

## SUPPLEMENTARY INFORMATION

### Online, interactive visualizations:

We provide the following resources online at <http://compstorylab.org/share/papers/dodds2014a/> and at <http://hedonometer.org>.

- Links to example scripts for parsing and measuring average happiness scores for texts, and for generating D3 word shifts: <http://compstorylab.org/share/papers/dodds2014a/code.html>
- Visualizations for exploring translation-stable word pairs across languages;
- Interactive, multi-language time series for over 10,000 works of literature including Moby Dick and Harry Potter;
- Jellyfish plots for all 24 corpora;
- An API for selected data streams and word lists at <http://hedonometer.org/api.html>
- Spatiotemporal hedonometric measurements of Twitter across all 10 languages, explorable at <http://hedonometer.org>.

### Corpora

We used the services of Appen Butler Hill (<http://www.appen.com>) for all word evaluations excluding English, for which we had earlier employed Mechanical Turk (<https://www.mturk.com/> [17]).

English instructions (see the example below) were translated to all other languages and given to participants along with survey questions, and an example of the English instruction page is below. Non-english language experiments were conducted through a custom interactive website built by Appen Butler Hill, and all participants were required to pass a stringent aural proficiency test in their own language.

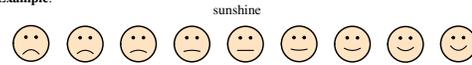
#### Measuring the Happiness of Words

Our overall aim is to assess how people feel about individual words. With this particular survey, we are focusing on the dual emotions of sadness and happiness. You are to rate 100 individual words on a 9 point unhappy-happy scale.

Please consider each word carefully. If we determine that your ratings are randomly or otherwise inappropriately selected, or that any questions are left unanswered, we may not approve your work. These words were chosen based on their common usage. As a result, a small portion of words may be offensive to some people, written in a different language, or nonsensical.

Before completing the word ratings, we ask that you answer a few short demographic questions. We expect the entire survey to require 10 minutes of your time. Thank you for participating!

#### Example:



Read the word and click on the face that best corresponds to your emotional response.

#### Demographic Questions

1. What is your gender? (Male/Female)
2. What is your age? (Free text)
3. Which of the following best describes your highest achieved education level?  
Some High School, High School Graduate, Some college, no degree, Associates degree, Bachelors degree, Graduate degree (Masters, Doctorate, etc.)
4. What is the total income of your household?
5. Where are you from originally?
6. Where do you live currently?
7. Is \_\_\_\_\_ your first language? (Yes/No) If it is not, please specify what your first language is.
8. Do you have any comments or suggestions? (Free text)

Corpus:	# Words	Reference(s)
English: Twitter	5000	[18]
English: Google Books Project	5000	[14]
English: The New York Times	5000	[18]
English: Music lyrics	5000	[16]
Portuguese: Google Web Crawl	7133	[15]
Portuguese: Twitter	7119	Twitter API
Spanish: Google Web Crawl	7189	[15]
Spanish: Twitter	6415	Twitter API
Spanish: Google Books Project	6379	[14]
French: Google Web Crawl	7056	[15]
French: Twitter	6569	Twitter API
French: Google Books Project	6192	[14]
Arabic: Movie and TV subtitles	9999	The MITRE Corporation
Indonesian: Twitter	7044	Twitter API
Indonesian: Movie subtitles	6726	The MITRE Corporation
Russian: Twitter	6575	Twitter API
Russian: Google Books Project	5980	[14]
Russian: Movie and TV subtitles	6186	[15]
German: Google Web Crawl	6902	[15]
German: Twitter	6459	Twitter API
German: Google Books Project	6097	[14]
Korean: Twitter	6728	Twitter API
Korean: Movie subtitles	5389	The MITRE Corporation
Chinese: Google Books Project	10000	[14]

TABLE S1. Sources for all corpora.

Language	Participants' location(s)	Number of participants	Average words scored
English	United States of America, India	384	1302
German	Germany	196	2551
Indonesian	Indonesia	146	3425
Russian	Russia	125	4000
Arabic	Egypt	185	2703
French	France	179	2793
Spanish	Mexico	236	2119
Portuguese	Brazil	208	2404
Simplified Chinese	China	128	3906
Korean	Korea, United States of America	109	4587

TABLE S2. Number and main country/countries of location for participants evaluating the 10,000 common words for each of the 10 languages we studied. Also recorded is the average number of words evaluated by each participant (rounded to the nearest integer). We note that each word received 50 evaluations from distinct individuals. The English word list was evaluated via Mechanical Turk for our initial study [17]. The nine languages evaluated through Appen-Butler Hill yielded a higher participation rate likely due to better pay and the organization's quality of service.

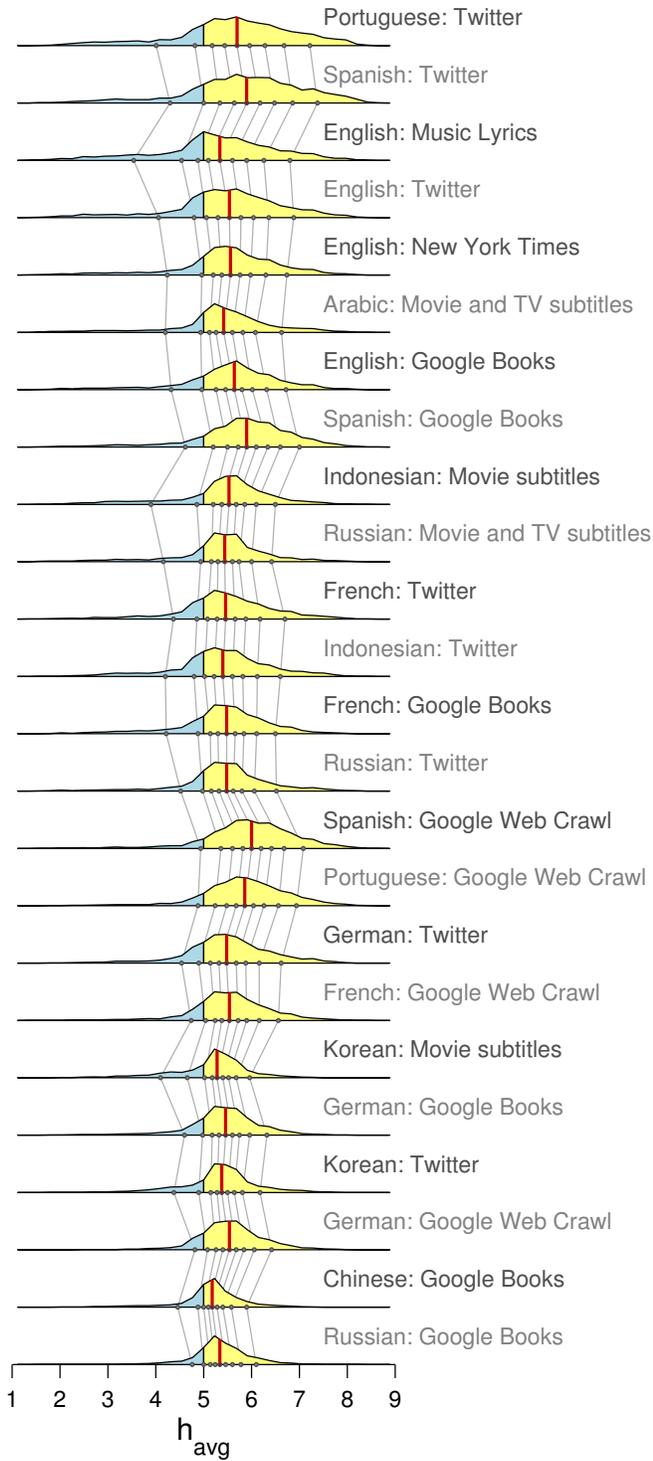


FIG. S1. The same average happiness distributions shown in Fig. 1 re-ordered by increasing variance. Yellow indicates above neutral ( $h_{avg} = 5$ ), blue below neutral, red vertical lines mark each distribution's median, and the gray background lines connect the deciles of adjacent distributions.

	Spanish	Portuguese	English	Indonesian	French	German	Arabic	Russian	Korean	Chinese
Spanish	1.00, 0.00	1.01, 0.03	1.06, -0.07	1.22, -0.88	1.11, -0.24	1.22, -0.84	1.13, -0.22	1.31, -1.16	1.60, -2.73	1.58, -2.30
Portuguese	0.99, -0.03	1.00, 0.00	1.04, -0.03	1.22, -0.97	1.11, -0.33	1.21, -0.86	1.09, -0.08	1.26, -0.95	1.62, -2.92	1.58, -2.39
English	0.94, 0.06	0.96, 0.03	1.00, 0.00	1.13, -0.66	1.06, -0.23	1.16, -0.75	1.05, -0.10	1.21, -0.91	1.51, -2.53	1.47, -2.10
Indonesian	0.82, 0.72	0.82, 0.80	0.88, 0.58	1.00, 0.00	0.92, 0.48	0.99, 0.06	0.89, 0.71	1.02, 0.04	1.31, -1.53	1.33, -1.42
French	0.90, 0.22	0.90, 0.30	0.94, 0.22	1.09, -0.52	1.00, 0.00	1.08, -0.44	0.99, 0.12	1.12, -0.50	1.37, -1.88	1.40, -1.77
German	0.82, 0.69	0.83, 0.71	0.86, 0.65	1.01, -0.06	0.92, 0.41	1.00, 0.00	0.91, 0.61	1.07, -0.25	1.29, -1.44	1.32, -1.36
Arabic	0.88, 0.19	0.92, 0.08	0.95, 0.10	1.12, -0.80	1.01, -0.12	1.10, -0.68	1.00, 0.00	1.12, -0.63	1.40, -2.14	1.43, -2.01
Russian	0.76, 0.88	0.80, 0.75	0.83, 0.75	0.98, -0.04	0.89, 0.45	0.93, 0.24	0.89, 0.56	1.00, 0.00	1.26, -1.39	1.25, -1.05
Korean	0.62, 1.70	0.62, 1.81	0.66, 1.67	0.77, 1.17	0.73, 1.37	0.78, 1.12	0.71, 1.53	0.79, 1.10	1.00, 0.00	0.98, 0.28
Chinese	0.63, 1.46	0.63, 1.51	0.68, 1.43	0.75, 1.07	0.71, 1.26	0.76, 1.03	0.70, 1.41	0.80, 0.84	1.02, -0.29	1.00, 0.00

TABLE S3. Reduced Major Axis (RMA) regression fits for row language as a linear function of the column language:  $h_{\text{avg}}^{(\text{row})}(w) = mh_{\text{avg}}^{(\text{column})}(w) + c$  where  $w$  indicates a translation-stable word. Each entry in the table contains the coefficient pair  $m$  and  $c$ . See the scatter plot tableau of Fig. 2 for further details on all language-language comparisons. We use RMA regression, also known as Standardized Major Axis linear regression, because of its accommodation of errors in both variables.

	Spanish	Portuguese	English	Indonesian	French	German	Arabic	Russian	Korean	Chinese
Spanish	1.00	0.89	0.87	0.82	0.86	0.82	0.83	0.73	0.79	0.79
Portuguese	0.89	1.00	0.87	0.82	0.84	0.81	0.84	0.84	0.79	0.76
English	0.87	0.87	1.00	0.88	0.86	0.82	0.86	0.87	0.82	0.81
Indonesian	0.82	0.82	0.88	1.00	0.79	0.77	0.83	0.85	0.79	0.77
French	0.86	0.84	0.86	0.79	1.00	0.84	0.77	0.84	0.79	0.76
German	0.82	0.81	0.82	0.77	0.84	1.00	0.76	0.80	0.73	0.74
Arabic	0.83	0.84	0.86	0.83	0.77	0.76	1.00	0.83	0.79	0.80
Russian	0.73	0.84	0.87	0.85	0.84	0.80	0.83	1.00	0.80	0.82
Korean	0.79	0.79	0.82	0.79	0.79	0.73	0.79	0.80	1.00	0.81
Chinese	0.79	0.76	0.81	0.77	0.76	0.74	0.80	0.82	0.81	1.00

TABLE S4. Pearson correlation coefficients for translation-stable words for all language pairs. All  $p$ -values are  $< 10^{-118}$ . These values are included in Fig. 2 and reproduced here for to facilitate comparison.

	Spanish	Portuguese	English	Indonesian	French	German	Arabic	Russian	Korean	Chinese
Spanish	1.00	0.85	0.83	0.77	0.81	0.77	0.75	0.74	0.74	0.68
Portuguese	0.85	1.00	0.83	0.77	0.78	0.77	0.77	0.81	0.75	0.66
English	0.83	0.83	1.00	0.82	0.80	0.78	0.78	0.81	0.75	0.70
Indonesian	0.77	0.77	0.82	1.00	0.72	0.72	0.76	0.77	0.71	0.71
French	0.81	0.78	0.80	0.72	1.00	0.80	0.67	0.79	0.71	0.64
German	0.77	0.77	0.78	0.72	0.80	1.00	0.69	0.76	0.64	0.62
Arabic	0.75	0.77	0.78	0.76	0.67	0.69	1.00	0.74	0.69	0.68
Russian	0.74	0.81	0.81	0.77	0.79	0.76	0.74	1.00	0.70	0.66
Korean	0.74	0.75	0.75	0.71	0.71	0.64	0.69	0.70	1.00	0.71
Chinese	0.68	0.66	0.70	0.71	0.64	0.62	0.68	0.66	0.71	1.00

TABLE S5. Spearman correlation coefficients for translation-stable words. All  $p$ -values are  $< 10^{-82}$ .

Language: Corpus	$\rho_p$	$p$ -value	$\rho_s$	$p$ -value	$\alpha$	$\beta$
Spanish: Google Web Crawl	-0.114	$3.38 \times 10^{-22}$	-0.090	$1.85 \times 10^{-14}$	$-5.55 \times 10^{-5}$	6.10
Spanish: Google Books	-0.040	$1.51 \times 10^{-3}$	-0.016	$1.90 \times 10^{-1}$	$-2.28 \times 10^{-5}$	5.90
Spanish: Twitter	-0.048	$1.14 \times 10^{-4}$	-0.032	$1.10 \times 10^{-2}$	$-3.10 \times 10^{-5}$	5.94
Portuguese: Google Web Crawl	-0.085	$6.33 \times 10^{-13}$	-0.060	$3.23 \times 10^{-7}$	$-3.98 \times 10^{-5}$	5.96
Portuguese: Twitter	-0.041	$5.98 \times 10^{-4}$	-0.030	$1.15 \times 10^{-2}$	$-2.40 \times 10^{-5}$	5.73
English: Google Books	-0.042	$3.03 \times 10^{-3}$	-0.013	$3.50 \times 10^{-1}$	$-3.04 \times 10^{-5}$	5.62
English: New York Times	-0.056	$6.93 \times 10^{-5}$	-0.044	$1.99 \times 10^{-3}$	$-4.17 \times 10^{-5}$	5.61
German: Google Web Crawl	-0.096	$1.11 \times 10^{-15}$	-0.082	$6.75 \times 10^{-12}$	$-3.67 \times 10^{-5}$	5.65
French: Google Web Crawl	-0.105	$9.20 \times 10^{-19}$	-0.080	$1.99 \times 10^{-11}$	$-4.50 \times 10^{-5}$	5.68
English: Twitter	-0.097	$6.56 \times 10^{-12}$	-0.103	$2.37 \times 10^{-13}$	$-7.78 \times 10^{-5}$	5.67
Indonesian: Movie subtitles	-0.039	$1.48 \times 10^{-3}$	-0.063	$2.45 \times 10^{-7}$	$-2.04 \times 10^{-5}$	5.45
German: Twitter	-0.054	$1.47 \times 10^{-5}$	-0.036	$4.02 \times 10^{-3}$	$-2.51 \times 10^{-5}$	5.58
Russian: Twitter	-0.052	$2.38 \times 10^{-5}$	-0.028	$2.42 \times 10^{-2}$	$-2.55 \times 10^{-5}$	5.52
French: Google Books	-0.043	$6.80 \times 10^{-4}$	-0.030	$1.71 \times 10^{-2}$	$-2.31 \times 10^{-5}$	5.49
German: Google Books	-0.003	$8.12 \times 10^{-1}$	+0.014	$2.74 \times 10^{-1}$	$-1.38 \times 10^{-6}$	5.45
French: Twitter	-0.049	$6.08 \times 10^{-5}$	-0.023	$6.31 \times 10^{-2}$	$-2.54 \times 10^{-5}$	5.54
Russian: Movie and TV subtitles	-0.029	$2.36 \times 10^{-2}$	-0.033	$9.17 \times 10^{-3}$	$-1.57 \times 10^{-5}$	5.43
Arabic: Movie and TV subtitles	-0.045	$7.10 \times 10^{-6}$	-0.029	$4.19 \times 10^{-3}$	$-1.66 \times 10^{-5}$	5.44
Indonesian: Twitter	-0.051	$2.14 \times 10^{-5}$	-0.018	$1.24 \times 10^{-1}$	$-2.50 \times 10^{-5}$	5.46
Korean: Twitter	-0.032	$8.29 \times 10^{-3}$	-0.016	$1.91 \times 10^{-1}$	$-1.24 \times 10^{-5}$	5.38
Russian: Google Books	+0.030	$2.09 \times 10^{-2}$	+0.070	$5.08 \times 10^{-8}$	$+1.20 \times 10^{-5}$	5.35
English: Music Lyrics	-0.073	$2.53 \times 10^{-7}$	-0.081	$1.05 \times 10^{-8}$	$-6.12 \times 10^{-5}$	5.45
Korean: Movie subtitles	-0.187	$8.22 \times 10^{-44}$	-0.180	$2.01 \times 10^{-40}$	$-9.66 \times 10^{-5}$	5.41
Chinese: Google Books	-0.067	$1.48 \times 10^{-11}$	-0.050	$5.01 \times 10^{-7}$	$-1.72 \times 10^{-5}$	5.21

TABLE S6. Pearson correlation coefficients and  $p$ -values, Spearman correlation coefficients and  $p$ -values, and linear fit coefficients, for average word happiness  $h_{\text{avg}}$  as a function of word usage frequency rank  $r$ . We use the fit is  $h_{\text{avg}} = \alpha r + \beta$  for the most common 5000 words in each corpora, determining  $\alpha$  and  $\beta$  via ordinary least squares, and order languages by the median of their average word happiness scores (descending). We note that stemming of words may affect these estimates.

Language: Corpus	$\rho_p$	$p$ -value	$\rho_s$	$p$ -value	$\alpha$	$\beta$
Portuguese: Twitter	+0.090	$2.55 \times 10^{-14}$	+0.095	$1.28 \times 10^{-15}$	$1.19 \times 10^{-5}$	1.29
Spanish: Twitter	+0.097	$8.45 \times 10^{-15}$	+0.104	$5.92 \times 10^{-17}$	$1.47 \times 10^{-5}$	1.26
English: Music Lyrics	+0.129	$4.87 \times 10^{-20}$	+0.134	$1.63 \times 10^{-21}$	$2.76 \times 10^{-5}$	1.33
English: Twitter	+0.007	$6.26 \times 10^{-1}$	+0.012	$4.11 \times 10^{-1}$	$1.47 \times 10^{-6}$	1.35
English: New York Times	+0.050	$4.56 \times 10^{-4}$	+0.044	$1.91 \times 10^{-3}$	$9.34 \times 10^{-6}$	1.32
Arabic: Movie and TV subtitles	+0.101	$7.13 \times 10^{-24}$	+0.101	$3.41 \times 10^{-24}$	$9.41 \times 10^{-6}$	1.01
English: Google Books	+0.180	$1.68 \times 10^{-37}$	+0.176	$4.96 \times 10^{-36}$	$3.36 \times 10^{-5}$	1.27
Spanish: Google Books	+0.066	$1.23 \times 10^{-7}$	+0.062	$6.53 \times 10^{-7}$	$9.17 \times 10^{-6}$	1.26
Indonesian: Movie subtitles	+0.026	$3.43 \times 10^{-2}$	+0.027	$2.81 \times 10^{-2}$	$2.87 \times 10^{-6}$	1.12
Russian: Movie and TV subtitles	+0.083	$7.60 \times 10^{-11}$	+0.075	$3.28 \times 10^{-9}$	$1.06 \times 10^{-5}$	0.89
French: Twitter	+0.072	$4.77 \times 10^{-9}$	+0.076	$8.94 \times 10^{-10}$	$1.07 \times 10^{-5}$	1.05
Indonesian: Twitter	+0.072	$1.17 \times 10^{-9}$	+0.072	$1.73 \times 10^{-9}$	$8.16 \times 10^{-6}$	1.12
French: Google Books	+0.090	$1.02 \times 10^{-12}$	+0.085	$1.67 \times 10^{-11}$	$1.25 \times 10^{-5}$	1.02
Russian: Twitter	+0.055	$6.83 \times 10^{-6}$	+0.053	$1.67 \times 10^{-5}$	$7.39 \times 10^{-6}$	0.91
Spanish: Google Web Crawl	+0.119	$4.45 \times 10^{-24}$	+0.106	$2.60 \times 10^{-19}$	$1.45 \times 10^{-5}$	1.23
Portuguese: Google Web Crawl	+0.093	$4.06 \times 10^{-15}$	+0.083	$2.91 \times 10^{-12}$	$1.07 \times 10^{-5}$	1.26
German: Twitter	+0.051	$4.45 \times 10^{-5}$	+0.050	$5.15 \times 10^{-5}$	$7.39 \times 10^{-6}$	1.15
French: Google Web Crawl	+0.104	$2.12 \times 10^{-18}$	+0.088	$9.64 \times 10^{-14}$	$1.27 \times 10^{-5}$	1.01
Korean: Movie subtitles	+0.171	$1.39 \times 10^{-36}$	+0.185	$8.85 \times 10^{-43}$	$2.58 \times 10^{-5}$	0.88
German: Google Books	+0.157	$6.06 \times 10^{-35}$	+0.162	$4.96 \times 10^{-37}$	$2.17 \times 10^{-5}$	1.03
Korean: Twitter	+0.056	$4.07 \times 10^{-6}$	+0.062	$4.25 \times 10^{-7}$	$6.98 \times 10^{-6}$	0.93
German: Google Web Crawl	+0.099	$2.05 \times 10^{-16}$	+0.085	$1.18 \times 10^{-12}$	$1.20 \times 10^{-5}$	1.07
Chinese: Google Books	+0.099	$3.07 \times 10^{-23}$	+0.097	$3.81 \times 10^{-22}$	$8.70 \times 10^{-6}$	1.16
Russian: Google Books	+0.187	$5.15 \times 10^{-48}$	+0.177	$2.24 \times 10^{-43}$	$2.28 \times 10^{-5}$	0.81

TABLE S7. Pearson correlation coefficients and  $p$ -values, Spearman correlation coefficients and  $p$ -values, and linear fit coefficients for standard deviation of word happiness  $h_{\text{std}}$  as a function of word usage frequency rank  $r$ . We consider the fit is  $h_{\text{std}} = \alpha r + \beta$  for the most common 5000 words in each corpora, determining  $\alpha$  and  $\beta$  via ordinary least squares, and order corpora according to their emotional variance (descending).



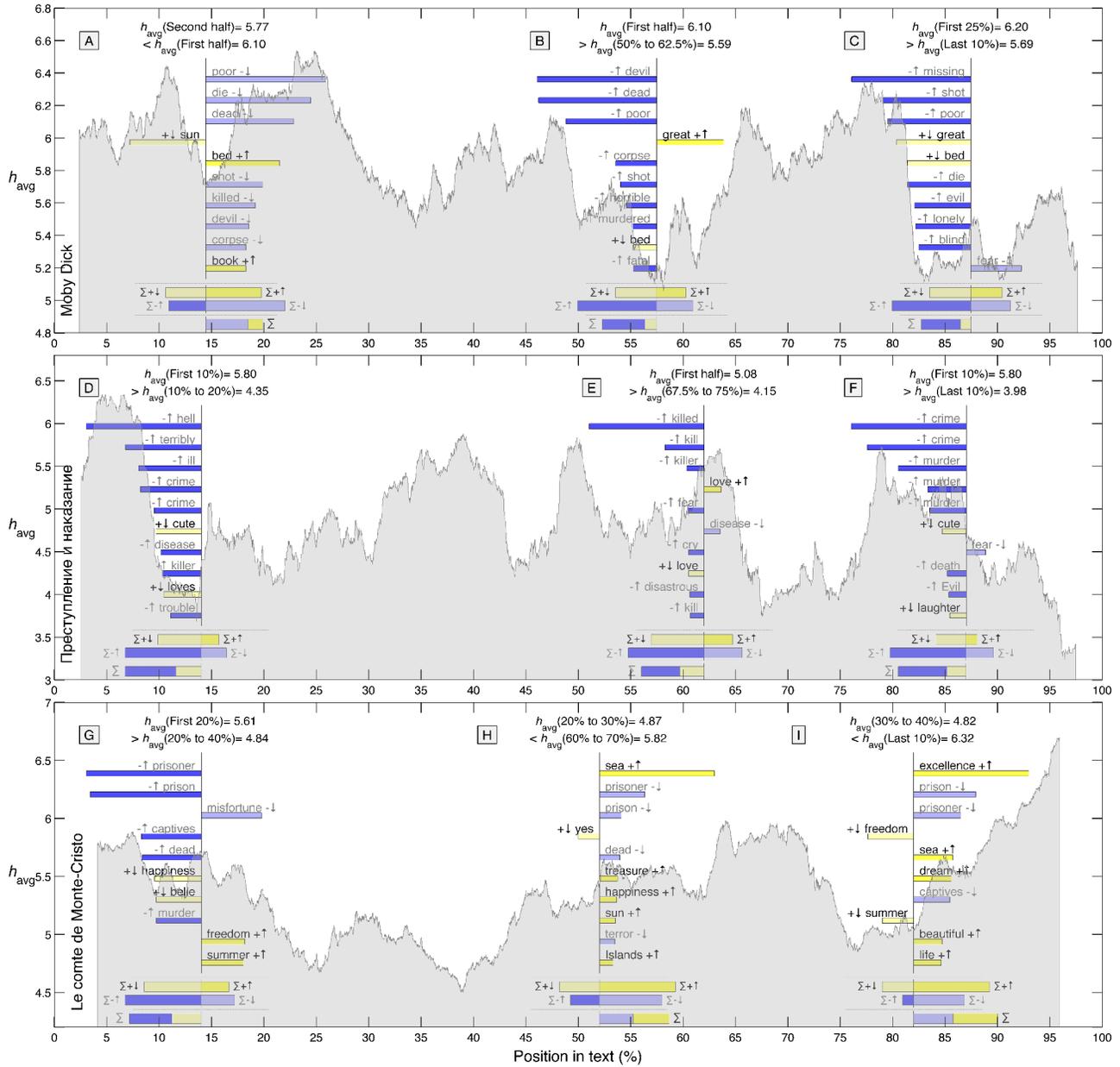


FIG. S3. Fig. 4 from the main text with Russian and French translated into English. Online, interactive visualizations of over 10,000 books can be found here: <http://hedonometer.org/books.html>.

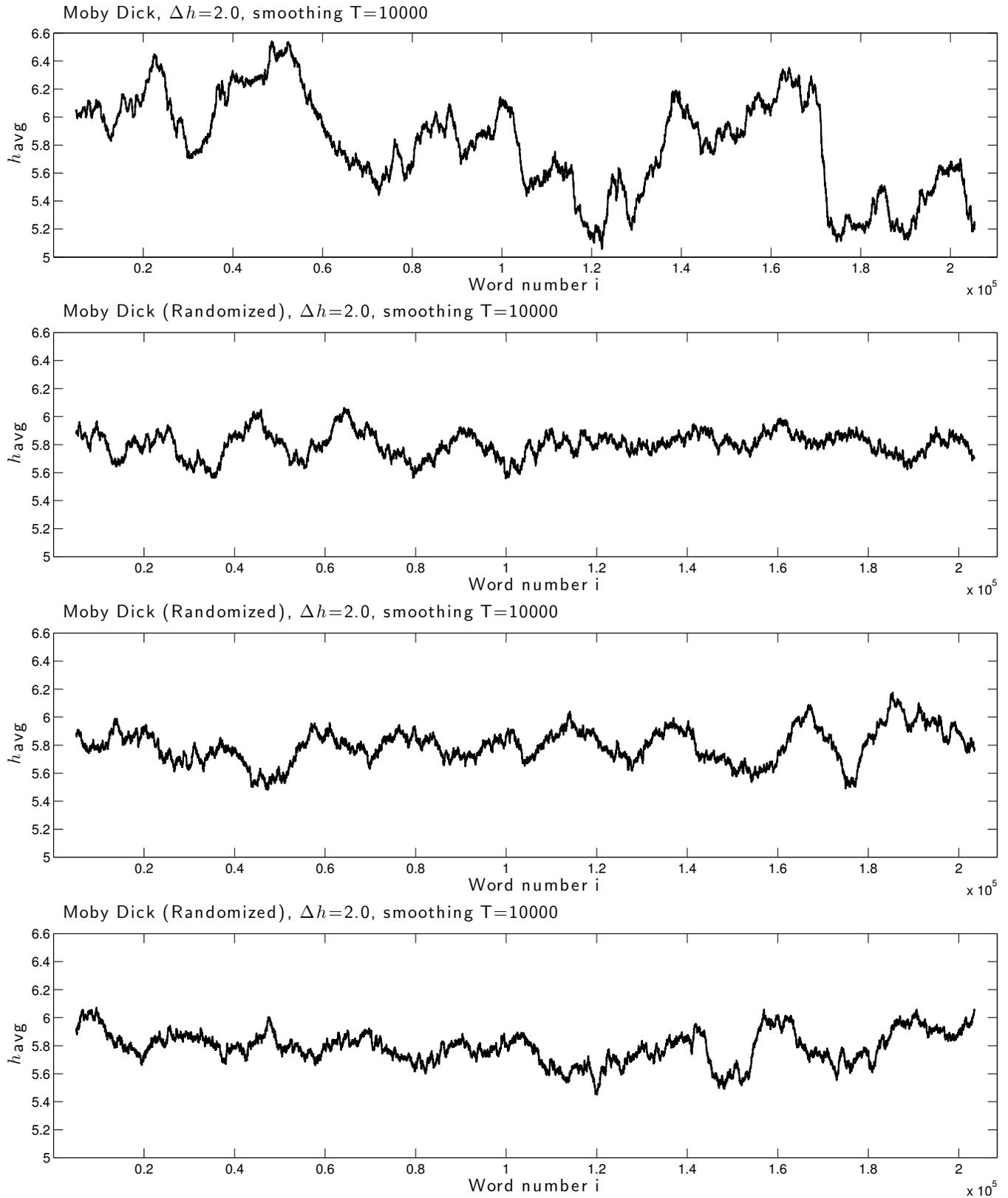
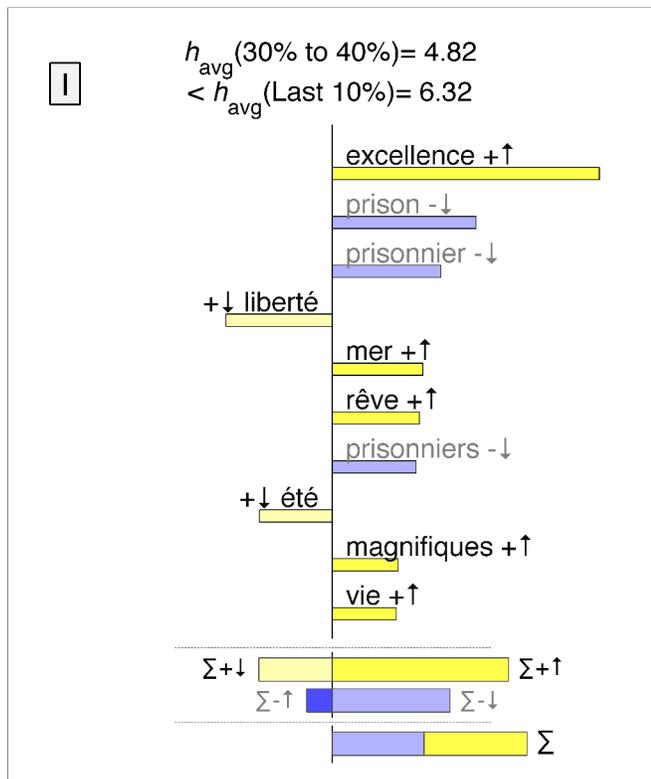


FIG. S4. Comparison of the emotional trajectory of Moby Dick with the results for three example randomized versions of the same text, showing the loss of structure and variability.

## EXPLANATION OF WORD SHIFTS

In this section, we explain the word shifts included in Figs. 4 and S3. We expand upon the approach described in [16] and [18] to rank and visualize how words contribute to this overall upward shift in happiness.

Shown below is the third inset word shift used in Fig 4 for the Count of Monte Cristo, a comparison of words found in the last 10% of the book ( $T_{\text{comp}}$ ,  $h_{\text{avg}} = 6.32$ ) relative to those used between 30% and 40% ( $T_{\text{ref}}$ ,  $h_{\text{avg}} = 4.82$ ). For this particular measurement, we employed the ‘word lens’ which excluded words with  $3 < h_{\text{avg}} < 7$ .



We will use the following probability notation for the normalized frequency of a given word  $w$  in a text  $T$ :

$$\Pr(w|T; L) = \frac{f(w|T; L)}{\sum_{w' \in L} f(w'|T; L)}, \quad (1)$$

where  $f(w|T; L)$  is the frequency of word  $w$  in  $T$  with word lens  $L$  applied [16]. (For the example word shift above, we have  $L = \{[1, 3], [7, 9]\}$ .) We then estimate the happiness score of any text  $T$  as

$$h_{\text{avg}}(T; L) = \sum_{w \in L} h_{\text{avg}}(w) \Pr(w|T; L), \quad (2)$$

where  $h_{\text{avg}}(w)$  is the average happiness score of a word as determined by our survey.

We can now express the happiness difference between

two texts as follows:

$$\begin{aligned} & h_{\text{avg}}(T_{\text{comp}}; L) - h_{\text{avg}}(T_{\text{ref}}; L) \\ &= \sum_{w \in L} h_{\text{avg}}(w) \Pr(w|T_{\text{comp}}; L) - \sum_{w \in L} h_{\text{avg}}(w) \Pr(w|T_{\text{ref}}; L) \\ &= \sum_{w \in L} h_{\text{avg}}(w) [\Pr(w|T_{\text{comp}}; L) - \Pr(w|T_{\text{ref}}; L)] \\ &= \sum_{w \in L} [h_{\text{avg}}(w) - h_{\text{avg}}(T_{\text{ref}}; L)] \\ &\quad \times [\Pr(w|T_{\text{comp}}; L) - \Pr(w|T_{\text{ref}}; L)], \end{aligned} \quad (3)$$

where we have introduced  $h_{\text{avg}}(T_{\text{ref}}; L)$  as base reference for the average happiness of a word by noting that

$$\begin{aligned} & \sum_{w \in L} h_{\text{avg}}(T_{\text{ref}}; L) [\Pr(w|T_{\text{comp}}; L) - \Pr(w|T_{\text{ref}}; L)] \\ &= h_{\text{avg}}(T_{\text{ref}}; L) \sum_{w \in L} [\Pr(w|T_{\text{comp}}; L) - \Pr(w|T_{\text{ref}}; L)] \\ &= h_{\text{avg}}(T_{\text{ref}}; L) [1 - 1] = 0. \end{aligned} \quad (4)$$

We can now see the change in average happiness between a reference and comparison text as depending on how these two quantities behave for each word:

$$\delta_h(w) = [h_{\text{avg}}(w) - h_{\text{avg}}(T_{\text{ref}}; L)] \quad (5)$$

and

$$\delta_p(w) = [\Pr(w|T_{\text{comp}}; L) - \Pr(w|T_{\text{ref}}; L)]. \quad (6)$$

Words can contribute to or work against a shift in average happiness in four possible ways which we encode with symbols and colors:

- $\delta_h(w) > 0$ ,  $\delta_p(w) > 0$ : Words that are more positive than the reference text’s overall average and are used more in the comparison text (+↑, strong yellow).
- $\delta_h(w) < 0$ ,  $\delta_p(w) < 0$ : Words that are less positive than the reference text’s overall average but are used less in the comparison text (-↓, pale blue).
- $\delta_h(w) > 0$ ,  $\delta_p(w) < 0$ : Words that are more positive than the reference text’s overall average but are used less in the comparison text (+↓, pale yellow).
- $\delta_h(w) < 0$ ,  $\delta_p(w) > 0$ : Words that are more positive than the reference text’s overall average and are used more in the comparison text (-↑, strong blue).

Regardless of usage changes, yellow indicates a relatively positive word, blue a negative one. The stronger colors indicate words with the most simple impact: relatively positive or negative words being used more overall.

We order words by the absolute value of their contribution to or against the overall shift, and normalize them as percentages.

### Simple Word Shifts

For simple inset word shifts, we show the 10 top words in terms of their absolute contribution to the shift.

Returning to the inset word shift above, we see that an increase in the abundance of relatively positive words ‘excellence’ ‘mer’ and ‘rêve’ (+↑, strong yellow) as well as a decrease in the relatively negative words ‘prison’ and ‘prisonnier’ (−↓, pale blue) most strongly contribute to the increase in positivity. Some words go against this trend, and in the abbreviated word shift we see less usage of relatively positive words ‘liberté’ and ‘été’ (+↓, pale

yellow).

The normalized sum total of each of the four categories of words is shown in the summary bars at the bottom of the word shift. For example,  $\Sigma+\uparrow$  represents the total shift due to all relatively positive words that are more prevalent in the comparison text. The smallest contribution comes from relatively negative words being used more (−↑, strong blue).

The bottom bar with  $\Sigma$  shows the overall shift with a breakdown of how relatively positive and negative words separately contribute. For the Count of Monte Cristo example, we observe an overall use of relatively positive words and a drop in the use of relatively negative ones (strong yellow and pale blue).