ESSENCE SUMMER SCHOOL, EDINBURGH, AUGUST 2015

STRUCTURED REPRESENTATIONS FOR ROBOT BEHAVIOUR

NICK HAWES

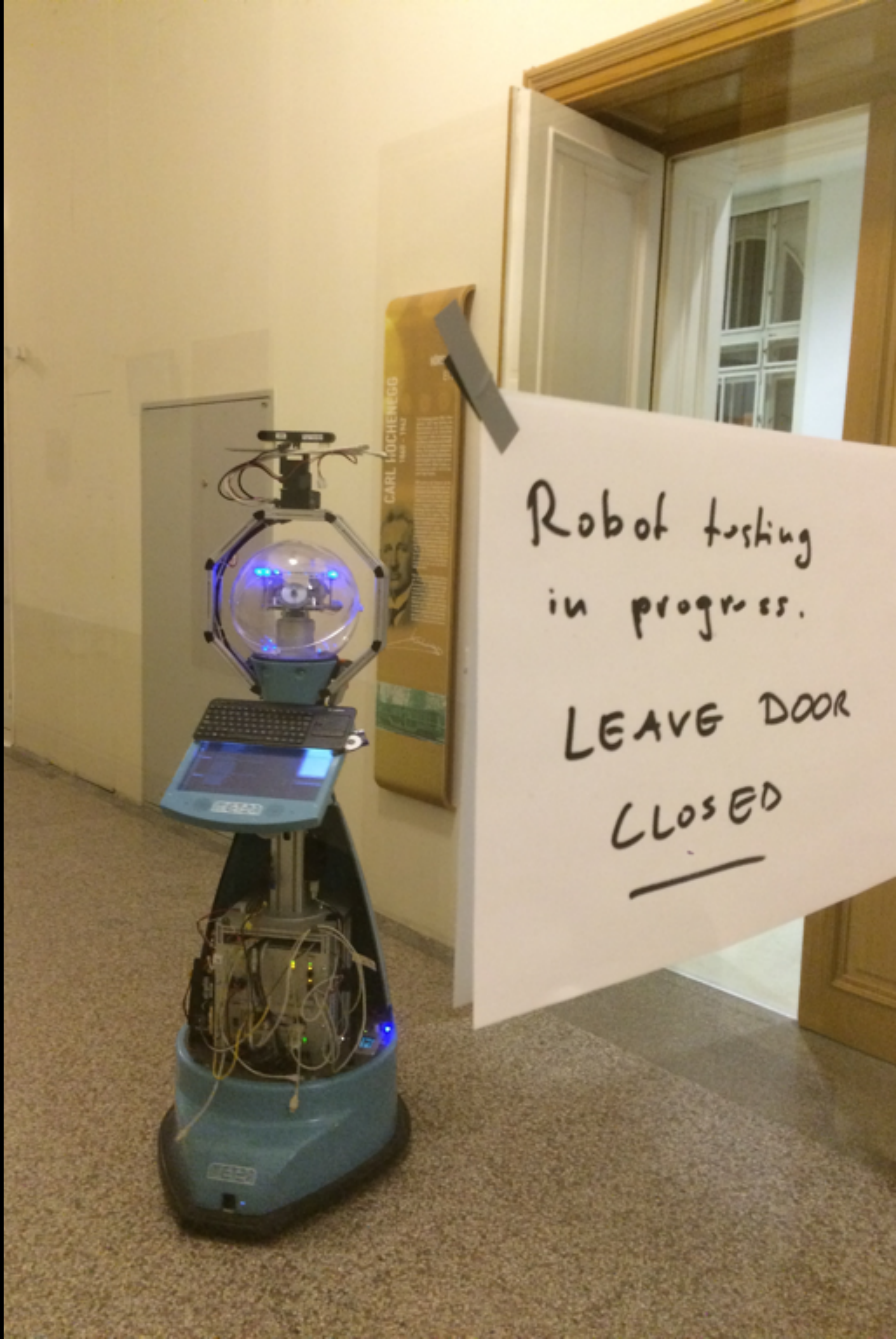
SCHOOL OF COMPUTER SCIENCE, UNIVERSITY OF BIRMINGHAM

N.A.HAWES@CS.BHAM.AC.UK

HTTP://WWW.CS.BHAM.AC.UK/~NAH @HAWESIE

ABOUT ME

- Research interests in applying AI to make robots smarter
- I've worked on robots and video games, planning, language, vision etc.
- Coordinator of the EU STRANDS project (which I will draw on a lot)
- Any questions, please just ask!



STRUCTURE

- Autonomous Mobile Robots
- Knowledge of Space
- Break
- Understanding Change
- The Unknown

STRUCTURE

- **Autonomous Mobile Robots**
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What is the problem? The creation of autonomous mobile robots that act intelligently in real world domains.

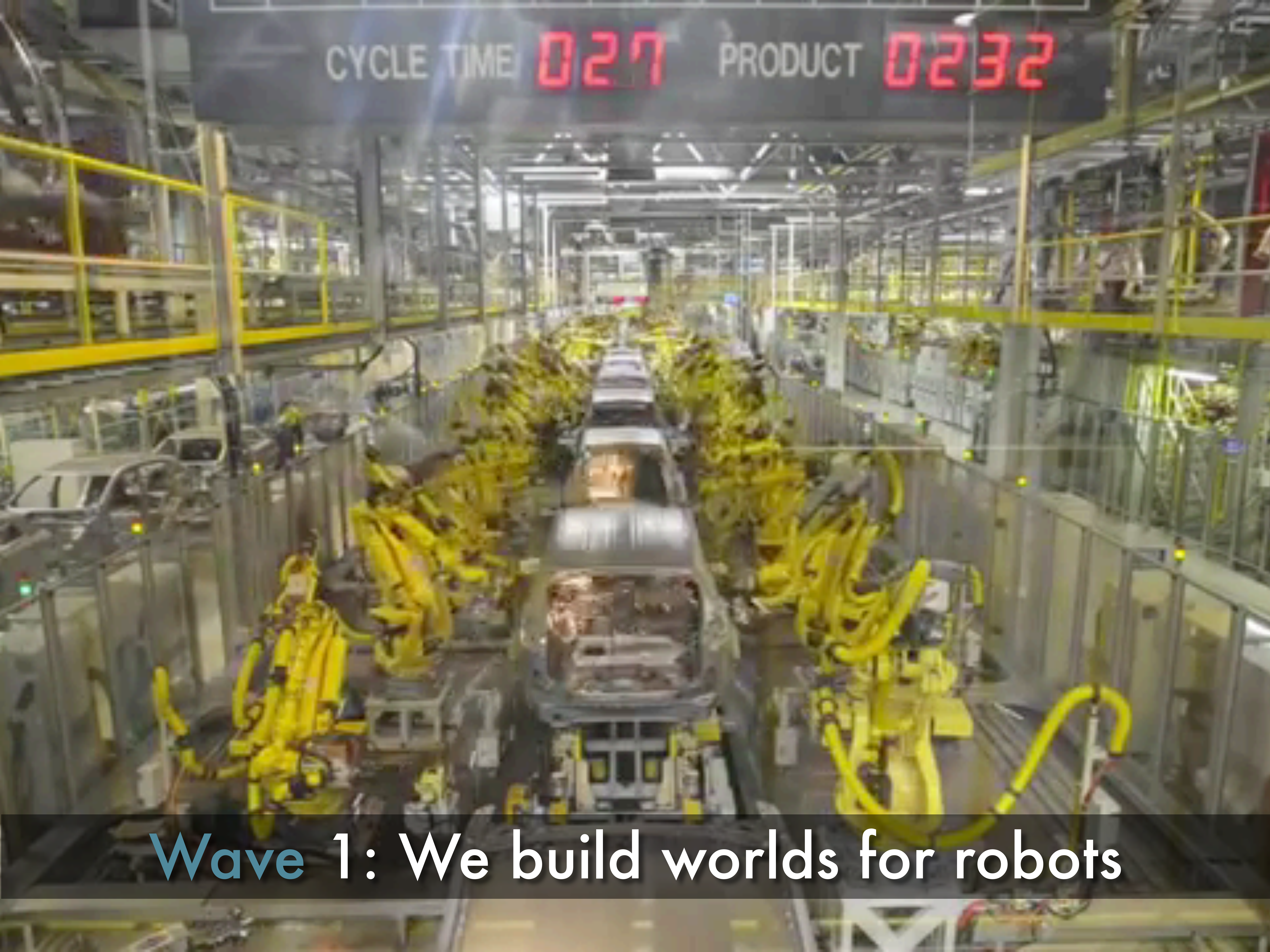
AUTONOMOUS MOBILE ROBOTS

Why is it hard? The integration of a range of different functionalities to create a robust, intelligent system is hard both in theory and practice

Wave 1

Wave 2

Wave 3

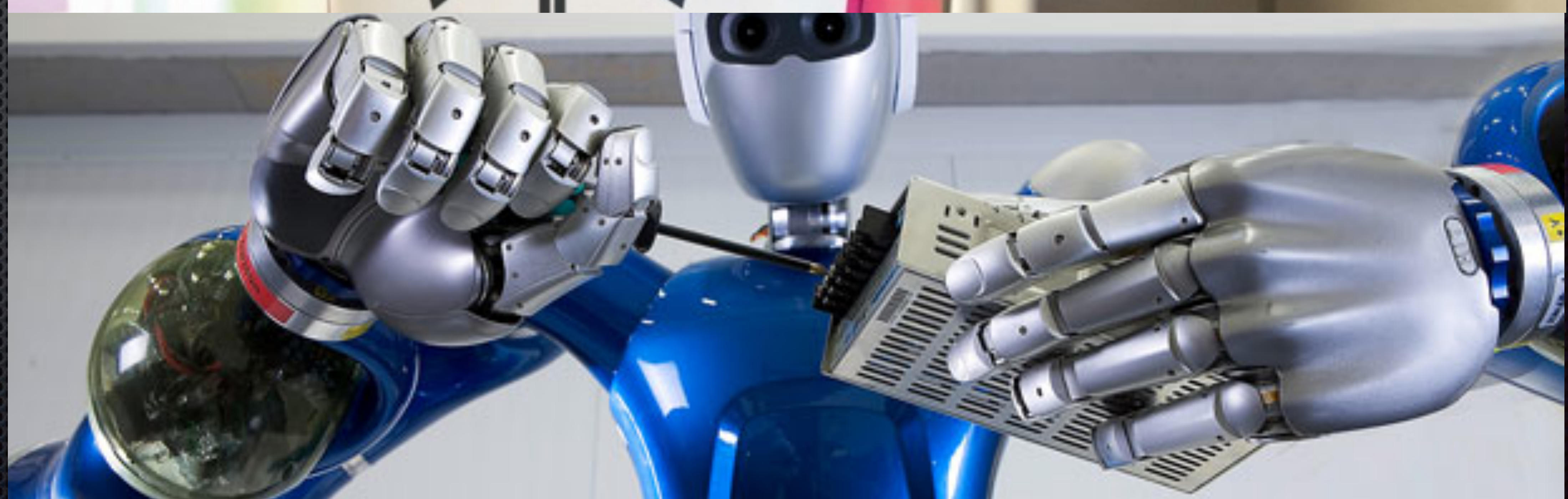


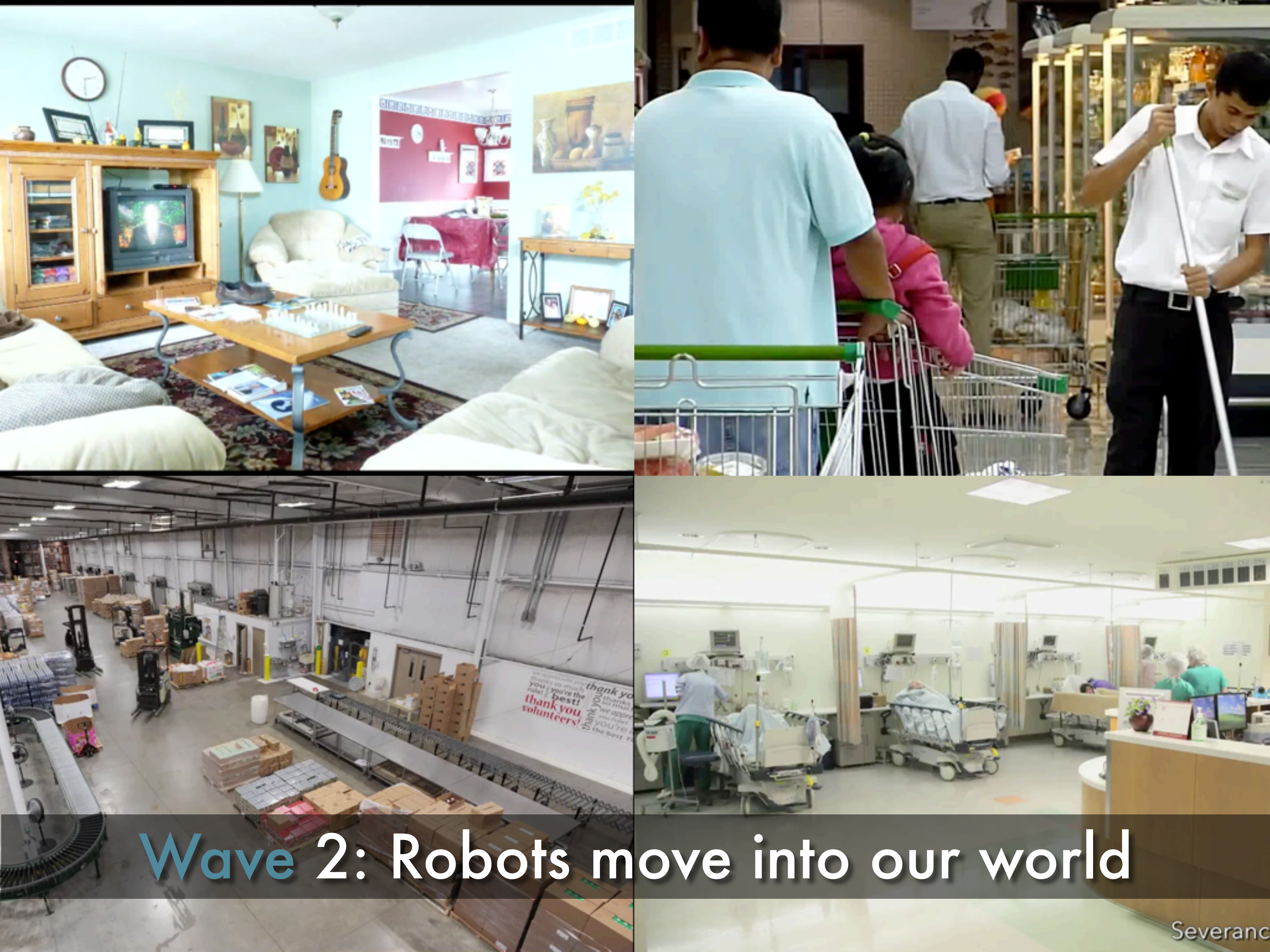
Wave 1: We build worlds for robots

Wave 1

Wave 2

Wave 3





Wave 2: Robots move into our world

Wave 1

Wave 2

Wave 3

FREQ.	PROCESSING	OUTPUT
Asynch.	World model, planning, sensor anchoring/symbol grounding	Behaviour or task plans, actions at locations
<5Hz	Discretisation of continuous state, topological localisation	Navigation between sequence of discrete locations, generates paths
~15Hz	State estimation, continuous localisation	Trajectory planning, robot velocities
>30Hz	Hardware interfaces, drivers	Velocity control to motor control

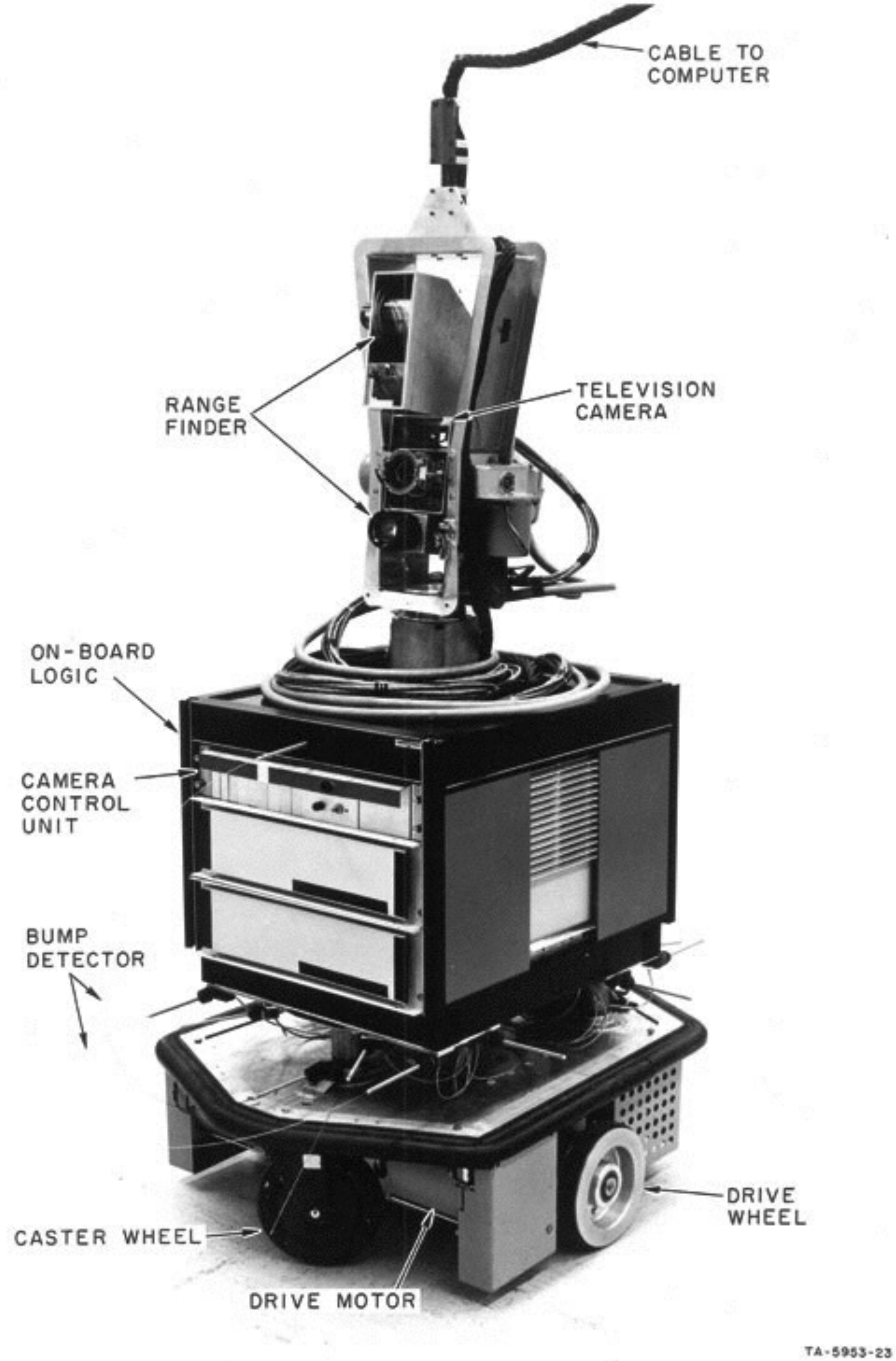
AUTONOMOUS MOBILE ROBOTS

Shakey

SRI International

1966 - 1972

- STRIPS
- A* search algorithm
- the Hough transform



Minerva and Rhino

CMU/Bonn

1995 - 1998?

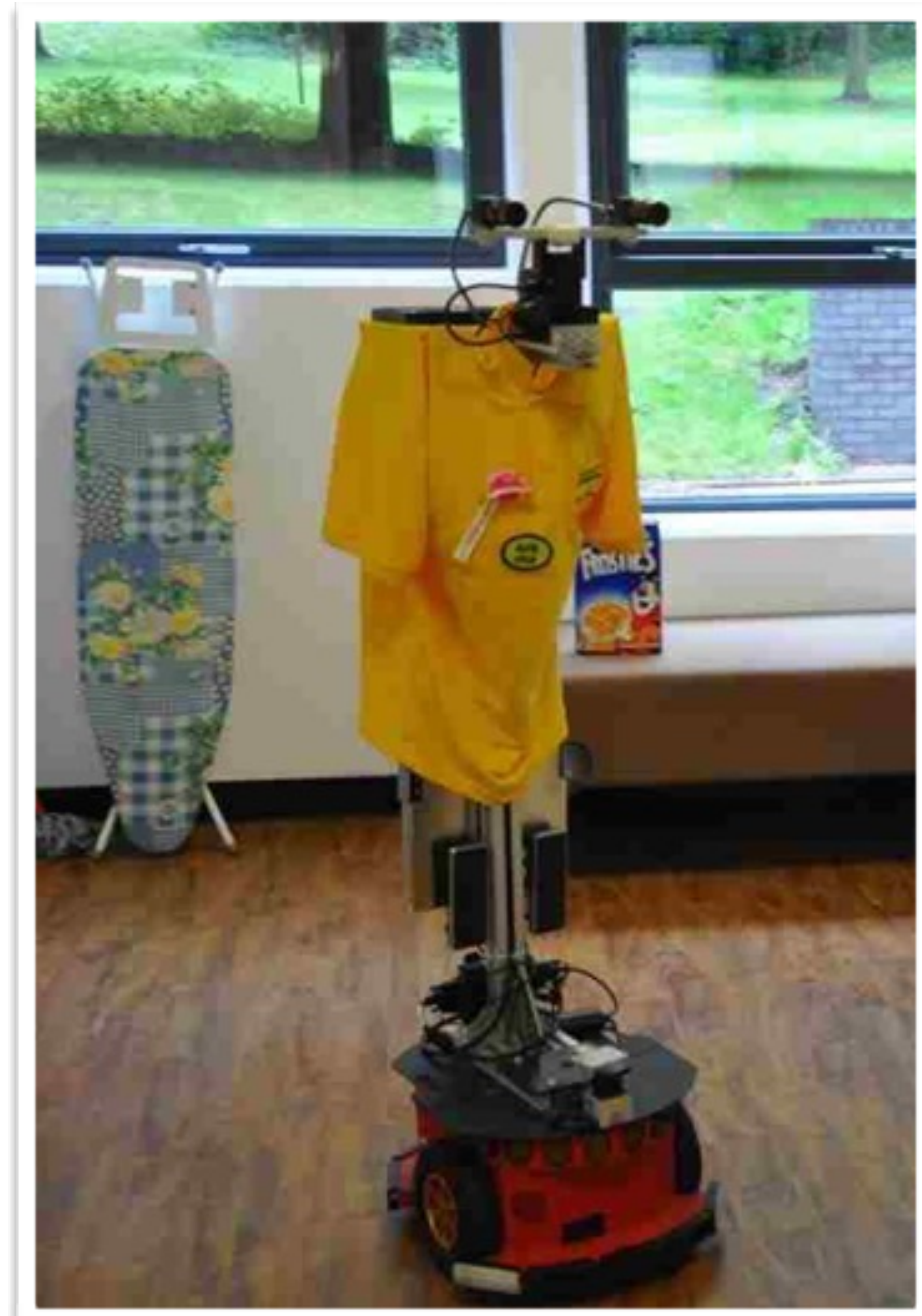
- Dynamic Window
- Topological Mapping
- Particle Filtering

Dora

EU CogX Project

2008 - 2012

- Conceptual Mapping
- Motivation System
- Knowledge Self-Extension

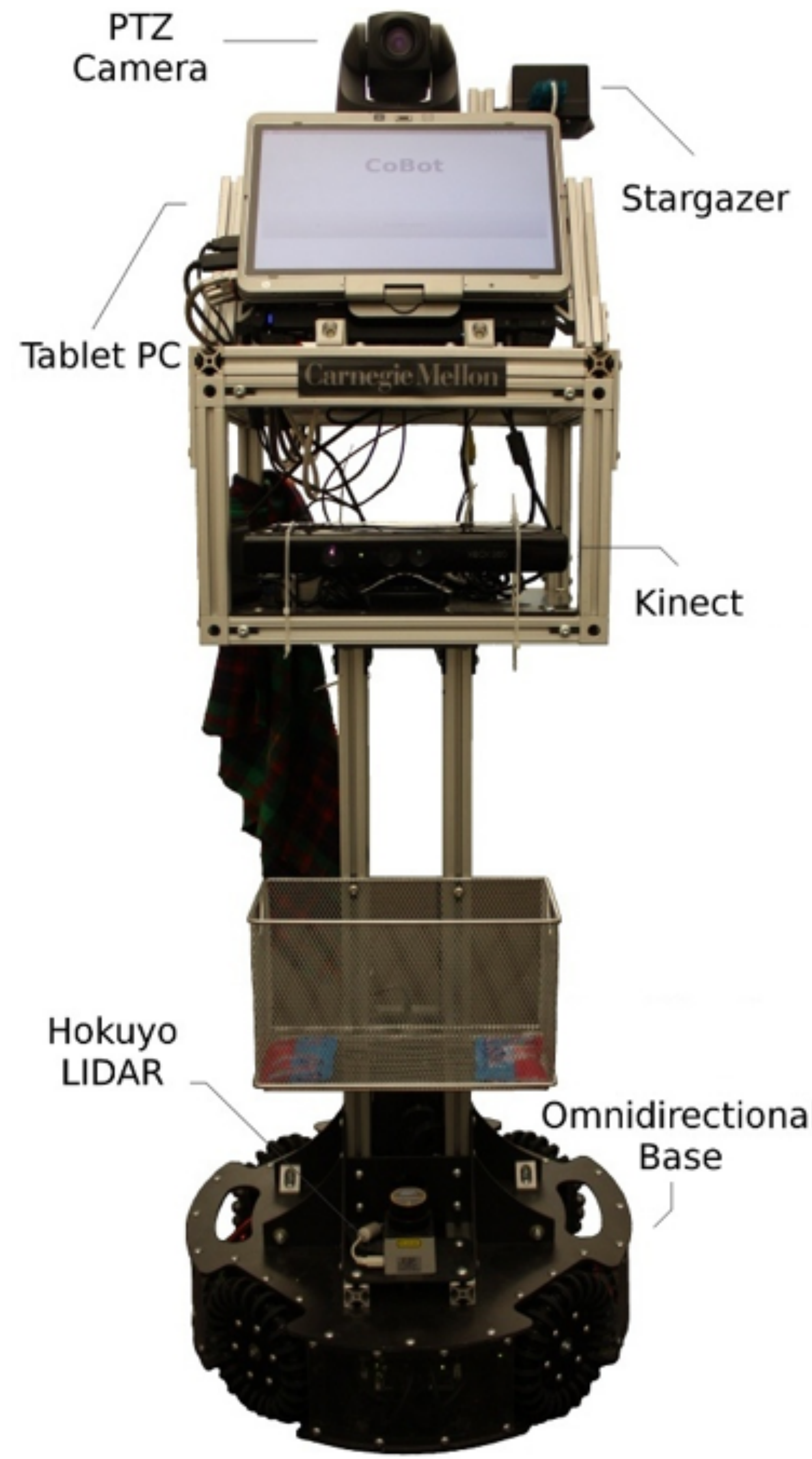


CoBot

CMU

2009 - present

- 1,000km of autonomous localization and navigation!
- Symbiotic autonomy
- Task scheduling



STRANDS Robots

EU STRANDS Project

2013 - present

- Aiming for 120 days autonomy in *real-world environments*
- Qualitative representations
- Modelling temporal dynamics

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STRUCTURE

- Autonomous Mobile Robots
- **Knowledge of Space**
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What is the problem? Giving robots an understanding of space

KNOWLEDGE OF SPACE

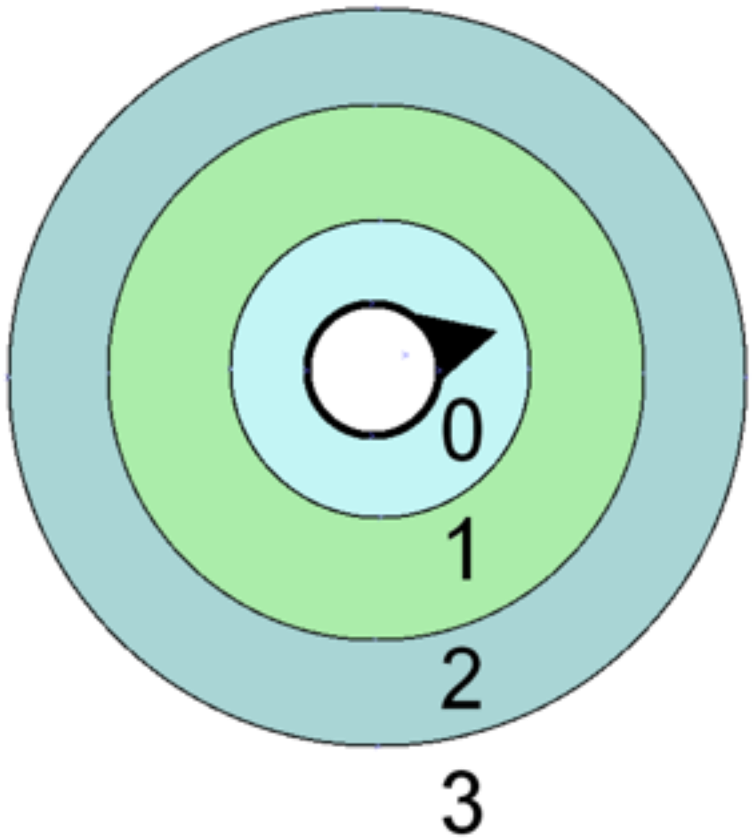
Why is it hard? Finding the right abstraction for the right problem, avoid complexity yet providing reasoning power

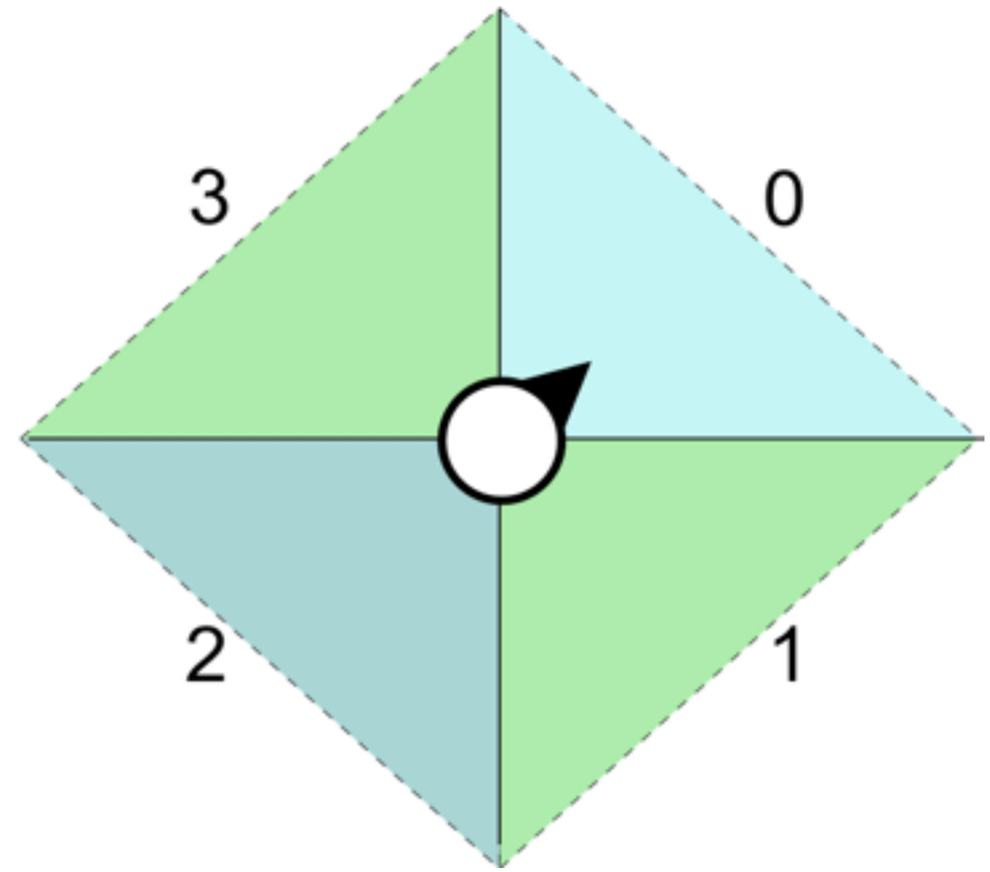
Qualitative representations of **space** and **time**

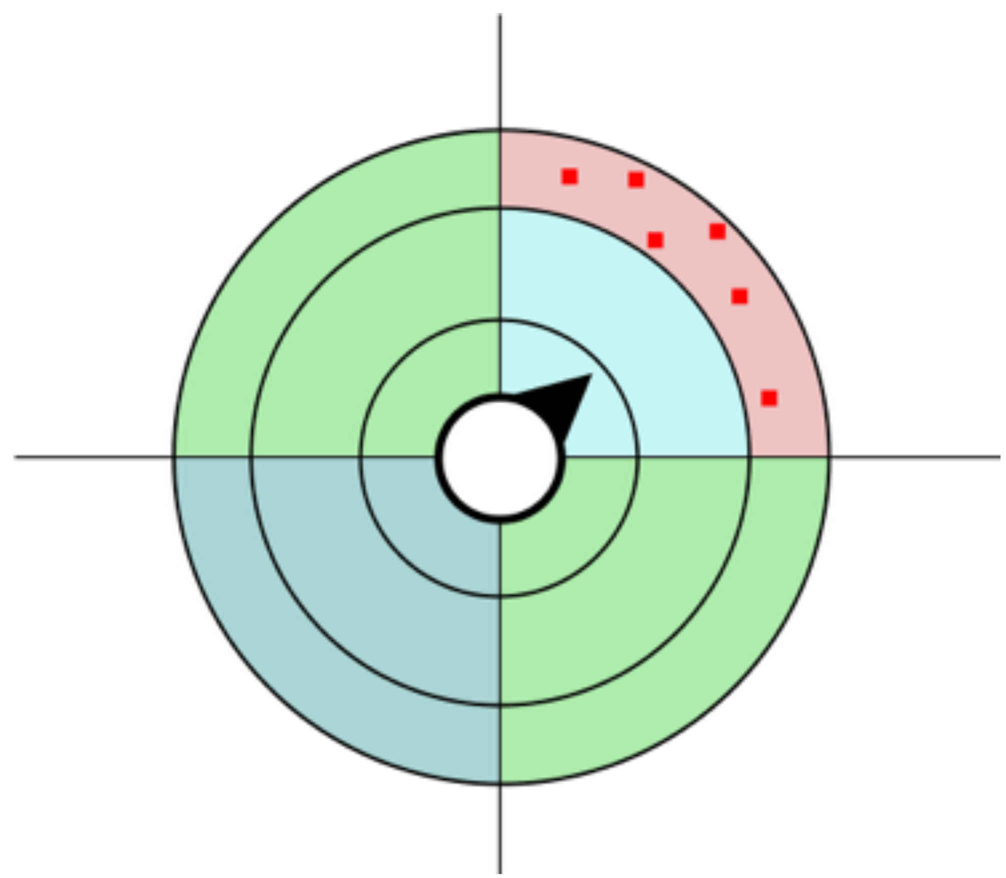
Compress/abstract multiple **quantitative states** into a single **qualitative state**

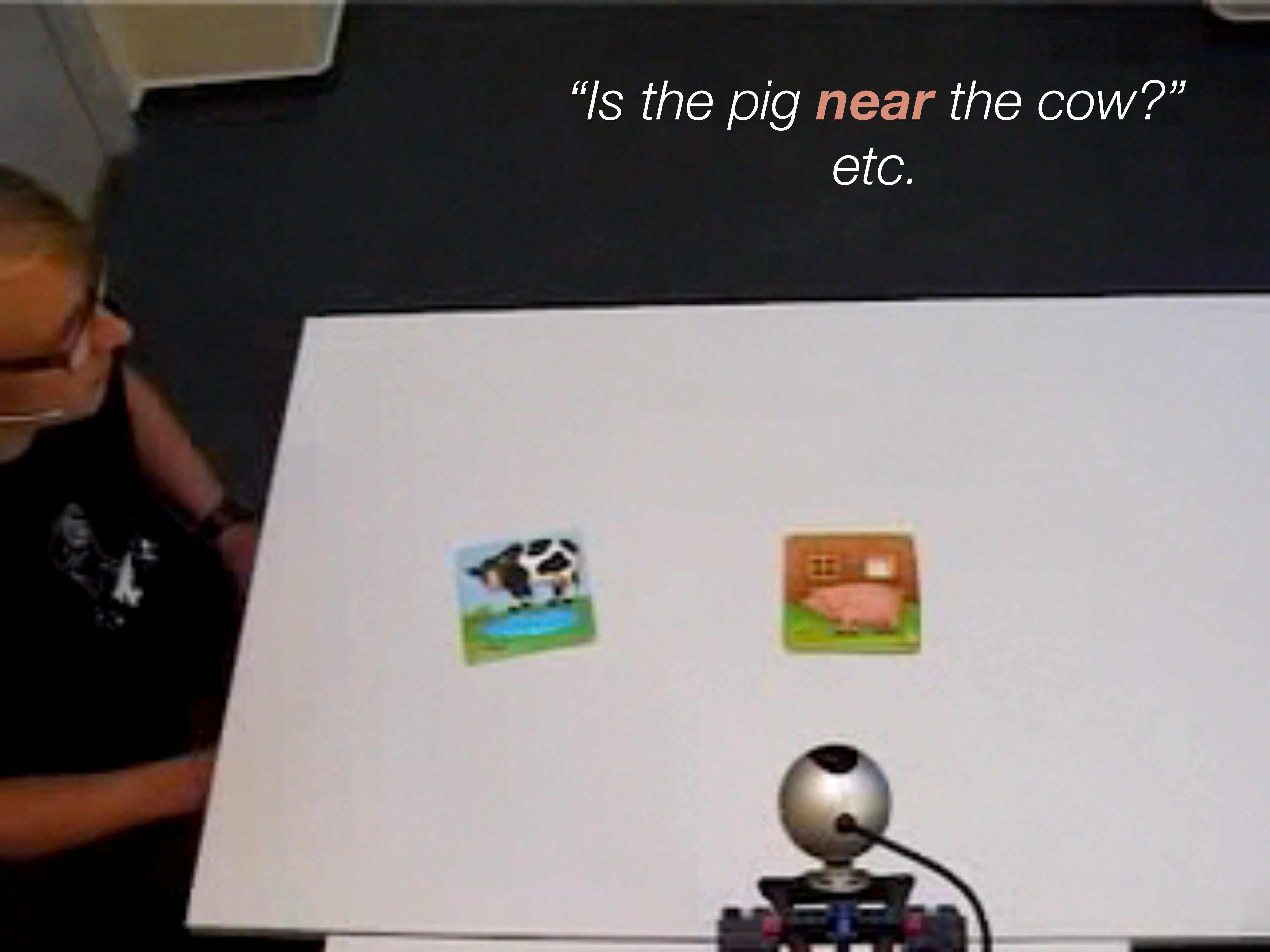
Often used to capture the **inherent** or **assumed structure** in a **spatial** or **temporal domain**

Representations are often **relational**, providing **relative** rather than **absolute** information

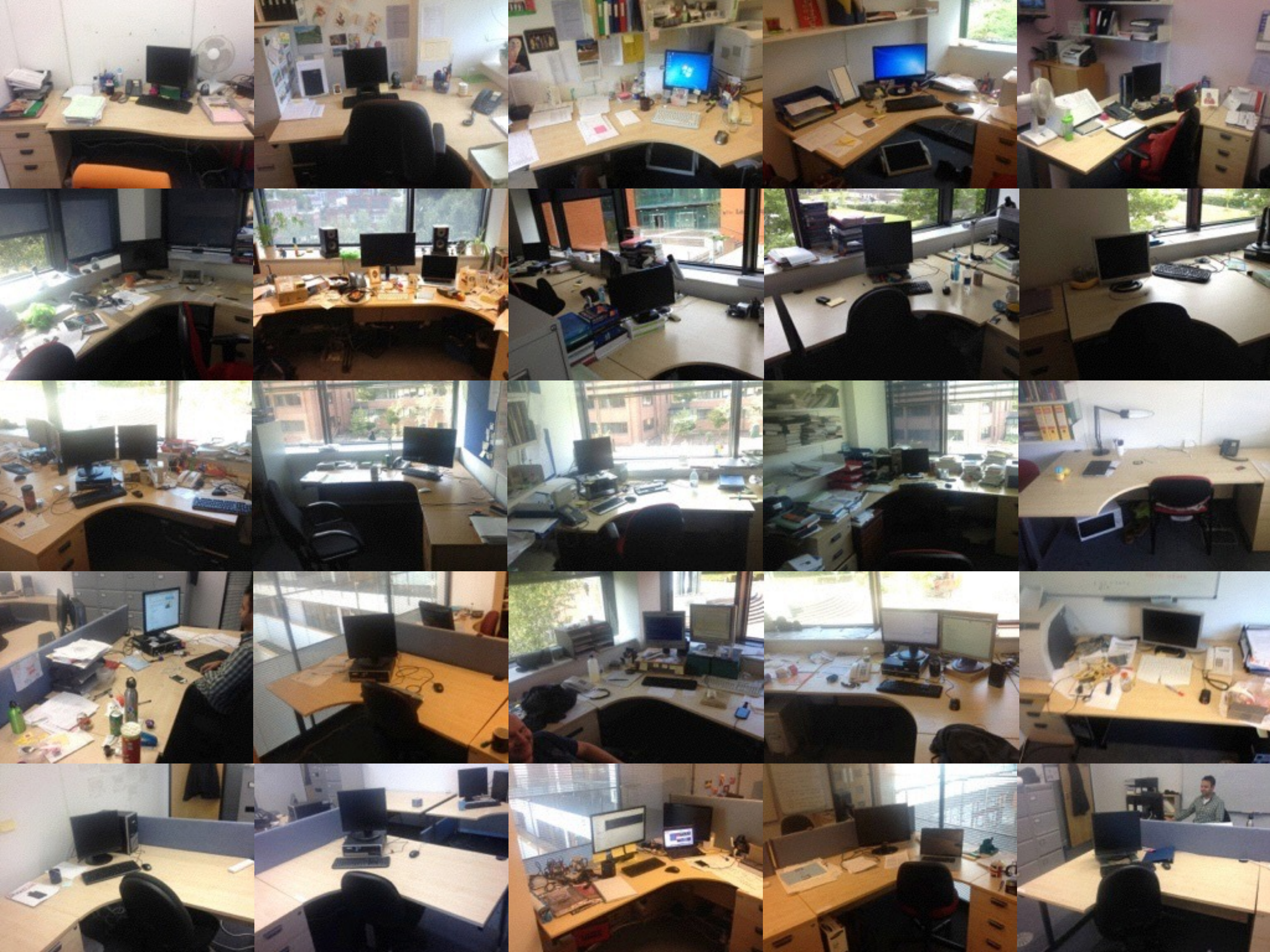

0
1
2
3


3
0
2
1

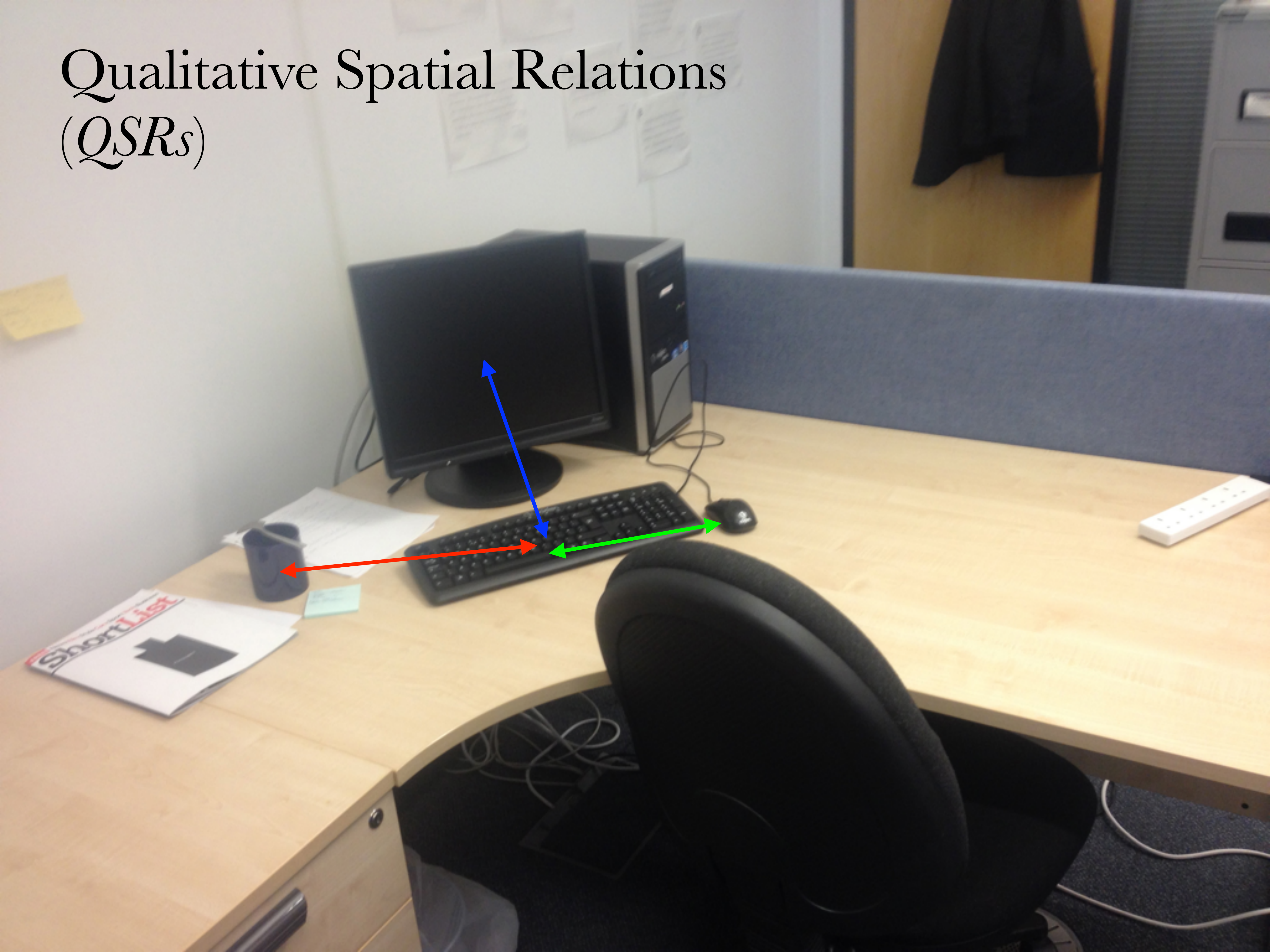


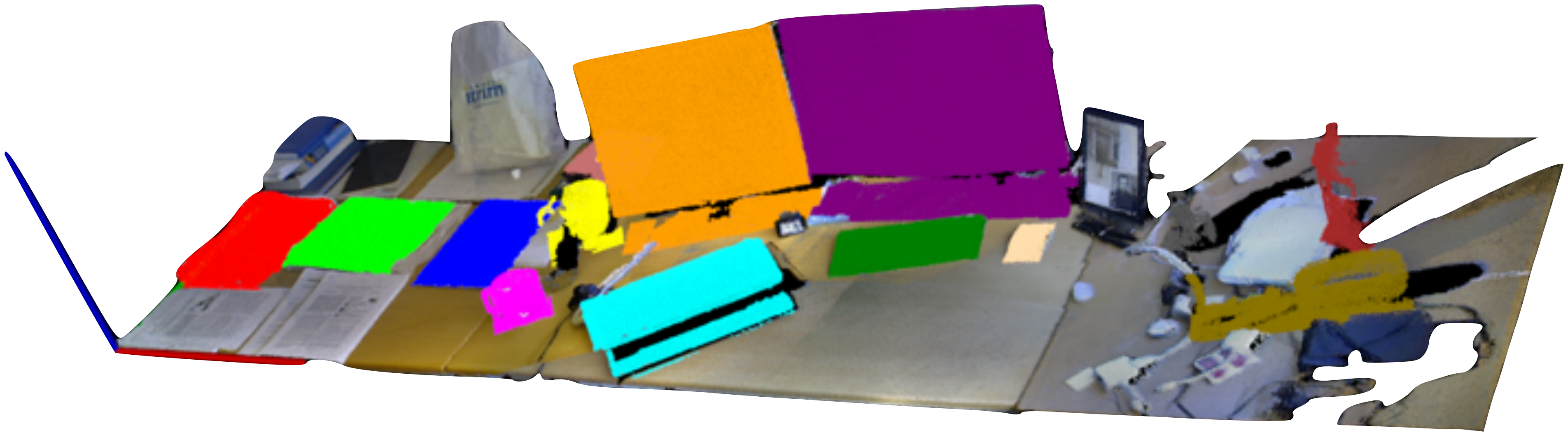

“Is the pig **near** the cow?”
etc.


“Put the blue box ***to the right of*** *the red box”*

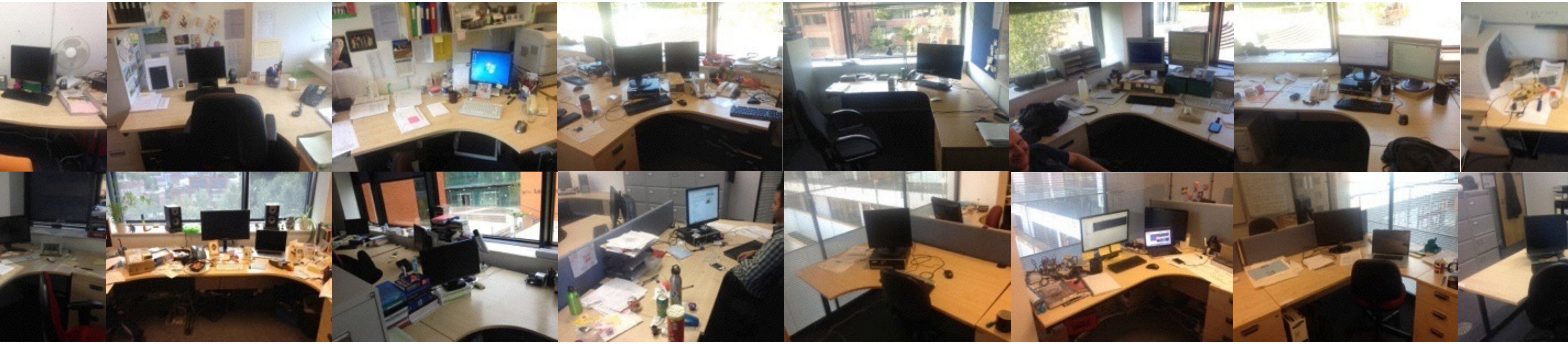


Qualitative Spatial Relations (*QSRs*)



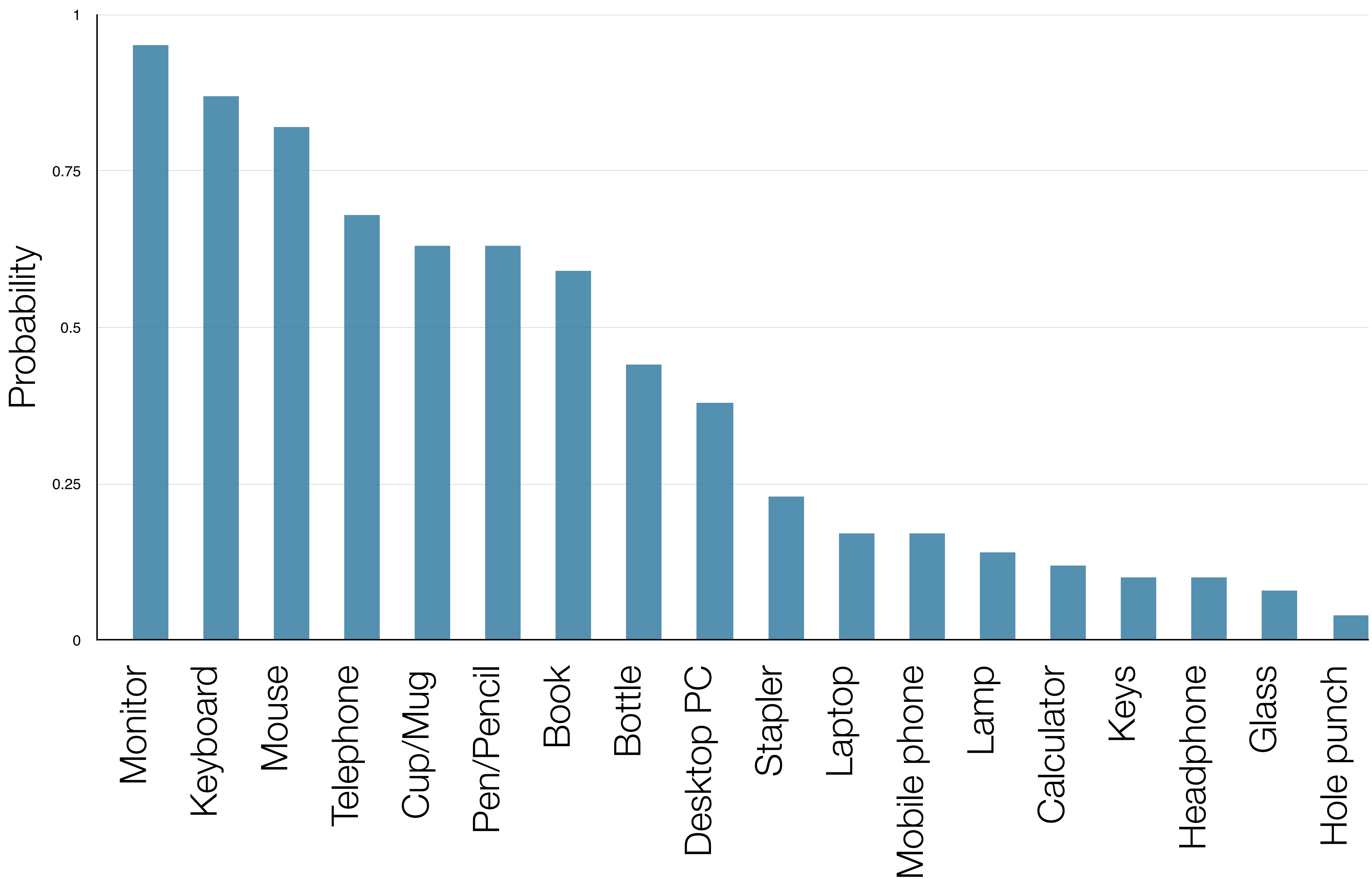


Akshaya Thippur et al. *KTH-3D-TOTAL: A 3D Dataset for Discovering Spatial Structures for Long-Term Autonomous Learning*. In SAIS'14.



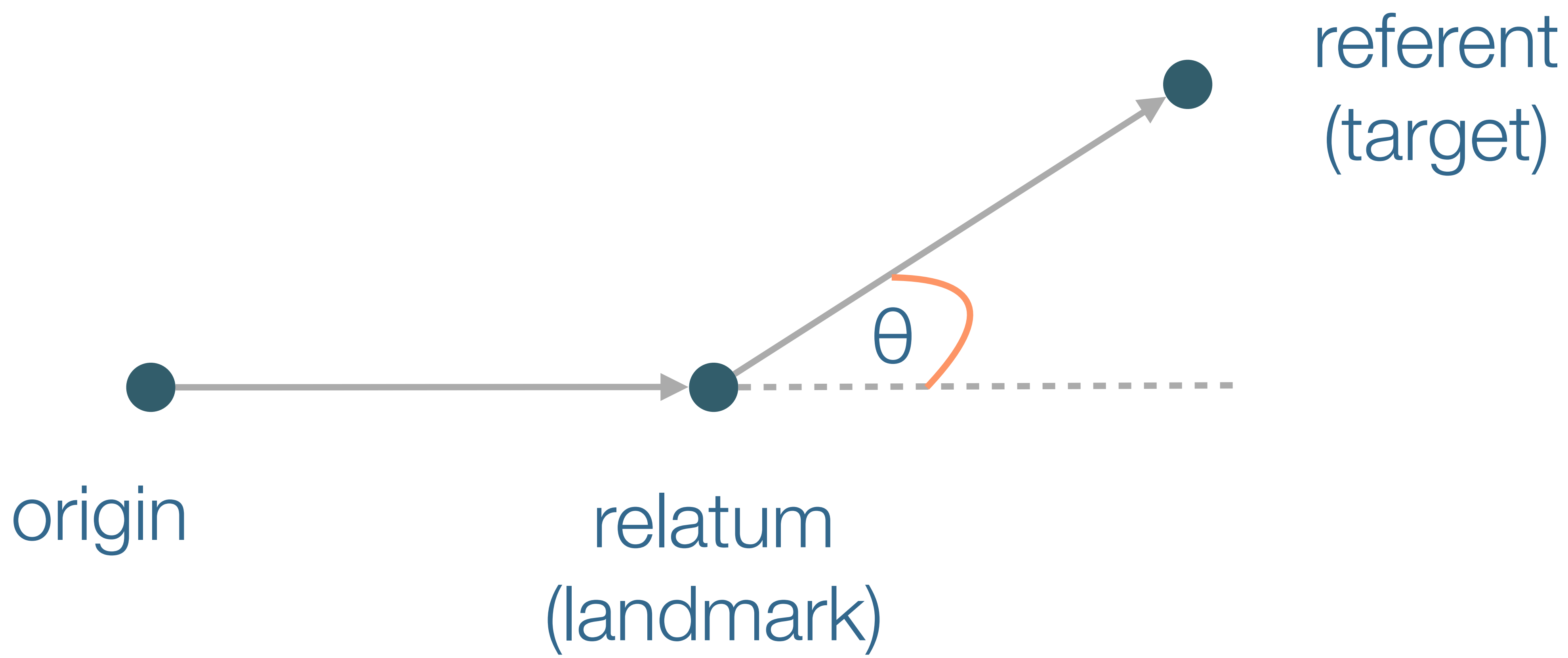
Lars et al. *Bootstrapping probabilistic models of qualitative spatial relations for active visual object search*. In AAAI SS 2014 on Qualitative Representations for Robots

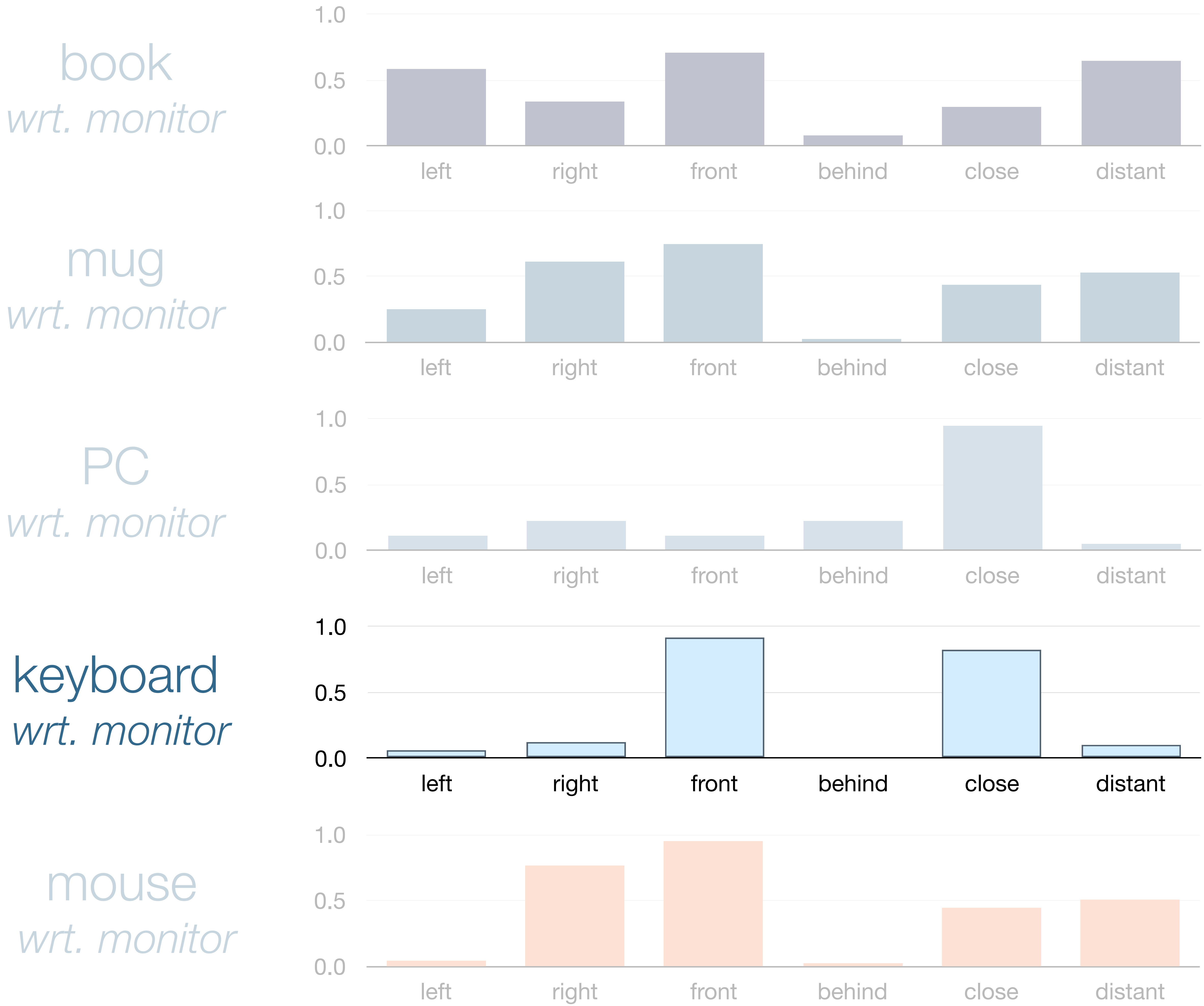
Object Presence Probability



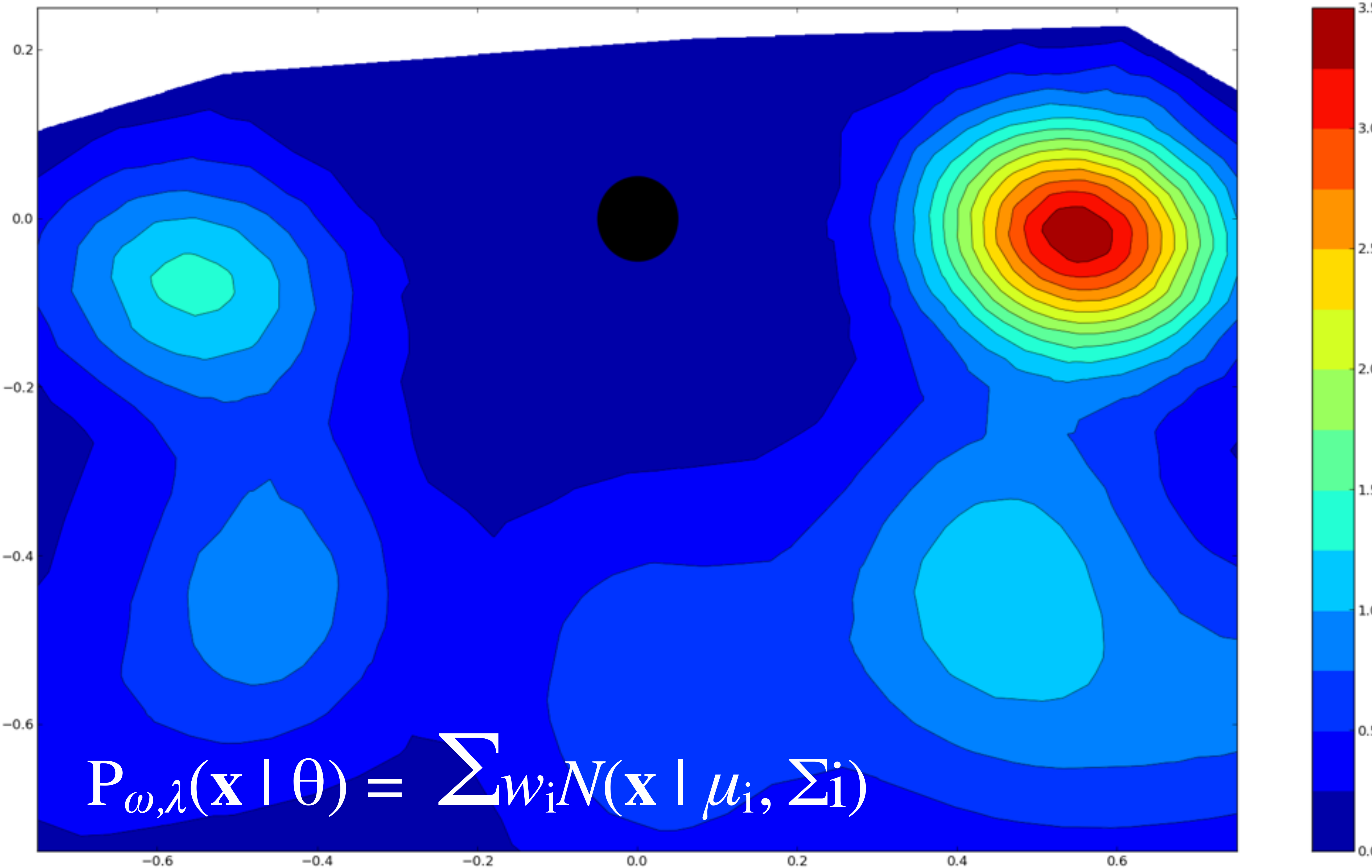
Ternary Point Calculus

Moratz, Nebel, and Freksa, *Qualitative spatial reasoning about relative position. Spatial Cognition III*, 2003.



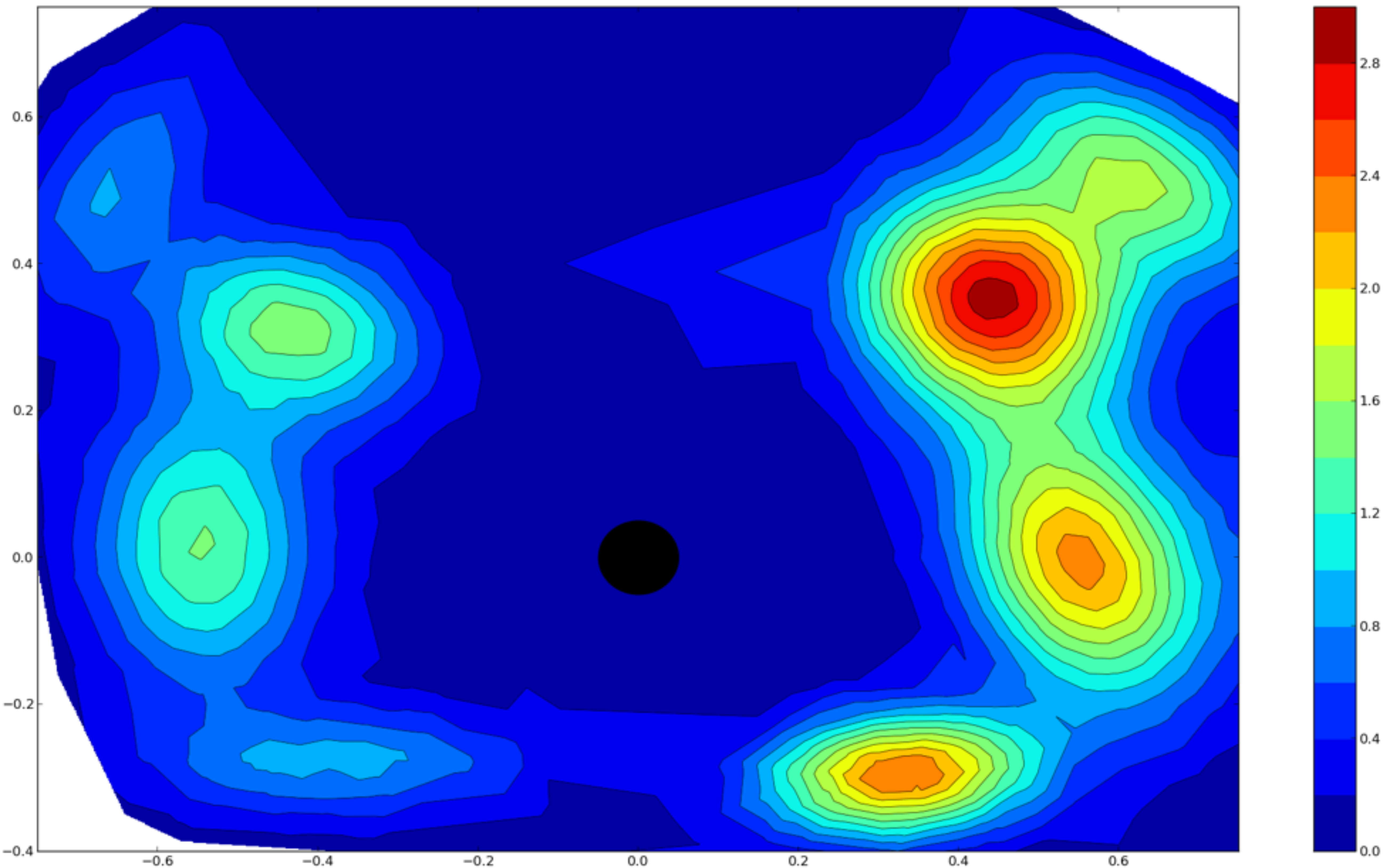

book
wrt. monitor
mug
wrt. monitor
PC
wrt. monitor
keyboard
wrt. monitor
mouse
wrt. monitor
1.0
0.5
0.0
left
right
front
behind
close
distant

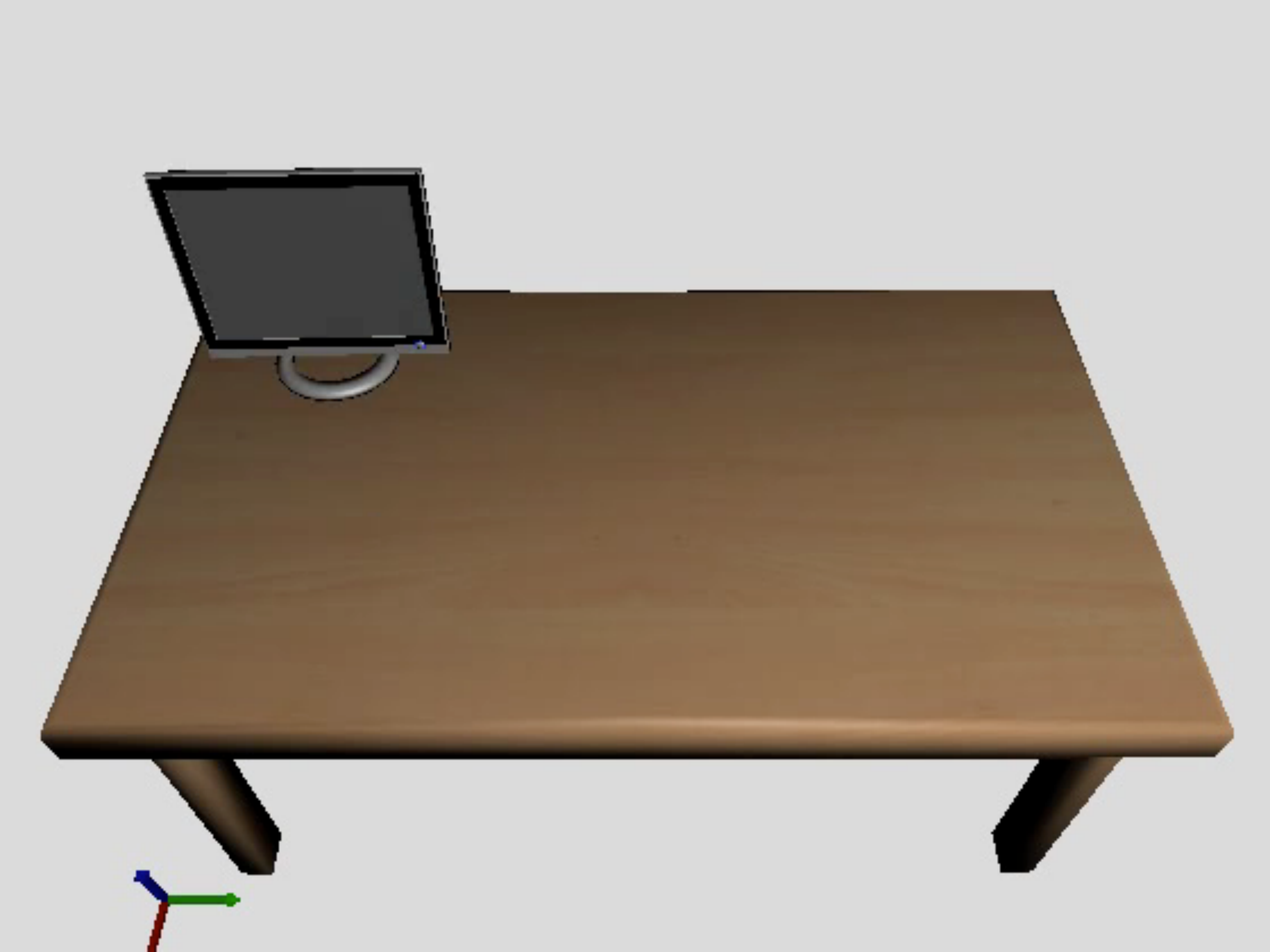
Position of cup relative to monitor



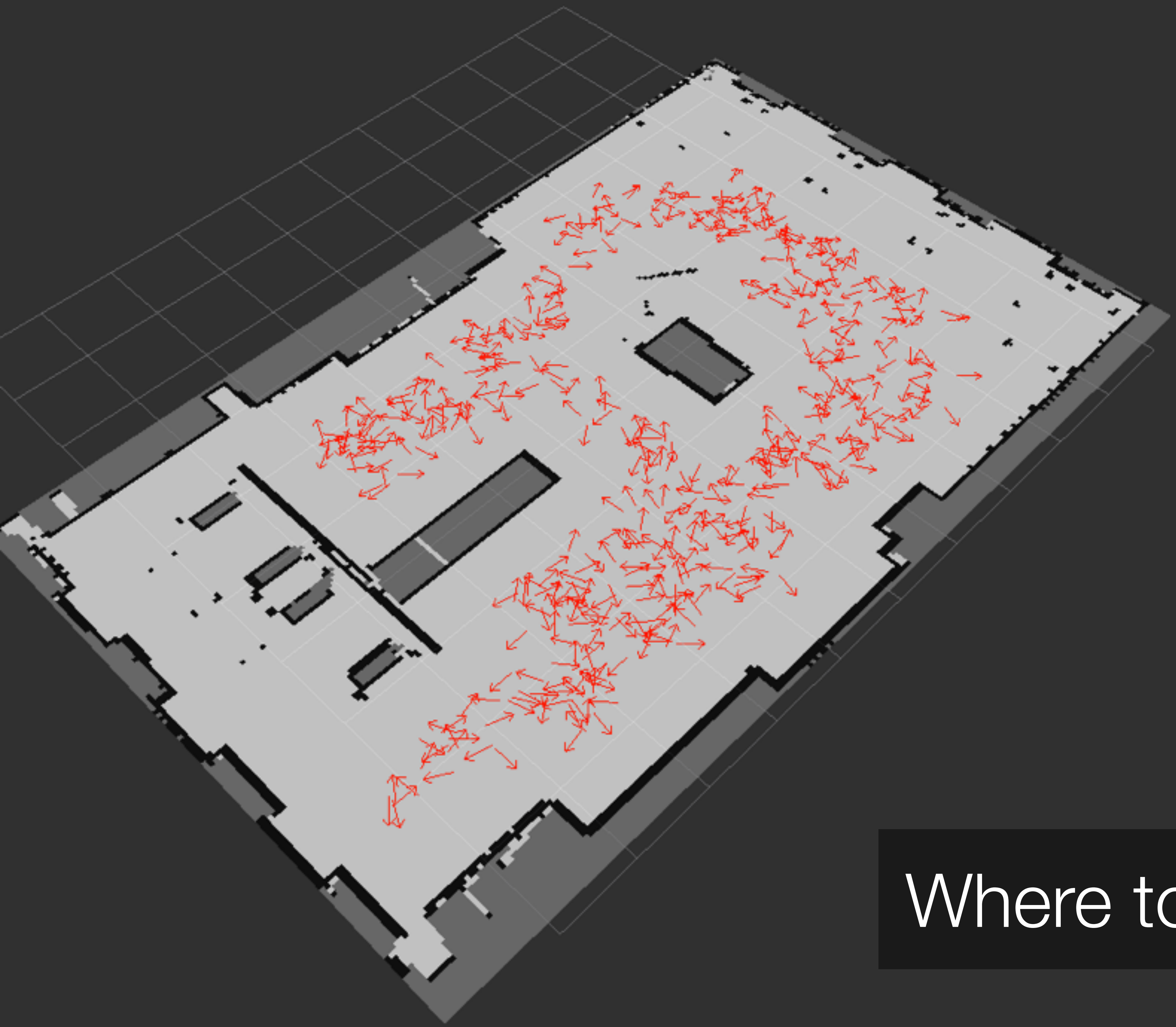
$$P_{\omega,\lambda}(\mathbf{x} \mid \theta) = \sum w_i N(\mathbf{x} \mid \mu_i, \Sigma i)$$

Position of cup relative to keyboard

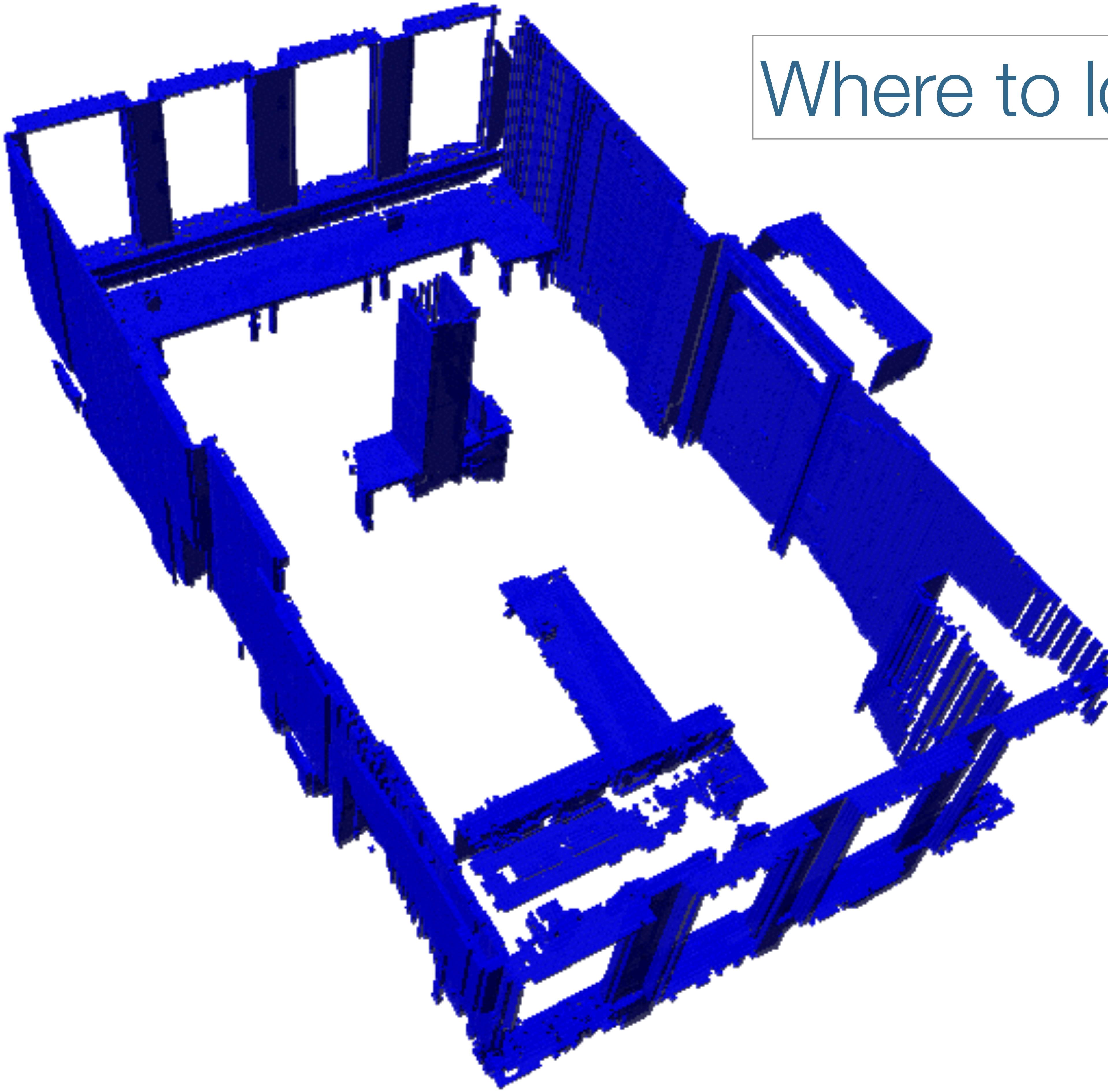





Where should a robot look for objects?

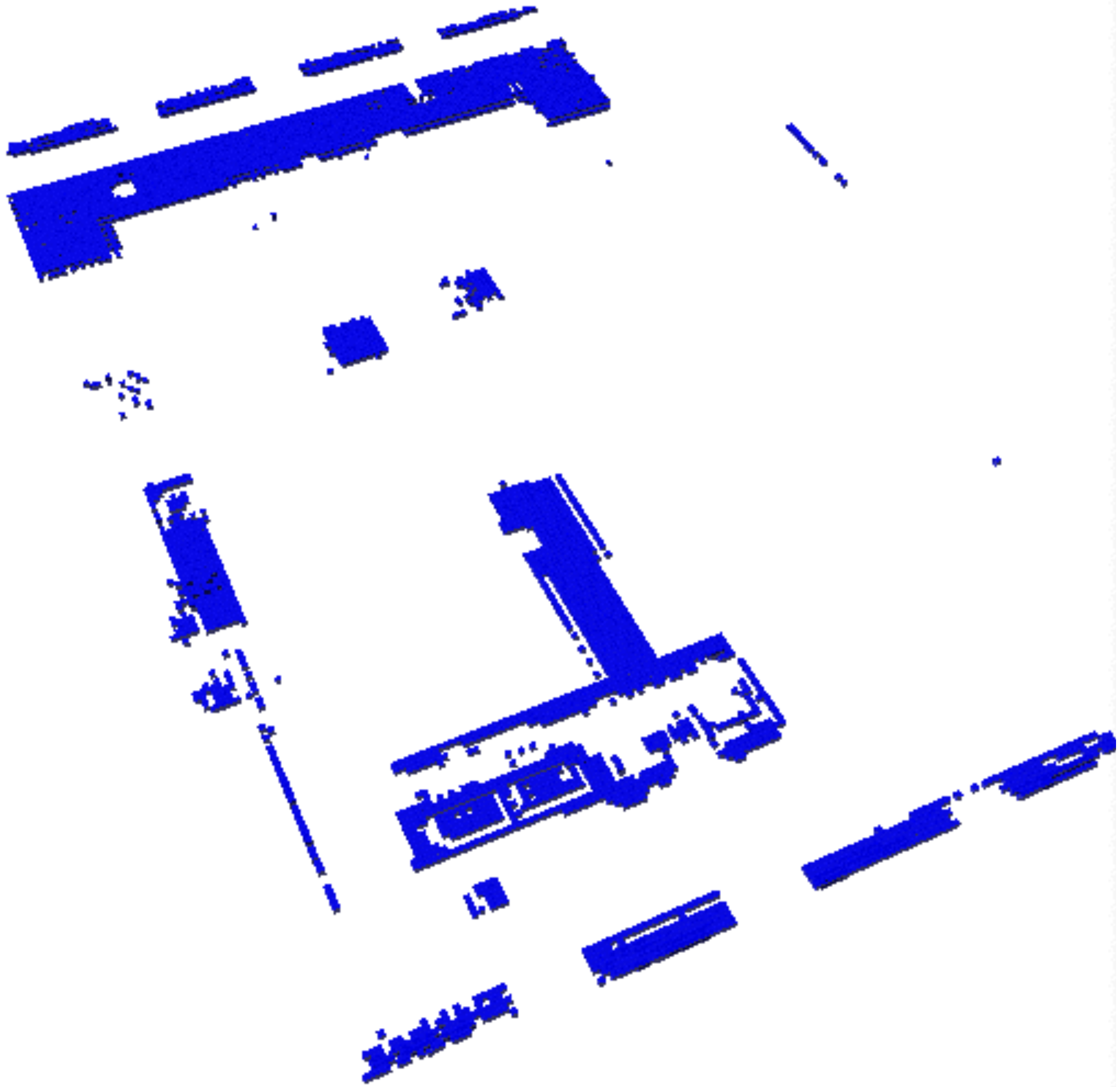


Where to stand?

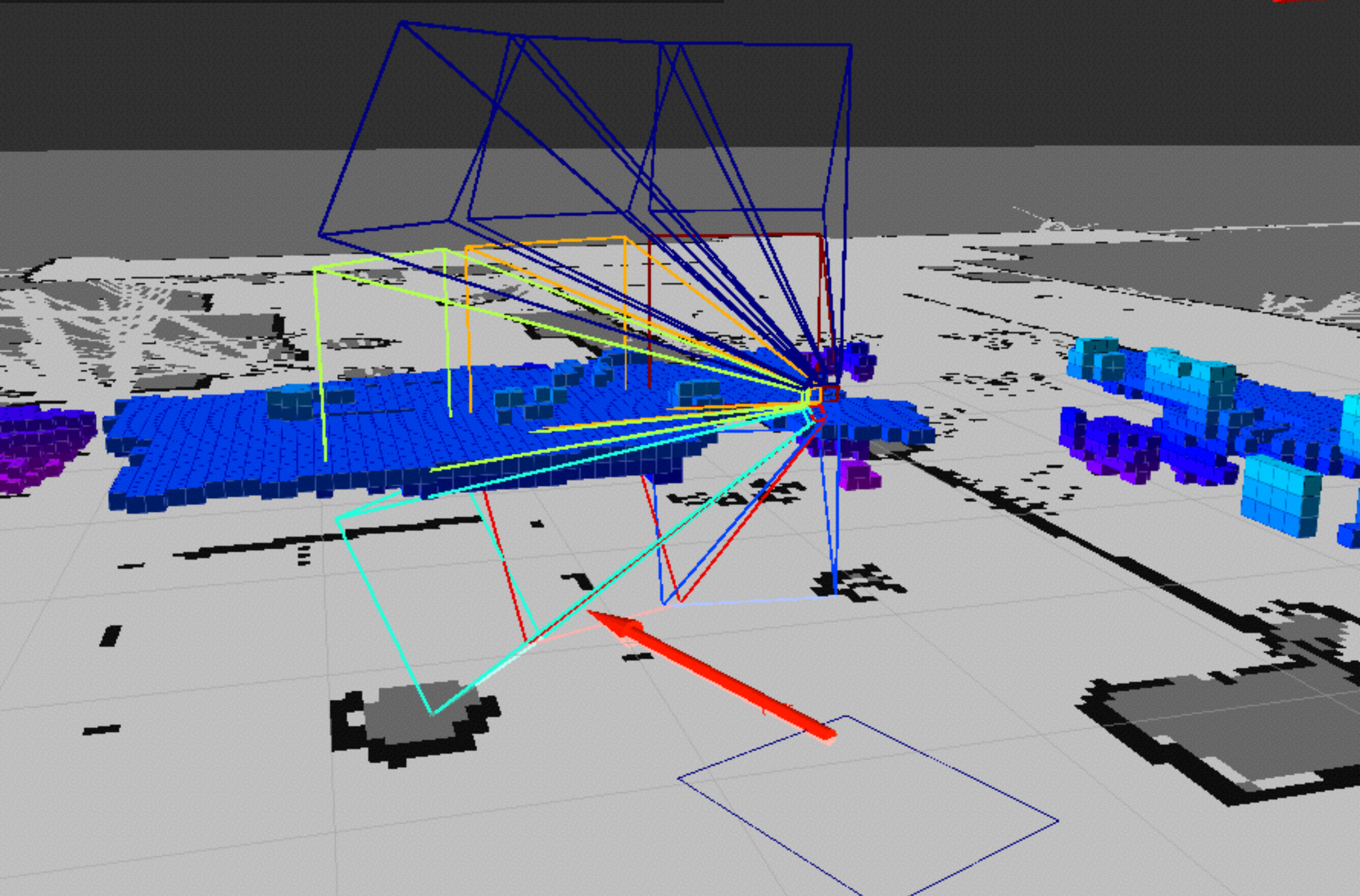


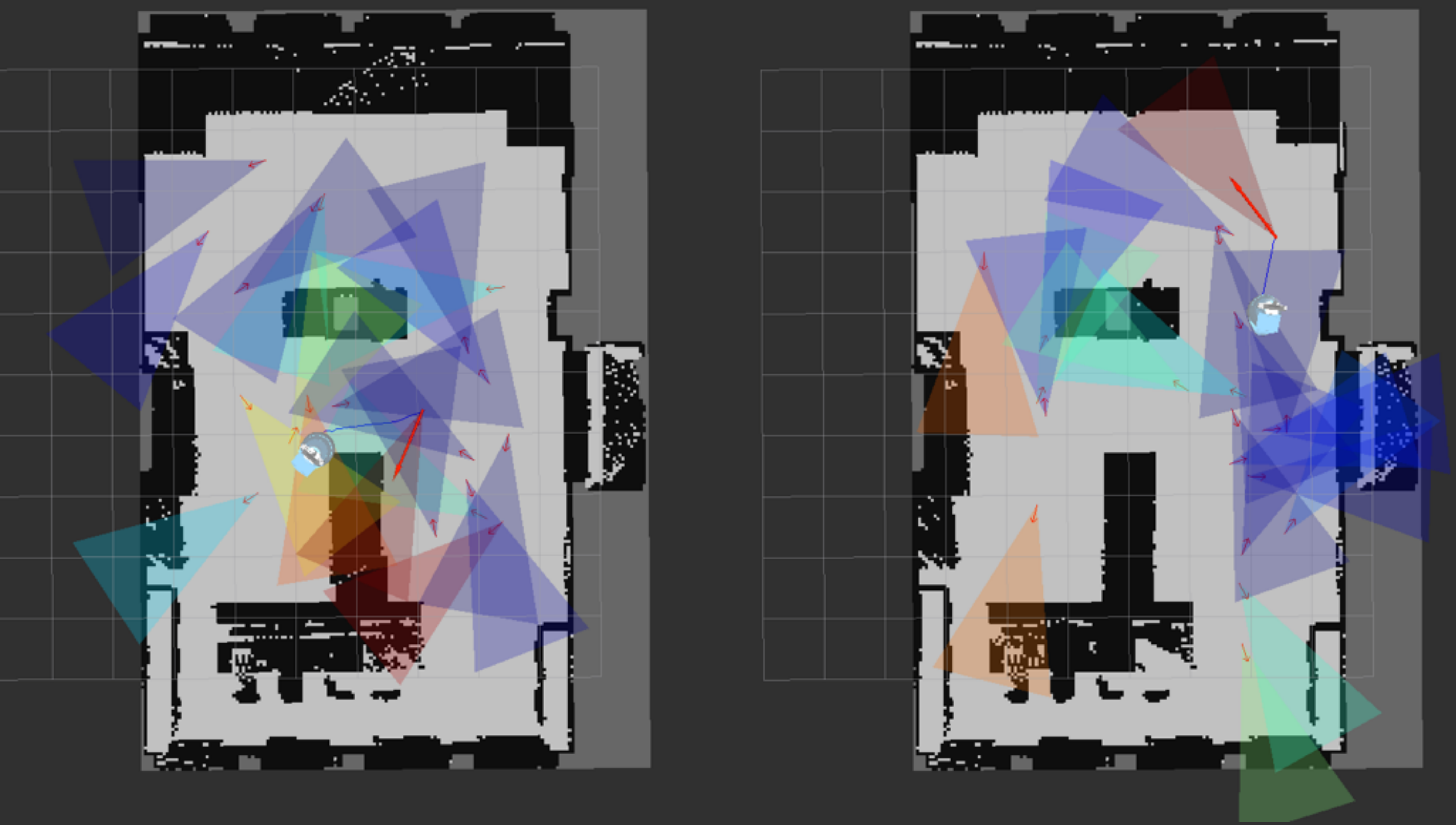
Where to look?

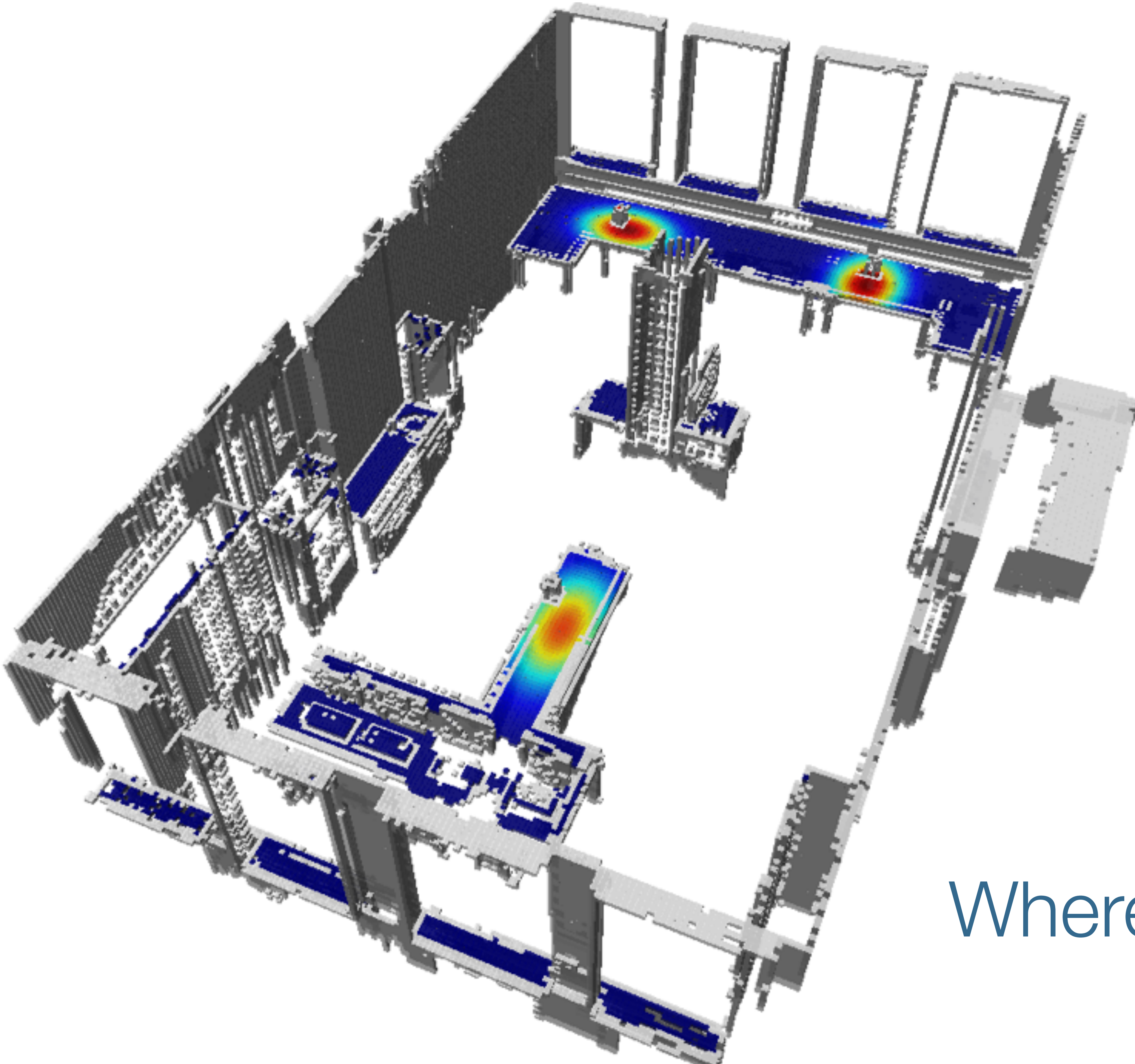
Where to look?

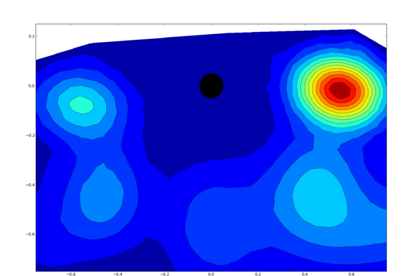


What am I likely to see?



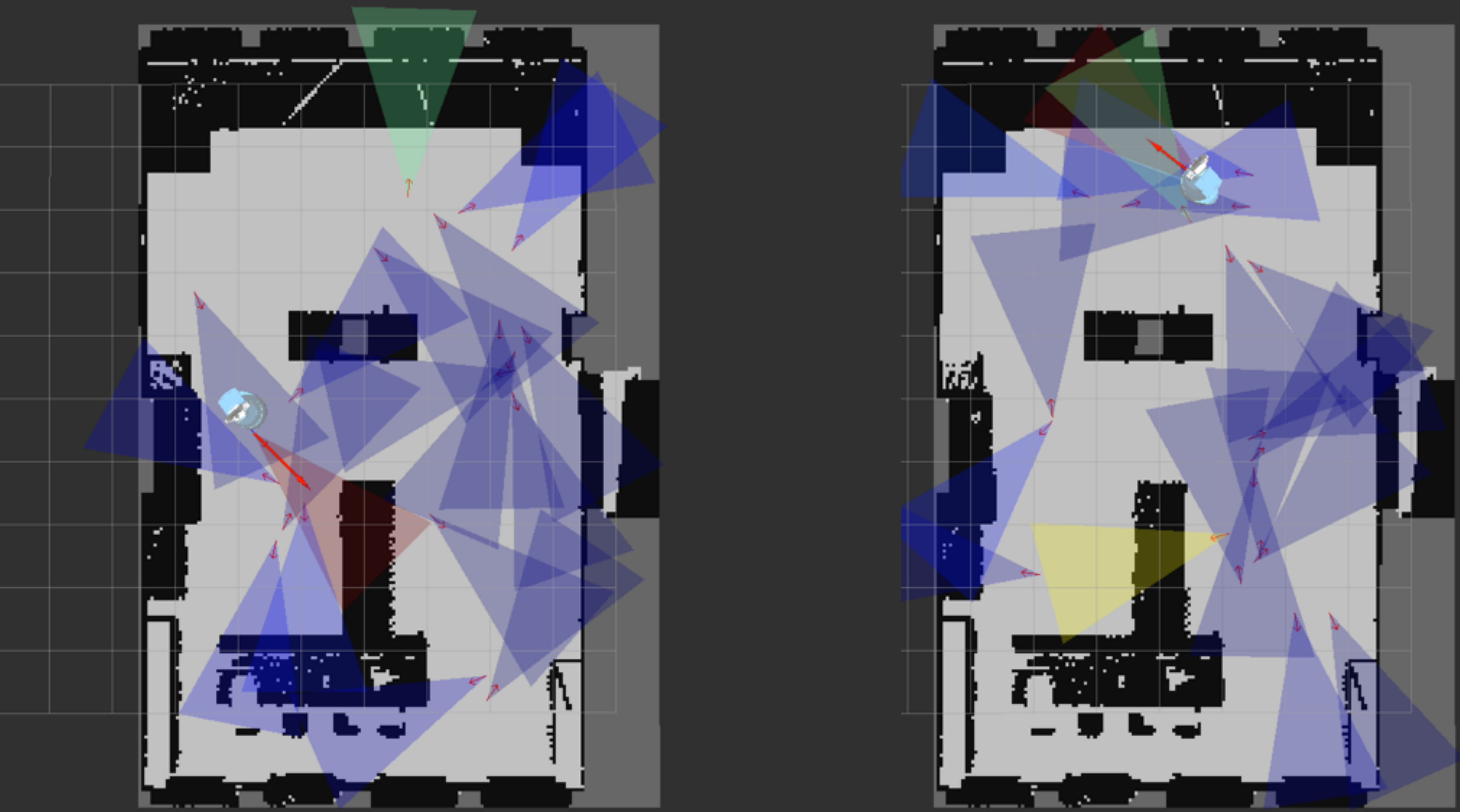


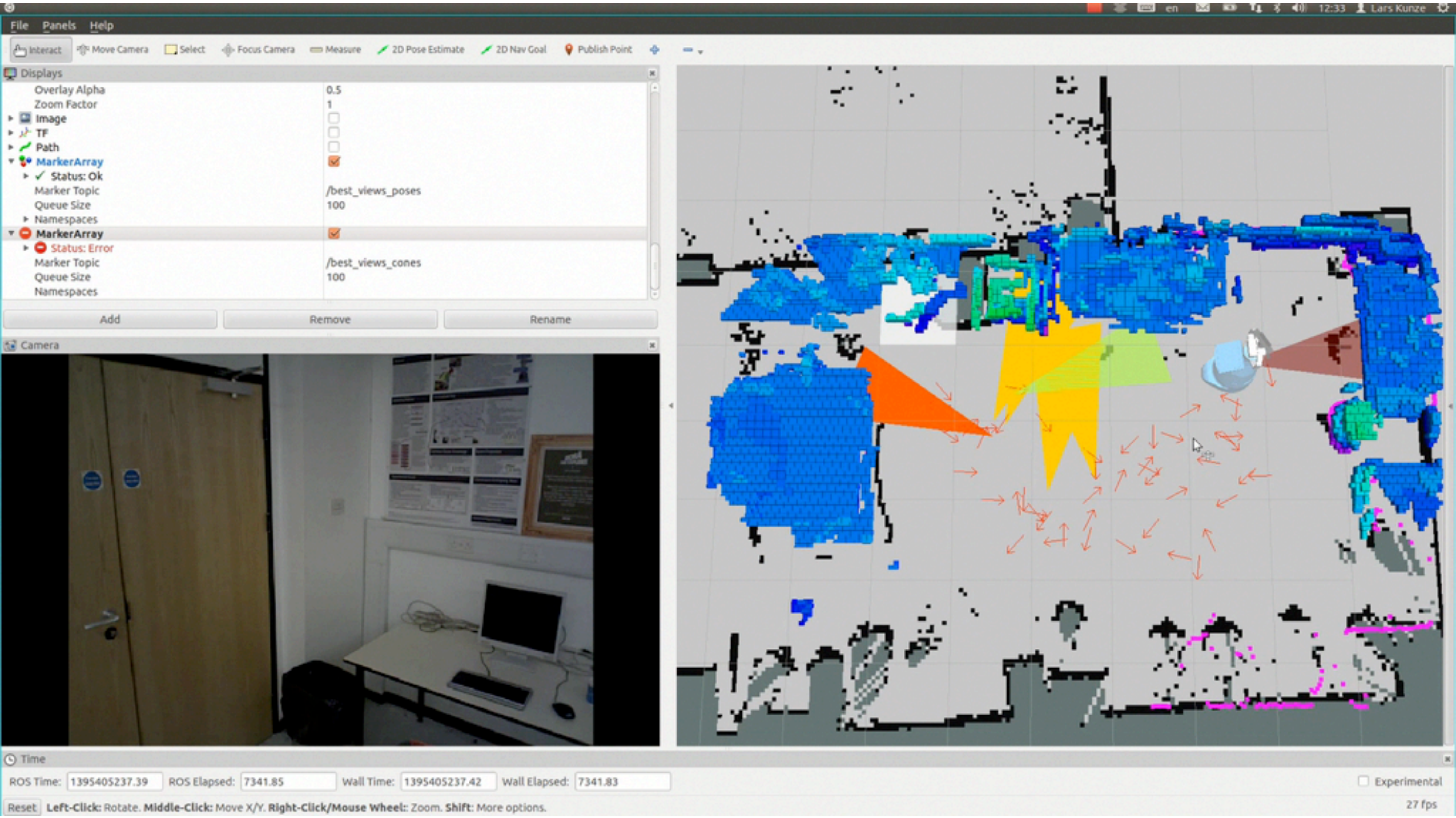




Where to look?

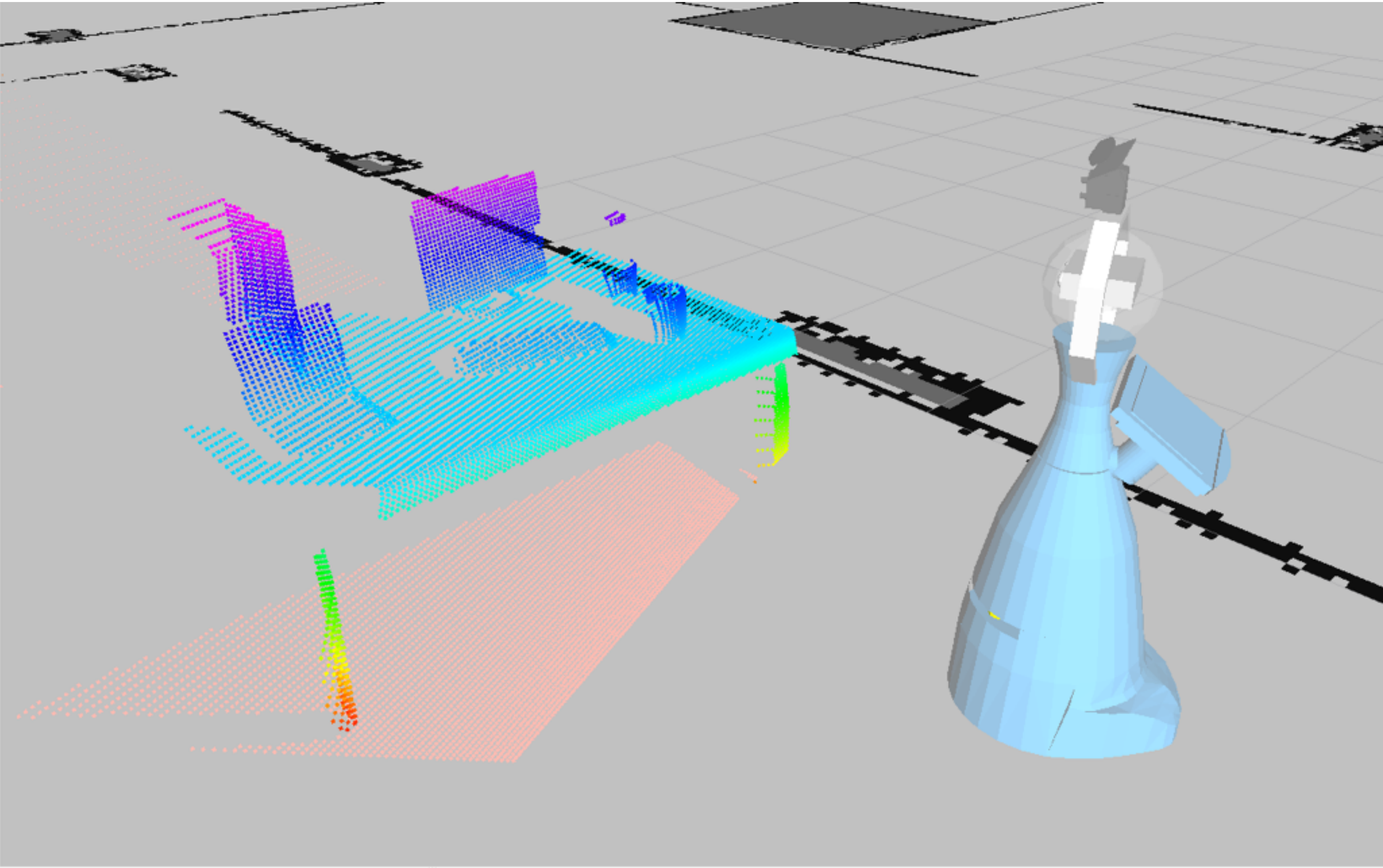
$$\operatorname{argmax} \sum P_{QSR}(v_i \mid \omega, \Lambda)\, In(v_i, Viewcone(\psi))$$

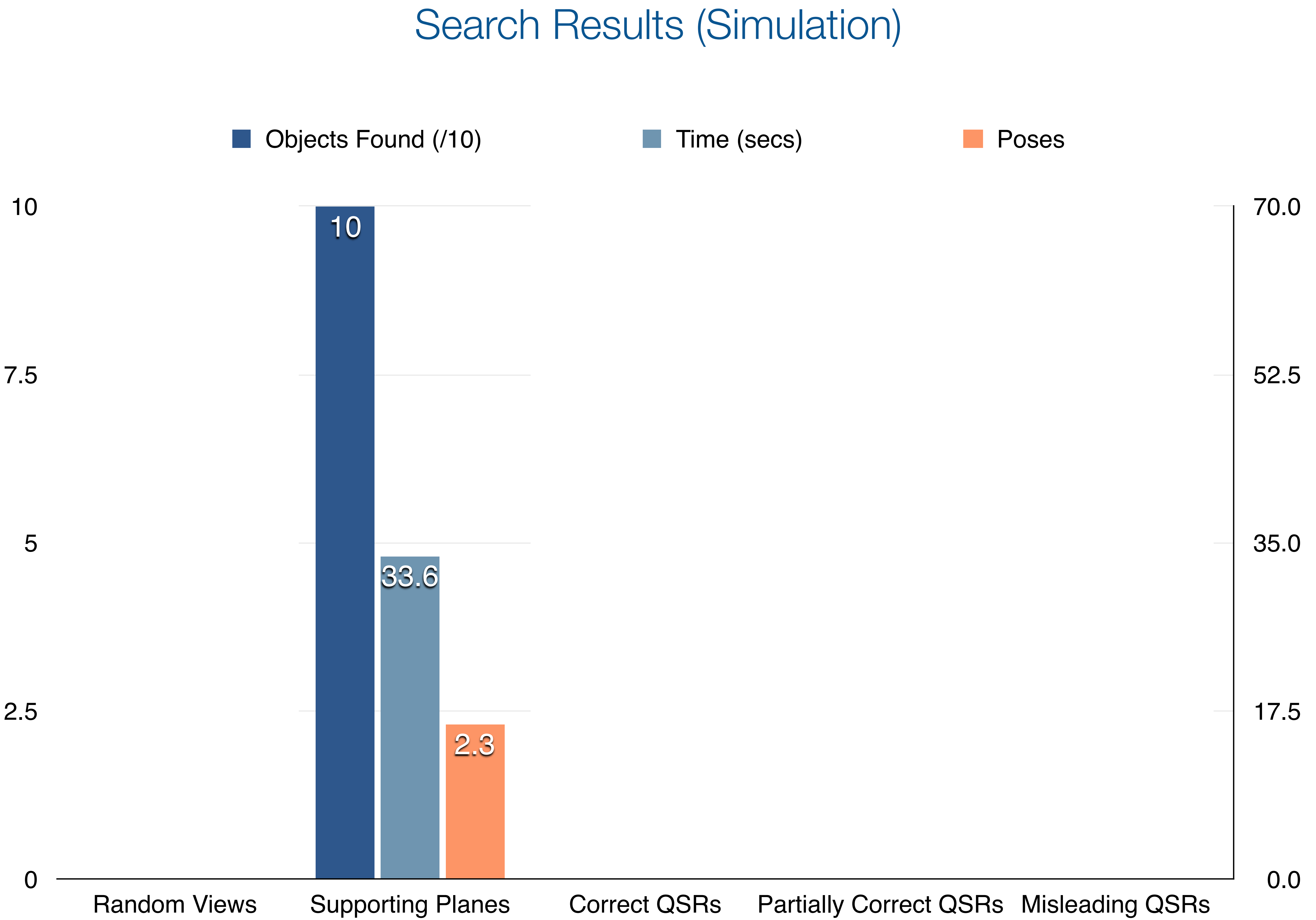


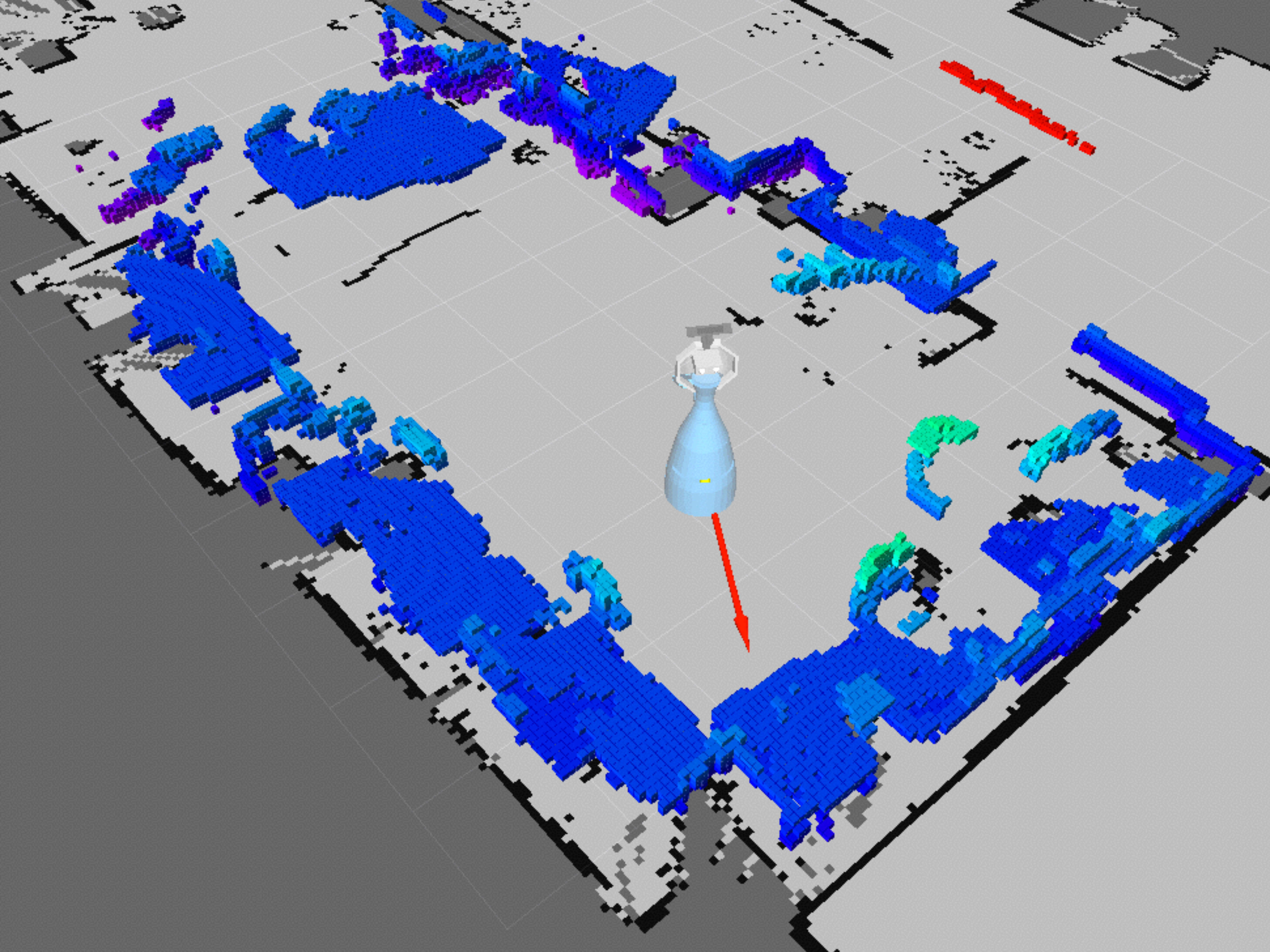

File
Panels
Help
Interact
Move Camera
Select
Focus Camera
Measure
2D Pose Estimate
2D Nav Goal
Publish Point
en
12:33
Lars Kunze
Displays
Overlay Alpha
0.5
Zoom Factor
1
Image
TF
Path
MarkerArray
Status: Ok
Marker Topic
/best_views_poses
Queue Size
100
Namespaces
MarkerArray
Status: Error
Marker Topic
/best_views_cones
Queue Size
100
Namespaces
Add
Remove
Rename
Camera
Time
ROS Time:
1395405237.39
ROS Elapsed:
7341.85
Wall Time:
1395405237.42
Wall Elapsed:
7341.83
Experimental
Reset
Left-Click: Rotate. Middle-Click: Move X/Y. Right-Click/Mouse Wheel:: Zoom. Shift: More options.
27 fps

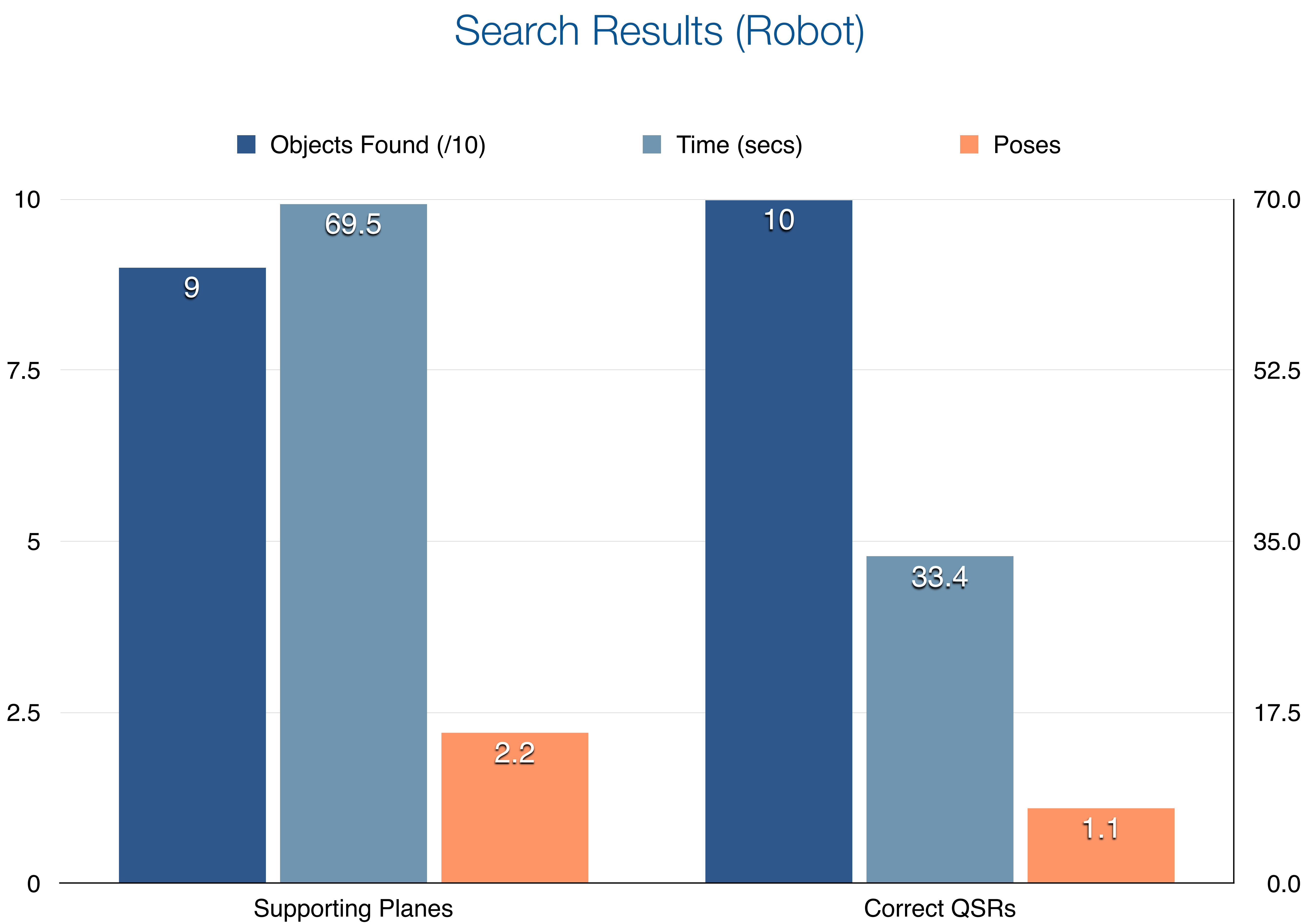
Supporting planes vs QSRs
10 trials
3 out of 8 tables
choose 1/500 sim. desks

L. Kunze, K. K. Doreswamy and N. Hawes. *Using Qualitative Spatial Relations for Indirect Object Search*. In ICRA'14.



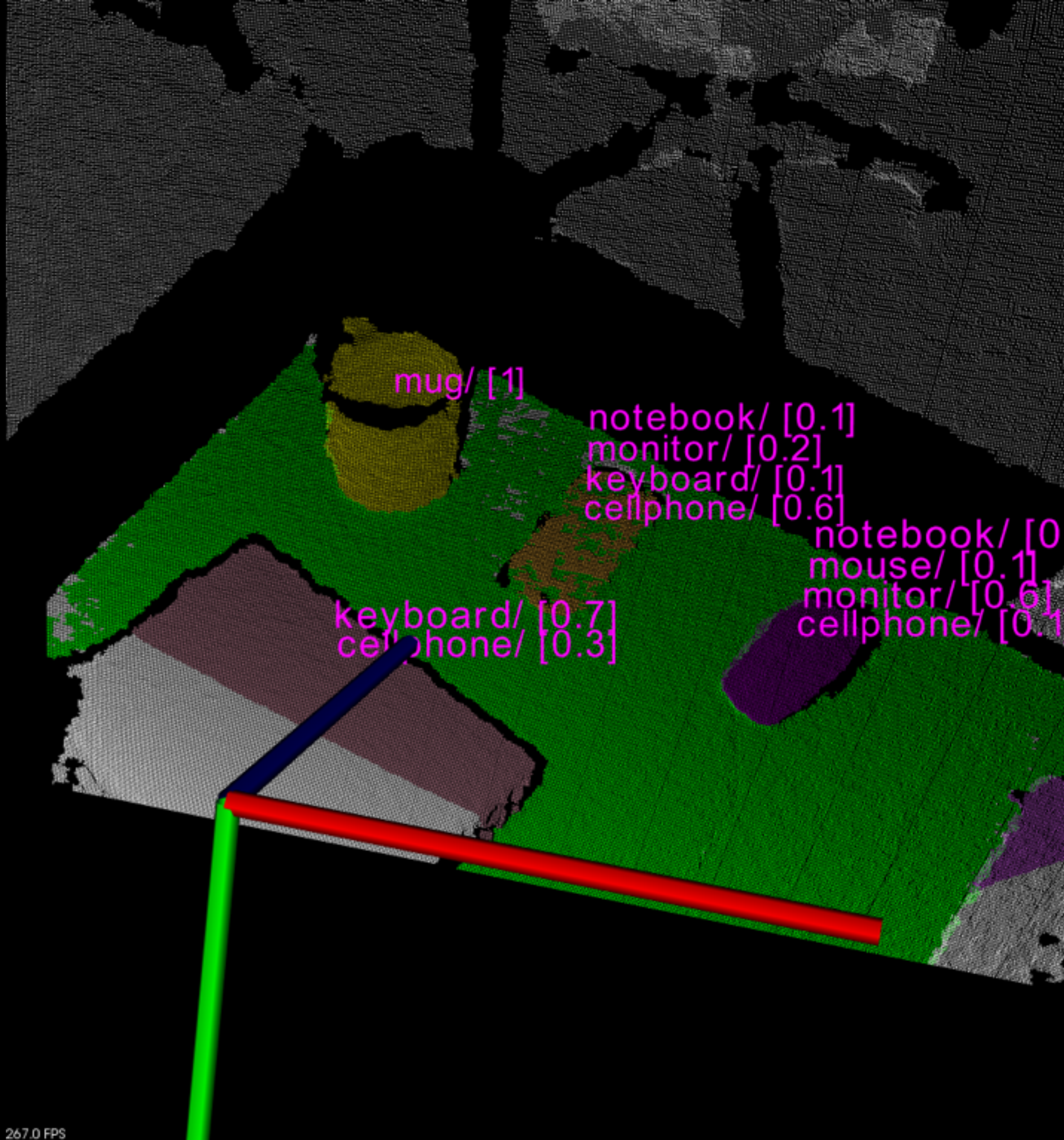

Search Results (Simulation)
Objects Found (/10)
Time (secs)
Poses
10
7.5
5
2.5
0
70.0
52.5
35.0
17.5
0.0
10
33.6
2.3
Random Views
Supporting Planes
Correct QSRs
Partially Correct QSRs
Misleading QSRs



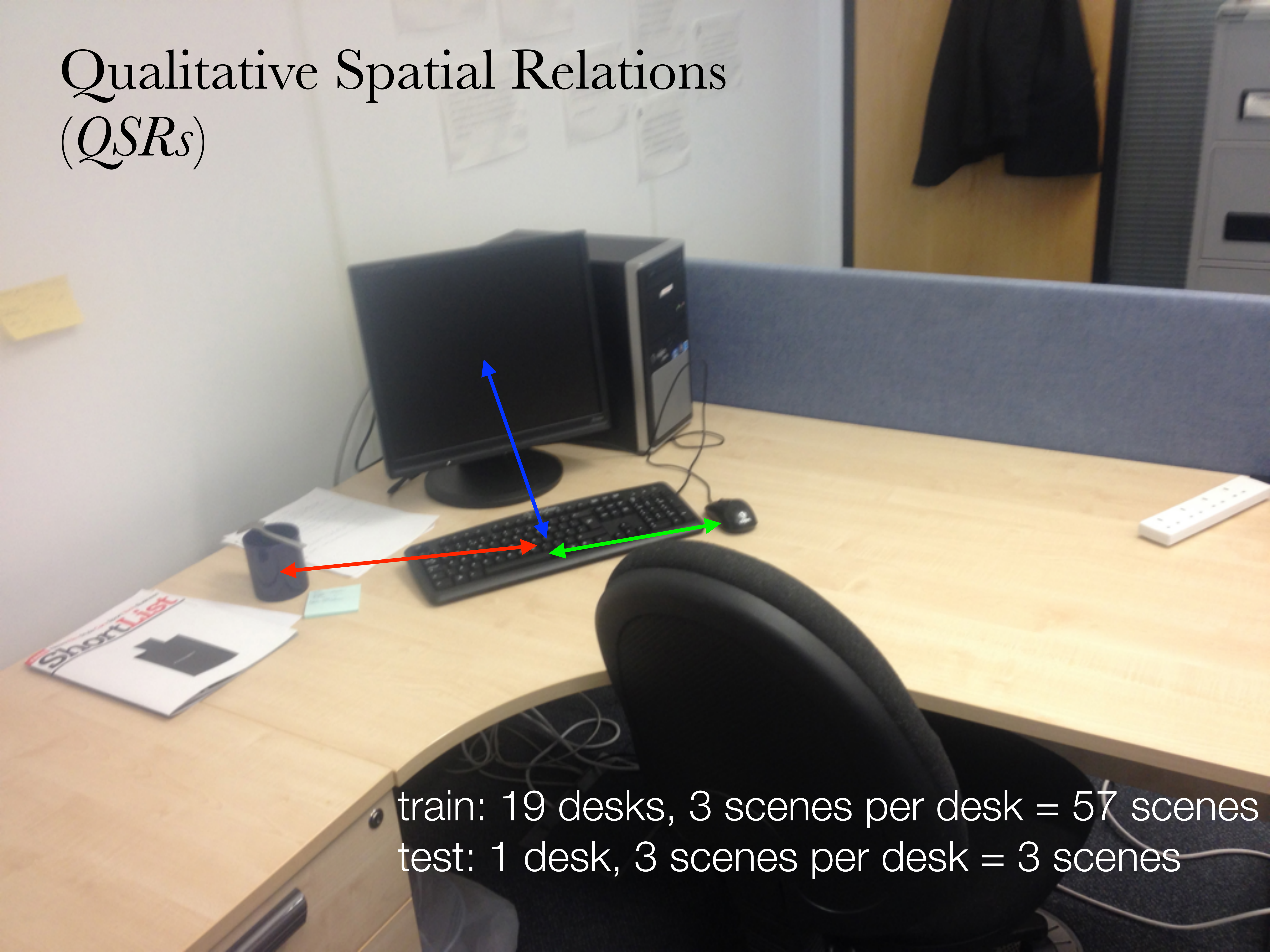


Search Results (Robot)
Objects Found (/10)
Time (secs)
Poses
10
7.5
5
2.5
0
70.0
52.5
35.0
17.5
0.0
9
69.5
2.2
10
33.4
1.1
Supporting Planes
Correct QSRs


TEAM 9

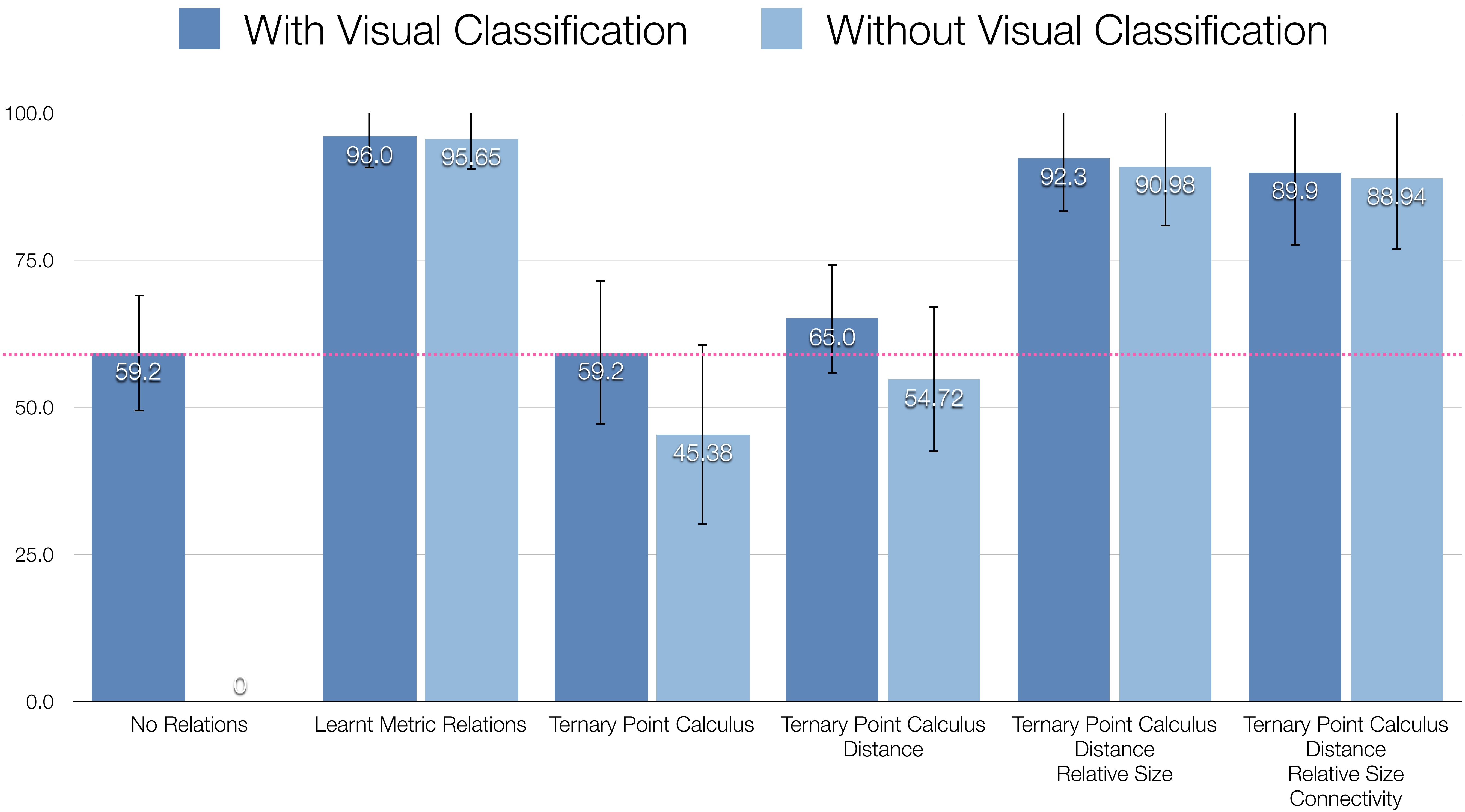

mug/ [1]
notebook/ [0.1]
monitor/ [0.2]
keyboard/ [0.1]
cellphone/ [0.6]
notebook/ [0.
mouse/ [0.1]
monitor/ [0.6]
cellphone/ [0.1]
keyboard/ [0.7]
cellphone/ [0.3]
267.0 FPS

Qualitative Spatial Relations (*QSRs*)



train: 19 desks, 3 scenes per desk = 57 scenes
test: 1 desk, 3 scenes per desk = 3 scenes

Classification Results (Robot)



Lars Kunze et al. *Combining Top-down Spatial Reasoning and Bottom-up Object Class Recognition for Scene Understanding*. In IROS '14.

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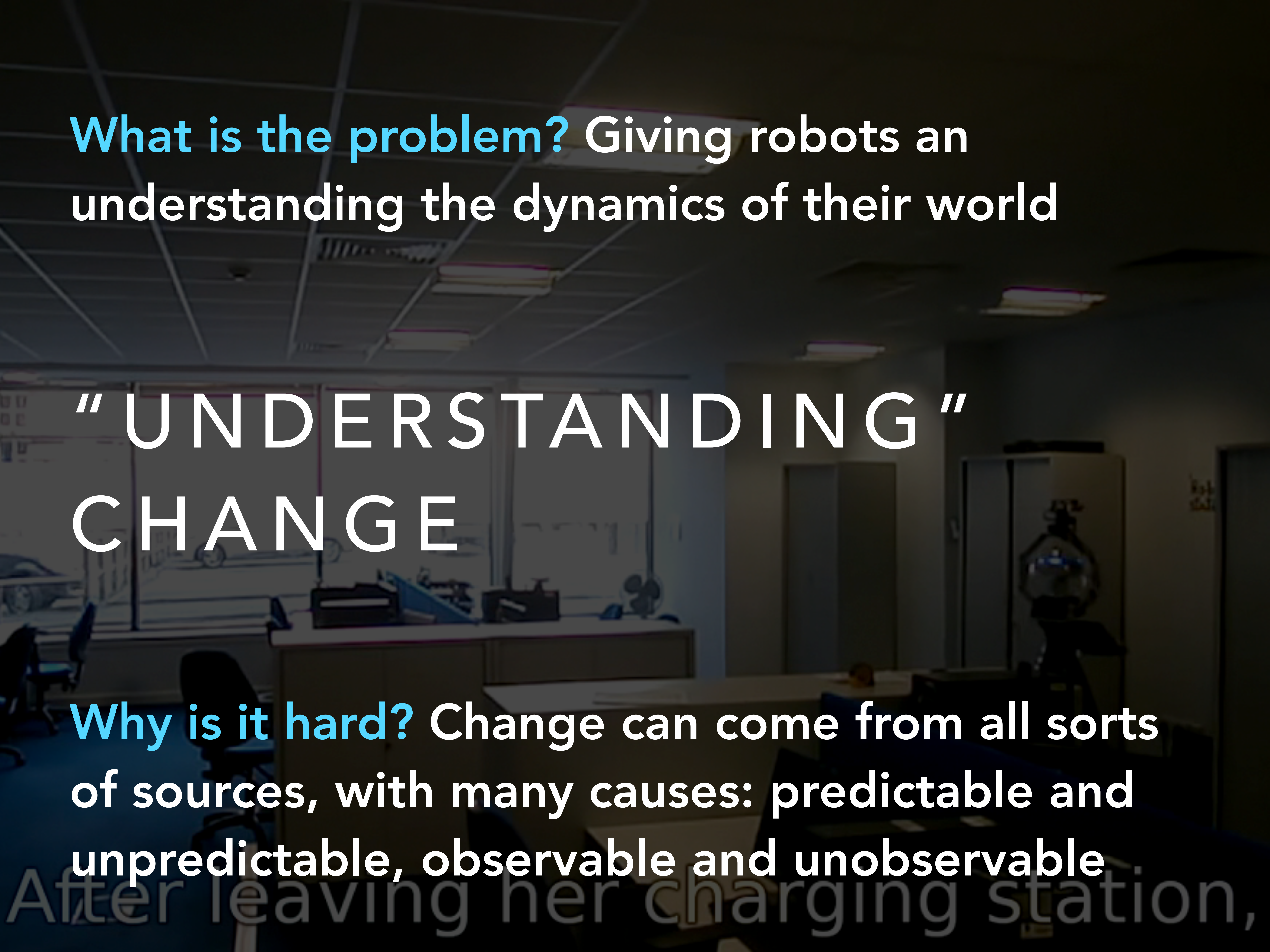
What is the problem? Giving robots an understanding the dynamics of their world

“UNDERSTANDING” CHANGE

Why is it hard? Change can come from all sorts of sources, with many causes: predictable and unpredictable, observable and unobservable



Envisioning the Effects of Robot Manipulation Actions using Physics-based Simulations

Kunze and Beetz, *Artificial Intelligence* 2015

The robot's actions are a major source of change in tasks

How can action parameters be chosen such that the change is the desired outcome

Envisioning: logic to simulation to logic again

How to pour the pancake mix?

where to hold it?
at what height?
at what angle?
how long for?

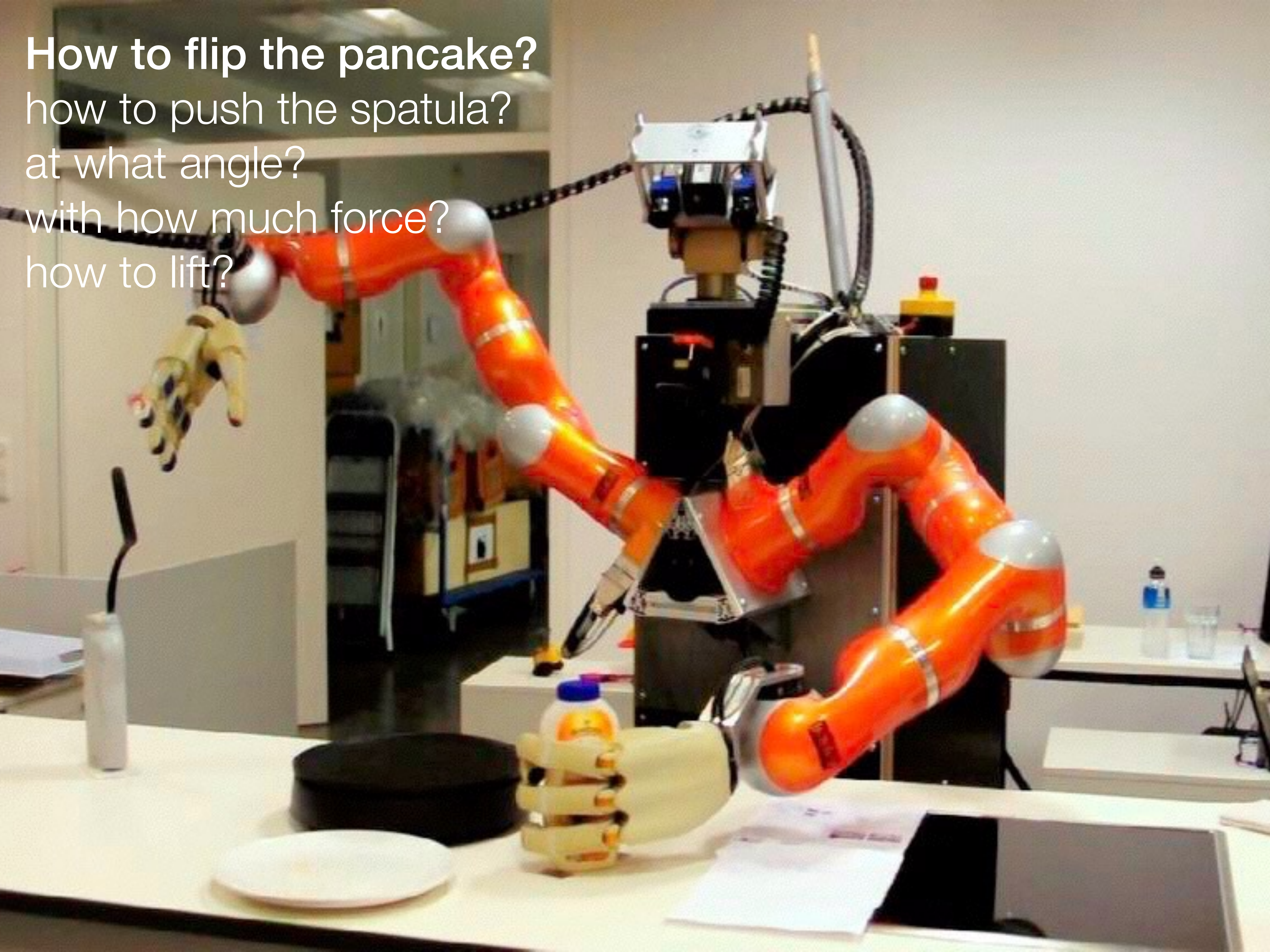
How to flip the pancake?

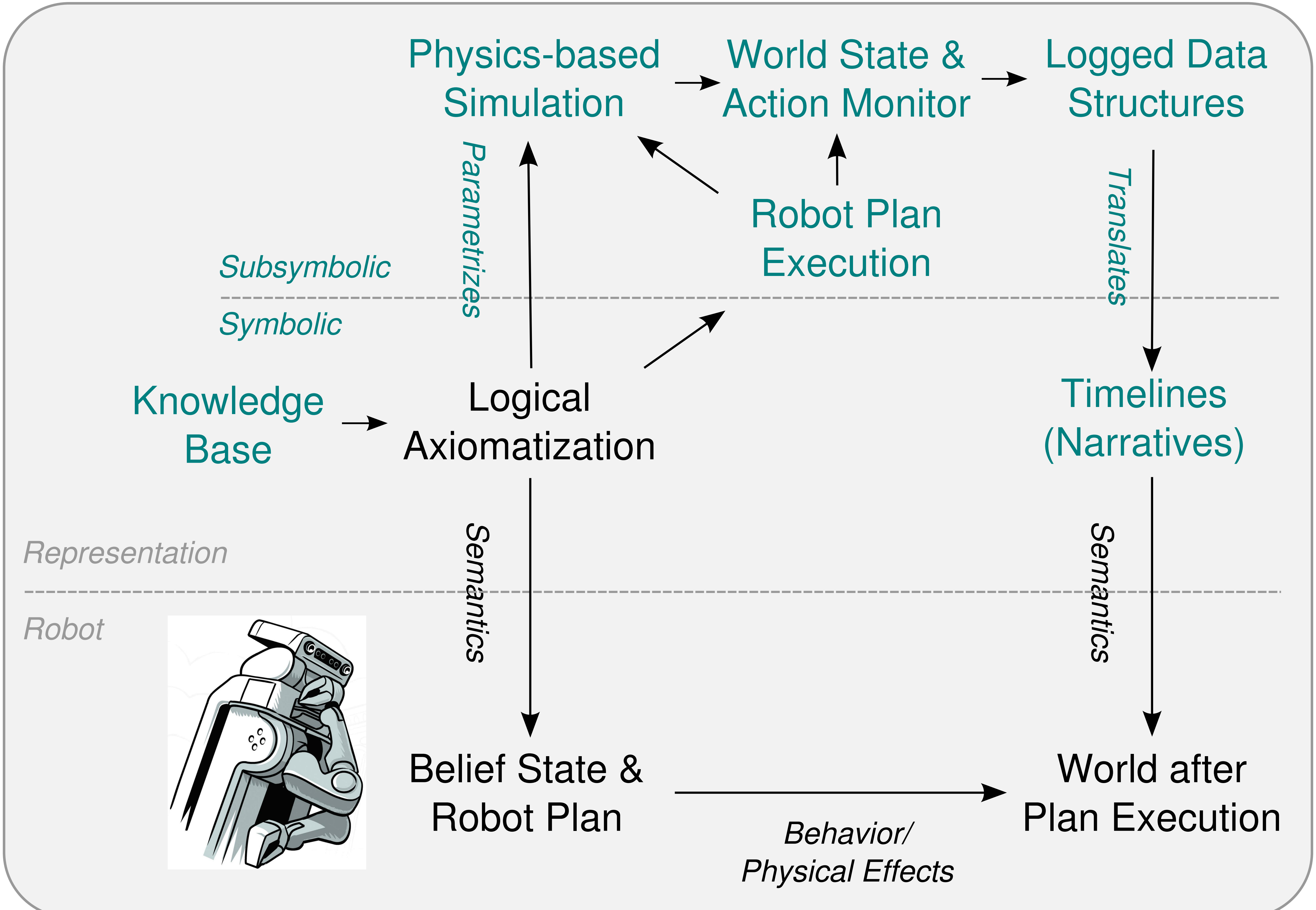
how to push the spatula?

at what angle?

with how much force?

how to lift?

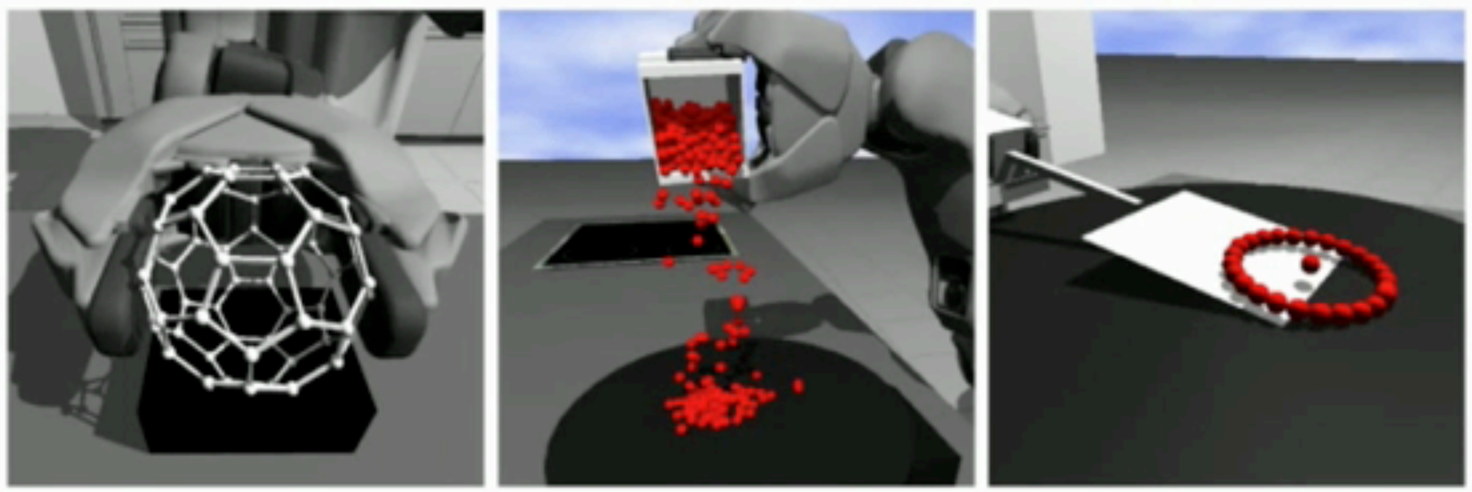




Physics-based Simulation
World State & Action Monitor
Logged Data Structures
Parametrizes
Robot Plan Execution
Translates
Subsymbolic
Symbolic
Knowledge Base
Logical Axiomatization
Timelines (Narratives)
Representation
Semantics
Semantics
Robot
Belief State & Robot Plan
World after Plan Execution
Behavior/ Physical Effects

Logic Programming with Simulation-based Temporal Projection for Everyday Robot Object Manipulation

Lars Kunze, Mihai Emanuel Dolha and Michael Beetz



Intelligent Autonomous Systems


ROS
PR2
16x


Humans cause a lot of the environmental dynamics experienced by a robot

Action Recognition

Activity/**Action**/**Plan**/**Intent**/**Event**
Recognition**/**Recognition**/**Prediction**/**Forecasting

Build **models** of **actions**

Recognise when a human is performing an **action**

Predict the next **action** in the **activity**

This is a very **large** and **diverse** field

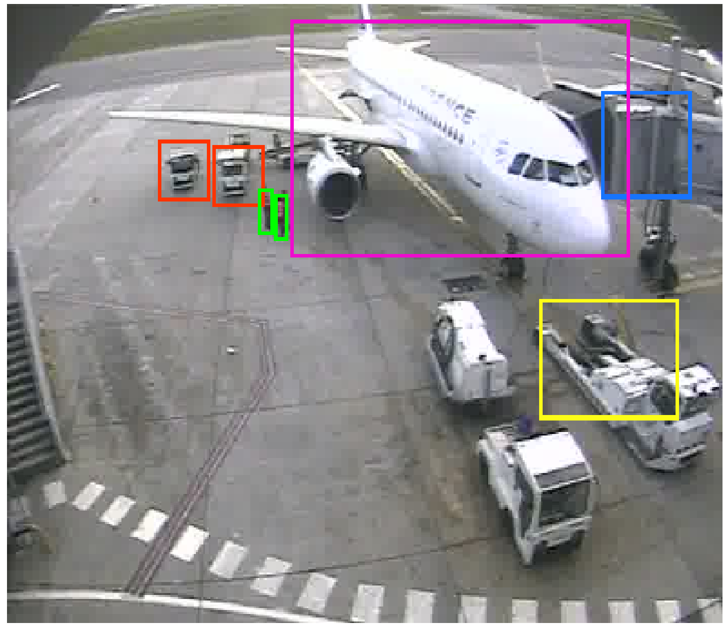
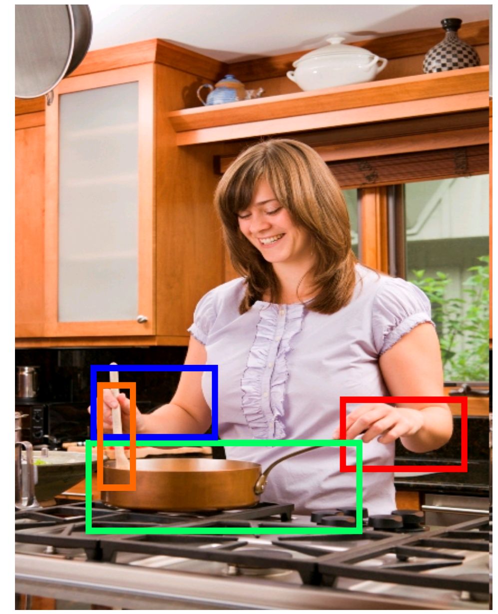
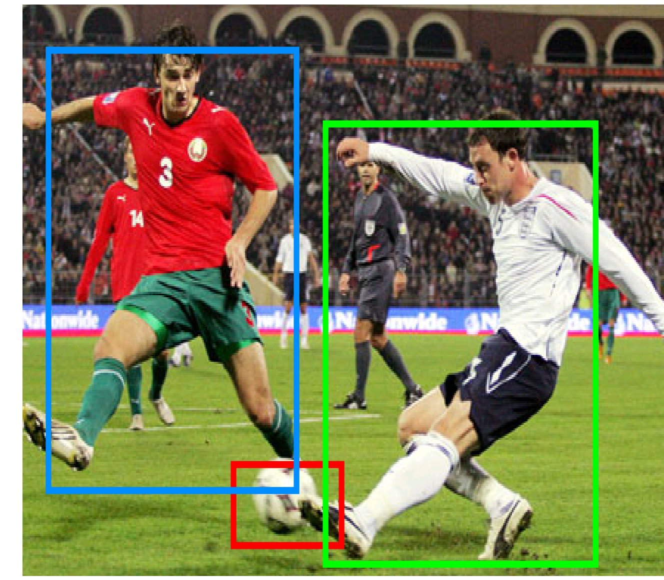
Requires knowledge of **space** and **time**

Build **models** of **actions**

Recognise when a human is performing an **action**

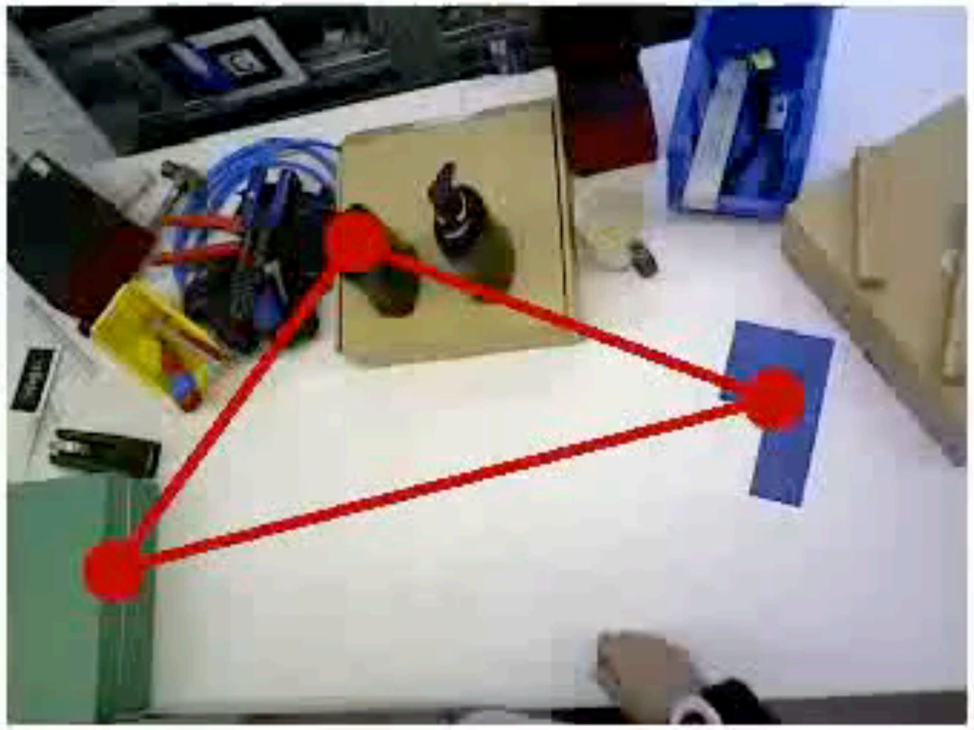
Predict the next **action** in the **activity**

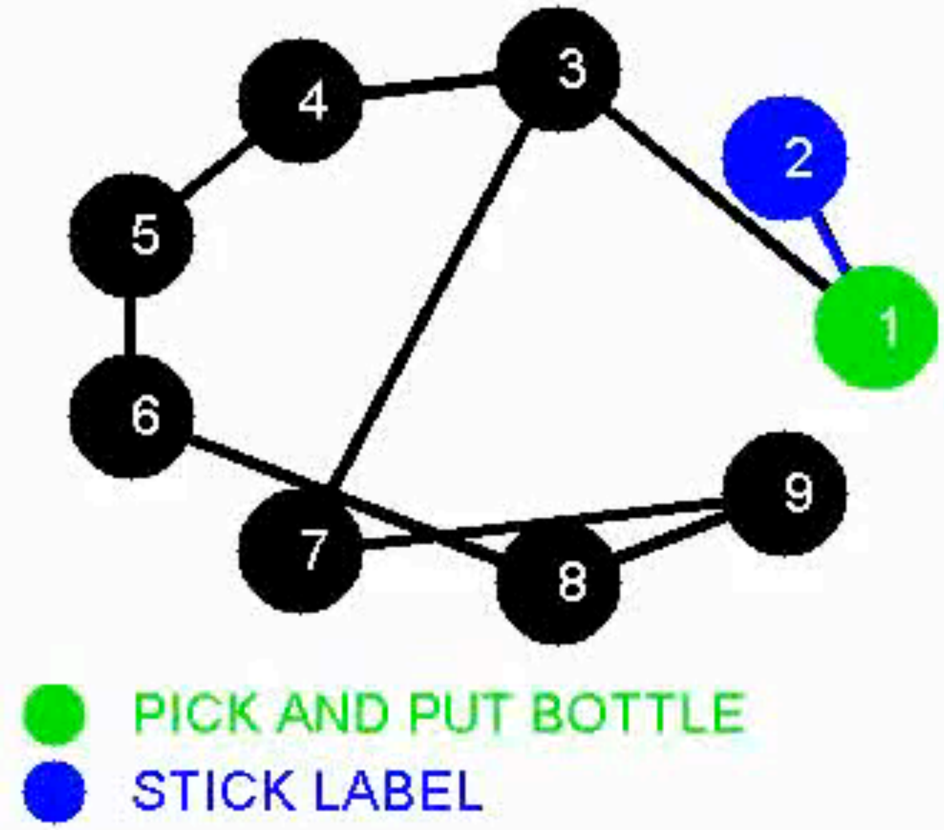
plus **learning** and **probabilistic reasoning**

Activities			
Event Classes	Unloading Bridge On	Baking a cake Making Coffee	Tackle Goal kick
Object Classes	Plane Trolley	Spoon Cup	Player Ball

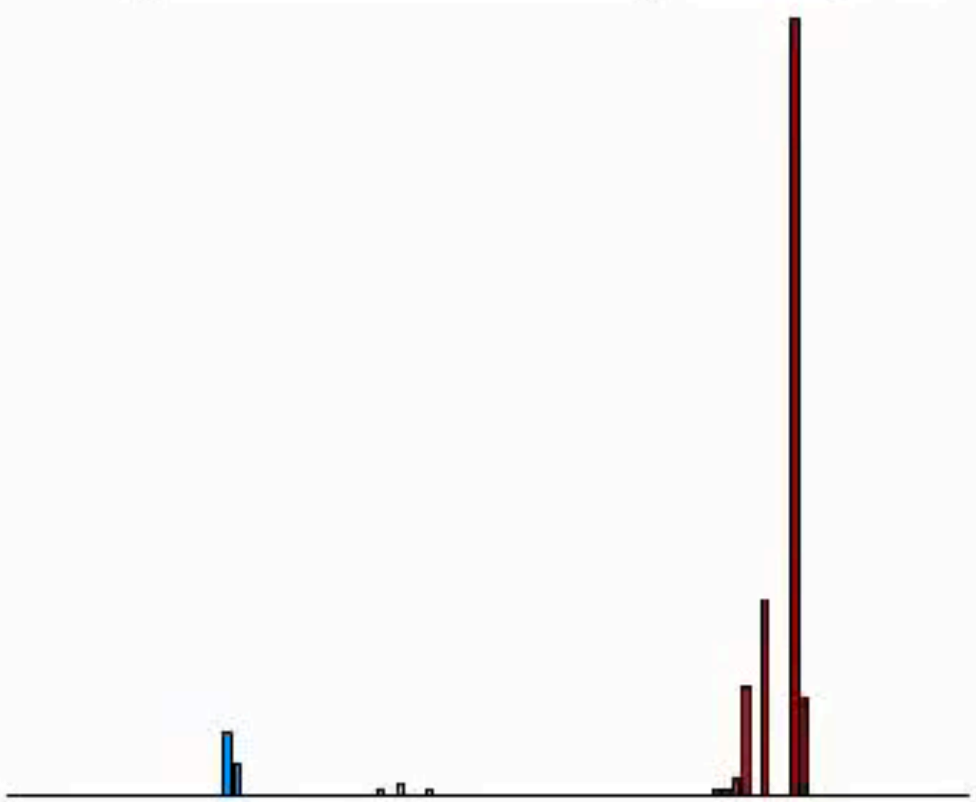
Unsupervised Learning of Event and Object Classes from Video
Sridhar, PhD Thesis, 2010.

Relational Graph

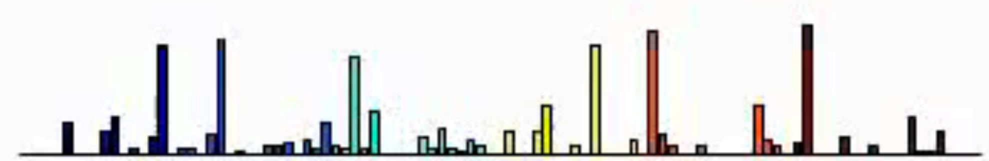




Bag-of-Relations : Object-Object



Bag-of-Relations : Upper-Body Model



Tony Cohn et al, University of Leeds for the RACE Project

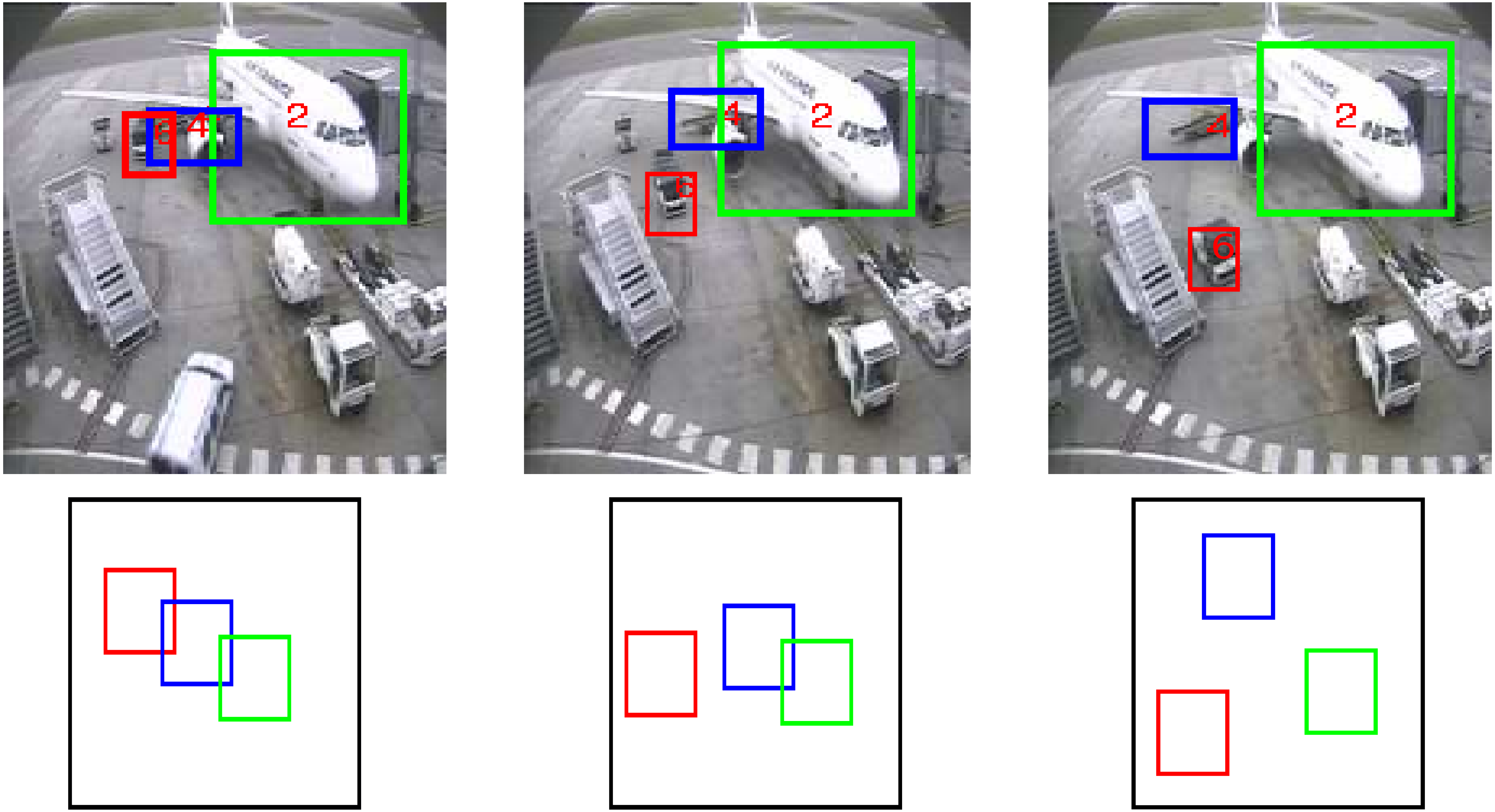
Unsupervised Learning of Event Classes from Video

Sridhar, Cohn and Hogg. In *AAAI'10*.

Automatically learn models of activities from video, then recognise them in new videos

Events are sequences of spatial interactions between objects

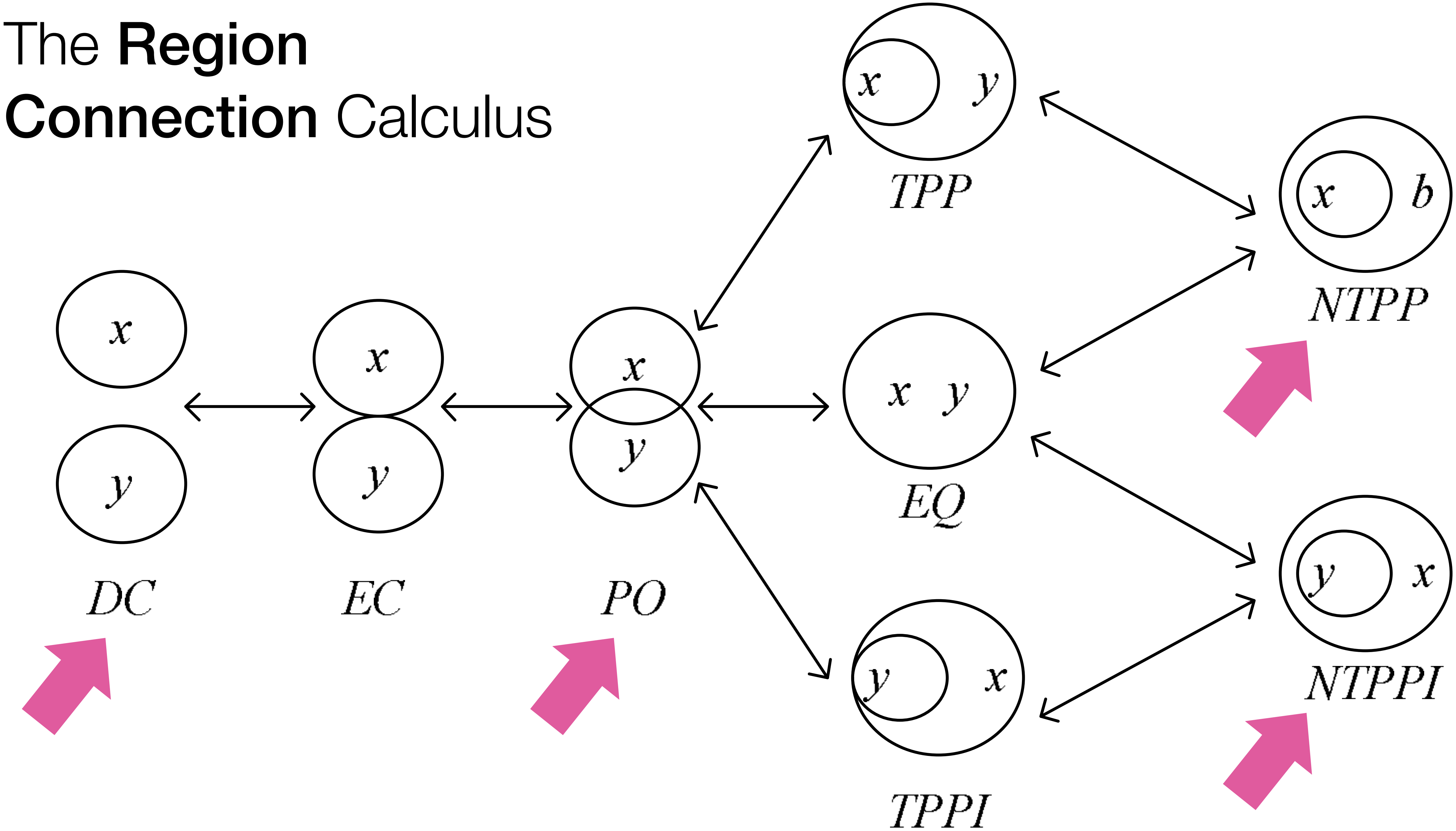
Activities are collections of events with related objects that cooccur.



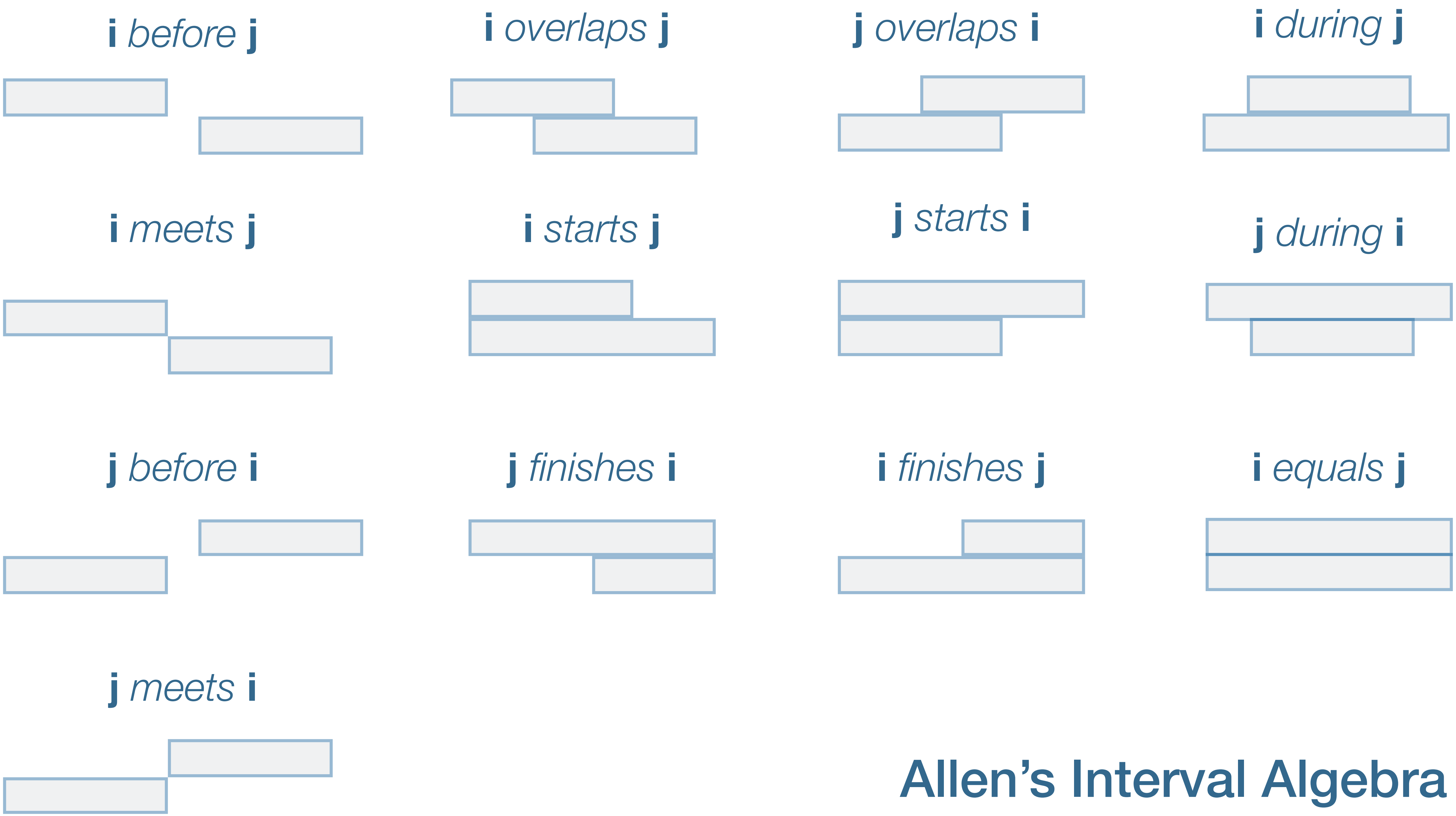
Unsupervised Learning of Event and Object Classes from Video

Sridhar, PhD Thesis, 2010.

The **Region Connection** Calculus

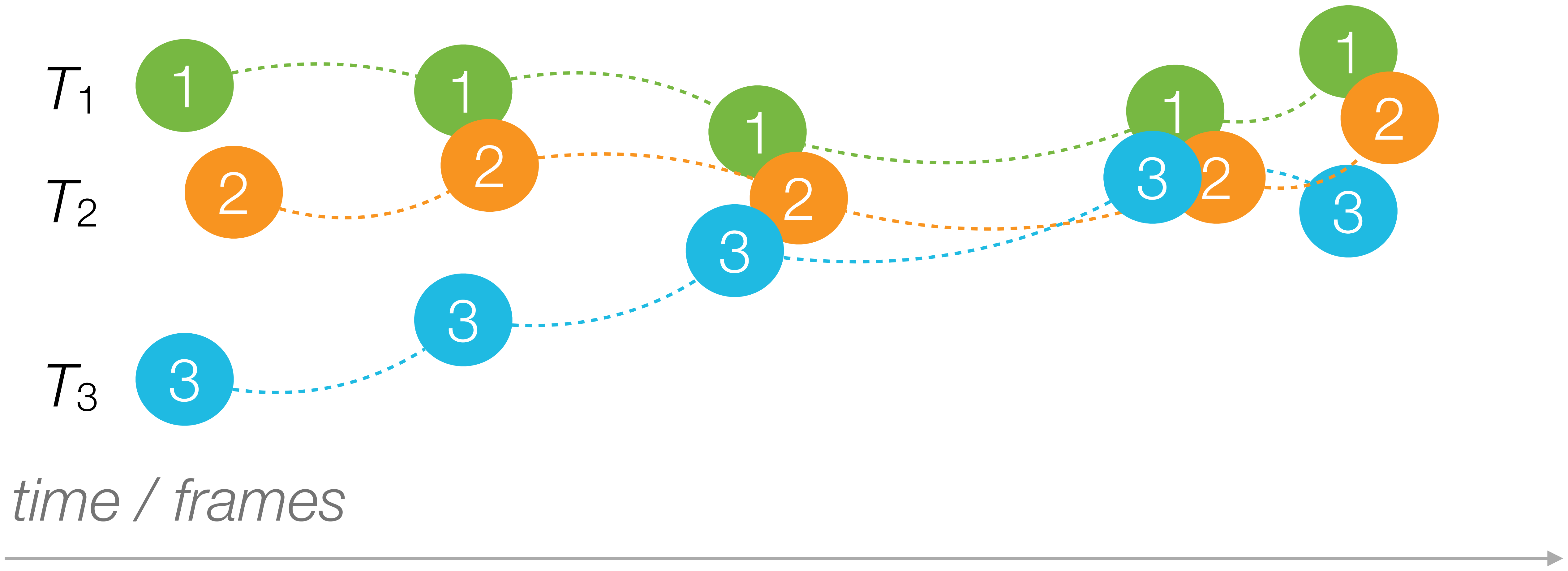


Qualitative spatial representation and reasoning with the region connection calculus. A. G. Cohn, B. Bennett, J. Gooday, and N. M. Gotts. *GeoInformatica*, 1(3):275–316, 1997.



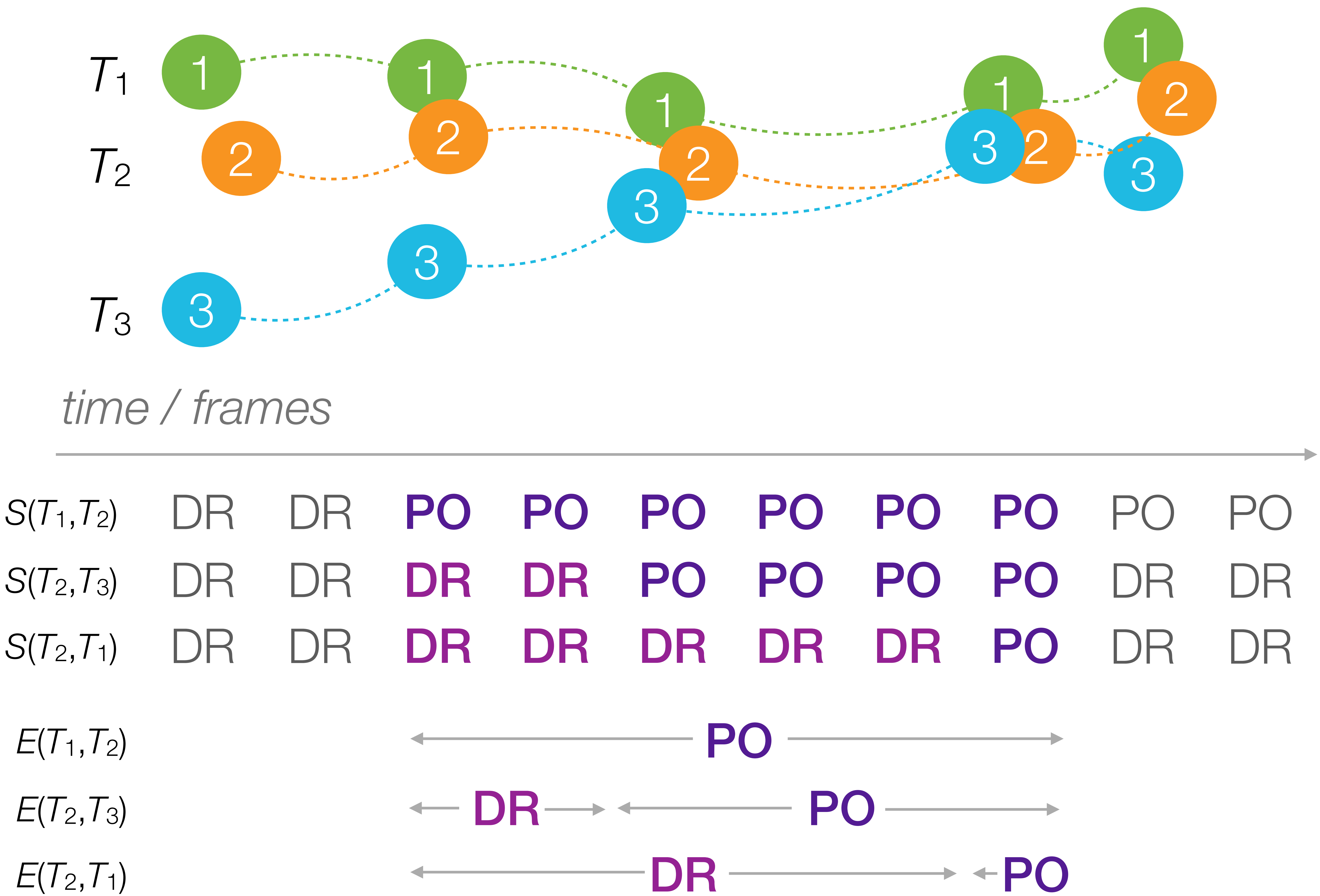
Allen's Interval Algebra

J. F. Allen. *Maintaining knowledge about temporal intervals. Communications of the ACM*, 26(11):832– 843, 1983.

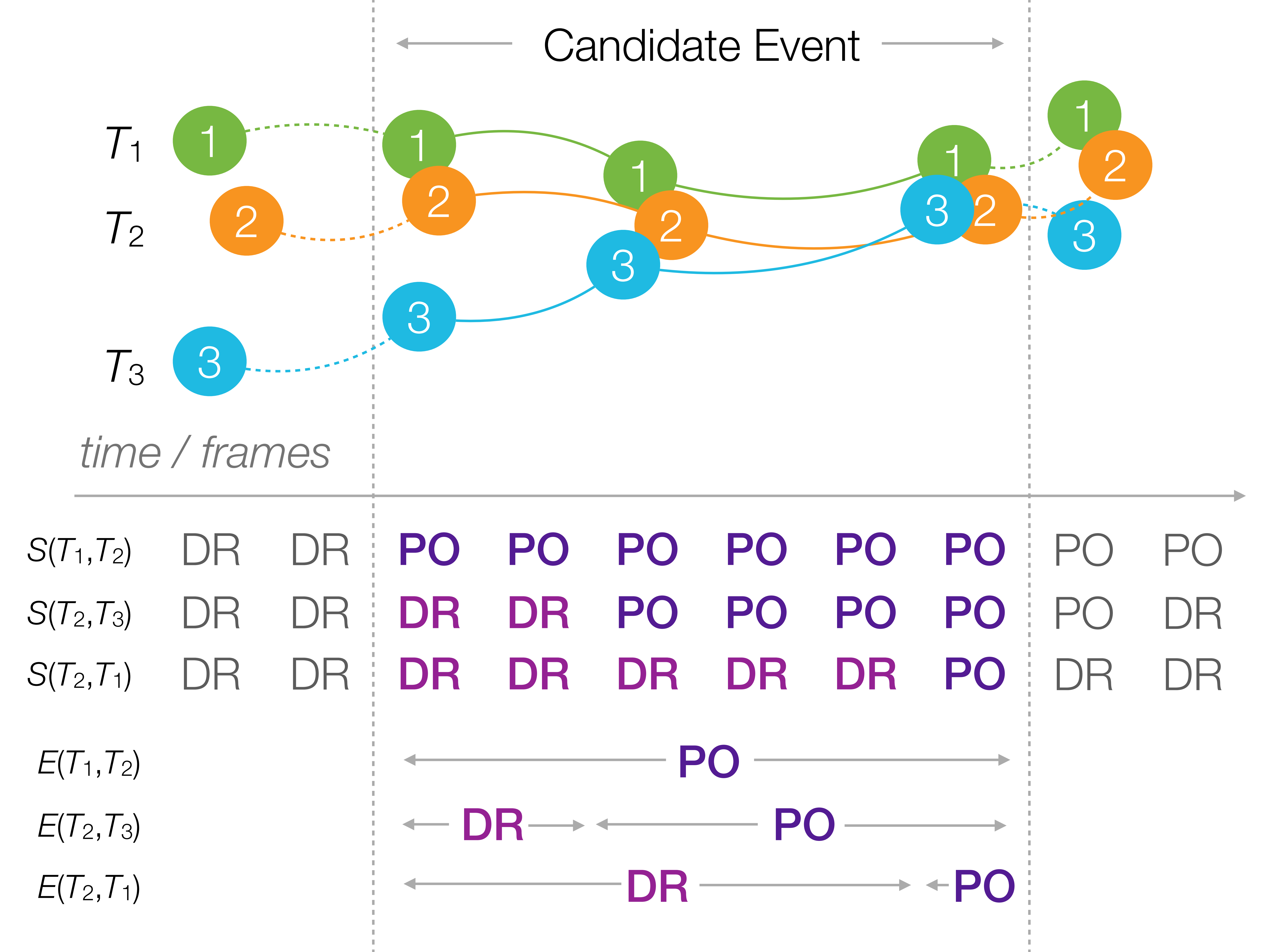


How can we **segment** events from this stream of data?

How can we **compare** events?

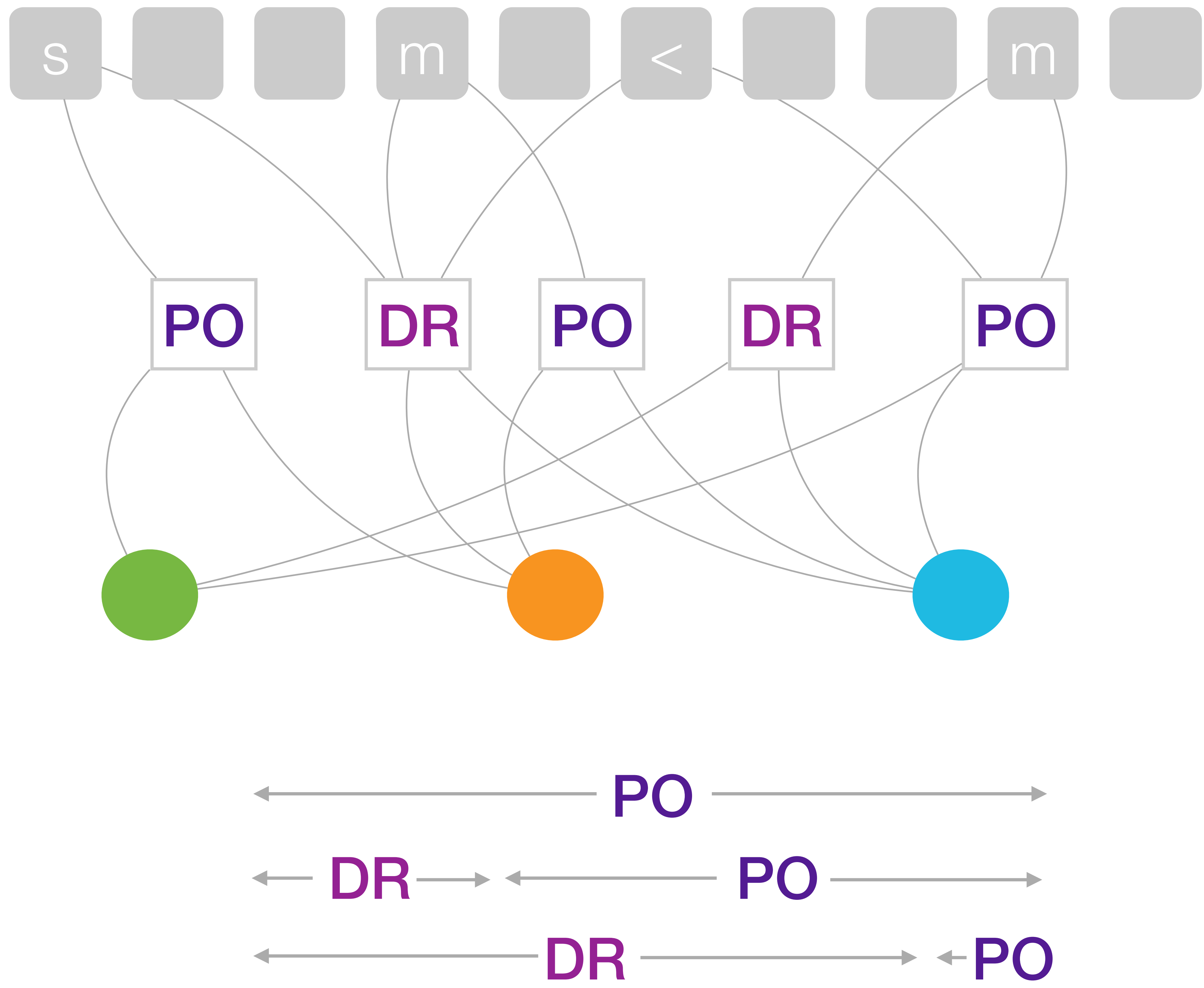


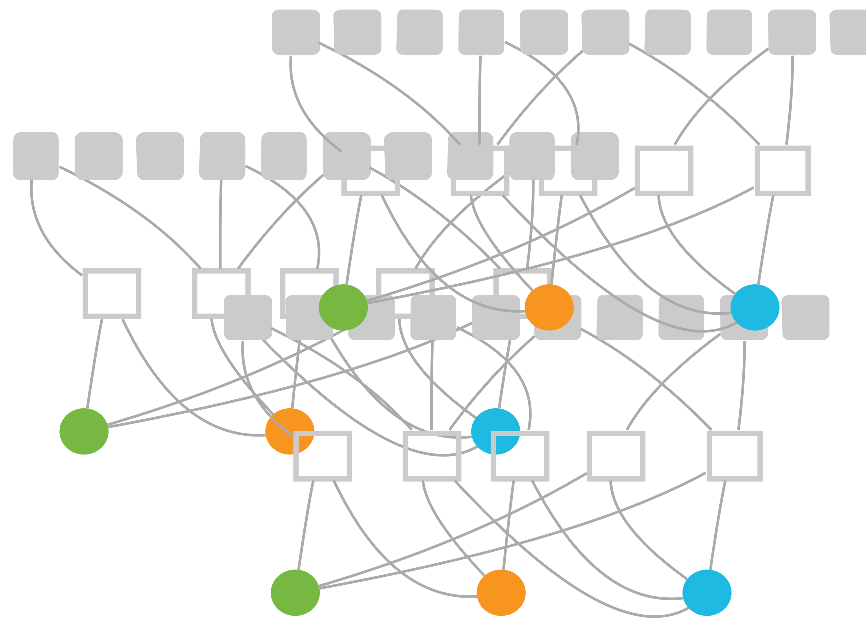
T1
T2
T3
time / frames
S(T1,T2) DR DR PO PO PO PO PO PO PO PO
S(T2,T3) DR DR DR DR PO PO PO PO DR DR
S(T2,T1) DR DR DR DR DR DR DR PO DR DR
E(T1,T2) PO
E(T2,T3) DR PO
E(T2,T1) DR PO

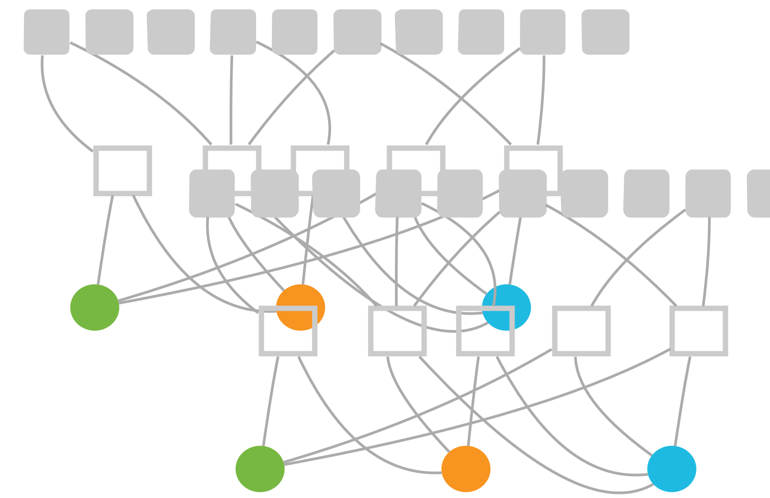


Candidate Event
T_1
T_2
T_3
1
2
3
time / frames
$S(T_1,T_2)$ DR DR PO PO PO PO PO PO PO PO
$S(T_2,T_3)$ DR DR DR DR PO PO PO PO PO DR
$S(T_2,T_1)$ DR DR DR DR DR DR DR PO DR DR
$E(T_1,T_2)$ PO
$E(T_2,T_3)$ DR PO
$E(T_2,T_1)$ DR PO

Candidate Event Graph

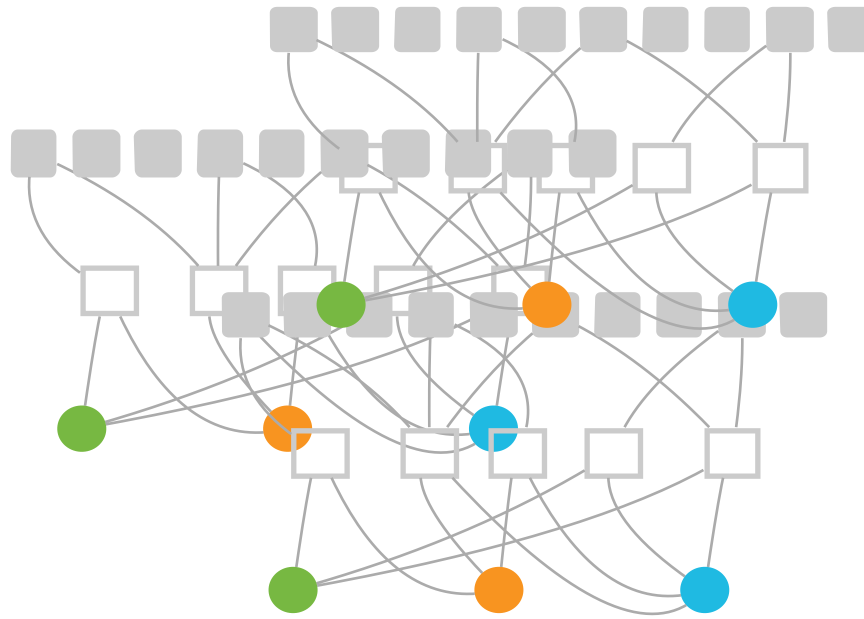


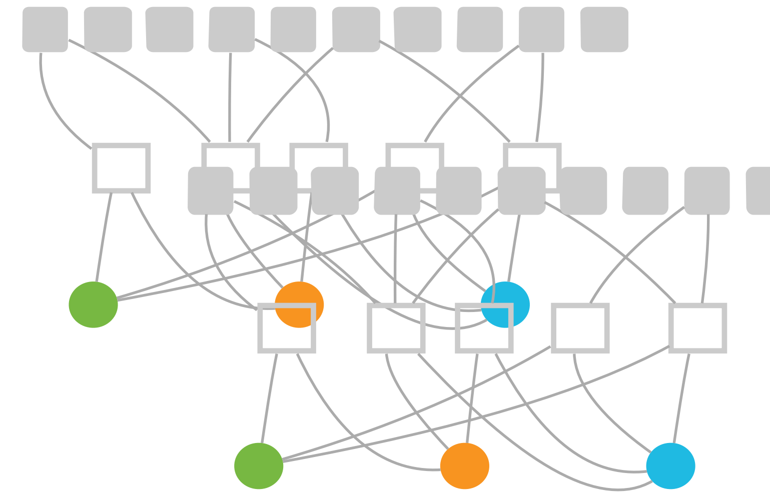




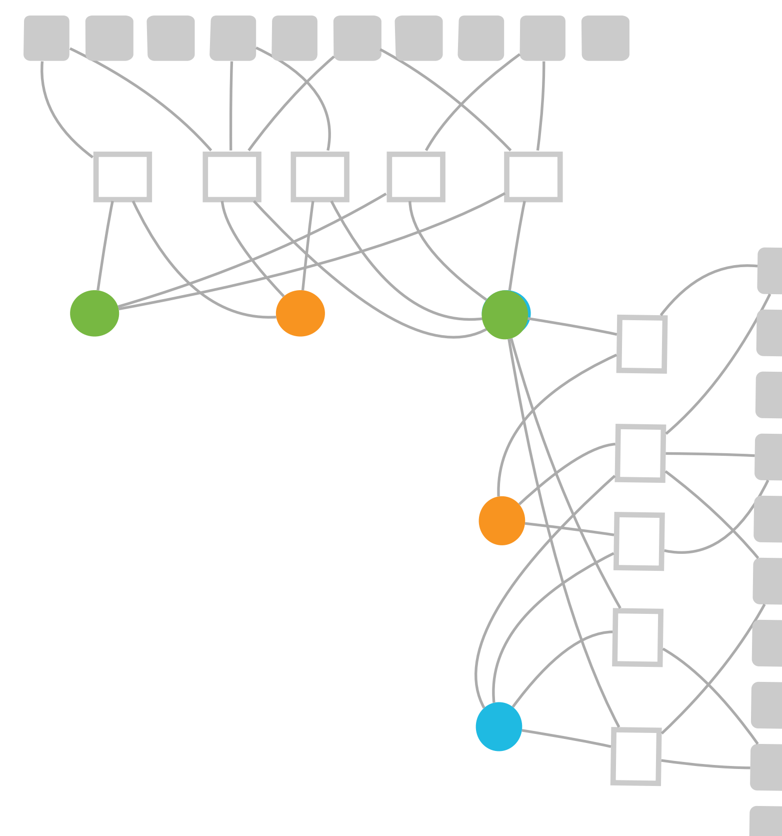
Over the course of a video, common graph/event structure are extracted into **classes** following rules

Events in the same **activity** can share objects



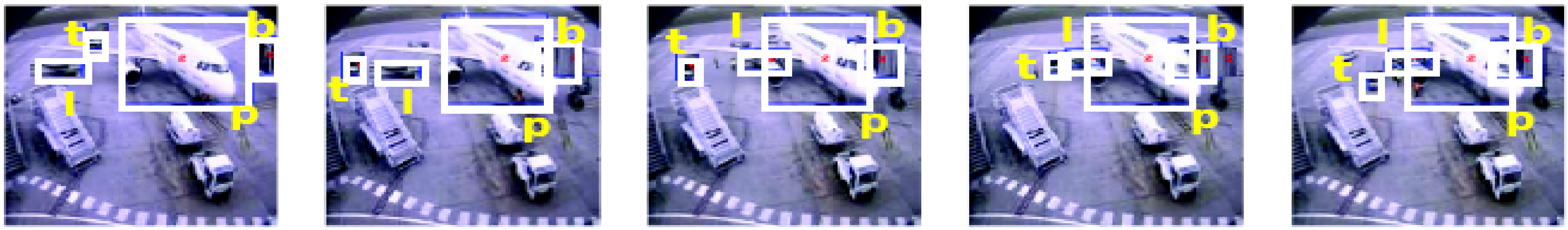


The recognition process tries to find events which provide the most likely explanation for the data

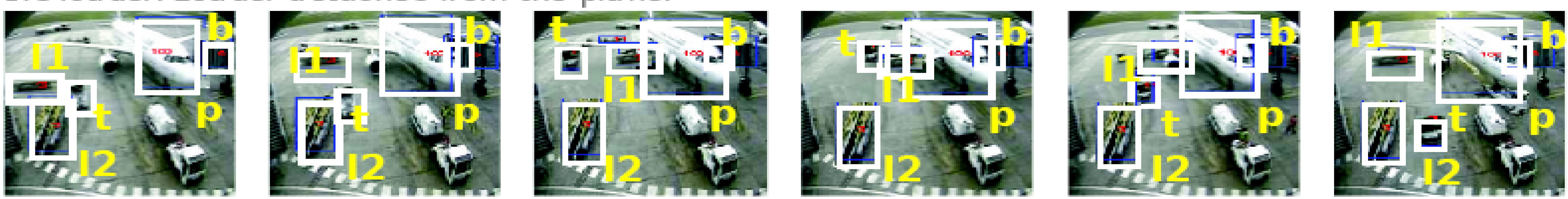



1
2
3
4

Bridge attaches to plane. Loader attaches to the plane. Trolley attaches and then detaches from the loader.



Bridge attaches to plane. Loader attaches to the plane. Trolley attaches and then detaches from the loader. Loader detaches from the plane.



Action Recognition

High-level/semantic representation of change

of **actions**

Recognise when a … an **action**

Predict the next **action** in th…

monitor (0.420000)
monitor (0.940000)
monitor (0.520000)

Spectral Analysis for Long-Term Robotic Mapping
Krajník, Fentanes, Cielniak, Dondrup and Duckett. In *ICRA'14*.

Change in the environment is often the result of **human activity**

Human activities are often **periodic**

Other dynamics are **periodic** too (day/night etc.).

(a) Variations introduced by illumination

Semantic Modelling of Space. Pronobis, Jensfelt, Sjöö, Zender, Kruijff, Mozos, and Burgard. In volume 8 of *Cognitive Systems Monographs*, 2010.

Corridor | One-person office | Two-persons office

(b) Variations observed over time

Semantic Modelling of Space. Pronobis, Jensfelt, Sjöö, Zender, Kruijff, Mozos, and Burgard. In volume 8 of *Cognitive Systems Monographs*, 2010.

Spectral Analysis for Long-Term Robotic Mapping
Krajník, Fentanes, Cielniak, Dondrup and Duckett. In *ICRA'14*.

Change in the environment is often the result of **human activity**

Human activities are often **periodic**

Other dynamics are **periodic** too (day/night etc.).

Therefore use ***frequency analysis*** to learn and predict the dynamics of the environment

assuming **binary states**
cell occupancy, door open/closed, feature presence/absence

value of j^{th} state: $s_j = \{0, 1\}$

probability of j^{th} state: $p_j = P(s_j = 1)$

probability of j^{th} state at time t: $p_j(t)$

Bayesian models tell us how to update $p_j(t)$ given uncertain observations, but assume a **static world**

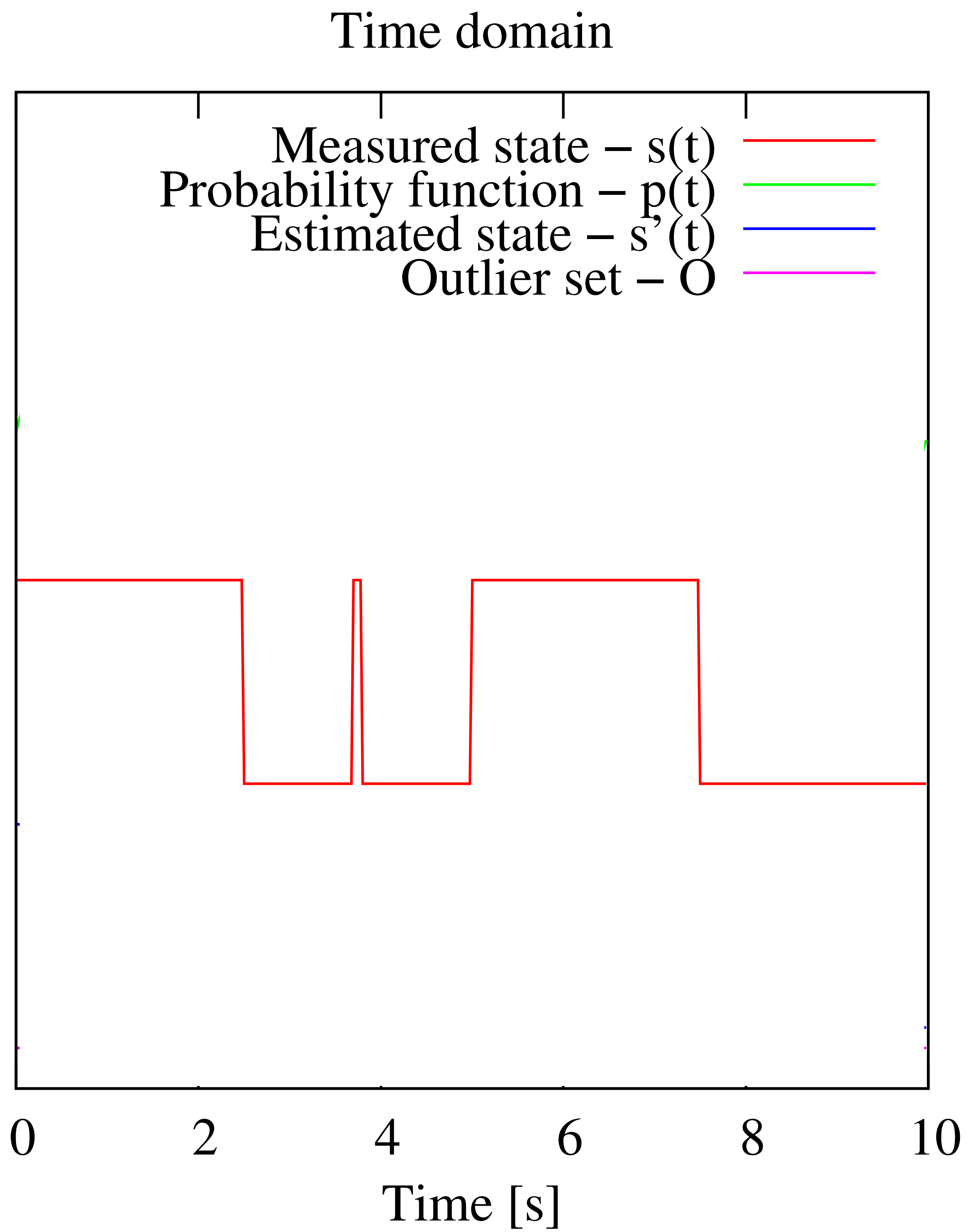
use the **Fourier Transform**
to get a compact, predictive model for s

sequence of states: $s(t)$

frequency spectrum of sequence: $S(\omega) = FT(s(t))$

the spectral model $\mathcal{P}$ is the n most prominent frequencies $S(\omega)$

$\mathcal{P}$ can be used to generate a smoothed sequence $\tilde{s}(t)$
and a predicted sequence $s'(t)$ and outlier set O


Time domain
Measured state – s(t)
Probability function – p(t)
Estimated state – s'(t)
Outlier set – O
0
2
4
6
8
10
Time [s]

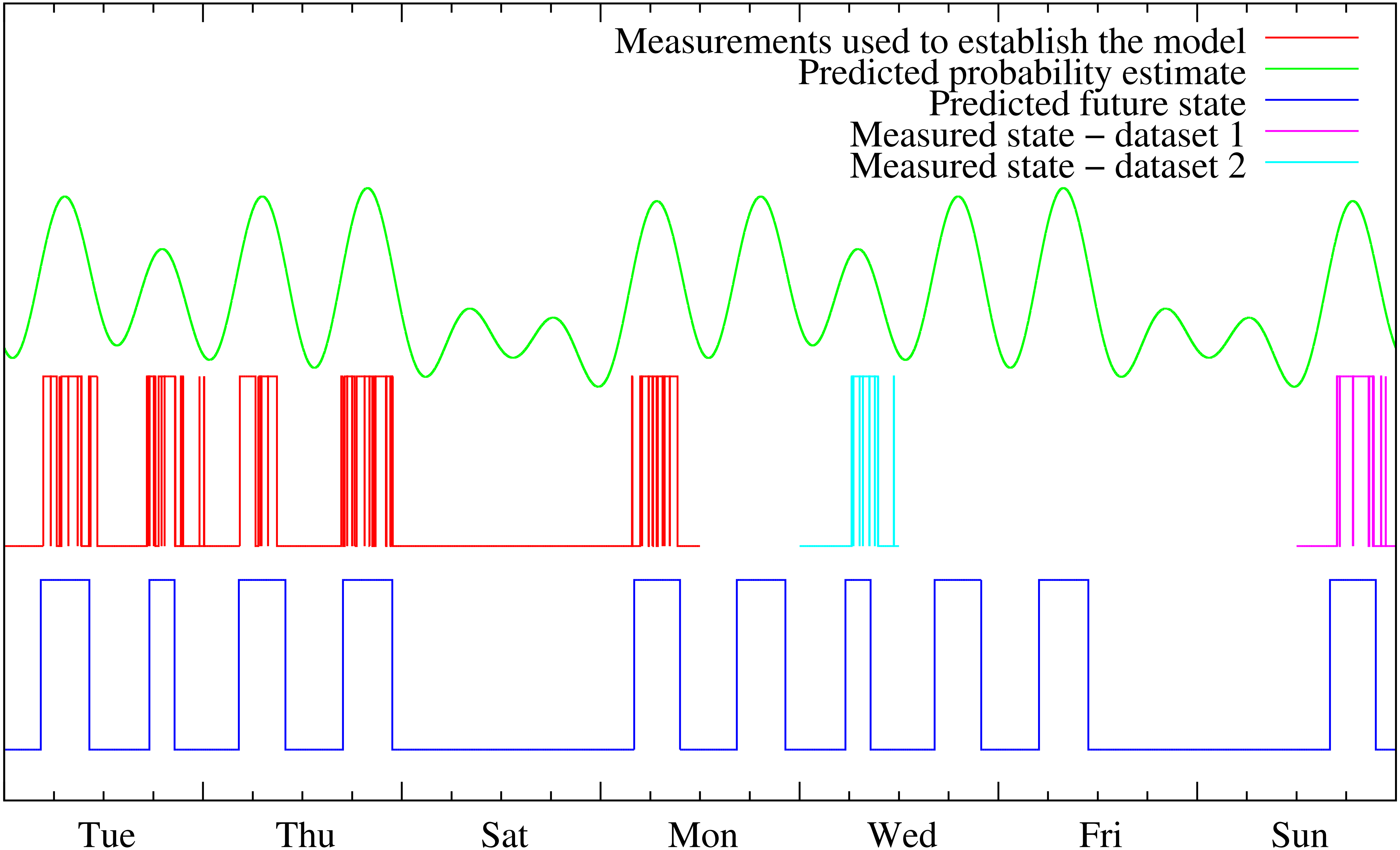
state **estimation**

$$s'(t) = p(t) > 0.5 = \varsigma(IFT(\mathcal{P})) > 0.5$$

state **reconstruction**

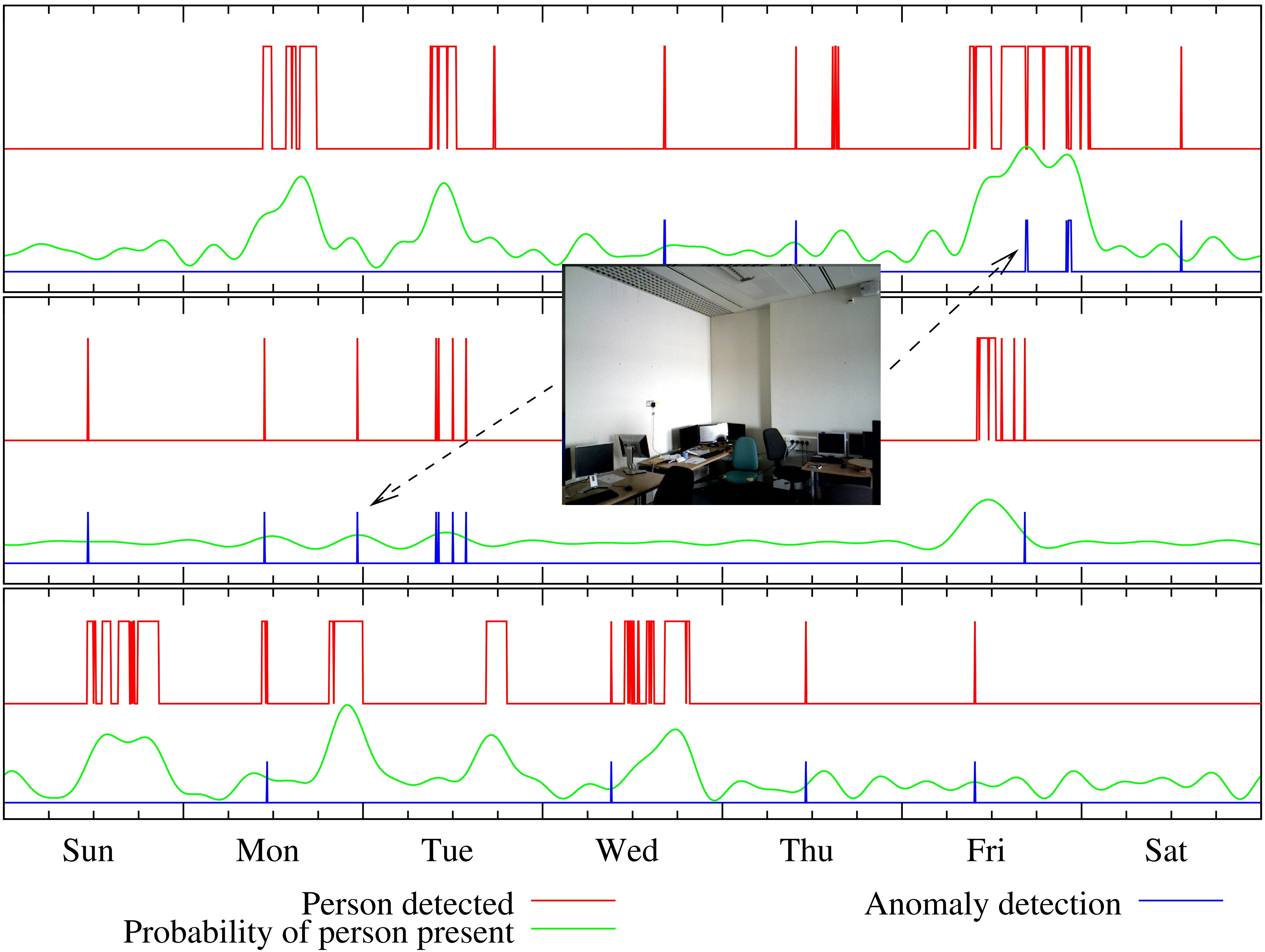
$$s(t) = s'(t) \oplus (t \notin O) = \varsigma(IFT(\mathcal{P})) > 0.5 \oplus (t \notin O)$$

(*estimation xor with outlier set*)



Office door open/closed model.

Compresses 18 million readings to 3 frequencies


Sun
Mon
Tue
Wed
Thu
Fri
Sat
Person detected
Probability of person present
Anomaly detection

Lincoln Centre for Autonomous Systems, United Kingdom
Royal Institute of Technology, Sweden

T. Krajník, J.P. Fentanes, O.M. Mozos
T. Duckett, J. Ekekrantz, M. Hanheide

Long-Term Topological Localisation for Service Robots in Dynamic Environments using Spectral Maps

Dataset collection and processing

Supported by EU ICT project 600623 'STRANDS'

https://youtu.be/Qw1kS_5zVwE

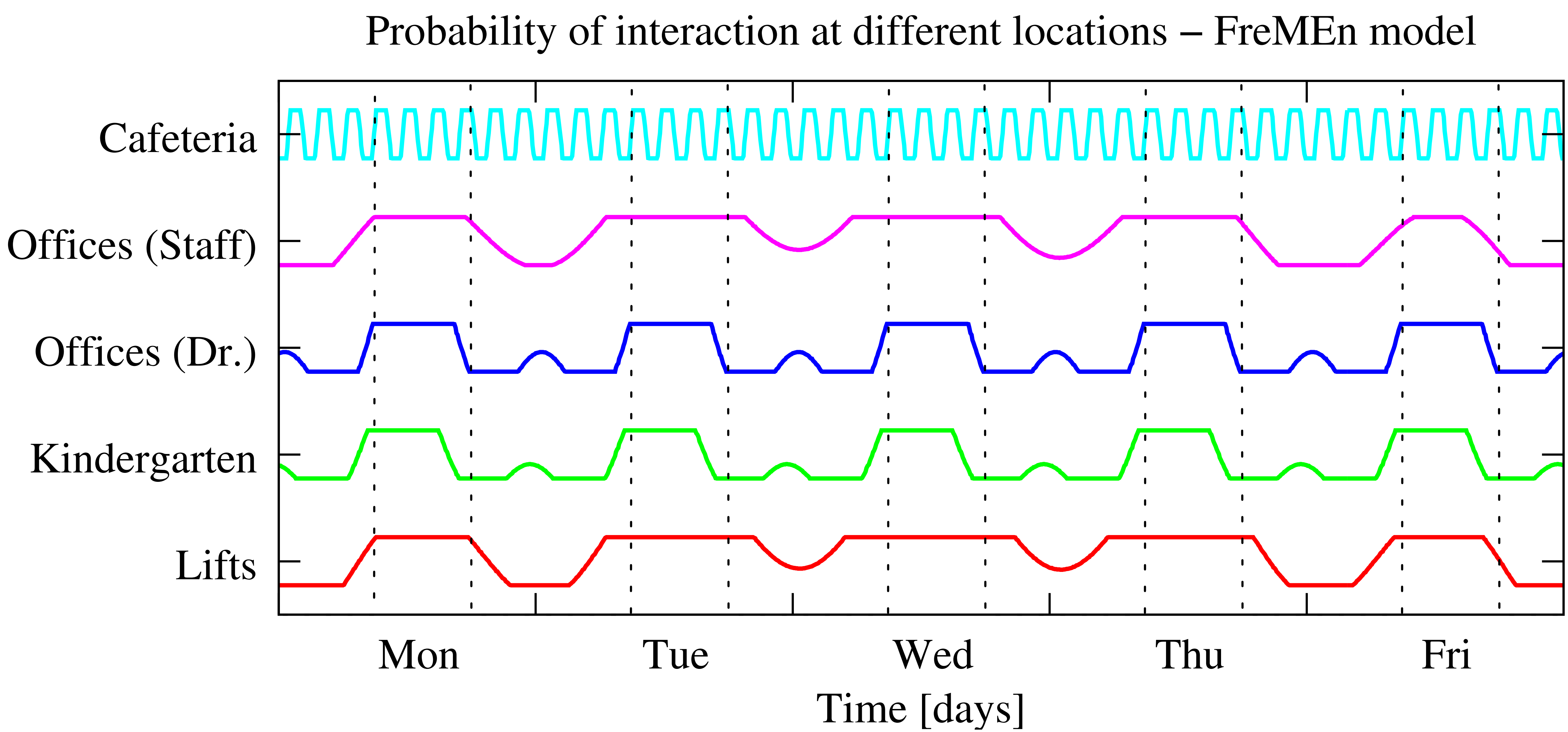
TABLE I

OVERALL LOCALIZATION ERROR (%)

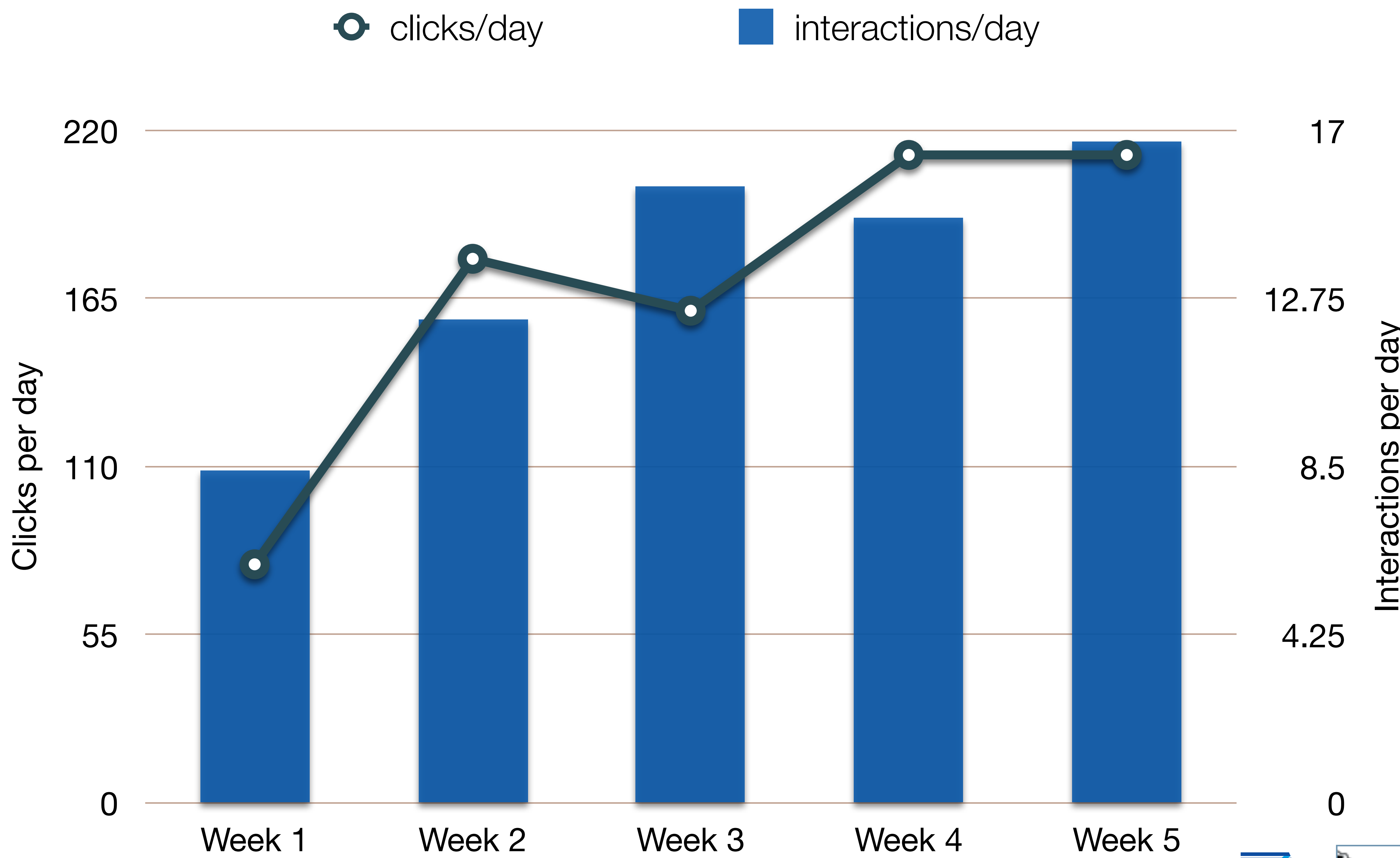
Model type	Model order	Image features Nov	Image features Feb	Occupancy grids Nov	Occupancy grids Feb
statical	-	35%	45%	21%	17%
spectral	1	25%	26%	14%	13%
spectral	2	22%	27%	14%	8%
spectral	3	18%	24%	14%	17%
spectral	4	17%	29%	7%	17%

Info Terminal

Info Terminal



Info Terminal



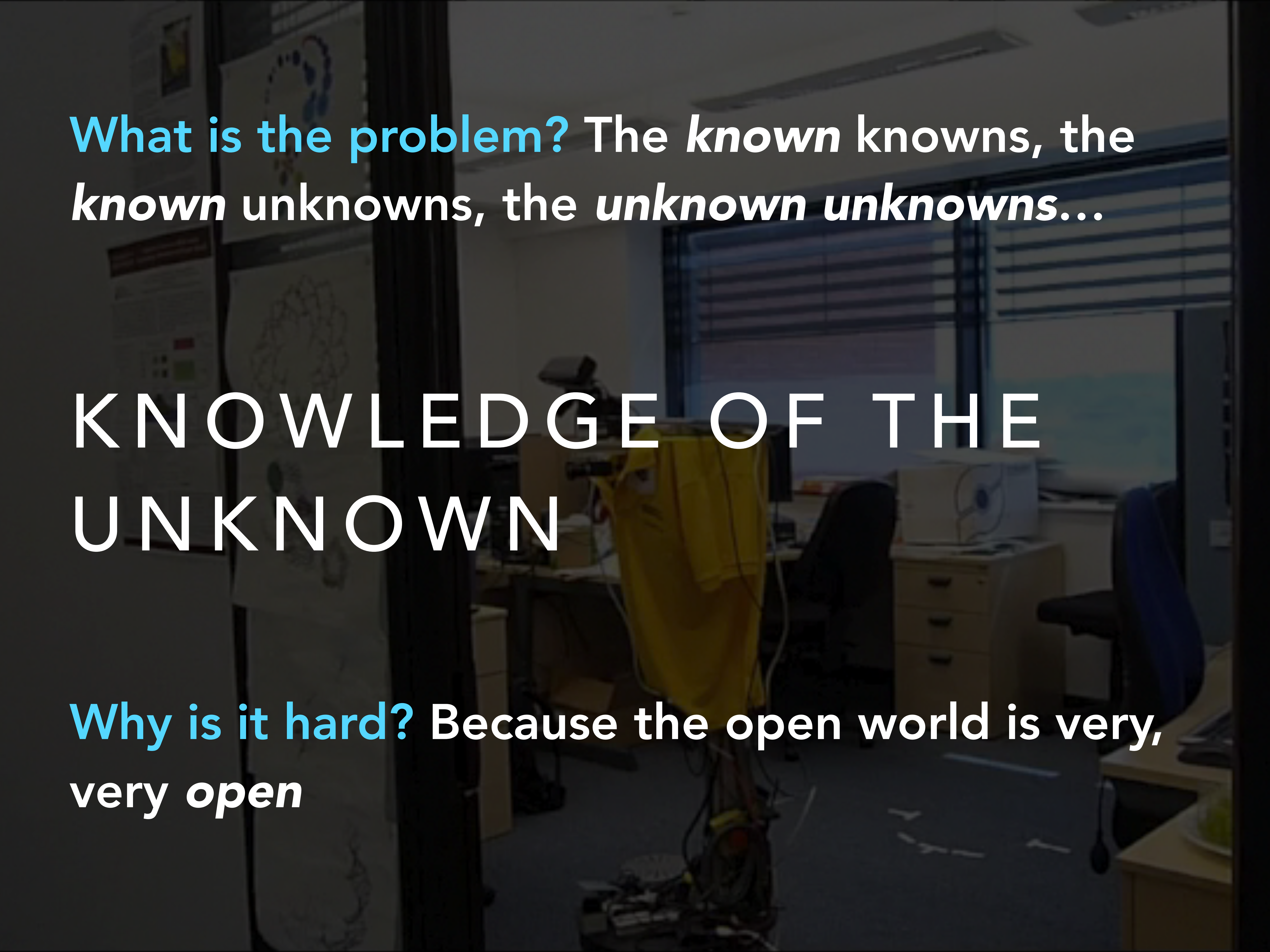
SEVENTH FRAMEWORK PROGRAMME
STRANDS

STRUCTURE

- Autonomous Mobile Robots
- Knowledge of Space
- Break
- **Understanding Change**
- The Unknown

STRUCTURE

- Autonomous Mobile Robots
- Knowledge of Space
- Break
- Understanding Change
- **The Unknown**



What is the problem? The ***known*** knowns, the ***known*** unknowns, the ***unknown unknowns***…

KNOWLEDGE OF THE UNKNOWN

Why is it hard? Because the open world is very, very ***open***

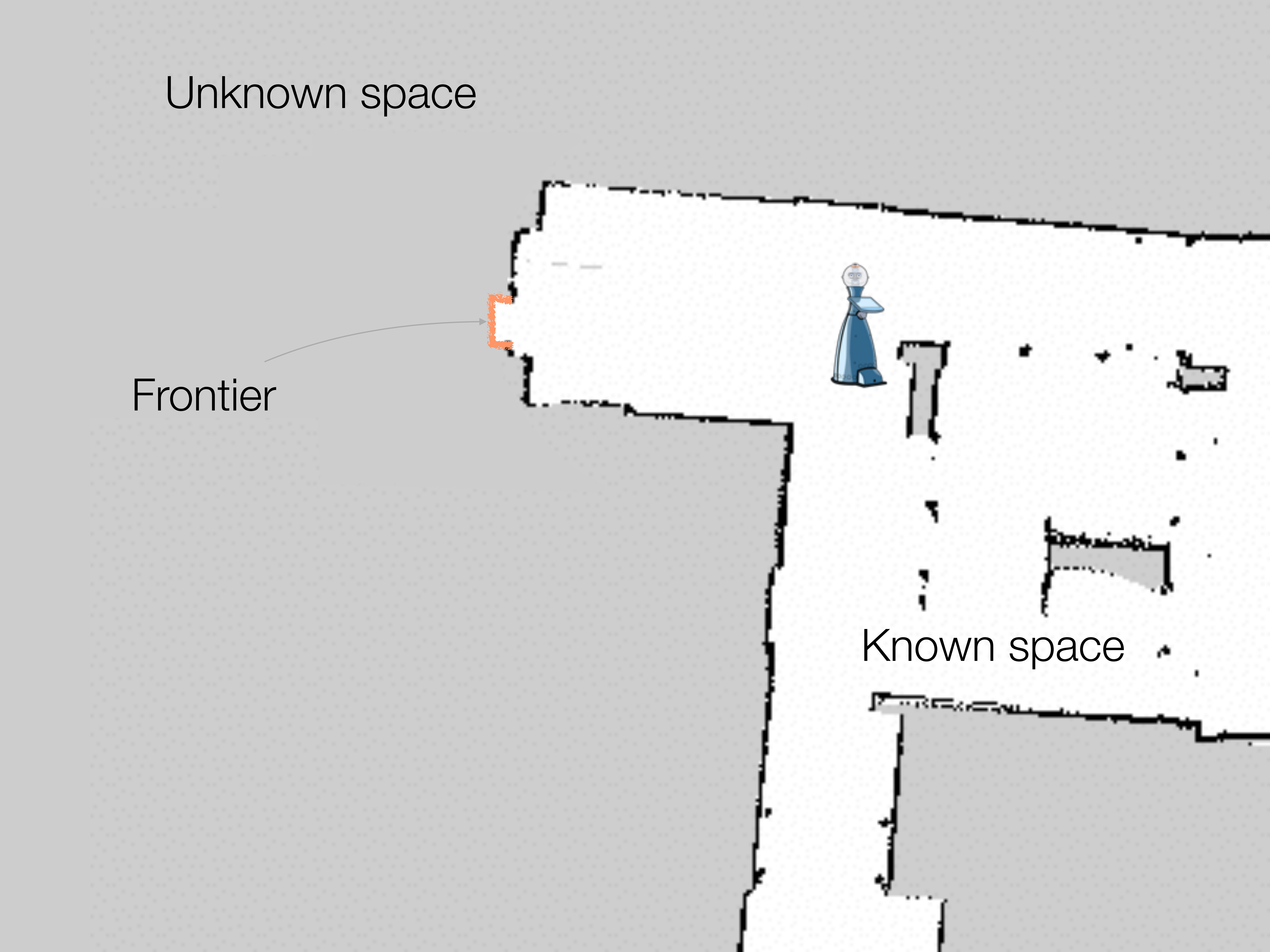
A Frontier-Based Approach for Autonomous Exploration
Yamauchi. In *CIRA '97*.

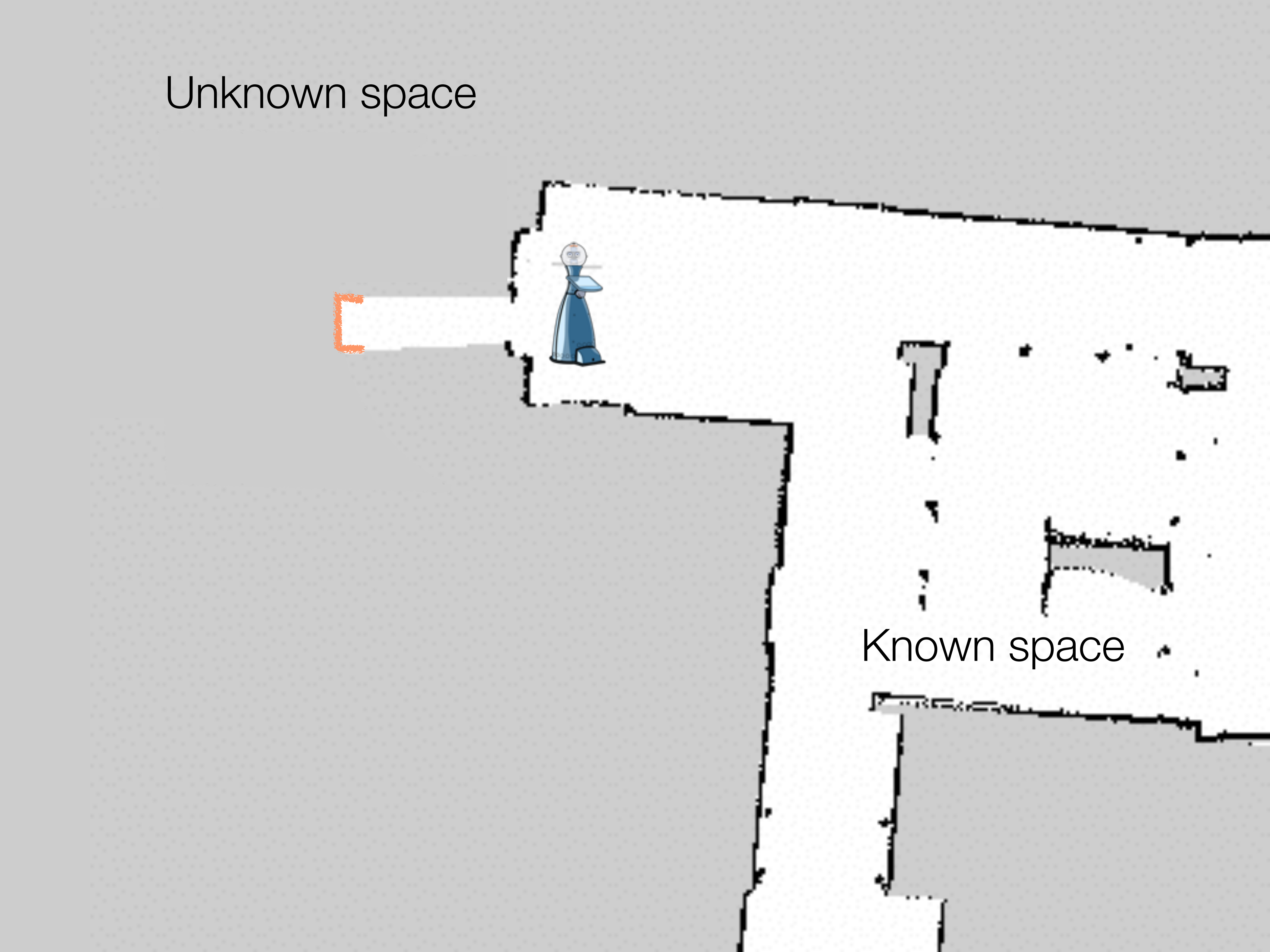
For mobile robots a **unknown space**
is a crucial problem.

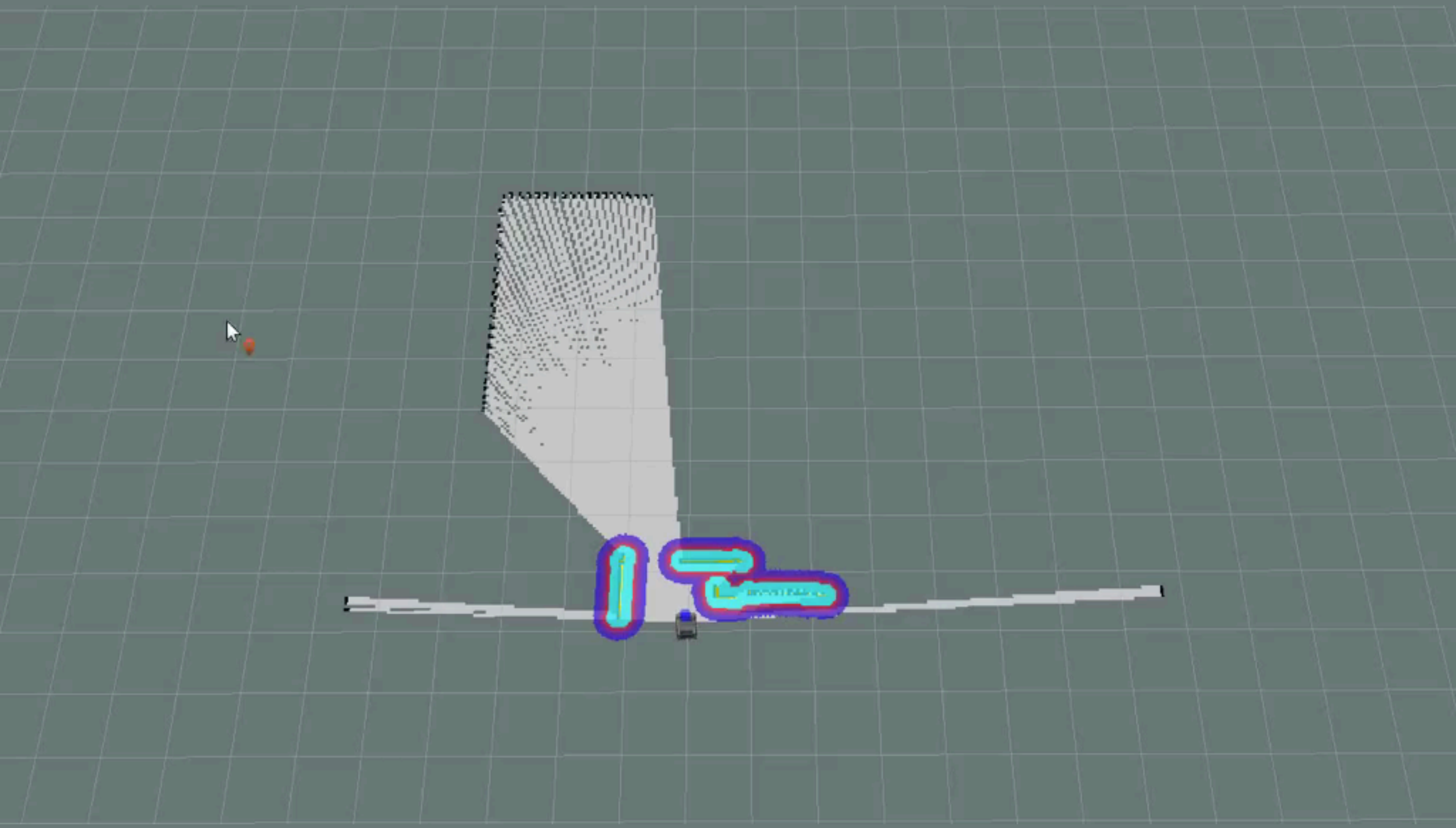
So **autonomous exploration** is a desirable capability

Exploration can be driven using **frontiers**.

These are boundaries between **known, open space** and the UNKNOWN


Unknown space
Frontier
Known space


Unknown space
Known space

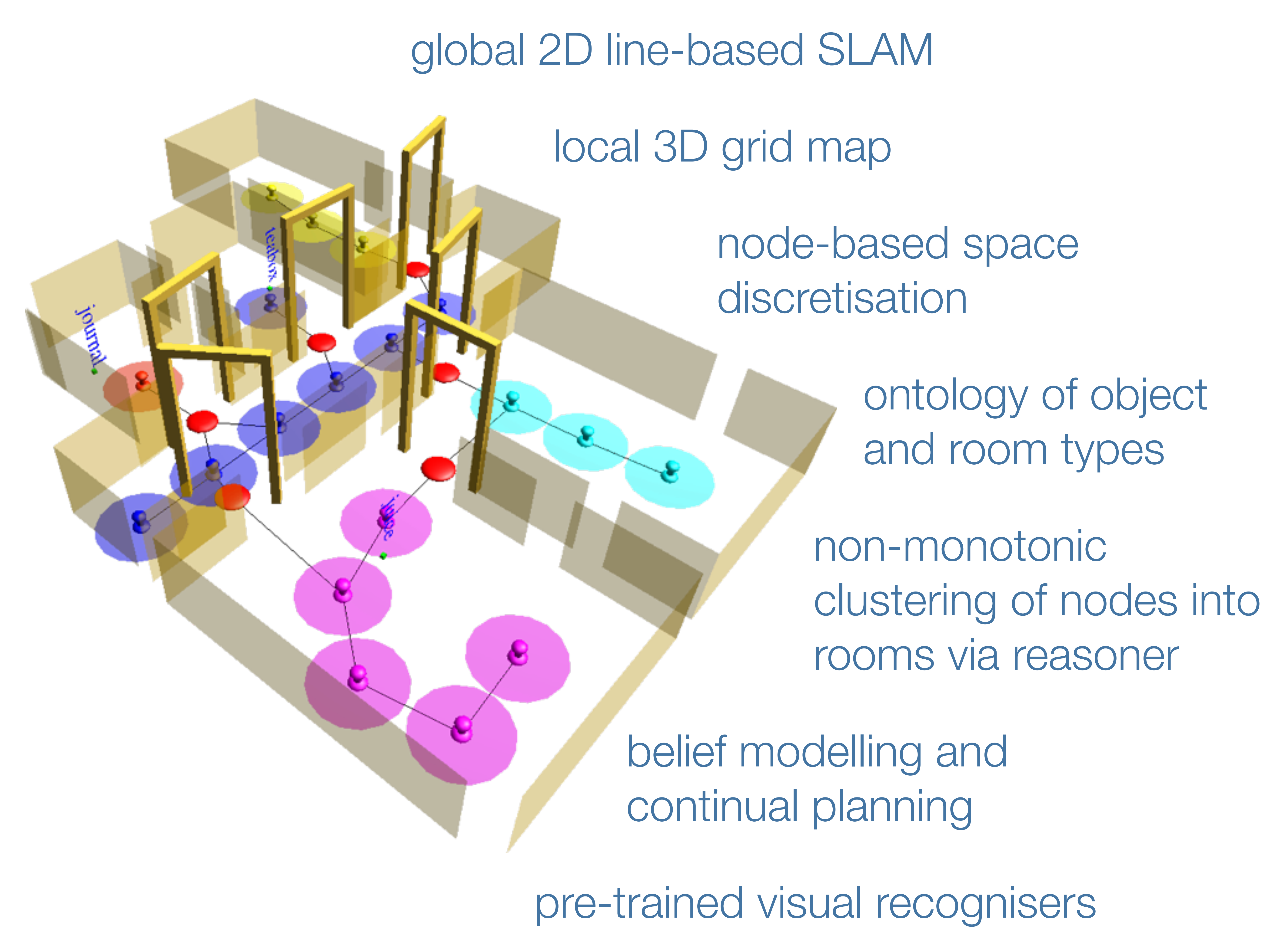


https://youtu.be/3W1ufJ7rpCA

DORA the EXPLORER

COGX

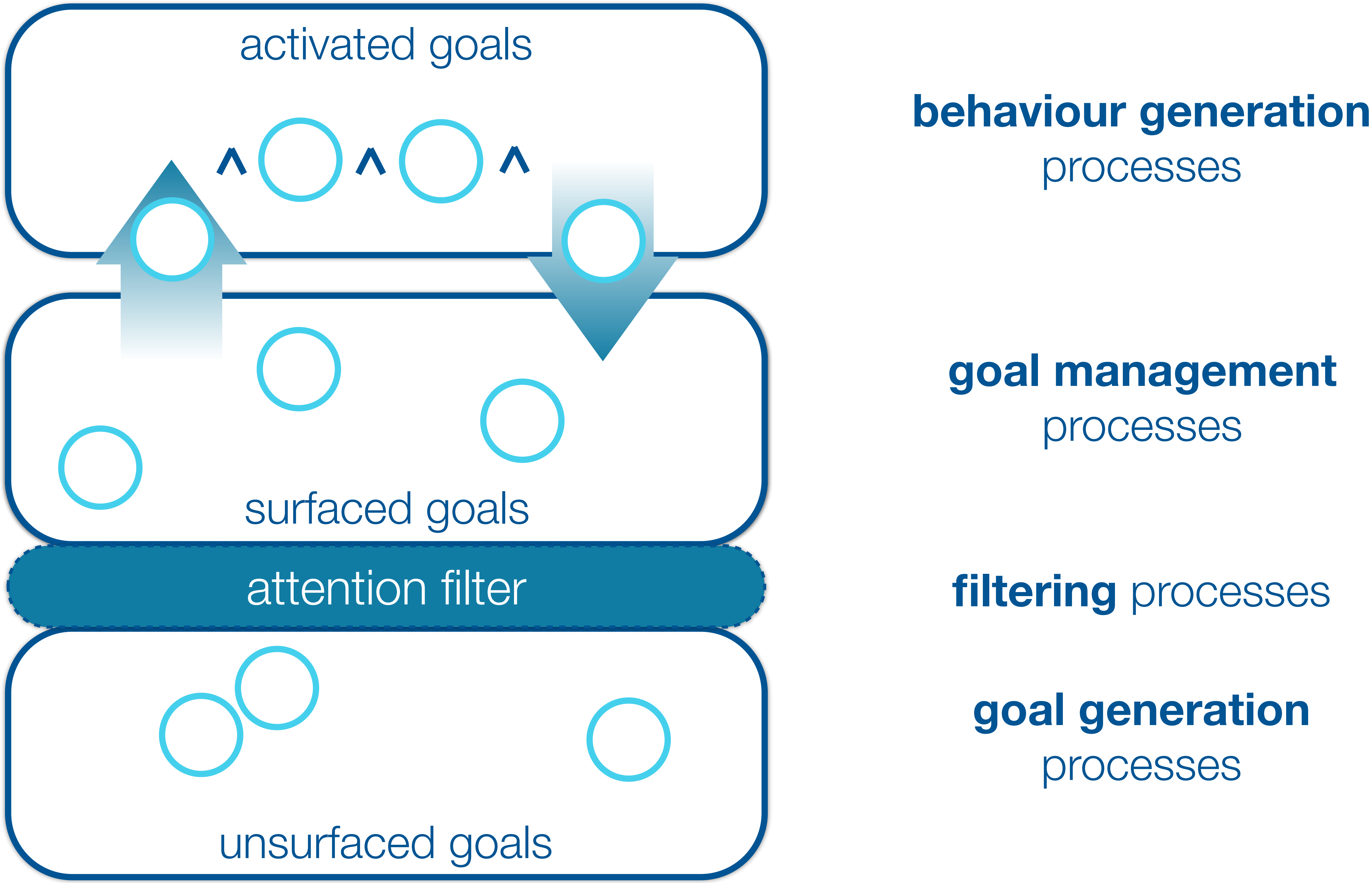
http://cogx.eu/results/dora/



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 via reasoner
belief modelling and continual planning
pre-trained visual recognisers
journal
teabox

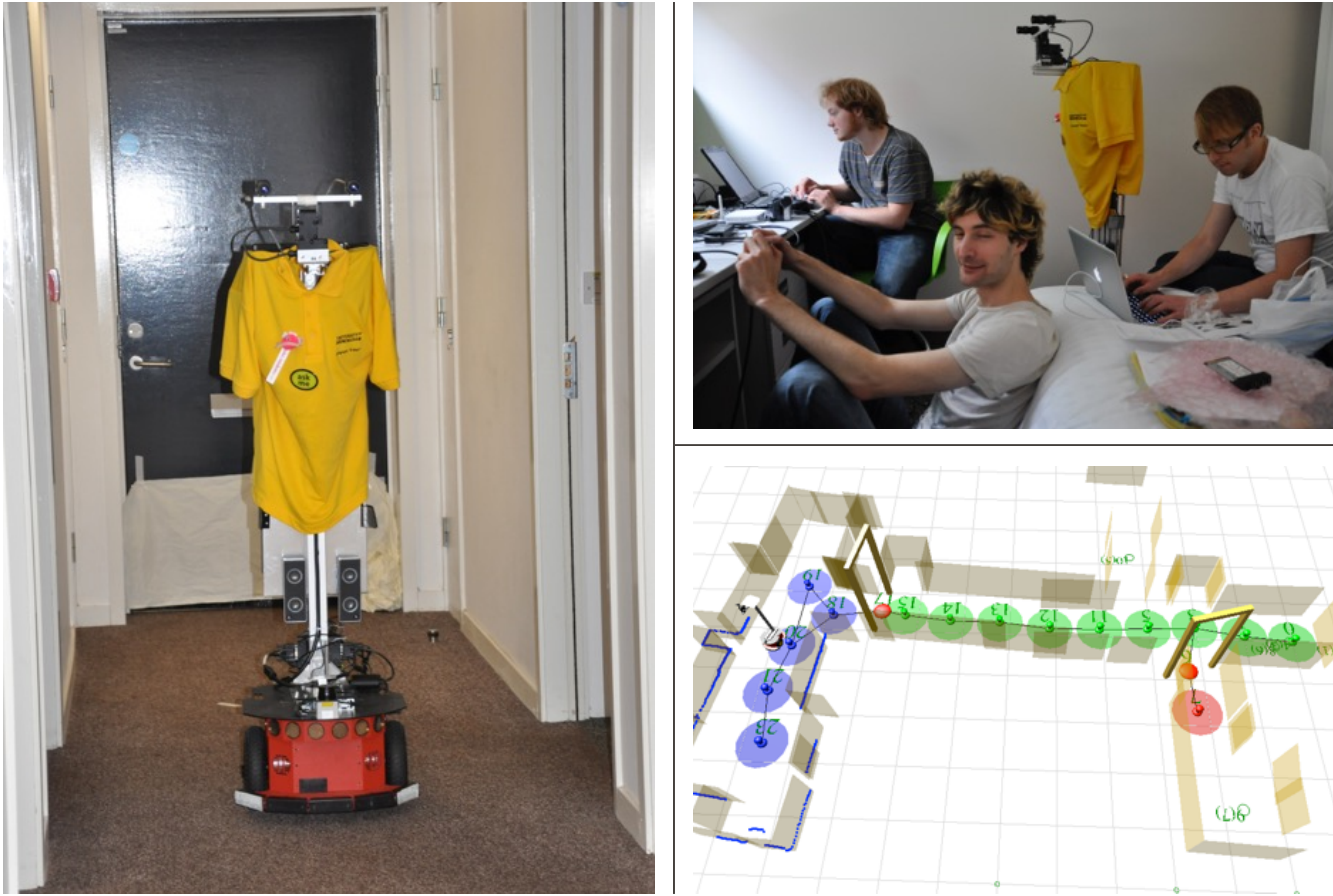
Add goal strings

- Go to a location
- Explore a place hypothesis
- Know the location of an object
- Know the type of a room

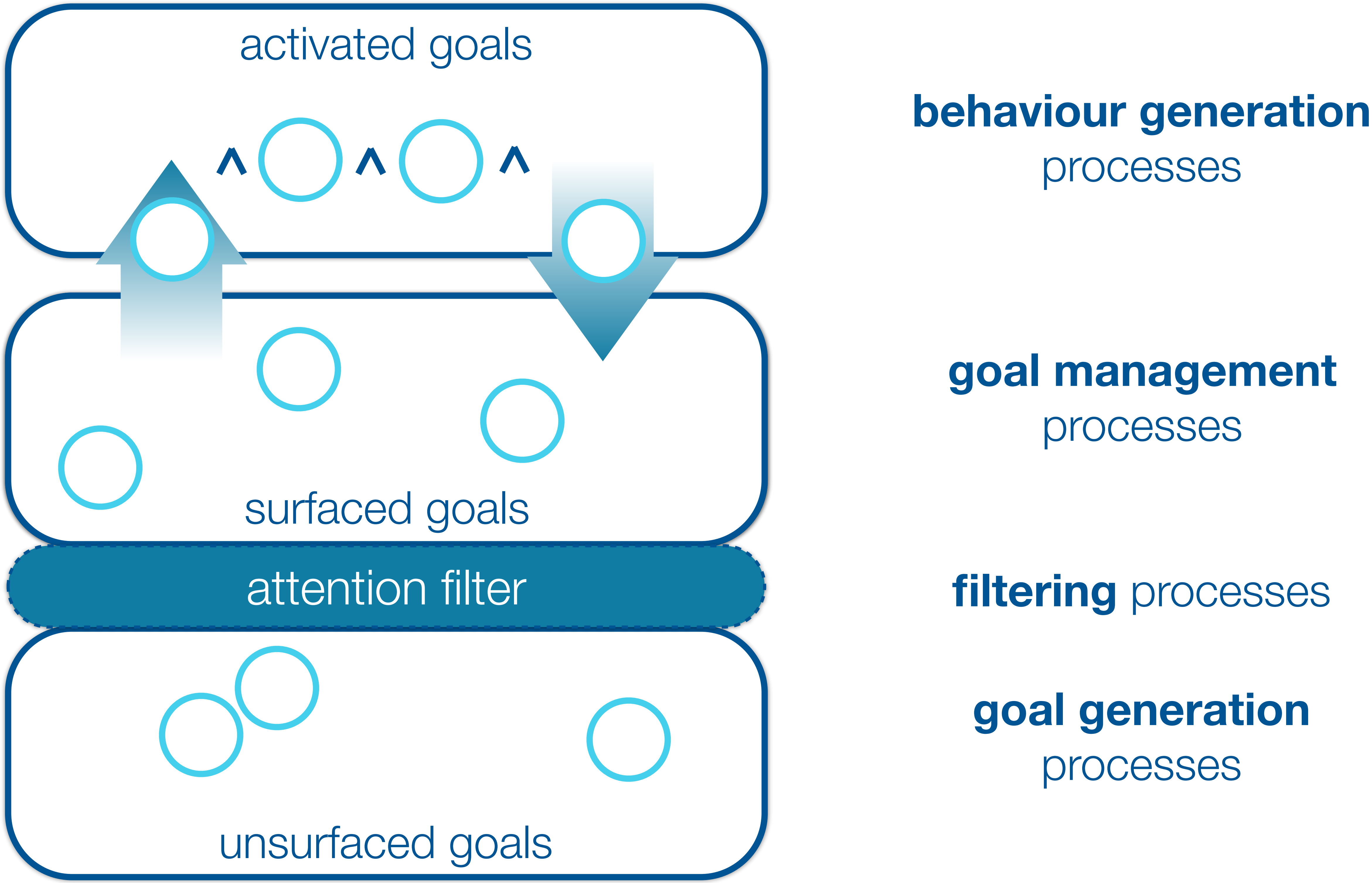


N. Hawes. **A survey of motivation frameworks for intelligent systems**. *Artificial Intelligence*, 175(5-6):1020 – 1036, 2011.

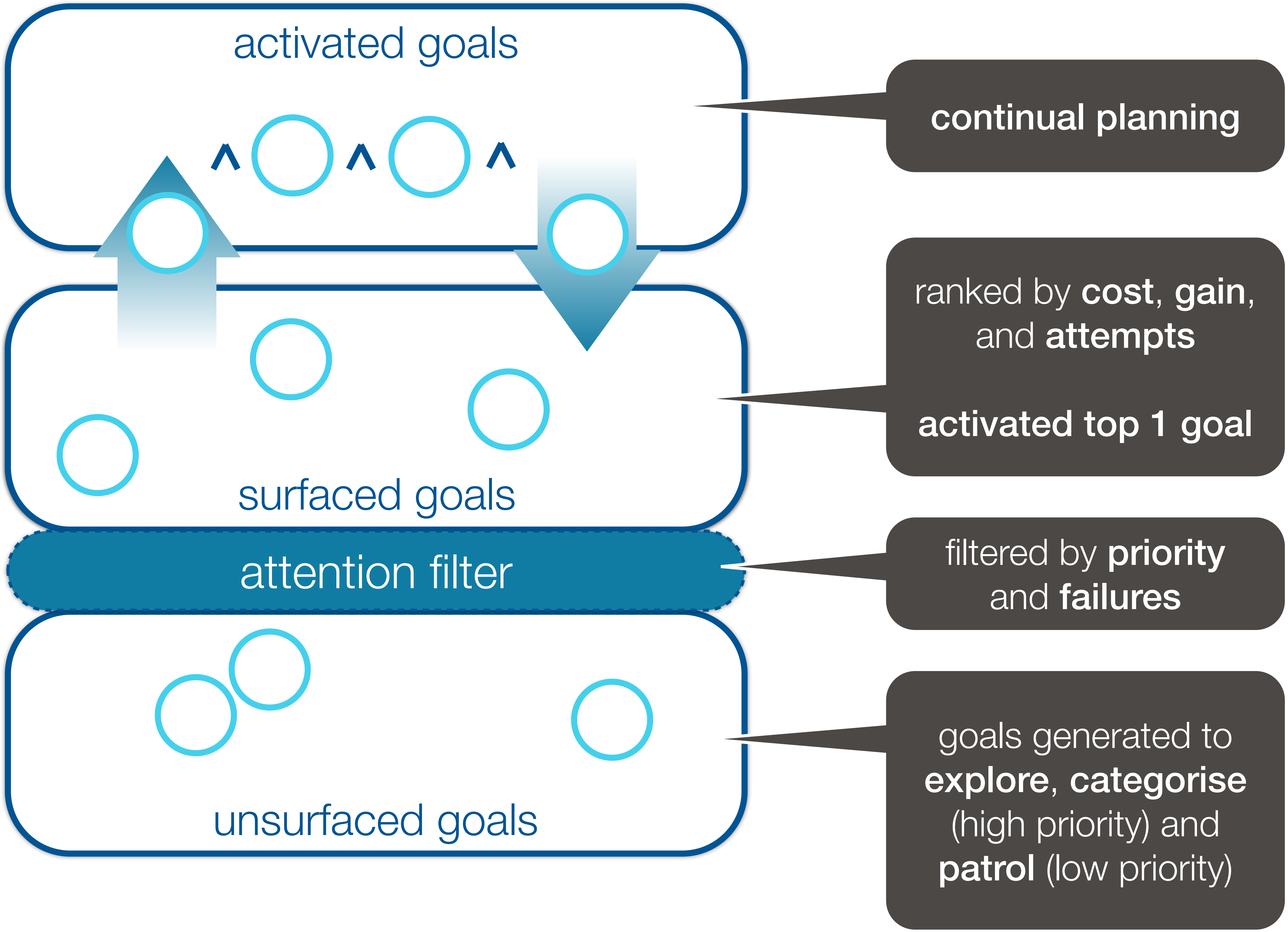
J. L. Wyatt, A. Aydemir, M. Brenner, M. Hanheide, N. Hawes, P. Jensfelt, M. Kristan, G.-J. M. Kruijff, P. Lison, A. Pronobis, K. Sjöö, D. Skočaj, A. Vrečko, H. Zender, and M. Zillich. **Self-understanding and self-extension: A systems and representational approach**. *IEEE Transactions on Autonomous Mental Development*, 2(4):282 – 303, December 2010.



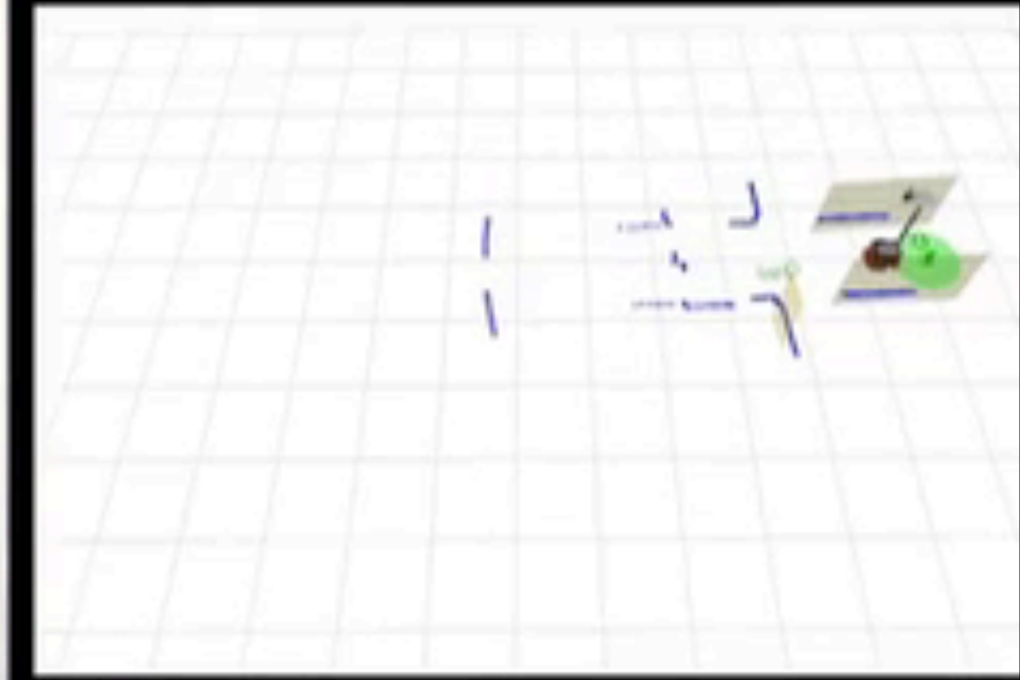
N. Hawes, M. Hanheide, J. Hargreaves, B. Page, H. Zender, and P. Jensfelt. **Home alone: Autonomous extension and correction of spatial representations**. In *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA '11)*, 2011.



N. Hawes, M. Hanheide, J. Hargreaves, B. Page, H. Zender, and P. Jensfelt. **Home alone: Autonomous extension and correction of spatial representations**. In *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA '11)*, 2011.



N. Hawes, M. Hanheide, J. Hargreaves, B. Page, H. Zender, and P. Jensfelt. **Home alone: Autonomous extension and correction of spatial representations**. In *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA '11)*, 2011.

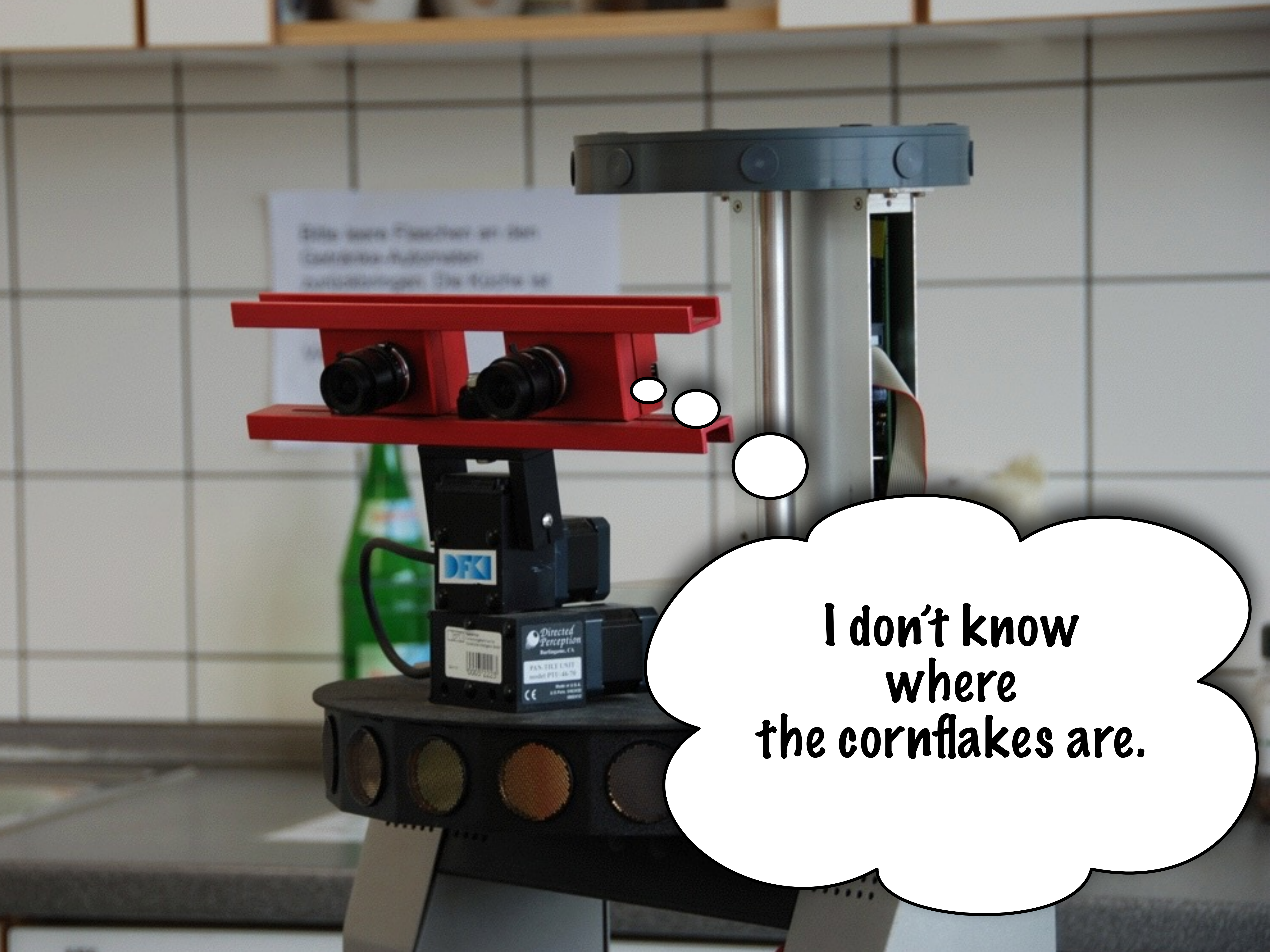


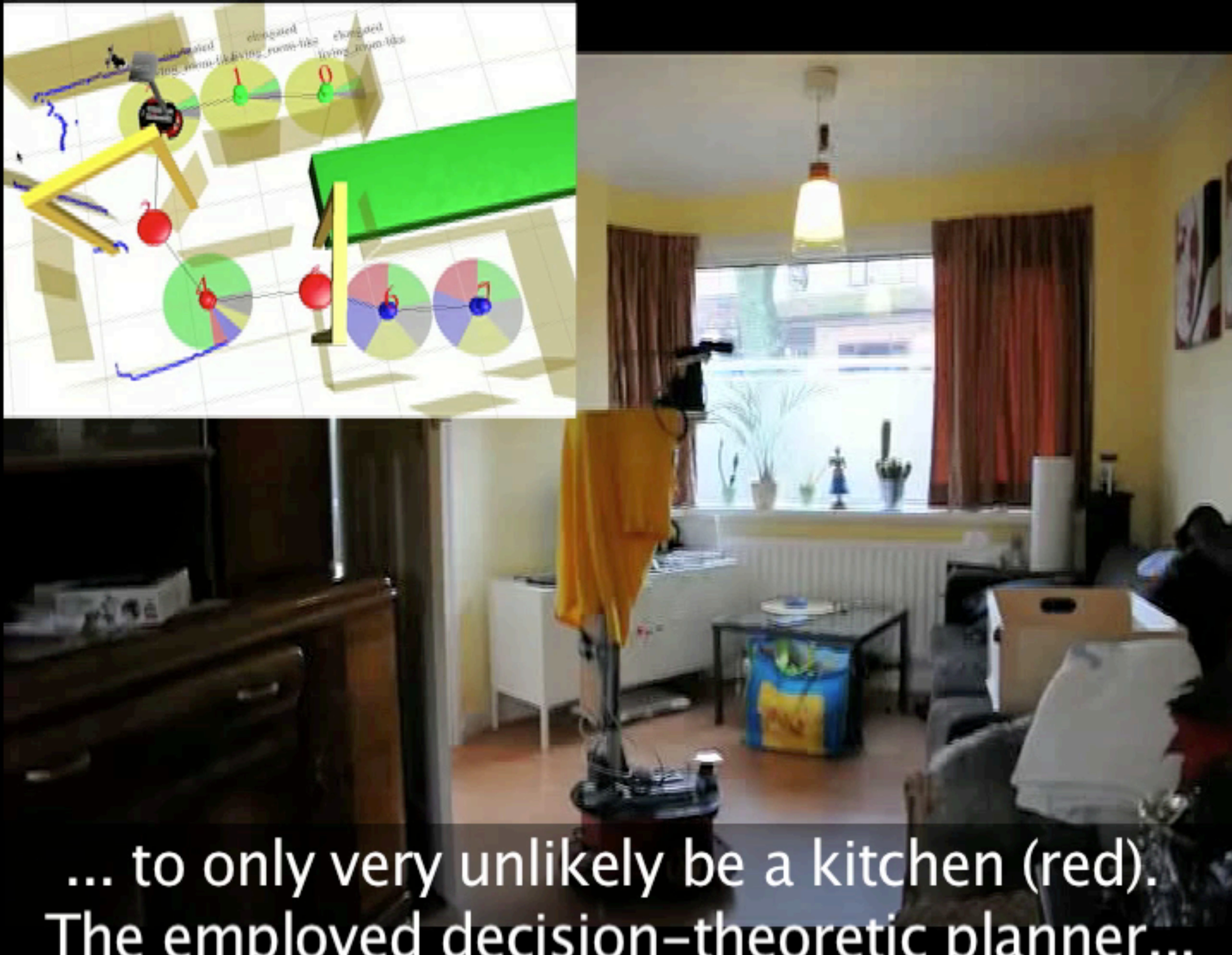
Go Dora, go go go!

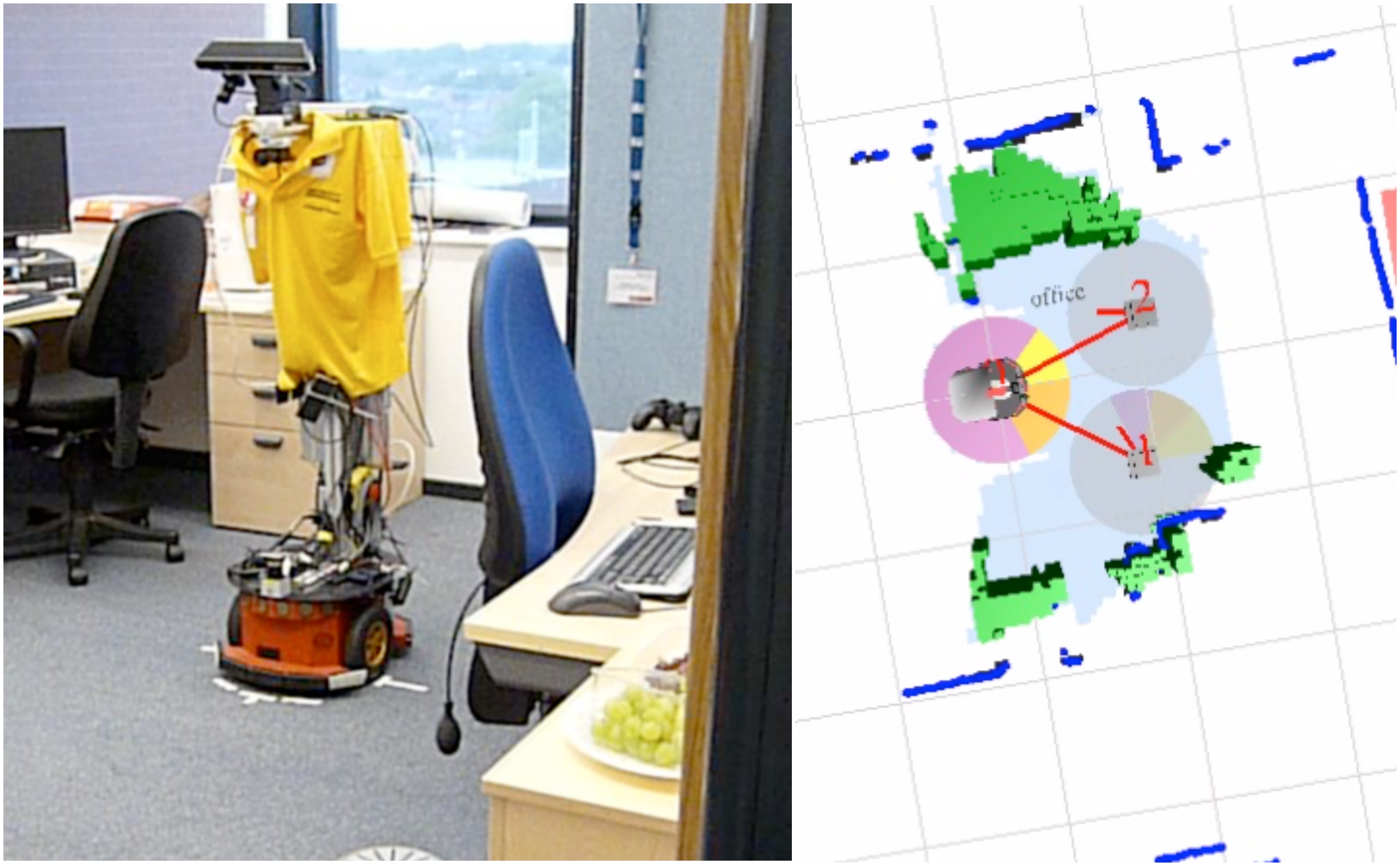
18/21	runs were successful
5/18	required recovery from a missed placeholder
1/18	required recovery from a mis-detected door
13/18	required recovery from action failures and time-outs

N. Hawes, M. Hanheide, J. Hargreaves, B. Page, H. Zender, and P. Jensfelt. **Home alone: Autonomous extension and correction of spatial representations**. In *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA '11)*, 2011.


Dora, get me a box of cornflakes.
Vollmilch

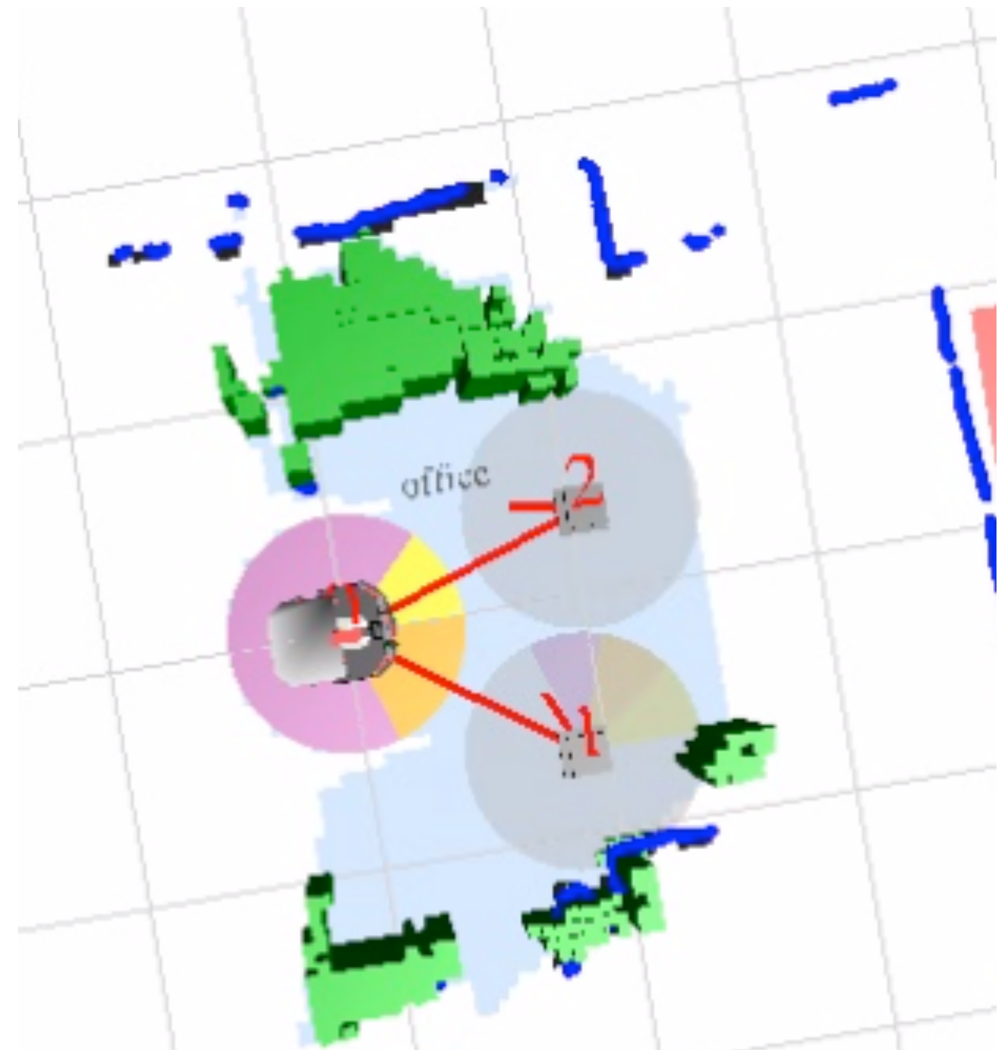

DFKI
Directed Perception
I don't know
where
the cornflakes are.

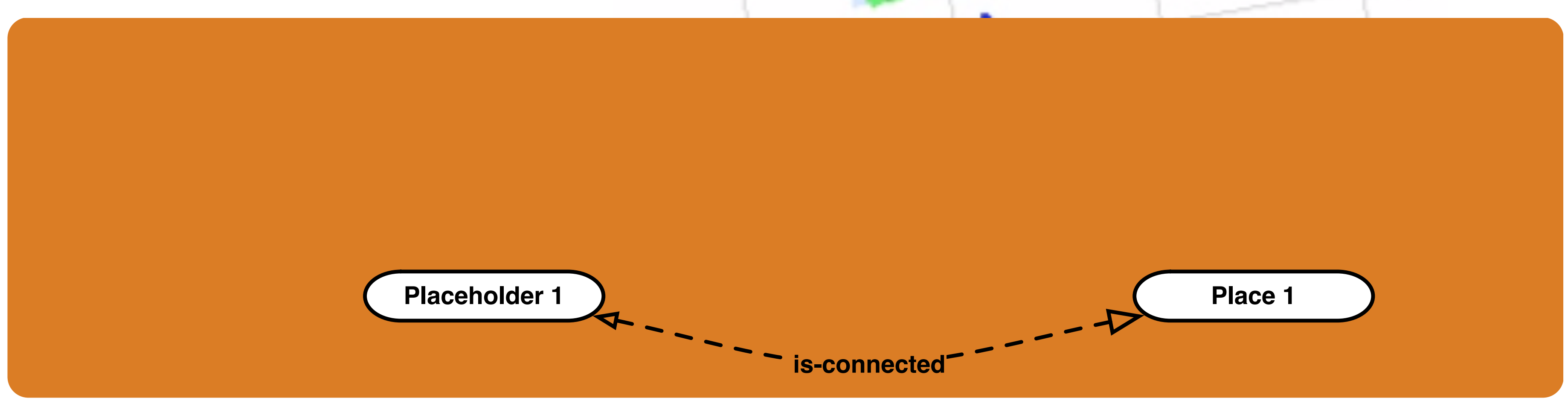

... to only very unlikely be a kitchen (red).
The employed decision-theoretic planner...


office
2
1

Instance Knowledge

Relational Map





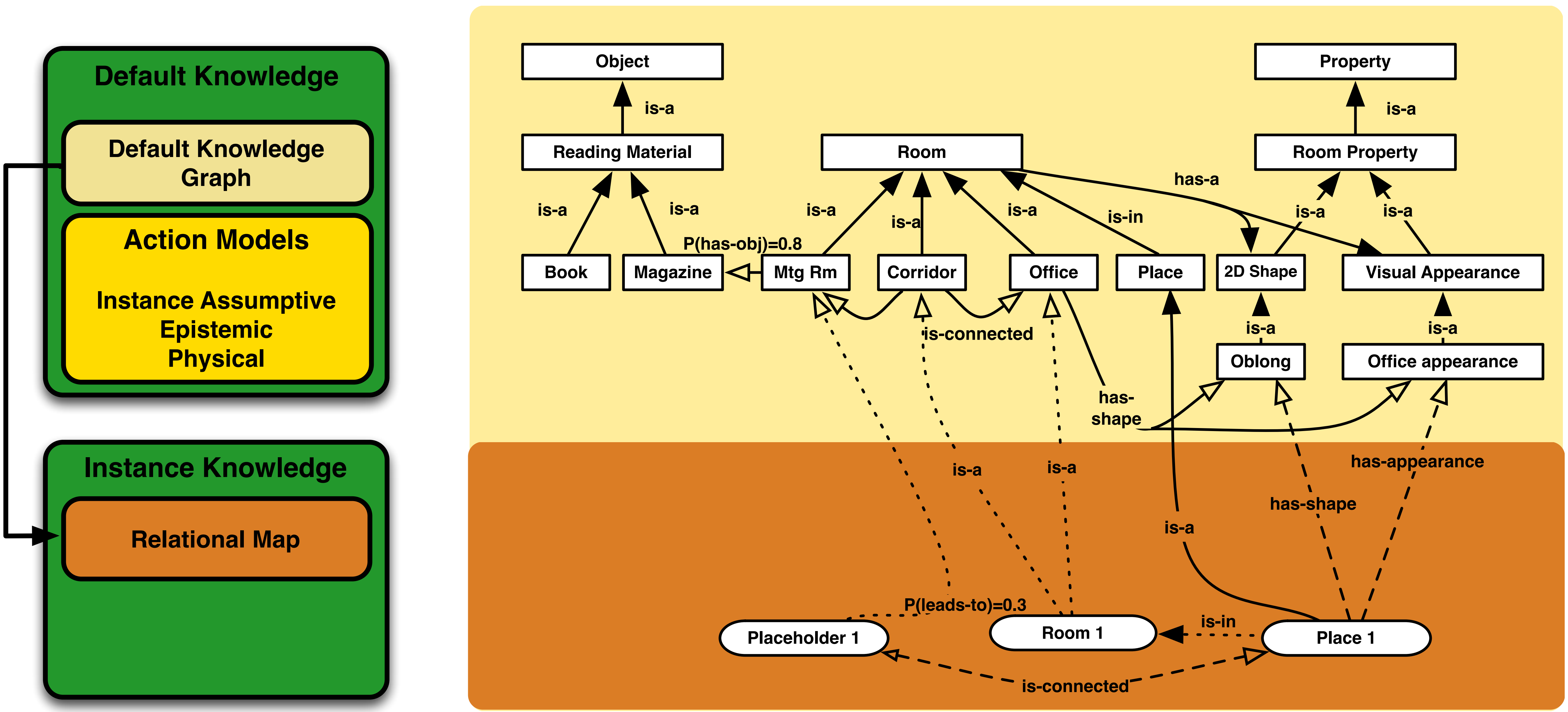
Robot Task Planning and Explanation in Open and Uncertain Worlds

Hanheide, Hawes, Wyatt *et al*. *Artificial Intelligence,* 2015.

“Dora, find me a magazine”

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

But how can Dora create a plan for this?



Default Knowledge
Default Knowledge Graph
Action Models
Instance Assumptive
Epistemic
Physical
Instance Knowledge
Relational Map
Object
is-a
Reading Material
is-a
is-a
Book
Magazine
P(has-obj)=0.8
Mtg Rm
Room
is-a
is-a
is-a
is-in
Corridor
Office
Place
has-a
Property
is-a
Room Property
is-a
is-a
2D Shape
Visual Appearance
is-a
is-a
Oblong
Office appearance
is-connected
has-
shape
is-a
is-a
is-a
has-appearance
has-shape
P(leads-to)=0.3
Placeholder 1
Room 1
is-in
Place 1
is-connected

Physical Effects

```
(move
      :pre (and (connected ?from ?to)
                (= (is-in ?a) ?from))

      :eff (and (assign (is-in ?a) ?to)
           ))
```

Probabilistic Effects

```
(observe-object
      . . .

      :eff (when (= (is-in ?o) ?pl)
                 (prob 0.7 (observe ?o))
           ))
```

Knowledge Effects

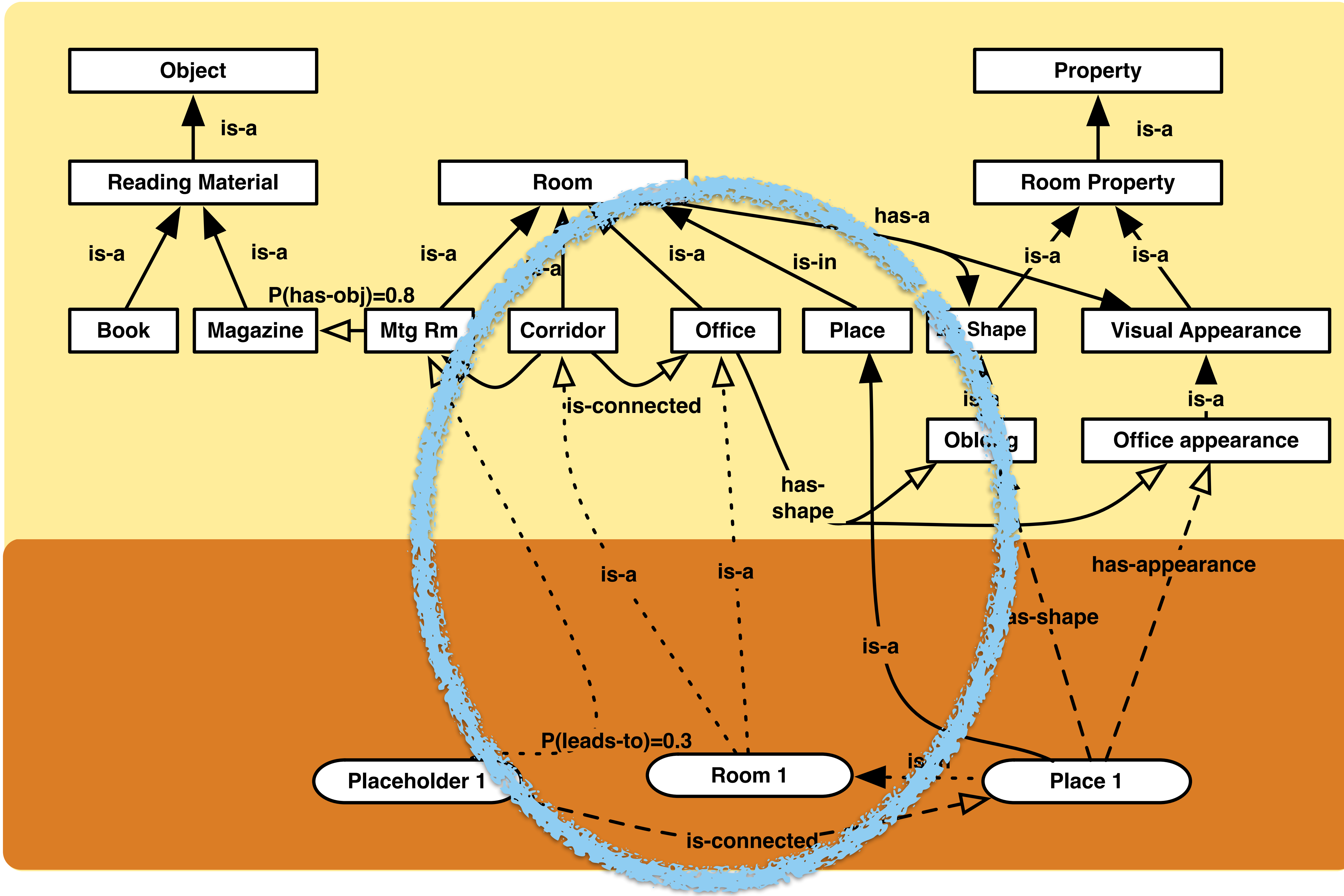
```
(move
      :pre (and (connected ?from ?to)
                (= (is-in ?a) ?from))

      :eff (and (assign (is-in ?a) ?to)
                (K (in-room ?to))))
```

Conditional Effects

```
(search-for-object
      . . .

      :eff (when (A (position ?o) ?room)
                 (K (position ?o))))
```

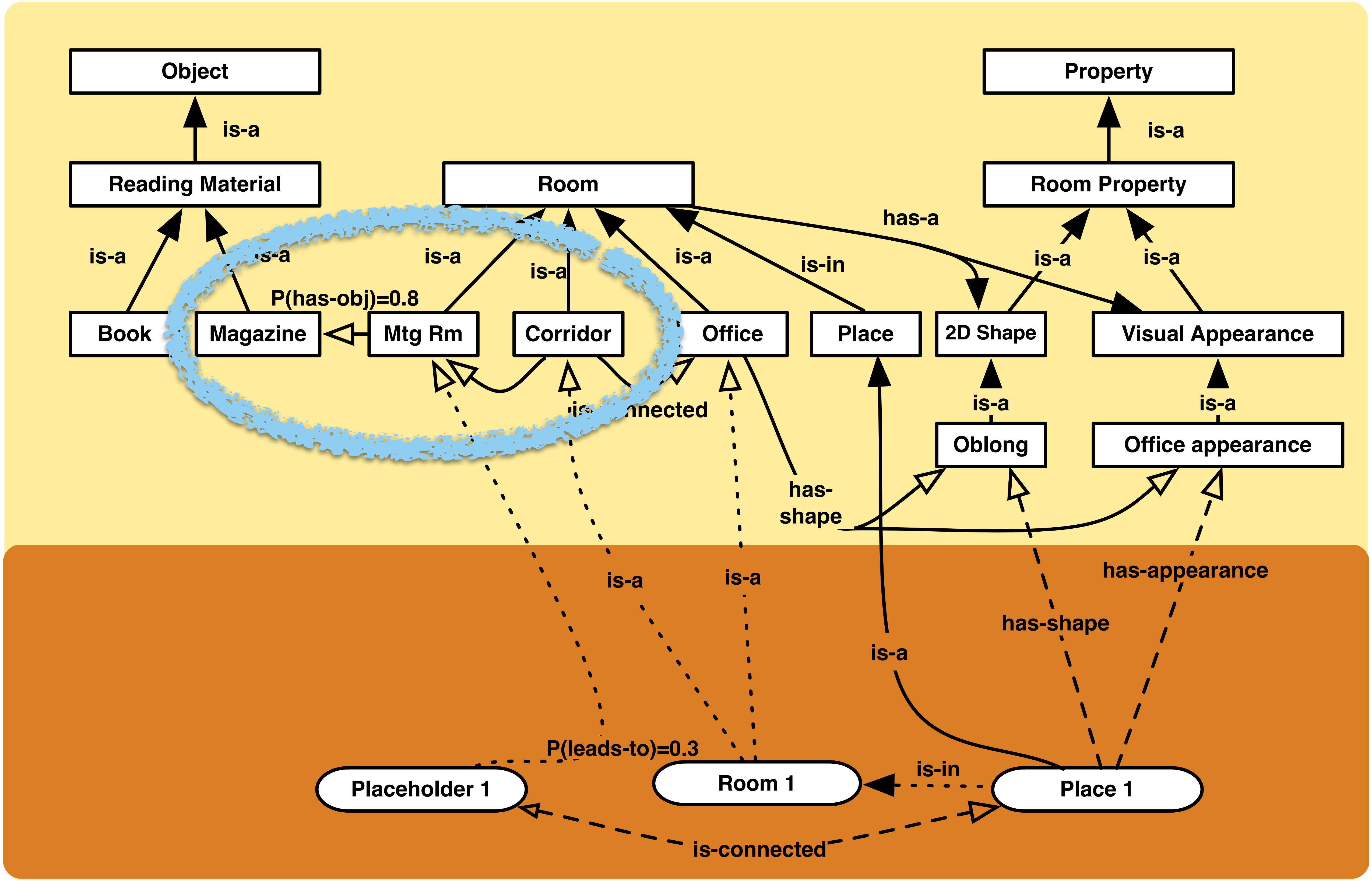


Object
is-a
Reading Material
Room
Property
is-a
Room Property
is-a
is-a
is-a
has-a
is-a
is-in
is-a
is-a
P(has-obj)=0.8
Book
Magazine
Mtg Rm
Corridor
Office
Place
Shape
Visual Appearance
is-connected
is-a
Office appearance
has-
shape
is-a
is-a
has-appearance
has-shape
is-a
P(leads-to)=0.3
Placeholder 1
Room 1
Place 1
is-connected

Assumptive Effects

```
(assumption is-room1-office
      :eff (A (is-a room1) office)
                (prob 0.52)))
```

Assumptions about **instance** state from **instance** state

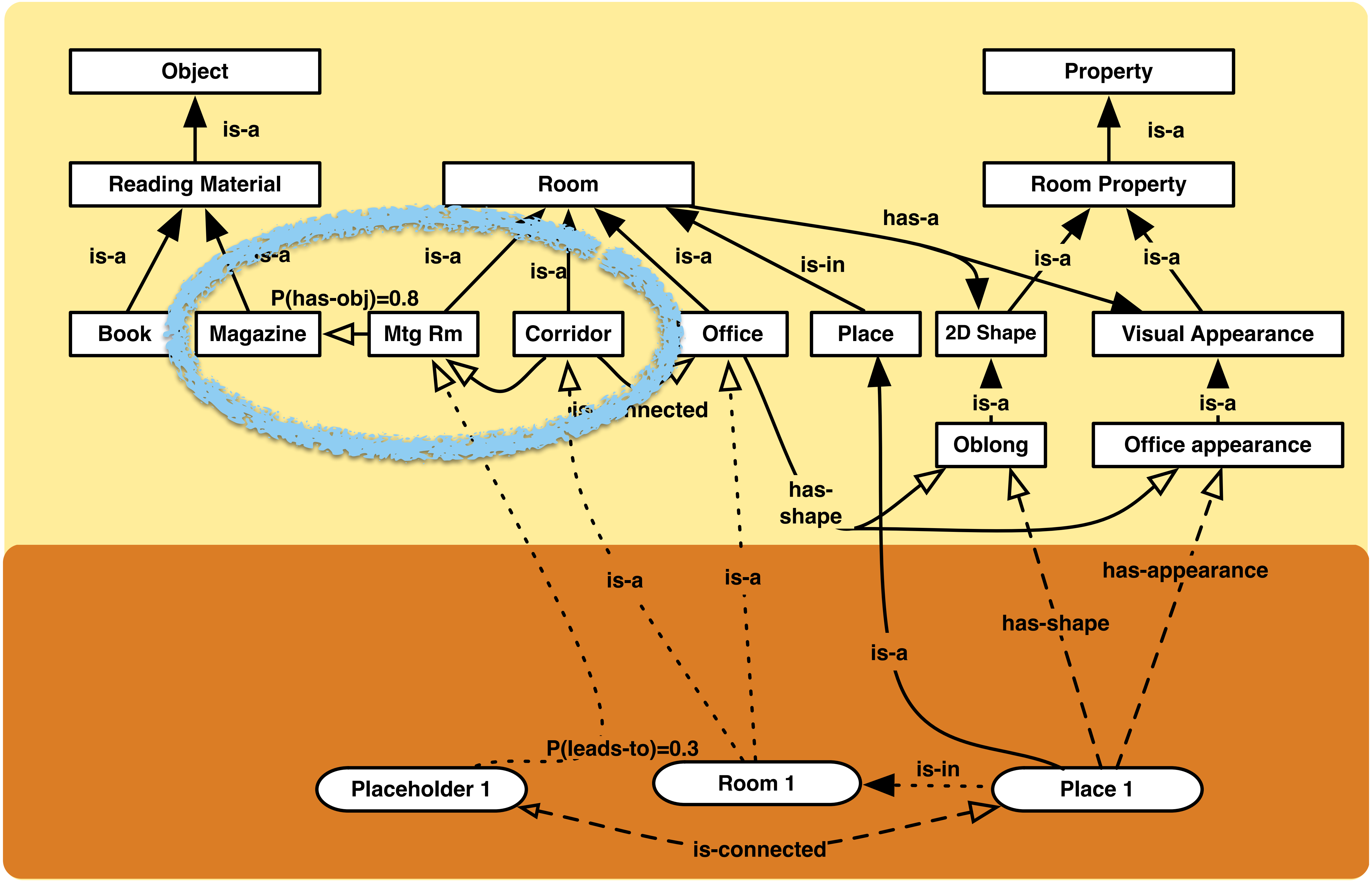


Object
is-a
Reading Material
is-a
is-a
Book
Magazine
P(has-obj)=0.8
Mtg Rm
Corridor
Room
is-a
is-a
is-a
Office
is-in
Place
has-a
Property
is-a
Room Property
is-a
is-a
2D Shape
Visual Appearance
is-a
is-a
Oblong
Office appearance
is-connected
has-
shape
is-a
is-a
is-a
has-appearance
has-shape
P(leads-to)=0.3
Placeholder 1
Room 1
is-in
Place 1
is-connected

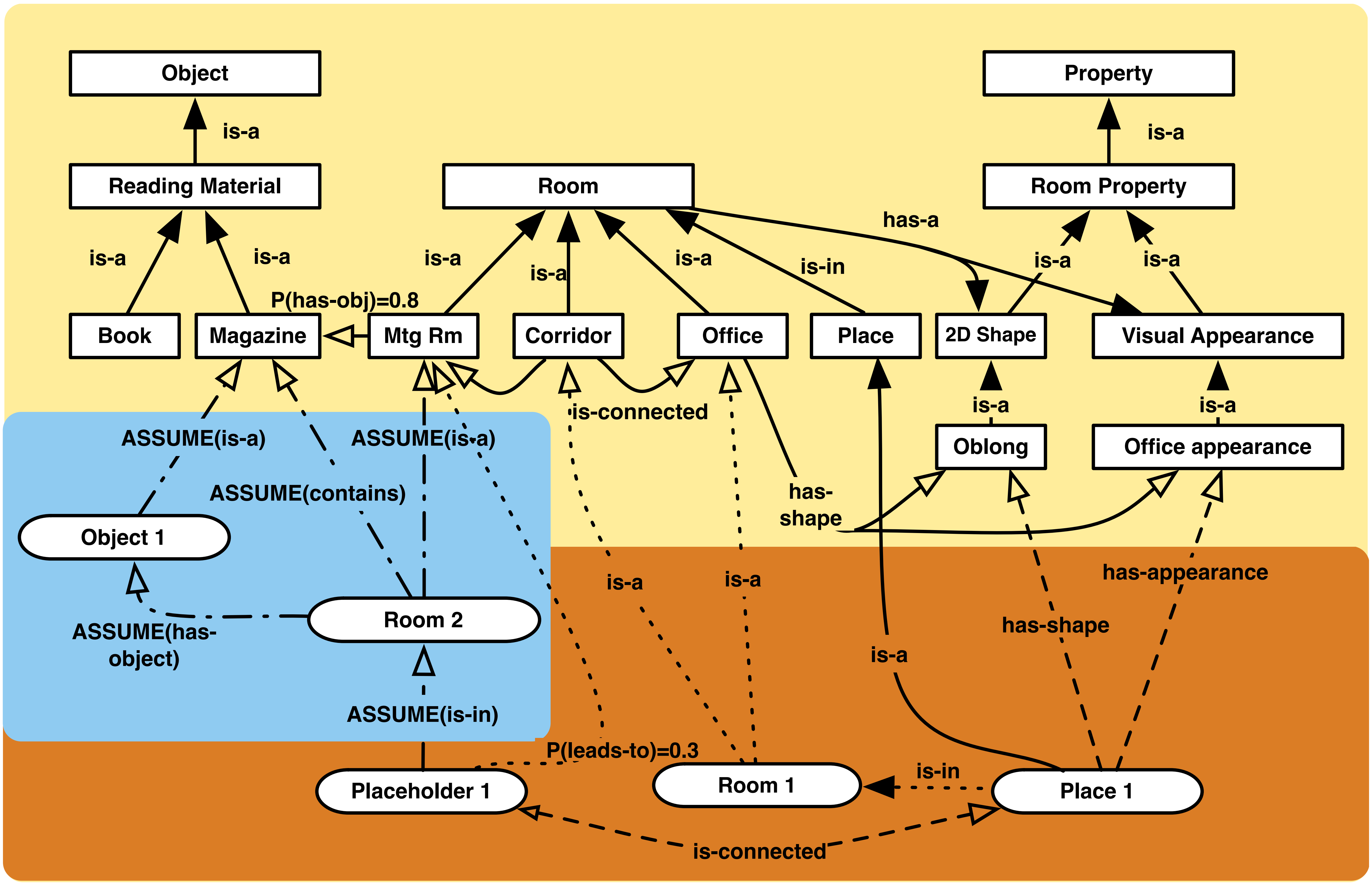
Assumptive Effects

```
(assumption object-in-room
  :pre (A (is-a ?room) ?room-type)
  :eff (and
        (A (is-in ?room ?obj-type) T)
        (assign prob
         (default-P (is-in ?room-type ?obj-type))
        )))
```

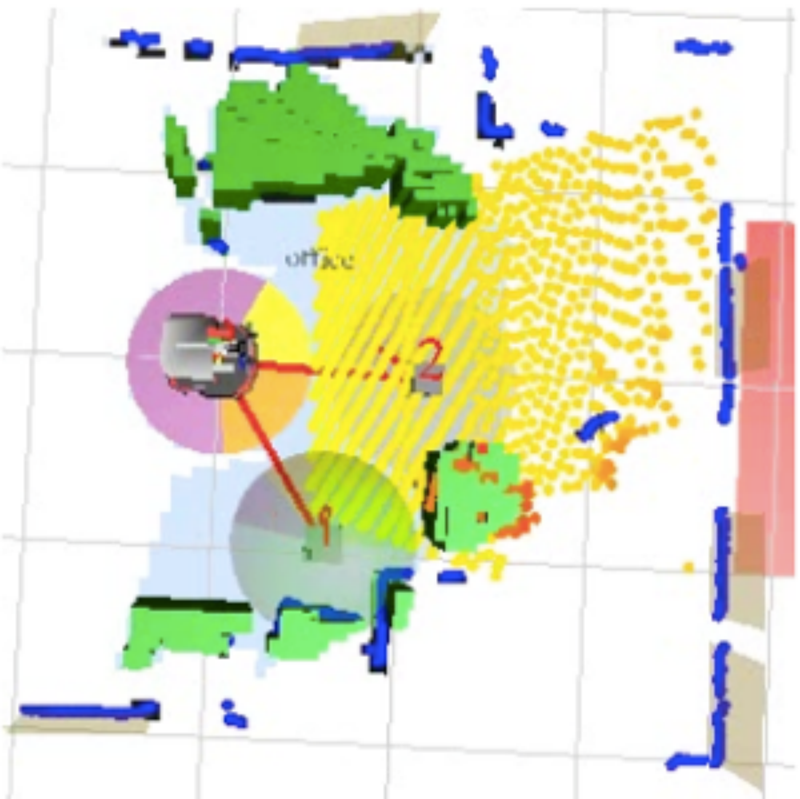
Assumptions about **instance** state from **default knowledge**



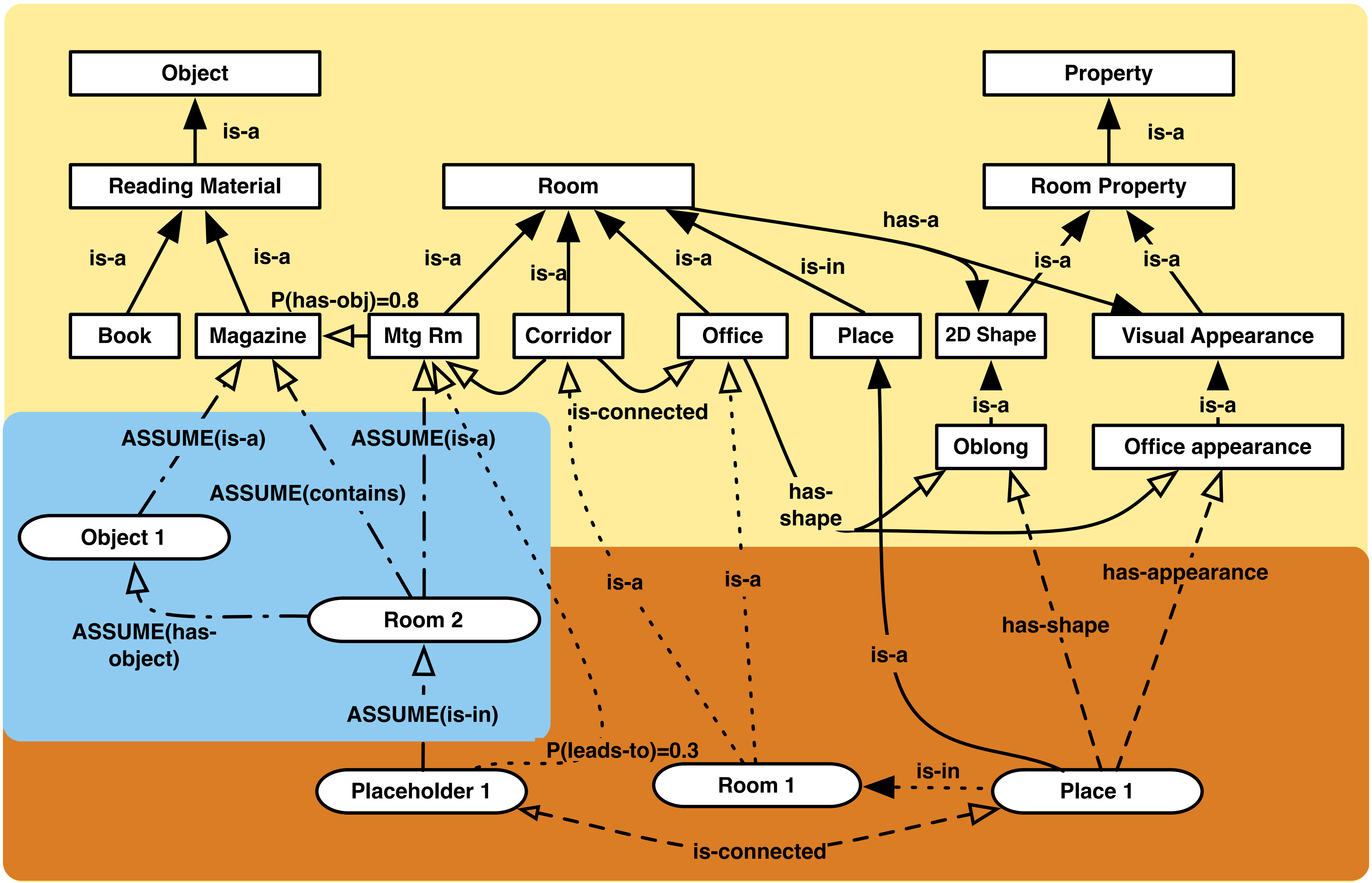
Object
Property
is-a
is-a
Reading Material
Room
Room Property
has-a
is-a
is-a
is-a
is-a
is-in
is-a
is-a
is-a
P(has-obj)=0.8
Book
Magazine
Mtg Rm
Corridor
Office
Place
2D Shape
Visual Appearance
is-a
is-a
Oblong
Office appearance
has-
shape
is-a
is-a
has-appearance
has-shape
is-a
P(leads-to)=0.3
is-in
Placeholder 1
Room 1
Place 1
is-connected



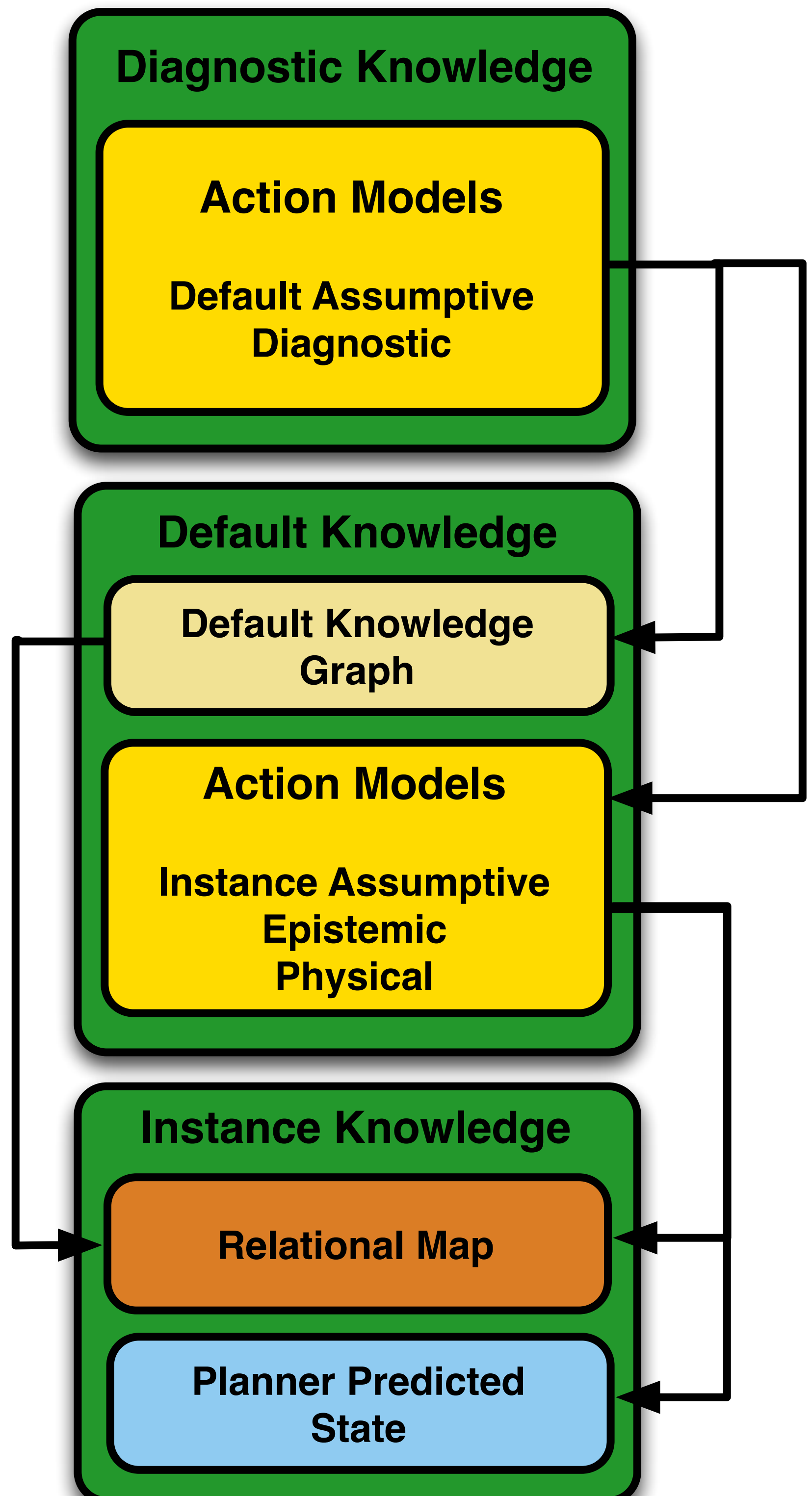
Object
is-a
Reading Material
is-a
is-a
Book
Magazine
P(has-obj)=0.8
Room
is-a
is-a
is-a
is-in
has-a
Mtg Rm
Corridor
Office
Place
Property
is-a
Room Property
is-a
is-a
2D Shape
Visual Appearance
is-a
is-a
Oblong
Office appearance
is-connected
has-
shape
ASSUME(is-a)
ASSUME(is-a)
ASSUME(contains)
Object 1
Room 2
ASSUME(has-
object)
ASSUME(is-in)
is-a
is-a
is-a
has-shape
has-appearance
P(leads-to)=0.3
Placeholder 1
Room 1
is-in
Place 1
is-connected



Action	**Cost**	**Prob.**	**Status**
leads-to-room-placeholder1-meetingroom	0	0.30	DONE
room-from-placeholder placeholder1 room2 meetingroom	0	1.00	DONE
object-in-room magazine room2 meetingroom	0	0.80	DONE
virtual-object-position object1 magazine room2	0	1.00	DONE
move dora place1 placeholder1	2	1.00	RUNNING
create-cones dora magazine room2 placeholder1	5	1.00	
search-for-object dora magazine room2 placeholder1 object1	200	1.00	
Total:	**207**	**0.243**	



Object
is-a
Property
is-a
Reading Material
Room
Room Property
is-a
is-a
is-a
is-a
is-a
has-a
is-in
is-a
is-a
P(has-obj)=0.8
Book
Magazine
Mtg Rm
Corridor
Office
Place
2D Shape
Visual Appearance
is-connected
is-a
is-a
ASSUME(is-a)
ASSUME(is-a)
Oblong
Office appearance
ASSUME(contains)
has-
shape
Object 1
is-a
is-a
has-appearance
Room 2
has-shape
ASSUME(has-
object)
is-a
ASSUME(is-in)
P(leads-to)=0.3
Placeholder 1
Room 1
is-in
Place 1
is-connected


Diagnostic Knowledge
Action Models
Default Assumptive
Diagnostic
Default Knowledge
Default Knowledge
Graph
Action Models
Instance Assumptive
Epistemic
Physical
Instance Knowledge
Relational Map
Planner Predicted
State

STRUCTURE

- Autonomous Mobile Robots
- Knowledge of Space
- Break
- Understanding Change
- **The Unknown**

ESSENCE SUMMER SCHOOL, EDINBURGH, AUGUST 2015

STRUCTURED REPRESENTATIONS FOR ROBOT BEHAVIOUR

NICK HAWES
SCHOOL OF COMPUTER SCIENCE, UNIVERSITY OF BIRMINGHAM

N.A.HAWES@CS.BHAM.AC.UK
HTTP://WWW.CS.BHAM.AC.UK/~NAH @HAWESIE