# Modelling how social network algorithms can influence opinion polarization 

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## Introduction

- Many opinion models have been proposed based on different aspects of the interaction between people;
- Objective: propose a model to incorporate the information on the relationship between social network users and the social network;
- Our model simulates how the information from outside of the social network influences the opinions.



## Motivation



Twitter networks: examples of polarization in the United States

## Model: Post transmission



Transmission probability:



We tested four different user behaviors.

## Model: Post reception



Reception probability:

$$
\begin{aligned}
& y=\left|b_{i}-b_{j}\right| \\
& y_{1}=|-0.9-0.2|=1.1 \quad P_{d}^{I I}\left(y_{1}\right)=0.42 \\
& y_{2}=|-0.9-1.0|=1.9 \quad P_{d}^{I I}\left(y_{2}\right)=0.01 \\
& y_{3}=|-0.9-(-0.3)|=0.6 \quad P_{d}^{I I}\left(y_{3}\right)=0.79 \\
& y_{4}=|-0.9-(-0.9)|=0.0 \quad P_{d}^{I I}\left(y_{4}\right)=1.00
\end{aligned}
$$



This step simulates the social network algorithm.
We tested several possibilities of algorithms.

## Model: Atraction



People update their opinions on topics after interacting or in a discussion and can become more polarized doing so.
D.J. Isenberg, Group polarization. A critical review and meta-analysis, Journal of Personality and Social Psychology 50 (1986) 1141-1151.
S. Moscovici, M. Zavalloni, The group as a polarizer of attitudes, Journal of Personality and Social Psychology 12 (1969) 125-135.

## Model: Rewiring



Twitter users are less likely to unfollow friends who have acknowledged them.

## Model


(a)

(b)

(c)

Reception probability

|  | $\begin{gathered} \phi=0 \\ b_{i}=-0.9 \end{gathered}$ |
| :---: | :---: |
| $y=\left\|b_{i}-b_{j}\right\|$ |  |
| $y_{1}=\|-0.9-0.2\|=1.1$ | $P_{d}^{I I}\left(y_{l}\right)=0.42$ |
| $y_{2}=\|-0.9-1.0\|=1.9$ | $P_{d}^{I I}\left(y_{2}\right)=0.01$ |
| $y_{3}=\|-0.9-(-0.3)\|=0.6$ | $P_{d}^{I I}\left(y_{3}\right)=0.79$ |
| $y_{4}=\|-0.9-(-0.9)\|=0.0$ | $P_{d}^{I I}\left(y_{4}\right)=1.00$ |


(e)

Attraction probability
$\xi\left(\theta, b_{j}\right)=1-\left|\theta-b_{j}\right| / 2$
$\xi_{1}(-0.4,0.2)=0.7$
$\xi_{3}(-0.4,-0.3)=0.95$
$\xi_{4}(-0.4,-0.9)=0.75$

$$
\Delta=0.1
$$

$$
\begin{array}{ll}
y_{1}=|-0.9-0.3|=1.2 & P_{\text {rewire }}\left(y_{1}\right)=0.1 \\
y_{4}=|-0.9-(-1.0)|=0.1 & P_{\text {rewire }}\left(y_{4}\right)=0.0
\end{array}
$$


(h)
(i)

## Results analyses

Bimodality coefficient

(a) Consensus

(b) Echo chamber,

(c) Diverse

$$
B C=\frac{g^{2}+1}{k+\frac{3(n-1)^{2}}{(n-2)(n-3)}}
$$

where $n$ is the number of samples, and $g$ and $k$ are the skewness and kurtosis of the analyzed distribution, respectively.

A $B_{\text {critic }}=5 / 9$ was empirically found . For values higher and lower than
$B C_{\text {critic }}$, it tends to be bi-modal and unimodal, respectively.

[^0]Results: Analysis of the dynamics


## Temporal analysis

- Example of dynamics without rewiring;
- In this case, the dynamics goes from bimodal to unimodal, with consensus close to an extreme opinion.



## Main conclusions

- This model was found to be flexible and can give rise to a wide range of outcomes representing different scenarios;
- In some cases, there is the polarization of opinions but without the formation of echo chambers (mainly when rewiring is not considered);
- If the users do not care about the information they post, the algorithm (post reception) can lead to polarization and the formation of echo chambers.


## For more information

Our paper is published in:
de Arruda, H. F., Cardoso, F. M., de Arruda, G. F., Hernández, A. R., Costa, L. da F., \& Moreno, Y. (2022). Modelling how social network algorithms can influence opinion polarization. Information Sciences, 588, 265-278.

The source code can be found in: https://github.com/hfarruda/OpinionPolarization

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## Thank you!

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[^0]:    W. Cota, S.C. Ferreira, R. Pastor-Satorras, M. Starnini, Quantifying echo chamber effects in information spreading over political communication networks, EPJ Data Science 8 (2019) 35.
    R. Pfister, K.A. Schwarz, M. Janczyk, R. Dale, J. Freeman, Good things peak in pairs: a note on the bimodality coefficient, Frontiers in Psychology 4 (2013) 700.

