The Social Science Data Revolution

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The Changing Evidence Base of Social Science Research

The Last 50 Years:

- Survey research
- Aggregate government statistics
- In depth studies of individual places, people, or events

The Next 50 Years: Spectacular increases in new data sources, due to...

- Much more of the above — improved, expanded, and applied
- Shrinking computers & the growing Internet: data everywhere
- The replication movement: academic data sharing (e.g., Dataverse)
- Governments encouraging data collection, distribution, experimentation (e.g., GovData)
- Advances in statistical methods, informatics, & software
- *The march of quantification*: through academia, professions, government, & commerce (*SuperCrunchers*, *The Numerati*, *MoneyBall*)

Examples of what's now possible

- Opinions of activists: A few thousand interviews $\rightsquigarrow$ millions of political opinions in social media posts (1B tweets/week)
- Exercise: A survey: "How many times did you exercise last week? $\rightsquigarrow$ 500K people carrying cell phones with accelerometers
- Social contacts: A survey: "Please tell me your 5 best friends" $\rightsquigarrow$ continuous record of phone calls, emails, text messages, bluetooth, social media connections, electronic address books
- Economic development in developing countries: Dubious or nonexistent governmental statistics $\rightsquigarrow$ satellite images of human-generated light at night, or networks of roads and other infrastructure
- Expert-vs-Statistician contests: Whenever enough information is quantified (& a right answer exists), stats wins every time
- Many, many more...

How to make progress in the new data-rich world?

1. Computer-assisted methods: Traditional quantitative-only or qualitative-only approaches are infeasible
2. Large-scale, interdisciplinary, collaborative research
3. New statistical methods & engineering required
4. Better theory: to respond to massive new evidence, privacy challenges, data-driven science

$\rightsquigarrow$ Bigger changes in the practice of social science then ever before

Two Examples

of Automated Text Analysis

Example 1: How to Read a Billion Blog Posts

(& Classify Deaths without Physicians)

- Daniel Hopkins and Gary King. "Extracting Systematic Social Science Meaning from Text" *AJPS*, $\leadsto$ commercialized via:

crimson hexagon $\leadsto$

$\leadsto$

Fast Company Names Crimson Hexagon Number Seven on "The 10 Most Innovative Companies in Web" List Leading Social Intelligence Firm Recognized For Revolutionary Measurement of Consumer Opinions in Social Media

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CAMBRIDGE, Mass., Mar 16, 2011 (BUSINESS WIRE) -- Fast Company named

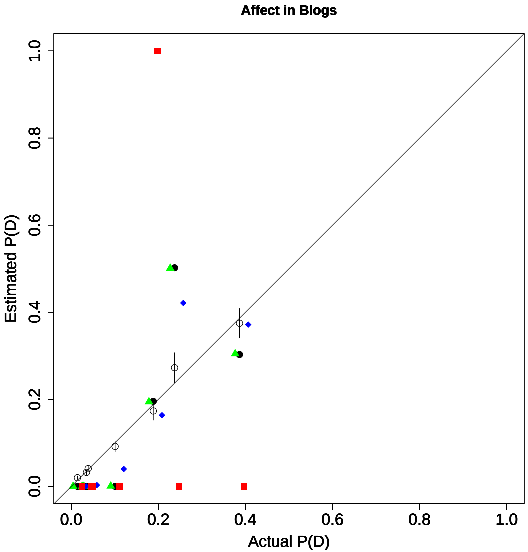
- Gary King and Ying Lu. "Verbal Autopsy Methods with Multiple Causes of Death," *Statistical Science* $\leadsto$ used by (among others):

World Health Organization

Data and Quantities of Interest

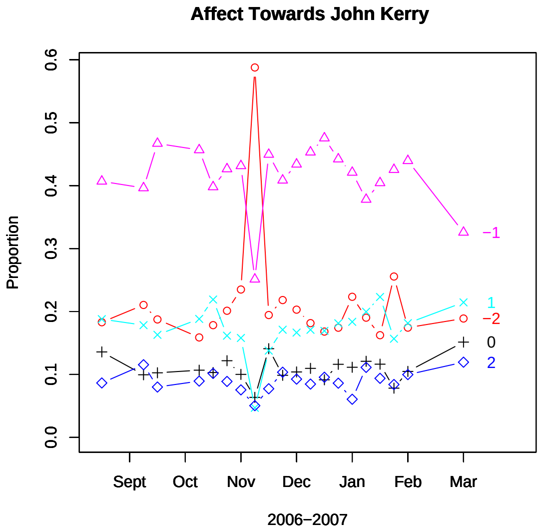
- Input Data:
  - Large set of text documents (e.g., all English language blog posts)
  - Categories (posts about US candidates): extremely negative, negative, neutral, positive, extremely positive, no opinion, not a blog
  - A small "training set" of documents hand-coded into the categories
- Quantities of interest
  - Computer science: individual document classifications (spam filters, Google searches)
  - Social Science: proportion in each category (proportion of email which is spam; proportion extremely negative comment about Pres Bush)
- Estimation
  - *Can* get the 2nd by counting the 1st (if 1st is accurate)
  - High classification accuracy $\not\Rightarrow$ unbiased category proportions
  - 70% classification accuracy is high $\Rightarrow$ disaster for category proportions
  - New methodology: unbiased category proportions, even when classification accuracy is low

Out-of-sample Comparison: 60 Seconds vs. 8.7 Days



Reactions to John Kerry's Botched Joke

You know, education — if you make the most of it . . . you can do well. If you don't, you get stuck in Iraq.



Example 2: Computer-Assisted "Reading"

- Justin Grimmer and Gary King. 2011. "General-Purpose Clustering and Conceptualization" *Proceedings of the National Academy of Sciences*.
- Conceptualization through Classification: "one of the most central and generic of all our conceptual exercises. . . . Without classification, there could be no advanced conceptualization, reasoning, language, data analysis or,for that matter, social science research." (Bailey, 1994).
- Cluster Analysis: simultaneously (1) invents categories and (2) assigns documents to categories

What's Hard about Clustering?

(Why Johnny Can't Classify)

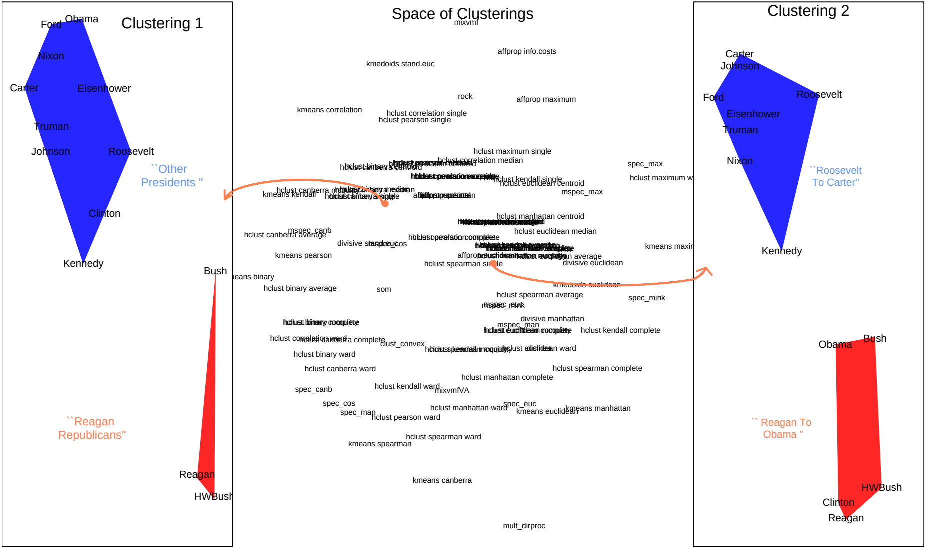
- Goal: Computer-assisted conceptualization & clustering
- Bell(n) $=$ number of ways of partitioning n objects
- Bell(2) $= 2$ (AB, A B)
- Bell(3) $= 5$ (ABC, AB C, A BC, AC B, A B C)
- Bell(5) $= 52$
- Bell(100) $\approx 10^{28} \times$ Number of elementary particles in the universe
- Now imagine choosing the *optimal* classification scheme by hand!
- Available compromises pursue different goals:
  - Standard Approach: Fully automated methods $\rightsquigarrow$ no method works well in general; impossible to know which to apply!
  - Our Approach: Computer-assisted methods $\rightsquigarrow$ You, not some computer algorithm, decides what's important, but with help

Switch from Fully Automated to Computer Assisted

- Computer-Assisted Clustering
  - Easy in theory: list all clusterings; choose the best
  - Impossible in practice: Too hard for us mere humans!
  - An organized list will make the search possible
  - Insight: Many clusterings are perceptually identical
  - E.g.,: consider two clusterings that differ only because one document (of 10,000) moves from category 5 to 6
- Question: How to organize clusterings so humans can understand?

How to Zoom Out while Reading

You choose one (or more) clustering, based on insight, discovery, useful information,. . .



Evaluation: More Informative Discoveries

- Found 2 scholars analyzing lots of textual data for their work
- Created 6 clusterings:
  - 2 clusterings selected with our method (biased against us)
  - 2 clusterings from each of 2 other methods (varying tuning parameters)
- Created info packet on each clustering (for each cluster: exemplar document, automated content summary)
- Asked for $\binom{6}{2}=15$ pairwise comparisons
- User chooses $\Rightarrow$ only care about the one clustering that wins
- Both cases a Condorcet winner:

"Immigration":

Our Method 1 $\rightarrow$ vMF 1 $\rightarrow$ vMF 2 $\rightarrow$ Our Method 2 $\rightarrow$ K-Means 1 $\rightarrow$ K-Means 2

"Genetic testing":

Our Method 1 $\rightarrow$ {Our Method 2, K-Means 1, K-means 2} $\rightarrow$ Dir Proc. 1 $\rightarrow$ Dir Proc. 2

Evaluation: What Do Members of Congress Do?

Example Discovery

Taunting ruins deliberation

Sen. Lautenberg
on Senate Floor
4/29/04

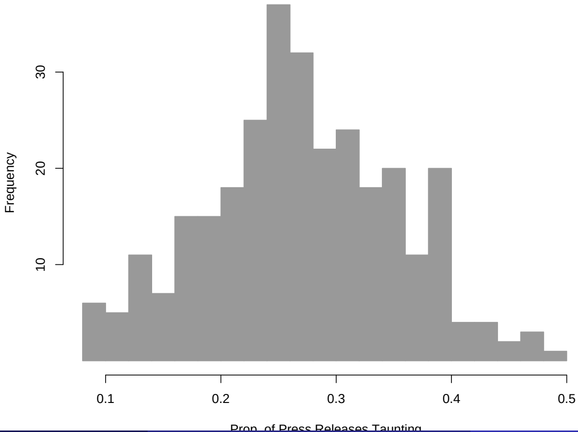
- "Senator Lautenberg Blasts Republicans as 'Chicken Hawks' " [Government Oversight]

Out of Sample Confirmation of Partisan Taunting

- Discovered using 200 press releases; 1 senator.

Out of Sample Confirmation of Partisan Taunting

- Discovered using 200 press releases; 1 senator.
- Confirmed using 64,033 press releases; 301 senator-years.
- Apply supervised learning method: measure proportion of press releases a senator taunts other party



Normative Implications of Taunting

- Partisan taunting:
  - Very common
  - Makes deliberation less likely
  - Occurs more often in homogeneously partisan districts (i.e., when preaching to the choir)
- Incompatibility of the principles of representative democracy
  - To get <u>reflection</u>: Homogeneous (noncompetitive) districts
  - To get <u>deliberation</u> (no taunting): Heterogeneous (competitive) districts
  - $\rightsquigarrow$ you can't have both!

Some New Data Types

1. Unstructured text: emails (1 LOC every 10 minutes), speeches, government reports, blogs, social media updates, web pages, newspapers, scholarly literature
2. Commercial activity: credit cards, sales data, and real estate transactions, product RFIDs
3. Geographic location: cell phones, Fastlane or EZPass transponders, garage cameras
4. Health information: digital medical records, hospital admittances, google/MS health, and accelerometers and other devices being included in cell phones
5. Biological sciences: effectively becoming social sciences as genomics, proteomics, metabolomics, and brain imaging produce huge numbers of *person-level variables*.
6. Satellite imagery: increasing in scope, resolution, and availability.
7. Electoral activity: ballot images, precinct-level results, individual-level registration, primary participation, and campaign contributions

Some More New Data Examples

8. Social media: facebook, twitter, social bookmarking, blog comments, product reviews, virtual worlds, game behavior, crowd sourcing
9. Web surfing artifacts: clicks, searches, and advertising clickthroughs. (Google collects 1 petabyte/72 minutes on human behavior!)
10. Multiplayer web games and virtual worlds: Billions of highly controlled experiments on human behavior
11. Government bureaucracies: moving from paper to electronic data bases, increasing availability
12. Governmental policies: requiring more data collection, such e.g., "No Child Left Behind Act"; allowing randomized policy experiments; Obama pushing data distribution
13. Scholarly data: the replication movement in academia, led in part by political science, is massively increasing data sharing

Enormous Emerging Opportunities for Social Scientists

- For the first time: technologies, policies, data, and methods are making it feasible to attack some of the most vexing problems that afflict human society
- A massive change from studying problems to understanding and solving problems
- Opportunities require a change in our job descriptions, with new:
  1. Computer-assisted methods: Traditional quantitative-only or qualitative-only approaches are infeasible
  2. Large-scale, interdisciplinary, collaborative research
  3. New statistical methods & engineering required
  4. Better theory: to respond to massive new evidence, privacy challenges, data-driven science
- And then there's you & me:
  - In most legislatures, courts, academic departments, . . . , change comes from replacement not conversion
  - Will we wait to be replaced? or put in the effort to convert and learn how to use the new information?

For more information

http://GKing.Harvard.edu