

what to do when ...

Individuals' attributes are heterogeneous

**Individuals' interactions are complex, nonlinear,
discontinuous, or discrete**

**Agents exhibit complex behaviour, including learning and
adaptation**

**Topology of the interactions is heterogeneous and complex
(social networks are rarely homogeneous, but clustered)**

Space is crucial and the agents' positions are not fixed

Analytical approaches often fail at this level of complexity

**Agent-based simulations are capable of studying this
complexity at the cost of generality that analytical
methods provide**

**BUT: ABM and analytical methods do not oppose but
complement each other**

what are agent-based simulations?

definition
and aim of
ABM

Rule-based computational modelling

Based on dynamic interactions among agents/individuals

Goal of Agent-based simulations

Model **components** of a system and simulate their interactions, which are based on a pre-defined set of rules

Gain insight into **collective behaviour** of agents following simple rules

what are agent-based simulations?

characteristics

Modularity

Individuals can be added and removed from system

Rules can easily be changed without changing entire model

Complexity

Allows complex low level interactions, and changes to agents and environment

Emergence

Local interactions among agents can lead to higher level patterns

what are examples for agent-based simulations?

Ecosystem and natural-resource management

Land-use and agricultural policy

Control disease outbreaks

Marketing

Private-sector logistics and strategy

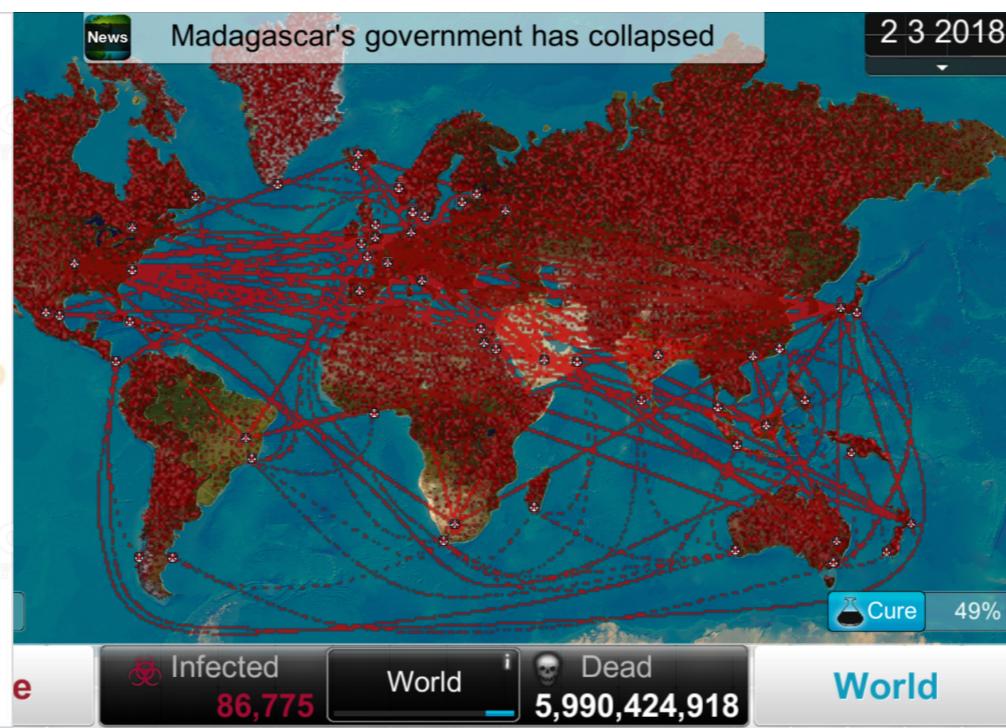
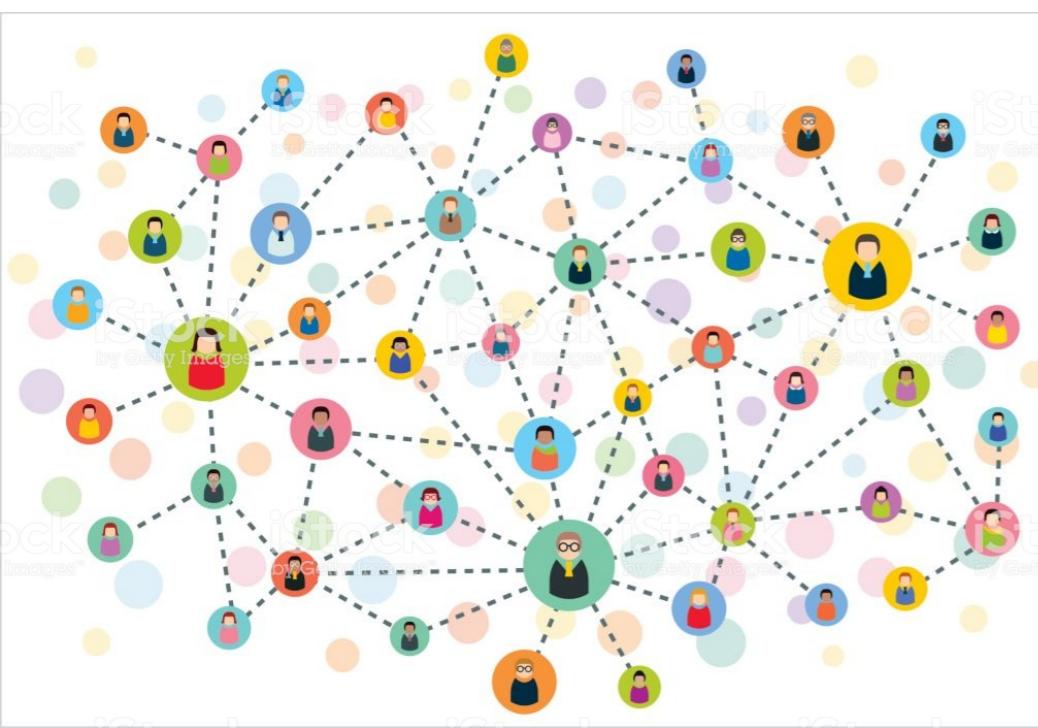
Stock exchange

Electoral design

Social media dynamics

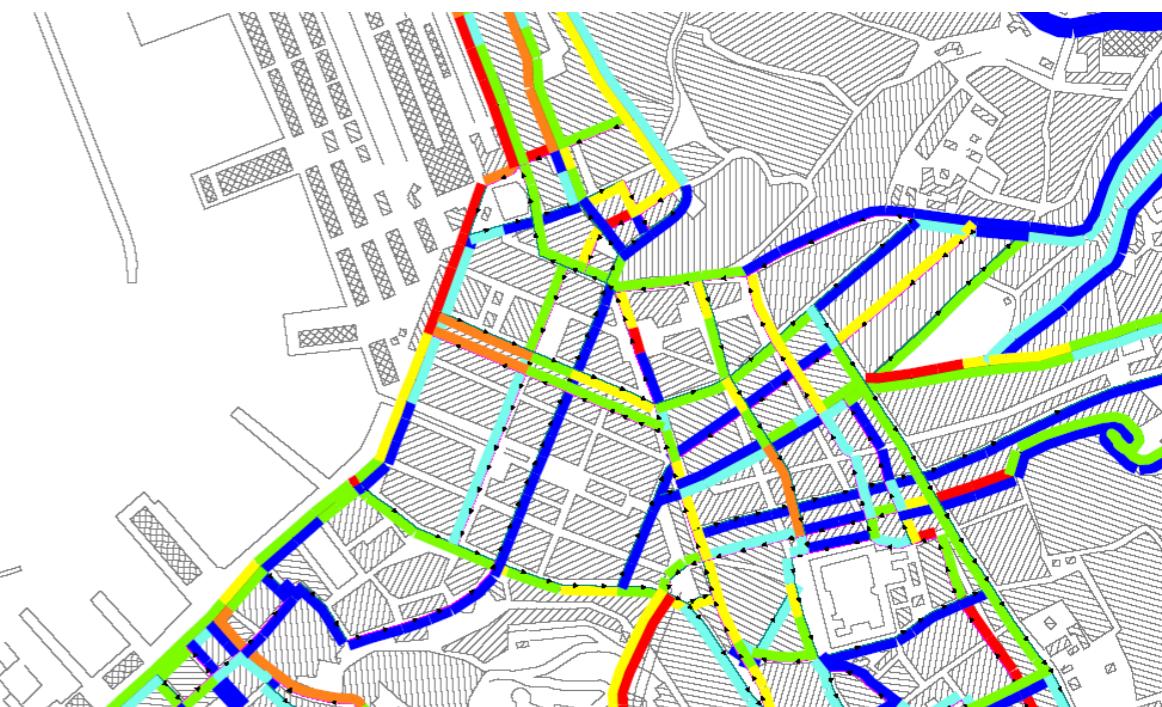
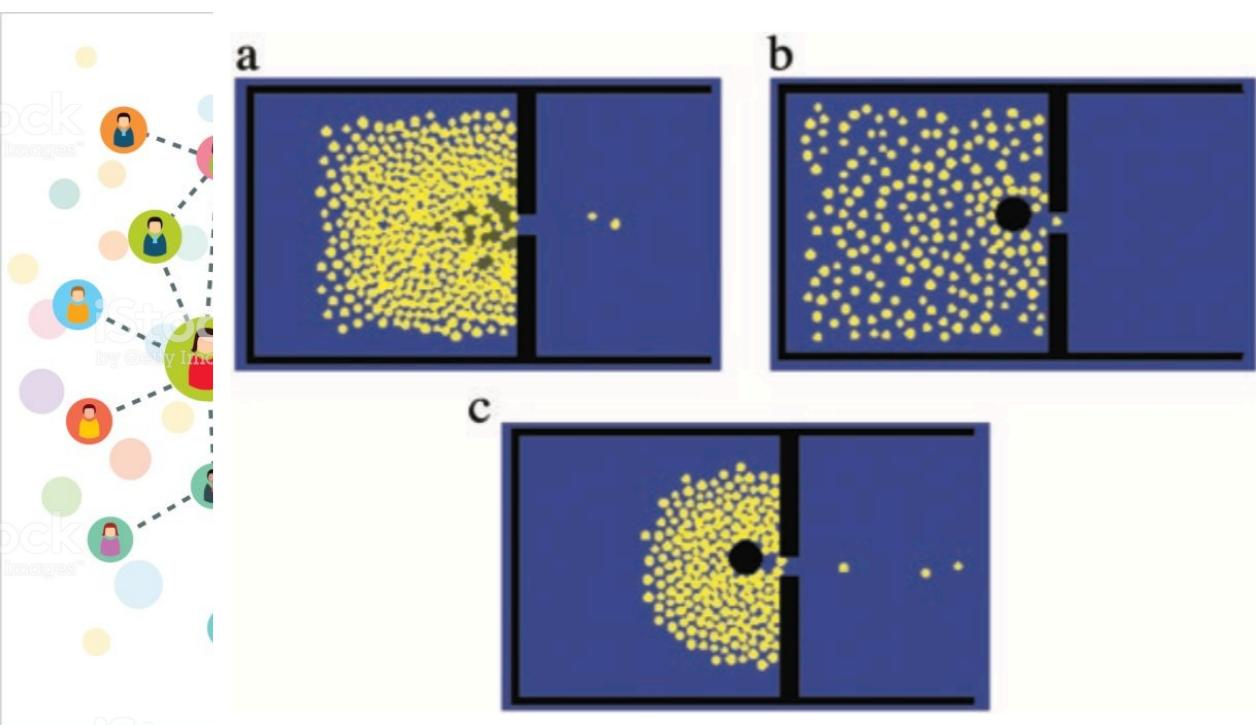
Emergency escape planning

Traffic planning



what are examples for agent-based simulations?

- Ecosystem and natural-resource management
- Land-use and agricultural policy
- Control disease outbreaks
- Marketing
- Private-sector logistics and strategy
- Stock exchange
- Electoral design
- Social media dynamics
- Emergency escape planning
- Traffic planning



what are the components of an agent-based model?

Properties, Actions, Rules, Time, and Environment

Agents

Context

Properties

what defines the individual? (age, sex, size, wealth, etc.)

are these properties fixed or can they change throughout simulation?

Actions

what can the individual do? (move, eat, communicate or learn from neighbour)

do activities affect only the individual, or also neighbours and the environment?

Rules

based on environmental input, or time, or others' states or behaviours?

Time

the unit in which rules, actions, and changes in agent properties or the environment occur
can be fixed for all components, or vary e.g. spread of information in a network versus the
change in the network topology

Environment

structure of the environment (e.g. lattice, ring, torus, checkerboard)

can change over time (e.g. turnover of quality of resources patches)

looking at an example in more detail

flocking
behaviour



looking at an example in more detail

Emergent pattern appears complex, however, it can be explained with relatively simple heuristics as shown in various agent-based models.

flocking behaviour



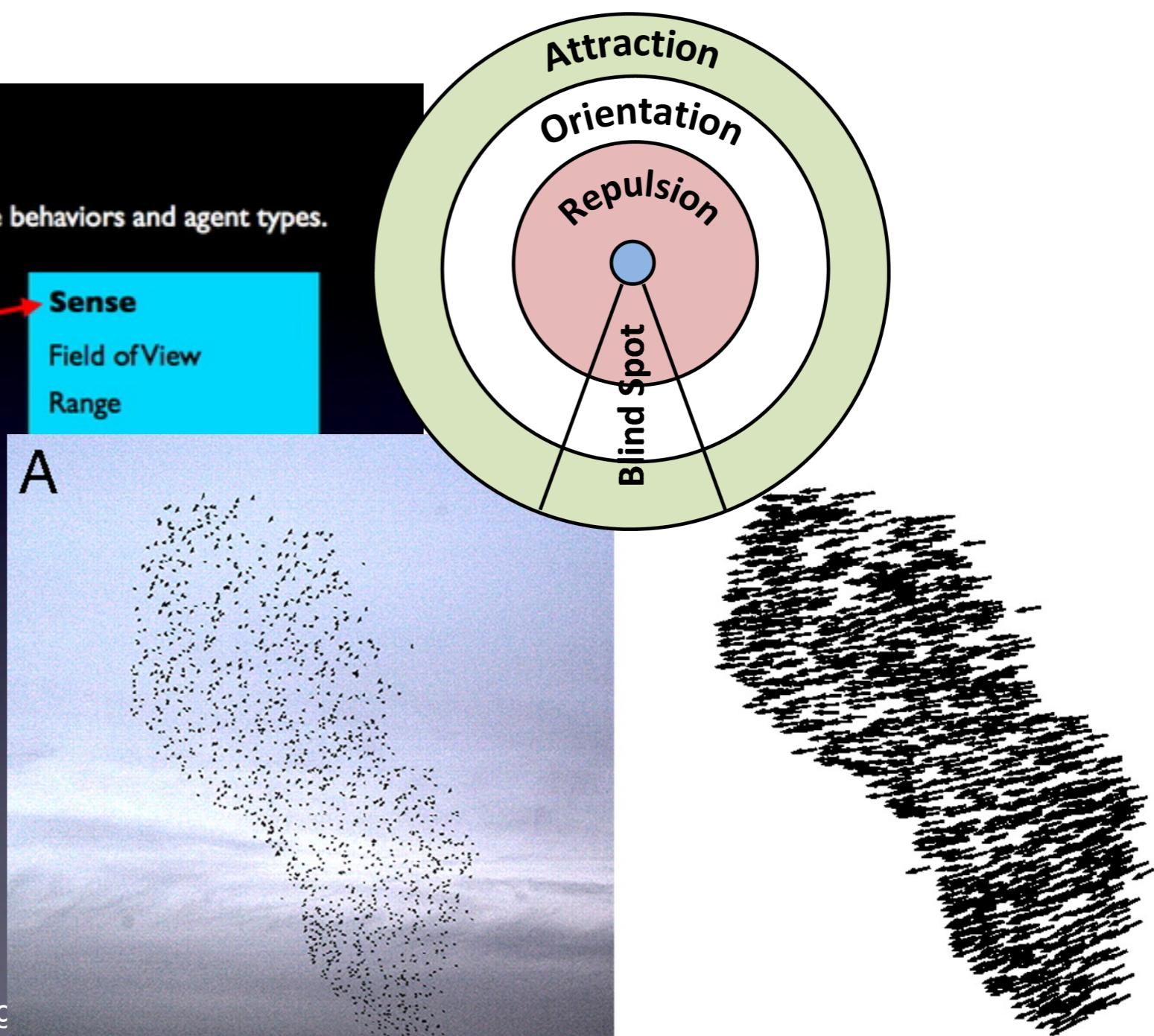
looking at an example in more detail

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flocking behaviour

Implementation

The key feature of my implementation is support for multiple behaviors and agent types.



developing an abm

1. Define question and goal of the simulation model

2. Model scope and conceptual design

informed choice of key concepts, structures, relationships (from literature)

3. Model specification

decisions on how to implement components from step 2 in a simulation model

4. Model implementation

translating concepts and components into a executable program and run with test parameters

5. Analysis

1. Testing, calibration, debugging

check whether model behaves as expected and adjust if necessary

2. Designing experiments and conducting analysis

use model to test hypothesis

3. Sensitivity analysis

sweep parameter space to identify where small changes in parameter values can cause drastic changes in model outcomes and to test the effect of assumptions that have been made during model design

6. Synthesis and reporting

compile statistical analysis and visualisations

exemplary case study on social learning

competition effects on social and individual learning

when is social learning adaptive?

Social Learning Strategies Tournament



Rendell et al., 2010

winning strategy: almost only social learning

can resource competition explain the pattern?



honeybees

Grüter et al. 2008



sometimes individuals rely less on social information even when available



goats

Baciadonna et al. 2003



guppies

Kendal et al. 2004



Smolla M, Gilman RT, Galla T, Shultz S. 2015 **Competition for resources can explain patterns of social and individual learning in nature.** *Proc. R. Soc. B* 282: 20151405.

<http://dx.doi.org/10.1098/rspb.2015.1405>

producer-scrounger game

Patches with different payoffs Q



learning in a foraging context



Individual learner

Information producer

Social learner

Information scrounger

10,000 rounds
100 individuals
100 patches
0.01 turnover rate

Why use an ABM approach?

- Learning (innovation & imitation)
- Memory
- Local interactions

producer-scrounger game

Patches with different payoffs Q



learning in a foraging context



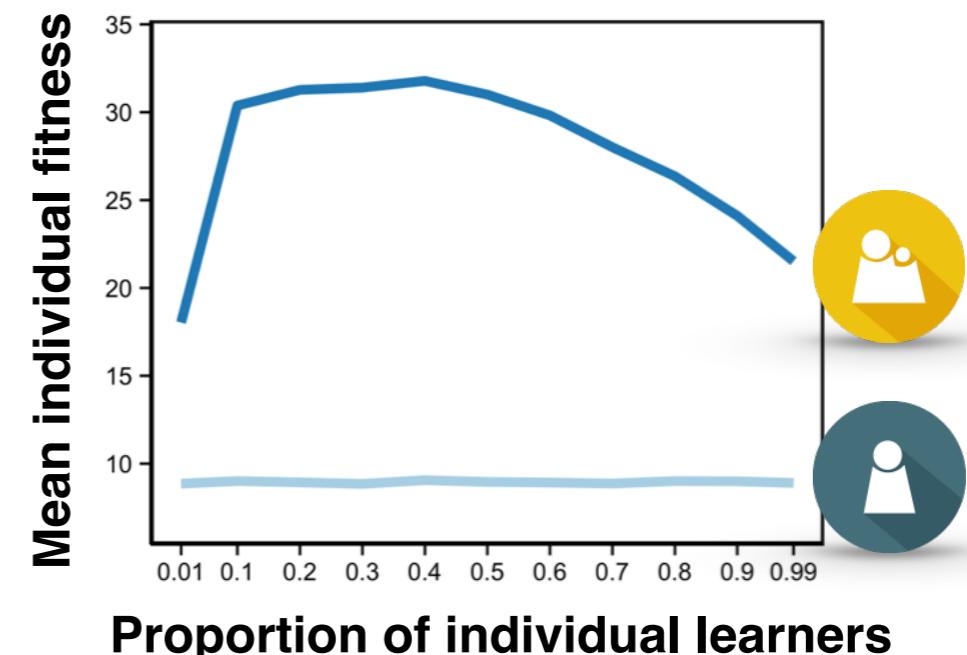
Individual learner

Information producer

10,000 rounds
100 individuals
100 patches
0.01 turnover rate

Social learner

Information scrounger



free-riding social learners always dominate individual learners

resource competition

Q amount of accessible resources in a patch

no competition



competition



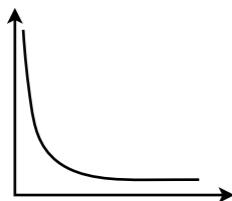
a single individual receives

Q

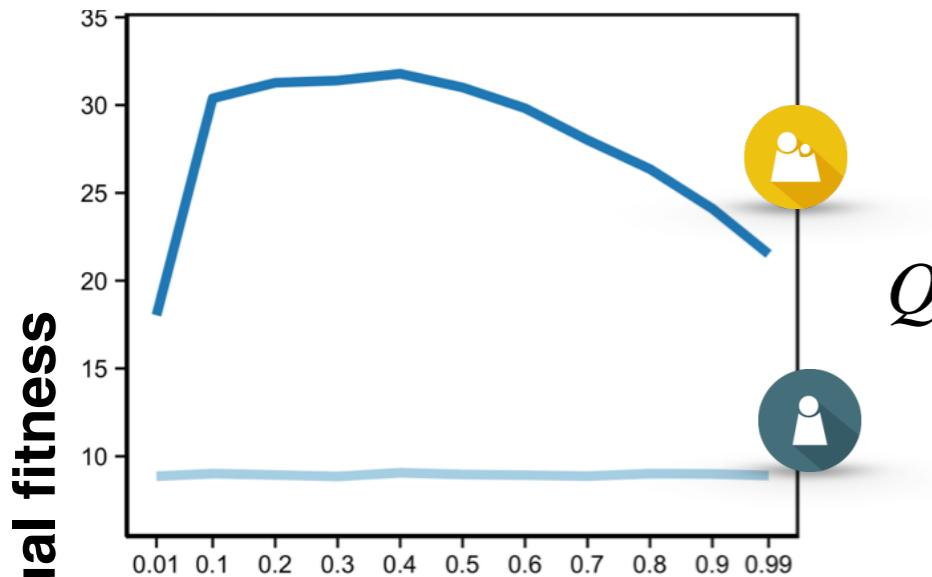
$$\frac{Q}{N} \quad (\text{number of individuals in patch})$$

how to formalise competition?

effect of competition

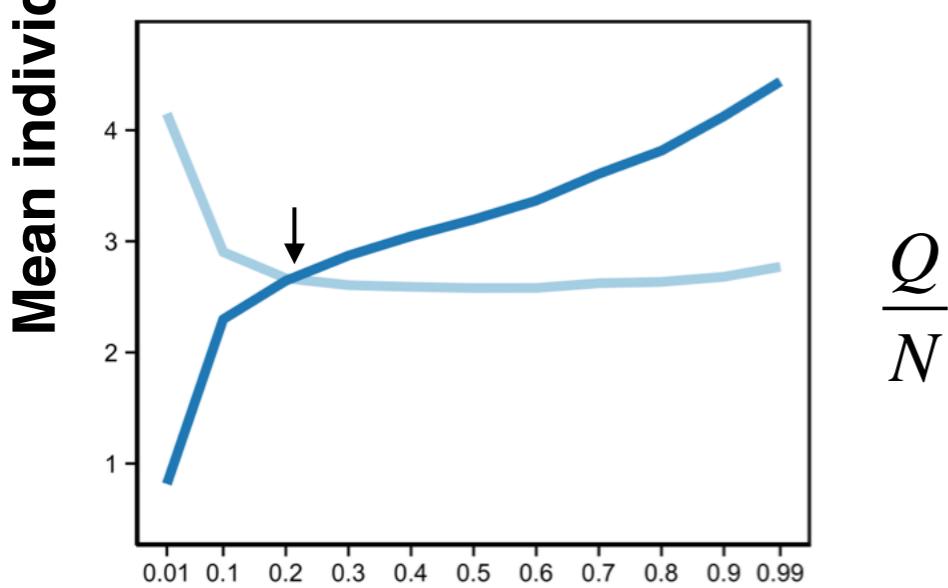


Uneven resources



Q

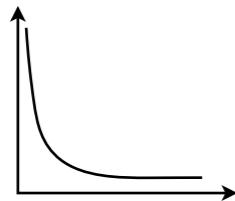
$\frac{Q}{N}$



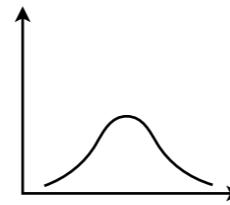
Proportion of individual learners

finding the stable state between two strategies

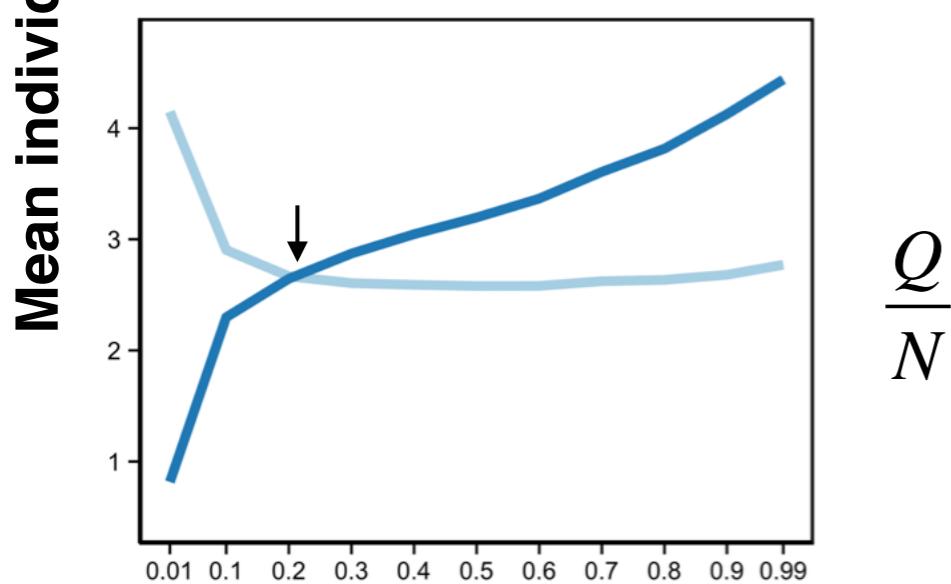
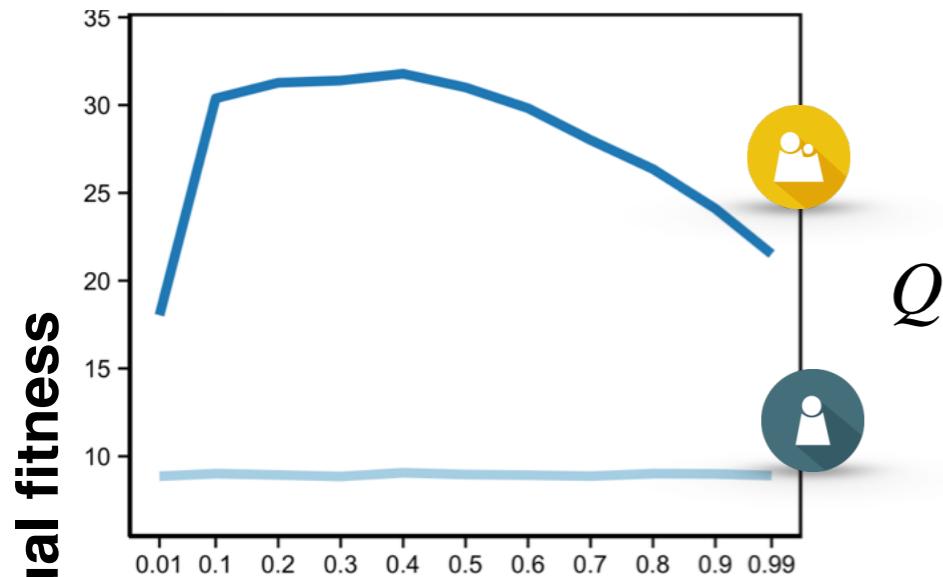
effect of competition



Uneven resources



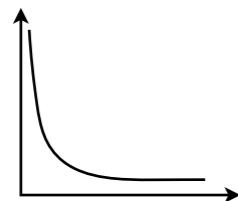
Even resources



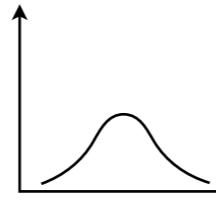
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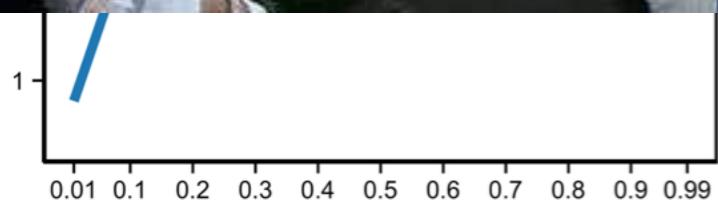


Uneven resources



Even resources

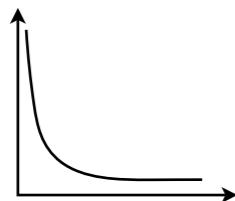
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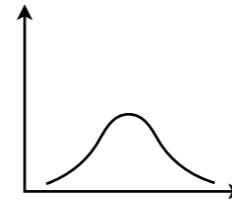
Proportion of individual learners

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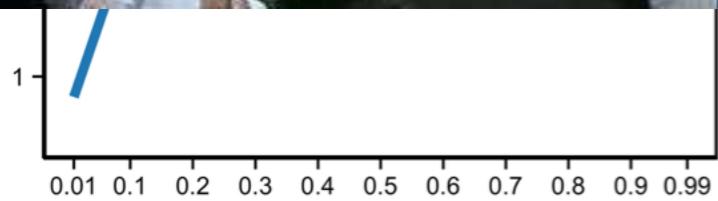


Uneven resources



Even resources

35

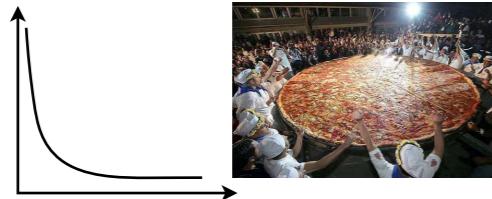


Proportion of individual learners

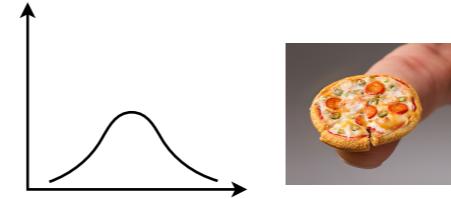
finding the



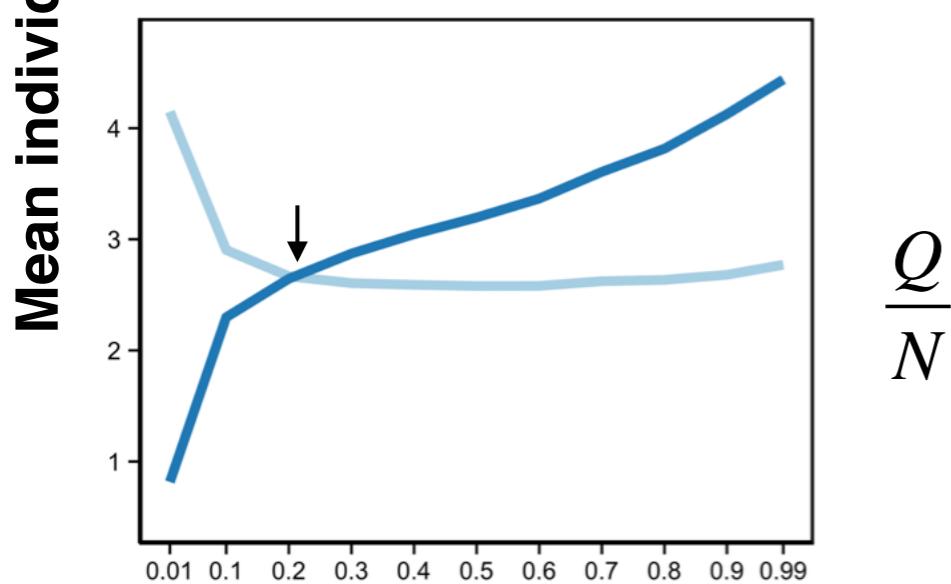
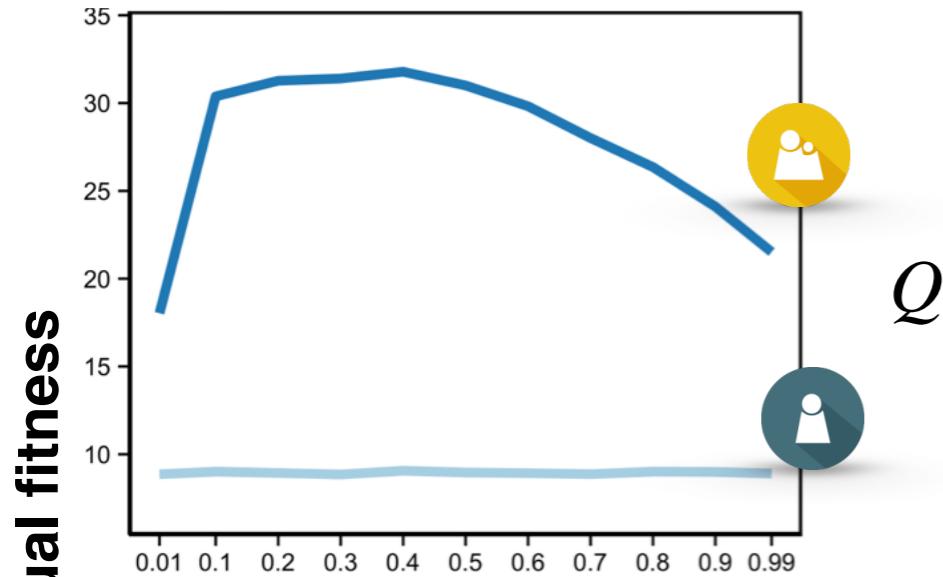
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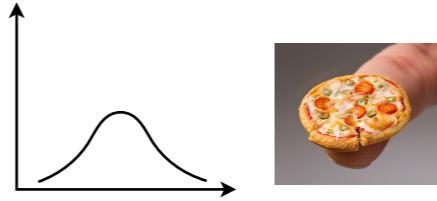
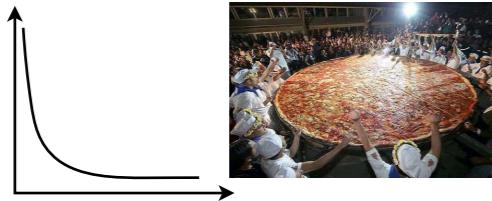
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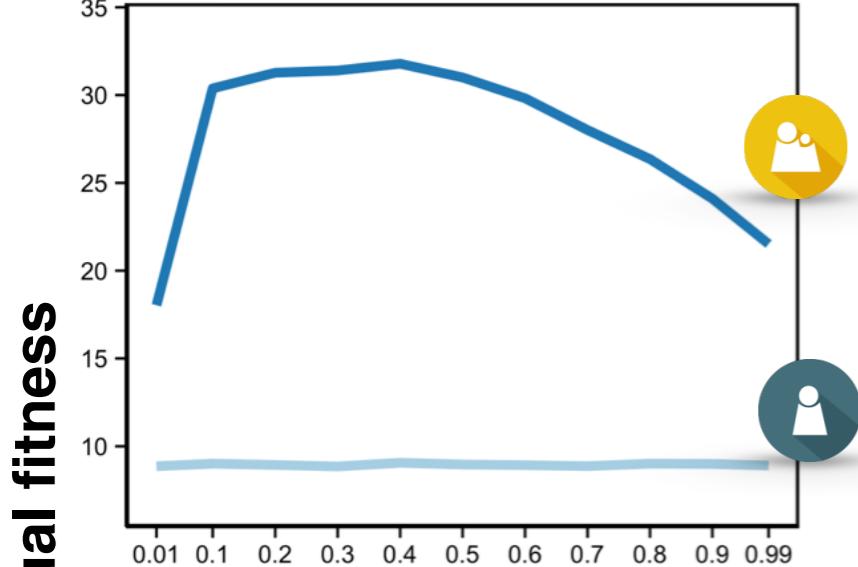
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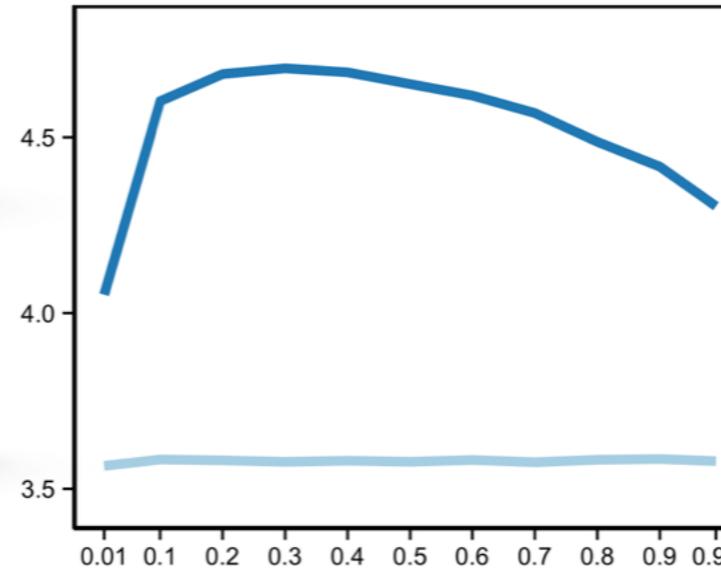
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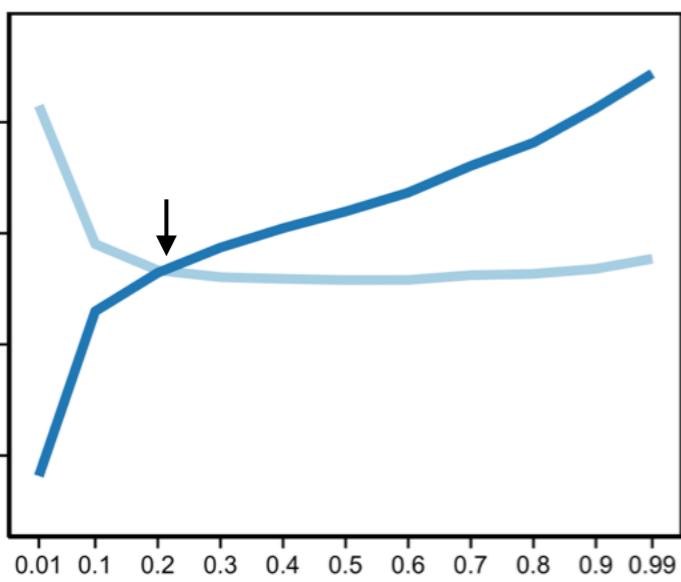
Uneven resources



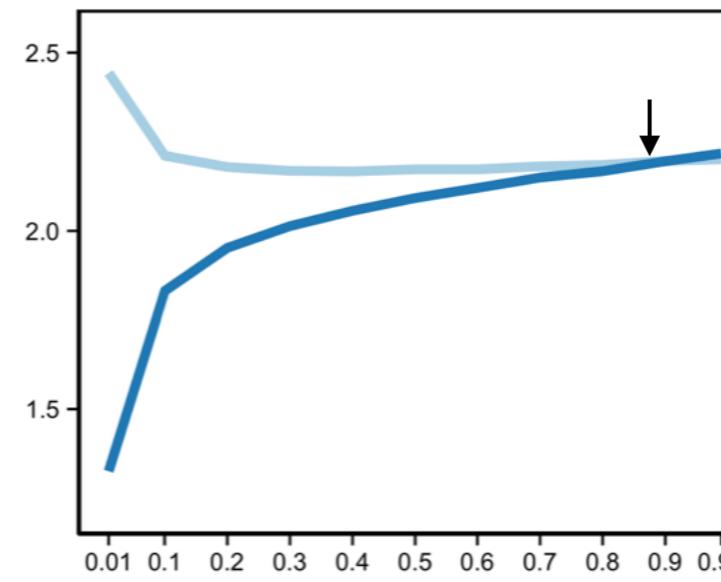
Even resources



Mean individual fitness



Proportion of individual learners



Q

$\frac{Q}{N}$

finding the stable state between two strategies

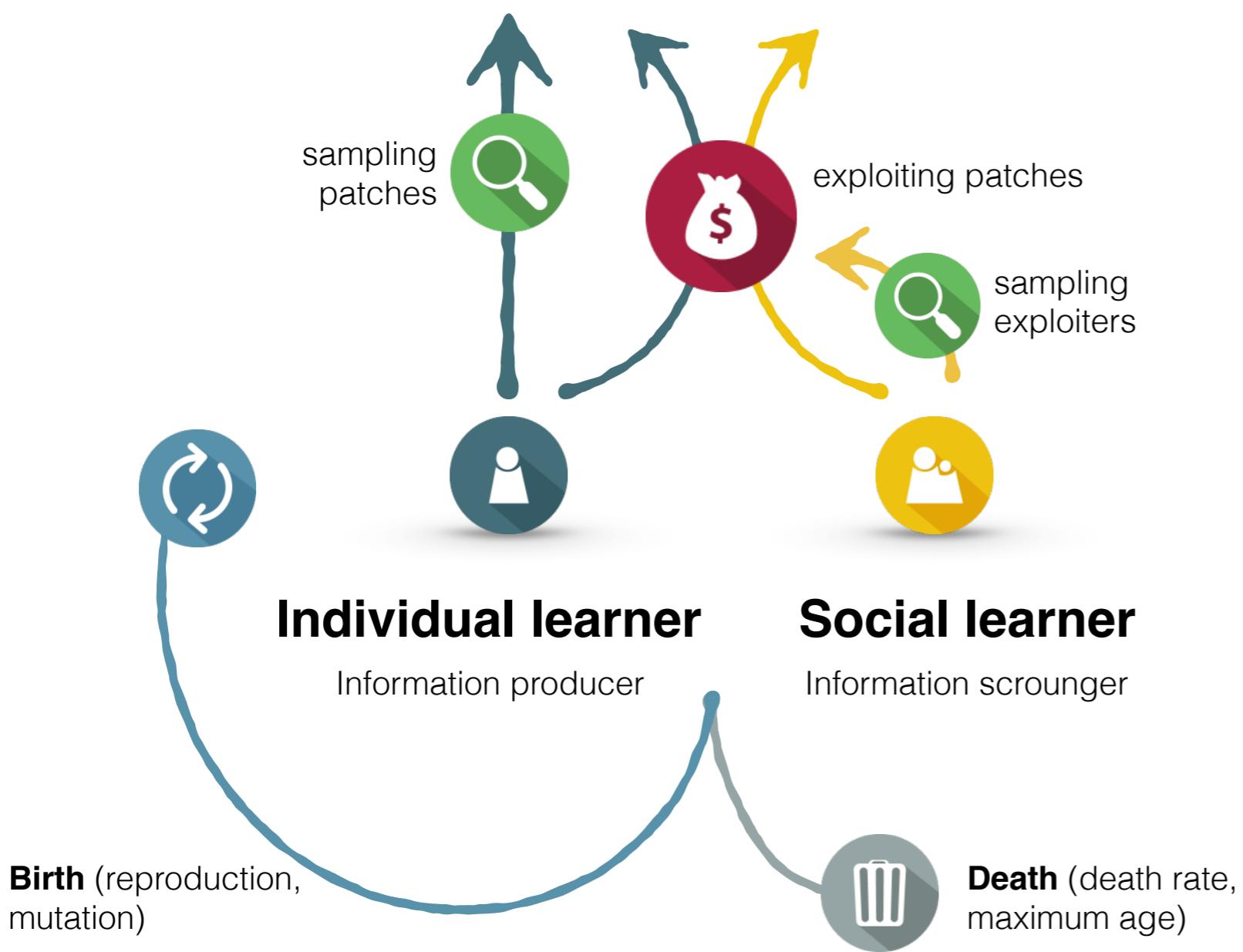
the stable state is affected by the payoff distribution

evolving producer- scrounger game

Patches with different payoffs Q



evolutionary
model to find
strategy
equilibrium



effect of the environment

frequent changes



Environmental turnover

10^0

10^{-1}

10^{-2}

10^{-3}

10^{-4}

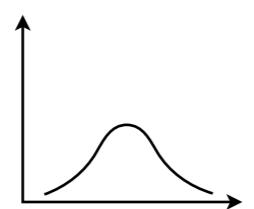
stable environment



0.1 0.2 0.4 0.6 0.8

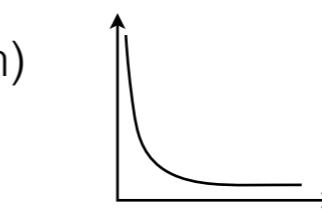
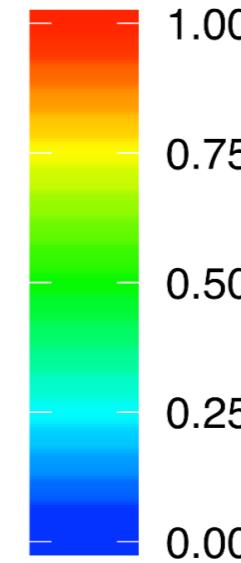
Gini index

(resource distribution)



Even resources

Proportion of individual learners



Uneven resources

a wide range of environmental parameters in an evolving system

effect of the environment

frequent changes



Environmental turnover

7

10⁰

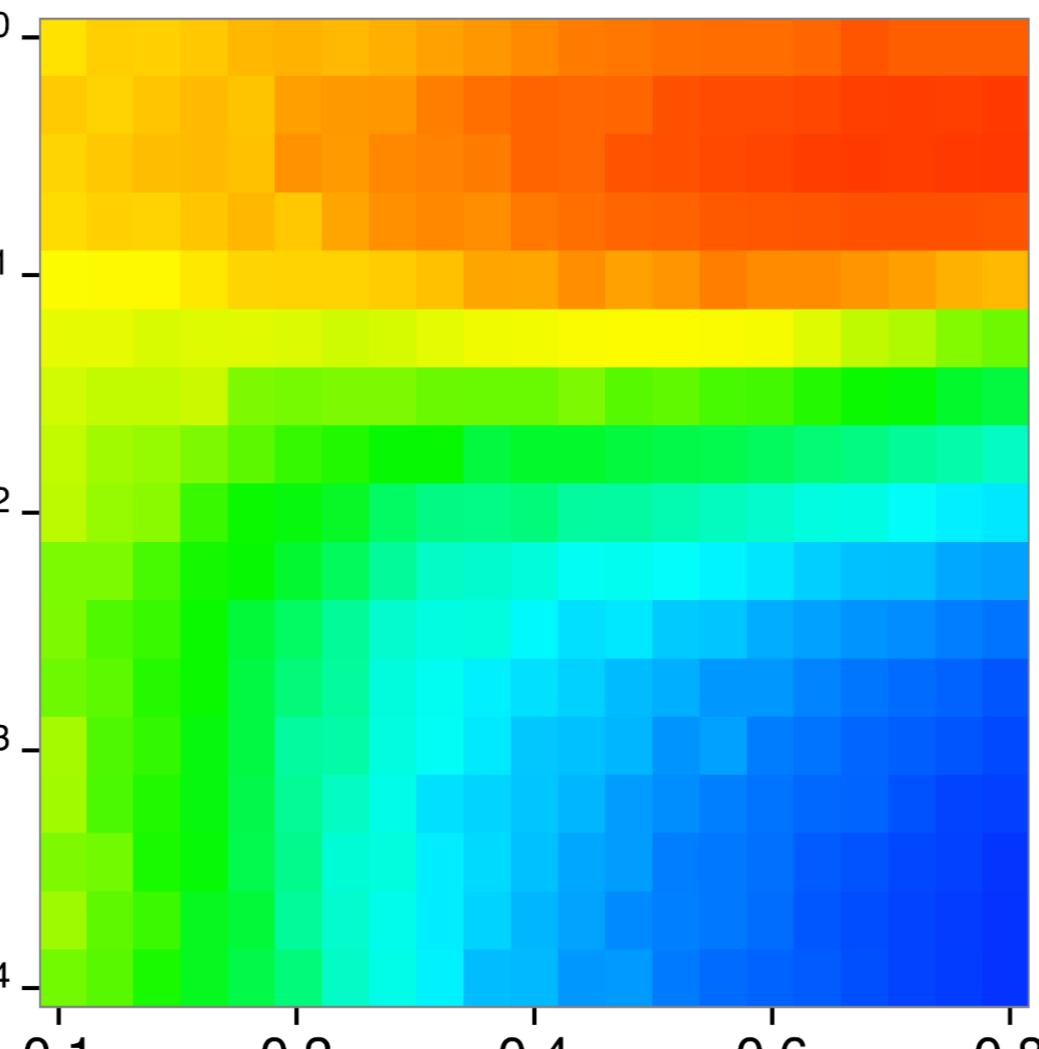
10⁻¹

10⁻²

10⁻³

10⁻⁴

(probability per patch and round)



Proportion
of individual
learners

1.00

0.75

0.50

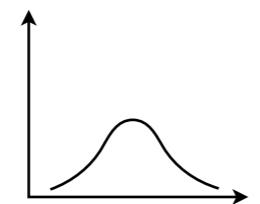
0.25

0.00

stable
environment

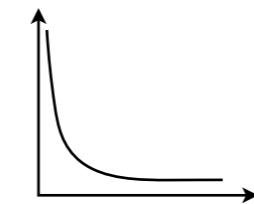


Gini index



Even resources

(resource distribution)

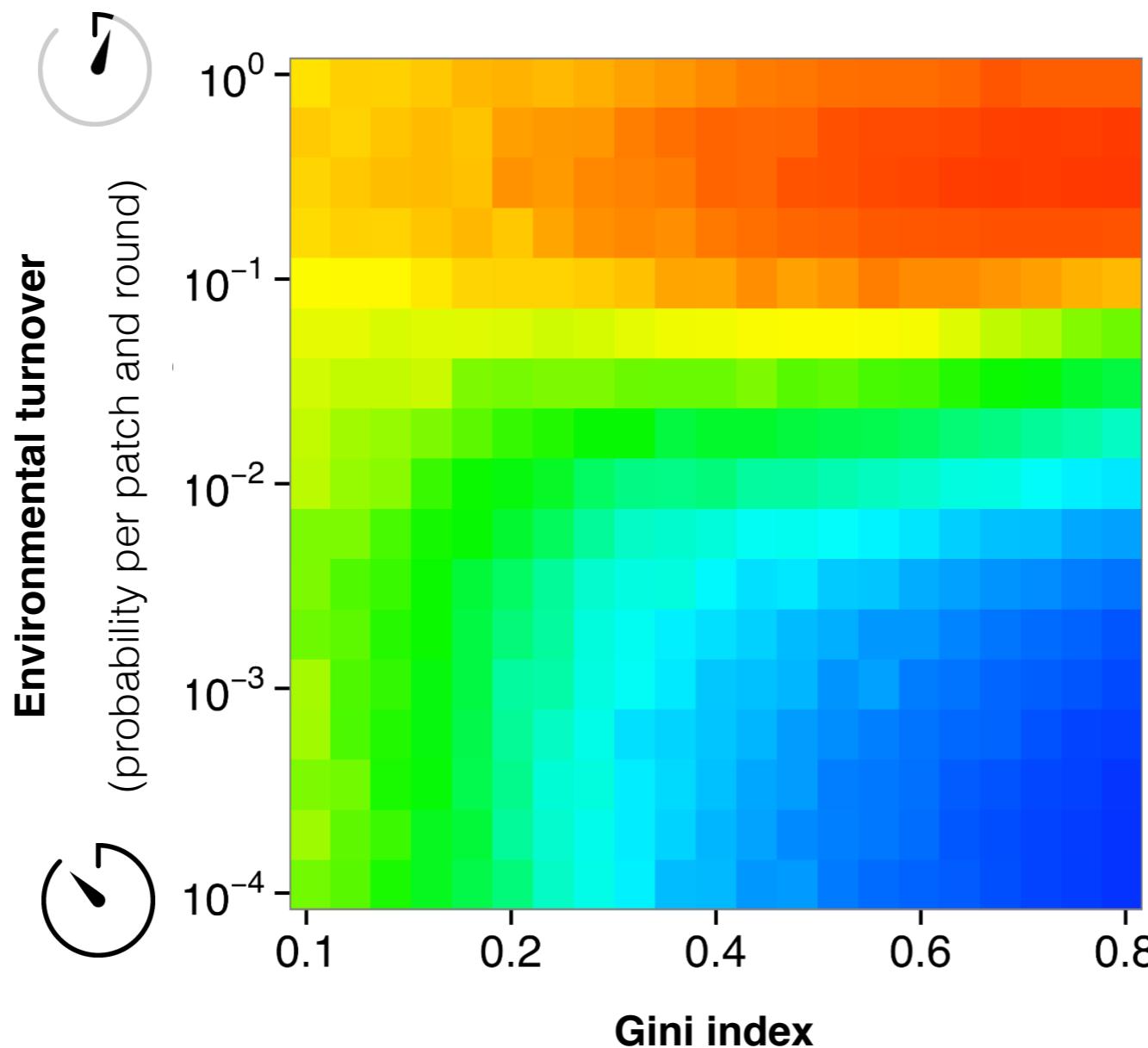


Uneven resources

a wide
range of
environmental
parameters in
an evolving
system

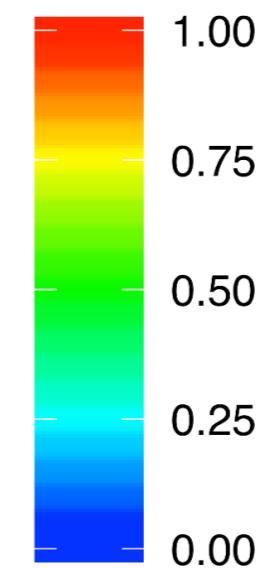
effect of the environment

frequent changes

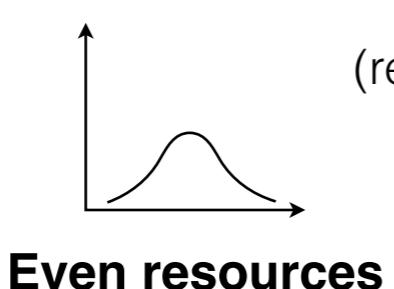


stable environment

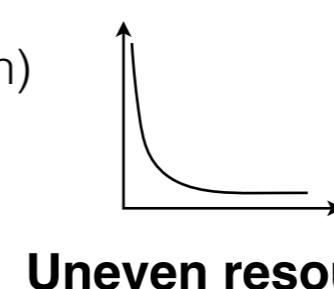
Proportion
of individual
learners



a wide range of environmental parameters in an evolving system



(resource distribution)



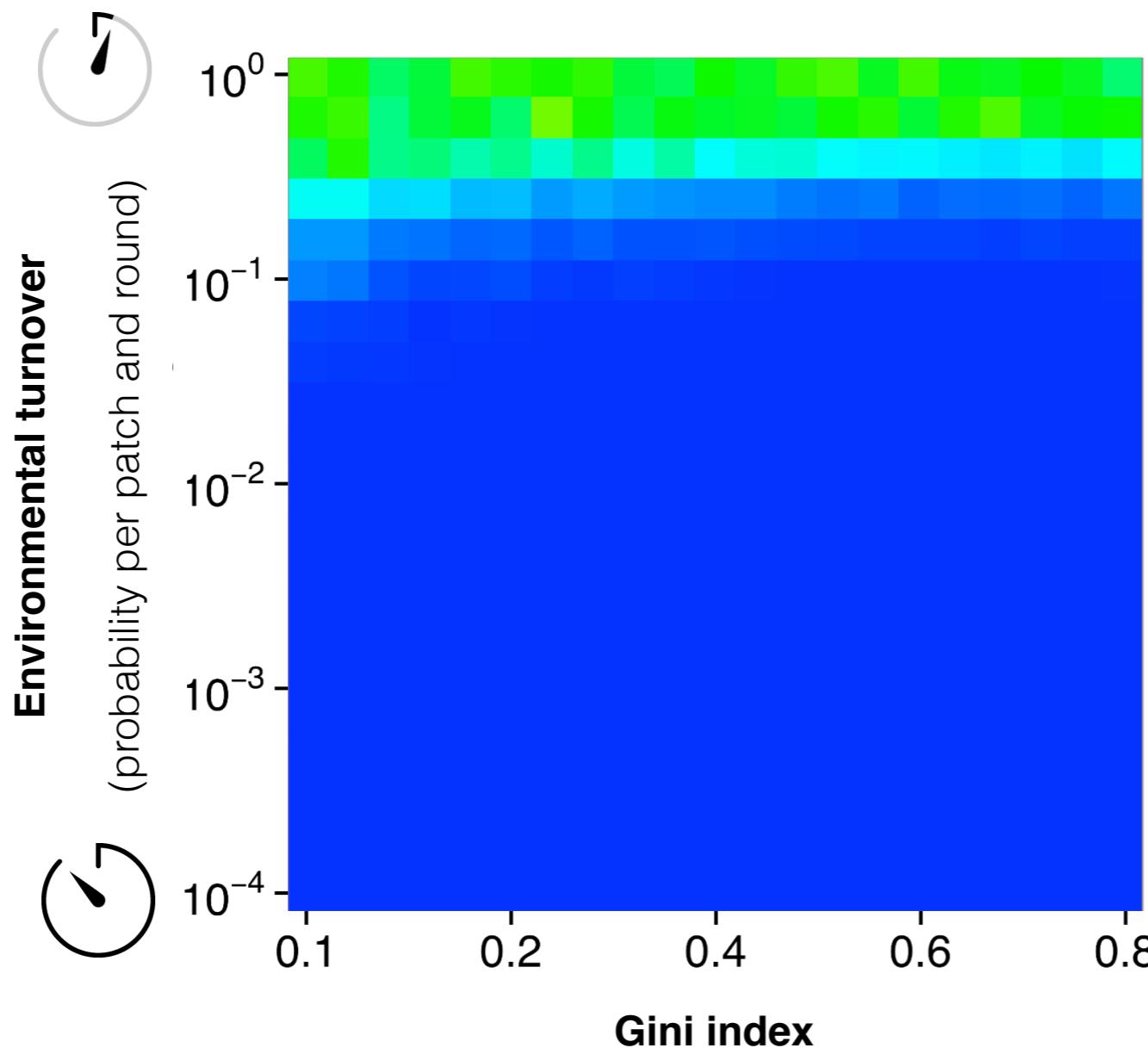
Uneven resources

copying others is advantageous if:

- payoffs are highly skewed
- payoffs are stable

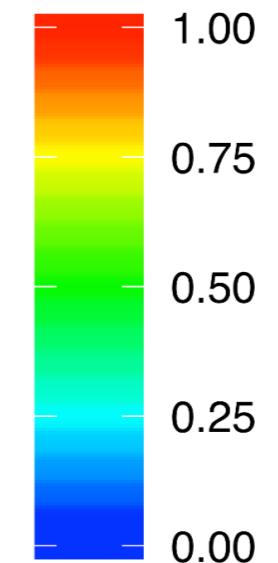
effect of the environment

frequent changes

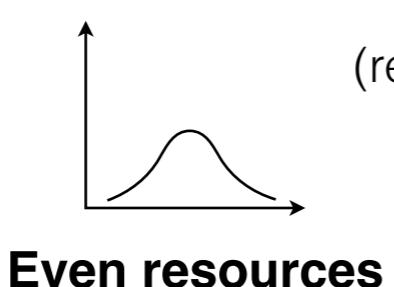


stable environment

Proportion
of individual
learners

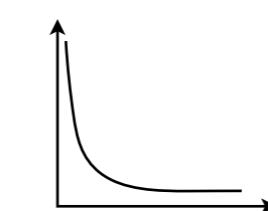


a wide range of environmental parameters in an evolving system



(resource distribution)

Even resources



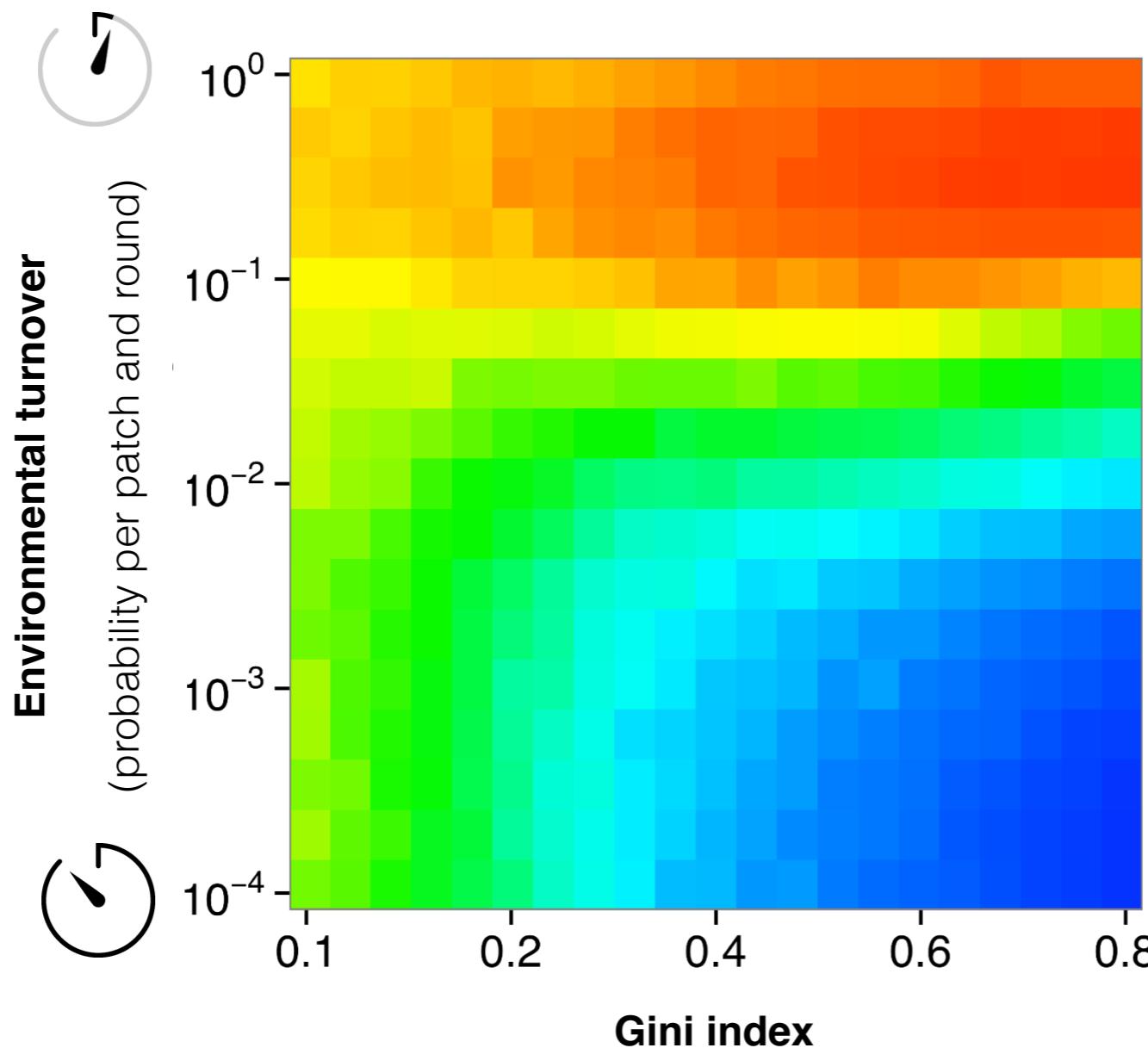
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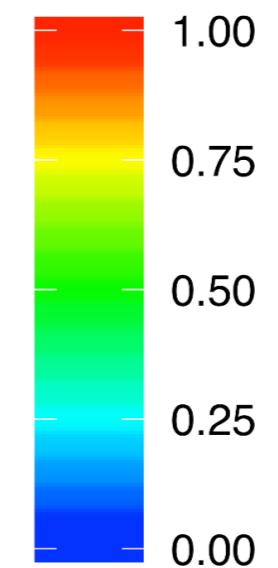
effect of the environment

frequent changes

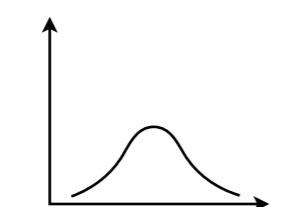


stable environment

Proportion
of individual
learners



(resource distribution)



Even resources



Uneven resources

copying others is
advantageous if:

- payoffs are highly
skewed
- payoffs are stable

resource competition

Q amount of resources in a patch accessible for a single individual

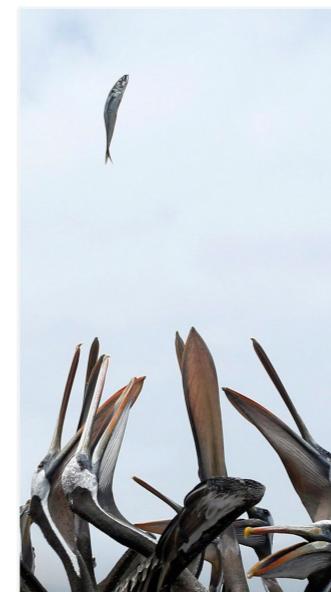
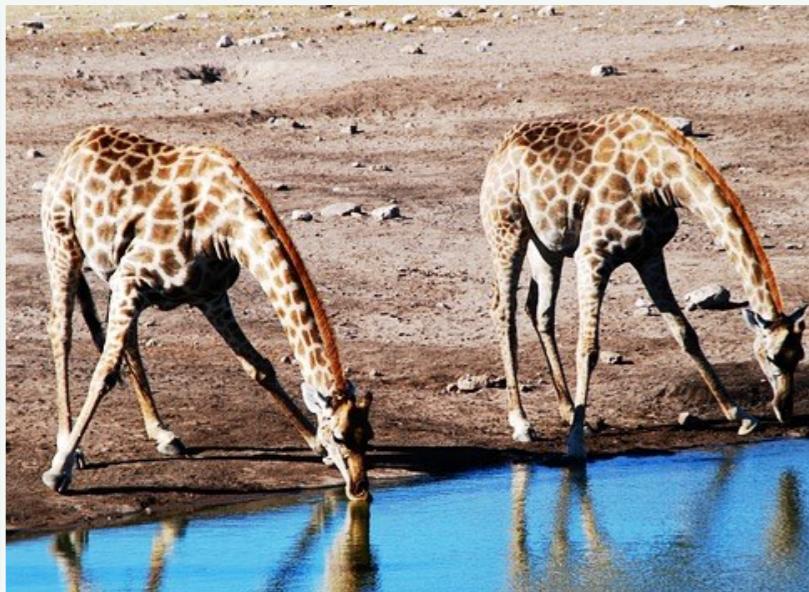
no competition

exploit competition

stronger interference

competition strength c

how to formalise competition?



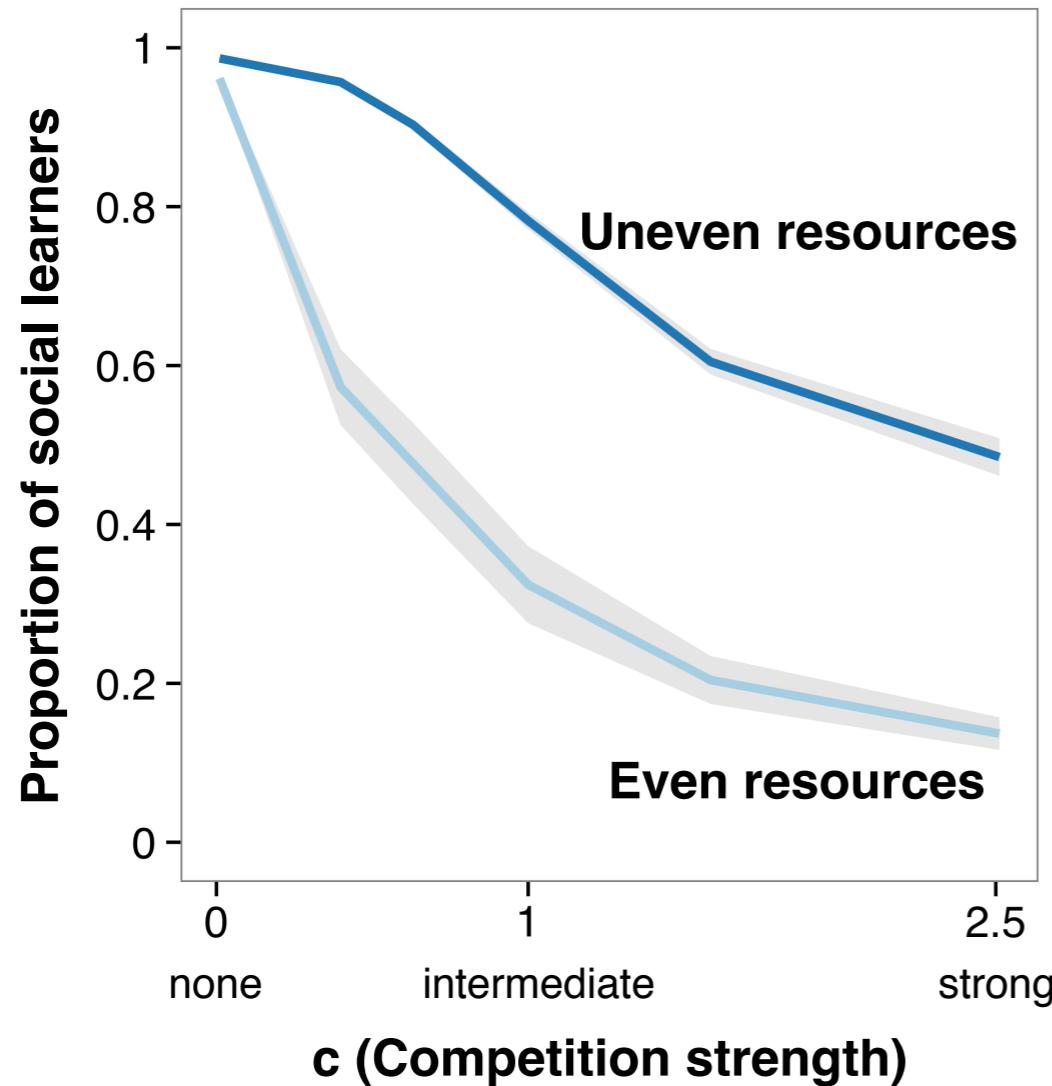
q amount of resources collected by a single individual

$$q = \frac{Q}{N^0}$$

$$q = \frac{Q}{N^1}$$

$$q = \frac{Q}{N^c}$$

effect of different competition strength



Grand and Dill, 1998

with increasing competition social learning decreases

programming our own agent based model
(jupyter notebook)

when are ABMs useful?

Conditional behaviour changes

Learning

Imitation

Evolution

Geographical representation

Social network structures

Emergence (bottom-up)

In-silico experiments

Asses effect of interventions and policies

Help plan data collection

Communication

ABM best practice

1. **Start with a clear question or goal** and let this drive early modelling decisions
2. **Take an “agent” perspective** in initial design, identifying key actors in the system that will be the focus of the model
3. **Start with (relatively) simple models** and build up complexity iteratively, one step at a time
4. **Assumptions should be well grounded** and have a strong **motivation**
5. **Use care in translation** of an ABM design into computational code
6. Conduct **error-checking** and **partial testing** as models are implemented
7. **Retrieve a known, neutral case** with the model (e.g. ideal-free distribution)
8. Fully **document model specification and implementation**, and maintain up-to-date documentation throughout the process
9. Conduct thorough and appropriate **sensitivity analysis**
10. **Design clear experiments** to yield clear insights
11. **Always investigate surprising results**, and make sure that you understand how they arise
12. Draw **appropriate conclusions** from the model analysis

Verification

debugging model code so that model behaves as intended

Validation

making sure right model has been build

challenges in ABM

Generalisations are often not possible

Statements only hold for those parameter(s/ sets) that have been simulated

Defining rules, agents, and the environment

Important to choose, motivate, and justify behavioural rules, agent and environmental characteristics

Pitfall: programming results into the model mechanics

References

Bialek et al., (2012). "Statistical mechanics for natural flocks of birds." *Proceedings of the National Academy of Sciences* 109.13: 4786-4791.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*, 99(Supplement 3), 7280–7287.
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