Things to help pull up our SOCKS

Last updated: 2023/08/24, 08:16:49 EDT

Principles of Complex Systems, Vols. 1, 2, & 3D CSYS/MATH 6701, 6713, & a pretend number, 2023–2024| @pocsvox

Prof. Peter Sheridan Dodds | @peterdodds

Computational Story Lab | Vermont Complex Systems Center
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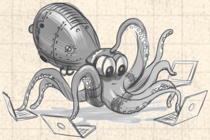
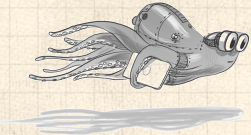




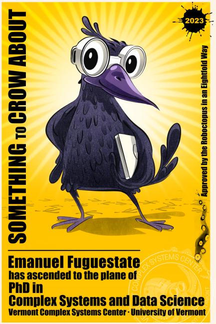
vermontcomplexsystems.org

Leveling up—Scaffolded educational mission:

- Data Science Undergrad.
- Graduate Certificate in Complex Systems and Data Science
- Fall, 2015–: MS in Complex Systems and Data Science
- Fall, 2018–: PhD in ~~The Study of Interesting Things~~ Complex Systems and Data Science

All the words: http://vermontcomplexsystems.org.

Dipoloma-posters:



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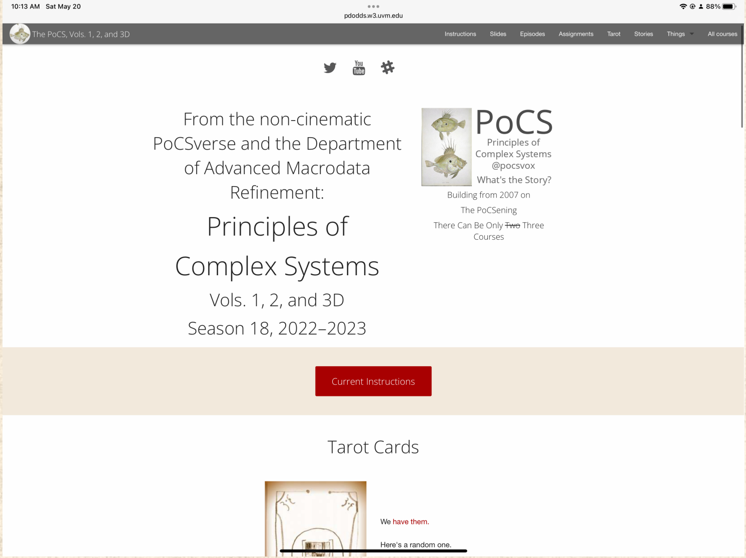

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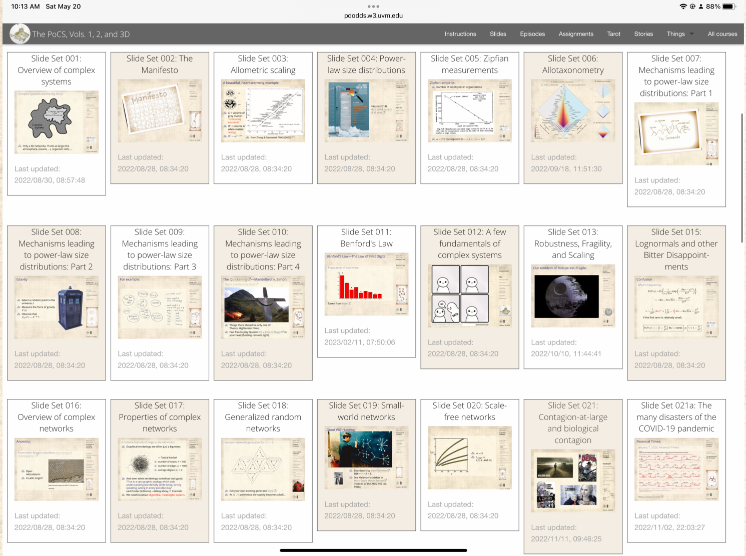

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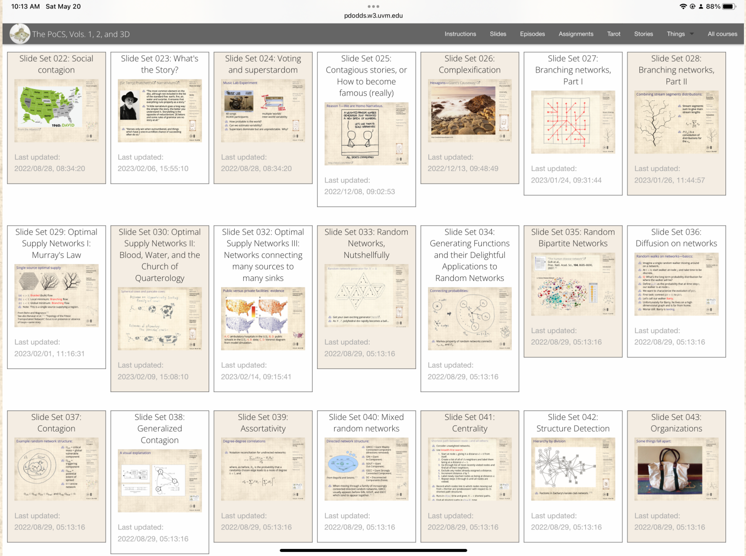

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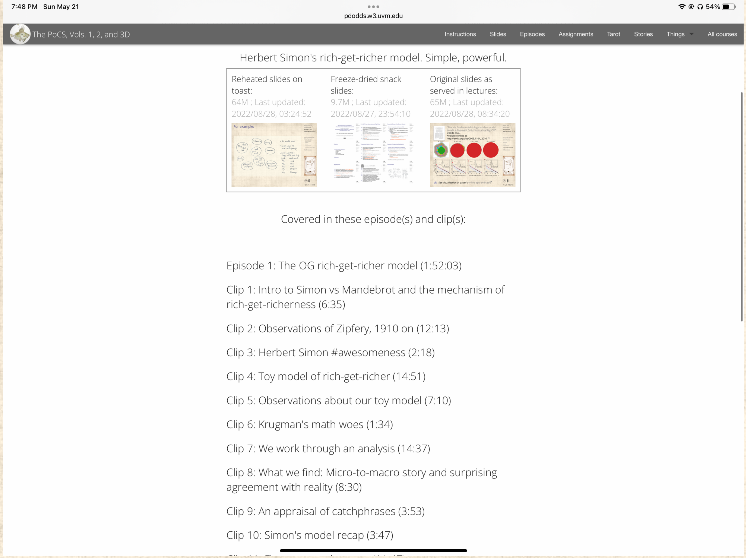

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The PoCS, Vols. 1, 2, and 3D

Instructions Slides Episodes Assignments Tarot Stories Things All courses

Herbert Simon's rich-get-richer model. Simple, powerful.

Reheated slides on toast:	Freeze-dried snack slides:	Original slides as served in lectures:
64M ; Last updated: 2022/08/28, 03:24:52	9.7M ; Last updated: 2022/08/27, 23:54:10	65M ; Last updated: 2022/08/28, 08:34:20

Covered in these episode(s) and clip(s):

Episode 1: The OG rich-get-richer model (1:52:03)

Clip 1: Intro to Simon vs Mandebrot and the mechanism of rich-get-richerness (6:35)

Clip 2: Observations of Zipfery, 1910 on (12:13)

Clip 3: Herbert Simon #awesomeness (2:18)

Clip 4: Toy model of rich-get-richer (14:51)

Clip 5: Observations about our toy model (7:10)

Clip 6: Krugman's math woes (1:34)

Clip 7: We work through an analysis (14:37)

Clip 8: What we find: Micro-to-macro story and surprising agreement with reality (8:30)

Clip 9: An appraisal of catchphrases (3:53)

Clip 10: Simon's model recap (3:47)

Exciting details regarding these slides:

- Three servings (all in pdf):
    1. Fresh: For in-class Deliveration.
    2. On toast: Flattened for page-turning joy.
    3. Freeze-dried: Pack-and-go, 3x3 slides per page.
- ~~Presentation versions are hyperly navigable: back + search + forward.~~
- Web links look like this.
- References in slides link to full citation at end. [2]
- Citations contain links to pdfs for papers (if available).
- Some books will be linked to on Amazon.
- Brought to you by a frightening melange of XƎLaTeX, Beamer, perl, PerlTeX, fevered command-line madness, and an almost fanatical devotion to the indomitable emacs. #totallynormal


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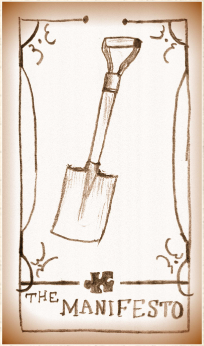
THE MANIFESTO

The Science of Complex Systems Manifesto:

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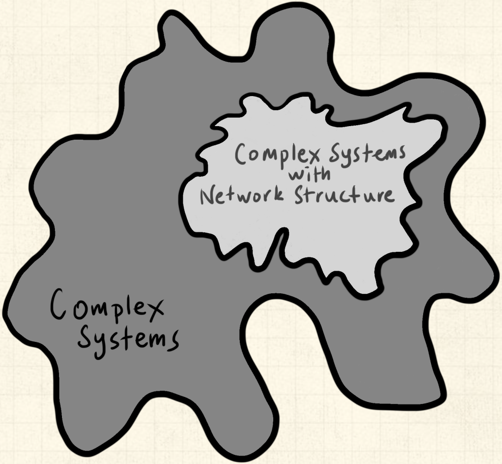
   - 6.2 We can simulate, model, and create complex systems in extraordinary detail.

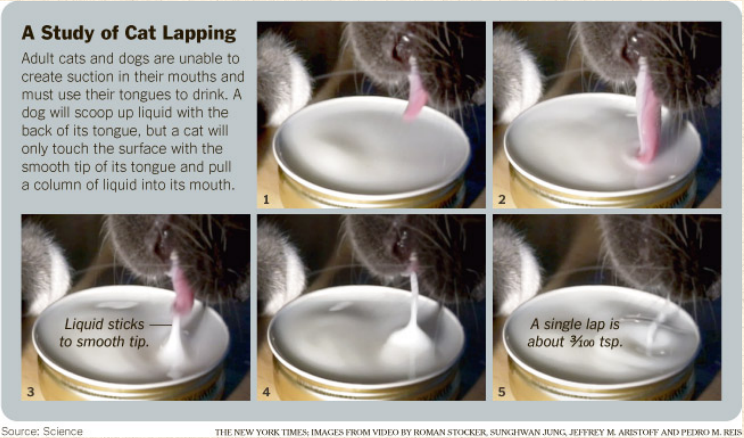
Complex Systems is the Big Story:



- Only sometimes a bit networky: Fluids-at-large (the atmosphere, oceans, ...), organism cells, ...

Rather silly but great example of real science:

"How Cats Lap: Water Uptake by *Felis catus*"
Reis et al., *Science*, 2010.

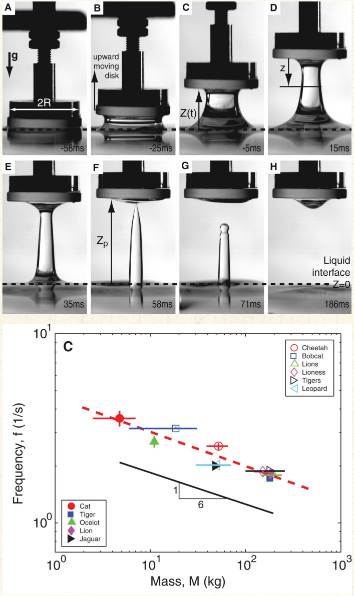


Amusing interview here

Another great, great moment in scaling:

$$f \sim M^{-1/6}$$

The balance of inertia and gravity yields a prediction for the lapping frequency of other felines. Assuming isometry within the Felidae family (i.e., that lapping height H scales linearly with tongue width R and animal mass M scales as R^3), the finding that Fr* is of order one translates to the prediction $f \sim R^{-1/2} \sim M^{-1/6}$. Isometry or marginally positive allomety among the Felidae has been demonstrated for skull (*20*, *21*) and limb bones (*22*). Although variability by function can lead to departures from isometry in interspecific scalings (*23*), reported variations within the Felidae (*23*, *24*) only minimally affect the predicted scaling $f \sim M^{-1/6}$. We tested this –1/6 power-law dependence by measuring the lapping frequency for eight species of felines, from videos acquired at the Zoo New England or available on YouTube (*16*). The lapping frequency was observed to decrease with animal mass as $f = 4.6\,M^{-0.181 \pm 0.024}$ (f in s^{-1}, M in kg) (Fig. 4C), close to the predicted $M^{-1/6}$. This close agreement suggests that the domestic cat's inertia- and gravity-controlled lapping mechanism is conserved among felines.



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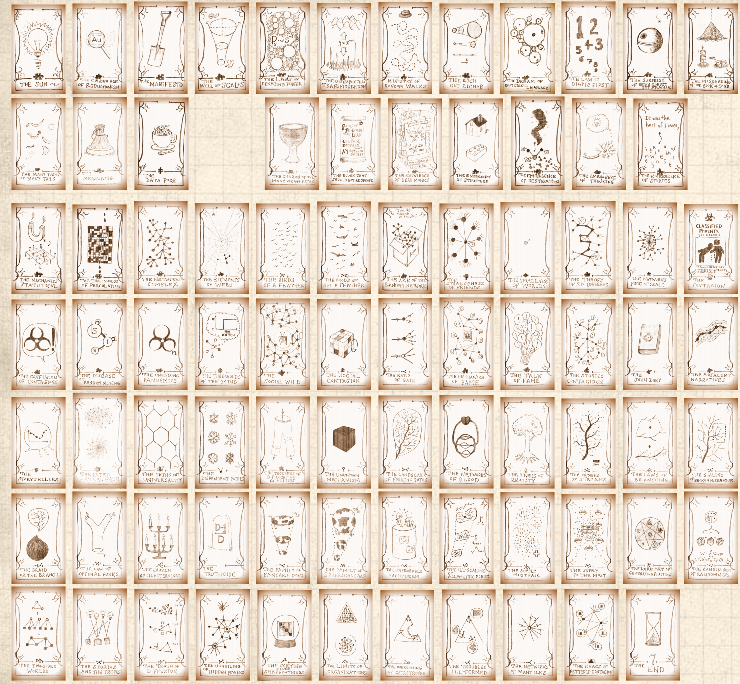
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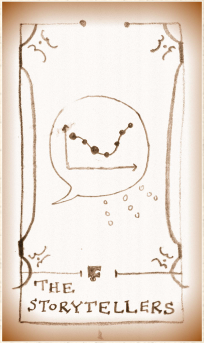
THE CHARMS OF THE MANY WRONG PATHS
THE DOORS THAT SHOULD NOT BE OPENED
THE KNOWLEDGE OF DEAD MONKS
THE EMERGENCE OF STRUCTURE
THE EMERGENCE OF DESTRUCTION
THE EMERGENCE OF THINKING
It was the best of times,
THE EMERGENCE OF STORIES
THE MECHANICS STATISTICAL
THE THRESHOLDS OF PERCOLATION
THE NETWORKS COMPLEX
THE ELEMENTS OF WEBS
THE BIRDS OF A FEATHER
THE BIRDS OF NOT A FEATHER
"I am the Monarch of the Sea."
THE ARK OF THE RANDOM NETWORK
THE STRANGENESS OF FRIENDS
THE SMALLNESS OF WORLDS
THE THEORY OF SIX DEGREES
THE NETWORKS FREE OF SCALE
CLASSIFIED
PHOENIX
THE CONTAGION
THE CONFUSION OF CONTAGIONS
THE DISEASE OF RANDOM MIXING
THE UNENDING PANDEMICS
THE THRESHOLDS OF THE MIND
THE SOCIAL WILD
THE SOCIAL CONTAGION
THE RATIO OF GAIN
THE MECHANICS OF FAME
THE TALK OF FAME
THE STORIES CONTAGIOUS
THE JOHN DORY
THE ADJACENT NARRATIVES
THE FATED ASTRAL PATH
THE PATHS OF UNIVERSALITY
THE DEPENDENT PATHS
THE TROUSERS OF BIFURCATING REALITIES
THE UNKNOWN MECHANISM
THE LANDSCAPES OF FORKING PATHS
THE NETWORKS OF BLOOD
THE TREES OF REALITY
THE ORDERS OF STREAMS
THE LAWS OF BRANCHING
THE SCALING OF BROKEN HIERARCHIES
THE BRAID OR THE BRANCH
THE LAW OF OPTIMAL FORKS
THE CHURCH OF QUARTEROLOGY
THE TRUTHICIDE
THE FAMILY OF PANCAKE COWS
THE FAMILY OF SPHERICAL COWS
THE IMPROBABLE PACHYDERM
THE ILL-SCALING OF ALLOMETRIC BODIES
THE SUPPLY MOST FAIR
THE SUPPLY TO THE MOST
THE DARK ART OF GENERATING FUNCTIONS
THE RANDOM SUM OF RANDOMNESS
THE TWO-SIDED WORLDS
THE STORIES AND THE TROPES
THE TRUTH OF DIFFUSION
THE UNVEILING OF HIDDEN POWERS
THE SCRYING FOR THE SHAPES OF THINGS
THE LIMITS OF ORGANIZATIONS
THE OVERCOMING OF CATASTROPHE
THE TROUBLES ILL-FORMED
THE NETWORKS OF MANY ILKS
THE CHAOS OF FETTERED CONTAGION
THE END


THE STORYTELLERS

Super Survival of the Stories:

The Desirability of 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.
- Like the best stories, the best storytellers reproduce more successfully.

Major competing storytelling entities:

- News.
- Books, magazines.
- Art.
- Music industry.
- Television, movie studios, Netflix, HBO, Disney.
- Social media: Facebook, Instagram, Snapchat, ...
- All sport.
- Video games.
- Religions, ideologies, belief systems, Freemasons, ...
- Enduring coherent groups: Cultures, countries, cities, ...

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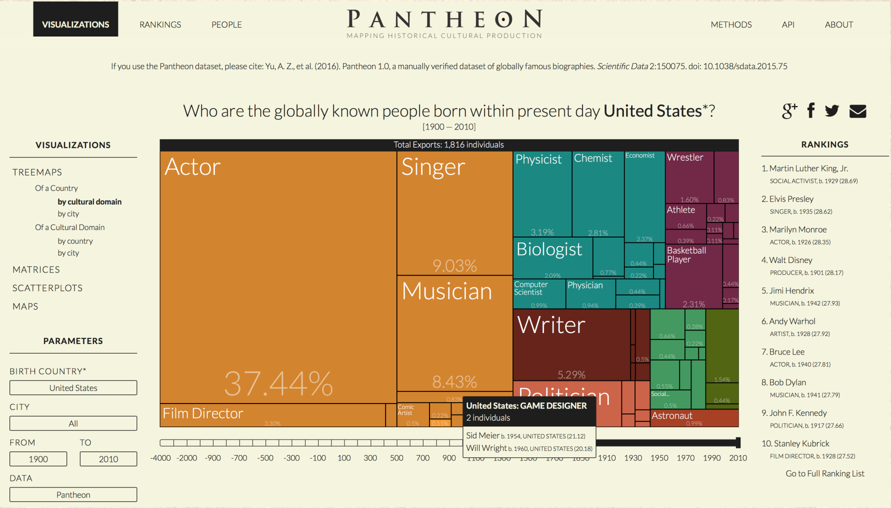
Cultural products from Pantheon:

- Writers, artists, movie directors, video game directors.

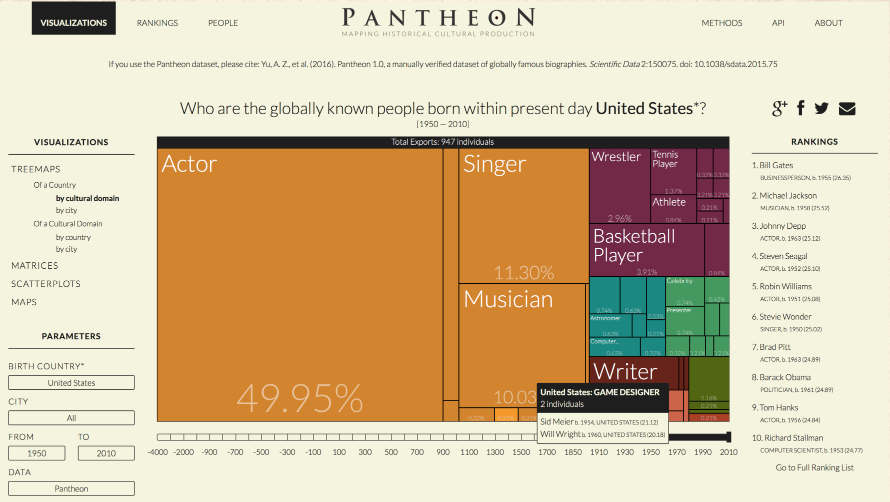
Storytellers win:



For people born 1900–

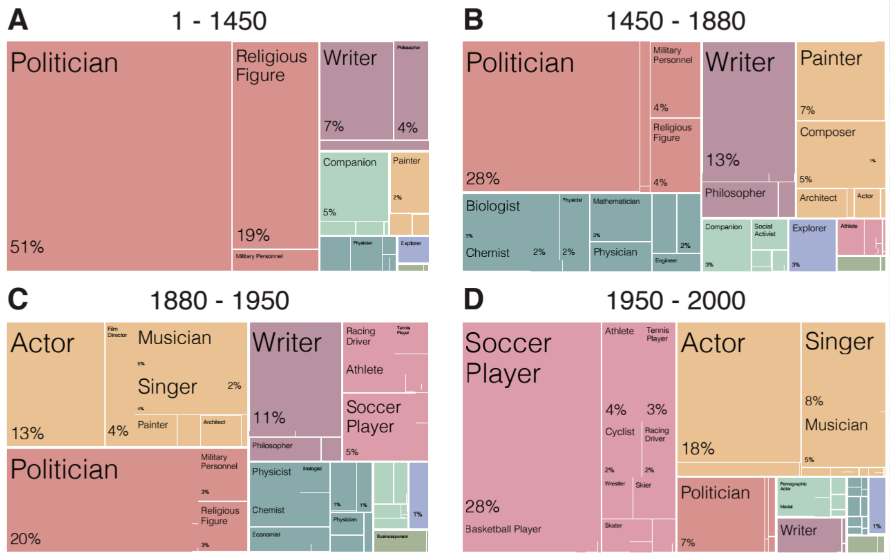
http://pantheon.media.mit.edu/treemap/country_exports/US/all/1900/2010/H15/pantheon

Storytellers win:

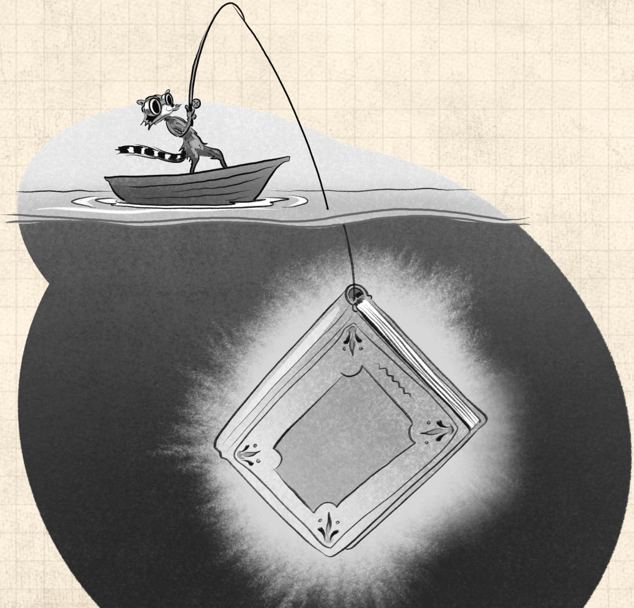


For people born 1950–

http://pantheon.media.mit.edu/treemap/country_exports/US/all/1950/2010/H15/pantheon

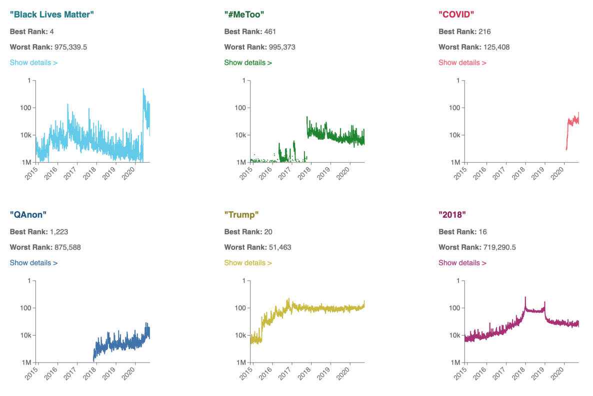


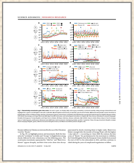
https://www.media.mit.edu/projects/pantheon-new/overview/



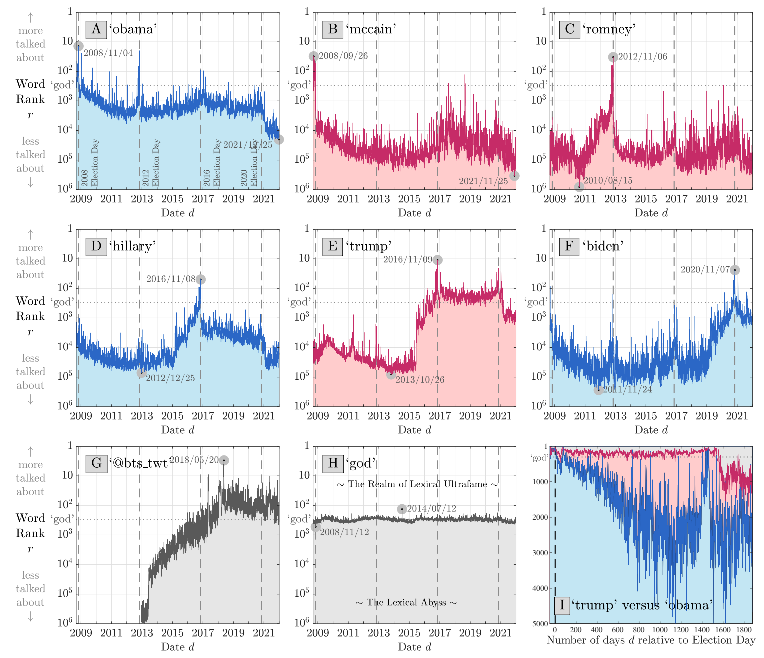
storywrangler
from the University of Vermont Computational Story Lab

https://storywrangling.org/

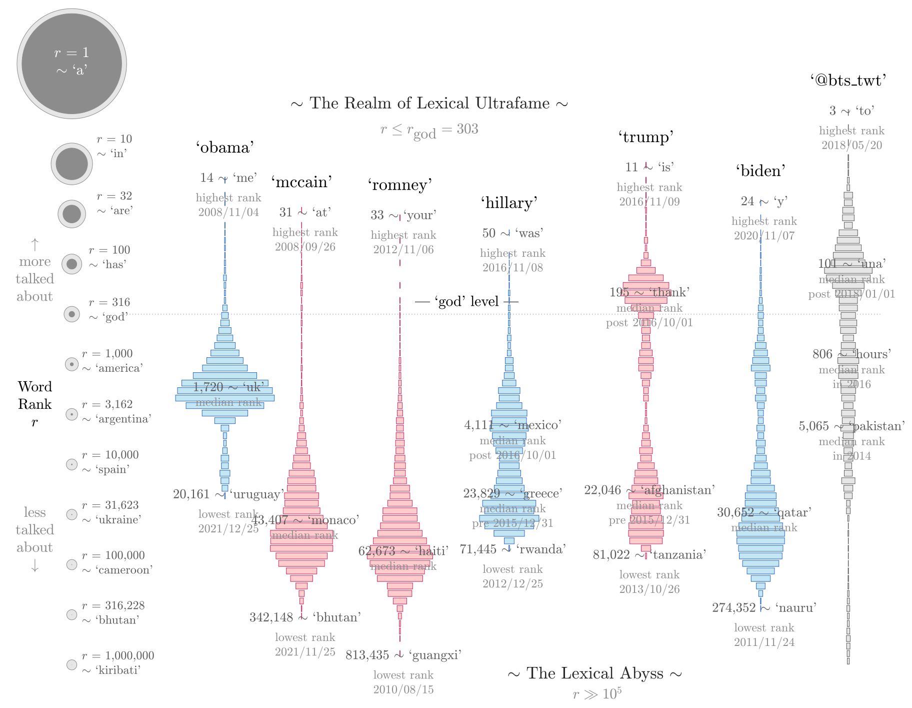




"Storywrangler: A massive exploratorium for sociolinguistic, cultural, socioeconomic, and political timelines using Twitter"
Alshaabi et al.,
Science Advances, **7**, eabe6534, 2021. [1]

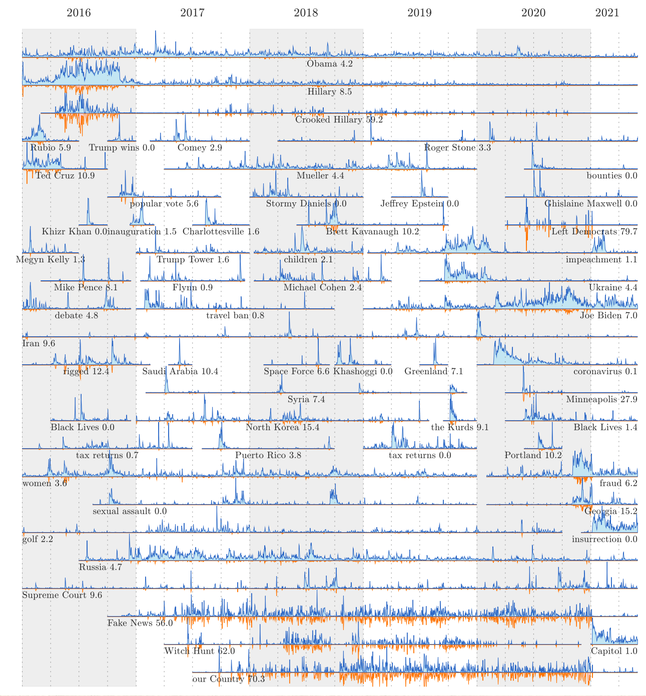


2011 Whitehouse Correspondents' Dinner



r = 1 ∼ 'a'
r = 10 ∼ 'in'
r = 32 ∼ 'are'
r = 100 ∼ 'has'
r = 316 ∼ 'god'
r = 1,000 ∼ 'america'
r = 3,162 ∼ 'argentina'
r = 10,000 ∼ 'spain'
r = 31,623 ∼ 'ukraine'
r = 100,000 ∼ 'cameroon'
r = 316,228 ∼ 'bhutan'
r = 1,000,000 ∼ 'kiribati'
↑ more talked about
Word Rank r
less talked about ↓
∼ The Realm of Lexical Ultrafame ∼
$r \le r_{\mathrm{god}} = 303$
— 'god' level —
∼ The Lexical Abyss ∼
$r \gg 10^5$
'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
43,407 ∼ '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
4,111 ∼ 'mexico'
median rank post 2016/10/01
23,829 ∼ 'greece'
median rank pre 2015/12/31
71,445 ∼ 'rwanda'
lowest rank 2012/12/25
'trump'
11 ∼ 'is'
highest rank 2016/11/09
195 ∼ 'thank'
median rank post 2016/10/01
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
30,652 ∼ 'qatar'
median rank
274,352 ∼ 'nauru'
lowest rank 2011/11/24
'@bts_twt'
3 ∼ 'to'
highest rank 2018/05/20
101 ∼ 'una'
median rank post 2018/01/01
806 ∼ 'hours'
median rank in 2016
5,065 ∼ 'pakistan'
median rank in 2014

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 4.9	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	Jussie Smollett 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	Lyin’ Ted 66.2	health care 0.0	Cambridge Analytica 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	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 5.7	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 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 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 15.7	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	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 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



2016
2017
2018
2019
2020
2021
Obama 4.2
Hillary 8.5
Crooked Hillary 59.2
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 0.0
inauguration 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 8.1
Flynn 0.9
Michael Cohen 2.4
Ukraine 4.4
debate 4.8
travel ban 0.8
Joe Biden 7.0
Iran 9.6
rigged 12.4
Saudi Arabia 10.4
Space Force 6.6
Khashoggi 0.0
Greenland 7.1
coronavirus 0.1
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 56.0
Witch Hunt 62.0
Capitol 1.0
our Country 70.3

The Boggoracle Speaks:

Panometer—Three kinds of lexical meters:

1. Principled lexical meters:
   - The Hedonometer.

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Panometer—Three kinds of lexical meters:

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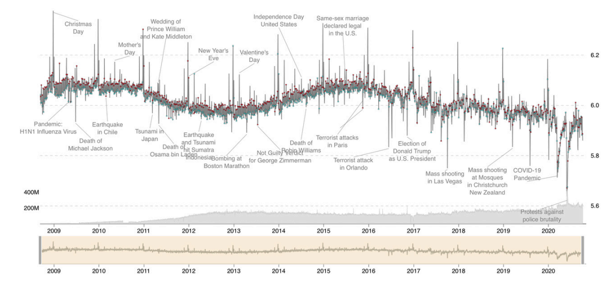
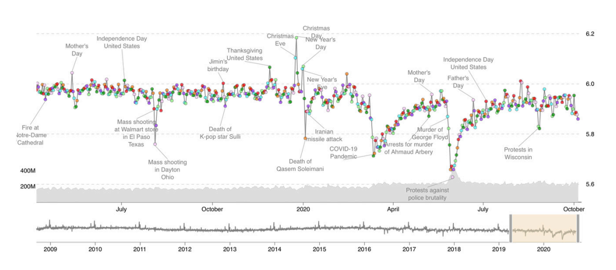
   - Lexicocalorimeter, POTUSometer, Ousiometer.
2. Ground truth lexical meters:
   - Insomniometer.
   - Hangoverometer.
3. Bootstrap lexical meters:
   - Boredometer.
   - Hashtagometers.

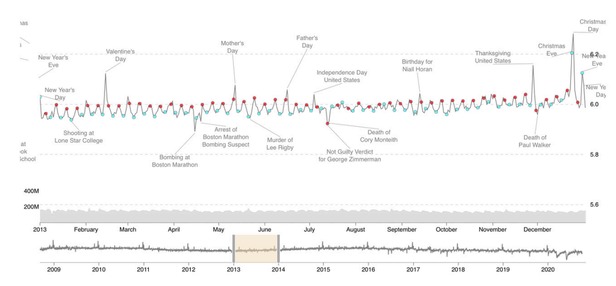
Emotional turbulence:

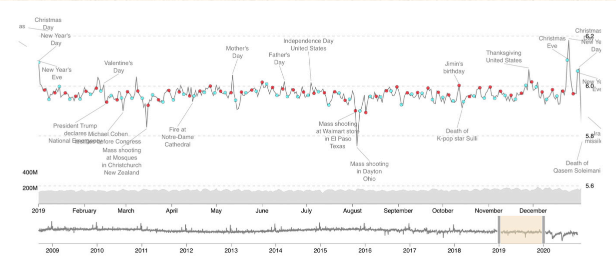




http://hedonometer.org/

Emotional turbulence:





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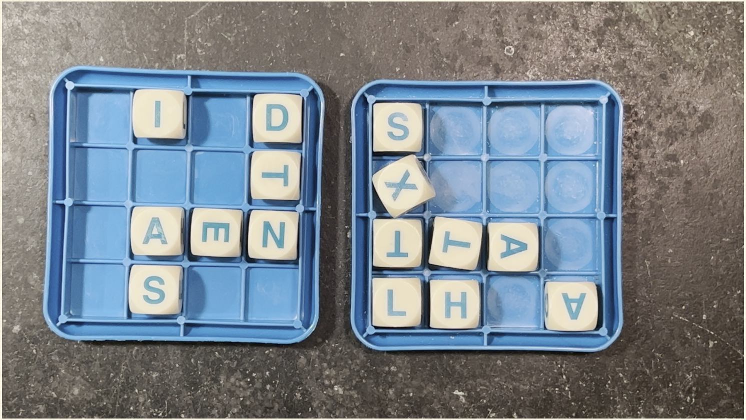
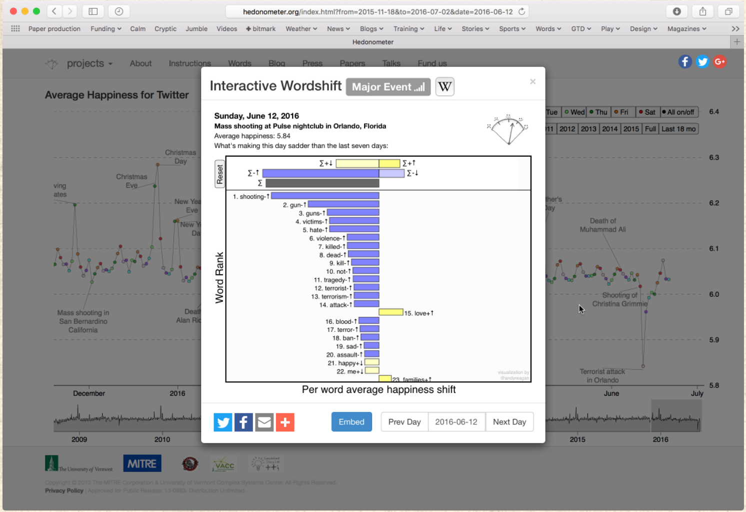
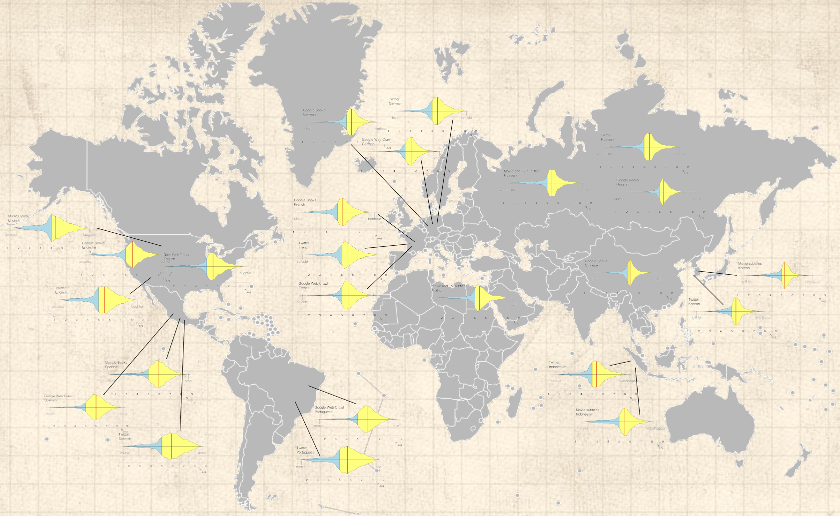


hedonometer.org—word shifts:



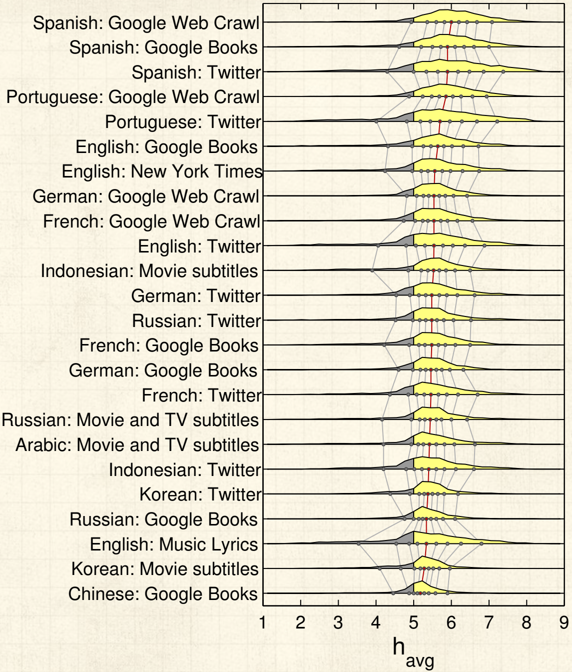


Dodds/Tivnan/Danforth et al.,
Proc. Natl. Acad. Sci. 2015,
"Human language reveals a universal positivity bias." [5]

Global press including National Geographic

Top 100 altmetric article, 2015

853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French: Google Web Crawl
English: Twitter
Indonesian: Movie subtitles
German: Twitter
Russian: Twitter
French: Google Books
German: Google Books
French: Twitter
Russian: Movie and TV subtitles
Arabic: Movie and TV subtitles
Indonesian: Twitter
Korean: Twitter
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1
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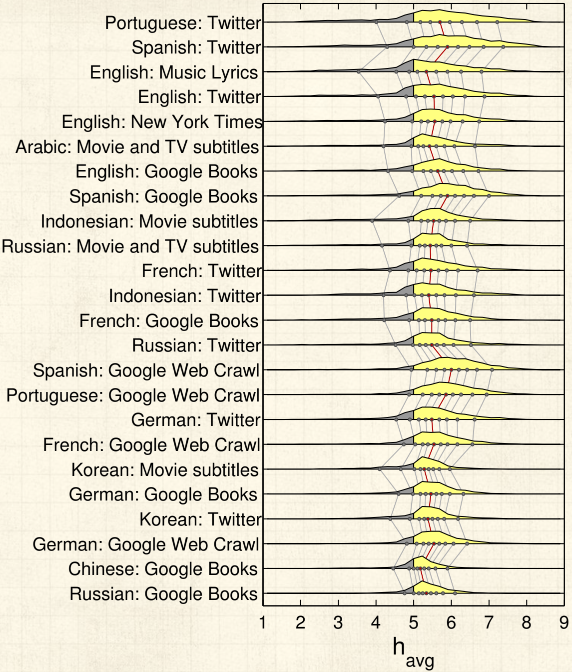
h_{avg}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English: Music Lyrics
English: Twitter
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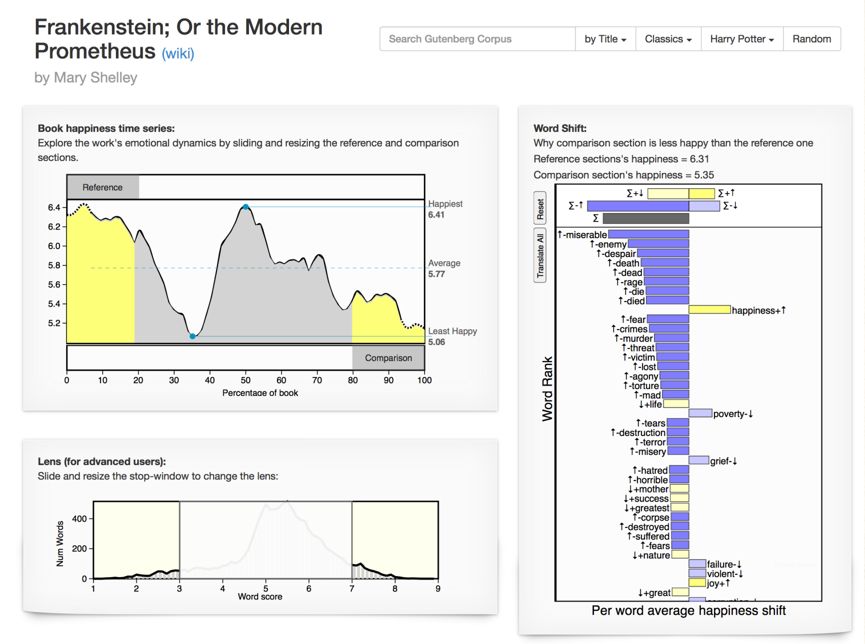
English: Google Books
Spanish: Google Books
Indonesian: Movie subtitles
Russian: Movie and TV subtitles
French: Twitter
Indonesian: Twitter
French: Google Books
Russian: Twitter
Spanish: Google Web Crawl
Portuguese: Google Web Crawl
German: Twitter
French: Google Web Crawl
Korean: Movie subtitles
German: Google Books
Korean: Twitter
German: Google Web Crawl
Chinese: Google Books
Russian: Google Books
1 2 3 4 5 6 7 8 9
h_{avg}

Kurt Vonnegut on the shapes of stories

Source: Kurt Vonnegut on the Shapes of Stories. Longer piece with bonus stories (Metamorphosis and Hamlet).

Online, interactive Emotional Shapes of Stories for 10,000+ books:



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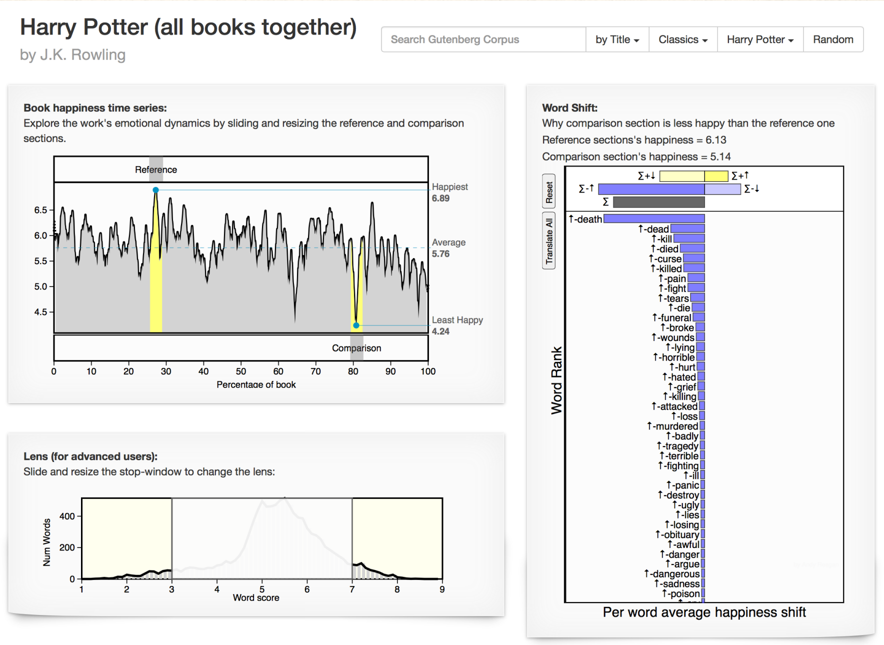


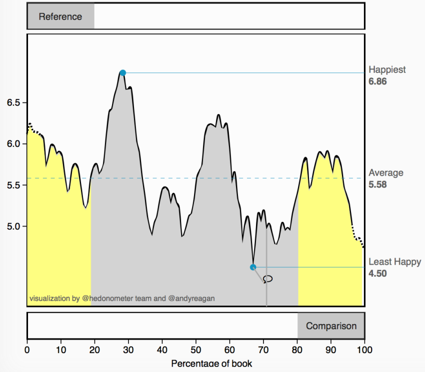
Online, interactive Emotional Shapes of Stories for 1,000+ movie scripts:

Pulp Fiction

directed by Quentin Tarantino

Search Movies | Classics | Team Picks | Random

Movie happiness time series:
Explore the work's emotional dynamics by sliding and resizing the reference and comparison sections.



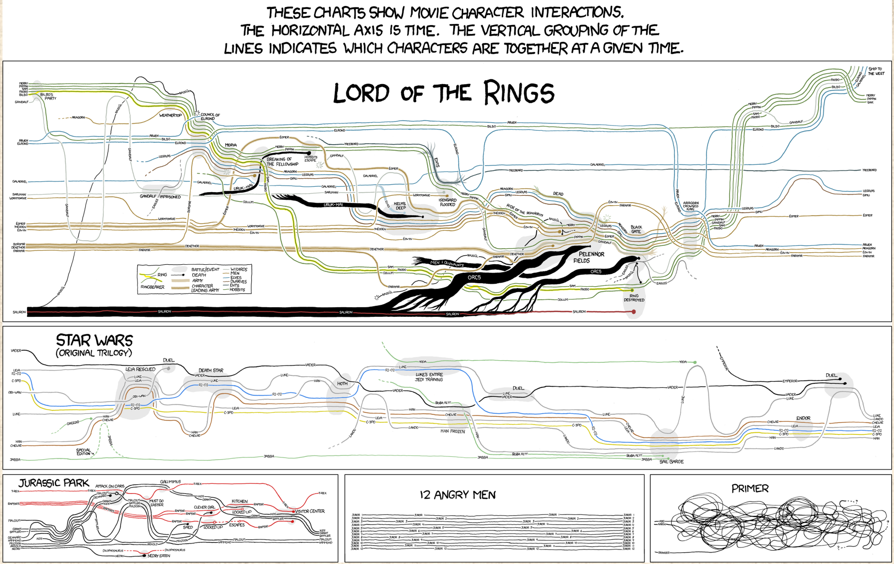
Movie script:
Portion of script scored for each point in timeseries.

```
Zed takes the chair, sits it in front of the two prisoners,
then lowers into it. Maynard hands The Gimp's leash to Zed,
then backs away.

                        MAYNARD
                   (to The Gimp)
             Down!

The Gimp gets on its knees.

Maynard hangs back while Zed appraises the two men.

                        MAYNARD
             Who's first?

                        ZED
             I ain't fer sure yet.

Then with his little finger, Zed does a silent "Eenie, meany,
miney, moe... " just his mouth mouthing the words and his
finger going back and forth between the two.

Butch are Marsellus are terrified.

Maynard looks back and forth at the victims.

The Gimps's eyes go from one to the other inside the mask.
```

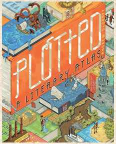
"So, in writing, there are six basic plots, and their sequels and derivative franchises."

The PoCSverse
The Science of OCKS
Storytellers
Characters
Nutshellfish
Extras
References

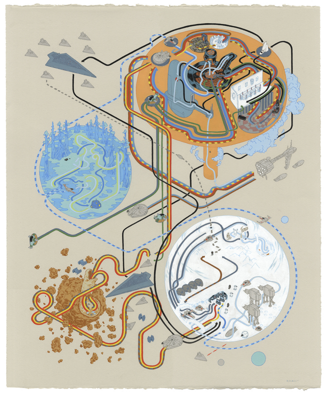
Emotional arcs are not plots. Neither are character paths:



https://xkcd.com/657/



"Plotted: A Literary Atlas"
by Andrew DeGraff (2015).[3]



http://www.andrewdegraff.com/moviemaps/

“Extraction and analysis of fictional character networks: A survey”, Labatut and Bost, ACM Computing Surveys (CSUR), **52**, 1–40, 2019. [12]

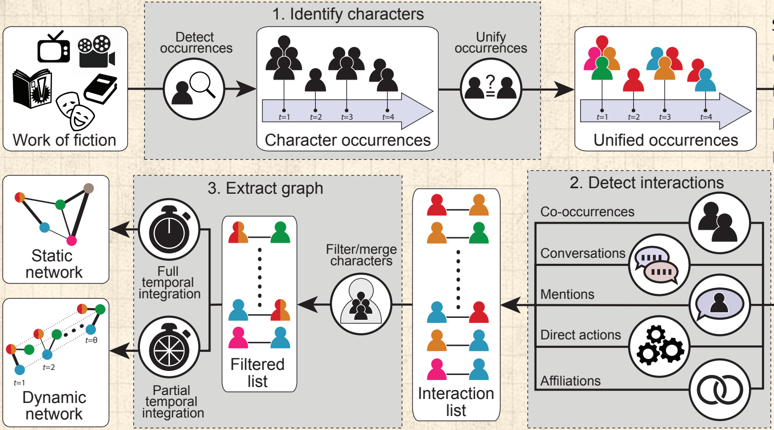
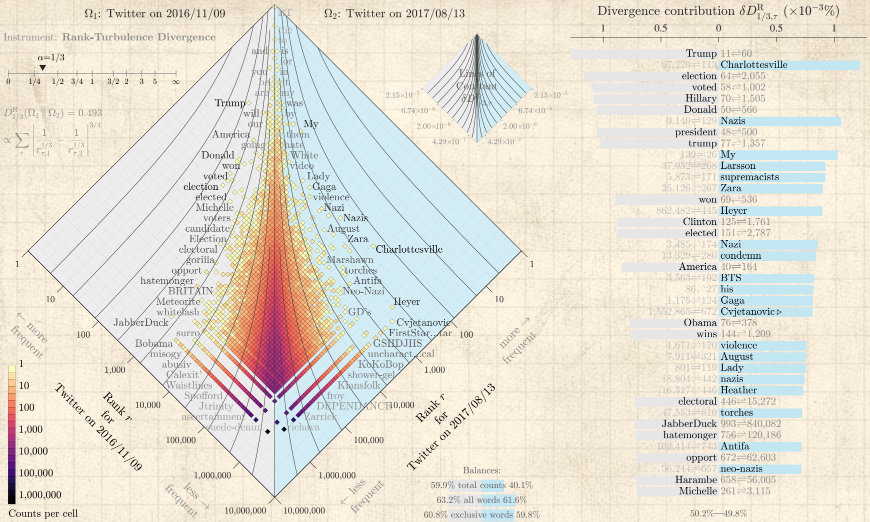


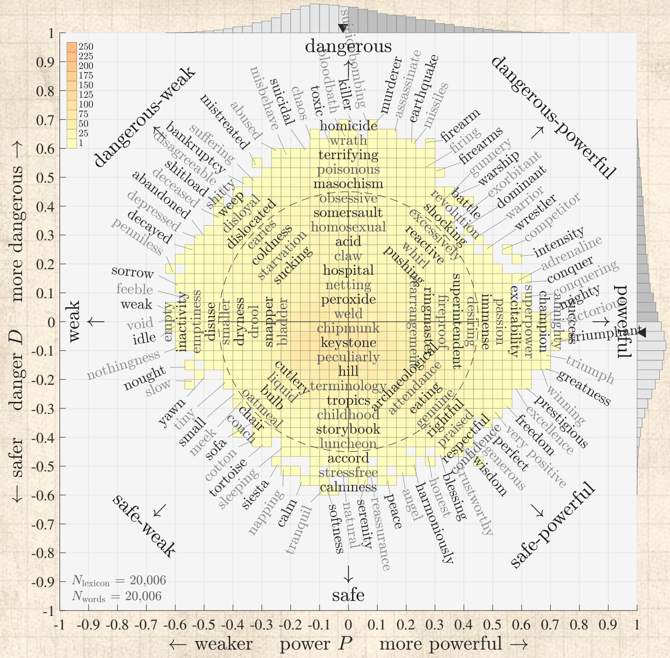
Fig. 1. Overview of the generic character network extraction process. Figure available at 10.6084/m9.figshare.7993040 under CC-BY license.



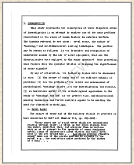
Allotaxonometry—
the comparison of complex systems:

http://compstorylab.org/allotaxonometry/

~ power-danger ousiogram for the NRC VAD lexicon ~



The meaning of pings:



I. INTRODUCTION

This study represents the convergence of three disparate areas of investigation in an attempt to analyze one of the many problems encountered in the study of human factors in undersea warfare. The domains referred to are these: naval sonar, the nature of "meaning," and multidimensional scaling techniques. The problem may be stated as follows: In the detection and recognition of underwater sounds by the use of sonar equipment, what are the discriminative cues employed by the sonar operator? More generally, what factors does the operator utilize in decoding the significance of sonar signals?

By way of orientation, the following topics will be discussed in turn: (1) the nature of sonar and of the auditory stimuli it provides; (2) how the problem of the nature and measurement of psychological "meaning" enters into our investigation; and finally, (3) an historical survey of the methodological approaches to the study of "meaning" and how, at the present time, multidimensional scaling techniques and factor analysis appear to be meeting the need for objective methodology.

A. Naval Sonar

The nature of sonar and of the auditory stimuli it provides is best described by Neff and Thurlow (12, pp. 219-220):

"Sonar makes use of sound waves which are transmitted readily through water; it picks up the sound signals from the water, amplifies them, and analyzes them in various ways so as to present to the operator of sonar equipment useful items of information about objects and their movement in the sea around him . . . Listening systems (Passive sonar) make use of the sounds emitted by objects in the water, e.g., the cavitation noise produced by the screws of a ship . . .

"A factorial study of complex auditory stimuli (passive sonar sounds)"
L. M. Solomon,
Unpublished Doctoral Dissertation, University of Illinois, **52**, , 1954. [17]

From the introduction:

'This study represents the convergence of three disparate areas of investigation in an attempt to analyze one of the many problems encountered in the study of human factors in undersea warfare.
The domains referred to are these:

- naval sonar,
- the nature of "meaning,"
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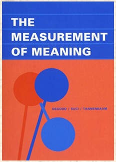
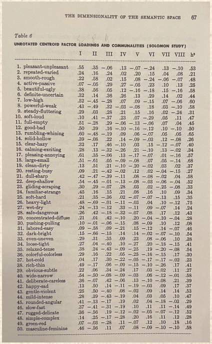
From pings to things:



"The Measurement of Meaning" by Osgood, Suci, and Tannenbaum (1957). [14]



THE DIMENSIONALITY OF THE SEMANTIC SPACE 67

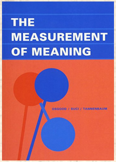
Table 6

UNROTATED CENTROID FACTOR LOADINGS AND COMMUNALITIES (SOLOMON STUDY)

	I	II	III	IV	V	VI	VII	VIII	h^2
1. pleasant-unpleasant	.55	.35	−.06	.13	−.07	−.24	.13	−.10	.53
2. repeated-varied	.24	.16	.24	.02	.20	.15	.04	.08	.21
3. smooth-rough	.22	.58	.02	.15	.08	−.24	−.06	−.07	.48
4. active-passive	.07	−.05	.29	.27	−.05	.23	.10	.13	.25
5. beautiful-ugly	.38	.56	.05	.12	−.16	−.18	.15	−.16	.58
6. definite-uncertain	.32	.14	.36	.26	.13	.29	.14	.02	.44
7. low-high	.52	−.45	−.28	.07	.09	−.15	.07	−.06	.60
8. powerful-weak	.43	−.49	.32	−.03	−.08	.18	.03	−.10	.58
9. steady-fluttering	.29	.03	.28	.21	.15	.16	.02	−.24	.31
10. soft-loud	.10	.41	−.37	.23	.07	−.29	.05	.11	.47
11. full-empty	.51	−.28	.29	−.06	−.13	−.06	.07	.04	.45
12. good-bad	.50	.39	.16	−.10	−.16	−.12	.10	−.10	.50
13. rumbling-whining	.60	−.48	−.19	.09	.06	−.07	.05	.05	.65
14. solid-hollow	.39	−.08	.22	.14	−.09	−.03	.12	−.08	.26
15. clear-hazy	.32	.17	.46	−.10	.03	.15	−.12	−.07	.40
16. calming-exciting	.28	.13	−.32	−.26	.21	−.10	.13	−.02	.34
17. pleasing-annoying	.61	.35	−.06	.13	−.17	−.07	.01	−.16	.57
18. large-small	.51	−.61	.05	−.09	−.08	.07	.05	−.14	.68
19. clean-dirty	.13	.51	.21	−.10	−.20	−.02	.03	.02	.37
20. resting-busy	.09	.21	−.42	−.02	.12	.02	−.04	−.15	.27
21. dull-sharp	.42	−.47	−.39	−.11	.08	−.08	−.02	.04	.58
22. deep-shallow	.54	−.45	−.01	−.13	−.08	−.03	−.06	−.04	.52
23. gliding-scraping	.30	.29	−.07	.28	.03	.02	−.25	−.08	.33
24. familiar-strange	.45	.16	.15	.21	.08	.16	.10	.09	.34
25. soft-hard	.21	.35	−.36	.02	−.07	−.07	−.13	.15	.35
26. heavy-light	.48	−.69	−.01	−.11	−.03	.04	.10	−.12	.75
27. wet-dry	.24	−.13	−.12	.33	−.11	.09	−.07	.14	.24
28. safe-dangerous	.26	.42	−.18	−.32	−.07	.08	.17	.12	.43
29. concentrated-diffuse	.21	.01	.42	−.10	.20	−.04	−.10	−.04	.28
30. pushing-pulling	.10	−.01	−.06	−.15	.08	−.09	.10	.12	.08
31. labored-easy	.09	−.58	.09	−.21	.15	−.12	.14	−.07	.46
32. dark-bright	.15	−.66	−.15	.14	.14	−.02	−.07	−.10	.54
33. even-uneven	.29	.31	.35	.09	.23	.08	−.06	.10	.38
34. loose-tight	.27	.04	−.40	.10	−.27	.20	−.18	−.15	.41
35. relaxed-tense	.38	.24	−.43	−.09	−.25	.19	−.20	−.08	.54
36. colorful-colorless	.29	.16	.22	.05	−.25	−.16	−.15	.17	.30
37. hot-cold	.04	.17	.30	−.22	−.05	−.17	−.17	−.02	.23
38. rich-thin	.49	−.17	.06	−.09	−.15	−.10	−.26	.17	.41
39. obvious-subtle	.22	.06	.34	−.24	.17	.03	−.02	.11	.27
40. wide-narrow	.54	−.50	−.08	−.09	−.03	.06	−.12	−.01	.58
41. deliberate-careless	.36	−.07	.42	−.06	.13	−.10	−.08	.21	.39
42. happy-sad	.13	.50	.14	−.11	−.19	−.03	.09	.17	.37
43. gentle-violent	.25	.50	−.40	.08	−.02	.09	.14	.14	.53
44. mild-intense	.28	.39	−.43	−.19	.04	.03	.05	.10	.47
45. rounded-angular	.41	−.13	−.17	.19	.02	.04	−.18	−.03	.29
46. slow-fast	.37	−.41	−.31	−.19	.10	.11	.11	−.14	.49
47. rugged-delicate	.36	−.56	.19	−.12	−.02	−.05	−.07	−.12	.52
48. simple-complex	.14	.25	−.17	−.28	.20	.16	.11	.12	.28
49. green-red	.07	−.03	−.28	.11	−.07	.12	.10	.18	.16
50. masculine-feminine	.46	−.56	.11	.07	.08	−.09	−.10	−.10	.58

- Osgood et al. used semantic differentials and factor analysis to identify a basis of three variables for meaning-space:

From pings to things:



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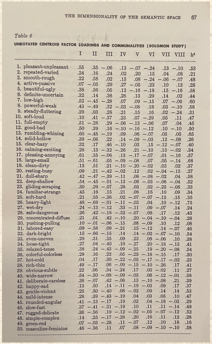

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12. good-bad	.50	.39	.16	−.10	−.16	−.12	.10	−.10	.50
13. rumbling-whining	.60	−.48	−.19	.09	.06	−.07	.05	.05	.65
14. solid-hollow	.39	−.08	.22	.14	−.09	−.03	.12	−.08	.26
15. clear-hazy	.32	.17	.46	−.10	.03	.15	−.12	−.07	.40
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19. clean-dirty	.13	.51	.21	−.10	−.20	−.02	.03	.02	.37
20. resting-busy	.09	.21	−.42	−.02	.12	.02	−.04	−.15	.27
21. dull-sharp	.42	−.47	−.39	−.11	.08	−.08	−.02	.04	.58
22. deep-shallow	.54	−.45	−.01	−.13	−.08	−.03	−.06	−.04	.52
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25. soft-hard	.21	.35	−.36	.02	−.07	−.07	−.13	.15	.35
26. heavy-light	.48	−.69	−.01	−.11	−.03	.04	.10	−.12	.75
27. wet-dry	.24	−.13	−.12	.33	−.11	.09	−.07	.14	.24
28. safe-dangerous	.26	.42	−.18	−.32	−.07	.08	.17	.12	.43
29. concentrated-diffuse	.21	.01	.42	−.10	.20	−.04	−.10	−.04	.28
30. pushing-pulling	.10	−.01	−.06	−.15	.08	−.09	.10	.12	.08
31. labored-easy	.09	−.58	.09	−.21	.15	−.12	.14	−.07	.46
32. dark-bright	.15	−.66	−.15	.14	.14	−.02	−.07	−.10	.54
33. even-uneven	.29	.31	.35	.09	.23	.08	−.06	.10	.38
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38. rich-thin	.49	−.17	.06	−.09	−.15	−.10	−.26	.17	.41
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46. slow-fast	.37	−.41	−.31	−.19	.10	.11	.11	−.14	.49
47. rugged-delicate	.36	−.56	.19	−.12	−.02	−.05	−.07	−.12	.52
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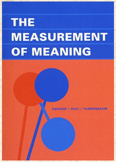
  - Evaluation: {bad ⇔ good}

From pings to things:



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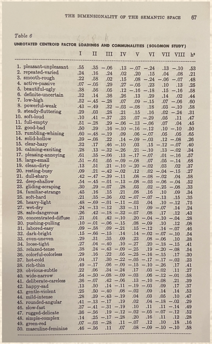

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13. rumbling-whining	.60	−.48	−.19	.09	.06	−.07	.05	.05	.65
14. solid-hollow	.39	−.08	.22	.14	−.09	−.03	.12	−.08	.26
15. clear-hazy	.32	.17	.46	−.10	.03	.15	−.12	−.07	.40
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19. clean-dirty	.13	.51	.21	−.10	−.20	−.02	.03	.02	.37
20. resting-busy	.09	.21	−.42	−.02	.12	.02	−.04	−.15	.27
21. dull-sharp	.42	−.47	−.39	−.11	.08	−.08	−.02	.04	.58
22. deep-shallow	.54	−.45	−.01	−.13	−.08	−.03	−.06	−.04	.52
23. gliding-scraping	.30	.29	−.07	.28	.03	.02	−.25	−.08	.33
24. familiar-strange	.45	.16	.15	.21	.08	.16	.10	.09	.34
25. soft-hard	.21	.35	−.36	.02	−.07	−.07	−.13	.15	.35
26. heavy-light	.48	−.69	−.01	−.11	−.03	.04	.10	−.12	.75
27. wet-dry	.24	−.13	−.12	.33	−.11	.09	−.07	.14	.24
28. safe-dangerous	.26	.42	−.18	−.32	−.07	.08	.17	.12	.43
29. concentrated-diffuse	.21	.01	.42	−.10	.20	−.04	−.10	−.04	.28
30. pushing-pulling	.10	−.01	−.06	−.15	.08	−.09	.10	.12	.08
31. labored-easy	.09	−.58	.09	−.21	.15	−.12	.14	−.07	.46
32. dark-bright	.15	−.66	−.15	.14	.14	−.02	−.07	−.10	.54
33. even-uneven	.29	.31	.35	.09	.23	.08	−.06	.10	.38
34. loose-tight	.27	.04	−.40	.10	−.27	.20	−.18	−.15	.41
35. relaxed-tense	.38	.24	−.43	−.09	−.25	.19	−.20	−.08	.54
36. colorful-colorless	.29	.16	.22	.05	−.25	−.16	−.15	.17	.30
37. hot-cold	.04	.17	.30	−.22	−.05	−.17	−.17	−.02	.23
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39. obvious-subtle	.22	.06	.34	−.24	.17	.03	−.02	.11	.27
40. wide-narrow	.54	−.50	−.08	−.09	−.03	.06	−.12	−.01	.58
41. deliberate-careless	.36	−.07	.42	−.06	.13	−.10	−.08	.21	.39
42. happy-sad	.13	.50	.14	−.11	−.19	−.03	.09	.17	.37
43. gentle-violent	.25	.50	−.40	.08	−.02	.09	.14	.14	.53
44. mild-intense	.28	.39	−.43	−.19	.04	.03	.05	.10	.47
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46. slow-fast	.37	−.41	−.31	−.19	.10	.11	.11	−.14	.49
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- Osgood et al. used semantic differentials and factor analysis to identify a basis of three variables for meaning-space:
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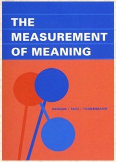

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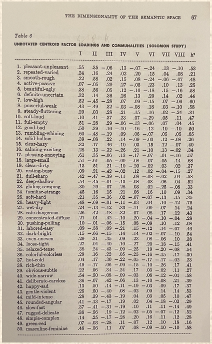

THE DIMENSIONALITY OF THE SEMANTIC SPACE 67

Table 6

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2. repeated-varied	.24	.16	.24	.02	.20	.15	.04	.08	.21
3. smooth-rough	.22	.58	.02	.15	.08	−.24	−.06	−.07	.48
4. active-passive	.07	−.05	.29	.27	−.05	.23	.10	.13	.25
5. beautiful-ugly	.38	.56	.05	.12	−.16	−.18	.15	−.16	.58
6. definite-uncertain	.32	.14	.36	.26	.13	.29	.14	.02	.44
7. low-high	.52	−.45	−.28	.07	.09	−.15	.07	−.06	.60
8. powerful-weak	.43	−.49	.32	−.03	−.08	.18	.03	−.10	.58
9. steady-fluttering	.29	.03	.28	.21	.15	.16	.02	−.24	.31
10. soft-loud	.10	.41	−.37	.23	.07	−.29	.05	.11	.47
11. full-empty	.51	−.28	.29	−.06	−.13	−.06	.07	.04	.45
12. good-bad	.50	.39	.16	−.10	−.16	−.12	.10	−.10	.50
13. rumbling-whining	.60	−.48	−.19	.09	.06	−.07	.05	.05	.65
14. solid-hollow	.39	−.08	.22	.14	−.09	−.03	.12	−.08	.26
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16. calming-exciting	.28	.13	−.32	−.26	.21	−.10	.13	−.02	.34
17. pleasing-annoying	.61	.35	−.06	.13	−.17	−.07	.01	−.16	.57
18. large-small	.51	−.61	.05	−.09	−.08	.07	.05	−.14	.68
19. clean-dirty	.13	.51	.21	−.10	−.20	−.02	.03	.02	.37
20. resting-busy	.09	.21	−.42	−.02	.12	.02	−.04	−.15	.27
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25. soft-hard	.21	.35	−.36	.02	−.07	−.07	−.13	.15	.35
26. heavy-light	.48	−.69	−.01	−.11	−.03	.04	.10	−.12	.75
27. wet-dry	.24	−.13	−.12	.33	−.11	.09	−.07	.14	.24
28. safe-dangerous	.26	.42	−.18	−.32	−.07	.08	.17	.12	.43
29. concentrated-diffuse	.21	.01	.42	−.10	.20	−.04	−.10	−.04	.28
30. pushing-pulling	.10	−.01	−.06	−.15	.08	−.09	.10	.12	.08
31. labored-easy	.09	−.58	.09	−.21	.15	−.12	.14	−.07	.46
32. dark-bright	.15	−.66	−.15	.14	.14	−.02	−.07	−.10	.54
33. even-uneven	.29	.31	.35	.09	.23	.08	−.06	.10	.38
34. loose-tight	.27	.04	−.40	.10	−.27	.20	−.18	−.15	.41
35. relaxed-tense	.38	.24	−.43	−.09	−.25	.19	−.20	−.08	.54
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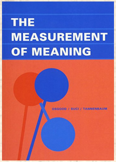

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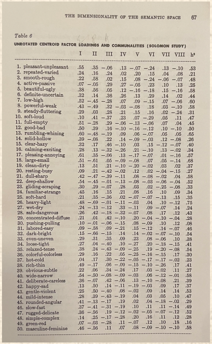

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12. good-bad	.50	.39	.16	−.10	−.16	−.12	.10	−.10	.50
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18. large-small	.51	−.61	.05	−.09	−.08	.07	.05	−.14	.68
19. clean-dirty	.13	.51	.21	−.10	−.20	−.02	.03	.02	.37
20. resting-busy	.09	.21	−.42	−.02	.12	.02	−.04	−.15	.27
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26. heavy-light	.48	−.69	−.01	−.11	−.03	.04	.10	−.12	.75
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29. concentrated-diffuse	.21	.01	.42	−.10	.20	−.04	−.10	−.04	.28
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34. loose-tight	.27	.04	−.40	.10	−.27	.20	−.18	−.15	.41
35. relaxed-tense	.38	.24	−.43	−.09	−.25	.19	−.20	−.08	.54
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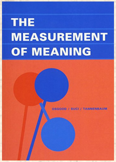

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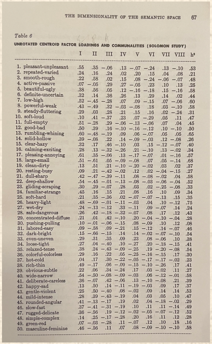

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10. soft-loud	.10	.41	−.37	.23	.07	−.29	.05	.11	.47
11. full-empty	.51	−.28	.29	−.06	−.13	−.06	.07	.04	.45
12. good-bad	.50	.39	.16	−.10	−.16	−.12	.10	−.10	.50
13. rumbling-whining	.60	−.48	−.19	.09	.06	−.07	.05	.05	.65
14. solid-hollow	.39	−.08	.22	.14	−.09	−.03	.12	−.08	.26
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16. calming-exciting	.28	.13	−.32	−.26	.21	−.10	.13	−.02	.34
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20. resting-busy	.09	.21	−.42	−.02	.12	.02	−.04	−.15	.27
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23. gliding-scraping	.30	.29	−.07	.28	.03	.02	−.25	−.08	.33
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27. wet-dry	.24	−.13	−.12	.33	−.11	.09	−.07	.14	.24
28. safe-dangerous	.26	.42	−.18	−.32	−.07	.08	.17	.12	.43
29. concentrated-diffuse	.21	.01	.42	−.10	.20	−.04	−.10	−.04	.28
30. pushing-pulling	.10	−.01	−.06	−.15	.08	−.09	.10	.12	.08
31. labored-easy	.09	−.58	.09	−.21	.15	−.12	.14	−.07	.46
32. dark-bright	.15	−.66	−.15	.14	.14	−.02	−.07	−.10	.54
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34. loose-tight	.27	.04	−.40	.10	−.27	.20	−.18	−.15	.41
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Semantic differentials from Osgood et al.: [14]

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32. dark-bright
33. even-uneven
34. loose-tight
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- To be distinguished from semantics, semiotics, ...
- οὐσία is the etymological root of the word ‘essence’.
- Ousiometry, ousiometer, ousiograms, ...

Definitions:

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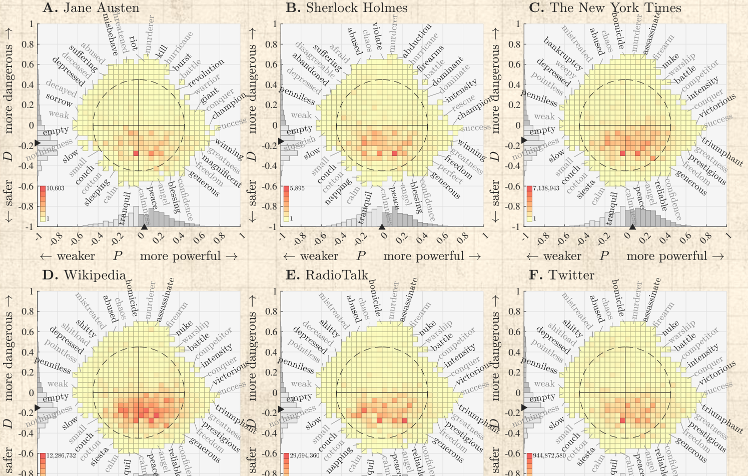
- To be distinguished from semantics, semiotics, ...
- οὐσία is the etymological root of the word ‘essence’.
- Ousiometry, ousiometer, ousiograms, ...
- Telegnomics: The distant sensing of knowledge (∼ distant reading [13])

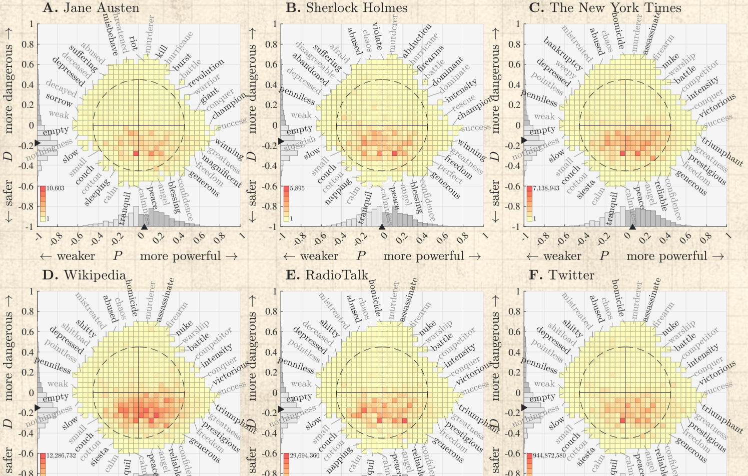
A special thing has happened:

- The PDS framework emerged only from analyzing a lexicon (types).

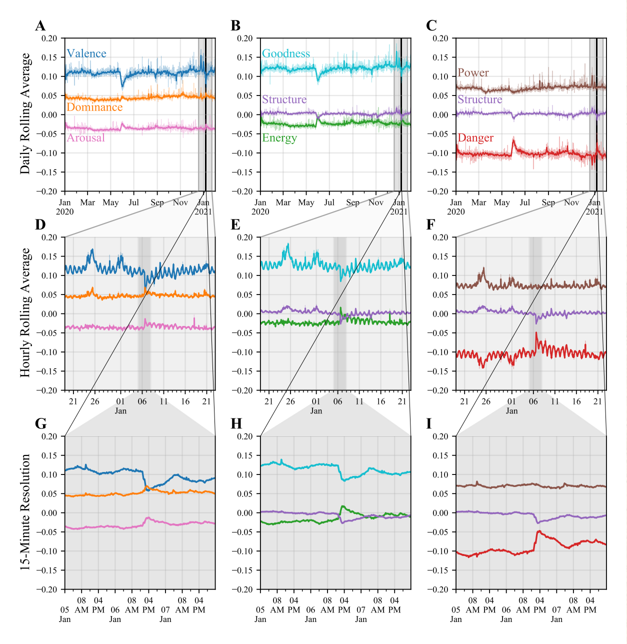


A special thing has happened:

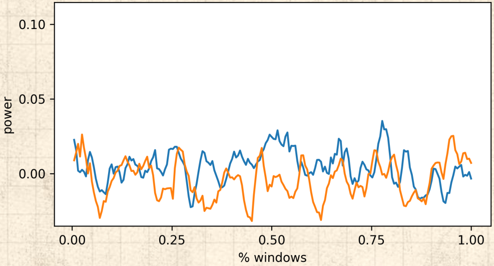
- The PDS framework emerged only from analyzing a lexicon (types).
- Applying PDS framework to disparate corpora (tokens) reveals a linguistic ‘safety bias’.

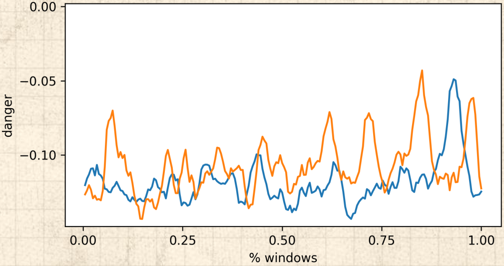


Prototype ousiometer—Twitter:



Prototype ousiometer—Harry Potter:

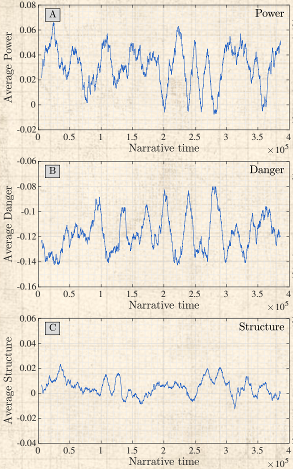




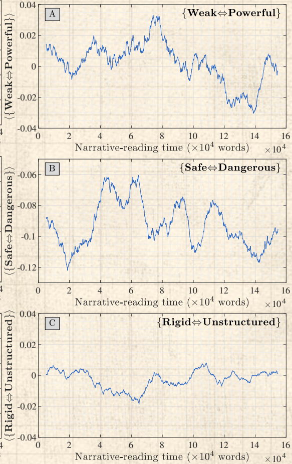
Blue: Harry Potter and the Half-Blood Prince
Orange: Harry Potter and the Deathly Hallows

Power and Danger time series for books:

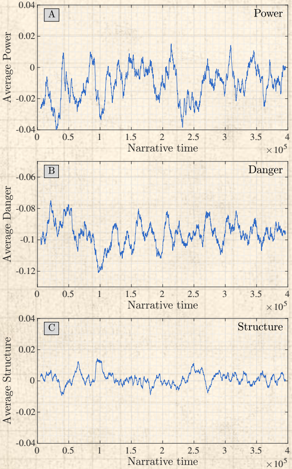
Ousiometrics for
“Anna Karenina”
(Peaver Volokhonsky translation)



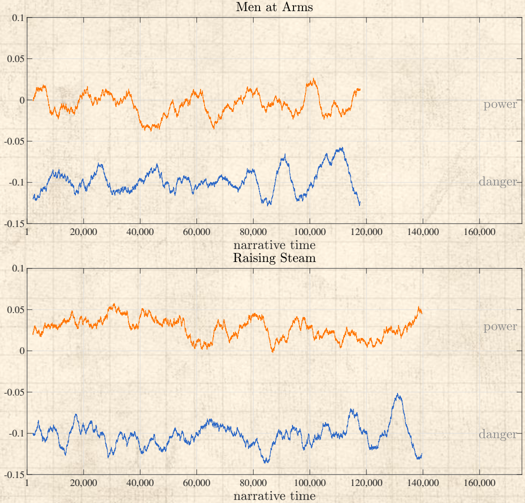
Ousiometrics for
“One Hundred Years of Solitude”
(English translation)

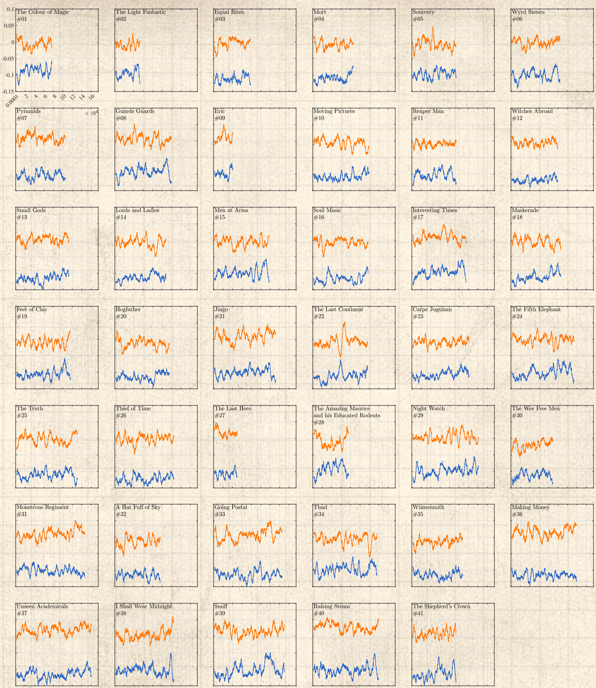


Ousiometrics for “Gravity’s Rainbow”



Prototype ousiometer—Terry Pratchett's Discworld:




0.1
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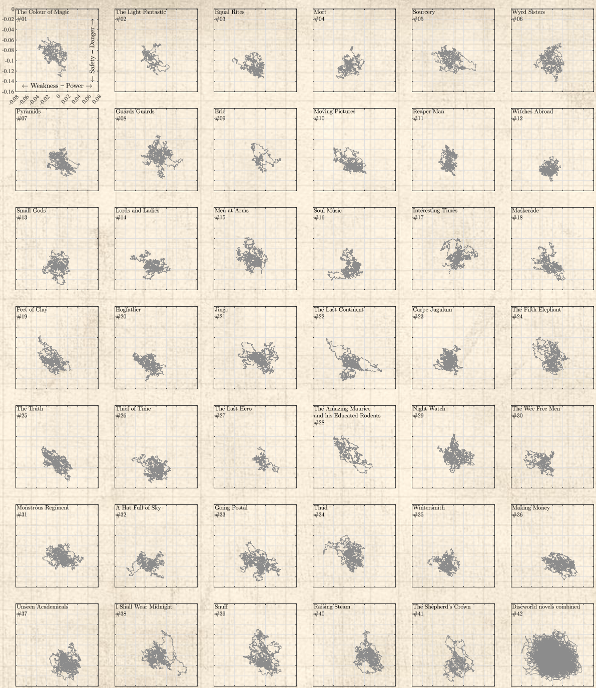
The Light Fantastic #02
Equal Rites #03
Mort #04
Sourcery #05
Wyrd Sisters #06
Pyramids #07
Guards Guards #08
Eric #09
Moving Pictures #10
Reaper Man #11
Witches Abroad #12
Small Gods #13
Lords and Ladies #14
Men at Arms #15
Soul Music #16
Interesting Times #17
Maskerade #18
Feet of Clay #19
Hogfather #20
Jingo #21
The Last Continent #22
Carpe Jugulum #23
The Fifth Elephant #24
The Truth #25
Thief of Time #26
The Last Hero #27
The Amazing Maurice and his Educated Rodents #28
Night Watch #29
The Wee Free Men #30
Monstrous Regiment #31
A Hat Full of Sky #32
Going Postal #33
Thud #34
Wintersmith #35
Making Money #36
Unseen Academicals #37
I Shall Wear Midnight #38
Snuff #39
Raising Steam #40
The Shepherd's Crown #41


The Colour of Magic
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I Shall Wear Midnight
#38
Snuff
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Raising Steam
#40
The Shepherd's Crown
#41
Discworld novels combined
#42
← Weakness – Power →
← Safety – Danger →
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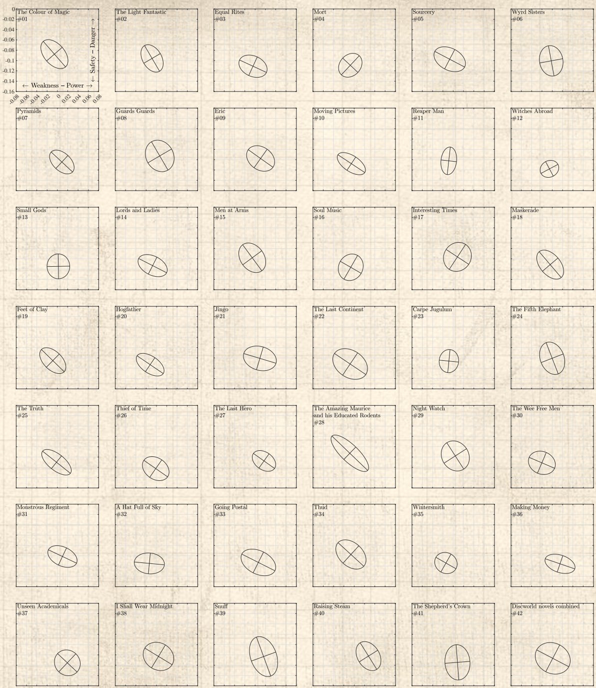
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← Weakness – Power →
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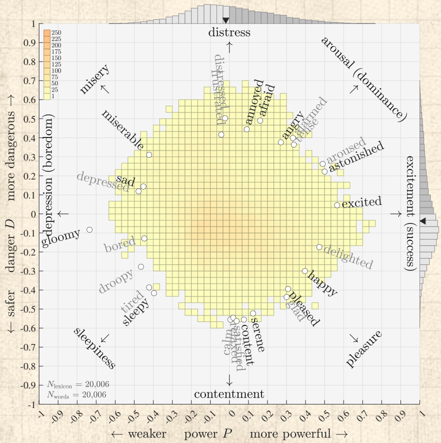
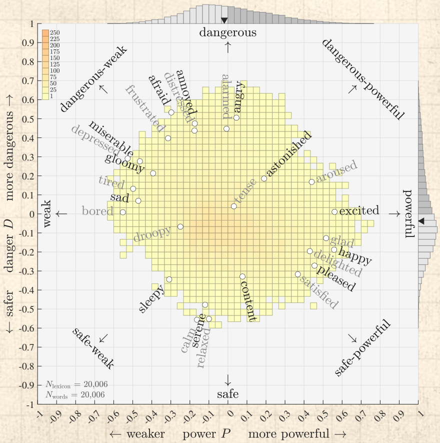
The Shepherd's Crown #41
Discworld novels combined #42

Rough agreement with Russell's circumplex model,[16] which itself doesn't disagree with a 2-d orthogonal framework.

A. Circumplex model of affect:



B. Power-danger coordinates for Russell's affect words:



Dungeons & Dragons—Two alignment axes for character:

[1]

{lawful ⇔ chaotic} (vertical) and {good ⇔ evil} (horizontal).

[1] From this Reddit thread, where, naturally, the choices are enthusiastically debated.

lawful-good $\sim$ structured-powerful-safe	neutral-good $\sim$ neutral-powerful-safe	chaotic-good $\sim$ unstructured-powerful-safe
lawful-neutral $\sim$ structured-neutral	(true) neutral	chaotic-neutral $\sim$ unstructured-neutral
lawful-evil $\sim$ structured-dangerous	neutral-evil $\sim$ neutral-dangerous	chaotic-evil $\sim$ unstructured-dangerous

Aligns with rotated version of Cipolla's Basic Laws of Human Stupidity:

↑
dangerous
"bandits"
(demons)

− harm others

\+ help themselves

← weak
"stupid people"
(fools)

powerful →
"intelligent people"
(heroes)

− harm themselves

"helpless people"
(angels)
safe
↓

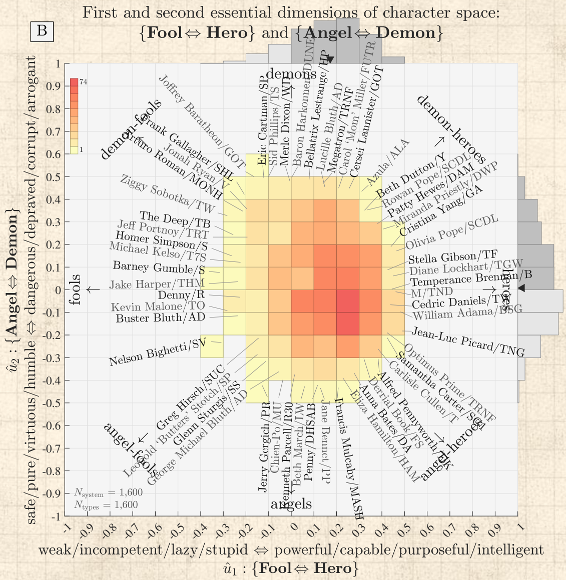
\+ help others

Data set:

- 1600 characters
- 400 traits as semantic differentials
- 364 traits after removing 35 emoji-based semantic differentials and one duplicate
- Shows $\sim$ Stories (television series and film)

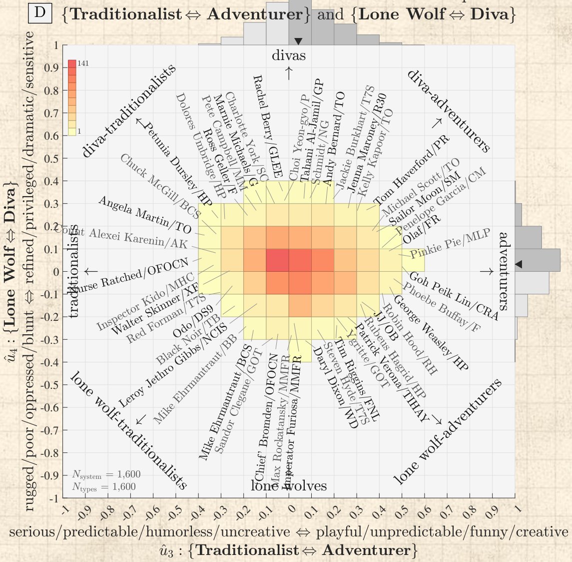
Most extreme characters:

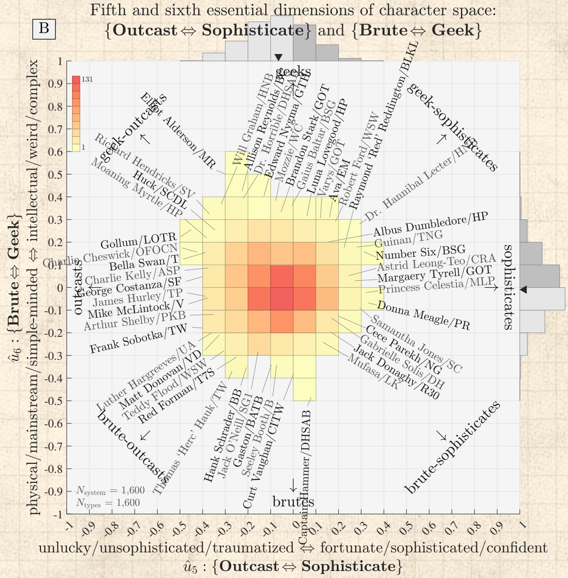
Rank. Character Storyverse	Size S	Top Three Archetypes (Essential Direction, Norm. Component/% Variance Explained) Third:	Second:	First:	$R^{\mathrm{ext}}_{\mathrm{arch}}$
1. Joffrey Baratheon GOT	100.0	Fool (−1, 26.4/7.0%)	Diva (+4, 31.7/10.0%)	Demon (+2, 80.1/64.1%)	6.4
2. Firelord Ozai ALA	98.9	Traditionalist (−3, 40.1/16.5%)	Hero (+1, 41.9/17.9%)	Demon (+2, 69.2/48.9%)	18.1
3. Logan Roy SUC	98.5	Traditionalist (−3, 34.7/12.4%)	Hero (+1, 49.2/24.9%)	Demon (+2, 66.8/45.9%)	14.7
4. Nurse Ratched OFOCN	95.6	Demon (+2, 41.7/19.0%)	Hero (+1, 44.8/21.9%)	Traditionalist (−3, 60.8/40.5%)	36.4
5. Tracy Jordan R30	95.5	Fool (−1, 17.9/3.5%)	Demon (+2, 52.8/30.5%)	Adventurer (+3, 62.8/43.2%)	20.9
6. Dolores Umbridge HP	95.1	Diva (+4, 36.5/14.7%)	Traditionalist (−3, 44.7/22.1%)	Demon (+2, 60.1/39.9%)	20.8
7. Eric Cartman SP	95.1	Fool (−1, 19.4/4.2%)	Adventurer (+3, 20.8/4.8%)	Demon (+2, 79.0/69.1%)	14.4
8. Malory Archer ARCH	94.9	Diva (+4, 24.0/6.4%)	Hero (+1, 44.0/21.5%)	Demon (+2, 68.1/51.5%)	10.9
9. Azula ALA	94.5	— (+9, 15.1/2.6%)	Hero (+1, 49.8/27.7%)	Demon (+2, 69.6/54.2%)	31.1
10. Sid Phillips TS	94.2	Fool (−1, 16.2/3.0%)	Outcast (−5, 33.4/12.6%)	Demon (+2, 79.7/71.6%)	6.0
11. Sterling Archer ARCH	93.9	— (−11, 15.0/2.5%)	Adventurer (+3, 41.2/19.3%)	Demon (+2, 70.7/56.7%)	14.4
12. Gollum LOTR	93.6	Geek (+6, 26.5/8.0%)	Outcast (−5, 46.9/25.1%)	Demon (+2, 60.5/41.8%)	14.6
13. Homelander TB	93.3	— (−8, 18.3/3.8%)	Diva (+4, 25.6/7.5%)	Demon (+2, 74.6/63.9%)	8.5
14. Baron Harkonnen DUNE	93.2	Diva (+4, 13.9/2.2%)	— (+7, 23.9/6.6%)	Demon (+2, 79.4/72.7%)	11.1
15. The Joker DK	93.0	Geek (+6, 27.3/8.6%)	Adventurer (+3, 36.5/15.4%)	Demon (+2, 66.3/50.9%)	7.2
16. Darlene Snell O	92.6	— (−8, 24.2/6.9%)	Outcast (−5, 33.0/12.7%)	Demon (+2, 71.9/60.3%)	7.2
17. Billy Butcher TB	92.4	Lone Wolf (−4, 28.6/9.6%)	Hero (+1, 38.1/17.0%)	Demon (+2, 63.9/47.9%)	7.1
18. Man in Black WSW	92.4	Traditionalist (−3, 18.5/4.0%)	Hero (+1, 43.0/21.7%)	Demon (+2, 68.5/55.1%)	18.2
19. Jenna Maroney R30	92.3	Adventurer (+3, 41.4/20.1%)	Diva (+4, 44.1/22.8%)	Demon (+2, 58.6/40.2%)	41.3
20. Ziggy Sobotka TW	92.2	Adventurer (+3, 36.6/15.7%)	Fool (−1, 45.2/24.0%)	Demon (+2, 52.5/32.4%)	5.8
21. Frank Gallagher SHL	92.2	Adventurer (+3, 26.5/8.3%)	Fool (−1, 33.2/12.9%)	Demon (+2, 67.4/53.5%)	7.2
22. Ron Swanson PR	92.1	Traditionalist (−3, 28.4/9.5%)	Lone Wolf (−4, 39.3/18.2%)	Hero (+1, 58.0/39.7%)	11.0
23. Mr. Burns S	92.1	Hero (+1, 23.9/6.7%)	Traditionalist (−3, 40.4/19.2%)	Demon (+2, 67.0/52.9%)	10.1
24. Dr. Hannibal Lecter HNB	92.0	Demon (+2, 30.2/10.7%)	Sophisticate (+5, 30.5/11.0%)	Hero (+1, 60.1/42.7%)	5.7
25. Red Forman T7S	91.8	Brute (−6, 32.0/12.1%)	Hero (+1, 46.9/26.1%)	Traditionalist (−3, 47.8/27.1%)	5.4


B
First and second essential dimensions of character space:
{Fool ⇔ Hero} and {Angel ⇔ Demon}
$\hat{u}_2$: {Angel ⇔ Demon}
safe/pure/virtuous/humble ⇔ dangerous/depraved/corrupt/arrogant
weak/incompetent/lazy/stupid ⇔ powerful/capable/purposeful/intelligent
$\hat{u}_1$: {Fool ⇔ Hero}
demons
angels
fools
heroes
demon-fools
demon-heroes
angel-fools
angel-heroes
74
1
N_{system} = 1,600
N_{types} = 1,600
Joffrey Baratheon/GOT
Frank Gallagher/SHL
Jonah Ryan/V
Arturo Roman/MONH
Ziggy Sobotka/TW
The Deep/TB
Jeff Portnoy/TRT
Homer Simpson/S
Michael Kelso/T7S
Barney Gumble/S
Jake Harper/THM
Denny/R
Kevin Malone/TO
Buster Bluth/AD
Nelson Bighetti/SV
Eric Cartman/SP
Sid Phillips/TS
Merle Dixon/WD
Baron Harkonnen/DUNE
Bellatrix Lestrange/HP
Lucille Bluth/AD
Megatron/TRNF
Carol 'Mom' Miller/FUTR
Cersei Lannister/GOT
Azula/ALA
Beth Dutton/Y
Rowan Pope/SCDL
Patty Hewes/DAM
Miranda Priestly/DWP
Cristina Yang/GA
Olivia Pope/SCDL
Stella Gibson/TF
Diane Lockhart/TGW
Temperance Brennan/B
M/TND
Cedric Daniels/TW
William Adama/BSG
Jean-Luc Picard/TNG
Optimus Prime/TRNF
Samantha Carter/SG1
Carlisle Cullen/T
Alfred Pennyworth/TDK
Derrial Book/FS
Anna Bates/DA
Eliza Hamilton/HAM
Francis Mulcahy/MASH
Jane Bennet/PP
Penny/DHSAB
Beth March/LW
Kenneth Parcell/R30
Chien-Po/MU
Jerry Gergich/PR
George Michael Bluth/AD
Glenn Sturgis/SS
Leopold 'Butters' Stotch/SP
Greg Hirsch/SUC

Third and fourth essential dimensions of character space:

$\boxed{\text{D}}$ {**Traditionalist** ⇔ **Adventurer**} and {**Lone Wolf** ⇔ **Diva**}




B
Fifth and sixth essential dimensions of character space:
{Outcast ⇔ Sophisticate} and {Brute ⇔ Geek}
geeks
brutes
outcasts
sophisticates
geek-outcasts
geek-sophisticates
brute-outcasts
brute-sophisticates
131
1
Elliot Alderson/MR
Richard Hendricks/SV
Huck/SCDL
Moaning Myrtle/HP
Will Graham/HNB
Allison Reynolds/BC
Dr. Horrible/DHSAB
Edward Nygma/GTH
Mozzie/WC
Brandon Stark/GOT
Gaius Baltar/BSG
Luna Lovegood/HP
Varys/GOT
Ava/EM
Robert Ford/WSW
Raymond 'Red' Reddington/BLKL
Dr. Hannibal Lecter/HNB
Albus Dumbledore/HP
Guinan/TNG
Number Six/BSG
Astrid Leong-Teo/CRA
Margaery Tyrell/GOT
Princess Celestia/MLP
Donna Meagle/PR
Samantha Jones/SC
Cece Parekh/NG
Gabrielle Solis/DH
Jack Donaghy/R30
Mufasa/LK
Gollum/LOTR
Charlie Cheswick/OFOCN
Bella Swan/T
Charlie Kelly/ASP
George Costanza/SF
James Hurley/TP
Mike McLintock/V
Arthur Shelby/PKB
Frank Sobotka/TW
Luther Hargreeves/UA
Matt Donovan/VD
Teddy Flood/WSW
Red Forman/T7S
Thomas 'Herc' Hauk/TW
Hank Schrader/BB
Jack O'Neill/SG1
Gaston/BATB
Seeley Booth/B
Curt Vaughan/CTTW
Captain Hammer/DHSAB
$N_{\text{system}} = 1{,}600$
$N_{\text{types}} = 1{,}600$
$\hat{u}_6$: {Brute ⇔ Geek}
physical/mainstream/simple-minded ⇔ intellectual/weird/complex
unlucky/unsophisticated/traumatized ⇔ fortunate/sophisticated/confident
$\hat{u}_5$: {Outcast ⇔ Sophisticate}

Base archetypes:

Essential Character Dimension 1, $\hat{u}_1$

Major archetype dimension: {**Fool** ⇔ **Hero**}

{weak/incompetent/lazy/stupid ⇔ powerful/capable/purposeful/intelligent}

A. Most aligned traits ($\hat{v}_1$)	Cos.	Var. Expl.	Comp. Size	Trait Size	Size Rank
1. incompetent ⇔ competent	0.94	88.6	81.1	86.2	17
2. helpless ⇔ resourceful	0.92	83.9	77.8	85.0	23
3. lazy ⇔ diligent	0.92	83.9	88.5	96.6	2
4. low IQ ⇔ high IQ	0.90	81.9	80.7	89.1	9
5. unobservant ⇔ perceptive	0.90	81.7	77.0	85.2	21

B. Traits by ($\hat{v}_1$) **largest component**	Cos.	Var. Expl.	Comp. Size	Trait Size	Size Rank
1. lazy ⇔ diligent	0.92	83.9	88.5	96.6	2
2. quitter ⇔ persistent	0.87	75.0	86.6	100.0	1
3. unmotivated ⇔ motivated	0.87	76.2	83.1	95.2	4
4. unambitious ⇔ driven	0.88	78.1	82.7	93.5	5
5. incompetent ⇔ competent	0.94	88.6	81.1	86.2	17

C. Most negatively aligned characters ($-\hat{u}_1$)	Cos.	Var. Expl.	Comp. Size	Char. Size	Size Rank
1. Barney Gumble S	-0.63	39.2	50.5	80.7	247
2. Kevin Malone TO	-0.62	38.2	45.1	73.1	574
3. Jake Harper THM	-0.59	34.5	37.7	64.2	1014
4. Nelson Bighetti SV	-0.58	34.1	49.4	84.5	142
5. Kermit SHL	-0.58	33.2	35.2	61.2	1147

D. Most positively aligned characters ($+\hat{u}_1$)	Cos.	Var. Expl.	Comp. Size	Char. Size	Size Rank
1. Kate Beckett CSTL	0.93	85.6	71.3	77.1	385
2. Olivia Benson SVU	0.90	81.6	72.6	80.4	257
3. Princess Leia SW	0.89	79.2	67.1	75.4	456
4. Miranda Bailey GA	0.89	78.7	73.0	82.3	200
5. Shirley Schmidt BL	0.89	78.4	68.8	77.7	364

E. Characters by largest negative component ($-\hat{u}_1$)	Cos.	Var. Expl.	Comp. Size	Char. Size	Size Rank
1. Barney Gumble S	-0.63	39.2	50.5	80.7	247
2. Nelson Bighetti SV	-0.58	34.1	49.4	84.5	142
3. Ziggy Sobotka TW	-0.49	24.0	45.2	92.2	20
4. Kevin Malone TO	-0.62	38.2	45.1	73.1	574
5. Homer Simpson S	-0.53	27.6	42.1	80.2	265

F. Characters by largest positive component ($+\hat{u}_1$)	Cos.	Var. Expl.	Comp. Size	Char. Size	Size Rank
1. Jean-Luc Picard TNG	0.86	73.5	78.4	91.4	30
2. William Adama BSG	0.85	72.3	77.2	90.8	37
3. Hermione Granger HP	0.88	78.1	76.4	86.4	95
4. Olivia Pope SCDL	0.85	72.0	74.4	87.6	76
5. Minerva McGonagall HP	0.88	76.8	74.2	84.7	140

TABLE I. Sets of top 5 traits and characters by various measures for the second essential dimension which we interpet as {**Fool** ⇔ **Hero**}. These lists are abbreviated versions of what we provide in the Supplementary Document SD1 in the Anciliary files. See Tabs. A3–A24 for the same set of six tables for the top 15 traits and characters for the first 11 essential dimensions. See Sec. A9 for story abbreviations.

A. Major essential character dimensions:

Archetypes ∼ Descriptors	Five factor model dimension(s)	Essential Meaning (Ousiometrics)	% Variance Explained	Primary Dimension
1. {**Fool** ⇔ **Hero**}	+{**conscientiousness**}	{**weak** ⇔ **powerful**}	25.7%	41.2% (9+651=660)
∼ {weak/incompetent/lazy/stupid ⇔ powerful/capable/purposeful/intelligent}				
2. {**Angel** ⇔ **Demon**}	−{**agreeableness**}	{**safe** ⇔ **dangerous**}	21.3%	27.5% (161+279=440)
∼ {safe/pure/virtuous/humble ⇔ dangerous/depraved/corrupt/arrogant}				
3. {**Traditionalist** ⇔ **Adventurer**}	+{**openness**}	{**structured** ⇔ **unstructured**}	14.1%	18.2% (52+240=292)
∼ {serious/predictable/humorless/uncreative ⇔ playful/unpredictable/funny/creative}				
			61.1%	87.0% (1392)

B. Minor essential character dimensions:

Archetypes ∼ Descriptors	Five factor model dimension(s)	% Variance Explained	Primary Dimension
4. {**Lone Wolf** ⇔ **Diva**}	+{**extroversion**}	6.4%	5.5% (12+76=88)
∼ {rugged/poor/oppressed/blunt ⇔ refined/privileged/dramatic/sensitive}			
5. {**Outcast** ⇔ **Sophisticate**}	−{**neuroticism**}	5.1%	5.1% (81+0=81)
∼ {unlucky/unsophisticated/traumatized ⇔ fortunate/sophisticated/confident}			
6. {**Brute** ⇔ **Geek**}	−{**extroversion**}, +{**neuroticism**}	3.7%	1.6% (13+13=26)
∼ {physical/mainstream/simple-minded ⇔ intellectual/weird/complex}			
		15.2%	12.2% (195)

C. Trait-level essential character dimensions:

Unnamed non-Archetype Essential Traits ∼ Descriptors	% Variance Explained	Primary Dimension
7. ∼ {young/attractive/dramatic ⇔ old/ugly/comedic}	2.1%	0.4% (5+2=7)
8. ∼ {spiritual/historical/rural ⇔ skeptical/modern/urban}	1.7%	0.2% (1+3=4)
9. ∼ {low tempo ⇔ high tempo}	1.5%	0.1% (1+0=1)
10. ∼ {feminine/low-tech/non-athletic ⇔ masculine/high-tech/athletic}	1.1%	0.0% (0+0=0)
11. ∼ {forthright/naive/rich ⇔ treacherous/street-wise/poor}	0.9%	0.1% (0+1=1)
	7.3%	0.8% (13)
12–364. All other essential dimensions combined:	16.4%	0.0% (0)

Most archetypal characters:

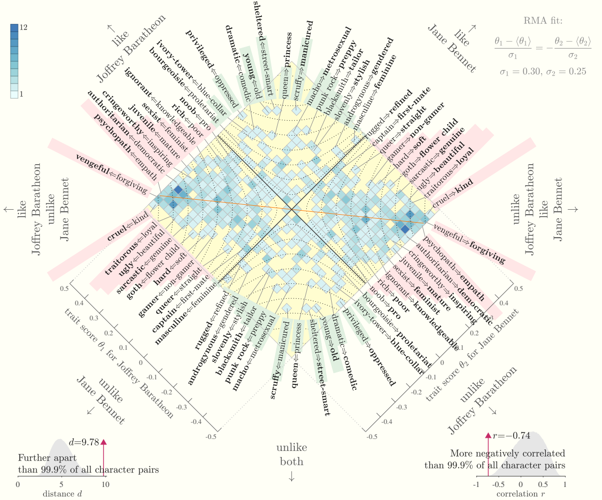
Rank by $R^{\text{ext}}_{\text{arch}}$. Character Story	Size S	Rank	Archetype class	(% var. exp., β_1, β_2)	$R^{\text{ext}}_{\text{arch}}$
1. Tywin Lannister Game of Thrones	90.9	36	Traditionalist-Demon-Hero	(88.5, 1.3)	66.6
2. Charlie Young The West Wing	82.5	191	Angel-Hero	(83.3, 1.7)	48.4
3. Kate Beckett Castle	77.1	385	Hero	(85.6, 1.8)	46.6
4. Kelly Kapoor The Office	81.1	234	Diva-Adventurer-Demon	(83.0, 1.9)	43.6
5. Dr. John Watson Sherlock	62.9	1058	Outcast-Angel-Hero	(83.8, 2.0)	41.5
6. Jenna Maroney 30 Rock	92.3	19	Diva-Adventurer-Demon	(81.1, 2.0)	41.3
7. Annie Porter Speed	61.4	1132	Adventurer-Angel-Hero	(74.2, 1.8)	41.1
8. Phoebe Buffay Friends	81.5	224	Adventurer	(80.4, 2.0)	39.6
9. Will Byers Stranger Things	62.6	1073	Geek-Outcast-Angel	(74.6, 1.9)	38.5
10. Marmee March Little Women	74.8	484	Angel-Hero	(81.4, 2.2)	36.9
11. Nurse Ratched One Flew Over the Cuckoo's Nest	95.6	4	Traditionalist-Demon-Hero	(79.1, 2.2)	36.4
12. Walter Skinner The X-Files	67.5	844	Traditionalist-Hero	(84.7, 2.4)	34.8
13. Avon Barksdale The Wire	75.5	453	Demon-Hero	(72.1, 2.1)	34.7
14. Regina Mills Once Upon a Time	76.3	423	Demon-Hero	(77.5, 2.3)	34.2
15. Pinkie Pie My Little Pony: Friendship Is Magic	87.1	81	Adventurer	(77.1, 2.3)	34.0
16. Sara Sidle CSI: Crime Scene Investigation	58.8	1236	Hero	(75.8, 2.3)	33.2
17. Rory Gilmore Gilmore Girls	69.7	738	Diva-Angel-Hero	(74.5, 2.2)	33.1
18. Prudence Night Chilling Adventures of Sabrina	75.7	437	Demon-Hero	(78.4, 2.4)	32.9
19. Principal Skinner The Simpsons	58.0	1264	Outcast-Diva-Traditionalist	(78.9, 2.4)	32.8
20. Beverly Crusher Star Trek: The Next Generation	76.5	417	Angel-Hero	(77.6, 2.4)	32.1
21. Rachel Chu Crazy Rich Asians	69.1	761	Adventurer-Angel-Hero	(81.5, 2.5)	32.1
22. Grace Van Pelt The Mentalist	58.9	1228	Angel-Hero	(76.0, 2.4)	31.6
23. Perry Cox Scrubs	78.3	338	Demon-Hero	(76.0, 2.4)	31.4
24. Dr. Madolyn Madden The Departed	56.9	1311	Diva-Angel-Hero	(68.2, 2.2)	31.1
25. Azula Avatar: The Last Airbender	94.5	9	Demon-Hero	(79.8, 2.6)	31.1

1. Joffrey Baratheon
Game of Thrones
Demon

Minor archetype: R_{arch}=6.4

2. Jane Bennet
Pride and Prejudice
Angel

Major archetype: R_{arch}=11.4



Standard correlation r

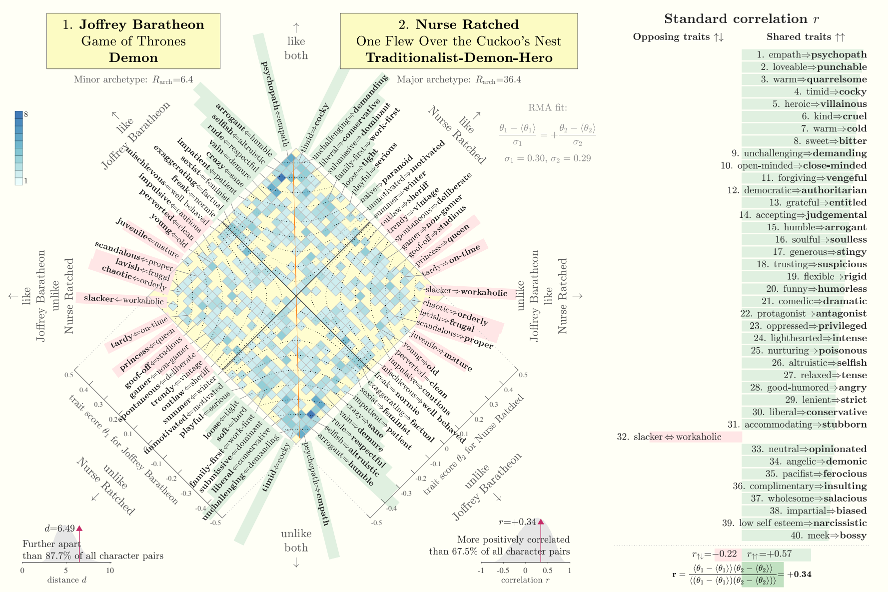
Opposing traits ↑↓ | **Shared traits ↑↑**

1. cruel ⇔ kind
2. rude ⇔ respectful
3. vengeful ⇔ forgiving
4. demonic ⇔ angelic
5. bitter ⇔ sweet
6. psychopath ⇔ empath
7. quarrelsome ⇔ warm
8. arrogant ⇔ humble
9. repulsive ⇔ attractive
10. poisonous ⇔ nurturing
11. punchable ⇔ loveable
12. angry ⇔ good-humored
13. bad boy ⇔ white knight
14. barbaric ⇔ civilized
15. perverted ⇔ clean
16. debased ⇔ pure
17. selfish ⇔ altruistic
18. impatient ⇔ patient
19. ferocious ⇔ pacifist
20. competitive ⇔ cooperative
21. villainous ⇔ heroic
22. mischievous ⇔ well behaved
23. trash ⇔ treasure
24. deranged ⇔ reasonable
25. judgemental ⇔ accepting
26. traitorous ⇔ loyal
27. lewd ⇔ tasteful
28. genocidal ⇔ not genocidal
29. interrupting ⇔ attentive
30. loud ⇔ quiet
31. animalistic ⇔ human
32. scandalous ⇔ proper
33. flamboyant ⇔ modest
34. salacious ⇔ wholesome
35. feisty ⇔ gracious
36. crazy ⇔ sane
37. cunning ⇔ honorable
38. ludicrous ⇔ sensible
39. ugly ⇔ beautiful
40. stingy ⇔ generous

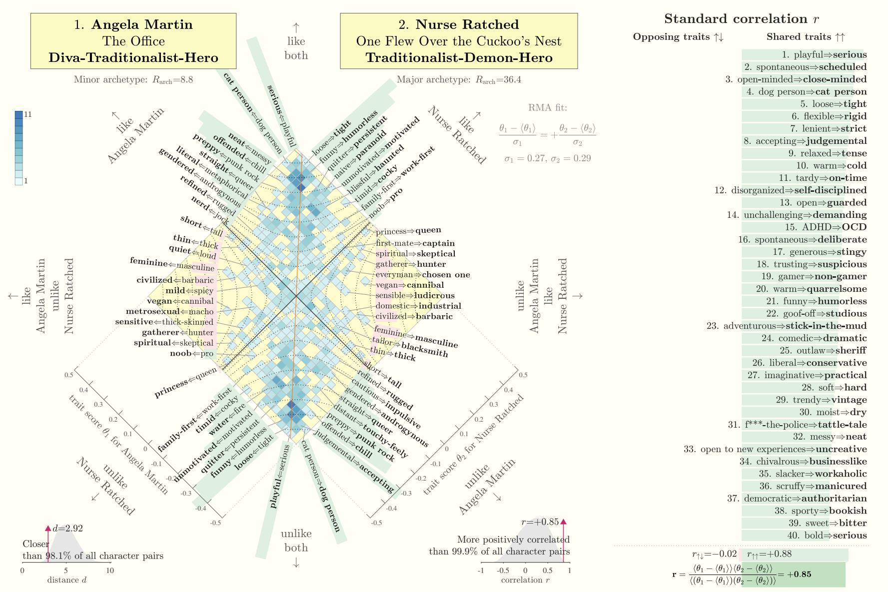
$r_{\uparrow\downarrow}=-0.81$ $r_{\uparrow\uparrow}=+0.07$

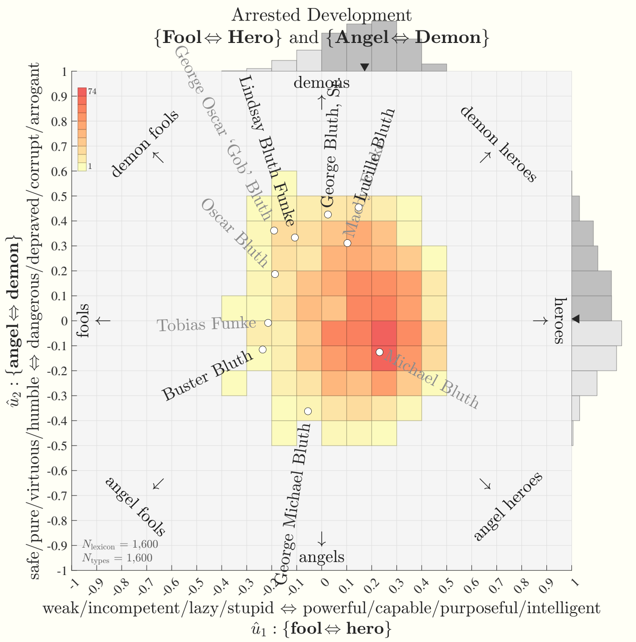
$$\mathbf{r} = \frac{\langle(\theta_1 - \langle\theta_1\rangle)(\theta_2 - \langle\theta_2\rangle)\rangle}{\langle(\theta_1 - \langle\theta_1\rangle)(\theta_2 - \langle\theta_2\rangle)\rangle} = \mathbf{-0.74}$$

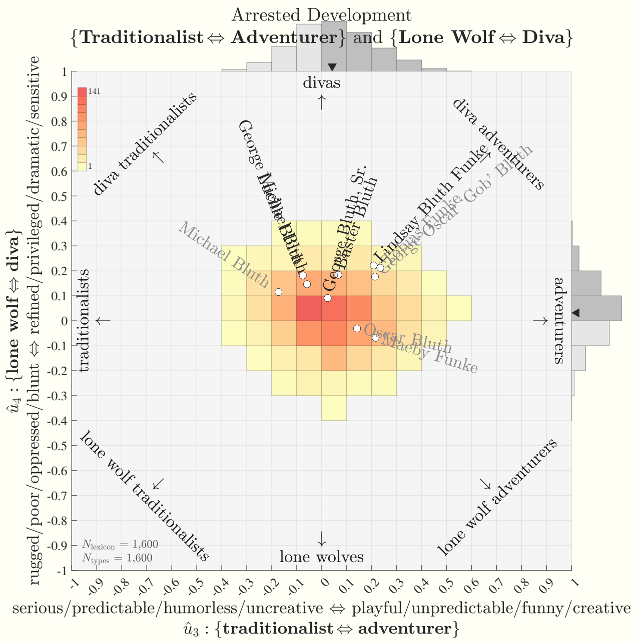
Two distinct villains:

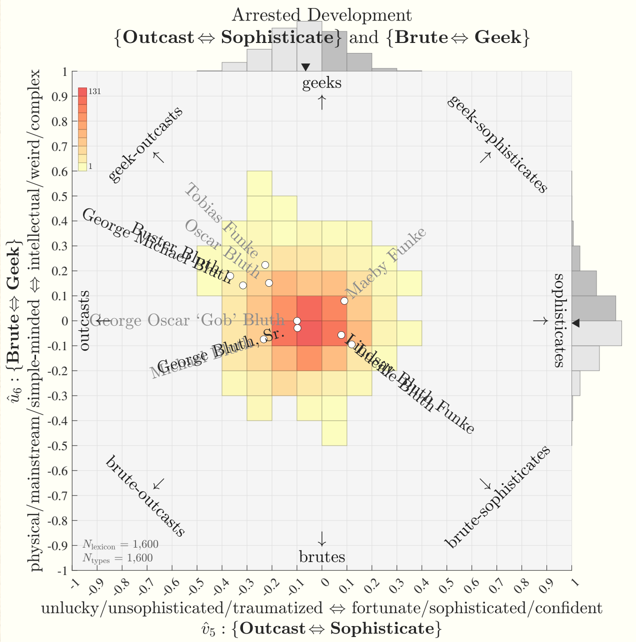


Two similar villains:



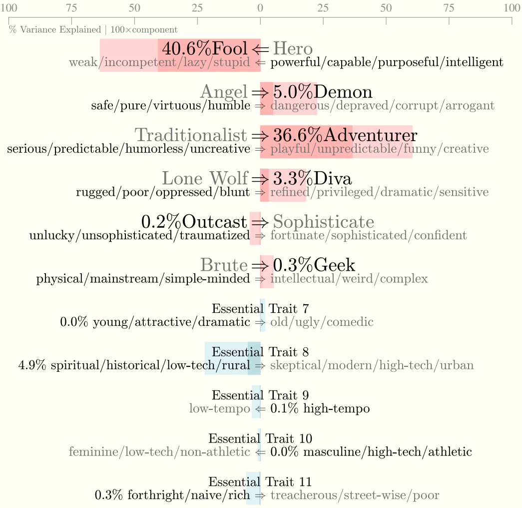

Arrested Development
{Fool ⇔ Hero} and {Angel ⇔ Demon}
demons
angels
fools
heroes
demon fools
demon heroes
angel fools
angel heroes
George Oscar 'Gob' Bluth
Lindsay Bluth Funke
George Bluth, Sr.
Lucille Bluth
Oscar Bluth
Tobias Funke
Buster Bluth
Michael Bluth
George Michael Bluth
74
1
N_{lexicon} = 1,600
N_{types} = 1,600
weak/incompetent/lazy/stupid ⇔ powerful/capable/purposeful/intelligent
$\hat{u}_1$: {fool ⇔ hero}
safe/pure/virtuous/humble ⇔ dangerous/depraved/corrupt/arrogant
$\hat{u}_2$: {angel ⇔ demon}


Arrested Development
{Traditionalist ⇔ Adventurer} and {Lone Wolf ⇔ Diva}
divas
diva traditionalists
diva adventurers
traditionalists
adventurers
lone wolf traditionalists
lone wolf adventurers
lone wolves
Michael Bluth
Lindsay Bluth Funke
Oscar Bluth
Maeby Funke
Buster Bluth
George Bluth, Sr.
141
1
N_{lexicon} = 1,600
N_{types} = 1,600
$\hat{u}_4$: {lone wolf ⇔ diva}
rugged/poor/oppressed/blunt ⇔ refined/privileged/dramatic/sensitive
serious/predictable/humorless/uncreative ⇔ playful/unpredictable/funny/creative
$\hat{u}_3$: {traditionalist ⇔ adventurer}

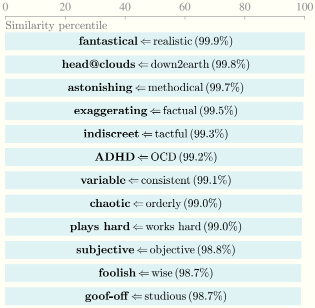

Arrested Development
{Outcast ⇔ Sophisticate} and {Brute ⇔ Geek}
geeks
brutes
outcasts
sophisticates
geek-outcasts
geek-sophisticates
brute-outcasts
brute-sophisticates
Tobias Funke
George Michael Bluth
Buster Bluth
Oscar Bluth
Maeby Funke
George Oscar 'Gob' Bluth
George Bluth, Sr.
Michael Bluth
Lindsay Bluth Funke
Lucille Bluth
131
1
N_{lexicon} = 1,600
N_{types} = 1,600
$\hat{u}_6$: {Brute ⇔ Geek}
physical/mainstream/simple-minded ⇔ intellectual/weird/complex
unlucky/unsophisticated/traumatized ⇔ fortunate/sophisticated/confident
$\hat{v}_5$: {Outcast ⇔ Sophisticate}

whimsical ⇐ rational

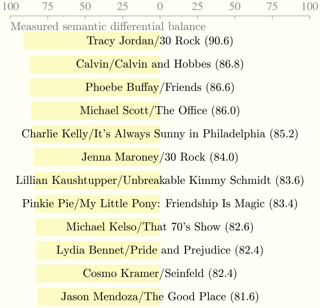
Relative trait strength 71%, 157/364



Most similar traits:

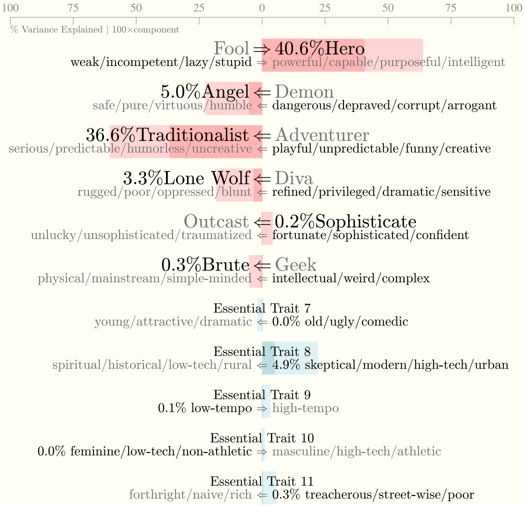


Characters with largest component:

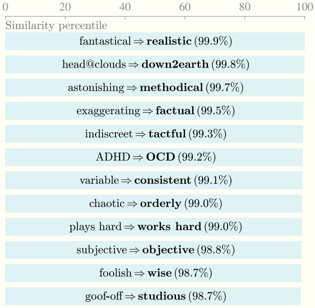


whimsical ⇒ **rational**

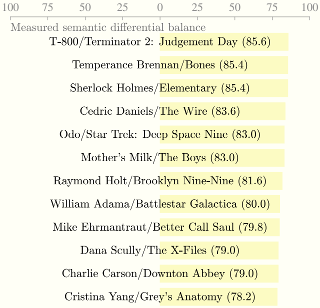
Relative trait strength 71%, 157/364



Most similar traits:



Characters with largest component:



Buffy Summers
Buffy the Vampire Slayer

Relative character size 74%, 508/1600 — Archetype ratio 13.0, 332/1600

Major Archetype: 73.0/73.6% **Adventurer-Hero**

100 75 50 25 0 25 50 75 100
Normalized component/%Variance Explained

Fool ⇒ 59.2/48.4% Hero
weak/incompetent/lazy/stupid ⇒ powerful/capable/purposeful/intelligent

Angel ⇒ 20.3/5.7% Demon
safe/pure/virtuous/humble ⇒ dangerous/depraved/corrupt/arrogant

Traditionalist ⇒ 44.1/26.8% Adventurer
serious/predictable/humorless/uncreative ⇒ playful/unpredictable/funny/creative

6.1/0.5% Lone Wolf ⇐ Diva
rugged/poor/oppressed/blunt ⇐ refined/privileged/dramatic/sensitive

2.2/0.1% Outcast ⇐ Sophisticate
unlucky/unsophisticated/traumatized ⇐ fortunate/sophisticated/confident

7.9/0.9% Brute ⇐ Geek
physical/mainstream/simple-minded ⇐ intellectual/weird/complex

Essential Trait 7
13.9/2.7% young/attractive/dramatic ⇐ old/ugly/comedic

Essential Trait 8
spiritual/historical/rural ⇒ 1.7/0.0% skeptical/modern/urban

Essential Trait 9
low-tempo ⇒ 12.7/2.2% high-tempo

Essential Trait 10
feminine/low-tech/non-athletic ⇒ 0.2/0.0% masculine/high-tech/athletic

Essential Trait 11
5.9/0.5% forthright/naive/rich ⇐ treacherous/street-wise/poor

Dominant underlying traits:

100 75 50 25 0 25 50 75 100
Measured semantic differential balance

antagonist ⇒ **protagonist** (89.6)
weakass ⇒ **badass** (88.0)
everyman ⇒ **chosen one** (88.0)
slothful ⇒ **active** (87.6)
quitter ⇒ **persistent** (87.2)
mundane ⇒ **extraordinary** (86.4)
morning lark ⇒ **night owl** (85.8)
helpless ⇒ **resourceful** (85.8)
first-mate ⇒ **captain** (85.2)
ugly ⇒ **beautiful** (85.2)
villainous ⇒ **heroic** (84.6)
repulsive ⇒ **attractive** (84.4)

Most similar characters:

0 20 40 60 80 100
Similarity percentile

Daisy ‘Skye’ Johnson/Agents of S.H.I.E.L.D. (99.9%)
Elizabeth Swann/Pirates of the Caribbean (99.8%)
Marion Ravenwood/Raiders of the Lost Ark (99.7%)
Thea Queen/Arrow (99.6%)
Emma Swan/Once Upon a Time (99.6%)
Max Mayfield/Stranger Things (99.4%)
Steven Hiller/Independence Day (99.3%)
Mikaela Banes/Transformers (99.2%)
Bellamy Blake/The 100 (99.2%)
Princess Fiona/Shrek (98.9%)
Nairobi/Money Heist (98.9%)
Sabrina Spellman/Chilling Adventures of Sabrina (98.9%)

Willow Rosenberg
Buffy the Vampire Slayer

Relative character size 70%, 732/1600 — Archetype ratio 7.3, 1031/1600

Minor Archetype: 65.3/66.9% **Geek-Angel-Hero**

100 75 50 25 0 25 50 75 100
Normalized component/%Variance Explained

Fool ⇒ 32.5/16.6% Hero
weak/incompetent/lazy/stupid ⇒ powerful/capable/purposeful/intelligent

46.9/34.5% Angel ⇐ Demon
safe/pure/virtuous/humble ⇐ dangerous/depraved/corrupt/arrogant

Traditionalist ⇒ 24.1/9.1% Adventurer
serious/predictable/humorless/uncreative ⇒ playful/unpredictable/funny/creative

Lone Wolf ⇒ 10.3/1.7% Diva
rugged/poor/oppressed/blunt ⇒ refined/privileged/dramatic/sensitive

15.3/3.6% Outcast ⇐ Sophisticate
unlucky/unsophisticated/traumatized ⇐ fortunate/sophisticated/confident

Brute ⇒ 33.7/17.8% Geek
physical/mainstream/simple-minded ⇒ intellectual/weird/complex

Essential Trait 7
young/attractive/dramatic ⇒ 4.4/0.3% old/ugly/comedic

Essential Trait 8
2.4/0.1% spiritual/historical/rural ⇐ skeptical/modern/urban

Essential Trait 9
low-tempo ⇒ 10.2/1.6% high-tempo

Essential Trait 10
feminine/low-tech/non-athletic ⇒ 2.1/0.1% masculine/high-tech/athletic

Essential Trait 11
forthright/naive/rich ⇒ 5.1/0.4% treacherous/street-wise/poor

Dominant underlying traits:

100 75 50 25 0 25 50 75 100
Measured semantic differential balance

- jock ⇒ **nerd** (89.2)
- sporty ⇒ **bookish** (89.0)
- sexist ⇒ **feminist** (83.4)
- low IQ ⇒ **high IQ** (82.4)
- drop out ⇒ **valedictorian** (82.4)
- ignorant ⇒ **knowledgeable** (80.6)
- pop ⇒ **indie** (80.0)
- lazy ⇒ **diligent** (79.8)
- soulless ⇒ **soulful** (78.8)
- receiving ⇒ **giving** (78.2)
- dunce ⇒ **genius** (78.2)
- trash ⇒ **treasure** (78.2)

Most similar characters:

0 20 40 60 80 100
Similarity percentile

- Amy Antsler/Booksmart (100.0%)
- Rosalind Walker/Chilling Adventures of Sabrina (99.9%)
- Ariadne/Inception (99.7%)
- Oliver Hampton/How To Get Away With Murder (99.7%)
- Daniel Jackson/Stargate SG-1 (99.5%)
- Leo Fitz/Agents of S.H.I.E.L.D. (99.4%)
- Cameron James/10 Things I Hate About You (99.4%)
- Molly Hooper/Sherlock (99.4%)
- Felicity Smoak/Arrow (99.2%)
- Will Byers/Stranger Things (99.1%)
- Lane Kim/Gilmore Girls (99.1%)
- Aram Mojtabai/The Blacklist (99.0%)

Sherlock Holmes
Sherlock

Relative character size 84%, 167/1600 — Archetype ratio 11.5, 440/1600

Major Archetype: 83.1/75.4% **Geek-Demon-Hero**

Normalized component/%Variance Explained

Fool ⇒ 57.9/36.6% Hero
weak/incompetent/lazy/stupid ⇒ powerful/capable/purposeful/intelligent

Angel ⇒ 50.7/28.1% Demon
safe/pure/virtuous/humble ⇒ dangerous/depraved/corrupt/arrogant

Traditionalist ⇒ 4.6/0.2% Adventurer
serious/predictable/humorless/uncreative ⇒ playful/unpredictable/funny/creative

2.9/0.1% Lone Wolf ⇐ Diva
rugged/poor/oppressed/blunt ⇐ refined/privileged/dramatic/sensitive

0.2/0.0% Outcast ⇐ Sophisticate
unlucky/unsophisticated/traumatized ⇐ fortunate/sophisticated/confident

Brute ⇒ 35.3/13.6% Geek
physical/mainstream/simple-minded ⇒ intellectual/weird/complex

Essential Trait 7
young/attractive/dramatic ⇒ 9.0/0.9% old/ugly/comedic

Essential Trait 8
spiritual/historical/rural ⇒ 10.3/1.2% skeptical/modern/urban

Essential Trait 9
low-tempo ⇒ 2.0/0.0% high-tempo

Essential Trait 10
feminine/low-tech/non-athletic ⇒ 3.7/0.1% masculine/high-tech/athletic

Essential Trait 11
24.5/6.6% forthright/naive/rich ⇐ treacherous/street-wise/poor

Dominant underlying traits:

Measured semantic differential balance

- low IQ ⇒ **high IQ** (93.6)
- spiritual ⇒ **skeptical** (89.4)
- dunce ⇒ **genius** (89.0)
- accommodating ⇒ **stubborn** (88.8)
- mundane ⇒ **extraordinary** (87.4)
- common sense ⇒ **analysis** (87.4)
- apprentice ⇒ **master** (86.6)
- unobservant ⇒ **perceptive** (86.6)
- noob ⇒ **pro** (85.0)
- slow-talking ⇒ **fast-talking** (84.8)
- quitter ⇒ **persistent** (84.8)
- obedient ⇒ **rebellious** (84.0)

Most similar characters:

Similarity percentile

- Sherlock Holmes/Elementary (100.0%)
- Dr. Gregory House/House, M.D. (98.9%)
- Beth Harmon/The Queen's Gambit (98.6%)
- Dr. Harry Wells/The Flash (97.4%)
- Annalise Keating/How To Get Away With Murder (96.2%)
- Kat Stratford/10 Things I Hate About You (95.8%)
- Mr. Robot/Mr. Robot (95.6%)
- Alex Vause/Orange is the New Black (94.9%)
- Walter White/Breaking Bad (94.7%)
- Amy Elliott Dunne/Gone Girl (94.6%)
- Magneto/X-Men (94.5%)
- Cristina Yang/Grey's Anatomy (93.9%)

Dr. John Watson
Sherlock

Relative character size 63%, 1058/1600 — Archetype ratio 41.5, 5/1600

Major Archetype: 65.9/83.8% Outcast-Angel-Hero

100 75 50 25 0 25 50 75 100

Normalized component/%Variance Explained

Fool ⇒ 40.5/31.6% Hero
weak/incompetent/lazy/stupid ⇒ powerful/capable/purposeful/intelligent

44.1/37.5% Angel ⇐ Demon
safe/pure/virtuous/humble ⇐ dangerous/depraved/corrupt/arrogant

7.0/1.0% Traditionalist ⇐ Adventurer
serious/predictable/humorless/uncreative ⇐ playful/unpredictable/funny/creative

Lone Wolf ⇒ 2.9/0.2% Diva
rugged/poor/oppressed/blunt ⇒ refined/privileged/dramatic/sensitive

29.6/16.9% Outcast ⇐ Sophisticate
unlucky/unsophisticated/traumatized ⇐ fortunate/sophisticated/confident

5.4/0.6% Brute ⇐ Geek
physical/mainstream/simple-minded ⇐ intellectual/weird/complex

Essential Trait 7
4.1/0.3% young/attractive/dramatic ⇐ old/ugly/comedic

Essential Trait 8
spiritual/historical/rural ⇒ 6.3/0.8% skeptical/modern/urban

Essential Trait 9
4.4/0.4% low-tempo ⇐ high-tempo

Essential Trait 10
2.8/0.2% feminine/low-tech/non-athletic ⇐ masculine/high-tech/athletic

Essential Trait 11
forthright/naive/rich ⇒ 2.7/0.1% treacherous/street-wise/poor

Dominant underlying traits:

100 75 50 25 0 25 50 75 100

Measured semantic differential balance

traitorous ⇒ **loyal** (87.6)
villainous ⇒ **heroic** (77.8)
unfaithful ⇒ **devoted** (76.2)
German ⇒ **English** (75.6)
cruel ⇒ **kind** (72.2)
lazy ⇒ **diligent** (72.0)
money-focused ⇒ **love-focused** (71.4)
trash ⇒ **treasure** (70.6)
cunning ⇒ **honorable** (70.2)
psychopath ⇒ **empath** (69.8)
flamboyant ⇒ **modest** (69.4)
animalistic ⇒ **human** (69.2)

Most similar characters:

0 20 40 60 80 100

Similarity percentile

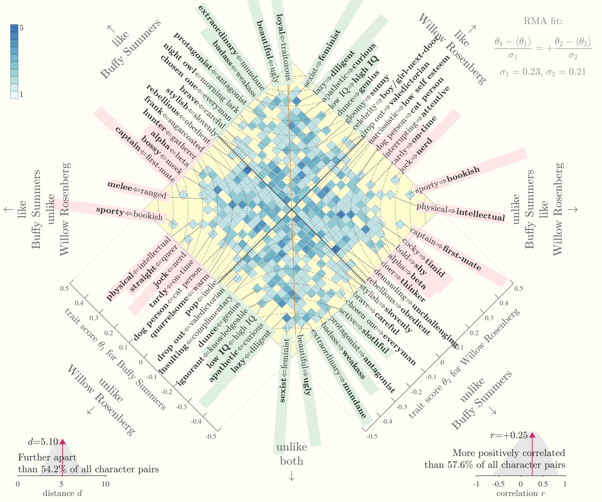
James Gordon/The Dark Knight (100.0%)
Dr. James Wilson/House, M.D. (100.0%)
Beatrice ‘Beadie’ Russell/The Wire (99.9%)
Kevin Ryan/Castle (99.9%)
D.I. Greg Lestrade/Sherlock (99.9%)
Davos Seaworth/Game of Thrones (99.9%)
David Rosen/Scandal (99.9%)
Ann Perkins/Parks and Recreation (99.9%)
Eric Murphy/Entourage (99.9%)
Anita ‘Needy’ Lesnicki/Jennifer’s Body (99.8%)
Pope/Outer Banks (99.8%)
Peeta Mellark/The Hunger Games (99.8%)

1. Buffy Summers
Buffy the Vampire Slayer
Adventurer-Hero

Major archetype: R_{arch}=13.0

2. Willow Rosenberg
Buffy the Vampire Slayer
Geek-Angel-Hero

Minor archetype: R_{arch}=7.3



Standard correlation r

Opposing traits ↑↓	Shared traits ↑↑
	1. sexist⇒**feminist**
2. sporty ⇔ bookish	
	3. traitorous⇒**loyal**
	4. ugly⇒**beautiful**
	5. mundane⇒**extraordinary**
	6. unmotivated⇒**motivated**
7. captain ⇔ first-mate	
	8. repulsive⇒**attractive**
	9. lazy⇒**diligent**
	10. trash⇒**treasure**
	11. soulless⇒**soulful**
	12. helpless⇒**resourceful**
	13. racist⇒**egalitarian**
	14. incompetent⇒**competent**
	15. quitter⇒**persistent**
	16. irrelevant⇒**important**
	17. unambitious⇒**driven**
18. physical ⇔ intellectual	
	19. villainous⇒**heroic**
	20. slacker⇒**workaholic**
	21. weakass⇒**badass**
22. jock ⇔ nerd	
	23. underachiever⇒**overachiever**
	24. money-focused⇒**love-focused**
	25. apathetic⇒**curious**
	26. uncreative⇒**open to new experiences**
	27. conservative⇒**liberal**
	28. stinky⇒**fresh**
	29. old⇒**young**
	30. dispassionate⇒**romantic**
	31. antagonist⇒**protagonist**
	32. scrub⇒**legit**
	33. tiresome⇒**interesting**
34. straight ⇔ queer	
	35. cruel⇒**kind**
	36. sickly⇒**healthy**
	37. slothful⇒**active**
	38. low IQ⇒**high IQ**
	39. unfaithful⇒**devoted**
	40. stingy⇒**generous**
$r_{\uparrow\downarrow}=-0.26$	$r_{\uparrow\uparrow}=+0.51$

$$\mathbf{r} = \frac{\langle(\theta_1 - \langle\theta_1\rangle)(\theta_2 - \langle\theta_2\rangle)\rangle}{\langle(\theta_1 - \langle\theta_1\rangle)(\theta_2 - \langle\theta_2\rangle)\rangle} = \mathbf{+0.25}$$

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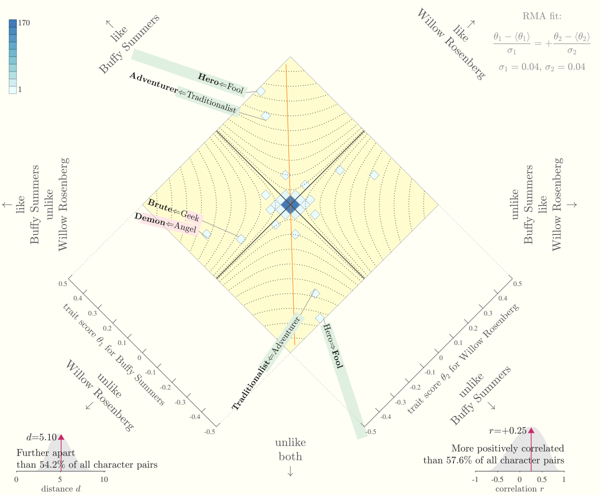
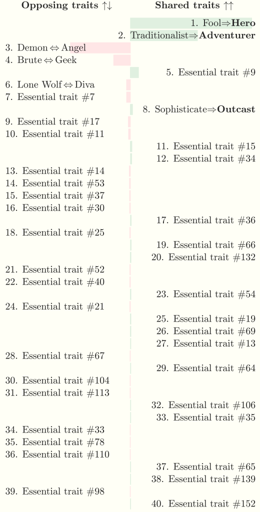


Standard correlation r



$r_{\uparrow\downarrow}=-0.25$ $r_{\uparrow\uparrow}=+0.50$

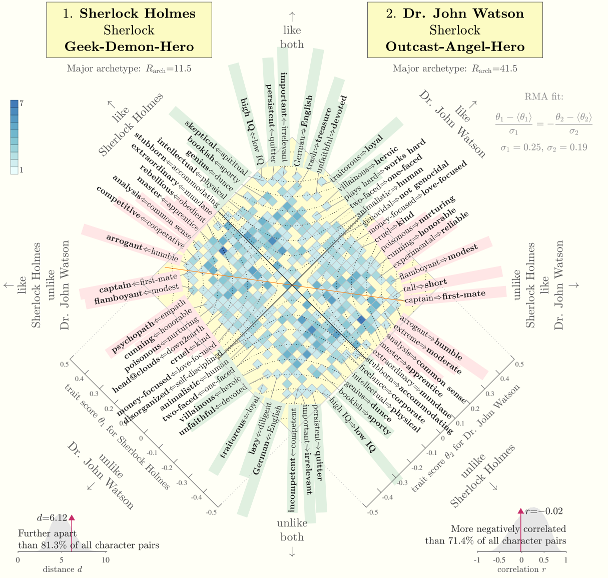
$$\mathbf{r} = \frac{\langle\theta_1 - \langle\theta_1\rangle\rangle\langle\theta_2 - \langle\theta_2\rangle\rangle}{\langle(\theta_1 - \langle\theta_1\rangle)(\theta_2 - \langle\theta_2\rangle)\rangle} = +\mathbf{0.25}$$

1. **Sherlock Holmes**
Sherlock
Geek-Demon-Hero

Major archetype: R_{arch}=11.5

2. **Dr. John Watson**
Sherlock
Outcast-Angel-Hero

Major archetype: R_{arch}=41.5



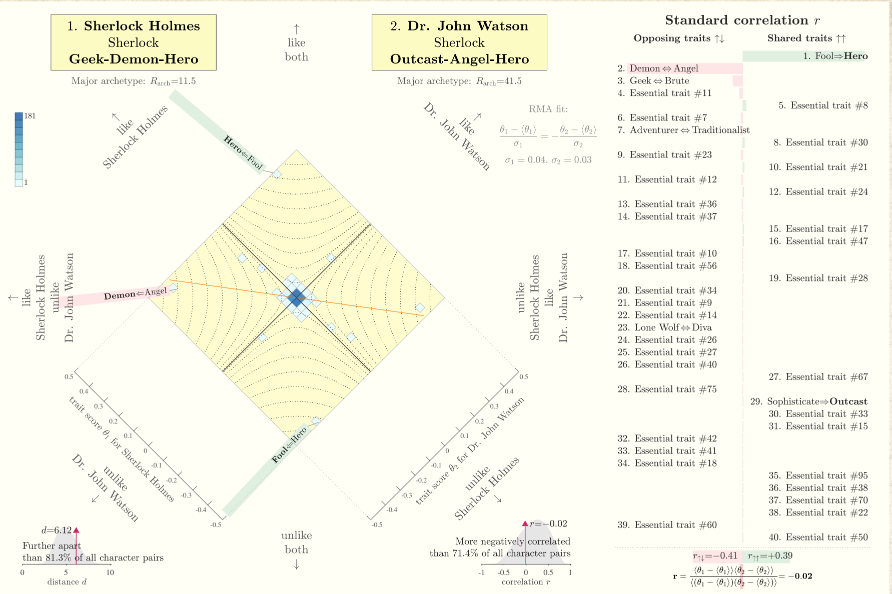
Standard correlation r

Opposing traits ↑↓ **Shared traits ↑↑**

1. German⇒**English**
2. irrelevant⇒**important**
3. slacker⇒**workaholic**
4. quitter⇒**persistent**
5. incompetent⇒**competent**
6. low IQ⇒**high IQ**
7. arrogant ⇔ humble
8. captain ⇔ first-mate
9. spiritual⇒**skeptical**
10. tall ⇔ short
11. flamboyant ⇔ modest
12. psychopath ⇔ empath
13. trash⇒**treasure**
14. racist⇒**egalitarian**
15. traitorous⇒**loyal**
16. rude ⇔ respectful
17. ignorant⇒**knowledgeable**
18. competitive ⇔ cooperative
19. antagonist⇒**protagonist**
20. random⇒**pointed**
21. narcissistic ⇔ low self esteem
22. artistic⇒**scientific**
23. lazy⇒**diligent**
24. extreme ⇔ moderate
25. helpless⇒**resourceful**
26. entitled ⇔ grateful
27. experimental ⇔ reliable
28. unfaithful⇒**devoted**
29. extravagant ⇔ thrifty
30. alpha ⇔ beta
31. cold ⇔ warm
32. analysis ⇔ common sense
33. mischievous ⇔ well behaved
34. cunning ⇔ honorable
35. sporty⇒**bookish**
36. relaxed⇒**tense**
37. unorthodox ⇔ traditional
38. jock⇒**nerd**
39. open⇒**guarded**
40. scrub⇒**legit**

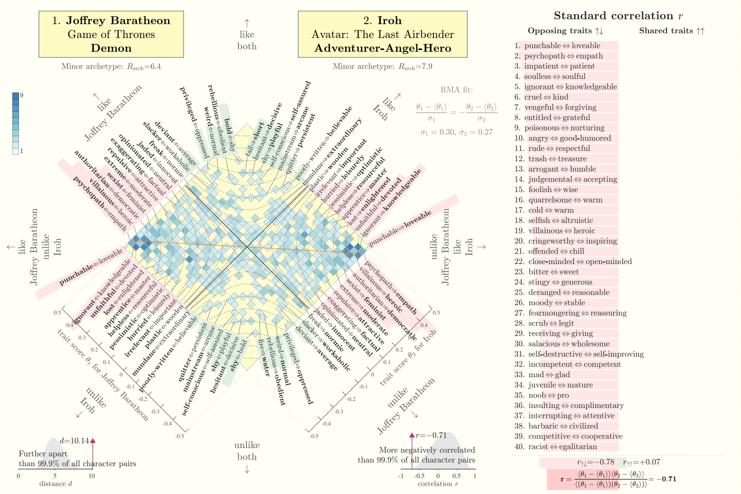
$r_{\uparrow\downarrow}$=−0.37 $r_{\uparrow\uparrow}$=+0.35

$$\mathbf{r}=\frac{\langle(\theta_1-\langle\theta_1\rangle)(\theta_2-\langle\theta_2\rangle)\rangle}{\langle(\theta_1-\langle\theta_1\rangle)(\theta_2-\langle\theta_2\rangle)\rangle}=-\mathbf{0.02}$$

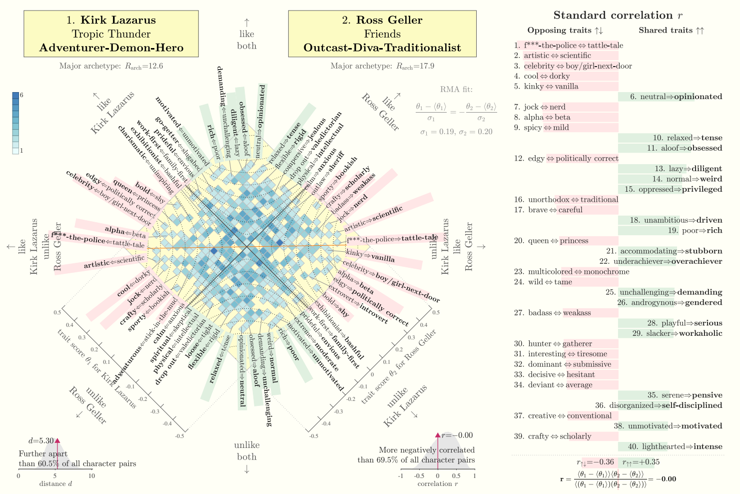


1. Sherlock Holmes
Sherlock
Geek-Demon-Hero
Major archetype: R_{arch}=11.5
↑ like both
2. Dr. John Watson
Sherlock
Outcast-Angel-Hero
Major archetype: R_{arch}=41.5
181
1
↖ like Sherlock Holmes
↗ like Dr. John Watson
RMA fit:
$\frac{\theta_1 - \langle\theta_1\rangle}{\sigma_1} = -\frac{\theta_2 - \langle\theta_2\rangle}{\sigma_2}$
$\sigma_1 = 0.04$, $\sigma_2 = 0.03$
Hero⇐Fool
Demon⇐Angel
Fool⇐Hero
← like Sherlock Holmes unlike Dr. John Watson
unlike Sherlock Holmes like Dr. John Watson →
trait score θ_1 for Sherlock Holmes
trait score θ_2 for Dr. John Watson
unlike Dr. John Watson ↙
unlike Sherlock Holmes ↘
unlike both ↓
d=6.12
Further apart than 81.3% of all character pairs
distance d
r=−0.02
More negatively correlated than 71.4% of all character pairs
correlation r
Standard correlation r
Opposing traits ↑↓
Shared traits ↑↑
1. Fool⇒Hero
2. Demon⇔Angel
3. Geek⇔Brute
4. Essential trait #11
5. Essential trait #8
6. Essential trait #7
7. Adventurer⇔Traditionalist
8. Essential trait #30
9. Essential trait #23
10. Essential trait #21
11. Essential trait #12
12. Essential trait #24
13. Essential trait #36
14. Essential trait #37
15. Essential trait #17
16. Essential trait #47
17. Essential trait #10
18. Essential trait #56
19. Essential trait #28
20. Essential trait #34
21. Essential trait #9
22. Essential trait #14
23. Lone Wolf⇔Diva
24. Essential trait #26
25. Essential trait #27
26. Essential trait #40
27. Essential trait #67
28. Essential trait #75
29. Sophisticate⇒Outcast
30. Essential trait #33
31. Essential trait #15
32. Essential trait #42
33. Essential trait #41
34. Essential trait #18
35. Essential trait #95
36. Essential trait #38
37. Essential trait #70
38. Essential trait #22
39. Essential trait #60
40. Essential trait #50
$r_{\uparrow\downarrow}$=−0.41
$r_{\uparrow\uparrow}$=+0.39
$\mathbf{r} = \frac{\langle(\theta_1 - \langle\theta_1\rangle)(\theta_2 - \langle\theta_2\rangle)\rangle}{\langle(\theta_1 - \langle\theta_1\rangle)(\theta_2 - \langle\theta_2\rangle)\rangle} = \mathbf{-0.02}$

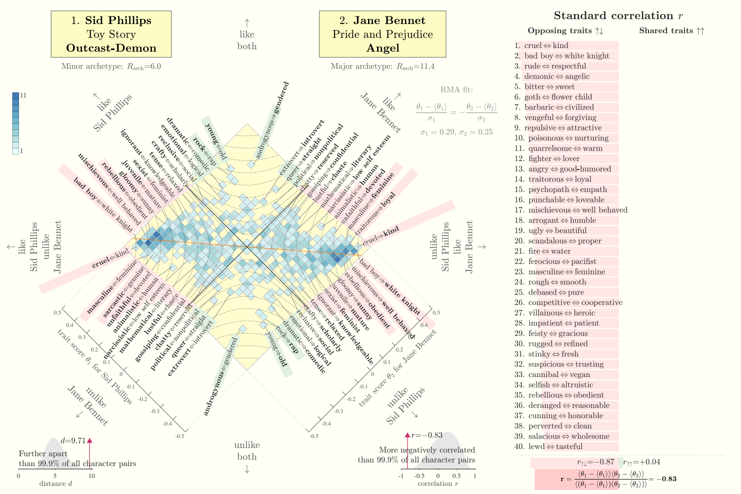
The two characters furthest apart:



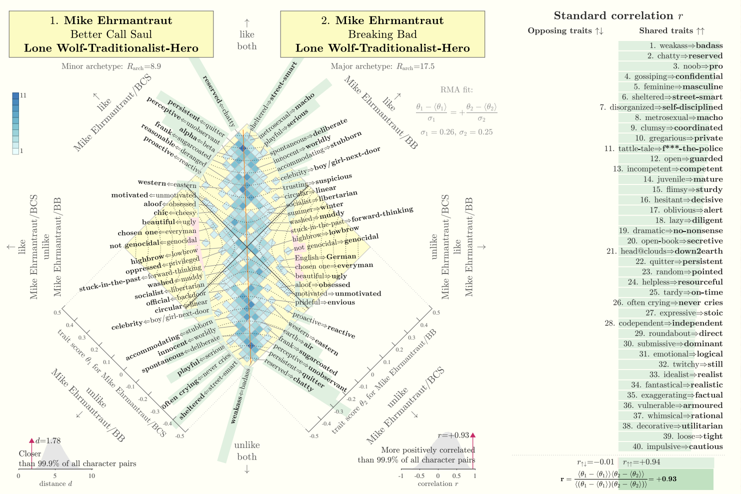
The most uncorrelated pair of characters:



The most negatively correlated characters:



Character evolution:



Some nutshelling

- Storywrangler framework is an exploratorium for temporally ordered large-scale texts

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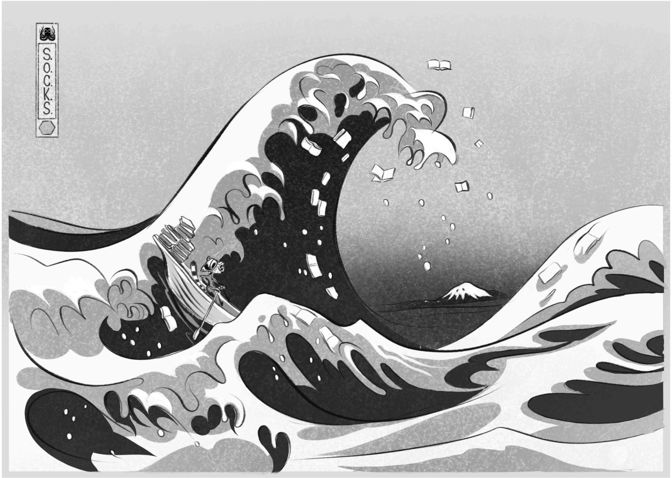
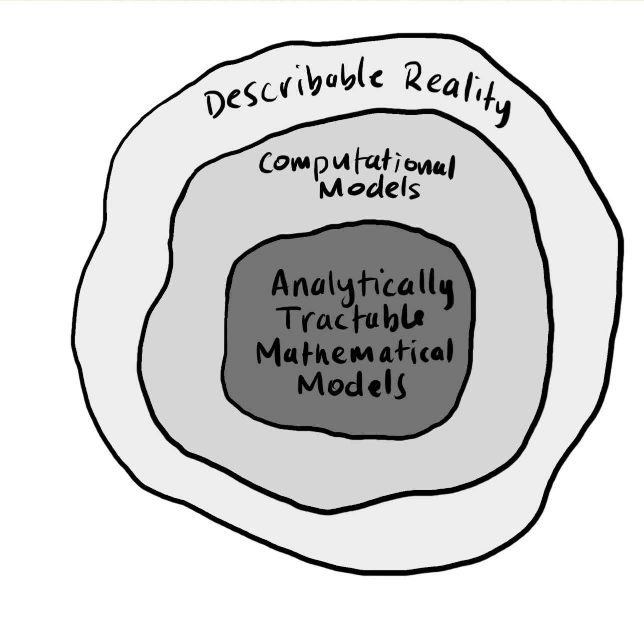
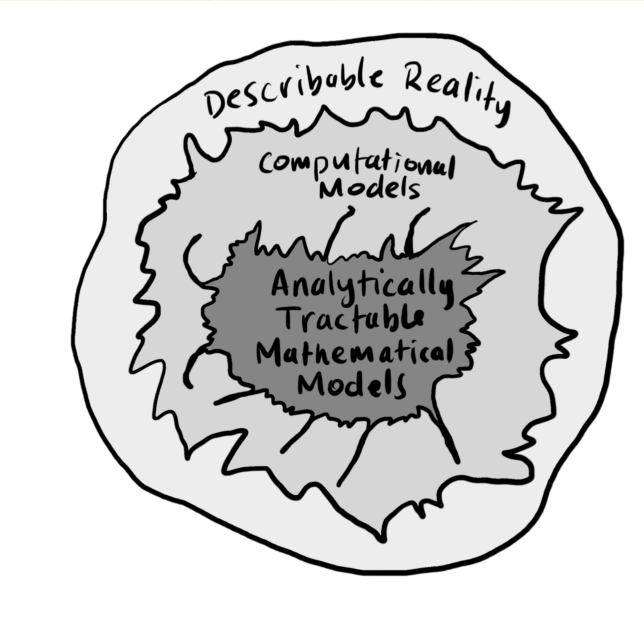
- Instruments are open boxes not closed boxes
- Stories $\sim$ Characters + Time
- Coming soon: The Essential Six Dimensions of Character Archetypes
- GPT is not (yet) a scientific instrument


S.O.C.K.S.


Describable Reality
Computational Models
Analytically Tractable Mathematical Models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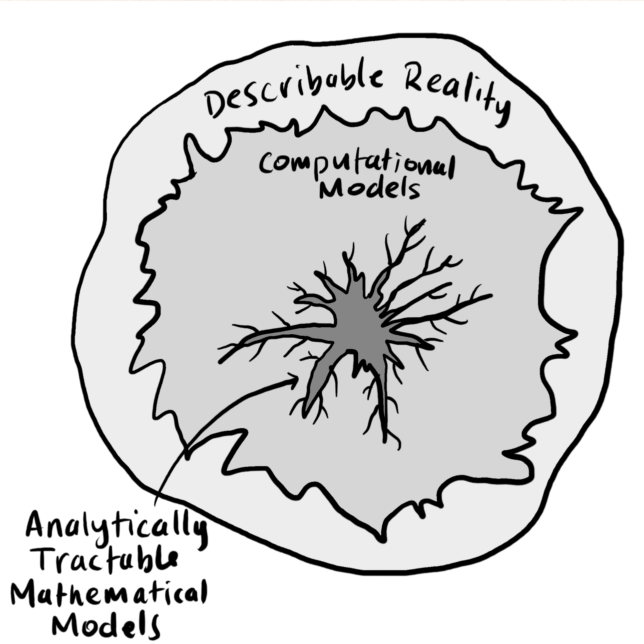
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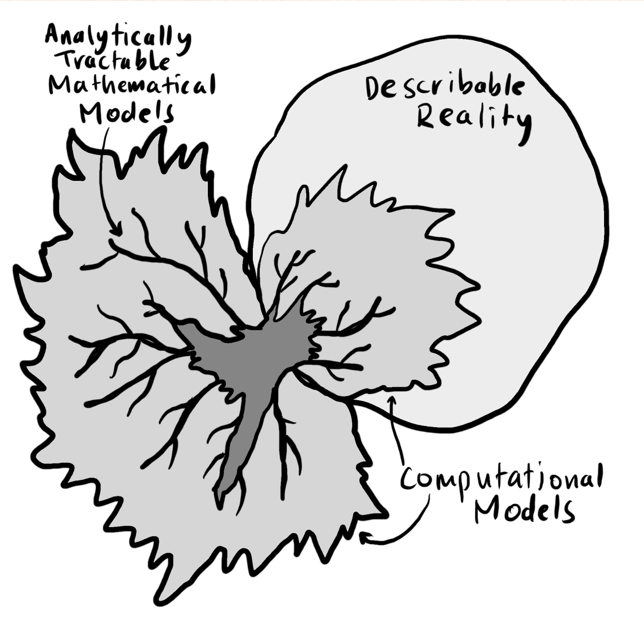
Analytically Tractable Mathematical Models
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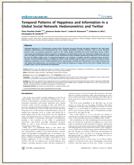
A few key papers:

"Measuring the happiness of large-scale written expression: Songs, blogs, and presidents.", Dodds and Danforth, Journal of Happiness Studies, **11**, 441–456, 2009. [6]


Temporal Patterns of Happiness and Information in a Global Social Network: Hedonometrics and Twitter

"Temporal patterns of happiness and information in a global social network: Hedonometrics and Twitter"
Dodds et al.,
PLoS ONE, **6**, e26752, 2011. [7]

"Positivity of the English language", Kloumann et al., PLoS ONE, **7**, e29484, 2012. [11]

"Human language reveals a universal positivity bias", Dodds et al., Proc. Natl. Acad. Sci., **112**, 2389–2394, 2015. [5]

A few more key papers:

"Sentiment analysis methods for understanding large-scale texts: A case for using continuum-scored words and word shift graphs", Reagan et al., EPJ Data Science, **6**, , 2017. [15]


EPJ Data Science
REGULAR ARTICLE
Open Access
Generalized word shift graphs: a method for visualizing and explaining pairwise comparisons between texts

"Generalized word shift graphs: A method for visualizing and explaining pairwise comparisons between texts"
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Available online at https://arxiv.org/abs/1910.00149, 2019. [8]

"Computational timeline reconstruction of the stories surrounding Trump: Story turbulence, narrative control, and collective chronopathy"
Dodds et al.,
, 2020. [9]

- POTUSometer with the Smorgasdashbord: http://compstorylab.org/potusometer/
- Stories surrounding Trump: http://compstorylab.org/trumpstoryturbulence/

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Measuring the happiness of large-scale written expression: Songs, blogs, and presidents.
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