# Non-Parametric Modeling of Spatio-Temporal Human Activity Based on Mobile Robot Observations

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Institute of Mechatronic Systems
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# Human Activity Modeling

## Environment dynamics

- Robots should adapt to human behavior

→ Models of human activity can improve navigation, task planning and -execution

(a) Cleaning robot[1]

(b) Security robot[2]

(c) Guiding robot[3]

(d) Delivery robot[4]

Figure: Robots in human-populated environments

[1] LG airport cleaning robot, photo: ©AP Photo/Ahn Young-joon, [2] Knightscope K5, photo: ©Steve Marcus

[3] Care-o-Bot, photo: ©Saturn, [4] Starship Technologies, photo: ©Christian Sinibaldi/The Guardian

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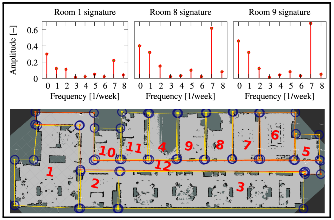
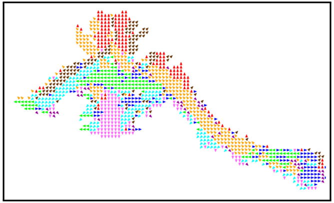
## State-of-the-art

- Few models consider temporal (long-term) effects
- Approaches neglect spatial interdependencies




(a) Jovan et al., 2016[1]



(b) Molina et al., 2021[2]

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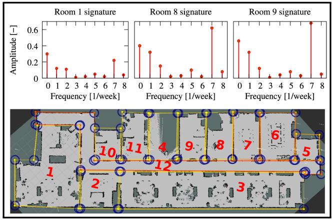
## Non-parametric modeling

+ Spatio-temporal interdependencies as prior

+ Consider noisy data, data gaps and predictive uncertainty

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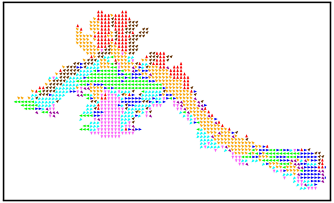

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# Regression Problem

## Data creation

- Moving robot → sparse/heterogeneous data distribution
- Input data

$$\boldsymbol{X} = \{(x_{1,i}, x_{2,i}, t_i)\}_{i=0}^{n}$$

- Target

$$\boldsymbol{y} = \{c_i/\Delta_i\}_{i=0}^{n}$$

People count ↑ ↑ Observation duration

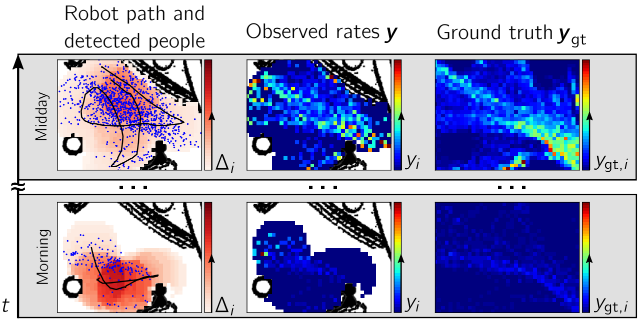


Figure: Input data and resulting observations for different points in time

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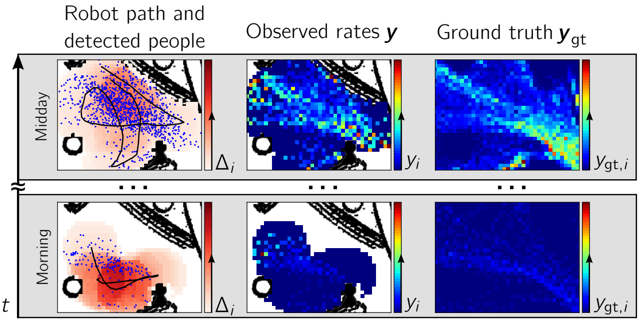


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## Goal

- Given inputs $\boldsymbol{X} = \{\boldsymbol{x}_i \in \mathbb{R}^3\}_{i=1}^{n}$ and target $\boldsymbol{y} = \{y_i \in \mathbb{R}\}_{i=1}^{n}$ infer $f : \mathbb{R}^3 \to \mathbb{R}$
- Heteroscedastic Gaussian Process Regression: $y_i \sim \mathcal{N}(f(\boldsymbol{x}_i), \sigma_i^2)$, $\sigma_i^2 = \zeta\left(g(\boldsymbol{x}_i)\right)$

$\mathcal{GP}(\mu_f(\boldsymbol{x}), k_f(\boldsymbol{x}, \boldsymbol{x}'))$ ⟶ $f(\boldsymbol{x}_i)$

$g(\boldsymbol{x}_i)$ ⟵ $\mathcal{GP}(\mu_g(\boldsymbol{x}), k_g(\boldsymbol{x}, \boldsymbol{x}'))$

# Defining the Gaussian Process

## Multidimensional product kernel

- Separate each $\boldsymbol{x}_i = [\boldsymbol{x}_\mathrm{s}, x_\mathrm{t}]_i^\top$ , $\quad \boldsymbol{x}_\mathrm{s} \in \mathbb{R}^2,\ x_\mathrm{t} \in \mathbb{R}$
- Spatio-temporal covariance function

$$k_f\left(\boldsymbol{x}_\mathrm{s}, x_\mathrm{t}, \boldsymbol{x}_\mathrm{s}', x_\mathrm{t}'\right) = k_\mathrm{s}\left(\|\boldsymbol{x}_\mathrm{s} - \boldsymbol{x}_\mathrm{s}'\|_2\right) \cdot k_\mathrm{t}\left(|x_\mathrm{t} - x_\mathrm{t}'|\right)$$

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Leibniz Universität Hannover

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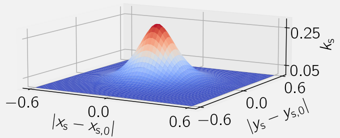

# Defining the Gaussian Process

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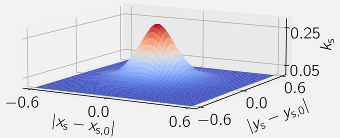
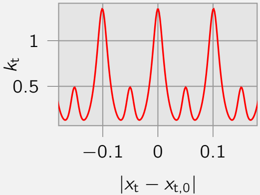



## Temporal kernel (Periodic)

Hyperparameters:
Periods and amplitudes



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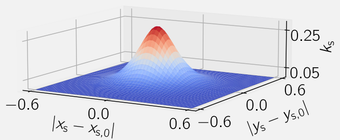


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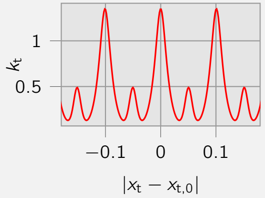
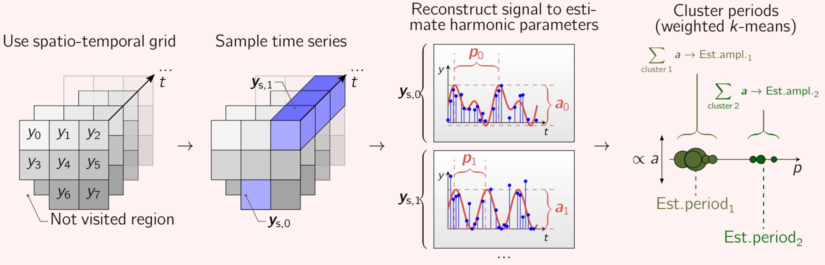



## Initialize periodic hyperparameters



# Results: Service Disturbance

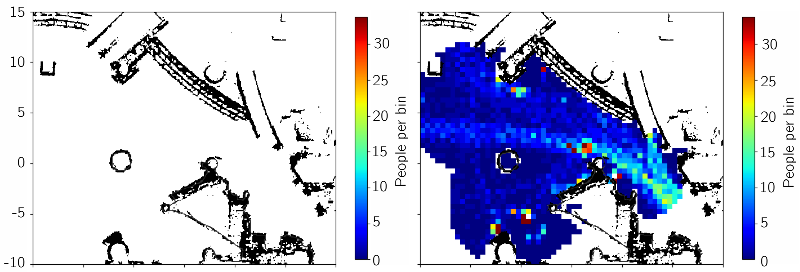
## Application-related evaluation (Vintr et al., 2020)[1]

- **Idea:** Use model to avoid disturbance of people
- Service disturbance with *servicing ratio r*

$$E(\lfloor pr \rfloor) = \sum_{k=1}^{\lfloor pr \rfloor} e_k$$

- $p$ imaginary navigation scenarios at different times
- Expected encounters

$$EE = \int_0^1 \sum_{k=1}^{pr} e_k \mathrm{d}r$$




Ground truth

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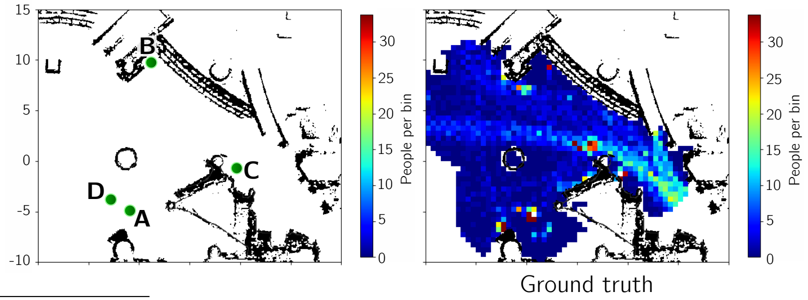


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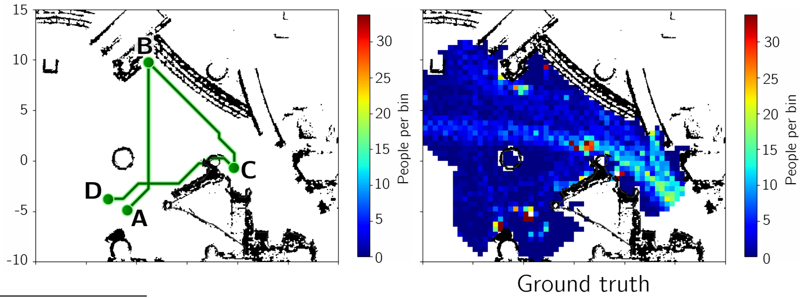


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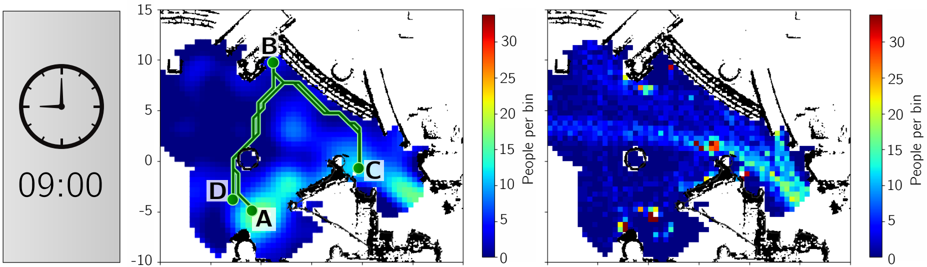


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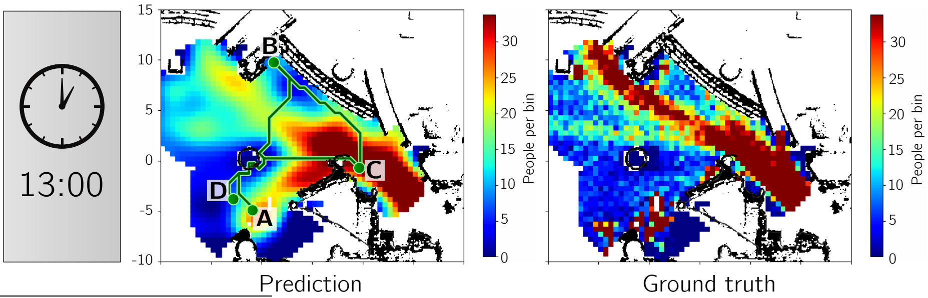


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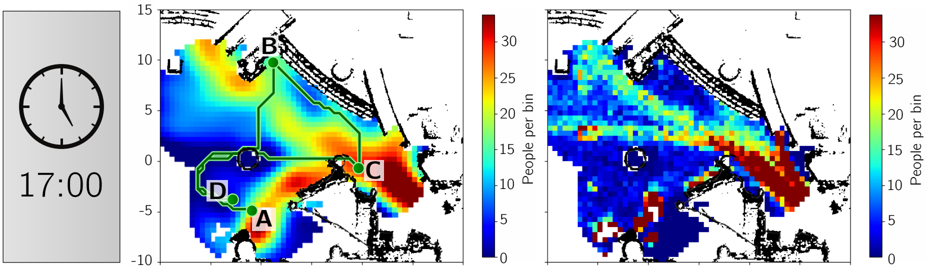


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# Some results

## Evaluation

- 4 days, 12 hours per day and 5 navigation tasks per hour $\Rightarrow p = 240$
- *How many encounters with people occurred, when a ratio $r$ of navigation tasks must be executed*

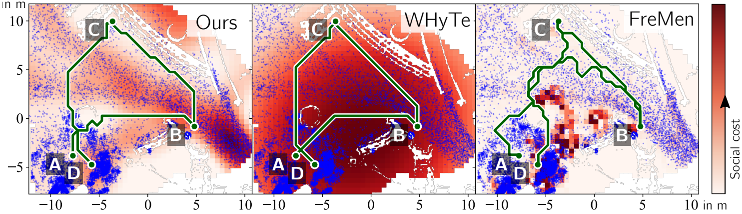



Figure: Our method leads to smooth paths and avoidance of high density areas

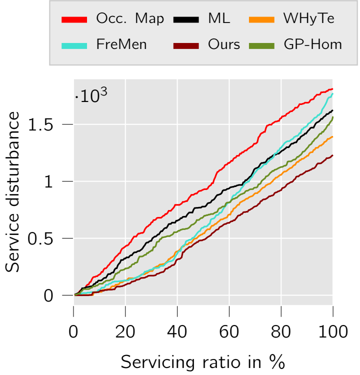
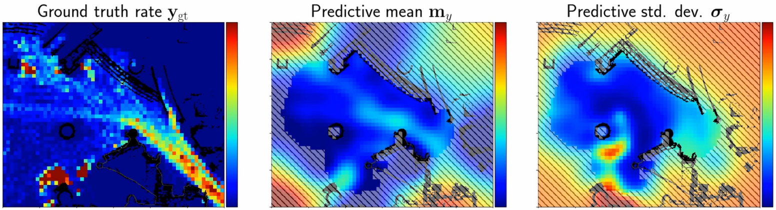



Figure: Service disturbance (encounters) depending on servicing ratio $r$

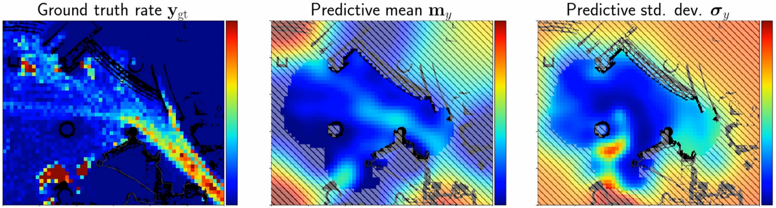
# Summary




## Prediction

Day: 11, 10:00

# Summary




Prediction
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- Encode prior knowledge of dependencies and periodicities into **kernel**
- Use **heteroscedastic** Gaussian Process for **continuous** modeling of sparse data
- **Variational inference** to allow for fast, repeated model training
- Code available: `https://github.com/MarvinStuede/copa-map`

# Thank you!

**Contact:**
Marvin.Stuede@imes.uni-hannover.de

# References I

Jovan, Ferdian et al. (2016). "A Poisson-spectral model for modelling temporal patterns in human data observed by a robot". In: *IEEE/RSJ IROS*, pp. 4013–4018.

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