Computational History

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Principles of Complex Systems, Vols. 1 & 2
CSYS/MATH 300 and 303, 2021–2022 | @pocsvox

Prof. Peter Sheridan Dodds | @peterdodds

Computational Story Lab | Vermont Complex Systems Center
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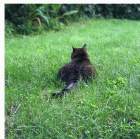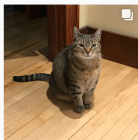
 On Instagram at pratchett_the_cat⬈

Outline

THE MECHANICS OF FAME

THE TALK OF FAME

THE STORIES CONTAGIOUS

THE SOCIAL WILD

Fame by rank

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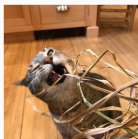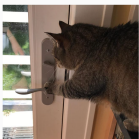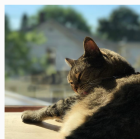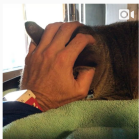Sociotechnical time series
Adjacent Narratives

Extras
Memory & Turbulence

References

Nature (2014): Most cited papers of all time⇗

Word frequency:

Brown Corpus 🔗 ($\sim 10^6$ words):

rank	word	% q	rank	word	% q
1.	the	6.8872	1945.	apply	0.0055
2.	of	3.5839	1946.	vital	0.0055
3.	and	2.8401	1947.	September	0.0055
4.	to	2.5744	1948.	review	0.0055
5.	a	2.2996	1949.	wage	0.0055
6.	in	2.1010	1950.	motor	0.0055
7.	that	1.0428	1951.	fifteen	0.0055
8.	is	0.9943	1952.	regarded	0.0055
9.	was	0.9661	1953.	draw	0.0055
10.	he	0.9392	1954.	wheel	0.0055
11.	for	0.9340	1955.	organized	0.0055
12.	it	0.8623	1956.	vision	0.0055
13.	with	0.7176	1957.	wild	0.0055
14.	as	0.7137	1958.	Palmer	0.0055
15.	his	0.6886	1959.	intensity	0.0055

Jonathan Harris's Wordcount: ⬈

A word frequency distribution explorer:

WORD**COUNT**

◄ PREVIOUS WORD   NEXT WORD ►

the of and to a in that is was for you he with as the but it they you with the then that

1   2   3   4 5 6 7

CURRENT WORD

FIND WORD: [   ] ►   BY RANK: [   ] ►   REQUESTED WORD: **THE**   86800 WORDS IN ARCHIVE

RANK: **1**   ABOUT WORDCOUNT

WORD**COUNT**

◄ PREVIOUS WORD   NEXT WORD ►

spitsbergeneyles**turboprop**pahdra

55059   55060   55061   55062

CURRENT WORD

FIND WORD: [   ] ►   BY RANK: [   ] ►   REQUESTED WORD: **SPITSBERGEN**   86800 WORDS IN ARCHIVE

RANK: **55059**   ABOUT WORDCOUNT

"Thing Explainer: Complicated Stuff in Simple Words " 🅐,⎚
by Randall Munroe (2015). [14]

BOAT THAT GOES UNDER THE SEA

We've always had boats that go under the sea, but in the last few hundred years, we've learned to make ones that come back up.

At first, we used those boats to shoot at other boats, make holes in them, or stick things to them that blew up.
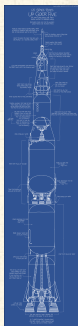
Later, we found a new use for these boats: keeping our city-burning machines hidden, safe, and ready to use if there's a war.

WORLD-ENDING BOAT
The boat shown here carries up to two dozen city-turning war machines. People have added up the power used during the Second World War—all the machines that blew up, all the guns that fired, and all the cities that burned. It's a lot of fire power. Each of these boats carries several times that much.

SPECIAL SEA WORDS
Most of the time, if you call a really big boat a "boat," people who know a lot about boats will get mad at you. But boats that go under the sea are really called "boats."

HEAVY METAL POWER MACHINE
These boats are powered by heavy metal, just like some power buildings. The means they can stay hidden for a long time without running out of power.
Any time heavy metal is used for power, people worry about something going wrong. Of course, given what these boats are built for, people worry even more about the idea of one of them working right!

Pusher
Wing
turners

Machines that turn the pusher

Door for people

Machines for making fresh air

Door for people

BREATHING STICK
This brings fresh air into the boat, but the boat can also make its own air by breaking water into the parts it's made of. This takes a lot of power, but the boat is powered by heavy metal, so it has enough power to do whatever it wants.

SLEEPING ROOMS
The normal people on the boat sleep on either side of the city-burning machines.

Goes for city-burning machines

Room for putting people to go

Offices

Hallway making choices

MIRROR LOOKERS
When the boat is hiding under the sea, it can come near the surface and use these sticks with mirrors in them to let the people inside see out of the water.

SOUND LOOKERS
Light can't go far under water, so these boats "see" with sound. The boat makes sound, which hits things and comes back. By listening carefully, the people in the boat can tell what's around them without seeing—just like those sea birds that catch flies in the dark.

Room for flying boats

Radio

Eating room

Computers

Flying carrier control room

Rooms into hit with sound to make the boat go under the sea anymore.

EMPTY ROOMS
A while ago, everyone decided the world didn't need so many city-burning machines. This country agreed to turn off two of the two dozen flying machine carriers in each boat, leaving only twenty.

MACHINES FOR BURNING CITIES
Each of these rooms has a flying carrier full of city-burning machines. While hiding under the water, the boats can shoot the machines into space. Any of these boats can send a machine anywhere in the world in under an hour.

Machine that makes power from fire water (in case there's a problem with the heavy metal)

MACHINES FOR SHOOTING BOATS
This boat can shoot these tiny machines under the water at other boats to make holes in them. They blow up, but don't use heavy metal.

Boats used to carry more guns and machines like this, but boats don't really fight each other anymore.

OTHER BOATS THAT GO UNDER THE SEA
These are some other boats, drawn to show how big they are next to the world-ending boat above.

Up goer five⎚

The everywhereness of algorithms and stories:

"On the Origin of Stories: Evolution, Cognition, and Fiction" a,⤢
by Brian Boyd (2010). [3]

"The Storytelling Animal: How Stories Make Us Human" a,⤢
by Jonathan Gottschall (2013). [10]

"The Written World: How Literature Shaped Civilization" a,⤢
by Martin Puchner (2017). [17]

Algorithms, recipes, stories, …

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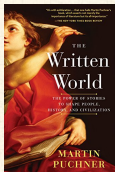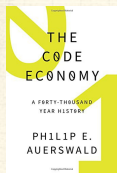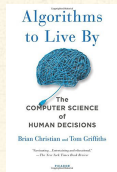
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References

"The Code Economy: A Forty-Thousand Year History" 🅰, ⤤
by Philip E Auerswald (2017). [1]

"Algorithms to Live By" 🅰 ⤤
by Christian and Griffiths (2016). [6]

"Once Upon an Algorithm" 🅰 ⤤
by Martin Erwig (2017). [9]

Also: Numerical Recipes in C [16] and How to Bake π [4]

The famous are storytellers—Japan:

For people born 1950–

http://pantheon.media.mit.edu/treemap/country_exports/JP/all/1900/2010/H15/pantheon

https://www.media.mit.edu/projects/pantheon-new/overview/

Super Survival of the Stories:

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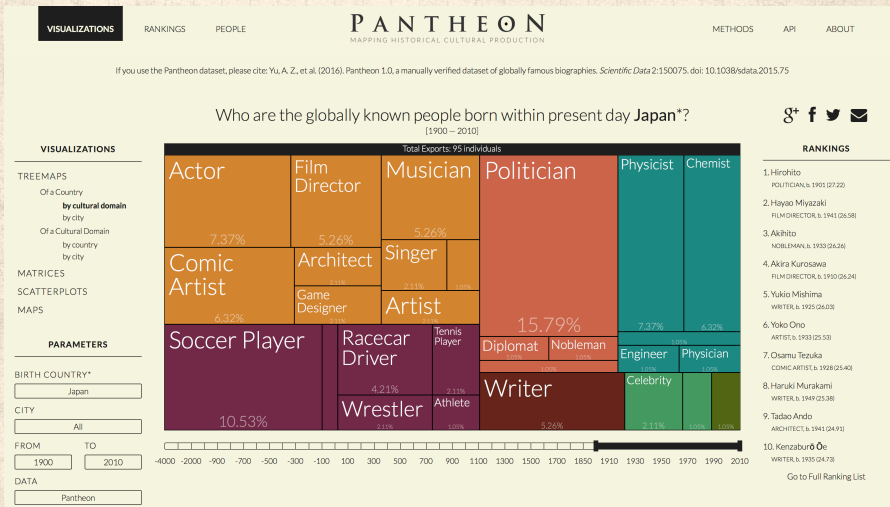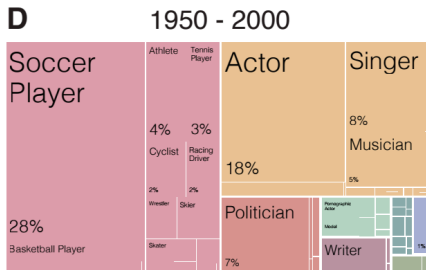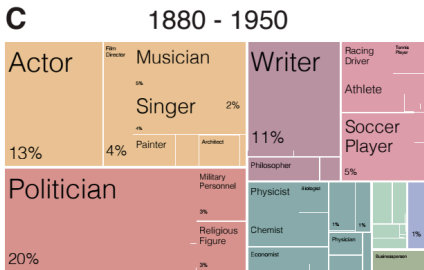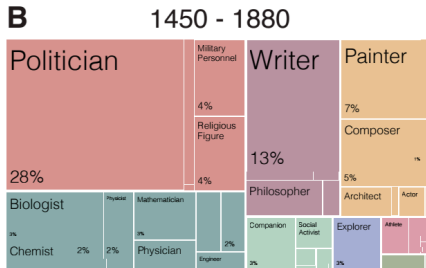
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The Desirability
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Storytellers ,
The Atlantic,
Ed Yong,
2017-12-05.

- 🎲 Study of Agta, Filipino hunter-gatherers.
- 🎲 Storytelling valued well above all other skills
  including hunting.
- 🎲 Stories encode prosocial norms such as
  cooperation.

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- 🎲 Storytelling valued well above all other skills including hunting.
- 🎲 Stories encode prosocial norms such as cooperation.
- 🎲 Like the best stories, the best storytellers reproduce more successfully.

The most famous painting in the world:

The dismal predictive powers of editors ......

Twelve ...

The completely unpredicted fall of Eastern Europe:

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References

Timur Kuran: [12] "Now Out of Never: The Element of Surprise in the East European Revolution of 1989"

We understand bushfire stories:

1. Sparks start fires.

We understand bushfire stories:

1. Sparks start fires.
2. System properties control a fire's spread.

We understand bushfire stories:

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3. But for three reasons, we make two mistakes
   about Social Fires ...

We understand bushfire stories:

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1. Sparks start fires.
2. System properties control a fire's spread.

3. But for three reasons, we make two mistakes about Social Fires ...

Reason 1—We are Homo Narrativus.

http://xkcd.com/904/

Reason 2—"We are all individuals." ↗

Archival footage:

🧊 Individual narratives are not enough to
understand distributed, networked minds.

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Reason 3—We are spectacular imitators.

BBC/David Attenborough.

Mistake 1:
Success is due to intrinsic properties

See "Becoming Mona Lisa" by David Sassoon ⬀

Mistake 1:
Success is due to intrinsic properties

it's just so disappointingly small

See "Becoming Mona Lisa" by David Sassoon ⎘

Mistake 1:
Success is due to intrinsic properties

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Stolen in 1913, recovered in 1915.

See "Becoming Mona Lisa" by David Sassoon ⬀

Mistake 1:
Success is due to intrinsic properties

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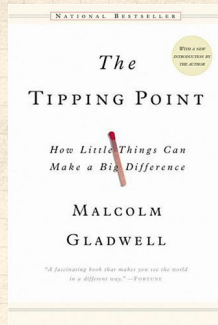Extras
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Hidden during WWII.

See "Becoming Mona Lisa" by David Sassoon ⬀

Mistake 1:
Success is due to intrinsic properties

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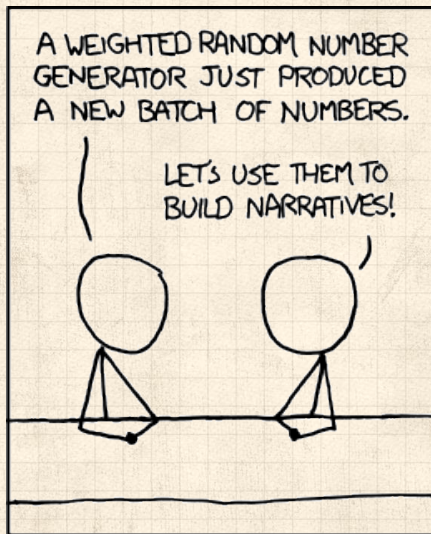
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Repeatedly vandalised and attacked. ⬀

See "Becoming Mona Lisa" by David Sassoon ⬀

48 songs
30k participants

Exp 1— weak social

Exp. 2—strong social

"An experimental study of inequality and unpredictability in an artificial cultural market"

Salganik, Dodds, and Watts, Science, **311**, 854–856, 2006. [18]

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Resolving the paradox:

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Increased social awareness leads to
Stronger inequality + Less predictability.

Payola/Deceptive advertising hurts us all:

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"Mistake" 2:
Seeing success is 'due to social' and wanting to say 'all your interactions are belong to us'

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"This is truly the last time, believe me"

The Washington Post

Business • Analysis

14 years of Mark Zuckerberg saying sorry, not sorry

By Geoffrey A. Fowler and Chiqui Esteban April 9, 2018

Do you trust Mark Zuckerberg?

From the moment Mark Zuckerberg entered the public eye in 2003 for creating a Harvard student network and rating site, he's been apologizing. So we collected this abbreviated history of his public mea culpas.

It reads like a record on repeat. Zuckerberg, who made "move fast and break things" his slogan, says sorry for being naive, and then promises solutions such as privacy "controls," "transparency" and better policy "enforcement." And then he promises it again the next time. You can track his sorries in orange and promises in blue in the timeline below.

All the while, Facebook's access to our personal data increases and little changes about the way Zuckerberg handles it. So as Zuckerberg prepares to apologize for the first time in front of Congress, the question that lingers is: What will be different this time?

Robert Godwin Sr.

" Our hearts go out to the family and friends of Robert Godwin Sr., and we have a lot of work — and we will keep doing all we can to prevent tragedies like this from happening. "

September 2017
While revealing a nine-step plan to stop nations from using Facebook to interfere in one another's elections, noting that the amount of "problematic content" found so far is "relatively small."

" I care deeply about the democratic process and protecting its integrity. ... It is a new challenge for internet communities to deal with

December 2007
After launching Beacon, which opted-in everyone to sharing with advertisers what they were doing in outside websites and apps.

" We simply did a bad job with this release, and I apologize for it. ... People need to be able to explicitly choose what they share. "

February 2009
After unveiling new terms of service that angered users.

" Over the past couple of days, we received a lot of questions and comments. ... Based on this feedback, we have decided to return to our previous terms of use while we resolve the issues. "

" We won't prevent all mistakes or abuse, but we currently make too many errors enforcing our policies and preventing misuse of our tools. ... This will be a serious year of self-improvement and I'm looking forward to learning from working to fix our issues together. "

March 2018
After details emerged about Cambridge Analytica taking user data.

" We have a responsibility to protect your data, and if we can't then we don't deserve to serve you. ... We will learn from this experience to secure our platform further and make our community safer for everyone going forward. "

Commission for deceiving consumers about privacy.

" I'm the first to admit we've made a bunch of mistakes. ... Facebook has always been committed to being transparent about the information you have stored with us — and we have led the internet in building tools to give people the ability to see and control what they share "

July 2014
After an academic paper exposed that Facebook conducted psychological tests on nearly 700,000 users without their knowledge.
(Apology by Facebook COO Sheryl Sandberg)

" It was my mistake, and I'm sorry. ... There's more we can do here to limit the information developers can access and put more safeguards in place to prevent abuse. "

Related stories
Facebook: Most users may have had public data 'scraped'
Facebook COO Sheryl Sandberg on data leak: 'I am really sorry, we are late'
As Facebook confronts data misuse, foreign governments might force real change
What if you paid for Facebook — instead of letting it spy on us for free?

About this story
Photo/illustration based on photos by Tony Avelar/Bloomberg News, Drew Angerer/Getty Images, Jeff Roberson/AP, Jim Watson/Getty Images, Craig Ruttle/AP, Paul Sakuma/AP, Stephen Lam/Reuters, Jose Gomez/Reuters, Richard Drew/AP

☐ 232 Comments

More stories
The Facebook ads Russians showed to different groups
Facebook has said these ads were created by the internet

The hypodermic model of influence:
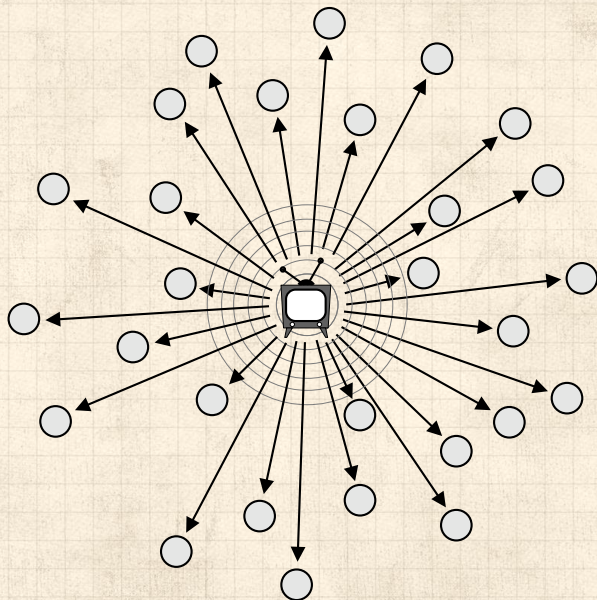
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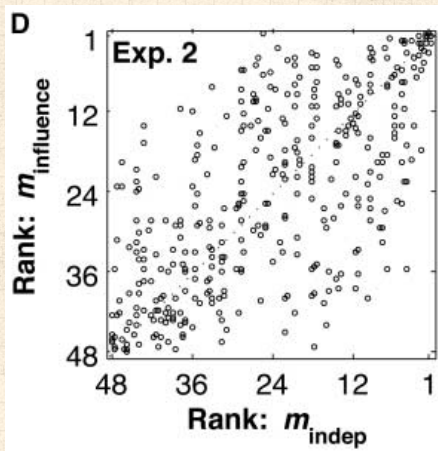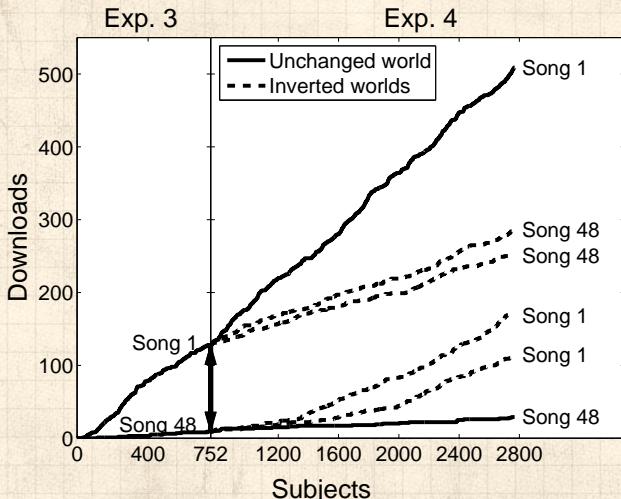
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The two step model of influence: [11]
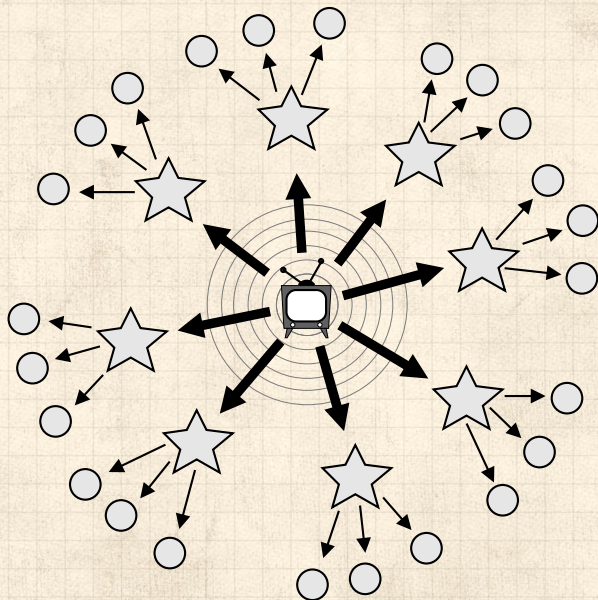
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The network model of influence:

The network model of influence:

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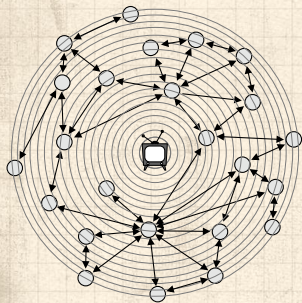
How supersreading works:

Many interconnected, average, trusting people
must benefit from both
receiving and sharing a message
far from its source.

"Influentials, Networks, and Public Opinion Formation" 🔗
Watts and Dodds,
J. Consum. Res., **34**, 441–458, 2007. [19]

Etymological clarity:

Fate—from the Latin *fatus*: meaning "spoken".

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- Fate—from the Latin *fatus*: meaning "spoken".
- Fate is talk that has been done.
  "It is written", fore-tell, pre-dict.

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- Fate is talk that has been done.
  "It is written", fore-tell, pre-dict.
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- Destiny is probablistic.

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- Fame—from the Latin *fāma*: meaning "to talk."

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- Destiny is probablistic.

- Fame—from the Latin *fāma*: meaning "to talk."

- Fame is inherently the social discussion about the thing, not the thing itself.

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- ⬡ Fate—from the Latin *fatus*: meaning "spoken".
- ⬡ Fate is talk that has been done.
  "It is written", fore-tell, pre-dict.
- ⬡ "There is no such thing as fate, only the story of fate." ↗
- ⬡ Destiny is probablistic.
- ⬡ Fame—from the Latin *fāma*: meaning "to talk."
- ⬡ Fame is inherently the social discussion about the thing, not the thing itself.
- ⬡ Renown ↗: Repeatedly named, talked about. Old French renon, from re- + non ("name").

Etymological clarity:

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fate." ↗

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shout" (again). Connected to "lowing".

Oscar Wilde, The Picture of Dorian Gray: Raw Fame

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and that is

not being talked about."

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"Fame and Ultrafame: Measuring and comparing daily levels of 'being talked about' for United States' presidents, their rivals, God, countries, and K-pop" ↗
Dodds et al.,
Available online at
https://arxiv.org/abs/1910.00149, 2019. [7]

"Computational timeline reconstruction of the stories surrounding Trump: Story turbulence, narrative control, and collective chronopathy" ↗
Dodds et al.,
, 2020. [8]

🧊 POTUSometer with the Smorgasdashbord:
http://compstorylab.org/potusometer/ ↗

🧊 Stories surrounding Trump:
http://compstorylab.org/trumpstoryturbulence/ ↗

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↑
more
talked
about

Word
Rank
r

less
talked
about
↓

'trump'

2020/11/04

'god'

Election Day

2021/11/20

↑
more
talked
about

Word
Rank
r

less
talked
about
↓

'biden'

2020/11/0?

'god'

2019/01/31

Election Day

Ultrafame:
Nobody expects ~~the Spanish Inquisition~~ K-pop:

Vox (2019-04-17):
BTS, the band that changed K-pop, explained ☐

Figure: Word rank time series for various terms on Twitter. Panels A–I show the rank r of words over dates d from roughly 2009 to 2021.

A 'obama' — 2008/11/04, 'god', 2021/11/25

B 'mccain' — 2008/09/26, 'god', 2021/11/25

C 'romney' — 2012/11/06, 'god', 2010/08/15

D 'hillary' — 2016/11/08, 'god', 2012/12/25

E 'trump' — 2016/11/09, 'god', 2013/10/26

F 'biden' — 2020/11/07, 'god', 2021/11/24

G '@bts_twt' — 2018/05/20

H 'god' — ~ The Realm of Lexical Ultrafame ~, 2014/07/12, 'god', 2008/11/12, ~ The Lexical Abyss ~

I 'trump' versus 'obama'

Axis labels: "more talked about ↑", "less talked about ↓", "Word Rank r", with tick marks at 1, 10, 10^2, 10^3, 10^4, 10^5, 10^6. Horizontal axis "Date d" with years 2009, 2011, 2013, 2015, 2017, 2019, 2021. Dashed vertical lines marked "Election Day" for 2008, 2012, 2016, 2020.

~ The Realm of Lexical Ultrafame ~

$r \leq r_{\text{god}} = 303$

$r = 1$ ~ 'a'

$r = 10$ ~ 'in'

$r = 32$ ~ 'are'

$r = 100$ ~ 'has'

↑ more talked about

$r = 316$ ~ 'god'

$r = 1,000$ ~ 'america'

Word Rank r

$r = 3,162$ ~ 'argentina'

$r = 10,000$ ~ 'spain'

$r = 31,623$ ~ 'ukraine'

less talked about ↓

$r = 100,000$ ~ 'cameroon'

$r = 316,228$ ~ 'bhutan'

$r = 1,000,000$ ~ 'kiribati'

'obama'

14 ↴ 'me'
highest rank
2008/11/04

1,720 ~ 'uk'
median rank

20,161 ↴ 'uruguay'
lowest rank
2021/12/25

'mccain'

31 ↰ 'at'
highest rank
2008/09/26

13,407 ↴ 'monaco'
median rank

342,148 ↰ 'bhutan'
lowest rank
2021/11/25

'romney'

33 ↰ 'your'
highest rank
2012/11/06

62,673 ↴ 'haiti'
median rank

813,435 ↴ 'guangxi'
lowest rank
2010/08/15

'hillary'

50 ↰ 'was'
highest rank
2016/11/08

— 'god' level —

4,112 ↴ 'mexico'
median rank
post 2016/10/01

23,829 ↴ 'greece'
highest rank
2015/12/31

71,445 ↴ 'rwanda'
lowest rank
2012/12/25

'trump'

11 ↰ 'is'
highest rank
2016/11/09

195 ~ 'frank'
median rank
post 2019/10/01

22,046 ↴ 'afghanistan'
median rank
pre 2015/12/31

81,022 ↴ 'tanzania'
lowest rank
2013/10/26

'biden'

24 ↦ 'y'
highest rank
2020/11/07

30,632 ↴ 'qatar'
median rank

274,352 ~ 'nauru'
lowest rank
2011/11/24

'@bts_twt'

3 ↰ 'to'
highest rank
2018/05/20

101 ~ 'ema'
median rank
post 2019/01/01

806 ~ 'hours'
median rank
in 2016

5,065 ~ 'pakistan'
median rank
in 2014

~ The Lexical Abyss ~
$r \gg 10^5$

Ultrafame—Percentage of days per year ranked above 'god'

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
'barack'	1.8%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
'obama'	54.4%	6.9%	0.5%	0.5%	2.2%	0.3%	0.0%	0.3%	2.2%	2.2%	0.5%	0.0%	0.3%	0.0%
'@barackobama'	0.0%	0.0%	0.0%	0.0%	0.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
'john'	3.5%	0.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.3%	0.8%	0.3%	0.5%	0.0%
'mccain'	39.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.3%	1.1%	0.0%	0.0%	0.0%
'@senjohnmccain'	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
'mitt'	0.0%	0.0%	0.0%	0.0%	0.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
'romney'	0.0%	0.0%	0.0%	0.0%	1.6%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.3%	0.0%
'@mittromney'	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
'hillary'	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	10.4%	0.0%	0.0%	0.0%	0.0%	0.4%
'clinton'	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	7.7%	0.0%	0.0%	0.0%	0.0%	0.0%
'@hillaryclinton'	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.1%	0.0%	0.0%	0.0%	0.0%	0.0%
'donald'	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	2.7%	0.5%	0.0%	0.0%	1.6%	0.6%
'trump'	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.5%	47.8%	98.6%	93.7%	92.3%	100.0%	10.2%
'@realdonaldtrump'	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	2.7%	26.8%	41.4%	62.7%	90.2%	2.2%
'joe'	3.5%	2.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	8.2%	0.6%
'biden'	1.8%	0.0%	0.0%	0.0%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	23.8%	6.1%
'@joebiden'	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	4.1%	0.3%
'@bts_twt'	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.5%	8.5%	50.7%	100.0%	100.0%	98.9%	93.1%

Relative median rates of 'being talked about' in the 8 weeks (56 days) pre-election day:

	2008	2012	2016	2020
'barack'	128	11	11	13
'obama'	1000	132	135	71
'@barackobama'	9	24	10	17
'john'	307	66	72	65
'mccain'	757	1	2	3
'@senjohnmccain'	0	0	1	0
'mitt'	3	50	2	2
'romney'	2	120	3	3
'@mittromney'	0	14	1	1
'hillary'	20	3	357	30
'clinton'	42	8	326	23
'@hillaryclinton'	0	0	130	19
'donald'	7	5	178	135
'trump'	4	3	656	1001
'@realdonaldtrump'	0	4	219	656
'joe'	128	39	32	287
'biden'	67	4	5	504
'@joebiden'	0	1	1	212
'@bts_twt'	0	0	166	1037
'god'	400	484	362	380
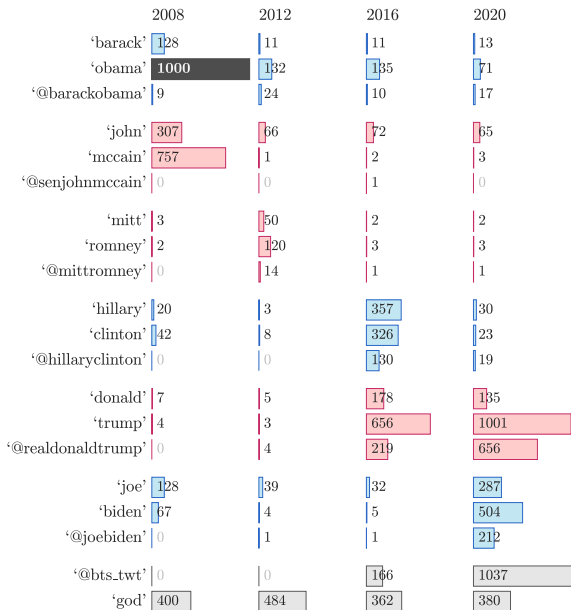
Relative median rates of 'being talked about' per year:

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
'barack'	50	38	17	9	10	7	8	11	14	15	14	14	19	3
'obama'	897	379	152	87	97	79	91	103	156	160	129	106	104	17
'@barackobama'	10	8	11	10	17	15	16	13	13	17	17	13	24	5
'john'	405	274	188	126	117	104	113	121	118	129	128	114	108	82
'mccain'	579	11	4	2	2	2	1	1	3	15	7	5	3	2
'@senjohnmccain'	0	2	1	0	0	1	1	1	1	9	2	0	0	0
'mitt'	5	8	5	6	25	6	5	4	4	2	2	3	3	2
'romney'	3	1	1	4	42	2	1	1	4	1	1	3	4	1
'@mittromney'	0	0	0	0	5	0	0	0	1	0	0	1	1	0
'hillary'	28	10	5	3	3	4	6	30	169	72	61	43	33	6
'clinton'	62	25	16	10	8	6	8	27	140	65	62	45	32	8
'@hillaryclinton'	0	0	0	0	0	0	1	11	71	22	19	21	23	3
'donald'	11	17	11	11	8	6	7	44	166	145	114	104	143	43
'trump'	7	20	10	7	4	3	3	77	583	1000	865	808	1134	229
'@realdonaldtrump'	0	0	0	1	2	3	2	32	219	468	555	652	888	1
'joe'	157	187	138	87	66	58	44	46	50	48	44	78	197	117
'biden'	72	7	3	1	2	2	2	3	5	3	4	52	284	221
'@joebiden'	0	0	0	0	0	0	0	0	1	1	2	18	162	28
'@bts_twt'	0	0	0	0	0	5	36	123	242	595	2487	1802	1440	1437
'god'	666	851	687	694	791	719	607	616	601	590	612	611	612	510

Ratiometrics:
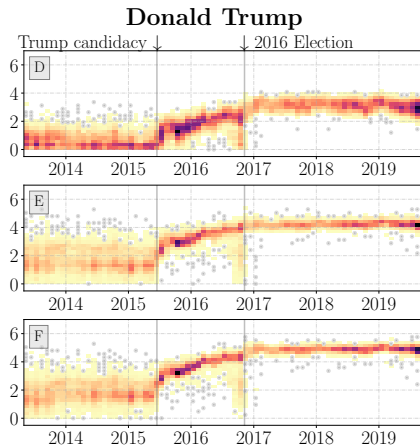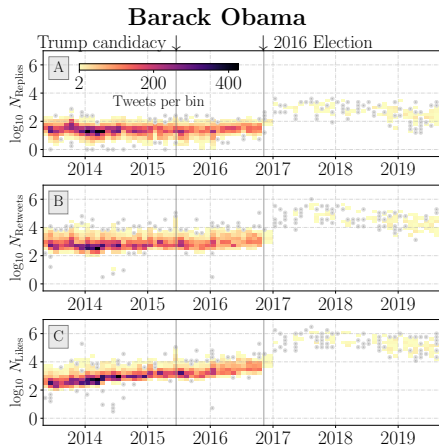
Barack Obama   **Donald Trump**

"Ratioing the President: An exploration of public engagement with Obama and Trump on Twitter,"

Minot et al., 2020 [13]

Ratiometrics:
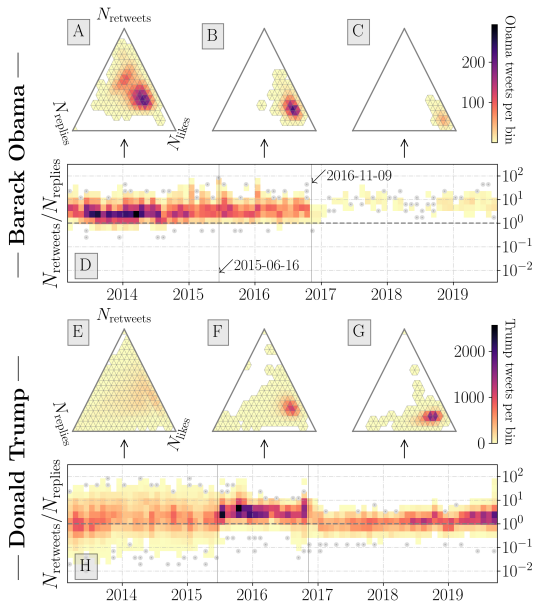
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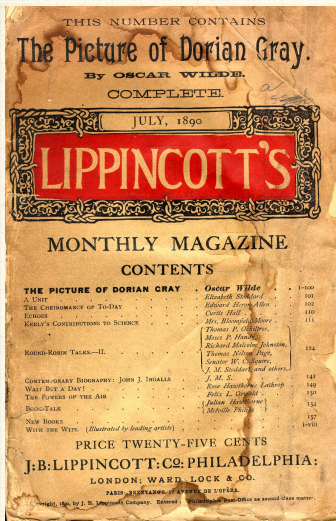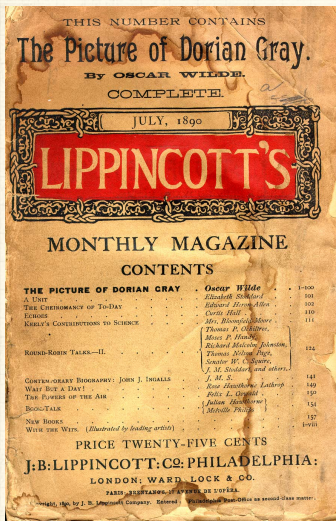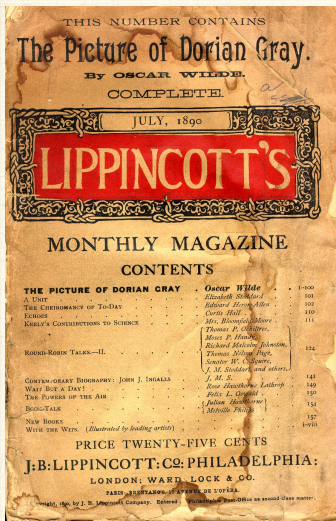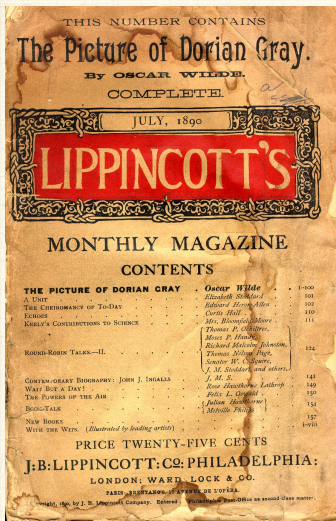Sociotechnical time series
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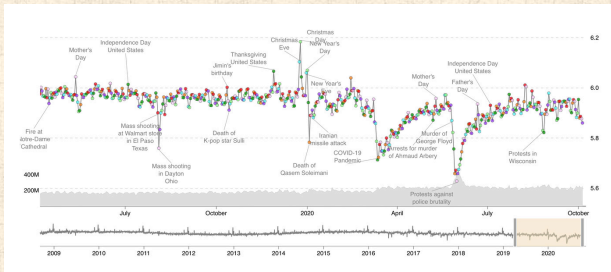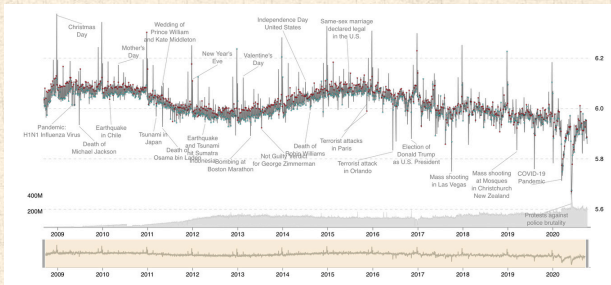
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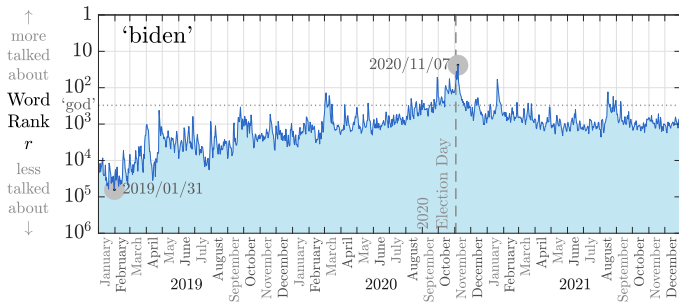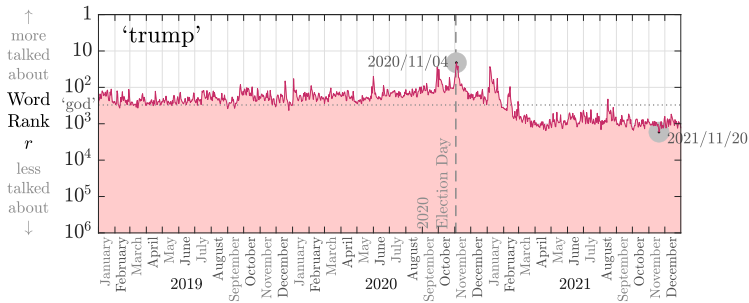Lexical Ultrafame

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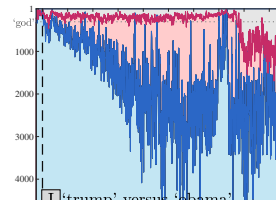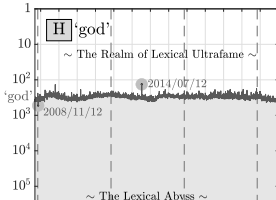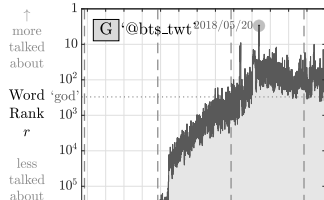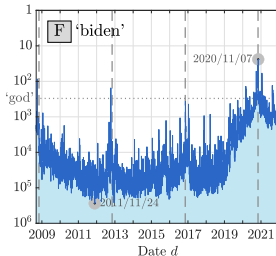Adjacent Narratives

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http://hedonometer.org/ ⬀

Allotaxonometry—
the comparison of complex systems:
http://compstorylab.org/allotaxonometry/

2016/01/01

2016 → 2020

01/01

top 10 most narratively dominant words

most narratively dominant word at day-scale

most narratively dominant word at week-scale

2020/10/05

12/31

narrative control

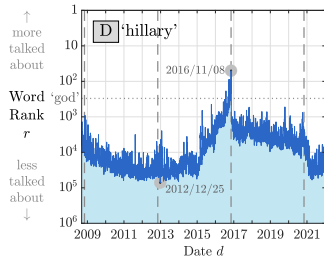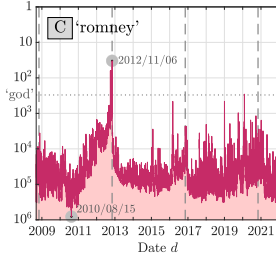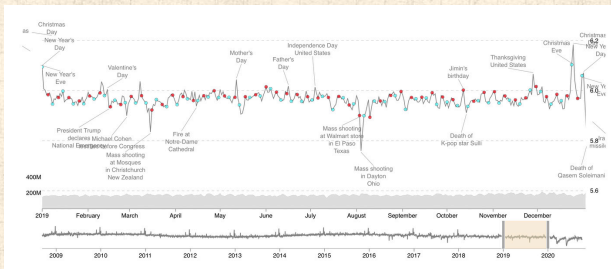| Week	2016	2017	2018	2019	2020
1. 01/01-01/07	Hillary 34.7	hacking 28.6	Bannon 2.2	shutdown 0.0	Iran 9.6
2. 01/08-01/14	Cruz 1.0	Meryl 5.0	Mueller 0.0	shutdown 0.0	Soleimani 5.9
3. 01/15-01/21	Cruz 10.7	inauguration 0.6	DACA 6.7	Poland 6.6	Parnas 0.0
4. 01/22-01/28	Cruz 10.6	inauguration 3.1	Mueller 2.7	border 0.0	culture 5.5
5. 01/29-02/04	Cruz 11.2	ban 2.1	Mueller 0.0	border 0.0	impeachment 0.0
6. 02/05-02/11	Cruz 5.3	Bannon 0.0	Mueller 0.0	memo 2.3	Vindman 2.5
7. 02/12-02/18	Cruz 9.9	Flynn 0.0	Mueller 0.0	emergency 0.0	Barr 2.2
8. 02/19-02/25	Rubio 3.8	Sweden 4.9	Parkland 0.3	Jussie 0.0	Bloomberg 6.3
9. 02/26-03/04	Rubio 9.2	Russia 6.4	Mueller 0.0	Cohen 3.7	coronavirus 0.0
10. 03/05-03/11	Cruz 1.9	Russia 4.8	border 0.0	Nadler 13.7	coronavirus 0.0
11. 03/12-03/18	Cruz 5.7	tax 1.8	Mueller 2.2	emergency 1.6	coronavirus 0.0
12. 03/19-03/25	Arizona 16.8	Nunes 0.0	Mueller 2.2	Barr 0.0	coronavirus 0.0
13. 03/26-04/01	women 8.3	Russia 9.9	Stormy 0.0	Schiff 5.2	coronavirus 0.5
14. 04/02-04/08	Cruz 1.5	Russia 2.8	Mueller 0.0	returns 0.0	coronavirus 0.0
15. 04/09-04/15	Cruz 1.7	Syria 6.4	Mueller 0.0	Barr 2.4	coronavirus 0.0
16. 04/16-04/22	Cruz 10.5	Russia 0.5	Mueller 0.0	Barr 0.1	coronavirus 0.0
17. 04/23-04/29	Cruz 3.0	days 0.1	Kanye 8.0	Biden 6.0	coronavirus 0.0
18. 04/30-05/06	Indiana 11.5	Trumpcare 0.0	Mueller 0.0	Barr 0.0	coronavirus 0.0
19. 05/07-05/13	Ryan 2.5	Comey 2.8	Iran 6.6	Barr 0.0	coronavirus 0.0
20. 05/14-05/20	Bernie 25.3	Comey 1.0	ZTE 4.5	Barr 0.0	coronavirus 0.0
21. 05/21-05/27	Clinton 9.5	budget 0.0	Korea 18.2	Barr 0.0	pandemic 0.0
22. 05/28-06/03	Hillary 11.9	Kathy 4.4	Roseanne 4.0	USS 3.0	Minneapolis 32.1
23. 06/04-06/10	Clinton 11.1	Comey 0.8	pardon 0.0	Mexico 27.6	police 4.2
24. 06/11-06/17	Orlando 12.4	Russia 0.0	Kim 4.1	foreign 2.0	Tulsa 1.0
25. 06/18-06/24	Hillary 23.3	Trumpcare 0.0	children 1.0	Iran 12.9	Tulsa 2.1
26. 06/25-07/01	Clinton 13.0	Russia 5.8	Justice 8.3	Moon 29.9	bounties 0.0
27. 07/02-07/08	Crooked 80.6	CNN 0.0	toddlers 0.0	parade 0.0	Rushmore 2.3
28. 07/09-07/15	Crooked 71.5	Putin 0.0	NATO 13.8	Epstein 0.0	coronavirus 0.0
29. 07/16-07/22	Pence 2.3	Mueller 0.0	Helsinki 3.1	racist 0.8	coronavirus 0.0
30. 07/23-07/29	DNC 6.1	Scouts 0.0	Cohen 0.0	Baltimore 13.6	Portland 11.8
31. 07/30-08/05	Khan 6.5	Mueller 0.0	LeBron 0.7	Baltimore 9.4	pandemic 0.0
32. 08/06-08/12	Crooked 55.2	Korea 5.8	Paso 7.6		USPS 0.0
33. 08/13-08/19	Manafort 0.0	Charlottesville 1.5	Omarosa 9.5	Greenland 0.0	USPS 0.0
34. 08/20-08/26	Clinton 7.6	Charlottesville 3.8	Cohen 2.7	Greenland 8.0	Biden 6.0
35. 08/27-09/02	Crooked 57.4	Harvey 0.0	Ohr 14.0	Dorian 12.2	Kenosha 9.5
36. 09/03-09/09	Bondi 0.0	DACA 2.4	resign 0.0	Poland 0.0	Atlantic 4.8
37. 09/10-09/16	deplorable 0.0	ESPN 2.7	Puerto 7.5	flavored 0.0	Woodward 2.6
38. 09/17-09/23	Clinton 6.5	Kim 4.9	Kavanaugh 1.7	Ukraine 4.5	coronavirus 0.0
39. 09/24-09/30	debate 6.9	Puerto 4.7	Kavanaugh 9.5	Ukraine 6.8	ballots 0.7
40. 10/01-10/07	Pence 4.9	Puerto 2.1	Kavanaugh 6.8	Ukraine 5.1	Covid 0.0
41. 10/08-10/14	sexual 0.3	Puerto 1.8	Kavanaugh 4.3	Kurds 8.2	
42. 10/15-10/21	rigged 0.1	Puerto 0.2	Saudi 5.3	Kurds 3.7	
43. 10/22-10/28	star 0.0	Mueller 0.0	caravan 0.0	impeachment 0.0	
44. 10/29-11/04	FBI 5.9	Mueller 0.0	caravan 0.0	impeachment 0.0	
45. 11/05-11/11	Clinton 0.9	Gillespie 12.0	Whitaker 6.2	Ukraine 0.0	
46. 11/12-11/18	Bannon 0.0	sexual 1.7	caravan 0.0	Ukraine 0.0	
47. 11/19-11/25	Hamilton 12.4	LaVar 21.3	Saudi 1.6	Ukraine 3.5	
48. 11/26-12/02	recount 0.0	Moore 0.0	Moscow 0.1	impeachment 3.1	
49. 12/03-12/09	Taiwan 7.8	Moore 0.0	Cohen 2.1	impeachment 0.0	
50. 12/10-12/16	Russia 2.9	Moore 0.0	Cohen 8.9	impeachment 0.0	
51. 12/17-12/23	inauguration 11.8	Mueller 0.0	wall 9.8	impeachment 1.4	
52. 12/24-12/31	inauguration 3.2	Mueller 0.0	wall 20.4	impeachment 7.6	

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Week	2016	2017	2018	2019	2020	2021
1. 01/01–01/07	Hillary 34.7	hacking 28.6	Bannon 2.2	shutdown 0.0	Iran 9.6	Georgia 14.7
2. 01/08–01/14	Cruz 1.0	Meryl 5.0	Mueller 0.0	shutdown 0.0	Soleimani 9.9	Capitol 0.1
3. 01/15–01/21	Cruz 10.7	inauguration 0.0	DACA 6.7	Pelosi 6.8	Parnas 0.0	Capitol 0.0
4. 01/22–01/28	Cruz 10.6	inauguration 3.1	Mueller 0.0	Pelosi 2.6	Vindman 3.3	insurrection 0.0
5. 01/29–02/04	Cruz 11.2	ban 2.1	Mueller 0.0	border 0.1	impeachment 0.0	Greene 0.0
6. 02/05–02/11	Cruz 5.1	Bannon 0.0	memo 2.3	Whitaker 0.0	Vindman 2.5	insurrection 0.0
7. 02/12–02/18	Cruz 6.9	Flynn 0.0	Mueller 0.0	emergency 0.0	Barr 2.2	Capitol 0.0
8. 02/19–02/25	Rubio 3.8	Sweden 4.9	Parkland 0.3	Jussie 0.0	Bloomberg 6.3	Capitol 0.0
9. 02/26–03/04	Rubio 9.2	Russia 6.4	Mueller 0.0	Cohen 3.7	coronavirus 0.0	Capitol 0.0
10. 03/05–03/11	Cruz 1.0	Russian 4.8	Mueller 0.0	Nadler 13.7	coronavirus 0.0	insurrection 0.0
11. 03/12–03/18	Cruz 5.7	tax 1.8	Mueller 2.2	emergency 1.6	coronavirus 0.0	Biden 0.0
12. 03/19–03/25	Arizona 16.8	Nunes 0.0	Mueller 2.2	Barr 0.0	coronavirus 0.0	Biden 0.0
13. 03/26–04/01	women 8.3	Russia 9.9	Stormy 0.0	Schiff 5.2	coronavirus 0.5	Capitol 0.0
14. 04/02–04/08	Cruz 1.5	Russia 2.8	Mueller 0.0	returns 0.0	coronavirus 0.0	Matt 0.0
15. 04/09–04/15	Cruz 1.7	Syria 0.4	Mueller 2.0	Barr 2.4	coronavirus 5.0	Capitol 0.0
16. 04/16–04/22	Cruz 10.5	Russia 0.5	Mueller 0.0	Barr 0.1	coronavirus 0.0	audit 0.0
17. 04/23–04/29	Cruz 3.0	days 0.1	Kanye 0.0	Biden 0.0	coronavirus 0.0	audit 0.0
18. 04/30–05/06	Indiana 11.5	Trumpcare 0.0	Mueller 0.0	Barr 0.0	coronavirus 0.0	Cheney 0.0
19. 05/07–05/13	Ryan 2.5	Comey 2.8	Iran 6.6	Barr 0.0	coronavirus 0.0	Cheney 0.0
20. 05/14–05/20	Bernie 25.3	Comey 1.0	ZTE 4.5	Barr 0.0	coronavirus 0.0	Cheney 0.0
21. 05/21–05/27	Clinton 9.5	budget 0.0	Korea 18.2	Barr 0.0	pandemic 0.0	Weisselberg 0.0
22. 05/28–06/03	Hillary 11.9	Kathy 4.4	Roseanne 0.0	USS 33.0	Minneapolis 0.0	reinstated 0.0
23. 06/04–06/10	Clinton 11.1	Comey 0.8	pardon 0.0	Mexico 27.6	police 4.2	McGahn 0.0
24. 06/11–06/17	Orlando 12.4	Mueller 0.0	Kim 4.1	foreign 2.0	Tulsa 4.5	DOJ 0.0
25. 06/18–06/24	Hillary 23.9	Trumpcare 0.0	children 1.0	Iran 12.9	Tulsa 2.1	Capitol 0.0
26. 06/25–07/01	Clinton 13.0	Russia 5.8	Justice 8.3	Moon 29.9	bounties 0.0	Organization 0.0
27. 07/02–07/08	OS Crooked 80.6	CNN 0.7	toddlers 0.0	parade 0.0	Rushmore 2.3	Weisselberg 0.0
28. 07/09–07/15	Crooked 71.5	Russian 1.2	NATO 13.0	racist 0.8	coronavirus 0.0	CPAC 0.0
29. 07/16–07/22	Pence 2.9	Mueller 0.0	Helsinki 3.1	racist 0.8	coronavirus 0.0	vaccinated 0.0
30. 07/23–07/29	DNC 6.1	Scouts 0.0	Cohen 0.0	Baltimore 13.6	Portland 11.8	Jan 0.0
31. 07/30–08/05	Khan 6.5	Mueller 0.0	LeBron 0.7	Baltimore 9.4	pandemic 0.0	Capitol 0.0
32. 08/06–08/12	Crooked 55.2	Korea 5.8	Omarosa 0.4	Paso 7.6	USPS 0.0	Rosen 0.0
33. 08/13–08/19	Manafort 0.0	Charlottesville 1.5	Omarosa 9.5	Greenland 6.9	USPS 0.0	Taliban 0.0
34. 08/20–08/26	Clinton 7.6	Charlottesville 3.8	Cohen 2.7	Greenland 8.0	Biden 6.6	Taliban 0.0
35. 08/27–09/02	Crooked 57.4	Harvey 0.0	Ohr 14.0	Dorian 12.2	Kenosha 9.5	Taliban 0.0
36. 09/03–09/09	Bondi 0.0	DACA 2.4	Kavanaugh 2.1	Dorian 12.6	Atlantic 4.8	Afghanistan 0.0
37. 09/10–09/16	deplorable 0.0	ESPN 2.7	Puerto 7.5	flavored 0.0	Woodward 2.6	Milley 0.0
38. 09/17–09/23	Clinton 6.5	Kim 4.9	Kavanaugh 1.7	Ukraine 4.5	coronavirus 0.0	Eastman 0.0
39. 09/24–09/30	debate 4.9	Puerto 0.4	Kavanaugh 9.5	Ukraine 6.8	ballots 0.7	audit 0.0
40. 10/01–10/07	Pence 4.9	Puerto 2.1	Kavanaugh 6.8	Ukraine 4.1	Covid 1.4	Bannon 0.0
41. 10/08–10/14	sexual 0.3	Puerto 1.8	Kavanaugh 4.3	Kurds 3.7	COVID 3.4	Powell 0.0
42. 10/15–10/21	rigged 10.1	Puerto 0.0	Saudi 5.3	Kurds 4.5	Biden 8.2	Powell 0.0
43. 10/22–10/28	star 0.0	Mueller 0.0	caravan 0.0	impeachment 0.0	Biden 9.2	Jan 0.0
44. 10/29–11/04	FBI 5.9	Mueller 0.0	caravan 0.0	impeachment 0.0	Biden 10.0	Youngkin 0.0
45. 11/05–11/11	Clinton 0.9	Gillespie 12.0	Whitaker 6.2	Ukraine 6.2	votes 3.4	infrastructure 0.0
46. 11/12–11/18	Bannon 0.0	sexual 1.7	caravan 0.0	Ukraine 5.2	Dominion 23.2	Christie 0.0
47. 11/19–11/25	Hamilton 12.4	LaVar 21.3	Saudi 1.6	Ukraine 3.5	Sidney 0.1	Rittenhouse 0.0
48. 11/26–12/02	recount 0.0	Moore 0.0	Moscow 0.1	impeachment 3.1	votes 24.1	Waukesha 0.0
49. 12/03–12/09	Taiwan 7.8	Mueller 0.0	Cohen 2.1	impeachment 0.0	Georgia 20.2	Meadows 0.0
50. 12/10–12/16	Russia 2.9	Mueller 0.0	Cohen 6.9	impeachment 0.0	vaccine 11.1	Meadows 0.0
51. 12/17–12/23	inauguration 11.8	Mueller 0.0	wall 9.8	impeachment 1.4	vaccine 15.4	Manchin 0.0
52. 12/24–12/31	inauguration 3.2	Mueller 0.0	wall 20.4	impeachment 7.6	Election 60.2	Trump 0.0

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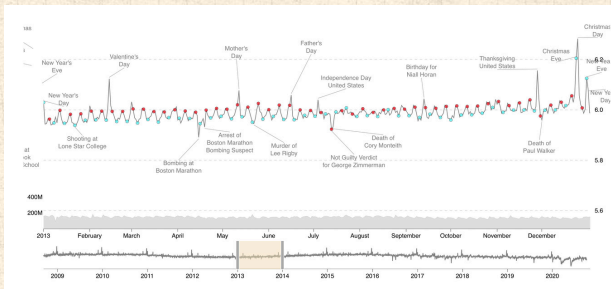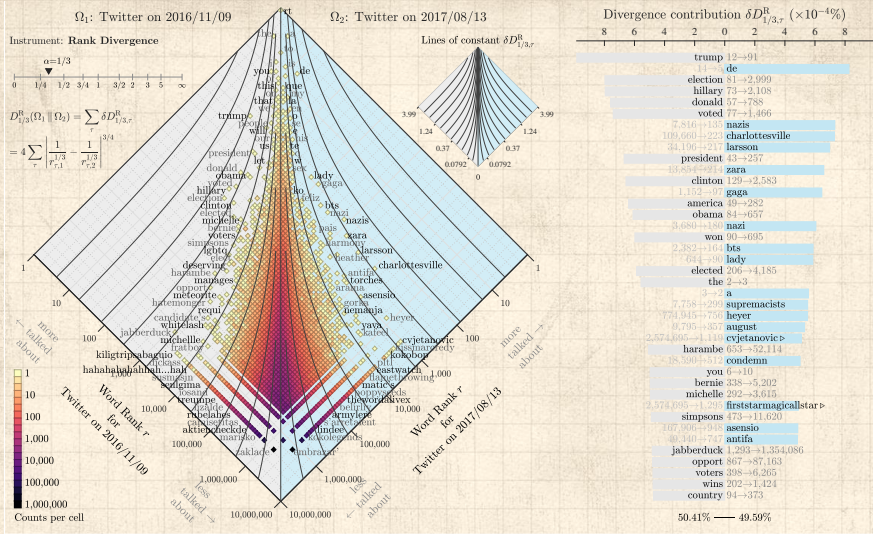Extras
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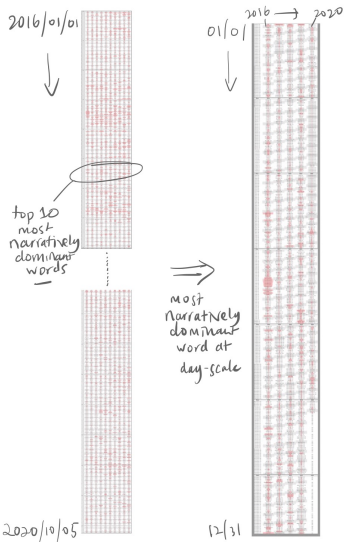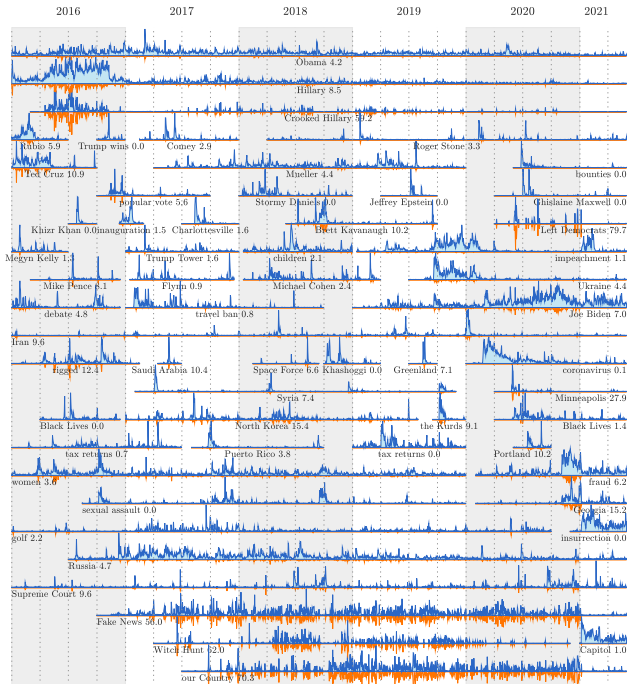Adjacent Narratives
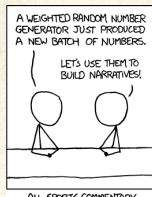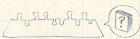
Extras
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References

Week	2016	2017	2018	2019	2020	2021
1. 01/01–01/07	Hillary Clinton 32.7	plant in 85.1	Steve Bannon 5.7	the government 0.0	a war 6.6	in Georgia 20.2
2. 01/08–01/14	Trump rally 0.0	Meryl Streep 6.6	shithole countries 0.0	the border 1.0	impeachment trial 0.0	the Capitol 0.0
3. 01/15–01/21	Ted Cruz 26.0	Trump's inauguration 0.0	the government 1.4	Cohen to 0.0	impeachment trial 0.0	the Capitol 0.0
4. 01/22–01/28	Megyn Kelly 4.2	executive order 0.0	the FBI 5.6	the government 0.0	impeachment trial 0.0	the Capitol 0.0
5. 01/29–02/04	Ted Cruz 19.7	travel ban 1.6	the FBI 9.4	Ralph Northam 0.0	impeachment trial 0.0	the Capitol 0.0
6. 02/05–02/11	New Hampshire 19.6	travel ban 1.1	military parade 0.0	El Paso 4.7	Alexander Vindman 0.0	the Capitol 0.0
7. 02/12–02/18	Ted Cruz 15.7	Michael Flynn 0.0	school shooting 3.1	national emergency 0.0	Roger Stone 4.0	the Capitol 0.0
8. 02/19–02/25	Ted Cruz 30.1	Trump administration 0.0	the NRA 0.0	Jussie Smollett 0.0	Bernie Sanders 13.6	the Capitol 0.0
9. 02/26–03/04	vote for 4.4	to Russia 12.9	Hope Hicks 0.0	Michael Cohen 5.3	the coronavirus 0.0	the Capitol 0.0
10. 03/05–03/11	Ted Cruz 2.4	travel ban 0.0	Stormy Daniels 0.0	Tim Apple 0.0	the coronavirus 0.0	voted for 0.0
11. 03/12–03/18	Trump is 0.0	Meals on 0.0	Stormy Daniels 0.0	New Zealand 17.9	the coronavirus 0.0	Lara Trump 0.0
12. 03/19–03/25	Lyin' Ted 66.2	health care 0.0	Cambridge Analytica 0.0	Robert report 0.0	the coronavirus 0.0	the border 0.0
13. 03/26–04/01	Trump is 0.0	Freedom Caucus 20.8	Stormy Daniels 0.0	Mueller report 0.0	the coronavirus 0.0	Matt Gaetz 0.0
14. 04/02–04/08	Ted Cruz 3.9	Susan Rice 0.3	National Guard 0.0	tax returns 0.0	the coronavirus 0.0	Matt Gaetz 0.0
15. 04/09–04/15	New York 19.3	in Syria 0.2	sanctuary cities 5.3	the coronavirus 0.0	the coronavirus 0.0	Matt Gaetz 0.0
16. 04/16–04/22	Ted Cruz 28.1	turnout for 0.0	Michael Cohen 2.4	Mueller report 0.0	the coronavirus 0.0	Maxine Waters 0.0
17. 04/23–04/29	Trump rally 0.0	tax plan 0.0	the Korean 0.0	Mueller report 0.0	the coronavirus 0.0	Liz Cheney 0.0
18. 04/30–05/06	Ted Cruz 5.5	health care 0.0	Stormy Daniels 0.0	Mueller report 0.0	treated worse 0.0	Liz Cheney 0.0
19. 05/07–05/13	Paul Ryan 2.0	James Comey 6.7	the Iran 9.0	tax returns 0.0	tested positive 0.0	Liz Cheney 0.0
20. 05/14–05/20	Hillary Clinton 26.5	Saudi Arabia 12.5	are animals 0.0	Lindsey Graham 0.0	the pandemic 0.0	Kevin McCarthy 0.0
21. 05/21–05/27	Hillary Clinton 24.8	Saudi Arabia 8.2	the FBI 23.3	Nancy Pelosi 12.5	a mask 6.3	the January 0.0
22. 05/28–06/03	Trump University 3.4	Kathy Griffin 5.1	Samantha Bee 4.4	John McCain 0.0	photo op 0.0	Memorial Day 0.0
23. 06/04–06/10	Hillary Clinton 10.5	Justin Trudeau 8.5	with Mexico 39.2	Joe Biden 0.0	Left Democrats 75.1	Jean Carroll 0.0
24. 06/11–06/17	Trump is 0.0	obstruction of 12.6	their parents 0.9	the FBI 8.5	in Tulsa 2.1	Trump DOJ 0.0
25. 06/18–06/24	Hillary Clinton 20.6	Karen Handel 16.6	their parents 3.4	need soap 0.0	in Tulsa 7.2	in Tulsa 0.0
26. 06/25–07/01	Hillary Clinton 20.5	Fake News 31.6	Supreme Court 3.7	Jean Carroll 0.0	American soldiers 0.0	Trump Organization 0.0
27. 07/02–07/08	Crooked Hillary 82.8	North Korea 28.6	Trump administration 0.0	Jeffrey Epstein 0.0	Mount Rushmore 3.9	Ashli Babbitt 0.0
28. 07/09–07/15	Crooked Hillary 73.3	Trump Jr 0.0	Supreme Court 7.9	Jeffrey Epstein 0.0	Roger Stone 0.0	the Capitol 0.0
29. 07/16–07/22	Mike Pence 6.8	Secret Service 0.0	in Helsinki 1.7	a racist 0.0	in Portland 0.0	Tom Barrack 0.0
30. 07/23–07/29	Crooked Hillary 79.6	Boy Scouts 0.0	Walk of 0.0	Elijah Cummings 27.2	in Portland 8.9	the Capitol 0.0
31. 07/30–08/05	Khizr Khan 0.0	Maxine Waters 0.0	enemy of 22.2	El Paso 11.1	the election 3.4	the Capitol 0.0
32. 08/06–08/12	Hillary Clinton 10.5	North Korea 5.7	Space Force 11.1	El Paso 7.7	Social Security 0.0	overturn the 0.0
33. 08/13–08/19	Trump campaign 0.0	white supremacists 0.0	security clearance 0.0	New Hampshire 26.5	the USPS 0.0	the Taliban 0.0
34. 08/20–08/26	Hillary Clinton 8.5	Joe Arpaio 3.5	Michael Cohen 4.3	Greenland 28.7	Joe Biden 5.9	the Taliban 0.0
35. 08/27–09/02	Crooked Hillary 61.8	Hurricane Harvey 0.1	John McCain 9.6	Hurricane Dorian 0.0	Joe Biden 2.7	the Taliban 0.0
36. 09/03–09/09	in Detroit 0.0	to end 0.0	Brett Kavanaugh 7.6	the Taliban 3.0	Joe Biden 0.0	Robert 0.0
37. 09/10–09/16	tax returns 0.0	white supremacist 0.0	Puerto Rico 8.4	Dan Bishop 37.7	Joe Biden 13.3	to overturn 0.0
38. 09/17–09/23	Trump Jr 0.0	North Korea 12.8	Blasey Ford 0.0	a foreign 4.3	Supreme Court 7.3	to overturn 0.0
39. 09/24–09/30	Hillary Clinton 7.5	Puerto Rico 5.2	Brett Kavanaugh 15.3	impeachment inquiry 0.0	Supreme Court 0.0	debt ceiling 0.0
40. 10/01–10/07	Mike Pence 8.9	Puerto Rico 2.6	Supreme Court 4.9	Adam Schiff 4.3	Walter Reed 5.7	the debt 0.0
41. 10/08–10/14	sexual assault 0.0	Puerto Rico 0.0	Kanye West 0.0	the Kurds 11.3	Biden is 26.5	the January 0.0
42. 10/15–10/21	Hillary Clinton 19.9	families of 0.0	Saudi Arabia 6.6	the Kurds 3.8	Joe Biden 12.1	the January 0.0
43. 10/22–10/28	Hillary Clinton 6.7	Myeshia Johnson 0.0	the bombs 0.0	World Series 0.0	Joe Biden 10.1	Alec Baldwin 0.0
44. 10/29–11/04	Hillary Clinton 6.5	Twitter employee 0.0	birthright citizenship 0.0	the impeachment 0.0	Joe Biden 16.2	in Virginia 0.0
45. 11/05–11/11	Trump wins 0.0	mental health 0.0	Jim Acosta 0.0	pro quo 8.1	the election 2.2	infrastructure bill 0.0
46. 11/12–11/18	Steve Bannon 0.0	Roy Moore 0.1	president who 0.0	impeachment inquiry 0.0	the election 7.5	Chris Christie 0.0
47. 11/19–11/25	Mike Pence 24.3	Roy Moore 6.8	Saudi Arabia 2.5	quid pro 1.3	the election 6.7	Kyle Rittenhouse 0.0
48. 11/26–12/02	popular vote 7.4	Native American 0.0	Trump Tower 2.5	Hong Kong 0.0	voter fraud 2.2	Donald Trump 0.0
49. 12/03–12/09	Air Force 18.2	Roy Moore 3.5	campaign finance 0.0	to impeach 7.7	in Georgia 12.9	Donald Trump 0.0
50. 12/10–12/16	of State 7.6	of sexual 0.0	Michael Cohen 7.8	articles of 0.0	the election 9.0	Mark Meadows 0.0
51. 12/17–12/23	Electoral College 5.8	tax bill 0.0	the wall 13.7	Christianity Today 8.1	election fraud 13.9	the Capitol 0.0

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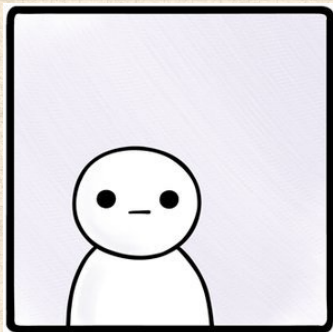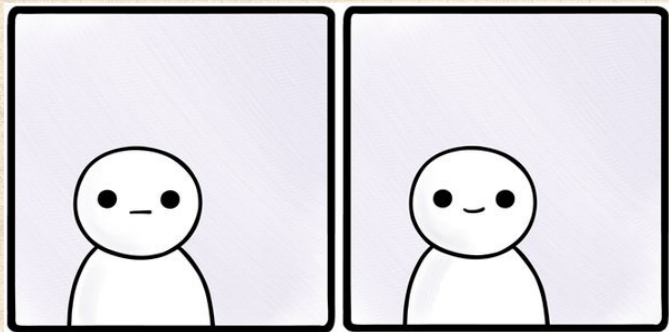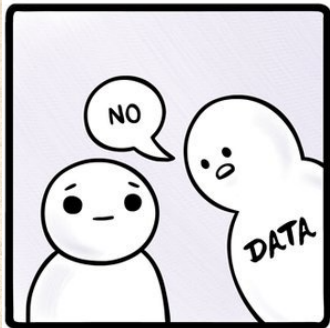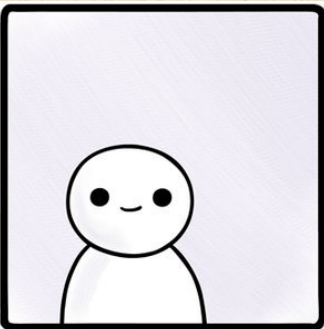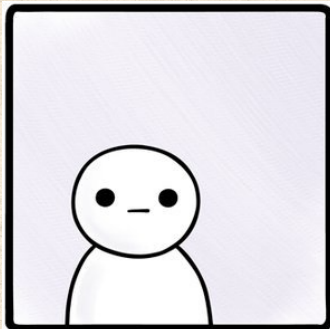Adjacent Narratives

Extras
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References

2016   2017   2018   2019   2020   2021

Obama 4.2
Hillary 8.5
Crooked Hillary 4.2
Rubio 5.9   Trump wins 0.0   Comey 2.9   Roger Stone 3.3
Ted Cruz 10.9   Mueller 4.4   bounties 0.0
popular vote 5,6   Stormy Daniels 0.0   Jeffrey Epstein 0.0   Ghislaine Maxwell 0.0
Khizr Khan 0.0inauguration 1.5 Charlottesville 1.6   Brett Kavanaugh 10.2   Left Democrats 79.7
Megyn Kelly 1.3   Trump Tower 1.6   children 2.1   impeachment 1.1
Mike Pence 6.1   Flynn 0.9   Michael Cohen 2.4   Ukraine 4.4
debate 4.8   travel ban 0.8   Joe Biden 7.0
Iran 9.6   coronavirus 0.1
figg-t 12.4   Saudi Arabia 10.4   Space Force 6.6 Khashoggi 0.0   Greenland 7.1
Syria 7.4   Minneapolis 27.9
Black Lives 0.0   North Korea 15.4   the Kurds 9.1   Black Lives 1.4
tax returns 0.7   Puerto Rico 3.8   tax returns 0.0   Portland 10.2
women 3.6   fraud 6.2
sexual assault 0.0   Georgia 15.2
golf 2.2   insurrection 0.0
Russia 4.7
Supreme Court 9.6
Fake News 50.0
Witch Hunt 62.0   Capitol 1.0
our Country 76.3

A. Chronopathic equivalency heat map for δ-days-ago surrounding Trump

$D^{\mathrm{R}}_{1/4}$

B. Number-of-days-ago chronopathically equivalent to 14-days-ago in April, 2020

C. Number-of-days-ago chronopathically equivalent to 56-days-ago in May, 2020

D. Number-of-days-ago chronopathically equivalent to 182-days-ago in August, 2020

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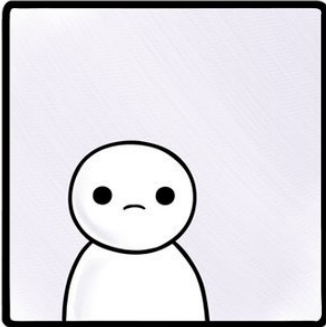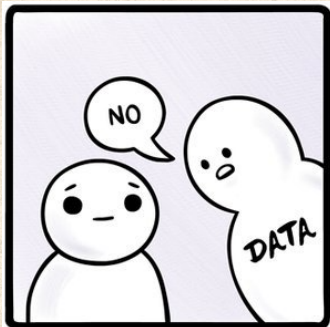Extras
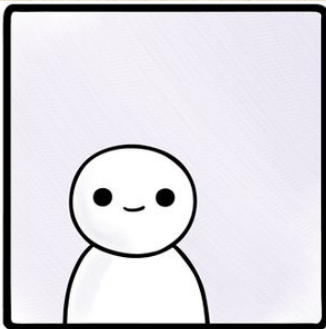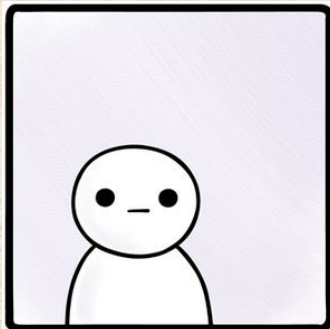Sociotechnical time series
Adjacent Narratives

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A WEIGHTED RANDOM NUMBER
GENERATOR JUST PRODUCED
A NEW BATCH OF NUMBERS.

LET'S USE THEM TO
BUILD NARRATIVES!

ALL SPORTS COMMENTARY

xkcd.com/904/⌐

- Toward a Science of Stories.
- Claim: Homo narrativus⌐—we run on stories.
- "What's the John Dory?"
- "They've lost the plot/thread"
- Narrative hierarchies and scalability of stories⌐.
- Research: Real-time and offline extraction of metaphors, frames, plots, narratives, conspiracy theories, and stories from large-scale text.
- Research: The taxonomy of human stories.
- To be built: Storyscopes—improvable, online, interactive instruments.

ding!

On Instagram at pratchett_the_cat

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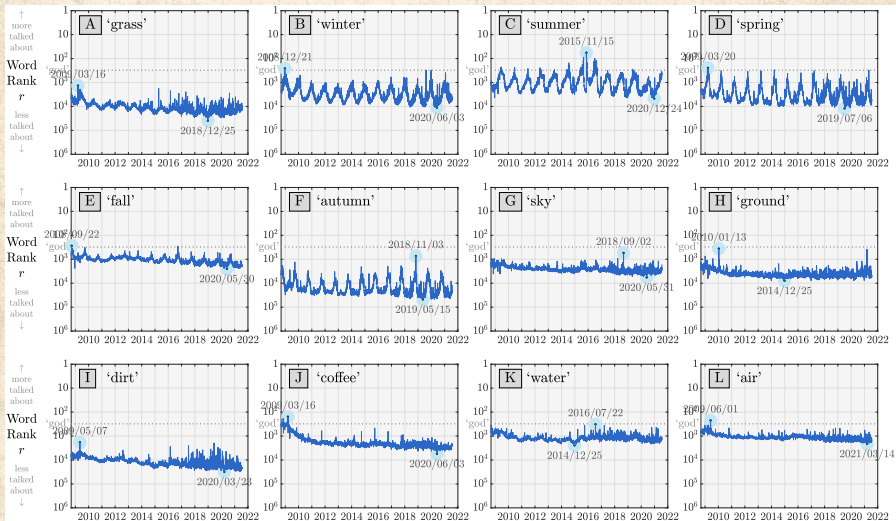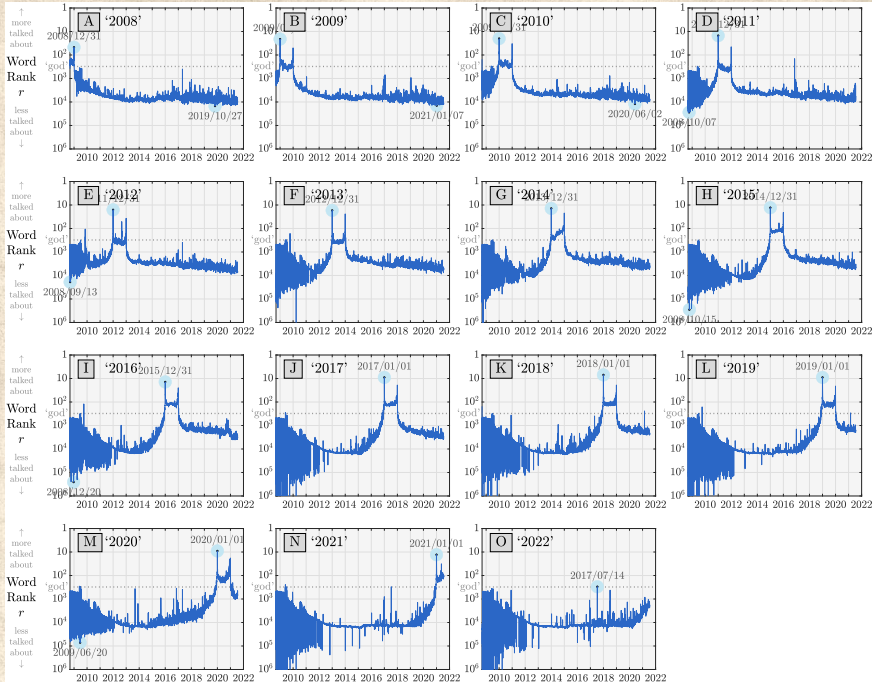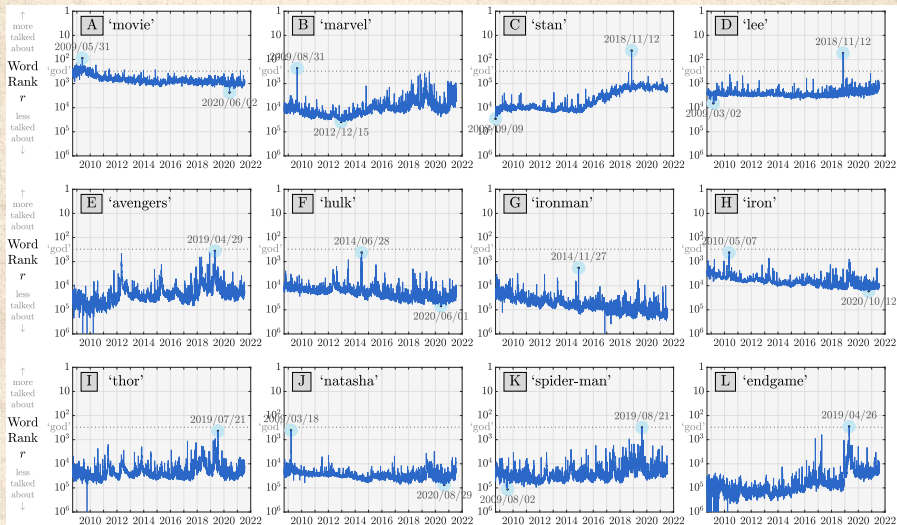Turbulent times

Extras
Sociotechnical time series
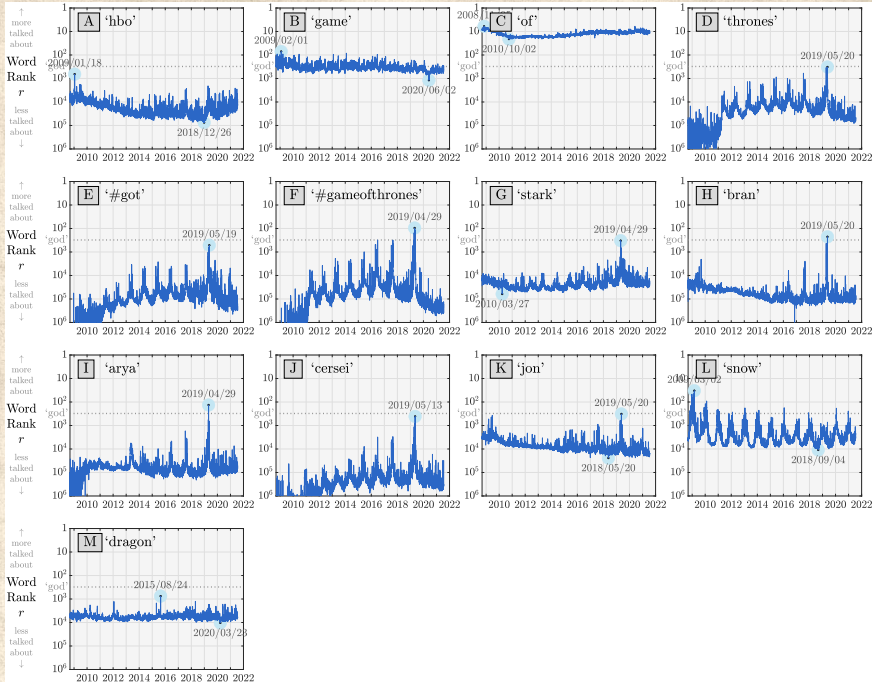Adjacent Narratives

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Memory & Turbulence

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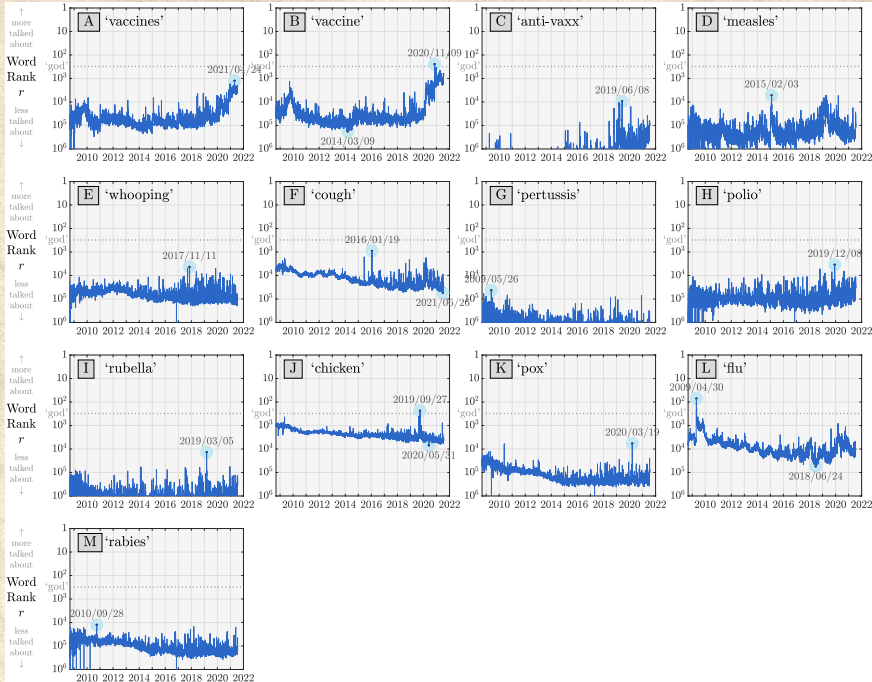Adjacent Narratives

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Word Rank r plots for twelve Marvel-related search terms.

- **A** 'movie' — 2000/05/31, 2020/06/02
- **B** 'marvel' — 2009/08/31, 2012/12/15
- **C** 'stan' — 2018/11/12, 2008/09/09
- **D** 'lee' — 2018/11/12, 2009/03/02
- **E** 'avengers' — 2019/04/29
- **F** 'hulk' — 2014/06/28, 2020/06/01
- **G** 'ironman' — 2014/11/27
- **H** 'iron' — 2010/05/07, 2020/10/12
- **I** 'thor' — 2019/07/21
- **J** 'natasha' — 2017/03/18, 2020/08/29
- **K** 'spider-man' — 2019/08/21, 2009/08/02
- **L** 'endgame' — 2019/04/26

Figure showing word rank timelines (2010–2022) for eight terms, each in its own panel labeled A–H. The vertical axis for each panel is "Word Rank r", ranging from more talked about (↑) at top to less talked about (↓) at bottom, with a dotted reference line marked 'god'.

- **A** 'ipo' — 2012/05/18
- **B** 'uber' — 2011/02/18, 2013/12/01
- **C** 'lyft' — 2017/01/01
- **D** 'airbnb' — 2021/04/14
- **E** 'pinterest' — 2021/02/23
- **F** 'tumblr' — 2010/12/06, 2020/03/18
- **G** 'grindr' — 2019/08/14
- **H** 'tinder' — 2018/08/23

Figure showing Word Rank time series plots (2008–2022) for hurricane-related terms:

- **A** 'hurricane' — 2012/10/29, 2021/05/05
- **B** 'sandy' — 2012/10/29, 2020/01/04
- **C** 'irene' — 2011/08/27, 2008/09/20
- **D** 'harvey' — 2017/08/29, 2020/09/30
- **E** 'houston' — 2012/02/11, 2020/04/18
- **F** 'irma' — 2017/09/10
- **G** 'maria' — 2011/03/29, 2020/05/31
- **H** 'puerto' — 2017/09/30, 2020/05/10
- **I** 'rico' — 2017/09/30, 2009/03/16

Each plot has vertical axis labeled "Word Rank r" ranging from more talked about (top) to less talked about (bottom), with a dotted reference line labeled 'god'.

Word Rank r over time for a series of K-pop related search terms. The y-axis ranges from more talked about (top) to less talked about (bottom), with the 'god' reference line marked.

- **A** '@bts_twt' 2018/05/20
- **B** 'bts' 2019/04/24 2008/12/26
- **C** '#bts' 2018/12/14
- **D** '@weareoneexo' 2017/02/25
- **E** 'exo' 2016/12/02
- **F** '#exo' 2018/11/02
- **G** 'superm' 2019/10/04

A 'messi' 2014/07/13 2009/09/14

B 'ronaldo' 2016/07/10 2009/10/05

C 'neymar' 2014/07/04

D 'gagibol' 2019/09/17

E 'lebron' 2010/07/08 2008/10/16

F 'brady' 2017/02/05 2020/06/09

G 'belichick' 2019/09/07

H 'phelps' 2016/08/09

I 'kohli' 2016/03/27

A 'serena' 2018/09/09 2020/03/25

B 'wozniacki' 2007/02/19

C 'hingis' 2015/07/11

D 'sharapova' 2016/03/07

E 'federer'

F 'nadal'

G 'djokovic'

Word Rank r

↑ more talked about

↓ less talked about

'god'

Word Rank r over time for various words related to political and legal figures and proceedings.

A 'mcgahn' — 2019/05/21

B 'giuliani' — 2018/05/03

C 'manafort' — 2017/10/30

D 'papadopolous' — 2017/10/30

E 'cypher' — 2017/05/09

F 'conviction' — 2009/08/23

G 'trial' — 2020/01/24, 2012/12/25

H 'nunes' — 2016/12/31

I 'stone' — 2019/01/25, 2020/03/31

J 'flynn' — 2017/02/14

K 'cohen' — 2019/02/27, 2020/03/11

L 'lewandowski' — 2013/04/24

The figure consists of 15 small multiples (labeled A through O), each showing a time series of Word Rank r (vertical axis, logarithmic scale from 1 to 10^6, with "more talked about" at top and "less talked about" at bottom) versus year (horizontal axis, 2010 to 2022). Each panel is annotated with a Twitter handle and a highlighted date.

Panel	Handle	Annotated date
A	'@realdonaldtrump'	2020/11/07
B	'@andrewyang'	2020/02/11
C	'@waynemessam'	2019/03/28
D	'@sethmoulton'	2017/05/18
E	'@timryan'	2021/05/19
F	'@joesestak'	2009/11/01
G	'@tomsteyer'	2020/03/05
H	'@marwilliamson'	2019/07/31
I	'@michaelbennet'	2019/08/14
J	'@governorbullock'	2019/10/22
K	'@billdeblasio'	2019/09/20
L	'@hickenlooper'	2020/09/21
M	'@johndelaney'	2019/07/31
N	'@jayinslee'	2020/06/11
O	'@mikebloomberg'	2020/02/19

THE LAWS OF
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$P \sim S$

THE END

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Mt.
Very surprising

Mts. Most of
the time

Mt.
OMG!

Mt.
Exogenous

Mt.
Financial
Collapse

The Unexpected Mountains
of Reality

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$t^{1/2}$

t

The Snormals

The Random Road
through the Forests of Forgettable Events

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$t^{\frac{1}{2}+\alpha}$

t

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Size

The Road of Surprises
through the Disconcerting Woods

The Unexpected
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Money
≡
Belief

"Building a better America—One wealth quintile at a time"
Norton and Ariely, 2011. [15]

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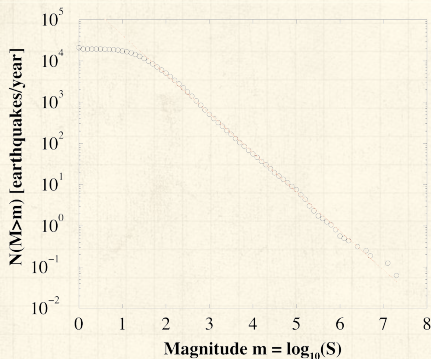Superspreading

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Two questions about wealth distribution in the
United States:

"Building a better America—One wealth quintile at a time"
Norton and Ariely, 2011. [15]

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Two questions about wealth distribution in the United States:

1. Estimate the percentage of all wealth owned by individuals when grouped into quintiles.

"Building a better America—One wealth quintile at a time"
Norton and Ariely, 2011. [15]

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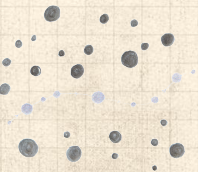Adjacent Narratives
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Two questions about wealth distribution in the United States:

1. Estimate the percentage of all wealth owned by individuals when grouped into quintiles.
2. Estimate what you believe each quintile should own, ideally.

"Building a better America—One wealth quintile at a time"
Norton and Ariely, 2011. [15]

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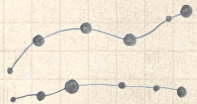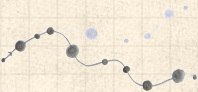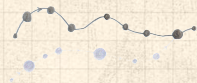Adjacent Narratives
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Money
$\equiv$
Belief

Two questions about wealth distribution in the
United States:

1. Estimate the percentage of all wealth owned by
   individuals when grouped into quintiles.
2. Estimate what you believe each quintile should
   own, ideally.
3. Extremes: 100, 0, 0, 0, 0 and 20, 20, 20, 20, 20

"Building a better America—One wealth quintile at a time"
Norton and Ariely, 2011. [15]

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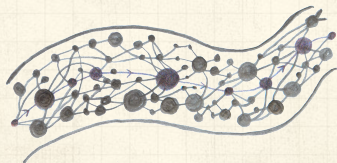Sociotechnical time series
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Wealth distribution in the United States: [15]
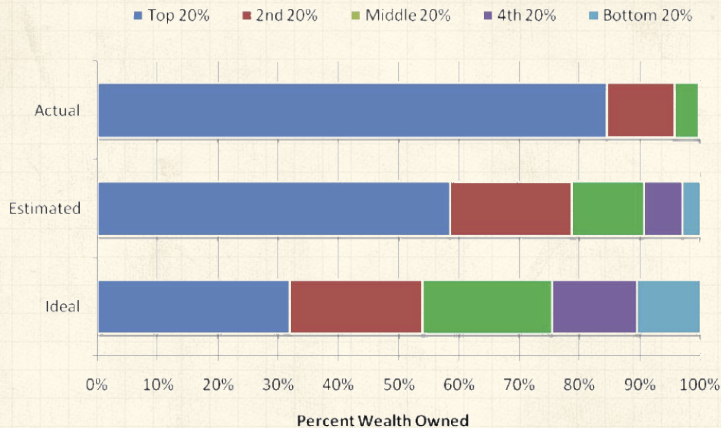
Fig. 2. The actual United States wealth distribution plotted against the estimated and ideal distributions across all respondents. Because of their small percentage share of total wealth, both the "4th 20%" value (0.2%) and the "Bottom 20%" value (0.1%) are not visible in the "Actual" distribution.

"Building a better America—One wealth quintile at a time"
Norton and Ariely, 2011. [15]

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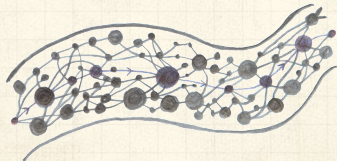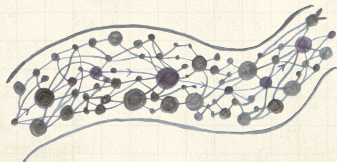
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Wealth distribution in the United States: [15]

Fig. 3. The actual United States wealth distribution plotted against the estimated and ideal distributions of respondents of different income levels, political affiliations, and genders. Because of their small percentage share of total wealth, both the "4th 20%" value (0.2%) and the "Bottom 20%" value (0.1%) are not visible in the "Actual" distribution.

Aside: The 1% framing may be effective but makes no sense.

My, what big words you have …

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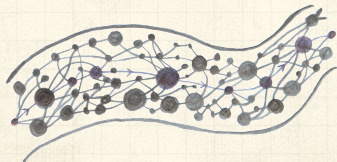
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Test your vocab — *How many words do you know?*

🧩 Test ⧉ capitalizes on word frequency following a heavily skewed frequency distribution with a decaying power-law tail.

🧩 This Man Can Pronounce Every Word in the Dictionary ⧉ (story here ⧉)

🧩 Best of Dr. Bailly ⧉

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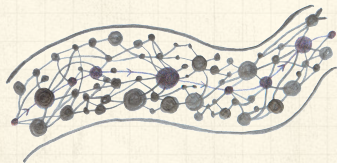Adjacent Narratives
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Gutenberg-Richter law 🔗

🦣 Log-log plot

🦣 Base 10

🦣 Slope = -1

$$N(M > m) \propto m^{-1}$$

🦣 From both the very awkwardly similar Christensen et al. and Bak et al.:
"Unified scaling law for earthquakes" [5, 2]

Outline

THE ADJACENT NARRATIVES

Adjacent narratives ☐—why mistruths and conspiracy theories ☐ exist and flourish:
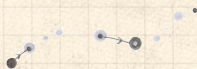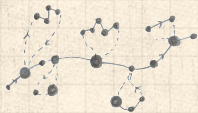
Why adjacent narratives exist and untrue stories flourish:

1/4. A real story is never recorded and retold completely

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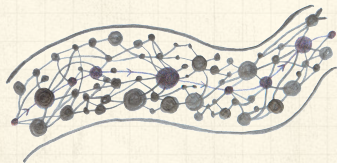
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1/4. A real story is never recorded and retold completely

- 🧊 Impossible to record every detail.

Why adjacent narratives exist and untrue stories flourish:

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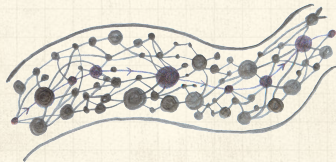Adjacent Narratives
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1/4. A real story is never recorded and retold completely

- Impossible to record every detail.
- Recording entails compression to scale of medium (narrative hierarchy).

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1/4. A real story is never recorded and retold completely

- 🧊 Impossible to record every detail.
- 🧊 Recording entails compression to scale of medium (narrative hierarchy).
- 🧊 Story logic will be favored, and seemingly irrelevant aspects discarded.

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2/4. The infinitude of adjacent stories will afford "better" stories

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2/4. The infinitude of adjacent stories will afford "better" stories

🎲 Better = More engaging, more motivating to spread, more durable under spreading.

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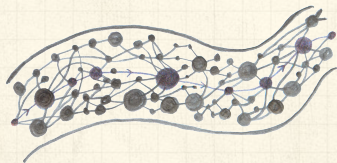Sociotechnical time series
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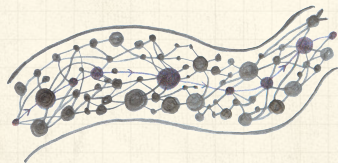
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2/4. The infinitude of adjacent stories will afford "better" stories

- 🎲 Better = More engaging, more motivating to spread, more durable under spreading.
- 🎲 Better stories exist for truthful recorders and retellers (journalists).

Why adjacent narratives exist and untrue stories flourish:

3/4. The infinitude of adjacent stories means "better" stories exist for those who would disinform

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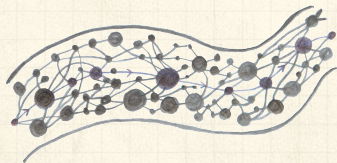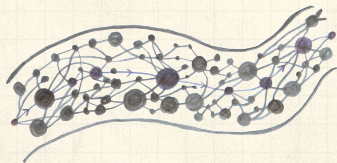
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3/4. The infinitude of adjacent stories means "better" stories exist for those who would disinform

- Adjacent stories may be truth-limited and/or falsehood-bearing.

Why adjacent narratives exist and untrue stories flourish:

3/4. The infinitude of adjacent stories means "better" stories exist for those who would disinform

- Adjacent stories may be truth-limited and/or falsehood-bearing.
- There may exist adjacent stories that conform to a world view/ideology.

Why adjacent narratives exist and untrue stories flourish:

3/4. The infinitude of adjacent stories means "better" stories exist for those who would disinform

- Adjacent stories may be truth-limited and/or falsehood-bearing.
- There may exist adjacent stories that conform to a world view/ideology.
- Even the seemingly non-adjacent must have some plausibility (Pizzagate).

Why adjacent narratives exist and untrue stories flourish:

4/4. Character is the short cut to story

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4/4. Character is the short cut to story

- The barely implausible can be believed if the character can make it so.

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4/4. Character is the short cut to story

- ⬡ The barely implausible can be believed if the character can make it so.
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4/4. Character is the short cut to story

- 📦 The barely implausible can be believed if the character can make it so.
- 📦 A believe-to-be evil character can do anything.
- 📦 Iterate between character and story to make the character fixed.

Things that spread quickly:

:-p

LOL win omg cute geeky trashy fail wtf

+ News + Conspiracy Theories …

buzzfeed.com🗗:

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The three fundamental events of (non-clone) life:

The boiled-down essence of stories:

The three fundamental events of (non-clone) life:

- Hatchings, Matchings, and Dispatchings.

The boiled-down essence of stories:

The three fundamental events of (non-clone) life:

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⚖ Stories encode survival algorithms.

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The three fundamental events of (non-clone) life:

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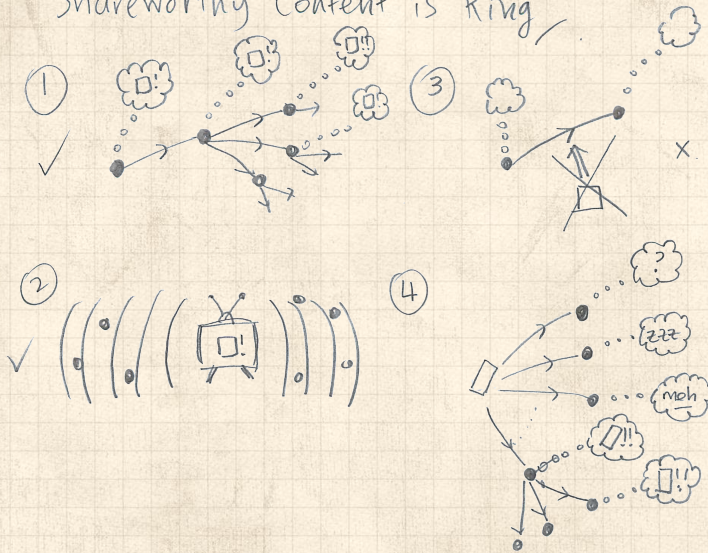Sociotechnical time series
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- 🧊 Stories encode survival algorithms.
- 🧊 Survival algorithms are for both individuals and groups.
- 🧊 Stories are dynamic paths of the true, the possible, the unlikely.
- 🧊 The unifying theme of existence is existence.

Deep fame:

Shareworthy Content is King

① ✓

② ✓

③ ✗

④

Shareworthy Content is "King":

1. Build entities/messages/stories that have intrinsic
   and social value out in the Social Wild.

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5. Essential implication: Billions of people can be harmoniously wrong.

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6. Beware the evil, payola version.

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5. Essential implication: Billions of people can be harmoniously wrong.

6. Beware the evil, payola version.

7. Challenge: What's the societal vaccine for conspiracy theories?

Fame: Zipfian rank-frequency plots

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George Kingsley Zipf:

🎲 Noted various rank distributions
have power-law tails, often with exponent near -1
(word frequency, city sizes, species numbers, ...)

🎲 Zipf's 1949 Magnum Opus ⬀:

"Human Behaviour and the Principle of
Least-Effort" ⓐ ⬀
by G. K. Zipf (1949). [20]

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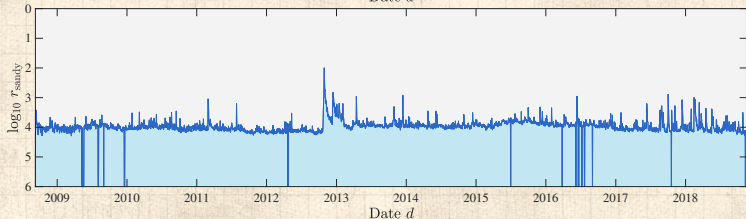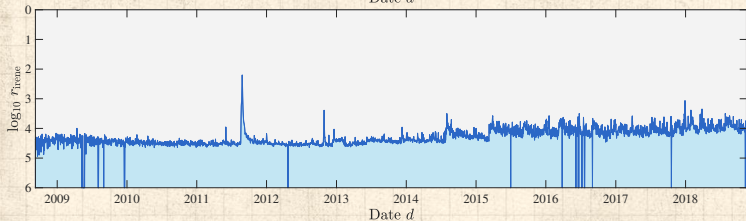Extras
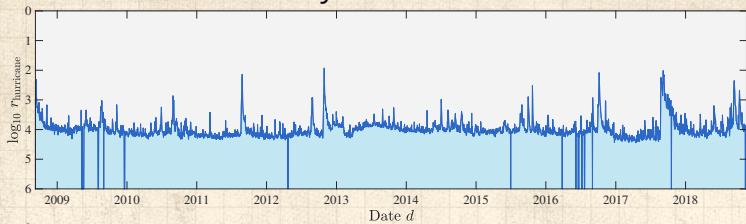Sociotechnical time series
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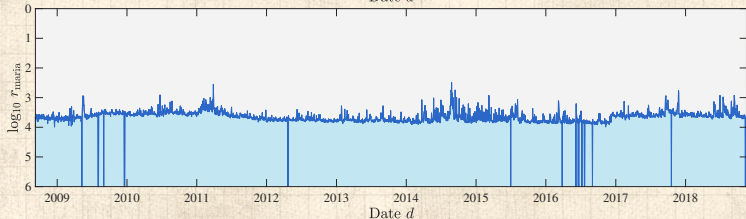Sociotechnical time series
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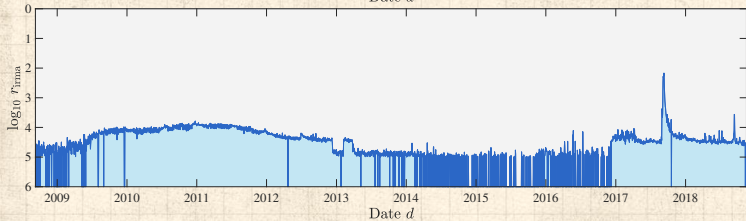Extras
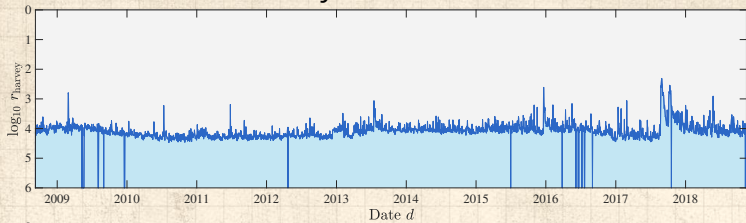Sociotechnical time series
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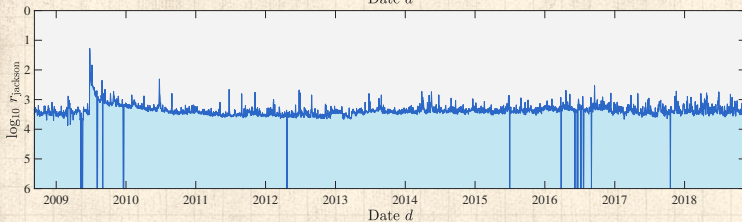Sociotechnical time series
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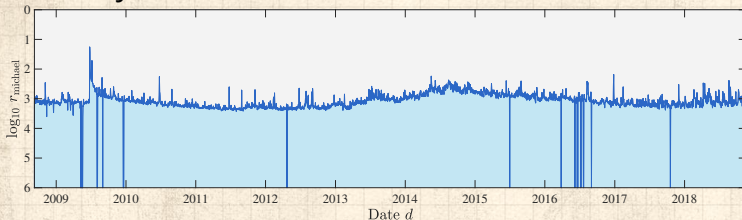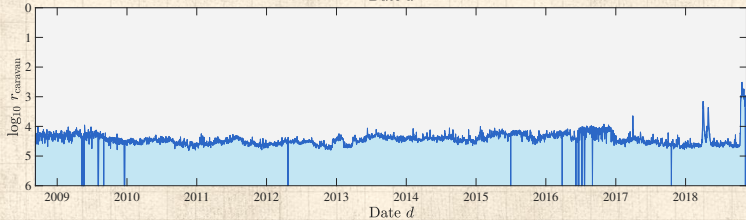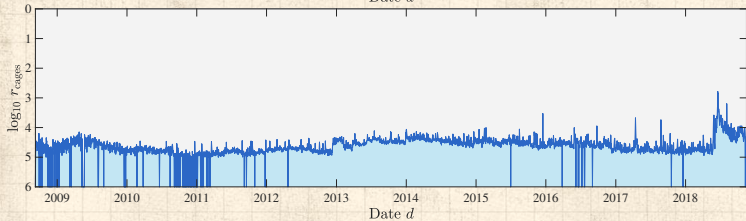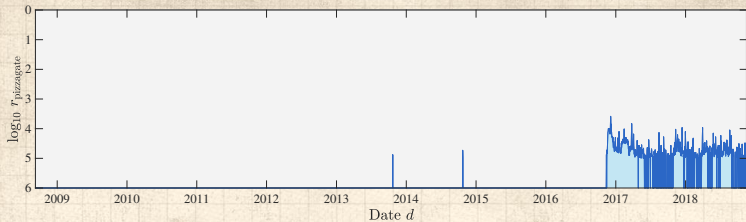Sociotechnical time series
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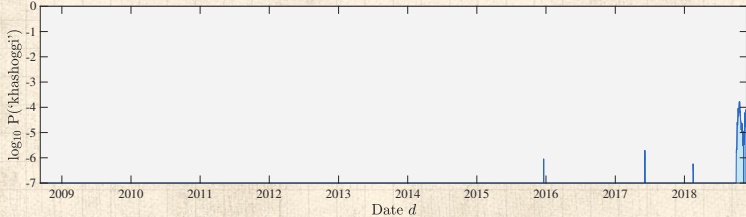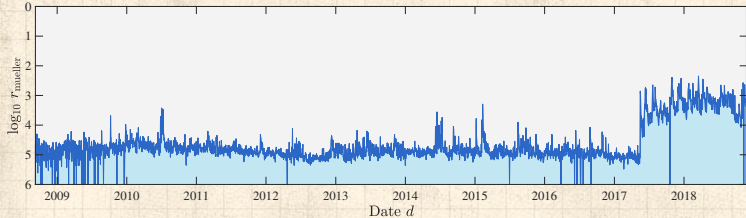Lexical Ultrafame

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Story turbulence:

2012	2013	2014	2015	2016	2017	2018
1.6 m	3.3 w	5.1 d	2.5 d	1.9 d	1.3 d	1.0 d
1.1 y	1.2 y	1.1 y	4.7 m	2.4 m	5.7 d	2.0 d
1.3 y	1.5 y	1.3 y	1.1 y	8.3 m	2.6 w	3.0 d
1.4 y	2.0 y	1.6 y	1.2 y	1.2 y	1.7 m	1.1 w
1.6 y	2.1 y	2.1 y	1.3 y	1.3 y	3.1 m	2.1 w
2.1 y	2.3 y	2.3 y	1.7 y	2.0 y	1.2 y	3.0 m
2.2 y	2.4 y	2.6 y	2.1 y	2.1 y	1.5 y	6.1 m
2.1 y	2.3 y	2.3 y	1.7 y	2.1 y	1.2 y	1.0 y
2.4 y	2.7 y	3.2 y	2.3 y	2.3 y	2.2 y	2.0 y

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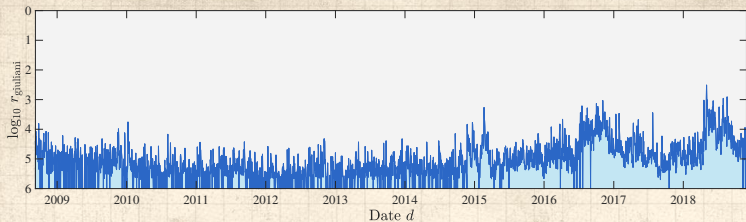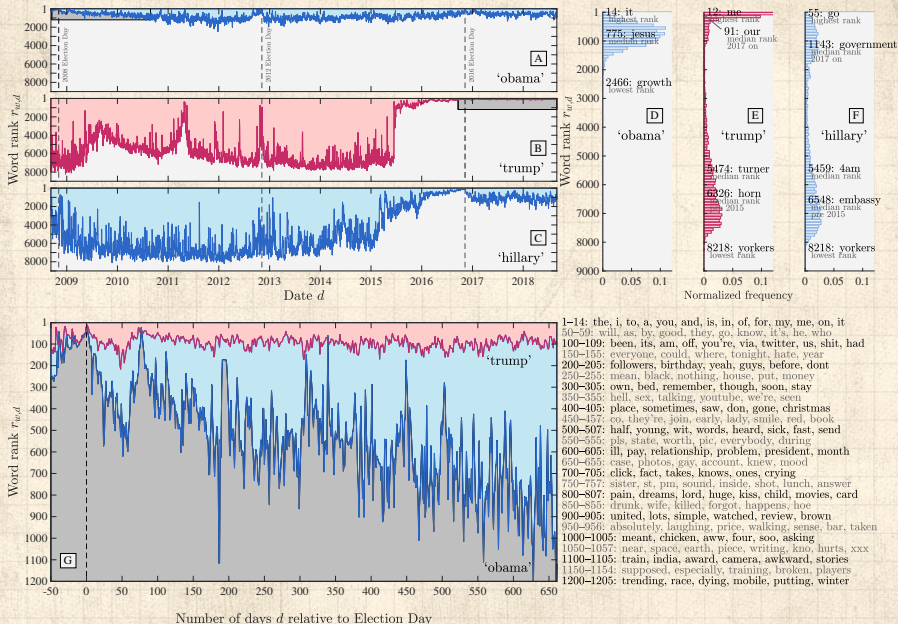Superspreading
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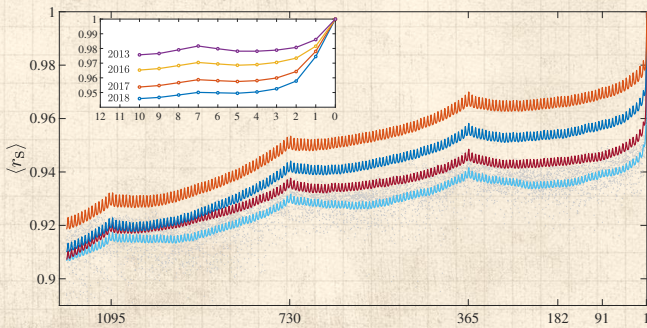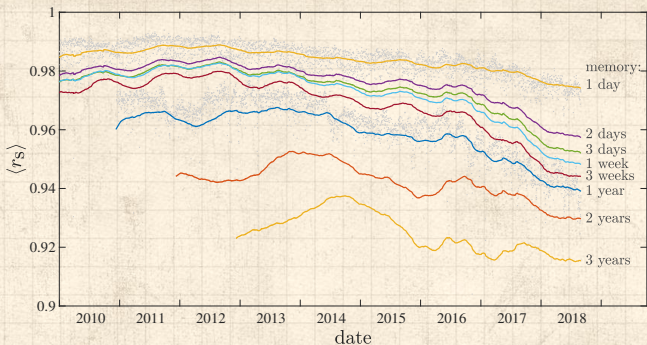Extras
Memory & Turbulence
References

[1] P. E. Auerswald.
     The Code Economy: A Forty-Thousand Year
     History.
     Oxford University Press, 2017.

[2] P. Bak, K. Christensen, L. Danon, and T. Scanlon.
     Unified scaling law for earthquakes.
     Phys. Rev. Lett., 88:178501, 2002. pdf

[3] B. Boyd.
     On the Origin of Stories: Evolution, Cognition, and
     Fiction.
     Belknap Press, 2010.

[4] E. Cheng.
     How to bake pi: An edible exploration of the
     mathematics of mathematics.
     Basic Books, 2015.

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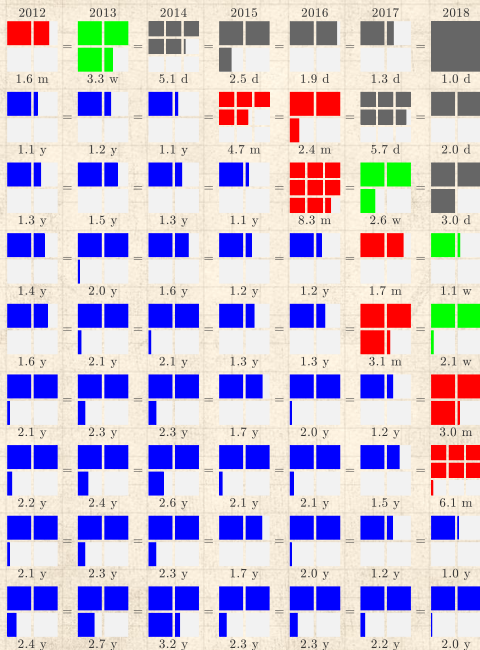Extras
Sociotechnical time series
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References II

[5] K. Christensen, L. Danon, T. Scanlon, and P. Bak.
Unified scaling law for earthquakes.
Proc. Natl. Acad. Sci., 99:2509–2513, 2002. pdf

[6] B. Christian and T. Griffiths.
Algorithms to Live By.
Macmillan, 2016.

[7] P. S. Dodds, J. R. Minot, M. V. Arnold, T. Alshaabi,
J. L. Adams, D. R. Dewhurst, A. J. Reagan, and C. M.
Danforth.
Fame and Ultrafame: Measuring and comparing
daily levels of 'being talked about' for United
States' presidents, their rivals, God, countries, and
K-pop, 2019.
Available online at
https://arxiv.org/abs/1910.00149. pdf

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[8] P. S. Dodds, J. R. Minot, M. V. Arnold, T. Alshaabi,
     J. L. Adams, A. J. Reagan, and C. M. Danforth.
     Computational timeline reconstruction of the
     stories surrounding Trump: Story turbulence,
     narrative control, and collective chronopathy,
     2020.
     https://arxiv.org/abs/2008.07301. pdf

[9] M. Erwig.
     Once Upon an Algorithm.
     MIT Press, 2017.

[10] J. Gottschall.
     The Storytelling Animal: How Stories Make Us
     Human.
     Mariner Books, 2013.

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References

[11] E. Katz and P. F. Lazarsfeld.
Personal Influence.
The Free Press, New York, 1955.

[12] T. Kuran.
Now out of never: The element of surprise in the
east european revolution of 1989.
World Politics, 44:7–48, 1991. pdf ☑

[13] J. R. Minot, M. V. Arnold, T. Alshaabi, C. M.
Danforth, and P. S. Dodds.
Ratioing the President: An exploration of public
engagement with Obama and Trump on Twitter,
2020.
Available online at
https://arxiv.org/abs/2006.03526. pdf ☑

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References

[14] R. Munroe.
Thing Explainer: Complicated Stuff in Simple
Words.
Houghton Mifflin Harcourt, 2015.

[15] M. I. Norton and D. Ariely.
Building a better America—One wealth quintile at
a time.
Perspectives on Psychological Science, 6:9–12,
2011. pdf 🗗

[16] W. H. Press, S. A. Teukolsky, W. T. Vetterling, and
B. P. Flannery.
Numerical Recipes in C.
Cambridge University Press, second edition, 1992.

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[17] M. Puchner.
The Written World: How Literature Shaped
Civilization.
Random, 2017.

[18] M. J. Salganik, P. S. Dodds, and D. J. Watts.
An experimental study of inequality and
unpredictability in an artificial cultural market.
Science, 311:854–856, 2006. pdf ☑

[19] D. J. Watts and P. S. Dodds.
Influentials, networks, and public opinion
formation.
Journal of Consumer Research, 34:441–458, 2007.
pdf ☑

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[20] G. K. Zipf.
Human Behaviour and the Principle of
Least-Effort.
Addison-Wesley, Cambridge, MA, 1949.