Lecture Two

Stories of Complex Sociotechnical Systems: Measurement, Mechanisms, and Meaning
Lipari Summer School, Summer, 2012

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Outline

Papers and so on:

"Temporal patterns of happiness and information in a global social network: Hedonometrics and Twitter"
Dodds et al., PLoS ONE, 2011 [7]
Much better version here:
http://arxiv.org/abs/1101.5120 (⊞)

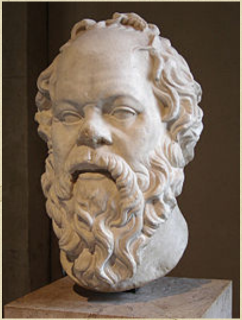
- "Positivity of the English Language"
  Kloumann et al., PLoS ONE, 2012 [11]
- "Measuring the Happiness of Large-Scale Written Expression: Songs, Blogs, and Presidents"
  Dodds and Danforth, Journal of Happiness Studies, 2009 [6]
- language assessment by Mechanical Turk (labMT 1.0)
- http://www.onehappybird.com (⊞)

Press...

- “Social Scientists wade into the Tweet stream” by Greg Miller, Science, **333**, 1814–1815, 2011 [15]
- “Does a Nation’s Mood Lurk in Its Songs and Blogs?” by Benedict Carey New York Times, August 2009. (⊞)

- More here: http://www.uvm.edu/∼pdodds/research/ (⊞)

Happiness:



Socrates et al.:
eudaimonia [8]

Bentham:
hedonistic calculus

Jefferson:
. . . the pursuit of happiness

Early drafts:

that among these are:

Life,

Liberty, and ?? ~~Money~~?

~~Libations~~ ... ~~Alcohol~~

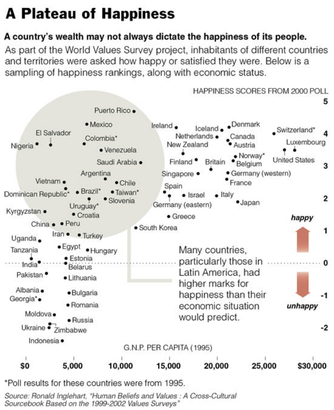
~~Property~~ ~~Foot-the-ball~~

~~Beer~~

Happiness

Desiring happiness—not just for boffins:

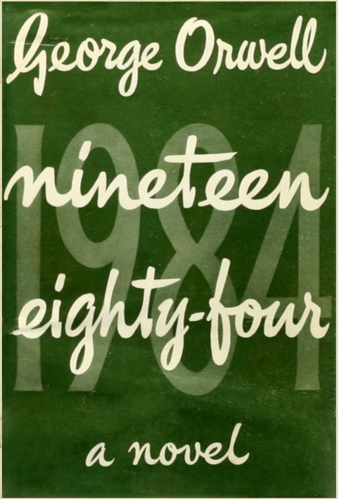
- Average people routinely report being happy is what they want most in life [12, 13, 5]
- And it matters: “Happy people live longer:. . . ” Survey by Diener and Chan. [5]



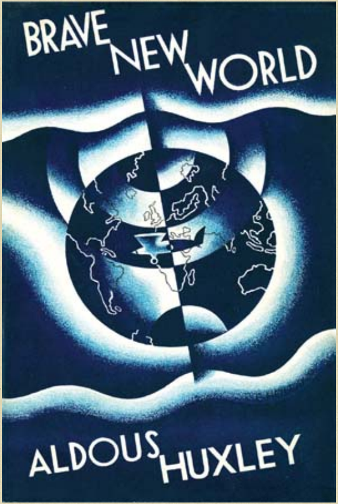
National indices of well-being:

- Bhutan
- France
- Australia

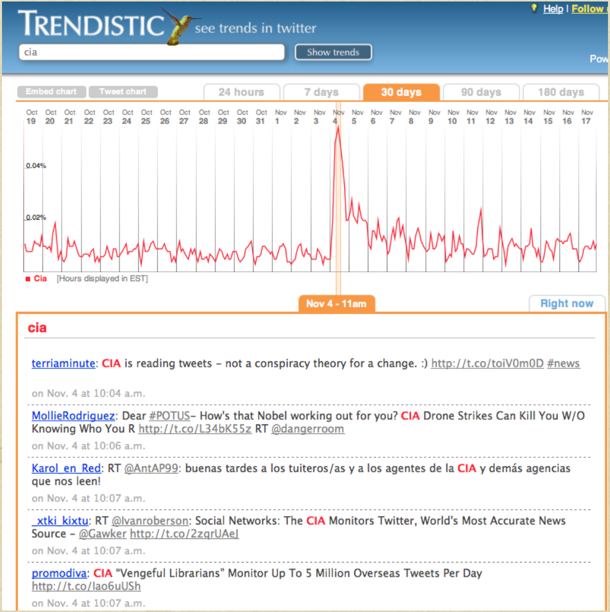
An easy knock:



Science = Orwell



Policy = Brave New World



- See story here (⊞) for example [slate].

Emotional content

So how does one measure

1. happiness?
2. levels of other emotional states?

Just ask people how happy they are.

- Experience sampling [2, 4, 3] (Csikszentmihalyi et al.)
- Day reconstruction [9] (Kahneman et al.)

But self-reporting has some drawbacks:

- relies on memory and self-perception
- induces misreporting [14]
- costly

Happiness, attention, and doing:

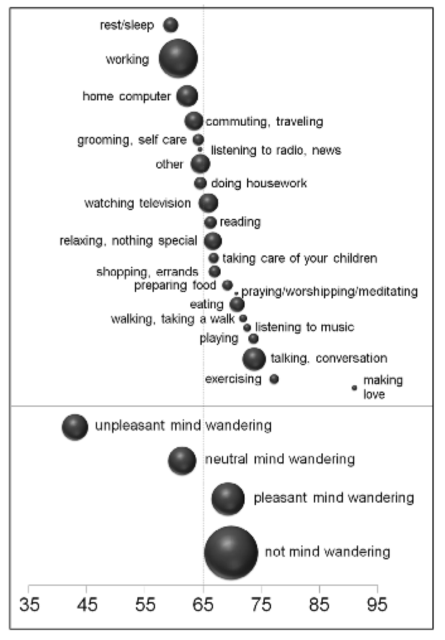
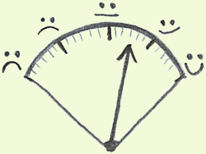


Fig. 1. Mean happiness reported during each activity (**top**) and while mind wandering to unpleasant topics, neutral topics, pleasant topics or not mind wandering (**bottom**). Dashed line indicates mean of happiness across all samples. Bubble area indicates the frequency of occurrence. The largest bubble ("not mind wandering") corresponds to 53.1% of the samples, and the smallest bubble ("praying/worshipping/meditating") corresponds to 0.1% of the samples.

Killingsworth and Gilbert, Science, 2010 [10]

We'd like to build an 'hedonometer':



- An instrument to 'remotely-sense' emotional states and levels, in real time or post hoc.

Ideally:

- Transparent
- Fast
- Based on written expression
- Uses human evaluation
- Non-reactive
- Complementary to self-reported measures
- Improvable

Some possibilities:

- Natural language processing (e.g., OpinionFinder)
- Declared mood levels in blogs (e.g., Livejournal) [16]

ANEW study

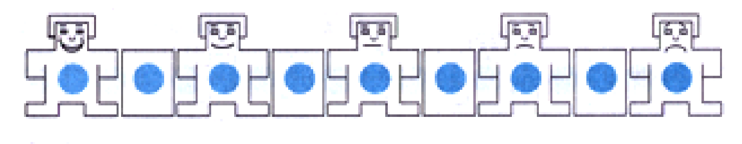
- ANEW = “Affective Norms for English Words”

- Study: participants shown lists of isolated words
- Asked to grade each word’s valence, arousal, and dominance level
- Integer scale of 1–9

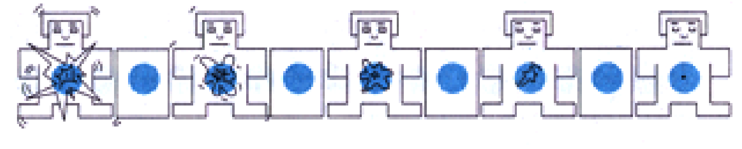
- N =1034 words—previously identified as bearing emotional weight
- Participants = College students (*cough*)
- Results published by Bradley and Lang (1999) [1]

ANEW study—three 1–9 scales:

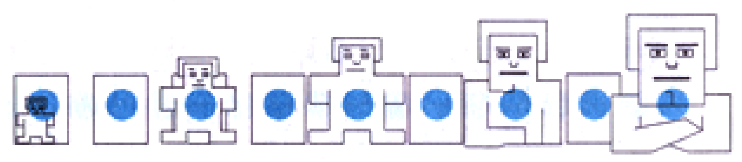
valence:



arousal:



dominance:



ANEW study words—examples

love/paradise/triumphant
glory/luxury/trophy
optimism/pancakes/church
engine/paper/street
derelict/neurotic/vanity
fault/corrupt/lawsuit
trauma/hostage/disgusted
funeral/rape/suicide

ANEW = "Affective Norms for English Words" [1]

Analysing text:

Lyrics for Michael Jackson's Billie Jean

"She was more like a beauty queen
from a movie scene.
⋮
And mother always told me,
be careful who you love.
And be careful of what you do
'cause the lie becomes the truth.

Billie Jean is not my lover,
She's just a girl who claims
that I am the one.
⋮

ANEW words	v_k	f_k
k=1. love	8.72	1
2. mother	8.39	1
3. baby	8.22	3
4. beauty	7.82	1
5. truth	7.80	1
6. people	7.33	2
7. strong	7.11	1
8. young	6.89	2
9. girl	6.87	4
10. movie	6.86	1
11. perfume	6.76	1
12. queen	6.44	1
13. name	5.55	1
14. lie	2.79	1

$$v_{\text{text}} = \frac{\sum_k v_k f_k}{\sum_k f_k}$$

$$v_{\text{Billie Jean}} = 7.1$$

$$v_{\text{Thriller}} = 6.3$$

$$v_{\text{Michael Jackson}} = 6.4$$

Data sets:

Texts:

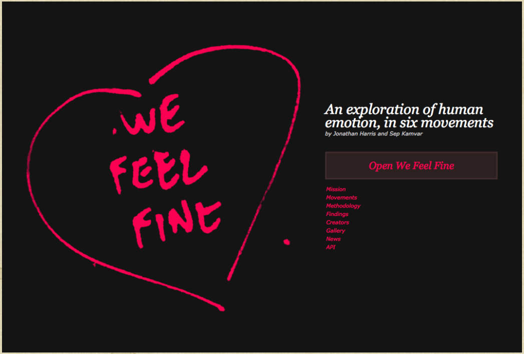
1. Song lyrics (1960–2007)
2. Song titles (1960–2008)
3. State of the Union (SOTU) Addresses (1790–2008)

Sources:

- hotlyrics.com (⊞)
- freedb.com (⊞)
- American Presidency Project: www.presidency.ucsb.edu (⊞).

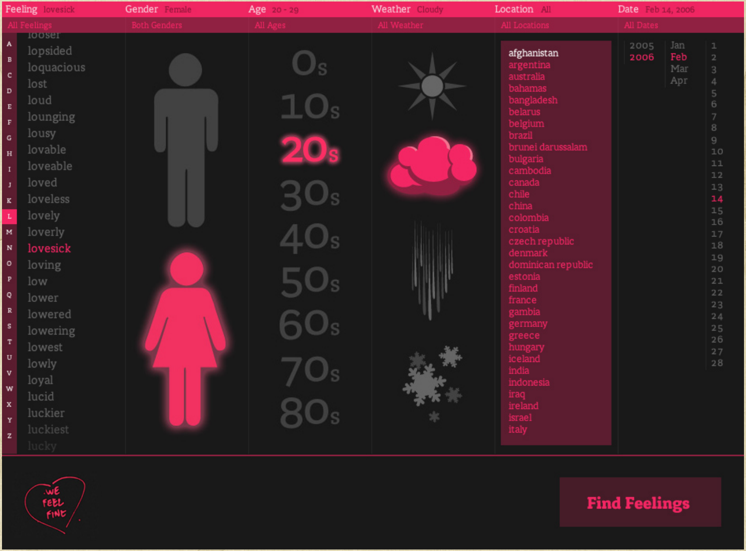
Data sets:

4. Blog phrases containing "I feel...", "I am feeling", etc., taken from wefeelfine.org (⊞) (API, 2005–2010)



- Created by Jonathan Harris & Sep Kamvar

wefeelfine.org:



More data sets:

5. twitter
6. New York Times (20 years)
7. Gutenberg.org
8. Google Books: http://ngrams.googlelabs.com/ (⊞)
9. …

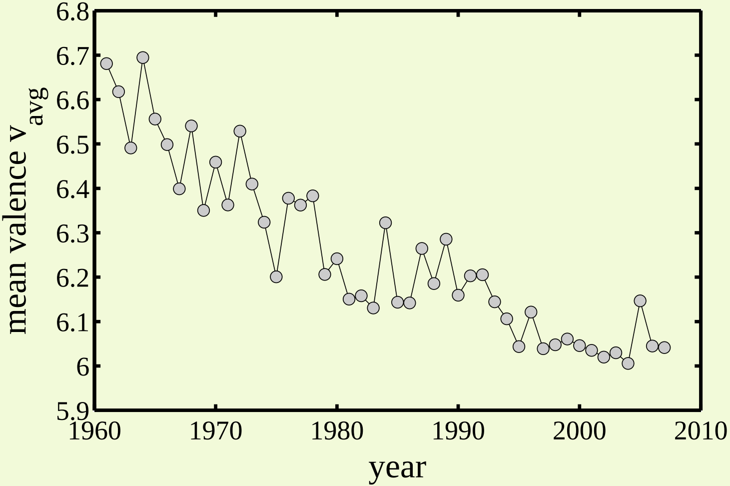
Some numbers:

Counts	Song lyrics	Song titles
All words	58,610,849	60,867,223
ANEW words	3,477,575 (5.9%)	5,612,708 (9.2%)
Individuals	$\sim$ 20,000	$\sim$ 632,000

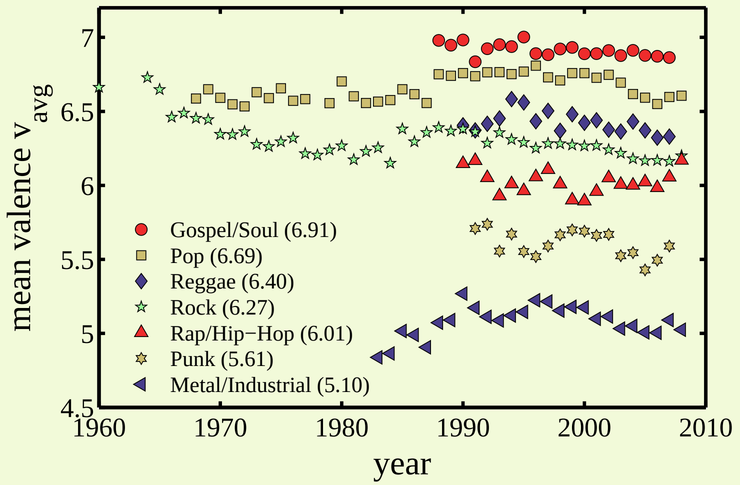
Counts	blogs	SOTU
All words	155,667,394	1,796,763
ANEW words	8,581,226 (5.5%)	61,926 (3.5%)
Individuals	$\sim$ 2,335,000	43

Counts	Twitter
All words	$\sim$ 100 billion
Tweets	$\sim$ 10 billion
Individuals	$\sim$ 100 million

Song Lyrics—average happiness (valence)

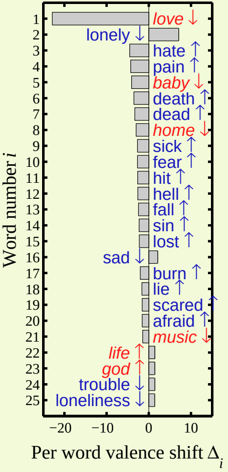


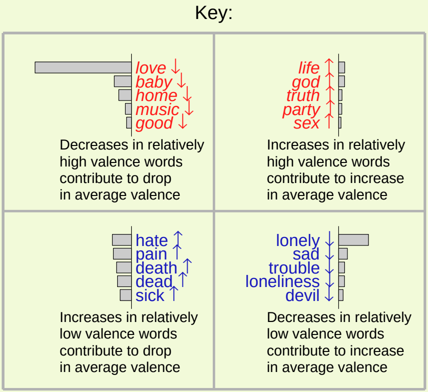
Song Lyrics—average happiness of genres:



Happiness Word Shift Graph:

Per word drop in valence of lyrics from 1980−2007 relative to valence of lyrics from 1960





Top 16 of $\simeq$ 20,000 artists:

Rank	Artist	Valence
1	All-4-One	7.15
2	Luther Vandross	7.12
3	S Club 7	7.05
4	K Ci & JoJo	7.04
5	Perry Como	7.04
6	Diana Ross & The Supremes	7.03
7	Buddy Holly	7.02
8	Faith Evans	7.01
9	The Beach Boys	7.01
10	Jon B	6.98
11	Dru Hill	6.96
12	Earth Wind & Fire	6.95
13	Ashanti	6.95
14	Otis Redding	6.93
15	Faith Hill	6.93
16	NSync	6.93

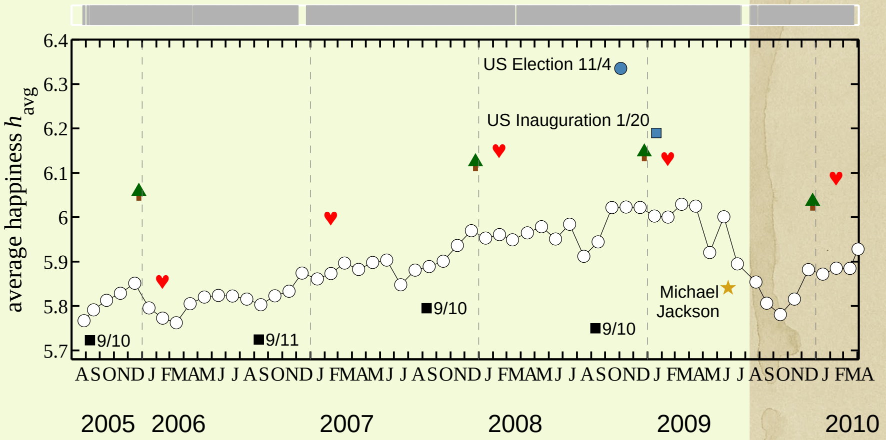
(criteria: $\geq$ 50 songs and $\geq$ 1000 ANEW words)

Bottom 16 of $\simeq$ 20,000 artists:

Rank	Artist	Valence
1	Slayer	4.80
2	Misfits	4.88
3	Staind	4.93
4	Slipknot	4.98
5	Darkthrone	4.98
6	Death	5.02
7	Black Label Society	5.05
8	Pig	5.08
9	Voivod	5.14
10	Fear Factory	5.15
11	Iced Earth	5.16
12	Simple Plan	5.16
13	Machine Head	5.17
14	Metallica	5.19
15	Dimmu Borgir	5.20
16	Mudvayne	5.21

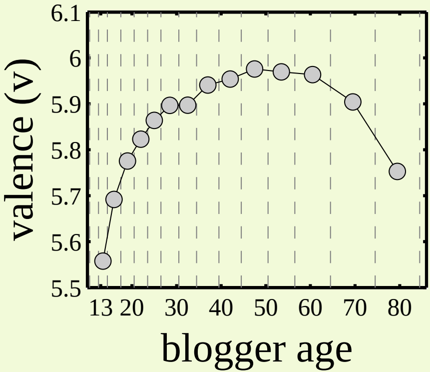
(criteria: $\geq$ 50 songs and $\geq$ 1000 ANEW words)

Blogs—Overall trend

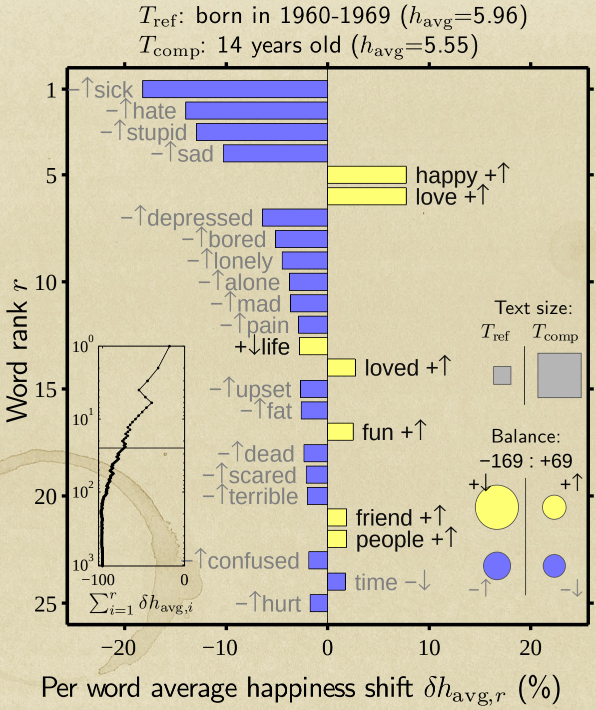


Text:	$h_{\rm avg}$	Words with a similar score:
Soul/Gospel lyrics [6]	6.9	chocolate (6.88), leisurely (6.88), penthouse (6.81)
Pop lyrics [6]	6.7	dream (6.73), honey (6.73), sugar (6.74)
Dante's Paradise	6.5	muffin (6.57), rabbit (6.57), smooth (6.58)
Tweets, 9/9/2008 to 12/31/2010	6.4	thought (6.39), face (6.39), blond (6.42)
Rock lyrics [6]	6.3	church (6.28), tree (6.32), air (6.34)
Enron Emails (⊞)	6.2	clouds (6.18), alert (6.20), computer (6.24)
State of the Union Messages [6]	6.1	grass (6.12), idol (6.12), bottle (6.15)
New York Times (1987–2007) [17]	6.0	hotel (6.00), tennis (6.02), wonder (6.03)
Blogs [6]	5.8	owl (5.80), whistle (5.81), humble (5.86)
Dante's Inferno	5.5	glacier (5.50), repentant (5.53), mischief (5.57)
Heavy Metal lyrics [6]	5.4	lamp (5.41), elevator (5.44), truck (5.47)

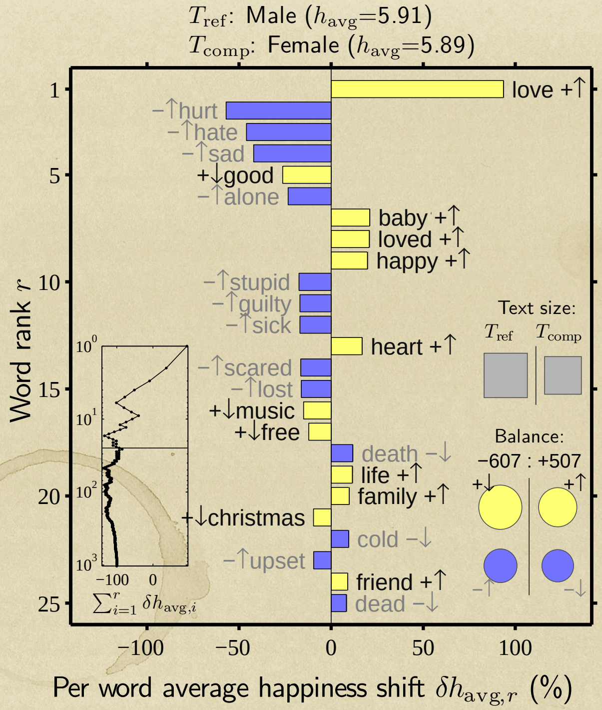
Blogs



- Average happiness as a function of the age bloggers report they will turn in the year of their posting.

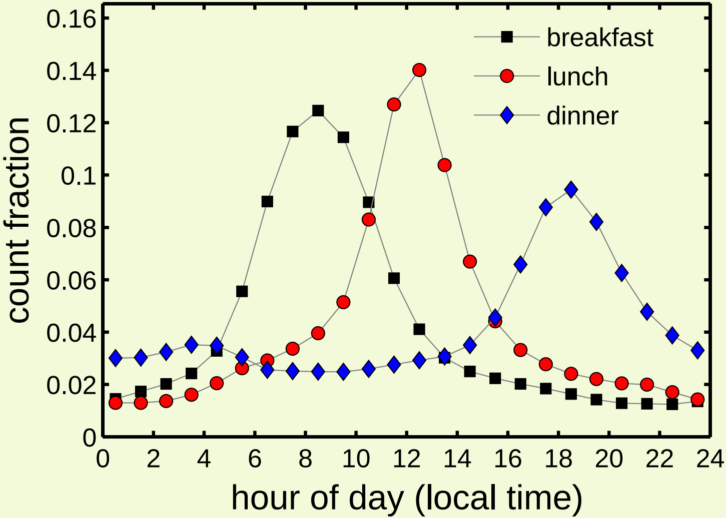


T_{ref}: born in 1960-1969 (h_{avg}=5.96)
T_{comp}: 14 years old (h_{avg}=5.55)
−↑sick
−↑hate
−↑stupid
−↑sad
happy +↑
love +↑
−↑depressed
−↑bored
−↑lonely
−↑alone
−↑mad
−↑pain
+↓life
loved +↑
−↑upset
−↑fat
fun +↑
−↑dead
−↑scared
−↑terrible
friend +↑
people +↑
−↑confused
time −↓
−↑hurt
Text size:
T_{ref} T_{comp}
Balance:
−169 : +69
+↓ +↑
−↑ −↓
Word rank r
1
5
10
15
20
25
−20
−10
0
10
20
Per word average happiness shift $\delta h_{\text{avg},r}$ (%)
10^0
10^1
10^2
10^3
−100
0
$\sum_{i=1}^{r} \delta h_{\text{avg},i}$

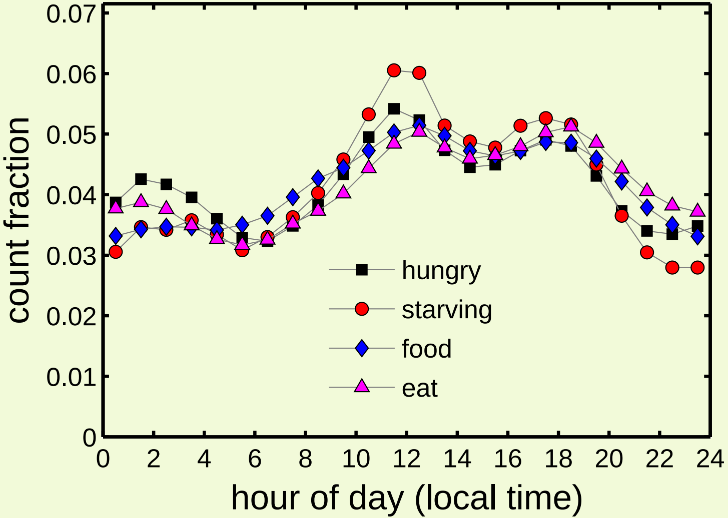


Measuring Happiness
Some motivation
Measuring emotional content
Data sets
Analysis
Songs
Blogs
Tweets
Positivity Bias
References

Twitter—living in the now:



Twitter—living in the now:



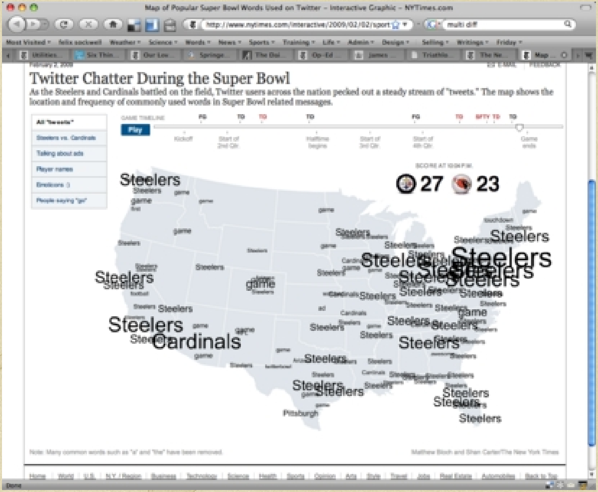
Words most correlated with obesity levels in cities:

Word	h_{avg}	r_s	p-value
stomach	5.40	0.37	1.98894e-07
mcdonalds	5.98	0.30	2.60824e-05
hungry	3.38	0.27	0.000206297
wings	6.52	0.25	0.000388915
ham	5.66	0.24	0.000763101
starving	2.58	0.22	0.00272286
spaghetti	0.00	0.20	0.00689403
ihop	0.00	0.19	0.0100034
noodles	0.00	0.18	0.0106139
ketchup	0.00	0.18	0.0145088
fat	3.24	0.18	0.0148845
sprite	0.00	0.17	0.0175705
cookin	0.00	0.17	0.0182976
heartburn	0.00	0.17	0.0200551
sugar	6.74	0.15	0.0329359
kool-aid	0.00	0.15	0.0354226
miller	5.36	0.15	0.036325

Words most anti-correlated with obesity levels in cities:

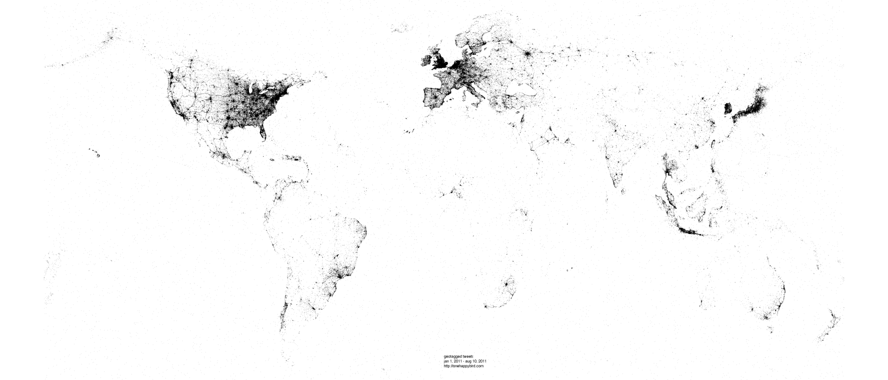
brunch	6.32	-0.41	6.37431e-09
bar	5.82	-0.35	5.54374e-07
banana	6.86	-0.35	5.67492e-07
barista	0.00	-0.35	7.29324e-07
delicious	7.92	-0.34	1.09807e-06
dinner	7.40	-0.34	1.35413e-06
coffee	7.18	-0.34	2.04145e-06
espresso	0.00	-0.33	4.45903e-06
cocktails	0.00	-0.32	4.96518e-06
booze	0.00	-0.32	6.38461e-06
mimosa	0.00	-0.31	1.24472e-05
spiced	0.00	-0.31	1.52074e-05
veggie	0.00	-0.31	1.60439e-05
sushi	5.40	-0.31	1.71997e-05
wines	6.28	-0.31	1.7432e-05
tofu	0.00	-0.31	1.86278e-05
panini	0.00	-0.31	1.86719e-05
gnocchi	0.00	-0.30	2.51419e-05

Twitter—living in the now:



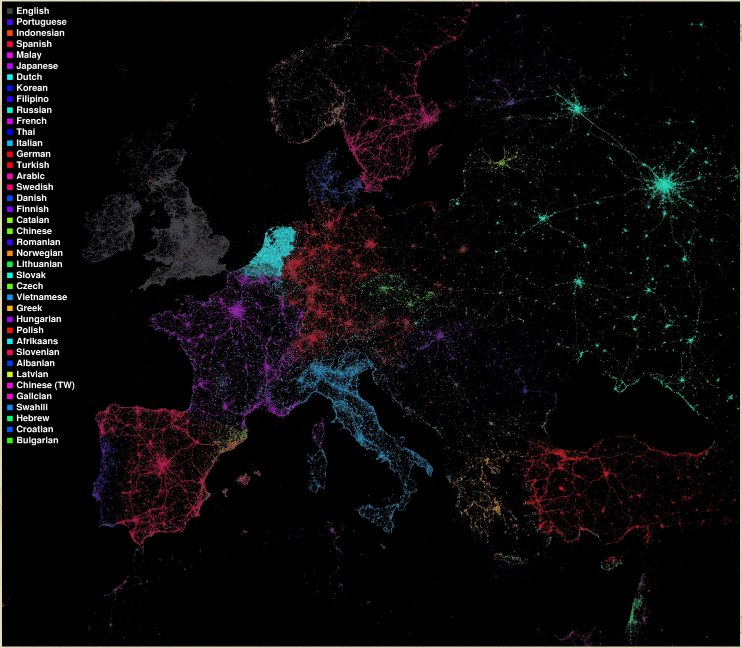
Tweeting the Superbowl (⊞) [NY Times]

{"in_reply_to_user_id_str":null,"id_str":"122740606790410240","in_reply_to_user_id":null,"text":"RT @outrage_molly: #occupydenver we will be marching down E Colfax first with a shout out to @occupythehood","created_at":"Sat Oct 08 18:30:15 +0000 2011","contributors":null,"retweeted_status":{"in_reply_to_user_id_str":null,"id_str":"122739523930169344","in_reply_to_user_id":null,"text":"#occupydenver we will be marching down E Colfax first with a shout out to @occupythehood","created_at":"Sat Oct 08 18:25:57 +0000 2011","contributors":null,"geo":null,"favorited":false,"source":"\u003Ca href=\"http:\/\/ubersocial.com\" rel=\"nofollow\"\u003EUberSocial for BlackBerry\u003C\/a\u003E","retweet_count":1,"in_reply_to_screen_name":null,"coordinates":null,"entities":{"hashtags":[{"text":"occupydenver","indices":[0,13]}],"urls":[],"user_mentions":[{"id_str":"379936422","indices":[74,88],"name":"Occupy The Hood ","id":379936422,"screen_name":"OccupyTheHood"}]},"retweeted":false,"in_reply_to_status_id":null,"in_reply_to_status_id_str":null,"place":null,"user":{"id_str":"165386225","show_all_inline_media":false,"contributors_enabled":false,"following":null,"profile_background_image_url_https":"https:\/\/si0.twimg.com\/profile_background_images\/123611013\/web_graphic2-1.jpg","created_at":"Sun Jul 11 12:17:25 +0000 2010","profile_background_color":"d9571f","profile_image_url":"http:\/\/a0.twimg.com\/profile_images\/1069877121\/mollykate3_normal.jpg","profile_background_tile":false,"favourites_count":24,"follow_request_sent":null,"time_zone":"Mountain Time (US & Canada)","profile_sidebar_fill_color":"d9a4db","url":null,"description":"May the road rise with you. Anger is an energy. Rise. ~PiL\r | Public Policy grad student. Views are mine. Go 99%. ","default_profile":false,"geo_enabled":false,"profile_sidebar_border_color":"52014a","followers_count":462,"is_translator":false,"profile_image_url_https":"https:\/\/si0.twimg.com\/profile_images\/1069877121\/mollykate3_normal.jpg","listed_count":6,"profile_use_background_image":true,"friends_count":622,"location":"Denver","profile_text_color":"333333","protected":false,"lang":"en","verified":false,"profile_background_image_url":"http:\/\/a2.twimg.com\/profile_background_images\/123611013\/web_graphic2-1.jpg","name":"Molly","notifications":null,"profile_link_color":"507d4b","id":165386225,"default_profile_image":false,"statuses_count":2399,"utc_offset":-25200,"screen_name":"outrage_molly"},"id":122739523930169344,"truncated":false},"geo":null,"favorited":false,"source":"web","retweet_count":1,"in_reply_to_screen_name":null,"coordinates":null,"entities":{"hashtags":[{"text":"occupydenver","indices":[19,32]}],"urls":[],"user_mentions":[{"id_str":"165386225","indices":[3,17],"name":"Molly","id":165386225,"screen_name":"outrage_molly"},{"id_str":"379936422","indices":[93,107],"name":"Occupy The Hood ","id":379936422,"screen_name":"OccupyTheHood"}]},"retweeted":false,"in_reply_to_status_id":null,"in_reply_to_status_id_str":":null,"place":null,"user":{"id_str":"362705928","show_all_inline_media":false,"contributors_enabled":false,"following":null,"profile_background_image_url_https":"https:\/\/si0.twimg.com\/images\/themes\/theme1\/bg.png","created_at":"Fri Aug 26 21:10:18 +0000 2011","profile_background_color":"C0DEED","profile_image_url":"http:\/\/a3.twimg.com\/profile_images\/1514944353\/284683_780784519822_42112934_38358736_4257516_n_normal.jpg","profile_background_tile":false,"favourites_count":1,"follow_request_sent":null,"time_zone":"Mountain Time (US & Canada)","profile_sidebar_fill_color":"DDEEF6","url":null,"description":"From The Ruins Are Born The Spark","default_profile":true,"geo_enabled":false,"profile_sidebar_border_color":"C0DEED","followers_count":154,"is_translator":false,"profile_image_url_https":"https:\/\/si0.twimg.com\/profile_images\/1514944353\/284683_780784519822_42112934_38358736_4257516_n_normal.jpg","listed_count":11,"profile_use_background_image":true,"friends_count":70,"location":"","profile_text_color":"333333","protected":false,"lang":"en","verified":false,"profile_background_image_url":"http:\/\/a0.twimg.com\/images\/themes\/theme1\/bg.png","name":"DonRhetorick","notifications":null,"profile_link_color":"0084B4","id":362705928,"default_profile_image":false,"statuses_count":1975,"utc_offset":-25200,"screen_name":"DonRhetorick"},"id":122740606790410240,"truncated":false}

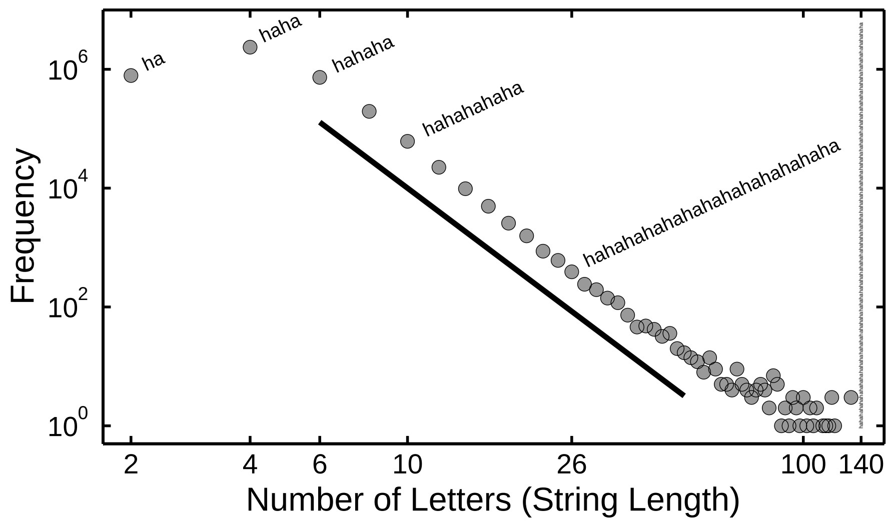


http:/www.onehappybird.com (⊞)

http://flowingdata.com/2011/10/27/language-communities-of-twitter/ (⊞)



The happiest distribution:



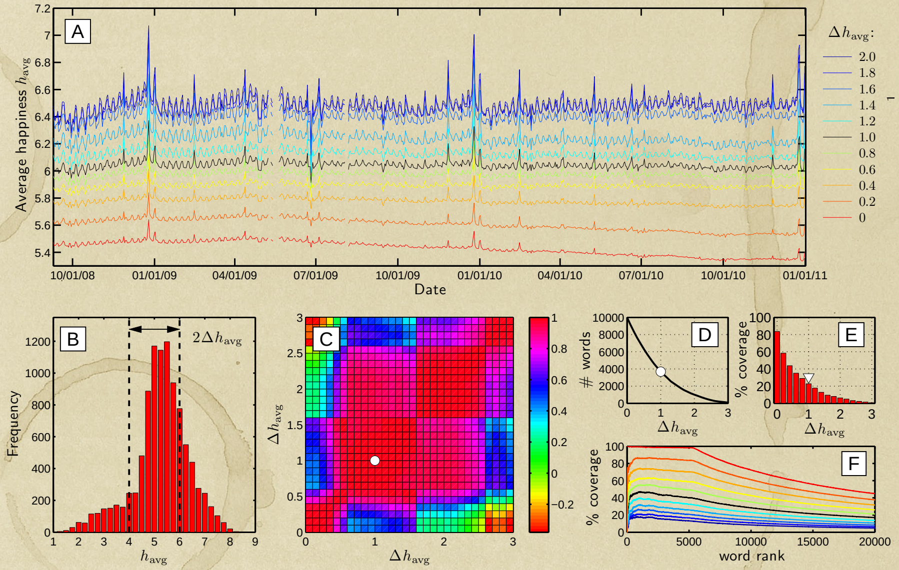
labMT 1.0:
language assessment by Mechanical Turk

valence rank	word	valence	std dev	twitter rank	g-books rank	nyt rank	lyrics rank
1	laughter	8.50	0.93	3600	–	–	1728
2	happiness	8.44	0.97	1853	2458	–	1230
3	love	8.42	1.11	25	317	328	23
4	happy	8.30	0.99	65	1372	1313	375
5	laughed	8.26	1.16	3334	3542	–	2332
6	laugh	8.22	1.37	1002	3998	4488	647
7	laughing	8.20	1.11	1579	–	–	1122
8	excellent	8.18	1.10	1496	1756	3155	–
9	laughs	8.18	1.16	3554	–	–	2856
10	joy	8.16	1.06	988	2336	2723	809
11	successful	8.16	1.08	2176	1198	1565	–
12	win	8.12	1.08	154	3031	776	694
13	rainbow	8.10	0.99	2726	–	–	1723
14	smile	8.10	1.02	925	2666	2898	349
15	won	8.10	1.22	810	1167	439	1493
16	pleasure	8.08	0.97	1497	1526	4253	1398
17	smiled	8.08	1.07	–	3537	–	2248
18	rainbows	8.06	1.36	–	–	–	4216
19	winning	8.04	1.05	1876	–	1426	3646
20	celebration	8.02	1.53	3306	–	2762	4070
21	enjoyed	8.02	1.53	1530	2908	3502	–
22	healthy	8.02	1.06	1393	3200	3292	4619
23	music	8.02	1.12	132	875	167	374
24	celebrating	8.00	1.14	2550	–	–	–
25	congratulations	8.00	1.63	2246	–	–	–
26	weekend	8.00	1.29	317	–	833	2256
27	celebrate	7.98	1.15	1606	–	3574	2108
28	comedy	7.98	1.15	1444	–	2566	–
29	jokes	7.98	0.98	2812	–	–	3808
30	rich	7.98	1.32	1625	1221	1469	890
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

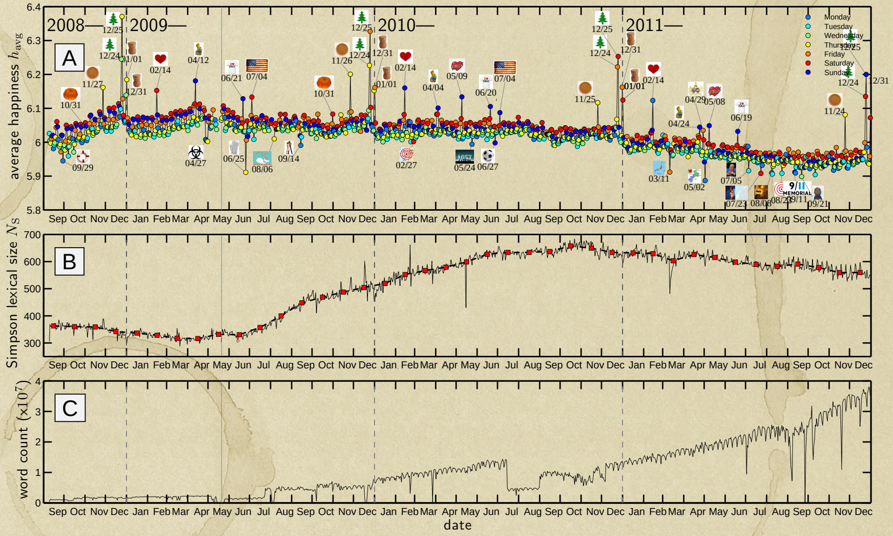
valence rank	word	valence	std dev	twitter rank	g-books rank	nyt rank	lyrics rank
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
10193	violence	1.86	1.05	4299	1724	1238	2016
10194	cruel	1.84	1.15	2963	–	–	1447
10195	cry	1.84	1.28	1028	3075	–	226
10196	failed	1.84	1.00	2645	1618	1276	2920
10197	sickness	1.84	1.18	4735	–	–	3782
10198	abused	1.83	1.31	–	–	–	4589
10199	tortured	1.82	1.42	–	–	–	4693
10200	fatal	1.80	1.53	–	4089	–	3724
10201	killings	1.80	1.54	–	–	4914	–
10202	murdered	1.80	1.63	–	–	–	4796
10203	war	1.80	1.41	468	175	291	462
10204	kills	1.78	1.23	2459	–	–	2857
10205	jail	1.76	1.02	1642	–	2573	1619
10206	terror	1.76	1.00	4625	4117	4048	2370
10207	die	1.74	1.19	418	730	2605	143
10208	killing	1.70	1.36	1507	4428	1672	998
10209	arrested	1.64	1.01	2435	4474	1435	–
10210	deaths	1.64	1.14	–	–	2974	–
10211	raped	1.64	1.43	–	–	–	4528
10212	torture	1.58	1.05	3175	–	–	3126
10213	died	1.56	1.20	1223	866	208	826
10214	kill	1.56	1.05	798	2727	2572	430
10215	killed	1.56	1.23	1137	1603	814	1273
10216	cancer	1.54	1.07	946	1884	796	3802
10217	death	1.54	1.28	509	307	373	433
10218	murder	1.48	1.01	2762	3110	1541	1059
10219	terrorism	1.48	0.91	–	–	3192	–
10220	rape	1.44	0.79	3133	–	4115	2977
10221	suicide	1.30	0.84	2124	4707	3319	2107
10222	terrorist	1.30	0.91	3576	–	3026	–

std dev rank	word	valence	std dev	twitter rank	g-books rank	nyt rank	lyrics rank
1	fϟ@king	4.64	2.93	448	–	–	620
2	f✫✫kin	3.86	2.74	1077	–	–	688
3	f✫✫ked	3.56	2.71	1840	–	–	904
4	pussy	4.80	2.66	2019	–	–	949
5	whiskey	5.72	2.64	–	–	–	2208
6	slut	3.57	2.63	–	–	–	4071
7	cigarettes	3.31	2.60	–	–	–	3279
8	f✫✫k	4.14	2.58	322	–	–	185
9	mortality	4.38	2.55	–	3960	–	–
10	cigarette	3.09	2.52	–	–	–	2678
11	motherf✫✫kers	2.51	2.47	–	–	–	1466
12	churches	5.70	2.46	–	2281	–	–
13	motherf✫✫king	2.64	2.46	–	–	–	2910
14	capitalism	5.16	2.45	–	4648	–	–
15	porn	4.18	2.43	1801	–	–	–
16	summer	6.40	2.39	896	1226	721	590
17	beer	5.92	2.39	839	4924	3960	1413
18	execution	3.10	2.39	–	2975	–	–
19	wines	6.28	2.37	–	–	3316	–
20	zombies	4.00	2.37	4708	–	–	–
21	aids	4.28	2.35	2983	3996	1197	–
22	capitalist	4.84	2.34	–	4694	–	–
23	revenge	3.71	2.34	–	–	–	2766
24	mcdonalds	5.98	2.33	3831	–	–	–
25	beatles	6.44	2.33	3797	–	–	–
26	islam	4.68	2.33	–	4514	–	–
27	pay	5.30	2.32	627	769	460	499
28	alcohol	5.20	2.32	2787	2617	3752	3600
29	muthaf✫✫kin	3.00	2.31	–	–	–	4107
30	christ	6.16	2.31	2509	909	4238	1526
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

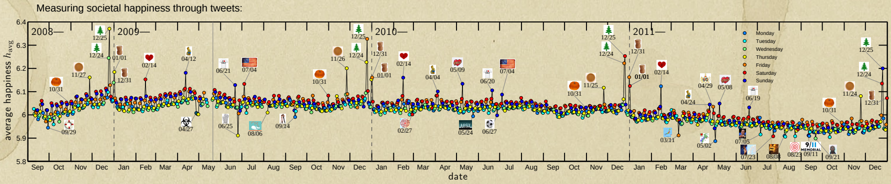
The very surprising tunable hedonometer:



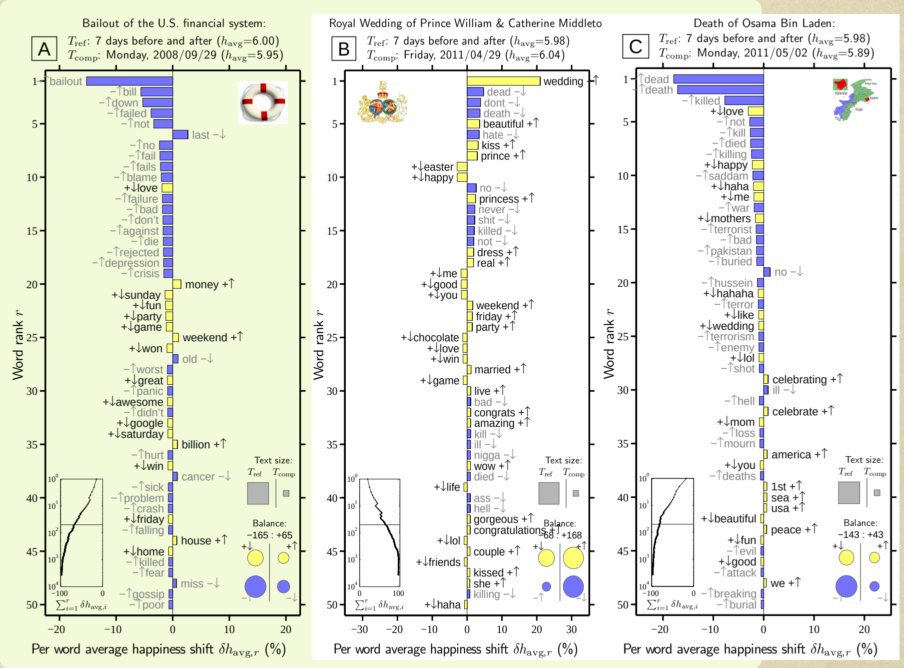
Twitter—overall time series:



Twitter—overall time series:

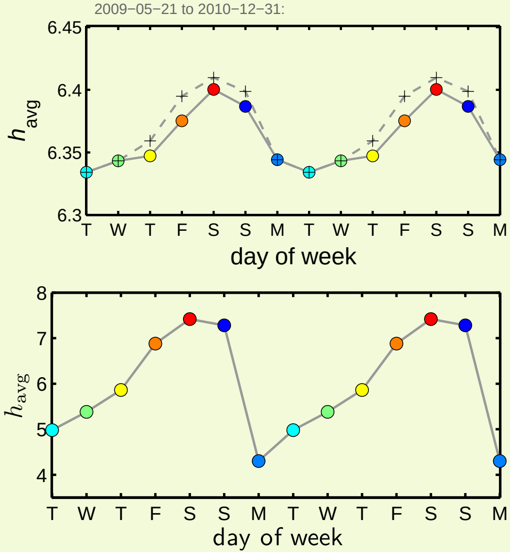


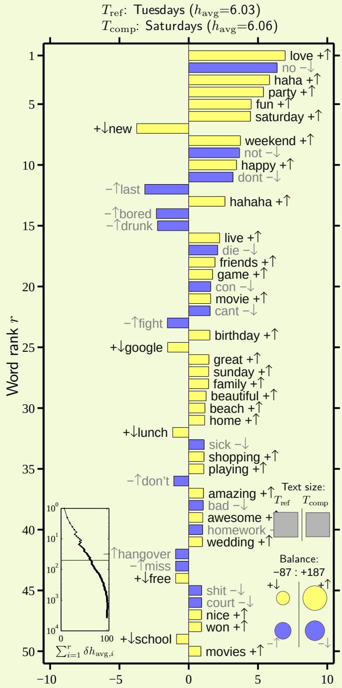
- Global happiness spikes = predictable rituals.
- Global sadness spikes = unpredictable, exogeneous shocks.
- No accidental happiness outbreaks.



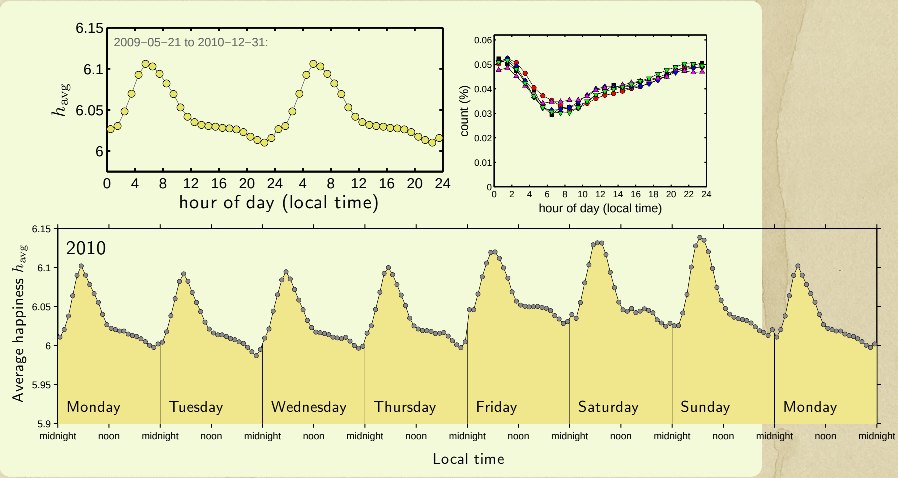
A
Bailout of the U.S. financial system:
$T_{\rm ref}$: 7 days before and after ($h_{\rm avg}$=6.00)
$T_{\rm comp}$: Monday, 2008/09/29 ($h_{\rm avg}$=5.95)
bailout, bill, down, failed, not, last, no, fail, fails, blame, love, failure, bad, don't, against, die, rejected, depression, crisis, money, sunday, fun, party, game, weekend, won, old, worst, great, panic, awesome, didn't, google, saturday, billion, hurt, win, cancer, sick, problem, crash, friday, falling, house, home, killed, fear, miss, gossip, poor
Text size: $T_{\rm ref}$ $T_{\rm comp}$
Balance: −165 : +65
B
Royal Wedding of Prince William & Catherine Middleto
$T_{\rm ref}$: 7 days before and after ($h_{\rm avg}$=5.98)
$T_{\rm comp}$: Friday, 2011/04/29 ($h_{\rm avg}$=6.04)
wedding, dead, dont, death, beautiful, hate, kiss, prince, easter, happy, no, princess, never, shit, killed, not, dress, real, me, good, you, weekend, friday, party, chocolate, love, win, married, game, live, bad, congrats, amazing, kill, ill, nigga, wow, died, life, ass, hell, gorgeous, congratulations, lol, couple, friends, kissed, she, killing, haha
Text size: $T_{\rm ref}$ $T_{\rm comp}$
Balance: −68 : +168
C
Death of Osama Bin Laden:
$T_{\rm ref}$: 7 days before and after ($h_{\rm avg}$=5.98)
$T_{\rm comp}$: Monday, 2011/05/02 ($h_{\rm avg}$=5.89)
dead, death, killed, love, not, kill, died, killing, happy, saddam, haha, me, war, mothers, terrorist, bad, pakistan, buried, no, hussein, hahaha, terror, like, wedding, terrorism, enemy, lol, shot, celebrating, ill, hell, celebrate, mom, loss, mourn, america, you, deaths, 1st, sea, usa, beautiful, peace, fun, evil, good, attack, we, breaking, burial
Text size: $T_{\rm ref}$ $T_{\rm comp}$
Balance: −143 : +43
Word rank r
Per word average happiness shift $\delta h_{{\rm avg},r}$ (%)
$\sum_{i=1}^{r} \delta h_{{\rm avg},i}$

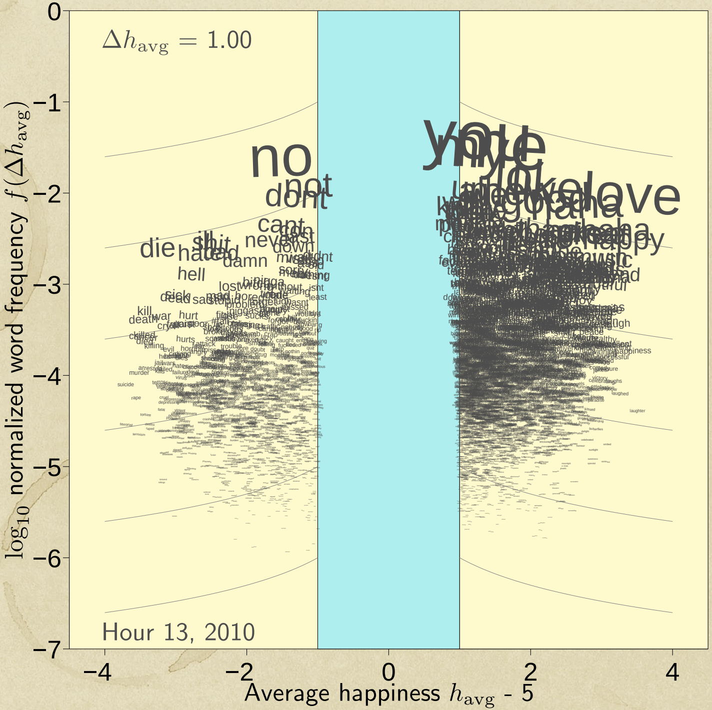
Twitter—weekly time series:



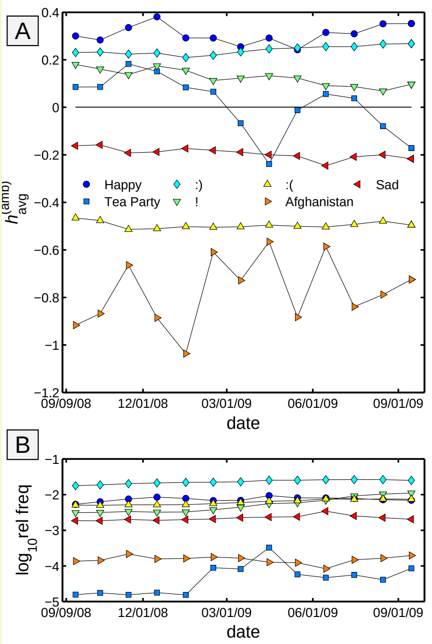

$T_{\rm ref}$: Tuesdays ($h_{\rm avg}$=6.03)
$T_{\rm comp}$: Saturdays ($h_{\rm avg}$=6.06)
Word rank r
love +↑
no −↓
haha +↑
party +↑
fun +↑
saturday +↑
+↓new
weekend +↑
not −↓
happy +↑
dont −↓
−↑last
hahaha +↑
−↑bored
−↑drunk
live +↑
die −↓
friends +↑
game +↑
con −↓
movie +↑
cant −↓
−↑fight
birthday +↑
+↓google
great +↑
sunday +↑
family +↑
beautiful +↑
beach +↑
home +↑
+↓lunch
sick −↓
shopping +↑
playing +↑
−↑don't
amazing +↑
bad −↓
awesome +
homework
wedding +↑
−↑hangover
−↑miss
+↓free
shit −↓
court −↓
nice +↑
won +↑
+↓school
movies +↑
Text size:
$T_{\rm ref}$ $T_{\rm comp}$
Balance:
−87 : +187
$\sum_{i=1}^{r} \delta h_{{\rm avg},i}$

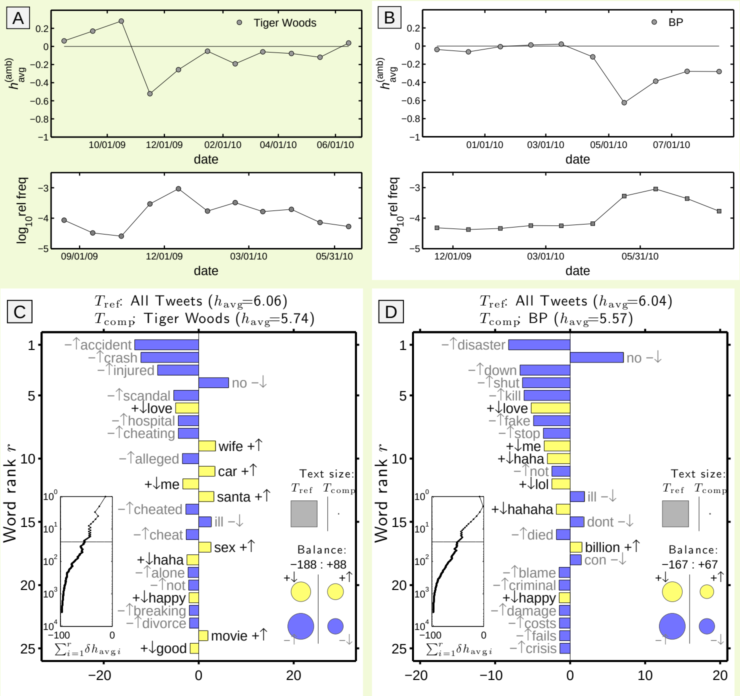
The daily unravelling of the human mind:

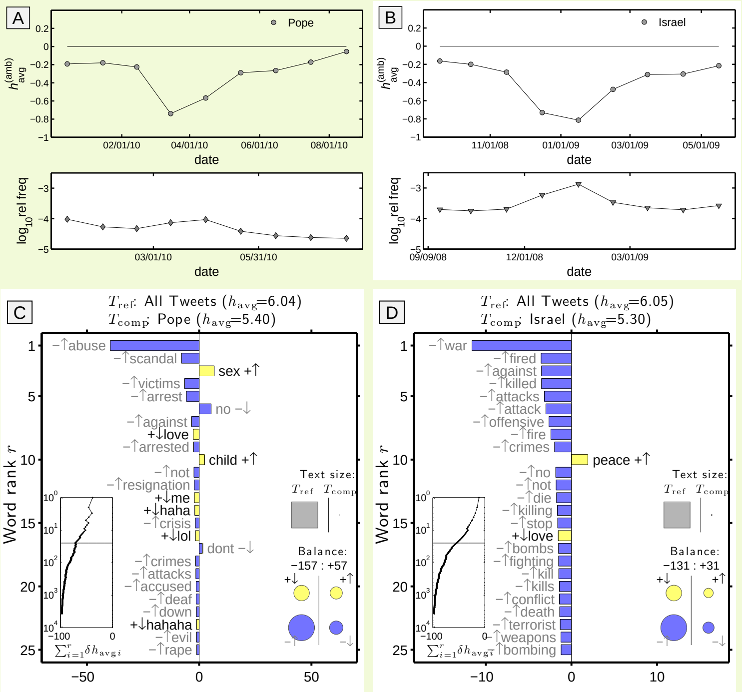




$\Delta h_{\text{avg}} = 1.00$
Hour 13, 2010
log$_{10}$ normalized word frequency $f(\Delta h_{\text{avg}})$
Average happiness h_{avg} - 5
0
−1
−2
−3
−4
−5
−6
−7
−4
−2
0
2
4
no
not
dont
cant
never
die
hate
shit
damn
hell
lost
sick
dead
sad
kill
death
war
hurt
killed
died
killing
murder
suicide
rape
you
me
my
lol
love
haha
happy
laughter
happiness


A
0.4
0.2
0
−0.2
−0.4
−0.6
−0.8
−1
−1.2
$h_{avg}^{(amp)}$
Happy
Tea Party
:)
!
:(
Afghanistan
Sad
09/09/08
12/01/08
03/01/09
06/01/09
09/01/09
date
B
−1
−2
−3
−4
−5
$\log_{10}$rel freq
09/09/08
12/01/08
03/01/09
06/01/09
09/01/09
date


A
Tiger Woods
$h_{avg}^{(amb)}$
date
10/01/09 12/01/09 02/01/10 04/01/10 06/01/10
$\log_{10}$rel freq
09/01/09 12/01/09 03/01/10 05/31/10
B
BP
01/01/10 03/01/10 05/01/10 07/01/10
12/01/09 03/01/10 05/31/10
C
T_{ref}: All Tweets (h_{avg}=6.06)
T_{comp}: Tiger Woods (h_{avg}=5.74)
Word rank r
−↑accident
−↑crash
−↑injured
no −↓
−↑scandal
+↓love
−↑hospital
−↑cheating
wife +↑
−↑alleged
car +↑
+↓me
santa +↑
−↑cheated
ill −↓
−↑cheat
sex +↑
+↓haha
−↑alone
−↑not
+↓happy
−↑breaking
−↑divorce
movie +↑
+↓good
Text size:
T_{ref} T_{comp}
Balance:
−188 : +88
$\sum_{i=1}^{r} \delta h_{avg\,i}$
D
T_{ref}: All Tweets (h_{avg}=6.04)
T_{comp}: BP (h_{avg}=5.57)
−↑disaster
no −↓
−↑down
−↑shut
−↑kill
+↓love
−↑fake
−↑stop
+↓me
+↓haha
−↑not
+↓lol
ill −↓
+↓hahaha
dont −↓
−↑died
billion +↑
con −↓
−↑blame
−↑criminal
+↓happy
−↑damage
−↑costs
−↑fails
−↑crisis
Balance:
−167 : +67


A
Pope
$h^{(amb)}_{avg}$
date
02/01/10
04/01/10
06/01/10
08/01/10
$\log_{10}$ rel freq
03/01/10
05/31/10
B
Israel
11/01/08
01/01/09
03/01/09
05/01/09
09/09/08
12/01/08
C
T_{ref}: All Tweets (h_{avg}=6.04)
T_{comp}: Pope (h_{avg}=5.40)
Word rank r
−↑abuse
−↑scandal
sex +↑
−↑victims
−↑arrest
no −↓
−↑against
+↓love
−↑arrested
child +↑
−↑not
−↑resignation
+↓me
+↓haha
−↑crisis
+↓lol
dont −↓
−↑crimes
−↑attacks
−↑accused
−↑deaf
−↑down
+↓hahaha
−↑evil
−↑rape
Text size:
T_{ref} T_{comp}
Balance:
−157 : +57
$\sum_{i=1}^{r} \delta h_{avg\,i}$
D
T_{ref}: All Tweets (h_{avg}=6.05)
T_{comp}: Israel (h_{avg}=5.30)
−↑war
−↑fired
−↑against
−↑killed
−↑attacks
−↑attack
−↑offensive
−↑fire
−↑crimes
peace +↑
−↑no
−↑not
−↑die
−↑killing
−↑stop
+↓love
−↑bombs
−↑fighting
−↑kill
−↑kills
−↑conflict
−↑death
−↑terrorist
−↑weapons
−↑bombing
Balance:
−131 : +31

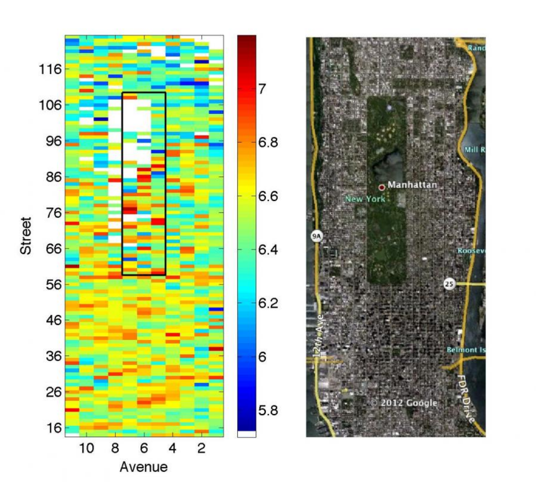
Word	$h_{\text{avg}}^{(\text{amb})}$	Total Tweets	Total ANEW
1. love	+1.42	46,687,476 (6)	85,269,499 (5)
2. happy	+1.32	16,541,968 (13)	32,442,529 (8)
3. win	+1.26	7,981,856 (26)	14,640,728 (20)
4. kiss	+1.21	1,697,405 (59)	3,162,330 (48)
5. cash	+1.21	1,279,236 (63)	2,468,496 (51)
6. vacation	+1.11	934,501 (67)	1,783,270 (56)
7. Christmas	+1.03	4,887,968 (35)	10,645,630 (25)
8. God	+0.95	8,576,364 (25)	17,867,768 (16)
9. party	+0.93	6,438,886 (29)	12,090,597 (23)
10. sex	+0.89	3,551,767 (39)	7,087,972 (31)
11. Valentine	+0.85	247,288 (84)	464,914 (75)
12. family	+0.79	5,014,816 (32)	10,629,361 (26)
13. sun	+0.65	2,385,348 (52)	4,602,627 (44)
14. life	+0.50	14,006,454 (17)	27,770,768 (10)
15. hope	+0.48	11,833,337 (18)	22,952,366 (13)
16. heaven	+0.43	741,878 (71)	1,485,702 (59)
17. :)	+0.42	10,470,483 (20)	6,787,678 (35)
18. income	+0.36	510,425 (76)	418,161 (77)
19. friends	+0.33	7,669,719 (27)	7,541,106 (29)
20. snow	+0.32	2,596,165 (49)	5,011,785 (40)
21. :-)	+0.32	1,680,165 (60)	1,102,512 (67)
22. night	+0.29	17,089,505 (12)	17,606,796 (17)
23. vegan	+0.28	183,889 (90)	178,676 (86)
24. Jesus	+0.27	2,027,720 (56)	1,673,992 (58)
25. girl	+0.25	10,070,132 (22)	19,886,691 (14)
26. USA	+0.23	2,157,172 (54)	1,204,585 (65)
27. you	+0.22	173,276,993 (3)	145,464,084 (2)
28. our	+0.21	14,062,465 (16)	14,437,899 (21)
29. ;)	+0.20	2,618,940 (48)	1,475,221 (60)
30. health	+0.20	2,575,543 (50)	4,950,202 (41)
31. tomorrow	+0.20	10,379,637 (21)	8,899,406 (28)
32. !	+0.16	3,463,257 (40)	1,385,072 (62)
33. summer	+0.13	2,998,785 (43)	2,554,459 (50)
34. we	+0.13	39,132,934 (7)	34,513,587 (7)
35. today	+0.13	25,588,506 (9)	23,619,518 (12)
36. man	+0.12	15,856,341 (14)	29,558,118 (9)
37. woman	+0.10	2,543,036 (51)	5,603,347 (39)
38. Stephen Colbert	+0.10	23,778 (99)	14,697 (99)
39. ;-)	+0.10	943,413 (66)	516,171 (73)
40. RT	+0.06	339,055,724 (1)	142,219,359 (3)
41. coffee	+0.04	2,800,972 (46)	2,399,867 (52)
42. church	+0.03	1,812,251 (58)	3,452,171 (45)
43. work	+0.02	18,415,618 (11)	16,191,802 (18)
44. I	+0.02	307,960,343 (2)	282,865,043 (1)
45. yes	+0.02	11,593,356 (19)	7,499,840 (30)
46. them	0.00	15,352,295 (15)	14,398,889 (22)
47. hot	-0.01	7,122,144 (28)	6,286,163 (37)
48. boy	-0.01	4,933,333 (33)	9,670,512 (27)
49. yesterday	-0.01	3,077,761 (42)	2,852,623 (49)

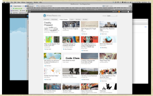
Word	$h_{\text{avg}}^{(\text{amb})}$	Total Tweets	Total ANEW
51. me	-0.06	144,342,098 (4)	88,088,051 (4)
52. ?	-0.07	2,333,283 (53)	674,679 (69)
53. commute	-0.09	90,126 (94)	90,092 (92)
54. gay	-0.09	2,727,309 (47)	1,697,177 (57)
55. right	-0.10	19,166,480 (10)	15,850,283 (19)
56. school	-0.11	9,264,217 (24)	6,924,193 (34)
57. Republican	-0.13	229,773 (86)	188,338 (85)
58. they	-0.16	27,442,360 (8)	27,150,189 (11)
59. winter	-0.19	1,255,945 (64)	1,217,225 (64)
60. lose	-0.19	2,056,468 (55)	2,091,540 (53)
61. Jon Stewart	-0.20	52,084 (97)	33,086 (96)
62. gas	-0.22	1,022,879 (65)	812,029 (68)
63. no	-0.22	95,129,093 (5)	38,894,616 (6)
64. Democrat	-0.23	93,193 (93)	75,450 (93)
65. left	-0.27	4,893,634 (34)	4,611,878 (43)
66. Senate	-0.29	447,732 (78)	316,835 (80)
67. election	-0.30	560,184 (75)	375,055 (78)
68. Sarah Palin	-0.34	225,577 (87)	150,096 (88)
69. Obama	-0.35	2,981,150 (44)	1,998,326 (54)
70. economy	-0.36	608,878 (73)	460,834 (76)
71. Congress	-0.36	391,510 (79)	279,695 (81)
72. drugs	-0.39	509,606 (77)	469,091 (74)
73. Muslim	-0.42	215,300 (88)	146,506 (89)
74. George Bush	-0.43	32,341 (98)	23,102 (98)
75. climate	-0.44	364,177 (80)	229,129 (83)
76. Pope	-0.51	152,320 (91)	135,955 (90)
77. oil	-0.53	1,377,355 (62)	1,148,990 (66)
78. I feel	-0.54	5,173,513 (31)	4,702,352 (42)
79. Glenn Beck	-0.54	113,991 (92)	101,090 (91)
80. Islam	-0.54	187,223 (89)	70,311 (94)
81. :-(	-0.65	341,141 (81)	244,215 (82)
82. :(	-0.70	2,907,145 (45)	1,891,225 (55)
83. flu	-0.75	901,403 (68)	639,000 (70)
84. rain	-0.78	3,233,464 (41)	5,959,903 (38)
85. BP	-0.78	582,167 (74)	326,100 (79)
86. mosque	-0.79	69,812 (95)	46,736 (95)
87. dark	-0.95	1,577,553 (61)	3,233,911 (47)
88. Lehman Brothers	-1.08	8,500 (100)	4,280 (100)
89. Goldman Sachs	-1.08	52,703 (96)	30,769 (97)
90. Afghanistan	-1.15	273,519 (83)	172,637 (87)
91. Iraq	-1.37	238,931 (85)	213,425 (84)
92. cold	-1.39	3,670,447 (36)	7,015,518 (32)
93. gun	-1.81	680,903 (72)	1,263,217 (63)
94. hate	-2.43	9,652,881 (23)	18,158,870 (15)
95. hell	-2.49	6,266,162 (30)	11,056,735 (24)
96. sick	-2.55	3,576,058 (37)	6,783,395 (36)
97. sad	-2.56	3,563,745 (38)	6,951,686 (33)
98. war	-2.63	1,955,901 (57)	3,417,588 (46)
99. depressed	-2.64	280,872 (82)	541,394 (72)

Text element and context correlate in happiness scores:

- Compare ambient happiness with text element happiness.
- Spearman correlation coefficient: $r_s \simeq 0.79$, p-value $< 10^{-10}$.
- An on-average result: says nothing about any individual sentence.
- Extra random piece: stemming fails.

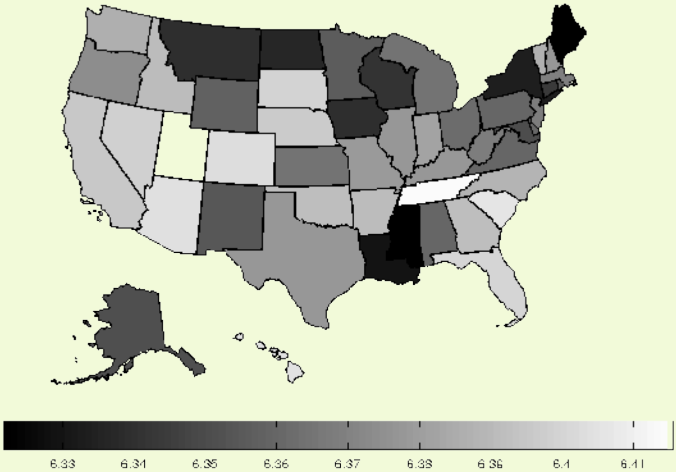
Happiness in Manhattan (just for fun):



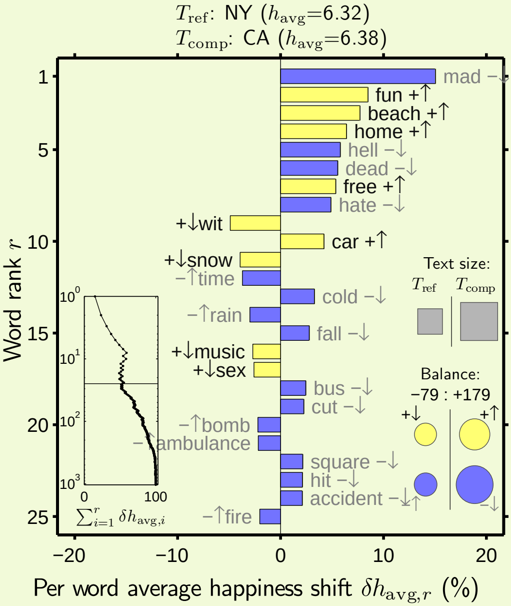


See Blog post on onehappybird (⊞)

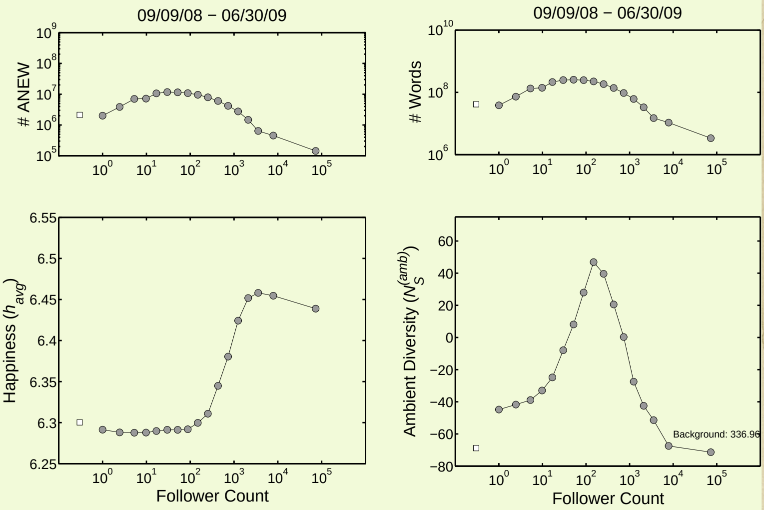
Twitter—location:



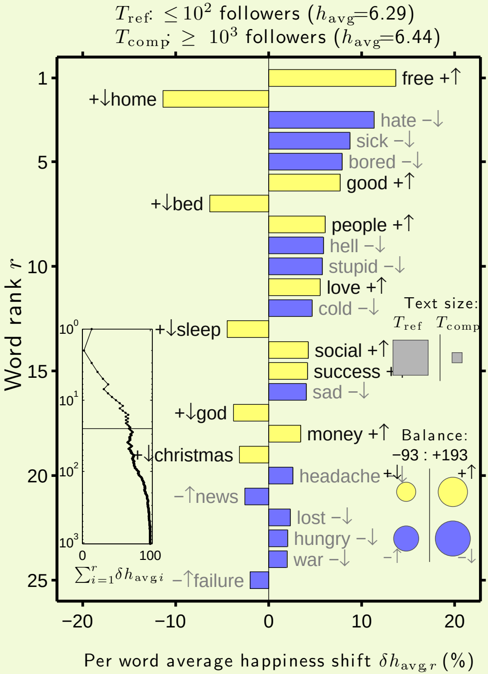
Twitter—location:



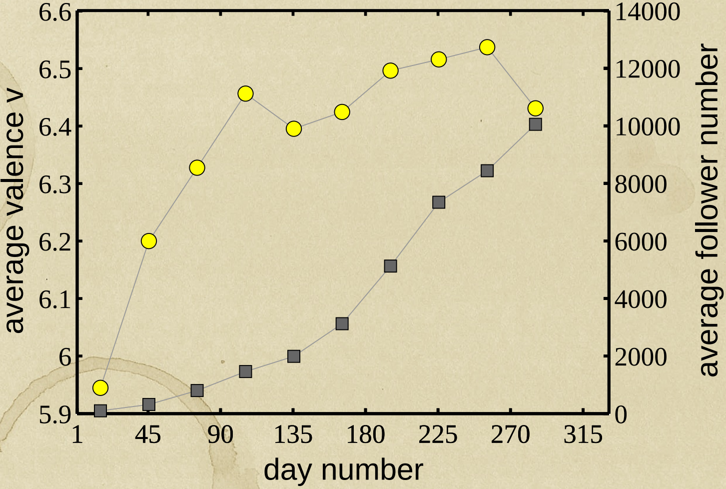
Twitter—popularity based on follower count:



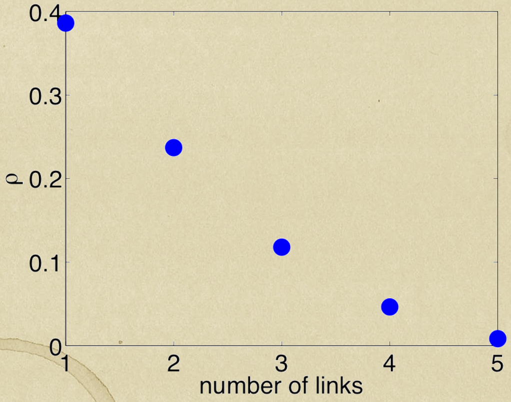
- Dunbar's number $\simeq$ 150.



T_{ref}: $\leq 10^2$ followers (h_{avg}=6.29)
T_{comp}: $\geq 10^3$ followers (h_{avg}=6.44)
free +↑
+↓home
hate −↓
sick −↓
bored −↓
good +↑
+↓bed
people +↑
hell −↓
stupid −↓
love +↑
cold −↓
+↓sleep
social +↑
success +↑
sad −↓
+↓god
money +↑
+↓christmas
headache −↓
−↑news
lost −↓
hungry −↓
war −↓
−↑failure
Text size:
T_{ref} T_{comp}
Balance:
−93 : +193
+↓ +↑
−↑ −↓
$\sum_{i=1}^{r} \delta h_{\text{avg}\,i}$
Word rank r
Per word average happiness shift $\delta h_{\text{avg}\,r}$ (%)

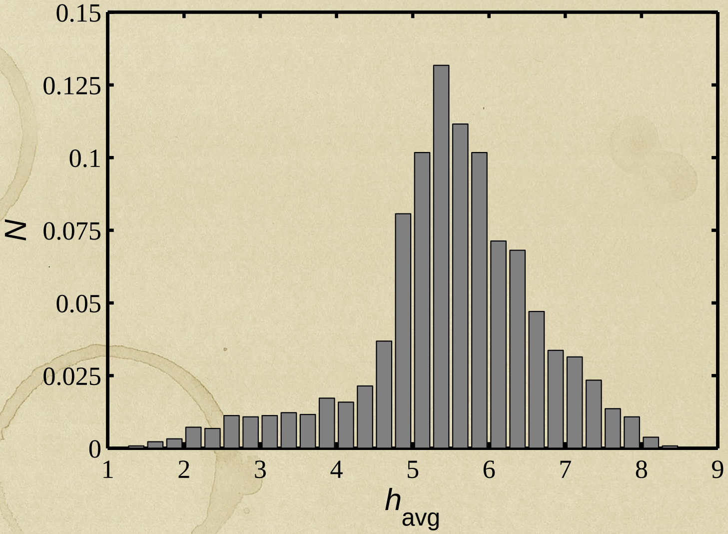

average valence v
6.6
6.5
6.4
6.3
6.2
6.1
6
5.9
1
45
90
135
180
225
270
315
day number
14000
12000
10000
8000
6000
4000
2000
0
average follower number

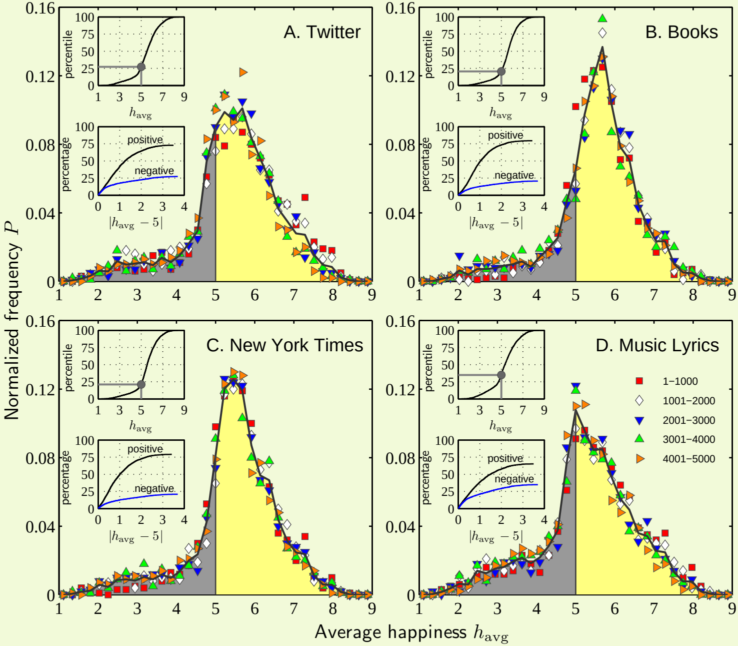
Twitter—interactions:

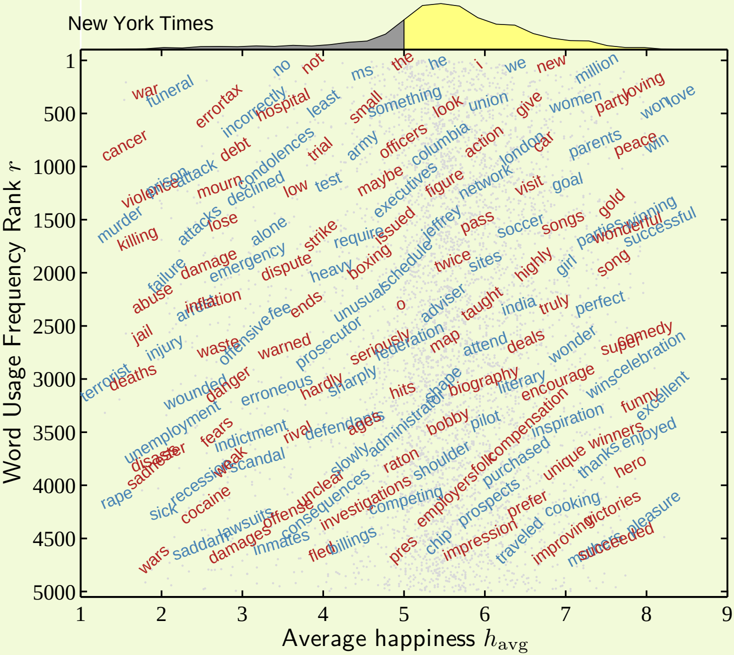


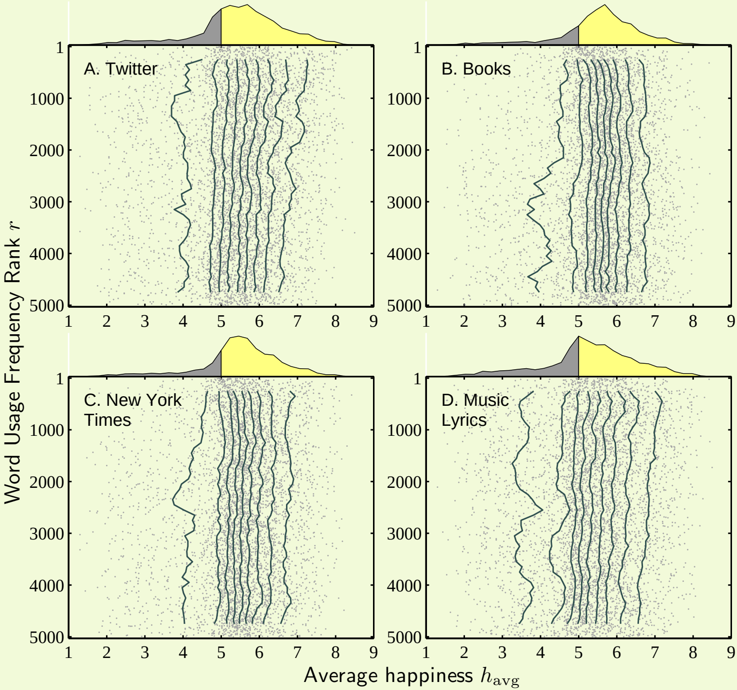
- Decay in happiness correlation in social network.
- ρ = Spearman's correlation coefficient.

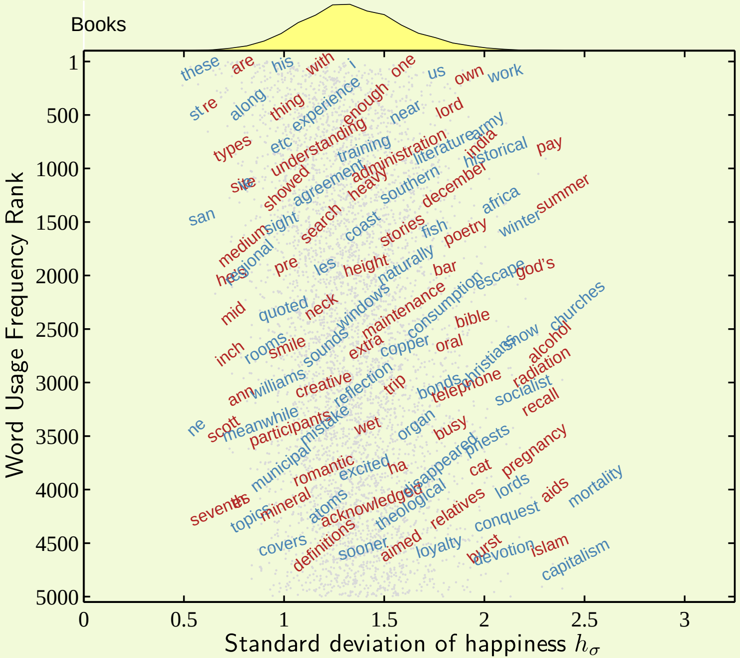
Positive bias in the English language:

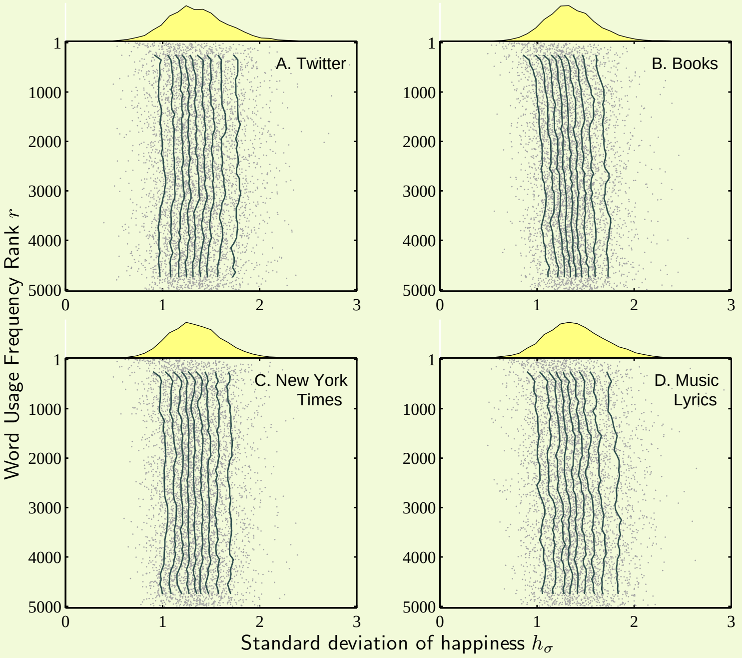



A. Twitter
B. Books
C. New York Times
D. Music Lyrics
Normalized frequency P
Average happiness h_{avg}
percentile
percentage
positive
negative
h_{avg}
$|h_{\mathrm{avg}} - 5|$
1–1000
1001–2000
2001–3000
3001–4000
4001–5000


New York Times
Word Usage Frequency Rank r
Average happiness h_{avg}
1
500
1000
1500
2000
2500
3000
3500
4000
4500
5000
1
2
3
4
5
6
7
8
9
war
funeral
errortax
no
not
ms
the
he
i
we
new
million
incorrectly
hospital
least
small
something
look
union
give
women
party
loving
won
love
cancer
debt
trial
army
officers
columbia
action
london
car
parents
peace
win
violence
prison
attack
mourn
condolences
declined
low
test
maybe
executives
figure
network
visit
goal
murder
killing
attacks
lose
alone
strike
require
issued
jeffrey
pass
soccer
songs
gold
parties
winning
wonderful
successful
failure
damage
emergency
dispute
heavy
boxing
schedule
twice
sites
highly
girl
song
abuse
inflation
fee
ends
unusual
o
adviser
taught
india
truly
perfect
jail
injury
waste
offensive
warned
prosecutor
seriously
federation
map
attend
deals
wonder
super
comedy
terrorist
deaths
wounded
danger
erroneous
hardly
sharply
hits
shape
biography
literary
encourage
wins
celebration
unemployment
fears
indictment
rival
defendants
ages
administrator
bobby
pilot
compensation
inspiration
funny
excellent
disaster
scandal
slowly
raton
shoulder
purchased
unique
winners
thanks
enjoyed
hero
rape
sick
recession
cocaine
unclear
consequences
investigations
competing
employers
folk
prospects
prefer
cooking
victories
pleasure
wars
saddam
lawsuits
damages
offense
inmates
fled
billings
pres
chip
impression
traveled
improving
succeeded


A. Twitter
B. Books
C. New York Times
D. Music Lyrics
1
1000
2000
3000
4000
5000
1 2 3 4 5 6 7 8 9
Word Usage Frequency Rank r
Average happiness h_{avg}


Books
Word Usage Frequency Rank
Standard deviation of happiness h_σ
1
500
1000
1500
2000
2500
3000
3500
4000
4500
5000
0
0.5
1
1.5
2
2.5
3
these are his with i one us own work
st re along thing experience enough near lord
types etc understanding training administration literature army
site showed agreement heavy southern december india historical pay
san medium sight search coast stories fish africa summer
regional pre les height naturally poetry winter
mid quoted neck windows bar consumption escape god's
inch rooms smile sounds maintenance bible churches
ann williams creative extra copper oral christians snow alcohol
ne scott meanwhile participants reflection trip bonds telephone radiation socialist
mistake wet organ busy priests recall
sevenths municipal romantic excited ha disappeared cat pregnancy
topics mineral atoms acknowledged theological relatives lords aids mortality
covers definitions sooner aimed loyalty conquest burst devotion islam capitalism


A. Twitter
B. Books
C. New York Times
D. Music Lyrics
Word Usage Frequency Rank r
Standard deviation of happiness h_σ
1
1000
2000
3000
4000
5000
0
1
2
3

Random other things (now and next):

- Gross National Happiness Index, hedonometer.org (in development)
- Prediction ...
- Scores for letters, phonemes, as a function of tense.
- Fifteen additional languages being scored on Mechanical Turk
- How does happiness vary with proximity to nature? to Walmart?
- Emotional contagion.
- Quantifying metaphor and narrative and stories ...

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