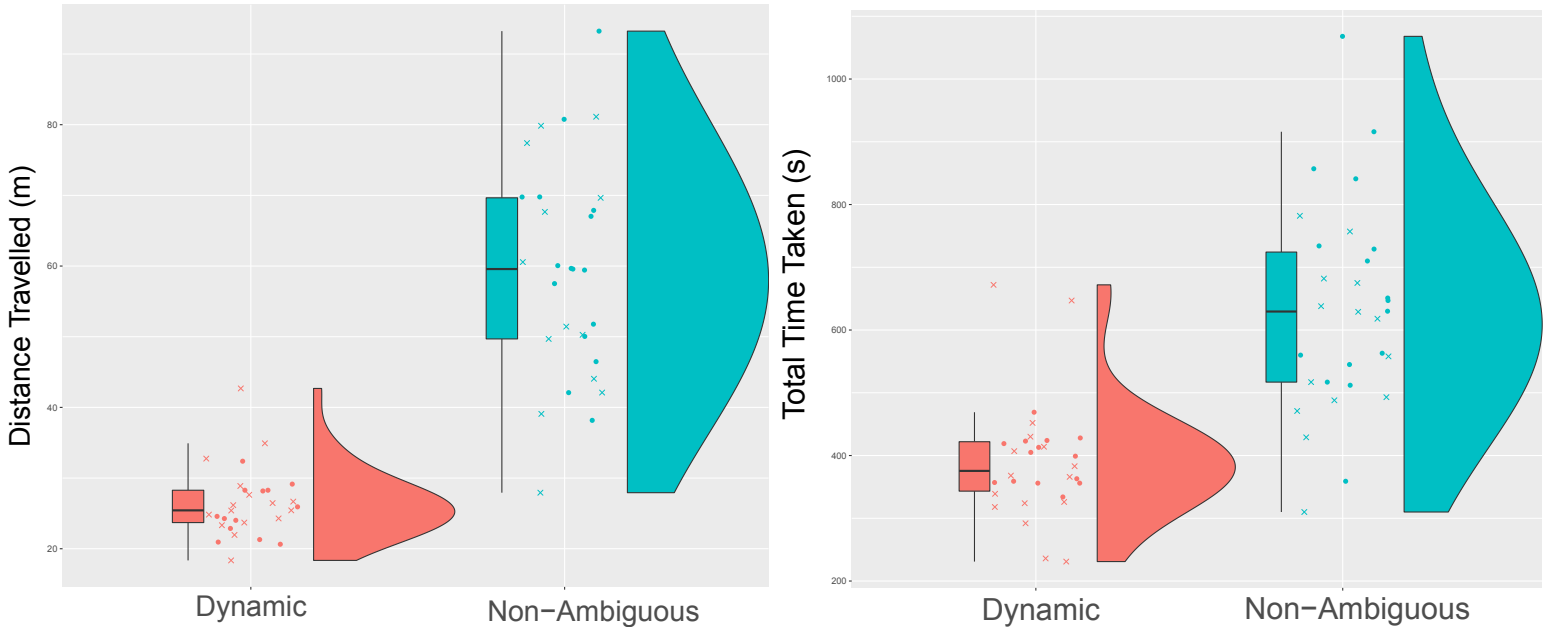
Condition Non-ambiguous: "A grey barrel is next to a grey barrel, next to a silver barrel and next to a green barrel."

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 Wallbr



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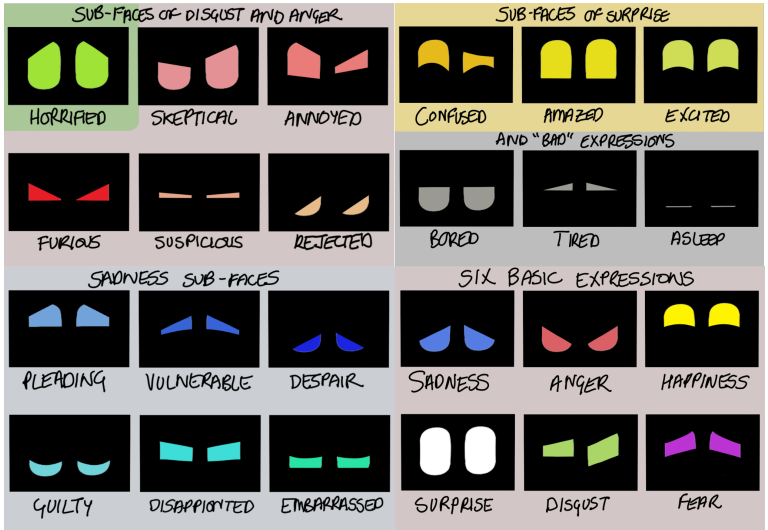
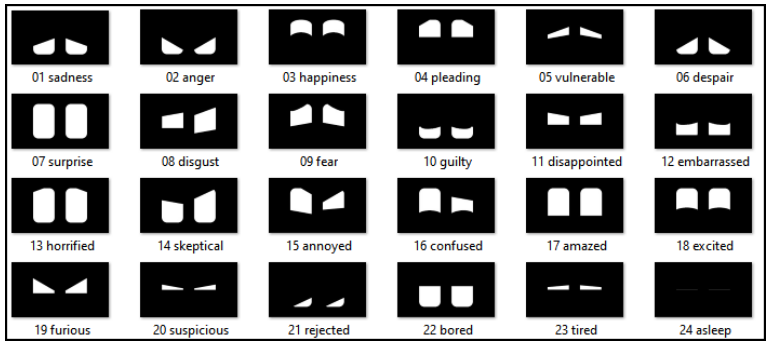
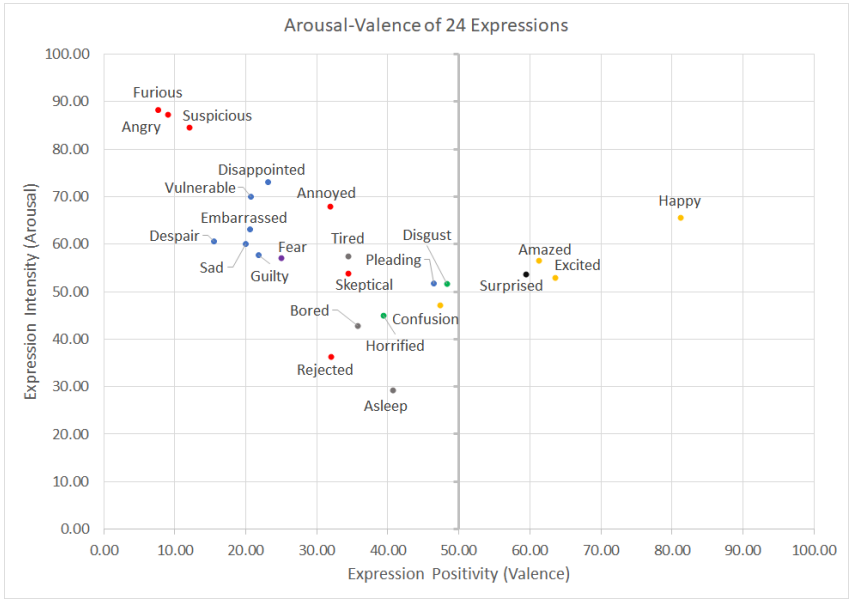
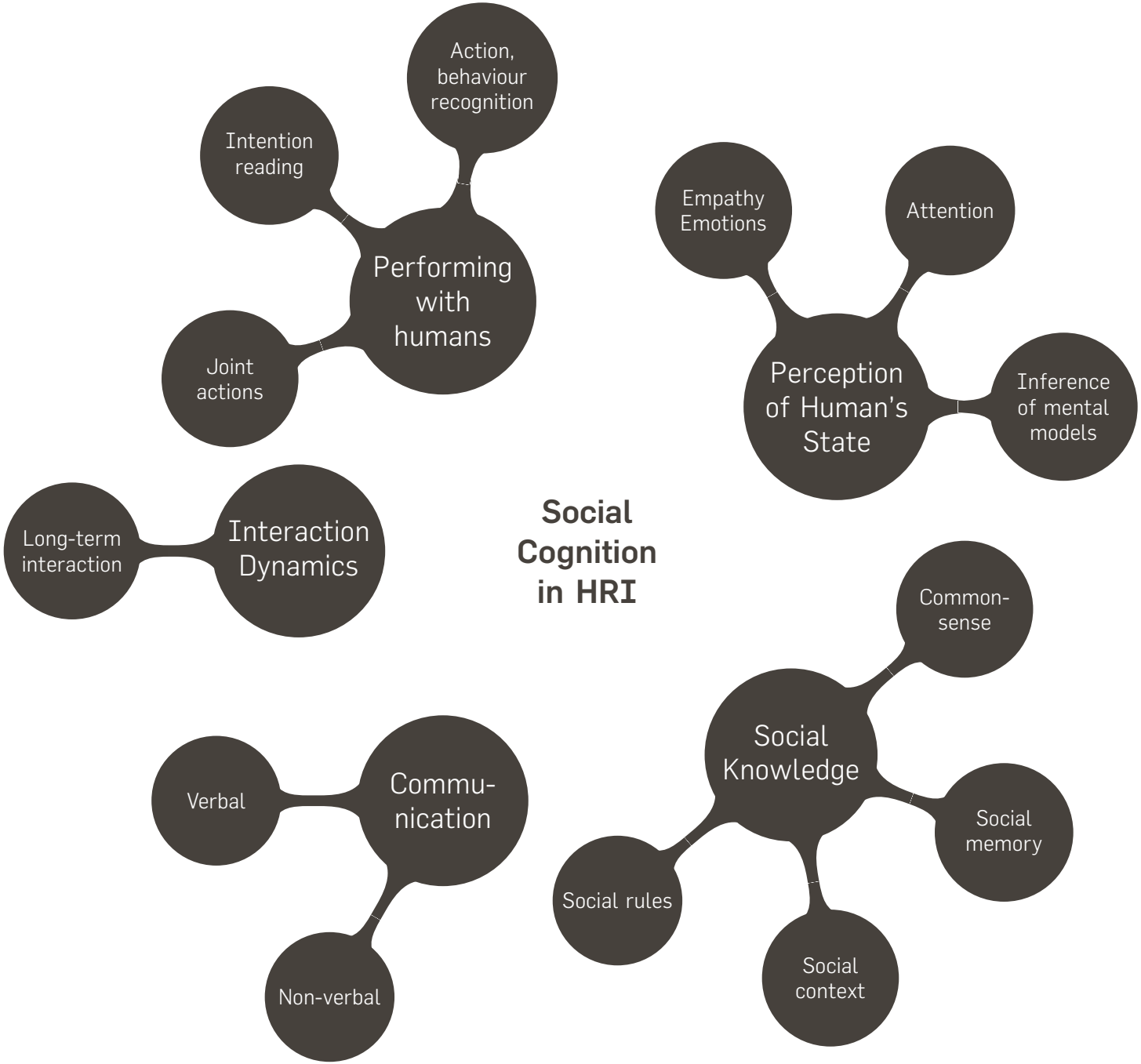
EXPRESSIVE EYES





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




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

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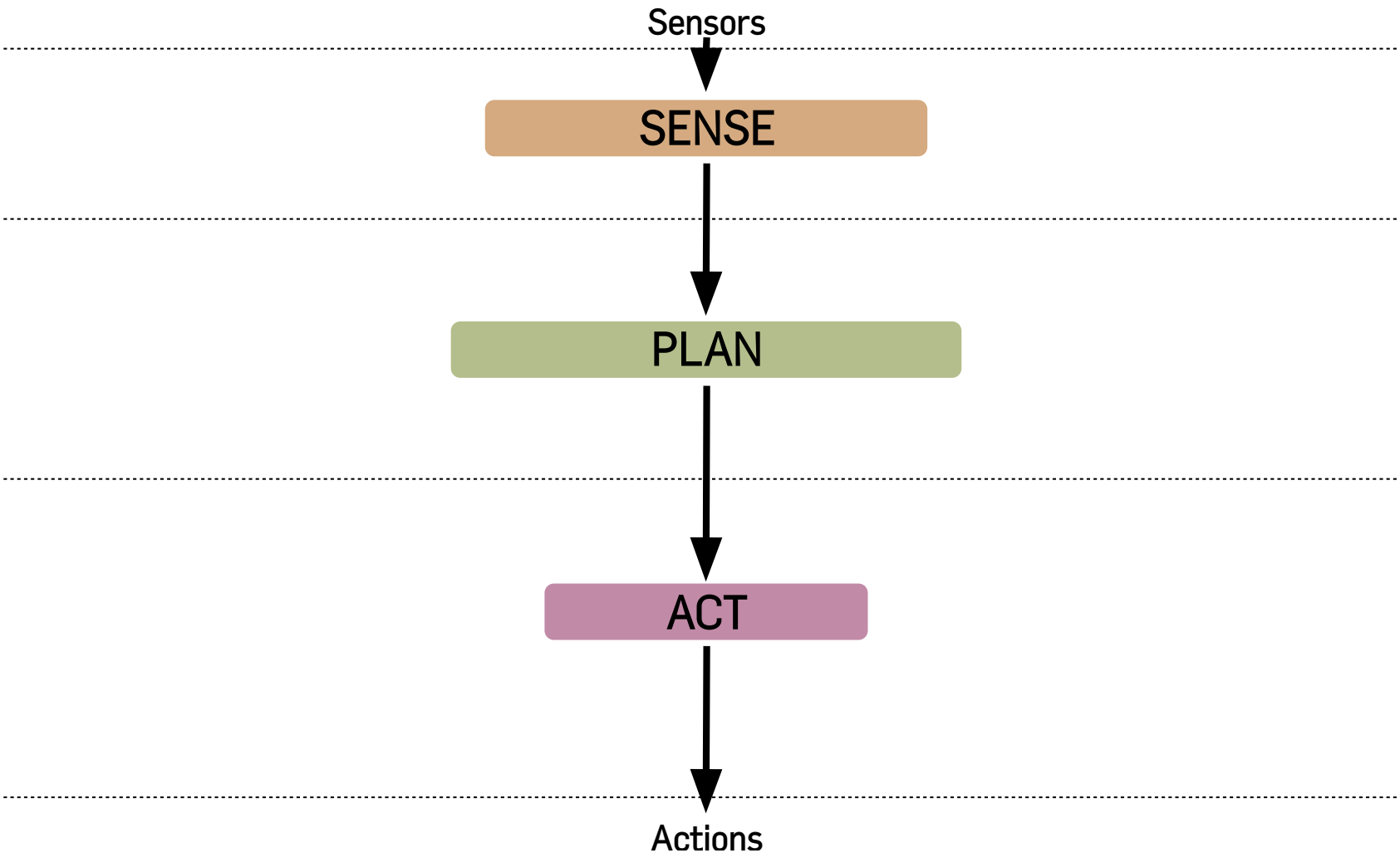
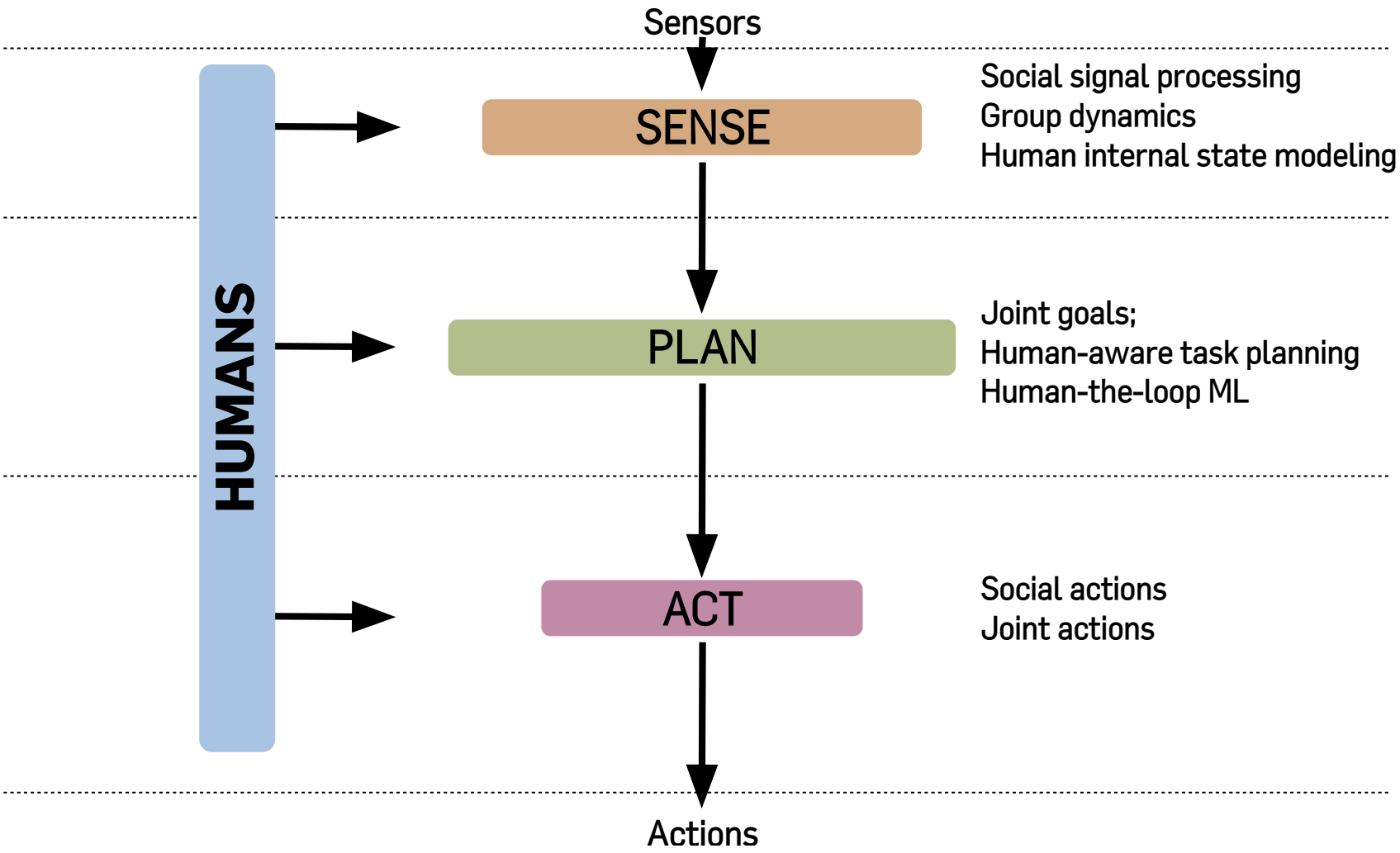
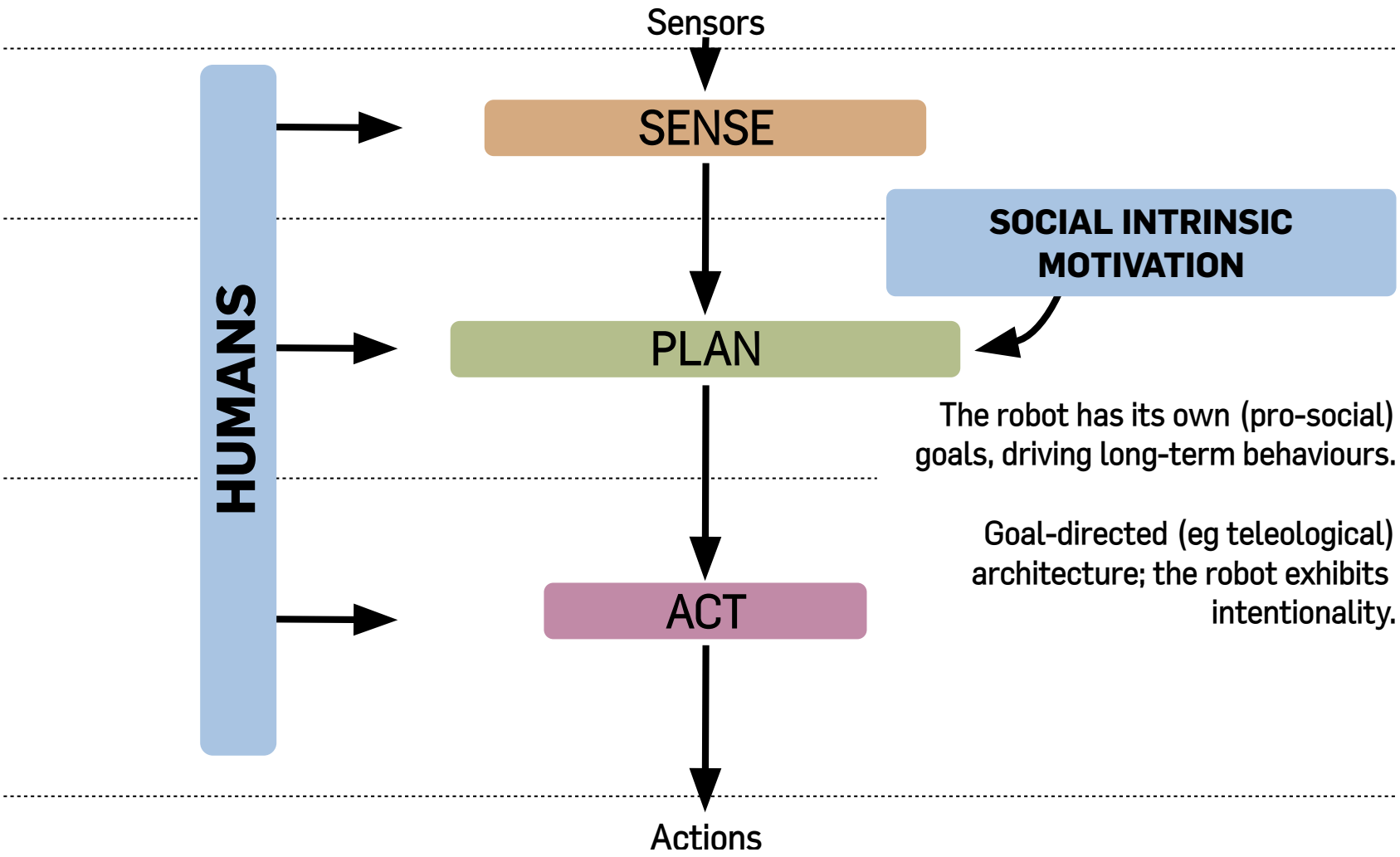
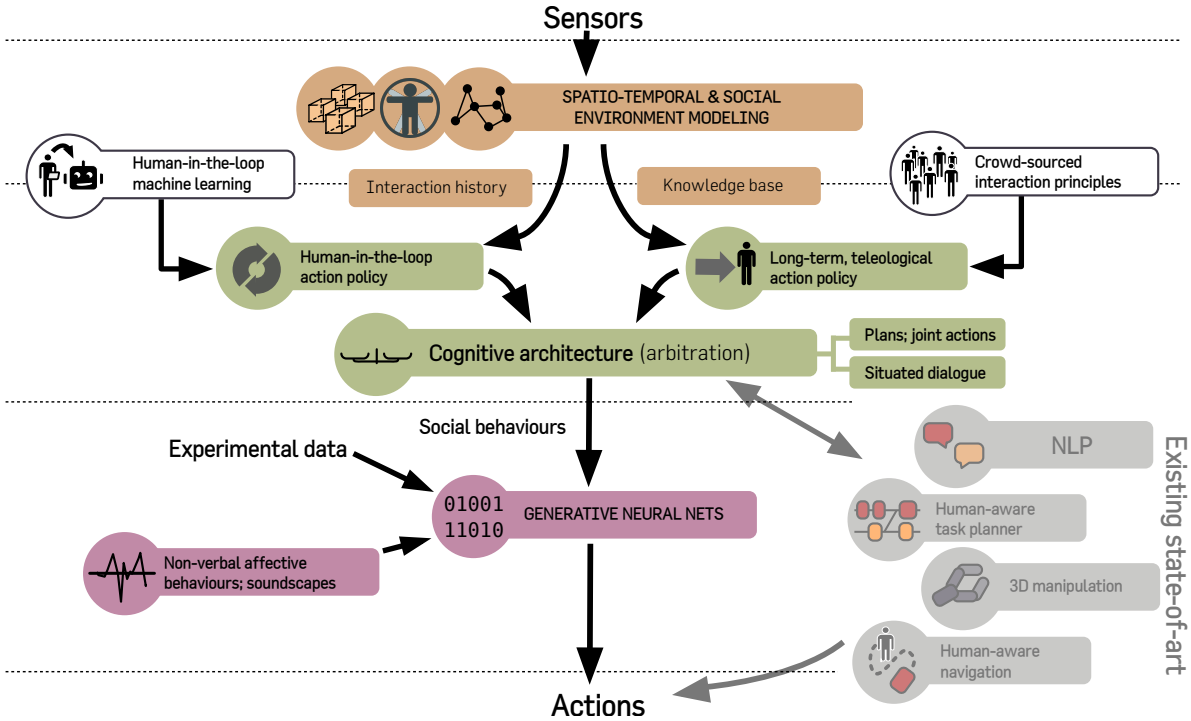
Socially-Driven Autonomous Robots for Real-world Human-Robot Interactions


Sensors
SENSE
PLAN
ACT
Actions


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

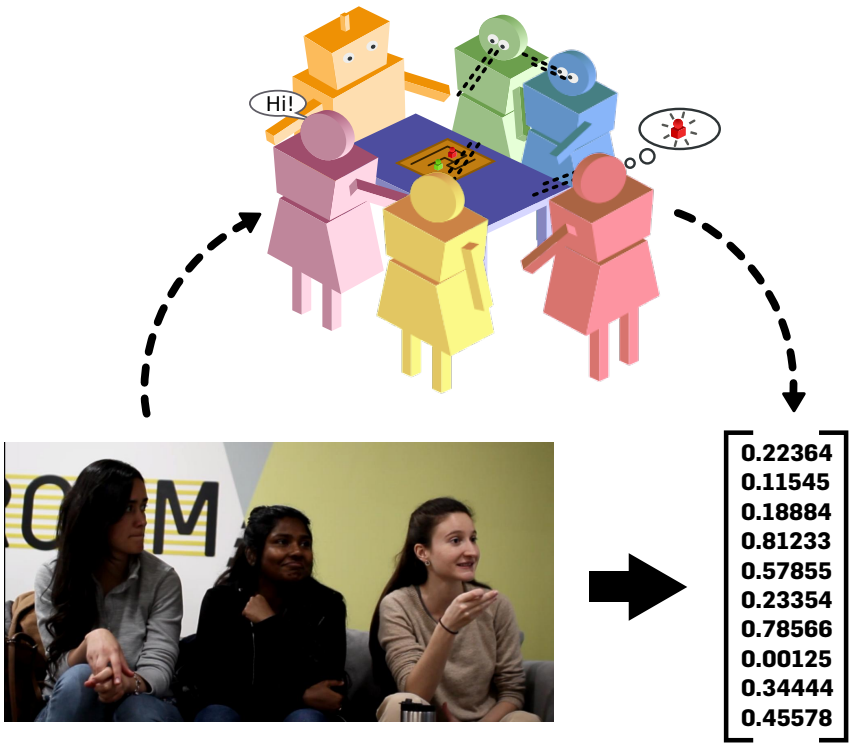

Sensors
SENSE
SOCIAL INTRINSIC MOTIVATION
HUMANS
PLAN
ACT
Actions
The robot has its own (pro-social) goals, driving long-term behaviours.
Goal-directed (eg teleological) architecture; the robot exhibits intentionality.

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**

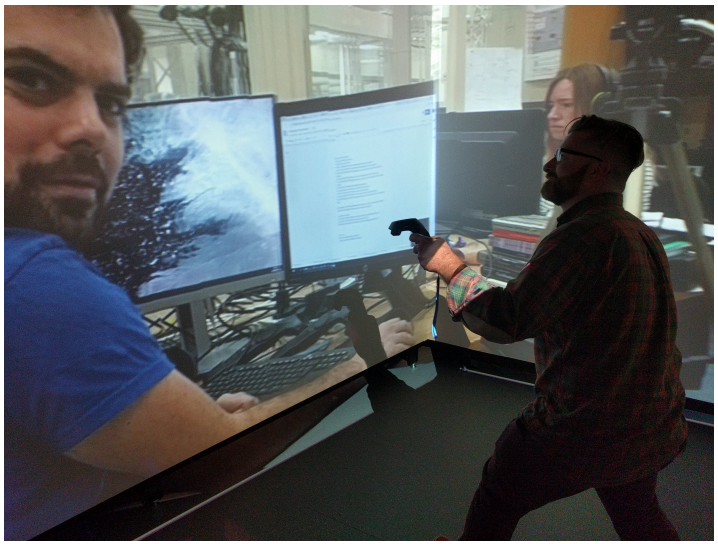
IDEA: SOCIAL EMBEDDINGS



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

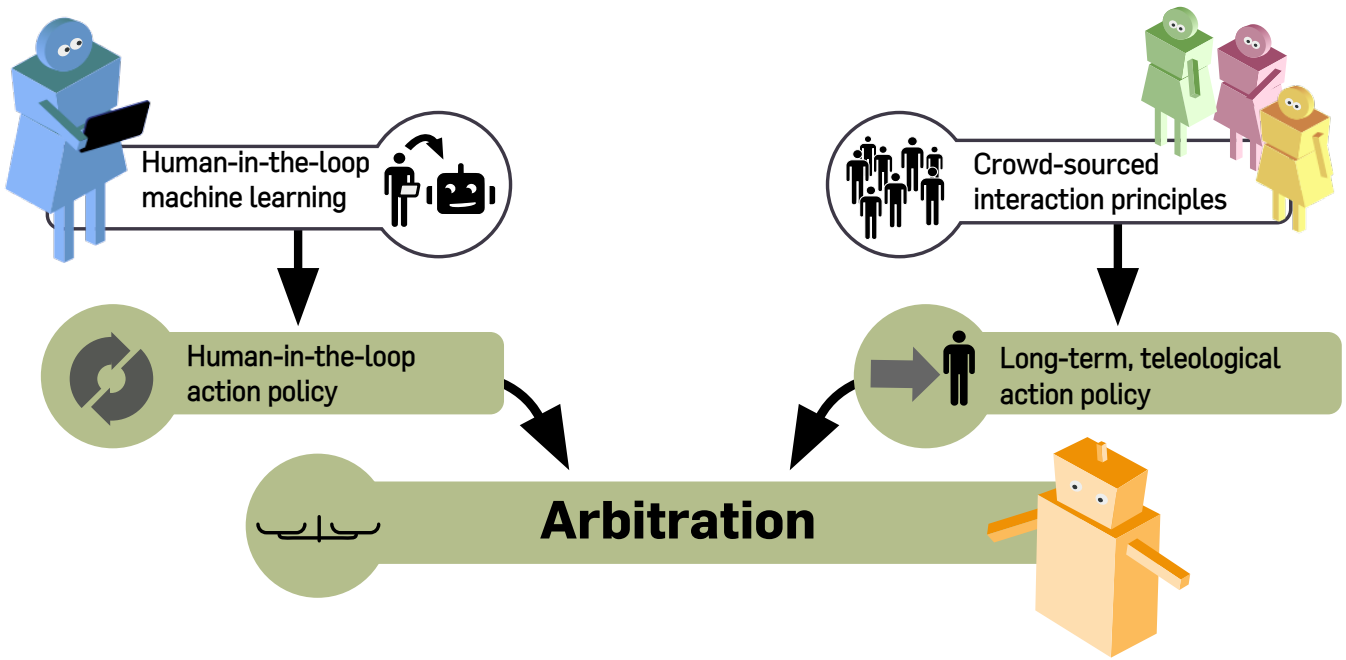
- real-world social interactions are highly dynamic, noisy, multi-modal
- hard for the robot to model and reason about
- → **learn an embedding**: Attention nets, Deep graph nets
- can be used by the robot to **recognise social situation** and **generate congruent social behaviours**

IDEA: GENERATIVE NON-REPETITIVE SOCIAL BEHAVIOURS



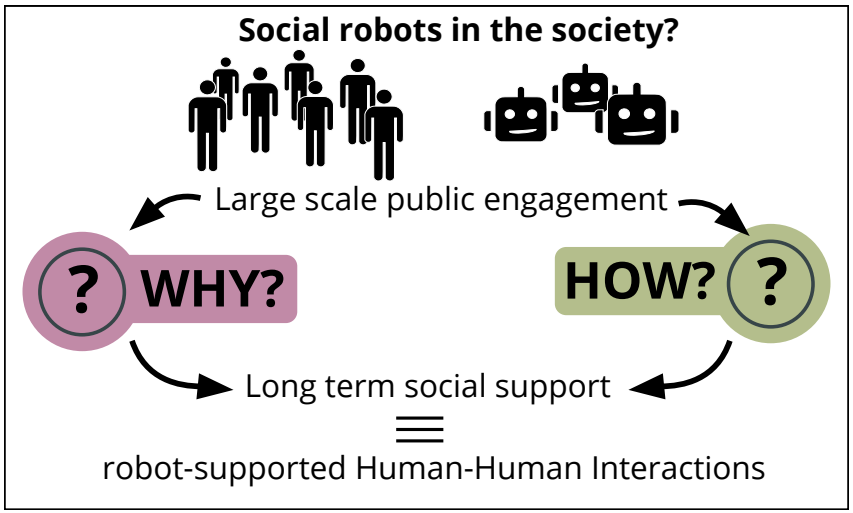
- Cracking the '**non-repetitive, socially congruent**' behaviour generation problem
- Extend **Generative Adversarial Networks** *à la* AppGAN to complex behaviours (re-use *social embeddings*)
- **Immersive technologies** to build datasets
- **Transdiscplinary approach**, incl. arts: choreographer,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

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**

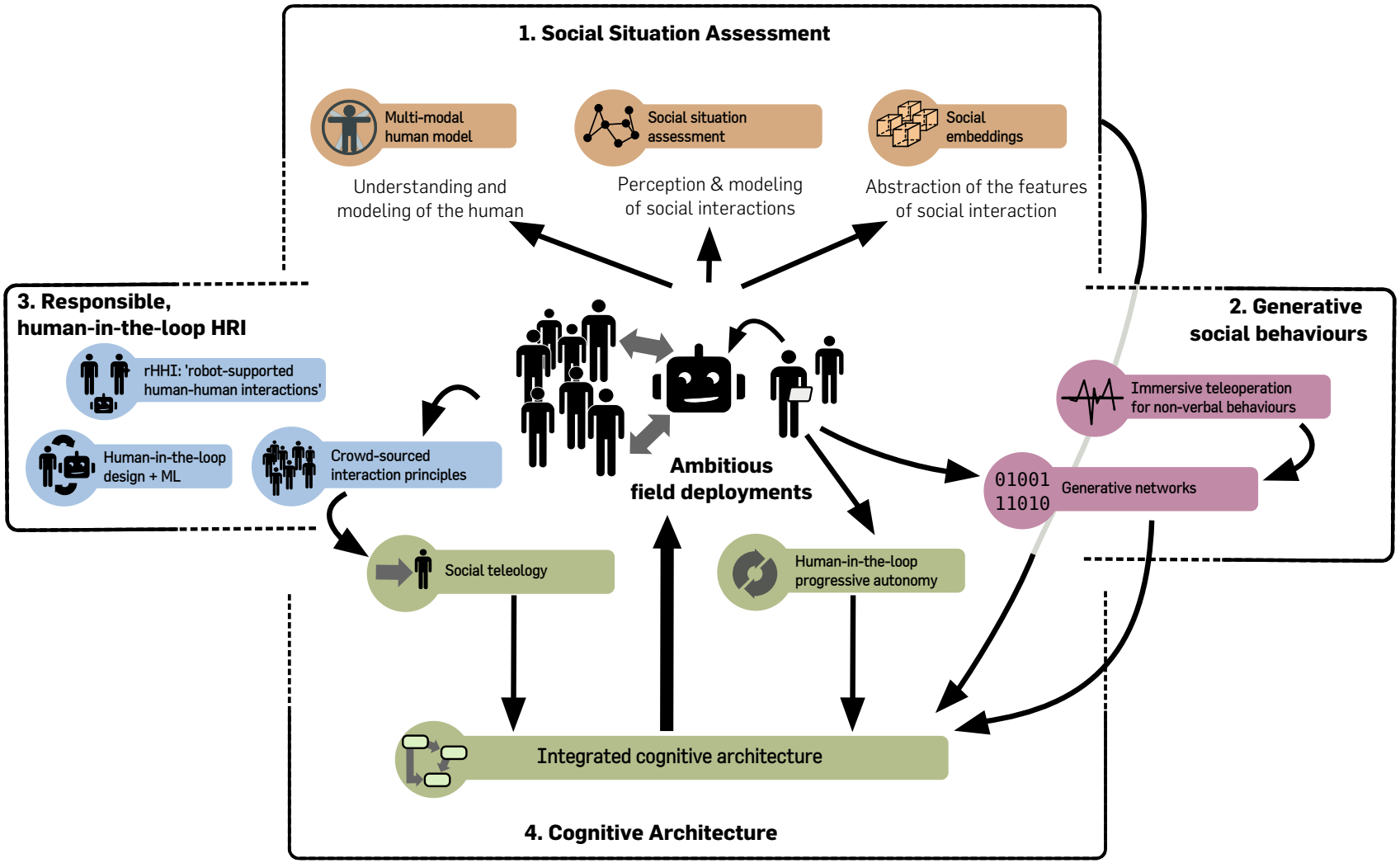
IDEA: ROBOT-SUPPORTED HUMAN-HUMAN INTERACTIONS



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)*