Data Science

Gaurav Sood

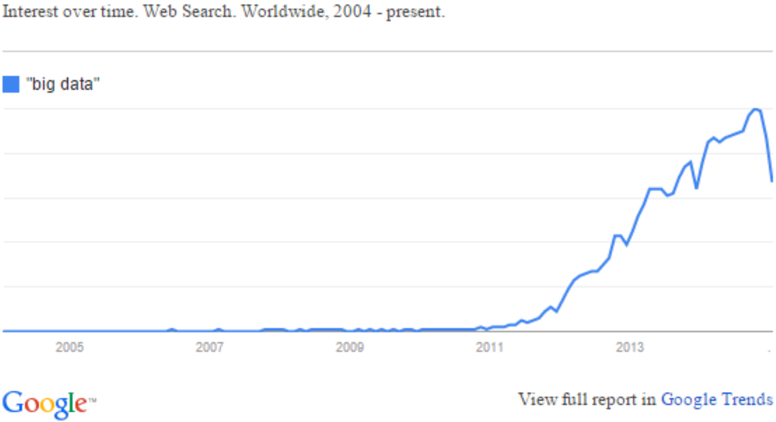
Spring 2015

Big Data

Big Data

Lots of hype recently.

Big Data



Interest over time. Web Search. Worldwide, 2004 - present.
"big data"
2005
2007
2009
2011
2013
Google™
View full report in Google Trends

Big Data

But where's the cheese?

Some examples

Fishing Out Fishy Figures


Previous | Next | Latest Americas view

All latest updates

Statistics in Argentina

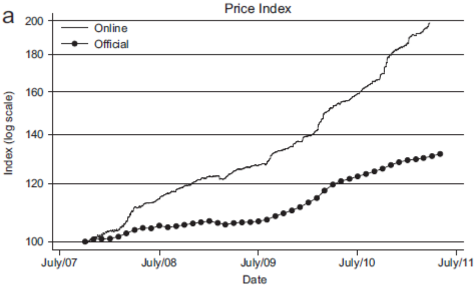
Fishy figures

Sep 17th 2014, 19:53 BY H.C. | BUENOS AIRES

Timekeeper Like 107 Tweet 9

"The CPINu's August inflation figure of 1.3% is less than half the 2.65% of the CPI Congreso, a compilation of private estimates gathered by opposition members of Congress." (Economist)

Fishing Out Fishy Figures



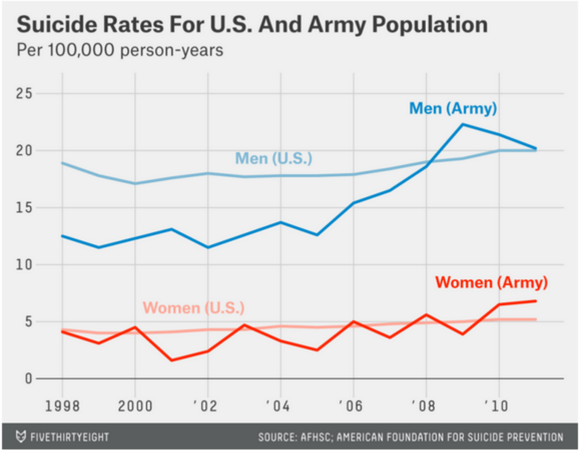
Source: Online vs Official Price Indexes: Measuring Argentina's Inflation By Alberto Cavallo

Suicide Prevention in the Army

Suicide Prevention in the Army

"In 2012, more soldiers committed suicide than died while fighting in Afghanistan: 349 suicides compared to 295 combat deaths."

Suicide Prevention in the Army



Suicide Prevention in the Army

"Research has repeatedly shown that doctors are not accurate in predicting who is at risk of suicide."

Suicide Prevention in the Army

"The soldiers with the highest 5 percent of risk scores committed over half of all suicides in the period covered — at an extraordinary rate of about 3,824 suicides per 100,000 person-years."

538 Article
STARRS paper

Reducing Crime

Minority Report

Reducing Crime

Predictive, ‘CompStat’, ‘HotSpot’ Policing

Reducing Crime

PredPol: Predictive Policing

LAPD, Atlanta PD

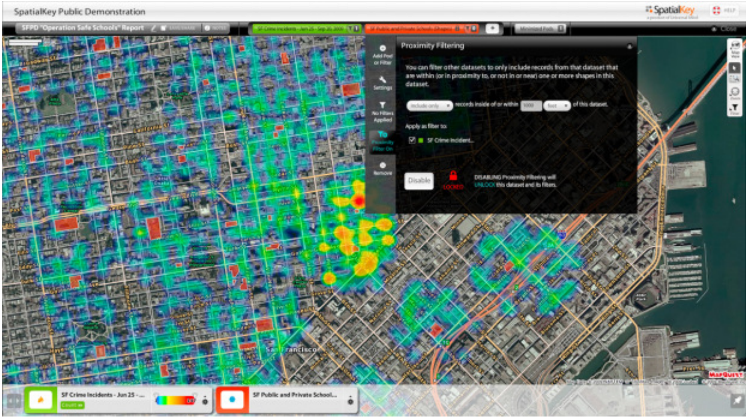
Based off earthquake prediction algorithm

Reducing Crime

"During a four-month trial in Kent, 8.5% of all street crime occurred within PredPol's pink boxes, with plenty more next door to them; predictions from police analysts scored only 5%. An earlier trial in Los Angeles saw the machine score 6% compared with human analysts' 3%."

Economist

Reducing Crime



Web Search

Web Search

What's New
Check Email
YAHOO!
Personalize
Help
Yahoo! Pager
instant messaging
Yahoo! Pager
now works with chat
Yahoo! Mail
free email for life
Search
advanced search
Yahoo! Auctions - 1000's of items to bid on - Pokemon, Beanie Babies, video games, Furbys...
Shopping - Yellow Pages - People Search - Maps - Travel Agent - Classifieds - Personals - Games - Chat
Email - Calendar - Pager - My Yahoo! - Today's News - Sports - Weather - TV - Stock Quotes - more...
Arts & Humanities
Literature, Photography...
News & Media
Full Coverage, Newspapers, TV...
Business & Economy
Companies, Finance, Jobs...
Recreation & Sports
Sports, Travel, Autos, Outdoors...
Computers & Internet
Internet, WWW, Software, Games...
Reference
Libraries, Dictionaries, Quotations...
Education
College and University, K-12...
Regional
Countries, Regions, US States...
Entertainment
Cool Links, Movies, Humor, Music...
Science
Biology, Astronomy, Engineering...
Government
Military, Politics, Law, Taxes...
Social Science
Archaeology, Economics, Languages...
Health
Medicine, Diseases, Drugs, Fitness...
Society & Culture
People, Environment, Religion...
In the News
· NATO - Serbia war
· Giant bacterium discovered
· Lakers release Rodman
more...
Marketplace
· Charity Auctions - for the Kosovo relief effort
· Find a new job!
more...
Inside Yahoo!
· Y! Movies - showtimes, reviews
· Y! Clubs - create your own
· Y! Visa - instant credit while you wait
more...

Web Search

– Human Curation, Ad-hoc automation

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- Page Rank

Side-effects of Drugs

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"Adverse drug events cause substantial morbidity and mortality and are often discovered after a drug comes to market."

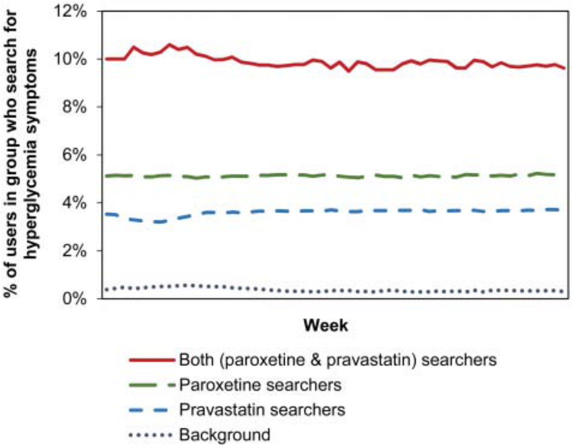
Side-effects of Drugs

FDA collects this information from “physicians, pharmacists, patients, and drug companies” but these reports “are incomplete and biased”

Side-effects of Drugs

"paroxetine and pravastatin, whose interaction was reported to cause hyperglycemia after the time period of the online logs used in the analysis"

Side-effects of Drugs



Web-scale Pharmacovigilance: Listening to Signals from the Crowd. By White et al.

Flu Season

How many got the sniffles?

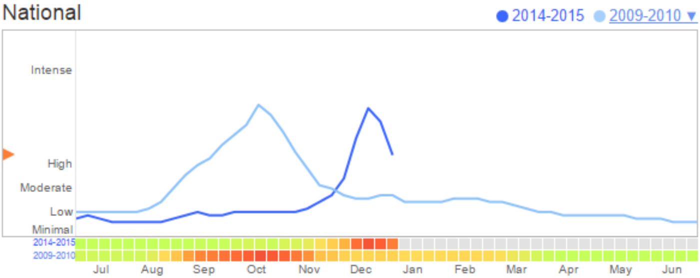
Flu Season

How many got the sniffles in the past month?

Flu Season

Explore flu trends - United States

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 »]

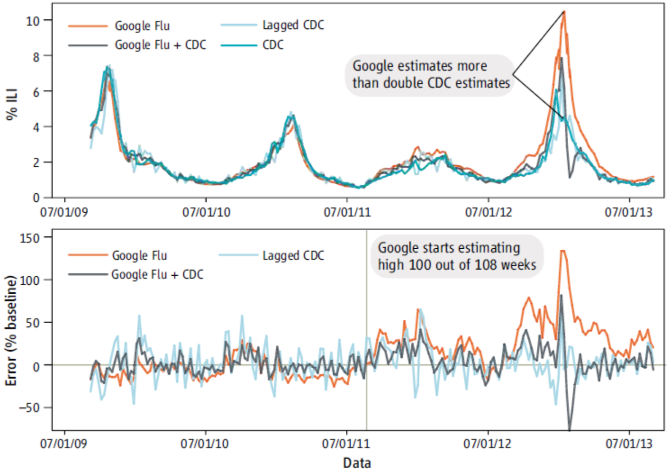


Google Flu Trends

Flu Season

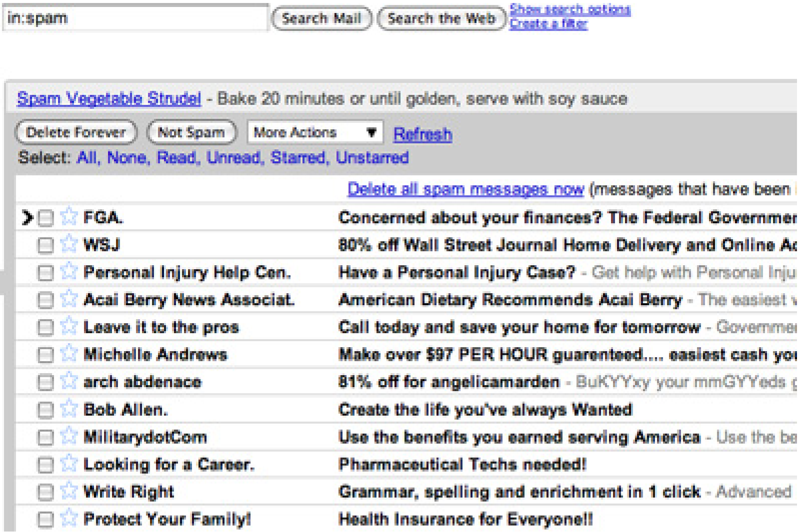
Google Flu is sick.

Flu Season



The Parable of Google Flu: Traps in Big Data Analysis. By Lazer et al.

Spam or Ham


in:spam
Search Mail
Search the Web
Show search options
Create a filter
Spam Vegetable Strudel - Bake 20 minutes or until golden, serve with soy sauce
Delete Forever
Not Spam
More Actions
Refresh
Select: All, None, Read, Unread, Starred, Unstarred
Delete all spam messages now (messages that have been
FGA.
Concerned about your finances? The Federal Governmer
WSJ
80% off Wall Street Journal Home Delivery and Online Ac
Personal Injury Help Cen.
Have a Personal Injury Case? - Get help with Personal Inju
Acai Berry News Associat.
American Dietary Recommends Acai Berry - The easiest
Leave it to the pros
Call today and save your home for tomorrow - Governme
Michelle Andrews
Make over $97 PER HOUR guarenteed.... easiest cash yo
arch abdenace
81% off for angelicamarden - BuKYYxy your mmGYYeds
Bob Allen.
Create the life you've always Wanted
MilitarydotCom
Use the benefits you earned serving America - Use the be
Looking for a Career.
Pharmaceutical Techs needed!
Write Right
Grammar, spelling and enrichment in 1 click - Advanced
Protect Your Family!
Health Insurance for Everyone!!

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- $logit[p(spam)] = \alpha + f'\beta$ where f is frequencies.

Vote


A 61-million-person experiment in social influence and political mobilization

Robert M. Bond[1], Christopher J. Fariss[1], Jason J. Jones[2], Adam D. I. Kramer[3], Cameron Marlow[3], Jaime E. Settle[1] & James H. Fowler[1,4]

Human behaviour is thought to spread through face-to-face social networks, but it is difficult to identify social influence effects in observational studies[9–13], and it is unknown whether online social with all users of at least 18 years of age in the United States who accessed the Facebook website on 2 November 2010, the day of the US congressional elections. Users were randomly assigned to a 'social

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.39% direct effect, and .01 to .1% indirect effect.

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– Used SQL database Vertica for ‘speed-of-thought’ analyses.

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- ‘Big data’ is high **volume**, high **velocity** and high **variety** information assets that demand cost-effective, innovative forms of information processing[.]

  Gartner, Inc.’s “3Vs” definition.

Sources of (Big) Data

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- Data as the primary goal of activities

  Telescopes, Genetic sequencers, 61 million person experiments . . .

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  Passive observation as things change arbitrarily may help

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- For really big data: N*log(N)

  Traversing a binary tree, sort and search N log(N)

  Streaming application

MapReduce and PageRank

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  - Distributed programming can be very very hard.

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- Simple programming model

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– Implementation - Hadoop (via Yahoo)/Apache

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  - Send different words to different computers
  - Combine

```
map(String input_key, String input_value):
    // input_key: document name
    // input_value: document contents
    for each word w in input_value:
      EmitIntermediate(w, ``1'');


  reduce(String output_key, Iterator intermediate_values):
    // output_key: a word
    // output_values: a list of counts
    int result = 0;
    for each v in intermediate_values:
      result += ParseInt(v);
    Emit(AsString(result));
```

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  - Web - lots of false positives. Some of it malware peddling sites.

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- Innovation: see Internet as a graph
  Nodes = webpages, Edges = hyperlinks
  Ranks based on linking patterns alone.
- Currency is in-links.

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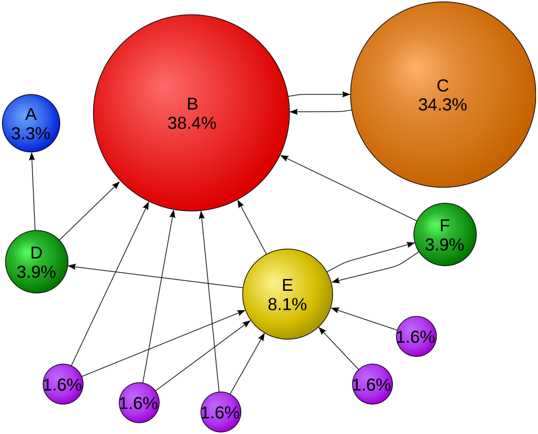
  - Say page i has importance r_i, and n outgoing links, each vote $= r_i/n$

Page Rank Example



Source: Wikipedia

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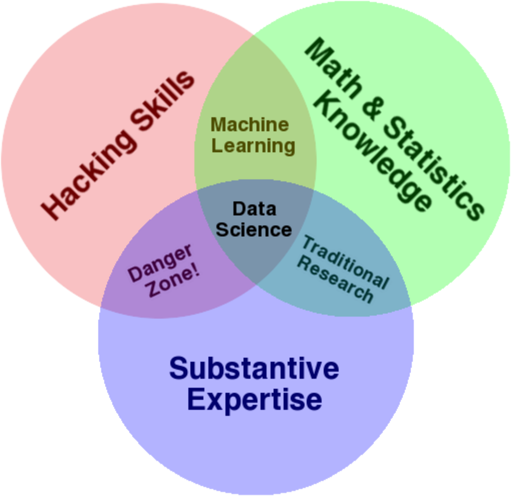
$$r_i = \sum \frac{r_j}{d_j}$$

over j where j tracks all the pages pointing to i.

Class

Data Science



Data Science Venn Diagram. By Drew Conoway

Course Outline

- Get your own (big) data

  Scrape it, clean it

  Basics of webscraping

  Basics of regular expressions

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- Analyze your (big) data
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  Numerical Optimization

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