IEEE/RSJ International Conference on Intelligent Robots and Systems

GETTING THE BEST OUT OF N REPRESENTATIONS

PERSPECTIVES FROM TWO INTEGRATING PROJECTS ON AUTONOMOUS SYSTEMS

Marc Hanheide
Lincoln Centre for Autonomous System

UNIVERSITY OF LINCOLN
marc@hanheide.net
@MarcHanheide
L-CAS

“ROBOTICS IS INTEGRATION SCIENCE !”

Renaud Champion,
co-founder and partner of
ROBOLUTION Capital,
Berlin, 2013

Software AND Representations

INTEGRATED SYSTEMS

COGX

STRANDS

Spatio-Temporal Representation and Activities for Cognitive Control in Long-Term Scenarios

"ROBOTICS IS INTEGRATION SCIENCE !"

integrating projects

Autonomy

Interaction

Uncertainty

Long-term experience

SYNOPSIS

Intelligent Robotics is integrated AI: Examples of different representations

Robots do fail: Dealing with uncertainty and errors in goal-driven autonomy

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

SYNOPSIS

Intelligent Robotics is integrated AI: Examples of different representations

Probabilistic Sequential Models of Qualitative States

with goal-

Uncertain Belief States

Metric and Topologic Maps

Em Periodic Probability Density Functions

Prosp of

Long-term Autonomy and Interaction

Deterministic and Probabilistic Domain knowledge

SYNOPSIS

Intelligent Robotics is integrated AI:
Examples of different representations

Robots do fail: Dealing with uncertainty and errors in goal-driven autonomy

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

Uncertain Belief States

Probabilistic Sequential Models of Qualitative States

Periodic Probability Density Functions

Metric and Topologic Maps

Deterministic and Probabilistic Domain knowledge

ROBOTS DO FAIL: LONG-TERM AUTONOMY

```
(exists
  (?o - object)
  (and
    (= (label
    (K (positi
  )
)
```

Robots do fail: Dealing with uncertainty and errors in goal-
utonomy

Disclaimer: This is a brief recap of what Andrzej Prognosis talked about earlier on.

utonomy

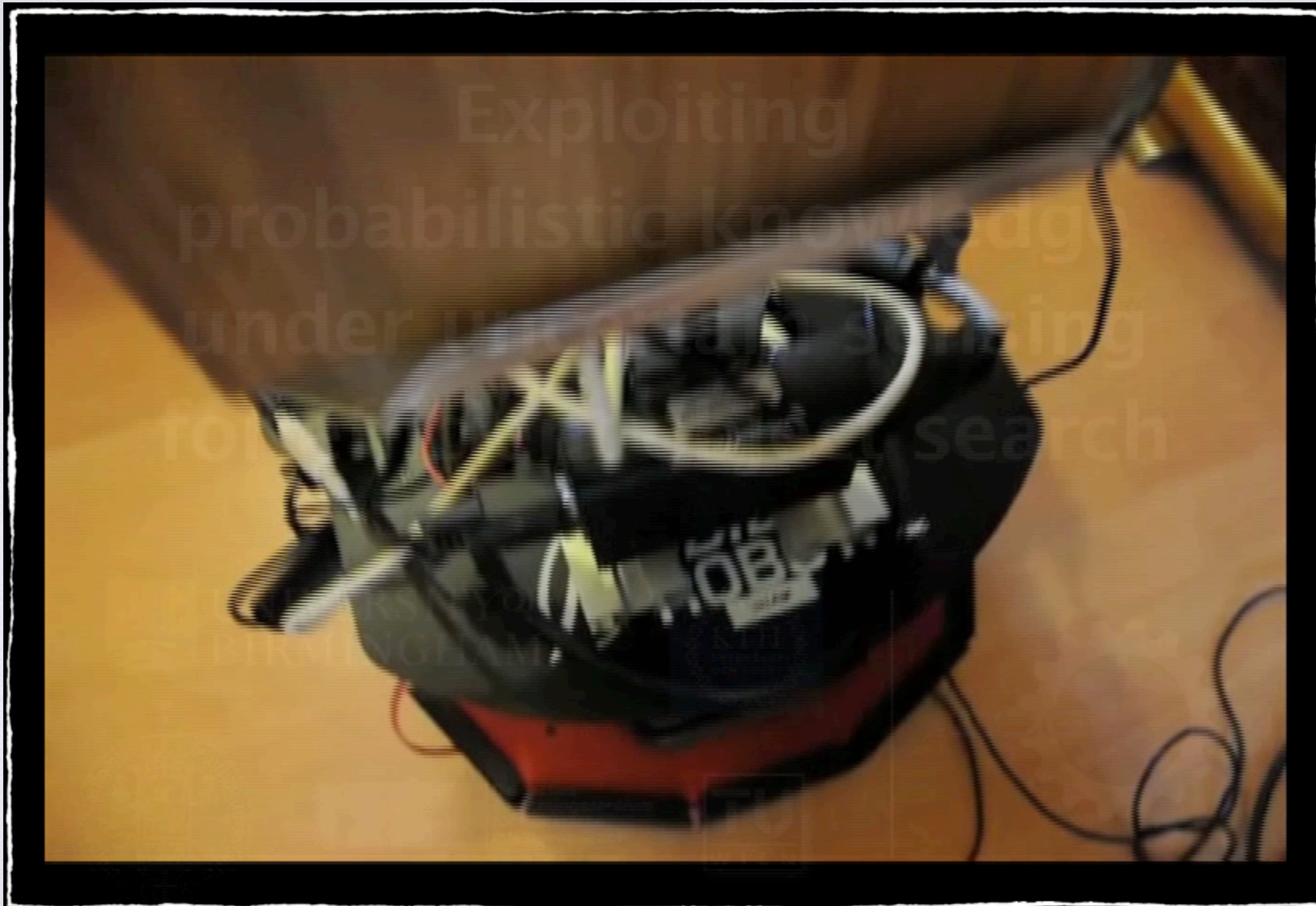
hat to achieve,
chieve it

- but it's all very uncertain and prone to failure
  - requires re-planning when failing

UNIVERSITY OF LINCOLN

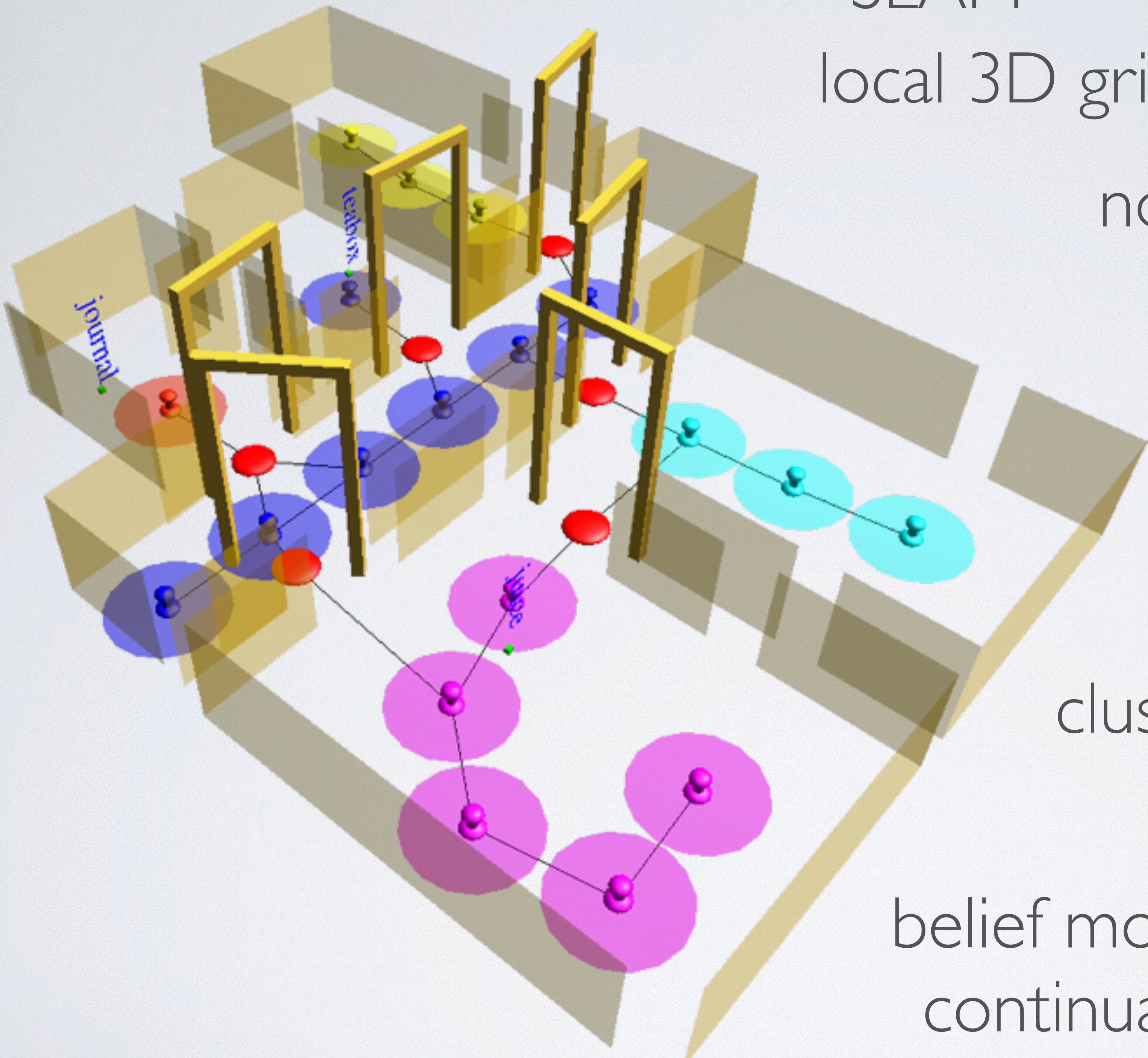
L-CAS

DORA IN MY (OLD) HOME



global 2D line-based SLAM

local 3D grid map



node-based space discretisation

ontology of object and room types

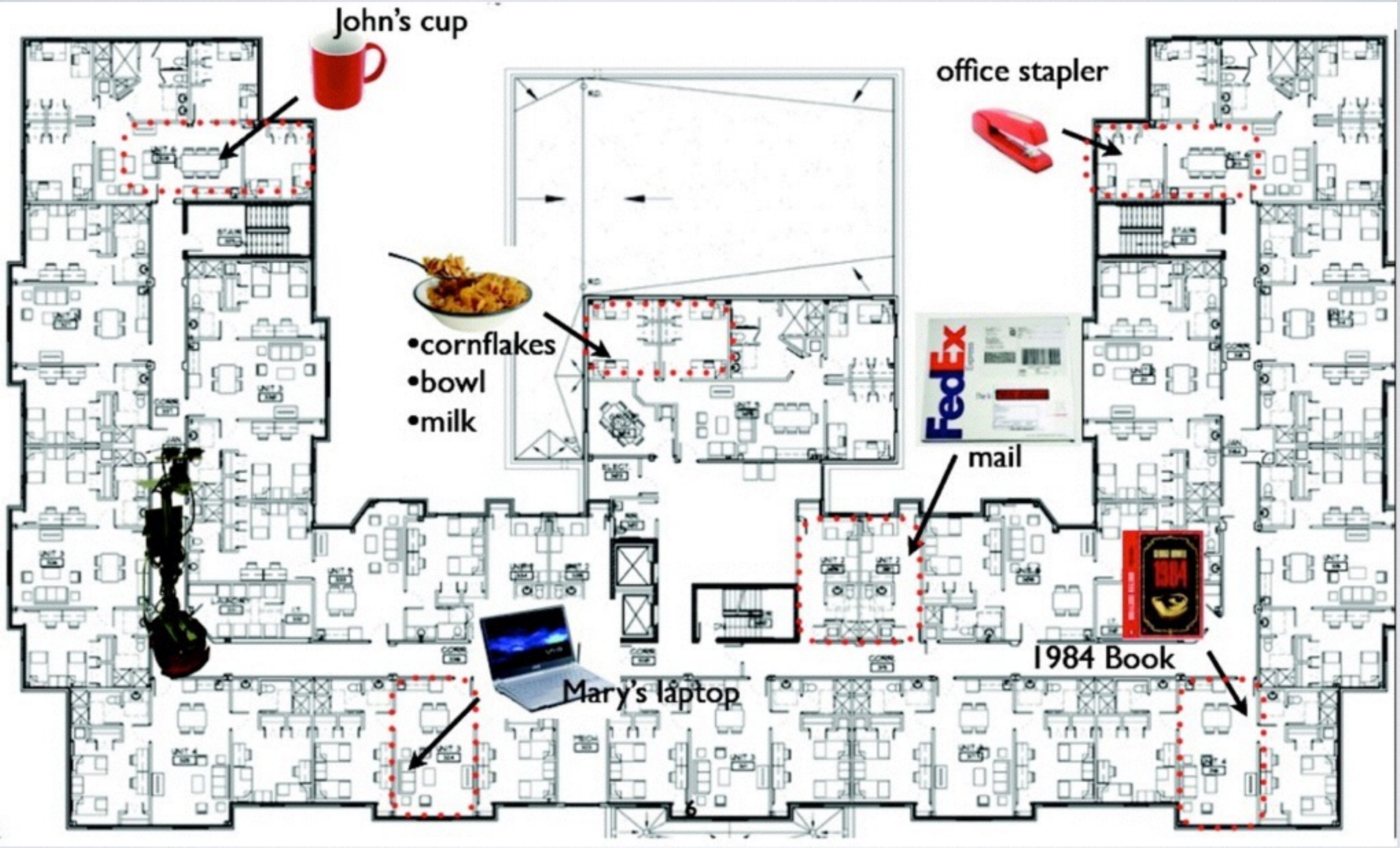
non-monotonic clustering of nodes into rooms

belief modelling and continual planning

Metric and Topologic Maps

pre-trained visual recognisers

DORA SEARCHING


John's cup
office stapler
•cornflakes
•bowl
•milk
mail
1984 Book
Mary's laptop

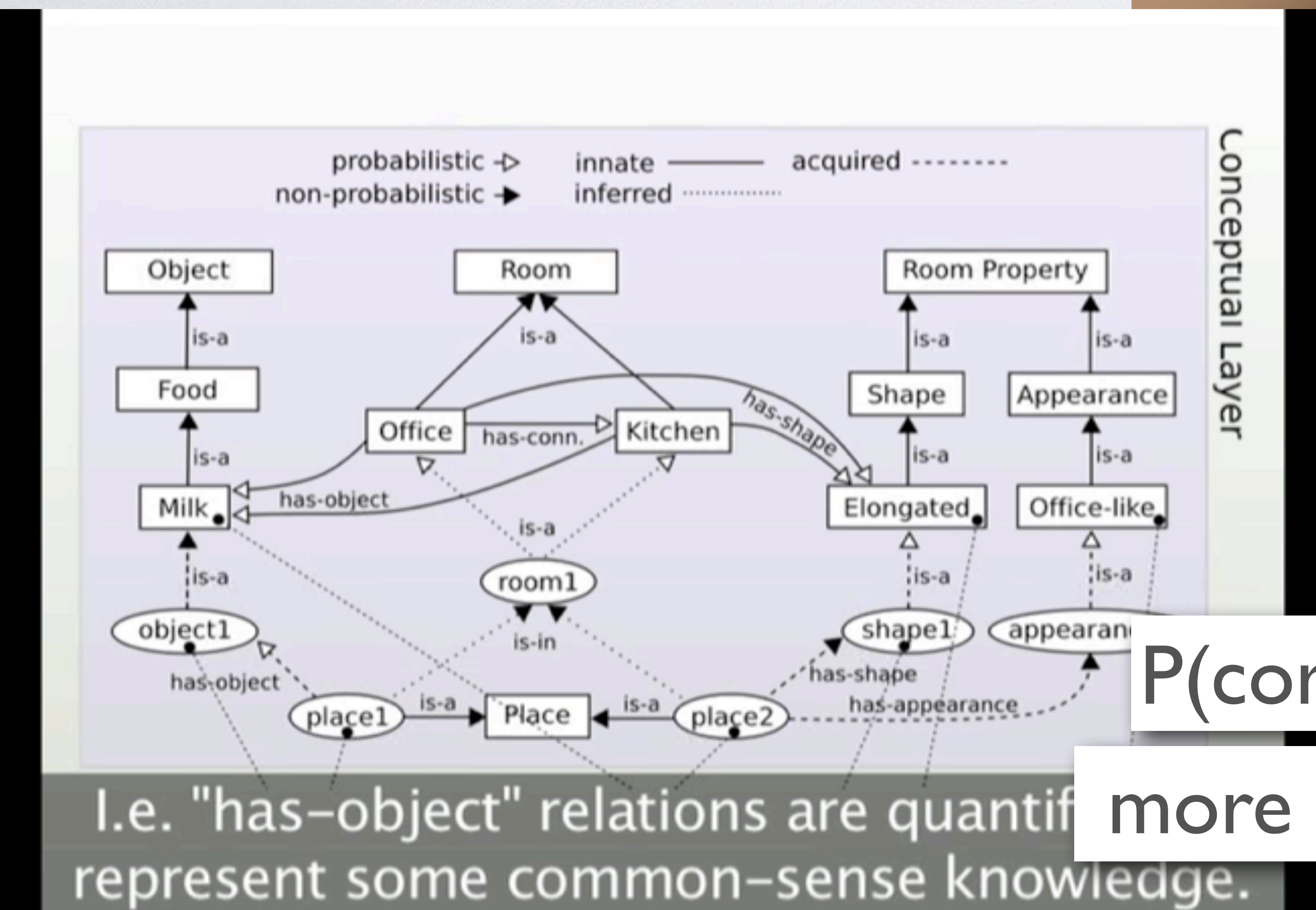
cereals are found in kitchens

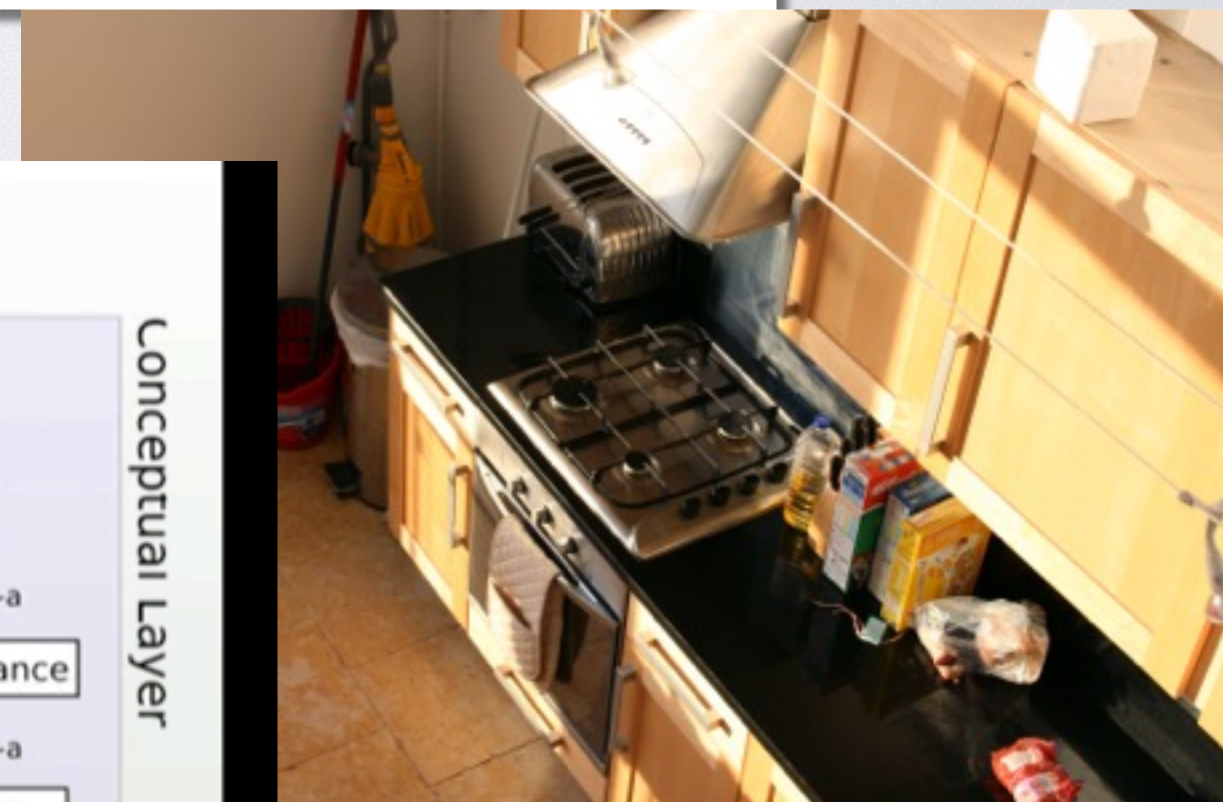
dining rooms

living rooms?

OPEN MIND

Deterministic and Probabilistic Domain knowledge



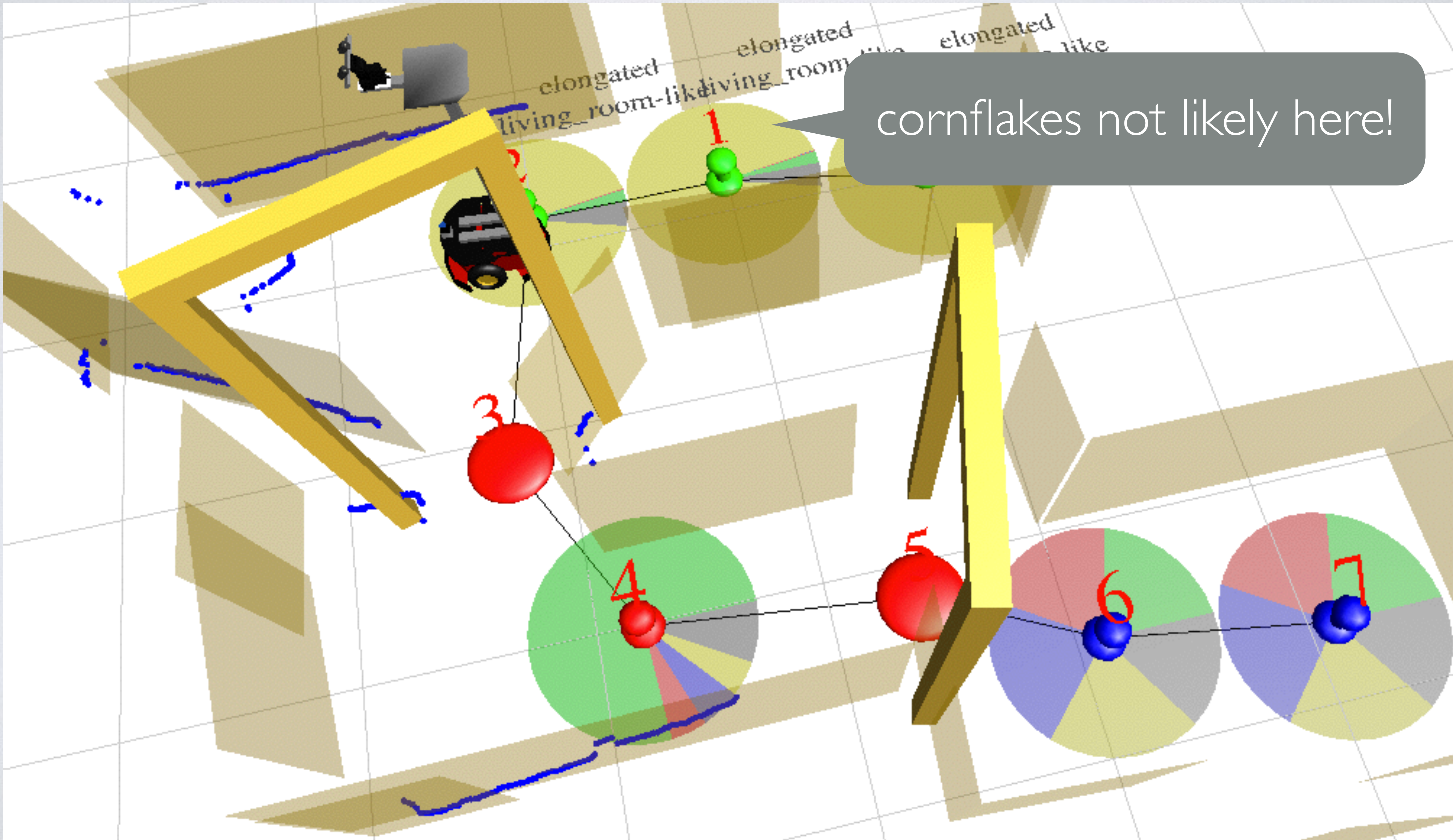


P(cornflakes|kitchen)=0.4

more an “educated guess”!

(see Pronobis’ talk)

WHERE TO SEARCH?



cornflakes not likely here!

How to **reason** about knowledge and perception?

How to make **informed choices** of actions?

How to find object most **efficiently**?

A **DOMAIN-INDEPENDENT** PLANNING APPROACH

From a given (perceived) current **belief state**

```
(is-in 'robot' place-3)
(prob (obj-located
    cornflakes kitchen)
  0.6)
...
```

Uncertain Belief States

find a **sequence of actions**

```
(goto 'robot' place-4)
...
```

to reach an intended **goal** state

```
(and (kval 'robot' (related-to object-3)) (label object-3
```

DEALING WITH UNCERTAINTY

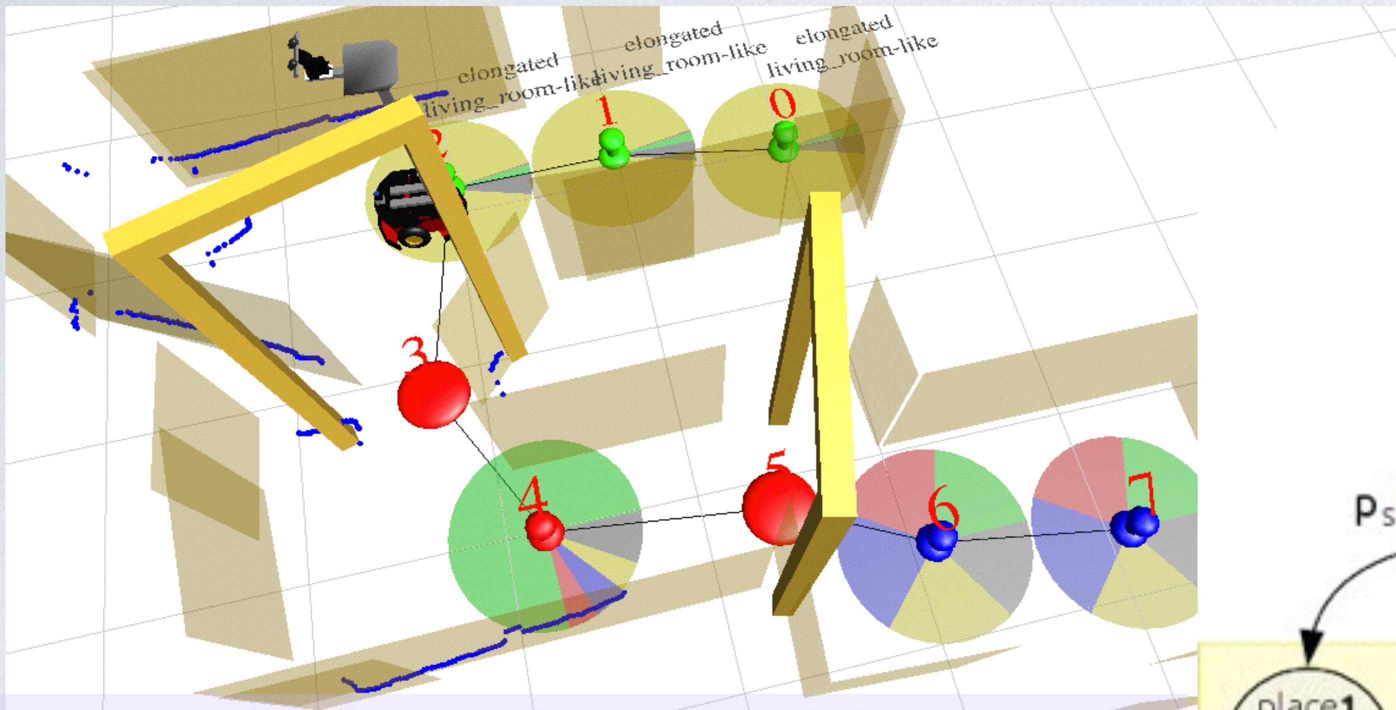
- sensing algorithms can fail
  - not seeing the object
  - mis-classifying a room
- common-sense knowledge can be wrong, even though useful in most cases

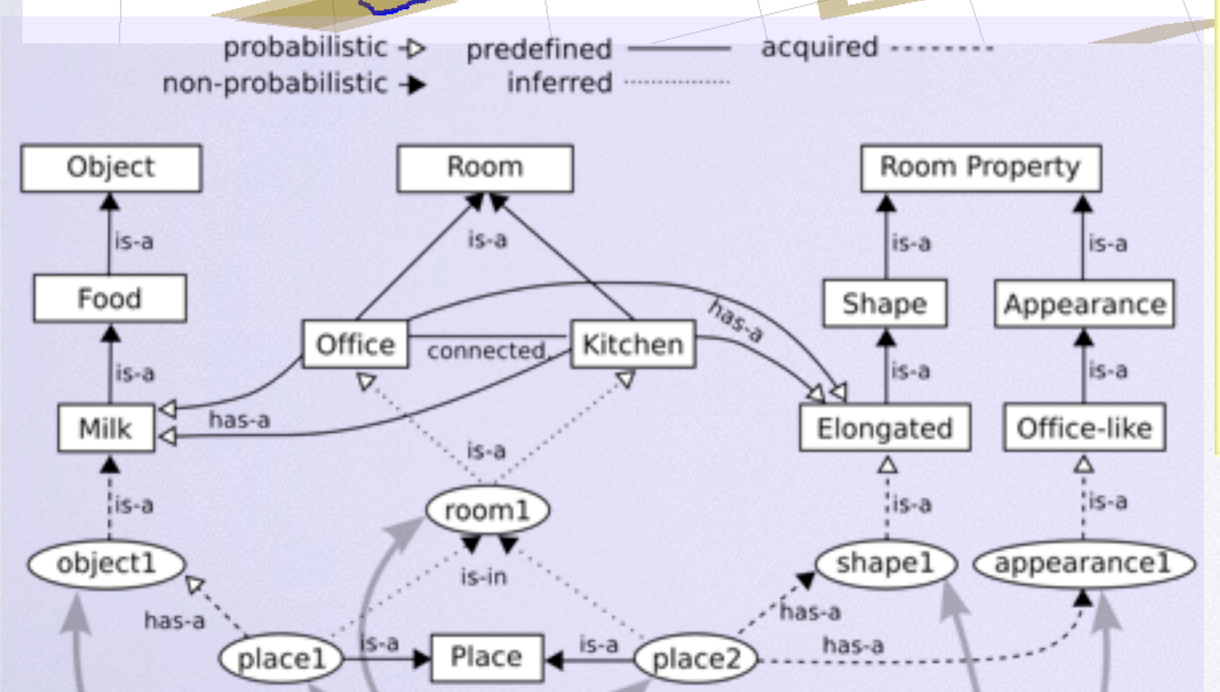
it's all so uncertain... how to deal with it?

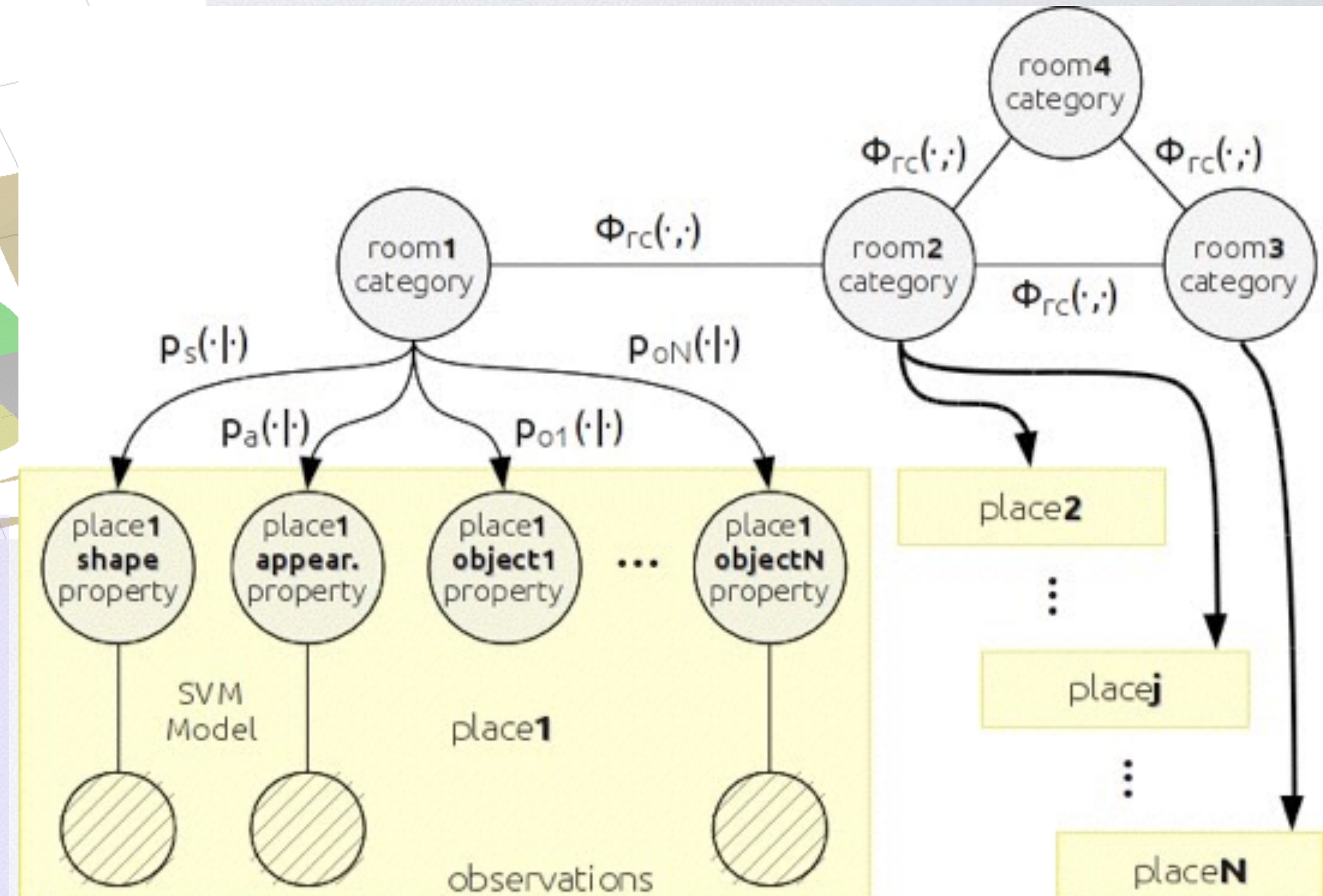
Hanheide et al.: IJCAI, 2011

KNOWLEDGE REPRESENTATION

Uncertain Belief States

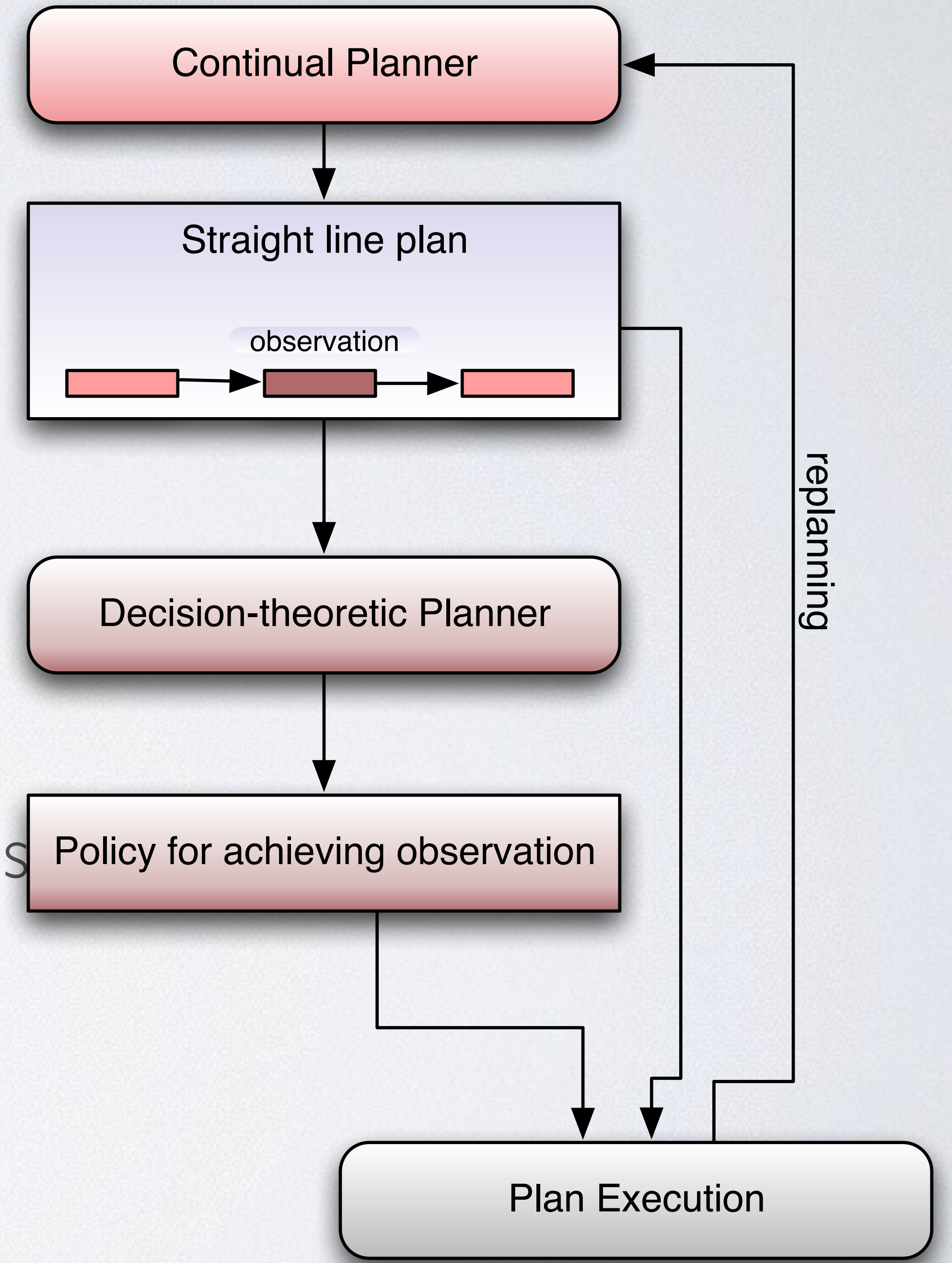






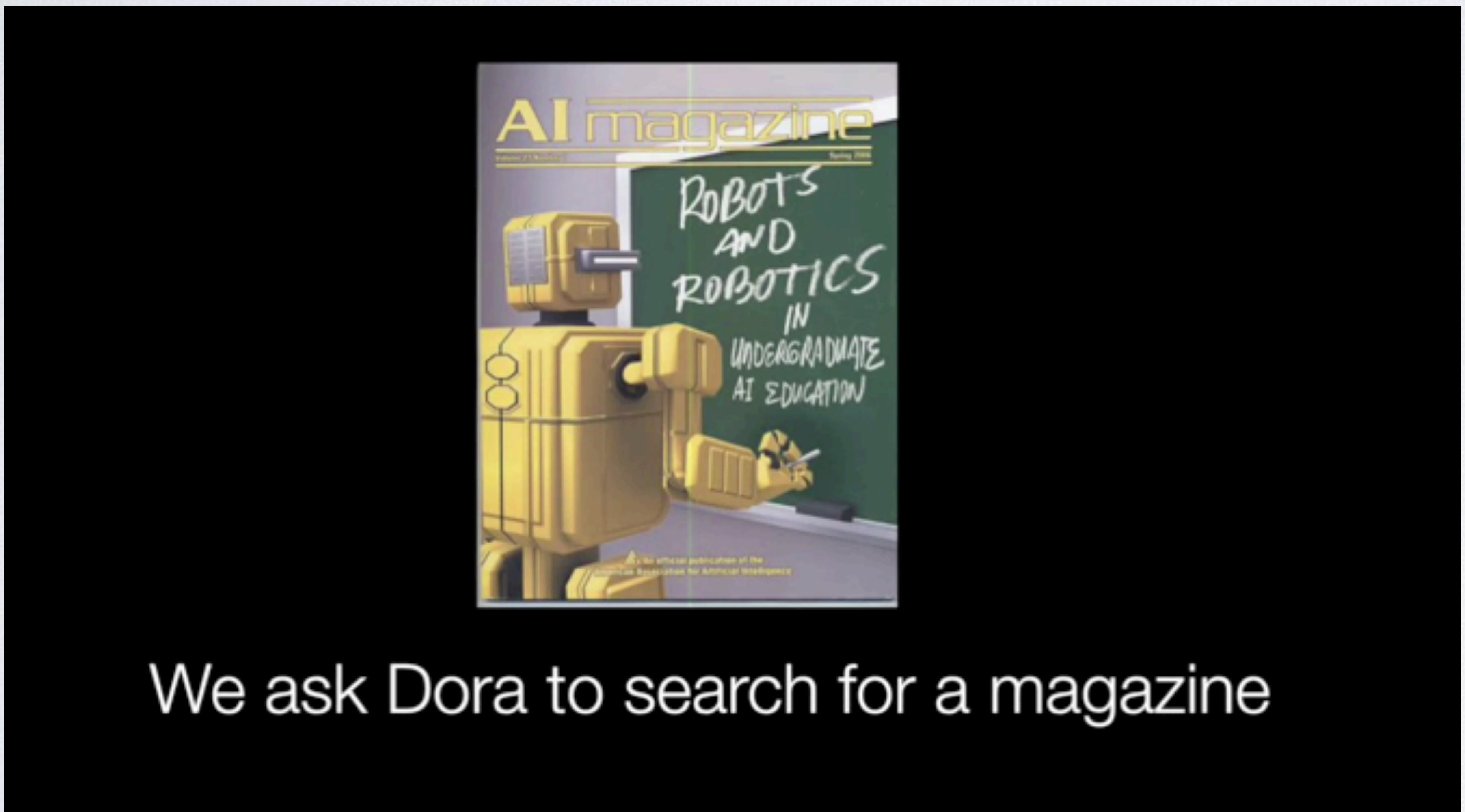
PLANNING UNDER UNCERTAINTY

- world state cannot be observed directly (it's computer vision after all)
- probabilistic state space can be intractably huge
- domain-independent solution: *switching planner*
    - make *assumptions* in a *sequential* session to generate most rewarding sequence of actions
    - *contingent* session for observation planning
    - (dis)confirmation of assumptions by contingent session



Hanheide et al., AIJ 2016
Göbelbecker et al., AAAI 2011

INCOMPLETE KNOWLEDGE: DORA SEARCHING A MAGAZINE



http://lncn.eu/aijvideo

```
(exists
  (?o - object)
  (and
    (= (label ?o) magazine)
    (K (position ?o))
  )
)
```

- explore the environment to extend knowledge
- model uncertainty
- replan in case of errors

Hanheide, M. et al., 2016. Robot task planning and explanation in open and uncertain worlds. Artificial Intelligence.

DORA SEARCHING A MAGAZINE MAKING ASSUMPTIONS EXPLICIT

Deterministic and Probabilistic Domain knowledge

Key Idea 7:

An assumption succeeds with a probability determined by the instance and default knowledge.

http://lncn.eu/aijvideo

```
(exists
  (?o - object)
  (and
    (= (label ?o) magazine)
    (K (position ?o))
  )
)
```

- Modelling uncertainty probabilistically and plan with it
- explicit expect change

Hanheide, M. et al., 2016. Robot task planning and explanation in open and uncertain worlds. Artificial Intelligence.

UNIVERSITY OF LINCOLN

L-CAS

DORA SEARCHING A MAGAZINE DEALING WITH & EXPLAINING ERRORS

Key Idea 9:

A surprise is the difference between expectation and experience.

http://lncn.eu/aijvideo

```
(exists
  (?o - object)
  (and
    (= (label ?o) magazine)
    (K (position ?o))
  )
)
```

- a principled approach to dealing with surprise
- resolve them interactively

UNIVERSITY OF LINCOLN

Hanheide, M. et al., 2016. Robot task planning and explanation in open and uncertain worlds. Artificial Intelligence.

L-CAS

SYNOPSIS

Dealing with change was very limited so far

Robots do fail: Dealing with uncertainty and errors in goal-driven autonomy

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

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

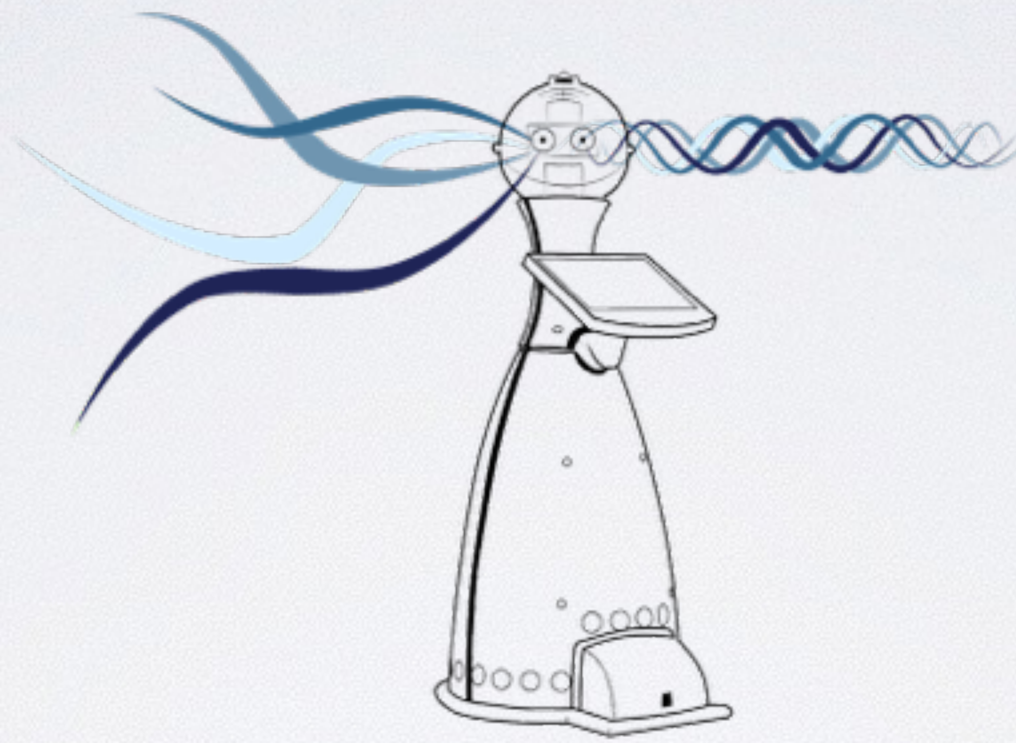
Robust, intelligent, autonomous behaviour

running for weeks

Long run-times in everyday environments

Novel opportunities to learn structure environment

Exploitation of structure for improved performance



UNIVERSITY OF LINCOLN

STRANDS

LINCOLN ROBOTICS

LONG-LIVED *AND* INTELLIGENT

working 24/7

working intelligently

plus video streams annotated with detected

2	MS6	30 days	20%	$1000m^3$

This milestone extends the functionality o

3	MS8	60 days	30%	$2000m^3$

4	MS10	120 days	30%	$2000m^3$

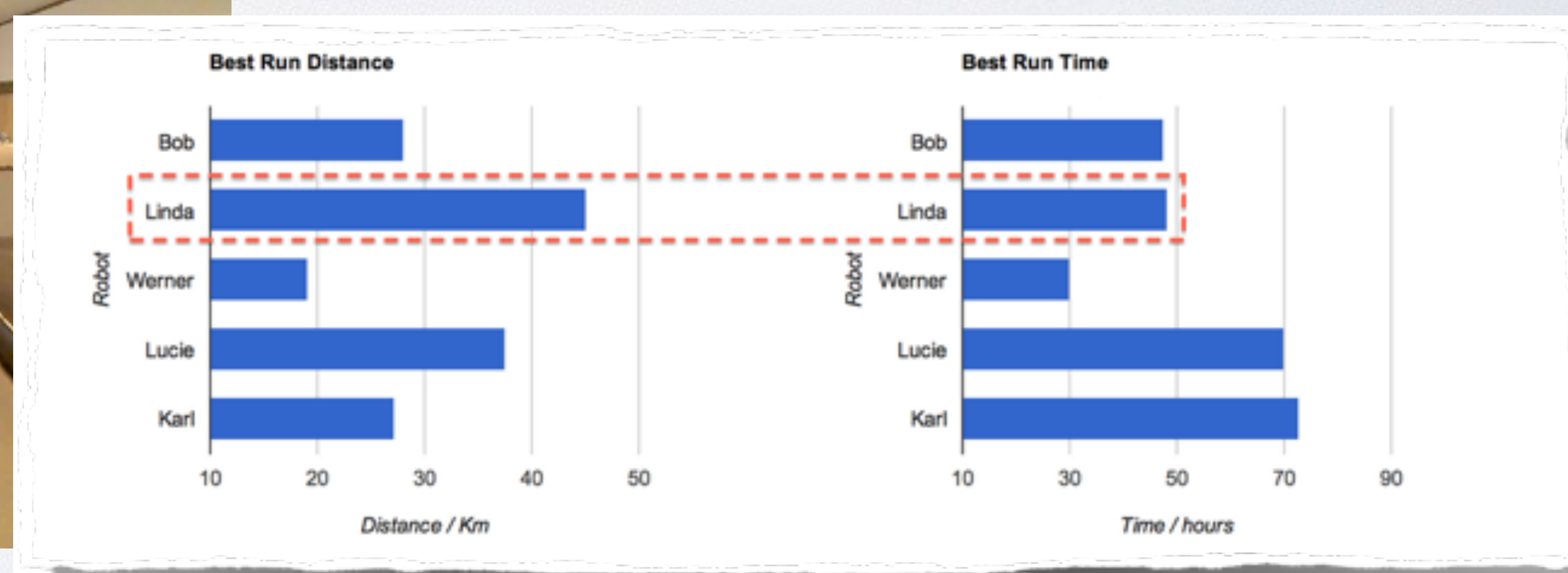
exploiting long-term experience

UNIVERSITY OF LINCOLN

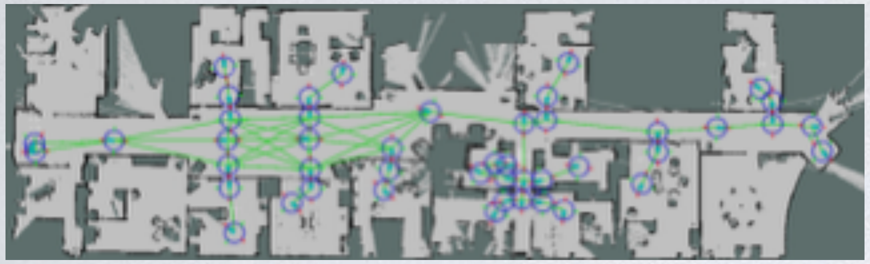
STRANDS

LINCOLN ROBOTICS

eu Robotics Week

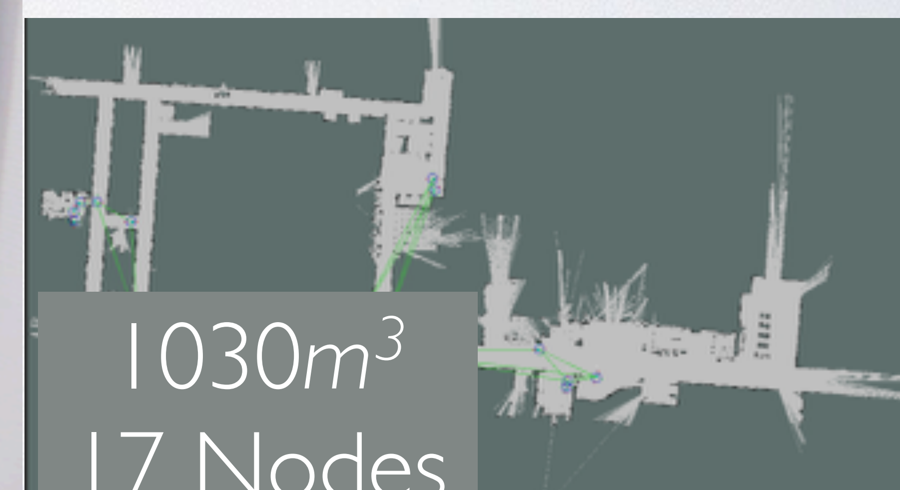


Bob at
G4S Technology, UK



690m^3
46 Nodes
16 days

Henry at
Haus der Barmherzigkeit,
Austria



1030m^3
17 Nodes
14 days

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

Robust, intelligent, autonomous behaviour

running for weeks

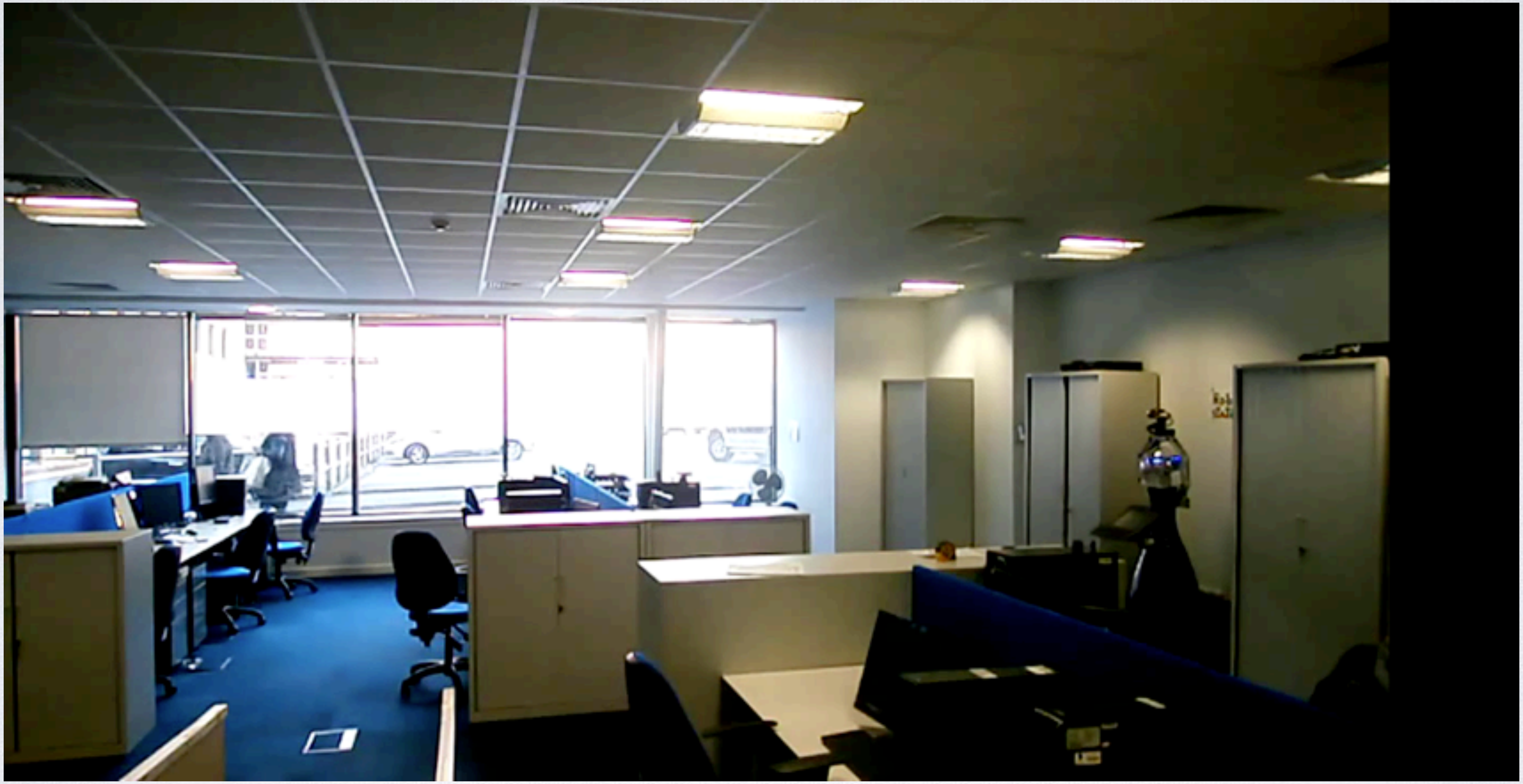
Long run-times in everyday environments

learn how the world changes

Novel opportunities to learn structure environment

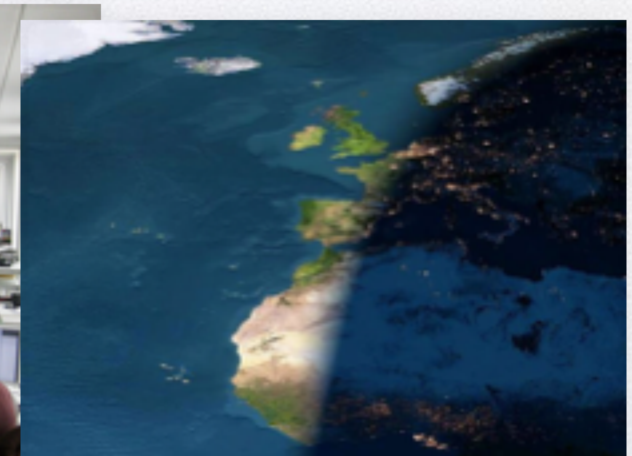
Exploitation of structure for improved performance

A ROBOT PATROLLING (ONE WEEK)



The world is not static!

But it’s full of routines
(nearly cyclostationary processes)



WHY AND HOW TO MODEL ROUTINES?

- Why:
  - better localisation
  - better planning
  - detect deviations
  - predict the future

- 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 the most prominent S

Periodic Probability Density Functions

WHY AND HOW TO MODEL ROUTINES?

- Why:
  - better localisation
  - better planning
  - detect deviations
  - predict the future
- 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 the most prominent S

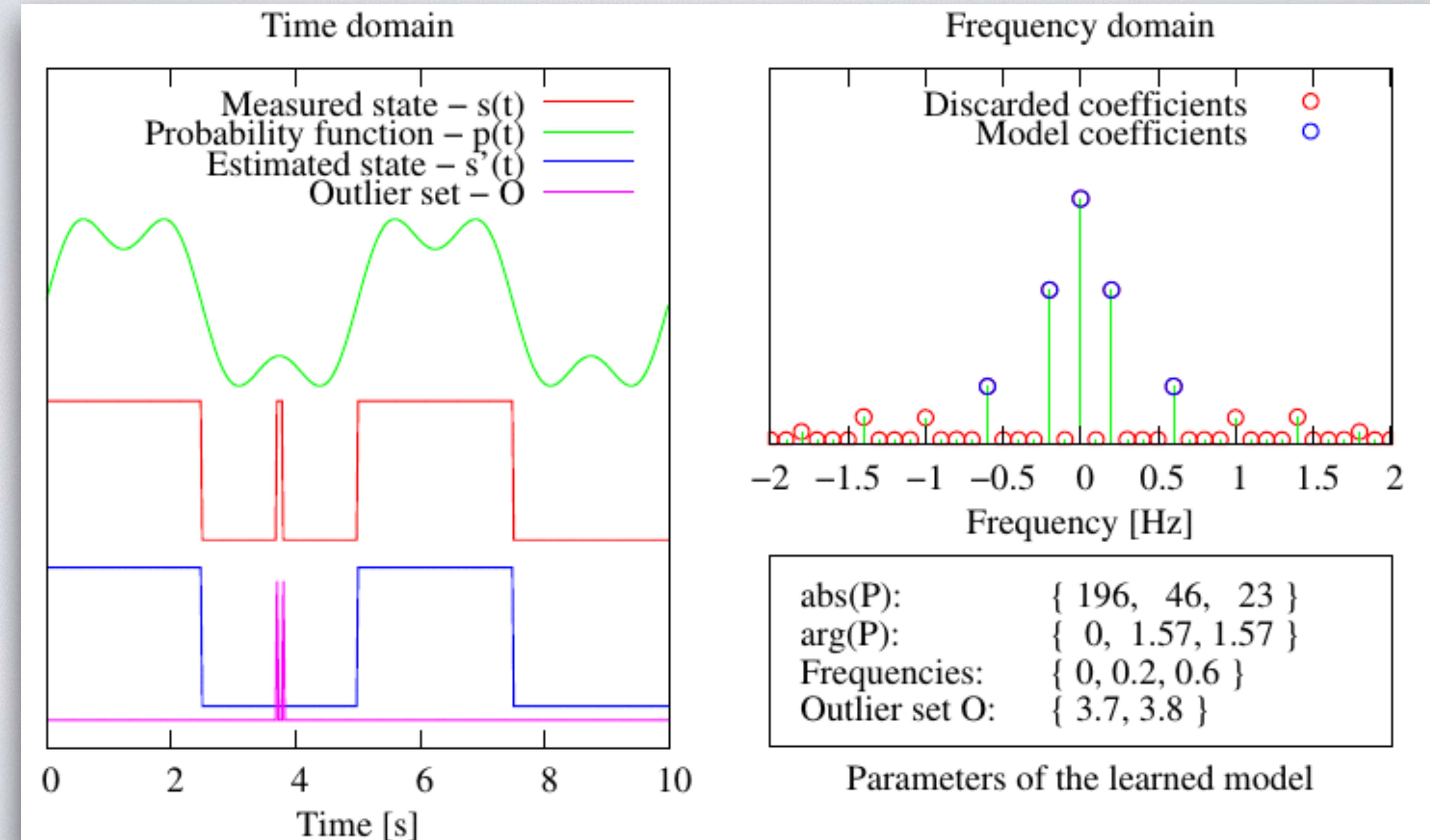
now extended to real-valued states and non-uniform sampling

Indeed, our recent model also takes recency into account

UNIVERSITY OF LINCOLN

L-CAS

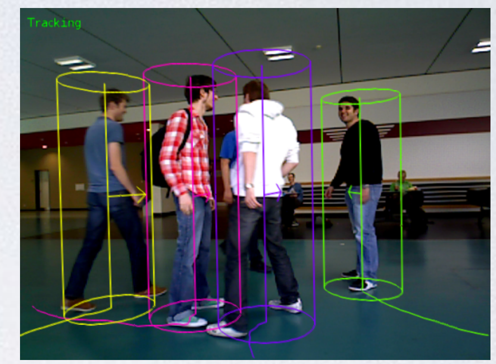
FREQUENCY MAP ENHANCEMENT

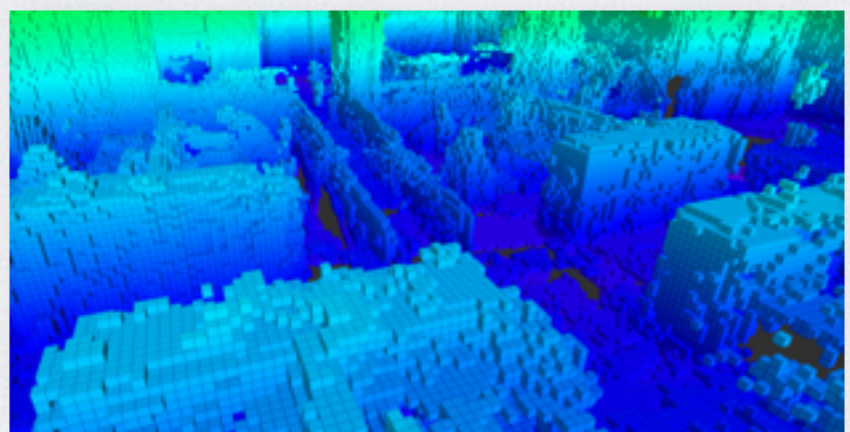


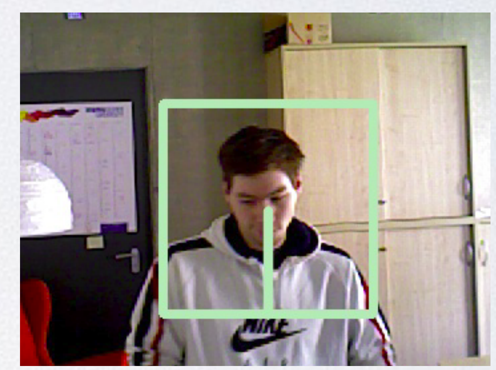
UNIVERSITY OF LINCOLN
STRANDS
LINCOLN ROBOTICS

STATES?

- Could be almost anything

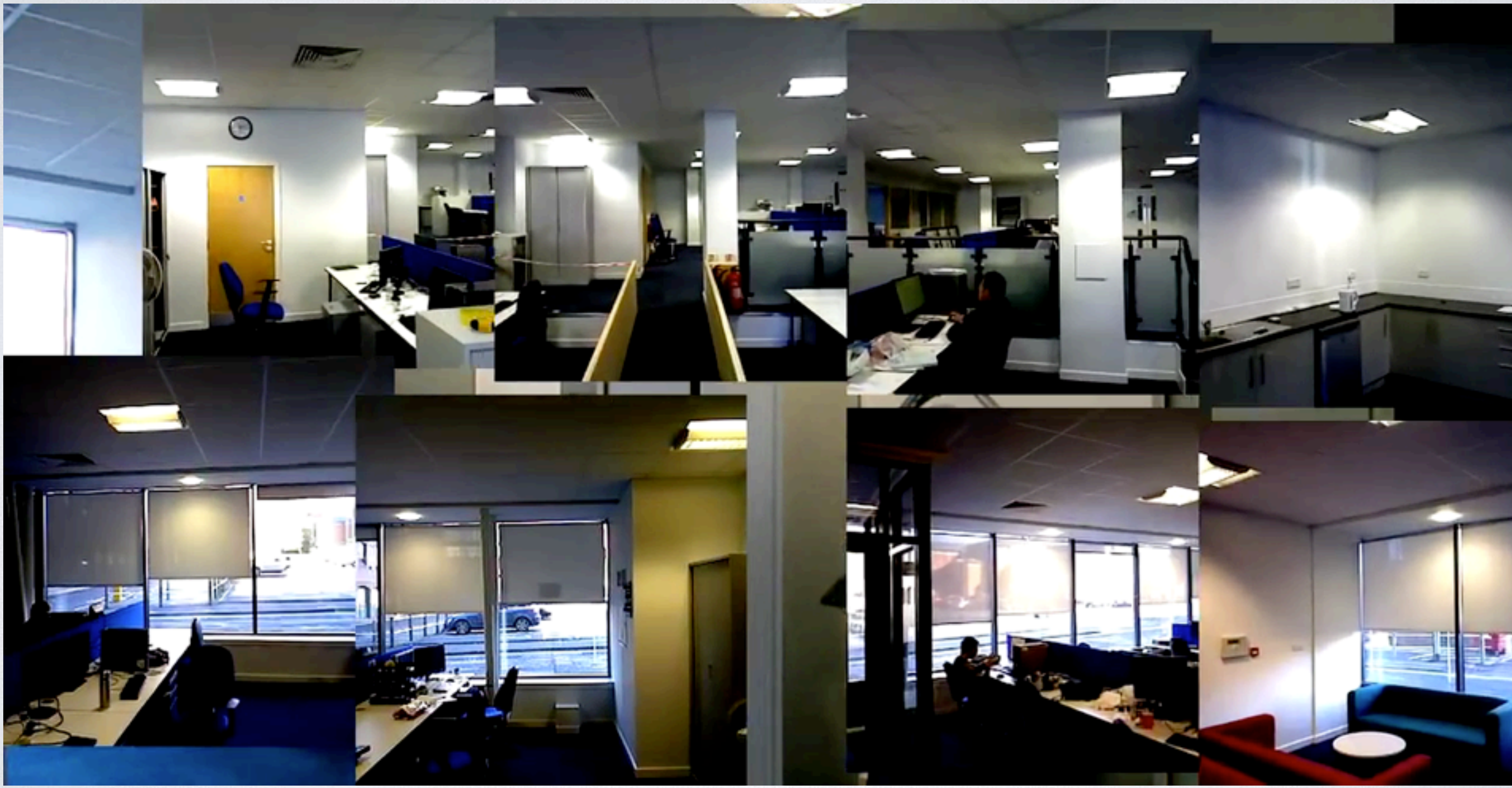






$$
\begin{aligned}
&\mathit{scene}(\mathit{Monitor}, \mathit{Keyboard}, \mathit{Laptop}, \mathit{Cup}, \mathit{Bottle}) \Leftrightarrow \\
&\quad \mathit{in\text{-}front\text{-}of}(\mathit{Keyboard}, \mathit{Monitor}) \wedge \\
&\quad \mathit{left\text{-}of}(\mathit{Laptop}, \mathit{Keyboard}) \wedge \\
&\quad \mathit{right\text{-}of}(\mathit{Cup}, \mathit{Keyboard}) \wedge \\
&\quad \mathit{behind\text{-}of}(\mathit{Bottle}, \mathit{Cup}) \wedge \\
&\quad \mathit{close\text{-}to}(\mathit{Bottle}, \mathit{Cup}).
\end{aligned}
$$

VISUAL TOPOLOGICAL LOCALISATION



["Long-Term Topological Localisation for Service Robots in Dynamic Environments using Spectral Maps" that will be presented at IEEE/RSJ International Conference on Intelligent Robots and Systems 2014]

UNIVERSITY OF LINCOLN

STRANDS

LINCOLN ROBOTICS

A FEW RESULTS

TABLE I

OVERALL LOCALIZATION ERROR (%)

1 week prediction

3 months prediction

Model type	Model order	Image features Nov	Image features Feb	Occupancy grids Nov	Occupancy grids Feb
static	-	35%	45%	21%	17%
spectral	1	25%	26%	14%	13%
spectral	2	22%	27%	14%	8%
spectral	3	18%	24%	14%	17%
spectral	4	17%	29%	7%	17%

[Krajnic et al "Long-Term Topological Localisation for Service Robots in Dynamic Environments using Spectral Maps", IEEE/RSJ International Conference on Intelligent Robots and Systems 2014]

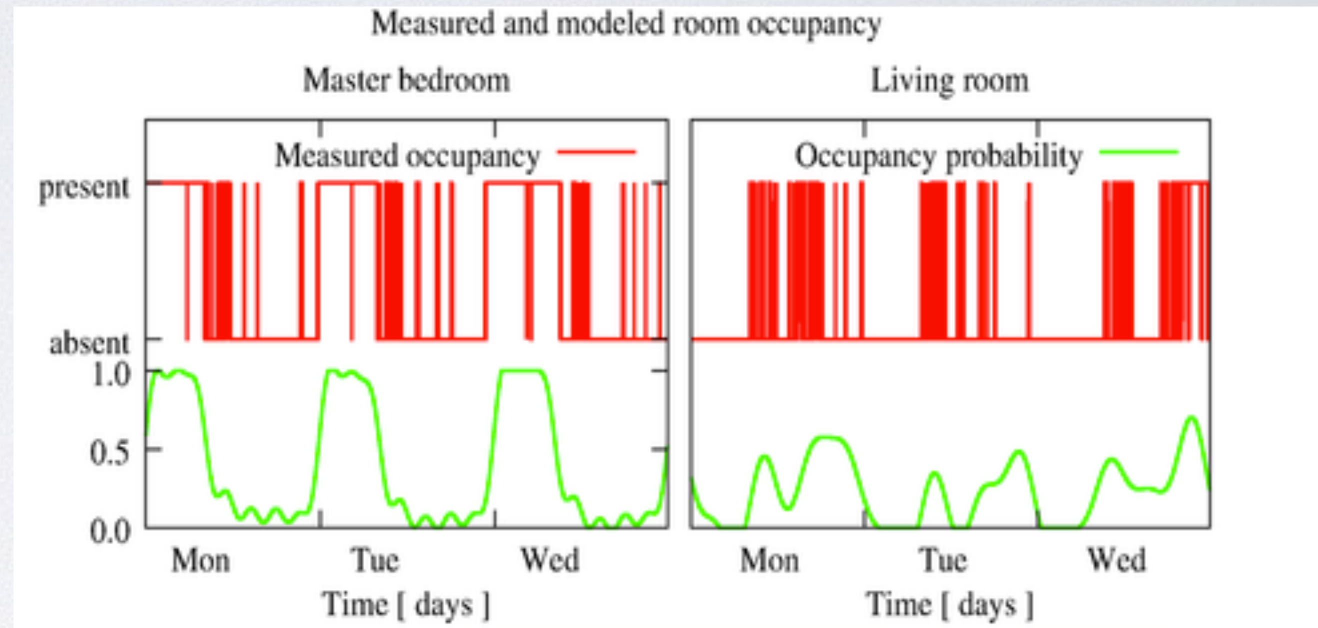
PREDICT PRESENCE OF HUMANS

related: Th, 10:20
Paper ThT11.19

- use spectral models to model presence of people/people
- similar to *Dora*, but dynamic prediction
- find people/objects faster

TABLE I: Mean (μ) and median ($\tilde{t}$) time to find a person

Model		Dataset			
		Aruba		Brayford	
type	order	$\mu[s]$	$\tilde{t}[s]$	$\mu[s]$	$\tilde{t}[s]$
Static	-	44	41	19	23
FreMEn	1	36	15	14	9
FreMEn	2	33	15	14	9
FreMEn	3	34	15	16	9
PerGaM	1	34	15	14	15
PerGaM	2	33	15	14	15
PerGaM	3	33	15	14	15

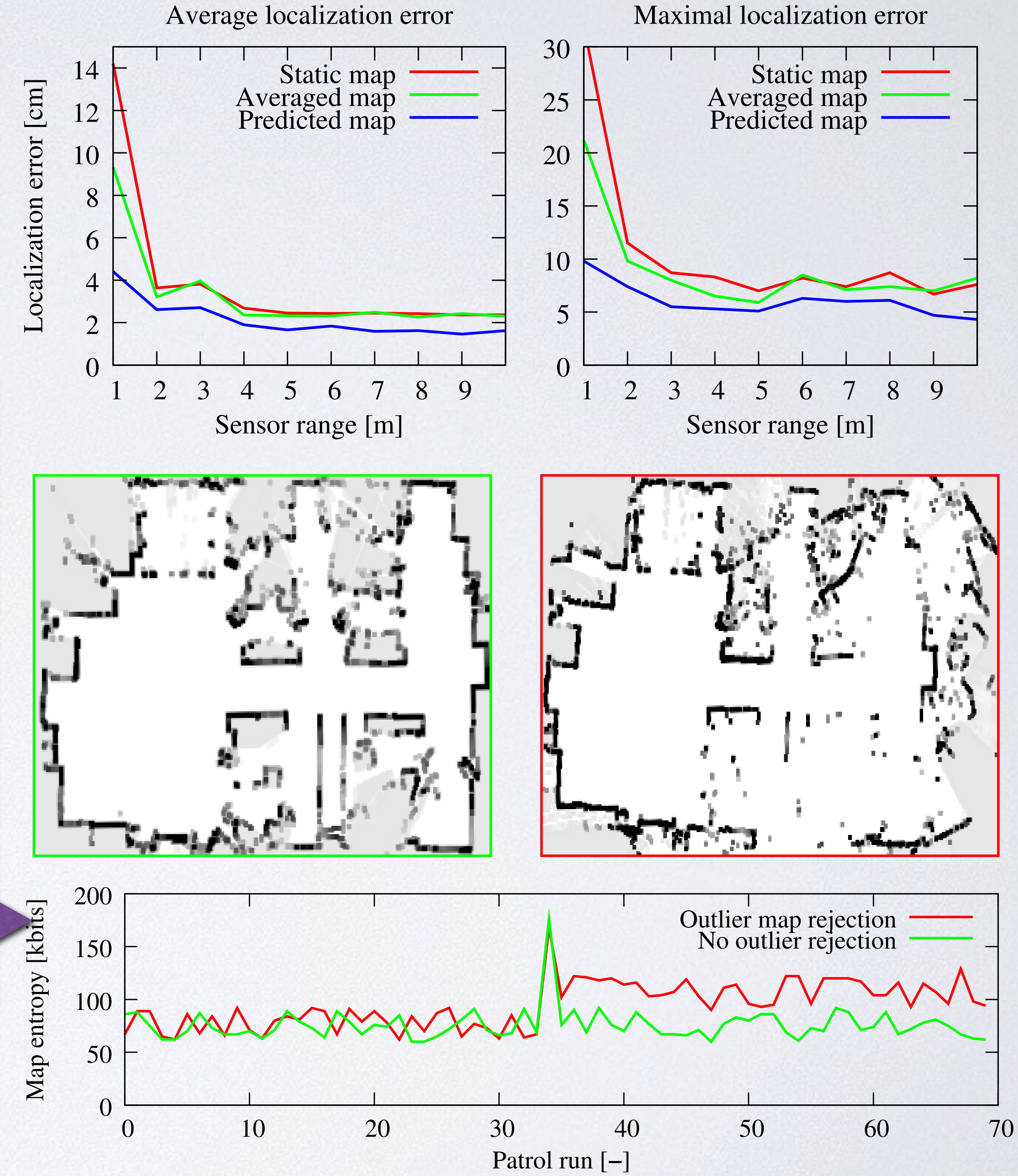


[Krajnic et al, "Where's Waldo at time t? Using Spatio-Temporal Models for Mobile Robot Search.", ICRA 2015]

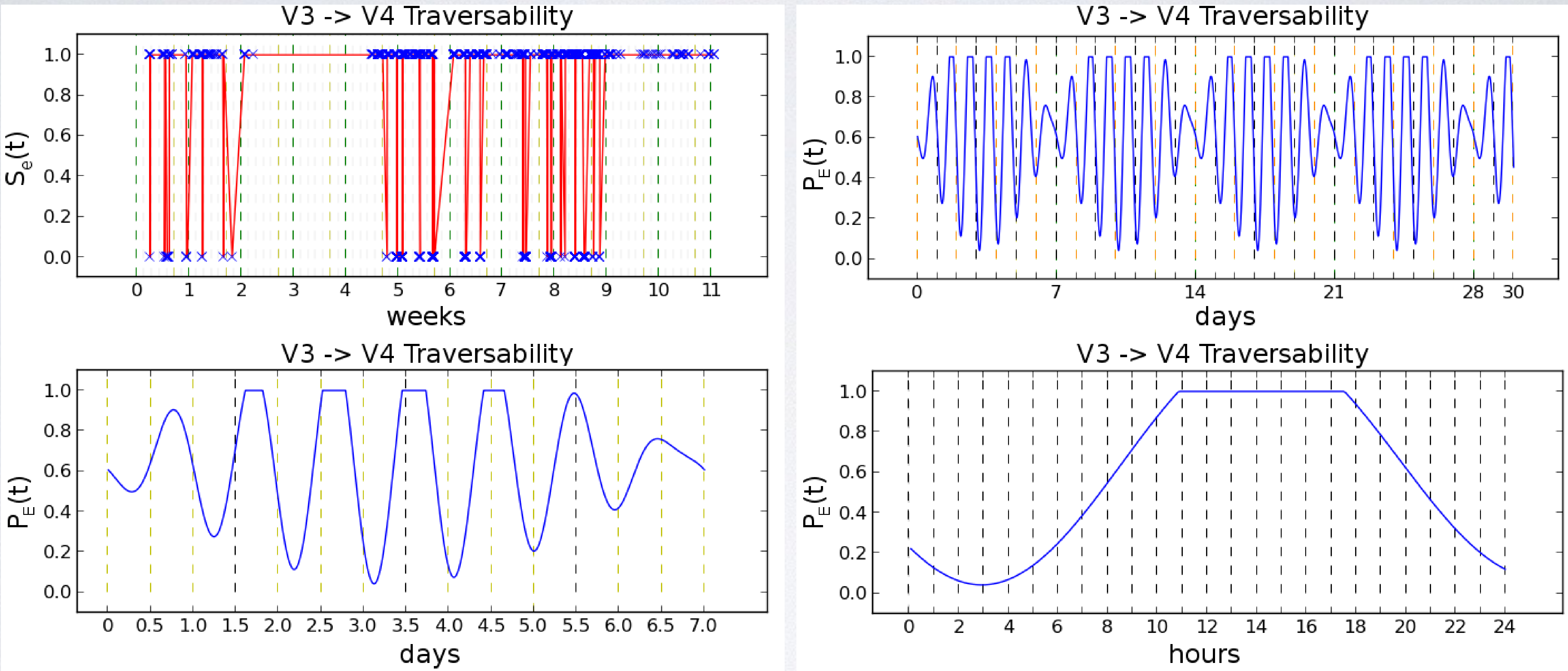
PREDICT 2D GRID MAPS

- better accuracy and robustness in localisation

more on Th, 14:05
Paper ThT21.10:
Persistent Localization and Life-Long Mapping in Changing Environments Using the Frequency Map Enhancement

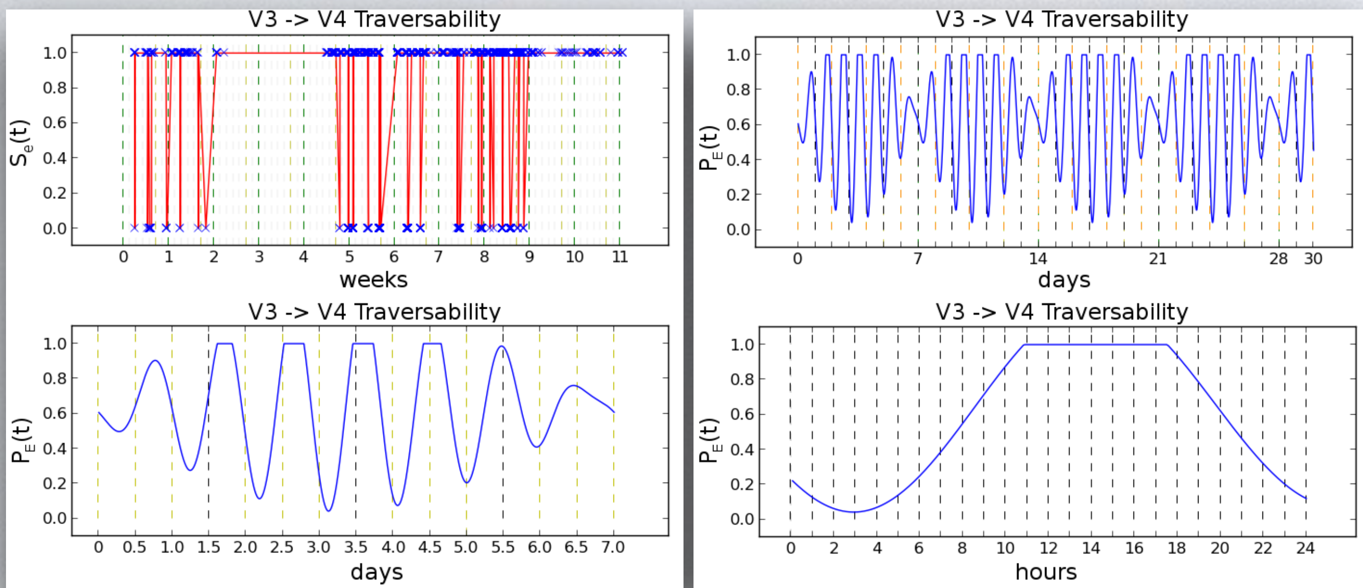


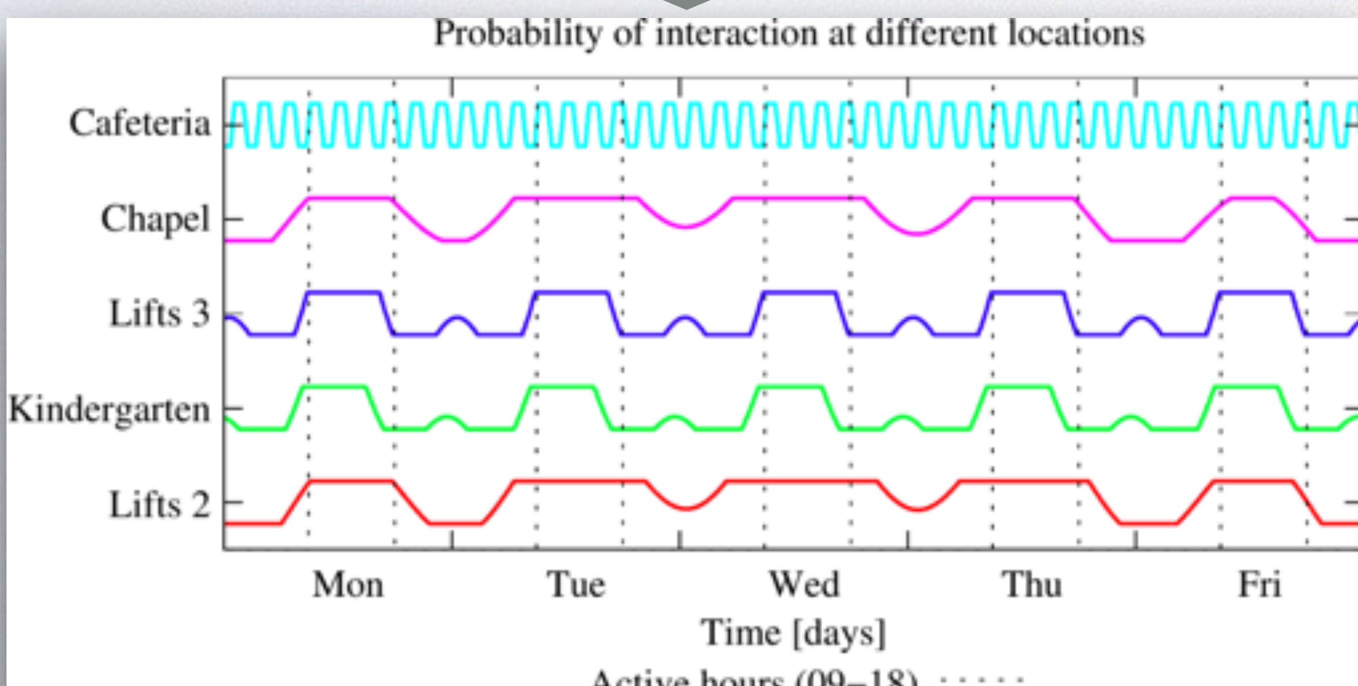
TOPOLOGICAL EDGE TRAVERSABILITY MODELLING USING FREMEN



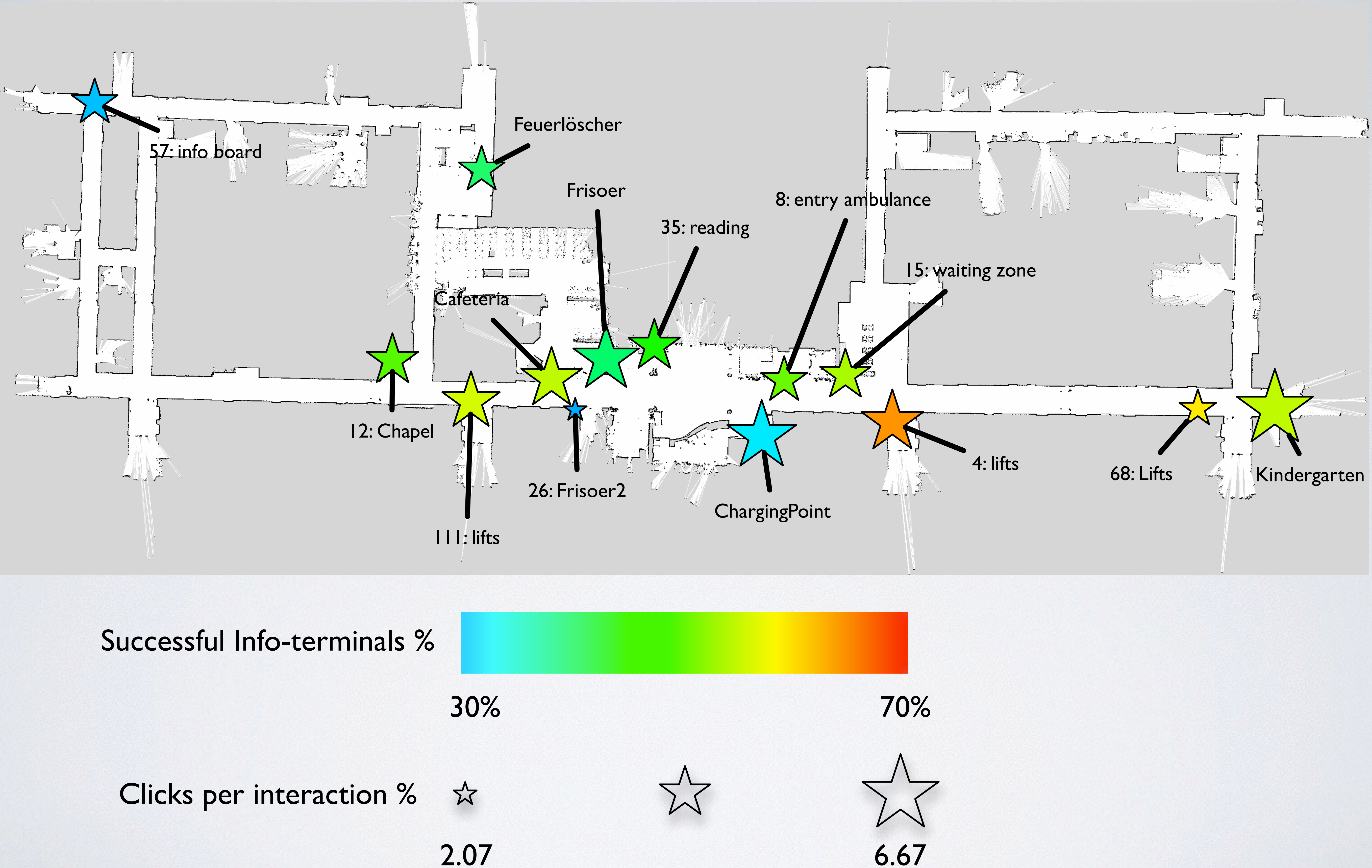
J. Pulido Fentanes, B. Lacerda, T. Krajník, N. Hawes, and M. Hanheide. Now or later? predicting and maximising success of navigation actions from long-term experience. In ICRA, 2015.

ANTICIPATING USERS' TASKS

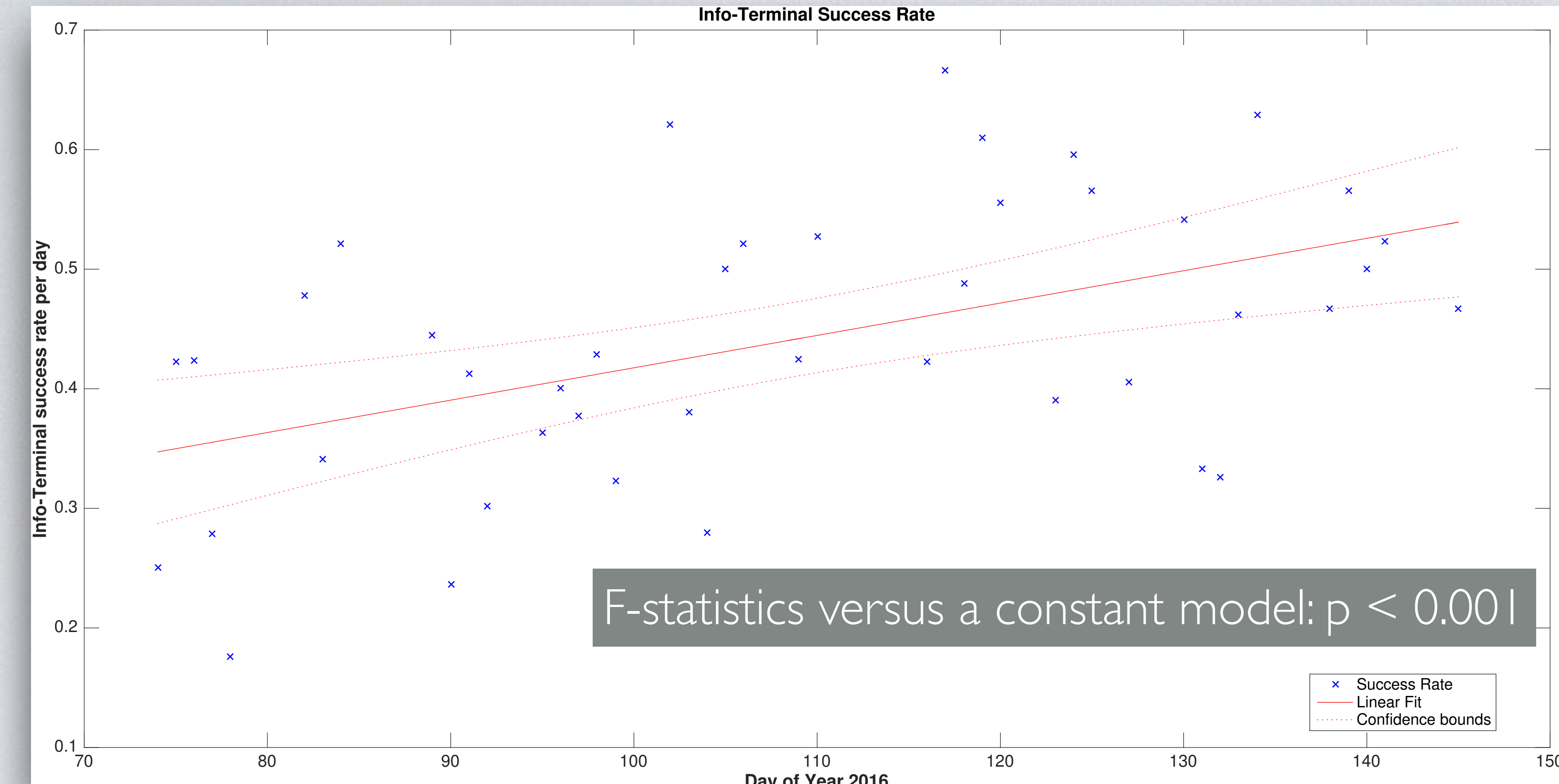




- Model probability of interaction "success" as periodic probability distribution
- Exploit prediction to improve where the service is offered when
- Explore actively to learn
- greedy 50/50 exploration/ exploitation


57: info board
Feuerlöscher
Frisoer
8: entry ambulance
35: reading
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

ADAPTIVE AUTONOMY



user's needs / intentions might be well captured by periodic models

from experience learn to do what your users want

	Kindergarten	Ambulance	Feuerloescher	Waiting Zone	Lifts 1	Cafeteria	Reading Zone	Chapel	Lifts 2	Lifts 3	Infoboard	Frisoer 1	Frisoer 2	SUM
Menu	25	61	23	34	43	48	34	36	69	49	23	37	7	489
Weather	29	37	28	34	35	44	36	28	45	33	10	20	7	386
News	21	33	24	34	31	29	14	22	36	29	13	41	3	330
Photo	165	127	96	128	79	110	111	110	170	62	71	69	10	1308
SUM	240	258	171	230	188	231	195	196	320	173	117	167	27	2513

SYNOPSIS

Exploiting experience from and for interaction

Robots do fail: Dealing with uncertainty and errors in goal-driven autonomy

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

Robust, intelligent, autonomous behaviour

running for weeks

Exploitation of structure for improved performance

Long run-times in everyday environments

learn improved represen-tations

Novel opportunities to learn structure environment

learn how the world changes

UNIVERSITY OF LINCOLN

STRANDS

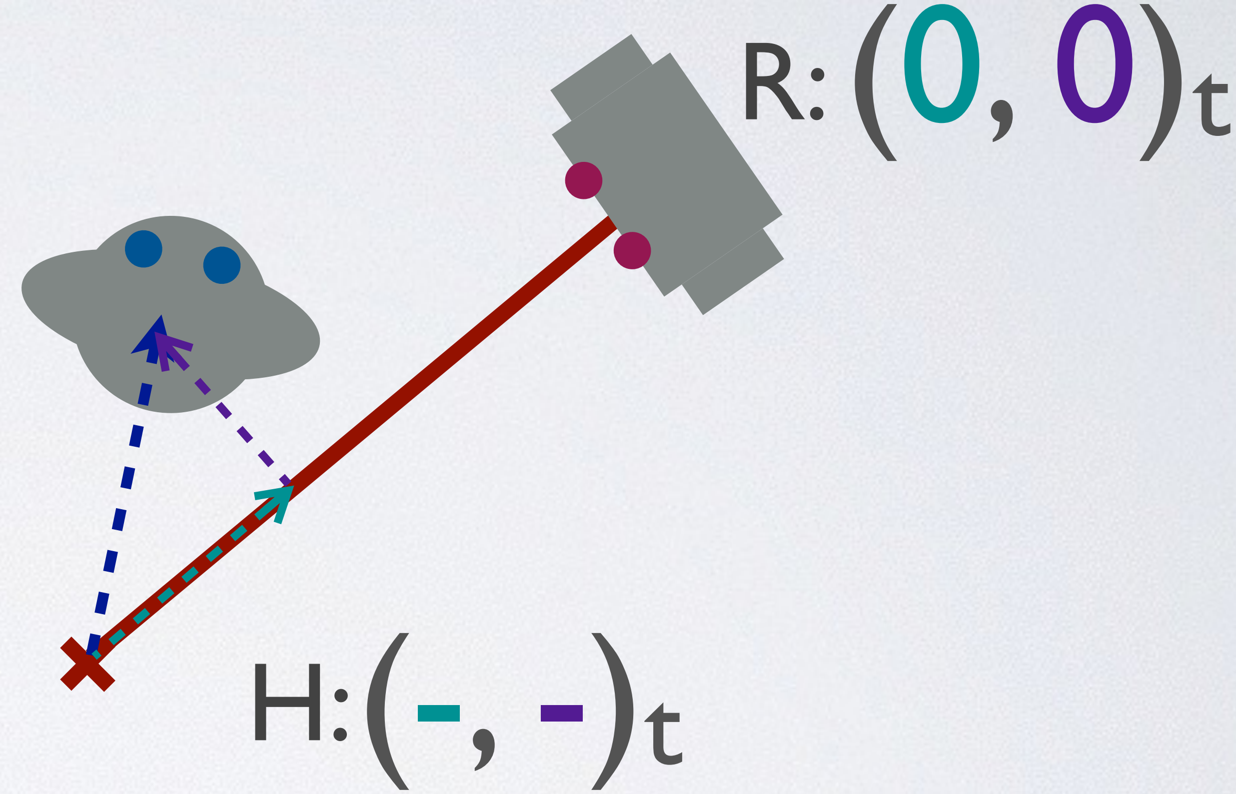
LINCOLN ROBOTICS

PROBABILISTIC TIME SERIES OF QUALITATIVE STATES

- Qualitative Spatial Relations (QSR) are well established technique to model human activities
  - A QSR calculus is a well founded theoretical model
- An activity is a sequence of different qualitative states

1. Cohn, A.G. & Renz, J., 2008. Chapter 13 Qualitative Spatial Representation and Reasoning. In F. van Harmelen, V. Lifschitz, & B. Porter, eds. Handbook of Knowledge Representation. Elsevier, pp. 551–596.
2. Sridhar, M., Cohn, A.G. & Hogg, D.C., 2010. Unsupervised learning of event classes from video. In Proceedings of the AAAI Conference on Artificial Intelligence (AAAI). pp. 1631–1638. Available at: http://www.aaai.org/ocs/index.php/AAAI/AAAI10/paper/viewFile/1846/2268.
3. Van de Weghe, N. et al., 2006. A qualitative trajectory calculus as a basis for representing moving objects in Geographical Information Systems. Control and Cybernetics, 35(1), pp.97–119. Available at: http://control.ibspan.waw.pl:3000/contents/export?filename=Weghe-et-al.pdf.

QSR SEQUENCES FOR HUMAN-ROBOT COLLABORATION AND INTERACTION

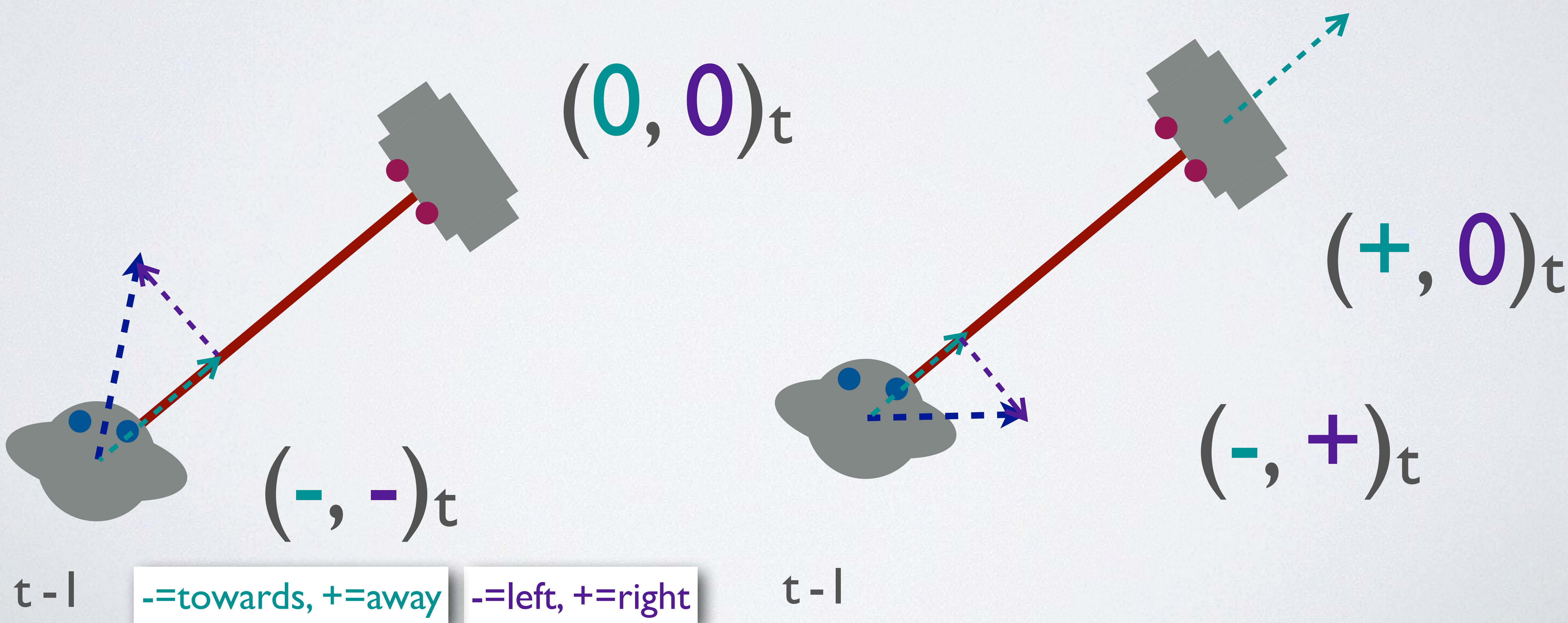


- idea: predict **humans' intention** from (partial) movement sequences
- model the mutual movement of human and robot using **QTC**

Probabilistic Sequential Models of Qualitative States

QTC_C - BY EXAMPLE

QTC_C represents the relative motion of two points in a time interval with respect to the reference line that connects them on a 2D plane.



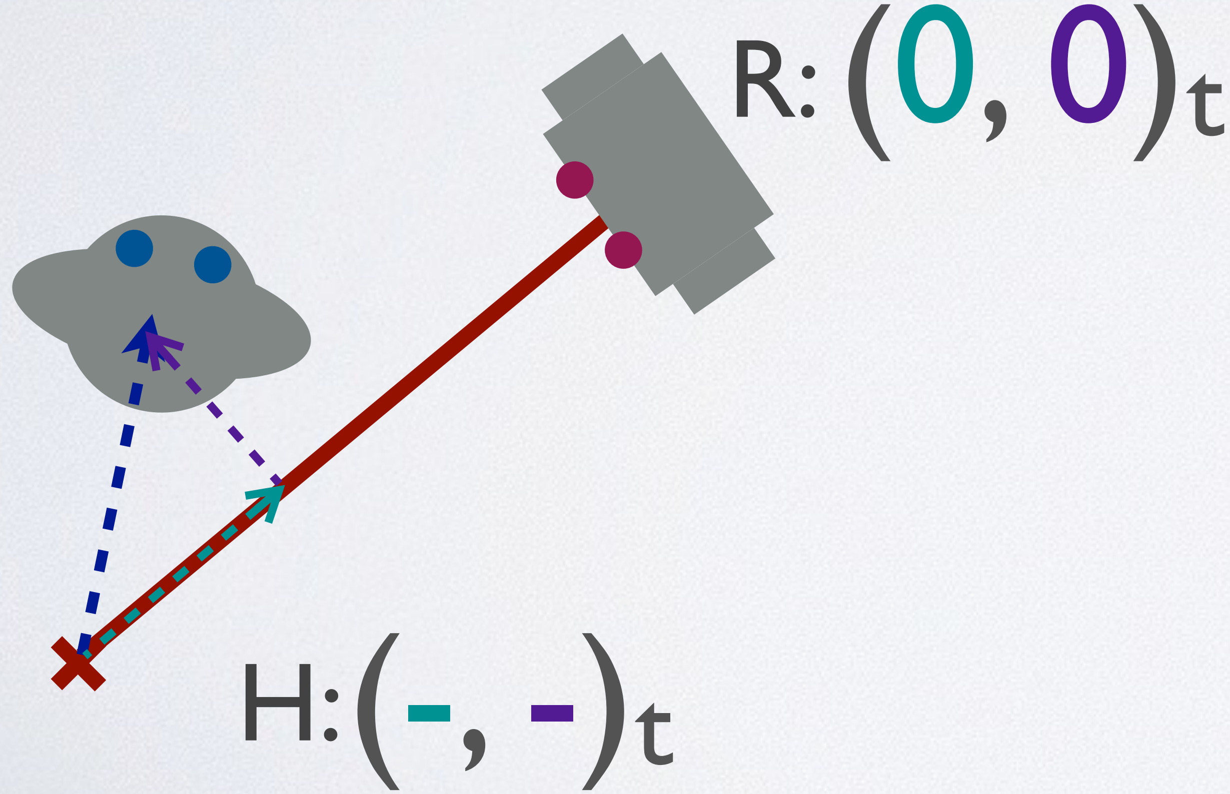
QTC$_C$ - BY EXAMPLE

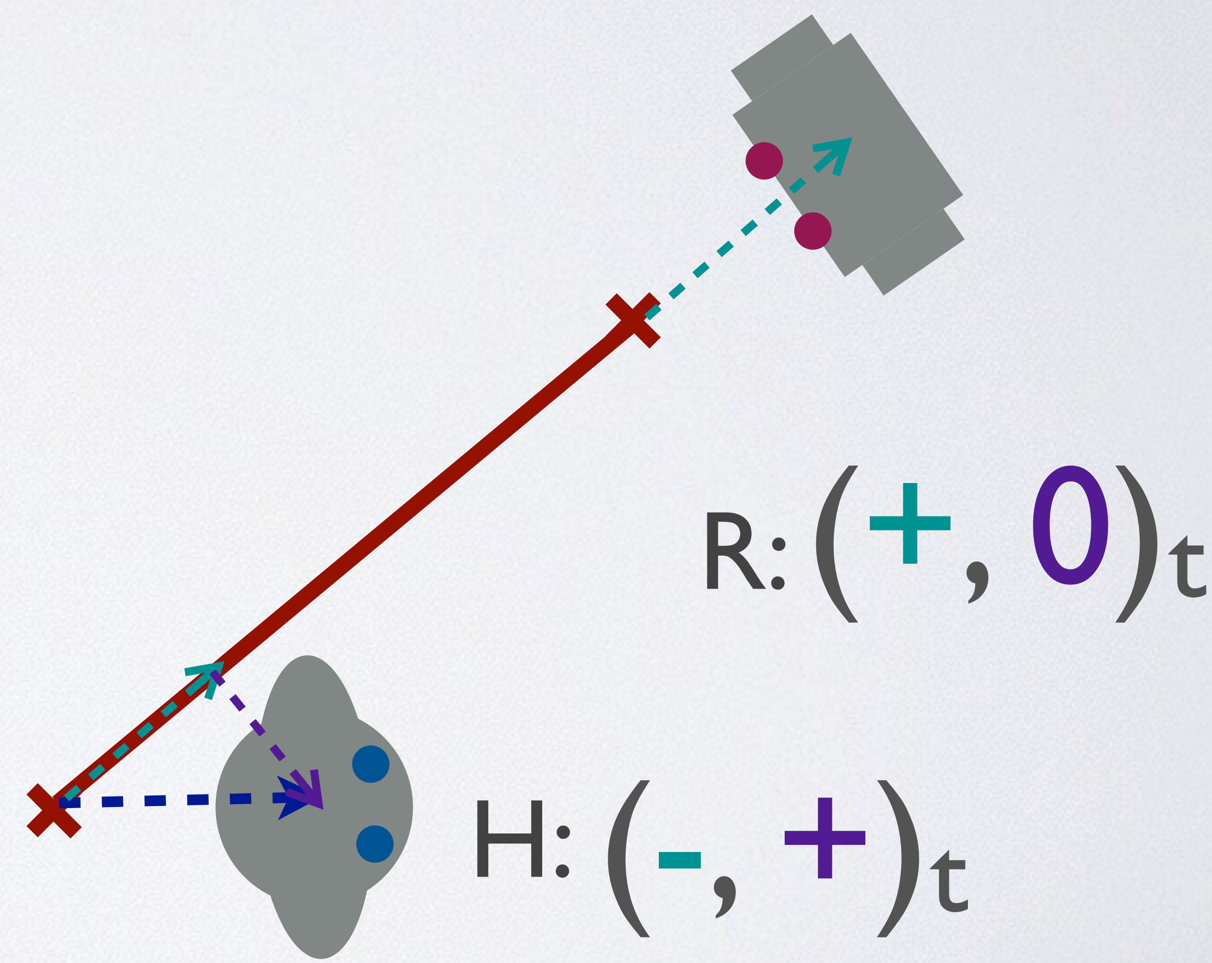
$(-, 0, -, 0)_t$

H R H R

$(-, +, +, 0)_t$

H R H R



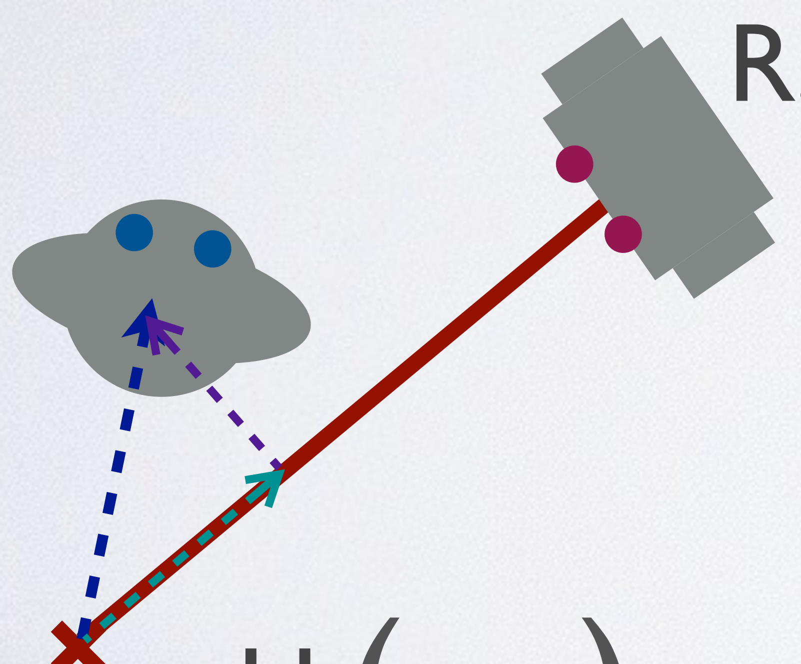


QTC$_C$ STATE

$(-, 0, -, 0)_t$

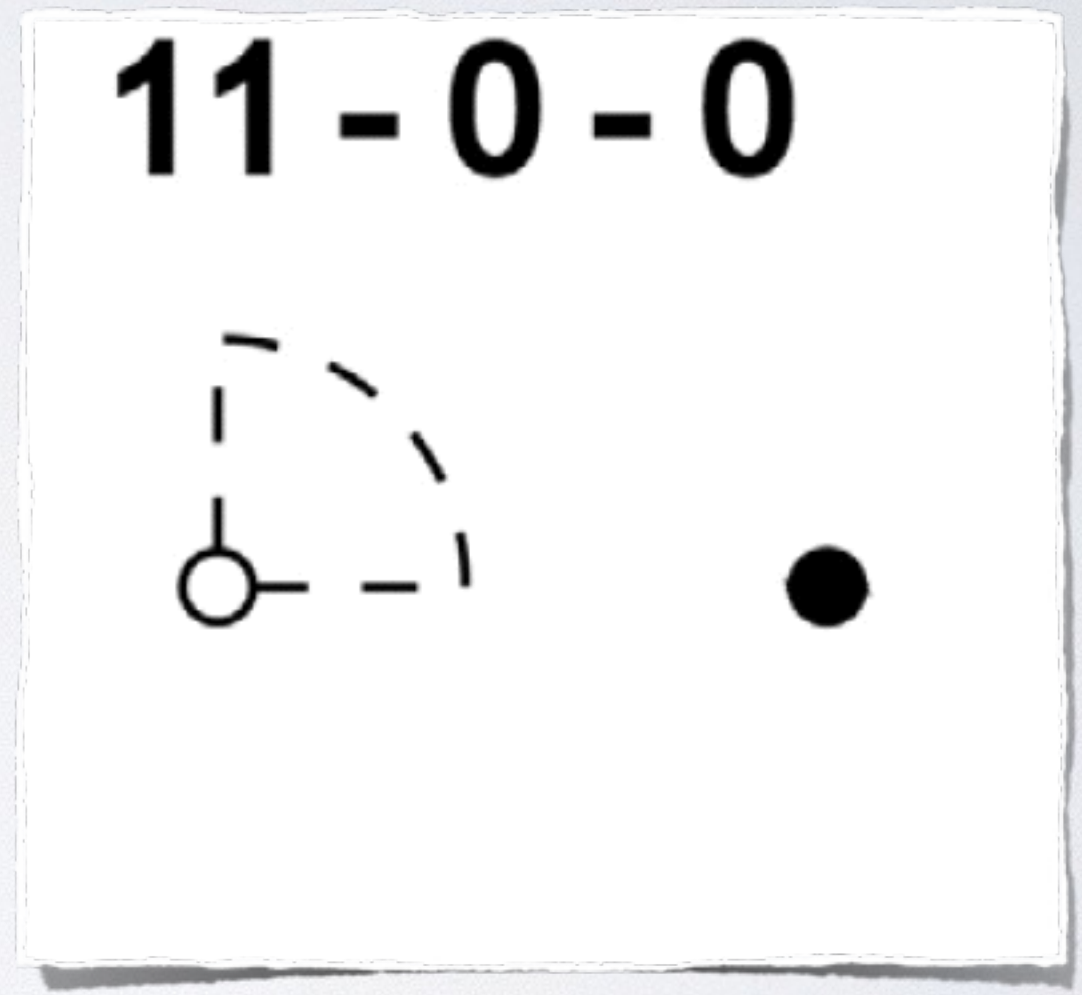
H R H R

state no. H R H R



R: $(0, 0)_t$

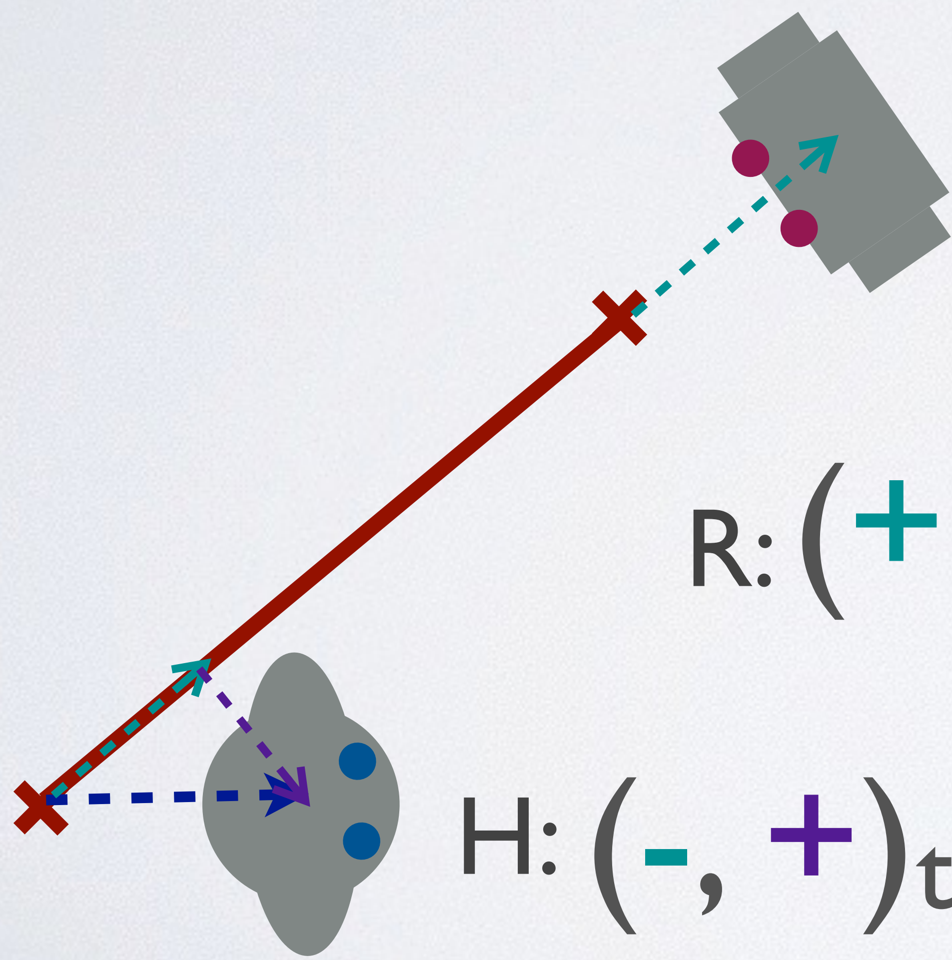
H: $(-, -)_t$



QTC$_C$ STATE

$(-, +, +, 0)_t$

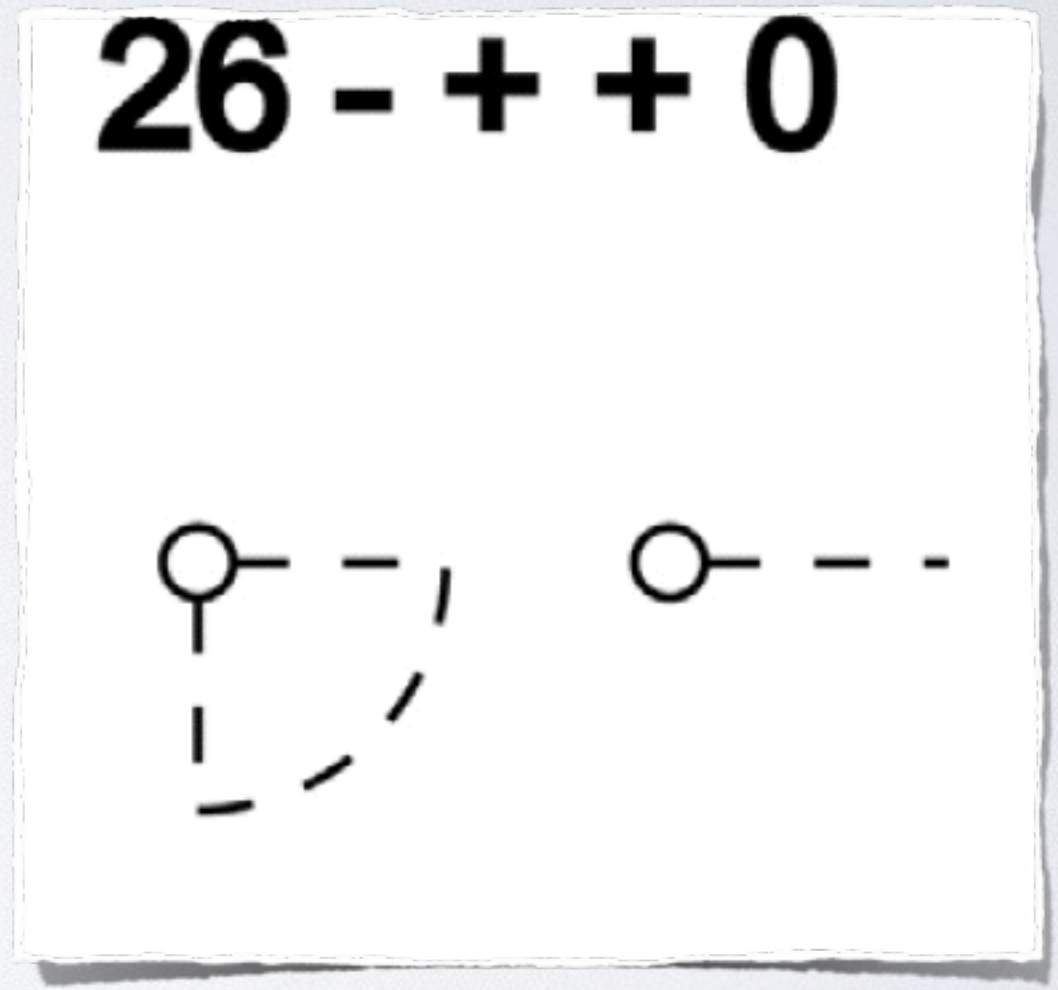
H R H R



R: $(+, 0)_t$

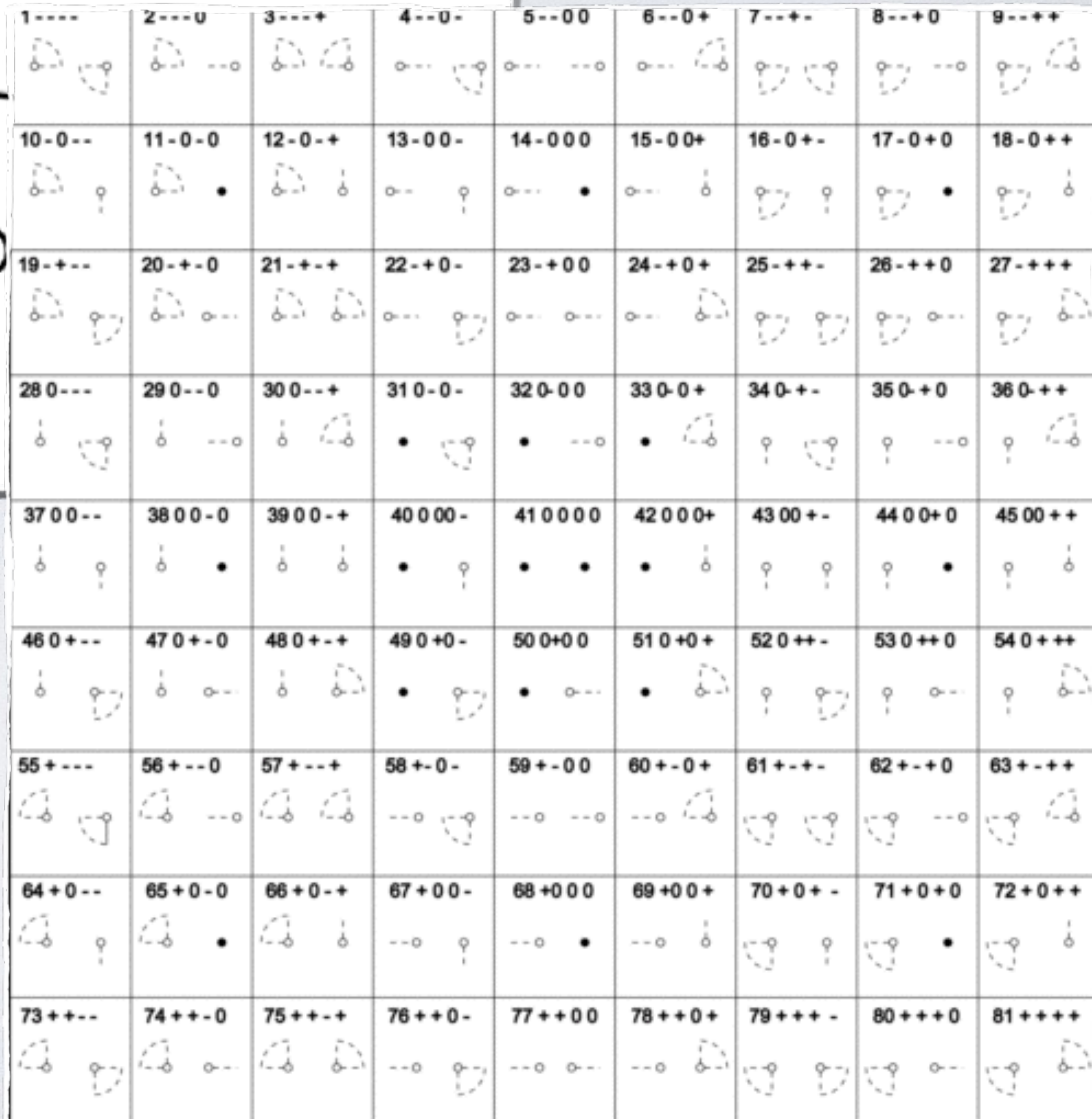
H: $(-, +)_t$

state no. H R H R



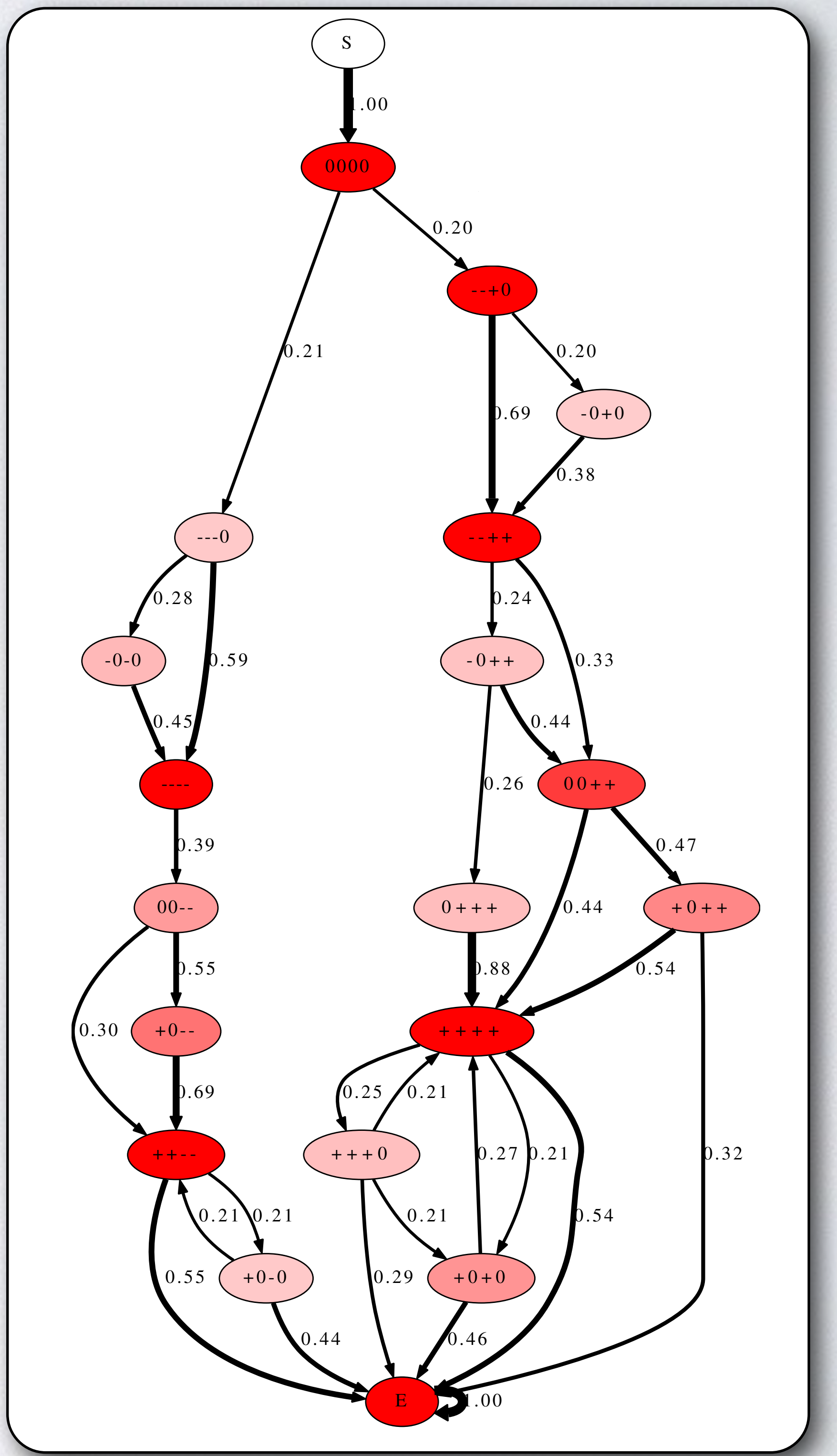
11 - 0 - 0

4 = 81


1 - - - -
2 - - - 0
3 - - - +
4 - - 0 -
5 - - 0 0
6 - - 0 +
7 - - + -
8 - - + 0
9 - - + +
10 - 0 - -
11 - 0 - 0
12 - 0 - +
13 - 0 0 -
14 - 0 0 0
15 - 0 0 +
16 - 0 + -
17 - 0 + 0
18 - 0 + +
19 - + - -
20 - + - 0
21 - + - +
22 - + 0 -
23 - + 0 0
24 - + 0 +
25 - + + -
26 - + + 0
27 - + + +
28 0 - - -
29 0 - - 0
30 0 - - +
31 0 - 0 -
32 0 - 0 0
33 0 - 0 +
34 0 - + -
35 0 - + 0
36 0 - + +
37 0 0 - -
38 0 0 - 0
39 0 0 - +
40 0 0 0 -
41 0 0 0 0
42 0 0 0 +
43 0 0 + -
44 0 0 + 0
45 0 0 + +
46 0 + - -
47 0 + - 0
48 0 + - +
49 0 + 0 -
50 0 + 0 0
51 0 + 0 +
52 0 + + -
53 0 + + 0
54 0 + + +
55 + - - -
56 + - - 0
57 + - - +
58 + - 0 -
59 + - 0 0
60 + - 0 +
61 + - + -
62 + - + 0
63 + - + +
64 + 0 - -
65 + 0 - 0
66 + 0 - +
67 + 0 0 -
68 + 0 0 0
69 + 0 0 +
70 + 0 + -
71 + 0 + 0
72 + 0 + +
73 + + - -
74 + + - 0
75 + + - +
76 + + 0 -
77 + + 0 0
78 + + 0 +
79 + + + -
80 + + + 0
81 + + + +

REPRESENTING HRSI BEHAVIOUR AS QTC-MM

- create a Markov Model topology
- Discretise Motion of Human and Robot into QTC states
- Train from long-term experience

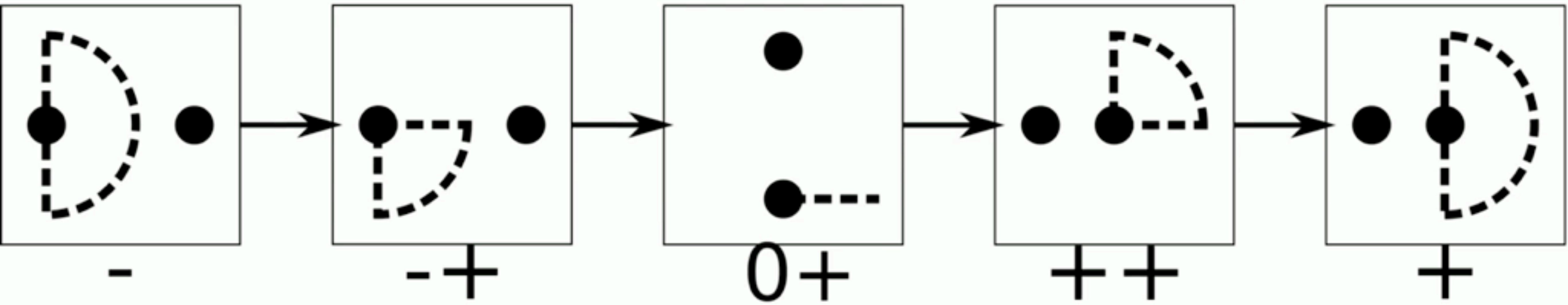


[Dondrup et al. A computational model of human-robot spatial interactions based on a qualitative trajectory calculus. Robotics, 4 (1). 2015]

UNIVERSITY OF LINCOLN

L-CAS

PLANNING CONSTRAINTS FROM PREDICTED QSR



IT WORKS

PERCENTAGE OF TRAJECTORIES COLLIDING WITH THE HUMAN

	Simulation		Robot	
	Pass-by	Path Crossing	Pass-by	Path Crossing
DWA	100%	100%	53.3%	86.7%
G-Global	0%	100%	22.2%	75.0%
G-Local	100%	0%	33.3%	100%
Vel-Maps	0%	0%	12.5%	13.3%

[Dondrup et al: Qualitative Constraints for Human-aware Robot Navigation using Velocity Costmaps, ICRA 2016. submitted]

SOME CONCLUSIONS

Robots do fail: Dealing with uncertainty and errors in goal-driven autonomy

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

Uncertain Belief States

Probabilistic Sequential Models of Qualitative States

Periodic Probability Density Functions

Metric and Topologic Maps

Deterministic and Probabilistic Domain knowledge

SOME CONCLUSIONS

- Dora show-cases an **integrated planning approach** to deal with uncertainty, surprise and **goal-directed** behaviour
- Deal with the ***expected***, and the ***unexpected*** change in real world environments
- **Verify explanations** (surprises) (inter-)actively by planning more knowledge gathering

Uncertain Belief States

abilistic Sequential Models of Qualitative States

Periodic Probability Density Functions

Metric and Topologic Maps

Deterministic and Probabilistic Domain knowledge

Robots do fail: Dealing with uncertainty and errors in goal-driven autonomy

SOME CONCLUSIONS

- Learning **routines** can help building more effective and efficient systems, spectral models are very powerful here
- Long-term autonomy is a challenge to develop **common-sense** and **self-improve**
- Change is mostly **human-made**, and humans are the most **unpredictable entities** in an environment, but they can explain it

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

Uncertain Belief States

Probabilistic Sequential Models of Qualitative States

Periodic Probability Density Functions

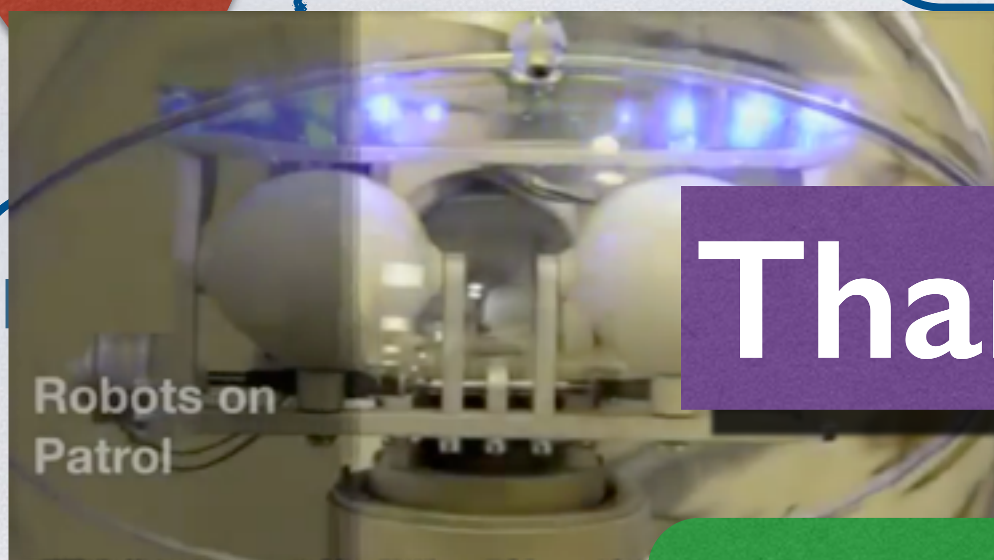
Metric and Topologic Maps

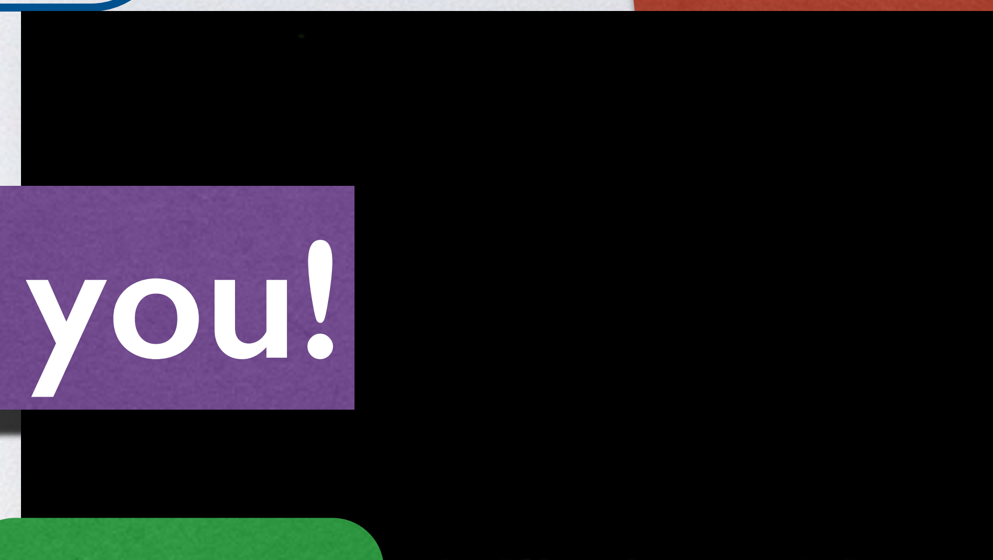
Deterministic and Probabilistic Domain knowledge

experienced-based autonomy

Robust, intelligent, autonomous behaviour

running for weeks





Thank you!

Carpe Diem

Carpe Noctem

learn improved represen-tations

learn how the world changes

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

UNIVERSITY OF LINCOLN

STRANDS

LINCOLN ROBOTICS

ADVERTISEMENT!

marc@hanheide.net

@MarcHanheide

We are hiring:

- **Associate/Assistant Professors** (tenured) in "*Learning in Autonomous Systems*"
- **PostDocs and PhD students** in "*Long-Term Autonomy for Mobile Robots in Intra-Logistics*"

http://lncn.eu/lcasjobs or Google "**l-cas lincoln**"