Swarm Robotics – an overview –

Vito Trianni, PhD
Institute of Cognitive Sciences and Technologies
National Research Council
vito.trianni@istc.cnr.it

swarm robotics

- *swarm robotics* studies robotic systems composed of a multitude of interacting units
    - homogeneous systems or few heterogeneous groups
    - each unit is relatively simple and inexpensive
- individual limitations, absence of global information
    - limitations can be physical or functional
    - access to local and incomplete information only
- decentralised control
    - no *single point of failure*
    - *redundancy* is built-in in the system
- expected properties:
    - parallelism
    - robustness
    - adaptivity
    - scalability
    - efficiency

swarm robotics

- simple individuals and simple behaviours
- complexity results from cooperation
- research mainly focuses on:
  - development of specific hardware to support communication and physical interactions
  - development and test of swarm control systems
- *problem:* how to define individual rules?

design of decentralised systems

- distributed
- large number of interconnected agents
- self-organised

SWARM ROBOTICS

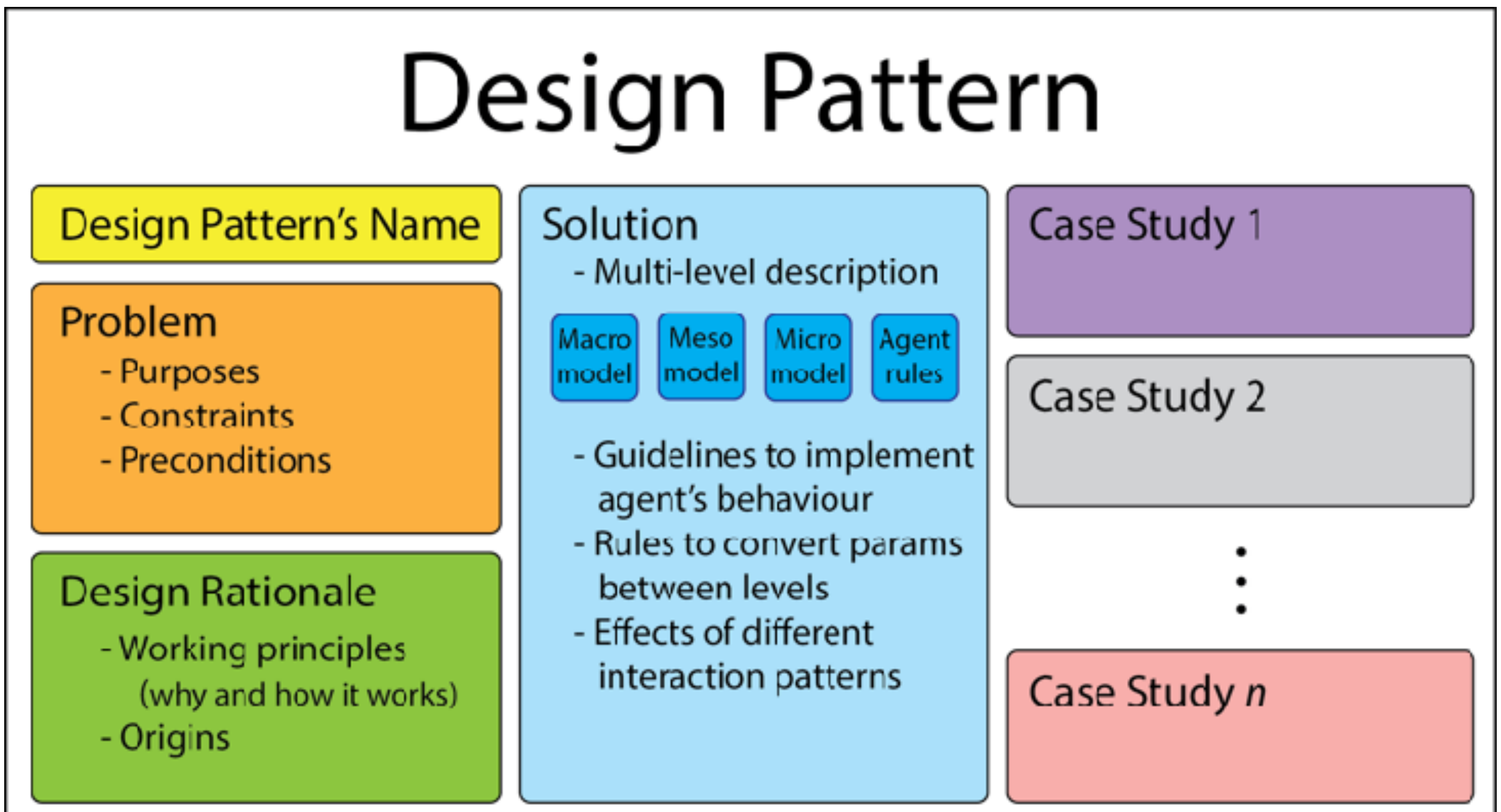
WIRELESS SENSOR NETWORKS

macroscopic behaviour → DESIGN PROBLEM → individual agent rules

Reina, A., Valentini, G., Fernández-Oto, C., Dorigo, M., & Trianni, V. (2015). A Design Pattern for Decentralised Decision Making. PLoS ONE, 10(10), e0140950–18.

design patterns

- reusable solutions for a specific class of problems
- leverage on the principled understanding of theoretical models of collective systems



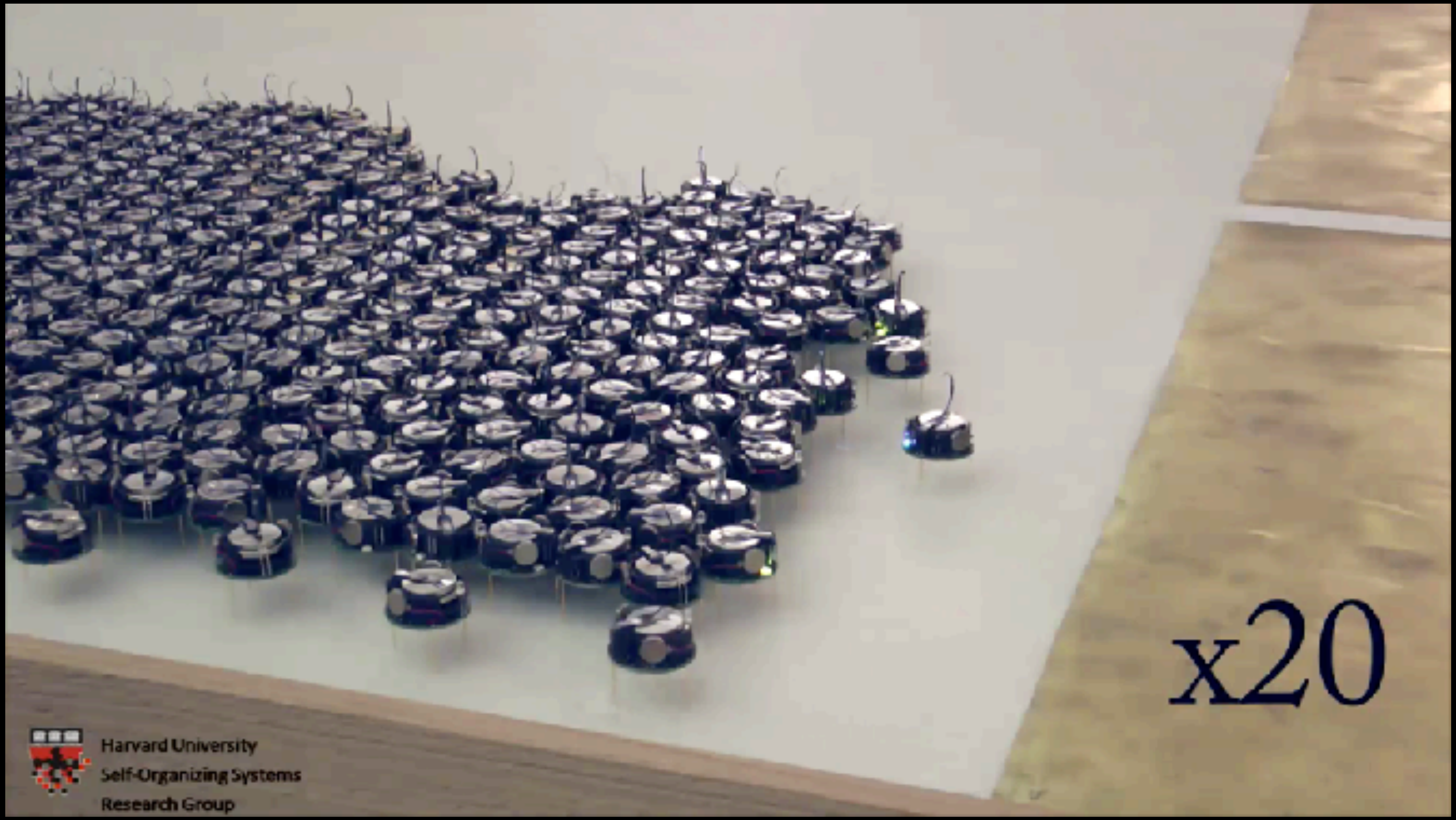
what design rationale
for robot swarms?

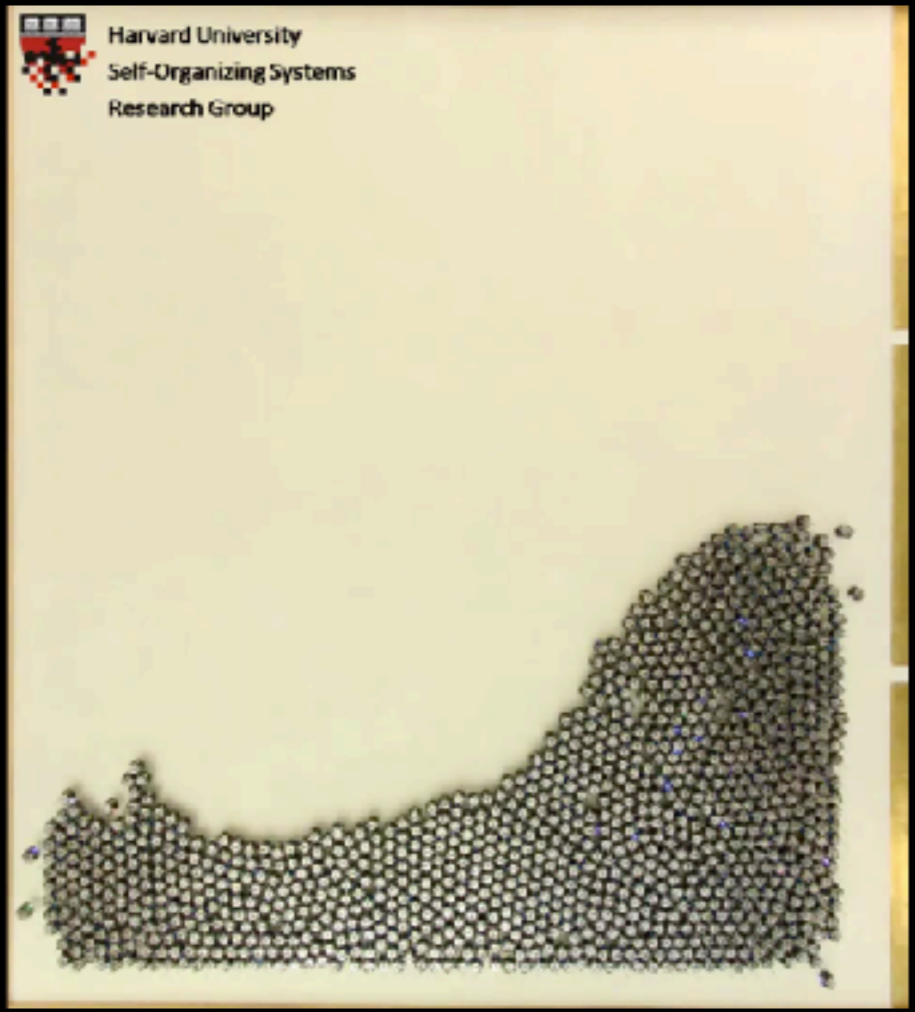
super-organisms

Swarm-Bots (2004)

Swarmanoid (2011)

Kilobots (2014)


x20
Harvard University
Self-Organizing Systems
Research Group


Harvard University
Self-Organizing Systems
Research Group

Verity Studios (2017)

perspectives

- potential application domains
  - agriculture and precision farming
  - security, search&rescue
  - logistics
  - space exploration
- swarm robotics still confined into the lab
- more research needed for higher cognitive skills
  - collective decision-making
  - task allocation
  - categorisation
  - learning

collective decisions

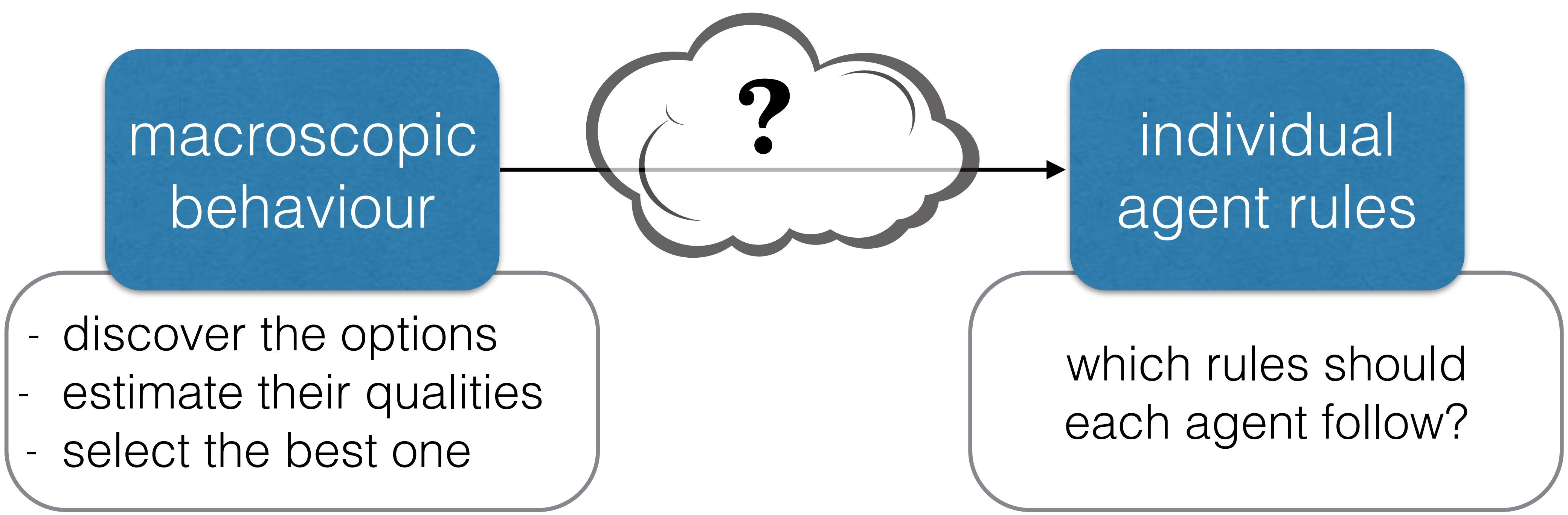
collective decisions

- *definition*:
  the process that leads a group to identify
  the best option out of several alternatives
- *precondition*:
  partial/noisy information about the available alternatives
- *postcondition*:
  the group (or a large majority) shares the same choice
- *constraints*:
  individuals cannot know/compare all alternatives

decentralised decision making

- best-of-*n* decision problem
- set of *n* options
- each option *i* has a quality v_i

- GOAL: select the best (or equal-best) option



design rationale

nest-site selection in honeybees

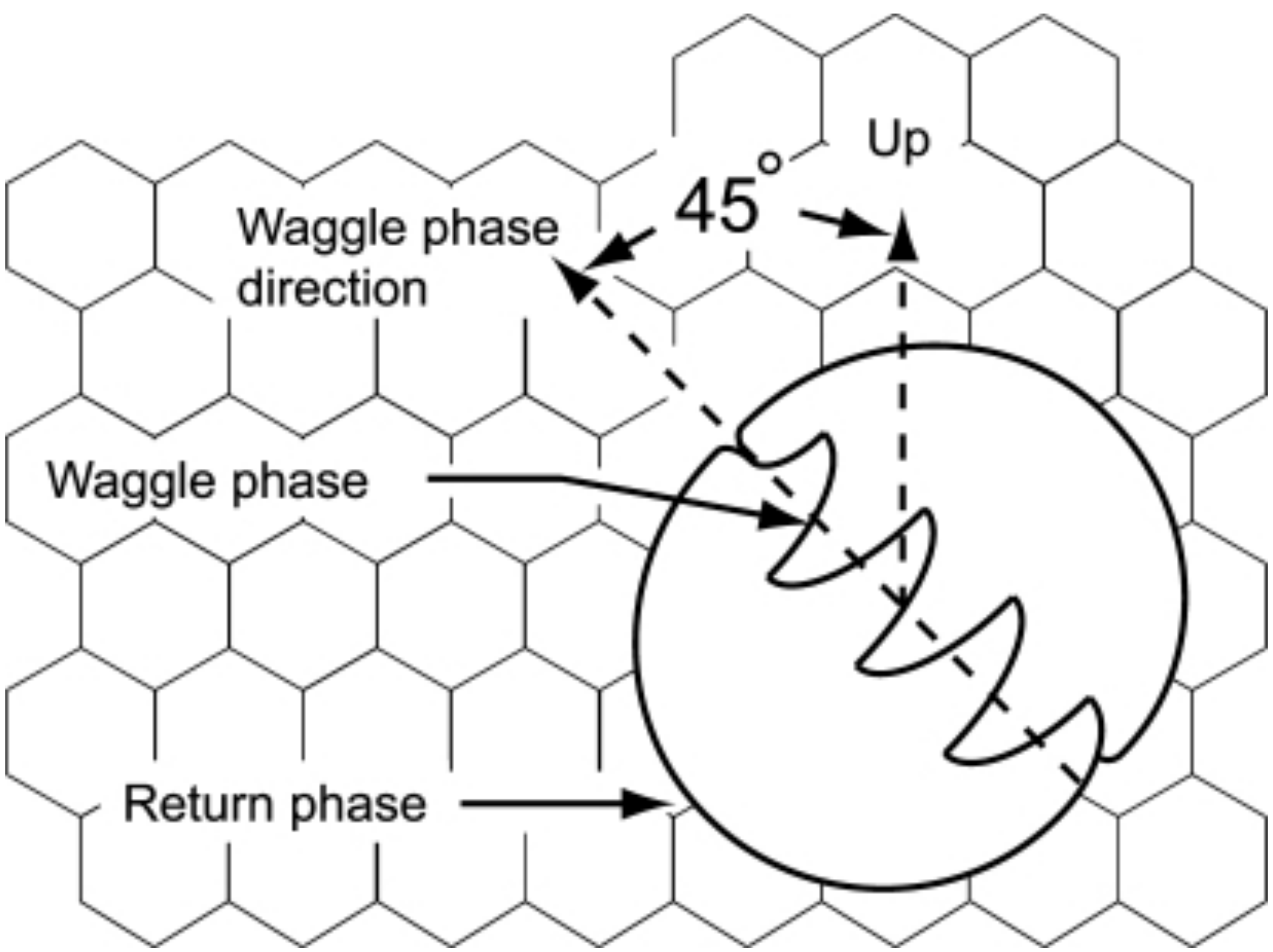
+ attains near-optimal speed-accuracy tradeoff
+ no need of direct comparison between option qualities
+ adaptive mechanisms to tune decision speed and break symmetry deadlocks

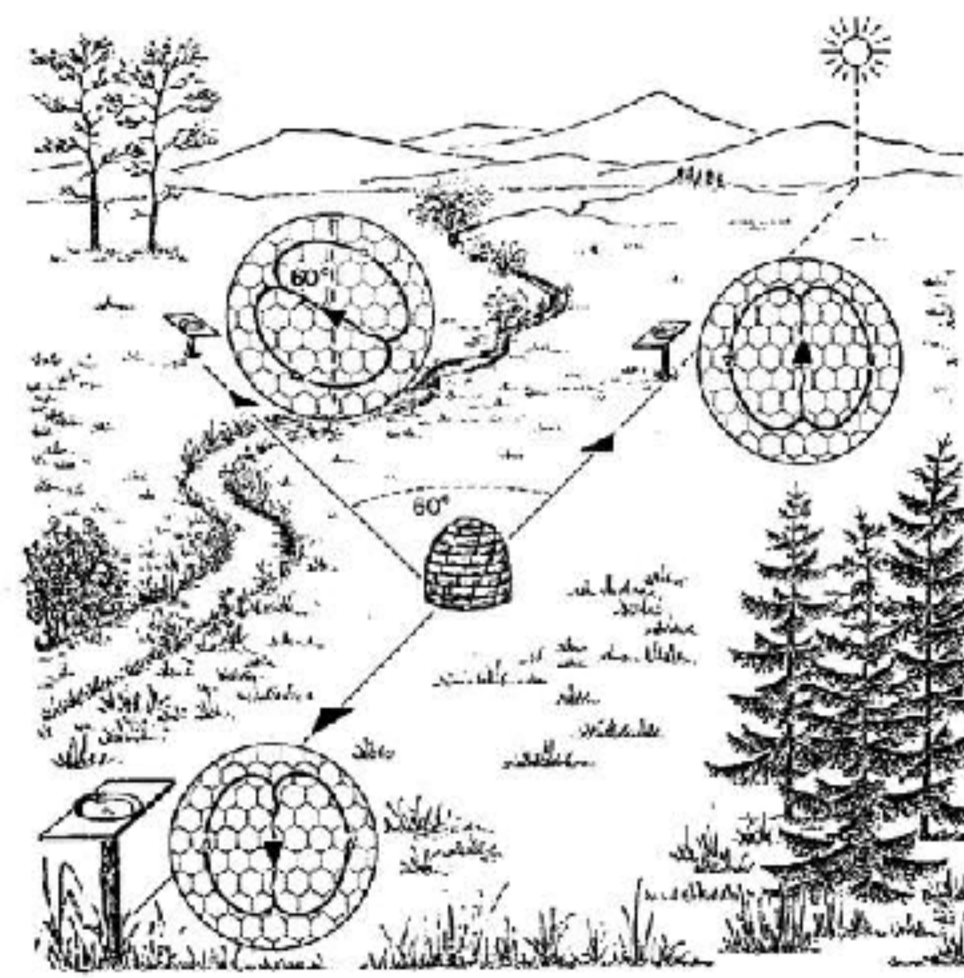
collective decisions in bees

a swarm needs to select the new nesting site

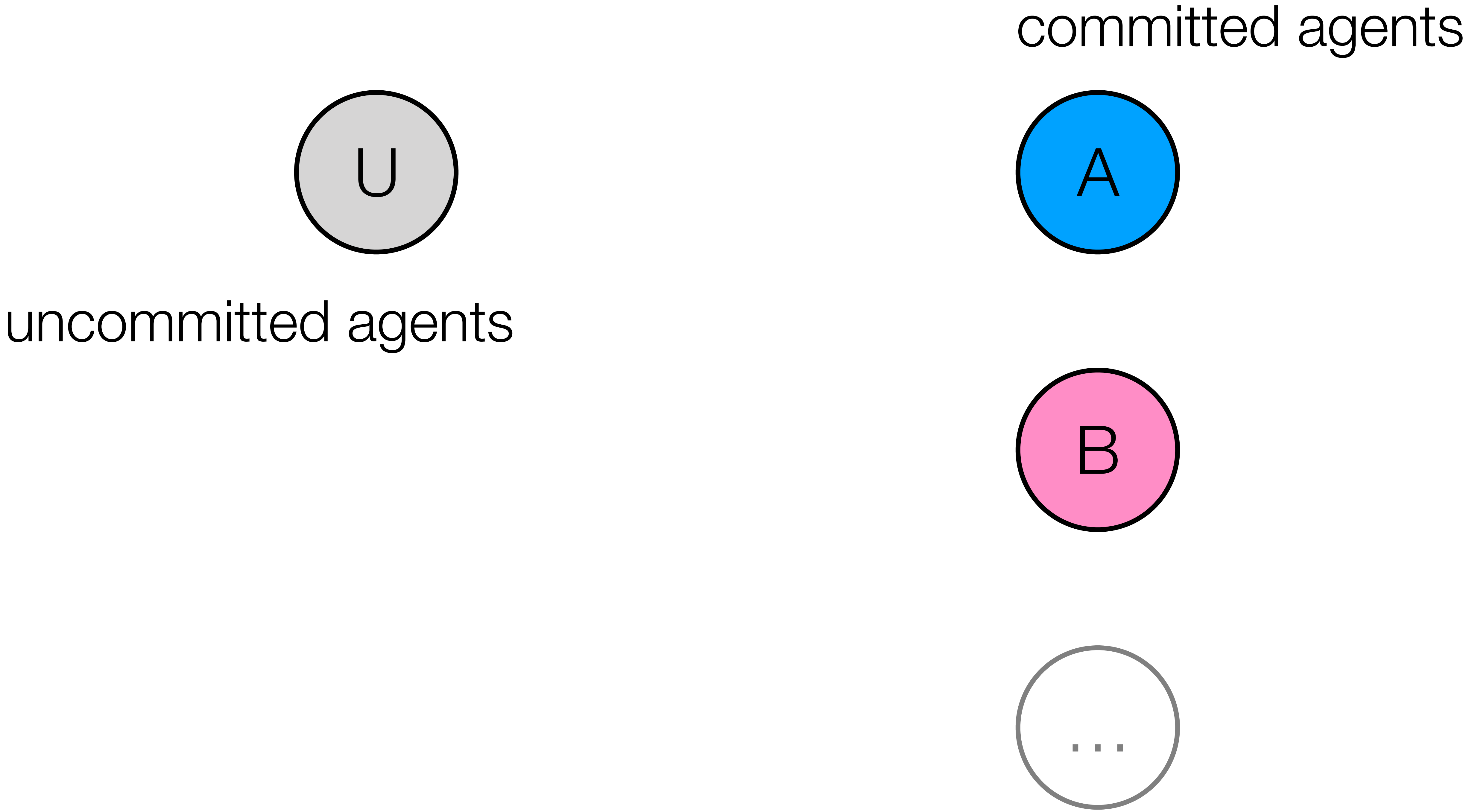
collective decisions in bees

scout bees identify the available alternatives and share information through the ‘waggle dance’

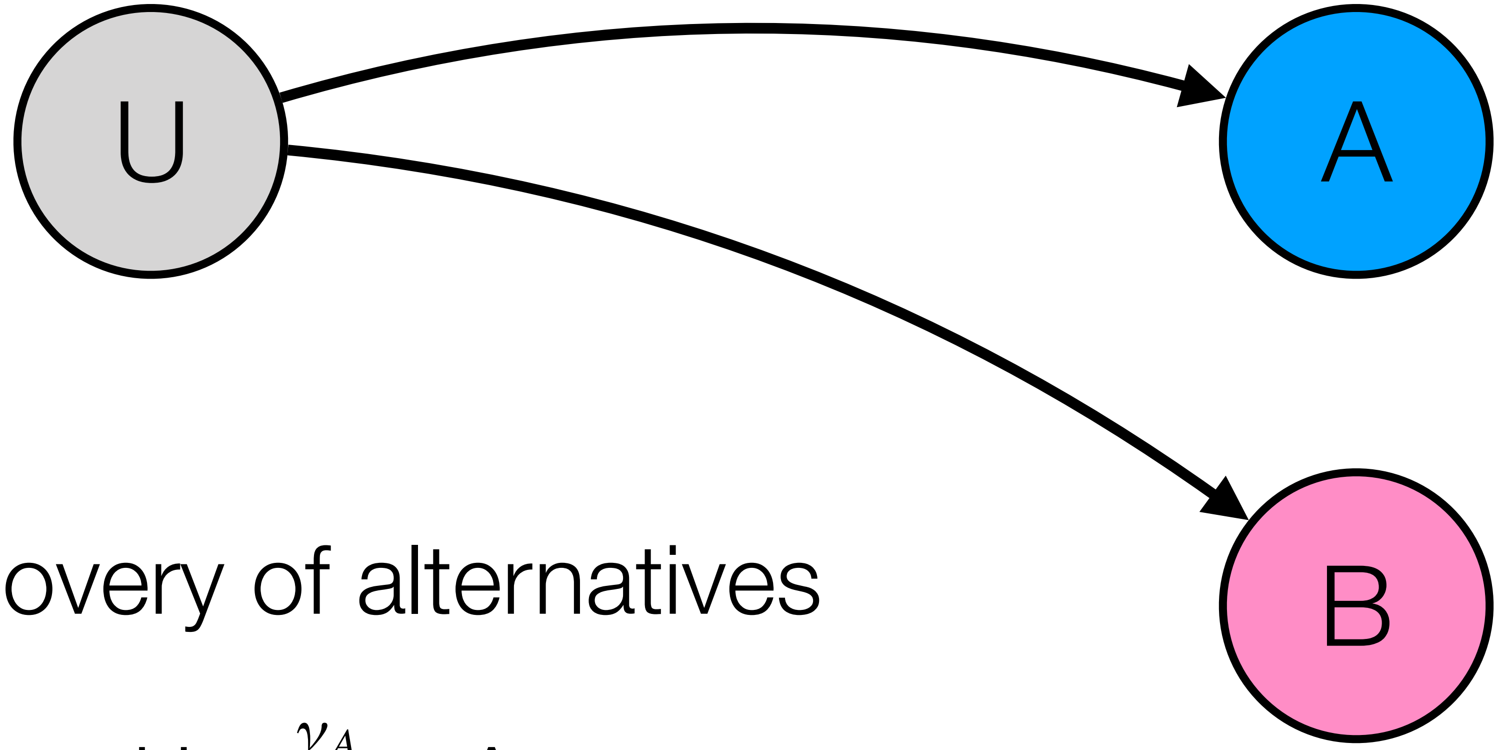




modelling collective decisions



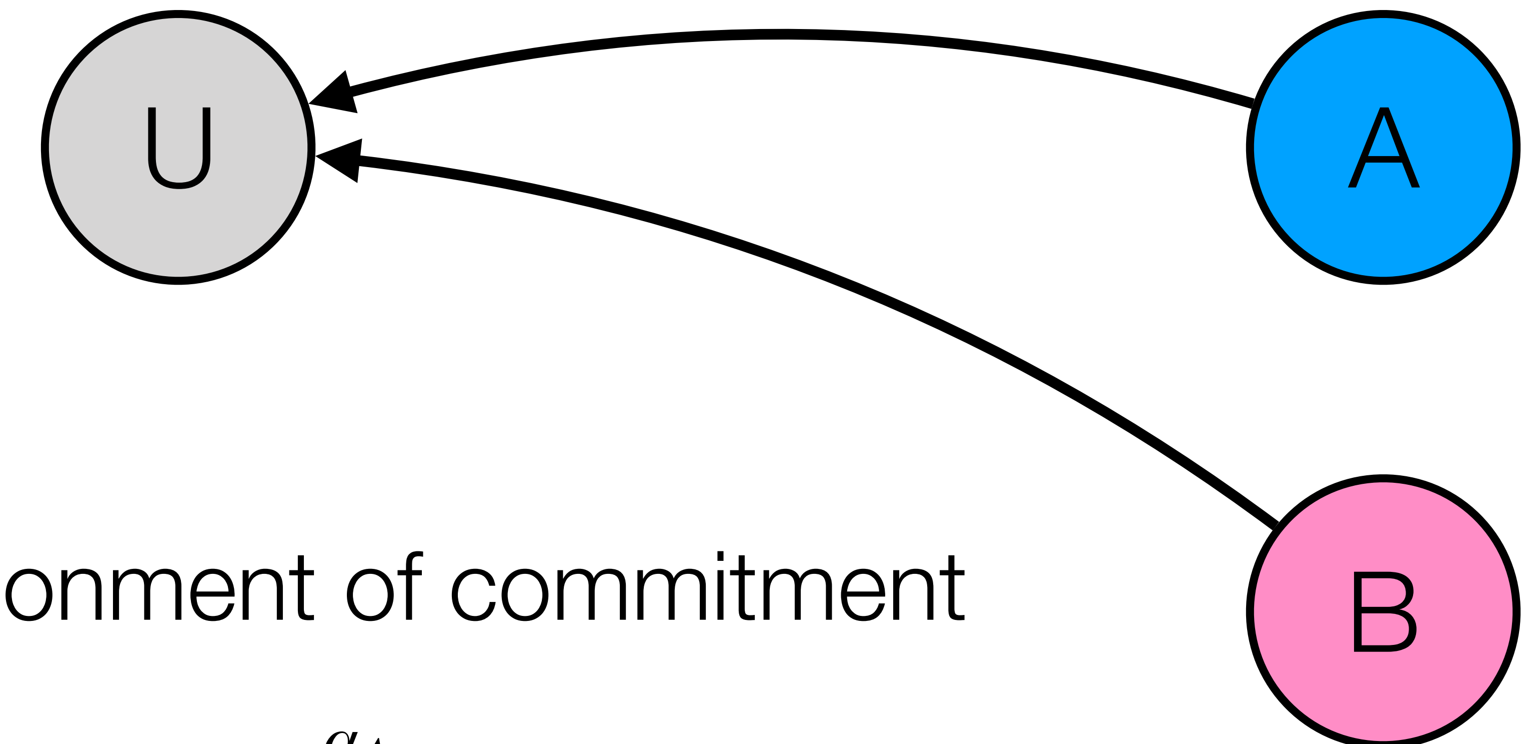
modelling collective decisions



discovery of alternatives

$$U \xrightarrow{\gamma_A} A$$
$$U \xrightarrow{\gamma_B} B$$

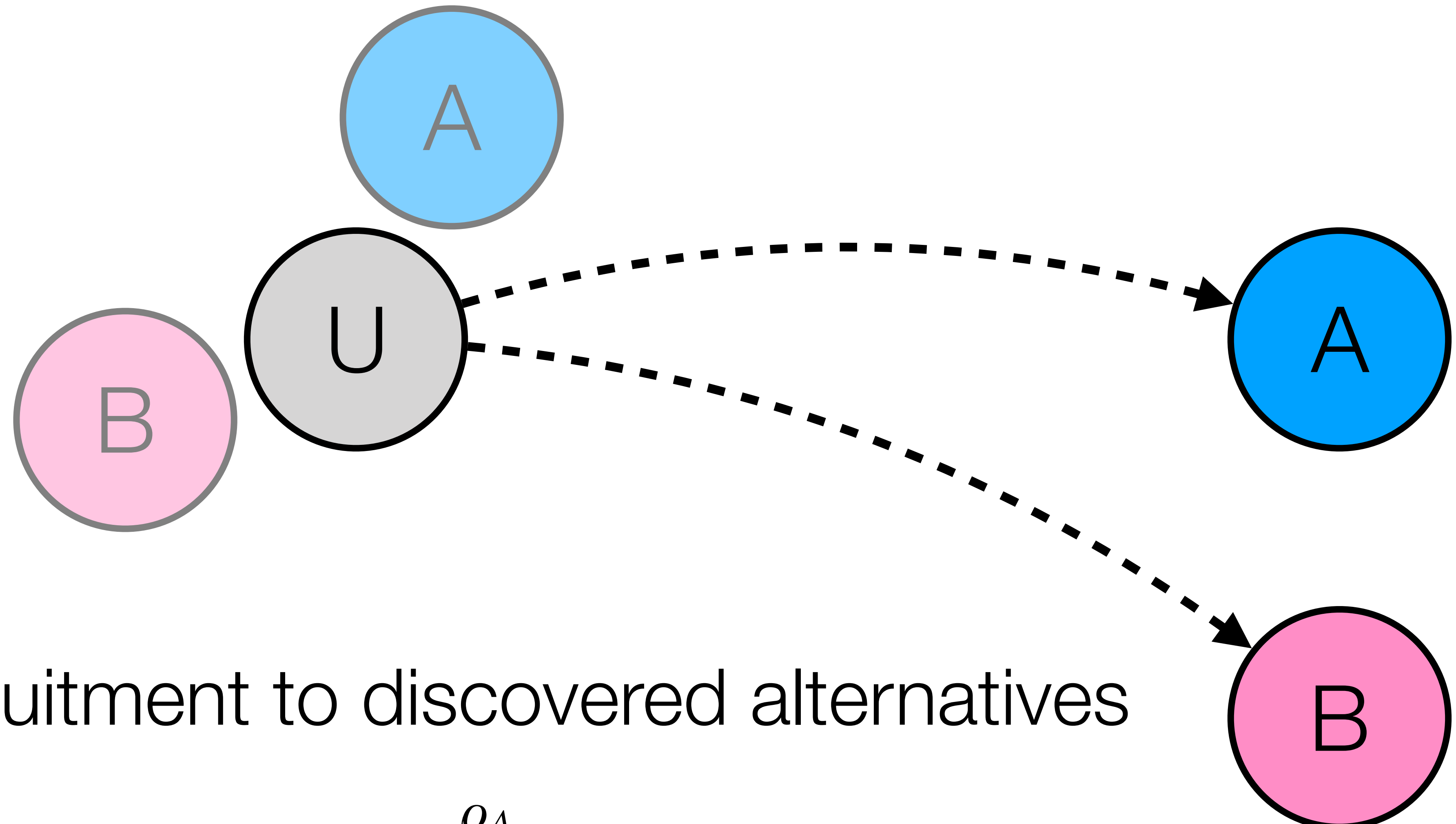
modelling collective decisions



abandonment of commitment

$$A \xrightarrow{\alpha_A} U$$
$$B \xrightarrow{\alpha_B} U$$

modelling collective decisions



recruitment to discovered alternatives

$$U+A \xrightarrow{Q_A} A+A$$
$$U+B \xrightarrow{Q_B} B+B$$

nest-site selection model

discovery:

$$U \longrightarrow A$$
$$U \longrightarrow B$$

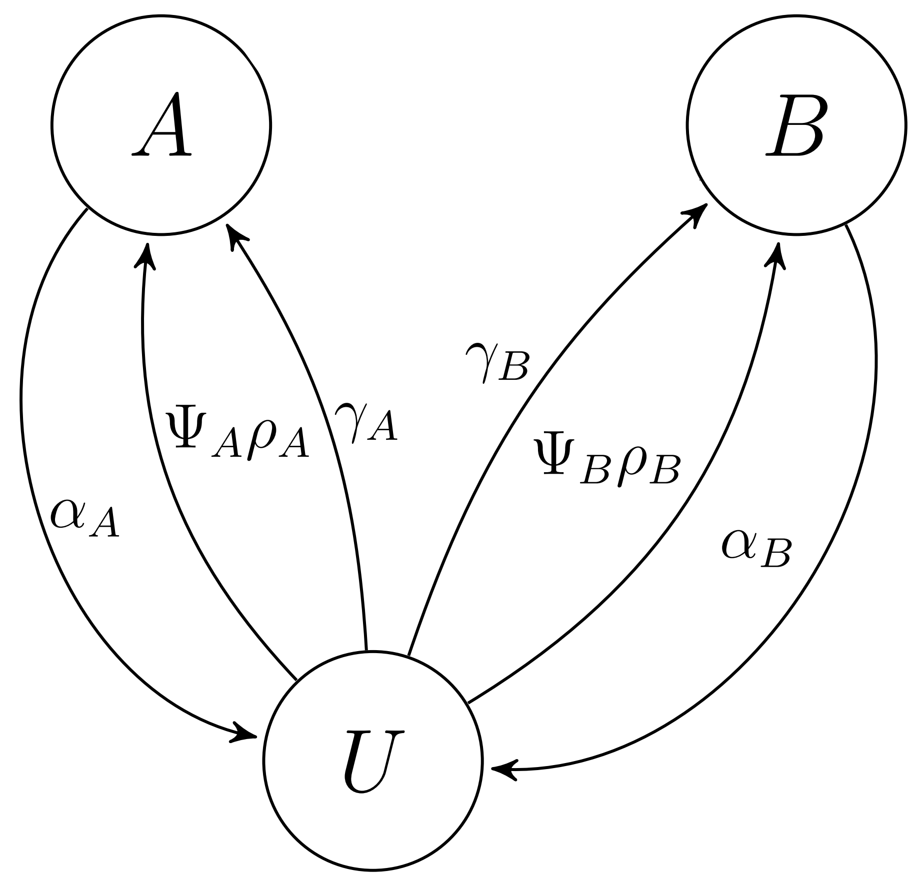
abandonment:

$$A \longrightarrow U$$
$$B \longrightarrow U$$

recruitment:

$$A+U \longrightarrow A+A$$
$$B+U \longrightarrow B+B$$

$$\begin{cases} \dot{\Psi}_A &= \gamma_A \Psi_U - \alpha_A \Psi_A + \rho_A \Psi_A \Psi_U \\ \dot{\Psi}_B &= \gamma_B \Psi_U - \alpha_B \Psi_B + \rho_B \Psi_B \Psi_U \\ \Psi_U &= 1 - \Psi_A - \Psi_B \end{cases}$$



nest-site selection model

discovery:

$$U \longrightarrow A$$
$$U \longrightarrow B$$

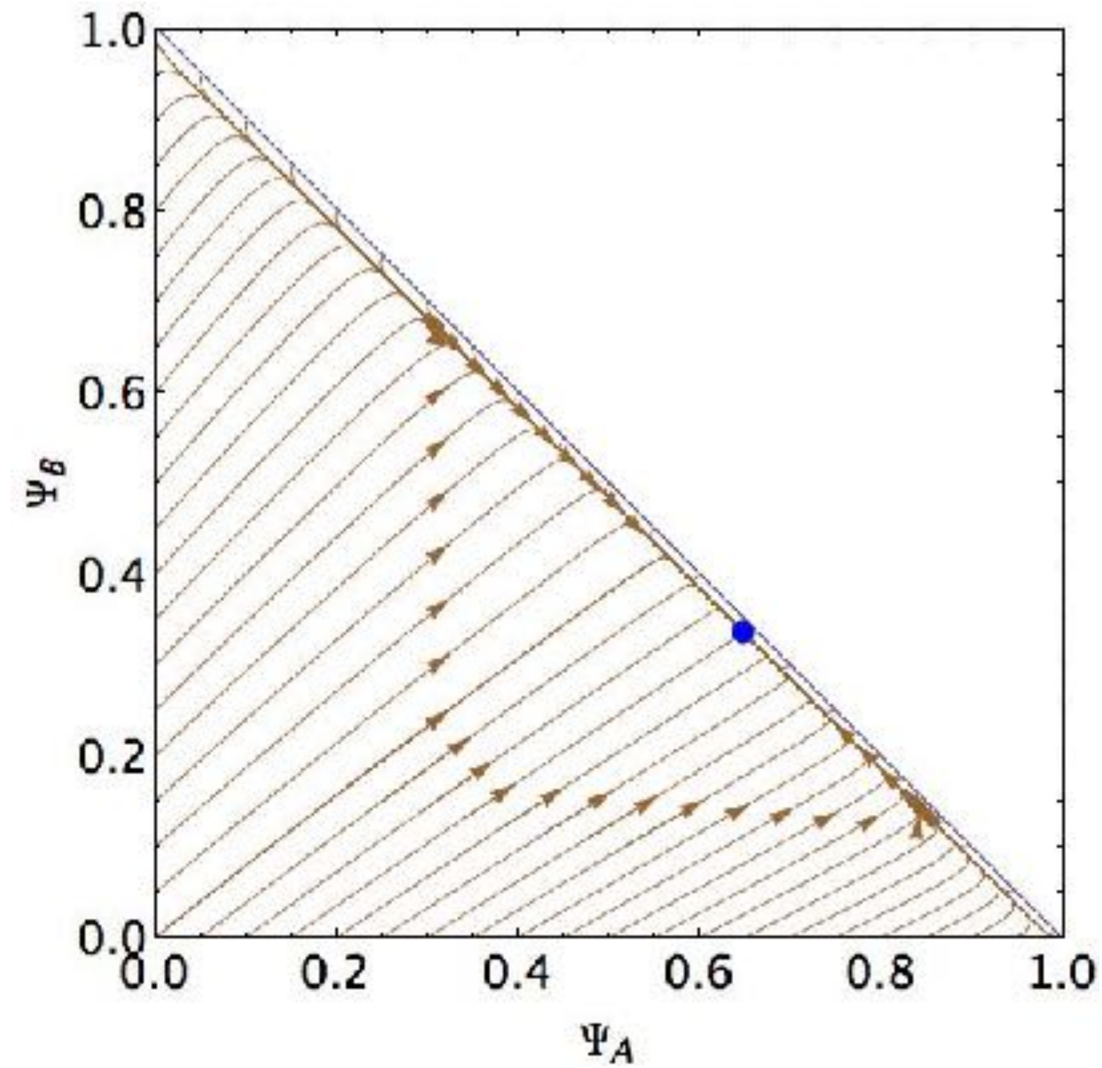
$$\begin{cases} \dot{\Psi}_A &= \gamma_A \Psi_U - \alpha_A \Psi_A + \rho_A \Psi_A \Psi_U \\ \dot{\Psi}_B &= \gamma_B \Psi_U - \alpha_B \Psi_B + \rho_B \Psi_B \Psi_U \\ \Psi_U &= 1 - \Psi_A - \Psi_B \end{cases}$$

abandonment:

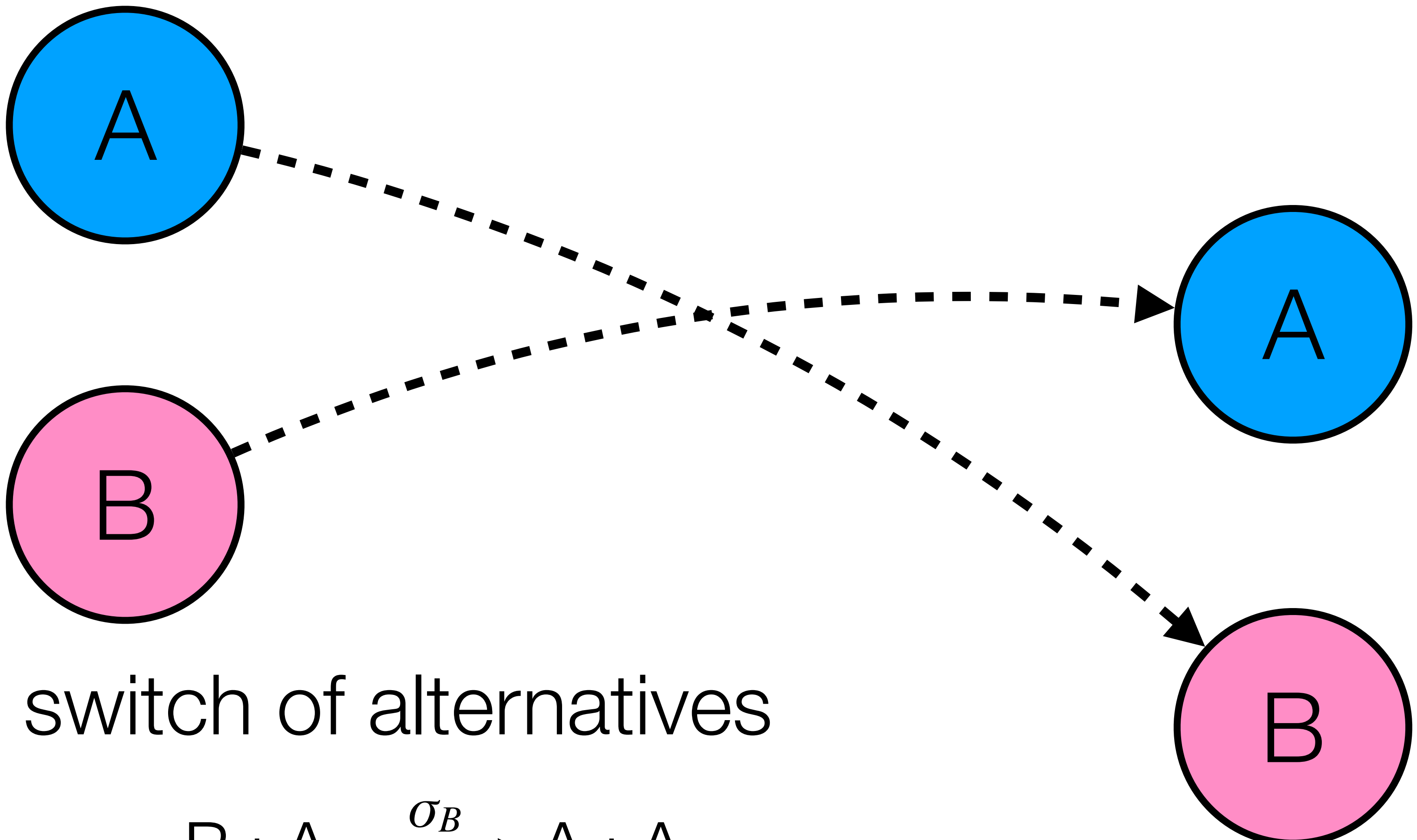
$$A \longrightarrow U$$
$$B \longrightarrow U$$

recruitment:

$$A+U \longrightarrow A+A$$
$$B+U \longrightarrow B+B$$



modelling collective decisions



switch of alternatives

$$\mathrm{B+A} \xrightarrow{\sigma_B} \mathrm{A+A}$$
$$\mathrm{A+B} \xrightarrow{\sigma_A} \mathrm{B+B}$$

nest-site selection model

discovery:

$$U \longrightarrow A$$
$$U \longrightarrow B$$

$$\begin{cases} \dot{\Psi}_A & = \gamma_A \Psi_U - \alpha_A \Psi_A + \rho_A \Psi_A \Psi_U - (\sigma_B - \sigma_A) \Psi_A \Psi_B \\ \dot{\Psi}_B & = \gamma_B \Psi_U - \alpha_B \Psi_B + \rho_B \Psi_B \Psi_U - (\sigma_A - \sigma_B) \Psi_A \Psi_B \\ \Psi_U & = 1 - \Psi_A - \Psi_B \end{cases}$$

abandonment:

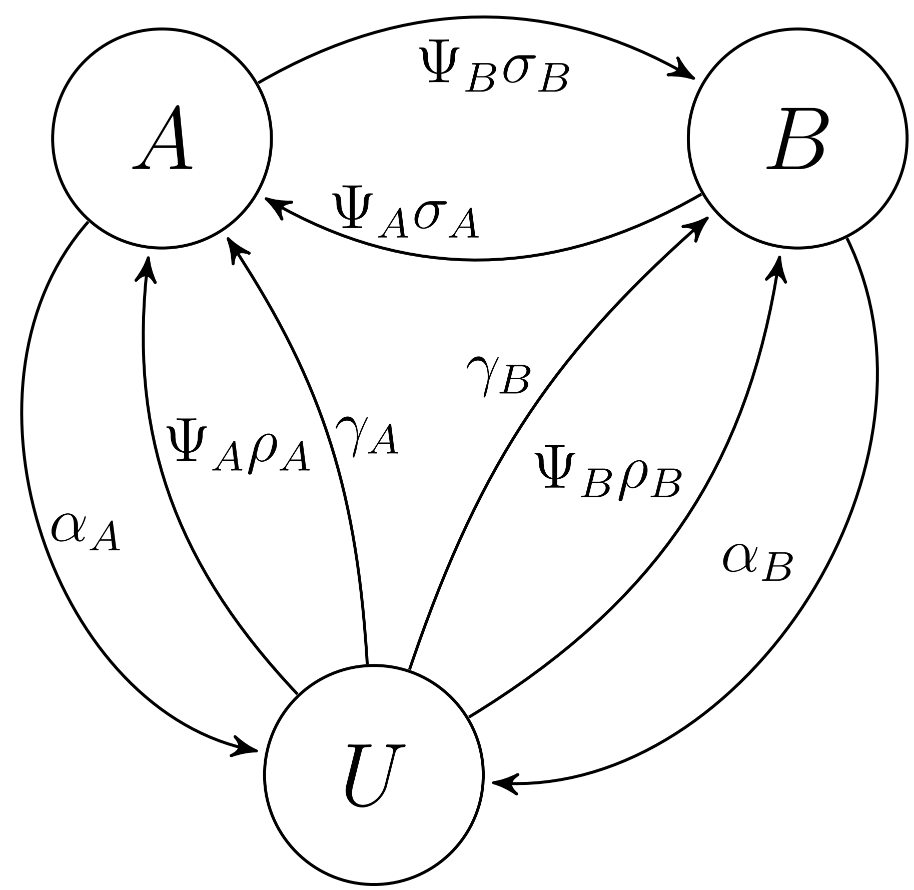
$$A \longrightarrow U$$
$$B \longrightarrow U$$

recruitment:

$$A+U \longrightarrow A+A$$
$$B+U \longrightarrow B+B$$

direct switch:

$$A+B \longrightarrow A+A$$
$$B+A \longrightarrow B+B$$



nest-site selection model

discovery:

U ⟶ A
U ⟶ B

$$
\begin{cases}
\dot{\Psi}_A &= \gamma_A \Psi_U - \alpha_A \Psi_A + \rho_A \Psi_A \Psi_U - (\sigma_B - \sigma_A)\Psi_A \Psi_B \\
\dot{\Psi}_B &= \gamma_B \Psi_U - \alpha_B \Psi_B + \rho_B \Psi_B \Psi_U - (\sigma_A - \sigma_B)\Psi_A \Psi_B \\
\Psi_U &= 1 - \Psi_A - \Psi_B
\end{cases}
$$

abandonment:

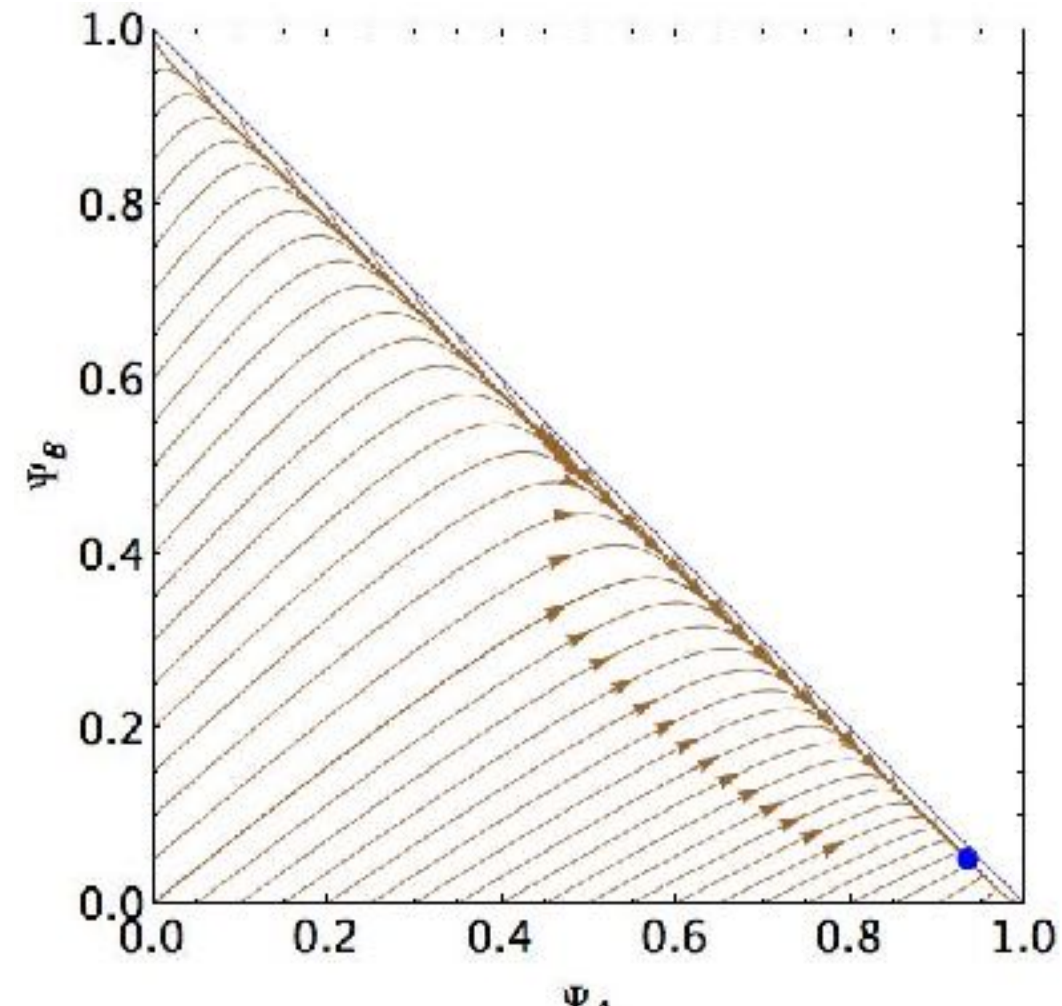
A ⟶ U
B ⟶ U

recruitment:

A+U ⟶ A+A
B+U ⟶ B+B

direct switch:

A+B ⟶ A+A
B+A ⟶ B+B



nest-site selection model

discovery:

$$U \longrightarrow A$$
$$U \longrightarrow B$$

$$\begin{cases} \dot{\Psi}_A &= \gamma_A \Psi_U - \alpha_A \Psi_A + \rho_A \Psi_A \Psi_U - (\sigma_B - \sigma_A) \Psi_A \Psi_B \\ \dot{\Psi}_B &= \gamma_B \Psi_U - \alpha_B \Psi_B + \rho_B \Psi_B \Psi_U - (\sigma_A - \sigma_B) \Psi_A \Psi_B \\ \Psi_U &= 1 - \Psi_A - \Psi_B \end{cases}$$

abandonment:

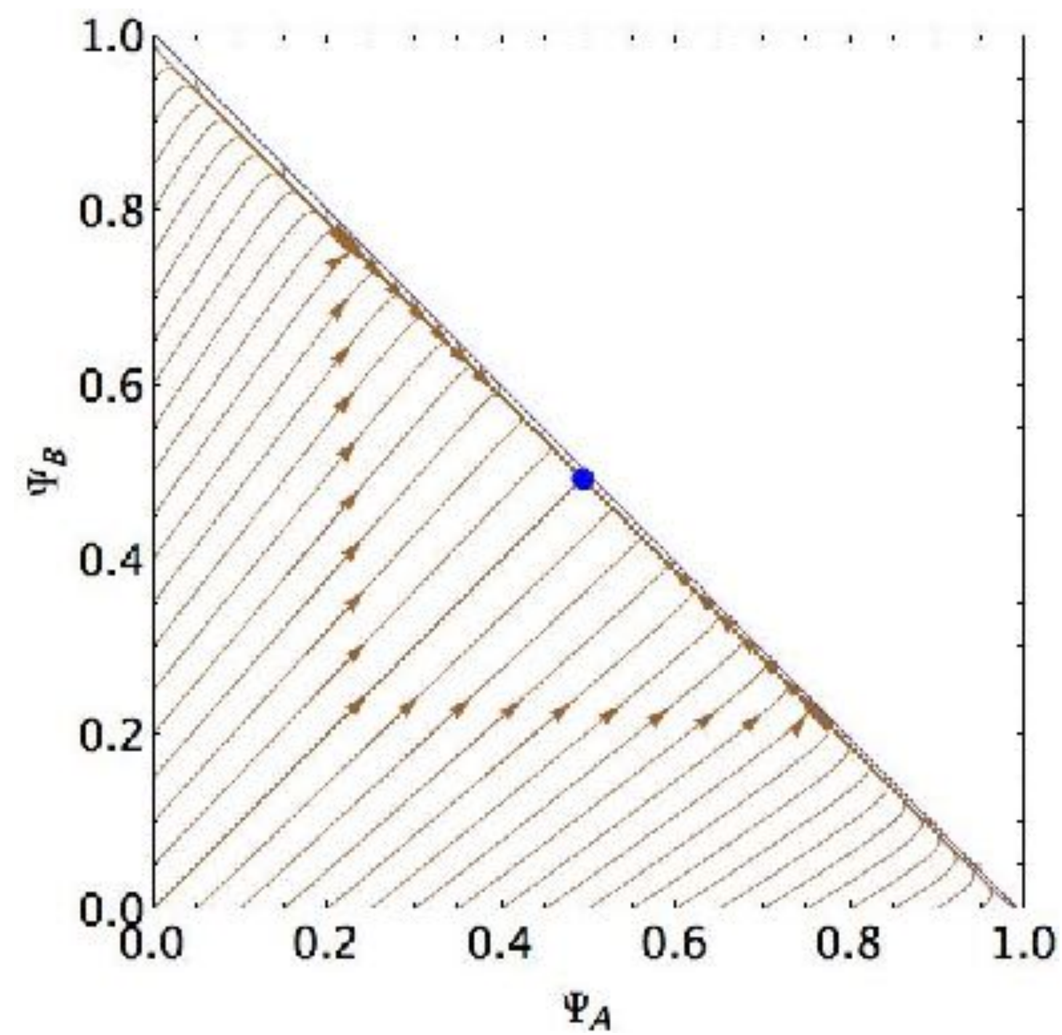
$$A \longrightarrow U$$
$$B \longrightarrow U$$

recruitment:

$$A+U \longrightarrow A+A$$
$$B+U \longrightarrow B+B$$

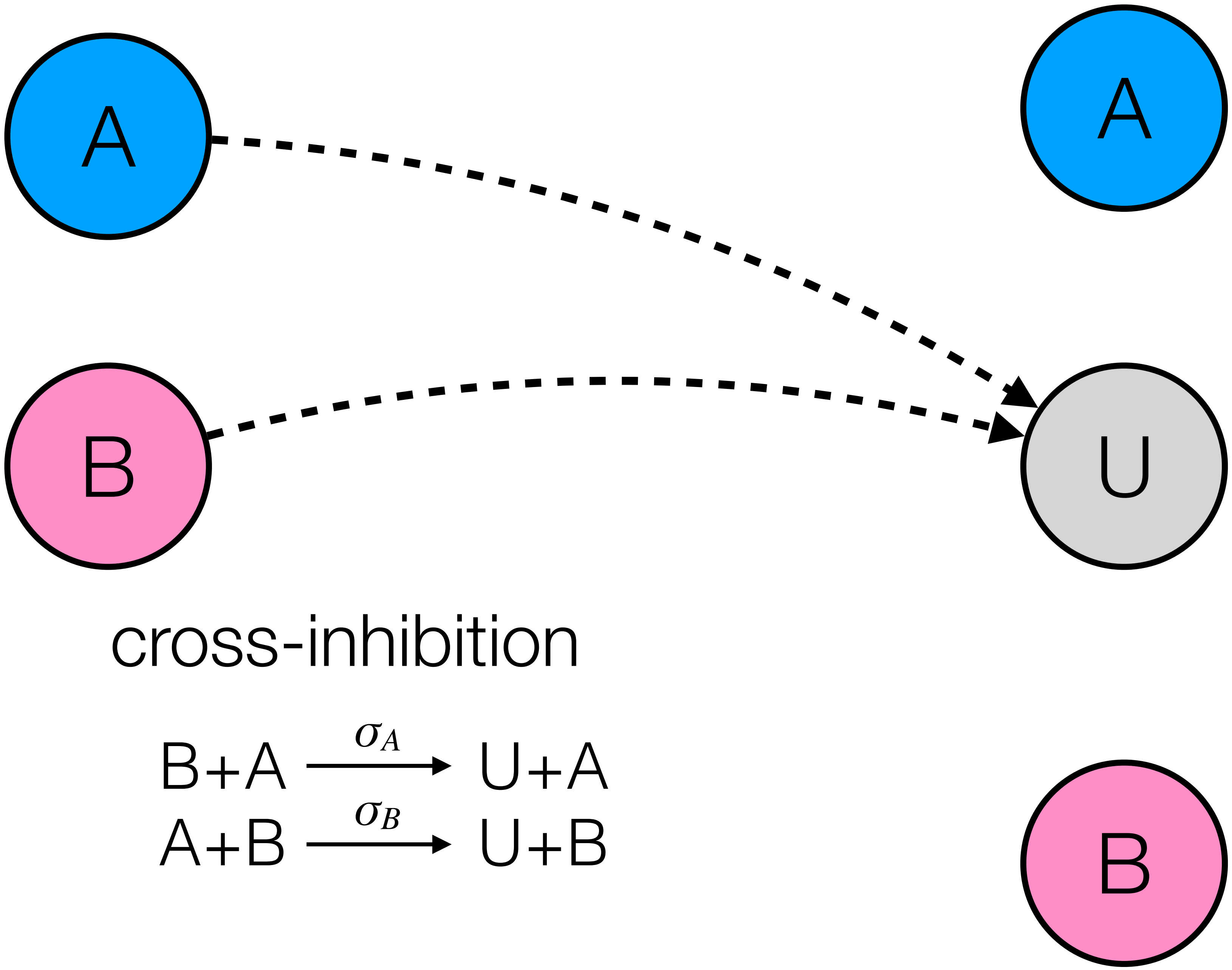
direct switch:

$$A+B \longrightarrow A+A$$
$$B+A \longrightarrow B+B$$



T. D. Seeley, P. K. Visscher, T. Schlegel, P. M. Hogan, N. R. Franks, and J. A. R. Marshall, “Stop Signals Provide Cross Inhibition in Collective Decision-Making by Honeybee Swarms”. Science, vol. 335, no. 6064, pp. 108–111, 2012.

modelling collective decisions



cross-inhibition

$$B + A \xrightarrow{\sigma_A} U + A$$
$$A + B \xrightarrow{\sigma_B} U + B$$

nest-site selection model

discovery:

$$U \longrightarrow A$$
$$U \longrightarrow B$$

$$\begin{cases} \dot{\Psi}_A = \gamma_A \Psi_U - \alpha_A \Psi_A + \rho_A \Psi_A \Psi_U - (\sigma_A - \sigma_B)\Psi_A \Psi_B \\ \dot{\Psi}_B = \gamma_B \Psi_U - \alpha_B \Psi_B + \rho_B \Psi_B \Psi_U - (\sigma_B - \sigma_A)\Psi_A \Psi_B \\ \Psi_U = 1 - \Psi_A - \Psi_B \end{cases}$$

abandonment:

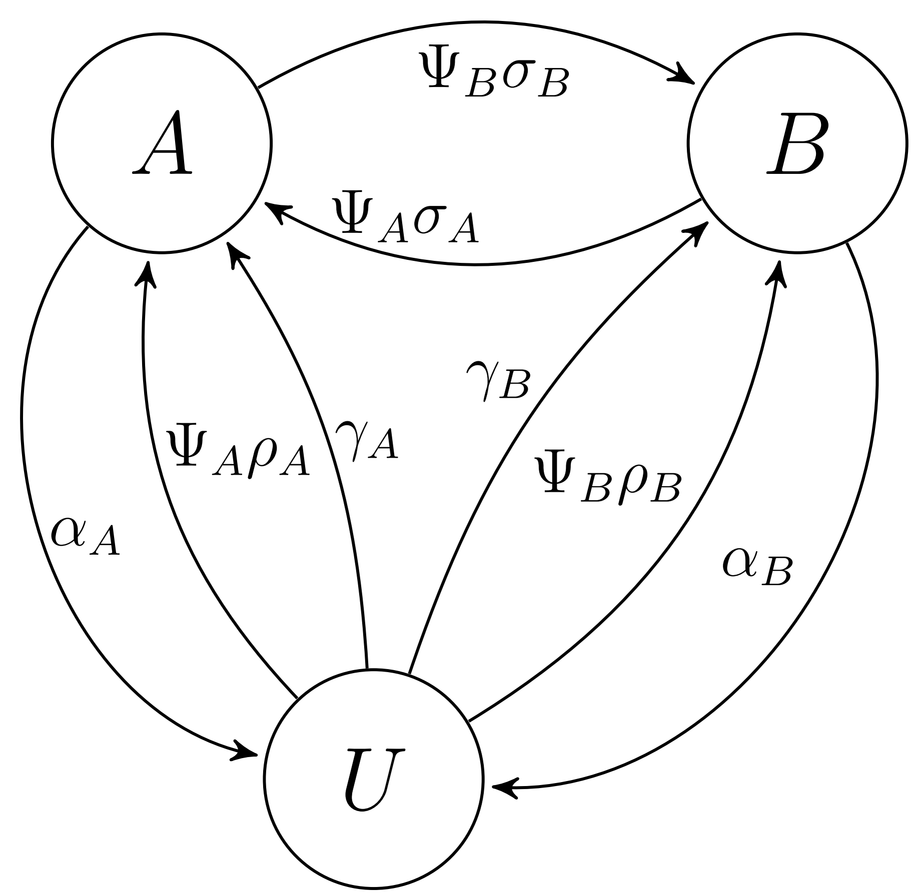
$$A \longrightarrow U$$
$$B \longrightarrow U$$

recruitment:

$$A+U \longrightarrow A+A$$
$$B+U \longrightarrow B+B$$

direct switch:

$$A+B \longrightarrow A+A$$
$$B+A \longrightarrow B+B$$



nest-site selection model

discovery:

$$\mathrm{U} \longrightarrow \mathrm{A}$$
$$\mathrm{U} \longrightarrow \mathrm{B}$$

abandonment:

$$\mathrm{A} \longrightarrow \mathrm{U}$$
$$\mathrm{B} \longrightarrow \mathrm{U}$$

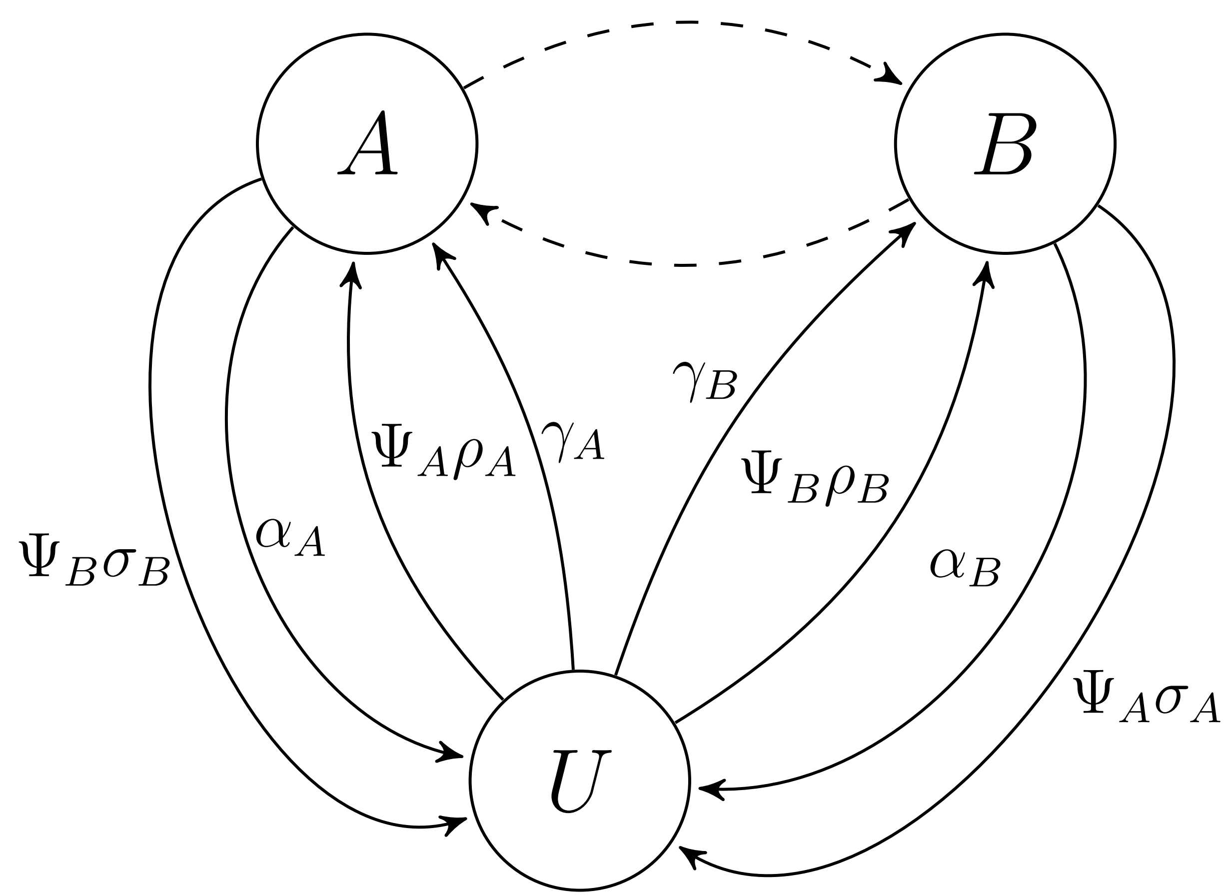
recruitment:

$$\mathrm{A+U} \longrightarrow \mathrm{A+A}$$
$$\mathrm{B+U} \longrightarrow \mathrm{B+B}$$

cross-inhibition

$$\mathrm{A+B} \longrightarrow \mathrm{A+U}$$
$$\mathrm{B+A} \longrightarrow \mathrm{B+U}$$

$$\begin{cases} \dot{\Psi}_A = \gamma_A \Psi_U - \alpha_A \Psi_A + \rho_A \Psi_A \Psi_U - \sigma_B \Psi_A \Psi_B \\ \dot{\Psi}_B = \gamma_B \Psi_U - \alpha_B \Psi_B + \rho_B \Psi_B \Psi_U - \sigma_A \Psi_A \Psi_B \\ \Psi_U = 1 - \Psi_A - \Psi_B \end{cases} ,$$



nest-site selection model

discovery:

$$U \longrightarrow A$$
$$U \longrightarrow B$$

abandonment:

$$A \longrightarrow U$$
$$B \longrightarrow U$$

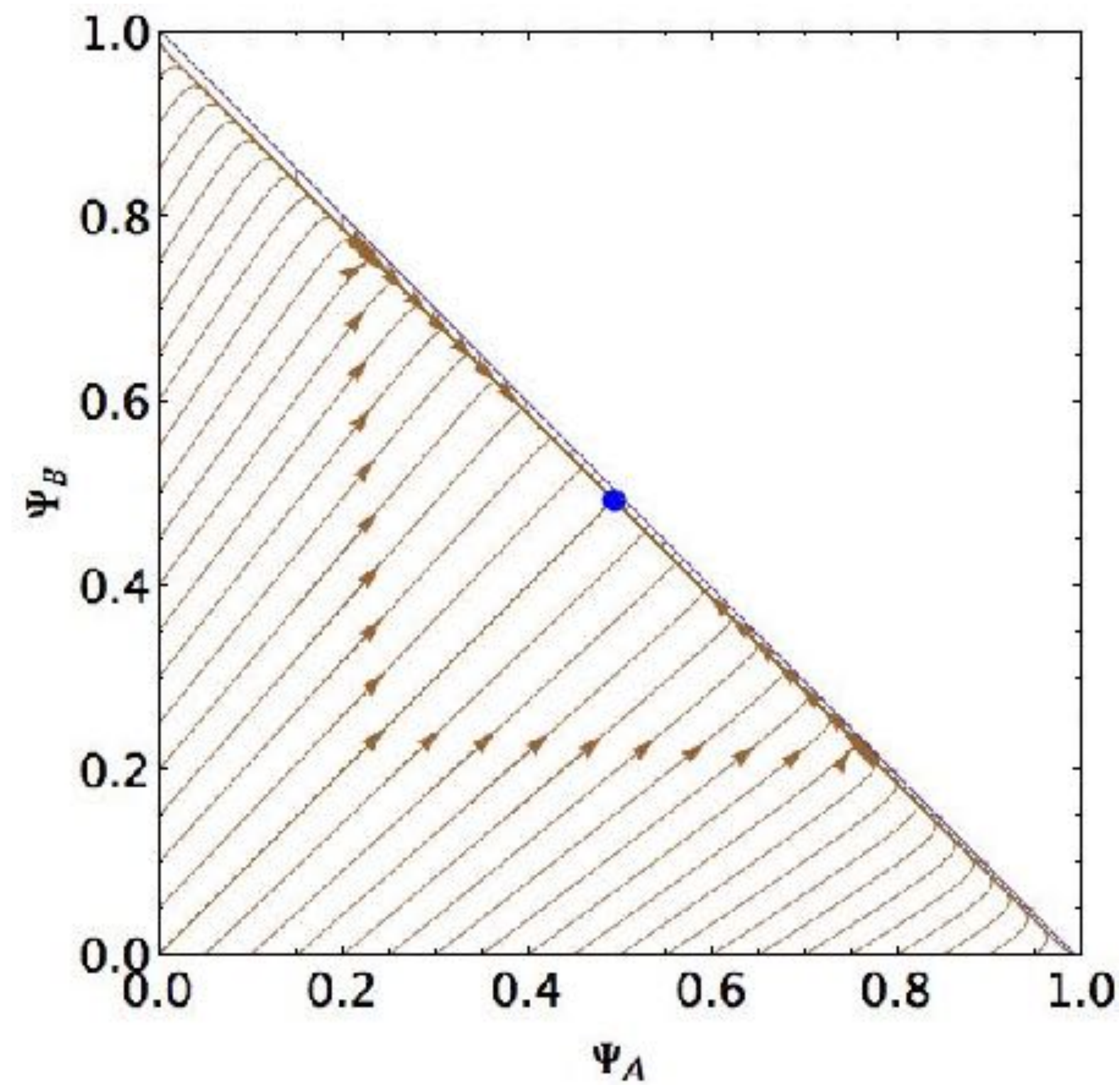
recruitment:

$$A+U \longrightarrow A+A$$
$$B+U \longrightarrow B+B$$

cross-inhibition

$$A+B \longrightarrow A+U$$
$$B+A \longrightarrow B+U$$

$$\begin{cases} \dot{\Psi}_A = \gamma_A \Psi_U - \alpha_A \Psi_A + \rho_A \Psi_A \Psi_U - \sigma_B \Psi_A \Psi_B \\ \dot{\Psi}_B = \gamma_B \Psi_U - \alpha_B \Psi_B + \rho_B \Psi_B \Psi_U - \sigma_A \Psi_A \Psi_B \\ \Psi_U = 1 - \Psi_A - \Psi_B \end{cases},$$



nest-site selection model

discovery:

$$U \longrightarrow A$$
$$U \longrightarrow B$$

abandonment:

$$A \longrightarrow U$$
$$B \longrightarrow U$$

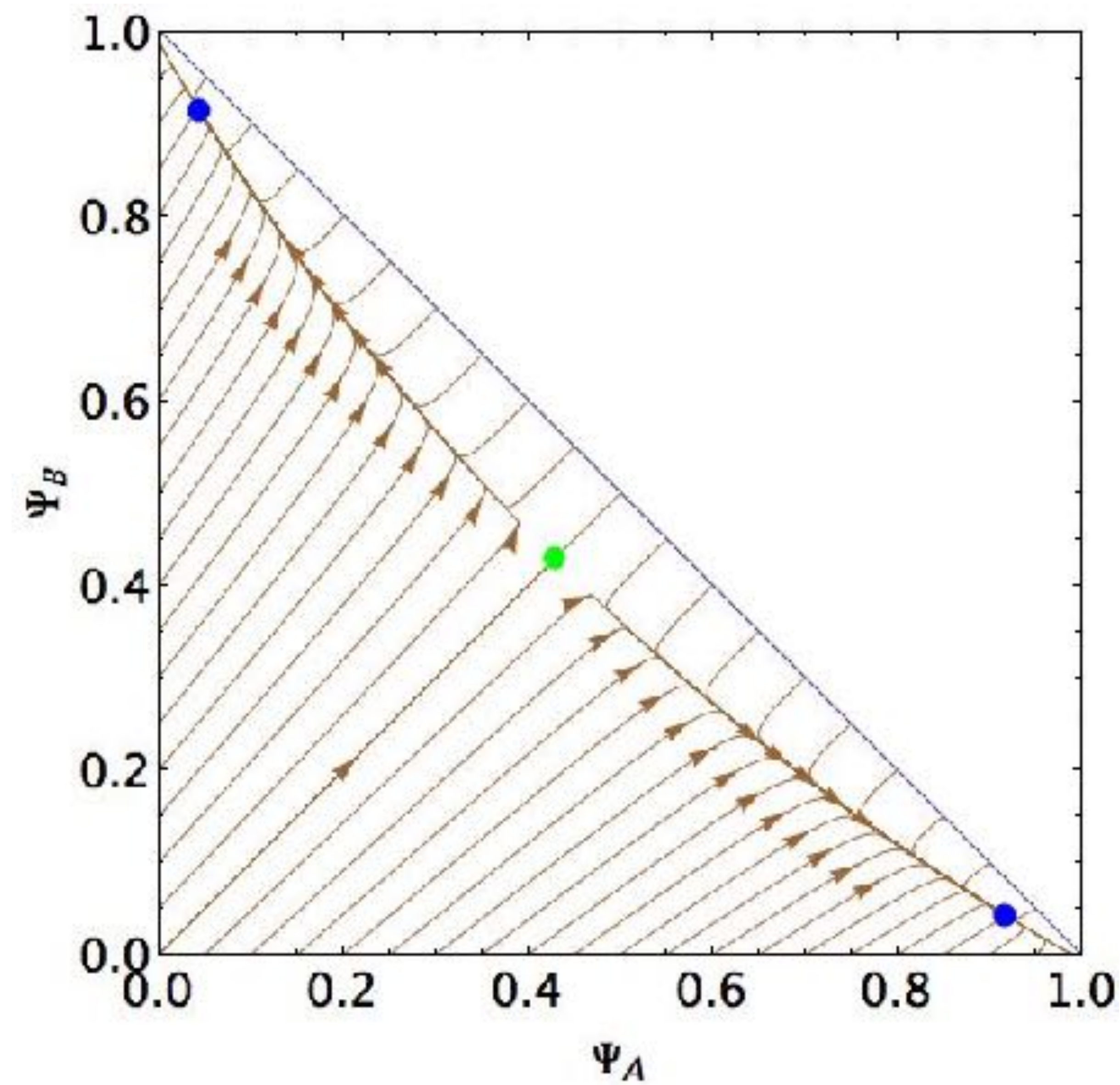
recruitment:

$$A+U \longrightarrow A+A$$
$$B+U \longrightarrow B+B$$

cross-inhibition

$$A+B \longrightarrow A+U$$
$$B+A \longrightarrow B+U$$

$$\begin{cases} \dot{\Psi}_A = \gamma_A \Psi_U - \alpha_A \Psi_A + \rho_A \Psi_A \Psi_U - \sigma_B \Psi_A \Psi_B \\ \dot{\Psi}_B = \gamma_B \Psi_U - \alpha_B \Psi_B + \rho_B \Psi_B \Psi_U - \sigma_A \Psi_A \Psi_B \\ \Psi_U = 1 - \Psi_A - \Psi_B \end{cases},$$



design pattern solution

multi-level description of the decision process

Reina, A., Valentini, G., Fernández-Oto, C., Dorigo, M., & Trianni, V. (2015). A Design Pattern for Decentralised Decision Making. PLoS ONE, 10(10), e0140950–18.

design pattern solution

multi-level description of the decision process

Macroscopic description	Macroscopic description	Microscopic description
infinite-size deterministic time continuous	finite-size stochastic time continuous	agent-based stochastic time discrete

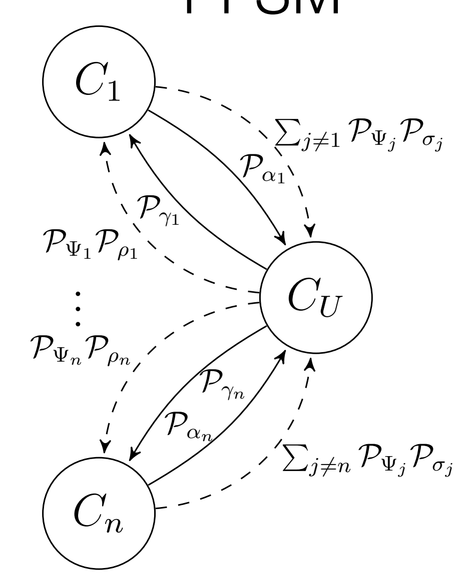
System of ODEs

$$\begin{cases} \dot{\Psi}_i &= \gamma_i \Psi_U - \alpha_i \Psi_i + \rho_i \Psi_i \Psi_U - \sum_{j \neq i} \sigma_j \Psi_i \Psi_j \\ \Psi_U &= 1 - \sum_i \Psi_i \end{cases}$$

Master equation

$$\frac{\delta}{\delta t} P(\mathbf{N}, t) = \sum_{k=1}^{4n} [\beta_k - P(\mathbf{N}, t) \mathscr{Q}_k], \quad \forall \mathbf{N}$$

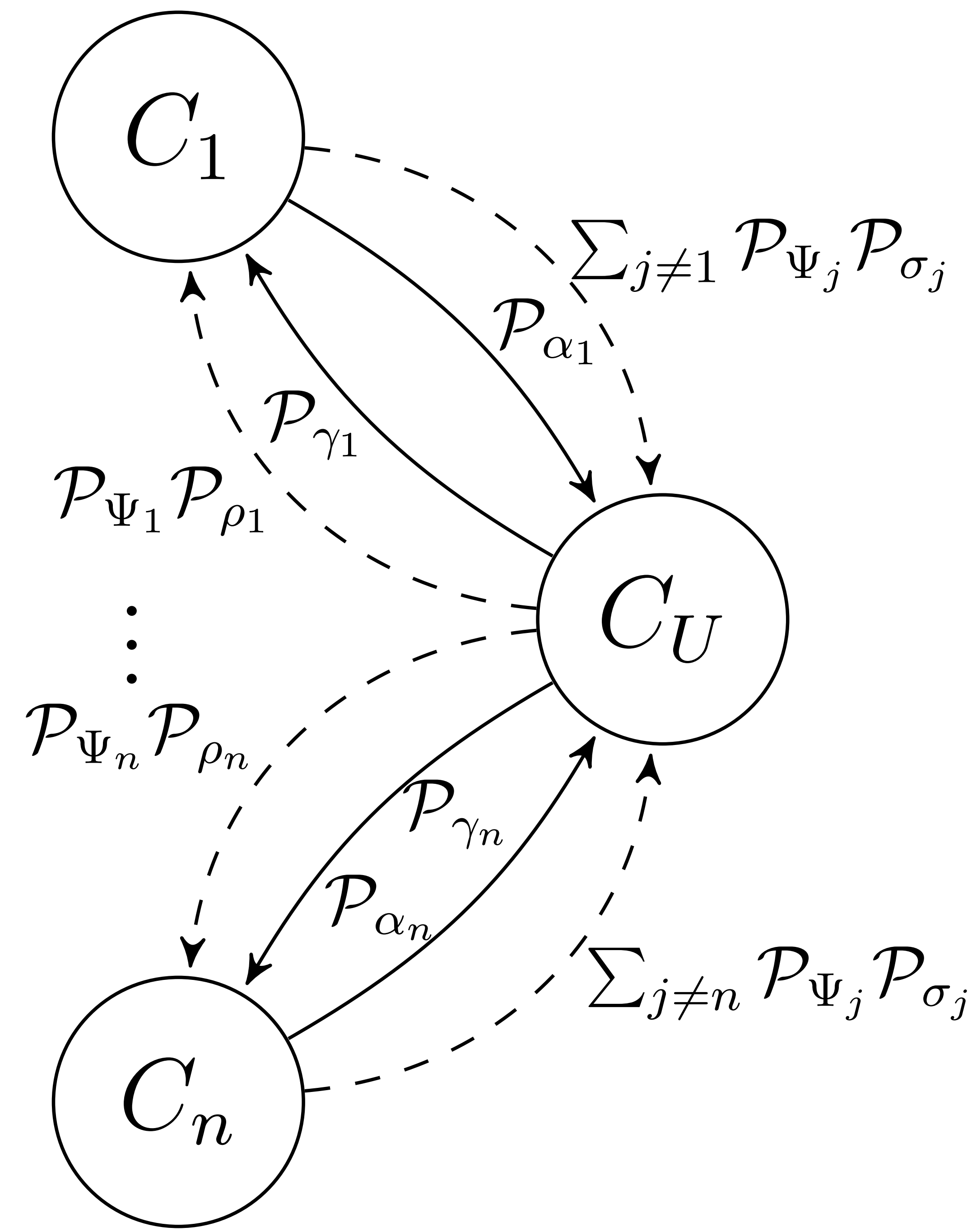
PFSM



Reina, A., Valentini, G., Fernández-Oto, C., Dorigo, M., & Trianni, V. (2015). A Design Pattern for Decentralised Decision Making. PLoS ONE, 10(10), e0140950–18.

design pattern solution

multi-level description of the decision process

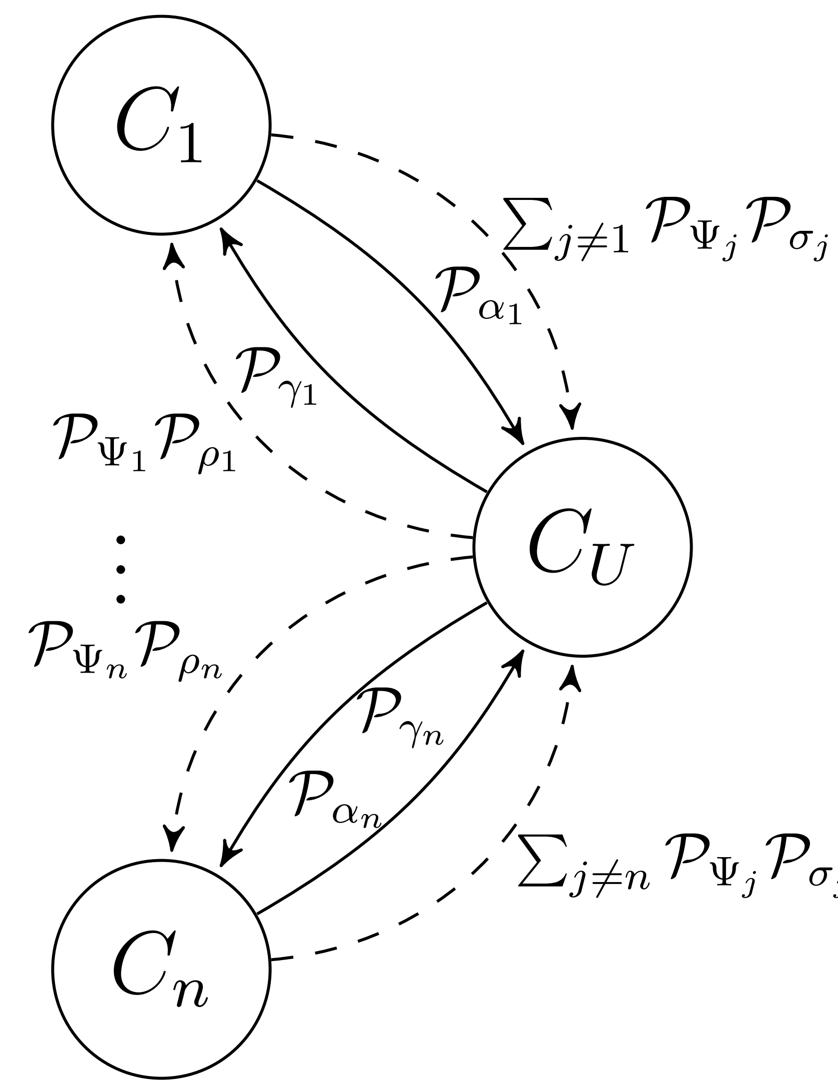


Reina, A., Valentini, G., Fernández-Oto, C., Dorigo, M., & Trianni, V. (2015). A Design Pattern for Decentralised Decision Making. PLoS ONE, 10(10), e0140950–18.

micro-macro link

transform parameters of the macroscopic model into the probabilities of the individual PFSM

$$
\begin{cases}
\dot{\Psi}_i = \gamma_i \Psi_U - \alpha_i \Psi_i + \\
\qquad\qquad \rho_i \Psi_i \Psi_U - \sum_{j \neq i} \sigma_j \Psi_i \Psi_j \\
\Psi_U = 1 - \sum_i \Psi_i
\end{cases}
$$



micro-macro link

transform parameters of the macroscopic model into the probabilities of the individual PFSM

$$\lambda_i = f_\lambda(v_i) \;\rightarrow\; \mathcal{P}_\lambda(v_i) = f_\lambda(v_i)\tau, \qquad \begin{array}{c} \lambda \in \{\gamma, \alpha, \rho, \sigma\} \\ i \in \{1, \ldots, n\} \end{array}$$

usage of the design pattern

1. Choice of the macroscopic parameterisation, including application specific constraints

2. Derivation of the microscopic parameterisation

3. Implementation and testing

macroscopic parameterisation

- The choice depends on the expected properties with respect to the options value
- Value-sensitive decision-making

$$\gamma_i = \rho_i = \frac{1}{\alpha_i} = v_i \qquad \sigma_i = \hat{\sigma}$$

Pais et al. (2013). A Mechanism for Value-Sensitive Decision-Making. PLoS ONE, 8(9), e73216

- Best-of-N decisions

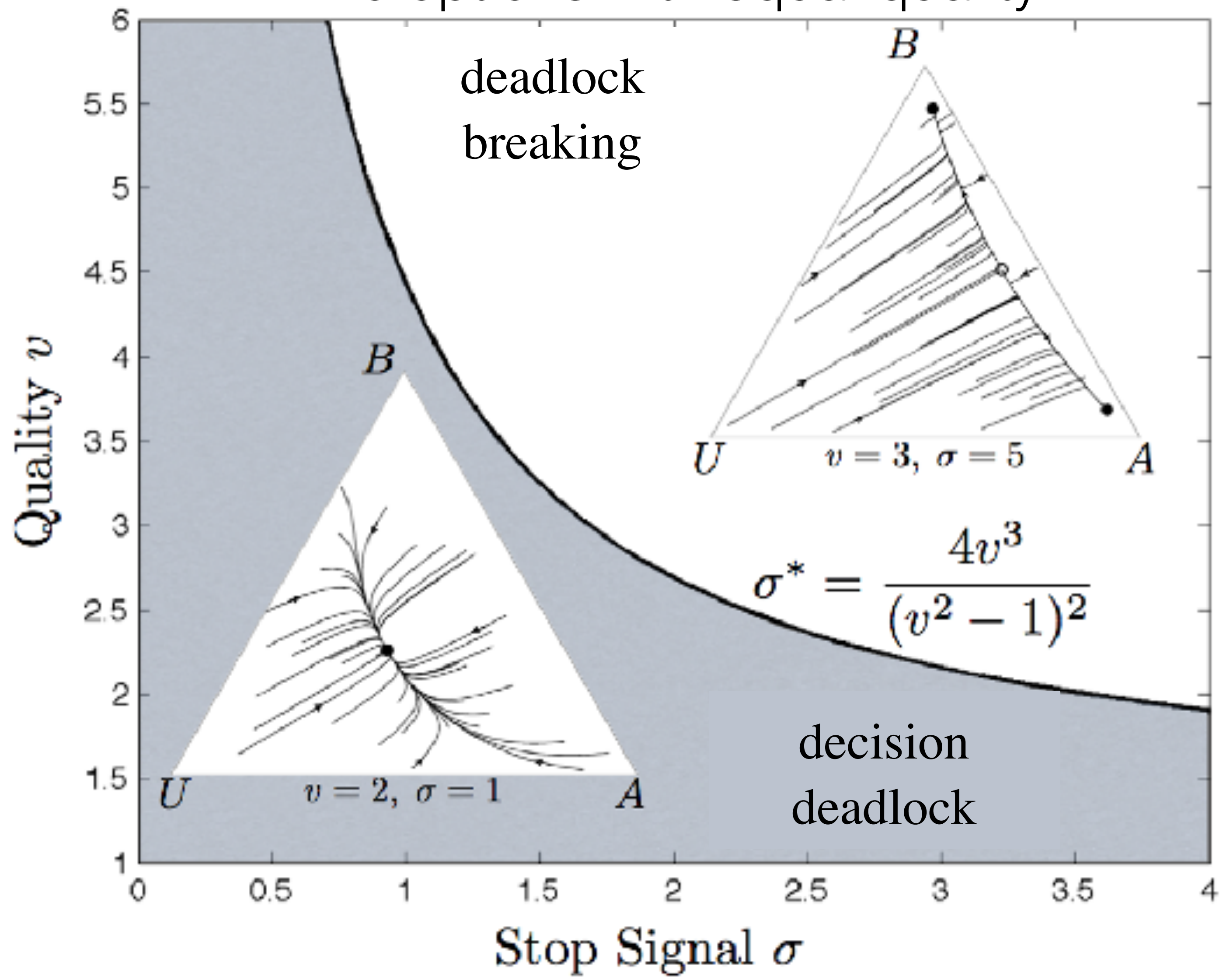
$$\gamma_i = \frac{1}{\alpha_i} = kv_i \qquad \rho_i = \sigma_i = hv_i \qquad r = \frac{h}{k}$$

Reina et al. (2017). Model of the best-of-N nest-site selection process in honeybees. Physical Review E, 95(5), 052411–15

value sensitivity

$$\gamma_i = \rho_i = \frac{1}{\alpha_i} = v_i \qquad \sigma_i = \hat{\sigma}$$

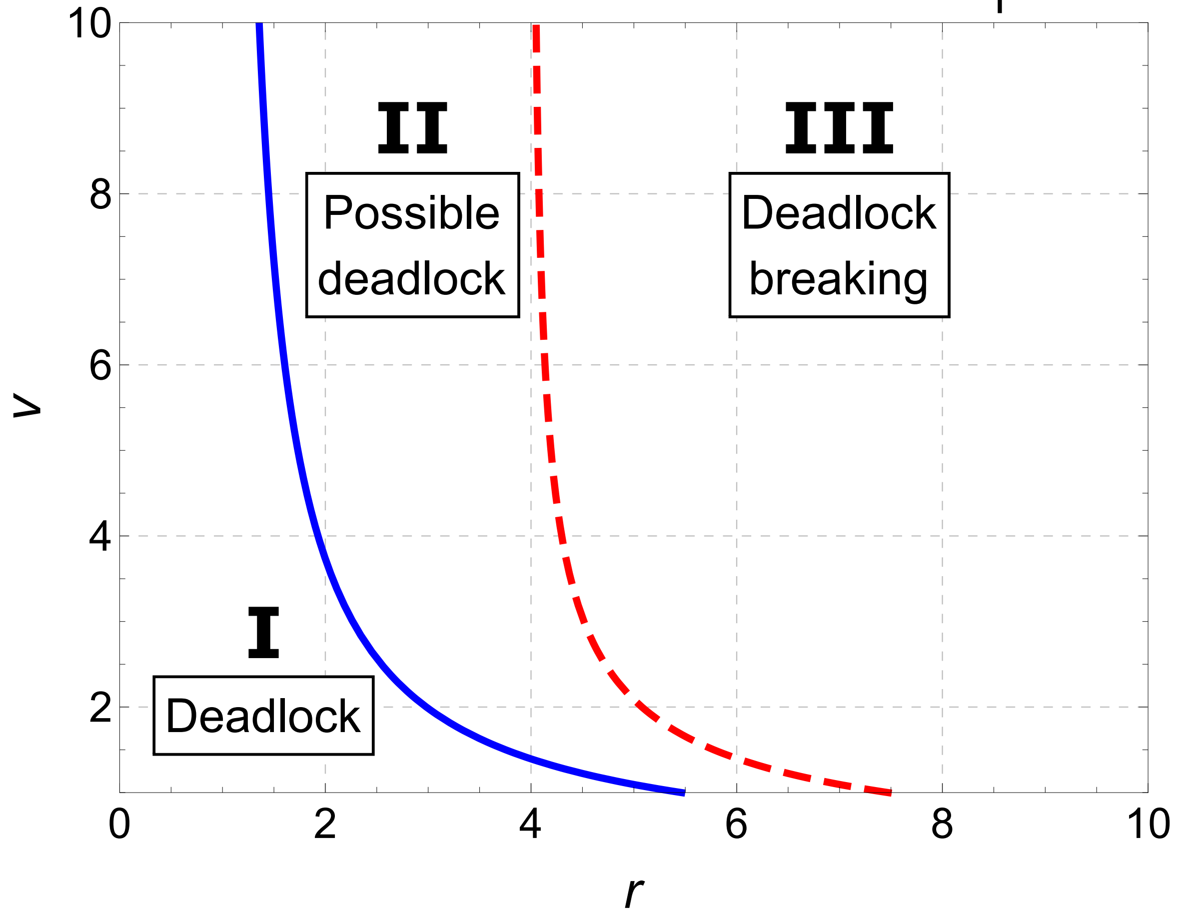
Two options with equal quality

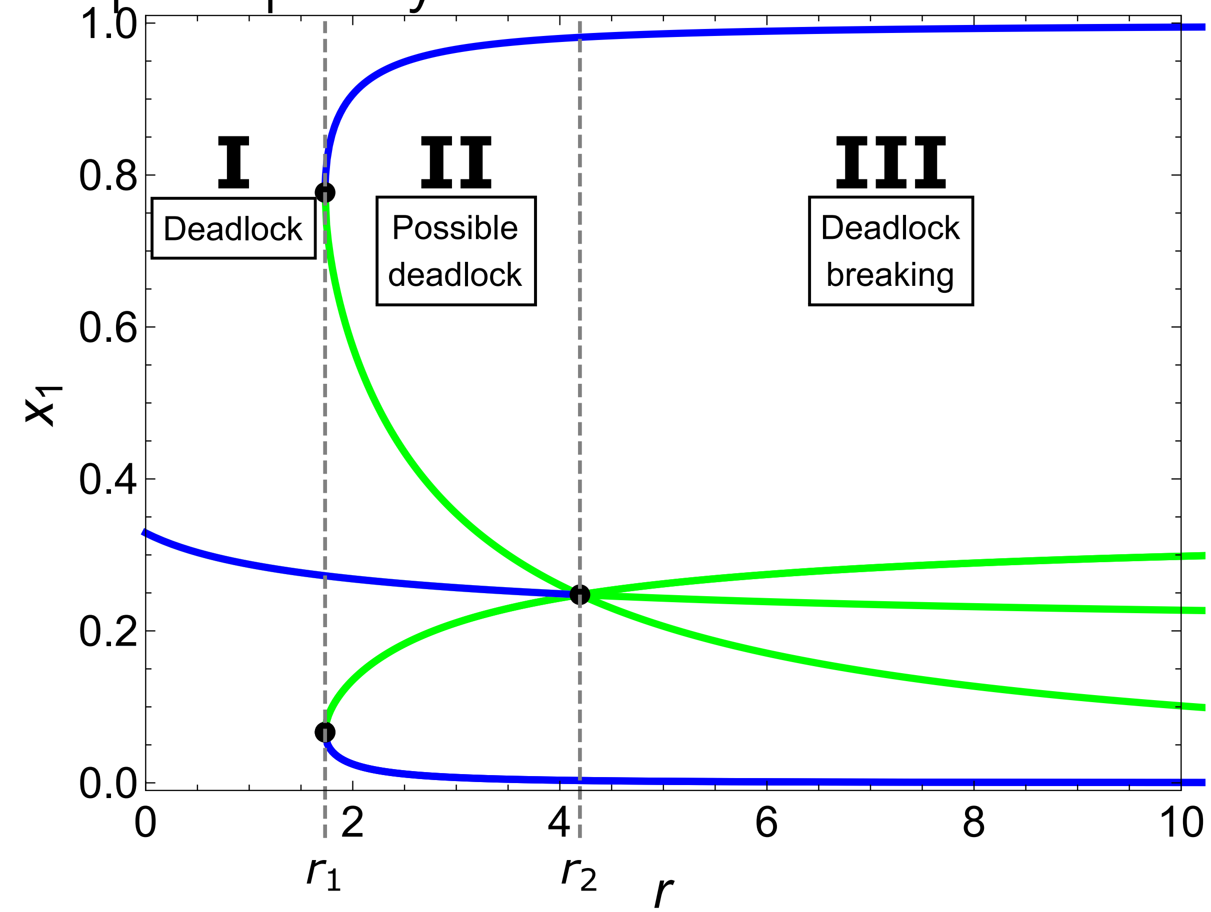


best-of-N decisions

$$\gamma_i = \frac{1}{\alpha_i} = k v_i \qquad \rho_i = \sigma_i = h v_i \qquad r = \frac{h}{k}$$

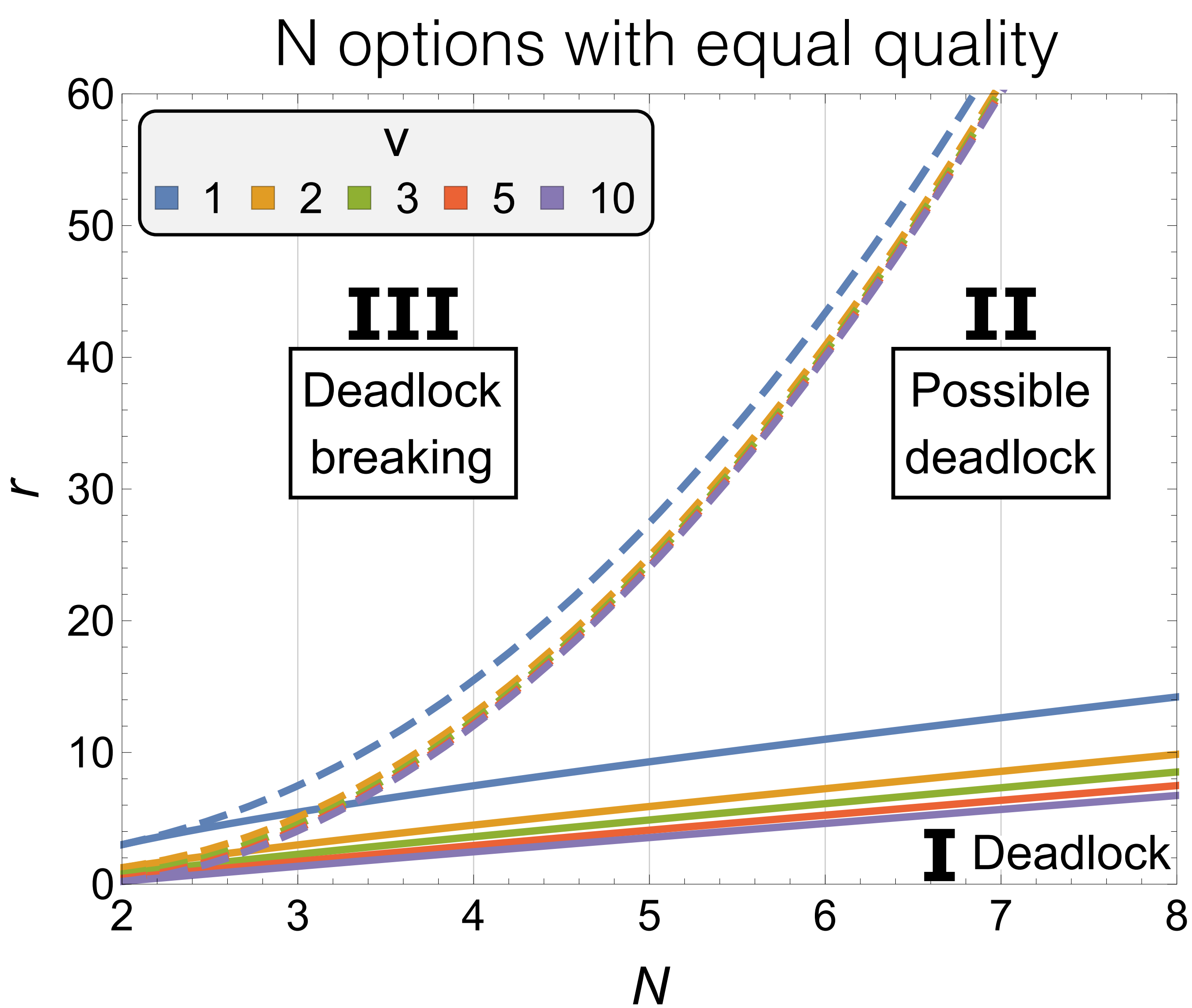
Three options with equal quality





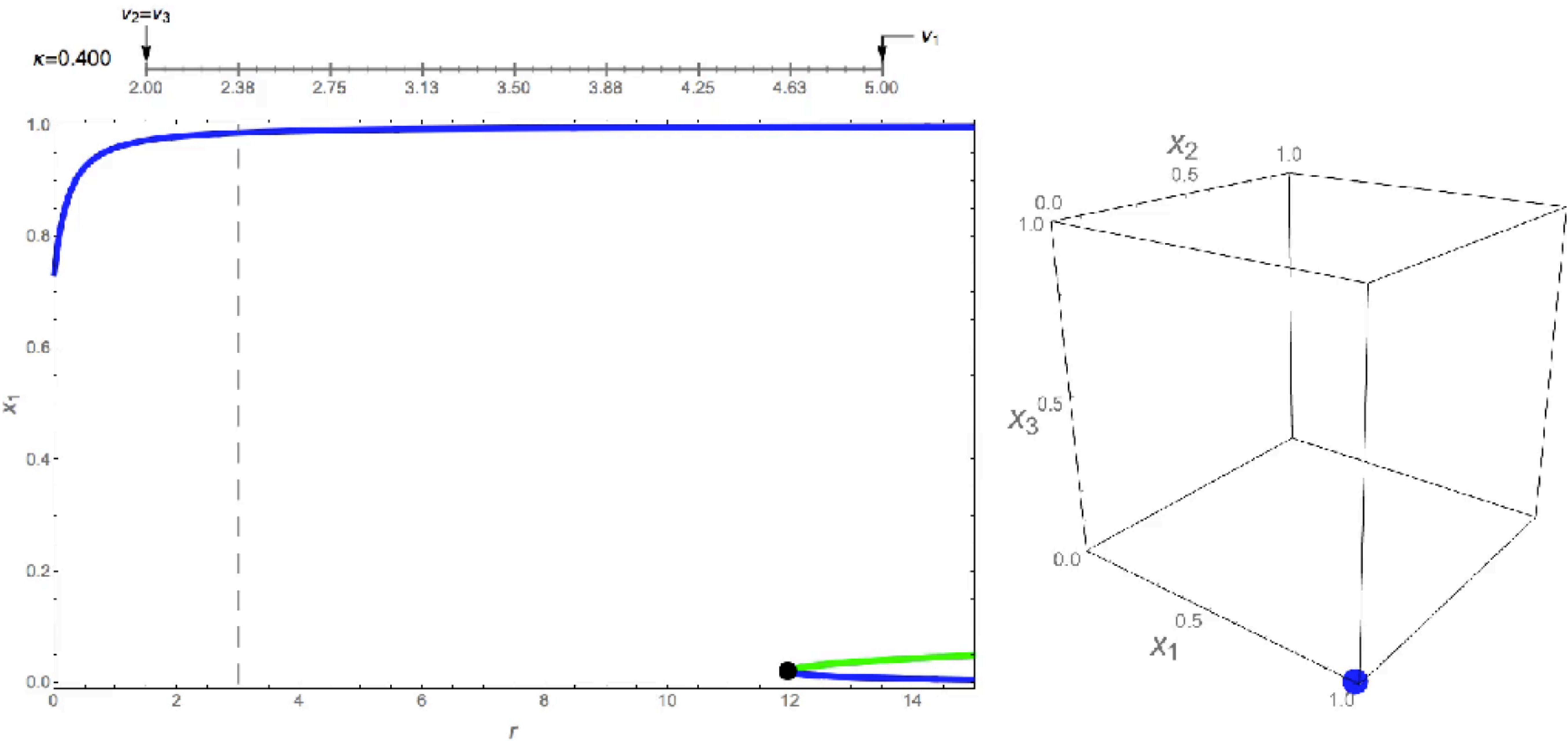
best-of-N decisions

$$\gamma_i = \frac{1}{\alpha_i} = k v_i \qquad \rho_i = \sigma_i = h v_i \qquad r = \frac{h}{k}$$



best-of-N decisions

One superior and two inferior options



case studies

.1. Multiagent simulations on fully-connected networks

Basic case study to investigate several parameterisations

.2. Multiagent simulations for search & exploration

Mobile point-size particles capable to move in a 2D environment

.3. Swarm robotics system for search & exploitation

Robots exemplify embodiment challenges

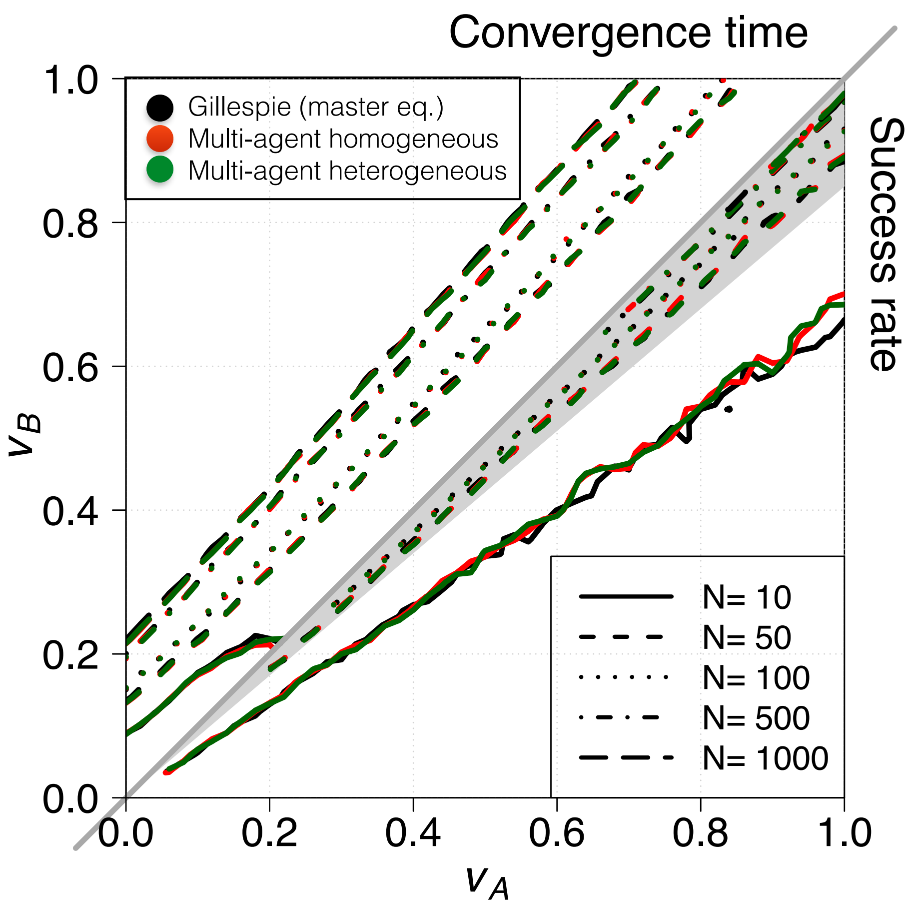
.4. Coexistence in heterogeneous cognitive networks

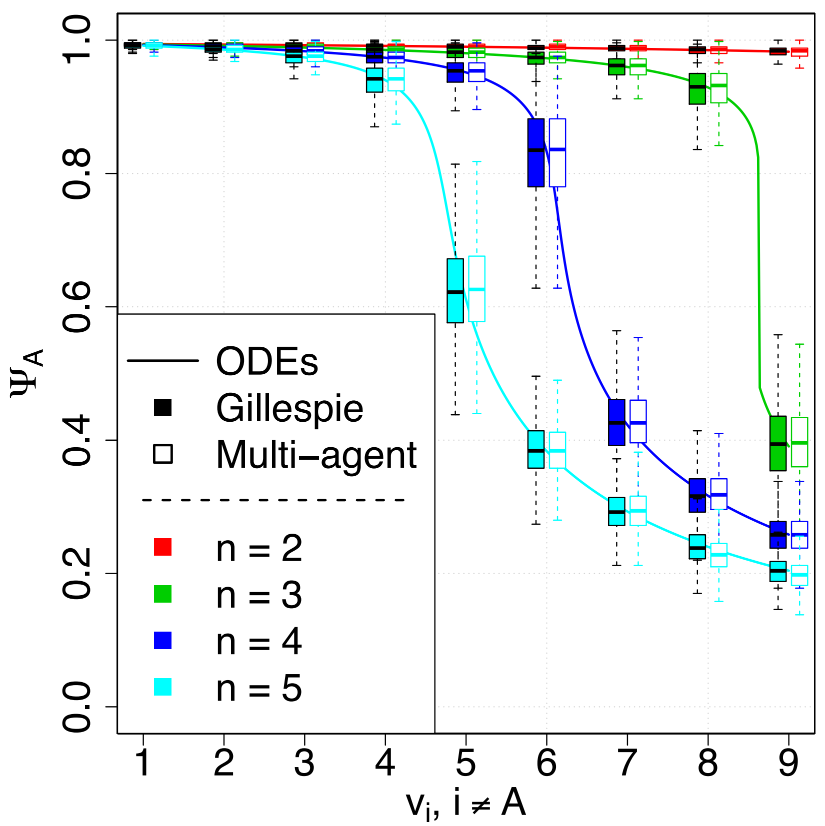
fully-decentralised solution for channel selection in cognitive radio networks

case study #1

.1.
Multiagent simulations on fully-connected networks

Basic case study to investigate several parameterisations



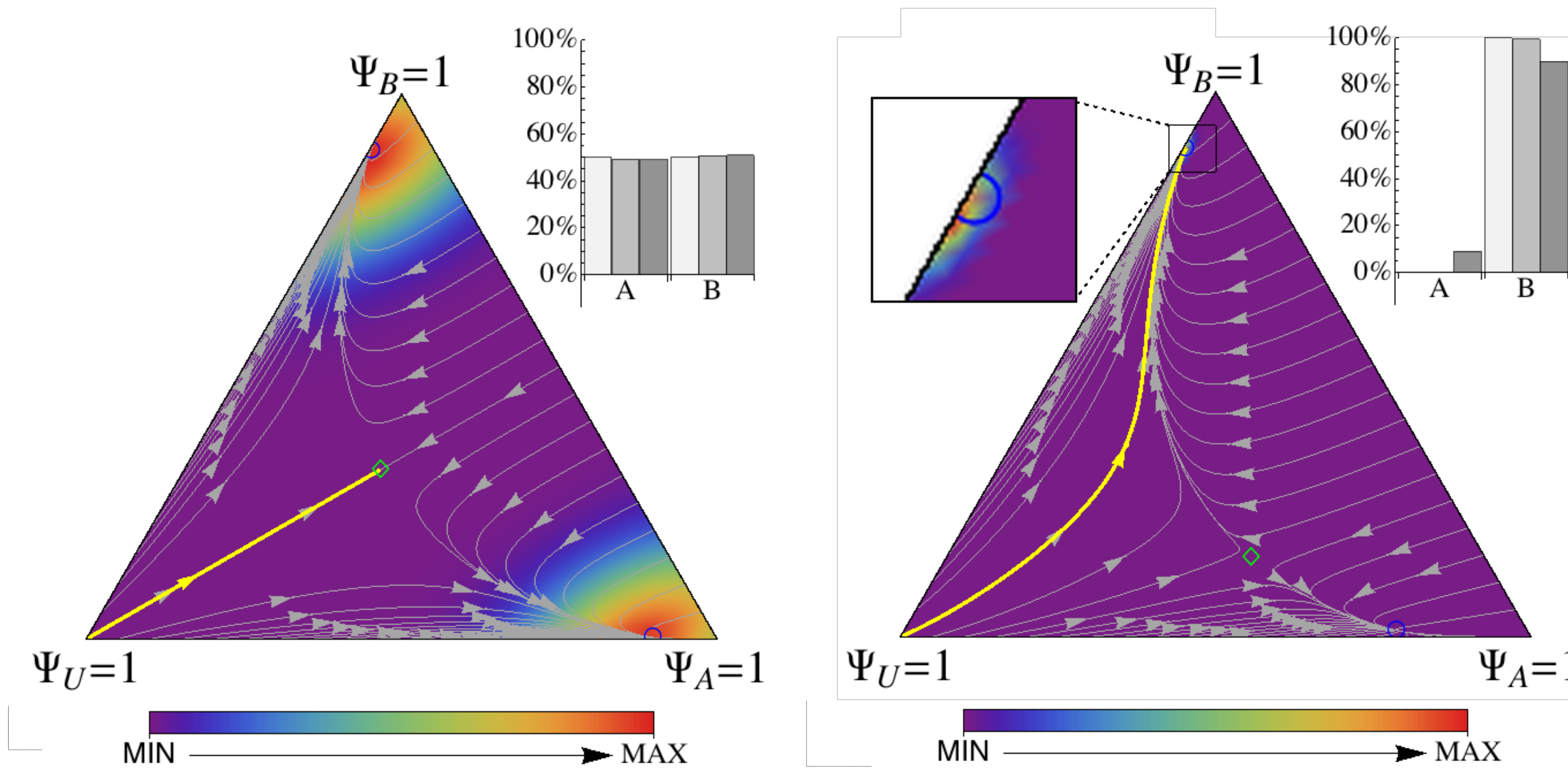


Reina, A., Valentini, G., Fernández-Oto, C., Dorigo, M., & Trianni, V. (2015). A Design Pattern for Decentralised Decision Making. PLoS ONE, 10(10), e0140950–18.

case study #2

.2.
Multiagent simulations for search & exploration

Mobile point-size particles capable to move in a 2D environment

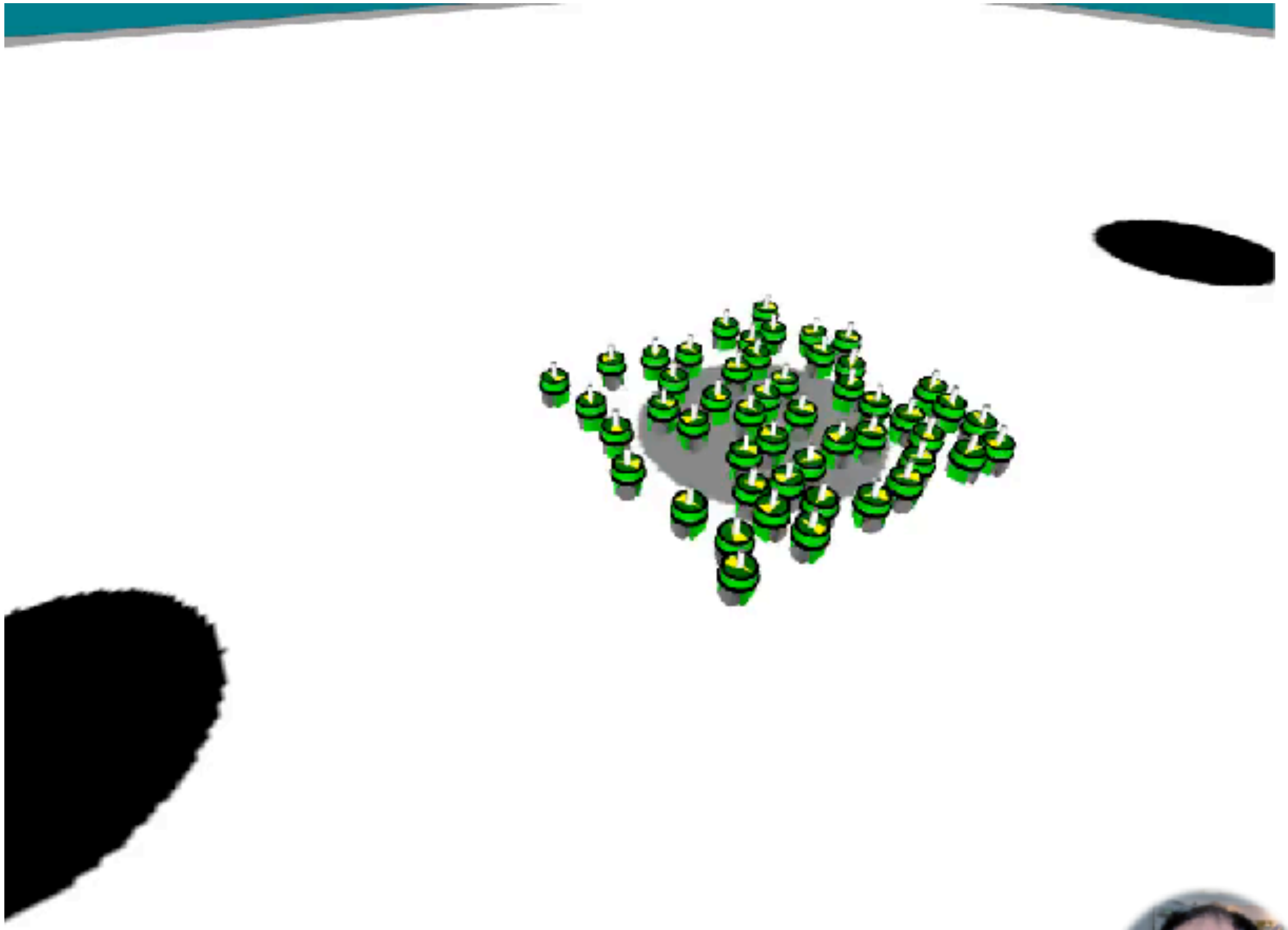


Reina, A., Valentini, G., Fernández-Oto, C., Dorigo, M., & Trianni, V. (2015). A Design Pattern for Decentralised Decision Making. PLoS ONE, 10(10), e0140950–18.

case study #3

.3.
Swarm robotics system for search & exploitation

Robots exemplify embodiment challenges



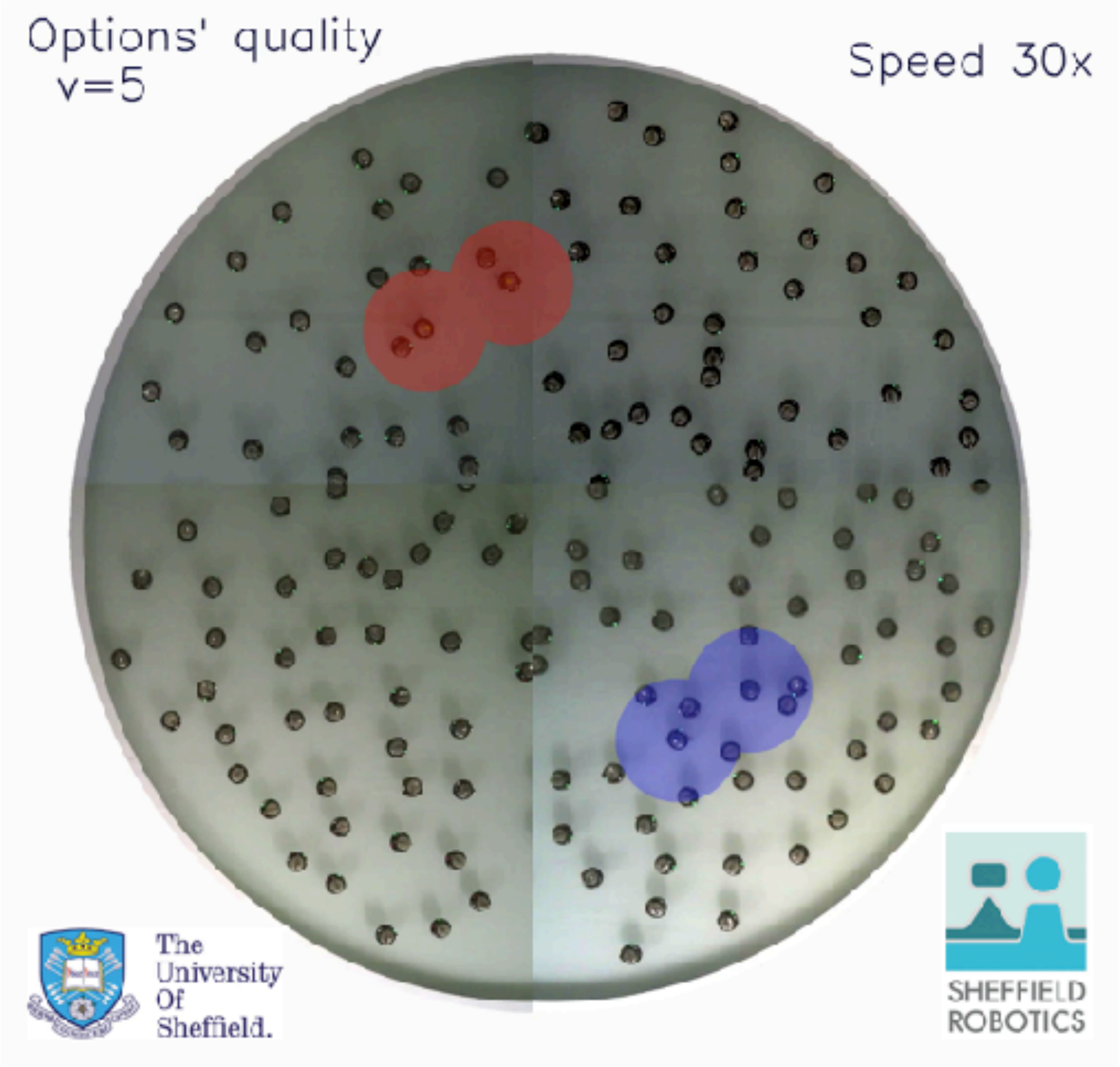
video by A. Reina

Reina, A., Miletitch, R., Dorigo, M., & Trianni, V. (2015). A quantitative micro–macro link for collective decisions: the shortest path discovery/selection example. Swarm Intelligence, 9(2-3), 75–102.

case study #3

.3.
Swarm robotics system for search & exploitation

Robots exemplify embodiment challenges



video by A. Reina

Reina et al (2016): Effects of Spatiality on Value-Sensitive Decisions Made by Robot Swarms.
In: Proceedings of DARS 2016, pp. 1–8, Natural History Museum in London, UK

task allocation

task allocation

- *definition*:
  the process that leads a group to (equally) divide labour among the group members

- *precondition*:
  a set of tasks with different labour demands (utility)

- *postcondition*:
  agents are deployed to execute one or more tasks

- *constraints*:
  individuals do not know task requirements and other's preferences/choices

task allocation: variants

- single-task (ST) versus multi-task robots (MT)
- single-robot (SR) versus multi-robot tasks (MR)
- instantaneous (IA) versus time-extended assignment (TA)

Gerkey, B. P., & Matarić, M. J. (2004). A Formal Analysis and Taxonomy of Task Allocation in Multi-Robot Systems. The International Journal of Robotics Research, 23(9), 939–954.

TA via response thresholds

Theraulaz, G., Bonabeau, E., & Denuebourg, J. N. (1998). Response threshold reinforcements and division of labour in insect societies. Proceedings of the Royal Society of London. Series B: Biological Sciences, 265(1393), 327–332.

TA via response thresholds

- tasks are associated with a utility (stimulus)

$$S_j, j \in \{1, \ldots, M\}$$

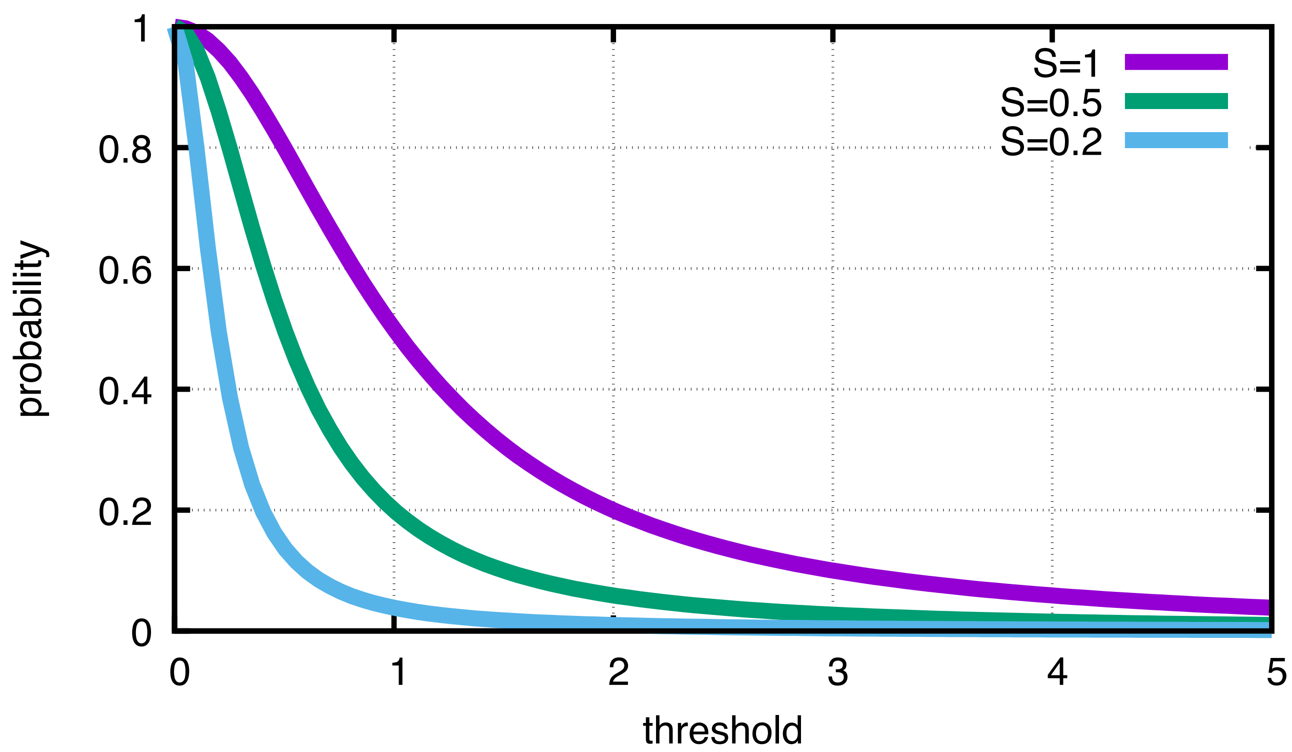
- agents have a response threshold for each task

$$\theta_{ij}, i \in \{1, \ldots, N\}$$

TA via response thresholds

- agents apply a simple decision rule

$$\mathcal{P}_i(S_j) = \frac{S_j^2}{S_j^2 + \theta_{ij}^2}$$



- task utility varies over time

spontaneous growth

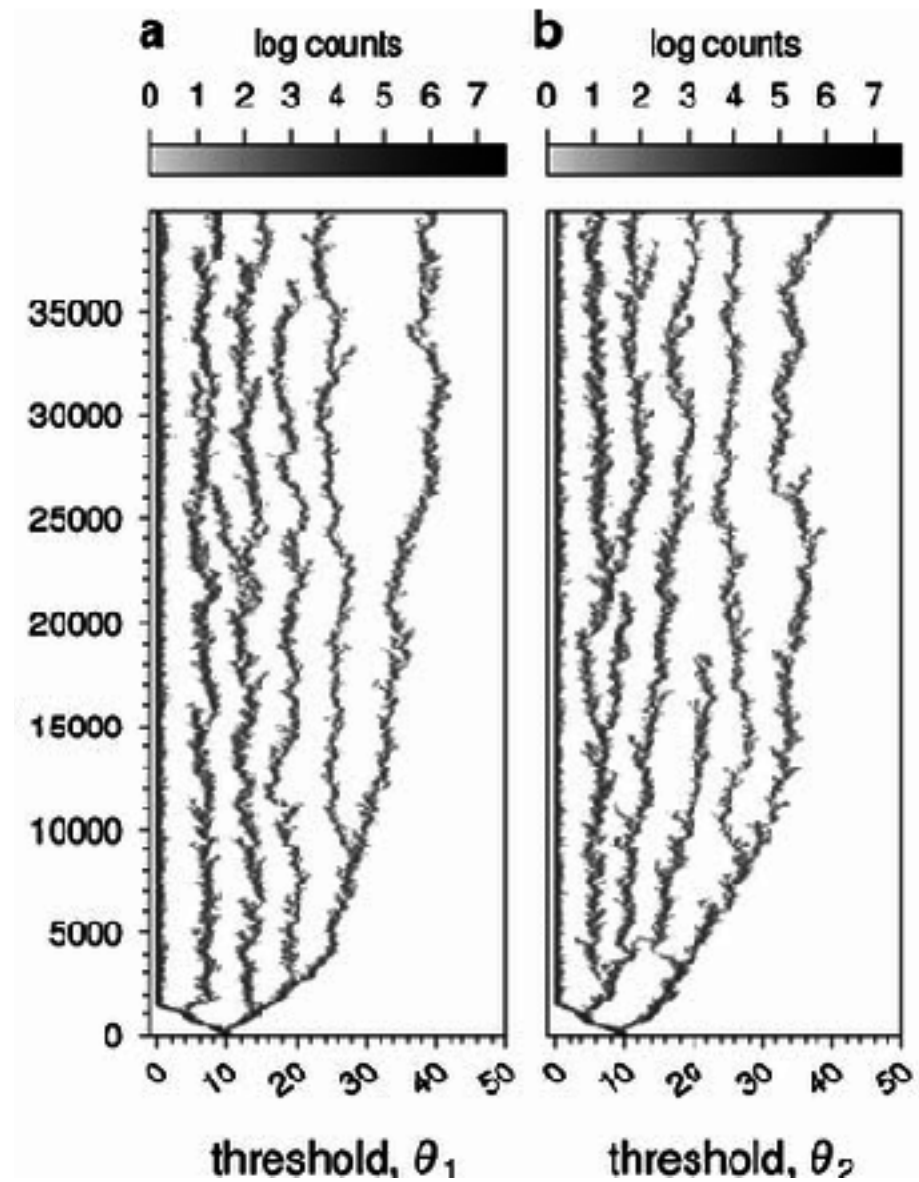
$$\dot{S}_j = \delta - \alpha \frac{n_j}{N}$$

enrolled agents

individual execution rate

TA via response thresholds

- How to distribute thresholds for optimal task allocation?
- How to assign threshold to have specialised agents? What about generalists?
- Adaptive response thresholds:



$$\theta_{ij} \leftarrow \theta_{ij} - \xi \Delta t \quad \text{if agent } i \text{ performs task } j$$

$$\theta_{ij} \leftarrow \theta_{ij} + \xi \Delta t \quad \text{if agent } i \text{ does not perform task } j$$

confronting TA with CD

task allocation

- discover tasks and evaluate utility
- leave tasks when completed
- recruit workers to tasks that need attention
- …

collective decision

- discover alternatives and evaluate quality
- abandon commitment for low quality options
- recruit agents to favourable options
- cross-inhibition between competing options

coupled dynamical models

- the utility of executing a task is dependent on the number of enrolled agents:

$$\dot{u}_i = -u_i n_i(\delta n_i - \xi n_i^2), \quad u_i \in [0, 1].$$

- the optimal number of agents depends on the utility dynamics:

$$n^\star = \frac{2\delta}{3\xi}$$

- coupled dynamics of task allocation and utility:

$$\begin{aligned}
\gamma_i &= k u_i \\
\alpha_i &= k\mathcal{H}(\nu - u_i) \\
\rho_i &= h u_i \\
\sigma_{ij} &= h u_i \frac{2\delta - 3\xi n_j}{2\delta}, \quad i \neq j \\
\sigma_{ii} &= \frac{(3\xi N - 2\delta)(3\xi N \gamma_i + 2\delta \rho_i)}{4\delta^2}
\end{aligned}$$

coupled dynamical models

- the utility of executing a task is dependent on the number of enrolled agents:

$$\dot{u}_i = -u_i n_i(\delta n_i - \xi n_i^2), \quad u_i \in [0, 1].$$

- the optimal number of agents depends on the utility dynamics:

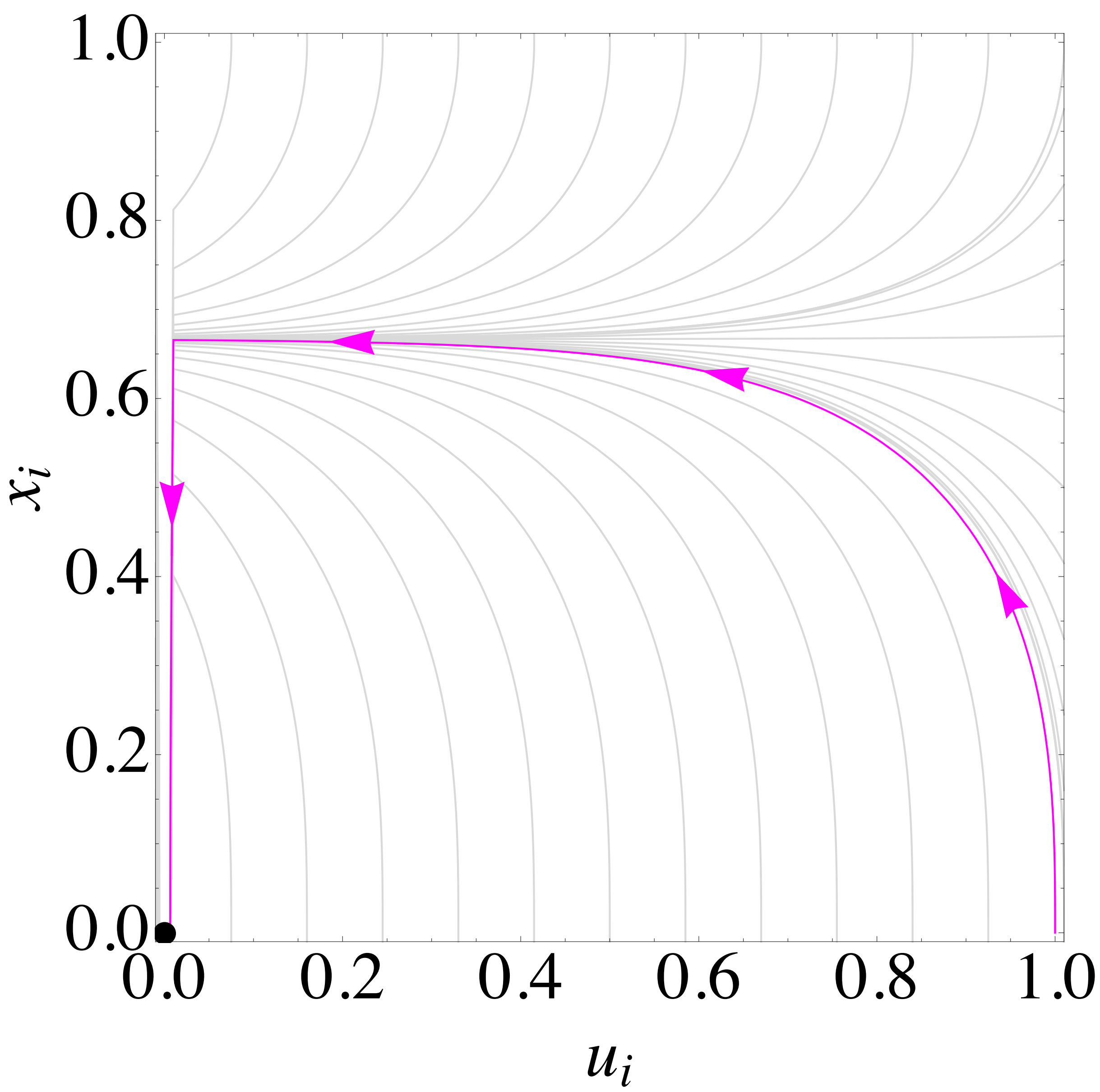
$$n^\star = \frac{2\delta}{3\xi}$$

- coupled dynamics of task allocation and utility:

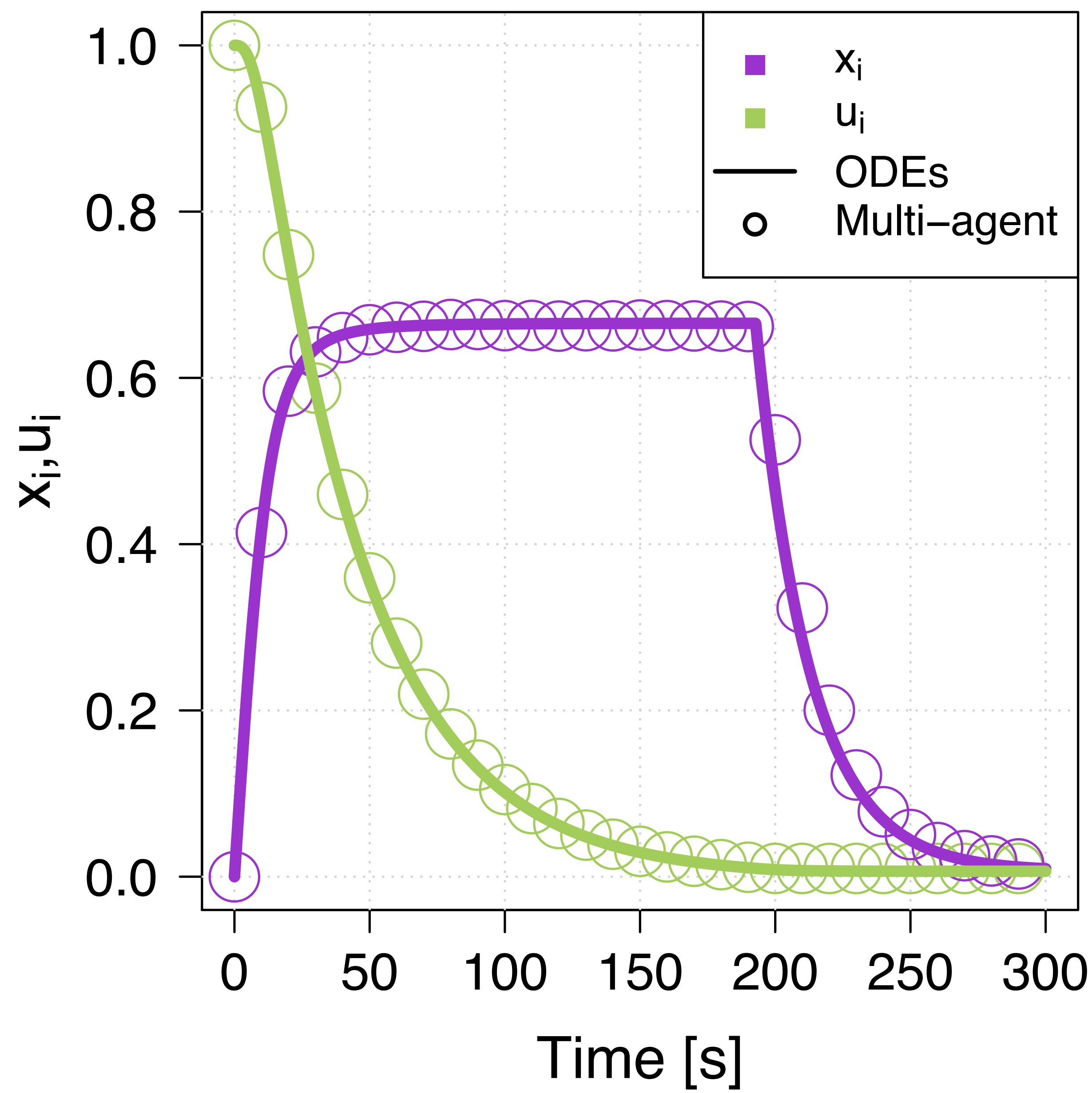
- dynamics controlled by the ratio between interactive and spontaneous transitions

$$r = \frac{h}{k}$$

single task

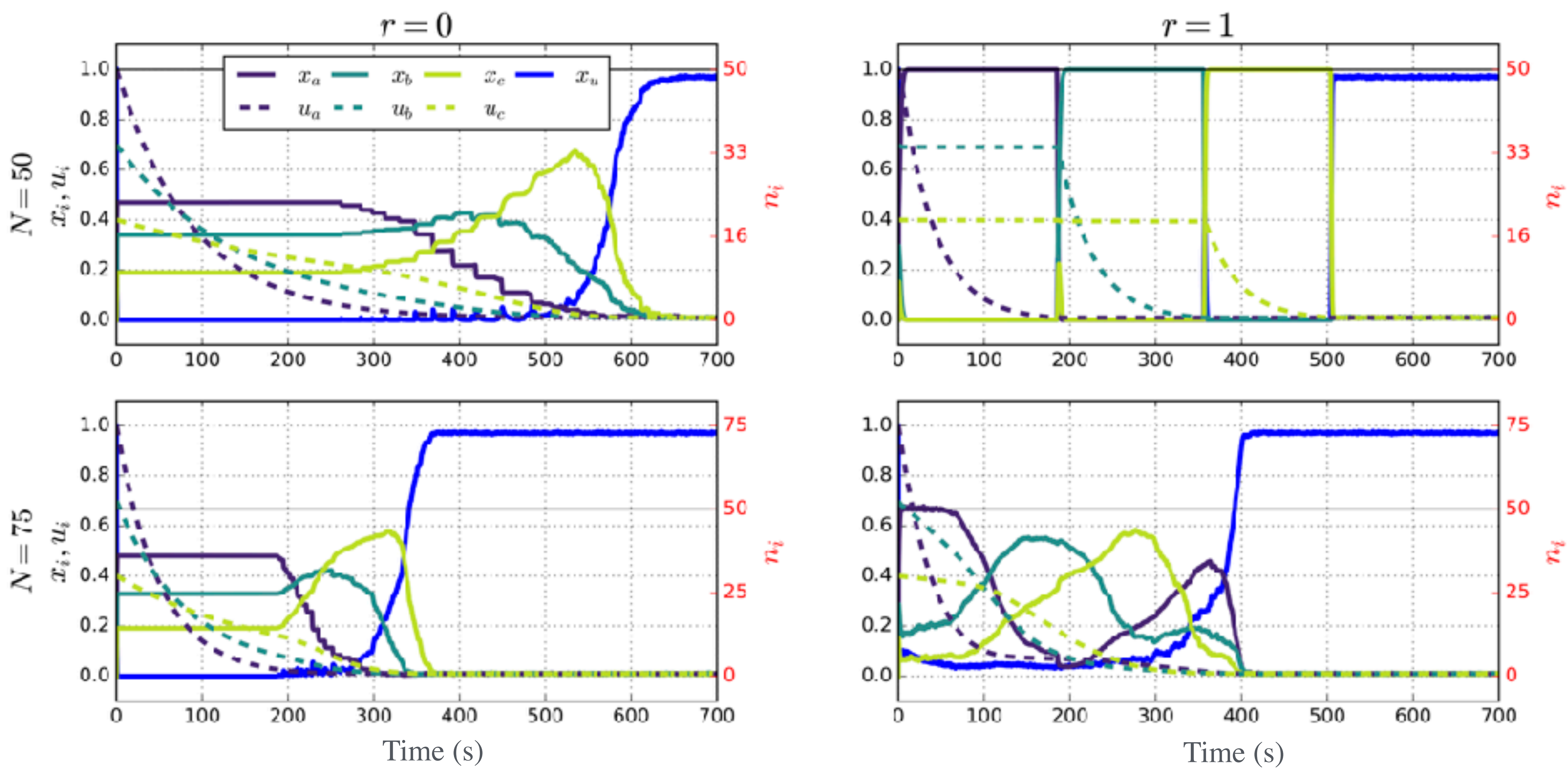


1.0
0.8
0.6
0.4
0.2
0.0
x_i
0.0 0.2 0.4 0.6 0.8 1.0
u_i



x_i
u_i
ODEs
Multi–agent
1.0
0.8
0.6
0.4
0.2
0.0
x_i, u_i
0 50 100 150 200 250 300
Time [s]

three tasks



$r = 0$
$r = 1$
x_a
x_b
x_c
x_u
u_a
u_b
u_c
$N = 50$
$N = 75$
x_i, u_i
n_i
0.0
0.2
0.4
0.6
0.8
1.0
0
16
33
50
25
75
100
200
300
400
500
600
700
Time (s)

TA in a nutshell

- task allocation and collective decisions
  share many important aspects

- recruitment and inhibition dynamics provide means to implement different task allocation strategies

- strategies varies from utility-proportional to
  winner-take-all strategies

- giving more importance to interactions,
  task allocation becomes responsive to changes in utility


Thanks for
your attention