Lecture 18: Social media and society

Matthew J. Salganik

Sociology 204: Social Networks
Princeton University

Feedback on the feedback from quiz 6

Social media:

- Lecture 17: Social media and individuals
- Lecture 18: Social media and society
- Lecture 19: Social ads in social media
- Lecture 20: Fixing social media
- Lecture 21: Facebook Files

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- Allcott et al. do a randomized controlled trial to measure the effect of FB on a sample of American users
- Being off FB for one month leads to 1) reduced online activity and increased offline activity 2) reduced factual news knowledge and political polarization 3) increased subjective well-being and 4) caused a large persistent reduction in post-experiment Facebook use
- Being off FB for one month also leads to new awareness about the good and bad aspects of FB

Community minute

Social media:

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- What is going viral? Lies and outrage

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- Who is more responsible algorithms or people? Hard to say
  - Most focused on people: Vosoughi et al.
  - In between: Brady et al.
  - Most focussed on algorithms: Bakshy et al.

Background

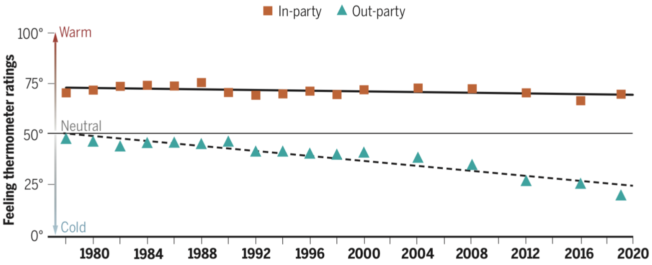
SOCIAL SCIENCE

Political sectarianism in America

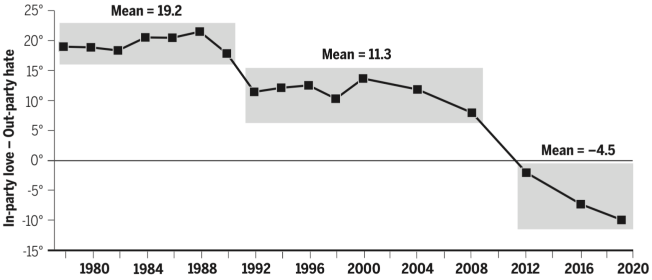
A poisonous cocktail of othering, aversion, and moralization poses a threat to democracy

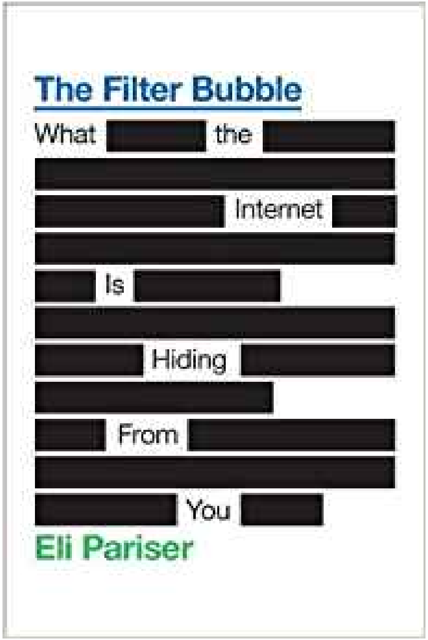
By **Eli J. Finkel[1], Christopher A. Bail[2], Mina Cikara[3], Peter H. Ditto[4], Shanto Iyengar[5], Samara Klar[6], Lilliana Mason[7], Mary C. McGrath[1], Brendan Nyhan[8], David G. Rand[9], Linda J. Skitka[10], Joshua A. Tucker[11], Jay J. Van Bavel[11], Cynthia S. Wang[1], James N. Druckman[1]**

Warmth toward the opposing party (out-party) has diminished for decades

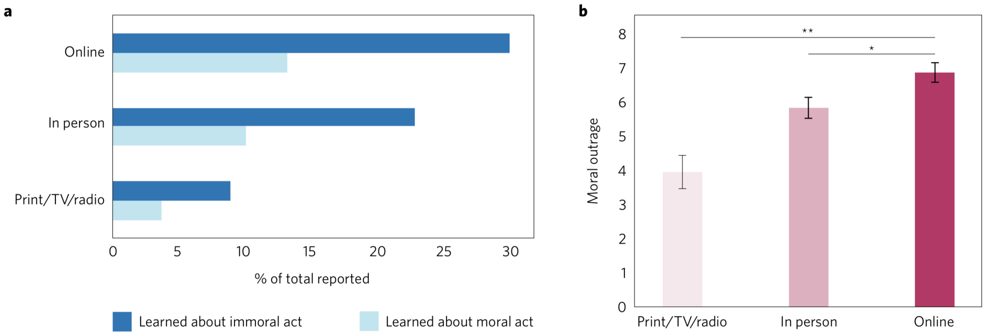


Out-party hate has emerged as a stronger force than in-party love

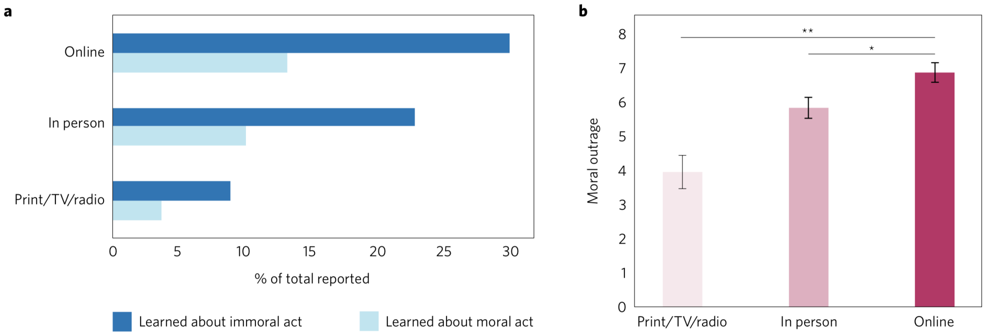



The Filter Bubble
What the
Internet
Is
Hiding
From
You
Eli Pariser

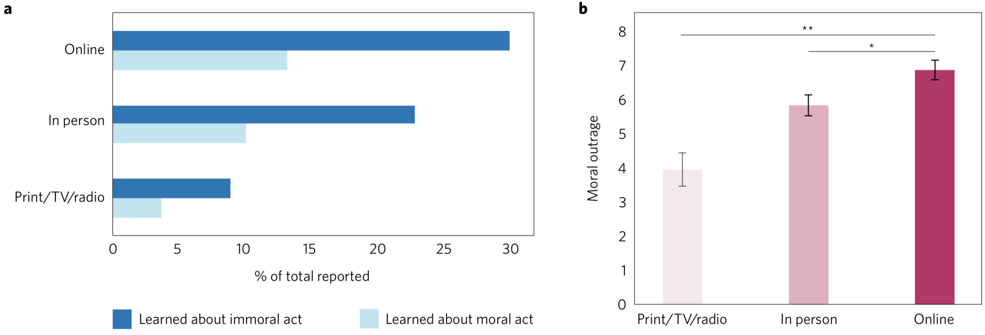
What goes viral? Moral outrage and lies



- People more likely to learn about immoral acts online than through other media



- People more likely to learn about immoral acts online than through other media
- Outrageous acts that people see online lead to more outrage



- People more likely to learn about immoral acts online than through other media
- Outrageous acts that people see online lead to more outrage
- "Digital media transform moral outrage by changing both the nature and prevalence of the stimuli that trigger it."

SOCIAL SCIENCES

How social learning amplifies moral outrage expression in online social networks

William J. Brady[1]*, Killian McLoughlin[1], Tuan N. Doan[2], Molly J. Crockett[1]*

- two observational studies and two experiments (all preregistered)

SOCIAL SCIENCES

How social learning amplifies moral outrage expression in online social networks

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- two observational studies and two experiments (all preregistered)
- reinforcement learning and norm learning, both of which are controlled in part by design of social media platforms

“A person can be viewed as expressing moral outrage if:

- they have feelings in response to a perceived violated of their personal morals
- their feelings are comprised of emotions such as anger, disgust, and contempt
- the feelings are associated with specific reactions including blaming people/events/things, holding them responsible or wanting to punish them.”

They labeled a many example tweets and then built a Digital Outrage Classifier

https://www.youtube.com/watch?v=b2AYlD8ReeA&t=11m26s

Supporting our hypotheses, we found that daily outrage expression was significantly and positively associated with the amount of social feedback received for the previous day's outrage expression (Study 1: $b = 0.03$, $p <.001$, 95% CI = [0.03, 0.03]; Study 2: $b = 0.02$, $p <.001$, 95% CI = [0.02, 0.03]). For our model, this effect size translates to an expected 2-3% increase in outrage expression on the following day of tweeting if a user received a 100% increase in feedback for expressing outrage on a given day. For instance, a user who averaged 5 likes/shares per tweet, and then received 10 likes/shares when they expressed outrage, would be expected to increase their outrage expression on the next day by 2-3%. While this effect size is small, it can easily scale on social media over time, become notable at scale at the network level, or for users who maintain a larger followership and could experience much higher than 100% increases in social feedback for tweeting outrage content (e.g., political leaders). For other model specifications to test the robustness of the effect, see SOM, Section 2.0.

Three main findings from observational studies

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- “outrage expression on Twitter can be explained in part by variation in social feedback that people receive via the platform”
- “users are more likely to express outrage in more ideologically extreme social networks”
- “in more ideologically extreme social networks, users’ outrage expression behavior is less sensitive to social feedback.”

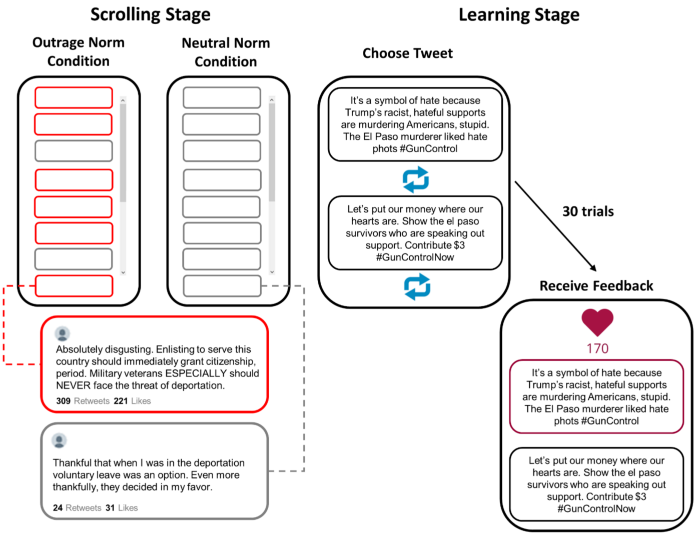
Finding are consistent with reinforcement learning and norm learning, but there are limits to what they can learn just from watching without controlling the environment

Experimental evidence of massive-scale emotional contagion through social networks

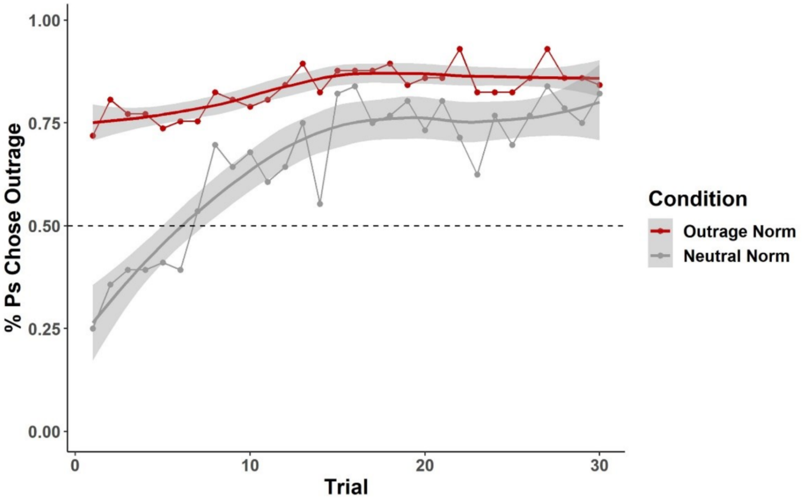
Adam D. I. Kramer[a,1], Jamie E. Guillory[b,2], and Jeffrey T. Hancock[b,c]

[a]Core Data Science Team, Facebook, Inc., Menlo Park, CA 94025; and Departments of [b]Communication and [c]Information Science, Cornell University, Ithaca, NY 14853

We also observed a withdrawal effect: People who were exposed to fewer emotional posts (of either valence) in their News Feed were less expressive overall on the following days, addressing the question about how emotional expression affects social engagement online. This observation, and the fact that



- Now researchers can vary the environment (norms) and feedback (reinforcement)



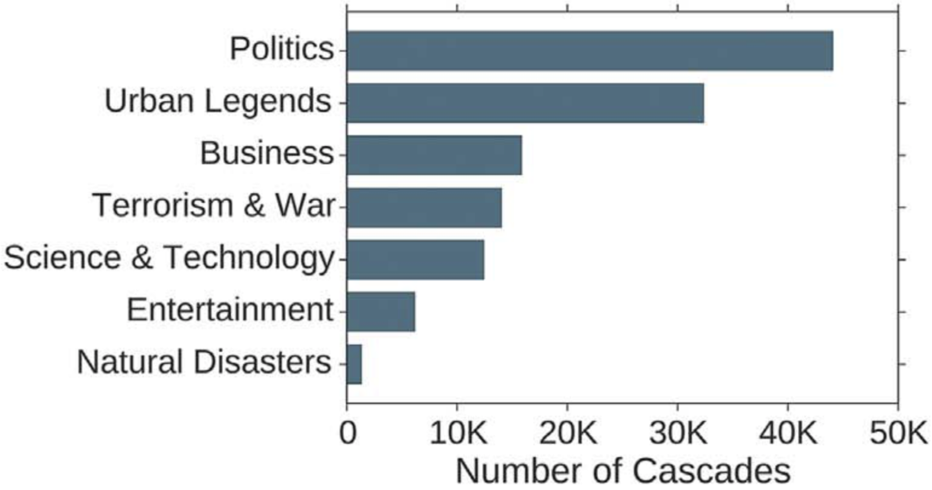
- Norms matter and people learn to choose outrage

Who is responsible? People are doing it, but what about the architects?

What goes viral? Moral outrage and lies

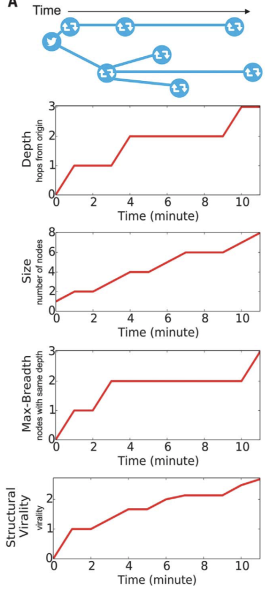
The spread of true and false news online

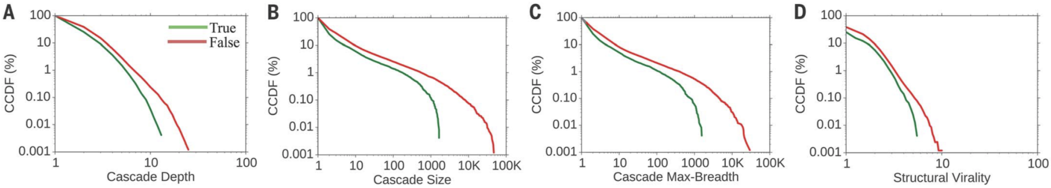
Soroush Vosoughi,[1] Deb Roy,[1] Sinan Aral[2]*



Unlike Goel et al. these are measured as true or false based on 6 fact checking websites

A


Time
Depth
hops from origin
Time (minute)
Size
number of nodes
Time (minute)
Max-Breadth
nodes with same depth
Time (minute)
Structural Virality
virality
Time (minute)



- false rumors spread deeper, are more retweeted, spread more broadly, and are more viral than true rumors

What might explain this pattern?

What might explain this pattern? False rumors are more novel than true rumors and so people decide to retweet them.

- Is this because the face checked rumors are somehow different?

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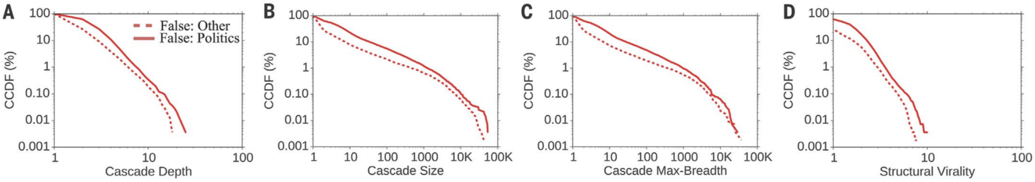
- Why does this matter?

- Is this because the face checked rumors are somehow different? No. Newly, independently checked rumors show similar pattern.
- Is this because of bots? No. If you remove bots you get similar patterns
- Why does this matter? It impacts which policy you might use to intervene (e.g., labeling for humans, training for humans vs bot removal)



- political rumors spreads deeper, are more retweeted, spread more broadly, and are more viral than true rumors

All of this might make you think that we are awash in false rumors about politics, but. . . . .

Fake news on Twitter during the 2016 U.S. presidential election

Nir Grinberg[1,2]*, Kenneth Joseph[3]*, Lisa Friedland[1]*,
Briony Swire-Thompson[1,2], David Lazer[1,2]†

The spread of fake news on social media became a public concern in the United States after the 2016 presidential election. We examined exposure to and sharing of fake news by registered voters on Twitter and found that engagement with fake news sources was extremely concentrated. Only 1% of individuals accounted for 80% of fake news source exposures, and 0.1% accounted for nearly 80% of fake news sources shared. Individuals most likely to engage with fake news sources were conservative leaning, older, and highly engaged with political news. A cluster of fake news sources shared overlapping audiences on the extreme right, but for people across the political spectrum, most political news exposure still came from mainstream media outlets.

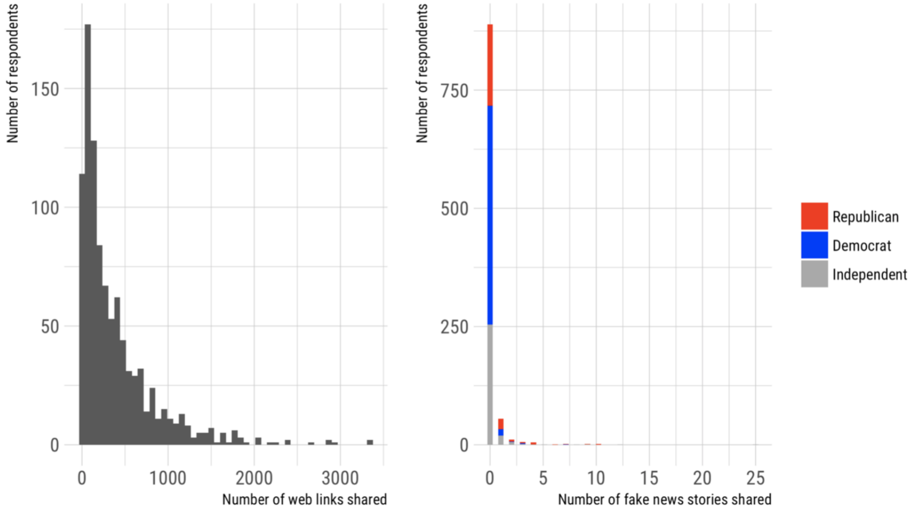
Twitter, 2016 US election, `https://dx.doi.org/10.1126/science.aau2706`

Less than you think: Prevalence and predictors of fake news dissemination on Facebook

Andrew Guess[1]*, Jonathan Nagler[2], Joshua Tucker[2]

So-called "fake news" has renewed concerns about the prevalence and effects of misinformation in political campaigns. Given the potential for widespread dissemination of this material, we examine the individual-level characteristics associated with sharing false articles during the 2016 U.S. presidential campaign. To do so, we uniquely link an original survey with respondents' sharing activity as recorded in Facebook profile data. First and foremost, we find that sharing this content was a relatively rare activity. Conservatives were more likely to share articles from fake news domains, which in 2016 were largely pro-Trump in orientation, than liberals or moderates. We also find a strong age effect, which persists after controlling for partisanship and ideology: On average, users over 65 shared nearly seven times as many articles from fake news domains as the youngest age group.

Facebook, 2016 US election, `https://dx.doi.org/10.1126/sciadv.aau4586`



- people share links of Facebook, just not fake news

Also, we have no good estimates (that I've seen) about the *impact* of any of these false rumors on people's beliefs

The science of fake news

Addressing fake news requires a multidisciplinary effort

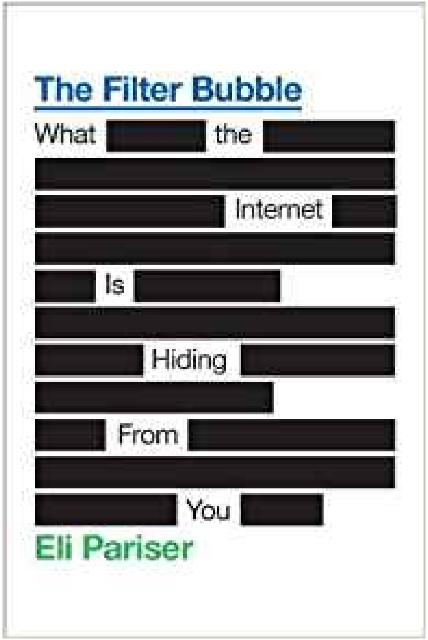
By **David M. J. Lazer, Matthew A. Baum, Yochai Benkler, Adam J. Berinsky, Kelly M. Greenhill, Filippo Menczer, Miriam J. Metzger, Brendan Nyhan, Gordon Pennycook, David Rothschild, Michael Schudson, Steven A. Sloman, Cass R. Sunstein, Emily A. Thorson, Duncan J. Watts, Jonathan L. Zittrain**

https://dx.doi.org/10.1126/science.aao2998

Next lets focus on one specific algorithm thought to be related to political polarization: Facebook NewsFeed

Exposure to ideologically diverse news and opinion on Facebook

Eytan Bakshy,[1*†] Solomon Messing,[1†] Lada A. Adamic[1,2]

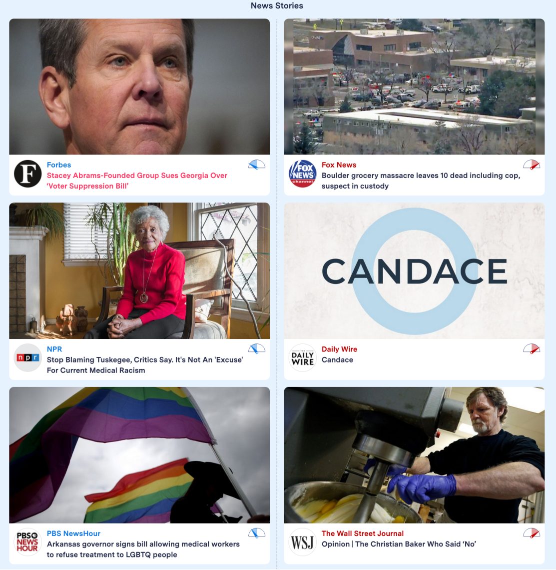

The Filter Bubble
What the
Internet
Is
Hiding
From
You
Eli Pariser

Citizen Browser

Split Screen

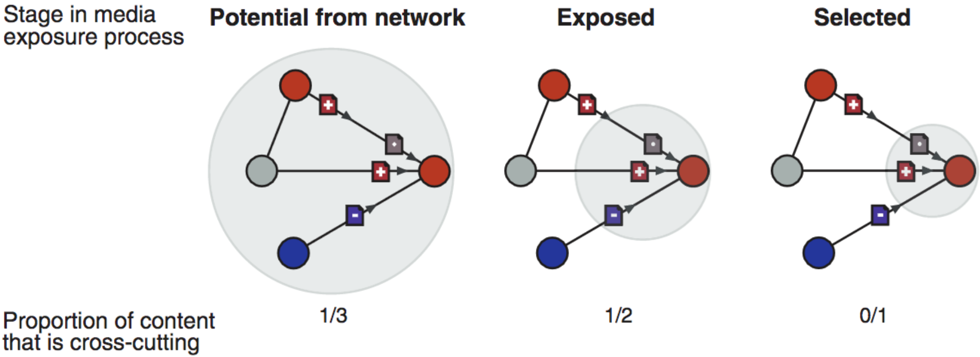
How Different Are Americans' Facebook Feeds?

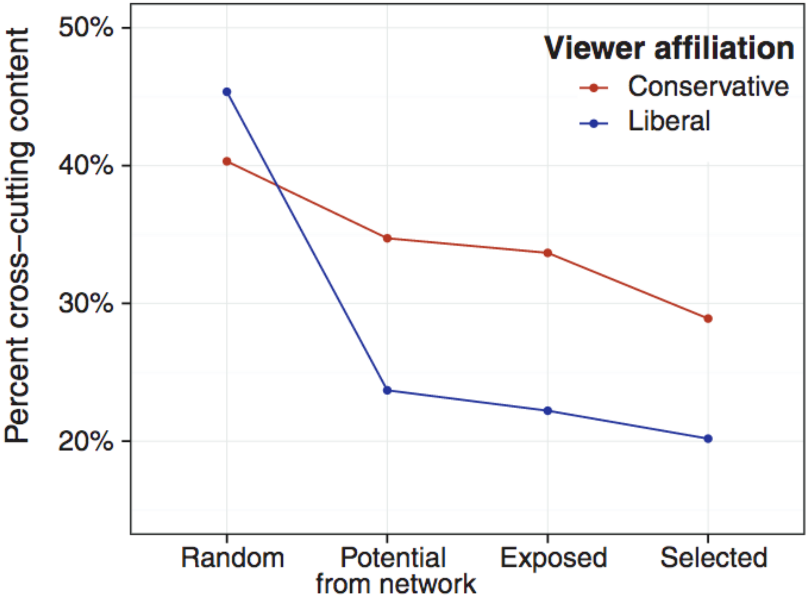
Snapshots from the Facebook feeds of our Citizen Browser panelists illuminate how Facebook's recommendation algorithm siloes information on the platform. See how we built this tool



Note that these are all political stories, and most stories in NewsFeeds are not political.
More info: `https://themarkup.org/citizen-browser/2021/03/11/introducing-split-screen`

Information exposure on FB is a multi-step process




Viewer affiliation
Conservative
Liberal
Percent cross–cutting content
50%
40%
30%
20%
Random
Potential from network
Exposed
Selected

How did they measure the ideology of the subject?

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All Facebook users can self-report their political affiliation; 9% of U.S. users over 18 do. We mapped the top 500 political designations on a five-point, -2 (Very Liberal) to +2 (Very Conservative) ideological scale; those with no response or with responses such as “other” or “I don’t care” were not included. 46% of those who entered their political affiliation on their profiles had a response that could be mapped to this scale. We validated a sample of these labels against a survey of 79 thousand U.S. users in which we asked for a 5-point very-liberal to very-conservative ideological affiliation; the Spearman rank correlation between the survey responses and our labels was 0.78.

How did they measure the ideology of the post?

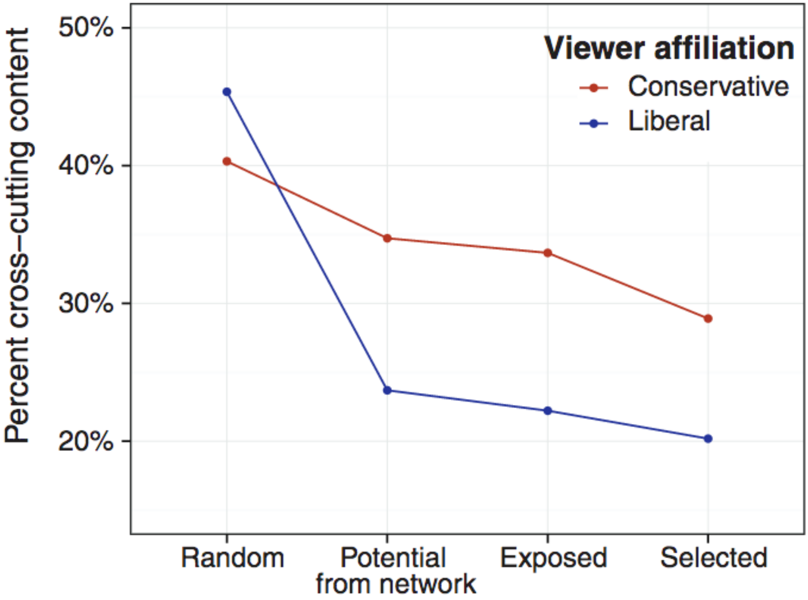
How did they measure the ideology of the post?
"We derive the alignment score A of an individual URL by averaging the political alignment of the set of people who share the URL."

What kind of posts?

What kind of posts?

“We classified stories as either “hard” (such as national news, politics, or world affairs) or “soft” content (such as sports, entertainment, or travel) by training a support vector machine on unigram, bigram, and trigram text features (details are available in the supplementary materials, section S1.4.1).”

Approximately 13% were classified as hard news. Or approximately 87% were classified as soft news. This only counts links shared, not baby pictures. So we are talking about a small slice of a small slice.


Viewer affiliation
Conservative
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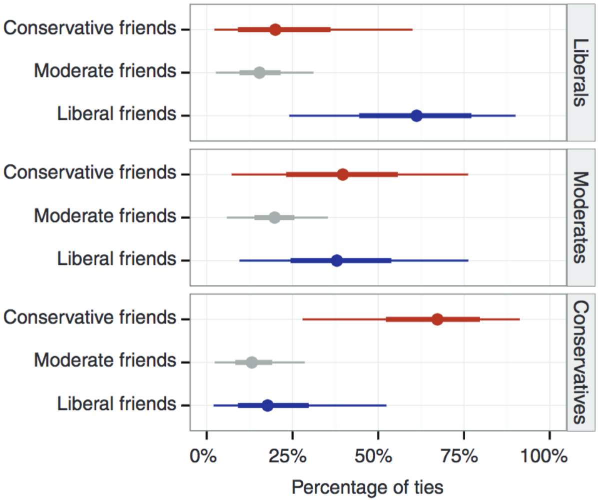
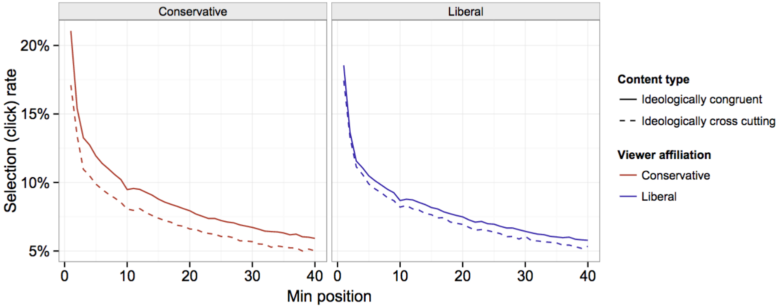
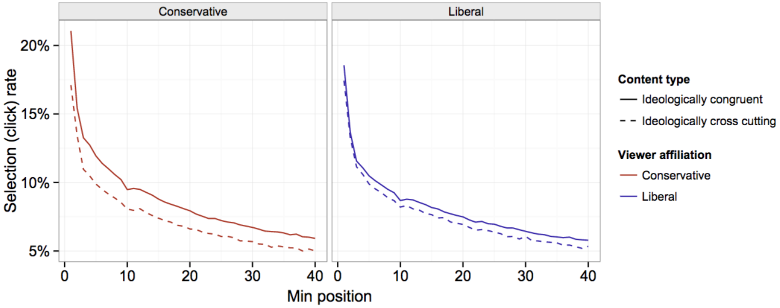
Two non-filter bubble findings



People are more likely to be friends with people of a similar political ideology, but there are cross-cutting ties



- people are more likely to click on content at the top of their feed (this might remind you of MusicLab), suggests that design of NewsFeed is important



- people are more likely to click on content at the top of their feed (this might remind you of MusicLab), suggests that design of NewsFeed is important
- both liberals and conservatives are more likely to click on ideologically congruent content

Is Facebook's NewsFeed algorithm driving political tribalism in the United States? Is it Facebook's fault?

- "Compared with algorithmic ranking, individuals' choices played a stronger role in limiting exposure to cross-cutting content."

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- "Compared with algorithmic ranking, individuals' choices played a stronger role in limiting exposure to cross-cutting content."
- "Within the population under study here, individual choices more than algorithms limit exposure to attitude-challenging content in the context of Facebook."

Is Facebook's NewsFeed algorithm driving political tribalism in the United States? Is it Facebook's fault?

- "Compared with algorithmic ranking, individuals' choices played a stronger role in limiting exposure to cross-cutting content."
- "Within the population under study here, individual choices more than algorithms limit exposure to attitude-challenging content in the context of Facebook."
- "...our work suggests that the power to expose oneself to perspectives from the other sided in social media lies first and foremost with individuals"

Commentary and criticism:

- https://www.wired.com/2015/05/facebook-not-fault-study/
- https://medium.com/message/how-facebook-s-algorithm-suppresses-content-diversity-modestly-how-the
- https://thesocietypages.org/cyborgology/2015/05/07/facebook-fair-and-balanced/
- http://crookedtimber.org/2015/05/07/why-doesnt-science-publish-important-methods-info-prominently/

Also, we don't know to what extent these findings from July 7, 2014 to January 7, 2015 are true today.

Descriptive vs normative

Thermostat problem:

- Facebook can control the amount of cross-cutting content that people see. How should they set the thermostat?

Exposure to opposing views on social media can increase political polarization

Christopher A. Bail[a,1], Lisa P. Argyle[b], Taylor W. Brown[a], John P. Bumpus[a], Haohan Chen[c], M. B. Fallin Hunzaker[d], Jaemin Lee[a], Marcus Mann[a], Friedolin Merhout[a], and Alexander Volfovsky[e]

[a]Department of Sociology, Duke University, Durham, NC 27708; [b]Department of Political Science, Brigham Young University, Provo, UT 84602; [c]Department of Political Science, Duke University, Durham, NC 27708; [d]Department of Sociology, New York University, New York, NY 10012; and [e]Department of Statistical Science, Duke University, Durham, NC 27708

More cross-cutting content can lead to more polarized attitudes (backfire effect)

Are algorithm filter bubbles different from other processes that create filter bubbles?

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The measurement of partisan sorting for 180 million voters

Jacob R. Brown[1,2] and Ryan D. Enos[1,2]

Segregation across social groups is an enduring feature of nearly all human societies and is associated with numerous social maladies. In many countries, reports of growing geographic political polarization raise concerns about the stability of democratic governance. Here, using advances in spatial data computation, we measure individual partisan segregation by calculating the local residential segregation of every registered voter in the United States, creating a spatially weighted measure for more than 180 million individuals. With these data, we present evidence of extensive partisan segregation in the country. A large proportion of voters live with virtually no exposure to voters from the other party in their residential environment. Such high levels of partisan isolation can be found across a range of places and densities and are distinct from racial and ethnic segregation. Moreover, Democrats and Republicans living in the same city, or even the same neighbourhood, are segregated by party.

https://www.nytimes.com/interactive/2021/03/17/upshot/partisan-segregation-maps.html

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https://www.nytimes.com/interactive/2021/03/17/upshot/partisan-segregation-maps.html

I think yes. Algorithmic filter bubbles are centrally controlled and set for profit.

- Social media seems to amplify moral outrage and false rumors

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- This happens because of the choices of people and the choices of social media architects

- Social media seems to amplify moral outrage and false rumors
- This happens because of the choices of people and the choices of social media architects
- It is hard to isolate how much of this caused by human behavior and how much is magnified by the architecture of the environment

Next class: Social ads in social media

- Duhigg, C. (2012). How companies learn your secrets. *New York Times*.
- Goel, S. (2010). Birds of a feather shop together. *Messy Matters blog*.
- Goel, S. and Goldstein D.G. (2014). Predicting Individual Behavior with Social Networks. *Marketing Science*.
- Bakshy, E. et al. (2012). Social influence in social advertising: Evidence from field experiments. *EC*