

POIR 613: Computational Social Science

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Course website:

pablobarbera.com/POIR613/

Today

1. Computational social science research: challenges and opportunities
2. Discussion: ethics of Big Data research.
 - ▶ Hargittai 2018
 - ▶ Vlasceanu and Amodio 2022
3. Good coding practices
4. Efficient programming in R

Logistics

1. Referee reports:
 - ▶ You should all have already signed up
 - ▶ Due day before class at 8pm
2. Future readings for discussion:
 - ▶ Focus on the readings that people will be presenting

Computational Social Science



Shift in communication patterns



Digital footprints of human behavior

Computational Social Science

Two different approaches in the growing field of computational social science:

1. Big data as a new source of information
 - ▶ Behavior, opinions, and latent traits
 - ▶ Interpersonal networks
 - ▶ Elite behavior
 - ▶ Affordable online experiments
2. How big data and social media affect social behavior
 - ▶ Collective action and social movements
 - ▶ Political campaigns
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Behavior, opinions, and latent traits

- ▶ Digital footprints: check-ins, conversations, geolocated pictures, likes, shares, retweets, . . .
- Non-intrusive measurement of behavior and public opinion



Regular Article

Every tweet counts? How sentiment analysis of social media can improve our knowledge of citizens' political preferences with an application to Italy and France

Andrea Ceron, Luigi Curini, Stefano M Iacus

Università degli Studi di Milano, Italy

Giuseppe Porro

Università degli Studi dell'Insubria, Italy

new media & society

2014, Vol. 16(2) 340–358

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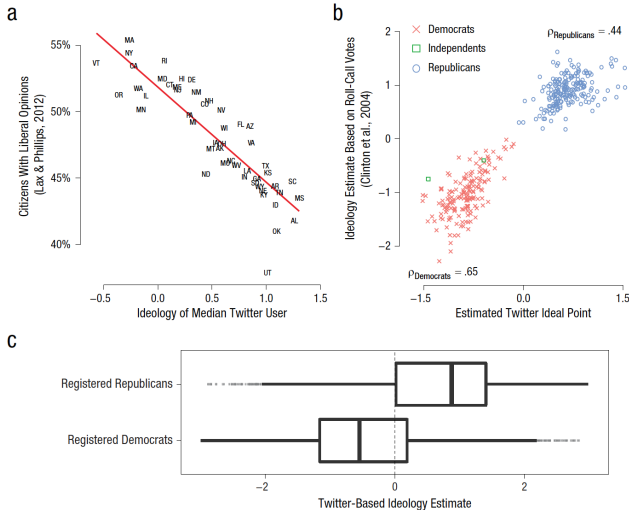
DOI: 10.1177/1461444813480466

nms.sagepub.com



Behavior, opinions, and latent traits

→ Inference of latent traits: political knowledge, ideology, personal traits, socially undesirable behavior, . . .



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Interpersonal networks

- ▶ Political behavior is social, strongly influenced by peers

Today is Election Day [What's this?](#) • [close](#)



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

I Voted

01155376
People on Facebook Voted



 Jaime Settle, Jason Jones, and 18 other friends have voted.

Bond et al, 2012, "A 61-million-person experiment in social influence and political mobilization", *Nature*

- ▶ Costly to measure network structure
- ▶ High overlap across online and offline social networks

OPEN ACCESS Freely available online

 **PLOS** | ONE

Inferring Tie Strength from Online Directed Behavior

Jason J. Jones^{1,2*}, Jaime E. Settle², Robert M. Bond², Christopher J. Fariss², Cameron Marlow³, James H. Fowler^{1,2}

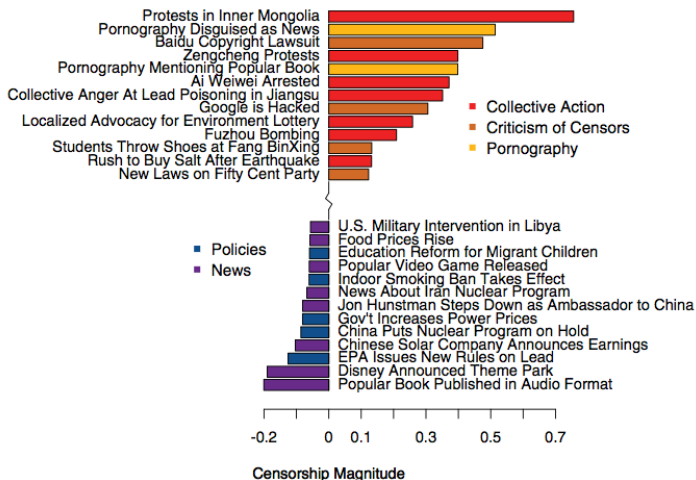
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Elite behavior

- ▶ Authoritarian governments' response to threat of collective action



King et al, 2013, "How Censorship in China Allows Government Criticism but Silences Collective Expression", *APSR*

- ▶ How elected officials communicate with constituents

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 - ▶ [Affordable online experiments](#)
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Affordable field experiments



[Political Behavior](#)

September 2017, Volume 39, [Issue 3](#), pp 629–649 | [Cite as](#)

Tweetment Effects on the Tweeted: Experimentally Reducing Racist Harassment

Authors

[Authors and affiliations](#)

Kevin Munger 

Original Paper

First Online: 11 November 2016

2.7k

Shares

12k

Downloads

3

Citations



[Redacted]

13 Sep 2015

@ [Redacted] don't be a nigger



Rasheed [Redacted]

@Rasheed [Redacted]

@ [Redacted] Hey man, just remember that there are real people who are hurt when you harass them with that kind of language

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slacktivism?

why the revolution will not be tweeted

*When the sit-in movement spread from Greensboro throughout the South, it did not spread indiscriminately. It spread to those cities which had preexisting “movement centers” – a **core of dedicated and trained activists** ready to turn the “fever” into action.*

*The kind of activism associated with social media isn't like this at all. [...] Social networks are effective at increasing participation – by **lessening the level of motivation** that participation requires.*

Gladwell, *Small Change* (New Yorker)

*You can't simply join a revolution any time you want, contribute a comma to a random revolutionary decree, rephrase the guillotine manual, and then slack off for months. **Revolutions prize centralization and require fully committed leaders**, strict discipline, absolute dedication, and strong relationships.*

*When every node on the network can send a message to all other nodes, **confusion is the new default equilibrium**.*

Morozov, *The Net Delusion: The Dark Side of Internet Freedom*

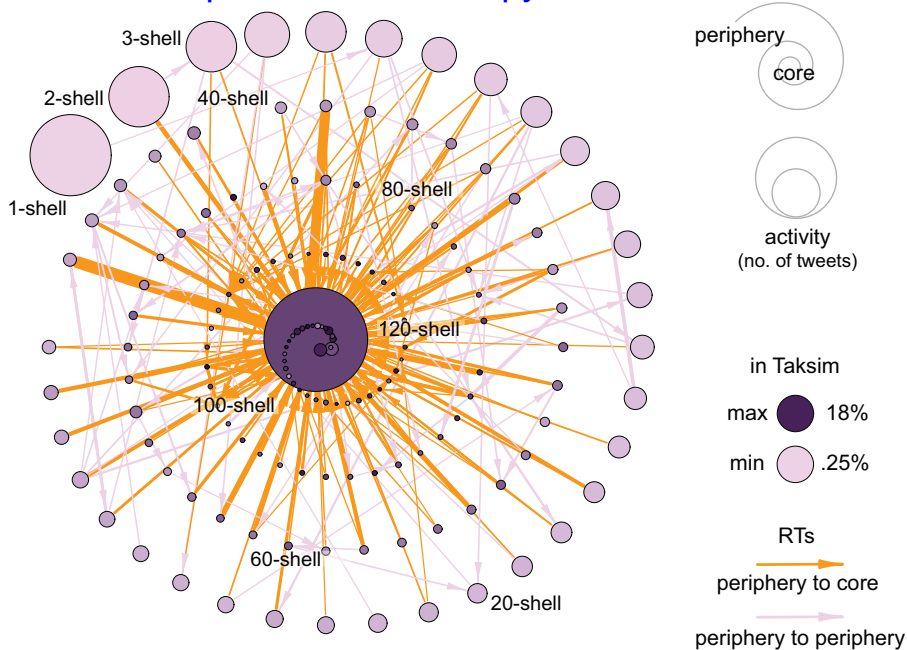
RESEARCH ARTICLE

The Critical Periphery in the Growth of Social Protests

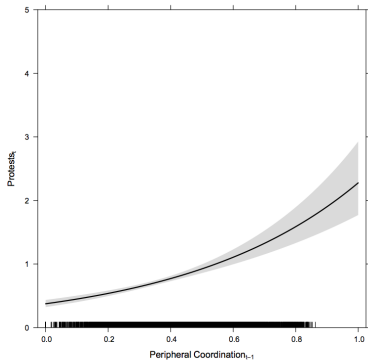
Pablo Barberá^{1*}, Ning Wang², Richard Bonneau^{3,4}, John T. Jost^{1,5,6}, Jonathan Nagler⁶, Joshua Tucker⁶, Sandra González-Bailón^{7*}

- ▶ Structure of online protest networks:
 1. **Core**: committed minority of resourceful protesters
 2. **Periphery**: majority of less motivated individuals
- ▶ Our argument: key role of peripheral participants
 1. Increase reach of protest messages (positional effect)
 2. Large contribution to overall activity (size effect)

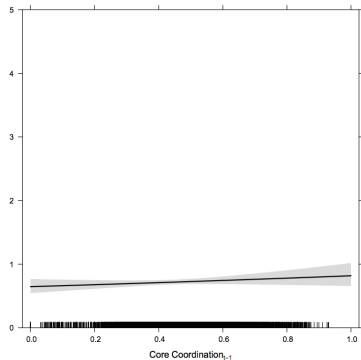
k-core decomposition of #OccupyGezi network



Peripheral mobilization during the Arab Spring



(a) Increase in protest as peripheral coordination increases



(b) Coordination does not come through core individuals

Steinert-Threlkeld (APSR 2017) “Spontaneous Collective Action”

Social media and democracy

FROM LIBERATION TO TURMOIL: SOCIAL MEDIA AND DEMOCRACY

*Joshua A. Tucker, Yannis Theodoridis, Margaret E. Roberts,
and Pablo Barberá*

*“How can one technology – social media – simultaneously give rise to hopes for liberation in authoritarian regimes, be used for repression by these same regimes, and be harnessed by antisystem actors in democracy? We present a simple framework for reconciling these contradictory developments based on two propositions: 1) that social media **give voice to those previously excluded from political discussion** by traditional media, and 2) that although social media democratize access to information, the platforms themselves are neither inherently democratic nor nondemocratic, but represent a **tool political actors can use for a variety of goals**, including, paradoxically, illiberal goals.”*

***Journal of Democracy*, 2017**

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Barack Obama ✓
@BarackObama



+ Follow

Four more years.



RETWEETS

756,411

FAVORITES

288,867



11:16 PM - 6 Nov 2012

Political persuasion

Social media as a new campaign tool:

“Let me tell you about Twitter. I think that maybe I wouldn’t be here if it wasn’t for Twitter. [...] Twitter is a wonderful thing for me, because I get the word out... I might not be here talking to you right now as president if I didn’t have an honest way of getting the word out.”

Donald Trump, March 16, 2017 (Fox News)

- ▶ Diminished **gatekeeping** role of journalists
 - ▶ Part of a trend towards citizen journalism (Goode, 2009)
- ▶ Information is contextualized within **social layer**
 - ▶ Messing and Westwood (2012): social cues can be as important as partisan cues to explain news consumption through social media
- ▶ **Real-time broadcasting** in reaction to events
 - ▶ e.g. *dual screening* (Vaccari et al, 2015)
- ▶ **Micro-targeting**
 - ▶ Affects how campaigns perceive voters (Hersh, 2015), but unclear if effective in mobilizing or persuading voters

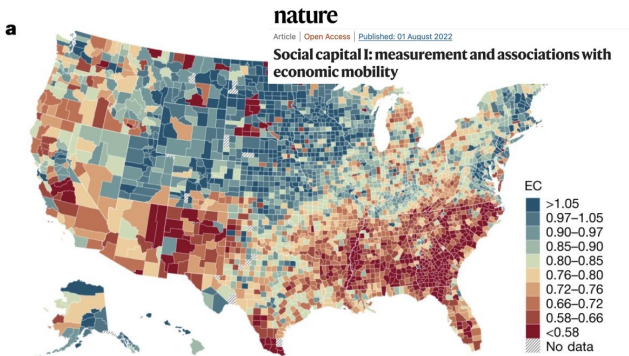
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Social capital

- ▶ Social connections are essential in democratic societies, but online interactions do not facilitate creation and strengthening of social capital (Putnam, 2001)
- ▶ Online networking sites facilitate and transform how social ties are established



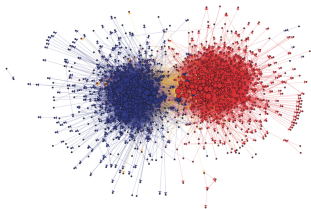
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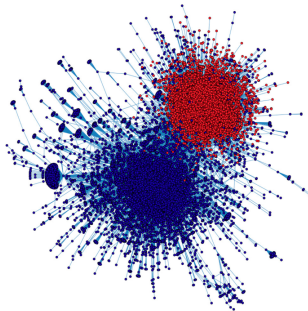
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Social media as echo chambers?

- ▶ communities of like-minded individuals (homophily, influence)



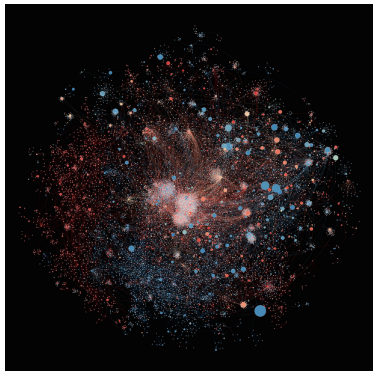
Adamic and Glance (2005)



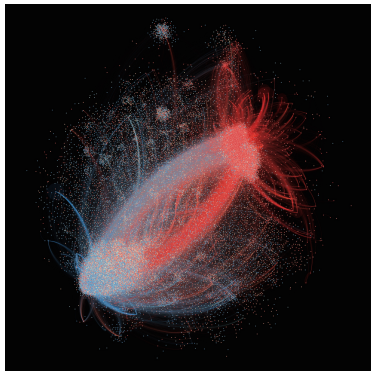
Conover et al (2012)

- ▶ ...generates selective exposure to congenial information
- ▶ ...reinforced by ranking algorithms – “filter bubble” (Pariser)
- ▶ ...increases political polarization (Sunstein, Prior)

Social media as echo chambers?



2013 SuperBowl



2012 Election

Barberá et al (2015) "Tweeting From Left to Right: Is Online Political Communication More Than an Echo Chamber?" *Psychological Science*

Fake news?



- ▶ Guess et al (2018, 2019); Grinberg et al (2019): **who consumes misinformation?**
 - ▶ 25% Americans exposed to fake news sites in 2016; 6% of all news consumption; but heavily concentrated (1% saw 80%)
 - ▶ Older, conservative people more likely to be exposed
 - ▶ Fact-check does not reach consumers of misinformation
- ▶ Allcott and Gentzkow (2017): **does it matter?**
 - ▶ Survey experiment with real and placebo fake news stories
 - ▶ Most people do not remember seeing fake news stories
 - ▶ Unlikely to affect behavior for most people

Overall impact of social media in politics?

American Economic Review 2020, 110(3): 629–676
<https://doi.org/10.1257/aer.20190658>

The Welfare Effects of Social Media[†]

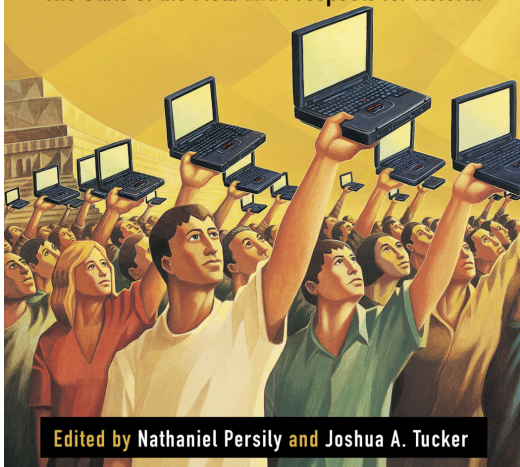
By HUNT ALLCOTT, LUCA BRAGHIERI, SARAH EICHMEYER,
AND MATTHEW GENTZKOW*

The rise of social media has provoked both optimism about potential societal benefits and concern about harms such as addiction, depression, and political polarization. In a randomized experiment, we find that deactivating Facebook for the four weeks before the 2018 US midterm election (i) reduced online activity, while increasing offline activities such as watching TV alone and socializing with family and friends; (ii) reduced both factual news knowledge and political polarization; (iii) increased subjective well-being; and (iv) caused a large persistent reduction in post-experiment Facebook use. Deactivation reduced post-experiment valuations of Facebook, suggesting that traditional metrics may overstate consumer surplus. (JEL D12, D72, D90, I31, L82, L86, Z13)

SSRC Anxieties of Democracy

SOCIAL MEDIA and DEMOCRACY

The State of the Field **and** Prospects for Reform



Edited by Nathaniel Persily **and** Joshua A. Tucker

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What are the most important challenges when working with Big Data?

Big data and social science: challenges

1. Big data, big bias?
2. The end of theory?
3. Spam and bots
4. The privacy paradox
5. Generalizing from online to offline behavior
6. Ethical concerns

1. Big data, big bias?

SOCIAL SCIENCES

Social media for large studies of behavior

Large-scale studies of human behavior in social media need to be held to higher methodological standards

By Derek Ruths^{1*} and Jürgen Pfeffer²

On 3 November 1948, the day after Harry Truman won the United States presidential elections, the *Chicago Tribune* published one of the most famous erroneous headlines in newspaper history: “Dewey Defeats Truman” (1, 2). The headline was informed by telephone surveys, which had inadver-

different social media platforms (8). For instance, Instagram is “especially appealing to adults aged 18 to 29, African-American, Latinos, women, urban residents” (9) whereas Pinterest is dominated by females, aged 25 to 34, with an average annual household income of \$100,000 (10). These sampling biases are rarely corrected for (if even acknowledged).

Proprietary algorithms for public data. Platform-specific sampling problems, for example, the highest-volume source of pub-

The rise of “embedded research” among researchers who have special relationships with providers that give them access to platform-specific data, algorithms, and resources) is creating a divided social media research community. Such researchers, for example, can see a platform’s inner workings and make accommodations, but may not be able to reveal their color or the data used to generate their findings.

Ruths and Pfeffer, 2015, “Social media for large studies of behavior”,
Science

Big data, big bias?

Sources of bias (Ruths and Pfeffer, 2015; Lazer et al, 2017)

- ▶ **Population bias**

- ▶ Sociodemographic characteristics are correlated with presence on social media

- ▶ **Self-selection within samples**

- ▶ Partisans more likely to post about politics (Barberá & Rivero, 2014)

- ▶ **Proprietary algorithms for public data**

- ▶ Twitter API does not always return 100% of publicly available tweets (Morstatter et al, 2014)

- ▶ **Human behavior and online platform design**

- ▶ e.g. *Google Flu* (Lazer et al, 2014)

1. Big data, big bias?

Reducing biases and flaws in social media data

DATA COLLECTION

- 1. Quantifies platform-specific biases (platform design, user base, platform-specific behavior, platform storage policies)
- 2. Quantifies biases of available data (access constraints, platform-side filtering)
- 3. Quantifies proxy population biases/mismatches

METHODS

- 4. Applies filters/corrects for nonhuman accounts in data
- 5. Accounts for platform and proxy population biases
 - a. Corrects for platform-specific and proxy population biases
 - OR
 - b. Tests robustness of findings
- 6. Accounts for platform-specific algorithms
 - a. Shows results for more than one platform
 - OR
 - b. Shows results for time-separated data sets from the same platform
- 7. For new methods: compares results to existing methods on the same data
- 8. For new social phenomena or methods or classifiers: reports performance on two or more distinct data sets (one of which was not used during classifier development or design)

Issues in evaluating data from social media. Large-scale social media studies of human behavior should i address issues listed and discussed herein (further discussion in supplementary materials).

Ruths and Pfeffer, 2015, “Social media for large studies of behavior”,
Science

2. The end of theory?

Petabytes allow us to say: "Correlation is enough." We can stop looking for models. We can analyze the data without hypotheses about what it might show. We can throw the numbers into the biggest computing clusters the world has ever seen and let statistical algorithms find patterns where science cannot.

Chris Anderson, [Wired](#), June 2008

Correlations are a way of catching a scientist's attention, but the models and mechanisms that explain them are how we make the predictions that not only advance science, but generate practical applications.

John Timmer, [Ars Technica](#), June 2008

(Big) social media data as a complement - not a substitute - for theoretical work and careful causal inference.

3. Spam and bots



“Follow your coordinators. We need to start tweeting, all at the same time, using the hashtag #ItsTimeForMexico. . . and don’t forget to retweet tweets from the candidate’s account...”

***Unidentified PRI campaign manager
minutes before the May 8, 2012 Mexican Presidential debate***

3. Spam and bots



Ferrara et al, 2016, *Communications of the ACM*

4. The privacy paradox

Online data present a paradox in the protection of privacy: Data are at once too revealing in terms of privacy protection, yet also not revealing enough in terms of providing the demographic background information needed by social scientists.

Golder & Macy, *Digital footprints*, 2014

5. Generalizing from online to offline behavior

What makes online behavior different:

- ▶ Platform affordances may distort behavior (e.g. anonymity encourages vitriol)
- ▶ Tools extend innate capacities (e.g. Dunbar's number)
- ▶ Asymmetries between online behavior and self-reported survey responses

6. Ethical concerns

1. Shifting notion of *informed consent*

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}

^aCore Data Science Team, Facebook, Inc., Menlo Park, CA 94025; and Departments of ^bCommunication and ^cInformation Science, Cornell University, Ithaca, NY 14853

Edited by Susan T. Fiske, Princeton University, Princeton, NJ, and approved March 25, 2014 (received for review October 23, 2013)

Emotional states can be transferred to others via emotional contagion, leading people to experience the same emotions without their awareness. Emotional contagion is well established in laboratory experiments, with people transferring positive and negative emotions to others. Data from a large real-world social network, collected over a 20-y period suggests that longer-lasting moods (e.g., depression, happiness) can be transferred through networks [Fowler JH, Christakis NA (2008) *BMJ* 337:a2338], although the results are controversial. In an experiment with people who use Facebook, we test whether emotional contagion occurs

demonstrated that (i) emotional contagion occurs via text-based computer-mediated communication (7); (ii) contagion of psychological and physiological qualities has been suggested based on correlational data for social networks generally (7, 8); and (iii) people's emotional expressions on Facebook predict friends' emotional expressions, even days later (7) (although some shared experiences may in fact last several days). To date, however, there is no experimental evidence that emotions or moods are contagious in the absence of direct interaction between experimenter and target.

On Facebook, people frequently express emotions, which are

2. Most personal data can be de-anonymized

[Ethics and Information Technology](#)

December 2010, Volume 12, [Issue 4](#), pp 313–325

“But the data is already public”: on the ethics of research in Facebook

Principles for ethical research with Big Data

From Salganik, Chapter 6:

1. **Respect for persons:** treating persons as autonomous and respecting their wishes (informed consent)
2. **Beneficence:** (1) do not harm, and (2) maximize possible benefits and minimize (probability and severity of) possible harms.
3. **Justice:** risks and benefits of research should be distributed fairly
4. **Respect for Law and Public Interest:** compliance with law and transparency-based accountability

For next week

1. Submit coding challenge
2. Skim background reading – Guess (2021)
3. Readings for discussion:
 - ▶ Bond et al (2012)
 - ▶ King et al (2014)
 - ▶ Siegel and Badaán (2017)
 - ▶ Asimovic et al (2018) – no presentation