Asking the right questions

Getting the right answers from your data

Shannon McWeeney, PhD

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Data After Dark

OHSU BD2K Data Science Workshop

Importance of Question + Scope

Guidelines for Study Design

Study Design

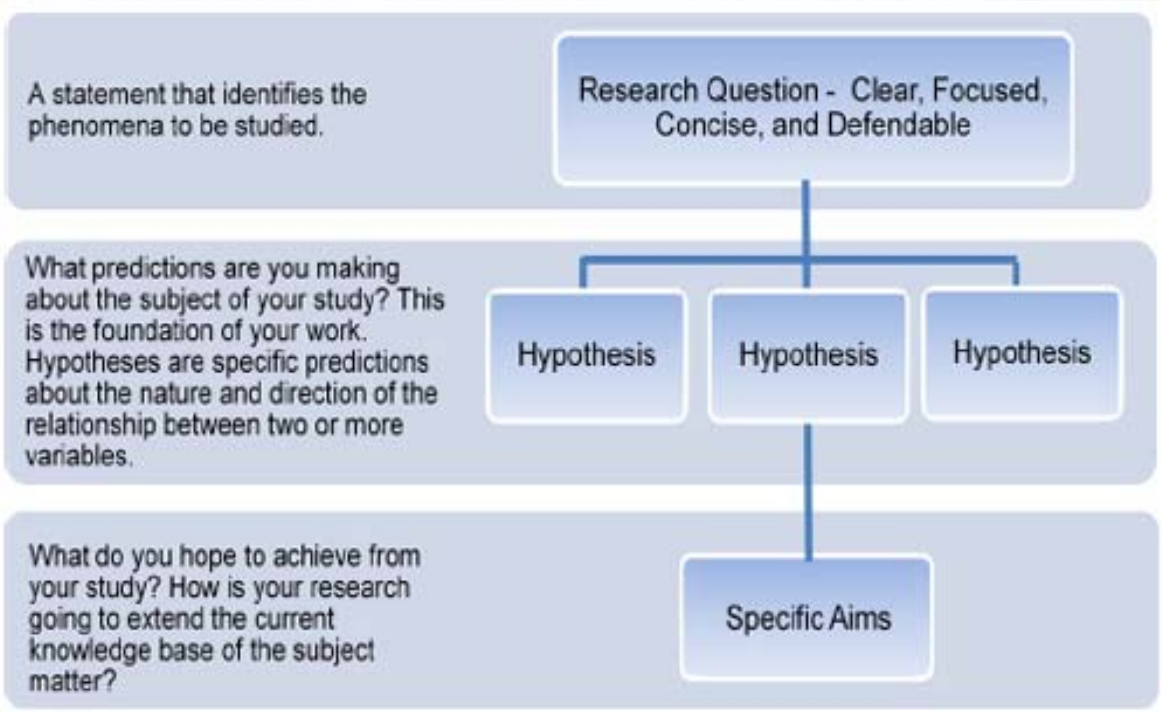
- Define Question
- Type of Study / Method of data Generation
- Sampling Considerations

Defining Your Question

- Why is this research important?
- What is it that we don't know or fully understand?
- What have other researchers in my field done?
- What areas need further exploration?
- Can my study help fill in these gaps or lead to greater understanding?

From Question->Hypothesis

- Characteristics of a good hypothesis
  - Gives insight into the proposed research question;
  - Is measurable and testable;
  - Is developed directly from the experiences of the researcher and should have a well-founded rationale for all proposed hypotheses.



Guidelines for Good Design

- **Clarity**
  - Clear hypothesis.
  - **Does your question match your analysis method?**
- **Simplicity**
  - Multiple Questions
  - Data Snooping

Guidelines for Good Design

- **Confounding Factors**
  - Distinguish between variation of interest and other sources of variation.

- **Replicates**
  - Type of replicates
  - Can you detect the effect if it is present?

Assessing Significance

- *P* value (R.A. Fisher): Informal way to judge whether evidence was "significant" (i.e., worthy of a second look)
  - Formulate 'Null hypothesis'
  - Set up statistical test assuming null hypothesis is true
  - Calculate the chances of getting results at least as extreme as what was actually observed. This probability = *P* value.
  - Smaller *P* value = greater the likelihood that the straw-man null hypothesis was false
  - Context: Part of the research process / life-cycle

Evidence Based Decisions

- Rigourous and Objective Framework
  - Key Concepts:
    - Statistical Power
    - Estimation of False positives and False Negatives
    - Explicit statements about effect size and variability

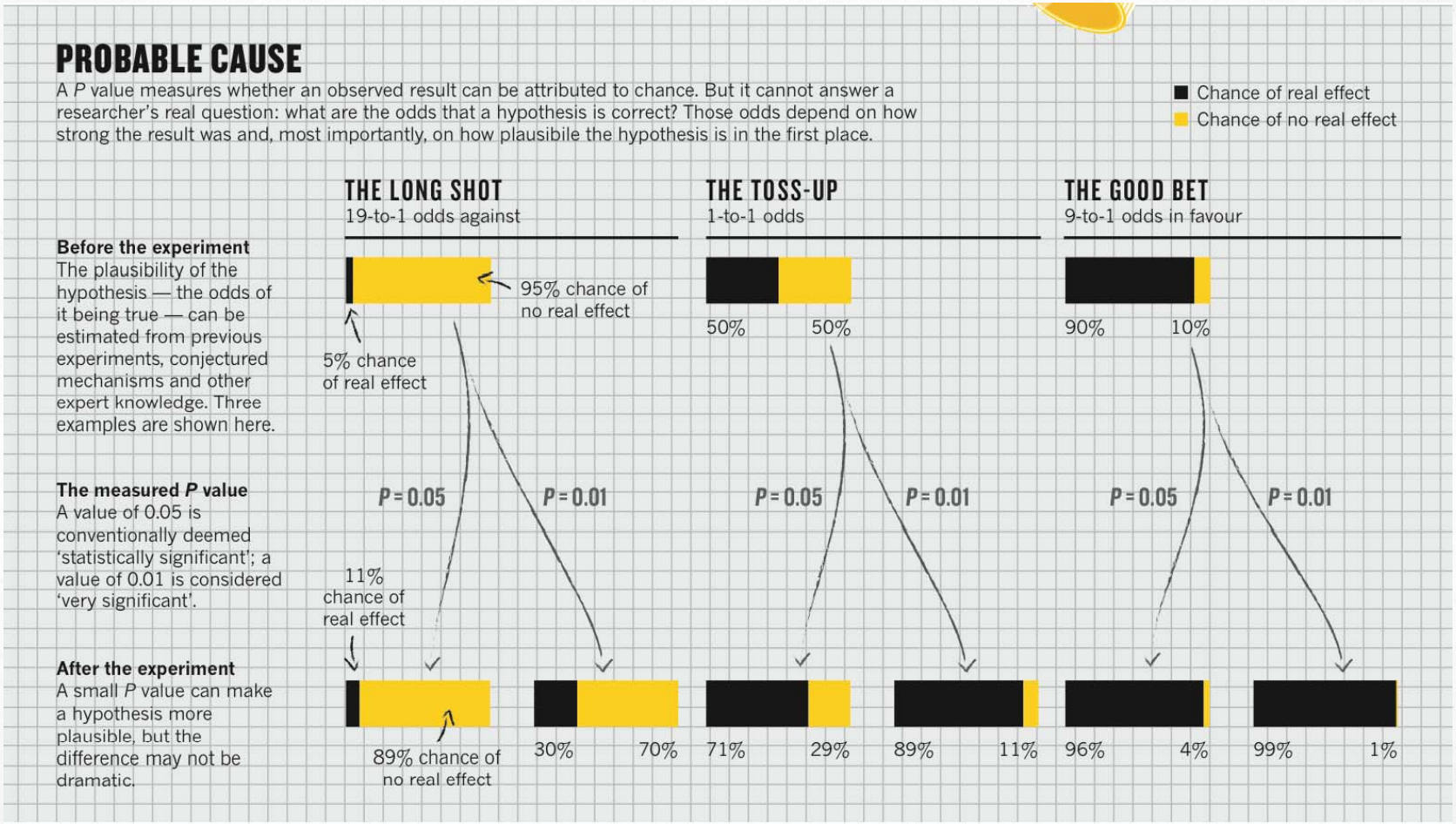
This framework was incorrectly hybridized with P-value concept.

"THE P VALUE WAS NEVER MEANT TO BE USED THE WAY IT'S USED TODAY"

What we should be asking

- What are the odds that a hypothesis is correct?
  - Depends on how plausible the hypothesis is in the first place.

Rephrasing the Question



Key Danger

- “P-hacking” : “is trying multiple things until you get the desired result, even unconsciously
  - Monitoring data while it is being collected
  - Exploratory studies confused with confirmatory studies

Three Questions

- What is the evidence?
- What should I believe?
- What should I do?

Case Study

Google Flu

What Do we have here?

- A patient comes into your office in January with the following complaints:
  - Body aches, muscle and joint pain, headache, a sore throat and a unproductive cough with occasionally harsh breathing
  - Fever, which ranged from 100 to 104 F and lasted for a few days
  - Felt sudden dizziness, weakness and pain while at work
  - Constipation
  - Bloody nose, red mucous membranes
  - Family members have noted he is “not acting like himself”

What is a possible diagnosis?

What If I told you....

- The year is not 2016 but 1918
  - All of those symptoms were what was being reported in medical literature at the time
  - Excerpts from JAMA, 10/3/1918 and 1/25/1919
  - At time, most basic clinical guideline was the temperature
  - Other Data collected:
    - Pulse rate "the pulse was remarkably slow," (JAMA, 4/12/1919)
    - Respiration rate
    - White blood cells counts

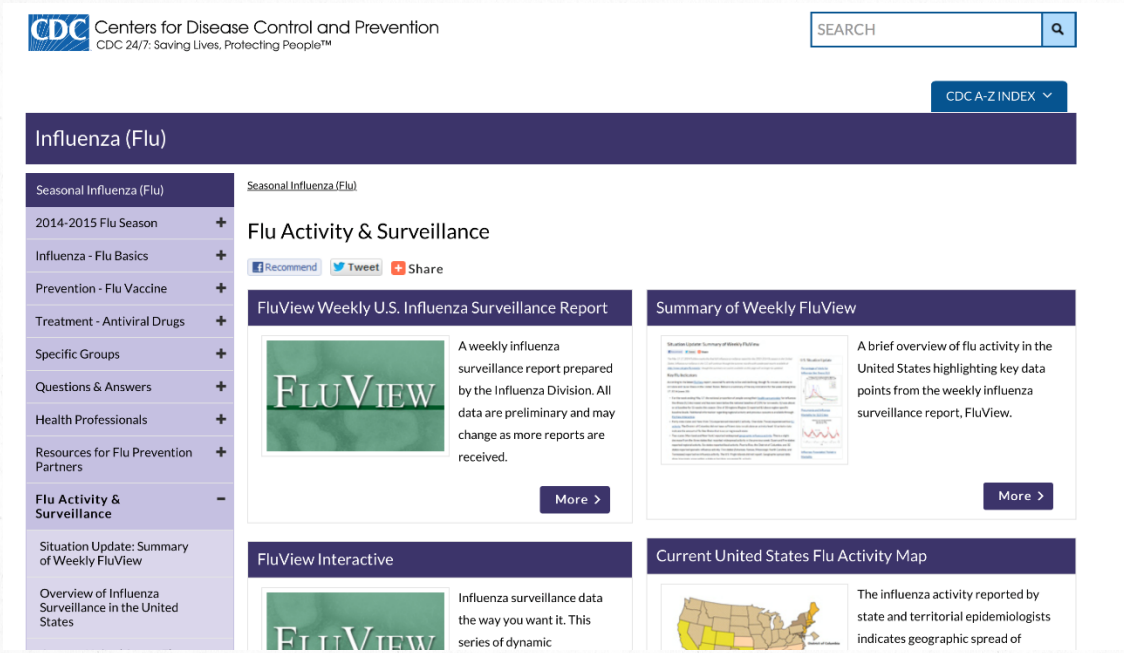
Estimated Mortality Rate

Untreated Plague	100%
Untreated Anthrax	90%
Smallpox	30%
Spanish Influenza	2.5%

Public Health Reports (2001) Supp 2 / Vol.116

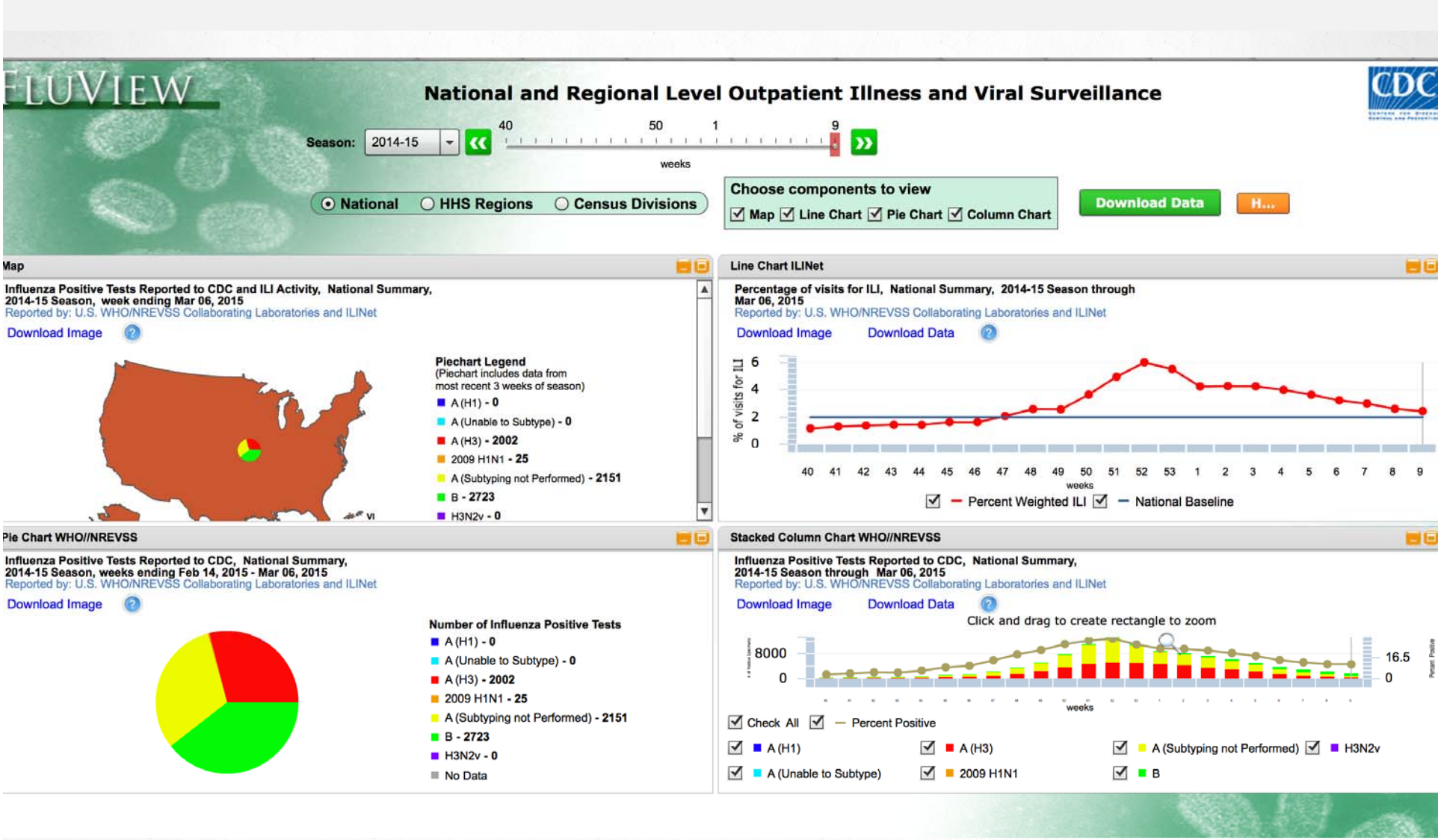
1918 Spanish Influenza

Traditional Surveillance



- US Centers for Disease Control and Prevention (CDC) and European Influenza Surveillance Scheme (EISS)
  - Rely on both virological and clinical data, including influenza-like illness (ILI) physician visits.

CDC publishes national and regional data from these surveillance systems on a weekly basis, typically with a 1–2-week reporting lag



http://gis.cdc.gov/grasp/fluview/fluportaldashboard.html

google.org Flu Trends

Language: English (United States)

Google.org home

Dengue Trends

Flu Trends

Home

Select country/region

How does this work?

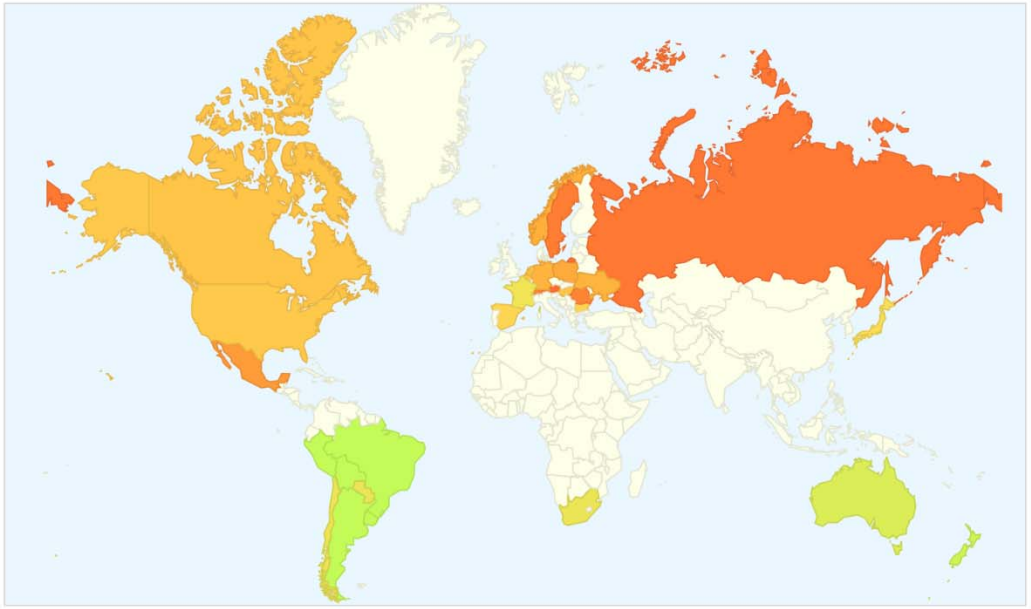
FAQ

Flu activity

- Intense
- High
- Moderate
- Low
- Minimal

Explore flu trends around the world

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 »



Download world flu activity data - Animated flu trends for Google Earth - Compare flu trends across regions in Public Data Explorer

https://www.google.org/flutrends/

Problems Amenable to Analytics

When do we need Big Data

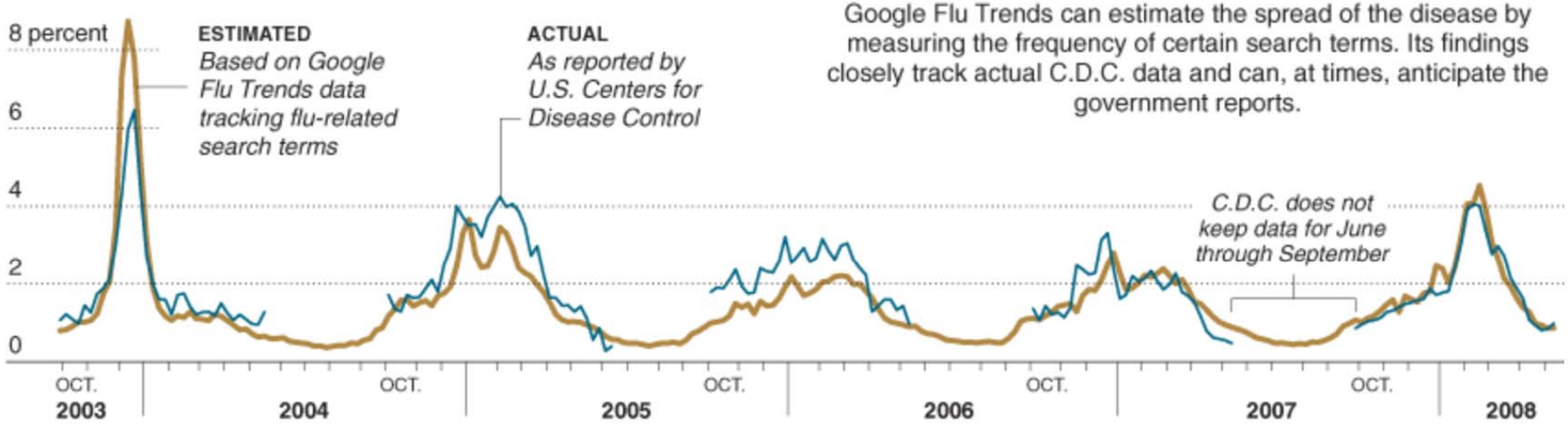
The New York Times

November 12, 2008

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

Using Google to Monitor the Flu

Google Flu Trends can estimate the spread of the disease by measuring the frequency of certain search terms. Its findings closely track actual C.D.C. data and can, at times, anticipate the government reports.



Sources: Google; Centers for Disease Control

THE NEW YORK TIMES

Google Flu Approach

- 5 years (2003-2008) of Google web search logs for modeling
- Time series of weekly counts: 50 million most common search queries (US only)
- No information about the identity of any user was retained
- Normalized by dividing the count for each query in a particular week by the total number of online search queries submitted in that location during the week (query fraction)
- Used the public historical CDC Influenza Sentinel Provider Surveillance Network data
  - Reported influenza-like illness (ILI) physician visits

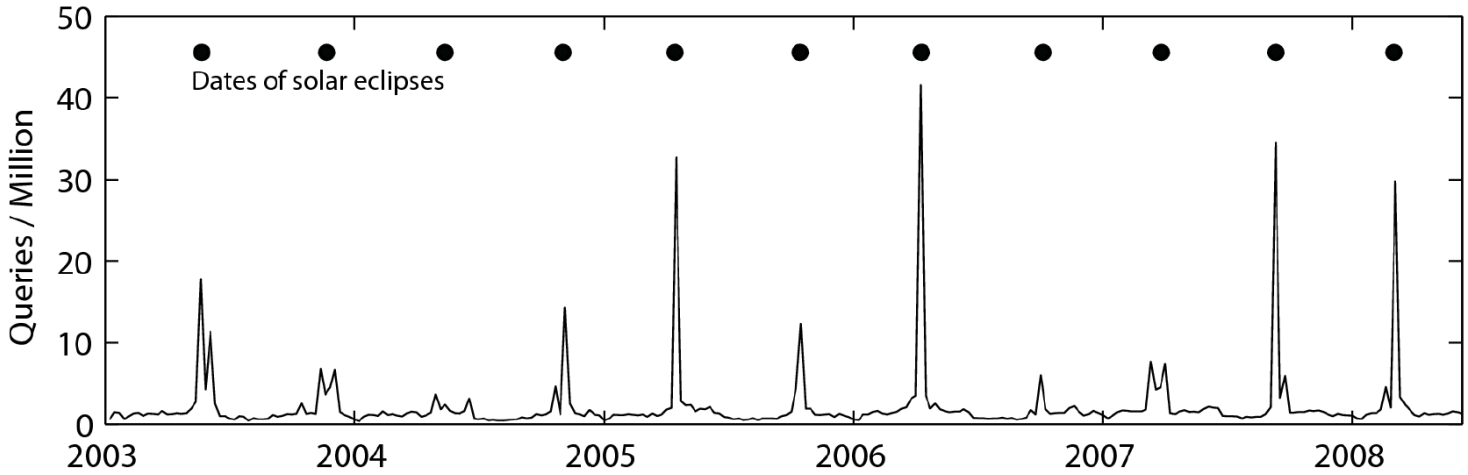
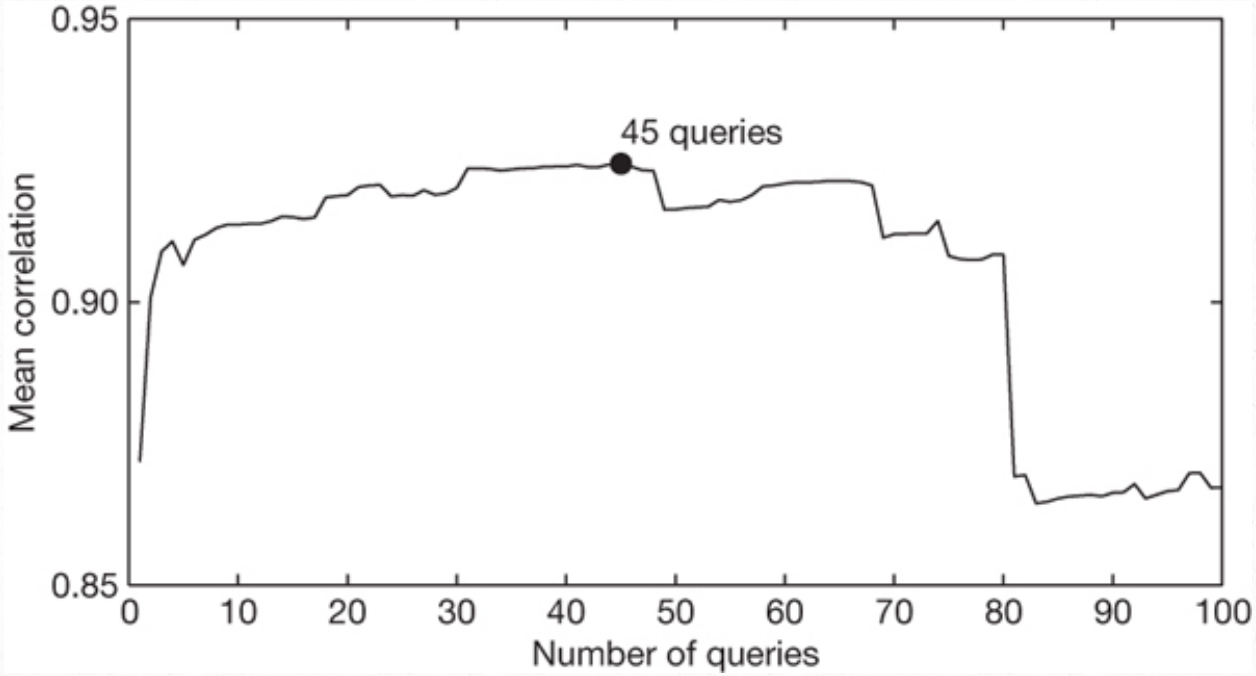


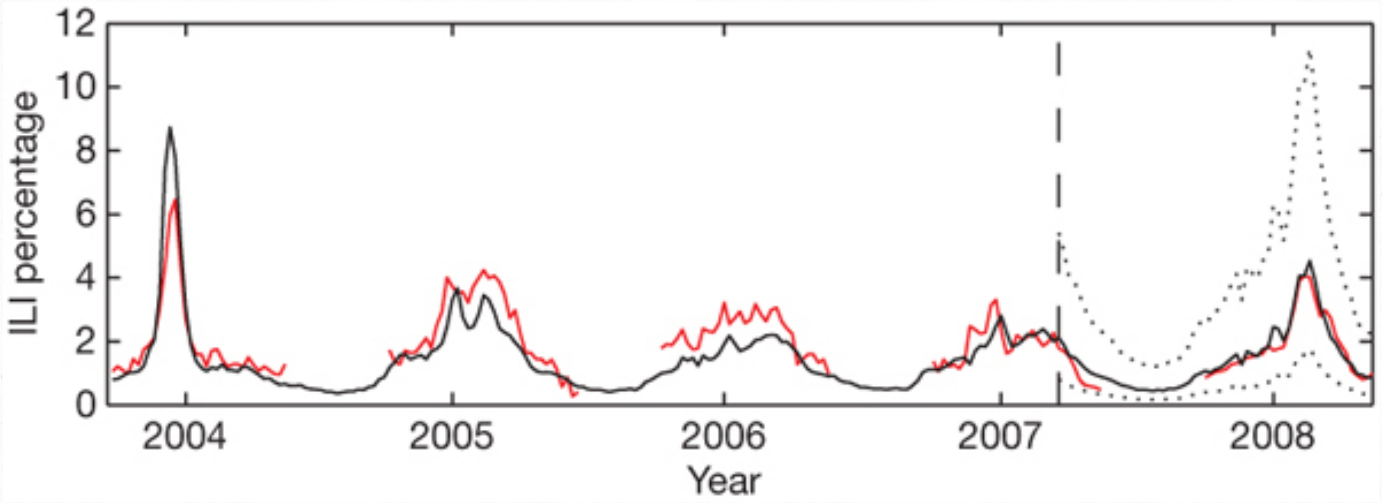
Figure 1: Weekly frequency of the search query “solar eclipse” in the United States from January 2003 to May 2008 and occurrences of solar eclipses, indicated by black dots.

Automated Approach

- Requires no previous knowledge about influenza
- Measure how effectively model would fit the regional CDC ILI data if they used only a single query as the explanatory variable, $Q(t)$
- Each of 50 million candidate queries was separately tested, to identify search queries which most accurately modeled the CDC regional ILI visit %
- Approach rewarded queries that showed regional variations similar to the regional variations in CDC ILI data
  - Motivation: the chance that a random search query can fit the ILI percentage in all nine regions is considerably less than the chance that a random search query can fit a single location



J Ginsberg *et al. Nature* **000**, 1-3 (2008) doi:10.1038/nature07634



J Ginsberg *et al. Nature* **000**, 1-3 (2008) doi:10.1038/nature07634

nature

Model estimates for the mid-Atlantic region (black)
CDC-reported ILI percentages (red)

SCIENCE BIG DATA

Google's Flu Project Shows the Failings of Big Data

Data Fail! How Google Flu Trends Fell Way Short

Posted: 03/16/2014 8:12 pm EDT | Updated: 03/16/2014 8:59 pm EDT

Google Flu Trends gets it wrong three years running

› 18:00 13 March 2014 by **Hal Hodson**
› For similar stories, visit the **Bird Flu** Topic Guide

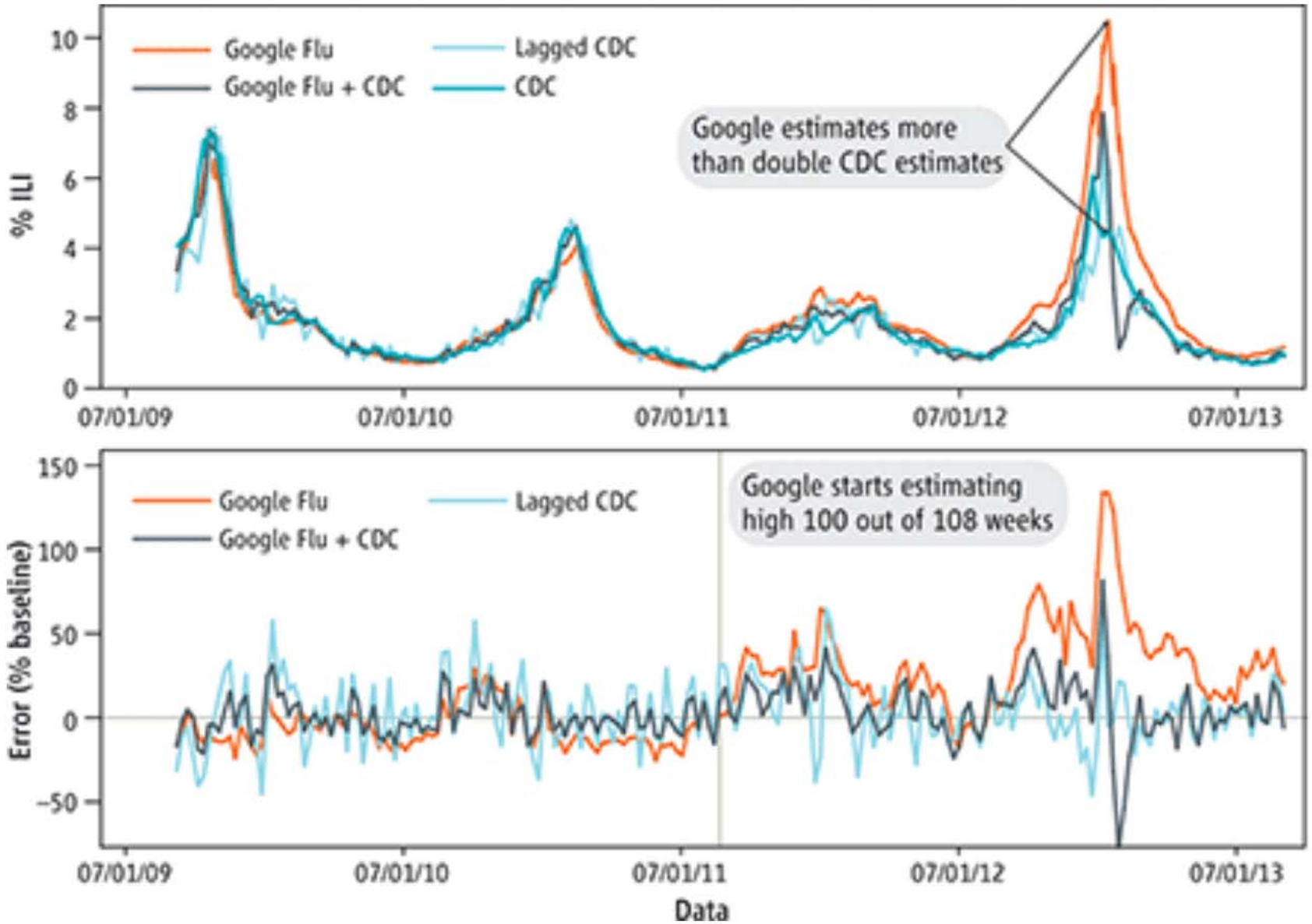
PHARMA & HEALTHCARE 3/23/2014 @ 9:00AM | 47,878 views

Why Google Flu Is A Failure

“Houston we have a problem….”

Combining the $n = 45$ highest-scoring queries was found to obtain the best fit. These 45 search queries, although selected automatically, appeared to be consistently related to ILIs. Other search queries in the top 100, not included in our model, included topics like ‘high school basketball’, which tend to coincide with influenza season in the United States (Table 1).

50 million search terms to fit 1152 data points!


Google Flu
Google Flu + CDC
Lagged CDC
CDC
Google estimates more than double CDC estimates
% ILI
10
8
6
4
2
0
07/01/09
07/01/10
07/01/11
07/01/12
07/01/13
Google Flu
Google Flu + CDC
Lagged CDC
Google starts estimating high 100 out of 108 weeks
Error (% baseline)
150
100
50
0
−50
07/01/09
07/01/10
07/01/11
07/01/12
07/01/13
Data

Big data Hubris

- Assumption that big data are a substitute for, rather than a supplement to, traditional data collection and analysis

- Core challenge: most big data are not the output of instruments designed to produce valid and reliable data amenable for scientific analysis.

Concept of Measurement

- Is the instrumentation actually capturing the theoretical construct of interest?
- Is measurement stable and comparable across cases and over time?
- Are measurement errors systematic?

Big Data vs Small Data

- Choice depends on question being **asked**

“You just brought a tote bag full of David Sedaris books to a knife fight” – Jon Stewart