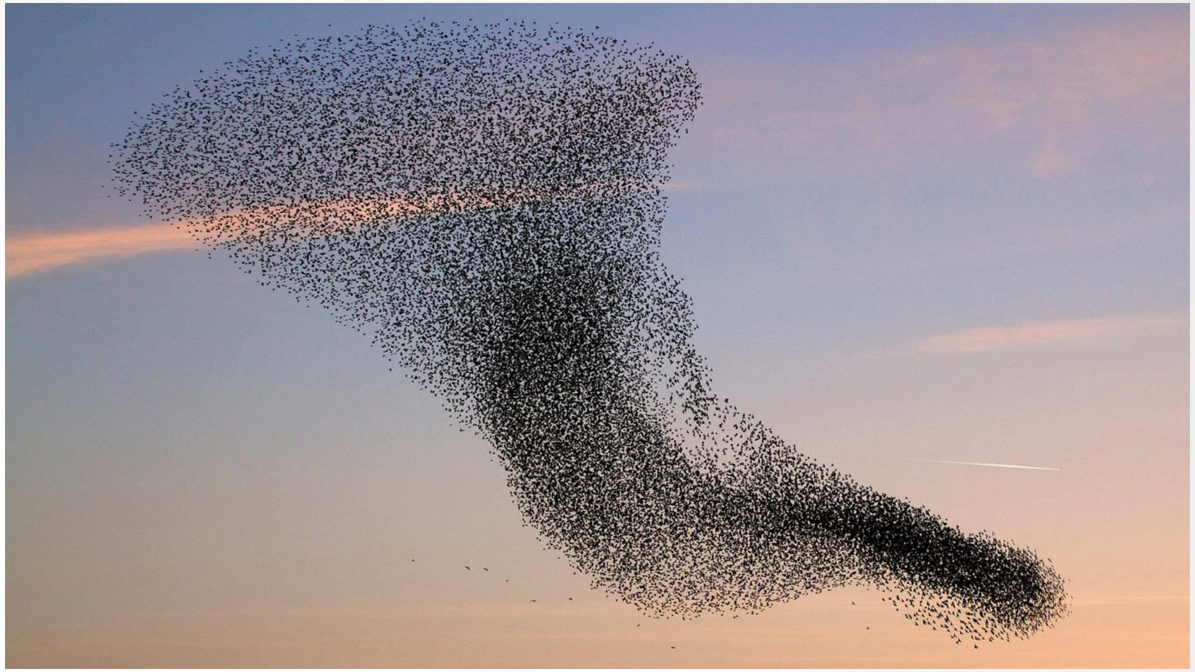
Complex systems: An introduction to modeling, networks & ABM

Pablo Balenzuela. DF-UBA & CONICET

balen@df.uba.ar

@polbalen in Twitter

What is a complex system?



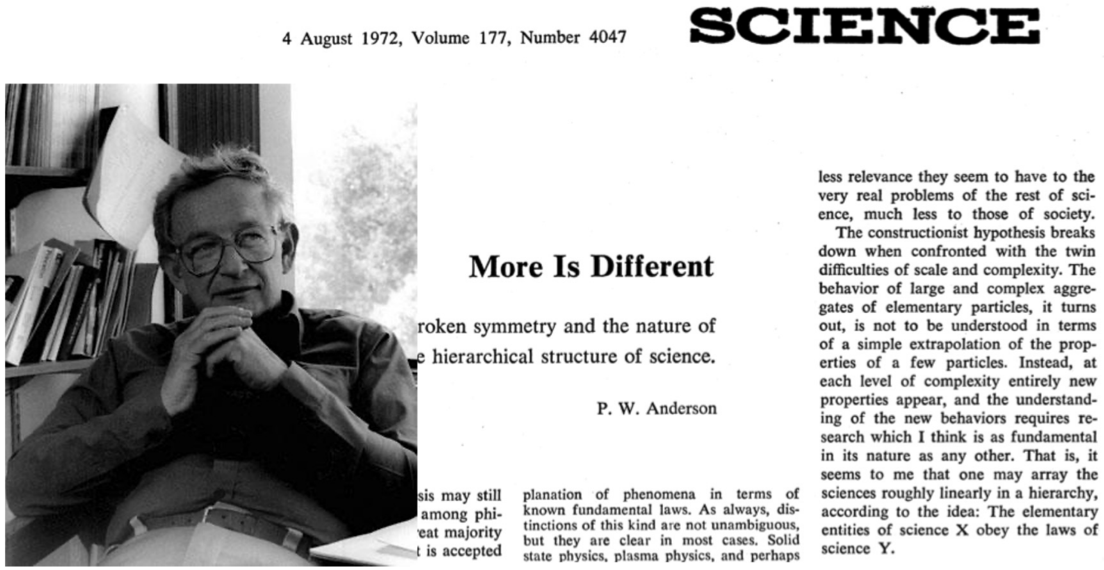
Two essential features distinguish a complex from a merely complicated system:

- **Emergence**: the whole is greater that the sum of the parts

- **Self – organization**: The systems tends spontaneously towards some level of organization

Physics & emergence

The ability to reduce everything to simple fundamental laws does not imply the ability to start from those law and reconstruct the universe.



4 August 1972, Volume 177, Number 4047

SCIENCE

More Is Different

roken symmetry and the nature of
e hierarchical structure of science.

P. W. Anderson

sis may still
among phi-
eat majority
t is accepted

planation of phenomena in terms of known fundamental laws. As always, distinctions of this kind are not unambiguous, but they are clear in most cases. Solid state physics, plasma physics, and perhaps

less relevance they seem to have to the very real problems of the rest of science, much less to those of society.

The constructionist hypothesis breaks down when confronted with the twin difficulties of scale and complexity. The behavior of large and complex aggregates of elementary particles, it turns out, is not to be understood in terms of a simple extrapolation of the properties of a few particles. Instead, at each level of complexity entirely new properties appear, and the understanding of the new behaviors requires research which I think is as fundamental in its nature as any other. That is, it seems to me that one may array the sciences roughly linearly in a hierarchy, according to the idea: The elementary entities of science X obey the laws of science Y.

Phillip Anderson, 1972

- The behavior of a large and complex aggregates of elementary particles can not be understood in terms of a simple extrapolation of properties of a few particles.

- At each level of complexity, new properties appear, and the understanding of the new behavior requires research as fundamental in its nature as any others

Physics & Complexity

concepts

The bigger picture

Tamas Vicsek

If a concept is not well defined, it can be abused. This is particularly true of complexity, an inherently interdisciplinary concept that has penetrated a range of intellectual fields from physics to linguistics,

understand reality through simplification and analysis. Some important simple systems are successful idealizations or primitive models of particular real situations — for example, a perfect sphere rolling down an absolutely smooth slope in a vacuum. This is the world of newtonian mechanics, and it

Complexity

The laws that describe the behaviour of a complex system are qualitatively different from those that govern its units.

and scaling (for example, power-law depen-

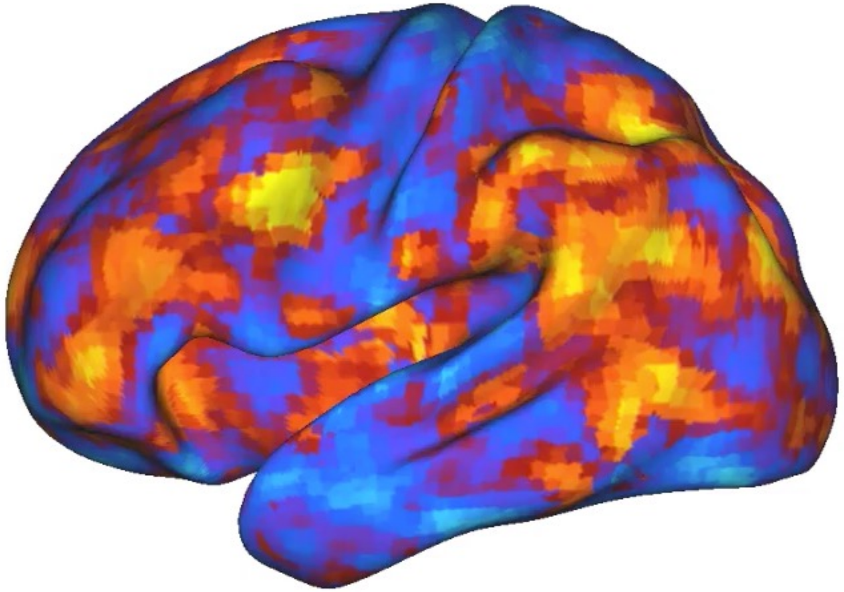
- Complexity is an inherent interdisciplinary concept that range from physics to linguistics and with no underlying unified theory.

- News features emerge as one moves from one scale to another, so the science of complexity deals with the principles that govern the way these new properties appear.

- The description of the entire system’s behavior requires a qualitatively new theory because the laws that describe its behavior are qualitatively different from those that govern its individual units.

T.Vicsek, Nature 418 (2002)

Physics & Complexity: 2 examples



Can we explain the behavior of the flock by merely extrapolating the behavior of a single bird?

Can we explain the behavior of the Brain from the dynamics of a single neuron?

Starling flocks

-Starlings moves in coordinated flocks

-Flocks of different sizes have the same movement pattern

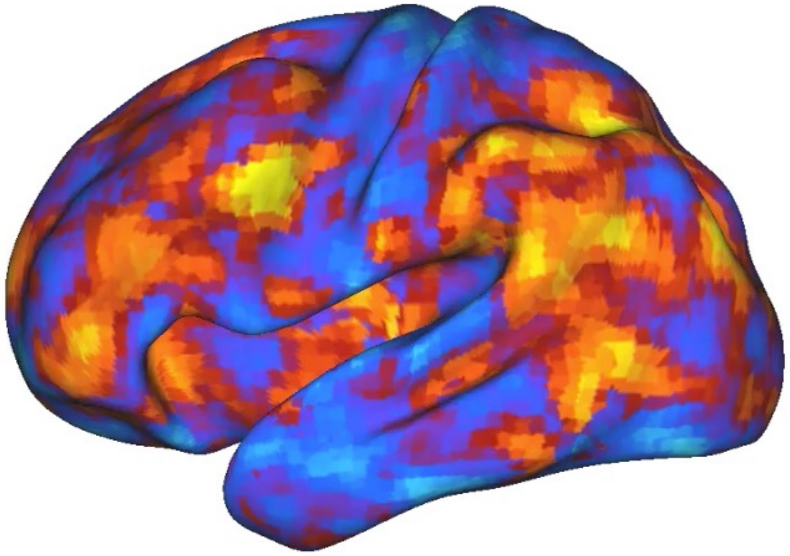
-Each bird only sees those who are near

-How are they coordinated then?

Andrea Cavagna, Universidad de la Sapienza, Italia. “Starling Flocks”

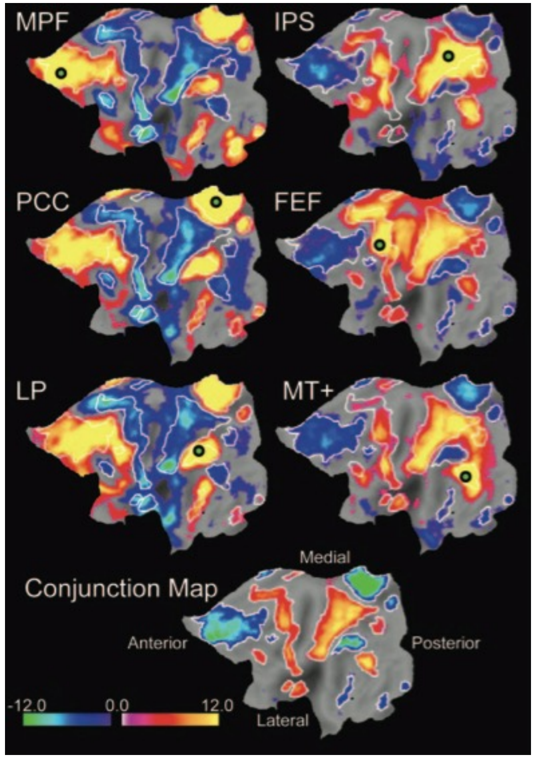
“Scale-free correlations in starling flocks” A. Cavagna, Al. Cimarelli, I. Giardina, G. Parisi, R. Santagati, F. Stefanini, and M. Viale
PNAS June 29, 2010 107 (26) 11865-11870; https://doi.org/10.1073/pnas.1005766107

Brain Activity: Resting state networks



The human brain is intrinsically organized into dynamic, anticorrelated functional networks

Michael D. Fox*†, Abraham Z. Snyder*‡, Justin L. Vincent*, Maurizio Corbetta‡, David C. Van Essen§, and Marcus E. Raichle*‡§¶



During performance of attention-demanding cognitive tasks, certain regions of the brain routinely increase activity, whereas others routinely decrease activity. In this study, we investigate the extent to which this task-related dichotomy is represented intrinsically in the resting human brain through examination of spontaneous fluctuations in the functional MRI blood oxygen level-dependent signal. We identify two diametrically opposed, widely distributed brain networks on the basis of both spontaneous correlations within each network and anticorrelations between networks. One network consists of regions routinely exhibiting task-related activations and the other of regions routinely exhibiting task-related deactivations. This intrinsic organization, featuring the presence of anticorrelated networks in the absence of overt task performance, provides a critical context in which to understand brain function. We suggest that both task-driven neuronal responses and behavior are reflections of this dynamic, ongoing, functional organization of the brain.

- B Biswal, FZ Yetkin, VM Haughton, JS Hyde. (1995).

-M.D. Fox, A.Z. Snyder, J.L. Vincent, M. Corbetta, D.C. van Essen, M.E. Raichle. (2005).

Opinion formation process

Last years research

✓Collective behavior:

Process of agreeing

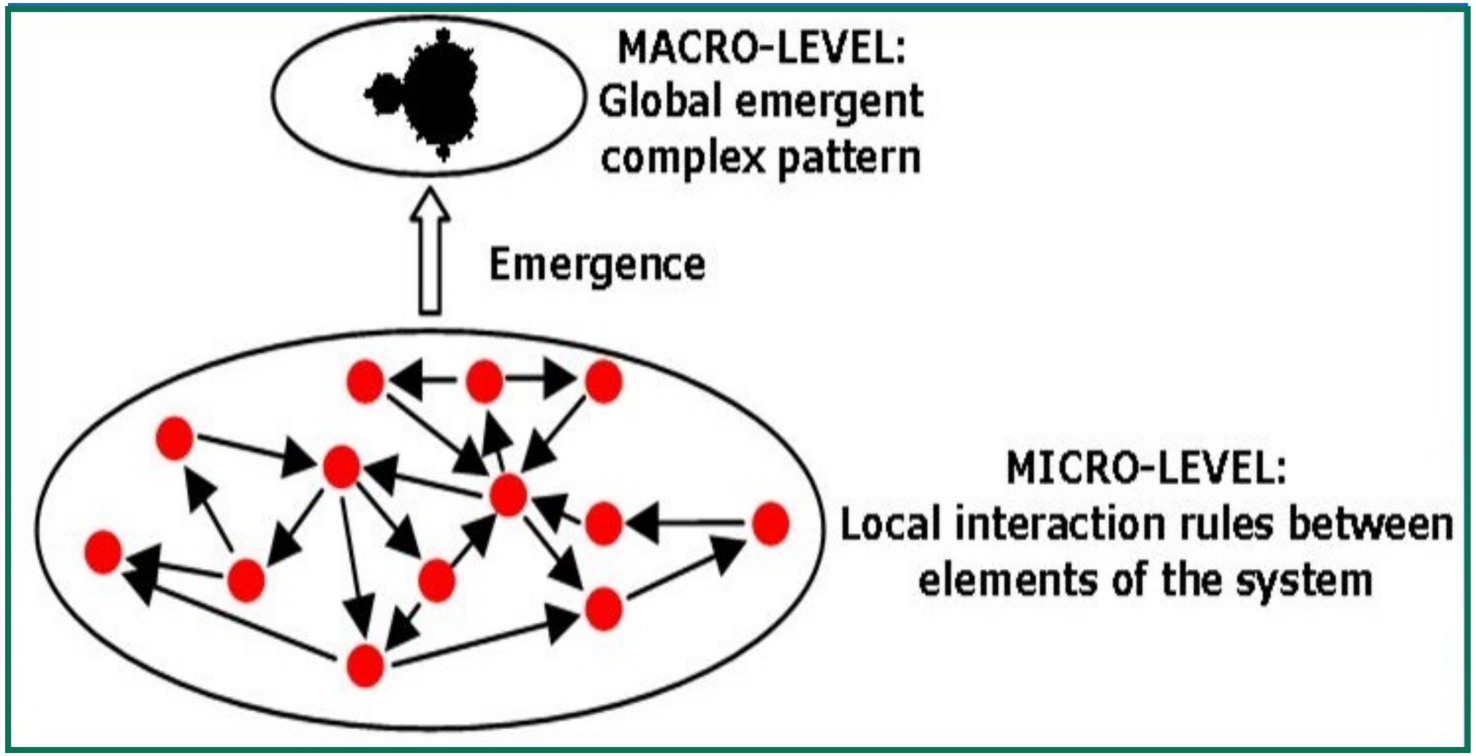
✓ People in a group tend to change their opinion

✓What are the mechanisms?

- Social Pressure
- Imitation
- Adaptation to the environment
- Exchange of arguments

Common elements in complex systems

- Is a system composed of many components which may interact with each other.
- No central authority
- Local Non-linear interactions
- Emergent behavior
- *"The action of the whole is more than the sum of its parts" (Holland 2014)*



Physics, Biologics, Technicals, Socials, etc

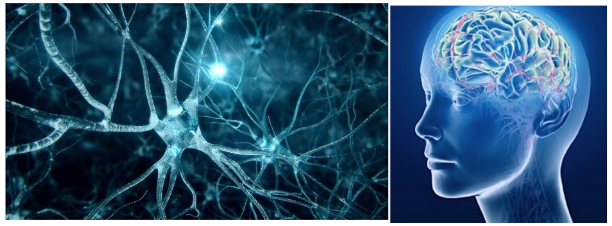
Pattern formation
○ = matter

Biological development
○ = cell

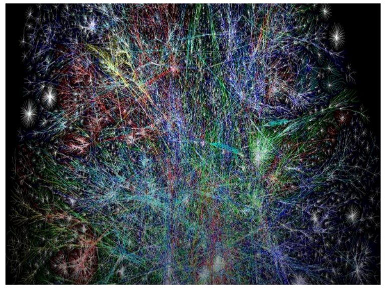
anthill
○ = ants

Flocks
○ = starling

shoal
○ = fish



Brain & Cognición
○ = neuron



Internet & Web
○ = host/webpage

Social Networks
○ = people

Theoretical framework

Agents	Ensemble	Behavior
People	Social Groups Social Networks Societies	• Opinion formation • Group behavior • Pedestrian Dynamics • Language Dynamics • Culture dynamics • Migration dynamics
Neurons Brain regions	Brain	•Thoughts •Actions •Movements •Memory
Insects, birds, fishes	Colonies	• Search for food • Collective movements
Molecules	Gas / Liquids / Solids	• Phase transitions • Estate equations • New global properties

Modeling Complex systems

- Physicist have learned how to build relatively simple models that can produce complicated behavior
- Also, those who works on inherently very complex systems (biologist, sociologist, neuroscientist) are uncovering ways to interpret their subjects in terms of interacting well defined units (such as proteins)
- We are witnessing a change of paradigm in our attempts to understand the world. The laws of the whole can not be deduced by digging deeper into the details.
- Computer have allowed a new way of learning:
- **By directly modeling a system made of many units we can observe, manipulate and understand the behavior of the whole system much better than before.**

concepts

The bigger picture

Tamas Vicsek

If a concept is not well defined, it can be abused. This is particularly true of complexity, an inherently interdisciplinary concept that has penetrated a range of intellectual fields from physics to linguistics,

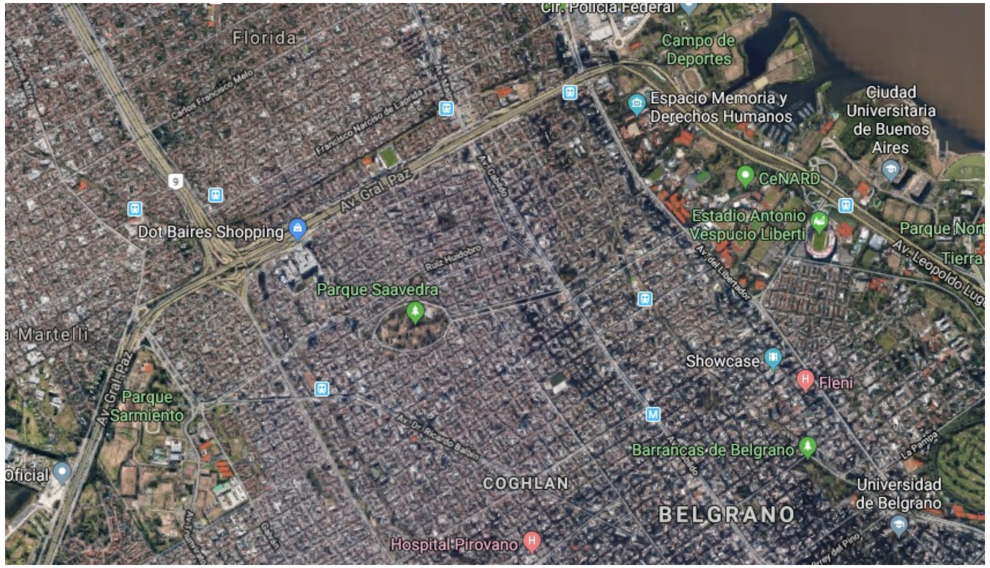
understand reality through simplification and analysis. Some important simple systems are successful idealizations or primitive models of particular real situations — for example, a perfect sphere rolling down an absolutely smooth slope in a vacuum. This is the world of newtonian mechanics, and it

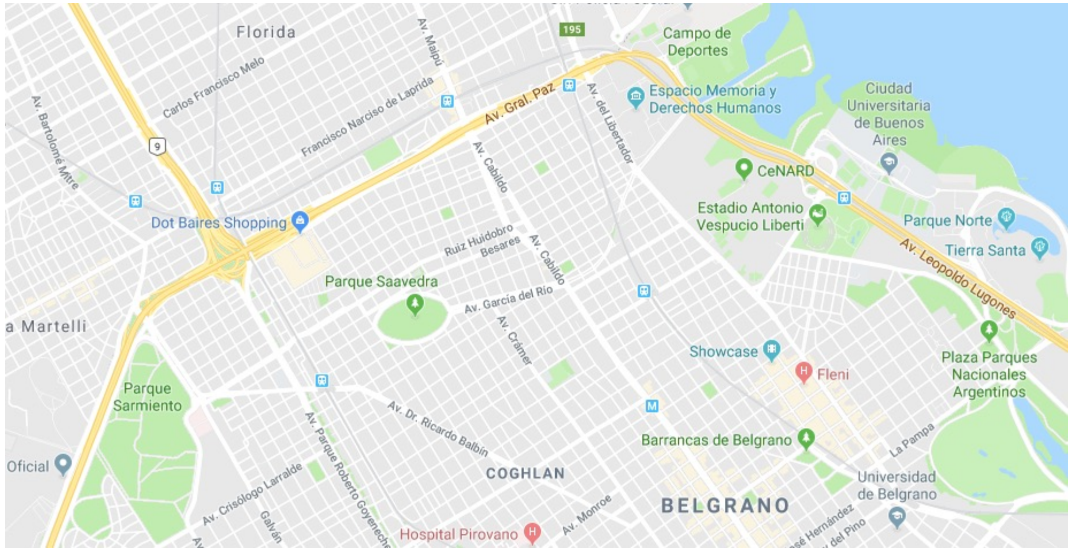
Complexity

The laws that describe the behaviour of a complex system are qualitatively different from those that govern its units.

and scaling (for example, power-law depen-

Complex systems: We are used to models!!!





- ✓ Maps are simplified models we use in our daily life.
- ✓ They leave out a lot of unnecessary details.
- ✓ They are useful simplifications that help us in many tasks.

Complex Adaptive Systems, J.H Miller & S.E.Page

Complex Systems Models

Social and economic systems have a multitude of factors
Include them all in a model is unattainable

Our understanding: Abstract, limited, idealized, description of reality that still captures a specific phenomenon. *Very limited number of variables*

Models in this realm are not intended to reproduce *reality* but to shed light on mechanisms behind specific observed phenomena

Complex Systems Models:

Three main features

- **Finite in size & time:**
  - Some models are solvable in the limit N ⇢ ∞, but finite size fluctuations could be relevant in the observed behavior
  - Social or biological process are frequently limited in time and the equilibrium hypothesis could be misleading in many cases.
- **Heterogeneity:**
  - Can crucially affect the observed properties of a given system and it should taken into account
- **Interactions:**
  - Agents do not act in isolation but interact with others.
  - The nature of interactions could dramatically change the global properties of the system.
  - The structure of the interactions can be described via complex networks.

Complex Systems: The standing ovation problem

From https://www.gettyimages.com/

The standing ovation problem

- Though ostensibly simple, the social dynamics responsible for a standing ovation are complex.
- As the performance ends, each audience member must decide whether to stand. Of course, if the decision to stand is simply a personal choice based on the individual’s own assessment of the worth of the performance, the problem becomes trivial.
- However, people do not stand solely based upon their own impressions of the performance. A seated audience member surrounded by people standing might be tempted to stand, even if he hated the performance.
- This behavioral mimicry could be strategic (the agents wants to send the right signal to the lecturer), informational (maybe the lecture was better than he thought), or conformal (he stands to not feel awkward).

Complex Adaptative Systems: An introduction to computational models of social life, J. Miller & S. Page
Mircromotives & Macrobehaviors, Thomas Schelling 1978

Modeling the standing ovation problem

- Let's assume an audience of N people.
- Each one receives a signal that depends on the quality of the performance, q: <u>$s_i(q)$ is the signal received by the agent i.</u>
- We could also hypothesize a functional form for $s_i(q)$ even adding some diversity to each signal by adding a white noise term (ζ_i) with zero mean and standard deviation σ : $s_i(q) = q + \zeta_i$.
- <u>Dynamics</u>: We hypothesize that each person "stands" if and only if $s_i(q) > T$, where T is some critical threshold above which people are so moved by the performance that they stand up and applaud.

Complex Adaptative Systems: An introduction to computational models of social life, J. Miller & S. Page

Modeling the standing ovation problem
Model 1: The simplest model

- But people could not only respond (standing and applauding) because the quality of the performance, but because other people do.
- Let's add an additional parameter α that gives the percentage of people who must stand in order to ignore the initial signal and decide to stand up.
- <u>Outcomes</u>: If the initial group of standing people exceed α ($N_0 > \alpha$), everyone stands and $N_{up}=N$. Otherwise, it remains in the initial group standing ($N_{up} = N_0 \leq \alpha$).
- Even though the model is simple and elegant, we know that real ovations often exhibit gradual waves of participation and noticeable spatial patterns across the auditorium.

Complex Adaptative Systems: An introduction to computational models of social life, J. Miller & S. Page

Modeling the standing ovation problem Model 2: A more complex model

- The first step could be placing every person in a seat of the auditorium.
- Also people have connections with others. People use to arrive and sit in the auditorium with acquaintances.
- If the model allows people to sit in a space and locate near friends, the driving forces begin to change. People seated in one part of the theater (side of the aisle, for instance) receive different set of signals than others.
- Locations may also reflects a priori preferences for the performance that is about to begin.
- Also people may differentially weight the signals sent by their friends, either because or peer pressure or friendships were initially forged on common traits.
- Now, identical individuals can behave different depending on where, and with whom they are seated.

Complex Adaptative Systems: An introduction to computational models of social life, J. Miller & S. Page

Modeling the standing ovation problem Comparison between models

Feature	Model 1 (simplest)	Model 2 (richer)
Dynamics	An initial decision to stand followed by a second decision based on how many people stood initially	The first round of standing will induce others to stand, and this action will cause others to react. The systems can display cascades of behavior that may not settle down anytime soon.
Size of standing people	An initial group of $N_0 \leq \alpha$ or everybody	Any size
Rounds of applause	two	Several cascades of behaviors are possible
Social influence	Everyone's influence is equal	Influence depends on friendship or seat location

Complex Adaptative Systems: An introduction to computational models of social life, J. Miller & S. Page

Research questions for the Standing Ovation problem

- Do performances that attract more groups lead to more ovations?
- How does changing the design of the theater by, say, adding balconies, influence ovations?
- If you want to start an ovation, where should you place your shills?
- If people are seated based on their preferences for the performance, say, left or right side of the aisle or more expensive seats up front, do you see different patterns of ovations?

Hands on: proposal 1

- Implement the model 2 with spatial structure and location based infuence.
- Implement the model 2 with spatial structure, location based and acquaintances infuences.
- Implement a version of model 3 where some of the previous research questions could be addressed

Tools to describe Complex Systems (among others)

- How to simplify but keeping the complexity?
- How to model a complex system?

1 – Agent Based Models (ABM)

2 – Complex networks (You will see this with Prof. Semeshenko)

- Describing the backbone of the interactions among agents
- Could be used to describe emergent behavior (functional networks)

Agent Based Models

Agents (person, voter, institutions, neuron, brain region,etc). Each one could be defined by a given state or an individual dynamics

+

Interactions between agents

=

Global emergent behavior

Goal:
To Investigate how large-scale effects arise from the microscopic processes of agent interactions.

Methodology:

- Make assumptions about agents and their interactions.
- Use computer simulations to observe consequences of those assumptions (experiment).

Granovetter (1978)
How to model collective behavior?

Mark Granovetter

Joan Butler Ford Professor and Chair of Sociology
Joan Butler Ford Professor in the School of Humanities and Sciences

A.B. Princeton University 1965 Modern History
Ph.D. Harvard Unversity 1970 Sociology

Download CV

STANFORD DIRECTORY »

About

Mark Granovetter's main interest is in the way people, social networks and social institutions interact and shape one another. He has written extensively on this subject, including his two most widely cited articles "The Strength of Weak Ties" (1973) and "Economic Action and Social Structure: The Problem of Embeddedness" (1985). In recent years, his focus has been on the social foundations of the economy, and he is working on a book entitled *Society and Economy* , to be published by Harvard University Press in two volumes. The first volume wil be broadly theoretical, treating the role in the economy of social networks, norms, values, culture, "institutional logics", trust, power and the intersection of social institutions. The second volume will use this framework to illuminate the study of such important topics as corruption, corporate governance, organizational form and the emergence of new industries such as the American electricity industry and the high-tech industry of Silicon Valley.

Collective Behavior of Crowds

<u>Sociological theories in ‘70:</u>

- Norms
- Preferences
- Motives
- Beliefs

Emphasis on the individual

Theories assume a group relationship too simple

Collective Behavior of Crowds

Sociological theories in ‘70:

- Norms
- Preferences
- Motives
- Beliefs

Emphasis on the individual

Theories assume a group relationship too simple

Granovetter

Theory of Collective Behaviors

- **Interrelation**: Interrelated behaviors of agents
- **Variability or heterogeneity:** Different individuals

Collective Behaviors Contrary to Preferences Individuals

Question

How to study collective behaviors in situations where subjects have two alternatives and the cost / benefit of choosing one of them depends on how many others make the same decision? Example: <u>A Riot</u>

Model

<u>Threshold</u>: the proportion of the group he would must see join before he would do so.

Leader!!

Radicals:
Lower threshold

Conservatives
(higher thresholds)

Granovetter M (1978) Threshold models of collective behavior. American Journal of Sociology 83: 1420–1443 doi: 10.1086/226707

There is a riot or not?

<u>Situation</u>: milling around in a square (a potential riot situation).
<u>Starting Point</u>: The instigator engages in riot behavior (i.e., breaks a window)
<u>Question</u>: Do we have a riot or not?
<u>Goal</u> of the threshold model:
Given an initial threshold distribution→ Can we predict the outcome?

Case 1

-Uniform threshold distribution (Thr)
one w/ Thr=0; other with Thr=1, another con Thr=2,…

Instigator

- **<u>Result</u>**: Bandwagon effect!!
Green (Thr=0) → Start the riot
Light Blue (Thr=1) → join to the riot because green.
Red (Thr=2)→ Also join because….

All the people join the riot!!
Equilibrium situation: r_e=All!

There is a riot or not?

Let's perturb slightly the previous distribution
How will the final solution change?

Case 2

- **Almost uniform** threshold distribution (Thr)
One w/ Thr=0; **<u>Nobody</u>** with Thr=1,
two with thr=2,…

Instigator

<u>Result</u>:
- Green (Thr=0) → Start the riot
- Light blue or red (Thr=2) → He/She would join if at least were two but…

¡¡Absolut failure!!

Nobody join to he riot!
Equilibrium solution: $r_e=1$

There is a riot or not?

The day after news

Case 1

Case 2

What does this simple-minded example suggest?

it is hazardous to infer individual dispositions from aggregate outcomes

- ✓ Two almost identical crowds produce radically different collective behaviors
- ✓ The differences between both results comes from the aggregation process (in particular from the gap in the frequency distribution in the case 2)

¿How to describe mathematically?

- f(x)= Threshold distribution (how many people has threshold equal to x)
- F(x) = Cumulated threshold distribution(how many people has threshold less or equal to x)

- r(t) =Fraction on individuals joined to the riot at time “t”.
- The evolution of the systems is given by: r(t+1)=F(r(t))

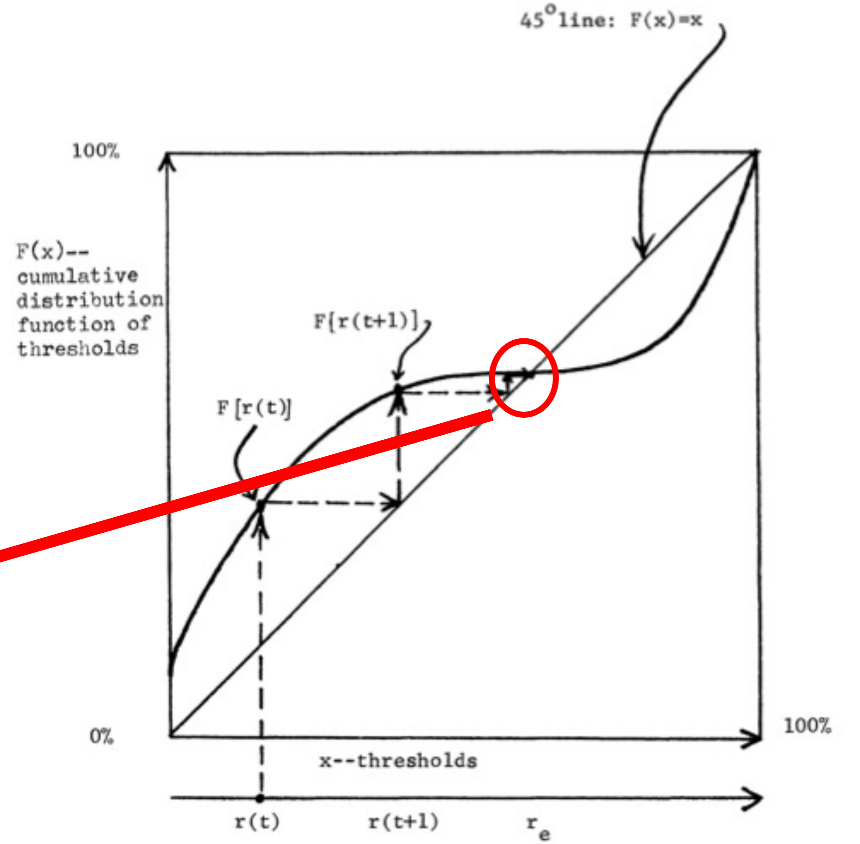


FIG. 1.—Graphical method of finding the equilibrium point of a threshold distribution. $r(t)$ = proportion having rioted by time t.

<u>Equilibrium point:</u>
How many people finally join the riot (r_e→r(t+1)=r(t))

Starting from a single rioter

The Initial truncated normal distribution case

Why?

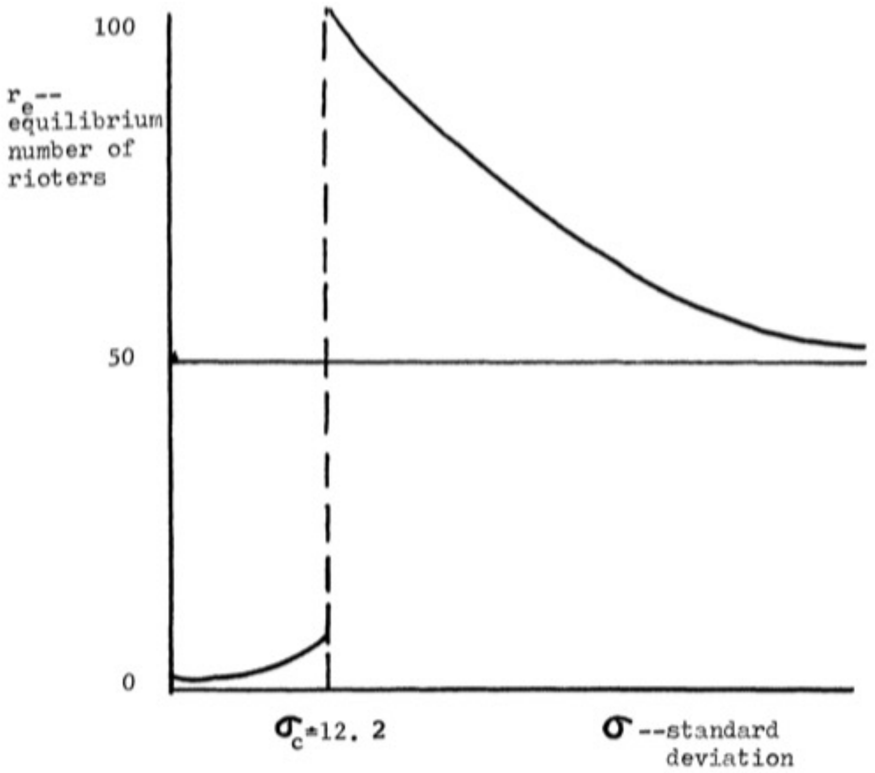


FIG. 2.—Equilibrium number of rioters plotted against standard deviation of normal distributions of thresholds with mean = 25, N = 100.

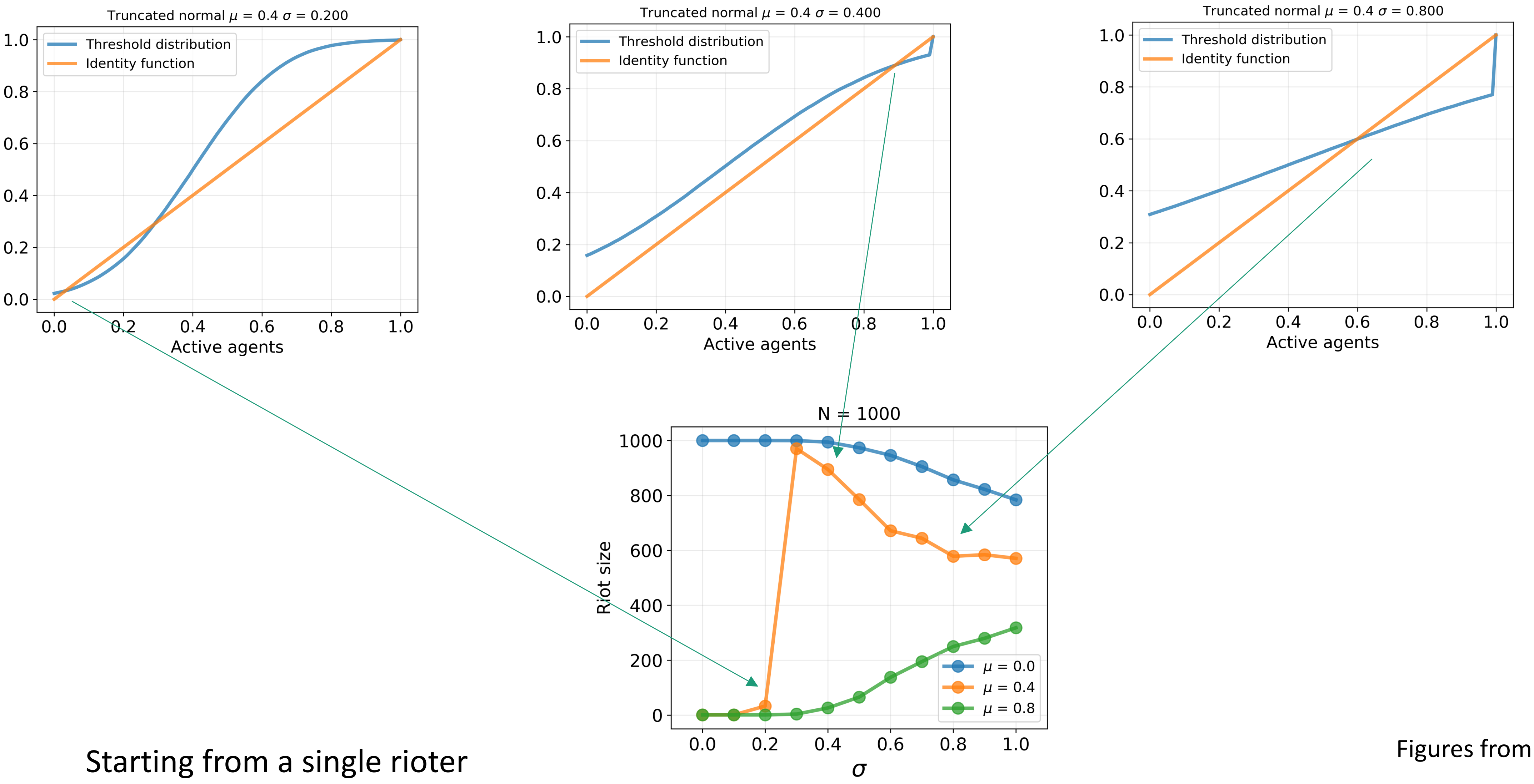
Starting from a single rioter

- There is no obvious sociological way to explain why a slight perturbation of the normal distribution around the critical standard deviation should have a wholly discontinuous, striking qualitative effect

- This example shows again how two crowds whose average preferences are nearly identical could generate entirely different results.

The Initial truncated Normal Distribution case

Truncated Normal Distributions N(μ,σ). μ=0.4, varying σ

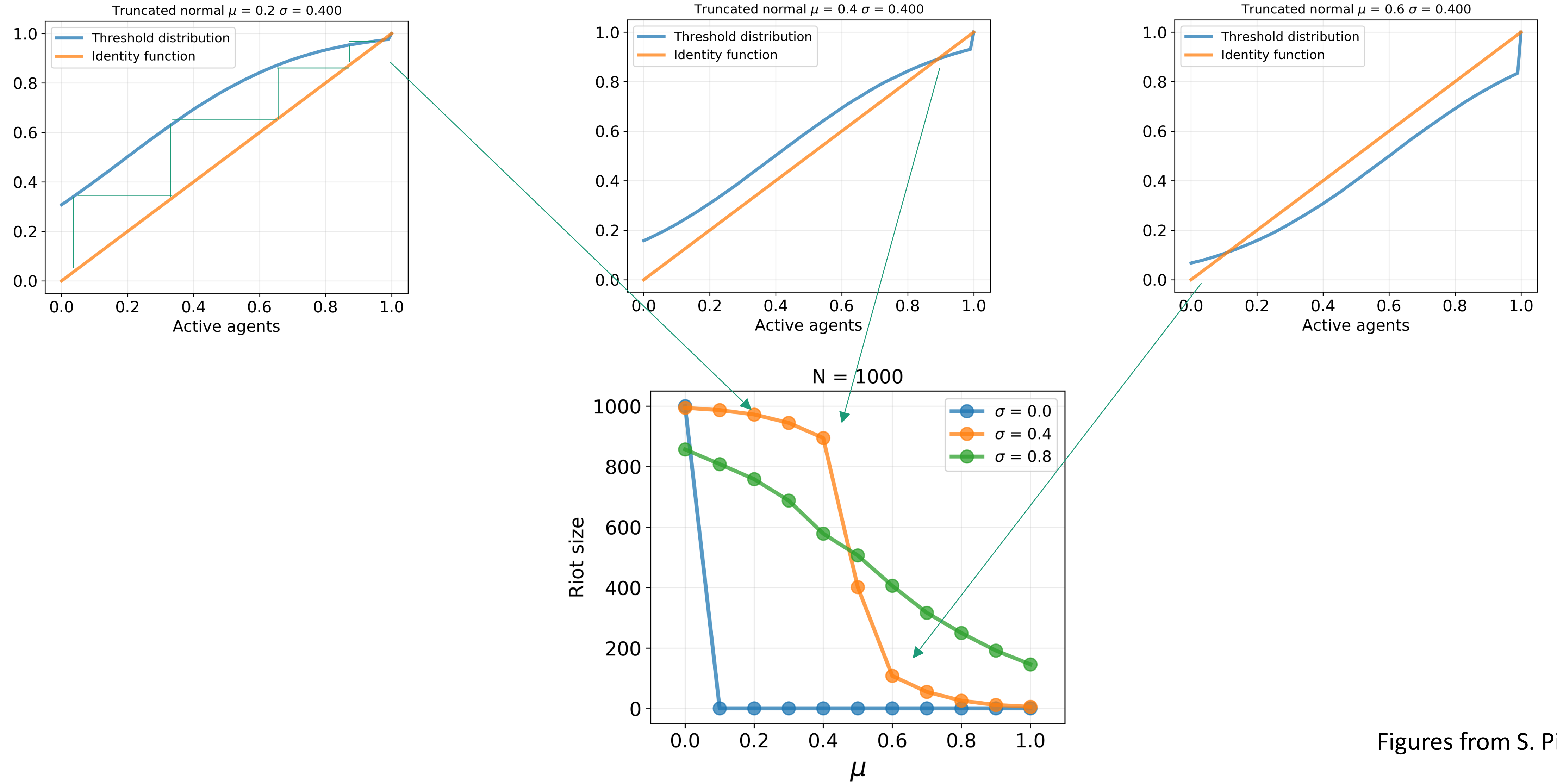


Starting from a single rioter

Figures from S. Pinto

The Initial truncated Normal Distribution case

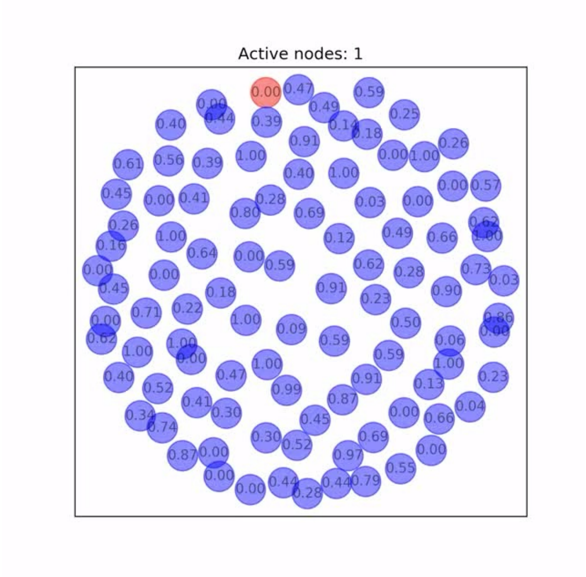
Truncated Normal Distributions N(μ,σ). σ=0.4, varyng μ

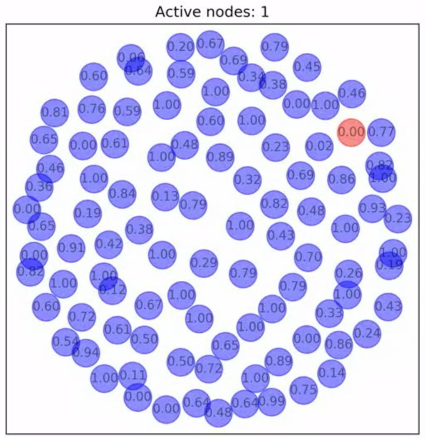


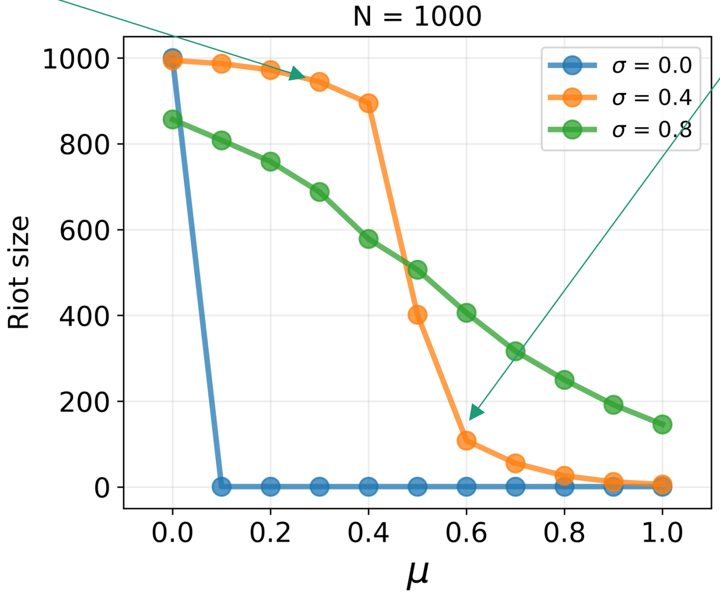
Figures from S. Pinto

The Initial truncated Normal Distribution case

Truncated Normal Distributions N(μ,σ). σ=0.4, varyng μ





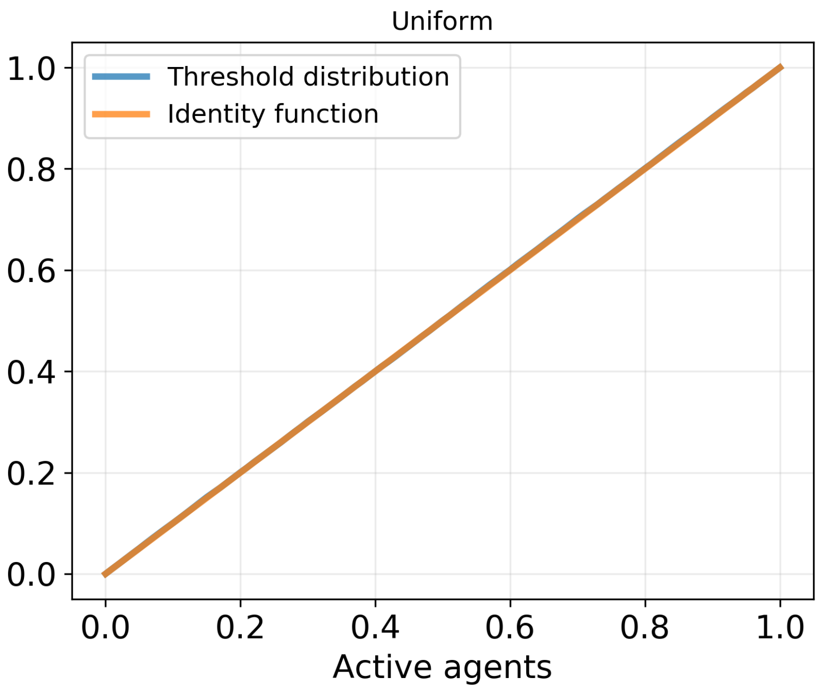


Figures from S. Pinto

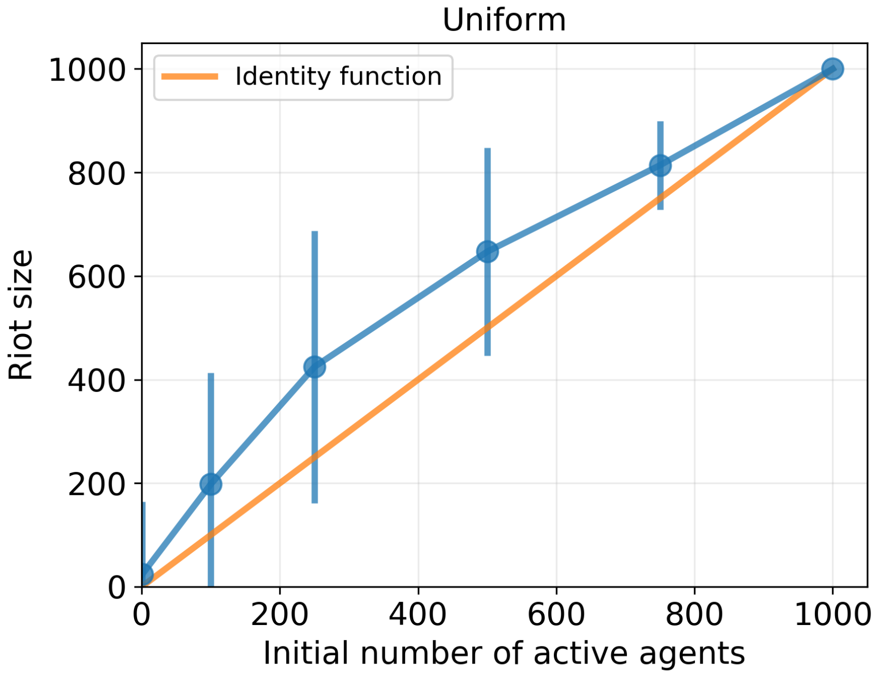
The Uniform Initial Condition

Equilibrium Condition: r = F(r)

U[0,1] : Multiple equilibriums state



U[0,1] : Multiple equilibriums state

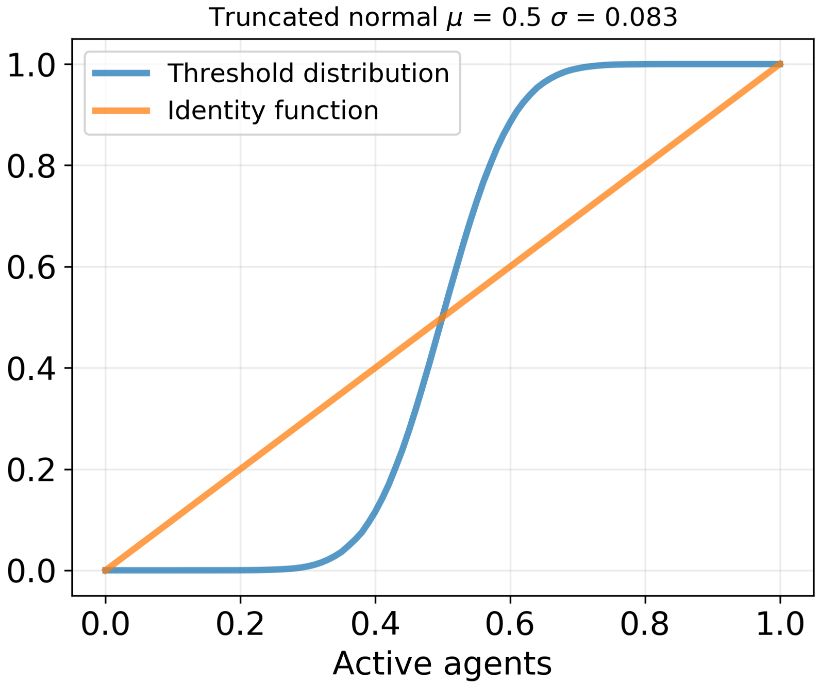


Figures from S. Pinto

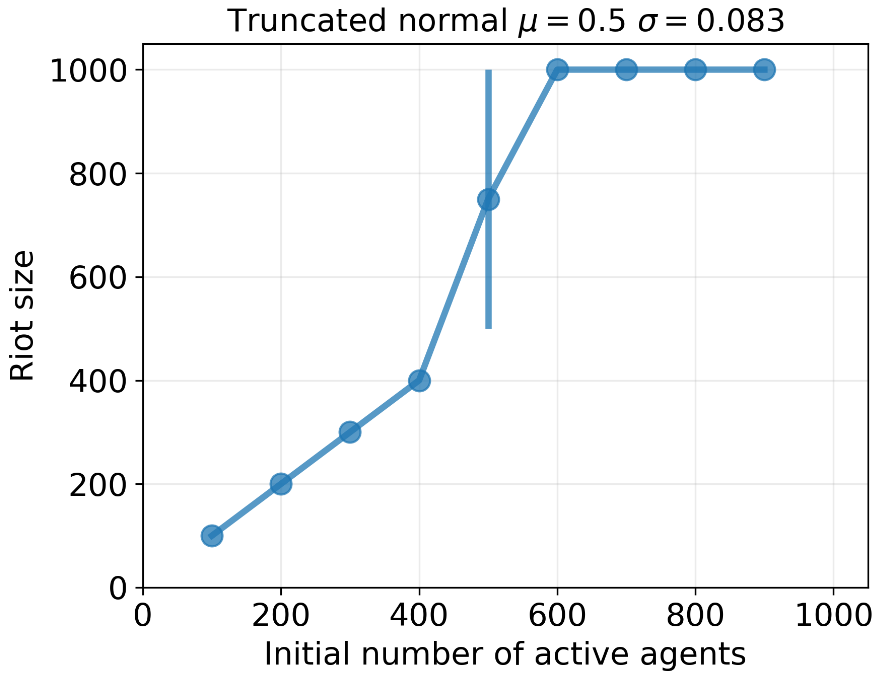
The Normal truncated Initial Condition

Equilibrium Condition: r = F(r)

N(0.5;0.083): A single state equilibrium state



N(0.5;0.083): A single state equilibrium state



Figures from S. Pinto

What this example show us?

- This example shows again how two crowds whose average preferences

are nearly identical could generate entirely different results.

- Threshold models take the two elements of collective behavior which are central to explain the results:
  - substantial heterogeneity of preferences.
  - interdependence of decisions over time.

More ingredients to be considered

Social structure

- It is not the same if a stranger joined one or several friends.
- How to weigh the friendship?
- Formalize the concept of "Perceived Threshold" → Weighted social matrix

Temporal and spatial effects

- Not everyone is connected to everyone(as assumed in the first version)
- Include a time dependent connectivity network between agents.

Hands on, proposal 2: implement a new version of the trheshold model with some of these ingredients

Formalizing the threshold model

Let <u>N agents</u> in the system. Each one can adopt a binary state "*s*":

- *s*=1 (engaged, interested,etc)
- *s*=0 (not engaged, not interested,etc)

The collective state of the system will be described in terms of the fraction of engaged / interested agents:

$$p = \sum_{i=1}^{N} s_i/_N$$

<u>Interactions:</u> The agents are also described by a threshold τ_i , which represents the fraction of engaged / interested people to induce engagement / interest on agent "*i*":

- Si $p \geq \tau_i \rightarrow s_i(t+1) = 1$
- Si $p < \tau_i \rightarrow s_i(t+1) = 0$

(Thresholds are random variables between 0 and 1 from a probability density $f(\tau)$)

Master Equations for the threshold model

Let $q(p_k,t)$ the probability that the fraction of interested agents at time t be p_k/N.
Then, the master equation for $q(p_k,t)$ is:

$$\boxed{\frac{dq(p_k,t)}{dt} = Q(1|p_{k-1})q(p_{k-1},t) + Q(0|p_{k+1})q(p_{k+1},t) - Q(1|p_k)q(p_k,t) - Q(0|p_k)q(p_k,t) \quad (1)}$$

Where $Q(1|p_k)$ and $Q(0|p_k)$ are the transitions probabilities that a given agent become engaged / interested or disengaged / not-interested given p_k:

- $Q(1|p_k) = (1 - p_k)\, S(p_k)$
- $Q(0|p_k) = p_k\, [1 - S(p_k)]$

Where $S(p_k) = \int_0^{p_k} f(\tau)d\tau$, is the cumulative distribution function of $f(\tau)$ and therefore :
$S(p_k) \equiv P(\tau < p_k)$ is the fraction of agents whose thresholds are below p_k .

Master Equations for the threshold model

In the limit of infinite agents $(N \to \infty), p_k \to p$ $(\mathrm{p} \in [0,1])$, we take the following approximations:

$$p_{k\pm1} \to p \pm \Delta$$
$$q(p_{k\pm1}, t) \to q(p,t) \pm \frac{\partial q(p,t)}{\partial p}\Delta$$
$$S(p_{k\pm1}) \to S(p) \pm \frac{\partial S(p)}{\partial p}\Delta$$

With Δ=1/N. Replacing these expresions in master equation (1) and neglecting terms of Δ^2 order:

$$\frac{\partial q(p)}{\partial t} = -\frac{\partial}{\partial p}\left[\left(-p + S(p)\right)q(p,t)\right]\Delta \qquad (2)$$

For a well defined initial condition, $q(p,0) = \delta(p - p_0)$ and rescaling $t \to Nt$ the solution of equation (2) is:

$$\boxed{\frac{dp}{dt} = -p + S(p)}$$

Which stationary solution is: $p_e = S(p_e)$ as we have seen before

Hands on: proposal 3

- Can you add an external field to the Granovetter model?
- Read the following manuscript and see how to:

Reconstructing social sensitivity from evolution of content volume in Twitter

Sebastián Pinto,[1,2,*] Marcos A Trevisan,[1,2] and Pablo Balenzuela[1,2]

[1] *Departamento de Física, FCEN, Universidad de Buenos Aires. Pabellón 1, Ciudad Universitaria, 1428EGA, Buenos Aires, Argentina.*

[2] *Instituto de Física de Buenos Aires, CONICET. Ciudad Universitaria, 1428EGA, Buenos Aires, Argentina.*

(Dated: May 10, 2022)

The consumption of news produces uneven social reactions. In most cases, people share information and discuss their opinions; public interest remains therefore bounded to the field of debate. A few cases, in contrast, fuel up the collective sensibility and give rise to social movements. To explain the dynamics that underlie the emergence of these reactive states, we set up a simple mathematical model for public interest in terms of media coverage and social interactions. We test the model on a series of events related to violence in the US during 2020. The volume of tweets and retweets is used as a proxy of public interest, and the volume of news as a proxy of media coverage. We show that the model succesfully fits the data and allows inferring a measure of social engagement that correlates with human mobility data. Our findings suggest that this low-dimensional model captures the basic ingredients that regulate social responses capable of ignite social mobilizations.

https://arxiv.org/abs/2112.11644

Summary

- Complex systems approach to social systems it to capture mechanisms behind emergent phenomena**. It is not about detailed description of reality**
- Social systems have a multitude of details that render their complete description an unattainable task.
- However, stylized models can capture mechanisms behind some of their observed properties.
- When these mechanisms are at work the microscopic details become unimportant to have a qualitative understanding.
- For quantitative understanding complementary tools are needed.

See you in next class