Chapter 14

Diffusion: Opinion Dynamics

Summary

- Modeling Opinions
- Polarization, Fragmentation, Bias
- Modeling Algorithmic Bias
- Opinions and Topology

Reading

- “Opinion dynamics: models, extensions and external effects.” Sirbu et al.

Modelling Opinions

Opinion Dynamics

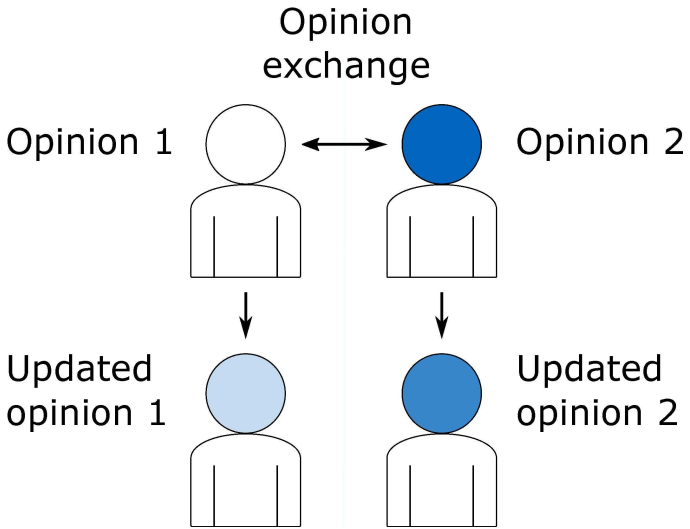
Model evolution of opinions in a population

Opinions are at the base of human behaviour

- understand behaviour - which mechanisms are important?
- trigger changes in behaviour ~ intervention methods in spreading, less explored

Broadly part of complex contagion modelling: peer effects through social network.

Simple representations of opinions - one variable.

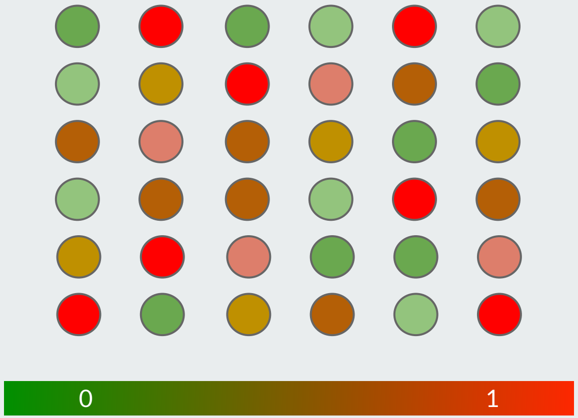


Opinions

Continuous

Individual status is identified by a (bounded) real value:

- e.g., opinions, beliefs,...

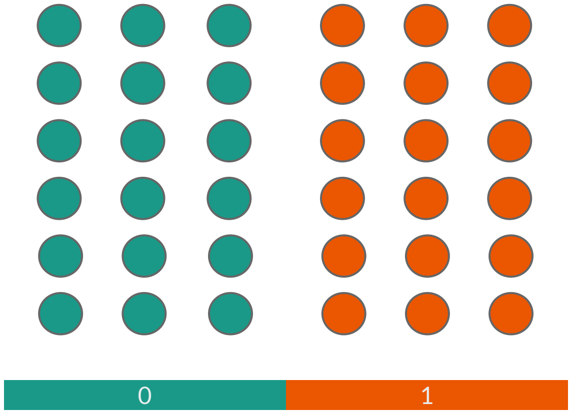


Opinions

Discrete

Individual status is identified by a discrete value:

- e.g., political party affiliation...



Sîrbu, Alina, et al. *"Opinion dynamics: models, extensions and external effects."* Participatory sensing, opinions and collective awareness. (2017).

Models

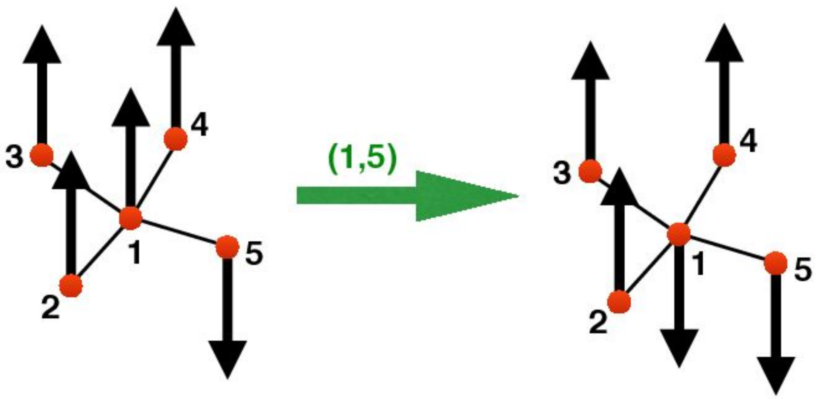
Voter

Originally introduced to analyse competition of species, then applied to electoral competitions.

Discrete opinions: {-1, 1}

Iteration:

- A random agent i is selected with one of its neighbors j
- i takes j's opinion



R. Holley and T. Liggett, *"Ergodic theorems for weakly interacting infinite systems and the voter model,"* Ann. Probab., (1975).

Models

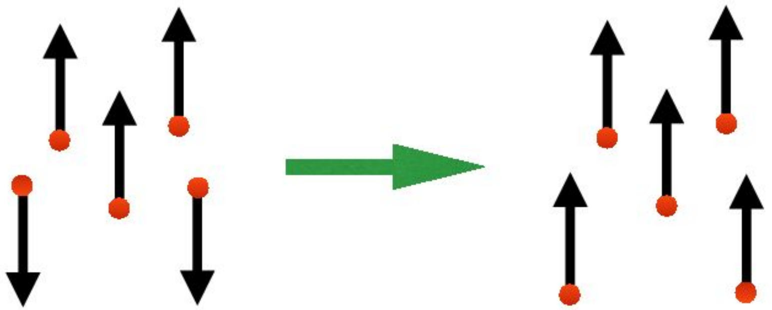
Majority Rule

Originally introduced to describe public debates
(e.g., global warming, H1N1 pandemic).

Discrete opinions: {-1, 1}

Iteration:
- A random group of r agents is selected
- The agents take the majority opinion within the group

r odd: majority always exists
r even: possibility of tied configurations.
To address them, bias toward an opinion is introduced (social inertia)



S.Galam, *"Minority opinion spreading in random geometry."* Eur.Phys. J. B, (2002).
R.Friedman and M.Friedman, *"The Tyranny of the Status Quo."* Harcourt Brace Company (1984).

Models

Sznajd

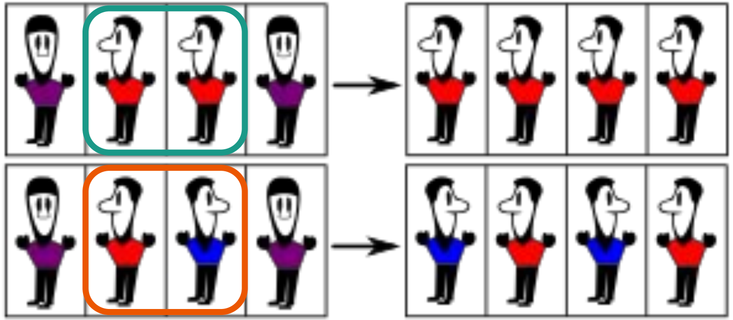
A group of individuals having the same opinion can influence their neighbors more than a single individual

Discrete opinions: {-1, 1}

Iteration:

- A random agent i is selected with one of its neighbors j
- if i and j opinions coincide all their neighbors take that opinion, otherwise the neighbors take contrasting opinions

The model converge to one of the two contrasting stationary states



Sznajd-Weron and J. Sznajd, *"Opinion evolution in closed community,"* International Journal of Modern Physics C, (2001).

Models

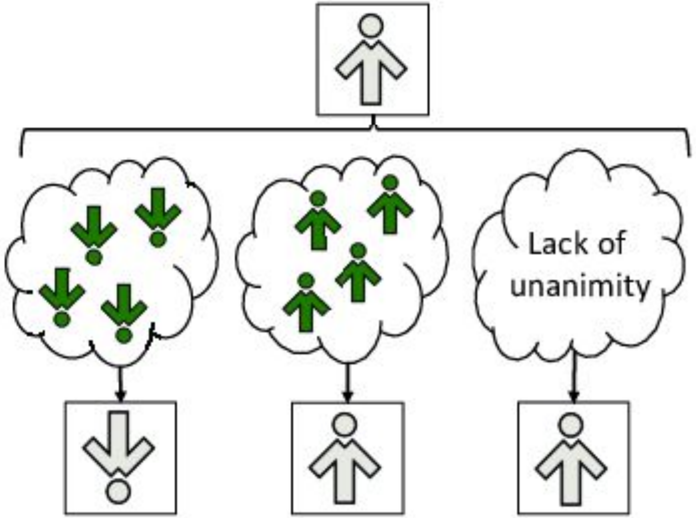
Q-Voter

Generalization of the Voter and Sznajd models

Discrete opinions: {-1, 1}

Iteration:

- q neighbours are chosen and, if they agree, they influence one neighbour chosen at random
- If the group does not agree, the agent flips its opinion with probability ε



C. Castellano, M. A. Munoz, and R. Pastor-Satorras, *"The non-linear q-voter model,"* Physical Review E, (2009).

Models

Deffuant Model

Simple model of opinion formation, with bounded confidence

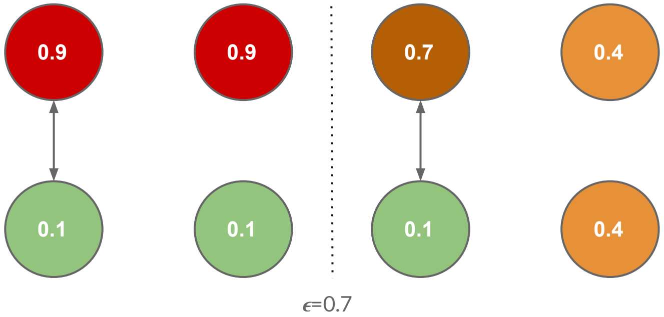
Opinions $x_i \in [0,1]$ (Continuous values)

Discrete time steps

Iteration:

Two random individuals interact with bounded confidence ϵ (open-mindness)

- $x_i(t+1) = x_j(t+1) = (x_i(t)+x_j(t))/2$
- only if $|x_i(t+1)-x_j(t+1)| < \epsilon$



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

Behaviour

Continuous

One or more clusters
(depending on the bounded confidence parameter.)

- Extreme information → segregation
- Mild information → consensus

Extensions:

- Noise, heterogeneous bounds of confidence → consensus
- Contrarians → fragmentation, extremism, agreement with external information

Behaviour

Discrete

Consensus on one of the two opinions

Questions:

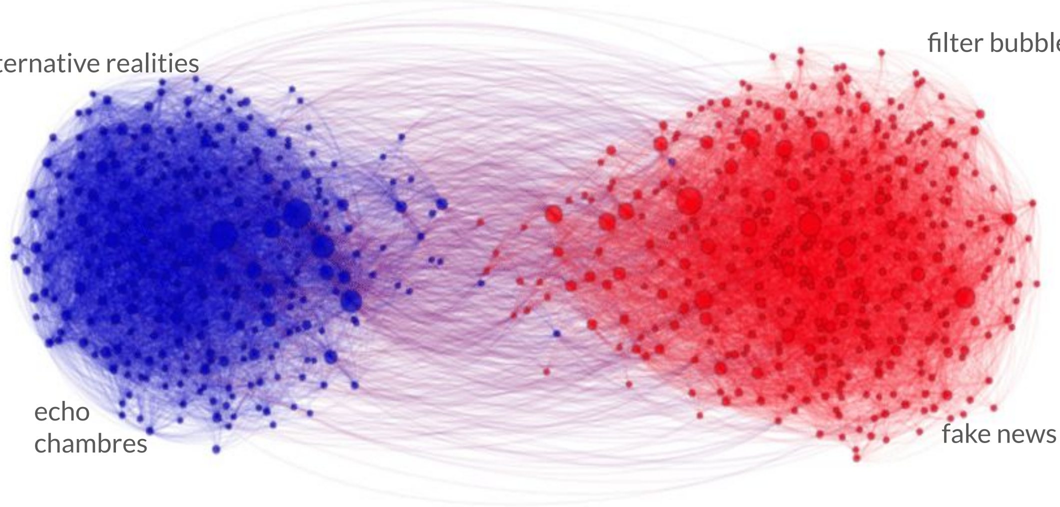
- Exit probability: prob. to obtain consensus on +1/-1
- Consensus time for a population of size N

Extensions:

- contrarians, inflexibles (zealots), independents (noise).
- Consensus breaks → clusters of opinion.

Polarization and Fragmentation in Social Media

Polarization of the public debate

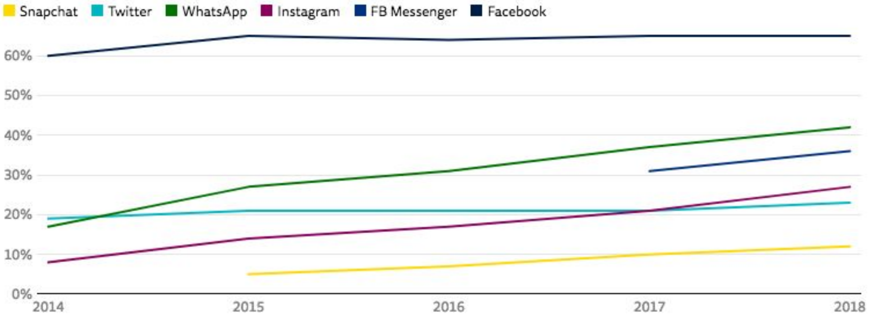


Adamic, Lada A., and Natalie Glance. *"The political blogosphere and the 2004 US election: divided they blog."* ACM (2005).

Online News Consumption

PROPORTION THAT USED EACH SOCIAL NETWORK FOR ANY PURPOSE IN THE LAST WEEK (2014–18)

Selected markets



Q12A. Which, if any, of the following have you used for any purpose in the last week?

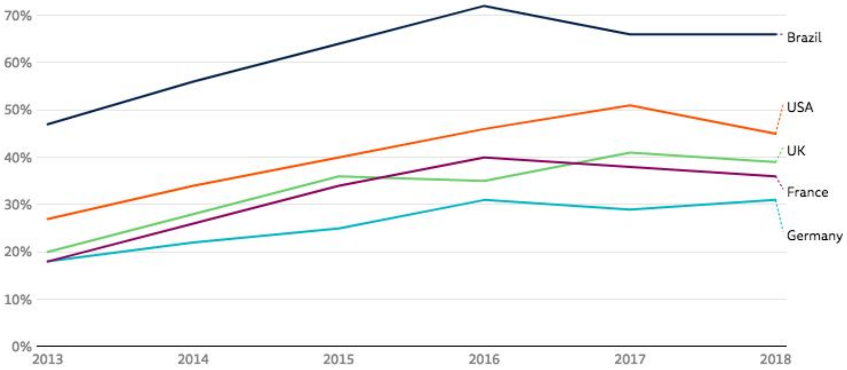
Base: Total sample across selected markets: 2014 = 18859, 2015 = 23557, 2016 = 24814, 2017 = 24487, 2018 = 24735.

Note: From 2015–18, the 12 markets included are UK, US, Germany, France, Spain, Italy, Ireland, Denmark, Finland, Japan, Australia, Brazil. In 2014, we did not poll in Australia or Ireland.

Get the data • Embed

PROPORTION THAT USED SOCIAL MEDIA AS A SOURCE OF NEWS IN THE LAST WEEK (2013–18)

Selected countries



Q3. Which, if any, of the following have you used in the last week as a source of news?

Base: Total 2013–2018 sample in each market.

Get the data • Embed

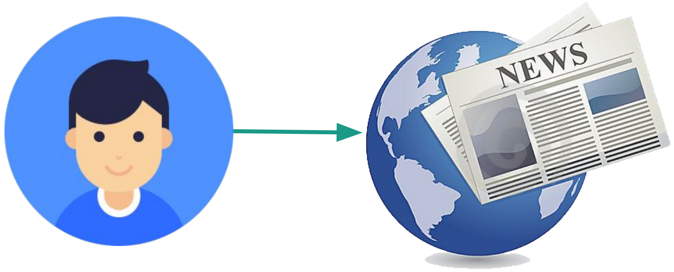
Online consumption of information

Interaction of

- *users*,
- with *media* content

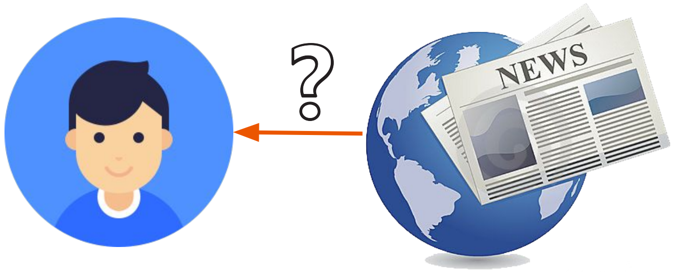
mediated by computer programs

1st scenario



Users actively search for news

2nd scenario



Users are passively fed of news

Online consumption of information

The aim of the computer programs is to maximise the usage of the platform

To fulfill such goal they carefully taylor the information shown to their users

Confirmation Bias
"[is the] tendency to search for, interpret, favor, and recall information in a way that ***confirms one's preexisting beliefs*** *or hypotheses."*

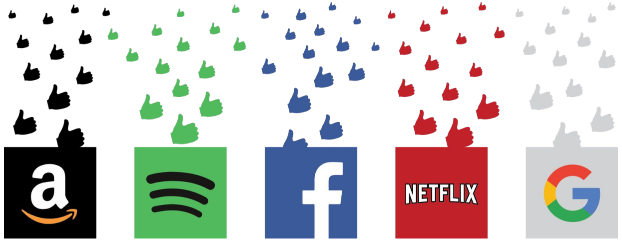
Recommender Systems

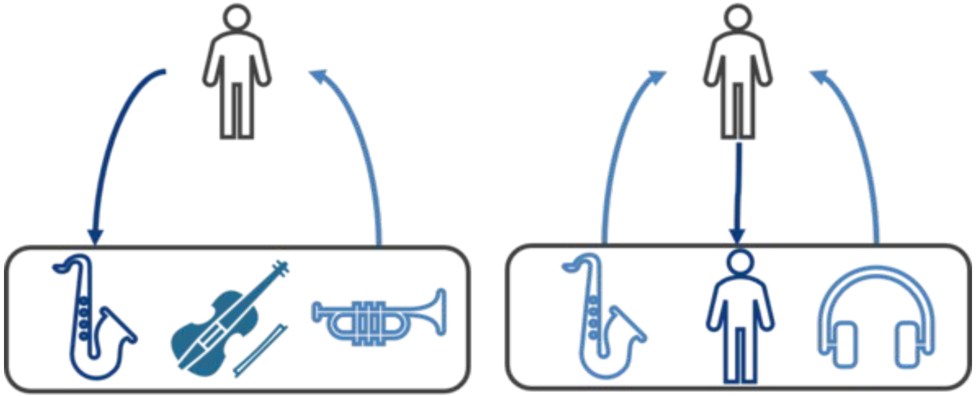
Leveraging user’s history

Recommendations are built on top of user’s past choices...

- type of news searched, product bought…

As well as on top of “similar” users’ ones





A product is recommended that is **similar to products** the customer has already looked at.

The customer is shown products that customers with **similar data profiles** have found interesting.

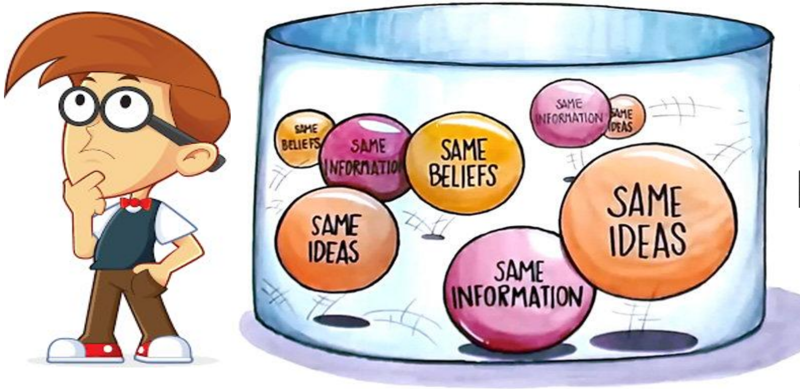
Online consumption of information

Users are mostly shown opinions that are close to their own (algorithmic bias)

- News about topics we like,
- Posts from close friends,
- ...

Users do not even get confronted with narratives different from their favorite ones

- or they get in contact with extreme opposite narratives



Modeling Algorithmic Bias

Models

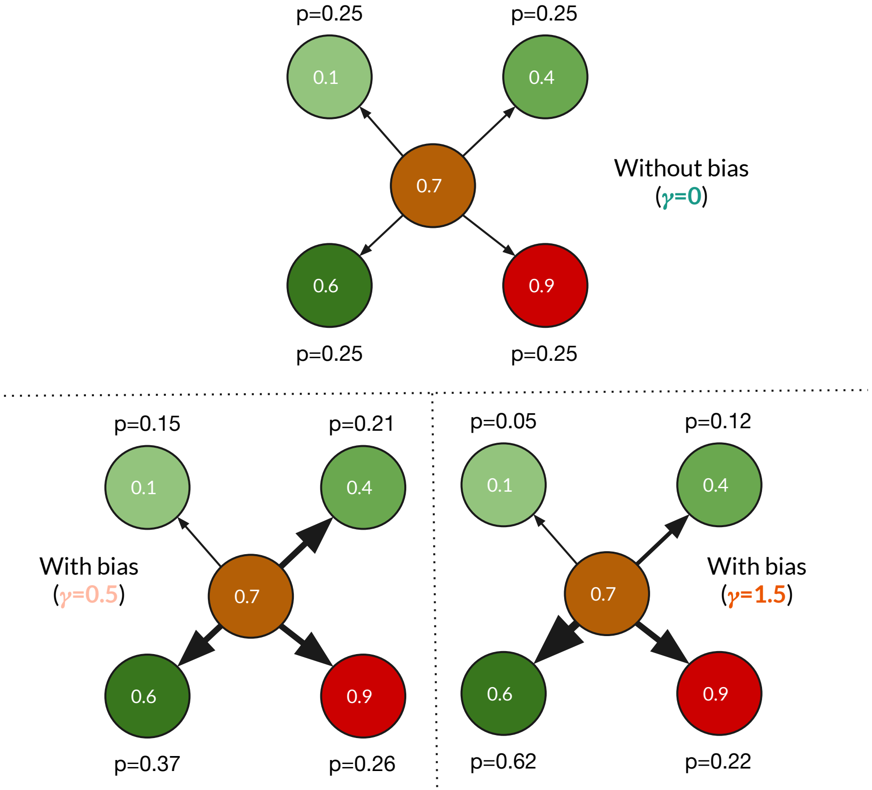
Algorithmic Bias

Modified Deffuant model

Probability to select interaction partner depends by
- the opinion distance, d_{ij}
- the bias strength, γ

$$p_i(j) = \frac{d_{ij}^{-\gamma}}{\sum_{k \neq i} d_{ik}^{-\gamma}}$$

The more similar the opinions, the more likely that the interaction will take place.



Sîrbu, Alina, et al. *"Algorithmic bias amplifies opinion fragmentation and polarization: A bounded confidence model." PloS One* (2019)

Deffuant

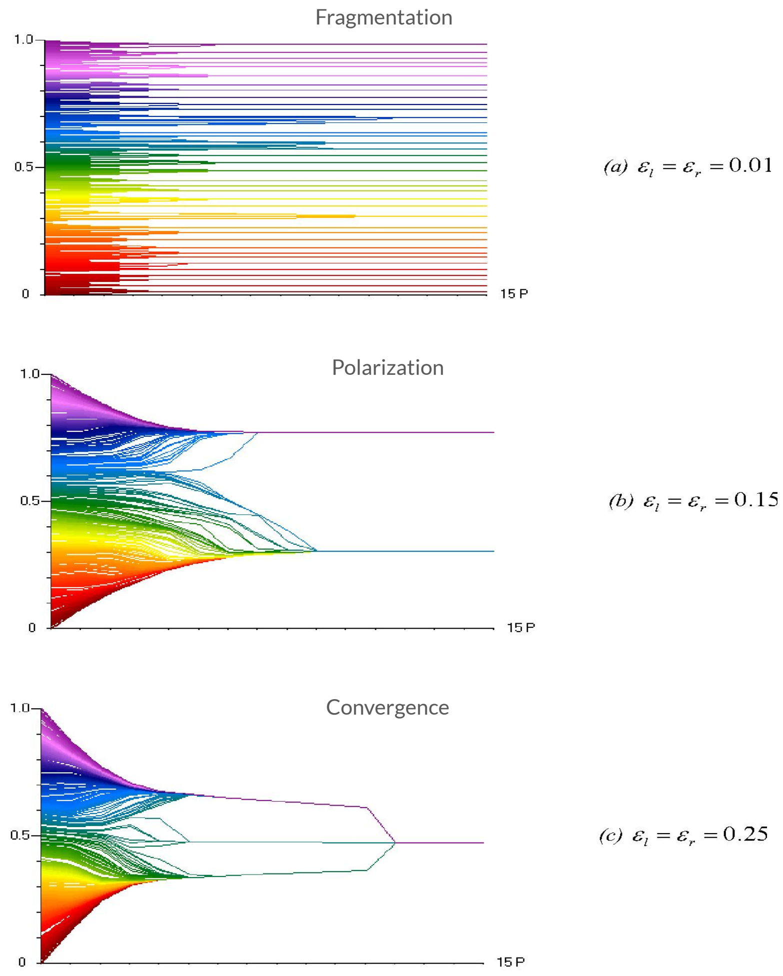
Simulations

Recap:

Reducing the bounded confidence threshold value opinion fragmentation (polarization) intensifies

Interpretation:

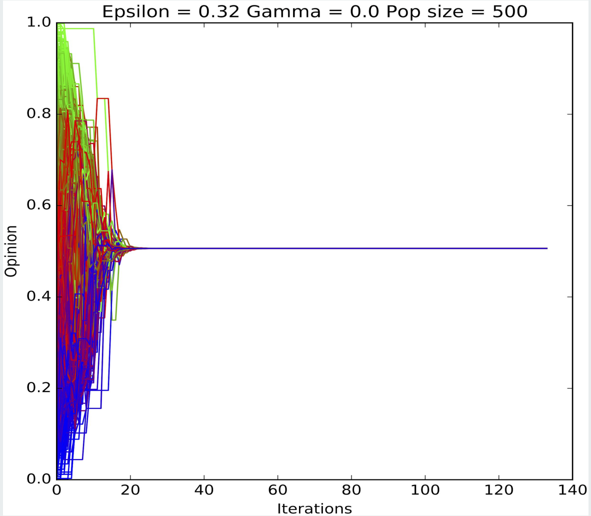
The larger the open-mindedness value, the more likely that consensus will be reached



Deffuant

Without Bias

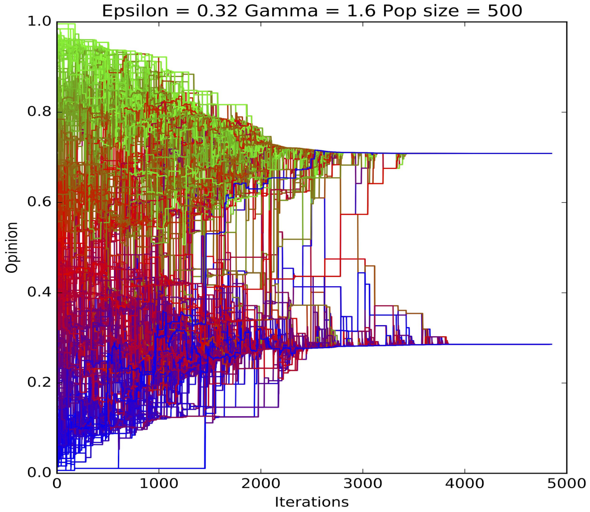
Convergence to common opinion



Deffuant

With Bias

Opinion Polarization, Fragmentation,
Convergence slow-down (instability)



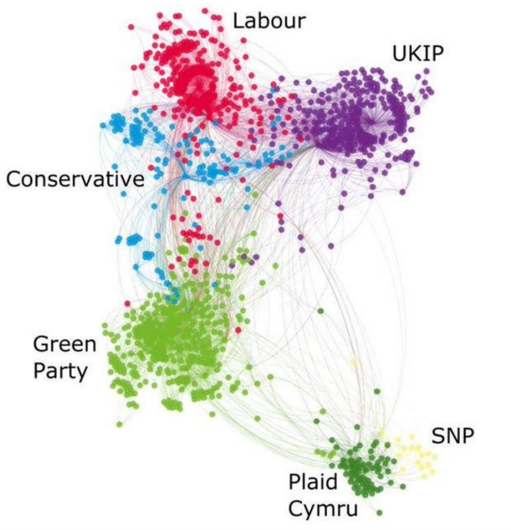
Algorithmic Bias

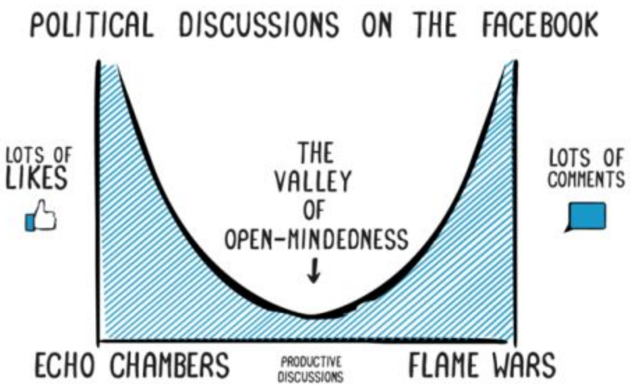
Is this the whole story?

Unfortunately, it is not.

The situation in reality is even worse

- Simulations performed in mean field
- The observed effects can be exacerbated by the topology of the social network





Social Tissue as Shaped By Opinions

A feedback loop model

Models

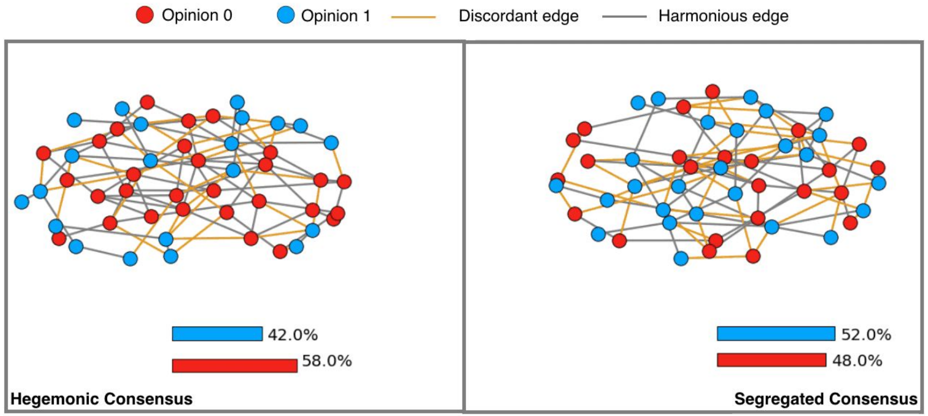
Co-Evolving Voter Model

Opinion dynamics may affect network topology

Discrete opinions: {-1, 1}

Iteration:

- A random agent **i** is selected with one of its neighbors **j**
- If they share the same opinion nothing happens. Otherwise,
  - with probability **p**:
    i detaches from j and attaches randomly to a node **z** that shares i's opinion;
  - with probability **1-p**:
    i adopts j's opinion



F. Vazquez, V.M. Eguíluz and M. San Miguel. *Generic absorbing transition in coevolution dynamics.* Phys. Rev. Lett., 2008).

Summarizing

Conclusion

Opinions, as well as viruses, are “objects” that spread over a social tissue.

Different assumptions on how they diffuse allow the design of (simplified and controllable) “what if” scenarios so to study specific social phenomena.

01	**Discrete Opinions**	• Voter, Q-Voter • Majority • Sznaid
02	**Continuous Opinions**	• Deffuant • Algorithmic Bias
03	**Dynamic On & Of**	• Co-Evolving Voter

Chapter 14

Conclusion

Take Away Messages

1. Opinions diffuse through social interactions
2. They can be modeled as continuous as well as discrete variables
3. Different models design adhoc “what if” scenarios that allow analyzing real phenomena

Suggested Readings

- “Algorithmic bias amplifies opinion fragmentation and polarization: A bounded confidence model." Sirbu et al.

What’s Next

Chapter 15: