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Understanding epistemic grouping, networking and division of labour

What can simple macroscopic models do?

International Conference
Modeling Epistemic and Scientific Groups: Interdisciplinary Perspectives
Nancy, MSH Lorraine, November 25 - 26, 2013

Structure of the talk

1. The idea of simple macroscopic models
2. The BC-model: A short analysis of the most simple version
3. Truth, truth seekers and cognitive division of labour – A first CASE-study
4. Modelling networking
5. Epistemic grouping and networking A second CASE study
6. Two-dimensional opinion spaces, epistemic landscapes, climbers and followers – A third CASE study
7. Some perspectives and ideas for CASE-studies

§1
The idea of simple macroscopic models

For the start: Let‘s suppose ...

- a group of people, for instance a *group of experts* on something;
- each expert has an *opinion* on the topic under discussion, for instance the probability of a certain type of accident;
- *nobody is totally sure* that he is totally right;
- to some degree everybody is *willing to revise* his opinion when informed about the opinions of others, especially the opinions of '*competent*' *others*;
- the revisions produce a new opinion distribution which may lead to further revisions of opinions, and so on and so on.... .

De Vergadering (The meeting), Willy Belinfante

Two „*simple macroscopic models*“:

- There is a set of n *agents*; $i, j \in I$.
- Time is *discrete*; $t = 0, 1, 2, \ldots$.
- Each agent i starts with a certain *opinion* given by a *real number* $x_i(t_0) \in [0,1]$.
- The *profile* of all opinions at time t is: $X(t) = x_1(t), \ldots, x_i(t), x_j(t), \ldots, x_n(t)$.
- *Updating* idea: *Averaging* over the opinions, but based on *competence* (*respect*, *seriousness*, …).

linear model

Each agent i assigns to each agent j a weight w_{ij} that expresses the supposed competence.

It holds:

$$w_{ij} \in [0,1] \text{ and } \sum_{j \in I} w_{ij} = 1$$

Updating is compentence-weighted averaging over all opinions:

$$x_i(t+1) = \sum_{j \in I} w_{ij} x_j(t)$$

non-linear model

Each agent i regards as competent the set of agents j whose opinions are *not too far away*, i.e. for which $|x_i(t) - x_j(t)| \leq \varepsilon$ (*confidence interval*).

The (time dependent !) *set* of agents j that i regards as competent is:

$$I(i, X(t)) = \{ j \,|\, |x_i(t) - x_j(t)| \leq \varepsilon \}$$

Updating is averaging over all opinions within one's confidence interval:

$$x_i(t+1) = \frac{1}{\#(I(i, X(t)))} \sum_{j \in I(i, X(t))} x_j(t)$$

number of elements (of $\#$)

"Bounded Confidence Model"

Note:
The opinions – *more* than probabilities only!

„… *opinion*, given by a *real number* $x_i(t_0) \in [0,1]$."

<u>Possible types opinions:</u>

- probabilities / degrees of belief for any quantitative or qualitative proposition
- real valued quantitative propositions (the normalized range [0,1] does not matter).
- intensity or importance of a wish or preference (*iff* intersubjectively comparable!)
- moral praiseworthiness (0: extremely bad, 0.5: neutral, 1: extremely good)
- budget share

<u>Not covered:</u>

Non continous opinions (e.g. discrete or even binary)

An ultra-short history of the two models

linear model

1956 — John R. P. French

A directed graph represents the *power to influence* the opinions of others in a group. Some convergence results.

1959 — Frank Harary

Harary *translates* French's approach into the theory of stochastic matrices and Markov chains. Direct transfer of analytical results from there.

1974 — Morris H. DeGroot

Explicit Definition of the linear model. Framing: Chances to reach consensus in a group of experts that discuss probabilities. Transfer of formal results from the theory of stochastic matrices and Markov chains.

1981 — Keith Lehrer & Carl Wagner

Give the linear model a *normative* interpretation and propose to use it as a *mechanical devise* to resolve disagree- ment in science and society *rationally*.

Problems in the linear model:

- How to assign weights?
- Can't weights change over time?
- Arn't weights depending upon another's opinion?

non-linear model

1997 — Ulrich Krause

Explicit definition of the non-linear model

1998 conference proceedings 2000

Coins the concept "*bounded confidence*" model. Proof of a sufficient condition for consensus.

2000 — Guillaume Deffuant et al.

A broad simulation based study of a *variant* of the non-linear model; main difference: *random pairwise updating*.

2002 — Rainer Hegselmann & Ulrich Krause

A broad analytical and simulation based study of the BC-model in its elementary version and some extensions (biased confidence intervals).

§2
The BC-model: A short analysis of the most simple version

Basics of the bounded confidence model

Each individual takes seriously only those others whose opinions are '*reasonable*', '*not too strange*', i.e. not too far away from one's own opinion.

- There is a set of *n individuals; i, j* $\in$ *I.*
- Time is *discrete;* $t = 0, 1, 2, \ldots$.
- Each individual starts with a certain *opinion*, given by a *real number*; $x_i(t_0) \in [0,1]$.
- The *profile* of all opinions at time t is

$$x(t) = x_1(t), \ldots, x_i(t), x_j(t), \ldots, x_n(t).$$

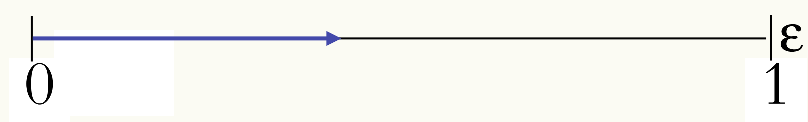
- Each individual *i* takes into account only '*competent*' others. Competent are those individuals whose opinions are not too far away, i.e. for which $|x_i(t) - x_j(t)| \leq \varepsilon$ (*confidence interval*). The *set* of all others that *i* takes into account at time *t* is:

$$I(i,x(t)) = \{ j \mid |x_i(t) - x_j(t)| \leq \varepsilon \}.$$

- The individuals *update* their opinions. The next period's opinion of individual *i* is the *average* opinion of all those which *i* takes seriously:

$$x_i(t+1) = \left| I\left(i, x(t)\right) \right|^{-1} \sum_{j \in I(i,x(t))} x_j(t)$$

How to analyse the model?



Confidence intervals: [0,1] as parameter space.

Heuristics:
‚Walking' from 0 direction 1

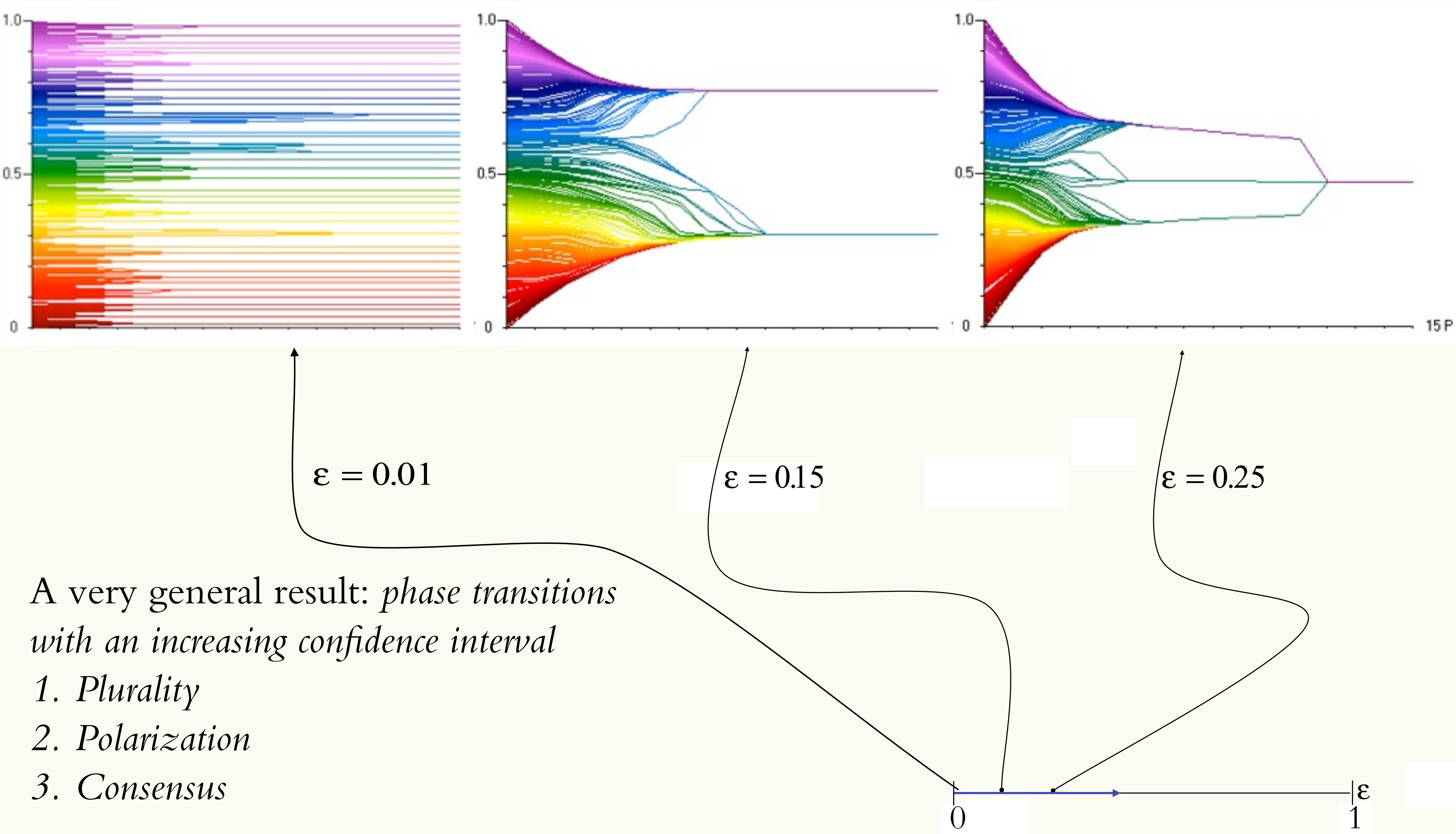
Research Questions:

- Does such a dynamics stabilize?
- Are there typical final results?
- When is consensus feasible?

KISS-principle: "Keep it simple, stupid!"

- Confidence intervals: *symmetric, homogeneous,* and *constant over time.*
- Start distributions:
  random uniform distribution: $x_i(t_0) \in [0,1]$
- Updating: *simultaneous*

Effects of different confidence intervals



A very general result: *phase transitions with an increasing confidence interval*

1. *Plurality*
2. *Polarization*
3. *Consensus*

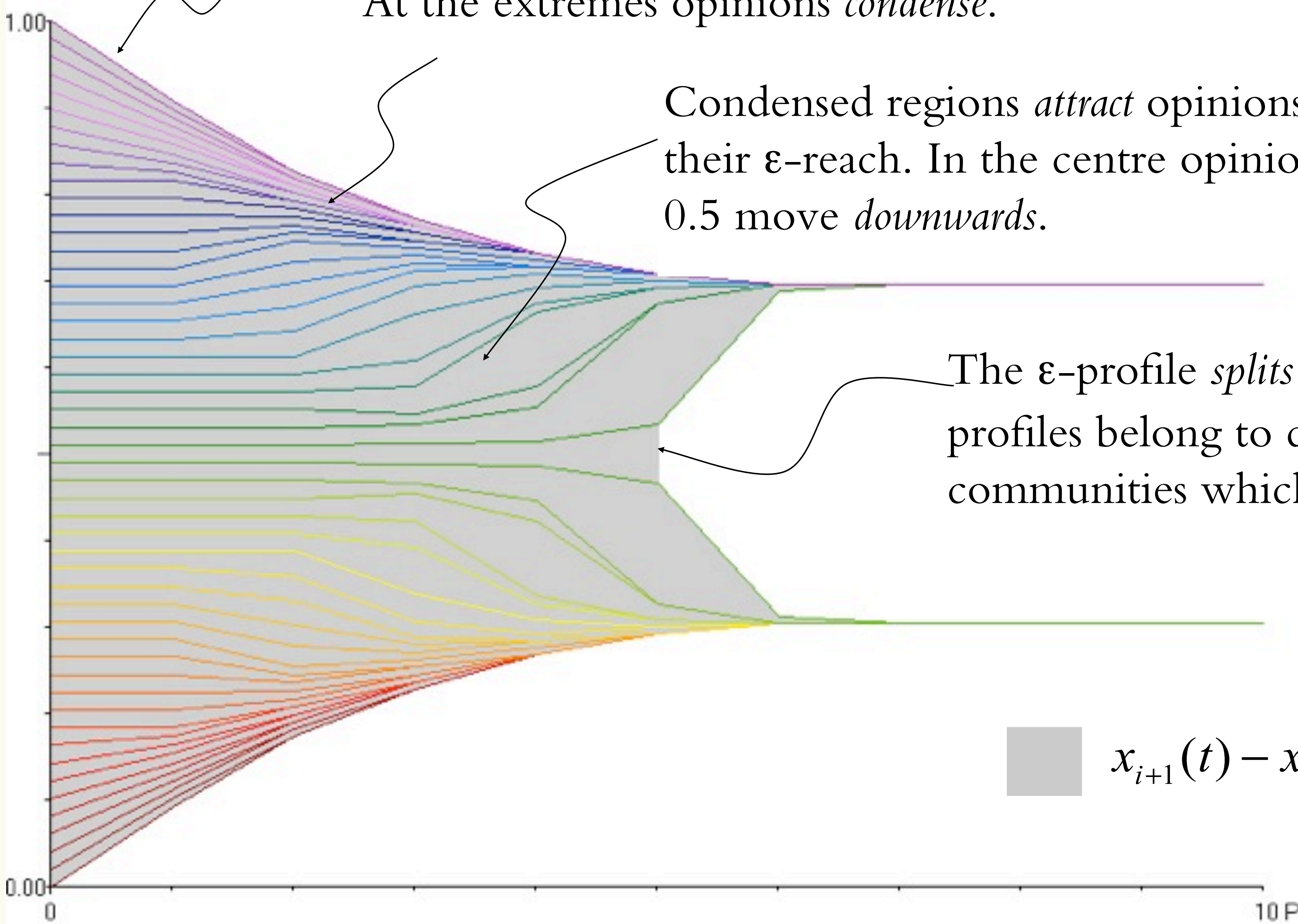
Understanding fragmentation: The ε-split

Extreme opinions are under a *one sided influence* and move direction centre. The range of the profile *shrinks*.

At the extremes opinions *condense*.

Condensed regions *attract* opinions from less populated areas within their ε-reach. In the centre opinions > 0.5 move *upwards*, opinions < 0.5 move *downwards*.

The ε-profile *splits* in t_6. From now on the split sub-profiles belong to different 'opinion worlds' or communities which *do no longer interact*.



$x_{i+1}(t) - x_i(t) \leq \varepsilon$

Dynamics with 50 opinions, simultaneous updating, regular start profile, ε = 0.2.

Understanding fragmentation: Some terminology

Definition 1

The opinion profile

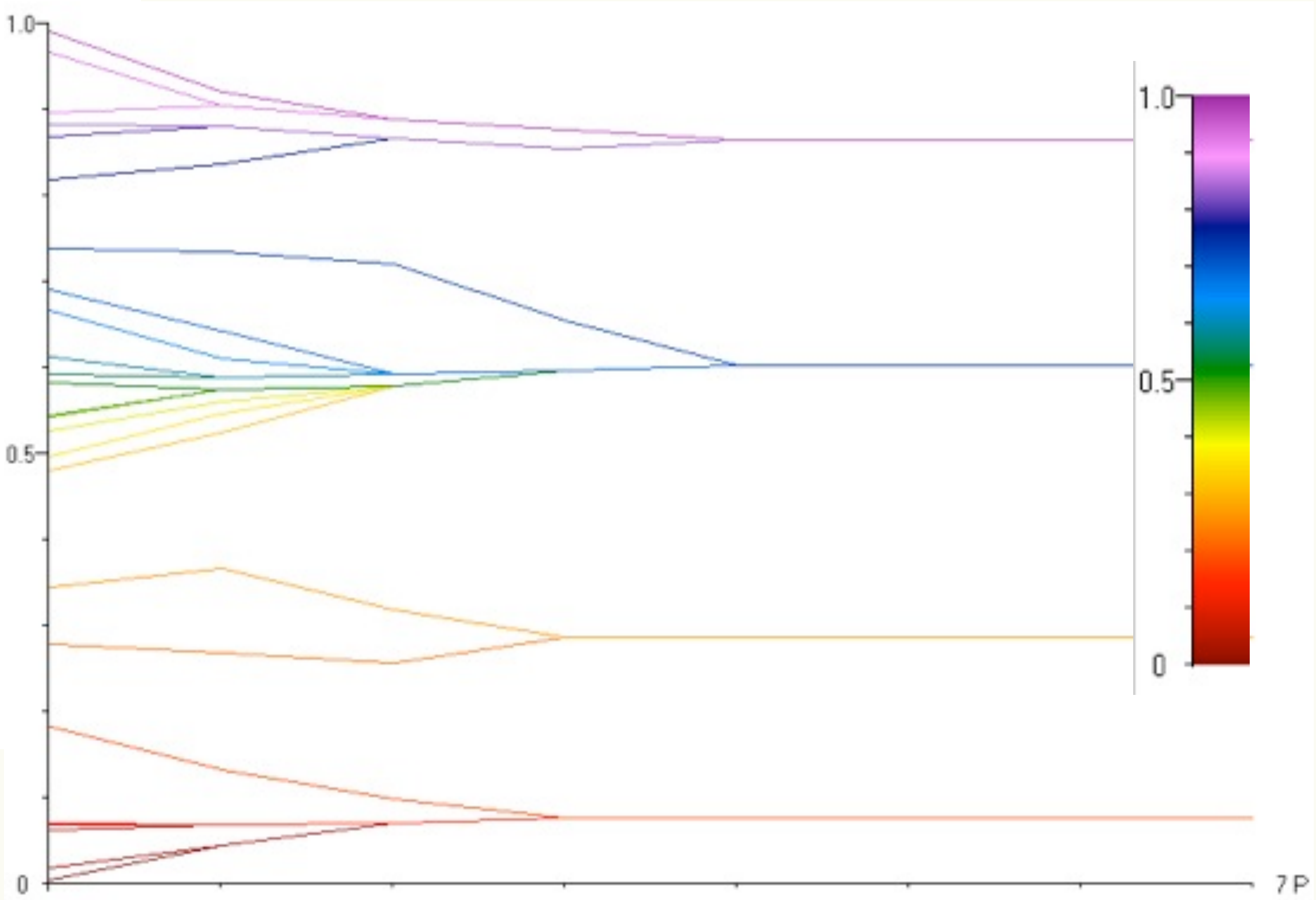
$x(t) = x_1(t), x_2(t), \ldots, x_i(t), \ldots x_n(t)$

is an *ordered opinion profile* iff

$0 \leq x_1(t), \leq x_2(t) \leq .. \leq x_i(t) \leq \ \ldots \leq x_n(t)$

Definition 2:

An ordered opinion profile is an ε–*profile* iff for all $i = 2, \ldots, n$ it holds $(x_{i+1} - x_i) \leq \varepsilon$.



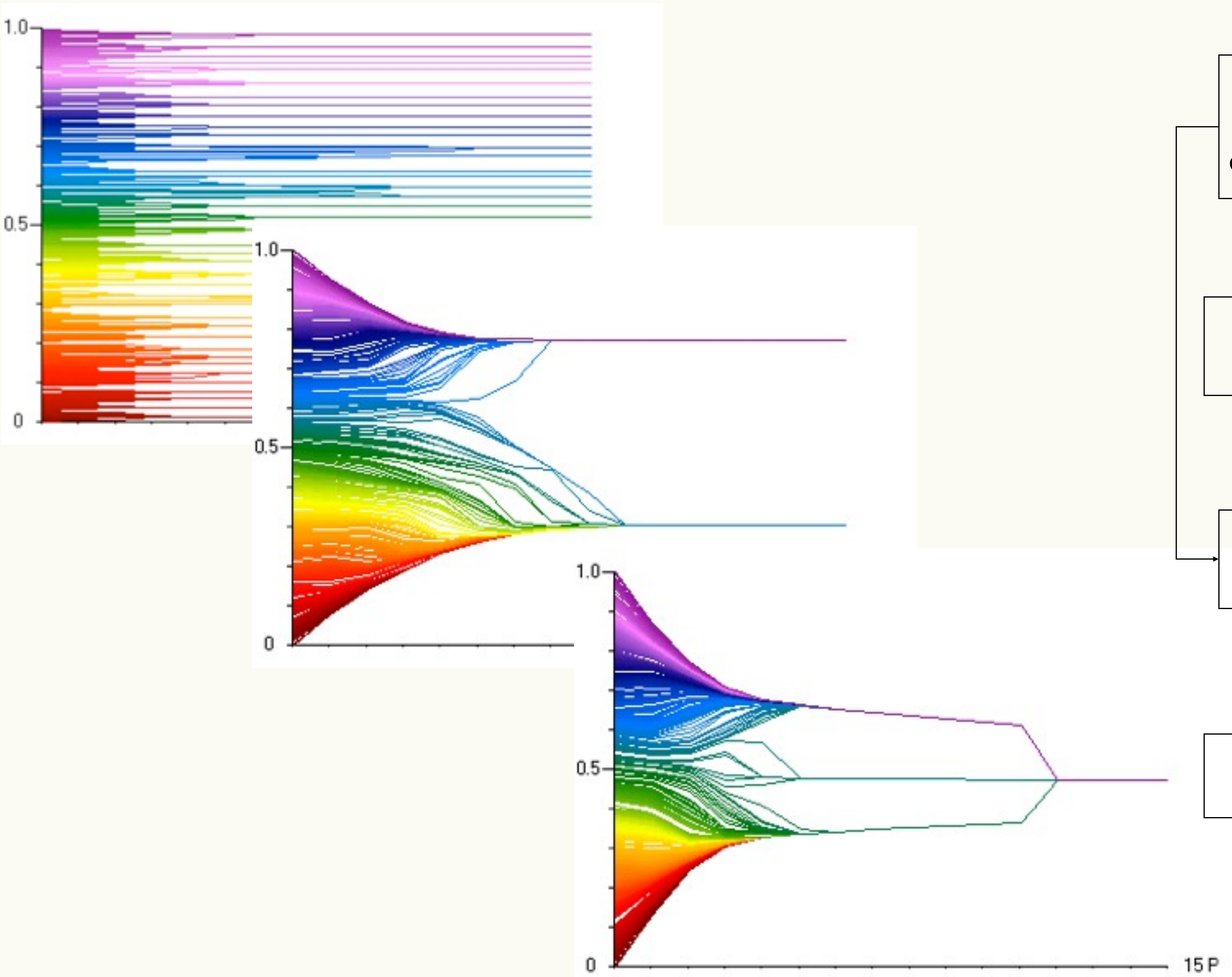
Note:

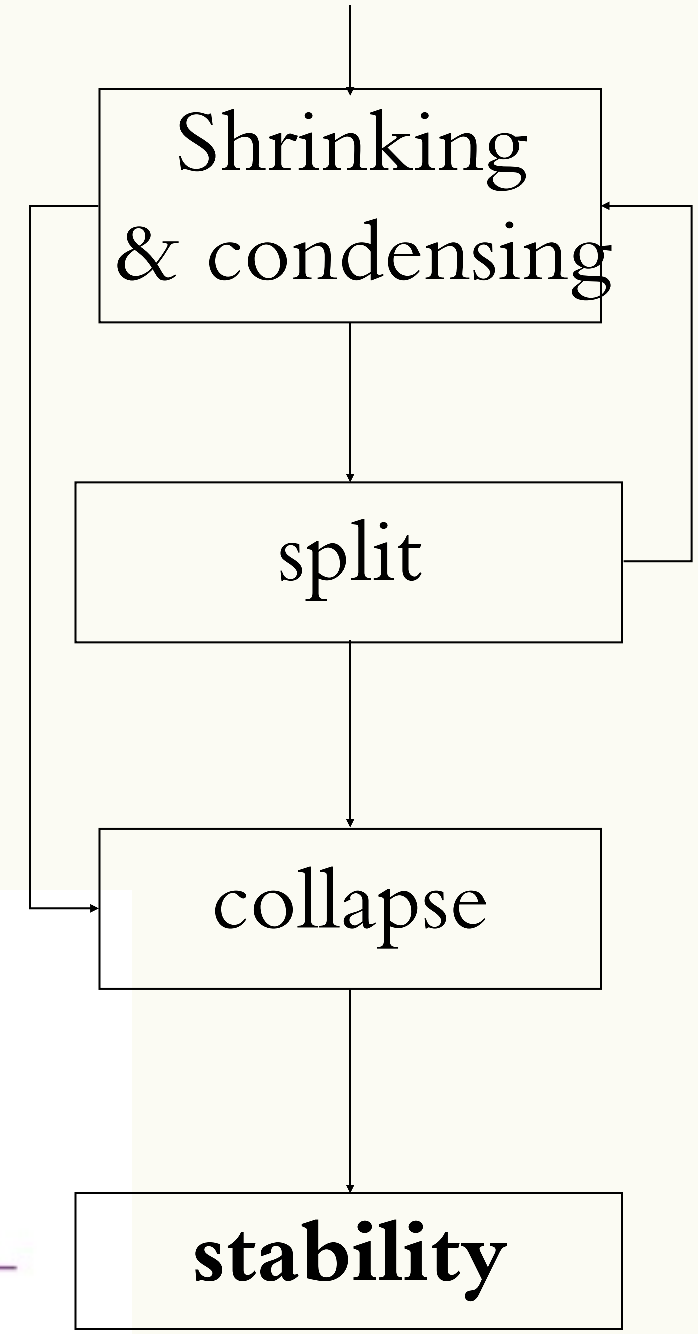
- We always *start* in t_0 with an *ordered* opinion profile

Please believe:

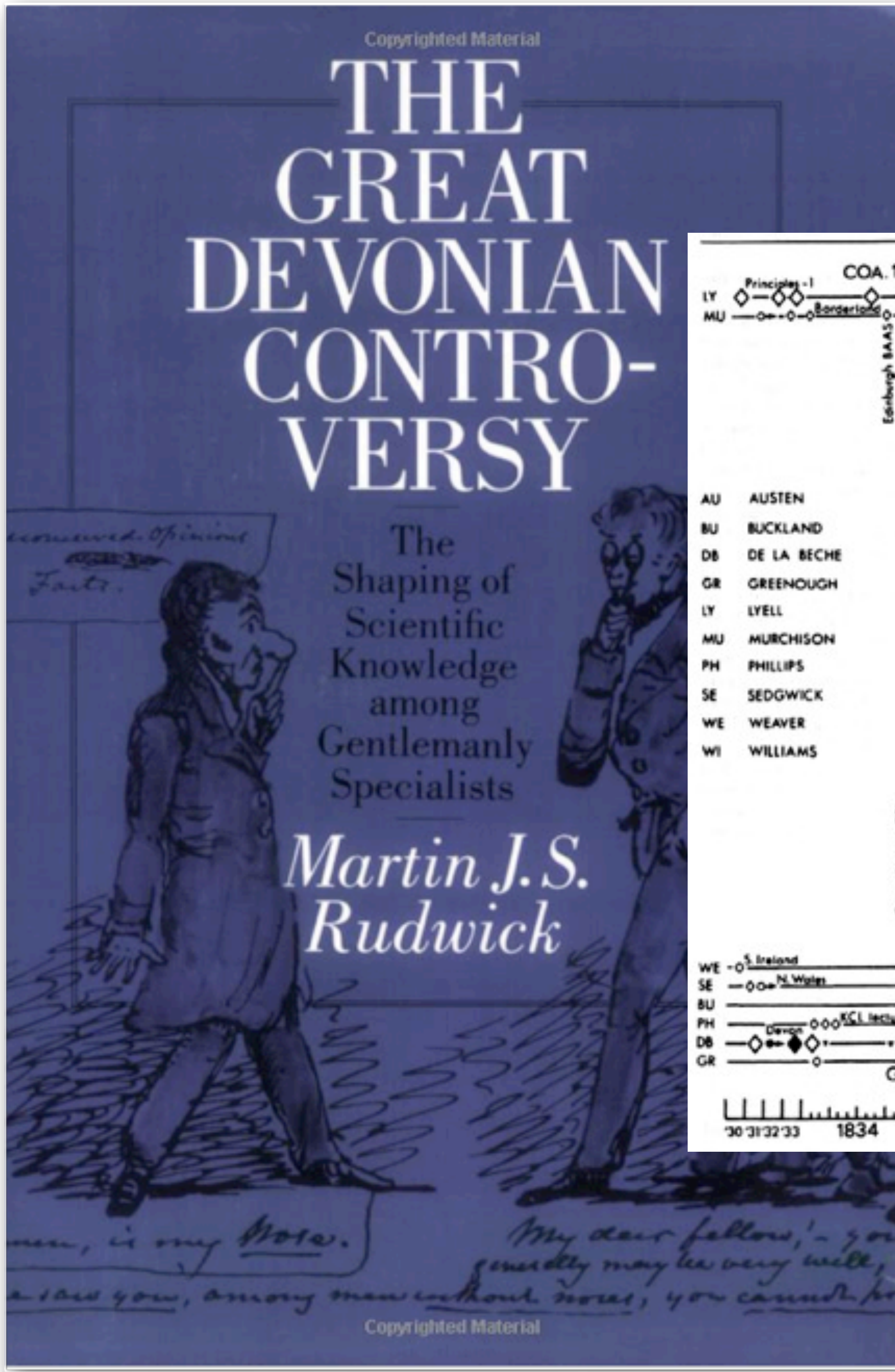
- *Simultaneous* updating will never disorder an opinion profile over time.

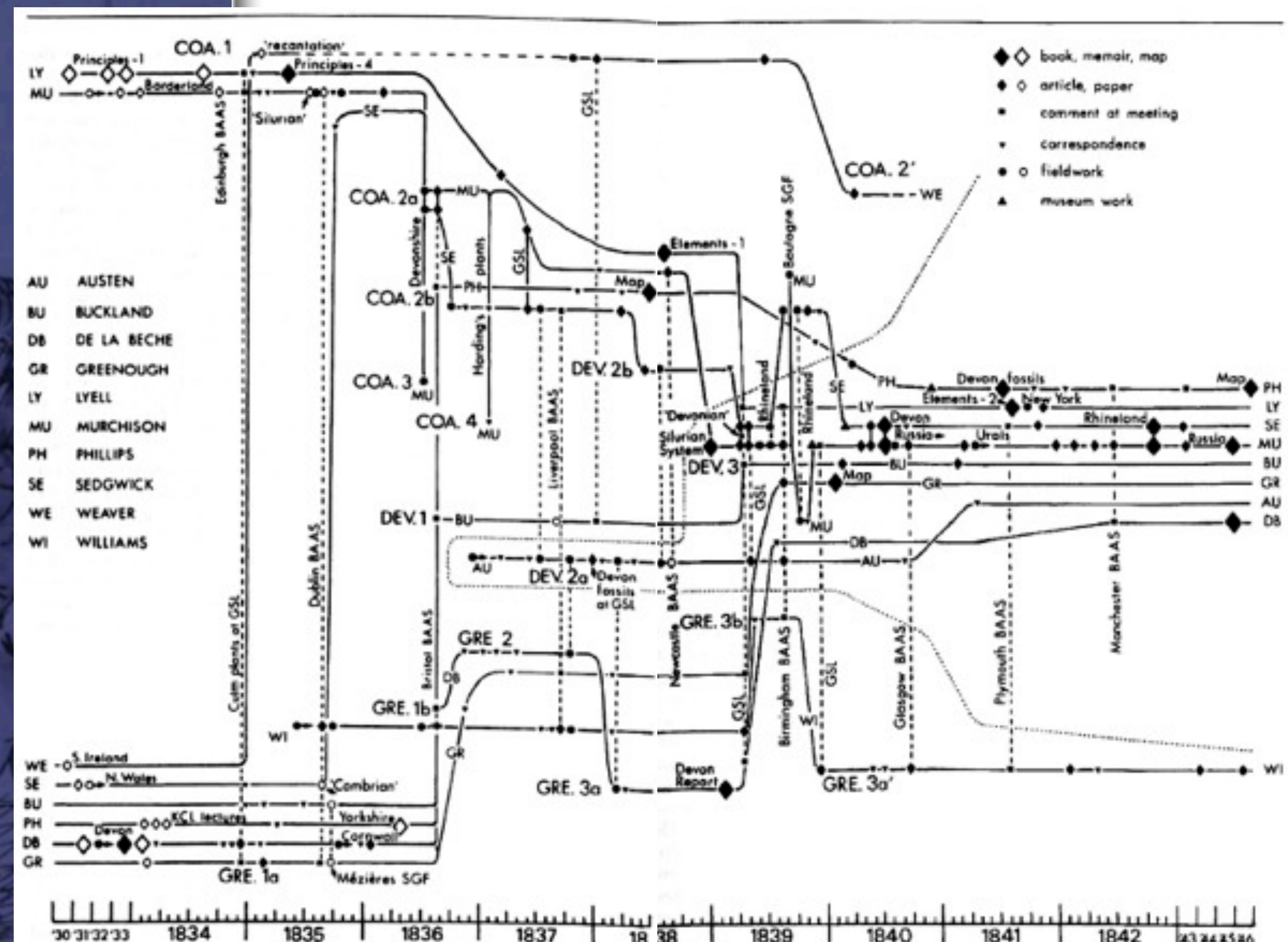
Understanding fragmentation: summary



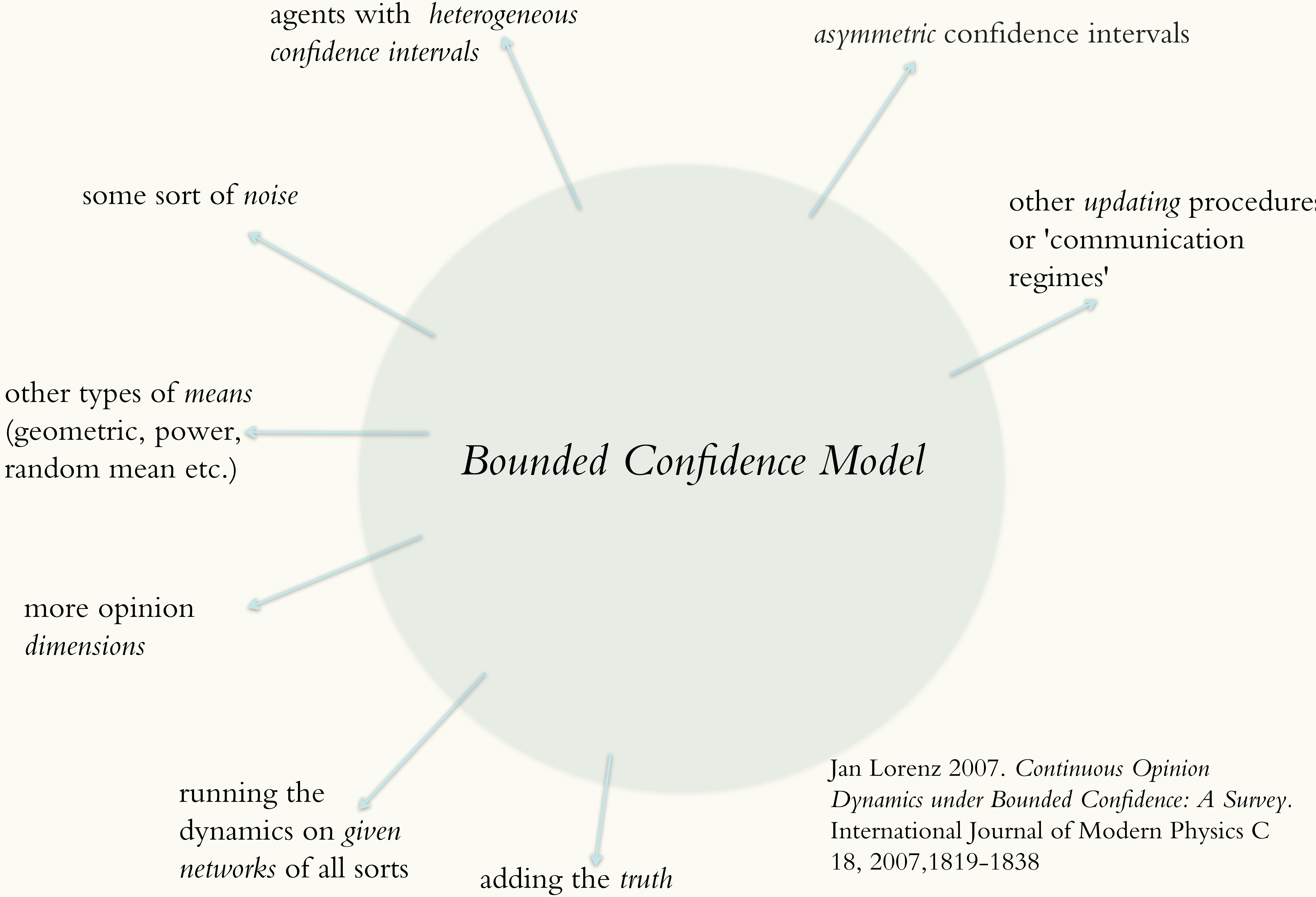


An example from history of science?





Modifications, extensions, variations



Jan Lorenz 2007. *Continuous Opinion Dynamics under Bounded Confidence: A Survey*. International Journal of Modern Physics C 18, 2007,1819-1838

Article in JASSS

JASSS

Rainer Hegselmann and Ulrich Krause (2002)

Opinion dynamics and bounded confidence: models, analysis and simulation

Journal of Artificial Societies and Social Simulation vol. 5, no. 3
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Abstract

When does opinion formation within an interacting group lead to consensus, polarization or fragmentation? The article investigates various models for the dynamics of continuous opinions by analytical methods as well as by computer simulations. Section 2 develops within a unified framework the classical model of consensus formation, the variant of this model due to Friedkin and Johnsen, a time-dependent version and a nonlinear version with bounded confidence of the agents. Section 3 presents for all these models major analytical results. Section 4 gives an extensive exploration of the nonlinear model with bounded confidence by a series of computer simulations. An appendix supplies needed mathematical definitions, tools, and theorems.

Keywords:
Bounded Confidence; Consensus/dissent; Nonlinear Dynamical; Opinic

Because of the complex mathematical notation in this articl format. To read the article you will need a copy of the Adob

The artic

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Titel	Opinion dynamics and bounded confidence: models, analysis and simulation
Autoren	Rainer Hegselmann, Ulrich Krause
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Beschreibung	Abstract When does opinion formation within an interacting group lead to consensus, polarization or fragmentation? The article investigates various models for the dynamics of continuous opinions by analytical methods as well as by computer simulations. Section 2 develops within a unified framework the classical model of consensus formation, the variant of this model due to Friedkin and Johnsen, a time-dependent version and a nonlinear version with bounded confidence of the agents. Section 3 presents for all these models ...
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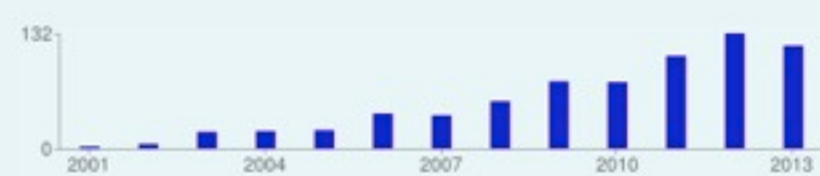
Zitate pro Jahr	



§3
Truth, truth seekers and cognitive division of labour
A first CASE-study

*(**C**omputer **A**ided **S**ocial **E**pistemology)*

Opinion dynamics & truth seeking: A radically simplifying, macroscopic approach

opinion profile of n agents at time t. $x_i(t) \in [0, 1]$

$$x(t) = \underbrace{\left(x_1(t), x_2(t), \ldots, x_i(t), \ldots, x_n(t)\right)}_{\text{social process function } f_i}$$

$$\downarrow$$

$$x_i(t+1)$$

f_i^{BC} (*Bounded confidence* model): Averaging over all opinions that are ‚not too strange', i.e. within *i*'s *confidence interval* ε.

f_i^{LW} (*Lehrer/Wagner* model): Weighted averaging. The subjectively assigned weights w_{ij} reflect competences.

To some degree α_i with $0 \leq \alpha_i \leq 1$ an agent *i* is ‚driven direction truth T' (*objective* component). An agents updated opinion is a *convex combination* of the social and the objective component:

$$[D]: \quad x_i(t+1) = \alpha_i \cdot T + \overbrace{(1-\alpha_i) \cdot f_i}$$

'objective' component $T \in]0,1]$

social component

To avoid misunderstandings ....

$$[D]: \quad x_i(t+1) = \alpha_i \cdot T + (1-\alpha_i) \cdot \boldsymbol{f}_i$$

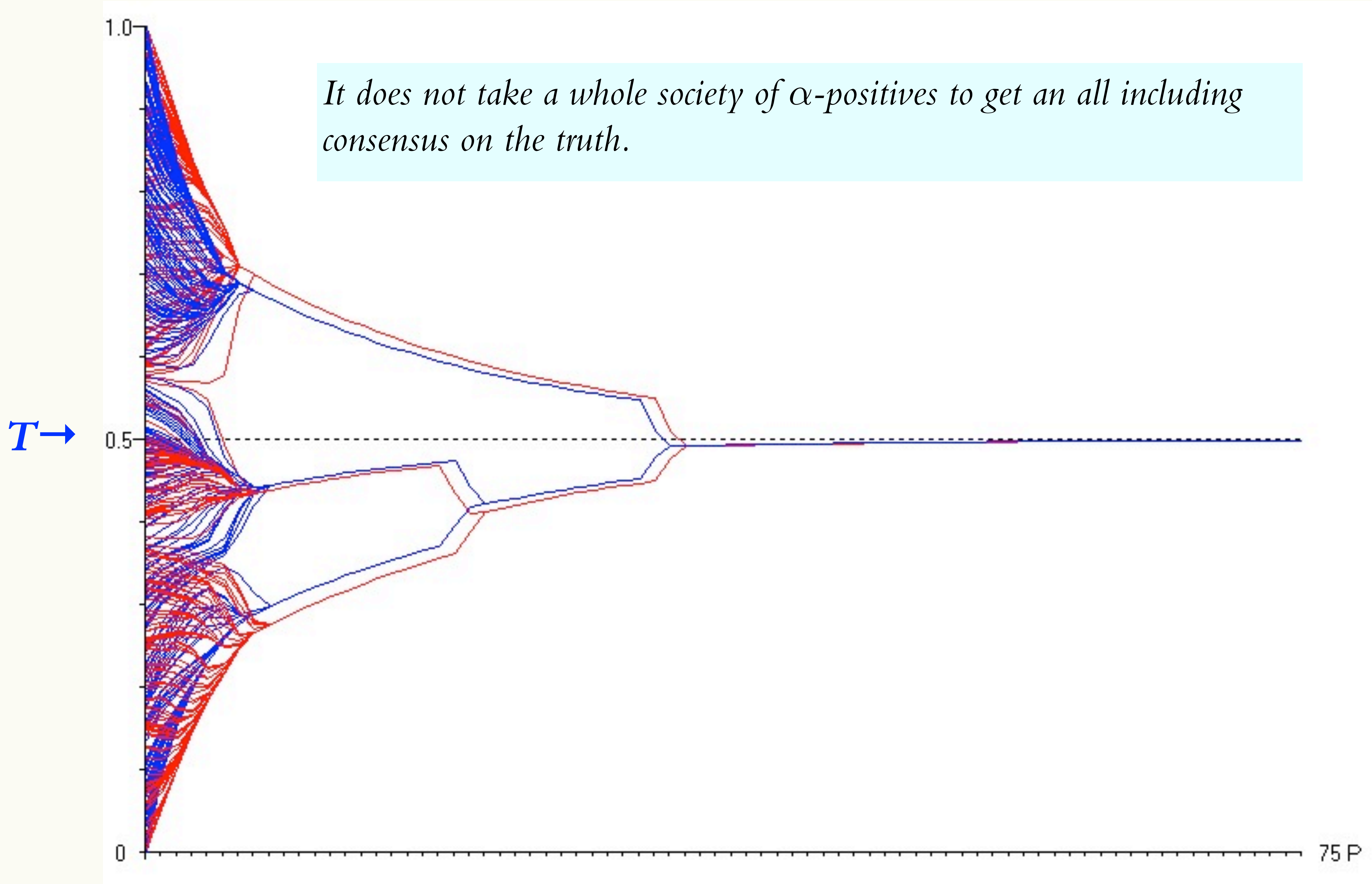
‚objective‘ component *social component*

- α_i ($0 \leq \alpha_i \leq 1$) controls the strength of the ‚attraction‘ of the truth. That allows to *distinguish* truth-seekers ($\alpha_i > 0$) and non-truth-seekers ($\alpha_i = 0$), a kind of *cognitive division of labour.*
- For any positive α_i the truth T attracts. However, exchange of opinions with one‘s epistemic fellows may pull one‘s opinion in another direction.
- If $\forall i$ ($\alpha_i = 0$), then we have again the classical bounded confidence model in which truth *does not* play any role.

BUT, please, note:

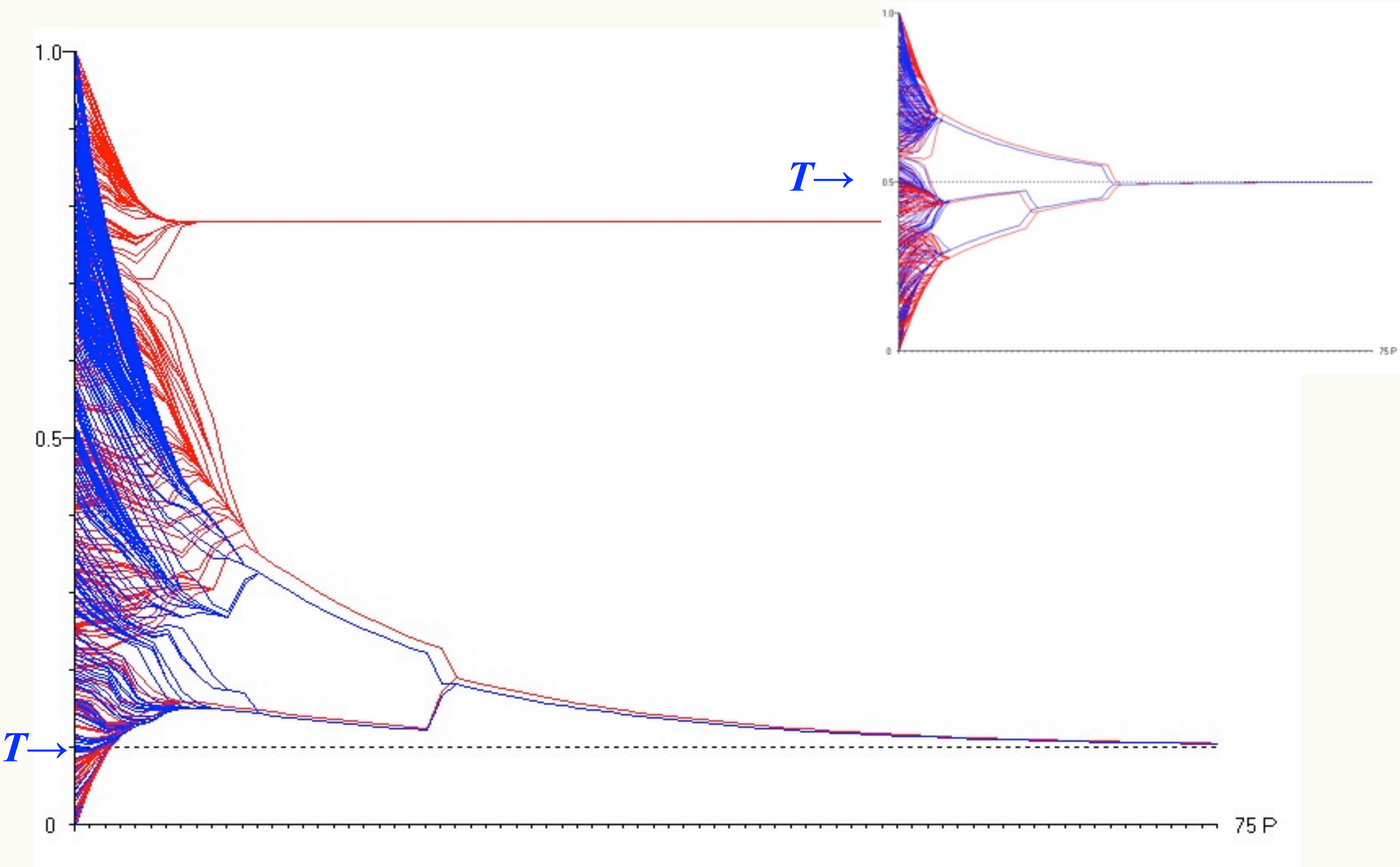
- D is ***not*** meant to be the *intentional* and *explicit* updating procedure of an agent!
- D is meant to describe the ***overall effects*** of research and investigations of all sorts, e.g. deliberative exchange, reflections and (re)thinking.
- Our approach is a ***low-resolution approach***, different from the typically *high*-resolution approaches in *formal dialectics, epistemic game theory, belief revision, or (non-monotonic) logic* research programs.

50 % $\alpha = 0$ – Nevertheless: Consensus on T!



500 individuals, 50 % α =0, all others α =0.1, $\varepsilon = 0.1$, $T = 0.5$

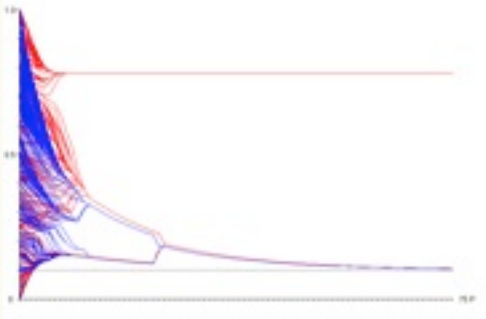
The position of *T* matters!

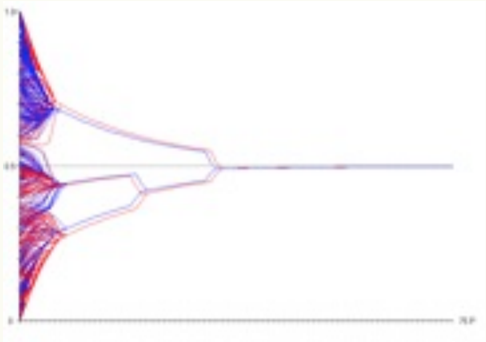


500 individuals, 50 % α =0, all others α =0.1, ε = 0.1, T = 0.1

The veritistic perspective: *Truth deviation* $\tau(t)$

To compare results we need to measure societal distance to the truth.





<u>Idea:</u>
We define and measure the *truth deviation* similar to the standard deviation.

The *standard deviation* is defined as:

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \mu\right)^2}$$

arithmetic mean of n values $x_1, x_2, \ldots x_n$

We define the *truth deviation* analogously as the root mean square deviation from the truth *T*:

$$\tau(t) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_i(t) - T\right)^2}$$

the dispersion of values (i.e. time dependent opinions) is measured aginst the truth T

T, $F_{\alpha=0}$, ε and α probably matter! How to get an overview?

Simplifying assumptions:

- *homogeneous, symmetric*, and *constant* confidence intervals ε for all individuals.
- *homogeneous and constant* strength of the truth-directedness α for all α-positives.
- *fixed number* of 625 individuals.
- *uniform* start distributions.
- *simultaneous* updating.

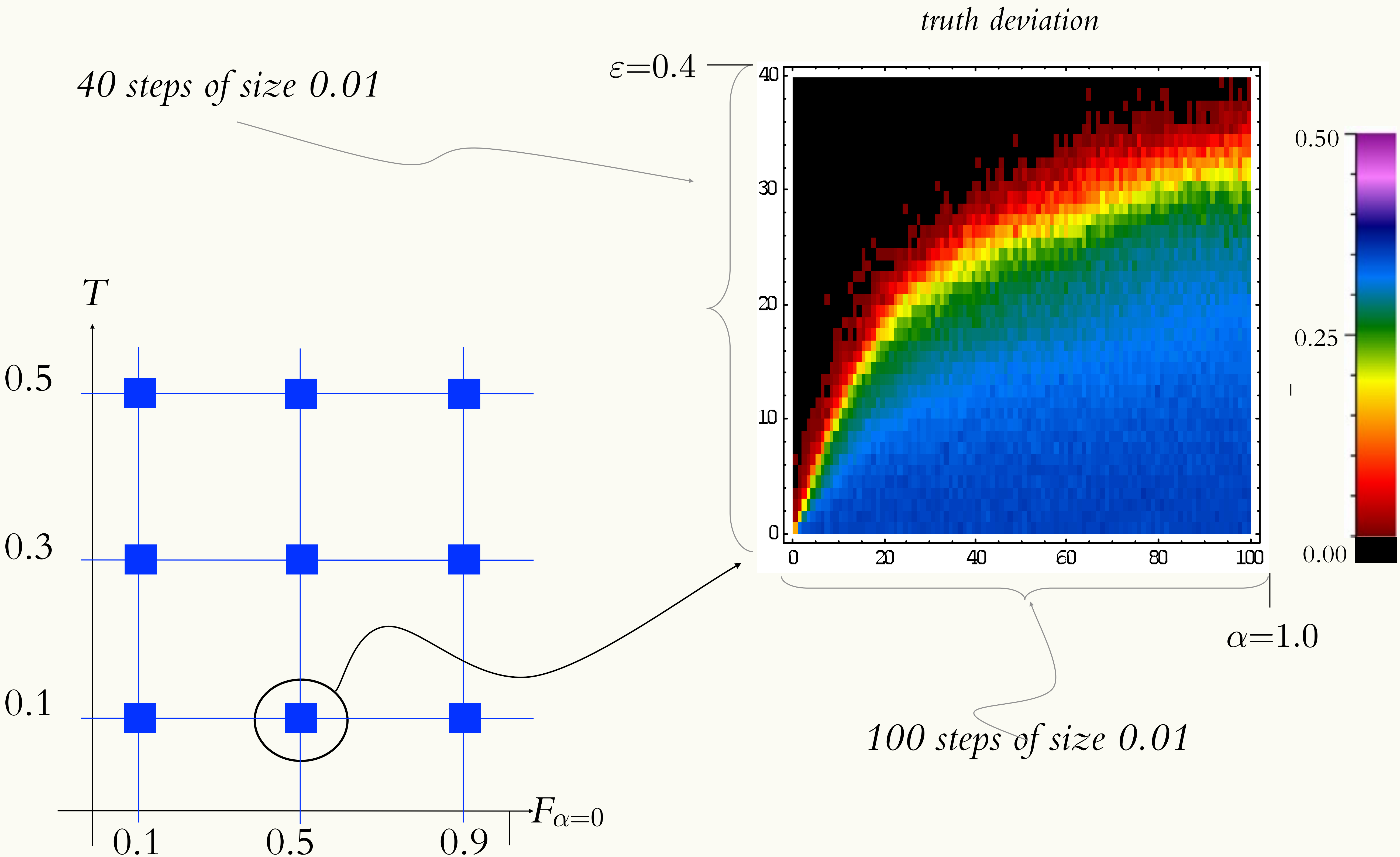
Parameters we vary:

1. The *position of the truth T*: $T = 0.1$; $T = 0.3$; $T = 0.5$.
2. The *frequency* $F_{\alpha=0}$ of α-positives: 90%, 50%, 10%.
3. The *size of the confidence interval*: $\varepsilon = 0.01, 0.02, \ldots, 0.4$; i.e. 40 steps.
4. The *strength of the truth directedness*: $\alpha = 0.01, 0.02, \ldots, 1.0$; i.e. 100 steps.

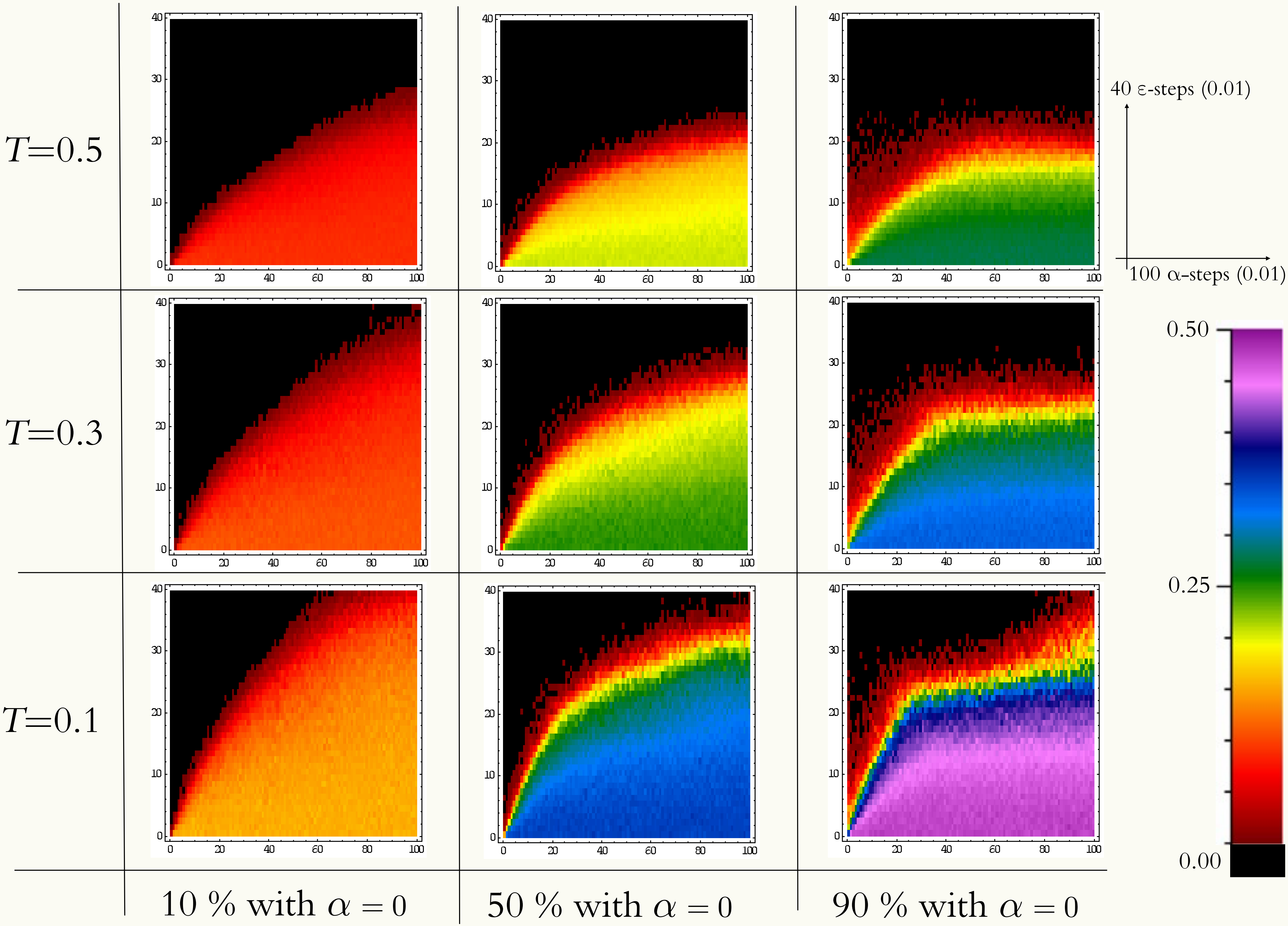
Methode:

Systematic *simulations*. 50 repetitions for each constellation $<T, F_{\alpha=0}, \varepsilon, \alpha>$. Thus a total of $3 \times 3 \times 40 \times 100 \times 50 = 1.8$ Mio runs. Each run until stability is reached.

T, $F_{\alpha=0}$, ε and α probably matter!
How to get an overview? Scenarios & Grids



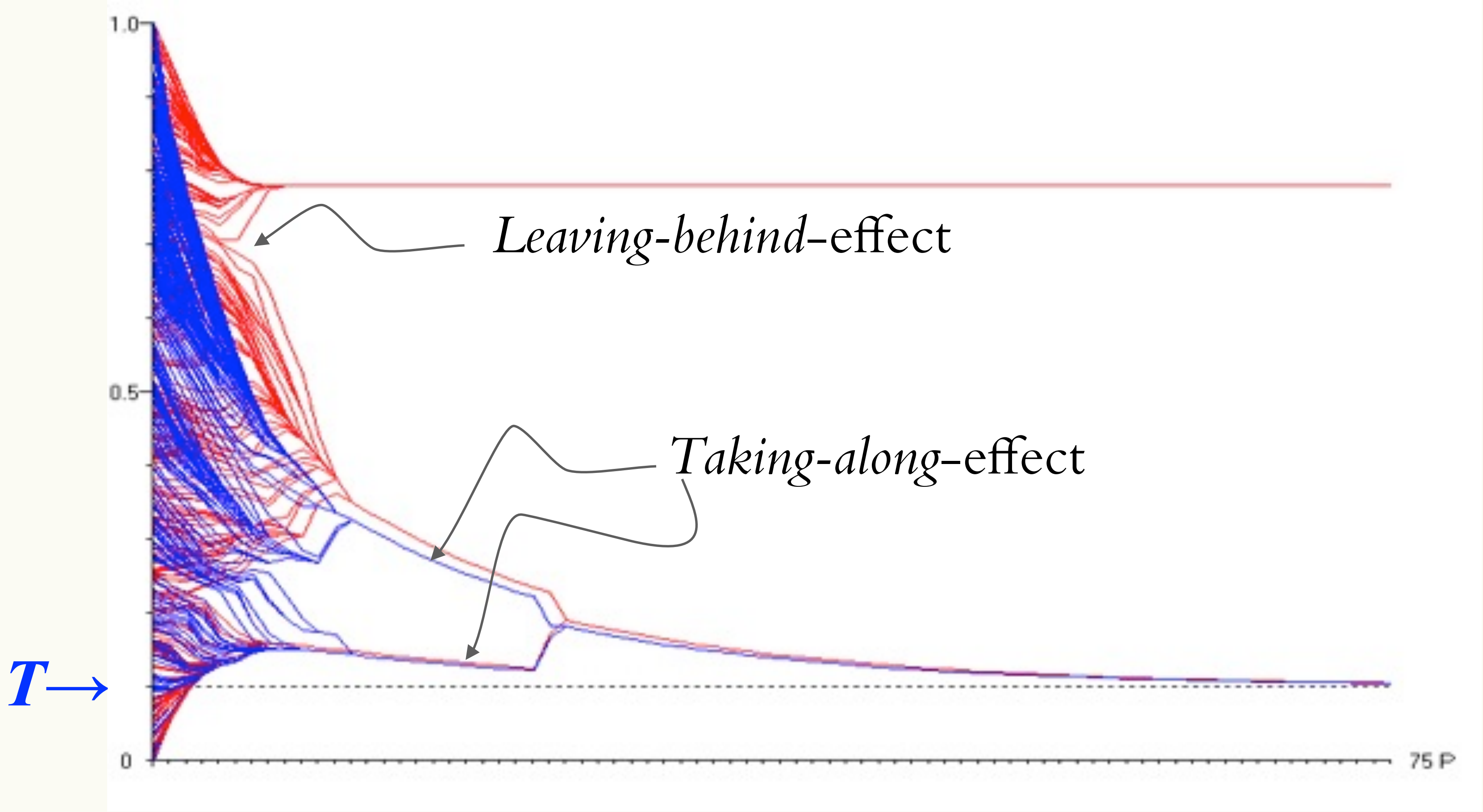
Final truth deviation: Means



Lesson: To get all at the truth, not all have to be truth seekers!

1. Whether there is a tiny minority or even an overwhelming majority of α-positives, for suitable values of ε and α *the whole society may nevertheless end up with the truth.*

2. That observation *holds for a remarkably huge area of the parameter space* of ε and α.



Article in JASSS

JASSS

Rainer Hegselmann and Ulrich Krause (2006)

Truth and Cognitive Division of Labour: First Steps Towards a Computer Aided Social Epistemology

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Abstract

The paper analyzes the chances for the truth to be found and broadly accepted under conditions of cognitive division of labour combined with a social exchange process. Cognitive division of labour means, that only some individuals are active truth seekers, possibly with different capacities. The social exchange process consists in an exchange of opinions between all individuals, whether truth seekers or not. We de- velop a model which is investigated by both, mathematical tools and computer simulations. As an analytical result the Funnel theorem states that under rather weak conditions on the social process a consensus on the truth will be reached if all individuals posses an arbitrarily small inclination for truth seeking. The Leading the pack theorem states that under certain conditions even a single truth seeker may lead all individuals to the truth. Systematic simulations analyze how close and how fast groups can get to the truth depending on the frequency of truth seekers, their capacities as truth seekers, the position of the truth (more to the extreme or more in the centre of an opinion space), and the willingness to take into account the opinions of others when exchanging and updating opinions. A tricky movie visualizes simulations results in a parameter space of higher dimensions.

Keywords:
Opinion Dynamics, Consensus/dissent, Bounded Confidence, Truth, Social Epistemology

§4
Modelling networking

A *missing* universal societal phenomenon: networking of all sorts

It may well be the case that, *for instance*, ...

- ... some or all *truth seekers* ($\alpha_i > 0$) look for close relations to *other* truth seekers;
- ... some or all *excellent* truth-seekers (comparatively high α_i) look for close relations to other *excellent* truth-seekers;
- ... some or all non-truth-seekers ($\alpha_i = 0$) try to keep distance to the 'damned intellectuals' ($\alpha_i > 0$);
- ... some or all of the damned intelletuals, the *englihteners*, try to get into close contact with non-truth-seekers while avoiding contact with those truth-seekers that disdain the 'simple minded'.
- ...
- ... and that is an *ongoing process that (almost) never comes to an end*.

Research questions:

- How does ongoing segregating, grouping, in short, *networking of all sorts* affect societal truth deviation?
- How can we model networking in epistemic contexts?

A classic: Schelling's models of segregation

Journal of Mathematical Sociology
1971, Vol. 1, pp 143–186

issue 2

DYNAMIC MODELS OF SEGREGATION†

THOMAS C. SCHELLING
Harvard University

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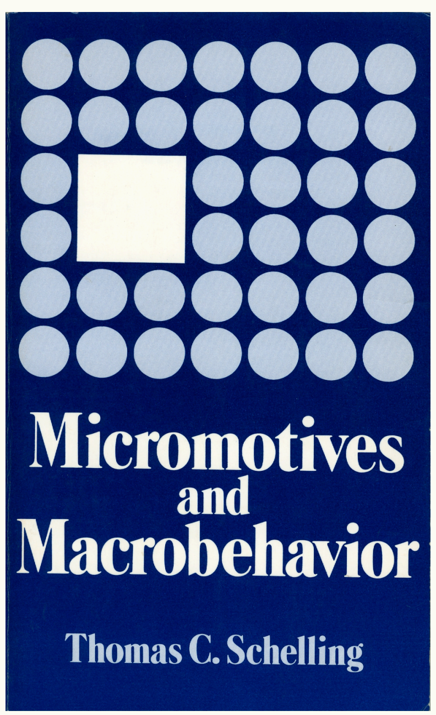
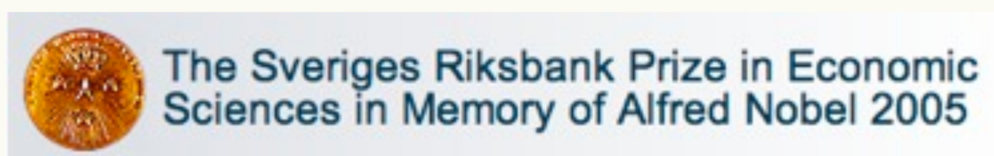


chapter 4:
Sorting and Mixing



December 10, 2005

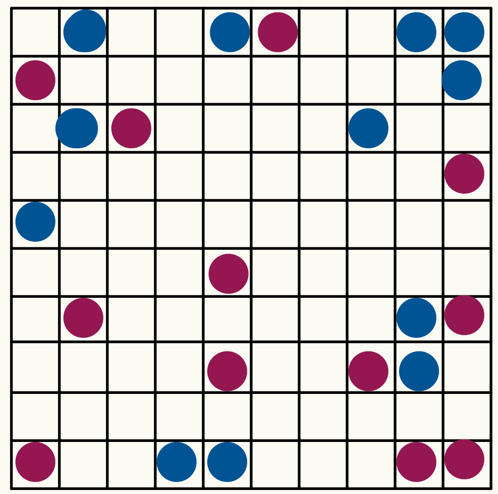
"Why Does Segregation Arise?

... Schelling showed that even rather weak preferences regarding the share of like persons in a neighborhood can result in strongly segregated living patters. In other words, no extreme preferences on the part of individuals are required in order for a social problem to arise."

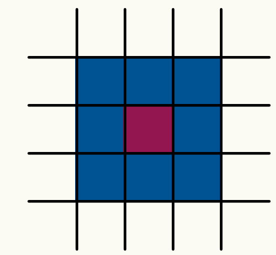
October 10, 2005

Schelling's model$_{\text{standard}}$: A short description

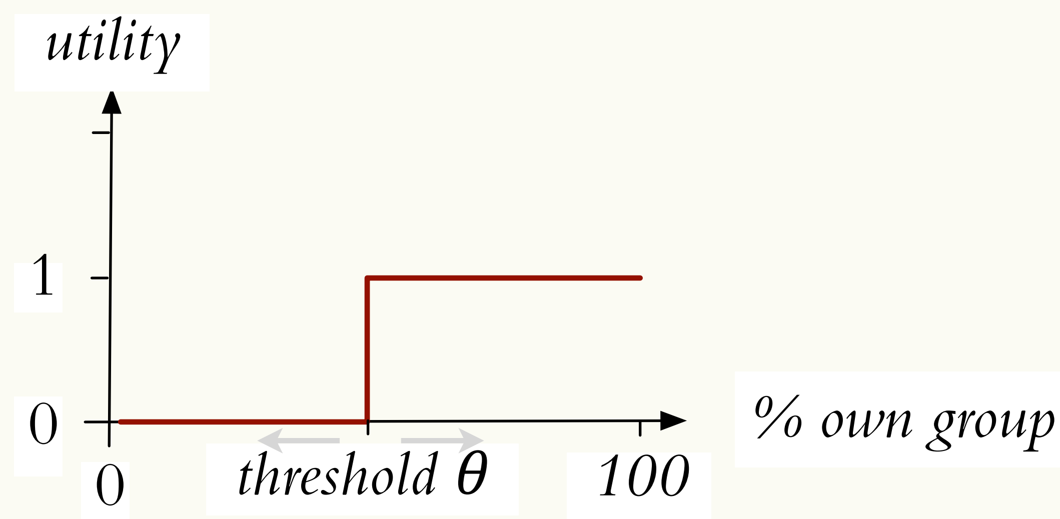
Two groups live on a checkerboard.



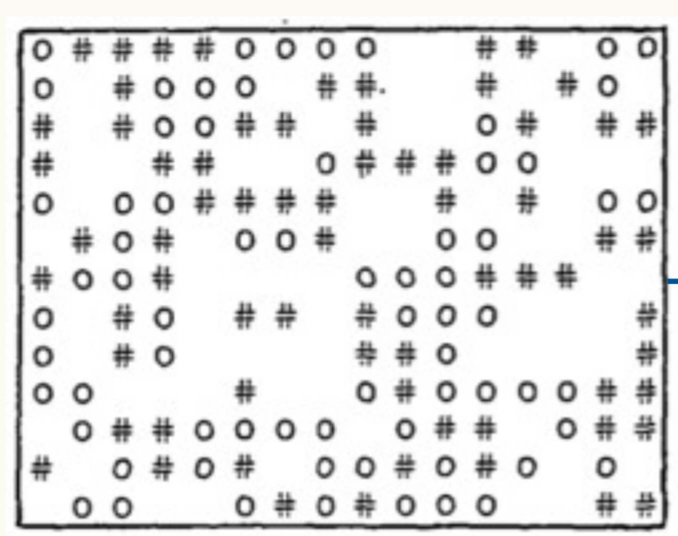
Each individual has a 3x3 *neighborhood*.



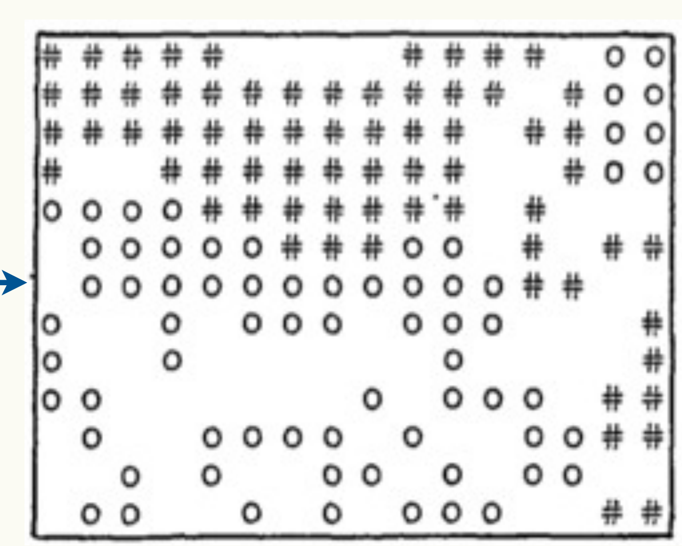
Neighborhood *evaluation* based on a utility function



Migration:
Who is discontent at his acutal location, moves to a best location–if available.



manual table top exercise,
warning against computers



An unknown: James Minoru Sakoda

The Journal of
MATHEMATICAL
SOCIOLOGY

Journal of Mathematical Sociology
1971, Vol. 1, pp 119–132

the very first issue

THE CHECKERBOARD MODEL OF SOCIAL INTERACTION†

JAMES M. SAKODA
Brown University

The checkerboard model is a computer simulation of social interaction among members of two groups. The checkerboard represents a social field on which two groups of checkers move on the board on the basis of positive, neutral or negative attitudes toward one another assigned to them. The resulting pattern of positions of the pieces represents the social structure. The theoretical basis for the checker-board model is explained and the r
illustrative runs named Crossroads, I
Boy-Girl, Couples and Husband-Wi
each. It is concluded that the checkerb
between attitudes of group members
social interactional process and to th

forgotten as a scientist,
still known as a paper folder

BRITISH ORIGAMI SOCIETY

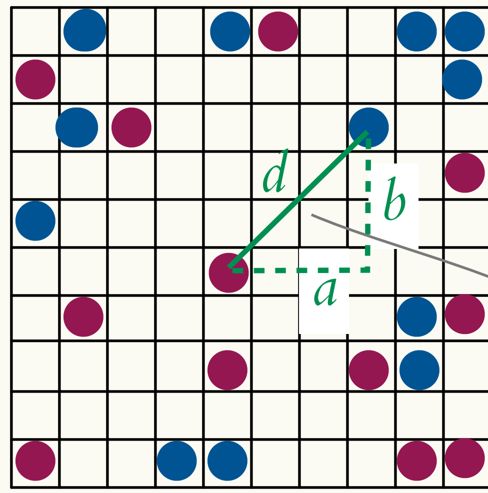
The Lister List

James Minoru Sakoda 1916-2005

I am sure that I am only one among hundreds of paper folders who are deeply saddened to read the news that James Sakoda died on 12th June 2005 at the age of 89. I am amazed to read that he was aged 89 because he seemed much younger and was certainly young in spirit. Unlike many paperfolders in the academic world, he did not have a mathematical background. He was survived by his wife, Hettie and his son, Bill.

Sakoda's model: A short description

Two groups live on a checkerboard.

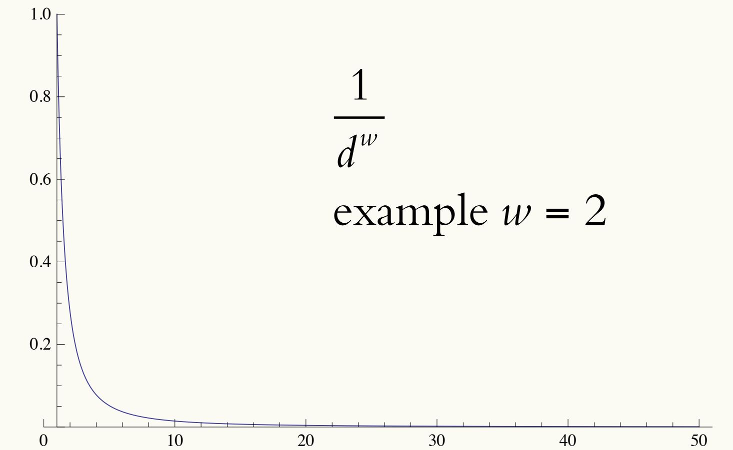


Neighborhood is the whole world. But more distant others count less.

$d = \sqrt{a^2 + b^2}$

eucledian distance

distance depending weight of others



$\frac{1}{d^w}$

example $w = 2$

Neighborhood *evaluation* based on an "*attitude matrix*"

[*modernized*: utility matrix]

	g_1	g_2
g_1	u_{11}	u_{12}
g_2	u_{21}	u_{22}

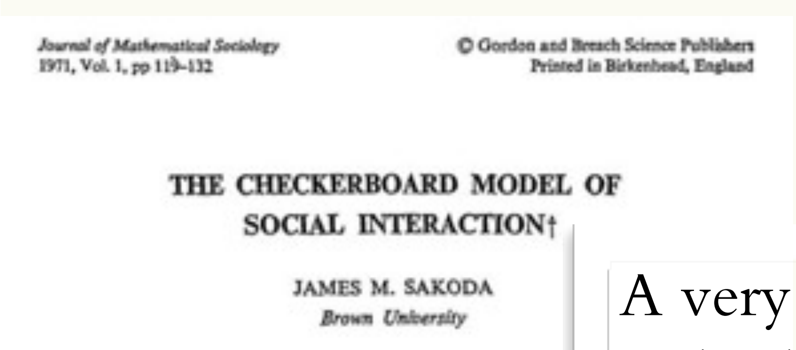
$u_{ij} \in \{-1, 0, +1\}$

Migration:

Agent i moves to an empty cell where

$$U = \sum_{\text{whole world}} \frac{u_{ij}}{d^w}$$

is *maximized*.


Journal of Mathematical Sociology
1971, Vol. 1, pp 119–132

THE CHECKERBOARD MODEL OF SOCIAL INTERACTION†

JAMES M. SAKODA
Brown University

A very general claim:

"The checkerboard model provides a concrete means of portraying social interaction as an ongoing process among members of groups"

In some sense: Schelling$_{standard}$ is just an instance of Sakoda

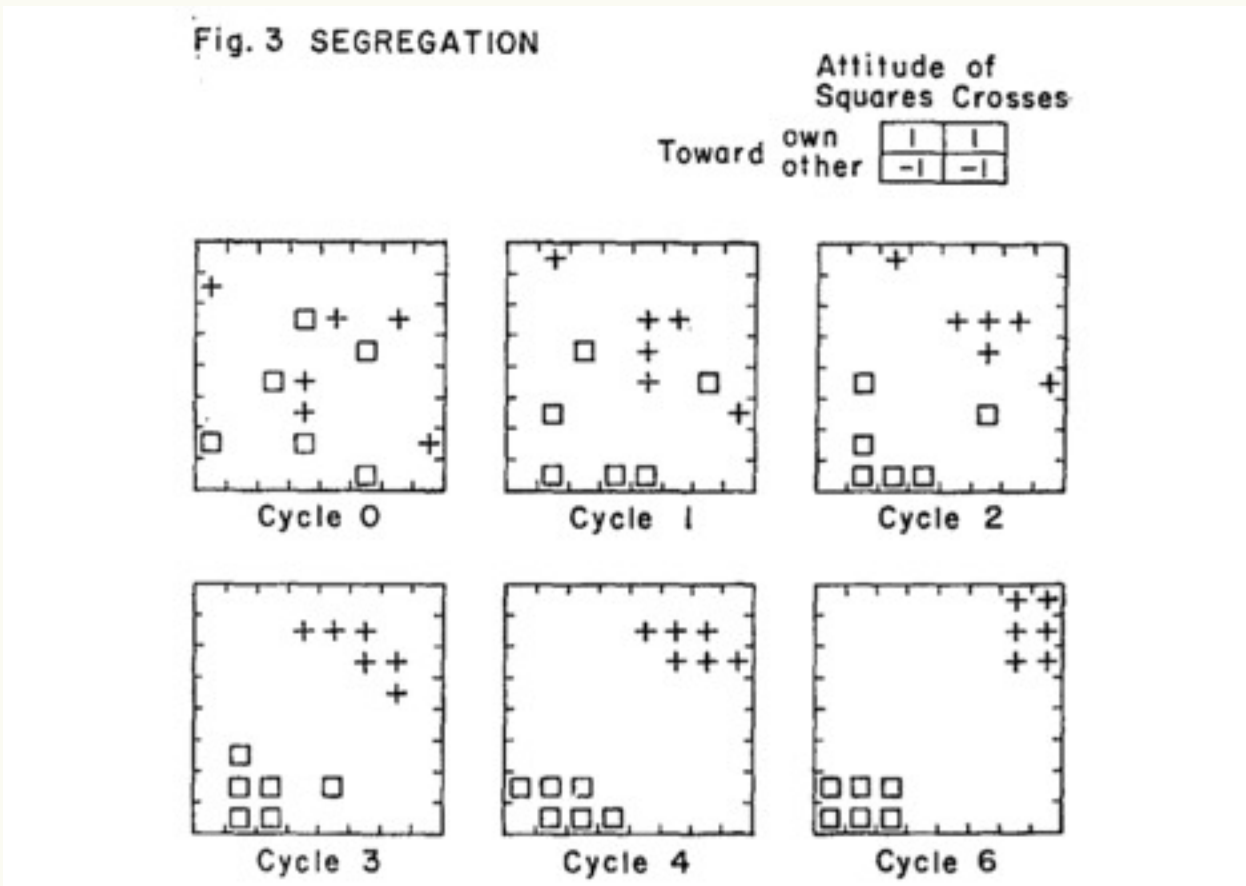
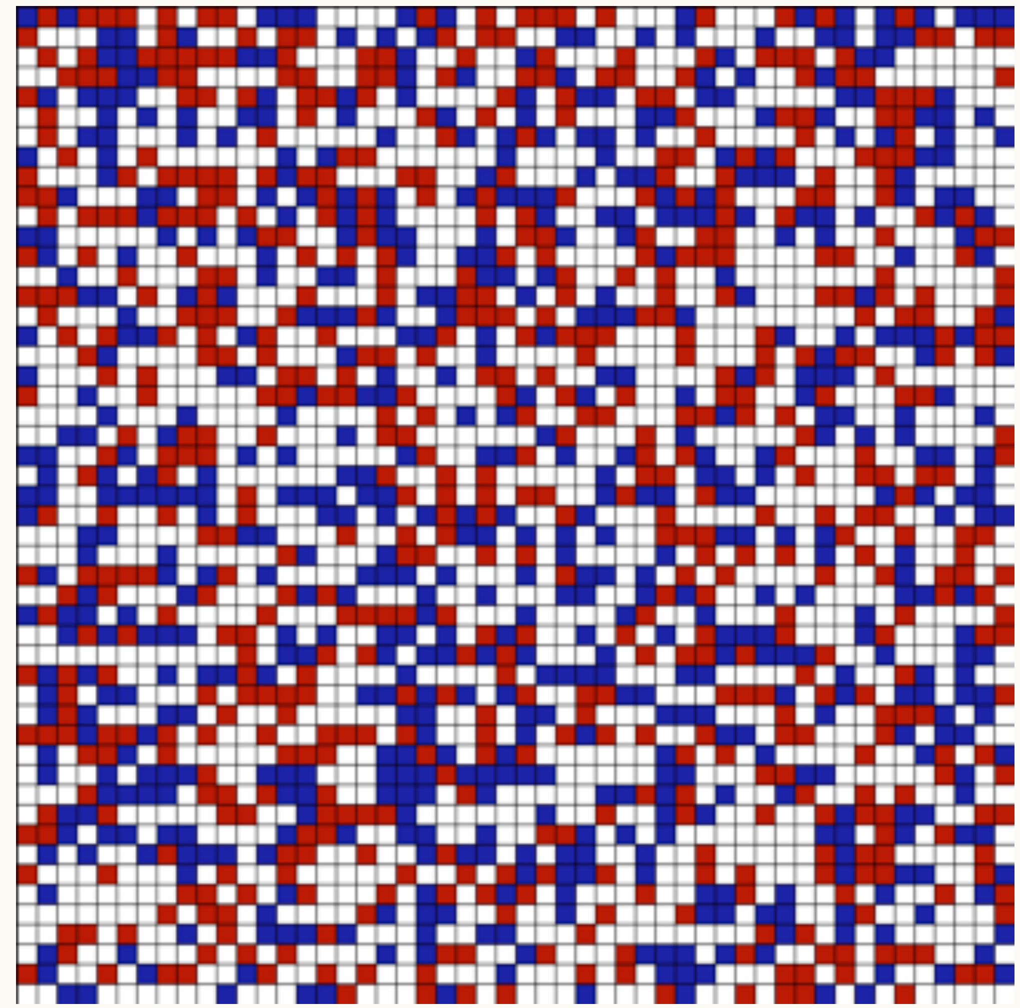
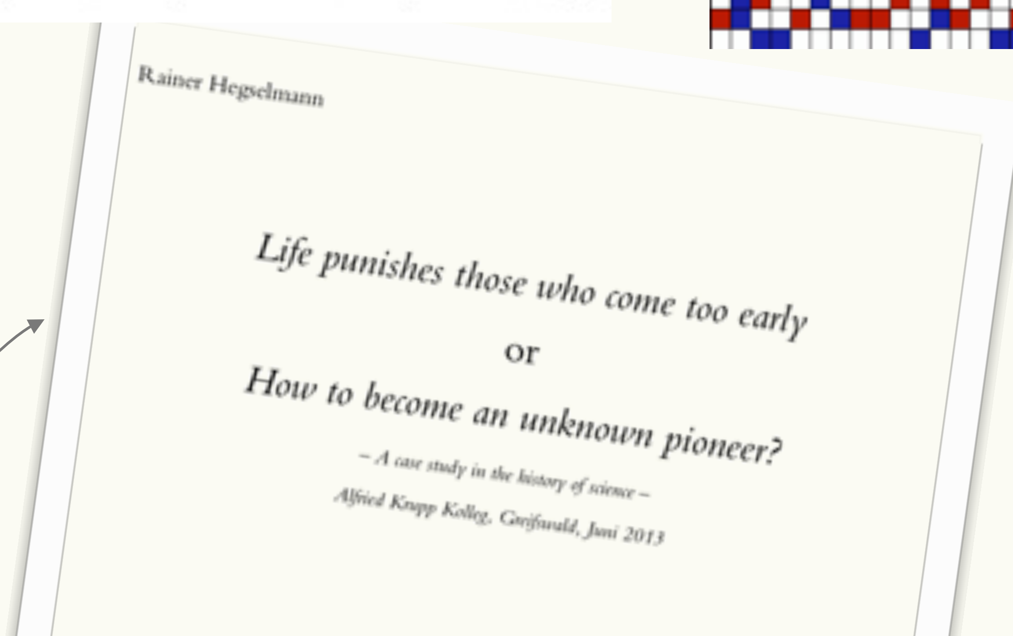


FIGURE 3 *Segregated Groups* (Squares: 1 to Own, −1 to Others, Crosses: 1 to Own, −1 to Others).





another talk,
(if you want)

Generalizing Sakoda's approach

***Group structure* G** partitions the population *P* of *n* agents into *m* groups.

↓

***Social space* S** is given by the vertices *V* and edges *E* of a *connected graph* G= (*V*,*E*) . The nodes can be inhabited by agents that live and move on the graph. The social space *may be* based on a *grid* of any sort or dimension—*or not*.

↓

***Evaluation E of network positions*:** Basis of the evaluation is the *attitude matrix* $A=(a_{i,j}) \in \mathbb{R}^{m\times(m+1)}$. Then *aggregation* with distance depending weights over group depending utilities of all neighbors (close by or far distant).

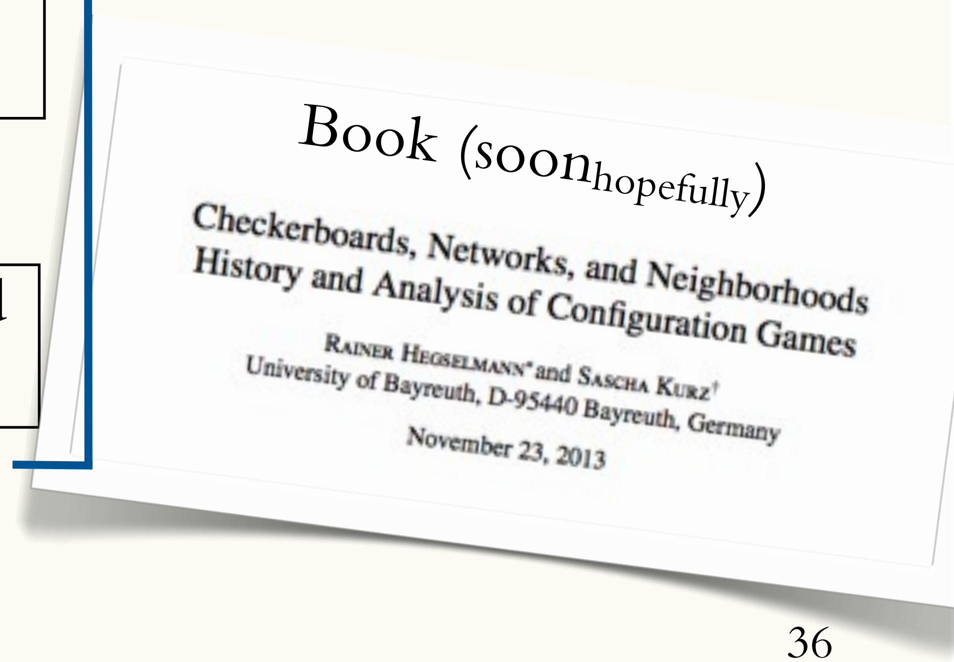
↓

Migration regime M specifies how migration options are assigned and used.

→ **⟨*G,S,E,M* ⟩**

Configuration Game

sakoda-ian in spirit!


Book (soon$_{hopefully}$)

Checkerboards, Networks, and Neighborhoods
History and Analysis of Configuration Games

Rainer Hegselmann* and Sascha Kurz†
University of Bayreuth, D-95440 Bayreuth, Germany

November 23, 2013

§5
Epistemic grouping and networking
A second CASE-study

Problem: How does networking affect the spreading of the truth?

Suppose that ...

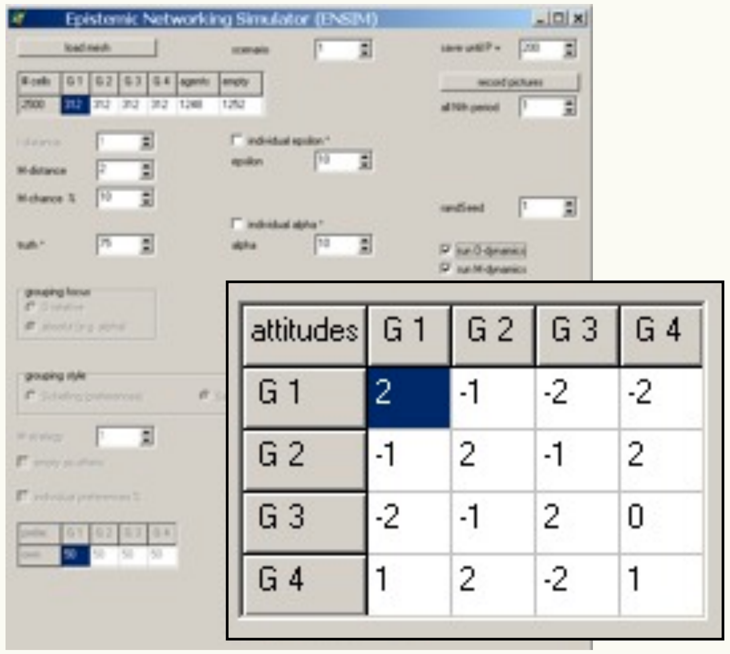
... agents *exchange* their opinions with others to which they are *connected in a network*.

... agents *differ* in their epistemic *attitudes* and *capabilities*: some are interested in the truth, others not; some are better truth seekers than others ...

... the networks in which agents exchange their opinions are *dynamic*: Depending upon their own and the others' epistemic attitudes and capabilities, agents find network positions more or less attractive and, therefore, establish or give up network connection.

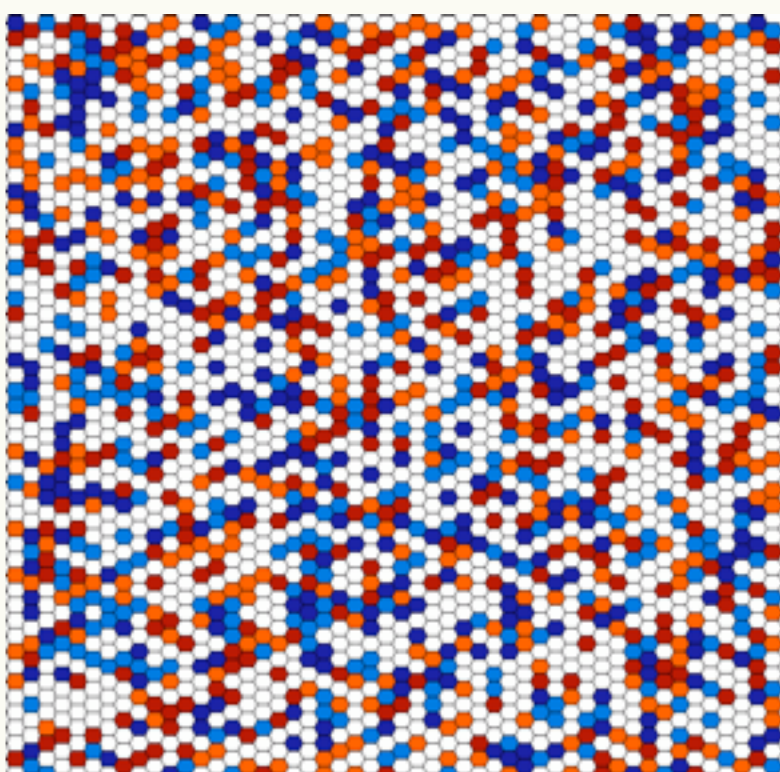
What are the epistemic effects of such a combined opinion *and* network dynamics?

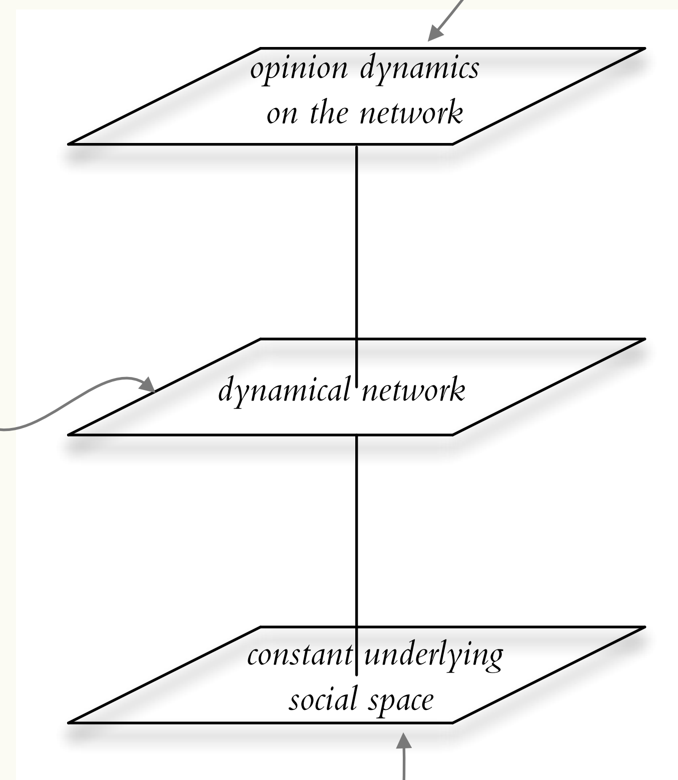
Co-evolution: networking & opinion dynamics

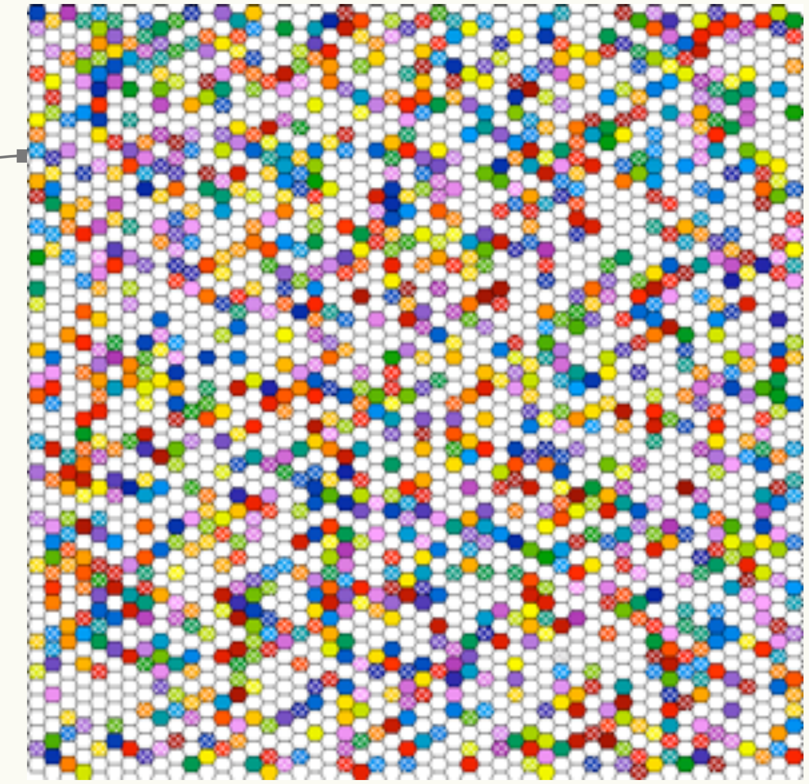


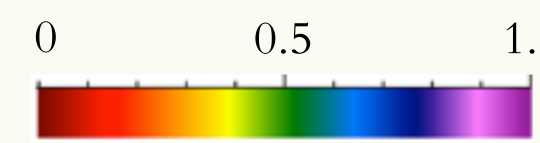
attitudes	G 1	G 2	G 3	G 4
G 1	2	-1	-2	-2
G 2	-1	2	-1	2
G 3	-2	-1	2	0
G 4	1	2	-2	1

- G1: *arrogant* truth-seekers
- G2: *modest* truth-seekers (enlighteners)
- G3: *arrogant* non-truth seekers
- G4: *modest* non-truth-seekers









for all agents $\varepsilon = 0.1$

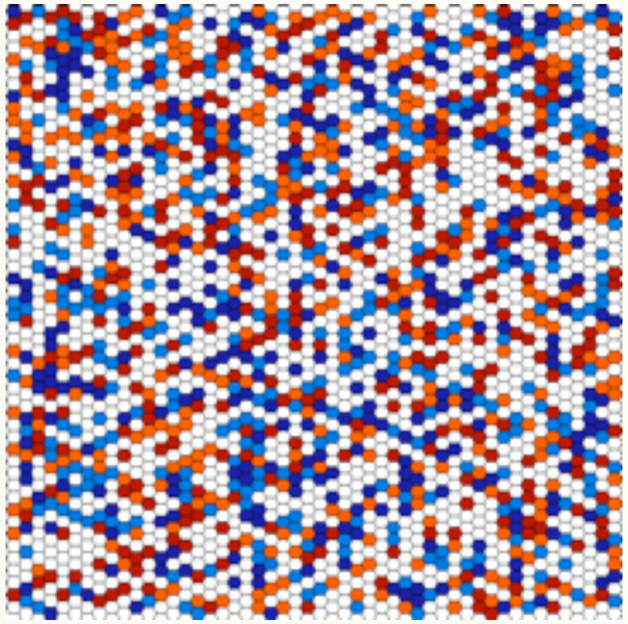
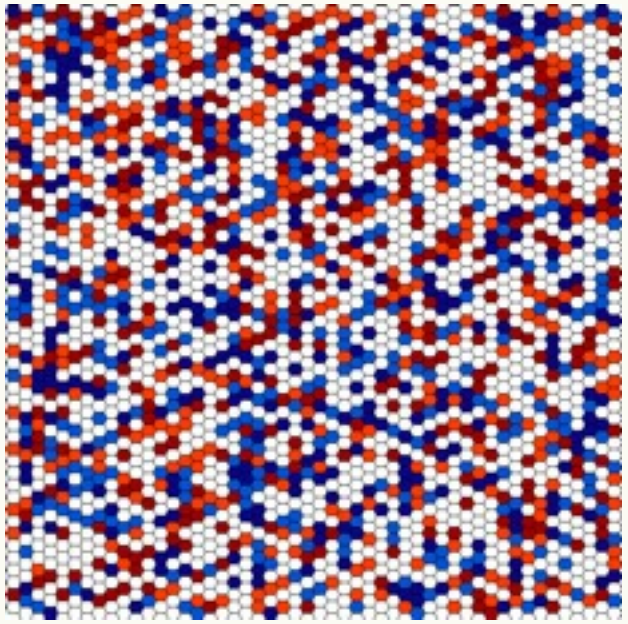
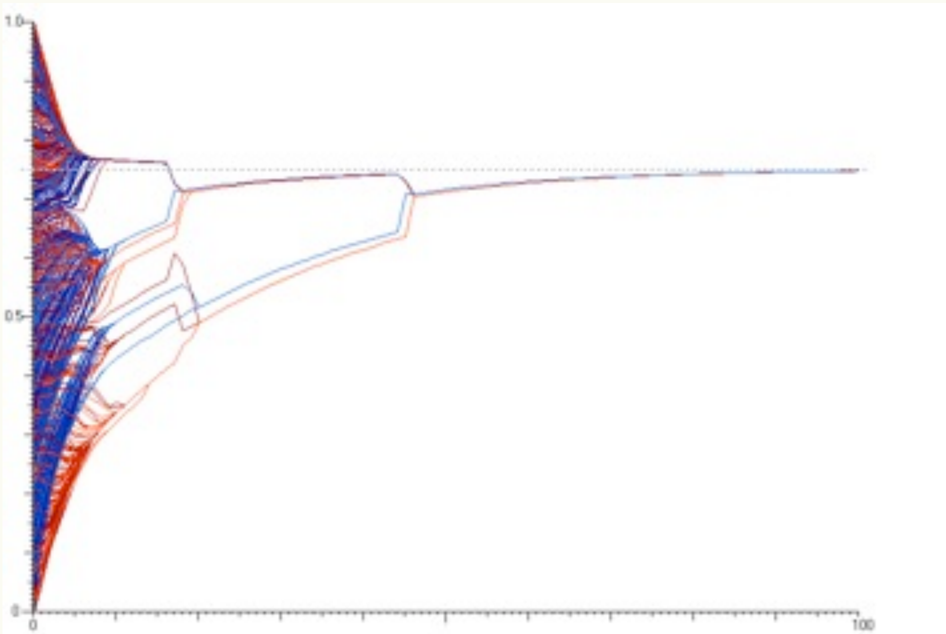
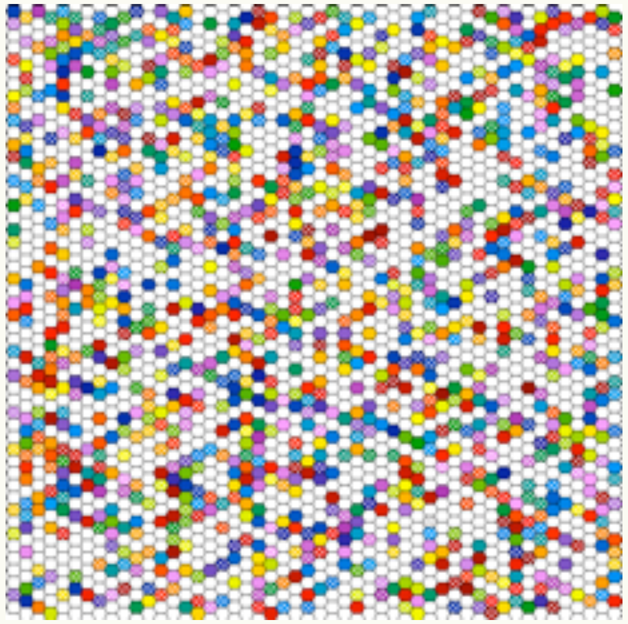
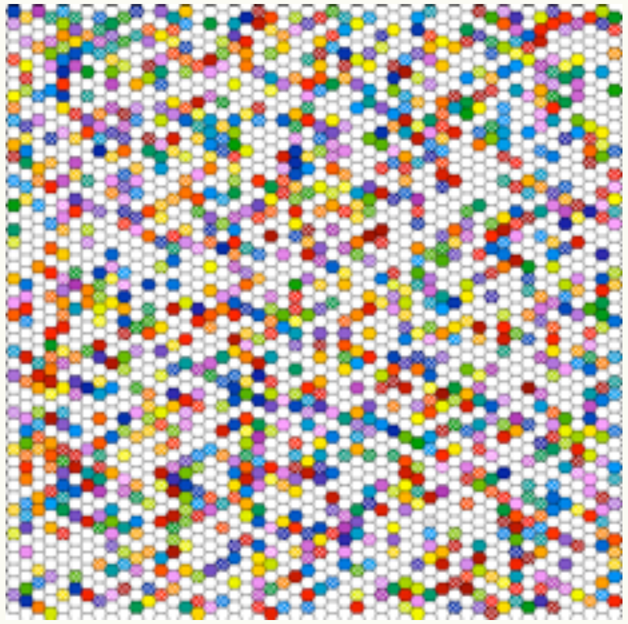
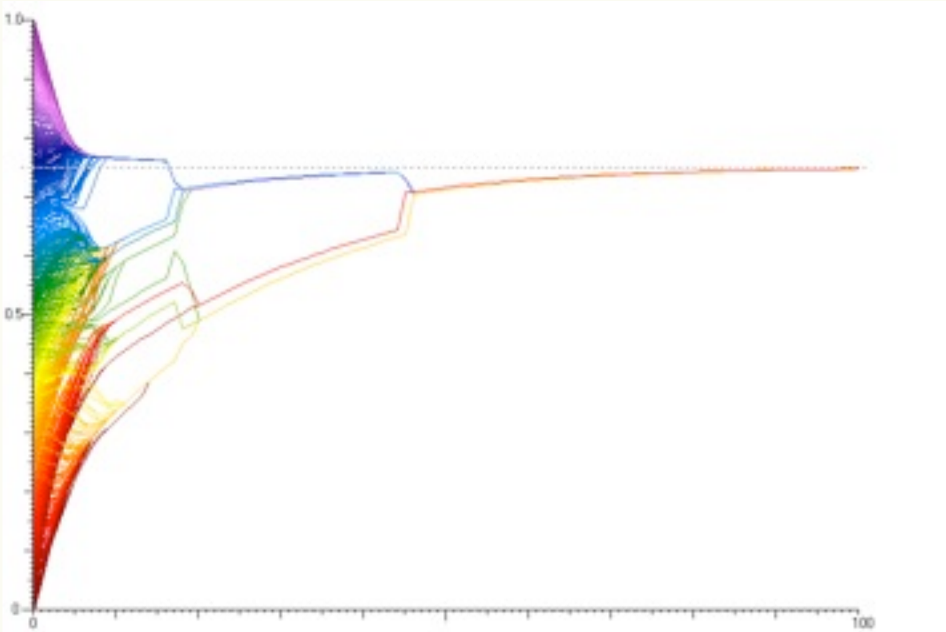
truth seekers: $\alpha = 0.1$

non-truth-seekers: $\alpha = 0$

Truth: $T = 0.75$

hexagonal grid on a torus as a logical constraint on evolving network structures, based on migration and interaction windows.

The effects of epistemic networking: Comparing *three* worlds

	with networking ***N*-world**	constant original structure ***OS*-world**	no networks at all ***NoN*-world**
groups			
opinions			

Methodological strategy: *Parallel* computing of three possible worlds

In *all* three possible worlds the agents '*are the same*' or 'have their *counterparts*' with respect to their:

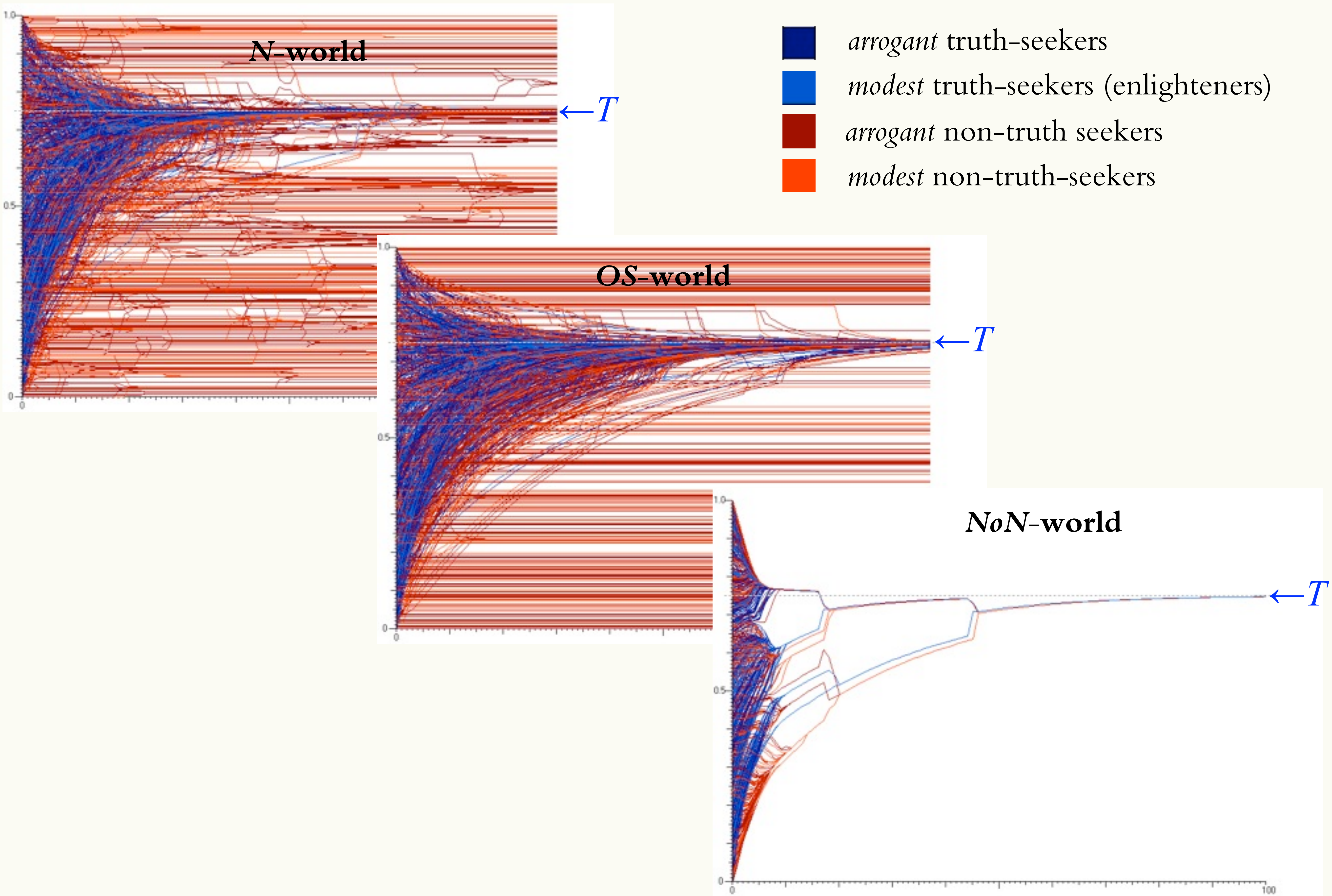
* start opinion $x_i(0)$,
* confidence interval ε,
* truth attraction α.

***N*-world:**
Networking, *migration* and *local* interaction.

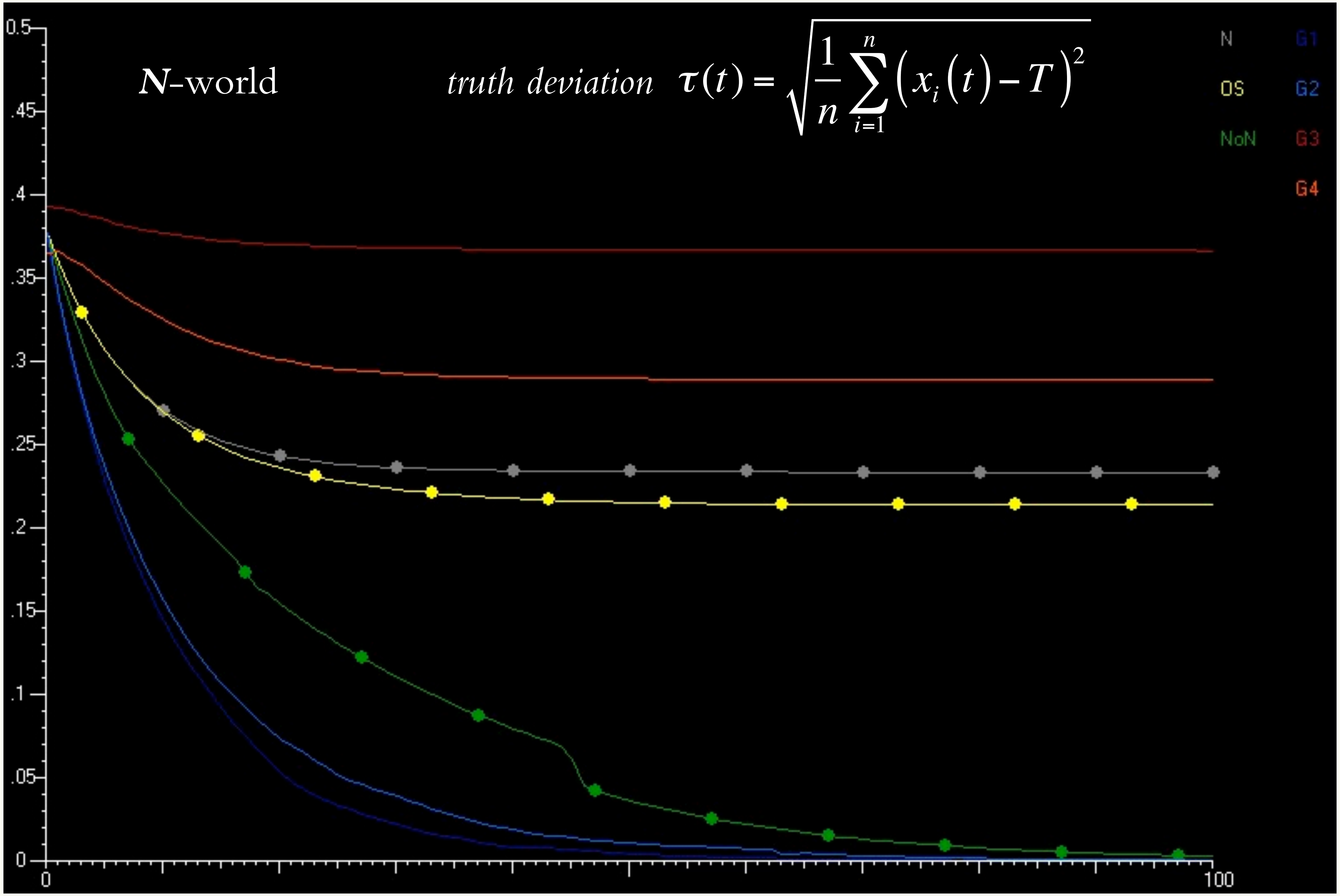
***OS*-world:**
Original network structure is *kept constant*, i.e. no migration. Interactions are *local*.

***NoN*-world:**
No networking, *no* migration, *no* locality restriction on interactions.

O-dynamics in three *parallel* worlds



Networking: costs and benefits, winners and losers



∅ truth deviation ***N***-world

∅ truth deviation ***OS***-world

∅ truth deviation ***NoN***-world

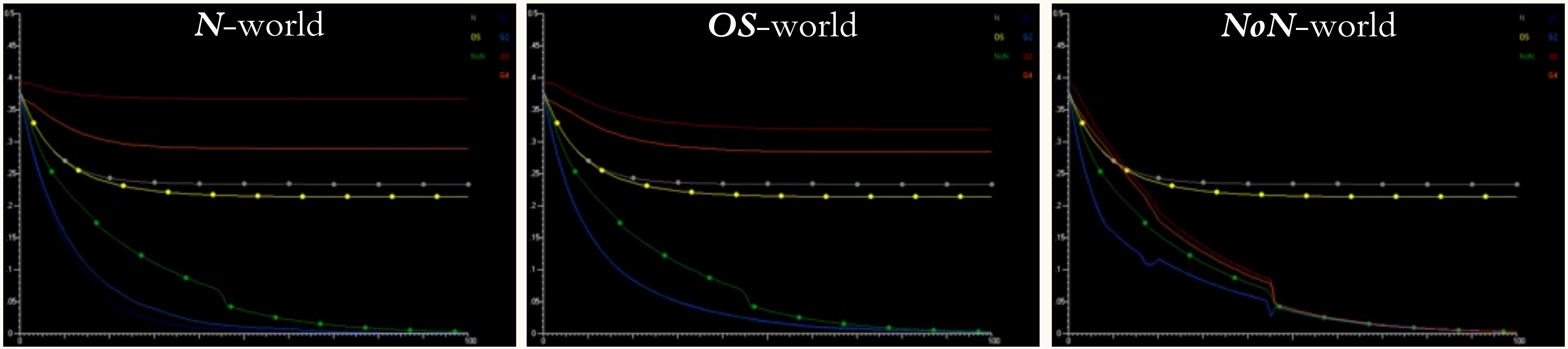
arrogant truth-seekers

modest truth-seekers (enlighteners)

arrogant non-truth seekers

modest non-truth-seekers

Lesson: Networking comes at significant costs in terms of societal truth deviation !



- ∅ truth deviation ***N***-world
- ∅ truth deviation ***OS***-world
- ∅ truth deviation ***NoN***-world

- *arrogant* truth-seekers
- *modest* truth-seekers (enlighteners)
- *arrogant* non-truth seekers
- *modest* non-truth-seekers

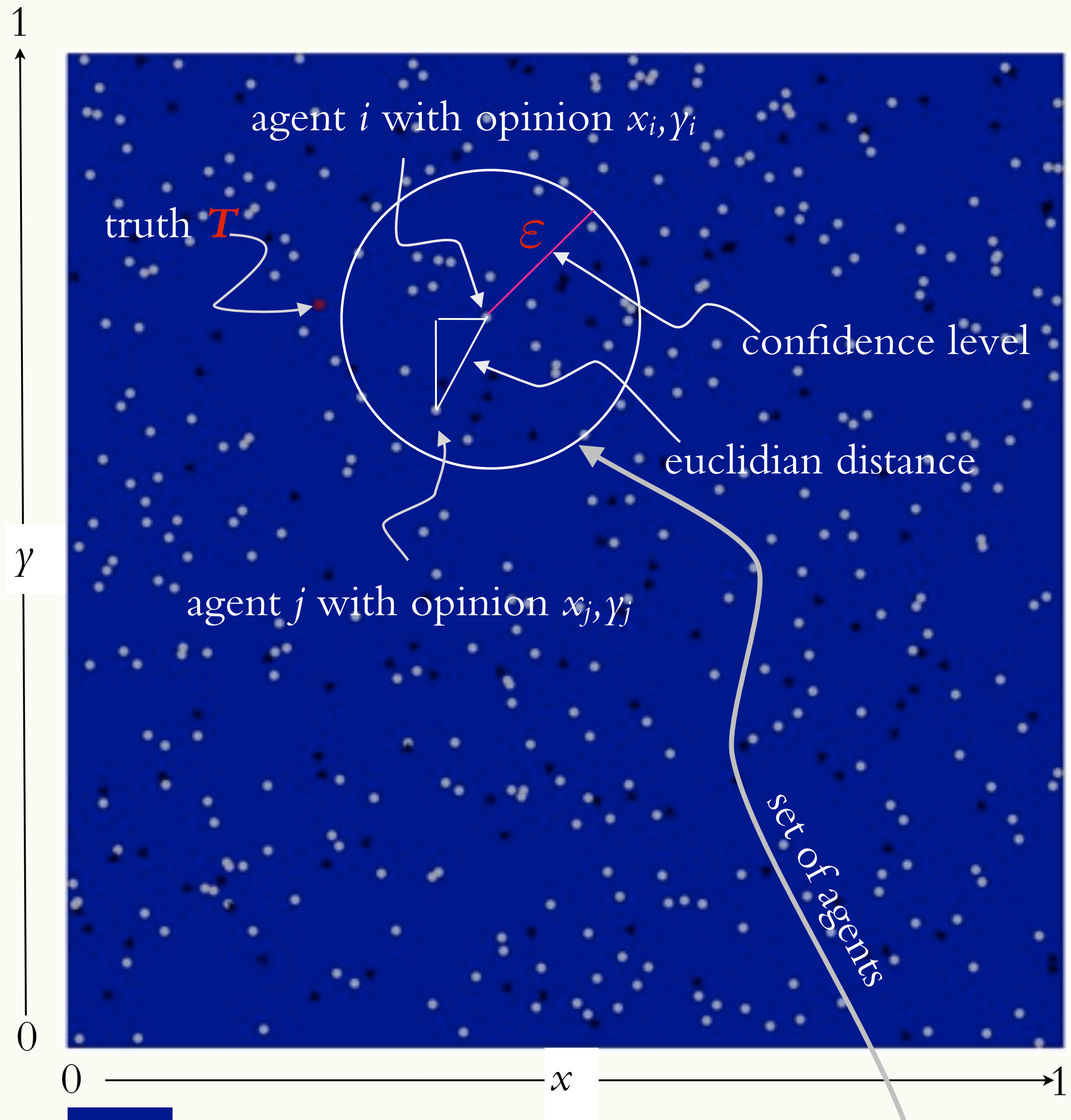
truth deviation $\tau(t) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_i(t) - T\right)^2}$

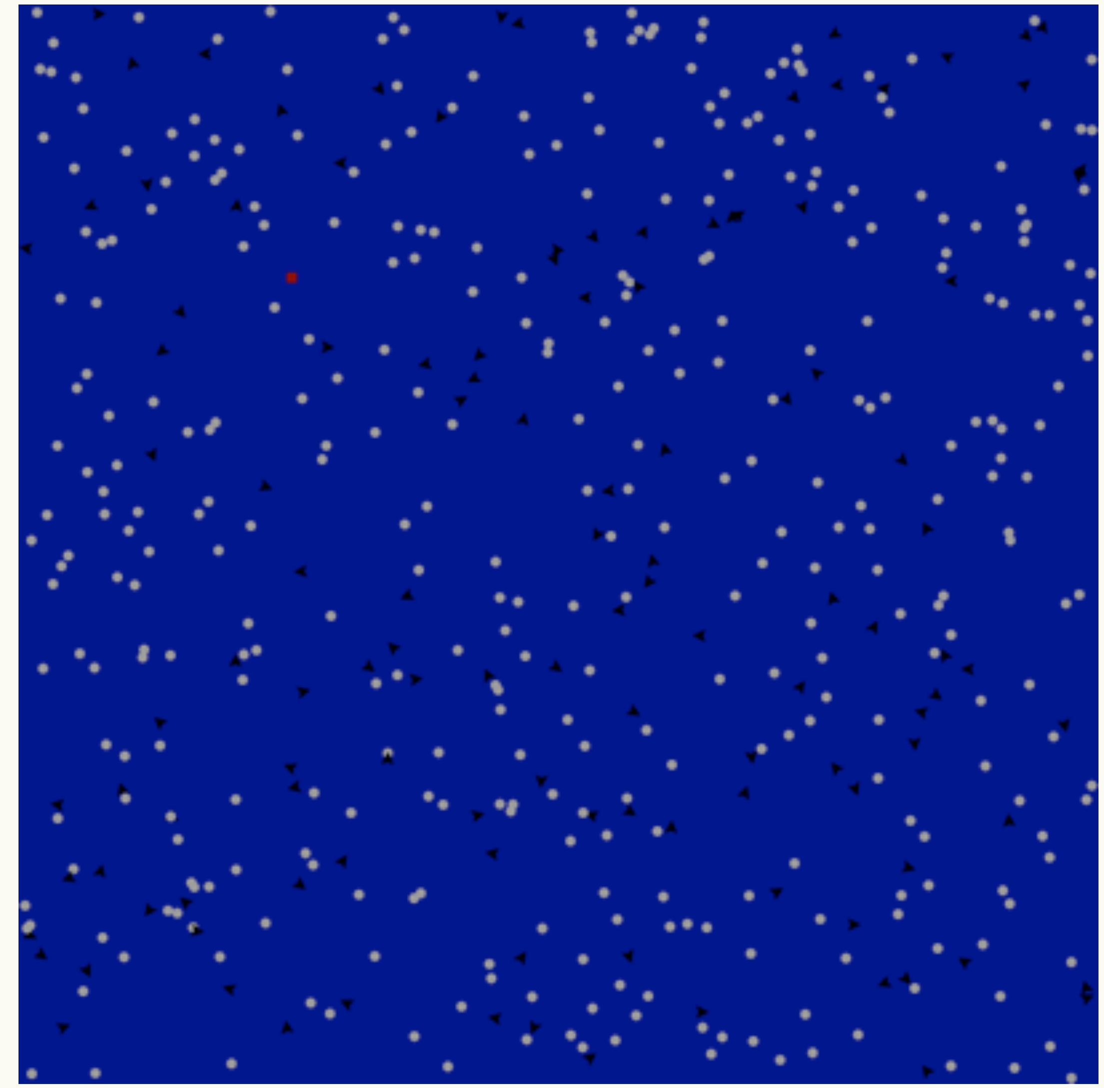
§6

2-dimensional opinion spaces, epistemic landscapes, climbers and followers

A third CASE-study

Two opinion dimensions and a truth T





truth seeker ($\alpha_i > 0$)

non-truth seekers, followers ($\alpha_i = 0$)

$$I(i, X(t), Y(t)) = \left\{ j \,\middle|\, \sqrt{\left(x_i(t) - x_j(t)\right)^2 + \left(y_i(t) - y_j(t)\right)^2} \le \varepsilon \right\}$$

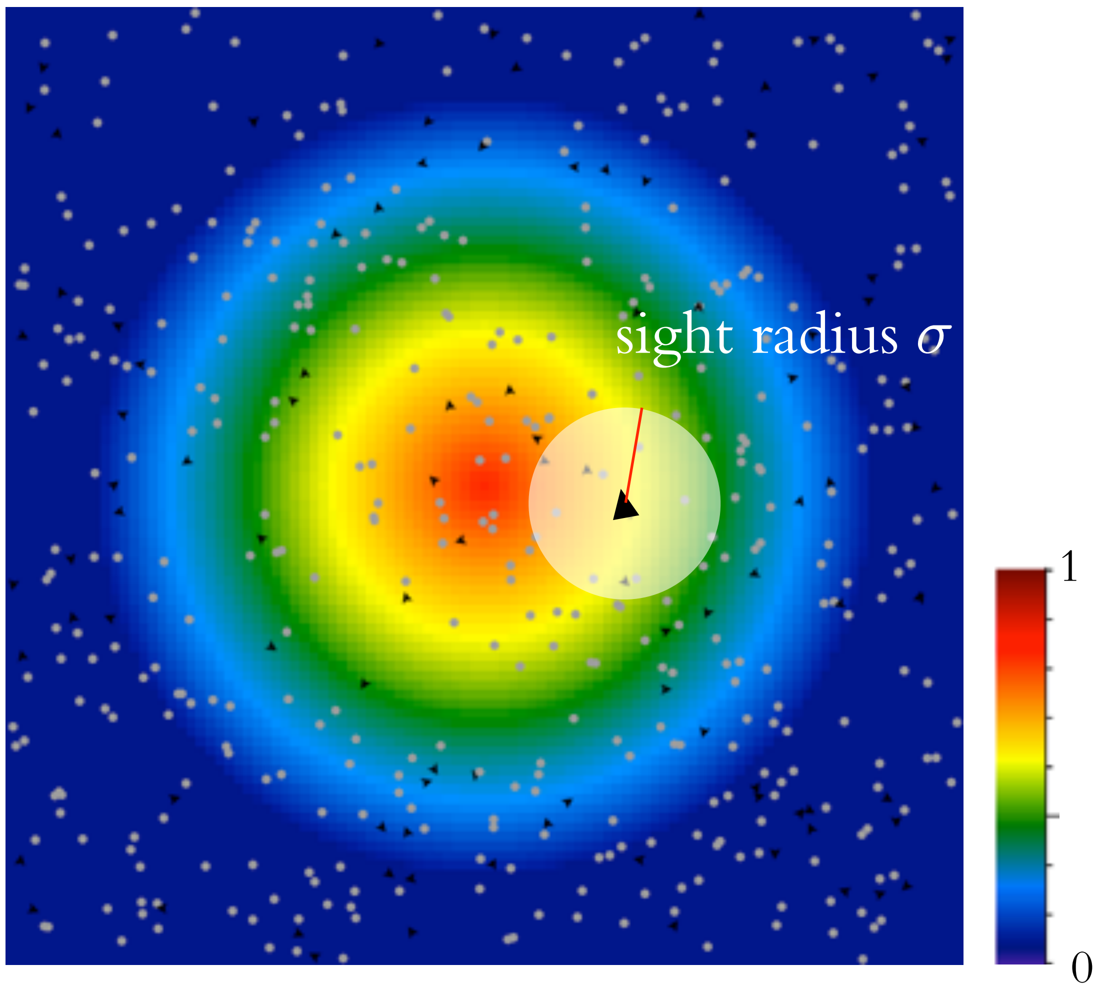
Update:

$$\begin{cases} x_i(t+1) = \alpha_i [x]_T + (1-\alpha_i) \dfrac{1}{\#\left(I(i, X(t), Y(t))\right)} \displaystyle\sum_{j \in I(i, X(t), Y(t))} x_j(t) \\ y_i(t+1) = \alpha_i [y]_T + (1-\alpha_i) \dfrac{1}{\#\left(I(i, X(t), Y(t))\right)} \displaystyle\sum_{j \in I(i, X(t), Y(t))} y_j(t) \end{cases}$$

x-coordinate of T (annotating $[x]_T$)

y-coordinate of T (annotating $[y]_T$)

Climbing an epistemic peak

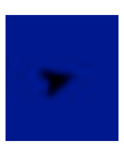


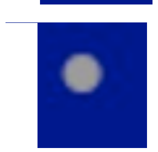
Climbers recognize within the sight radius σ the epistemic values of all opinions.

$E_{i,\sigma}^{\max}$: an opinion with a highest epistemic value within the sight radius σ of agent i with opinion x_i, y_i.

Climbers may go in the direction of

- *any* randomly chosen element of $E_{i,\sigma}^{\max}$
- a *nearest* (randomly chosen) element of $E_{i,\sigma}^{\max}$ (status quo bias)


climbers ($\alpha_i > 0$)


followers ($\alpha_i = 0$)

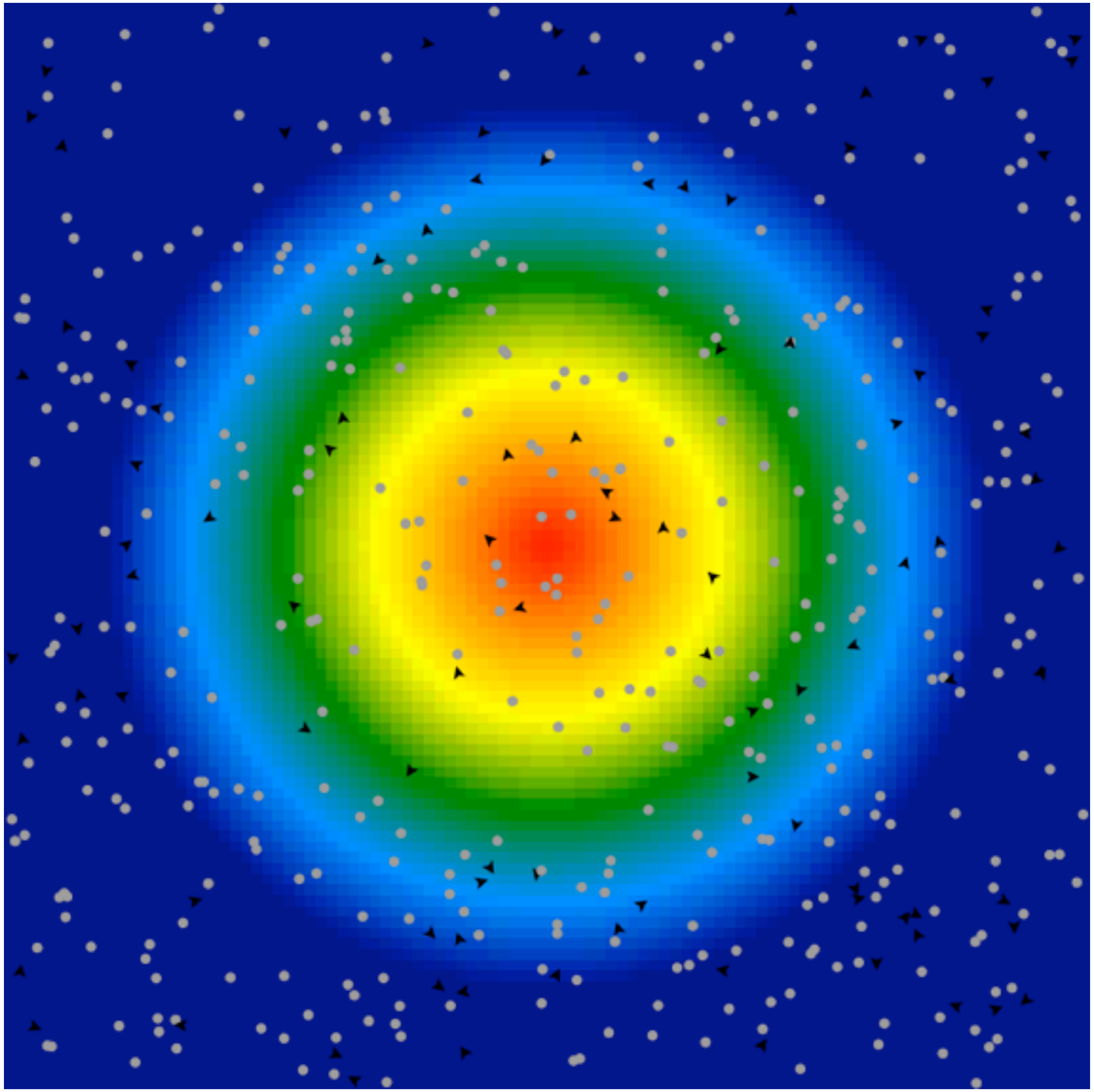
$$I\left(i, X(t), Y(t)\right) = \left\{ j \,\middle|\, \sqrt{\left(x_i(t) - x_j(t)\right)^2 + \left(y_i(t) - y_j(t)\right)^2} \leq \varepsilon \right\}$$

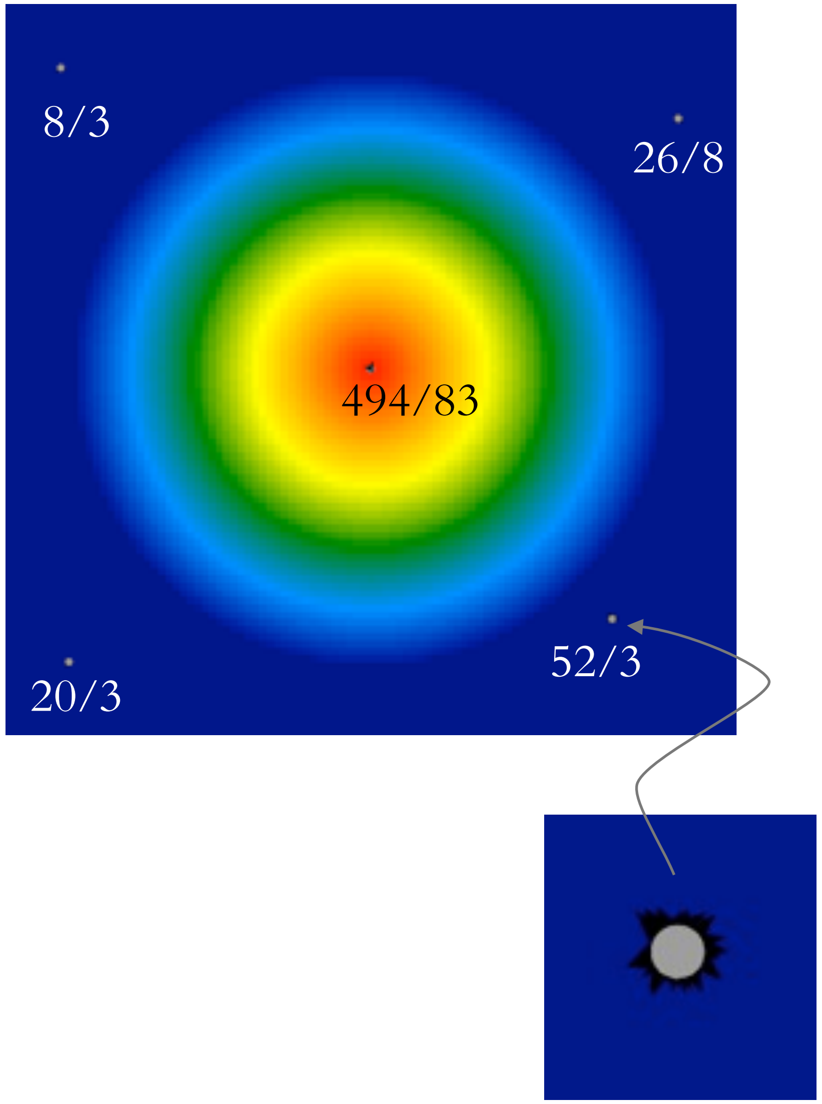
x-coordinate of $E_{i,\sigma}^{\max}$

Update:
$$\begin{cases} x_i(t+1) = \alpha_i \left[x\right]_{E_{i,\sigma}^{\max}} + \left(1-\alpha_i\right) \dfrac{1}{\#\left(I\left(i, X(t), Y(t)\right)\right)} \displaystyle\sum_{j \in I(i, X(t), Y(t))} x_j(t) \\ y_i(t+1) = \alpha_i \left[y\right]_{E_{i,\sigma}^{\max}} + \left(1-\alpha_i\right) \dfrac{1}{\#\left(I\left(i, X(t), Y(t)\right)\right)} \displaystyle\sum_{j \in I(i, X(t), Y(t))} y_j(t) \end{cases}$$

y-coordinate of $E_{i,\sigma}^{\max}$

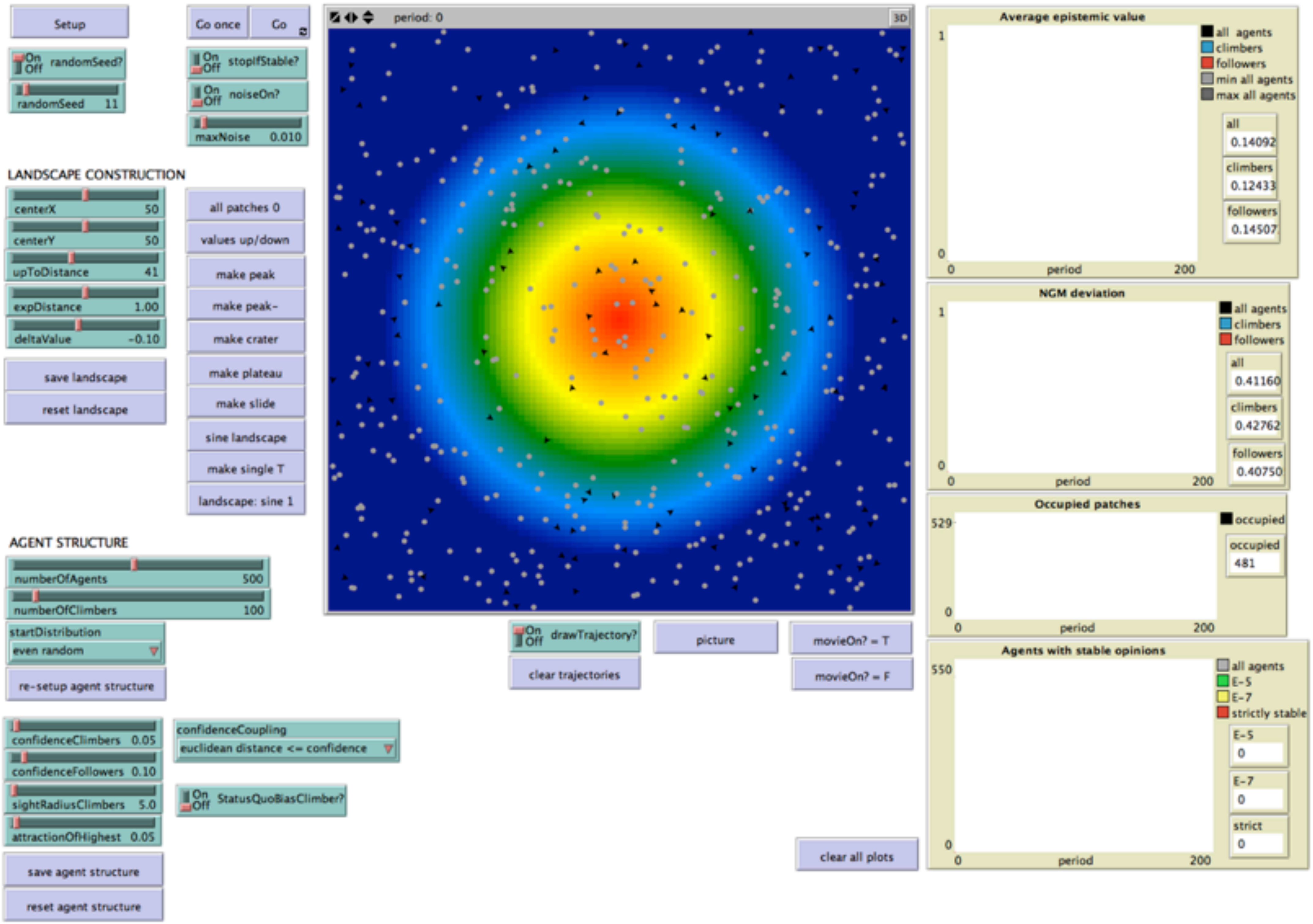
Climbing an epistemic peak



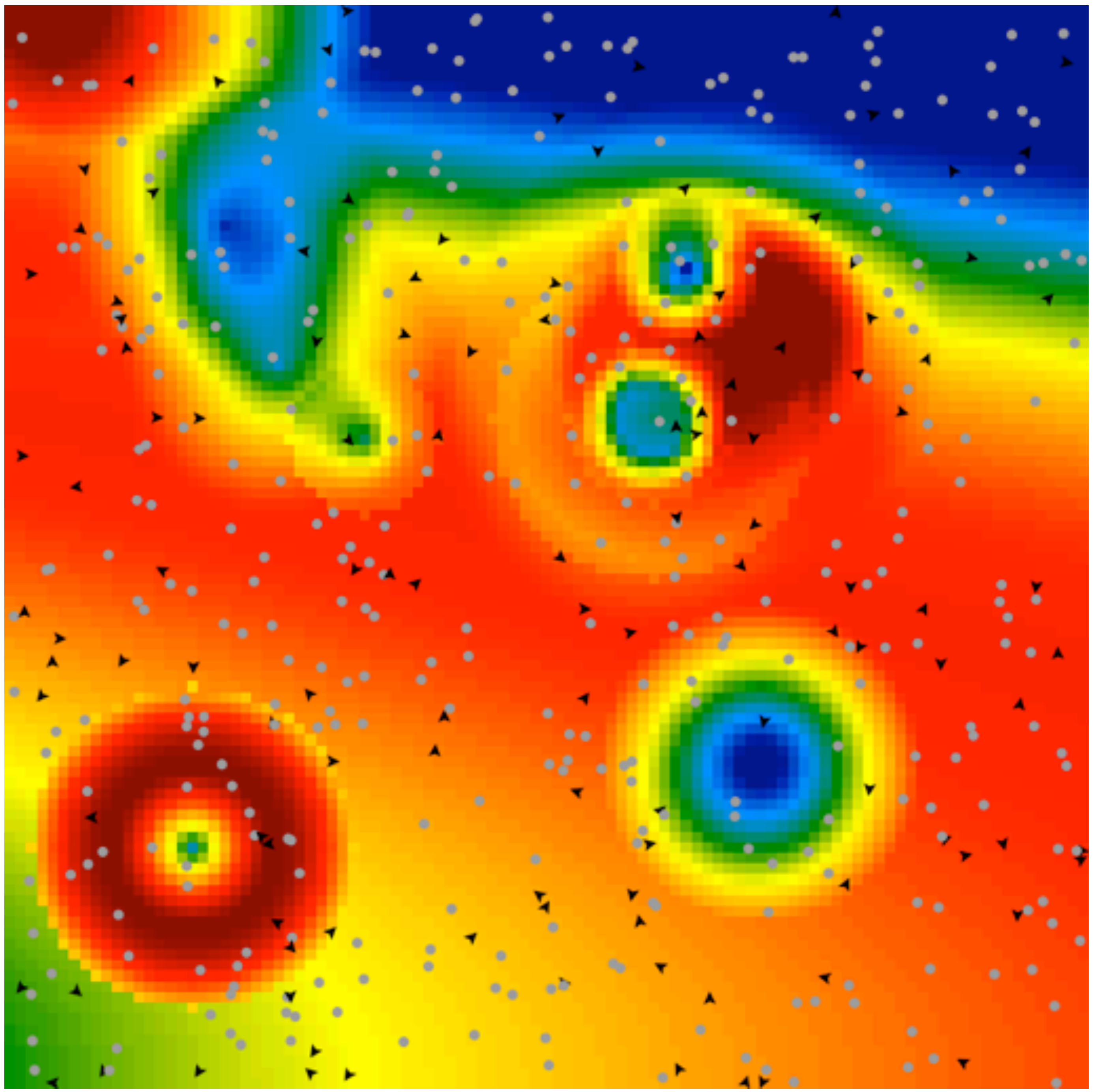


- 100 climbers, $\alpha = 0.05$, $\varepsilon/\sigma = 0.05$
- 500 followers, $\varepsilon = 0.1$
- 1250 periods

The NetLogo simulator



Climbers and followers in a cliffy landscape



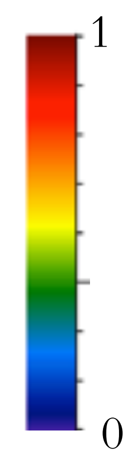
agents: 484

climbers: 121 (25%)

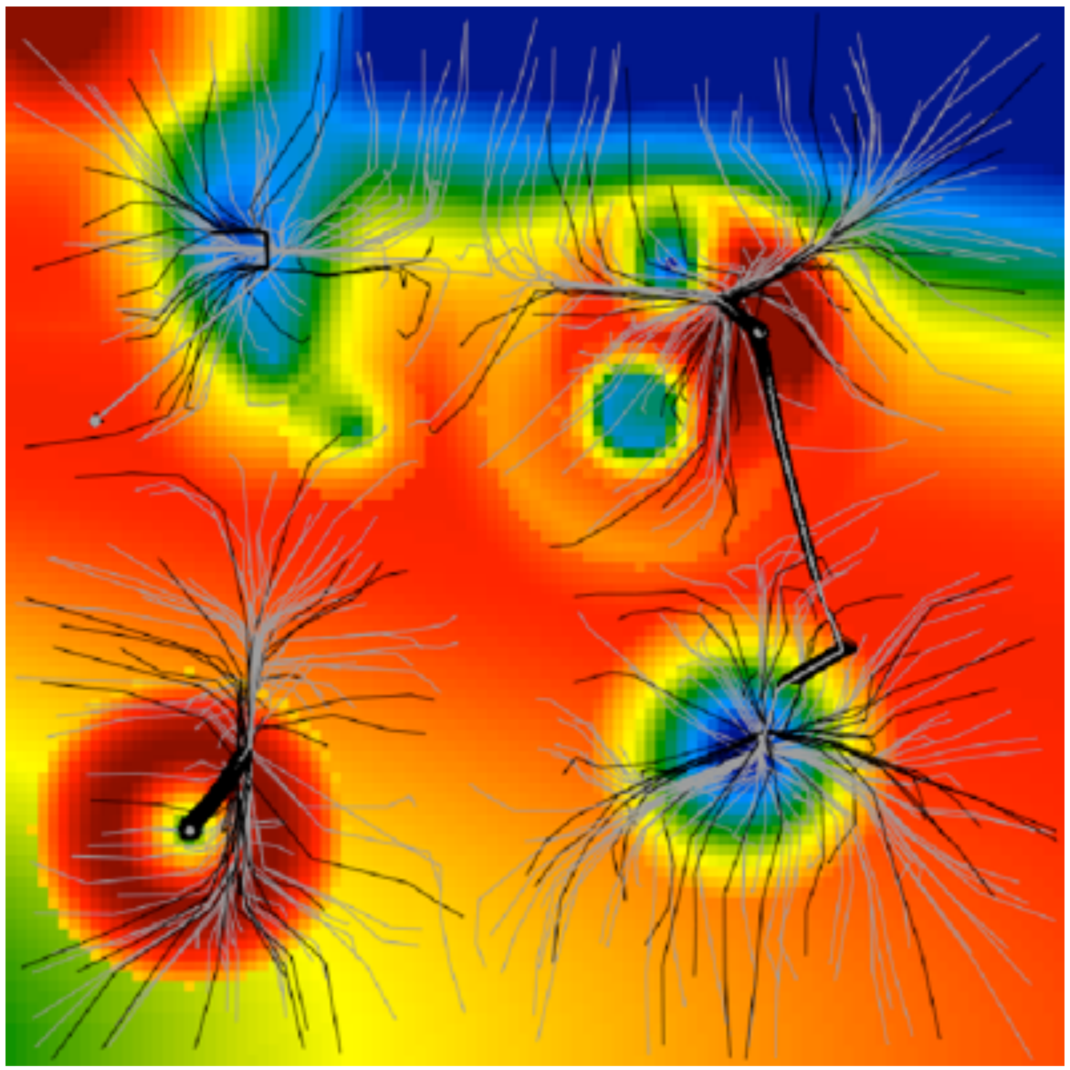
confidence $\varepsilon = 0.2$

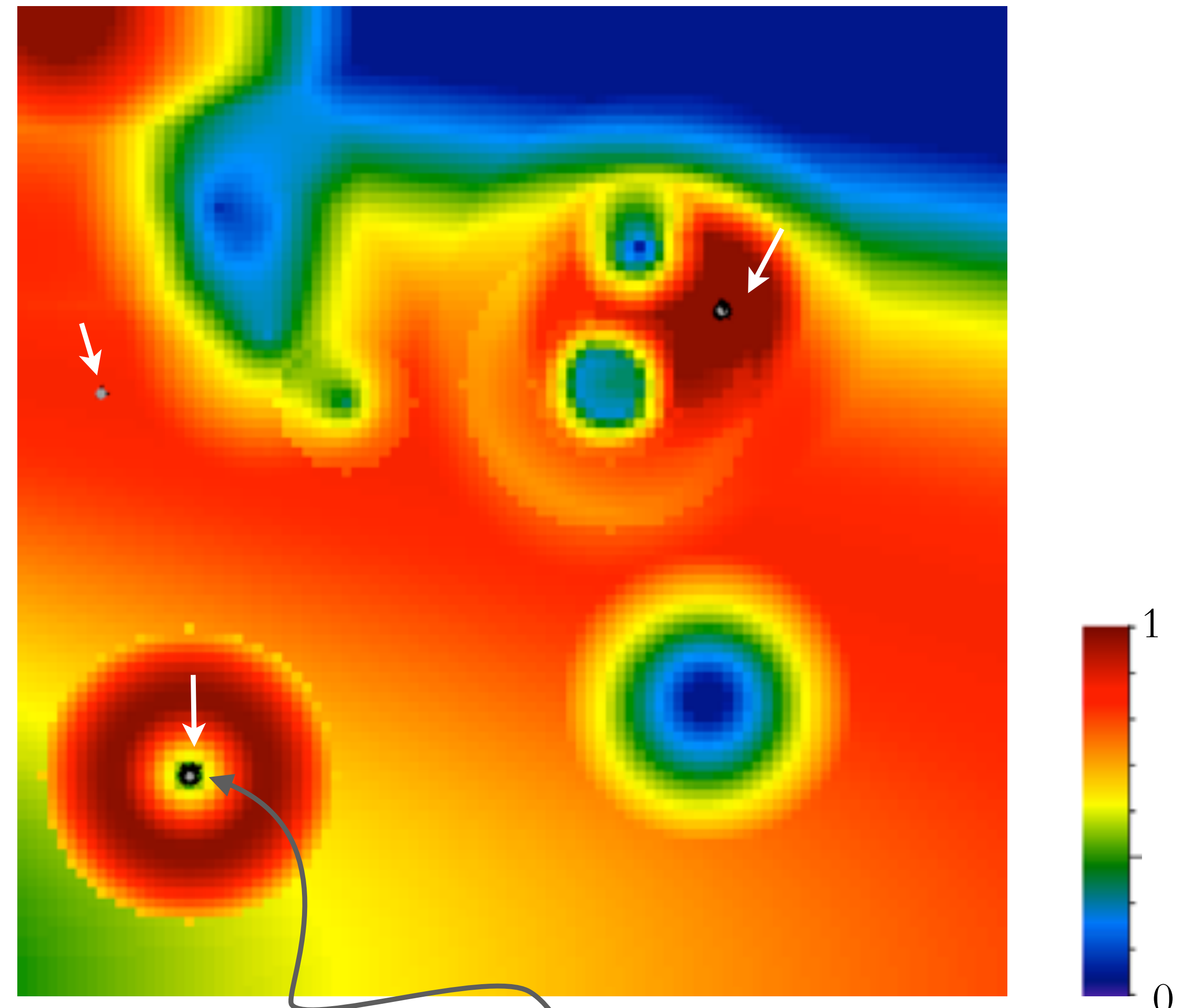
sight radius $\sigma = 0.2$

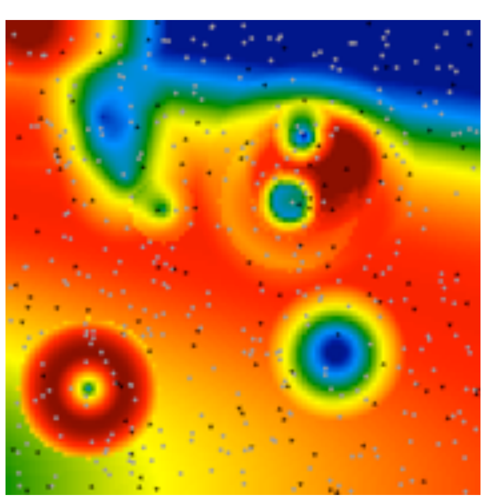
attraction $\alpha = 0.1$



Climbers and followers in cliffy landscapes







agents: 484

climbers: 121 (25%)

confidence $\varepsilon = 0.2$

sight radius $\sigma = 0.2$

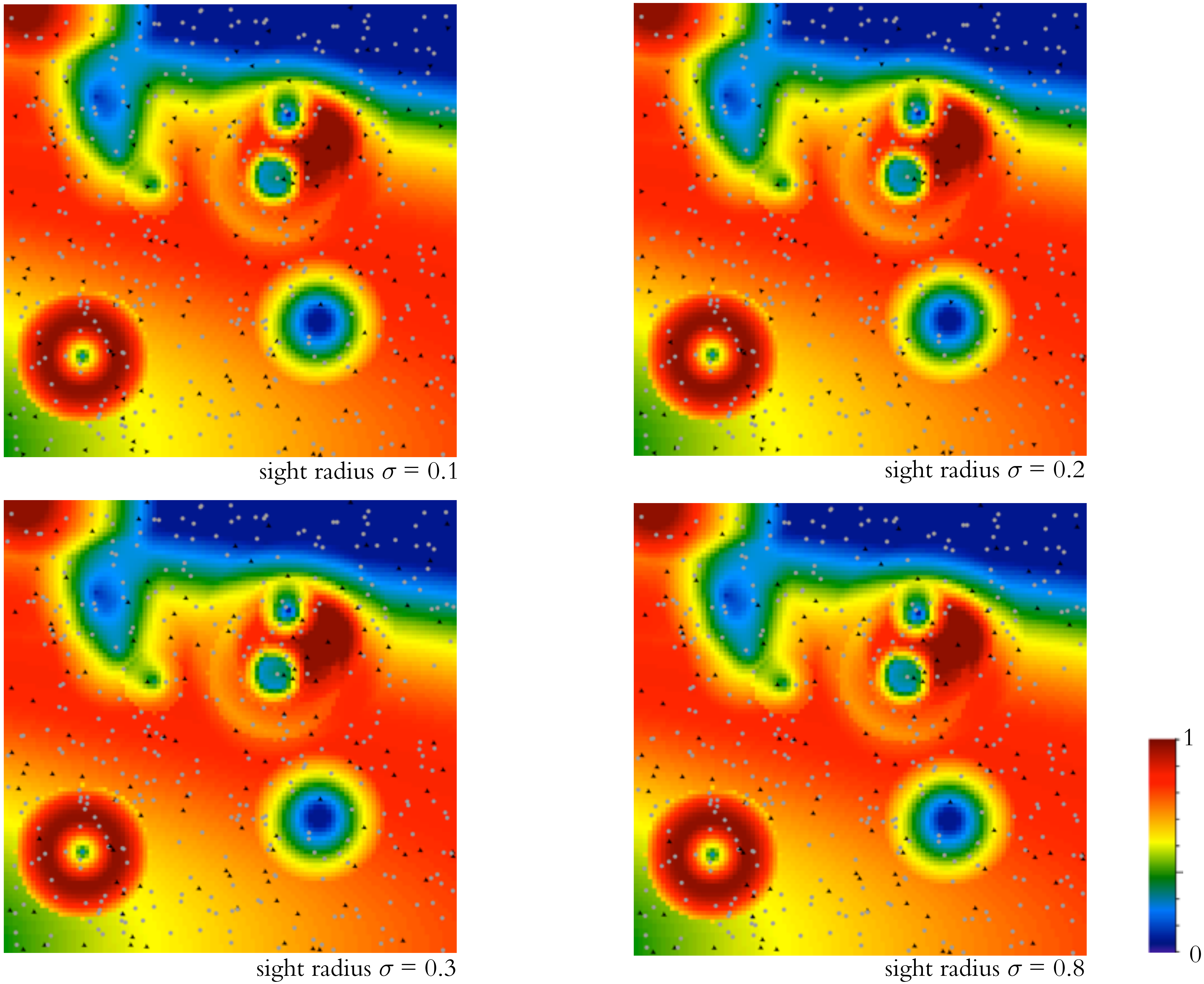
attraction $\alpha = 0.1$

How comes?

Climbers moved in the direction of a randomly chosen highest peak within their sight radius.

Alternative: nearest highest (*status quo bias*)

Climbing with different sight radii



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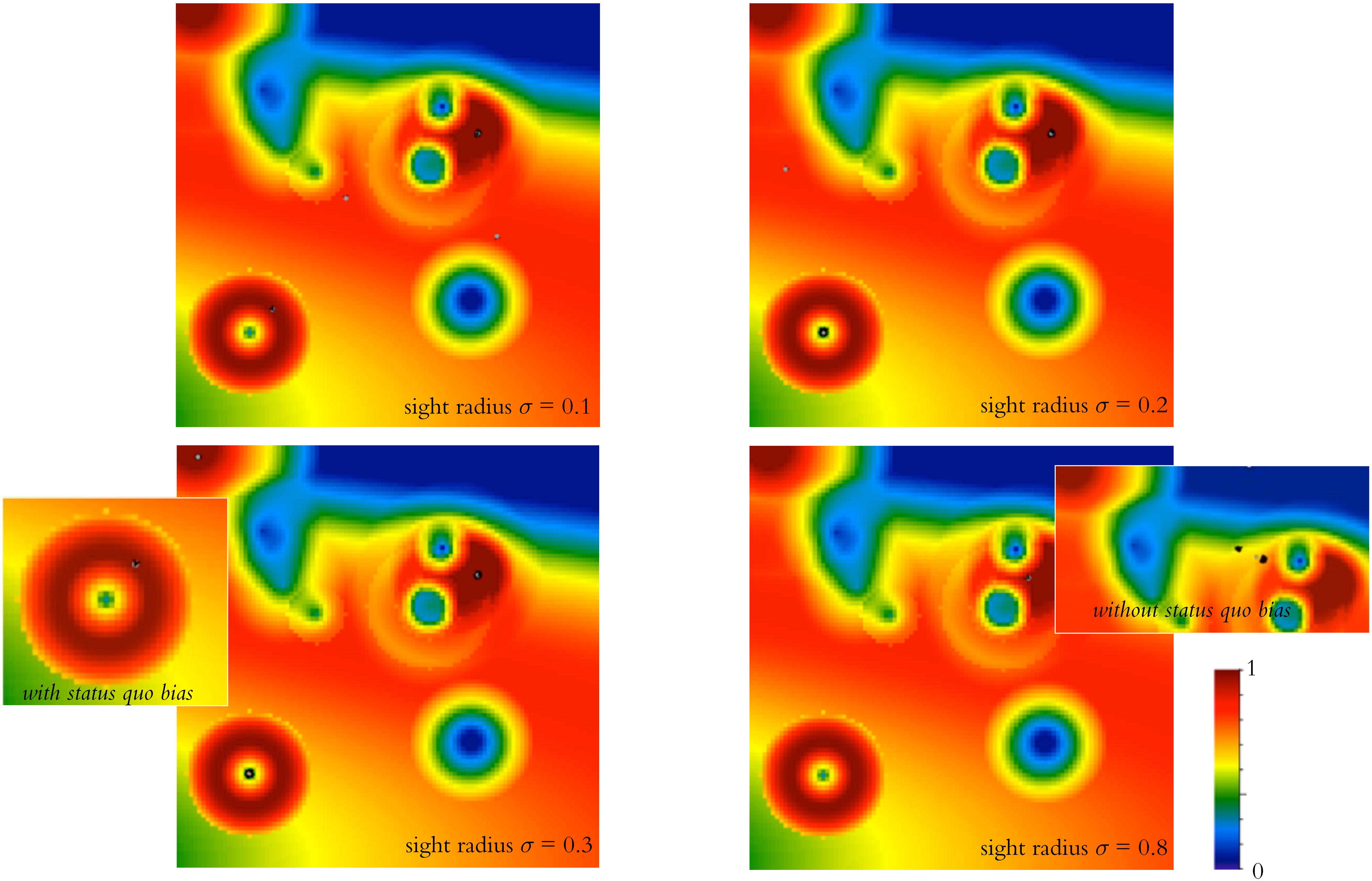
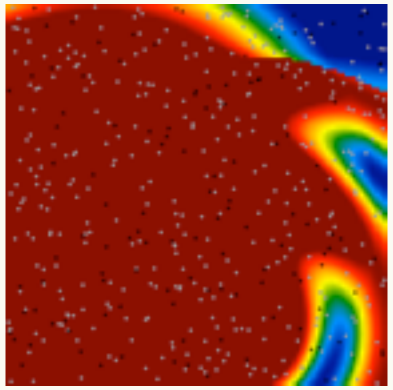
Climbers and followers in cliffy landscapes

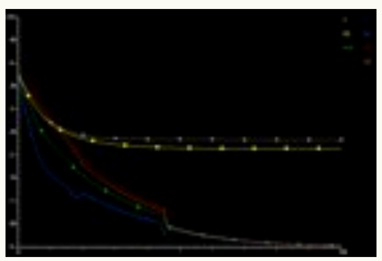


§7
Some perspectives and ideas for CASE-studies

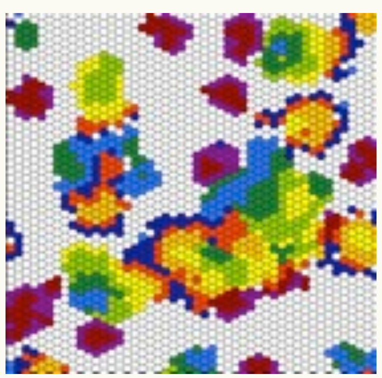
Macroscopic CASE-studies: Some perspectives



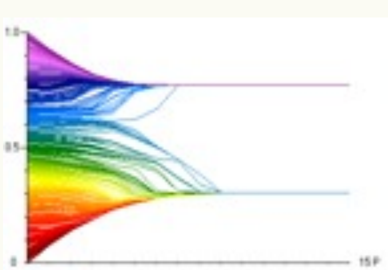
- Classification of interesting epistemic landscapes. Efficiency analysis with regard to the frequency of climbers, confidence levels, sight radius, climber skills, different heuristics (e.g. status quo bias) etc.



- Using higher dimensional opinion spaces to model cognitive interaction between specialized scientific groups: The groups have different truth-seeker/ climber-skills in different dimensions. The confidence levels may be different in different dimensions. What's about the chances for the truth to spread throughout the whole community? Whats about the chances that the globally highest peak is finally found by all? What's about the time that it takes?



- Characterization and analysis of epistemically interesting scenarios of epistemic groups and the effects of combined network & opinion dynamics:
  - opinion dynamics of laymen, (disaggreeing) experts, and media in public debates
  - modeling and analysis of evidence and truth distorting campaigns (e.g. intelligent design, smoking-lung cancer, climate debate)



- Optimal control of (network based) opinion streams: Analysis and development of efficient campaigning strategies (Where in the opinion space should one place opinions? Whom should one try to influence? Between whom should one try to establish links? Which strategy works faster? (WARNING: Can be used for all purposes – good or bad!)

Many thanks for your attention!