

# Computational History


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Principles of Complex Systems, Vols. 1, 2, & 3D  
CSYS/MATH 6701, 6713, & a pretend number, 2024–2025

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Computational Story Lab | Vermont Complex Systems Center  
Santa Fe Institute | University of Vermont



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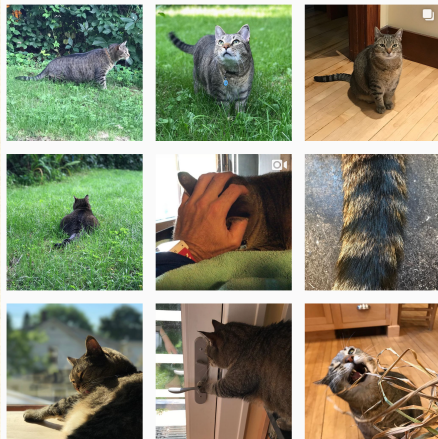
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# Outline

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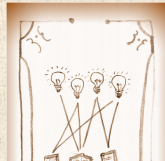
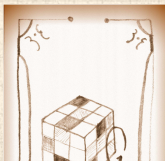
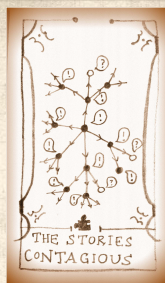
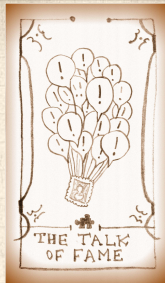
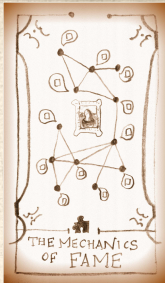
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# Word frequency:

Brown Corpus ↗ ( $\sim 10^6$  words):

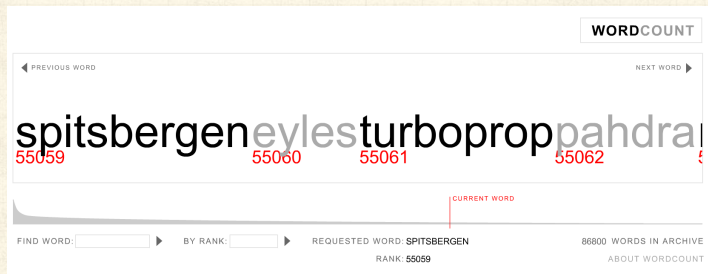
rank	word	% q
1.	the	6.8872
2.	of	3.5839
3.	and	2.8401
4.	to	2.5744
5.	a	2.2996
6.	in	2.1010
7.	that	1.0428
8.	is	0.9943
9.	was	0.9661
10.	he	0.9392
11.	for	0.9340
12.	it	0.8623
13.	with	0.7176
14.	as	0.7137
15.	his	0.6886

rank	word	% q
1945.	apply	0.0055
1946.	vital	0.0055
1947.	September	0.0055
1948.	review	0.0055
1949.	wage	0.0055
1950.	motor	0.0055
1951.	fifteen	0.0055
1952.	regarded	0.0055
1953.	draw	0.0055
1954.	wheel	0.0055
1955.	organized	0.0055
1956.	vision	0.0055
1957.	wild	0.0055
1958.	Palmer	0.0055
1959.	intensity	0.0055



# Jonathan Harris's Wordcount:

A word frequency distribution explorer:



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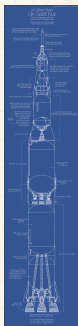






# “Thing Explainer: Complicated Stuff in Simple Words”

by Randall Munroe (2015). [12]



## 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-burning war machines. People have added on the power used during the Second World War—the machines that blow up all the guns that fire, and all the ships that guard it. 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 bit 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. This 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, green-what, these boats are built for people worry even more about the idea of one of them working right.

### BREATHING STICK

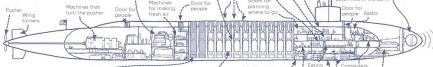
This brings fresh air into the boat, but the boat can also make its own air by breaking water into the parts it's made of. This takes a lot of power, but the boat is powered by heavy metal, so it has enough power to do whatever it wants.

### 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 all around them without seeing out. Like if those skin bands that catch flies in the dark.



### EMPTY ROOMS

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

### MACHINES FOR BURNING CITIES

Each of these rooms has a firing carrier full of city-burning machines. When firing under the sea, the boats can shoot the machines into space. Any of these boats can do it as much as anywhere in the world in under an hour.

### 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.

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Up goer five ↗



## The everywhere-ness of algorithms and stories:



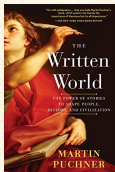
“On the Origin of Stories: Evolution, Cognition, and Fiction” [a](#)

by Brian Boyd (2010). <sup>[2]</sup>



“The Storytelling Animal: How Stories Make Us Human” [a](#)

by Jonathan Gottschall (2013). <sup>[8]</sup>

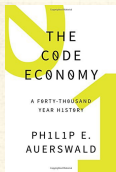


“The Written World: How Literature Shaped Civilization” [a](#)

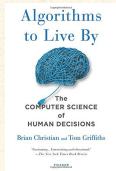
by Martin Puchner (2017). <sup>[14]</sup>



# Algorithms, recipes, stories, ...



“The Code Economy: A Forty-Thousand Year History” [a](#) [↗](#)  
by Philip E Auerswald (2017). [1]



“Algorithms to Live By” [a](#) [↗](#)  
by Christian and Griffiths (2016). [4]



“Once Upon an Algorithm” [a](#) [↗](#)  
by Martin Erwig (2017). [7]

Also: Numerical Recipes in C [13] and How to Bake  $\pi$  [3]

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# The famous are storytellers—Japan:

VISUALIZATIONS

RANKINGS

PEOPLE

PANTHEON  
MAPPING HISTORICAL CULTURAL PRODUCTION

METHODS

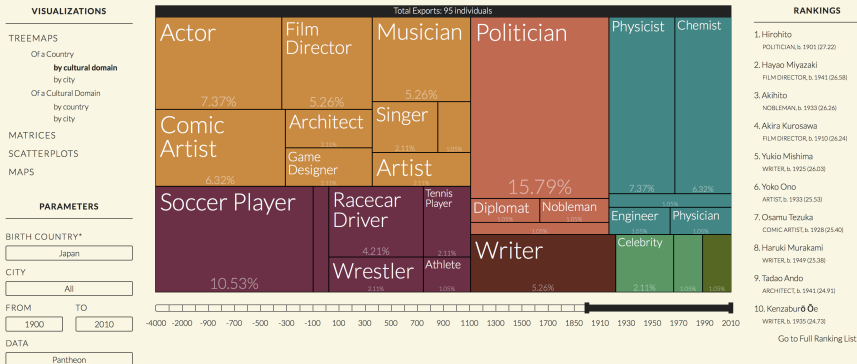
API

ABOUT

If you use the Pantheon dataset, please cite: Yu, A. Z., et al. (2016). Pantheon 1.0, a manually verified dataset of globally famous biographies. *Scientific Data* 2:150075. doi: 10.1038/sdata.2015.75

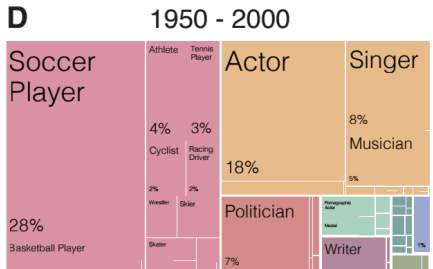
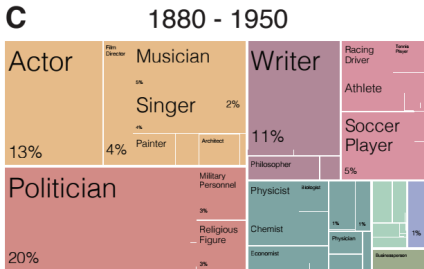
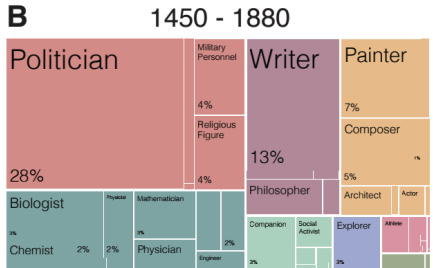
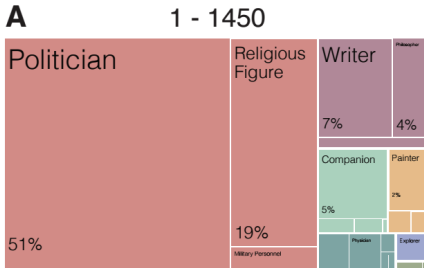
## Who are the globally known people born within present day Japan\*?

[1900 – 2010]



## For people born 1950–


[http://pantheon.media.mit.edu/treemap/country\\_exports/JP/all/1900/2010/H15/pantheon](http://pantheon.media.mit.edu/treemap/country_exports/JP/all/1900/2010/H15/pantheon)



## Super Survival of the Stories:







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


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



## Super Survival of the Stories:



-  Study of Agta, Filipino hunter-gatherers.
-  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 Desirability of  
Storytellers , The  
Atlantic,  
Ed Yong,  
2017-12-05.



# The most famous painting in the world:



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

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Twelve ...



# The completely unpredicted fall of Eastern Europe:



Timur Kuran: <sup>[10]</sup> “Now Out of Never: The Element of Surprise in the East European Revolution of 1989”

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# We understand bushfire stories:



1. Sparks start fires.

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# We understand bushfire stories:



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

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# We understand bushfire stories:



1. Sparks start fires.
2. System properties control a fire's spread.
3. But for three reasons, we make two mistakes about **Social Fires** ...

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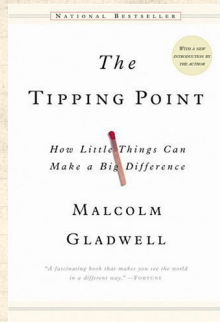
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# We understand bushfire stories:



1. Sparks start fires.
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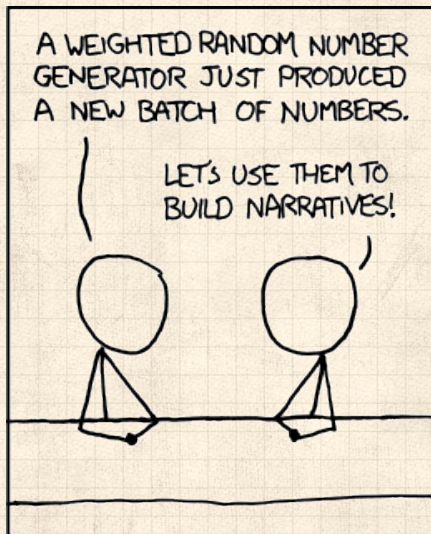
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## Reason 1—We are Homo Narrativus.



ALL SPORTS COMMENTARY

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## Reason 2—“We are all individuals.”

Archival footage:

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





## Reason 3—We are spectacular imitators.

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BBC/David Attenborough.



# Mistake 1: Success is due to intrinsic properties



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See “Becoming Mona Lisa” by David Sassoon 



# Mistake 1: Success is due to intrinsic properties



it's just so disappointingly small

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See “Becoming Mona Lisa” by David Sassoon 



# Mistake 1: Success is due to intrinsic properties



Stolen in 1913, recovered in 1915.

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See “Becoming Mona Lisa” by David Sassoon 



# Mistake 1: Success is due to intrinsic properties



Hidden during WWII.

See “Becoming Mona Lisa” by David Sassoon 

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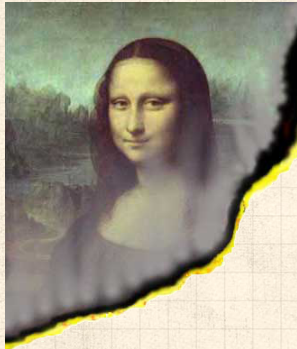
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# Mistake 1: Success is due to intrinsic properties



Repeatedly vandalised and attacked. ↗

See “Becoming Mona Lisa” by David Sassoon ↗

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48 songs  
30k participants

## Exp 1— weak social

	RIP	(RIP)	(RIP)	RIP
WATERGATE	20	10	10	24
THEY'RE NOT MESSING WITH ME	19	10	10	24
DEEP FRODOLO TO DIE	17	10	10	24
THE TURTLE	16	10	10	24
THE BROTHERS PROCLAIM	15	10	10	24
THE NEW GAMES	14	10	10	24
THE NEW GAMES	13	10	10	24
THE NEW GAMES	12	10	10	24
THE NEW GAMES	11	10	10	24
THE NEW GAMES	10	10	10	24
THE NEW GAMES	9	10	10	24
THE NEW GAMES	8	10	10	24
THE NEW GAMES	7	10	10	24
THE NEW GAMES	6	10	10	24
THE NEW GAMES	5	10	10	24
THE NEW GAMES	4	10	10	24
THE NEW GAMES	3	10	10	24
THE NEW GAMES	2	10	10	24
THE NEW GAMES	1	10	10	24

## Exp. 2—strong social

	RIP	(RIP)	(RIP)	RIP
WATERGATE	20	10	10	24
THEY'RE NOT MESSING WITH ME	19	10	10	24
DEEP FRODOLO TO DIE	17	10	10	24
THE TURTLE	16	10	10	24
THE BROTHERS PROCLAIM	15	10	10	24
THE NEW GAMES	14	10	10	24
THE NEW GAMES	13	10	10	24
THE NEW GAMES	12	10	10	24
THE NEW GAMES	11	10	10	24
THE NEW GAMES	10	10	10	24
THE NEW GAMES	9	10	10	24
THE NEW GAMES	8	10	10	24
THE NEW GAMES	7	10	10	24
THE NEW GAMES	6	10	10	24
THE NEW GAMES	5	10	10	24
THE NEW GAMES	4	10	10	24
THE NEW GAMES	3	10	10	24
THE NEW GAMES	2	10	10	24
THE NEW GAMES	1	10	10	24

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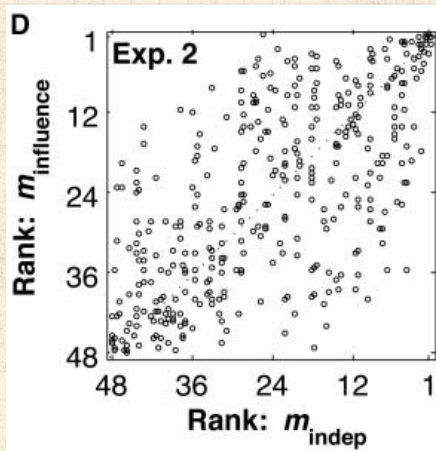
References



“An experimental study of inequality and unpredictability in an artificial cultural market” ↗  
Salganik, Dodds, and Watts,  
Science, 311, 854–856, 2006. [15]



## Resolving the paradox:



Increased social awareness leads to **Stronger** inequality + **Less** predictability.





# Payola/Deceptive advertising hurts us all:

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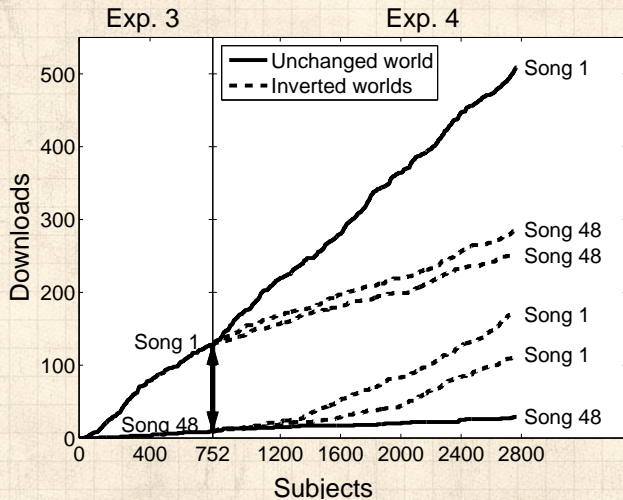
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“Mistake” 2:

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 Christl Eitelman April 8, 2018

Do you trust Mark Zuckerberg?

From the moment the Facebook founder entered the public eye in 2005 for creating a Harvard student hot-or-not 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 [tweets to Congress](#) and [statements to the press](#) on 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 that we've made a branch of mistakes. ... Facebook has always been committed to being transparent about the information you have shared 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. (Honorary 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 say they had public data 'strapped'](#)

[Facebook COO Sheryl Sandberg on data leak: 'I am really sorry, we are later'](#)

[As Facebook confronts data misuse, foreign governments might force real change](#)

[What if we paid for Facebook — instead of letting it spy on us for free?](#)

About this story

Photo/illustrations based on photos by Tony Avelay/Bloomberg News, Drew Angerer/Getty Images, Jeff Robinson/AP, Jim Westcott/Getty Images, Craig Rutten/AP Photo/Outlines/AP, Stephen Loring Reuters, Jesse Garcia/Reuters, Richard Dowd/AP

322 Comments

More stories

The Facebook ads Russians showed to different groups

Facebook has said these ads were created by the Internet

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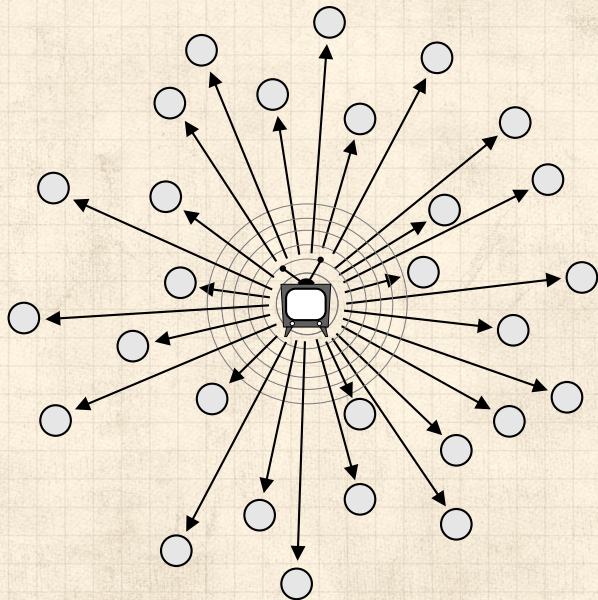
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# The hypodermic model of influence:



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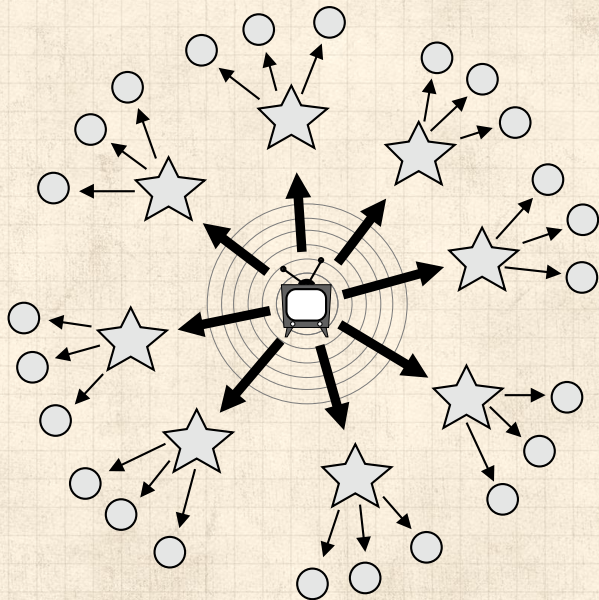
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# The two step model of influence: [9]



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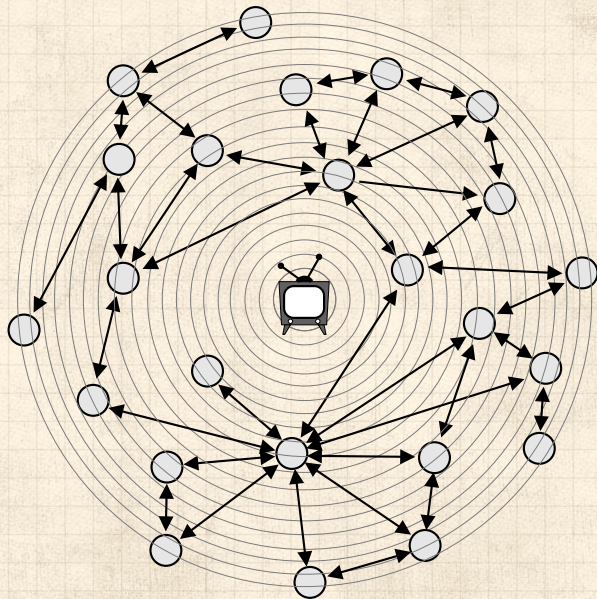
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# The network model of influence:



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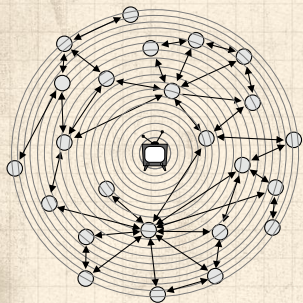
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# The network model of influence:



## How superspreading 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. <sup>[16]</sup>




## Etymological clarity:


 **Fate**—from the Latin *fatus*: meaning “spoken”.






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 **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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 Réclame . “Clamo”—Proto-Indo-European: “to shout” (again).





## Etymological clarity:


 **Fate**—from the Latin *fatus*: meaning “spoken”.



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“It is written”, fore-tell, pre-dict.



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 Destiny is probablistic.

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

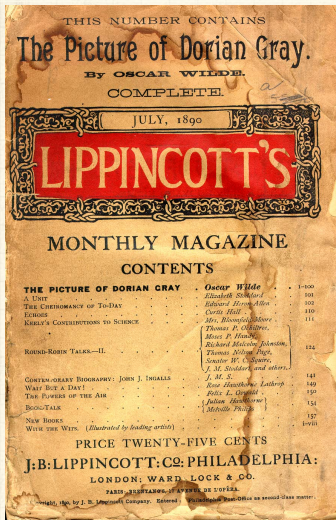
 Renown : Repeatedly named, talked about. Old French *renon*, from re- + non (“name”).

 Réclame . “Clamo”—Proto-Indo-European: “to shout” (again). Connected to “lowing”.





# Oscar Wilde, The Picture of Dorian Gray: Raw Fame



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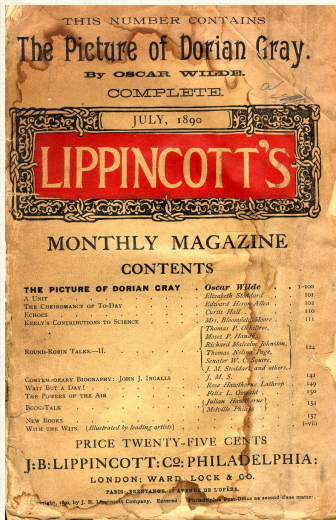
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# Oscar Wilde, The Picture of Dorian Gray: Raw Fame



“There is only one thing in the world

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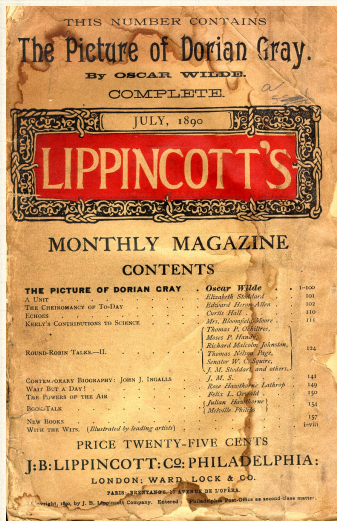
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# Oscar Wilde, The Picture of Dorian Gray: Raw Fame



“There is only one thing in  
the world  
worse than being talked  
about,

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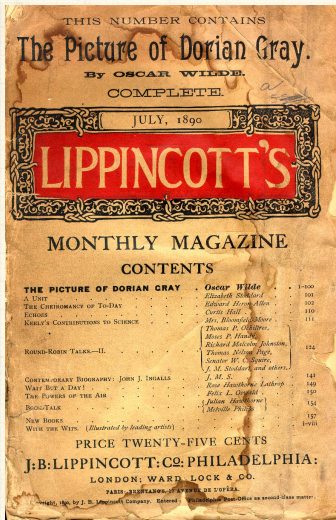
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# Oscar Wilde, The Picture of Dorian Gray: Raw Fame



“There is only one thing in  
the world  
worse than being talked  
about,  
and that is

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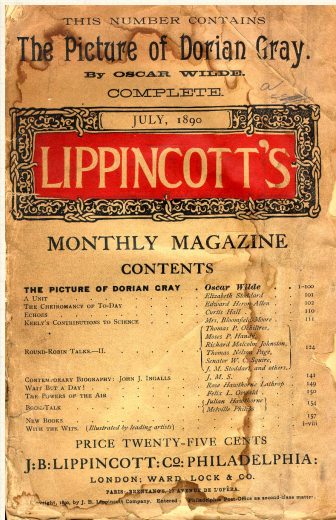
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# Oscar Wilde, The Picture of Dorian Gray: Raw Fame



“There is only one thing in the world worse than being talked about, and that is not being talked about.”

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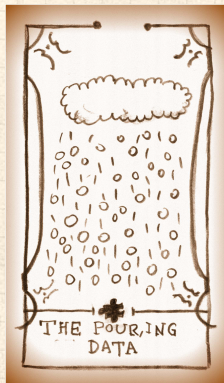
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“Fame and Ultrafame: Measuring and comparing daily levels of ‘being talked about’ for United States’ presidents, their rivals, God, countries, and K-pop” ↗

Dodds et al.,

Available online at

<https://arxiv.org/abs/1910.00149>, 2019. [5]



“Computational timeline reconstruction of the stories surrounding Trump: Story turbulence, narrative control, and collective chronopathy” ↗

Dodds et al.,

, 2020. [6]



POTUSometer with the Smorgasdashbord:

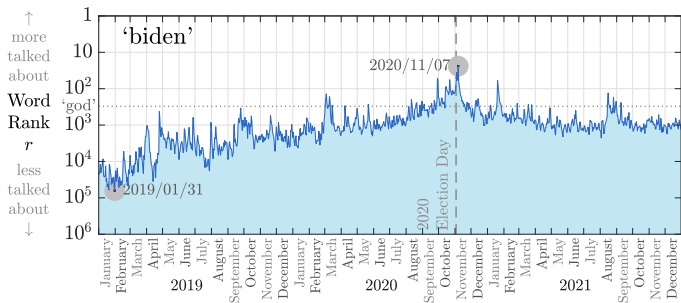
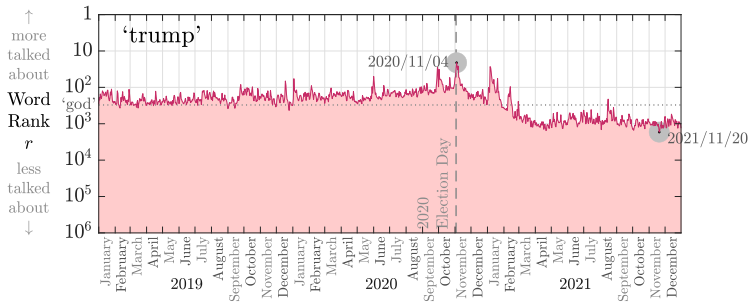
<http://compstorylab.org/potusometer/> ↗



Stories surrounding Trump:

<http://compstorylab.org/trumpstoryturbulence/> ↗







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



Vox (2019-04-17):  
BTS, the band that changed K-pop, explained [↗](#)

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Distant reading by smashing texts into storyons:

```
cd ~/work/stories/2019-10story-turbulence-trump/data/1grams  
261G
```

```
more updateall.sh
```

```
file names:
```

```
compute_rank_turbulence_divergence_sweep_the_leg
```

Zip files:

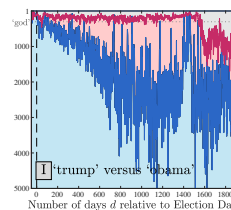
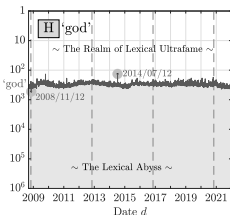
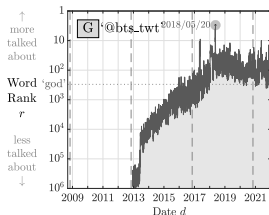
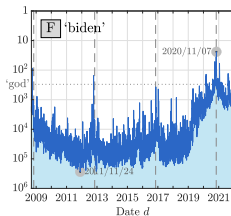
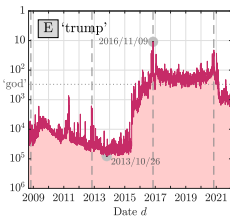
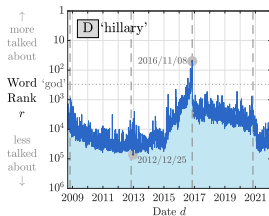
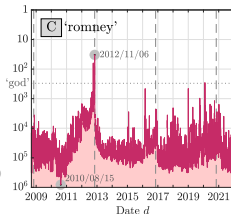
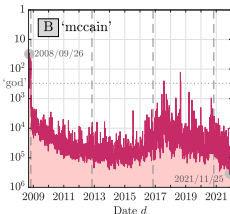
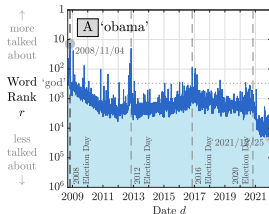
```
zless 2018-01-06/1grams/en_*.tar.tsv
```

```
zless 2021-01-05/1grams/en_*.tar.tsv
```

```
zless 2021-01-06/1grams/en_*.tar.tsv
```

```
zless 2021-01-07/1grams/en_*.tar.tsv
```

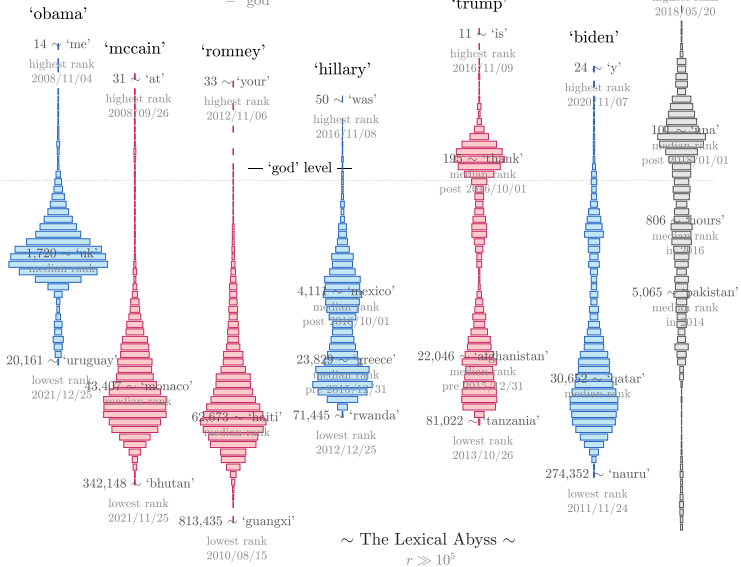






~ The Realm of Lexical Ultraframe ~

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



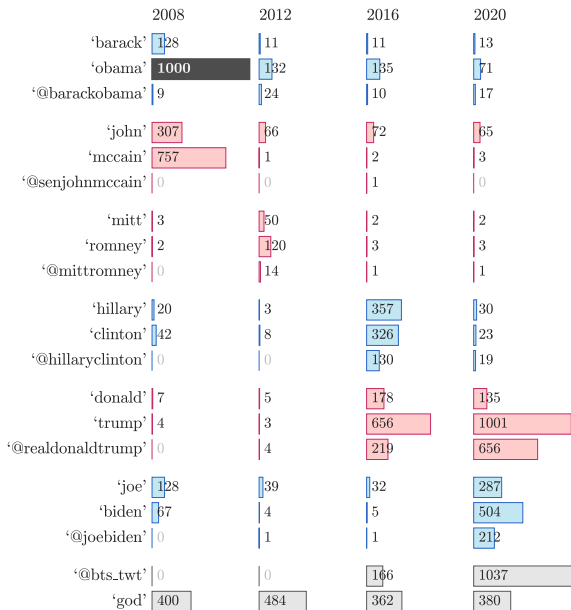
~ The Lexical Abyss ~

$r \gg 10^5$

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%	0.0%
‘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%

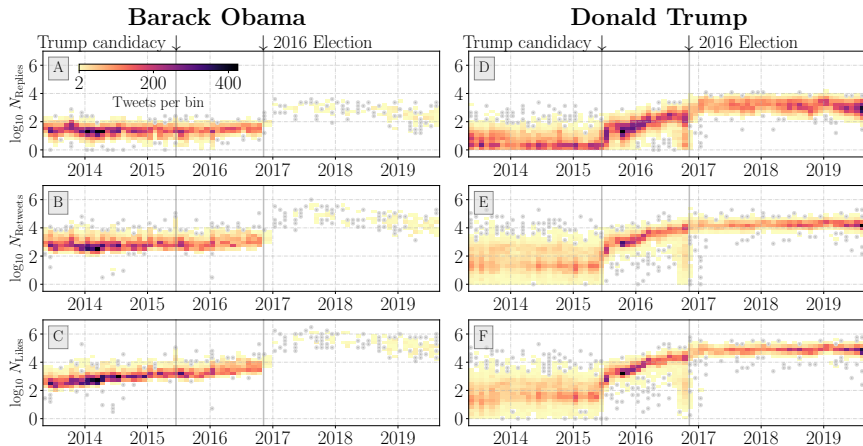
Relative median rates of 'being talked about'  
in the 8 weeks (56 days) pre-election day:



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	56	60	329	106	104	17
'@barackobama'	10	8	11	10	17	15	16	13	13	17	17	13	24	5
'john'	405	274	388	226	117	104	113	21	18	29	28	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	69	72	61	43	33	6
'clinton'	62	25	16	10	8	6	8	27	40	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	66	45	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'	57	87	38	87	66	58	44	46	50	48	44	78	97	17
'biden'	72	7	3	1	2	2	2	3	5	3	4	52	24	21
'@joebiden'	0	0	0	0	0	0	0	0	1	1	2	18	62	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:



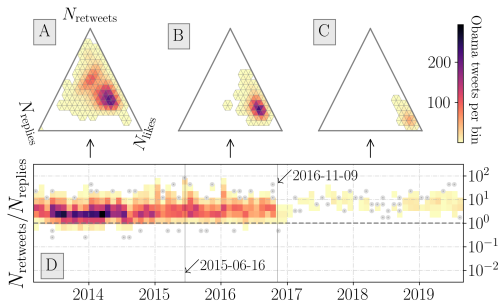
“Ratioing the President: An exploration of public engagement with Obama and Trump on Twitter,” Minot et al.,

2020 [11]

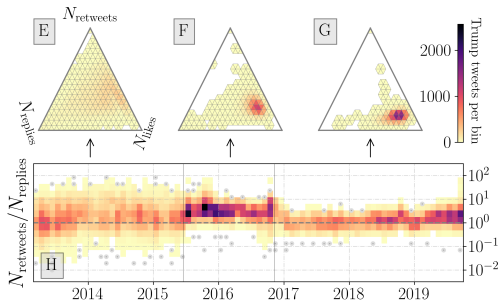


# Ratiometrics:

— Barack Obama —



— Donald Trump —



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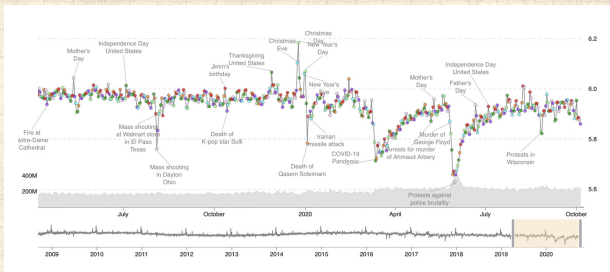
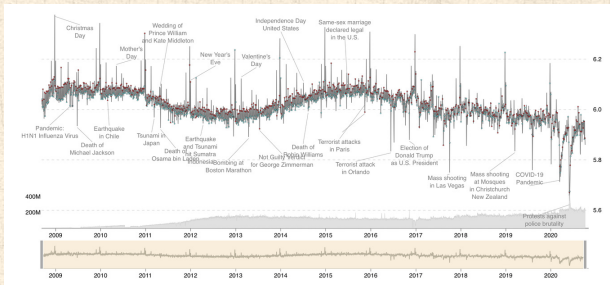
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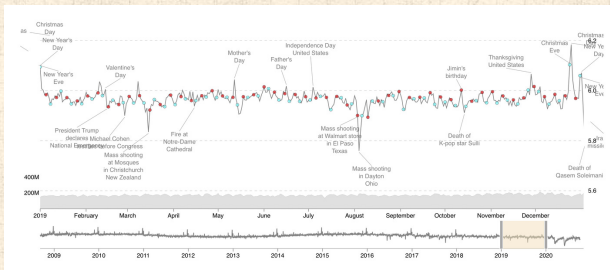
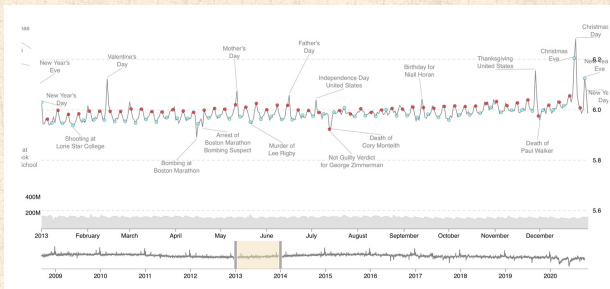
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# Emotional turbulence:



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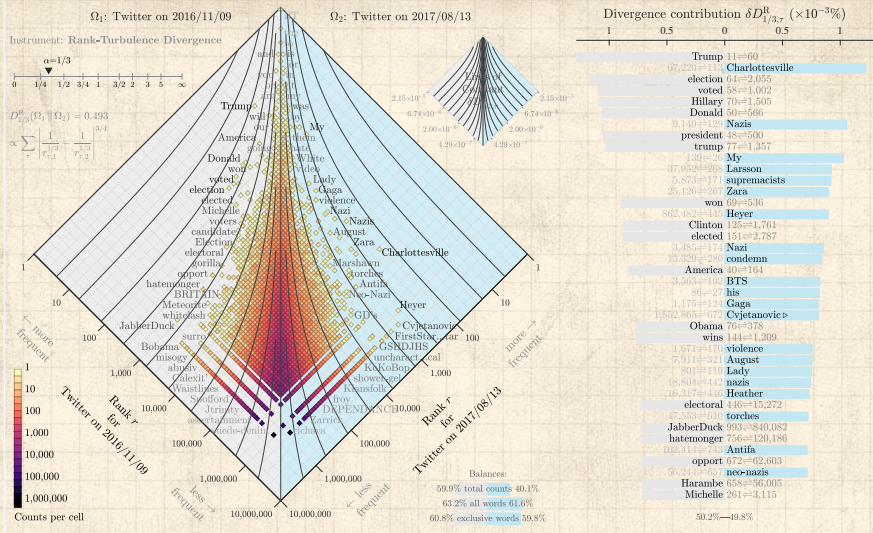
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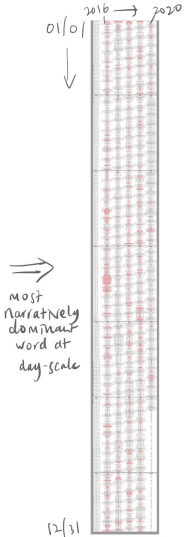




## Allotaxonomy—

the comparison of complex systems:

<http://compstorylab.org/allotaxonomy/>



most narratively dominant word at week-scale

narrative control

Week	2016	2017	2018	2019	2020	
1.	01/01-01/07	Hillary 34.7	hashtag 28.6	Bannon 2.2	shutdown 0.0	Iran 9.6
2.	01/08-01/14	Cruz 1.0	Meiji 0.0	Mueller 0.0	shutdown 0.0	Schindler 5.9
3.	01/15-01/21	Cruz 10.7	inauguration 0.6	DACA 6.7	Pelosi 6.8	Parnas 0.0
4.	01/22-01/28	Cruz 10.6	inauguration 3.1	Mueller 0.0	Pelosi 2.6	Ukraine 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 5.1	Bannon 0.0	menç 2.3	Whitaker 0.0	Vindjian 2.5
7.	02/12-02/18	Cruz 6.9	Flynn 0.0	Mueller 0.0	emergency 0.0	Barr 2.2
8.	02/19-02/25	Rubio 3.8	Sweden 4.9	Farkland 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 1.0	Russia 4.8	Mueller 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 0.4	Mueller 2.0	Barr 2.4	coronavirus 0.0
16.	04/16-04/22	Cruz 10.5	Russia 0.5	Mueller 0.1	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	Iraq 6.6	Barr 0.0	coronavirus 0.0
20.	05/14-05/20	Beatie 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	Koçak 18.2	Barr 0.0	pandemic 0.0
22.	05/28-06/03	Hillary 11.9	Katip 4.4	Roseanne 4.0	USS 1.0	Mitsunobu 22.1
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	Mueller 0.0	Kin 4.1	feet 2.0	Tubi 4.5
25.	06/18-06/24	Hillary 23.9	Trumpcare 0.0	children 1.0	Iraq 12.9	Tubi 2.1
26.	06/25-07/01	Clinton 13.0	Russia 5.8	Justice 8.3	boonties 0.0	boonties 0.0
27.	07/02-07/08	Crooked 80.6	CNN 0.7	toilets 0.0	parade 0.0	Rubini 2.3
28.	07/09-07/15	Crooked 71.5	Russia 1.2	NATO 13.0	Egyptin 0.0	coronavirus 0.0
29.	07/16-07/22	Penç 2.9	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	Korç 5.8	Omarosa 0.4	Pisa 7.6	USPS 0.0
33.	08/13-08/19	Manafort 0.0	Charlottesville 1.5	Omarosa 9.5	Greenland 6.9	USPS 0.0
34.	08/20-08/26	Clinton 7.6	Charlottesville 3.8	Cohen 2.7	Greenland 8.0	Biden 6.6
35.	08/27-09/02	Crooked 57.4	Harvey 0.0	Oh 14.0	Dortch 12.2	Keselha 9.5
36.	09/03-09/09	Boodi 0.0	DACA 2.4	Kavanaugh 2.1	Dortch 12.6	Atlantic 4.8
37.	09/10-09/16	deplorable 6.0	ESPN 2.7	Puerto 7.5	flavored 0.0	Woodward 2.6
38.	09/17-09/23	Clinton 6.5	Kin 4.9	Kavanaugh 1.7	Ukraine 4.5	coronavirus 0.0
39.	09/24-09/30	debate 4.9	Puerto 4.7	Kavanaugh 9.5	Ukraine 6.8	Ukraine 6.8
40.	10/01-10/07	Penç 4.9	Puerto 2.1	Kavanaugh 6.8	Ukraine 5.1	ballots 0.0
41.	10/08-10/14	sexual 0.5	Puerto 1.8	Kavanaugh 4.3	Kurd 8.2	Covid 0.0
42.	10/15-10/21	rigged 10.1	Puerto 0.2	Sund 5.3	Kurd 3.7	
43.	10/22-10/28	star 0.0	Mueller 0.0	caravan 0.0	impeachment 0.0	impeachment 0.0
44.	10/29-11/04	FBI 5.9	Mueller 0.0	caravan 0.0	impeachment 0.0	impeachment 0.0
45.	11/05-11/11	Clinton 0.9	Gillespie 12.0	Whitaker 6.2	Ukraine 6.2	Ukraine 6.2
46.	11/12-11/18	Bangsa 0.0	sexual 1.7	caravan 0.0	Ukraine 5.2	Ukraine 5.2
47.	11/19-11/25	Hans 12.4	LaVie 21.3	Sund 1.6	Ukraine 3.5	Ukraine 3.5
48.	11/26-12/02	recife 0.0	Moore 0.0	Moore 0.1	impeachment 3.1	impeachment 3.1
49.	12/03-12/09	Taiwan 7.8	Mueller 0.0	Cohen 2.1	impeachment 0.0	impeachment 0.0
50.	12/10-12/16	Russia 2.9	Mueller 0.0	Cohen 6.9	impeachment 0.0	impeachment 0.0
51.	12/17-12/23	inauguration 11.8	Mueller 0.0	wall 9.8	impeachment 1.4	impeachment 1.4
52.	12/24-12/31	inauguration 3.2	Mueller 0.0	wall 20.4	impeachment 7.6	impeachment 7.6

<http://compstorylab.org/trumpstoryturbulence/>

open ~/papers/stories/2020-05story-turbulence-trump/package/anc/.

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 5.9	Capitol 0.1
3. 01/15-01/21	Cruz 10.7	inauguration 0.6	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	Ukraine 5.5	insurrection 0.0
5. 01/29-02/04	Cruz 11.2	ban 2.1	Mueller 0.0	border 0.0	impeachment 0.0	Greene 0.0
6. 02/05-02/11	Cruz 5.1	Bannon 0.0	memo 2.3	Whittaker 0.0	Vindinan 2.5	insurrection 0.0
7. 02/12-02/18	Cruz 6.9	Flynn 0.0	Mueller 0.0	emergency 0.0	Bar 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	Mueller 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	insurrection 0.0
12. 03/19-03/25	Arizona 16.8	Nunes 0.0	Mueller 2.2	Bar 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	Biden 0.0
14. 04/02-04/08	Cruz 1.5	Russia 2.8	Mueller 0.0	returus 0.0	coronavirus 0.0	Capitol 0.0
15. 04/09-04/15	Cruz 1.7	Syria 0.4	Mueller 2.0	Bar 2.4	coronavirus 0.0	Capitol 0.0
16. 04/16-04/22	Cruz 10.5	Russia 0.5	Mueller 0.1	Bar 0.1	coronavirus 0.0	Capitol 0.0
17. 04/23-04/29	Cruz 3.0	days 0.1	Kanye 8.0	Biden 6.0	coronavirus 0.0	audit 0.0
18. 04/30-05/06	Indiana 11.5	Trumpcare 0.0	Mueller 0.0	Bar 0.0	coronavirus 0.0	Cheney 0.0
19. 05/07-05/13	Ryan 2.5	Comey 2.8	Iran 6.6	Bar 0.0	coronavirus 0.0	Cheney 0.0
20. 05/14-05/20	Bernie 25.3	Comey 1.0	ZTE 4.5	Bar 0.0	coronavirus 0.0	Cheney 0.0
21. 05/21-05/27	Clinton 9.5	budget 0.0	Korea 18.2	Bar 0.0	pandemic 0.0	Weisselberg 0.0
22. 05/28-06/03	Hillary 11.9	Kathy 4.4	Roseanne 4.0	US\$ 3.0	Minneapolis 32.1	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	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	Epstein 0.0	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	Charlotteville 1.5	Omarosa 9.5	Greenland 6.9	USPS 0.0	Taliban 0.0
34. 08/20-08/26	Clinton 7.6	Charlotteville 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	Oltr 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	Estimote 0.0
39. 09/24-09/30	debate 4.9	Puerto 4.7	Kavanaugh 9.5	Ukraine 6.8	ballots 0.0	audit 0.0
40. 10/01-10/07	Pence 4.9	Puerto 2.1	Kavanaugh 6.8	Ukraine 5.1	Covidi 1.4	Bannon 0.0
41. 10/08-10/14	sexual 0.3	Puerto 1.8	Kavanaugh 4.3	Kurds 8.2	COVID 1.4	Jan 0.0
42. 10/15-10/21	rigged 10.1	Puerto 0.2	Saudi 5.3	Kurds 3.7	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	Whittaker 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	LaYar 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	Brandon 0.0

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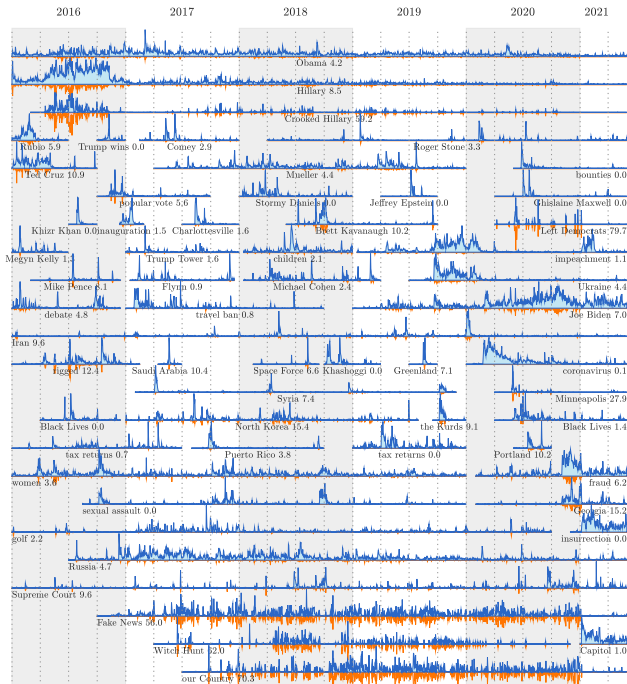
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References





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	shit-hole countries 1.0	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 be 0.0	impeachment trial 0.0	the Capitol 0.0
4. 01/22-01/28	Megyn Kelly 4.9	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 26.0	impeachment trial 0.0	the Capitol 0.0
6. 02/05-02/11	New Hampshire 19.5	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	Justice Sotomayor 0.0	Bernie Sanders 13.6	the Capitol 0.0
9. 02/26-03/04	vote for 4.4	to Russia 22.0	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 0.1	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	Lynne Ted 06.2	health care 0.0	Cambridge Analytics 0.0	Mueller 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	Michael Cohen 0.0	sanctuary cities 5.3	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	Michael Cohen 2.4	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 6.0
22. 05/28-06/03	Trump University 3.4	Kathy Griffin 5.7	Samantha Bee 4.4	John McCain 0.0	photo op 0.0	Memorial Day 0.0
23. 06/04-06/10	Hillary Clinton 18.6	James Comey 0.2	Justin Trudeau 8.5	with Mexico 39.2	Left Democrats 75.1	Jean Carroll 0.0
24. 06/11-06/17	Trump is 0.0	obstruction of 12.6	their parents 0.0	the FBI 8.5	in Tulsa 7.4	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 2.2	the Capitol 0.0
26. 06/25-07/01	Hillary Clinton 20.5	Fake News 37.6	Supreme Court 3.7	Jean Carroll 0.0	American soldiers 0.0	Trump Organization 7.0
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 19.1	Joe Arpaio 3.5	Michael Cohen 4.3	Prime Minister 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 0.2	Hurricane Dorian 9.6	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 3.4	Robert E 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	the Taliban 0.0
38. 09/17-09/23	Trump Jr 0.0	North Korea 12.8	Blasey Ford 0.0	a foreign 6.4	Supreme Court 7.3	to overturn 0.0
39. 09/24-09/30	Hillary Clinton 7.5	Puerto Rico 5.2	Brett Kavanaugh 15.0	Impeachment inquiry 0.0	Supreme Court 5.7	debt ceiling 0.0
40. 10/01-10/07	Mike Pence 8.9	Puerto Rico 2.6	Supreme Court 6.9	Adam Schiff 13.3	Walter Reed 5.7	the debt 0.0
41. 10/08-10/14	sexual assault 0.0	Puerto Rico 2.2	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 11.7	Myshia 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 12.6	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	ban on 0.0	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 0.0	Saudi Arabia 2.5	quid pro 1.3	the election 6.7	Kyle Rittenhouse 0.0
48. 11/26-12/02	popular vote 17.4	Native American 0.1	Trump Tower 2.5	Hong Kong 0.0	voter fraud 32.2	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
52. 12/24-12/31	Trump next 0.0	the FBI 0.1	Border Security 70.6	the Senate 29.1	on January 16.7	Donald Trump 0.0







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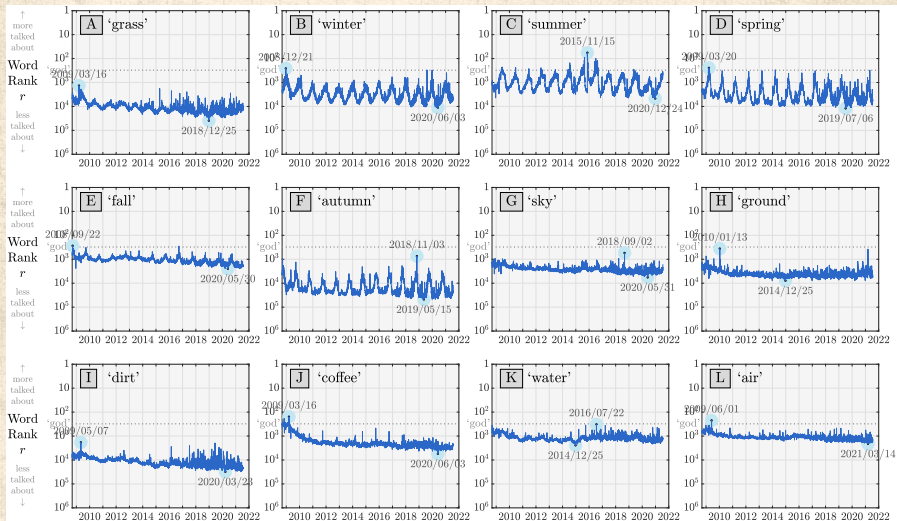
Extras

Sociotechnical time series

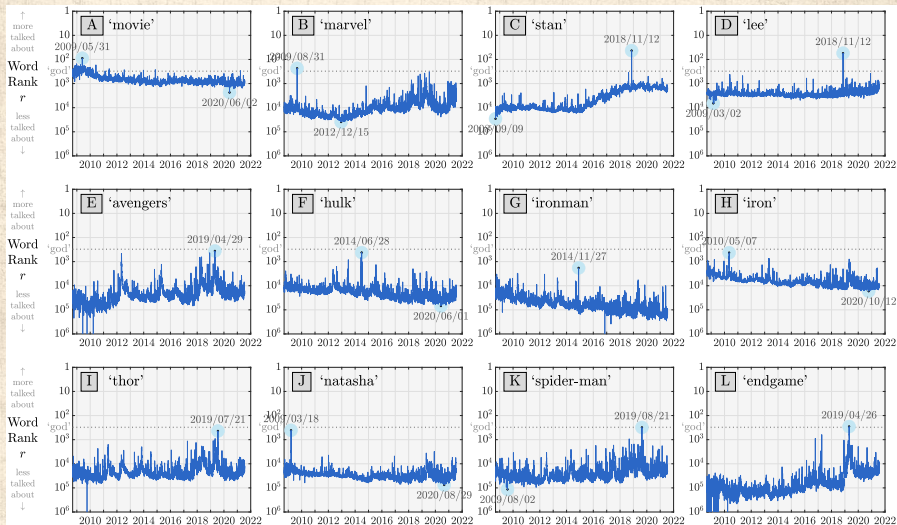
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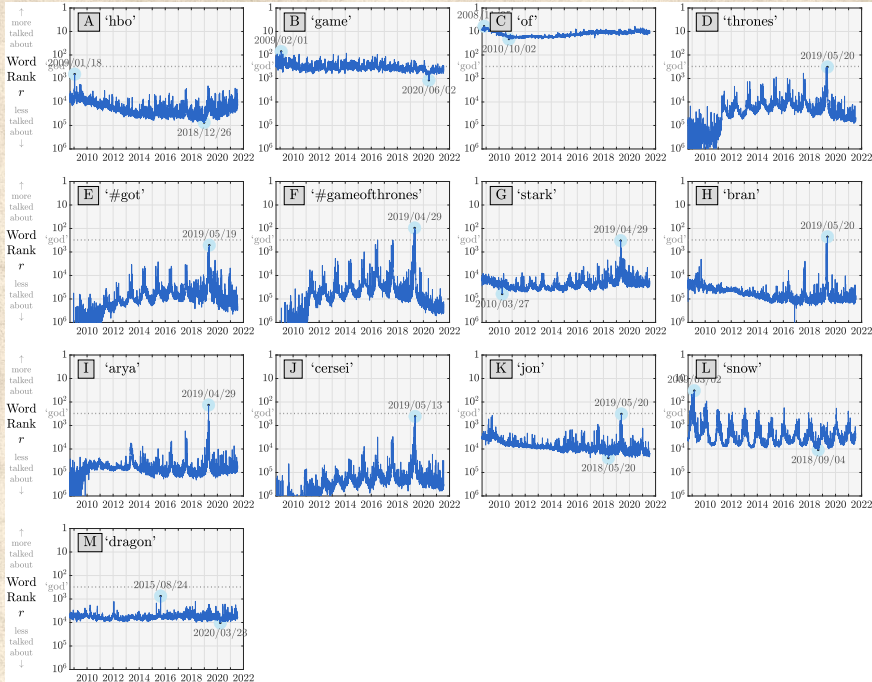
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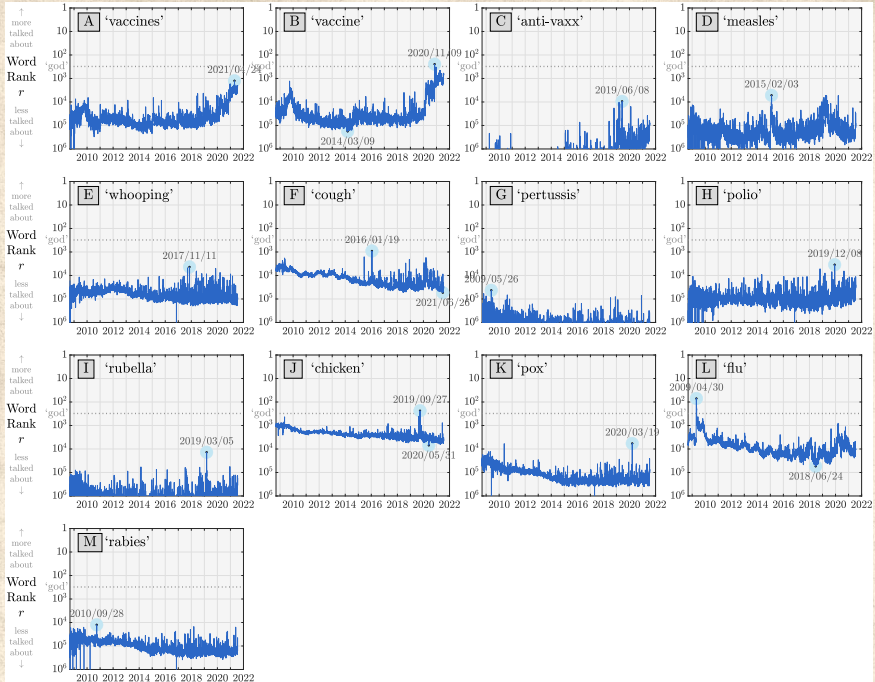


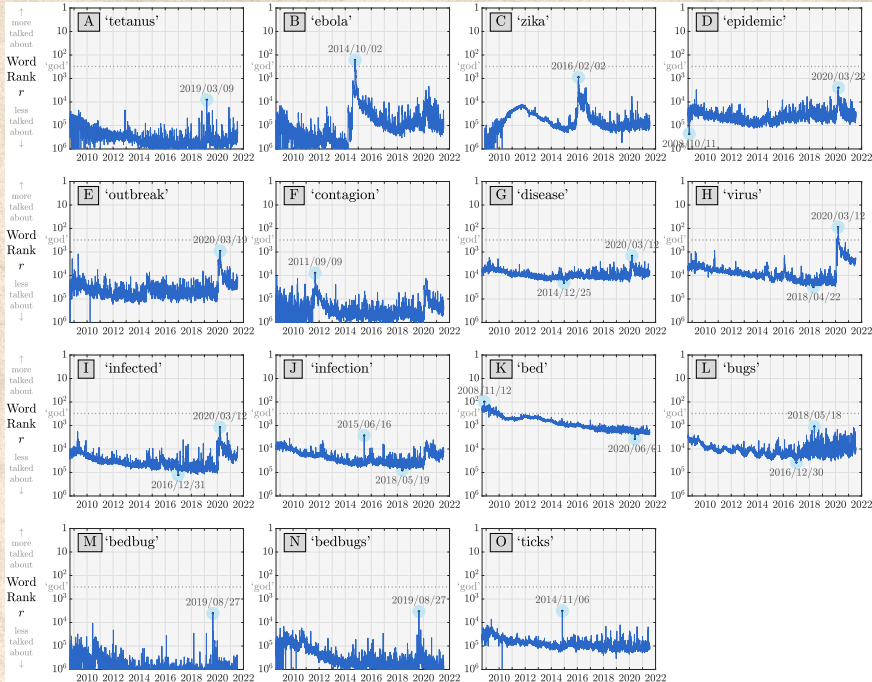




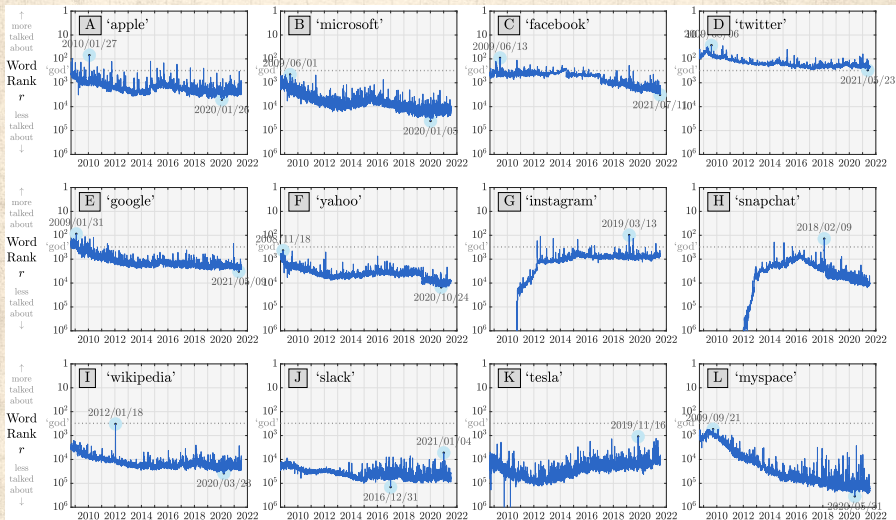


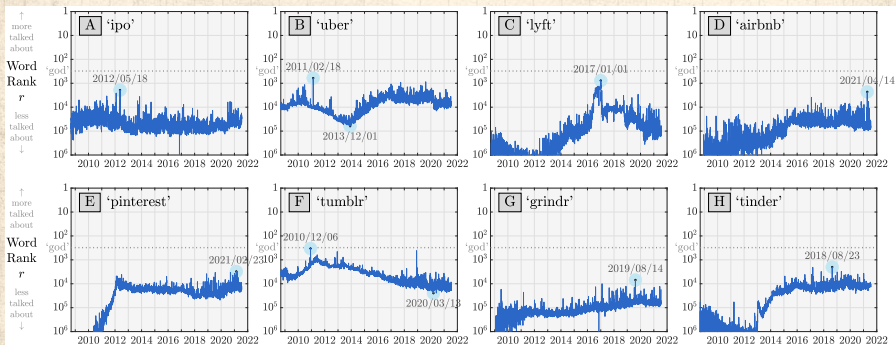


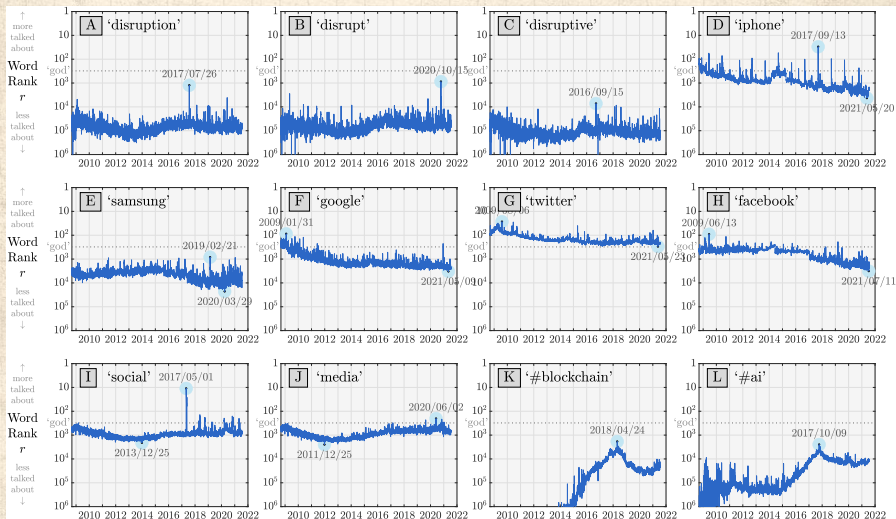




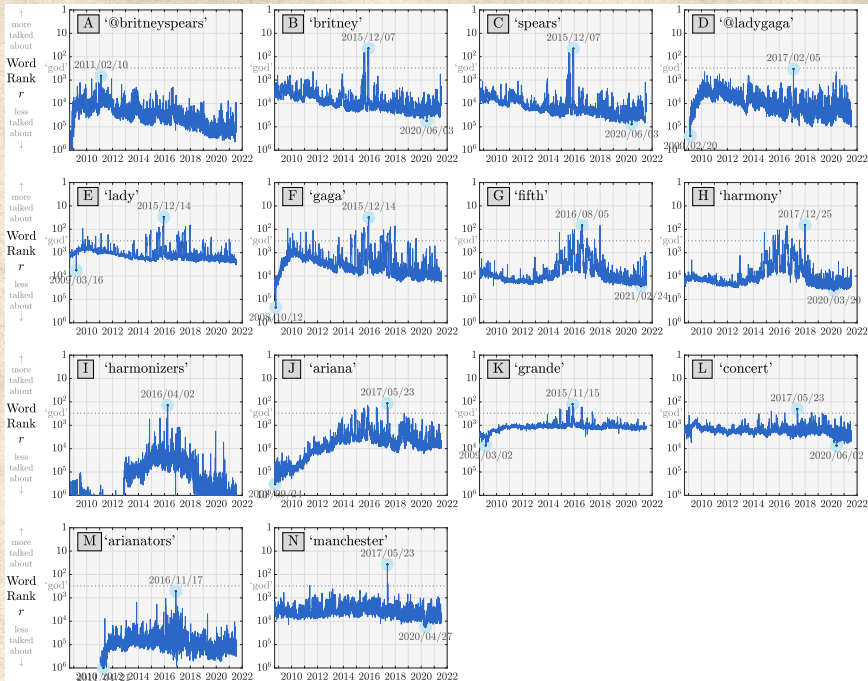


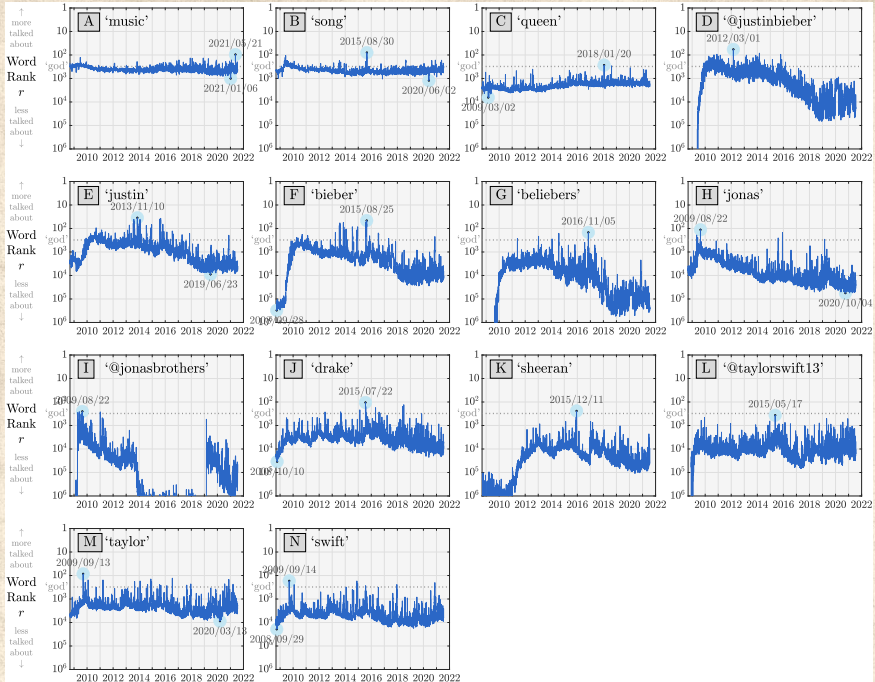








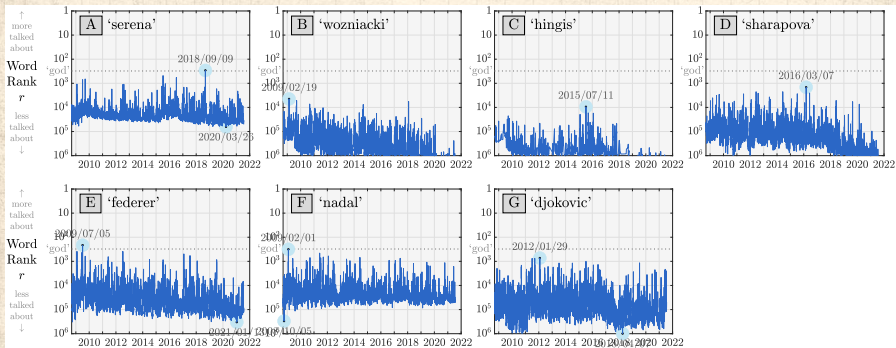


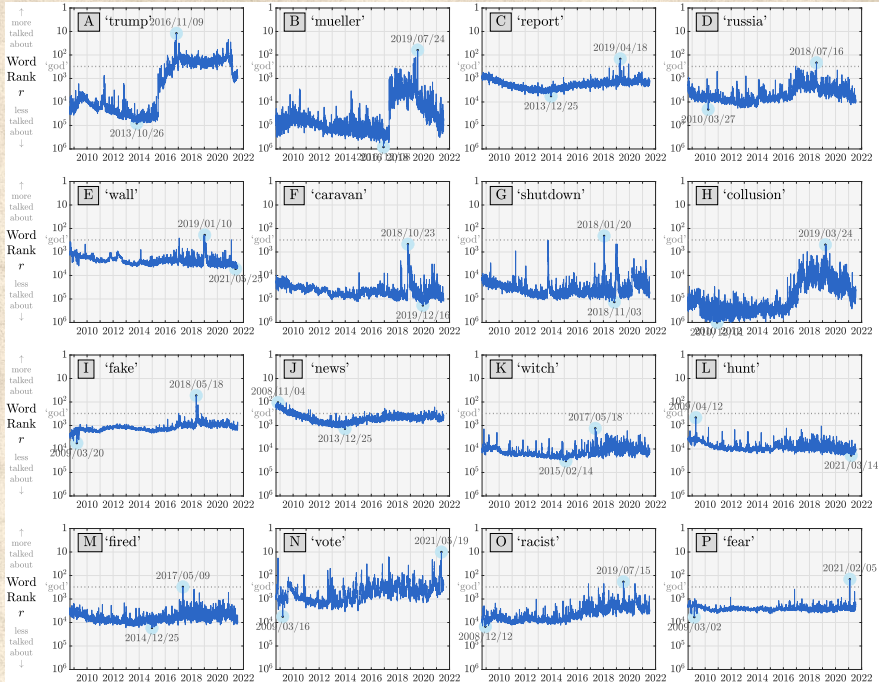


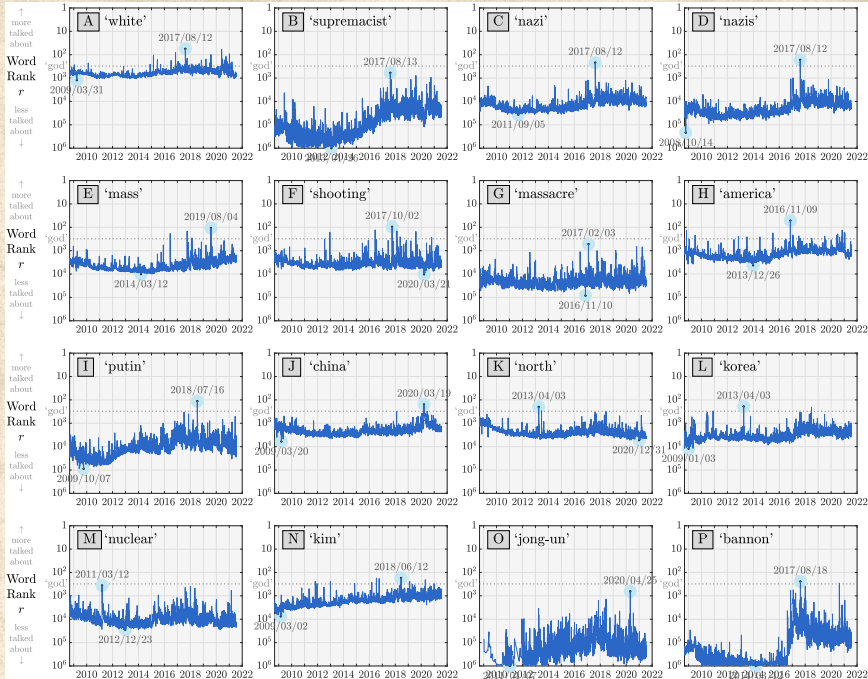


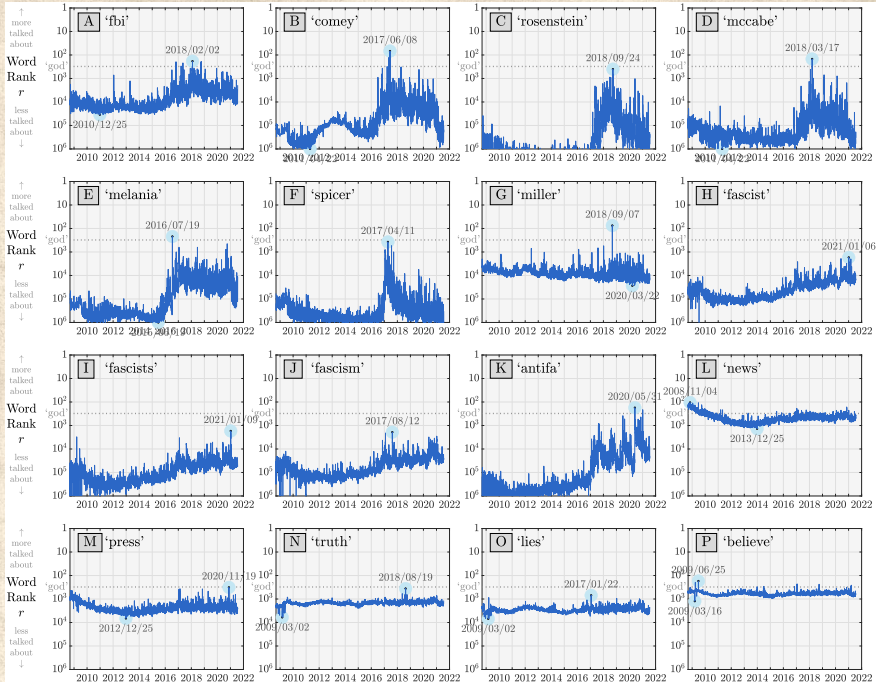


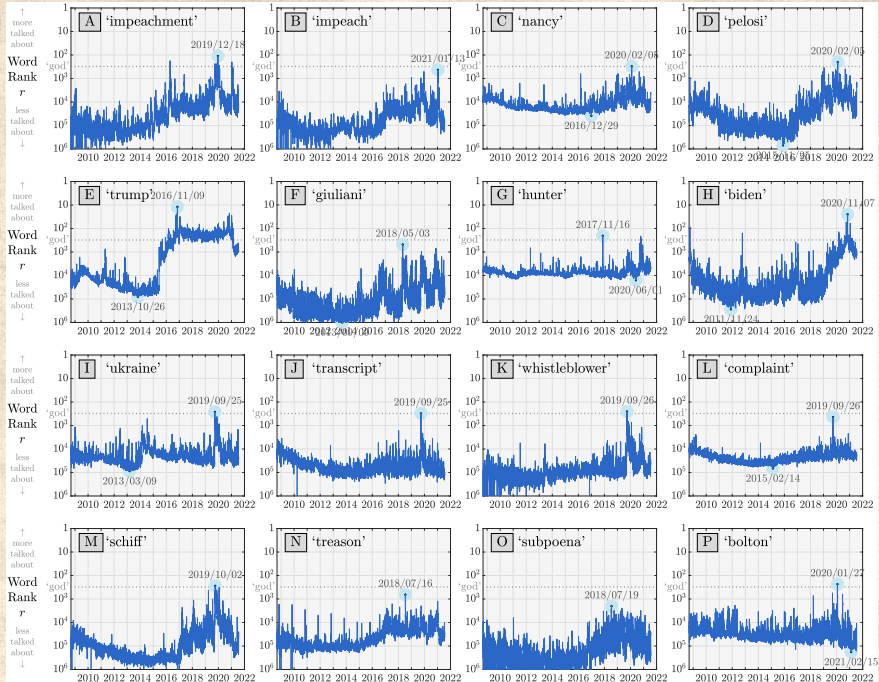


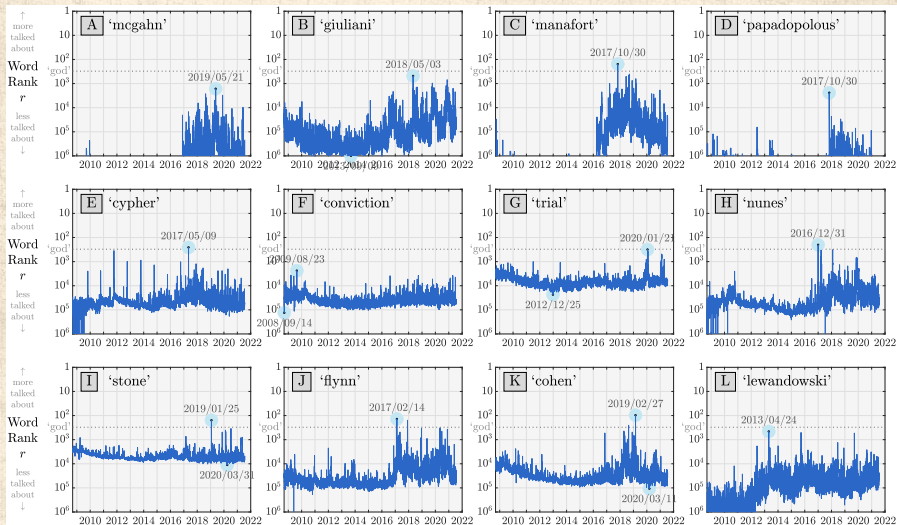


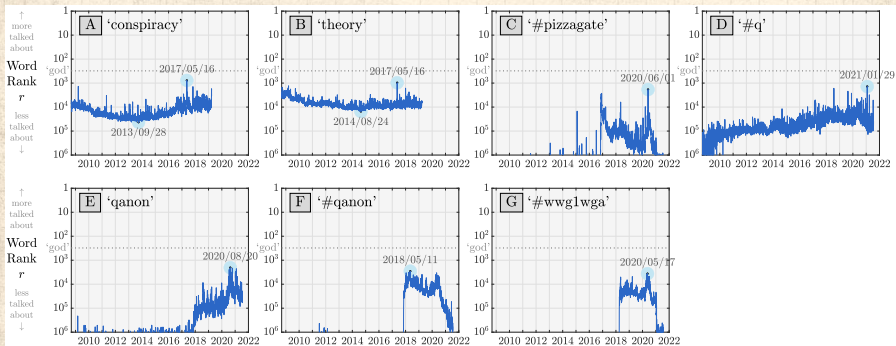


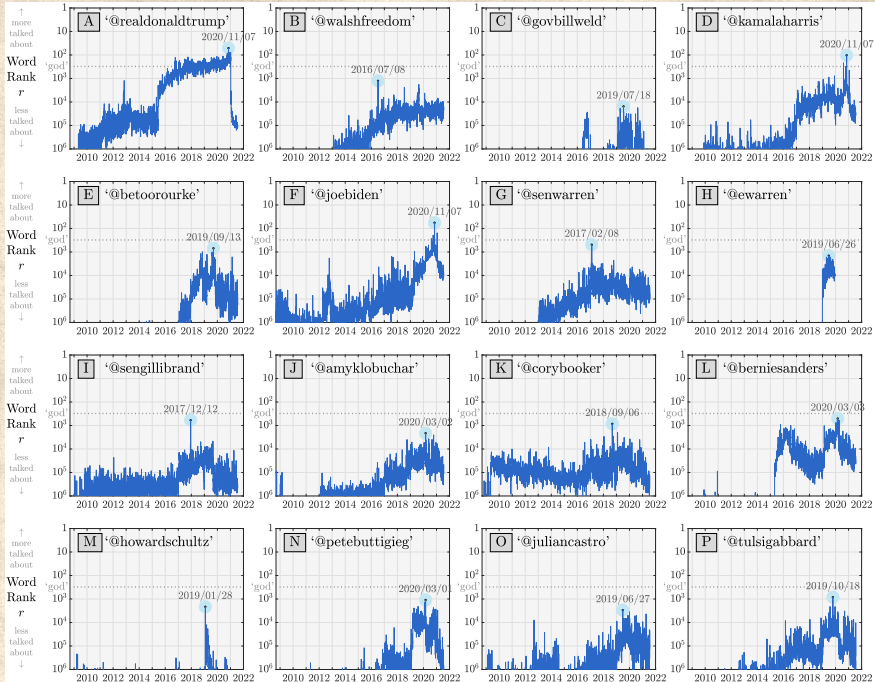




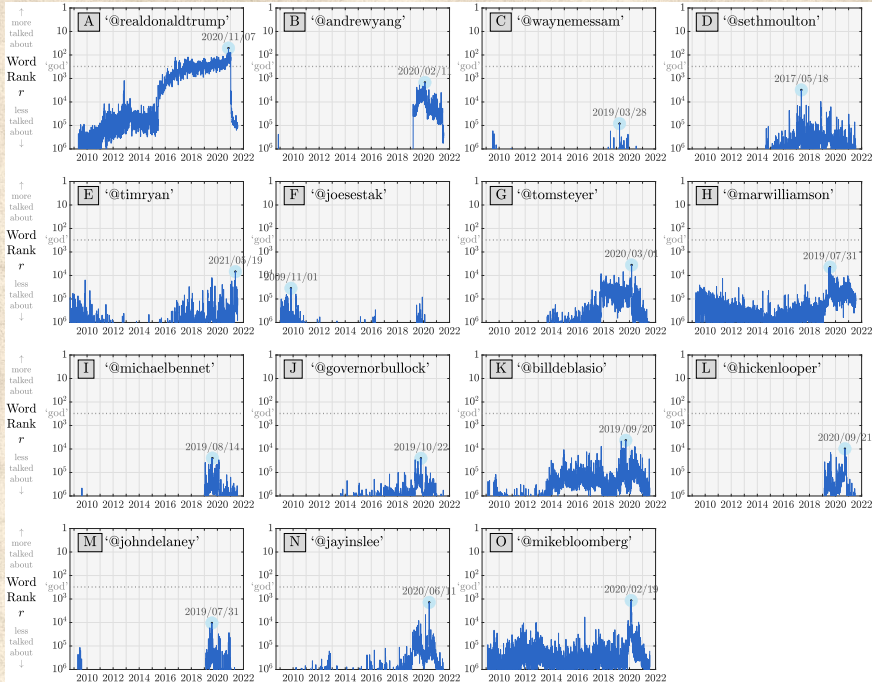












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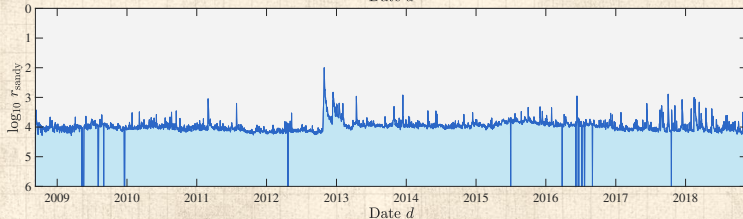
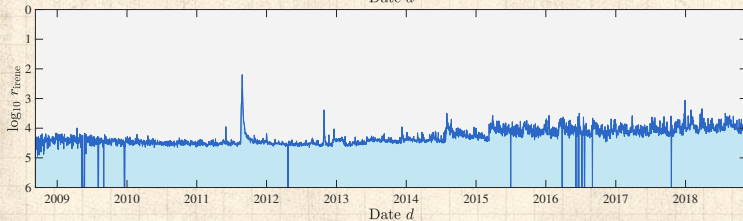
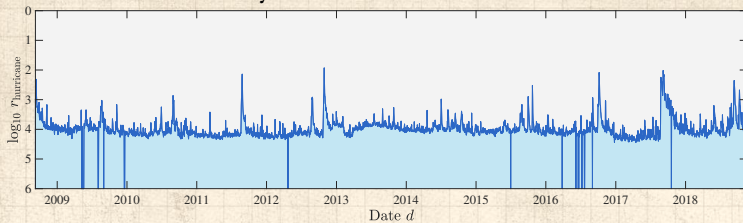
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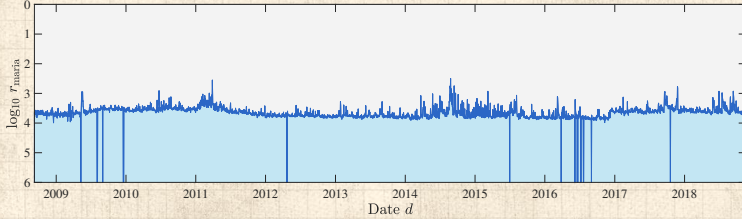
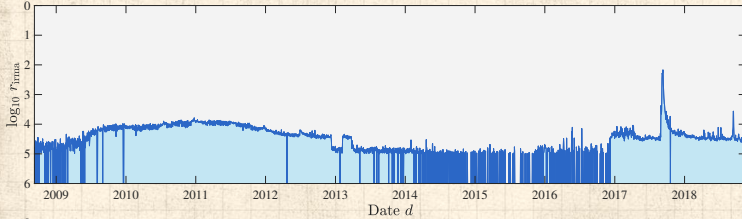
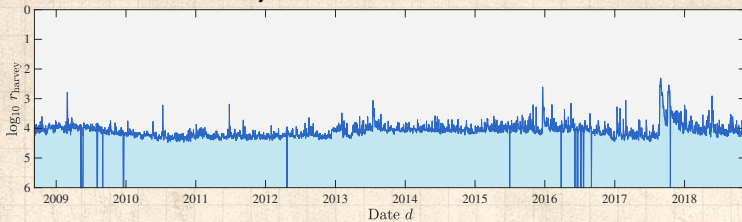
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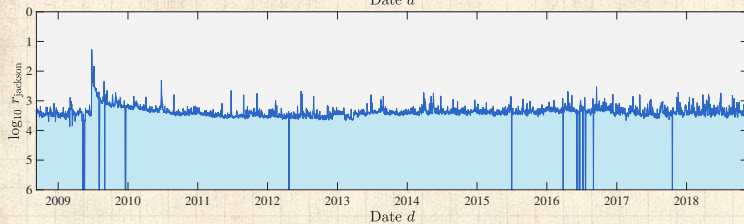
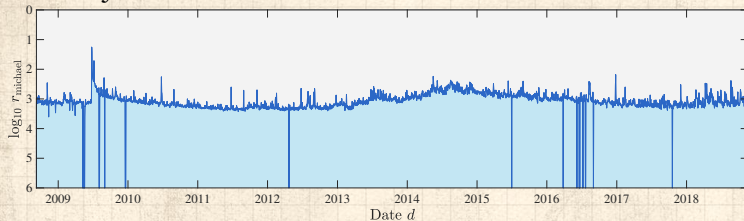
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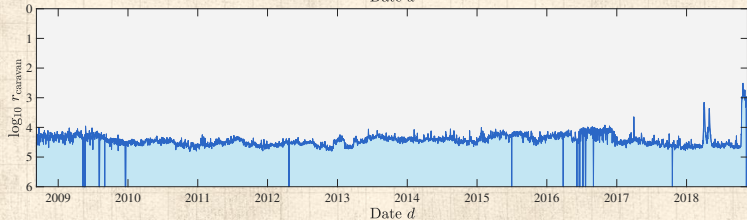
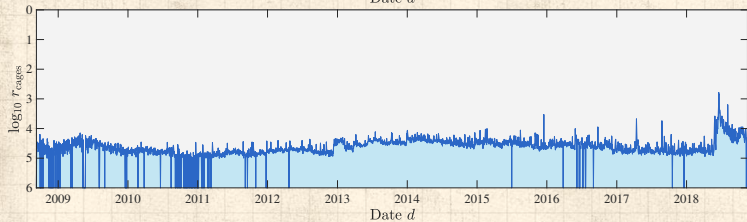
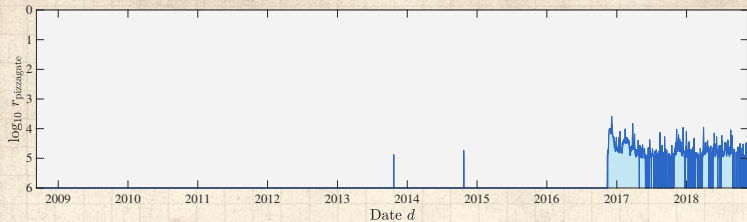
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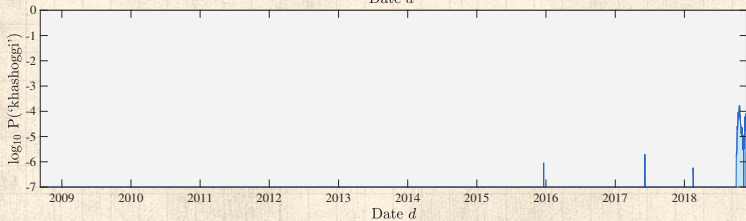
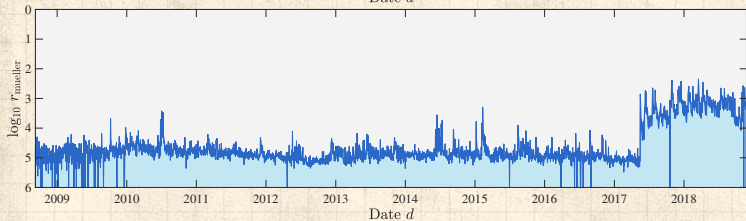
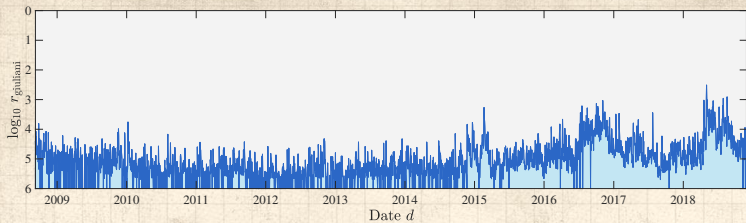
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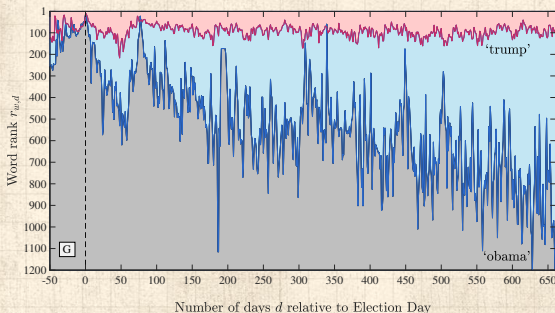
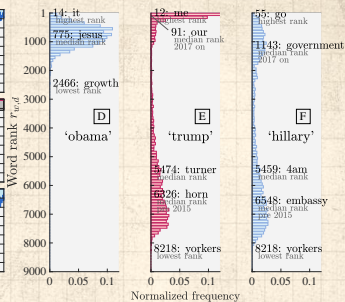
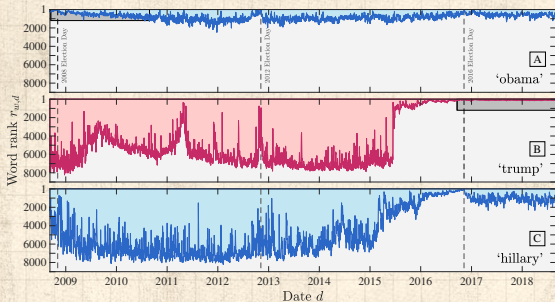
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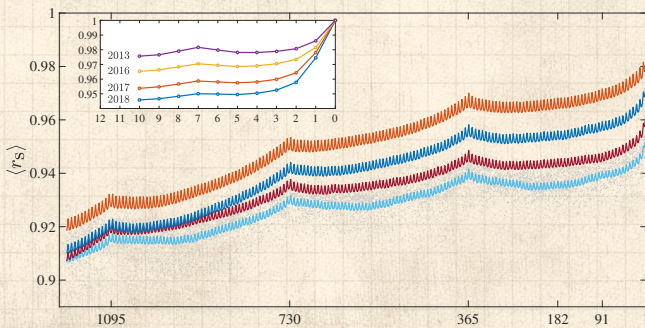
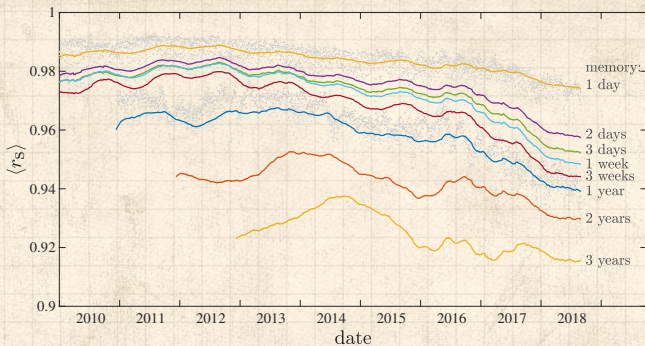
# Lexical fame of POTUSes and possible POTUSes:



- 1-14: the, i, to, a, you, and, is, in, of, for, my, me, on, it
- 50-59: will, as, by, good, they, go, know, it's, he, who
- 100-109: been, its, am, off, you're, via, twitter, us, shit, had
- 150-155: everyone, could, where, tonight, hate, year
- 200-205: followers, birthday, yeah, guys, before, dont
- 250-255: mean, black, nothing, house, put, money
- 300-305: own, bed, remember, though, soon, stay
- 350-355: hell, sex, talking, youtube, we're, seen
- 400-405: place, sometimes, saw, don, gone, christmas
- 450-457: co, they're, join, early, lady, smile, red, book
- 500-507: half, young, wit, words, heard, sick, fast, send
- 550-555: pls, state, worth, pic, everybody, during
- 600-605: ill, pay, relationship, problem, president, month
- 650-655: case, photos, gay, account, knew, mood
- 700-705: click, fact, takes, knows, ones, crying
- 750-757: sister, st, pau, sound, inside, shot, lunch, answer
- 800-807: pain, dreams, lord, huge, kiss, child, movies, card
- 850-855: drunk, wife, killed, forgot, happens, hoe
- 900-905: united, lots, simple, watched, review, brown
- 950-956: absolutely, laughing, price, walking, sense, bar, taken
- 1000-1005: meant, chicken, aww, four, soo, asking
- 1050-1057: near, space, earth, piece, writing, kno, hurts, xxx
- 1100-1105: train, india, award, camera, awkward, stories
- 1150-1154: supposed, especially, training, broken, players
- 1200-1205: trending, race, dying, mobile, putting, winter



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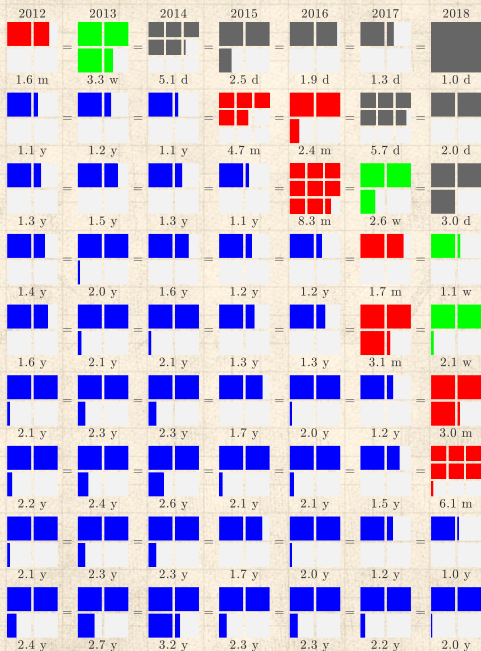
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# Story turbulence:





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