Frequency Map Enhancement for Long-term Autonomy in Changing Environments

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Czech Technical University in Prague

Czech Technical University in Prague:

- Oldest non-military technical university
- Alumni: Christian Doppler, Simon Wiesenthal
- $\sim$ 420 fields of study, $\sim$ 25000 students
- strong in AI and robotics

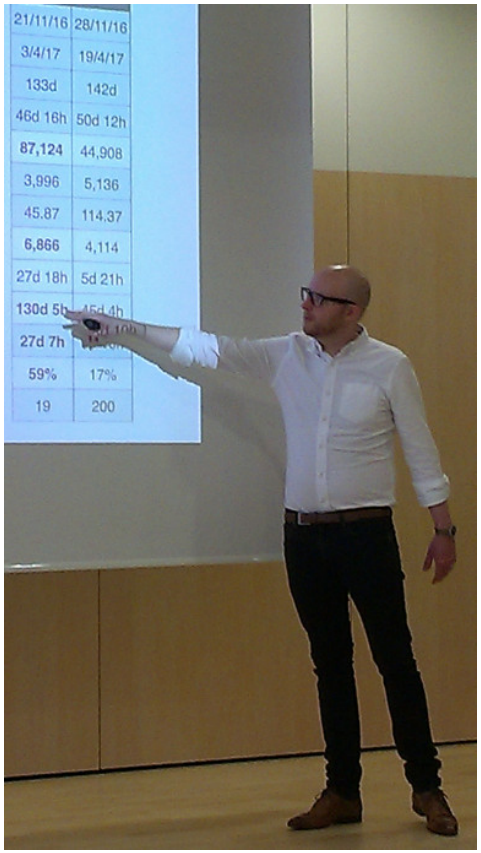
Come for a visit:

- Outdoor robot navigation challenge RoboTour (annually)
- CTU Poster Student Conference (annually) - free
- 2019 - European Conference on Mobile Robots (ECMR)
- 2021 - Intelligent Robots and Systems (IROS)

Mapping in changing environments - MBZIRC

Outdoor object mapping for a multi-UAV system.

Mapping in changing environments - EU FP7 STRANDS



Autonomous operation at a care homes for >4 months.

Addressing Long-Term Environment Changes

Oxford	*Churchill et al.*:	place-specific ‘experiences’
CMU	*Biswas et al.*:	static/dynamic separation
Örebro	*Lowry et al.*:	condition-invariant appearance
Freiburg	*Tipaldi et al.*:	Markov models
MIT	*Rosen et al.*:	persistence filter
QUT	*Sünderhauf et al.*:	appearance prediction

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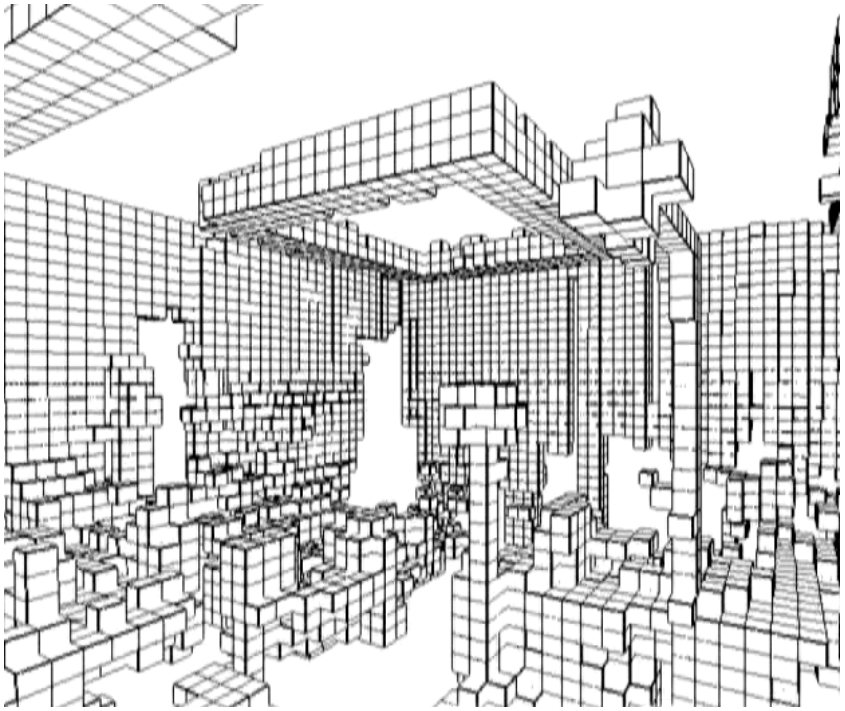
Spatial representations in robotics

Discretised, independent components with binary states

- Occupancy grids
  - cells empty or full
- Landmark-based
  - landmarks (in)visible
- Topological
  - edges (in)traversable
  - nodes (un)reachable
- Semantic
  - door open or closed
  - people present/absent



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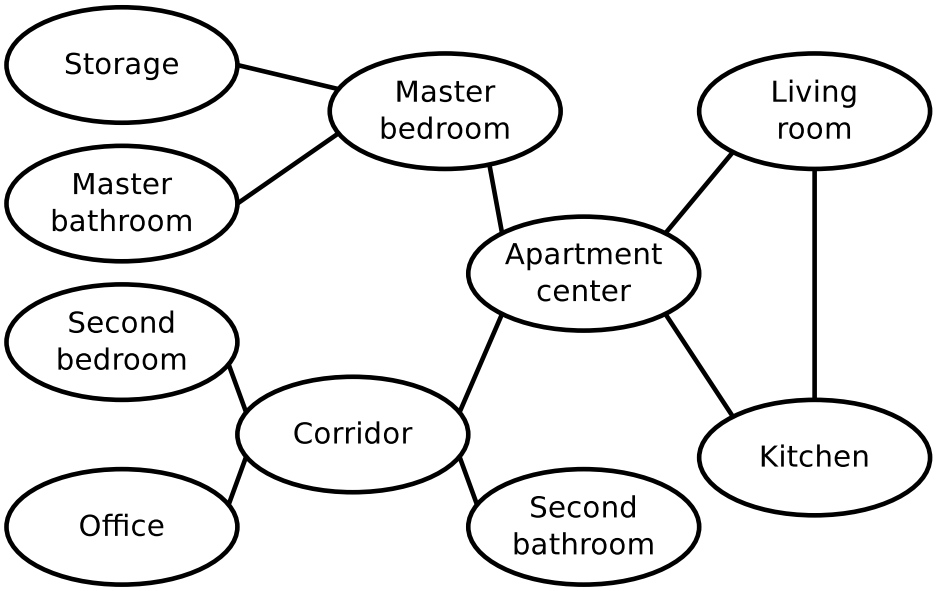

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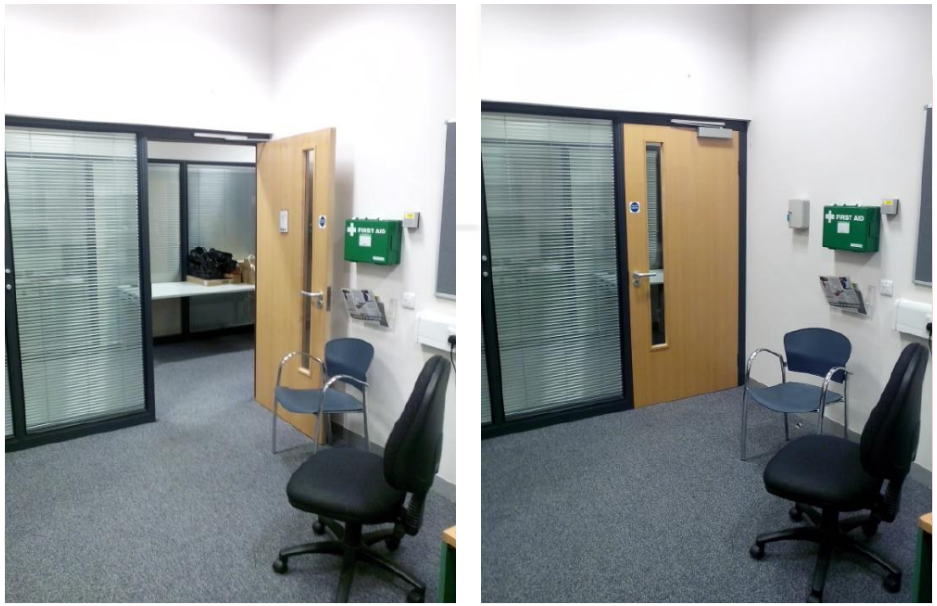
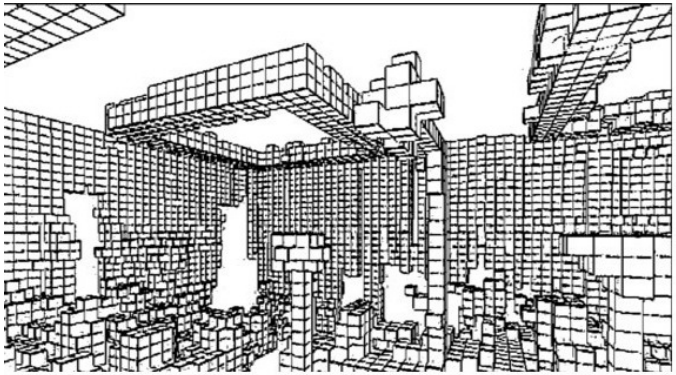


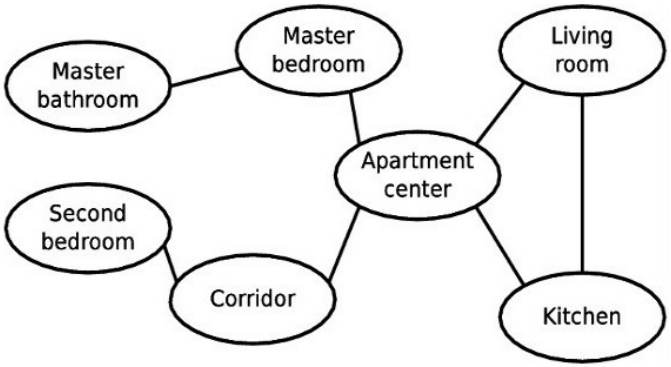
Towards Spatio-Temporal Domain Modeling



P(occupied) ⟶

P(open) ⟶

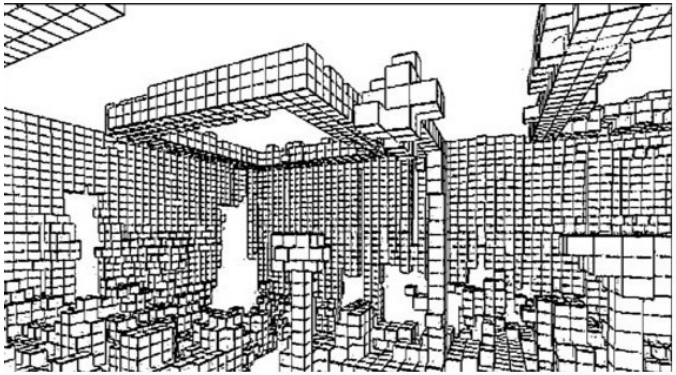
$$p(t) = p_0$$

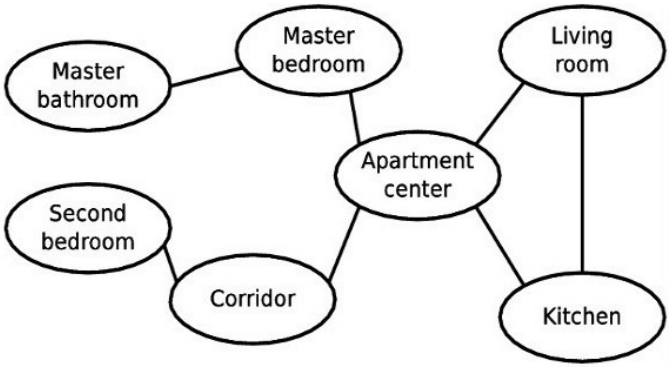


⟵ P(traversable)

⟵ P(visible)

Towards Spatio-Temporal Domain Modeling





P(occupied) ⟶

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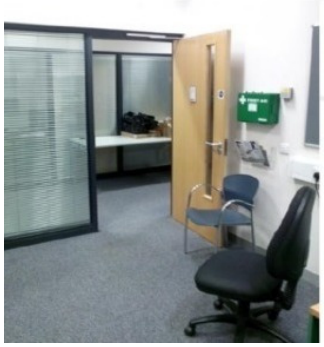
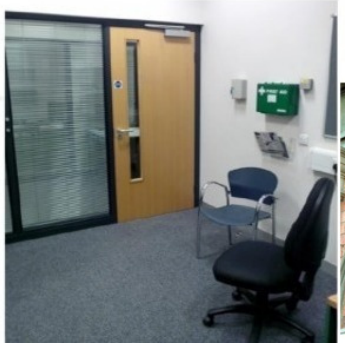
$p(t) = p_0$

Environment changes

⟵ P(traversable)

⟵ P(visible)





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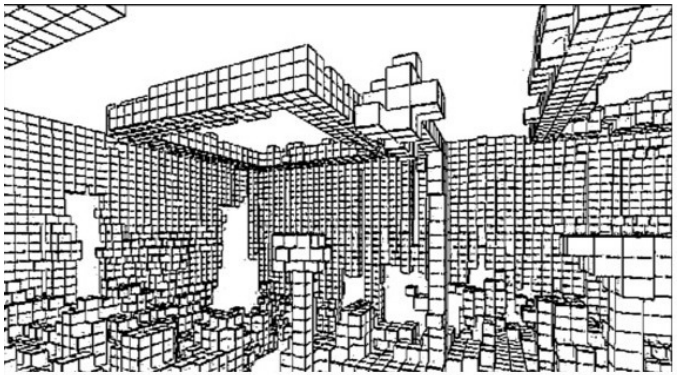
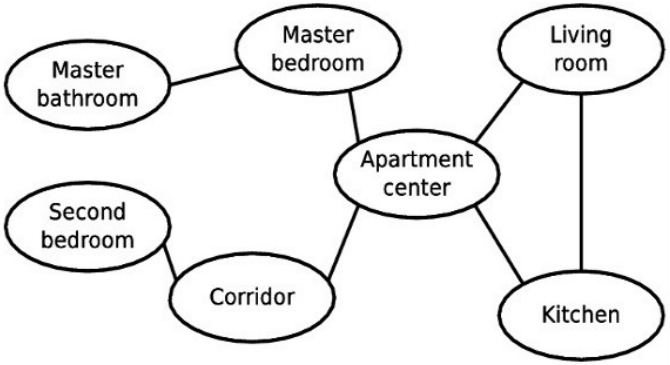




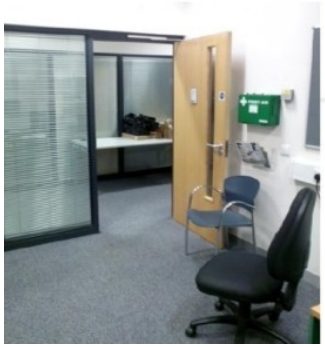
P(occupied) ⟶

P(open) ⟶

$$p(t) = p_0 + \sum_{j=1}^{n} p_j cos(\omega_j t + \varphi_j)$$

⟵ P(traversable)

⟵ P(visible)



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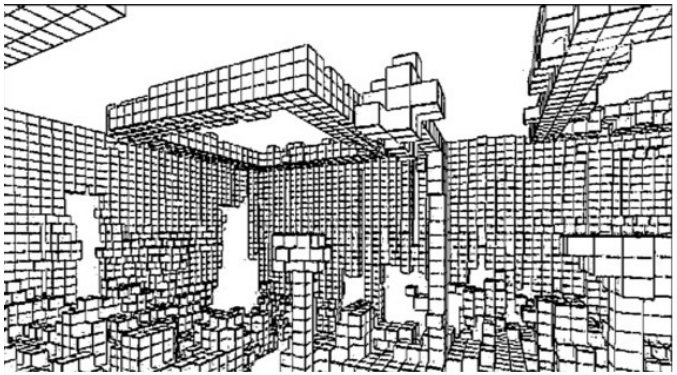

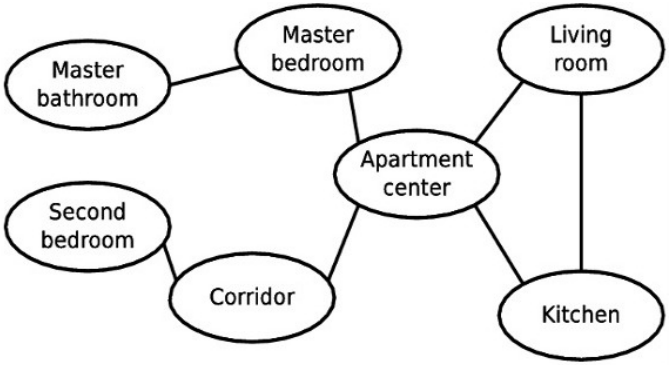

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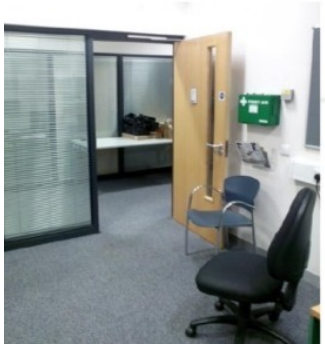
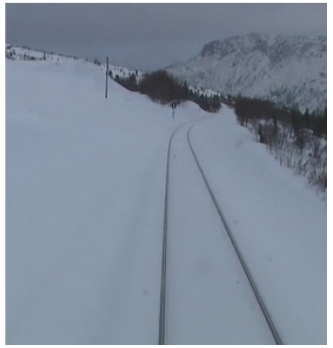


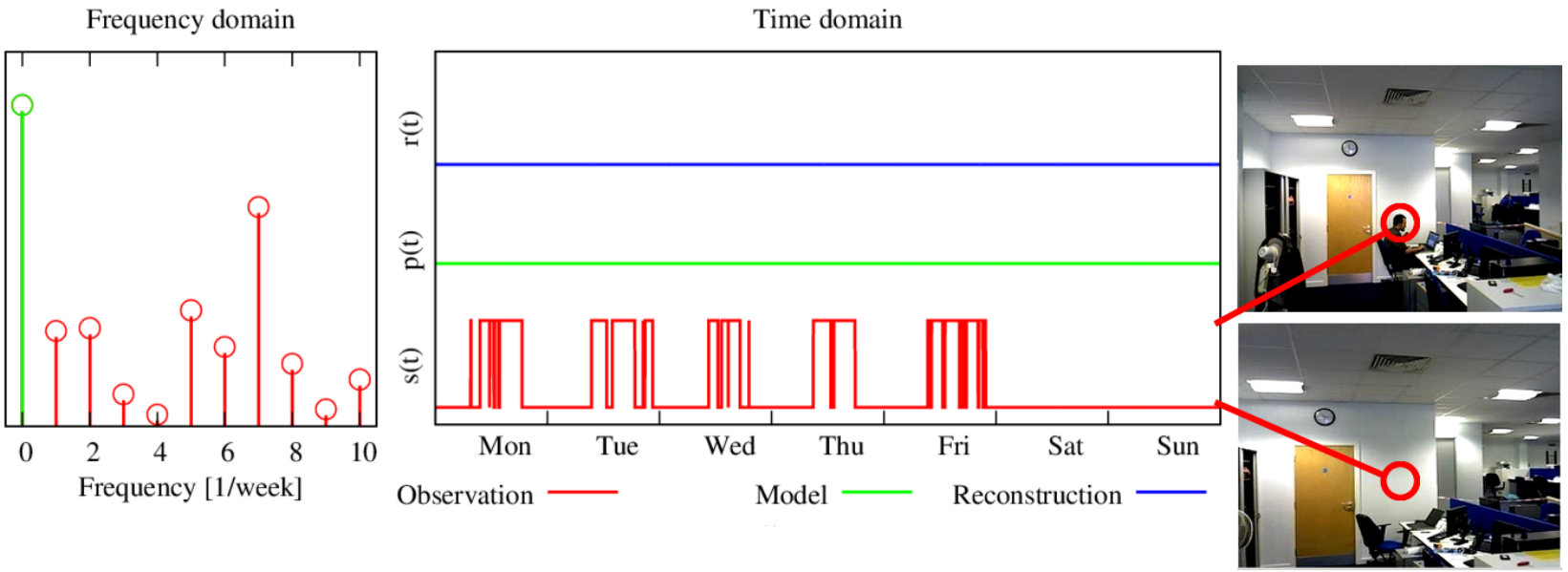


Example: Modeling a single state

Continuous observation of an image feature

Static model:

$s'(t)$ matches the observations in 74% of cases

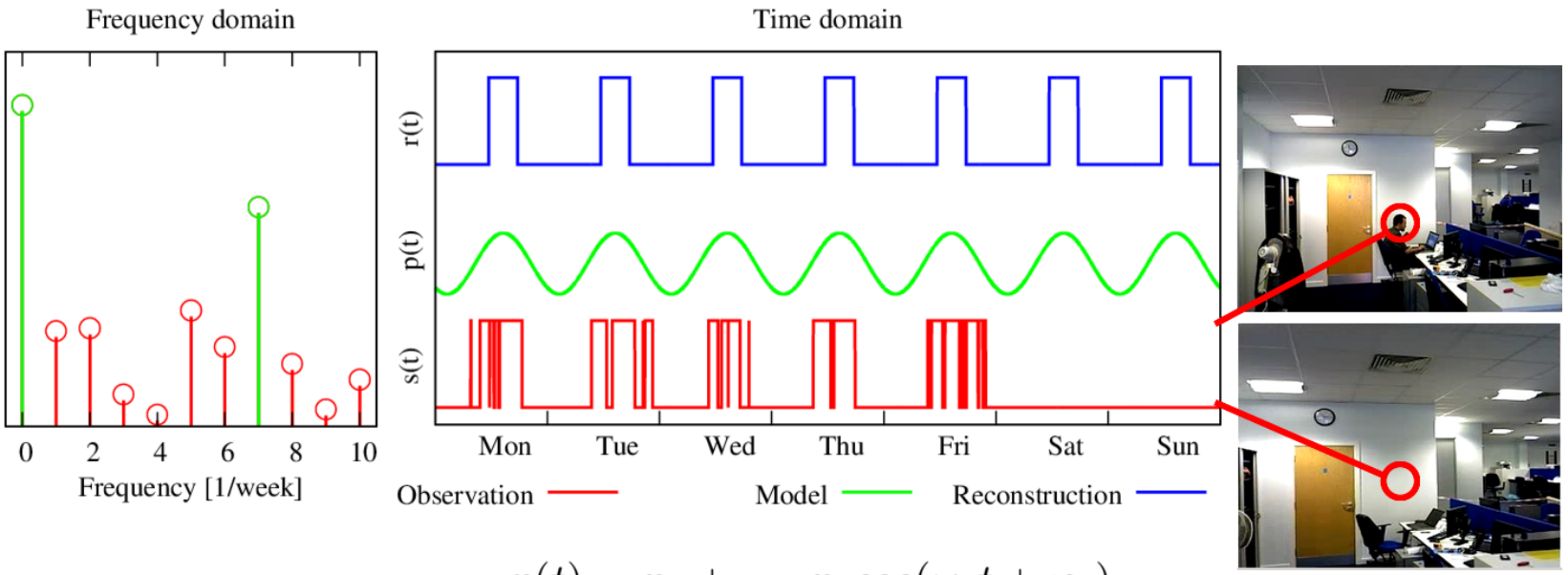


$p \quad = p_0$

Example: Modeling a single state

Continuous observation of an image feature

Dynamic model with one periodic process:
$s'(t)$ matches the observations in 80% of cases

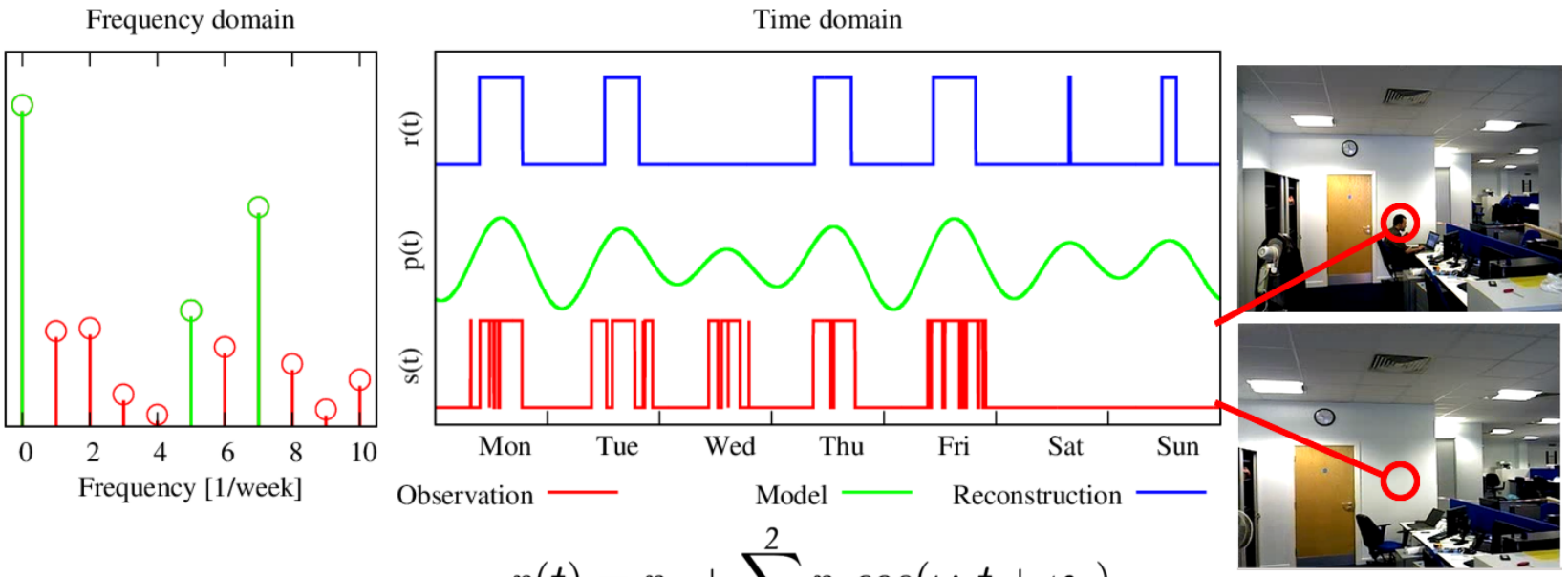


$$p(t) = p_0 + \quad p_1 cos(\omega_1 t + \varphi_1)$$

Example: Modeling a single state

Continuous observation of an image feature

Dynamic model with two periodic processes:
$s'(t)$ matches the observations in 87% of cases



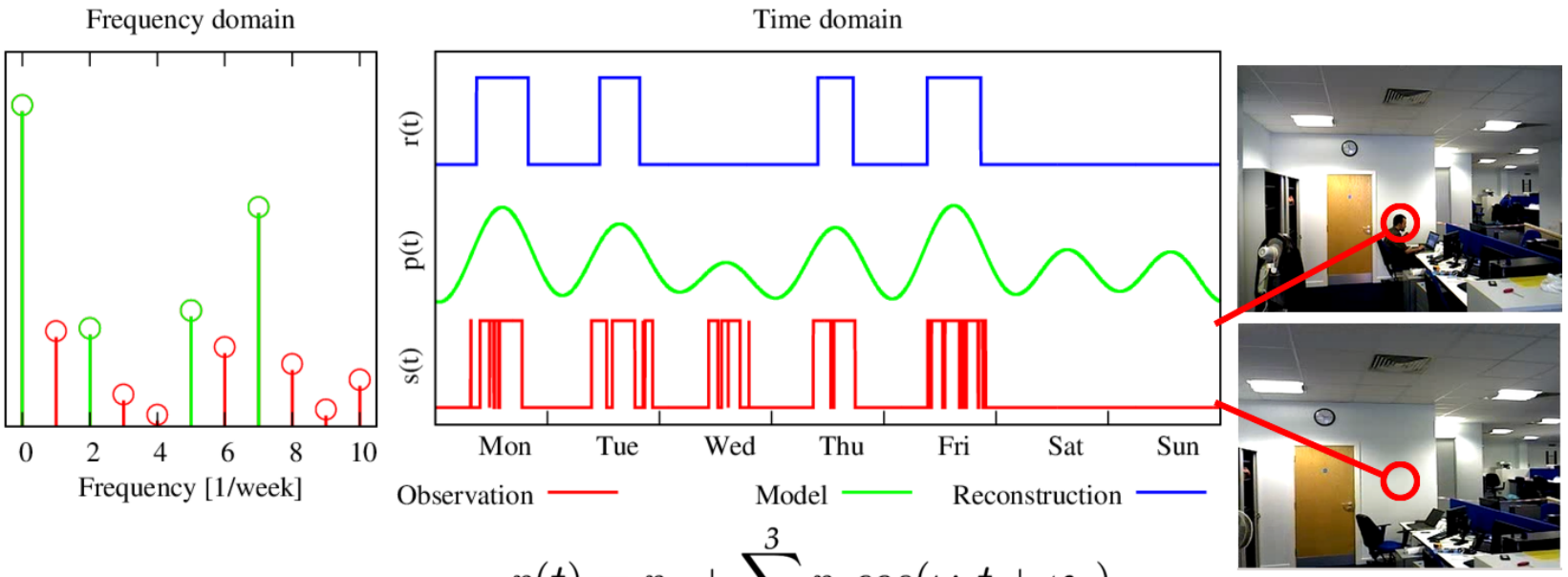
$$p(t) = p_0 + \sum_{j=1}^{2} p_j cos(\omega_j t + \varphi_j)$$

Example: Modeling a single state

Continuous observation of an image feature

Dynamic model with n periodic processes:

$s'(t)$ matches the observations in $90\% - 95\%$ of cases



$$p(t) = p_0 + \sum_{j=1}^{3} p_j cos(\omega_j t + \varphi_j)$$

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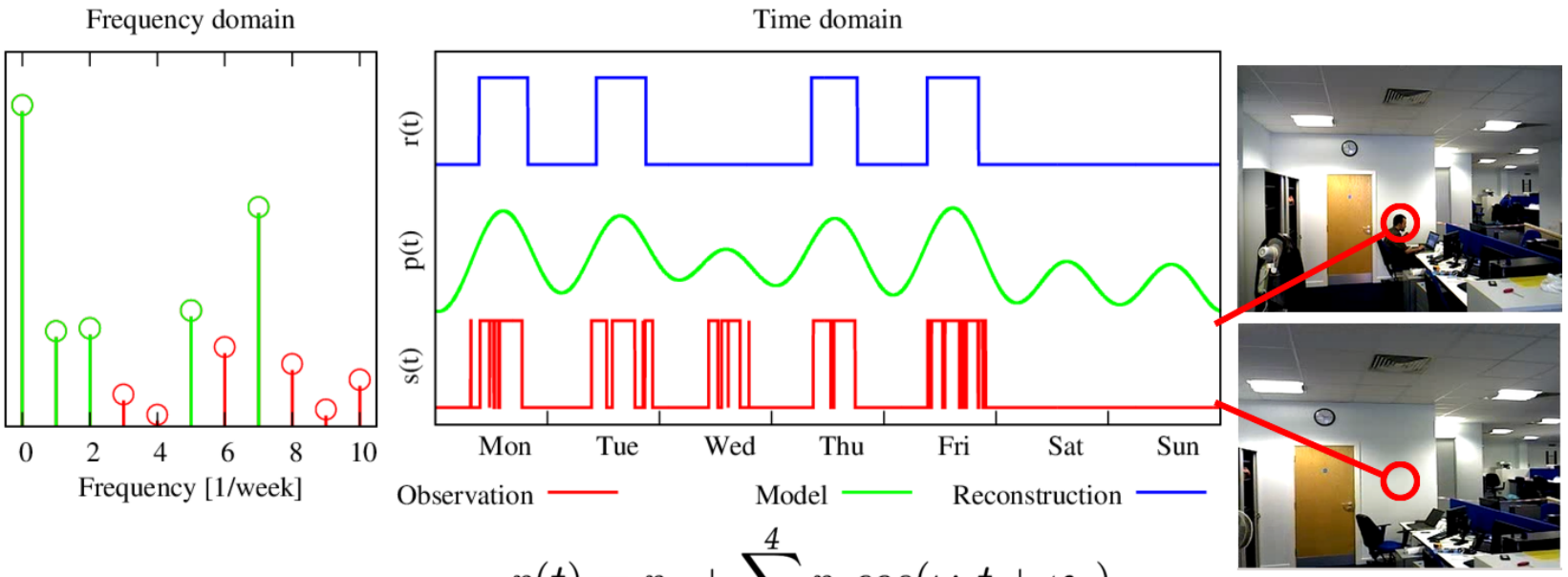

$$p(t) = p_0 + \sum_{j=1}^{4} p_j cos(\omega_j t + \varphi_j)$$

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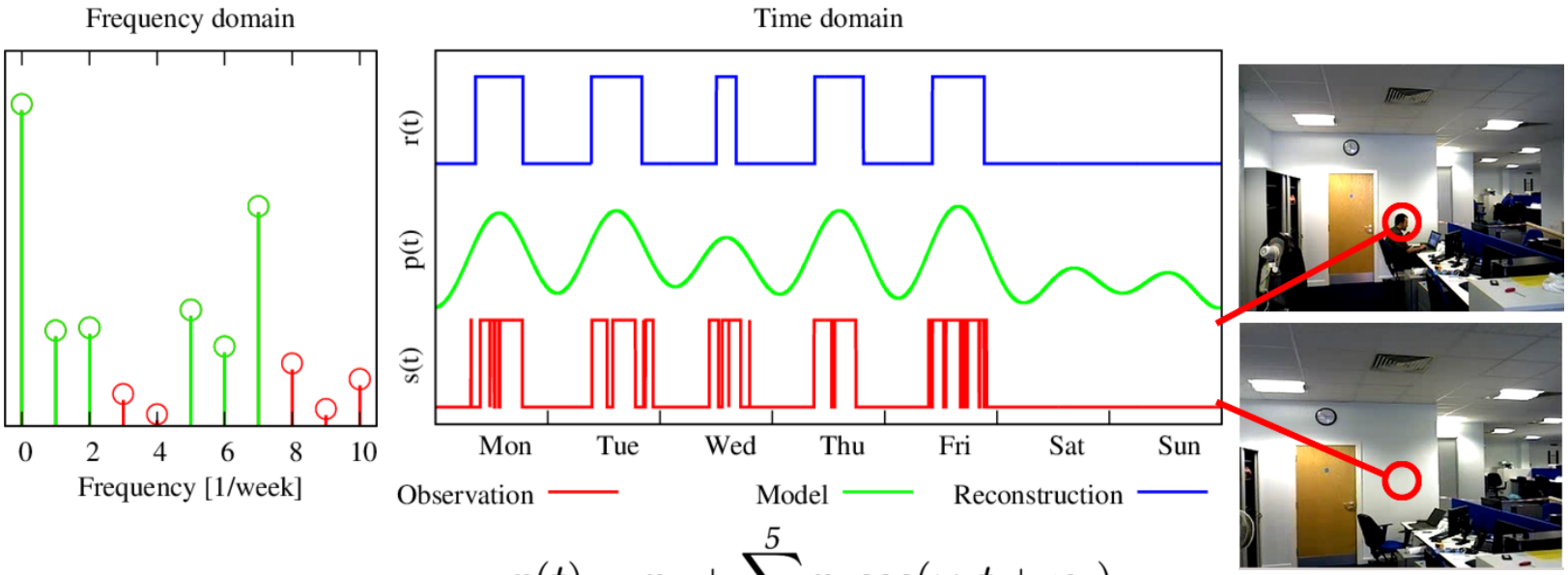

$$p(t) = p_0 + \sum_{j=1}^{5} p_j cos(\omega_j t + \varphi_j)$$

Video 1: Feature-based topological localization

Feature-based topological localization

Task: Decide robot locations based on visual features visible.
Feature visibility modeled by FreMEn.

Spatial:
- 100 BRIEFs
- 8 locations

Temporal:
- one year
- every 10min

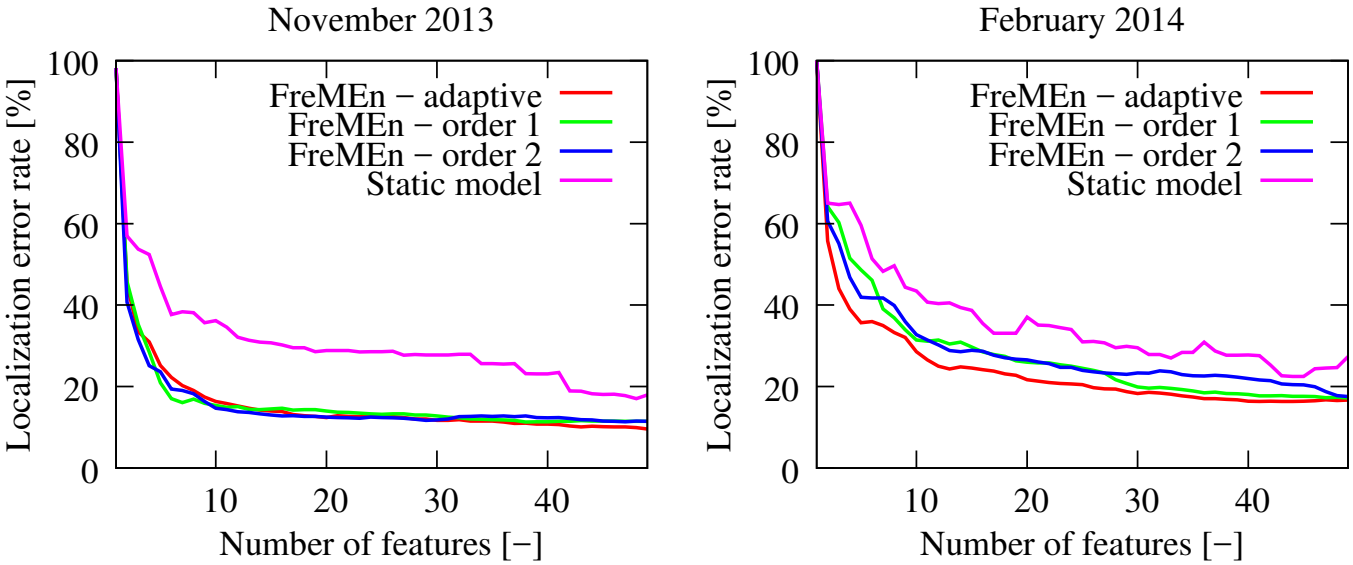

Figure: Localization error one week and three months after training.

Feature-based topological localization

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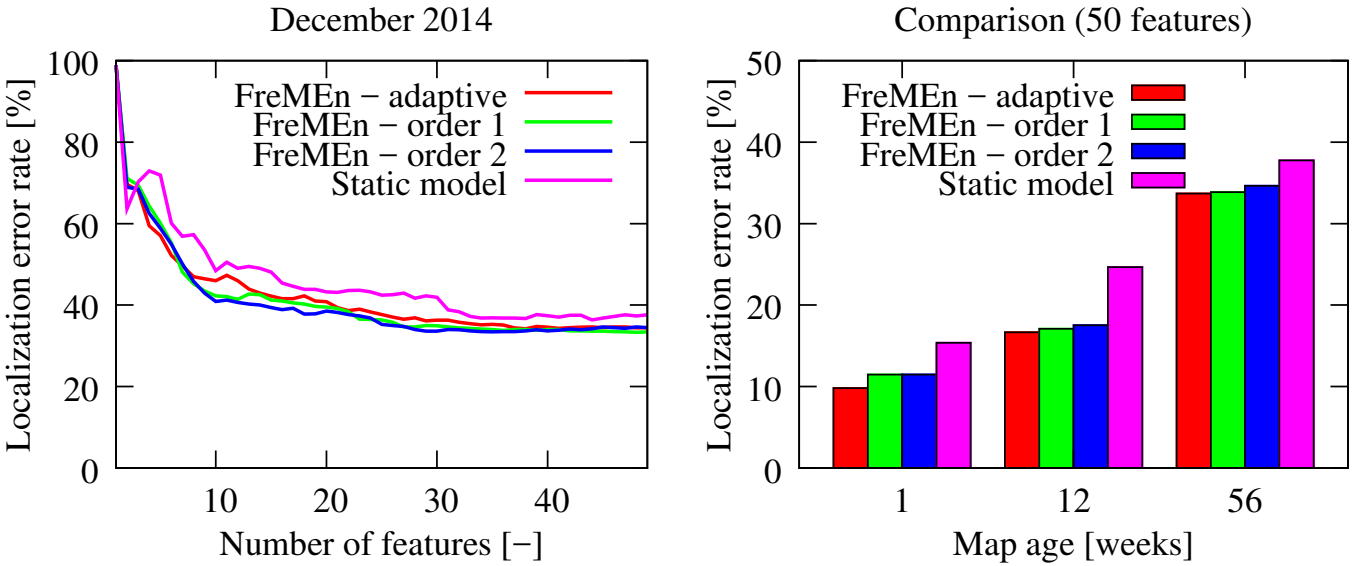


Figure: Localization error one year + error summary.

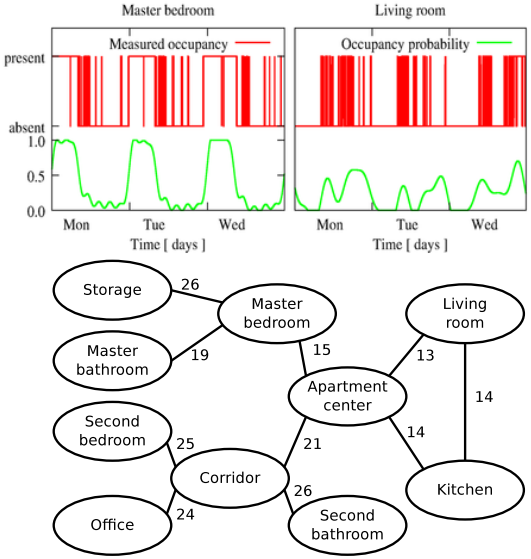
Object search scenario

Task: Find a person in shortest time possible.
Topological map, spectral-based model of room occupancies.

Spatial:
- 1 person
- 9 locations

Temporal:
- 16 weeks
- every minute

Figure: The CASAS-Aruba environment.



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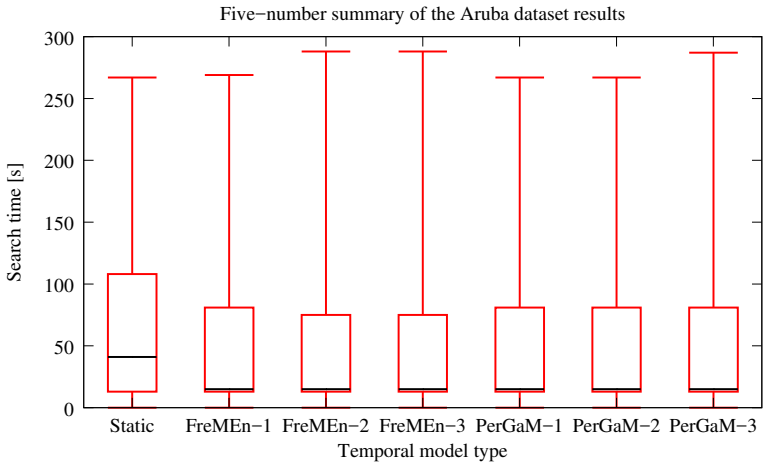
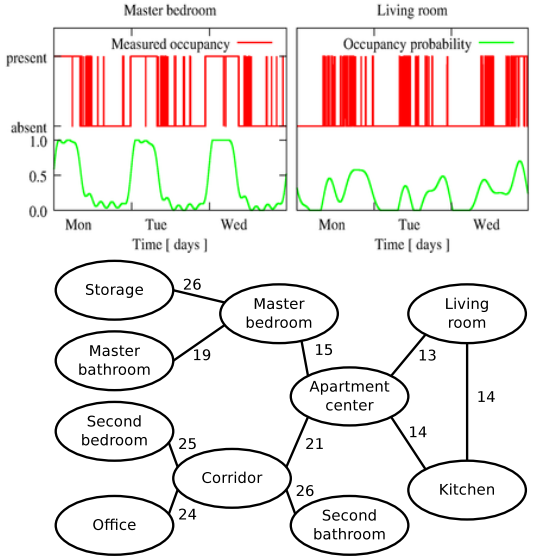


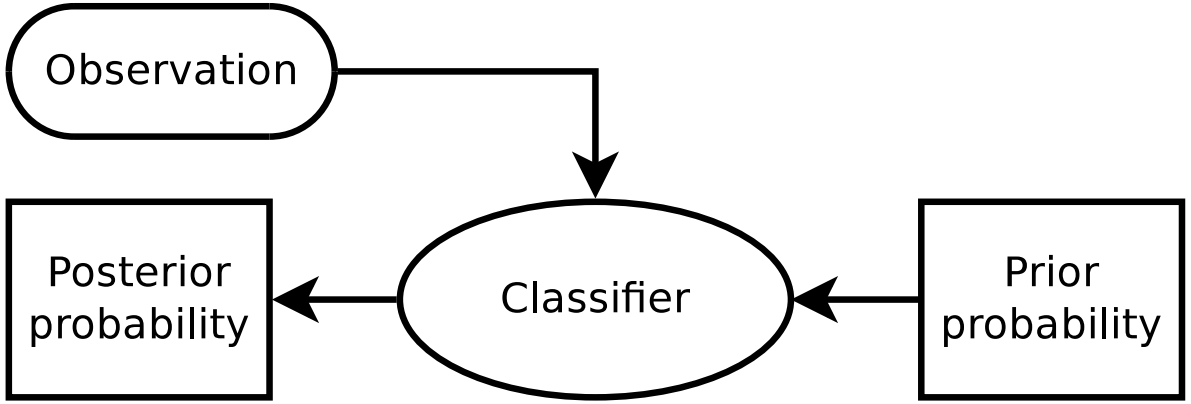
Figure: Time to find a person in the 'Aruba' flat.



Temporal context for activity recognition

Task: Classify person activity.

$$p(activity|observation) = \frac{p(observation|activity)}{p(observation)} p(activity)$$



Classification pipeline.

Temporal context for activity recognition

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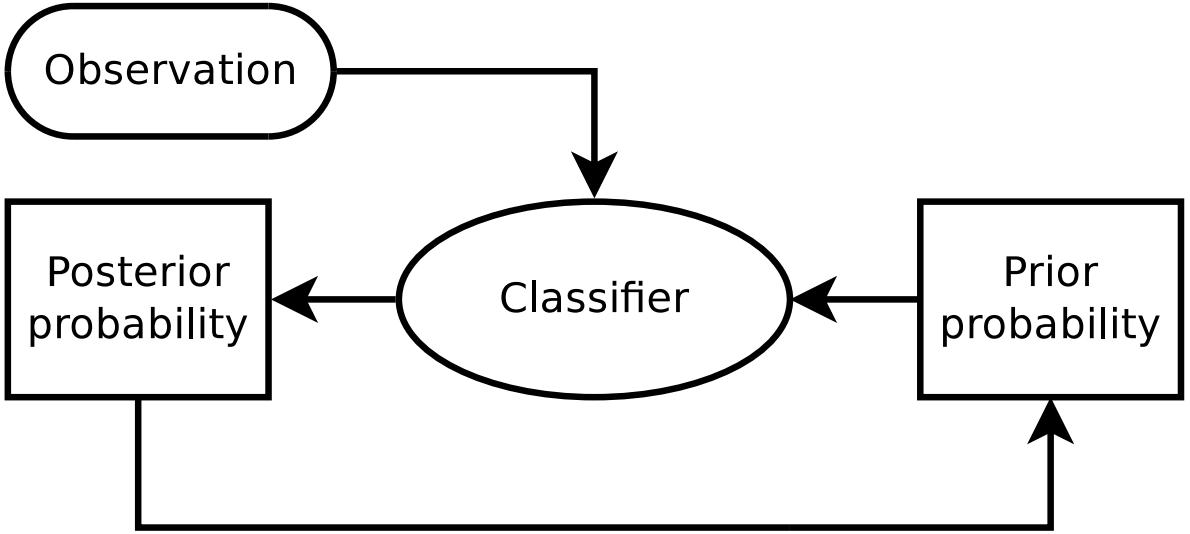
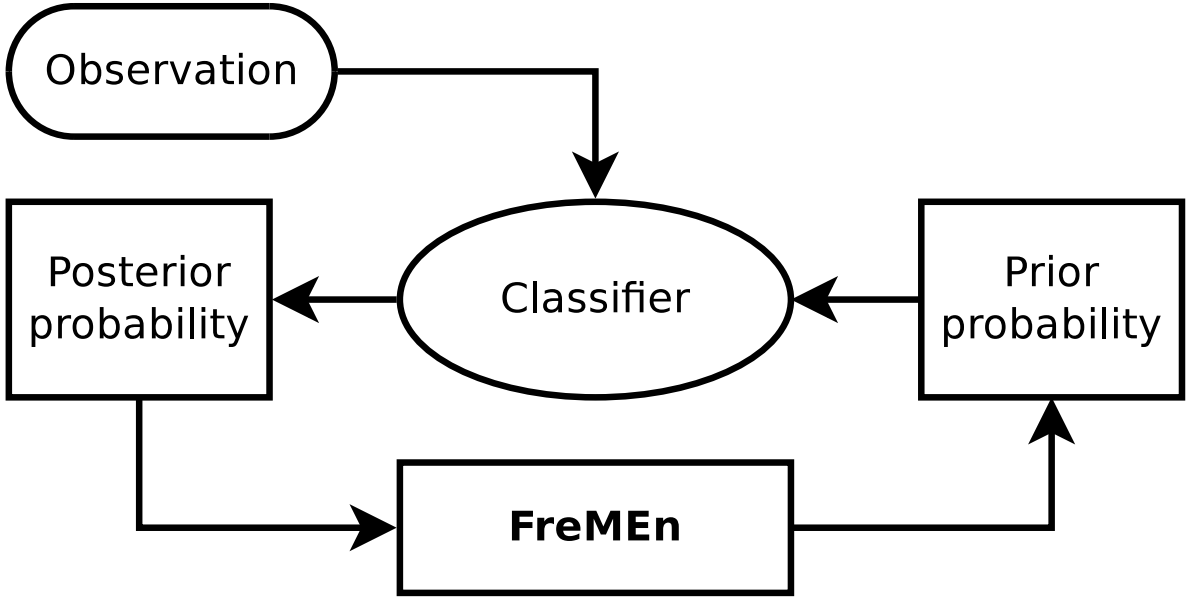


Classification pipeline + learning priors.

Temporal context for activity recognition

Task: Classify person activity.

$$p(activity|observation, t) = \frac{p(observation|activity)}{p(observation,t)} p(activity, t)$$



Classification pipeline + temporal priors.

Temporal context for activity recognition

Task: Classify person activity.
Use FreMEn-aided temporal models as priors.

$$p(activity, t|observation) \sim p(observation|activity)p(activity, t)$$

Household:
- 9 locations
- 12 activities

Office:
- 10 locations
- 10 activities

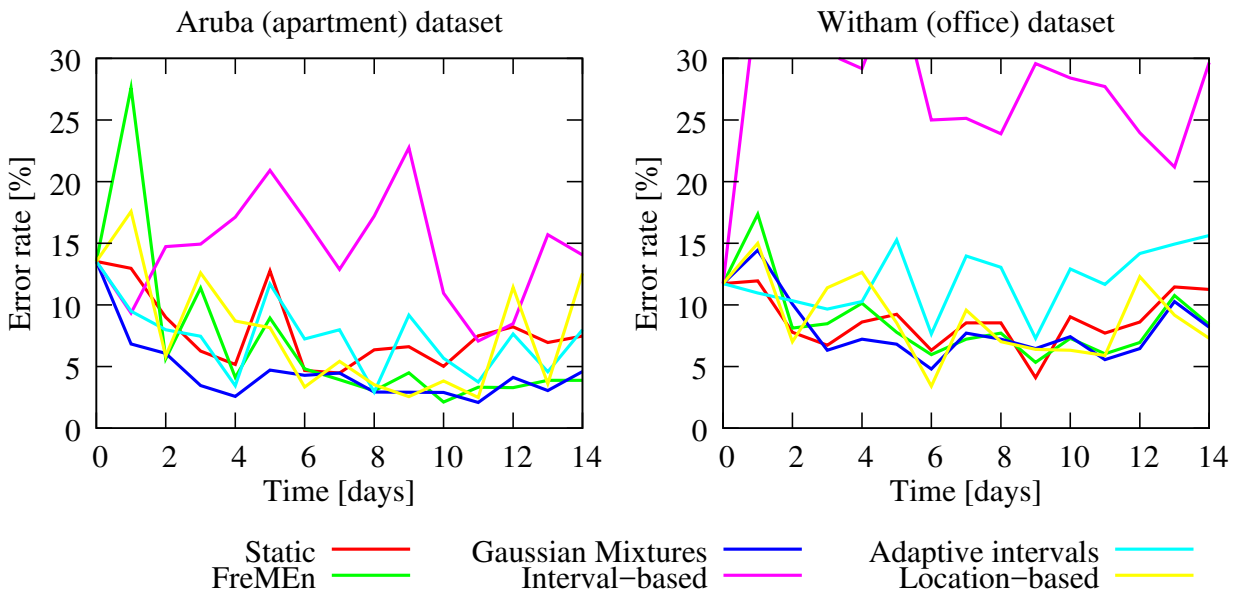


Figure: Error rate of activity recognition.

SPEctral Robotic Mapping

Modeling long-term observations in the frequency domain

- can extend static environment models with discrete states
- into models that capture long-term environment dynamics.

The approach allows for

- efficient representation of long-term observations,
- environment state/appearance prediction,
- and long-term planning in changing environments.

However, it's very impractical, because

$$S(k) = \frac{1}{N} \sum_{n=1}^{N} s(nT) e^{-2\pi jkn/N} \quad k \in \mathbb{N}$$

requires tedious and brittle learning, followed by deployment.

FREquency Map ENhancement

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- into models that capture long-term environment dynamics.

The approach allows for

- efficient representation of long-term observations,
- environment state/appearance prediction,
- and long-term planning in changing environments.

To allow for sparse and non-uniform sampling

$$S(\omega_k) = \frac{1}{N} \sum_{n=1}^{N} s(t_n) e^{-j\omega_k t_n} \quad \omega_k \in \Omega$$

which can be used for incremental, on-the-fly learning.

Frequency Map Enhancement (FreMEn)

Can build spatio-temporal models **incrementally** from **sparse** and **irregular** observations. Allows **on-the-fly** learning.

Addition of a new measurement:

μ	$\leftarrow$	$\frac{1}{n+1}\,(\,n\mu + s(t)\,),$		mean probability
α_k	$\leftarrow$	$\frac{1}{n+1}\,(\,n\alpha_k + s(t)\,e^{-jt\omega_k}\,)$	$\forall\,\omega_k \in \omega,$	state spectrum
β_k	$\leftarrow$	$\frac{1}{n+1}\,(\,n\beta_k + e^{-jt\omega_k}\,)$	$\forall\,\omega_k \in \omega,$	observation spectrum
n	$\leftarrow$	$n+1,$		num of observations

Performing predictions:

γ_k	$\leftarrow$	$\alpha_k - \mu\,\beta_k$	predictive spectrum
$\gamma_{1..m}$	$\leftarrow$	$\mathrm{argmax}\,\lvert\gamma_k\rvert$	m components γ_k with highest abs. value
$p(t)$	=	$\mu + \sum_{j=1}^{m} \lvert\gamma_j\rvert\, cos(\omega_j t + \arg(\gamma_j))$	actual prediction

Topological path planning

Decide the best time to navigate to a particular location.
Topological map with FreMEn edge traversability.

Spatial:
- 14 nodes
- 26 edges

Temporal:
- two months
- $\sim 10\times$ per day

Nav. success rate:
- Static: 60%
- FreMEn: 90%

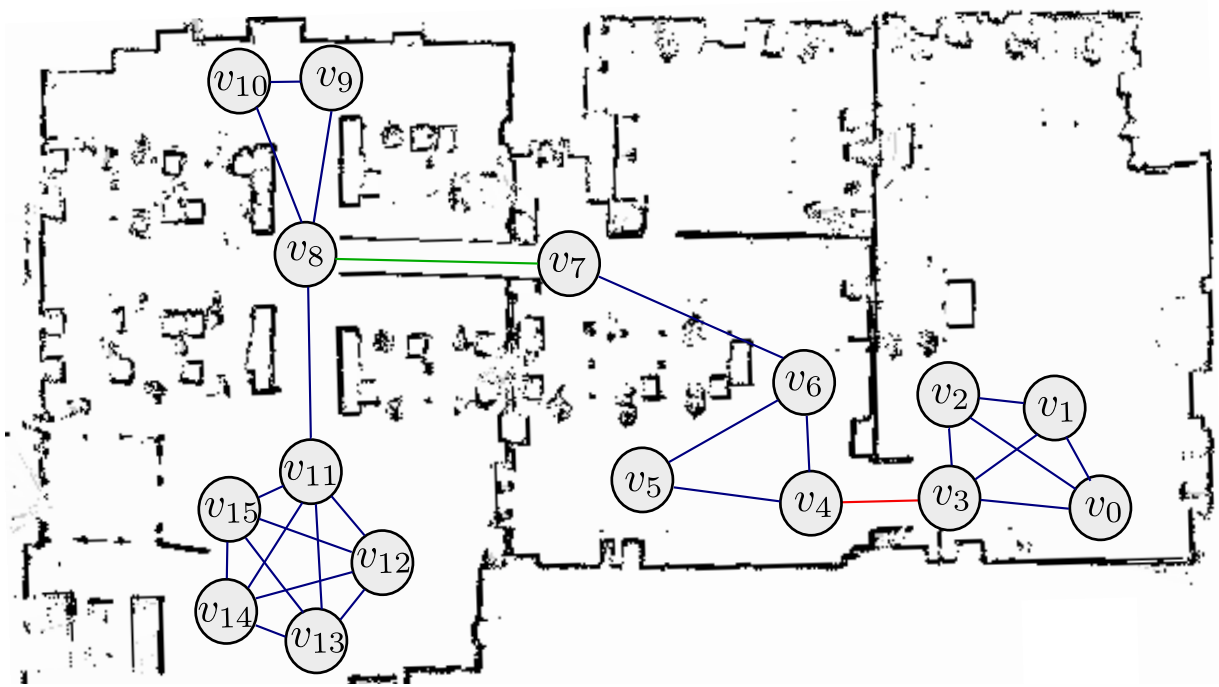

Figure: Topological/metric map overlay of the LCAS offices.

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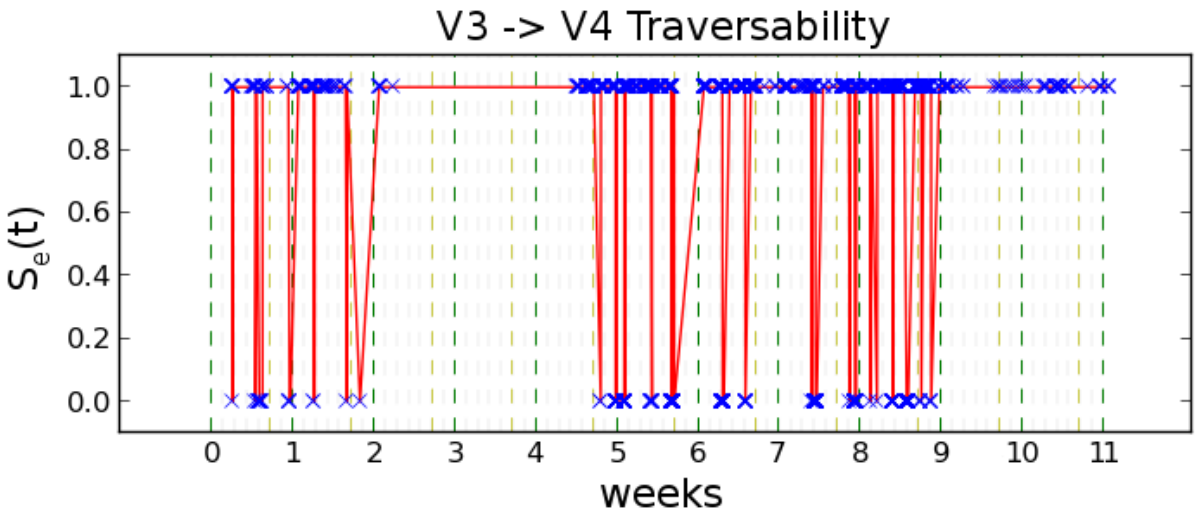

Edge V3->V4: Navigation success over time.

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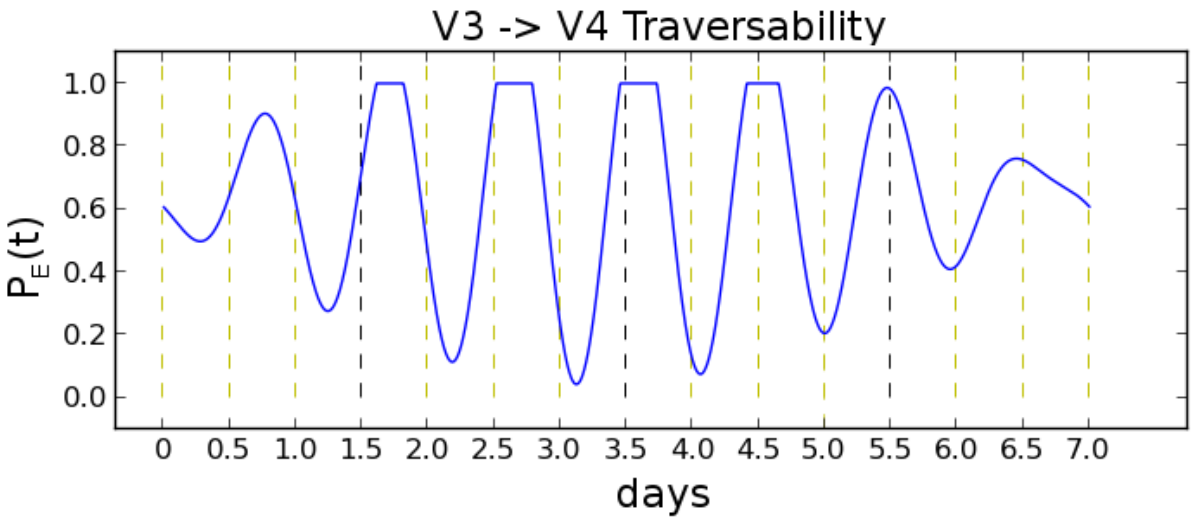

Edge V3->V4: FreMEn model for one week.

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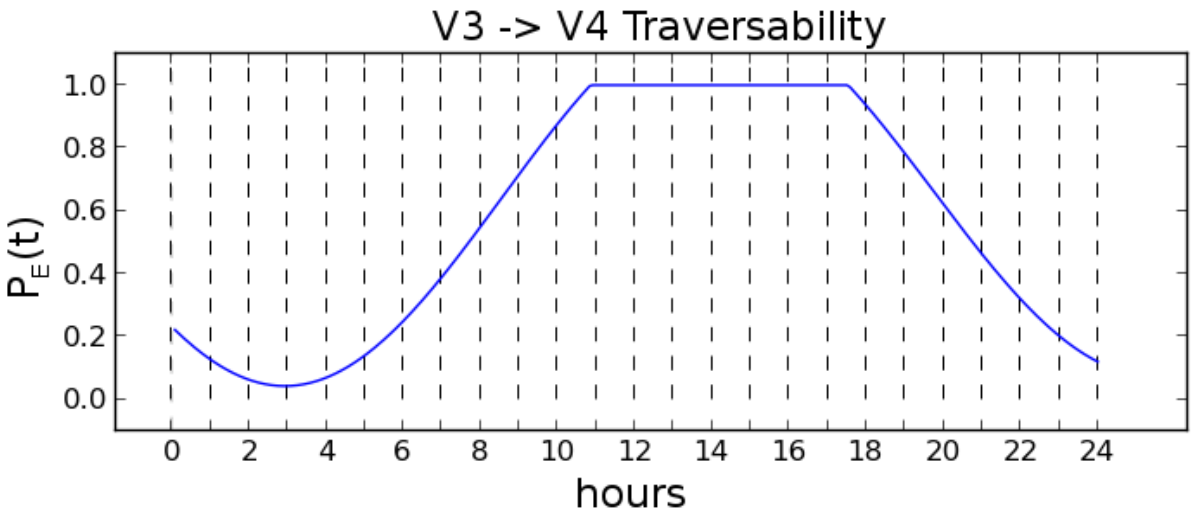
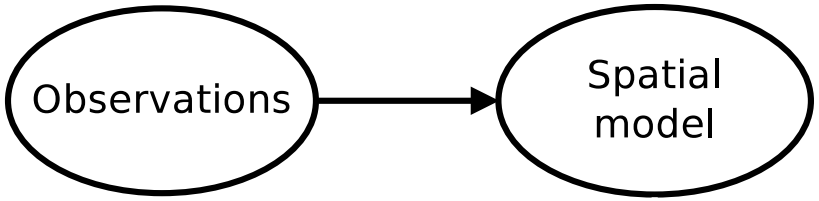


Edge V3->V4: FreMEn model for Thursday

Towards Spatio-Temporal Exploration

Create accurate spatial models.

Mapping pipeline:

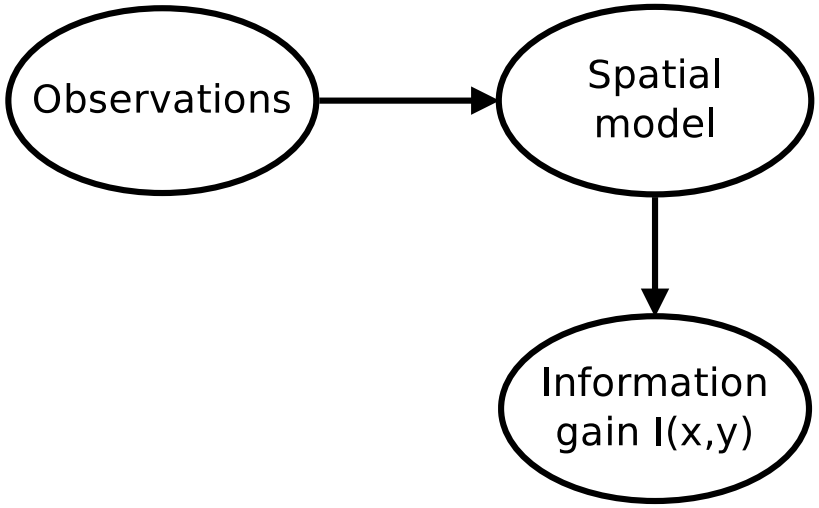


Observations gathered during routine operation

Towards Spatio-Temporal Exploration

Create accurate spatial models.

Spatial exploration pipeline:

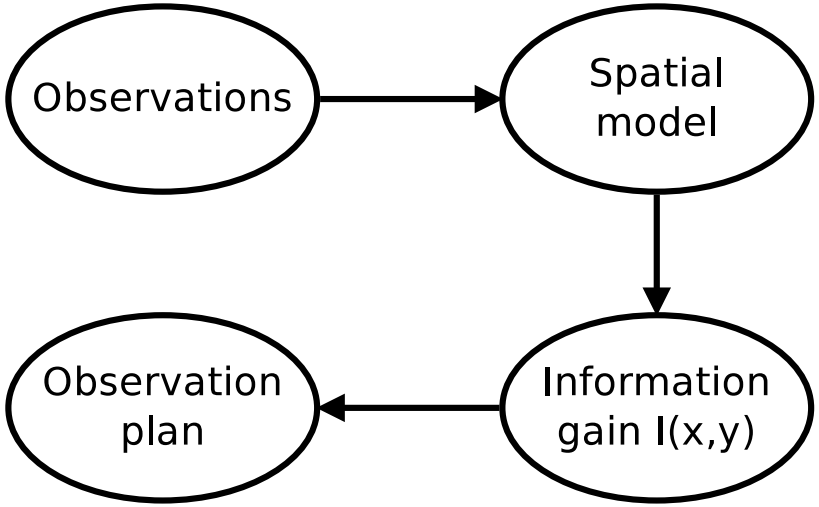


Robot decides **where** to perform observations

Towards Spatio-Temporal Exploration

Create accurate spatial models.

Spatial exploration pipeline:



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Towards Spatio-Temporal Exploration

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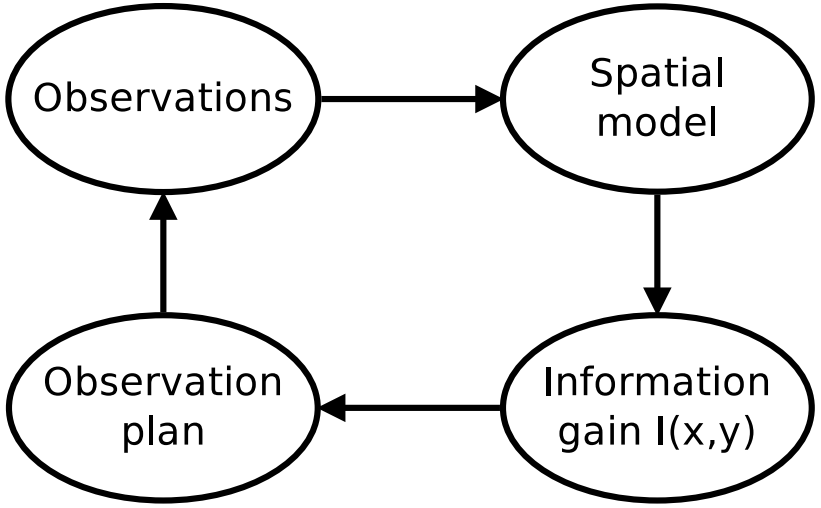
Spatial exploration pipeline:

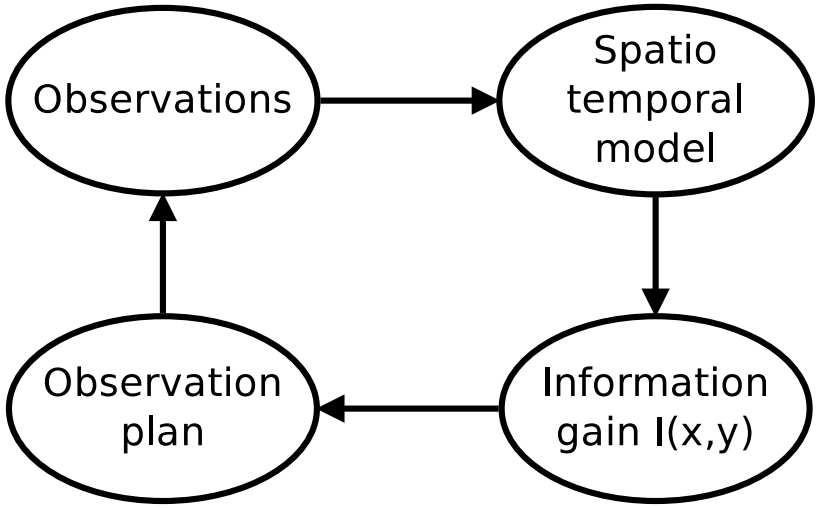


Robot decides **where** to perform observations

Towards Spatio-Temporal Exploration

Create and maintain accurate spatial-temporal models.

Spatio-temporal exploration pipeline:

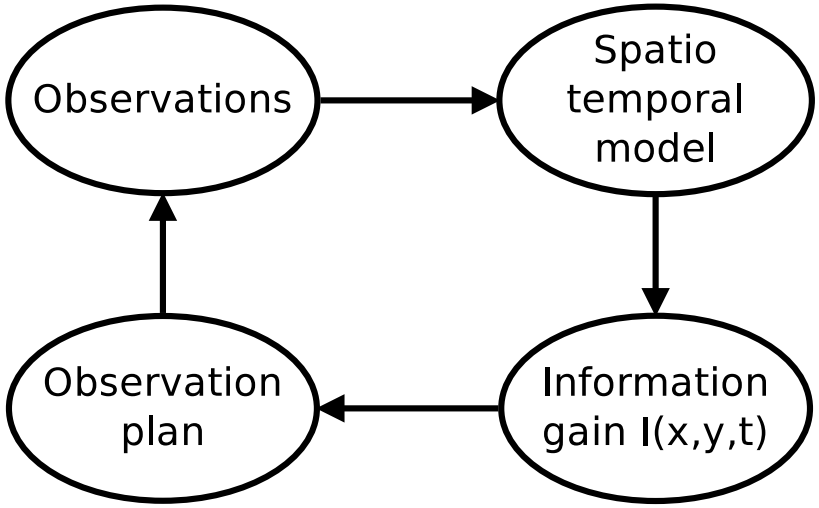


Robot decides **where** and **when** to perform observations

Towards Spatio-Temporal Exploration

Create and maintain accurate spatial-temporal models.

Spatio-temporal exploration pipeline:

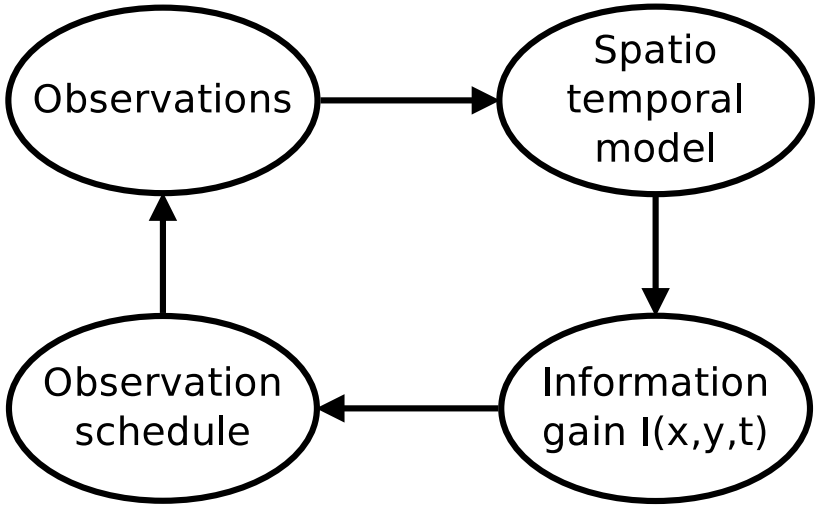


Robot decides **where** and **when** to perform observations

Towards Spatio-Temporal Exploration

Create and maintain accurate spatial-temporal models.

Spatio-temporal exploration pipeline:

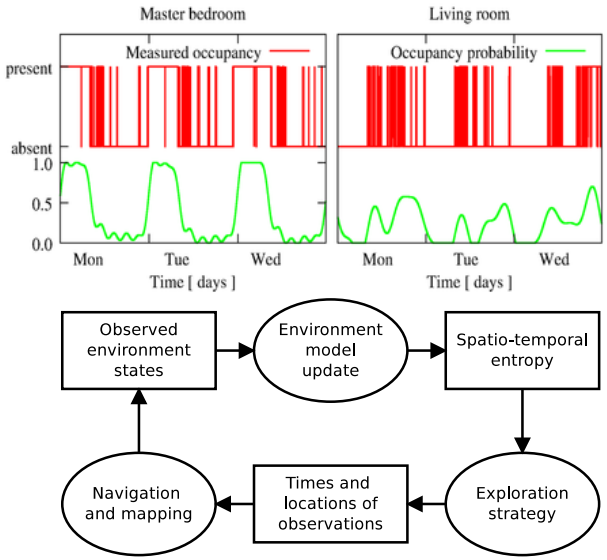


Robot decides **where** and **when** to perform observations

Information-theoretic spatio-temporal exploration

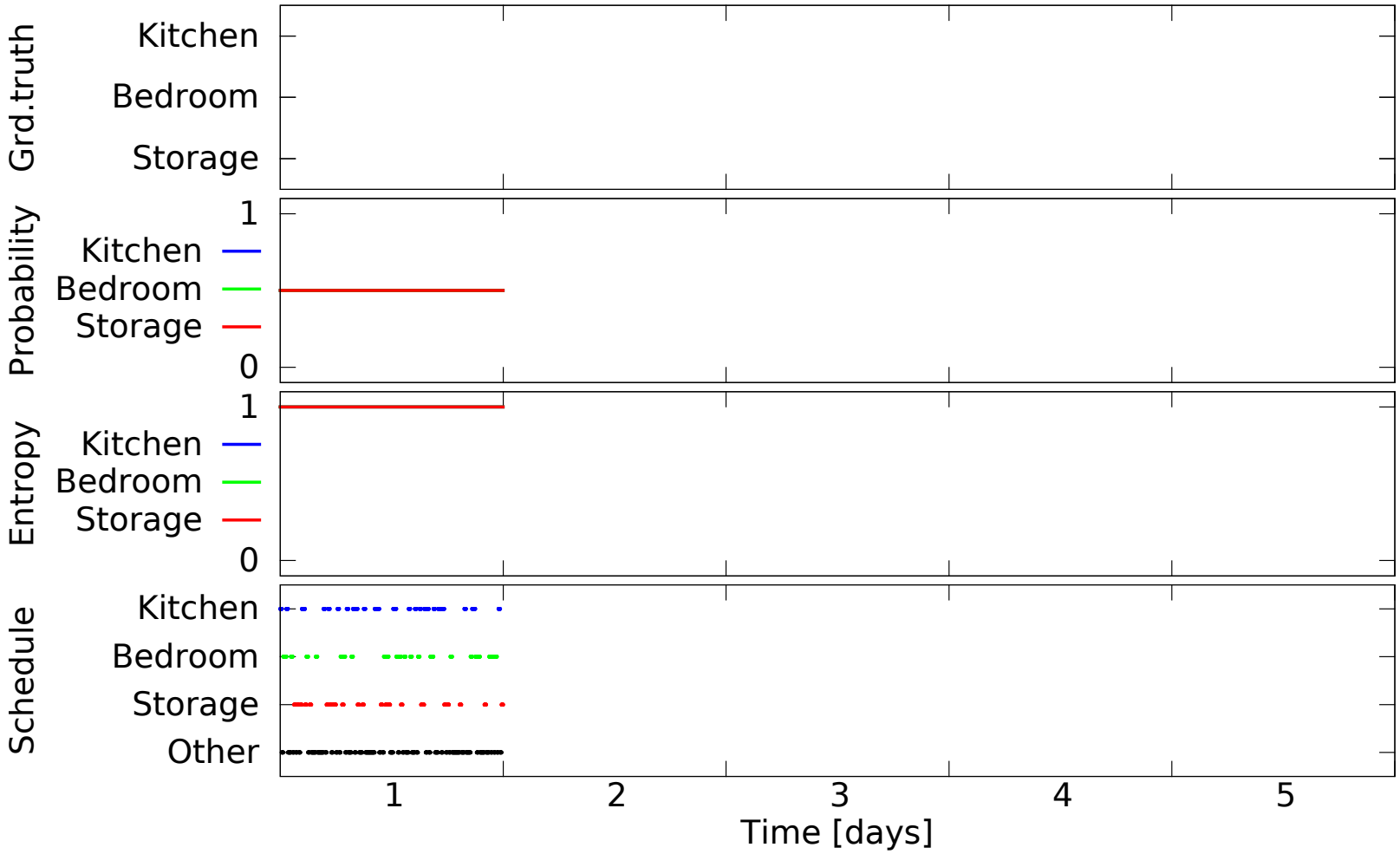
Create and maintain accurate spatio-temporal models.
Decide **where** and **when** to perform observations
Probability p(t) $\rightarrow$ Entropy H(t) $\rightarrow$ Prob. of observation o(t)
'Next Best Time and Location'

Figure: The CASAS-Aruba environment.



Spatio-temporal exploration

Decide **where** and **when** to go to make observations.
Spatio-temporal entropy + information-gain-based methods.



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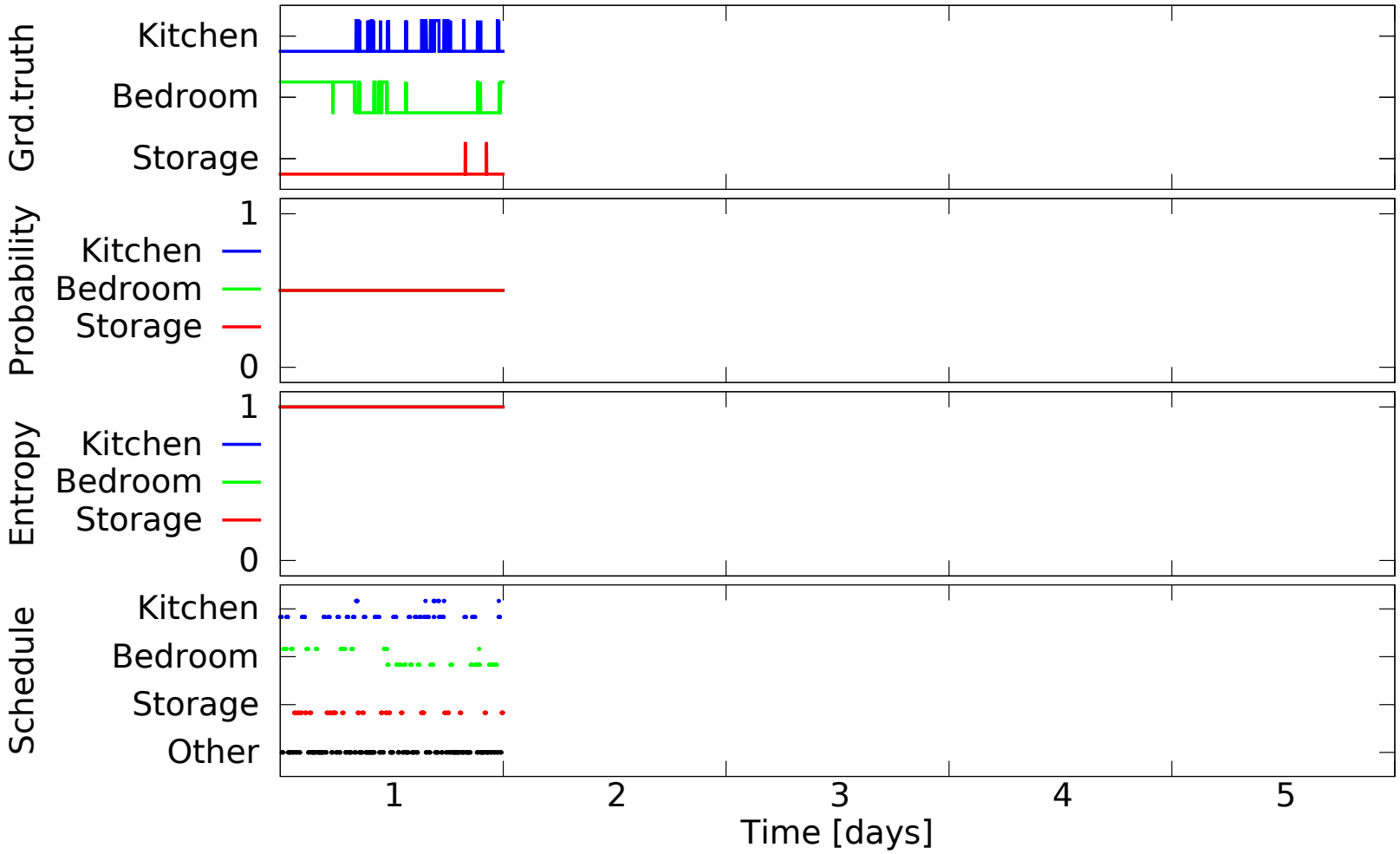

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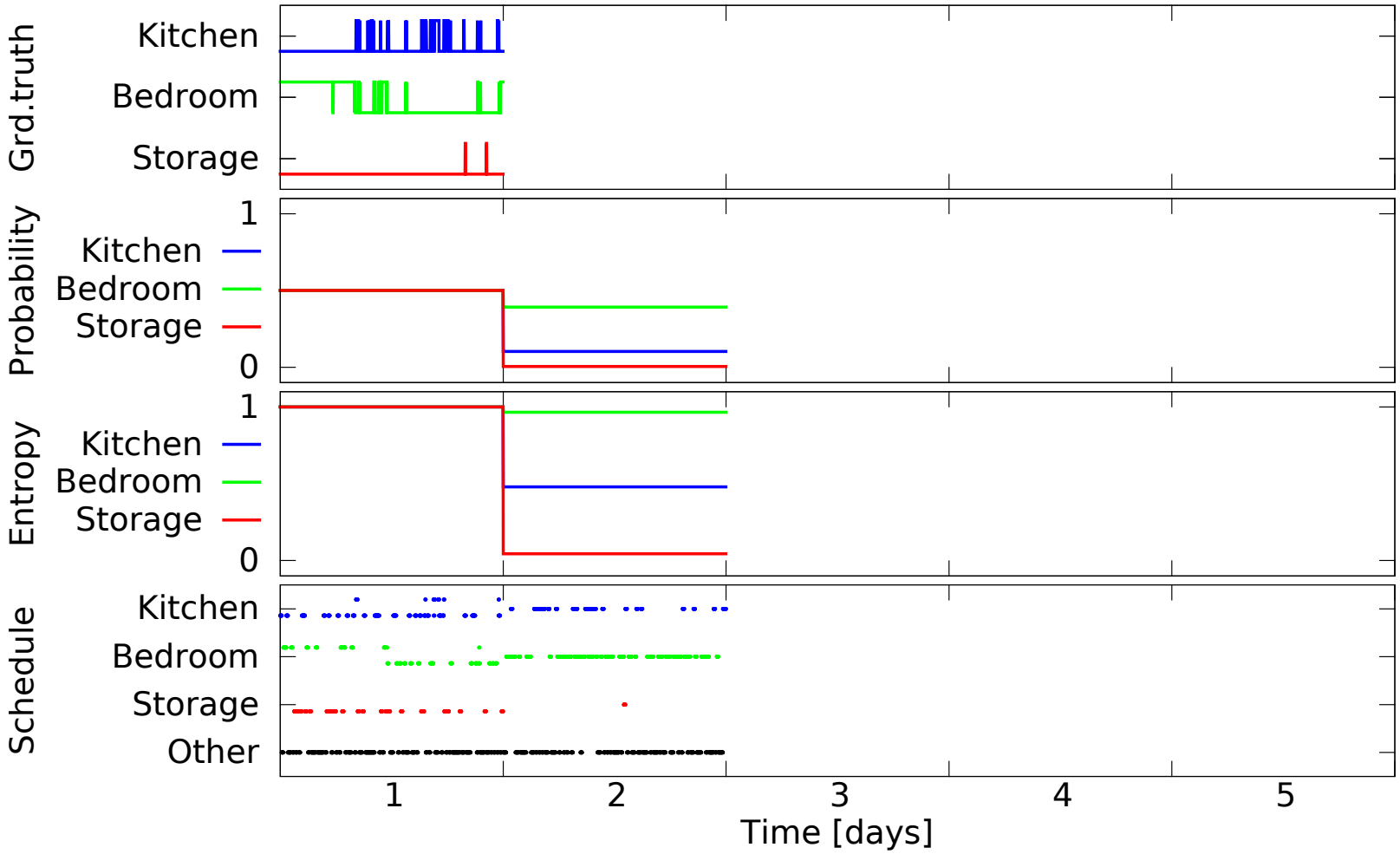

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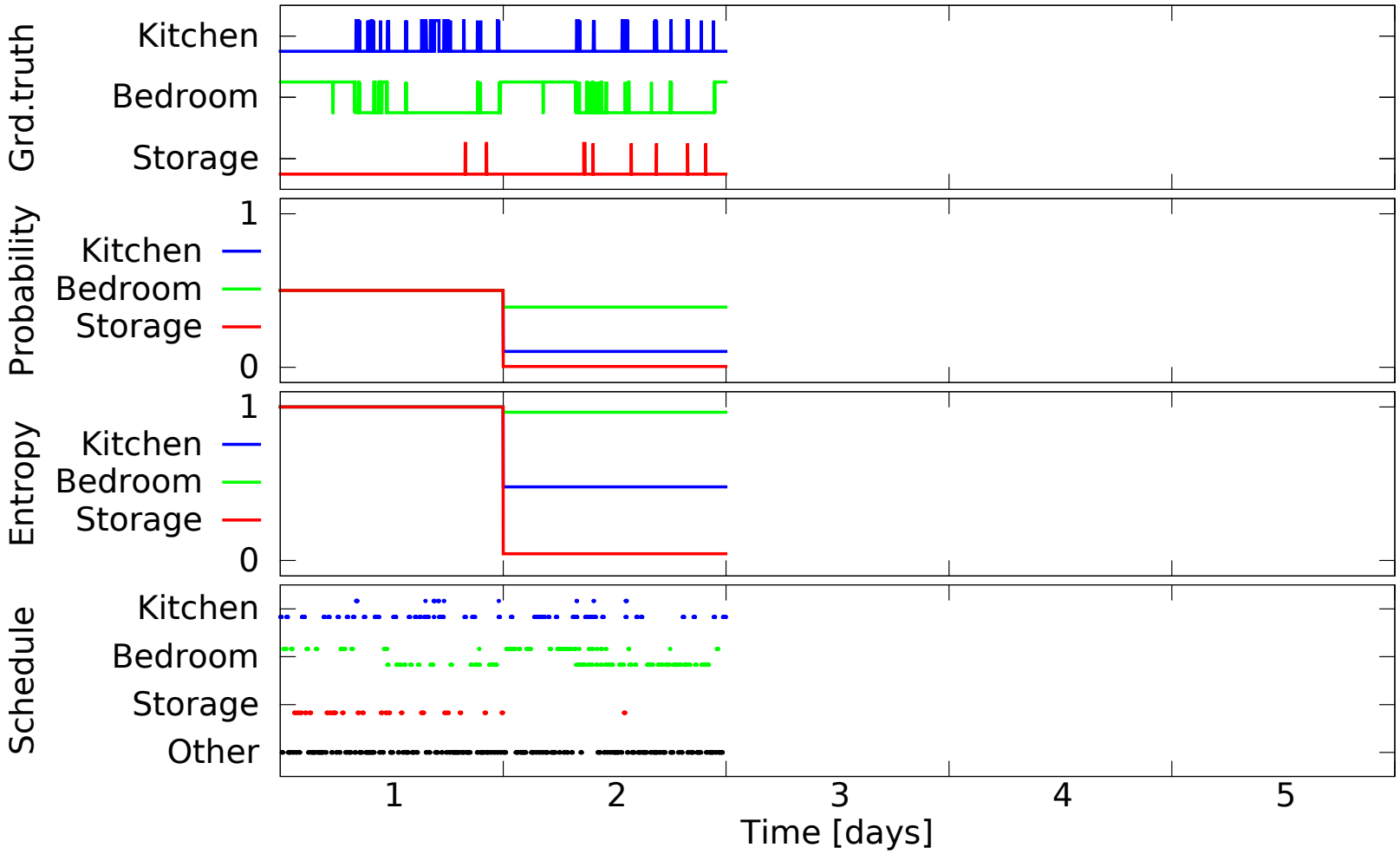

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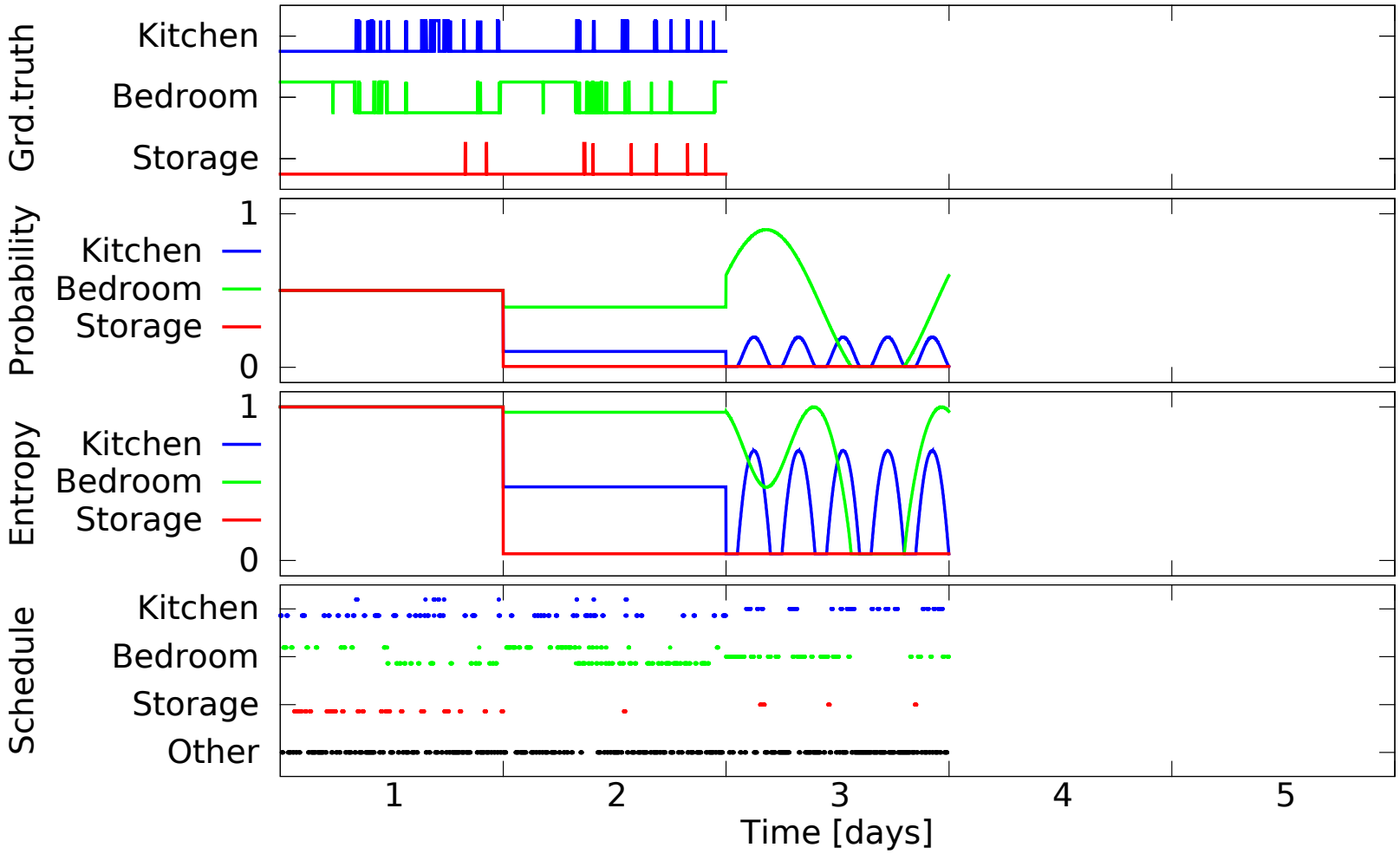

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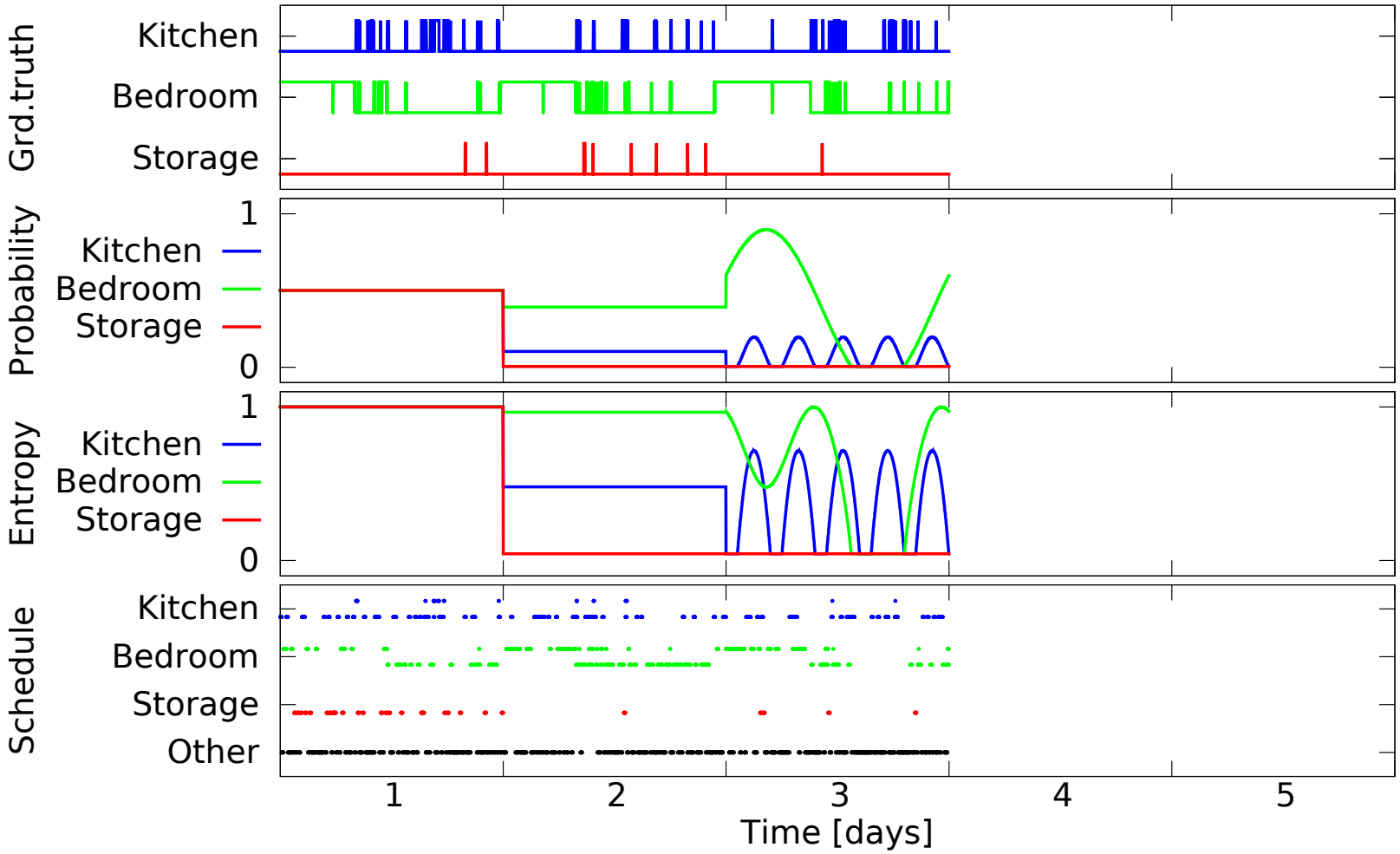

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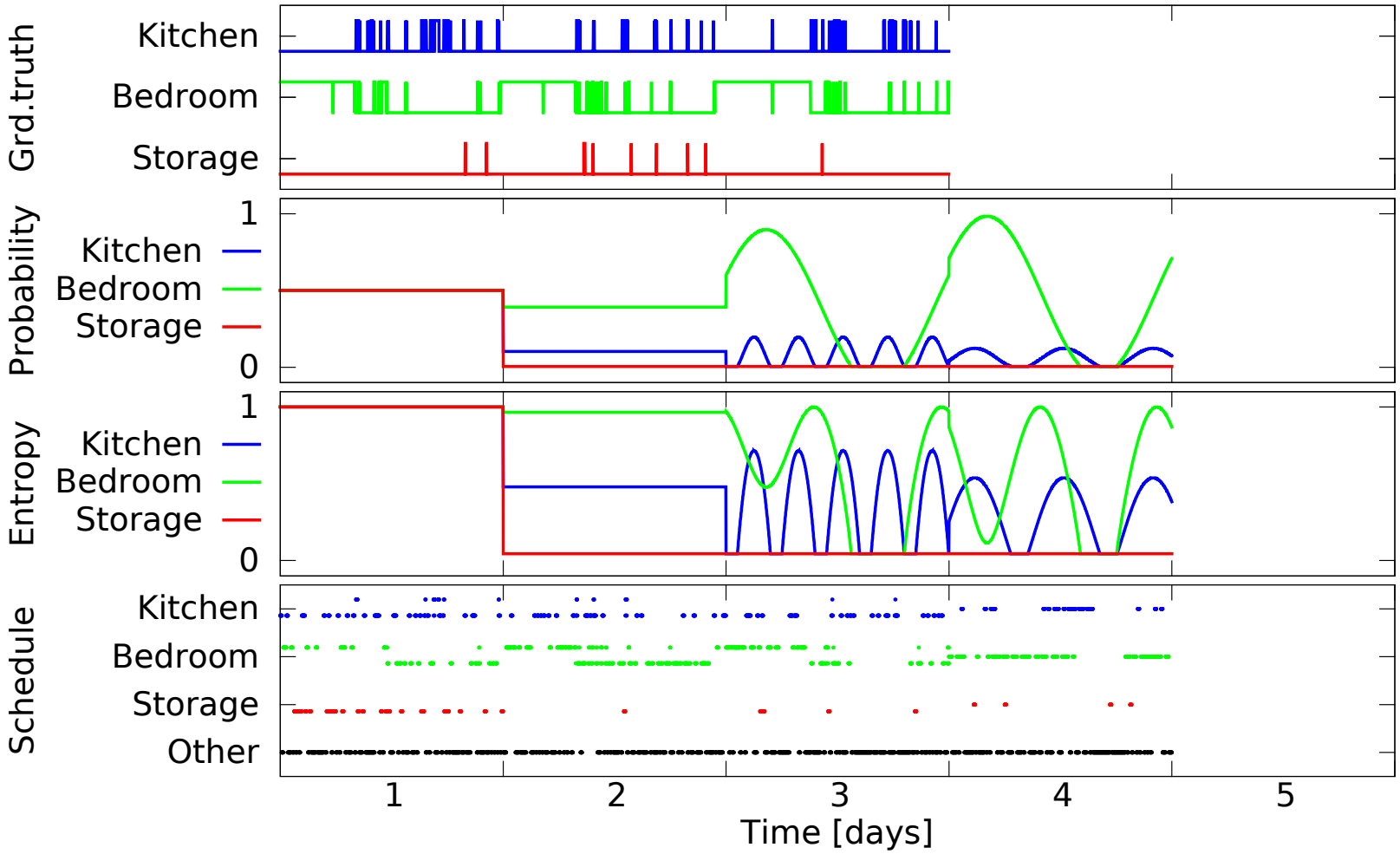

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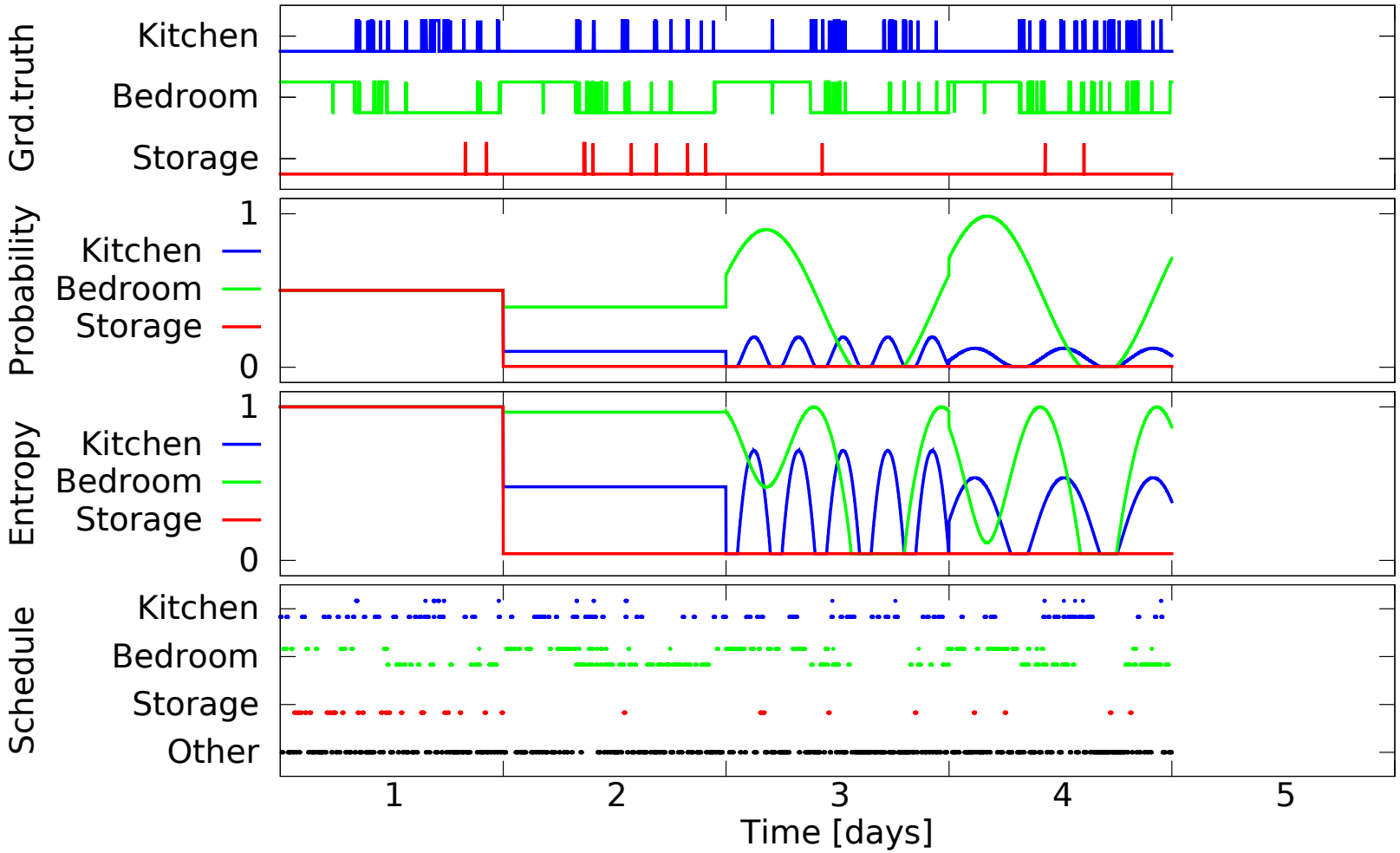

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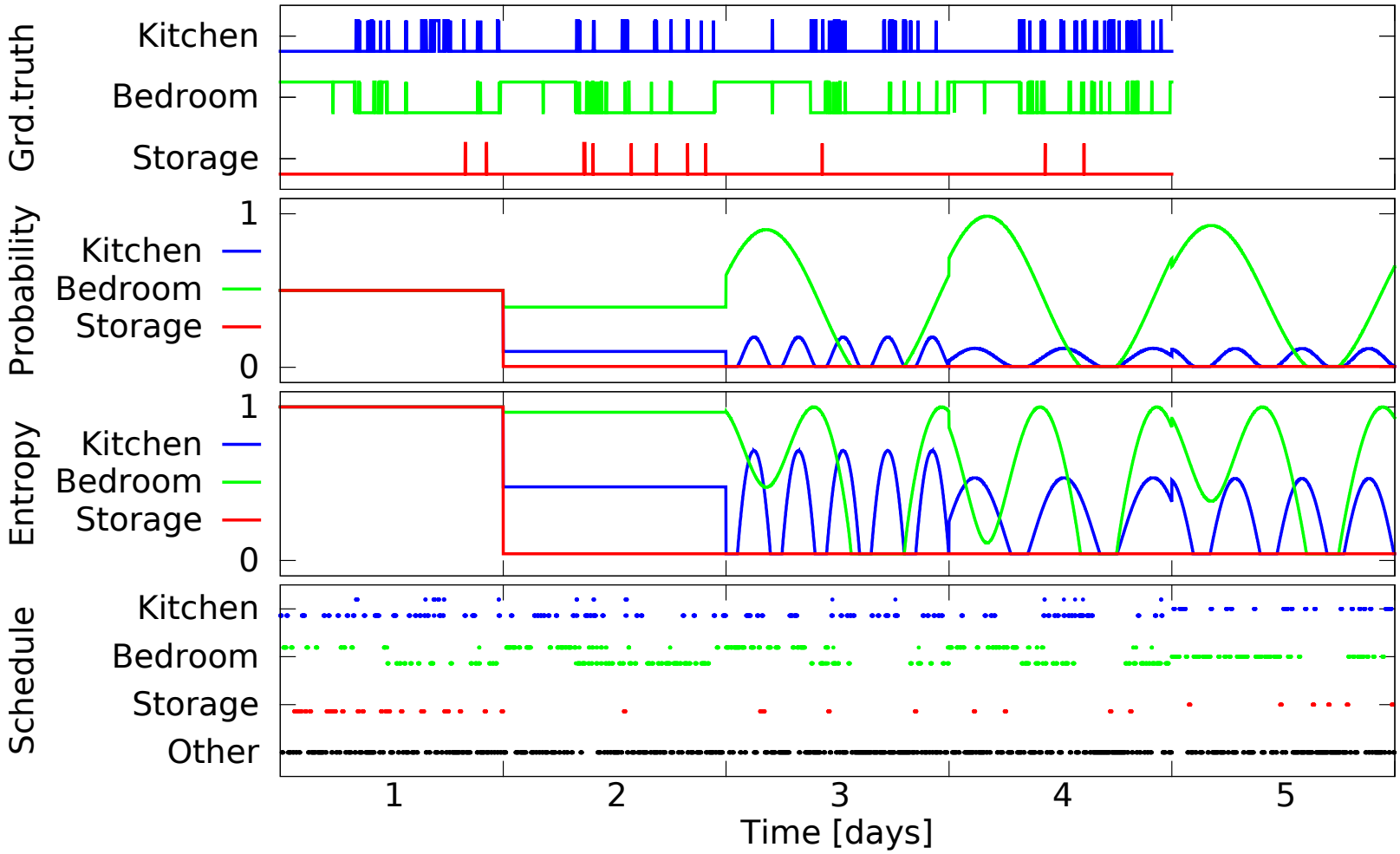

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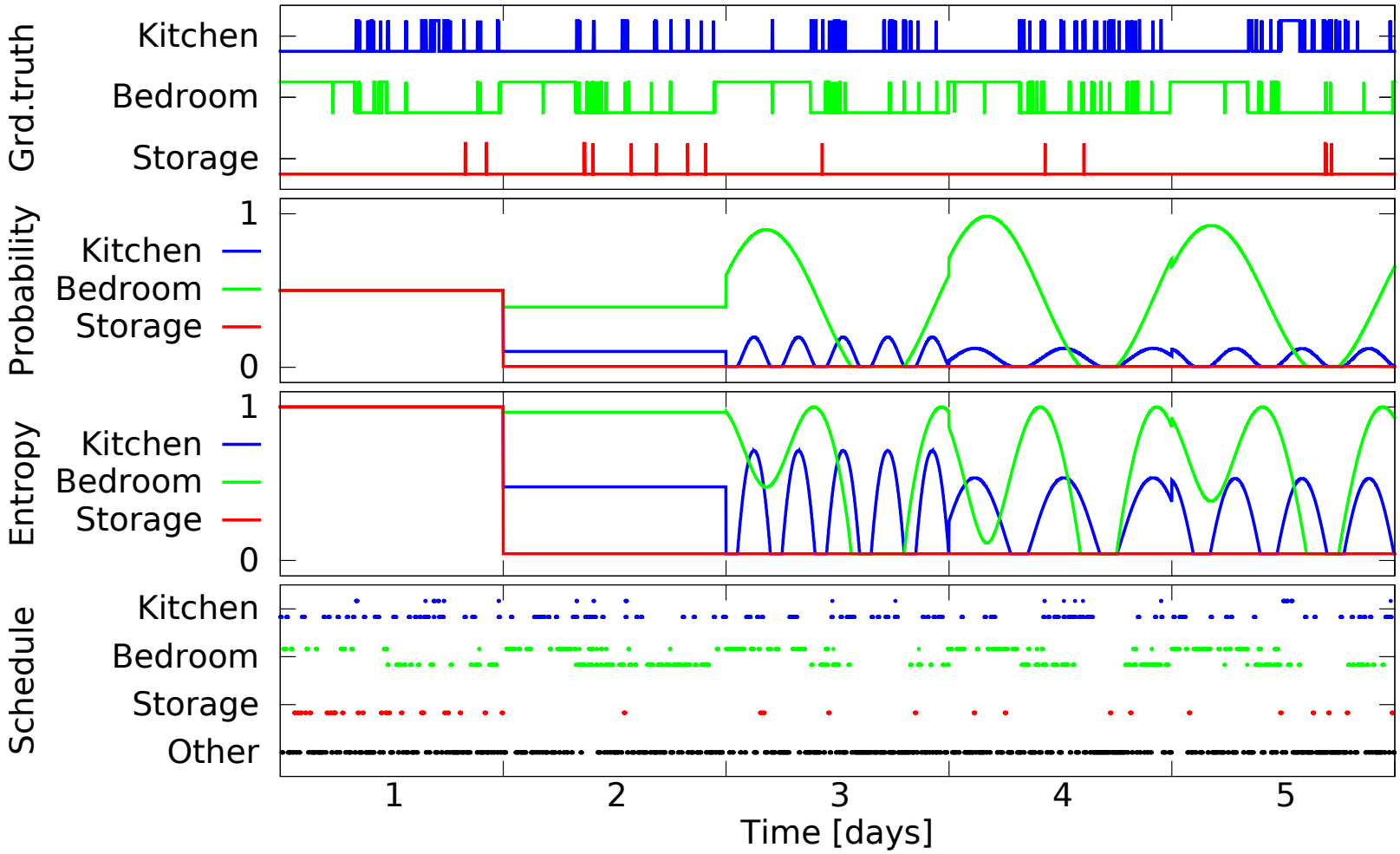
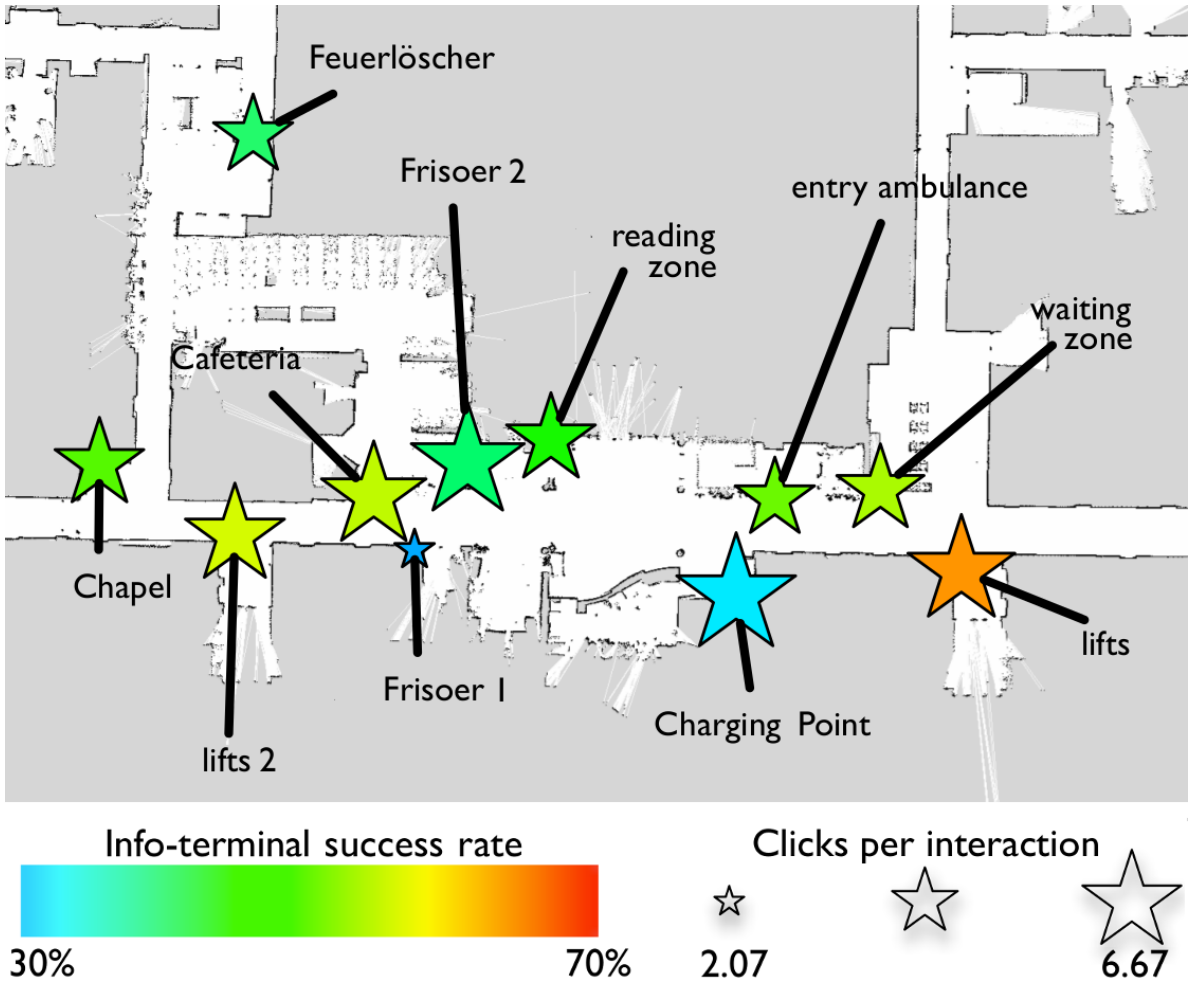


Mobile Infoterminal - exploration/exploitation

Decide the best time and location to provide an info-terminal service in a hospital. Maximise number of interactions.



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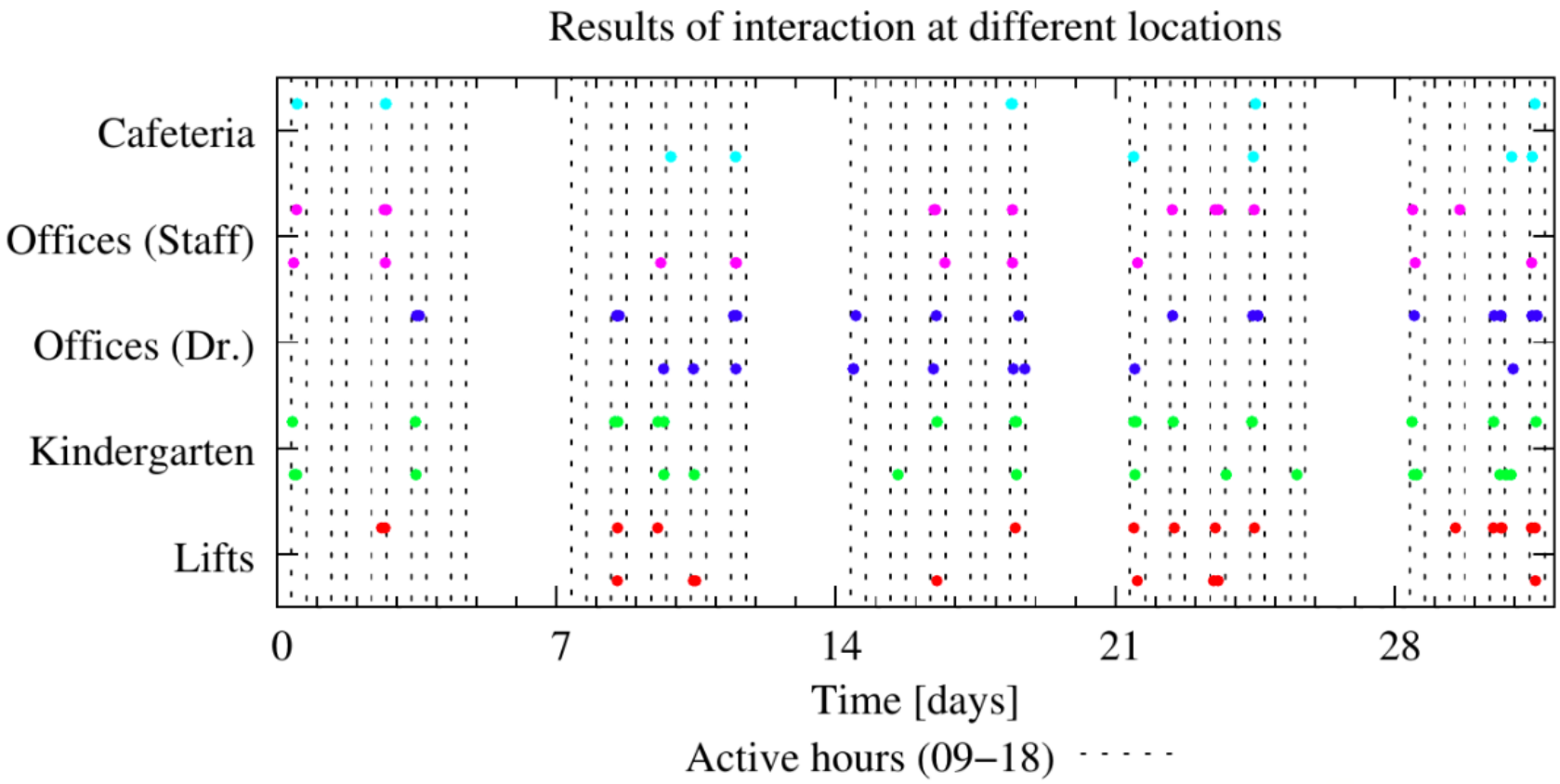

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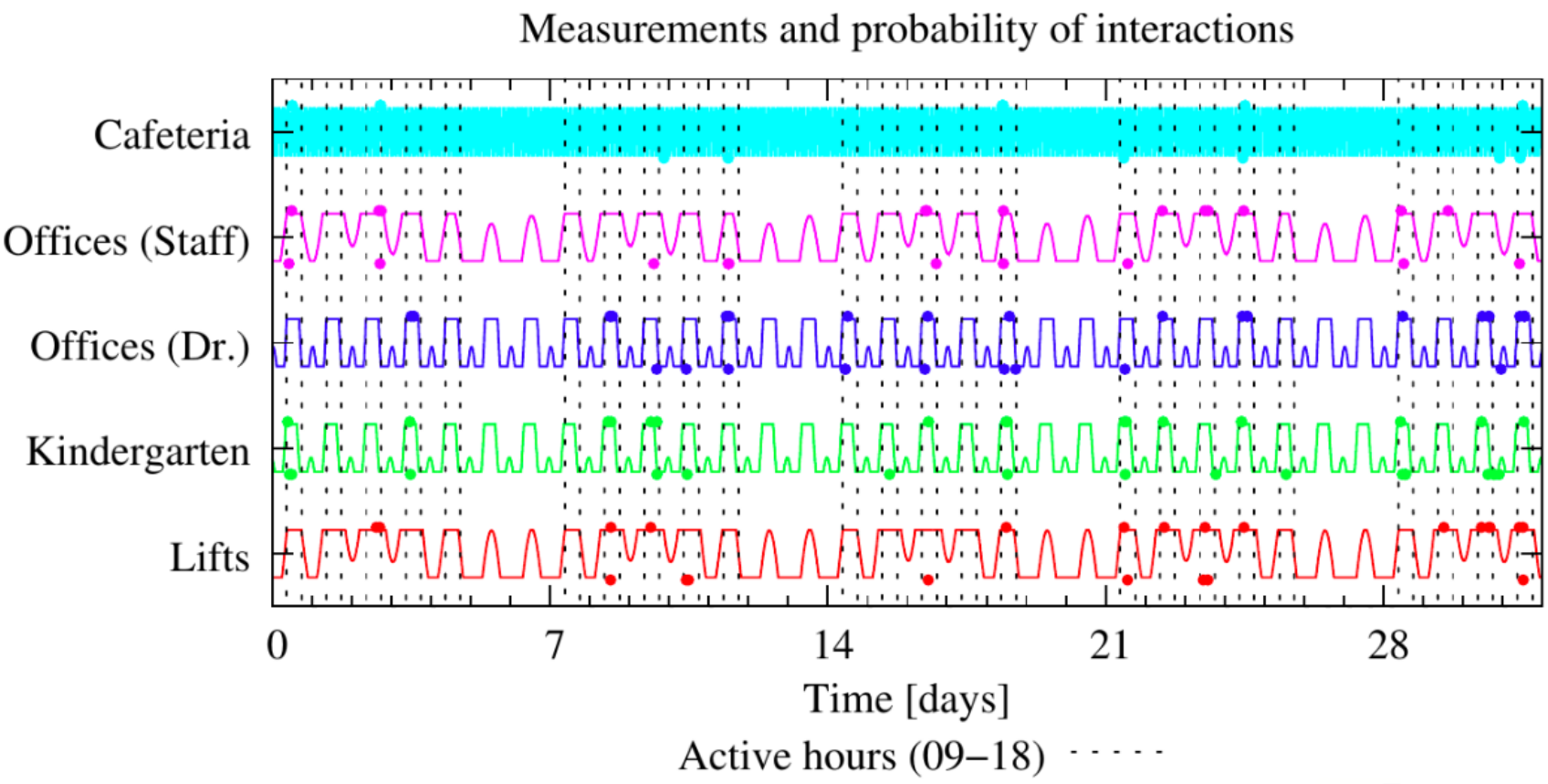

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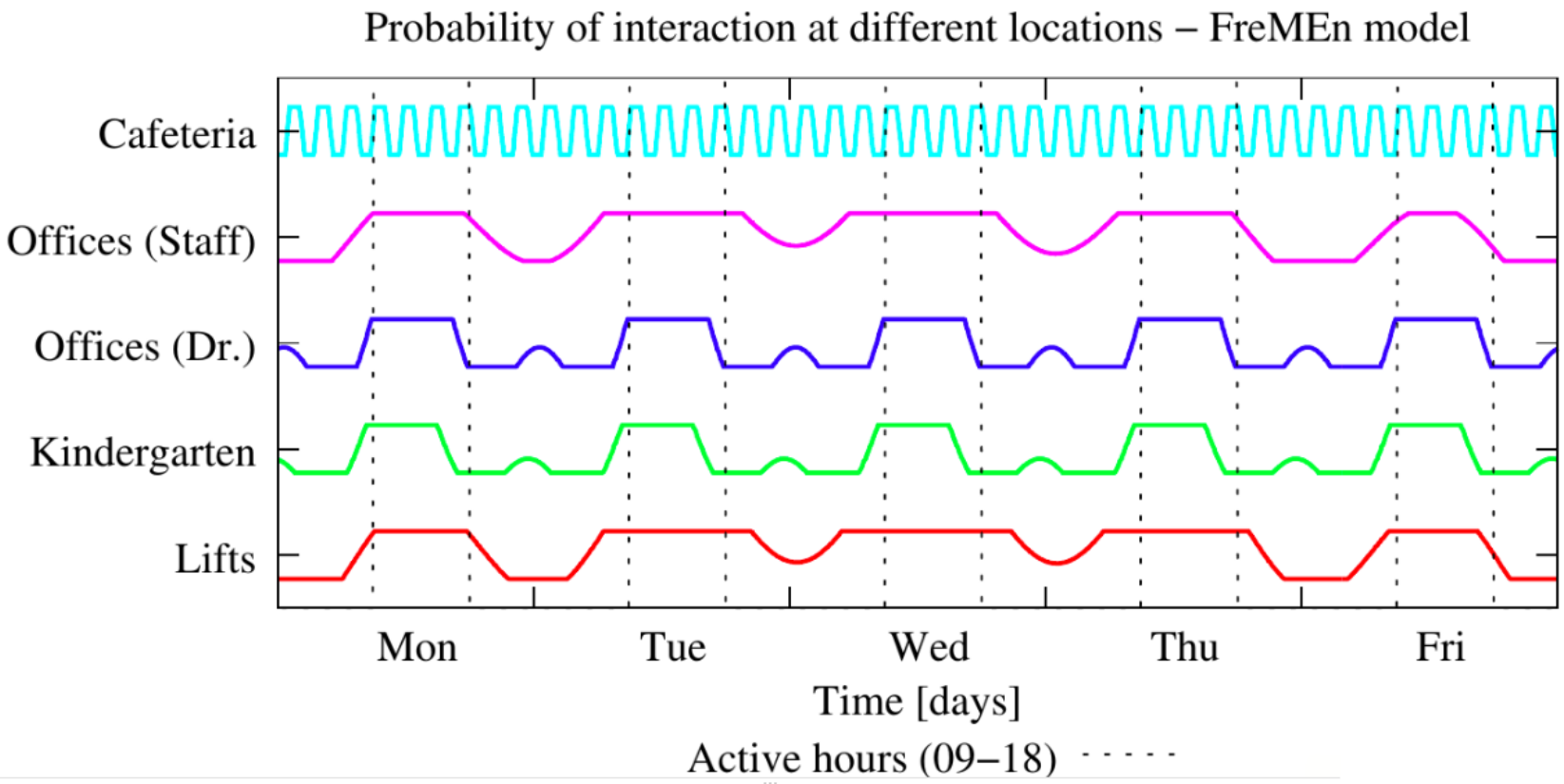

4D Spatio-Temporal Exploration

Spatio-temporal Information-driven Next Best View.
FreMEn 3D grid + spatio-temporal entropy + next best path

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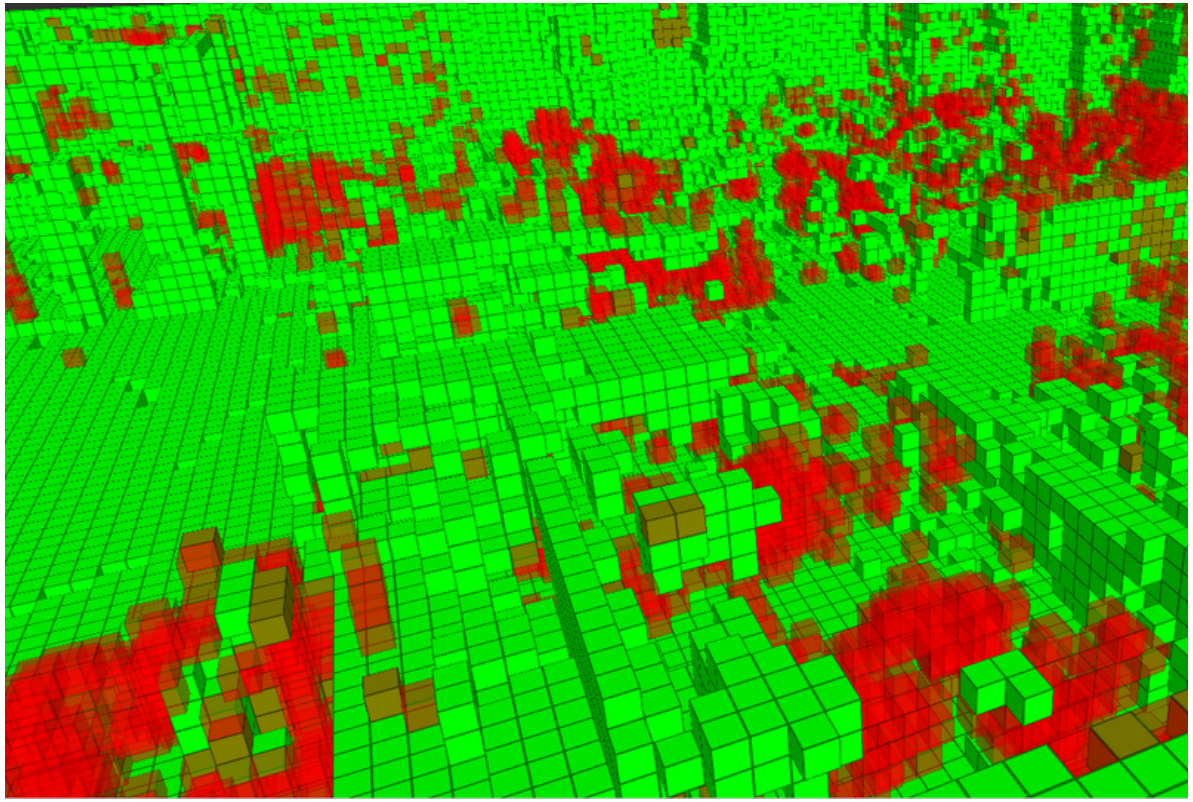

4D Spatio-Temporal Exploration

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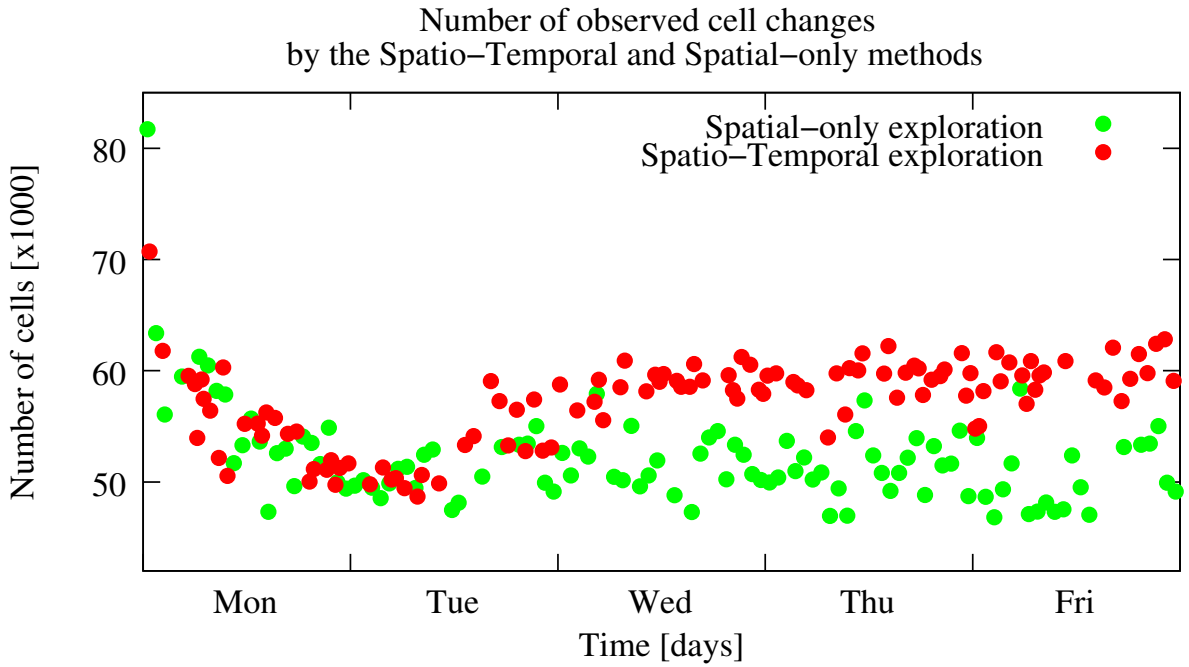
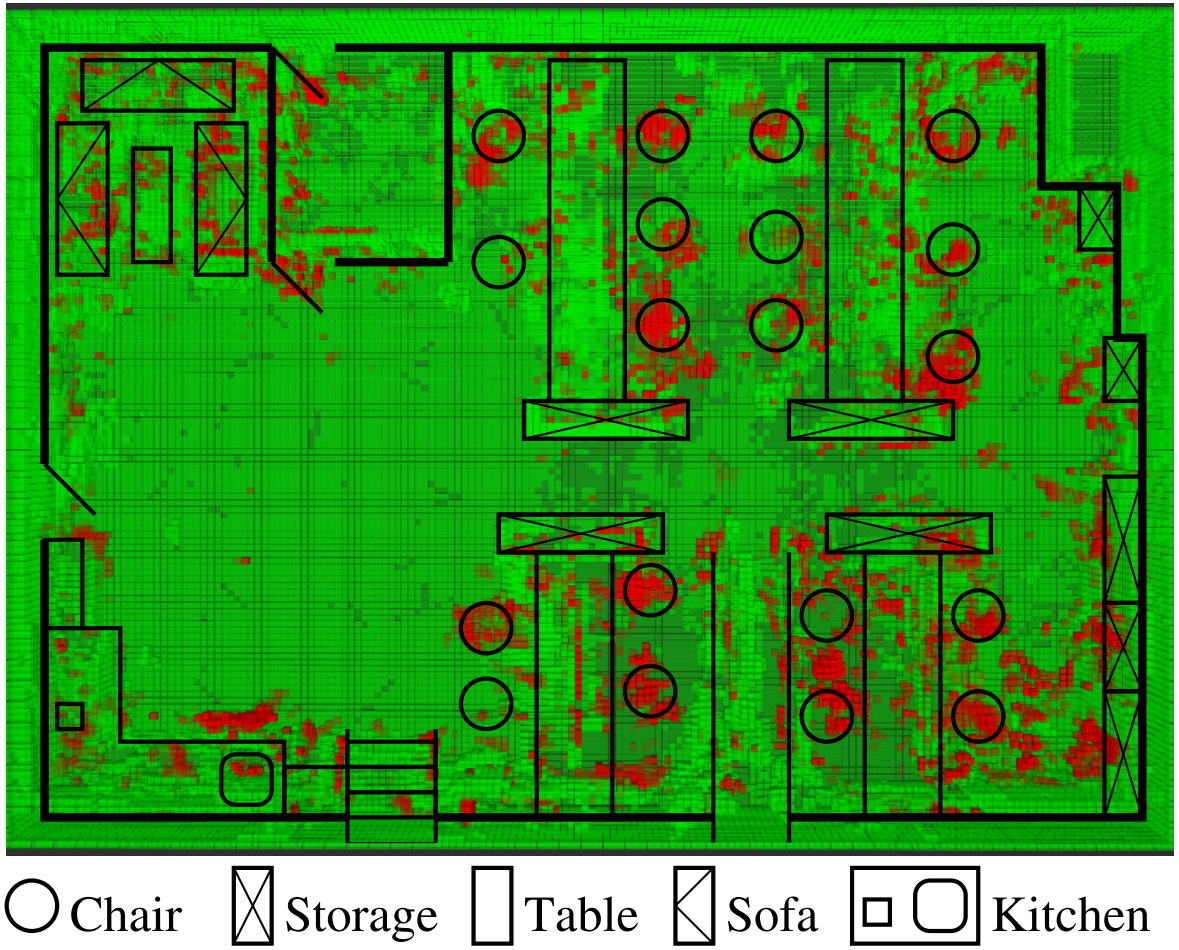


4D Spatio-Temporal Exploration

Spatio-temporal Information-driven Next Best View.
FreMEn 3D grid + spatio-temporal entropy + next best path



Video 2: 4D maps

FreMEn + persistence

Addition of a new measurement:

μ	$\leftarrow$	$\frac{1}{n+1}\,(\,n\mu + s(t)\,),$		mean probability
α_k	$\leftarrow$	$\frac{1}{n+1}\,(\,n\alpha_k + s(t)\,e^{-jt\omega_k}\,)$	$\forall\,\omega_k \in \omega,$	state spectrum
β_k	$\leftarrow$	$\frac{1}{n+1}\,(\,n\beta_k + e^{-jt\omega_k}\,)$	$\forall\,\omega_k \in \omega,$	observation spectrum
n	$\leftarrow$	$n+1,$		num of observations

Performing predictions:

γ_k	$\leftarrow$	$\alpha_k - \mu\,\beta_k$	predictive spectrum
$\gamma_{1..m}$	$\leftarrow$	$\mathrm{argmax}\,\lvert\gamma_k\rvert$	m components γ_k with highest abs. value
$p(t)$	=	$(\mu + \sum_{j=1}^{m} \lvert\gamma_j\rvert\, cos(\omega_j t + \arg(\gamma_j)))$	

FreMEn + persistence

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n	$\leftarrow$	$n+1,$		num of observations
τ^{-1}	$\leftarrow$	$\frac{1}{n+1}\,(\,n\tau^{-1} + \frac{\lvert s(t)-s(t_l)\rvert}{t-t_l}\,),$		rate of change
$s(t_l)$	$\leftarrow$	$s(t),$		last observation
t_l	$\leftarrow$	t		last observation time

Performing predictions:

γ_k	$\leftarrow$	$\alpha_k - \mu\,\beta_k$	predictive spectrum
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$p(t)$	=	$(\mu + \sum_{j=1}^{m} \lvert\gamma_j\rvert\, cos(\omega_j t + \arg(\gamma_j)))(1 - e^{\frac{t_l - t}{\tau}}) + s(t_l)e^{\frac{t_l - t}{\tau}}$	

FreMEn + persistence models

Short term predictions should consider recent observations.
Need to estimate persistence of a given state.

Adding a new measurement:

$$
\begin{aligned}
\mu &\leftarrow \tfrac{1}{n+1}\left(n\mu + s(t) \right), && \text{- mean probability} \\
\alpha_k &\leftarrow \tfrac{1}{n+1}\left(n\alpha_k + (s(t) - \mu)\, e^{-jt\omega_k} \right) \quad \forall\, \omega_k \in \Omega, && \text{- spectral components} \\
n &\leftarrow n + 1, && \text{- number of samples}
\end{aligned}
$$

Performing prediction:

$$
\begin{aligned}
\gamma_{1..m} &\leftarrow m \text{ spectral componets } \alpha \text{ with highest absolute value} \\
p(t) &= \varsigma(\mu + \textstyle\sum_{l=1}^{m} 2|\gamma_l| cos(\omega_l t + \mathtt{arg}(\gamma_l)))
\end{aligned}
$$

FreMEn + persistence models

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n & \leftarrow & n+1, & \text{- number of samples} \\
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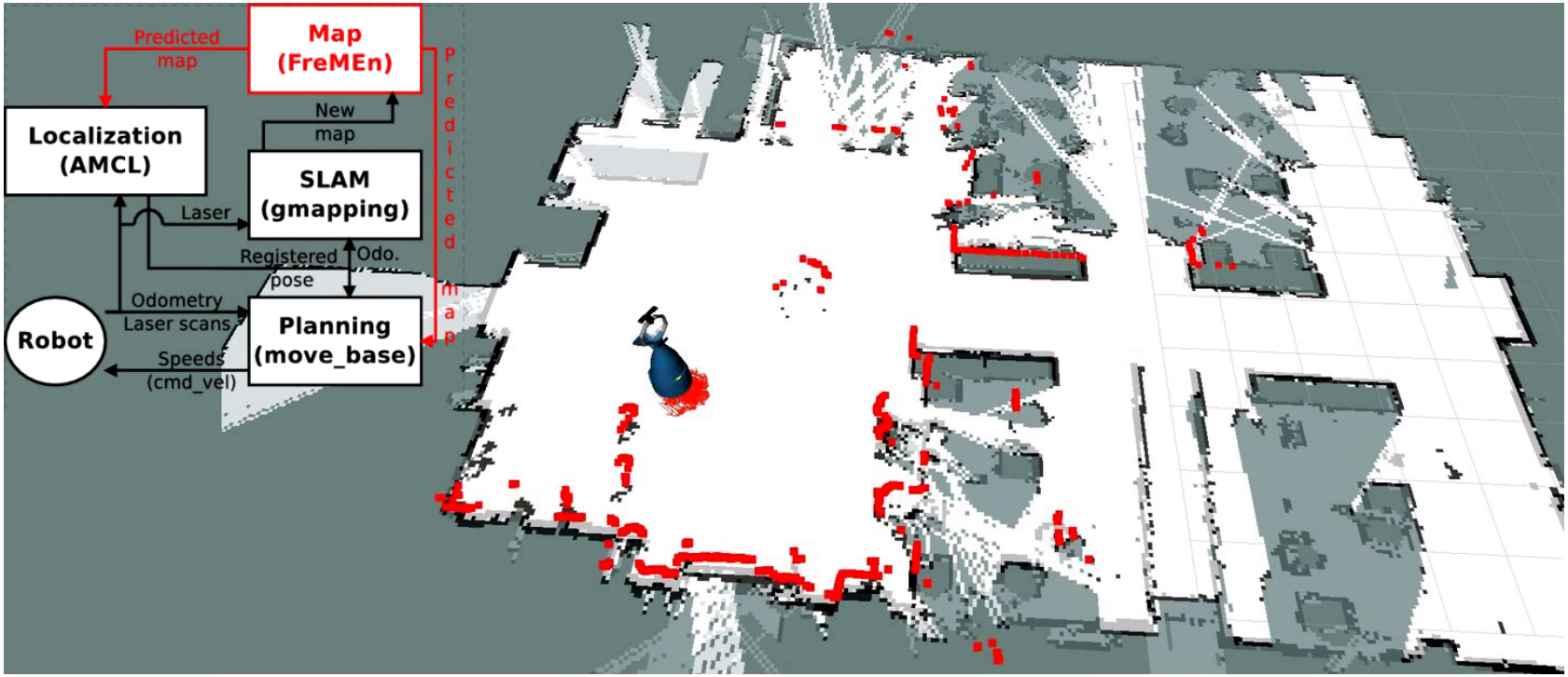
$$

Performing prediction:

$$
\begin{array}{lcl}
\gamma_{1..m} & \leftarrow & m \text{ spectral componets } \alpha \text{ with highest absolute value} \\
p(t) & = & \varsigma(\mu + \sum_{l=1}^{m} 2|\gamma_l| cos(\omega_l t + \mathtt{arg}(\gamma_l)))(1 - e^{\frac{t_l - t}{\tau}}) + s(t_l)\,e^{\frac{t_l - t}{\tau}}
\end{array}
$$

2D metric-based localization

Extended the temporal model by the notion of recency.
Extended 2D occupancy grids and integrate with ROS.



Localisation improvement only marginal for long-range sensors.

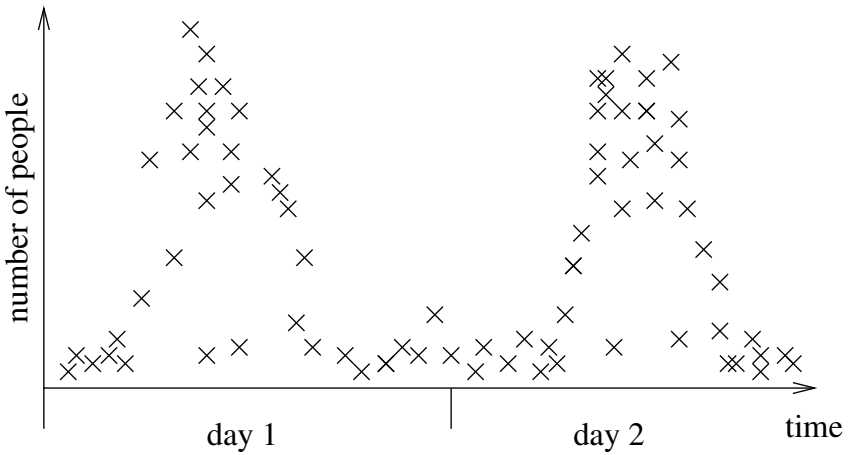
Video 3: ROS-based dynamic 2d grids

Video 4: People movement

FreMEn warped hypertime

Not all environment states are binary.

Example: number of people within a given area (video).



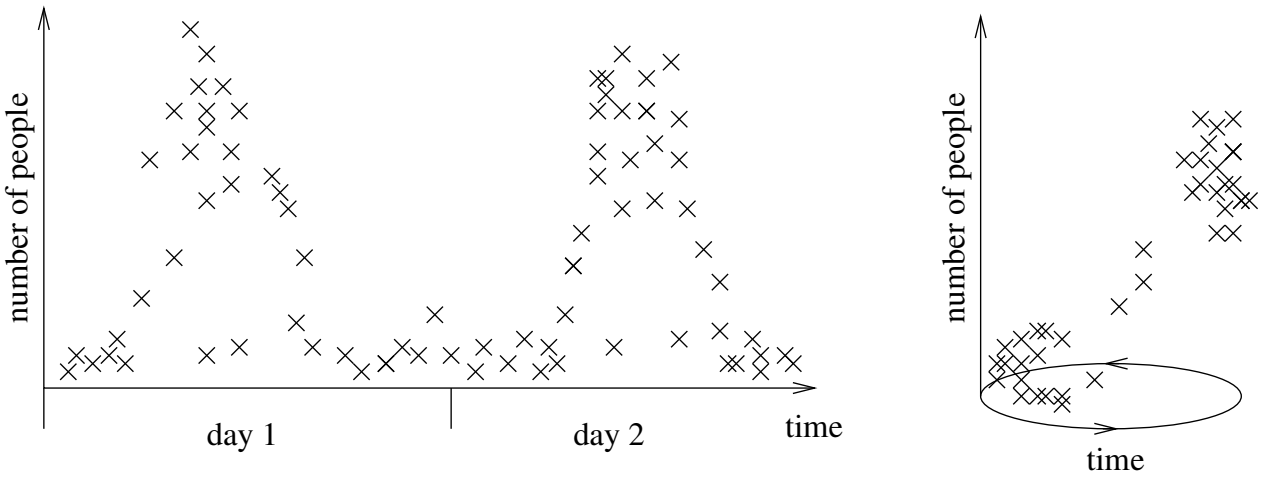
(x,t)

Use FreMEn to find dominant periodicity T,

FreMEn warped hypertime

Not all environment states are binary.

Example: number of people within a given area (video).



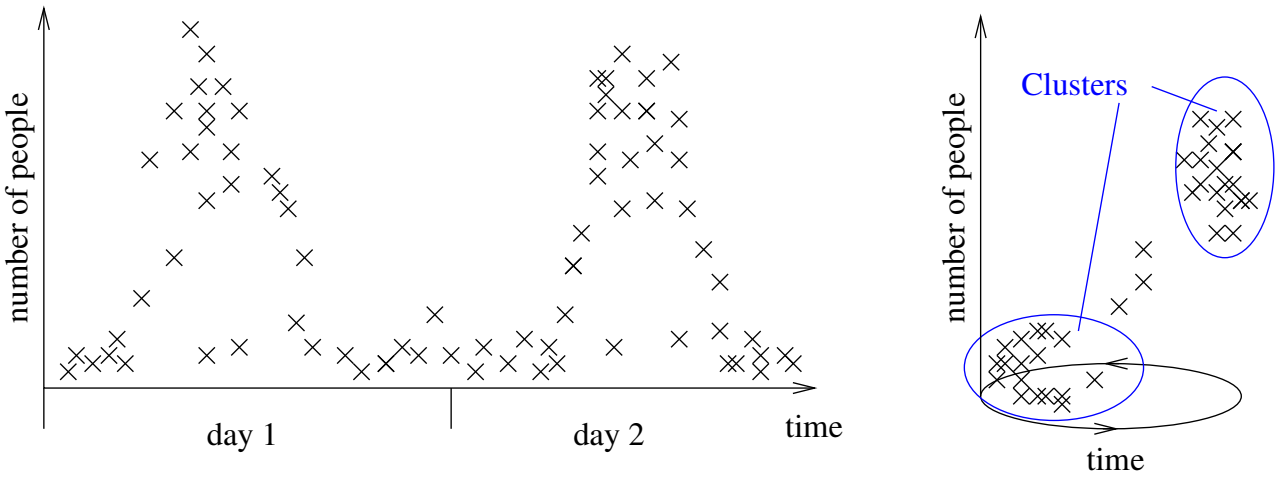
$$(x,t) \longrightarrow (x, \cos(2\pi\, t/T), \sin(2\pi\, t/T))$$

project time in ‘2d warped hypertime’

FreMEn warped hypertime

Not all environment states are binary.

Example: number of people within a given area (video).



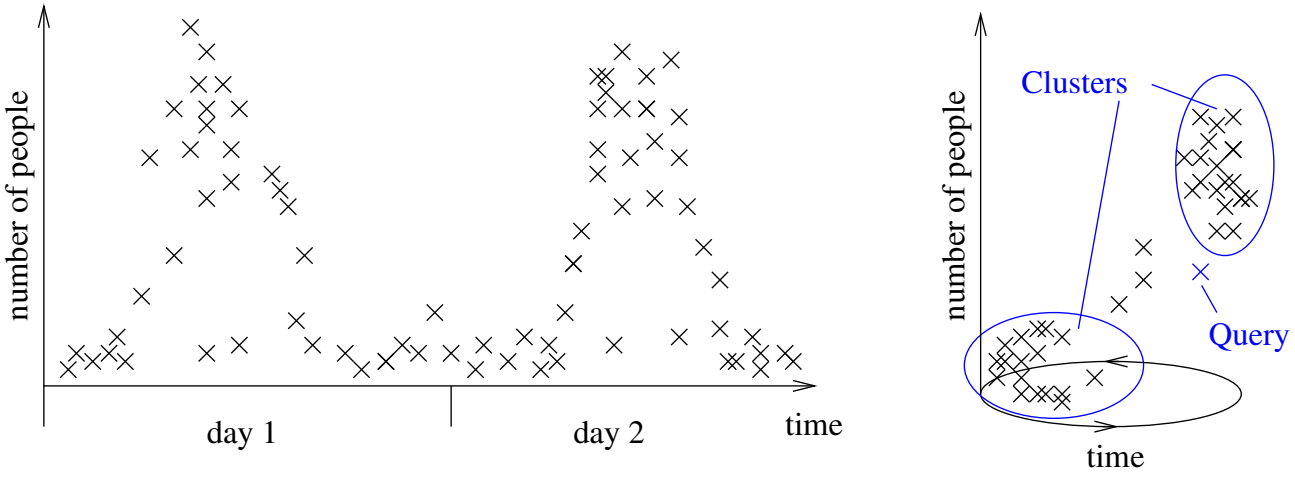
(x,t) ⟶ (x,cos(2pi t/T), sin(2pi t/T))

cluster the data, (and repeat).

FreMEn warped hypertime

Not all environment states are binary.

Example: number of people within a given area (video).



(x,t) ⟶ (x,cos(2pi t/T), sin(2pi t/T))

Predict the future states.

Video 5: People occurrences across time

Predictive database

FreMEn integrated into MongoDB.
A database that predicts future states.

Conclusions

FREquency Map ENhancement (FreMEn)

- models probability over time in the spectral domain,
- converts static representations into models that explicitly represent how the environment changes over time,
- improves localization [1], mapping [2], path planning [3], task scheduling [4], activity recognition [5], human-robot interaction [6], and enables spatio-temporal exploration [7].

[1] Krajník et al.: FreMEn: Frequency Map Enhancement.... IEEE T-RO 2017
[2] Krajník et al.: FROctomap: An Efficient Spatio-Temporal Environment Representation. In TAROS 2014
[3] Fentanes et al.: Now or later? Predicting and Maximising Success of Navigation Actions... In ICRA 2015
[4] Krajník et al.: Where's Waldo at time t? Using Spatio-Temporal Models for Robot Search. In ICRA 2015
[5] Coppola et al.: Temporal Models for Activity Recognition... In ECAI 2016
[6] M.Hanheide et al.: The When, Where, and How: An Adaptive Robotic Info-Terminal for Care... In HRI 2017
[7] Santos et al.: Life-long Information-based Exploration... RAL 2016

Publication timeline

[01] Krajník et al.: Spectral Analysis for Long-Term Robotic Mapping. In ICRA 14
[02] Duckett et al.:A frequency-based approach to long-term robotic mapping. (Keynote) ICRA LTAW 14
[03] Krajník et al.: FROctomap: An Efficient Spatio-Temporal Environment Representation. In TAROS 14
[04] Krajník et al.: Long-term topological localisation for service robots in dynamic environ... In IROS 14
[05] Krajník et al.: Long-term mobile robot localization in dynamic environments... (video) AAAI 15
[06] Krajník et al.: Where's Waldo at time t? Using Spatio-Temporal Models for Robot Search. In ICRA 15
[05] Fentanes et al.: Now or later? Predicting and Maximising Success of Navigation Actions... In ICRA 15
[07] Krajník et al.: Life-long exploration of dynamic environments. In ICRA LTB 15.
[08] Krajník et al.: FreMEN: ... for long-term mobile robot autonomy in changing envs... In ICRA VPRiCE 15
[09] Krajník et al.: Life-Long Spatio-Temporal Exploration of Dynamic Environments. In ECMR 15
[10] Krajník: FreMEn: Frequency Map Enhancement for Long-term Autonomy of UAVs (Invited) GRASP UPENN 16
[11] M.Kulich et al.: To Explore or to Exploit? Learning Humans' Behaviour to Maximize... In MESAS 2016
[12] Krajník: FreMEn: Frequency Map Enhancement for Long-term Autonomy of M.Robots **(Invited) MIT CSAIL 16**
[13] Krajník et al.: FreMEn: Introducing Dynamics into Static Environment Models. (Keynote) ICRA AILTA 16
[14] Coppola et al.: Temporal Models for Activity Recognition... In ECAI 16
[15] Krajnik: Mobile Robot Navigation in Changing Environments (Keynote) In PAIR 16
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Ongoing work

- Spatio-temporal Representations for Life-long Robot Navigation
- Czech Science Foundation

Project aims:

- visual teach and repeat for outdoor navigation,
- alternative transforms to model short events,
- Bayesian update scheme to handle sensor uncertainty,
- mining state dependencies to infer env. conditions,
- learning to infer temporal behaviour from appearance,

Questions

Check the presented approach at

http://fremen.uk

Questions?