Using Social Media for Health Studies

Ingmar Weber
Social Computing, Qatar Computing Research Institute
@ingmarweber

My Journey


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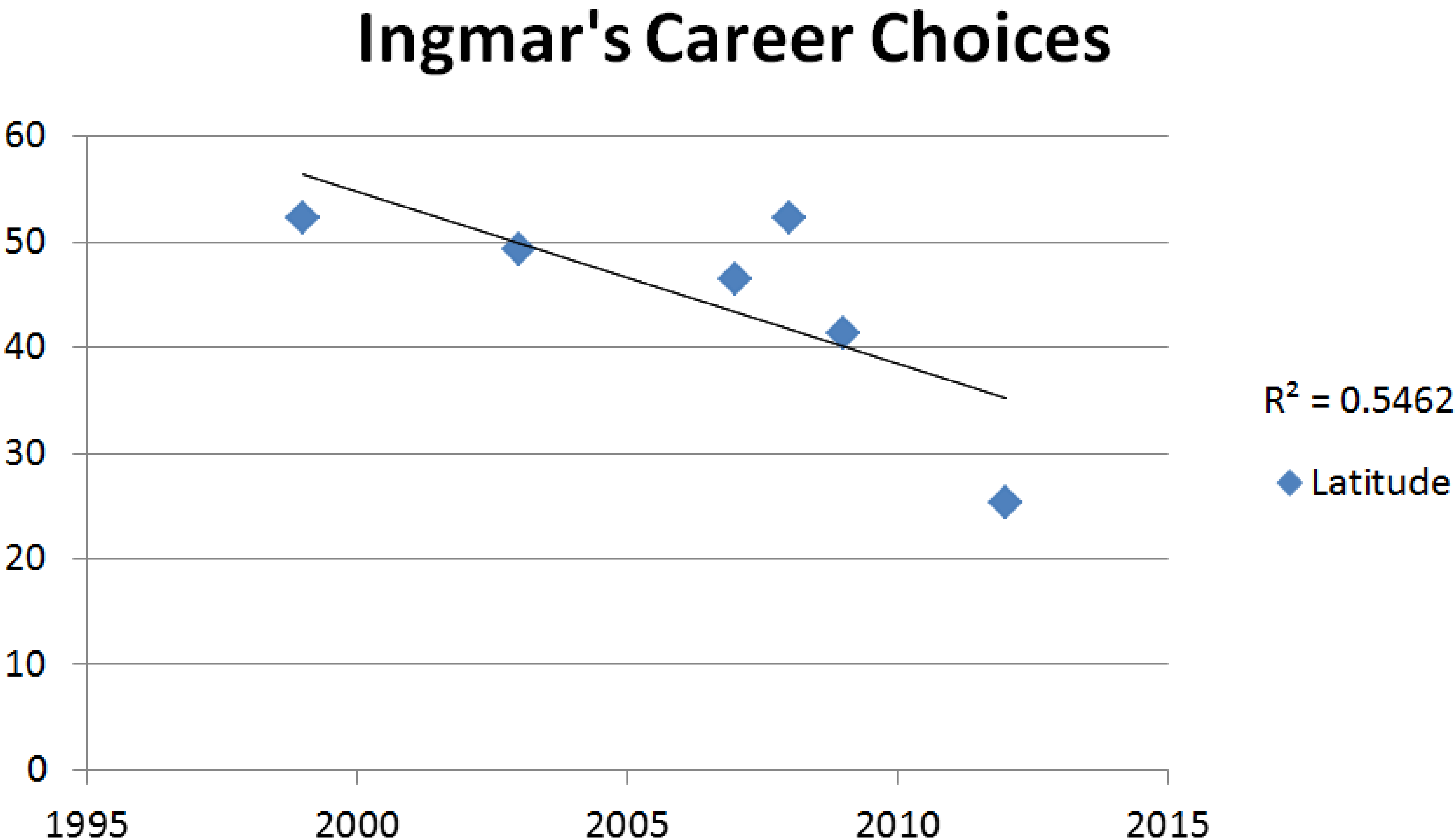
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2010
2015
R^2 = 0.5462
Latitude

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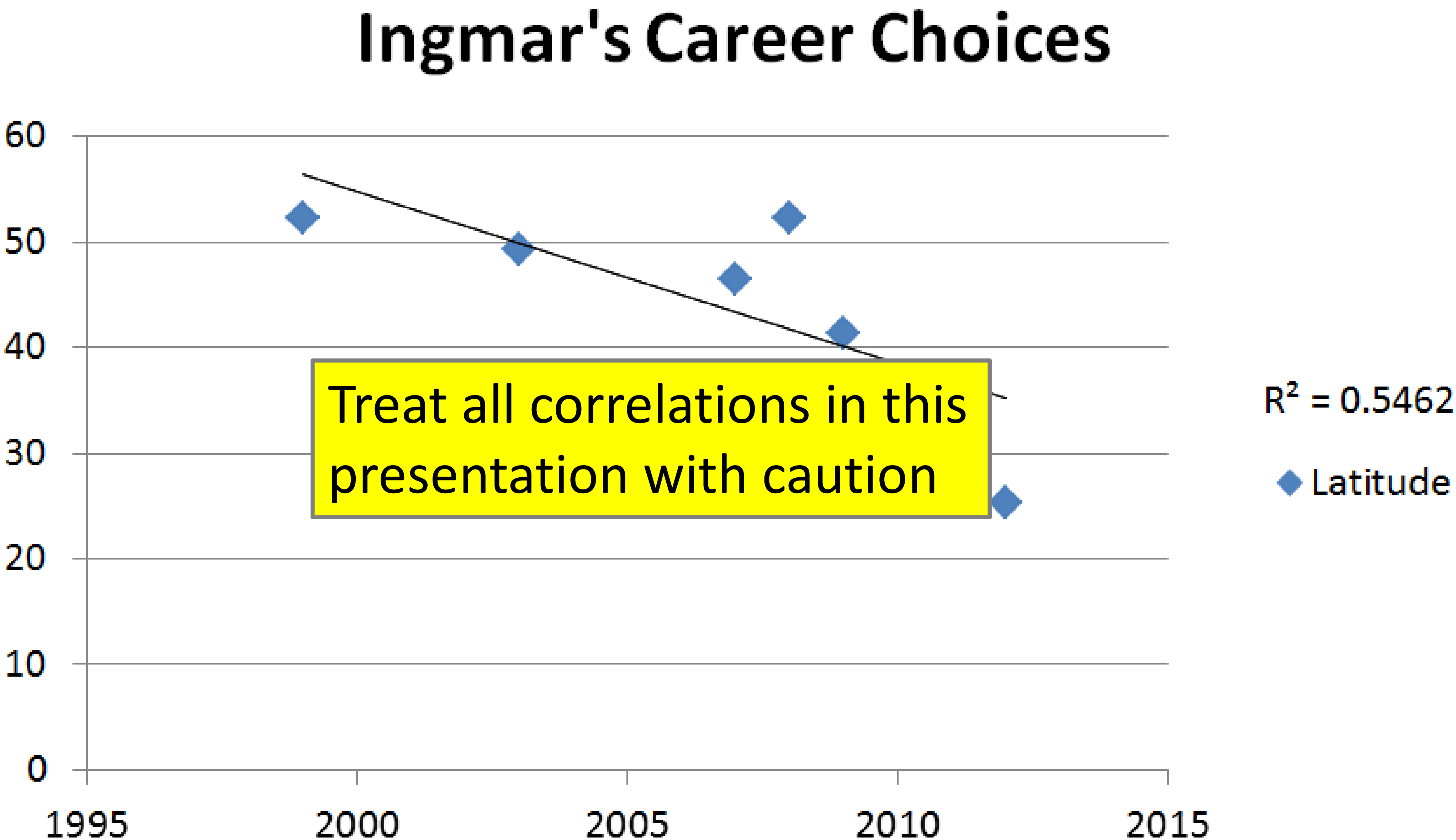
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Treat all correlations in this presentation with caution

Social Media and Healthcare

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PRESENTATIONS

JANUARY 25, 2014

The Intersection of Health Care, Social Media, and Digital Strategy

BY SUSANNAH FOX

Social Media and Healthcare

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BY SUSANNAH

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HEALTHCARE // CLINICAL INFORMATION SYSTEMS

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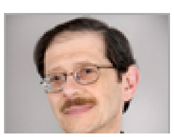
10:15 AM

Will Social Media Revolutionize Healthcare?



Without a doubt. In fact, several medical providers and IT vendors are plowing ahead already.

Social Media and Healthcare

Social Media and Healthcare

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How Healthcare Can Use Social Media Effectively And Compliantly

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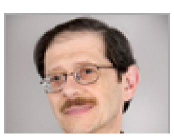

Without a doubt. In fact, several medical providers and IT vendors are plowing ahead already.

Social Media and Healthcare

Social Media as a *Data Source*

- Part 1: Three Example Studies
  - Twitter Flu Trend
  - Lifestyle and Correlates of Health
  - Studying Obesity Through Food Tweets
- Part 2: Opportunities and Challenges
  - Image Analysis
  - Network Influence
  - Social Media Meets Quantified Self
  - Interventions for Individual Health

Classification of Health Research

	Acute condition **Short-term concerns**	**Chronic condition** **Long-term concerns**
Public health **Population-centric** **Campaigns + policies**		
Individual health **Individual-centric** **Treatment + therapies**		

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Individual health **Individual-centric** **Treatment + therapies**	Nothing?	SM forums/messages as interventions

Later: Not

Why Bother with Social Media?

- Lots of it
  - Often also across countries
- Cheap to collect
  - Keyword/geographic-based collection standard
- (Semi-)Longitudinal data
  - Last 3,200 tweets, more for money
- Social network data
  - Usually not part of surveys
- Lifestyle data
  - Lifestyle diseases, public health

Example 1: National and Local Influenza Surveillance through Twitter: An Analysis of the 2012-2013 Influenza Epidemic

David Broniatowski, Michael Paul, Mark Dredze

PLOS ONE, Dec 2013

Using Google to Track Flu Epidemics

google.org Flu Trends

Google.org home

Dengue Trends

Flu Trends

Home

Sweden

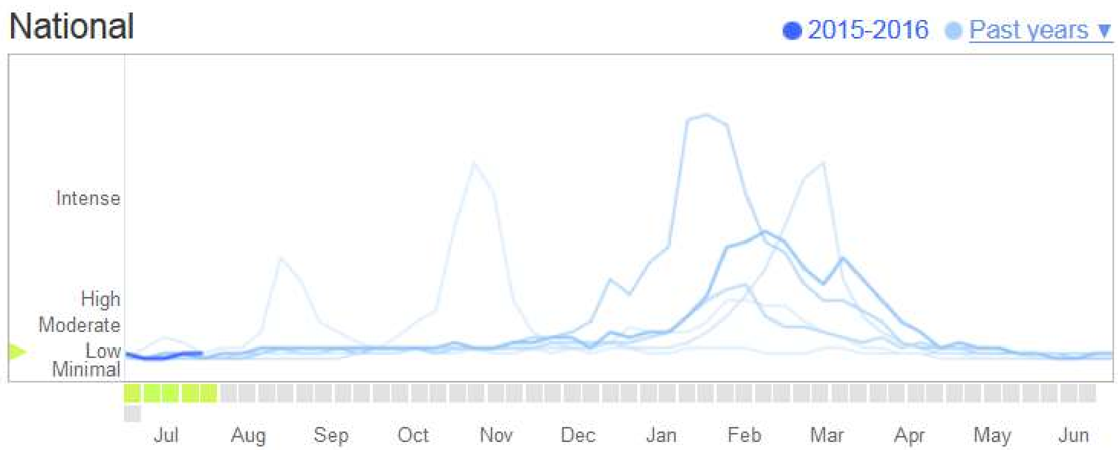
Download data

How does this work?

FAQ

Explore flu trends - Sweden

We've found that certain search terms are good indicators of flu activity. Google Flu Trends uses aggregated Google search data to estimate flu activity. Learn more »



Using Google to Track Flu Epidemics

nature International weekly journal of science

NATURE | NEWS

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When Google got flu wrong

US outbreak foxes a leading web-based method for tracking seasonal flu.

Declan Butler

13 February 2013

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Using Google to Track Flu Epidemics

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Science 14 March 2014:
Vol. 343 no. 6176 pp. 1203-1205
DOI: 10.1126/science.1248506

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POLICY FORUM

BIG DATA

The Parable of Google Flu: Traps in Big Data Analysis

David Lazer[1,2,*], Ryan Kennedy[1,3,4], Gary King[3], Alessandro Vespignani[5,6,3]

+ Author Affiliations

[*]Corresponding author. E-mail: d.lazer@neu.edu.

In February 2013, Google Flu Trends (GFT) made headlines but not for a reason that Google executives or the creators of the flu tracking system would have hoped. *Nature* reported that GFT was predicting more than double the proportion of doctor visits for influenza-like illness (ILI) than the Centers for Disease Control and Prevention (CDC), which bases its estimates on surveillance reports from laboratories across the United States (*1*, *2*). This happened despite the fact that GFT was built to predict CDC reports. Given that GFT is often held up as an exemplary use of big data (*3*, *4*), what lessons can we draw from this error?

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Read Full Text to Comment (1)

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Can Twitter give a
- more transparent prediction?
- more robust prediction (re context)?

*Corresponding author. E-mail: d.lazer@neu.edu.

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Read the Full Text

Can We Do it (Better?) With Twitter?

- Many people have tried
  - 40+ papers on the topic
- Typically a straightforward setup
  - Collect Twitter data for a set of keywords (fever, …)
  - Do some post-filtering (Saturday Night Fever)
  - Show temporal correlation/predictive power
- Major weaknesses
  - Only work with a single flu season
  - Done in retrospect (hard to get historical data)

Recent Breakthrough?

Sections ≡ The Washington Post

To Your Health

A better flu tracker using Twitter, not Google

A | 0

By **Lenny Bernstein** March 19, 2014 Follow @LennyMBernstein

There have been a number of efforts to track the flu with social media, including the recently criticized Google flu tracker. Now scientists from Johns Hopkins University and George Washington University say their approach, which uses Twitter, has proven highly accurate at the task.

During the 2012-2013 flu season, the technique was 93 percent accurate when compared to actual national flu data collected by the Centers for Disease Control and Prevention, and 88 percent accurate when applied in New York

Most Read National

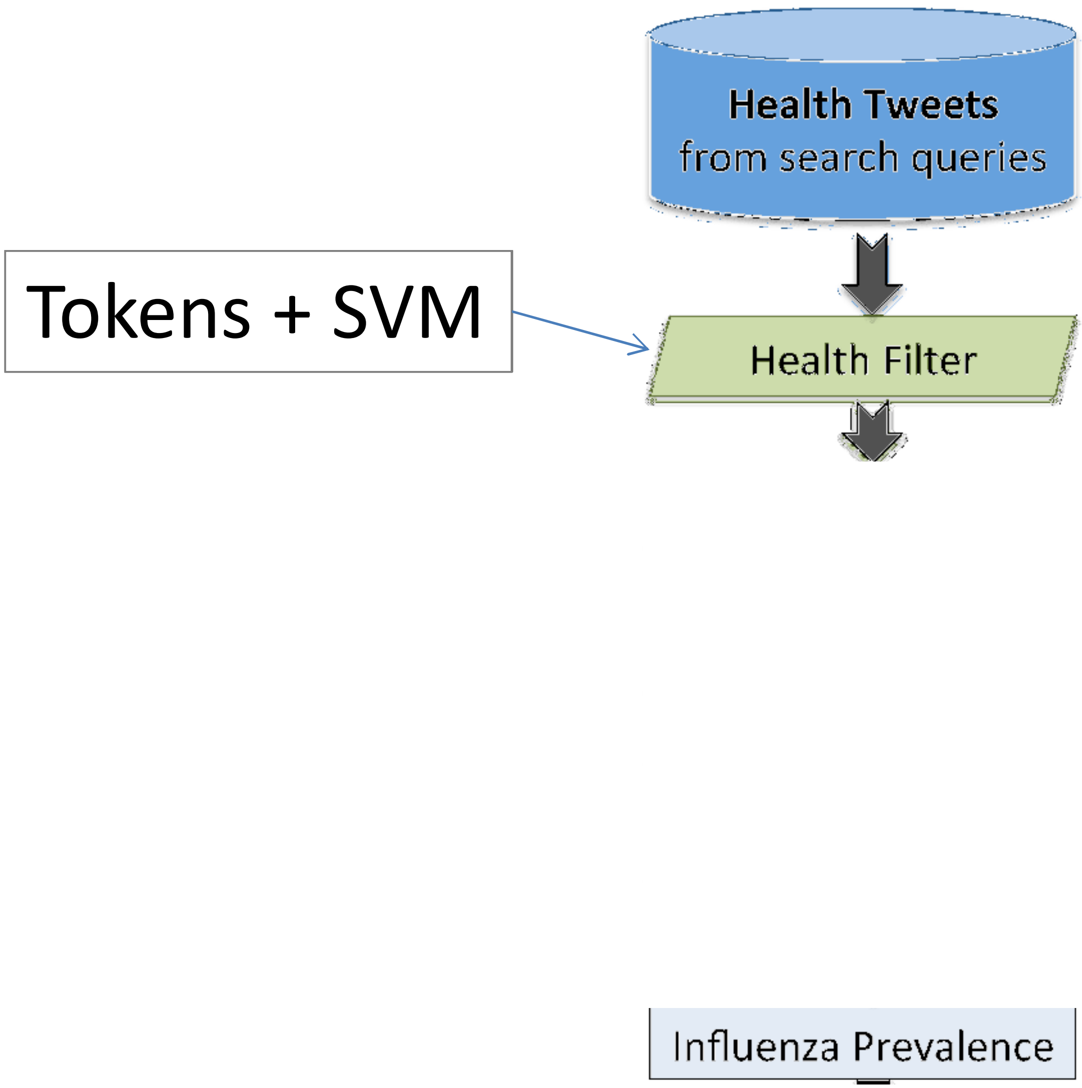
1 **At least 24 dead, more than 300 rescued after twin train derailments in India**

2 **Photo of cop aiming gun at woman goes viral, but report paints different picture**

3 **Zimbabwean hunter**

How It Works

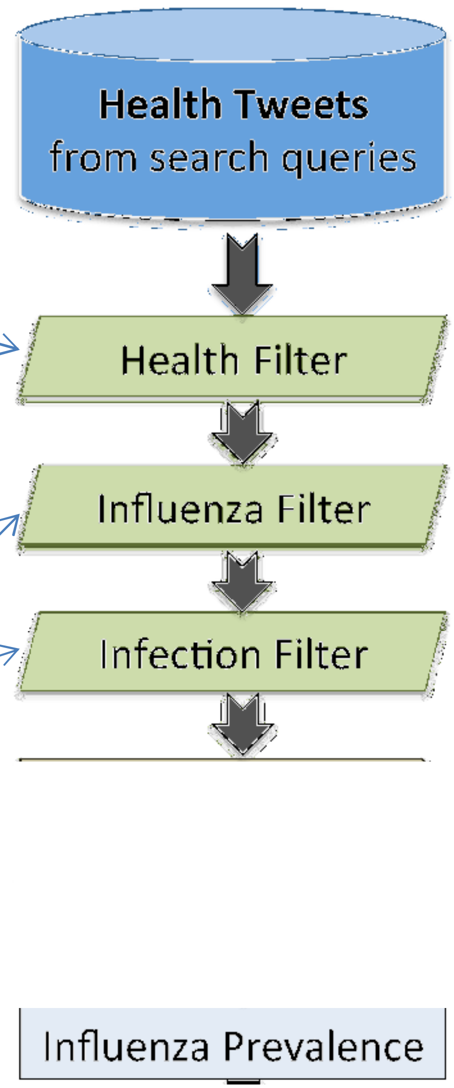
How It Works


Health Tweets
from search queries
Tokens + SVM
Health Filter
Influenza Prevalence

How It Works

Tokens + SVM

Word classes (noun, …)
RT, @, Emoticons
Part-of-Speech tagging
Verb-phrases
Pairs with pronouns
Verb-noun pairs
…
Log-linear w/ L_2 regulariz.



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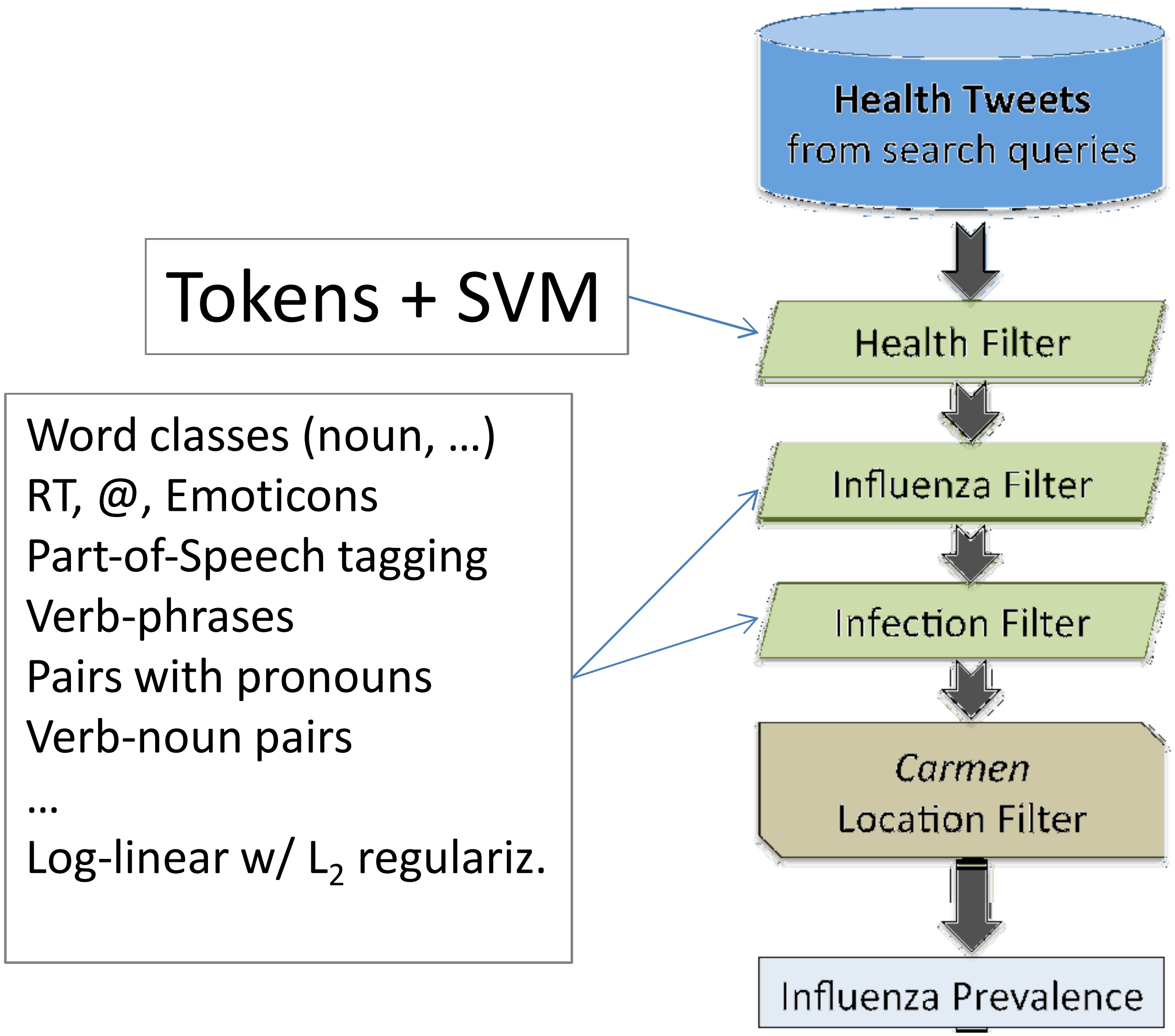
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Infection Filter
Carmen
Location Filter
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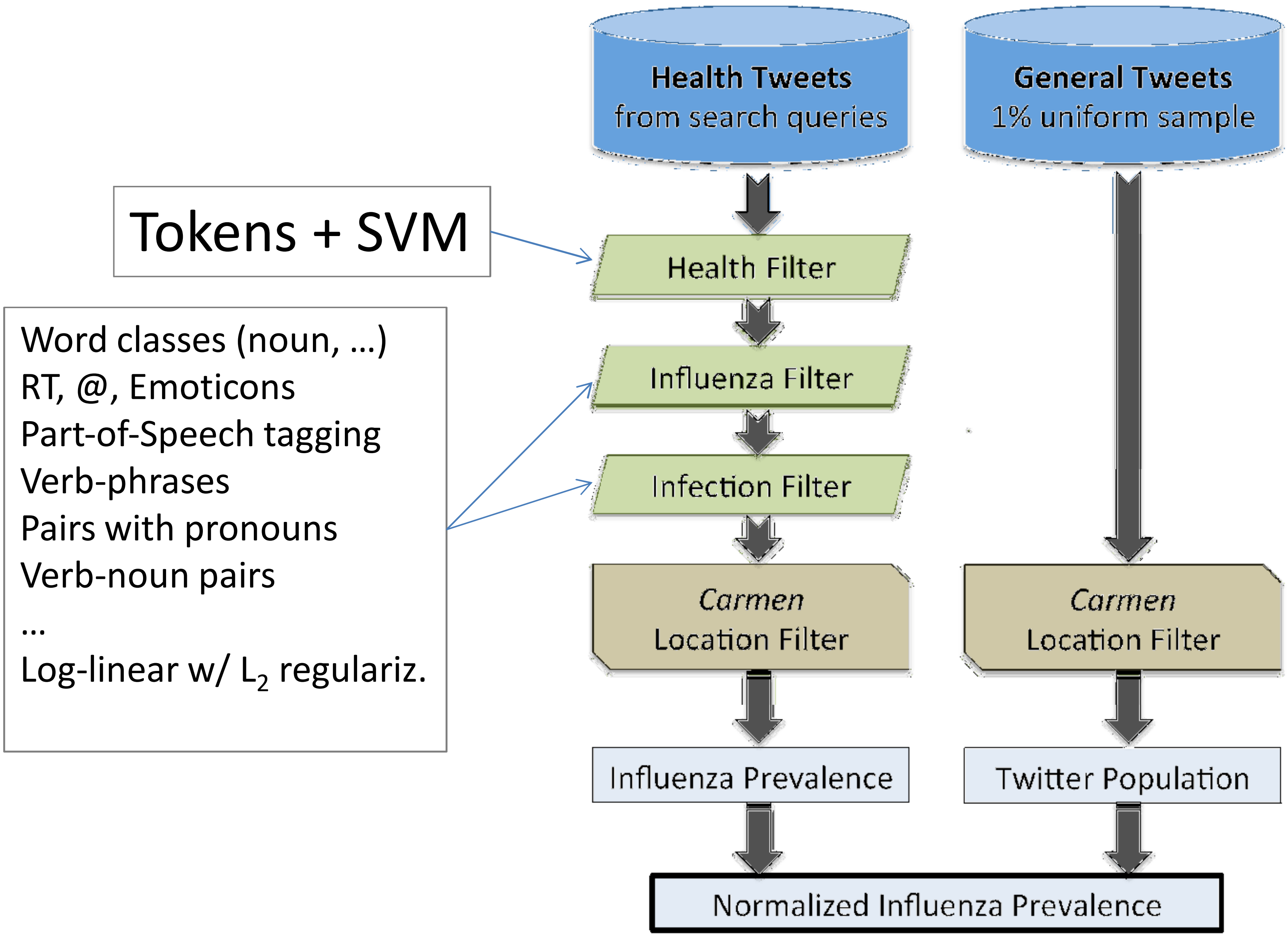
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Health Tweets
from search queries
General Tweets
1% uniform sample
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Influenza Filter
Infection Filter
Carmen
Location Filter
Carmen
Location Filter
Influenza Prevalence
Twitter Population
Normalized Influenza Prevalence

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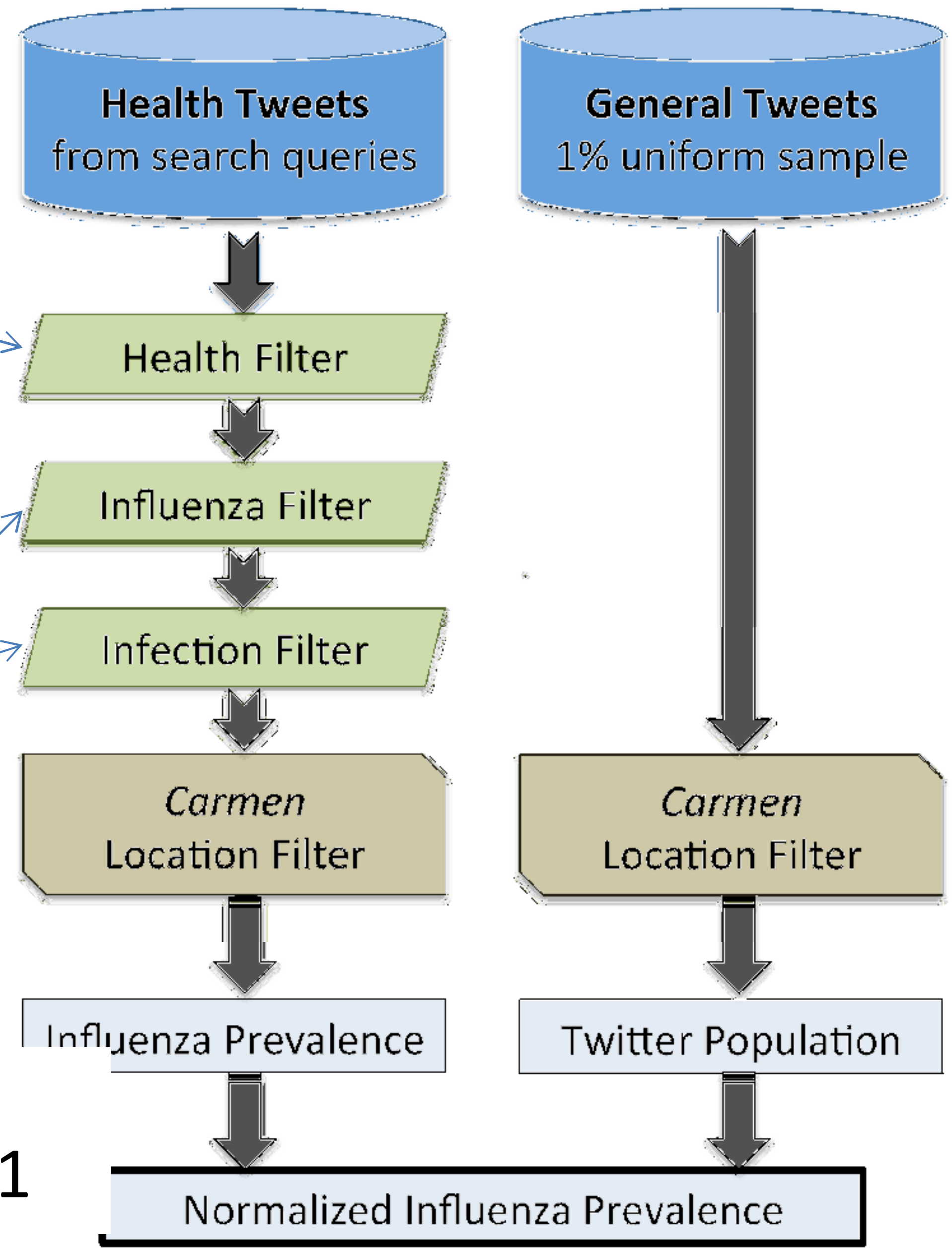


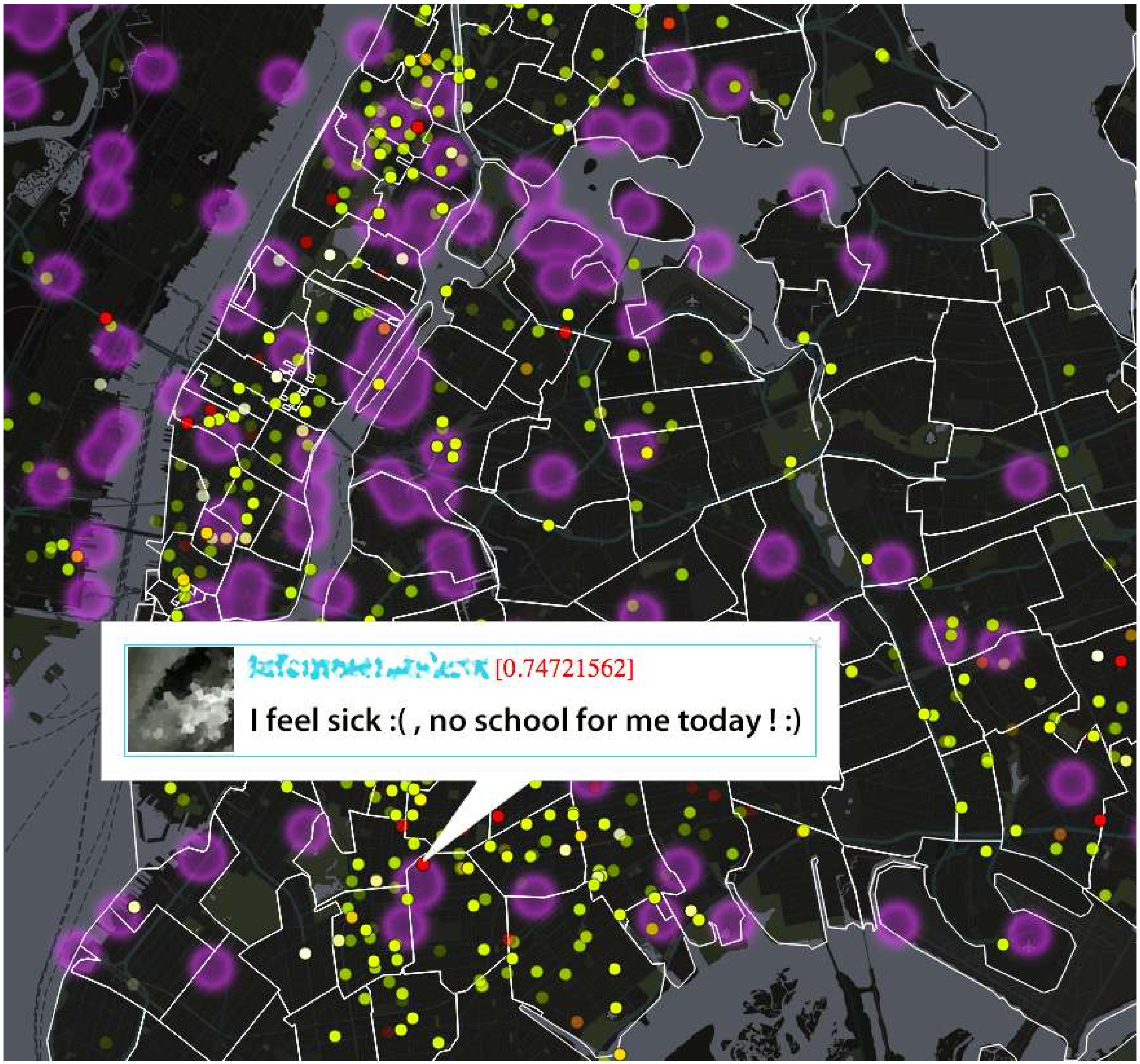
US-level: $r = 0.93$, $p < .001$
NYC-level: $r = 0.88$, $p < .001$

Example 2:
Modeling the Impact of Lifestyle on Health at Scale

Adam Sadilek, Henry Kautz

WSDM'13

Geo-Tagged “Sick” Tweets from NYC



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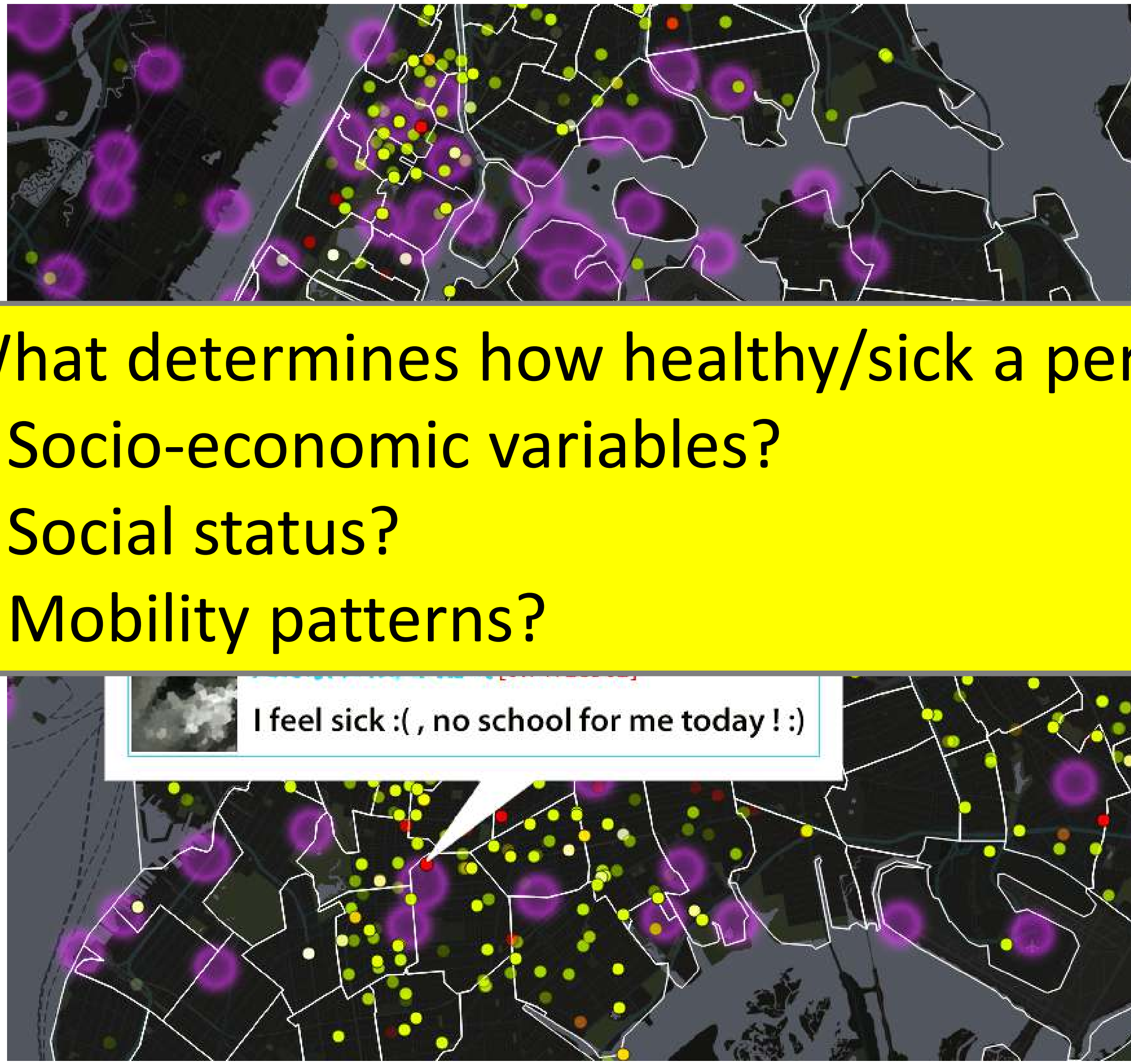


What determines how healthy/sick a person is?

- Socio-economic variables?
- Social status?
- Mobility patterns?

Data Collection

- May 19 – June 19, 2010
- periodically queried Twitter r=100km of NYC
  - Re Twitter streaming API?
- 16 million tweets, 630k unique users
- 6,237 users with 100+ geo-tagged tweets

Sick-or-Not SVM Classifier

- Cast to lower case & basic “cleaning”
- Extract uni-, bi- and tri-grams
- 5 MT workers label “sick” or “other”
- Train an SVM
- .98 precision, .97 recall (class distribution?)
- Convert SVM output to probability (Platt?)
- Probability of u’s message being “sick”

$$P_S = \frac{1}{|M|} \sum_{t \in M} \Pr\big[t \text{ is sick}\big]$$

Discriminative Features

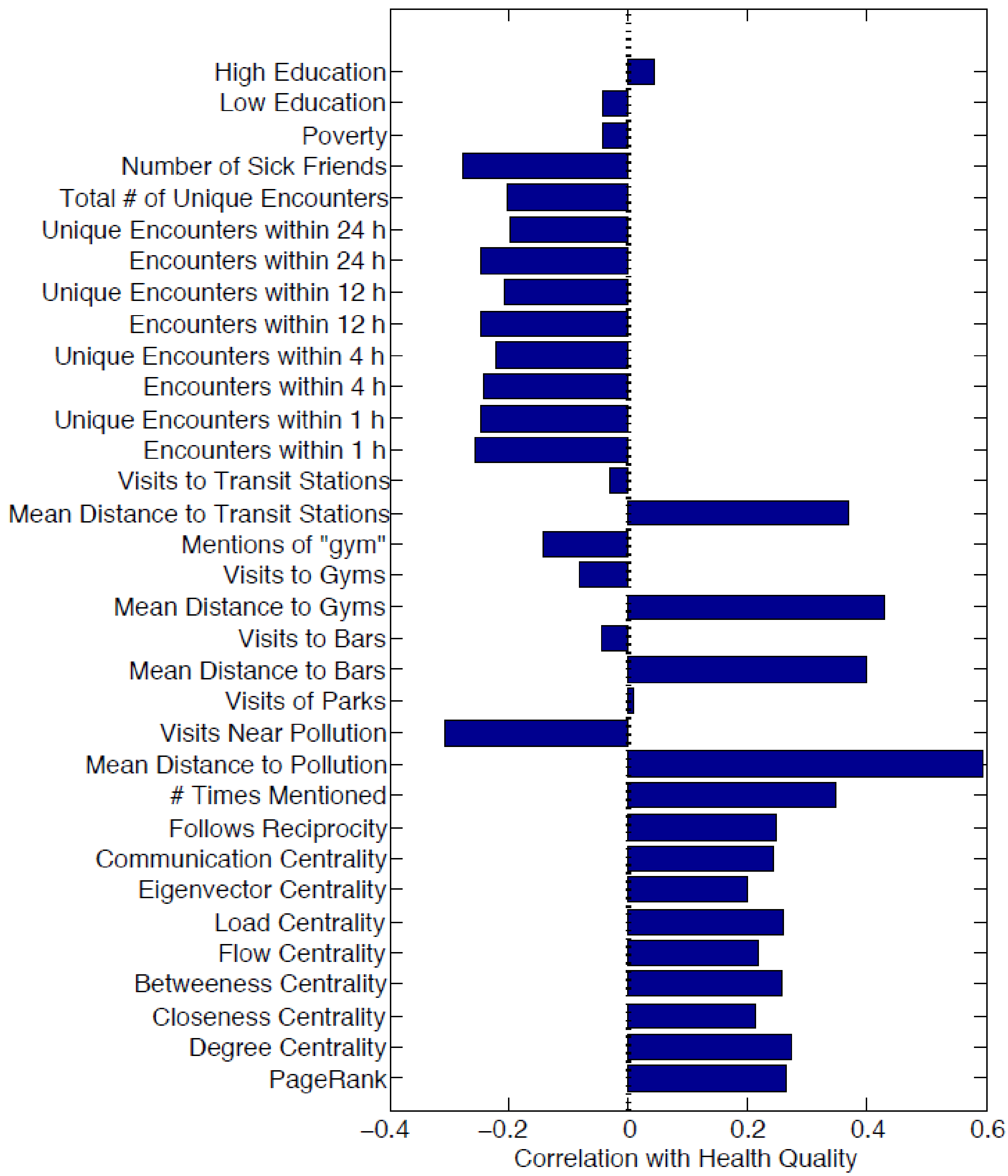
Positive Features		Negative Features	
Feature	**Weight**	**Feature**	**Weight**
sick	0.9579	sick of	−0.4005
headache	0.5249	you	−0.3662
flu	0.5051	lol	−0.3017
fever	0.3879	love	−0.1753
feel	0.3451	i feel your	−0.1416
coughing	0.2917	so sick of	−0.0887
being sick	0.1919	bieber fever	−0.1026
better	0.1988	smoking	−0.0980
being	0.1943	i'm sick of	−0.0894
stomach	0.1703	pressure	−0.0837
and my	0.1687	massage	−0.0726
infection	0.1686	i love	−0.0719
morning	0.1647	pregnant	−0.0639

Variables to Study

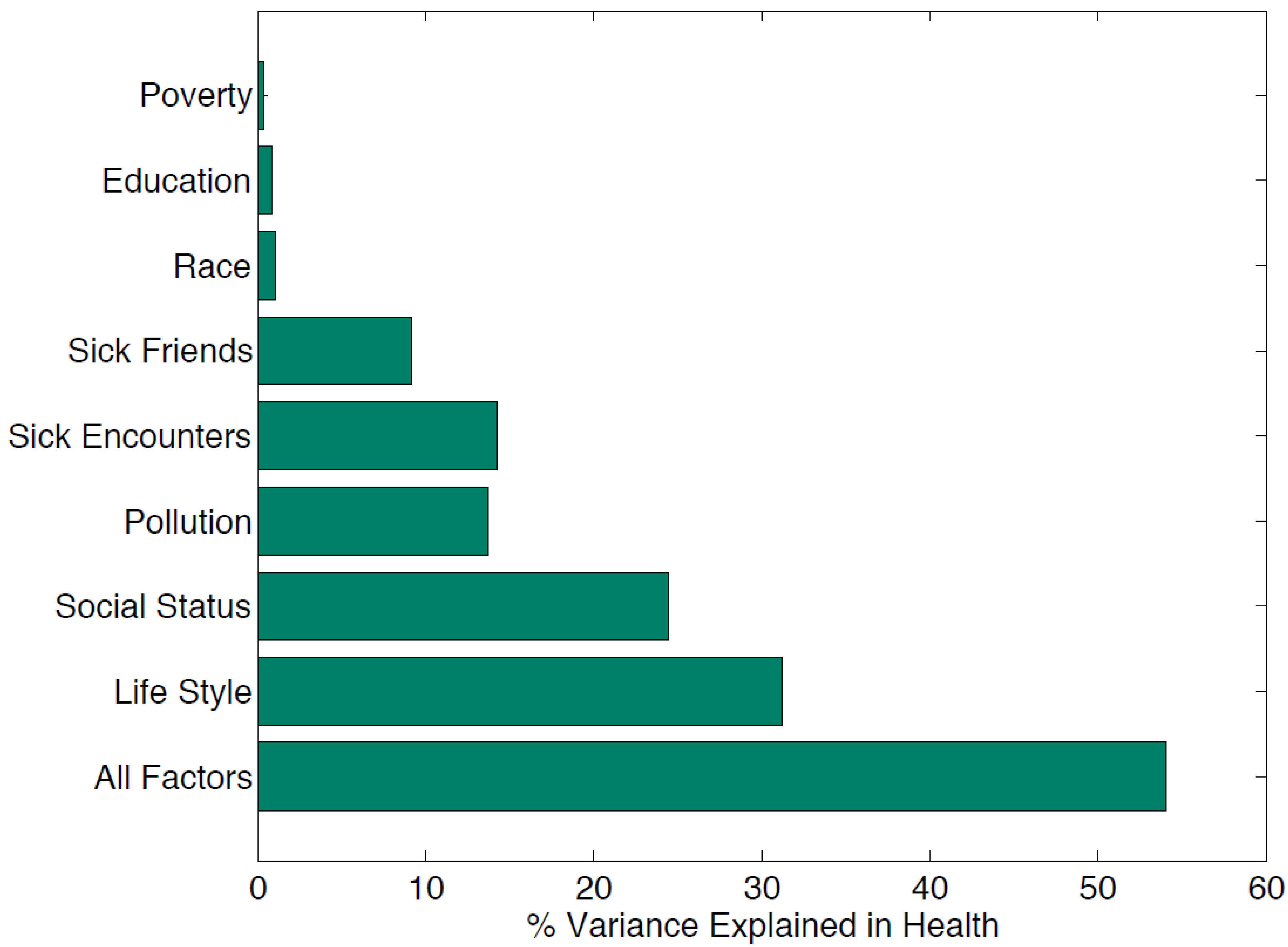
- “Physical encounters”
  - <100 m within 1, 4, 24 hours
- Sick friends (mutual following)
- 25k Google Places
  - Bars, nights clubs, transit stations, parks, gyms
  - Tweeting within 100m of venue
- Pollution
- Socio-economic indicators

Predict P_S using these variables

Correlation With Health ($-P_S$)



Grouped by Variable Class



Example 3: You Tweet What You Eat: Studying Food Consumption Through Twitter

Sofiane Abbar, Yelena Mejova, Ingmar Weber

CHI’15

“Pointless Babble” == Great Data!

“Twitter Study Reveals Interesting Results - About Usage 40% is Pointless Babble” (Pear Analytics, 2009)

Pointless Babble

These are the “I am eating a sandwich now” tweets.

“Pointless Babble” == Great Data!

“Twitter Study Reveals Interesting Results - About Usage 40% is Pointless Babble” (Pear Analytics, 2009)

Pointless Babble

These are the “I am eating a sandwich now” tweets.

Can we use food tweets to study obesity patterns?

[redacted]

Having a BBQ **sandwich** for lunch cuz I ran out of fillings, spread and ketchup

[redacted] · 2h

i've been kinda **having a** crisis about being directionless but bae said just do things that make me happy so i got **a** bagel **sandwich**

1 4

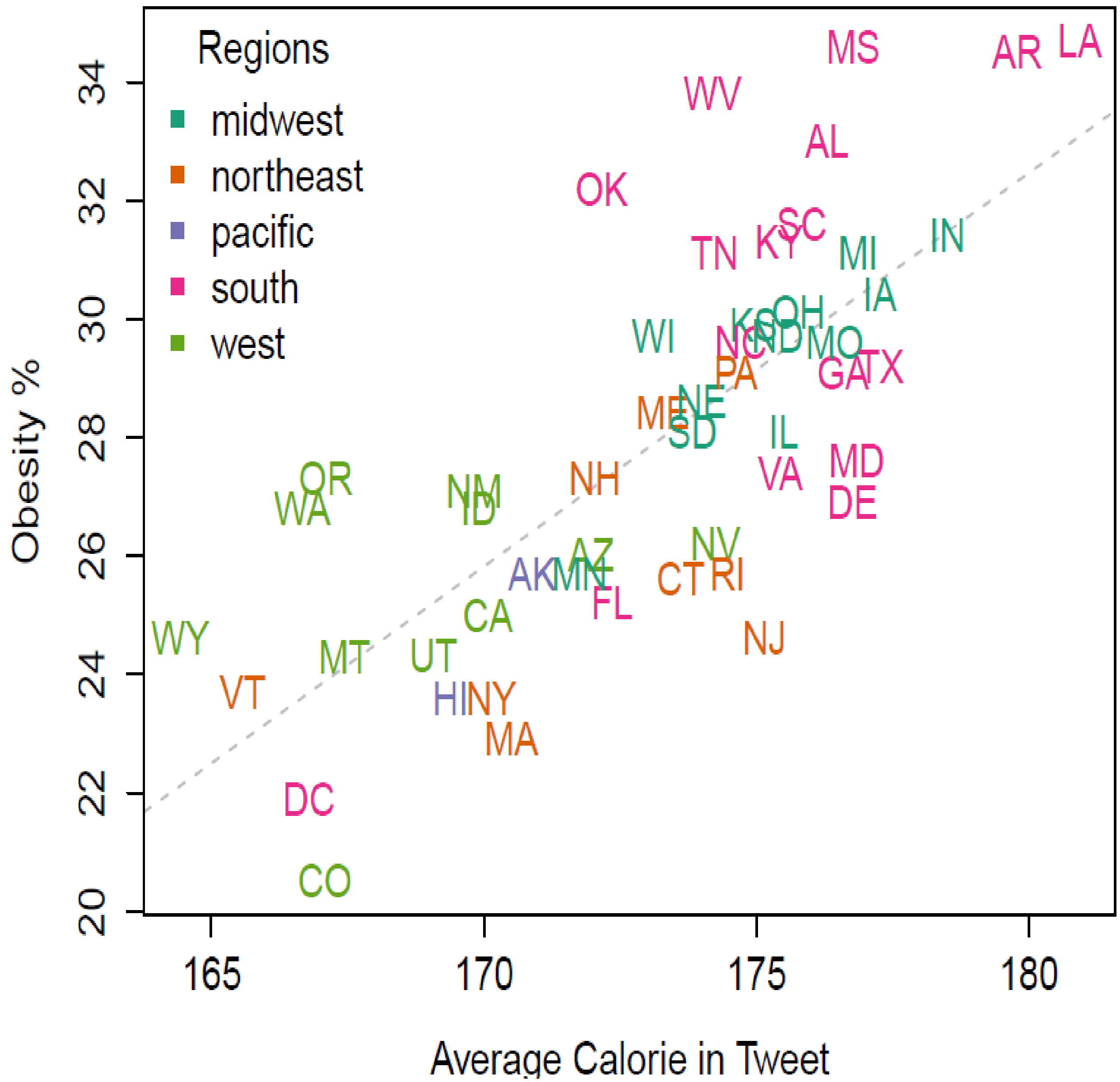
[redacted] · 9h

Having a breakfast **sandwich** for dinner at 10pm is totally ok, right? #adulthood

Data Collection

- Streaming API filter for “eat”, “cook”, “lunch”, …
- Collect 50M tweets during Nov 2013
- 892K geo-tagged tweets from 400K users
  - Use (lat, long) to map to ZIP and census data
  - Get data for 210K random user subset
- 3,200 public tweets, profile, friends, followers
- 503M tweets, 32M distinct friends
- Label eat-co-occurring terms as “is food”
  - 460 uni- and bigrams with mapping to calories
  - Pizza 478, fruit salad 99, … [link]
- Average calories for users

Calories vs. Obesity



Calories vs. Obesity

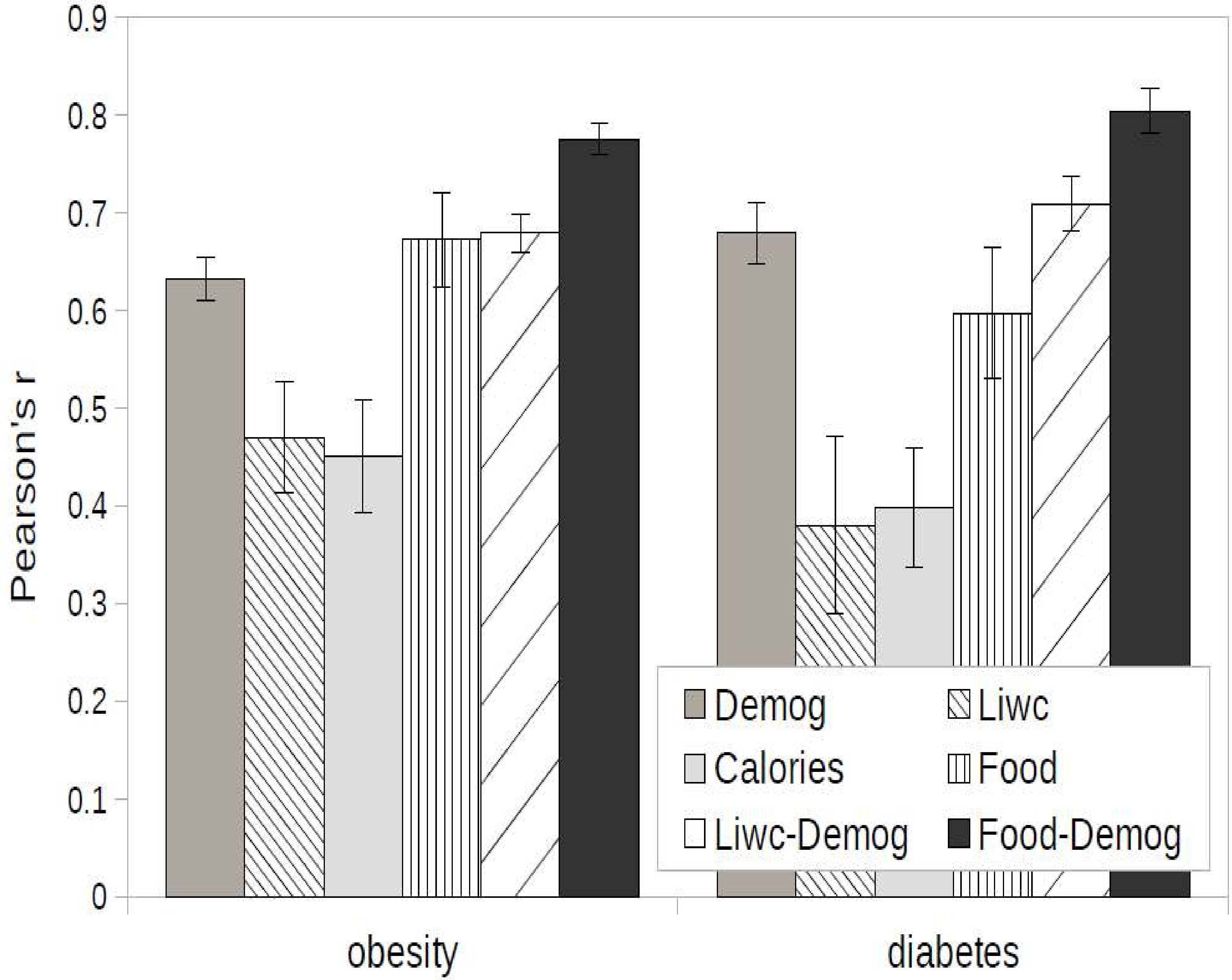
	Obesity		Diabetes	
	Pearson	Spearman	Pearson	Spearman
All	0.772^{***}	0.784^{***}	0.658^{***}	0.657^{***}
Food	0.629^{***}	0.643^{***}	0.538^{***}	0.517^{**}
Beverage	0.762^{***}	0.786^{***}	0.646^{***}	0.622^{***}
Alcoholic bev.	0.445^{*}	0.430^{*}	0.073	-0.007

Significance: $p < 0.0001$ ***, $p < 0.001$ **, $p < 0.01$ *

Zooming-In to Counties

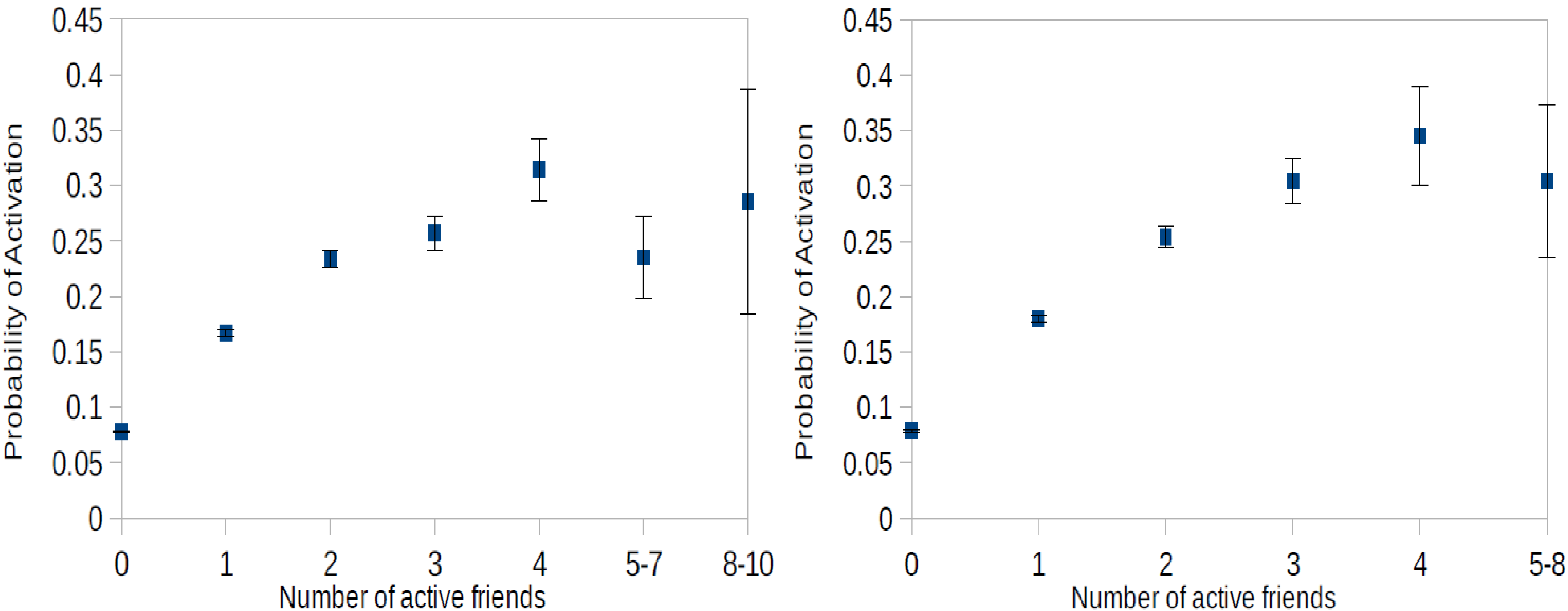
- Try to predict county-level obesity
  - avCal
  - Food names
  - LIWC categories (re Culotta'14)
  - Demographic
- Ridge regression with 5-fold cross validation

Prediction Performance



Social Network Effects

- Call a user in predicted top 10% “active”



(a) Obesity spread in FN

(b) Obesity spread in MN

Example n:
Lots of Studies

Lots of People

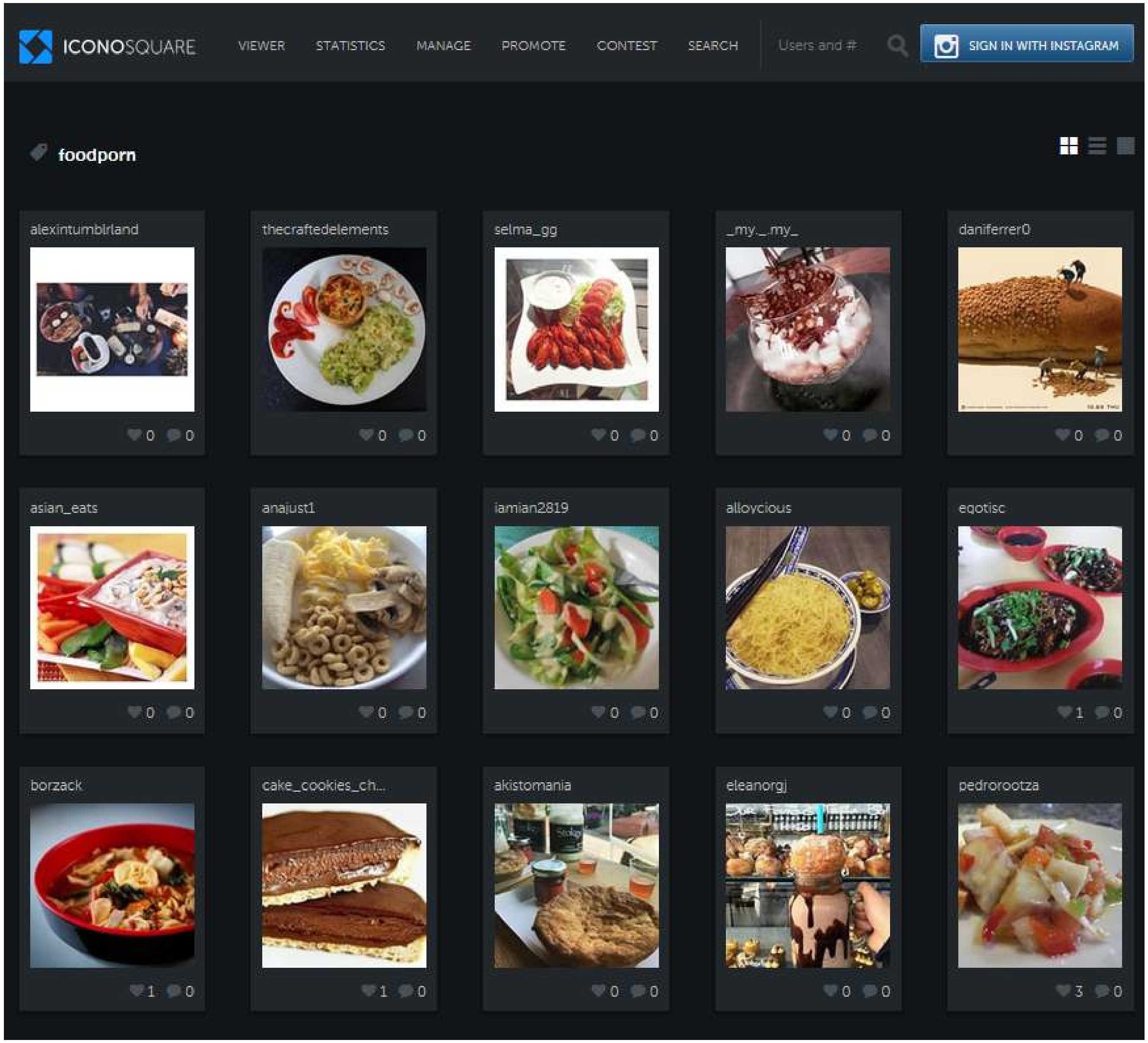
Lots of Venues

More Example Domains

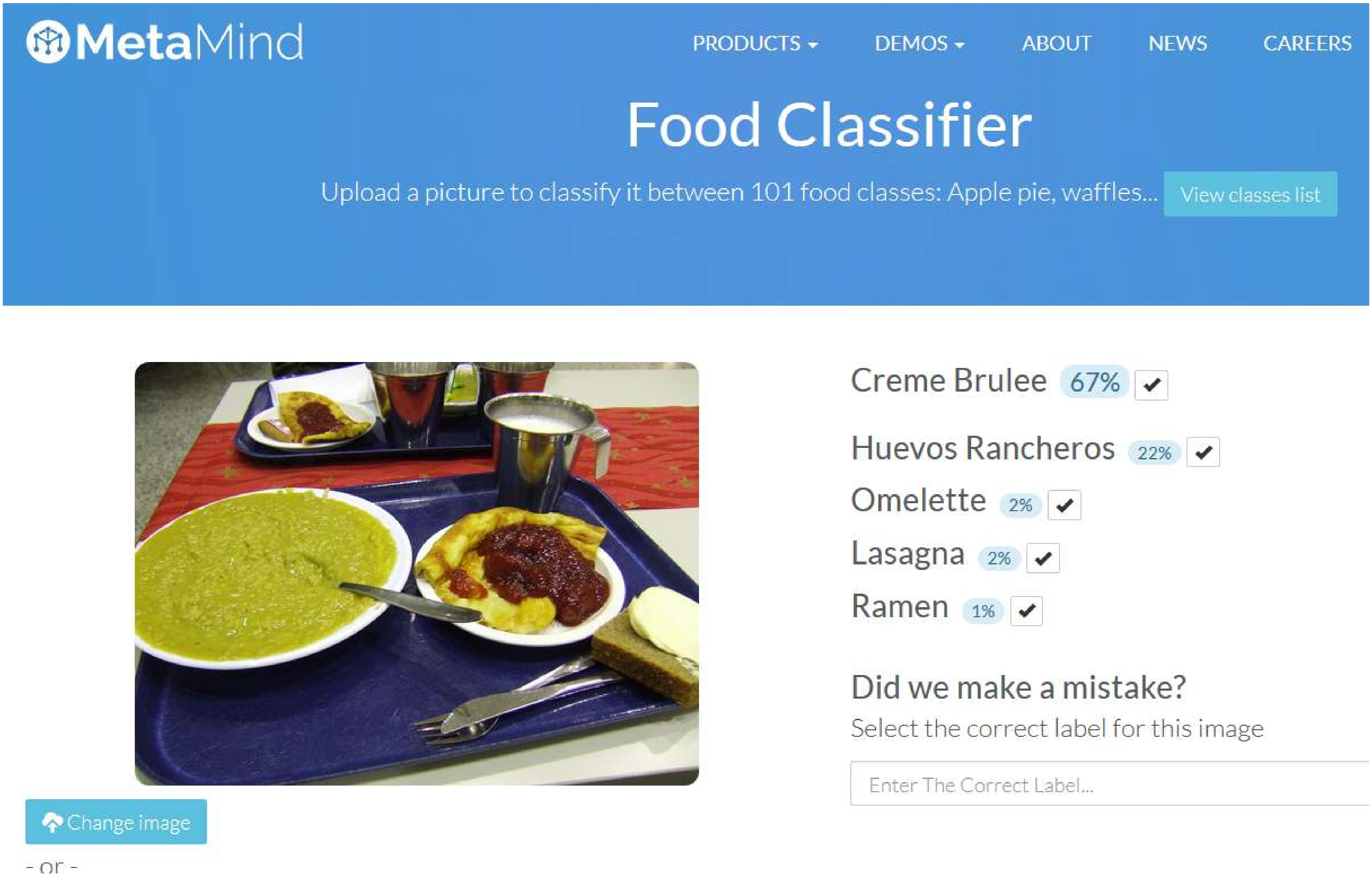
- Finding Adverse Drug Reactions (ADRs)
- Tracking mental health
- Dedicated social media such as forums
- Social media for health communication
- …

Research Opportunities And Challenges

Opportunity 1: Mining Social Media *Images*



Opportunity 1:
Mining Social Media *Images*



Opportunity 1:
Mining Social Media *Images*

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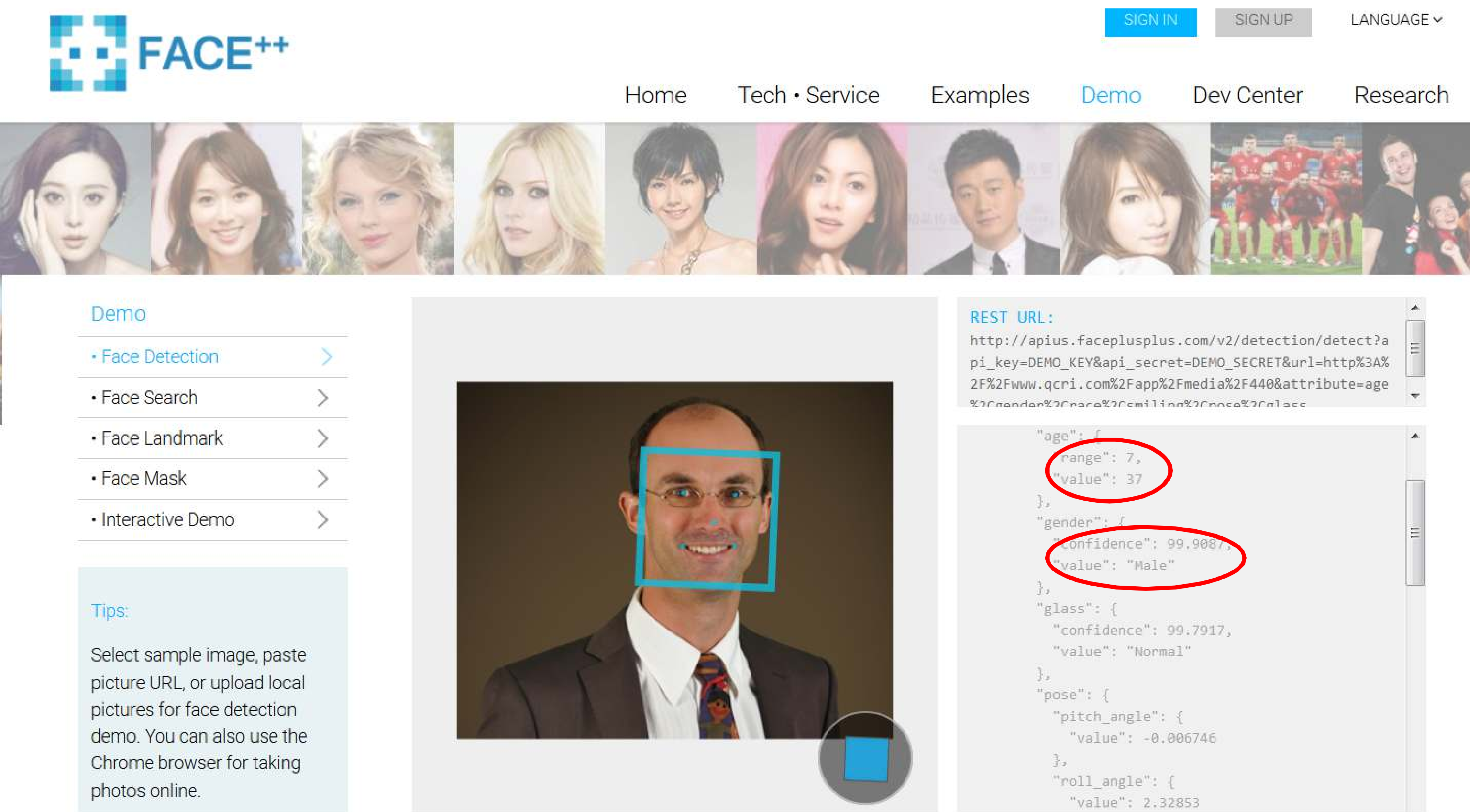

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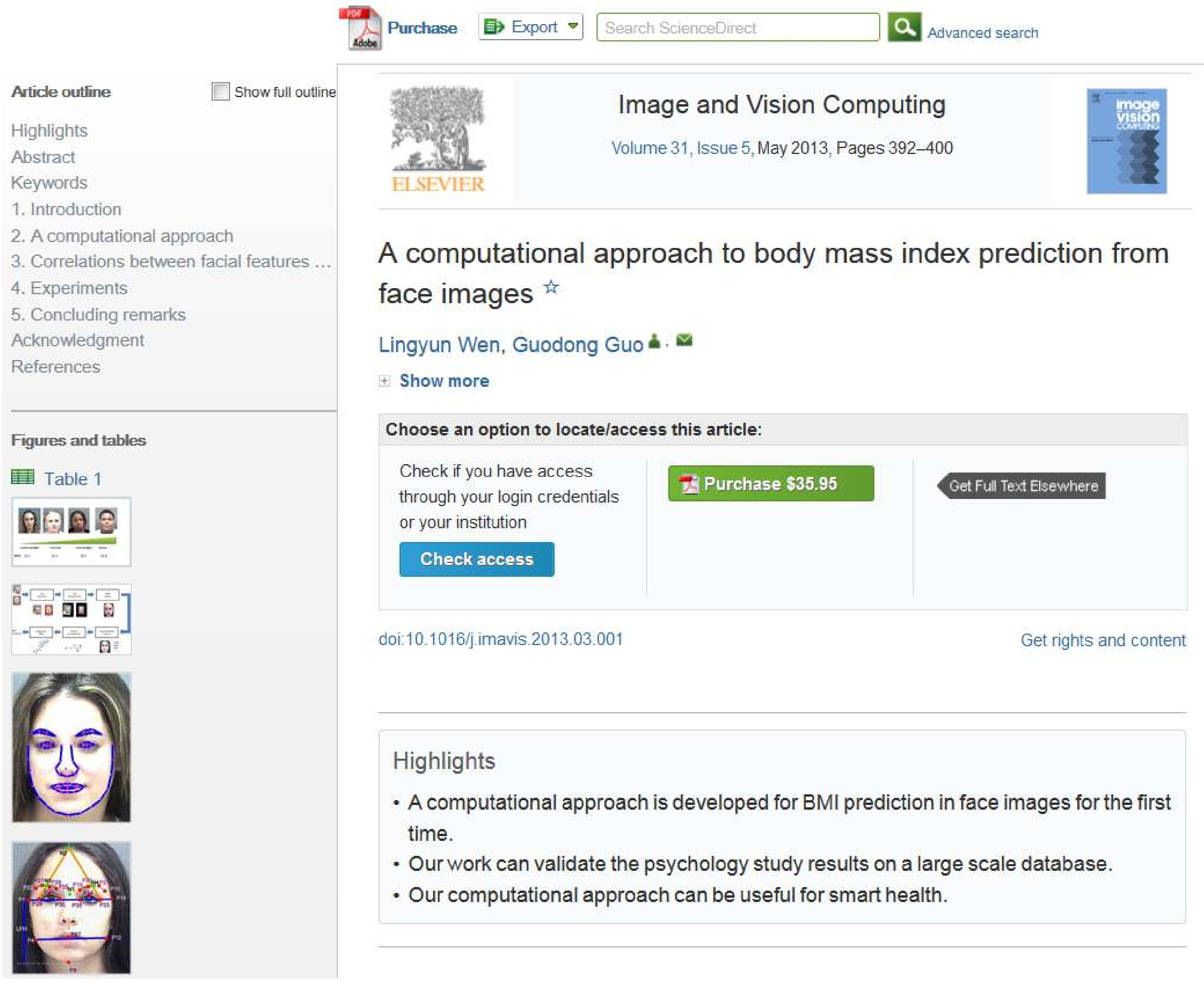
Mining Social Media *Images*



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Article outline Show full outline

Highlights
Abstract
Keywords
1. Introduction
2. A computational approach
3. Correlations between facial features …
4. Experiments
5. Concluding remarks
Acknowledgment
References

Figures and tables

Table 1

ELSEVIER

Image and Vision Computing

Volume 31, Issue 5, May 2013, Pages 392–400

A computational approach to body mass index prediction from face images ☆

Lingyun Wen, Guodong Guo

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doi:10.1016/j.imavis.2013.03.001

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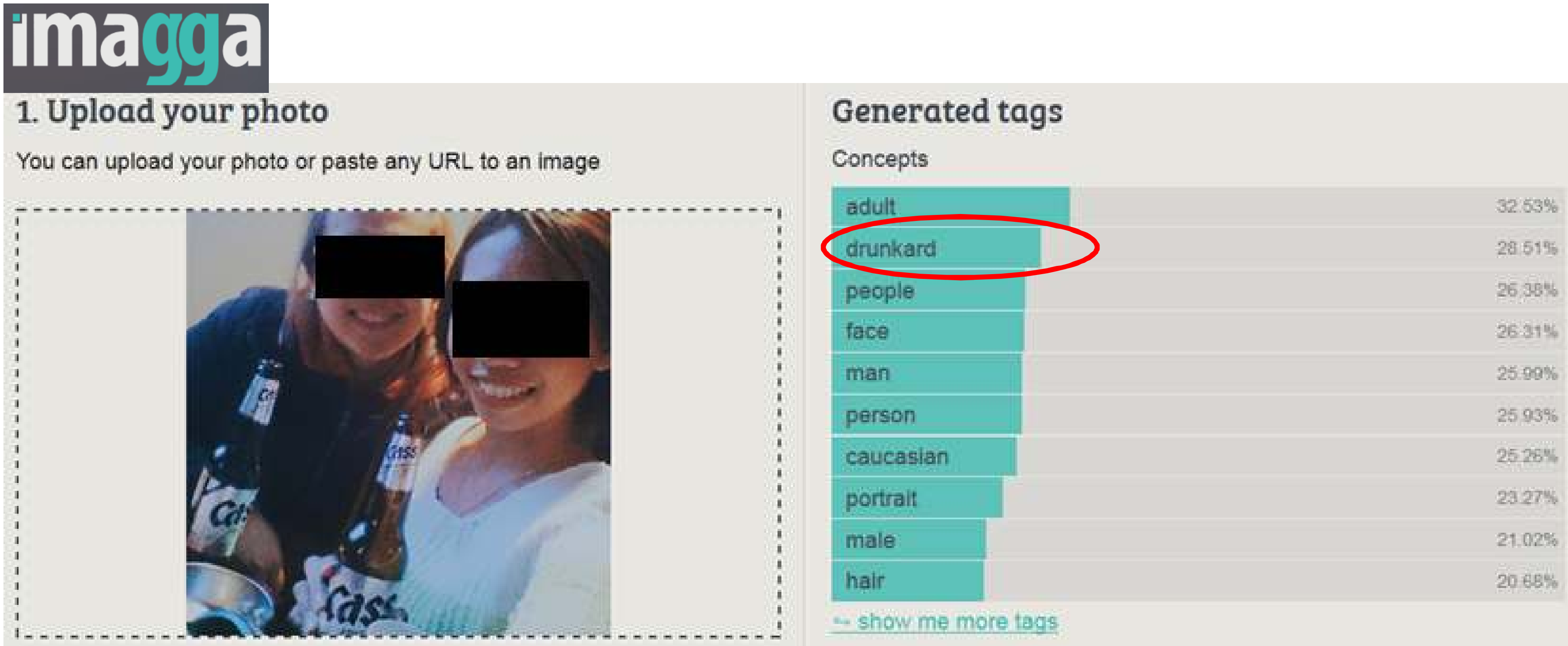
Highlights

- A computational approach is developed for BMI prediction in face images for the first time.
- Our work can validate the psychology study results on a large scale database.
- Our computational approach can be useful for smart health.

Opportunity 1:
Mining Social Media *Images*



- Helps to model variation in “excessive drinking”
  - Contact me for submission (under review)

Opportunity 2: Network Influence

The NEW ENGLAND JOURNAL of MEDICINE

HOME | ARTICLES & MULTIMEDIA | ISSUES | SPECIALTIES & TOPICS | FOR AUTHORS | CME

SPECIAL ARTICLE

The Spread of Obesity in a Large Social Network over 32 Years

Nicholas A. Christakis, M.D., Ph.D., M.P.H., and James H. Fowler, Ph.D.

N Engl J Med 2007; 357:370-379 | July 26, 2007 | DOI: 10.1056/NEJMsa066082

Share:

Abstract | Article | References | Citing Articles (1122) | Glossary | Letters

BACKGROUND

The prevalence of obesity has increased substantially over the past 30 years. We performed a quantitative analysis of the nature and extent of the person-to-person spread of obesity as a possible factor contributing to the obesity epidemic.

MEDIA IN THIS ARTICLE

Animation

Opportunity 2: Network Influence

The NEW ENGLAND JOURNAL of MEDICINE

A person's chances of becoming obese increased by 57% (95% confidence interval [CI], 6 to 123) if he or she had a friend who became obese in a given interval. Among pairs of adult siblings, if one sibling became obese, the chance that the other would become obese increased by 40% (95% CI, 21 to 60). If one spouse became obese, the likelihood that the other spouse would become obese increased by 37% (95% CI, 7 to 73).

Share:

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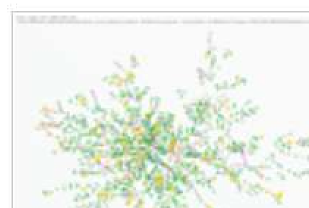

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The NEW ENGLAND JOURNAL of MEDICINE

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Share:

The spread of obesity in a large social network over 32 years

NA Christakis, JH Fowler - New England journal of medicine, 2007 - Mass Medical Soc

Background The prevalence of obesity has increased substantially over the past 30 years. We performed a quantitative analysis of the nature and extent of the person-to-person spread of obesity as a possible factor contributing to the obesity epidemic.

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Opportunity 2:
Network Influence

The New York Times

Health

Study Says Obesity Can Be Contagious

By GINA KOLATA
Published: July 25, 2007

Obesity can spread from person to person, much like a virus, researchers are reporting today. When a person gains weight, close friends tend to gain weight, too.

Multimedia

Their study, published in the New England Journal of Medicine, involved a detailed analysis of a large social network of 12,067 people who had been closely followed for 32 years,

Opportunity 2:
Network Influence

PMC
US National Library of Medicine
National Institutes of Health

PMC

Limits Advanced Journal list

Sociol Methods Res. Author manuscript; available in PMC 2012 Apr 18.
Published in final edited form as:
Sociol Methods Res. 2011 May; 40(2): 211–239.
doi: 10.1177/0049124111404820

PMCID: PMC3328971
NIHMSID: NIHMS364906

Author Manuscript

Homophily and Contagion Are Generically Confounded in Observational Social Network Studies

Cosma Rohilla Shalizi[1] and Andrew C. Thomas[1]

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See other articles in PMC that cite the published article.

Abstract

Go to:

The authors consider processes on social networks that can potentially involve three factors: homophily, or the formation of social ties due to matching individual traits; social contagion, also known as social

Opportunity 2:
Network Influence

The New York Times

HEALTH

Catching Obesity From Friends May Not Be So Easy

By GINA KOLATA AUG. 8, 2011

Lars Leetaru

Email

Does obesity spread like a virus through networks of friends and friends of friends? Do smoking, loneliness, happiness, depression and illegal drug use

Opportunity 2: Network Influence

The New York Times

HEALTH

Catching Obesity From Friends May Not Be So Easy

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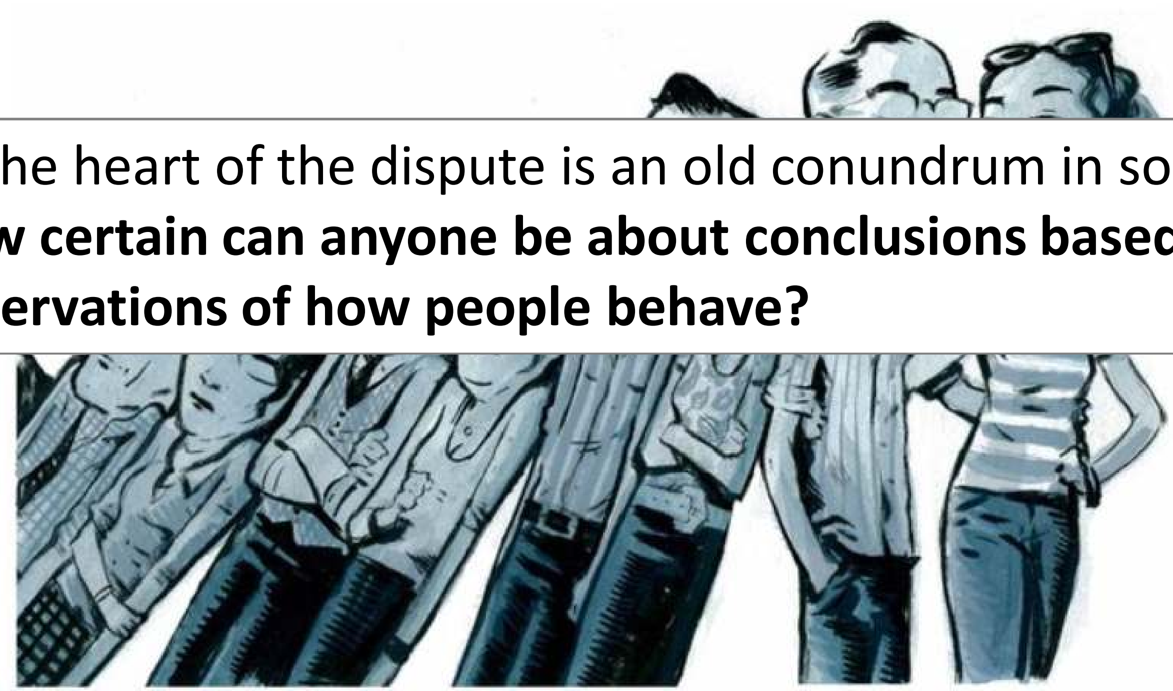


At the heart of the dispute is an old conundrum in social science: **How certain can anyone be about conclusions based on observations of how people behave?**

Lars Leetaru

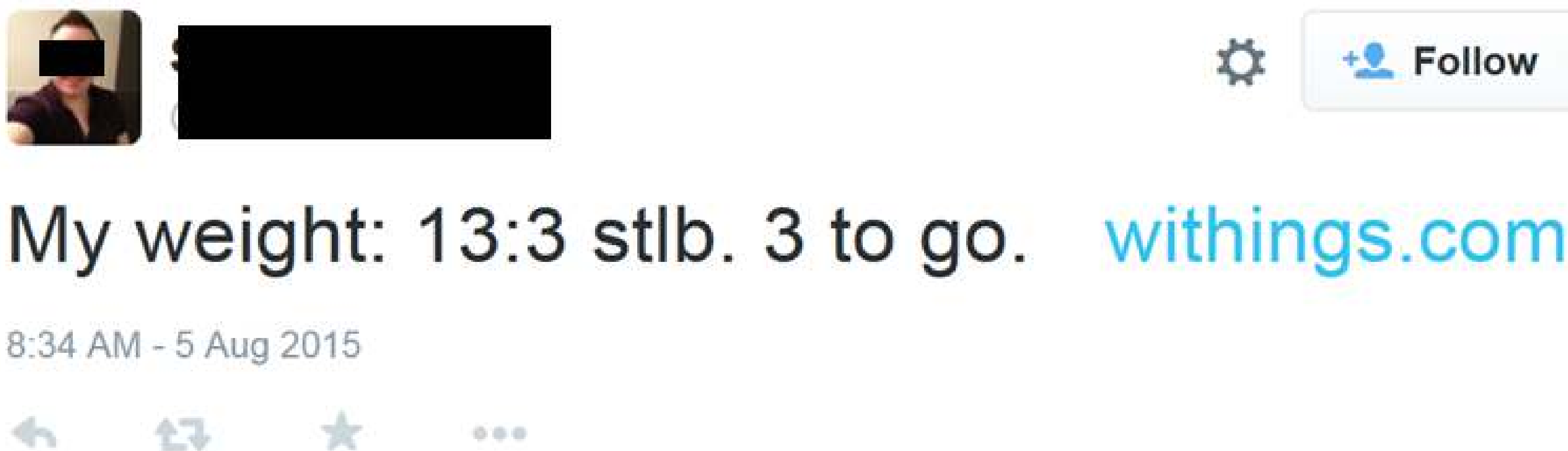
Email

Does obesity spread like a virus through networks of friends and friends of friends? Do smoking, loneliness, happiness, depression and illegal drug use

Opportunity 2: Network Influence

- No randomized controlled trial (RCT)
  - Only observational data
- Hard to tease apart
  - Homophily: friends are similar to you
  - Environment: friends are exposed to similar factors
  - Social influence: friends *make* you similar
- Possible solution: Natural experiments
  - Weather?
  - Local campaigns?

Opportunity 3:
Social Media Meets Quantified Self



Opportunity 3:
Social Media Meets Quantified Self

Opportunity 3:
Social Media Meets Quantified Self

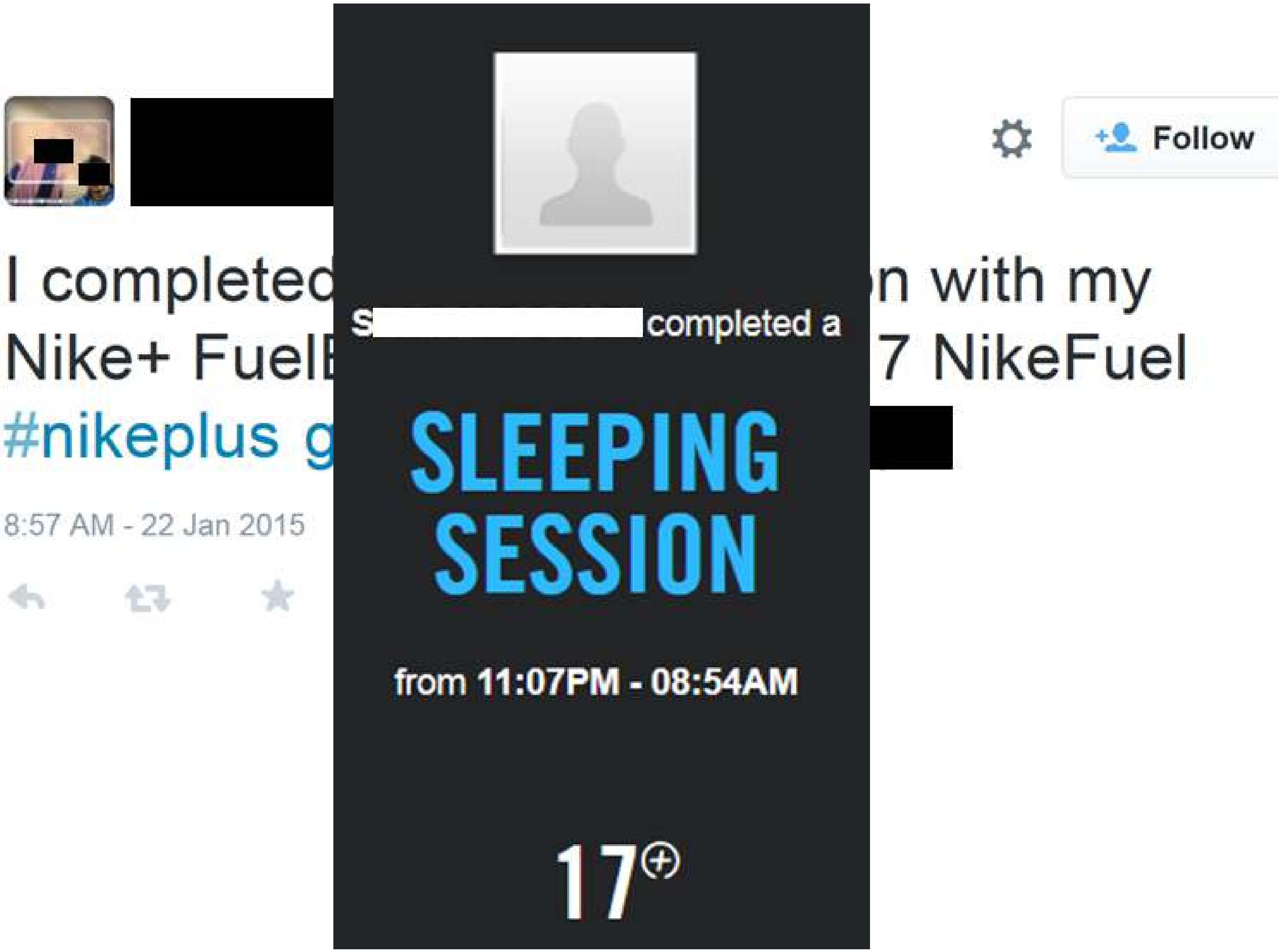
[redacted]

Follow

I completed a sleeping Session with my Nike+ FuelBand and earned 17 NikeFuel #nikeplus go.nike.com/[redacted]

8:57 AM - 22 Jan 2015

Opportunity 3:
Social Media Meets Quantified Self



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Social Media Meets Quantified Self

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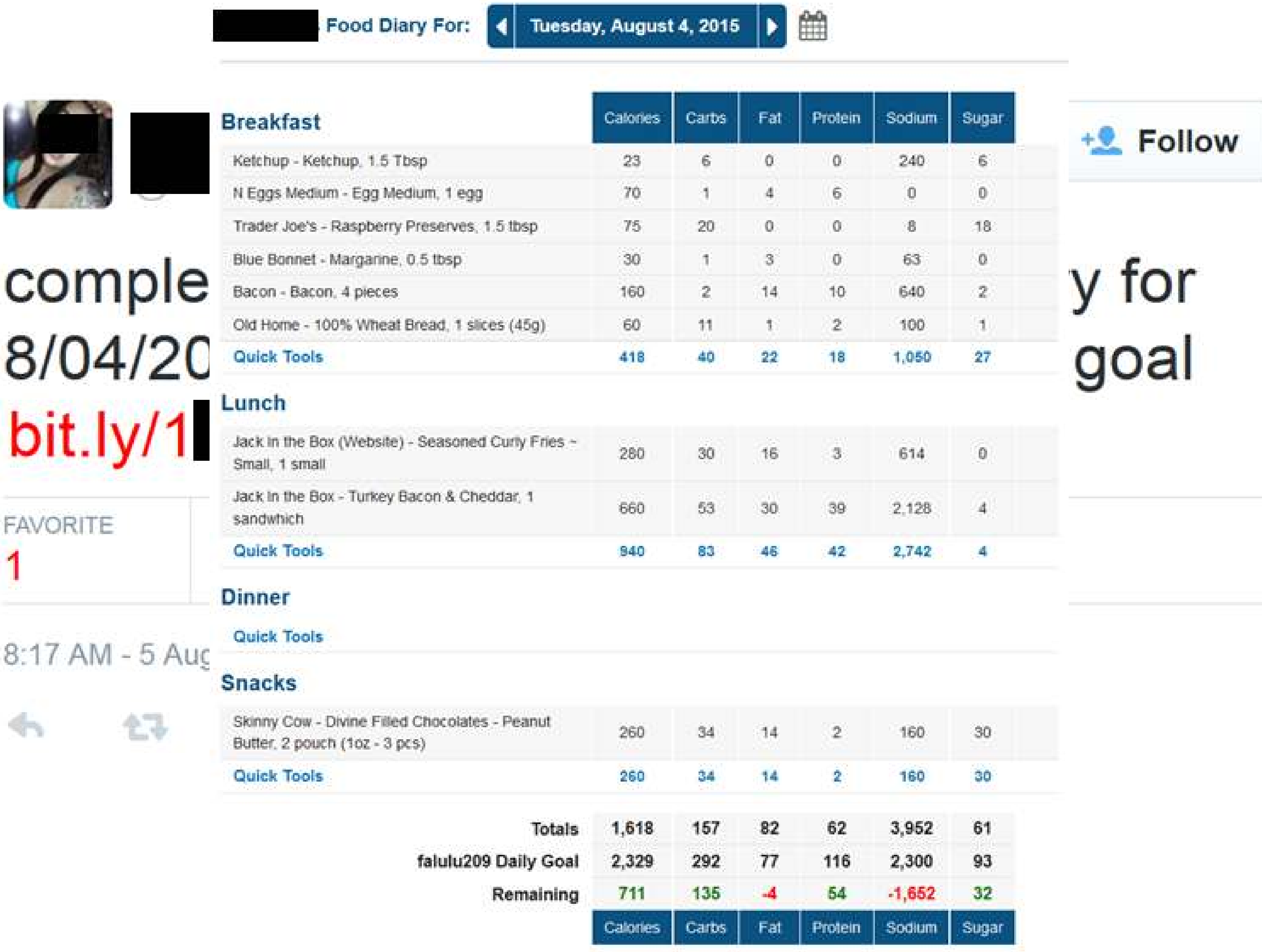
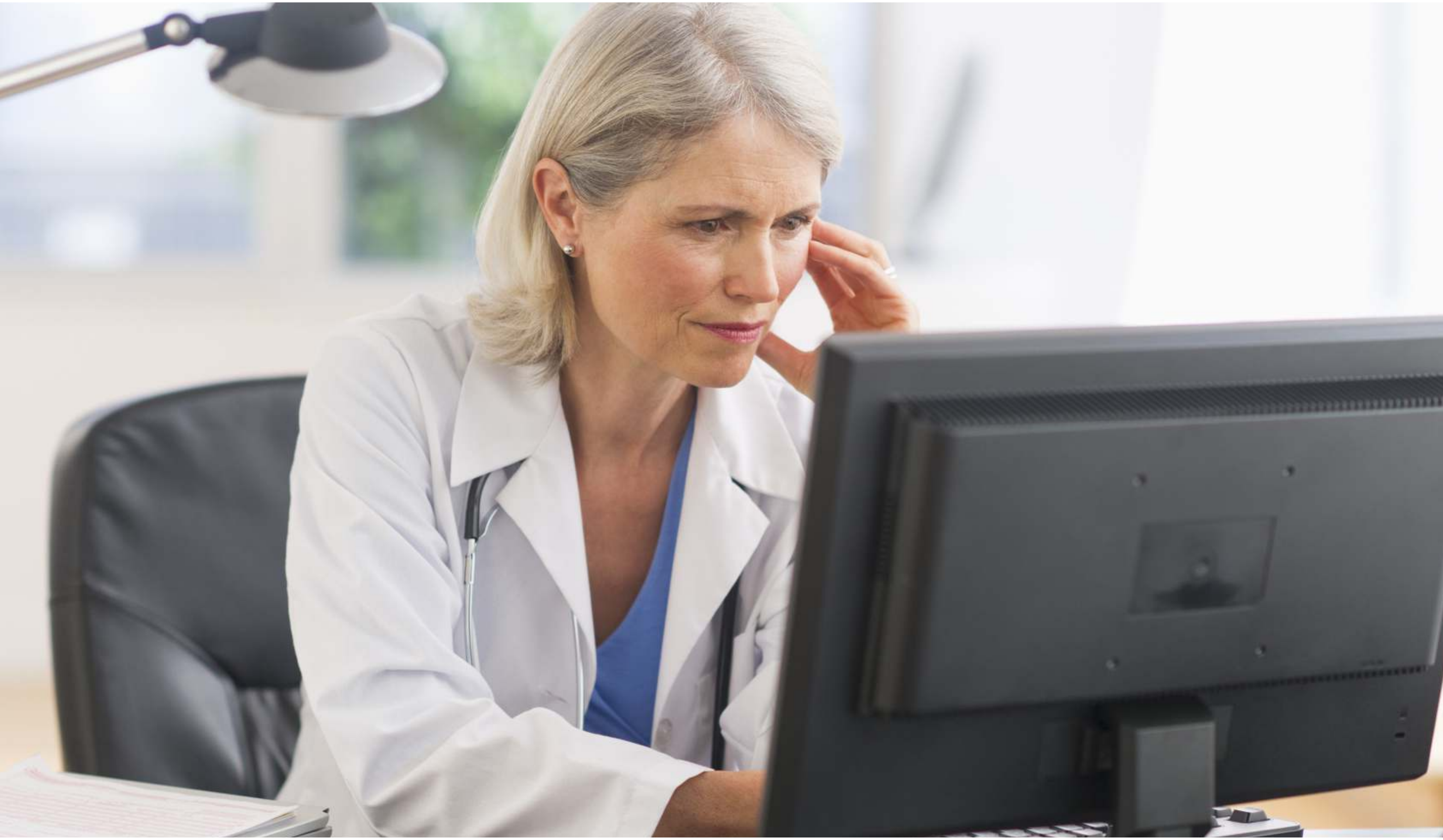


[redacted] Food Diary For: Tuesday, August 4, 2015

Breakfast	Calories	Carbs	Fat	Protein	Sodium	Sugar
Ketchup - Ketchup, 1.5 Tbsp	23	6	0	0	240	6
N Eggs Medium - Egg Medium, 1 egg	70	1	4	6	0	0
Trader Joe's - Raspberry Preserves, 1.5 tbsp	75	20	0	0	8	18
Blue Bonnet - Margarine, 0.5 tbsp	30	1	3	0	63	0
Bacon - Bacon, 4 pieces	160	2	14	10	640	2
Old Home - 100% Wheat Bread, 1 slices (45g)	60	11	1	2	100	1
Quick Tools	418	40	22	18	1,050	27
Lunch						
Jack in the Box (Website) - Seasoned Curly Fries ~ Small, 1 small	280	30	16	3	614	0
Jack in the Box - Turkey Bacon & Cheddar, 1 sandwhich	660	53	30	39	2,128	4
Quick Tools	940	83	46	42	2,742	4
Dinner						
Quick Tools						
Snacks						
Skinny Cow - Divine Filled Chocolates - Peanut Butter, 2 pouch (1oz - 3 pcs)	260	34	14	2	160	30
Quick Tools	260	34	14	2	160	30
Totals	1,618	157	82	62	3,952	61
falulu209 Daily Goal	2,329	292	77	116	2,300	93
Remaining	711	135	-4	54	-1,652	32
	Calories	Carbs	Fat	Protein	Sodium	Sugar

Opportunity 4:
Information for Individual Health



Opportunity 4:
Information for Individual Health

Opportunity 4:
Information for Individual Health

Opportunity 4: Information for Individual Health

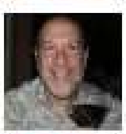
HEALTHBOOK

Search

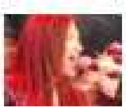
- Wall
- **Info**
- Photos (826)
- Questions

Family

Karen Zuckerberg
Runner



Edward Zuckerberg
Drinker



Randi Zuckerberg
Influencer

Mark Zuckerberg

Has posted unhealthy food pics. No exercise posts.

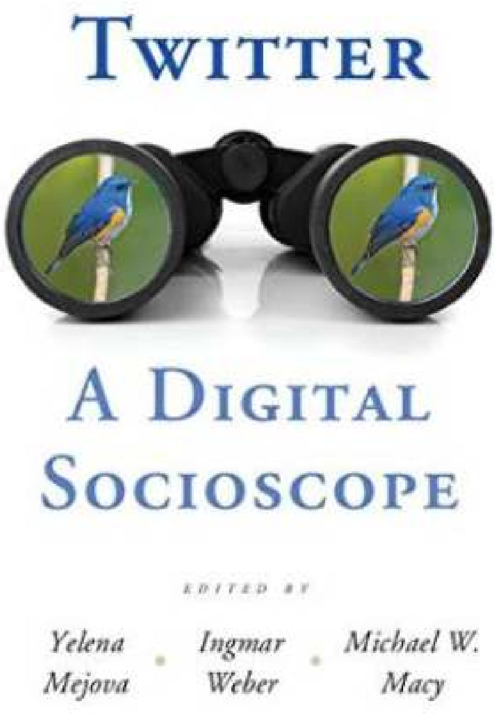
Education and Work

Mood	Large drop in positive mood since April. Possibly coincides with increased usage of #work.
Interests	Sedentary: online social networks, tv series, advertising Active: [none]

Challenges

- Ethical
  - Big Brother
  - “Informed” Consent
- Attitudinal
  - Medical doctors to listen
  - “Social Media Cures Cancer”
- Data quality
  - Selection bias: Who’s on Social Media? Who’s using QS?
  - Reporting bias: Who tweets about food? About STDs?
- Lack of individual level ground truth
  - Who has the flu? Who is obese? Who is smoking?
- Having *interventions*
  - So far only communication-based interventions
  - A/B testing on the “inside”

Twitter For Sociological Studies



Twitter: A Digital Socioscope Kindle Edition

by Yelena Mejova (Editor), Ingmar Weber (Editor), Michael W. Macy (Editor)

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Tack! Thanks!