

# Verifying Data in Space and Time

*Mieke Massink*

joint work mostly with Vincenzo Ciancia, Diego Latella and Michele Loreti



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GIF

*Space: the final frontier*

# Introduction

Origins of Spatial Reasoning

“Space, like time, is one of the most fundamental categories of human cognition.

It structures all our activities and relationships with the external world.

It also structures many of our reasoning capabilities: it serves as the basis for many metaphors, including temporal, and gave rise to mathematics itself, geometry being the first formal system known.”



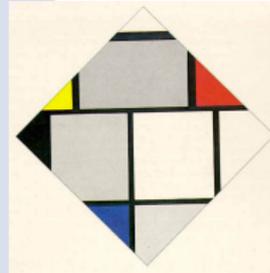
(Laure Vieu, 1997)

Physical Sciences

Ordinary/  
Partial  
Differential  
Equations



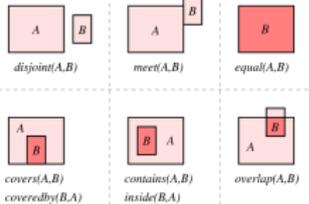
Pure Mathematics



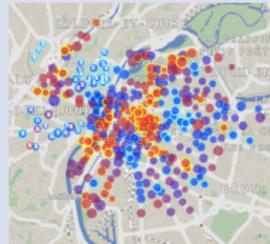
Topology  
Modal Logics  
Decidability  
Satisfiability

SPACE

Region  
Connection  
Calculus



Artificial Intelligence



Model checking

Collective Adaptive Systems

# Collective Adaptive Systems

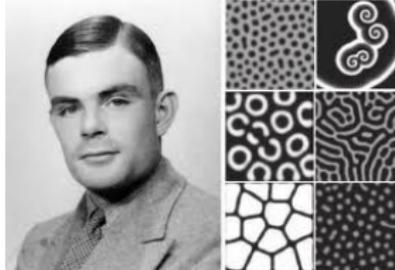
Examples of decentralised collective adaptive behaviour in nature:



Insects crossing. Ants foraging along an experimental trail set up in the laboratory.  
Credit: Audrey Dussanourt/University of Sydney



Research shows  
how complex systems  
rule everyday life



# Designing CAS for a smart society

The development of a formal verification framework for **smart urban transport** and **smart grid**.



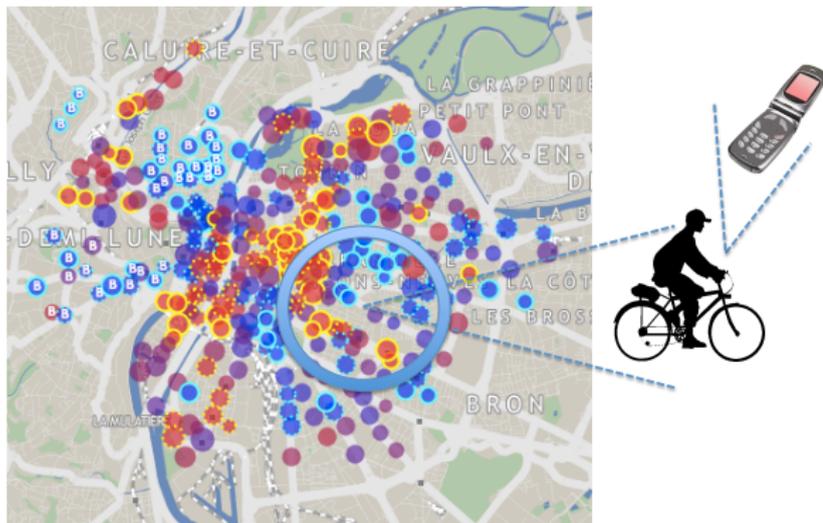
The long term objective is to support fair and efficient management of resources in **large scale systems** of heterogenous components that are **spatially distributed** and have possibly competing goals.

quanticol

[blog.inf.ed.ac.uk/quanticol/](http://blog.inf.ed.ac.uk/quanticol/)

# A Bike Sharing System

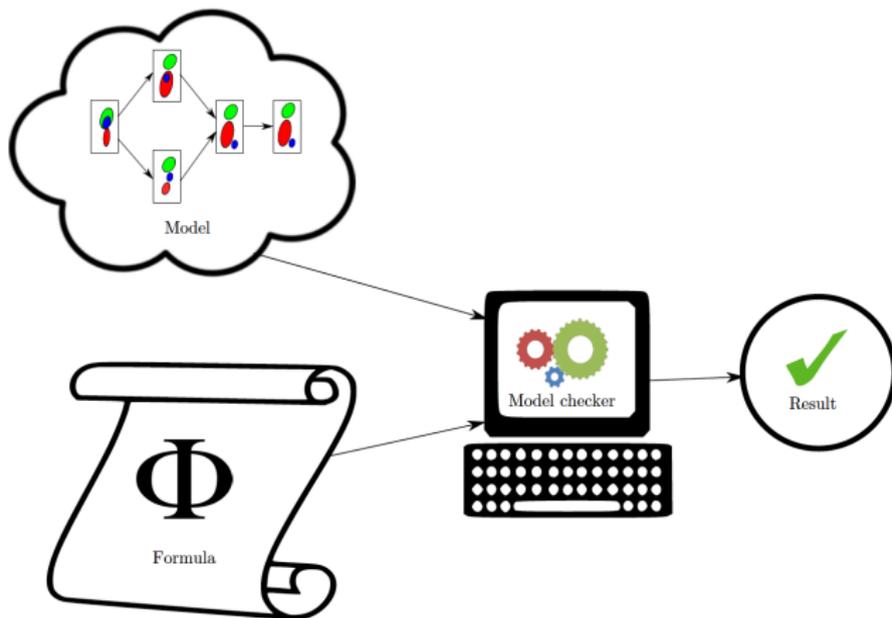
Continuous or discrete space? Space and time? Images? Points or sets?



Continuous space, discrete regular grid, graph of stations, street map

O'Brien's map of bike sharing [www.citylab.com](http://www.citylab.com)

# Spatial-temporal Model Checking?



# Unified Framework for Spatial Model Checking?

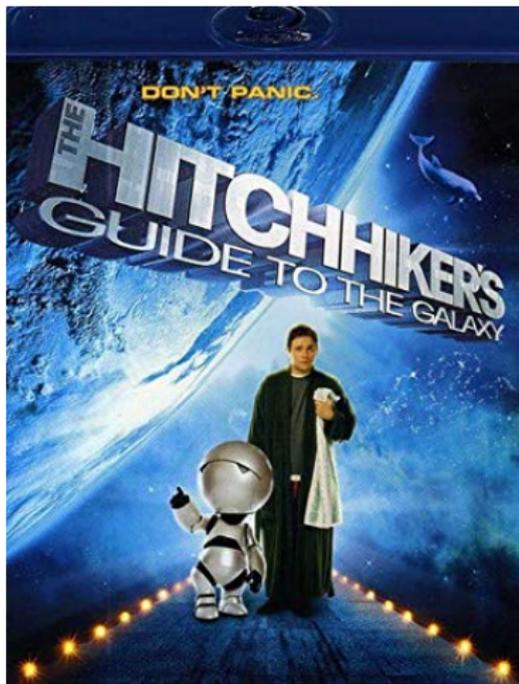
- Generalising some topological notions
- Bridging the gap between continuous and discrete space
- Spatial Logics for Model Checking

Bringing us to explore

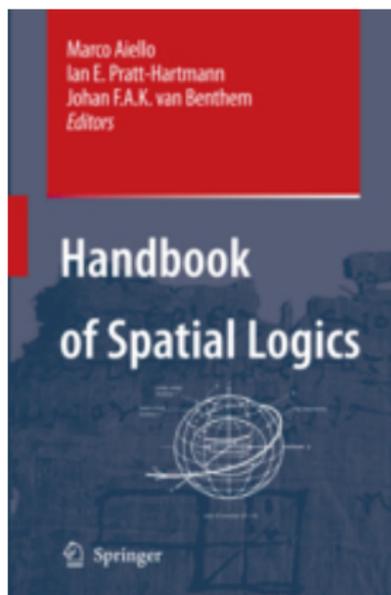
Closure Spaces and Quasi-discrete Closure Spaces

following up on work by, a.o., A. Galton and M. B. Smyth et al.

# Hitchhikers Guide to the Galaxy



# Handbook of Spatial Logics



Handbook of Spatial Logics

Aiello, Pratt-Hartmann and van Benthem (Eds.), Springer, 2007

# PART I

Logics and Space

# Topological Space

A pair  $(X, \mathcal{O})$  where

- $X \neq \emptyset$  is a set
- $\mathcal{O}$  is a collection of open sets  $\mathcal{O} \subseteq \mathcal{P}(X)$

such that

- $\emptyset, X \in \mathcal{O}$
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## Example: Euclidian space (2D)



open set

- open balls (in  $\mathbb{R}^n$ ) are open sets



closed set

- $\mathcal{I}^T(S)$  is the *largest open set* contained in  $S$
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# Modal Logic

$$\Phi ::= p \mid \top \mid \perp \mid \neg\Phi \mid \Phi \wedge \Phi \mid \Phi \vee \Phi \mid \Box\Phi \mid \Diamond\Phi$$

A topological space  $(X, O)$

- $X$  a set of points
- $O$  the set of open sets of  $X$

A model  $\mathcal{M} = ((X, O), \mathcal{V})$

- $(X, O)$  a topological space
- $\mathcal{V} : P \rightarrow \mathcal{P}(X)$  a valuation function

$\mathcal{V}$  assigns to each atomic proposition the set of points that satisfy it.

$$\mathcal{M}, x \models \top \iff \text{true}$$

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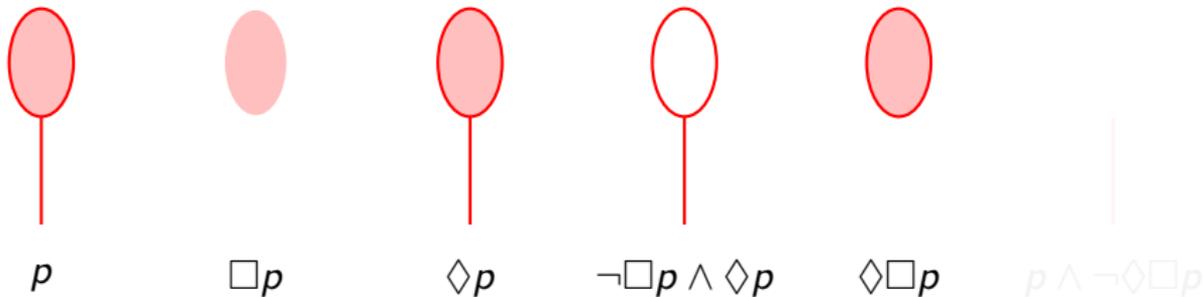
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# Alternative characterisation of Topological Space

[Kuratowski]

A topological space is a pair  $(X, \mathcal{C}^T)$  with  $\mathcal{C}^T : 2^X \rightarrow 2^X$  such that

for each  $A, B \subseteq X$ :

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Interior and closure are duals:

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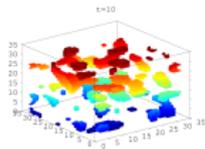
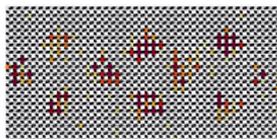
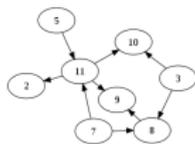
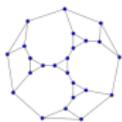
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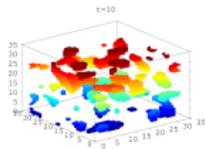
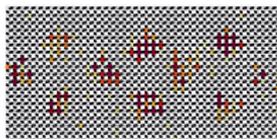
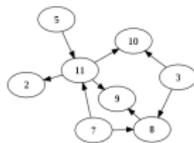
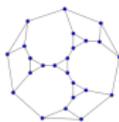
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We want to be able to deal also with

*GENERIC GRAPHS*

as models of space(s)

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# Čech Spaces or Closure Spaces

A *closure space* is a pair  $(X, \mathcal{C})$  with  $\mathcal{C} : 2^X \rightarrow 2^X$  such that

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- $A \subseteq \mathcal{C}(A)$
- $\mathcal{C}(\mathcal{C}(A)) = \mathcal{C}(A)$

Define:

- $\mathcal{I}(A) = \overline{\mathcal{C}(\overline{A})}$
- $A$  is *open* iff  $A = \mathcal{I}(A)$
- $A$  is *closed* iff  $A = \mathcal{C}(A)$
- $A$  is a *neighbourhood* of  $x \in X$  iff  $x \in \mathcal{I}(A)$

Interior and closure are duals:

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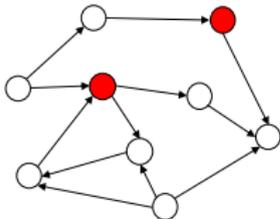
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## Graphs as Closure Spaces

A graph is a set of nodes  $X$  and a binary relation  $R \subseteq X \times X$

$$\mathcal{C}_R(A) = A \cup \{x \in X \mid \exists a \in A. (a, x) \in R\}$$

The pair  $(X, \mathcal{C}_R)$  is a closure space

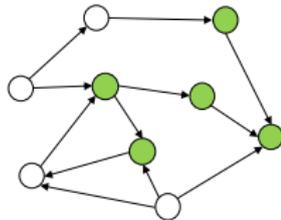
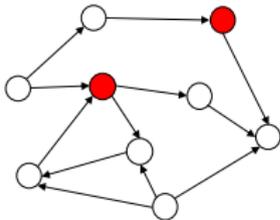


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# Quasi-discrete Closure Spaces

A closure space  $(X, \mathcal{C})$  is *quasi-discrete* if and only if either one of the following holds:

- each  $x \in X$  has a *minimal neighbourhood*  $N_x$
- for each  $A \subseteq X$ ,  $\mathcal{C}(A) = \bigcup_{a \in A} \mathcal{C}(\{a\})$

$A$  is a neighbourhood of  $x \in X$  iff  $x \in \mathcal{I}(A)$

## Theorem

$(X, \mathcal{C})$  is quasi-discrete iff there is  $R \subseteq X \times X$  such that  $\mathcal{C} = \mathcal{C}_R$

## Lemma

$\mathcal{C}_R$  is idempotent iff the reflexive closure  $R^\equiv$  of  $R$  is transitive

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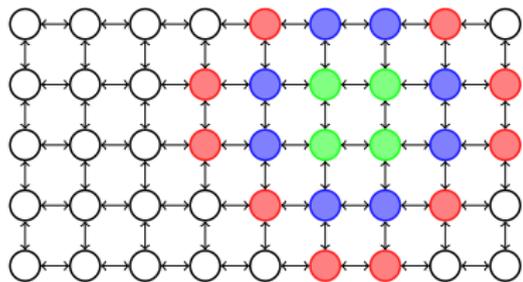
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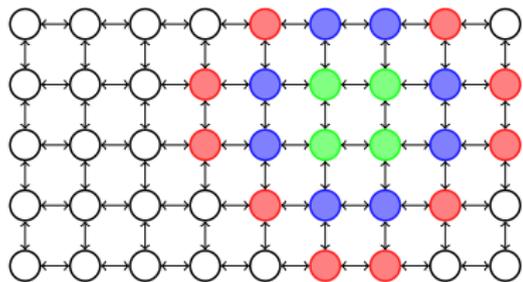
# Graphs inducing Quasi Discrete Closure Spaces



- $A = \{\bullet, \bullet\}$
- $\mathcal{I}(A) = \{\bullet\}$  and  $\mathcal{C}(A) = \{\bullet, \bullet, \bullet\}$
- $B(A) = \mathcal{C}(A) \setminus \mathcal{I}(A) = \{\bullet, \bullet\}$
- $B^-(A) = A \setminus \mathcal{I}(A) = \{\bullet\}$
- $B^+(A) = \mathcal{C}(A) \setminus A = \{\bullet\}$

But also graphs with an **uncountable** set of nodes/points such as  $(\mathbb{R}, \leq)$  are quasi-discrete closure spaces

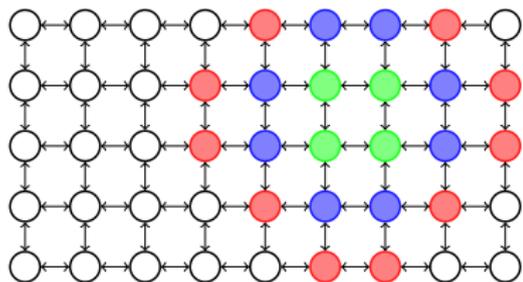
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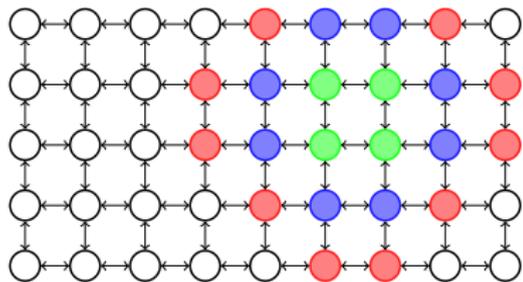
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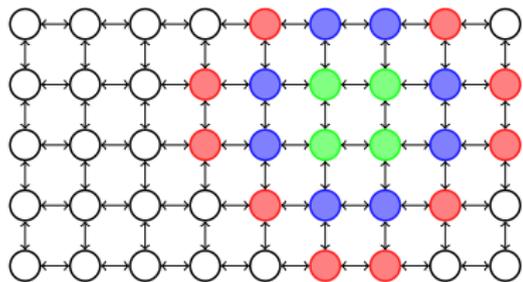
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- $\mathcal{B}^-(A) = A \setminus \mathcal{I}(A) = \{\bullet\}$
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But also graphs with an **uncountable** set of nodes/points such as  $(\mathbb{R}, \leq)$  are quasi-discrete closure spaces

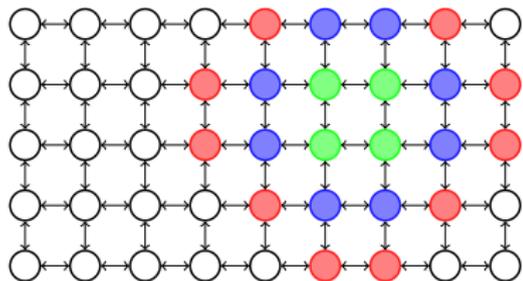
# Graphs inducing Quasi Discrete Closure Spaces



- $A = \{\bullet, \bullet\}$
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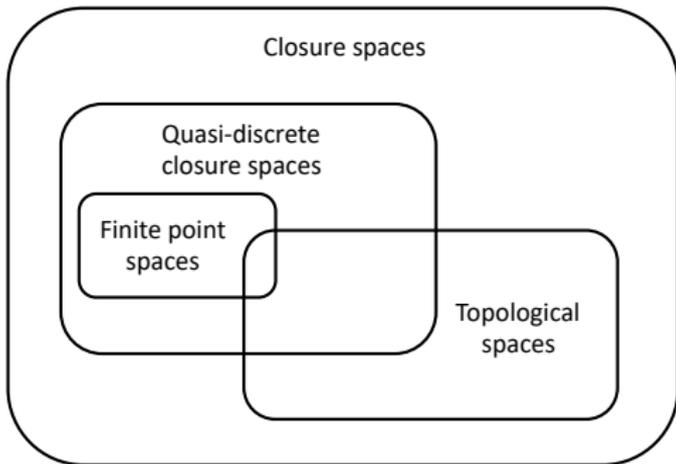
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But also graphs with an **uncountable** set of nodes/points such as  $(\mathbb{R}, \leq)$  are quasi-discrete closure spaces

# Hierarchy of Closure Spaces



# PART II

Spatial Logic for Closure Spaces

## Spatial Logic for Closure Spaces (SLCS)



..... a little alchemy ...

What if we interpret Temporal Logics operators (e.g.  $\mathcal{U}$ ) on structures which represent space?

$\Phi_1 \mathcal{U} \Phi_2$



The points in space which  
satisfy  $\Phi_1$  and  
are *surrounded* by points satisfying  $\Phi_2$

What if we interpret Temporal Logics operators (e.g.  $\mathcal{U}$ ) on structures which represent space?

$\Phi_1 \mathcal{U} \Phi_2$

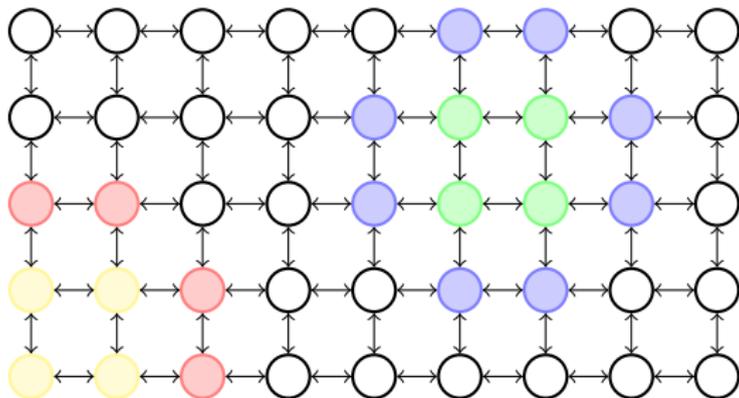


The points in space which  
satisfy  $\Phi_1$  and  
are *surrounded* by points satisfying  $\Phi_2$

## SLCS syntax

$$\begin{array}{l} \Phi ::= p \quad [\text{ATOMIC PROPOSITION}] \\ | \top \quad [\text{TRUE}] \\ | \neg\Phi \quad [\text{NOT}] \\ | \Phi \wedge \Phi \quad [\text{AND}] \\ | \mathcal{N}\Phi \quad [\text{NEAR}] \\ | \Phi \mathcal{S} \Phi \quad [\text{SURROUNDED}] \end{array}$$

## Spatial operators: intuition

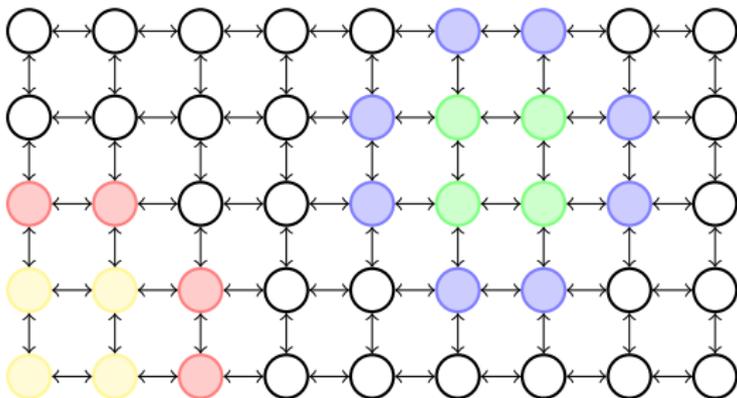


All red and yellow points satisfy  $\mathcal{N}_{yellow}$

Green points satisfy *green S blue*

Yellow points satisfy *yellow S red*

## Spatial operators: intuition

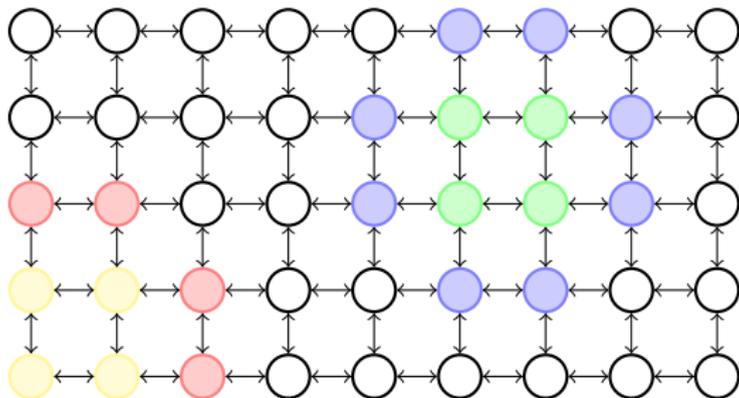


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## Spatial operators: intuition



All red and yellow points satisfy  $\mathcal{N} \text{ yellow}$

Green points satisfy  $\text{green } \mathcal{S} \text{ blue}$

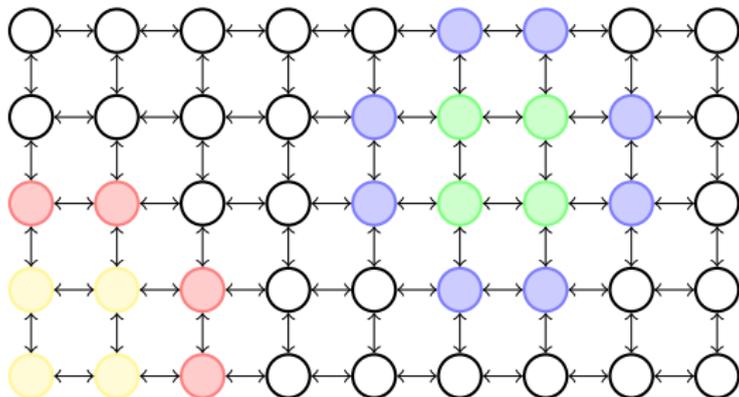
Yellow points satisfy  $\text{yellow } \mathcal{S} \text{ red}$

## Semantics of SLCS

Satisfaction  $\mathcal{M}, x \models \phi$  of formula  $\phi$  at point  $x$  in quasi-discrete closure model  $\mathcal{M} = ((X, \mathcal{C}), \mathcal{V})$  is defined, by induction on terms, as follows:

$\mathcal{M}, x \models p$	$\iff$	$x \in \mathcal{V}(p)$
$\mathcal{M}, x \models \top$	$\iff$	<i>true</i>
$\mathcal{M}, x \models \neg\phi$	$\iff$	<b>not</b> $\mathcal{M}, x \models \phi$
$\mathcal{M}, x \models \phi \wedge \psi$	$\iff$	$\mathcal{M}, x \models \phi$ <b>and</b> $\mathcal{M}, x \models \psi$
$\mathcal{M}, x \models \mathcal{N}\phi$	$\iff$	$x \in \mathcal{C}(\{y \in X \mid \mathcal{M}, y \models \phi\})$
$\mathcal{M}, x \models \phi \mathcal{S} \psi$	$\iff$	$\exists A \subseteq X. x \in A \wedge \forall y \in A. \mathcal{M}, y \models \phi \wedge$ $\forall z \in \mathcal{B}^+(A). \mathcal{M}, z \models \psi$

## Derived operators



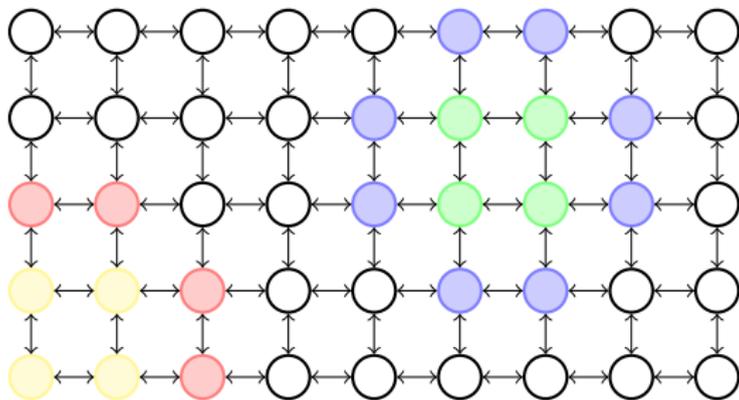
$$\mathcal{I}\phi \triangleq \neg(\mathcal{N}\neg\phi) \quad [\text{INTERIOR}]$$

$$\delta\phi \triangleq (\mathcal{N}\phi) \wedge (\neg\mathcal{I}\phi) \quad [\text{BOUNDARY}]$$

$$\delta^-\phi \triangleq \phi \wedge (\neg\mathcal{I}\phi) \quad [\text{INTERNAL/INTERIOR BOUNDARY}]$$

$$\delta^+\phi \triangleq (\mathcal{N}\phi) \wedge (\neg\phi) \quad [\text{EXTERNAL/CLOSURE BOUNDARY}]$$

# Derived operators<sup>1</sup>



$$\begin{aligned}\mathcal{E}\phi &\triangleq \phi \mathcal{S} \perp && [\text{EVERYWHERE}] \\ \mathcal{F}\phi &\triangleq \neg\mathcal{E}(\neg\phi) && [\text{SOMEWHERE}]\end{aligned}$$

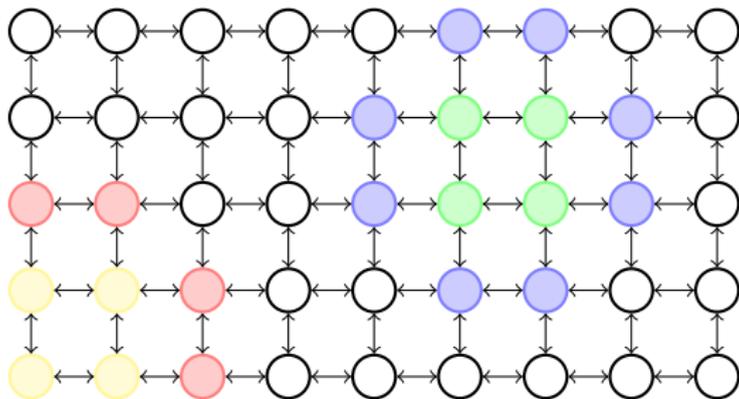
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<sup>1</sup>[John H. Reif, A. Prasad Sistla, ICALP 1983]

# Derived operators

$$\phi \mathcal{R} \psi \triangleq \neg((\neg\psi) \mathcal{S}(\neg\phi)) \quad [\text{REACHABILITY}]$$

$$\phi \mathcal{T} \psi \triangleq \phi \wedge ((\phi \vee \psi) \mathcal{R} \psi) \quad [\text{FROM-TO}]$$



$\phi \mathcal{R} \psi$ : either  $\psi$  holds in  $x$ , or there exists a sequence of points after  $x$ , all satisfying  $\phi$  leading to a point satisfying both  $\phi$  and  $\psi$

$(white \vee blue) \mathcal{R} blue$  satisfied by  $\{\bullet, \bullet, \circ, \bullet\}$

$white \mathcal{T} blue$  satisfied by  $\{\circ\}$

# PART III

Model Checking Spatial Logics

## Spatial Model checking (finite models)

Model checking in quasi-discrete closure spaces is analysis of a graph

Efficient algorithm  $O(\text{nodes} + \text{arcs})$  for checking  $\phi \mathcal{S} \psi$

Implemented as a “flooding” algorithm

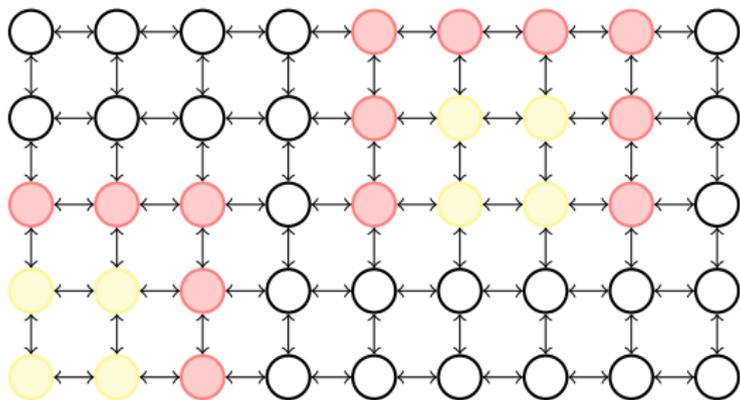
## Efficient algorithm

The algorithm identifies “*bad*” areas, where  $\neg\phi$  can be reached *without* passing by points satisfying  $\psi$

Implemented recursively as an operator that enlarges the set of “bad” points at each application

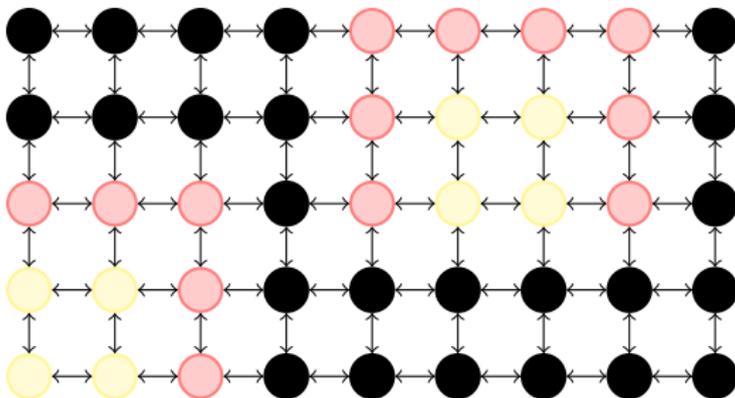
Upon fixed point: the points where  $\phi$  holds, that are not “bad”, satisfy  $\phi \mathcal{S} \psi$ .

$\text{Sat}(\mathcal{M}, \text{yellow } S \text{ red})$



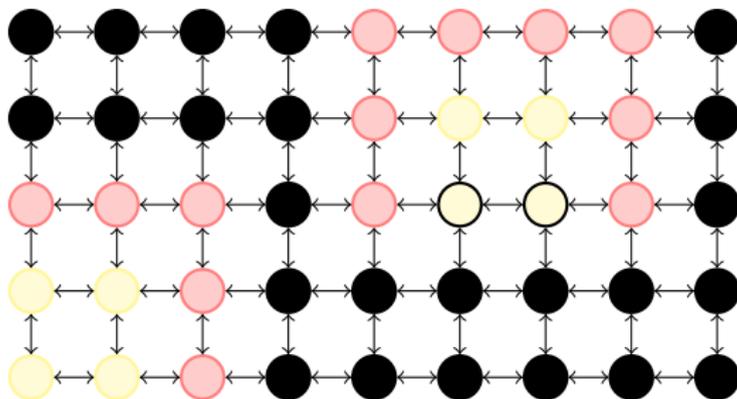
Find points satisfying *yellow S red*

$\text{Sat}(\mathcal{M}, \text{yellow } S \text{ red})$



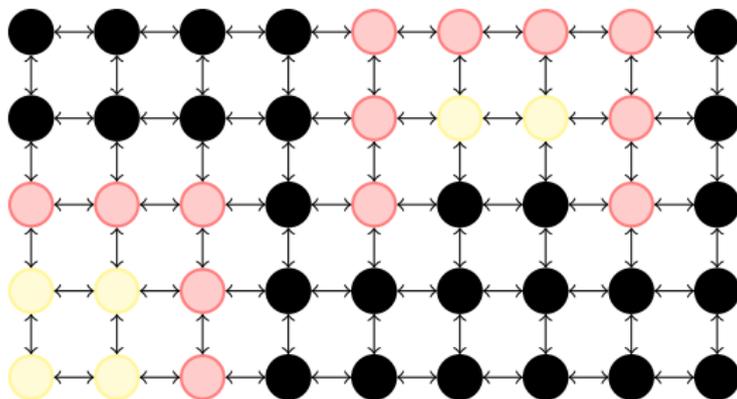
1) Find points satisfying neither *yellow* nor *red* and make them black

$\text{Sat}(\mathcal{M}, \text{yellow } S \text{ red})$



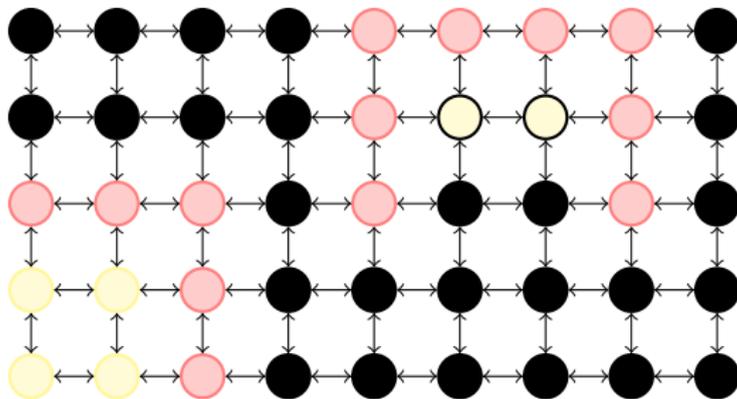
2) Identify yellow points in  $\mathcal{C}(\text{black})$  . . .

$\text{Sat}(\mathcal{M}, \text{yellow } S \text{ red})$



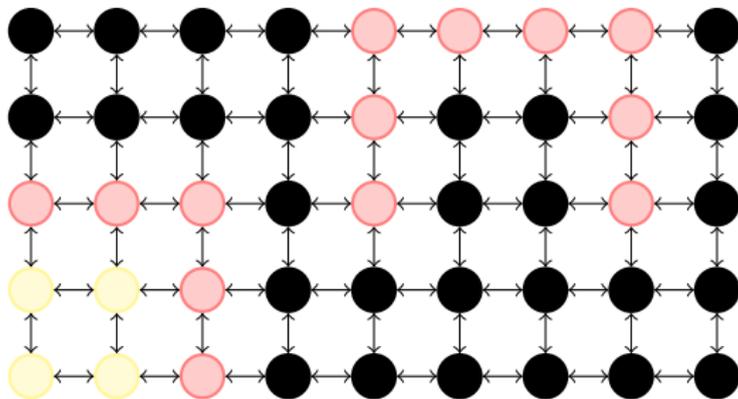
3) . . . and make them black

$\text{Sat}(\mathcal{M}, \text{yellow } S \text{ red})$



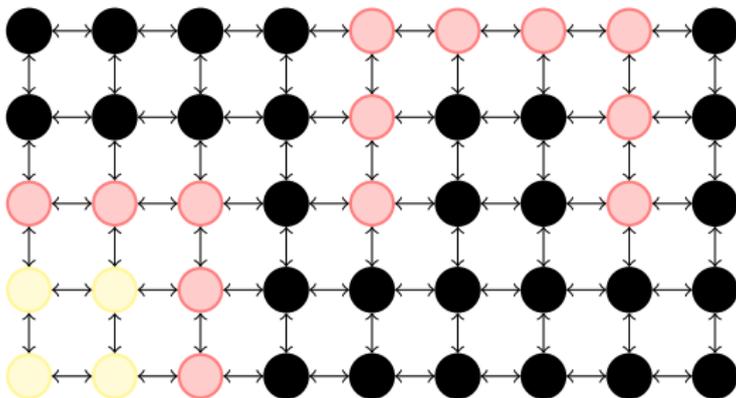
4) Identify yellow points in  $\mathcal{C}(\text{black})$  . . .

$\text{Sat}(\mathcal{M}, \text{yellow } S \text{ red})$



5) . . . and make them black

$\text{Sat}(\mathcal{M}, \text{yellow } S \text{ red})$



Fixed point reached, the yellow points satisfy *yellow S red*

# Model Checking Algorithm

**Function**  $\text{Sat}(\mathcal{M}, \phi)$

**Input:** Finite, quasi-discrete closure model

$\mathcal{M} = ((X, \mathcal{C}), \mathcal{V})$ , formula  $\phi$

**Output:** Set of points  $\{x \in X \mid \mathcal{M}, x \models \phi\}$

**Match**  $\phi$

case  $\top$  : return  $X$

case  $p$  : return  $\mathcal{V}(p)$

case  $\neg\phi_1$  :

    let  $P = \text{Sat}(\mathcal{M}, \phi_1)$

    return  $X \setminus P$

case  $\phi_1 \wedge \phi_2$  :

    let  $P = \text{Sat}(\mathcal{M}, \phi_1)$

    let  $Q = \text{Sat}(\mathcal{M}, \phi_2)$

    return  $P \cap Q$

case  $\mathcal{N}\phi_1$  :

    let  $P = \text{Sat}(\mathcal{M}, \phi_1)$

    return  $\mathcal{C}(P)$

case  $\phi_1 \mathcal{S} \phi_2$  :

    return  $\text{CheckSurr}(\mathcal{M}, \phi_1, \phi_2)$

**Function**  $\text{CheckSurr}(\mathcal{M}, \phi_1, \phi_2)$

**Input:** Finite, quasi-discrete closure model

$\mathcal{M} = ((X, \mathcal{C}), \mathcal{V})$ , formulas  $\phi_1, \phi_2$

**Output:** Set of points  $\{x \in X \mid \mathcal{M}, x \models \phi_1 \mathcal{S} \phi_2\}$

var  $V := \text{Sat}(\mathcal{M}, \phi_1)$

let  $Q = \text{Sat}(\mathcal{M}, \phi_2)$

var  $T := \mathcal{B}^+(V \cup Q)$

while  $T \neq \emptyset$  do

    var  $T' := \emptyset$

    for  $x \in T$  do

        let  $N = \text{pre}(x) \cap V$

$V := V \setminus N$

$T' := T' \cup (N \setminus Q)$

$T := T'$ ;

return  $V$

## Correctness and Complexity

### Theorem

For any finite quasi-discrete closure model  $\mathcal{M} = ((X, \mathcal{C}), \mathcal{V})$  and SLCS formula  $\phi$ ,  $x \in \text{Sat}(\mathcal{M}, \phi)$  if and only if  $\mathcal{M}, x \models \phi$

### Proposition

For any finite quasi-discrete model  $\mathcal{M} = ((X, \mathcal{C}_R), \mathcal{V})$  and SLCS formula  $\phi$  of size  $k$ , function  $\text{Sat}(\mathcal{M}, \phi)$  terminates in  $\mathcal{O}(k \cdot (|X| + |R|))$  steps

# PART IV

Some applications

# Some Recent Results<sup>2</sup>

## Theory, Algorithms and Tools:

- **closure spaces**: graphs, images (based on Galton's work)
- new operators: *reach*, *surrounded*, *touch*, ...
- **topochecker**: spatio-temporal & collective model checking
- topochecker + MultiVeSTa: statistical spatio-temporal MC
- [topochecker.isti.cnr.it](http://topochecker.isti.cnr.it)
- **VoxLogica**: image analysis
- [github.com/vincenzoml/VoxLogica](https://github.com/vincenzoml/VoxLogica)

## Applications:

- smart transportation (bike sharing, buses, train control);
- image analysis (medical domain)

---

[Ciancia, Latella, Loreti, Massink - LMCS 2016]

<sup>2</sup>[Ciancia, Latella, Massink, Paškauskas, Vandin, ISoLA 2016]

[Ciancia, Gilmore, Grilletti, Latella, Loreti, Massink, STTT 2018]

[Banci Buonamici, Belmonte, Ciancia, Latella, Massink, STTT 2019]

[Ciancia, Belmonte, Latella, Massink, TACAS 2019]

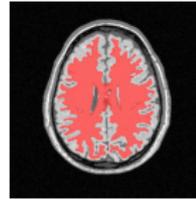
# Selected Applications



*A maze*



*Smart buses GPS*



*Medical Imaging*



*London bike sharing*



*Turing patterns*

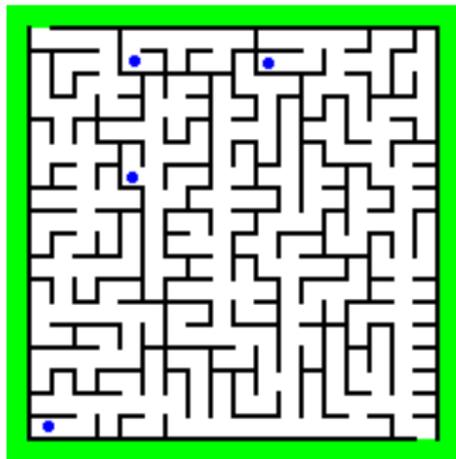


*Embedding RCC8D*

# Digital images

Any digital image can be treated as a finite, quasi discrete, closure space

Atomic propositions: white, green, black, blue

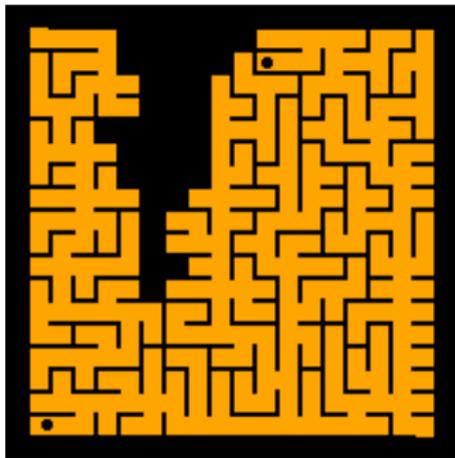
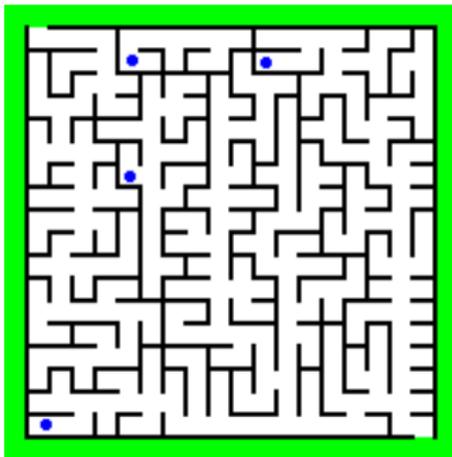


```
toExit = [white] T [green] {●}
```

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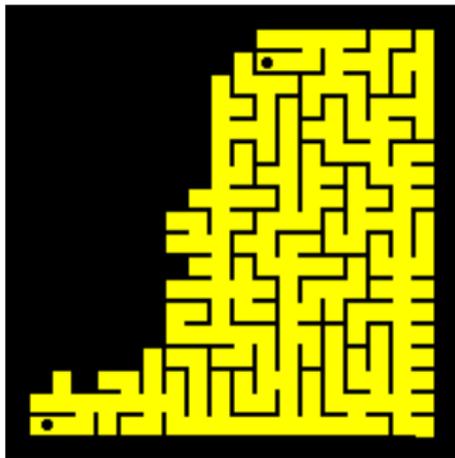
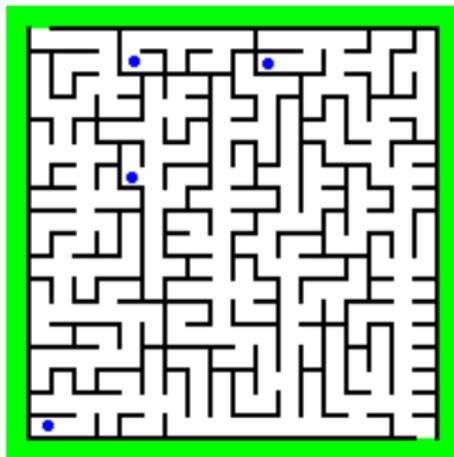
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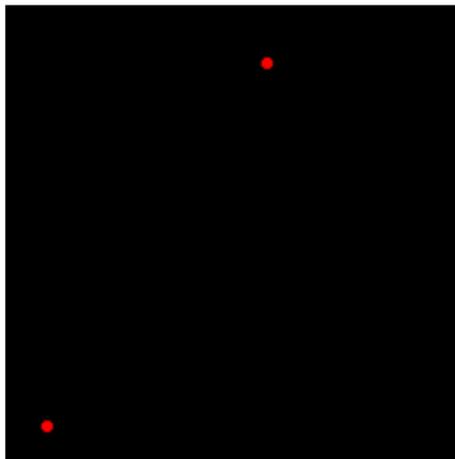


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```

# Implausible data in GPS traces of Edinburgh buses

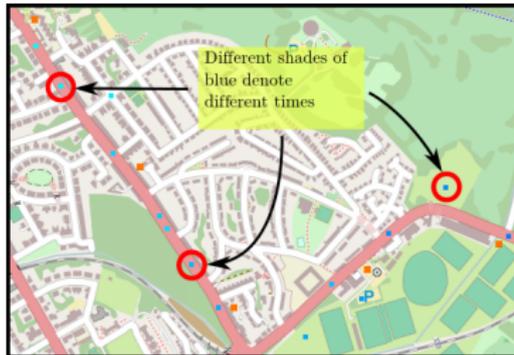


Spatial ordering of data points

“not on a main street”

“not on a street at all”

[Ciancia, Gilmore, Grilletti et al., STTT 2018]



spatial model



model checking result

*back*

# Medical Image Analysis: **ImgQL**

[Banci Buonamici, Belmonte, Ciancia, Latella, Massink, STTT 2019]

[Ciancia, Belmonte, Latella, Massink, TACAS 2019]

## ImgQL variant of SLCS

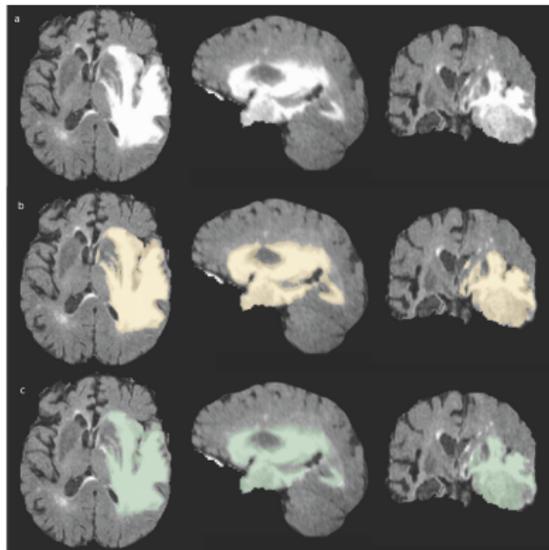
$$\Phi ::= p \mid \neg \Phi \mid \Phi_1 \vee \Phi_2 \mid \mathcal{N}\Phi \mid \Phi_1 \mathcal{S} \Phi_2 \mid \mathcal{D}'\Phi$$

### Derived:

- Surrounded
- Region Growing

### Domain specific:

- Distance Operator
- Statistical Texture Similarity Operator
- Percentiles
- Tool: **VoxLogicA**



GTV for TCIA 471 patient from BraTS 2017 dataset

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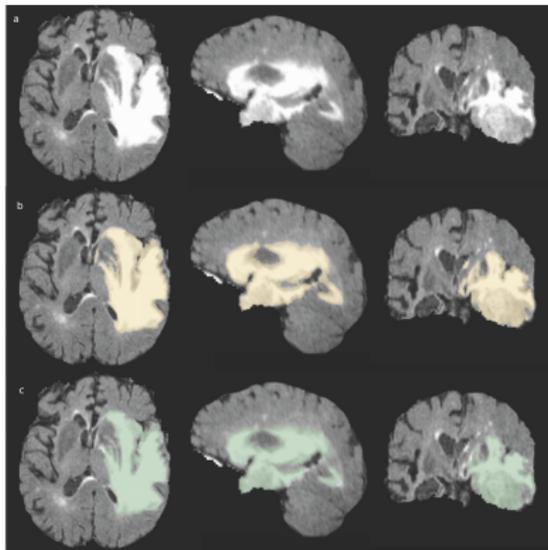
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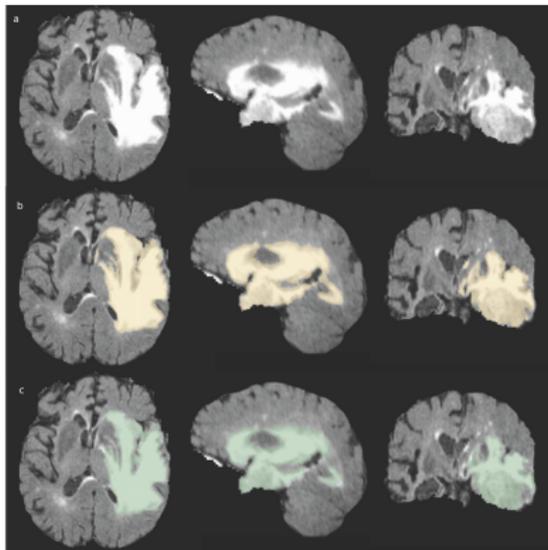
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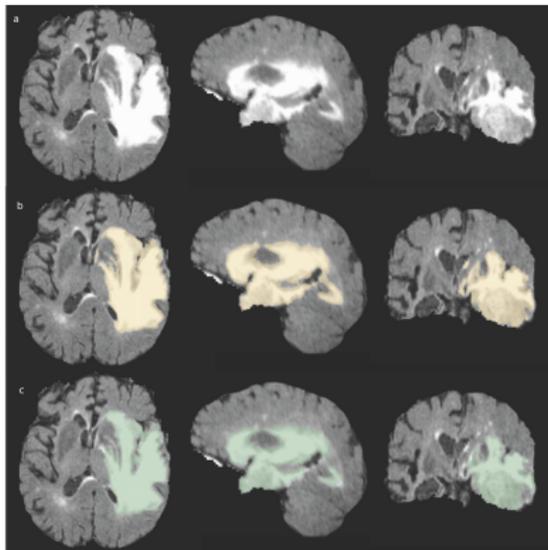
$$\Phi ::= p \mid \neg \Phi \mid \Phi_1 \vee \Phi_2 \mid \mathcal{N}\Phi \mid \rho \Phi_2[\Phi_1] \mid \mathcal{D}'\Phi$$

### Derived:

- $\Phi_1 \mathcal{S} \Phi_2 \triangleq \Phi_1 \wedge \neg \rho (\neg(\Phi_1 \vee \Phi_2))[\neg \Phi_2]$
- $grow(\Phi_1, \Phi_2) \triangleq \Phi_1 \vee touch(\Phi_2, \Phi_1)$

### Domain specific:

- Distance Operator
- Statistical Texture Similarity Operator
- Percentiles
- Tool: **VoxLogicA**



GTV for TCIA 471 patient from BraTS 2017 dataset

# Domain Specific Operators

## Distance Operator

A point  $x$  satisfies  $\mathcal{D}^I \Phi$  iff the distance of  $x$  from the *set of points* satisfying  $\Phi$  falls into interval  $I$ ; ( $\text{dist}(x, \emptyset) = \infty$ ,  $\text{dist}(x, A) = \inf \{ \text{dist}(x, y) | y \in A \}$ )

## Statistical Texture Similarity Operator

A point  $x$  satisfies  $\Delta_{\bowtie c} \left[ \begin{matrix} m & M & k \\ r & a & b \end{matrix} \right] \Phi$  iff, letting  $h_a$  be the histogram of the *sphere* of radius  $r$  centred in  $x$  and  $h_b$  that of the  $\Phi$ -area, we have *cross-correlation*( $h_a, h_b$ )  $\bowtie c$

White matter<sup>3</sup>:

original MRI

---

<sup>3</sup>Original MRI: Pat04 from [Aubert-Broche et al. IEEE Trans. on Med. Im., 25(11), 2006]

# Domain Specific Operators

## Distance Operator

A point  $x$  satisfies  $\mathcal{D}'\Phi$  iff the distance of  $x$  from the *set of points* satisfying  $\Phi$  falls into interval  $I$ ; ( $\text{dist}(x, \emptyset) = \infty, \text{dist}(x, A) = \inf\{\text{dist}(x, y) | y \in A\}$ )

## Statistical Texture Similarity Operator

A point  $x$  satisfies  $\Delta_{\bowtie c} \left[ \begin{matrix} m & M & k \\ r & a & b \end{matrix} \right] \Phi$  iff, letting  $h_a$  be the histogram of the *sphere* of radius  $r$  centred in  $x$  and  $h_b$  that of the  $\Phi$ -area, we have *cross-correlation*( $h_a, h_b$ )  $\bowtie c$

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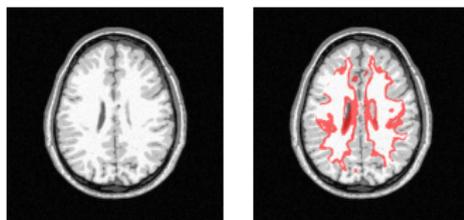
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## White matter<sup>3</sup>:



original MRI

likely white

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# Domain Specific Operators

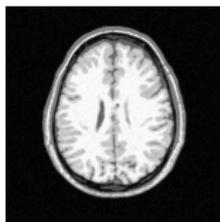
## Distance Operator

A point  $x$  satisfies  $\mathcal{D}^I \Phi$  iff the distance of  $x$  from the *set of points* satisfying  $\Phi$  falls into interval  $I$ ; ( $\text{dist}(x, \emptyset) = \infty, \text{dist}(x, A) = \inf \{\text{dist}(x, y) | y \in A\}$ )

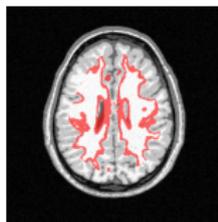
## Statistical Texture Similarity Operator

A point  $x$  satisfies  $\Delta_{\bowtie c} \left[ \begin{matrix} m & M & k \\ r & a & b \end{matrix} \right] \Phi$  iff, letting  $h_a$  be the histogram of the *sphere* of radius  $r$  centred in  $x$  and  $h_b$  that of the  $\Phi$ -area, we have *cross-correlation*( $h_a, h_b$ )  $\bowtie c$

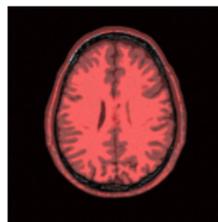
## White matter<sup>3</sup>:



original MRI



likely white



similarity score

<sup>3</sup>Original MRI: Pat04 from [Aubert-Broche et al. IEEE Trans. on Med. Im., 25(11), 2006]

# Domain Specific Operators

## Distance Operator

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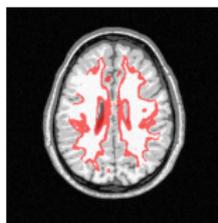
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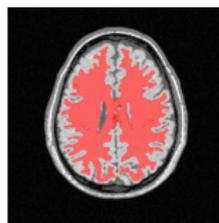
original MRI



likely white



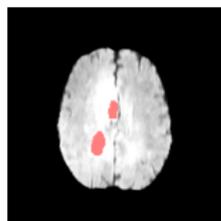
similarity score



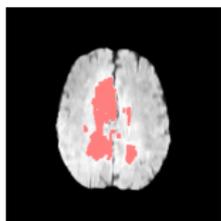
highly similar

<sup>3</sup>Original MRI: Pat04 from [Aubert-Broche et al. *IEEE Trans. on Med. Im.*, 25(11), 2006]

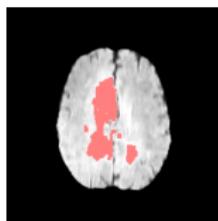
# 3D Magnetic Resonance Tumour Segmentation<sup>4,5</sup>



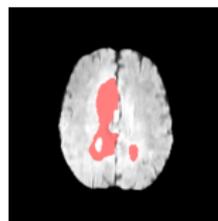
hyper intense  
(hl)



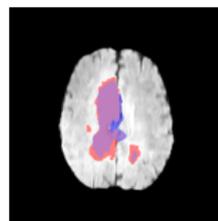
very intense  
(vl)



grow(hl,vl)  
(c)



similar texture  
(d)



gtv=grow(c,d)  
manual (blue)

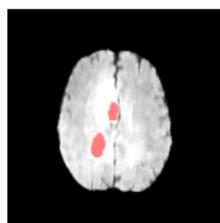
---

<sup>4</sup> [Belmonte, Ciancia, Latella, Massink, TACAS19]

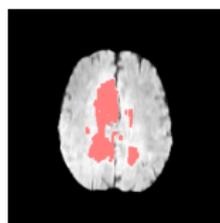
[Banci Buonamici, Belmonte, Ciancia, Latella, Massink, STTT 2019 and ESMRBM19]

<sup>5</sup> Image: Brats17\_2013\_2.1 from BraTS 2017 database

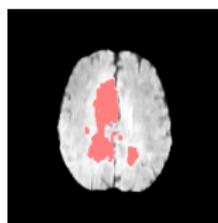
# 3D Magnetic Resonance Tumour Segmentation<sup>4,5</sup>



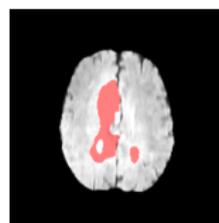
hyper intense  
(hl)



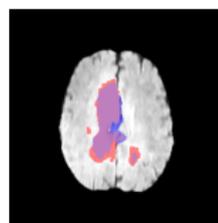
very intense  
(vl)



grow(hl,vl)  
(c)



similar texture  
(d)



gtv=grow(c,d)  
manual (blue)

## Brain Tumor Image Segmentation Benchmark (BraTS) 2017

Comparison of 18 BraTS17 techniques that analyse at least 100 cases:  
Similarity score (Dice GTV): 0.88 (avg.) 0.64-0.96 (range)

*more ...*

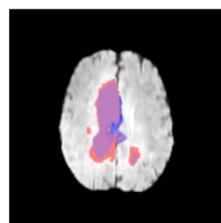
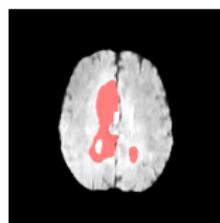
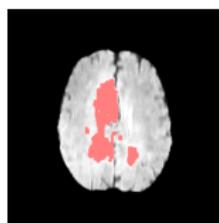
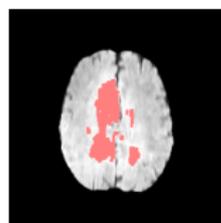
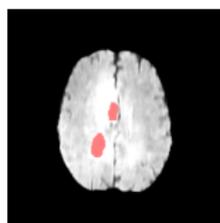
Our score on 193 cases: **0.85** (avg.) **0.10** (std.)

<sup>4</sup> [Belmonte, Ciancia, Latella, Massink, TACAS19]

[Banci Buonamici, Belmonte, Ciancia, Latella, Massink, STTT 2019 and ESMRBM19]

<sup>5</sup> Image: Brats17\_2013.2.1 from BraTS 2017 database

# 3D Magnetic Resonance Tumour Segmentation<sup>4,5</sup>



hyper intense  
(hl)

very intense  
(vl)

grow(hl,vl)  
(c)

similar texture  
(d)

gtv=grow(c,d)  
manual (blue)

## Brain Tumor Image Segmentation Benchmark (BraTS) 2017

Comparison of 18 BraTS17 techniques that analyse at least 100 cases:  
Similarity score (Dice GTV): 0.88 (avg.) 0.64-0.96 (range)

*more ...*

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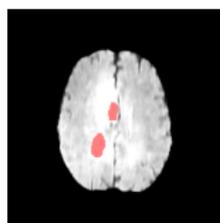
About 10 seconds on Intel Core i7 7700 (8 cores), ~ 9 million voxels

<sup>4</sup> [Belmonte, Ciancia, Latella, Massink, TACAS19]

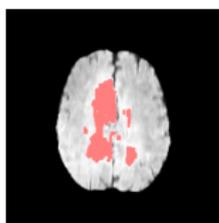
[Banci Buonamici, Belmonte, Ciancia, Latella, Massink, STTT 2019 and ESMRBM19]

<sup>5</sup> Image: Brats17\_2013.2.1 from BraTS 2017 database

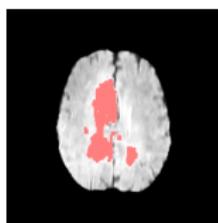
# 3D Magnetic Resonance Tumour Segmentation<sup>4,5</sup>



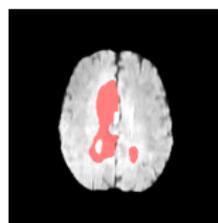
hyper intense  
(hl)



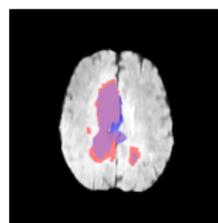
very intense  
(vl)



grow(hl,vl)  
(c)



similar texture  
(d)



gtv=grow(c,d)  
manual (blue)

## Brain Tumor Image Segmentation Benchmark (BraTS) 2017

Comparison of 18 BraTS17 techniques that analyse at least 100 cases:  
Similarity score (Dice GTV): 0.88 (avg.) 0.64-0.96 (range)

*more ...*

Our score on 193 cases: **0.85** (avg.) **0.10** (std.) **In line with state-of-the-art!**

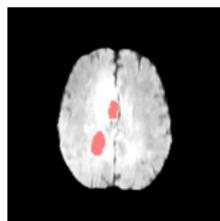
About 10 seconds on Intel Core I7 7700 (8 cores), ~ 9 million voxels

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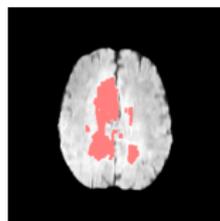
[Banci Buonamici, Belmonte, Ciancia, Latella, Massink, STTT 2019 and ESMRBM19]

<sup>5</sup> Image: Brats17\_2013.2.1 from BraTS 2017 database

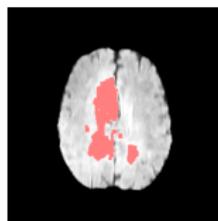
# 3D Magnetic Resonance Tumour Segmentation<sup>4,5</sup>



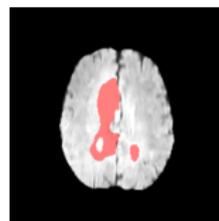
hyper intense  
(hl)



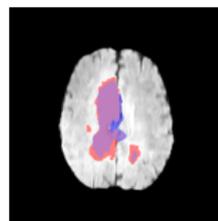
very intense  
(vl)



grow(hl,vl)  
(c)



similar texture  
(d)



gtv=grow(c,d)  
manual (blue)

```
let background = touch(intensity <. 0.1, border)
let brain = !background

let pflair = percentiles(intensity, brain)
let hl = pflair >. 0.95
let vl = pflair >. 0.86
let hyperIntense = flt(5.0, hl)
let veryIntense = flt(2.0, vl)

let growTum = grow(hyperIntense, veryIntense)
let tumSim = similarTo(growTum)
let tumStatCC = flt(2.0, tumSim >. 0.6)
let gtv = grow(growTum, tumStatCC)
```

background removal

[back](#)

thresholding

region growing and  
texture similarity

<sup>4</sup> [Belmonte, Ciancia, Latella, Massink, TACAS19]

[Banci Buonamici, Belmonte, Ciancia, Latella, Massink, STTT 2019 and ESMRBM19]

<sup>5</sup> Image: Brats17\_2013\_2.1 from BraTS 2017 database

# Spatio-Temporal Logics (SLCS+CTL)

## Syntax

$\Phi ::=$	$\top$	[TRUE]	}	<i>Spatial</i>
	$p$	[ATOMIC PROPOSITION]		
	$\neg\Phi$	[NOT]		
	$\Phi \vee \Phi$	[OR]		
	$\mathcal{N}\Phi$	[NEAR]		
	$\Phi \mathcal{S} \Phi$	[SURROUNDED]		
	$A\varphi$	[ALL PATHS]	}	<i>Temporal</i>
	$E\varphi$	[EXIST PATH]		
$\varphi ::=$	$\mathcal{X}\Phi$	[NEXT]	}	<i>Path formulas</i>
	$\Phi \mathcal{U} \Psi$	[UNTIL]		

# Spatio-Temporal Logics (STLCS)

## Semantics

Satisfaction  $\mathcal{M}, x, s \models \Phi$  of an STLCS formula  $\Phi$  at point  $x$  and state  $s$  in model  $\mathcal{M} = ((X, \mathcal{C}), (S, R), \mathcal{V}_{s \in S})$  is defined as follows:

$$\begin{aligned} \mathcal{M}, x, s &\models \top \\ \mathcal{M}, x, s &\models p \quad \Leftrightarrow \quad x \in \mathcal{V}_s(p) \\ \mathcal{M}, x, s &\models \neg\Phi \quad \Leftrightarrow \quad \mathcal{M}, x, s \not\models \Phi \\ \mathcal{M}, x, s &\models \Phi \vee \Psi \quad \Leftrightarrow \quad \mathcal{M}, x, s \models \Phi \text{ or } \mathcal{M}, x, s \models \Psi \\ \mathcal{M}, x, s &\models \mathcal{N}\Phi \quad \Leftrightarrow \quad x \in \mathcal{C}(\{y \in X \mid \mathcal{M}, y, s \models \Phi\}) \\ \mathcal{M}, x, s &\models \Phi \mathcal{S} \Psi \quad \Leftrightarrow \quad \exists A \subseteq X. x \in A \wedge \forall y \in A. \mathcal{M}, y, s \models \Phi \wedge \\ &\quad \wedge \forall z \in \mathcal{B}^+(A). \mathcal{M}, z, s \models \Psi \\ \mathcal{M}, x, s &\models \mathbf{A}\varphi \quad \Leftrightarrow \quad \forall \sigma \in \mathcal{P}_s. \mathcal{M}, x, \sigma \models \varphi \\ \mathcal{M}, x, s &\models \mathbf{E}\varphi \quad \Leftrightarrow \quad \exists \sigma \in \mathcal{P}_s. \mathcal{M}, x, \sigma \models \varphi \\ \mathcal{M}, x, \sigma &\models \mathcal{X}\Phi \quad \Leftrightarrow \quad \mathcal{M}, x, \sigma(1) \models \Phi \\ \mathcal{M}, x, \sigma &\models \Phi \mathcal{U} \Psi \quad \Leftrightarrow \quad \exists n. \mathcal{M}, x, \sigma(n) \models \Psi \text{ and} \\ &\quad \forall n' \in [0, n). \mathcal{M}, x, \sigma(n') \models \Phi \end{aligned}$$

# Bike sharing: Clusters of full docking stations

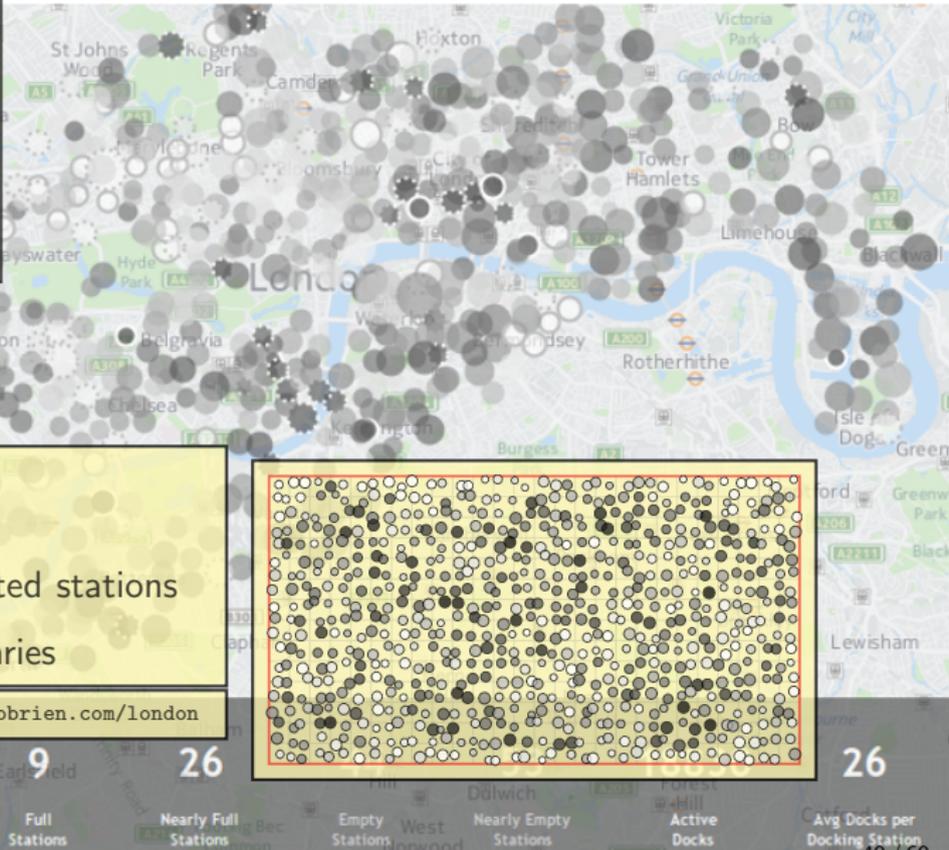
[Ciancia et al, SEFMWS15].[Massink, Paškauskas, ITSC15]

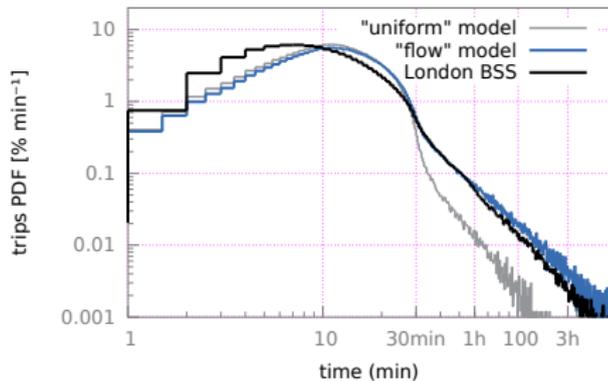
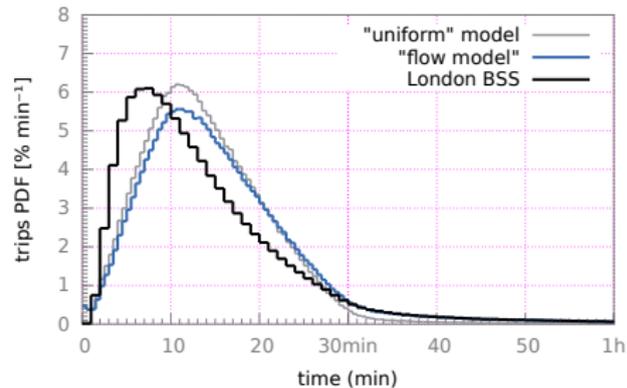
Key	Value
-----	-------

Stations	742
Capacity	19,000
Bike Fleet	11,500
Trips·h <sup>-1</sup>	1,120
Area (km <sup>2</sup> )	90

- Rectangular map
- Randomly distributed stations
- Bird's flight itineraries

Background img.: <http://bikes.oobrien.com/london>





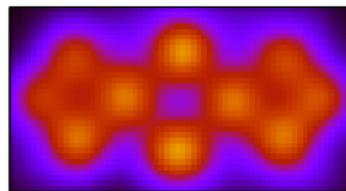
Expected Trips( $> 30$ )min = 0%

Uniform Multi-agent, uniform OD

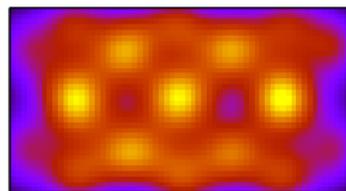
- Trips( $> 30$ )min = 2%

Flow Multi-agent, non-uniform OD

- Trips( $> 30$ )min = 7.7% Bingo!



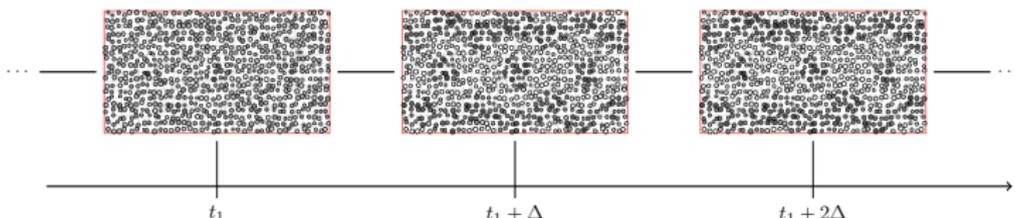
hiring probabilities



returning probabilities

Soft control: dissolve clusters

## Detecting the emergence of clusters of full stations

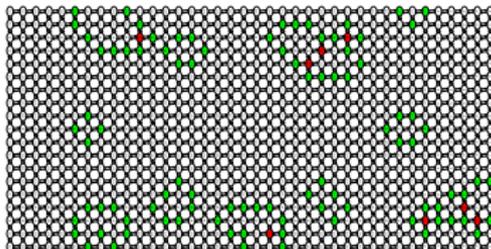


- Define cluster:

`cluster = I(full)`

- Cluster boundary:

`(!EF cluster) & (N EF cluster)`



[[topochecker](https://github.com/vincenzoml/topochecker),  
[www.github.com/vincenzoml/topochecker](https://www.github.com/vincenzoml/topochecker)]

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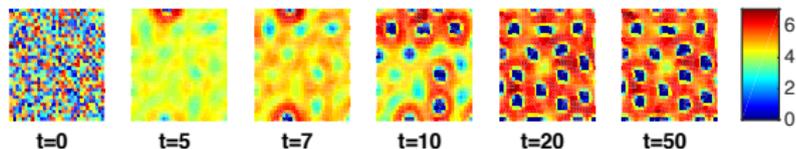
$$\begin{aligned} \mathcal{M}, x, s &\models \top \\ \mathcal{M}, x, s &\models p \quad \Leftrightarrow \quad x \in \mathcal{V}_s(p) \\ \mathcal{M}, x, s &\models \neg\Phi \quad \Leftrightarrow \quad \mathcal{M}, x, s \not\models \Phi \\ \mathcal{M}, x, s &\models \Phi \vee \Psi \quad \Leftrightarrow \quad \mathcal{M}, x, s \models \Phi \text{ or } \mathcal{M}, x, s \models \Psi \\ \mathcal{M}, x, s &\models \mathcal{N}\Phi \quad \Leftrightarrow \quad x \in \mathcal{C}(\{y \in X \mid \mathcal{M}, y, s \models \Phi\}) \\ \mathcal{M}, x, s &\models \Phi \mathcal{S} \Psi \quad \Leftrightarrow \quad \exists A \subseteq X. x \in A \wedge \forall y \in A. \mathcal{M}, y, s \models \Phi \wedge \\ &\quad \wedge \forall z \in \mathcal{B}^+(A). \mathcal{M}, z, s \models \Psi \\ \mathcal{M}, x, s &\models \mathbf{A}\varphi \quad \Leftrightarrow \quad \forall \sigma \in \mathcal{P}_s. \mathcal{M}, x, \sigma \models \varphi \\ \mathcal{M}, x, s &\models \mathbf{E}\varphi \quad \Leftrightarrow \quad \exists \sigma \in \mathcal{P}_s. \mathcal{M}, x, \sigma \models \varphi \\ \mathcal{M}, x, \sigma &\models \mathcal{X}\Phi \quad \Leftrightarrow \quad \mathcal{M}, x, \sigma(1) \models \Phi \\ \mathcal{M}, x, \sigma &\models \Phi \mathcal{U} \Psi \quad \Leftrightarrow \quad \exists n. \mathcal{M}, x, \sigma(n) \models \Psi \text{ and} \\ &\quad \forall n' \in [0, n). \mathcal{M}, x, \sigma(n') \models \Phi \end{aligned}$$

# Spatio-temporal analysis of Turing patterns (SSTL)

[Nenzi, Bortolussi, Latella, Loreti, Massink, RV15 + LMCS 2018]

Morphogenesis: Two chemical substances  $A$  and  $B$  in a  $K \times K$  grid

$$\begin{cases} \frac{dx_{i,j}^A}{dt} = R_1 x_{i,j}^A x_{i,j}^B - x_{i,j}^A + R_2 + D_1(\mu_{i,j}^A - x_{i,j}^A) \\ \frac{dx_{i,j}^B}{dt} = R_3 x_{i,j}^A x_{i,j}^B + R_4 + D_2(\mu_{i,j}^B - x_{i,j}^B) \end{cases}$$



$$\phi_{\text{pattern}} := \mathcal{F}_{[\tau_{\text{pattern}}, \tau_{\text{pattern}} + \delta]} \mathcal{G}_{[0, \tau_{\text{end}}]}((x^A \leq h) S_{[w_1, w_2]}(x^A > h))$$

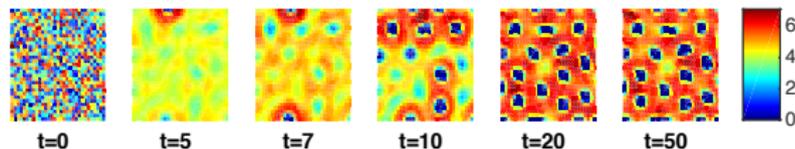
Detecting emergent spots and their persistence in time, including their robustness to small perturbations

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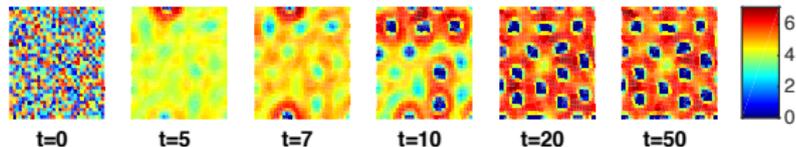
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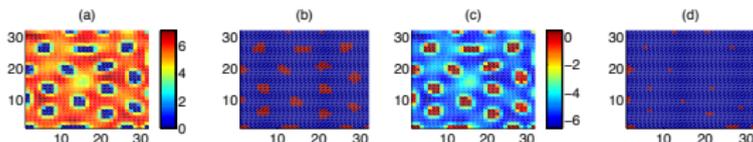
[Nenzi, Bortolussi, Latella, Loreti, Massink, RV15 + LMCS 2018]

Morphogenesis: Two chemical substances  $A$  and  $B$  in a  $K \times K$  grid

$$\begin{cases} \frac{dx_{i,j}^A}{dt} = R_1 x_{i,j}^A x_{i,j}^B - x_{i,j}^A + R_2 + D_1(\mu_{i,j}^A - x_{i,j}^A) \\ \frac{dx_{i,j}^B}{dt} = R_3 x_{i,j}^A x_{i,j}^B + R_4 + D_2(\mu_{i,j}^B - x_{i,j}^B) \end{cases}$$

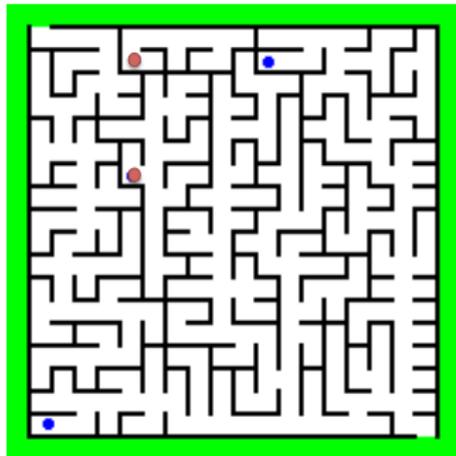


$$\phi_{\text{pattern}} := \mathcal{F}_{[T_{\text{pattern}}, T_{\text{pattern}} + \delta]} \mathcal{G}_{[0, T_{\text{end}}]} ((x^A \leq h) \mathcal{S}_{[w_1, w_2]} (x^A > h))$$



Detecting emergent spots and their persistence in time, including their robustness to small perturbations

## Collective Spatial Logic<sup>6</sup>



model

The sets of points in blue can collectively reach an exit

# Collective Spatial Logic

## Syntax

$\Phi ::= p$  [ATOMIC PROPOSITION]  
|  $\top$  [TRUE]  
|  $\neg\Phi$  [NOT]  
|  $\Phi \wedge \Phi$  [AND]  
|  $\mathcal{N}\Phi$  [NEAR]  
|  $\Phi \mathcal{S} \Phi$  [SURROUNDED]

$\Psi ::= \neg\Psi$  [COLLECTIVE NOT]  
|  $\Psi_1 \wedge \Psi_2$  [COLLECTIVE AND]  
|  $\Phi \prec \Psi$  [SHARE]  
|  $\mathcal{G}\Phi$  [GROUP]

# Collective Spatial Logic

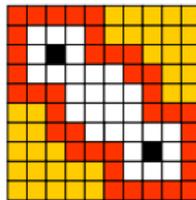
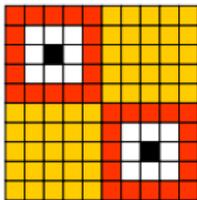
## Semantics

*Satisfaction*  $\mathcal{M}, Y \models_C \Psi$  of a collective formula  $\Psi$  at set  $Y \subseteq X$  in model  $\mathcal{M} = ((X, \mathcal{C}), \mathcal{V})$  is defined by induction on the structure of formulas:

$$\begin{aligned} \mathcal{M}, Y \models_C \neg \Psi &\Leftrightarrow \mathcal{M}, Y \models_C \Psi \text{ does not hold} \\ \mathcal{M}, Y \models_C \Psi_1 \wedge \Psi_2 &\Leftrightarrow \mathcal{M}, Y \models_C \Psi_1 \text{ and } \mathcal{M}, Y \models_C \Psi_2 \\ \mathcal{M}, Y \models_C \Phi \prec \Psi &\Leftrightarrow \mathcal{M}, \{x \in Y \mid \mathcal{M}, x \models \Phi\} \models_C \Psi \\ \mathcal{M}, Y \models_C \mathcal{G} \Phi &\Leftrightarrow \text{there exists } Z \subseteq X \text{ such that} \\ &\quad Y \subseteq Z \text{ and } Z \text{ is path-connected and} \\ &\quad \text{for all } z \in Z \text{ we have: } \mathcal{M}, z \models \Phi \end{aligned}$$

# Collective Spatial Logic

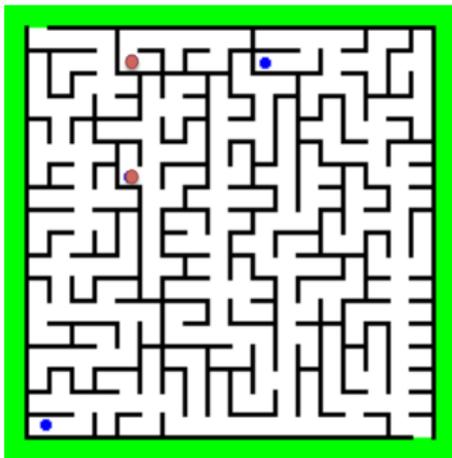
Simple example



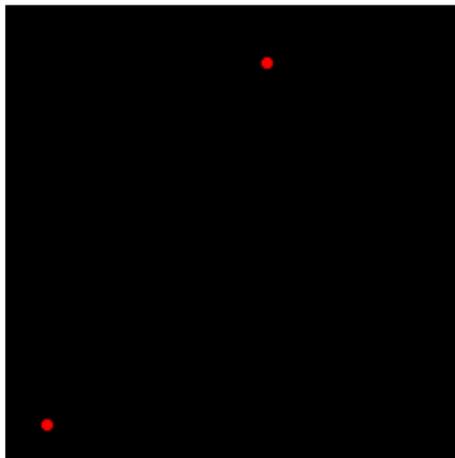
$\Phi: (black \vee white) S red$

$\mathcal{M}, \{y | y \text{ is black}\} \models_c \mathcal{G}(\Phi)$

# Collective Spatial Logic



model



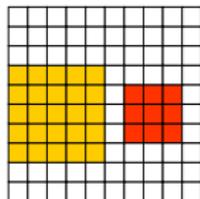
result

The set of blue points can collectively reach an exit

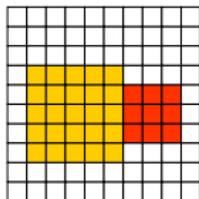
$$\mathcal{M}, \{y \mid y \text{ is blue}\} \models_C \mathcal{G}(\text{white} \vee \text{startCanExit}) \{\bullet\}$$

# Embedding of Discrete Region Connection Calculus (RCC8D)<sup>7</sup>

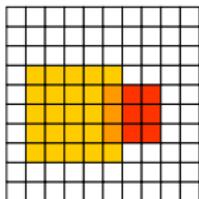
[Randell, Cui, Cohn, KR'92, 1992]



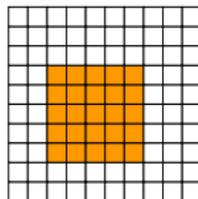
*DC*



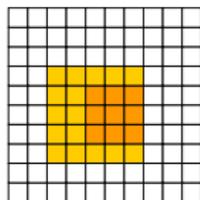
*EC*



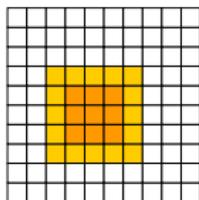
*PO*



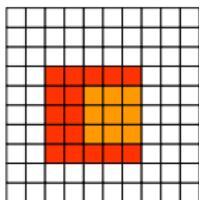
*EQ*



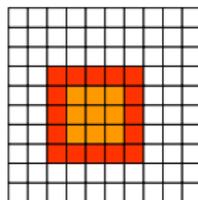
*TPP*



*NTPP*



*TPPi*



*NTPPi*

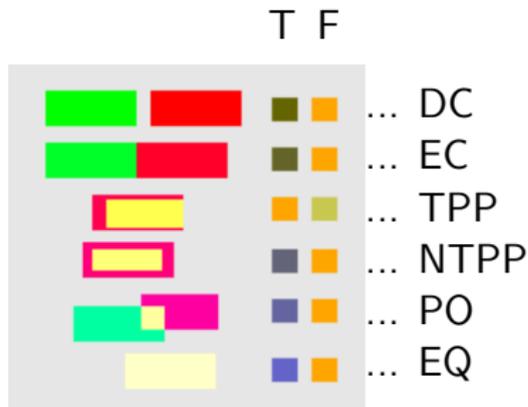
more ...

<sup>7</sup>[Ciancia, Latella, Massink, LNCS 11665, 2019]

# Embedding RCC8D in CSLCS<sup>8</sup>

Verification with *topochecker*

TPP(*Green*, *Red*)



Produced using the *spatio-temporal* model-checker *topochecker*  
<http://topochecker.isti.cnr.it/>

*back*

<sup>8</sup>[Ciancia, Latella, Massink, LNCS 11665, 2019]

## Conclusions and Outlook

“Nothing is more practical than a good theory”<sup>9</sup>

Future work:

- Spatial Model Reduction
- Spatial Monitoring and Spatial Computing
- Medical Imaging
- Data and Topology

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<sup>9</sup>Kurt Lewin, 1951

Thanks for listening!

Hope you enjoyed your travel through space!



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$$\Phi_2 \vee (\Phi_1 \mathcal{S} \Phi_2) \equiv A(\Phi_1 \mathcal{W} \Phi_2)$$

where:

- $A$  is the *path universal quantifier*
- $\mathcal{W}$  the weak-until operator

# Similarity indexes in Medical Imaging

$$Dice = 2 * TP / (2 * TP + FN + FP)$$

with

TP = True Positive

FN = False Negative

FP = False Positive

Sensitivity is the fraction of True Positives:

$$Sens = TP / (TP + FP)$$

Specificity is the fraction of True Negatives:

$$Spec = TN / (TN + FN)$$

## Embedding RCC8D in CSLCS

Let  $(X, \mathcal{C})$  a closure space and  $\mathcal{M} = ((X, \mathcal{C}), \mathcal{V})$  a finite model.

Predicate  $p_Y$  denotes the set  $Y \subseteq X$  s.t.  $\mathcal{V}(p_Y) = Y$ .

Encoding of standard set-theoretic and closure operators in CSLCS:

$\llbracket Y \rrbracket$	$= p_Y, \text{ for all } Y \subseteq X$	[CONSTANT]
$\llbracket \bar{\gamma} \rrbracket$	$= \neg \llbracket \gamma \rrbracket$	[COMPLEMENT]
$\llbracket \gamma_1 \cap \gamma_2 \rrbracket$	$= \llbracket \gamma_1 \rrbracket \wedge \llbracket \gamma_2 \rrbracket$	[INTERSECTION]
$\llbracket \mathcal{C}(\gamma) \rrbracket$	$= \mathcal{N}(\llbracket \gamma \rrbracket)$	[CLOSURE]

where  $\gamma, \gamma_1, \gamma_2$  range over expressions on sets built out of constants, complement, intersection and closure

## Embedding RCC8D in CSLCS

Tests on the empty set, on set-inclusion and set-equality:

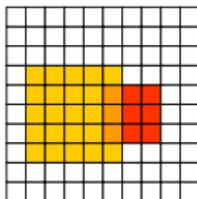
$$\begin{aligned} \llbracket \gamma = \emptyset \rrbracket &= \llbracket \gamma \rrbracket \prec \mathcal{G} \perp && \text{[EMPTY]} \\ \llbracket \gamma_1 \subseteq \gamma_2 \rrbracket &= \llbracket (\gamma_1 \cap \overline{\gamma_2}) = \emptyset \rrbracket && \text{[INCLUSION]} \\ \llbracket \gamma_1 = \gamma_2 \rrbracket &= \llbracket \gamma_1 \subseteq \gamma_2 \rrbracket \wedge \llbracket \gamma_2 \subseteq \gamma_1 \rrbracket && \text{[EQUALITY]} \end{aligned}$$

## Embedding RCC8D in CSLCS

$$\begin{aligned} \llbracket P(Y_1, Y_2) \rrbracket &= \llbracket Y_1 \subseteq Y_2 \rrbracket \wedge \neg \llbracket Y_1 = \emptyset \rrbracket && \text{[PARTHOOD]} \\ \llbracket O(Y_1, Y_2) \rrbracket &= \neg \llbracket Y_1 \cap Y_2 = \emptyset \rrbracket && \text{[OVERLAP]} \end{aligned}$$

PARTIAL OVERLAP:

$$\llbracket PO(Y_1, Y_2) \rrbracket = \llbracket O(Y_1, Y_2) \rrbracket \wedge \neg \llbracket P(Y_1, Y_2) \rrbracket \wedge \neg \llbracket P(Y_2, Y_1) \rrbracket$$



For all RCC8D formulas  $F$  the following holds:

$F$  holds in an adjacency model  $\mathcal{M}$  if and only if  $\mathcal{M}, X \models_c \llbracket F \rrbracket$ .