+ Group behavior

Imitation

Opinion Dynamics

Pablo Balenzuela. DF-UBA & CONICET

balen@df.uba.ar

@polbalen in Twitter

Group behaviors

Reservoir Dogs, Quentin Tarantino
(Persuasive Arguments)

Continuous opinion models

De Groot (1974): A simple model of continuous opinions

- N agents. Each one has opinion o_i.
- o_i distributed uniformly in [-1;1] at t=0.
- Every time step, each agent know the opinion of all other agents and update if opinion according to a weighted average of all group members:
- $O_i(t+1) = a_{i1}O_1(t) + \cdots + a_{iN}O_N(t)$
- Where $a_{i1} + \cdots + a_{iN} = 1 \;\forall\, i = 1, N$ represents the normalized weights that agent "i" assigns to the opinions of all members in the group.
- If a_{ij} =0 it means that agent "i" does not have into account opinion of agent "j".
- If a_{ii} =1 it means that a_{ij} =0 $\forall\, j \neq i$. Agent "i" is a stubborn.

In this mechanism of social influence, each agents try to become more like the group

DeGroot, M. H. "Reaching a consensus", Journal of the American Statistics Association, 1974.

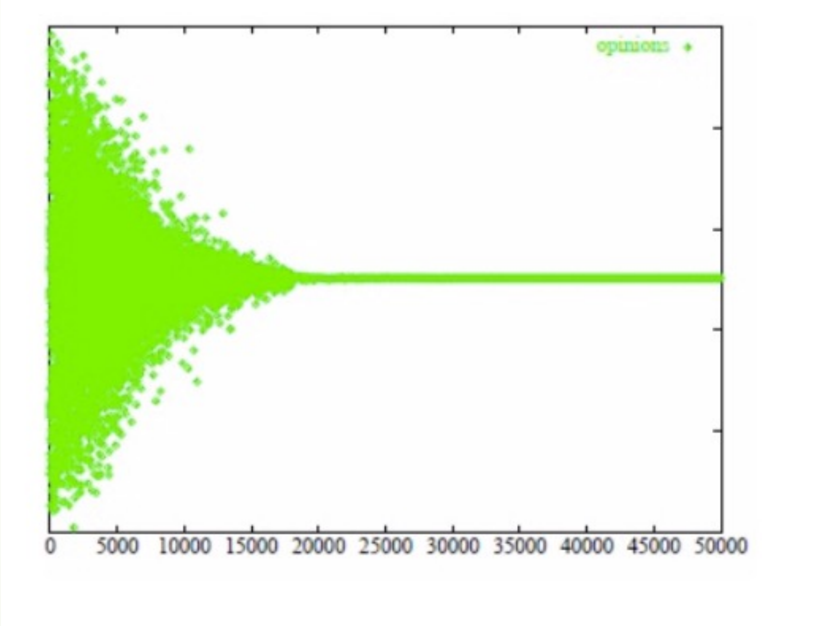
De Groot (1974): There is convergence to consensus in this model?

- It will depend on the weight's distribution a_{ij} !!
- If there is enough $a_{ij} \neq 0$, then the system always converge to consensus.
- Obs: the most extreme opinions in each iteration are softened every time we averaged.

Simplified DeGroot with pairwise interactions:

- Two agents are picked at random and they become similar:

$$O_i(t+1) = \frac{1}{2}(O_i(t) + O_j(t)) = O_i(t) + \frac{1}{2}(O_j(t) - O_i(t))$$
$$O_j(t+1) = \frac{1}{2}(O_i(t) + O_j(t)) = O_j(t) + \frac{1}{2}(O_i(t) - O_j(t))$$



- The mean opinion is constant $O_m = \sum_{i=1}^{N} O_i(t) \ \forall t$
- The dispersion goes to zero.

The problem with classical models

- These models usually predicts consensus of opinions, but empirically opinion dynamics show diversity of opinions

- Puzzled by this, Abelson wondered in 1964 "what on earth one must assume in order to generate the bimodal outcome of community cleavage studies?"

Bounded Confidence models

An explanation for Abelson's puzzle:

Agents tend to interact with similar ones and avoid influence from dissimilar ones

- This notion is supported by two theories (Byrne 1971)

  1. **The reinforcement approach** (Byrne 1961): When humans interacts with similar ones, they feel rewarded because their interaction partners offer them validations by indicating that his percepts and concepts are congruent with ours. At the same time, dissimilar ones constitutes negatives stimulus because we learn that our opinions can be wrong.

  2. **Explanation based in cognitive theories** (Festinger 1957, Heider 1967): We have positive emotions toward persons who are similar to us and negatives to people who are dissimilar

- Empirical research support these assumptions (see Byrne 1971)

The Deffuant's model

They implement the previous idea via the bounded confidence concept:

- N agents
- Each one has an opinion $x_i \in [-1,1]$.
- Two agents are picked at random and if $|x_i - x_j| \leq d$ they become more similar:

$$x_i(t+dt) = x_i(t) + \mu[x_j(t) - x_i(t)]$$
$$x_j(t+dt) = x_j(t) + \mu[x_i(t) - x_j(t)]$$

- Where "d" is the confidence threshold.

Deffuant, G., Neau, D., Amblard, F., Weisbuch, G. "Mixing beliefs among interacting agents", Advances in Complex Systems, 2000.

Master equation of the Deffuant's model

Let's write down the master equation (ME) for the evolution.
First, we define ***u*(x,*t*)** as the probability of find an agent with opinion **x** at time ***t***:

$$\int_{-1}^{+1} u(x,t)dx = 1$$

Then, the ME can be written as:

$$\frac{\partial u}{\partial t} = \int_{-1}^{+1} [\underbrace{\beta(x|y,t)u(y,t)}_{\text{Gain}} - \underbrace{\beta(y|x,t)u(x,t)}_{\text{Loss}}]\, dy$$

$\beta(x|y,t)$: Conditional probability of going fron state y at time t to state x at t+dt

Master equation of the Deffuant's model

Loss: $\equiv \int_{-1}^{+1} u(x)u(x+y)dy$

Loss term: If an agent with opinion x interacts with any agent with opinion y (satisfying that $|x-y| \leq d$) then his/her opinion (in t+dt) will be different from x and u(x,t) decreases, being ${}^{\partial u}/_{\partial t} < 0$.

Gain: $\equiv \int dy\, u(x+y) \int dz\, u(x+z)\delta\{[(x+y) - \mu((x+z) - (x+y))] - x\}$

Gain term: An agent will have opinion x at time (t+dt) (and therefore u(x,t) increases, being ${}^{\partial u}/_{\partial t} > 0$ if two agents with opinions different from x interact according to the model rules:

$$x = (x+y) + \mu[(x+z) - (x+y)]$$

where $x_i(t) = (x+y)$, $x_j(t) = (x+z)$ and $x_i(t+dt)=x$

Master equation of the Deffuant's model

The Gain term becomes:

$$\text{Gain:} \equiv \int dy\, u(x+y) \int dz\, u(x+z)\delta(y+\mu(z-y))$$

And the δ function becomes 1 if $z = \frac{\mu-1}{\mu} y$ and:

$$\text{Gain:} \quad \equiv \int_{-\mu d}^{\mu d} dy\, u(x+y)u(x+\frac{\mu-1}{\mu}y)$$

Where we use that $\left|(x+y) - \left(x + \frac{\mu-1}{\mu}y\right)\right| \leq d$ which gives $|y| \leq d$, setting the integration limits.

Master equation of the Deffuant's model

Putting gain and loss term together, we obtain the ME for u(x,t):

$$\boxed{\frac{\partial u}{\partial t} = \int_{-\mu d}^{\mu d} dy\, u(x+y)u(x+\frac{\mu-1}{\mu}y) \; - \int_{-1}^{+1} u(x)u(x+y)dy} \qquad \text{(ME)}$$

This equation can be solved in the limit of d<<1, by expanding u in Taylor series:

$$u(x+cy) = u(x) + cy\frac{\partial u}{\partial x} + \frac{c^2y^2}{2}\frac{\partial^2 u}{\partial x^2}$$

Replacing this in the (ME) and performing the integrals of linear and quadratic terms:

…

$$\boxed{\frac{\partial u}{\partial t} = \mu(\mu-1)\frac{2d^3}{3}\frac{\partial^2 u^2}{\partial x^2}}$$

Master equation of the Deffuant's model

ME is like heat equation with time reversal : departing from uniform initial condition, it evolves towards a delta function as time goes on.

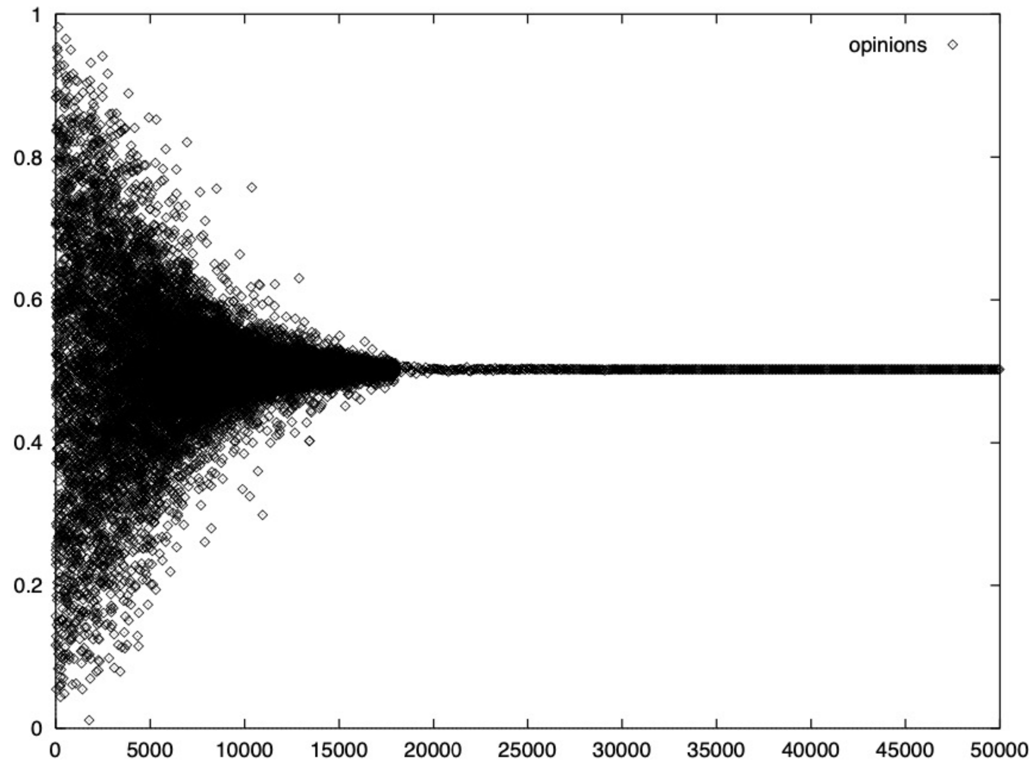
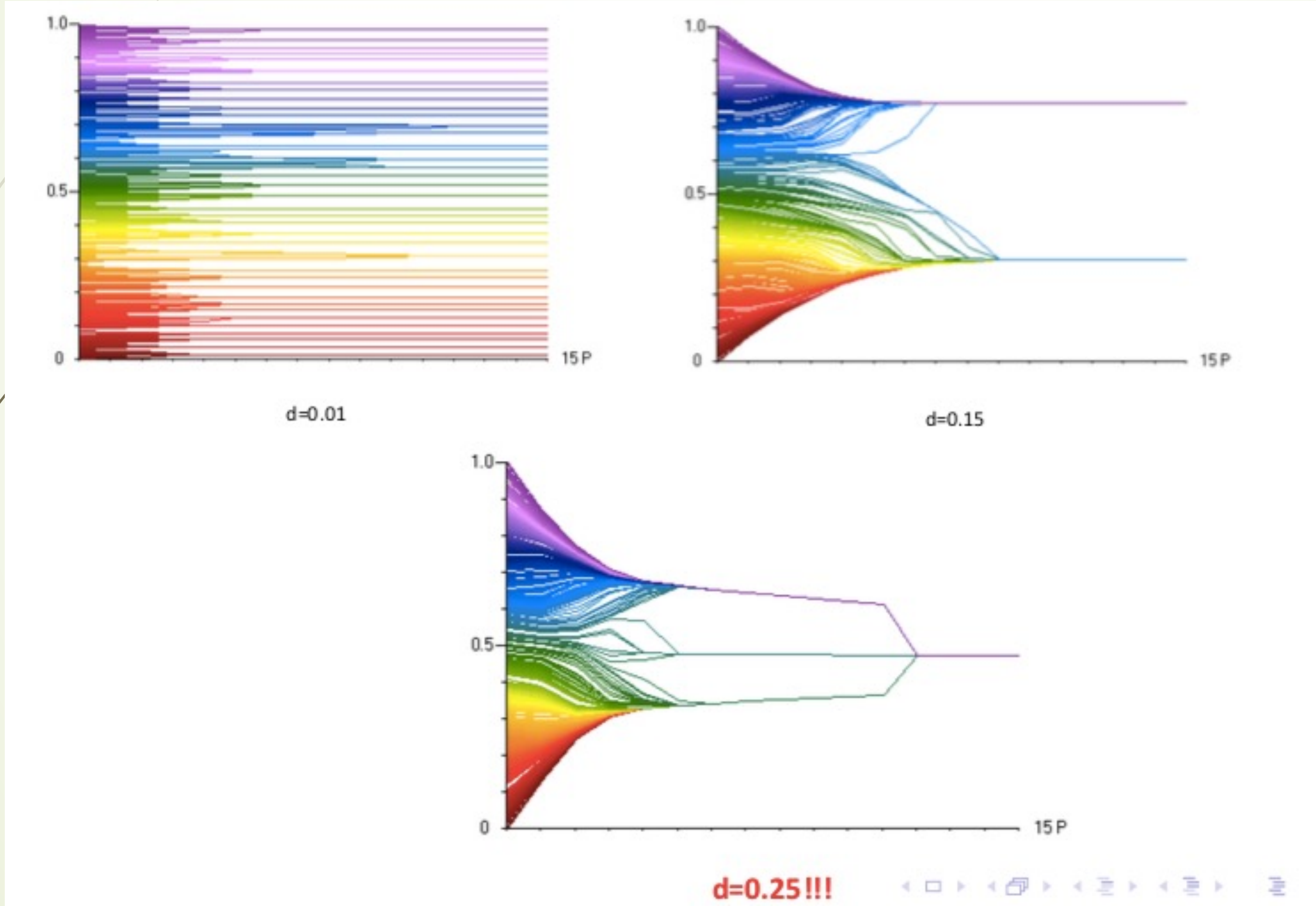


Figure 1. *Time chart of opinions* ($d = 0.5 \quad \mu = 0.5 \quad N = 2000$). *One time unit corresponds to sampling 1000 pairs of agents.*

The Deffuant's model

The population becomes fragmented depending on the threshold



Figs from Hegselmann – Krause (2002)

- For d>025 the population reach consensus

- When d decrease the population breaks in n_c clusters of similar opinions

- The smaller d, the larger n_c

Asymmetric bounded confidence

- Hegselmann & Krause (Opinion Dynamics and bounded confidence models, analysis and simulation", Journal of Artificial Societies and Social Simulation, 2002.)
- They implements asymmetric bounded confidence in order to weight different opinions from left or right.

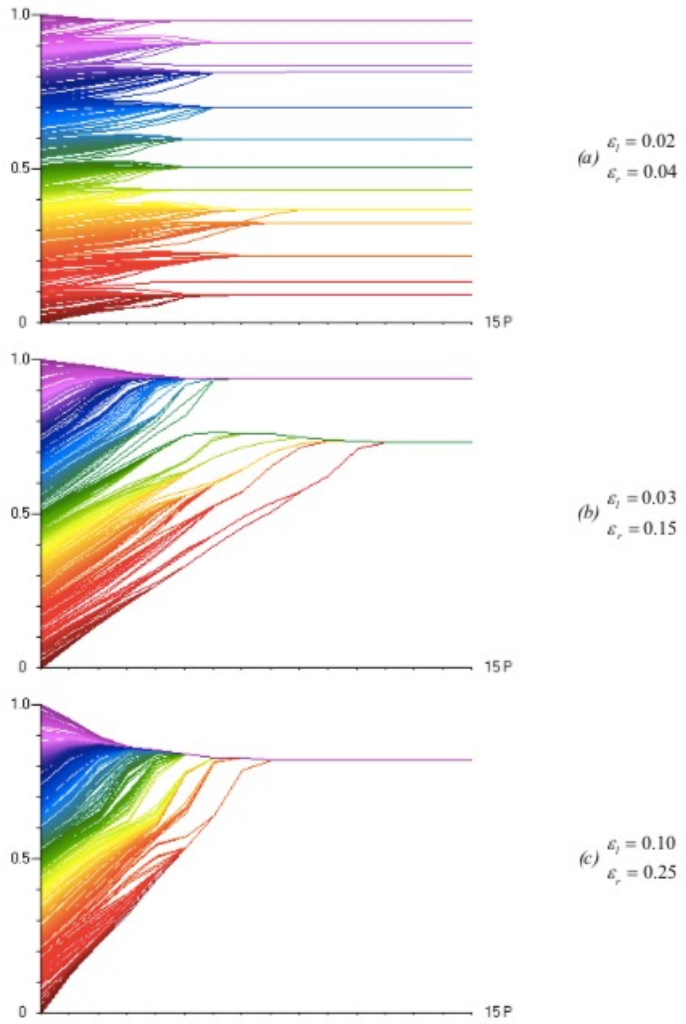


Figure 10: Single runs, 625 opinions, random start profile.

The problem with bounded confidence models

The bounded confidence mechanism has two problematic assumptions:

- Propose the agents to refuse interactions with dissimilar ones and this can be too strict to assume.
- They generate clusters only when the agents have very different opinion at the beginning. But if not enought initial diversity is assumed, the model fails in create diversity. There is no mechanism creating diversity

Negative Influence models

Negative Influence & striving for uniqueness

- Positive influence: change opinion to move closer to position of influential others.
- Negative influence: change opinion to move away from position of influential others
- Two versions of negative influence:
    - Striving for uniqueness [supported by psychological research (Imhoff et al. 2009; Maslach et al. 1985; Snyder et al. 1980)]. People wants to become different from the group.
    - Xenophobia or Negative Influence: Agent's distance themselves from disliked or dissimilar others.
        - Xenophobia: if opinion differences are too large, relations become negative.
        - Negative Influence: If relations are negative, agents increase opinion distance

Models of Negative Influence in De Groot's framework.

$$O_i(t+1) = O_i(t) + C\sum_{j=1}^{N} w_{i,j}(t)(O_j(t) - O_i(t)) + \xi_i(t)$$

Striving for uniqueness

$$\xi_i(t) = N\left(0, \sum_{j=1}^{N} e^{-|O_i - O_j|}\right)$$

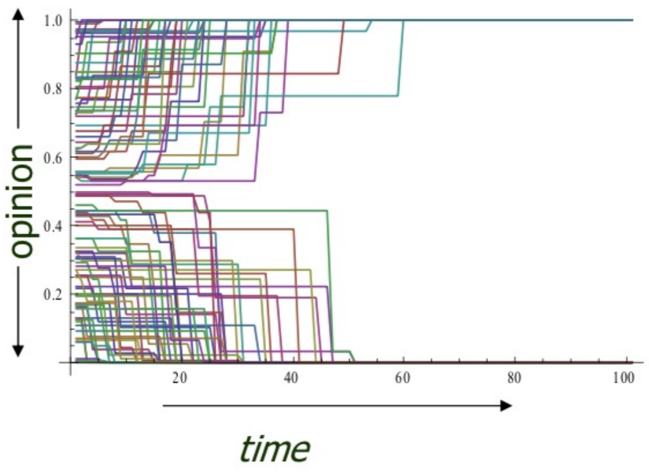
- Changes can be + or –
- Small opinions are more probable

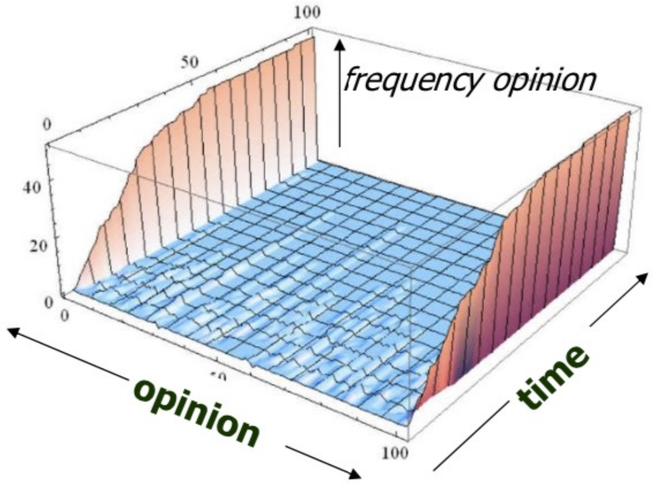
Striving for uniqueness: Is modeled as white noise. Plays a role of a disintegrating force.
- Mäs, Flache & Helbing 2010, PLoS Comp Biol
- Mäs, Flache & Kitts 2014, Perspectives on Culture and Agent-based Simulations

Negative Influence: Is modeled with negative weights in this framework.

Various models include xenophobia and negative influence (Macy, Kitts, Flache, Benard 2003, see also Mark 2oo3, Jager & Amblard 2004, Baldassari & Bearman 2007, Flache & Mäs 2008, Fent, Groeber & Schweitzer 2007, ...)

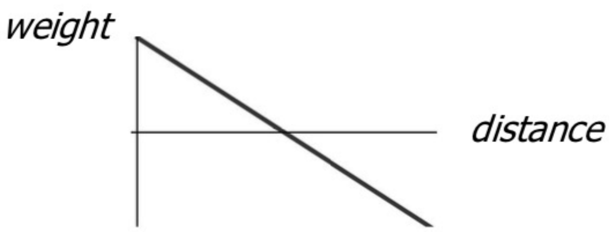
The interplay between positive and negative influence.
Typical result
Initial uniformity turns into bipolarization





- Initially random uniform
- N=100, 1000 iterations
- Asynchronous updating

e.g.
Macy et al 2003
Jager & Amblard 2005 CMOT



Micro-level "minimize cognitive dissonance"

Figs from A. Flaché

Persuasive Arguments models

Bipolarization without Negative Influence: A Persuasive Arguments Theory (PAT)

Differentiation without Distancing. Explaining Bi-Polarization of Opinions without Negative Influence

Michael Mäs[1]*, Andreas Flache[2]

1 Chair of Sociology, in particular Modeling and Simulation, ETH Zurich, Zurich, Switzerland, 2 Department of Sociology/ICS, University of Groningen, Groningen, The Netherlands

Abstract

Explanations of opinion bi-polarization hinge on the assumption of negative influence, individuals' striving to amplify differences to disliked others. However, empirical evidence for negative influence is inconclusive, which motivated us to search for an alternative explanation. Here, we demonstrate that bi-polarization can be explained without negative influence, drawing on theories that emphasize the communication of arguments as central mechanism of influence. Due to homophily, actors interact mainly with others whose arguments will intensify existing tendencies for or against the issue at stake. We develop an agent-based model of this theory and compare its implications to those of existing social-influence models, deriving testable hypotheses about the conditions of bi-polarization. Hypotheses were tested with a group-discussion experiment (*N* = 96). Results demonstrate that argument exchange can entail bi-polarization even when there is no negative influence.

- Here, authors propose that initially homogeneous populations can fall apart into subgroups with opposing opinions even though individuals do not seek to distance themselves from any other member of the population and social influence is only positive.

Bipolarization without Negative Influence: A Persuasive Arguments Theory (PAT)

Differentiation without Distancing. Explaining Bi-Polarization of Opinions without Negative Influence

Michael Mäs[1]*, Andreas Flache[2]

1 Chair of Sociology, in particular Modeling and Simulation, ETH Zurich, Zurich, Switzerland, 2 Department of Sociology/ICS, University of Groningen, Groningen, The Netherlands

Abstract

Explanations of opinion bi-polarization hinge on the assumption of negative influence, individuals' striving to amplify differences to disliked others. However, empirical evidence for negative influence is inconclusive, which motivated us to search for an alternative explanation. Here, we demonstrate that bi-polarization can be explained without negative influence, drawing on theories that emphasize the communication of arguments as central mechanism of influence. Due to homophily, actors interact mainly with others whose arguments will intensify existing tendencies for or against the issue at stake. We develop an agent-based model of this theory and compare its implications to those of existing social-influence models, deriving testable hypotheses about the conditions of bi-polarization. Hypotheses were tested with a group-discussion experiment ($N = 96$). Results demonstrate that argument exchange can entail bi-polarization even when there is no negative influence.

Model: "Argument-communication theory of bi-polarization" (ACTB)
Ingredients:

- Homophily (Individuals tend to interact with similar ones)
- Persuasive Arguments Theory (Individuals base their opinions in pro and cons arguments).

The model

- N agents, each one with a given opinion, a time t, represented as a continuous variable in the interval [-1,1]: $-1 \leq o_i(t) \leq +1$.
- It assumes that there is a limited number of arguments, N_{ars}, that address the issue.
- There are available, for each agent, P pro arguments with weight $a_l=+1$ and C con argument with weight $a_l=-1$.
- Supported by empirical evidence, agent "i" holds his/her opinion in a limited amount of arguments S_i (t). (S_i (t)< P+C).
- They define a relevance vector for agent "i", $r_i(l)$ with P+C elements. If $r_i(l)=1$, the argument a_l is considered by the agent. Otherwise, $r_i(l)=0$.
- They assume that all arguments have the same persuasiveness:

$$o_i(t) = \frac{1}{S_i(t)} \sum_{i=1}^{S_i(t)} a_l r_i(l)$$

- An agent with 6 pro arguments has o=1. Another one with 3 pro and 3 con argument, has o=0

Dynamics of the model

- At each time step, a given agent "i" is randomly selected.
- **Homophily:** Then an interaction partner "j" is selected with probability P_{ij} given by their similarity. The more similar, the more probable they interact. The strength of homophily is given by a parameter h.

$$sim_{i^*,j,t} = \frac{1}{2}\left(2 - |o_{i^*,t} - o_{j,t}|\right)$$

$$p_{j,t} = \frac{\left(sim_{i^*,j,t}\right)^h}{\sum_{p=1,p\neq i^*}^{N-1} \left(sim_{i^*,p,t}\right)^h}$$

- **Social Influence:** Agent "i" is influenced by agent "j" based in argument's persuasive mechanism: An argument a_l is picked from the relevant arguments of agent "j" and adopted by agent "i" with highest relevancy, discarding one of his/her previous arguments. All relevant arguments are equally probable of being selected.
- Repeat previous steps until systems of N agents reach equilibrium.
- The model displays two stable states:
  - Consensus
  - Maximal bipolarization

Emergent behavior of the model

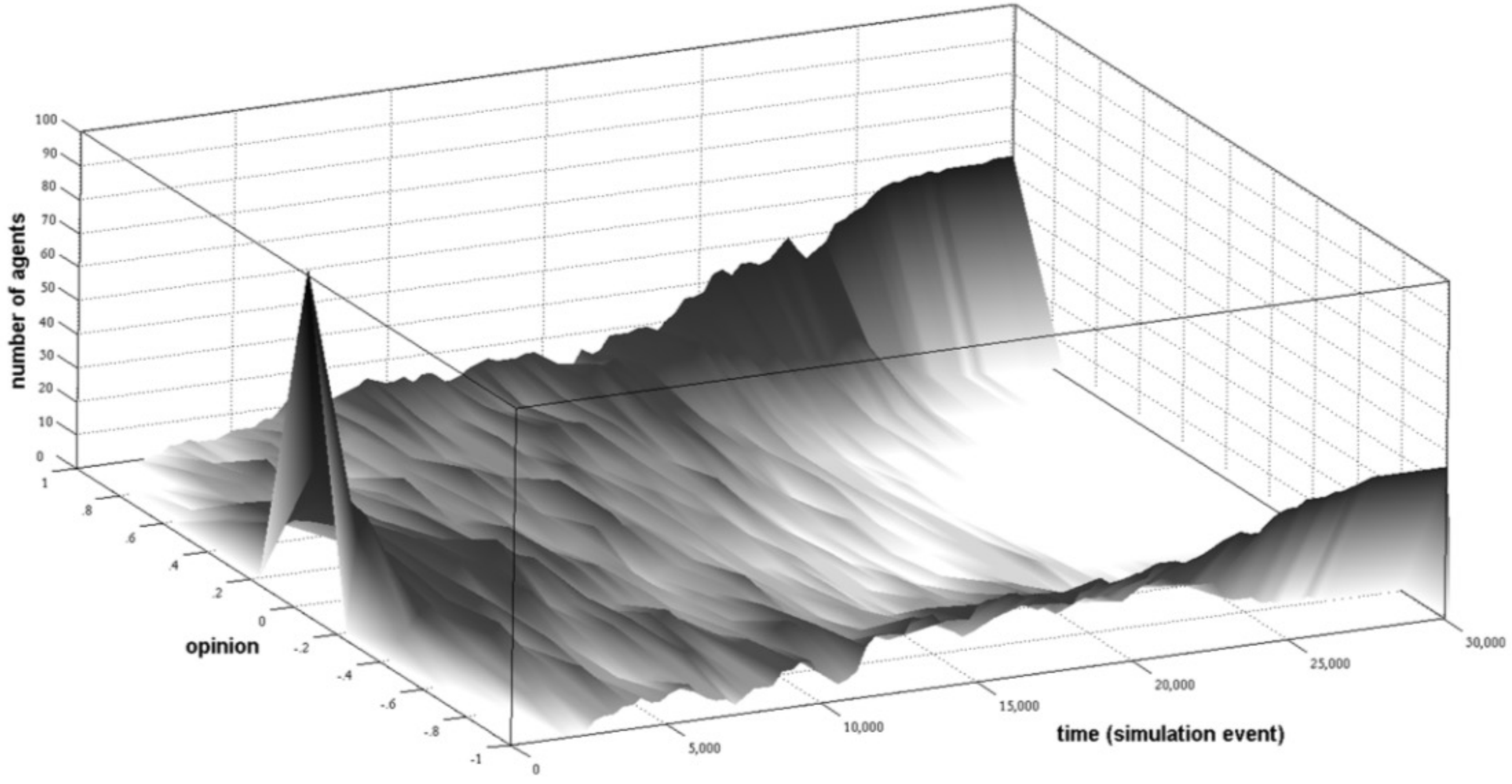


Figure 2. Bi-polarization generated by argument exchange and homophily ($N=100$, $P=C=30$, $S=10$, $h=9$).
doi:10.1371/journal.pone.0074516.g002

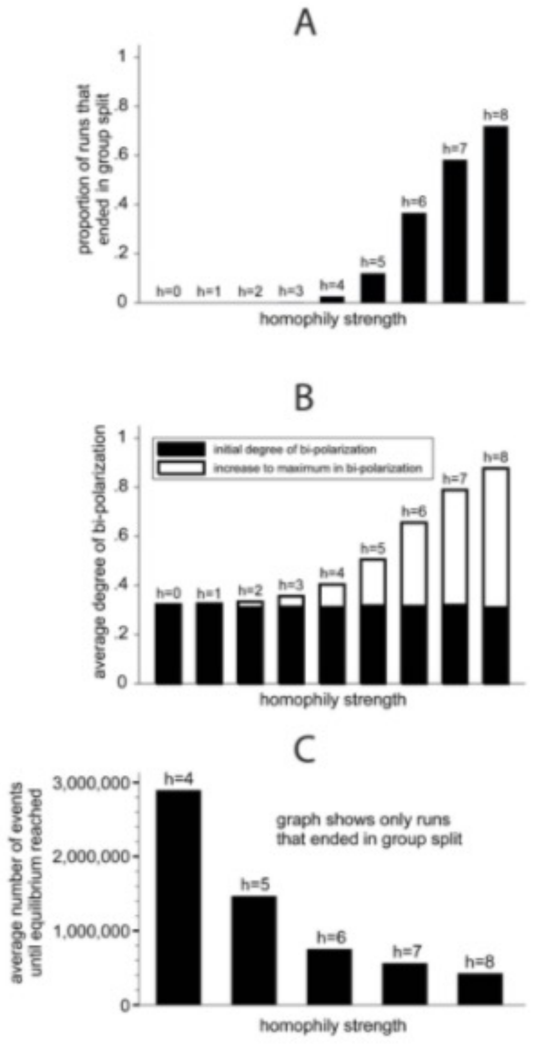


Figure 3. Results from simulation experiment on the effects of homophily on the degree of bi-polarization (500 runs per condition, $N=20$, $P=C=20$, $S=6$).
doi:10.1371/journal.pone.0074516.g003

What this article does not say

- They only explore the dependence of the solution with homophily parameter h
- The results strongly depends on the ratio between the amount of agents (N) and the number of available arguments (N_{ars})
- The bipolarized solution appears in a narrow region of the parameter space.
- Another model with PAT hypothesis can be found here:

Polarizing crowds: Consensus and bipolarization in a persuasive arguments model

Cite as: Chaos **30**, 063141 (2020); doi: 10.1063/5.0004504
Submitted: 12 February 2020 · Accepted: 5 June 2020 ·
Published Online: 19 June 2020

View Online Export Citation CrossMark

Federico Barrera Lemarchand,[1,2,3,a)] Viktoriya Semeshenko,[4] Joaquín Navajas,[1,3] and Pablo Balenzuela[2,5]

Experimental setup & comparison with model

Hand on: Any group would like to tell us how they do experiments?

Which is the problem with previous model?

- Opinions change too much
- People do not change their opinion so often
- However, interactions change perception, information and beliefs
- So, how to implement a model with social influence that consider these ingredients?

Information Threshold models

Pro, cons, undecided and degree of confidence

http://elgatoylacaja.com/confianza-ciega/

A threshold- information model driven by cumulative changes

Goal

- To design a model with discrete opinions and continuous leaning compatible with Persuasive Argument Theory.

Ingredients

- Social Influence: The social interactions produces cumulative changes that, eventually, can produce change in opinion.
- Threshold: When the cumulate of change is above a given threshold, the agent changes his/her opinion.

Opinion change by interchange between agents

PLOS | ONE

RESEARCH ARTICLE

The Undecided Have the Key: Interaction-Driven Opinion Dynamics in a Three State Model

Pablo Balenzuela[1☯*], Juan Pablo Pinasco[2☯], Viktoriya Semeshenko[3,4☯]

1 Departamento de Física, Facultad de Ciencias Exactas y Naturales, Universidad de Buenos Aires and IFIBA, CONICET, Buenos Aires, Argentina, **2** Departamento de Matemática, Facultad de Ciencias Exactas y Naturales, Universidad de Buenos Aires and IMAS UBA-CONICET, Buenos Aires, Argentina, **3** Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET), Buenos Aires, Argentina, **4** Instituto Interdisciplinario de Economía Política de Buenos Aires (IIEP-BAIRES), Facultad de Ciencias Económicas, Universidad de Buenos Aires, Buenos Aires, Argentina

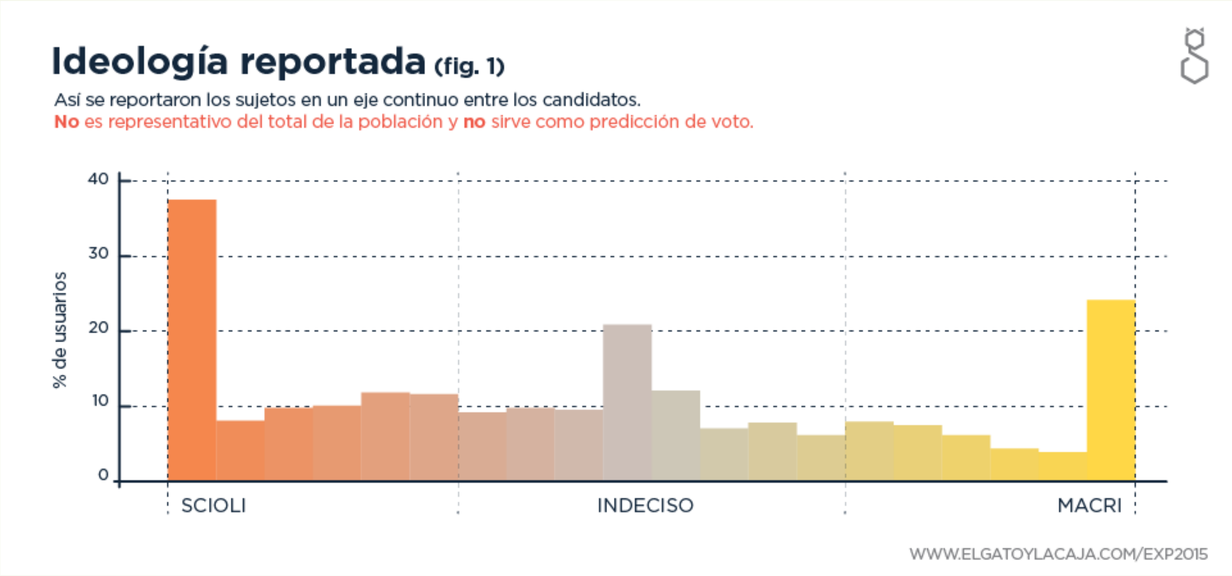
☯ These authors contributed equally to this work.
* balen@df.uba.ar

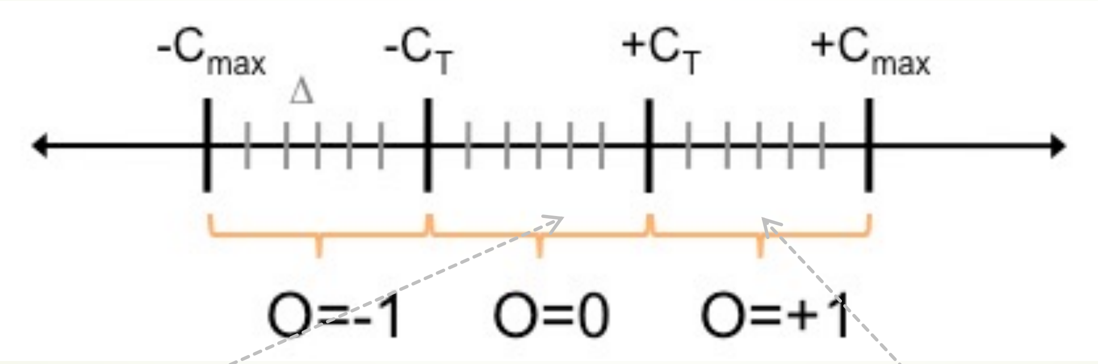
CrossMark
click for updates

Detailed Ingredients

- We place the agents in a linear scale, represented by a variable called C which represent the leaning between two extremes.
- Given a situation in which each agent should define his/her opinion, we choose a three options scenario: pro O=+1), against (O=-1), undecided or centrist(O=0)
- The agents can change their opinions by interaction with other agents.
- We assume that during interactions, agents are no exposed to the influence of an external source of information (MM).
- We assume that the interaction process is given by an interchange of arguments. This process leads to change the leaning of the agent in the discussed issue (represented by the variable C) because new information is incorporate by each agent.
- The process of opinion change is then cumulative and depending on a threshold. This threshold could represent the amount of information needed by an individual to adopt one of the opposing opinion.

Description





-hm.. (?)
It could be but I don't know

(O=0, C=0.5)

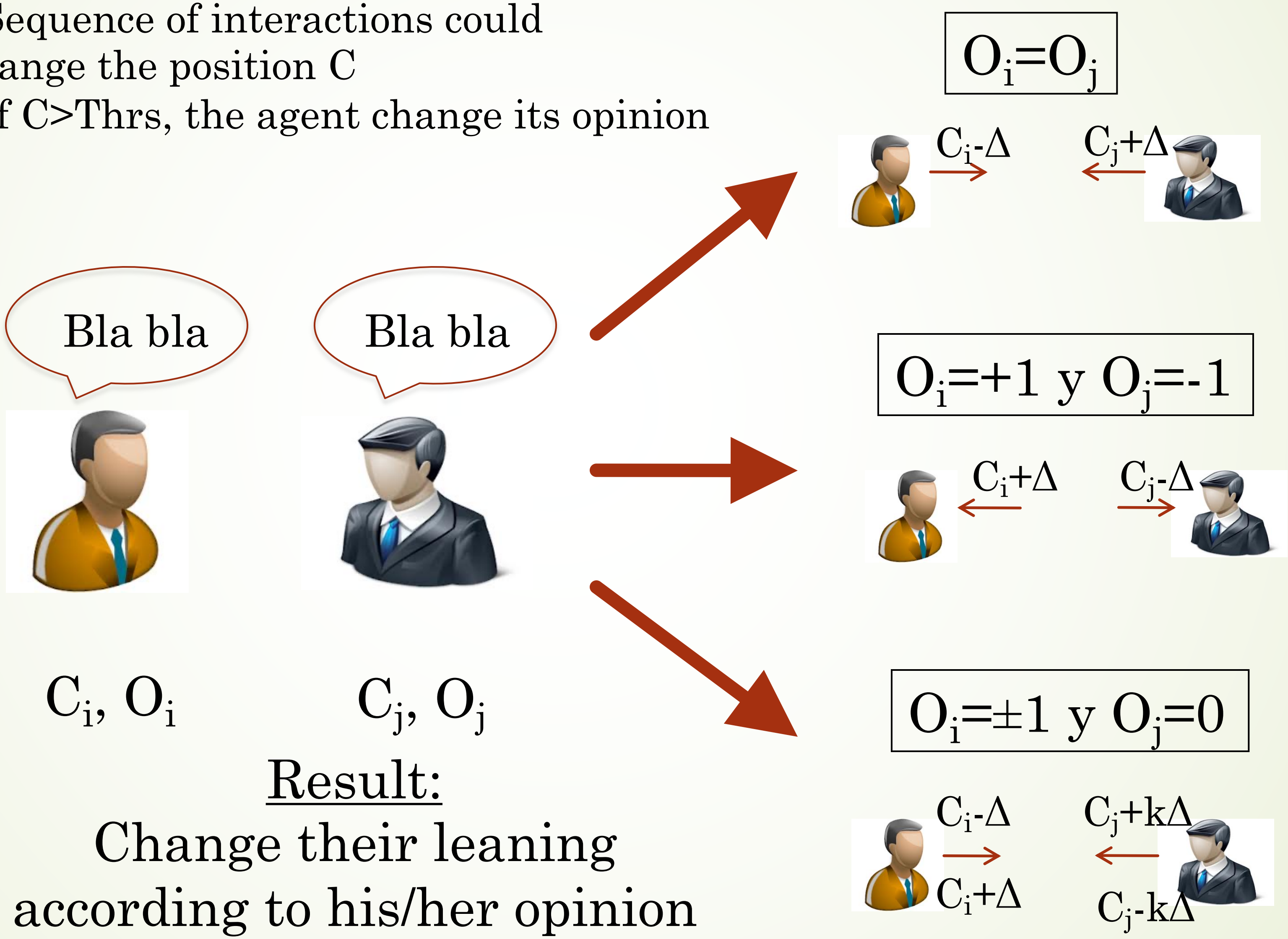
-Yes!!
I don't have any doubts

(O=+1, C=2.9)

Dynamics

Interactions

- Sequence of interactions could change the position C
- If C>Thrs, the agent change its opinion



<u>Result:</u>

Change their leaning according to his/her opinion

Phase Diagram: Stationary states as a function of P_0 y Δ

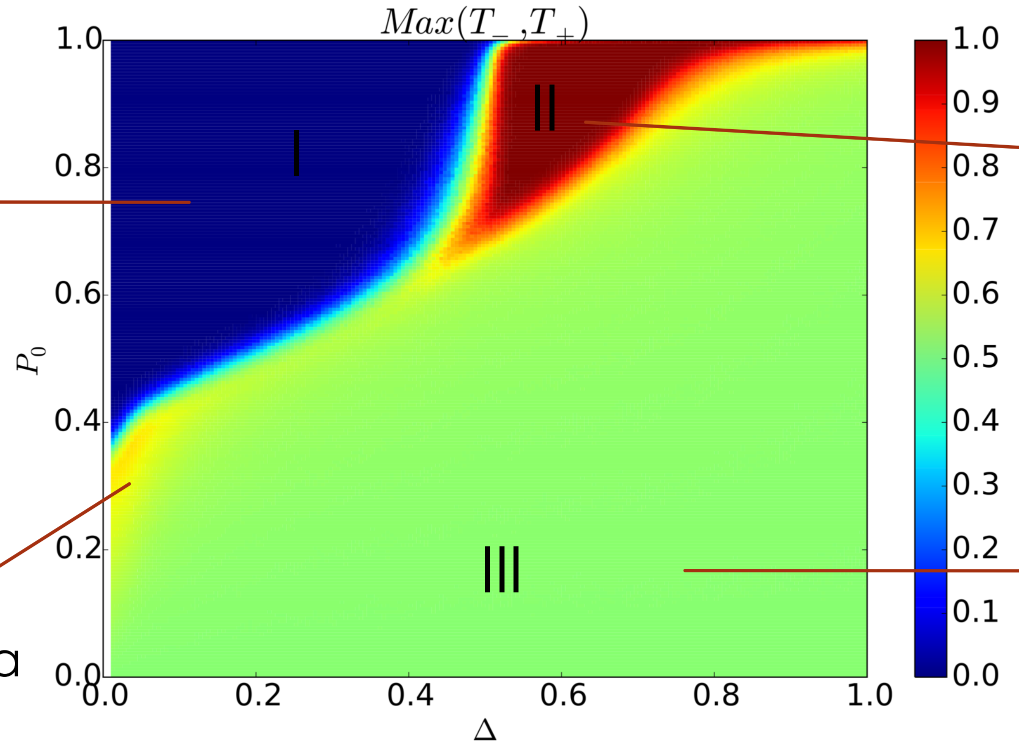
P_0: Fraction of Initial Undecided agents
Δ: Sensitivity to interaction

4 possible stationary states

- ✓ (I) Convergence on undecided
- ✓ (II) Opinion consensus +1/-1
- ✓ (III) Polarization

All undecided

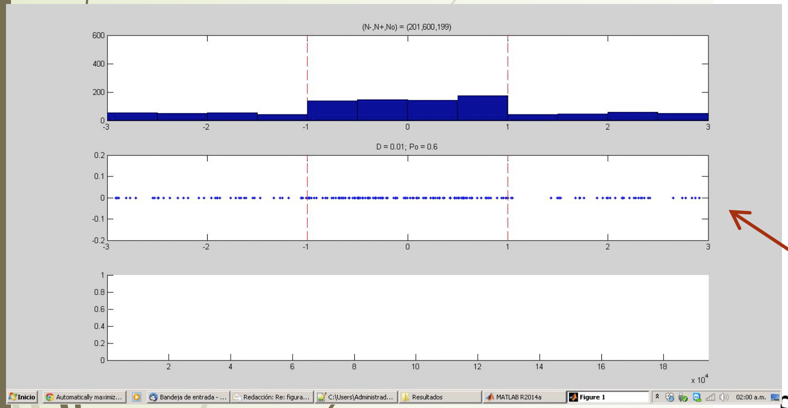
Consensus of a single opinion

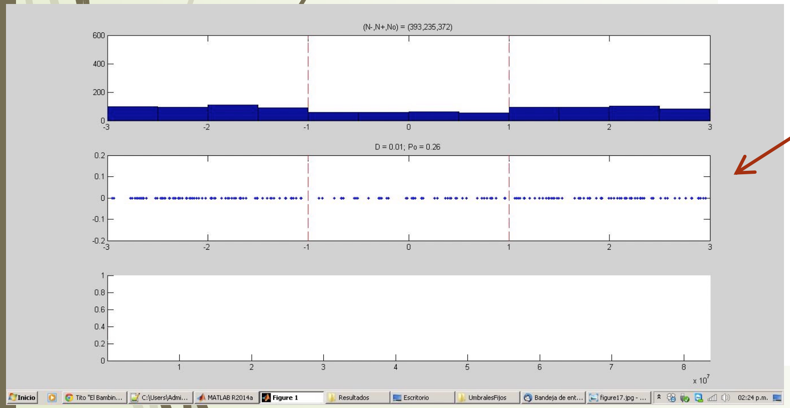


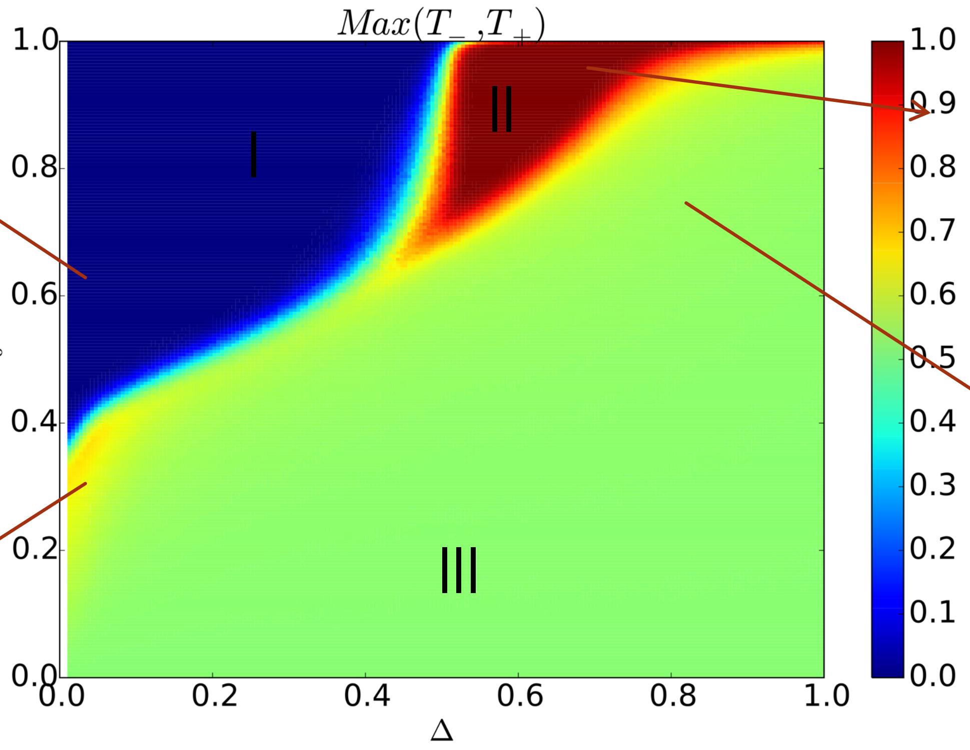
Bipolarization with a dominant opinion

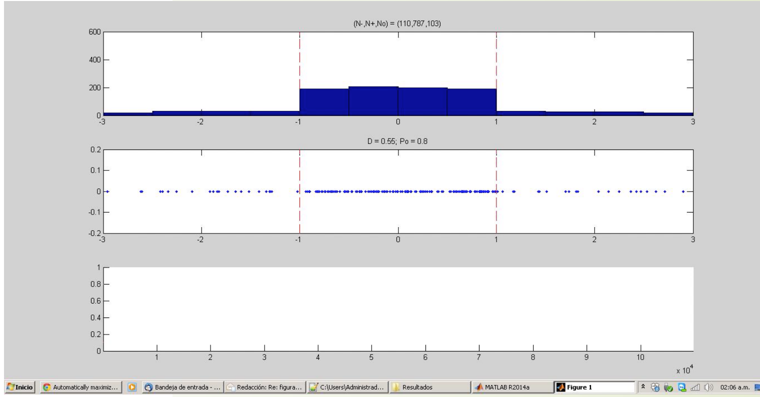
Bipolarization without a dominant opinion

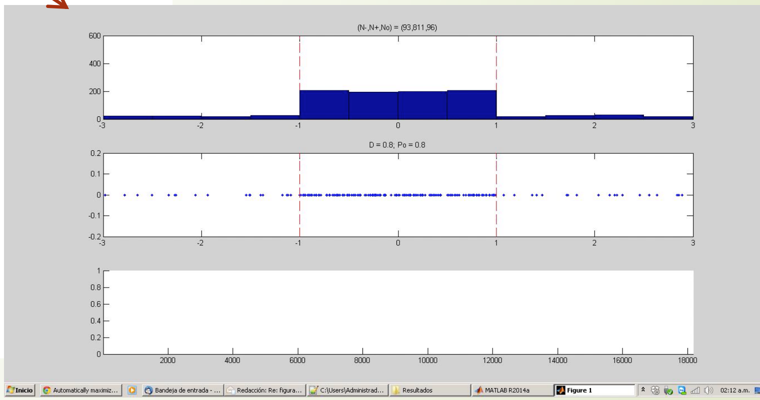
Dynamics for representative values of P_0 y Δ





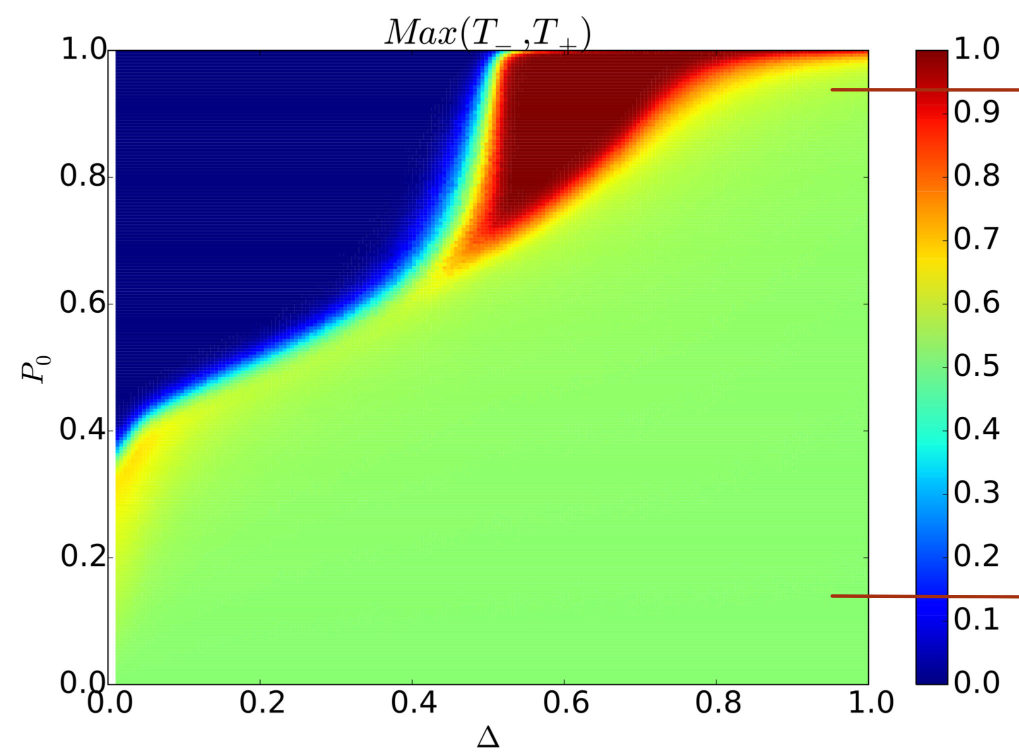






Videos from G. Pasqualetti

Observations



Larger values of P_0:
3 possible states

Typical scenario for low information situations:
E.g.: Fracking discussion o College Decision

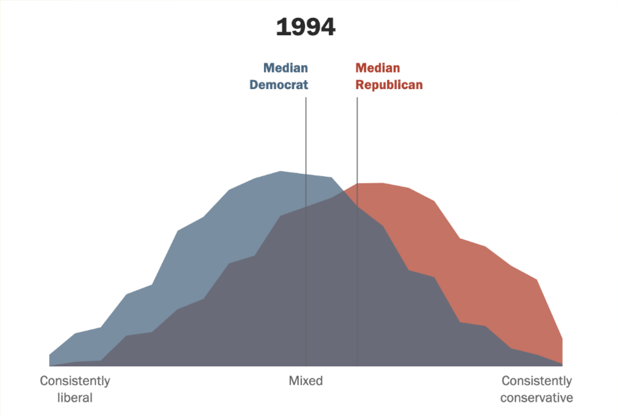
Low values of P_0:
Only bipolarization

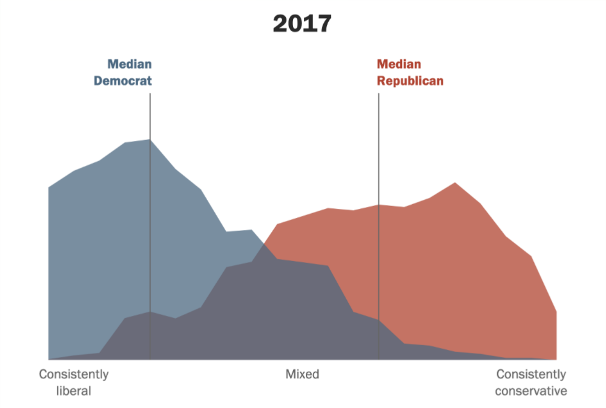
Typical scenario for political elections with two candidates (10-15% of undecided)

It is possible to change any feature of the model in order to increase the diversity of collective states in the low undecided agent's regime?

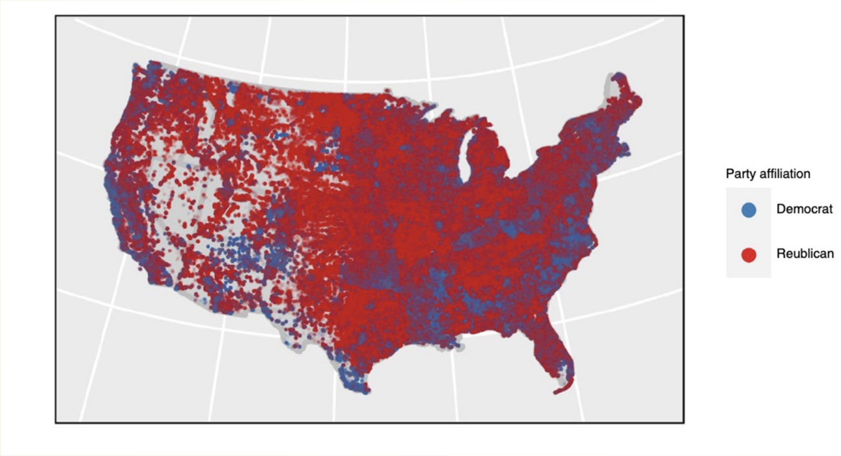
Political Polarization & Echo Chambers

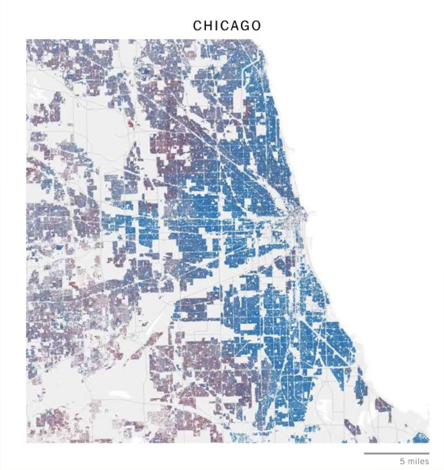
Political polarization is a growing phenomenon worldwide and leads to extremes of **segregation** by **ideological affinity**.





https://www.pewresearch.org/politics/interactives/political-polarization-1994-2017/





Political Polarization on Twitter

Political Polarization on Twitter

M. D. Conover, J. Ratkiewicz, M. Francisco, B. Gonçalves, A. Flammini, F. Menczer
Center for Complex Networks and Systems Research
School of Informatics and Computing
Indiana University, Bloomington, IN, USA

45.000 nodos totales
23.800 no aislados
18.300 en la componente gigante

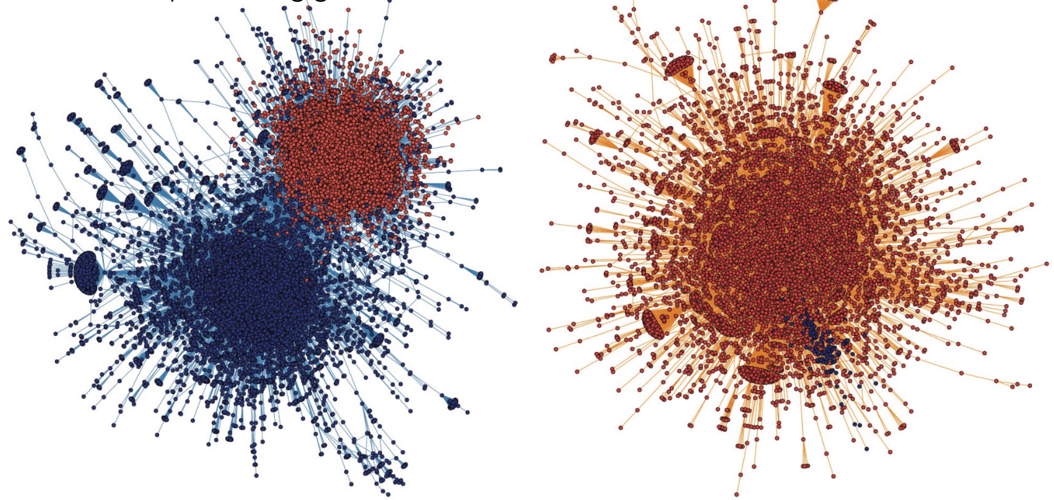


Figure 1: The political retweet (left) and mention (right) networks, laid out using a force-directed algorithm. Node colors reflect cluster assignments (see § 3.1). Community structure is evident in the retweet network, but less so in the mention network. We show in § 3.3 that in the retweet network, the red cluster A is made of 93% right-leaning users, while the blue cluster B is made of 80% left-leaning users.

- US midterm elections
- Use hashtags with political content to select tweets
- Measure content homogeneity (from cosine distance of hashtags vector)
- Measure political polarization (by hand)

Retweet's network

Highly modular structure.
Two homogeneous communities (political left and right).

Mention´s Network

It does not exhibit this type of political segregation, users are exposed to individuals and information that they probably would not have chosen beforehand.

Proceedings of the Fifth International AAAI Conference on Weblogs and Social Media (2011)

Echo chambers in social media

The echo chamber effect on social media

Matteo Cinelli[a], Gianmarco De Francisci Morales[b], Alessandro Galeazzi[c], Walter Quattrociocchi[d,1], and Michele Starnini[b]

[a]Department of Environmental Sciences, Informatics and Statistics, Ca'Foscari Univerity of Venice, 30172 Venice, Italy; [b]Institute for Scientific Interchange (ISI) Foundation, 10126 Torino, Italy; [c]Department of Information Engineering, University of Brescia, 25123 Brescia, Italy; and [d]Department of Computer Science, Sapienza University of Rome, 00185 Rome, Italy

Twitter: Gun Control / Obamacare / Abortion
Facebook: Pro / Anti Vaccines

They characterize echo chambers with observables that can be quantified and empirically measured:
1 – Leaning toward a specific topic
2 – Structure of social interactions

x_i= They infer individual leaning of a user $x_i \in [-1,+1]$ by averaging the news organizations' scores linked by user i

x^N_i= neighbor´s average leaning

Modeling echo chambers

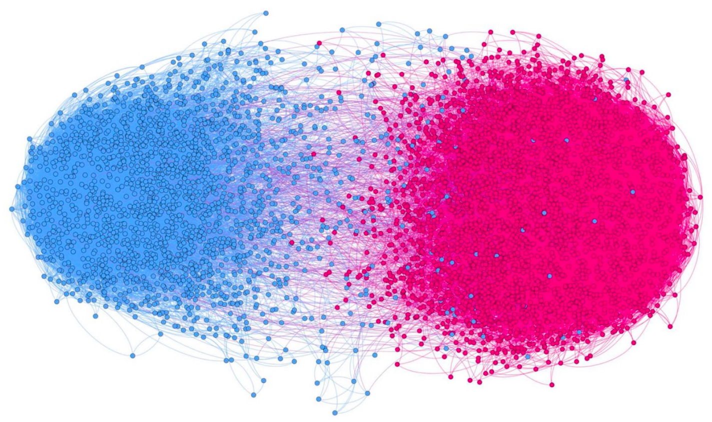

Journal of Computational Social Science (2021) 4:381–402 383

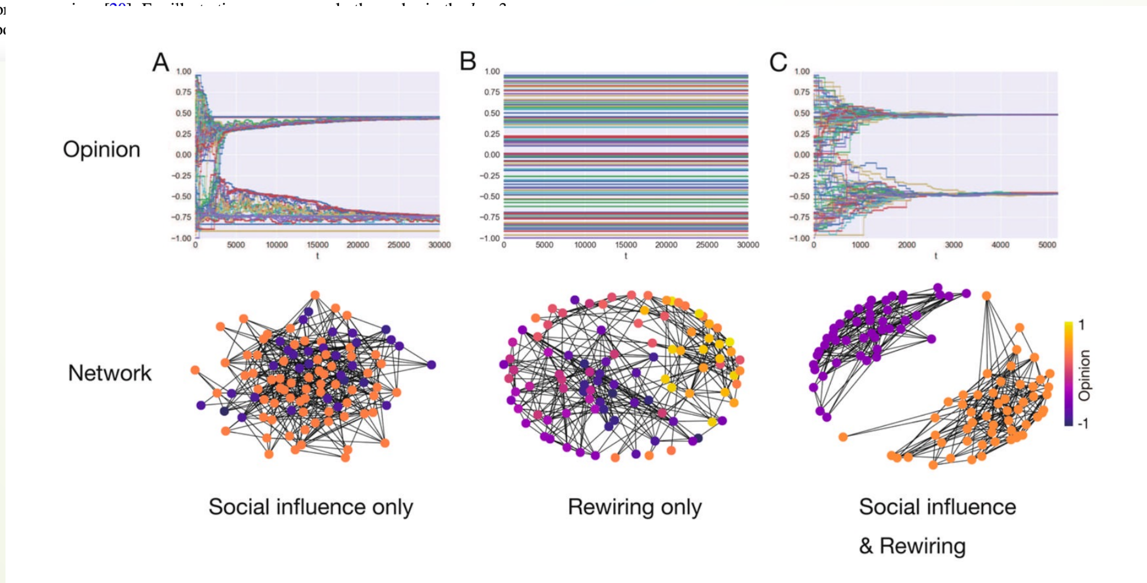
Fig. 1 Example of a polarized and segregated network on Twitter. The network visualizes retweets of political hashtags from the 2010 US midterm elections. The nodes represent Twitter users and there is a directed edge from node i to node j if user j retweeted user i. Colors represent political preference: red for conservatives and blue fo[…]
are visualized. See Metho[…]

Model with Bounded Confidence + rewiring

$$o_i(t+1) = o_i(t) + \mu \frac{\sum_{j=1}^{l} I_\epsilon(o_i(t), m_j)(m_j - o_i(t))}{\sum_{j=1}^{l} I_\epsilon(o_i(t), m_j)}, \quad (1)$$

where μ is an influence strength parameter, the sum runs over the messages in i's screen, and I_ϵ is an indicator function for concordant opinions based on the confidence bound ϵ:

$$I_\epsilon(o, m) = \begin{cases} 1 & \text{if } |o - m| < \epsilon \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$



Sasahara et al, Journal of Computational Social Science (2021) 4:381–402

Conclusions

- It implements an original dynamic of the opinion formation process as a cumulative threshold process. The opinion of each subject can change due to the constant interactions with their peers.
- The model presents consensus and polarization solutions for different values of the relevant parameters
- On going: Social experiments

Summary

- We have seen different models where individual opinions is represented with a continuous variable in a finite interval
- We have seen mechanism as bounded confidence, negative influence, persuasive arguments and threshold cumulative information.
- Polarization appears in model and data
- How to develop data-driven models?

See you next class!!