AUTONOMOUS ROBOTS IN THE WILD

ADAPTING **FROM** AND **FOR** INTERACTION

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Director Lincoln Centre for Autonomous Systems
Director EPSRC Centre for Doctoral Training in Agri-Food Robotics

SoRAIM Winter School

UNIVERSITY OF LINCOLN

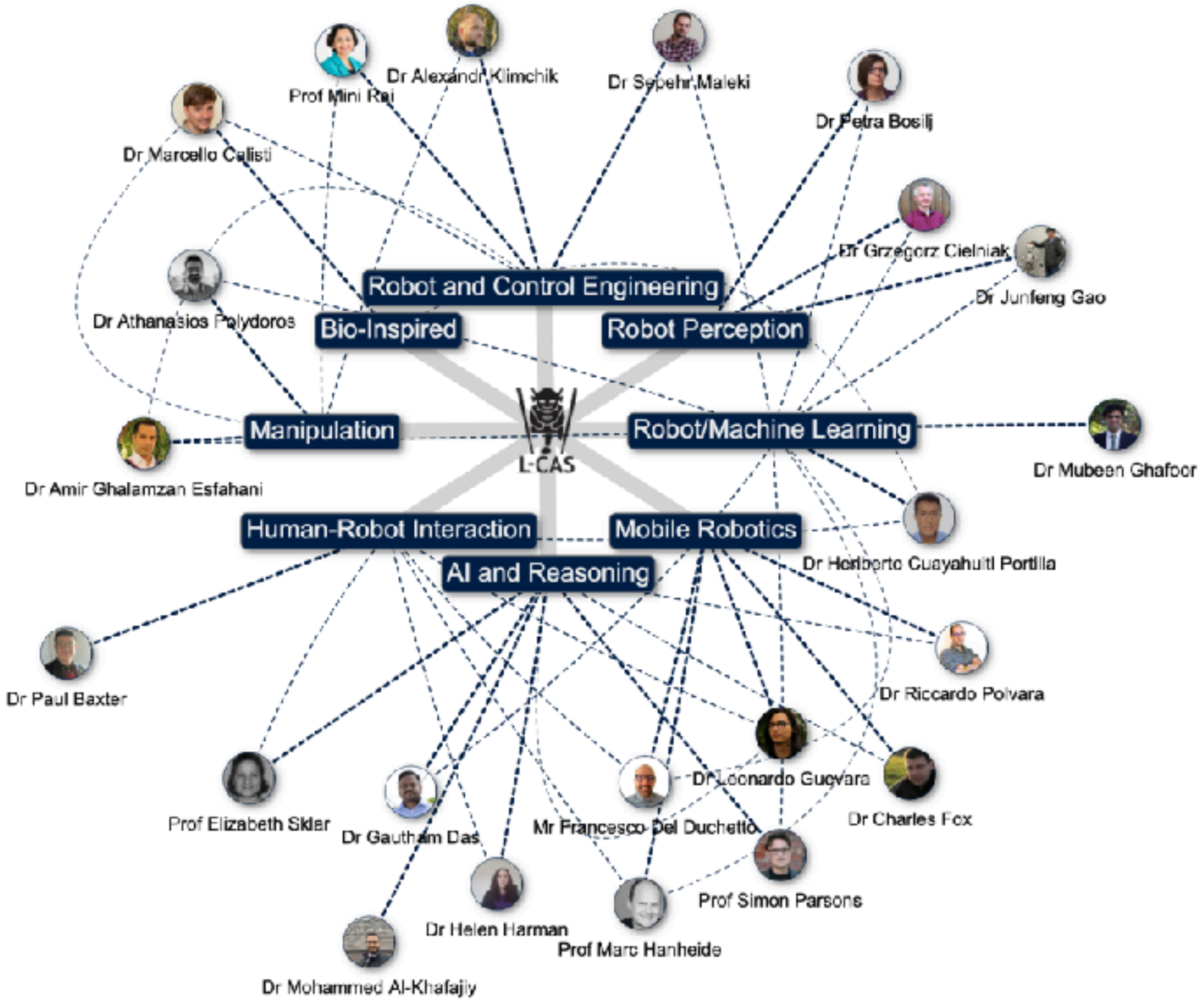
L-CAS

https://www.hanheide.net/
https://lcas.lincoln.ac.uk

Marc Hanheide, L-CAS, University of Lincoln

Agri FoRwArdS

EPSRC Centre for Doctoral Training in Agri-Food Robotics



- Interested in *long-term autonomy* for (mobile) robots in human-shared spaces
- Aspects of *actual* and *perceived safety* in HRI
- Software architectures for *dependable*, adaptive, long-term robotic systems
- In agriculture, nuclear robotics, homes, and public spaces

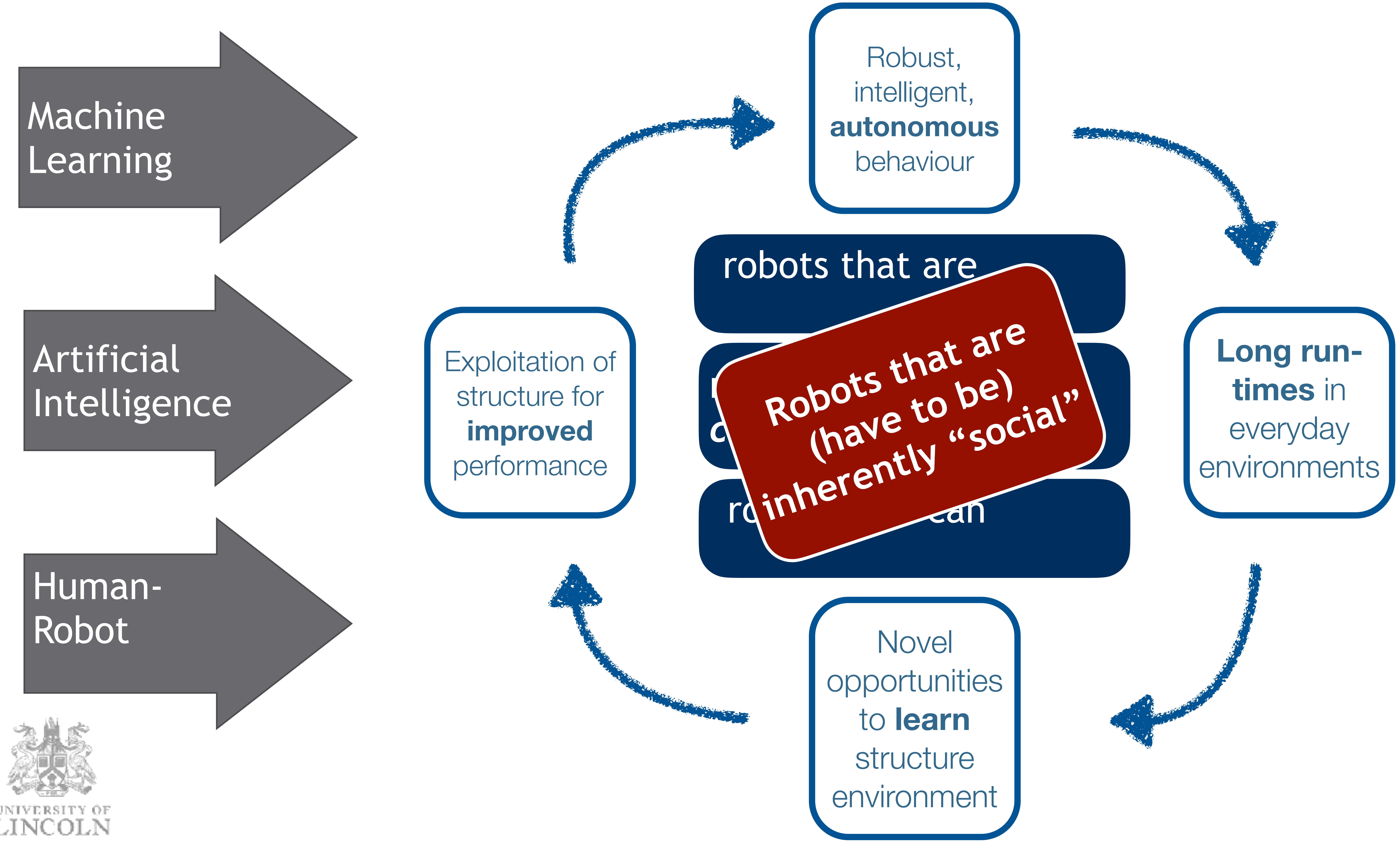
@MarcHanheide

robots that are

robots that have some *common-sense*

robots that can

L-CAS


Machine Learning
Artificial Intelligence
Human-Robot
Robust, intelligent, **autonomous** behaviour
Long run-times in everyday environments
Novel opportunities to **learn** structure environment
Exploitation of structure for **improved** performance
robots that are
can
Robots that are (have to be) inherently “social”

Robust Mobile Robotic Systems for Long-term Deployment

- “Response” to Severin:
  - Been in charge for System Integration and Deployment in 5 EU projects since 2002 (and many other as contributor)
  - Software engineering challenges in (mostly/only??) academia

STRANDS

The Strands Project:

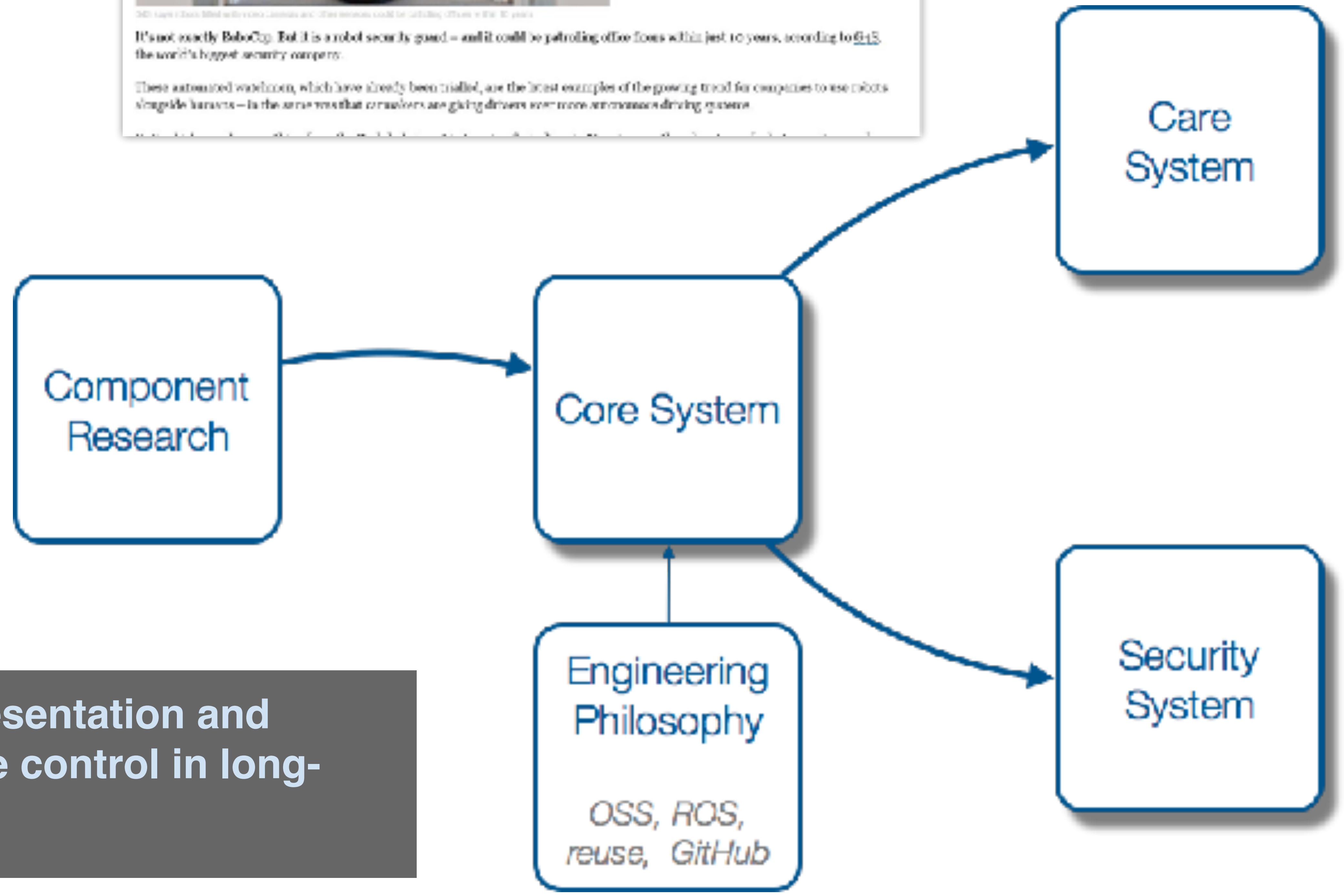
Long-Term Autonomy at its Heart, “Social Robotics” as a (~~un~~)welcomed Necessity

http://strands.acin.tuwien.ac.at/


FINANCIAL TIMES

G4S powers up robotic security

- Long-term autonomy requires robust software
- 6 robots, shared software, 2 application domains
- > 30+ developers



Spatio-temporal representation and activities for cognitive control in long-term scenarios

Betty at
Transport Systems Catapult,
Milton Keynes, UK

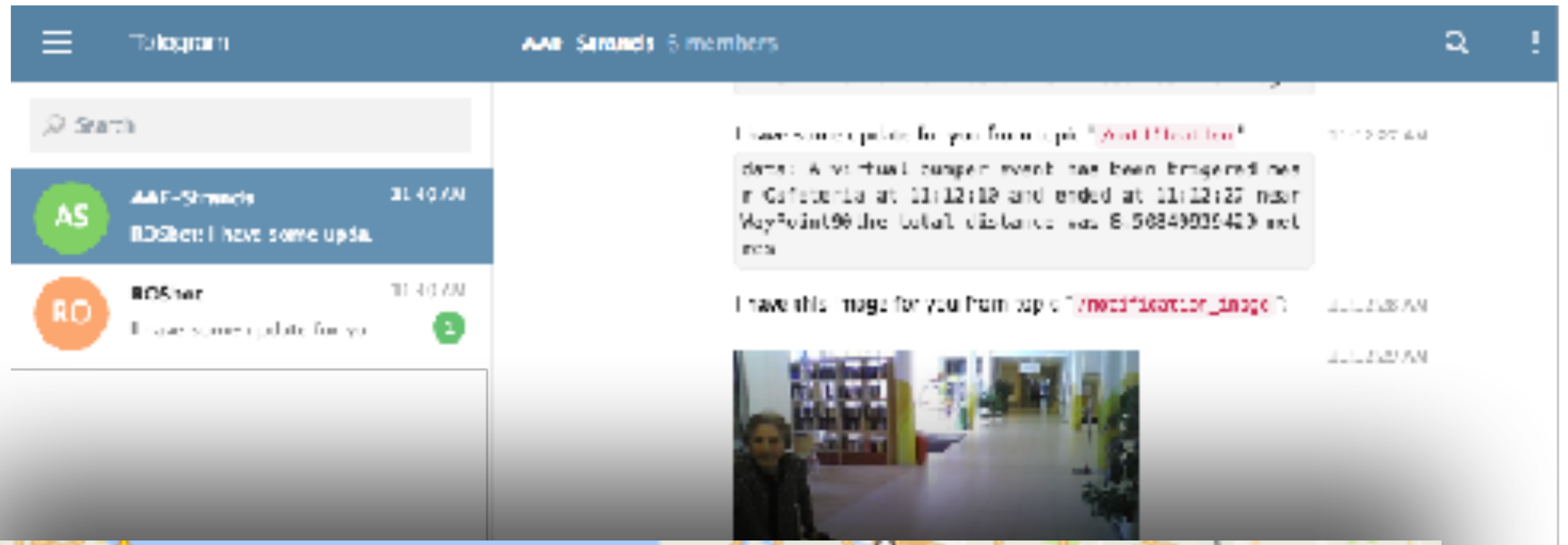
STRANDS

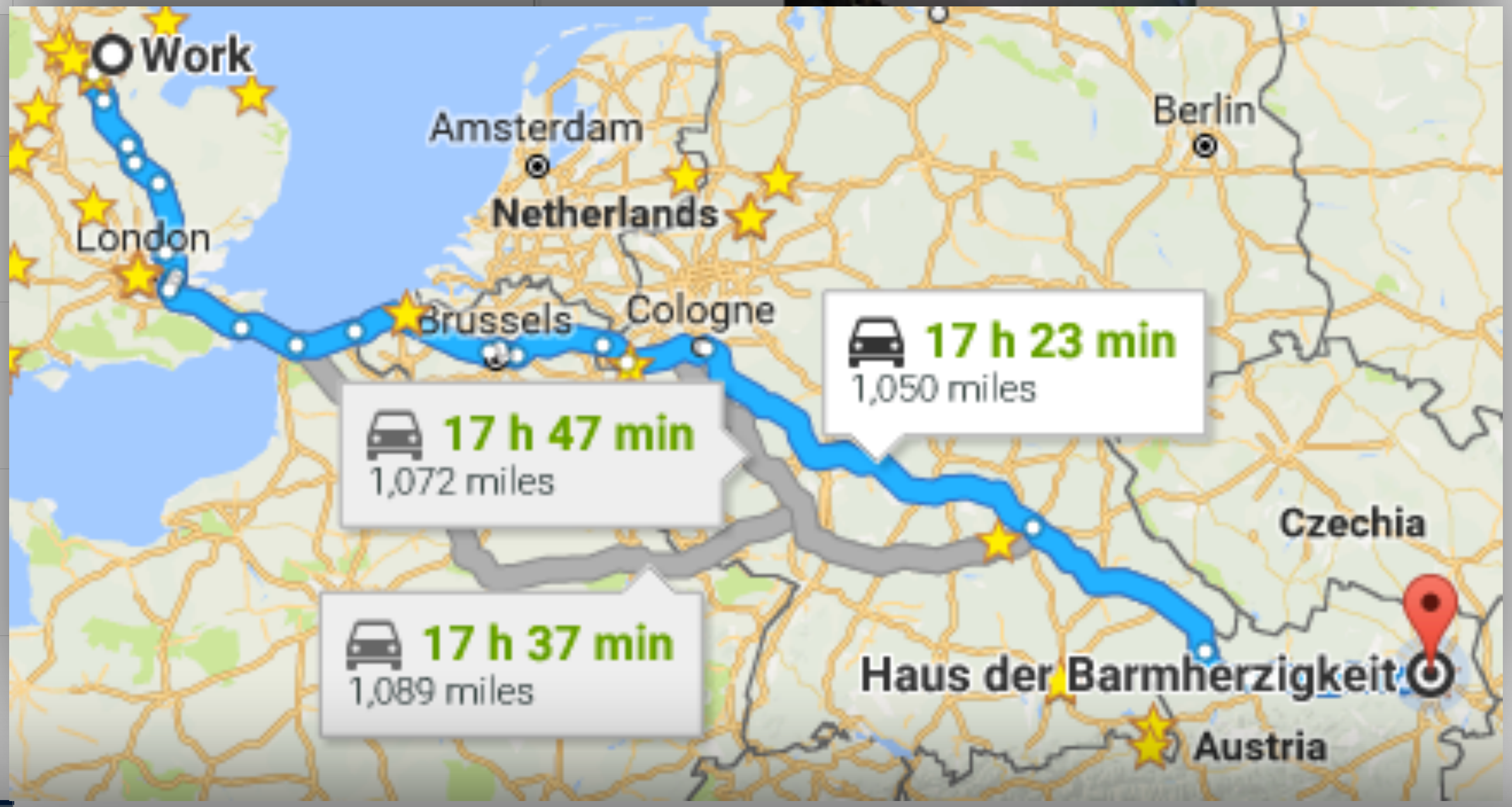
Henry at
Haus der Barmherzigkeit,
Vienna, Austria

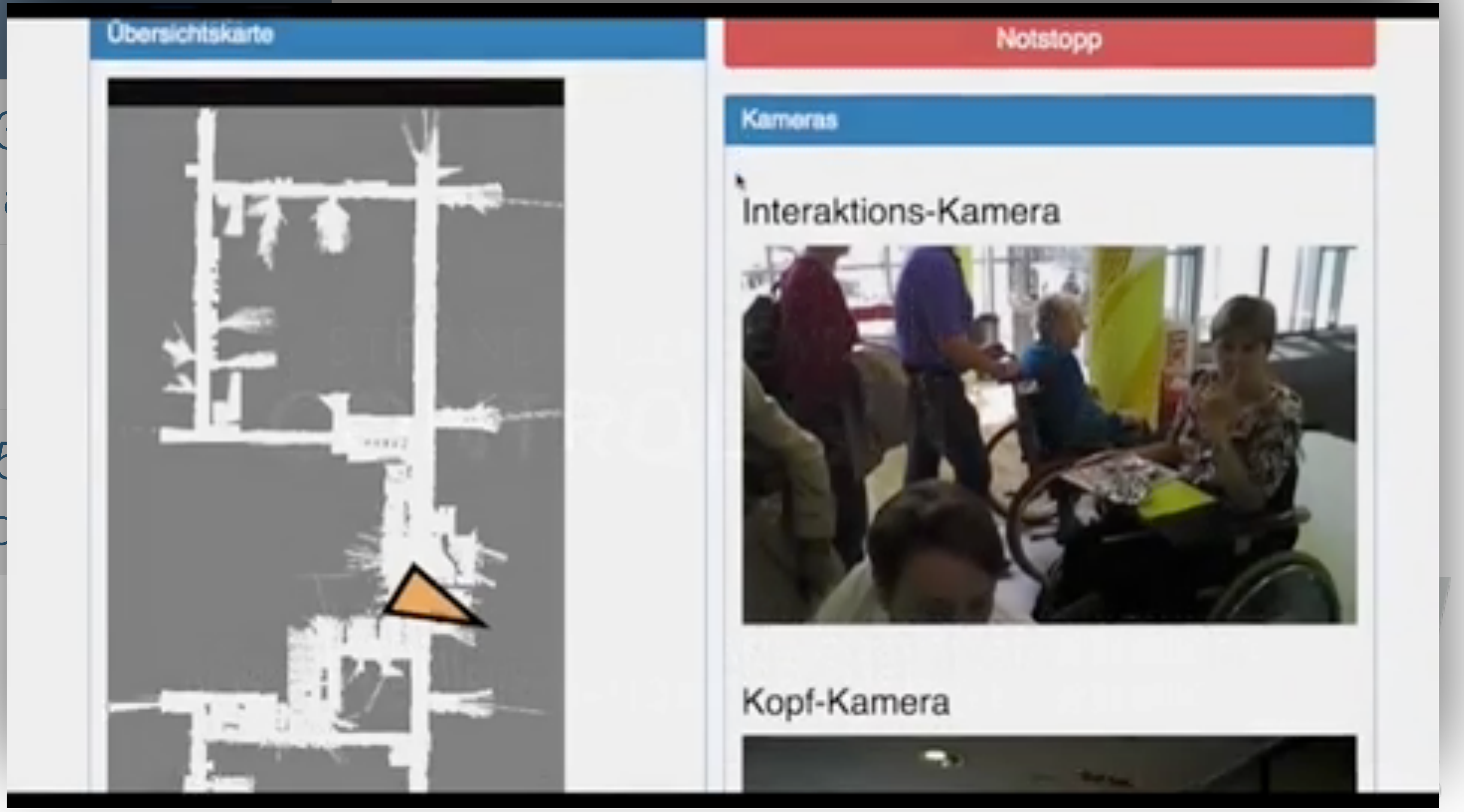
L-CAS

	Care Y3	Care Y2
Deployment	21/3/16 to 27/5/16	18/5/15 to 17/6/15
Working Hours	Weekdays days 7.00 to 19.00	Most days 8.00 to 21.00
Distance	~50km	23.41km
Tasks	1890	865
Available Work Time	529 hours, 13 minutes	252 hours, 54 minutes
Autonomous Time	[illegible], 13 minutes	135 hours, 20 minutes
A%	[illegible].53%	53.51%
	[illegible] System Lifetime (TSL)	
Max	25 days, 11:29 hours (includes 8 days off)	15 days, 5:[illegible] (includes 5 d[illegible]
2nd best	15 days, 9:30 hours (includes 4 days off)	
Cumulative	55 days, 9:57 hours (includes 16 days off)	29 days, 5:5[illegible] (includes 10 [illegible]

no developers/ engineers on-site







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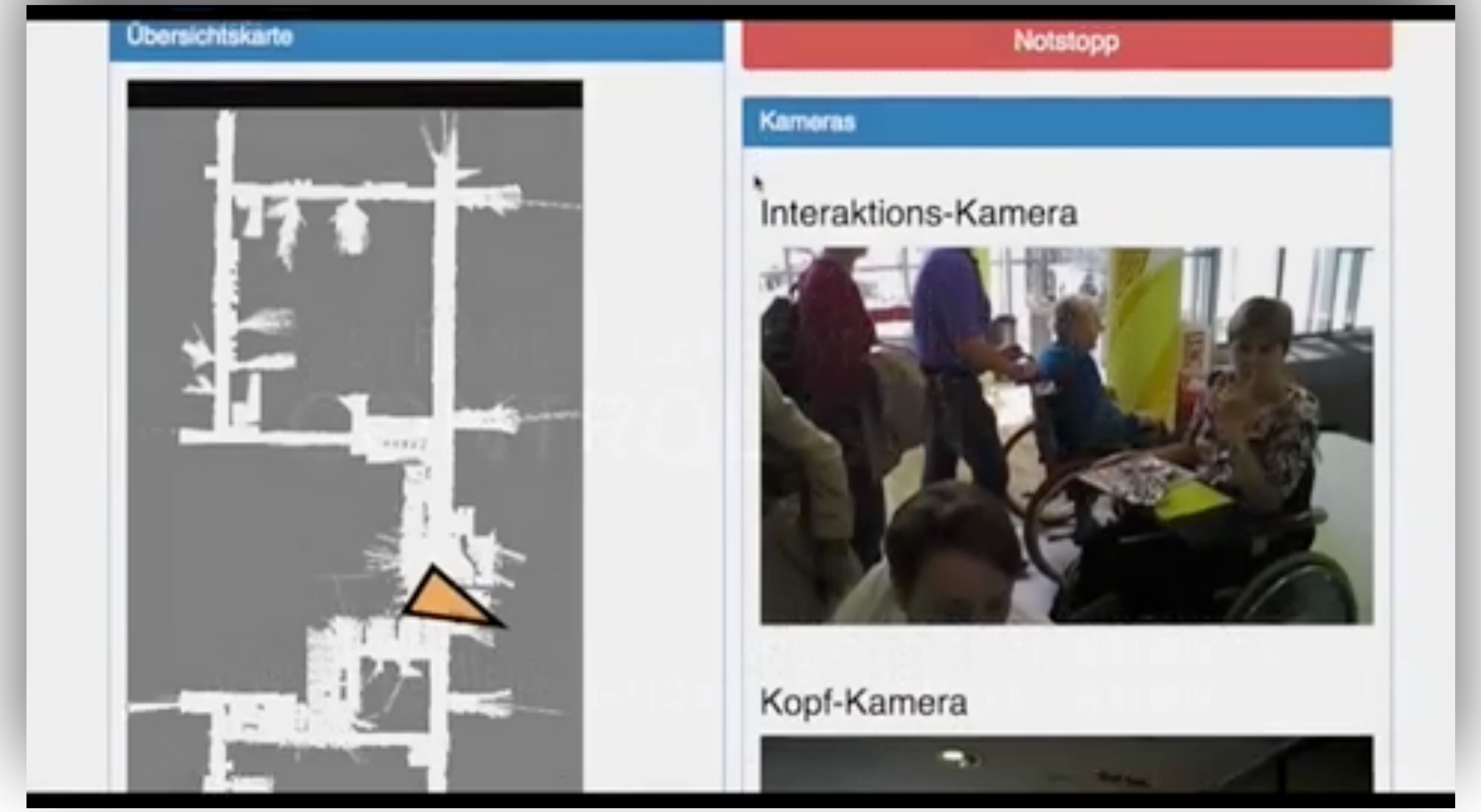
Bellbot

Walking Group

"The first autonomous mobile robot engaged in physical therapy"



Info Terminal
(later)

It’s not as easy as it may seem

- Build on top of off-the-shelf ROS components

ROS

- long-term autonomy requires **robust software**

Fork me on GitHub

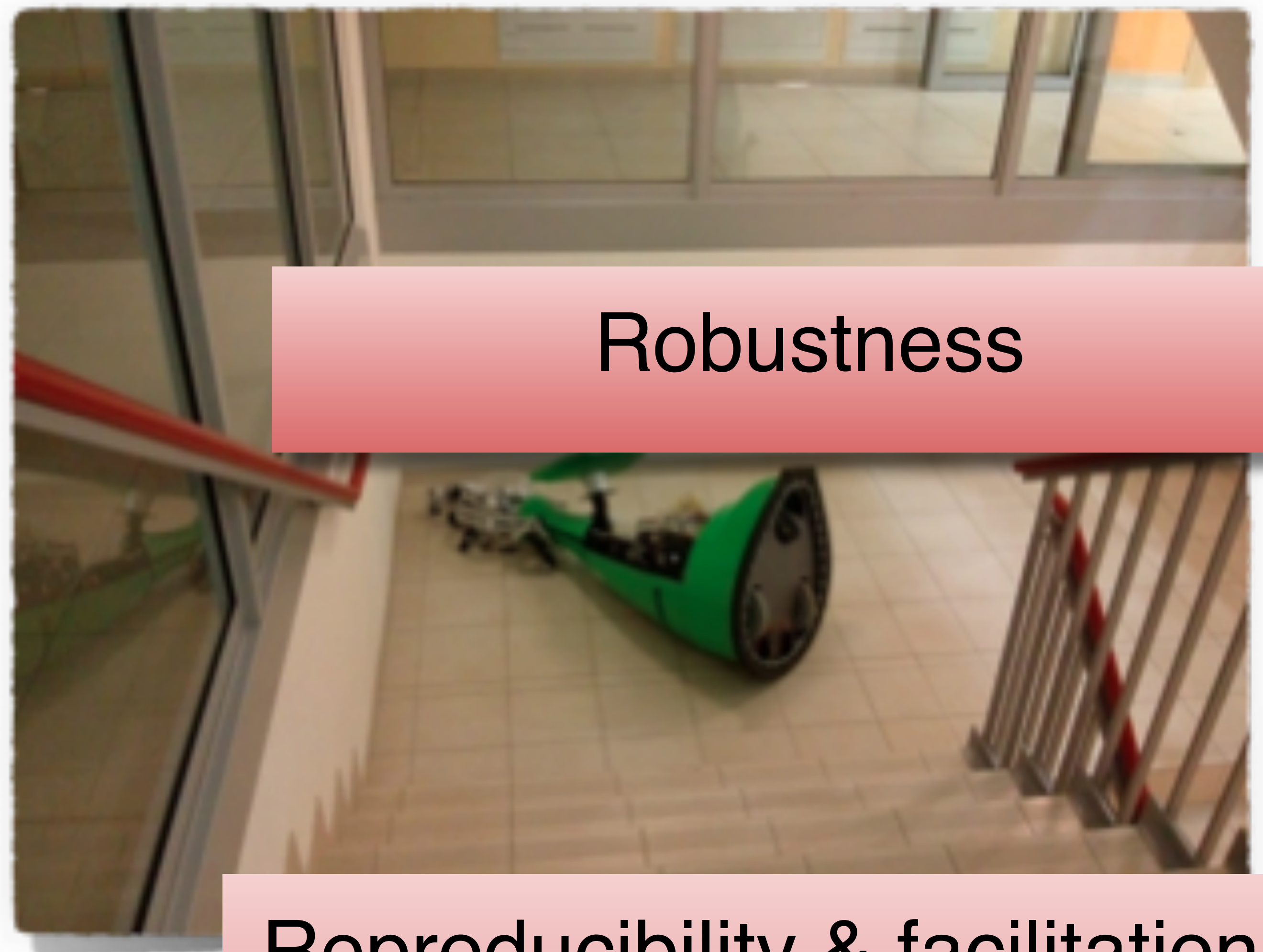
Challenges

Heterogeneous (and independent) group of developers

"Hacking for paper" attitude

not well-trained developers

Supervisors' focus on publications (rightly so)



Robustness

Reproducibility & facilitation of system science (for team and community)

Deployment to test-sites

Some (for us) working solutions back then and now

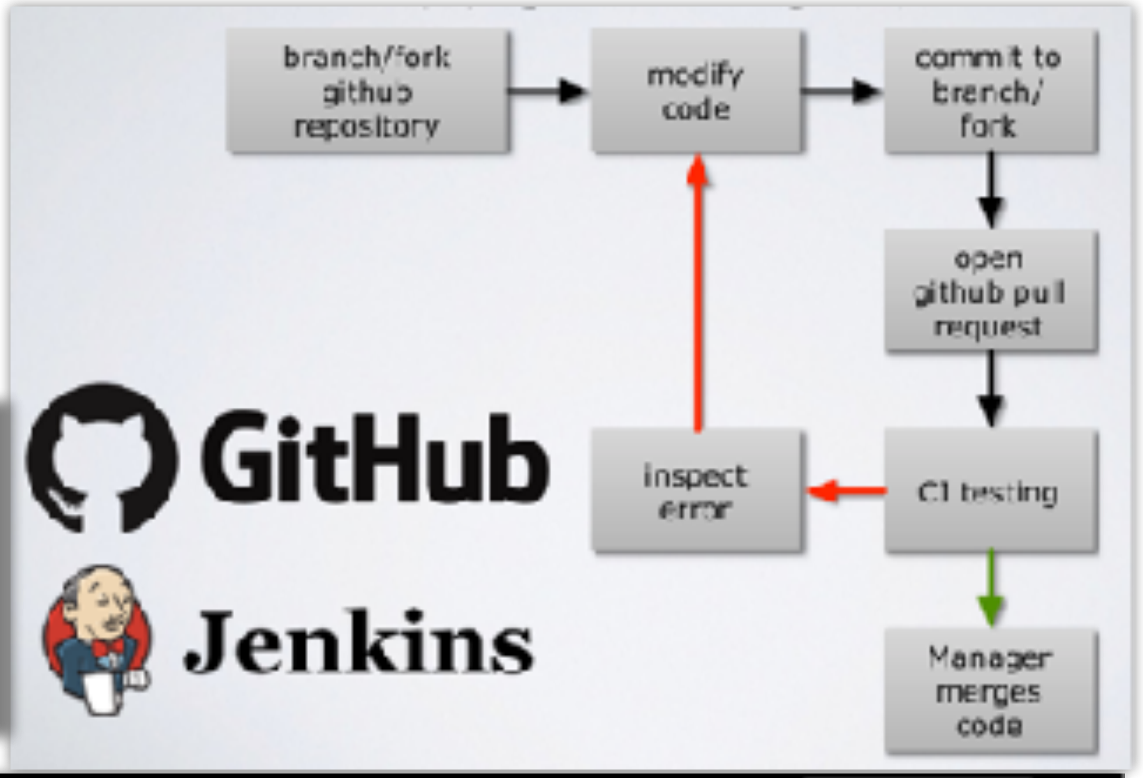
Heterogeneous (and independent) group of developers

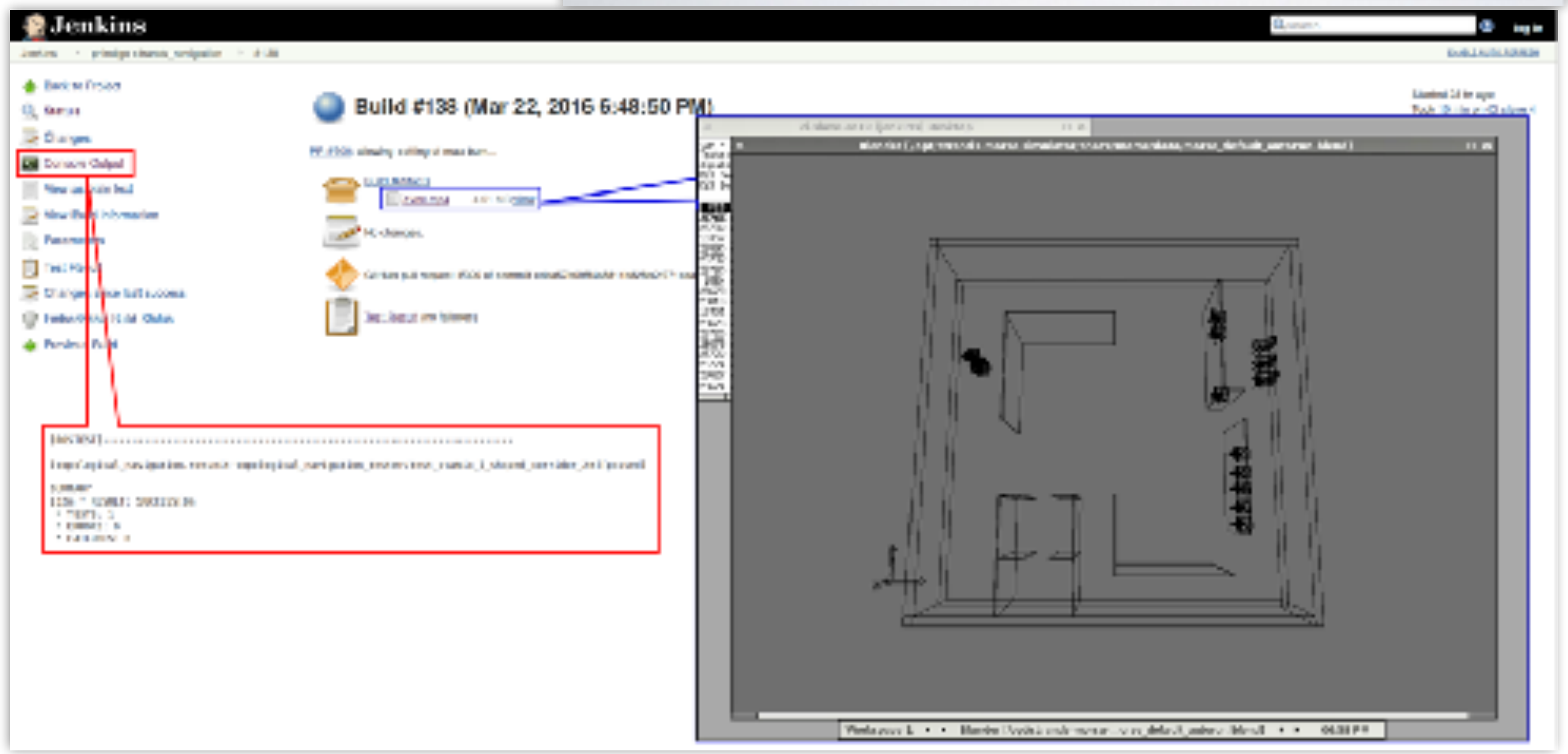
not well-trained developers

Robustness

2016

Adopt OSRF (ROS) build farm and extend it



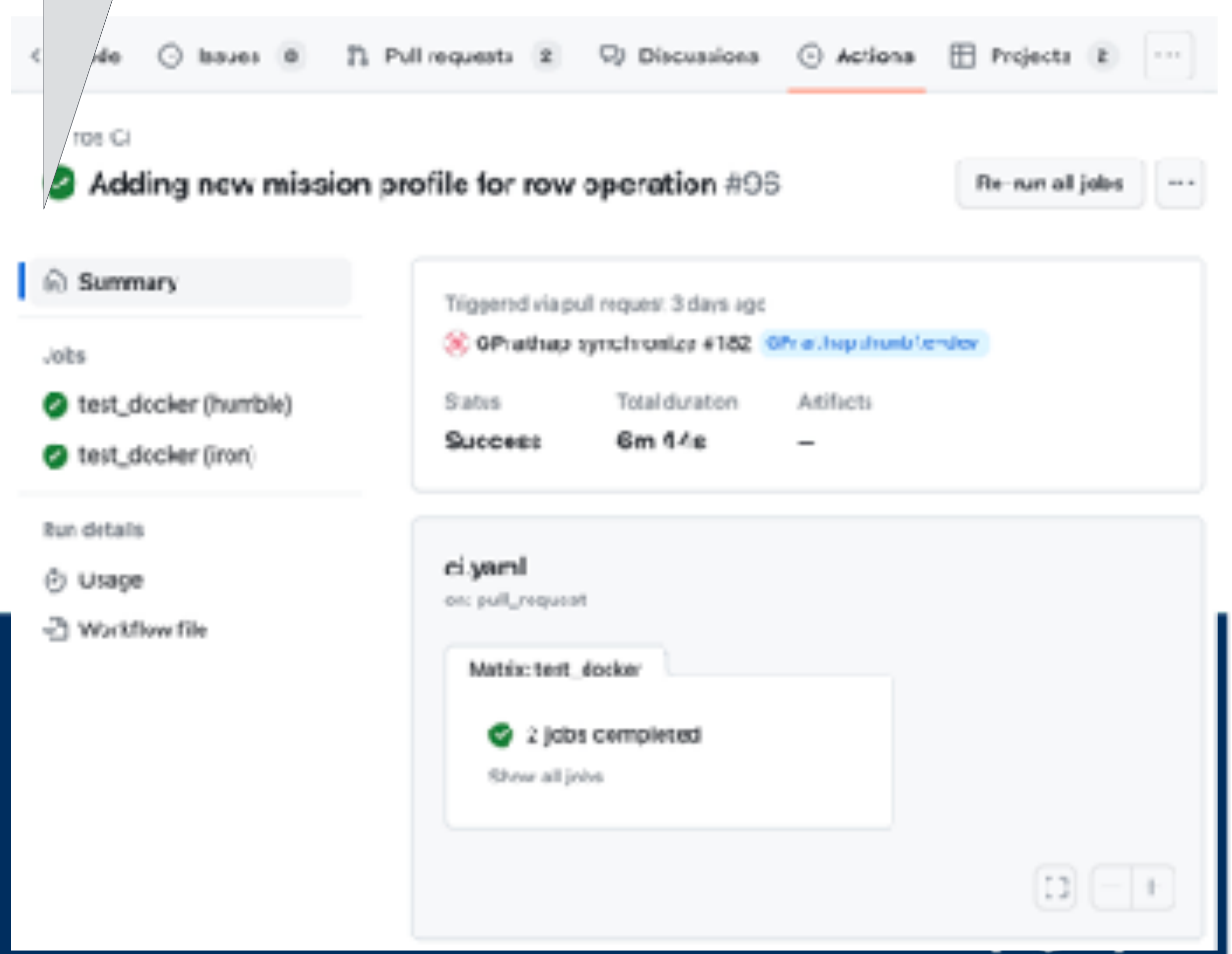


2023

Containerisation

GitHub Actions

Standardised Dev Container

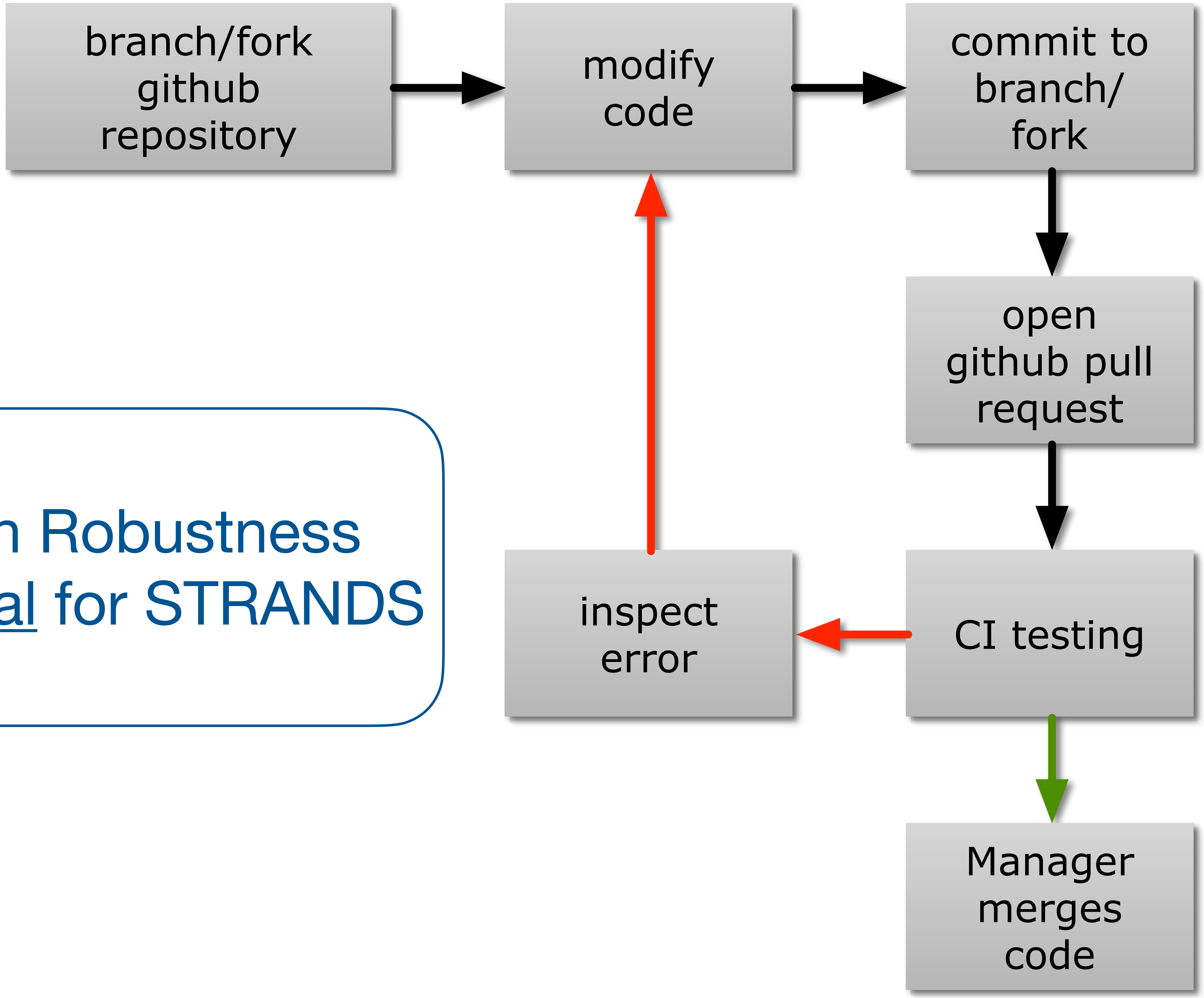


- ❑ "Force" developers to share code (github) and adopt fork and pull model and continuous integration with email notification
- ❑ Team of 3-4 software managers, who review code and approve releases
- ❑ Utilise **Continuous Integration** and **DevContainers**

Example: Robust and dependable Navigation

GitHub

Jenkins



Navigation Robustness was <u>crucial</u> for STRANDS

Simulation-based Robot testing

github pull request

↓

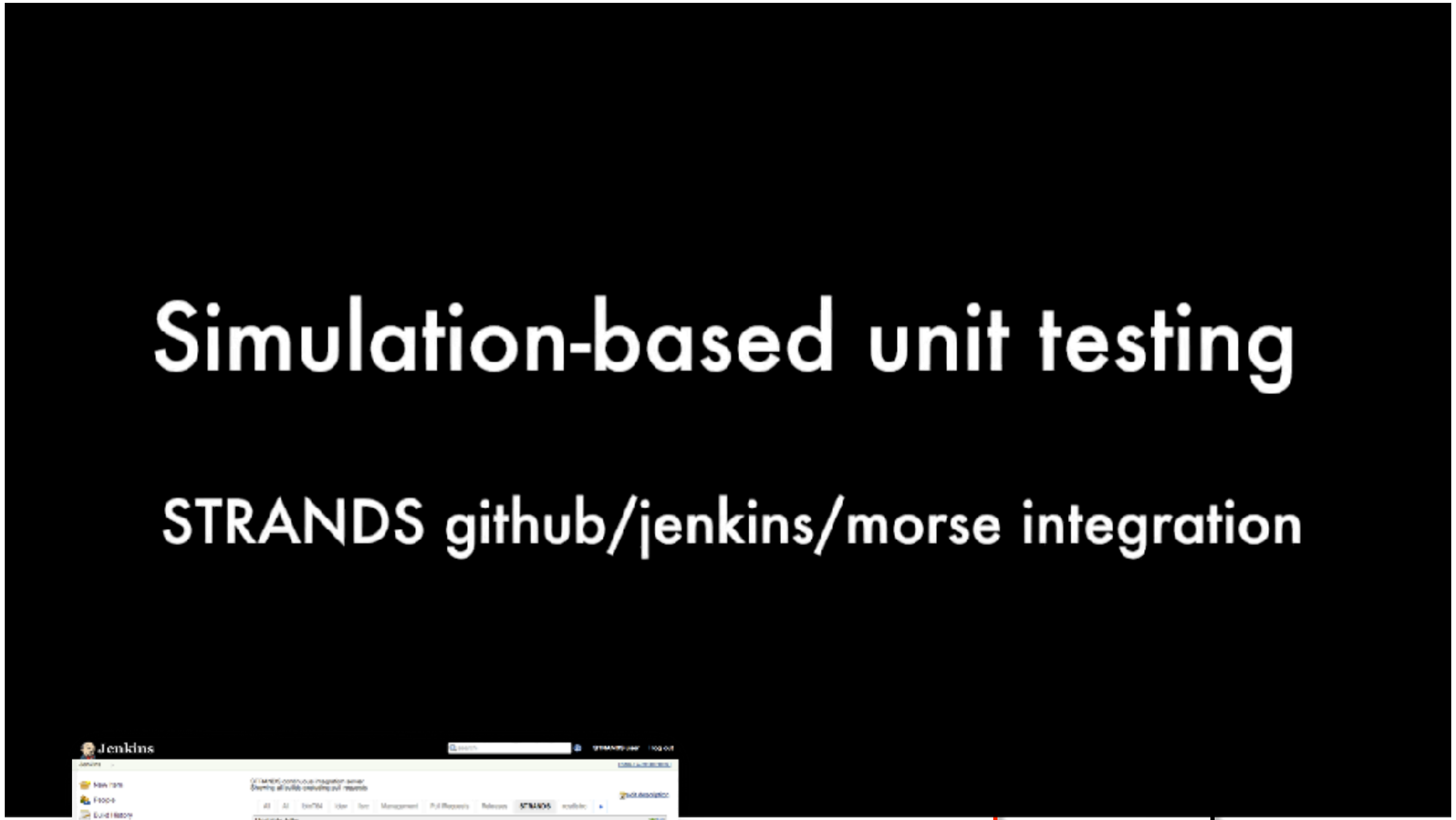
jenkins pull request builder

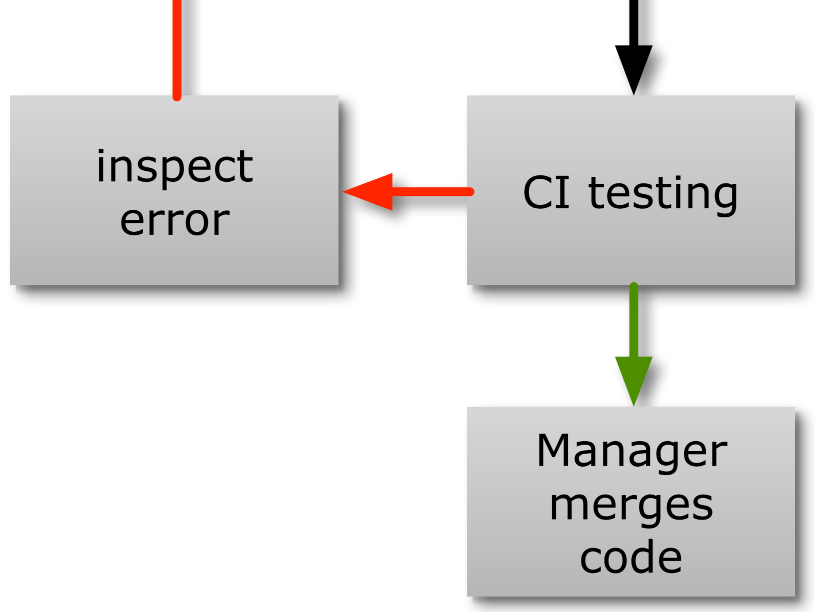
↓

launch MORSE simulation

↓

run defined unit test & record result





Robot testing is also about reality

… and even the best maintained system will fail and have to recover

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L-CAS

Strands Navigation (sub-) Architecture (still alive!)

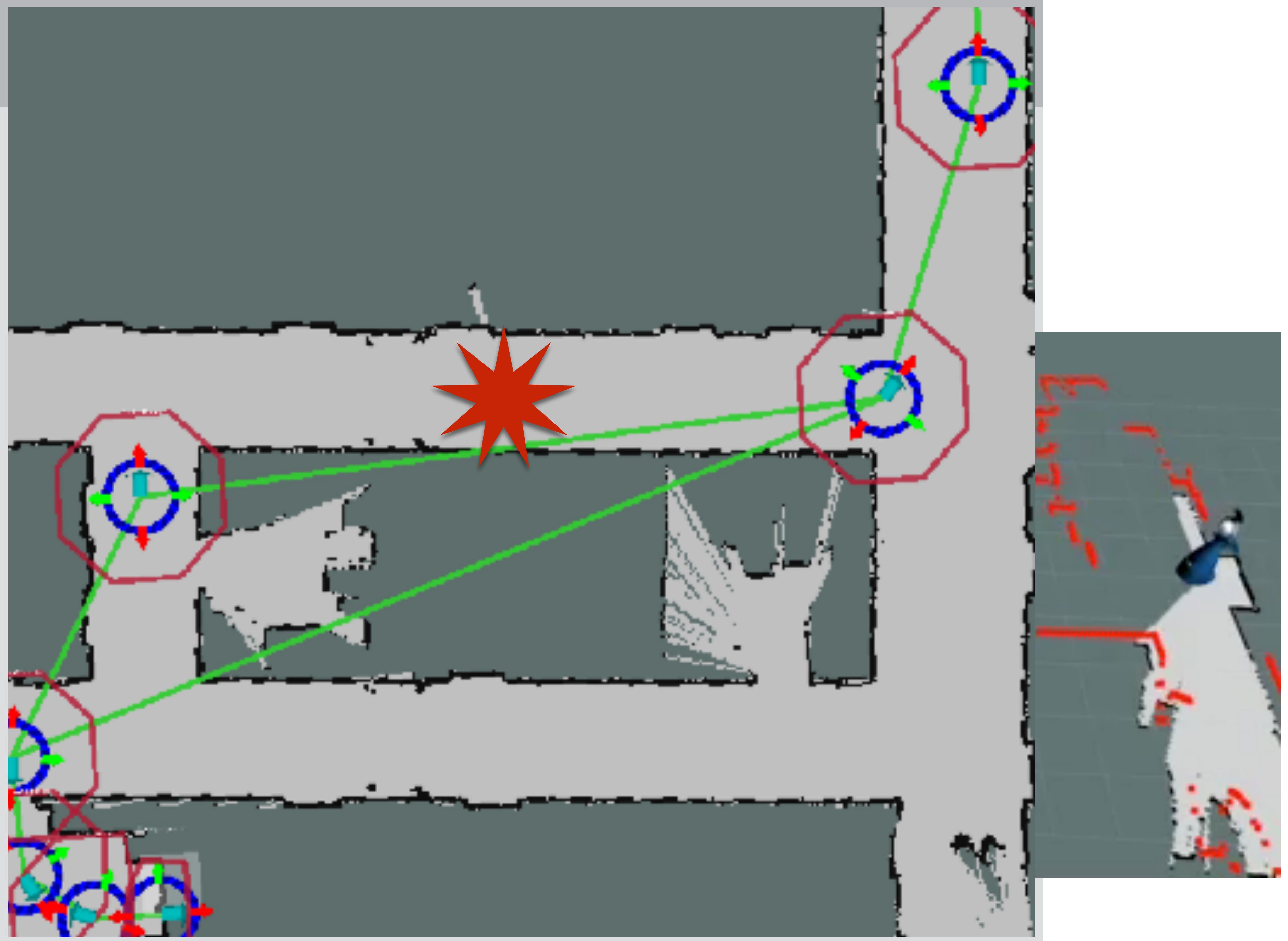
Executive Control

- Task Executor
- Scheduler
- Nav Learning

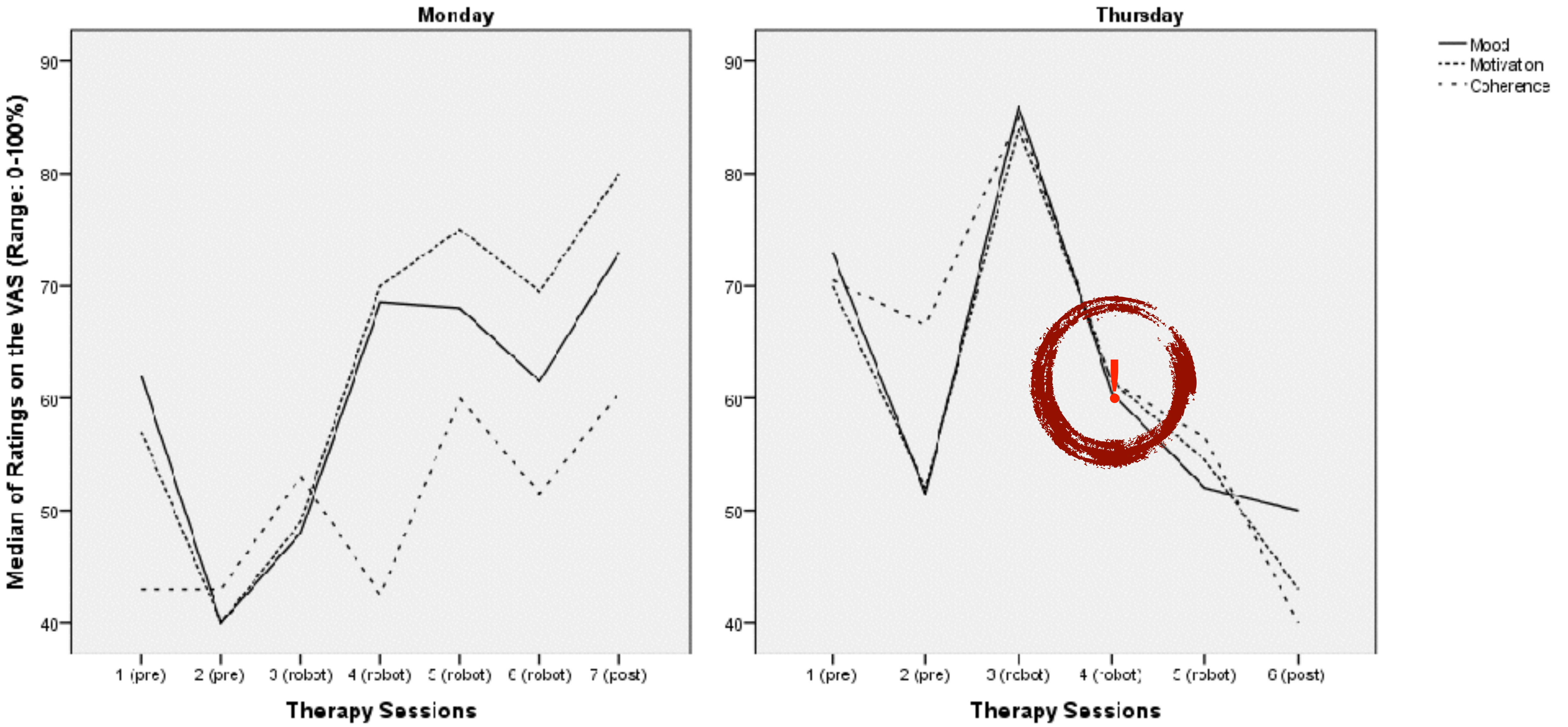
Localisation & Navigation

- Request help
- Backtrack
- Sleep and retry
- **Monitoring**
- **Topological**
- **Continuous**

move-base and/or thin-navigation + specific nav behaviours



Failures and Trust!



Medians of subjective ratings of therapists and observers across slow and fast patient groups for:

overall atmosphere/mood (0=aggrieved, 100=cheerful),
motivation (0=demotivated, 100=very motivated),
group coherence (0=loose, 100=strong)

Capacity

MDMT: Multi-Dimensional Measure of Trust

Daniel Ullman & Bertram F. Malle

CAPACITY TRUST
Reliable Subscale: *reliable, predictable, someone you can count on, consistent* (α = .92)
Capable Subscale: *capable, skilled, competent, meticulous* (α = .92)

MORAL TRUST
Ethical Subscale: *ethical, respectable, principled, has integrity* (α = .81)
Sincere Subscale: *sincere, genuine, candid, authentic* (α = .79)

Morality

Taxonomy of Trust-Relevant Failures and Mitigation Strategies

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Table 1: Types of actions which cause a loss of trust: we call these failures

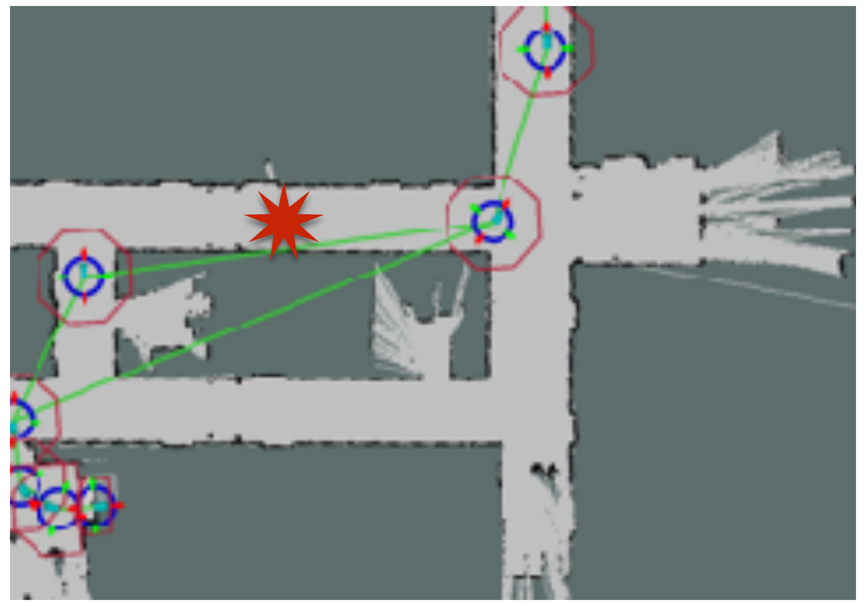
Failure type:	Action by	Meant to act this way	In retrospect, should actor behave this way?	Description
Design	System	Yes	No	System does what it's been made to do, but in retrospect the system should not actually behave this way
System	System	No	No	System doesn't do what it's been made to do
Expectation	System	Yes	Yes	System does what it's been made to do, but user expected something different to happen. In retrospect system should still behave this way
User	User	No	If design fail: yes If expectation fail: no	User behaves in a way they are not supposed to. (Only a problem if leading to other type of failure)

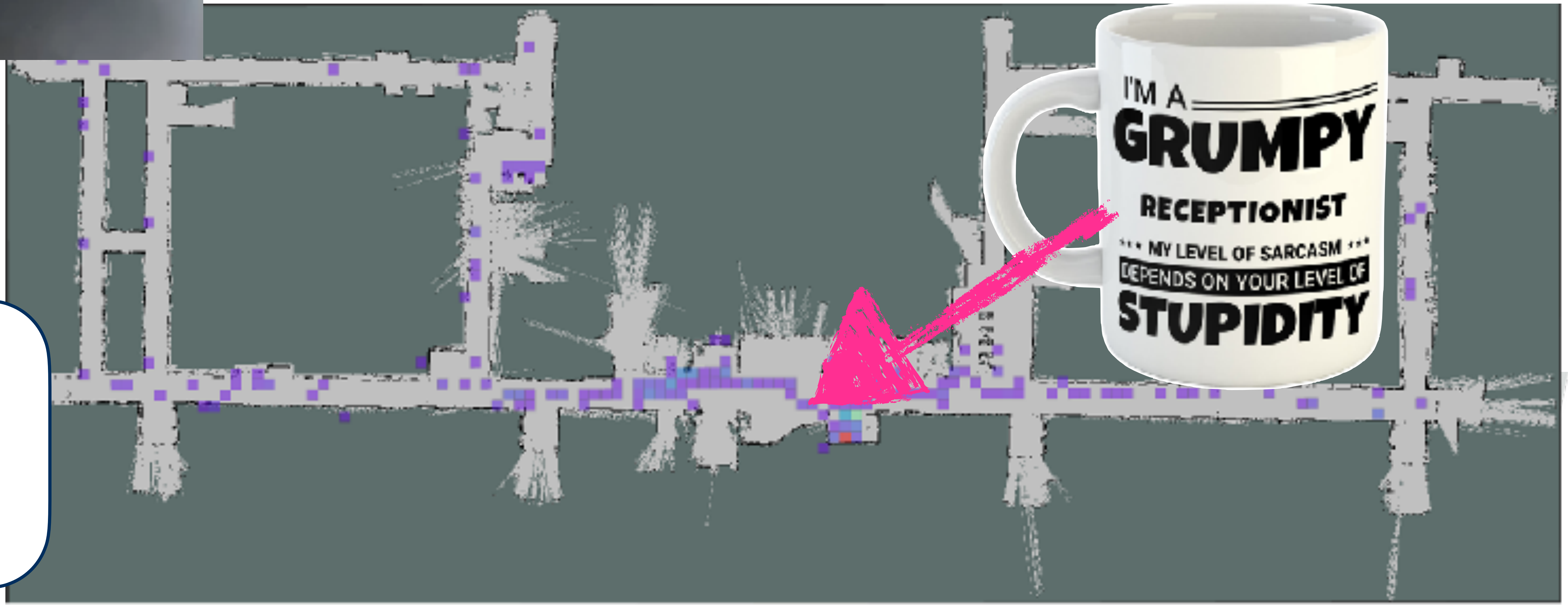
Requesting Human's help (empowerment to increase trust)

Appearance explains incompetence / lack of capacity (Transparent)

Capacity?!

People are willing to help robots (to some extent)





Unacceptable Incompetence

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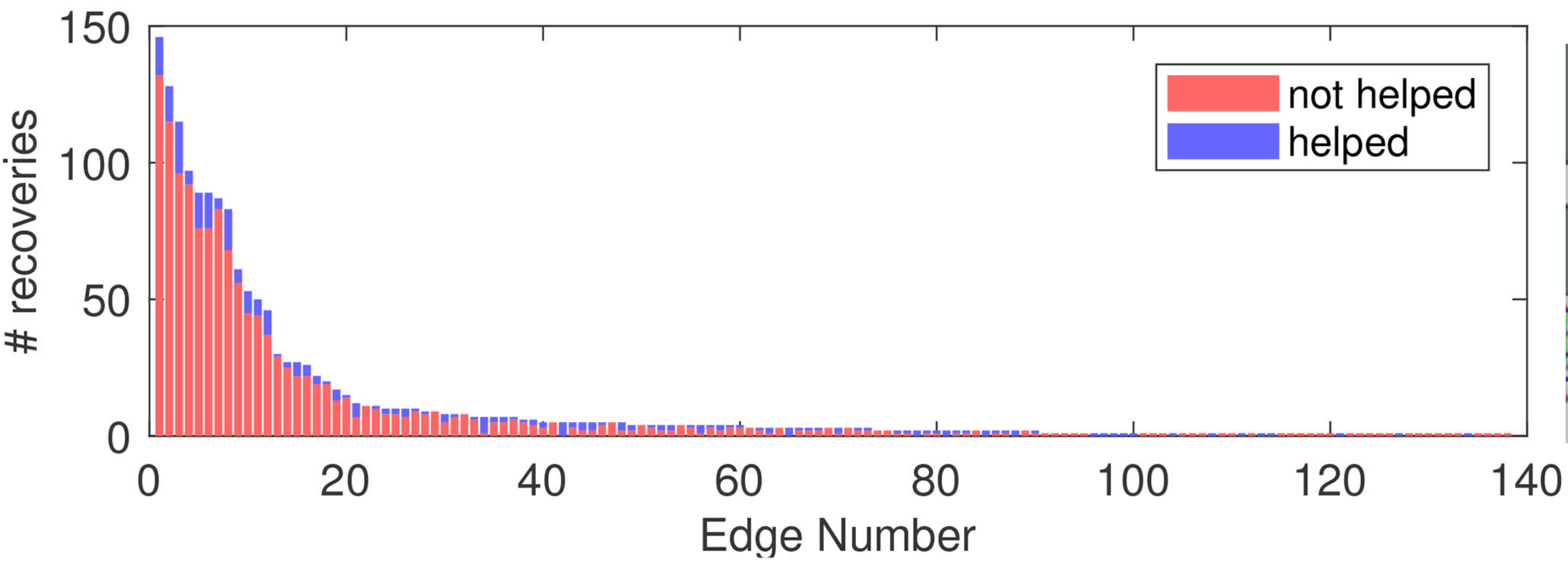
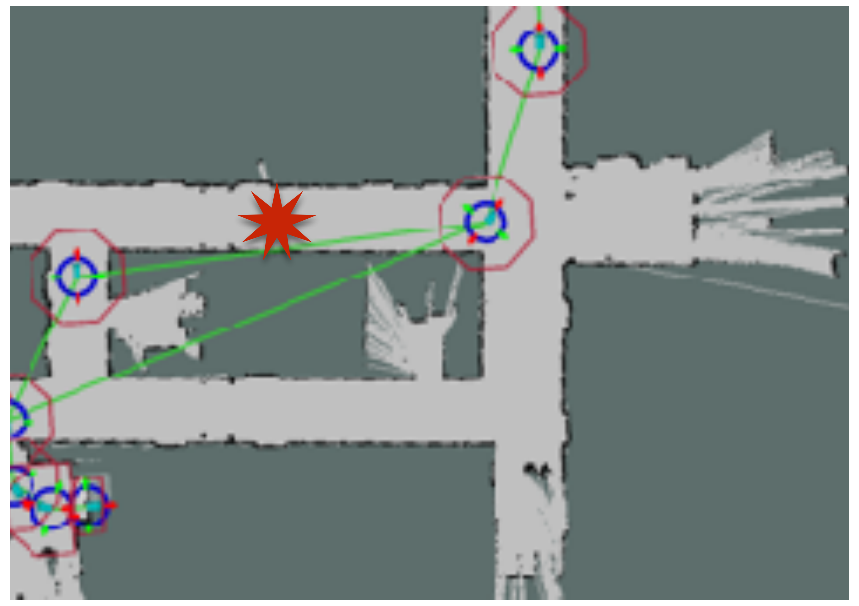
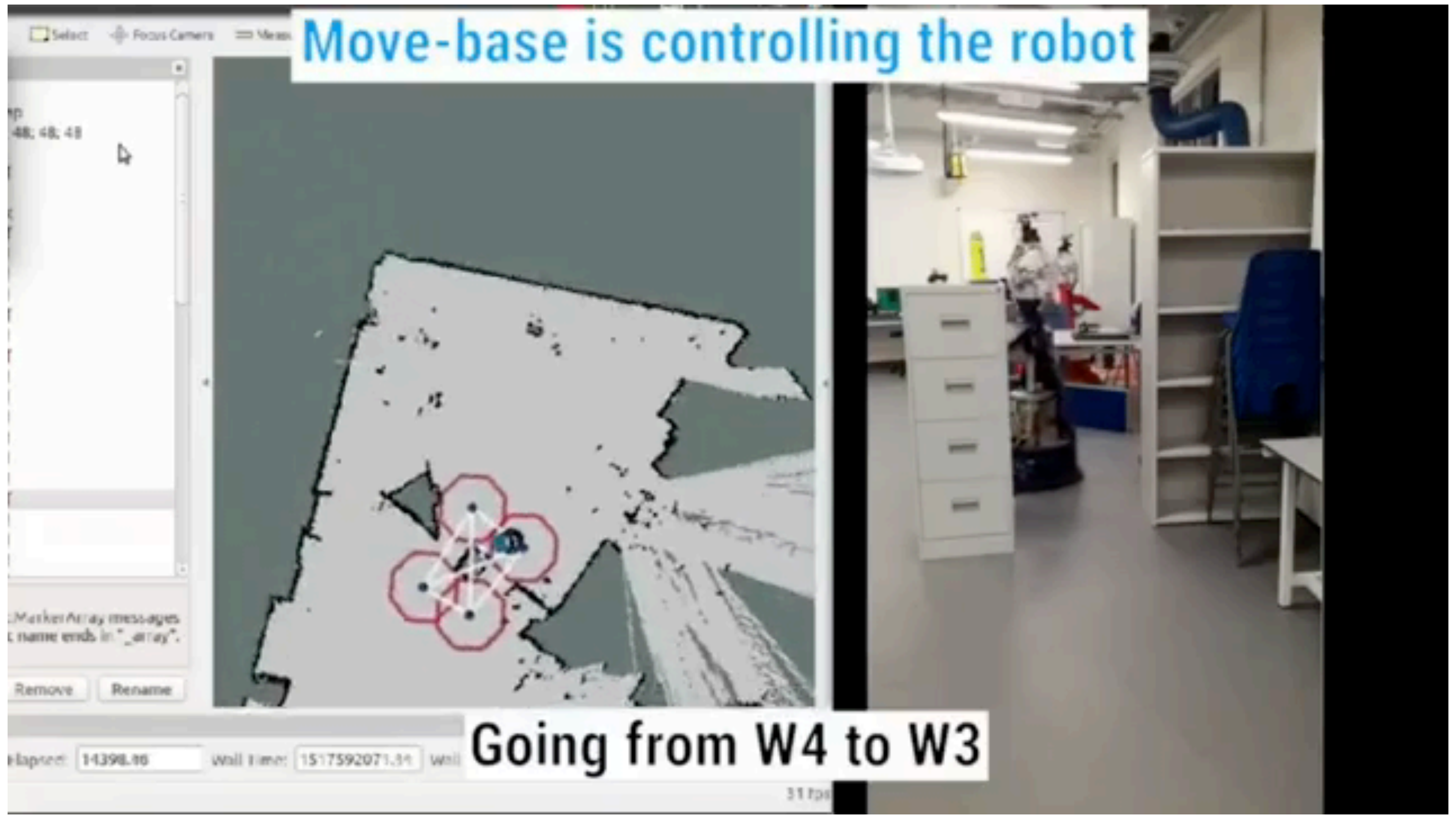
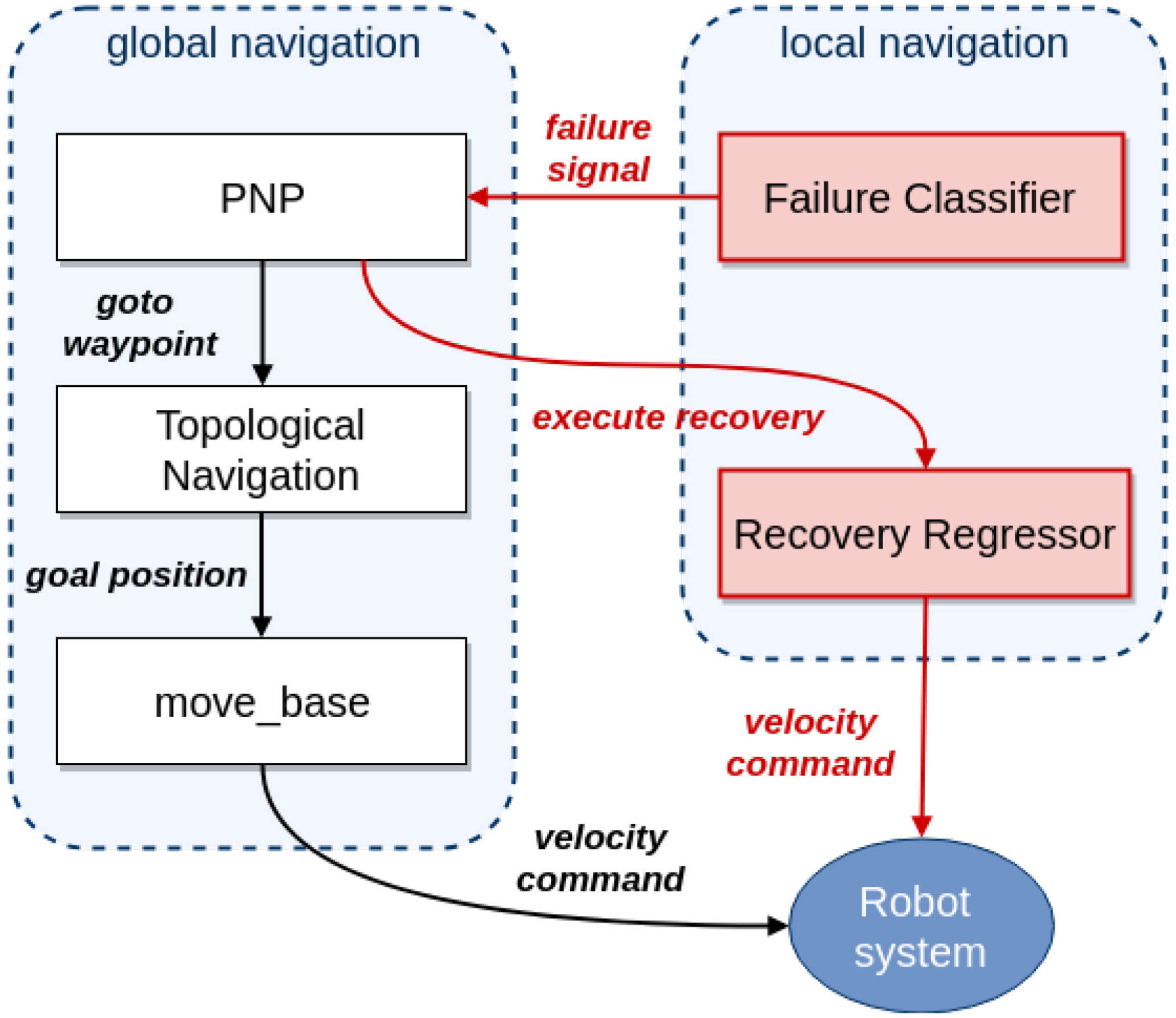
Don’t make the same mistake again!
Learning by Demonstration (in the wild)

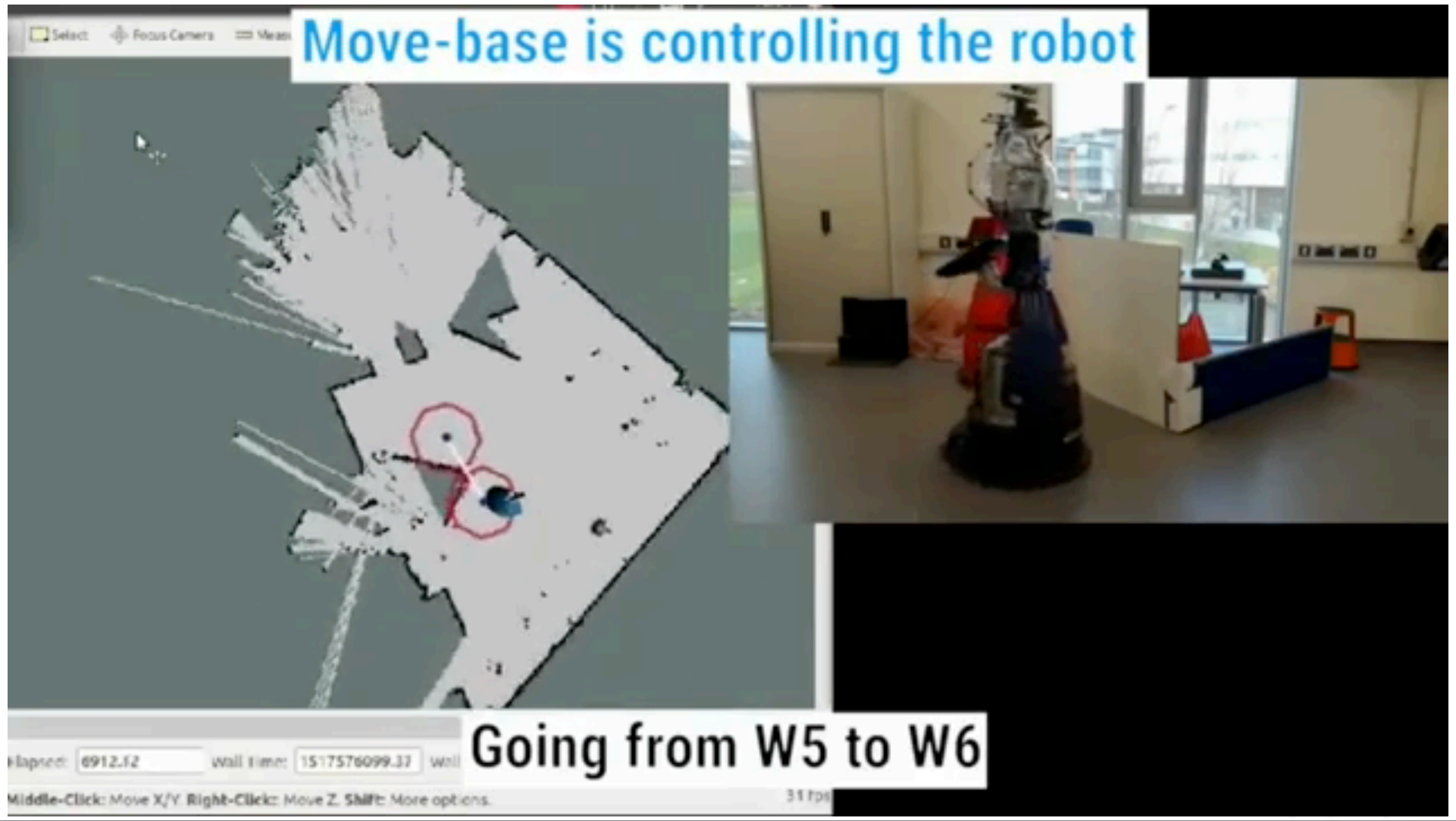






	TOTAL Y1-Y4 Care & Security
Distance (km)	**362.48**
Mon nav events	**8,362**
MNE / km	**22.81**
m / MNE	**43.84**

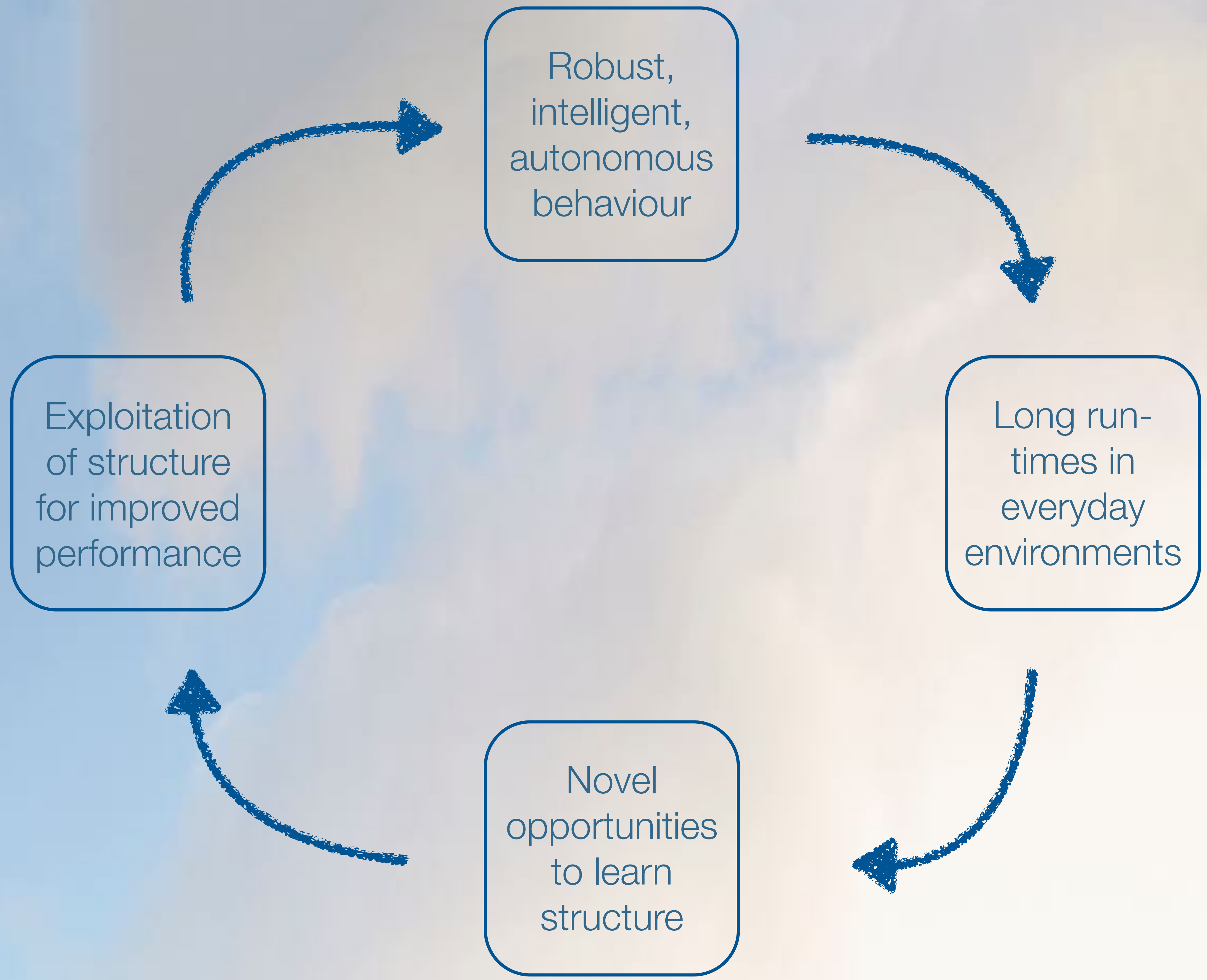




F. Del Duchetto et al., “Do Not Make the Same Mistakes Again and Again: Learning Local Recovery Policies for Navigation From Human Demonstrations,” IEEE Robot. Autom. Lett., vol. 3, no. 4, pp. 4084-4091, Oct. 2018.

Learning about your Users & Usage Patterns

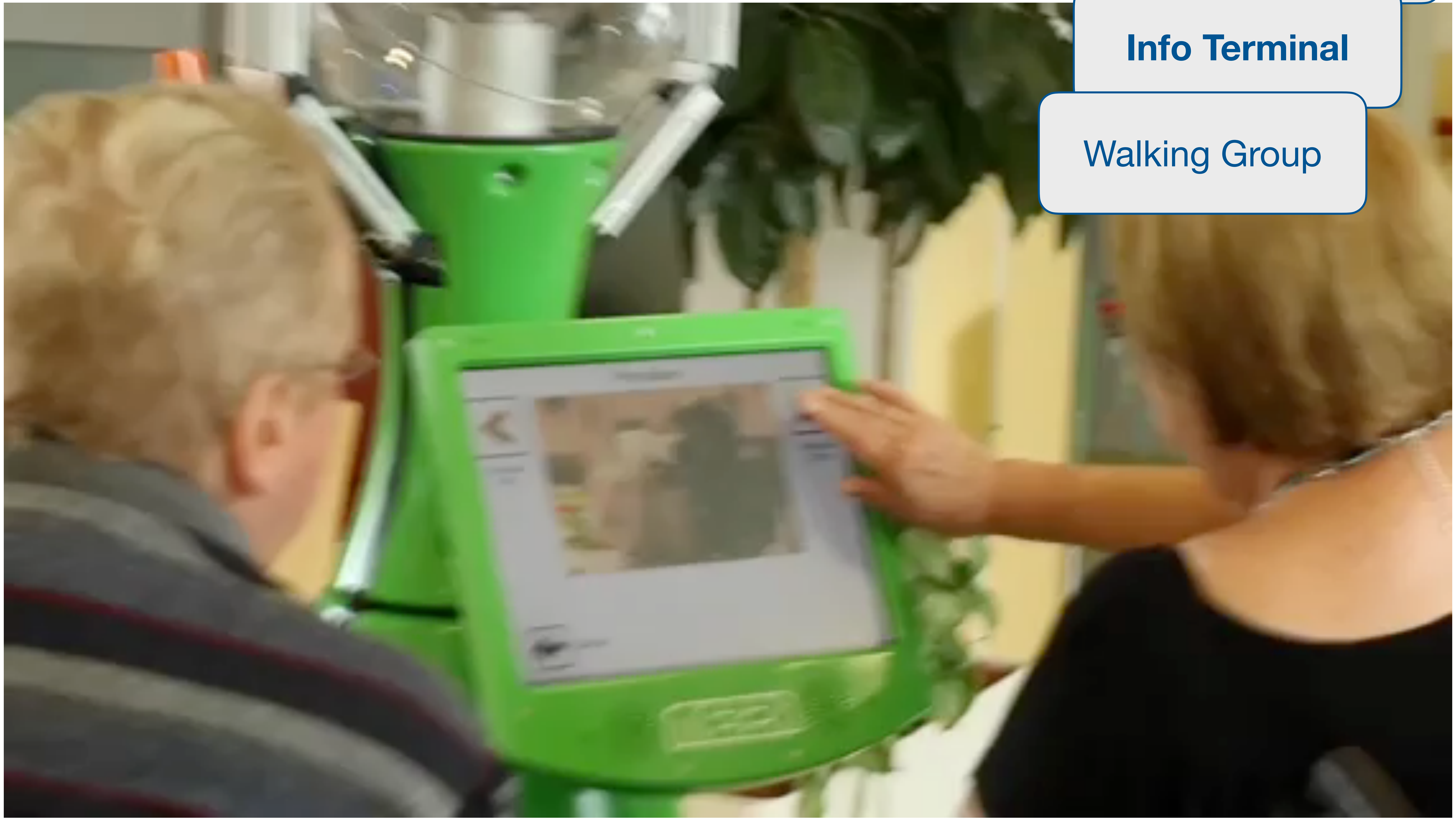
“Getting better on the job”



Bellbot

Info Terminal

Walking Group



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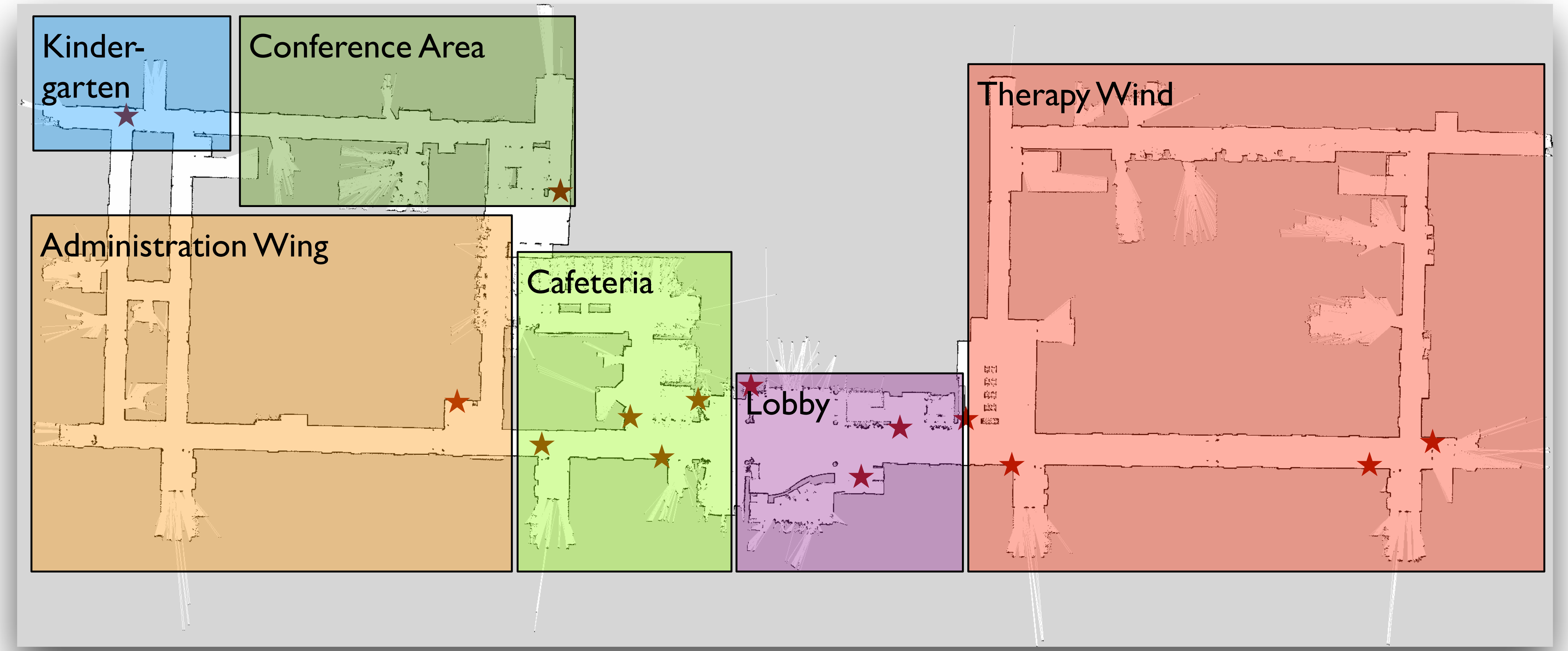
L-CAS

Adaptive Info-Terminal



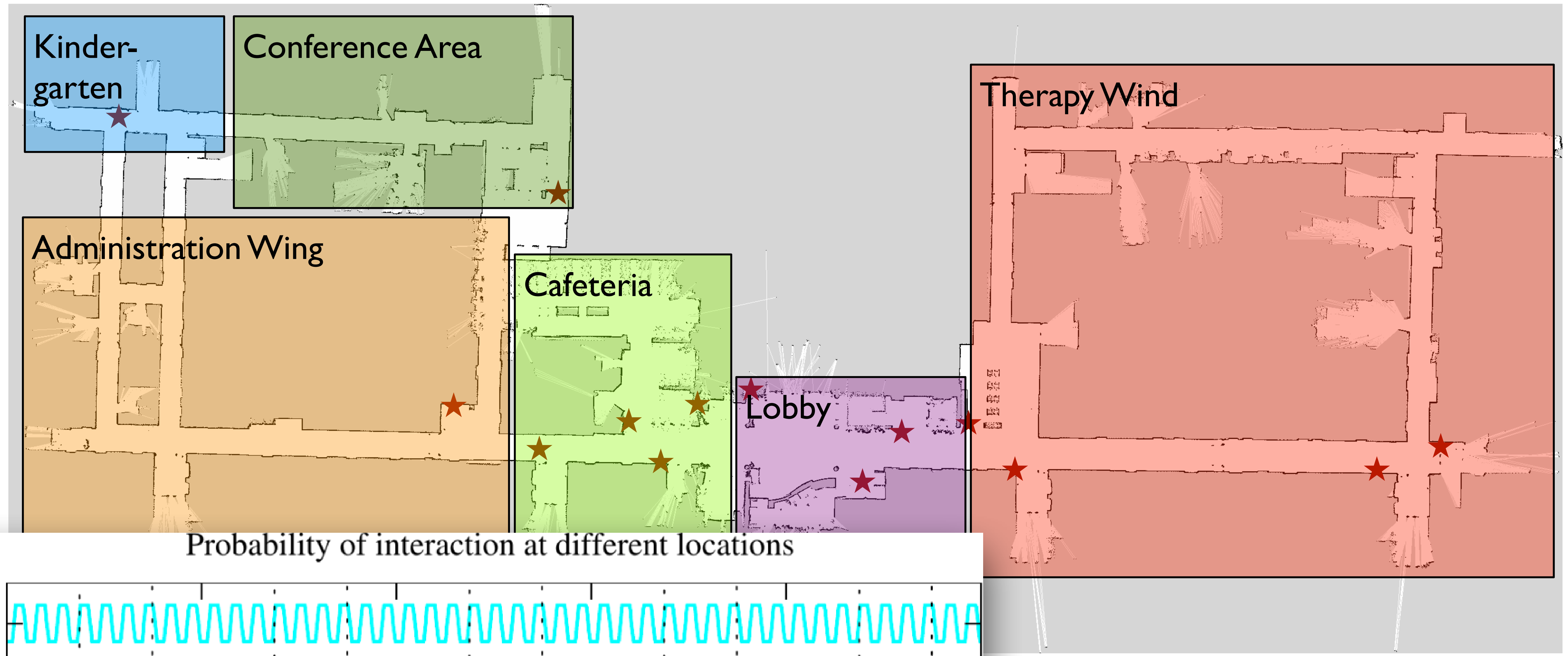
- data recorded:
  - **where** is the robot **when**?
  - **did** people use the robot where it was? (success!)

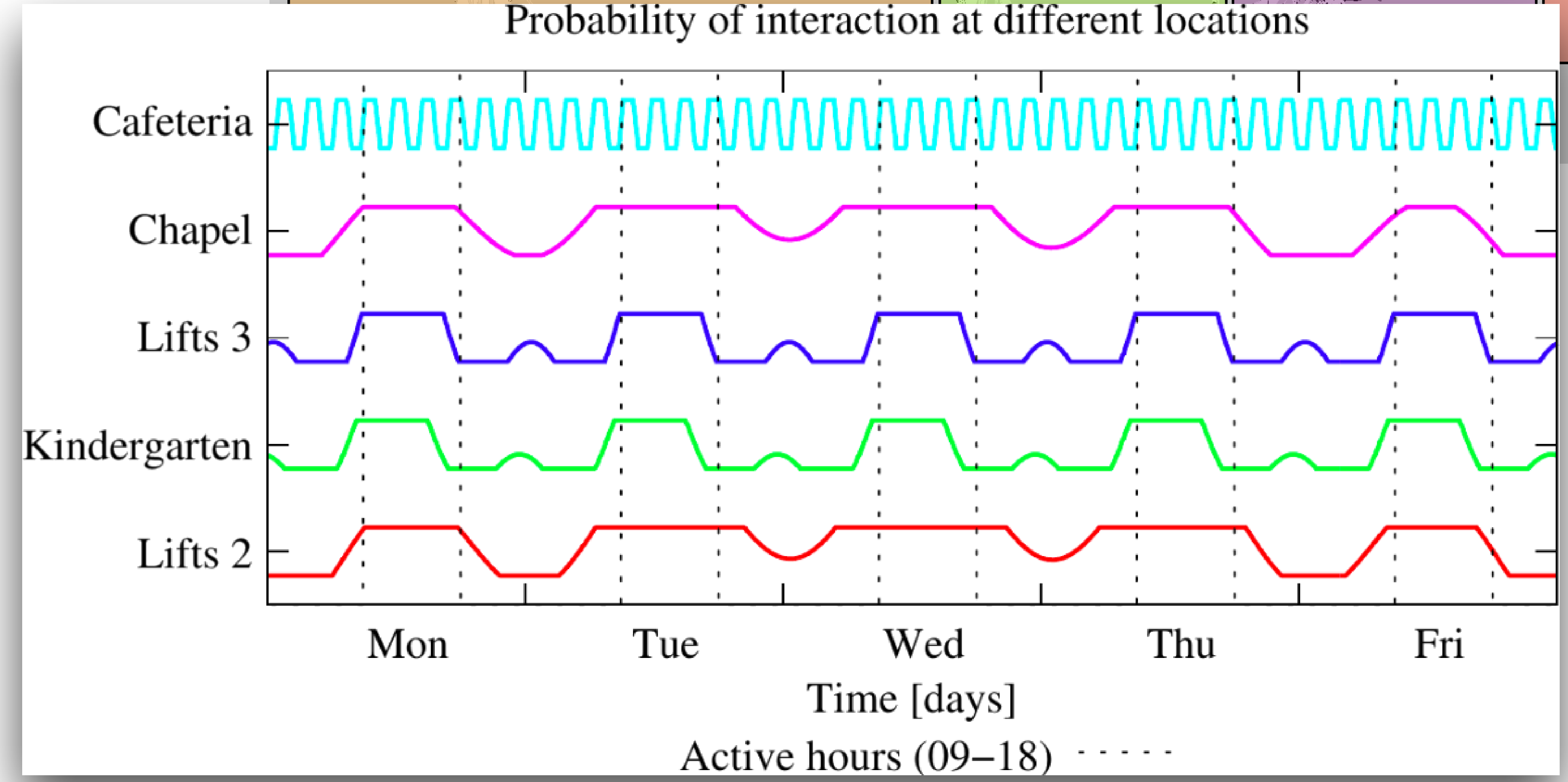
l t

$a_l(t)$

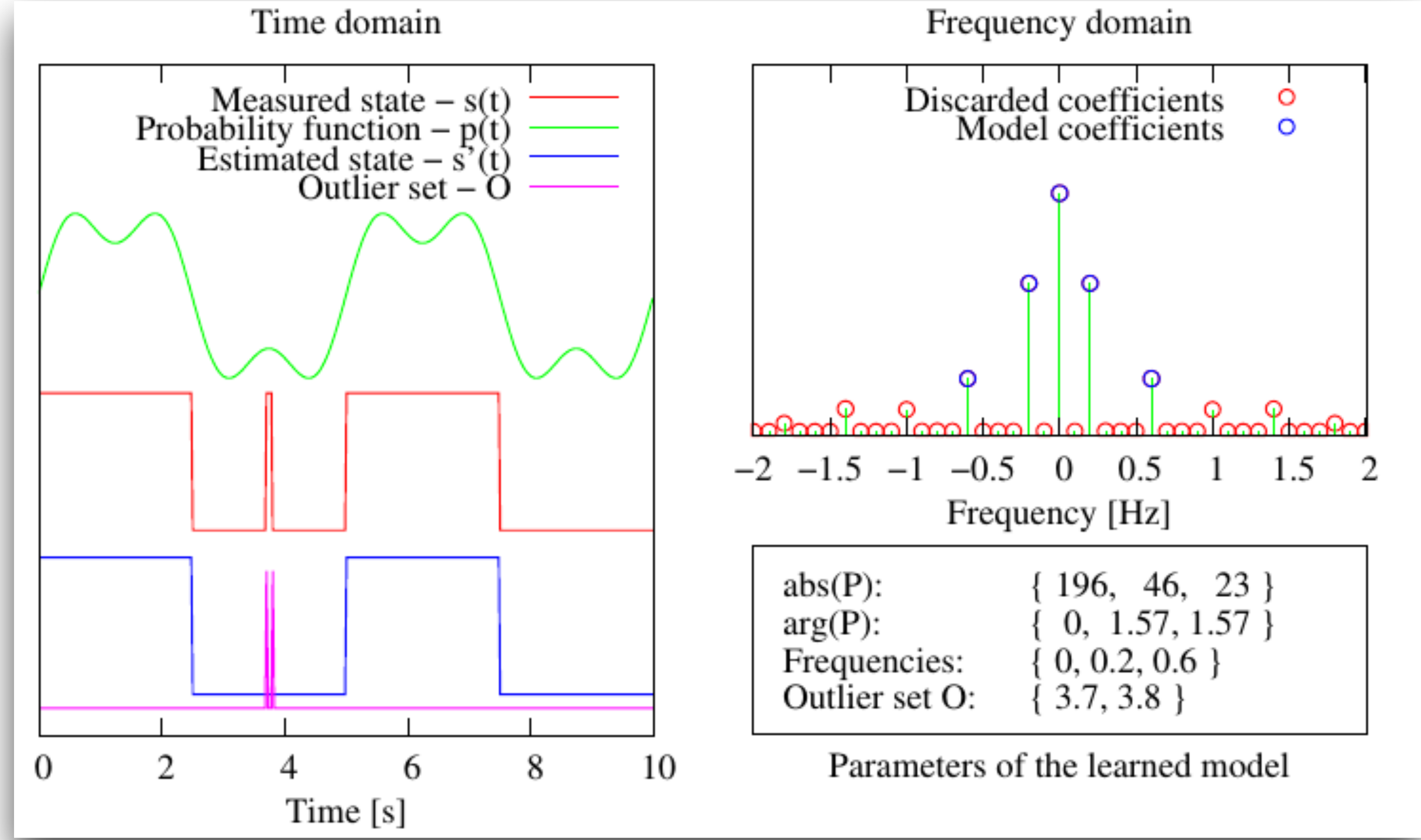
Spatio-Temporal Modelling

- FreMEn method assumes that the probabilities of the some phenomena are influenced by hidden processes which might be **periodic**.





FreMEn?



- How:
  - (binary) states

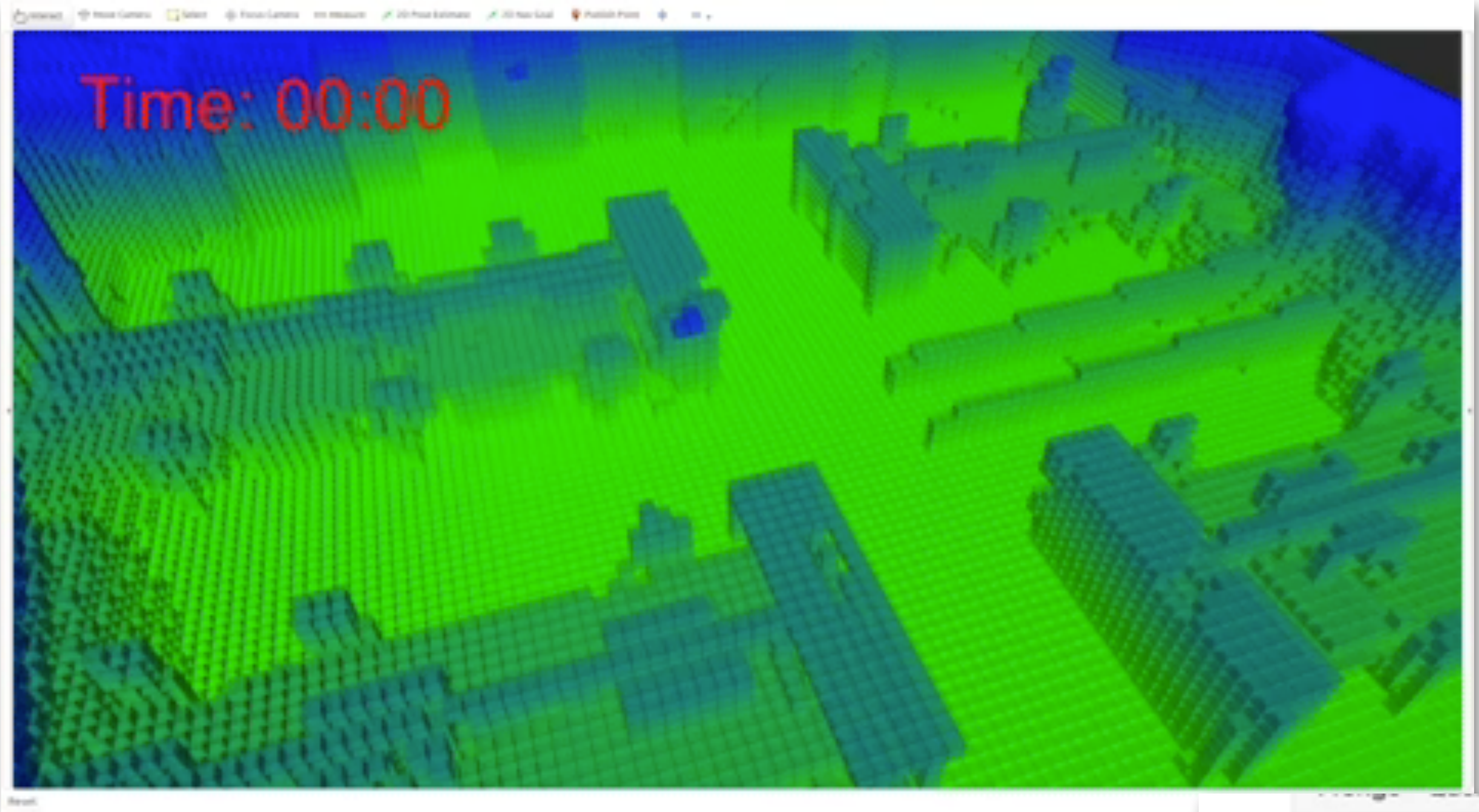
$$s_j(t)=\{0,1\}$$
$$s(t)=[s_1(t),s_2(t),\ldots,s_J(t)]^T$$

  - derive spectral model using FT

$$S(\omega)=FT(s(t))$$

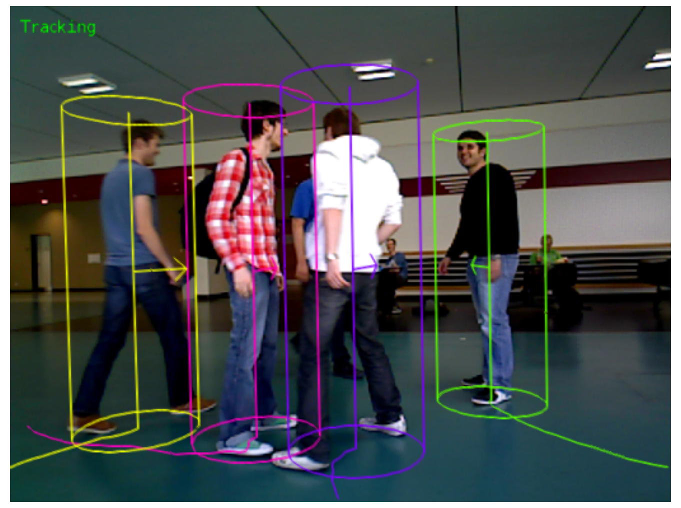
  - keep N the most prominent S

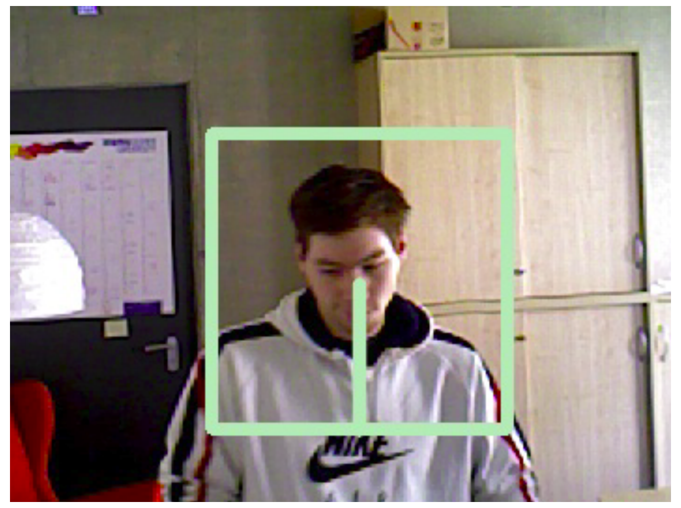
Periodicity in all sort of states?!

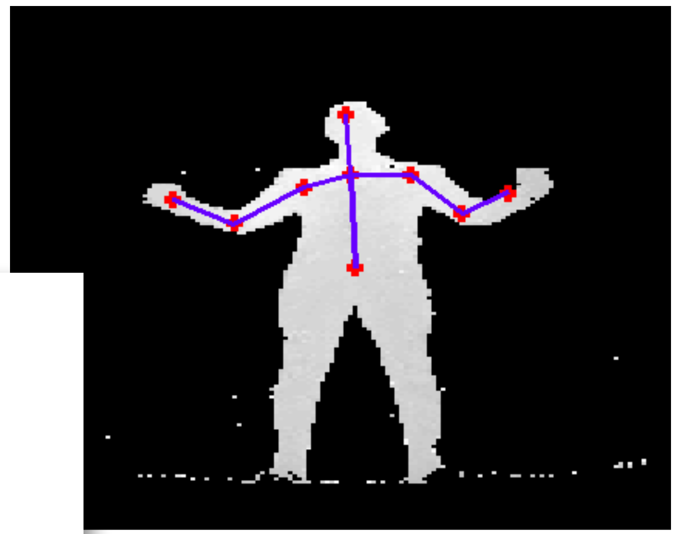


$$s(t)=[s_1(t),s_2(t),\dots,s_J(t)]^T$$

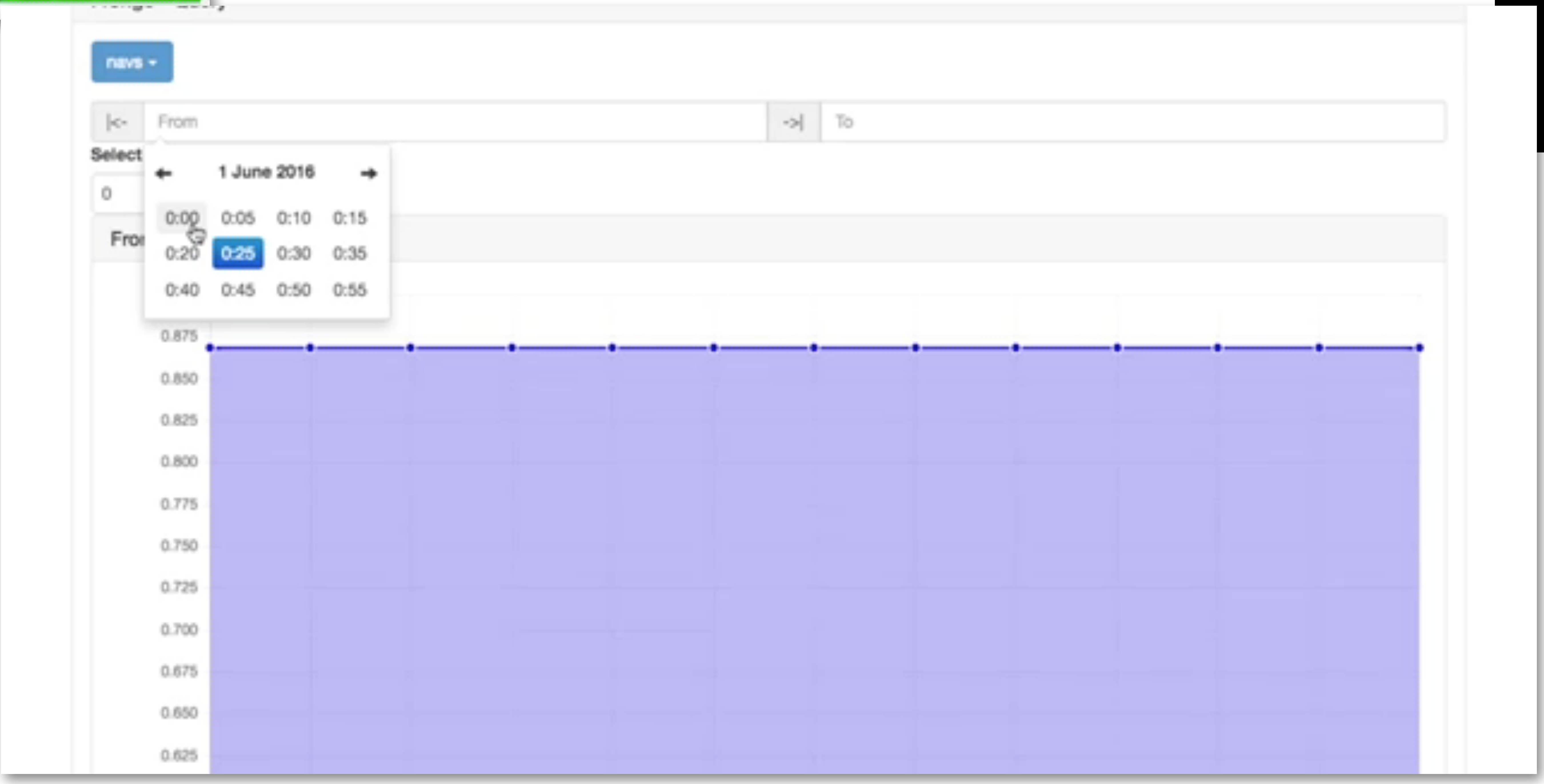
$$S(\omega)=FT(s(t))$$







scene(Monitor, Keyboard, Laptop, Cup, Bottle) ⇔
in-front-of(Keyboard, Monitor)∧
left-of(Laptop, Keyboard)∧
right-of(Cup, Keyboard)∧
behind-of(Bottle, Cup)∧
close-to(Bottle, Cup).



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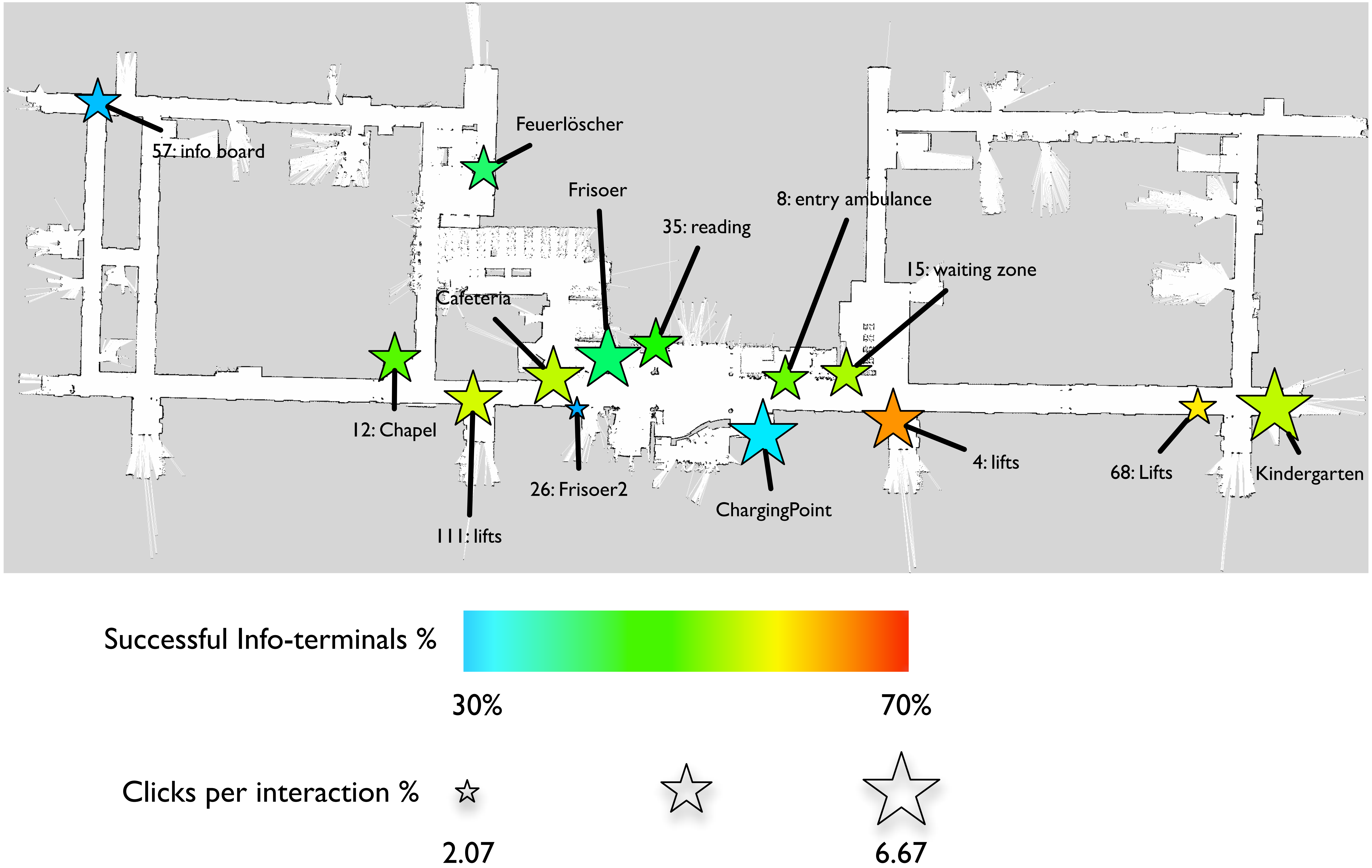
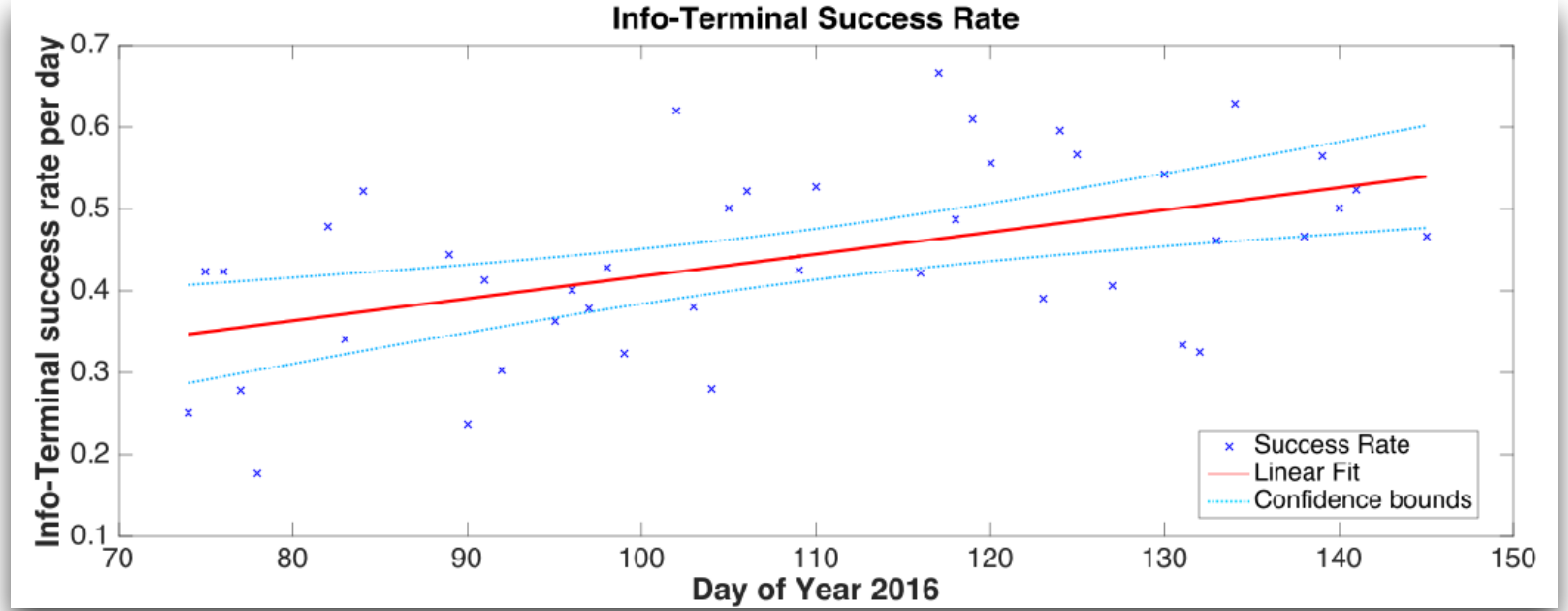
L-CAS

Choosing the next location

- predicted utility of a location *l:* $$u_l(t) = \epsilon\, h(p_l(t)) + (1-\epsilon)\, p_l(t)$$
- use utility to sample next location to go, greedily, new place every 10 minutes
- Here we set ***ε=0.5*** (exploration-exploitation ratio)
- start with ***$p_l(t)$ = 0.5*** at the beginning
- more on exploitation-exploration and planning horizons in
  Kulich, M., Krajnik, T., Preucil, L., and Duckett, T. To explore or to exploit? Learning humans’ behaviour to maximize interactions with them. In Proceedings of the Workshop on Modelling and Simulation for Autonomous Systems (MESAS)


57: info board
Feuerlöscher
Frisoer
35: reading
8: entry ambulance
15: waiting zone
Cafeteria
12: Chapel
26: Frisoer2
111: lifts
ChargingPoint
4: lifts
68: Lifts
Kindergarten
Successful Info-terminals %
30%
70%
Clicks per interaction %
2.07
6.67

More and more interactions



- Linear regression on average success rates per day.
- rejection of H0 (constant number of interactions) with *p=0.000674*.

Lindsey in the Museum
2018-2023

https://lcas.lincoln.ac.uk/wp/projects/lindsey-a-robot-tour-guide/

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L-CAS

Total deployment duration:

3.3 years

Days of operation:

446 days (1.2 years)

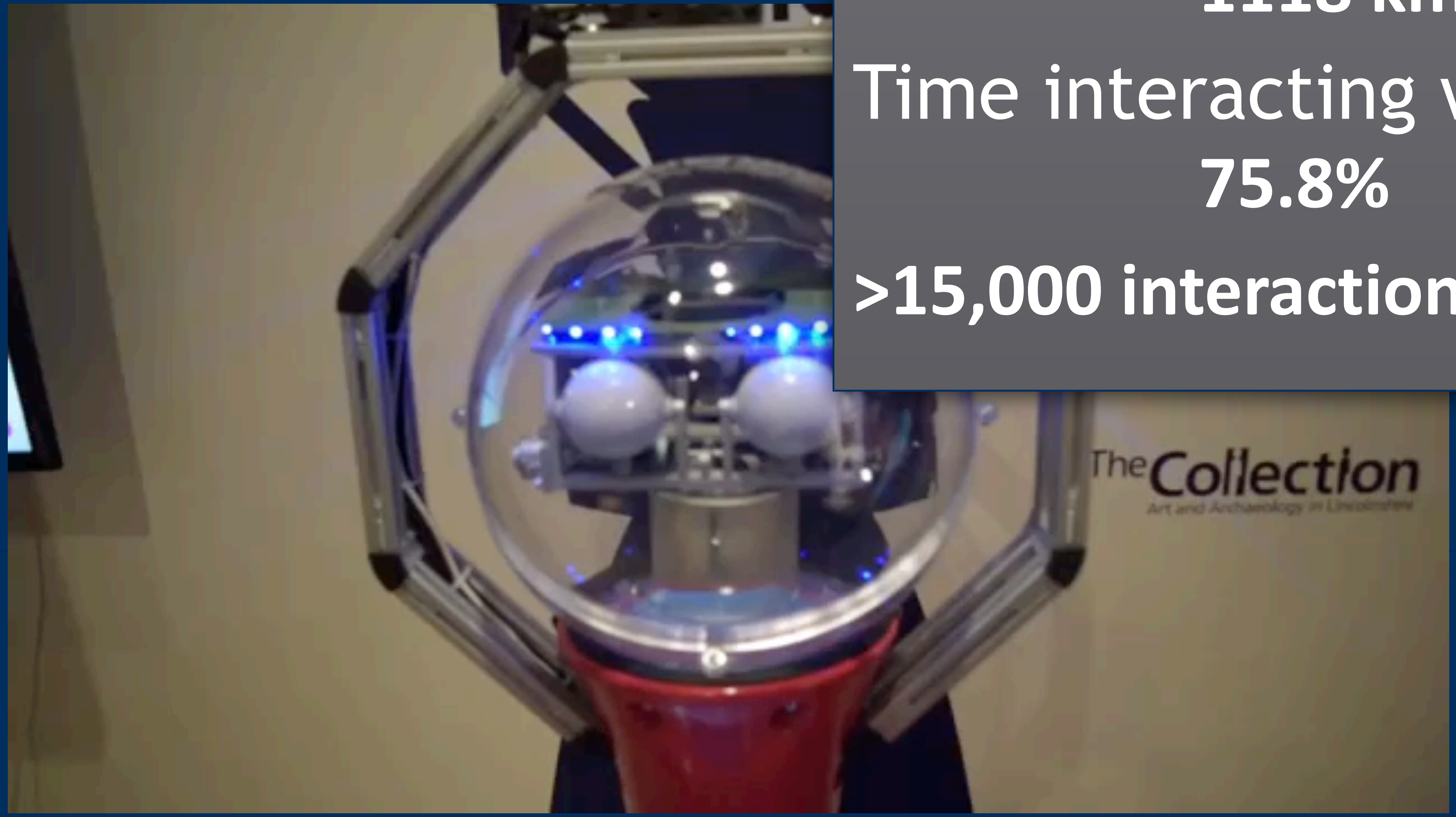
Distance travelled:

1118 km

Time interacting with visitors:

75.8%

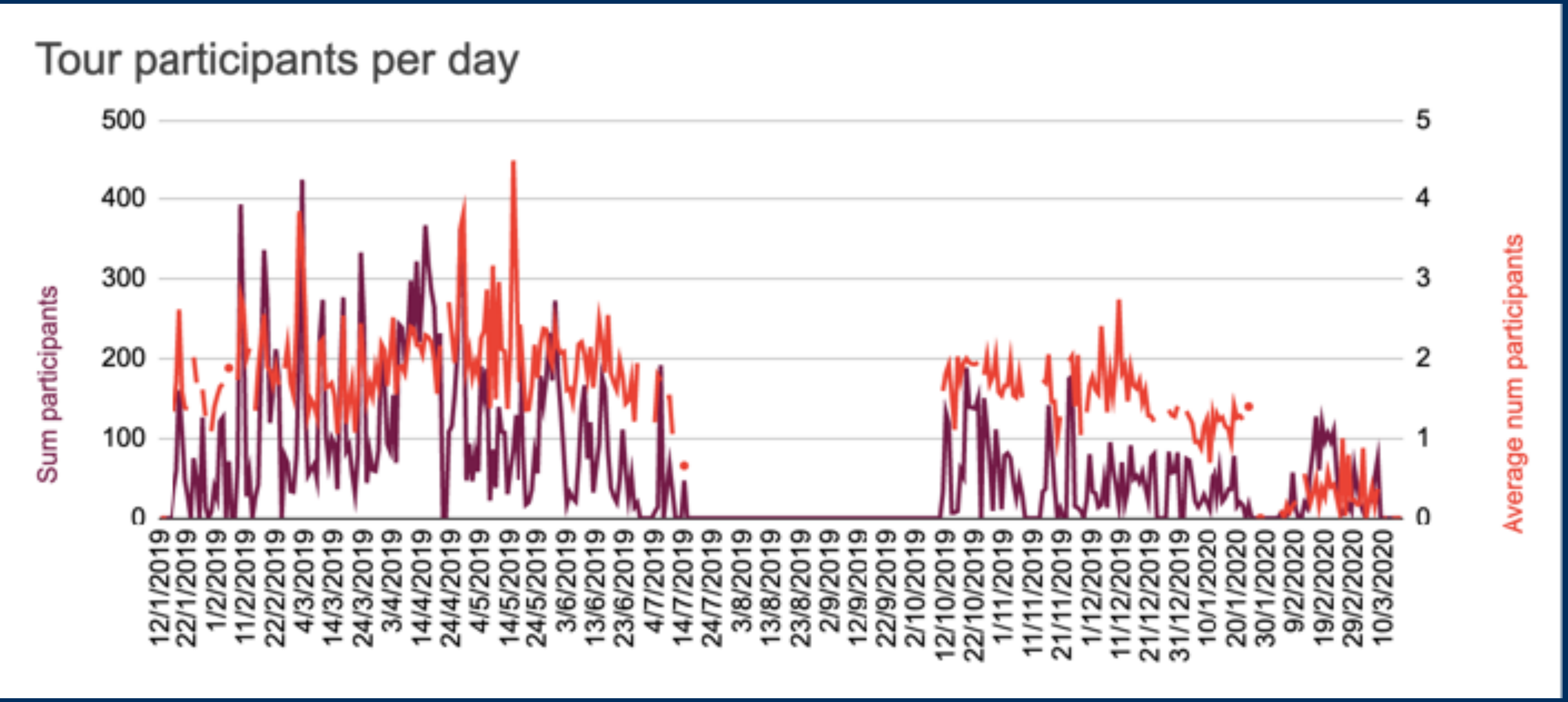
>15,000 interactions with the museum's visitors



Reinforcement learning in the public domain?

- Lindsey is a tour guide robot in The Collection Archeological Museum
- *Can we learn better tours through long-term interaction with the public?*

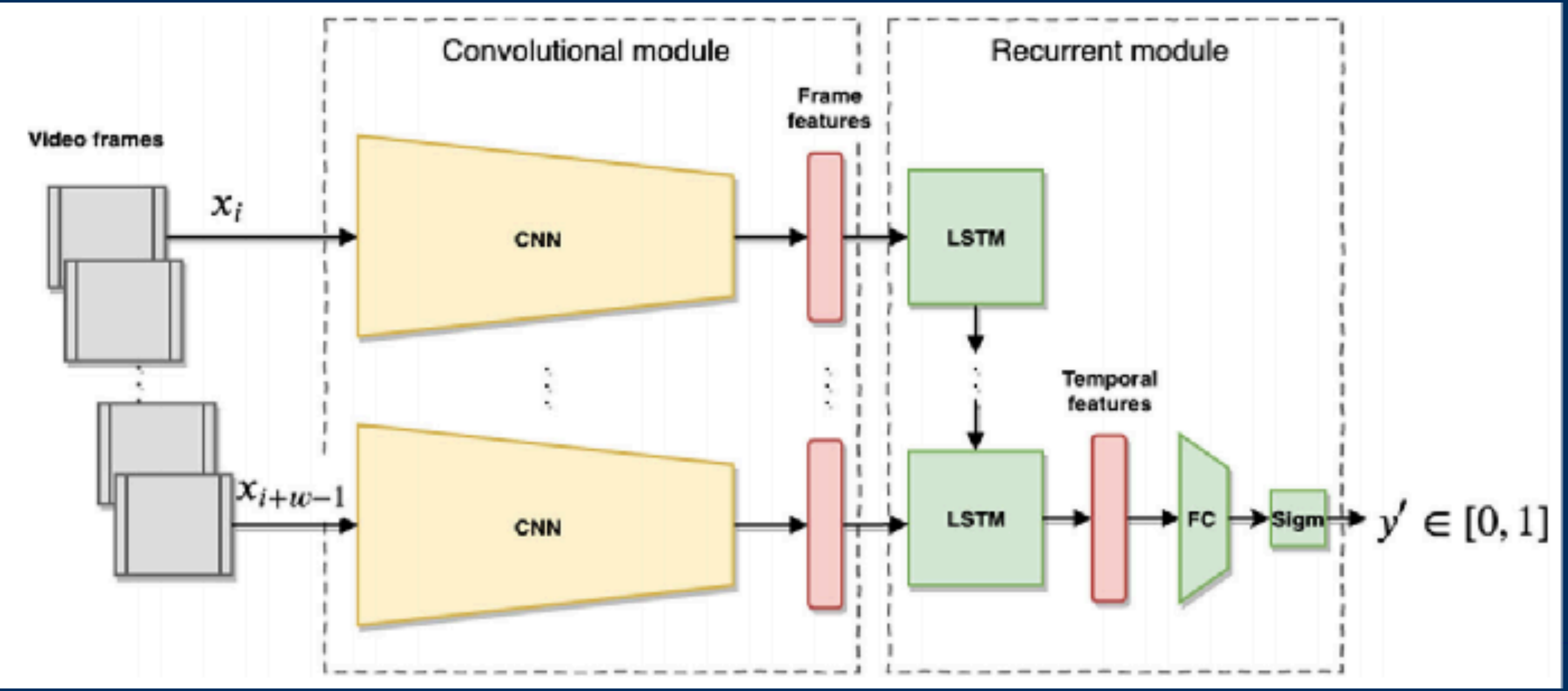
"Getting better on the job"

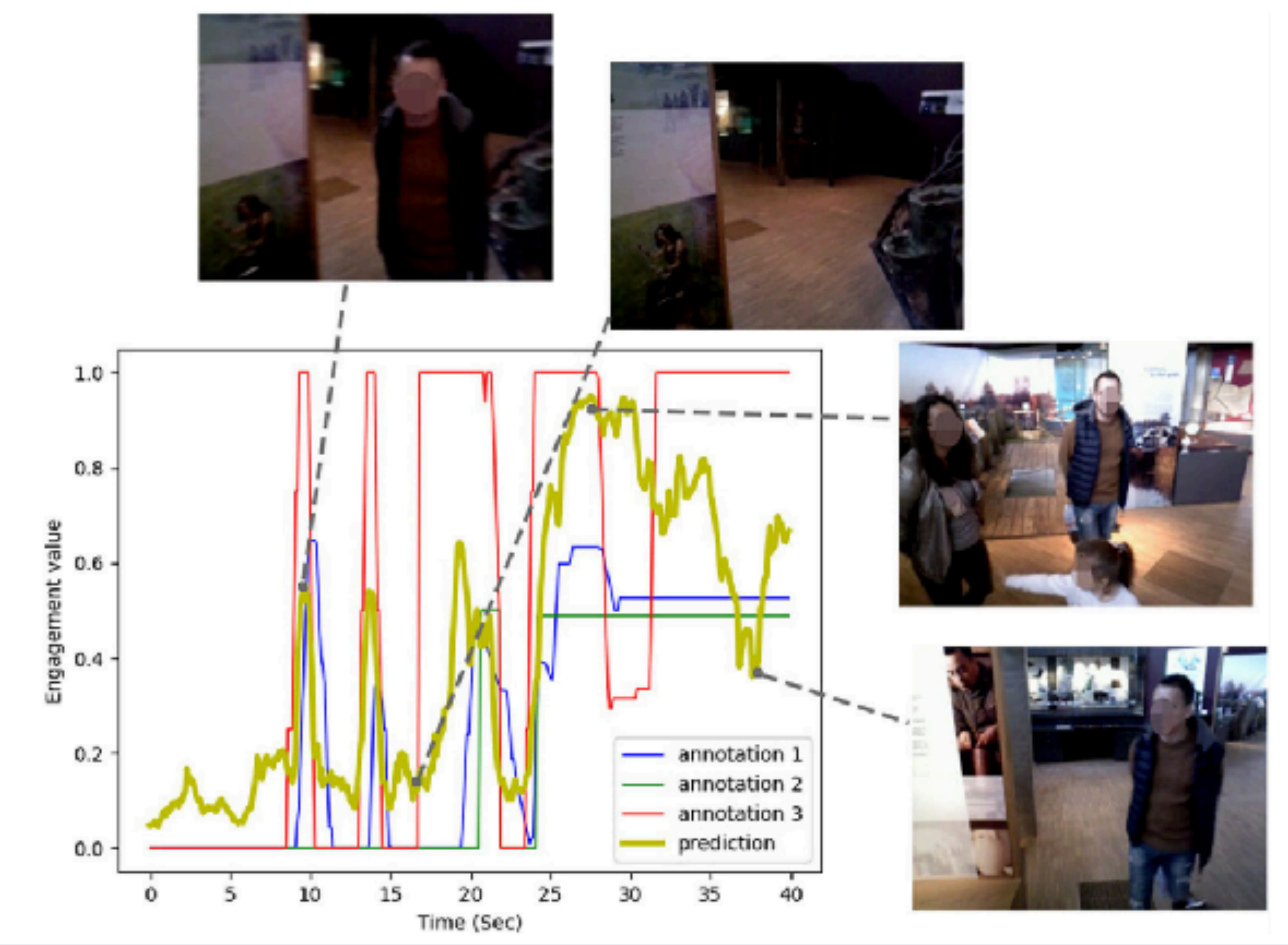


Are You Still With Me? Continuous Engagement Assessment From a Robot's Point of View

Francesco Del Duchetto, Paul Baxter and Marc Hanheide*

Lincoln Centre for Autonomous Systems, School of Computer Science, University of Lincoln, Lincoln, United Kingdom





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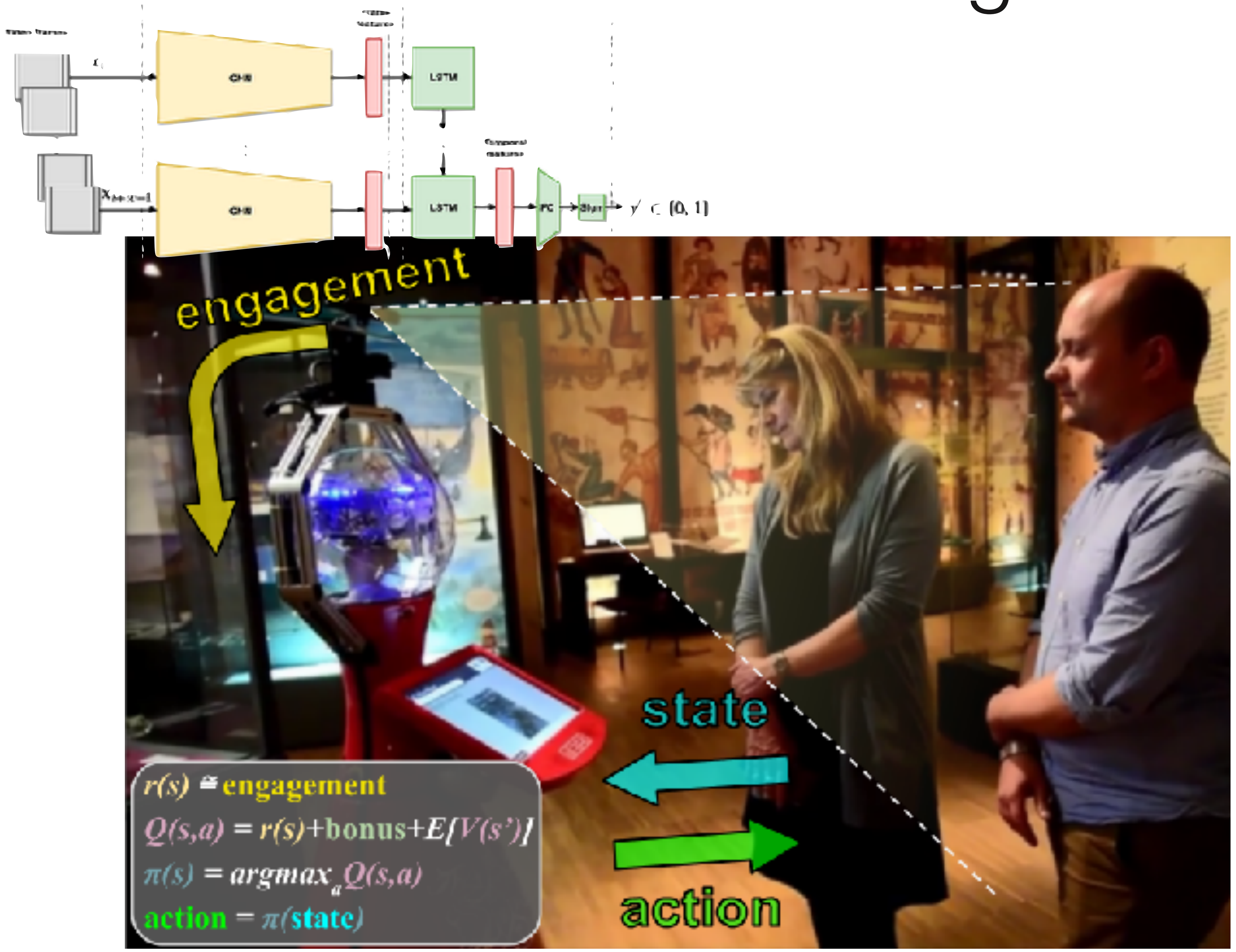
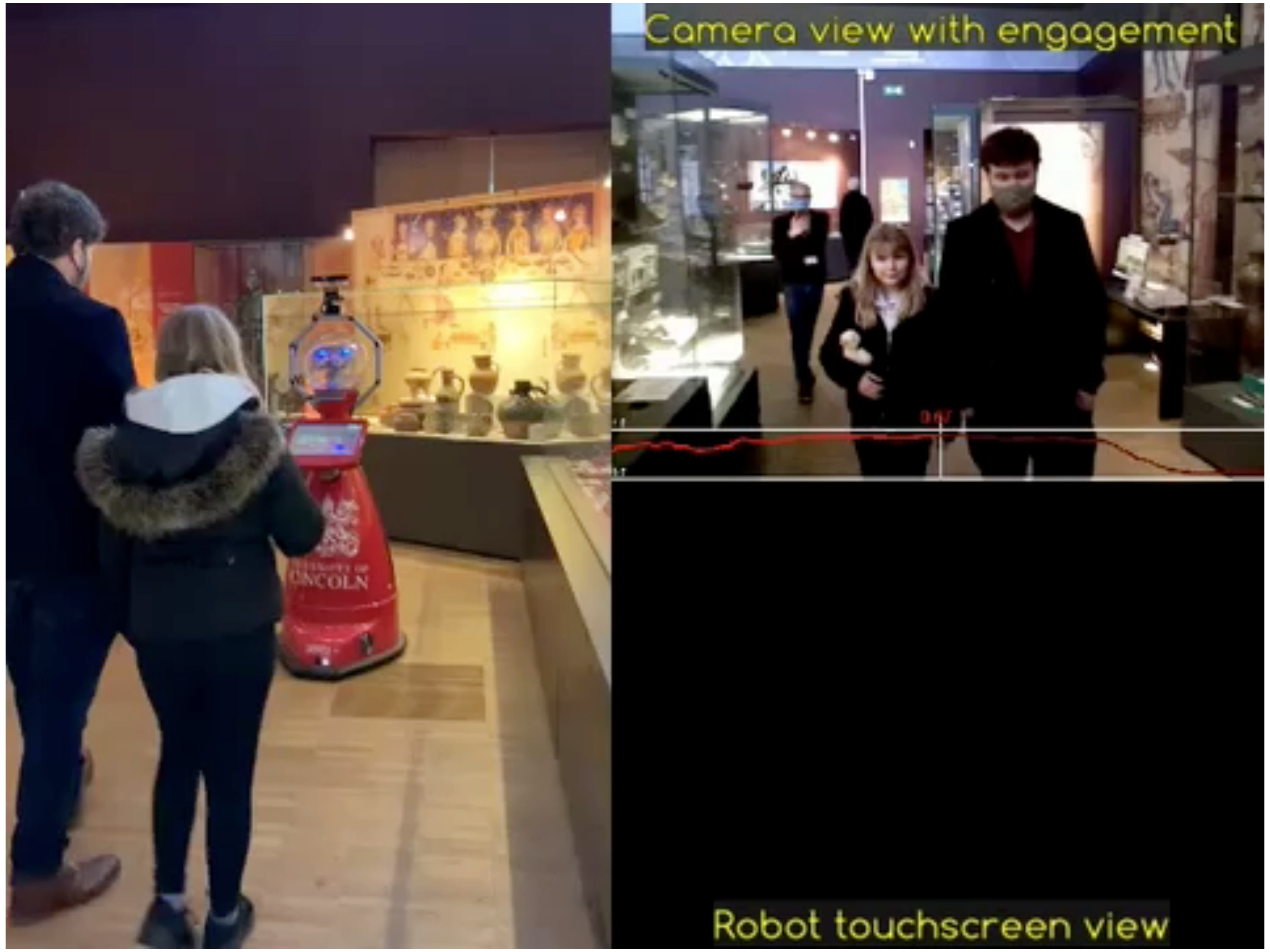
ROS4HRI ??

https://github.com/LCAS/engagement_detector

L-CAS

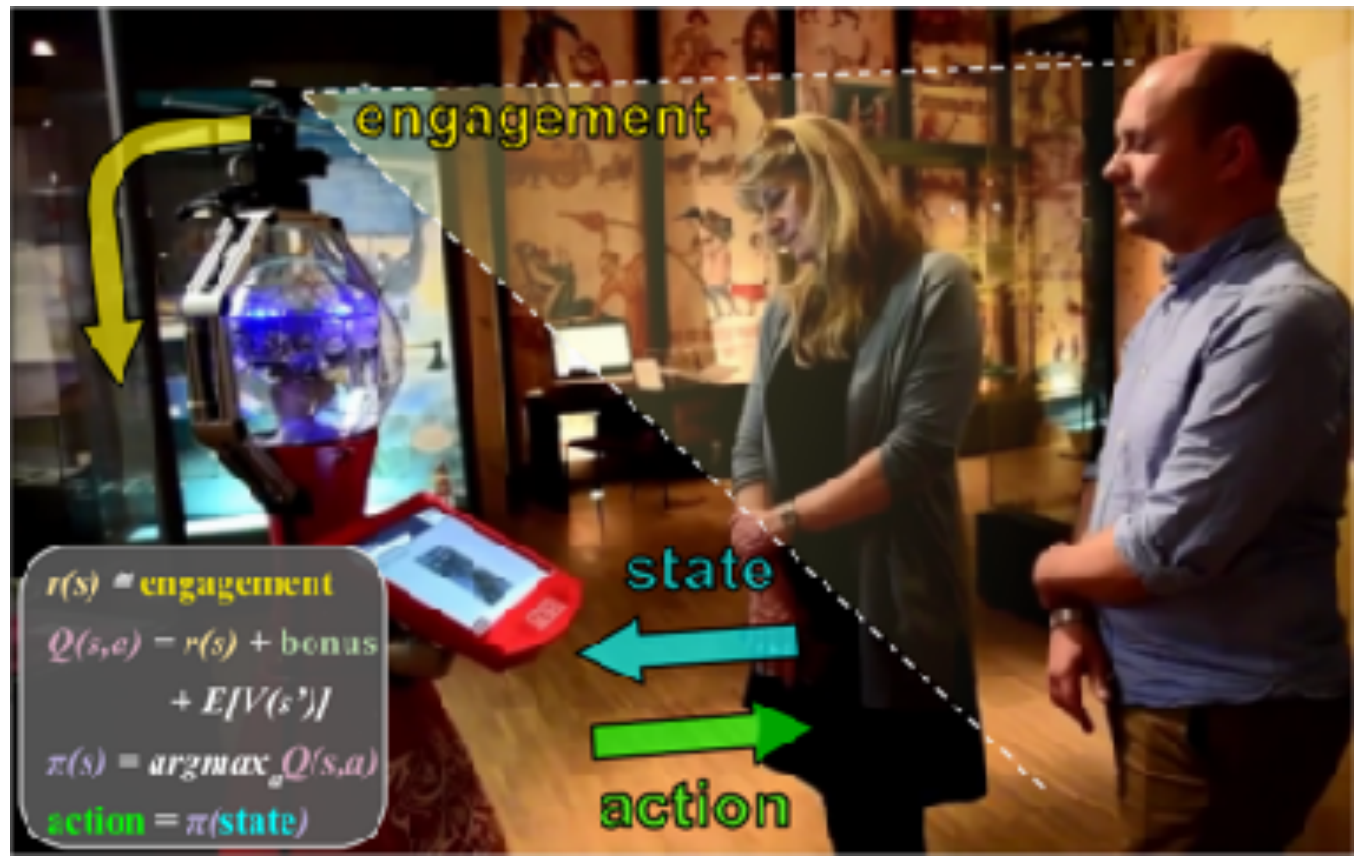
Reinforcement learning in the public domain?

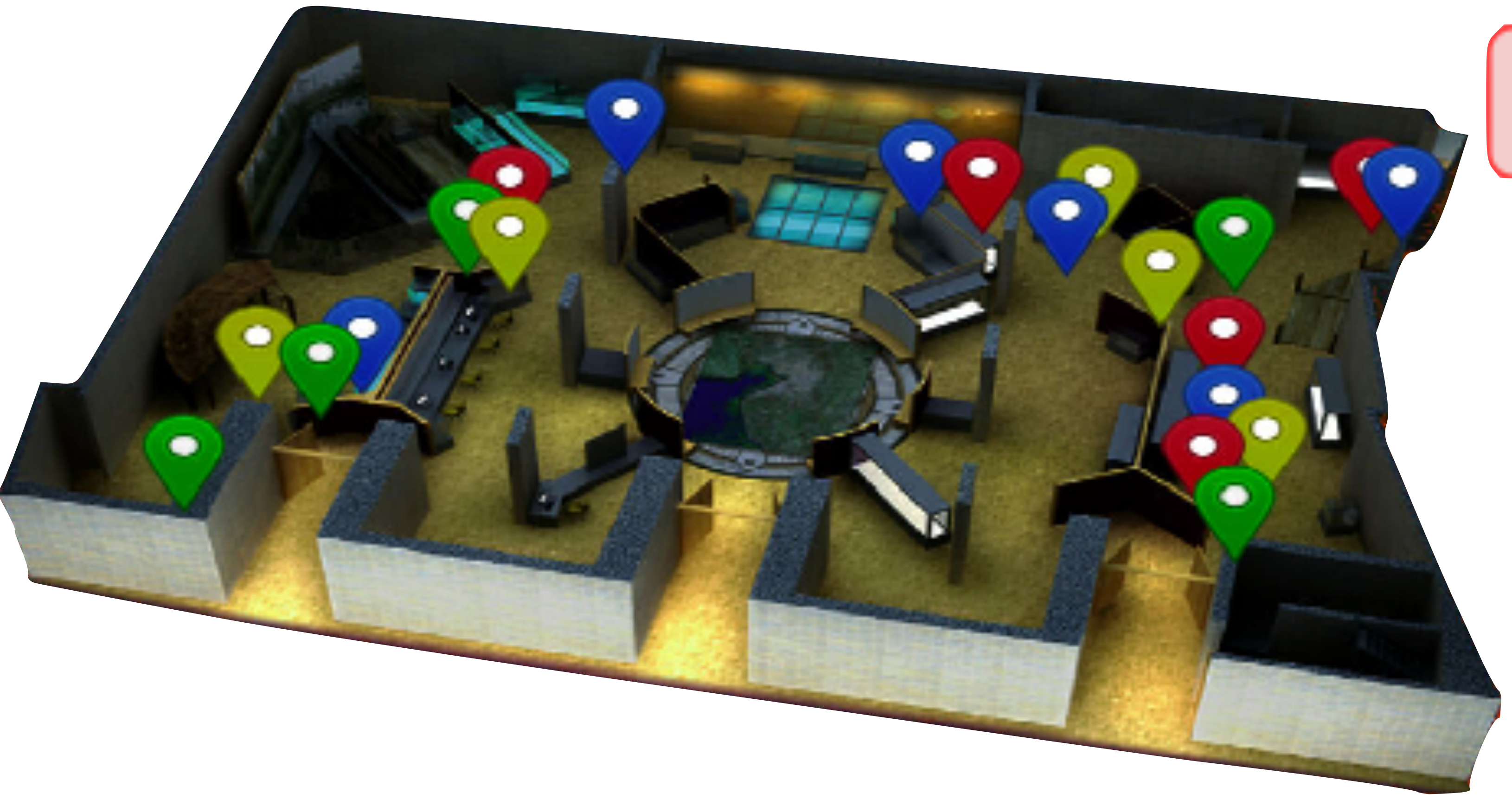


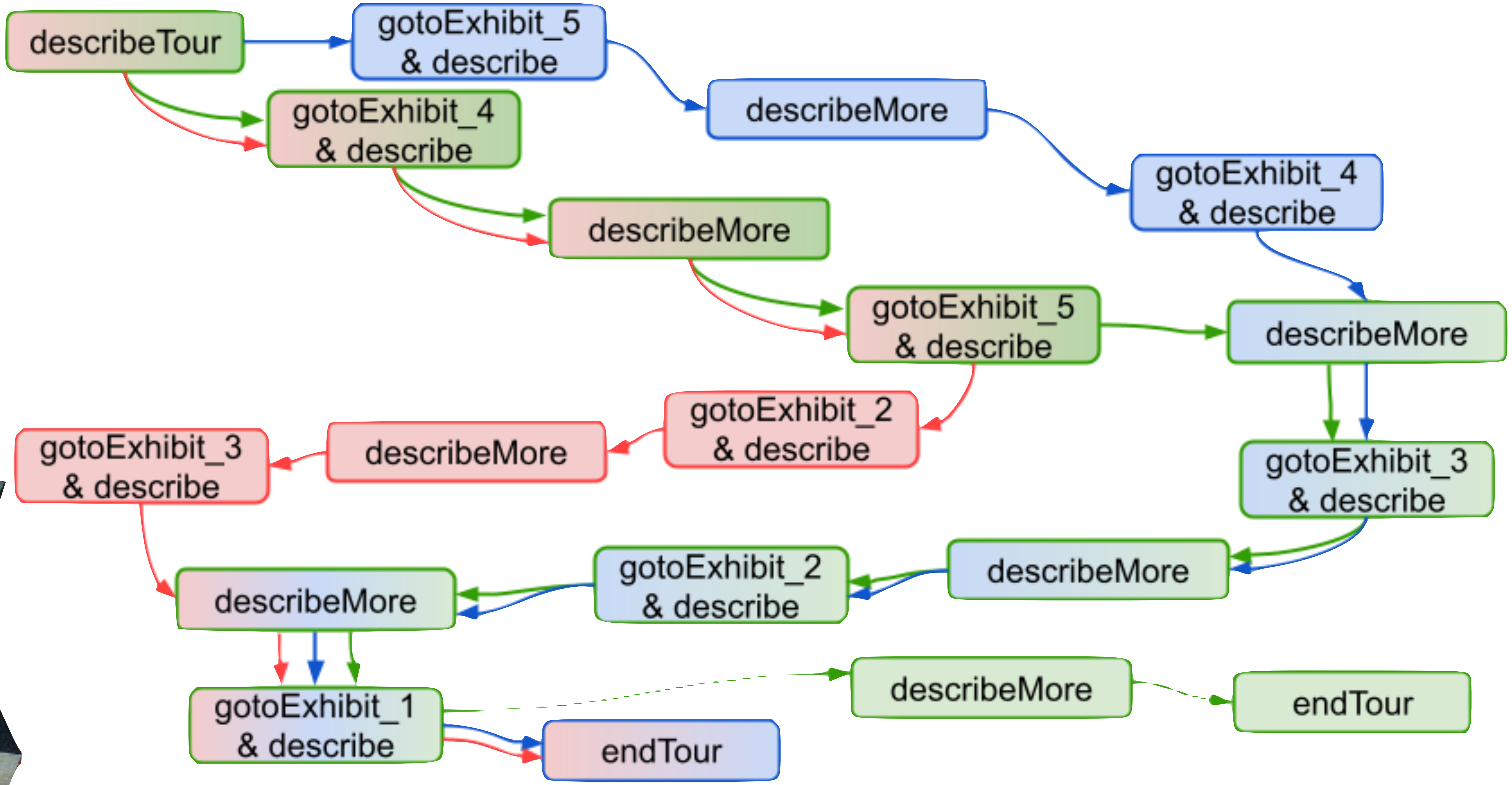


Del Duchetto, F., Baxter, P., & Hanheide, M. (2020). Are you still with me? Continuous engagement assessment from a robot's point of view. *Frontiers in Robotics and AI*, 116.

Tour structure depending on current engagement and state

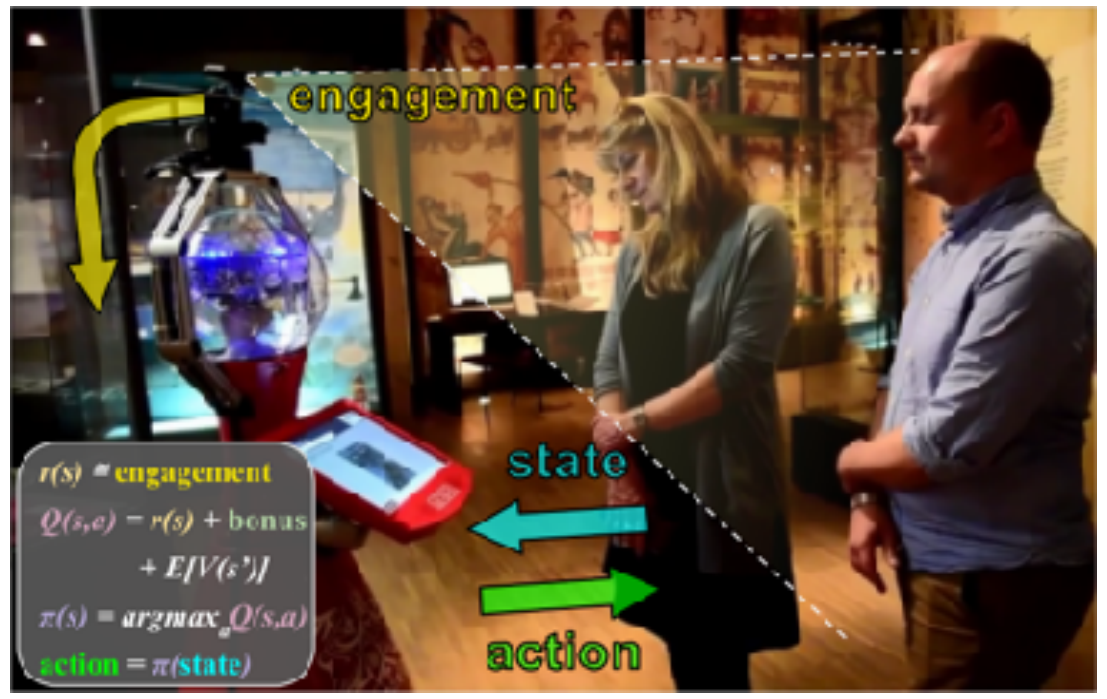


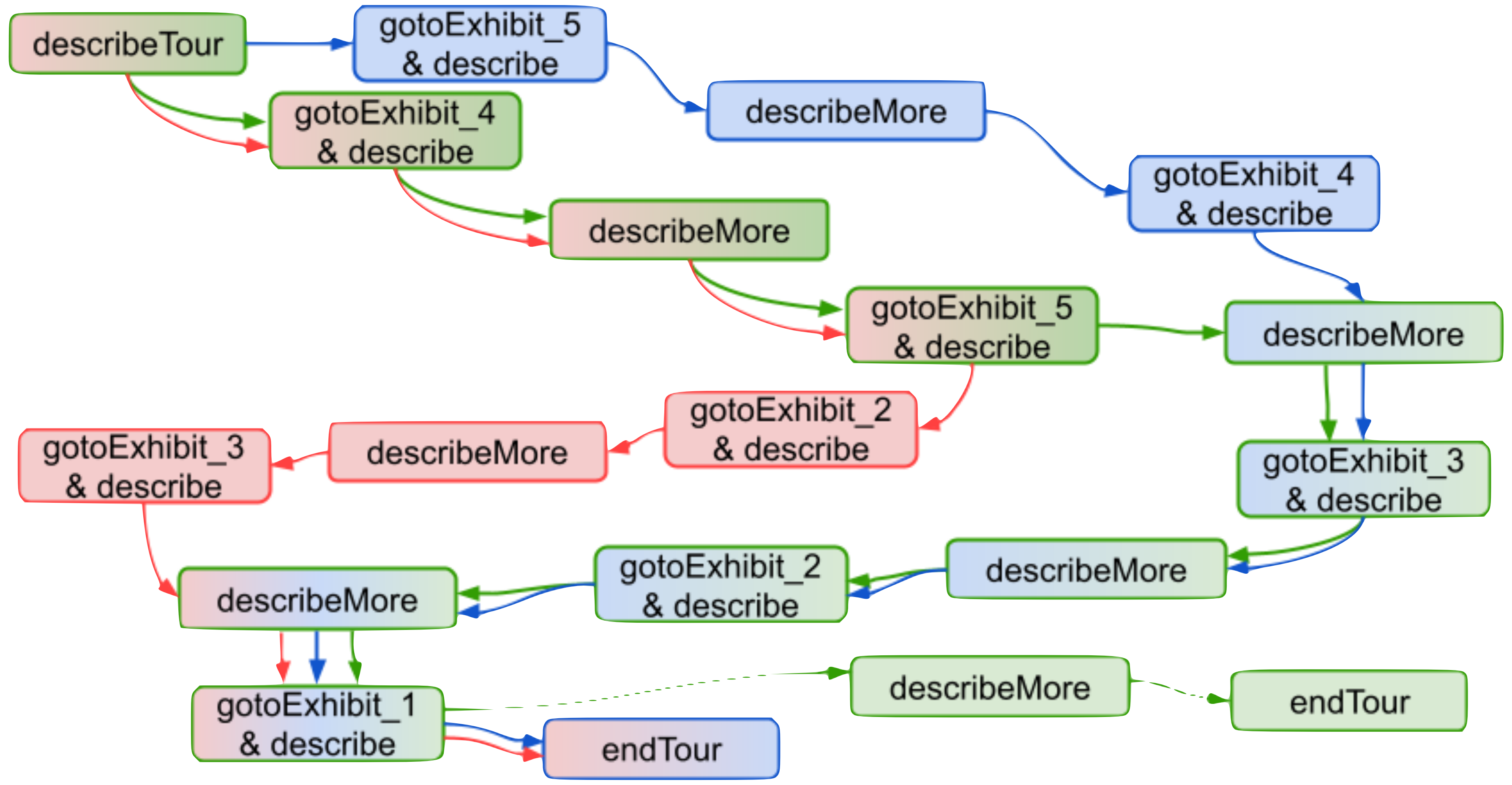


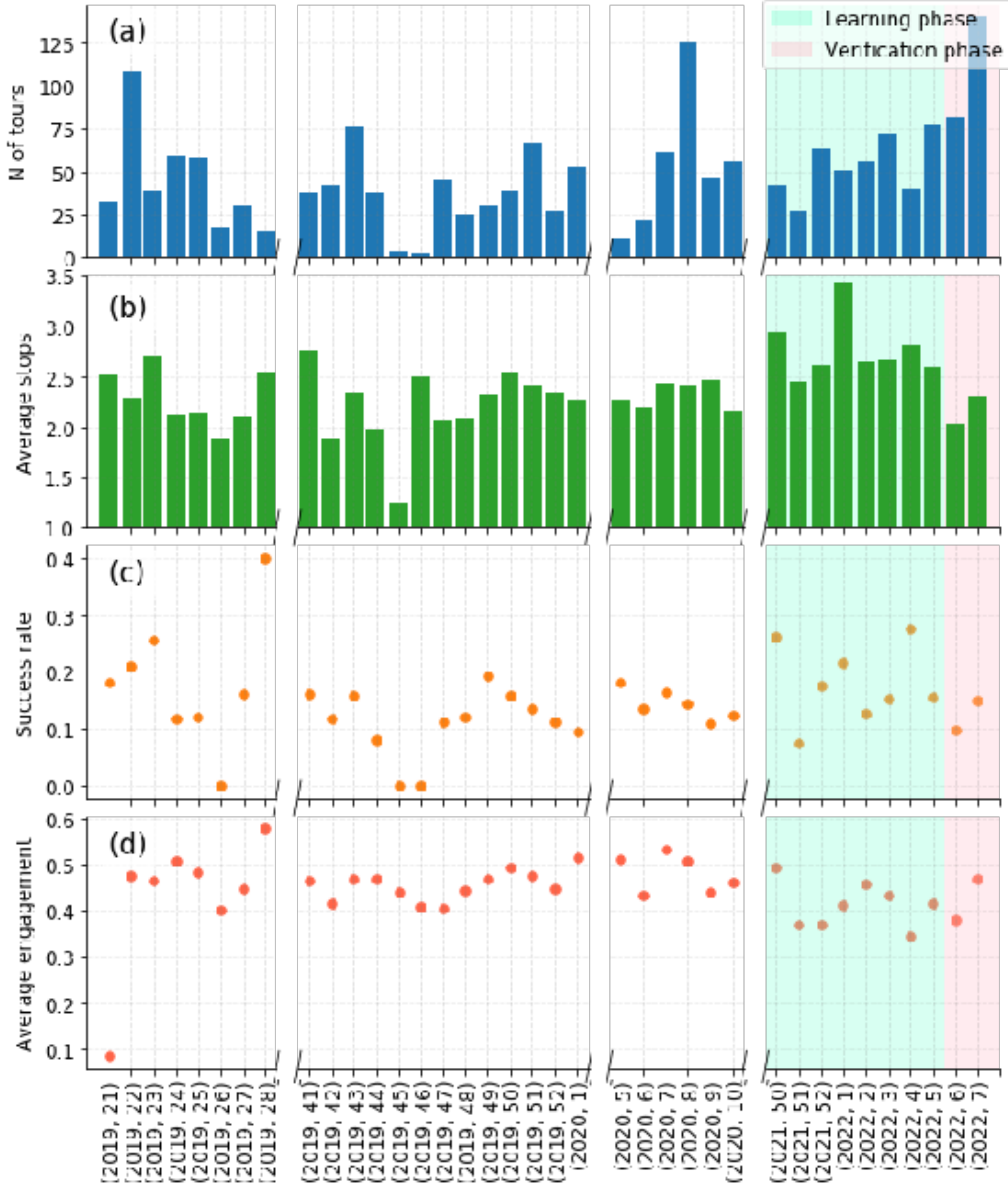


Different actions chosen by the learned policy for the tour art at different levels of engagement. Engagement values are red for LOW, blue for MEDIUM and green for HIGH

Getting better on the job!







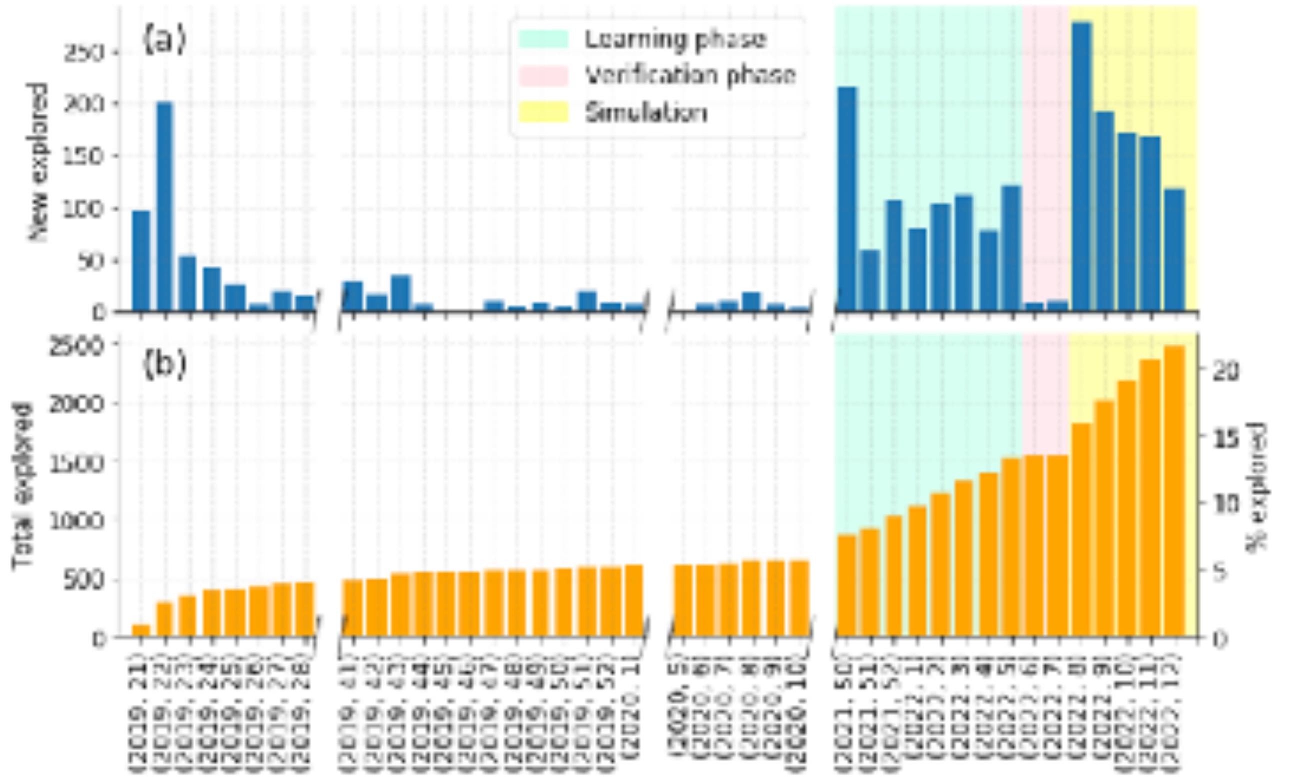
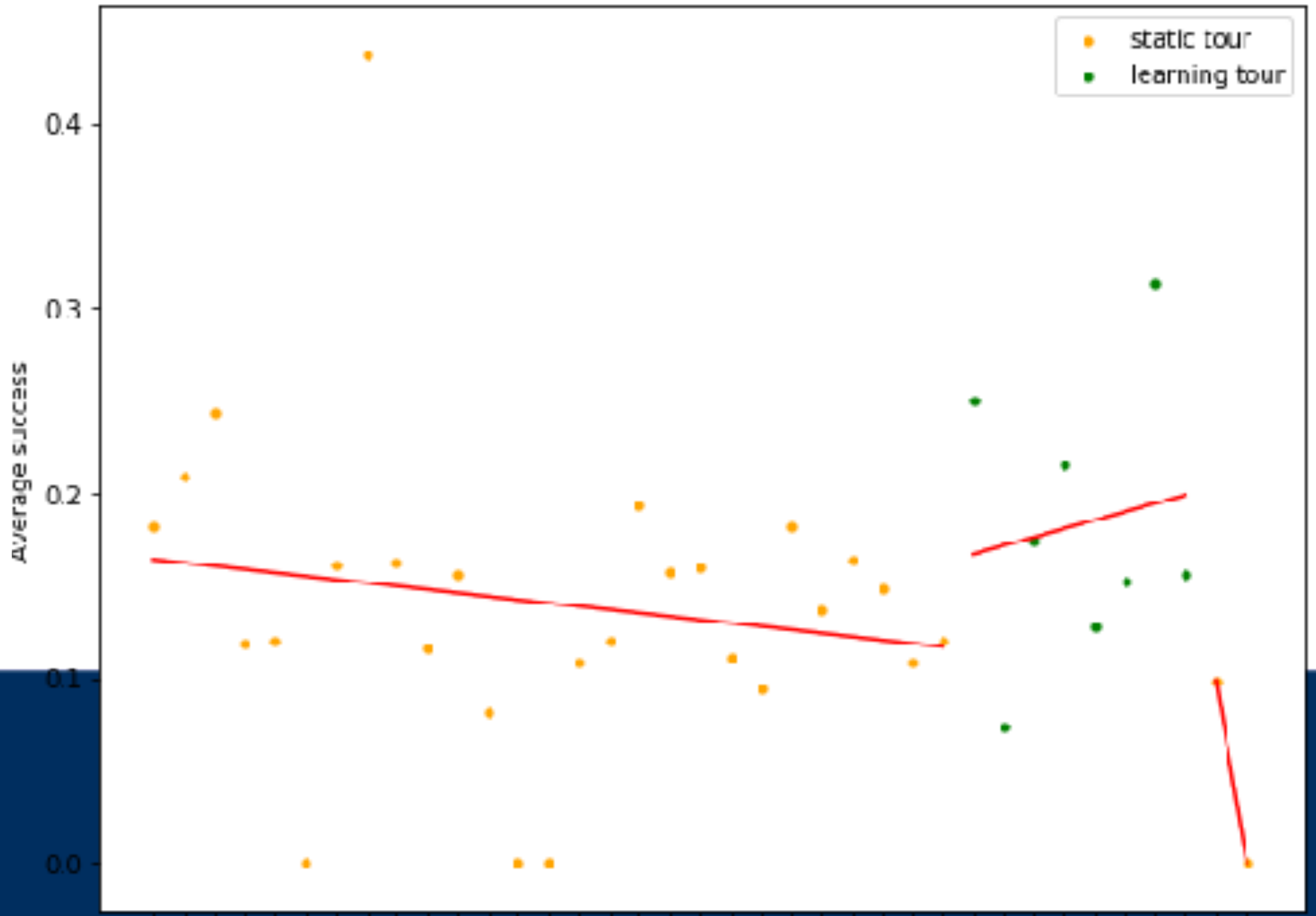


Fig. 9: Exploration of the state-action space of the policy per week. (a) Number of newly explored state-action pairs, (b) cumulative exploration.



Robot Highways

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Social HRI in Agriculture

Innovate UK

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L-CAS

- supporting fruit pickers
- up to 20% productivity gain through autonomous transport

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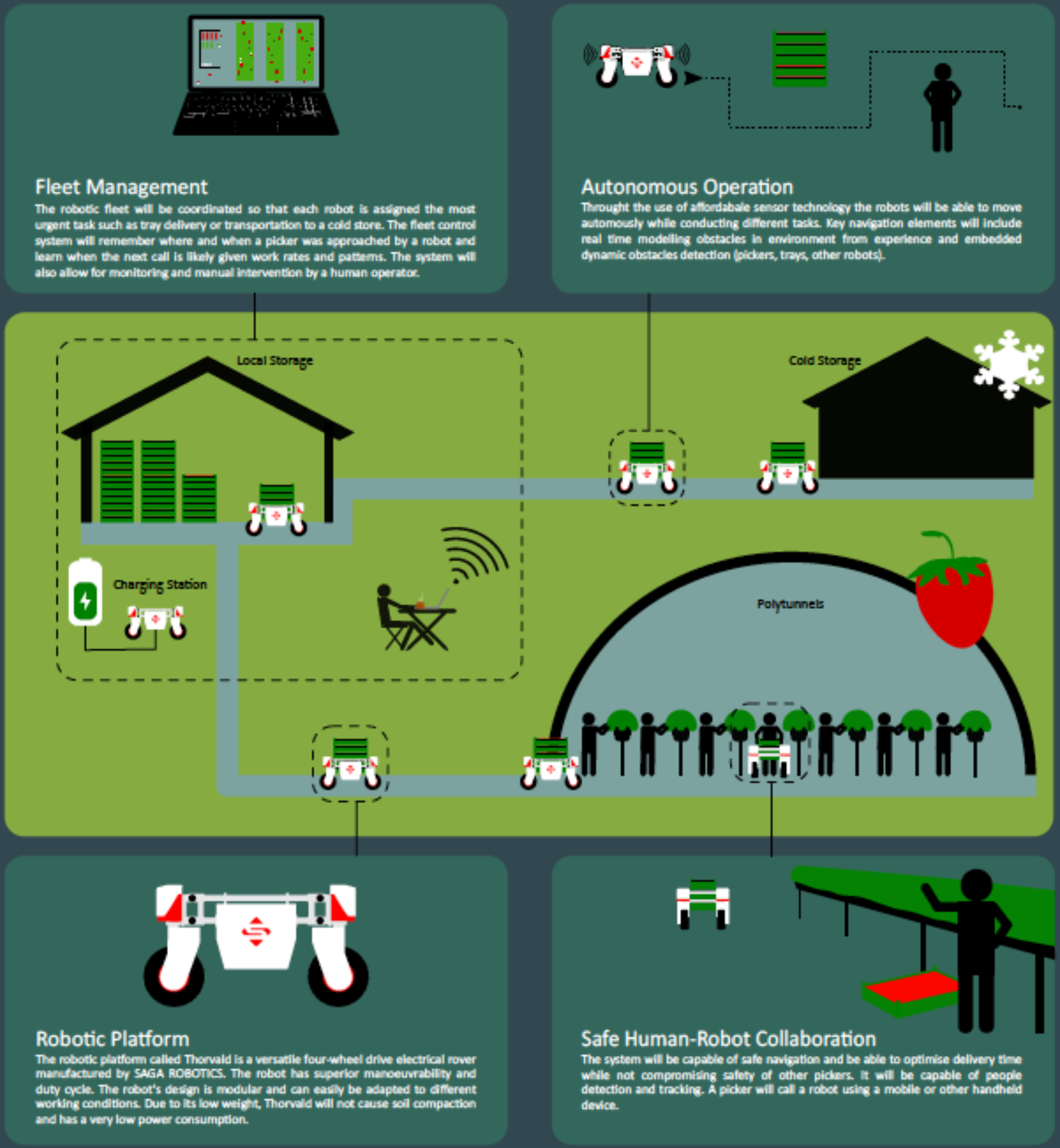
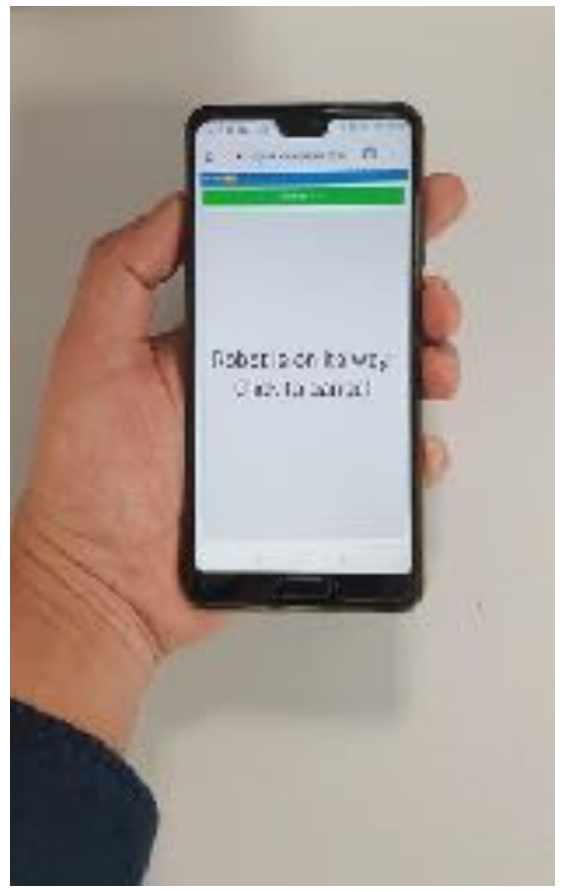
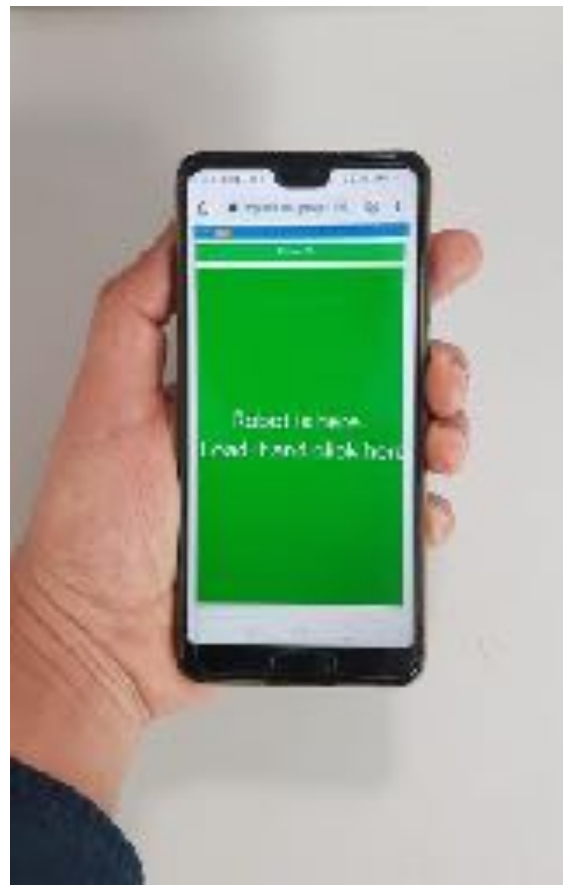
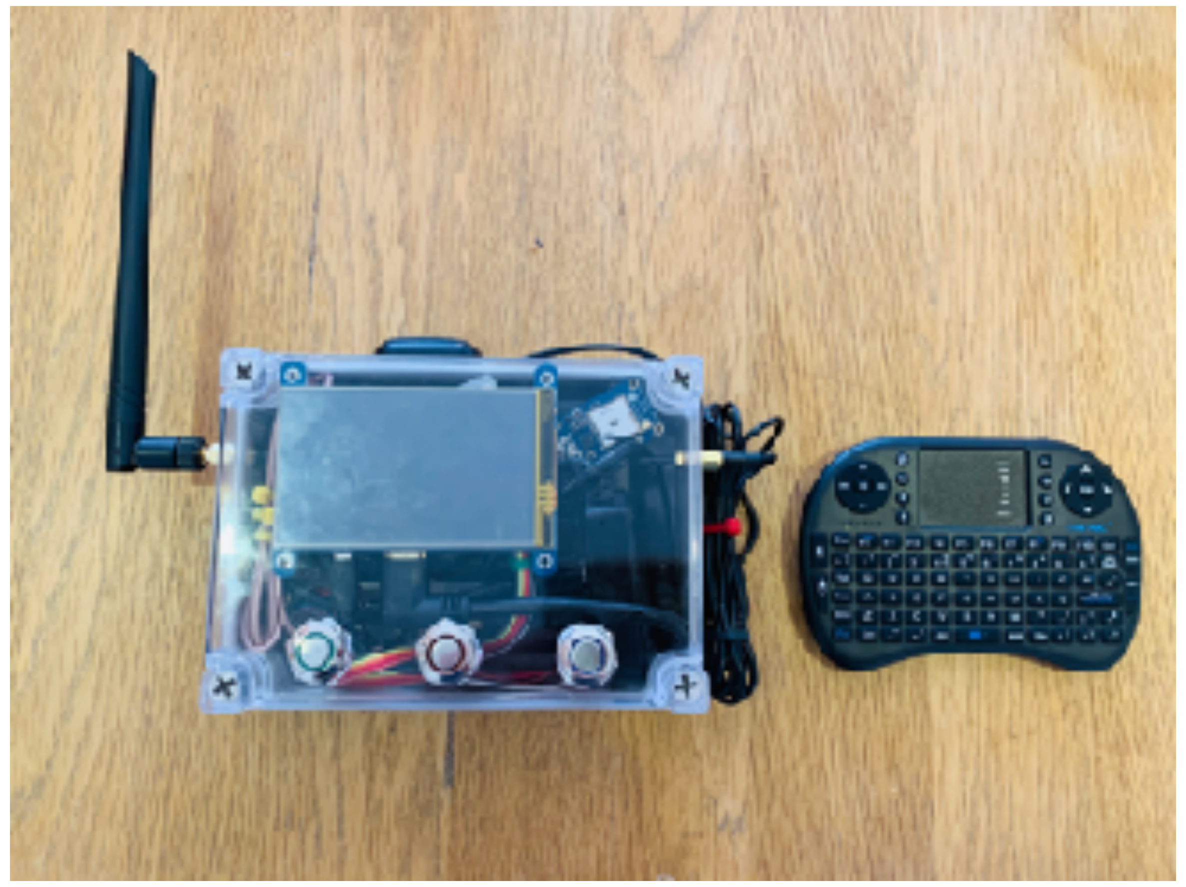


Summon a robot to help

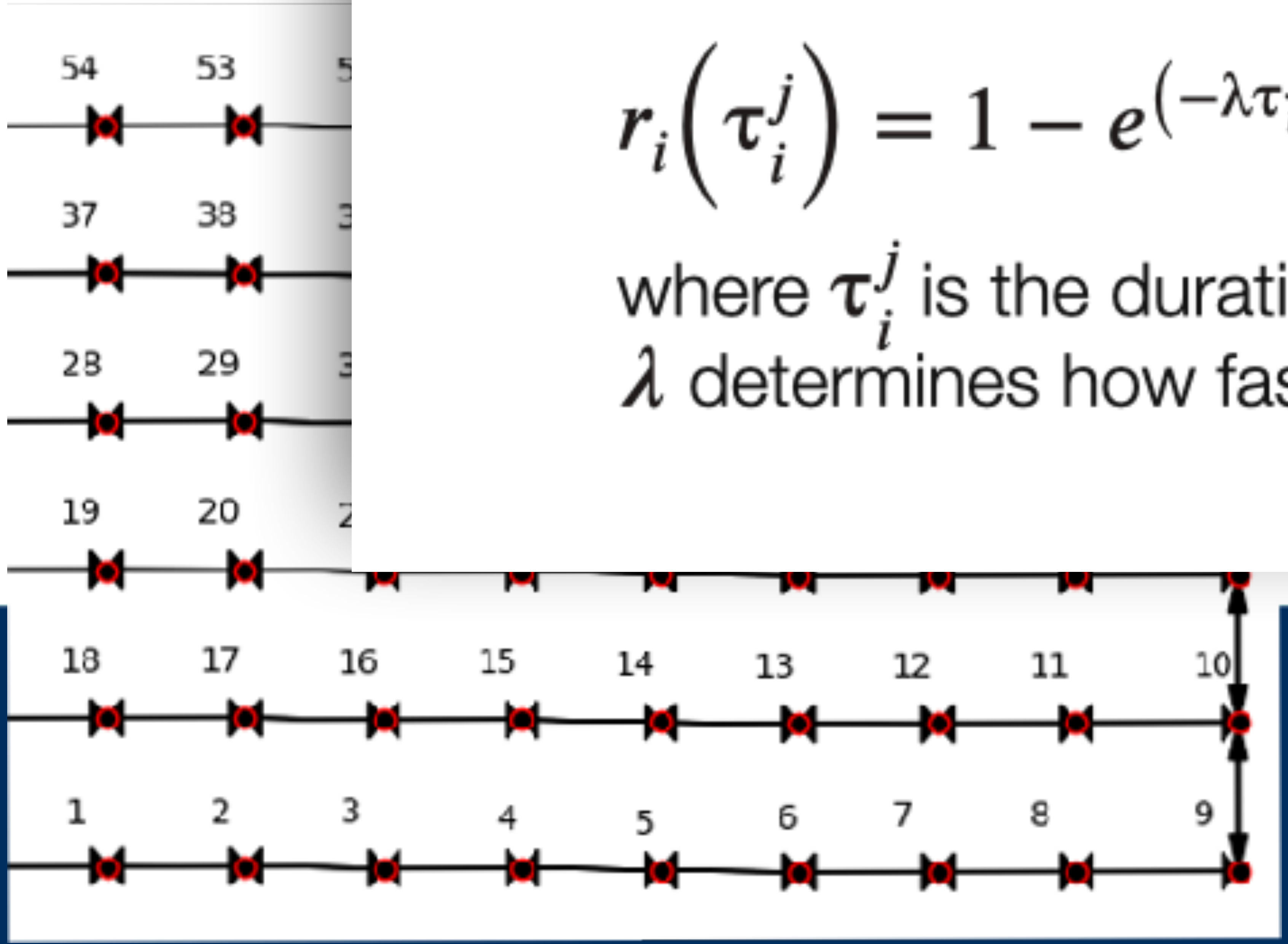




- Embedded “Smart Trolley” system
  - GPS
  - 4G/5G communication

Using Robotics Tech to improve “noisy” sensors

- GPS noisy (~3m) measu
(even worse in tunnels v
beams)
- Idea:
  - Use knowledge of “roa



1. Initialisation (t=0): $p^i_{t=0}(\,.\,) \sim \mathcal{N}\left(g_{t=0},\ \sigma\right)$

   where p^i_0 is i^{th} particle and g_0 is the GNSS location at t=0

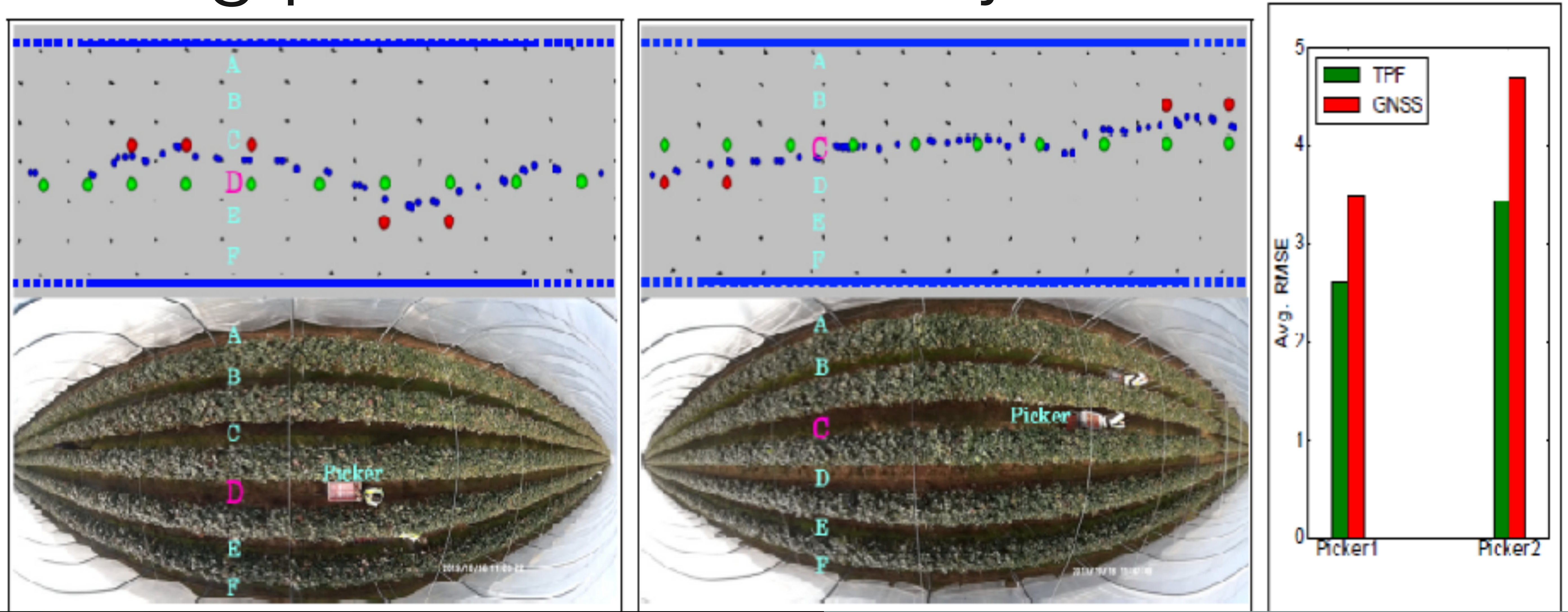
2. Prediction (t>0): Predict future states of particles.
   - Particles can only move to nodes connected by edges (neighbour)
   - Probability of a particle i moving out from a node j:

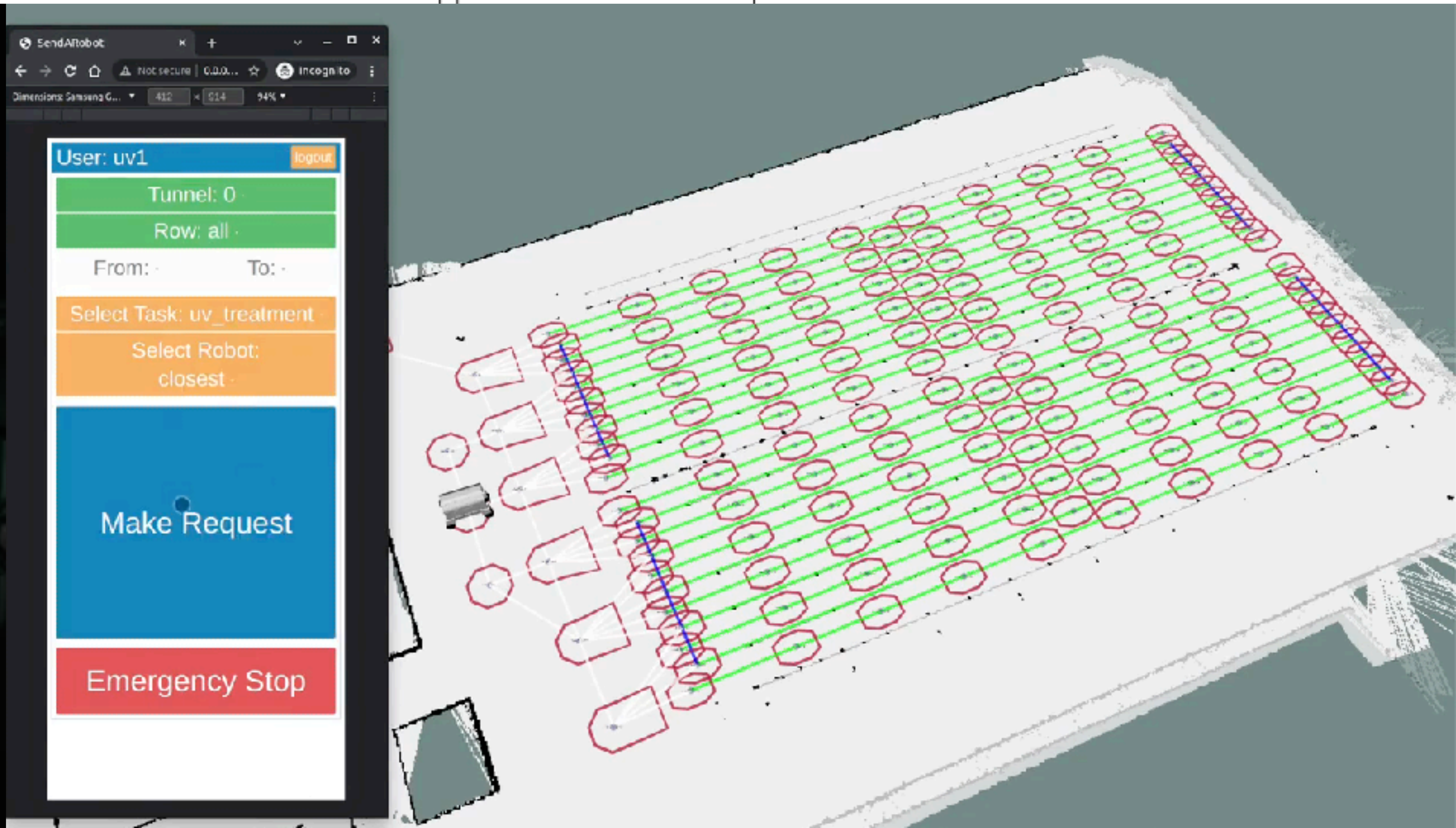
$$r_i\left(\tau^j_i\right) = 1 - e^{\left(-\lambda\tau^j_i\right)}$$

Continuous Time: exponential distribution of leaving a node to go to neighbour node

where τ^j_i is the duration of particle i at node j and λ determines how fast the picker is moving

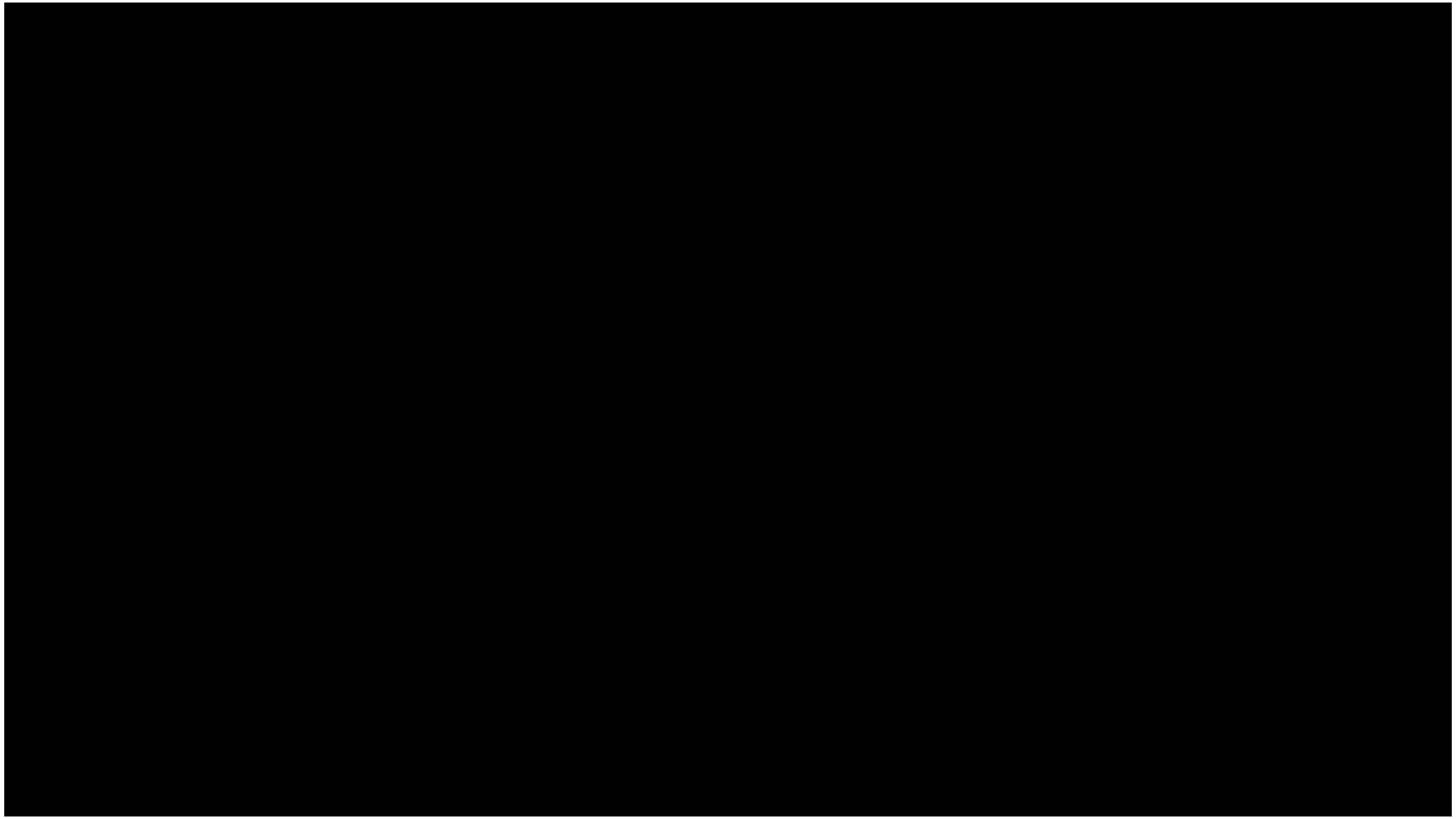
Robots supporting pickers and other jobs in strawberry fields





MesaPro

- Interaction modalities vary greatly by domain
- Regulations and safety play a key role in the workplace (and other domains)

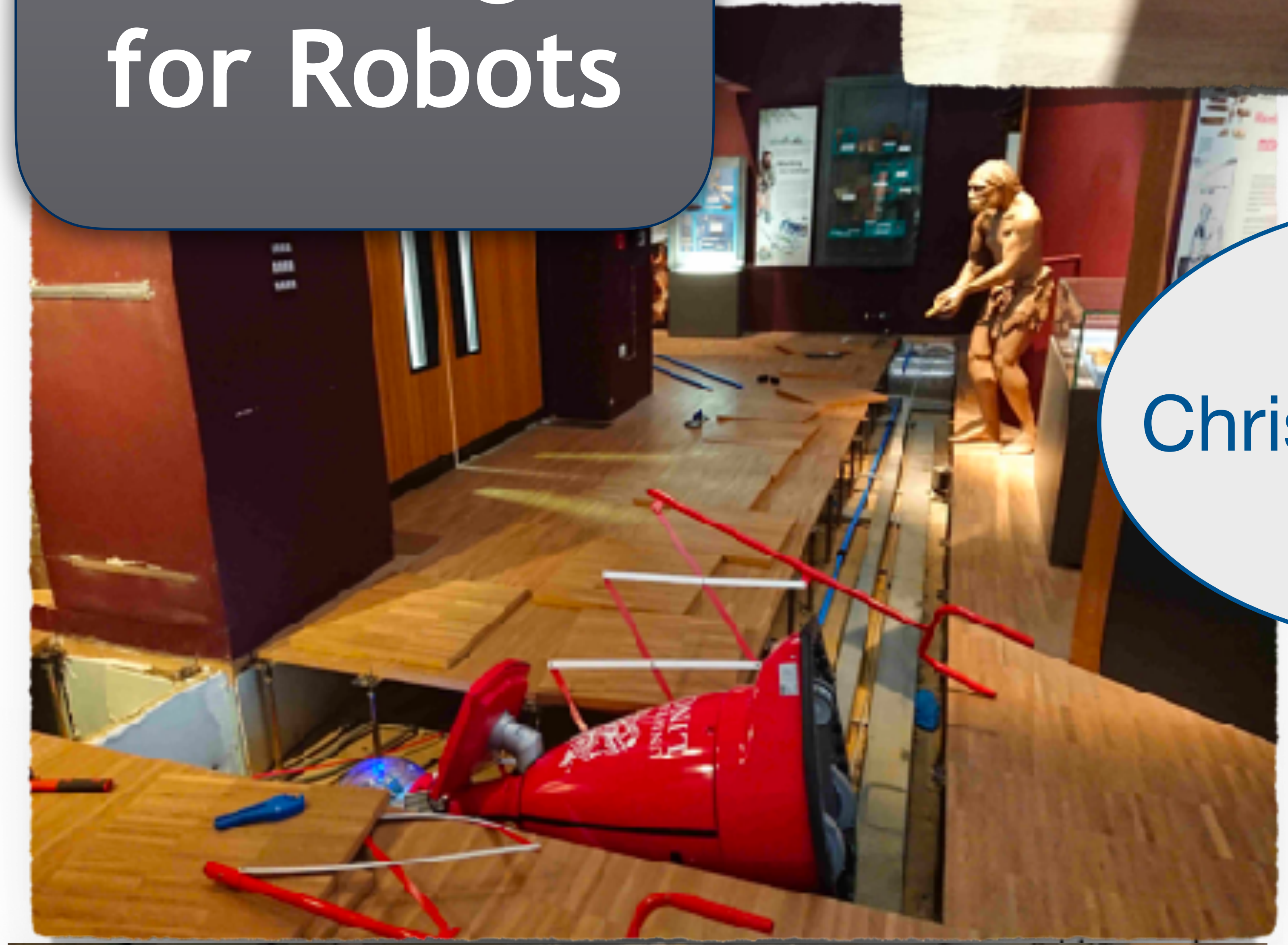


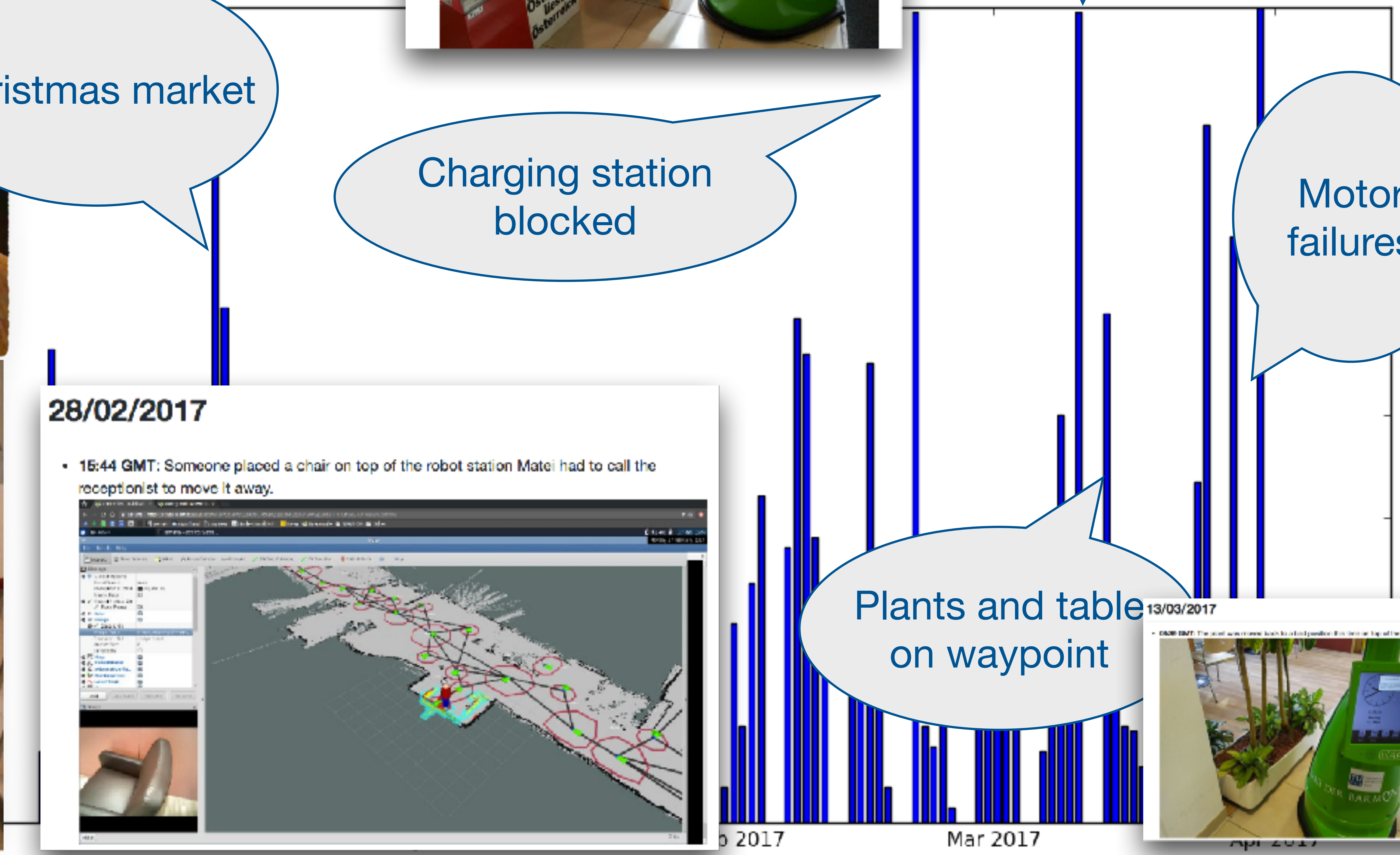
Embrace the Change: Prospects and Challenges of Long-term Autonomy and Interaction

Robots do fail: (interactive) Recovery behaviours are needed. Robust software is prerequisite.

Learning **routines** can help building more effective and efficient systems, spectral models are very powerful to improve long-term navigation.

Remaining Challenges for Robots





That's all Folks!

https://lcas.lincoln.ac.uk/

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