Dynamics of Democracy

Part I (MS100)
3:10-4:50 PM

Heather Brooks
University of California, Los Angeles

Joseph Tien
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Part II (MS112)
5:00-6:40 PM

Carlos Castillo-Chavez
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Alexandria Volkening
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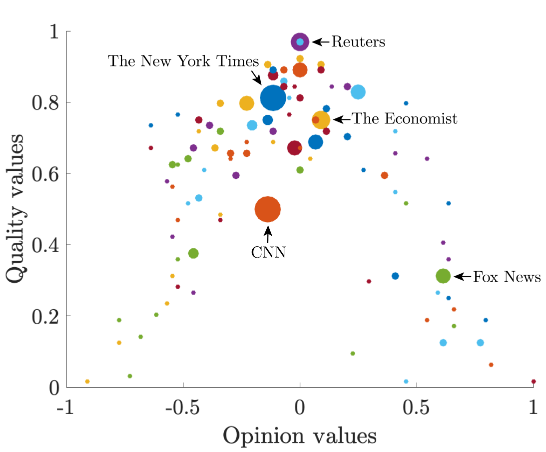

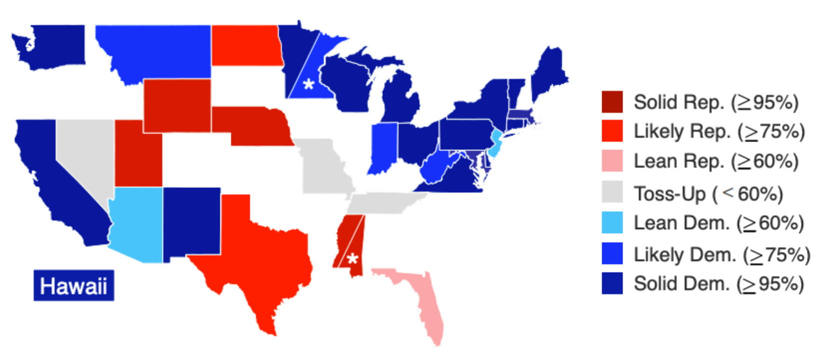

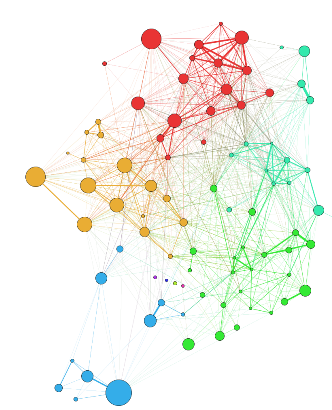

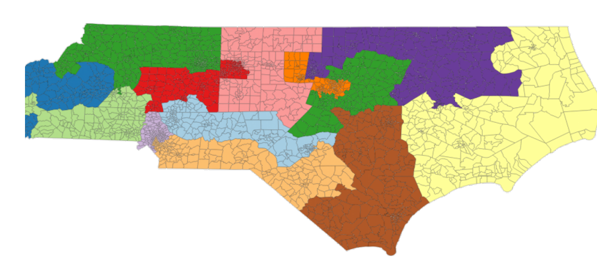

A Model for the Influence of Media on the Ideology of Content in Online Social Networks

Heather Zinn Brooks
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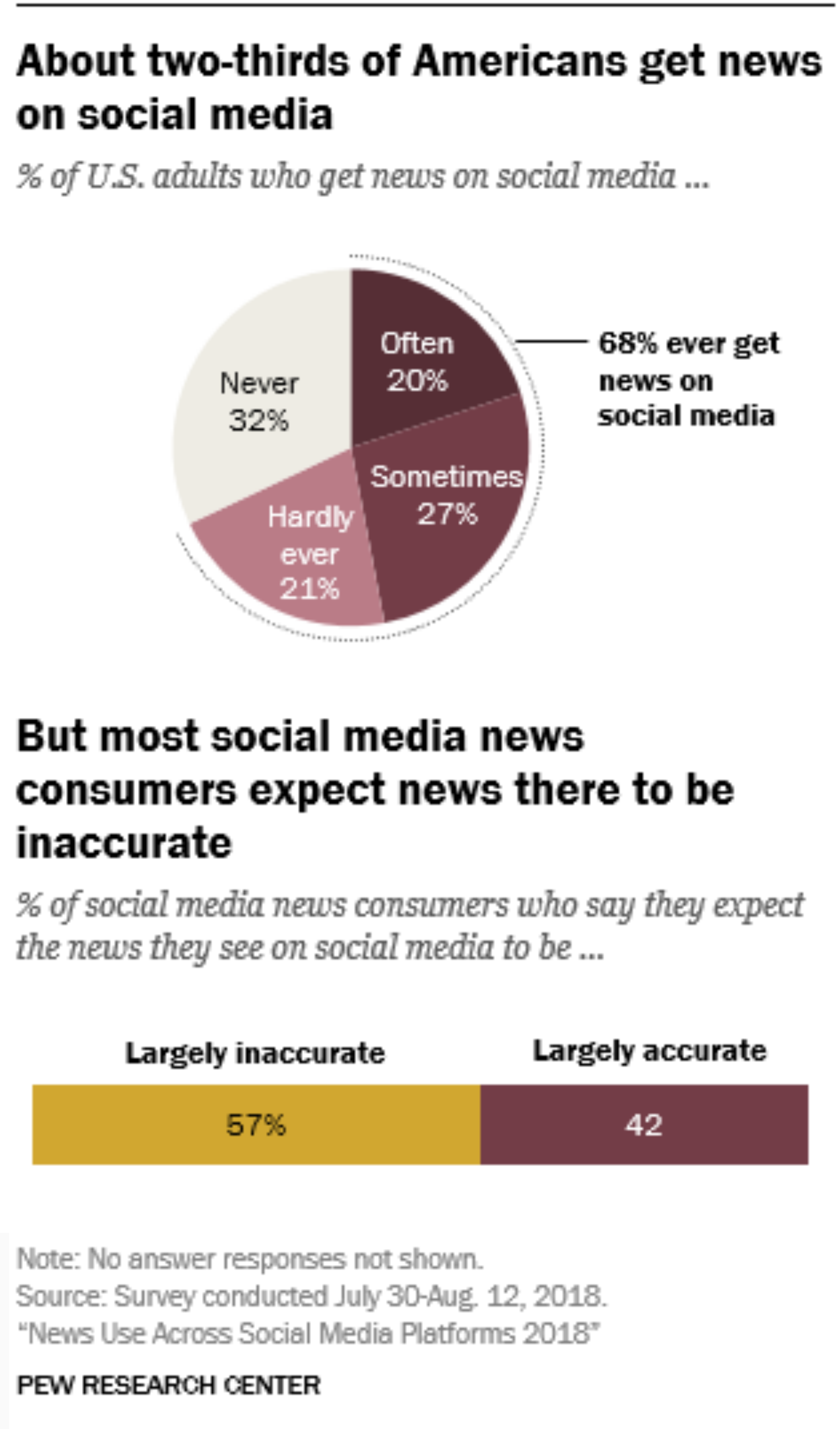
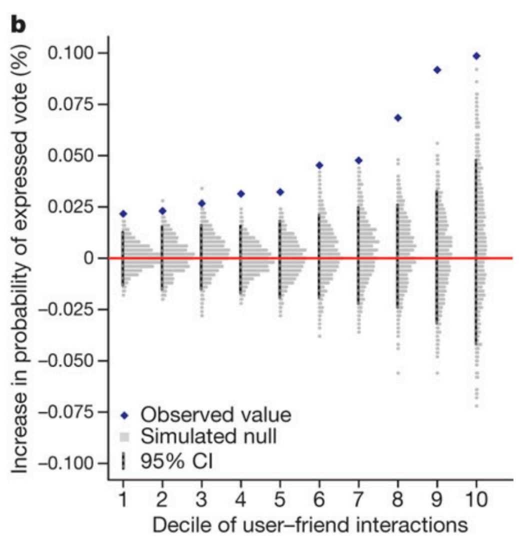
Joint work with Mason A. Porter, UCLA

People are increasingly reliant on online social networks as sources of news and information



The spread of information online affects policy, opinion, and personal interactions



LETTER

doi:10.1038/nature11421

A 61-million-person experiment in social influence and political mobilization

Robert M. Bond[1], Christopher J. Fariss[1], Jason J. Jones[2], Adam D. I. Kramer[3], Cameron Marlow[3], Jaime E. Settle[1] & James H. Fowler[1,4]

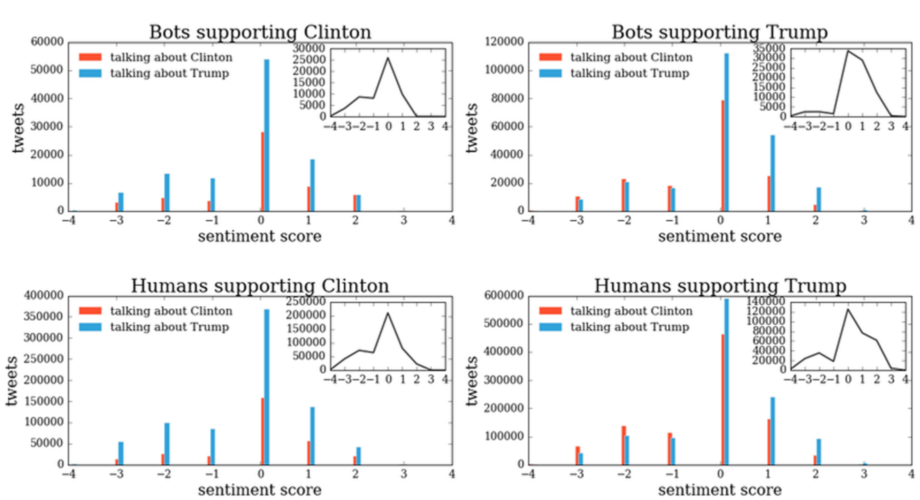
Social Bots Distort the 2016 US Presidential Election Online Discussion

First Monday, Volume 21, Number 11 - 7 November 2016

14 Pages • Posted: 8 Jun 2017

Alessandro Bessi
University of Southern California - Information Sciences Institute

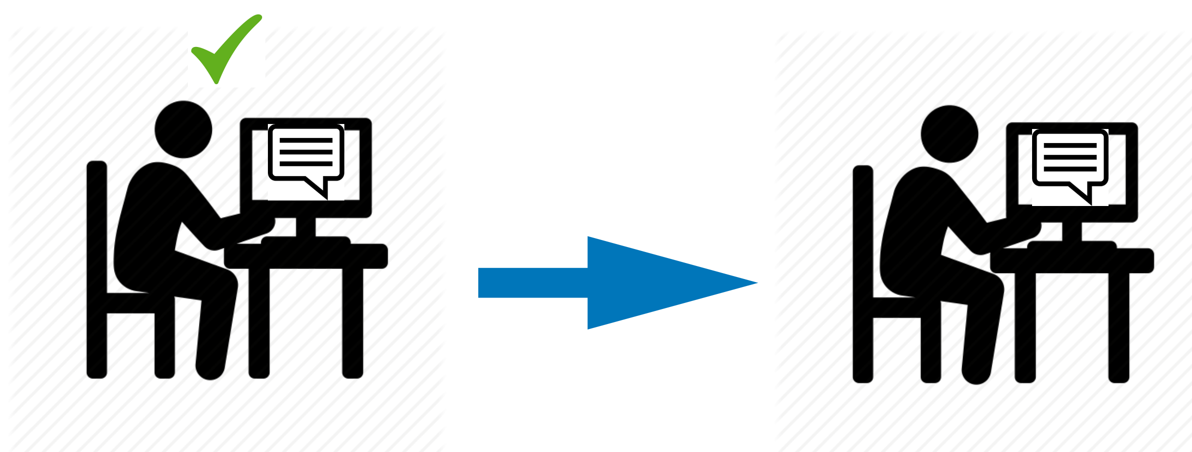
Emilio Ferrara
University of Southern California - Information Sciences Institute



How is content spread?

User preference:

Users are more likely to share a false story if it confirms or supports their biases



Manipulation of content spread:

Bot, cyborg, and sockpuppet accounts

Today's talk

- Building our model: social network structure
- Building our model: content updating dynamics
- Quantifying media impact
- Effects of network parameters
- Model upgrade: content spread with bias and quality

A Model for the Influence of Media on the Ideology of Content in Online Social Networks

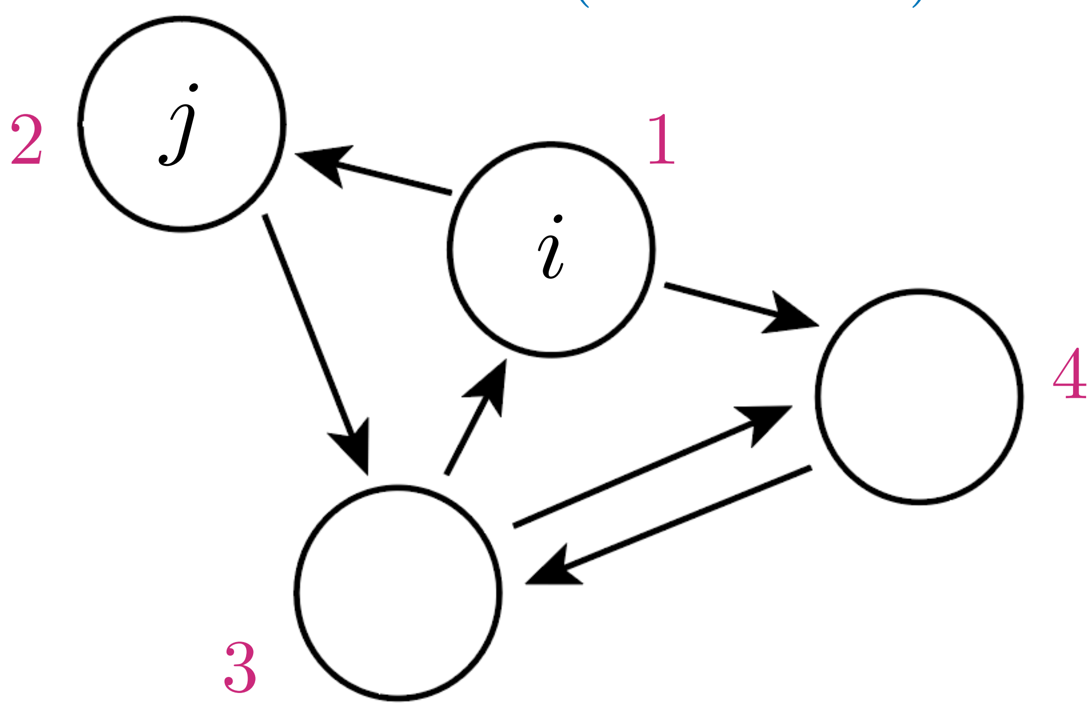
Heather Z. Brooks, Mason A. Porter

(Submitted on 19 Apr 2019)

We represent online social media network structure with a directed graph

$$G(\mathcal{V}_N, \mathcal{E})$$

set of (non-media) accounts   set of follower relationships



$$A = \begin{pmatrix} 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix}$$

Account i is a follower of account j if there is a directed edge from i to j

This graph can be represented with adjacency matrix A

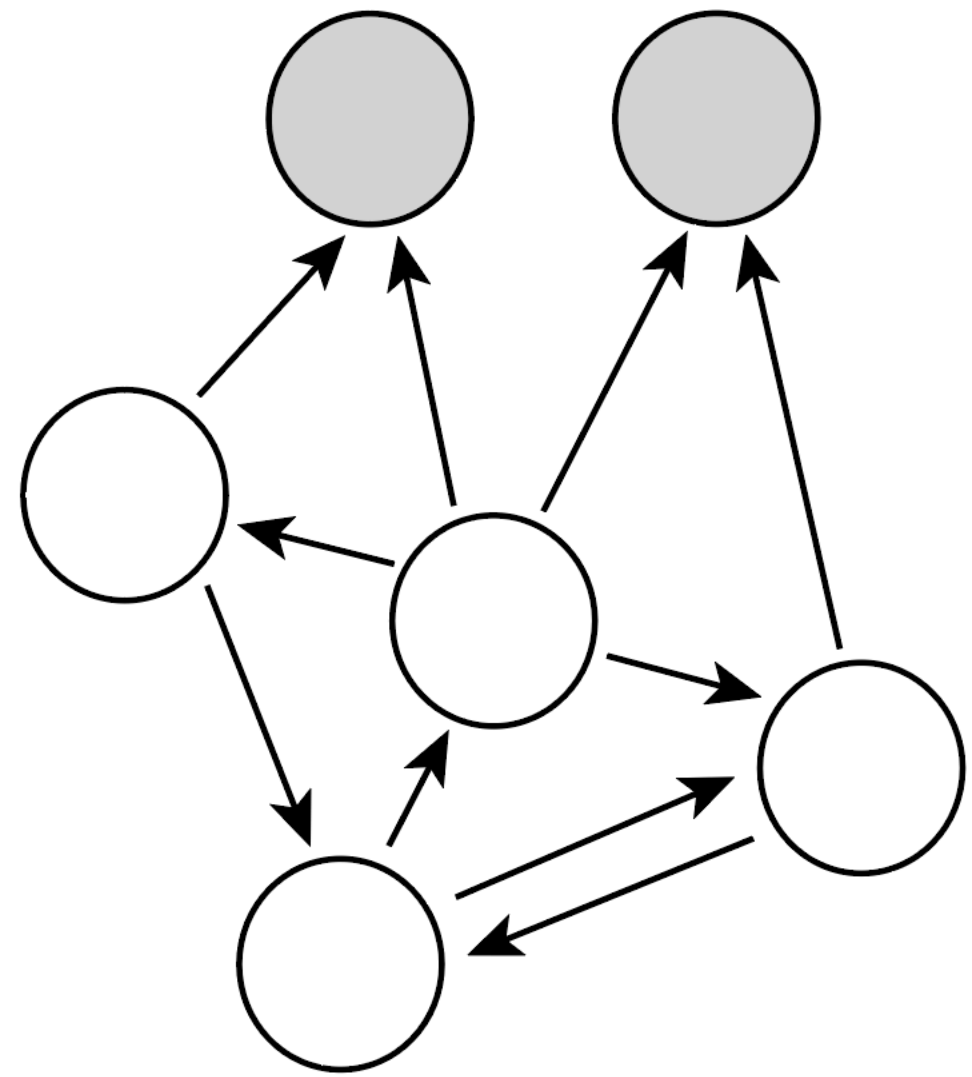
We add media accounts as influencer nodes

Assume: media accounts are not influenced (they do not follow other accounts)

M = number of media accounts

n_M = number of followers per media account

$$A = \begin{pmatrix} 0 & 1 & 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$



Bounded-confidence mechanism for content updating

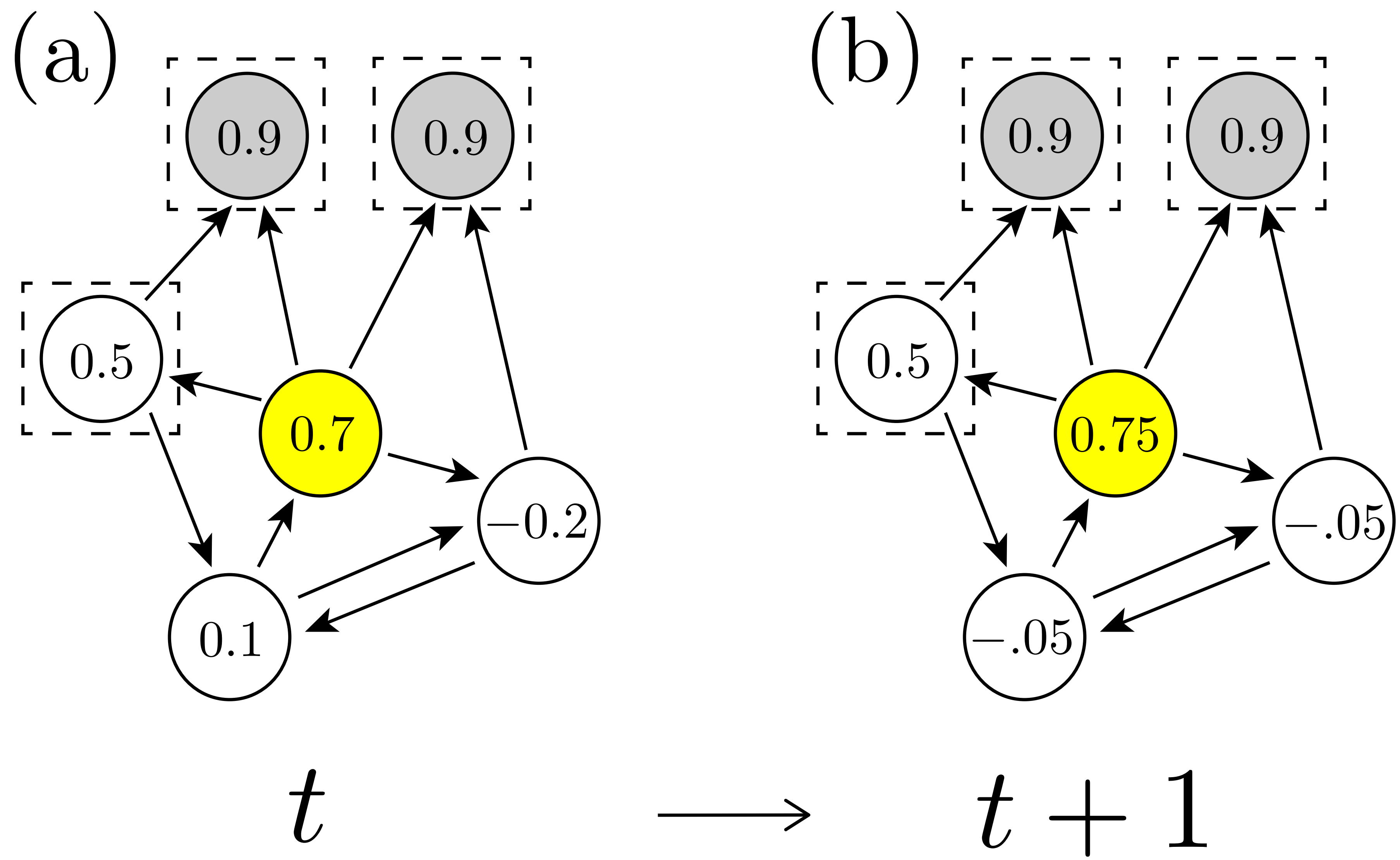
Content ideology of node i at time t is $\mathbf{x}_i^t \in [-1,1]^d$ which is updated according to

$$\boxed{\mathbf{x}_i^{t+1} = \frac{1}{|I_i|+1}\left(\mathbf{x}_i^t + \sum_{j=1}^{N+M} A_{ij}\mathbf{x}_j^t f(\mathbf{x}_j^t, \mathbf{x}_i^t)\right)}$$

where $\begin{cases} f(\mathbf{x}_j, \mathbf{x}_i) = 1 & \mathrm{dist}(\mathbf{x}_j, \mathbf{x}_i) < c \\ f(\mathbf{x}_j, \mathbf{x}_i) = 0 & \text{otherwise} \end{cases}$

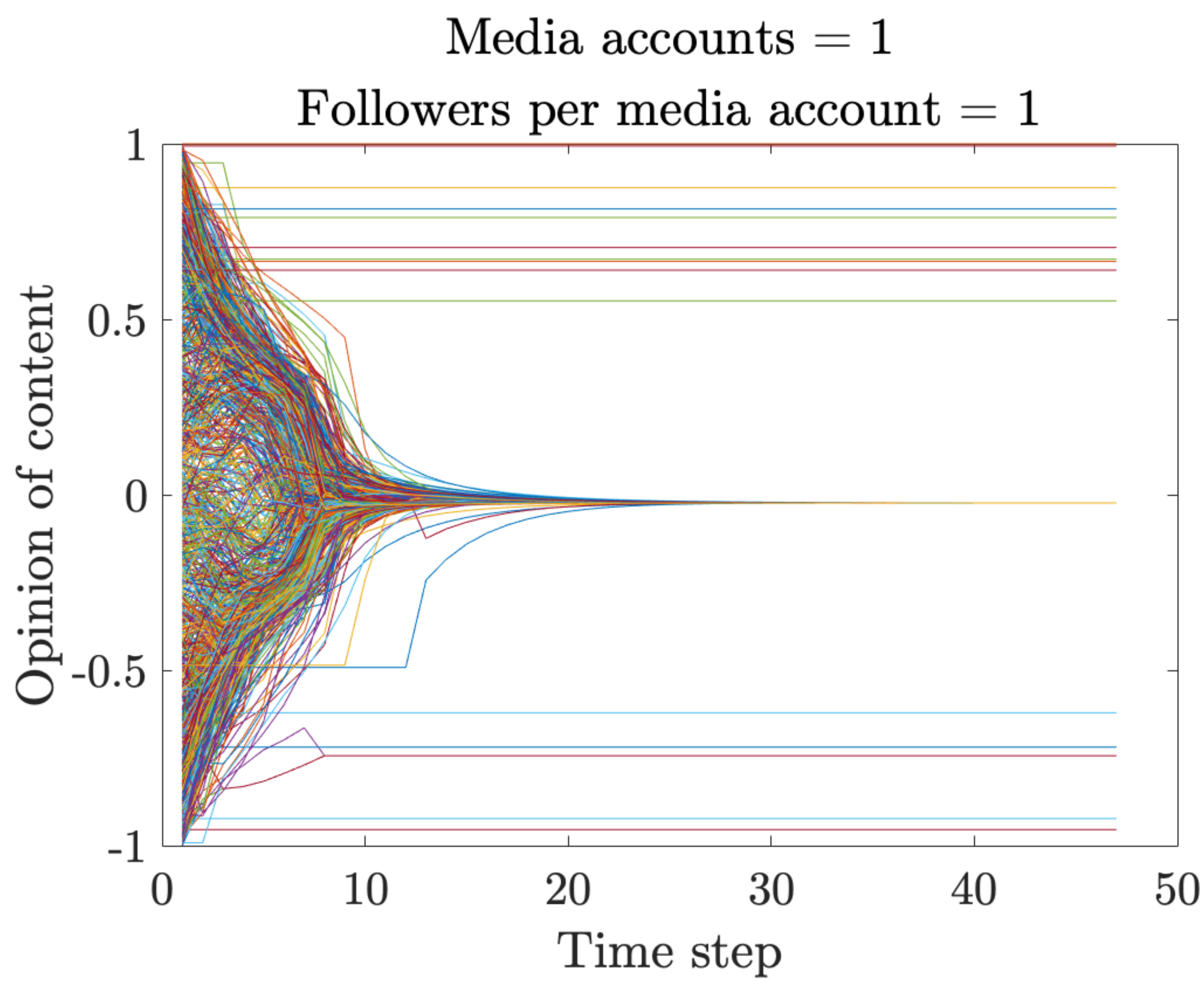
and $I_i = \{j \in \{1, \ldots, N+M\} | A_{ij} = 1; \mathrm{dist}(\mathbf{x}_j, \mathbf{x}_i) < c\}$

Schematic of content updating rule



$$x^{t+1} = \frac{1}{4}\left(0.7 + 0.5 + 0.9 + 0.9\right) = 0.75$$

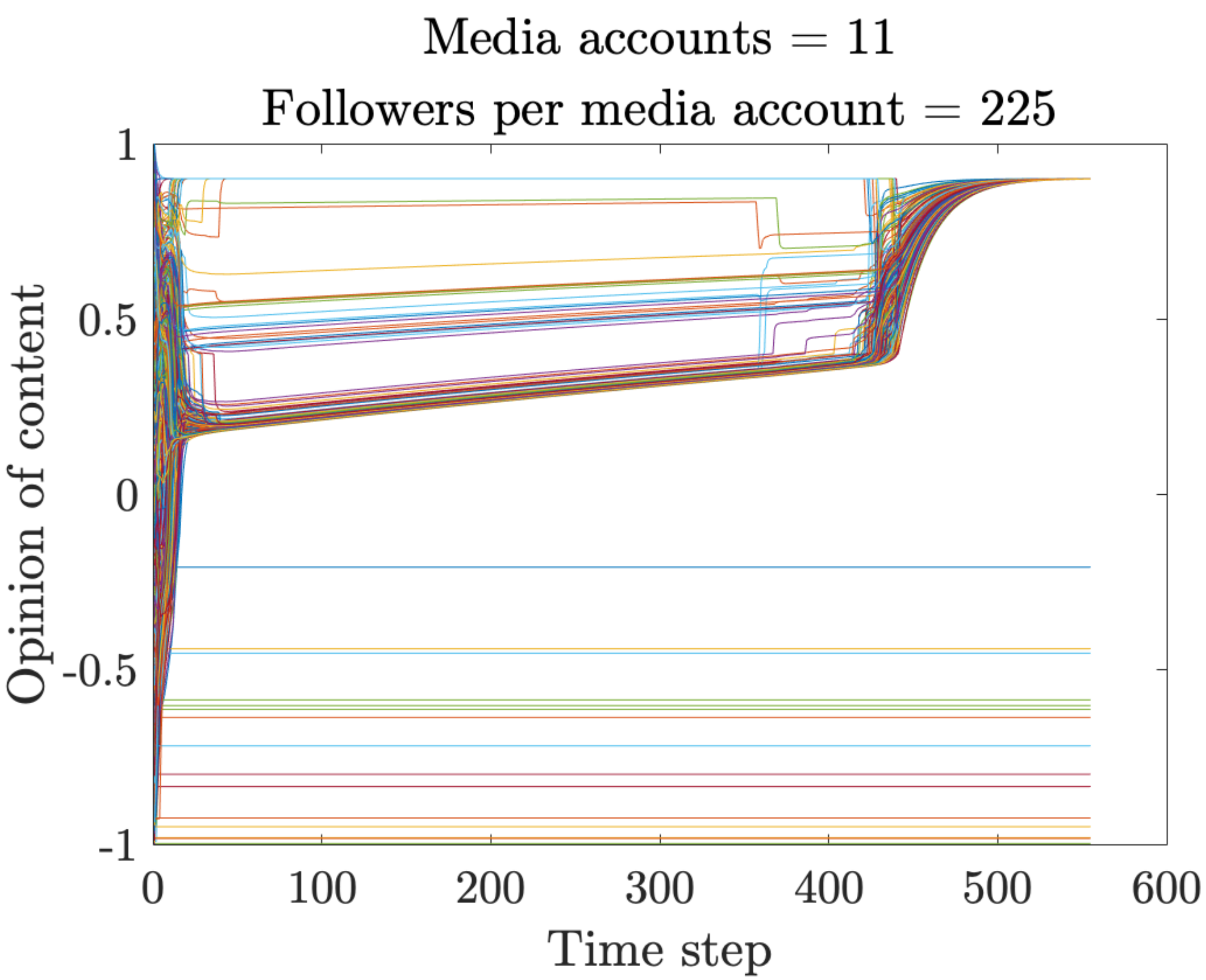
Example: simulation of one trial with a one-dimensional ideology space

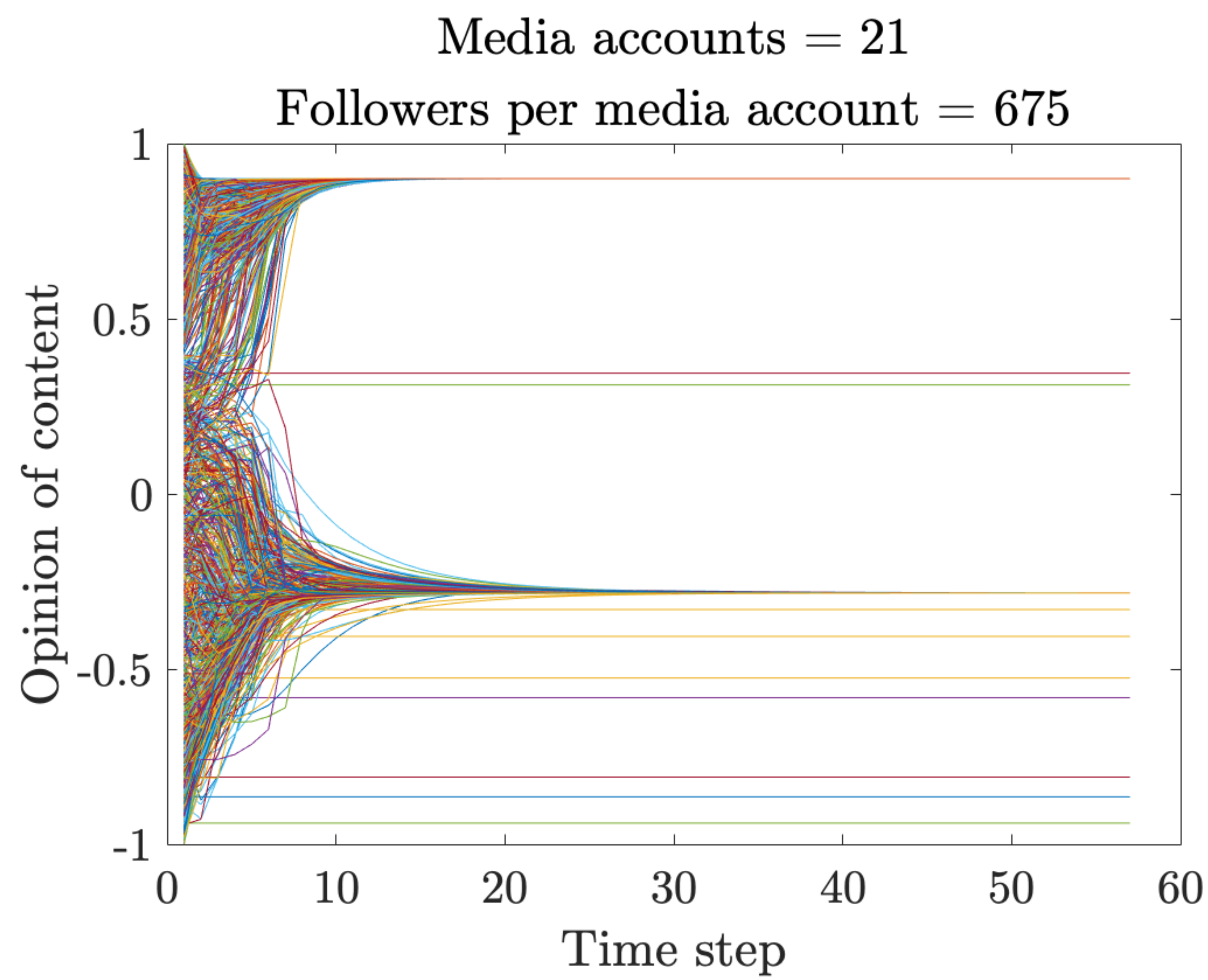


Network architecture: Facebook100 Reed College (N=962)

Media ideology: $x_M = 0.9$

Increasing media accounts and number of followers per account leads to different dynamics





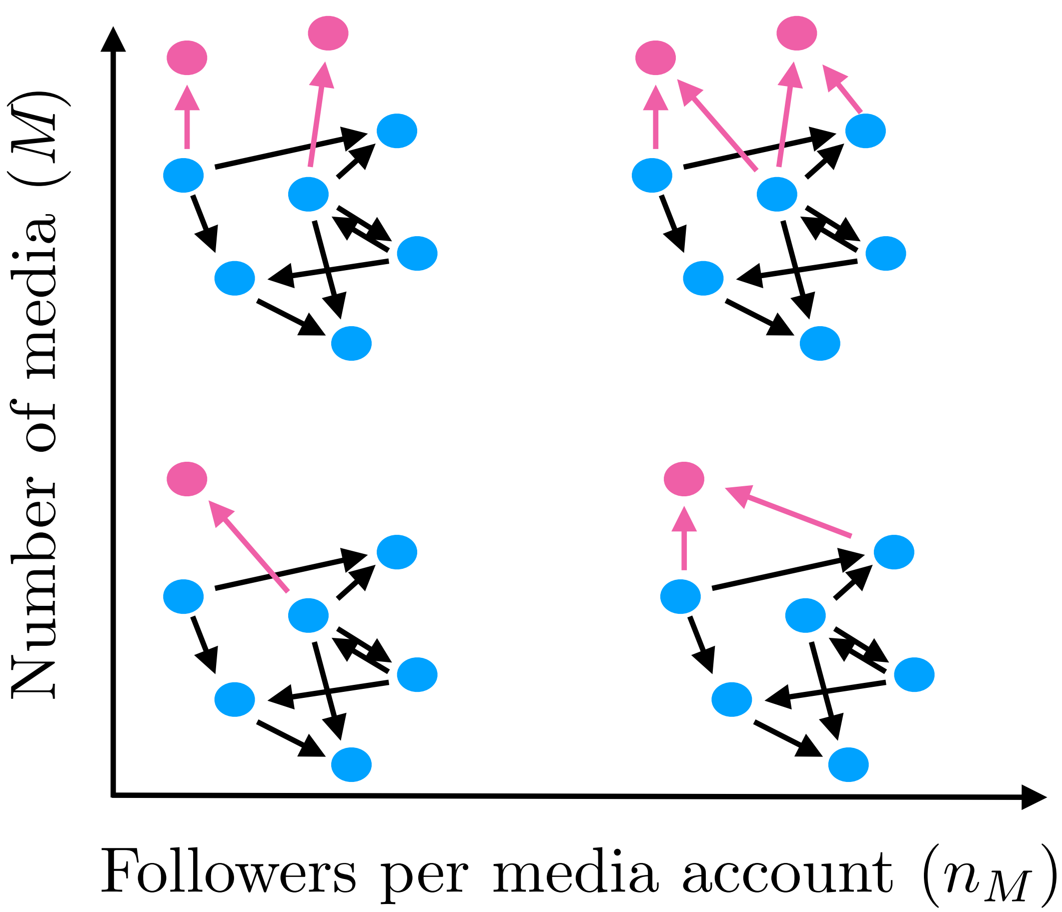
Network architecture: Facebook100 Reed College (N=962)

Media ideology: $x_M = 0.9$

How to quantify impact of media accounts on the network

For each (n_M, M) pair, calculate impact summary diagnostic

$$\overline{R} = \frac{\overline{R_0}}{\overline{R_i}}$$



where the order parameter for ideology without media is

$$R_0 = \frac{1}{N} \sum_{i=1}^{N} \|x_i^b - x_M\|_2$$

and with media is

$$R_i = \frac{1}{N} \sum_{i=1}^{N} \|x_i^* - x_M\|_2$$

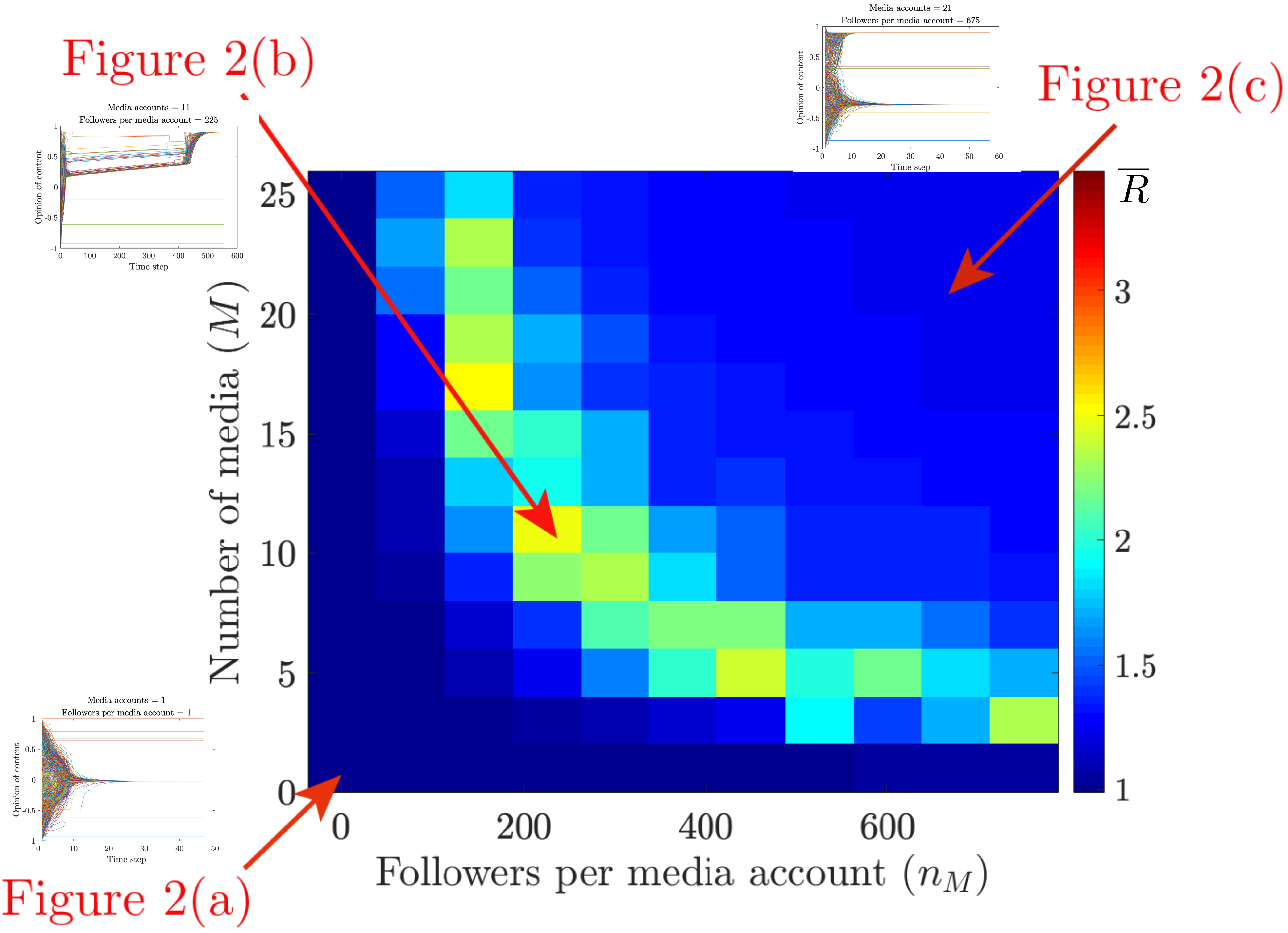
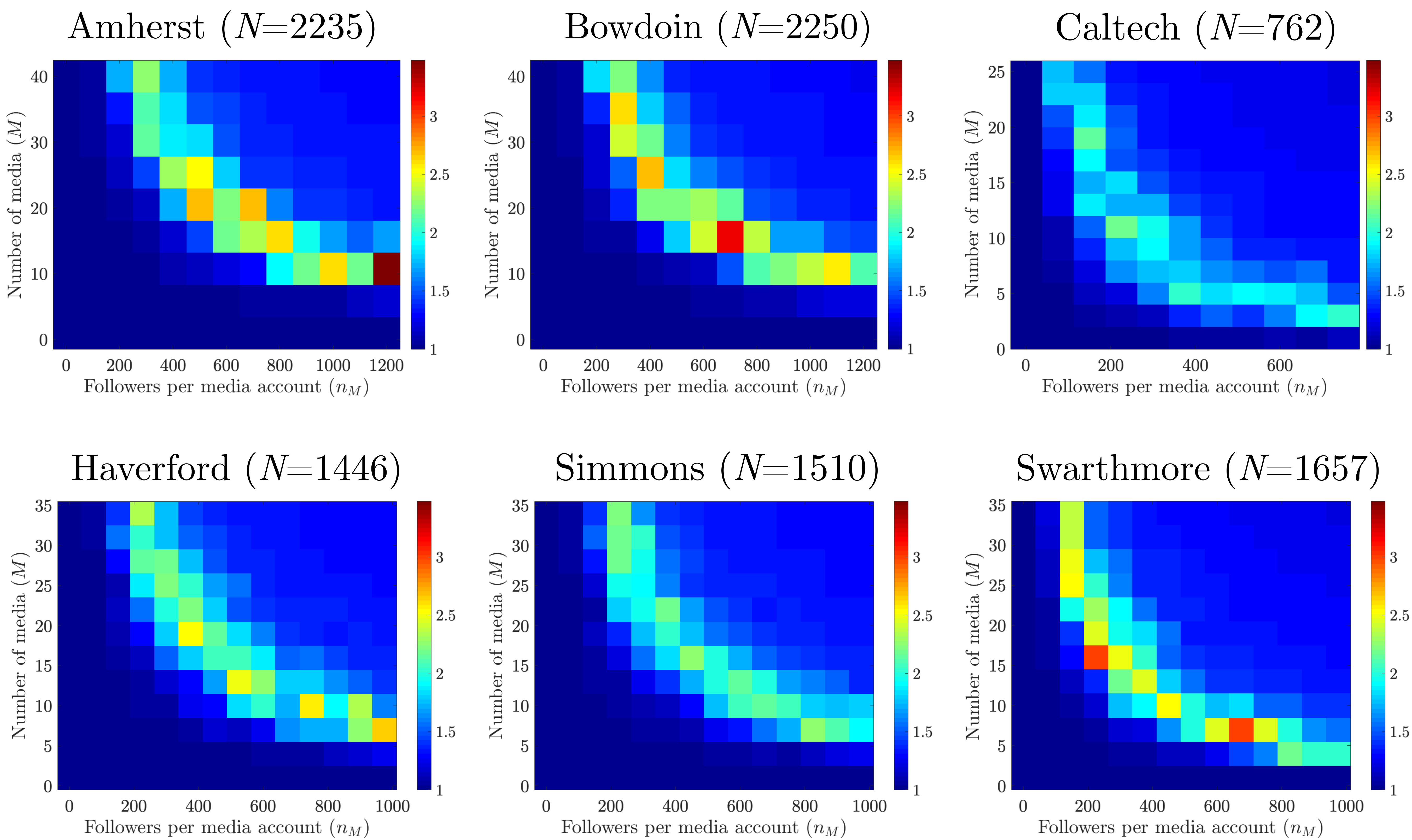
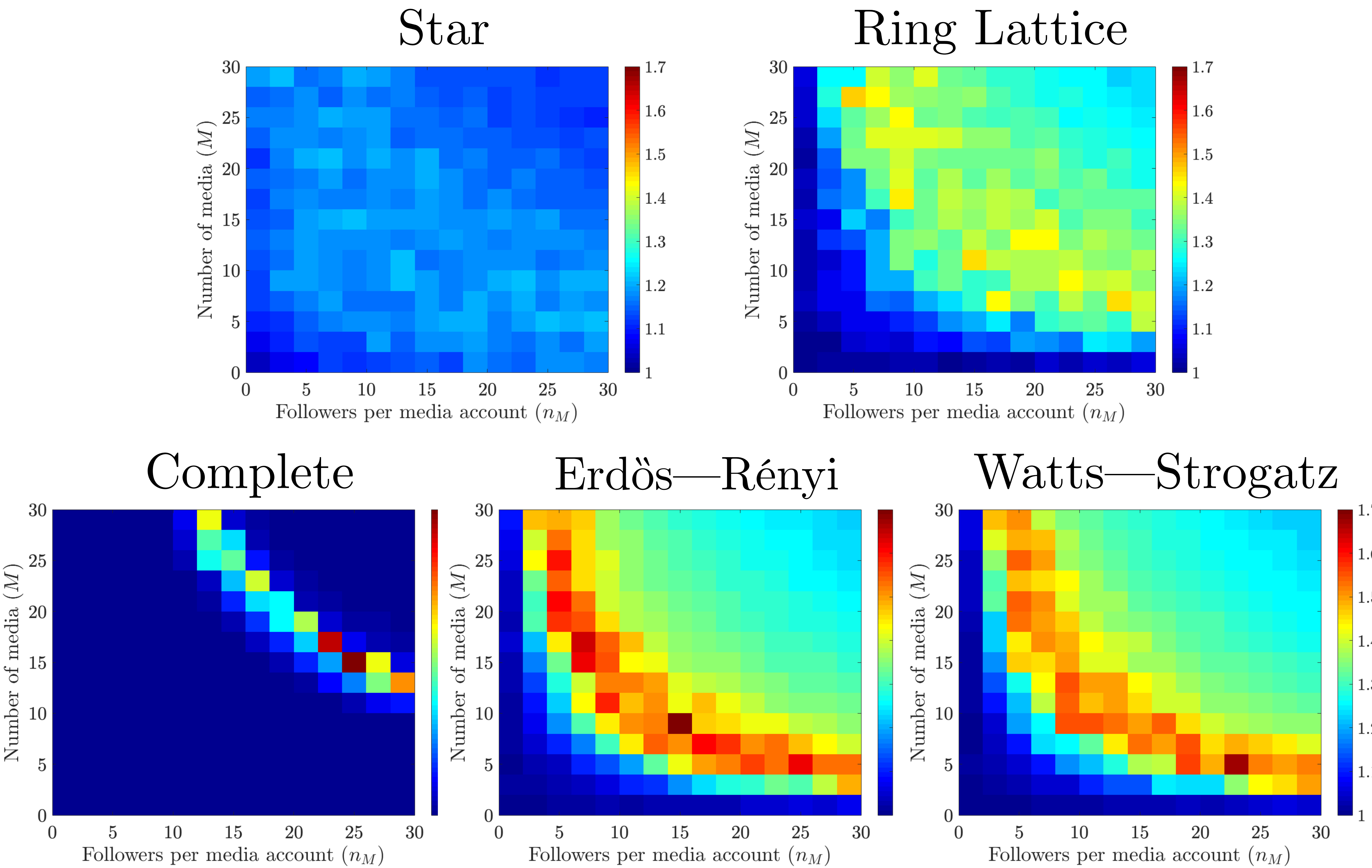


Figure 2(b)
Media accounts = 11
Followers per media account = 225
Opinion of content
Time step
Media accounts = 21
Followers per media account = 675
Opinion of content
Time step
Figure 2(c)
Media accounts = 1
Followers per media account = 1
Opinion of content
Time step
Figure 2(a)
Number of media (M)
Followers per media account (n_M)
$\overline{R}$

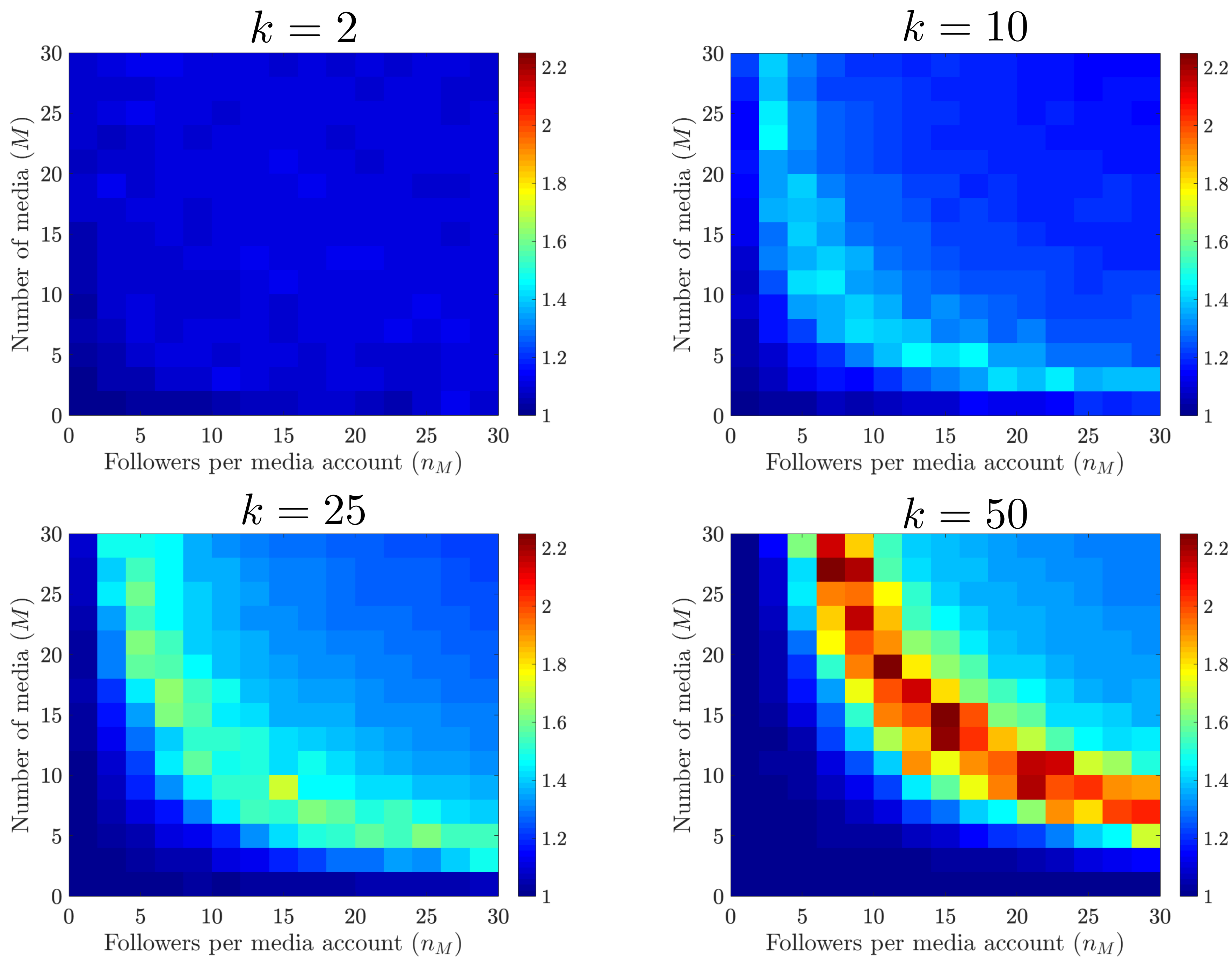
Media entrainment in Facebook100 networks



Media entrainment in synthetic networks

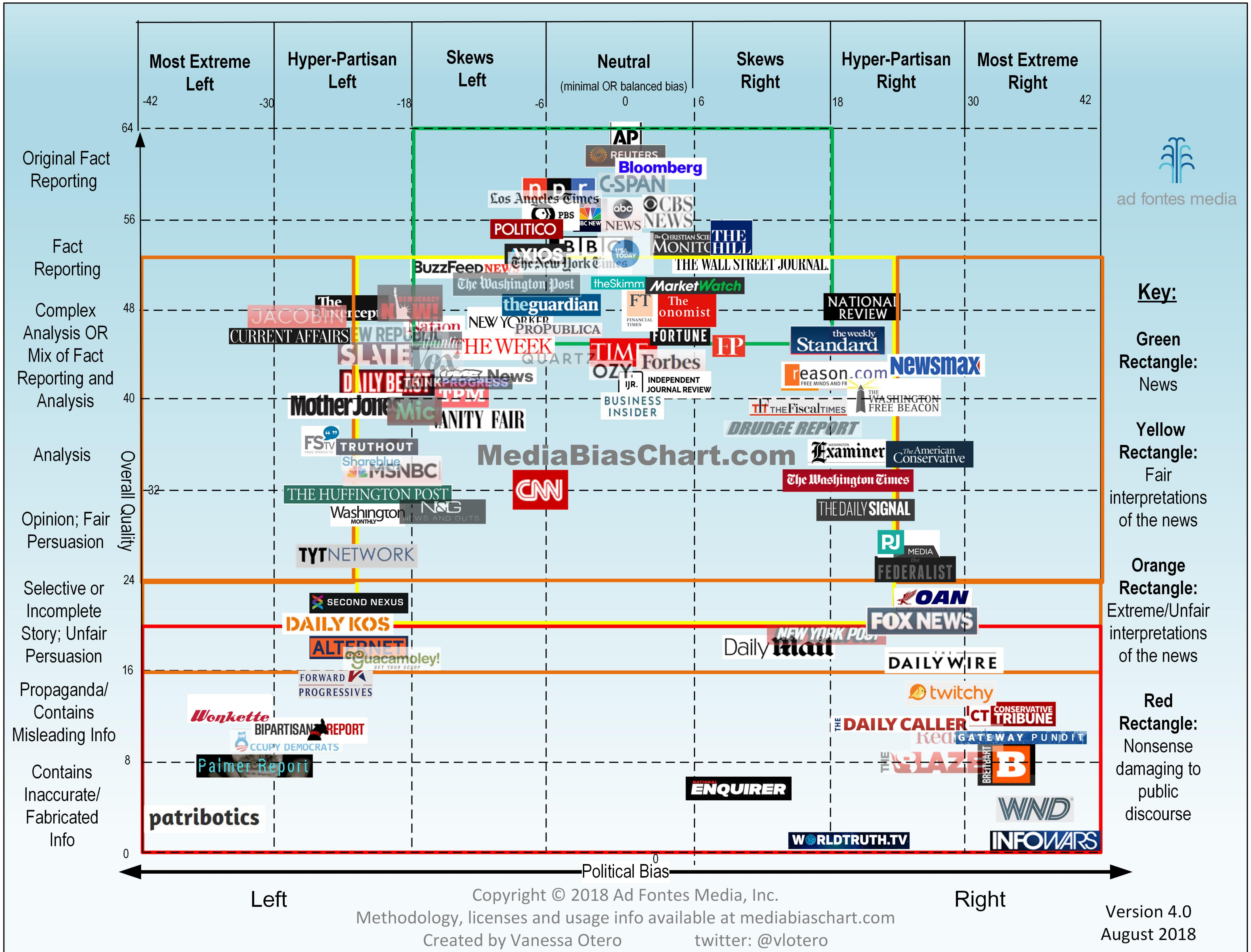


Increasing k, the average number of non-media followers, increases media entrainment



We also observe increased entrainment when increasing number of non-media accounts and increasing receptiveness parameter

Media in real online networks: their content has a distribution of ideological bias and quality



Our model with content ideology and quality

Content state of node i at time t is $\mathbf{x}_i \in [-1, 1]^d \times [0, 1]$

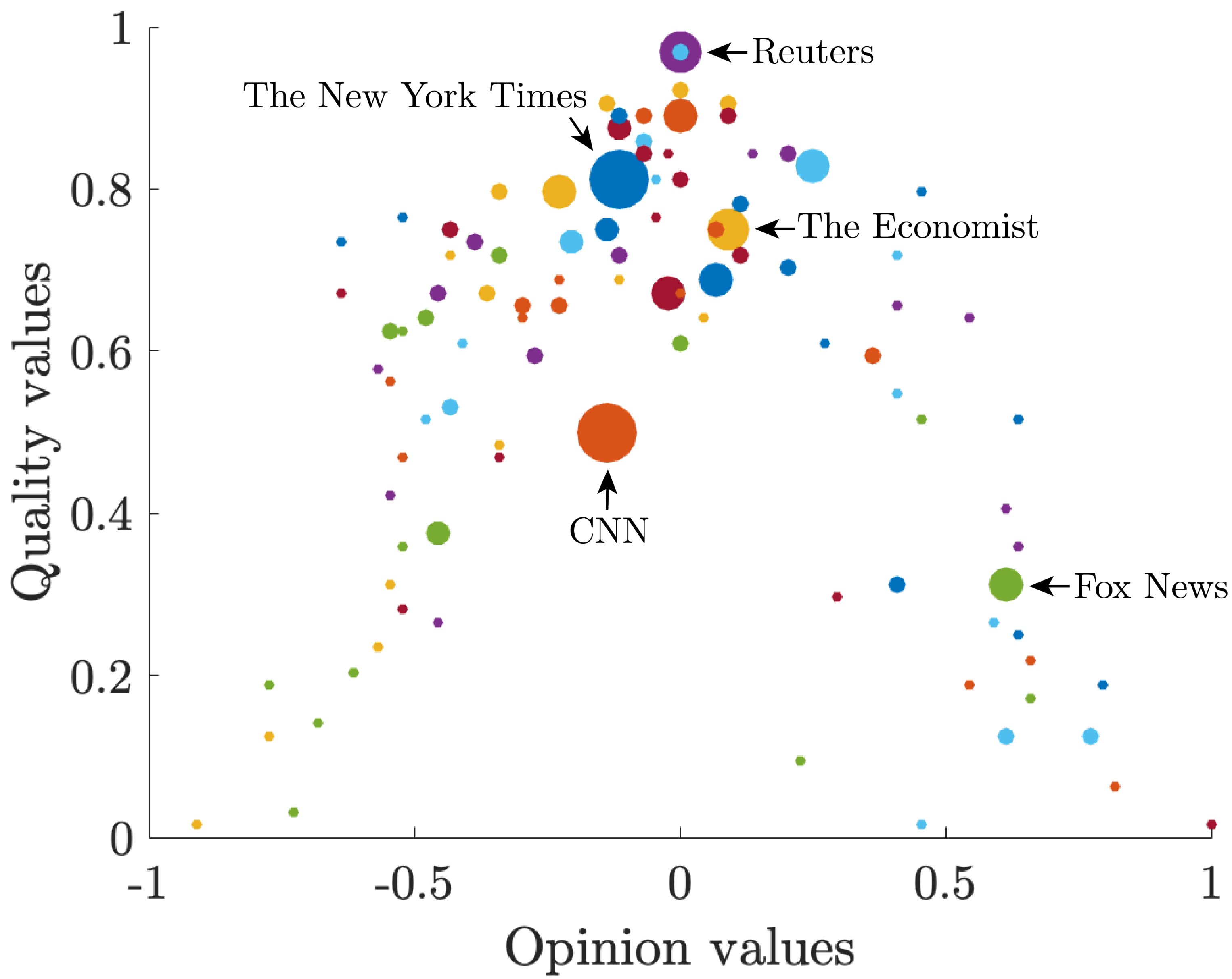
content ideology content quality

$$\boxed{\mathbf{x}_i^{t+1} = \frac{1}{|I_i| + 1} \left(\mathbf{x}_i^t + \sum_{j=1}^{N+M} A_{ij} \mathbf{x}_j^t g(\mathbf{x}_i^t, \mathbf{x}_j^t) \right)}$$

$$\text{where } g(\mathbf{x}_i^t, \mathbf{x}_j^t) = \begin{cases} 1\,, & \text{if } x_{2,j} \geq q_{i,j} \\ 0\,, & \text{otherwise} \end{cases}$$

$$\text{and } q_{i,j} = \frac{1}{c} \mathrm{dist}(x_{1,i}, x_{1,j})$$

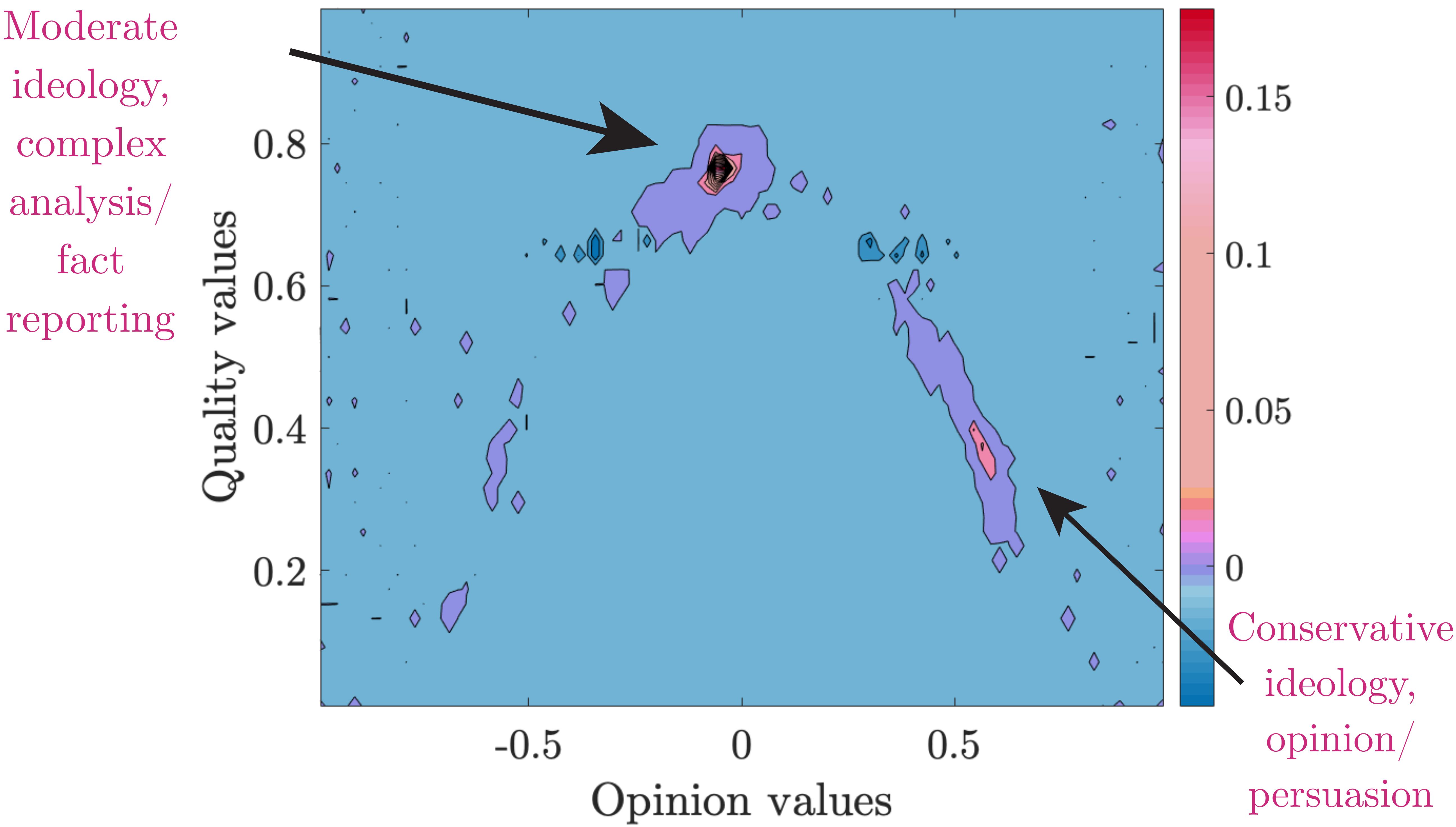
Create media distribution in ideology-quality space based on the Ad Fontes Media Bias Chart



M=103 media accounts

We choose the number of followers per media account to be proportional to the approximate number of followers that each media source had on Twitter on 15 Feb 2019 at 17:36 PST (under the constraint that each media source in the model has at least one follower)

We observe the emergence of two primary communities ("echo chambers") of content



Colors of contour plot show values of media impact function over 200 trials

There are many next steps!

- Mathematical analysis of media entrainment
- Incorporating account heterogeneity
- Structural homophily (particularly in ideology)
- Incorporating multiple types of social media: generalizing to a multilayer network
- Sentiment analysis of online content to get ideologies inferred from data
- Transient dynamics and time-dependent networks (rewiring followers)

Our model of content spread is very generalizable, and we hope this work will build the theory of online content spread and provide a step toward the development of control strategies and novel algorithms for mitigating the spread of undesirable content.

Thank you!

Mason Porter (UCLA)

Franca Hoffmann (Caltech)

Andrew Stuart (Caltech)

Yi Ming Lai (Nottingham)

UCLA Department of Mathematics

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Find me at:

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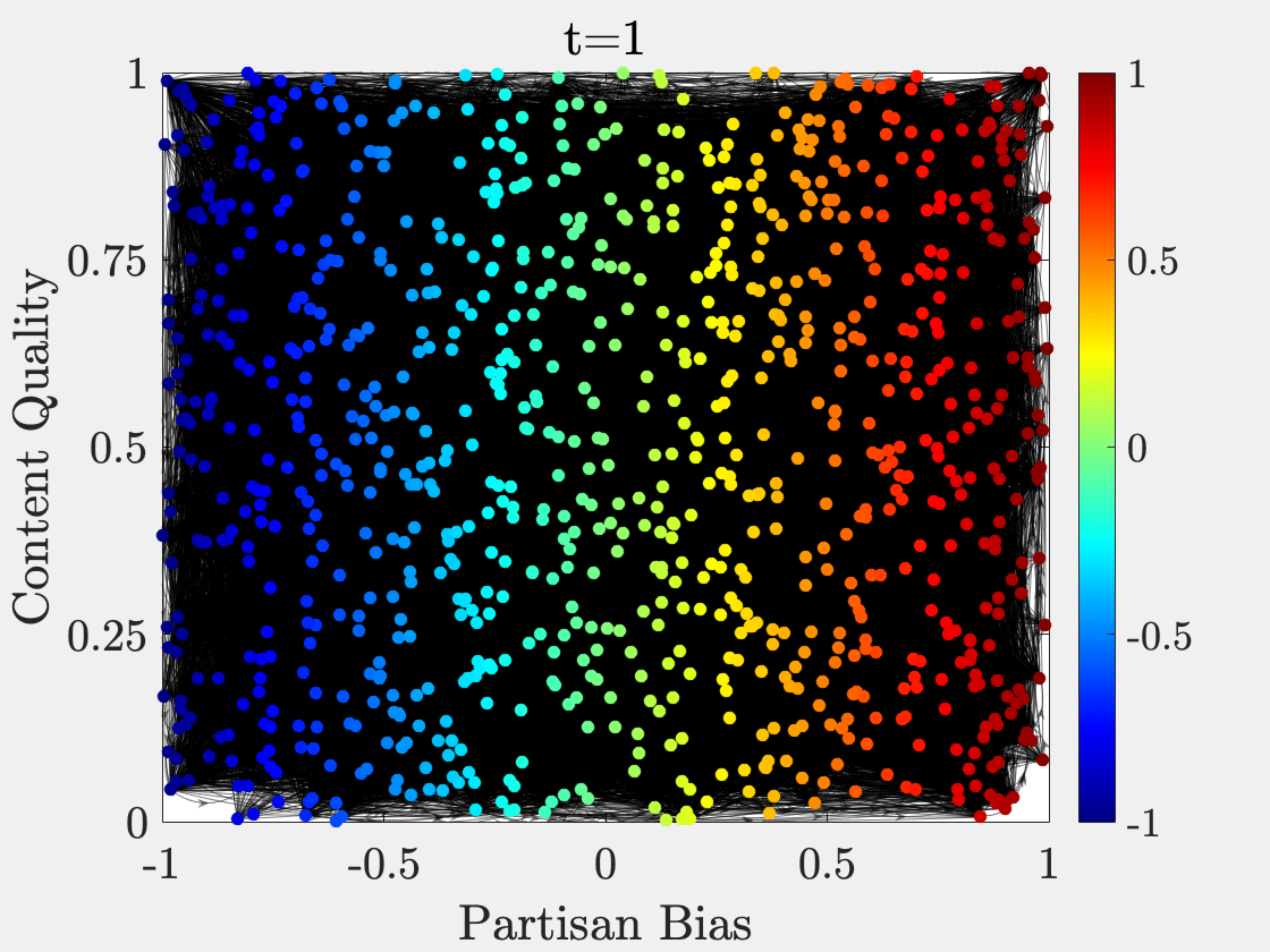
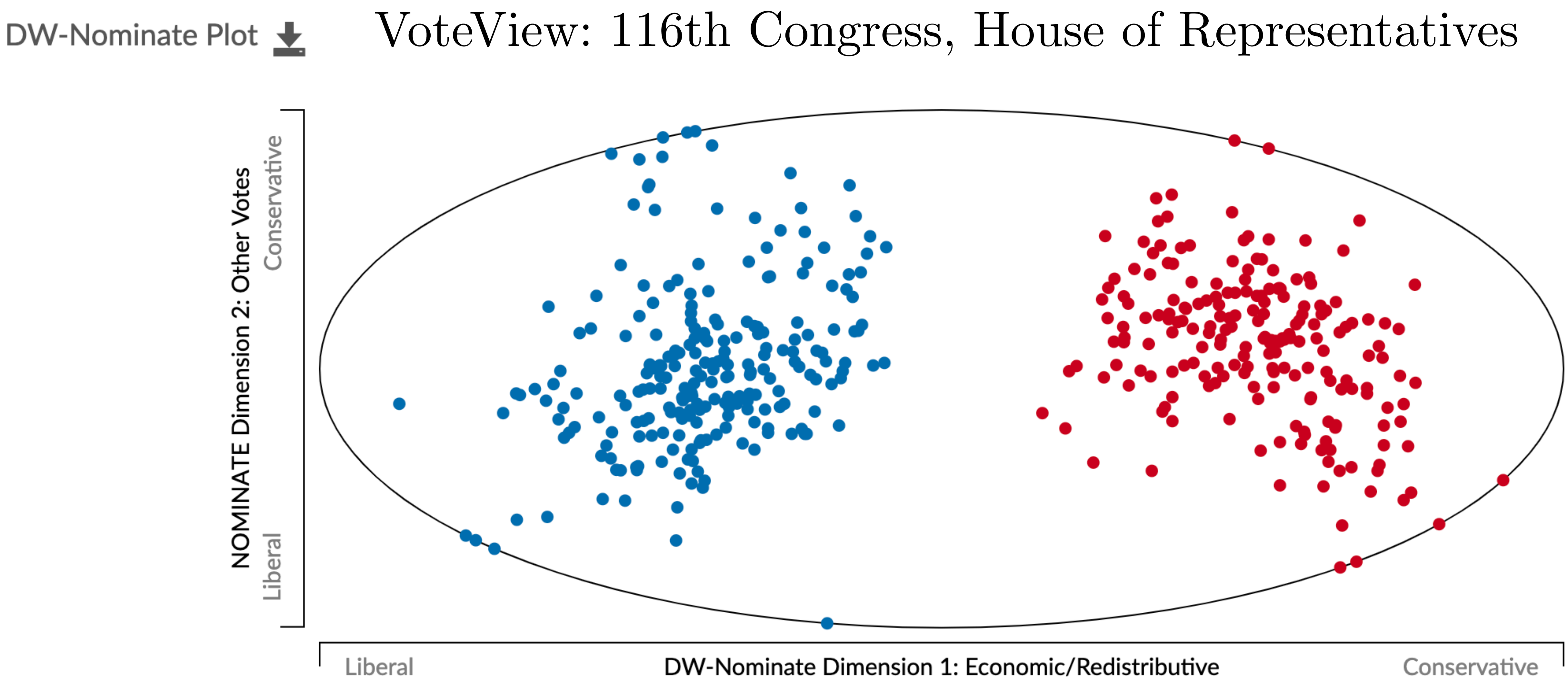
The paper is now on arXiv: 1904.09238

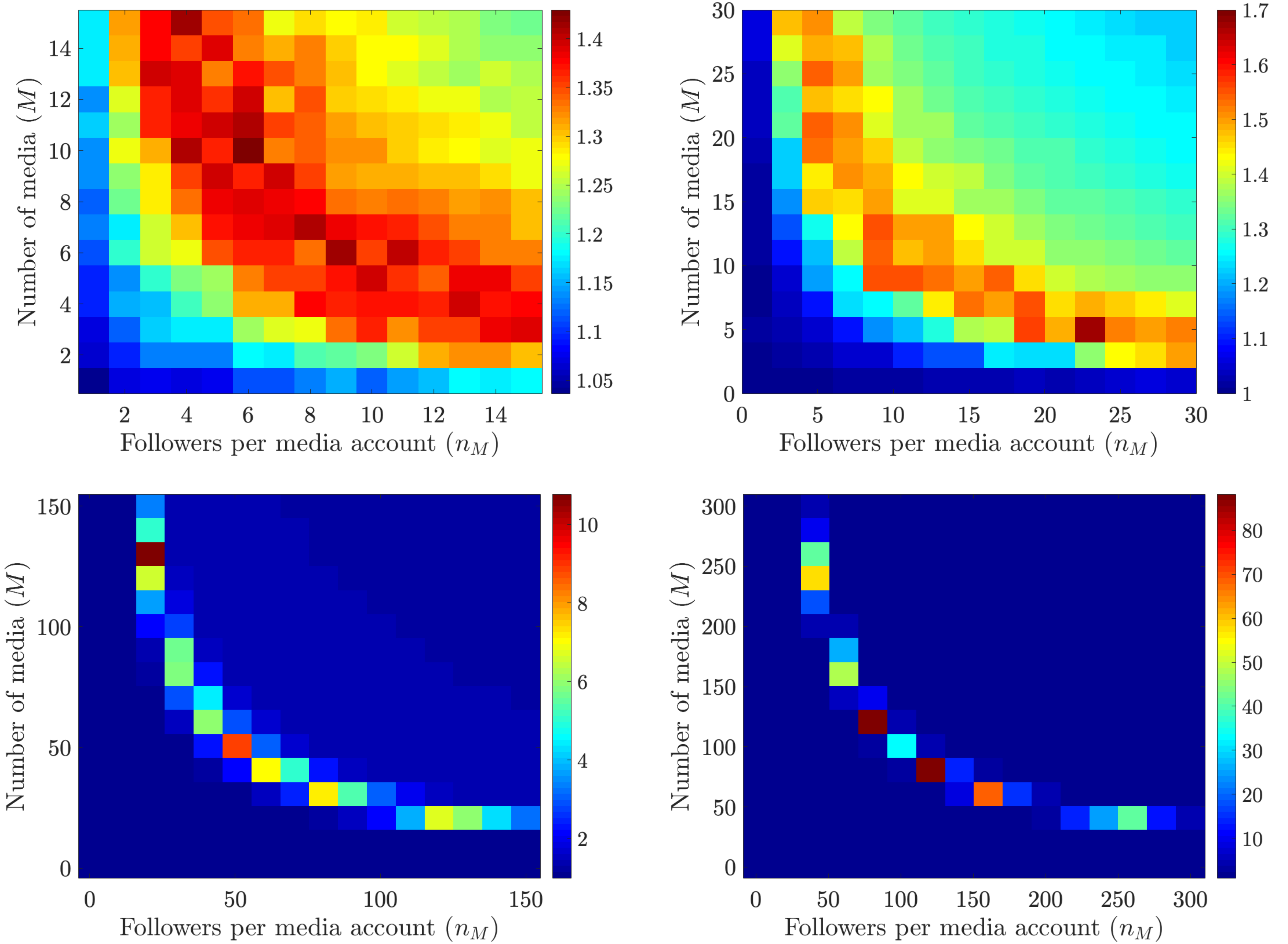


t=1
Content Quality
Partisan Bias
1
0.75
0.5
0.25
0
-1
-0.5
0
0.5
1
1
0.5
0
-0.5
-1

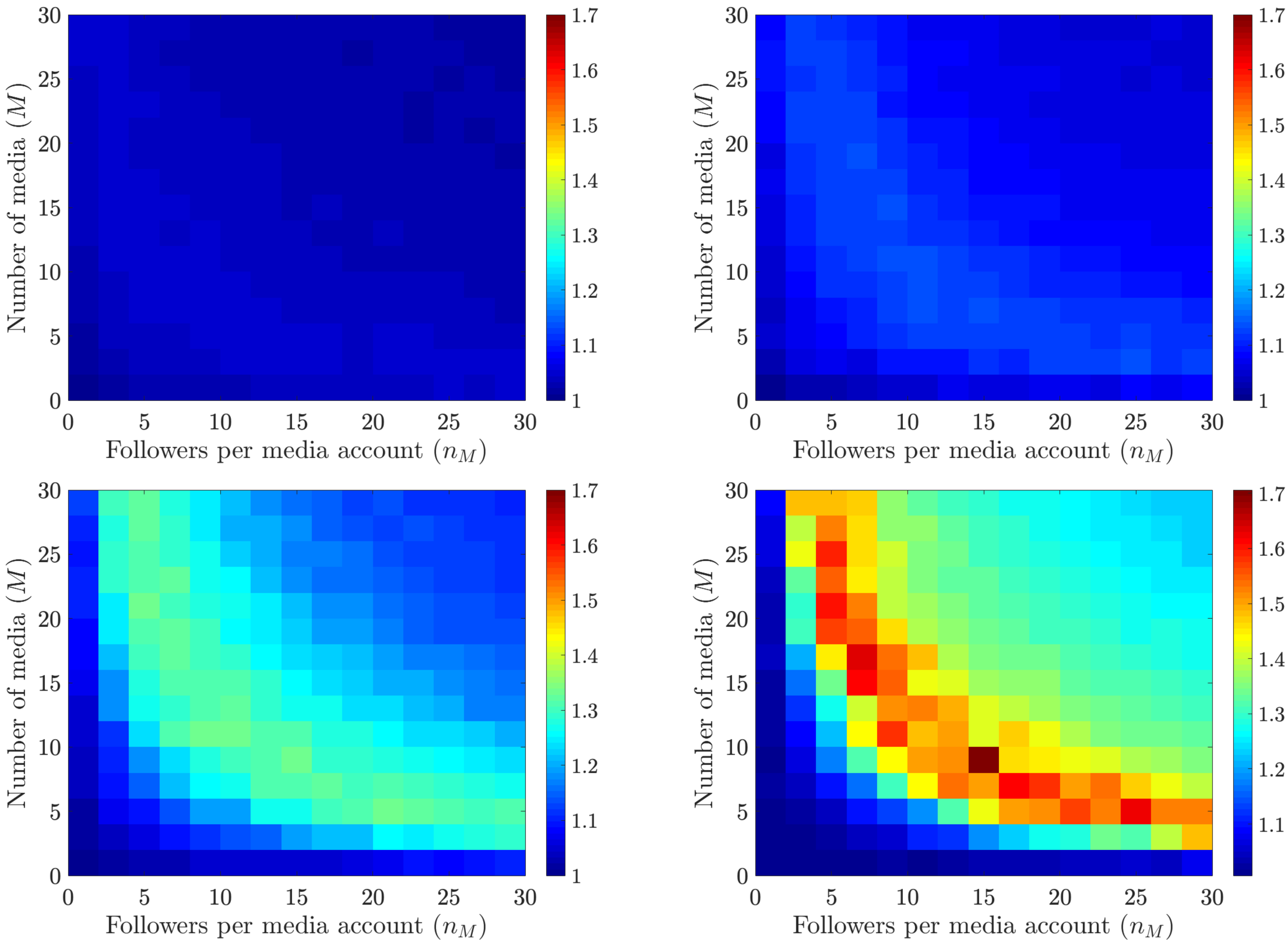
Two key factors: ideology and quality



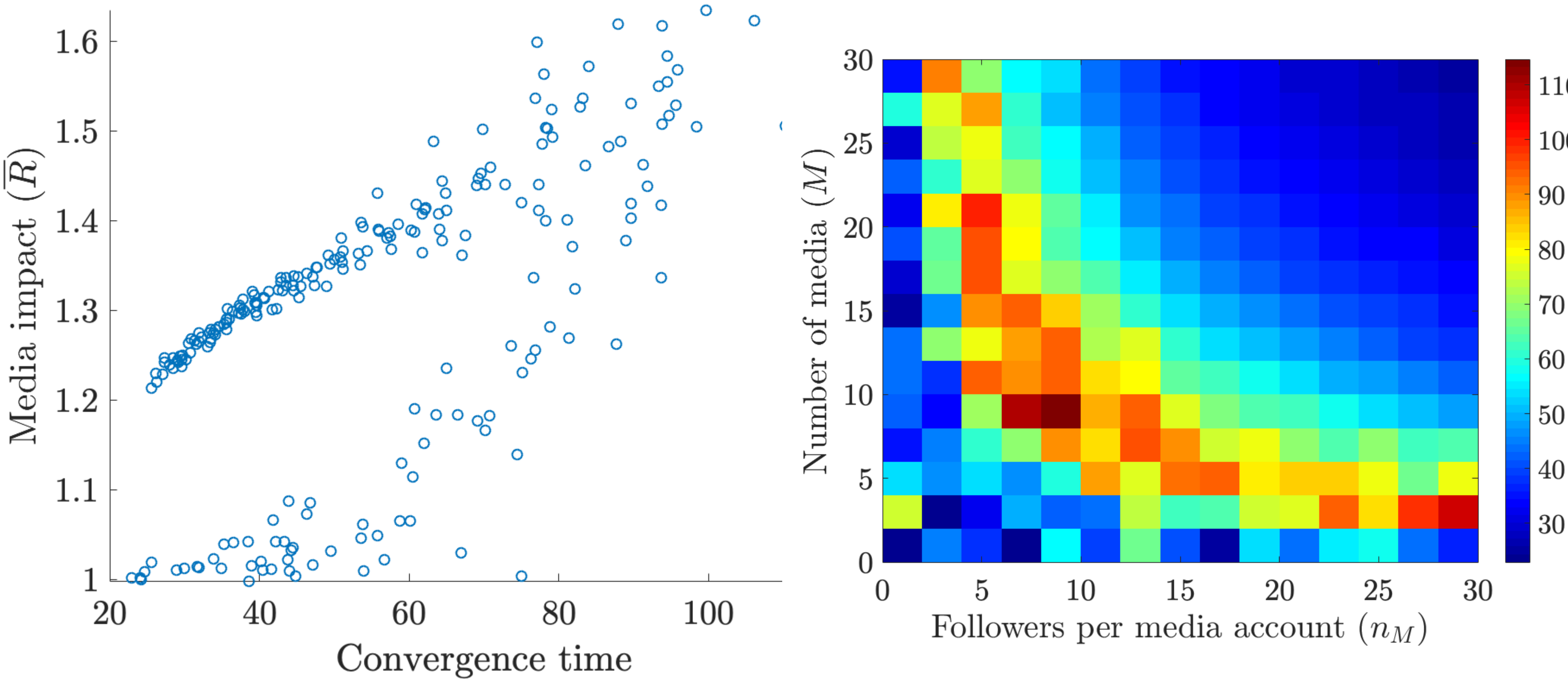
Increasing N narrows region of media entrainment



Increasing c increases media entrainment



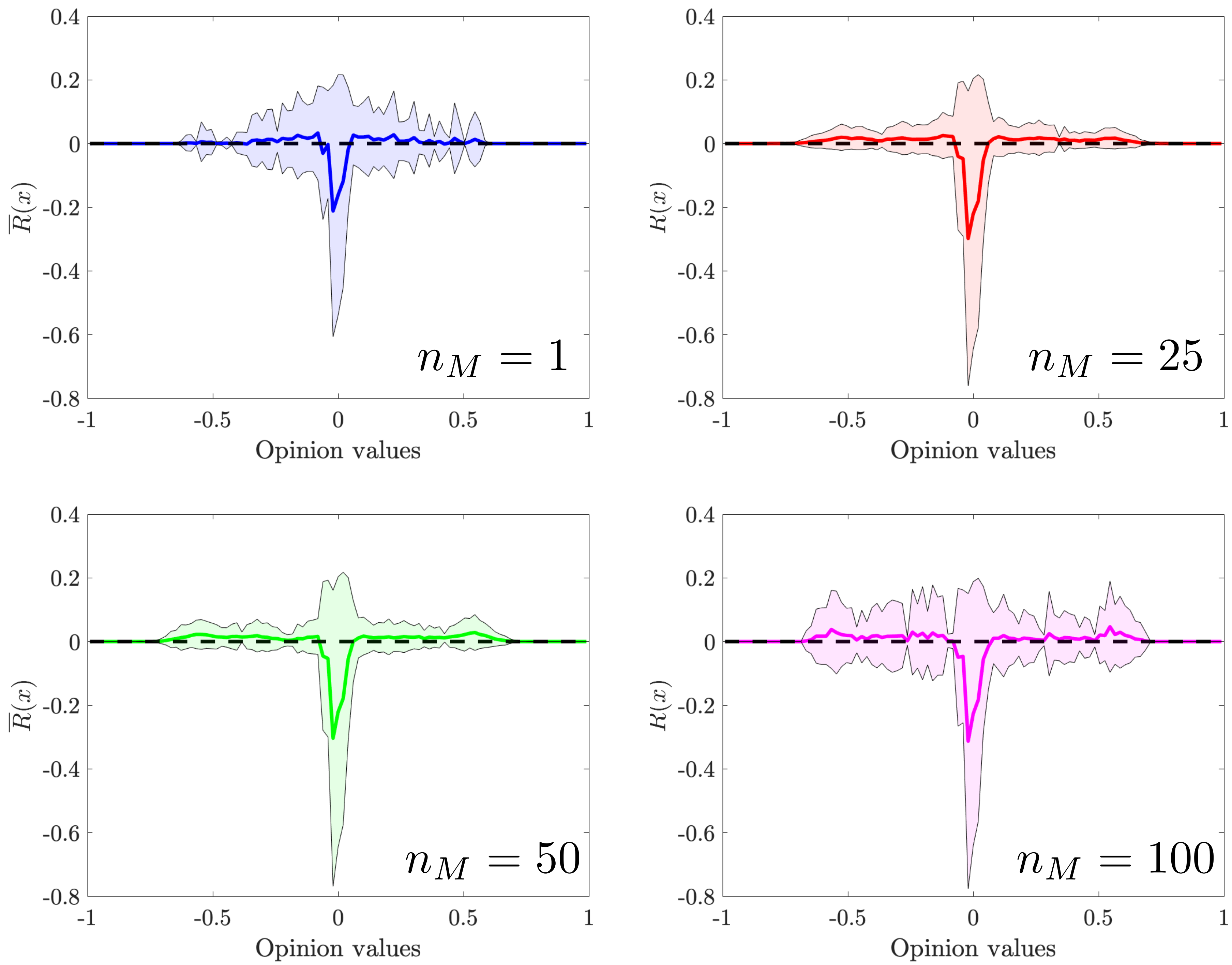
Media impact positively correlates with convergence time



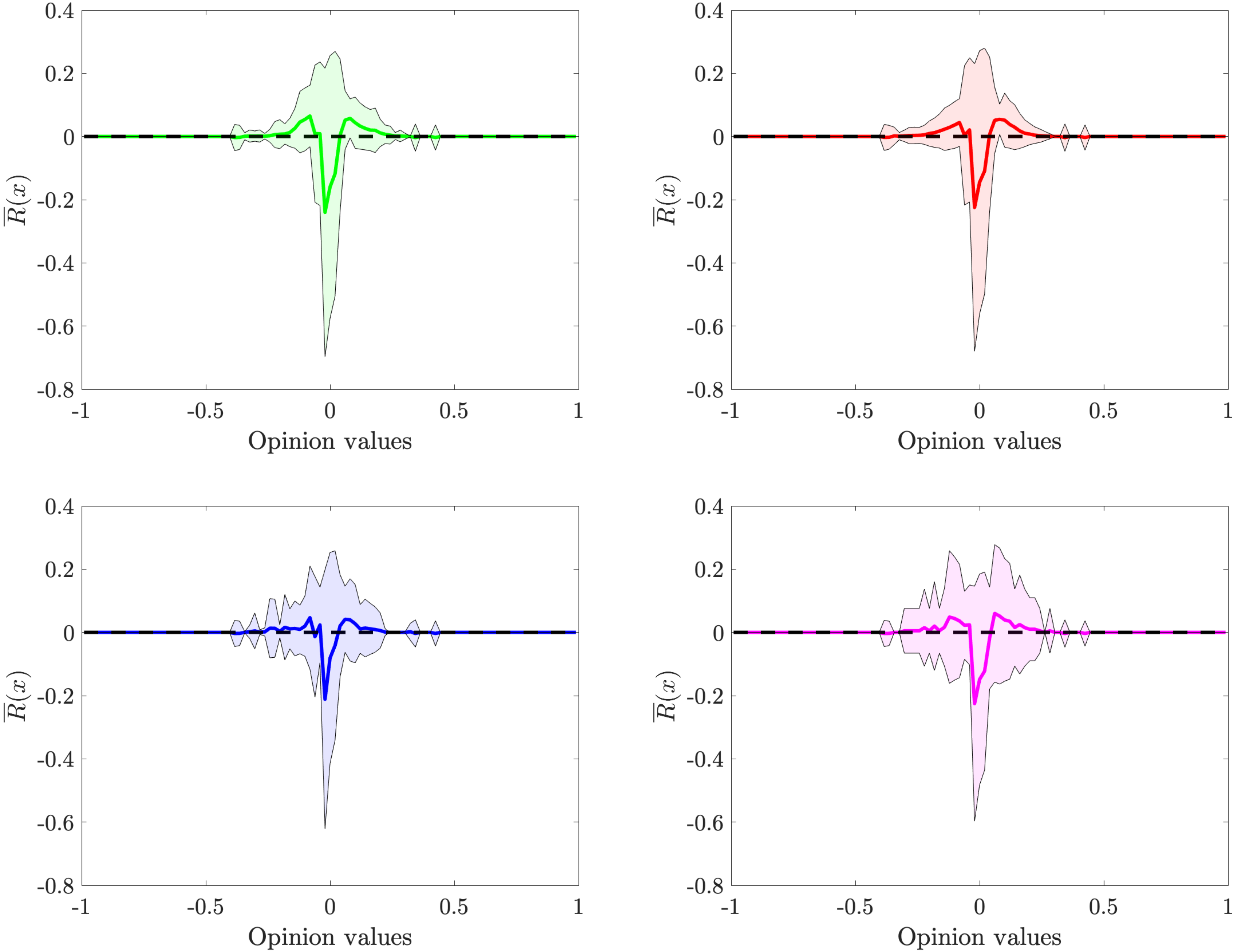
Each dot represents one trial for Erdős—Rényi graph with N=100, k=25.

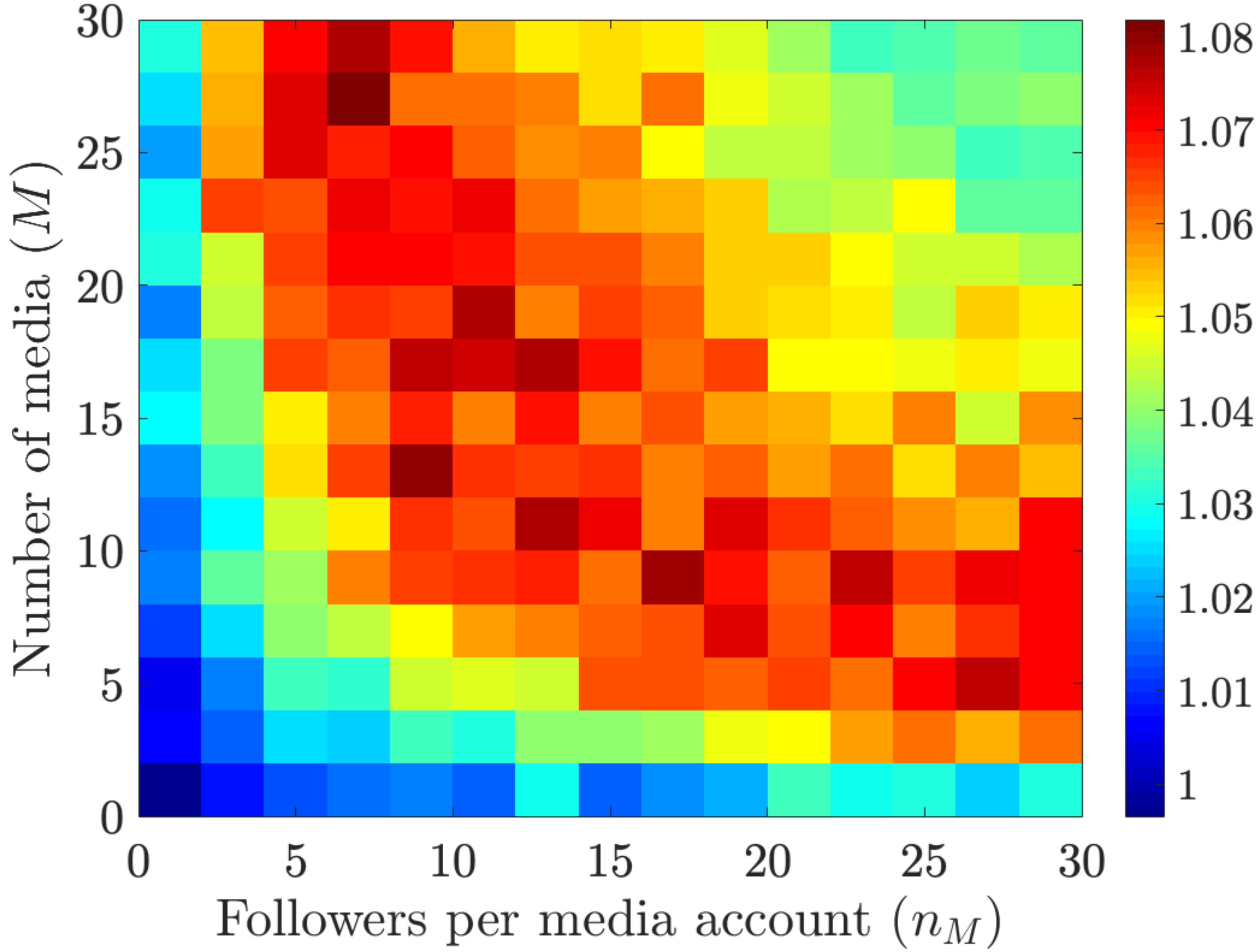
Color in heat map represents number of time steps to convergence

We can also measure impact for media ideologies drawn from distributions

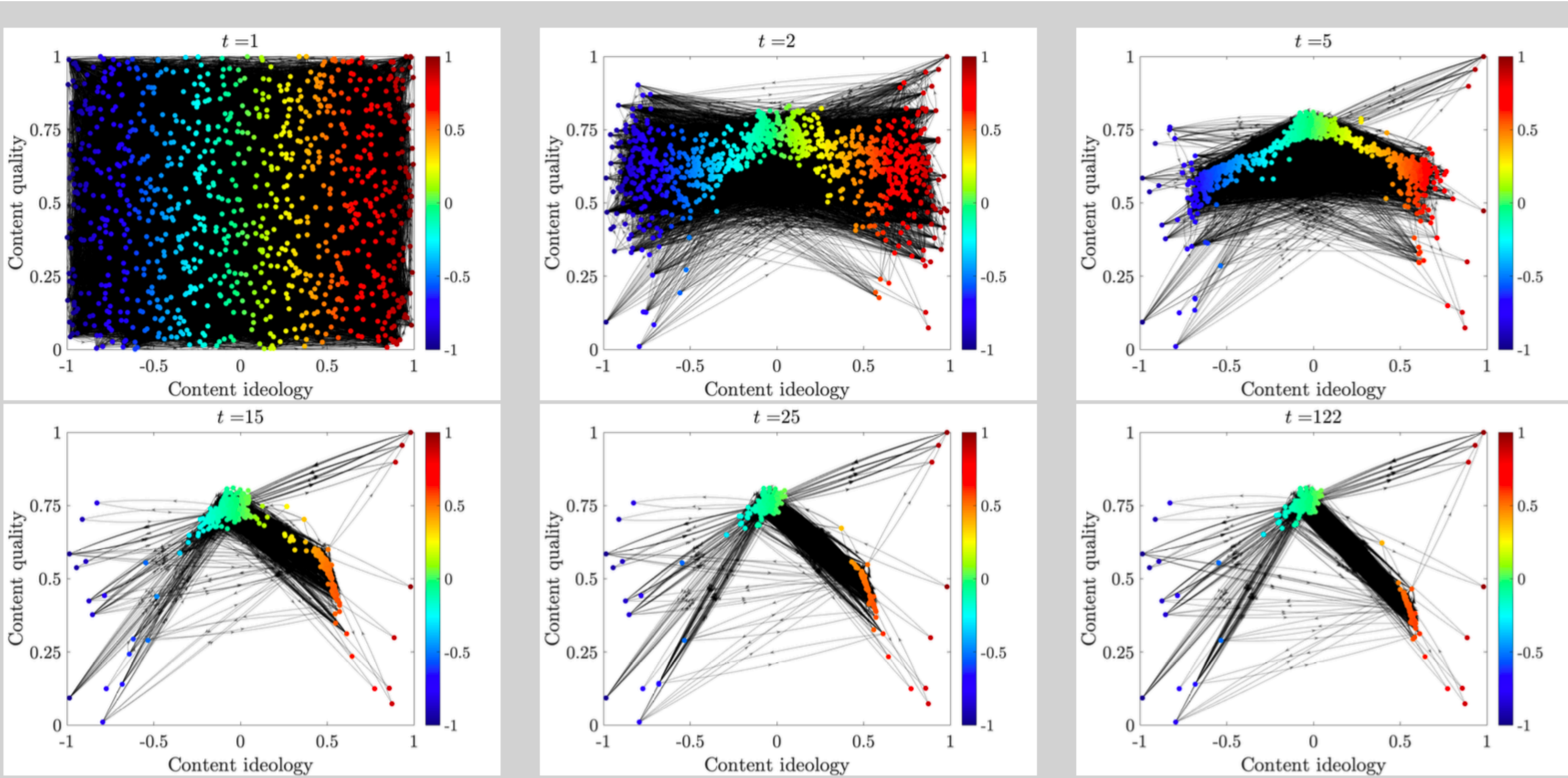


M=100 media drawn from a uniform random distribution on [-1,1]


0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
$\overline{R}(x)$
-1
-0.5
0
0.5
1
Opinion values

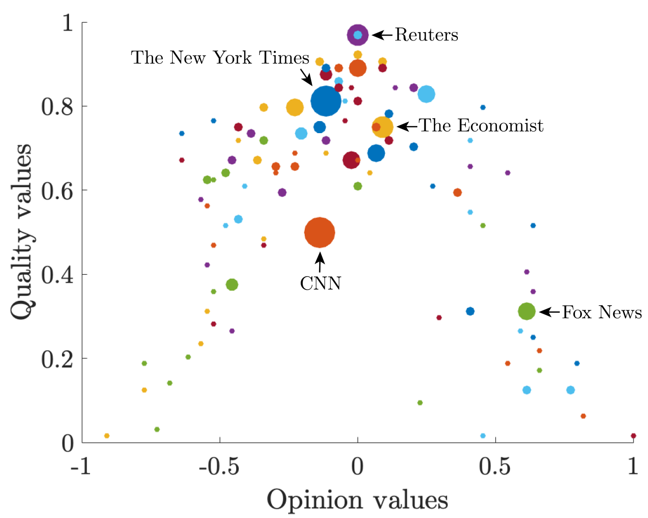


Two ideological dimensions



t =1
t =2
t =5
t =15
t =25
t =122
Content quality
Content ideology

Dynamics of democracy



Influence of Media on Opinion Dynamics in Social Networks

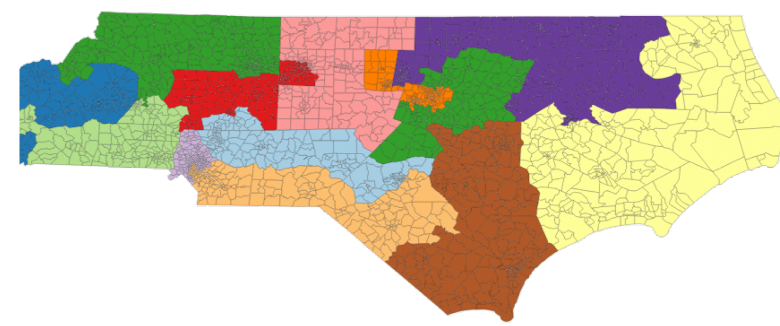
`Very Fine People on Both Sides' of Twitter: Analyzing the Network Structure of the Online Conversation about #Charlottesville

The Effect of the Convergence Parameter in the Deffuant Model of Opinion Dynamics

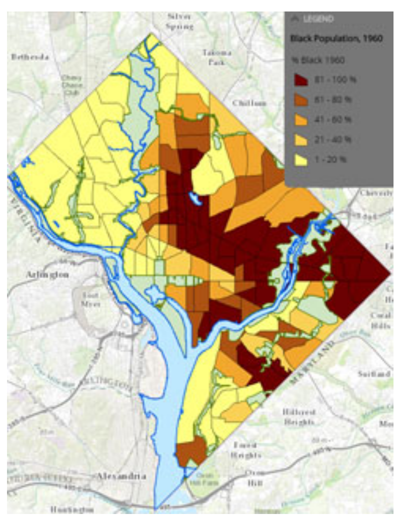
A Network Model of Immigration: Enclave Formation vs. Cultural Integration

Dynamics of democracy

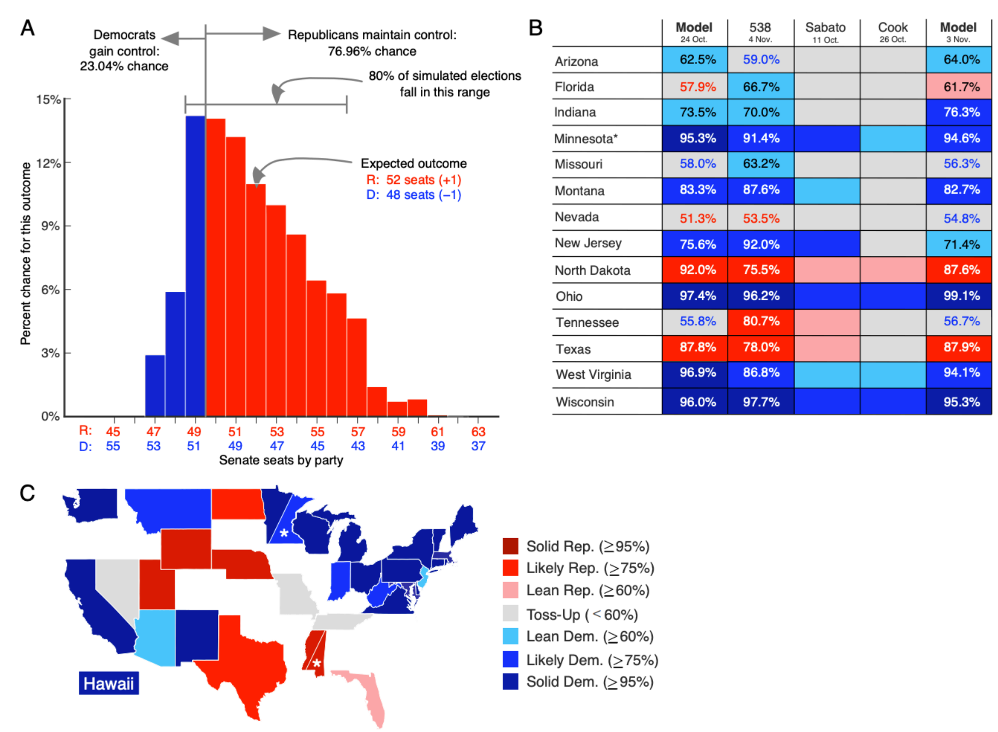
Interdisciplinary Inclusive Communities of Undergraduates doing Social-Justice Inspired Research



Quantifying Gerrymandering using Random Dynamics



Forecasting U.S. Elections using Compartmental Models



	Model 24 Oct.	538 4 Nov.	Sabato 11 Oct.	Cook 26 Oct.	Model 3 Nov.
Arizona	62.5%	59.0%			64.0%
Florida	57.9%	66.7%			61.7%
Indiana	73.5%	70.0%			76.3%
Minnesota*	95.3%	91.4%			94.6%
Missouri	58.0%	63.2%			56.3%
Montana	83.3%	87.6%			82.7%
Nevada	51.3%	53.5%			54.8%
New Jersey	75.6%	92.0%			71.4%
North Dakota	92.0%	75.5%			87.6%
Ohio	97.4%	96.2%			99.1%
Tennessee	55.8%	80.7%			56.7%
Texas	87.8%	78.0%			87.9%
West Virginia	96.9%	86.8%			94.1%
Wisconsin	96.0%	97.7%			95.3%

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