Big Data is Not About the Data!

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The Data In Big Data (about people)
The *Data* In Big Data (about people)

The Last 50 Years:

- Survey research
- Aggregate government statistics
- One off studies of individual places, people, or events

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

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

Impact:

- Changed most Fortune 500 firms
- Established new industries
- Altered friendship networks, political campaigns, public health, legal analysis, policing, economics, sports, public policy, literature, etc., etc., etc.
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The Value in Big Data: the Analytics

Data:
- easy to come by; often a free byproduct of IT improvements
- becoming commoditized
- Ignore it & every institution will have more every year
- With a bit of effort: huge data production increases

Where the Value is: the Analytics
- Output can be highly customized
- Moore's Law (doubling speed/power every 18 months)
- v. One good data scientist (1000x speed increase in 1 day)
- $2M computer v. 2 hours of algorithm design
- Low cost; little infrastructure; mostly human capital needed
- Innovative analytics: enormously better than off-the-shelf
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Exciting Data, But Useless without Novel Analytics
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• Opinions of activists:

A few thousand interviews ⇝ billions of political opinions in social media posts (650M/day)

• Exercise:

A survey: “How many times did you exercise last week?” ⇝ 500K people carrying cell phones with accelerometers

• Social contacts:

A survey: “Please tell me your 5 best friends” ⇝ continuous record of phone calls, emails, text messages, bluetooth, social media connections, address books

• Economic development in developing countries:

Doubtful or nonexistent governmental statistics ⇝ satellite images of human-generated light at night, road networks, other infrastructure

• Many, many, more. . .

In each: without new analytics, the data are useless.
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Examples of Bad Analytics:
- Physicians' "Verbal Autopsy" analysis
- Sentiment analysis via word counts

Unrelated substantive problems, same analytics solution:
- Key to both methods: classifying (deaths, social media posts)
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Bias in U.S. Social Security Administration Forecasts

• Social Security: single largest government program; lifted a whole generation out of poverty; extremely popular

• Forecasts: used for programs comprising >50% of the US expenditures; e.g., if retirees draw benefits longer than expected, the Trust Fund runs out

• First evaluation of SSA forecasts in 85 years:
  • Methods: little changed; mostly qualitative; a time when we've learned more about forecasting than at any time in history
  • Results: unbiased until 2000; systematically biased after
  • Actuaries hunkered down, insulated themselves, refused to budge when Democrats & Republicans pushed hard for changes
  • In the process, they also insulated themselves from the facts: Especially since 2000, Americans started living unexpectedly longer lives (due to statins, early cancer detection, etc.)

• New customized analytics we developed:
  • Logical consistency (e.g., older people have higher mortality)
  • Far more accurate forecasts
  • Trust fund needs >$800 billion more than SSA thought

• Many other applications to different types of forecasts
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• **Social Security:** single largest government program; lifted a whole generation out of poverty; extremely popular

• **Forecasts:** used for programs comprising > 50% of the US expenditures; e.g., if retirees draw benefits longer than expected, the Trust Fund runs out

• **First evaluation of SSA forecasts in 85 years:**

  - **Methods:** little changed; mostly qualitative; a time when we've learned more about forecasting than at any time in history

  - **Results:** unbiased until 2000; systematically biased after

  - Actuaries hunkered down, insulated themselves, refused to budge when Democrats & Republicans pushed hard for changes

  - In the process, they also insulated themselves from the facts: Especially since 2000, Americans started living unexpectedly longer lives (due to statins, early cancer detection, etc.)

  - **New customized analytics we developed:**

    - Logical consistency (e.g., older people have higher mortality)

    - Far more accurate forecasts

    - **Trust fund needs > $800 billion more than SSA thought**

    - Many other applications to different types of forecasts
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Thresher: Finding Those Hiding in Plain Sight
Example Substitution 1:
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1:

自由
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1:

自由  “Freedom”
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1:

自由 “Freedom”

Example Substitution 2:

和 谐 “Harmonious [Society]” (official slogan)
河 蟹 “River crab” (irrelevant)
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Example Substitution 1:

自由
自由

“Freedom”

Example Substitution 2:

和
谐

“Harmonious [Society]” (official slogan)

They can't follow the conversation; Thresher can.

The same task:

(1) Long tail search,
(2) Government and industry analyst's job,
(3) language drift (#BostonBombings ⇝ #BostonStrong),
(4) Child pornographers,
(5) Look-alike modeling,
(6) Starting point for other automated text methods,
(7) Infinitely improvable classification, eDiscovery, etc., etc.
Thresher: Finding Those Hiding in Plain Sight

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自由 自由 “Freedom”
目 田 “Eye field”
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1:

自由 自由 = “Freedom”
目田 目田 = “Eye field” (nonsensical)
### Example Substitution 1: Homograph

<table>
<thead>
<tr>
<th>自由</th>
<th>“Freedom”</th>
</tr>
</thead>
<tbody>
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- Categorization: (1) advertising, (2) position taking, (3) credit claiming
- New Insight: partisan taunting
  - Joe Wilson during Obama's State of the Union: "You lie!"
  - "Senator Lautenberg Blasts Republicans as 'Chicken Hawks'"
  - Basically anything said by a 2016 presidential candidate!
- How common is it?
  - 27% of all Senatorial press releases!
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- How common is it? 27% of all Senatorial press releases!
Modern Analytics to Improve Student Learning

The problem:
- How many students buy the book? < 50%
- How many students do reading assignments? 20-30%
- How much time do instructors have to write detailed quizzes?

Our solution:
Perusall
- A new type of collaborative e-reader, with novel data analytics, and cutting-edge behavioral research
- > 90% of students do the reading
- Solitary reading assignments ⇝ engaging collective activities
- Intrinsic motivation: collaborative annotation in threads
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Reverse Engineering Censorship in China

• Previous approach: watch a few posts; see what's removed
• Data: Download all posts before the Chinese censor them
• Novel methods of automated text analysis to discover patterns

What Could be the Goal?

1. Stop collective action

• Implications: Social Media is Actionable!

• Chinese leaders:
  • measure criticism: to judge local officials
  • censor: to stop events with collective action potential

• Thus, we can use criticism & censorship to predict:
  • Officials in trouble, likely to be replaced
  • Dissident arrests; new peace treaties; emerging scandals
  • Disagreements between central and local leaders
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Reverse Engineering China’s 50c Party
The Government Surreptitiously Fabricating Social Media Posts
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• Prevailing view of scholars, activists, journalists, social media participants:
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• Prevailing view of scholars, activists, journalists, social media participants: 50c party argues against those who criticize the government, its leaders, and their policies
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Existing evidence?
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Our evidence:
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Existing evidence? A few anecdotes; “no ground truth”; “no successful attempts to quantify” 50c party activity; even several analyses with made up dependent variables!
Our evidence: (1) Found a leaked archive of 50c posts too hard to analyze,
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Our evidence: (1) Found a leaked archive of 50c posts too hard to analyze, (2) developed methods of automated text analysis to decipher,
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- Prevailing view of scholars, activists, journalists, social media participants: 50c party argues against those who criticize the government, its leaders, and their policies

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Our evidence: (1) Found a leaked archive of 50c posts too hard to analyze, (2) developed methods of automated text analysis to decipher, (3) discovered patterns and extrapolated to all of China, (4) did a poll(!) and predicted 50c members acknowledged their behavior
Reverse Engineering China’s 50c Party
The Government Surreptitiously Fabricating Social Media Posts

• Prevailing view of scholars, activists, journalists, social media participants: 50c party argues against those who criticize the government, its leaders, and their policies **Wrong**
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- Fabricates 450M social media posts a year!
Reverse Engineering China’s 50c Party
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- Fabricates 450M social media posts a year!
- Does not argue; does not engage on controversial issues
- Distracts; redirects public attention from criticism and central issues to cheerleading and positive discussions of valence issues
The End of The Quantitative-Qualitative Divide

• The Quant-Qual divide exists in every field.

• Qualitative researchers: overwhelmed by information; need help

• Quantitative researchers: recognize the huge amounts of information in qualitative analyses, starting to analyze unstructured text, video, audio as data

• Expert-vs-analytics contests: Whenever enough information is quantified, a right answer exists, and good analytics are applied: analytics wins

• Moral of the story:
  • Fully human is inadequate
  • Fully automated fails
  • We need computer assisted, human controlled technology
  • (Technically correct, & politically much easier)
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Moral of the story:
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- It's cheap and powerful; don't skimp!
- Off-the-shelf analytics ⇝ big advances
- Innovative analytics ⇝ immensely better than off-the-shelf
- Save it for last first!

- The goal is "inference": using facts you know to learn about facts you don’t know
- The uncertainties in inference: not having the facts you need (most statistics are designed solely to overcome data problems)
- Building analytics during design: avoids problems before they occur; saves a fortune, opens many more possibilities
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For more information

GaryKing.org

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