Pre-read for Thursday, November 5: Disease empirics

Matthew J. Salganik

COS 597E/SOC 555 Limits to prediction
Fall 2020, Princeton University

Detecting influenza epidemics using search engine query data

Jeremy Ginsberg[1], Matthew H. Mohebbi[1], Rajan S. Patel[1], Lynnette Brammer[2], Mark S. Smolinski[1] & Larry Brilliant[1]

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]

readymades

custommades

https://commons.wikimedia.org/wiki/File:Duchamp_Fountaine.jpg
https://commons.wikimedia.org/wiki/File:%27David%27_by_Michelangelo_JBU0001.JPG

Reading notes:

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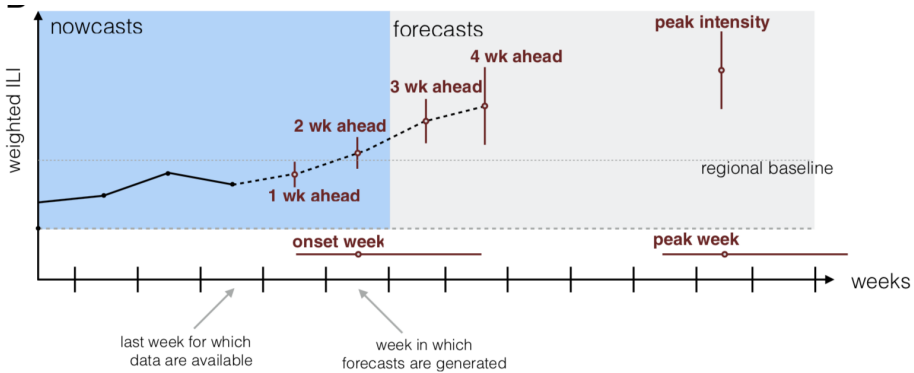
- After you read Lazer et al. see how your guesses compare to what they argue.
- Do you think the problems with Google Flu Trends are fixable or fundamental? Does the fact that Google Flu Trends is now discontinued change your guess?

Predicting the present vs predicting the future, but which is more important?

A collaborative multiyear, multimodel assessment of seasonal influenza forecasting in the United States

Nicholas G. Reich[a,1], Logan C. Brooks[b], Spencer J. Fox[c], Sasikiran Kandula[d], Craig J. McGowan[e], Evan Moore[a], Dave Osthus[f], Evan L. Ray[g], Abhinav Tushar[a], Teresa K. Yamana[d], Matthew Biggerstaff[e], Michael A. Johansson[h], Roni Rosenfeld[i], and Jeffrey Shaman[d]


nowcasts
forecasts
peak intensity
4 wk ahead
3 wk ahead
2 wk ahead
1 wk ahead
weighted ILI
regional baseline
onset week
peak week
weeks
last week for which data are available
week in which forecasts are generated

Predictions are evaluated using (modified) log score.
Here are some predictions from the ReichLab-KDE model (the baseline model).

1	Location	Target	Type	Unit	Bin_start_incl	Bin_end_notincl	Value
203	US National	1 wk ahead	Point	percent	NA	NA	3
204	US National	1 wk ahead	Bin	percent	0	0.1	9.99E-06
205	US National	1 wk ahead	Bin	percent	0.1	0.2	9.99E-06
206	US National	1 wk ahead	Bin	percent	0.2	0.3	9.99E-06
207	US National	1 wk ahead	Bin	percent	0.3	0.4	9.99E-06
208	US National	1 wk ahead	Bin	percent	0.4	0.5	9.99E-06
209	US National	1 wk ahead	Bin	percent	0.5	0.6	9.99E-06
210	US National	1 wk ahead	Bin	percent	0.6	0.7	2.00E-05
211	US National	1 wk ahead	Bin	percent	0.7	0.8	2.00E-05
212	US National	1 wk ahead	Bin	percent	0.8	0.9	0.00018975
213	US National	1 wk ahead	Bin	percent	0.9	1	0.00039948
214	US National	1 wk ahead	Bin	percent	1	1.1	0.00084889
215	US National	1 wk ahead	Bin	percent	1.1	1.2	0.00149804
216	US National	1 wk ahead	Bin	percent	1.2	1.3	0.00348543

If the true ILI% was between 1.2 and 1.3 percent, then this model would get $ln(0.00348543)$. You get more points putting on your probability weight on what happened.

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If the true ILI% was between 1.2 and 1.3 percent, then this model would get $ln(0.00348543)$. You get more points putting on your probability weight on what happened.
CDC uses modified version of log score so that you get you get full credit if you with 0.5 percentage points.

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- They are trying to predict the percentage of doctor visits that are related to influenza-like illness. How might this impact which kinds of approaches (statistical vs compartmental/mechanistic) are more or less effective?
- How does the debate about what scoring metric to use recall some of the debates that we had on October 15?

Epidemic Forecasting is Messier Than Weather Forecasting: The Role of Human Behavior and Internet Data Streams in Epidemic Forecast

Kelly R. Moran,[1] Geoffrey Fairchild,[1] Nicholas Generous,[1] Kyle Hickmann,[2] Dave Osthus,[3] Reid Priedhorsky,[4] James Hyman,[2,5] and Sara Y. Del Valle[1]

[1]Analytics, Intelligence, and Technology Division, [2]Theoretical Division, [3]Computer, Computational & Statistical Sciences Division, [4]High Performance Computing Division, Los Alamos National Laboratory, New Mexico; and [5]Department of Mathematics, Tulane University, New Orleans, Louisiana

From class on October 24

The following conditions make prediction easier for weather than many of the others domains we have studied in the past:

- Many groups make public predictions every day at multiple time scales (5-day forecast, 10-day forecast), and we can all see how accurate they are

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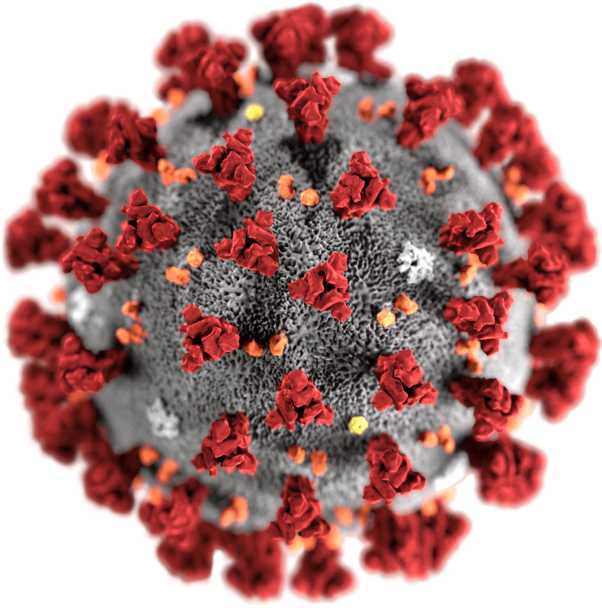
- Predictions based a real physical model
- Business and governments invests in improved performance

So even though this system is fundamentally unpredictable it has a lot going for it.



https://phil.cdc.gov/Details.aspx?pid=23312

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