PUBLIC HEALTH MEETS SOCIAL MEDIA:
MINING HEALTH INFO FROM TWITTER

Michael Paul (@mjp39)
Johns Hopkins University

Crowdsourcing and Human Computation
Lecture 18

Learning about the real world through Twitter

- Millions of people share on the web what they are doing every day
- Can analyze social media to infer what is happening in a population
  - Can make inferences about the population's **health**
- **Passive** data monitoring
  - Work with data that's already out there
  - vs active methods: soliciting data from people (e.g. surveys)
- Faster, cheaper than traditional data collection – but noisier

This lecture: Key ideas

- Applications
  - What can we learn about health?
    (and why would we want to do that?)
- Methods
  - How do you mine Twitter?
- Evaluation
  - How accurate is the mined data?
- Ethics
  - How does social media mining fit in with current medical research practices?

Twitter: Data

- Free streams of data provide 1% random sample of public status messages (tweets)

- Search streams provide tweets that match certain **keywords**
  - Still capped at 1%, but more targeted
  - We collect tweets matching any of 269 health keywords

```
,sick,cold,body,pain,hurts,sore,nose,hospital,doctor,cancer,u
,burning,flu,exhausted,medicine,surgery,knee,cough,fever,doct
ise,cure,eaten,dentist,vision,bedtime,physical,treatment,pill
t,ache,ankle,pill,numb,recovery,physically,wrist,depression,h
y,clinic,pains,jaw,sneeze,lungs,swollen,puke,anxiety,appt,rec
petite,resting,coughing,infection,diabetes,migraine,sickness,
```

  - https://dev.twitter.com/docs/streaming-apis/keyword-matching
  - https://github.com/mdredze/twitter_stream_downloader

Twitter: Location data

- **Geolocation:** often we need to identify where the authors of tweets are located

- Some tweets tagged with GPS coordinates
  - Only 2-3% of tweets/users
  - Can improve coverage by tenfold by also considering self-reported location in user profiles

Twitter: Location data

- **Geolocation:** often we need to identify where the authors of tweets are located

- *Carmen*
  - Identifies where a tweet is from using GPS + user profile info, e.g.

```
{"city": "Baltimore",
"state": "Maryland",
"country": "United States"}
```

  - Java (python coming soon) software available:
    - https://github.com/mdredze/carmen

Twitter: Health data?

- Twitter is a **noisy** data source

- 2012 study (André, Bernstein, Luther):

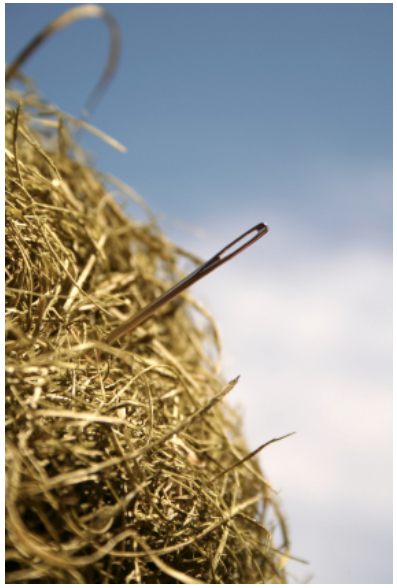
> ratings on Twitter updates. Using our dataset of over 43,000 voluntary ratings, we find that nearly 36% of the rated tweets are worth reading, 25% are not, and 39% are middling. These results suggest that users tolerate a large amount of less-desired content in their feeds. We find that

Twitter: Health data?

- My estimate: about **0.1%** of tweets are about tweeters' health
  - (1.6 million out of 2 billion tweets in an earlier study)

- 0.1% of Twitter is still a lot of data!
  - **~ half a million** tweets per day

- Lots of data, but hard to find in noise
  - Absolutely huge
  - Relatively tiny



Finding health tweets

- Step 1: keyword filtering
  - Filter out tweets unlikely to be about health
  - Large set of 20,000 keywords

- Not all tweets containing keywords are actually about someone's health
  - This tweet contains lots of health keywords:

- Step 2: supervised machine learning

Finding health tweets

- Step 2: supervised machine learning

- Labeled data
  - **5,128** tweets
  - *About health* | *Unrelated to health* | *Not English*

- Labels collected through Mechanical Turk
  - Each tweet labeled by 3 annotators
  - Final label determined by majority vote
  - 10 labels per HIT
  - Each HIT contained 1 gold-labeled tweet to identify poor-quality annotators

Finding health tweets

- About **1%** of tweets contained the 20,000 health keywords
- About **15%** of those were tagged as relevant by the health machine learning classifier

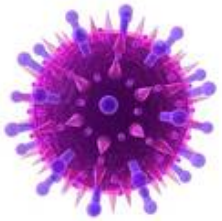
about **0.1%** of all tweets are health-related

- **1.6 million** health tweets from 2009-2010
- Over **150 million** collected since Aug 2011

Health tweets

- So we can we do with health tweets?

Flu surveillance

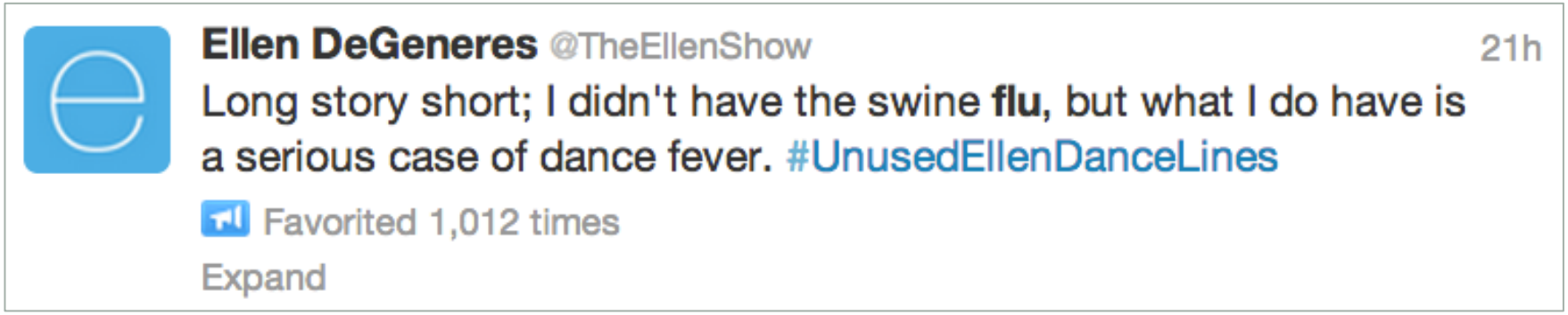


- Idea: people tweet about being sick
- More sick tweets will appear when the flu is going around
  - https://twitter.com/search?q=flu&src=typd&f=realtime
- Why do we care?
  - Cheap data source to complement primary disease surveillance systems (e.g. hospital data, lab work)
  - Real-time, can be automated
  - Lofty goal: early detection of novel, serious epidemics

Flu surveillance

- Goal: identify and count tweets that indicate the user is sick with the flu
  - Proxy for how many people in the population have the flu

- Challenge: not all tweets that mention “flu” actually indicate a person is sick



Finding flu tweets

- As before: supervised machine learning
- Labeled data
  - **11,990** tweets
  - *Flu infection* | *General flu awareness* | *Unrelated to flu*

- Same quality control measures as before
  - Also hand-verified all labels in the end
    - Changed 14% of labels

Finding flu tweets

- Machine learning classifiers identify tweets that indicate **flu infection**

- Many features beyond n-grams:
  - Retweets, user mentions, URLs
  - Part-of-speech information
  - Word classes:

Infection	getting, got, recovered, have, having, had, has, catching, catch, …
Disease	bird, the flu, flu, sick, epidemic
Concern	afraid, worried, scared, fear, worry, nervous, dread, terrified
Treatment	vaccine, vaccines, shot, shots, mist, tamiflu, jab, nasal spray
…	…

Flu surveillance

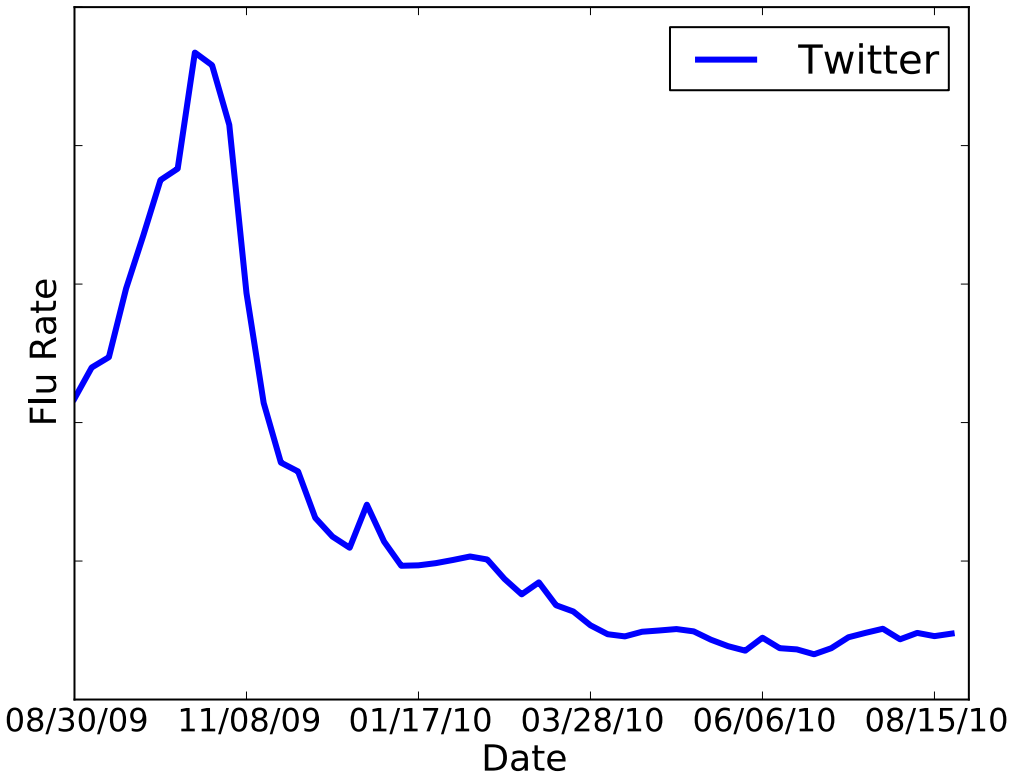
- Estimated weekly rate of flu on Twitter:

$$\frac{\text{\# tweets about flu infection that week}}{\text{\# of all tweets that week}}$$

- Normalize by number of all tweets to adjust for change in Twitter volume over time

Flu surveillance (2009-10)

- Large spike of flu activity around October
  - This was during the swine flu pandemic



- Is this accurate?

Flu surveillance: Evaluation

- Compare our estimates to “ground truth” data

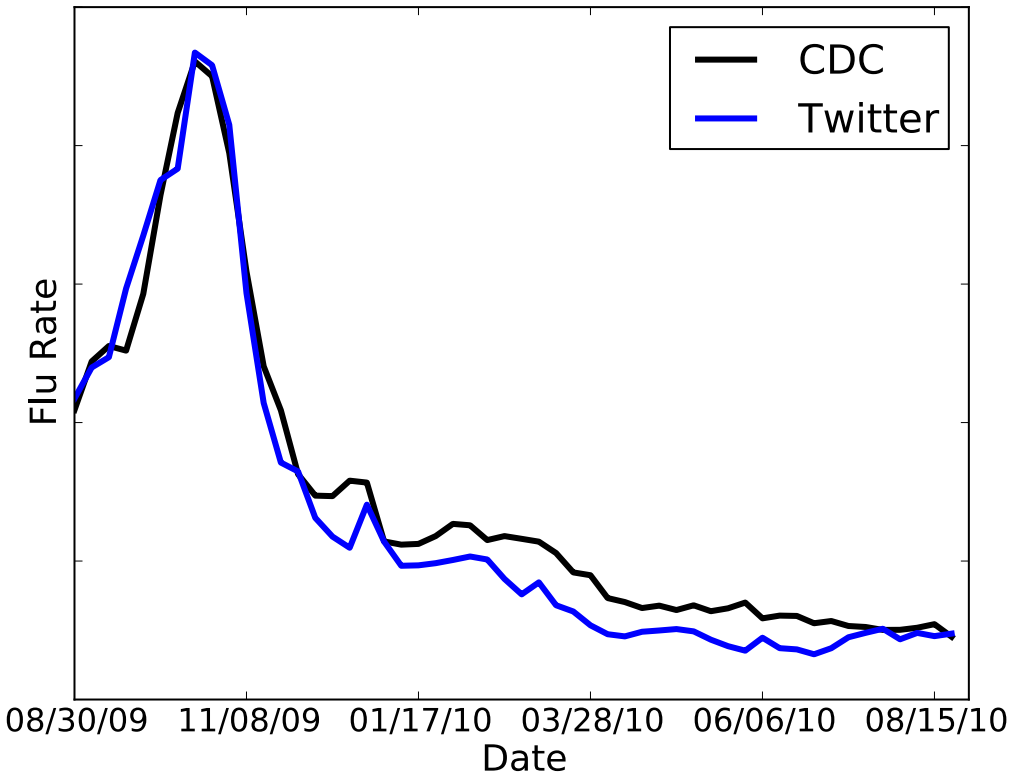
- We take government surveillance data to be ground truth
  - from the CDC (Centers for Disease Control and Prevention)
  - weekly counts of hospital outpatient visits for influenza-like symptoms

- Common metric: Pearson correlation
  - compare temporal trend of Twitter estimates against CDC data

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}}$$

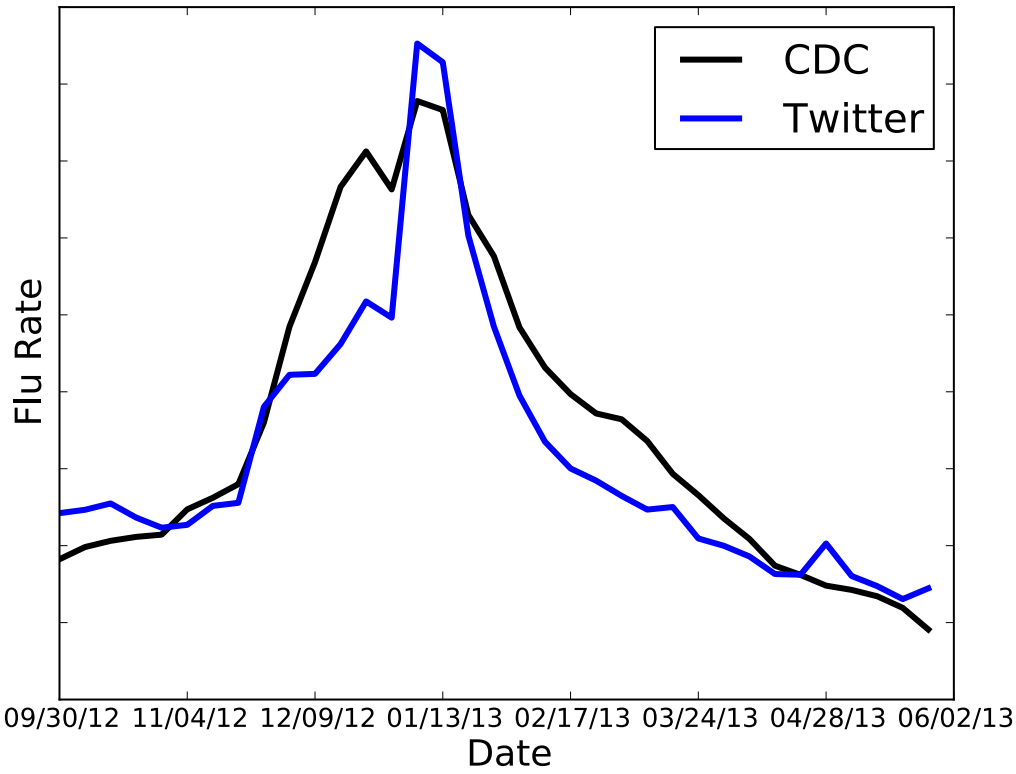
Flu surveillance (2009-10)

- Correlation with CDC: 0**.99**



Flu surveillance (2012-13)

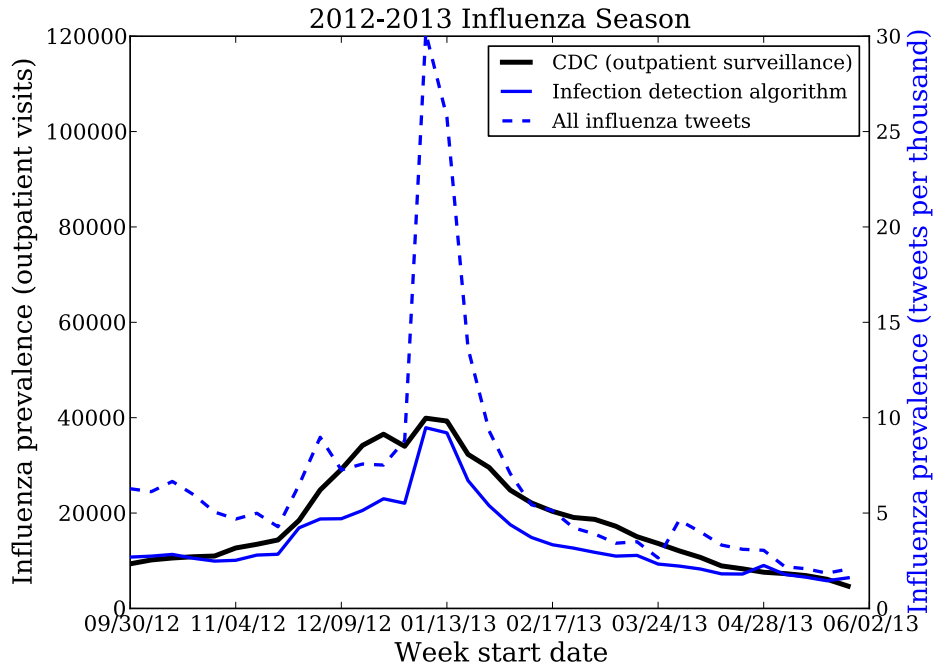
- Correlation with CDC: 0**.93**



Flu surveillance: More evaluation

- What if we just estimate the flu rate by counting tweets containing the words “flu” or “influenza”?

- Not as highly correlated:
  - 2009-10: 0.97 (2% reduction)
  - 2012-13: 0.75 (20% reduction)

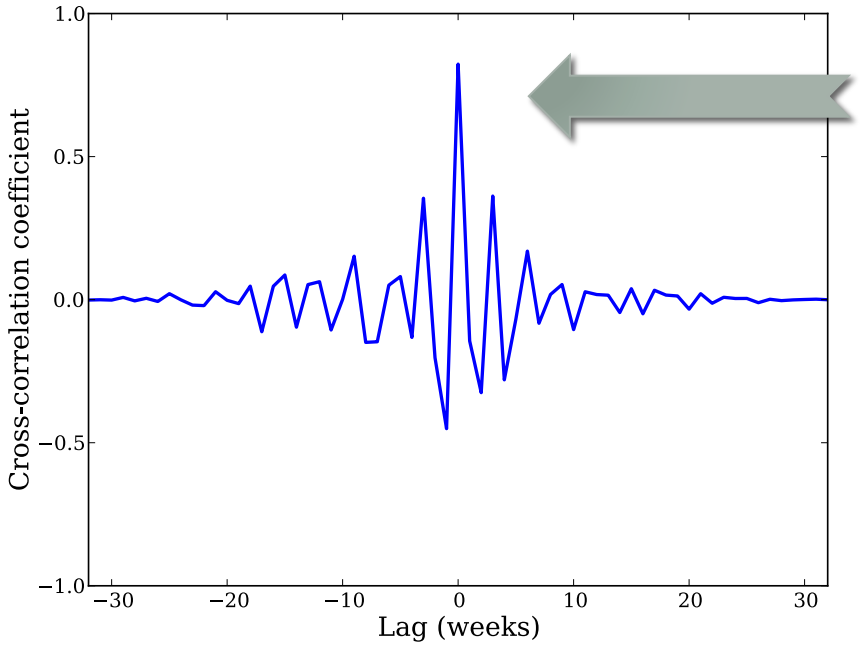


- More spurious spikes from keyword matching

Flu surveillance: More evaluation

- Cross-correlation
  - Measures similarity between curves when one of the trends is offset by some number of weeks (lead/lag)

$$(f \star g)(t) \stackrel{\text{def}}{=} \int_{-\infty}^{\infty} f^*(\tau)\ g(t+\tau)\, d\tau$$



Twitter neither leads/lags CDC (but maybe certain keywords do?)

Flu surveillance: More evaluation

- Basic correlation may overstate how good you are doing
  - As long as the peak weeks have above-average rates and the off-season weeks are below-average, you'll get a pretty high number
  - Especially true if trend has high **autocorrelation** (cross-correlation with itself) at nonzero lag
- Trend **differencing**
  - Subtract previous week's rate from current week
  - Measures correlation of week-to-week increase/decrease
    - More directly measures what you probably care about
- Box-Jenkins methods
  - Guidelines for applying differencing

Flu surveillance: More evaluation

- Simple accuracy
  - How often does the weekly direction of the trend (up or down) match CDC?
- Maybe more interpretable than correlation
- Our Twitter infection classifier:
  - **85%** direction accuracy (2012-13)
  - Simple keyword matching: 46%

Beyond flu

- The flu project was an in-depth study of one disease
  - Machine learning with human annotations
  - Time/labor intensive
  - Rich set of features

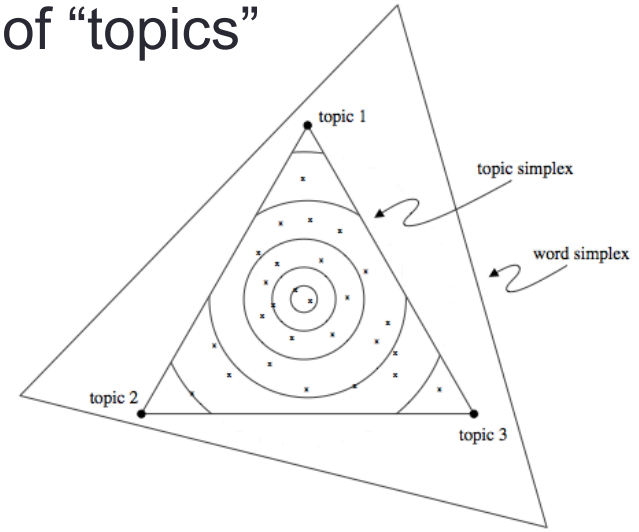
Beyond flu

- The flu project was an in-depth study of one disease
  - Machine learning with human annotations
  - Time/labor intensive
  - Rich set of features

- Alternative approach: broad, exploratory analysis
  - Find lots of diseases on Twitter
  - **Unsupervised** machine learning
    - No human input
  - Simple keyword-based models

Topic modeling

- Statistical model of text generation
  - decomposes data set into small number of “topics”
  - the topics are not given as labels
    - **unsupervised** model

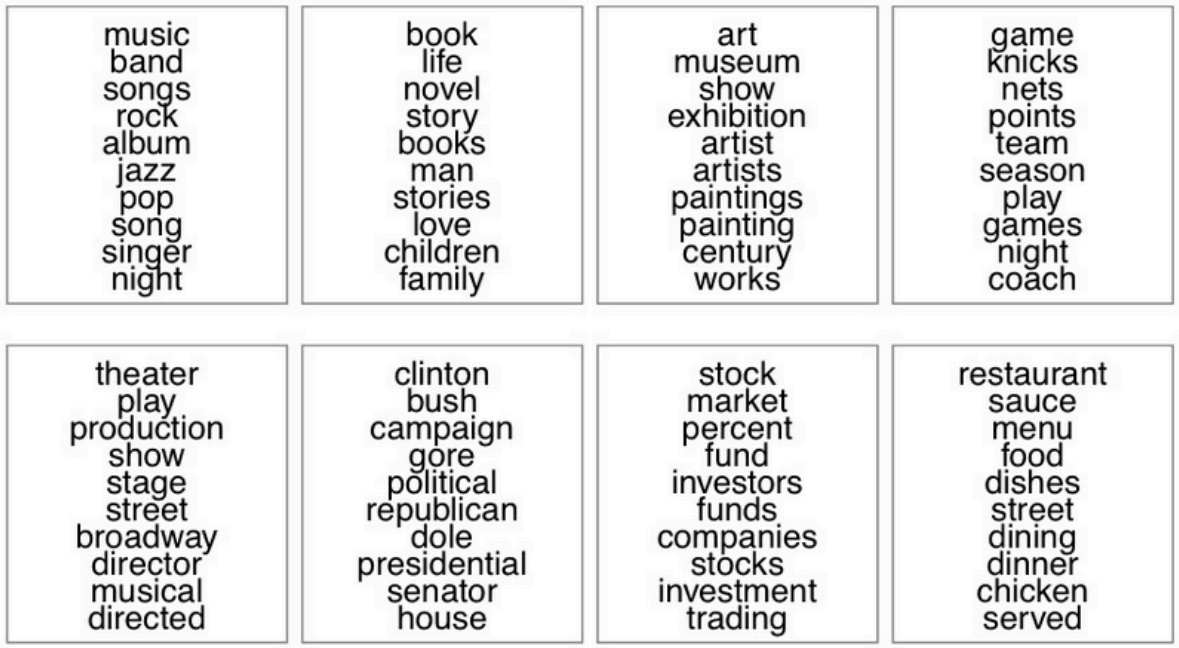


- Two types of parameters:
  - **p(topic|document)** for each document
  - **p(word|topic)** for each topic

- Optimize parameters to fit model to data (a collection of documents)

Topic modeling

- Automatically groups words into topics
- Automatically labels documents with topics
- Example when applied to New York Times articles:

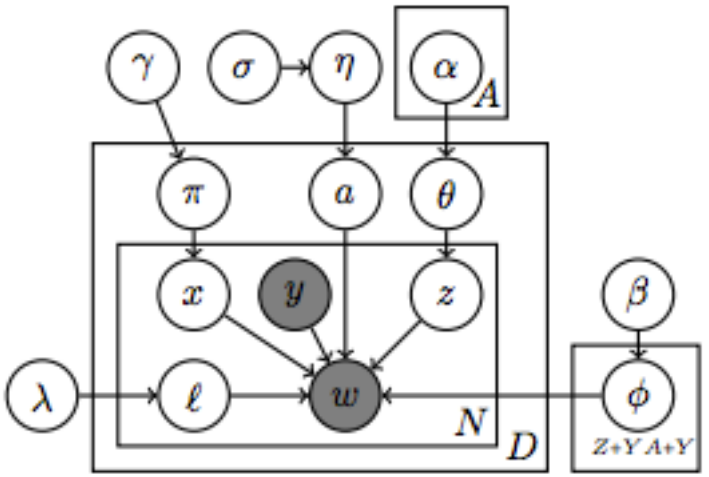


- from Hoffman, Blei, Wang, Paisley

Topic modeling health tweets

- We created a topic model specifically for finding health topics in Twitter

- Ailment Topic Aspect Model (ATAM)
  - Distinguishes health topics from other topics in the data
  - Breaks down health topics by general words, symptom words, treatment words



Topic modeling health tweets

"Aches and Pains"

Topic modeling health tweets

"Insomnia"

Topic modeling health tweets

"Allergies"

Topic modeling: Evaluation

- How accurately do these word clusters correspond to real-world concepts?

- As before: find existing data sources to compare to

Topic modeling: Diet and exercise

- Compare the “diet and exercise” health topic to government survey data about lifestyle factors
- Track rates across U.S. states
  - Geographic trends (vs temporal trends)
- Positively correlated with rates of physical activity and aerobic exercise
  - **0.61** and **0.53**
- Negatively correlated with rates of obesity
  - **-0.63**

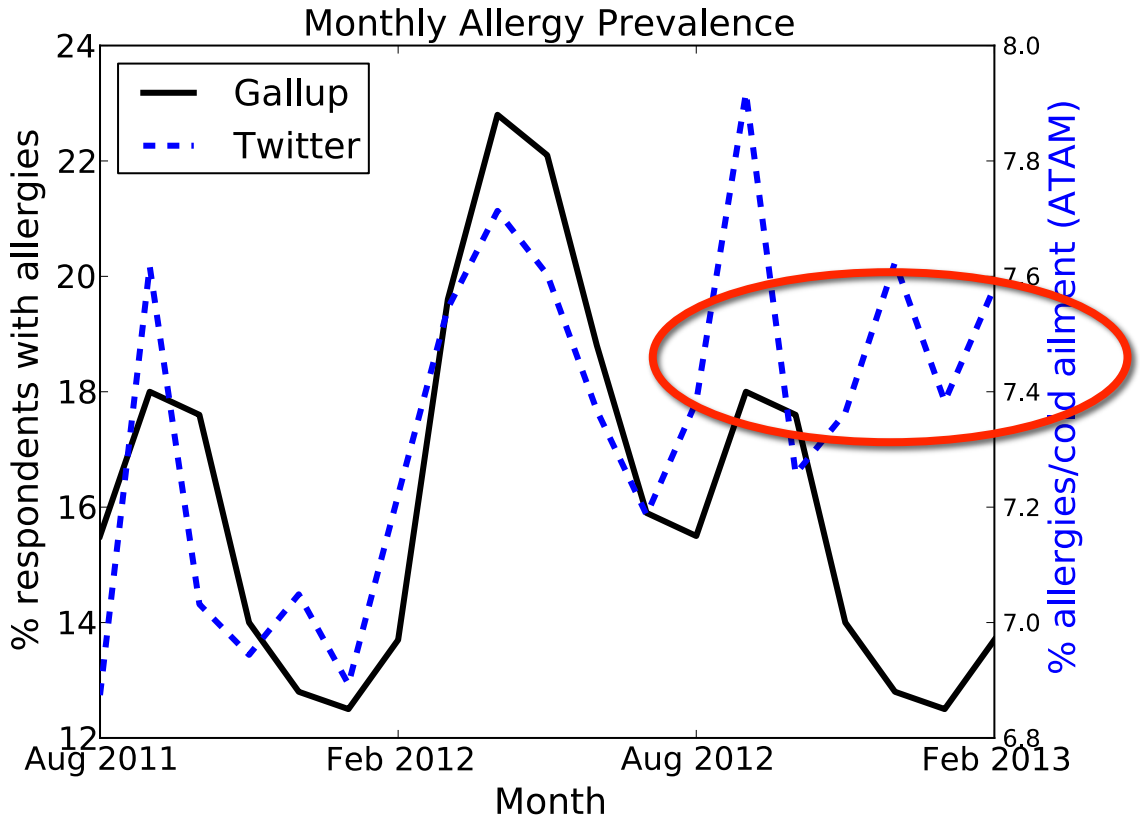
Topic modeling: Allergies

- Allergies aren't part of CDC surveillance systems
  - But private data sources exist

- We compared to phone survey results from Gallup
  - "Were you sick with allergies yesterday?"

Topic modeling: Allergies

- Correlation: **0.48**
  - 2011-12 season only: **0.84**



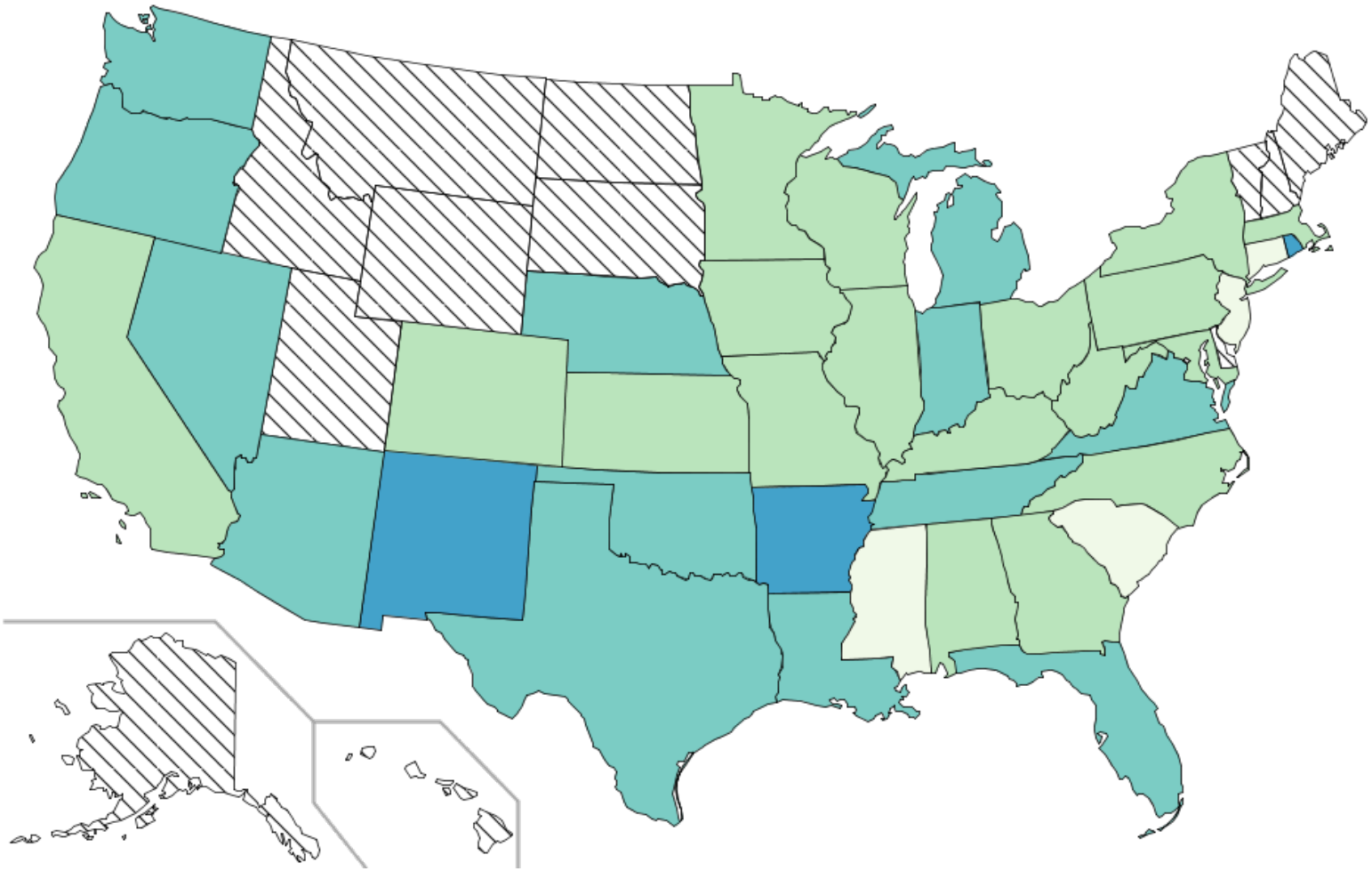
higher predictions in 2012-13; conflated with strong flu season (similar symptoms: coughing, sneezing)

Topic modeling: Evaluation

- Informal evaluation: visualize, check against intuition
- Do word clusters make sense?
  - Is there obvious noise?
    - e.g. cold/flu symptoms mixed with allergies
- Do geographic patterns make sense?
  - Are rates similar in nearby states?

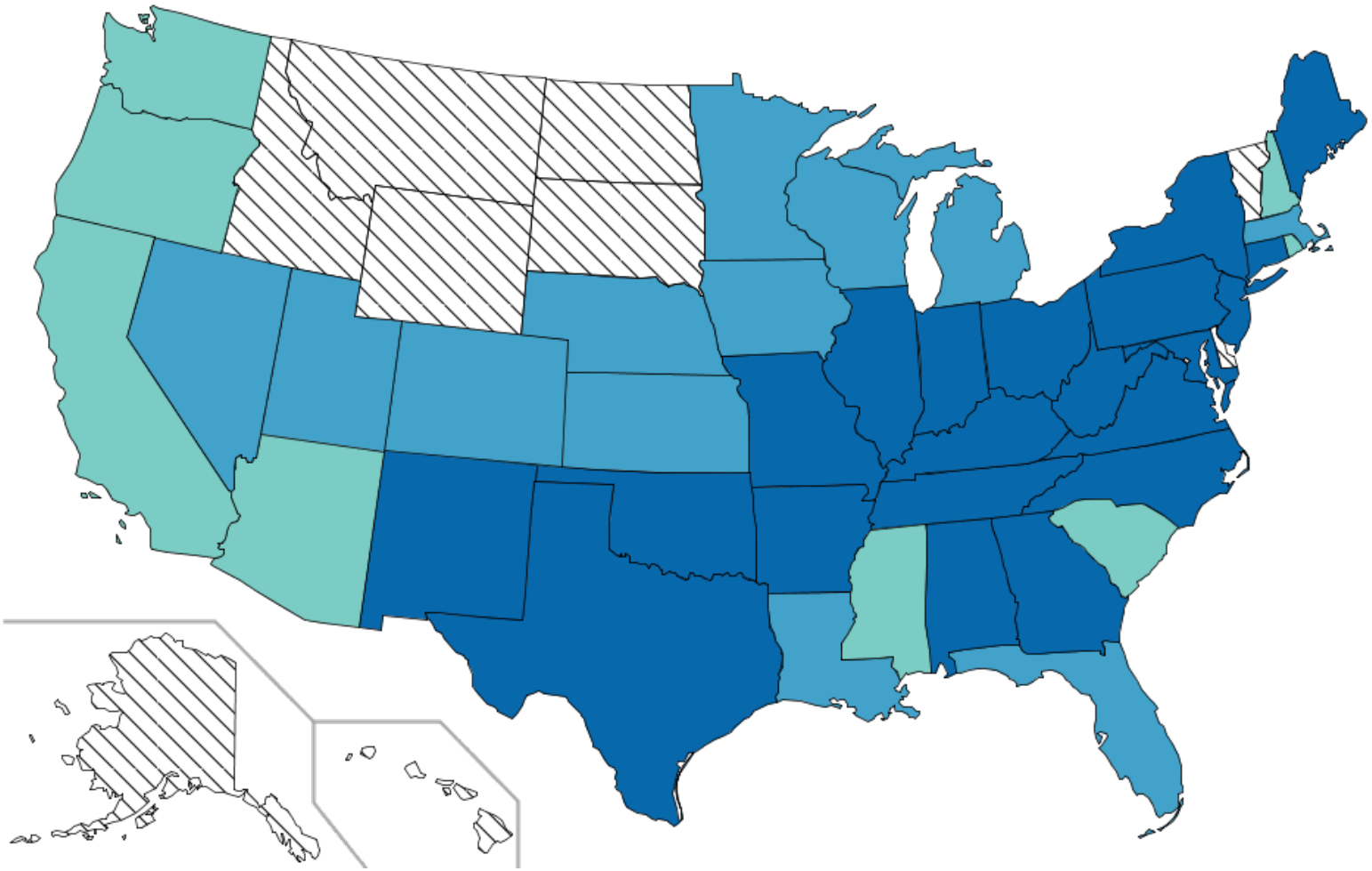
Topic modeling: Allergies

February 2010



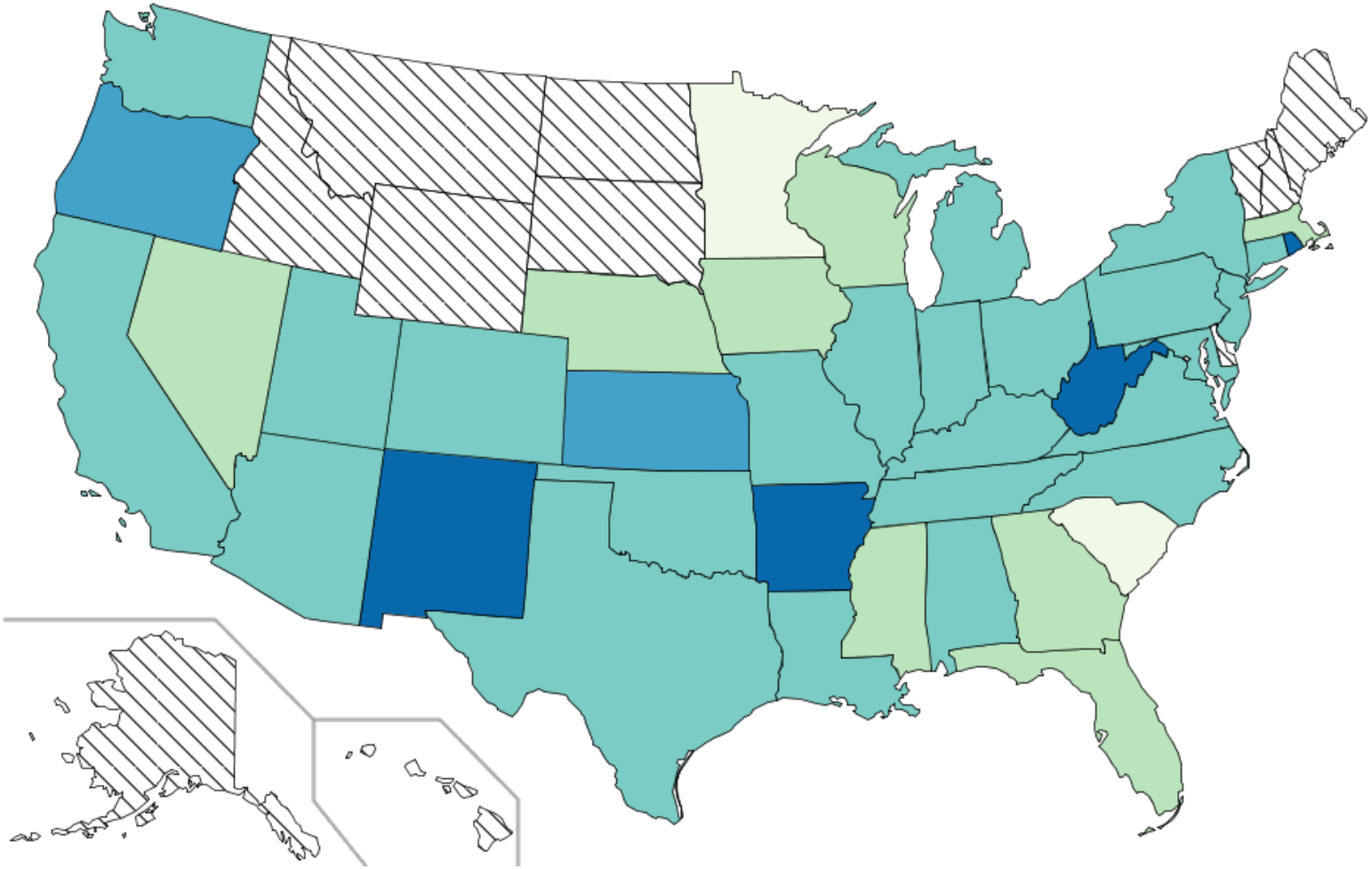
Topic modeling: Allergies

April 2010



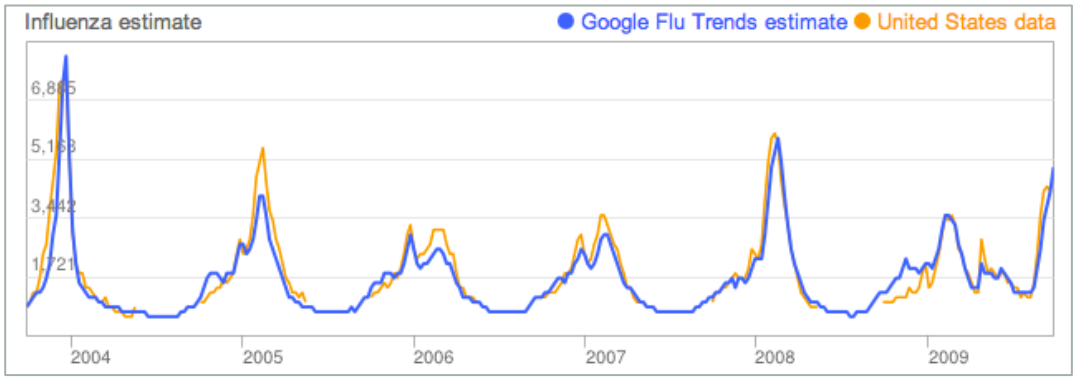
Topic modeling: Allergies

June 2010



Other methods

- (Linear) Regression
  - Explicitly train your system to predict ground-truth data
  - Approach used by Google Flu Trends (and others)



- Manual analysis by humans
  - “small data” approach
  - Good option for ideas too difficult to automate with machine learning

Other applications

- Broad health applications seem to work well enough
  - but the data may not support deeper medical questions
  - people share a lot but not everything
  - demographics differ between real world and social media
    - and can vary a lot between different social media sites

- More hype than substance in many applications
  - Can Twitter predict the **stock market**?
    - I don't know of anyone who has gotten rich from this yet…
  - Can Twitter predict **elections**?
    - If it could, Ron Paul would be president…

Ethics/Privacy

- Ethics is an important part of human subject research
- But there aren't comparable guidelines for "human computation" research
- So here are some things to think about…

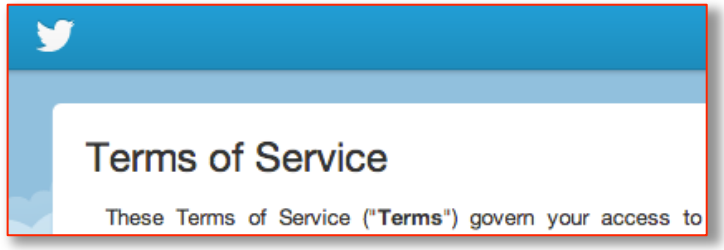
Ethics: Guidelines

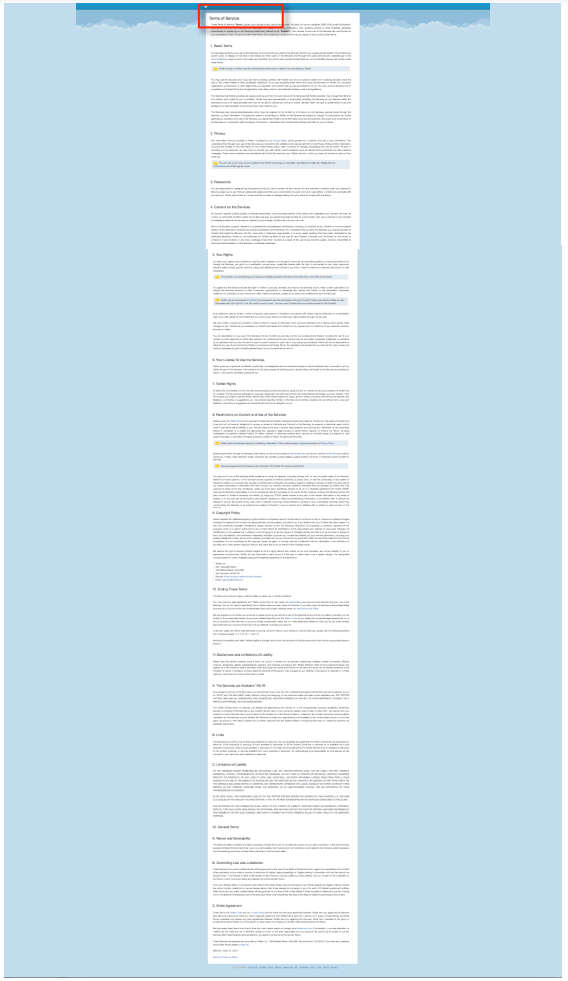
- Modern medical research guided by IRBs (institutional review board)

- IRB policy on social media data mining:
  - Data is public, therefore no approval required
    - This applied to what I showed you today
  - This policy may eventually change

- There are still privacy norms surrounding public data
  - and it's possible to use public data in creepy ways

Ethics: Guidelines





- Informed consent?
- Technically, if people actually read this:
- Tweets are public by default
  - not all users realize this
- Even if users are aware the data is public, they might not expect it to be used in certain ways

Ethics: Privacy

- Aggregate statistics generally preserve privacy
  - as long as they aren't aggregated in a town of 20 people

- Analysis of individual users may deviate from privacy expectations

  - Sadilek, Kautz, Silenzio 2012

Ethics: Privacy

- Health information is particularly sensitive and should be treated differently

- Courtesy of MappyHealth by Social Health Insights

Ethics: Privacy

- Hard to fully anonymize data
  - Same issue with medical records

- Can be de-anonymized with more data, more context

Ethics: Rules of thumb

- Stick to large-scale aggregate analysis
- Don’t use more data than a user likely intended to share
- Don’t use data that you don’t need for what you’re doing
- Think about how users will react to your app or research

- Good reading:
  - Slides by Caitlin Rivers: “Ethical user of Twitter for digital disease detection”
    - http://figshare.com/articles/Ethical_use_of_Twitter_for_DigDisDet/805198
  - Danah Boyd and Kate Crawford. 2012. Critical questions for Big Data. *Information, Communication & Society*: 15(5).

See more

- socialmediahealthresearch.org
- CIKM 2013 tutorial: Twitter and the real world
  - https://sites.google.com/site/twitterandtherealworld/
- Conference on Digital Disease Detection
  - http://healthmap.org/ddd/
- Apps/startups:
  - GermTracker – germtracker.org
  - MappyHealth – mappyhealth.com
  - Sickweather – sickweather.com