Cyber-Physical Systems

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Università degli Studi di Trieste

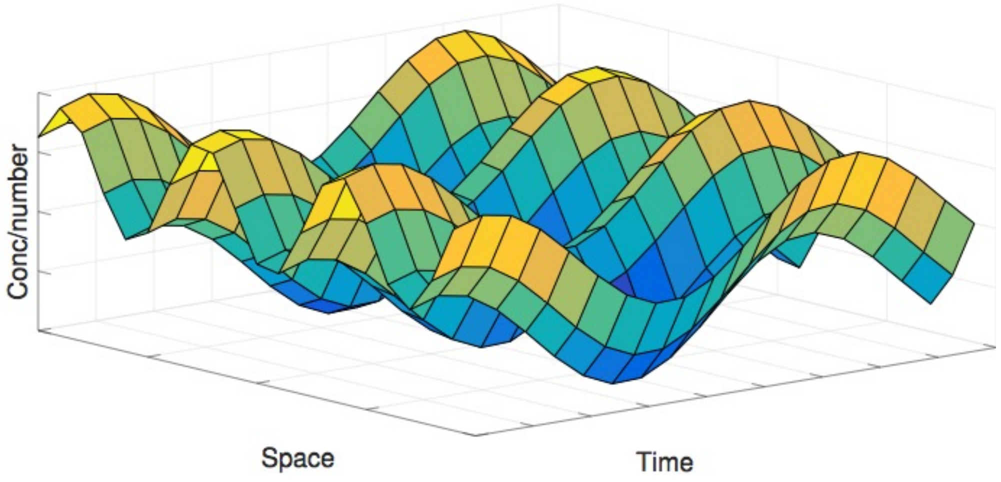
II Semestre 2021

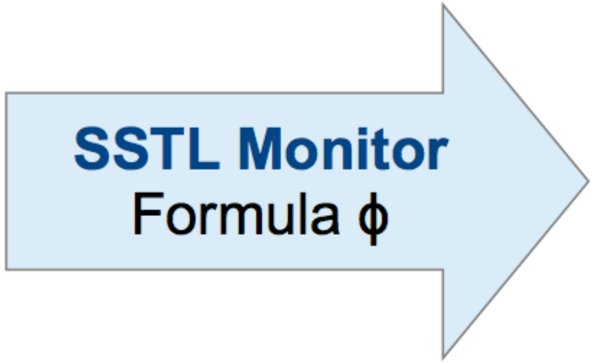
Lecture: Spatio-Temporal Reach and Escape Logic

Offline Monitoring Algorithm

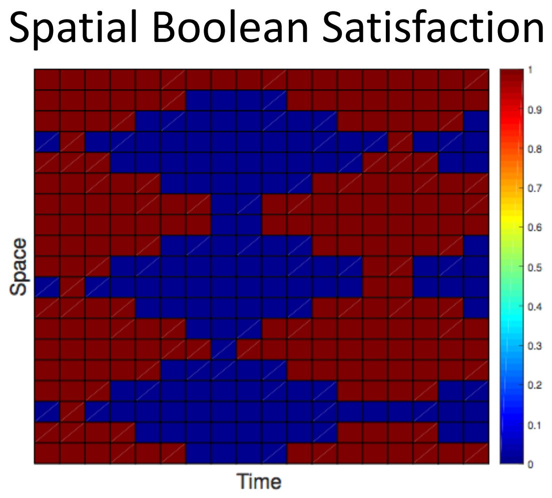
Spatial Boolean Signal

$s_\varphi : L \to [0, T] \to \{0, 1\}$ such that $s_\varphi(\ell, t) = 1 \Leftrightarrow (\mathcal{S}, \vec{x}, \ell, t) \models \varphi$





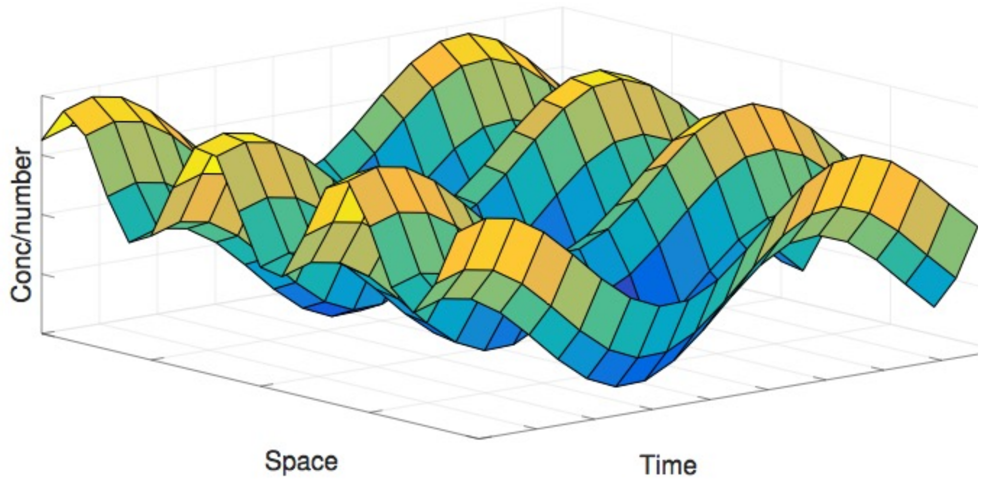
$s_\varphi(\ell, 0)$

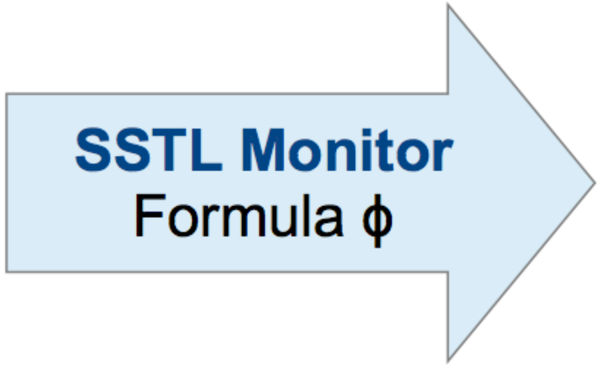


Offline Monitoring Algorithm

Spatial Quantitative Signal

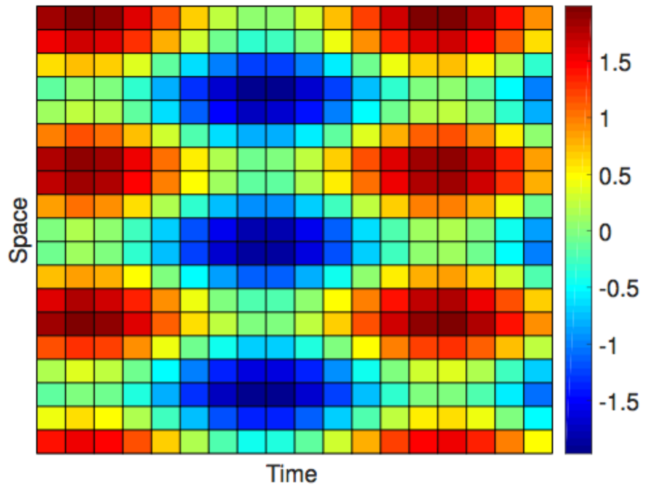
$\rho_\varphi : L \to [0, T] \to \mathbb{R} \cup \pm\infty$ such that $\rho_\varphi(\ell, t) = \rho(\mathcal{S}, \vec{x}, \ell, t)$

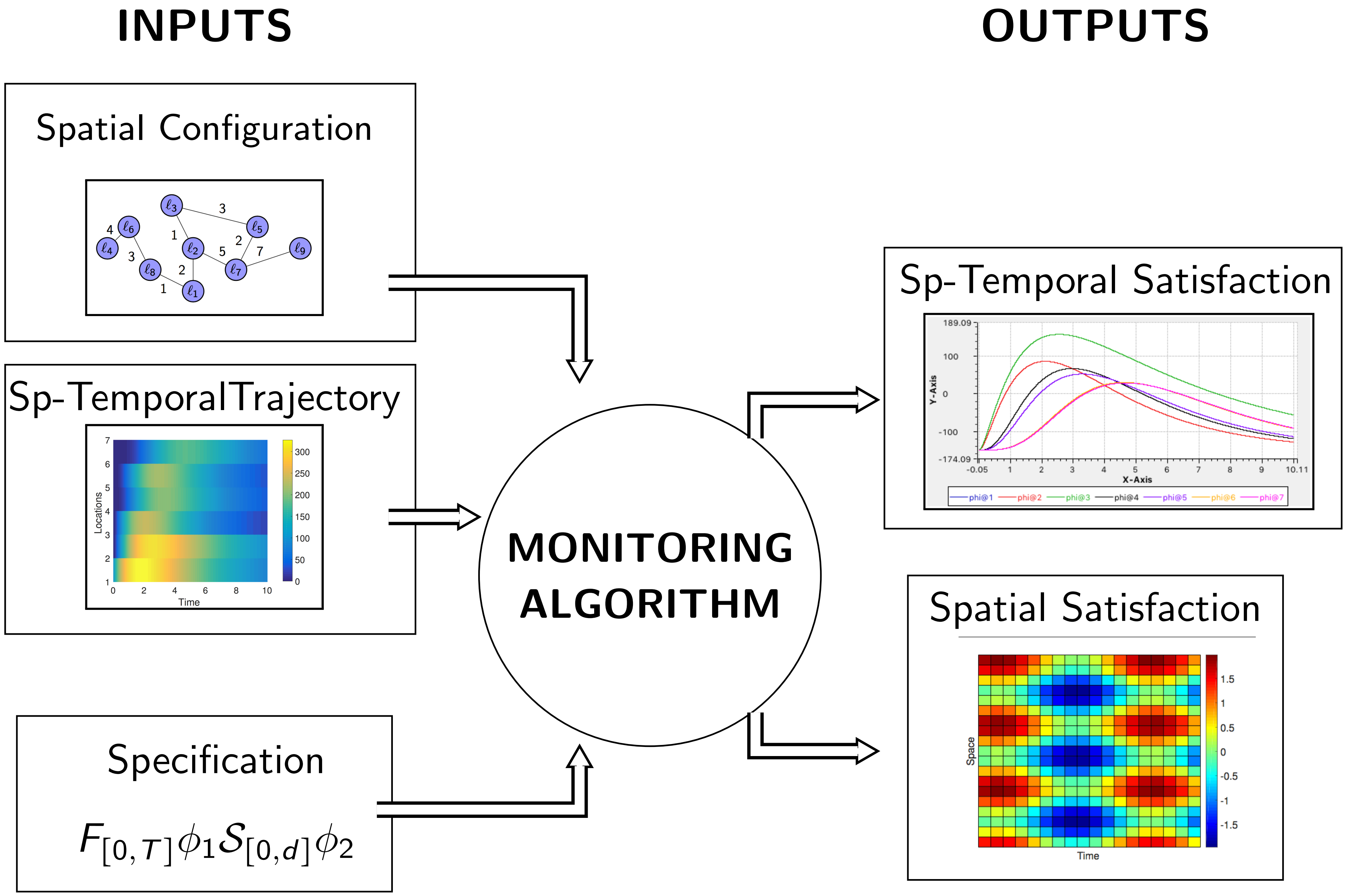




$\rho_\varphi(\ell, 0)$

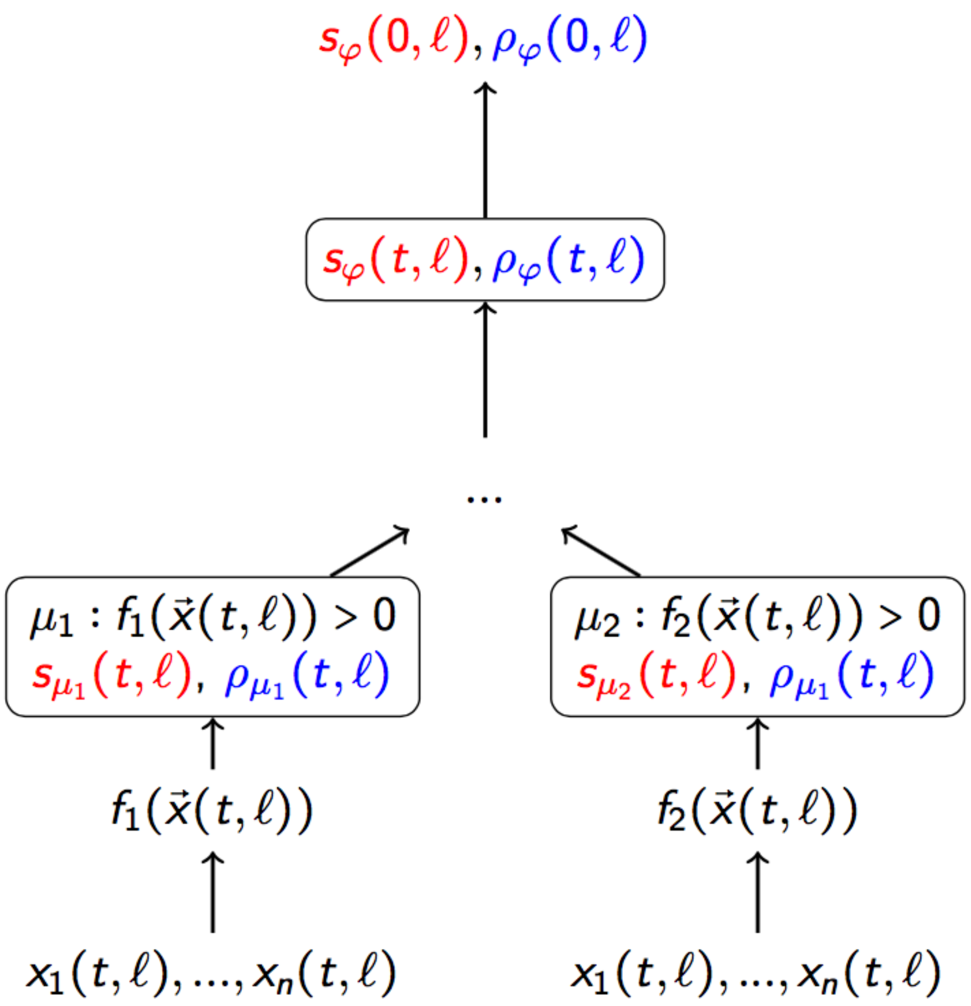
Spatial Quantitative Satisfaction





INPUTS
OUTPUTS
Spatial Configuration
Sp-TemporalTrajectory
Specification
$F_{[0,T]}\phi_1\mathcal{S}_{[0,d]}\phi_2$
MONITORING ALGORITHM
Sp-Temporal Satisfaction
Spatial Satisfaction
Locations
Time
X-Axis
Y-Axis
Space

Offline Monitoring Algorithm



Spatial Boolean satisfaction
Spatial Quant. satisfaction

Spatial Boolean signals
Spatial Quant. signals

Secondary signals

Primary signals

Computational consideration

- Temporal operators: like in STL monitoring [1] is **linear** in the length of the signal times the number of locations in the spatial model.

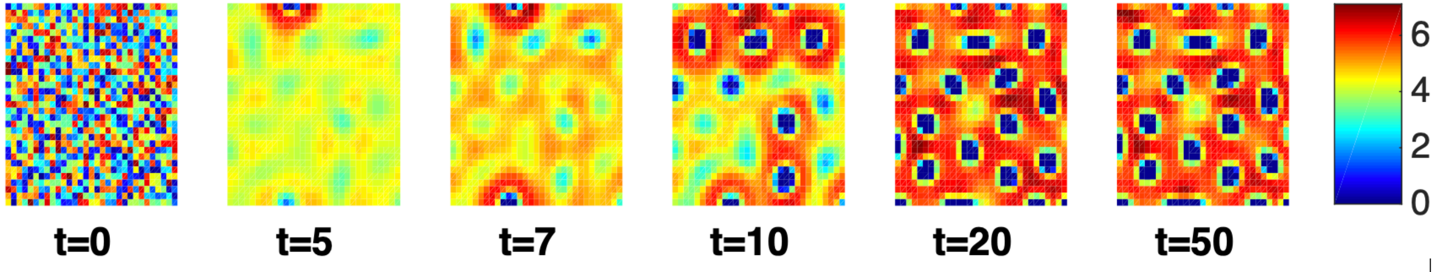
- Spatial properties are more expensive, they are based on a variations of the classical Floyd-Warshall algorithm.
  The number of operations to perform is **quadratic** for the reach operator and **cubic** for the escape

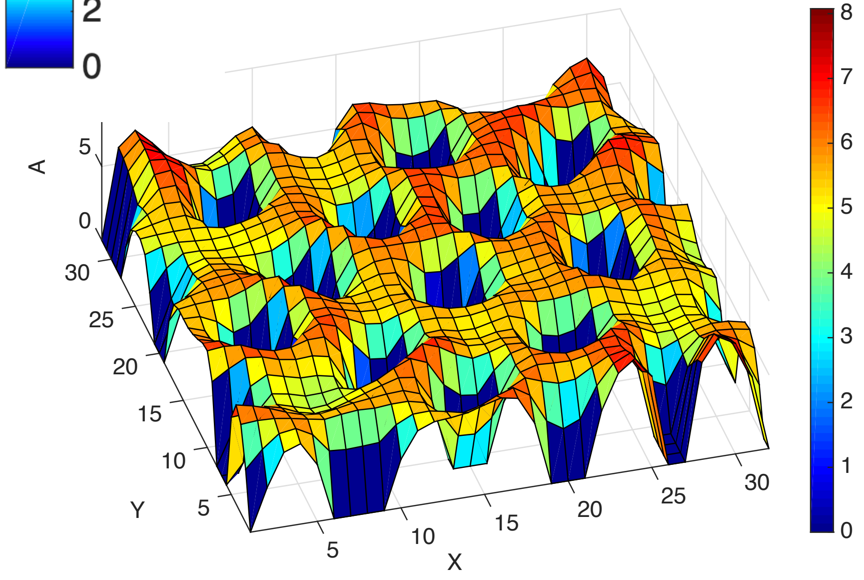
[1] O. Maler, T. Ferrére, and D. Nickovic. Efficient Robust Monitoring for STL. In Proc.CAV 2010

Static Space and Regular Grid

The formation of Patterns

The production of skin pigments that generate spots in animal furs:



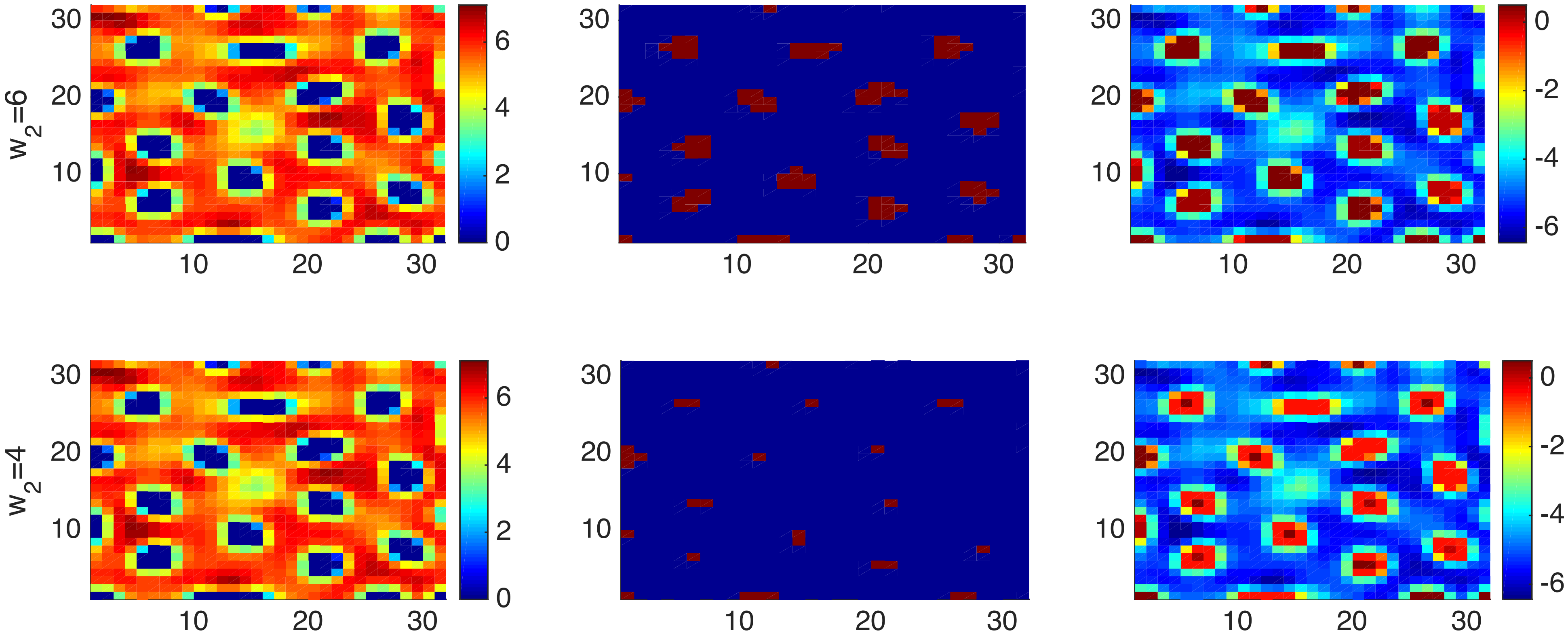


Space model: a K×K grid treated as a graph, cell$(i, j) \in L = \{1, \ldots, K\} \times \{1, \ldots, K\}$

Spatio-Temporal Trajectory: $x: L \rightarrow \mathbb{T} \rightarrow \mathbb{R}^2$ s.t. $x(\ell) = (x_A, x_B)$

Spot formation property

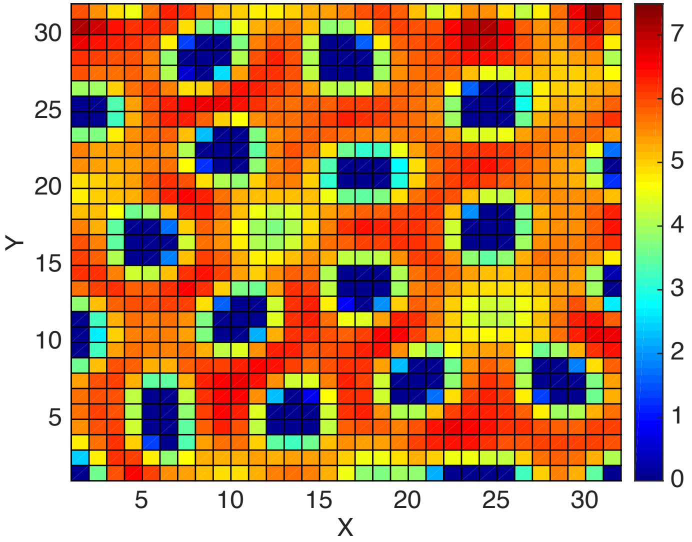
$$\phi_{spot_{form}} = F_{[19,20]} G((A \leq 0.5) \circledcirc^{hops}_{[1,w_2]} (A > 0.5))$$

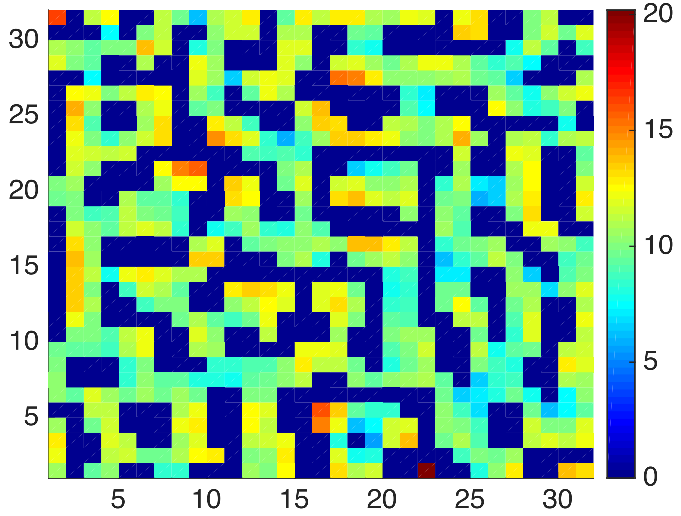
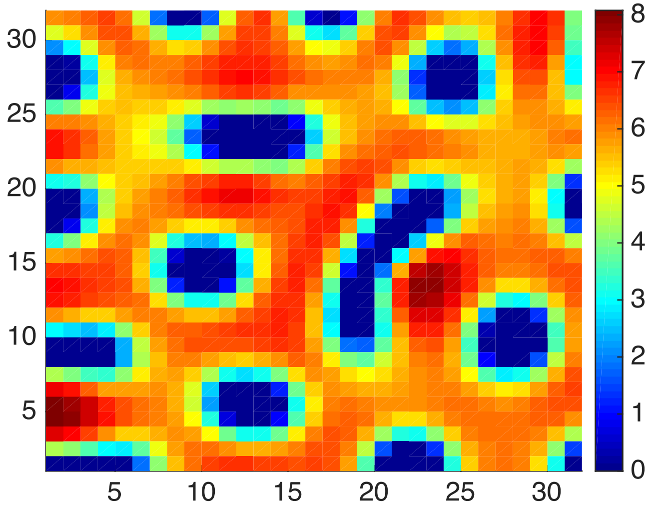


$\mathbf{x_A}(50, \ell)$ **Boolean sat.** **Quantitative sat.**

The formation of Patterns

$$\phi_{pattern} := \boxdot^{hops} \diamondsuit^{hops}_{[0,15]} \phi_{spot_{form}}$$

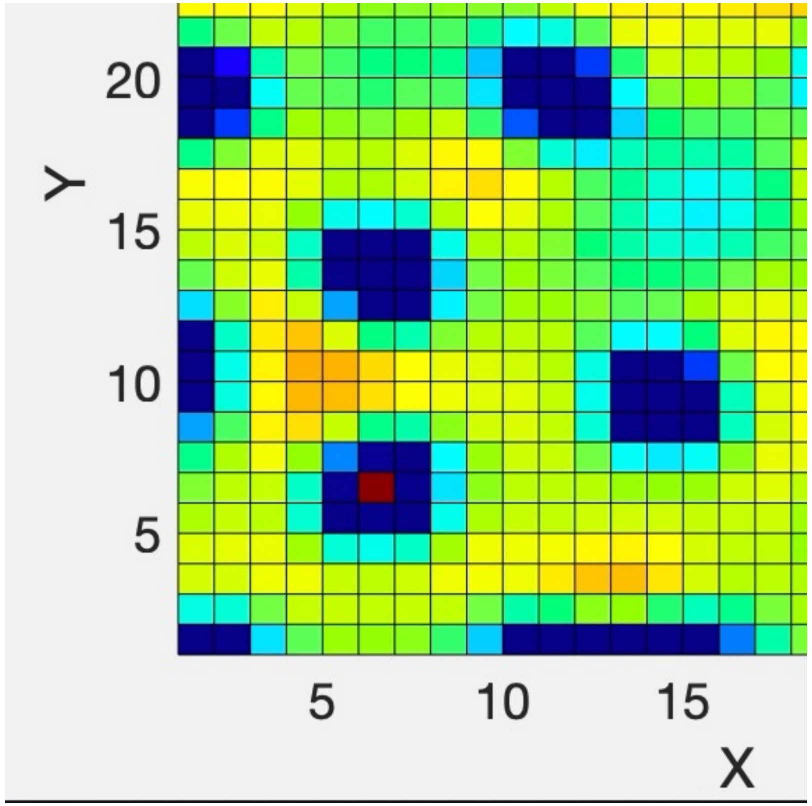


Perturbation Property

$$\phi_{\mathrm{pert}} := (x_A \geq 10) \wedge (\phi_{absorb} \circledcirc^{hops}_{[1,2]} \phi_{no\_effect})$$

- $\phi_{absorb} = F_{[0,1]} G_{[0,10]} (x_A < 3);$
- $\phi_{noeffect} := G_{[0,20]} (x_A < 3)$



Static Space and Stochastic Systems

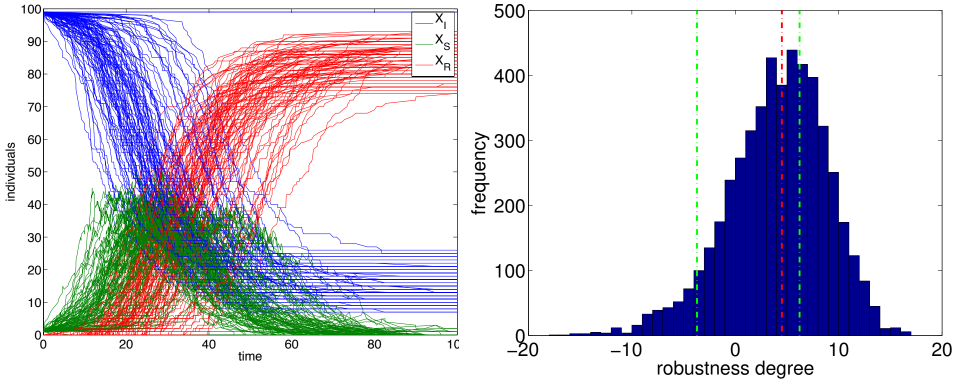
Application to Stochastic Systems

STREL can be applied on stochastic systems considering methodologies as Statistical Model Checking (SMC)

Stochastic process $\mathcal{M} = (\mathcal{T}, \mathcal{A}, \mu)$ where $\mathcal{T}$ is a trajectory space and $\boldsymbol{\mu}$ is a probability measure on a σ-algebra of $\mathcal{T}$

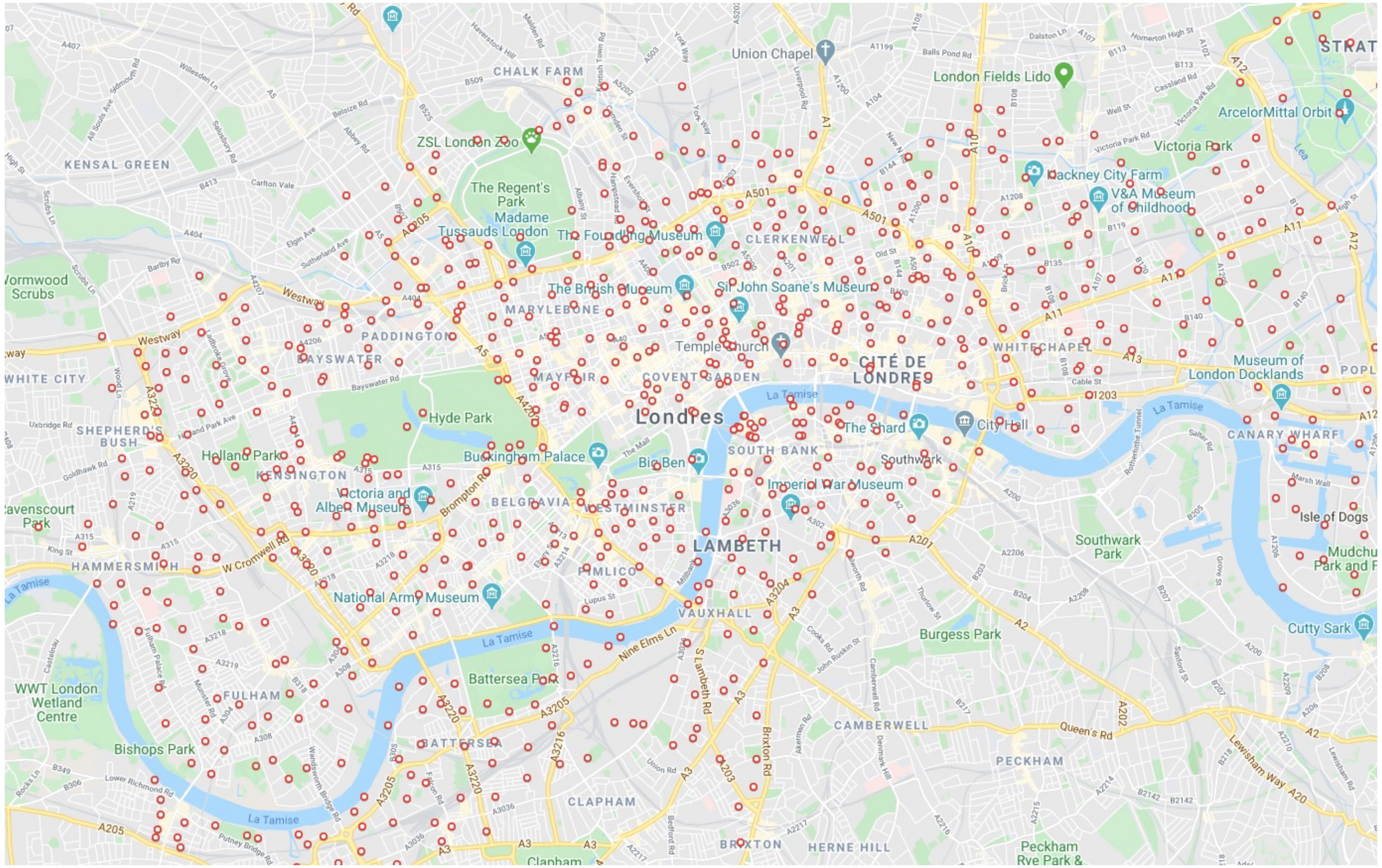
We approximate the satisfaction probability $S(\varphi, t)$, i.e. the probability that a trajectory generated by the stochastic process $\mathcal{M}$ satisfies the formula ϕ.

We can do something similar with the quantitative semantics computing the robustness distribution



Bike Sharing Systems (BSS)

London Santander Cycles Hire network



- 733 bike stations (each with 20-40 slots)
- a total population of 57,713 agents (users) picking up and returning bikes

We model it as a Population Continuous Time Markov Chain (PCTMC) with time-dependent rates, using historic journey and bike availability data.

Prediction for 40 minutes.

Bike Sharing Systems (BSS)

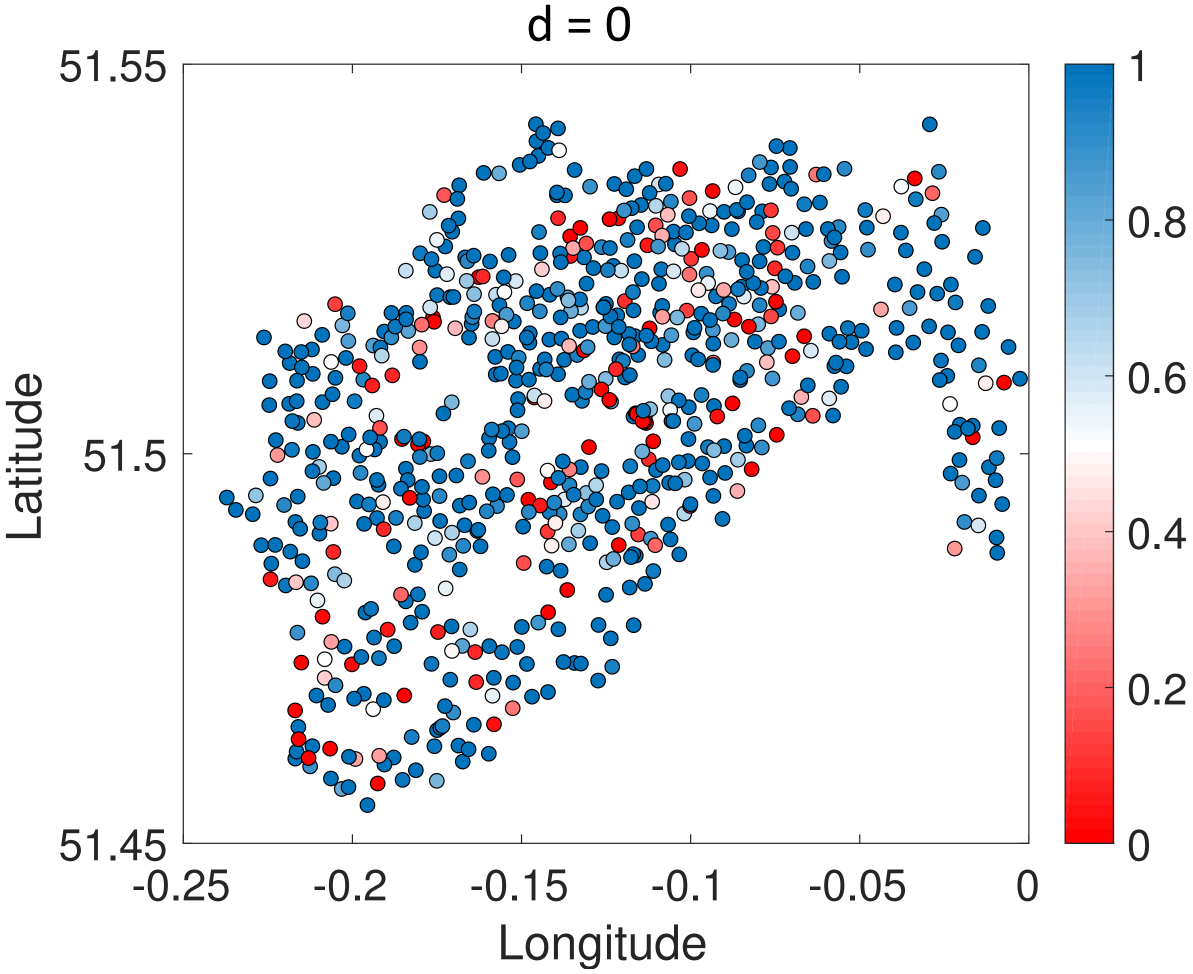
Spatio-Temporal Trajectory: $x: L \rightarrow \mathbb{T} \to \mathbb{Z}^2$ s.t. $x(i,t) = \left(B_i(t), S_i(t)\right)$

Space model

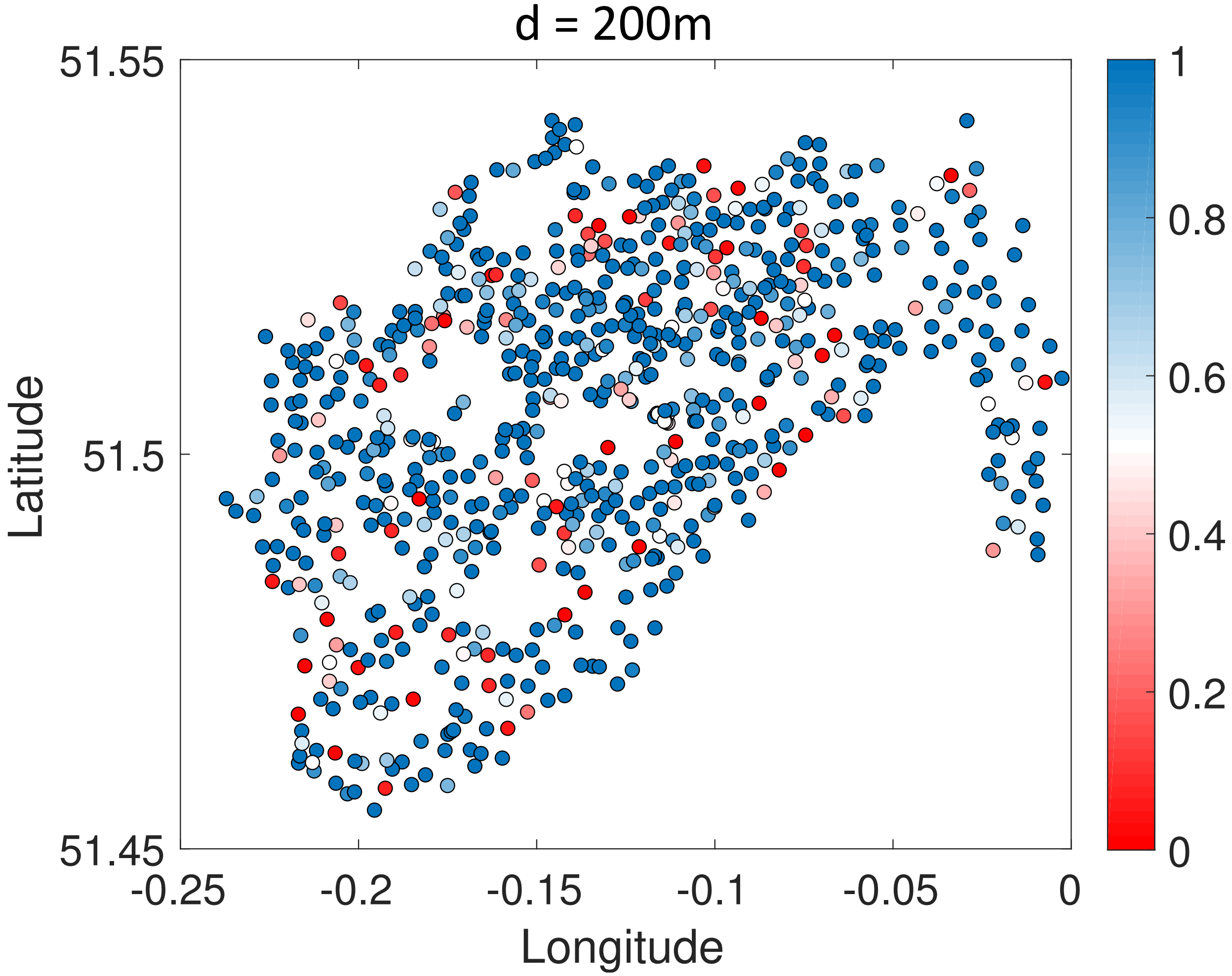
- Locations: $L = \{bike\ stations\}$,
- Edges: $\left(\ell_i, w, \ell_j\right) \in W$ iff $\mathrm{w} = \parallel \ell_i - \ell_j \parallel < 1\ kilometer$

Availability of Bikes

$$\phi_1 = \mathrm{G}\{\diamondsuit^{weight}_{[0,d]}(B > 0) \wedge \diamondsuit^{weight}_{[0,d]}(S > 0)\}$$



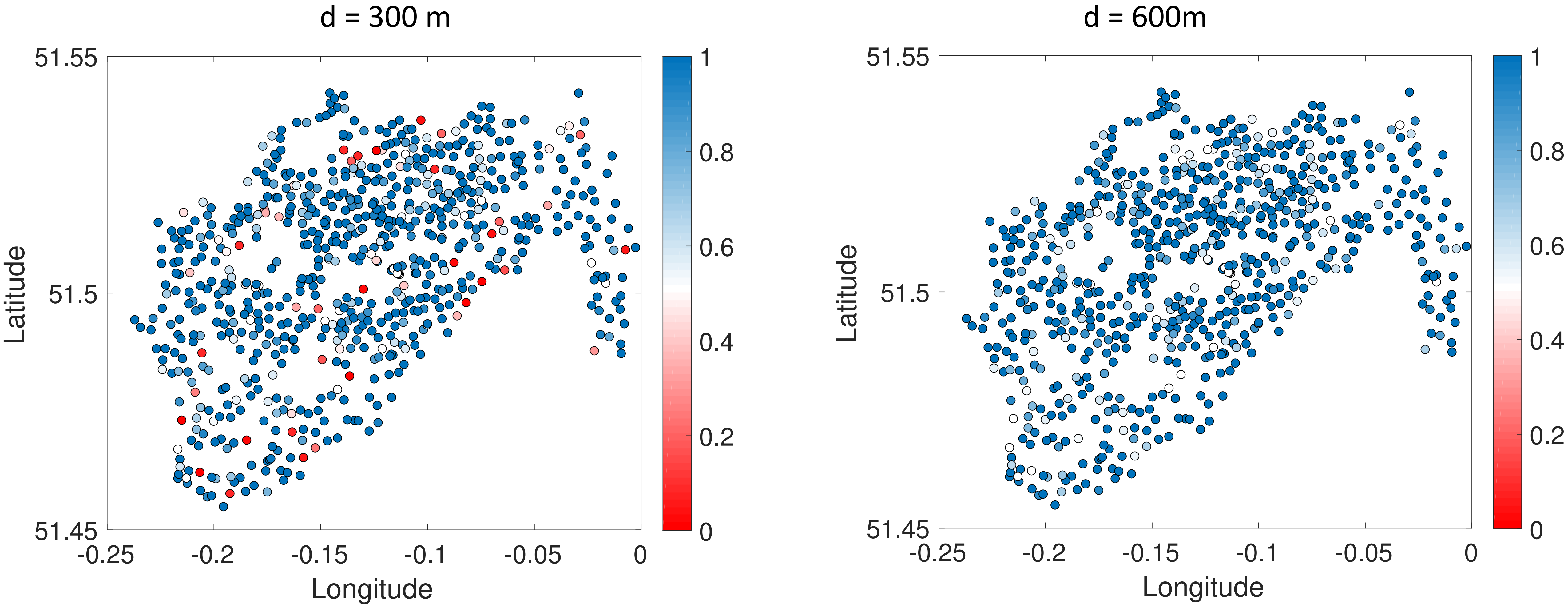
std in [0, 0.0158] , mean std = 0.0053.



std in [0, 0.0158] , mean std = 0.0039.

Availability of Bikes

$$\phi_1 = \mathrm{G}\{\diamondsuit^{weight}_{[0,d]}(B > 0) \wedge \diamondsuit^{weight}_{[0,d]}(S > 0)\}$$



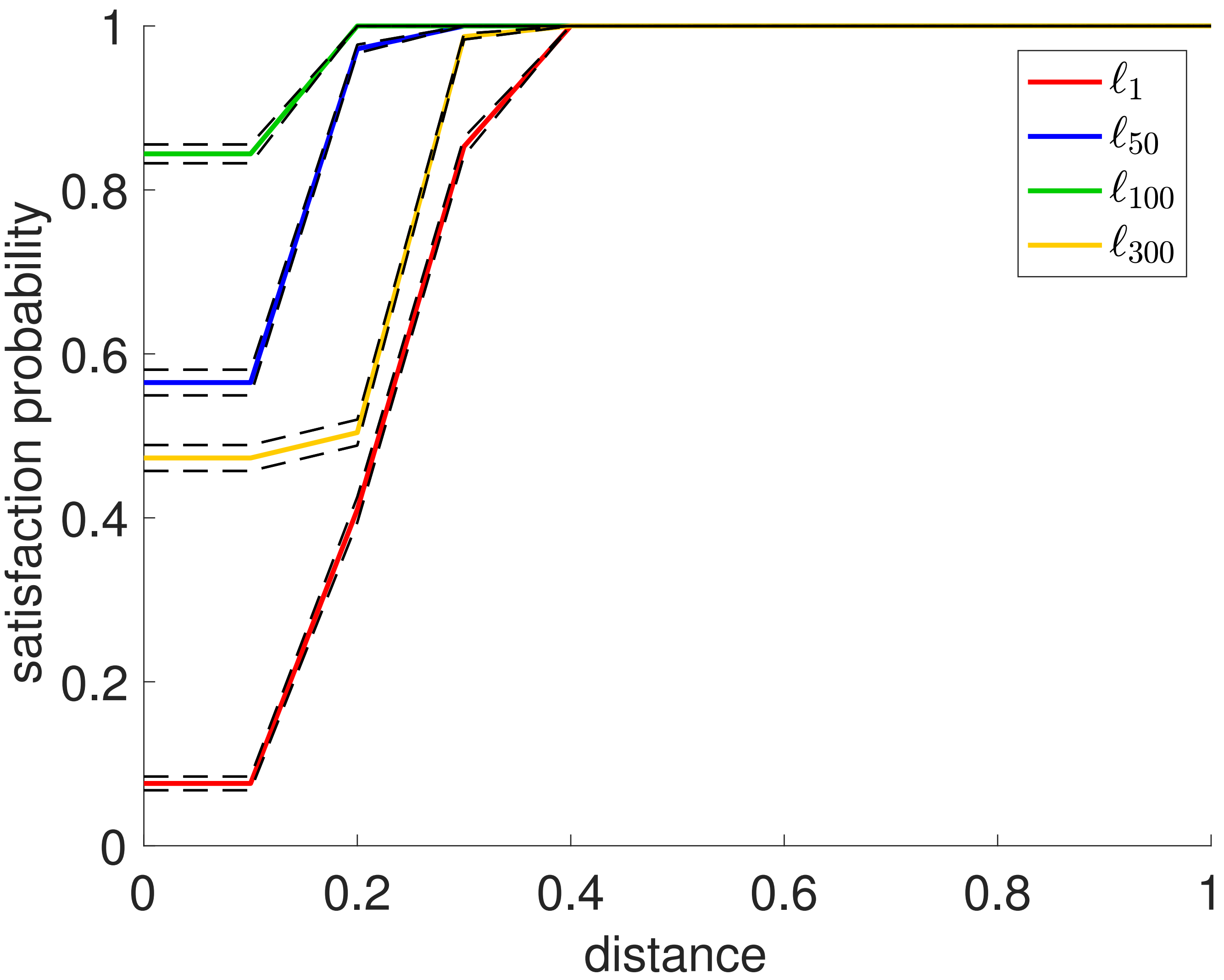
std in [0, 0.0151] , mean std = 0.0015.

std in [0, 0.0142] , mean std = 0.0002.

Availability of Bikes

$$\phi_1 = G\{\diamondsuit^{weight}_{[0,d]}(B > 0) \wedge \diamondsuit^{weight}_{[0,d]}(S > 0)\}$$

Satisfaction probability of some BBS stations vs distance d=[0,1.0]



Bike Sharing Systems (BSS)

$$\psi_1 = \mathrm{G}\{\diamondsuit_{[0,d]}^{weight}(\mathrm{F}_{[t_w,t_w]}B > 0) \wedge \diamondsuit_{[0,d]}^{weight}(\mathrm{F}_{[t_w,t_w]}S > 0)\}$$

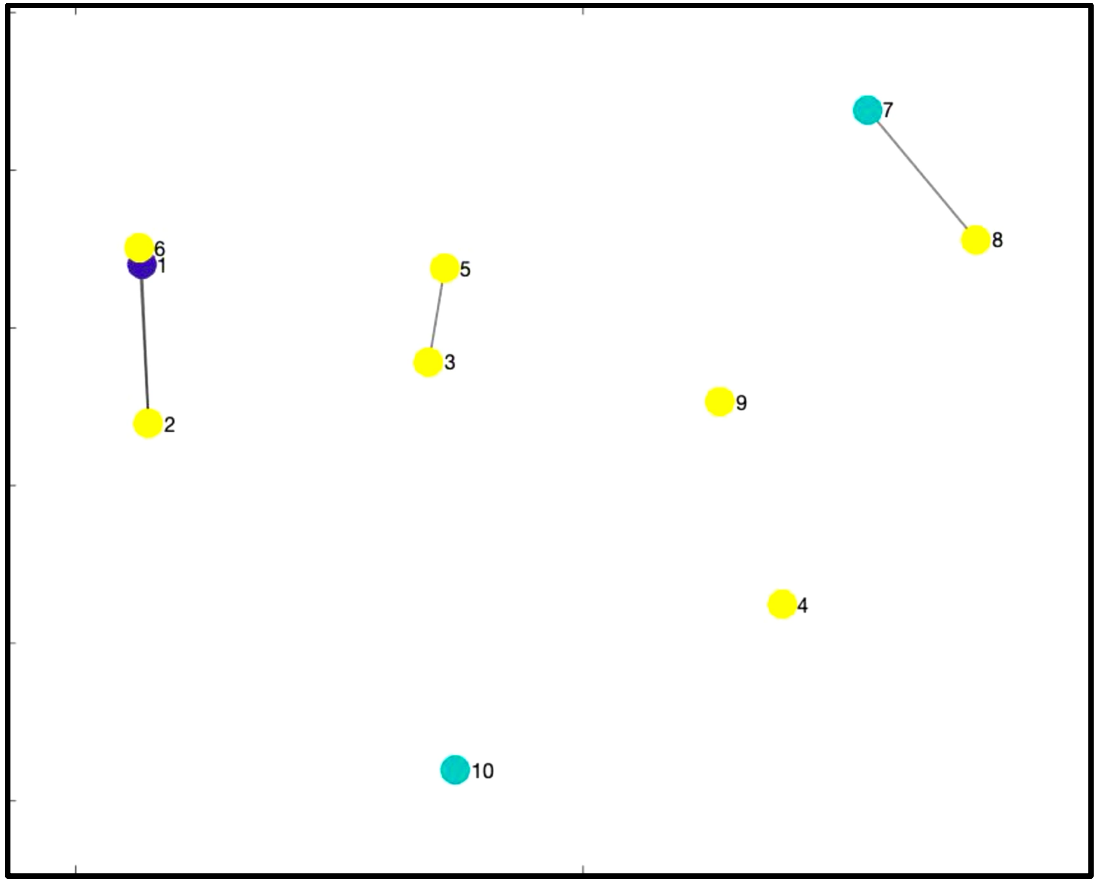
Average walking speed of 6.0 km/h, e.g. d = 0.5 km -> t_w = 6 minutes

The results similar to the results of previous property

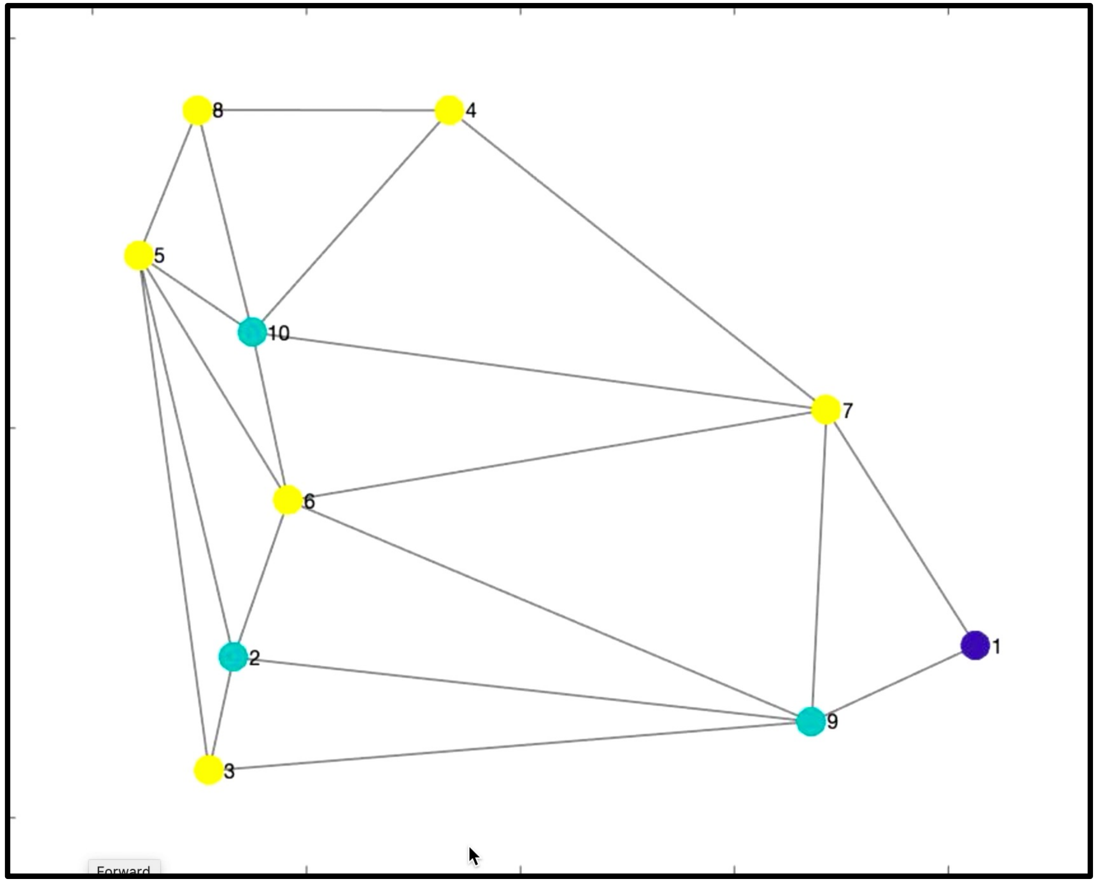
Dynamic Space

Mobile Ad-hoc sensor NETwork (MANET)

Coordinator Router End-devices



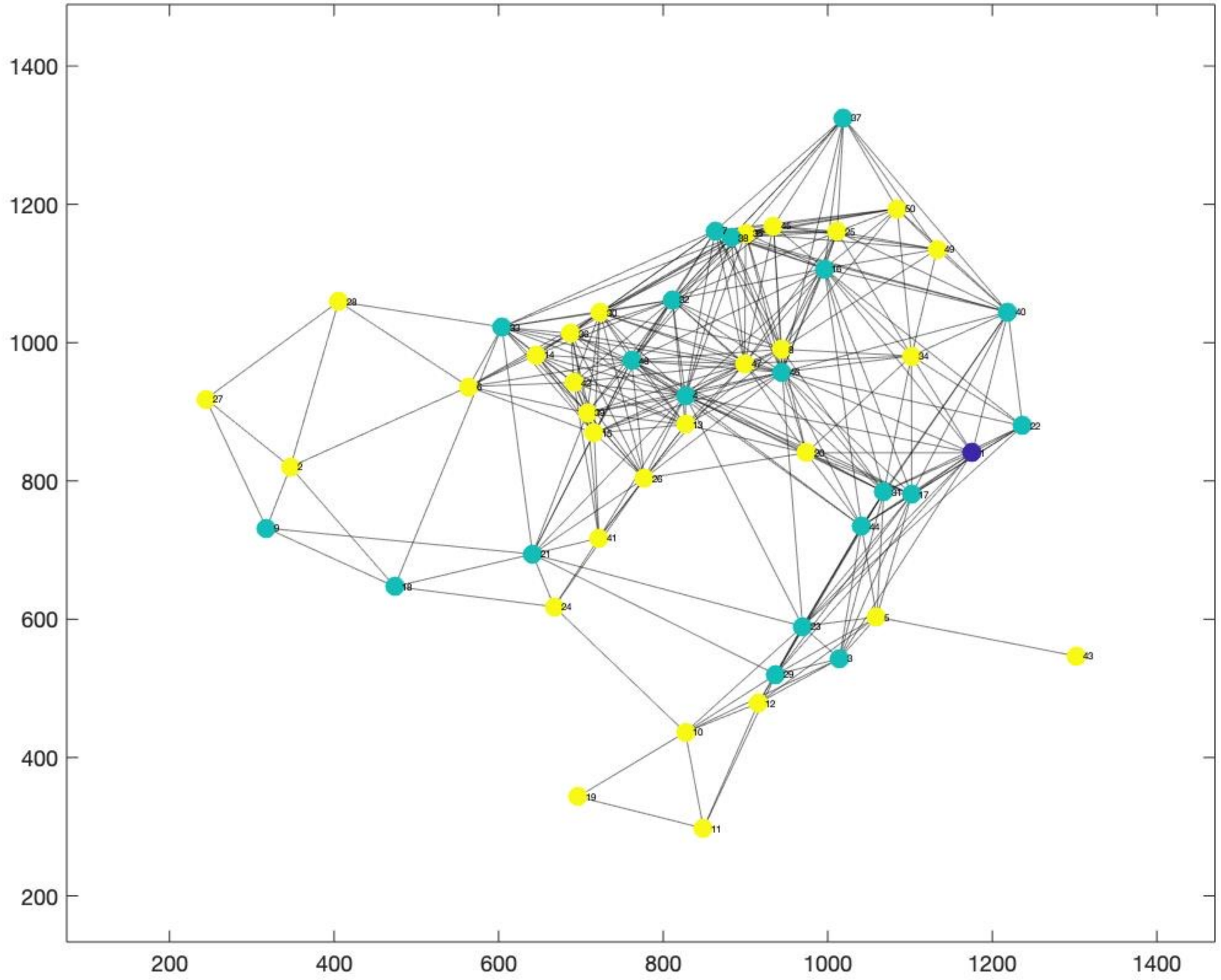
Connectivity Graph



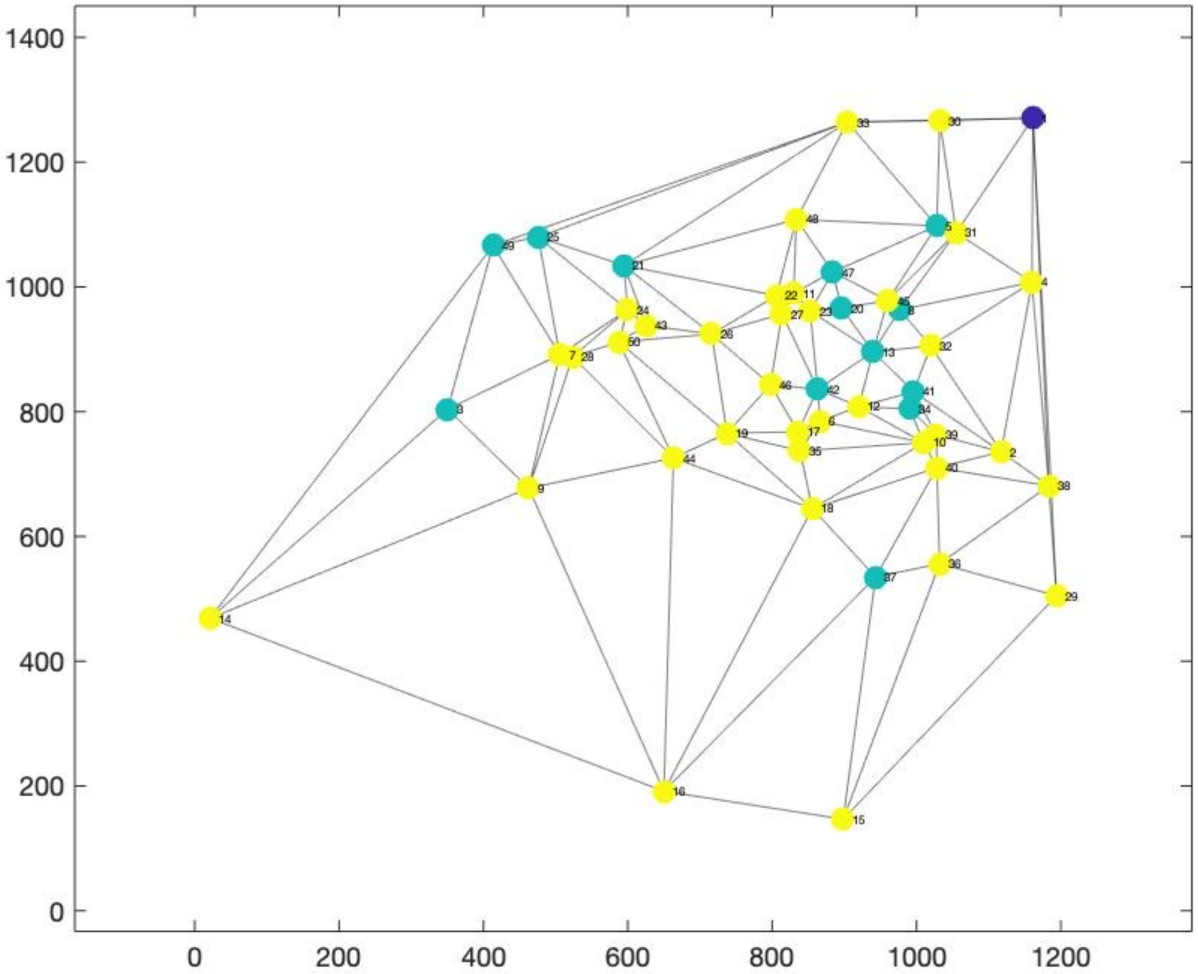
Proximity Graph

Mobile Ad-hoc sensor NETwork (MANET)

Coordinator Router End-devices



Connectivity Graph



Proximity Graph

Mobile Ad-hoc sensor NETwork (MANET)

Space model $S(t)$

- Locations: $L = \{devices\}$,
- Edges: $(\ell_i, w, \ell_j) \in W$ iff $\mathrm{w} = \| \ell_i - \ell_j \| < \min(r_i, r_j)$

Spatio-Temporal Trajectory: $x: L -> \mathbb{T} \rightarrow \mathbb{Z} \times \mathbb{R}^2$ s.t.

$x(i, t) = (nodeType, battery, temperature\ )$

$nodeType = 1, 2, 3$ for coordinator, rooter, and end_device

Connectivity in a MANET

“an end device is either connected to the coordinator or can reach it via a chain of routers”

“broken connection is restored within h time units”

Connectivity in a MANET

“an end device is either connected to the coordinator or can reach it via a chain of routers”

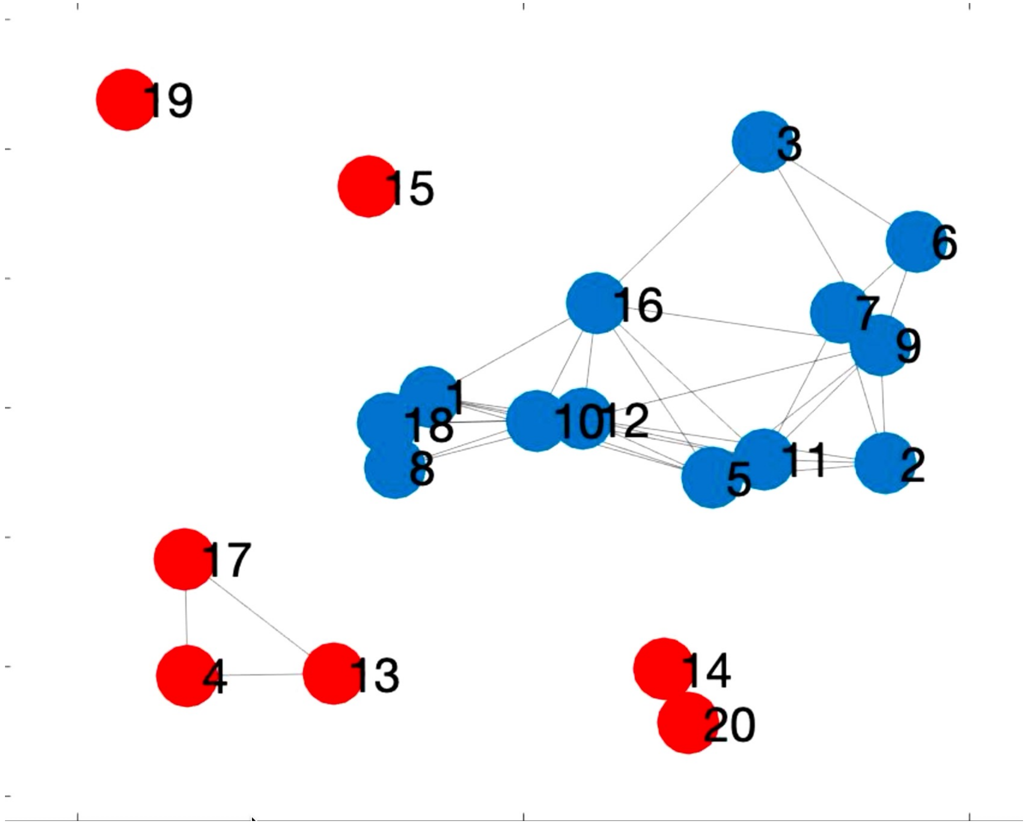
$$\phi_{connect} = device\mathcal{R}^{hop}_{[0,1]}(router\mathcal{R}^{hop}coord)$$

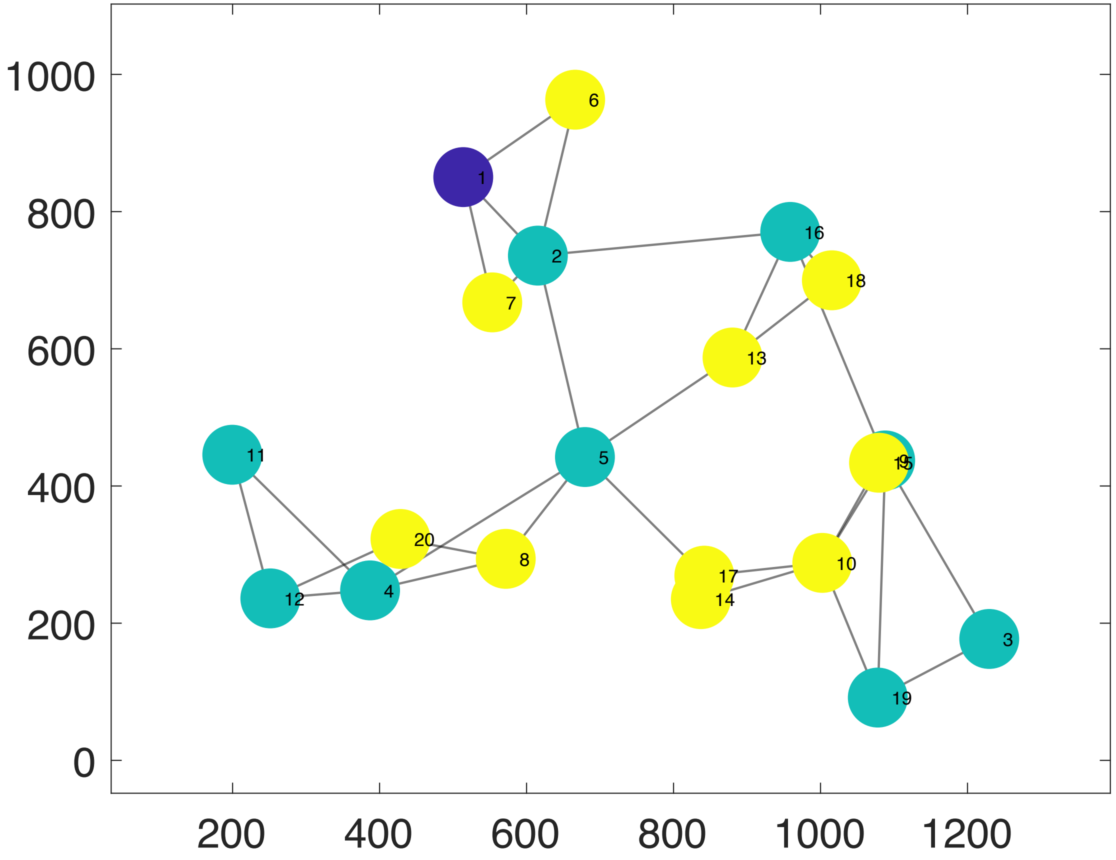
“broken connection is restored within h time units”

$$\phi_{connect\_restore} = \mathrm{G}(\neg\phi_{connect} \rightarrow \mathrm{F}_{[0,h]}\phi_{connect})$$

Boolean Satisfaction at each time step

$$\phi_{connect} = device\mathcal{R}^{hop}_{[0,1]}(router\mathcal{R}^{hop}coord)$$





Delivery in a MANET

"from a given location, we can find a path of (hops) length at least 5 such that all nodes along the path have a battery level greater than 0.5"

$$\psi_3 = \mathcal{E}^{hops}_{[5,\infty]}(battery > 0.5)$$

Reliability in a MANET

“reliability in terms of battery levels, e.g. battery level above 0.5

$$\phi_{reliable\_router} = ((battery > 0.5) \wedge router)\mathcal{R}^{hop} coord$$

$$\phi_{reliable\_connect} = device\mathcal{R}^{hop}_{[0,1]}(\phi_{reliable\_router})$$

Moonlight: https://github.com/MoonLightSuite/MoonLight/wiki

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Home

Simone edited this page on 1 Jul · 30 revisions

MoonLight build passing codecov 39%

MoonLight is a light-weight Java-tool for monitoring temporal, spatial and spatio-temporal properties of distributed complex systems, as *Cyber-Physical Systems* and *Collective Adaptive Systems*.

It supports the specification of properties written with the *Reach and Escape Logic* (STREL). STREL is a linear-time temporal logic, in particular, it extends the *Signal Temporal Logic* (STL) with a number of spatial operators that permit to described complex spatial behaviors as being surround, reaching target locations, and escaping from specific regions.

MoonLightis implemented in Java, but it features also a MATLAB interface that allows the monitoring of spatio-temporal signals generated within the MATLAB framework. A Python Interface is under development.

Getting Started

First, you need to download JAVA (version 8) and set the environmental variable

`JAVA_HOME= path to JAVA home directory`

Then you need to get or generate the executable for Python or MATLAB.

First, you need to clone our repository

`$ git clone https://github.com/MoonLightSuite/MoonLight.git`

or download it (link).

Then you need to compile it by executing the following Gradle tasks in the console

Pages 5

- Moonlight
- Script Syntax
- Matlab
  - Installation
  - Getting Started
- Python
- License

Clone this wiki locally

`https://github.com/Moor`

```
(atomicExpression)
| ! Formula
| Formula & Formula
| Formula | Formula
| Formula => Formula
| Formula until [a b] Formula
| Formula since [a b] Formula
| eventually [a b] Formula
| globally [a b] Formula
| once [a b] Formula
| historically [a b] Formula
| escape(distanceExpression)[a b] Formula
| Formula reach (distanceExpression)[a b] Formula
| somewhere(distanceExpression) [a b] Formula
| everywhere (distanceExpression) [a b] Formula
| {Formula}
```

Bibliography

Mining Requirements:

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