Things to help pull up our SOCKS

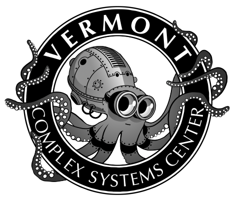
Last updated: 2023/08/24, 07:09:41 EDT

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
Santa Fe Institute | University of Vermont

Outline



Describe | Explain | Create | Share | Ethos: Play

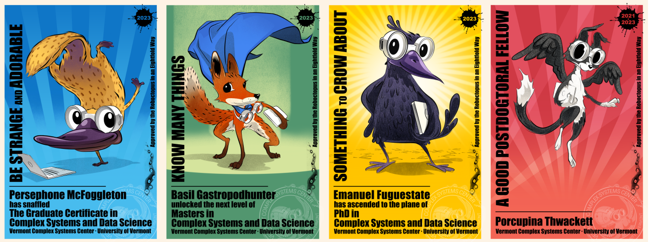
vermontcomplexsystems.org

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

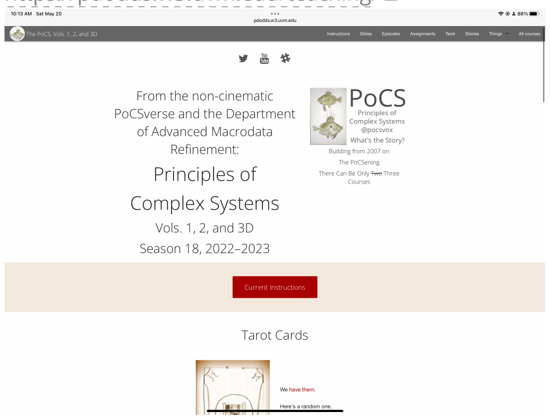
All the words: http://vermontcomplexsystems.org.

Dipoloma-posters:



Principles of Complex Systems, Vols. 1, 2, and 3D

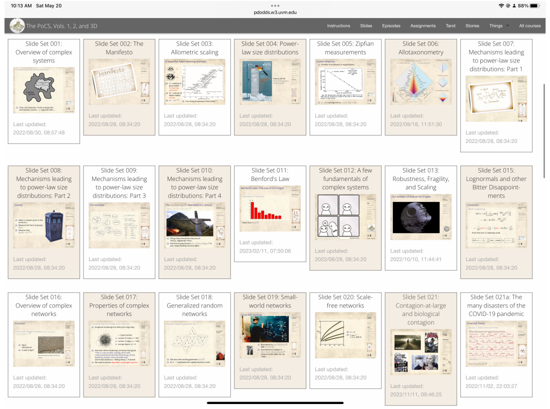
https://pdodds.w3.uvm.edu/teaching/



150,000 lines of LaTeX ...

Principles of Complex Systems, Vols. 1, 2, and 3D

https://pdodds.w3.uvm.edu/teaching/courses/pocsverse/slides/



Principles of Complex Systems, Vols. 1, 2, and 3D

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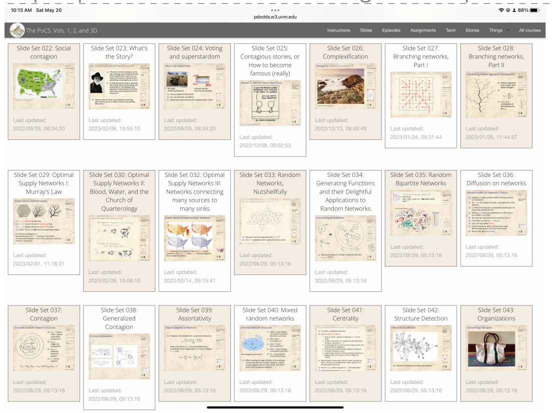
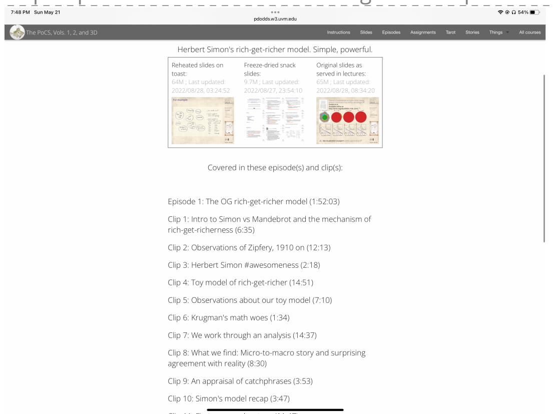


Principles of Complex Systems, Vols. 1, 2, and 3D

https://pdodds.w3.uvm.edu/teaching/courses/pocsverse/slides/



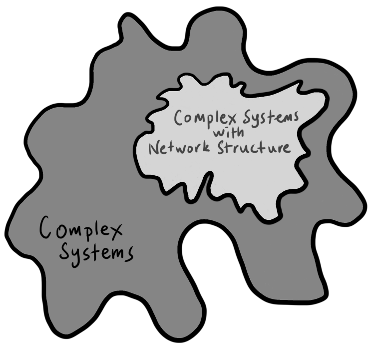
Exciting details regarding these slides:

- 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

The Science of Complex Systems Manifesto:

1. Systems are ubiquitous and systems matter.
2. Consequently, much of science is about understanding how pieces dynamically fit together.
3. 1700 to 2000 = Golden Age of Reductionism: Atoms!, sub-atomic particles, DNA, genes, people, ...
4. Understanding and creating systems (including new 'atoms') is the greater part of science and engineering.
5. Universality: systems with quantitatively different micro details exhibit qualitatively similar macro behavior (fate, but real and limited)
6. Computing advances make the Science of Complex Systems possible:
   6.1 We can measure and record enormous amounts of data, research areas continue to transition from data scarce to data rich.
   6.2 We can simulate, model, and create complex systems in extraordinary detail.

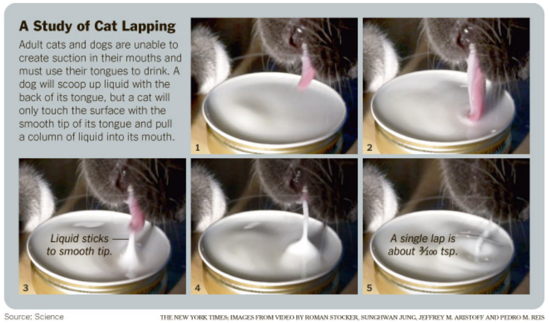
Complex Systems is the Big Story:



- 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.

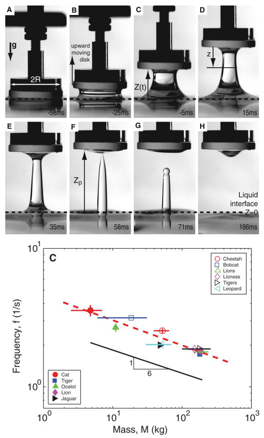


Amusing interview here

- 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.



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.

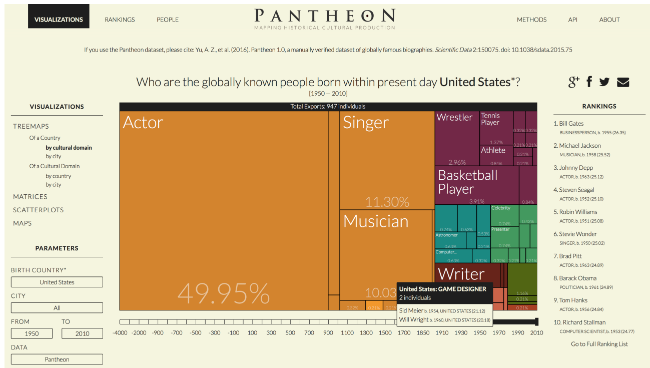
Major competing storytelling entities:

- 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, ...

Cultural products from Pantheon:

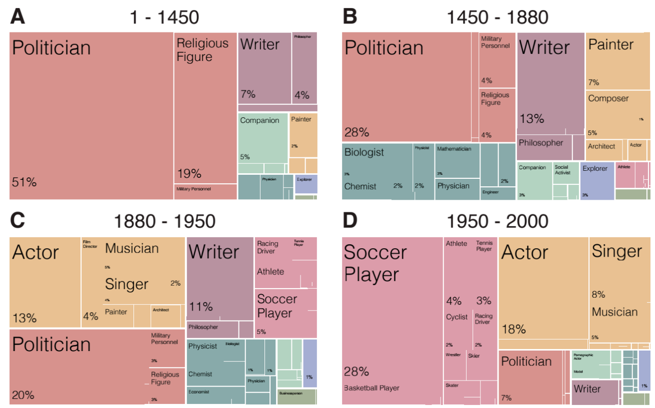
- Writers, artists, movie directors, video game directors.

Storytellers win:

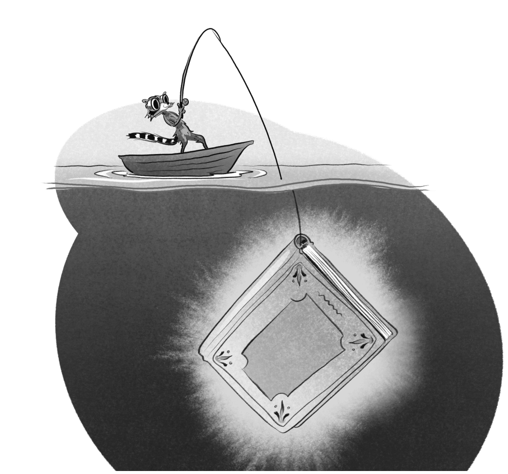


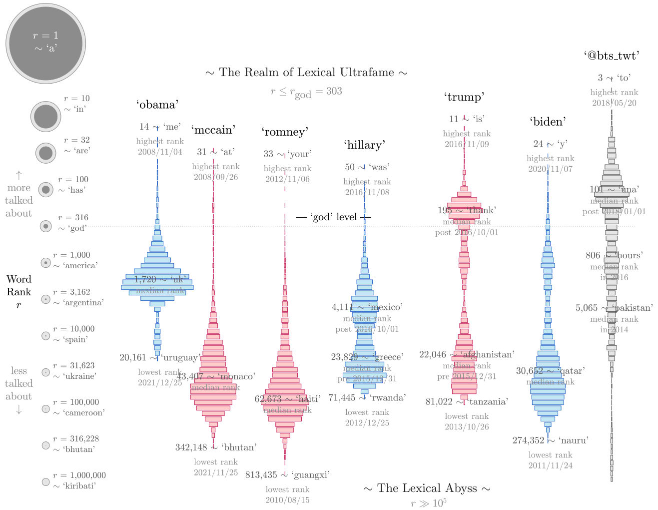
For people born 1950–

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

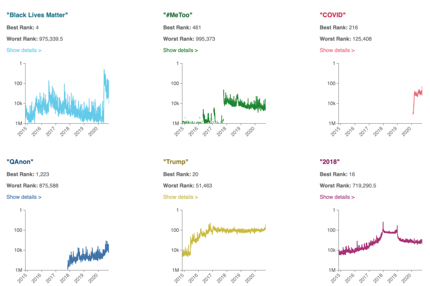


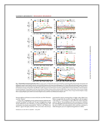
https://www.media.mit.edu/projects/pantheon-new/overview/



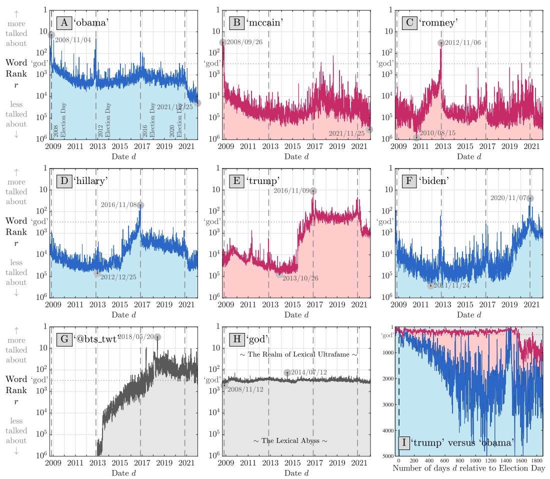


storywrangler https://storywrangling.org/



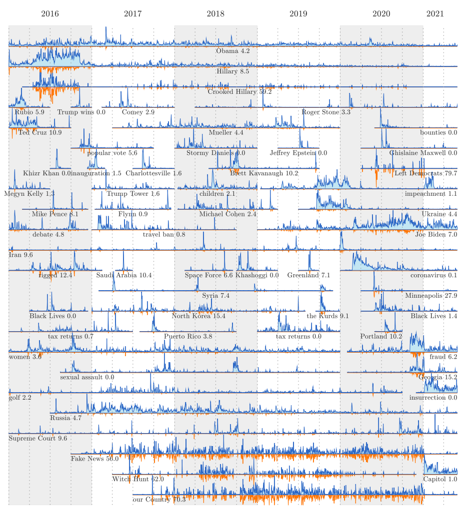


"Storywrangler: A massive exploratorium for sociolinguistic, cultural, socioeconomic, and political timelines using Twitter"
Alshaabi et al.,
Science Advances, **7**, eabe6534, 2021. [1]



2011 Whitehouse Correspondents' Dinner

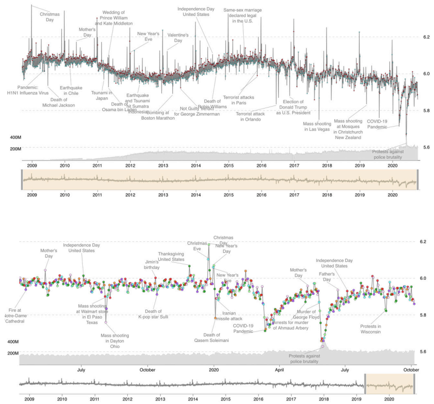
Week	2016	2017	2018	2019	2020	2021
1. 01/01–01/07	Hillary Clinton 32.7	plant in 85.1	Steve Bannon 5.7	the government 0.0	a war 6.6	in Georgia 20.2
2. 01/08–01/14	Trump rally 0.0	Meryl Streep 6.6	shithole countries 0.0	the border 1.0	impeachment trial 0.0	the Capitol 0.0
3. 01/15–01/21	Ted Cruz 26.0	Trump's 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



Panometer—Three kinds of lexical meters:

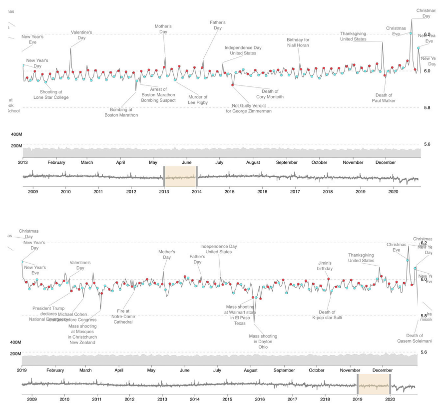
1. Principled lexical meters:
   - The Hedonometer.
   - Lexicocalorimeter, POTUSometer, Ousiometer.
2. Ground truth lexical meters:
   - Insomniometer.
   - Hangoverometer.
3. Bootstrap lexical meters:
   - Boredometer.
   - Hashtagometers.

Emotional turbulence:



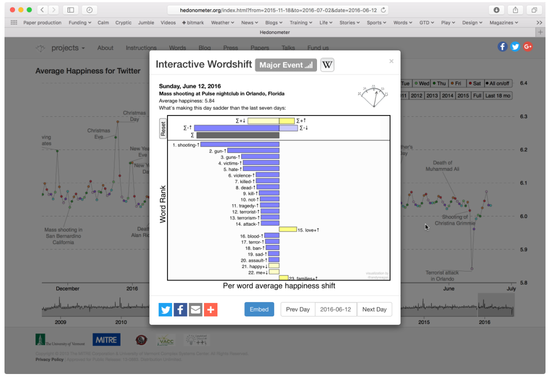
http://hedonometer.org/

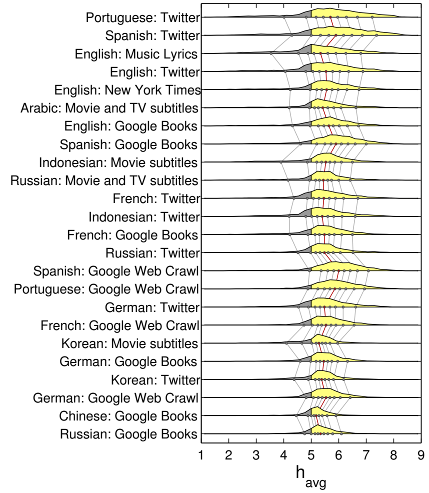
Emotional turbulence:



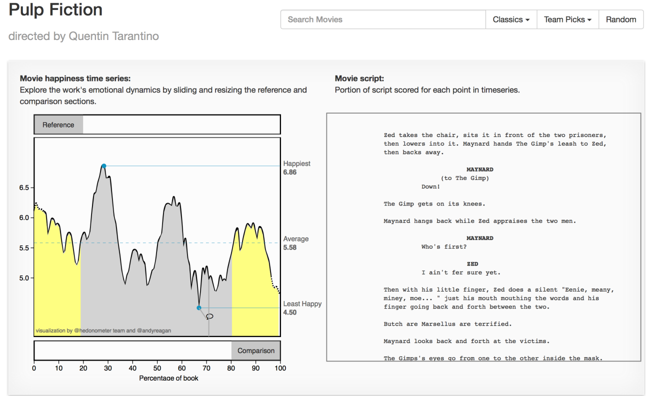
http://hedonometer.org/

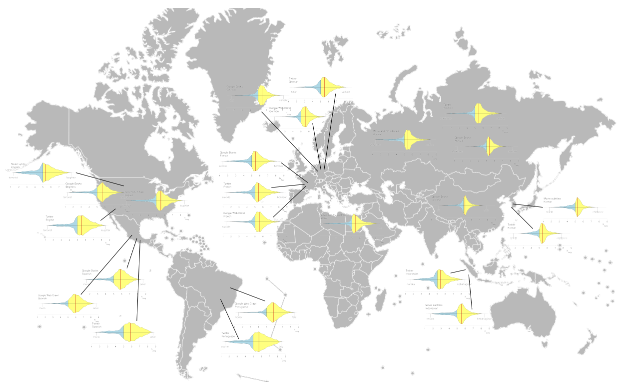
hedonometer.org—word shifts:





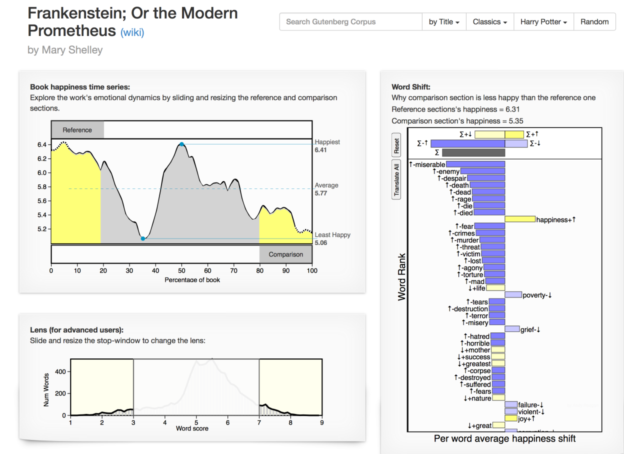
Online, interactive Emotional Shapes of Stories for 1,000+ movie scripts:



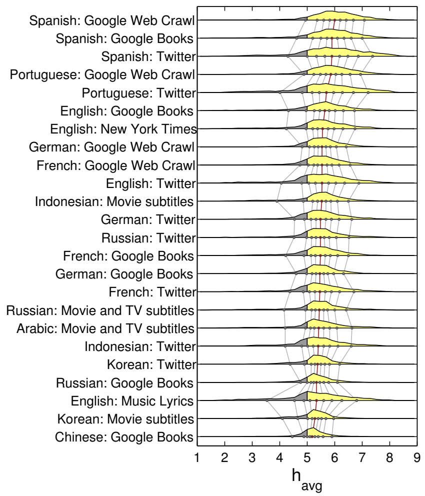


Dodds/Tivnan/Danforth et al.,
Proc. Natl. Acad. Sci. 2015,
"Human language reveals a universal positivity bias."[5]
Global press including National Geographic
Top 100 altmetric article, 2015

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

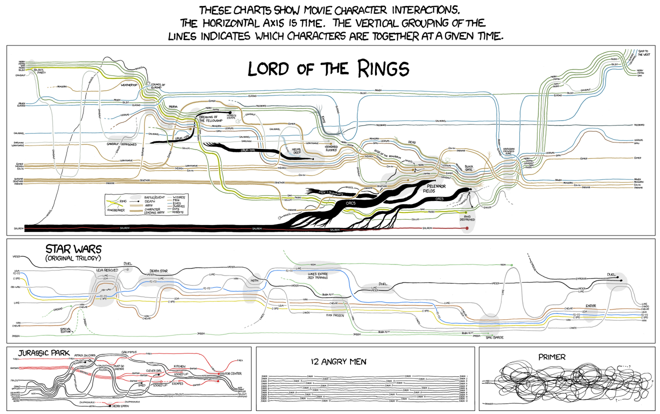


"So, in writing, there are six basic plots, and their sequels and derivative franchises."

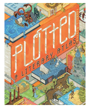


Online, interactive Emotional Shapes of Stories for 10,000+ books:

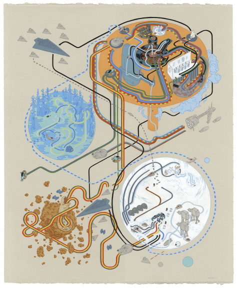
Emotional arcs are not plots. Neither are character paths:



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]

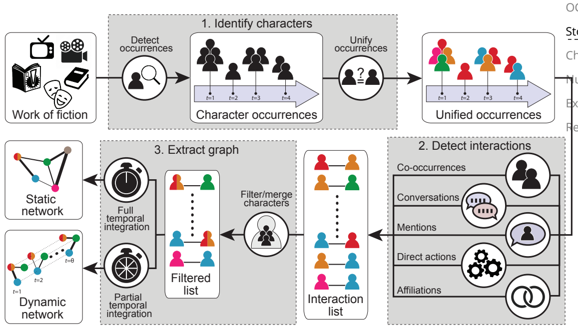
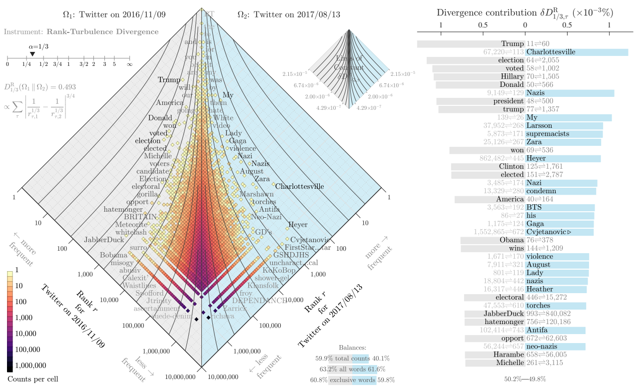
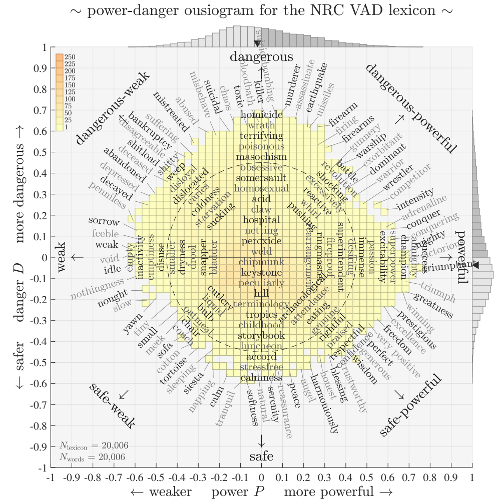


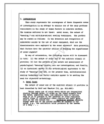
Fig. 1. Overview of the generic character network extraction process. Figure available at 10.6084/m9.figshare.7993040 under CC-BY license.



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



The meaning of pings:



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

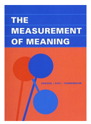
From the introduction:

'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:

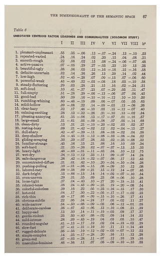
- naval sonar,
- the nature of "meaning,"
- and multidimensional scaling techniques.

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?'

From pings to things:

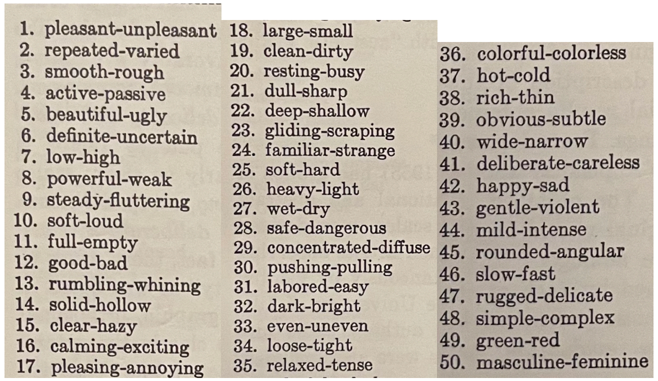


"The Measurement of Meaning" by Osgood, Suci, and Tannenbaum (1957). [14]



- Osgood et al. used semantic differentials and factor analysis to identify a basis of three variables for meaning-space:
  - Evaluation: {bad ⇔ good}
  - Potency: {weak ⇔ strong}
  - Activity: {passive ⇔ active}
- 100s of students, 10s of things, 50 semantic differentials
- "EPA framework"

Semantic differentials from Osgood et al.: [14]



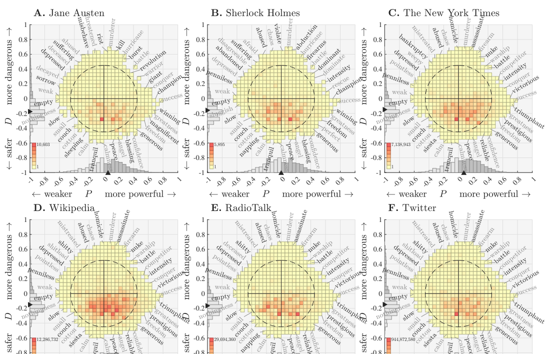
1. pleasant-unpleasant
2. repeated-varied
3. smooth-rough
4. active-passive
5. beautiful-ugly
6. definite-uncertain
7. low-high
8. powerful-weak
9. steady-fluttering
10. soft-loud
11. full-empty
12. good-bad
13. rumbling-whining
14. solid-hollow
15. clear-hazy
16. calming-exciting
17. pleasing-annoying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

Definitions:

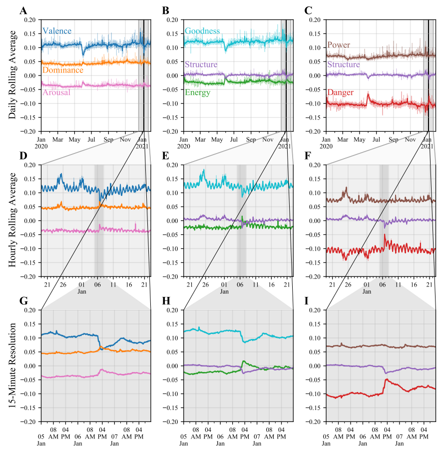
- Ousiometrics: The quantitative study of the essential meaningful components of an entity, however perceived.
- Used in philosophical and theological settings, the word 'ousia' comes from Ancient Greek οὐσία.
- To be distinguished from semantics, semiotics, …
- οὐσία is the etymological root of the word 'essence'.
- Ousiometry, ousiometer, ousiograms, …
- Telegnomics: The distant sensing of knowledge (∼ distant reading [13])

A special thing has happened:

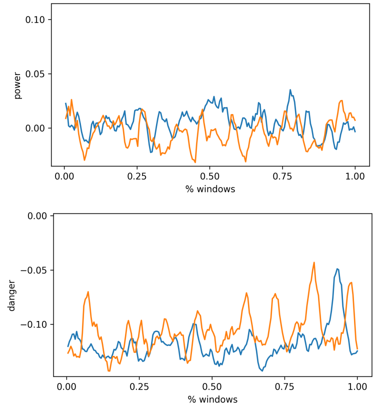
- The PDS framework emerged only from analyzing a lexicon (types).
- Applying PDS framework to disparate corpora (tokens) reveals a linguistic 'safety bias'.



Prototype ousiometer—Twitter:

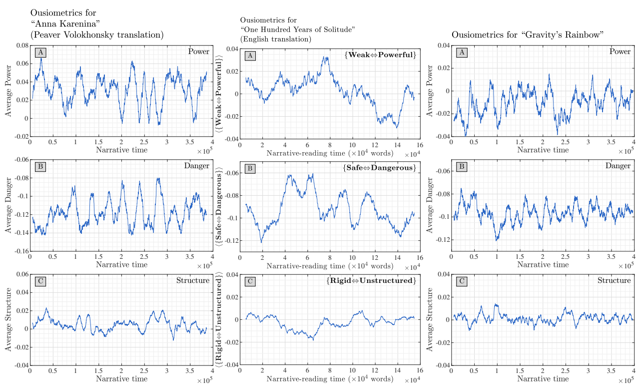


Prototype ousiometer—Harry Potter:

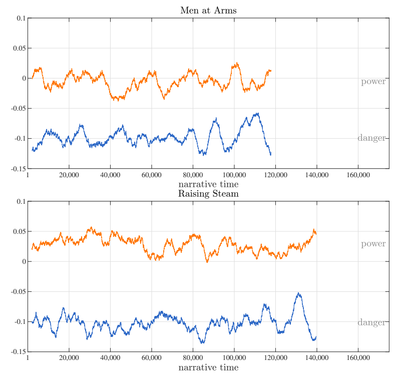


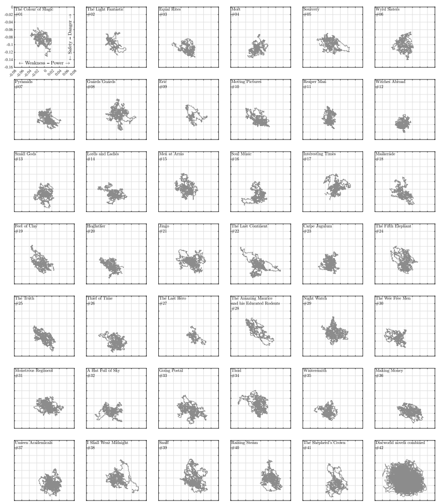
Blue: Harry Potter and the Half-Blood Prince
Orange: Harry Potter and the Deathly Hallows

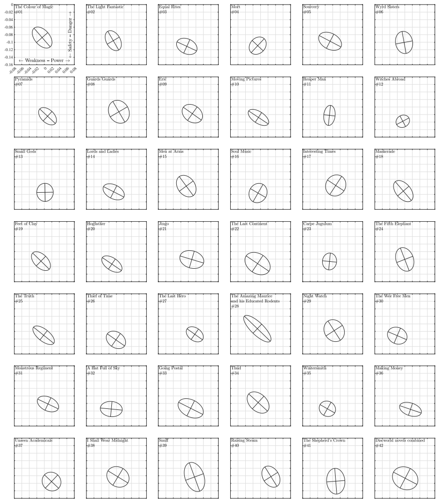
Power and Danger time series for books:



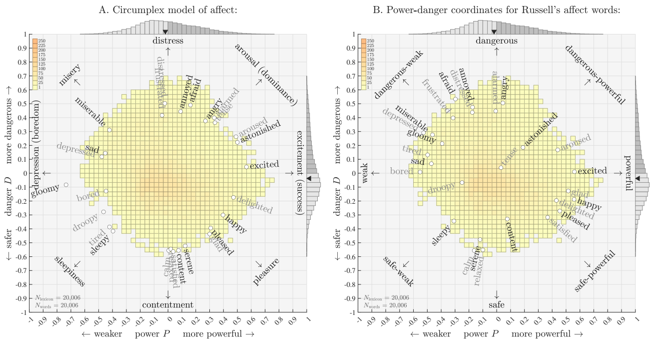
Prototype ousiometer—Terry Pratchett's Discworld:







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



Dungeons & Dragons—Two alignment axes for character:

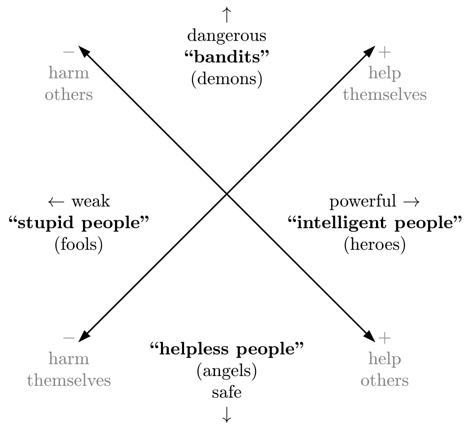
[1]

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

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

lawful-good ∼ structured-powerful-safe	neutral-good ∼ neutral-powerful-safe	chaotic-good ∼ unstructured-powerful-safe
lawful-neutral ∼ structured-neutral	(true) neutral	chaotic-neutral ∼ unstructured-neutral
lawful-evil ∼ structured-dangerous	neutral-evil ∼ neutral-dangerous	chaotic-evil ∼ unstructured-dangerous

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



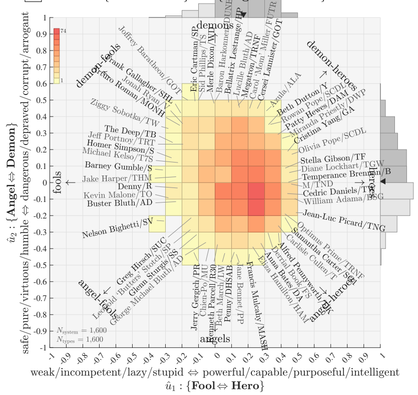
Data set:

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

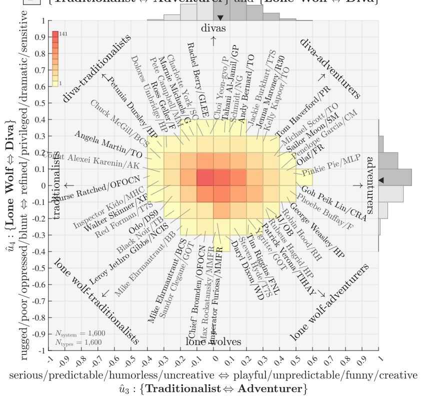
Most extreme characters:

Rank. Character Storyverse	Size S	Top Three Archetypes (Essential Direction, Norm. Component/% Variance Explained) Third:	Second:	First:	$R^{\text{ext}}_{\text{arch}}$
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

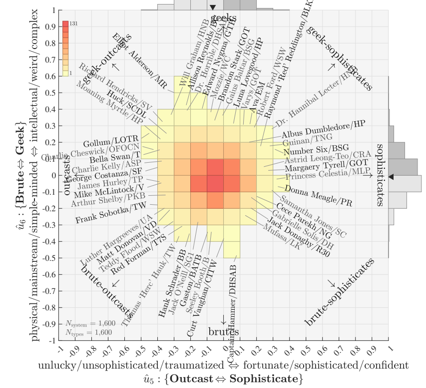
First and second essential dimensions of character space:
{**Fool** ⇔ **Hero**} and {**Angel** ⇔ **Demon**}



Third and fourth essential dimensions of character space:
{**Traditionalist** ⇔ **Adventurer**} and {**Lone Wolf** ⇔ **Diva**}



Fifth and sixth essential dimensions of character space:
{**Outcast** ⇔ **Sophisticate**} and {**Brute** ⇔ **Geek**}



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**} ∼ {weak/incompetent/lazy/stupid ⇔ powerful/capable/purposeful/intelligent}	+{**conscientiousness**}	{**weak** ⇔ **powerful**}	25.7%	41.2% (9+651=660)
2. {**Angel** ⇔ **Demon**} ∼ {safe/pure/virtuous/humble ⇔ dangerous/depraved/corrupt/arrogant}	−{**agreeableness**}	{**safe** ⇔ **dangerous**}	21.3%	27.5% (161+279=440)
3. {**Traditionalist** ⇔ **Adventurer**} ∼ {serious/predictable/humorless/uncreative ⇔ playful/unpredictable/funny/creative}	+{**openness**}	{**structured** ⇔ **unstructured**}	14.1%	18.2% (52+240=292)
			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**} ∼ {rugged/poor/oppressed/blunt ⇔ refined/privileged/dramatic/sensitive}	+{**extroversion**}	6.4%	5.5% (12+76=88)
5. {**Outcast** ⇔ **Sophisticate**} ∼ {unlucky/unsophisticated/traumatized ⇔ fortunate/sophisticated/confident}	−{**neuroticism**}	5.1%	5.1% (81+0=81)
6. {**Brute** ⇔ **Geek**} ∼ {physical/mainstream/simple-minded ⇔ intellectual/weird/complex}	−{**extroversion**}, +{**neuroticism**}	3.7%	1.6% (13+13=26)
		15.2%	12.2% (195)

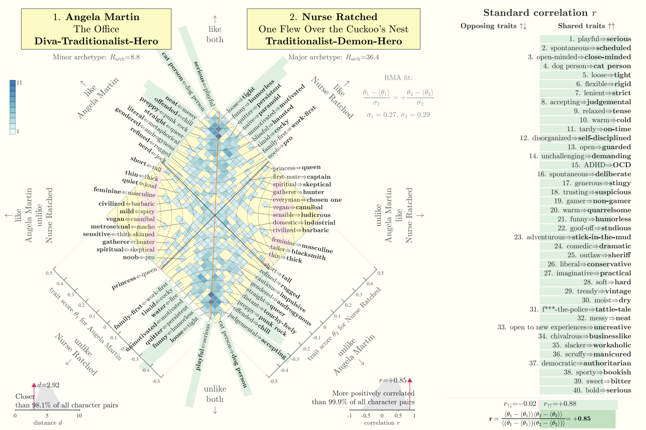
C. Trait-level essential character dimensions:

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)

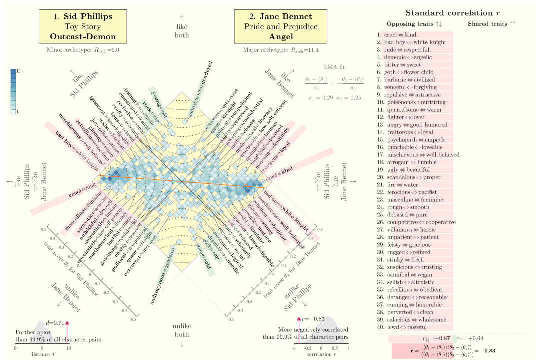
Most archetypal characters:

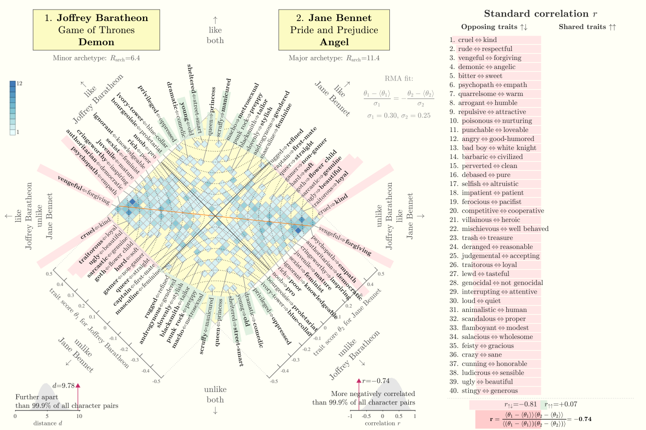
Rank by $R^{\text{ext}}_{\text{arch}}$. Character Story	Size S	Rank	Archetype class	(% var. exp., β_1, β_2)	$R^{\text{ext}}_{\text{arch}}$
1. Tywin Lannister Game of Thrones	90.9	36	Traditionalist-Demon-Hero	(88.5, 1.3)	66.6
2. Charlie Young The West Wing	82.5	191	Angel-Hero	(83.3, 1.7)	48.4
3. Kate 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

Two similar villains:

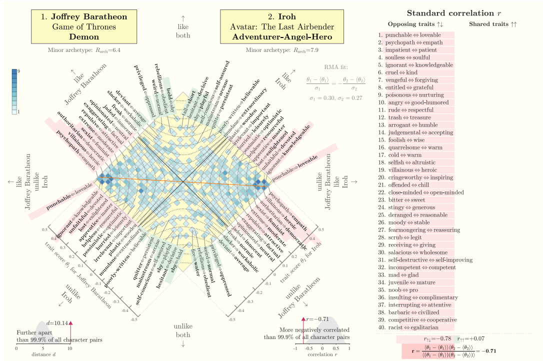


The most negatively correlated characters:

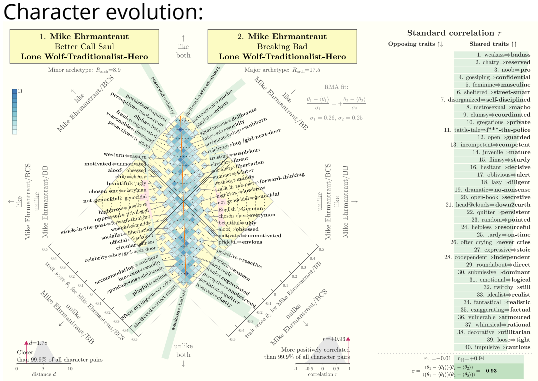




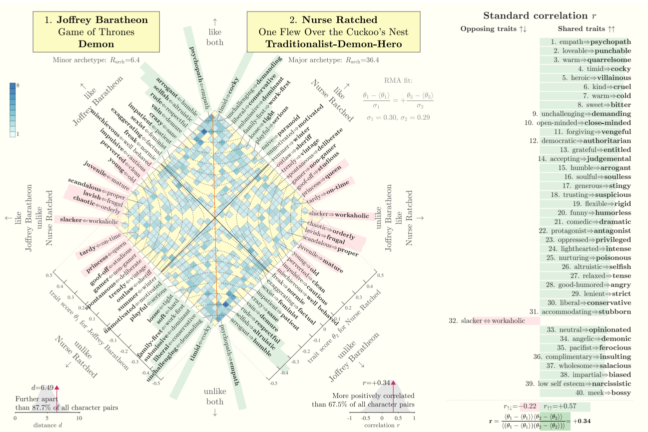
The two characters furthest apart:



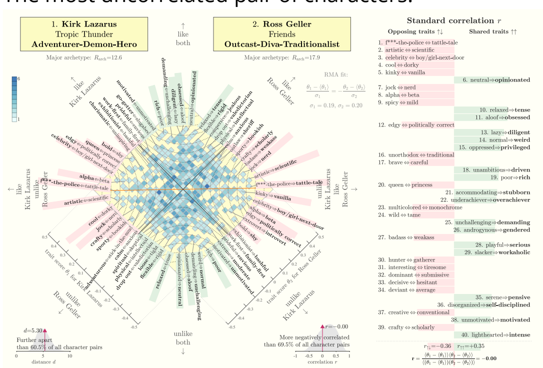
Character evolution:

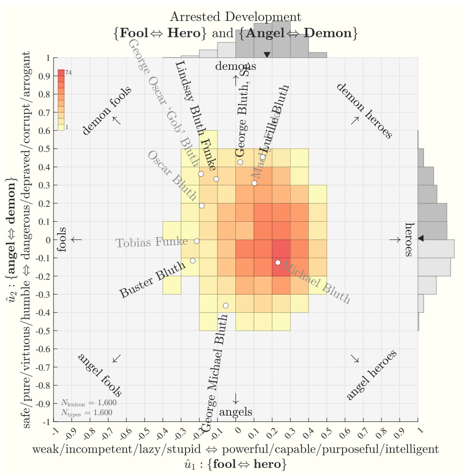


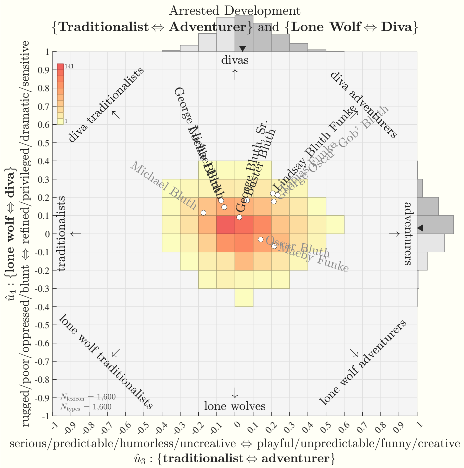
Two distinct villains:



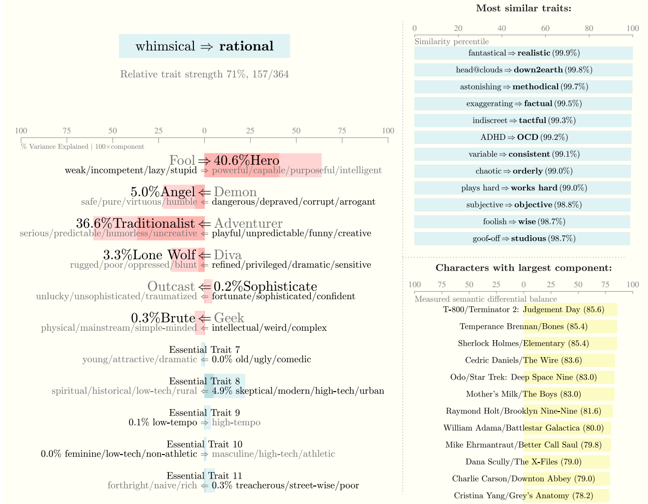
The most uncorrelated pair of characters:



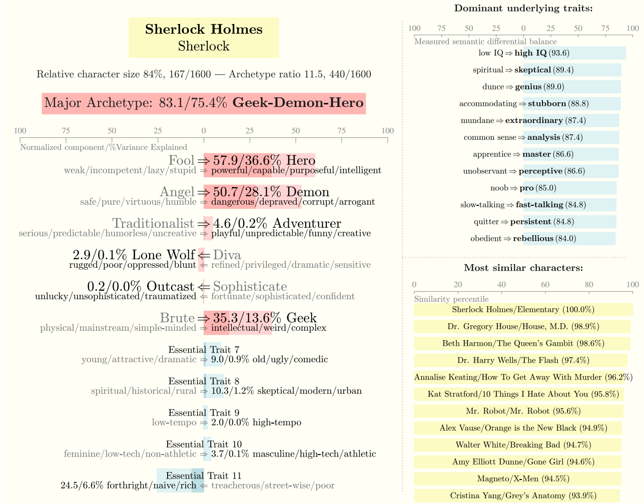




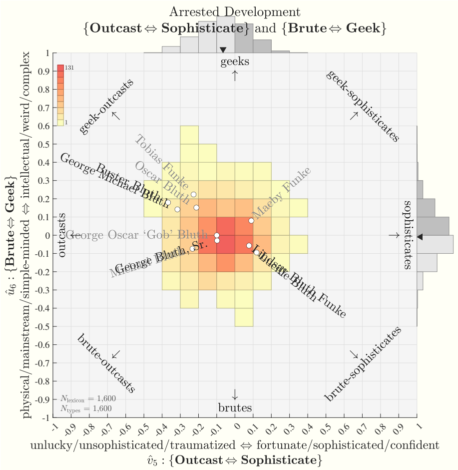
Arrested Development
{Traditionalist ⇔ Adventurer} and {Lone Wolf ⇔ Diva}
divas
lone wolves
traditionalists
adventurers
diva traditionalists
diva adventurers
lone wolf traditionalists
lone wolf adventurers
serious/predictable/humorless/uncreative ⇔ playful/unpredictable/funny/creative
$\hat{u}_3$: {traditionalist ⇔ adventurer}
$\hat{u}_4$: {lone wolf ⇔ diva}
rugged/poor/oppressed/blunt ⇔ refined/privileged/dramatic/sensitive



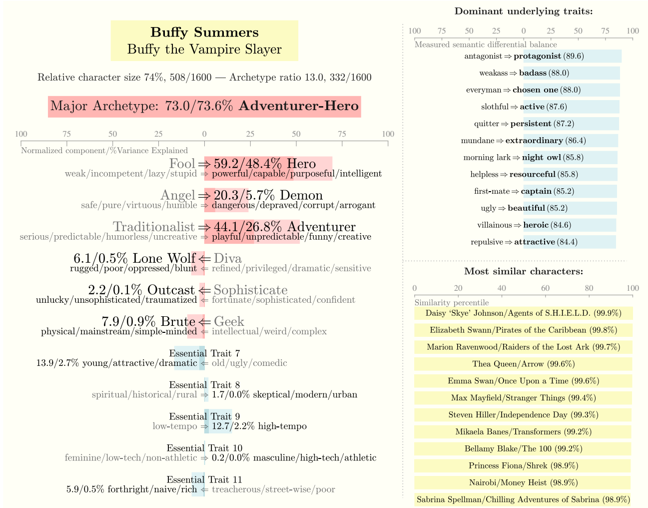
whimsical ⇒ rational
Relative trait strength 71%, 157/364
Most similar traits:
Characters with largest component:



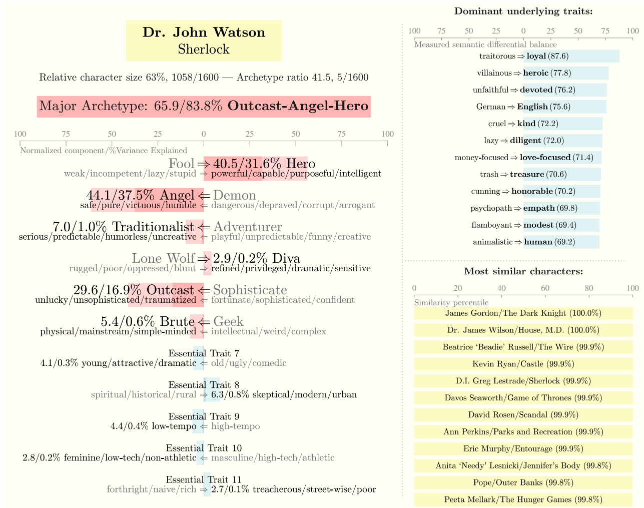
Sherlock Holmes
Sherlock
Relative character size 84%, 167/1600 — Archetype ratio 11.5, 440/1600
Major Archetype: 83.1/75.4% Geek-Demon-Hero
Dominant underlying traits:
Most similar characters:



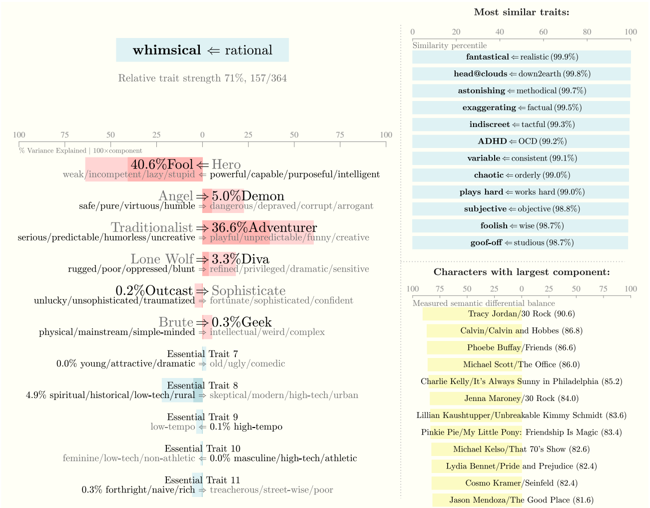
Arrested Development
{Outcast ⇔ Sophisticate} and {Brute ⇔ Geek}
geeks
brutes
outcasts
sophisticates
geek-outcasts
geek-sophisticates
brute-outcasts
brute-sophisticates
unlucky/unsophisticated/traumatized ⇔ fortunate/sophisticated/confident
$\hat{u}_5$: {Outcast ⇔ Sophisticate}
$\hat{u}_6$: {Brute ⇔ Geek}
physical/mainstream/simple-minded ⇔ intellectual/weird/complex



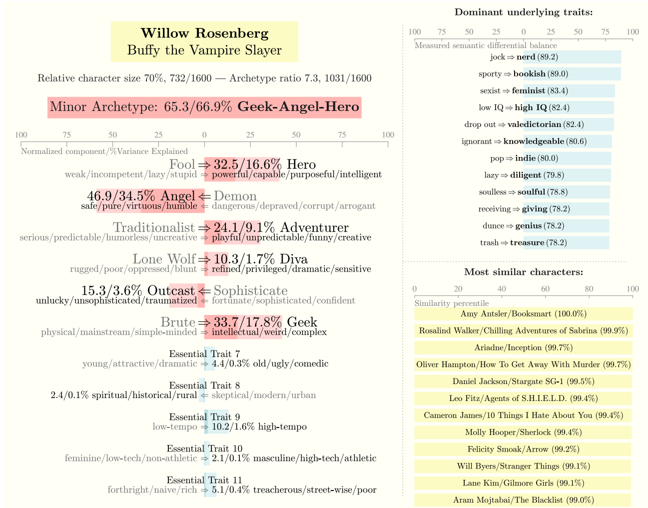
Buffy Summers
Buffy the Vampire Slayer
Relative character size 74%, 508/1600 — Archetype ratio 13.0, 332/1600
Major Archetype: 73.0/73.6% Adventurer-Hero
Dominant underlying traits:
Most similar characters:



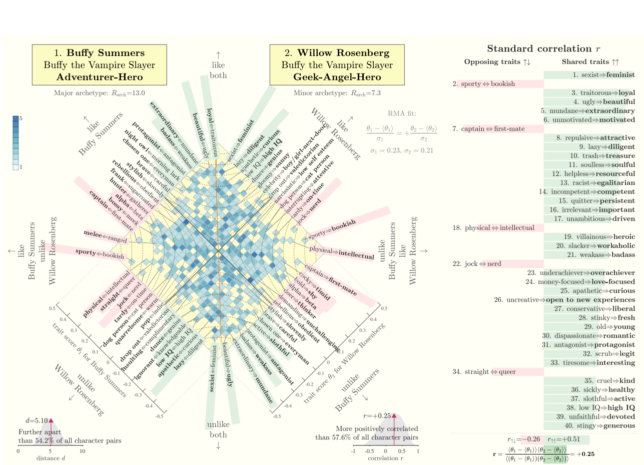
Dr. John Watson
Sherlock
Relative character size 63%, 1058/1600 — Archetype ratio 41.5, 5/1600
Major Archetype: 65.9/83.8% Outcast-Angel-Hero
Dominant underlying traits:
Most similar characters:



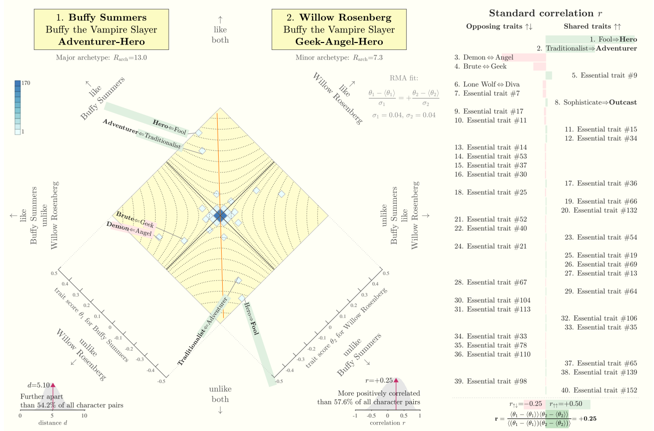
whimsical ⇐ rational
Relative trait strength 71%, 157/364
Most similar traits:
Characters with largest component:



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
Dominant underlying traits:
Most similar characters:

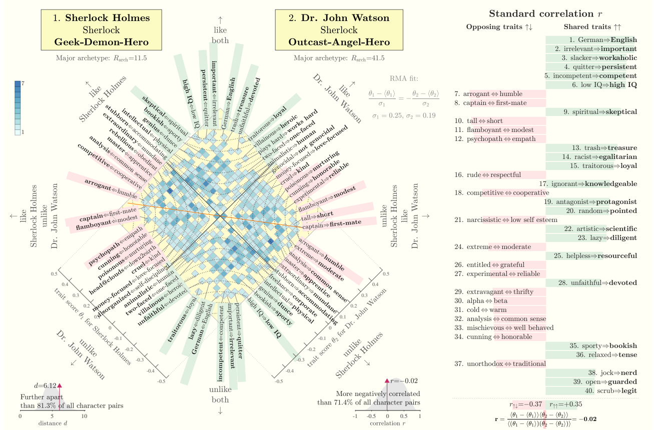


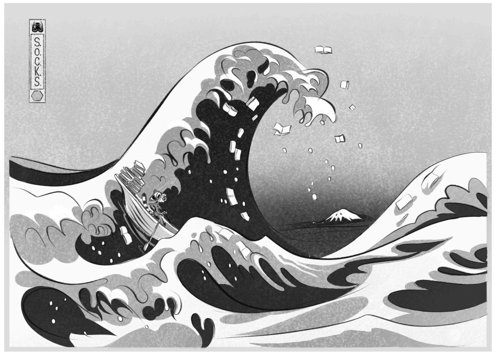
1. Buffy Summers
Buffy the Vampire Slayer
Adventurer-Hero
2. Willow Rosenberg
Buffy the Vampire Slayer
Geek-Angel-Hero
Standard correlation r
Opposing traits
Shared traits

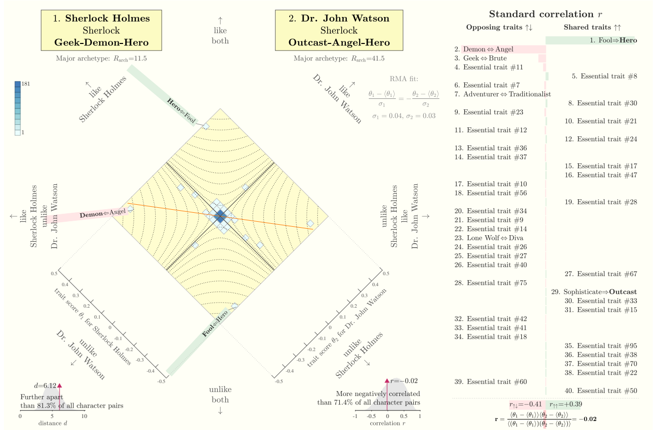


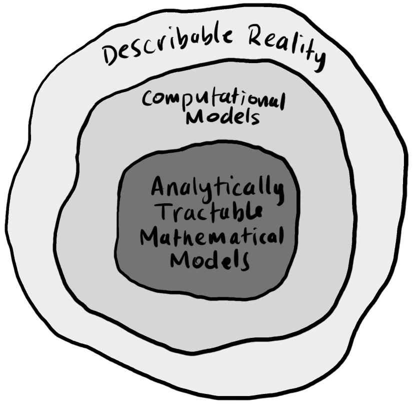
Some nutshelling

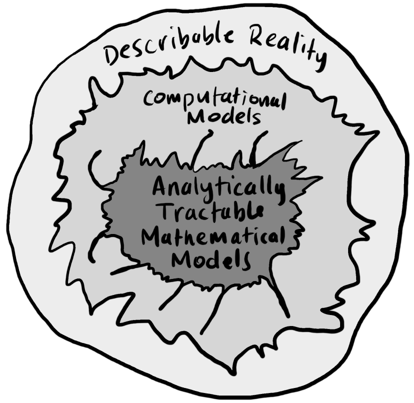
- Storywrangler framework is an exploratorium for temporally ordered large-scale texts
- Robust telescope-like lexical instruments
- Hedonometer, Ousiometer
- Happiness = Power + Safety
- Instruments enable lexical calculus (word shifts, allotaxonometry)
- Generalize from words to 'types' (species, cities, companies, ...)
- Instruments are open boxes not closed boxes
- Stories ~ Characters + Time
- Coming soon: The Essential Six Dimensions of Character Archetypes
- GPT is not (yet) a scientific instrument

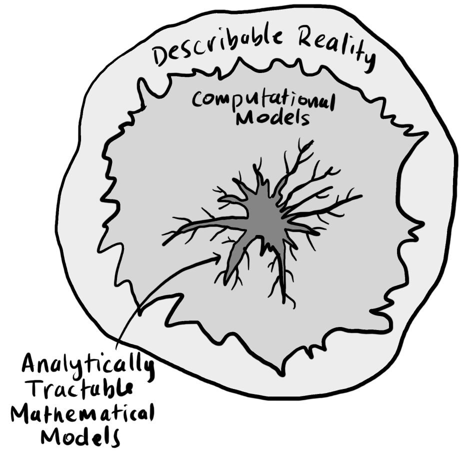


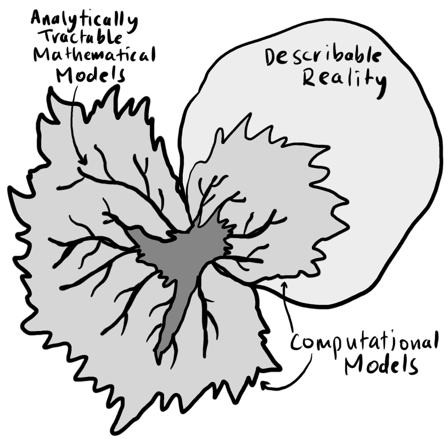












A few key papers:


"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"
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]

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"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]


"Generalized word shift graphs: A method for visualizing and explaining pairwise comparisons between texts"
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"Ousiometrics and Telegnomics: The essence of meaning conforms to a two-dimensional powerful-weak and dangerous-safe framework with diverse corpora presenting a safety bias"
Dodds et al.,
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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. [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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