Simplified approaches to opinion dynamics modelling

Duccio Fanelli

Dipartimento di Energetica,
University of Florence,
Italy.

Outline

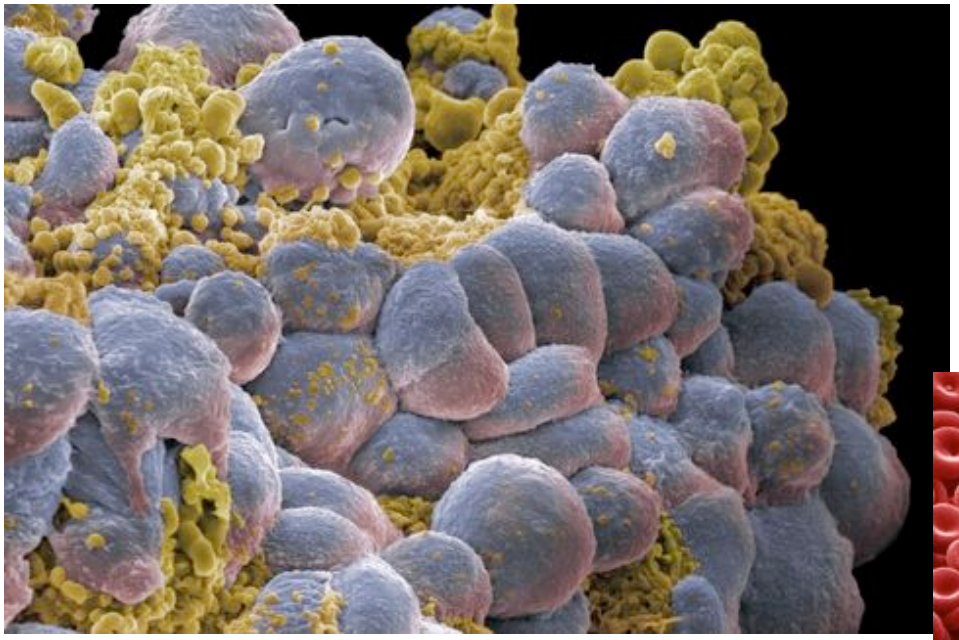
Modeling social systems: population, interactions, dynamics

The case of opinion dynamics: the Deffuant model

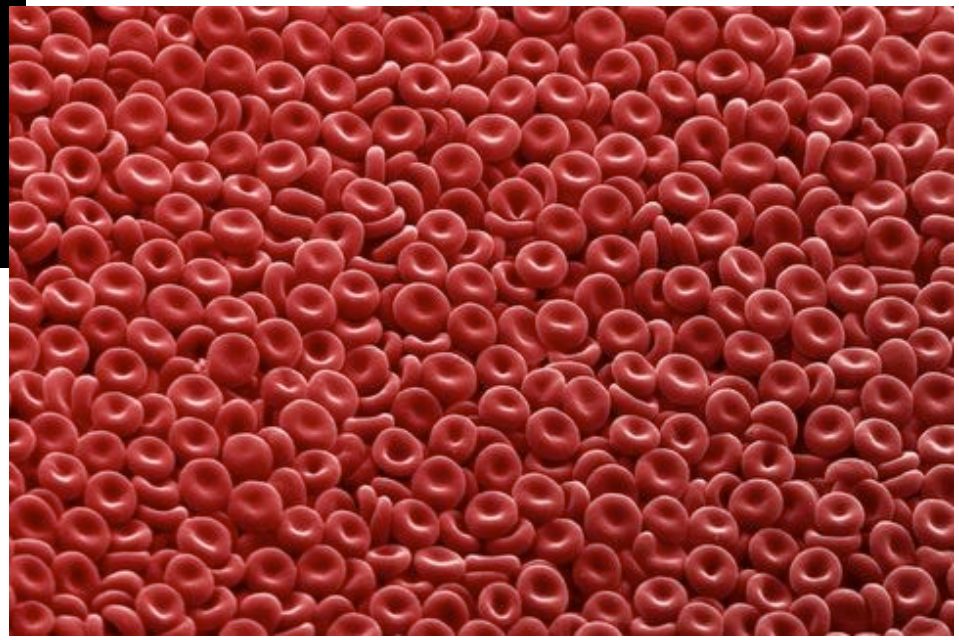
Heuristics and decision making: from psychology
to a simplified dynamical framework

Experiments vs. models: the virtual community laboratory

Natural phenomena often involve large assembly of simultaneously interacting bodies

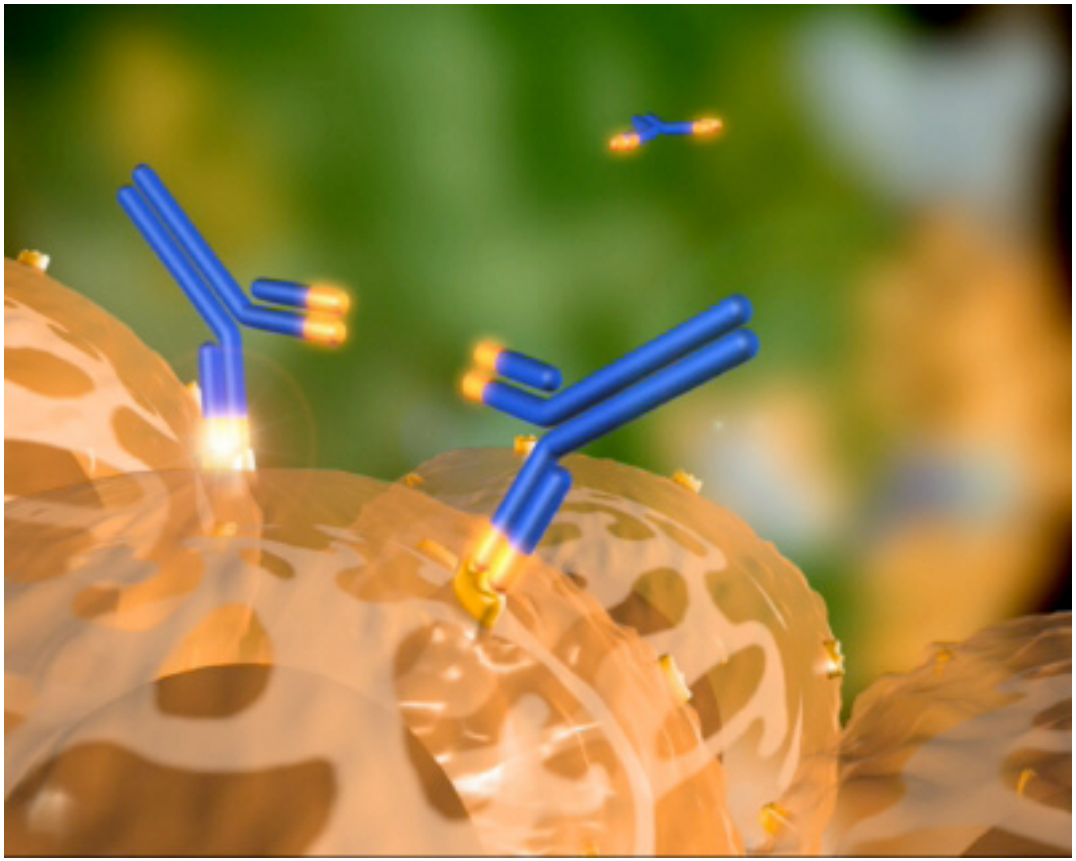


Interacting cells



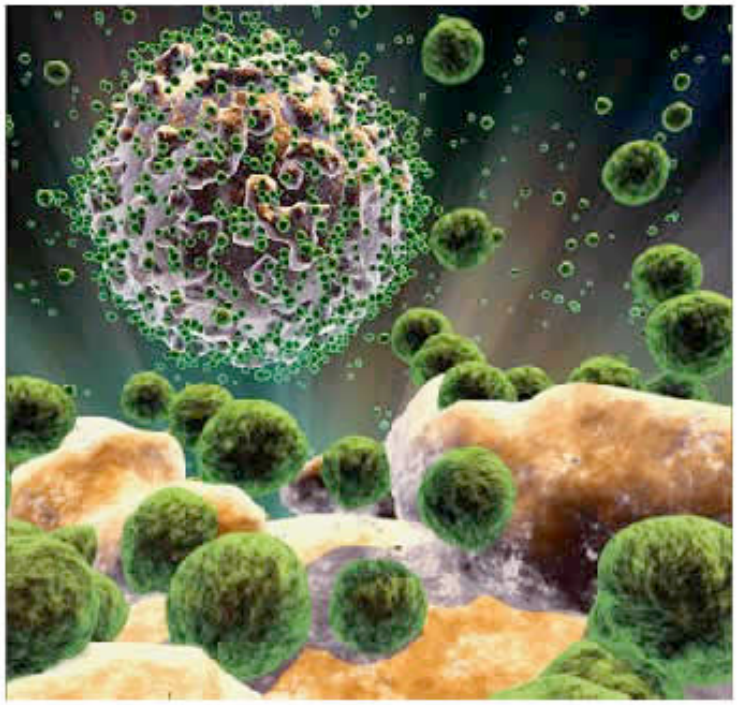
A red carpet of blood cells

Different processes occur at different scales…



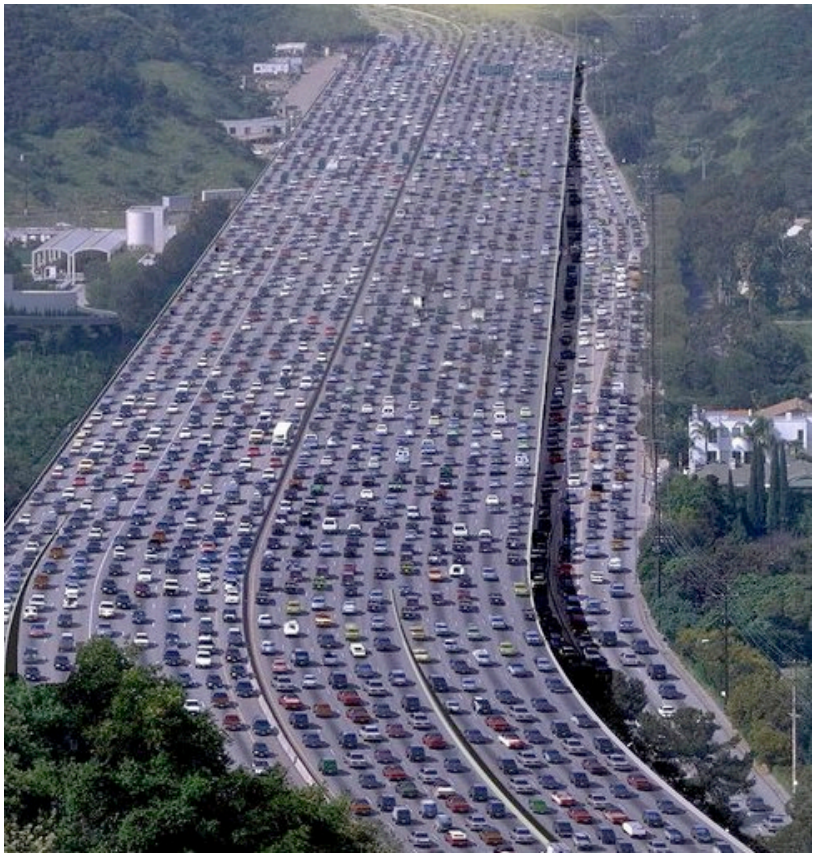
Different molecular actors belonging to distinct population in mutual competition (e.g. virus and antibodies)

Modeling the mutual interaction between interacting species is indeed a cross-disciplinary field of investigations



From life sciences (e.g. biology, ecology…)

…to e.g. social systems (traffic models, crowd dynamics)

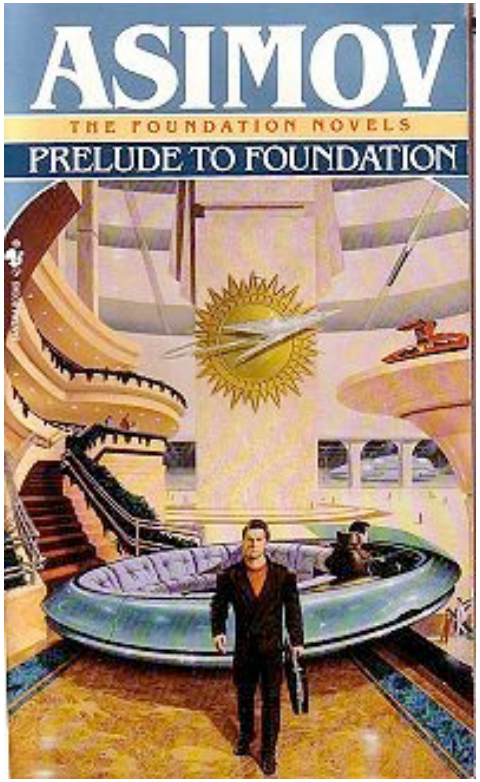


They all share similar tools and mathematical techniques

"Your Imperial Majesty ... consider the manner in which scientists have dealt with subatomic particles. There are enormous numbers of these, each moving or vibrating in random and unpredictable manner, but this chaos turns out to have an underlying order, so that we can work out a quantum mechanics that answers all the questions we know how to ask.

In studying society, we place human beings in the place of subatomic particles, but now there is the added factor of the human mind. Particles move mindlessly; human beings do not. To take into account the various attitudes and impulses of mind adds so much complexity that there lacks time to take care of all of it."

Prelude to Foundation by Isaac Asimov, 1988



It is particularly interesting to study the inherent dynamics of relatively small groups.

Individuals can debate on a specific issue and consequenly modify their opinion or believes.

The group can spontaneously organize an internal structure, e.g. by identifying the leader.

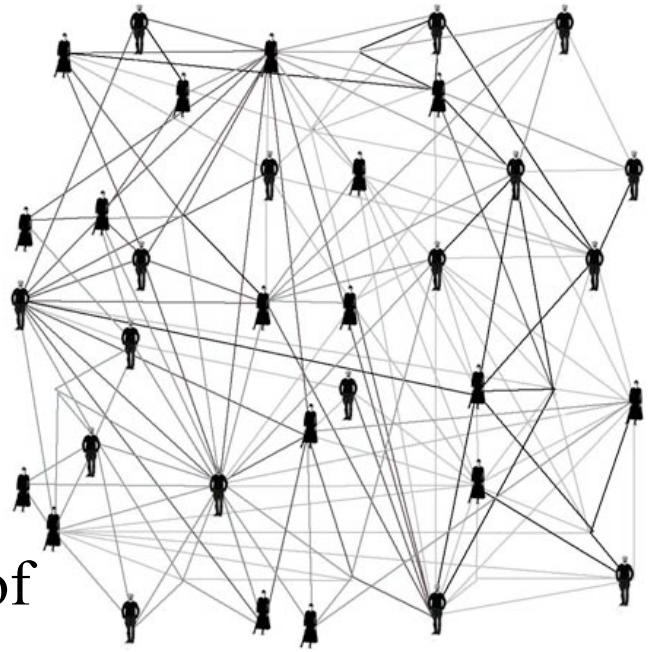
The opinion forming can be externally influenced by a "propaganda"

How to model these (and many more) effects within a self- consistent dyamical picture?

The physicist's approach:1D opinion representation

Consider N individual and imagine individual i to bear a specific (scalar) opinion O_i on a given topic

Individuals are linked together, via short vs. long range couplings, taking part of



People are nodes of an abstract network of connection, which can possibly account for the explicit notion of space.

Two different philosophies

Binary opinion

(0,1) / up-down

Ising model, Curie-Weiss, spin glasses

Magnetized phases correspond to configuration where consensus in the population has been reached

Continuous opinion

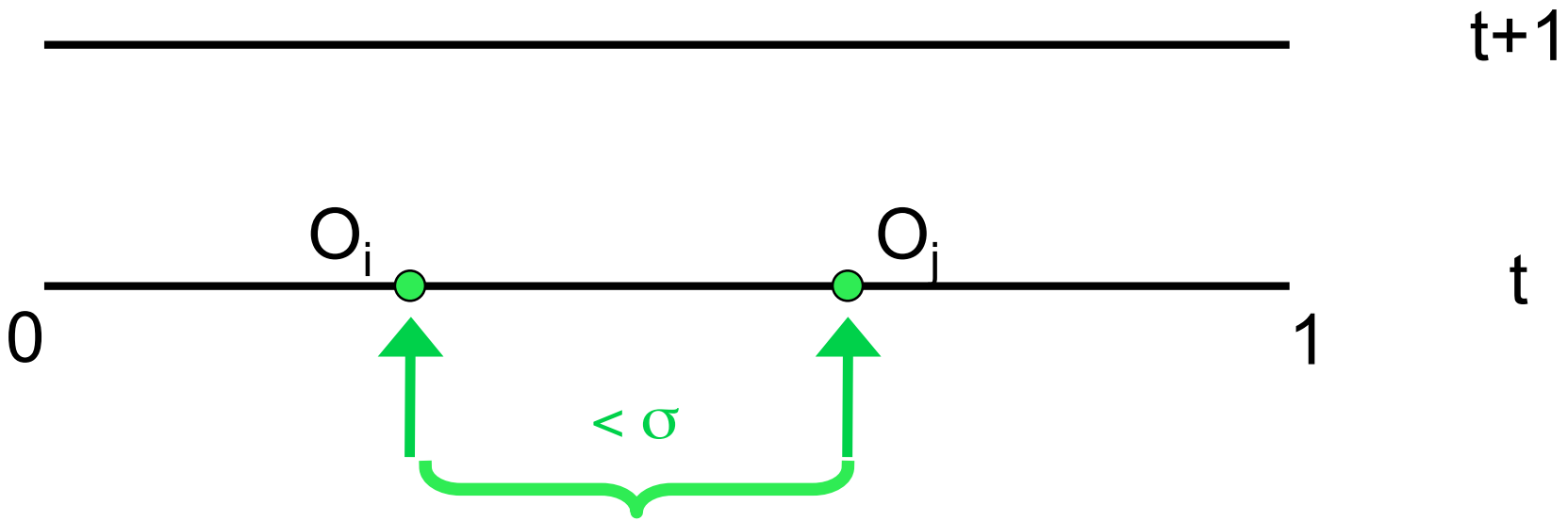
$0 < O_i < 1$

Deffuant et al.

Assigned specific rules of microscopic interactions

Deffuant's model

$$\begin{cases} |O_i(t) - O_j(t)| < \sigma \Rightarrow O_i(t+1) = O_i(t) + \mu |O_j(t) - O_i(t)| \\ |O_i(t) - O_j(t)| > \sigma \Rightarrow O_i(t+1) = O_i(t) \end{cases}$$



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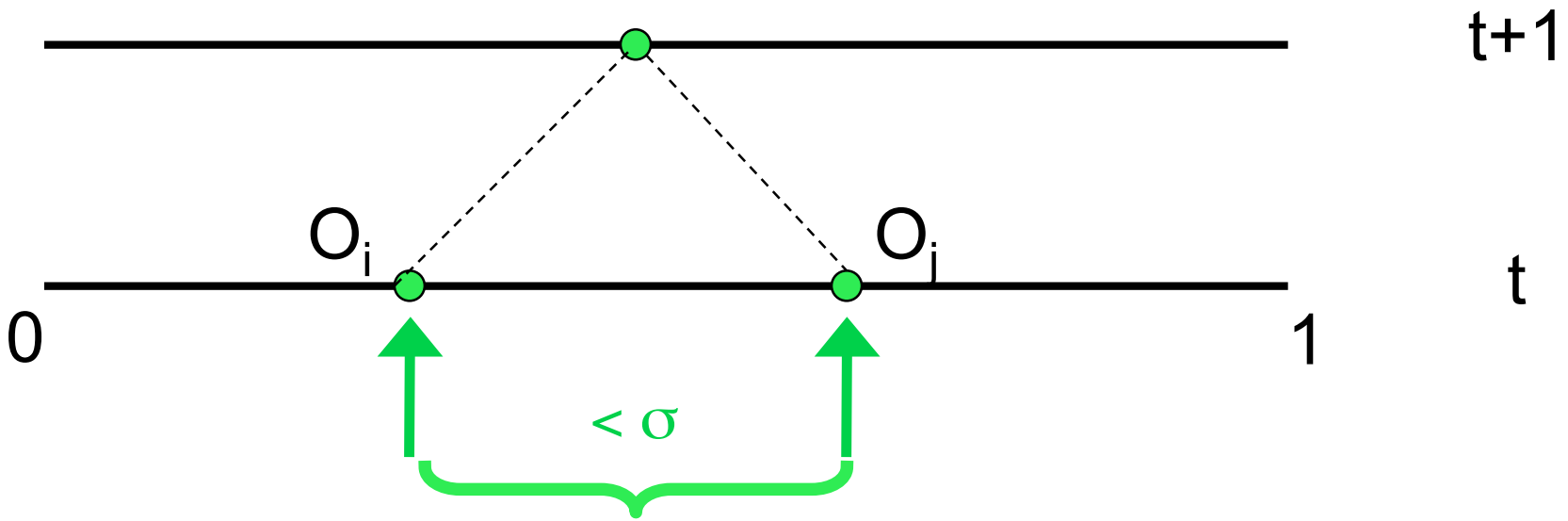

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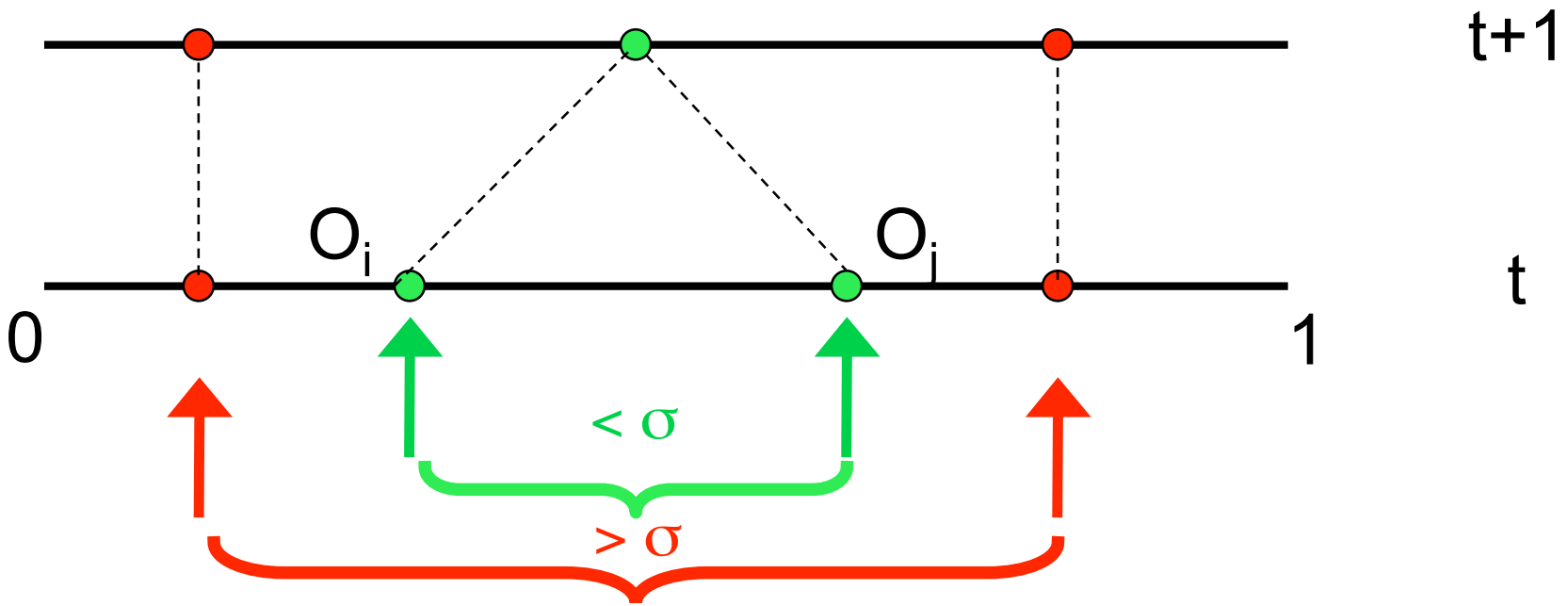

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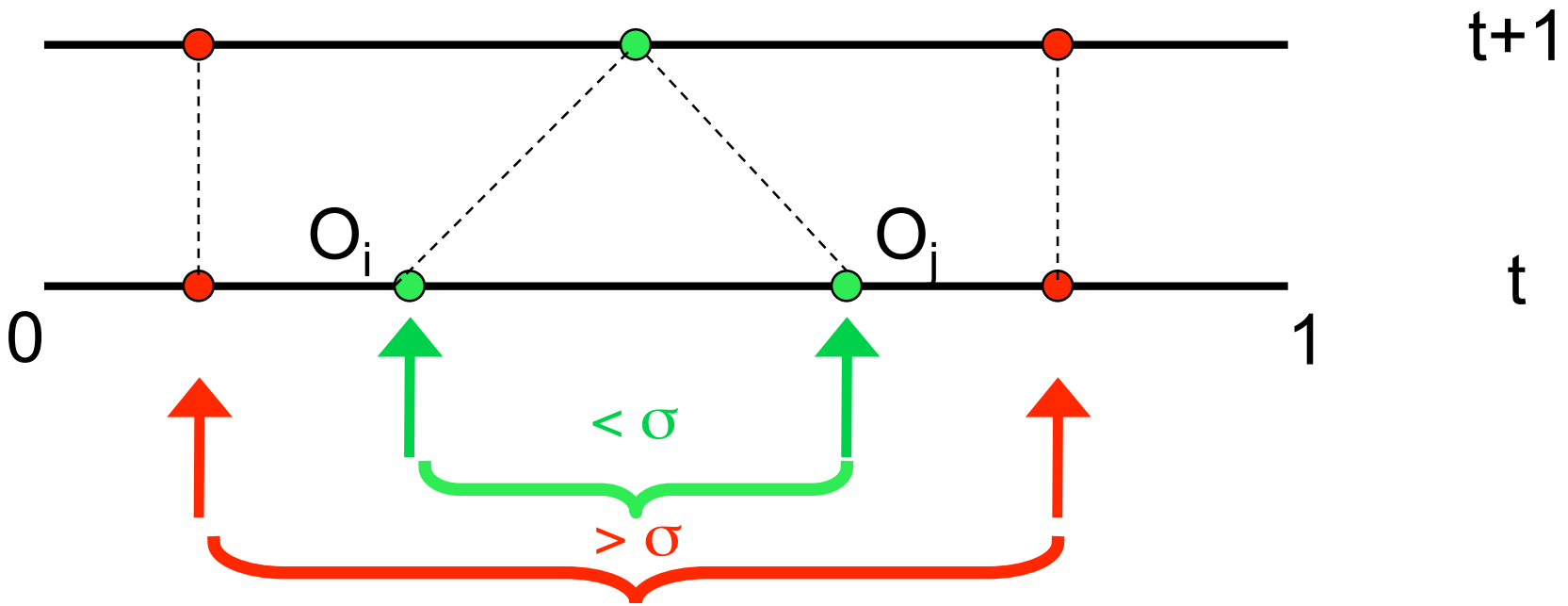
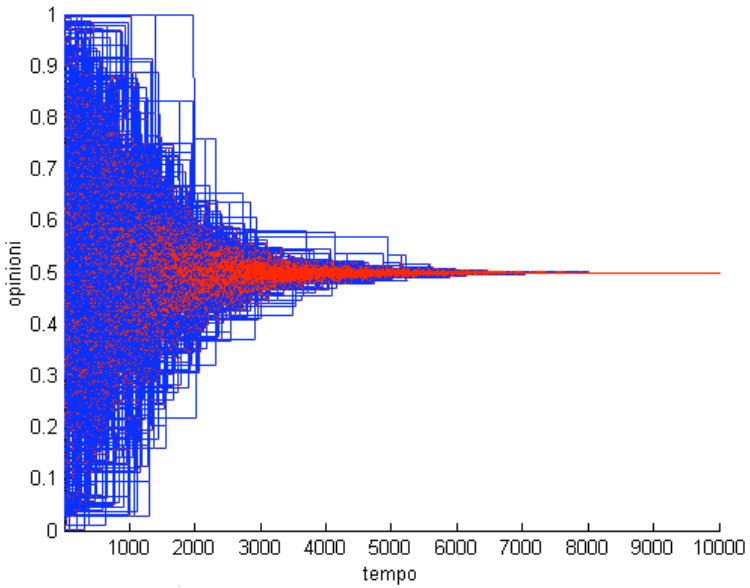
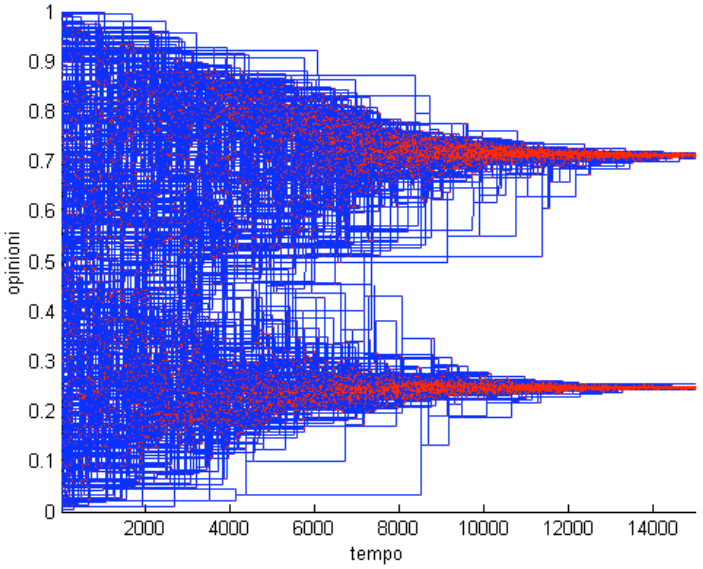
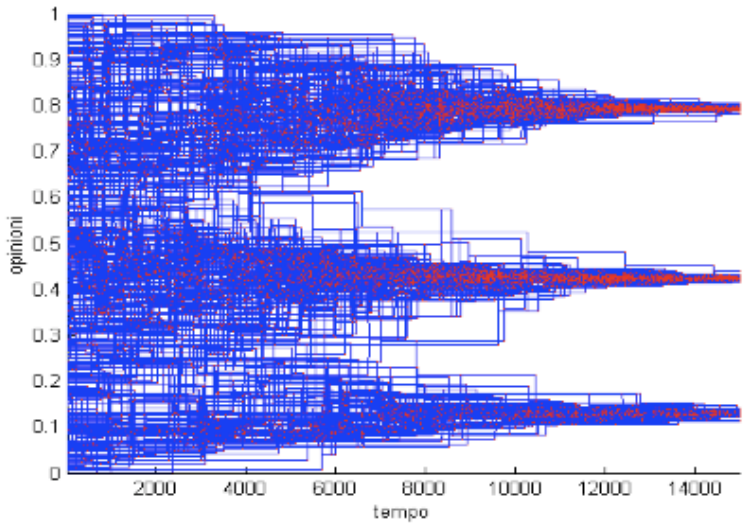


Opinion vs. time: different threshold amount

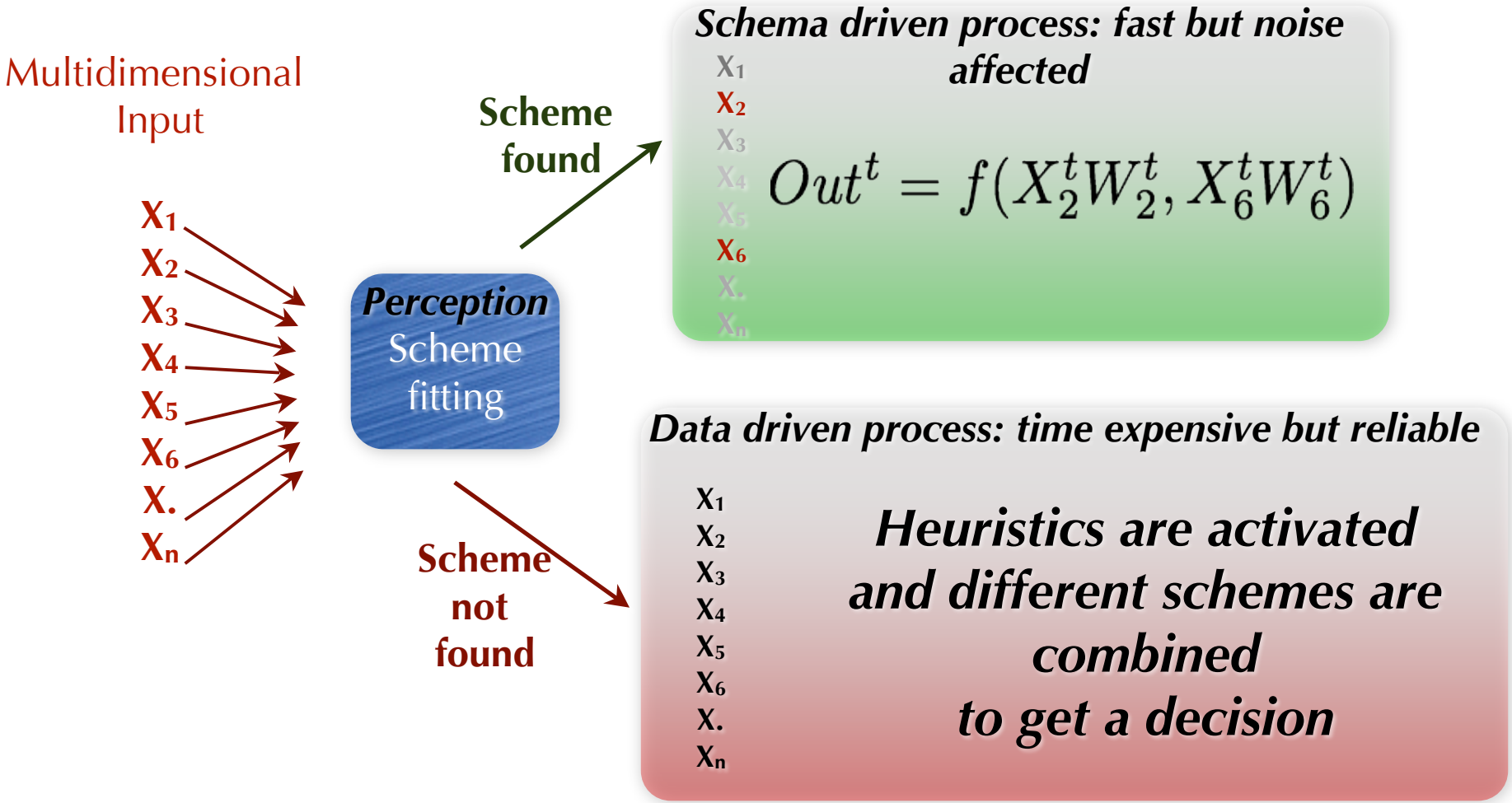




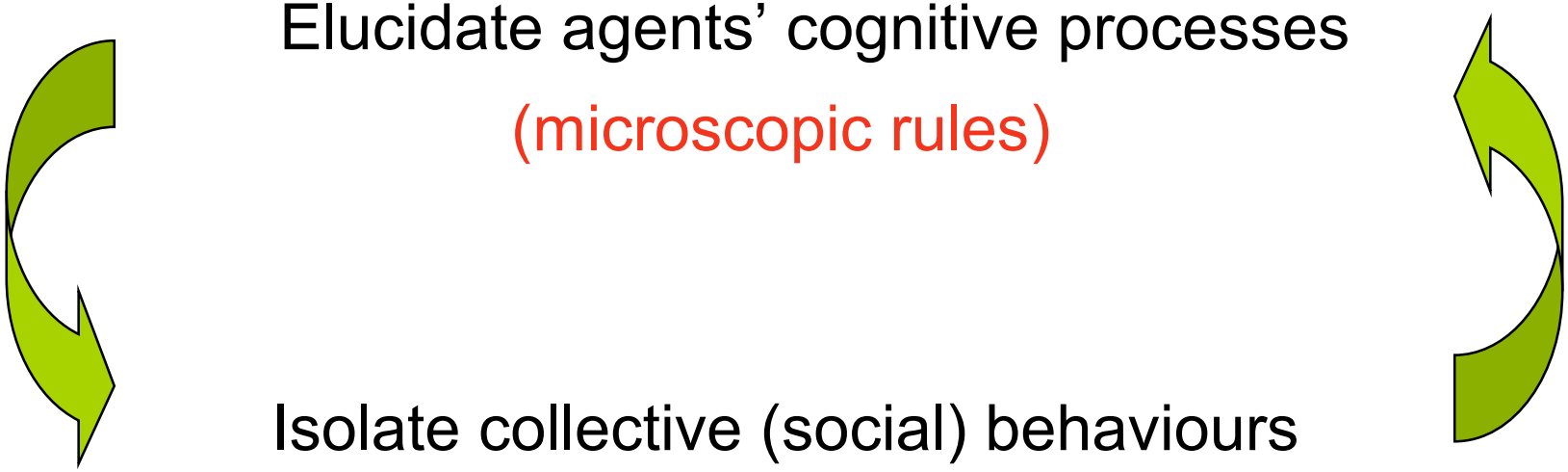


The number of clusters scales as $1/(2\sigma)$

In reality the process of opinion formation is rather complicated and involve detailed mechanisms studied by the psychological literature.



In general improving the model would necessitate…

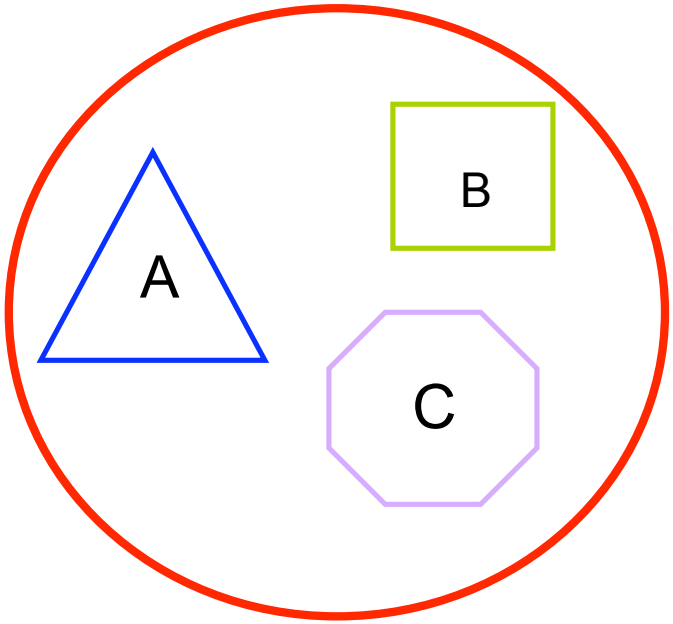


The degree of macroscopic complexity defines the level of microscopic coarse graining

The agent: decision making and cognitive strategies

Heuristics

In psychology, **simple**, **efficient** rules, hard-coded by evolution to explain decision making, judgment, and problem solving.



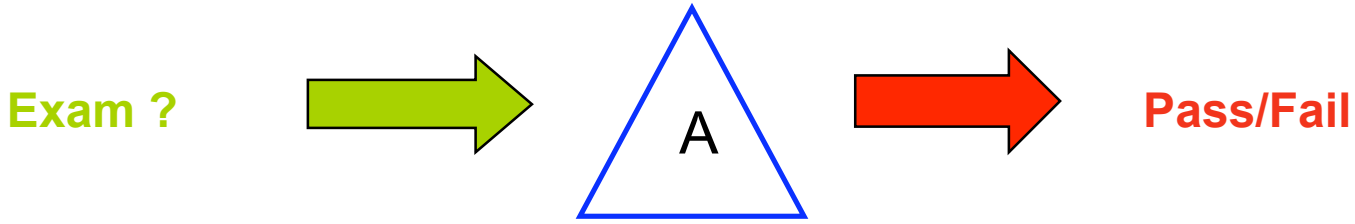
A. Representativeness

B. Avalaibility

C. Anchoring

A. Representativeness

Evaluate the similarity of selected features with respect to reference templates and judge accordingly.



Example Mike is a student you haven't met before. Will he pass the exam? To decide you compare with the *prototype* of successfull student and take a decision.

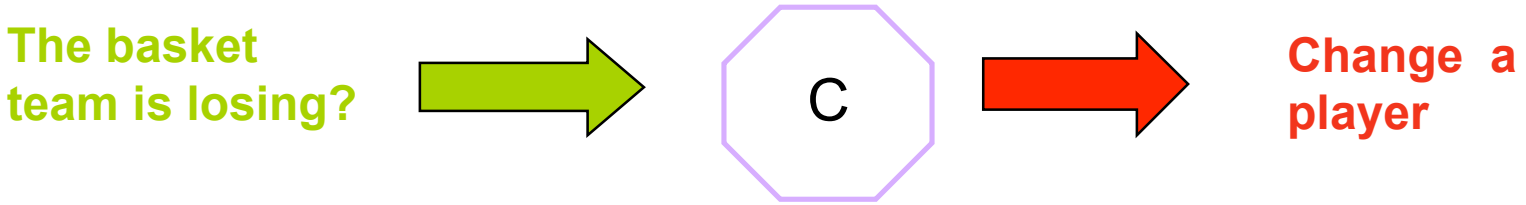
B. Availability

Assess the probability of an event on the basis of direct experience. The latter refers to the specific environment where the agent acts.

Example You live in Sweden and you are asked to estimate the percentage of individual with blond hair all over the world. Based on you daily experience (*feedback from the society*) you go for 70%.

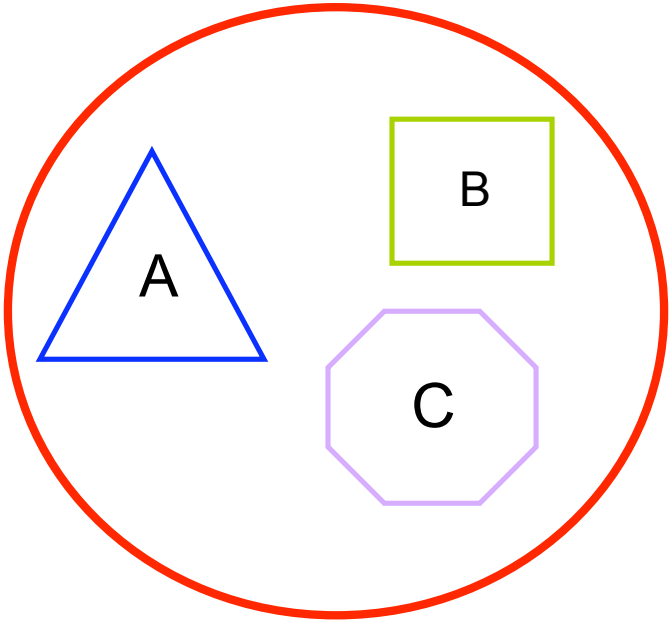
C. Anchoring

When asked to make a decision under uncertainty conditions, one refers to well established '***anchors***', which are adjusted *ad hoc* to serve the scope.



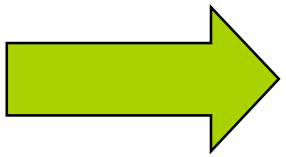
Example I am quite skilled in football and I know all about it. I am watching a basket match on TV. To interpret this new input I make use of an adjusted version of the schemes originally devised for the football.

Heuristics and coexistence of multiple inputs: the cognitive dissonance concept

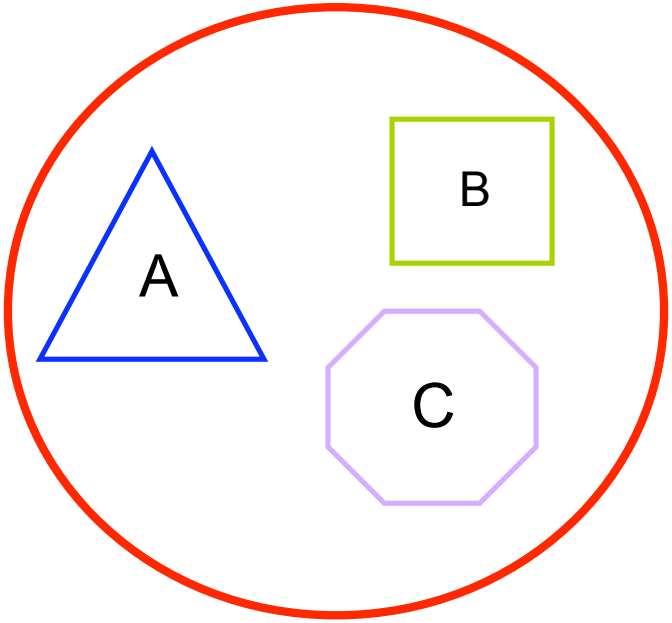


Heuristics and coexistence of multiple inputs: the cognitive dissonance concept

Input



Smokers have success with women



Heuristics and coexistence of multiple inputs: the cognitive dissonance concept

Input

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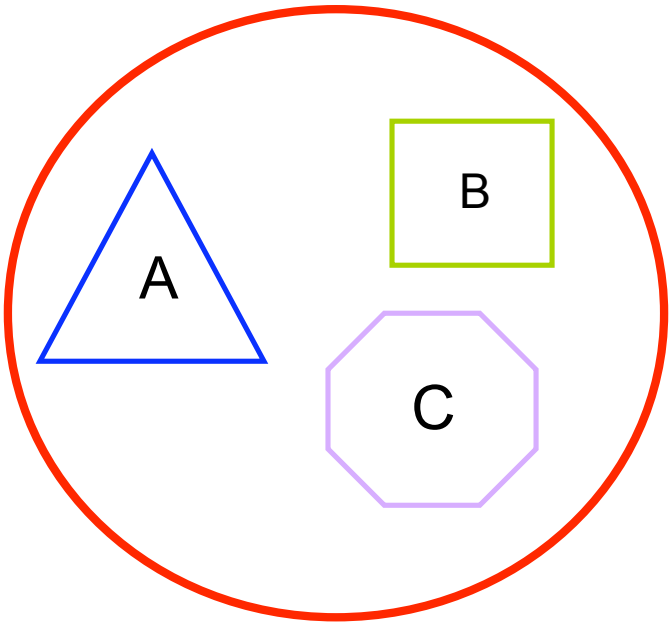
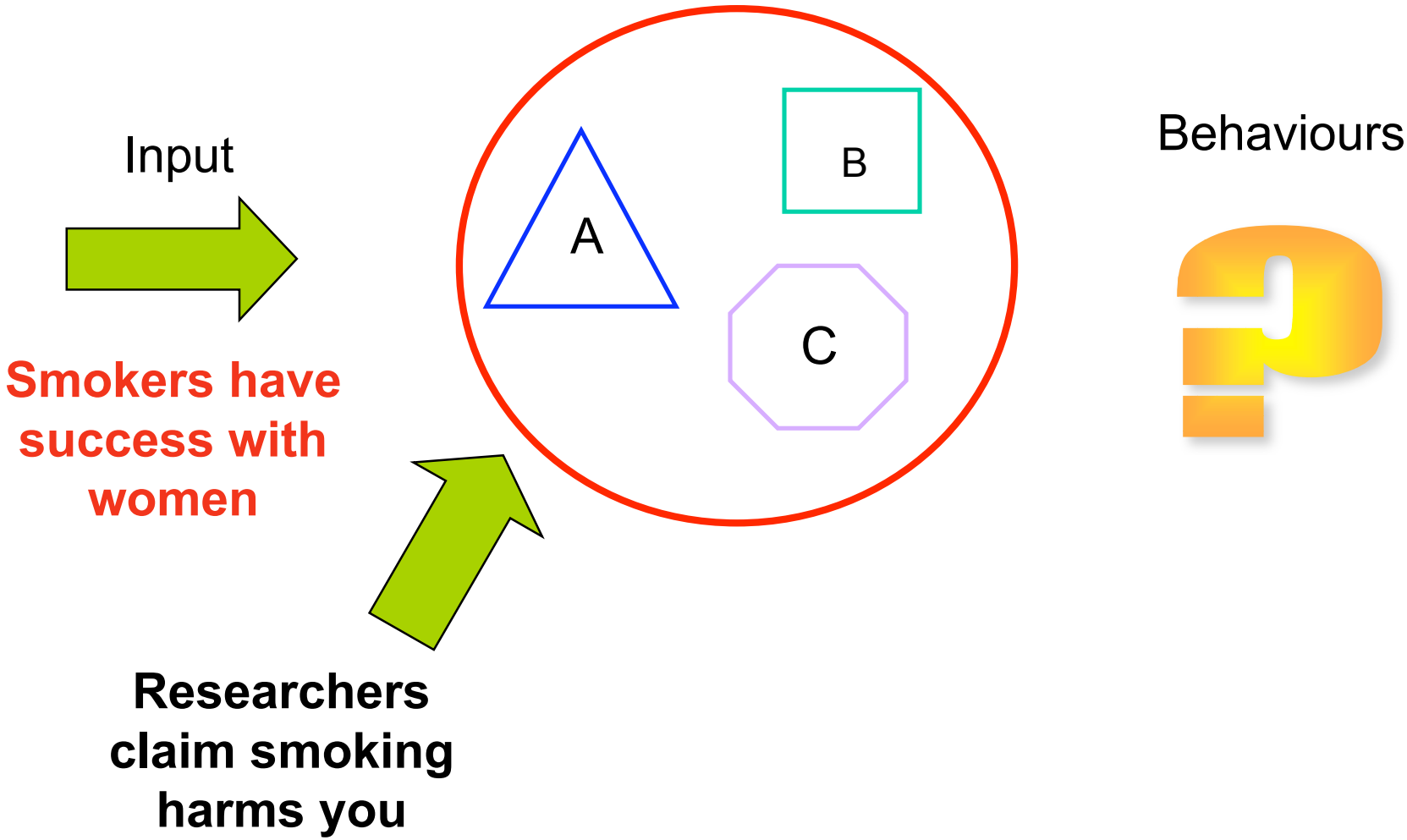


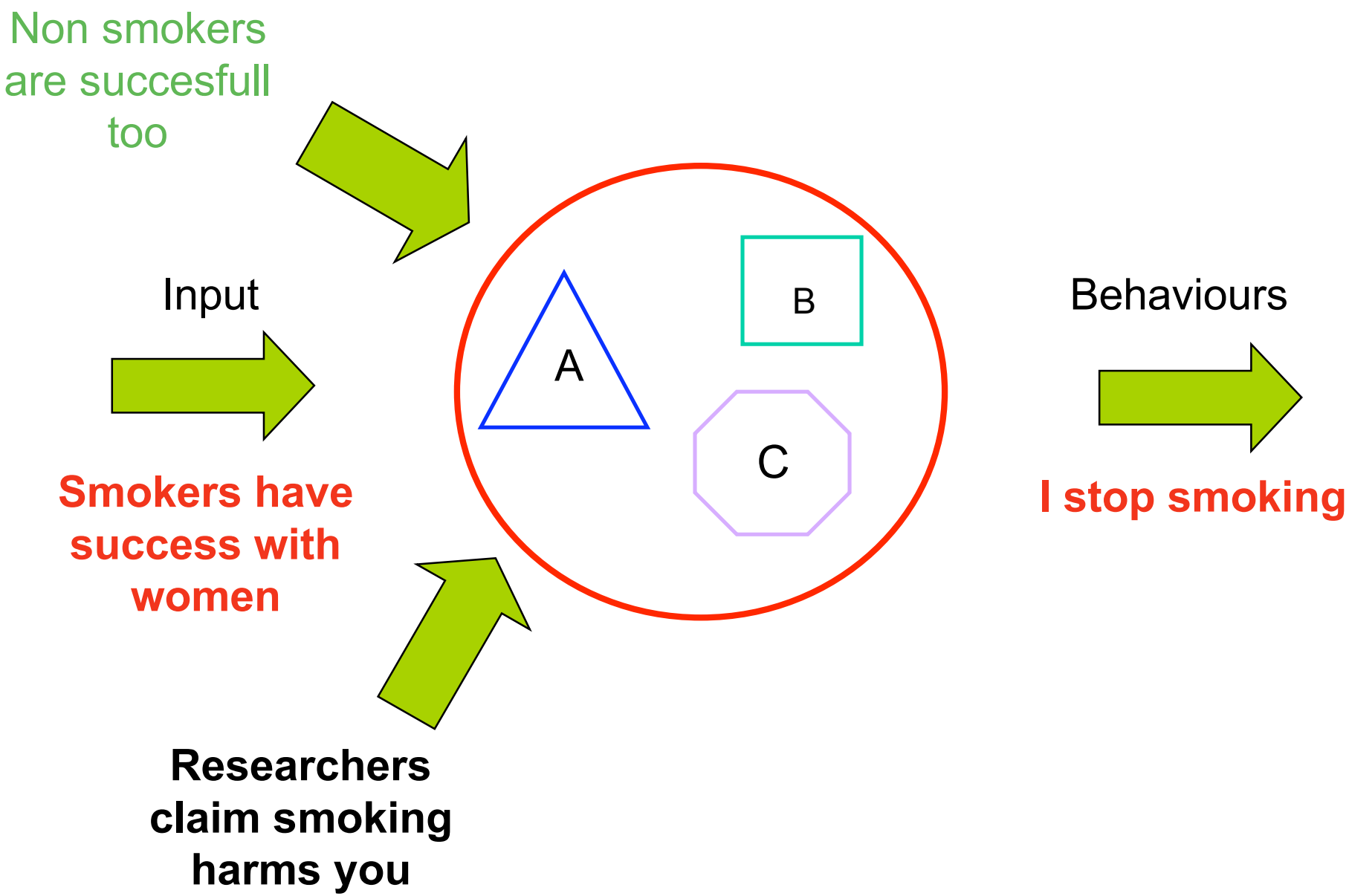
Behaviours

I smoke

A,B,C vs. cognitive dissonance

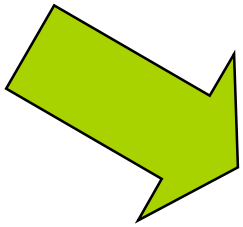


A,B,C vs. cognitive dissonance

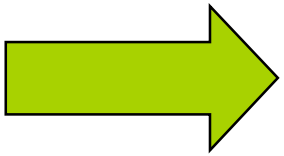


A,B,C vs. cognitive dissonance

Non smokers are succesfull too



Input



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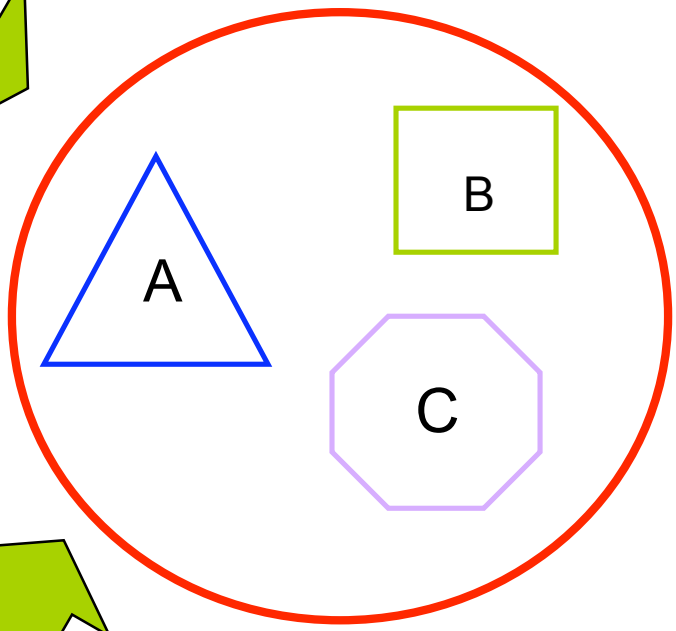
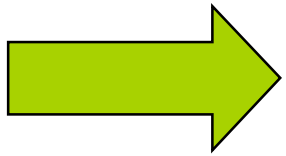


Behaviours



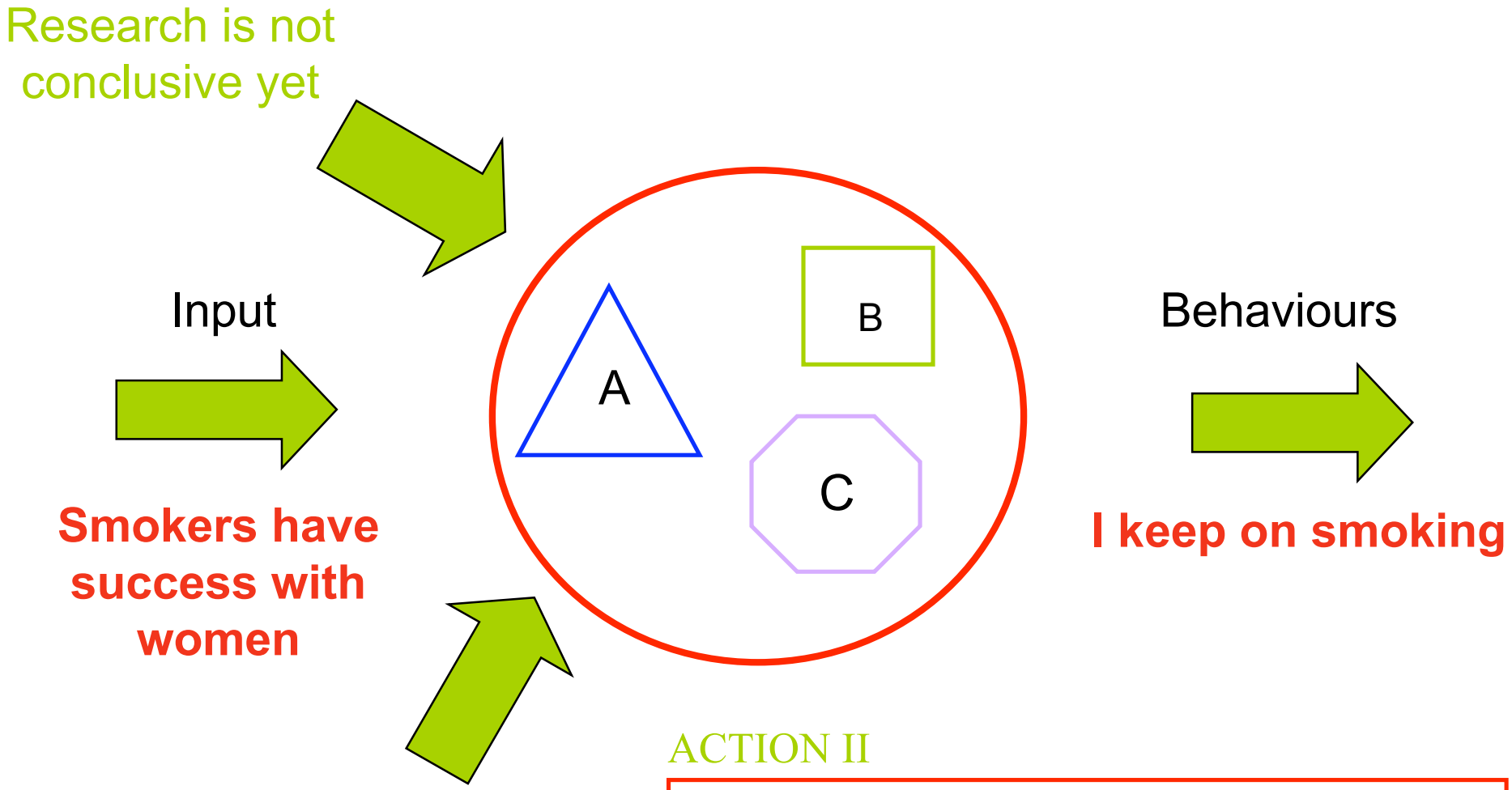
I stop smoking

Researchers claim smoking harms you

ACTION I

Researchers are a trustable source and I seek for further inputs that help mitigating the unpleasent tension state

A,B,C vs. cognitive dissonance



ACTION II

Research is still ongoing (researchers aren't a trustable source) and I keep on smoking

Developing a compherensive model which accounts for the aforementioned mechanism is a challenging task.

The number of variables/parameters is extremely large: when trying to match the (few) experimental observables, one probably faces a ill defined problem.

Analytical progress is difficult and one is forced to rely on simulations.

Can one incorporate some of the above mentioned ingredients in a simplified dynamical scheme, which extends over the simplified Deffuant's model?

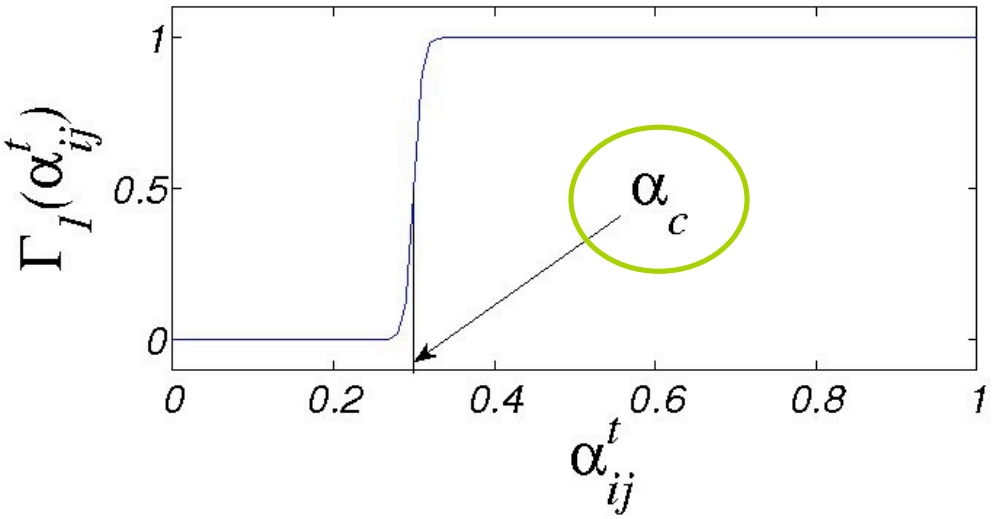
I. It seems plausible to assume that individuals take into account the trustability of a given source of information, when evaluating an external input.

II. This quantity, that we shall call affinity, evolve dynamically in time as follows the history of each individual.

III. The affinity can be modified (enhanced/depressed) so to resolve the tension that one faces when challenged by a conflicting viewpoint (resolve the dissonance).

Accounting for mutual affinity

$$O_i^{t+1} = O_i^t - \mu \Delta O_{ij}^t \Gamma_1 \left(\alpha_{ij}^t\right)$$



$$\Gamma_1 \left(\alpha_{ij}^t\right) = \frac{1}{2}\left[\tanh(\beta_1(\alpha_{ij}^t - \alpha_c)) + 1\right]$$

Accounting for mutual affinity

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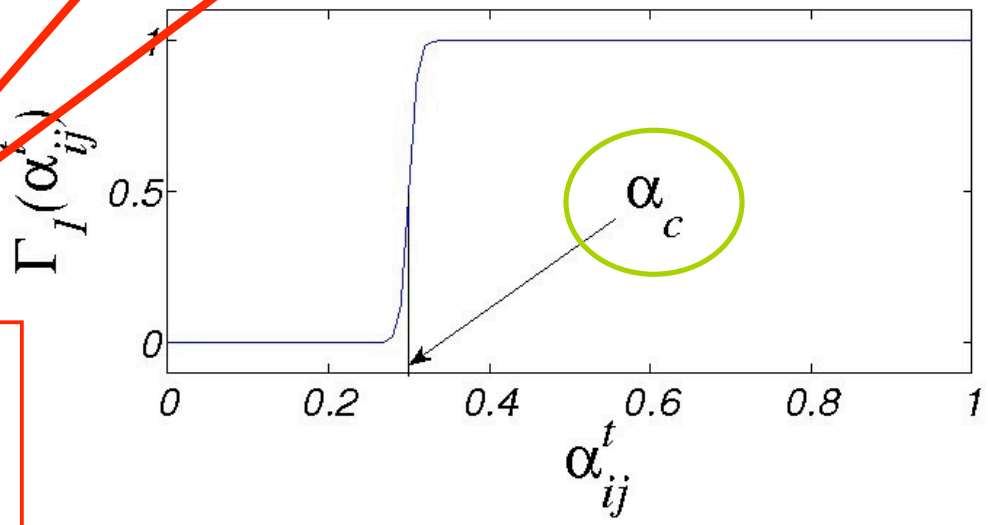


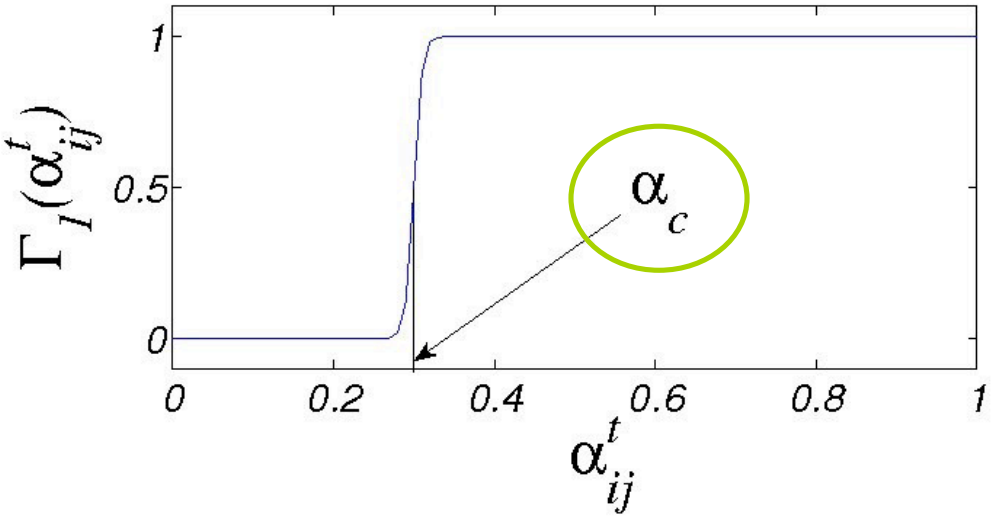
As in Deffuant's model

$$\Gamma_1 \left(\alpha_{ij}^t\right) = \frac{1}{2}\left[\tanh(\beta_1(\alpha_{ij}^t - \alpha_c)) + 1\right]$$

Accounting for mutual affinity

$$O_i^{t+1} = O_i^t - \mu \Delta O_{ij}^t \Gamma_1 \left(\alpha_{ij}^t \right)$$

NxN
affinity matrix



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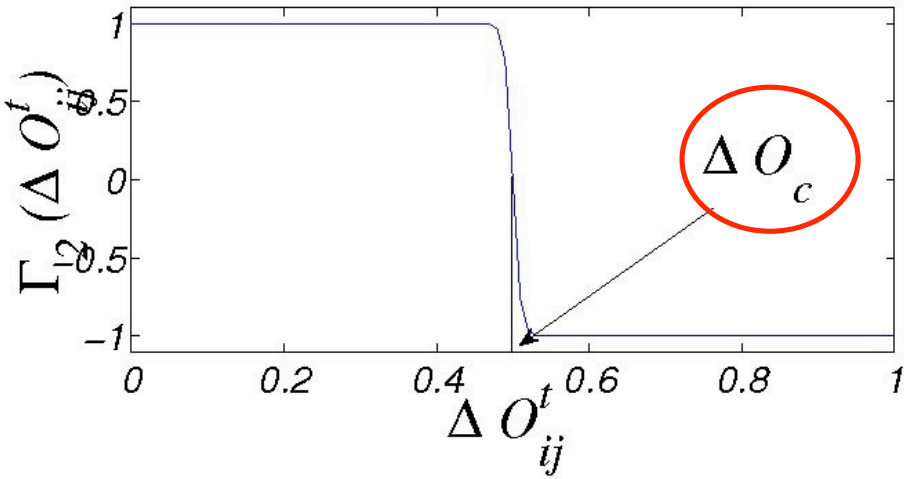
Accounting for mutual affinity

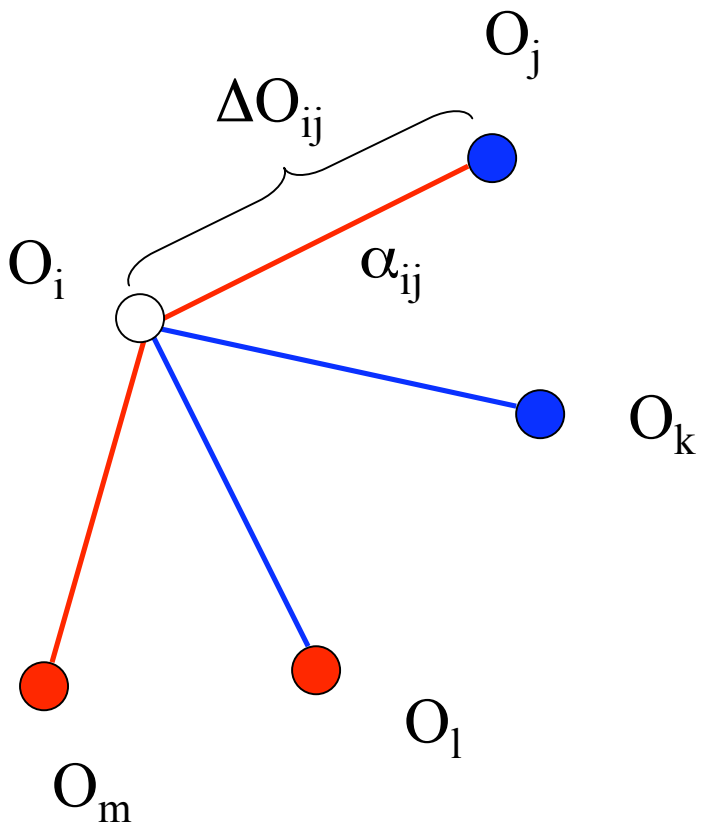
$$\alpha_{ij}^{t+1} = \alpha_{ij}^{t} + \alpha_{ij}^{t}[1 - \alpha_{ij}^{t}]\Gamma_2\left(\Delta O_{ij}\right)$$



$$\Gamma_2\left(\Delta O_{ij}\right) = -\tanh(\beta_2(|\Delta O_{ij}^t| - \Delta O_c))$$

$\Delta O \approx 1$ (different)

≈ 0 (similar)

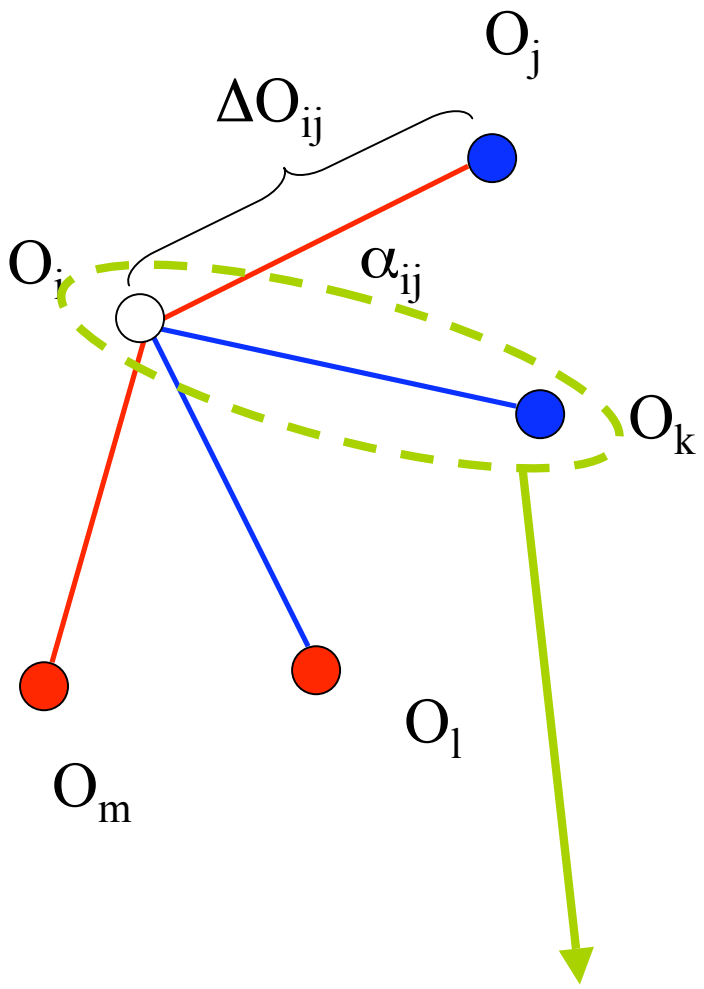


$\alpha_{ij} \approx 1$ (more affine)

≈ 0 (less affine)

$\Delta O \approx 1$ (different)

≈ 0 (similar)

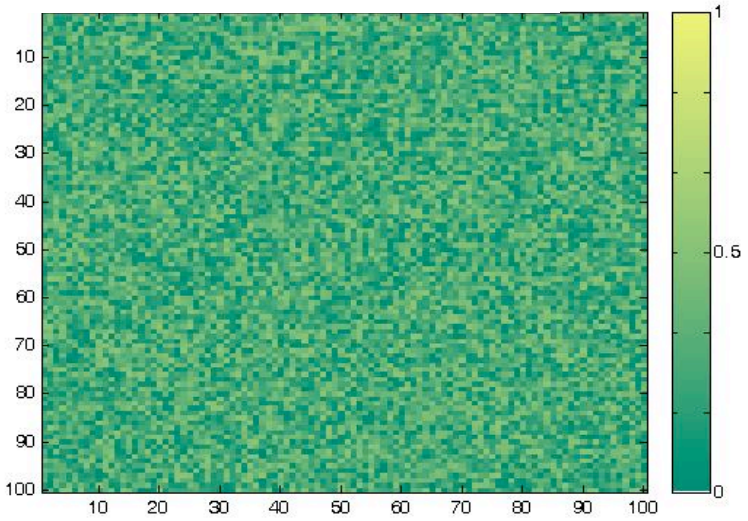


$\alpha_{ij} \approx 1$ (more affine)

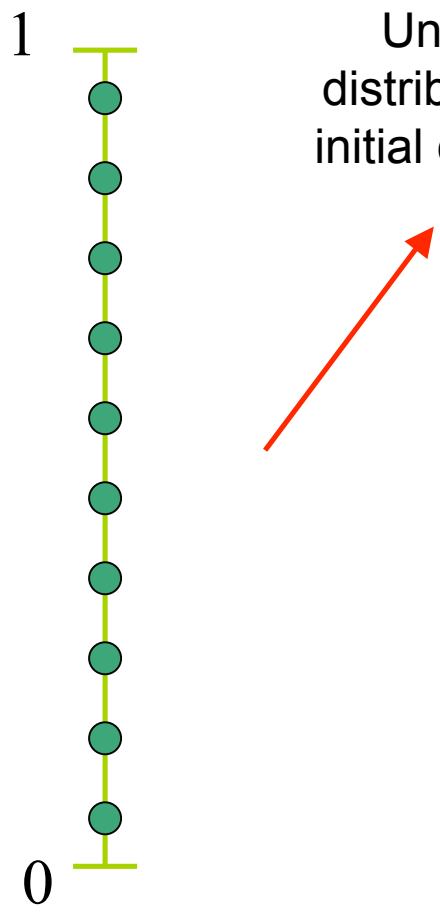
≈ 0 (less affine)

Individual k is the *ideal partner* of agent i

Initialising the system



Affinity matrix



Uniform distribution of initial opinions

1D opinion space

The selection rule: social temperature

I. $d_{ij}^t = \Delta O_{ij}^t (1 - \alpha_{ij}^t) \qquad j = 1, ..., N \qquad j \neq i.$

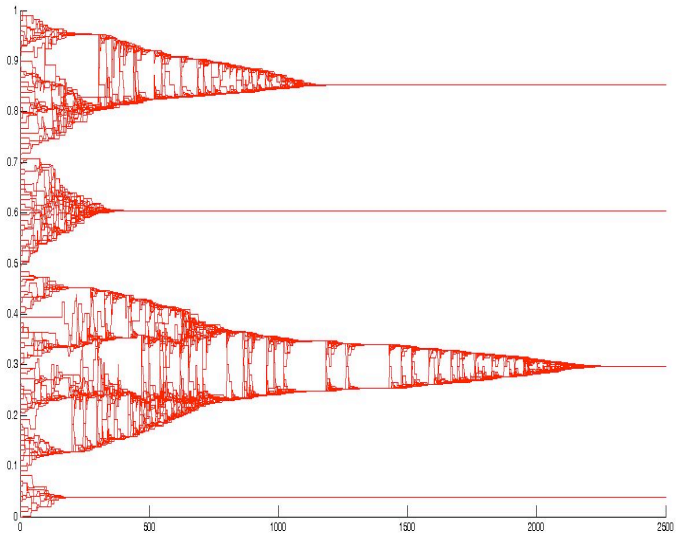
Distance among agents i and j In *social space*

Random Gaussian noise to represent *social mixing*

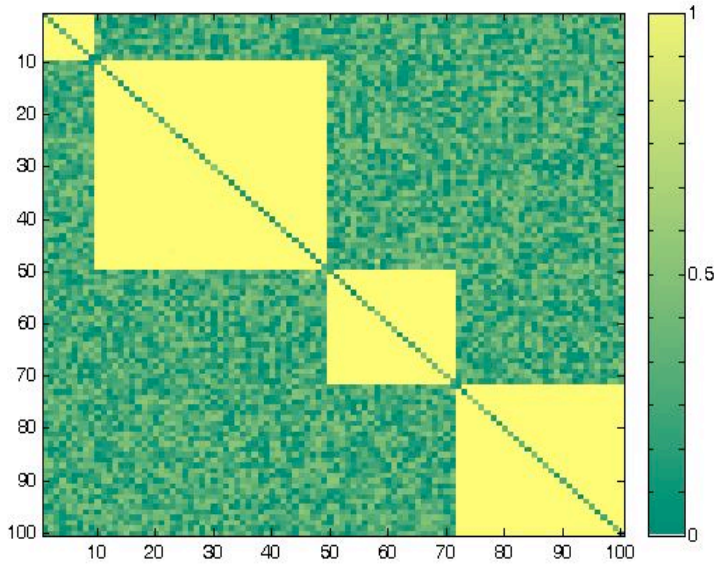
II. $D_{ij}^\eta = d_{ij}^t + \eta_j(0, \sigma)$

- Random selection of individual i
- Agent j follows from $min_j D_{ij}^{\eta}$

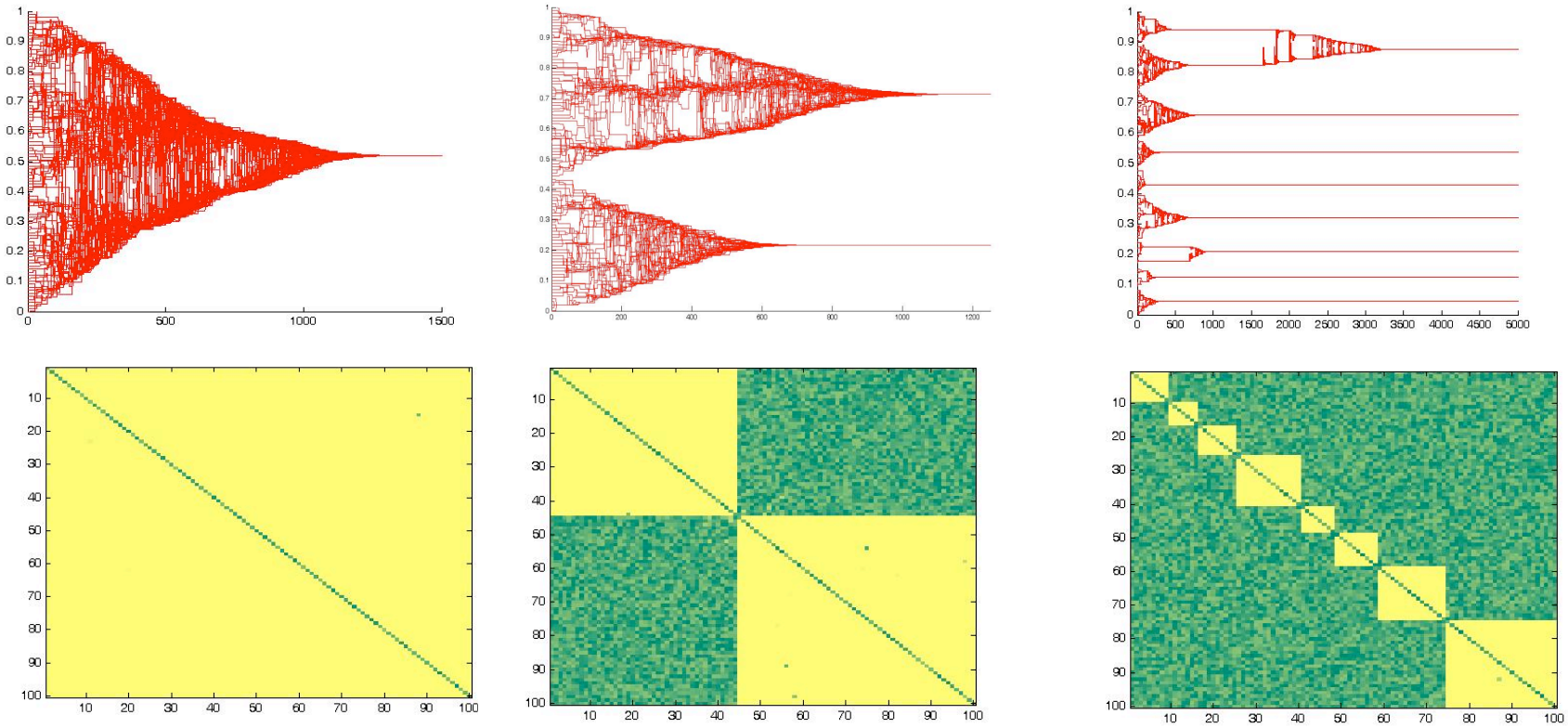
Evolution of opinion



Affinity Matrix

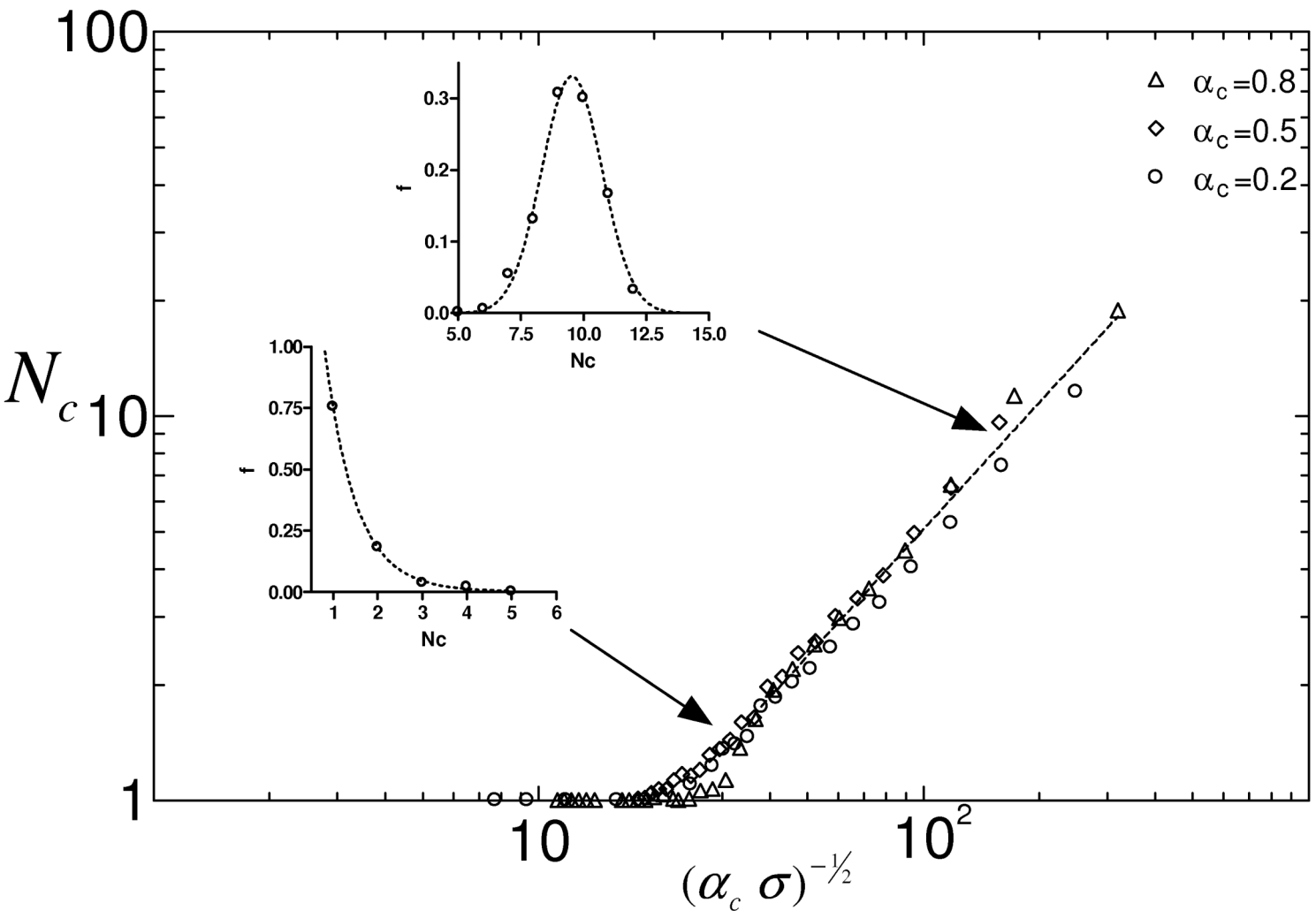


A. Polarization vs. fragmentation

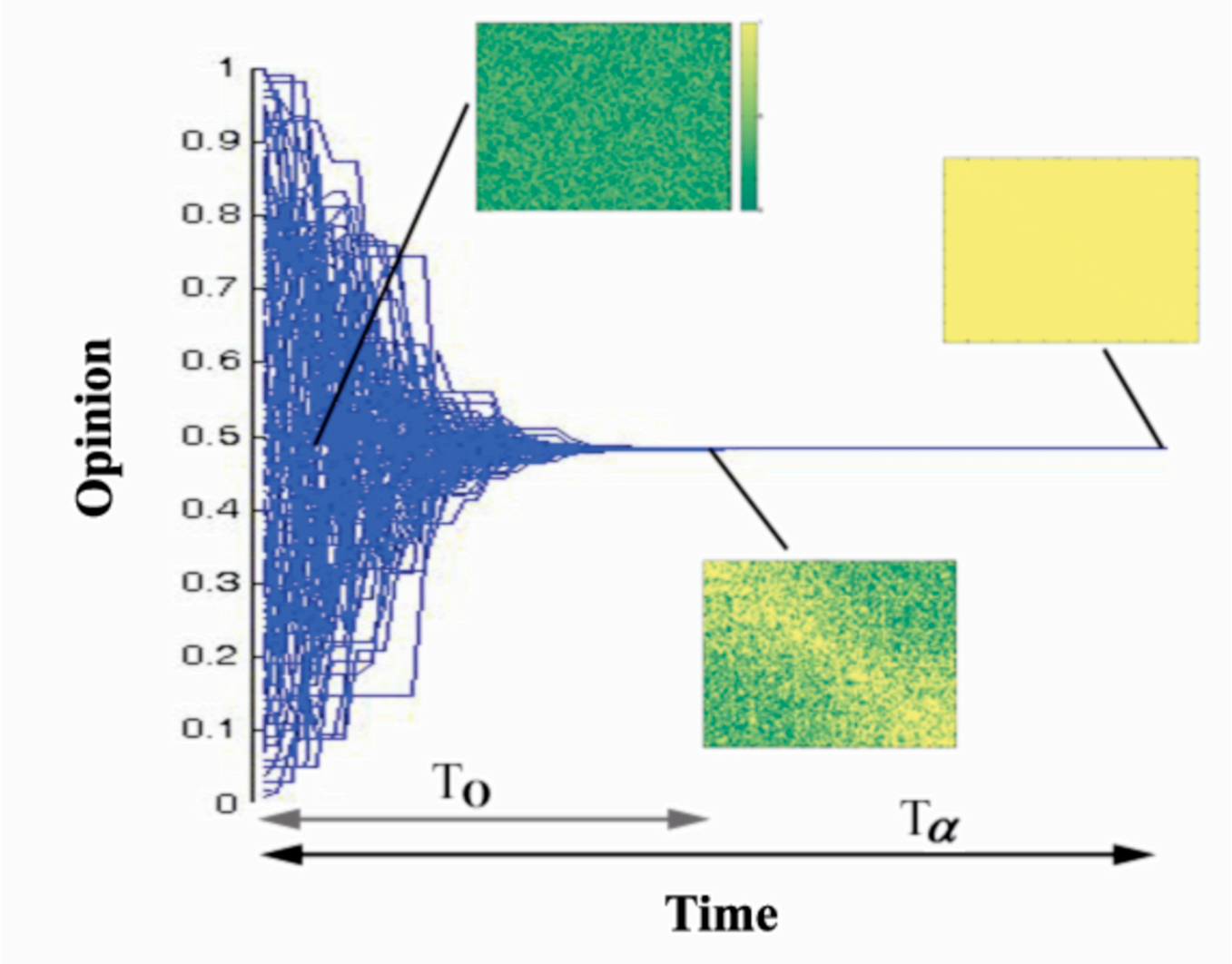


Decreasing mixing (social temperature)

Phase transition: from one to several (*metastable*) clusters



B. On the convergence time: T_o vs. T_α



Towards a characterization of T_α…

The **affinity matrix** measures the degree of connection among agents (weighted network)

AVERAGE CONNECTIVITY

$$< k >= \frac{1}{N(N-1)} \sum_{i,j} \alpha_{i,j}$$

$$\rightarrow \begin{cases} \bullet \quad k_0 \\ \bullet \quad < k > \rightarrow 1 \end{cases}$$

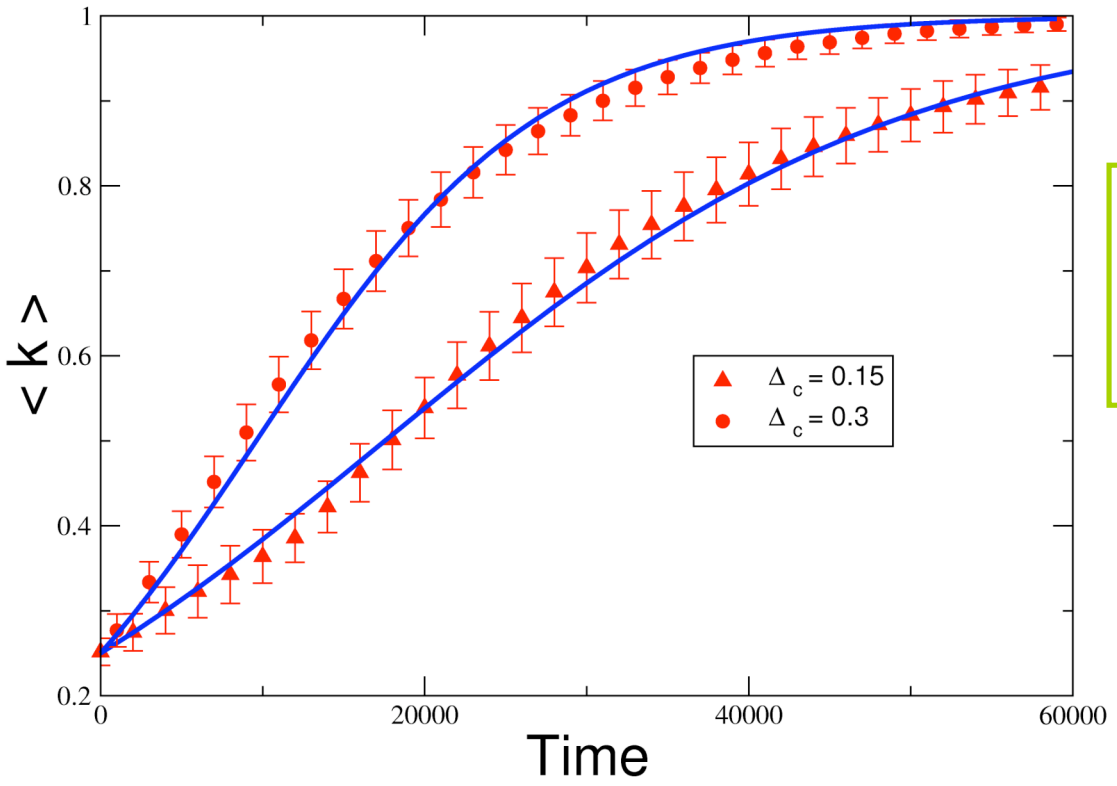
Accessing an estimate of T_α by monitoring the time evolution of <k>

DERIVING:

$$\frac{d < k >}{dt} = \frac{1}{N(N-1)} \sum_{i,j} \frac{d\alpha_{i,j}}{dt}$$

FOLLOWS FROM SYSTEM DYNAMICS

if $\sigma_\alpha^2 << 1$ then $\frac{d < k >}{dt} = \Gamma \left(< k > - < k >^2 \right)$

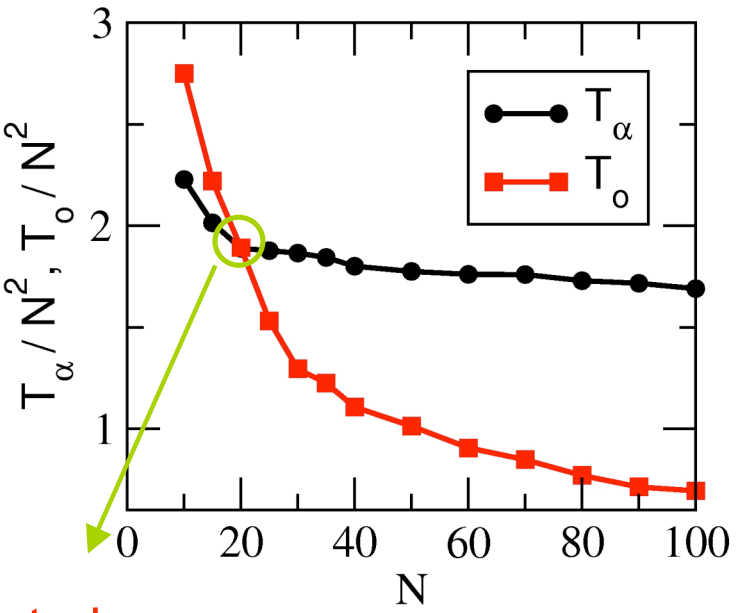


$$< k >= \frac{1}{1 + \frac{1-k_0}{k_0} \exp(-\Gamma t)}$$

For large enough N:

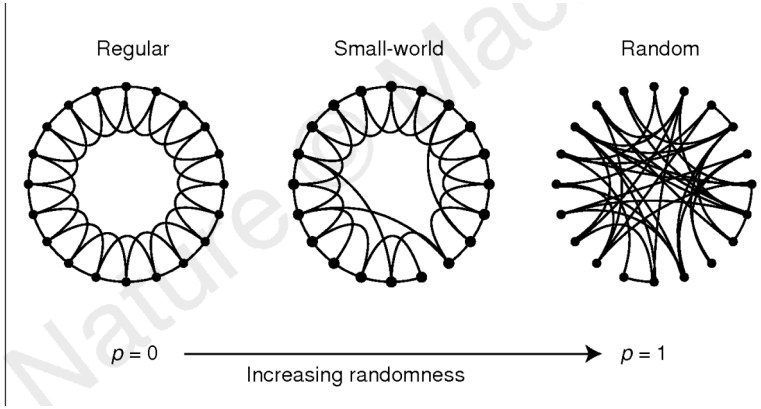
$$T_\alpha \propto N^2$$

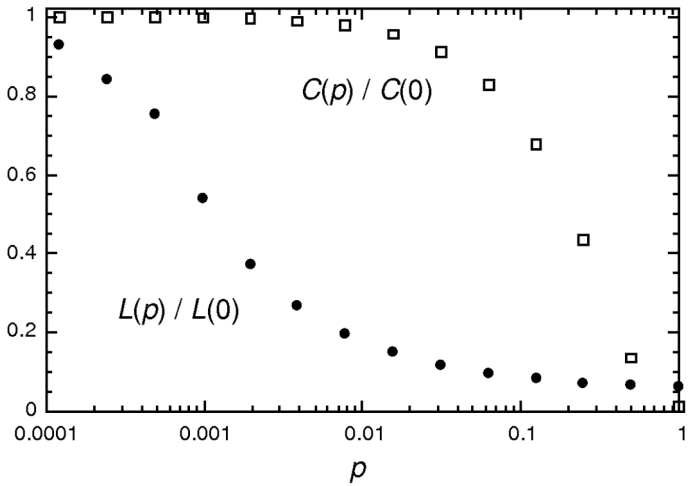
Existence of a **critical group size**, a mechanism that is reported in the psycological literature (Bjon). In a small group people get to know each other before converging to a final opinion, as opposed to the large group case.



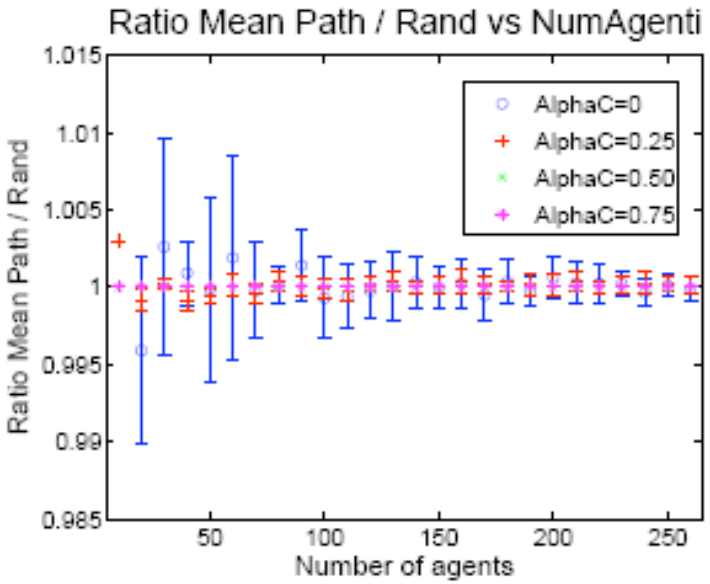
Crossover value predicted
by the theory for N ~ 20

C. Emerging topology of the social networks





Watts and Strogatz, Nature 1998

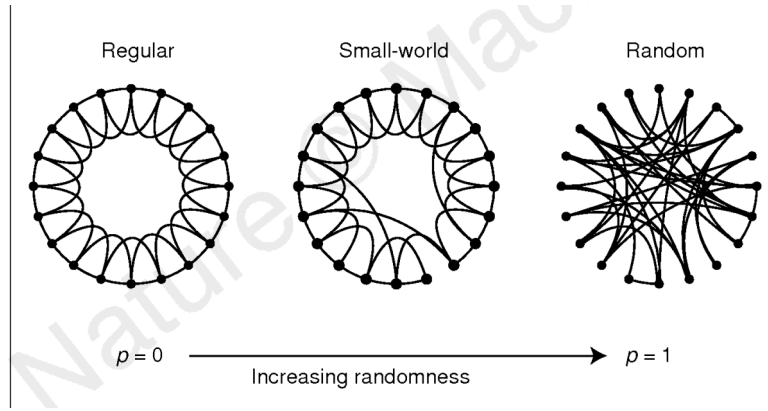


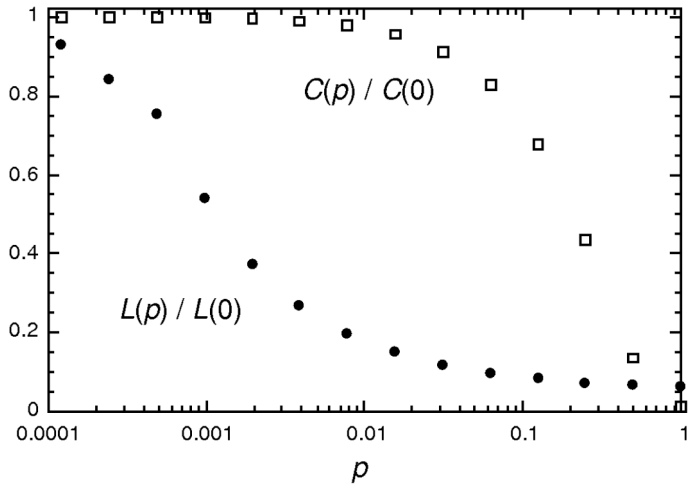
$$L = \frac{1}{N(N-1)} \sum_{i,j \in \mathcal{N}, i \neq j} d_{ij}$$

d_{ij} = length of geodesic path between i and j

$a_{ij} = [\alpha_{ij} - \alpha_f]$ adjacency matrix

C. Emerging topology of the social networks

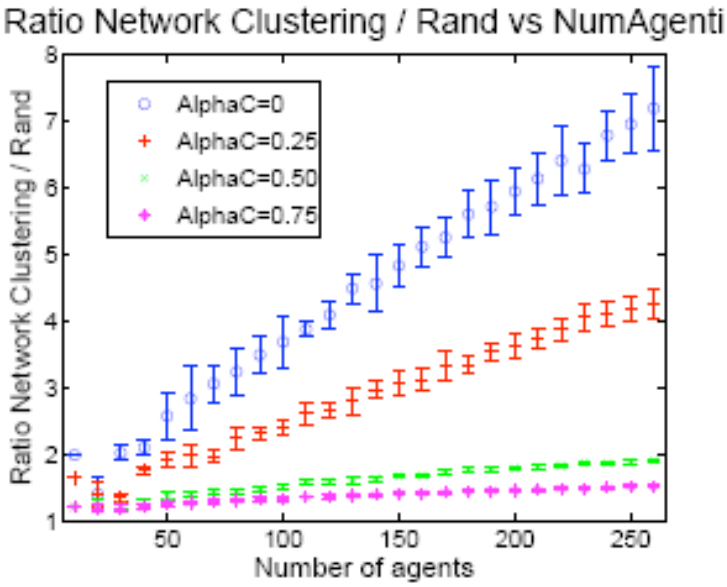




$$c_i = \frac{2e_i}{k_i(k_i-1)} = \frac{\sum_{j,m} a_{ij} a_{jm} a_{mi}}{k_i(k_i-1)}$$

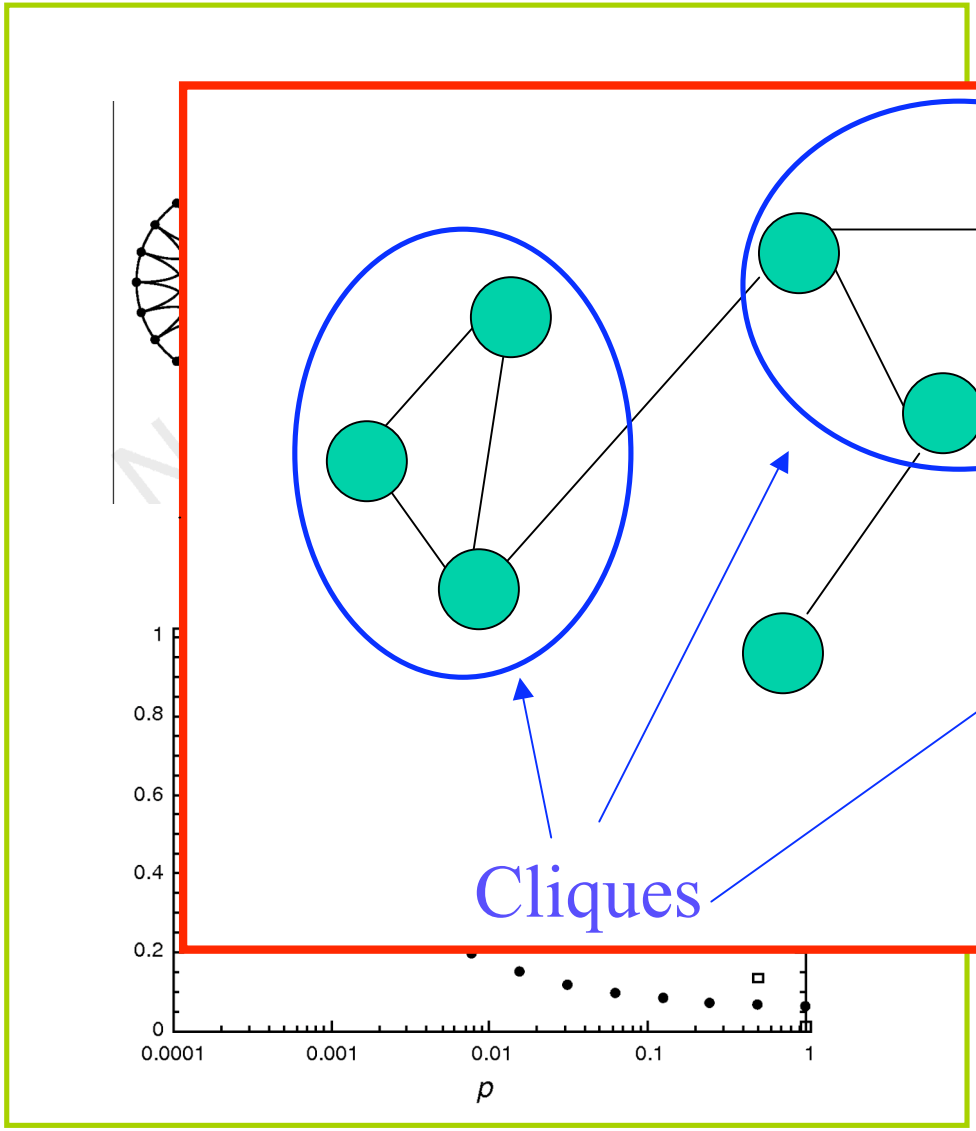
$$C = \langle c \rangle = \frac{1}{N} \sum_{i \in \mathcal{N}} c_i$$

e_i = nodes adjacent to node i



Watts and Strogatz, Nature 1998

C. Emerging topology of the social networks



Weak ties

Cliques

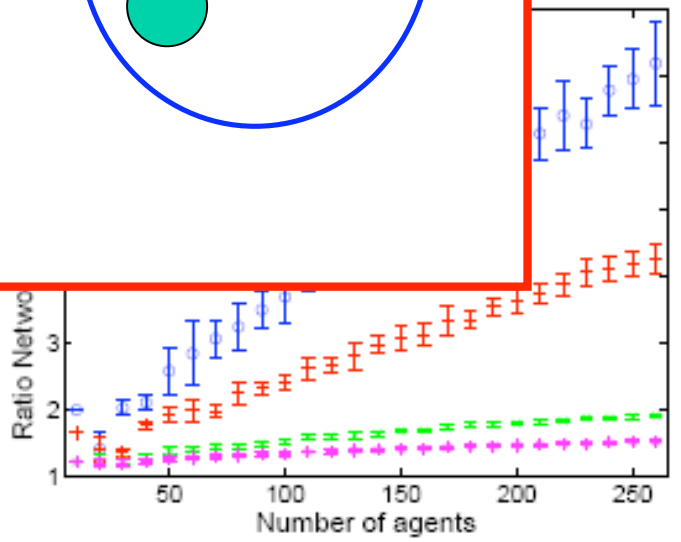
Watts and Strogatz, Nature 1998

$\sum_j a_{jm} a_{mi}$

$-1)$

node i

s NumAgenti



Summing up…..

PRO

I. Models do exist that enable us to study the opinion formation process

II. Consensus is an emerging feature, as opposed to fragmentation

III. Models can incorporate specific psychological aspect within a self-consistent dynamical framework

CONS

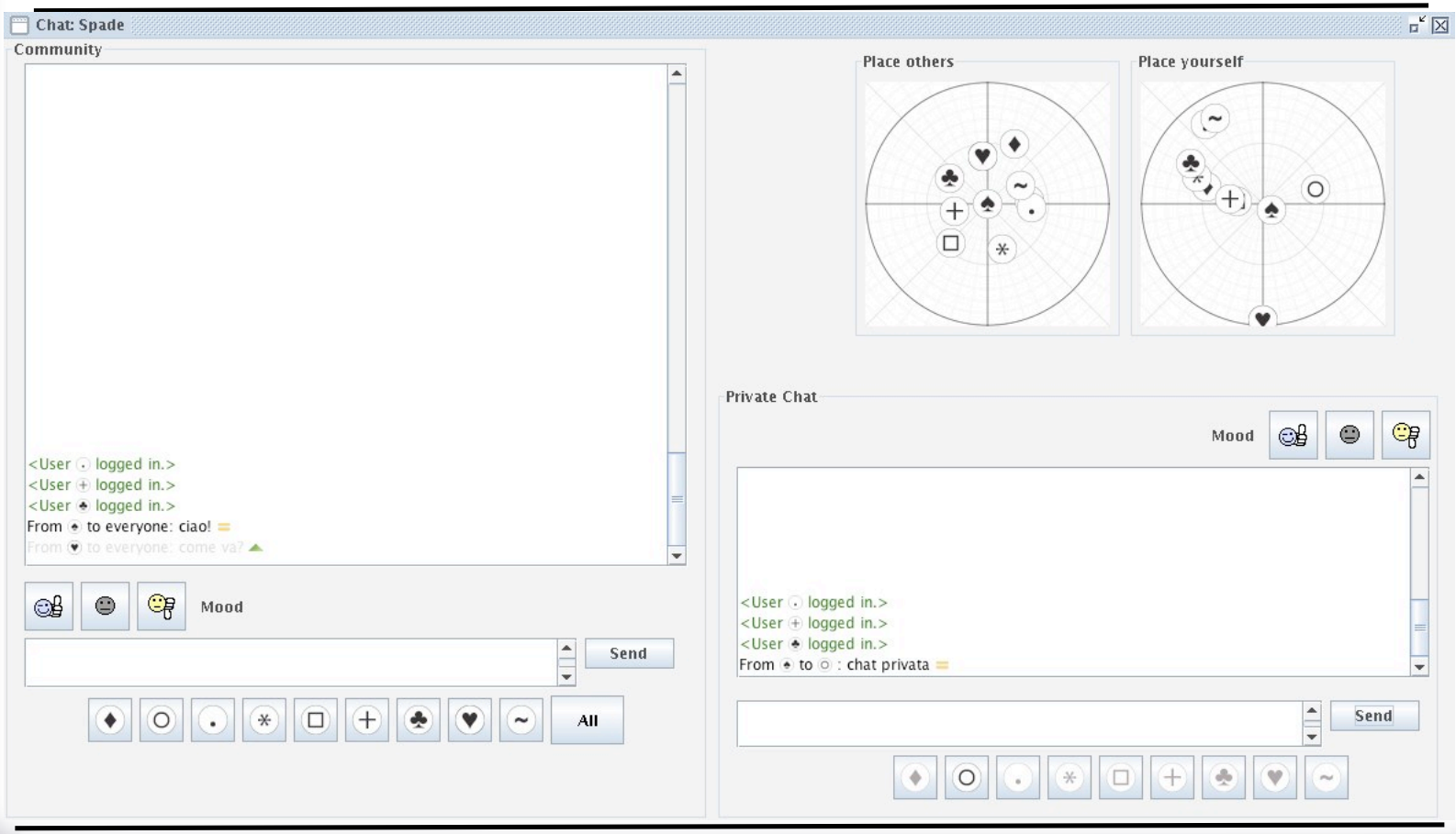
A. Too high degree of arbitrariness in setting up the models

B. Need for experimental inputs that allows to constraint the model

C. The level of model complexity has to be tuned so to reflect the richeness of the experimental inputs

The virtual community experiment (Andrea Guazzini et al.)

The chat interface



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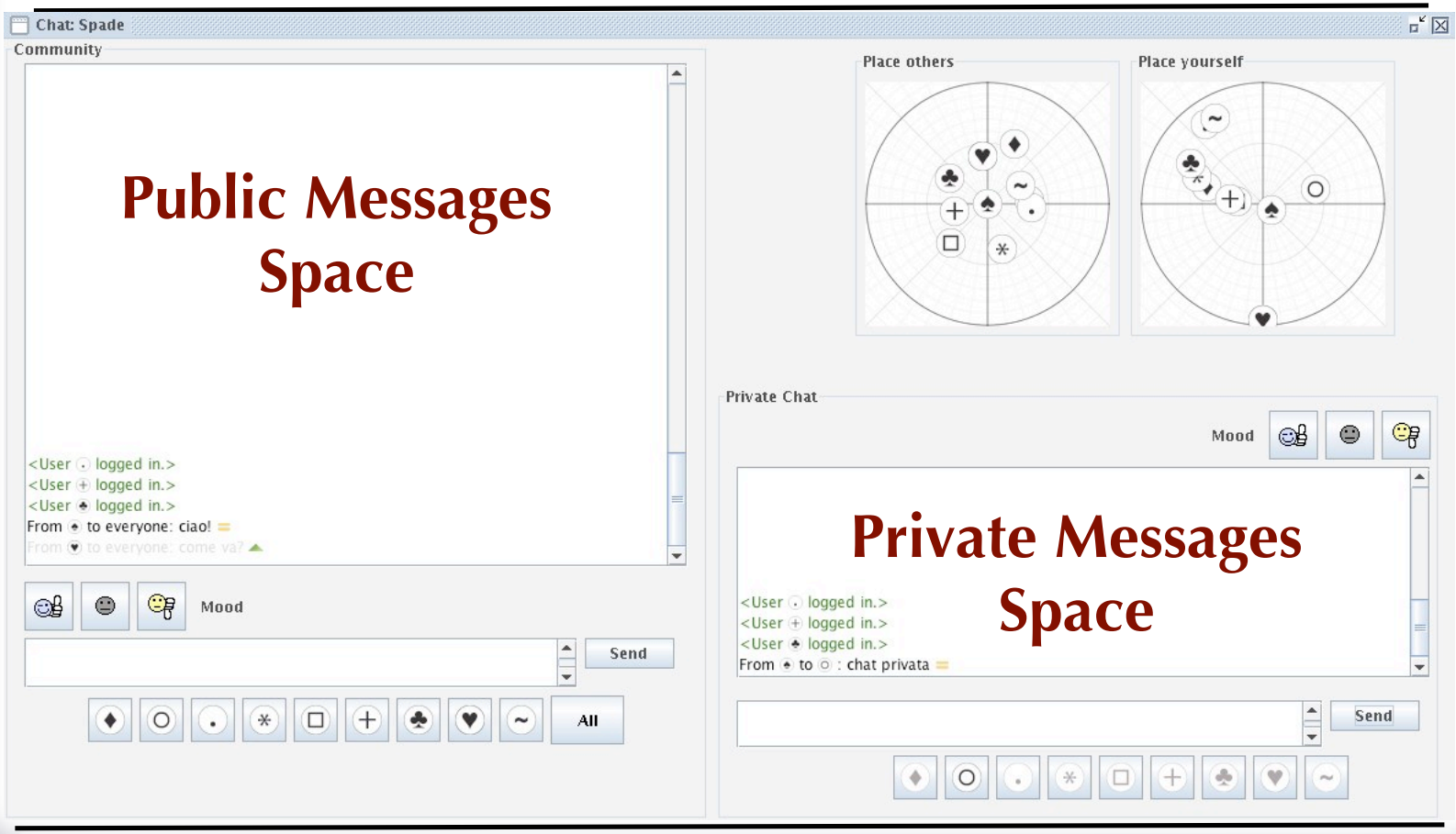

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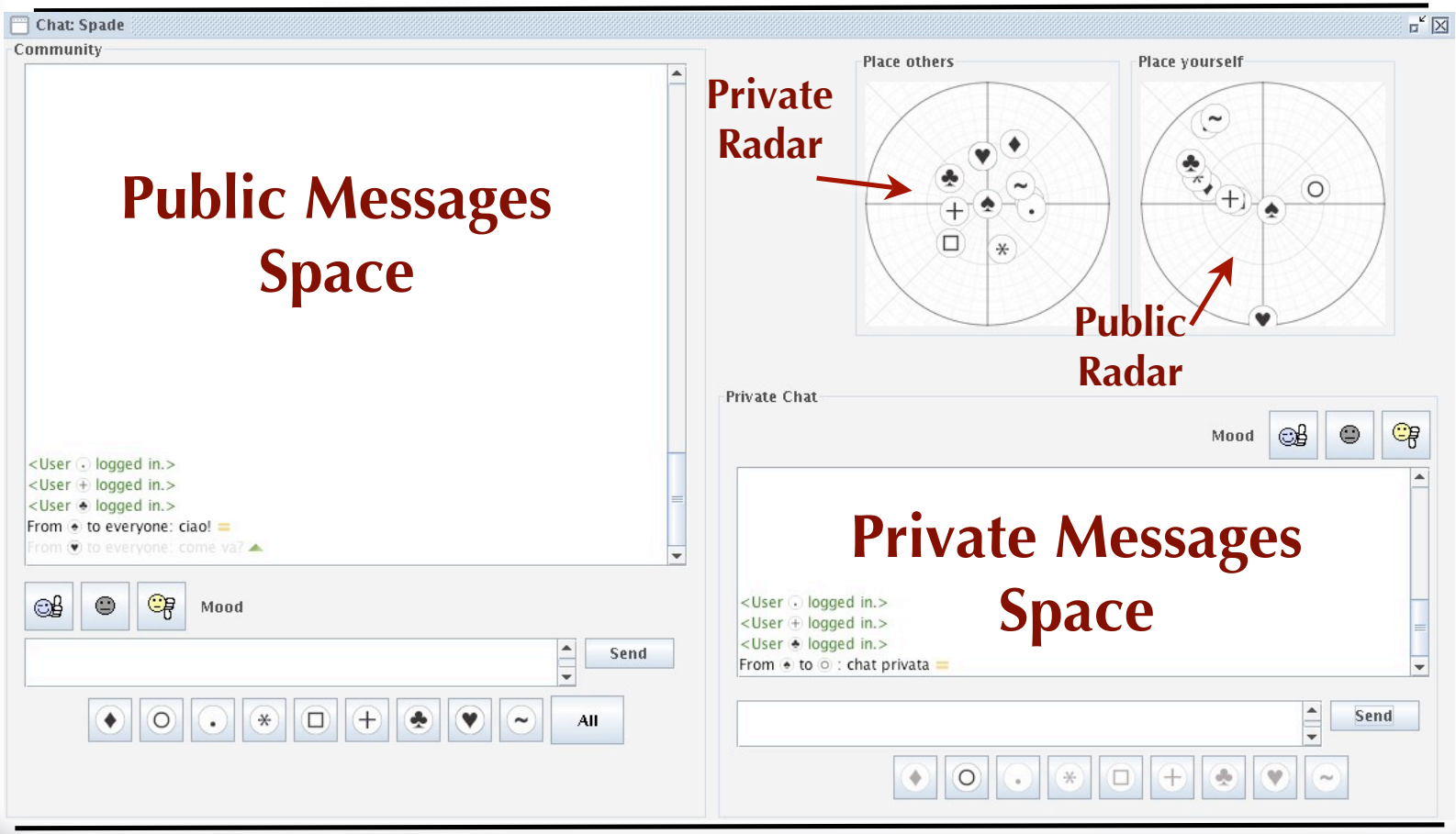

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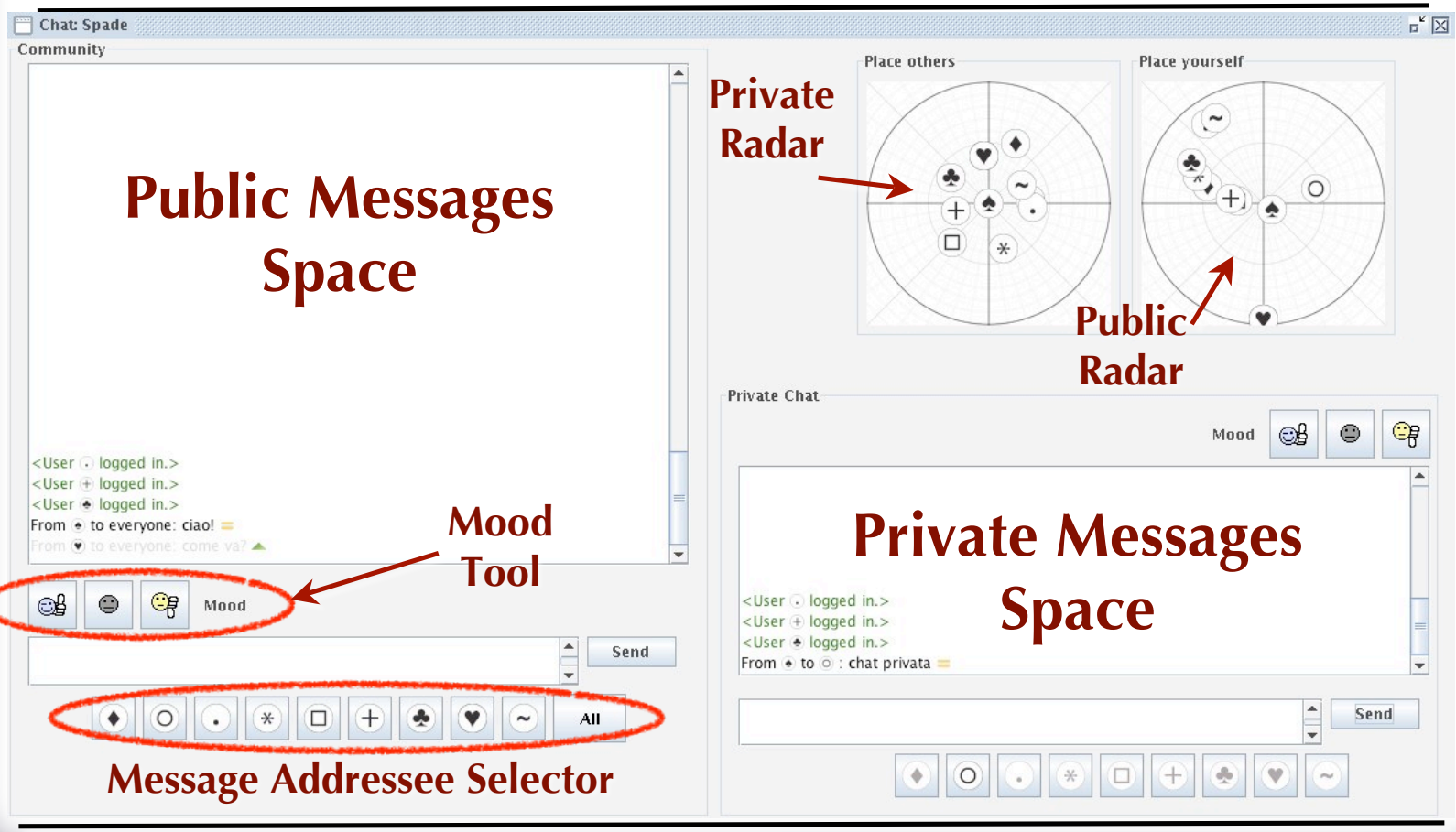

In collaboration with:

F. Bagnoli, University of Florence

T. Carletti and S. Righi, FUNDP, Namur

A. Guarino, Universite de la Polynesie Francaise

A. Guazzini, CNR Pisa