Outline

Measuring Happiness & Health
   Introduction
   The Hedonometer
   Mental Health
How do I look in these tweets? Gauging well-being through “caloric content” of tweets

Sharon E. Alajajian, Jake R. Kerr, and Xiaoxia Wang

We provide all data in the Supporting Information and with the paper’s Online Appendices:

address a sim-

food-based Twitter metric.

within a city may not be a large enough sample for any

we have not tried using the metric on counties or Cen-

the physical activity phrase list (just over 13,400 phras-

food list (just over 1400 phrases) is much smaller than

findings may be due to several factors: (a) the size of the

the food list was not. We believe that these preliminary

ty list to be robust to random partitioning [36], whereas

city level, but the food measure may not be accurate on

activity metric on its own may be quite e

IV. METHODS AND MATERIALS

In order to attempt to estimate the “caloric content”

We propose to use crowdsourcing as a way to build a

more comprehensive food phrase list that includes com-

In our LEAD model, we rank 64 food items (covering

An archived visualization by

The Lexicocalorimeter: Gauging public health input through caloric input and output on social media." 2017.
"Instagram photos reveal predictive markers of depression." 2017.
"Forecasting the onset and course of mental illness with Twitter data." 2017.
Outline

Measuring Happiness & Health

Introduction
The Hedonometer
Mental Health
Measuring the happiness of words

Goal:

- Our overall aim is to assess how people feel about individual words.
- With this particular survey, we are focusing on the dual emotions of happiness and sadness.

Time required:

- 6 to 8 minutes.

Instructions and Example:

- You are to rate individual words on a 9 point unhappy-happy scale:

  sunshine

1. Read the word, ("sunshine" in the above example) and observe your emotional response.
2. Click on the face that best corresponds to your response.
Hedonometer
Measuring Happiness & Health

Introduction
The Hedonometer
Mental Health

Prediction and Catastrophe
Winning: it's not for everyone

The Theory of Anything

References

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### Measuring Happiness & Health

**Introduction**

The Hedonometer

**Mental Health**

Frame 7/49

#### Language Assessment by Mechanical Turk

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A Frequency-Independent Happiness Bias

![Bar chart showing frequency distribution of happiness values.](chart.png)
A Frequency-Independent Happiness Bias

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Table I: Details of the four corpora we examined for positivity bias.

![Graphs showing positivity bias in the English language](image_url)
Add Pinker

Past studies have shown a strong consistency of happiness ratings across different languages. Each of our corpora was restricted to certain regions or countries, for example, Brazilian Portuguese, Korean, Simplified Chinese, Russian, Spanish, Portuguese, Indonesian, and Arabic. The sources of our corpora were varied, including English: Music Lyrics, Russian: Google Books, Korean: Twitter, Indonesian: Twitter, Arabic: Movie and TV subtitles, French: Google Books, German: Twitter, English: New York Times, Spanish: Google Books, and Portuguese: Twitter.

For each language, we paid native speakers to rate how they felt in response to individual words on a 1 to 9 scale, with 1 corresponding to most negative or saddest, 5 neutral, and 9 happiest. We used word usage frequency as the primary organizational measure, and perception of language components as a differential scale functions as a measure of a word's importance. Such a data-driven approach is crucial for both understanding the structure of language and for creating linguistic instruments.

On the increase in altruism, the New York Times. It's surprising; people think negativity will be there.

The meaningful atoms of language encode a prosocial focus...
To explore the positivity of human language, we conducted surveys to assess the perceived happiness of words. For each language, we paid native speakers to rate how happy or sad they felt in response to individual words on a 1 to 9 scale, with 1 corresponding to most negative or saddest, 5 neutral, and 9 extremely positive. Overall, we collected 50 ratings per word.

In Fig. 1, we show the distributions of perceived average word happiness across different languages. The histograms represent the frequency distribution of word happiness ratings. Each histogram is normalized to fit the shape of natural language, and even after language translation, the shape remains consistent across different languages.

The red vertical line indicates the median value of happiness ratings, and the background color (green, yellow, blue) reflects the spread of ratings, with green indicating negativity, yellow indicating positivity, and blue indicating neutrality. The distributions are arranged according to increasing variance, and the deciles of adjacent distributions are highlighted to show the spread of happiness ratings.

The meaningful atoms of language encode a prosocial component, which is reflected in the positive bias observed across different languages.

Past studies have shown a strong consistency of happiness evaluations for words, varying little with demographic details. This semantic distribution of language is approximately 10,000 words for each language. By contrast, earlier studies focusing on meaning and emotion restricted to certain regions or countries, for example, the New York Times or Google Web Crawl.

We take word usage frequency as the primary organizing factor for principled measurements. The sources of our corpora contain between 5,000–10,000 of the most frequently used words, chosen so that we have culturally diverse languages including English, Spanish, Portuguese, Arabic, Chinese, and others. The distributions are ordered by increasing median (red vertical line). The background grey negativity (green) and extremity positivity (yellow) are indicated.

One or two intro paragraphs.

Negative emotional responses help us avoid danger. On the increase in altruism, earlier studies focusing on meaning and emotion, and perception of language.
KRAMER: what did you go up there to heckle her for JERRY? because she came down to the club and heckled me give her a taste of her own medicine. opening monologue to me the thing about birthday parties is that the first birthday party you have and the last birthday party you have are actually complex, you know you just kind of sit there you're the least excited person at the party you don't even really realize that there is a party. you don't know what's going on behind the scenes. people have to kinda help you blow out the candles you can't do it yourself. you don't even know why you're doing it. there's this thing that is going on. it's also the only two birthday parties where other people have to gather your friends for you sometimes they do it on their own. even your friends then make the invitations then bring em in and then sit down and then tell you these are your friends tell them thank you for coming to my birthday party. KRAMER: yeah then after the ambulance left i found the toe so i put it in a cracker jack box filled it with ice and took off for the hospital. KRAMER: holy cow KRAMER: yeah yeah then all of a sudden this guy pulls out a gun well i knew any delay is gonna cost her pinky toe. i'm out of the seat and i started walking towards him he says do you think you're gonna crack me. i said well i got a little prize for ya buddy knocked him out cold. KRAMER: how could you do that KRAMER: then everybody is screaming because the driver he's put out of the whole commotion the bus is out of control so i grab him by the collar i take him out of the seat i get behind the wheel and now i'm drivin the bus. KRAMER: i'm batman. KRAMER: yeah yeah i am batman then the mugger he comes to and he starts choking me so i'm fighting him off with one hand and i kept drivin the bus with the other i'm screamin then i managed to open up the door and i kicked him out the door. you know with my foot you know at the next stop JERRY: you kept makin all the stops KRAMER: well people kept ringing the bell. KRAMER: how what about the toe what the little guy is back in place at the end of the line. KRAMER: you did all this for a pinky toe what KRAMER: well it's a valuable appendage.
Unhappiness (we’re working on it)

Some obvious problems/issues:

- Partial coverage of all words.
Unhappiness (we’re working on it)

Some obvious problems/issues:

- Partial coverage of all words.
- Context is ignored.
Unhappiness (we’re working on it)

Some obvious problems/issues:

- Partial coverage of all words.
- Context is ignored.
- Word evaluations distributed in space, time.
Unhappiness (we’re working on it)

Some obvious problems/issues:

- Partial coverage of all words.
- Context is ignored.
- Word evaluations distributed in space, time.

Clearly:

- Only suitable for large-scale texts.
Outline

Measuring Happiness & Health
  Introduction
  The Hedonometer
  Mental Health
Twitter—Spontaneous Bursts of Being

Daily trends

count fraction

hour of day (local time)

starving (0.06)
chicken (0.35)
hungry (0.42)
eat (0.98)
food (1.00)

Dodds et al. PLoS ONE 2011
Twitter—The Happiest Distribution...

Breaking: Two Explosions in the White House and Barack Obama is injured
Breaking: Two Explosions in the White House and Barack Obama is injured.
Twitter—Cartography
Twitter—Manhattan Happiness
Twitter—Manhattan Happiness
Standing at the happiest spot in NYC!
onehappybird.com/2012/03/22/que ...
pic.twitter.com/7IZUDlik9Y
TELL US WHY
YOU'RE HAPPY
FOR A CHANCE
TO WIN A TRIP
FOR 2 TO JAMAICA!

INCLUDE
#HAPPYNYC
IN YOUR TWEET TO ENTER

Clear Channel Outdoor

JAMAICA
Once you go, you know.

TIMES SQUARE IS THE HAPPIEST PLACE IN NEW YORK!

compiled by tracking tweets that included specific "happy" and "sad" words. - the university of vermont

complete terms and conditions available at facebook.com/ccoutdoor
Twitter—Cities

Chicago, IL-IN

Total tweets: 407,239
Average happiness: 5.96

Mitchell et al. PLoS ONE 2013
Twitter—Cities

Durham, NC

Total tweets: 32544
Average happiness: 5.92
Eggheads find Beaumont IS the ‘saddest city’

Tuesday, February 19, 2013 by: gator

That’s what some eggheads at the Department of Mathematics and Statistics at the University of Vermont have determined.
I’ve lived in quite a few places. The most recently Beaumont, TX. It's a pure hellhole. Hot, humid, trashy, terrible schools, corrupt government, lots of crime, no public parks or activities, terrible culture (other than crawfish boils), completely lacks diversity. This study confirms my suspicions that cities don’t get any more miserable than this.
Beaumont
is not
ARS
Figure 1: Choropleth showing average word happiness for geotagged tweets in all US states collected during the calendar year 2011. The happiest 5 states, in order, are: Hawaii, Utah, Idaho, Maine and Washington. The saddest 5 states, in order, are: Louisiana, Mississippi, Maryland, Michigan and Delaware.

Using this method we identify Napa, California as the happiest city in the US with a score of 6.26, and Beaumont, Texas as the saddest city with a score of 5.83.

Perhaps surprisingly, several cities that ranked both highly and lowly by our measure rank similarly in more traditional survey-based efforts. For example, a Gallup-Healthways well-being survey for 2011 [16] showed Boulder, Colorado as the city with the fifth highest well-being index composite score (and twelfth highest happiness score in our list), while Flint, Michigan had the second lowest and Montgomery, Alabama the 21st-lowest well-being index (compared to 8th lowest and 14th lowest happiness scores on our list). The overall Spearman correlation between the rankings using Gallup's well-being index and with our measure is $\rho = 0.328$, with $p$-value $7.73 \times 10^{-6}$ (a scatter plot is presented in Appendix B). Whereas our list uses only word frequencies in the calculation of $h_{avg}$, the Gallup-Healthways score is an average of six indices which measure life evaluation, emotional health, work environment, physical health, healthy behaviors, and access to basic necessities. We remark that our method is (a) far more efficient to implement than a survey-based approach, and (b) provides a near real-time stream of information quantifying well-being in cities.

To investigate why the average word happiness varies across urban areas, we study the word shift graphs [7, 8] for each city. These graphs show how...
**Happiness**: Average word happiness calculated using LabMT 1.0 and geotagged tweets from 2011

**Gun violence**: Shootings per 100,000 people (2011)

**Peace Index**: Composite index of Homicides per 100,000 people, violent crimes per 100,000 people, Jailed population per 100,000 people, Police officers per 100,000 people, ease of access to small arms (2011)

**AHR Score**: America’s Health Ranking, composite index of Behavior, Community & Environment, Policy and Clinical Care metrics (2011)

**BRFSS Score**: Average score from the Behavioral Risk Factor Surveillance System survey (2005–2008)

Mitchell et al. PLoS ONE 2013
The Daily Unravelling of the Human Mind

2009–05–21 to 2010–12–31:

\( h_{\text{avg}} \)

\begin{figure}
\begin{center}
\includegraphics[width=\textwidth]{figure}
\end{center}
\end{figure}

The Hedonometer

Measuring Happiness & Health

Introduction
The Hedonometer
Mental Health

Frame 27/49
Hedonometer
Measuring Happiness & Health
Introduction
The Hedonometer
Mental Health
#speller130 Andrew Toney spelled the word hedonometer correctly #spellingbee
HAPPINESS METER PROJECTION

An animated loop flashes the entire color spectrum, showing the association we're making between color and happiness.
Looking at the word differences between individuals with large and small radii of gyration in Figure 9, we see that individuals in the large radius group author the happier words than those with a small radius.

Individual word contributions held for 3 of the 4 urban areas (Los Angeles, San Francisco, and Chicago) visualized in Figure 8. Additional word shift comparisons for the four urban areas investigated earlier are provided in the Appendix.

To explain the difference in expressed happiness previously can be resolved by our hedonometer. Scores reflect a small signal, yet one that we have shown to persist through variation in binning and different measures of mobility.

For example, consider the difference between tweets authored close to home. Words going against the trend appear on the left, decreasing the happiness of the 2500km distance relative to the 1km group. Tweets close to home are more likely to contain the positive words ‘me’, ‘lol’, ‘love’, ‘like’, ‘haha’, ‘my’, ‘you’, and ‘good’. Moving clockwise, the three insets in Figure 6 show that happiness increases logarithmically with distance from expected location. Perhaps even more remarkably, we find that happiness increases logarithmically with distance from expected location (A), and gyradius (B). Starting with a large radius use happier words than those with a small radius.

Beyond this least happy distance, remarkably we find an almost identical trend when grouping together all words authored by individuals in each bin are gathered (B). These observed trends exhibited by different mobility groups, we turn to word shift graphs in Figure 6. Words appearing on the right increase the happiness of the average word happiness against the distance from expected location. The average happiness of words written at each distance is plotted (A). Expressed happiness grows logarithmically with distance from expected location. A similar trend is observed when individuals are grouped into ten equally populated bins by their gyradius, and all words authored by individuals in each bin are gathered (B). These observed trends are more likely to contain the negative words ‘no’, ‘don’t’, ‘not’, ‘hate’, ‘loathing’, ‘be in pain’, ‘can’t’, ‘damn’, and ‘never’ than tweets posted close to home. Words going against the trend appear on the left, decreasing the happiness of the 2500km distance relative 1km distance. For example, tweets authored far from an individual’s expected location are more likely to contain the negative words ‘no’, ‘don’t’, ‘not’, ‘hate’, ‘loathing’, ‘be in pain’, ‘can’t’, ‘damn’, and ‘never’ than tweets posted close to home. Words going against the trend appear on the left, decreasing the happiness of the 2500km distance relative 1km distance.

The average happiness of words written 1km away. The least happy words, on average, are individual’s expected location. The average happiness at distances of roughly 1km and 2500km away from an individual’s center of mass are slightly happier than those written 1km away. The least happy words, on average, are individuals rather than tweets, observing that happiness changes with location, we find that tweets written close to an individual’s expected location, and the 50 words listed make up roughly 50% of the total difference between the two bags of words. The happiness difference is the decrease in negative words and the increase in positive words.

The happiness differences between two large texts. As an example, consider the difference between tweets authored close to home. Words going against the trend appear on the left, decreasing the happiness of the 2500km distance relative to the 1km group. Tweets close to home are more likely to contain the positive words ‘me’, ‘lol’, ‘love’, ‘like’, ‘haha’, ‘my’, ‘you’, and ‘good’. Moving clockwise, the three insets in Figure 6 show that happiness increases logarithmically with distance from expected location. Perhaps even more remarkably, we find that happiness increases logarithmically with distance from expected location (A), and gyradius (B). Starting with a large radius use happier words than those with a small radius.

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Twitter—Happiness and Nature

Fig. 2. Affect before, during, and after park visit. Average affect for all user tweets (y-axis), within 24 hours of park exposure, binned by relative hour to in-park tweet (x-axis). The green vertical line represents the tweet in a San Francisco Park, with highest affect value. The blue range is the 95% Confidence Interval of mean affect for that hour bin based on 100 runs of randomly sampling 80% of tweets.

The mean affect benefit for all parks is 0.237 (0.227, 0.248) (Figure 3). As a point of reference, the average day on Twitter in 2016 had a sentiment of 6.04, and Christmas Day was the happiest day in 2016 with a sentiment of 6.26 (http://www.hedonometer.org). Thus, across our user pool, visiting an urban park had a similar affect benefit than did Christmas Day for Twitter as a whole.

Across all parks, we estimate the duration of elevated sentiment excluding tweets inside and within 1 hour of park visits. We find that affect remains elevated for six hours, compared to a baseline level averaged over 1 to 6 hours before park visitation. We estimated this by consecutively comparing the affect of each hour of tweets following park visits with the baseline group of tweets using the bootstrapping procedure.

Fig. 5A-D. Word frequency patterns before and after park visit. X-axis depicts hourly tweet bins from 12 hours before to 12 hours after in-park tweet, which is represented by green line. Y-axis ranges are scaled for each word's relative frequency. Relative frequencies (blue-lines) are smoothed as moving averages over 3 hours. Grey dashed line is mean frequency for entire 24-hour period around park visit.

Fig. 1. San Francisco Recreation and Parks Facility Map.

We constructed a list of Twitter users who had visited at least one park during the study period and queried the Twitter API for their 3,200 most recent tweets. A month later, we updated user histories with any tweets posted since the park visit. We used several heuristics to remove automated bots and businesses from the user sample and additionally removed any individual who made their account private in the period following their park tweet. Our process resulted in 5,065 user timelines.

2.2. Tweet Binning

Schwartz et al “Exposure to urban parks improves affect and reduces negativity on Twitter” In review 2018
Public Opinion

Hedonometer

Measuring Happiness & Health

Introduction

The Hedonometer

Mental Health

Cody et al., "Public Opinion Polling with Twitter". In review, 2017
How do I look in these tweets? Gauging well-being through “caloric content” of tweets

Sharon E. Alajajian, Jake R. Williams, Andrew J. Reagan, Stephen C. Alajajian, Morgan R. Frank, Lewis Mitchell, Jacob Lahne, Christopher M. Danforth, and Peter Sheridan Dodds

We provide all data in the Supporting Information and with the paper’s Online Appendices:

“The Lexicocalorimeter: Gauging public health through caloric input and output on social media”

Sharon E. Alajajian et al.,

"The Lexicocalorimeter: Gauging public health through caloric input and output on social media"

PLoS ONE, 2017
Alajajian et al.,
"The Lexicocalorimeter: Gauging public health through caloric input and output on social media"
PLoS ONE, 2017
Outline

Measuring Happiness & Health
- Introduction
- The Hedonometer
- Mental Health
Research Questions

1. Any difference?

Clinical Population

Healthy Population

2. Pre-diagnosis difference?

Timeline

Diagnosis

Timeline

3. Illness timeline?

Illness

Timeline

Clinical

Healthy
## Data Collection: Descriptives

**Total sample (Clinical sample)**

<table>
<thead>
<tr>
<th></th>
<th>Participants</th>
<th>Posts</th>
<th>Posts/Person</th>
</tr>
</thead>
<tbody>
<tr>
<td>Instagram: Depression</td>
<td>166 (71)</td>
<td>43,950 (24,811)</td>
<td>265 (349)</td>
</tr>
<tr>
<td>Twitter: Depression</td>
<td>204 (105)</td>
<td>279,951 (164,218)</td>
<td>1373 (1564)</td>
</tr>
<tr>
<td>Twitter: PTSD</td>
<td>174 (63)</td>
<td>243,775 (91,589)</td>
<td>1401 (1564)</td>
</tr>
</tbody>
</table>
Barrick et al (2002); Bruce & Hoff (1994); Carruthers et al (2010); DSM-IV (2000)
Compared to a century ago, the world is much better off, says Harvard scholar Steven Pinker
### Precision vs Recall

20 people
10 depressed
8 diagnosed

<table>
<thead>
<tr>
<th></th>
<th>Predict Healthy</th>
<th>Predict Depressed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Healthy</td>
<td>7</td>
<td>3</td>
</tr>
<tr>
<td>Actual Depressed</td>
<td>5</td>
<td>5</td>
</tr>
</tbody>
</table>

**Recall** = proportion of known cases discovered = \( \frac{3}{10} = 0.5 \)

**Precision** = proportion of diagnosed cases which are correct = \( \frac{5}{8} = 0.625 \)
Detecting Depression: “All Data” Models

Reece & Danforth, "Instagram photos reveal predictive markers of depression." EPJ Data Science, 2017
Reece et al., "Forecasting the onset & course of mental illness with Twitter data." Scientific reports, 2017
Detecting Depression: Pre-Diagnosis Models

Reece & Danforth, "Instagram photos reveal predictive markers of depression." EPJ Data Science, 2017
Reece et al., "Forecasting the onset & course of mental illness with Twitter data." Scientific reports, 2017
Both All-data and Pre-diagnosis models were decisively superior to a null model. All-data predictors were significant with 99% probability. 

Pre-diagnosis and All-data confidence levels were largely identical, with two exceptions: Pre-diagnosis Brightness decreased to 90% confidence, and Pre-diagnosis posting frequency dropped to 30% confidence, suggesting a null predictive value in the latter case.

Increased hue, along with decreased brightness and saturation, predicted target class observations. This means that photos posted by depressed individuals tended to be bluer, darker, and grayer (see Figure 1). The more comments Instagram posts received, the more likely they were posted by depressed participants, but the opposite was true for likes received. In the All-data model, higher posting frequency was also associated with depression. Depressed participants were more likely to post photos with faces, but had a lower average face count per photograph than healthy participants. Finally, depressed participants were less likely to apply Instagram filters to their posted photos.

A closer look at filter usage in depressed versus healthy participants provided additional texture. Instagram filters were used differently by target and control groups. Comparing point estimates of accuracy metrics is not as straightforward as it might seem. However, we felt it was more meaningful to reflect on our findings in a realistic context, rather than to benchmark against a naive statistical model that simply predicted the majority class for all observations.
Results

Both All-data and Pre-diagnosis models were decisively superior to a null model. All-data predictors were significant with 99% probability.

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Fig. 2. Magnitude and direction of results in All-data (N=24,713) and Pre-diagnosis (N=18,513) models. X-axis values represent the adjustment in odds of an observation belonging to the target class, per unit increase of each predictive variable. Odds were generated by exponentiating log-odds coefficients.

A closer look at filter usage in depressed versus healthy participants provided additional texture. Instagram filters were used differently by target and control groups.
Instagram filter usage difference between depressed and healthy users

- Valencia: Adds a high contrast and also makes your photos black and white.
- Inkwell: Edits high contrast and also makes your photos black and white.

Filter names:
- Valencia
- X-Pro II
- Hefe
- Amaro
- Rise
- Lo-fi
- Walden
- Kelvin
- Unknown
- Earlybird
- Clarendon
- Toaster
- 1977
- Mayfair
- Nashville
- Hudson
- Brannan
- Sierra
- Gotham
- Popsocket
- Maven
- Moon
- Vesper
- Ginza
- Lark
- Aden
- Gingham
- Ludwig
- Skyline
- Helena
- Dogpatch
- Sullo
- Perpetua
- June
- Aechy
- Slumber
- Sinson
- Reyes
- Willow
- Crema
- Inkwell

Usage difference (Chi^2 observed-expected):

- Healthy
- Depressed
Finding: Human and Machine assessments are uncorrelated
Instagram photos reveal predictive markers of depression: epjdatascience.springeropen.com/articles/10.11... My feed at height of my depression vs. now. #depression
In it for the good time
Tracking Depression onset with state-space modeling

Reece et al.
"Forecasting the onset and course of mental illness with Twitter data."
Scientific Reports, 2017
Reece et al.  
"Forecasting the onset and course of mental illness with Twitter data."  
Scientific Reports, 2017
#17 of 100

Instagram photos reveal predictive markers of depression

Studies in Human Society  |  Published in EP2 Data Science  |  August 2017

OPEN ACCESS

What do your social media posts say about you? This study analyzed the correlation between colours in Instagram photos and people's mental health - finding that those who used darker colours were more likely to have signs of or be suffering from depression.

Authors
Andrew C. Reece, Christopher M. Danforth

Institutions
Harvard University, University of Vermont

Countries
United States

The Washington Post

Your Instagram feed can tell us if you’re depressed, study suggests

The New York Times

The photos you share on Instagram may hold clues to your mental health, new research suggests

Your Instagram Posts May Hold Clues to Your Mental Health

From the colors in photos to the filters chosen, Instagram users with a history of depression present the world differently, a study suggests.

nytimes.com

8:55 AM - 10 Aug 2017

163 Retweets 324 Likes
Summary

- http://compstorylab.org
Summary

- http://compstorylab.org
- http://hedonometer.org
Summary

- http://compstorylab.org
- http://hedonometer.org
- Remote-sensing for public health
Thanks to NSF and MITRE for funding.