

# Fluid Approximation for the Analysis of Collective Adaptive Systems

Jane Hillston  
LFCS, University of Edinburgh

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# Outline

## 1 Introduction

- Collective Systems
- Quantitative Analysis
- Stochastic Process Algebra

## 2 Quantitative Analysis of Collective Systems

- Model construction
- Mathematical analysis: fluid approximation
- Numerical illustration
- Deriving properties: fluid model checking

## 3 Conclusions

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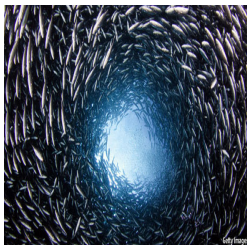
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# Collective Systems

We are surrounded by examples of **collective systems**:

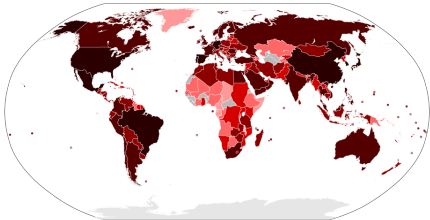
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We are surrounded by examples of **collective systems**:  
in the natural world ....



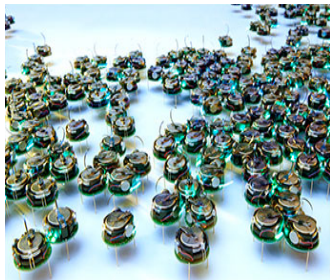
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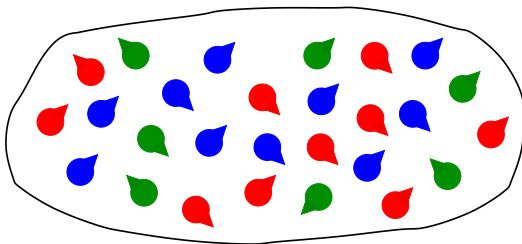
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Such systems are now becoming the reality, and many form collective adaptive systems, in which large numbers of computing elements collaborate to meet the human need.

For instance, many examples of such systems can be found in components of **Smart Cities**, such as **smart urban transport** and **smart grid electricity generation and storage**.

# Collective Systems

From a computer science perspective these systems can be viewed as being made up of a large number of interacting entities.

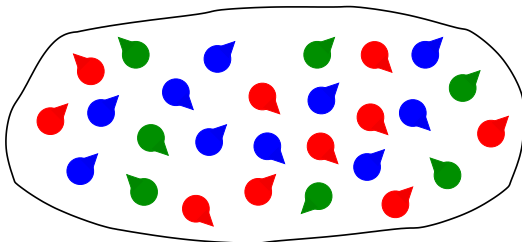


Each entity may have its own properties, objectives and actions.

At the system level these combine to create the **collective** behaviour.

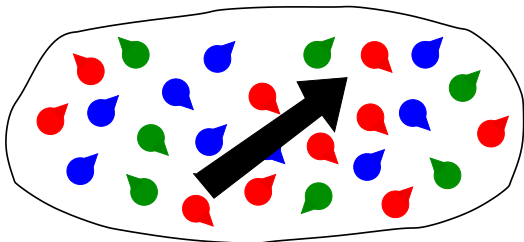
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The behaviour of the system is thus dependent on the behaviour of the individual entities.



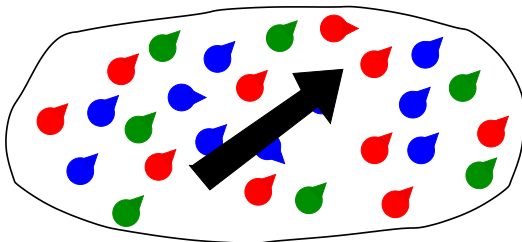
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And the behaviour of the individuals will be influenced by the state of the overall system.

# Quantitative Modelling

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Originally **queueing networks** were primarily used to construct models, and sophisticated analysis techniques were developed.

These techniques are no longer widely applicable for expressing the dynamic behaviour observed in distributed systems, and this is even more true of systems with **collective behaviour**.

# Performance Modelling: Motivation

## Capacity Planning

- How many clients can the existing server support and maintain reasonable response times?
- How many buses do I need to maintain service at peak time in a smart urban transport system?

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## System Tuning

- In an automated factory what speed of conveyor belt will minimize robot idle time and jamming but maximize throughput?
- What strategy can I use to maintain supply-demand balance within a smart electricity grid?

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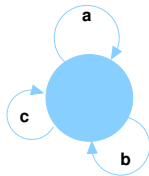
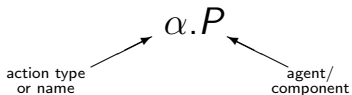
From these high-level system descriptions the underlying mathematical model (Continuous Time Markov Chain (CTMC)) can be **automatically generated**.

Primary examples include:

- **Stochastic Petri Nets** and
- **Stochastic/Markovian Process Algebras.**

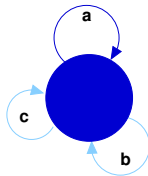
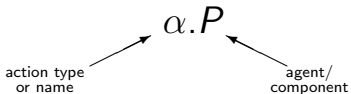
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- Models consist of **agents** which engage in **actions**.



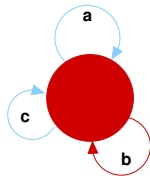
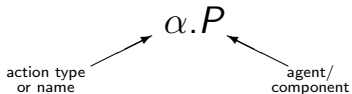
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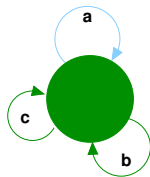
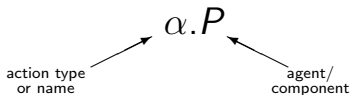
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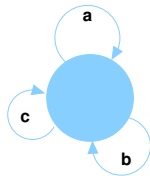
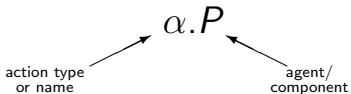
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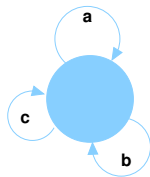
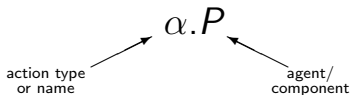
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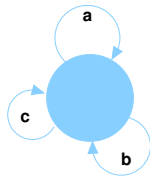
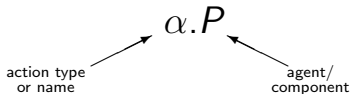
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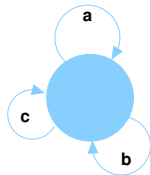
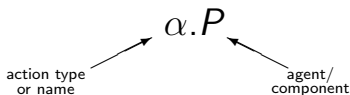
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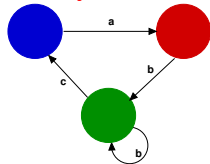


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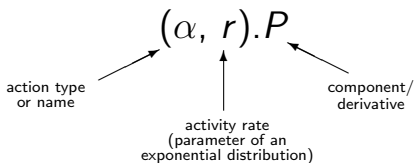


# Stochastic process algebras

Process algebras where models are decorated with quantitative information used to generate a stochastic process are **stochastic process algebras (SPA)**.

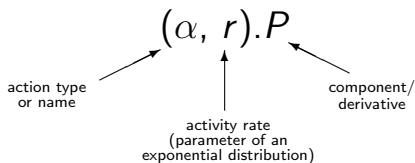
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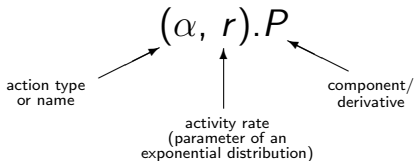
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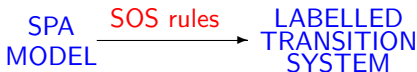
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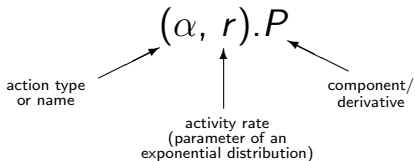


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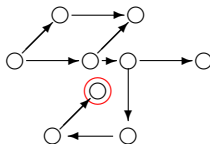
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# Integrated analysis

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## Reachability analysis

How long will it take  
for the system to arrive  
in a particular state?



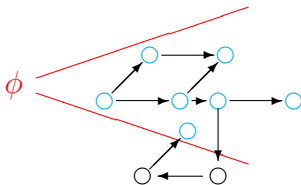


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## Model checking

Does a given property  $\phi$   
hold within the system  
with a given probability?

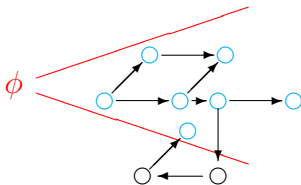


# Integrated analysis

**Qualitative** verification can now be complemented by **quantitative** verification.

## Model checking

For a given starting state  
how long is it until  
a given property  $\phi$  holds?



# Performance Evaluation Process Algebra

$(\alpha, f).P$	Prefix
$P_1 + P_2$	Choice
$P_1 \boxtimes_L P_2$	Co-operation
$P/L$	Hiding
$X$	Constant

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$P_1 \parallel P_2$  is a derived form for  $P_1 \boxtimes_{\emptyset} P_2$ .

When working with large numbers of entities, we write  $P[n]$  to denote an **array** of  $n$  copies of  $P$  executing in parallel.

$$P[5] \equiv (P \parallel P \parallel P \parallel P \parallel P)$$

# Structured Operational Semantics

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## Choice

$$\frac{E \xrightarrow{(\alpha, r)} E'}{E + F \xrightarrow{(\alpha, r)} E'}$$

$$\frac{F \xrightarrow{(\alpha, r)} F'}{E + F \xrightarrow{(\alpha, r)} F'}$$

# Structured Operational Semantics: Cooperation ( $\alpha \notin L$ )

## Cooperation

$$\frac{E \xrightarrow{(\alpha, r)} E'}{E \bowtie_L F \xrightarrow{(\alpha, r)} E' \bowtie_L F} \quad (\alpha \notin L)$$

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where  $R = \frac{r_1}{r_\alpha(E)} \frac{r_2}{r_\alpha(F)} \min(r_\alpha(E), r_\alpha(F))$

# Apparent Rate

$$r_{\alpha}((\beta, r).P) = \begin{cases} r & \beta = \alpha \\ 0 & \beta \neq \alpha \end{cases}$$

$$r_{\alpha}(P + Q) = r_{\alpha}(P) + r_{\alpha}(Q)$$

$$r_{\alpha}(A) = r_{\alpha}(P) \quad \text{where } A \stackrel{\text{def}}{=} P$$

$$r_{\alpha}(P \bowtie_L Q) = \begin{cases} r_{\alpha}(P) + r_{\alpha}(Q) & \alpha \notin L \\ \min(r_{\alpha}(P), r_{\alpha}(Q)) & \alpha \in L \end{cases}$$

$$r_{\alpha}(P/L) = \begin{cases} r_{\alpha}(P) & \alpha \notin L \\ 0 & \alpha \in L \end{cases}$$

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# Structured Operational Semantics: Constants

## Constant

$$\frac{E \xrightarrow{(\alpha, r)} E'}{A \xrightarrow{(\alpha, r)} E'} (A \stackrel{def}{=} E)$$

# A simple example: processors and resources

$$Proc_0 \stackrel{def}{=} (task1, r_1).Proc_1$$

$$Proc_1 \stackrel{def}{=} (task2, r_2).Proc_0$$

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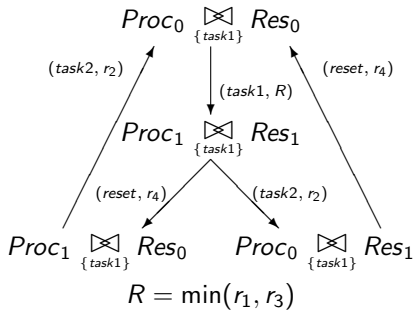
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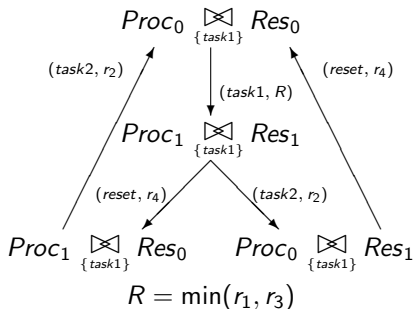
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$$Q = \begin{pmatrix} -R & R & 0 & 0 \\ 0 & -(r_2 + r_4) & r_4 & r_2 \\ r_2 & 0 & -r_2 & 0 \\ r_4 & 0 & 0 & -r_4 \end{pmatrix}$$



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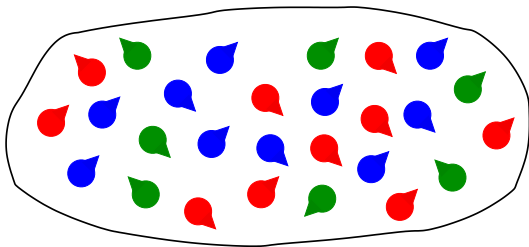
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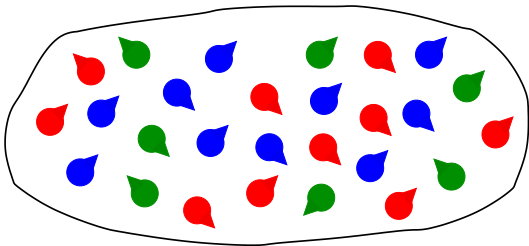
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High-level modelling formalisms allow this repetition to be captured at the high-level rather than explicitly.

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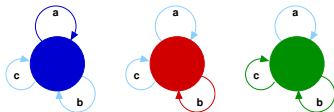
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Recent advances in analysis techniques for process algebras have made it possible to study such systems even when the number of entities and activities become huge.

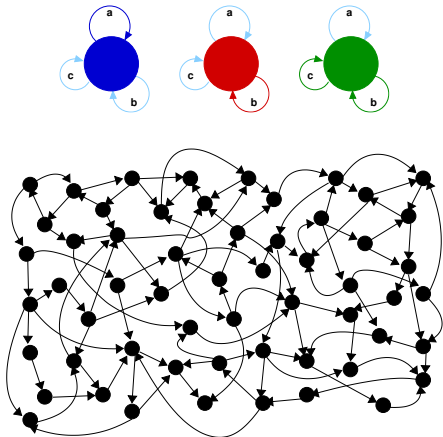
# Solving discrete state models

Under the SOS semantics a SPA model is mapped to a **CTMC** with global states determined by the local states of all the participating components.

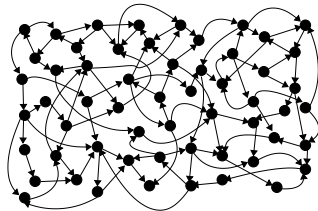


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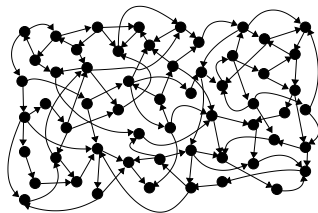


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When the size of the state space is not too large they are amenable to **numerical solution** (linear algebra) to determine a **steady state** or **transient probability distribution**.

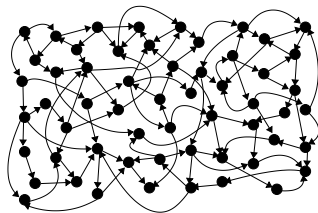
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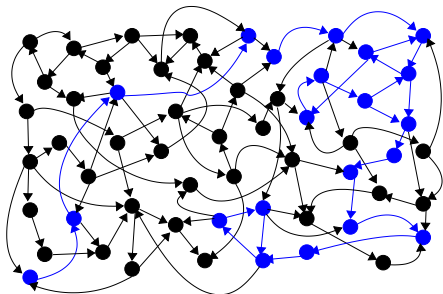
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$$\pi(t) = (\pi_1(t), \pi_2(t), \dots, \pi_N(t))$$

$$\pi(\infty)Q = 0$$

# Solving discrete state models

Alternatively they may be studied using **stochastic simulation**. Each run generates a single trajectory through the state space. Many runs are needed in order to obtain average behaviours.



# State space explosion

As the size of the state space becomes large it becomes infeasible to carry out numerical solution and extremely time-consuming to conduct stochastic simulation.



# Identity and Individuality

Collective systems are constructed from many instances of a set of components.

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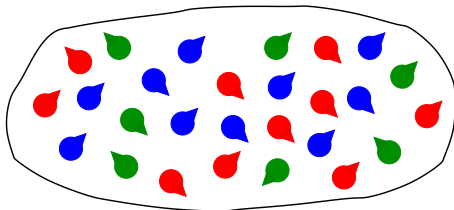
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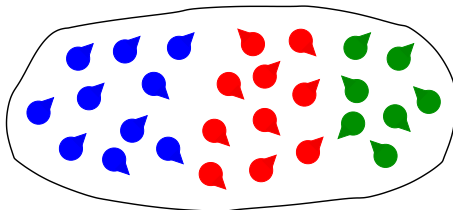
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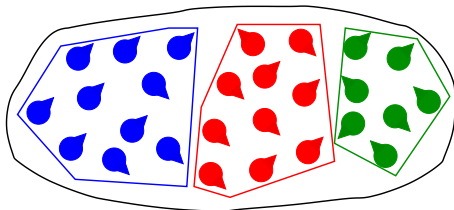
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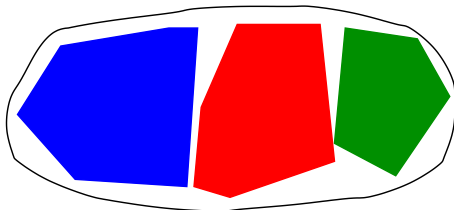


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We may choose to disregard the **identity** of components.

Even better reductions can be achieved when we no longer regard the components as **individuals**.

# Population statistics: emergent behaviour

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This allows us to model much larger systems than previously possible but in making the shift we are no longer able to collect any information about individuals in the system.

To characterise the behaviour of a population we calculate the **proportion** of individuals within the population that are exhibiting certain behaviours rather than tracking individuals directly.

Furthermore we make a **continuous approximation** of how the proportions vary over time.

# Continuous Approximation

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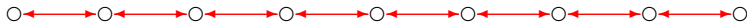
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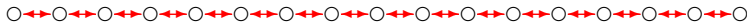
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We use **ordinary differential equations** to represent the evolution of those variables over time.



# Simple example revisited

$$Proc_0 \stackrel{def}{=} (task1, r_1).Proc_1$$

$$Proc_1 \stackrel{def}{=} (task2, r_2).Proc_0$$

$$Res_0 \stackrel{def}{=} (task1, r_3).Res_1$$

$$Res_1 \stackrel{def}{=} (reset, r_4).Res_0$$

$$Proc_0[N_P] \boxtimes_{\{task1\}} Res_0[N_R]$$

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## CTMC interpretation

Processors ( $N_P$ )	Resources ( $N_R$ )	States ( $2^{N_P+N_R}$ )
1	1	4
2	1	8
2	2	16
3	2	32
3	3	64
4	3	128
4	4	256
5	4	512
5	5	1024
6	5	2048
6	6	4096
7	6	8192
7	7	16384
8	7	32768
8	8	65536
9	8	131072
9	9	262144
10	9	524288
10	10	1048576

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$$Proc_0[N_P] \boxtimes_{\{task1\}} Res_0[N_R]$$

- *task1* decreases  $Proc_0$  and  $Res_0$
- *task1* increases  $Proc_1$  and  $Res_1$
- *task2* decreases  $Proc_1$
- *task2* increases  $Proc_0$
- *reset* decreases  $Res_1$
- *reset* increases  $Res_0$

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$$\frac{dx_1}{dt} = -\min(r_1 x_1, r_3 x_3) + r_2 x_2$$

$x_1 = \text{no. of } Proc_1$

- *task1* decreases  $Proc_0$
- *task1* is performed by  $Proc_0$  and  $Res_0$
- *task2* increases  $Proc_0$
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## ODE interpretation

$$\frac{dx_1}{dt} = -\min(r_1 x_1, r_3 x_3) + r_2 x_2$$

$x_1 = \text{no. of } Proc_1$

$$\frac{dx_2}{dt} = \min(r_1 x_1, r_3 x_3) - r_2 x_2$$

$x_2 = \text{no. of } Proc_2$

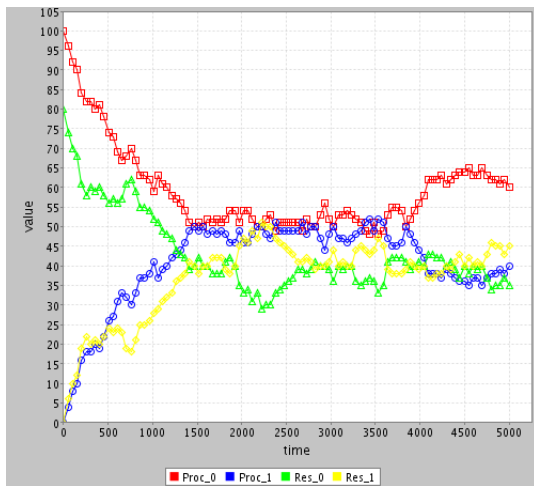
$$\frac{dx_3}{dt} = -\min(r_1 x_1, r_3 x_3) + r_4 x_4$$

$x_3 = \text{no. of } Res_0$

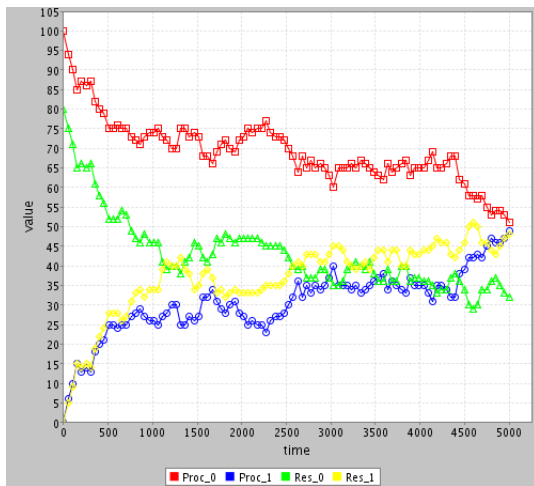
$$\frac{dx_4}{dt} = \min(r_1 x_1, r_3 x_3) - r_4 x_4$$

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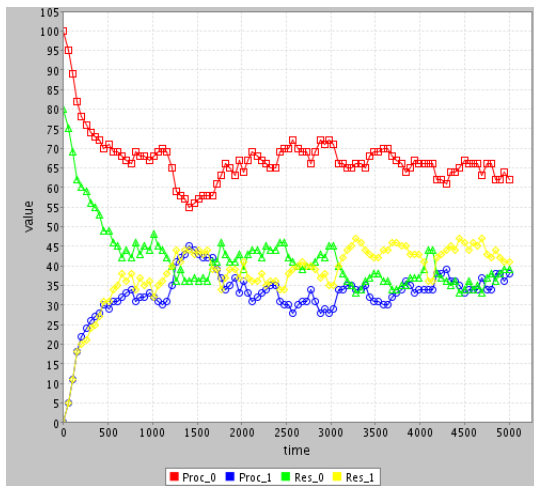
# 100 processors and 80 resources (simulation run A)



# 100 processors and 80 resources (simulation run B)

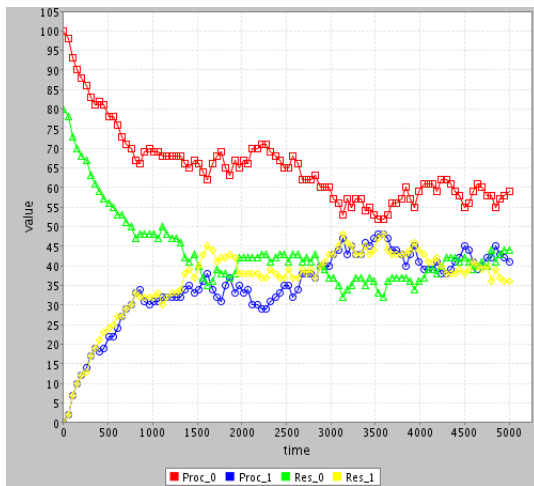


# 100 processors and 80 resources (simulation run C)

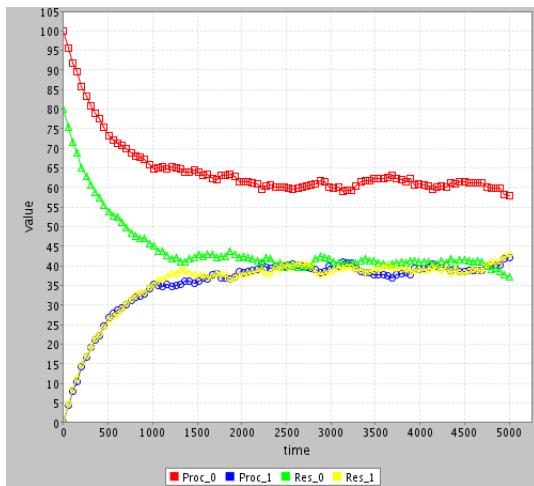




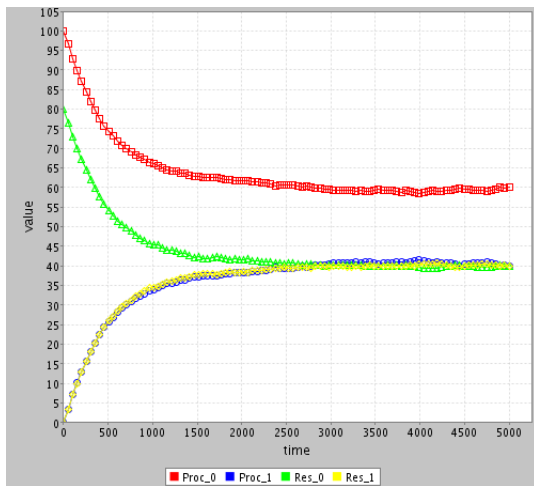
# 100 processors and 80 resources (simulation run D)



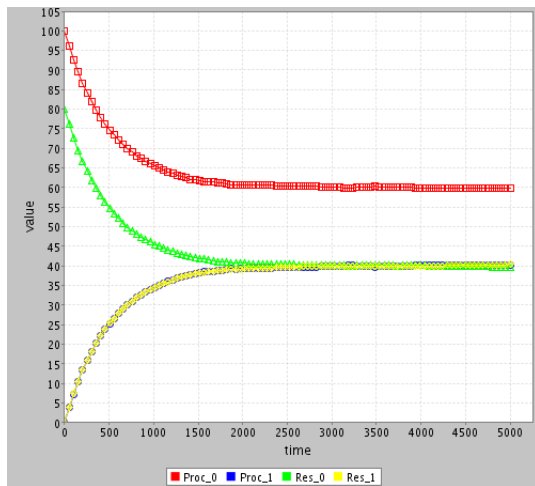
# 100 processors and 80 resources (average of 10 runs)



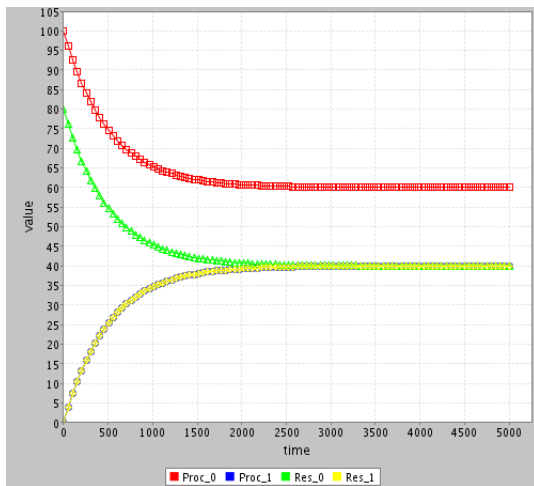
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# 100 processors and 80 resources (ODE solution)



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- 3 Calculate the rate of the transitions in terms of an arbitrary state of the CTMC.

Once this is done we can extract the **vector field**  $F_{\mathcal{M}}(x)$  from the jump multiset, under the assumption that the population size tends to infinity.

# Context Reduction

$$\begin{aligned}
 Proc_0 &\stackrel{def}{=} (task1, r_1).Proc_1 \\
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 Res_0 &\stackrel{def}{=} (task1, r_3).Res_1 \\
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 System &\stackrel{def}{=} Proc_0[N_P] \boxtimes_{\{transfer\}} Res_0[N_R]
 \end{aligned}$$

$$\Downarrow$$

$$\mathcal{R}(System) = \{Proc_0, Proc_1\} \boxtimes_{\{task1\}} \{Res_0, Res_1\}$$



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## Population Vector

$$\xi = (\xi_1, \xi_2, \xi_3, \xi_4)$$

# Location Dependency

$$System \stackrel{def}{=} Proc_0[N'_C] \underset{\{task1\}}{\boxtimes} Res_0[N_S] \parallel Proc_0[N''_C]$$

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$$\xi = (\xi_1, \xi_2, \xi_3, \xi_4, \xi_5, \xi_6)$$

# Fluid Structured Operational Semantics by Example

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 }{
 Proc_0 \boxtimes_{\{task1\}} Res_0 \xrightarrow{task1, r(\xi)} *_ Proc_1 \boxtimes_{\{task1\}} Res_1
 }$$



# Apparent Rate Calculation

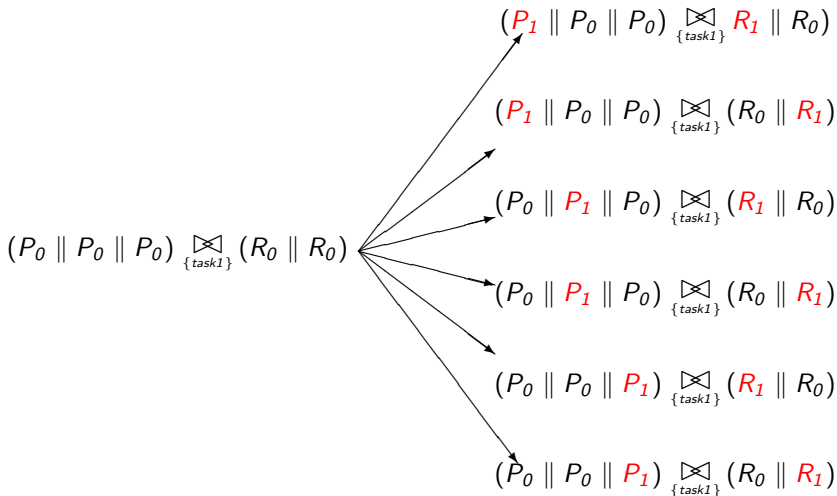
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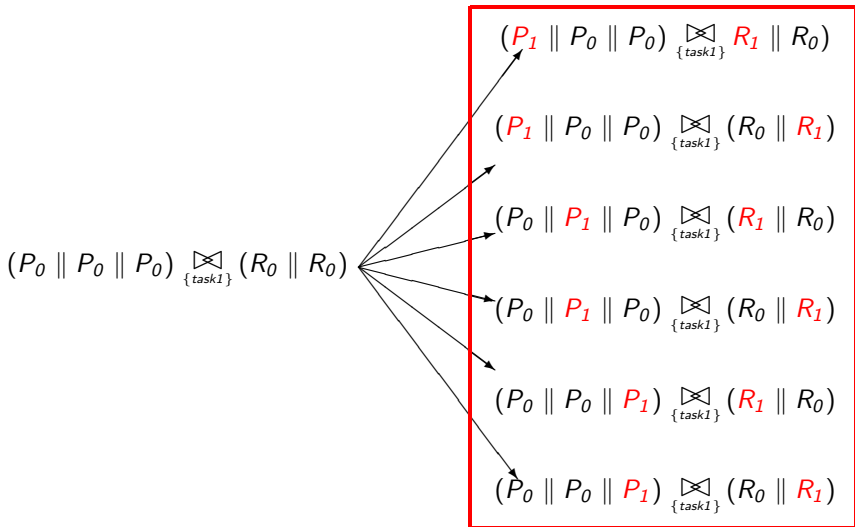
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 }$$

$$r(\xi) = \min(r_1 \xi_1, r_3 \xi_4)$$

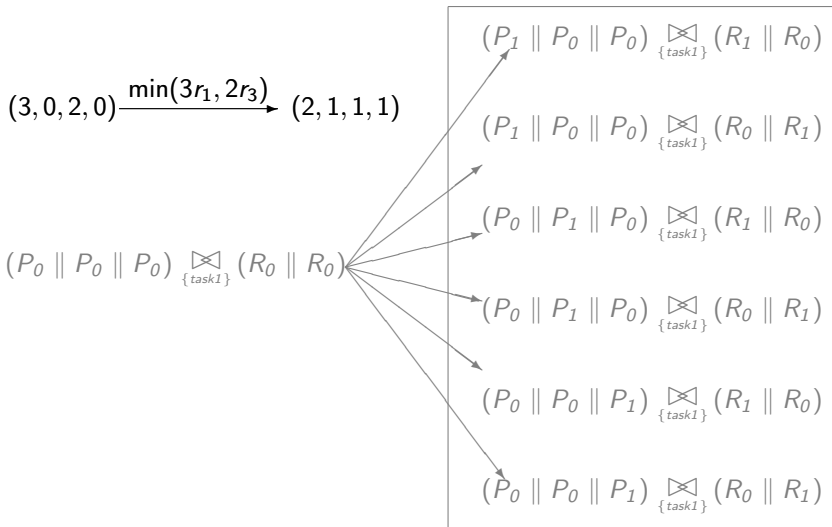
# $f(\xi, l, \alpha)$ as the Generator Matrix of the *Lumped* CTMC



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# Jump Multiset

$$\begin{array}{c}
 \textcolor{red}{Proc_0} \boxtimes_{\{task1\}} \textcolor{red}{Res_0} \xrightarrow{task1, r(\xi)}_* \textcolor{red}{Proc_1} \boxtimes_{\{task1\}} \textcolor{red}{Res_1} \\
 r(\xi) = \min(r_1\xi_1, r_3\xi_3)
 \end{array}$$

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$$Proc_0 \boxtimes_{\{task1\}} Res_1 \xrightarrow{reset, \xi_4 r_4}_* Proc_0 \boxtimes_{\{task1\}} Res_0$$



# Equivalent Transitions

Some transitions may give the same information:

$$\begin{array}{ccc}
 Proc_0 \boxtimes_{\{task1\}} Res_1 & \xrightarrow{\text{reset}, \xi_4 r_4} & Proc_0 \boxtimes_{\{task1\}} Res_0 \\
 Proc_1 \boxtimes_{\{task1\}} Res_1 & \xrightarrow{\text{reset}, \xi_4 r_4} & Proc_1 \boxtimes_{\{task1\}} Res_0
 \end{array}$$

i.e.,  $Res_1$  may perform an action independently from the rest of the system.

This is captured by the procedure used for the construction of the generator function  $f(\xi, l, \alpha)$

# Construction of $f(\xi, l, \alpha)$

$$Proc_0 \begin{array}{c} \boxtimes \\ \{task1\} \end{array} Res_1 \xrightarrow{\text{reset}, \xi_4 r_4}^* Proc_0 \begin{array}{c} \boxtimes \\ \{task1\} \end{array} Res_0$$

# Construction of $f(\xi, l, \alpha)$

$$Proc_0 \begin{array}{c} \boxtimes \\ \{task1\} \end{array} Res_1 \xrightarrow{\text{reset}, \xi_4 r_4} *_ Proc_0 \begin{array}{c} \boxtimes \\ \{task1\} \end{array} Res_0$$

- Take  $l = (0, 0, 0, 0)$

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- Take  $l = (0, 0, 0, 0)$
- Add  $-1$  to all elements of  $l$  corresponding to the indices of the components in the lhs of the transition

$$l = (-1, 0, 0, -1)$$

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- Add  $+1$  to all elements of  $l$  corresponding to the indices of the components in the rhs of the transition

$$l = (-1 + 1, 0, +1, -1) = (0, 0, +1, -1)$$

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$$f(\xi, (0, 0, +1, -1), reset) = \xi_4 r_4$$

# Construction of $f(\xi, l, \alpha)$

$$Proc_0 \boxtimes_{\{task1\}} Res_0 \xrightarrow{task1, r(\xi)}_* Proc_1 \boxtimes_{\{task1\}} Res_1$$

$$f(\xi, (-1, +1, -1, +1), task1) = r(\xi)$$

# Construction of $f(\xi, l, \alpha)$

$$\begin{array}{ccc}
 Proc_0 \boxtimes_{\{task1\}} Res_0 & \xrightarrow{task1, r(\xi)}_* & Proc_1 \boxtimes_{\{task1\}} Res_1 \\
 Proc_1 \boxtimes_{\{task1\}} Res_0 & \xrightarrow{task2, \xi_2 r'_2}_* & Proc_0 \boxtimes_{\{task1\}} Res_0
 \end{array}$$

$$\begin{aligned}
 f(\xi, (-1, +1, -1, +1), task1) &= r(\xi) \\
 f(\xi, (+1, -1, 0, 0), task2) &= \xi_2 r_2
 \end{aligned}$$



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 Proc_0 \boxtimes_{\{task1\}} Res_0 & \xrightarrow{task1, r(\xi)}_* & Proc_1 \boxtimes_{\{task1\}} Res_1 \\
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$$\begin{aligned}
 f(\xi, (-1, +1, -1, +1), task1) &= r(\xi) \\
 f(\xi, (+1, -1, 0, 0), task2) &= \xi_2 r_2' \\
 f(\xi, (0, 0, +1, -1), reset) &= \xi_4 r_4
 \end{aligned}$$

# Capturing behaviour in the Generator Function

$$\begin{aligned}
 Proc_0 &\stackrel{def}{=} (task1, r_1).Proc_1 \\
 Proc_1 &\stackrel{def}{=} (task2, r_2).Proc_0 \\
 Res_0 &\stackrel{def}{=} (task1, r_3).Res_1 \\
 Res_1 &\stackrel{def}{=} (reset, r_4).Res_0 \\
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## Numerical Vector Form

$$\xi = (\xi_1, \xi_2, \xi_3, \xi_4) \in \mathbb{N}^4, \quad \xi_1 + \xi_2 = N_P \quad \text{and} \quad \xi_3 + \xi_4 = N_R$$

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## Generator Function

$$\begin{aligned}
 f(\xi, l, \alpha) : \quad & f(\xi, (-1, 1, -1, 1), task1) = \min(r_1\xi_1, r_3\xi_3) \\
 & f(\xi, (1, -1, 0, 0), task2) = r_2\xi_2 \\
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 \end{aligned}$$

# Extraction of the ODE from $f$

## Generator Function

$$\begin{aligned}f(\xi, (-1, 1, -1, 1), task1) &= \min(r_1\xi_1, r_3\xi_3) \\f(\xi, (1, -1, 0, 0), task2) &= r_2\xi_2 \\f(\xi, (0, 0, 1, -1), reset) &= r_4\xi_4\end{aligned}$$

## Differential Equation

$$\begin{aligned}\frac{dx}{dt} &= F_{\mathcal{M}}(x) = \sum_{l \in \mathbb{Z}^d} l \sum_{\alpha \in \mathcal{A}} f(x, l, \alpha) \\&= (-1, 1, -1, 1) \min(r_1x_1, r_3x_3) + (1, -1, 0, 0)r_2x_2 \\&\quad + (0, 0, 1, -1)r_4x_4\end{aligned}$$

# Extraction of the ODE from $f$

## Generator Function

$$\begin{aligned}f(\xi, (-1, 1, -1, 1), task1) &= \min(r_1\xi_1, r_3\xi_3) \\f(\xi, (1, -1, 0, 0), task2) &= r_2\xi_2 \\f(\xi, (0, 0, 1, -1), reset) &= r_4\xi_4\end{aligned}$$

## Differential Equation

$$\begin{aligned}\frac{dx_1}{dt} &= -\min(r_1x_1, r_3x_3) + r_2x_2 \\ \frac{dx_2}{dt} &= \min(r_1x_1, r_3x_3) - r_2x_2 \\ \frac{dx_3}{dt} &= -\min(r_1x_1, r_3x_3) + r_4x_4 \\ \frac{dx_4}{dt} &= \min(r_1x_1, r_3x_3) - r_4x_4\end{aligned}$$

# Consistency results

- The vector field  $\mathcal{F}(x)$  is Lipschitz continuous i.e. all the rate functions governing transitions in the process algebra satisfy local continuity conditions.

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- We can prove this using Kurtz's theorem:  
**Solutions of Ordinary Differential Equations as Limits of Pure Jump Markov Processes**, T.G. Kurtz, J. Appl. Prob. (1970).
- Moreover Lipschitz continuity of the vector field guarantees existence and uniqueness of the solution to the initial value problem.

# Quantitative properties

The derived vector field  $\mathcal{F}(x)$ , gives an approximation of the **expected count** for each population over time.

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- Fluid approximation of **passage times** have been defined.

R.A.Hayden, A.Stefanek and J.T.Bradley. Fluid computation of passage-time distributions in large Markov models. TCS 2012.

# Fluid model checking

Since the vector field records only deterministic behaviour, LTL model checking can be used over a trace to give boolean results.

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But for the systems we are interested in we would like some more quantified answers, in the style of stochastic model checking.

Work on this is on-going but there are initial results for:

- **CSL properties of a single agent** within a population.

L.Bortolussi and J.Hillston. Fluid model checking. CONCUR 2012.

L.Bortolussi and J.Hillston. Model checking single agent behaviour by fluid approximation. Inf & Comp 2015.

- The **fraction of a population** that satisfies a property expressed as a one-clock deterministic timed automaton.

L.Bortolussi and R.Lanciani. Central Limit Approximation for Stochastic Model Checking. QEST 2013.

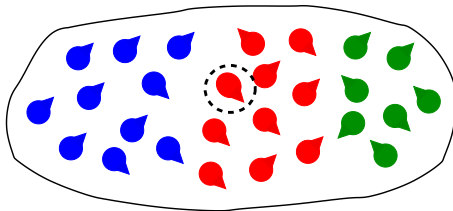
# CSL model checking of a single agent

We consider properties of a single agent within a population, expressed in the Continuous Stochastic Logic (CSL), usually used for model checking CTMCs.

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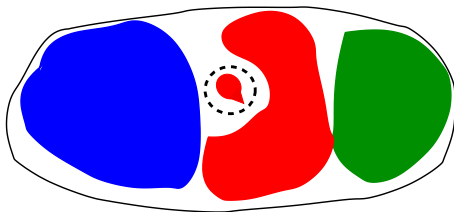
We consider an arbitrary member of the population.



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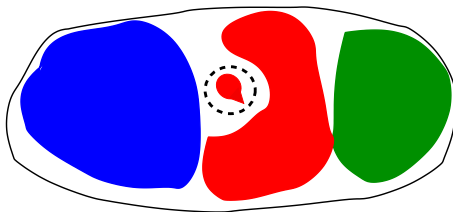
This agent is kept discrete, making transitions between its discrete states, but all other agents are treated as a **mean-field** influencing the behaviour of this agent.



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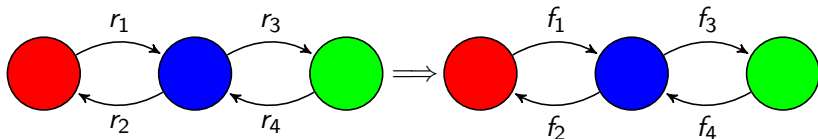
Essentially we keep a **detailed discrete-event representation of the one agent** and make a **fluid approximation of the rest** of the population.



# Inhomogeneous CTMC

The transition rates within the discrete-event representation will depend on the rest of the population.

i.e. it will depend on the vector field capturing the behaviour of the residual population.

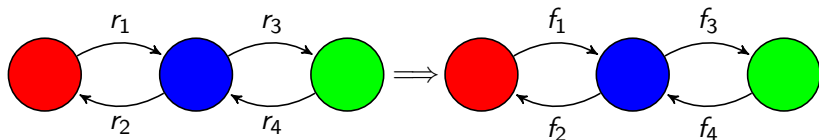


$$\text{where } f_i = f\left(\begin{array}{c} \text{blue pentagon} \quad \text{red pentagon} \quad \text{green pentagon} \end{array}\right)$$

# Inhomogeneous CTMC

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$$\text{where } f_i = f\left(\text{Diagram of three colored shapes (blue, red, green) inside an oval}\right)$$

It is an **inhomogeneous continuous time Markov chain**.

# Model checking the ICTMC

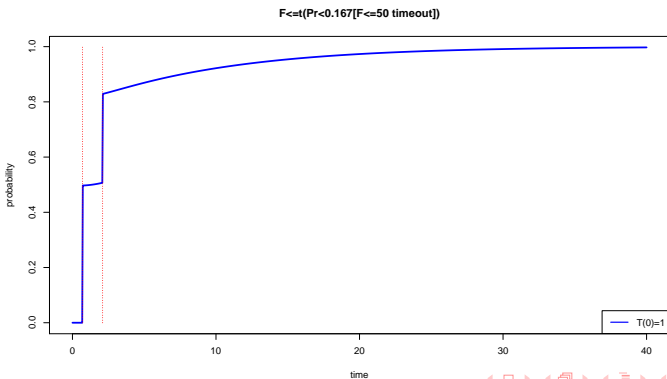
Care is needed to model check the ICTMC, which proceeds by explicitly calculating the reachability probabilities for states of interest (analogously to CSL model checking on CTMCs).



# Model checking the ICTMC

Care is needed to model check the ICTMC, which proceeds by explicitly calculating the reachability probabilities for states of interest (analogously to CSL model checking on CTMCs).

The inhomogeneous time within the model means that truth values may change with respect to time.



# Outline

## 1 Introduction

- Collective Systems
- Quantitative Analysis
- Stochastic Process Algebra

## 2 Quantitative Analysis of Collective Systems

- Model construction
- Mathematical analysis: fluid approximation
- Numerical illustration
- Deriving properties: fluid model checking

## 3 Conclusions

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# Conclusions

- Collective Systems are an interesting and challenging class of systems to design and construct.
- Their role within infrastructure, such as within smart cities, make it essential that quantitative aspects of behaviour is taken into consideration, as well as functional correctness.
- Fluid approximation based analysis offers hope for scalable quantitative analysis techniques, but there remain many interesting and challenging problems to be solved.
- In particular we currently seek to bring the fluid approximation techniques to systems with distinct locations.

# Thank you!

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Thanks to the other members of the QUANTICOL project

quanticol

[www.quanticol.eu](http://www.quanticol.eu)