Cognitive Science and Digital Technologies

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April 19, 2018

20th Century

21st Century

Lecture outline

Technology and human well-being: Quick overview

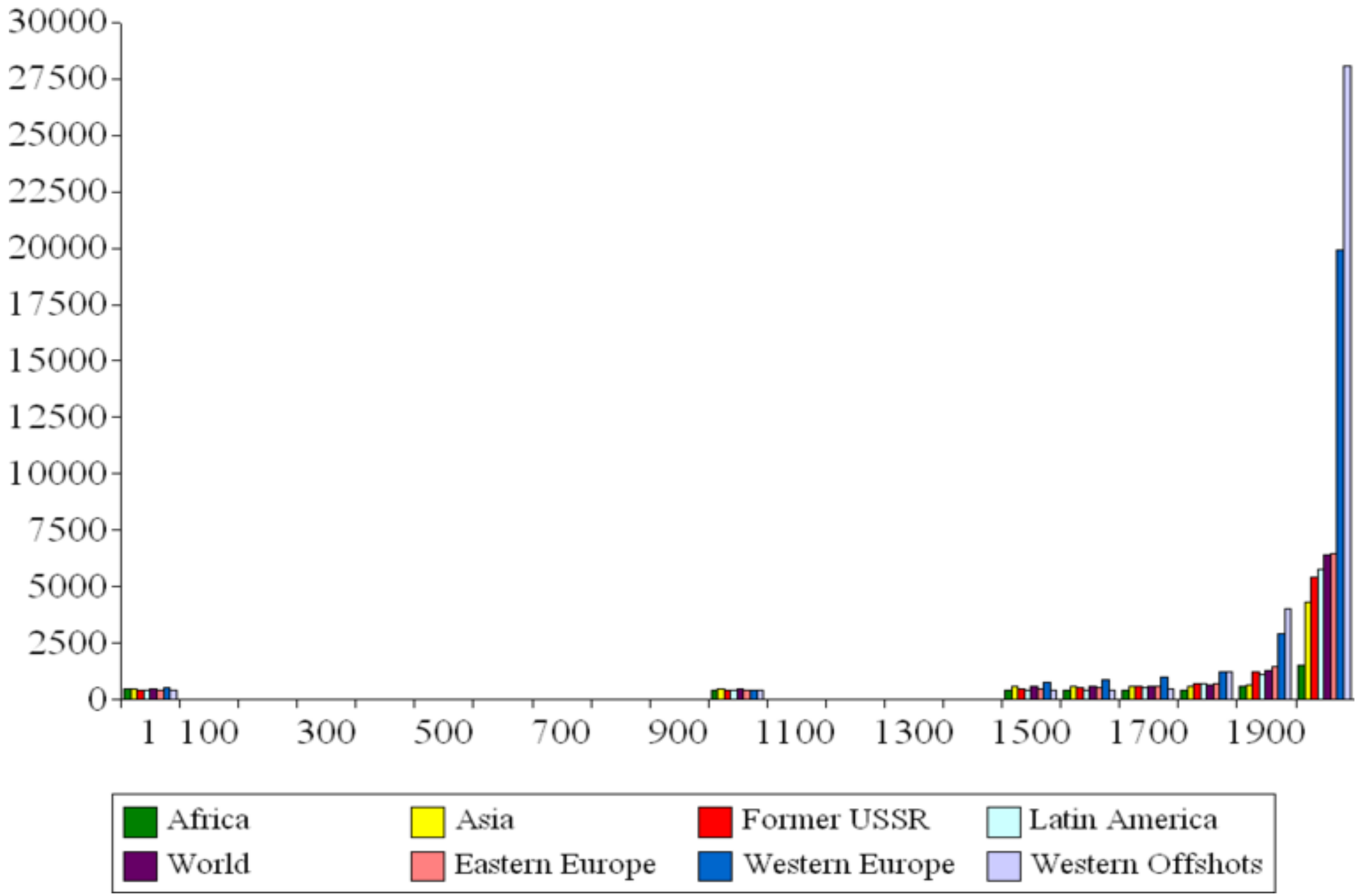
Media psychology: Case studies

Deep dive – online diffusion and virality

Computational psychology

Technology and Human Well-Being: A Quick Overview

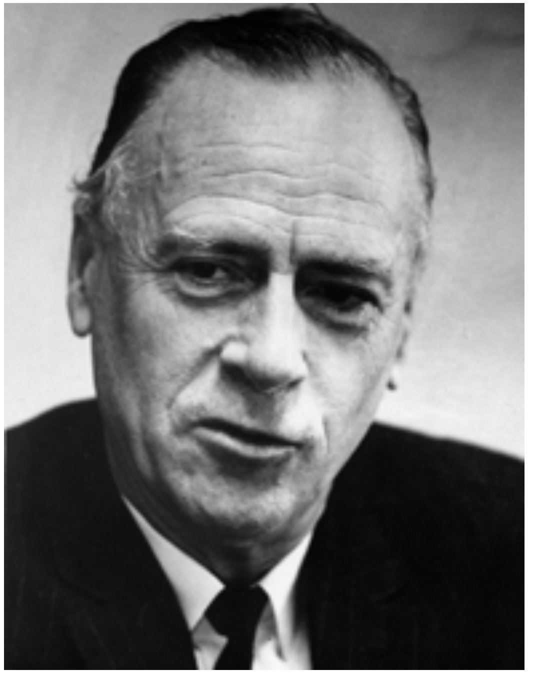
World GDP/capita 1-2003 A.D.



Information technology – major innovations

writing (4th Millennium BCE)
postal mail (Persia, 2nd/1st Mill. BCE)
printing press (1430s, Guttenberg)
telegraph (1830s), Morse code
telephone (1875, Bell)
phonographic recordings (1877, Edison)
radio/wireless communication (1880s-'90s)
television (1920s)
electronic computers (1940s)
satellite communication (early 60s)
Arpanet/Internet (late 60s, early 70s)
cell phones (70s and 80s)
World Wide Web (1991, Berners-Lee)
social media (early 2000s)

Marshall McLuhan (1911-1980)



technology drives history

media as "extensions of (hu)man(ity)"

McLuhan:
“the medium
is the message”

changes scale of human activity

example: the electric light as an information technology

Marshall McLuhan, *Understanding Media: The Extensions of Man*, 1964

The psychology of influence

McLuhan: global village

Digital technology makes us more dependent on mental shortcuts – fatigue, rush, overload

gives power to exploiters, e.g. of social proof

Robert Cialdini's answer: resist the exploiters!

Robert Cialdini, Influence: Science and Practice (4^{th} Edition), 2001

Technology and well-being

happiness has not increased in U.S. since 1946

higher inequality, depression, and anxiety

Amish are happier than most people

Richard Easterlin (1974)

money improves happiness dramatically for the poor

for the non-poor it has little effect

Richard Easterlin, “Does Economic Growth Improve the Human Lot? Some Empirical Evidence”, 1974

Daniel Kahneman and Angus Deaton (2010)

Income gains improve happiness up to about $75,000/year

Beyond that, there is little improvement

Daniel Kahneman and Angus Deaton, "High Income Improves Evaluation of Life But Not Emotional Outcomes", PNAS, 2010

Psychological mechanisms

loss aversion

myopic decision making

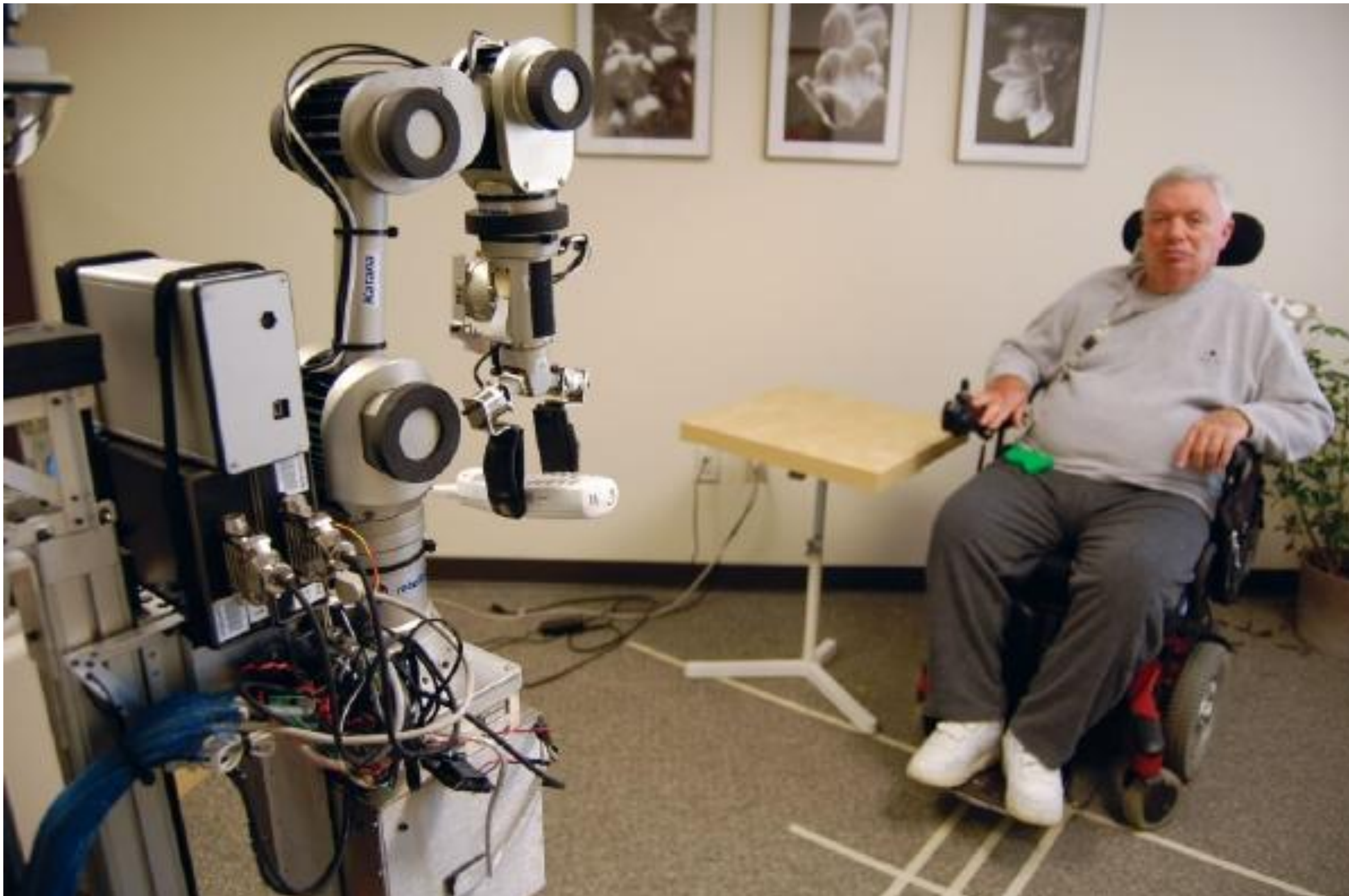
hedonic treadmill – adaptation to new wealth

Daniel Kahneman, *Thinking Fast and Slow*, 2011

Media Psychology: Case Studies

What is so special about “real”?

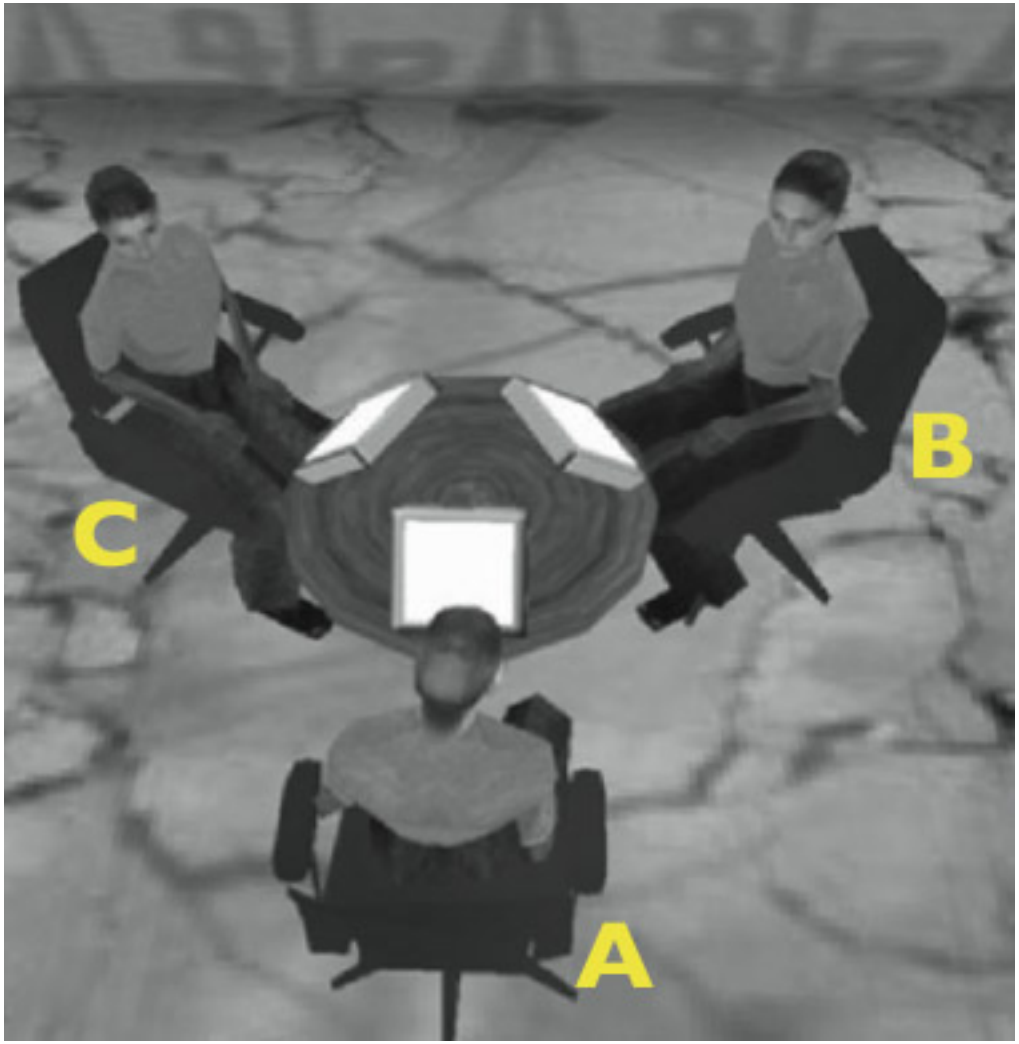
Robot caregivers



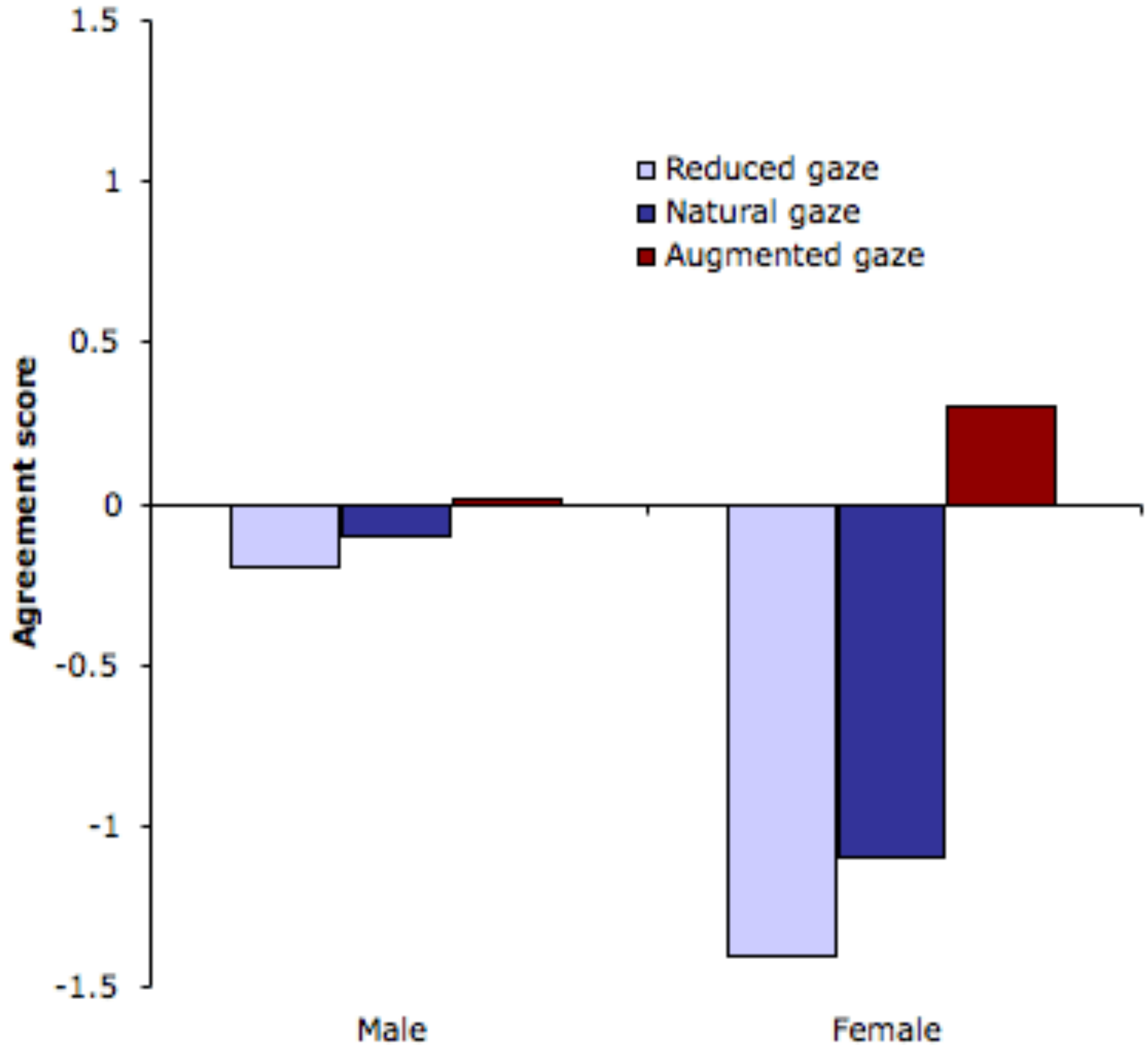
Sherry Turkle: Digital technologies give us "moments of more, and lives of less"

Sherry Turkle, *Alone Together: Why We Expect More from Technology and Less from Each Other*, 2011


Oculus
Development Kit 2



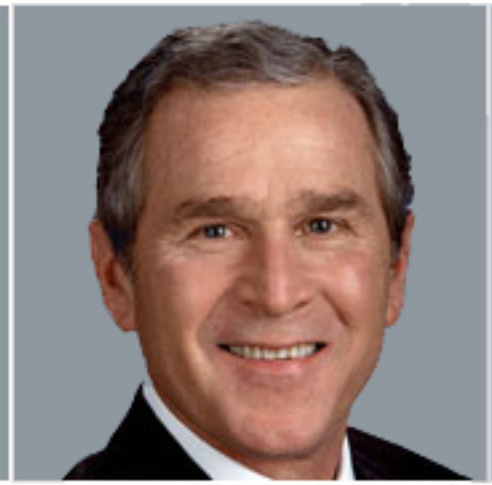
JEREMY N. BAILENSON, ANDREW C. BEALL, JACK LOOMIS, JIM BLASCOVICH, MATTHEW TURK, "Transformed Social Interaction, Augmented Gaze, and Social Influence in Immersive Virtual Environments", Human Communication Research, 2006



1.5
1
0.5
0
-0.5
-1
-1.5
Agreement score
Reduced gaze
Natural gaze
Augmented gaze
Male
Female

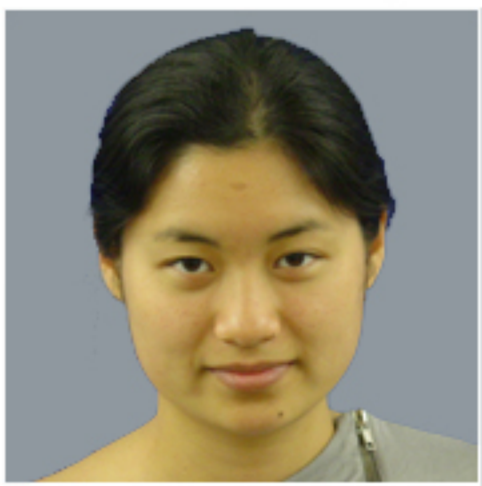
Morphing to Match

subject



"George Bush"

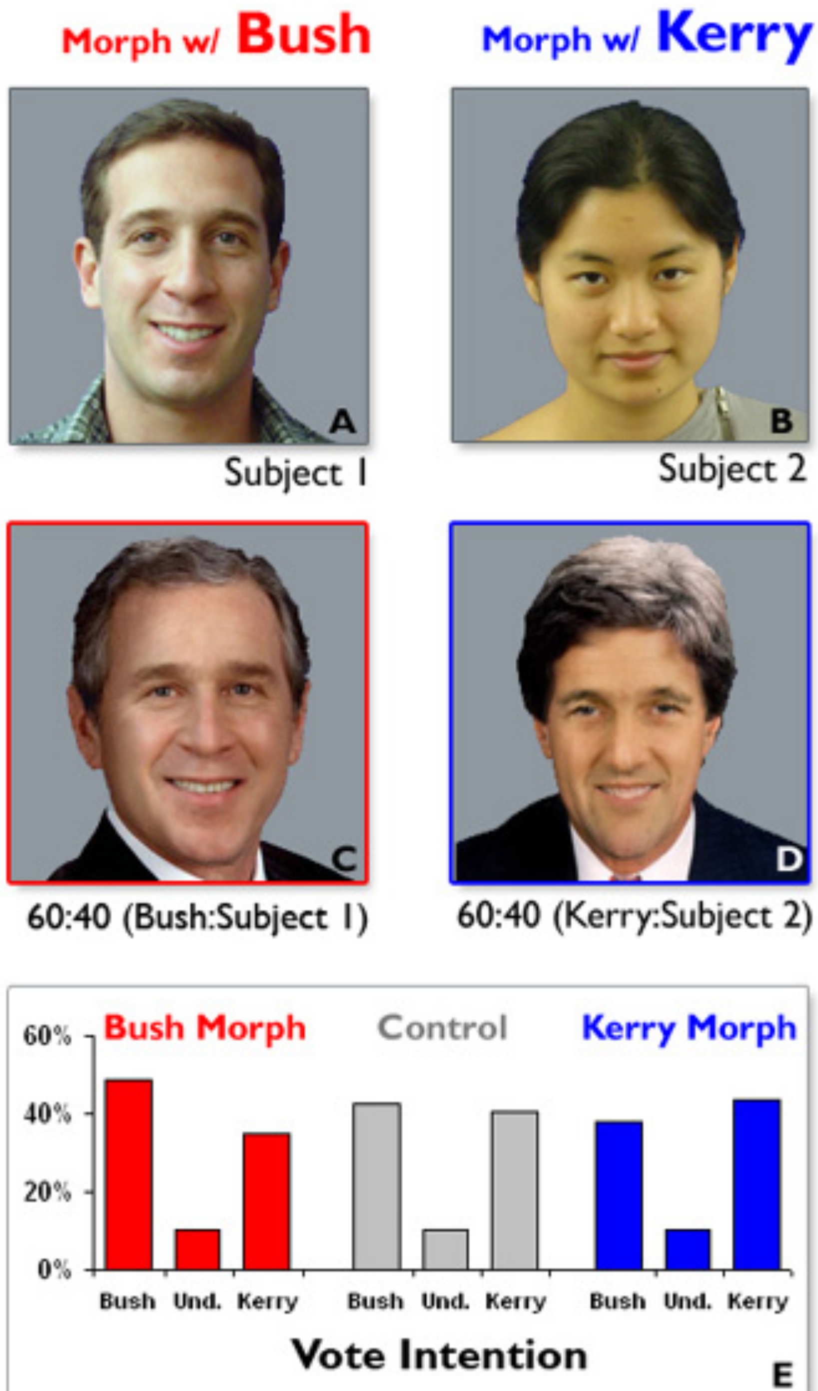
60:40 Blend

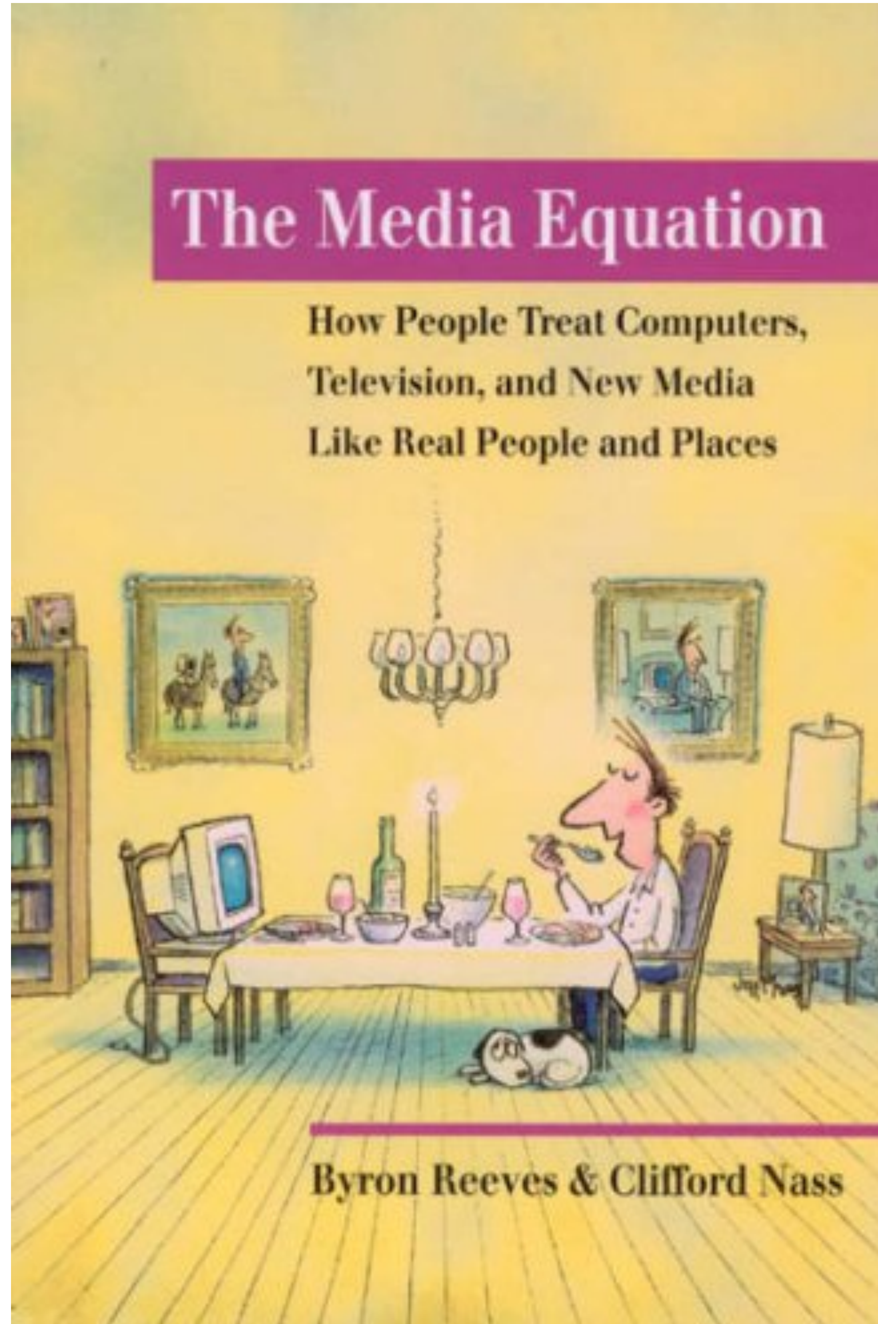


subject

"John Kerry"

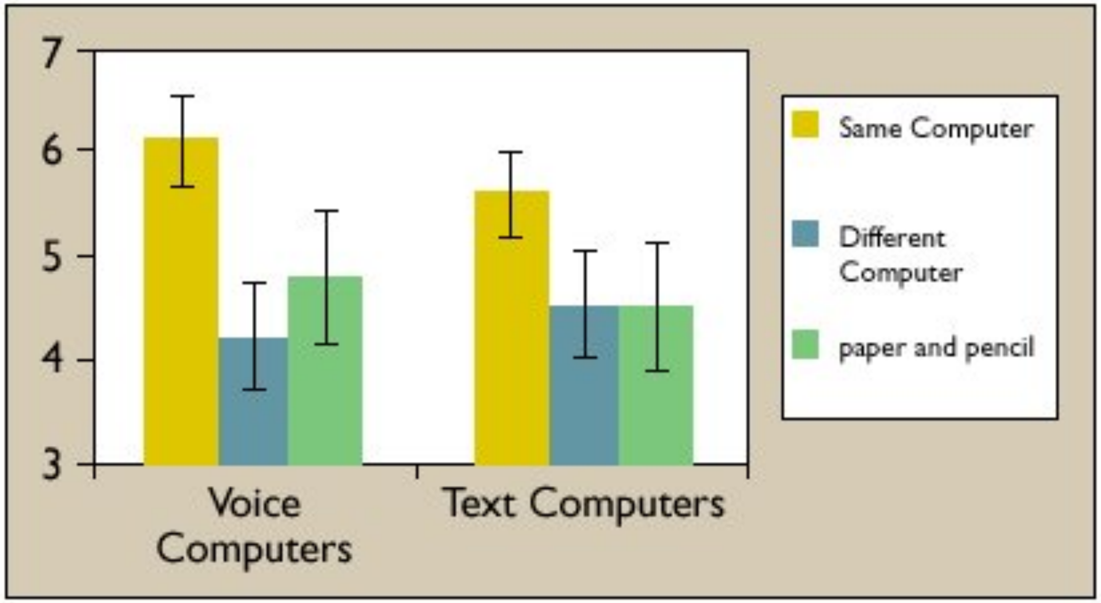
60:40 Blend

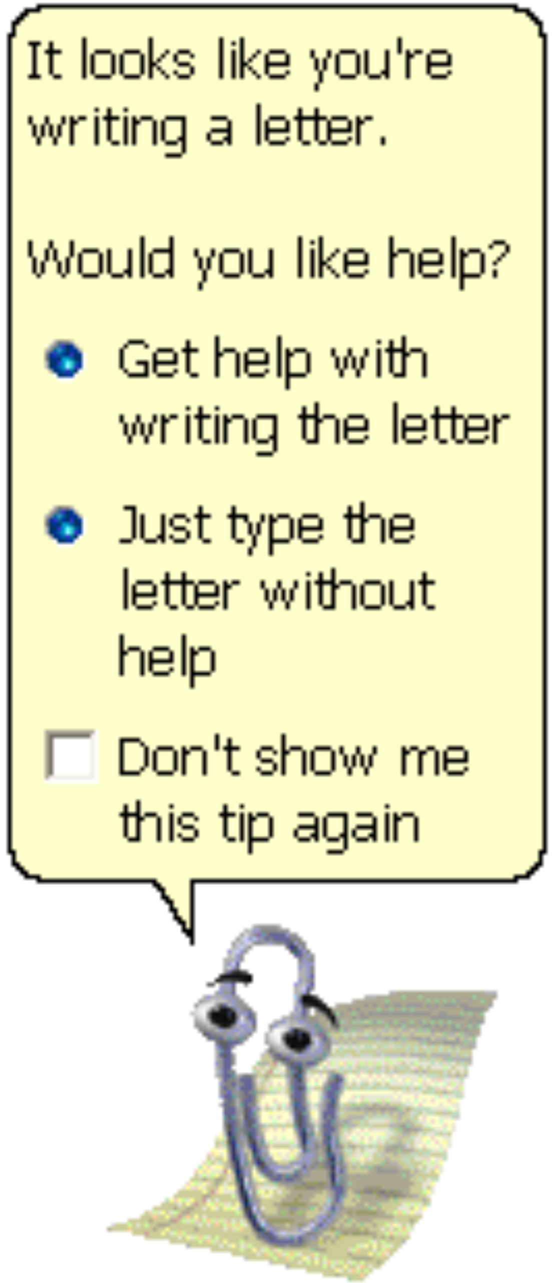

Morph w/ Bush
Morph w/ Kerry
A
B
Subject 1
Subject 2
C
D
60:40 (Bush:Subject 1)
60:40 (Kerry:Subject 2)
Bush Morph
Control
Kerry Morph
60%
40%
20%
0%
Bush
Und.
Kerry
Bush
Und.
Kerry
Bush
Und.
Kerry
Vote Intention
E


The Media Equation
How People Treat Computers,
Television, and New Media
Like Real People and Places
Byron Reeves & Clifford Nass

Do we treat computers like people?

Evaluation of
Training Experience




It looks like you're writing a letter.
Would you like help?
Get help with writing the letter
Just type the letter without help
Don't show me this tip again

Clifford Nass and colleagues’ findings on social media

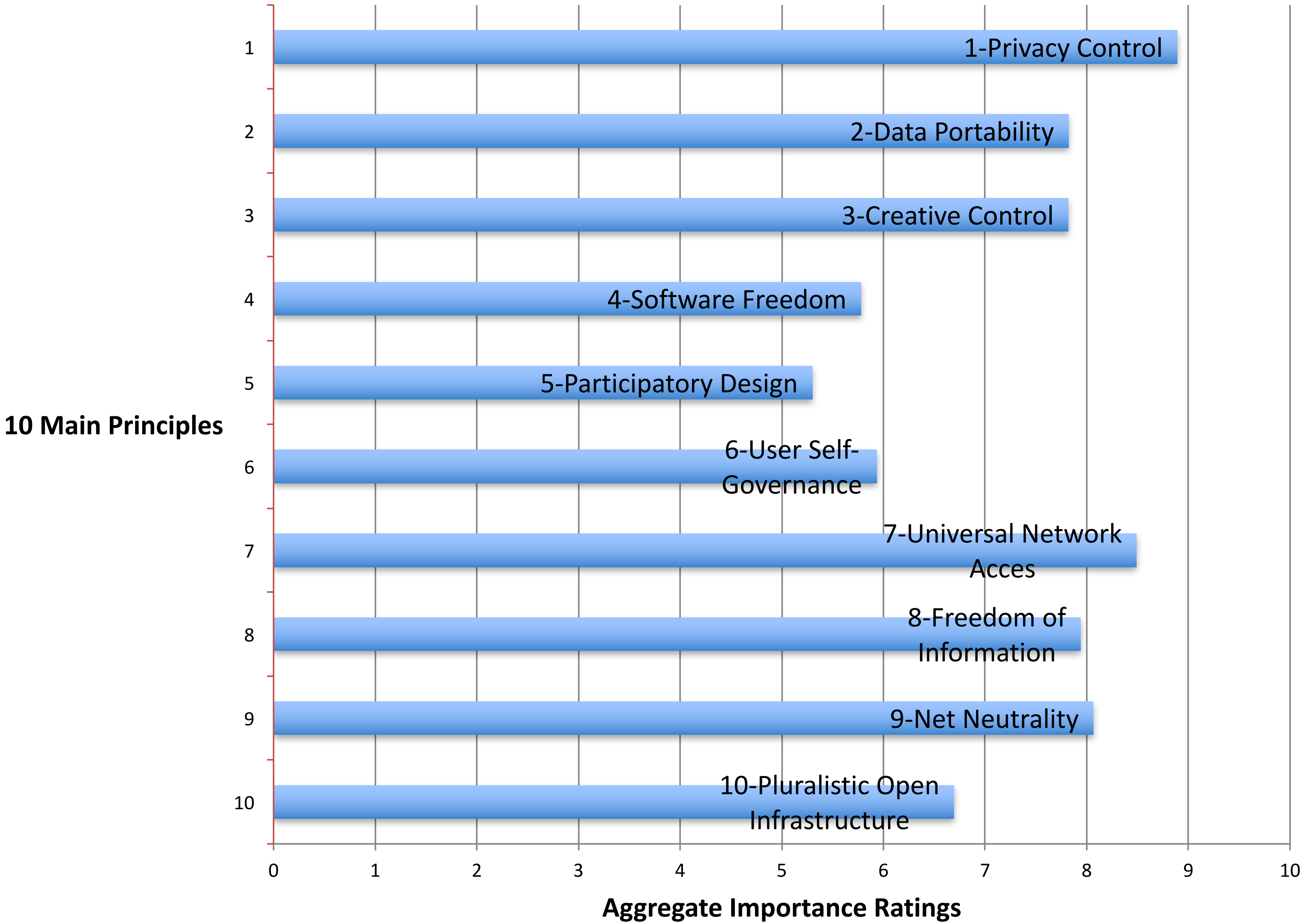
High “media multitaskers” have more difficulty focusing than low-MMers (Ophir, Nass, and Wagner, 2009)

Result extends to young people more than adults

Young people who are heavy users of social media are poorer at reading faces, less confident about social interactions

Eyal Ophir, Clifford Nass, and Anthony Wagner, ”Cognitive Control in Media Multitaskers”, *PNAS*, 2009


Mr. Mark Zuckerberg
© AFP/Getty Images



Todd Davies, "Digital Rights and Freedoms: A Framework for Surveying Users and Analyzing Policies", SocInfo 2014, Barcelona

Deep Dive: Online Diffusion

The Message or the Messenger? Inferring Virality and Diffusion Structure from Online Petition Signature Data

Chi Ling Chan[1] (ORCID 0000-0003-4665-714X), Justin Lai[1] (ORCID 0000-0002-2591-8673), Bryan Hooi[2] (ORCID 0000-0002-5645-1754), and Todd Davies[1] (ORCID 0000-0001-9082-4887)

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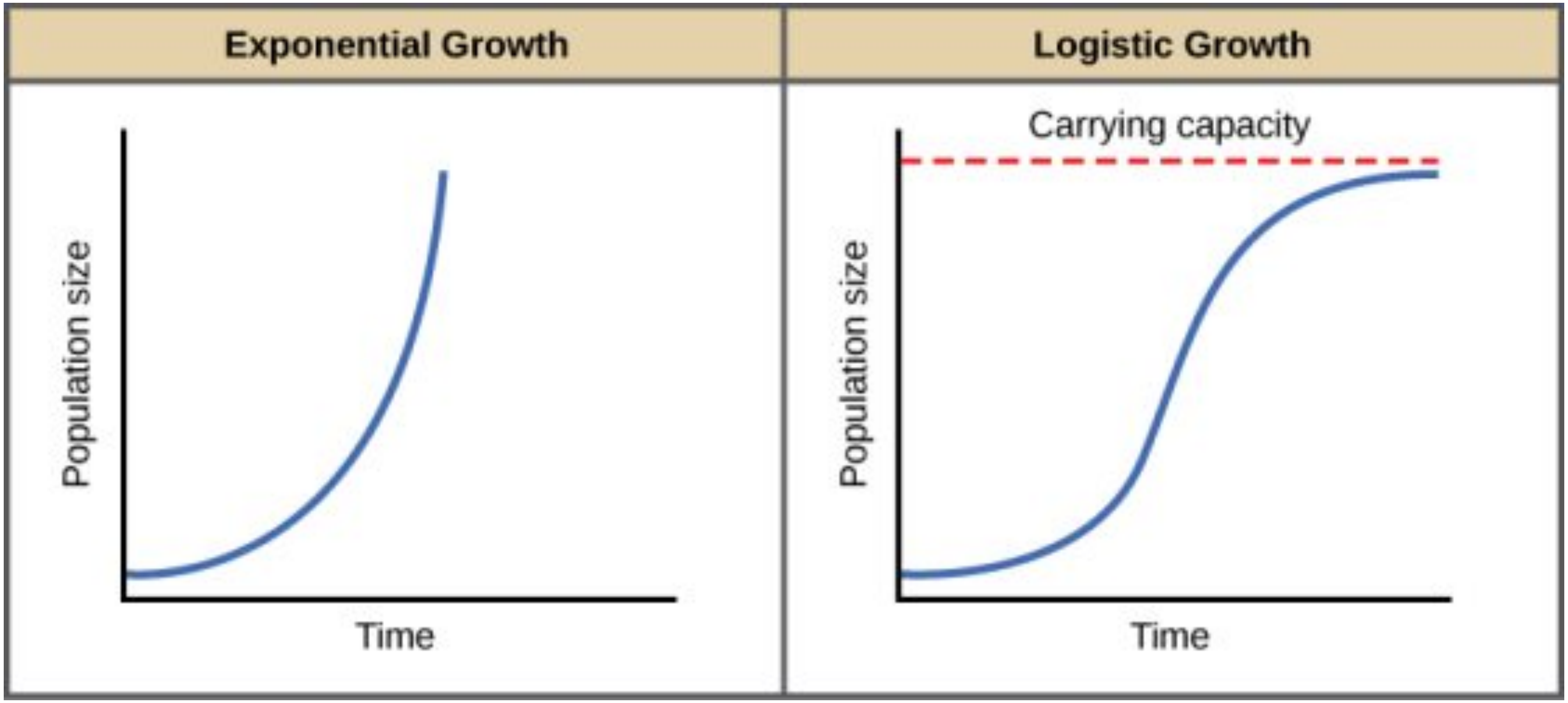
bhooi@andrew.cmu.edu

Abstract. Goel et al. [14] examined diffusion data from Twitter to conclude that online petitions are shared more virally than other types of content. Their definition of structural virality, which measures the extent to which diffusion follows a broadcast model or is spread person to person (virally), depends on knowing the topology of the diffusion cascade. But often the diffusion structure cannot be observed directly. We examined time-stamped signature data from the Obama White House's We the People petition platform. We developed measures based on temporal dynamics that, we argue, can be used to infer diffusion structure as well as the more intrinsic notion of virality sometimes known as infectiousness. These measures indicate that successful petitions are likely to be higher in both intrinsic and structural virality than unsuccessful petitions are. We also investigate threshold effects on petition signing that challenge simple contagion models, and report simulations for a theoretical model that are consistent with our data.

Keywords: petitions, virality, broadcast, diffusion

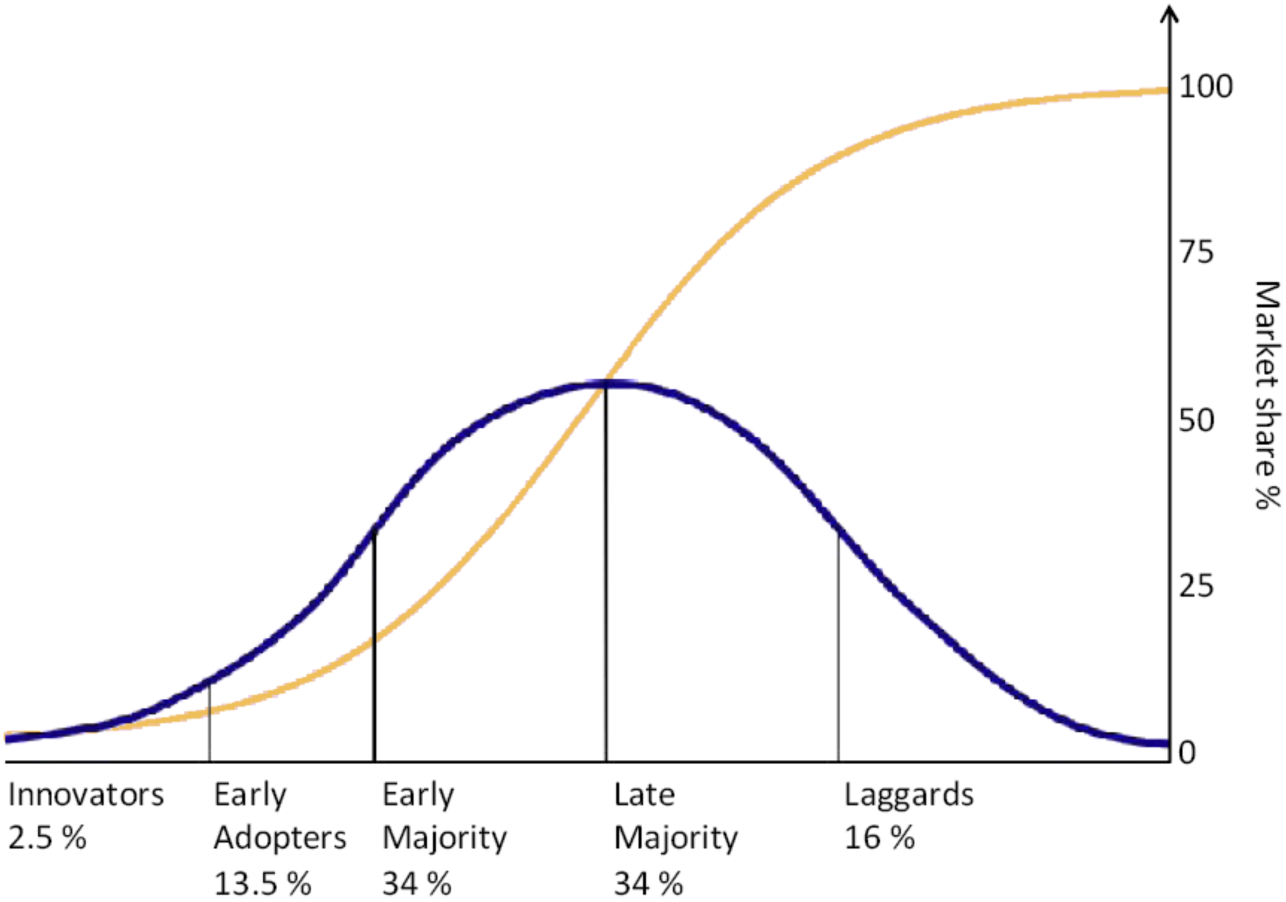
SocInfo 2017, Oxford

Viral marketing
(Faberge shampoo ad, 1982)



Graph from http://www.ubooks.pub/Books/ON/B0/E26R6789/P8C2S4U25.html

The classical adoption pattern



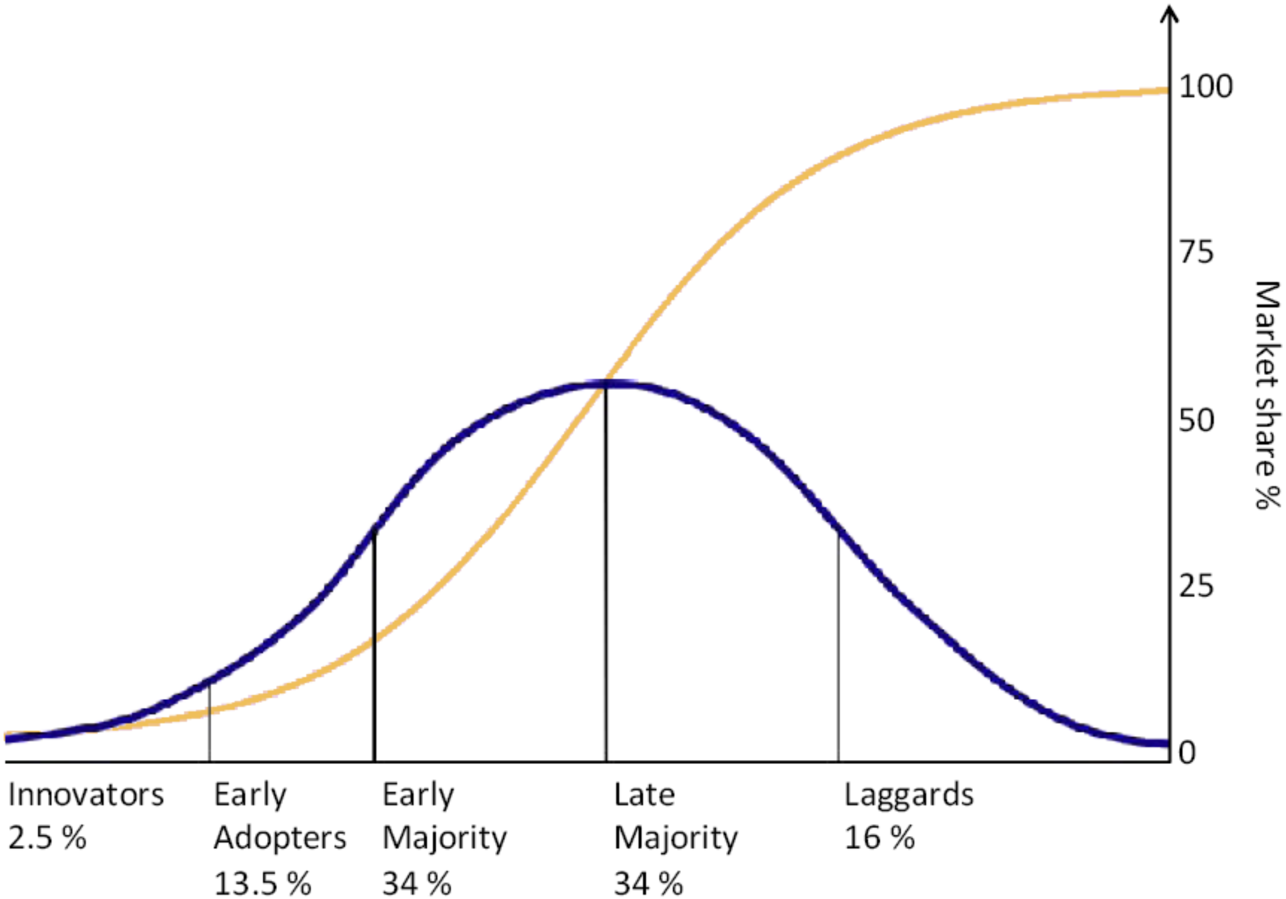
Graph from
https://commons.wikimedia.org/wiki/File:Diffusionofideas.PNG

Bandwagon effect

Photo and text from
https://en.wikipedia.org/wiki/Bandwagon_effect

“The bandwagon effect is a phenomenon whereby the rate of uptake of beliefs, ideas, fads and trends increases the more that they have already been adopted by others. In other words, the bandwagon effect is characterized by the probability of individual adoption increasing with respect to the proportion who have already done so. As more people come to believe in something, others also "hop on the bandwagon" regardless of the underlying evidence.” (Wikipedia)

The classical adoption pattern



Graph from
https://commons.wikimedia.org/wiki/File:Diffusionofideas.PNG

Experimental study of inequality and unpredictability in an artificial cultural market, MJ Salganik, PS Dodds, DJ Watts - *Science*, 2006

Influentials, networks, and public opinion formation, DJ Watts, PS Dodds - *Journal of Consumer Research*, 2007

Leading the herd astray: An experimental study of self-fulfilling prophecies in an artificial cultural market, MJ Salganik, DJ Watts - *Social Psychology Quarterly*, 2008

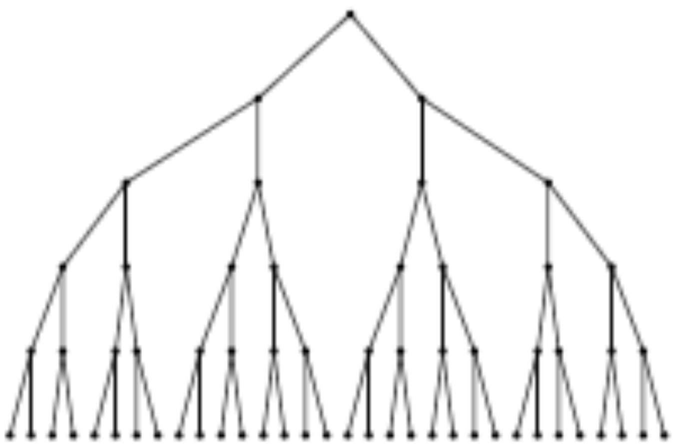
Web-based experiments for the study of collective social dynamics in cultural markets, MJ Salganik, DJ Watts - *Topics in Cognitive Science*, 2009

Schematic diffusion patterns

Broadcast

Messenger is important

Viral



Message is important (?)

Fig. 1 from Goel et al. (2016), "The Structural Virality of Online Diffusion"
(https://cs.stanford.edu/people/ashton/pubs/twiral.pdf)

Structural virality as the Wiener index
(Goel, Anderson, Hofman, & Watts 2016)

$$\nu(T) = \frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij}$$

$v(T)$ = the average distance between all pairs of nodes in a diffusion tree T (or, equivalently, the average depth of all nodes as roots)

for $n > 1$ nodes

d_{ij} = the shortest distance between nodes i and j

Random Twitter cascades ordered by structural virality

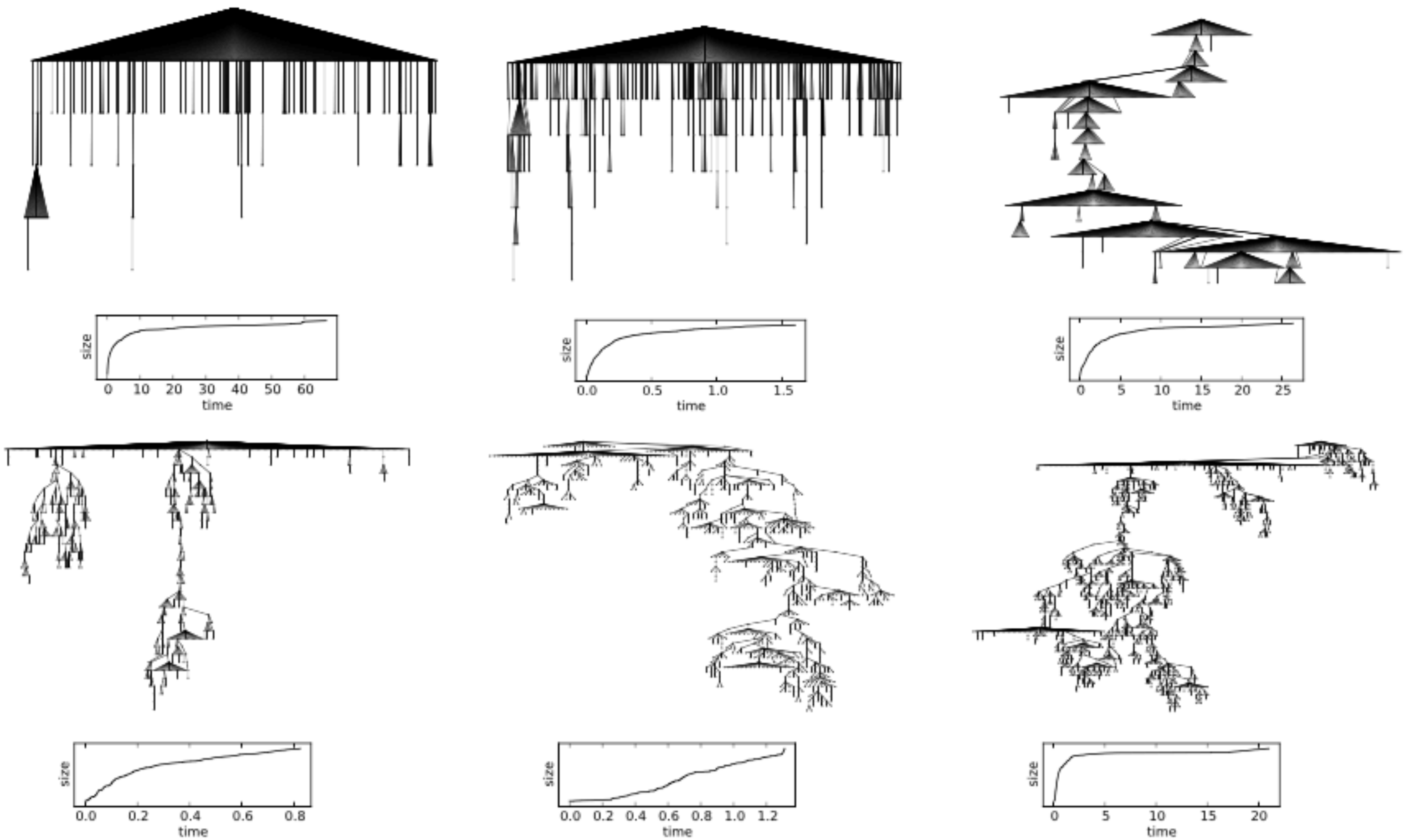


Fig. 3 from "The Structural Virality of Online Diffusion"
(https://cs.stanford.edu/people/ashton/pubs/twiral.pdf)

Structural virality by cascade size/popularity on Twitter, per domain

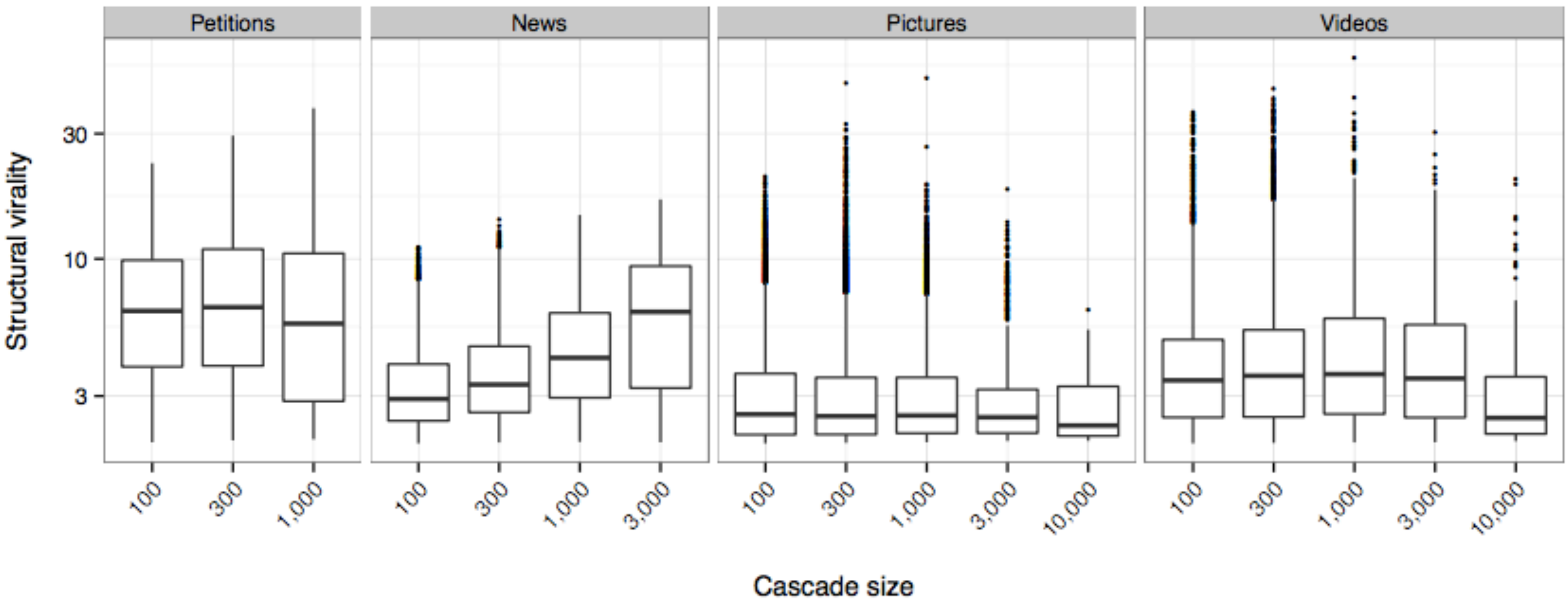


Fig. 5 from "The Structural Virality of Online Diffusion"
(https://cs.stanford.edu/people/ashton/pubs/twiral.pdf)

Correlation between popularity and structural virality for 4 domains

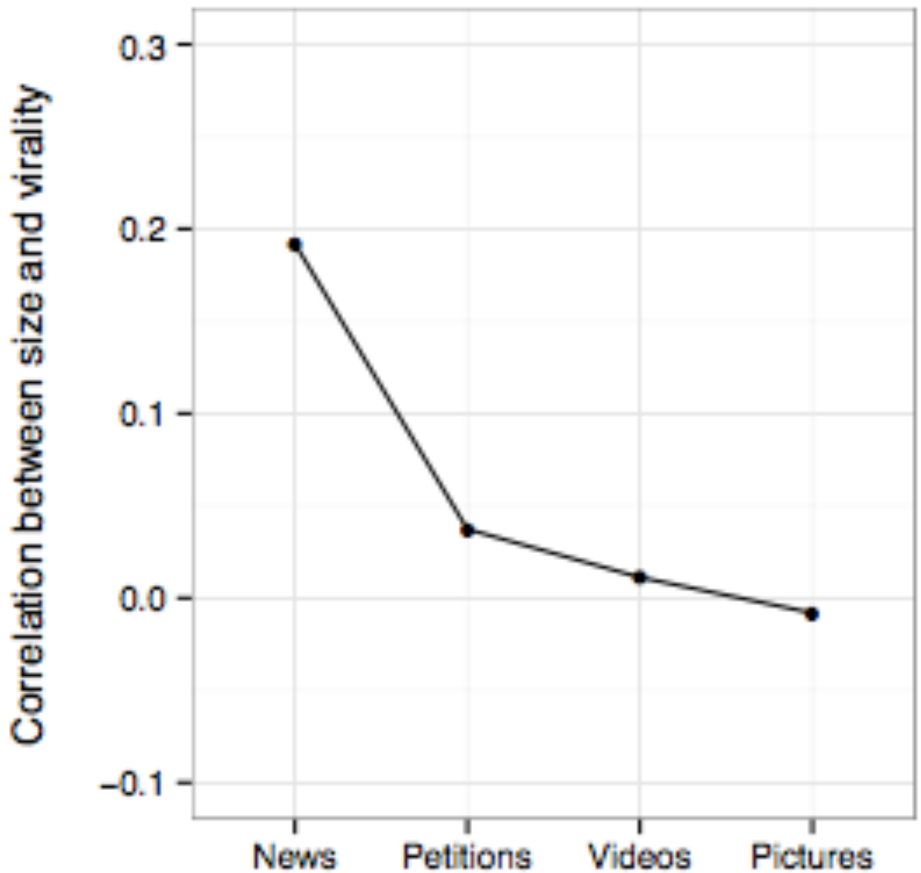


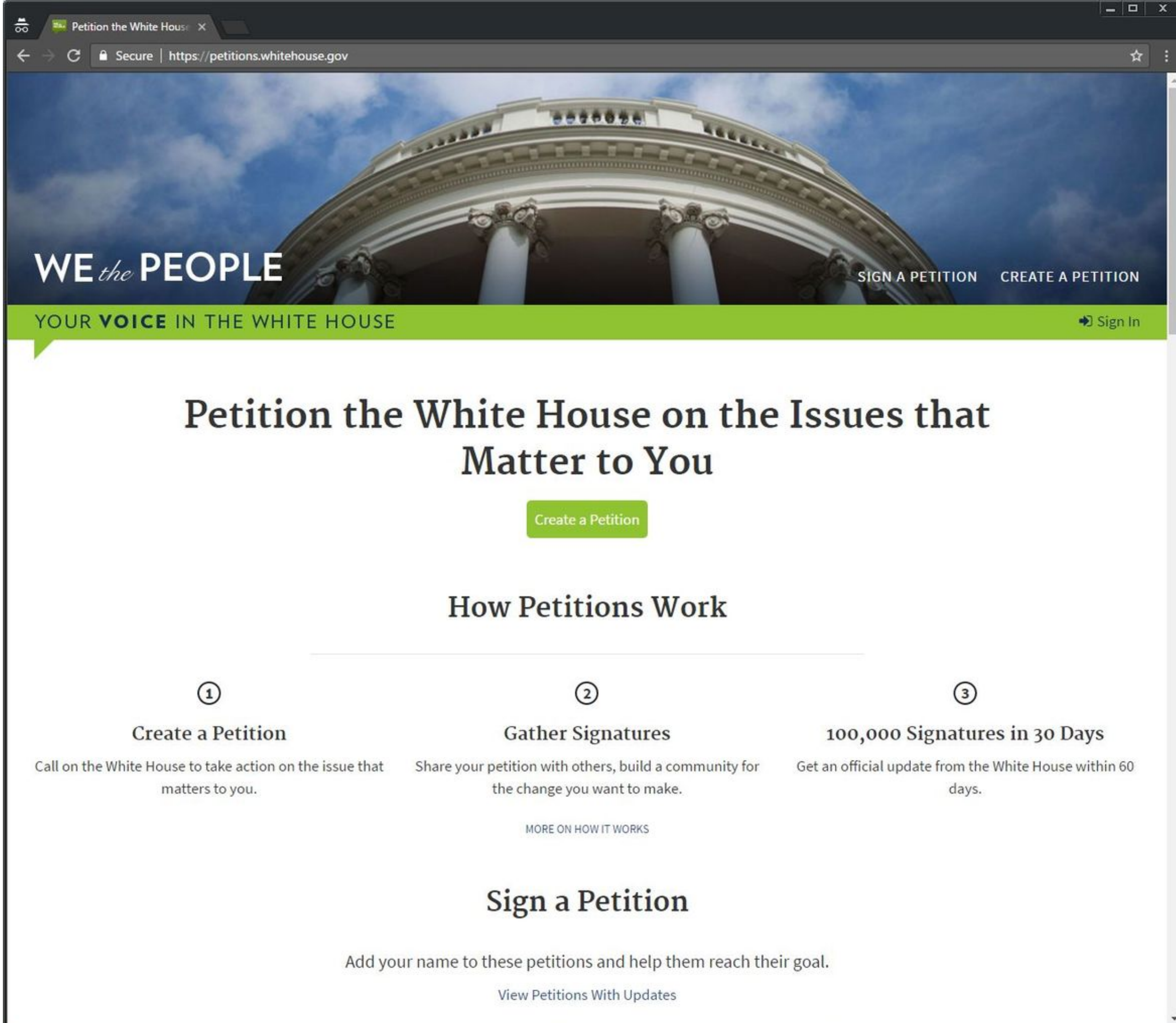
Fig. 6 from "The Structural Virality of Online Diffusion"
([https://cs.stanford.edu/people/ashton/pubs/twiral.pdf)](https://cs.stanford.edu/people/ashton/pubs/twiral.pdf)

Structural virality versus intrinsic virality (‘infectiousness’)

Main model in Goel et al. (2016) assumes constant infectiousness (intrinsic appeal of the content/message).

They say: “In other words, taking infectiousness as a proxy for quality, in our simulations the largest and most viral cascades are not inherently better than those that fail to gain traction, but are simply more fortunate (Watts 2002).”

So structural virality does not imply intrinsic virality/infectiousness.


Petition the White House
Secure | https://petitions.whitehouse.gov
WE the PEOPLE
SIGN A PETITION
CREATE A PETITION
YOUR VOICE IN THE WHITE HOUSE
Sign In
Petition the White House on the Issues that Matter to You
Create a Petition
How Petitions Work
1
Create a Petition
Call on the White House to take action on the issue that matters to you.
2
Gather Signatures
Share your petition with others, build a community for the change you want to make.
3
100,000 Signatures in 30 Days
Get an official update from the White House within 60 days.
MORE ON HOW IT WORKS
Sign a Petition
Add your name to these petitions and help them reach their goal.
View Petitions With Updates

Questions about petitions

Can we infer structural virality (or “broadcastness”) just from time-stamped signature data?

Are successful petitions on We The People more structurally viral than failed ones?

Is petition success predicted by infectiousness/intrinsic virality?

Do actual petition signature data show patterns at odds with what research using Twitter cascades would suggest?

A few other previous findings

First day signature total is very predictive of petition popularity/success on the No. 10 Downing Street petition site (Hale, Margetts, & Yasseri 2013)

Successful petitions on The Petition Site gather a large fraction of their signatures early on (Proskurnia et al. 2017)

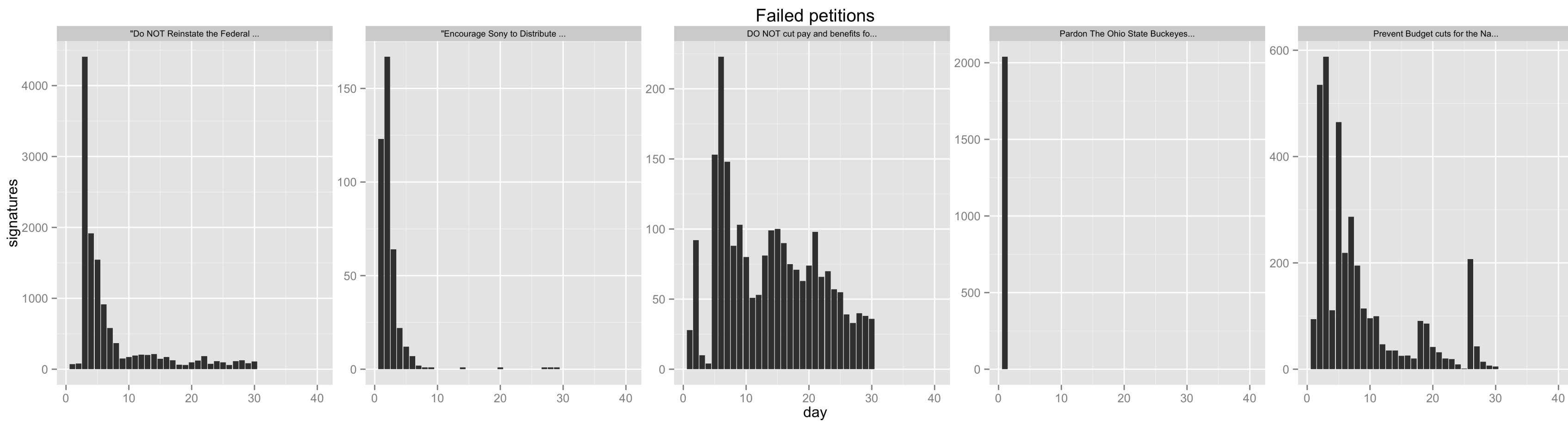
Successful/popular petitions are rare (many studies)

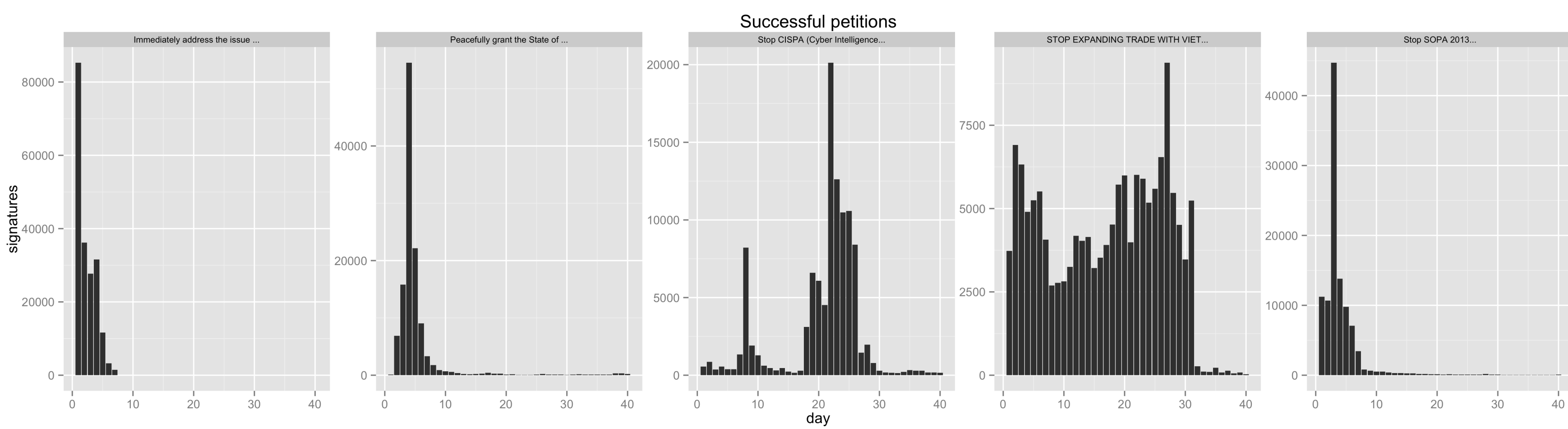
Data characterization

3682 WTP petitions collected between Sept. 20, 2011 and March 30, 2015

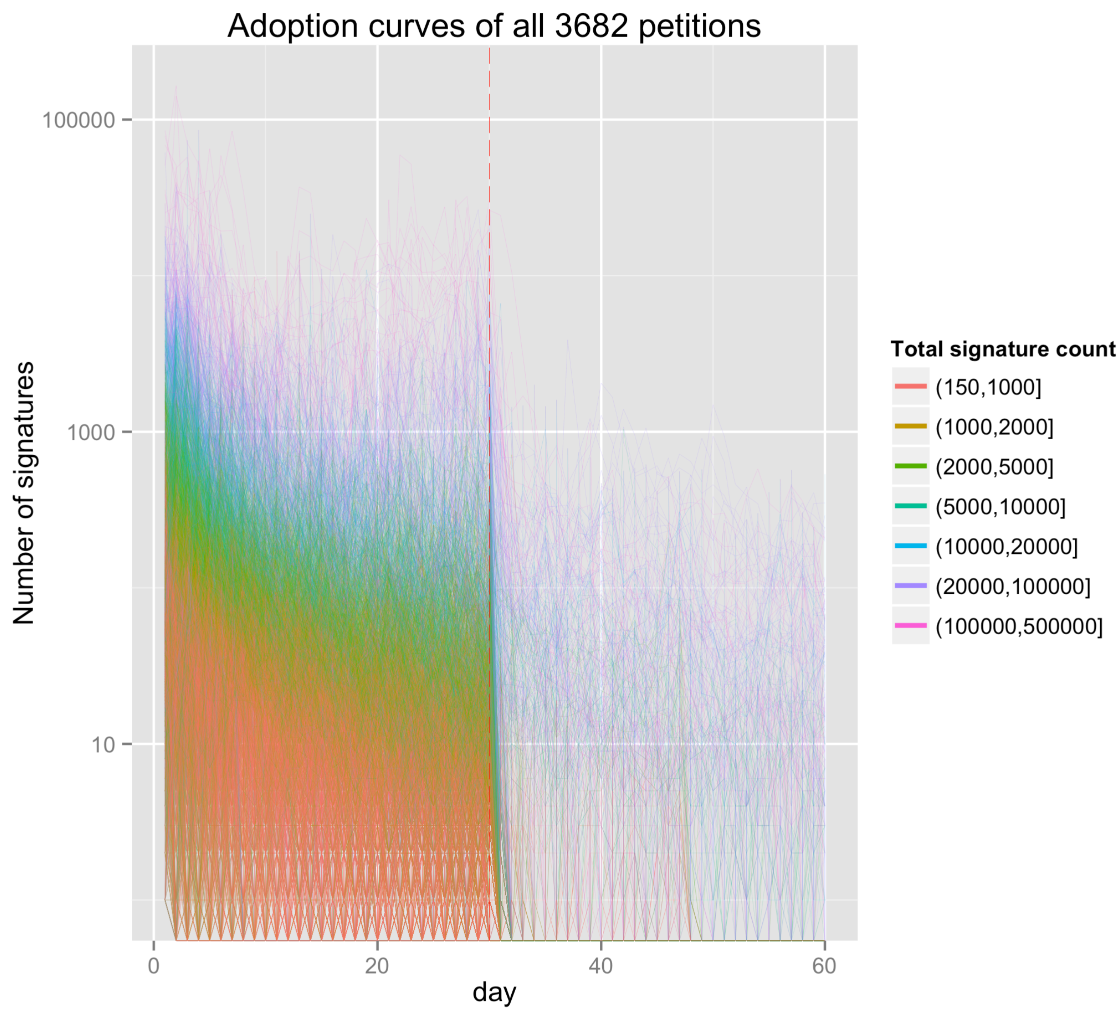
59 (1.6%) reached the signature threshold for a White House response

Signature graphs for randomly chosen failed vs. successful petitions

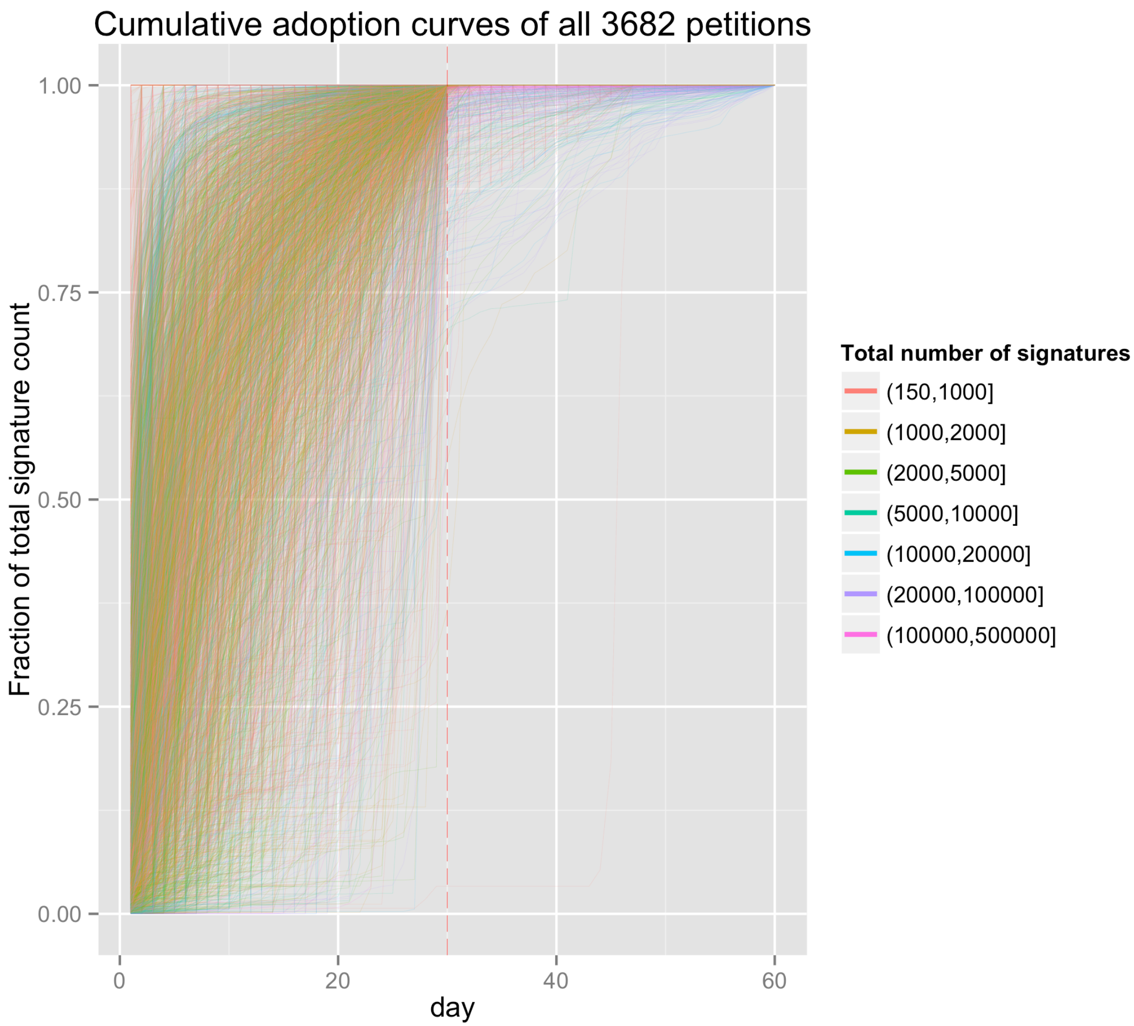




Day-by-day signature counts for petitions of different final popularities



Cumulative adoption curves for petitions of different popularities



Exceed ratios: inverse indicators of ***structural*** virality

- *Total exceed ratio* (an inverse measure of structural virality)

$$E_{Tot} = \frac{\Sigma_{i \in L}(S(i) - \max[S(i-1), S(i+1)])}{\Sigma_{i=1}^{T} S(i)}$$

for a given petition over *T* time periods, in which *S(i)* signatures are obtained in period *i*, and *L* is the set of all peak periods within *T*

- *Global-peak-only exceed ratio* E_{GPO} = adjacent-periods signature difference for just the global peak period divided by total signatures (an indicator of the largest broadcast event)

First day/second day (FDSD) ratio:
an indicator of ***intrinsic*** virality

Assumptions:

- Most petitions are launched by some kind of broadcast event on the first day

- Therefore, petitions that achieve more signatures on the second day than on the first day will be, on average, higher in intrinsic appeal than those with higher FDSD ratios

Average total exceed ratio E_{Tot} for all petitions: successful versus unsuccessful

	Successful (N = 59)	Unsuccessful (N = 3623)
Daily	0.152 (sd = .13)	0.224 (sd = .04)
Hourly	0.148 (sd = .09)	0.230 (sd = .03)

Failed petitions were 47.4% higher for daily total exceed ratio, and 55.4% higher for hourly (p < .0001 for both)

Daily global-peak-only exceed ratio E_{GPO} was 0.105 (sd=.11) for successful and 0.155 (sd=.19) for unsuccessful petitions (p = .042).

Cf. Goel et al., 2016: "If popularity is consistently related to any one feature, it is the size of the largest broadcast event."

FDSD Ratio:
Testing for intrinsic virality

Percentage of petitions with more signatures on the second day than on the first day

- Successful: 68% (N=59)
- Unsuccessful: 38% (N=3623)

($p < .00001$ by Chi-square)

Measures of shape
[with type of virality measured]

Measure of Shape	Interpretation
Skewness	Whether distribution has larger 'tails' extending to right (positive) [IV]
Kurtosis	How peaked a distribution is [SV]
Location of global peak	The day on which the petition received the most signatures [IV]
Number of local peaks	Number of days on which the petition received more signatures than on adjacent days [SV]

All these measures indicate higher structural and intrinsic virality for more popular petitions in the WTP data set.

Theoretical model: highlights

First broadcast event on day 1

Variable infectiousness for each petition (basic reproduction number R_0 = average number of signers in next period for each signer in present period): message strength

Constant average broadcast size X for all petitions after first broadcast: messenger strength

Simulation over 5000 petitions replicates qualitative patterns observed for regression of signature totals on measures of shape

Summary

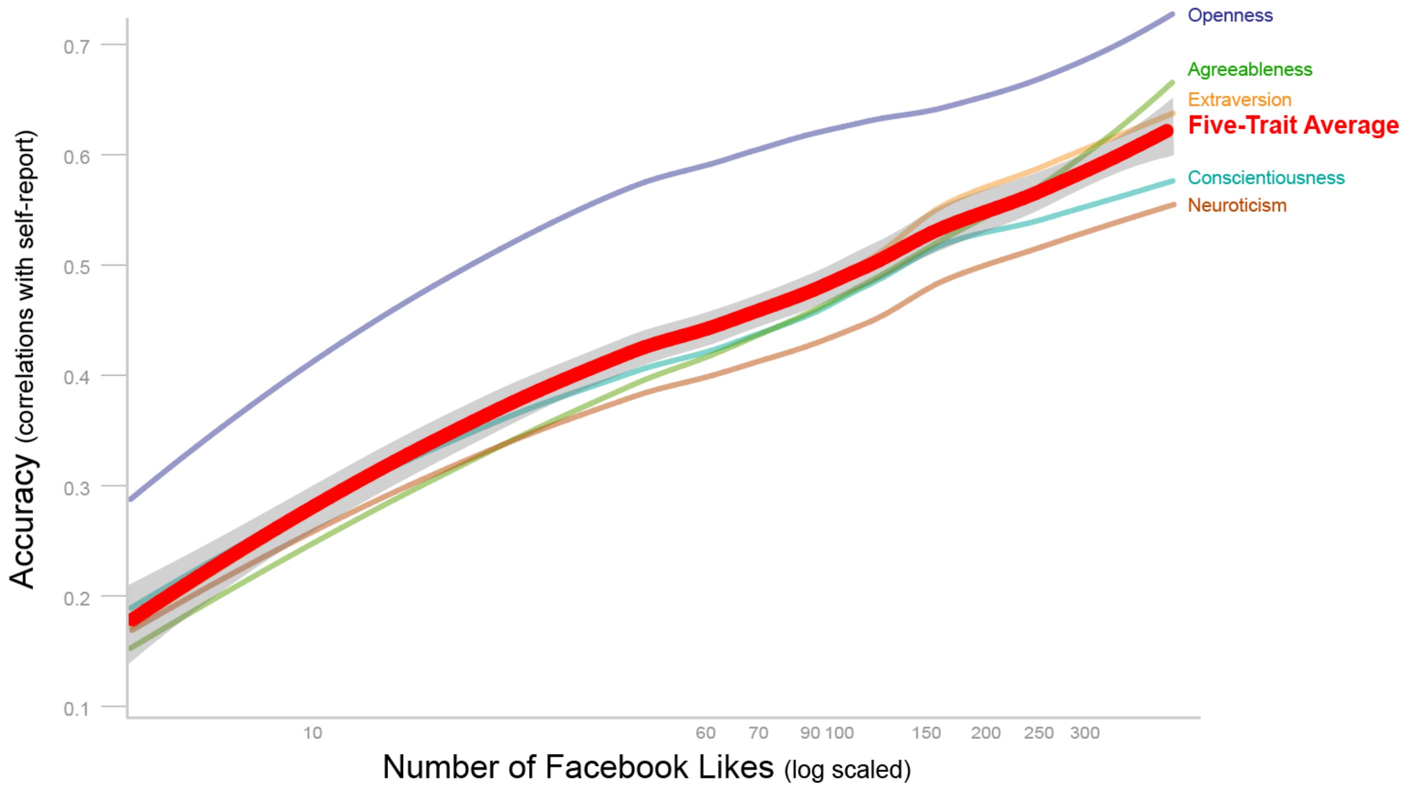
Analysis of We the People temporal signature data suggests more popular/successful petitions are higher in both structural and intrinsic virality than less popular / unsuccessful petitions, on all the measures chosen as indicators for SV and IV.

Our measure E_{GPO} indicates that successful petitions are less likely to depend on a single large broadcast event than unsuccessful ones for their signature totals.

Simulations support a model of petition signing in which intrinsic virality/infectiousness varies across petitions.

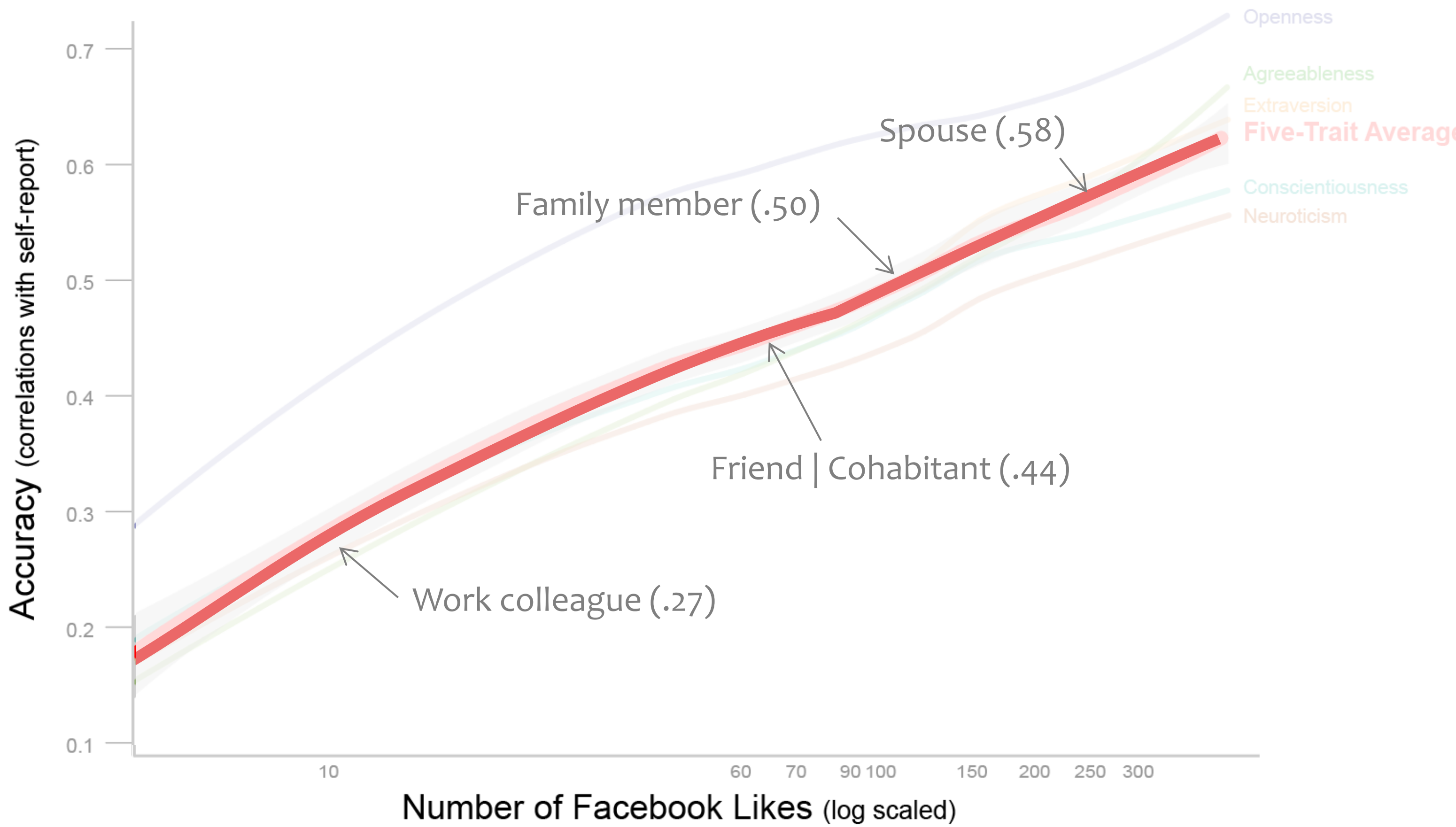
Computational Psychology

Predicting Personality from Facebook Likes



Kosinski, Stillwell & Graepel (2013) Private traits and attributes are predictable from digital records of human behavior. PNAS.

Predicting Personality from Facebook Likes



Youyou, Kosinski & Stillwell (2015) Computer-based personality judgements are more accurate than those made by humans. *PNAS.*

Further resources…

Marshall McLuhan, *Understanding Media: The Extensions of Man*, 1964

Daniel Kahneman and Angus Deaton, “High Income Improves Evaluation of Life But Not Emotional Outcomes”, PNAS, 2010

Sherry Turkle, *Alone Together: Why We Expect More from Technology and Less from Each Other*, 2011

Jeremy Bailenson, *Infinite Reality: The Hidden Blueprint of Our Virtual Lives*, 2012

Chi Ling Chan, Justin Lai, Bryan Hooi, and Todd Davies, ”The Message or the Messenger: Inferring Virality and Diffusion Structure from Online Petition Signature Data", SocInfo 2017

Michal Kosinski, ”The End of Privacy”, CeBIT 2017 [video]