The use of news alerts, Twitter microblogs, and Google searches as a complementary way to track disease activity

Case studies characterizing flu, dengue, Zika, and Ebola epidemics. Fondation Mérieux, December 6th, 2017



Mauricio Santillana, PhD

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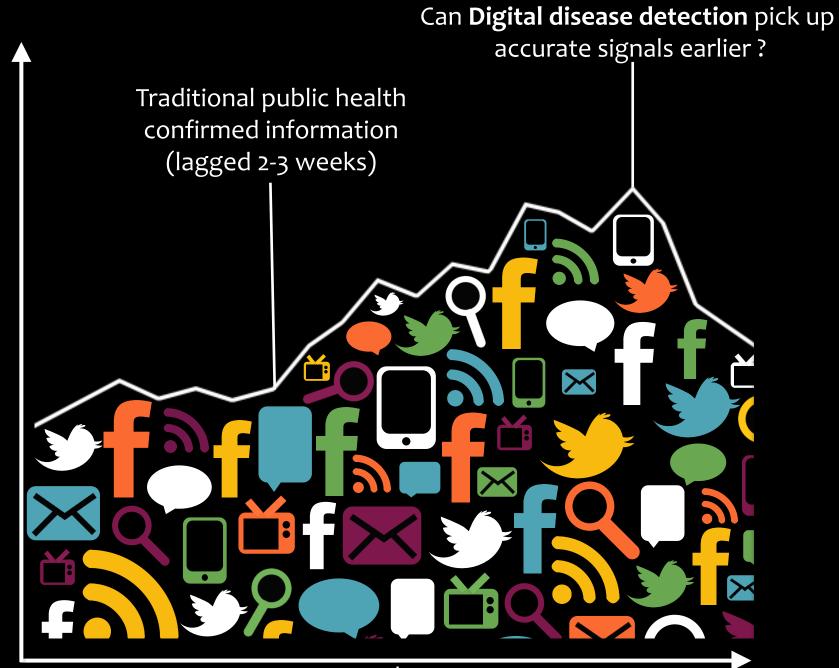
Collaborators: Sam C. Kou (Harvard Statistics), Shihao Yang (Harvard Statistics), Fred Lu (BCH), Nicholas Brooke (Break Dengue), Matt Biggerstaff (CDC), Julia Gunn (Boston Public Health Commission), Joe Conidi (Boston Public Health Commission), Michael Johansson (CDC), Nick Reich (Umass Amherst), Roni Rosenfeld (CMU), Kristin Baltrusaitis (Boston Univ), Alessandro Vespignani (Northeastern Univ), Nathan Kutz (Univ of Washington), Elaine Nsoesie (Univ of Washington), Rumi Chunara (NYU), John Brownstein (Harvard/BCH), Sarah McGough (Harvard), Leonardo C. Clemente (Inst. Politécnico Nacional, Mex), and many more





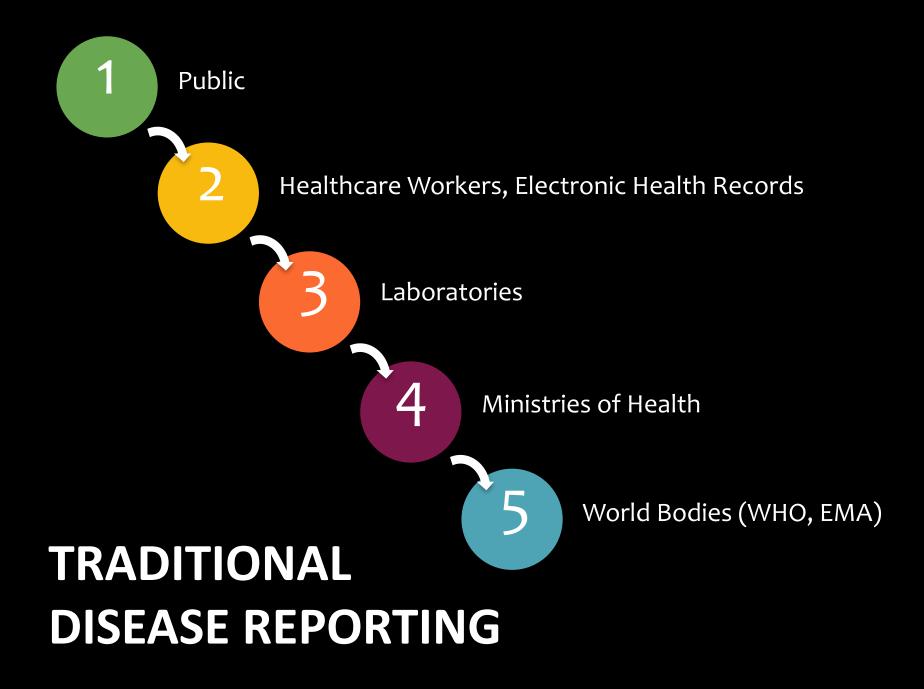


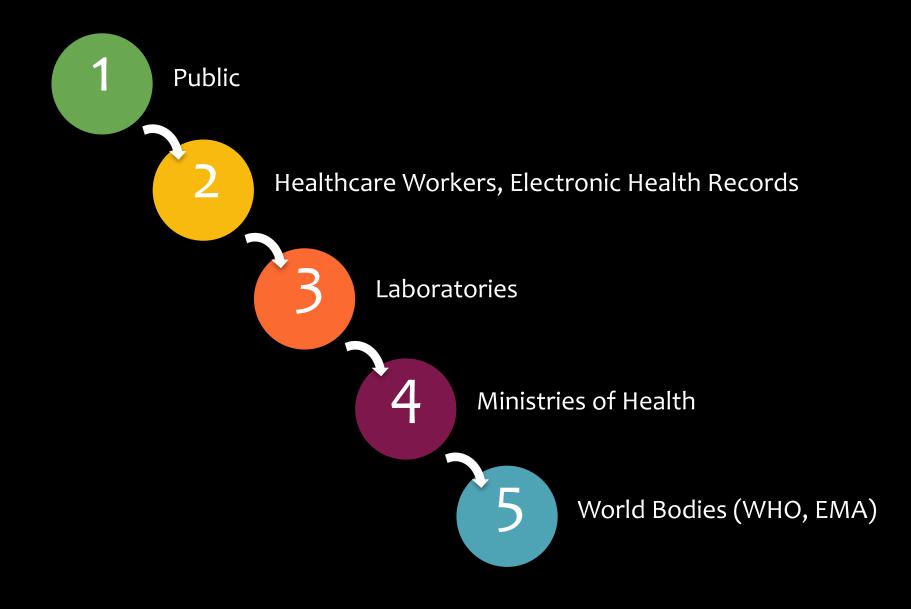


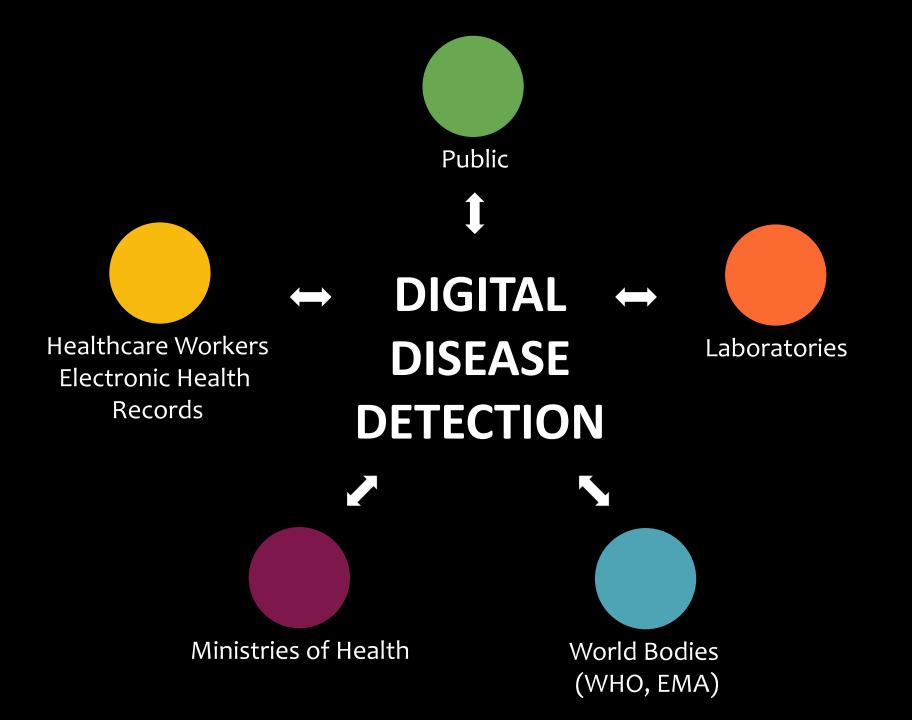


disease incidence

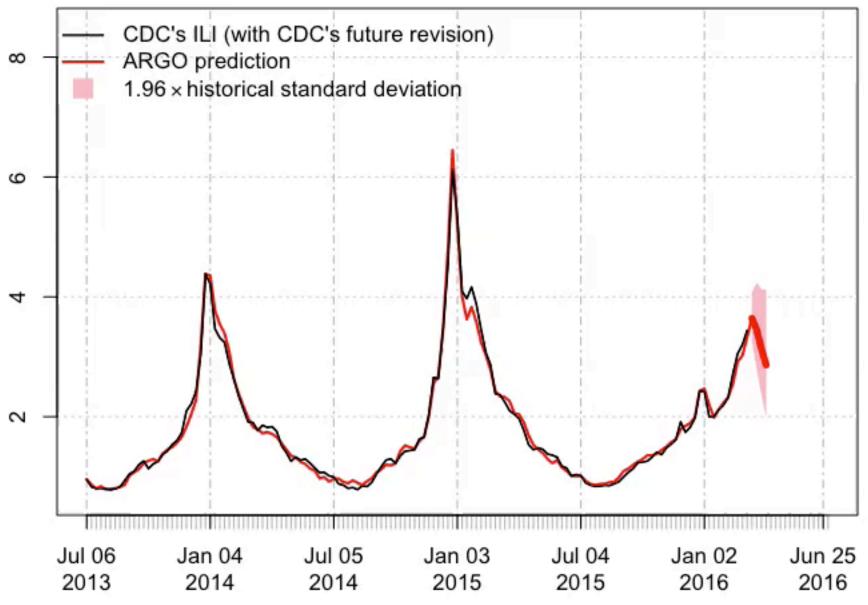
time



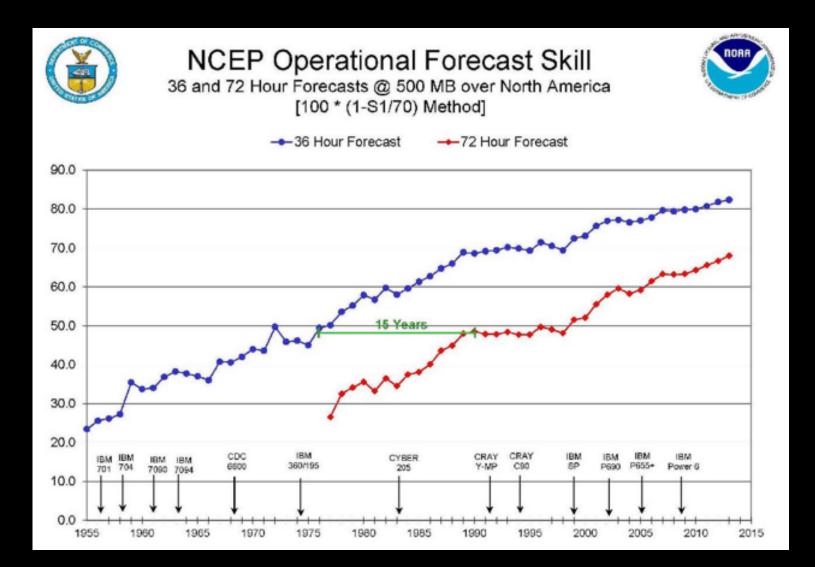




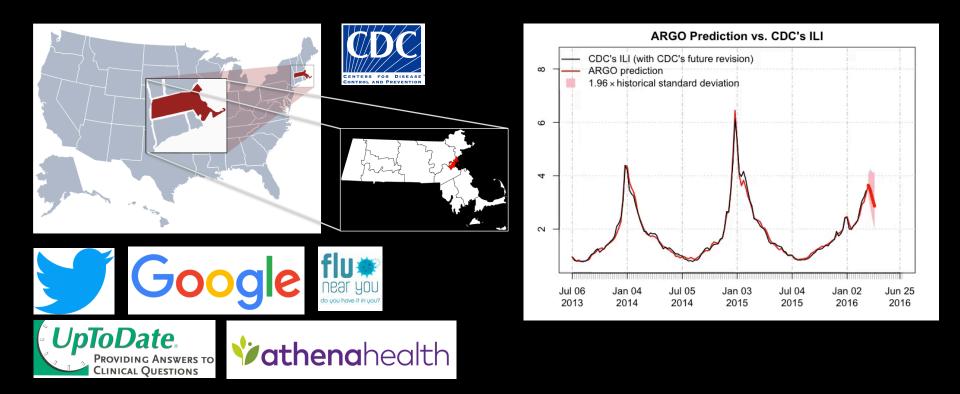
ARGO Prediction vs. CDC's ILI



Real-time tracking vs predictions of disease incidence/risk Similarities and differences with weather prediction



Part 1. Previous success stories in tracking and forecasting Influenza in data-rich high-income countries: USA



- 1. Multiple spatial resolutions: National, multi-state, state, city-level
- 2. Multiple data sources (hybrid systems): traditional healthcare-based, EHR, Google, Twitter, Crowd-sourced disease surveillance.

Part 2. Success stories in tracking and forecasting Flu, Zika, Dengue, Ebola in data-poor medium- to low-income countries.

Dengue, Zika, and Flu





- Latin America (Flu, Zika, Dengue)
- South-east Asia (Dengue)

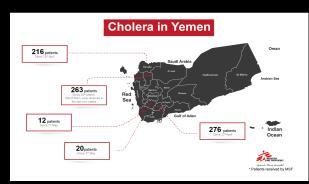
Ebola

Cholera



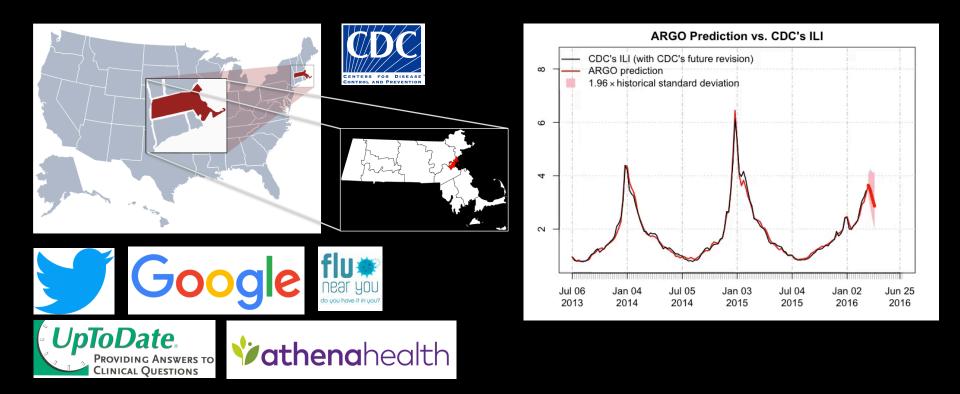


West Africa



• Middle East

Part 1. Previous success stories in tracking and forecasting Influenza in data-rich high-income countries: USA



- 1. Multiple spatial resolutions: National, multi-state, state, city-level
- 2. Multiple data sources (hybrid systems): traditional healthcare-based, EHR, Google, Twitter, Crowd-sourced disease surveillance.

Seminal work by Google

The promise of big data in public health

GOOGLE FLU TRENDS

nature International weekly journal of science

Google Flu Trends

Letter

Nature 457, 1012-1014 (19 February 2009) | doi:10.1038/nature07634; Received 14 August 2008; Accepted 13 November 2008; Published online 19 November 2008; Corrected 19 February 2009

Detecting influenza epidemics using search engine query data

Jeremy Ginsberg¹, Matthew H. Mohebbi¹, Rajan S. Patel¹, Lynnette Brammer², Mark S. Smolinski¹ & Larry Brilliant¹

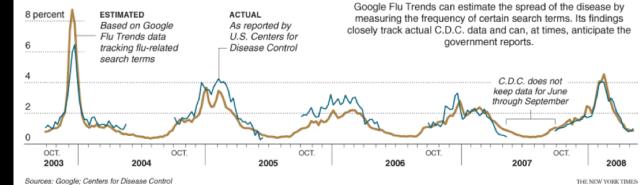
- 1. Google Inc., 1600 Amphitheatre Parkway, Mountain View, California 94043, USA
- 2. Centers for Disease Control and Prevention, 1600 Clifton Road, NE, Atlanta, Georgia 30333, USA

Correspondence to: Matthew H. Mohebbl¹ Correspondence and requests for materials should be addressed to J.G. or M.H.M. (Email: <u>flutrends-support@qoogle.com</u>).

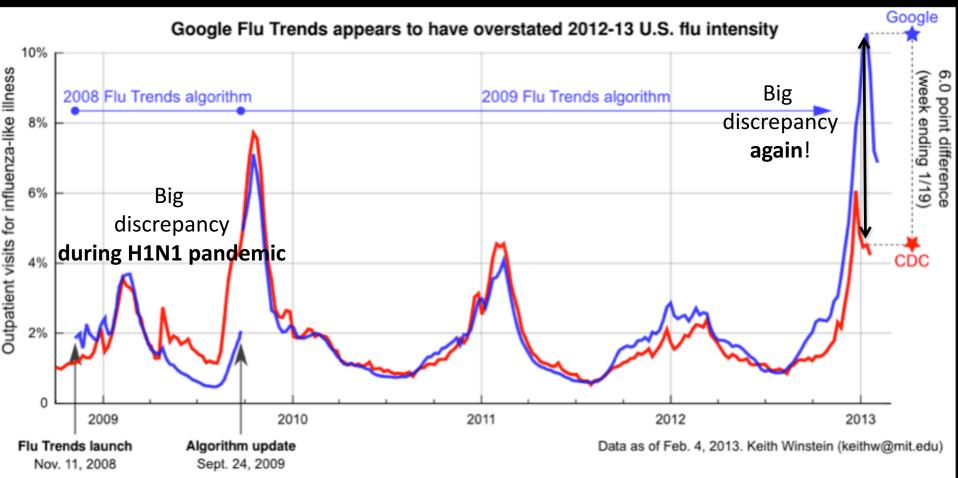
The New York Times

PERCENT OF HEALTH VISITS FOR FLU-LIKE SYMPTOMS Mid-Atlantic region

Using Google to Monitor the Flu



0



Sources: http://www.google.org/flutrends/us, CDC ILInet data from http://gis.cdc.gov/grasp/fluview/fluportaldashboard.html, Cook et al. (2011) Assessing Google Flu Trends Performance in the United States during the 2009 Influenza Virus A (H1N1) Pandemic.

Fixes were reported in: Cook et al. (2011) Assessing Google flu trends performance in the U.S. during the 2009 influenza virus A (H1N1) pandemic. PLoS One

Plot obtained from: http://blog.keithw.org/2013/02/q-how-accurate-is-google-flu-trends.html

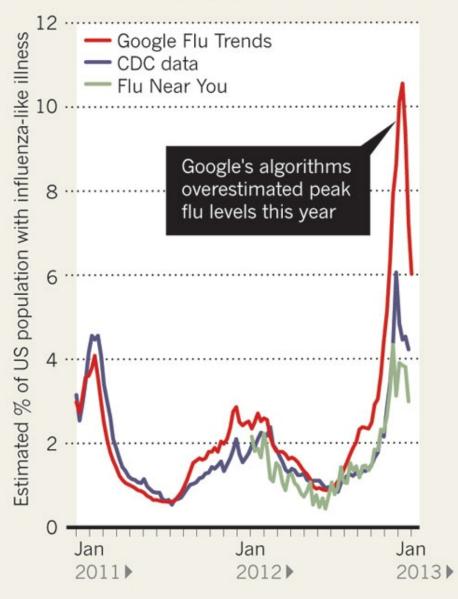
nature International weekly journal of science

When Google got flu wrong.

nature.com/news/when-google-got-flu-wrong.

FEVER PEAKS

A comparison of three different methods of measuring the proportion of the US population with an influenza-like illness.



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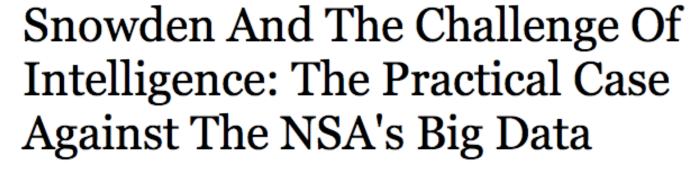
Lists The Forbes 400

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66 We should soon be able to keep track of most activities on the surface of the earth, day or night, in good weather or bad.

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Can Nate Silver's Data Culture Lead

Us Out of the NSA + Public Data

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RYAN COX | SEPTEMBER 18TH

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AMERICAN JOURNAL OF Preventive Medicine

A Journal of the American College of Preventive Medicine and Association for Prevention Teaching and Resear

What Can Digital Disease Detection Learn from (an External Revision to) Google Flu Trends?

Mauricio Santillana, PhD, MS, D. Wendong Zhang, MA, Benjamin M. Althouse, PhD, ScM, John W. Ayers, PhD, MA

© 2014 Published by Elsevier Inc. on behalf of American Journal of Preventive Medicine Am J Prev Med 2014;47(3):341-347 341 —CDC —Google flu trends ---Alternative 10 Original GFT Revised GFT CDC-reported ILI rate (%) 8 6 Post-H1N1 to 2012 season 2012-2013 season Wave 1 0 8/2/09 12/27/09 9/30/12 5/12/13

Figure 1. The alternative model outperforms Google Flu Trends

Google incorporated our proposed changes to GFT's engine in Oct 2014

We published a paper proposing changes to GFT's engine (2014)



Google Research Blog

The latest news from Research at Google

Google Flu Trends gets a brand new engine

Posted: Friday, October 31, 2014

222 Tweet {161 File {10

Posted by Christian Stefansen, Senior Software Engineer

Each year the flu kills thousands of people and affects millions around the world. So it's important that public health officials and health professionals learn about outbreaks as quickly as possible. In 2008 we launched Google Flu Trends in the U.S., using aggregate web searches to indicate when and where influenza was striking in real time. These models nicely complement other survey systems—they're more fine-grained geographically, and they're typically more immediate, up to 1-2 weeks ahead of traditional methods such as the CDC's official reports. They can also be incredibly helpful for countries that don't have official flu tracking. Since launching, we've expanded Flu Trends to cover 29 countries, and launched Dengue Trends in 10 countries.

8+1

The original model performed surprisingly well despite its simplicity. It was retrained just once per year, and typically used only the 50 to 300 queries that produced the best estimates for prior seasons. We then left it to perform through the new season and evaluated it at the end. It didn't use the official CDC data for estimation during the season—only in the initial training.

SCIENTIFIC **REP<mark>O</mark>RTS**

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Advances in nowcasting influenzalike illness rates using search query logs

Vasileios Lampos 📉, Andrew C. Miller, Steve Crossan & Christian Stefansen 🛛

Scientific Reports **5**, Article number: 12760 (2015) doi:10.1038/srep12760 Download Citation

Computer science Epidemiology

Applied mathematics

Influenza virus

Received: 07 May 2015 Accepted: 06 July 2015 Published online: 03 August 2015 Google and collaborators published a paper improving our AJPM 2014 methodology in August 2015

We improved last effort by Google team and published our results in PNAS in September 2015

Accurate estimation of influenza epidemics using Google search data via ARGO

Shihao Yang^a, Mauricio Santillana^{b,c,1}, and S. C. Kou^{a,1}

^aDepartment of Statistics, Harvard University, Cambridge, MA 02138; ^bSchool of Engineering and Applied Sciences, Harvard University, Cambridge, MA 02138; and ^cComputational Health Informatics Program, Boston Children's Hospital, Boston, MA 02115

Edited by Wing Hung Wong, Stanford University, Stanford, CA, and approved September 30, 2015 (received for review August 6, 2015)

Accurate real-time tracking of influenza outbreaks helps public health officials make timely and meaningful decisions that could save lives. We propose an influenza tracking model, ARGO (AutoRegression with GOogle search data), that uses publicly available online search data. In addition to having a rigorous statistical foundation, ARGO outperforms all previously available Google-search-based tracking models, including the latest version of Google Flu Trends, even though it uses only low-quality search data as input from publicly available Google Trends and Google Correlate websites. ARGO not only incorporates the seasonality in influenza epidemics but also captures changes in people's online search behavior over time. ARGO is also flexible, self-correcting, robust, and scalable, making it a potentially powerful tool that can be used for real-time tracking of other social events at multiple temporal and spatial resolutions.

CDC's ILI reports have a delay of 1–3wk due to the time for processing and aggregating clinical information. This time lag is far from optimal for decision-making purposes. To alleviate this information gap, multiple methods combining climate, demographic, and epidemiological data with mathematical models have been proposed for real-time estimation of flu activity (18, 21–25). In recent years, methods that harness Internet-based information have also been proposed, such as Google (1), Yahoo (2), and Baidu (3) Internet searches, Twitter posts (4), Wikipedia article views (5), clinicians' queries (6), and crowdsourced selfreporting mobile apps such as Influenzanet (Europe) (26), Flutracking (Australia) (27), and Flu Near You (United States) (28). Among them, GFT has received the most attention and has inspired subsequent digital disease detection systems (3, 8,

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Advances in nowcasting influenzalike illness rates using search query logs

Vasileios Lampos 🖾, Andrew C. Miller, Steve Crossan & Christian Stefansen

Scientific Reports 5, Article number: 12760 (2015) doi:10.1038/srep12760 **Download Citation**

Received: 07 May 2015 Accepted: 06 July 2015 Published online: 03 August 2015

Applied mathematics

Computer science Epidemiology

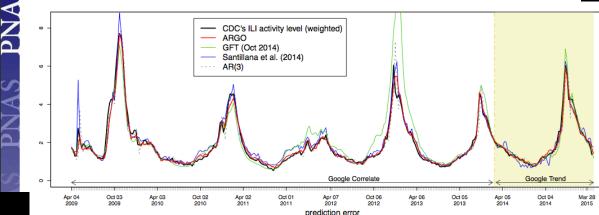
Influenza virus

Google and collaborators published a paper improving our AJPM 2014 methodology in August 2015

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Accurate estimation of influenza epidemics using Google search data via ARGO

Shihao Yang^a, Mauricio Santillana^{b,c,1}, and S. C. Kou^{a,1}





Google discontinues Flu Trends indefinitely!





The latest news from Research at Google

The Next Chapter for Flu Trends

Posted: Thursday, August 20, 2015

Instead of maintaining our own website going forward, we're now going to empower institutions who specialize in infectious disease research to use the data to build their own models. Starting this season, we'll provide Flu and Dengue signal data directly to partners including Columbia University's Mailman School of Public Health (to update their dashboard), Boston Children's Hospital/Harvard, and Centers for Disease Control and Prevention (CDC) Influenza Division. We will also continue to make historical Flu and Dengue estimate data available for anyone to see and analyze.

g+1



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NEWS

Google Flu Trends calls out sick, indefinitely

Google will pass along search queries related to the flu to health organizations so they can develop their own prediction models

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By Fred O'Connor Follow IDG News Service Aug 20, 2015 2:07 PM PT

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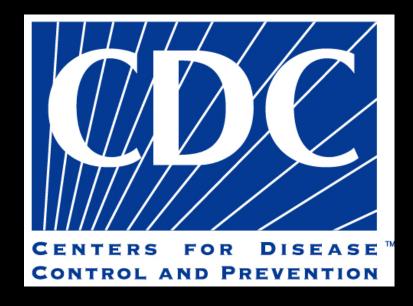
BIG DATA

Google discontinues Flu Trends, starts offering data to researchers

JORDAN NOVET AUGUST 20, 2015 12:17 PM

Our team at Boston Children's Hospital now has access to Google's search volumes, as one of the exclusive Google's partners.

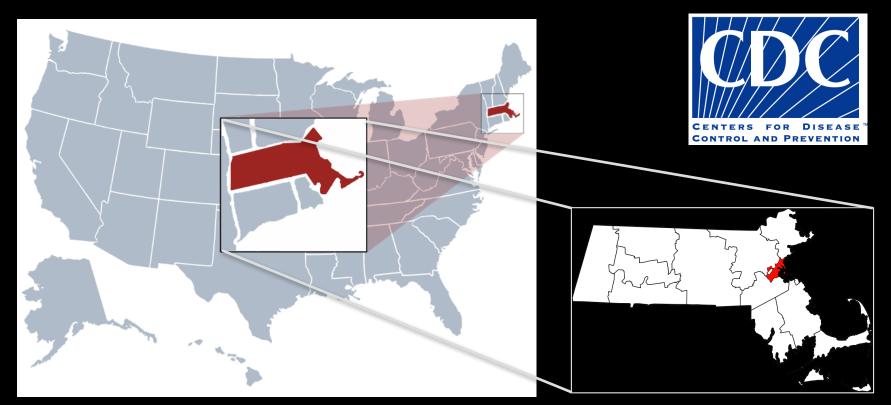
We are helping create a new improved disease forecasting platform funded by the Centers for Disease Control and Prevention



In collaboration with the CDC Influenza division, we are extending our work from National and Regional predictions, to state-level and city level (Boston as a pilot)

Grant: Centers for Disease Control and Prevention's Cooperative Agreement PPHF 11797-998G-15

Team members: *Fred Lu, Leonardo C. Clemente* CDC liaison and collaborator: *Matt Biggerstaff*





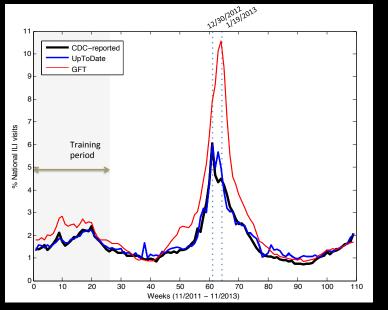
What are doctors searching for?



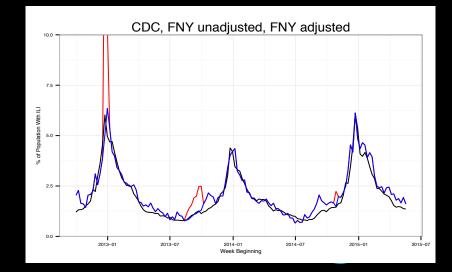


What are people tweeting? What are they reporting on crowd-sourced disease surveillance apps?

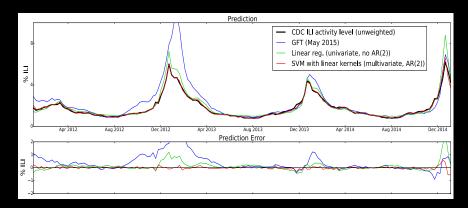


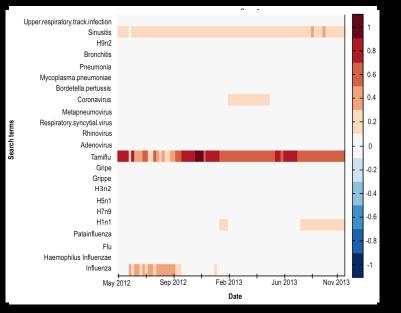


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What are doctors searching for?





What are people tweeting? What are they reporting on crowd-sourced disease surveillance apps?



OXFORD JOURNALS

Clinical Infectious Diseases

Using Clinicians' Search Query Data to Monitor Influenza Epidemics

Mauricio Santillana,^{1,2} Elaine O. Nsoesie,^{2,3} Sumiko R. Mekaru,² David Scales,^{2,4} and John S. Brownstein^{2,3,5}

¹School of Engineering and Applied Sciences, Harvard University, Cambridge, ²Children's Hospital Informatics Program, Boston Children's Hospital, ³Department of Polidistrics, Harvard Medical School, Boston, and ³Department of Internal Medicine, Cambridge Health Alliance, Massachusetts, and ³Department of Epidemiology, Biostatistics and Occupational Health, McGill University, Montreal, Quebec, Canado

Search query information from a clinician's database, UpTo-Date, is shown to predict influenza epidemics in the United States in a timely manner. Our results show that digital disease surveillance tools based on experts' databases may be able to provide an alternative, reliable, and stable signal for accurate predictions of influenza outbreaks.

Keywords. digital disease detection; Internet-based disease surveillance; prediction of influenza.

validated traditional surveillance systems and have the potential to provide timely epidemiologic intelligence to inform prevention messaging and healthcare facility staffing decisions.

The potential for the public's search activity to be influenced by anxiety, fears, and rumors raises concerns regarding reliability [10–13]. Although recent revisions to GFT have shown that these concerns can be partially mitigated [13–15], shifting Internet-based surveillance from the entire public to subjectmatter experts may maintain timeliness while generating a more reliable and stable signal requiring much less data. A recent small retrospective study using data on queries to a Finnish primary care guidelines database demonstrated, for example, that disease-specific queries for Lyme disease, tularemia, and other infectious diseases correlated well with concurrent confirmed cases [16].

Here, we show that UpToDate (www.uptodate.com), a physician-authored clinical decision support Internet resource that is used by 700 000 clinicians in 158 countries and almost 90% of academic medical centers in the United States, can be used for syndromic surveillance of influenza. Specifically, we use UpTo-Date's search query activity related to ILI to design a timely sentinel of influenza incidence in the United States.

What are doctors searching for?

veillance. Mobile phones, tablest, digital pers, and satellites are making it possible for surveillance and rapid response teams in even remote areas of the globe to carry out an essential function of public health to protect against outbreaks of infectious disease. To date, public health surveillance has been limited by the capacity of public health authorities to conduct case and contact tracing and a reliance outdate privided primarily

by the medical system. The increased use of digital communications technology is now making

2 Influenza Seasons

Digital communications technologies have rapidly

increased in use for public health disease sur-

it possible to enable the public to actively be part of the public health surveillance system.

Since 2003, participatory surveillance approaches have leveraged online survey technol-

ogy with syndromic surveillance of human

Objectives. We summarized Flu Near You (FNY) data from the 2012–2013 and 2013–2014 influenza seasons in the United States.

Methods. FNY collects limited demographic characteristic information upon registration, and prompts users each Monday to report symptoms of influenzalike illness (ILL) experienced during the previous week. We calculated the descriptive statistics and rates of ILI for the 2012-2013 and 2013-2014 seasons. We compared raw and noise-filtered ILI rates with ILI rates from the Centers for Disease Control and Prevention ILINet surveillance system.

Results. More than 61 000 participants submitted at least 1 report during the 2012-2013 season, totaling 327773 reports. Nearly 40 000 participants submitted at least 1 report during the 2013-2014 season, totaling 336933 reports. Rates of ILI as reported by FNY tracked closely with ILINet in both timing and magnitude.

Conclusions. With increased participation, FNY has the potential to serve as a viable complement to existing outpatient, hospital-based, and laboratory surveillance systems. Although many established systems have the benefits of specificity and credibility, participatory systems offer advantages in the areas of speed, sensitivity, and scalability. (Am J Public Health. Published online ahead of print August 13, 2015: e1-e7. doi:10.2106/AJPH.2015.302886)

What are people tweeting? What are they reporting on crowd-sourced disease surveillance apps?

AJPM American Journal of Preventive Medicine

Mark S. Smolinski, MD, MPH, Adam W. Crawley, MPH, Kristin Baltrusaitis, MA, Rumi Chunara, PhD, MS, Jennifer M. Olsen, DrPH, Oktawia Wójcik, PhD,

Flu Near You: Crowdsourced Symptom Reporting Spanning

Mauricio Santillana, PhD, MS, Andre Nguyen, and John S. Brownstein, PhD, MPH

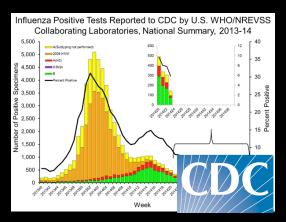
SCIENTIFIC REPORTS

OPEN Cloud-based Electronic Health Records for Real-time, Regionspecific Influenza Surveillance

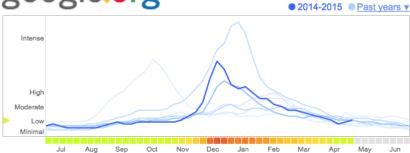
Received: 31 December 2015 M. Santillana^{1,2,3}, A. T. Nguyen³, T. Louie⁴, A. Zink⁵, J. Gray⁵, I. Sung⁵ & J. S. Brownstein^{1,2}

Ensemble approaches yield more accurate and more robust real-time and forecast flu estimates







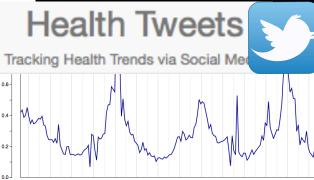






Products 8





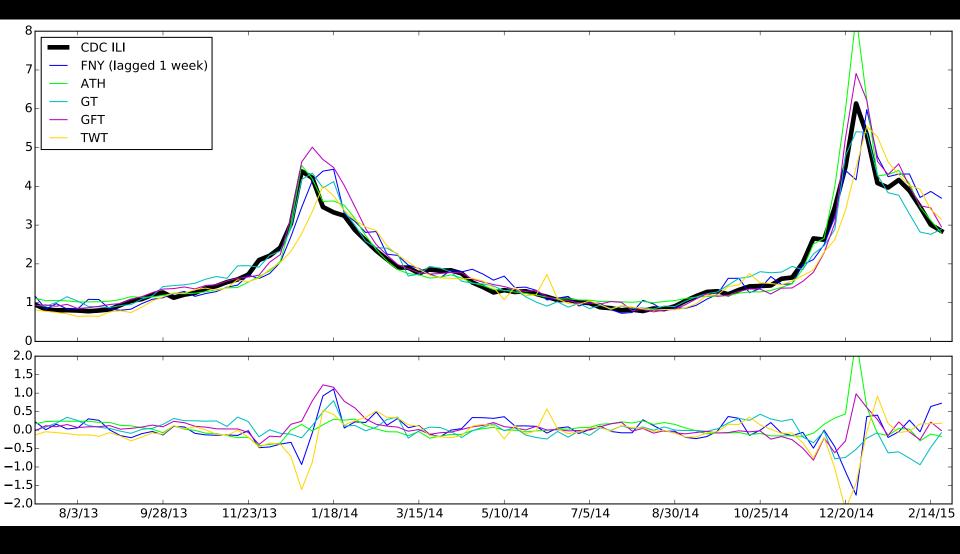
Performance of individual data sources

	CORR	RMSE (%ILI)	Rel RMSE (%)	RMAE (%)	Hit Rate
FNY	0.948	0.385	15.9	39.3	65.9
ATH	0.977	0.351	14.1	36.7	77.7
GT	0.978	0.245	13.3	42.9	65.9
GFT	0.980	0.333	12.3	35.3	75.3
TWT	0.937	0.414	15.1	50.1	62.4
CDC Baseline	0.930	0.501	18.2	46.7	68.2
CDC Virology	0.923	-	-	-	69.4

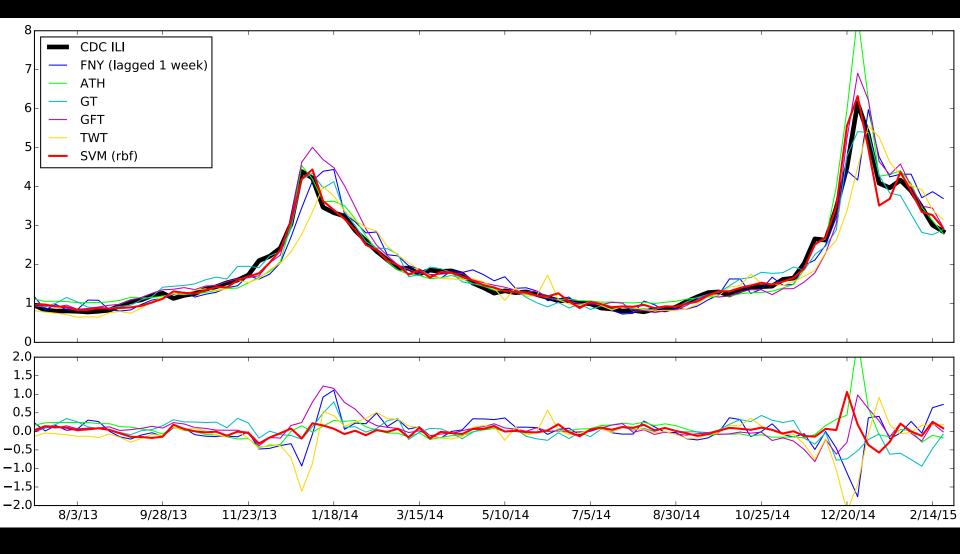
Performance ensemble

	CORR	RMSE ($\%$ ILI)	Rel RMSE (%)	RMAE (%)	Hit Rate
FNY	0.948	0.385	15.9	39.3	65.9
ATH	0.977	0.351	14.1	36.7	77.7
GT	0.978	0.245	13.3	42.9	65.9
GFT	0.980	0.333	12.3	35.3	75.3
TWT	0.937	0.414	15.1	50.1	62.4
CDC Baseline	0.930	0.501	18.2	46.7	68.2
CDC Virology	0.923	-	-	-	69.4
SVM (RBF)	0.989	0.176	8.27	23.6	69.4

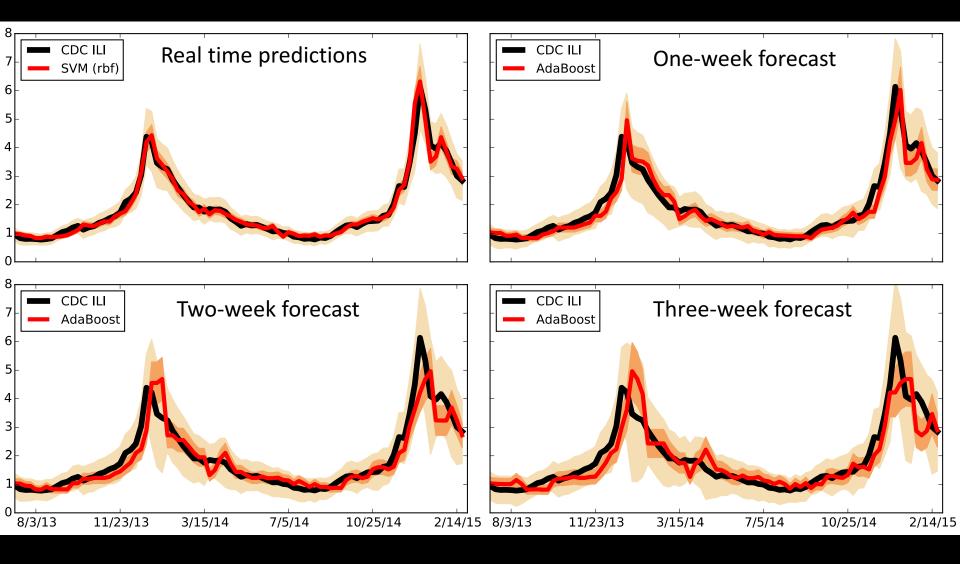
Performance of individual data sources



Performance ensemble



Real time predictions and Forecasts



Ensemble approaches yield more accurate and more robust real-time and forecast flu estimates

Yang et al. BMC Infectious Diseases (2017) 17:332 DOI 10.1186/s12879-017-2424-7	BMC Infectious Diseases
RESEARCH ARTICLE Using electronic health records and Internet search information for accu	Open Access
influenza forecasting	late

Shihao Yang¹, Mauricio Santillana^{2,3*}, John S. Brownstein^{2,3}, Josh Gray⁴, Stewart Richardson⁴ and S. C. Kou^{1*}

Abstract

Background: Accurate influenza activity forecasting helps public health officials prepare and allocate resources for unusual influenza activity. Traditional flu surveillance systems, such as the Centers for Disease Control and Prevention's (CDC) influenza-like illnesses reports, lag behind real-time by one to 2 weeks, whereas information contained in cloudbased electronic health records (EHR) and in Internet users' search activity is typically available in near real-time. We present a method that combines the information from these two data sources with historical flu activity to produce national flu forecasts for the United States up to 4 weeks ahead of the publication of CDC's flu reports.

Methods: We extend a method originally designed to track flu using Google searches, named ARGO, to combine information from EHR and Internet searches with historical flu activities. Our regularized multivariate regression model dynamically selects the most appropriate variables for flu prediction every week. The model is assessed for the flu seasons within the time period 2013–2016 using multiple metrics including root mean squared error (RMSE).

Results: Our method reduces the RMSE of the publicly available alternative (Healthmap flutrends) method by 33, 20, 17 and 21%, for the four time horizons: real-time, one, two, and 3 weeks ahead, respectively. Such accuracy improvements are statistically significant at the 5% level. Our real-time estimates correctly identified the peak timing and magnitude of the studied flu seasons.

Conclusions: Our method significantly reduces the prediction error when compared to historical publicly available Internet-based prediction systems, demonstrating that: (1) the method to combine data sources is as important as data quality; (2) effectively extracting information from a cloud-based EHR and Internet search activity leads to accurate forecast of flu.

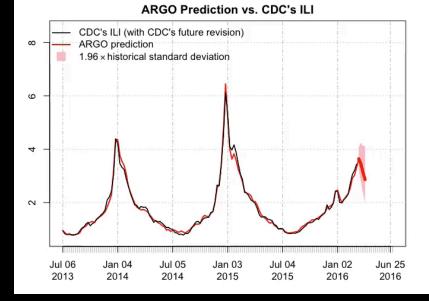
Keywords: Influenza-like illnesses reports, Digital disease detection, Dynamic error reduction, Validation test, Autoregression



RESEARCH ARTICLE

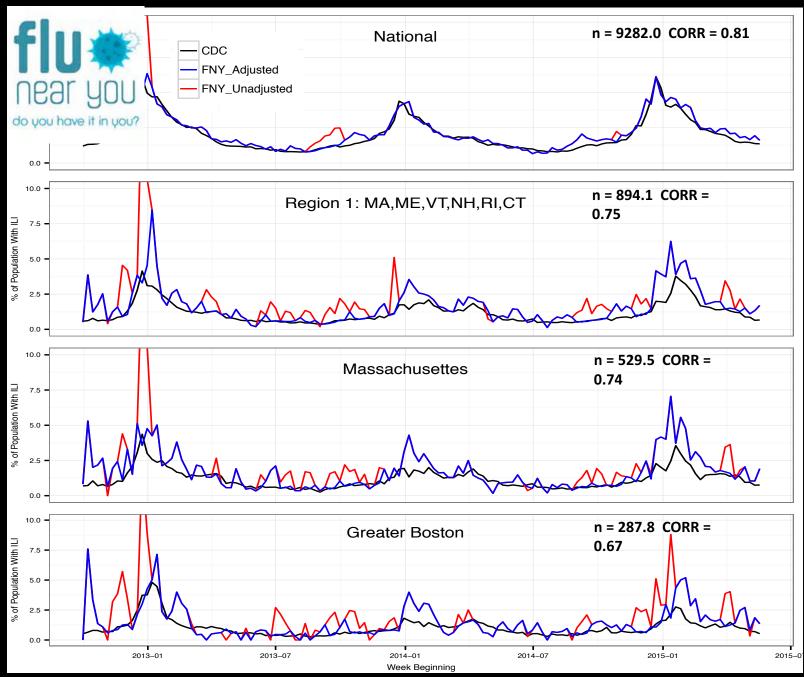
Combining Search, Social Media, and Traditional Data Sources to Improve Influenza Surveillance

Mauricio Santillana^{1,2,3}*, André T. Nguyen¹, Mark Dredze⁴, Michael J. Paul⁵, Elaine O. Nsoesie^{6,7}, John S. Brownstein^{2,3}

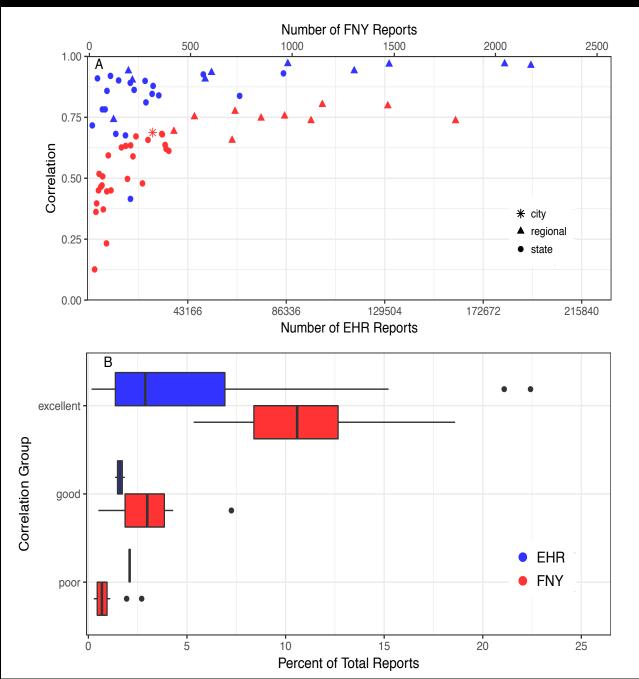


What about estimating flu in a regional level, state-level, city-level?

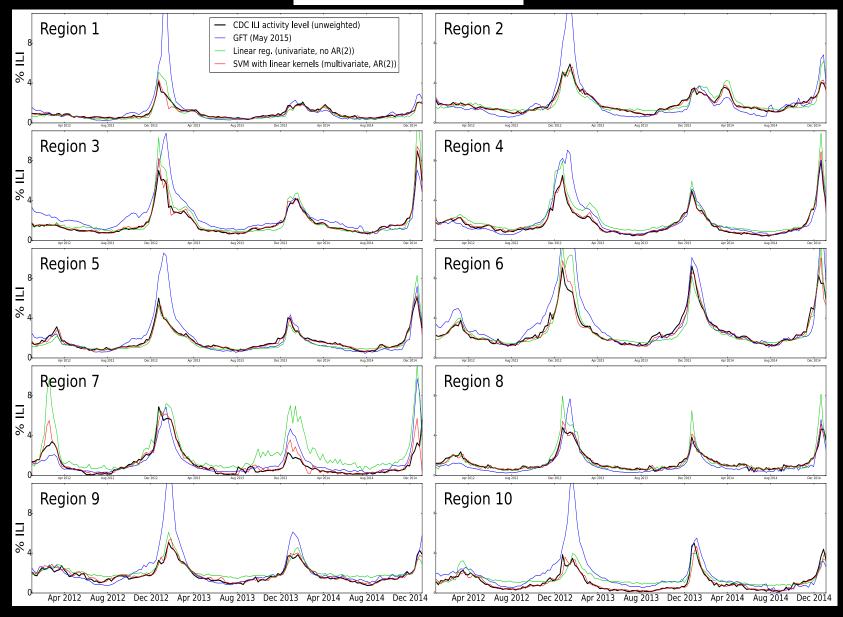
Correlation of FNY with CDC. Multiple Geographic Scales



Comparisons between CDC ILINet and FNY and Athenahealth in multiple spatial scales



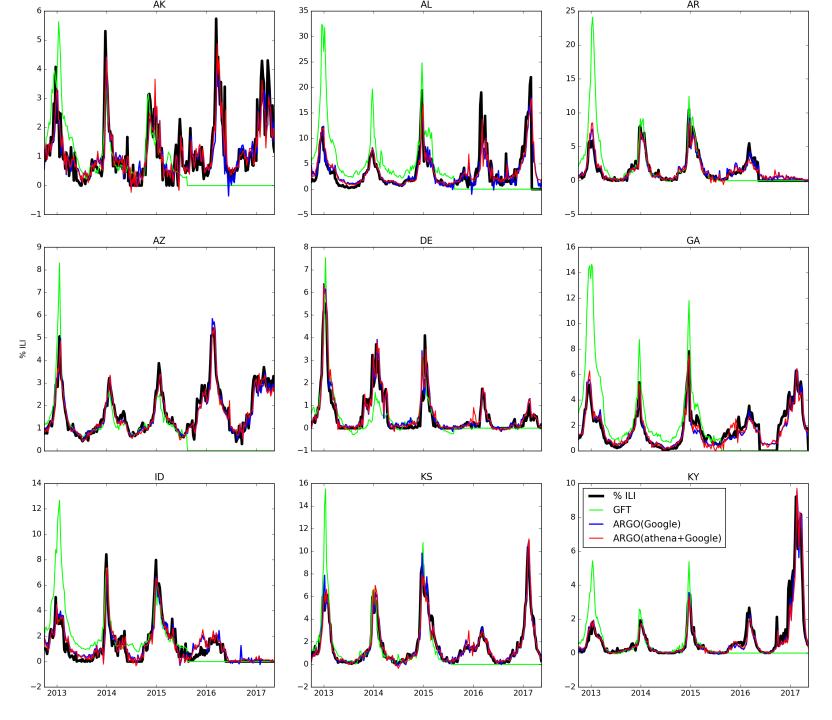
i athenahealth



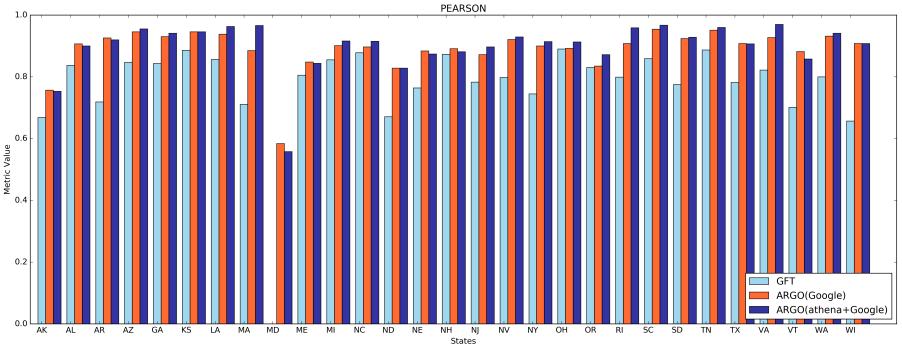
Santillana et al. 2016 Scientific Reports, 25732

How about state-level?





Metric	State	Model	2012-13	2013-14	2014-15	2015-16	2016-17	GFT Period	Whole Period
PEARSON	AK	GFT	0.673	0.932	0.768			0.669	0.669
		AR52	0.655	0.77	0.772	0.701	0.717	0.751	0.749
		ARGO(Google)	0.655	0.787	0.736	0.767	0.736	0.769	0.751
		ARGO(athena+Google)	0.682	0.828	0.73	0.814	0.801	0.795	0.766
	AL	GFT	0.915	0.867	0.939			0.837	0.837
		AR52	0.893	0.94	0.792	0.701	0.956	0.86	0.878
		ARGO(Google)	0.887	0.956	0.848	0.625	0.954	0.858	0.896
		ARGO(athena+Google)	0.962	0.958	0.85	0.564	0.964	0.859	0.905
	AR	GFT	0.913	0.949	0.968			0.719	0.719
		AR52	0.939	0.905	0.86	0.53		0.899	0.92
		ARGO(Google)	0.965	0.918	0.894	0.751		0.917	0.926
		ARGO(athena+Google)	0.966	0.923	0.893	0.758		0.905	0.916
	AZ	GFT	0.951	0.913	0.913			0.847	0.847
		AR52	0.89	0.902	0.955	0.91	0.898	0.942	0.933
		ARGO(Google)	0.949	0.944	0.953	0.938	0.892	0.952	0.958
		ARGO(athena+Google)	0.942	0.939	0.956	0.929	0.894	0.95	0.955
	DE	GFT	0.938	0.623	0.712			0.766	0.766
		AR52	0.927	0.702	0.81	0.623	0.692	0.887	0.875
		ARGO(Google)	0.96	0.732	0.778	0.912	0.83	0.907	0.891
		ARGO(athena+Google)	0.957	0.721	0.826	0.851	0.851	0.91	0.896
	GA	GFT	0.91	0.956	0.879			0.843	0.843
		AR52	0.95	0.895	0.815	0.676	0.847	0.913	0.907
		ARGO(Google)	0.969	0.953	0.896	0.87	0.915	0.932	0.936
-		ARGO(athena+Google)	0.973	0.962	0.909	0.296	0.918	0.927	0.941
	ID	GFT	0.862	0.903	0.956			0.638	0.638
		AR52	0.812	0.802	0.897	0.368		0.862	0.871
		ARGO(Google)	0.857	0.827	0.915	0.431		0.873	0.884
		ARGO(athena+Google)	0.824	0.85	0.917	0.303		0.876	0.892
	KS	GFT	0.88	0.954	0.957			0.886	0.886
		AR52	0.918	0.897	0.949	0.588	0.909	0.933	0.946
		ARGO(Google)	0.935	0.932	0.944	0.902	0.964	0.957	0.952
		ARGO(athena+Google)	0.943	0.94	0.933	0.793	0.962	0.95	0.944



How about city-level?

Refining the spatial resolution...

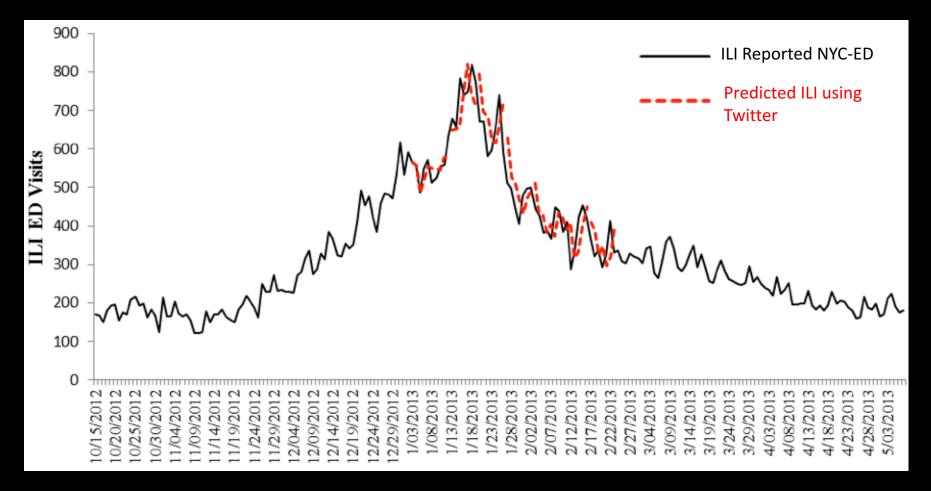


Tracking Flu using twitter (Daily analysis in NYC)



Work with R. Nagar, Q. Yuan, C. Freifeld, A. Nojima, R. Chunara, and J. S. Brownstein

Daily ILI visits (as reported by the NYC emergency department) compared to predicted ILI using twitter data



Nagar et al. (2014) Journal of Medical Internet Research. In press

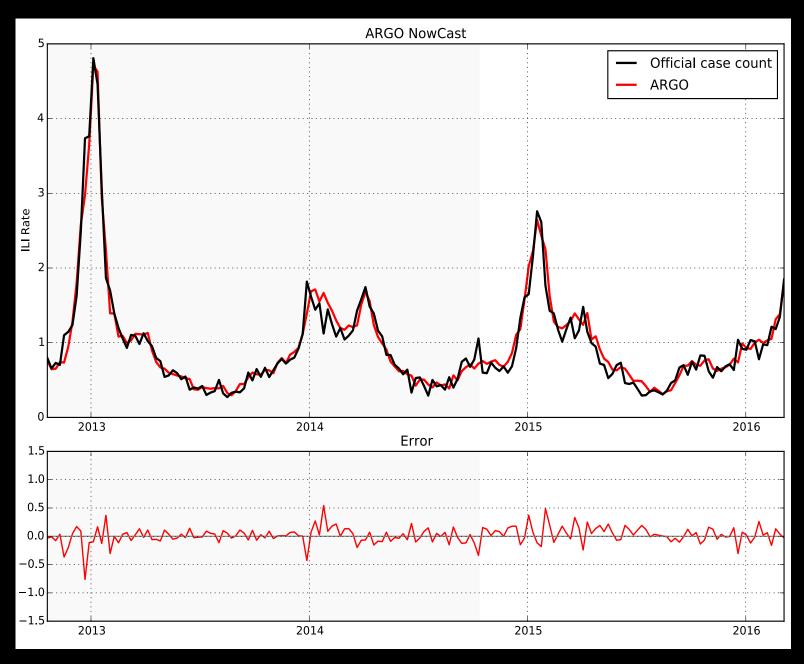
We will extend out methodology to finer spatial resolutions. Pilot projects:

- 1. State level: Massachusetts
 - 1. City level: Boston

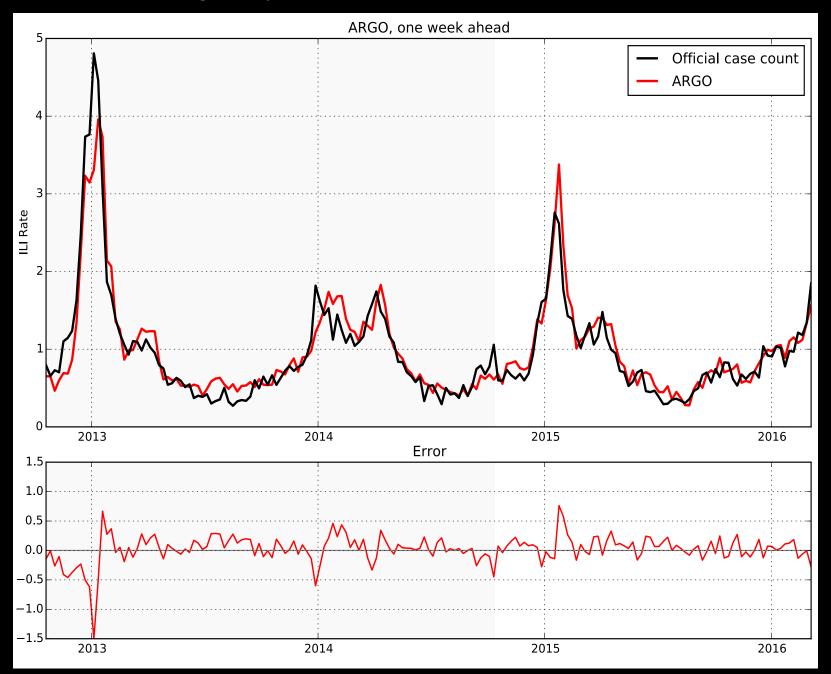
Team:

Fred Lu, Suqin Hou, Kristin Baltrusaitis, Joe Conidi, Julia Gunn, Jared Hawkins, John Brownstein, Mauricio Santillana

Using multiple data sources to track flu in Boston

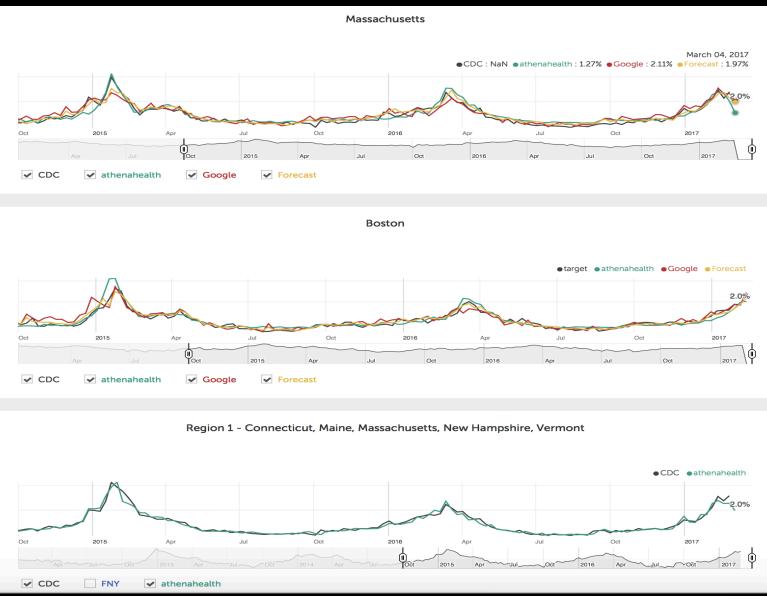


Using multiple data sources to forecast flu in Boston



Aim is to display these predictions in a joint CDC-BCH website

Using multiple data sources to track flu at the state-level in the USA



Part 2. Success stories in tracking and forecasting Flu, Zika, Dengue, Ebola in data-poor medium- to low-income countries.

Dengue, Zika, and Flu





- Latin America (Flu, Zika, Dengue)
- South-east Asia (Dengue)

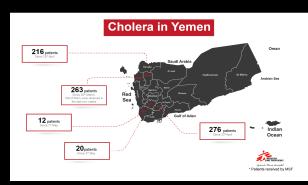
Ebola

Cholera





West Africa



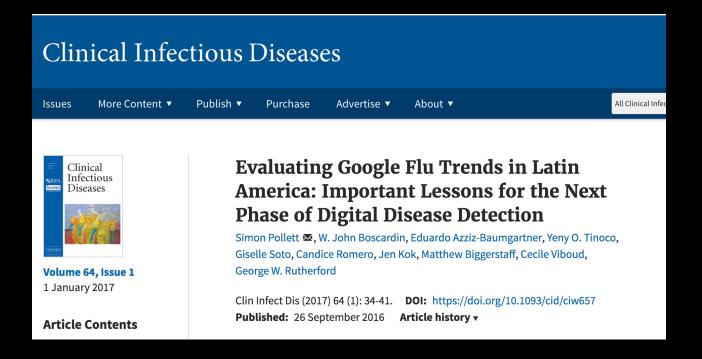
• Middle East

We are extending our tracking and forecasting systems to middle income countries

Now extending to Latin America

In response to a paper on *Clinical Infectious Diseases,* we have extended our methods to better predict flu in Latin America

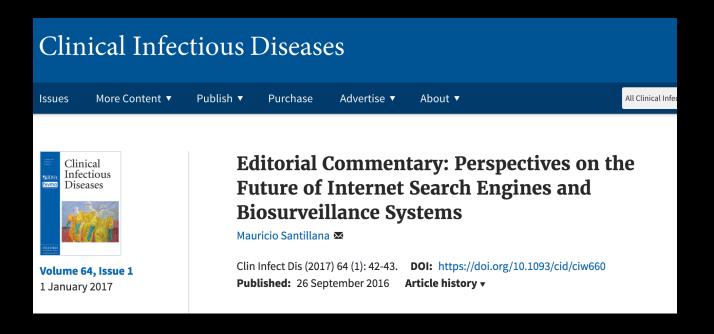
Team: Leonardo C. Clemente and Fred Lu



Now extending to Latin America

In response to a paper on *Clinical Infectious Diseases,* we have extended our methods to better predict flu in Latin America

Team: Leonardo C. Clemente and Fred Lu



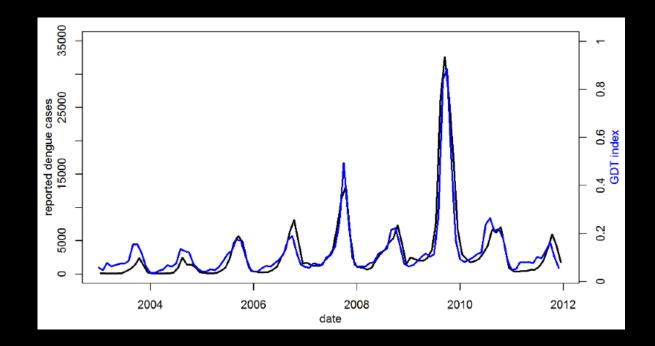
Evaluation of Internet-Based Dengue Query Data: Google Dengue Trends

Rebecca Tave Gluskin¹*, Michael A. Johansson², Mauricio Santillana³, John S. Brownstein¹

1 Children's Hospital Informatics Program, Children's Hospital Boston, Boston, Massachusetts, United States of America, 2 Dengue Branch, Division of Vector-Borne Diseases, Centers for Disease Control and Prevention, San Juan, Puerto Rico, 3 School of Engineering and Applied Sciences, Harvard University, Cambridge, Massachusetts, United States of America

PLOS REGLECTED

While Google Dengue Trends captures well the national incidence of disease



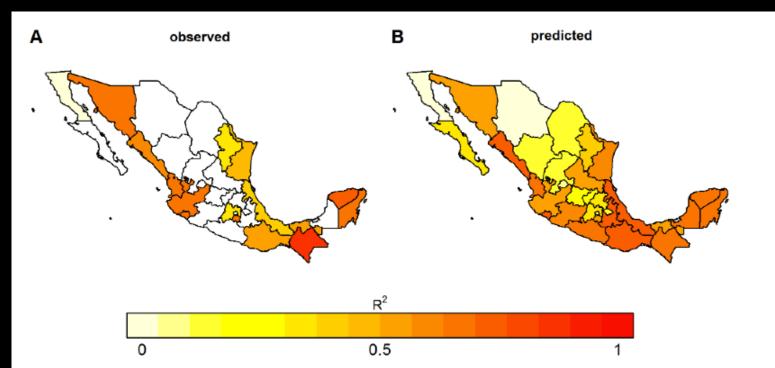
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PLOS NEGLECTED TROPICAL DISEASES

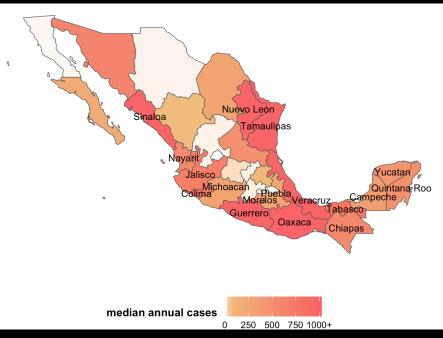
It fails to captures the incidence of dengue at the state level in multiple cases



Forecasting Dengue Incidence in Mexico

Establishing a prediction baseline





Team:

Mauricio Santillana (BCH, Harvard), Michael Johansson (CDC Puerto Rico), Aditi Hota (Columbia Univ), John Brownstein (BCH, Harvard), Nick Reich (Umass Amherts)



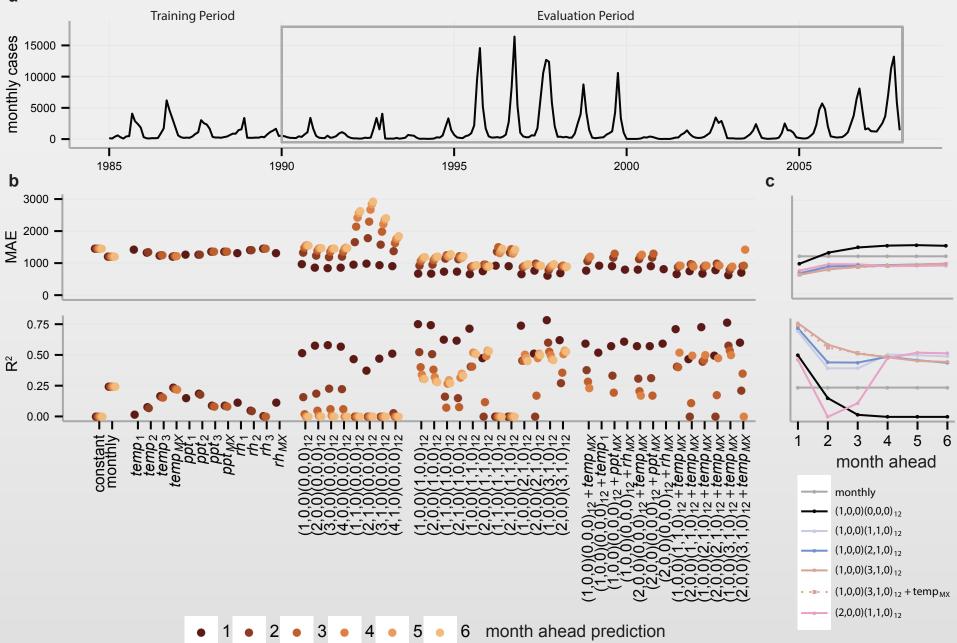
(2016)

doi:10.1038/srep33707

Download Citation

Received: 17 March 2016 Accepted: 24 August 2016 Published online: 26 September 2016

Mexico Dengue incidence (Country-level)



а



Extending use of Google searches to track Dengue in other countries:

Latin America: Mexico, Brazil

Southeast Asia: Thailand, Singapore, Taiwan



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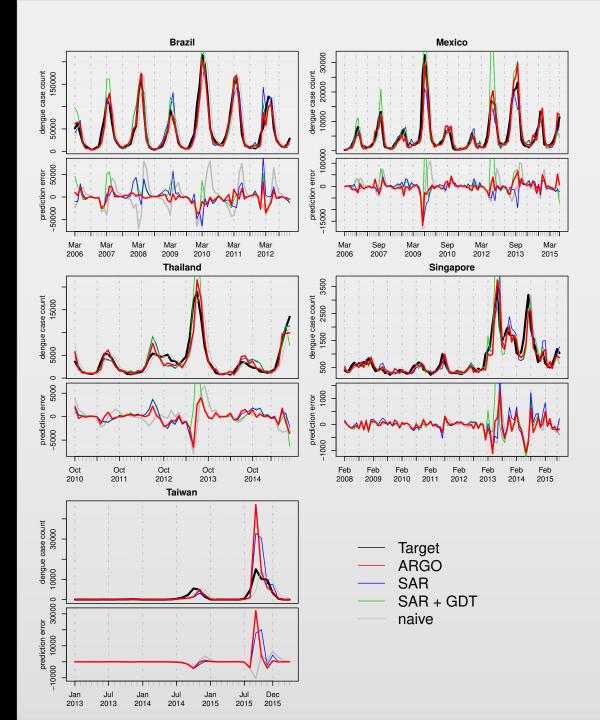
RESEARCH ARTICLE

Advances in using Internet searches to track dengue

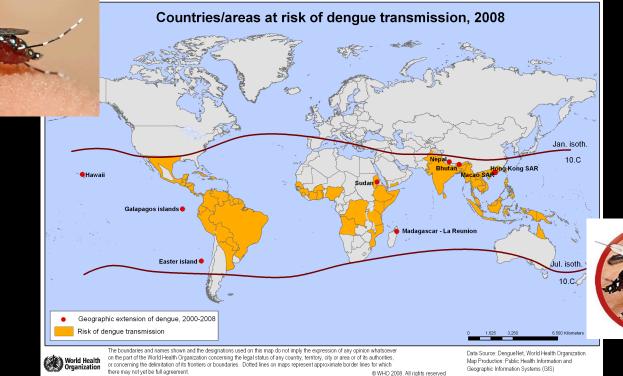
Shihao Yang, Samuel C. Kou 🖾, Fred Lu, John S. Brownstein, Nicholas Brooke, Mauricio Santillana 🔤

Published: July 20, 2017 • https://doi.org/10.1371/journal.pcbi.1005607

Article	Authors	Metrics	Comments	Related Content				
*								
Abstract								
Author summary	Abstract							
Introduction	Donguo is a mos	Dengue is a mosquito-borne disease that threatens over half of the world's population. Despite						
Materials and methods	being endemic to more than 100 countries, government-led efforts and tools for timely							
Results	ults identification and tracking of new infections are still lacking in many affected areas. Multiple methodologies that leverage the use of Internet-based data sources have been proposed as							



New alliance: Identifying hot spots for Dengue outbreaks

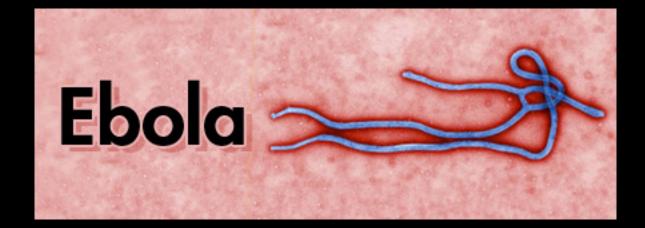








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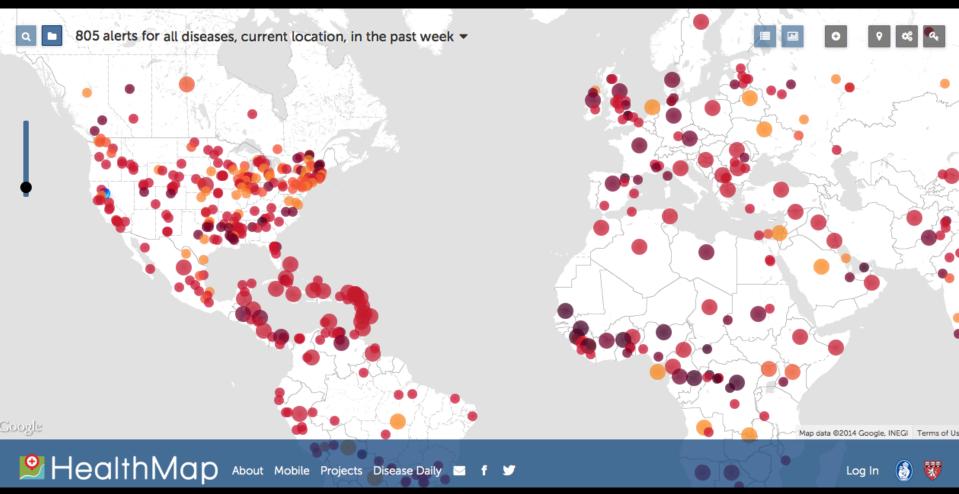


What if we could use **news reports** as a way to modulate predictions produced with models?

An example from the **Ebola** outbreak in 2015

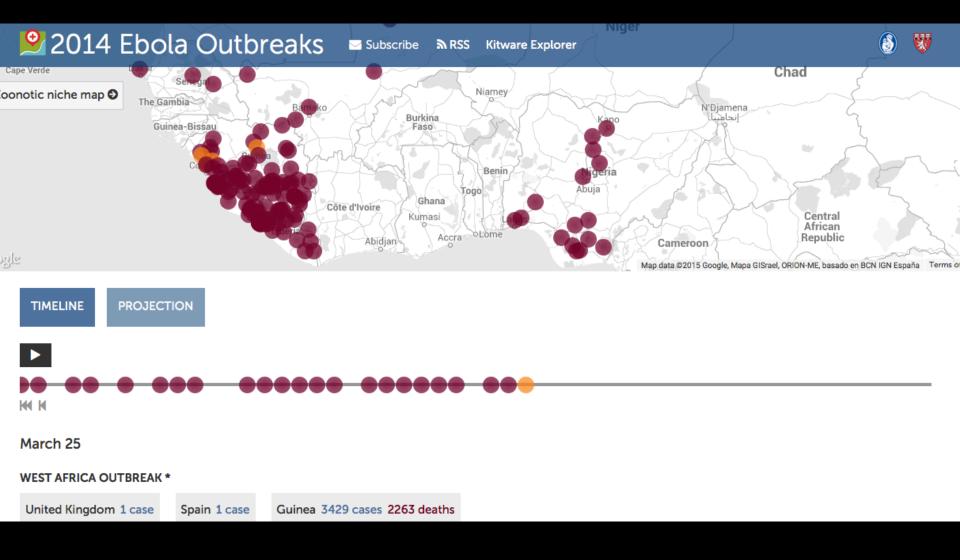
Healthmap.org

HealthMap brings together disparate data sources, including online news aggregators, eyewitness reports, expert-curated discussions and validated official reports, to achieve a unified and comprehensive view of the current global state of infectious diseases and their effect on human and animal health.



Through an automated process, updating 24/7/365, the system monitors, organizes, integrates, filters, visualizes and disseminates online information about emerging diseases in nine languages, facilitating early detection of global public health threats

Recent success story: Ebola outbreak identification and tracking



http://www.healthmap.org/ebola/#timeline



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2014 Ebola Outbreak: Media Events Track Changes in Observed Reproductive Number

APRIL 28, 2015 · COMMENTARY

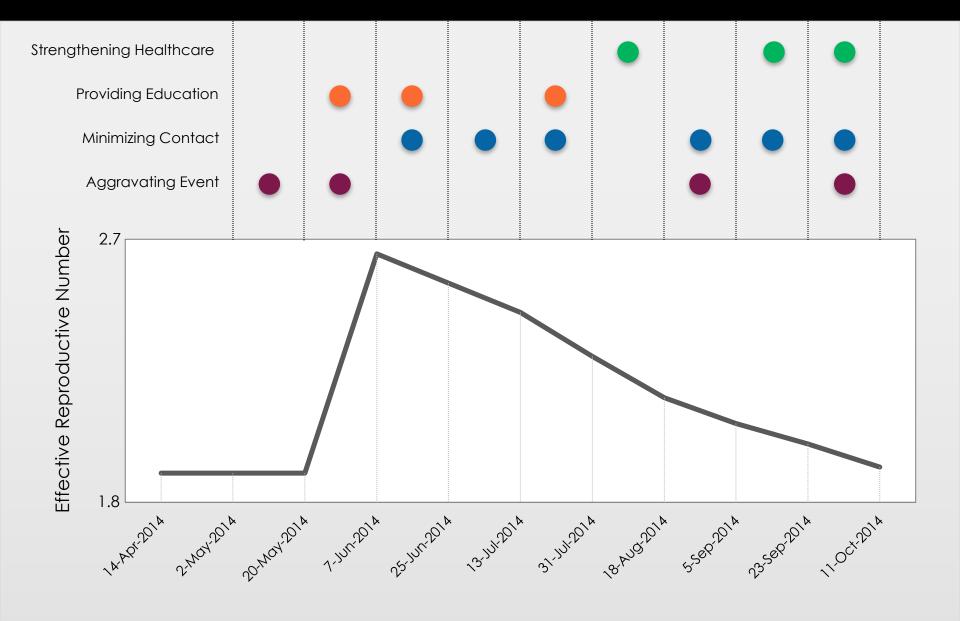


AUTHORS

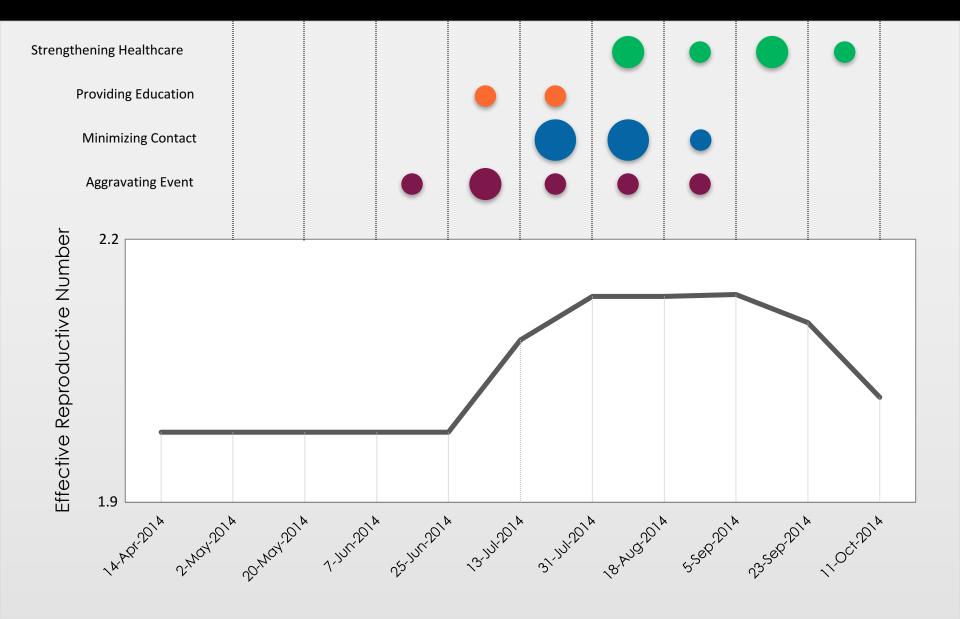
Maimuna S. Majumder Sheryl Kluberg Mauricio Santillana Sumiko Mekaru John S. Brownstein

ABSTRACT

In this commentary, we consider the relationship between early outbreak changes in the observed reproductive number of Ebola in West Africa and various media reported interventions and aggravating events. We find that media reports of interventions that provided education, minimized contact, or strengthened healthcare were typically followed by sustained transmission reductions in both Sierra Leone and Liberia. Meanwhile, media reports of aggravating events generally preceded temporary transmission increases in both countries. Given these preliminary findings, we conclude that media reported events could potentially be incorporated into future epidemic modeling efforts to improve mid-outbreak case projections.



Sierra Leone



Liberia

A more recent contribution on the 2015 Latin American **Zika** outbreak



Data-poor environments (Zika)

A more recent contribution on the 2015 Latin American Zika outbreak



🔒 JMIR Public Health and Surveillance

Published on 01.06.16 in Vol 2, No 1 (2016): Jan-Jun

This paper is in the following e-collection/theme issue:

⊗Infoveillance, Infodemiology and Digital Disease Surveillance ⊗Infodemiology and Infoveillance

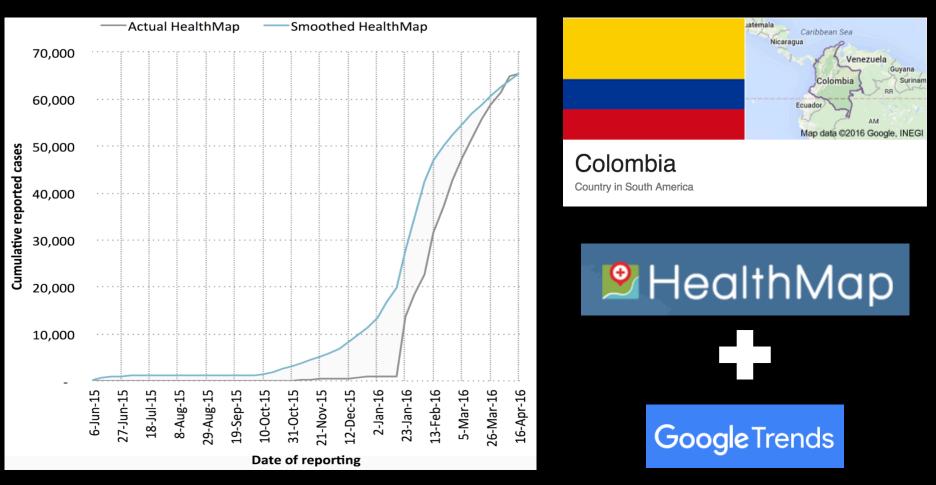


Utilizing Nontraditional Data Sources for Near Real-Time Estimation of Transmission Dynamics During the 2015-2016 Colombian Zika Virus Disease Outbreak

Maimuna S Majumder^{1,2}, MPH (D); Mauricio Santillana^{1,3,4}, PhD (D); Sumiko R Mekaru^{1,5}, PhD (D); Denise P McGinnis¹, ScD (D); Kamran Khan^{6,7}, MD (D); John S Brownstein^{1,4}, PhD (D)

Data-poor environments (Zika)

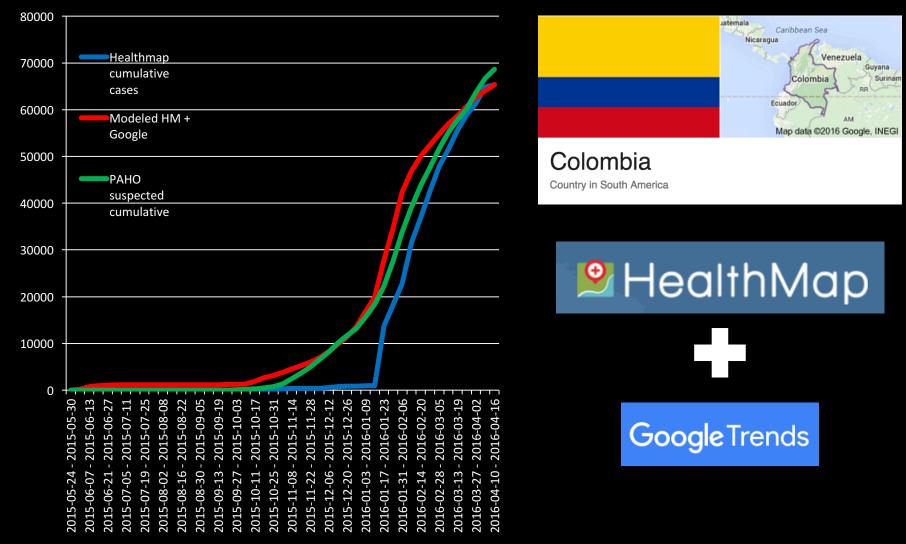
A more recent contribution on the 2015 Latin American Zika outbreak



With no access to traditional, government-lead disease surveillance information, we extracted the number of suspected cases as reported by **new reports** as a function of time. We then utilized the time behavior of Google searches of the word "zika" to smooth the news-reported incidence data.

Data-poor environments (Zika)

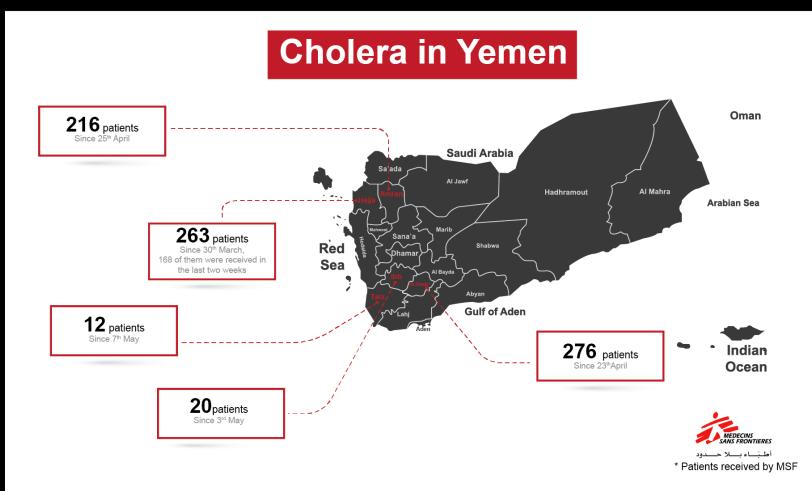
A more recent contribution on the 2015 Latin American Zika outbreak



When we gained access to government-lead disease surveillance information, we found great similarity with the curve we produced ahead of the publication of this information.

Data-poor environments (Cholera)

Extending work to characterize Cholera outbreak in Yemen

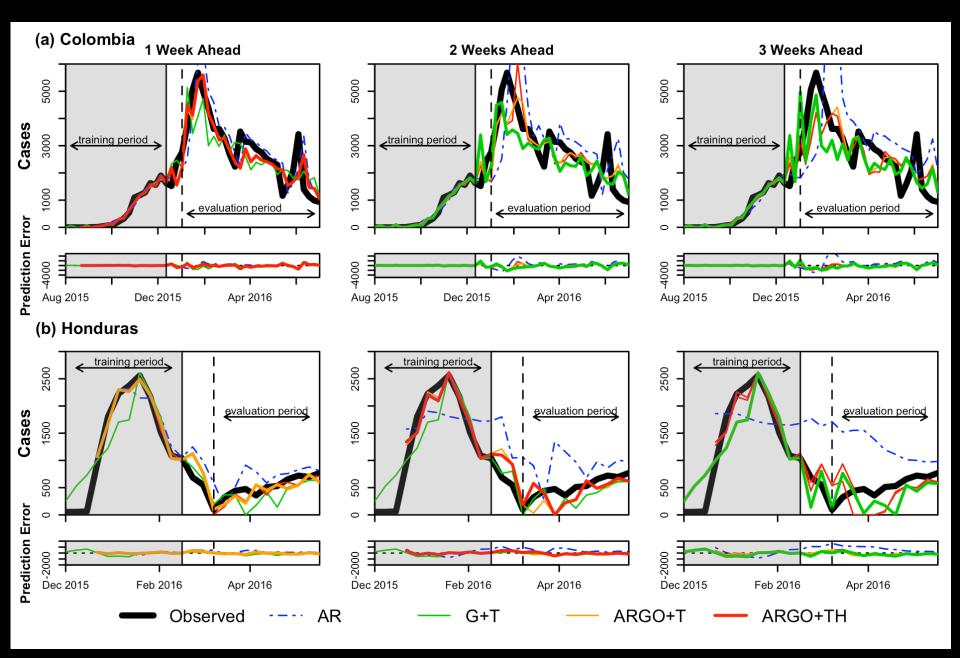


Forecasting Zika using Google searches and Twitter



Forecasting Zika using Google searches and Twitter

(with Sarah McGough)





Thank you!

Contact: msantill@fas.harvard.edu