Homophily: we like people similar to us, we are linked to people that share our own opinion/behaviors/social membership…

Mimicry: we tune our opinion/behaviors to the opinion/behaviors of (similar) others.

Social Influence / contagion: The tendency of individuals to become similar with each-other over time

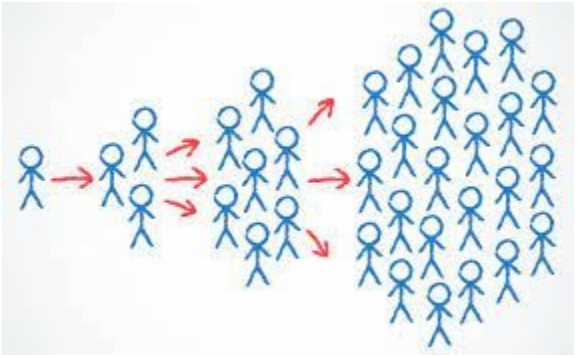
Eco-Chambers: environments in which the opinion, political leaning, or belief of users about a topic gets reinforced due to repeated interactions with peers or sources having similar tendencies and attitudes

Polarization: the opinion distribution is characterized by two well-separated peaks around the neutral consensus

Persuasion: free behavioral or attitudinal compliance toward a message whose intent was to convince the target

Social contagion theory: examining dynamic social networks and human behavior

Nicholas A. Christakis[a,b*†] and James H. Fowler[c,d]



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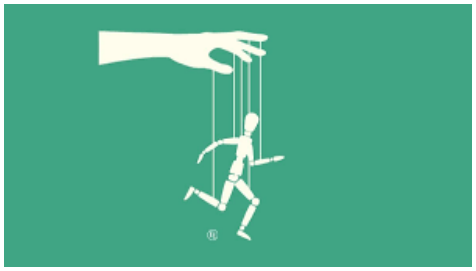
PLOS ONE

Detecting Emotional Contagion in Massive Social Networks

Lorenzo Coviello[1], Yunkyu Sohn[2], Adam D. I. Kramer[3], Cameron Marlow[3], Massimo Franceschetti[1], Nicholas A. Christakis[4,5], James H. Fowler[2,6*]



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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], and James H. Fowler[1,4]

Charles-Marie Gustave Le Bon was a leading French polymath whose areas of interest included anthropology, psychology, sociology, medicine, invention, and physics. He is best known for his 1895 work *The Crowd: A Study of the Popular Mind*, which is considered one of the seminal

Social contagion / behavior contagion

- The spread of ideas, attitudes, or behaviour patterns in a group through imitation and conformity.
- the propensity for a person to copy a certain behavior of others who are either in the vicinity, or whom they have been exposed to

Statistics
in Medicine

Featured Article

Received 22 November 2011, Accepted 21 February 2012 Published online 18 June 2012 in Wiley Online Library

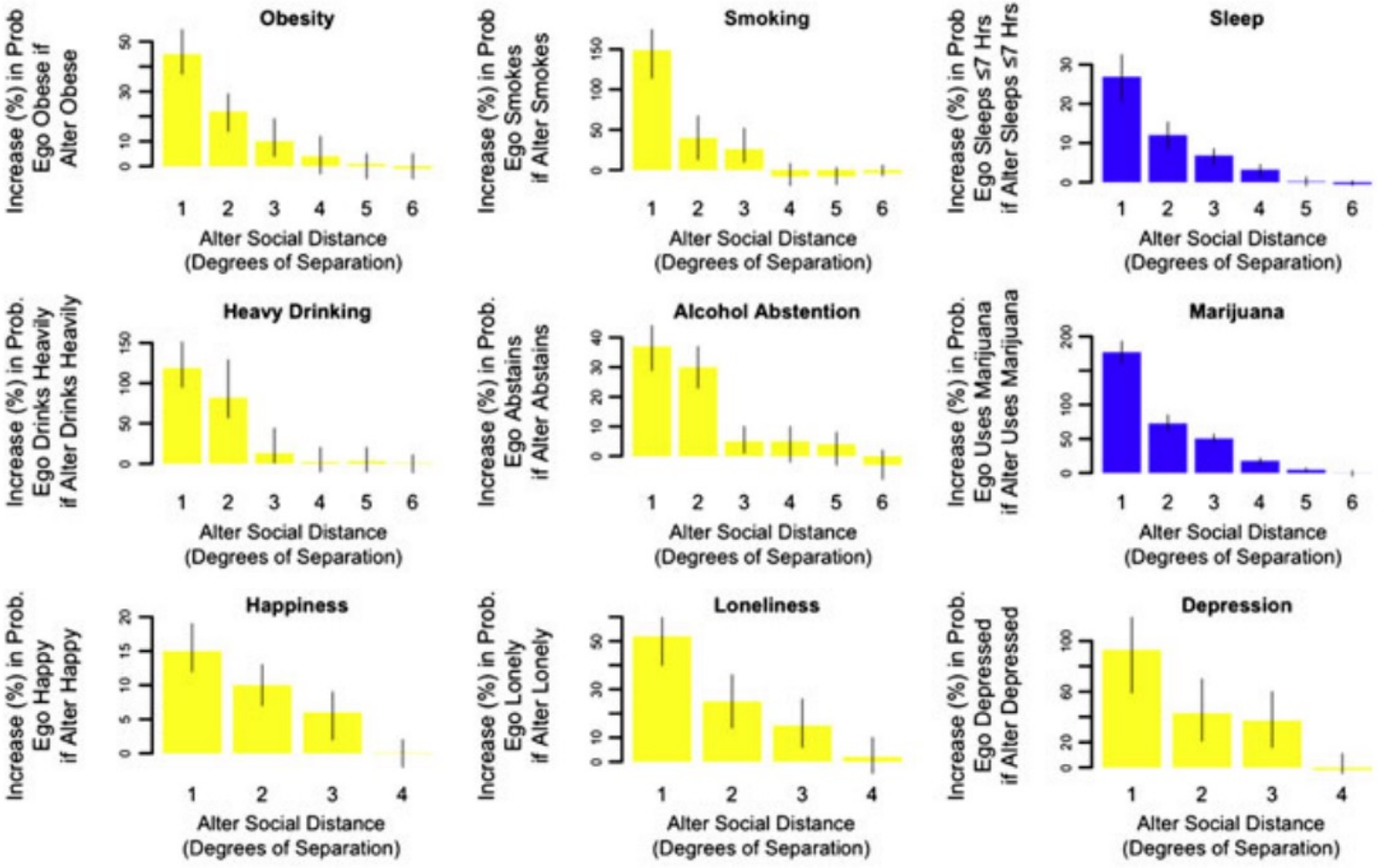
(wileyonlinelibrary.com) DOI: 10.1002/sim.5408

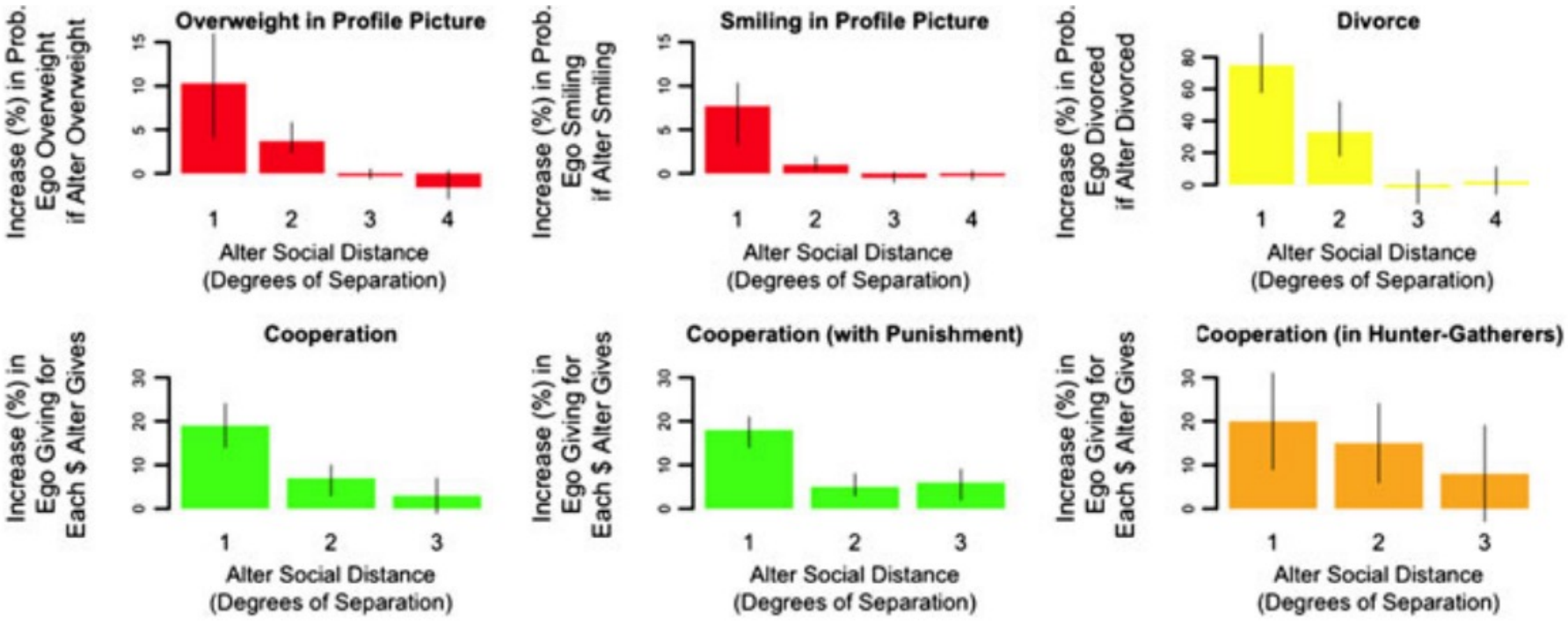
Social contagion theory: examining dynamic social networks and human behavior

Nicholas A. Christakis[a,b*†] **and James H. Fowler**[c,d]

Here, we review the research we have conducted on social contagion. We describe the methods we have employed (and the assumptions they have entailed) to examine several datasets with complementary strengths and weaknesses, including the Framingham Heart Study, the National Longitudinal Study of Adolescent Health, and other observational and experimental datasets that we and others have collected. We describe the regularities that led us to propose that human social networks may exhibit a 'three degrees of influence' property, and we review statistical approaches we have used to characterize interpersonal influence with respect to phenomena as diverse as obesity, smoking, cooperation, and happiness. We do not claim that this work is the final word, but we do believe that it provides some novel, informative, and stimulating evidence regarding social contagion in longitudinally followed networks. Along with other scholars, we are working to develop new methods for identifying causal effects using social network data, and we believe that this area is ripe for statistical development as current methods have known and often unavoidable limitations.

Keywords: social networks; contagion; human behavior; homophily; causal interence


Obesity
Increase (%) in Prob Ego Obese if Alter Obese
0 10 30 50
1 2 3 4 5 6
Alter Social Distance (Degrees of Separation)
Smoking
Increase (%) in Prob Ego Smokes if Alter Smokes
0 50 100 150
1 2 3 4 5 6
Alter Social Distance (Degrees of Separation)
Sleep
Increase (%) in Prob Ego Sleeps ≤7 Hrs if Alter Sleeps ≤7 Hrs
0 10 20 30
1 2 3 4 5 6
Alter Social Distance (Degrees of Separation)
Heavy Drinking
Increase (%) in Prob. Ego Drinks Heavily if Alter Drinks Heavily
0 50 100 150
1 2 3 4 5 6
Alter Social Distance (Degrees of Separation)
Alcohol Abstention
Increase (%) in Prob. Ego Abstains if Alter Abstains
0 10 20 30 40
1 2 3 4 5 6
Alter Social Distance (Degrees of Separation)
Marijuana
Increase (%) in Prob. Ego Uses Marijuana if Alter Uses Marijuana
0 50 100 200
1 2 3 4 5 6
Alter Social Distance (Degrees of Separation)
Happiness
Increase (%) in Prob. Ego Happy if Alter Happy
0 5 10 15 20
1 2 3 4
Alter Social Distance (Degrees of Separation)
Loneliness
Increase (%) in Prob. Ego Lonely if Alter Lonely
0 10 30 50
1 2 3 4
Alter Social Distance (Degrees of Separation)
Depression
Increase (%) in Prob. Ego Depressed if Alter Depressed
0 20 60 100
1 2 3 4
Alter Social Distance (Degrees of Separation)

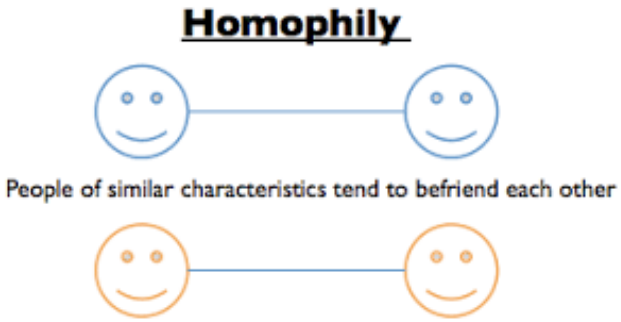


‘three degrees of influence’ property: the empirical regularity that clusters of behaviors or attributes extend to about three degrees of separation

the association fades within a few degrees in what seems like a systematic way across phenomena and datasets.

Explanations for such observed clusters

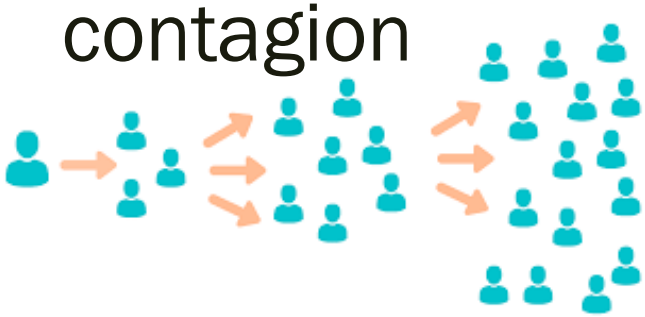
- (1) subjects might choose to associate with others exhibiting similar attributes (homophily);
- (2) subjects and their contacts might jointly experience unobserved contemporaneous exposures that cause their attributes to covary (omitted variables or confounding because of shared context);
- (3) subjects might be influenced by their contacts (social contagion).



Homophily

vs

Social contagion



If ties are more likely between similar nodes, their outcomes could be correlated because of inherent similarities in their characteristics

Linked nodes may directly influence one another to exhibit similar outcomes, creating viral contagions.

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PLOS ONE

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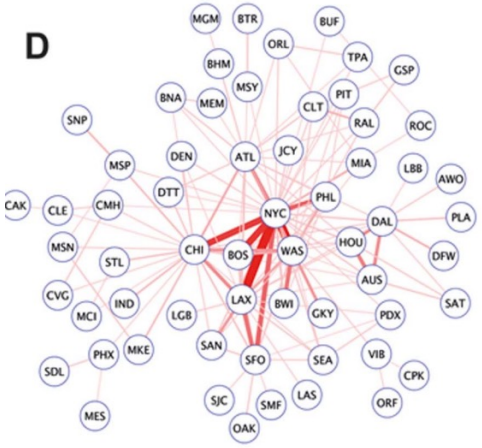
Lorenzo Coviello[1], Yunkyu Sohn[2], Adam D. I. Kramer[3], Cameron Marlow[3], Massimo Franceschetti[1], Nicholas A. Christakis[4,5], James H. Fowler[2,6]*

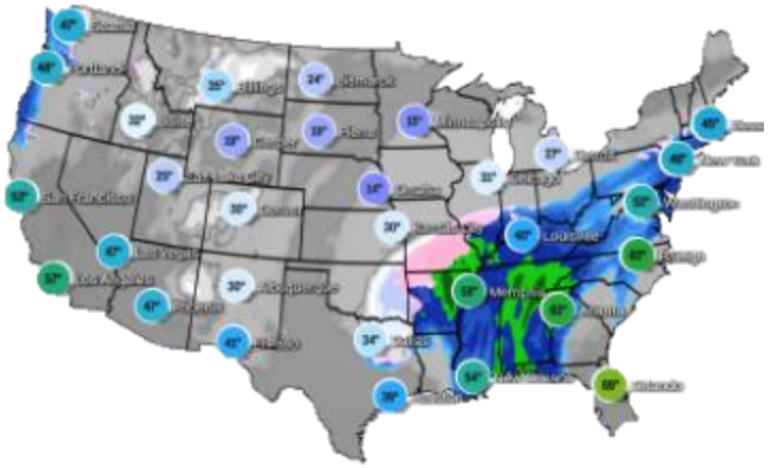
1 Electrical and Computer Engineering Department, University of California San Diego, San Diego, California, United States of America, **2** Political Science Department, University of California San Diego, San Diego, California, United States of America, **3** Facebook Inc., Menlo Park, California, United States of America, **4** Department of Sociology, Yale University, New Haven, Connecticut, United States of America, **5** Department of Medicine, Yale University, New Haven, Connecticut, United States of America, **6** Medical Genetics Division, School of Medicine, University of California San Diego, San Diego, California, United States of America

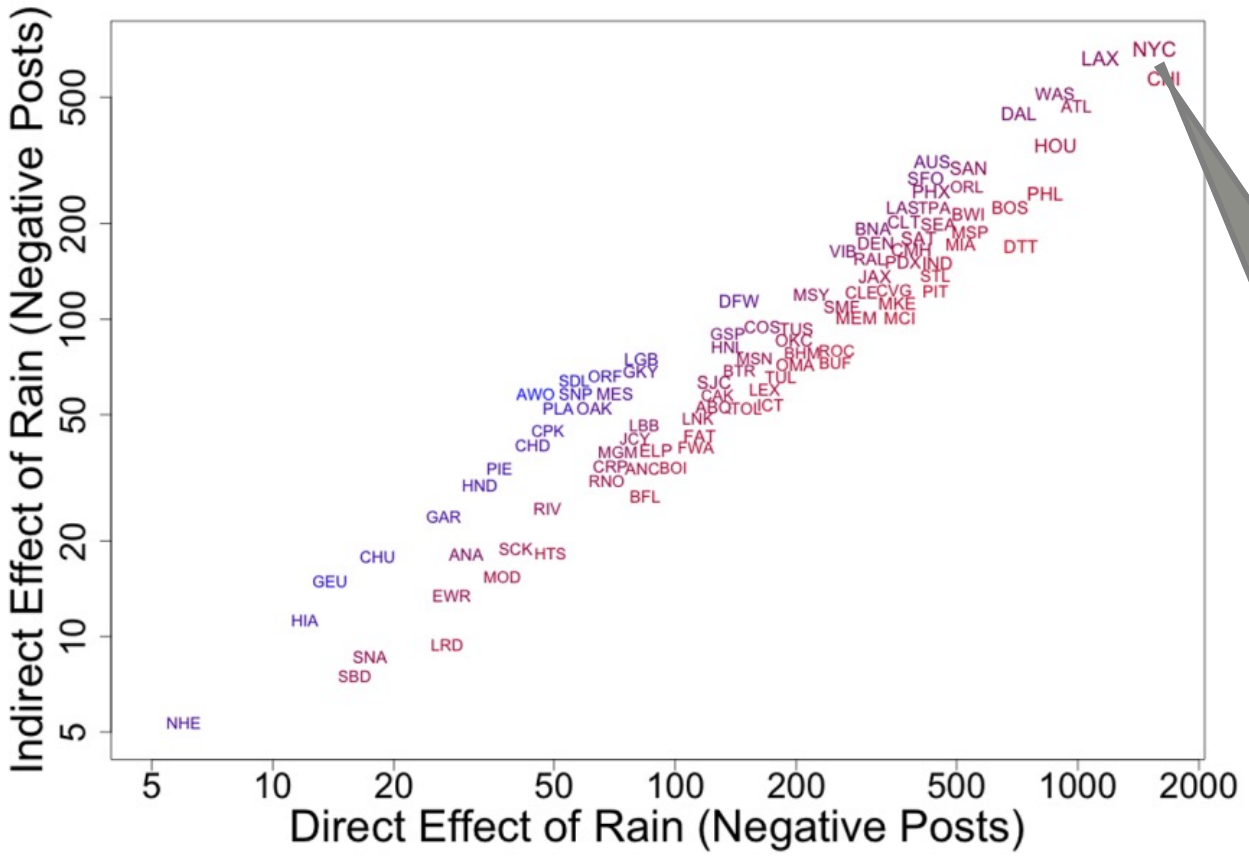
- data collected for 1180 days on **Facebook** from January 2009 to March 2012.
- To measure emotional expression, we use **"status updates"** (also called "posts") which are undirected text-based messages that a user's social contacts (Facebook friends) may view on their own News Feed.
- **Linguistic Inquiry Word Count**
  - *Posts' words express positive or negative emotions*

- aggregate individual observations by city and day, restricting our attention to all English-speaking Facebook users residing in the 100 most populous US cities.



- We matched these observations to publicly available meteorological records that indicate total precipitation for each day in each of these cities

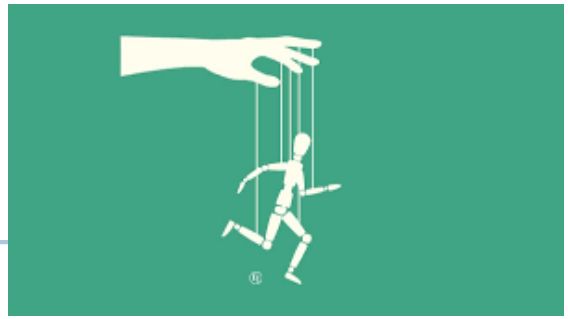




Predicted effects.

Total number of negative posts generated by a day of rainfall within a city (direct) and in other cities via contagion (indirect).

E.g., a rainy day in NYC directly yields an additional 1500 (95% CI 1100 to 2100) negative posts by users in NYC and about 700 (95% CI 600 to 800) negative posts by their friends elsewhere.



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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], and **James H. Fowler**[1,4]

[1]Political Science Department, University of California, San Diego, La Jolla, California 92093, USA

[2]Psychology Department, University of California, San Diego, La Jolla, California 92093, USA

[3]Data Science, Facebook, Inc., Menlo Park, California 94025, USA

[4]Medical Genetics Division, University of California, San Diego, La Jolla, California 92093, USA

nature

Main research question:

Can political behaviour spread through an online social network ?

-> whether online networks can be used effectively to increase the likelihood of behaviour change and social contagion

Field of application: voting behavior in national election (USA congressional election 2010)

- Voter turnout is significantly correlated among friends, family members and co-workers
- Voter mobilization efforts are effective at increasing turnout, particularly those conducted face-to-face and those that appeal to social pressure and social identity
- BUT: meta-analysis of email experiments suggests that online appeals to vote are ineffective

Small effects…yet remarkable

- most methods of contacting potential voters have small effects (if any) on turnout rates, ranging from 1% to 10%.
- However, the ability to reach large populations online means that even small effects could yield behaviour changes for millions of people.
- These changes could affect electoral outcomes.
  - *For example, in the 2000 US presidential election, George Bush beat Al Gore in Florida by 537 votes (less than 0.01% of votes cast in Florida). Had Gore won Florida, he would have won the election.*

Specific sample

- USA Facebook users aged >18
- All users who accessed the Facebook website on 2 November 2010 (congressional election day)

EXPERIMENTAL DESIGN

3 random groups

- «Social message» (n=60,055,176)
- «Informational message» (n =611,044)
- Control: no message (n=613,096)

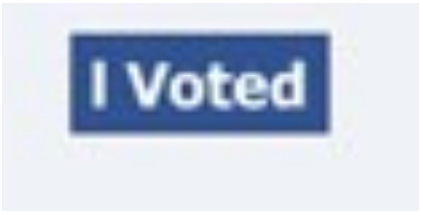
EXPERIMENTAL DESIGN

- SM group:
  - *invite people to vote at the top of their News Feed*
  - *providing a link to local polling*
  - *Clickable button reading «I Vote».*
  - *shows how many other Fb users vote*
  - *displayed six randomly selected profile from Facebook friends.*
- IM group: no friends faces shown.

Social message

a Informational message

Dependent Variables: direct effects



- Clicking the I Vote button (political self-expression)
- Clicking the polling-place link (user's desire to seek information about the election)
- Voting in the election (validated voting behaviour of 6.3 million users matched to publicly available voter records)

Network Definition

- Friendship network of Facebook users
- Average degree K=149 Facebook friends
- with whom users share social information

Hypothesis

Past research indicates that close friends have a stronger behavioural effect on each other than do acquaintances or strangers

- We therefore expected mobilization to spread more effectively online through ‘strong ties’.

Network boundaries

friends who interacted with each other at least once during the three months prior to the election.

Strenght of ties' operationalization

- As individuals vary in the degree to which they use the Facebook

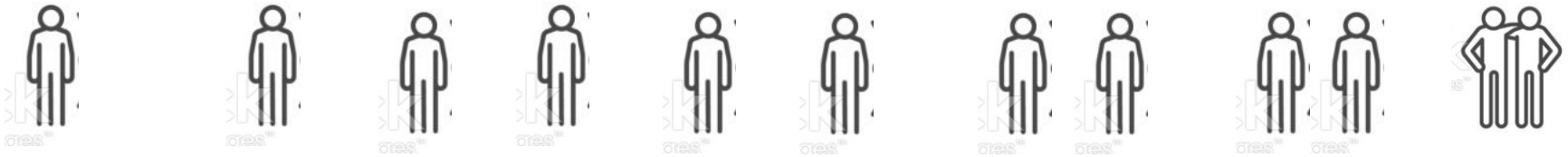
-> Normalization for each user:

$$\frac{\text{N° of interactions with a specific friend}}{\text{N° of interactions with all friends}}$$

- This gives a measure of the percentage of a user's interactions accounted for by each friend (for example, a user may interact 1% of the time with one friend and 20% of the time with another).

Strenght of ties' ranking

- Friendships **ranked** from lowest to highest percentage of interactions.



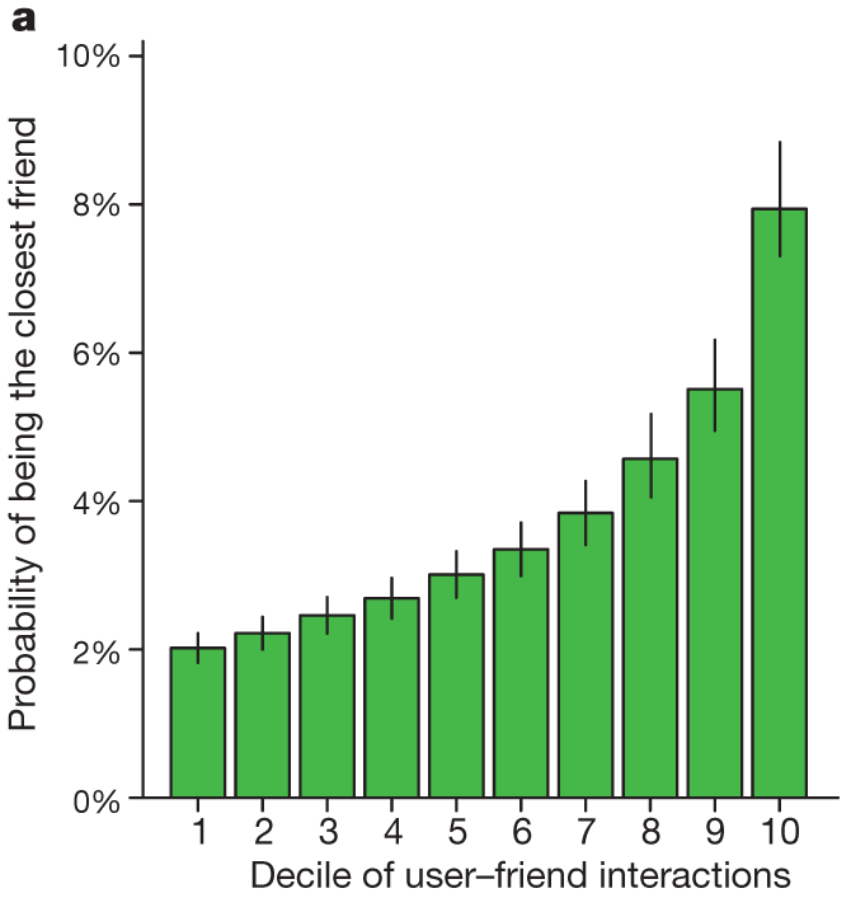
Justify the boundaries: validation study

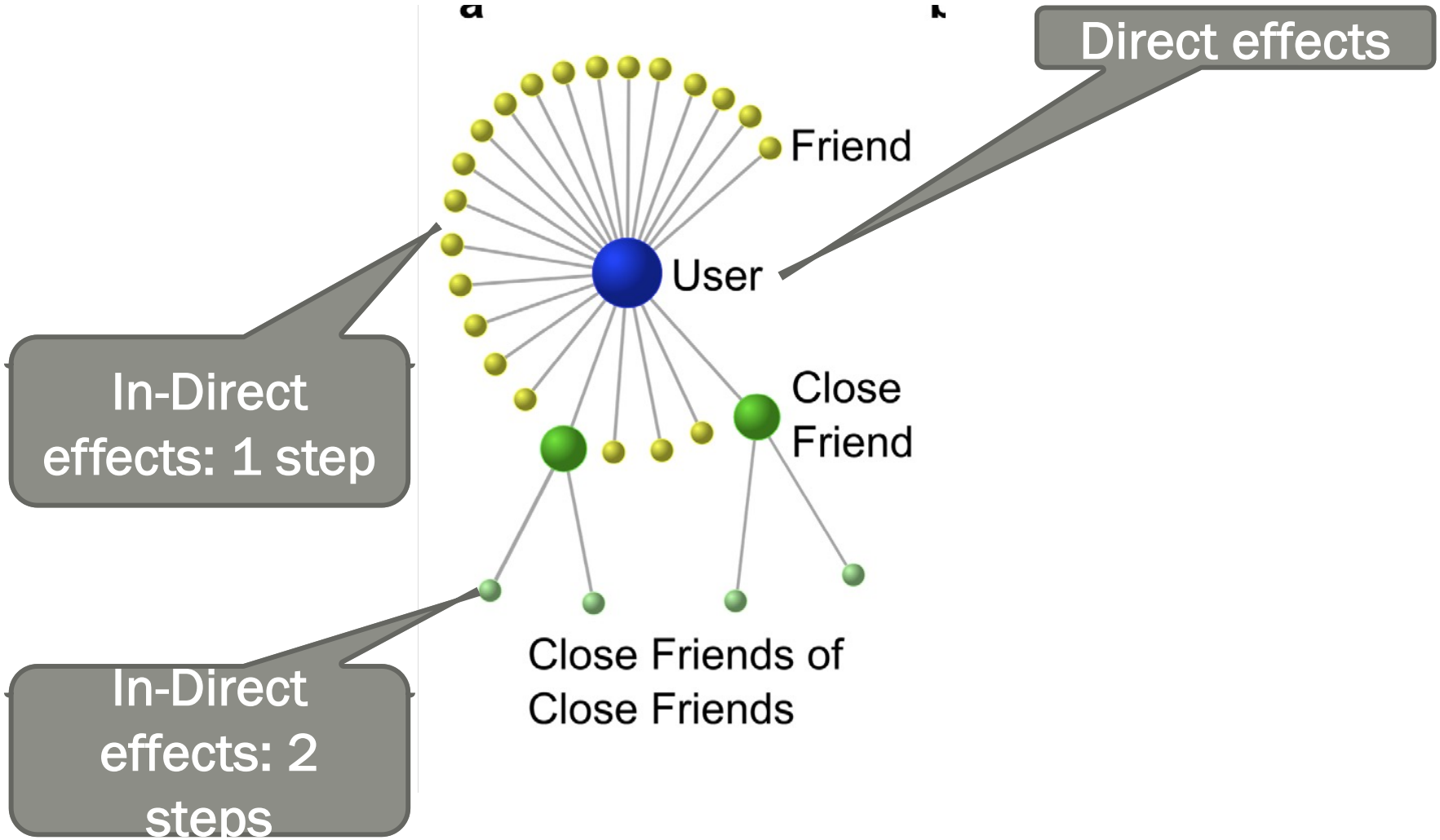
- measure of tie strength validated with a survey.
- N= 1656 users_between October 2010-jan 2011
- *“Think of the people with whom you have spent time in your life, friends with whom you have a close relationship. These friends might also be family members, neighbors, coworkers, classmates, and so on.*
  Who are your closest friends? “
- list of closest friends by pairing each survey respondent with the **first friend named** in response to the prompt.

Hyp: N° interactions is a good predictor of named closest friends.

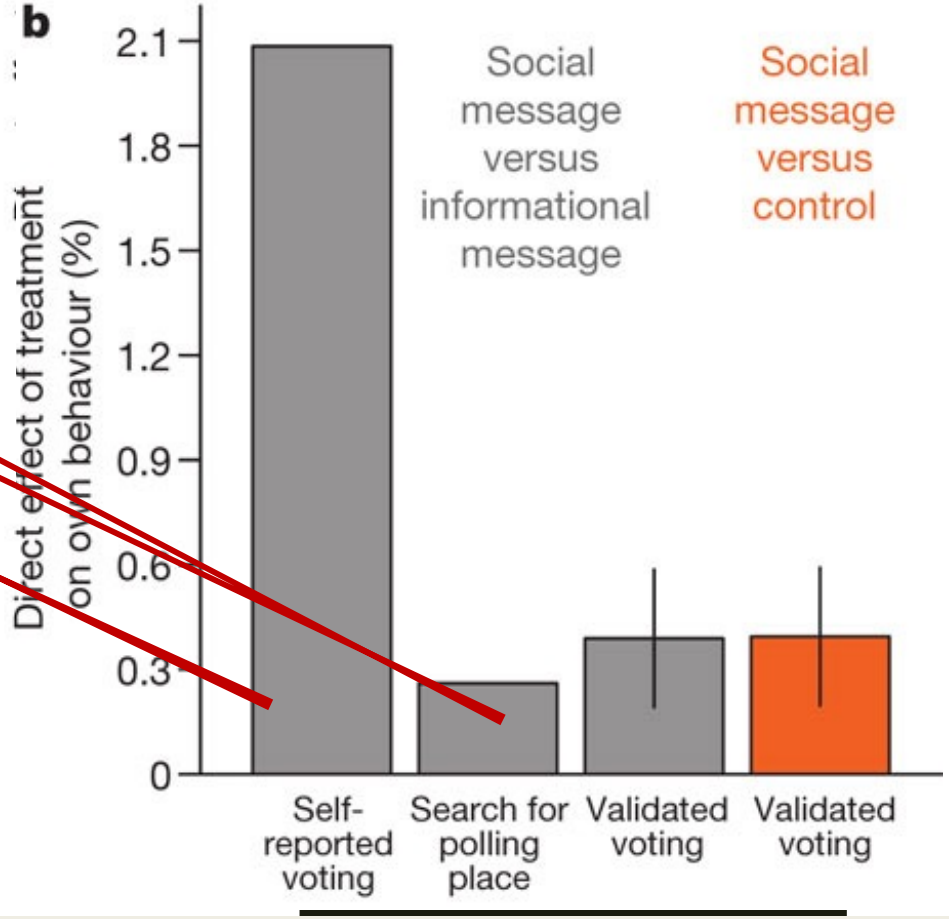
Justify the boundaries: validation study

Facebook friends are more likely to have a close real-world relationship




Direct effects
Friend
User
Close
Friend
In-Direct
effects: 1 step
Close Friends of
Close Friends
In-Direct
effects: 2
steps

DIRECT EFFECTS: Facebook behaviors



social mex 2.08% more likely to click on the I Voted button than info mex
social mex 0.26% more likely to click the polling-place information link than info mex

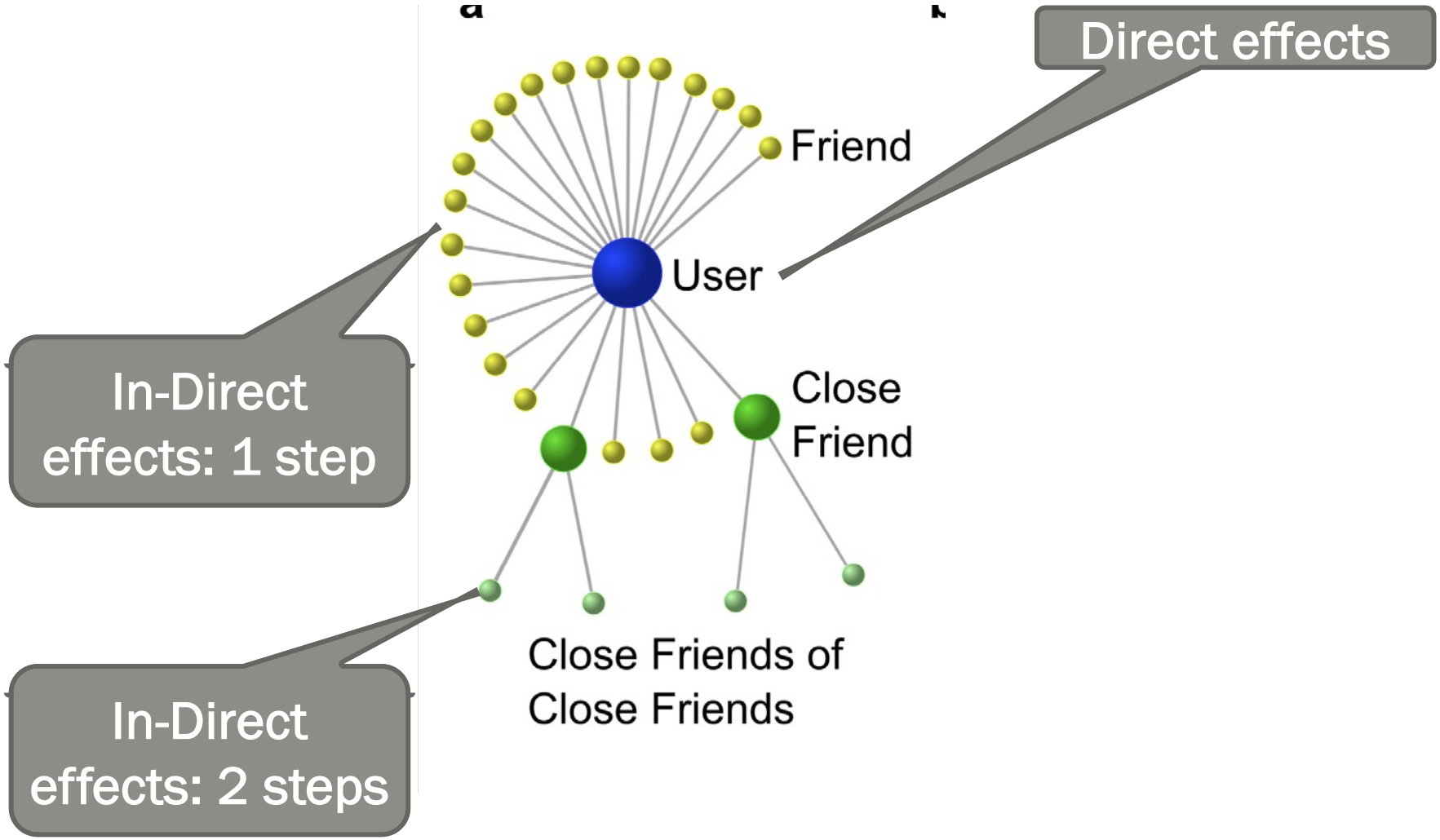
Direct effects: ACTUAL VOTING

- Social mex + 0.39% more likely to vote than control
- Social mex + 0.39% more likely to vote than informational mex
- Control = informational mex

-> seeing faces of friends significantly contributed to the overall effect of the message on real-world voting.

a Informational message

Social message


Direct effects
Friend
User
Close
Friend
In-Direct
effects: 1 step
Close Friends of
Close Friends
In-Direct
effects: 2 steps

INDIRECT EFFECTS 1 step: per friend treatment

- mean rate of behaviour for each user conditional on their friend's experimental condition
  - *Possible processes: imitation (social contagion)*
  - *Discussion (persuasion)*

per-friend treatment effect=

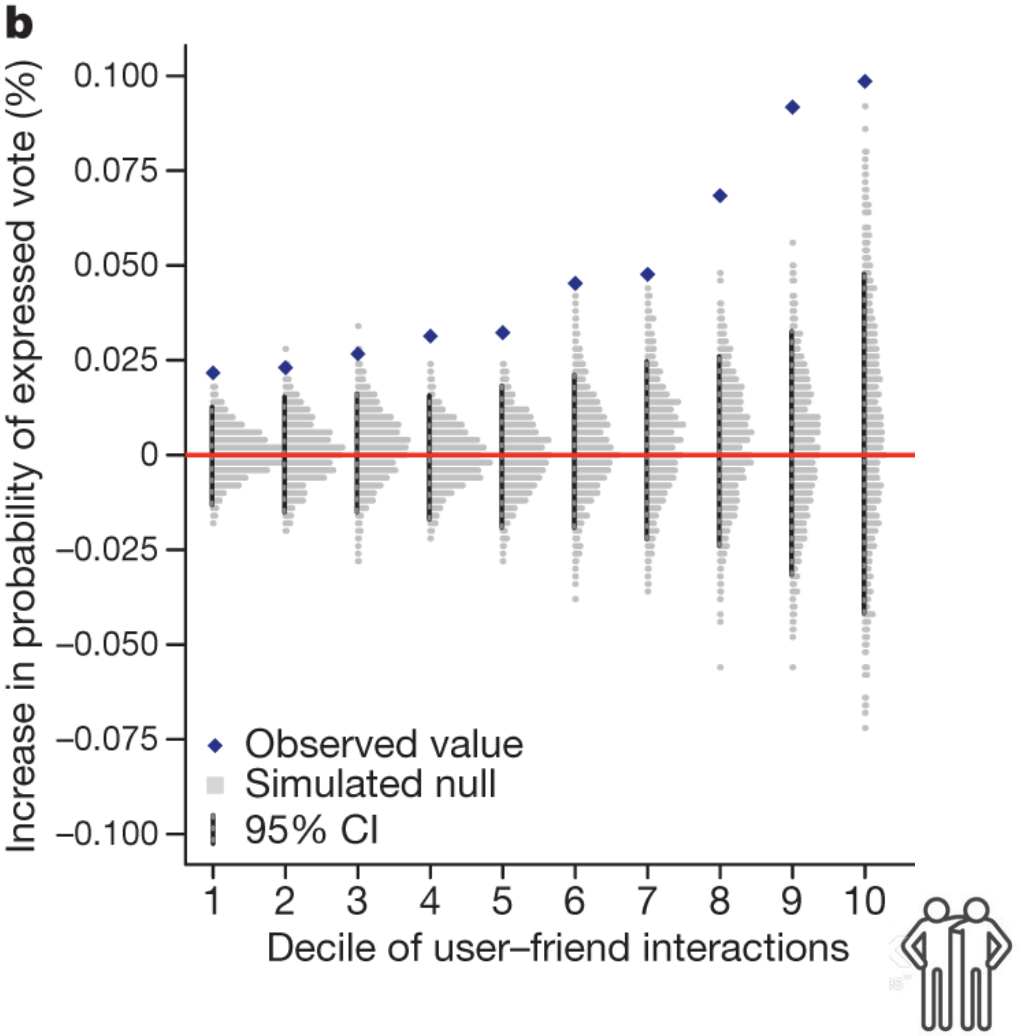
the rate of behaviour of the users whose friends were in the **treatment condition**

−

the rate of behaviour of the users whose friends were in the **control condition**

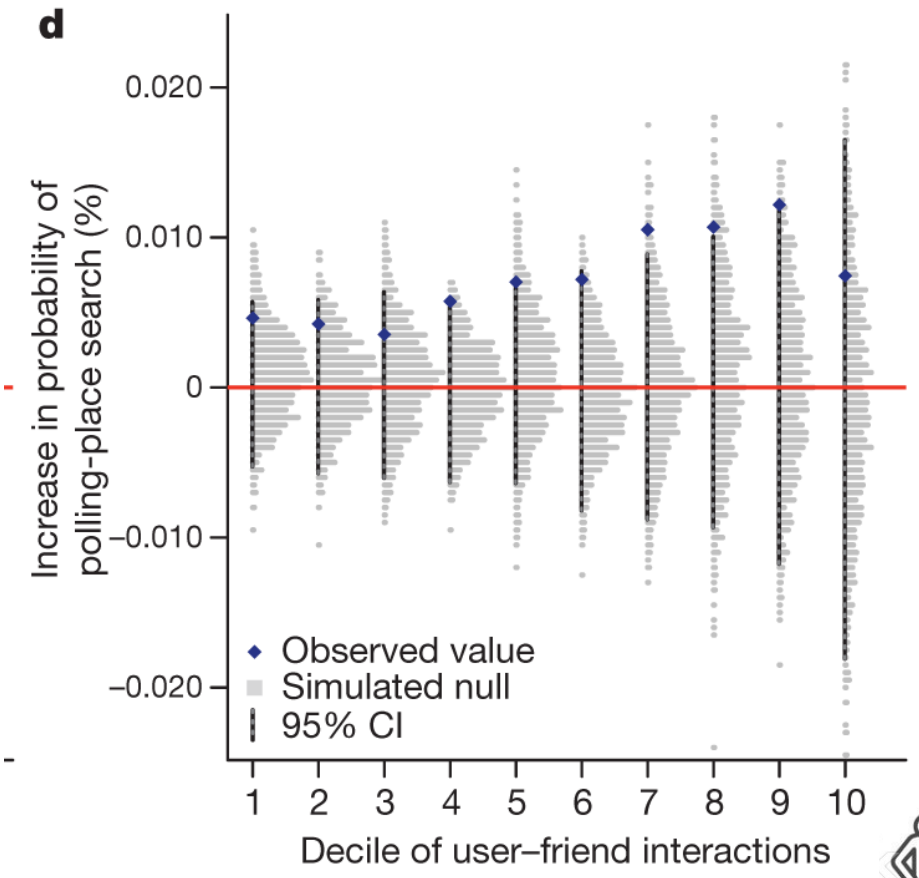
Indirect effects

As the interaction increases, so does the observed per-friend effect of friend's treatment on a user's expressed voting



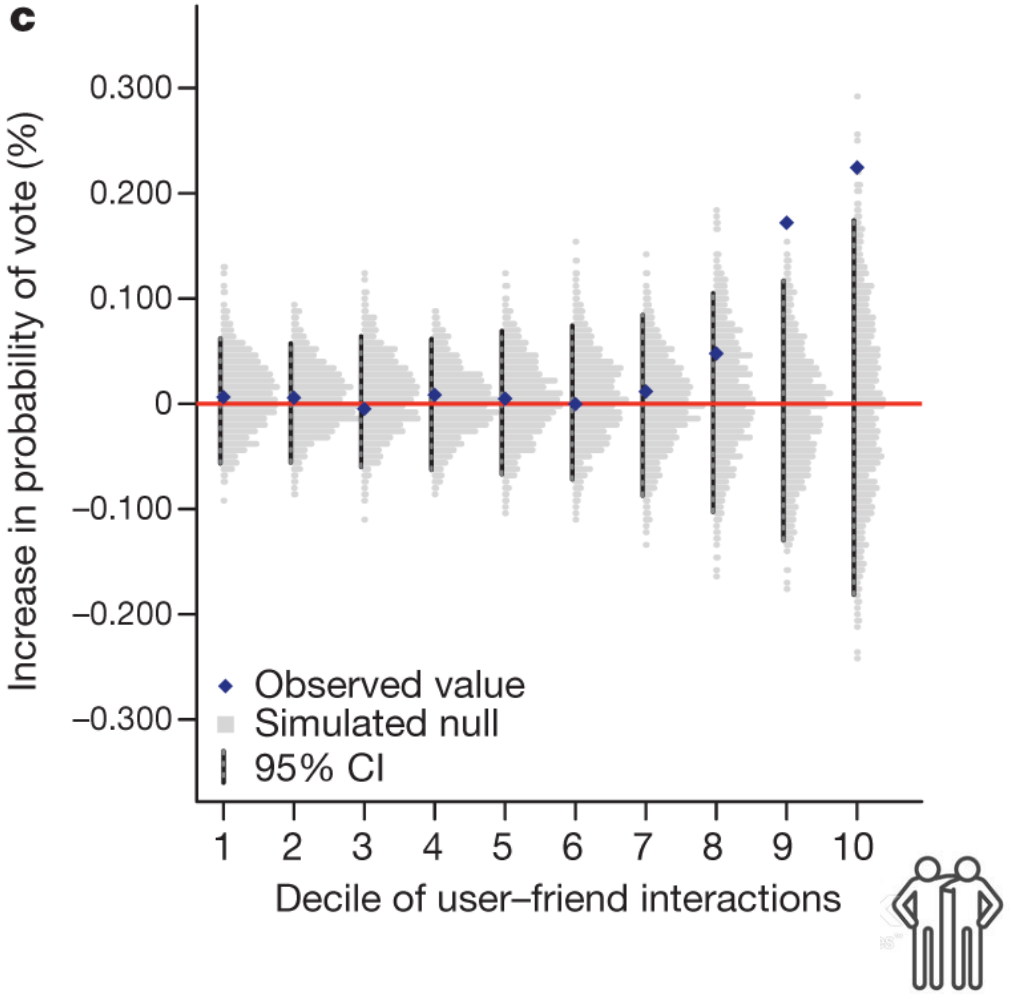
INDIRECT EFFECTS

As the interaction increases, so does the observed per-friend effect of friend's treatment on a user's polling-place search



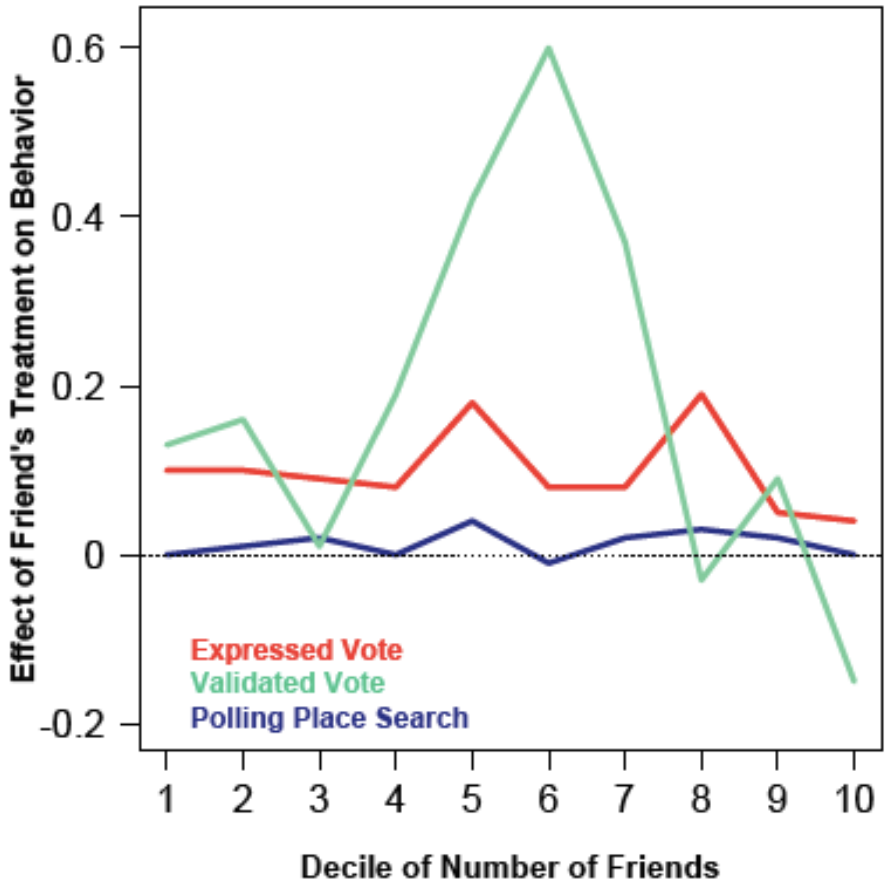
INDIRECT EFFECT

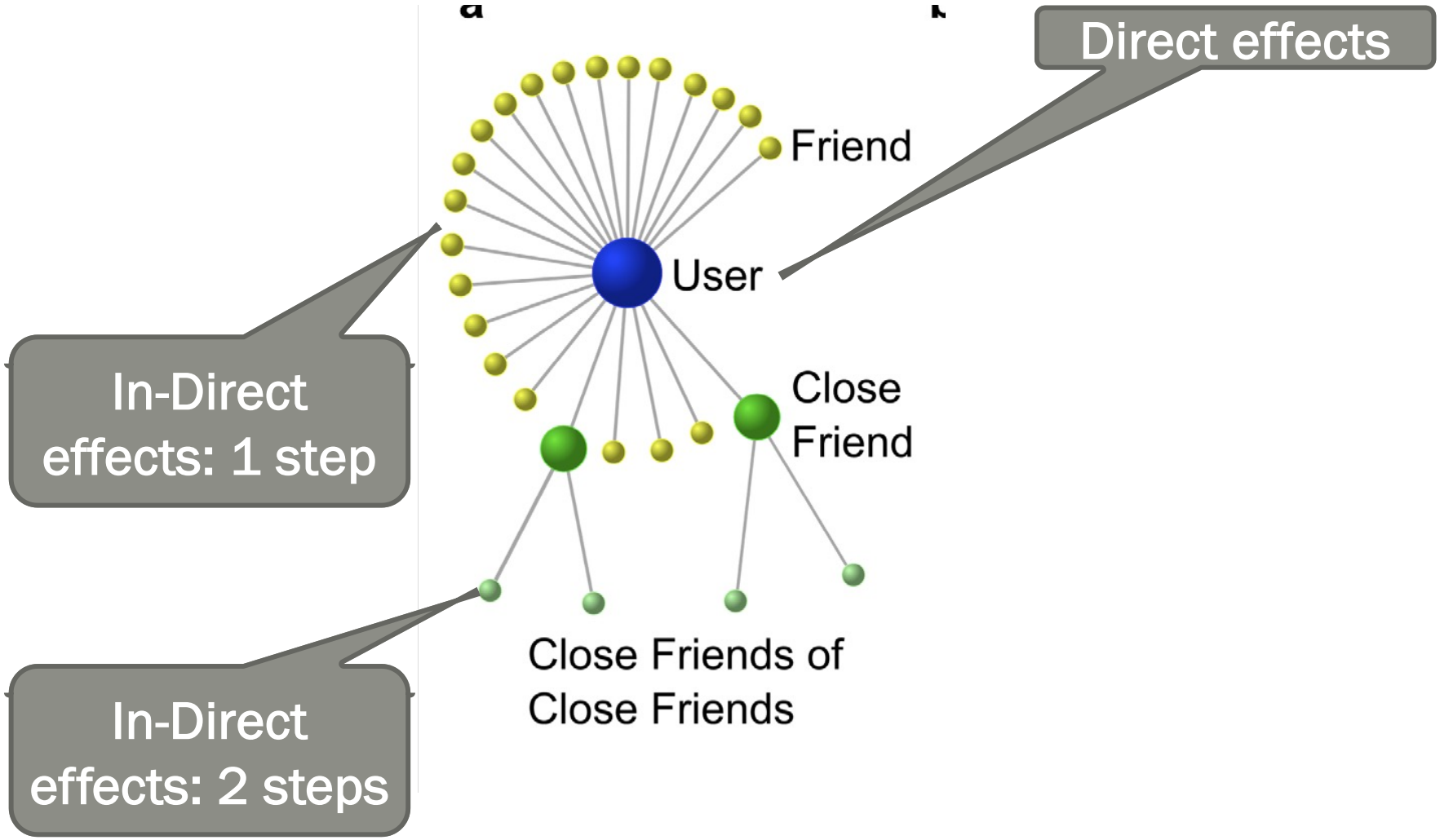
As the interaction increases, so does the observed per-friend effect of friend's treatment on a user's validated voting



Network size

- Effect on user behaviour (expressed vote, validated vote, polling place search) of a close friend receiving the social message (versus receiving no message), by decile of number of friends (Decile 1 = users with least friends, Decile 10 = users with most friends).




Direct effects
Friend
User
Close
Friend
In-Direct
effects: 1 step
Close Friends of
Close Friends
In-Direct
effects: 2 steps

Close friends of close friends

- expressed voting: the treatment effects were strong enough to be detectable at two degrees of separation.

For each *close friend of a close friend* who saw the social message, an individual was 0.022% more likely to express voting.

-> the treatment caused 1,025,000 close friends of close friends (2 degrees of separation) to express voting

Close friends of close friends

Find your polling place on the U.S. Politics Page and click the "I Voted" button to tell your friends you voted.

- For **validated voting** and **information seeking** we did not find significant effects for close friends of close friends

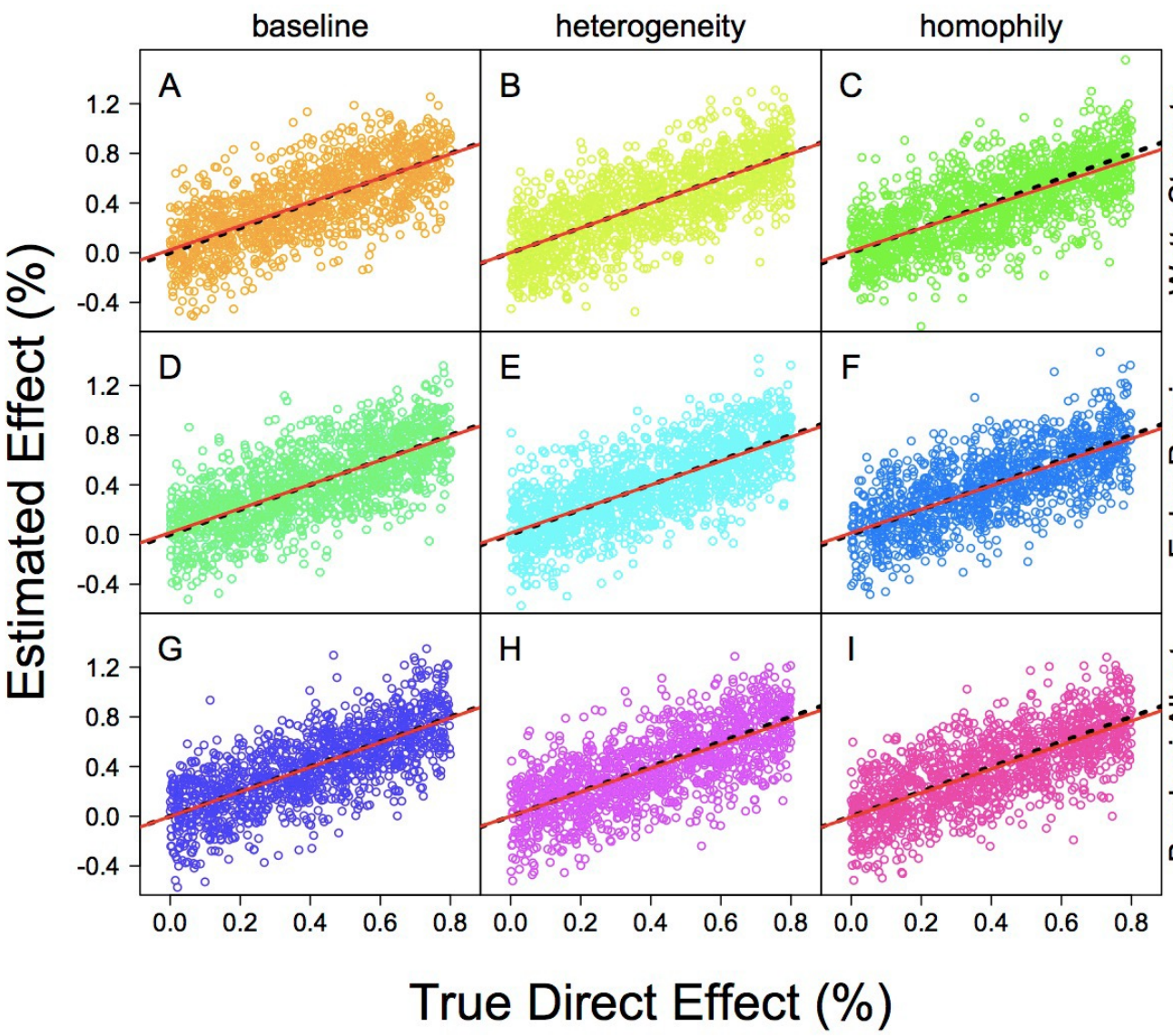
Network permutation

- the network permutation method allows to evaluate an observed correlation between a *treatment variable* and a *resulting behaviour* in the treated individual, the treated individual's friends, and the treated individual's friends of friends
- -> measure the likelihood that a correlation in observed behaviour between connected individuals in the network is due to chance

Montecarlo procedure

- 1) generates a network
- 2) endows individuals within the network with an initial likelihood of a behaviour
- 3) randomly assigns them to treatment and control groups
- 4) updates their likelihood of the behaviour according to treatment effects that we can assign (the “true” effects)
- 5) uses these probabilities to determine which individuals exhibit the behaviour.

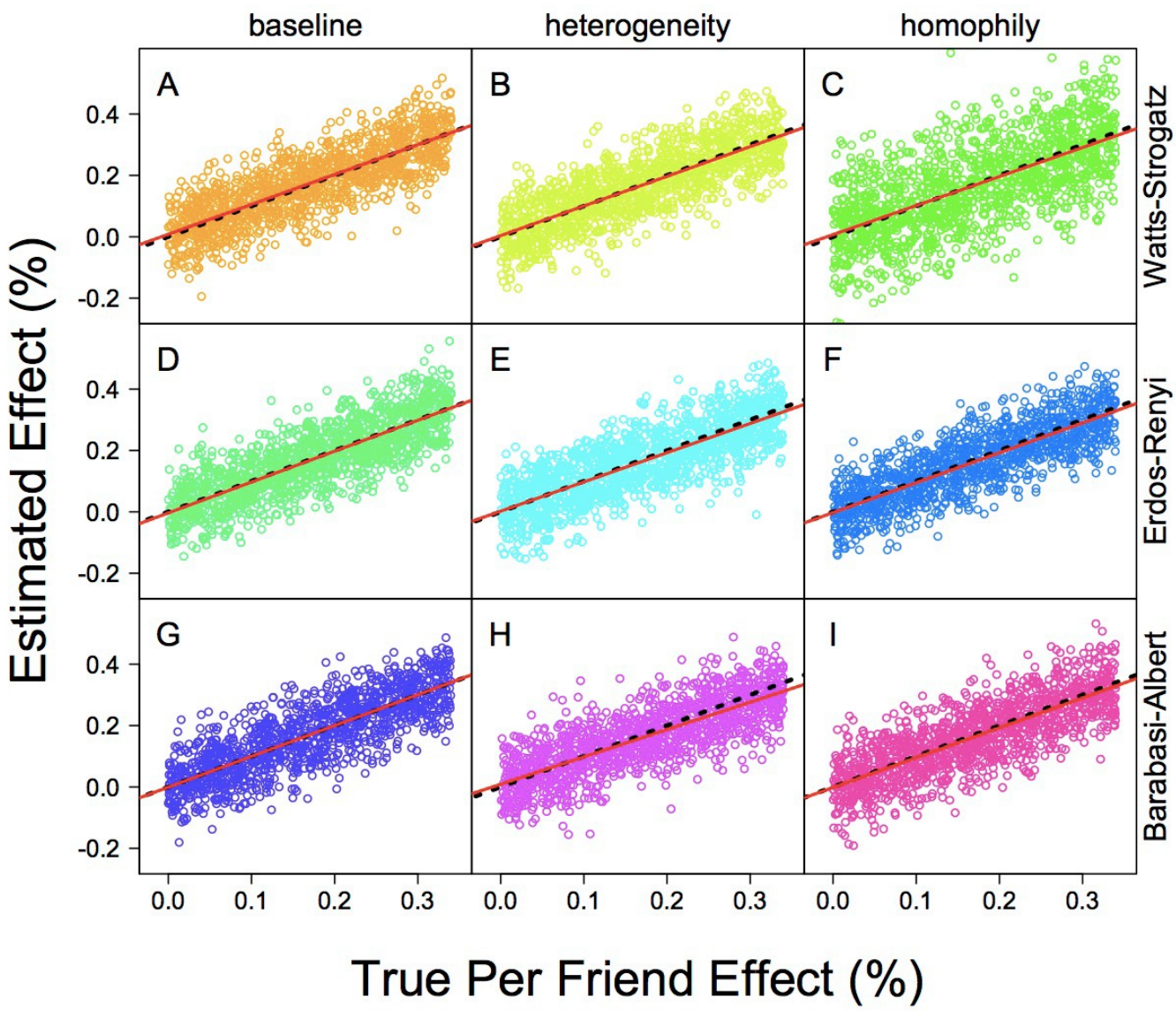
-> test the permutation procedure to see whether or not there is bias in the estimated treatment effects and the rate at which our estimation procedure produces false positives.



Small world

random network

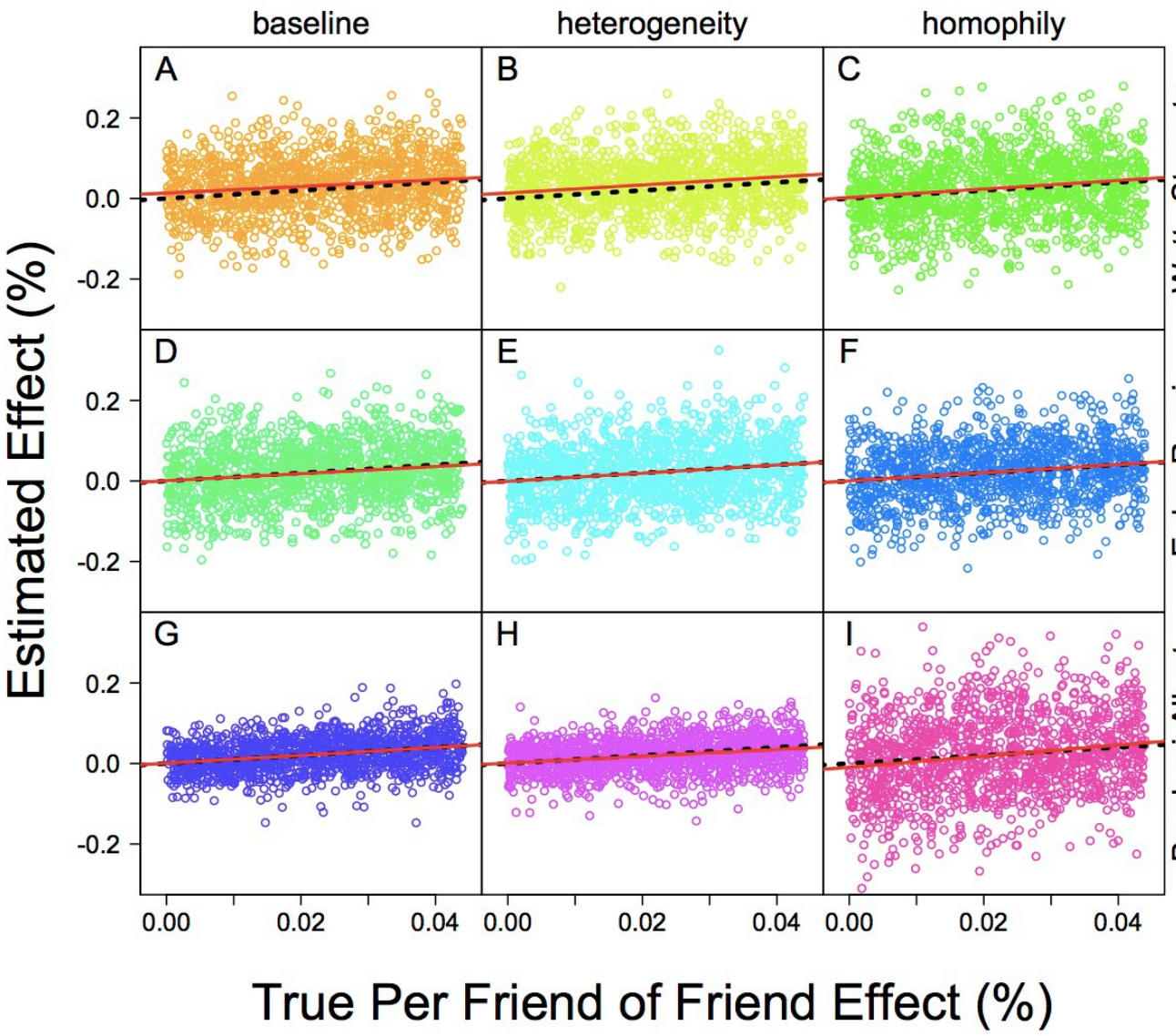
scale free" network



Small world

random network

scale free" network



Small world

random network

scale free" network

- The dotted line is the theoretical relationship between the “true” values we set and the values estimated by our method one would expect if there were no bias in the procedure, and the solid line is the actual relationship estimated by ordinary linear regression.
- in all cases the solid line lies very close to the dotted line.
- Conclusion: the estimates were not biased, no overestimation, no underestimation.

- Online political mobilization works.
- It induces political self-expression, but it also induces information gathering and real, validated voter turnout.

Facebook–Cambridge Analytica data scandal

20 languages

Article Talk Read Edit View history Tools

From Wikipedia, the free encyclopedia

In the 2010s, personal data belonging to millions of Facebook users was collected without their consent by British consulting firm Cambridge Analytica, predominantly to be used for political advertising.[1][a]

The data was collected through an app called "This Is Your Digital Life", developed by data scientist Aleksandr Kogan and his company Global Science Research in 2013.[2] The app consisted of a series of questions to build psychological profiles on users, and collected the personal data of the users' Facebook friends via Facebook's Open Graph platform.[2] The app harvested the data of up to 87 million Facebook profiles.[2] Cambridge Analytica used the data to analytically assist the 2016 presidential campaigns of Ted Cruz and Donald Trump.[3][4] Cambridge Analytica was also widely accused of interfering with the Brexit referendum, although the official investigation recognised that the company was not involved "beyond some initial enquiries" and that "no significant breaches" took place.[5][6]

This article is part of a series about

Meta Platforms

History (**Instagram** · **WhatsApp**) · **Acquisitions**

Products and services

Facebook [show]

Other products [show]

People

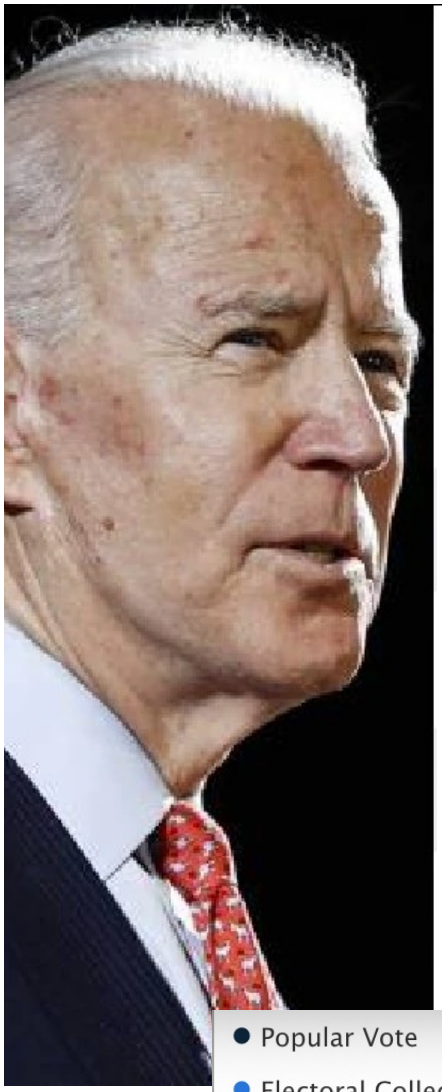
Executives and board members [show]

Notable employees [show]

Related organizations [show]

Business

Criticism [show]

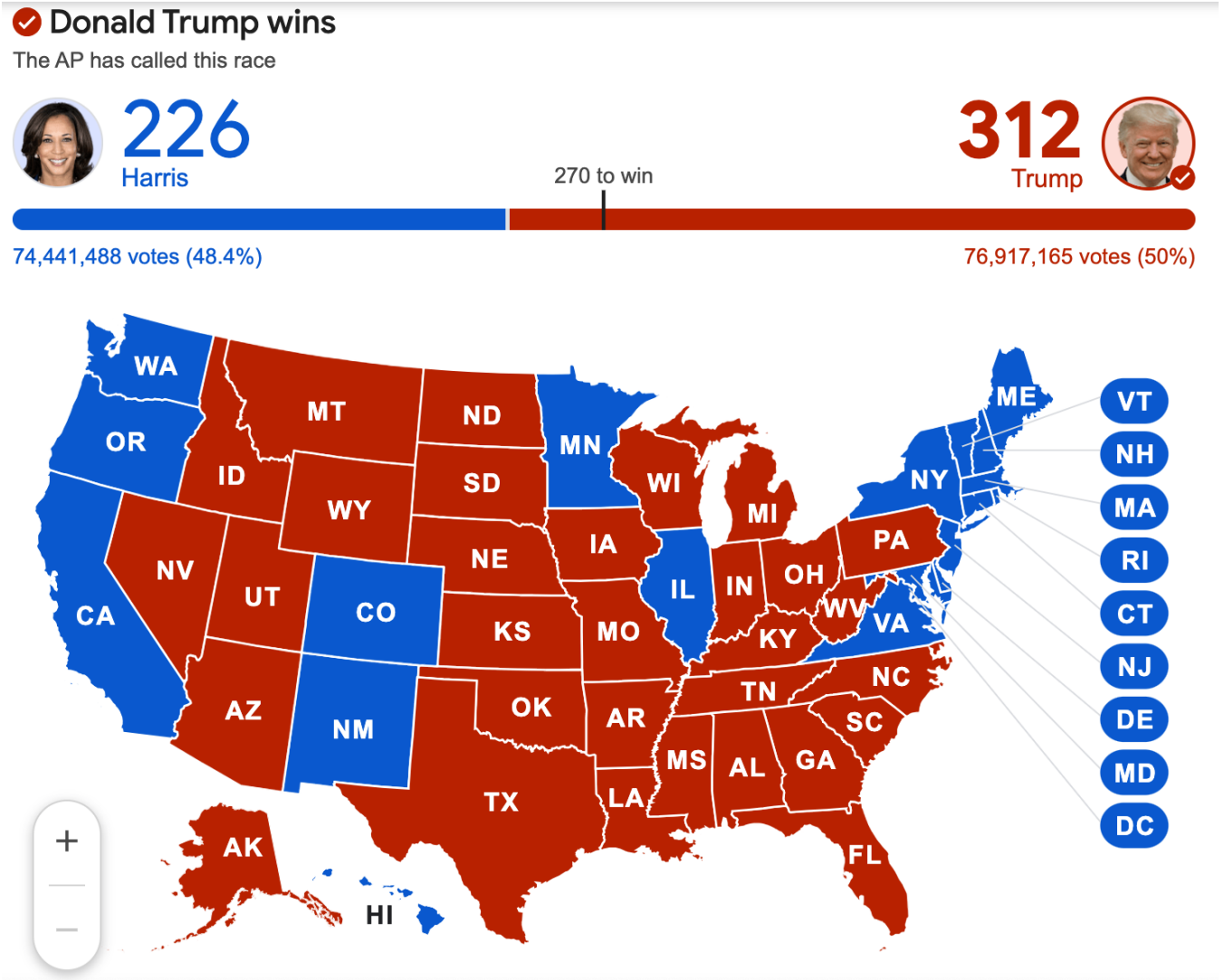


UNITED STATES PRESIDENTIAL ELECTIONS

WINNING MARGINS IN THE LAST 100 YEARS

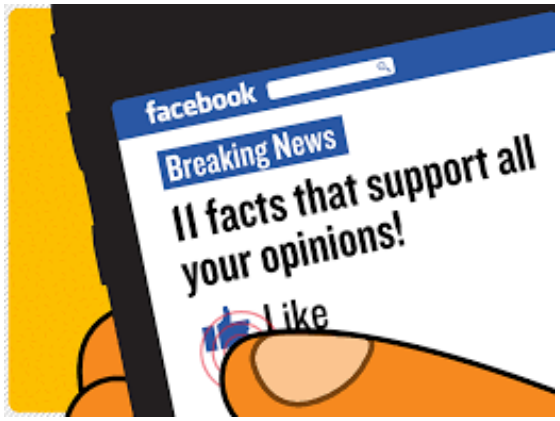
	Popular Vote	Electoral College
*2020: **Joe Biden** v Donald Trump	3.6%	13.75%
2016: **Donald Trump** v Hillary Clinton	-2.1%	14.3%
2012: **Barack Obama** v Mitt Romney	3.9%	23.24%
2008: **Barack Obama** v John McCain	7.2%	35.68%
2004: **George W. Bush** v John Kerry	2.4%	6.5%
2000: **George W. Bush** v Al Gore	-0.5%	0.93%
1996: **Bill Clinton** v Bob Dole	8.5%	40.9%
1992: **Bill Clinton** v George H. W. Bush	5.6%	37.54%
1988: **George H. W. Bush** v Michael S. Dukakis	7.7%	58.55%
1984: **Ronald Reagan** v Walter F. Mondale	18.2%	95.16%
1980: **Ronald Reagan** v Jimmy Carter	9.4%	81.78%
1976: **Jimmy Carter** v Gerald R. Ford	2%	10.59%
1972: **Richard Nixon** v George S. McGovern	23.2%	93.49%
1968: **Richard Nixon** v Hubert H. Humphrey	0.7%	20.45%
1964: **Lyndon B. Johnson** v Barry M. Goldwater	22.6%	80.66%

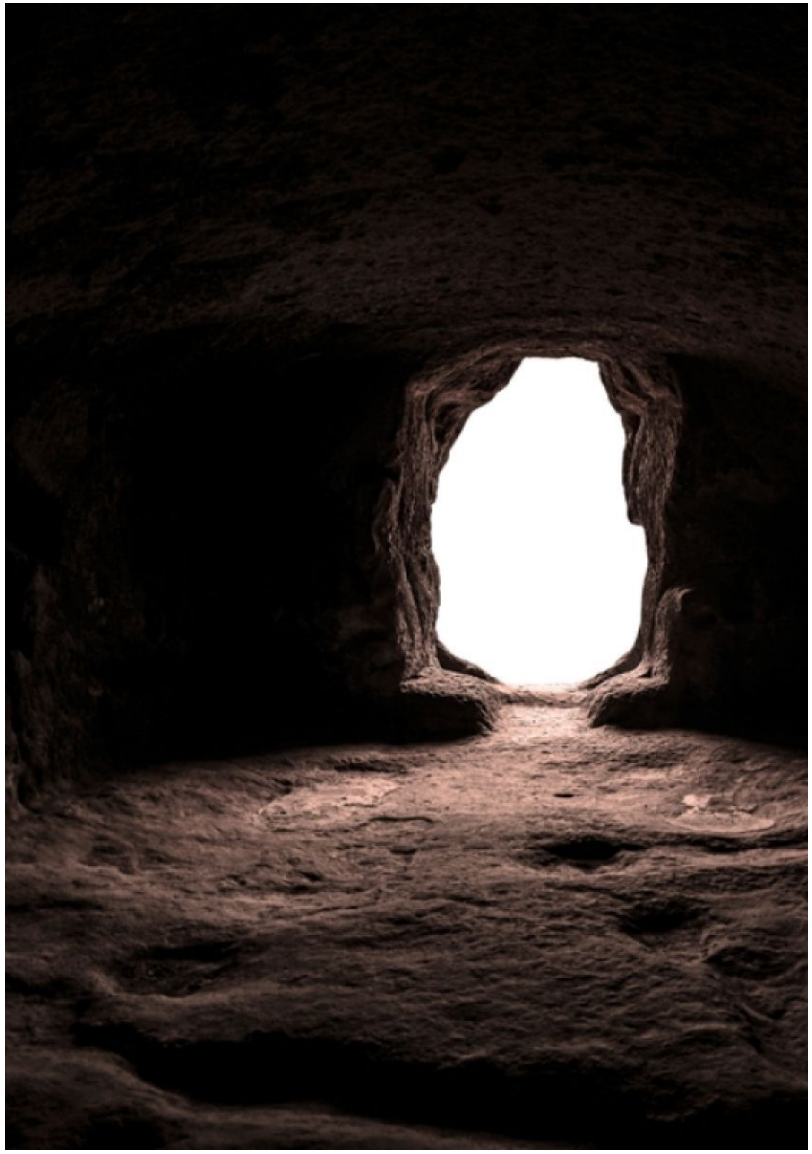
Popular vote margins: 1.48%



Eco-chambers

- situations in which one's opinion resonates with those of ones' social contacts
- an environment where a person only encounters information or opinions that reflect and reinforce their preexisting beliefs by communication and repetition inside a closed system and insulated from rebuttal
- segregation in the opinion space





Eco-chambers: processes

- Cognitive bases (selective exposure & confirmatory bias):
  - *people tend to privilege information aligned with their system of beliefs filter-out dissenting information*

- Algorithmic bases (filter bubbles): which information is eventually proposed to keep users as connected as possible, i.e. contents aligned with each users' viewpoint

- Homophily: users are surrounded by peers with similar leanings, and thus they get exposed, with a higher probability, to similar contents.

Eco-chambers -> polarization

- environments in which the opinion, political leaning, or belief of users about a topic gets reinforced due to repeated interactions with peers or sources having similar tendencies and attitudes
  - *groups of individuals who share similar views (particularly on contentious topics)* ***against opposing perspectives***
  - *framing and reinforcing a shared narrative*
  - *individuals opinions are polarized*
- polarization may catalyze misinformation

- Radicalization dynamics: Triggering segregation and hate speech

Quantification of ecochambers

The echo chamber effect on social media

Matteo Cinelli[a], Gianmarco De Francisci Morales[b], Alessandro Galeazzi[c], Walter Quattrociocchi[d,1], and Michele Starnini[b]

[a]Department of Environmental Sciences, Informatics and Statistics, Ca'Foscari Univerity of Venice, 30172 Venice, Italy; [b]Institute for Scientific Int (ISI) Foundation, 10126 Torino, Italy; [c]Department of Information Engineering, University of Brescia, 25123 Brescia, Italy; and [d]Department of Co Science, Sapienza University of Rome, 00185 Rome, Italy

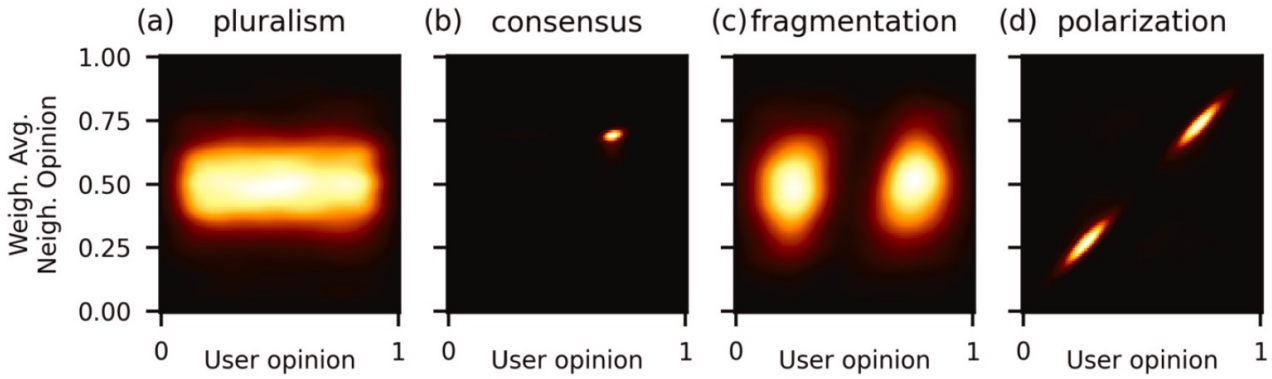
- 1) homophily in the interaction networks
- 2) bias in the information diffusion toward like-minded peers

- - based on user's attitude:
  - *content produced or endorsed (like) or shared (mentions or retweets)*
  - *explicit (e.g., arguments supporting a narrative) or implicit (e.g., framing and agenda setting)*

  - *How to code content?*
    - Language
    - Sentiment etc…
  - *How to code framing?*
    - External sources: https://mediabiasfactcheck.com/
    - Manual coding
    - Machine learning

Opinion dynamics models

- agents are usually represented as nodes of a graph endowed with some properties, namely opinions or attitudes
- Connections among nodes may represent social relationships (e.g. friendship) and allow agents to interact with each other.
- Simulations consist of updating agents' internal states and/or network connections **(rewiring) based on the opinions of neighboring others.**
- Usally considering social interaction strength among agents and the *controversialness* of the modeled topic
- interactions between individuals occur probabilistically, resulting in neighbours updating their opinions to become closer or farther from the opinion expressed in the post.
- the opinion of each user is updated according to a filtered subset of its nearest neighbors.
- The filtering mechanism mimicks the feed/recommendation algorithm's action on social media platforms that play a major role in shaping users online experience



PHYSICAL REVIEW LETTERS **124,** 048301 (2020)

Modeling Echo Chambers and Polarization Dynamics in Social Networks

Fabian Baumann,[1,*] Philipp Lorenz-Spreen,[2] Igor M. Sokolov,[1,3] and Michele Starnini[4,†]

[1]*Institute for Physics, Humboldt-University of Berlin, Newtonstraße 15, 12489 Berlin, Germany*

[2]*Center for Adaptive Rationality, Max Planck Institute for Human Development, Lentzeallee 94, 14195 Berlin, Germany*

[3]*IRIS Adlershof, Humboldt-University of Berlin, Newtonstraße 15, 12489 Berlin, Germany*

[4]*ISI Foundation, via Chisola 5, 10126 Torino, Italy*

- How moderate opinions become extreme,
- How echo chambers emerge,
- Why polarization appears despite open communication.

Model reproduces observed patterns in Twitter debates about:

- Abortion
- Gun control
- Obamacare

- Social influence
- Heterogeneous user activity (some are very active)
- Homophily (preference for interacting with similar users)

- Each user has an opinion value x_i:
- Sign = position (pro/contro)
- Magnitude = radicalization level
- K: strength of social influence
- α: controversialness of the topic
- A_{ij}: interaction network
- t: time

Opinion update rule over time

$$\dot{x}_i = -x_i + K \sum_j A_{ij}(t) \tanh(\alpha x_j)$$

System Outcomes

Depending on parameters:

- Neutral consensus
- One-sided radicalization
- Polarization into two opposing groups

Results

- **More active users become more extremec** (Seen in simulations and Twitter data)
- Users' opinions strongly correlate with those of their neighbors (Indicates **stable echo chambers**)
- **In controversial issues:** radicalization and polarization appear

- In the case of **controversial issues**, a reinforcement mechanism leads to radicalization dynamics and may drive groups of agents away from the global consensus.
- For weak homophily, the transition from consensus to radicalization dynamics can be predicted analytically.

Traditional concern:

- People cluster in **ideologically homogeneous groups**
- Limited exposure to opposing viewpoints

New trend (Di Martino et al., 2025):

- Entire platforms becoming ideological enclaves
- Example: Gab, Parler, BitChute mainly right-leaning
- Leads to fragmentation of the online ecosystem

Consequences of Fragmentation

- **Growing political polarization**
- Reduced shared public spaces
- Increased misinformation flow
- Harder for democratic societies to have shared debates

- Detecting Echo Platforms (3 Analytical Dimensions)
- Centrality:
  - *Central vs. peripheral roles in the information network*
- News consumption:
  - *Share of reliable vs. questionable sources*
- User ideology:
  - *Diverse vs. homogeneous political user bases*

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Research Report

Ideological fragmentation of the social media ecosystem: From echo chambers to echo platforms

Edoardo Di Martino[a,*], Alessandro Galeazzi[b], Michele Starnini[c,d], Walter Quattrociocchi[e] and Matteo Cinelli[e]

[a]Department of Social Sciences and Economics, Sapienza University of Rome, P.le Aldo Moro, 5, Rome 00185, Italy
[b]Department of Mathematics, University of Padova, Via Trieste, 63, Padua 35121, Italy
[c]Department of Engineering, Universitat Pompeu Fabra, Barcelona 08018, Spain
[d]CENTAI Institute, Turin 10138, Italy
[e]Department of Computer Science, Sapienza University of Rome, Viale Regina Elena, 295, Rome 00161, Italy
*To whom correspondence should be addressed: Email: edoardo.dimartino@uniroma1.it
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Further Relevant papers

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