



Modeling opinion dynamics under the impact of influencer and media strategies

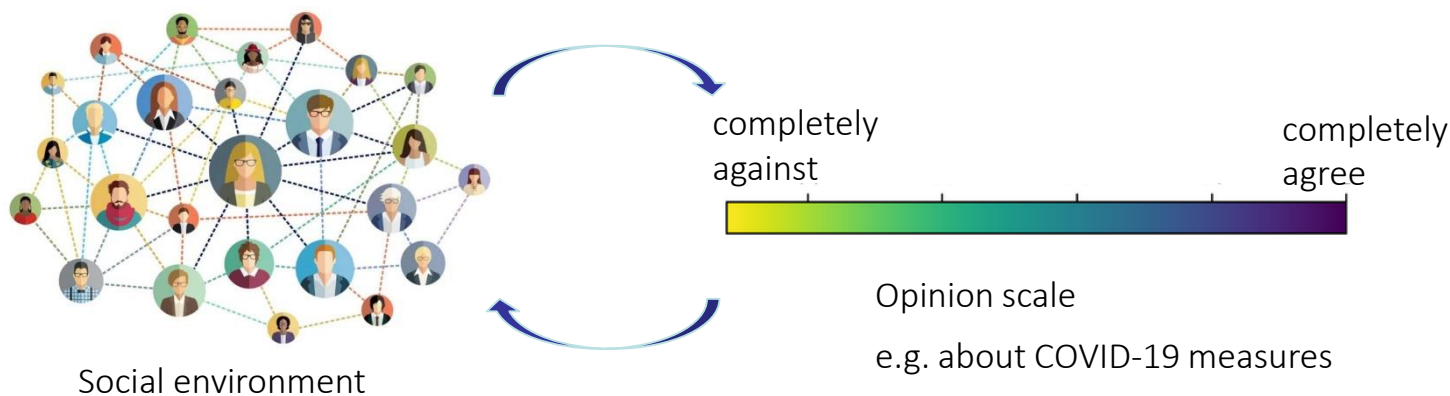
Nataša Djurdjevac Conrad
Zuse Institute Berlin

ASU/MATH+ Spring School
4.03.2024

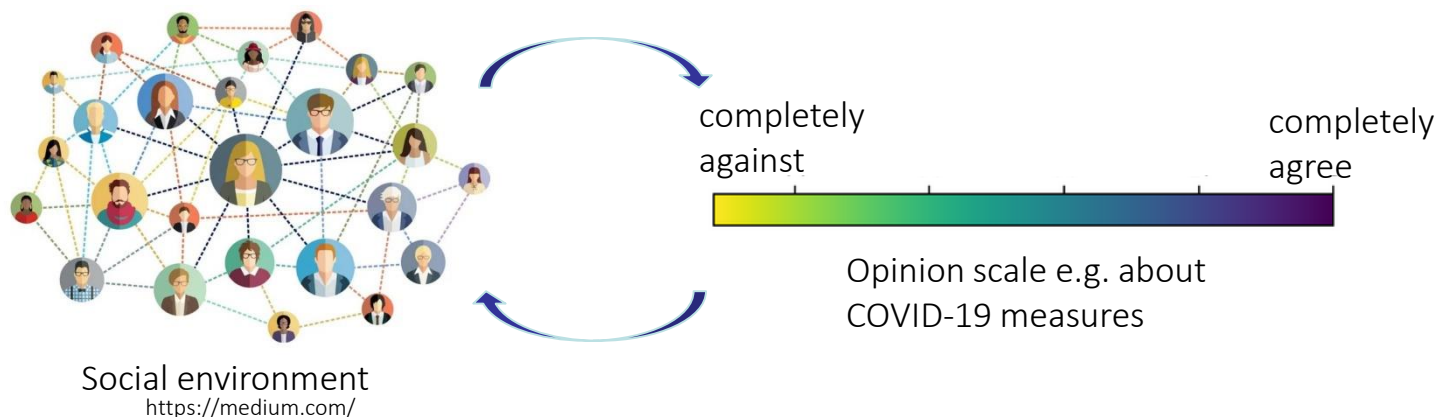
Understanding social&opinion dynamics

Main questions:

- How does our **social environment** influence our **opinion formation**?
- How do our **opinions** shape our **social environment**?

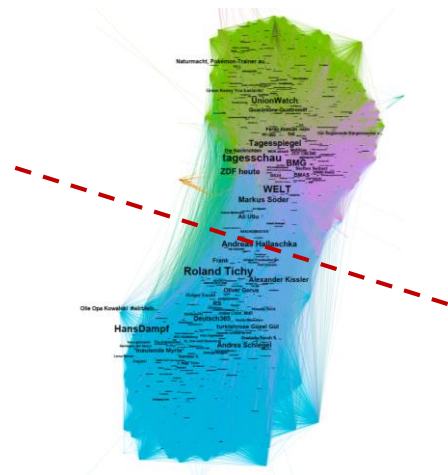


Understanding social&opinion dynamics



Application examples:

- understanding **online discourse** on e.g. COVID-19:
 - How do opinions (co)-evolve in a population?
 - How do different actors influence the opinion dynamics?
- studying **polarization** on e.g. the German Twitter:
 - Why/how/when does a society polarize?
 - Can polarization be prevented/reduced?



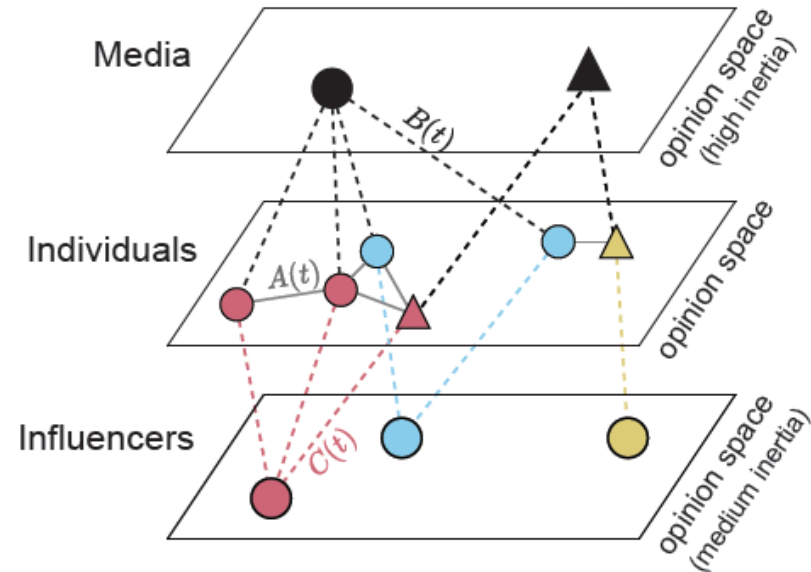
German retweet network (most active accounts)
keyword: "COVID", spring 2020, [Gidel, Lorenz-Spreen]

Modeling opinion dynamics under the impact of influencer and media strategies

Model features:

- ▶ Three types of agents:
 - ▶ individuals $i = 1, \dots, N$,
 - ▶ media $m = 1, \dots, M$,
 - ▶ influencers $l = 1, \dots, L$.

We assume $M < L \ll N$.

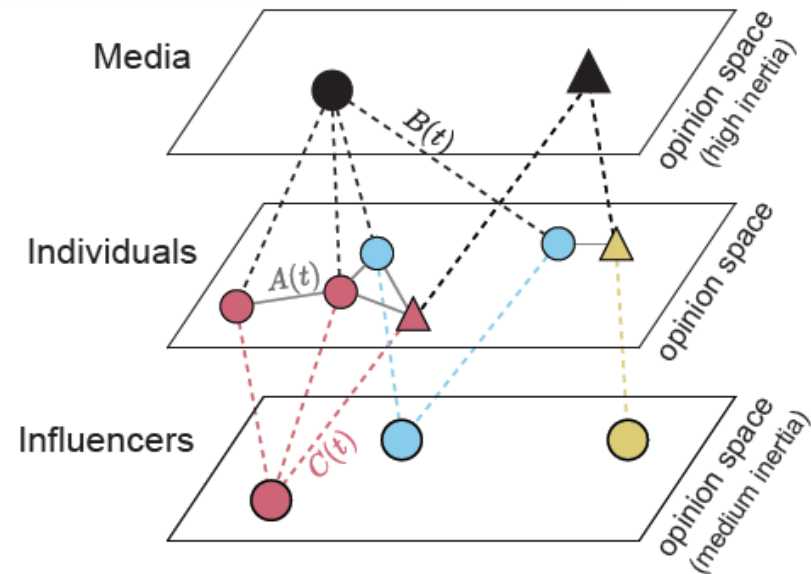


- ▶ Social environment at time t is given by social networks:
 - ▶ network between individuals $A(t) \in \{0, 1\}^{N \times N}$,
 - ▶ medium-follower network $B(t) \in \{0, 1\}^{N \times M}$,
 - ▶ influencer-follower network $C(t) \in \{0, 1\}^{N \times L}$.

Modeling opinion dynamics under the impact of influencer and media strategies

Original setting:

- A, B are constant in time;
- Each agent follows exactly 1 media and
- Each agent follows exactly 1 influencer.

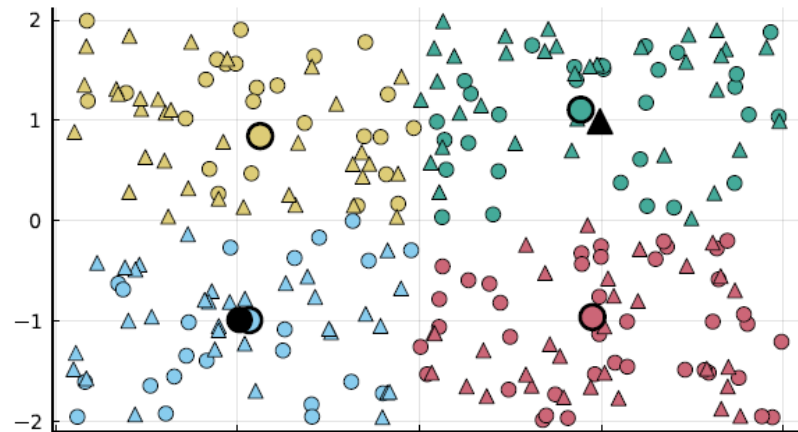


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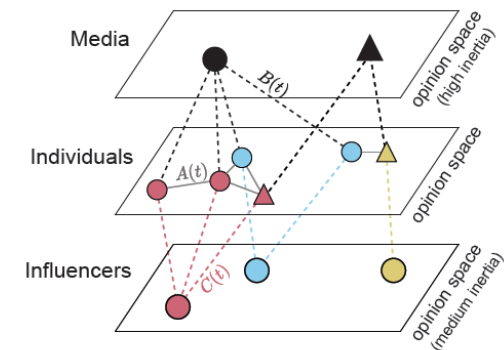
Modeling opinion dynamics under the impact of influencer and media strategies

- ▶ All agents have continuous opinions in an opinion space $D \subset \mathbb{R}^2$:

- ▶ opinions $x_i(t)$ of N individuals,
- ▶ opinions $y_m(t)$ of M media,
- ▶ opinions $z_l(t)$ of L influencers.



- ▶ Agents change their opinions on different time scales:
individuals (fast) - influencers, media (slow)
influencers (γ) - media ($\gamma < \Gamma$).



Modeling opinion dynamics

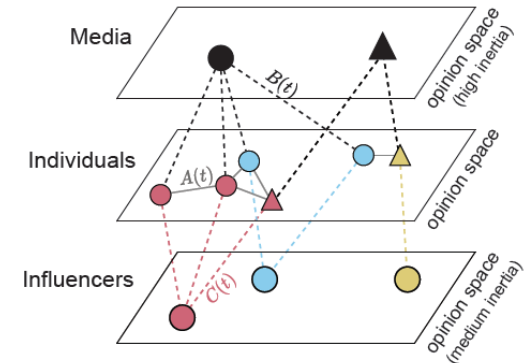
Opinion changes of individuals:

- ▶ opinion change of individual i given by

$$\frac{dx_i}{dt}(t) = \underbrace{F_i(x, y, z)}_{\text{interaction force on } i} + \underbrace{\sigma \frac{dW_i}{dt}(t)}_{\text{noise}}$$

- ▶ with (attractive) interaction force on individual i

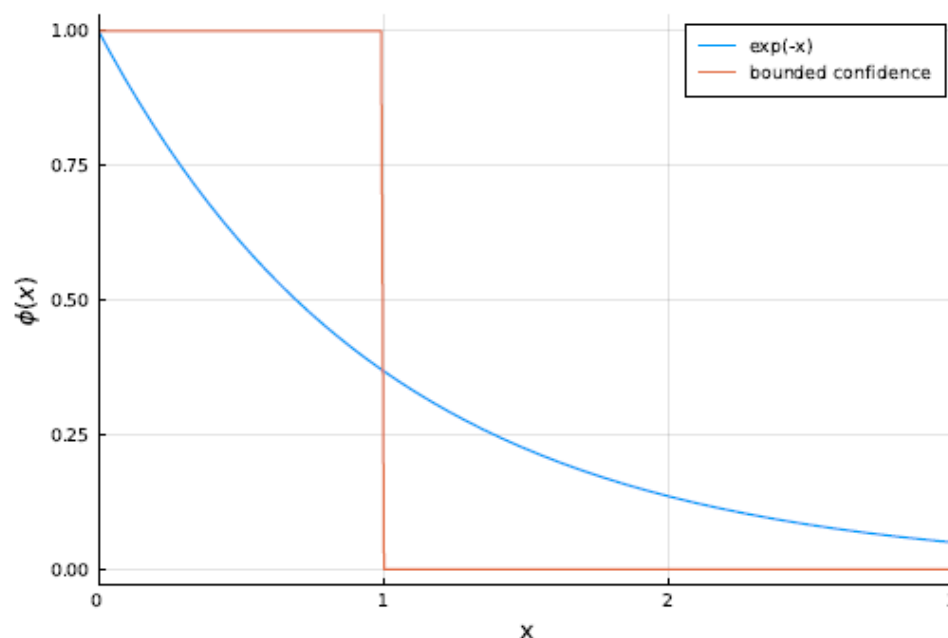
$$\begin{aligned} F_i(x, y, z) = & a \sum_{j=1}^N \frac{A_{ij}}{Z_i} \phi(|x_j(t) - x_i(t)|) (x_j(t) - x_i(t)) \\ & + b \sum_{m=1}^M B_{im} (y_m(t) - x_i(t)) \\ & + c \sum_{l=1}^L C_{il}(t) (z_l(t) - x_i(t)). \end{aligned}$$



Pairwise interaction function

possible pair functions $\phi(|x_j(t) - x_i(t)|)$:

- ▶ $\phi(x) = \exp(-x)$ (exponentially decaying in distance)
- ▶ $\phi(x) = 1_{[0,d]}(x)$ (bounded confidence)
- ▶ $\phi(x) = 1$ (DeGroot model)



Modeling opinion dynamics

Opinion changes of individuals:

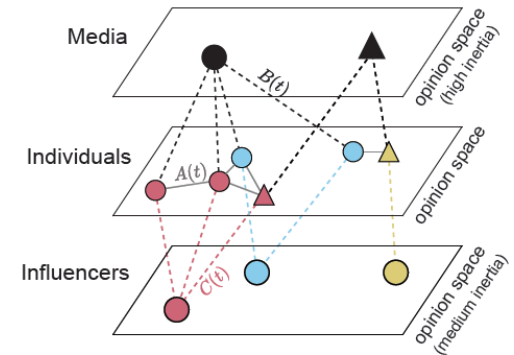
$$\frac{dx_i}{dt}(t) = \underbrace{F_i(x, y, z)}_{\text{interaction force on } i} + \underbrace{\sigma \frac{dW_i}{dt}(t)}_{\text{noise}}$$

Opinion changes of media:

$$\Gamma dy_m(t) = f(\tilde{x}_m(t) - y_m(t))dt + \tilde{\sigma} d\tilde{W}_m(t),$$

where the force function f can be used to model nonlinear influence effects but is set to $f(x) = x$ subsequently, i.e., media agents are drawn in the direction of the average opinion of their followers

$$\tilde{x}_m(t) = \frac{1}{\sum_k B_{km}(t)} \sum_{i=1}^N B_{im}(t) x_i(t).$$



Note: media and influencers adapt their opinions on a much slower timescale compared to individuals.

Modeling opinion dynamics

Opinion changes of individuals:

$$\frac{dx_i}{dt}(t) = \underbrace{F_i(x, y, z)}_{\text{interaction force on } i} + \underbrace{\sigma \frac{dW_i}{dt}(t)}_{\text{noise}}$$

Opinion changes of media:

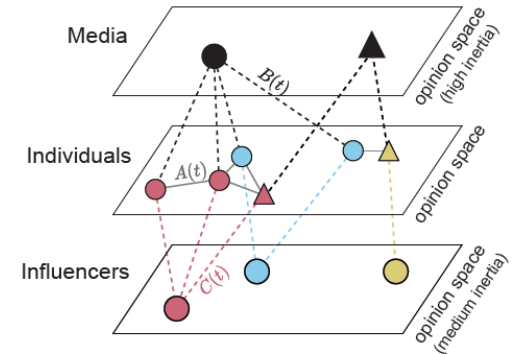
$$\underbrace{\Gamma}_{\text{resistance/inertia}} \frac{dy_m}{dt}(t) = \underbrace{\sum_{i=1}^N \frac{B_{im}}{\sum_k B_{km}} (x_i(t) - y_m(t))}_{\text{attraction force to average follower}} + \underbrace{\tilde{\sigma} \frac{d\tilde{W}_m}{dt}(t)}_{\text{noise}}$$

Opinion changes of influencers:

$$\gamma dz_l(t) = g(\hat{x}_l(t) - z_l(t))dt + \hat{\sigma} d\hat{W}_l(t),$$

where the average opinion of followers is given by

$$\hat{x}_l(t) = \frac{1}{\sum_k C_{kl}(t)} \sum_{i=1}^N C_{il}(t) x_i(t).$$



Note: media and influencers adapt their opinions on a much slower timescale compared to individuals.

Modeling opinion dynamics

Individuals:

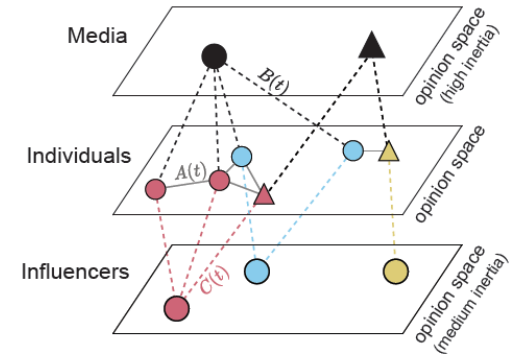
$$\frac{dx_i}{dt}(t) = \underbrace{F_i(x, y, z)}_{\text{interaction force on } i} + \underbrace{\sigma \frac{dW_i}{dt}(t)}_{\text{noise}}$$

Media:

$$\underbrace{\Gamma}_{\text{resistance/inertia}} \frac{dy_m}{dt}(t) = \underbrace{\sum_{i=1}^N \frac{B_{im}}{\sum_k B_{km}} (x_i(t) - y_m(t))}_{\text{attraction force to average follower}} + \underbrace{\tilde{\sigma} \frac{d\tilde{W}_m}{dt}(t)}_{\text{noise}}$$

Influencers:

$$\gamma \frac{dz_l}{dt}(t) = \sum_{i=1}^N \frac{C_{il}(t)}{\sum_k C_{kl}(t)} (x_i(t) - z_l(t)) + \hat{\sigma} \frac{d\hat{W}_l}{dt}(t)$$



How can individuals switch the influencer?

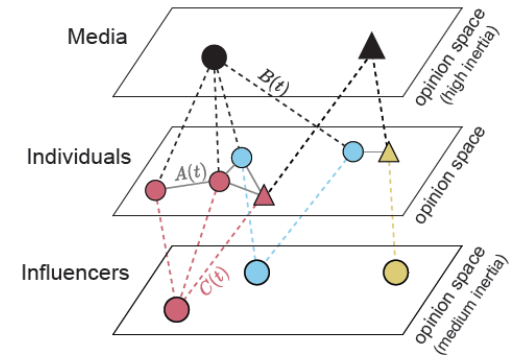
Each individual, following a media m , can at time t switch to influencer l with a given rate

$$\Lambda_m^{\rightarrow l}(x, t) = \eta \psi(|z_l - x|) r \left(\frac{n_{m,l}(t)}{\sum_{m'=1}^M n_{m',l}(t)} \right)$$

Scaling parameter

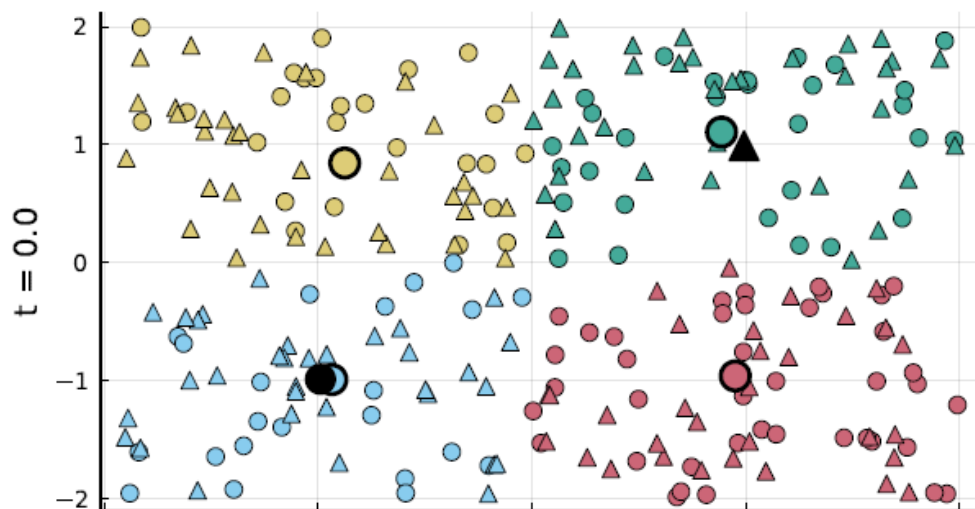
Influencer homophily: determines the rate of switching based on similarity of opinion z_l

Link recommendation function: individuals have a higher chance of switching to an influencer with a structurally similar followership



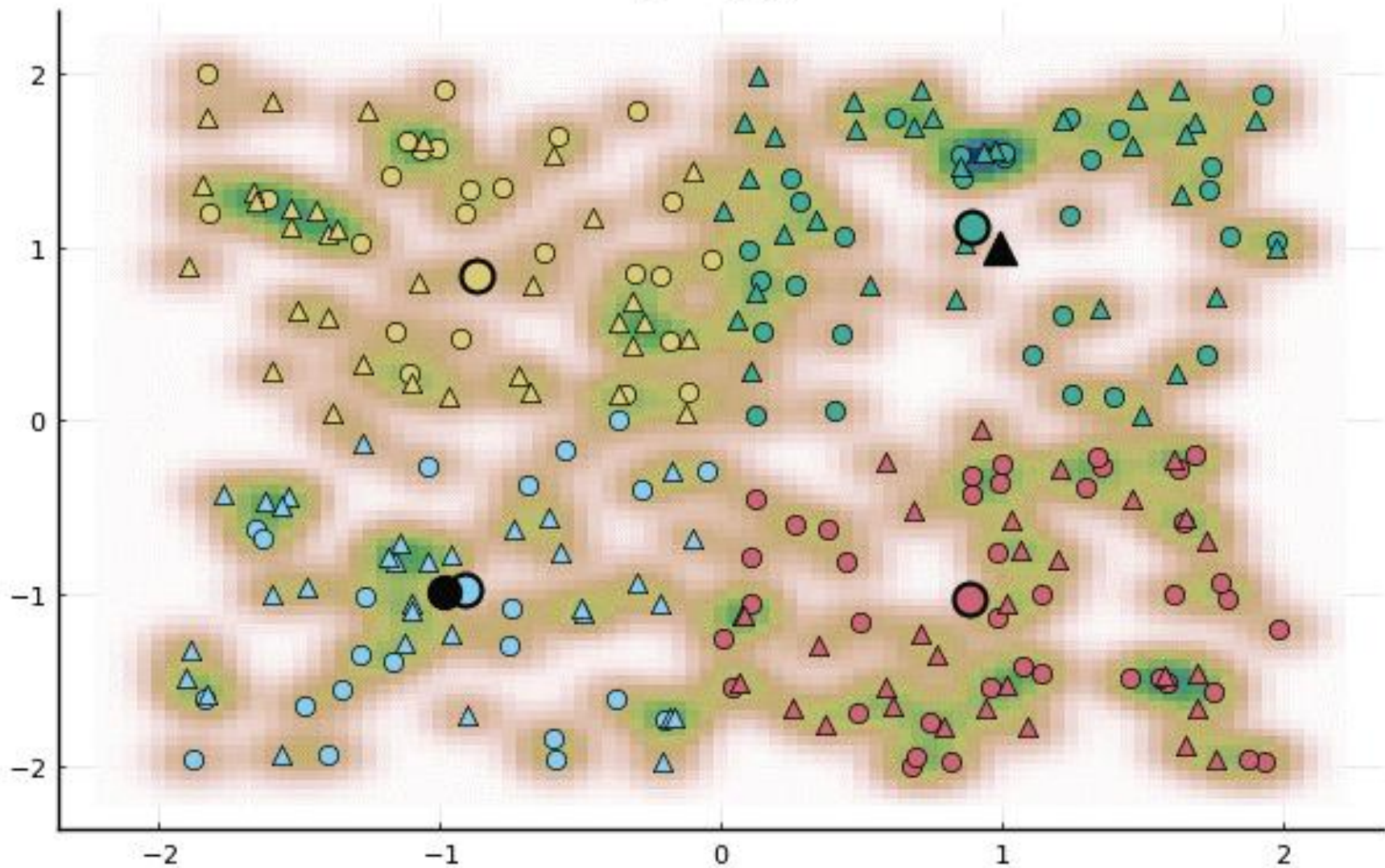
Example:

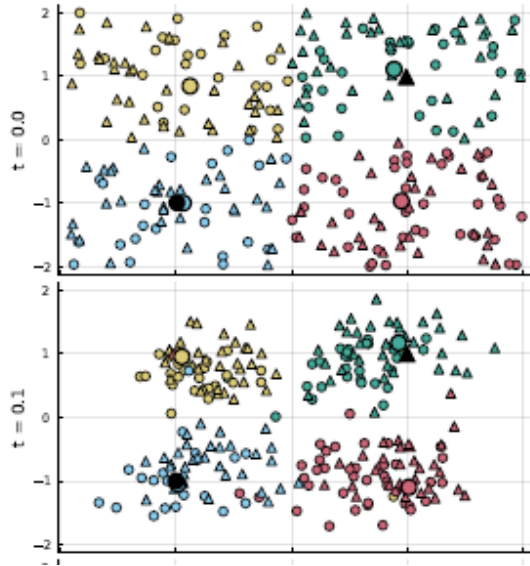
- 250 individuals, 2 media and 4 influencers.
- Initially individuals are **randomly distributed in opinion space** and uniformly at **random assigned to the 2 media**.
- The network A is **fully-connected**.
- Individuals in each of the 4 quadrants are **assigned to a different influencer**.
- Initial opinion of the influencer is set to the mean opinion of its followers.



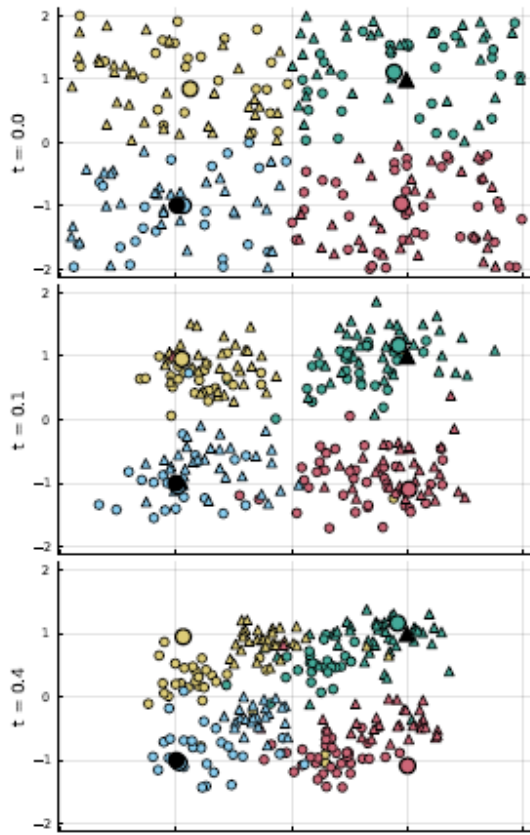
$$a = 1, b = 2, c = 4, \sigma = 0.5, \tilde{\sigma} = 0, \hat{\sigma} = 0, \Gamma = 100, \gamma = 10, \\ A_{ij} = 1 \text{ for all } (i, j), \phi(x) = \psi(x) = \exp(-x), \eta = 15.$$

$t = 0.0$



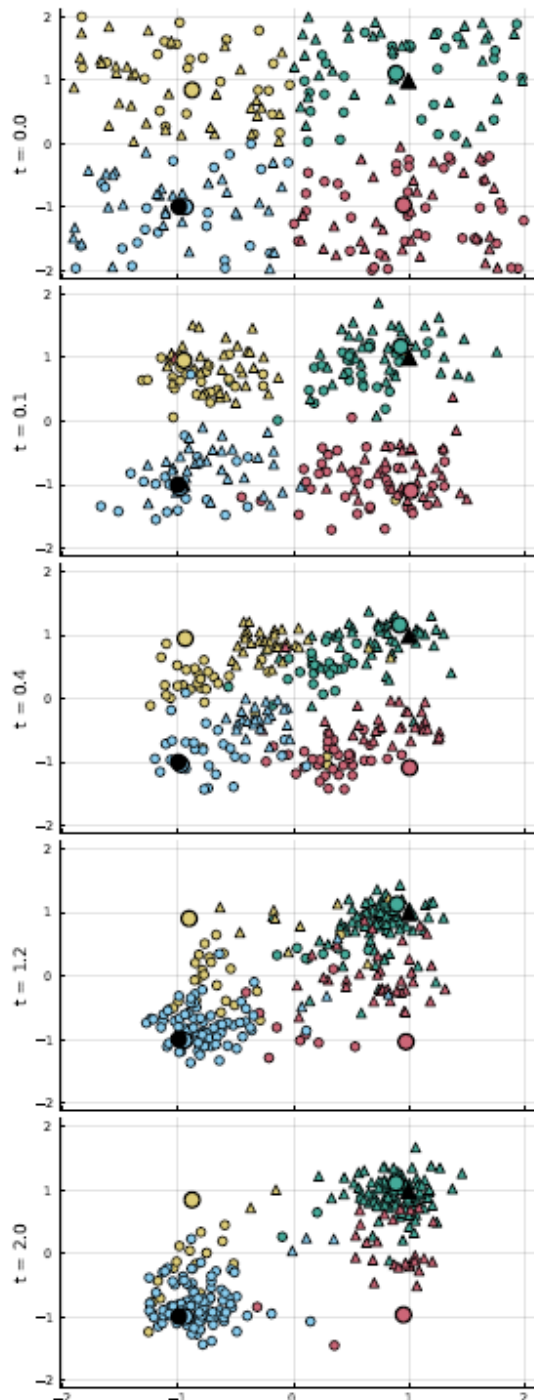


Individuals are quickly being attracted by their respective **influencer** and forming **4 clusters**



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After some time, the 4 clusters split further because individuals are also **attracted to their medium**, s.t. individuals now form **roughly 8 groups**.



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After some time, the 4 clusters split further because individuals are also **attracted to their medium**, s.t. individuals now form **roughly 8 groups**.

Some **individuals switch the influencer** to a more suitable influencer, i.e., one that is closer in opinion space and whose majority of followers are connected to the same medium as the individual. They then get attracted to the new influencer ($t = 1.2$), until finally ($t = 2$) **individuals have formed 2 mixed clusters near the 2 media opinions**.

More details

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Modelling opinion dynamics under the impact of influencer and media strategies

[Luzie Helfmann](#), [Nataša Djurdjevac Conrad](#), [Philipp Lorenz-Spreen](#) & [Christof Schütte](#) 


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Code in Julia-by L.Helfmann


SocialMediaModel
Public
Watch 2

master
6 Branches
0 Tags
Go to file
Add file
Code

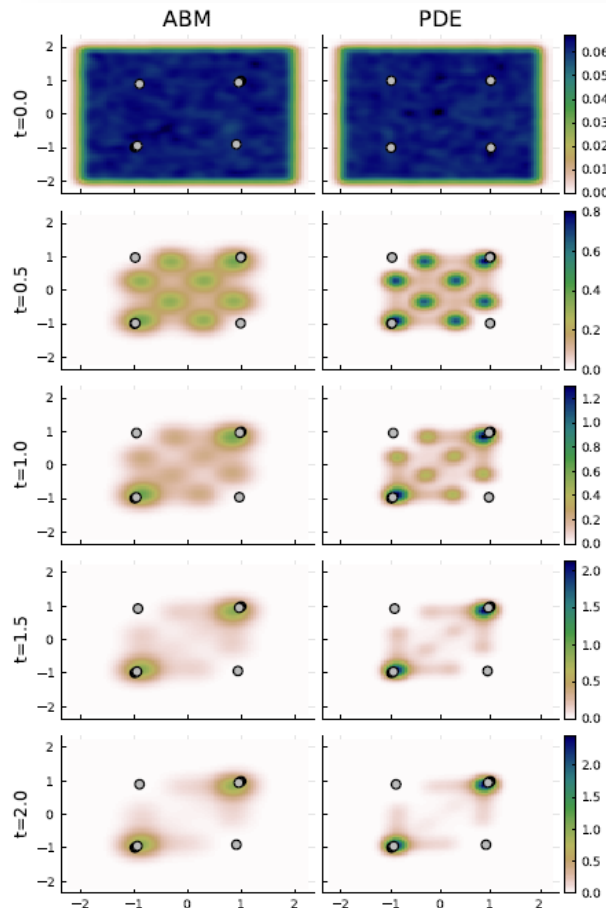

LuzieH
Update README.md

d20a90a · 3 months ago
149 Commits

data	make it a package	last year
img	added functions to plot spacetime clusters from Marcus and...	10 months ago
src	fixed cases abm influencer movement	9 months ago
test	minor updates	last year
.gitignore	some code cleaning	10 months ago
LICENSE	Create LICENSE	9 months ago
LocalPreferences.toml	renamed file to pde.jl, build in minor tweaks from pull reque...	2 years ago
Manifest.toml	manifest also corrected now	last year
Project.toml	deleted unused dependencies from project.toml	last year
README.md	Update README.md	3 months ago

`github.com/LuzieH/SocialMediaModel/tree/master`

Additional aspects



ABM: mean distribution over 1000 realizations with 250 agents;
PDE: discretized using a Finite Difference scheme.

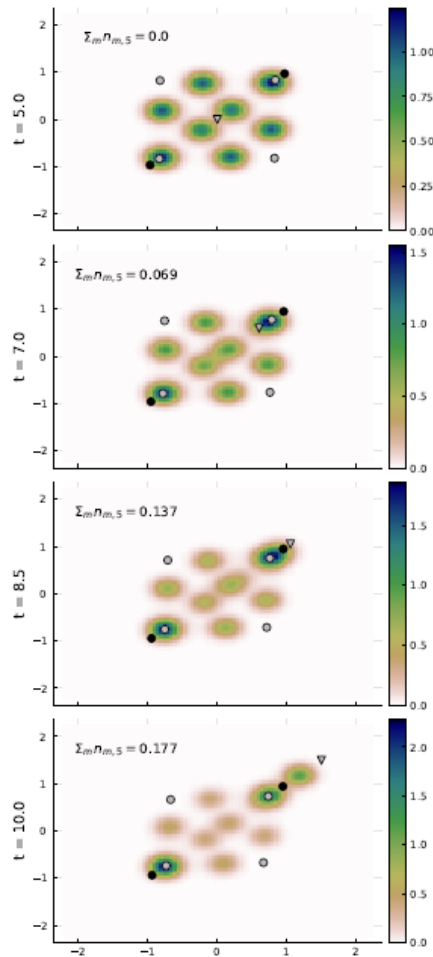
We derived a partial mean-field model many agents, few influencers and media.

Advantages of the mean-field model:

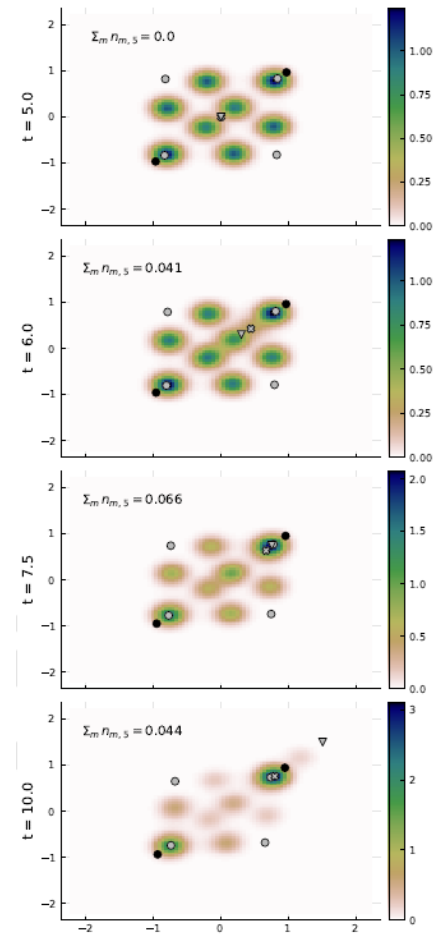
- Reduced computational cost that is not dependant on N .
- Deterministic model.
- Easier to study, e.g. the effect of influencer strategies in the attention economy.
- Allows for deriving optimal control schemes for counteracting actions that influence opinion distribution.

Strategies in the attention economy

Strategy of an influencer
(marked by a triangle)
to increase
followership:



Strategy of an influencer
(marked by a star)
to optimally counteract
the goal of another agent
(marked by a triangle)



Project from the ASU/MATH+ School 2023



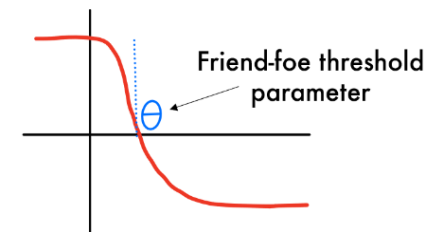
- Influencer feuds create polarized social networks
- Introduce influencer-influencer dynamics and repulsion mechanism driven by feuds

One More Lonely Girl



Inan Bostanci, Luzie Helfmann, Kristina Maier,
Nayely Vélez-Cruz,
and Adam Wiechman

Attraction-Repulsion Function ϕ



Code in Python

LuzieH / SocialMediaModelPy Public

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File	Commit Message	Time
img/frames	Create .keep	1 hour ago
src/SocialMediaModelPy	comment code	5 minutes ago
.gitignore	update setup file	1 hour ago
README.md	comment code	5 minutes ago
example.ipynb	comment code	5 minutes ago
setup.py	update setup file	1 hour ago

README.md

SocialMediaModelPy

Python code for the spring school in Arizona.

Usage

Install in editable mode in the SocialMediaModelPy directory with `pip install -e .`. Tests can be run in the command line with `pytest`.

github.com/LuzieH/SocialMediaModelPy

Open questions:

- How can we measure the clusters in the opinion distribution?
 - Number/size/diversity of clusters.
 - How clusters evolve: split and merge?
- How do the opinion distribution and the opinion clusters change in different settings?
 - for different parameters, networks, interaction functions, influencer/media dynamics, ...
- Realistic influencer+individual dynamics:
 - Individuals can follow more than 1 influencer/media,
 - adapt the influencer dynamics (e.g. stubborn agents), adapt the switching dynamics.
- Include an underlying network and that is changing in time (e.g. driven by homophily or “transitive homophily”).
- Neighbourhood effect = include the effect of friends of a friend: the influence of the opinion of a neighbour is proportional to the similarity of the mean opinions of the neighbours neighbours to their own opinion.
- In this model we consider only dyadic influences, study the effect of a 3-body interactions.

**Thank you
for your attention**

Questions?

Email: natasa.conrad@zib.de