Collective Adaptive Resource-sharing Markovian Agents (CARMA)

Jane Hillston

School of Informatics,
University of Edinburgh

8th April 2019

Outline

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Collective Systems

We are surrounded by examples of collective systems:

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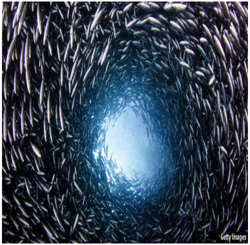
in the natural world ....



Collective Systems

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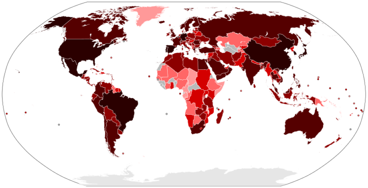
.... and in the man-made world



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an informatic environment

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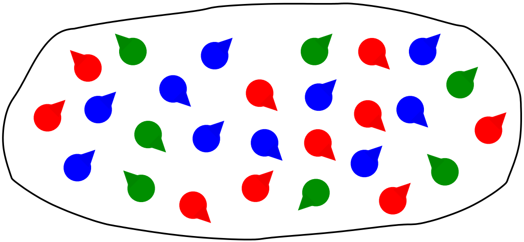
Most of these systems are also adaptive to their environment

Collective Adaptive Systems

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

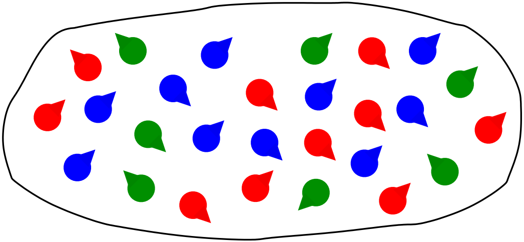


Each entity may have its own properties, objectives and actions.

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

Collective Adaptive Systems

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



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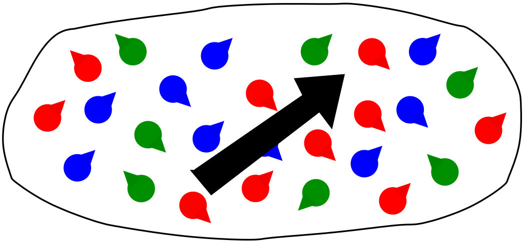

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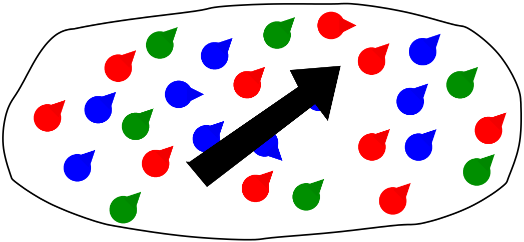
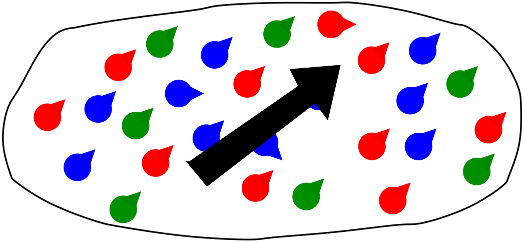


And the behaviour of the individuals will be influenced by the state of the overall system.

Collective Adaptive Systems

Such systems are often embedded in our environment and need to operate without centralised control or direction.



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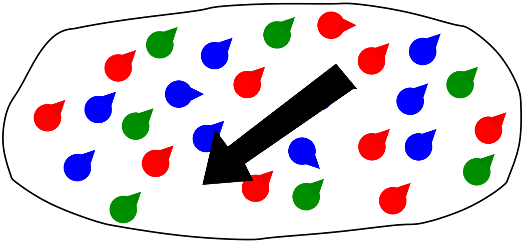

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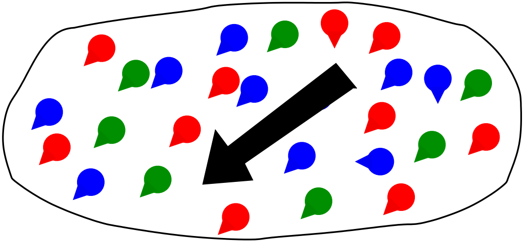

Moreover when conditions within the system change it may not be feasible to have human intervention to adjust behaviour appropriately.

Thus systems must be able to autonomously adapt.

The Informatic Environment

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

Performance Modelling for Smart Cities

Capacity planning

- How many buses do I need to maintain service at peak time in a smart urban transport system?

Performance Modelling for Smart Cities

System Configuration

- What capacity do I need at bike stations to minimise the movement of bikes by truck?

Performance Modelling for Smart Cities

System Tuning

- What strategy can I use to maintain supply-demand balance within a smart electricity grid?

Quantitative Modelling

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

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In the previous lecture we saw that the Stochastic Process Algebra, PEPA has been designed for this purpose.

Challenges for modelling CAS

The compositional framework provided by stochastic process algebras are well suited to modelling collective behaviour but leave a number of challenges:

- Open-ness and richer forms of interaction
- The influence of space on behaviour
- Capturing adaptivity

Open-ness

SPAs such as PEPA are conservative meaning that agents are neither created nor destroyed during the operation of the system.

In CAS agents may enter and leave the system at random times, either through faults (either within the agent or within the communication network) or choice (e.g. disconnect from a peer-to-peer network).

Thus the communication structure needs to be robust to missing partners, e.g. non-blocking

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Languages like SCEL offer these richer communication patterns, with components which include a knowledge store which can be manipulated by other components and attribute-based communication.

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For quantitative modelling there is a tension between keeping state spaces tractable and capturing local knowledge in agents.

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It would be preferable to model space explicitly but this poses significant challenges both for model expression and model solution.

Capturing adaptivity

Existing process algebras tend to work with a fixed set of actions for each entity type.

Some stochastic process algebras allow the rate of activity to be dependent on the state of the system.

But for truly adaptive systems there should also be some way to identify the goal or objective of an entity in addition to its behaviour.

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3. The environment where agents operate...
   - taking into account open ended-ness and adaptation;
   - taking into account resources, locations and visibility/reachability issues.

M.Loreti & J.Hillston, Modelling and Analysis of CAS with CARMA and its Tools. SFM 2016, LNCS 9700.

Interaction patterns in CAS

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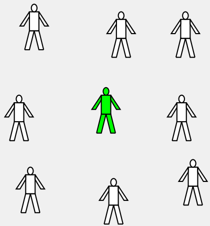

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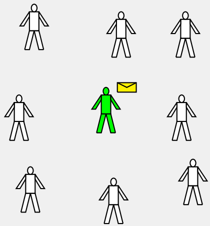

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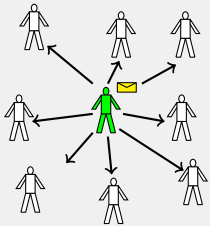

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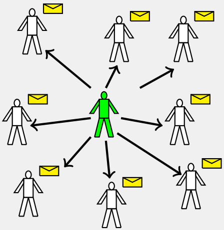

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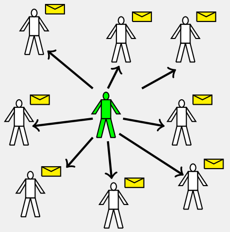

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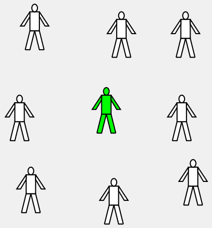

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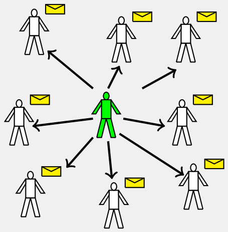

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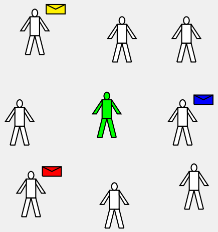

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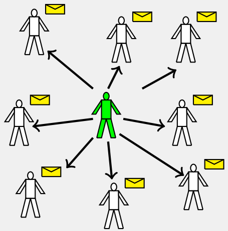

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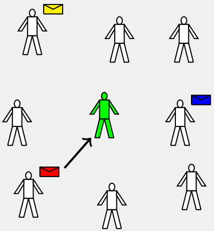

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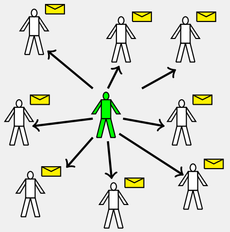

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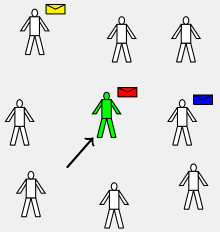
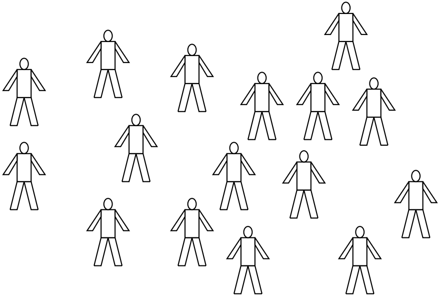


CAS: CARMA perspective

Collective



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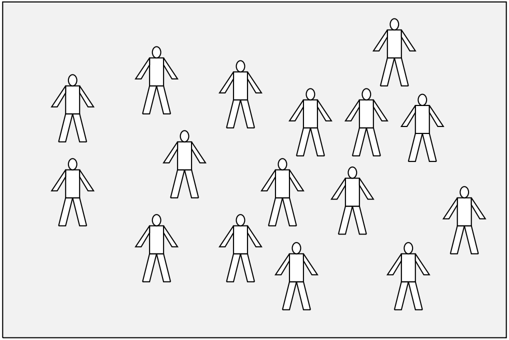
Collective **Environment**



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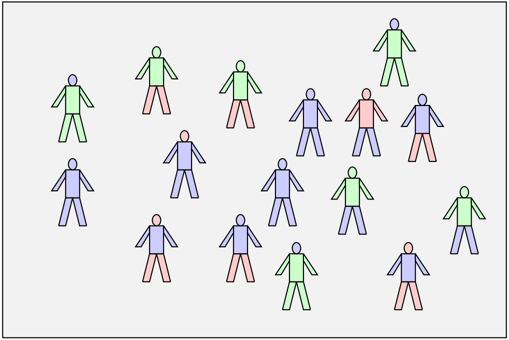

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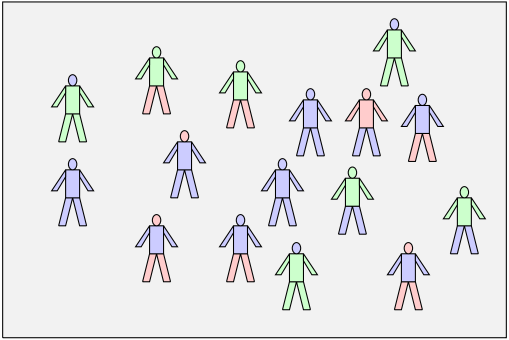

Processes are referenced via their attributes!

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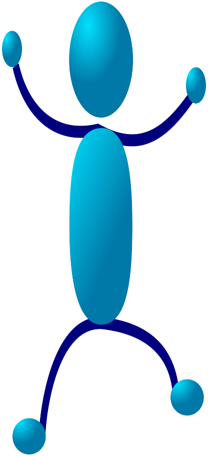
Environment...

- models the rules intrinsic to the context where agents operate;
- mediates and regulates agent interactions.

Agents in CARMA



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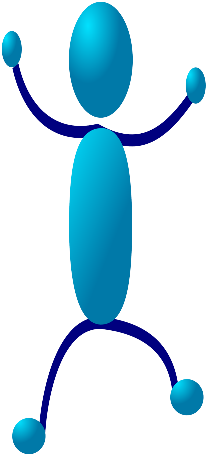

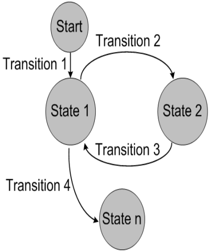

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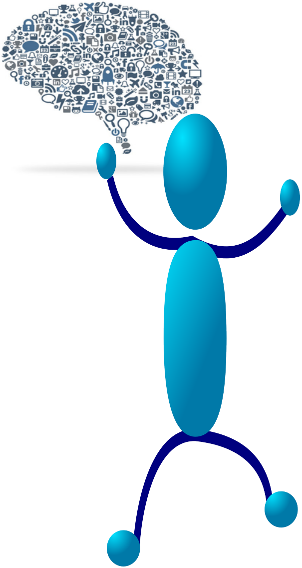

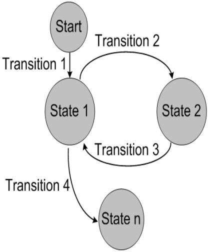

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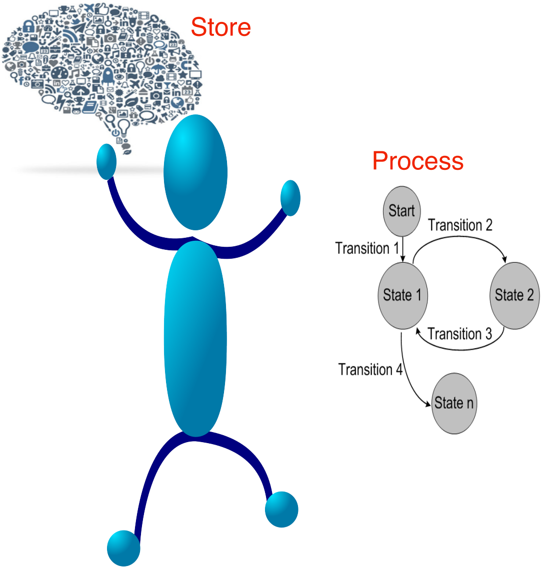
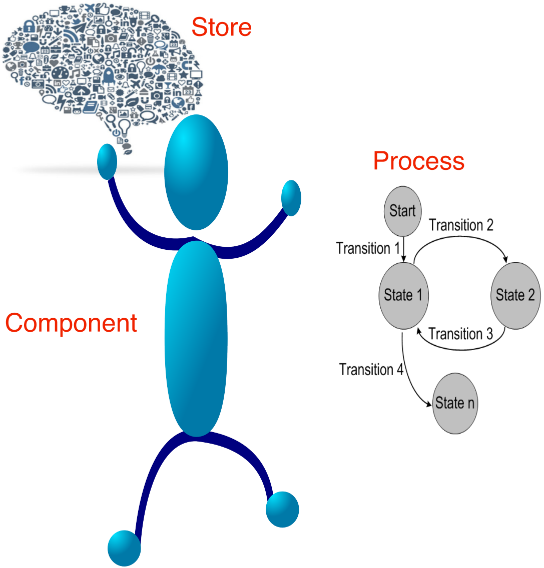


Components


Store
Process
Start
Transition 2
Transition 1
State 1
State 2
Transition 3
Component
Transition 4
State n

Components

Agents in CARMA are defined as components C of the form (P, γ) where...

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The participants of an interaction are identified via predicates...

- the counterpart of a communication is selected according its properties

Collective

Unicast communication

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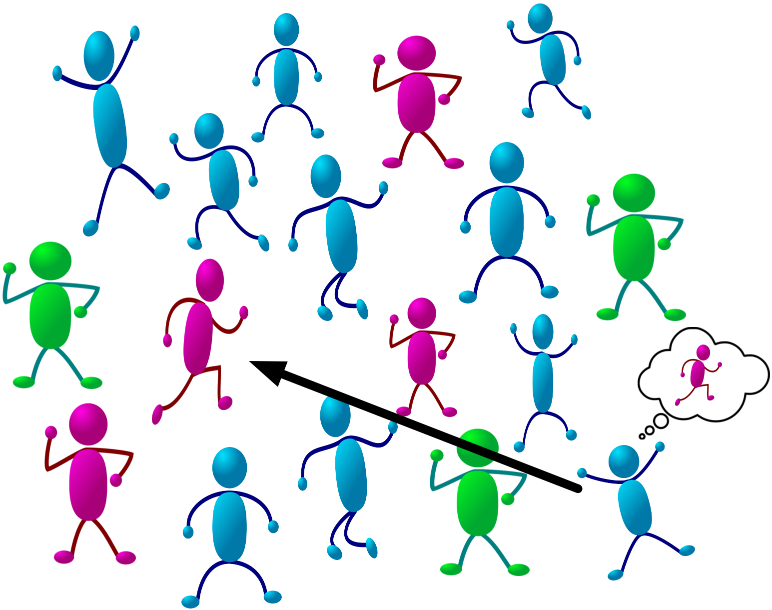

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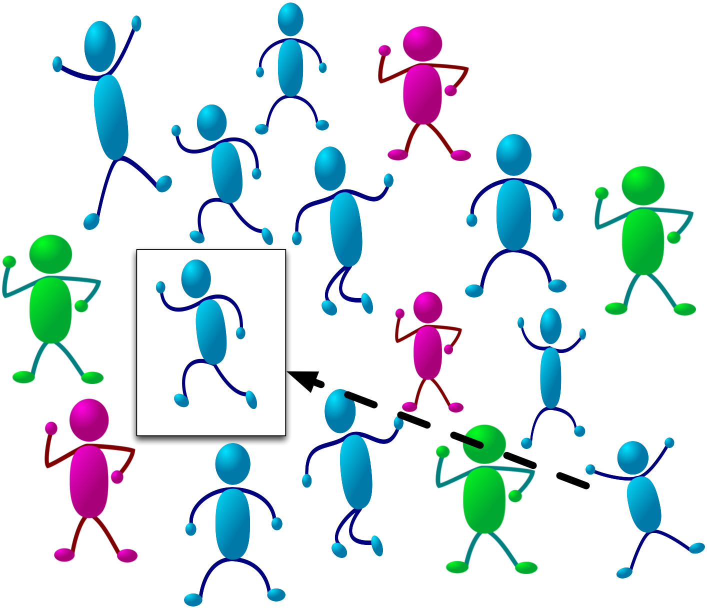

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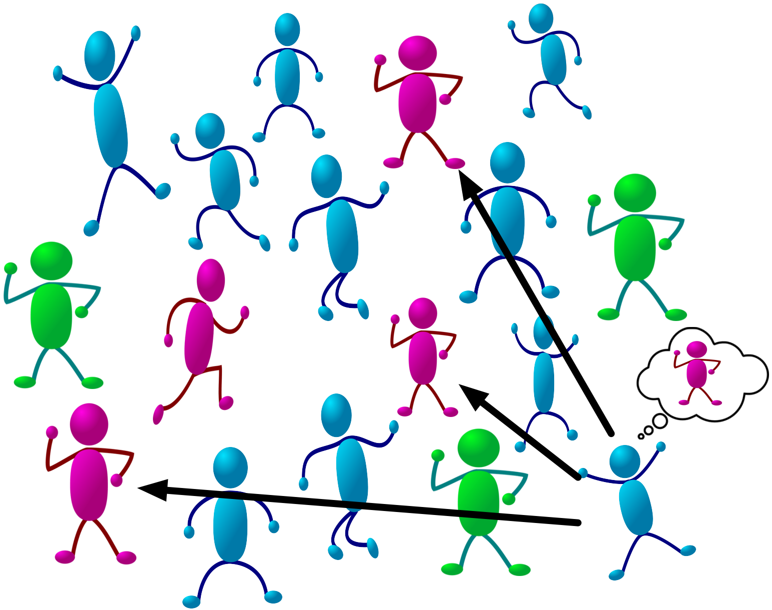

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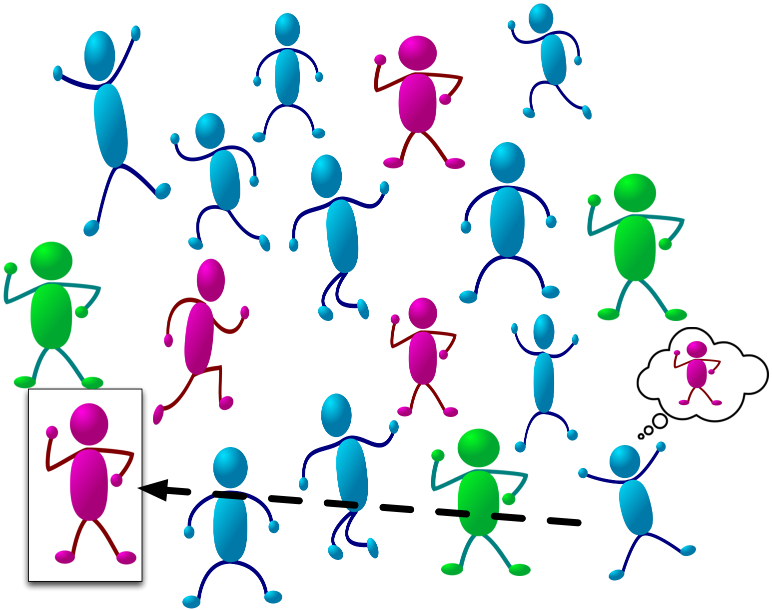

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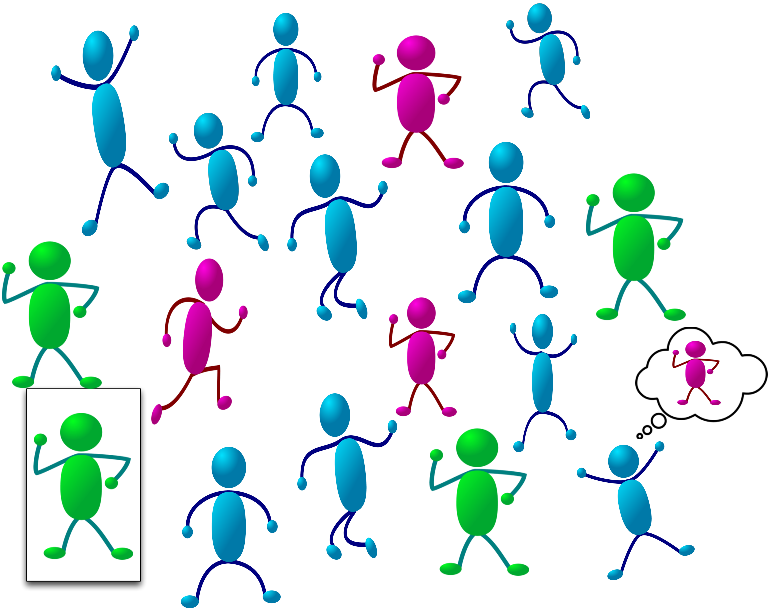

Interaction primitives

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The execution of an action takes an exponentially distributed time; the rate of each action is determined by the environment.

Interaction primitives
Syntax

act	$::=$	$\alpha^{\star}[\pi]\langle\overrightarrow{e}\rangle\sigma$	Broadcast output
	$\mid$	$\alpha^{\star}[\pi](\overrightarrow{x})\sigma$	Broadcast input
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- α is an action type;

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$$
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act & ::= & \alpha^{\star}[\pi]\langle\overrightarrow{e}\rangle\sigma & \text{Broadcast output}\\
& | & \alpha^{\star}[\pi](\overrightarrow{x})\sigma & \text{Broadcast input}\\
& | & \alpha[\pi]\langle\overrightarrow{e}\rangle\sigma & \text{Unicast output}\\
& | & \alpha[\pi](\overrightarrow{x})\sigma & \text{Unicast input}
\end{array}
$$

- α is an action type;
- π is a predicate;

Interaction primitives

Syntax

act	$::=$	$\alpha^{\star}[\pi]\langle\overrightarrow{e}\rangle\sigma$	Broadcast output
	$\mid$	$\alpha^{\star}[\pi](\overrightarrow{x})\sigma$	Broadcast input
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	$\mid$	$\alpha[\pi](\overrightarrow{x})\sigma$	Unicast input

- α is an action type;
- π is a predicate;
- σ is the effect of the action on the store.

Updating the store

After the execution of an action, a process can update the component store:

- σ denotes a function mapping each γ to a probability distribution over possible stores.

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Remark:

- Processes running in the same component can implicitly interact via the local store;
- Updates are instantaneous.

More on synchronisation

Predicates regulating broadcast/unicast inputs can refer also to the received values.

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Example:

A value greater than 0 is expected from a component with a *trust_level* less than 3:

$$\alpha^{\star}[(x > 0) \wedge (\mathit{trust\_level} < 3)](x)\sigma.P$$

Examples of interactions...

Broadcast synchronisation:

$$(\text{stop}^{\star}[\text{bl} < 5\%]\langle v\rangle\sigma_1.P \;, \{role = \text{“}master\text{”}\}) \parallel$$
$$(\text{stop}^{\star}[\text{role} = \text{“}master\text{”}](x)\sigma_2 \;.Q_1 \;, \{\text{bl} = 4\%\}) \parallel$$
$$(\text{stop}^{\star}[\text{role} = \text{“}super\text{”}](x)\sigma_3.Q_2 \;, \{\text{bl} = 2\%\}) \parallel$$
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$$\Downarrow$$

$$(P, \sigma_1(\{role = \text{“}master\text{''}\})) \parallel$$
$$(Q_1[v/x], \sigma_2(\{\text{bl} = 4\%\})) \parallel$$
$$(\text{stop}^\star[\text{role} = \text{“}super\text{''}](x)\sigma_3.Q_2, \{\text{bl} = 2\%\}) \parallel$$
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Modelling the environment

Interactions between components can be affected by the environment:

- a wall can inhibit wireless interactions;
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- is used to model the intrinsic rules that govern the physical context;
- consists of a pair (γ, ρ):
  - a global store γ, that captures knowledge at the system level;
  - an evolution rule ρ that regulates component interactions (receiving probabilities, action rates,...).

Example: Smart Taxi System

System description:

- We consider a set of taxis operating in a city, providing service to users;
- Both taxis and users are modelled as components.
- The city is subdivided into a number of patches arranged in a grid over the geography of the city.
- The users arrive randomly in different patches, at a rate that depends on the specific time of day.
- After arrival, a user makes a call for a taxi and then waits in that patch until they successfully engage a taxi and move to another randomly chosen patch.
- Unengaged taxis move about the city, influenced by the calls made by users.

J.Hillston and M.Loreti. Specification and analysis of open-ended systems with CARMA. In LNCS 9068, 2015.

Taxis and Users: stores

Both kinds of component use the local store to publish the relevant data that will be used to represent the state of the agent.

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Taxis

- *loc*: identifies current taxi location;
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- *dest*: if occupied, this attribute indicates the destination of the taxi journey.

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Users

- *loc*: identifies user location;
- *dest*: indicates user destination.

User processes

Users

process *User* =

$$Wait : \mathrm{call}^{\star}[\top]\langle \mathrm{my.loc.}x, \mathrm{my.loc.}y\rangle.Wait$$

$$+$$

$$\mathrm{take}[\mathrm{loc.}x == \mathrm{my.loc.}x \ \wedge\ \mathrm{loc.}y == \mathrm{my.loc.}y]$$

$$\langle \mathrm{my.dest.}x, \mathrm{my.dest.}y\rangle.\mathbf{kill}$$

endprocess

Taxi processes

Taxis

$$
\begin{aligned}
&\text{process } \mathit{Taxi} = \\
&\qquad F : \text{call}^{\star}[(\text{my.loc.x} \neq \text{posx}) \;\wedge\; \text{my.loc.y} \neq \text{posy}](\mathit{posx}, \mathit{posy}) \\
&\qquad\qquad\qquad\qquad \{\text{dest} := [x := \mathit{posx}, y := \mathit{posy}]\}.G \\
&\qquad\quad + \\
&\qquad\quad \text{take}[\top](\mathit{posx}, \mathit{posy}) \\
&\qquad\qquad\qquad \{\text{dest} := [x := \mathit{posx}, y := \mathit{posy}], \text{occupancy} := 1\}.G \\
&\qquad G : \text{move}^{\star}[\bot]\langle\circ\rangle \\
&\qquad\qquad \{\text{loc} := \text{dest}, \text{dest} := [x := 3, y := 3], \text{occupancy} := 0\}.F \\
&\text{endprocess}
\end{aligned}
$$

Modelling arrivals

The Arrivals process has a single attribute loc.

Arrivals process for users

$$
\begin{aligned}
&\text{process } \mathit{Arrivals} = \\
&\qquad A : \text{arrival}^{\star}[\bot]\langle\circ\rangle.A \\
&\text{endprocess}
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The precise role of this process will be clear when the environment is described.

The environment

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We also do not assume perfect communication, i.e. there may be a probability that an interaction will fail to complete even between components with appropriately match attributes.

The environment manages these aspects of system behaviour, and others in the evolution rule.

The evolution rule ρ

ρ is a function, dependent on current time, the global store and the current state of the collective, returns a tuple of functions $\varepsilon = \langle \mu_p, \mu_w, \mu_r, \mu_u \rangle$ known as the evaluation context

- $\mu_p(\gamma_s, \gamma_r, \alpha)$: the probability that a component with store γ_r can receive a broadcast message α from a component with store γ_s;
- $\mu_w(\gamma_s, \gamma_r, \alpha)$: the weight to be used to compute the probability that a component with store γ_r can receive a unicast message α from a component with store γ_s;
- $\mu_r(\gamma_s, \alpha)$ computes the execution rate of action α executed at a component with store γ_s;
- $\mu_u(\gamma_s, \alpha)$ determines the updates to the environment (global store and collective) induced by the execution of action α at a component with store γ_s.

Evolution rule: μ_p

Defining the probabilities of broadcast actions

$$\begin{array}{l} \mathsf{prob}\{ \\ \qquad \top, \mathsf{call}^\star : \mathsf{global.p}_{\mathsf{lost}} \\ \qquad \mathsf{default} \;\; 1 \\ \} \end{array}$$

- call* can be missed with a probability p_{lost} defined in the global store.
- All the other interactions occur with probability 1.

Evolution rule: μ_w

Defining the weights of unicast actions

$$
\begin{array}{l}
\text{prob}\{ \\
\qquad \top, \text{take} : \mathit{Takeprob}(\mathit{real}(\#\{\mathit{Taxi}[F] \mid \\
\qquad\qquad\qquad (\text{my.loc.x} == \text{sender.loc.x}) \wedge \\
\qquad\qquad\qquad (\text{my.loc.y} == \text{sender.loc.y})\})); \\
\}
\end{array}
$$

- Each taxi receives a user request (take) with a weight that depends on the number of taxis in the patch.

Evolution rule: μ_r

Defining the rates of actions

$$
\begin{array}{l}
\mathsf{rate}\{ \\
\quad \top, \mathsf{take} : \mathsf{global.r_t} \\
\quad \top, \mathsf{call}^\star : \mathsf{global.r_c} \\
\quad \top, \mathsf{move}^\star : \mathit{Mtime}(\mathsf{now}, \mathsf{sender.loc}, \mathsf{sender.dest}, 6) \\
\quad \top, \mathsf{arrival}^\star : \mathit{Atime}(\mathsf{now}, \mathsf{sender.loc}, 1) \\
\quad \mathsf{default} \;\; 0 \\
\}
\end{array}
$$

While take and call have constant rates, the rates of the actions move and arrival are functions that depend on time, reflecting shifting traffic patterns within the city over the course of a day.

Evolution rule: μ_u

In the taxi example, the arrival of a new user is achieved via the update rule:

Update rule

$$\begin{array}{l}\text{update}\{\\ \qquad \top, \text{arrival}^{\star} : \textbf{new } \text{User}(\text{sender.loc}, \text{DestLoc}(\text{now}, \text{sender.loc}), \text{Wait})\\ \}\end{array}$$

Measures

To extract data from a system, a CARMA specification also contains a set of measures.

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The number of waiting users at a location

$$\textbf{measure}\ \mathrm{WaitingUser}_{00}[i := 0] = \#\{\mathrm{User}[\mathrm{Wait}] \mid \mathrm{my.loc.x} == 0\ \wedge\ \mathrm{my.loc.y} == 0\};$$

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measure $\mathrm{WaitingUser}_{00}[i := 0] = \#\{\mathrm{User}[\mathrm{Wait}] \mid \mathrm{my.loc.x} == 0 \ \wedge \ \mathrm{my.loc.y} == 0\};$

The number of taxis relocating

measure $\mathrm{Taxi\_Relocating}[i := 1] = \#\{\mathrm{Taxi}[G] \mid \mathrm{my.occupancy} == 0\};$

Two Scenarios

We consider a grid of 3×3 patches, i.e., a set of locations (i, j) where $0 \leq i, j \leq 2$, and two different scenarios:

Scenario 1: Users arrive in all the patches at the same rate;

Scenario 2: At the beginning users arrive with a higher probability to the patches at the border of the grid; subsequently, users arrive with higher probability in the centre of the grid.

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Scenario 2: At the beginning users arrive with a higher probability to the patches at the border of the grid; subsequently, users arrive with higher probability in the centre of the grid.

These are investigated by placing the same collective in different environments.

Smart Taxi System Collective

collective {
  new : Arrival(0 : 2, 0 : 2);
  new Taxi(0 : 2, 0 : 2, 3, 3, 0, F);
}

Quantitative Analysis

The semantics of CARMA gives rise to a Continuous Time Markov Chain (CTMC).

This can be analysed by

- by numerical analysis of the CTMC for small systems;
- by stochastic simulation of the CTMC;
- by fluid approximation of the CTMC under certain restrictions (particularly on the environment).

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This can be analysed by

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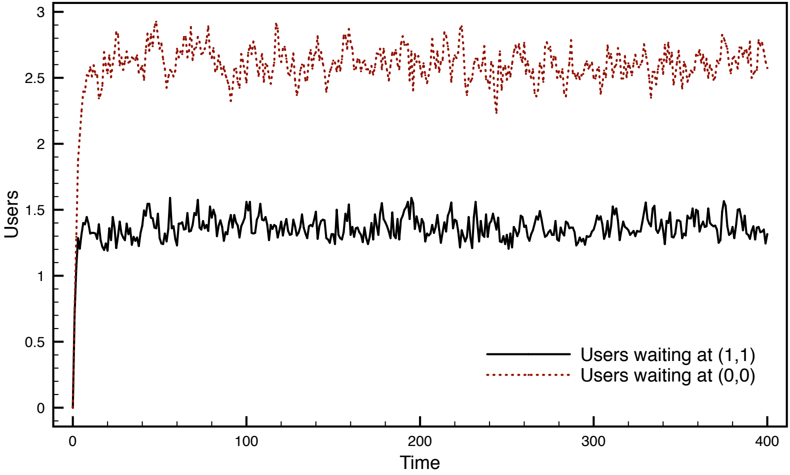
- by fluid approximation of the CTMC under certain restrictions (particularly on the environment).

Here we show the results of stochastic simulation.

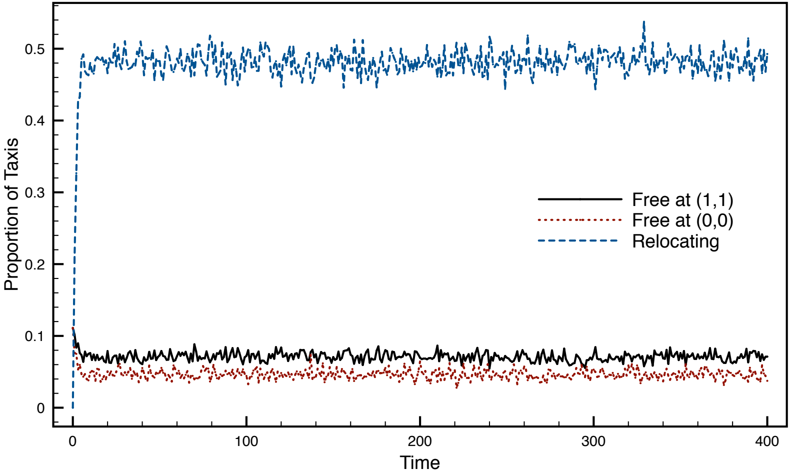
Scenario 1 results

Average number of users waiting at $(1, 1)$ and $(0, 0)$



Scenario 1 results

Proportion of free taxis at $(1,1)$ and $(0,0)$ and in transit

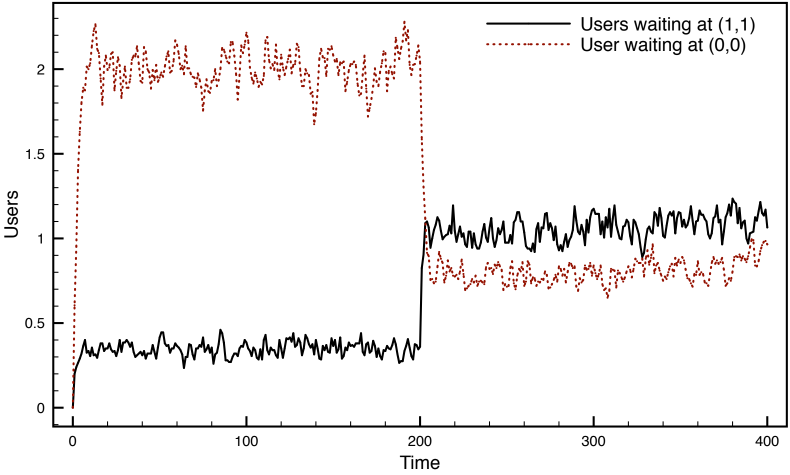


Comments: Scenario 1

- In Scenario 1 after an initial startup period, around 2.5 users are waiting for a taxi in the peripheral location while only 1.5 users are waiting for a taxi in location $(1, 1)$.
- In this scenario a larger fraction of users are delivered to location $(1, 1)$ so soon a larger fraction of taxis are available to collect users at the centre.
- A large fraction of taxis (around 50%) are continually moving between the different patches.

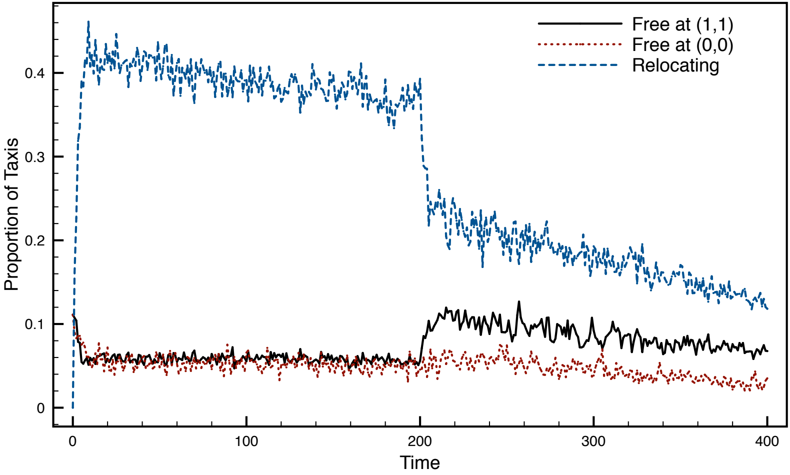
Scenario 2 results

Average number of users waiting at $(1, 1)$ and $(0, 0)$



Scenario 2 results

Proportion of free taxis at $(1, 1)$ and $(0, 0)$ and in transit



Comments: Scenario 2

- In Scenario 2 the location of new arrivals depends on the current time:
  - $[0, 200)$: 3/4 of users arrive on the border and only 1/4 in the centre;
  - $[200, 400)$: 1/4 of users arrive on the border and 3/4 in the centre.
- Results in the first phase are similar to Scenario 1.
- After time 200, the number of users waiting for a taxi in the border decreases below 1 whilst the average number waiting for a taxi in the centre increases to just over 1 and the fraction of taxis continually moving is reduced to 20%.

Outline

Concluding remarks

- Collective Systems are an interesting and challenging class of systems to design and construct.

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- CARMA aims to address many of these challenges, supporting rich forms of interaction, using attributes to capture explicit locations and the environment to allow adaptivity.

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- The complexity of these systems poses challenges both for model construction and model analysis.
- CARMA aims to address many of these challenges, supporting rich forms of interaction, using attributes to capture explicit locations and the environment to allow adaptivity.
- Fluid approximation based analysis offers hope for scalable quantitative analysis techniques, but this is yet to included in the tool.

Thanks!

Thanks!

Thanks to my collaborators and colleagues on the QUANTICOL project, especially Michele Loreti.

This work has been funded by the CEC through the FET-Proactive QUANTICOL project

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