Algorithmic bias and multidimensional political polarisation in online social networks

MMM Workshop, ETH Zurich

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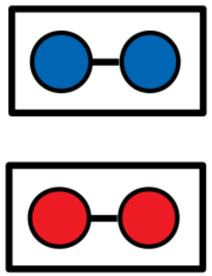
Deconstructing the (first) title…

SOCIAL
NETWORK STRUCTURE

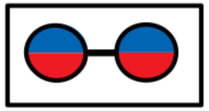
ROLE OF ALGORITHMIC BIAS

DYNAMICS OF
INFORMATION SPREADING

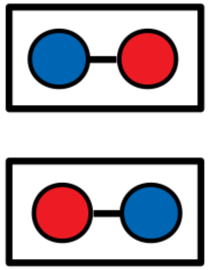
CONSENSUS



COEXISTENCE



POLARIZATION



Peralta, Iñiguez et al. *Phys. Rev. E* 104 (2021): 044312

Peralta, Iñiguez et al. *J. Phys. Comp.* 2 (2021): 045009

Five ways AI could improve the world: 'We can cure all diseases, stabilise our climate, halt poverty'

Greater longevity will come from scientific progress, aided by AI. Illustration: Leon Edler/The Guardian

'You can do both': experts seek 'good AI' while attempting to avoid the bad

While AI revolutionises medicine, bleaker alternatives present themselves, UN's AI for Good conference finds

onference

Five ways AI might destroy the world: 'Everyone on Earth could fall over dead in the same second'

Robots say they have no plans to steal jobs or rebel against humans

Humanoid robots speak - with some awkward pauses - in 'world first' press conference at Geneva AI summit

The nine
Photograp

Perspective

Measuring algorithmically infused societies

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Published online: 30 June 2021
Check for updates

Claudia Wagner[1,2,3], Markus Strohmaier[1,2,3], Alexandra Olteanu[4,5], Emre Kıcıman[6], Noshir Contractor[7] & Tina Eliassi-Rad[8]

It has been the historic responsibility of the social sciences to investigate human societies. Fulfilling this responsibility requires social theories, measurement models and social data. Most existing theories and measurement models in the social sciences were not developed with the deep societal reach of algorithms in mind. The emergence of 'algorithmically infused societies'—societies whose very fabric is co-shaped by algorithmic and human behaviour—raises three key challenges: the insufficient quality of measurements, the complex consequences of (mis)measurements, and the limits of existing social theories. Here we argue that tackling these challenges requires new social theories that account for the impact of algorithmic systems on social realities. To develop such theories, we need new methodologies for integrating data and measurements into theory construction. Given the scale at which measurements can be applied, we believe measurement models should be trustworthy, auditable and just. To achieve this, the development of measurements should be transparent and participatory, and include mechanisms to ensure measurement quality and identify possible harms. We argue that computational social scientists should rethink what aspects of algorithmically infused societies should be measured, how they should be measured, and the consequences of doing so.

Ethics Inf Technol (2013) 15:209–227
DOI 10.1007/s10676-013-9321-6

ORIGINAL PAPER

Bias in algorithmic filtering and personalization

Engin Bozdag

SPECIAL FEATURE

Check for updates

Link recommendation algorithms and dynamics of polarization in online social networks

Fernando P. Santos[a,b,1], Yphtach Lelkes[c], and Simon A. Levin[a]

[a]Department of Ecology and Evolutionary Biology, Princeton University, Princeton, NJ 08544; [b]Informatics Institute, University of Amsterdam, 1098XH Amsterdam, The Netherlands; and [c]Annenberg School for Communication Research, University of Pennsylvania, Philadelphia, PA 19104

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REVIEW
published: 17 September 2015
doi: 10.3389/fphy.2015.00078

CrossMark

Mechanistic models in computational social science

Petter Holme [1] and Fredrik Liljeros [2]*

[1] Department of Energy Science, Sungkyunkwan University, Suwon, South Korea, [2] Department of Sociology, Stockholm University, Stockholm, Sweden

Quantitative social science is not only about regression analysis or, in general, data inference. Computer simulations of social mechanisms have an over 60 years long history. They have been used for many different purposes—to test scenarios, to test the consistency of descriptive theories (proof-of-concept models), to explore emergent phenomena, for forecasting, etc… In this essay, we sketch these historical developments, the role of mechanistic models in the social sciences and the influences from the natural and formal sciences. We argue that mechanistic computational models form a natural common ground for social and natural sciences, and look forward to possible future information flow across the social-natural divide.

OPEN ACCESS

Keywords: computational social science, mechanistic models, simulation, complex systems, interdisciplinary science

BIOLOGY LETTERS

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Opinion piece

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Subject Areas:
bioengineering, bioinformatics, biomechanics, biotechnology

Keywords:
mechanistic modelling, machine learning, quantitative biology

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Biomechanics

Mechanistic models versus machine learning, a fight worth fighting for the biological community?

Ruth E. Baker[1,2], Jose-Maria Peña[4], Jayaratnam Jayamohan[5] and Antoine Jérusalem[3]

[1]Mathematical Institute, [2]St Hugh's College and [3]Department of Engineering Science, University of Oxford, Oxford, UK
[4]Lurtis Ltd, Madrid, Spain
[5]Department of Neurosurgery, Oxford University Hospitals, John Radcliffe Hospital, Oxford, UK

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Ninety per cent of the world's data have been generated in the last 5 years (*Machine learning: the power and promise of computers that learn by example*. Report no. DES4702. Issued April 2017. Royal Society). A small fraction of these data is collected with the aim of validating specific hypotheses. These studies are led by the development of mechanistic models focused on the causality of input–output relationships. However, the vast majority is aimed at supporting statistical or correlation studies that bypass the need for causality and focus exclusively on prediction. Along these lines, there has been a vast increase in the use of machine learning models, in particular in the biomedical and clinical sciences, to try and keep pace with the rate of data generation. Recent successes now beg the question of whether mechanistic models are still relevant in this area. Said otherwise, why should we try to understand the mechanisms of disease progression when we can use machine learning tools to directly predict disease outcome?

SCIENCE ADVANCES | RESEARCH ARTICLE

NETWORK SCIENCE

A Bayesian machine scientist to aid in the solution of challenging scientific problems

Roger Guimerà[1,2]*, Ignasi Reichardt[2], Antoni Aguilar-Mogas[2,3], Francesco A. Massucci[2,4], Manuel Miranda[2], Jordi Pallarès[5], Marta Sales-Pardo[2]

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Closed-form, interpretable mathematical models have been instrumental for advancing our understanding of the world; with the data revolution, we may now be in a position to uncover new such models for many systems from physics to the social sciences. However, to deal with increasing amounts of data, we need "machine scientists" that are able to extract these models automatically from data. Here, we introduce a Bayesian machine scientist, which establishes the plausibility of models using explicit approximations to the exact marginal posterior over models and establishes its prior expectations about models by learning from a large empirical corpus of mathematical expressions. It explores the space of models using Markov chain Monte Carlo. We show that this approach uncovers accurate models for synthetic and real data and provides out-of-sample predictions that are more accurate than those of existing approaches and of other nonparametric methods.

DYNAMICS **ON** NETWORKS – approximate master equations for binary dynamics

EPIDEMIC SPREADING

Node state -> Susceptible, infected, …
Edges -> Transmission of disease

SOCIAL CONTAGION

Node state -> Adopted, not adopted
Edges -> Transfer of ideas, behavior, …

OPINION FORMATION

Node state -> Opinion A, B, …
Edges -> Transfer of information

CULTURAL DYNAMICS

Node state -> Cultural features
Edges -> Similarity & interaction

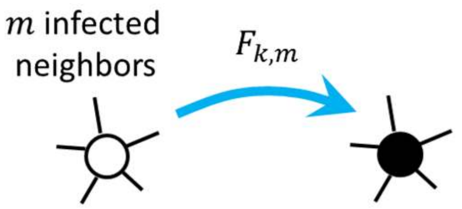
HUMAN MOBILITY

Node state -> Amount of people
Edges -> Roads, airways, etc.

divide network in groups of nodes with degree k and m infected neighbors

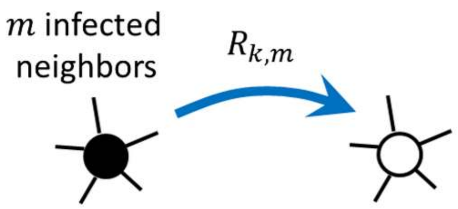
susceptible nodes (S)

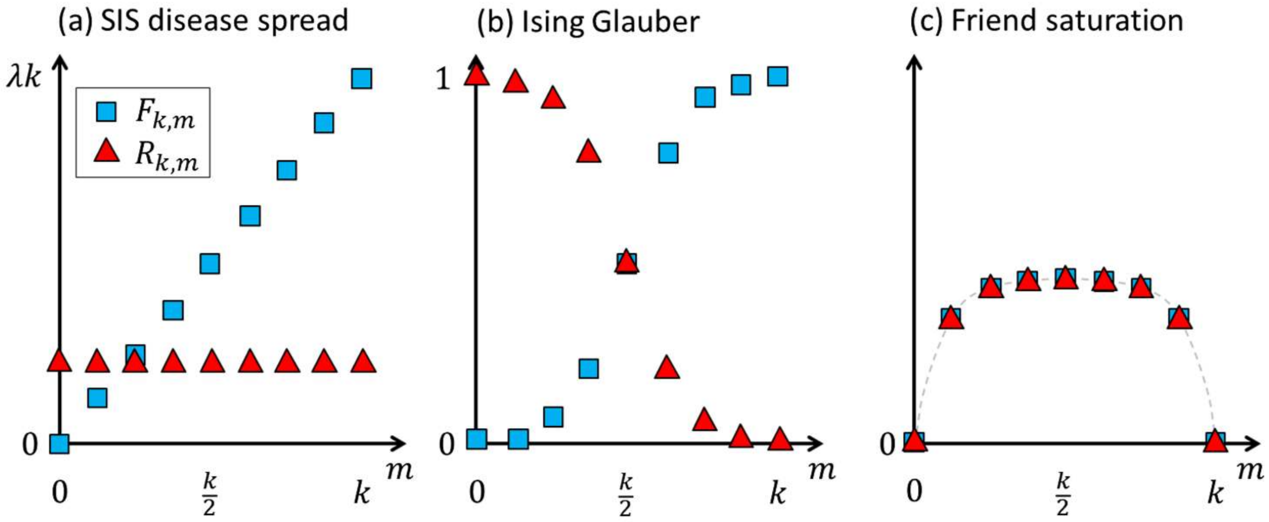
$$\frac{ds_{k,m}}{dt} = -F_{k,m}s_{k,m} + R_{k,m}i_{k,m} + \dots$$



infected nodes (I)

$$\frac{di_{k,m}}{dt} = -R_{k,m}i_{k,m} + F_{k,m}s_{k,m} + \dots$$





Gleeson, *Phys. Rev. Lett.* 107 (2011): 068701

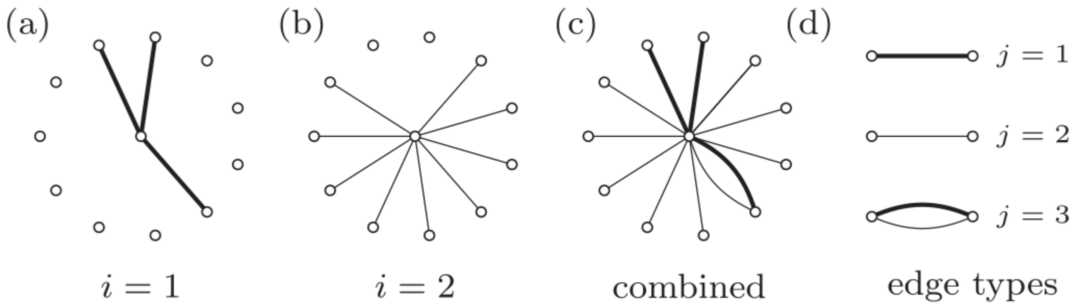
Gleeson, *Phys. Rev. X* 3 (2013): 021004

Porter et al. *Front. Appl. Dynam. Sys.*, Vol. 4 (Springer, 2016)

DYNAMICS **ON** NETWORKS – extending AMEs to arbitrary networks

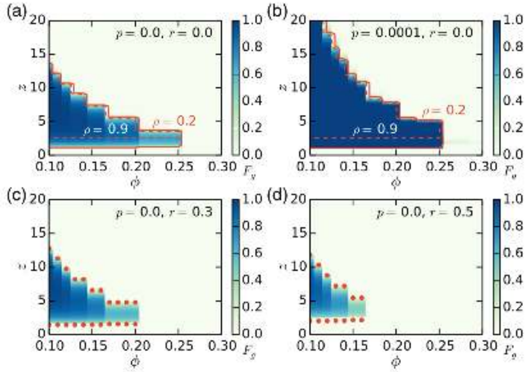
node group (k, m)

to vector $(\mathbf{k}, \mathbf{m})$

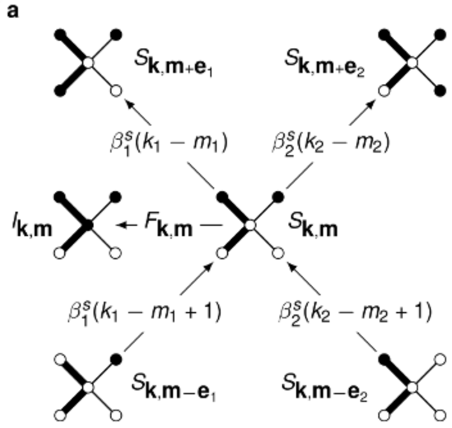


and extend AMEs

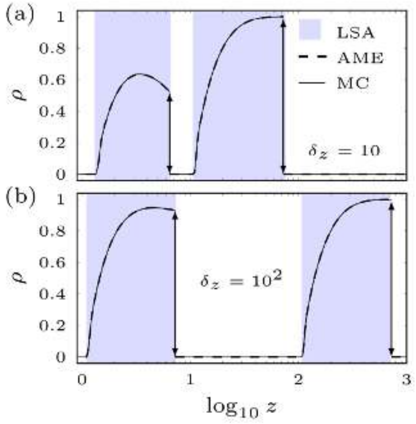
SIMPLE NETS



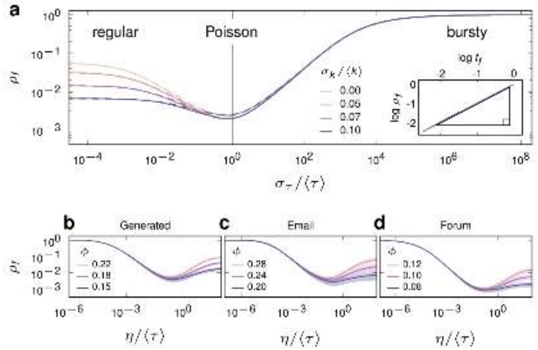
WEIGHTED NETS



MULTILAYER NETS



TEMPORAL NETS



Ruan, Iñiguez et al. *Phys. Rev. Lett.* 115 (2015): 218702

Karsai, Iñiguez et al. *Sci. Rep.* 6 (2016): 27178

Unicomb, Iñiguez, Karsai. *Sci. Rep.* 8 (2018): 3

Unicomb, Iñiguez et al. *Phys. Rev. E* 100 (2019): 040301(R)

So what about algorithmic bias?

SOCIAL
NETWORK STRUCTURE
(stochastic 1- & 2-block model)

ROLE OF
ALGORITHMIC BIAS

DYNAMICS OF
INFORMATION SPREADING
(binary opinion dynamics)

use of filtering algorithms to tailor user-specific content and avoid information overload

GENERAL POPULARITY

(most popular content)

SEMANTIC FILTERING

(content similar to what
user consumed before)

COLLABORATIVE FILTERING

(content similar to what
similar users consumed before)

Bozdag. *Ethics Inf. Technol.* 15 (2013): 209
Bakshy et al. *Science* 348 (2015): 1130
Pariser. *The Filter Bubble: What The Internet Is Hiding From You* (Penguin Books Limited, 2011)
Möller et al. *Inform. Commun. Soc.* 21 (2018): 959
Nikolov et al. *J. Assoc. Inf. Sci. Tech.* 70 (2018): 218

‘pair’ interactions

NOISY VOTER MODEL

Peralta, Iñiguez et al. *Phys. Rev. E* 104 (2021): 044312
Peralta, Iñiguez et al. *J. Phys. Comp.* 2 (2021): 045009

$$F_{k,m} = Q + (1-2Q)\frac{m}{k} \qquad R_{k,m} = Q + (1-2Q)\frac{k-m}{k}$$

Kirman. *Q. J. Econ.* 108 (1993): 137
Granovsky, Madras. *Stoch. Proc. Appl.* 55 (1995): 23

LANGUAGE MODEL

$$F_{k,m} = Q + (1-2Q)\left(\frac{m}{k}\right)^{\alpha} \qquad F_{k,m} = Q + (1-2Q)\left(\frac{k-m}{k}\right)^{\alpha}$$

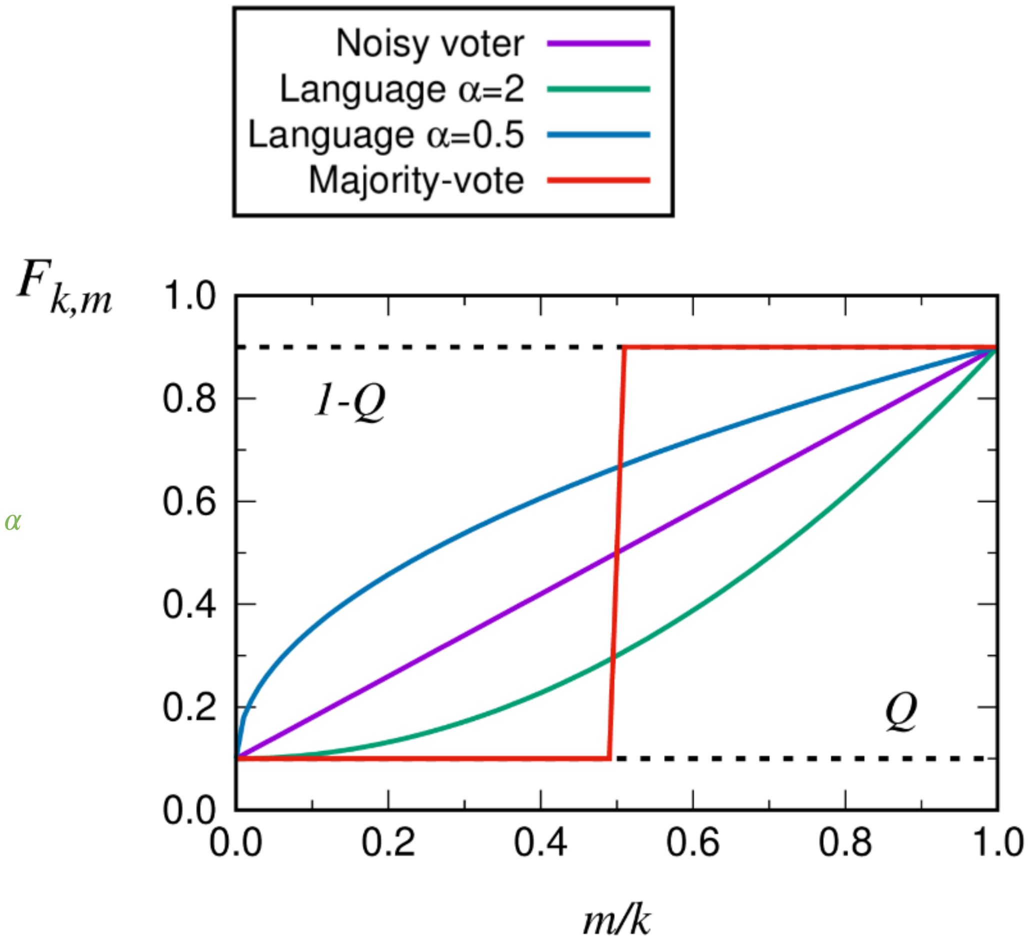
Abrams, Strogatz. *Nature* 424 (2003): 900
Peralta et al. *Chaos* 28 (2018): 075516

MAJORITY VOTE MODEL

$$F_{k,m} = \begin{cases} Q & \text{if} \quad m < k/2 \\ 1/2 & \text{if} \quad m = k/2 \\ 1-Q & \text{if} \quad m > k/2 \end{cases} \qquad R_{k,m} = \begin{cases} 1-Q & \text{if} \quad m < k/2 \\ 1/2 & \text{if} \quad m = k/2 \\ Q & \text{if} \quad m > k/2 \end{cases}$$

Liggett. *Interacting Particle Systems* (New York, 1985)
de Oliveira. *J. Stat. Phys.* 66 (1992): 273

‘group’ interactions



two model parameters:

Q (regulates noise)

α (tunes ‘group’ interactions)

minimal implementation of algorithmic bias

people disregard a fraction of friends w/ different opinion

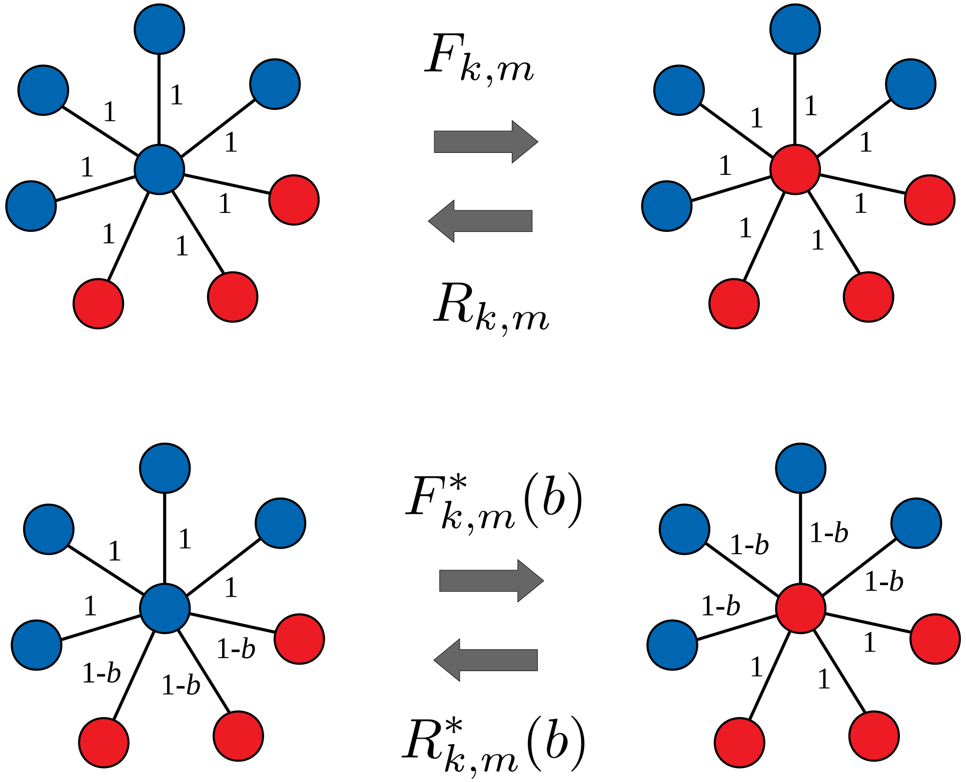
Parameters

NO BIAS
$(b = 0)$

(Q, α)

BIAS
$(b > 0)$

(Q, α, b)



Peralta, Iñiguez et al. *Phys. Rev. E* 104 (2021): 044312 Peralta, Iñiguez et al. *J. Phys. Comp.* 2 (2021): 045009

minimal implementation of algorithmic bias

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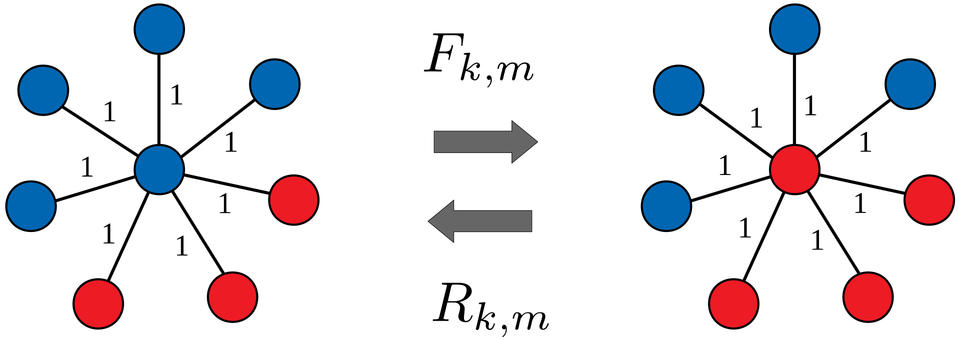
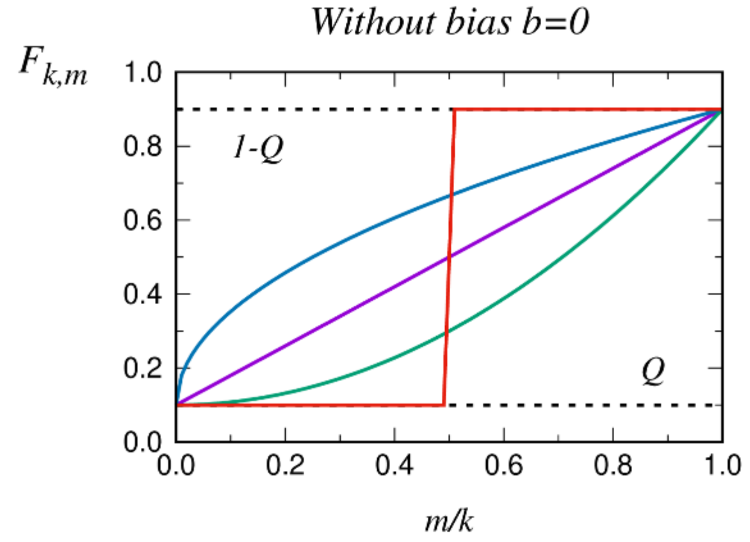
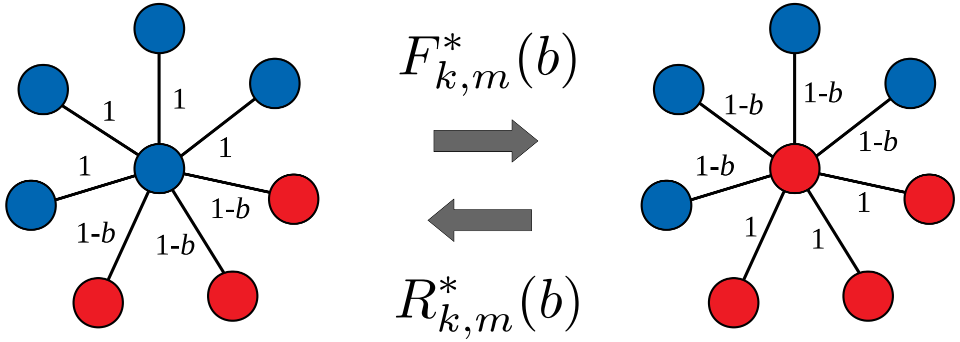


Parameters

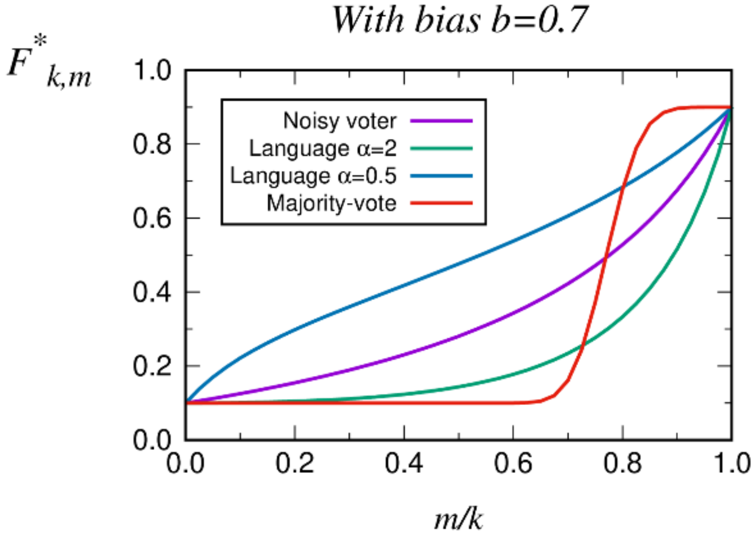
(Q, α)



BIAS
$(b > 0)$



(Q, α, b)



algorithmic bias amounts to
effective transition rates
(convolution w/ a binomial B)

$$F^*_{k,m}(b) = \sum_{i=0}^{m} B_{m,i}(1-b) F_{k-m+i,i}$$

$$R^*_{k,m}(b) = \sum_{s=0}^{k-m} B_{k-m,s}(1-b) R_{m+s,m}$$

Peralta, Iñiguez et al. *Phys. Rev. E* 104 (2021): 044312 Peralta, Iñiguez et al. *J. Phys. Comp.* 2 (2021): 045009

HOMOGENEOUS NETWORKS (degree dist P_k w/ large $z = \langle k \rangle$)

Peralta, Iñiguez et al. *Phys. Rev. E* 104 (2021): 044312
Peralta, Iñiguez et al. *J. Phys. Comp.* 2 (2021): 045009

MEAN FIELD
(for infection
density ρ)

$$\frac{d\rho}{dt} = \left(1-\rho\right) f\left[\frac{(1-b)\rho}{1-b\rho}\right] - \rho f\left[\frac{(1-b)(1-\rho)}{1-b(1-\rho)}\right]$$

$$f[x] = \sum_k P_k \sum_{m=0}^{k} F_{k,m} B_{k,m}(x)$$

CONSENSUS $\rho(\infty) = 0$, $\rho(\infty) = 1$

COEXISTENCE $\rho(\infty) = 1/2$

HOMOGENEOUS NETWORKS (degree dist P_k w/ large $z = \langle k \rangle$)

Peralta, Iñiguez et al. *Phys. Rev. E* 104 (2021): 044312
Peralta, Iñiguez et al. *J. Phys. Comp.* 2 (2021): 045009

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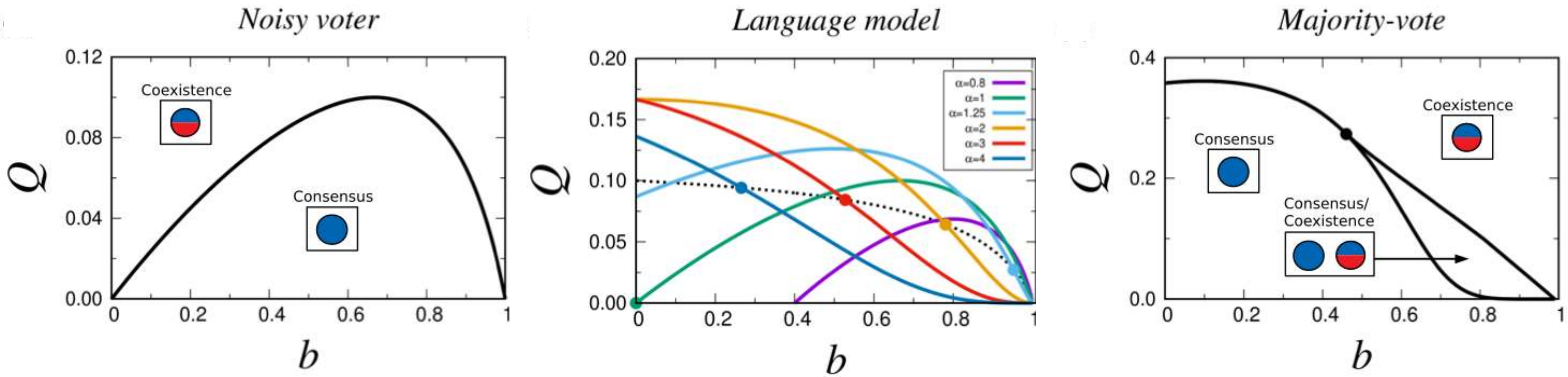


'pair' interactions:

ALGORITHMIC BIAS PROMOTES **CONSENSUS**!

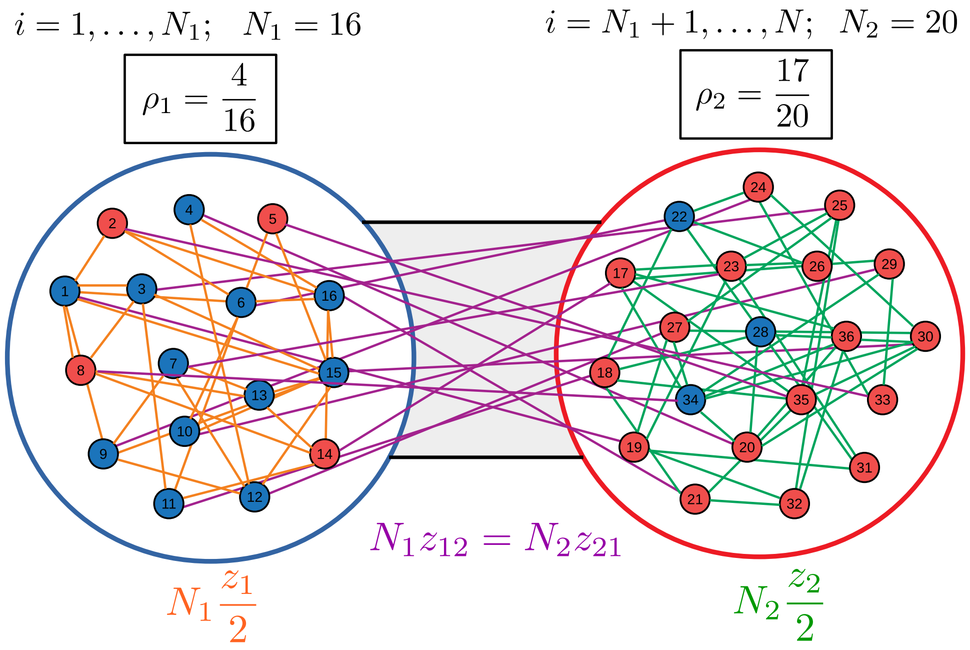
language model interpolates between behaviors

'group' interactions:

ALGORITHMIC BIAS PROMOTES **COEXISTENCE**!

HETEROGENEOUS NETWORKS (stochastic 2-block model)

Peralta, Iñiguez et al. *Phys. Rev. E* 104 (2021): 044312
Peralta, Iñiguez et al. *J. Phys. Comp.* 2 (2021): 045009



MEAN FIELD (for infection densities ρ_1, ρ_2)

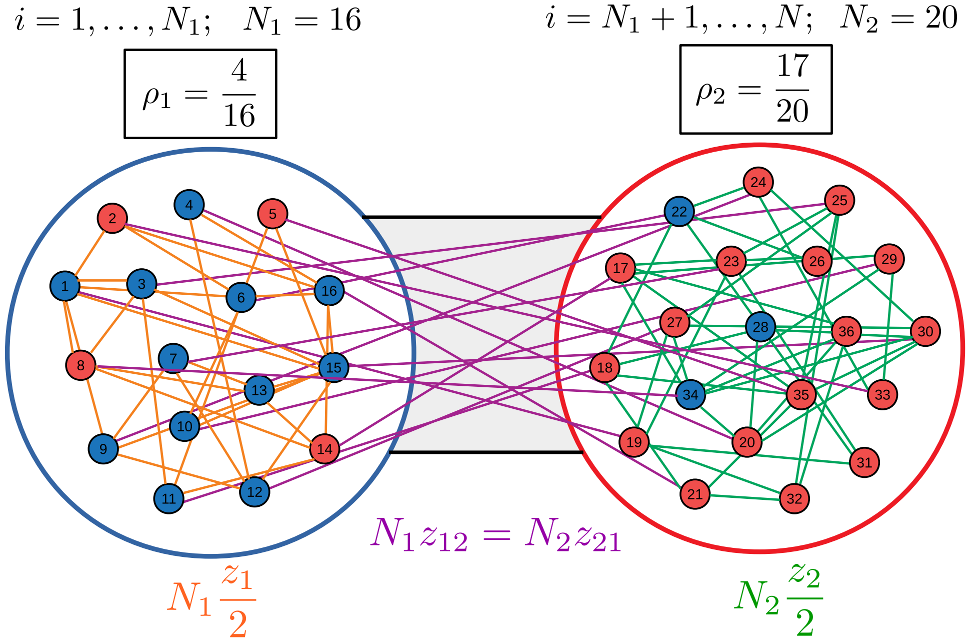
$$\frac{d\rho_1}{dt} = (1-\rho_1)\, f\left[\frac{(1-b)(\rho_1 + p_1\rho_2)}{1 + p_1 - b\left(\rho_1 + p_1\rho_2\right)}\right] - \rho_1 f\left[\frac{(1-b)(1-\rho_1 + p_1(1-\rho_2))}{1 + p_1 - b\left(1-\rho_1 + p_1(1-\rho_2)\right)}\right]$$

$$\frac{d\rho_2}{dt} = (1-\rho_2)\, f\left[\frac{(1-b)(\rho_2 + p_2\rho_1)}{1 + p_2 - b\left(\rho_2 + p_2\rho_1\right)}\right] - \rho_2 f\left[\frac{(1-b)(1-\rho_2 + p_2(1-\rho_1))}{1 + p_2 - b\left(1-\rho_2 + p_2(1-\rho_1)\right)}\right]$$

$$p_1 = N_2 z_{12}/N_1 z_1 \qquad p_2 = N_1 z_{21}/N_2 z_2$$

HETEROGENEOUS NETWORKS (stochastic 2-block model)

Peralta, Iñiguez et al. *Phys. Rev. E* 104 (2021): 044312
Peralta, Iñiguez et al. *J. Phys. Comp.* 2 (2021): 045009



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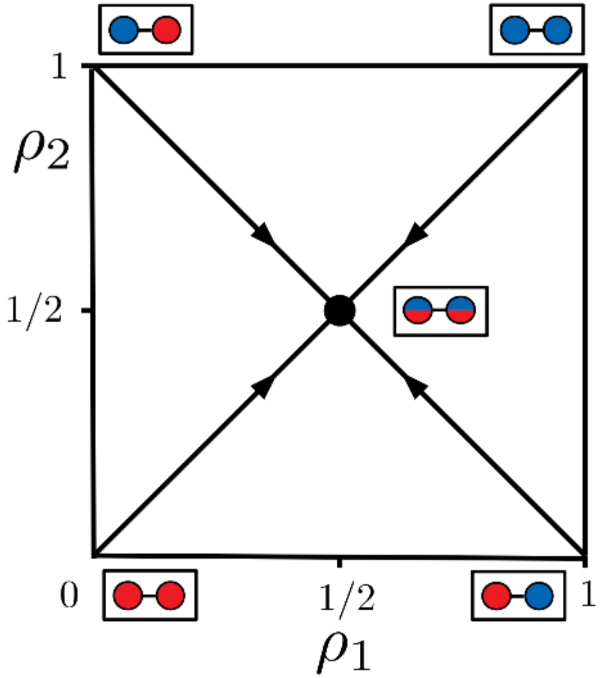
$$\frac{d\rho_2}{dt} = (1-\rho_2) f\left[\frac{(1-b)(\rho_2 + p_2\rho_1)}{1 + p_2 - b(\rho_2 + p_2\rho_1)}\right] - \rho_2 f\left[\frac{(1-b)(1-\rho_2 + p_2(1-\rho_1))}{1 + p_2 - b(1-\rho_2 + p_2(1-\rho_1))}\right]$$

$$p_1 = N_2 z_{12}/N_1 z_1 \qquad p_2 = N_1 z_{21}/N_2 z_2$$

POLARIZATION

$\rho_1(\infty) = 0, \qquad \rho_2(\infty) = 1$



CONSENSUS

$\rho_1(\infty) = \rho_2(\infty) = 1$

COEXISTENCE

$\rho_1(\infty) = \rho_2(\infty) = 1/2$

CONSENSUS

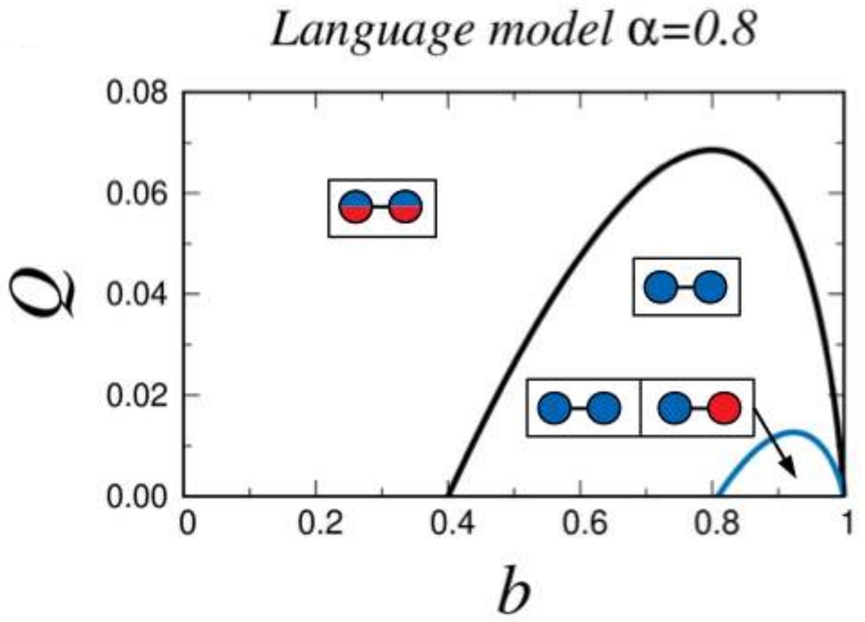
$\rho_1(\infty) = \rho_2(\infty) = 0$

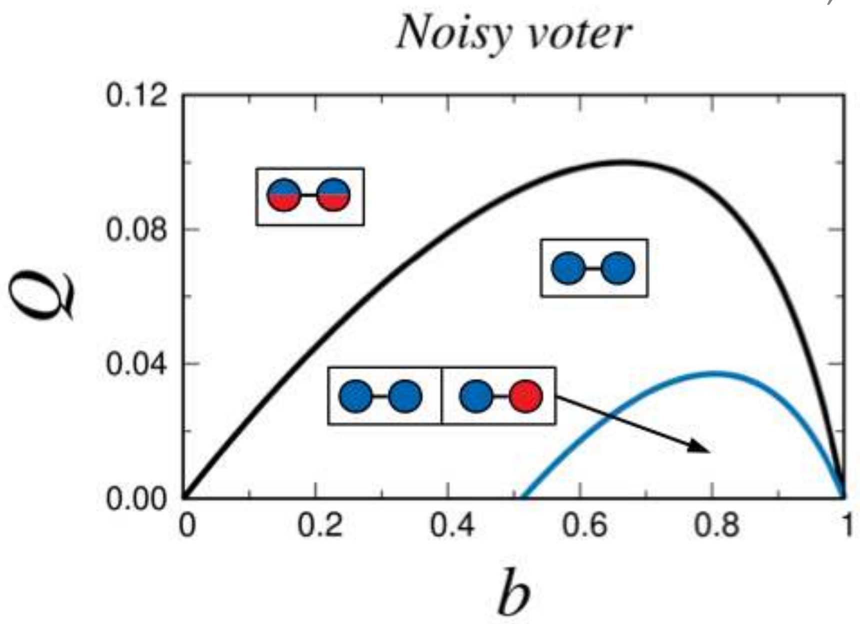
POLARIZATION

$\rho_1(\infty) = 1, \qquad \rho_2(\infty) = 0$

‘pair’ interactions

Peralta, Iñiguez et al. *Phys. Rev. E* 104 (2021): 044312
Peralta, Iñiguez et al. *J. Phys. Comp.* 2 (2021): 045009



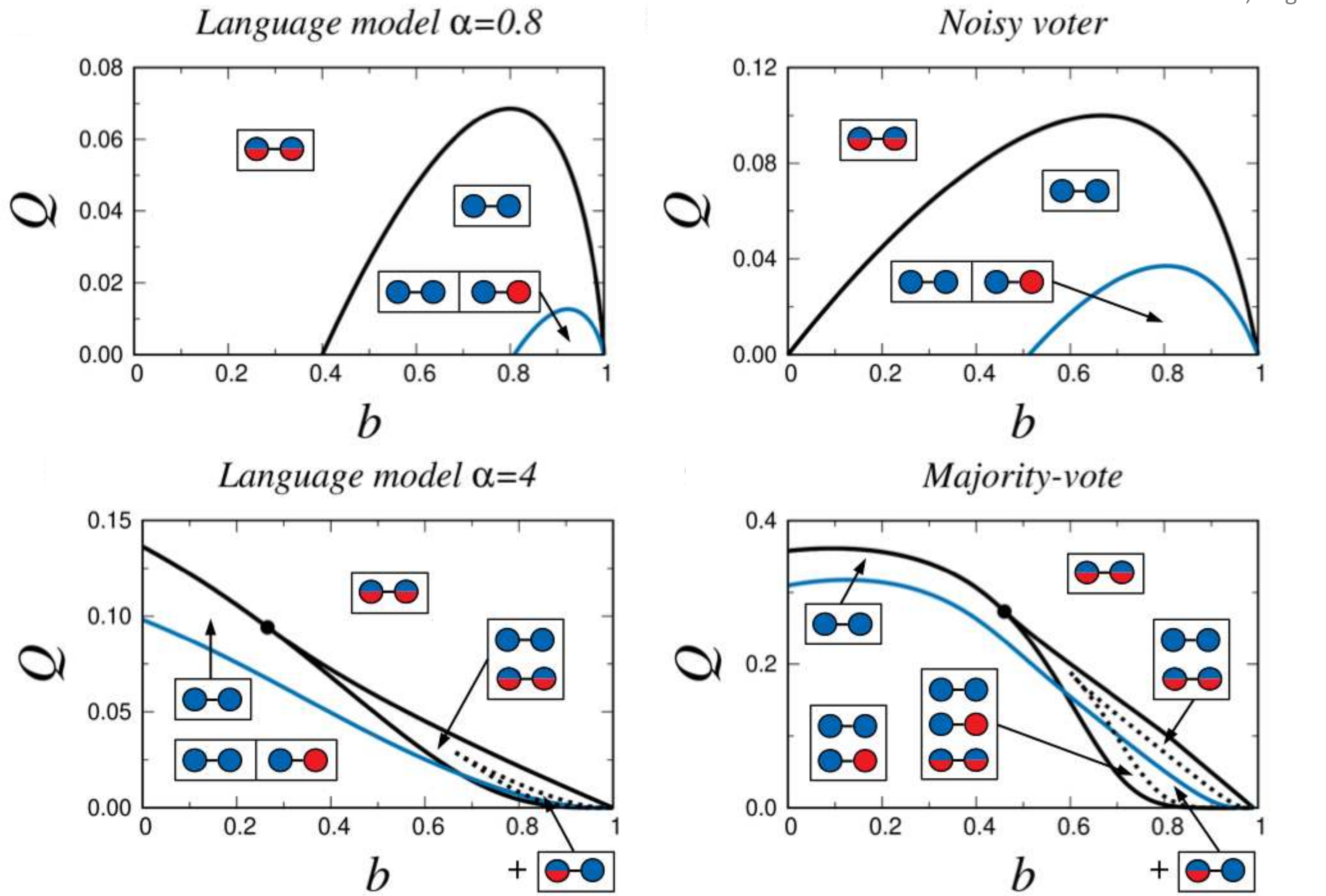


‘pair’ interactions:

INCREASING BIAS
leads to
CONSENSUS
and then
POLARIZATION

'pair' interactions

Peralta, Iñiguez et al. *Phys. Rev. E* 104 (2021): 044312
Peralta, Iñiguez et al. *J. Phys. Comp.* 2 (2021): 045009



'group' interactions

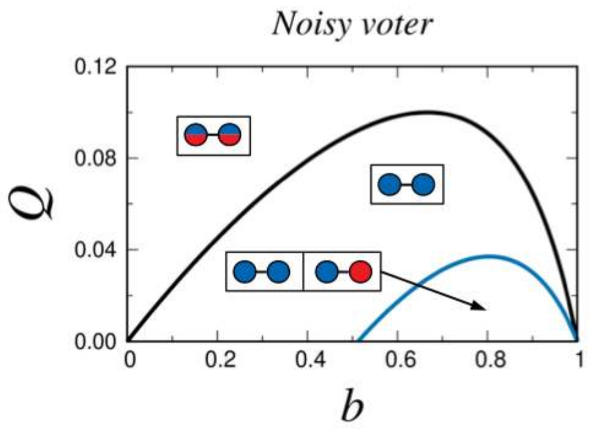
'pair' interactions:

INCREASING BIAS
leads to
CONSENSUS
and then
POLARIZATION

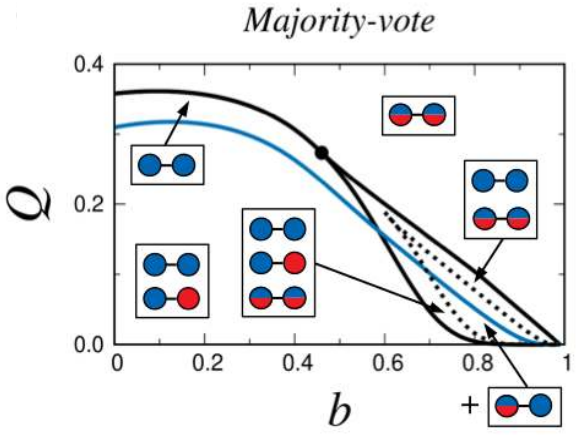
'group' interactions:

DECREASING BIAS
leads to
CONSENSUS
and then
POLARIZATION

(first) TAKE AWAY: What can we learn from the model?

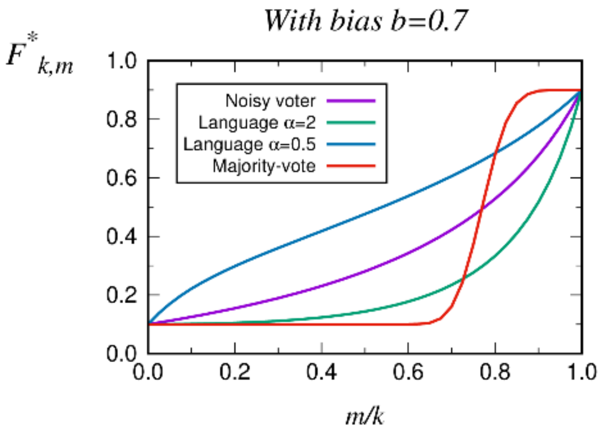


when **discussing one-on-one**, filtering out disagreeing views leads to **consensus**, and in the extreme, to **polarization**



when **discussing in groups** the opposite happens: filtering out disagreeing views promotes **coexistence**

polarization in social networks results from a nuanced interplay of **network structure**, **spreading dynamics**, & **content filtering**, and can be treated within a flexible framework



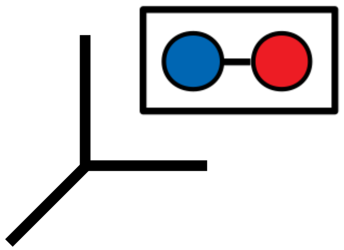
Deconstructing the (second) title…

SOCIAL
NETWORK STRUCTURE

ROLE OF
ONLINE PLATFORMS

DYNAMICS OF
POLITICAL IDEOLOGIES

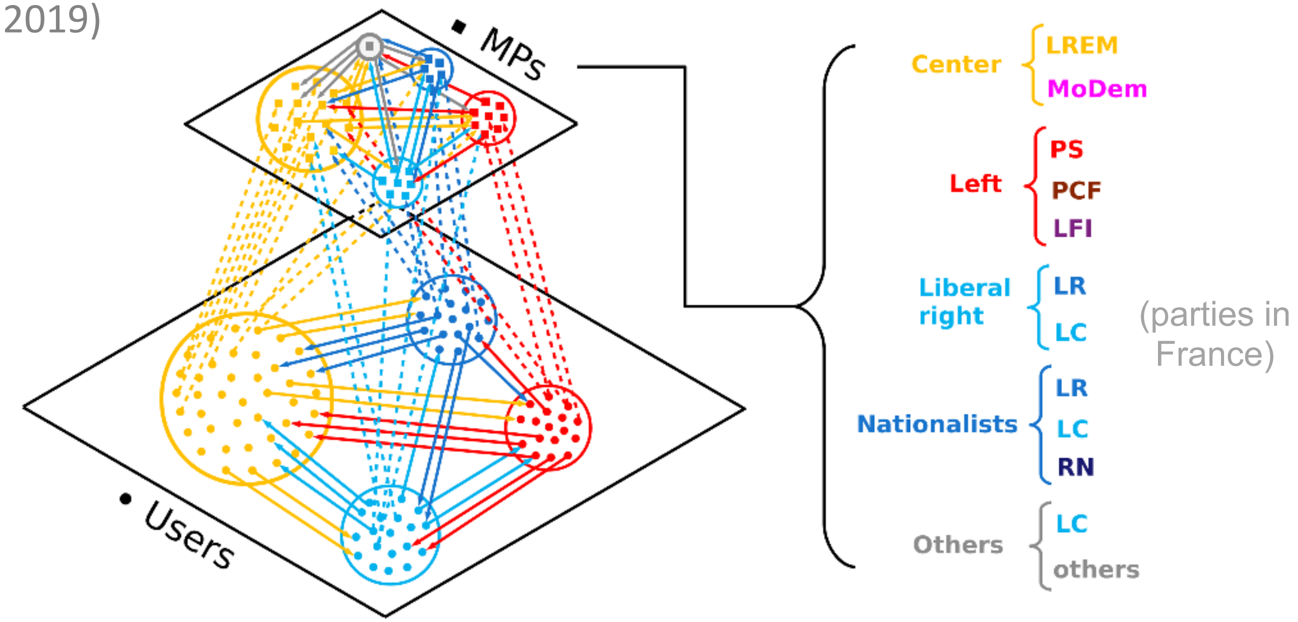
(multidimensional)
POLARIZATION



Ramaciotti, Iñiguez et al. *SNAM* 13 (2023): 14 Peralta, Iñiguez et al. *arXiv* (2023): 2305.02941

FRENCH TWITTER (2019)

813 Members of Parliament (MPs) & 230k followers



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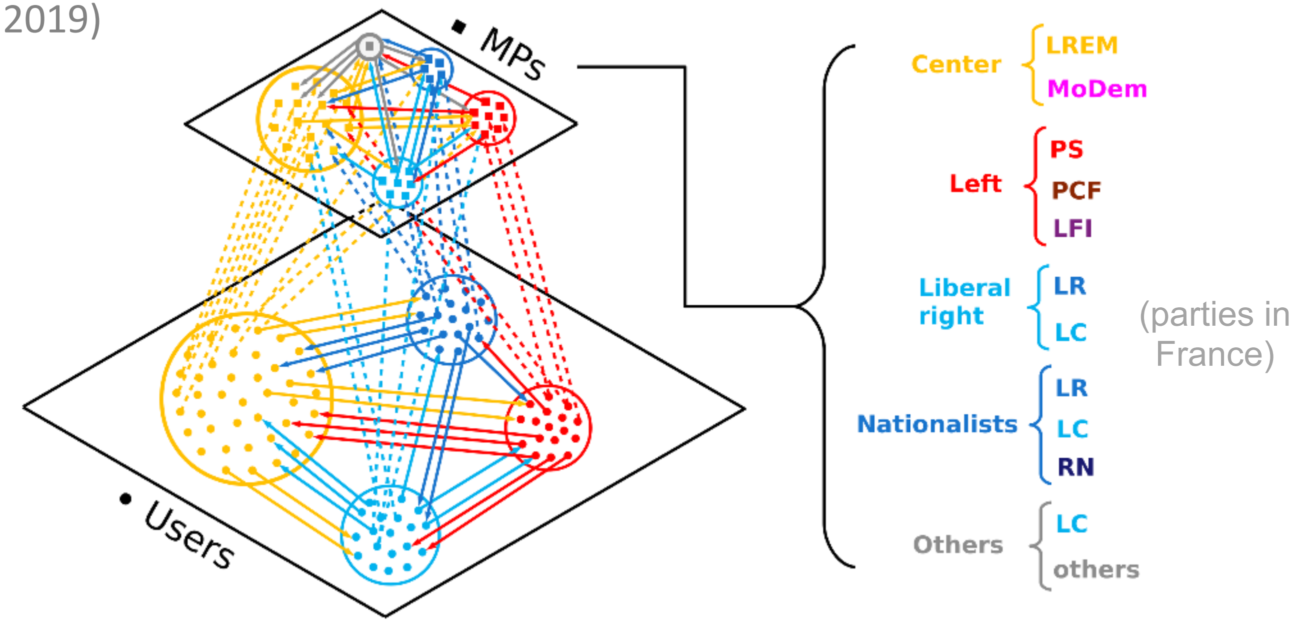
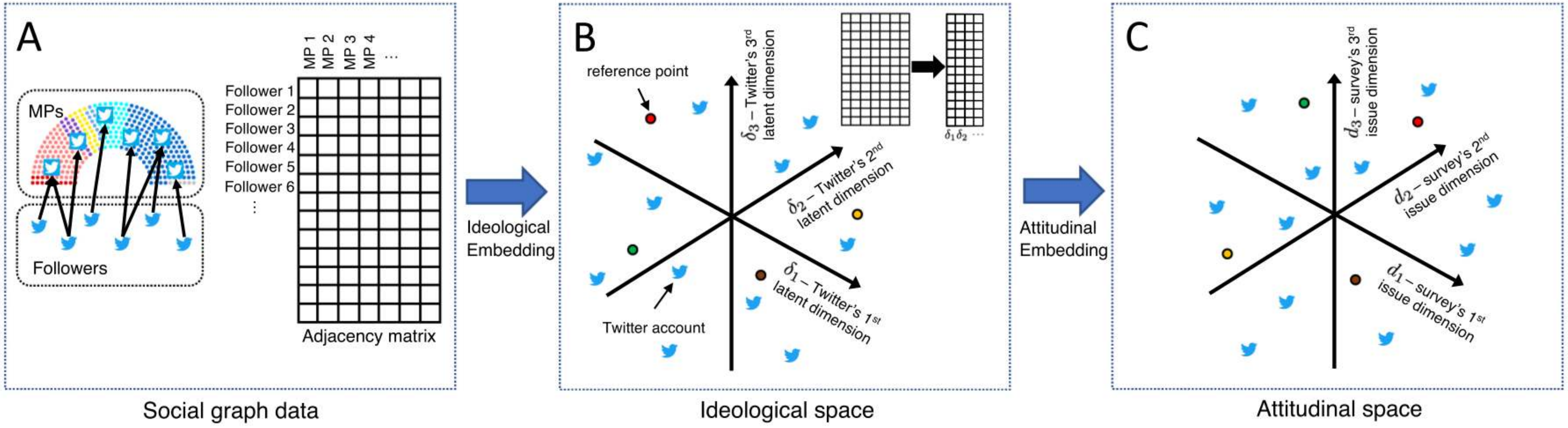


2-step LATENT SPACE EMBEDDING



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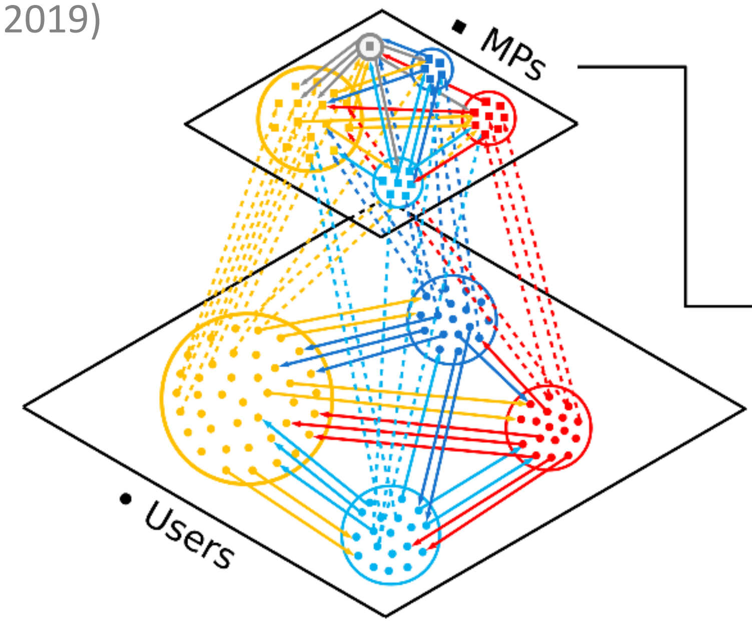
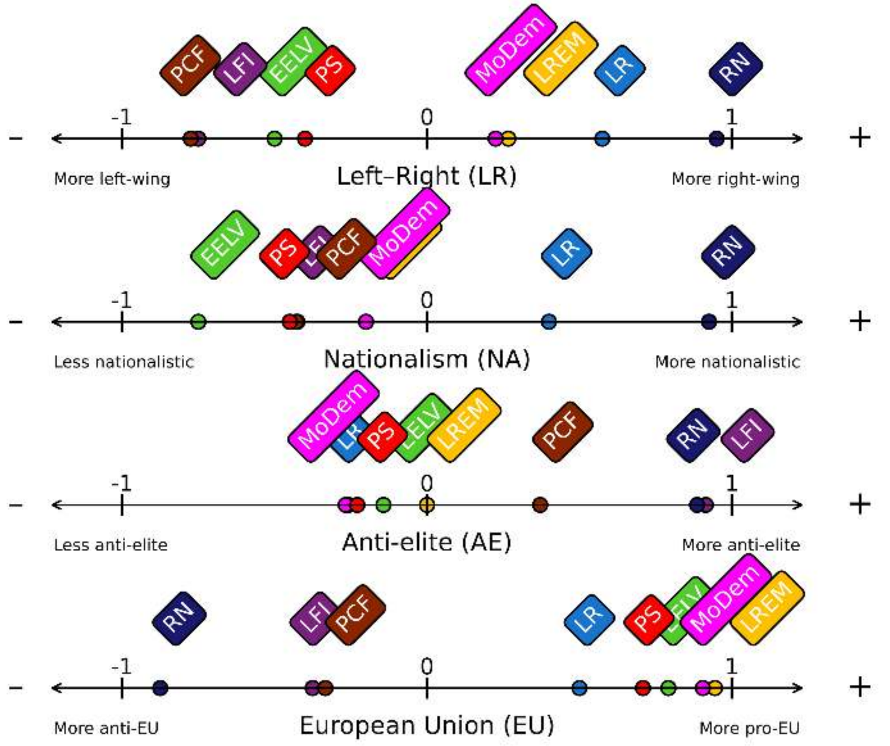


- **Center**: LREM, MoDem
- **Left**: PS, PCF, LFI
- **Liberal right**: LR, LC
- **Nationalists**: LR, LC, RN
- **Others**: LC, others

(parties in France)

4 identifiable political dimensions



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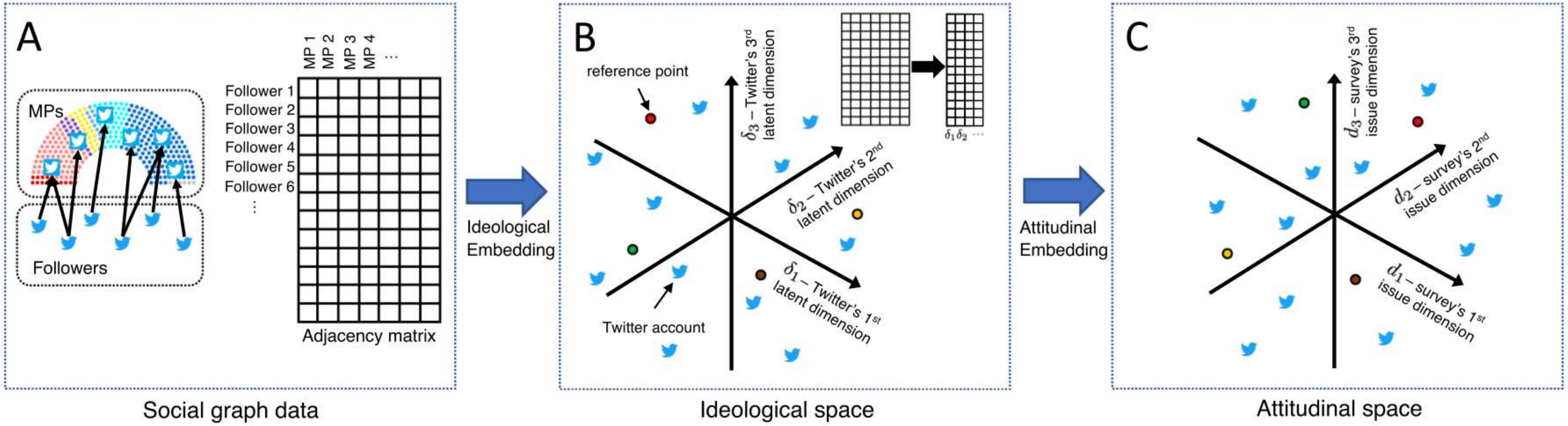
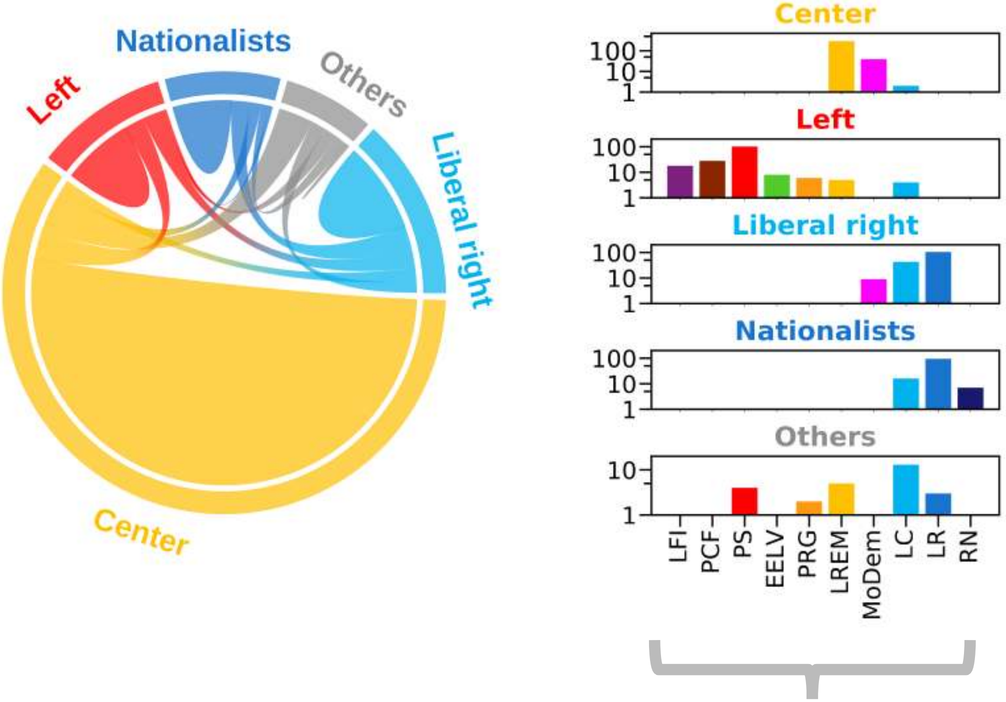


Ramaciotti, Iñiguez et al. *SNAM* 13 (2023): 14 Peralta, Iñiguez et al. *arXiv* (2023): 2305.02941

Latent space captures groups & ideologies of MPs and parties

COMMUNITY DETECTION

(stochastic block model + min description length)



(10 parties)

Ramaciotti, Iñiguez et al. *SNAM* 13 (2023): 14 Peralta, Iñiguez et al. *arXiv* (2023): 2305.02941

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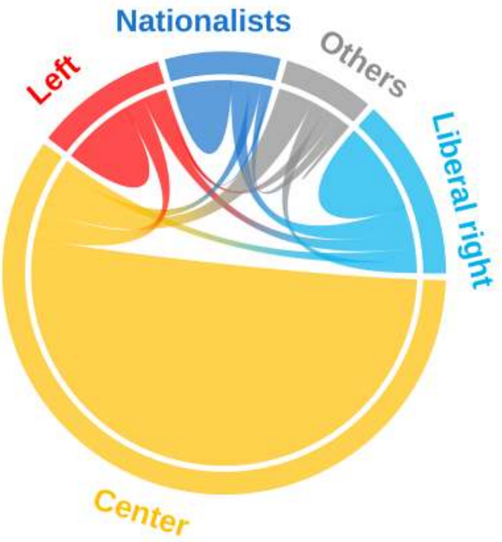
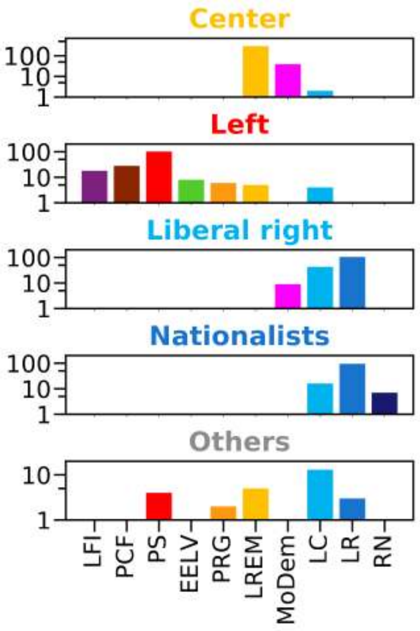
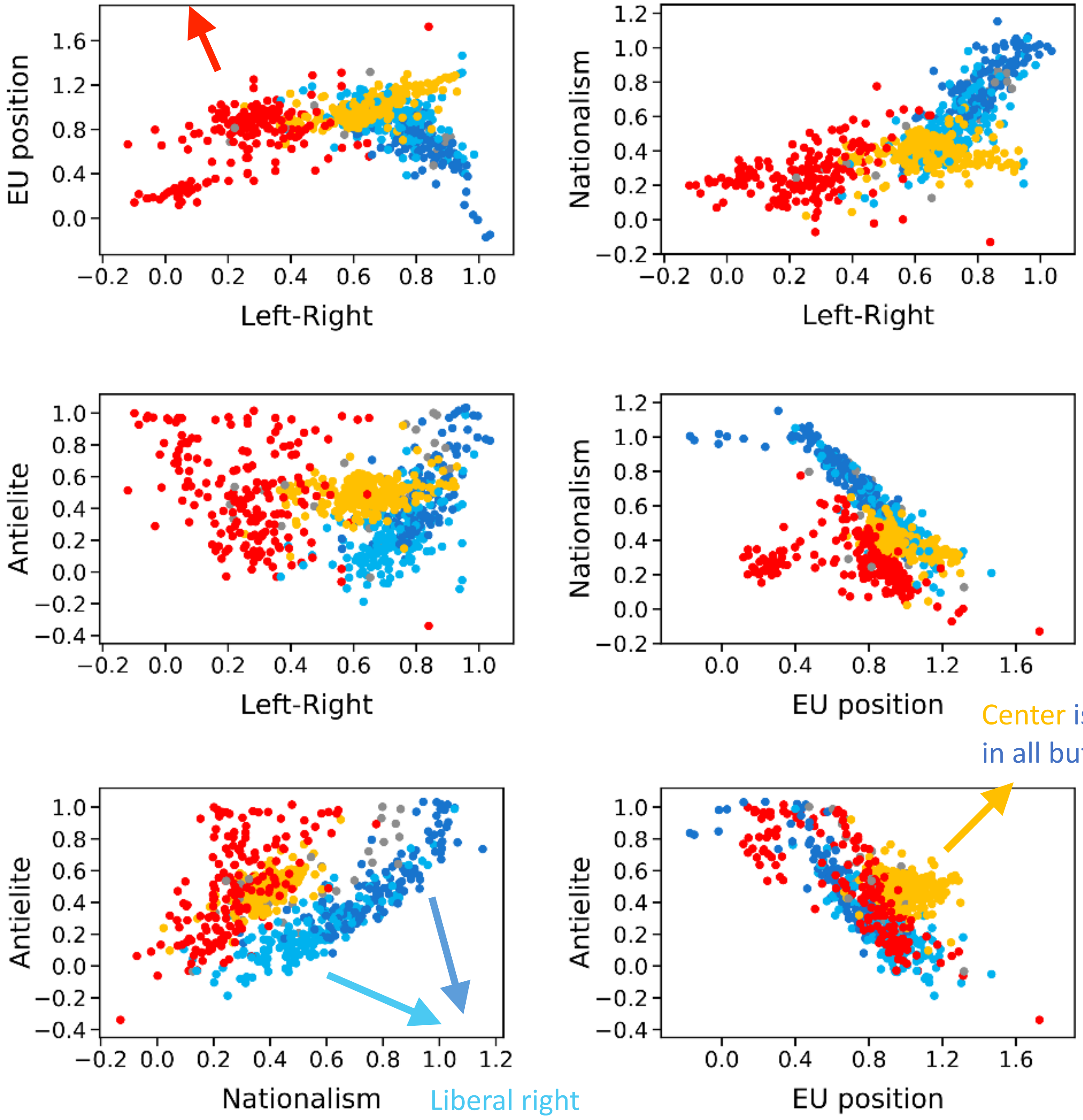




(10 parties)

Left is leftist!

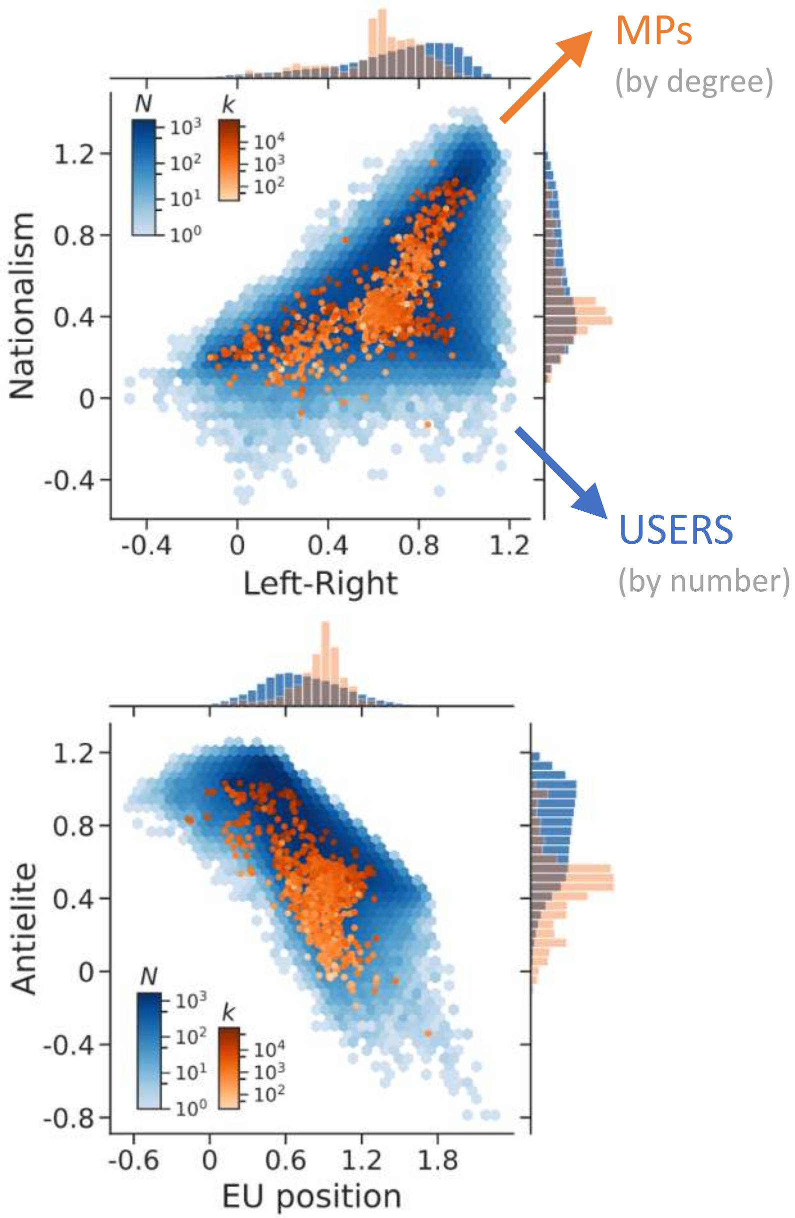


Center is centrist in all but EU!

Liberal right & Nationalists differ!

Ramaciotti, Iñiguez et al. *SNAM* 13 (2023): 14   Peralta, Iñiguez et al. *arXiv* (2023): 2305.02941

Twitter users are more extreme (& segregated) than MPs



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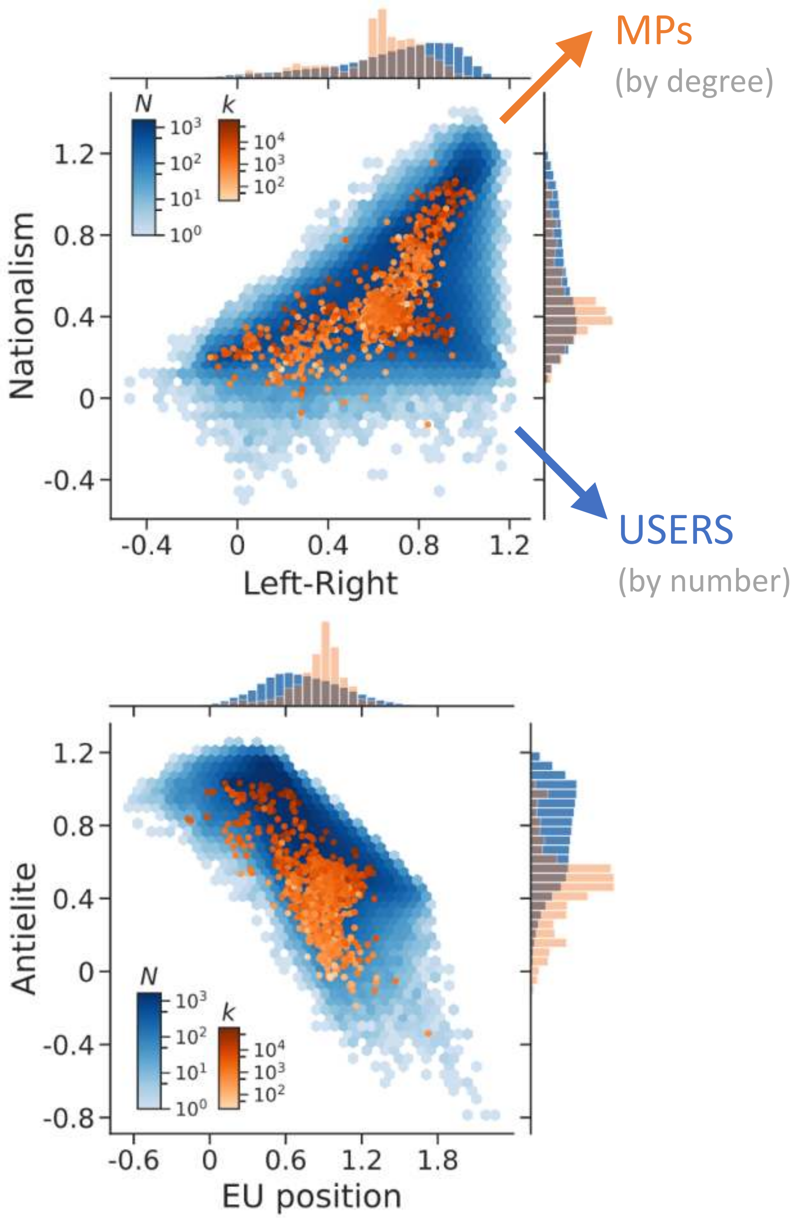

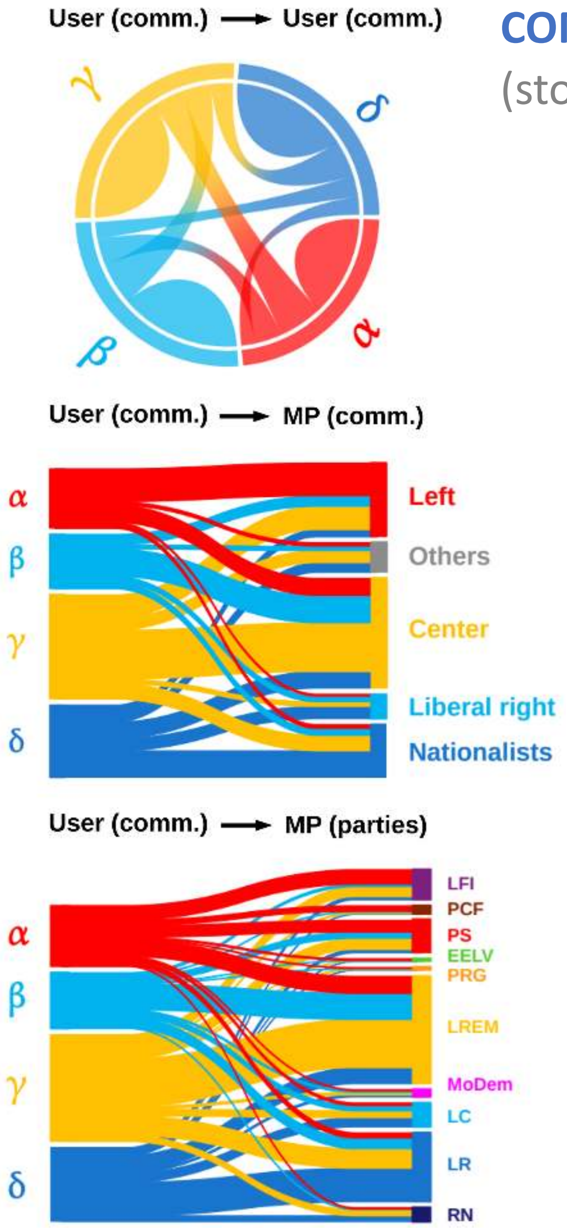

COMMUNITY DETECTION

(stochastic block model + 4 comms constraint)

Ramaciotti, Iñiguez et al. *SNAM* 13 (2023): 14 Peralta, Iñiguez et al. *arXiv* (2023): 2305.02941

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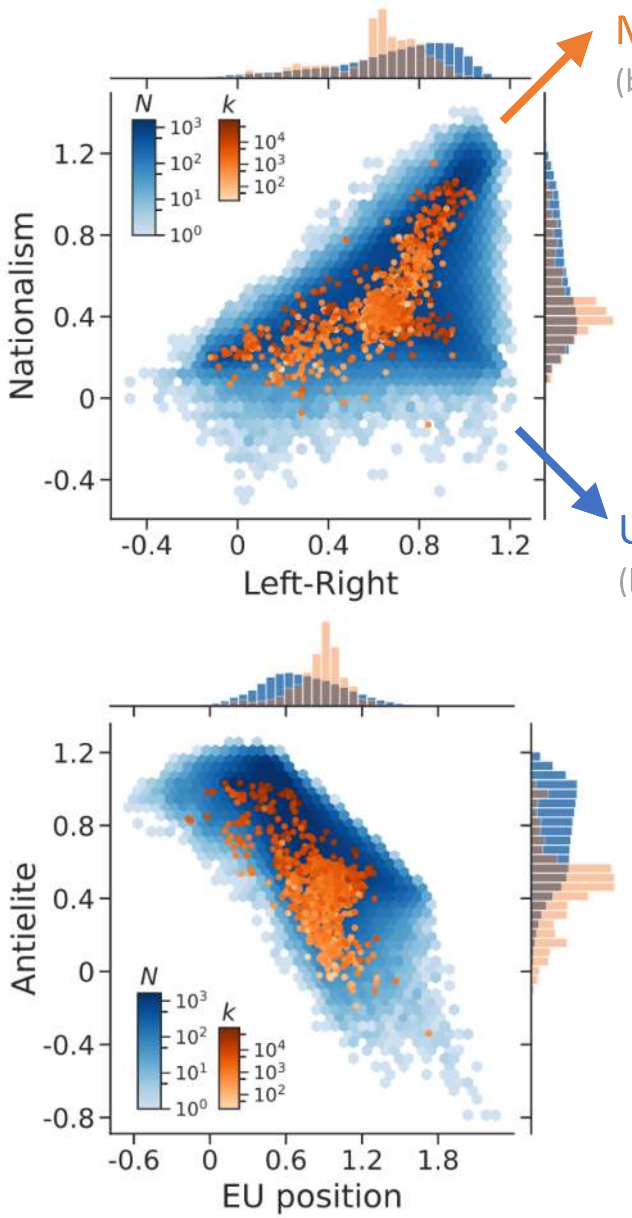
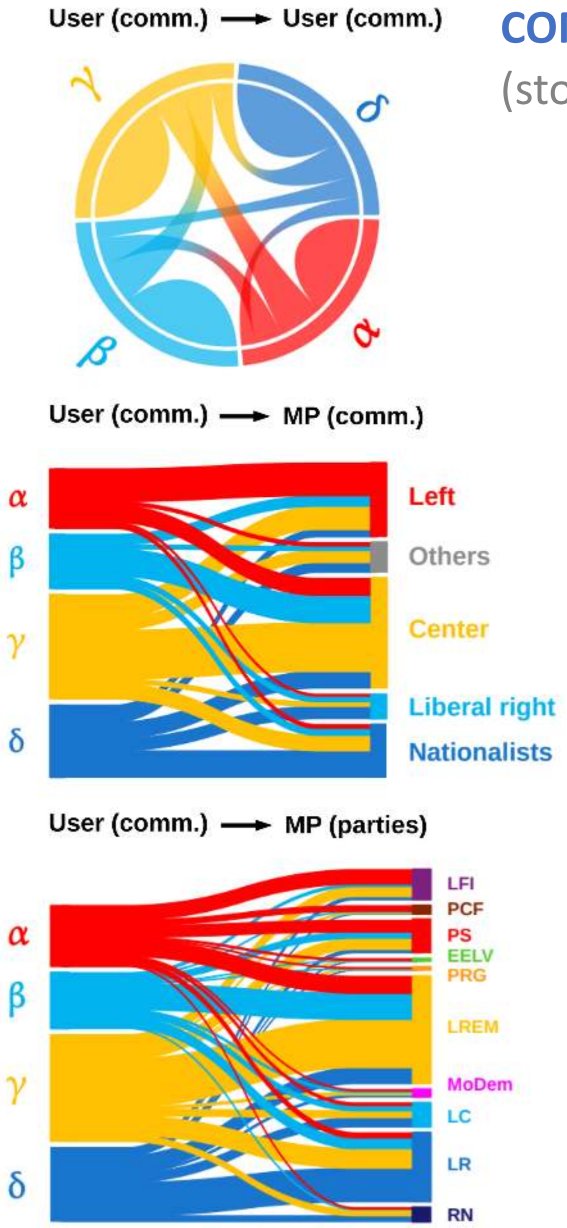


MPs
(by degree)

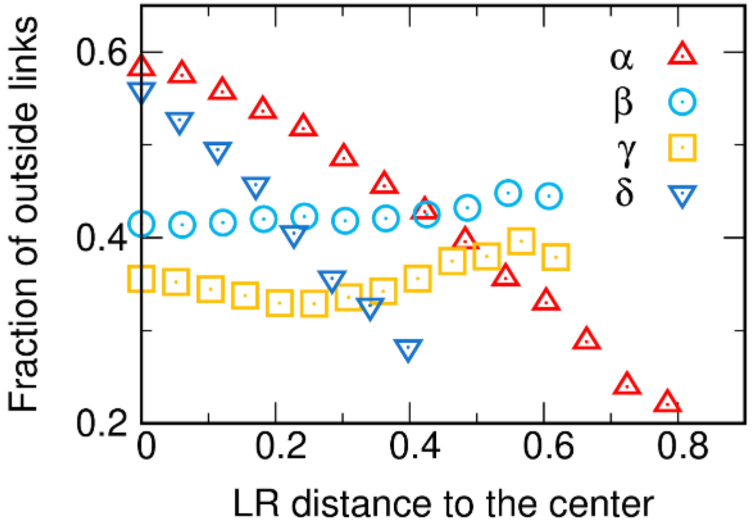
USERS
(by number)



COMMUNITY DETECTION

(stochastic block model + 4 comms constraint)

more centrist β and γ groups interact with others despite their differences



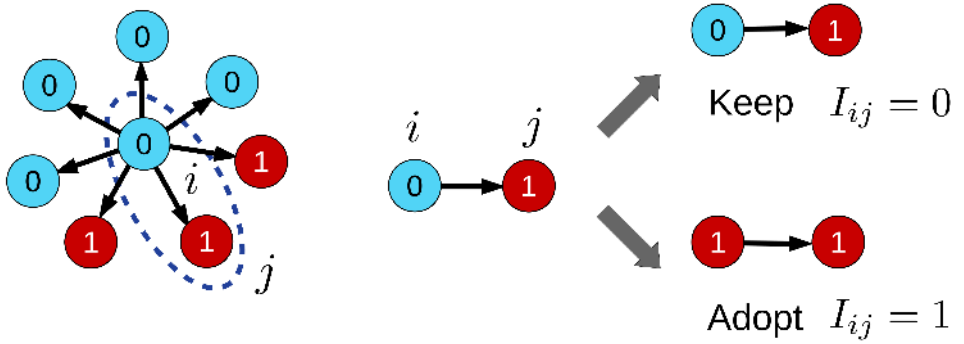
more extreme α and δ groups segregate as they diverge in ideology!

Ramaciotti, Iñiguez et al. *SNAM* 13 (2023): 14   Peralta, Iñiguez et al. *arXiv* (2023): 2305.02941

Modeling multidimensional political polarisation online

(variable) user 4D opinions $\vec{v}_i(t) = (x_i(t), y_i(t), z_i(t), w_i(t))$

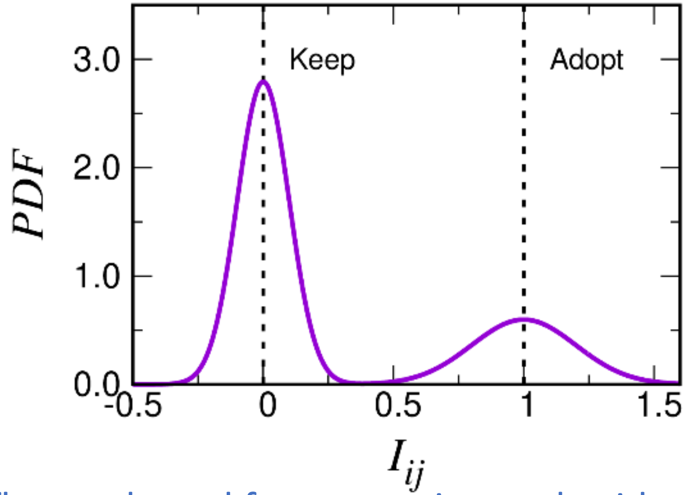
(fixed) MP 4D opinions $\vec{V}_m = (X_m, Y_m, Z_m, W_m)$



user <-> user $\vec{v}_i(t + \Delta t) = \vec{v}_i(t) + I_{ij}[\vec{v}_j(t) - \vec{v}_i(t)]$

user <-> MP $\vec{v}_i(t + \Delta t) = \vec{v}_i(t) + I_{im}[\vec{V}_m - \vec{v}_i(t)]$

(λ ratio of time scales)



influence kernel from experimental evidence

Chacoma, Zanette. *PloS ONE* 10 (2015): e0140406

Ramaciotti, Iñiguez et al. *SNAM* 13 (2023): 14

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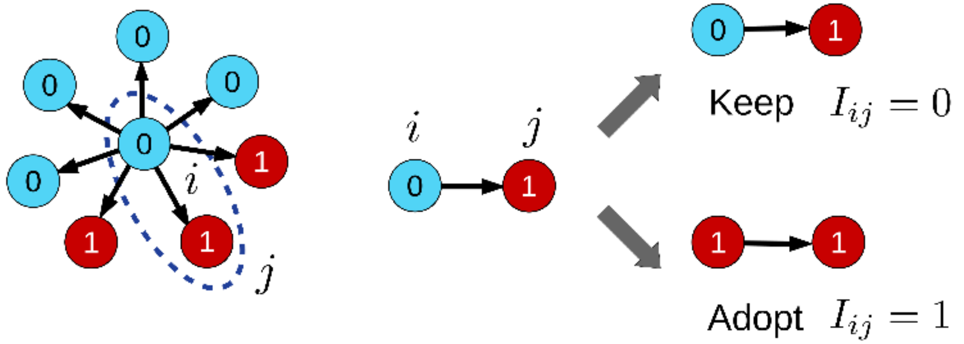

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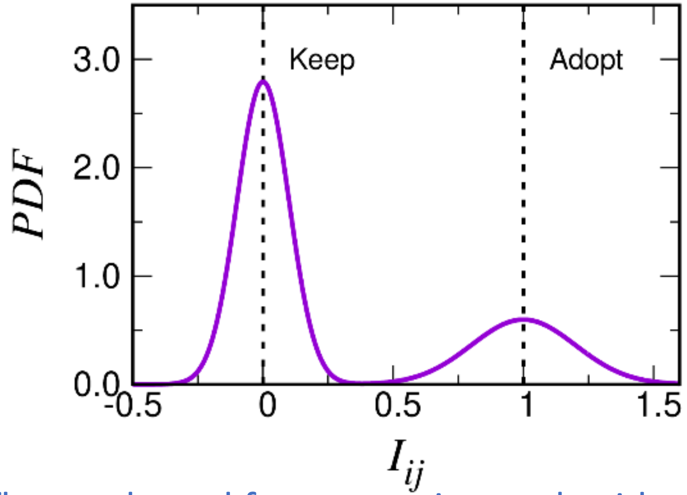
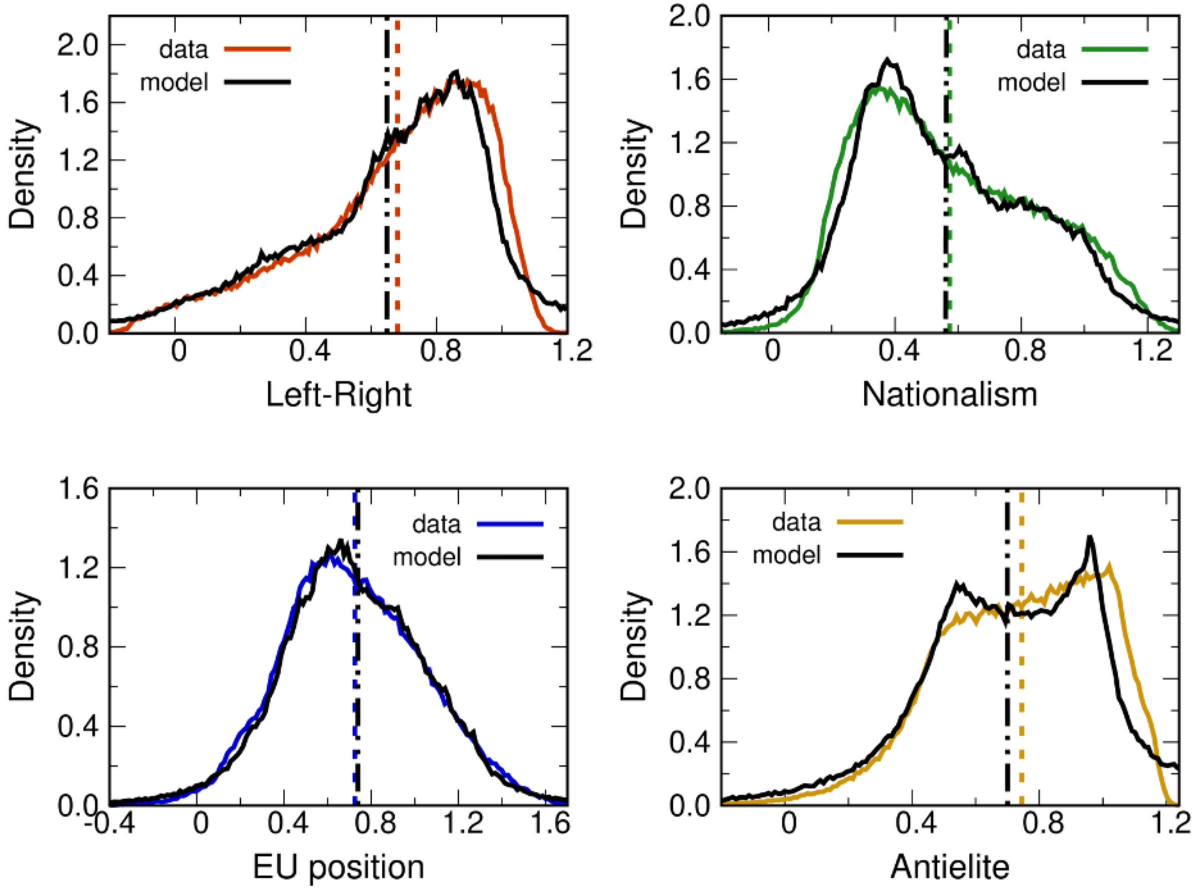


influence kernel from experimental evidence

Chacoma, Zanette. *PloS ONE* 10 (2015): e0140406

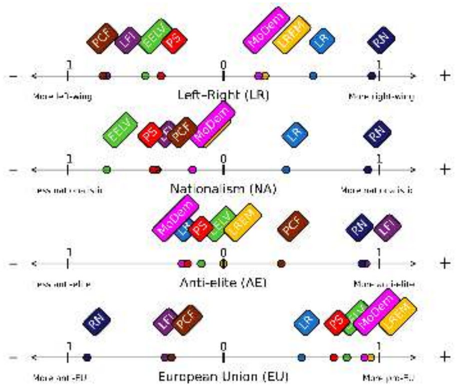
fitted model recovers ideological positions of most users



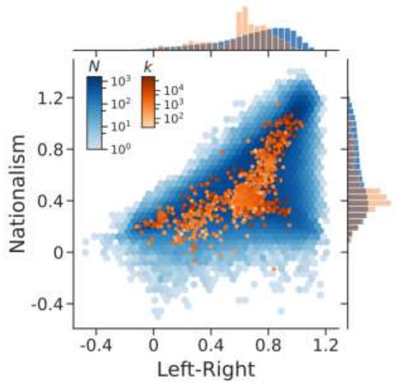
except for extremists in LR, NA, AE (different mechanisms?)

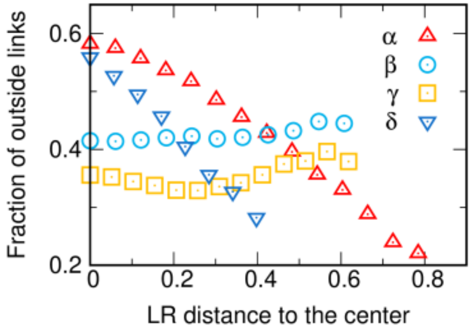
Ramaciotti, Iñiguez et al. *SNAM* 13 (2023): 14   Peralta, Iñiguez et al. *arXiv* (2023): 2305.02941

(second) TAKE AWAY: polarisation is inherently multidimensional



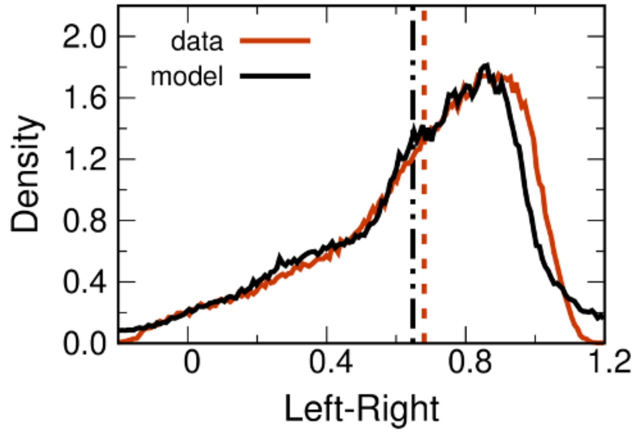
political **polarisation** is **not reducible** to a single dimension:
embedding Twitter data uncovers **4 dimensions** of political ideology in France





users and MPs form **groups** of similar people:
but users are **more extreme** & **segregated**, polarising Twitter

mechanisms of **opinion imitation** & **inertia** between users & MPs
are enough to **emulate ideologies** seen in data, at least for centrists



more info online:

Peralta, Neri, Kertész, Iñiguez

Effect of algorithmic bias and network structure on coexistence, consensus, and polarization of opinions

Physical Review E 104, 044312 (2021)

https://doi.org/10.1103/PhysRevE.104.044312

Peralta, Ramaciotti, Kertész, Iñiguez

Multidimensional political polarization in online social networks

Under review, arXiv:2305.02941 (2023)

https://doi.org/10.48550/arXiv.2305.02941

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